Optimizing the Wisdom of the Crowd: Inference, Learning, and Teaching

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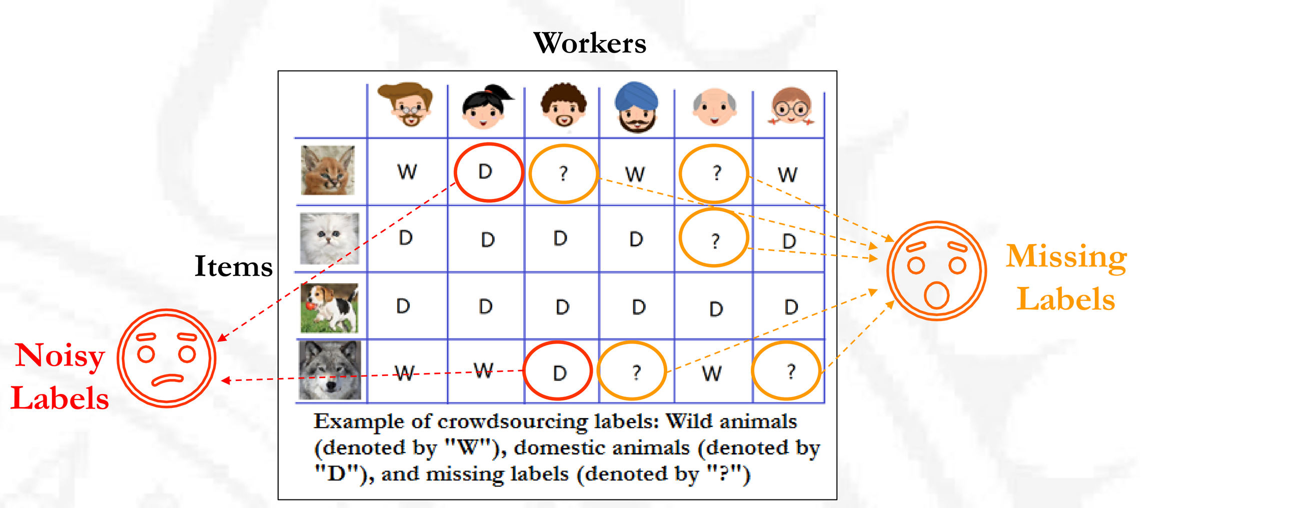
Background:

❑ Example 1: Crowdsourcing



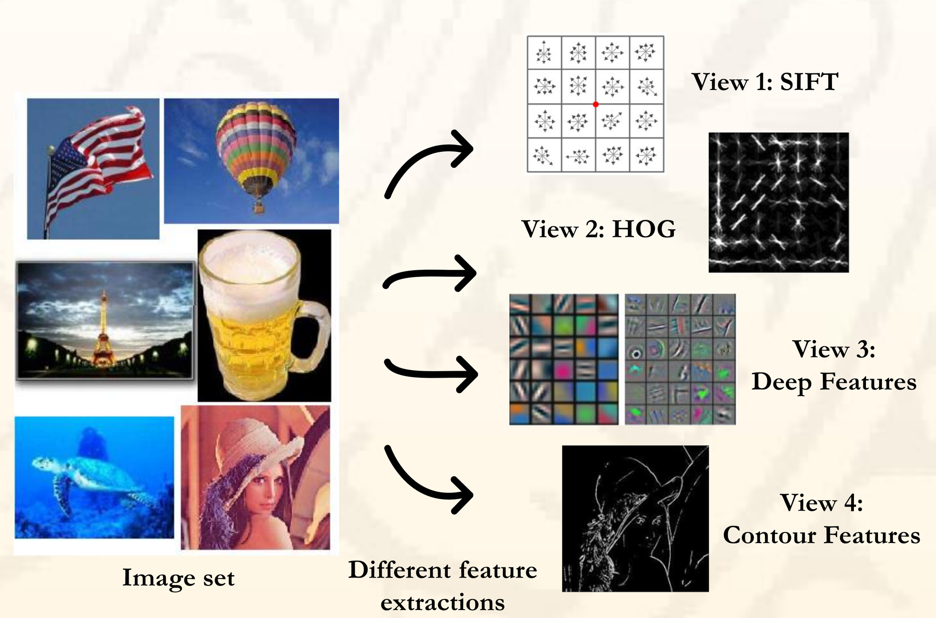
Example of crowdsourcing labels: Wild animals (denoted by "W"), domestic animals (denoted by "D"), and missing labels (denoted by "?")

Low cost: Collecting large amounts of labels is economic.

Low quality: Collected labels from the crowd (non-expert) are noisy.
Missing labels: Some workers are not willing to label all of the items.

❑ Example 2: Multi-task Learning

❑ Example 3: Multi-view Learning



Label Inference:

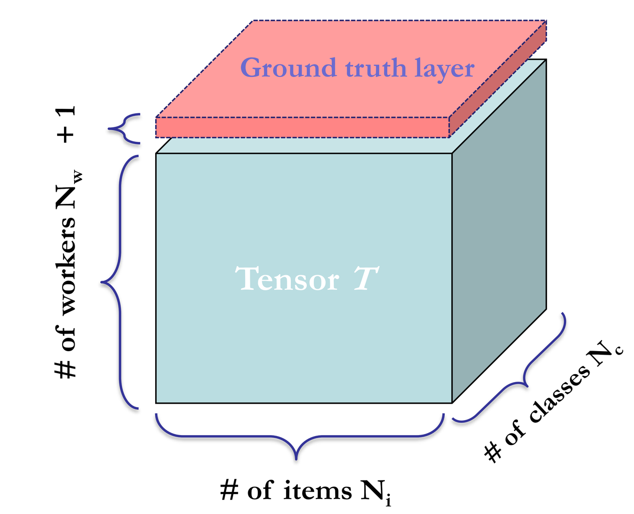
❑ Learning Goal

❖ Infer the true label of each item

❑ Main Principle

❖ Tensor Completion

$$\min_{\mathcal{X}, M_l} : \sum_{l=1}^{n} \alpha_l \|M_l\|_* + \frac{\beta_l}{2}\|\mathcal{X}_{(l)} - M_l\|_F^2 + R(\mathcal{X}_{i_g::})$$
$$s.t. : \mathcal{X}_\Omega = \mathcal{T}_\Omega$$



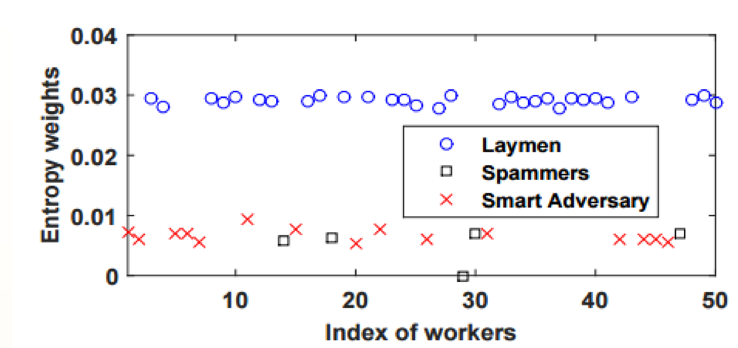
Heterogenous Learning:

❑ Problem Setting

❖ Learn a prediction function $f : \mathbf{x} \rightarrow y$, using the crowdsourced labels.

❑ Classifier Ensemble

$$\tilde{y} = \mathrm{sign}\left(\sum_{j=1}^{N_w} c_j \mathbf{w}_j^T \mathbf{x}_{test}\right)$$



❑ Main Principles

❖ **Multi-task Learning:**

➢ Tensor Rank Minimization

$$\min_{\mathcal{W}} \underbrace{\sum_{t=1}^{T}\sum_{i=1}^{N_t}\sum_{j=1}^{N_w} \mathrm{L}\left(Y_t(i,j), \mathcal{W}_{tj:}^T X_t(i,:)\right)}_{\text{Loss term}} + \underbrace{\mathrm{Rank}(\mathcal{W})}_{\text{Low rank term}} + \underbrace{\mathrm{R}(\mathcal{W})}_{\text{Regularization term}}$$

❖ **Multi-view Learning:**

➢ Worker Consensus & View Consistency + Feature Sparsity

$$\min_{W} \sum_{k=1}^{N_w}\sum_{i=1}^{N} \log\left(1 + \exp(-Y_{ik}\mathbf{w}_k^T \mathbf{x}_i)\right) + \sum_{l=1}^{2} \alpha_l \|\mathcal{A}_{(l)}\|_* + \lambda(\|W\|_G + \|W\|_{2,1})$$

Feature group sparsity

Feature common sparsity

l=1: worker consensus

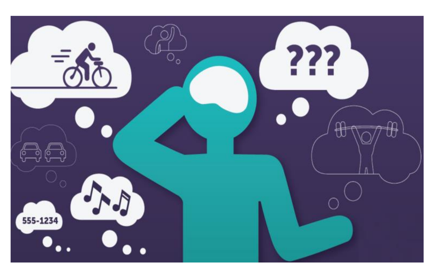
l=2: view consistency

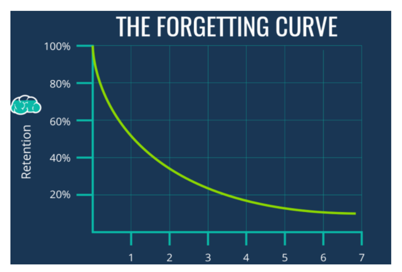
Crowd Teaching:

❑ JEDI Teaching Framework

❖ **A**d**J**ustable

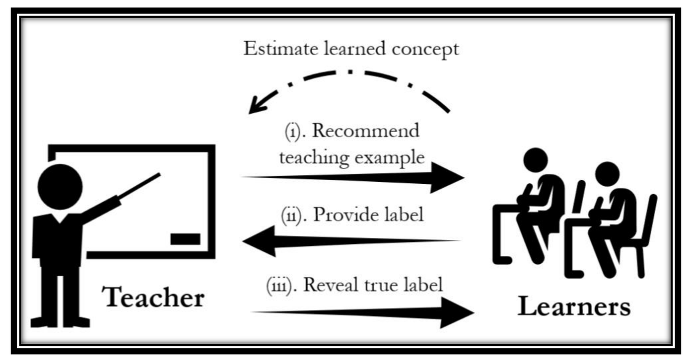
❖ **E**xponentially





❖ **D**ecayed Memory

❖ **I**nteractive Crowd Teaching



❑ Main principle

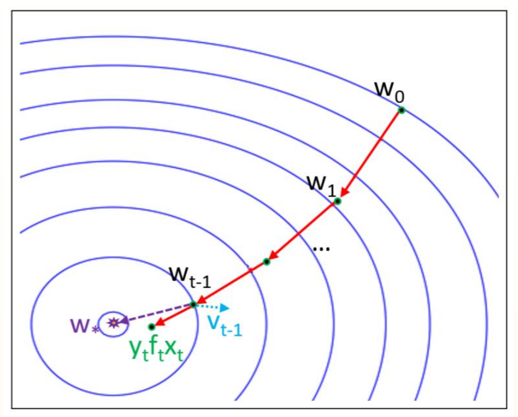
❖ Trade-off between *teaching usefulness* and *teaching diversity*

Maximize the teaching usefulness

$\langle \mathbf{w}_* - \mathbf{w}_{t-1}, y_t f_t \mathbf{x}_t \rangle$

target learning direction

teaching direction



Increase the teaching diversity

$\|y_t f_t \mathbf{x}_t - \mathbf{v}_{t-1}\|_2^2$

teaching direction

concept momentum

References:

1. **Zhou, Yao** and He, Jingrui. Crowdsourcing via Tensor Augmentation and Completion. *25th International Joint Conference on Artificial Intelligence* (**IJCAI 2016**)
2. **Zhou, Yao** and Ying, Lei and He, Jingrui. MultiC²: an Optimization Framework for Learning from Task and Worker Dual Heterogeneity. *SIAM International Conference on Data Mining* (**SDM 2017**)
3. **Zhou, Yao** and He, Jingrui. A Randomized Approach for Crowdsourcing in the Presence of Multiple Views. *IEEE International Conference on Data Mining* (**ICDM 2017**)
4. **Zhou, Yao** and Nelakurthi, Arun Reddy and He, Jingrui. Unlearn What You Have Learned: Adaptive Crowd Teaching with Exponentially Decayed Memory Learners. *ACM SIGKDD Conference on Knowledge Discovery and Data Mining* (**KDD 2018**)

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