Graph-based Active Learning for Semi-supervised Classification of SAR Data

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Our technology-rich and connected world produces lots of Data ...

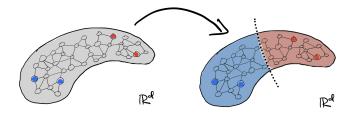
- Unlabeled Data : Inputs
 - Easy to Collect/Generate
- Labeled Data : Inputs + Outputs ("Labels")
 - Difficult to Collect/Generate



image credits: see references



Idea: Given a small amount of labeled data and a similarity graph created from all inputs, can I infer "accurate" labelings for the unlabeled data?





Great, you've leveraged using both labeled and unlabeled data!...

Why not try to improve?



Great, you've leveraged using both labeled and unlabeled data!...

Why not try to improve?

Hand-label the entire dataset...

COSTLY





Great, you've leveraged using both labeled and unlabeled data!...

Why not try to improve?

Hand-label the entire dataset...
COSTLY

Hand-label only a few more? DOABLE





Synthetic Aperture Radar Data

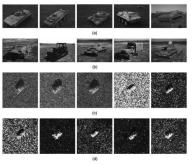


Fig. 2 MSTAR database. (a) and (b) Visible light images for BMP2, BTR70, T72, BTR60, 2S1, BRDM2, D7, T62, ZIL131, and ZSU234. (c) and (d) Corresponding SAR images for 10 targets measured at azimuth angle of 45 deg.

Figure 1: image credit: Perumal, Vasuki (2013)

MSTAR Dataset

- Synthetic Aperture Radar (SAR)
- Automatic Target Recognition (ATR)
- 6,784 images of size 88×88

Predefined train vs test split based on azimuth angle $(15^{\circ} \text{ vs } 17^{\circ})$

SAR Data Pipeline



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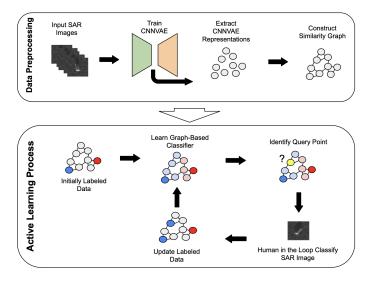


Figure 2: SAR Data Graph-Based Active Learning Pipeline

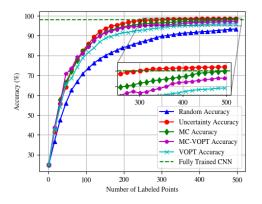
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With graph built from CNNVAE representations and *1 initially labeled point per class*, select 500 active learning query points sequentially.



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Results:

Achieve within 400 queries!

- 99% accuracy with < 10% training data</p>
- SOTA CNN: 98% Accuracy, but uses all training data

Figure 3: MSTAR Active Learning Results



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References |



Calder, Jeff, Brendan Cook, et al. "Poisson Learning: Graph Based Semi-Supervised Learning At Very Low Label Rates". In: *Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event.* Vol. 119. Proceedings of Machine Learning Research. PMLR, 2020, pp. 1306–1316. URL: http://proceedings.mlr.press/v119/calder20a.html.

Calder, Jeff, Dejan Slepčev, and Matthew Thorpe. Rates of Convergence for Laplacian Semi-Supervised Learning with Low Labeling Rates. 2020. arXiv: 2006.02765 [math.ST].

Christophe, Emmanuel, Corinne Mailhes, and P Duhamel. "Hyperspectral image compression: Adapting SPIHT and EZW to anisotropic 3-D wavelet coding". In: *IEEE transactions on image processing* 17 (2009). a publication of the IEEE Signal Processing Society, pp. 2334–46.

Maaten, Laurens van der and Geoffrey Hinton. "Visualizing Data using t-SNE". In: *Journal of Machine Learning Research* 9 (2008), pp. 2579–2605. URL: http://www.jmlr.org/papers/v9/vandermaaten08a.html.

Miller, Kevin, Hao Li, and Andrea L Bertozzi. "Efficient Graph-Based Active Learning with Probit Likelihood via Gaussian Approximations". en. In: *ICML* Workshop on Real-World Experiment Design and Active Learning (2020).

Perumal, Vasuki. "Automatic target classification of manmade objects in synthetic aperture radar images using Gabor wavelet and neural network". In: *Journal of Applied Remote Sensing* 7 (2013).

Rasmussen, Carl Edward and Christopher K. I. Williams. Gaussian processes for machine learning. Adaptive computation and machine learning. Cambridge, Mass: MIT Press, 2006. ISBN: 978-0-262-18253-9.

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Settles, Burr. "Active Learning". en. In: Synthesis Lectures on Artificial Intelligence and Machine Learning 6.1 (June 2012), pp. 1–114. ISSN: 1939-4608, 1939-4616. DOI: 10.2200/S00429ED1V01Y201207AIM018. URL: http://www.morganclaypool.com/doi/abs/10.2200/S00429ED1V01Y201207AIM018 (visited on 06/11/2020).

Zhu, Xiaojin, Zoubin Ghahramani, and John Lafferty. "Semi-supervised learning using Gaussian fields and harmonic functions". In: *Proceedings of the Twentieth International Conference on International Conference on Machine Learning*. ICML'03. Washington, DC, USA: AAAI Press, Aug. 2003, pp. 912–919. ISBN: 978-1-57735-189-4. (Visited on 06/11/2020).

Zhu, Xiaojin, John Lafferty, and Zoubin Ghahramani. "Combining Active Learning and Semi-Supervised Learning Using Gaussian Fields and Harmonic Functions". In: *ICML 2003 workshop on The Continuum from Labeled to Unlabeled Data in Machine Learning and Data Mining*. 2003, pp. 58–65.



- https://hocview.com/fitness-tracker-that-does-not-require-a-smartphone-or-computer/
- https://www.kenhub.com/en/library/anatomy/normal-chest-x-ray
- https://edu.gcfglobal.org/en/gmail/introduction-to-gmail/1/
- https://www.cs.toronto.edu/~kriz/cifar.html