

vehicle as a descriptor of the topic. We then posit a heuristic distance between

 $D(\hat{\phi}_{kw}, \hat{\phi}'_{kw}) = \sum \|\hat{\phi}_{kw} - \hat{\phi}'_{kw}\|$

Finally, we pose topic matching as a combinatorial optimization problem

 $\pi_r^* = \arg\min f(\pi(\phi_{kwr}))$

In practice, we solve the optimization in (3) using the Hungarian algorithm

[2], which provides a solution for each vehicle in $\mathcal{O}(K^3)$, giving an overall algo-

AUV 1 Topics

AUV 2 Topics

Figure 3: Optimization in (3) visualized as a bipartite graph matching problem, solvable via the

The complete algorithm is summarized below, where RefineTopics refers to the

here we seek to minimize the cost given by the total distance between top-

cs in (1). That is, the optimal topic permutation for robot r with respect to robot



Approximate Distributed Spatiotemporal Topic Models for Multi-Robot Terrain Characterization

missions that can^Kevin Doherty^{1,2}, Genevieve Flaspohler^{1,2}, Nicholas Roy¹, and Yogesh Girdhar² ¹Computer Science and Artificial Intelligence Laboratory (CSAIL), Massachusetts Institute of Technology (MIT) target spatiotemporaley Submergence Laboratory, Woods Hole Oceanographic Institution (WHOI) sparse, and previously.

unknown phenome ha, We leverage the per-topic word distribution given by $\hat{\phi}_{kw}$ learned by each

rithm complexity for our algorithm of $\mathcal{O}(RK^3)$.

 $D(\hat{\phi}_{1,1}, \hat{\phi}_{1,2})$

Gibbs sampling procedure given in (5).

// Local model updates

for each robot *r* in parallel **do**

enable a compute graph that spans multiple computers

for t from t_{curr} to $t_{curr} + T$ do

 $\mathbf{w}, \mathbf{x}, \mathbf{t} \leftarrow \text{ExtractWords}(I_t)$

// Receive global counts N_{kw}

 $\mathbf{z}, N_{kwr} \leftarrow \text{RefineTopics}(\mathbf{z}, \mathbf{w}, \mathbf{x}, \mathbf{t})$

Hungarian algorithm [2].

repeat

Algorithm AD-ROST-SIM

 $N_{kwr} \leftarrow N_{kw}$

end for

end for

these descriptors, given by:

is given as follows:

Problem

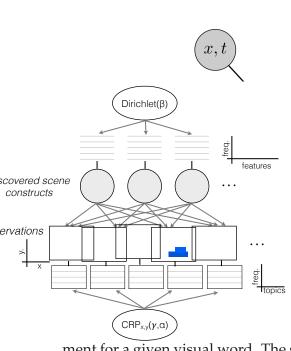
We aim to develop teams of under sea exploration robots capable of categorizing seabed terrains. This is chal lenging due to:

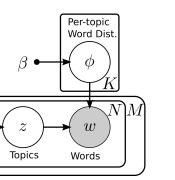
- Unsupervised models like topic models lack definitive "correspondence" between categories
- Communication-constraints underwater prevent highbandwidth solutions (e.g. transnission of raw images)

We seek improved consistency between local topic models with limited data transmissior

Spatiotemporal Topic Models

We focus on unsupervised categorization using Bayesian nonparametric inference. We use a "bag of words" model, where images are represented by a set of sual "words", i.e. image features.





in extreme

deepersea.

Figure 1: Two AUV's must merge local topic

models via a central node (ship)

environments-like the

odel of the ROST framework.

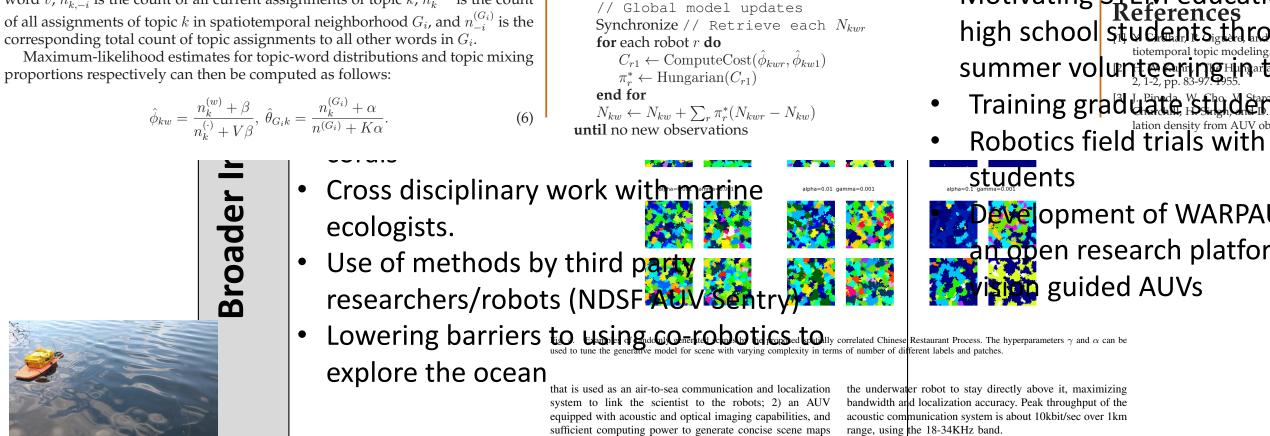
ral topic modeling (ROST) [1] to learn a set probability of word (i.e. image feature) w time *t* as follows:

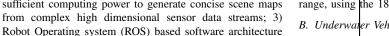
$$(w_i \mid z_i = k)p(z_i = k \mid x, t)$$

the posterior probability of a topic assignment for a given visual word. The sampling distribution is computed as follows:

$$p(z_i = k \mid \mathbf{z}_{-i}, \mathbf{w}) \propto \left[\frac{n_{k,-i}^{(v)} + \beta}{n_{k,-i}^{(\cdot)} + V\beta}\right] \left[\frac{n_k^{(G_i)} + \alpha}{n_{-i}^{(G_i)} + K\alpha}\right],$$

where $n_{k-i}^{(v)}$ is the count of assignments of topic k to every other observation of word v_i , $n_{k-i}^{(\cdot)}$ is the count of all current assignments of topic k_i , $n_k^{(G_i)}$ is the count of all assignments of topic k in spatiotemporal neighborhood G_i , and $n_{-i}^{(G_i)}$ is the corresponding total count of topic assignments to all other words in G_i . Maximum-likelihood estimates for topic-word distributions and topic mixing





B. Underwater Vehicle The underwater vehicle (Fig. 5.1) is based on the

Problem

We aim to develop teams of undersea exploration robots capable of categorizing seabed terrains. This is challenging due to:

- Unsupervised models like topic models lack definitive "correspondence" between categories
- Communication-constraints underwater prevent

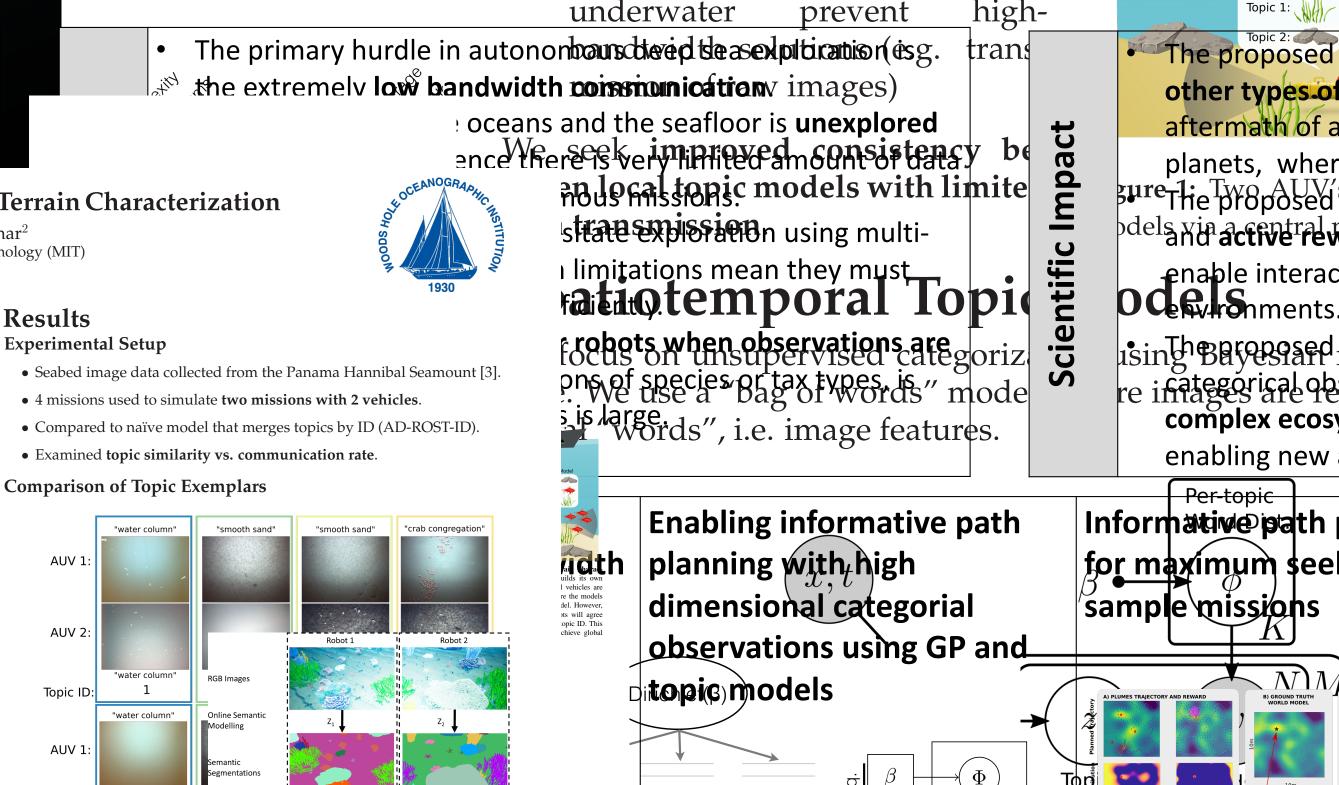


Figure 4: Comparison of maximum-likelihood topic exemplars from the first two missions. (Top) Topics learned by AD-ROST-ID. (Bottom): Topics learned using AD-ROST-SIM. **Topic Similarity vs. Communication Rate**

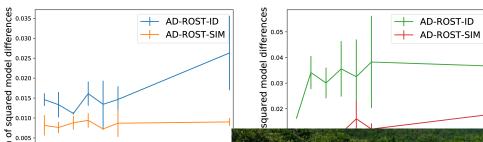


Figure 5: Topic distance (as in (3)) vs. numb • Motivating STEM education in high school students through aut summer volunteeringeringerinathendabe Training graduate studed the student salstor

Results

Experimental Setup

AUV 2

Topic ID:

AUV 1

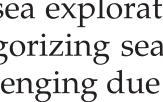
Development of WARPAUV as an open research platform for vision guided AUVs



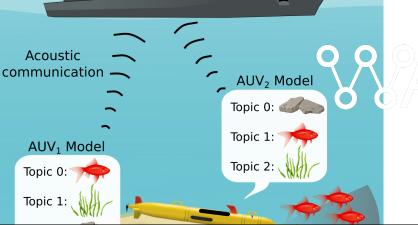


AUV 1 Per-topic Robot systems for distributed Informative path planning underwater exploration for maximum seek-andsample missions AUV 2 iodel of the ROST framework. n in (3) visualized as a bipa SlickLizard AS Flaspohler, G., Preston, V., Michel, A. P. M., torration-Guided to 1111 [2]. learn a set Soucie, J. S., Sogik, H. & Girdhar, Y. Gaussian robabidit Maximum onet and employing ge forded fre, N. Ucai, L., Belani, M., Claus, B. & Dirichlet Random Fields for Inference over High e 7 as follows Dimensional Observations in Girdhar, Y. [poster] WARPAOVCOBUPOLS, tasialgorithm is summarized k guided AUV for roboti Sriestarch in Northinst procedure given in (5). Robotics Colloquium (2019). Dimensional Categorical Observations. in 3782–3789 (2019). International Conference on Robotics and . in Automation (ICRA) (2020). $(w_i \parallel z_i = k) p(z_i = k \mid x, t)$ (4)<u>Algorithm AD-R</u>OST-SIM Quantifiable Impact repeat // Local model updates ility of a topic assign**for** each robot *r* in parallel **do** completeed conference papers • 1 journal paper // Receive global counts • Best paper award in service robotics $A_{kwr} \leftarrow N_{kw}$ α ICRA2020 for t from t_{curr} to $t_{curr} + T$ do \mathbf{F}_{K} in a list for best paper award at IROS 2018, $\mathbf{x}, \mathbf{t} \leftarrow \text{ExtractWords}(I_t)$ • First place prize at MIT Mechanical $\mathbf{z}, N_{kwr} \leftarrow \text{RefineTopics}(\mathbf{z}, \mathbf{w}, \mathbf{z})$ Engineering Research Exhibition 2019end for 10 students trained (graduate, undergraduate, high school the count // Global model updates odUse of methods by therd party Synchronize // Retrieve each wroederingers/robots (NDSFAUV Septry) ach robot r do a commutes for topic-word distributions and topic mixing $C_{r1} \leftarrow C\phimputeCost(\phi_{kwr}, \phi_{kw1})$ proportions respectively can then be computed as follows: $\underline{\pi_r^*} \leftarrow \operatorname{Hu}$ ngarian (C_{r1}) end for $N_{kw} \leftarrow N_{kw} + \sum_r \pi_r^* (N_{kwr} - N_{kw})$ (6) $() + K\alpha$ until no new observations

$$\hat{\phi}_{kw} = \frac{n_k^{(w)} + \beta}{n_k^{(\cdot)} + V\beta}, \ \hat{\theta}_{G_ik} = \frac{n_k^{(C_i)}}{n_k^{(C_i)} + V\beta}$$



Finding Topic Correspo



Topic 0:

Topic 1:

Topic 2:

We leverage the per-topic word distr chicle as a descriptor of the topic. We t hese descriptors, given by:

 $D(\hat{\phi}_{kw}, \hat{\phi}'_{kw}) = \sum$

Finally, we pose topic matching as a where we seek to minimize the cost giv ics in (1). That is, the optimal topic permu

• The proposed exploration approach generalized to many follows: other types of environments beyond the deep sea such as: aftermath of a natural disaster, caves and mines, and other planets, where there exist communication bottlenecks. ^{aure}The proposed distributed unsupervised scene understanding

dels yin active reward learning is, to our knowledge, the first to enable interactive exploration in communication constrained

ising Bayessand repretative model if or spatially distributed ce, we solve the optimization re intages are represented suggesting of the forth of the provides a solution for each ve complex ecosystem, habitats, and community streetings, exity for our algorithm of $\mathcal{O}($ enabling new applications in ecology.

 $\dot{n} = \arg m$ $f(\pi(\hat{\phi}_{kwr})) = \sum \left| \right|$