Summary

Overview:

Rose City Robotics (RCR), in collaboration with Portland State University (PSU), proposes a novel approach to robotic automation for electric vehicle (EV) battery disassembly. The project introduces an artificial intelligence (AI) system that leverages vision based sensing and information pursuit (IP) to address limitations in robotic adaptability, efficiency, and interpretability. IP actively updates a posterior distribution over the state (e.g. location and orientation) of target objects, such as bolts in EV battery packs. By selecting camera views that reduce the entropy of this posterior, the robot efficiently resolves uncertainty in real time. This enables fast, accurate localization and a transparent, continuously updated internal state that can be monitored by a human operator, crucial for safety critical, variable disassembly tasks.

At the heart of the project is an explainable generative AI system that builds and explores a learned embedding space: an abstract, low-dimensional representation of sensor data capturing task relevant features. This embedding allows robots to reason about complex environments using probabilistic models, reducing dependence on large datasets and rigid programming. Domain knowledge from drawings, documentation, and human behavior will inform a prior distribution that guides inference and accelerates convergence. RCR and PSU leverage this new level of intelligence to create truly adaptive machine perception.

The immediate application is a robotic work cell for EV battery disassembly, a task currently limited by manual labor due to varied battery designs. RCR's solution reduces safety risks, lowers costs, and improves recovery of critical minerals, strengthening U.S. supply chain resilience.

This project advances NSF goals by pushing the boundaries of AI, robotics, and probabilistic decision making while promoting innovation and workforce development in real world manufacturing.

Intellectual merit:

We propose to create an understandable and trustworthy system for robotic sensing that uses IP as a decision making layer on top of modern generative AI embeddings. While the IP algorithm was first presented about thirty years ago, it is still a technical challenge to implement it into a useful robotic system. However, recent progress in designing embeddings of data streams and distributions, Bayesian statistics, and generative models, provide new opportunities that will be exploited extensively during the time period of this grant. By the end of the project, we will create a real time demonstration of a robotic system driven by the IP algorithm, allowing it to locate the position and orientation of an object of interest using vision information only, while being robust to changes in the environment.

Broader impacts:

RCR is developing an intelligent robotic system for disassembling end-of-life batteries to secure America's mineral supply chains and strengthen national defense capabilities. As global threats and foreign dependencies jeopardize access to critical materials like lithium, cobalt, and nickel, RCR's autonomous systems provide a domestic solution to reclaim these strategic resources and repatriate supply chains. In partnership with PSU and national laboratories, RCR is advancing U.S. competitiveness through hands-on workforce training, applied research, and broad deployment of modular, American built systems for critical mineral recovery. This initiative anchors industrial jobs on U.S. soil, promotes ethical and explainable AI, and ensures automation enhances, not replaces, skilled labor in high risk environments.

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Project Description

1 Intellectual merit

1.1 Advances in artificial intelligence (AI) for robotics. Pixel-to-action research has gained momentum in both academic and commercial robotics communities. Recent breakthroughs in generative AI, particularly transformer neural networks (TNNs) [74], have enabled robots to learn complex bimanual manipulation tasks from human demonstrations, outperforming traditional programming approaches. The ALOHA project at Stanford [20, 83] exemplifies this trend, showing that neural networks can learn adaptable motion control from video and joint data [72]. Notably, Professor Chelsea Finn, the lead researcher behind ALOHA, cofounded Physical Intelligence, which secured a $400 million investment from major backers including Jeff Bezos and OpenAI [18]. Despite this momentum, skepticism remains. Professor Jonathan Hurst of Oregon State University and co-founder of Agility Robotics questions pixel-to-action methods, especially regarding safety critical applications [30]. Collecting enough data to handle all edge cases remains a major hurdle. For example, Waymo began collecting data in 2009 [53], and its systems still do not rely solely on pixel-to-action control [76].

Rose City Robotics (RCR) sees the main breakthrough of pixel-to-action research not in using TNNs for motion control, but in the unification of diverse data modalities into a shared embedding space that captures semantic relationships. This embedding underlies generative models that can synthesize new outputs from various input types. A promising development is the use of contrastive language-image pretraining (CLIP)[55], which partitions embedding spaces using natural language labels. When paired with diffusion models [67], CLIP enables synthesis of novel images from text prompts, thanks to shared embeddings for language and vision. The ALOHA robot similarly benefits from embedding video inputs and robotic joint outputs into a common space. Just as the brain integrates multiple sensory inputs, high-dimensional embeddings allow robotic systems to process diverse data streams. This also opens the door to natural language control [8]. By operating in the embedding space, diffusion, and potentially other generative processes, can be accelerated by orders of magnitude [59], underscoring the profound computational advantages of this unified representation.

RCR leverages this concept to develop novel capability: ***purposeful exploration of embedding spaces using Bayesian inference***. In a sense, RCR can endow robotic agents with imagination. Inspired by active inference (ActInf)[36, 61], a cognitive framework grounded in Bayesian reasoning [51], RCR will pursue a related but more streamlined framework called information pursuit (IP)[23]. Robots equipped with imagination could overcome major challenges in today's AI including:

1. hallucinations that reduce explainability and safety,
2. dependence on massive training datasets, and
3. poor handling of unexpected or novel inputs.

The core idea is to explore the embedding space by seeking states that provide the most novel information. The embedding represents a robot's internal model of reality, and it needs to generate samples from this model to "imagine", then select between various potential futures. For instance, in a task like removing a bolt, the embedding space can be partitioned into regions where the bolt is present, where removal has failed (e.g. robot collision), and where it has been successfully removed. Each future observation maps to one of these regions. The robot must find a path from its current state to a successful outcome. A human demonstration can serve as an initial guide, creating an informative prior for the IP algorithm. As the robot executes the task, it may encounter unexpected conditions. For example, the bolt is occluded or the surrounding material is damaged. In such cases, the robot must deviate from the original plan to gather new information. IP provides a decision making layer that can enable a robot to determine whether it needs to acquire more information to accurately perceive (identify and localize) an object. This project focuses on the feasibility of solving that problem as it is essential to commercialization. The motion planning problem to a known location can be solved with fast (< 10 ms) closed form equations [17]. IP enables this adaptability without requiring explicit programming or vast training datasets to handle every edge case.

While this capability has broad applications, RCR validated a critical need where current automation fails. Our first product will be a robotic work cell for that purpose, sold to critical mineral recovery companies, vehicle OEMs, and scrapyards focused on recovering critical minerals for domestic markets.

1.2 Background on information pursuit. The history of work on Information Pursuit (IP) can be summarized as follows. Jedynak and Geman (1996) [23] first proposed IP as a framework for actively testing and tracking roads in satellite images. Their method was semi-automatic, requiring a starting point and direction to guide the road tracking process. The core idea was to perform sequential tests, or queries, about a "true hypothesis" (e.g., the presence of a road segment) and use the information gained from each test to refine the tracking. IP evolved into a general approach for active testing, where a sequence of queries is adaptively selected to gain information about a target variable. The selection of queries is based on maximizing the mutual information (MI) between the potential query answer, a random quantity, and the target variable, given the history of previous queries and answers. Beyond road tracking, IP has found applications in face detection [69], localization, and tracking of surgical instruments [70, 71], as well as scene interpretation [31, 38]. More recently, IP has been identified as a framework for explainable AI, providing insights into the decision-making process by revealing the sequence of queries used to reach a prediction [10]. Still other applications include sensor management, active sensing, and information-driven adaptive data collection [34, 80]. But when is IP an optimal policy for gathering information in the presence of noise or hidden information? The framework of the game of 20 questions has provided answers [14, 32, 25]. Essentially, IP is a greedy policy that is shown to perform optimally or nearly optimally in a wide range of settings.

Information pursuit, optimal control and reinforcement learning. Reinforcement Learning (RL) and IP both involve sequential decision-making and learning from interaction. Both optimize to reduce uncertainty and achieve goals. RL focuses on an agent learning what actions to take in a dynamic environment to maximize cumulative reward. It is driven by a numerical feedback signal, aiming for an optimal long-term policy. Conversely, IP is an AI strategy whereby a system selects queries to efficiently gain knowledge for a confident prediction. Its goal is transparency and efficient information gain. RL typically involves physical interaction and reward, while IP centers on strategic information gathering for explainable classification or localization. Both represent distinct approaches to learning and decision-making.

Information pursuit and the free energy principle. The Free Energy Principle (FEP) from ActInf literature and IP both leverage information theory concepts like entropy and uncertainty. Both involve optimization processes aimed at reducing uncertainty or "surprise." However, their scopes differ significantly. FEP is a grand, unifying theory in neuroscience, positing that living systems minimize variational free energy to maintain their existence and predict sensory inputs through perception and action. It explains why systems behave adaptively. In contrast, Information Pursuit is an AI/machine learning strategy for efficient, interpretable prediction. It sequentially acquires specific, valuable information to classify or localize confidently.

Information pursuit in robotics. IP potentially equips robots with the ability to make intelligent decisions about where to go and what to perceive to efficiently reduce uncertainty and achieve the goals, particularly in complex and unknown environments. Examples of applications include autonomous exploration, in which robots use information gained to guide their exploration process. They can decide on the "next-best-viewpoint" or path to maximize the information acquired about the unknown environment, optimizing for factors like coverage or mapping accuracy. Another application is active Simultaneous Localization and Mapping [81, 37], where robots need to build a map of the environment while simultaneously determining their own position within that map. Still another application is sensor placement, where information theory is used to determine the optimal placement of sensors on a robot [27] or in an environment, thereby maximizing the information gathered for tasks such as system health monitoring or fault diagnosis.

1.3 Information pursuit algorithm. Here we describe the IP algorithm in the context of our specific robotic application. For specificity, consider a camera placed at the end of a robotic arm that can be positioned and oriented as desired. We denote by s the position and orientation of the camera. We will use the index t to reference algorithm steps. The image acquired during step t is denoted by $O(s_t)$. To reduce the high dimensionality resulting from the images and have the algorithm be driven exclusively by features essential to the problem, we propose working instead on a latent feature space represented by embeddings, denoted $X(s)$, mapped from images, $O(s)$.

Furthermore, let Z denote the vector describing the unknown position and orientation of the target object, which for our purposes is a bolt on a battery. The IP algorithm is a Bayesian iterative algorithm that sequentially acquires information about Z. We assume a prior distribution $p_0(z)$ and an initial position s_1. The time-step of the algorithm is initialized: $t = 1$. The history of past measurements is also initialized $h_0 = \emptyset$. A maximum number of iterations $\bar{T}$ is defined. The IP algorithm is presented in Alg. 1.

Algorithm 1 Vision-driven Information Pursuit algorithm

```
1: Learn embedding mapping g : O(·) → X(·)
2: Init: p_0, h_0 = ∅, s_1, t = 1, T̄.
3: while (t ≤ T̄) and (early stopping rule==false) do
4:     Acquire a picture O_t = O(s_t)
5:     Compute the embedding x_t = g(O_t)
6:     Update the history h_t = h_{t-1} ∪ x_t
7:     Compute the posterior distribution p_t(z) = P(z|h_t)
8:     Select the next position s_{t+1} = arg_{s∈S_t} max I(Z, X_{t+1}(s)|h_t)
9:     t = t + 1
10: end while
```

Iteratively, an image is acquired (line 4), its embedding is computed and added to the history (lines 5 and 6). The posterior distribution of the target is updated using Bayes' rule (line 7), and the position of the camera at the next step is chosen (line 8) by solving an optimization problem, where the cost function is the mutual information and the optimization domain is a set of camera locations that might depend on the step t. The time step of the algorithm is then incremented (line 9). Stopping occurs after a maximum number of steps or after an early stopping rule has been verified.

1.3.1 Mutual information. The mutual information (MI) function to be optimized in line 8 is a well-known information-theoretic quantity defined by Shannon in 1948 [62], which is given by

$$I(Z, X_{t+1}(s)|h_t) = H(Z|h_t) - H(Z|X_{t+1}(s), h_t) \tag{1}$$

The first term on the right-hand side is $E[-\log(p_t(Z))|h_t]$ (i.e., the Shannon entropy of p_t). It quantifies the current uncertainty in the position of the bolt. The second term represents the expected uncertainty that would remain in the location of the bolt if the camera were placed at s, an image were obtained there, and its image was mapped onto its embedding x_{t+1}. The difference between these two terms is always positive: on average, any observation provides information. However, aiming for a location s where this quantity is large will predominantly reduce the uncertainty in the location of the bolt, which explains the optimization in line 8 of the algorithm. Note that obtaining the very location where this quantity is the largest is not critical. The set $\mathcal{S}_t$ will be chosen such that the cost of moving to the location s is not too high. Note also that the actual observation at s could provide a bad surprise and increase the uncertainty in the location of the bolt. However, this occurs with vanishing probability on average when the algorithm is run for a large number of time-steps.

1.3.2 Posterior Estimation.

Note that, using Bayes rule

$$p_t(z) \propto \mathbb{P}(x_t|z, h_{t-1})p_{t-1}(z), \tag{2}$$

where $\propto$ means up to a multiplicative constant that does not depend on z. Although the likelihood $\mathbb{P}(x_t|z, h_{t-1})$ is not available, we may use samples from it using a digital twin of our system (*the simulator* henceforth) and use likelihood-free methods to estimate it.

Likelihood-free inference refers to methods that approximate a posterior distribution when it is either costly or impossible to evaluate the likelihood function ($\mathbb{P}(x_t|z, h_{t-1})$ in our case), but sampling from it is feasible, albeit expensive. This literature is large and growing, given the increasing complexity of modern problems. We will focus on three particular types of approaches, namely, Approximate Bayesian Computation, Kernel mean embedding of conditional distributions, and Bayes Rule by Triangular Transport, which we now briefly introduce.

Approximate Bayesian Computation (ABC). Among likelihood-free methods, Approximate Bayesian Computation (ABC) [5, 12] is perhaps the best-known approach. ABC methods approximate the posterior distribution using simulated samples from the likelihood, a summary statistic $S(\cdot)$, and a distance metric $d(\cdot, \cdot)$. Many variants of ABC algorithms exist. In its simplest form, at iteration t of the IP algorithm, ABC employs rejection sampling: first, a sample $z \sim p_{t-1}(z)$ is generated; second, a simulated value $x_t^{(sim)} \sim \mathbb{P}(x_t|z, h_{t-1})$ is obtained from the simulator conditional on z; third, the sampled parameter z is accepted if $d(S(x_t), S(x_t^{(sim)})) \leq \epsilon$, where ϵ is a prespecified tolerance. Repeating this procedure multiple times approximates the posterior:

$$p_t(z) \approx p_\epsilon(z|x_t, h_{t-1}) \propto \int \mathbb{I}\left(d(S(x_t), S(x_t^{(sim)})) \leq \epsilon\right) \mathbb{P}(x_t|z, h_{t-1})p_{t-1}(z)dx_t^{(sim)}. \tag{3}$$

Kernel Mean Embedding of Conditional Distributions (KMECD). Kernel methods [66] involve mapping data into a feature space of high or infinite dimension, a Hilbert space, using a nonlinear mapping and then performing linear operations in this feature space. The kernel trick enables these computations to be performed implicitly, without explicitly using the feature space representation.

An extension of these principles enables mapping probability distributions into a feature space and computing the expected values of nonlinear functions using an inner product, a linear operation [45]. Joint distributions, as well as conditional distributions, can also be represented in feature space, leading to a particular form of the Bayes rule [21] that closely resembles the Bayes rule for multivariate Normal distributions. It can be computed from samples of the joint distribution by solving a linear system of equations, obtaining an embedding of a conditional distribution at a reasonable computational cost.

Bayes Rule by Triangular Transport. Transport algorithms transform samples from a baseline distribution into samples from a target distribution using diffeomorphic mappings defined through dynamical systems and vector fields [2]. Triangular transport [4, 48] specifically generates samples from a conditional distribution using samples from a joint distribution by learning a suitable vector field. In our context, the dimension of this vector field maps from $\mathbb{R}^{d+r}$ to $\mathbb{R}^d$, where d is the dimension of z, and r is the dimension of the image embedding. Recent advances from our group [56, 57] offer efficient methods for learning such high-dimensional vector fields, which we intend to deploy to approach for this application.

1.4 Challenges. Algorithm 1 is straightforward in appearance; however, as with many other image-based learning approaches, if not developed carefully it will not use data efficiently and will struggle to generalize [60], especially with distracting, task-irrelevant elements in the observation space. Therefore, considerable hurdles remain for commercialization that require addressing several key questions, which are summarized below in a list of challenges to be targeted in this Phase I project.

First, what principles should guide the construction of the embedding function g to ensure robust performance? Second, how should the prior distribution p_0 be designed to improve algorithmic effectiveness? Third, in the absence of an explicit likelihood, what computationally efficient methods can be used to estimate the posterior $p_t(z)$ and how should we estimate the mutual information accurately? Lastly, how should an effective early-stopping rule be chosen? Answering these critical questions poses a significant technical challenge, especially given the computational limitations inherent in the online nature of the problem and the anticipated human-robot interaction. Solving these technical challenges will lead to real-world robotic systems utilizing IP.

Challenge 1: Generating the embedding function. Designing the embedding function g is critical for enabling the algorithm to perform efficiently and cost effectively by (1) reducing problem dimensionality and (2) extracting task relevant image features. We will use NVIDIA's IsaacSim to generate and label images for training. IsaacSim supports structured embedding development but does not guarantee that the resulting latent space will be smooth enough for interpolation. In particular, moving between two embedding points may not yield a valid intermediate state. The first objective of this Phase I project is to develop a suitable embedding and demonstrate that it supports feasible exploration.

Challenge 2: Designing the prior $p_0(z)$. Because it seems possible to fall back on easy-to-specify weakly-informative priors for the bolt location, Z, this task might mistakenly be thought of as trivial. Especially because weakly-informative priors are in many instances innocuous, and perhaps even conservative. However in vision problems, like the one we seek to tackle, an unsuitable choice of prior will impose a substantial performance penalty and would lack much needed (and available!) prior spatial and context-specific constraints (e.g., battery is unlikely to be close to ceiling, symmetries in bolt placement, etc.). An inadequately specified prior for the problem will inflate initial entropy, force wider posterior sample acceptance tolerances, and disperse simulator particles over regions the bolt can never occupy. The cascading effect is considerable: posterior accuracy is degraded, producing noisier mutual-information estimates, ultimately forcing the robotic arm to execute multiple times more moves than needed to reach the required precision. For an online system (where every additional move consumes time, energy, and hardware life) this inefficiency directly undermines the algorithm's value proposition.

To address this challenge, RCR will make use of all sources of relevant information available for prior design, and incorporate it in a way that allows the prior to combine both certainty when possible and flexibility when needed.

Challenge 3: Estimating the posterior $p_t(z)$. One of the main challenges associated with this problem is obtaining a suitable approximation of the posterior in equation (2). The difficulty stems from multiple sources. Chief among them is the fact that we have high dimensional image data with potentially complex textures, lighting variations, reflections, and partial occlusions. Also, the unknown form of the likelihood requires the use of likelihood free-methods, each bringing its own set of unique challenges. These issues can be exacerbated in this type of problem given that the posterior will most likely be a hard-to-estimate multi-modal function; as such, the number of samples needed from the simulator to achieve a reasonable precision can easily become an obstacle for online deployment of the algorithm.

ABC methods involve matching through a specific distance metric summaries of simulated and observed features within a prespecified tolerance. Both defining the distance metric and extracting meaningful low-dimensional summaries from these images is non-trivial, and mistakenly specifying either can severely degrade posterior quality. Furthermore, maintaining sufficiently small tolerances may become computationally prohibitive. Strategies to address these challenges include learning sufficient summary statistics via neural networks [82, 49], or bypassing summary statistics altogether by comparing directly the observed and simulated data through metrics such as Wasserstein distance [7], Maximum Mean Discrepancy (MMD) [50], and Kullback-Liebler divergence [33]. To mitigate sensitivity to the tolerance parameter, adaptive strategies such as Sequential Monte Carlo (SMC) [44, 65, 52], kernel weighting methods [46], and synthetic likelihood approaches [78, 54, 3] have been proposed. We plan on comparing several of these approaches to identify the one that is optimal for our specific application.

Challenge 4: Calculating mutual information from samples. A classic computation involving the rearrangement of sums provides an equivalent characterization of the mutual information in terms of Kullback-Leibler divergence, denoted KL, defined by Solomon Kullback in 1951 [35]:

$$I(Z, X_{t+1}(s)|h_t) = KL\left(\mathbb{P}(Z, X_{t+1}(s)|h_t), \mathbb{P}(Z|h_t)\mathbb{P}(X_{t+1}(s)|h_t)\right) \tag{4}$$

Estimating this quantity is a well-known challenging task. However, recent efforts have provided algorithms that are available for us to test and compare, but still require a high level of expertise as will be discussed below in Task 4.

1.5 Tasks and success criteria. The overall technical goal is to provide a vision-driven IP algorithm that is both accurate and fast. To this end, we plan to proceed in two steps:

(A) Design a baseline version of the algorithm. In the baseline version, the algorithm will run for a fixed number of steps;

(B) Improve upon this baseline by completing each of the challenges and evaluating the performance of the algorithm using two metrics: % improvement in accuracy of the predicted bolt location, and % improvement in execution time. We will sequentially address each challenge, measuring the improvement and choosing the best-performing strategy (or set of strategies) at each stage.

Our goal is to achieve one step of the IP algorithm at a rate of 0.5 Hertz [30] with a final bolt localization precision of 0.5 mm. By doing so, RCR and PSU will demonstrate that IP is a feasible approach for implementation in battery disassembly and that the commercialization of this technology should be pursued.

The position of the target (bolt) will be estimated using the maximum a posteriori estimator (MAP). The algorithm will be evaluated over 100 independent episodes (new bolt positions), each time randomizing the position of the target.

Accuracy will be measured using both the Root Mean Square Error (RMSE) between the true and the posterior mean for Z. Wall clock time (average and standard deviation (sd)) will measure the time-performance and the number of steps is used to measure the efficiency.

Baseline version. The baseline version of the algorithm builds upon past success from Jedynak in employing IP for vision tasks in [23, 69, 71]. The embedding function will be the identity. Simple alternatives include lower-resolution images obtained by blurring and subsampling. A weakly-informative prior on Z will be assumed as the baseline. The computation of the posterior (line 7) is obtained by using the standard ABC algorithm with uniform kernel shown in equation (3) with $d(\cdot, \cdot)$ set to be euclidean distance. The set of locations $\mathcal{S}_t$ considered in line 8 to identify s_{t+1}, will be obtained by simple random sampling. The mutual information is estimated using samples from the joint distribution and the standard empirical estimator using binning.

1.5.1 Task 1: Generating the embedding function. The success of the IP algorithm hinges on constructing a robust, task aware embedding function, $g : O(\cdot) \to X(\cdot)$ that maps high dimensional image observations into a lower dimensional latent space. This space must capture task relevant features (e.g., bolt location and orientation) while maintaining continuity for efficient Bayesian exploration. This work is structured into six subtasks, each with clear evaluation metrics.

(A) Data Generation with Domain Labels. Using NVIDIA's IsaacSim, we will generate a labeled dataset capturing substeps in bolt identification and localization. Labels will reflect expert knowledge from industry partners. Dataset quality will be assessed by number of configurations covered.

(B) Embedding Learning Strategies. We will compare three architectures: (1) a β-Variational Autoencoder (β-VAE)[29], (2) a contrastive vision transformer [16, 42] (e.g., SimCLR [11], CLIP), and (3) BYOL [24]. Models will be trained on the IsaacSim dataset and assessed using classification accuracy, interpolation fidelity, and semantic alignment with task substeps.

(C) Task Relevant Feature Encoding. We will assess how well embeddings represent task substeps using an multilayer perceptron classifier to distinguish phases such as bolt detection, localization, and alignment. Metrics include classification accuracy, silhouette scores, and alignment with CLIP-derived semantics. The top model from subtasks B & C will advance to subtask (D).

(D) Embedding Regularization. To enhance smoothness and generalization, we will adopt consistency regularization from NVIDIA's embedding robustness work [73]. We will minimize embedding divergence across perturbed inputs (e.g. crops, noise) and temporally adjacent frames. This subtask allows us to setup a quantitative metric to determine the feasibility of using IP on the embedding manifold. We expect a function g is *Lipschitz continuous* [47] if there exists a constant L such that

$$\|\nabla g(x) - \nabla g(y)\| \leq L\|x - y\| \quad \text{for all } x, y \text{ in the domain.}$$

The regularization loss using this method will help us estimate L in subtask E.

(E) Manifold Smoothness and Interpolation. We will analyze latent space continuity by interpolating between adjacent embedding samples and decoding the results. Realism of interpolated frames will be measured by reconstruction loss and embedding continuity. We are looking for an embedding with $10 \lesssim L \lesssim 100$, implying moderate curvature, smooth nonlinearities, and similar to ReLU nets.

This structured approach ensures the embedding compresses visual data while preserving the semantic features critical for robotic perception and decision-making. Architectural comparisons, task-grounded supervision, and robust regularization together support the development of robotic agents with actionable environmental understanding.

1.5.2 Task 2: Designing the prior.

Constructing a prior distribution over Z that incorporates physical constraints, plausible scene configurations, and human workflows will significantly reduce initial state entropy, stabilize mutual information estimates, and accelerate convergence.

To build this prior, we will integrate three sources of information, including 1) **Domain Knowledge:** Disassembly logs, handbooks, and CAD drawings provide details on bolt-free zones, symmetries, dimensions, fastener specs, nominal placements, and common obstructions. These define feasible bolt regions; 2) **Simulator Imagery:** While generating embeddings, we will sample diverse camera poses and bolt locations in simulation, improving prior robustness and realism; and 3) **Human Behavior:** Observations of expert disassembly will inform likely search strategies and spatial preferences, aligning the prior with practical workflows.

We will embed this knowledge into $p_0(z)$ through the following steps:

(A) Letting $p_0(z) = \int p_0(z|\kappa)p_0(\kappa)d\kappa$, where $\kappa :=$ battery center coordinates, define $p(\kappa)$ by encoding hard spatial constraints into explicit support limits for κ.

(B) Conditioning on κ, introduce soft and hard design constraints for possible bolt placements by defining $p_0(z|\kappa)$ as a mixture prior, centered on potential nominal bolt positions suggested by documentation and adjusted according to known model specifications.

(C) Calibrate the prior's hyper-parameters by leveraging the empirical distributions obtained from the simulator-generated imagery and human disassembly behavior to optimally match simulated feature statistics.

1.5.3 Task 3: Estimating the posterior. As mentioned earlier obtaining an accurate estimation of the posterior distribution at each step is critical for providing explainability and being able to monitor the robot. It is also a challenging task given real-time constraints. Thus, we will implement and contrast methods within three families of likelihood-free inferential strategies: Approximate Bayesian Computation (ABC), kernel mean embedding of conditional distributions, and transport methods.

(A) Evaluate if selected embeddings provide a sufficient reduction to work directly with adaptive ABC approaches (SMC, kernel weighting, synthetic likelihood).

(B) Assess ABC methods designed to directly compare observations (the embeddings x_t in our case) to simulations, using Wasserstein distance, MMD, and Kullback-Liebler divergence.

(C) Implement and assess the KMECD approach for conditional distributions, specifically evaluating the computational feasibility and accuracy of extending the fixed-point algorithm for this problem.

(D) Develop and test the triangular transport method, leveraging our group's recent methods for learning efficient vector fields, to generate conditional samples effectively.

RCR and PSU will rank the methods according to their accuracy and efficiency, and identify the three best strategies to estimate the posterior density and provide explainability.

1.5.4 Task 4: Estimating the mutual information and early stopping. Estimating mutual information (MI) between continuous distributions from finite samples is statistically challenging, particularly in high-dimensional embedding spaces. Key obstacles include the bias-variance trade-off and real-world data issues such as noise, sparsity, and heavy tails, especially in imaging.

Traditional estimators like Kernel Density Estimation (KDE)[43] and k-Nearest Neighbors (kNN)[64] are limited: KDE suffers from error amplification, while kNN struggles with paradoxical difficulty in quantifying strong dependencies. Newer approaches address these shortcomings. Direct density ratio estimation [68] avoids error propagation. Neural and variational estimators (e.g. MINE [6], InfoNCE [79]) and kernel methods [1] reformulate MI estimation as optimization problems, enabling scalability. However, they introduce challenges related to bias, hyperparameter sensitivity, and lack of ground truth for validation.

Effective practice in MI estimation necessitates a multi-pronged approach. General mitigation strategies, including sophisticated bias correction techniques, various variance reduction methods, and preprocessing steps like dimensionality reduction and feature selection, are indispensable. Furthermore, adaptive parameter selection and rigorous cross-validation are essential for robust and generalizable results.

For the Information Pursuit (IP) algorithm, early stopping will rely on mutual information gain thresholds: prolonged low gain will trigger termination. Alternatively, a low entropy posterior will signal convergence to the target's location.

We measure the accuracy of the bolt location determined by the algorithm at termination. If it is < 0.5 mm, and the algorithm converged in < 2 sec, then feasibility of our method for commercialization is proven.

1.6 Collaboration Plan. RCR and PSU senior personnel have monthly in-person meetings to discuss our collaboration, and this will continue throughout the project period. Students working under the subaward will meet with their advisors on a weekly basis. Short presentations of ongoing work, as well as current publications will keep the team synchronized internally and externally. The PIs and graduate students will meet on PSU campus as needed for intensive work sessions.

Tasks	Q1	Q2	Q3	Q4	Tasks	Q1	Q2	Q3	Q4
0a: Baseline utility code	RCR				**3a:** ABC posterior		PSU		
0b: IsaacSim virtual world	RCR				**3b:** KMECD posterior		PSU		
0c: Baseline algorithm	PSU				**3c:** Triangular transport			PSU	
1a: Learn embedding		RCR			**4a:** Test MI algorithms		PSU		
1b: Embedding analysis			RCR		**4b:** Test MI convergence			RCR	
2a: Design strong prior		PSU			**5:** Prepare final demo				All
2b: Compare to weak prior			PSU						

Table 1: Schedule of project activities for the duration of this award. Blue for RCR, Sepia for PSU task.

2 The Company / Team

2.1 The Company. RCR is a C-corporation founded in 2024 by Joseph Cole and Duncan Miller. The company was formed to commercialize a new class of intelligent robots that can learn directly from observation and experience, with a focus on real-world applications such as battery disassembly, critical mineral recovery, and industrial automation. Cole, a physicist and machine learning expert, and Miller, a seasoned entrepreneur, launched the company to accelerate the integration of advanced AI, particularly transformer neural networks and active inference, into robotics. RCR is headquartered in Portland, Oregon.

2.1.1 Core Competencies. Our multidisciplinary team brings deep technical, mathematical, and commercialization expertise. Cole leads the technical vision, drawing on extensive experience in algorithm design, system integration, and transformer architectures. He has delivered lectures on robotics and pixel-to-action technology and spent five years developing CUDA kernels for time-critical GPU tasks. Miller brings over 20 years of startup and business development experience, focusing on market strategy, partnerships, and workforce development. Jedynak, Maseeh Professor at Portland State University (PSU), offers 25+ years in machine learning, statistical modeling, and computer vision. His foundational work in IP and probabilistic modeling is directly applicable to intelligent, adaptive robotics. Taylor-Rodriguez, also at PSU, specializes in Bayesian testing, nonparametric models, and spatiotemporal inference. His expertise in uncertainty quantification supports the team's AI and simulation components. Together, the team integrates advanced mathematics, AI, robotics, and commercialization experience, positioning the project for both technical success and practical deployment.

2.1.2 Company Vision & Impact. RCR envisions a future where autonomous systems make critical mineral recovery safer, faster, and fully domestic. Our mission is to replace hazardous manual labor with intelligent robotic platforms for scalable, adaptive battery disassembly. By 2030, millions of tons of batteries will reach end-of-life (EOL) annually, yet recycling remains inefficient and labor intensive, constrained by the variety of proprietary pack designs. Our robots leverage imitation learning and information pursuit to generalize from demonstrations, enabling precise, safe disassembly, even under uncertainty. This capability supports both second-life reuse and direct recovery of critical minerals such as lithium (Li), cobalt (Co), and nickel (Ni) and graphite (C), strengthening U.S. supply chain resilience. By reducing reliance on smelting and manual labor, RCR can boost material recovery, cut emissions, and create high-skill jobs in robotic system operation and support. RCR aims to lead in battery disassembly automation by delivering robust, explainable AI solutions to a critical energy infrastructure challenge.

2.1.3 Revenue History. The company is currently earning revenue through technical consulting and workforce development; in addition, each founder has contributed $100,000 in initial capital.

2.2 Company Management Team.

2.2.1 Joseph Cole, Ph.D., CEO.
Dr. Cole is a physicist and brings more than two decades of experience in developing machine learning and computer vision algorithms, with prior roles at Northrop Grumman, Applied Materials, and YorLabs. He holds a Ph.D. in Applied Physics from Rice University and a graduate certificate in Applied Statistics from PSU. He also retired from the U.S. Army Reserves as a Major. Dr. Cole won the PSU F. S. Cater Prize in Mathematical Sciences and a NASA Graduate Student Researcher Program Fellowship at Rice University. Cole will be responsible for managing all grant deliverables and ensuring milestones are met on time and reported accurately from RCR and sub-awardees.

2.2.2 Duncan Miller, MBA, CFO.
Miller is a seasoned entrepreneur and business strategist. With an MBA from Babson College, he has over 20 years of experience building and leading bootstrapped business-to-business technology companies funded through cash flow. He is responsible for partner engagement, customer discovery, go-to-market strategy, and financial planning. Having previously successfully launched and transferred 4 commercial software products to market, Miller is highly capable of commercializing the proposed software solutions. Miller will be responsible for administering and tracking grant timelines as well as financial obligations.

2.3 Subawards.

2.3.1 Bruno Jedynak, DPhil, Professor, Portland State University.
Jedynak's research interests include machine learning, statistical learning, statistical modeling, and stochastic search. Applications in computer vision, medical image processing, natural language processing, bioinformatics, and computational neuroscience. Jedynak is the founder of the IP algorithm with D. Geman. Their paper [23] has been cited more than 700 times. Subsequent work on IP include [69, 70, 71, 32, 25, 26]. Jedynak will be in charge of the collaboration with RCR and the overall PSU subaward. Jedynak will also lead the research related to tasks 3 and 4: estimating the posterior and computing the mutual information.

2.3.2 Daniel Taylor-Rodriguez, Ph.D., Associate Professor, Portland State University.
Taylor-Rodriguez co-founded and currently leads the Computational and Data Enabled Science Consulting Lab. His work has largely focused on advancing Bayesian hierarchical modeling strategies for high-dimensional data with complex dependent structures, designing prior distributions for Bayesian testing that provide desirable posterior behavior, developing flexible nonparametric Bayesian testing techniques to sidestep distributional assumptions, and proposing efficient computational strategies for all of these approaches. Taylor-Rodriguez will lead the Bayesian methodological components of the project, designing and coordinating the implementation for the sampling strategies considered, proposing suitable prior specification alternatives, and supervising the work of students participating in the project.

2.4 Company Advisory Board.
RCR's advisory board consists of industry, policy and commercialization experts, Please refer to our Facilities, Equipment, and Other Resources section for a more complete description of board members.

RCR has also secured letters of support, available upon request, from leading critical mineral recovery stakeholders, including Cirba Solutions and American Battery Technology Company, as well as partners Polaris Battery Labs and Loupe Automation, reinforcing market validation and commercialization.

3 Broader Impacts

3.1 Strengthening National Security Through Critical Mineral Recovery.
The proposed development of an intelligent robotic system for battery disassembly addresses urgent national priorities: securing critical mineral supply chains, reducing dependence on foreign sources, and enhancing U.S. manufacturing capabilities. Modern defense systems rely on materials like Li, Co, Ni, C (graphite), all mostly imported. By

automating disassembly and recovery of these minerals from EOL batteries, RCR directly supports Defense Production Act priorities and mitigates vulnerabilities in the U.S. industrial base.

3.2 Technical Innovation and AI Advancement. RCR is advancing robotics by integrating biologically inspired active inference and Information Pursuit into neural network training workflows. These techniques allow robots to learn to operate efficiently under uncertainty, reducing data and programming requirements. The system is trained via human demonstration and active learning, allowing rapid adaptation to novel conditions. This innovation not only increases productivity in hazardous disassembly environments but also pushes the frontier of explainable and efficient AI in robotics.

3.3 Economic Growth and Job Creation. RCR's modular, low-cost systems enable distributed deployment to vehicle depots, scrapyards, and battery collection centers nationwide. This anchors high-value technical jobs in diverse regions, supporting workforce retraining in robotics, automation, and battery processing. By democratizing access to battery disassembly and critical material recovery, RCR contributes to the revitalization of American manufacturing. RCR estimates the adoption of the developed technology over the next 10 years to affect nearly 10,000 recovery centers nationwide.

3.4 Repatriating Supply Chains and Advancing U.S. Competitiveness. By shifting strategic material recovery to domestic facilities, RCR promotes critical mineral independence. This directly supports U.S. competitiveness in energy, advanced manufacturing, and national defense. With anticipated EOL battery supply reaching 20 million tons annually by 2040, the impact of this innovation is substantial and urgent.

3.5 Workforce Development and STEM Outreach. RCR is building America's next-generation workforce in robotics and materials recovery. Partnerships with Portland State University (PSU) enable undergraduate and graduate students to engage in real-world R&D. RCR will also contribute datasets from its teleoperation platform to academic curricula in computer vision and machine learning. Existing efforts include site tours, internships, and high school outreach programs to expose students to careers in intelligent automation and critical minerals. RCR tracks training efforts and to date has measured success criteria of tripling engagement rate and with over 1,000 trained students to-date.

3.6 Academic-Industry Collaboration. This project bridges the gap between fundamental research and industrial deployment. Collaborations with PSU and Oak Ridge National Laboratory enable transfer of cutting-edge research in machine learning and robotic control into a deployable product. RCR is uniquely qualified to transfer the fundamental research done to industrially relevant applications.

3.7 Enhancing Worker Safety in Hazardous Jobs. Manual battery disassembly exposes workers to high-voltage electrocution, toxic gas release, and explosive thermal runaway. RCR's teleoperated and autonomous robotic system physically isolates humans from these hazards. This not only protects human health but also establishes a model for automation-enhanced safety protocols in U.S. industry. RCR intends to track and measure the estimated number of workers better protected from significant risk as the technology developed is transferred to industrial facilities.

3.8 Minimizing Unintended Consequences. RCR is fully aware of the potential downsides of AI, particularly concerns about automation displacing skilled labor and increasing technological opacity in critical industries. To counter these risks, RCR's approach prioritizes explainable and human-guided AI, specifically through IP architectures that mimic human decision-making under uncertainty. Unlike traditional deep learning models, which are often opaque and data-hungry, IP models require significantly less training data, are more interpretable, and remain adaptable through human oversight. This ensures that automation enhances rather than replaces skilled labor roles, particularly in hazardous environments.

3.9 Upskilling and knowledge transfer. To mitigate workforce disruption, RCR emphasizes upskilling and knowledge transfer, offering ongoing training programs and internships in robotics and AI systems. The societal benefits of RCR's work including improved workforce safety, increased student engagement in STEM, and expanded regional access to technical jobs will be quantitatively tracked through metrics such as a) the number of students and interns trained, b) retention statistics from outreach programs, c) reductions in manual labor hours in hazardous tasks, and d) adoption rates of RCR technology in domestic critical mineral recovery centers. These indicators will be reviewed annually to guide program adjustments and ensure long-term impact.

4 Commercialization Potential

4.1 Market Analysis. By 2030, over 1.8 megatons of lithium-ion batteries (LiBs) will reach end-of-life (EOL) annually, a figure projected to rise to 20.5 megatons by 2040, growing at 25%/year. Meanwhile, demand for critical battery materials is surging while supply falls short. Projected demand exceeds U.S. domestic supply of Li, Ni, and Cu, requiring >50% of global Li and Ni reserves and over 200% of global Co reserves [9].

4.2 Business Model. RCR plans to license hardware and software to customers along with custom-built solutions for specific processes. The company will provide on-site system integration, training, and support. RCR will charge a monthly software subscription fee for access to their proprietary machine learning algorithm, software interfaces and data information system, enabling companies to build a competitive advantage through their own proprietary datasets of battery disassembly procedures and training data.

Despite being slow, dangerous, and expensive, manual disassembly remains the standard method for extracting materials. RCR interviewed Cirba Solutions, a U.S. critical mineral recovery company with 10,000 tons of capacity and plans to scale 10x by 2030 [58]. The process takes 1 to 3 hours/pack and is not scalable, even in centralized facilities [58, 28, 75]. Shredding whole packs yields only 35% black mass and 65% low-value material, whereas pre-disassembly boosts black mass recovery to 60% and extends equipment life [58].

OEMs like Daimler Trucks North America also disassemble batteries manually. EOL batteries are returned to a Michigan facility, where they are disassembled down to the module level [40]. Maximizing disassembly pre-shredding reduces mixing, improves black mass recovery, and protects equipment [58]. High-value batteries yield up to $600 in material profit/ton using current methods [9]. RCR's automated disassembly could increase that margin by 5x through materials recovery [15].

Alternatives to manual disassembly include pyrometallurgy (burning) and hydrometallurgy (shredding with acid); both are energy-intensive, generate waste, and often lose high-value materials (Li and graphite). For instance, a 1,100 lb NMC622 battery contains 23 lbs of lithium (worth >$100) and 159 lbs of spheroidized graphite, much of which is lost in pyrometallurgy [22, 77]. Recovery today is confined to a few specialized facilities as the process is complex, hazardous, and expensive. Transport adds further burden. Batteries are large, irregularly shaped, often damaged, and require fire-safe packaging, leading to higher logistics costs.

RCR proposes a modular, automated robotic disassembly platform to enable distributed processing. Disassembling at the point of collection improves economics in 3 key ways; 1) it preserves manufacturing value by identifying and redirecting viable modules and cells for second-life use, 2) it cuts transport costs by removing low-value decking material and eliminating inefficient full-pack handling, and 3) it enables higher-density shipping of critical materials by breaking packs into cells. Overall RCR's system reduces the cost of critical mineral recovery from $130 to $40 per ton, a 3x improvement over manual methods, making domestic processing economically viable for the first time at scale. See Table 3 below for revenue projections.

4.3 Customer Validation. RCR interviewed over a dozen potential customers across key market segments including critical battery materials firms, automotive OEMs, scrap yards, and logistics operators. Conversations with key stakeholders are summarized in the table below.

Table 2: Customer Validation Quotes

Name and Affiliation	Quote
Ryan Melsert, CEO and CTO, **American Battery Technology Company**	“This RCR technology has the potential to improve throughput, increase yields and reduce downstream costs of recycling. This innovation can help significantly increase the percentage of LiBs recovered as well as the quality and usefulness of materials. [41]”
Anthony Rogers, VP of Technology and Growth, **Cirba Solutions**	“RCR’s proposed automated disassembly technology could serve as a force multiplier that would enable our current disassembly team to greatly increase the number of packs they are able to disassemble while also providing them with an additional level of safety. [58]”
Travis Hesterberg, PhD, Director of Technology and Innovation, **Ecobat**	“We set up our plants to be very flexible on what incoming batteries we can accept. With large-format batteries we do typically need to do some level of disassembly to get them to fit. We definitely have some overlap in interest and capabilities, and depending on TRL/MRL we might even be a customer. [28]”
Apoorva Mathur*, ZTG Support Manager, **Daimler Trucks NA**	“The application is definitely there to your point in terms of broader vehicle OEM basis and even from a second life battery extension basis. A lot more OEMs are trying to understand how they can disassemble the packs that they get back from their customers, from their dealerships. [40]”
Carl Fletcher*, Remanufacturing Leader, **International Trucks**	“We see real benefit in the robotized dismantling of batteries from both a safety and economic perspective. Dismantling batteries ahead of shredding is a great way to improve black mass quality. [19]”
Joe Day*, Commercial Manager, **Li-Cycle**	“RCR emerging technology will provide a valuable solution to lithium-ion handlers and processors aiming to increase their efficiencies through automated pack and module disassembly. [13]”
Grayson Shor*, Battery Circularity Lead, **Amazon.com**	“We’re going to have a lot of end-of-life material that there’s not an industry really well set up to handle yet in the US. The more I can automate the process, the more it can reduce the costs, the more I can reduce safety risks, the more I can localize, the better. [63]”

* personal opinion that does not represent any company, and the statement should not be considered an endorsement of Rose City Robotics or the technology by the company.

4.4 Competitive Analysis. The most comparable solutions identified by RCR are tabled below.

4.5 Intellectual Property Strategy. Travis Woodland, Director of PSU’s Innovation, IP, and Business Development is guiding the team’s IP strategy. The initial RCR prototype is based on open-source hardware and software developed by Stanford, and the team is developing patentable IP around a purpose-built solution for batteries. In addition, the team is developing a generative AI model specifically for battery disassembly. RCR is also developing proprietary hardware-software interfaces by writing custom computer-based and spatial computing user interface software. This will allow battery technicians to better interact with the robot, teaching it new skills which can be disseminated to follower robots in real time.

4.6 Commercialization Strategy. RCR's commercialization plan, see Table 4 below, focuses on moving from prototype development to market deployment within 6 years, supported by phased R&D, strategic partnerships, and staged financing. In Year 1, RCR will complete Phase I R&D and identify strategic partners. In Year 2 the team will begin Phase II R&D. In Year 3, secure joint development agreements and co-develop the product with partners. In Year 4, finalize development, hire sales and marketing staff, and begin executing customer agreements. Year 5 will focus on growth, securing commercial contracts and preparing for expansion into a 2nd vertical (consumer electronics, military equipment, mineral mining). By Year 6, RCR expects to launch a prototype product for the second market.

4.7 Funding History & Support Needs. RCR has been bootstrapped to date, funded by co-founders Joseph Cole and Duncan Miller. Early R&D was supported through revenue from consulting and workforce development training. NSF STTR Phase I funding will enable critical algorithm development and early testing with commercialization partners. RCR anticipates Phase II and strategic investment to scale, with revenue projected from hardware and software sales in 2028.

Table 3: Revenue Projections ($000)

Category	**Yr 1**	**Yr 2**	**Yr 3**	**Yr 4**	**Yr 5**
SBIR funds	300	500	500	0	0
Software Sales	0	0	0	360	960
Hardware Sales	0	0	400	3,500	10,000
Workforce Dev	500	1,000	1,500	2,000	2,000
Total	800	1,500	1,400	3,860	12,960

Assumptions: Pricing for our hardware and software was estimated based on discussions with customers, who validated an initial cost point of $180/ton of annual capacity of automated disassembly systems (including labor), reducing to $90/ton at full autonomous operation and 100,000 tons/year capacity [75, 58, 41]. The cost of manual disassembly is estimated to be $0.05/pound [58]. Manual hours per battery is estimated at 1-3 hours [75, 58, 41, 28, 15]. A full-pack shredding system is estimated to cost $700/ton in capital cost, while a small-scale shredding system is estimated at $500/ton of capacity [58, 28, 39]

Table 4: Commercialization Plan

Activity	**Yr 1**	**Yr 2**	**Yr 3**	**Yr 4**	**Yr 5**	**Yr 6**
Conduct Phase I R&D Project	■					
Identify strategic partners		■				
Conduct Phase II R&D Project			■			
Identify strategic partners				■		
Execute joint development agreement				■		
Jointly complete product development					■	
Recruit & hire sales & marketing					■	
Execute customer agreements					■	
Identify & launch second vertical						■

Table 5: Competitive Analysis

Feature	Apple (Daisy)	Universe Energy	Posh Robotics	Molg	RCR
Designed for lithium-ion battery packs					
Handles large, non-uniform pack sizes					
Computer vision + AI for disassembly					
Fully autonomous robotic disassembly					
Modular, containerized deployment					
Enables second-life reuse					
Proprietary Information Pursuit ML					
Optimizes black mass yield					
Suitable for U.S. deployment					

4.8 Key Market Risks. Key uncertainties include the pace of battery adoption, evolving regulations, and fluctuations in critical mineral prices. RCR must also manage financial risks by balancing cash flow, R&D spending, and operational costs.

International competition, particularly from China's Made in China 2025 initiative and the EU's coordinated battery strategies, could threaten U.S. leadership in critical materials recovery.

Commodity pricing for Li, Ni, Co and Cu directly affects the economics of recovery. While short-term volatility is expected, long-term demand will outpace supply due to widespread lithium-ion battery adoption. RCR is positioning its technology to be viable under varied pricing conditions and evolving global dynamics.

4.9 Safety & Regulation. The system will be designed to meet industry safety standards (OSHA, ANSI, NFPA) and include automated safeguards for high-voltage, thermal, and chemical risks.

4.10 Ethical Commitments. RCR's approach prioritizes national security, domestic job creation, safer working conditions, and reduced reliance on offshore processing by empowering U.S.-based facilities with automated tools.

5 Results from prior NSF support

Jedynak and Taylor-Rodríguez are co-PIs of the RTG: Program in Computation and Data-Enabled Science #2136228, 5/15/2022-4/30/2027. This RTG aims to produce unique workforce additions possessing deep knowledge in specific areas of computational mathematics and statistics, as well as a broad understanding of current issues in data-driven science. Together, Jedynak and Taylor-Rodríguez have led the creation and development of the data science consulting lab, one of the major goals of this grant. With support from the CADES RTG program 13 postdocs, 9 PhD and 9 undergraduate students have been funded, 22 manuscripts have been published in total. This award does not overlap with the current proposal.

Jedynak was also a co-PI for CC* Compute: GPU-based Computation and Data Enabled Research and Education (G-CoDERE) at PSU #2019216, 7/1/2020-6/30/2022, which has enabled Portland State University to become a major provider of high-performance computing in Oregon. This award does not overlap with the current proposal.

References

[1] Kartik Ahuja. Estimating kullback-leibler divergence using kernel machines. In *2019 53rd Asilomar Conference on Signals, Systems, and Computers*, pages 690–696. IEEE, 2019.

[2] Michael S Albergo and Eric Vanden-Eijnden. Learning to sample better. *Journal of Statistical Mechanics: Theory and Experiment*, 2024(10):104014, 2024.

[3] Ziwen An, Leah F. South, David J. Nott, and Christopher C. Drovandi. Accelerating bayesian synthetic likelihood with the graphical lasso, 4 2019. ISSN 15372715.

[4] Ricardo Baptista, Bamdad Hosseini, Nikola B Kovachki, and Youssef Marzouk. Conditional sampling with monotone gans: from generative models to likelihood-free inference. *arXiv preprint arXiv:2006.06755*, 2020.

[5] Mark A. Beaumont. Approximate Bayesian Computation. *Annual Review of Statistics and Its Application*, 9:2021, 2022. doi: 10.1146/annurev-statistics-030718.

[6] Mohamed Ishmael Belghazi, Aristide Baratin, Sai Rajeswar, Sherjil Ozair, Yoshua Bengio, Aaron Courville, and R Devon Hjelm. Mine: mutual information neural estimation. *arXiv preprint arXiv:1801.04062*, 2018.

[7] Espen Bernton, Pierre E. Jacob, Mathieu Gerber, and Christian P. Robert. Approximate Bayesian computation with the Wasserstein distance. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, 81(2):235–269, 2019. ISSN 14679868. doi: 10.1111/rssb.12312.

[8] Kevin Black, Noah Brown, Danny Driess, Adnan Esmail, Michael Equi, Chelsea Finn, Niccolo Fusai, Lachy Groom, Karol Hausman, Brian Ichter, Szymon Jakubczak, Tim Jones, Liyiming Ke, Sergey Levine, Adrian Li-Bell, Mohith Mothukuri, Suraj Nair, Karl Pertsch, Lucy Xiaoyang Shi, James Tanner, Quan Vuong, Anna Walling, Haohuan Wang, and Ury Zhilinsky. π_0: A vision-language-action flow model for general robot control. *arXiv preprint arXiv:2410.24164*, 10 2024. Accessed June 30, 2025.

[9] Andreas Breiter, Martin Linder, Thomas Schuldt, Giulia Siccardo, and Nikola Vekic. Battery recycling takes the driver's seat. `https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/battery-recycling-takes-the-drivers-seat`, 2023. Accessed June 30, 2025.

[10] Aditya Chattopadhyay, Kwan Ho Ryan Chan, Benjamin D Haeffele, Donald Geman, and Rene Vidal. Variational information pursuit for interpretable predictions. *arXiv preprint arXiv:2302.02876*, 2023.

[11] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. *37th International Conference on Machine Learning, ICML 2020*, PartF168147-3:1575–1585, 2 2020.

[12] Katalin Csilléry, Michael GB Blum, Oscar E Gaggiotti, and Olivier François. Approximate bayesian computation (abc) in practice. *Trends in ecology & evolution*, 25(7):410–418, 2010.

[13] Joe Day. Interview li-cycle, 2024. Personal interview.

[14] Aditi Dhagat, Peter Gács, and Peter Winkler. On playing" twenty questions" with a liar. In *SODA*, volume 92, pages 16–22, 1992.

[15] Gaurav Dolwani. Interview lico materials, 2024. Personal interview.

[16] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. *ICLR 2021 - 9th International Conference on Learning Representations*, 10 2020.

[17] Alexander J. Elias and John T. Wen. Ik-geo: Unified robot inverse kinematics using subproblem decomposition. *Mechanism and Machine Theory*, 209:105971, 7 2025. ISSN 0094-114X. doi: 10.1016/J.MECHMACHTHEORY.2025.105971.

[18] Hayden Field. Jeff bezos and openai invest in robot startup physical intelligence. `https://www.cnbc.com/2024/11/04/jeff-bezos-and-openai-invest-in-robot-startup-physical-intelligence.html`, 11 2024. Accessed June 30, 2025.

[19] Carl Fletcher. Interview international trucks, 2024. Personal interview.

[20] Zipeng Fu, Tony Z. Zhao, and Chelsea Finn. Mobile aloha: Learning bimanual mobile manipulation with low-cost whole-body teleoperation. *arXiv preprint arXiv:2401.02117*, 1 2024.

[21] Kenji Fukumizu, Le Song, and Arthur Gretton. Kernel bayes' rule: Bayesian inference with positive definite kernels. *The Journal of Machine Learning Research*, 14(1):3753–3783, 2013.

[22] Linda Gaines. The future of automotive lithium-ion battery recycling: Charting a sustainable course. *Sustainable Materials and Technologies*, 1:2–7, December 2014. doi: 10.1016/j.susmat.2014.10.001.

[23] Donald Geman and Bruno Jedynak. An active testing model for tracking roads in satellite images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 18(1):1–14, 1996.

[24] Jean Bastien Grill, Florian Strub, Florent AltchÃ©, Corentin Tallec, Pierre H. Richemond, Elena Buchatskaya, Carl Doersch, Bernardo Avila Pires, Zhaohan Daniel Guo, Mohammad Gheshlaghi Azar, Bilal Piot, Koray Kavukcuoglu, RÃ©mi Munos, and Michal Valko. Bootstrap your own latent: A new approach to self-supervised learning. *Advances in Neural Information Processing Systems*, 2020-December, 6 2020. ISSN 10495258.

[25] Weidong Han, Peter I Frazier, and Bruno M Jedynak. Twenty questions for localizing multiple objects by counting: Bayes optimal policies for entropy loss. *arXiv preprint arXiv:1407.4446*, 2014.

[26] Weidong Han, Purnima Rajan, Peter I Frazier, and Bruno M Jedynak. Bayesian group testing under sum observations: A parallelizable two-approximation for entropy loss. *IEEE Transactions on Information Theory*, 63(2):915–933, 2016.

[27] Alfred O Hero and Douglas Cochran. Sensor management: Past, present, and future. *IEEE Sensors Journal*, 11(12):3064–3075, 2011.

[28] Travis Hesterberg and Colin Pelletier. Interview ecobat, 2024. Personal interview.

[29] Irina Higgins, Loic Matthey, Arka Pal, Christopher Burgess, Xavier Glorot, Matthew Botvinick, Shakir Mohamed, and Alexander Lerchner. β-vae: Learning basic visual concepts with a constrained variational framework. In *International Conference on Learning Representations (ICLR)*, Toulon, France, Apr 2017.

[30] Jonathan Hurst. Humanoid robots: From the warehouse to your house - youtube. `https://www.youtube.com/watch?v=VMVE4bq-CL8`, 4 2025. Accessed June 30, 2025.

[31] Ehsan Jahangiri, Erdem Yoruk, Rene Vidal, Laurent Younes, and Donald Geman. Information pursuit: A bayesian framework for sequential scene parsing. *arXiv preprint arXiv:1701.02343*, 2017.

[32] Bruno Jedynak, Peter I Frazier, and Raphael Sznitman. Twenty questions with noise: Bayes optimal policies for entropy loss. *Journal of Applied Probability*, 49(1):114–136, 2012.

[33] Bai Jiang, Tung-Yu Wu Wing, and Hung Wong. Approximate bayesian computation with kullback-leibler divergence as data discrepancy. In *Proceedings of the 21st conference on Artificial Intelligence and Statistics*. PMLR, 2018.

[34] Chris Kreucher, Keith Kastella, and Alfred O Hero Iii. Sensor management using an active sensing approach. *Signal Processing*, 85(3):607–624, 2005.

[35] Solomon Kullback and Richard A Leibler. On information and sufficiency. *The annals of mathematical statistics*, 22(1):79–86, 1951.

[36] Pablo Lanillos, Cristian Meo, Corrado Pezzato, Ajith Anil Meera, Mohamed Baioumy, Wataru Ohata, Alexander Tschantz, Beren Millidge, Martijn Wisse, Christopher L. Buckley, and Jun Tani. Active inference in robotics and artificial agents: Survey and challenges. *arXiv preprint arXiv:2112.01871*, 12 2021.

[37] Peng Li, Yupei Huang, Wenkai Chang, Chao Zhou, Shuo Wang, Junzhi Yu, and Zhengxing Wu. Active slam with dynamic viewpoint optimization for robust visual navigation. *IEEE Transactions on Instrumentation and Measurement*, pages 1–1, 2025. doi: 10.1109/TIM.2025.3579846.

[38] Daqi Liu, Miroslaw Bober, and Josef Kittler. Visual semantic information pursuit: A survey. *IEEE transactions on pattern analysis and machine intelligence*, 43(4):1404–1422, 2019.

[39] Jeremy Mankins. Interview shred-tech industrial shredding, 2024. Personal interview.

[40] Apoorva Mathur. Interview daimler trucks, 2024. Personal interview.

[41] Ryan Melsert. Interview american battery technologies, 2024. Personal interview.

[42] Shentong Mo, Zhun Sun, and Chao Li. Multi-level contrastive learning for self-supervised vision transformers. In *Proceedings - 2023 IEEE Winter Conference on Applications of Computer Vision, WACV 2023*, pages 2777–2786. Institute of Electrical and Electronics Engineers Inc., 2023. ISBN 9781665493468. doi: 10.1109/WACV56688.2023.00280.

[43] Young-Il Moon, Balaji Rajagopalan, and Upmanu Lall. Estimation of mutual information using kernel density estimators. *Physical Review E*, 52(3):2318, 1995.

[44] Pierre Del Moral, Arnaud Doucet, and Ajay Jasra. An adaptive sequential monte carlo method for approximate bayesian computation. *Statistics and Computing*, 22:1009–1020, 9 2012. ISSN 09603174. doi: 10.1007/s11222-011-9271-y.

[45] Krikamol Muandet, Kenji Fukumizu, Bharath Sriperumbudur, Bernhard Schölkopf, et al. Kernel mean embedding of distributions: A review and beyond. *Foundations and Trends® in Machine Learning*, 10 (1-2):1–141, 2017.

[46] Shigeki Nakagome, Kenji Fukumizu, and Shuhei Mano. Kernel approximate bayesian computation in population genetic inferences. *Statistical Applications in Genetics and Molecular Biology*, 12, 2013. ISSN 15446115. doi: 10.1515/sagmb-2012-0050.

[47] Jorge Nocedal and Stephen J. Wright. *Numerical Optimization*. Springer Series in Operations Research and Financial Engineering. Springer, 2nd edition, 2006. ISBN 9780387303031.

[48] Biraj Pandey, Bamdad Hosseini, Pau Batlle, and Houman Owhadi. Diffeomorphic measure matching with kernels for generative modeling. *arXiv preprint arXiv:2402.08077*, 2024.

[49] George Papamakarios, David C. Sterratt, and Iain Murray. Sequential neural likelihood: Fast likelihood-free inference with autoregressive flows. *AISTATS 2019 - 22nd International Conference on Artificial Intelligence and Statistics*, 89, 2020.

[50] Mijung Park, Wittawat Jitkrittum, and Dino Sejdinovic. K2-abc: Approximate bayesian computation with kernel embeddings. In Arthur Gretton and Christian C. Robert, editors, *Proceedings of the 19th International Conference on Artificial Intelligence and Statistics*, volume 51 of *Proceedings of Machine Learning Research*, pages 398–407, Cadiz, Spain, 09–11 May 2016. PMLR.

[51] Thomas. Parr, Giovanni. Pezzulo, and K. J.. Friston. *Active inference : the free energy principle in mind, brain, and behavior*. The MIT Press, 2022. ISBN 9780262369978.

[52] Thomas P. Prescott and Ruth E. Baker. Multifidelity approximate bayesian computation with sequential monte carlo parameter sampling. `https://arxiv.org/abs/2001.06256`, October 2020. Accessed June 30, 2025.

[53] Associated Press. Google's self-driving-car project becomes a separate company: Waymo - los angeles times. `https://www.latimes.com/business/autos/la-fi-hy-google-waymo-self-driving-20161213-story.html`, 2016. Accessed June 30, 2025.

[54] L. F. Price, C. C. Drovandi, A. Lee, and D. J. Nott. Bayesian synthetic likelihood. *Journal of Computational and Graphical Statistics*, 27:1–11, 1 2018. ISSN 15372715. doi: 10.1080/10618600.2017.1302882.

[55] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. *Proceedings of Machine Learning Research*, 139:8748–8763, 2 2021. ISSN 26403498.

[56] Victor Rielly, Kamel Lahouel, Ethan Lew, Michael Wells, Vicky Haney, and Bruno Jedynak. Learning high-dimensional nonparametric differential equations via multivariate occupation kernel functions. *arXiv preprint arXiv:2306.10189*, 2023.

[57] Victor Rielly, Kamel Lahouel, Chau Nguyen, and Bruno Jedynak. Rock: A variational formulation for occupation kernel methods in reproducing kernel hilbert spaces. *arXiv preprint arXiv:2503.13791*, 2025.

[58] Anthony Rogers and Lee Coval. Interview cirba solutions, 2024. Personal interview.

[59] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Bjorn Ommer. High-resolution image synthesis with latent diffusion models. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2022-June:10674–10685, 12 2021. ISSN 10636919. doi: 10.1109/CVPR52688.2022.01042.

[60] Sasha Salter, Dushyant Rao, Markus Wulfmeier, Raia Hadsell, and Ingmar Posner. Attention-privileged reinforcement learning. In *4th Conference on Robot Learning (CoRL 2020)*, 2020.

[61] Tim Schneider, Boris Belousov, Hany Abdulsamad, and Jan Peters. Active inference for robotic manipulation. *arXiv preprint arXiv:2206.10313*, 6 2022.

[62] Claude E. Shannon. A Mathematical Theory of Communication. *Bell System Technical Journal*, 27 (3-4):379–423, 623–656, July-October 1948. doi: 10.1002/j.1538-7305.1948.tb01338.x.

[63] Grayson Shor. Interview amazon, 2024. Personal interview.

[64] Shashank Singh and Barnabás Póczos. Analysis of k-nearest neighbor distances with application to entropy estimation. *arXiv preprint arXiv:1603.08578*, 2016.

[65] S. A. Sisson, Y. Fan, and Mark M. Tanaka. Sequential monte carlo without likelihoods. *Proceedings of the National Academy of Sciences*, 104(6):1760–1765, 2007. doi: 10.1073/pnas.0607208104.

[66] Alex J Smola and Bernhard Schölkopf. *Learning with kernels*, volume 4. Citeseer, 1998.

[67] Jascha Sohl-Dickstein, Eric A. Weiss, Niru Maheswaranathan, and Surya Ganguli. Deep unsupervised learning using nonequilibrium thermodynamics. *32nd International Conference on Machine Learning, ICML 2015*, 3:2246–2255, 3 2015.

[68] Masashi Sugiyama, Taiji Suzuki, and Takafumi Kanamori. Density ratio estimation: A comprehensive review. Technical Report RIMS Kōkyūroku Bessatsu B13, Research Institute for Mathematical Sciences, Kyoto University, Kyoto, Japan, 2010. Available at: `https://www.ms.k.u-tokyo.ac.jp/sugi/2010/RIMS2010.pdf`.

[69] Raphael Sznitman and Bruno Jedynak. Active testing for face detection and localization. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(10):1914–1920, 2010.

[70] Raphael Sznitman, Anasuya Basu, Rogerio Richa, Jim Handa, Peter Gehlbach, Russell H Taylor, Bruno Jedynak, and Gregory D Hager. Unified detection and tracking in retinal microsurgery. In *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2011: 14th International Conference, Toronto, Canada, September 18-22, 2011, Proceedings, Part I 14*, pages 1–8. Springer, 2011.

[71] Raphael Sznitman, Rogerio Richa, Russell H Taylor, Bruno Jedynak, and Gregory D Hager. Unified detection and tracking of instruments during retinal microsurgery. *IEEE transactions on pattern analysis and machine intelligence*, 35(5):1263–1273, 2012.

[72] Octo Model Team, Dibya Ghosh, Homer Walke, Karl Pertsch, Kevin Black, Oier Mees, Sudeep Dasari, Joey Hejna, Tobias Kreiman, Charles Xu, Jianlan Luo, You Liang Tan, Lawrence Yunliang Chen, Pannag Sanketi, Quan Vuong, Ted Xiao, Dorsa Sadigh, Chelsea Finn, and Sergey Levine. Octo: An open-source generalist robot policy. *arXiv preprint arXiv:2405:12213qq*, 5 2024.

[73] Hsueh ti Derek Liu, Alec Jacobson, Hsueh-Ti Derek Liu, Francis Williams, and Sanja Fidler. Learning smooth neural functions via lipschitz regularization. *arXiv preprint arXiv:2202.08345*, pages 1–13, 2 2022. doi: 10.1145/3528233.3530713.

[74] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in Neural Information Processing Systems*, 2017-December:5999–6009, 6 2017. ISSN 10495258.

[75] Paul Voigt. Interview redwood materials, 2024. Personal interview.

[76] Waymo. Self-driving car technology for a reliable ride - waymo driver. `https://waymo.com/waymo-driver/`, 2025. Accessed June 30, 2025.

[77] Shelley Whitlock. Interview polaris battery labs, 2024. Personal interview.

[78] Simon N. Wood. Statistical inference for noisy nonlinear ecological dynamic systems. *Nature*, 466: 1102–1104, 8 2010. ISSN 00280836. doi: 10.1038/nature09319.

[79] Mike Wu, Chengxu Zhuang, Milan Mosse, Daniel Yamins, and Noah Goodman. On mutual information in contrastive learning for visual representations. *arXiv preprint arXiv:2005.13149*, 2020.

[80] Scott Cheng-Hsin Yang, Daniel M Wolpert, and Máté Lengyel. Theoretical perspectives on active sensing. *Current opinion in behavioral sciences*, 11:100–108, 2016.

[81] Khalid Yousif, Alireza Bab-Hadiashar, and Reza Hoseinnezhad. An overview to visual odometry and visual slam: Applications to mobile robotics. *Intelligent Industrial Systems*, 1(4):289–311, 2015.

[82] Andrew Zammit-Mangion, Matthew Sainsbury-Dale, and Raphaël Huser. Neural Methods for Amortized Inference. *Annual Review of Statistics and Its Application*, 12(1):311–335, 2025. ISSN 2326831X. doi: 10.1146/annurev-statistics-112723-034123.

[83] Tony Z. Zhao, Vikash Kumar, Sergey Levine, and Chelsea Finn. Learning fine-grained bimanual manipulation with low-cost hardware. *arXiv preprint arXiv:2304.13705*, 4 2023.

2 Portland State University

OIT Research Cyberinfrastructure. Portland State University has a high degree of centralization of IT resources and support for academic and research computing. The Office of Information Technology's (OIT) Linux Applications Platform team in the Technology Infrastructure (TI) division provides central research computing support and provides free research computing resources, expertise, and training to students, faculty, and staff. The research computing staff work directly with researchers to identify their research computing needs in order to facilitate their research goals. TI's Data Center Operations and Networking teams provide data center and networking infrastructure support for central research systems.

The Office of Information Technology provides a highly functional, widely used campus cyberinfrastructure that effectively serves many PSU campus research projects. This is a thoughtfully integrated environment with mutually accessible file systems for home directory, labs shares, scratch volumes, and web directories to facilitate research work, data storage, and data sharing.

Computational Resources. OIT supports a number of computational systems that host a large range of scientific applications for computational mathematics, chemistry, biology, genetic analysis, hydrology, fluid dynamics, GIS, general purpose scientific, and statistical software. Support for applications, end-users, and custom systems (HPC, GIS) is provided by OIT Research Computing.

Coeus HPC cluster. *Coeus* is a general purpose HPC cluster, designed to address a broad range of computational requirements. Estimated peak performance of 110 TFLOPs, Intel Omni-Path high-performance network (100 Gb), and 200 TB scratch storage.

- Two login nodes and two management nodes head nodes:
  - 2x Intel Xeon E2630 v4, 10 cores @ 2.2 GHz
  - 64GB 2400 MHz RAM
- 128 compute nodes:
  - 2x Intel Xeon E2630 v4, 10 cores @ 2.2 GHz
  - 128 GB 2133 MHz RAM
  - 200 GB SSD
- 12 Intel Phi processor nodes:
  - Intel Xeon Phi 7210, 64 cores @ 2.2 GHz, 4 hyper-threads/core
  - 96 GB 2400 MHz RAM
  - 200 GB SSD drive
- 2 large-memory GPU compute nodes:
  - 2x Intel Xeon E2650 v4, 12 cores @ 2.2 GHz
  - 1x Nvidia V100 GPUs
  - 768 GB 1866 MHz RAM
  - 2 TB local scratch
- 10 GPU nodes:
  - AMD EPYC 7520P, 32 cores @ 2.5 GHz

- 4x Nvidia A40 or RTX A5000 GPUs
  - 2 TB NVMe local storage

- Data Transfer Node to support high-bandwidth data transfers:
  - Dual Intel Xeon E2650 v4, 12 cores @ 2.2 GHz
  - 256GB 2400 MHz RAM
  - 30 TB local disk storage transfer volume in a RAID 6 array

  - 200 TB NFS scratch storage
  - Dual Intel Xeon E2650 v4, 12 cores @ 2.2 GHz
  - 768 GB of 1866 MHz Registered ECC DDR4 memory
  - 32 x 8 TB SATA drives in a RAID 6 configuration
  - 2 TB NVME drive

- Intel Omni-Path high-performance network fabric

- 1 Gb ethernet cluster management and IPMI networks

Orca HPC cluster. The Orca cluster features 25 GPU-enabled compute nodes, each with 4 GPUs. Six nodes have Nvidia L40S GPUs, and 19 nodes have Nvidia A30 GPUs. All nodes have 64 core AMD EPYC Genoa 9534 2.45 GHz CPUs with 576 GB RAM and 480 GB SSD for local scratch storage.

High-Performance Storage. Scratch volume is provisioned on the Panasas ActiveStor Ultra parallel file system storage array consisting of three ASD-100 director nodes and 20 ASU-100 storage nodes. Total raw capacity of the array is 1,688 TB; half of that is provisioned as a scratch volume on the Coeus cluster. Panasas nodes have a 25GbE connection into the TOR switch that has a 100GbE uplink into the PSU network. Proprietary DirectFLOW client is deployed on all of the HPC nodes to provide parallel high storage performance but Panasas supports NFS and SMB protocols that can be used by non HPC clients to access the data. Data on Panasas is not backed up but Panasas snapshots are used to provide basic data recovery functionality. Currently, we preserve four 6-hour snapshots, four daily snapshots and four weekly snapshots.

PSU's NetApp storage array is used for the HPC data that is supposed to be kept beyond the runtime of the job. Multiple volumes are provisioned for the purpose of home directories, research projects, and software repositories using NFS to both Coeus nodes as well as standalone compute servers to provide ease of access for development and potential data movement.

Primary volumes are hosted on the FAS8700 NetApp array located in our primary datacenter while all of that data is also replicated to FAS8200 located in our hot site where it could be brought back online in case of the primary data center outage. All of the data is protected by the 4 months of NetApp snapshots as well as backups provided by our enterprise IT Commvault instance. NetApp array has multiple link aggregations to the 25 GbE network, providing robust and redundant network performance.

Networking. The Portland State campus core network includes dual, redundant 10 Gb paths between all science and research buildings and the data center. These buildings have 1 Gb networking to the desktop. Wireless 802.11b/g/n networking is available in common areas and classrooms at speeds up to 1 Gb. The Research and Innovation Network (RAIN) from CC* #1541469 and its Science DMZ provide an alternate 10 Gb path via Internet2 bypassing the campus firewall allowing high-speed data transfer on- and off-campus. Two data transfer nodes are available for high-speed data transfer on campus and off via Internet2.

OIT Personnel and Services. Computing research is supported by Portland State University's Office of Information Technology personnel. These efforts are led by Computing Infrastructure Associate Director and Chief Information Security Officer Gary Sandine, in coordination with Linux HPC staff Jim Stapleton, Marko Markoc, and Michael Ewan, Data Center Specialist Aaron Landreth, and Network Engineer Brian Lehigh. PSU's Linux systems administrators from OIT's Linux Applications Platform team provide after-hours on-call support for any critical hardware, performance, or security issues that arise. Virtualization is be facilitated by PSU's VMware enterprise infrastructure and supported by OIT's enterprise virtualization team which is a part of its Windows, Virtualization, Storage, and Backups team.

Research Colocation Facility. PSU's Office of Information Technology (OIT) manages a data center in the Fourth Avenue Building, which is currently used to house PSU's *Coeus* cluster. Racks in the data center are arranged in hot/cold aisles for warm-air extraction. A computer room air handler provides cooling for this facility, including a series of multistack dedicated heat recovery chillers. Two diverse utility power feeds power the data center, which is also protected by two 300 kVA Mitsubishi Uninterrupted Power Supply (UPS) units and two static transfer switches for power redundancy. In case of catastrophic power failure, the data center is also backed by a turbine generator. The total power available to the facility is 240 kVA. A Very Early Smoke Detection Apparatus (VESDA) with dry water pipe is system used in this facility. Hand-held Halotron fire extinguishers are also located on-site.

IDENTIFYING INFORMATION:

NAME: Cole, Joseph

ORCID iD: https://orcid.org/0009-0009-1938-5864

POSITION TITLE: Chief Executive Officer

PRIMARY ORGANIZATION AND LOCATION: Rose City Robotics, Inc., Portland, Oregon, United States

Professional Preparation:

ORGANIZATION AND LOCATION	DEGREE (if applicable)	RECEIPT DATE	FIELD OF STUDY
Portland State University, Portland, Oregon, United States	Graduate Certificate	01/2020	Applied Statistics
William Marsh Rice University, Houston, Texas, US	Ph.D.	12/2008	Applied Physics
The University of Texas at Austin, Austin, Texas, US	B.S.	12/2000	Electrical and Computer Engineering

Appointments and Positions

2024 - present Chief Executive Officer, Rose City Robotics, Inc., Portland, Oregon, United States

2021 - 2024 Staff Engineer - Ultrasound, YorLabs, Inc., Product Software Group, Portland, Oregon, United States

2019 - 2021 Chief Technology Officer, Koioc Incorporated, Portland, Oregon, United States

2012 - 2017 Algorithm Developer, Applied Materials (United States), Portland, Oregon, United States

2009 - 2011 Staff Seismic Imager, CGG Veritas, Houston, Texas, United States

2007 - 2008 Partner, Automated Creation Technologies, Houston, Texas, United States

2002 - 2008 Graduate Research Assistant, William Marsh Rice University, Applied Physics, Houston, Texas, US

2001 - 2002 Associate Engineer, Northrop Grumman (United States), Azusa, California, United States

2000 - 2000 Senior Student Associate, University of Texas at Austin Applied Research Laboratories, Austin, Texas, US

1997 - 2019 Major (Retired), United States Army Reserve, Joint Base Lewis McChord, Washington, United States

Products

Products Most Closely Related to the Proposed Project

Other Significant Products, Whether or Not Related to the Proposed Project

1. Marinescu Razvan V, Oxtoby Neil P, Young Alexandra L, Bron Esther E, Toga Arthur W, Weiner Michael W, Barkhof Frederik, Fox Nick C, Eshaghi Arman, Toni Tina,

Salaterski Marcin, Lunina Veronika, Ansart Manon, Durrleman Stanley, Lu Pascal, Iddi Samuel, Li Dan, Thompson Wesley K, Donohue Michael C, Nahon Aviv, Levy Yarden, Halbersberg Dan, Cohen Mariya, Liao Huiling, Li Tengfei, Yu Kaixian, Zhu Hongtu, Tamez-Peña José G, Ismail Aya, Wood Timothy, Bravo Hector Corrada, Nguyen Minh, Sun Nanbo, Feng Jiashi, Yeo BT Thomas, Chen Gang, Qi Ke, Chen Shiyang, Qiu Deqiang, Buciuman Ionut, Kelner Alex, Pop Raluca, Rimocea Denisa, Ghazi Mostafa M, Nielsen Mads, Ourselin Sebastien, Sørensen Lauge, Venkatraghavan Vikram, Liu Keli, Rabe Christina, Manser Paul, Hill Steven M, Howlett James, Huang Zhiyue, Kiddle Steven, Mukherjee Sach, Rouanet Anaïs, Taschler Bernd, Tom Brian DM, White Simon R. The Alzheimer's Disease Prediction Of Longitudinal Evolution (TADPOLE) Challenge: Results after 1 Year Follow-up. 2022. source-work-id: BASE:a53e3edb32e7e10db8677585a6af58944e852a74303ec9b49398daf3e0507465

2. Cole J, Mirin N, Knight M, Goodrich G, Halas N. Photothermal Efficiencies of Nanoshells and Nanorods for Clinical Therapeutic Applications. The Journal of Physical Chemistry C. 2009 June 11; 113(28):12090-12094. Available from: https://pubs.acs.org/doi/10.1021/jp9003592 DOI: 10.1021/jp9003592
3. Bardhan R, Grady N, Cole J, Joshi A, Halas N. Fluorescence Enhancement by Au Nanostructures: Nanoshells and Nanorods. ACS Nano. 2009 February 20; 3(3):744-752. Available from: https://pubs.acs.org/doi/10.1021/nn900001q DOI: 10.1021/nn900001q
4. Cole J, Halas N. Optimized plasmonic nanoparticle distributions for solar spectrum harvesting. Applied Physics Letters. 2006 October 09; 89(15):-. Available from: https://pubs.aip.org/apl/article/89/15/153120/143626/Optimized-plasmonic-nanoparticle-distributions-for DOI: 10.1063/1.2360918

Certification:

I certify that the information provided is current, accurate, and complete. This includes but is not limited to information related to domestic and foreign appointments and positions.

I also certify that, at the time of submission, I am not a party to a malign foreign talent recruitment program.

Misrepresentations and/or omissions may be subject to prosecution and liability pursuant to, but not limited to, 18 U.S.C. §§ 287, 1001, 1031 and 31 U.S.C. §§ 3729-3733 and 3802.

Certified by Cole, Joseph in SciENcv on 2025-06-11 14:34:18

IDENTIFYING INFORMATION:

NAME: Jedynak, Bruno

ORCID iD: https://orcid.org/0000-0002-0824-5745

POSITION TITLE: Professor

PRIMARY ORGANIZATION AND LOCATION: Portland State University, Portland, OR, United States

Professional Preparation:

ORGANIZATION AND LOCATION	DEGREE (if applicable)	RECEIPT DATE	FIELD OF STUDY
Universite Paris Sud Orsay, Paris France, Paris, Not Applicable, N/A, France	PHD	01/1995	Statistics
Universite Paris Sud Orsay, Paris, Not Applicable, N/A, France	BS	08/1989	Applied Mathematics

Appointments and Positions

2015 - present	Professor, Portland State University, Portland, OR, United States
2003 - 2015	Research Professor, Johns Hopkins University, Baltimore, MD, United States
1997 - 2003	Assistant Professor, University of Lille, Lille, Not Applicable, N/A, France

Products

Products Most Closely Related to the Proposed Project

1. Lahouel K, Wells M, Rielly V, Lew E, Lovitza D, Jedynak BM. Learning nonparametric ordinary differential equations from noisy data. J Comput Phys. 2024 Jun 15;507 PubMed Central PMCID: PMC11090484.
2. Sznitman R, Richa R, Taylor RH, Jedynak B, Hager GD. Unified detection and tracking of instruments during retinal microsurgery. IEEE Trans Pattern Anal Mach Intell. 2013 May;35(5):1263-73. PubMed PMID: 23520263; NIHMSID: NIHMS524361.
3. Sznitman R, Jedynak B. Active testing for face detection and localization. IEEE Trans Pattern Anal Mach Intell. 2010 Oct;32(10):1914-20. PubMed PMID: 20479494.
4. Geman D, Jedynak B. An active testing model for tracking roads in satellite images. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1996; 18(1):1-14. issn: 0162-8828
5. Geman D, Jedynak B. Shape recognition and twenty questions. INRIA; 1993.

Other Significant Products, Whether or Not Related to the Proposed Project

1. Han W, Rajan P, Frazier P, Jedynak B. Bayesian group testing under sum observations: A parallelizable two-approximation for entropy loss. IEEE Transactions on Information Theory. 2016; 63(2):915-933. issn: 0018-9448
2. Vogelstein JT, Watson BO, Packer AM, Yuste R, Jedynak B, Paninski L. Spike inference from calcium imaging using sequential Monte Carlo methods. Biophys J. 2009 Jul 22;97(2):636-55. PubMed Central PMCID: PMC2711341.

3. Huang H, Jedynak BM, Bader JS. Where have all the interactions gone? Estimating the coverage of two-hybrid protein interaction maps. PLoS Comput Biol. 2007 Nov;3(11):e214. PubMed Central PMCID: PMC2082503.
4. Izard C, Jedynak B, Stark CE. Spline-based probabilistic model for anatomical landmark detection. Med Image Comput Comput Assist Interv. 2006;9(Pt 1):849-56. PubMed PMID: 17354970.
5. Jedynak BM, Khudanpur S. Maximum likelihood set for estimating a probability mass function. Neural Comput. 2005 Jul;17(7):1508-30. PubMed PMID: 15901406.

Certification:

I certify that the information provided is current, accurate, and complete. This includes but is not limited to information related to domestic and foreign appointments and positions.

I also certify that, at the time of submission, I am not a party to a malign foreign talent recruitment program.

Misrepresentations and/or omissions may be subject to prosecution and liability pursuant to, but not limited to, 18 U.S.C. §§ 287, 1001, 1031 and 31 U.S.C. §§ 3729-3733 and 3802.

Certified by Jedynak, Bruno in SciENcv on 2025-06-12 18:31:53

IDENTIFYING INFORMATION:

NAME: Miller, Duncan

POSITION TITLE: Co-founder & CFO

PRIMARY ORGANIZATION AND LOCATION: Rose City Robotics, Portland, Oregon, United States

Professional Preparation:

ORGANIZATION AND LOCATION	DEGREE (if applicable)	RECEIPT DATE	FIELD OF STUDY
NVIDIA, San Jose, California, United States	Other training	01/2025 - 01/2025	Building LLM Applications with Prompt Engineering
Babson College, Wellesley, Massachusetts, United States	MBA	06/2007	Entrepreneurship
University of Massachusetts, Amherst, Massachusetts, United States	BBA	06/2002	Finance and Operations
Purdue University, West Lafayette, Indiana, United States	N/A	06/1999	Operations and Management

Appointments and Positions

2024 - present	Co-founder & CFO, Rose City Robotics, Portland, Oregon, United States
2025 - present	Limited Partner, E8 Angel Investors Fund, Seattle, Washington, United States
2025 - present	Head Coach, FIRST Robotics FTC Team #30603, Portland, Oregon, United States
2025 - present	Judge, Invent Oregon Competition, Portland, Oregon, United States
2024 - present	Community Liaison, Metro Region Innovation Hub, Portland, Oregon, United States
2024 - present	Mentor, Coach, Advisor, Portland State University, Portland, Oregon, United States
2024 - present	Organizer, Robotics Collaborative, Portland, Oregon, United States
2024 - present	Co-Organizer, Pacific Northwest Battery Collaborative, Seattle, Washington, United States
2022 - 2025	Founder & CEO, Waivolt Energy Professional Technical Training (merger), Portland, Oregon, United States
2022 - 2024	Founder & CEO, Shiro LLM Prompt Engineering Platform (exit), Portland, Oregon, United States
2010 - 2011	Consultant - Interim Financial Controller, Living Harvest (during acquisition by Cell-nique), Portland, Oregon, United States
2006 - 2023	Co-founder & CFO, HeatSpring Energy Professional Technical Training (exit), Cambridge, Massachusetts, United States

2005 - 2006 Consultant - Business Analyst, Symbol Technologies (during acquisition by Motorola), Holtsville, New York, United States

2002 - 2005 Implementation Consultant - Financial Information Systems, MEDITECH - Medical Technology Incorporated, Framingham, Massachusetts, United States

Products

Products Most Closely Related to the Proposed Project

1. Miller D. Business Website: Rose City Robotics. N/A. 2024. Available from: https://rosecityrobotics.com
2. Miller D. Open Source Software Repository: Large Language Model (LLM) Prompt Engineering. N/A. 2024. Available from: https://github.com/duncantmiller/llm_prompt_engineering
3. Miller D. Open Source Software Repository: Shiro Python Library. N/A. 2024. Available from: https://github.com/openshiro/shiro-python
4. Miller D. Business Website: Shiro. N/A. 2022. Available from: https://openshiro.com
5. Miller D. Video: PNW Battery Collaborative Event Host. N/A. 2025. Available from: https://www.youtube.com/watch?v=_jbkGpuzToI&ab_channel=RoseCityRobotics

Other Significant Products, Whether or Not Related to the Proposed Project

1. Miller D. Open Source Software Repository: Student Portfolio Website Template. N/A. 2025. Available from: https://github.com/duncantmiller/portfolio-website-bridgetown
2. Miller D. Open Source Software Repository: AI Developer Resources. N/A. 2023. Available from: https://github.com/RoseCityRobotics/ai-developer-resources
3. Miller D. Open Source Software Repository: Monopoly in Ruby. N/A. 2013. Available from: https://github.com/duncantmiller/monopoly-copy
4. Miller D. Open Source Software Repository: BotDevs AI Developer Job Board. N/A. 2023. Available from: https://github.com/duncantmiller/botdevs.ai
5. Miller D. Business Website: HeatSpring. N/A. 2006. Available from: https://www.heatspring.com

Certification:

I certify that the information provided is current, accurate, and complete. This includes but is not limited to information related to domestic and foreign appointments and positions.

I also certify that, at the time of submission, I am not a party to a malign foreign talent recruitment program.

Misrepresentations and/or omissions may be subject to prosecution and liability pursuant to, but not limited to, 18 U.S.C. §§ 287, 1001, 1031 and 31 U.S.C. §§ 3729-3733 and 3802.

Certified by Miller, Duncan in SciENcv on 2025-06-29 23:08:48

IDENTIFYING INFORMATION:

NAME: Taylor Rodriguez, Daniel

ORCID iD: https://orcid.org/0000-0002-2959-0281

POSITION TITLE: Associate Professor

PRIMARY ORGANIZATION AND LOCATION: Portland State University, Portland, Oregon, United States

Professional Preparation:

ORGANIZATION AND LOCATION	DEGREE (if applicable)	RECEIPT DATE	FIELD OF STUDY
University of Florida, Gainesville, FL, USA	PHD	08/2014	Interdisciplinary Ecology / Statistics
University of Florida, Gainesville, FL, USA	MSTAT	12/2011	Statistics
Universidad Nacional de Colombia, Bogota, Bogota, Colombia	BS	06/2007	Statistics
Universidad de Los Andes, Bogota, Bogota, Colombia	BS	06/2003	Economics

Appointments and Positions

2023 - present	Associate Professor, Portland State University, Portland, Oregon, United States
2017 - 2023	Assistant Professor, Portland State University, Portland, OR, United States
2016 - 2017	Research Associate Geospatial Lab, Michigan State University, East Lansing, MI, USA
2015 - 2016	Postdoctoral Associate, Duke University, Durham, NC, USA
2014 - 2015	Postdoctoral Fellow, SAMSI, Research Triangle Park, NC, USA

Products

Products Most Closely Related to the Proposed Project

1. Gutiérrez L, Barrientos A, González J, Taylor-Rodríguez D. A Bayesian Nonparametric Multiple Testing Procedure for Comparing Several Treatments Against a Control. Bayesian Analysis. 2019; 14(2):-. Available from: https://projecteuclid.org/journals/bayesian-analysis/volume-14/issue-2/A-Bayesian-Nonparametric-Multiple-Testing-Procedure-for-Comparing-Several-Treatments/10.1214/18-BA1122.full DOI: 10.1214/18-BA1122
2. Taylor-Rodriguez D, Finley AO, Datta A, Babcock C, Andersen HE, Cook BD, Morton DC, Banerjee S. Spatial Factor Models for High-Dimensional and Large Spatial Data: An Application in Forest Variable Mapping. Stat Sin. 2019;29:1155-1180. PubMed Central PMCID: PMC7731981.
3. Taylor-Rodriguez D, Womack A, Bliznyuk N. Bayesian Variable Selection on Model Spaces Constrained by Heredity Conditions. Journal of Computational and Graphical Statistics. 2016 May 10; 25(2):515-535. Available from: https://www.tandfonline.com/doi/full/10.1080/10618600.2015.1056793 DOI:

10.1080/10618600.2015.1056793

4. Taylor-Rodríguez D, Womack A, Fuentes C, Bliznyuk N. Intrinsic Bayesian Analysis for Occupancy Models. Bayesian Analysis. 2017; 12(3):-. Available from: https://projecteuclid.org/journals/bayesian-analysis/volume-12/issue-3/Intrinsic-Bayesian-Analysis-for-Occupancy-Models/10.1214/16-BA1014.full DOI: 10.1214/16-BA1014
5. Taylor-Rodríguez D, Kaufeld K, Schliep E, Clark J, Gelfand A. Joint Species Distribution Modeling: Dimension Reduction Using Dirichlet Processes. Bayesian Analysis. 2017 December 1; 12(4):-. Available from: https://projecteuclid.org/journals/bayesian-analysis/volume-12/issue-4/Joint-Species-Distribution-Modeling-Dimension-Reduction-Using-Dirichlet-Processes/10.1214/16-BA1031.full DOI: 10.1214/16-BA1031

Other Significant Products, Whether or Not Related to the Proposed Project

1. Martinez N, Sinedino LD, Bisinotto RS, Ribeiro ES, Gomes GC, Lima FS, Greco LF, Risco CA, Galvão KN, Taylor-Rodriguez D, Driver JP, Thatcher WW, Santos JE. Effect of induced subclinical hypocalcemia on physiological responses and neutrophil function in dairy cows. J Dairy Sci. 2014 Feb;97(2):874-87. PubMed PMID: 24359833.
2. de Rivera C, Bliss-Ketchum L, Lafrenz M, Hanson A, McKinney-Wise L, Rodriguez A, Schultz J, Simmons A, Taylor Rodriguez D, Temple A, Wheat R. Visualizing Connectivity for Wildlife in a World Without Roads. Frontiers in Environmental Science. 2022; 10:-. Available from: https://www.frontiersin.org/articles/10.3389/fenvs.2022.757954/full DOI: 10.3389/fenvs.2022.757954
3. Pereira LA, Taylor-Rodríguez D, Gutiérrez L. A Bayesian nonparametric testing procedure for paired samples. Biometrics. 2020 Dec;76(4):1133-1146. PubMed PMID: 32012223.
4. Pereira L, Gutiérrez L, Taylor-Rodríguez D, Mena R. Bayesian nonparametric hypothesis testing for longitudinal data analysis. Computational Statistics & Data Analysis. 2023 March; 179:107629-. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0167947322002092 DOI: 10.1016/j.csda.2022.107629
5. Dorazio R, Taylor Rodríguez D. A Gibbs sampler for Bayesian analysis of site occupancy data. Methods in Ecology and Evolution. 2012 August 20; 3(6):1093-1098. Available from: https://besjournals.onlinelibrary.wiley.com/doi/10.1111/j.2041-210X.2012.00237.x DOI: 10.1111/j.2041-210X.2012.00237.x

Certification:

I certify that the information provided is current, accurate, and complete. This includes but is not limited to information related to domestic and foreign appointments and positions.

I also certify that, at the time of submission, I am not a party to a malign foreign talent recruitment program.

Misrepresentations and/or omissions may be subject to prosecution and liability pursuant to, but not limited to, 18 U.S.C. §§ 287, 1001, 1031 and 31 U.S.C. §§ 3729-3733 and 3802.

Certified by Taylor Rodriguez, Daniel in SciENcv on 2025-06-16 21:23:28

Data Not Available

CURRENT AND PENDING (OTHER) SUPPORT INFORMATION

Provide the following information for the Senior/key personnel and other significant contributors.
Follow this format for each person.

*NAME: Cole, Joseph Raymond

PERSISTENT IDENTIFIER (PID) OF THE SENIOR/KEY PERSON: https://orcid.org/0009-0009-1938-5864

*POSITION TITLE: President and CEO

*ORGANIZATION AND LOCATION: Rose City Robotics, Inc., Portland, Oregon, United States

Proposals/Active Projects

***Proposal/Active Project Title:** STTR Phase I: Explainable Robotic Motion Planning in Unstructured Environments Using Information Pursuit for Critical Mineral Recovery

***Status of Support:** Pending

Proposal/Award Number: 261499

***Source of Support:** NSF STTR

***Primary Place of Performance:** 2130 SW 5th Ave, Suite 245B, Portland, OR 97201

***Proposal/Active Project Start Date: (MM/YYYY):** 01/2026

***Proposal/Active Project End Date: (MM/YYYY):** 12/2026

***Total Anticipated Proposal/Project Amount:** $305,000

*** Person Months per budget period Devoted to the Proposal/Active Project:**

Year	Person Months
2026	2.4

***Overall Objectives:** Develop an information pursuit algorithm for robotic applications.

***Statement of Potential Overlap:** No overlap. This is the proposal currently under consideration for funding.

Certification:

I certify that the information provided is current, accurate, and complete. This includes but is not limited to current, pending, and other support (both foreign and domestic) as defined in 42 U.S.C. § 6605.

I also certify that, at the time of submission, I am not a party to a malign foreign talent recruitment program.

Misrepresentations and/or omissions may be subject to prosecution and liability pursuant to, but not limited to, 18 U.S.C. §§ 287, 1001, 1031 and 31 U.S.C. §§ 3729-3733 and 3802.

Certified by Cole, Joseph in SciENcv on 2025-06-28 16:12:19

CURRENT AND PENDING (OTHER) SUPPORT INFORMATION

Provide the following information for the Senior/key personnel and other significant contributors.
Follow this format for each person.

*NAME: Jedynak, Bruno Michel

PERSISTENT IDENTIFIER (PID) OF THE SENIOR/KEY PERSON: https://orcid.org/0000-0002-0824-5745

*POSITION TITLE: Professor

*ORGANIZATION AND LOCATION: Portland State University, Portland, Oregon, United States

Proposals/Active Projects

***Proposal/Active Project Title:** Wisconsin Registry for Alzheimer Prevention (Renewal)

***Status of Support:** Current

Proposal/Award Number: R01AG027161

***Source of Support:** NIH

***Primary Place of Performance:** Portland State University

***Proposal/Active Project Start Date: (MM/YYYY):** 05/2023

***Proposal/Active Project End Date: (MM/YYYY):** 04/2028

***Total Anticipated Proposal/Project Amount:** $485,523

*** Person Months per budget period Devoted to the Proposal/Active Project:**

Year	Person Months
2023	1.8
2024	1.8
2025	1.8
2026	1.8
2027	1.8

***Overall Objectives:** The Portland State University team will develop statistical modeling methodology for the time continuous multivariate sequences of biomarkers acquired by WRAP

***Statement of Potential Overlap:** Potential overlap between The Longitudinal Course of Imaging Biomarkers in People At Risk of AD" (PREDICT) and "Wisconsin Registry for Alzheimer's Prevention" or (WRAP Renewal). In both cases, statistical methods for modeling the progression of Alzheimer's disease are developed. In PREDICT, we consider imaging biomarkers, while in WRAP, we focus on non-imaging biomarkers.

***Proposal/Active Project Title:** The Longitudinal Course of Imaging Biomarkers in People At Risk of AD (PREDICT)

***Status of Support:** Current

Proposal/Award Number: 5R01AG021155

***Source of Support:** NIH

***Primary Place of Performance:** Portland State University

***Proposal/Active Project Start Date: (MM/YYYY):** 04/2022

***Proposal/Active Project End Date: (MM/YYYY):** 03/2027

***Total Anticipated Proposal/Project Amount:** $547,808

*** Person Months per budget period Devoted to the Proposal/Active Project:**

Year	Person Months
2023	1.8
2024	1.8
2025	1.8
2026	1.8
2027	1.8

***Overall Objectives:** Develop novel statistical methods using imaging for the prediction of Alzheimer's disease progression.

***Statement of Potential Overlap:** Potential overlap between The Longitudinal Course of Imaging Biomarkers in People At Risk of AD" (PREDICT) and "Wisconsin Registry for Alzheimer's Prevention" or (WRAP Renewal). In both cases, statistical methods for modeling the progression of Alzheimer's disease are developed. In PREDICT, we consider imaging biomarkers, while in WRAP, we focus on non-imaging biomarkers.

***Proposal/Active Project Title:** Image processing of OCT and OCT-A for longitudinal analysis in multiple sclerosis

***Status of Support:** Current

Proposal/Award Number: R01EY032284

***Source of Support:** NIH NEI

***Primary Place of Performance:** Portland State University

***Proposal/Active Project Start Date: (MM/YYYY):** 03/2021

***Proposal/Active Project End Date: (MM/YYYY):** 02/2025

***Total Anticipated Proposal/Project Amount:** $491,308

*** Person Months per budget period Devoted to the Proposal/Active Project:**

Year	Person Months
2023	1.95
2024	1.95

***Overall Objectives:** Develop statistical methods for understanding the progression of Multiple Sclerosis

***Statement of Potential Overlap:** none

***Proposal/Active Project Title:** Collaborative Research: FDT-BioTech: Graph-Based Stochastic Processes for Biomedical Digital Twins

***Status of Support:** Pending

Proposal/Award Number:

***Source of Support:** NSF

***Primary Place of Performance:** Portland State University

***Proposal/Active Project Start Date: (MM/YYYY):** 01/2026

***Proposal/Active Project End Date: (MM/YYYY):** 12/2028

***Total Anticipated Proposal/Project Amount:** $669,551

*** Person Months per budget period Devoted to the Proposal/Active Project:**

Year	Person Months
2026	1
2027	1
2028	1

***Overall Objectives:** This proposal develops digital twins based on agent-based models, together with their large sample Gaussian approximations, organized along a graph structure, with specific applications to cancer development and tau-pathology evolution in connection with Alzheimer's disease. One of the main focuses is on the design of training algorithms in the presence of incomplete observations happening at multiple scales, and on the prediction of individual evolution based on personalized data.

***Statement of Potential Overlap:** no overlap

***Proposal/Active Project Title:** Information Pursuit for Robotics

***Status of Support:** Pending

Proposal/Award Number:

***Source of Support:** NSF

***Primary Place of Performance:** Portland State University

***Proposal/Active Project Start Date: (MM/YYYY):** 01/2026

***Proposal/Active Project End Date: (MM/YYYY):** 12/2026

***Total Anticipated Proposal/Project Amount:** $305,000

*** Person Months per budget period Devoted to the Proposal/Active Project:**

Year	Person Months
2026	0.5

***Overall Objectives:** Develop an information pursuit algorithm for robotic applications

***Statement of Potential Overlap:** no overlap

Certification:

I certify that the information provided is current, accurate, and complete. This includes but is not limited to current, pending, and other support (both foreign and domestic) as defined in 42 U.S.C. § 6605.

I also certify that, at the time of submission, I am not a party to a malign foreign talent recruitment program.

Misrepresentations and/or omissions may be subject to prosecution and liability pursuant to, but not limited to, 18 U.S.C. §§ 287, 1001, 1031 and 31 U.S.C. §§ 3729-3733 and 3802.

Certified by Jedynak, Bruno in SciENcv on 2025-06-21 02:30:10

CURRENT AND PENDING (OTHER) SUPPORT INFORMATION

Provide the following information for the Senior/key personnel and other significant contributors.
Follow this format for each person.

*NAME: Miller, Duncan

*POSITION TITLE: CFO

*ORGANIZATION AND LOCATION: Rose City Robotics, Portland, Oregon, United States

Proposals/Active Projects

***Proposal/Active Project Title:** STTR Phase I: Explainable Robotic Motion Planning in Unstructured Environments Using Information Pursuit for Critical Mineral Recovery

***Status of Support:** Pending

Proposal/Award Number: 261499

***Source of Support:** NSF STTR

***Primary Place of Performance:** 2130 SW 5th Ave, Suite 245B, Portland, OR 97201

***Proposal/Active Project Start Date: (MM/YYYY):** 01/2026

***Proposal/Active Project End Date: (MM/YYYY):** 12/2026

***Total Anticipated Proposal/Project Amount:** $305,000

*** Person Months per budget period Devoted to the Proposal/Active Project:**

Year	Person Months
2026	2.4

***Overall Objectives:** Develop an information pursuit algorithm for robotic applications.

***Statement of Potential Overlap:** No overlap. This is the proposal currently under consideration for funding.

Certification:

I certify that the information provided is current, accurate, and complete. This includes but is not limited to current, pending, and other support (both foreign and domestic) as defined in 42 U.S.C. § 6605.

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Certified by Miller, Duncan in SciENcv on 2025-06-30 14:39:24

CURRENT AND PENDING (OTHER) SUPPORT INFORMATION

Provide the following information for the Senior/key personnel and other significant contributors.
Follow this format for each person.

*NAME: Taylor Rodriguez, Daniel

PERSISTENT IDENTIFIER (PID) OF THE SENIOR/KEY PERSON: https://orcid.org/0000-0002-2959-0281

*POSITION TITLE: Associate Professor

*ORGANIZATION AND LOCATION: Portland State University, Portland, Oregon, United States

Proposals/Active Projects

***Proposal/Active Project Title:** RTG: Portland Program In Computation And Data Enabled Science

***Status of Support:** Current

Proposal/Award Number: 2136228

***Source of Support:** NSF DMS

***Primary Place of Performance:** Portland State University

***Proposal/Active Project Start Date: (MM/YYYY):** 03/2022

***Proposal/Active Project End Date: (MM/YYYY):** 03/2027

***Total Anticipated Proposal/Project Amount:** $1,969,747

*** Person Months per budget period Devoted to the Proposal/Active Project:**

Year	Person Months
2023	0.01
2024	0.01
2025	0.01
2026	0.01
2027	0.01

***Overall Objectives:** To produce unique workforce additions with deep knowledge in computational mathematics and statistics and a broad understanding of current issues in data-driven science. Research in CADES, being at the intersection of mathematics, statistics, and computing, is characterized by tremendous intellectual diversity of techniques. Integration across this diversity will result in enhanced research productivity and uniquely qualified trainees.

***Statement of Potential Overlap:** No overlap

***Proposal/Active Project Title:**	Assessment of anomia: improving efficiency and utility using item response theory
***Status of Support:**	Current
Proposal/Award Number:	R01DC01881301
***Source of Support:**	NIH/NIDCD
***Primary Place of Performance:**	Portland State University
***Proposal/Active Project Start Date: (MM/YYYY):**	09/2020
***Proposal/Active Project End Date: (MM/YYYY):**	08/2025
***Total Anticipated Proposal/Project Amount:**	$495,089

*** Person Months per budget period Devoted to the Proposal/Active Project:**

Year	Person Months
2021	0.5
2022	0.5
2023	0.5
2024	0.5
2025	1

***Overall Objectives:** To produce a powerful and flexible anomia assessment tool with utility for both research and clinical practice, improving the measurement technology available for assessing naming ability in persons with aphasia.

***Statement of Potential Overlap:** No overlap

Certification:

I certify that the information provided is current, accurate, and complete. This includes but is not limited to current, pending, and other support (both foreign and domestic) as defined in 42 U.S.C. § 6605.

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Certified by Taylor Rodriguez, Daniel in SciENcv on 2025-06-16 21:51:33

Table 1

1	Your Name:	Your Organizational Affiliation(s), last 12 mo	Last Active Date
	Cole, Joseph Raymond	Rose City Robotics, Inc.	

Table 2

2	Name:	Type of Relationship	Optional (email, Department)	Last Active Date

Table 3

3	Advisor/Advisee Name:	Organizational Affiliation	Optional (email, Department)
G	Halas, Naomi	Rice University, Houston, TX	
T	Nordlander, Peter	Rice University, Houston, TX	
T	Kelly, Kevin	Rice University, Houston, TX	

Table 4

4	Name:	Organizational Affiliation	Optional (email, Department)	Last Active Date

Table 5

5	Name:	Organizational Affiliation	Journal/Collection	Last Active Date

Table 1

1	Your Name:	Your Organizational Affiliation(s), last 12 mo	Last Active Date
	Jedynak, Bruno M	Portland State University	

Table 2

2	Name:	Type of Relationship	Optional (email, Department)	Last Active Date
R				

Table 3

3	Advisor/Advisee Name:	Organizational Affiliation	Optional (email, Department)
G	Geman Donald	Johns hopkins University	geman@jhu.edu
T	Rajan Purnima	Johns hopkins University	purnima@cs.jhu.edu
T	Bilgel Murat	National Institute of Health	murat.bilgel@nih.org
T	Variani Ehsan	Google, Inc	ehsan.variani@google.com
T	Sznitman Raphael	University of Bern	
T	Vogelstein Joshua	Johns hopkins University	
T	Vidal Camille	GE Healthcare	
T	Kruti Pandia	Intel corp.	
T	Victor Rielly	Portland State University	
T	Pierre-Emmanuel Poulet	INRIA	
T	Zheng Huicheng	Sun Yat-Sen University	

Table 4

4	Name:	Organizational Affiliation	Optional (email, Department)	Last Active Date
A	Prince Jerry L	Johns Hopkins University	prince@jhu.edu	
C	Johnson Sterling	U. of Wisconsin	scj@medicine.wisc.edu	
A	Resnick Susan	National Institute of Aging	resnicks@grc.nia.nih.gov	
A	Frazier Peter	Cornell University	pf98@cornell.edu	
A	Aaron Carass	johns Hopkins University	aaron_carass@jhu.edu	
A	Daniel Taylor Rodriguez	Portland State University	dtaylor2@pdx.edu	
A	Murat Bilgel	NIH NIA	murat.bilgel@nih.gov	
A	Peter Calabresi	Johns Hopkins University	pcalabr1@jhmi.edu	
A	Shiv Saida	johns Hopkins University	ssaidha2@jhmi.edu	
A	Fu Li	Portland State University	h8lf@pdx.edu	
A	Kamel Lahouel	the Translational Genomics Institute		

A	john Lipor	Portland State University		
A	Jay Gopalakrishnan	Portland State University		
A	Panayot Vassilevski	Portland State University		
A	Daniel Taylor Rodriguez	Portland State University		
A	Dacian Daescu	Portland State University		

Table 5

5	Name:	Organizational Affiliation	Journal/Collection	Last Active Date
B				
E				

Table 1

1	Your Name:	Your Organizational Affiliation(s), last 12 mo	Last Active Date
	Duncan Miller	Rose City Robotics	
		Metro Region Innovation Hub	06/30/25
		Portland State University (Mentor)	06/30/25
		Invent Oregon (Judge)	06/30/25
		E8 Angel Investment Fund	

Table 2

2	Name:	Type of Relationship	Optional (email, Department)	Last Active Date

Table 3

3	Advisor/Advisee Name:	Organizational Affiliation	Optional (email, Department)

Table 4

4	Name:	Organizational Affiliation	Optional (email, Department)	Last Active Date

Table 5

5	Name:	Organizational Affiliation	Journal/Collection	Last Active Date

Table 1

1	Your Name:	Your Organizational Affiliation(s), last 12 mo	Last Active Date
	Taylor-Rodriguez, Daniel	Portland State University	02/01/21

Table 2

2	Name:	Type of Relationship	Optional (email, Department)	Last Active Date
R				

Table 3

3	Advisor/Advisee Name:	Organizational Affiliation	Optional (email, Department)
G	Young, Linda	National Agricultural Statistical Service	Linda.J.Young@usda.gov
G	Bliznyuk, Nikolay	University of Florida	nblinyuk@uf.edu
T	Jacob Schultz	Portland State University	jschultz@pdx.edu
T	Ashlynn Crisp	Portland State University	acrisp@pdx.edu
T	Simon Lee	Portland State University	soonmlee@pdx.edu

Table 4

4	Name:	Organizational Affiliation	Optional (email, Department)	Last Active Date
A	Womack, Andrew J	Rice University		06/20/25
A	Fuentes, Claudio	Oregon State University		06/20/25
A	Finley, Andrew	Michigan State University		06/20/25
A	Gutierrez, Luis	Pontificia Universidad Catolica de Chile		01/01/24
A	Pereira, Luz A	Universidad del Valle		01/01/24
A	Mena, Ramses H	Universidad Autonoma de Mexico		01/01/24
C	Fergadiotis, Gerasimos	Portland State University		06/20/25
A	Hula, William	VA Pittsburgh Healthcare System		06/20/25
A	Holz, Andres	Portland State University		06/20/25
A	de Rivera, Catherine	Portland State University		12/01/23
A	Bliss-Ketchum, Leslie	Samara Group LLC		12/01/23
A	Lafrenz, Martin	Portland State University		12/01/23
A	Wheat, Rachel	Oregon Department of Fisheries and Wildlife		12/01/23
C	Cole, Joseph	Rosecity Robotics		06/20/25
C	Miller, Duncan	Rosecity Robotics		06/20/25
C	Jedynak, Bruno	Portland State University		06/20/25
C	Gopalakrishnan, Jay	Portland State University		06/20/25

C	Vasilevsky, Panayot	Portland State University		06/20/25
C	Orvall, Jeff	Portland State University		06/20/25
C	Nguyen, Nam	Portland State University		01/01/24
C	Daescu, Dacian	Portland State University		01/01/24
C	Chang, Heejun	Portland State University		08/01/24
A	Holz, Andres	Portland State University		06/20/25
A	Orvall, Jeff	Portland State University		01/01/24

Table 5

5	Name:	Organizational Affiliation	Journal/Collection	Last Active Date
B				
E				

Synergistic Activities - Joseph Cole

1 Training and Mentoring

I mentored two high school seniors as interns at Rose City Robotics during the spring of 2025, and currently I have four new interns for this summer. I helped them learn about simultaneous localization and mapping (SLAM) using the open source Robotis TurtleBot, as well as inverse kinematics using the OpenManipulator-X arm. We also have an ALOHA robot that one student is using to learn about the data collection process for human imitation learning, as well as the procedure to train transformer neural networks.

2 Curriculum Development

Rose City Robotics is currently developing a curriculum of robotics education courses to help interested high school students develop a portfolio of robotics projects they can showcase. Toward that end, I was accepted into the Portland State University Educational Leadership graduate certificate program beginning in the fall of 2025. My goal in joining this program is to deepen my understanding of adult developmental theory and to refine our curriculum design practices using proven pedagogical frameworks.

3 Software Development

In my last role, at the medical device startup YorLabs, I was the lead developer responsible for software architecture of a new cardiac ultrasound machine based on the NVIDIA Jetson ARM system-on-module. I developed beamforming and image processing algorithms to implement B, color doppler, and pulse wave doppler ultrasound modes. All of the ultrasound data processing occurs in real time on the GPU, giving me extensive experience developing CUDA kernels to parallelize time critical code. I also performed system integration of work products from experts on image quality, front-end user interface, and FPGA/hardware. This role required that I define and verify user requirements including frame rate and pipeline latency, and I had to ensure the system architecture could perform as expected. Ultimately, I demonstrated system performance both in lab and during two animal trials which led to successful closing of Series B and C investment rounds.

Prior to that, at Applied Materials, I designed algorithms in Matlab for the UVision UV microscope and SEMVision electron microscope platforms. These microscopes used high speed image processing and statistical algorithms for wafer inspection and defect review of semiconductor manufacturing process steps. I analyzed algorithmic gaps at a key customer site to focus company R&D efforts, earning Employee of the Quarter award (Q3, 2012). This role required daily frontline interactions with the customer that over time built relationships to fuel future tool sales. I improved software quality by testing early prototype versions of new algorithm features (e.g. subframe registration, 3D height measurements, process noise filters, etc.) on customer data, and I designed an edge segmentation algorithm for a new product line (Discrete Measurement Server). One of my algorithms, an image enhancement backlight algorithm, was developed on a compressed timeline to secure $6 million in SEMVision tool sales.

These roles, among others, demonstrate my proven capacity to lead an effort to implement and bring to market a revolutionary artificial intelligence algorithm.

Synergistic activities - Duncan Miller

1 Mentoring and Outreach Programs

At Portland State University, I serve as a mentor for student founders and entrepreneurs through the PSU Business Accelerator and Center for Entrepreneurship. I support a range of student-led ventures, offering guidance in product development, market analysis, and commercialization across initiatives like InventOR where I serve as both a judge and mentor. I also host meetups and workshops on robotics and artificial intelligence. As a University Ambassador for NVIDIA's Deep Learning Institute, I help students access cutting-edge AI curriculum and resources to support their academic and entrepreneurial goals. These efforts contribute to expanding the STEM pipeline and increasing participation in technology innovation among underrepresented groups.

2 Community Liaison for Regional Innovation

At the Metro Region Innovation Hub, I work to increase entrepreneurial access and innovation support for startup founders. The Innovation Hub is funded by Business Oregon and designed to bridge resource gaps across the innovation ecosystem. My role includes outreach to local entrepreneurs, and connecting them with education, mentoring, and capital programs. This work ensures that the benefits of scientific and engineering advancement are tied directly to regional economic resilience.

3 STEM Education and Robotics Training

I founded the Robotics Collaborative in Portland to promote access to hands-on robotics training. I also serve as a coach and mentor for a local FIRST Robotics FTC team, guiding high school students through the engineering design process, coding challenges, and competitive robotics events. Through these programs, I students build their confidence and capabilities in mechanical design, embedded systems, and artificial intelligence. These efforts directly address the national imperative to strengthen STEM education and cultivate the next generation of technical leaders.

4 Entrepreneurship and Technology Commercialization

Over the past 20 years, I have founded and led 4 technology startups in across energy, education, and software. Notably, I co-founded HeatSpring, an online education platform that served over 100,000 energy professionals and generated millions in revenue through bootstrapped growth. I also developed Shiro, a prompt engineering and testing platform for AI developers, which I exited in 2024. In 2025, I merged my AI-driven solar training platform Waivolt into Rose City Robotics. Across these ventures, I have lead product innovation, commercialization, and ecosystem development in to promote prosperity and leadership.

5 Innovation Network and Strategic Collaboration

I am a co-organizer of the Pacific Northwest Battery Collaborative, a consortium advancing battery innovation, manufacturing and recovery solutions. I also serve as a Limited Partner at E8 Angels, an investment network focused on early-stage ventures across North America. These roles allow me to support strategic resource repatriation and help mobilize investment into domestic critical materials recovery technologies. I also collaborate with partners, including Polaris Battery Labs and Loupe Robotics, and Oak Ridge National Laboratory to align research, training, and commercialization goals across the battery supply chain.

Synergistic activities - Bruno Jedynak

1 The CADES lab

Together with my colleague, Dr. Daniel Taylor-Rodriguez, I created the Computation and Data-Enabled Science (CADES) Consulting Lab in 2022, which was established as part of the NSF Research and Training Grant DMS-2136228. The lab offers consulting services to regional scientists. In doing so, it provides hands-on opportunities for trainees to experience the entire data analytics pipeline with real-world data and to develop the skills needed to connect theory with practice. Researchers from any discipline are welcome to consult on what computational techniques, data handling methods, or quantitative tools are best suited for their scientific pursuits.

To teach students how to communicate with clients effectively, student-led interactions were emphasized, rather than faculty or Lab staff orchestrating student-client interactions. Students organize and conduct interviews with clients, present weekly project updates, draft final consulting reports, and deliver a final presentation to their clients to debrief them on the results of their analysis.

Teams of students are composed of students from all academic levels. PhD students act as team leaders for their MSc and BSc classmates, while every team is under the guidance of a faculty. Teams are carefully chosen by the CADES Lab lead team, to balance student strengths (determined through an academic and coding background survey) and academic exposure to varying techniques and coursework.

2 Curriculum creation

Statistical Methods in Imaging. Created at Johns Hopkins University in Spring 2006. This course presented various statistical aspects of computational imaging. It introduced machine learning techniques for computer vision questions.

Statistical Learning. Created at Portland State University in 2018, this year-long sequence of three courses was focused on the probabilistic aspects of machine learning.

Kernel methods. Created in 2022 at Portland State University, this year-long sequence of three courses was focused on the presentation of kernel methods.

Synergistic activities - Daniel Taylor Rodriguez

1 TRAINING AND MENTORING

1.1 The CADES Consulting Lab. My colleague Bruno Jedynak and I established the Computation and Data-Enabled Science (CADES) Consulting Lab in 2022 under the NSF Research and Training Grant DMS-2136228. The lab offers consulting to local and regional scientists, providing students hands-on experience with complex real-world data to bridge theory and practice. Each term, we solicit project proposals from academic, government, and business partners, emphasizing computational methods, data management, and quantitative tools. We prioritize effective consulting communication (often overlooked in quantitative programs) through initial training sessions, after which students independently manage client interactions. Students conduct interviews, provide weekly updates, draft reports, and deliver final presentations. Teams include PhD, MSc, and BSc students to mirror real-world collaborative environments. PhD students typically lead, supported closely by faculty and staff.

1.2 PSU EAGLES Faculty Mentor. EAGLES is an NSF funded program designed to improve retention in STEM by supporting low-income undergraduate STEM students financially and with academic support/mentoring (2025-2027). I am currently mentor to three undergraduate students working towards a STEM degree (two in Computer Science and one in Chemistry) coming from low income backgrounds.

2 CURRICULAR DEVELOPMENT

2.1 Modernizing PSU's MS Stats program. As part of my commitment to advancing data science education, I co-led, alongside my colleague Bruno Jedynak, the comprehensive update of our department's MS Statistics program to include a Data Science emphasis. This enhanced program integrates modern computational tools, data management strategies, and advanced quantitative methods, aligning closely with current industry and research demands. Following successful approval, the revised MS Statistics + Data Science program is set to launch this upcoming Fall, significantly expanding our curriculum's relevance and appeal.

2.2 Creation of the BSc in Data Science at PSU. I played a leading role in establishing the BSc in Data Science program at Portland State University during 2019 and 2020. Specifically, I proposed and developed the statistical curriculum and designed several core requirements, ensuring alignment with industry standards and emerging research trends. This foundational work contributed significantly to the successful launch and ongoing development of the program, preparing students effectively for careers in data science. This program has been widely successful, and is currently one of the fastest growing programs in the University.

3 SOFTWARE DEVELOPMENT

Developed part of the statistical methodology and code built into the popular R package GJAM. R Software implementation of different Bayesian methods published in manuscripts: The software can be downloaded here: HCSelection https://github.com/dantaylor60/HCBayesianSelection.git and AutoBPFit https://github.com/dantaylor60/AutoBPFit.git

Data Management and Sharing Plan

All data generated in this NSF STTR Phase I project is considered proprietary.

Mentoring Plan

This comprehensive mentoring initiative is designed to support an undergraduate student, a graduate student, and a Senior Research Assistant II at Portland State University (PSU). The program aims to foster professional development through a range of activities, with progress evaluated via routine meetings with faculty advisors and an annual written report outlining individual advancement.

Program Orientation:

At the start, each participant will meet individually with project leads and attend group sessions with the broader research team. These meetings will clarify project goals, introduce available lab resources, and set expectations. Key areas of focus include promoting independent research, encouraging professional collaboration with team members, emphasizing timely and high-quality dissemination of results, and stressing proper documentation of methodologies and findings.

Scientific Communication and Professional Exposure:

Mentees will develop and present their research findings, often in collaboration with faculty investigators who will assist with writing, editing, and organizing manuscripts and conference presentations. Opportunities to share research will include weekly group meetings and national or international conferences, for which travel support is provided.

Career Development and Counseling:

The program offers guidance tailored to both short-term and long-term career planning. Participants will explore various career paths, including roles in academia, industry, and government. Mentors will facilitate engagement with the broader scientific community through conferences, technical meetings, and workshops, expanding professional networks and career prospects.

Development of Mentorship Skills:

Graduate students will mentor undergraduate researchers through summer internships at Portland State University. These internships are made available through the NSF Research and Training grant in Computation and Data Enabled Science. Faculty mentors will conduct bi-annual meetings to assess project progress, set research goals, and support career planning.

Ethics and Professional Conduct:

Ethical research practices and professionalism are integral to the training process, modeled through interactions with senior researchers. Participants will be encouraged to engage in peer review, help organize academic events, and serve the scientific community by joining relevant professional organizations.

Supplemental Mentoring Opportunities:

Additional support includes participation in specialized career development workshops, such as those focused on navigating academic job searches. Participants will give regular research updates to the group and receive constructive feedback. Opportunities will also be available in teaching undergraduate-level courses

Draft

Small Business Technology Transfer (STTR) Program Allocation Of Rights In Intellectual Property And Rights To Carry Out Follow-On Research, Development, Or Commercialization

This Agreement between Rose City Robotics, Inc., a small business concern organized as a C Corporation under the laws of Oregon and having a principal place of business at 11060 NW Copeland St., Portland, OR 97229 ____________________, ("SBC") and Portland State University, a research institution having a principal place of business at 1825 SW Broadway, Portland, OR 97201, ("RI") is entered into for the purpose of allocating between the parties certain rights relating to an STTR project to be carried out by SBC and RI (hereinafter referred to as the "PARTIES") under an STTR funding agreement that may be awarded by the National Science Foundation (NSF) to SBC to fund a proposal entitled "Explainable Robotic Motion Planning Using Information Pursuit for Critical Mineral Recovery "submitted, or to be submitted, to NSF by SBC on or about July 2, 2025.

1. Applicability of this Agreement

(a) This Agreement shall be applicable only to matters relating to the STTR project referred to in the preamble above.

(b) If a funding agreement for an STTR project is awarded to an SBC based upon the STTR proposal referred to in the preamble above, SBC will promptly provide a copy of such funding agreement to RI, and SBC will make a subaward to RI in accordance with the funding agreement, the proposal, and this Agreement. If the terms of such funding agreement appear to be inconsistent with the provisions of this Agreement, the Parties will attempt in good faith to resolve any such inconsistencies. However, if such resolution is not achieved within a reasonable period, SBC shall not be obligated to award nor RI to accept the subaward. If a subaward is made by SBC and accepted by RI, this Agreement shall not be applicable to contradict the terms of such subaward or of the funding agreement awarded by NSF to SBC except on the grounds of fraud, misrepresentation, or mistake, but shall be considered to resolve ambiguities in the terms of the subaward.

(c) The provisions of this Agreement shall apply to any and all consultants, subcontractors, independent contractors, or other individuals employed by SBC or RI for the purposes of this STTR project.

2. Background Intellectual Property

(a) "Background Intellectual Property" means property and the legal right therein of either or both parties developed before or independent of this Agreement including inventions, patent applications, patents, copyrights, trademarks, mask works, trade secrets and any information embodying proprietary data such as technical data and computer software.

(b) This Agreement shall not be construed as implying that either party hereto shall have the right to use Background Intellectual Property of the other in connection with this STTR project except as otherwise provided hereunder.

(1) The following Background Intellectual Property of SBC may be used nonexclusively and, except as noted, without compensation by RI in connection with research or development activities for this STTR project (if "none" so state): none:

(2) The following Background Intellectual Property of RI may be used nonexclusively and, except as noted, without compensation by SBC in connection with research or development activities for this STTR project (if "none" so state):
none:

(3) The following Background Intellectual Property of RI may be used by SBC nonexclusively in connection with commercialization of the results of this STTR project, to the extent that such use is reasonably necessary for practical, efficient and competitive commercialization of such results but not for commercialization independent of the commercialization of such results upon the condition that SBC pay to RI, in addition to any other royalty including any royalty specified in the following list, a royalty of __% of net sales or leases made by or under the authority of SBC of any product or service that embodies, or the manufacture or normal use of which entails the use of, all or any part of such Background Intellectual Property (if "none" so state): none.

3. Project Intellectual Property

(a) "Project Intellectual Property" means the legal rights relating to inventions (including Subject Inventions as defined in 37 CFR § 401), patent applications, patents, copyrights, trademarks, mask works, trade secrets and any other legally protectable information, including computer software, first made or generated during the performance of this STTR Agreement.

(b) Except as otherwise provided herein, ownership of Project Intellectual Property shall vest in the party whose personnel conceived the subject matter or first actually reduced the subject matter to practice, and such party may perfect legal protection therein in its own name and at its own expense. Jointly made or generated Project Intellectual Property shall be jointly owned by the Parties unless otherwise agreed in writing. The SBC shall have the first option to perfect the rights in jointly made or generated Project Intellectual Property unless otherwise agreed in writing.

(1) The ownership, including rights to any revenues and profits, resulting from any product, process, or other innovation or invention based on the cooperative shall be allocated between the SBC and the RI as follows:

SBC Percent: 50 RI Percent: 50

(2) Expenses and other liabilities associated with the development and marketing of any product, process, or other innovation or invention shall be allocated as follows: the SBC will be responsible for 50 percent and the RI will be responsible for 50 percent.

(c) The Parties agree to disclose to each other, in writing, each and every Subject Invention, which may be patentable or otherwise protectable under the United States patent laws in Title 35, United States Code. The Parties acknowledge that they will disclose Subject Inventions to each other and the awarding agency within 2 months after their respective inventor(s) first disclose the invention in writing to the person(s) responsible for patent matters of the disclosing Party. All written disclosures of such inventions shall contain sufficient detail of the invention, identification of any statutory bars, and shall be marked confidential, in accordance with 35 U.S.C. §205.

(d) Each party hereto may use Project Intellectual Property of the other nonexclusively and without compensation in connection with research or development activities for this STTR project, including inclusion in STTR project reports to the NSF and proposals to the NSF for continued funding of this STTR project through additional phases.

(e) In addition to the Government's rights under the Patent Rights clause of 37 CFR § 401.14, the Parties agree that the Government shall have an irrevocable, royalty free, nonexclusive license for any governmental purpose in any Project Intellectual Property.

(f) SBC will have an option to commercialize the Project Intellectual Property of RI, subject to any rights of the Government therein, as follows:

(1) Where Project Intellectual Property of RI is a potentially patentable invention, SBC will have an exclusive option for a license to such invention, for an initial option period of 24 months after such invention has been reported to SBC. SBC may, at its election and subject to the patent expense reimbursement provisions of this section, extend such option for an additional 24 months by giving written notice of such election to RI prior to the expiration of the initial option period. During the period of such option following notice by SBC of election to extend, RI will pursue and maintain any patent protection for the invention requested in writing by SBC and, except with the written consent of SBC or upon the failure of SBC to reimburse patenting expenses as required under this section, will not voluntarily discontinue the pursuit and maintenance of any United States patent protection for the invention initiated by RI or of any patent protection requested by SBC. For any invention for which SBC gives notice of its election to extend the option, SBC will, within 45 days after invoice, reimburse RI for the expenses incurred by RI prior to expiration or termination of the option period in pursuing and

maintaining (i) any United States patent protection initiated by RI and (ii) any patent protection requested by SBC. SBC may terminate such option at will by giving written notice to RI, in which case further accrual of reimbursable patenting expenses hereunder, other than prior commitments not practically revocable, will cease upon RI's receipt of such notice. At any time prior to the expiration or termination of an option, SBC may exercise such option by giving written notice to RI, whereupon the parties will promptly and in good faith enter into negotiations for a license under RI's patent rights in the invention for SBC to make, use and/or sell products and/or services that embody, or the development, manufacture and/or use of which involves employment of, the invention. The terms of such license will include: (i) payment of reasonable royalties to RI on sales of products or services which embody, or the development, manufacture or use of which involves employment of, the invention; (ii) reimbursement by SBC of expenses incurred by RI in seeking and maintaining patent protection for the invention in countries covered by the license (which reimbursement, as well as any such patent expenses incurred directly by SBC with RI's authorization, insofar as deriving from RI's interest in such invention, may be offset in full against up to of accrued royalties in excess of any minimum royalties due RI); and, in the case of an exclusive license, (iii) reasonable commercialization milestones and/or minimum royalties.

(2) Where Project Intellectual Property of RI is other than a potentially patentable invention, SBC will have an exclusive option for a license, for an option period extending until months following completion of RI's performance of that phase of this STTR project in which such Project Intellectual Property of RI was developed by RI. SBC may exercise such option by giving written notice to RI, whereupon the parties will promptly and in good faith enter into negotiations for a license under RI's interest in the subject matter for SBC to make, use and/or sell products or services which embody, or the development, manufacture and/or use of which involve employment of, such Project Intellectual Property of RI. The terms of such license will include: (i) payment of reasonable royalties to RI on sales of products or services that embody, or the development, manufacture or use of which involves employment of, the Project Intellectual Property of RI and, in the case of an exclusive license, (ii) reasonable commercialization milestones and/or minimum royalties.

(3) Where more than one royalty might otherwise be due in respect of any unit of product or service under a license pursuant to this Agreement, the parties shall in good faith negotiate to ameliorate any effect thereof that would threaten the commercial viability of the affected products or services by providing in such license(s) for a reasonable discount or cap on total royalties due in respect of any such unit.

4. Follow-on Research or Development

All follow-on work, including any licenses, contracts, subcontracts, sublicenses or arrangements of any type, shall contain appropriate provisions to implement the Project Intellectual Property rights provisions of this agreement and insure that the Parties and the Government obtain and retain such rights granted herein in all future resulting research, development, or commercialization work.

5. Confidentiality/Publication

(a) Background Intellectual Property and Project Intellectual Property of a party, as well as other proprietary or confidential information of a party, disclosed by that party to the other in connection with this STTR project shall be received and held in confidence by the receiving party and, except with the consent of the disclosing party or as permitted under this Agreement, neither used by the receiving party nor disclosed by the receiving party to others, provided that the receiving party has notice that such information is regarded by the disclosing party as proprietary or confidential. However, these confidentiality obligations shall not apply to use or disclosure by the receiving party after such information is or becomes known to the public without breach of this provision or is or becomes known to the receiving party from a source reasonably believed to be independent of the disclosing party or is developed by or for the receiving party independently of its disclosure by the disclosing party.

(b) Subject to the terms of paragraph (a) above, either party may publish its results from this STTR project. However, the publishing party will negotiate the right of refusal with the other party with respect to a proposed publication, as well as a day period in which to review proposed publications and submit comments, which will be given full consideration before publication. Furthermore, upon request of the reviewing party, publication will be deferred for up to additional days for preparation and filing of a patent application which the reviewing party has the right to file or to have filed at its request by the publishing party.

6. Liability

(a) Each party disclaims all warranties running to the other or through the other to third parties, whether express or implied, including without limitation warranties of merchantability, fitness for a particular purpose, and freedom from infringement, as to any information, result, design, prototype, product or process deriving directly or indirectly and in whole or part from such party in connection with this STTR project.

(b) SBC will indemnify and hold harmless RI with regard to any claims arising in connection with commercialization of the results of this STTR project by or under the authority of SBC. The PARTIES will indemnify and hold harmless the Government with regard to any claims arising in connection with commercialization of the results of this STTR project.

7. Termination

(a) This agreement may be terminated by either Party upon 14 days written notice to the other Party. This agreement may also be terminated by either Party in the event of the failure of the other Party to comply with the terms of this agreement.

(b) In the event of termination by either Party, each Party shall be responsible for its share of the costs incurred through the effective date of termination, as well as its share of the costs incurred after the effective date of termination, and which are related to the termination. The confidentiality, use, and/or non-disclosure obligations of this agreement shall survive any termination of this agreement.

AGREED TO AND ACCEPTED

Small Business Concern

By: ____

Date: _____________

Print name: Joseph R. Cole

Title: President & CEO

Research Institution

By: ____

Date: ____________

Print name: ____

Title: ____

Data Not Available

Research & Graduate Studies
Sponsored Projects Administration

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Portland State UNIVERSITY

June 25, 2025

Joseph Cole
Co-founder / CEO Rose City Robotics
2130 SW 5th Ave #245B
Portland, OR 97201
joe@rosecityrobotics.com

Reference: NSF 24-579: NSF Small Business Innovation Research /Small Business Technology Transfer Phase I Programs

Dear Joseph:

This letter confirms that the appropriate program and administrative personnel at Portland State University have reviewed the above referenced Statement of Work and budget and are committed to enter into an agreement with Rose City Robotics for the performance period of 01/05/2026 to 12/11/2026. The work to be performed by PSU does not include human or animal subjects.

The PSU Principal Investigator on this proposal is Bruno Jedynak for the project entitled: "Information pursuit for robotics." The PSU budget and scope of work are provided as separate enclosures to this letter. The estimated cost of the proposed subcontract will not exceed $165,048 and includes appropriate direct and indirect costs.

Furthermore, by submission of this commitment letter PSU and its Principal Investigator (PI) certify that the information submitted within the application is true, complete, and accurate to the best of PSU's knowledge. We certify Portland State University is in compliance with all assurances and certifications referenced in the application process and has institutional policies and procedures in place to ensure compliance with conflict of interest issues, as well as other applicable federal and state laws, rules and regulations.

Should an award be made to Portland State University, please forward to contract to the email awards@pdx.edu. If you have any questions, please contact the undersigned at spa_proposals@pdx.edu or (503) 725-9900.

Sincerely,

Addy Bareiss

Addy Bareiss, Proposal Manager
Authorized Organization Official

Enclosed: Budget, Budget Justification, Scope of Work

STATEMENT OF WORK

Subaward Site: Portland State University (PSU)

The work proposed by the PSU team aims to develop a vision-based Information-Pursuit algorithm that accurately identifies the location of bolts on electric vehicle (EV) batteries, the first step in the EV battery disassembly process. The successful formulation of this approach will serve as proof of concept, supporting the submission of an NSF SBIT/STTR Phase II proposal as a continuation of this project.

As site PI, Jedynak will complete the following tasks:

- Have primary responsibility for all activities related to sub-award management.
- Serve as liaison between PSU and Rose City Robotics.
- Recruit and hire a research associate and students who participate in the project.
- Share with Co-PI Taylor-Rodriguez the primary responsibility for ensuring the validity of the research conducted.
- Coordinate regular meetings with Rose City Robotics.
- Participate in weekly technical discussions.
- Contribute to the methodological development proposed.
- Contribute to the manuscripts resulting from the proposed work.
- Attend national conferences to disseminate the strategies that have been formulated.

As site Co-PI, Taylor-Rodriguez will

- Lead the methodological development of the project, including:
    - Formulation of a likelihood-free strategy to estimate the distributions required to power the information pursuit algorithm.
    - Designing an approach to estimate mutual information from samples.
    - Develop the guiding principles for obtaining the embeddings that yield the latent representation of the visual input received by the robotic arm.

- Lead and supervise the research associate and students during the software development, training, and testing stages of the project.
- Share with PI Jedynak the primary responsibility for ensuring the validity of the research conducted.
- Participate in regular meetings with Rose City Robotics.
- Coordinate and lead weekly technical discussions.
- Contribute to the manuscripts resulting from the proposed work.
- Attend national conferences to disseminate the strategies that have been formulated.

To Whom It May Concern:

If the proposal submitted by Dr. Joseph Cole entitled “STTR Phase I: Explainable Robotic Motion Planning in Unstructured Environments Using Information Pursuit for Critical Mineral Recovery” is selected for funding by NSF, it is my intent to collaborate and/or commit resources as detailed in the Project Description or the Facilities, Equipment and Other Resources section of the proposal.

Days Committed: 10

Daily Rate: $1000

Total: $10000

Sincerely,

Dakota Pellegrino

Dakota S Pellegrino

Principal

Callida Solutions LLC

Dakota.pellegrino@callida.solutions

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Data Not Available

Data Not Available