Active Learning Methods on Graphs for Image, Video and Multispectral Datasets

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Introduction

- **Supervised Learning** : Large amount of training (labeled) data
  - e.g. Convolutional neural network, support vector machine
- **Unsupervised Learning**: No training (labeled) data
  - e.g. Spectral clustering, k-means clustering, t-SNE embedding
- **Semi-supervised learning (SSL)**: Small amount of labeled data, but have unlabeled data as well
  - Graph-based SSL
    - Use similarity graph structure to aid in inferring classification of unlabeled data
    - Especially useful in low-label rate regime

Graph Construction

- Given inputs $Z = \{z_1, z_2, \ldots, z_n\}$, define a symmetric kernel function $k(z_i, z_j)$ between each pair of points
  - Larger $k(z_i, z_j)$ means higher similarity between the points
  - Define weight matrix, $W_{ij} = k(z_i, z_j)$
- For example, $$w_{ij} = exp(-d(z_i, z_j)^2/\tau)$$
  - **Metric (*d*)**: Euclidean, angular
  - **Scaling (*τ*)**:
    - Constant = Gaussian kernel
    - Distance with k^{th} nearest neighbor = Zelnik-Manor and Perona (ZMP)

Graph Construction: Degree and Graph Laplacian

- Degree of node z_i: $d_i = \Sigma_j w_{ij}$
  - Diagonal degree matrix: $D = \mathrm{diag}(d_1, d_2, \ldots, d_n)$

- Graph Laplacian: $L = D - W$
  - Common normalization: $L_s = D^{-1/2} L D^{-1/2}$ ("normalized graph Laplacian") - Hyperspectral Imagery
  - Positive semi-definite operator whose eigenvectors are useful for encoding clustering structure
    - E.g. Spectral Clustering

Accelerating the Diagonalization

Avoid costly computation of eigenvectors and eigenvalues on large, dense matrices.

- *k* nearest neighbor (kNN) graph
  - Only keep the weights of each node related to its *k* nearest neighbors ($k \ll n$)
  - Results in a **sparse** matrix
- Nyström Extension
  - **Low-rank approximation** of the dense weight matrix:
    - Constructs and stores only *k* columns ($k \ll n$)
  - Efficient computation of the eigenpairs of the graph Laplacian

Active Learning

Comparison of Goals:

- Semi-Supervised Learning : Accurate classification given current labeled data
- **Active Learning: "Optimally" select points to hand-label (classify) in order to improve underlying SSL classifier**

Active Learning Methods are usually more **explorative** or more **exploitative**

- **Exploration**: "Explore" the extent of the clustering structure of the underlying dataset
- **Exploitation:** "Exploit" the current level of knowledge about the classification of points in dataset

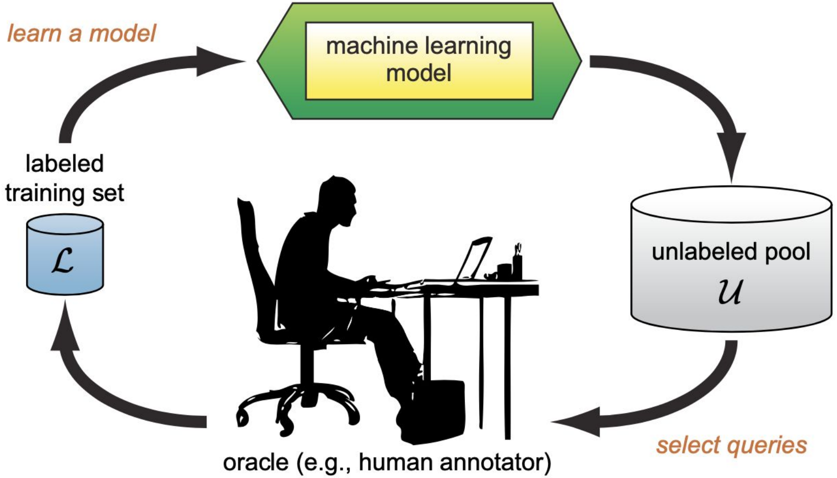
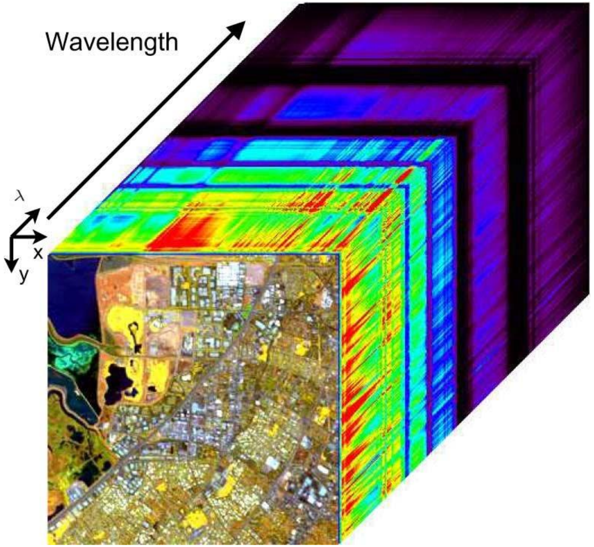


Image credit: Settles, Active Learning, 2013.

Application: Hyperspectral Imagery (HSI)



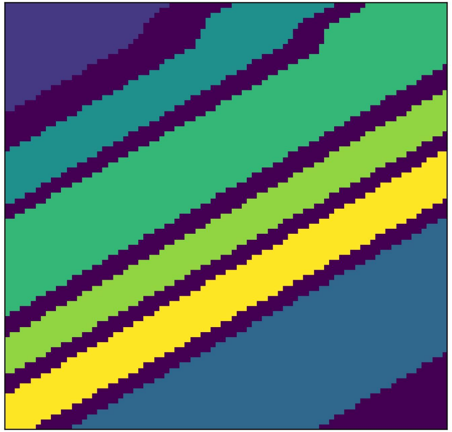
Hyperspectral images contain rich information about objects in the image, per the many wavelengths that are sampled when image is taken.

- Seek to classify the pixels into classes (e.g. water, dirt, grass, metal, etc)
- Noisy measurements, corrupted by weather and atmospheric effects

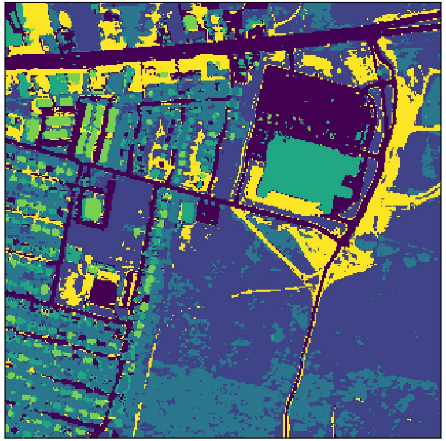
Apply active learning to incorporate human-in-the-loop to improve the accuracy of graph-based semi-supervised classification of pixels.

Image credit: Christophe, Emmanuel & Mailhes, Corinne & Duhamel, P. (2009)

HSI Datasets



Salinas-A: 6 classes of plant types



Urban: asphalt, grass, tree, roof, metal, and dirt

Graph Construction Details:

- 15-nearest neighbors graph
- Cosine similarity kernel, $k(x_i, x_j) = \langle x_i, x_j \rangle / ||x_i||\,||x_j||$

Active Learning with Graph-Based SSL

Given graph Laplacian L, define the energy $$\mathcal{J}(U;Y) := \frac{1}{2}\langle U, LU\rangle_F + \sum_{j\in\mathcal{L}} \ell(\mathbf{u}^j, \mathbf{y}^j)$$

- N x n_c matrix U (# pixels by # classes)
    - **u^j** = j^th row of matrix U
- **y^j** = "one-hot" encoding of classification of pixel j
- Loss functions:
    - Squared-Error $\ell(\mathbf{s},\mathbf{t}) = \frac{1}{2\gamma^2}\|\mathbf{s}-\mathbf{t}\|_2^2$ (will refer to as Multiclass Gaussian Regression, MGR)
    - Cross-Entropy (CE) $\ell(\mathbf{s},\mathbf{t}) = \sum_{c=1}^{n_c} s_c \ln t_c$

Look-Ahead Model

- "Hypothetical" model, *if were to label pixel k according to class* ***y^k.***

$$\mathcal{J}^{+k,\mathbf{y}^k}(U;Y,\mathbf{y}^k) := \frac{1}{2}\langle U, LU\rangle_F + \sum_{j\in\mathcal{L}} \ell(\mathbf{u}^j, \mathbf{y}^j) + \ell(\mathbf{u}^k, \mathbf{y}^k)$$

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How does labeling point k help our overall classification model?

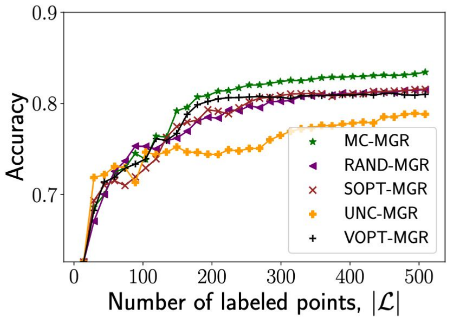
Active Learning Acquisition Functions

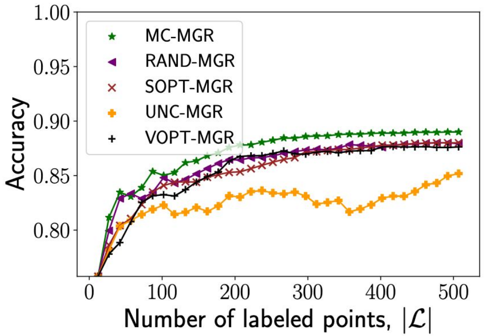
Acquisition function: Active learning criterion "function" that quantifies the utility of labeling an unlabeled point k

- **Random Sampling** : Select points uniformly at random
- **Uncertainty Sampling** : Select point that current classifier is "most uncertain" about
- **Variance Minimization** : Select point that will decrease the variance of the current classifier the most
    - **VOpt**: Minimize Trace of covariance matrix of Gaussian distribution of associated graph-based classifier
    - **SOpt**: "Sigma Optimality", variant of VOpt
- **Model Change** : Select point that will change the current classifier "the most"
    - Use look-ahead model with hypothetical "pseudo-label" to calculate

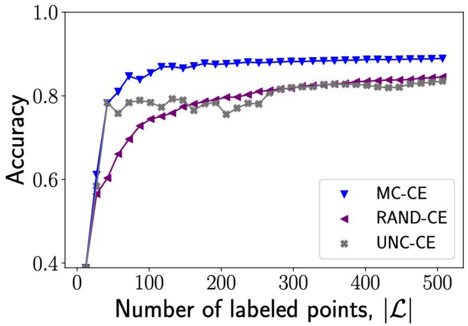
Results in HSI Application

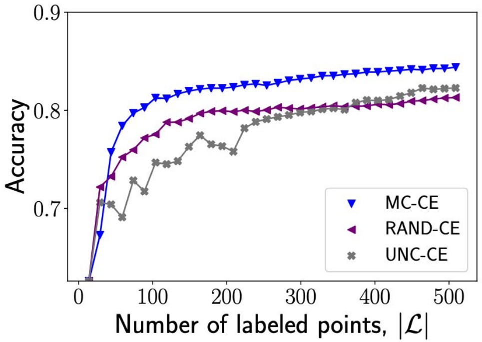
Multiclass Gaussian Regression





Cross-Entropy





Salinas-A (~7K total points)

Urban (~90K total points)

Synthetic Aperture Radar (SAR) Images

- Finer resolution images than standard radar
  - Mimic large antenna properties with multiple measurements from smaller antenna
  - Present in moving objects such as aircraft/spacecraft as well as drones
- Useful for Automatic Target Recognition (ATR) problems

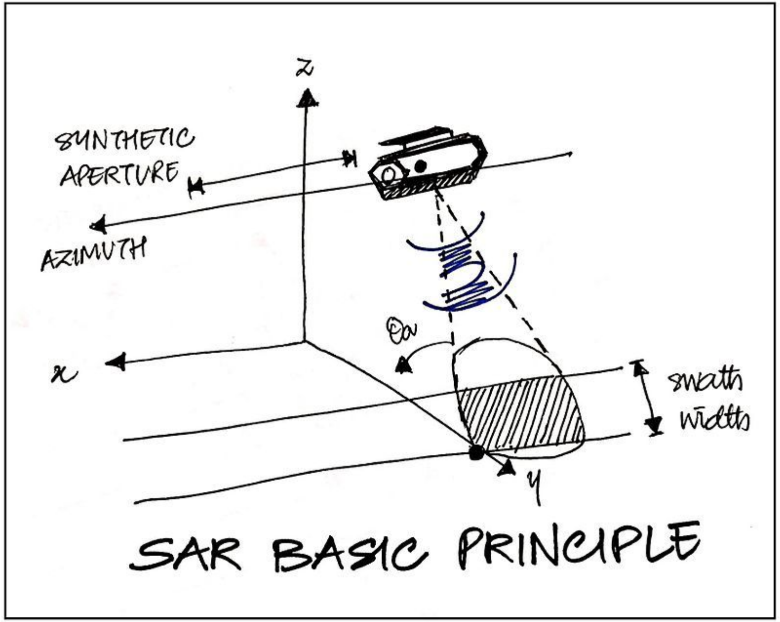


Image credit: https://commons.wikimedia.org/wiki/File:Synthetic_Aperture_Radar.jpg

MSTAR Dataset

- Collection of SAR images from 1995-1997.
  - 10 distinct types of ground vehicles such as tanks and trucks.
  - 6,874 images of size 88 x 88
- Magnitude and phase data

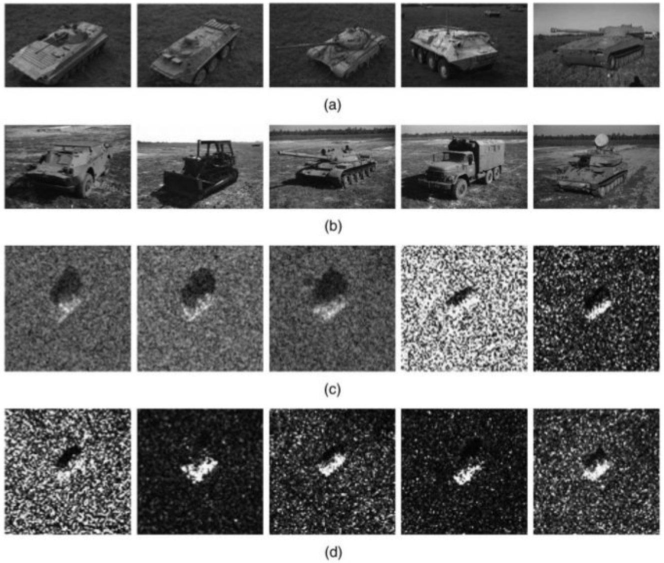


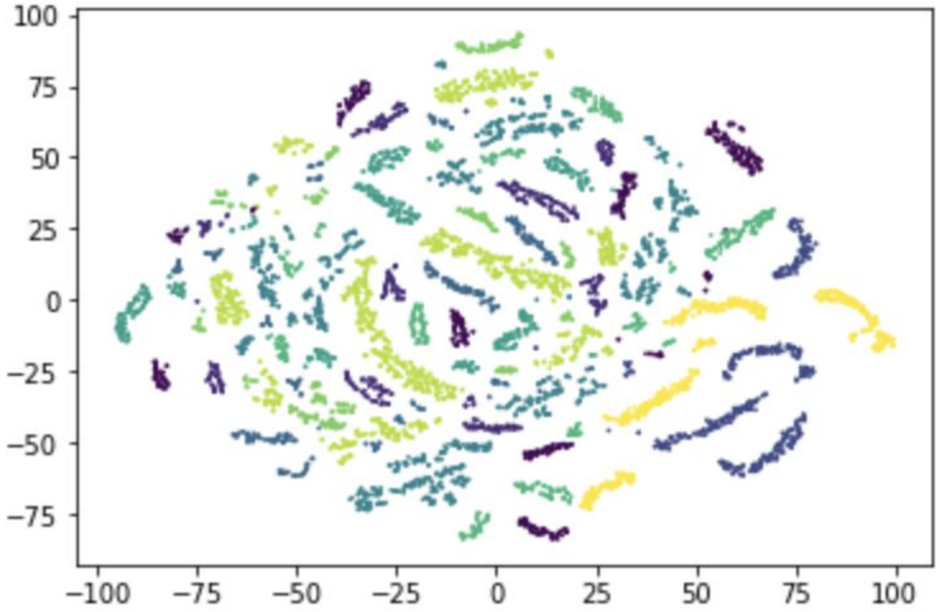
Fig. 2 MSTAR database. (a) and (b) Visible light images for BMP2, BTR70, T72, BTR60, 2S1, BRDM2, D7, T62, ZIL131, and ZSU23/4. (c) and (d) Corresponding SAR images for 10 targets measured at azimuth angle of 45 deg.

Image credit: Perumal, Vasuki (2013).

t-SNE Embedding of MSTAR for visualization

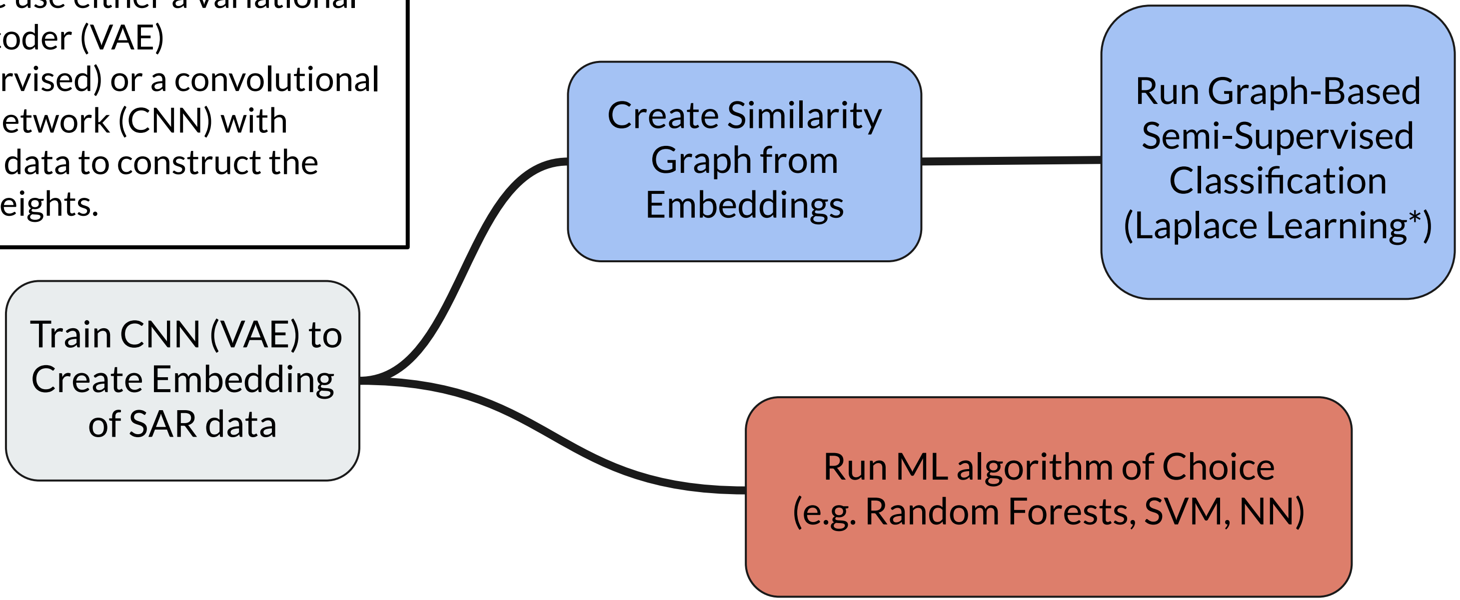
t-Distributed Stochastic Neighbor Embedding (t-SNE) is an unsupervised nonlinear embedding.   Analogous to PCA but preserving only small pairwise distances

- Each color represents a different class:
    - 2s1 gun
    - zsu23-4 gun
    - bmp2 tank
    - t62 tank
    - t72 tank
    - brdm2 truck
    - zill31 truck
    - btr60 transport
    - btr70 transport
    - bulldozer
- Seemingly “natural” clustering structure with minimal overlap
    - **Great candidate for graph-based learning!**



MSTAR Machine Learning Pipeline

Here we use either a variational autoencoder (VAE) (unsupervised) or a convolutional neural network (CNN) with training data to construct the graph weights.

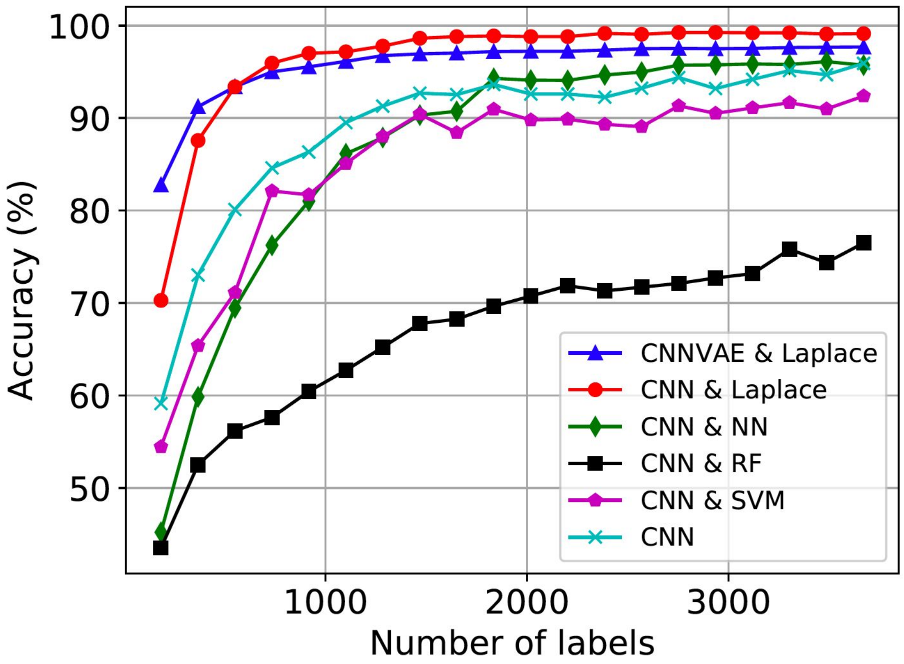


*Laplace Learning (AKA Label Propagation) of Zhu, Gharamani, and Lafferty (2003).

The Case for Graph Learning on MSTAR Data

- With CNN trained on 5%, 10%, 15%, … of training data, report the testing accuracies of various ML algorithms.
  - Provides “upper bound” on hoped for capability of unsupervised representations
- CNN-VAE representations trained on all of training data, **but without any label information**.

Graph Learning appears to be superior at using these learned representations!

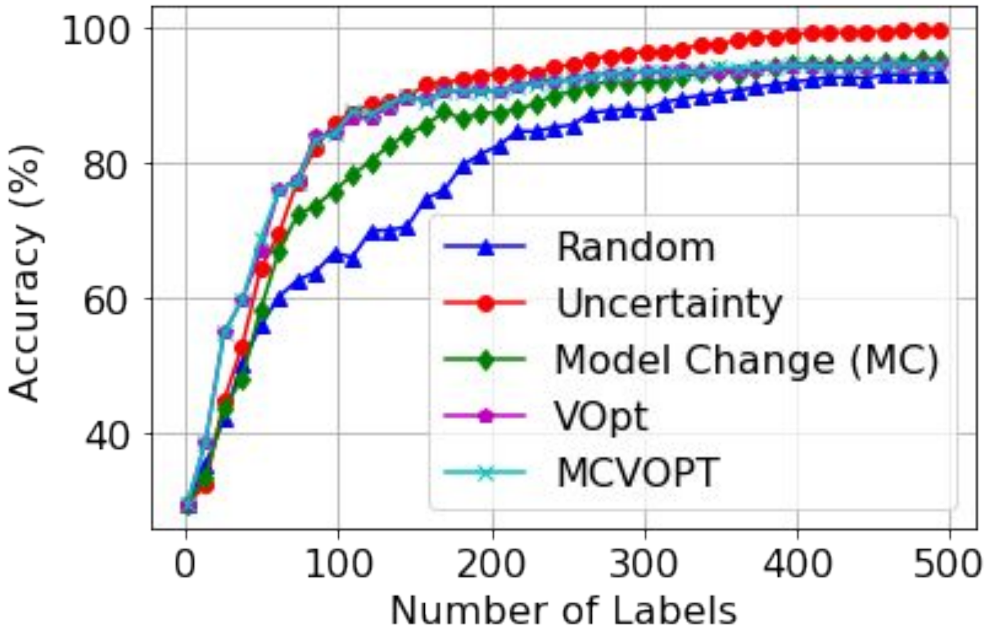


Active Learning on MSTAR

Given effectiveness of graph learning in low-label regime, we apply active learning to further improve the performance.

- Use CNN-VAE representations (i.e. no labeled data required for representation learning)
- Starting with *only 1 labeled point per class*, select 500 labeled points sequentially via the following acquisition functions:
    - Random sampling
    - Uncertainty
    - VOpt
    - Model Change (MC)
    - MCVOPT : A novel combination of VOpt and Model Change acquisition functions

Active Learning with Graph Learning on MSTAR



Here we use only the CNN-VAE for graph construction **without** any labels

Top performing: **Uncertainty Sampling**

- Related to geometry of dataset with many, distinct small clusters
- Exploration **and** Exploitation as a result

Conclusion

- Active learning in conjunction with graph-based learning is effective and efficient way to improve semi-supervised learning
- The natural clusters in MSTAR dataset ideal for graph learning
  - Clustering structure allows even simple acquisition functions (i.e. Uncertainty Sampling) to perform well
- Code available on GitHub
  - HSI experiments (https://github.com/millerk22/model-change-paper/)
  - MSTAR experiments (https://github.com/jwcalder/MSTAR-Active-Learning/)

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MSTAR, HSI, and SAR References 1

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