Collaborative Active Learning of a Kernel Machine Ensemble for Recognition

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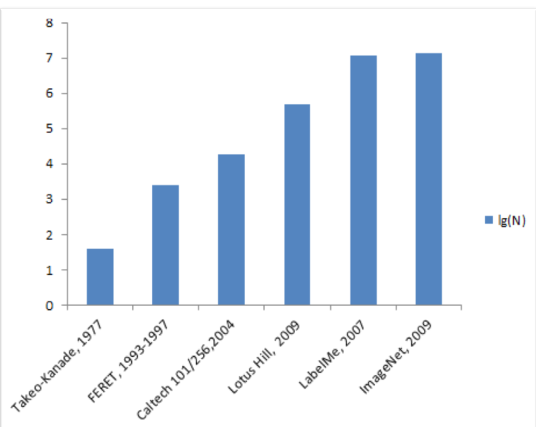
Background and motivation



Datasets	Description	How to collect labels
Takeo-Kanade	20 subjects, 40 face images	Labeled by the researchers.
FERET	856 subjects, 2413 face images	Government hired vendors to collect
Caltech 101/256	>100 categories, serveral tens of images per category	Collect by students
Lotus Hill	280 categories, 500k images	Hired professional artists to label
LabelMe	180 categories, 12M images	Used a web-based annotation tool
ImageNet	21841 synsets, > 14 images	Used Amazon Mechanical Turk

Crowd-sourcing labeling
- ➢Pros: cheap and fast to obtain large quantity of label data.
- ➢Cons: the obtained labels can be very noisy.

Previous work
- ➢Majority voting based confidence. [Donez et al 2009-2010]
- ➢Incremental relabeling mechanism. [Zhao et al 2011]

Disadvantage
- ➢Cannot handle label noise during the labeling process.
- ➢The label quality will be heavily affect if the malicious labelers occur at the early stage.
- ➢Only investigate the case where a single copy of labels is engaged.

Motivation
- ➢We introduce the active learning strategy into the framework.
- ➢We want to enable the collaborative work among the multiple labelers.
- ➢We want to handle the label noise during the labeling process.
- ➢We want to detect and even kick out the irresponsible labelers at the early stage.
- ➢We also want to make full use of multiple copies of labels.

Datasets

ImageNet dataset (10 categories, LLC features)
Gender face dataset (9441 face images)

Comparisons

Comparisons:
- CAL: collaborative active learning (ours).
- CRL: collaborative random learning (ours).
- MIAL: multiple independent active learning (remove cross term from CAL).
- MIRL: multiple independent random learning (remove cross term from CAL).
- SVM-MIAL: multiple independent active learning SVM.
- SVM-MIRL: multiple independent random learning SVM.
- MVAL: single classifier with majority voted labels using logistic loss.
- SVM-MVAL: single classifier with majority voted labels using hinge loss.
- ML-Bernoulli-AL: active learning with multiple labelers (Bernoulli version) proposed by Yan Yan et al. [ICML 2011]
- ML-Gaussian-AL: active learning with multiple labelers (Gaussian version) proposed by Yan Yan et al. [ICML 2011]

Sponsors

Learning kernel machine

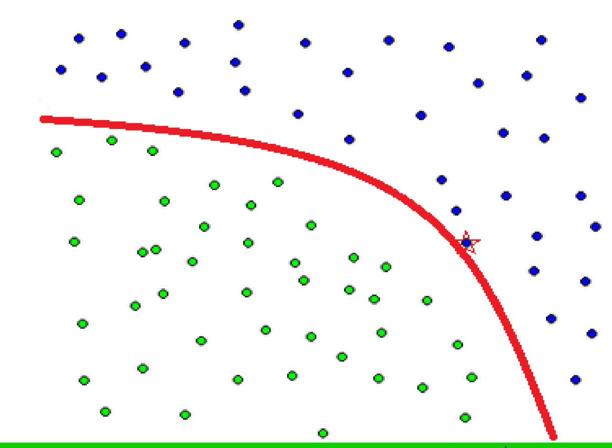
Objective function:
$$\mathcal{L}(\mathcal{D}) = \sum_{i=1}^{K}\sum_{x_j\in\mathcal{L}_i} L_i(y_i(j), f_i(\mathbf{x}_j)) \text{ ---- Individual term}$$
$$+ \sum_{1\le i\ne j\le K}\sum_{x_k\in\mathcal{D}_i\cap\mathcal{D}_j} L_C^i(y_k(j), f_i(\mathbf{x}_k)) \text{ ---- cross term}$$
$$+ \lambda\sum_{i=1}^{K}\Omega(\|f_i\|_{\mathcal{H}}) \text{ ---- regularization term}$$

Kernel form classifier: $f_i(\mathbf{x}) = \sum_{\mathbf{x}_j\in\mathcal{D}_i}\alpha_{ij}\mathbf{k}(\mathbf{x}_j,\mathbf{x})$

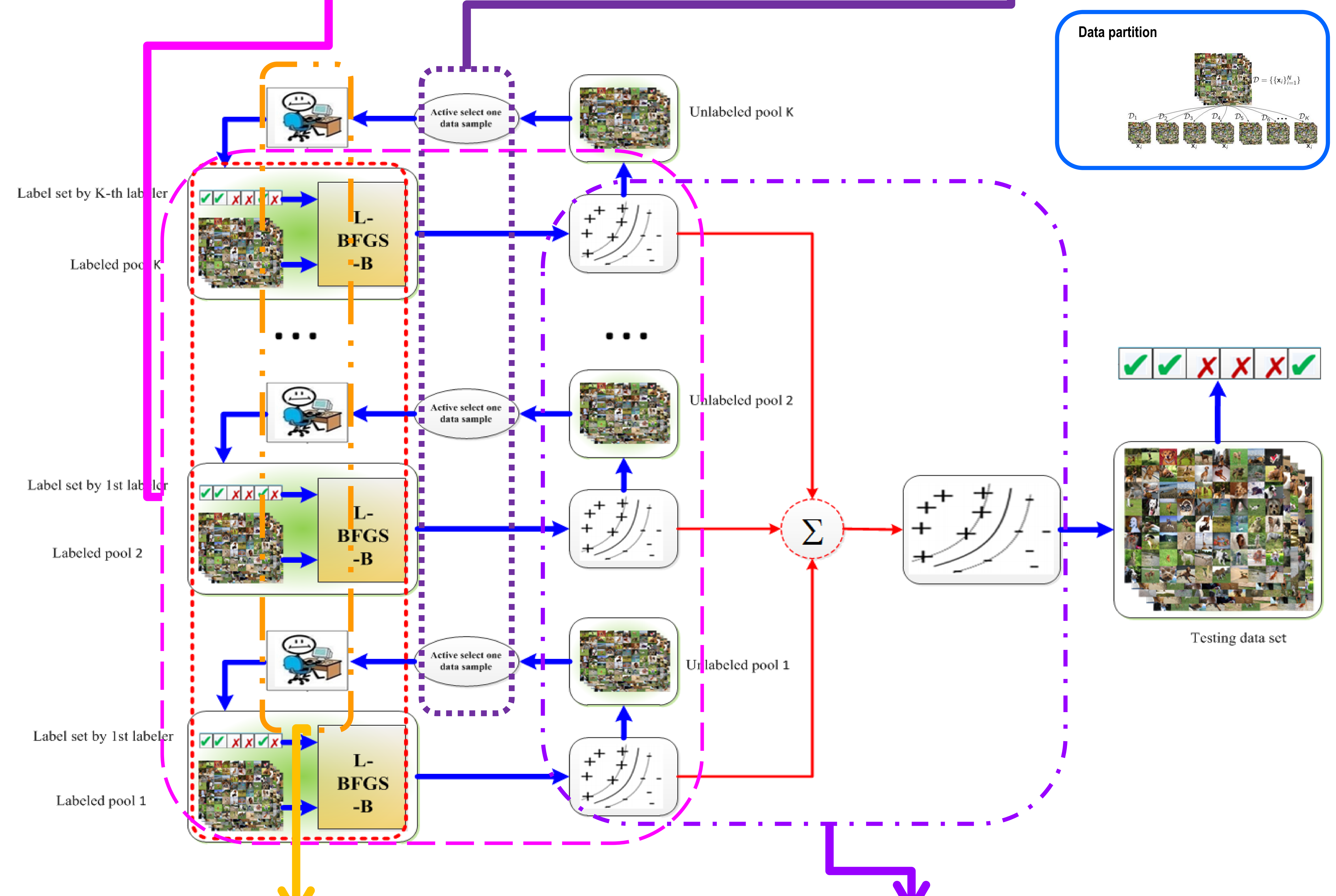
Objective function: $\mathcal{L}(\mathcal{D}) = \sum_{i=1}^{K}\mathbf{1}^T\log\{1+e^{-\mathbf{K}_i^i(\mathbf{y}_i)\vec{\alpha}_i}\} + \sum_{i\ne j}\mathbf{1}^T\log\{1+e^{-\mathbf{K}_j^i(\mathbf{y}_j^i)\vec{\alpha}_i}\} + \lambda\sum_i\vec{\alpha}_i^T\mathbf{K}_i\vec{\alpha}_i$

Active learning strategy

For labeler i, select $\mathbf{x}_k\in\mathcal{U}_i$ that closest to the decision boundary.



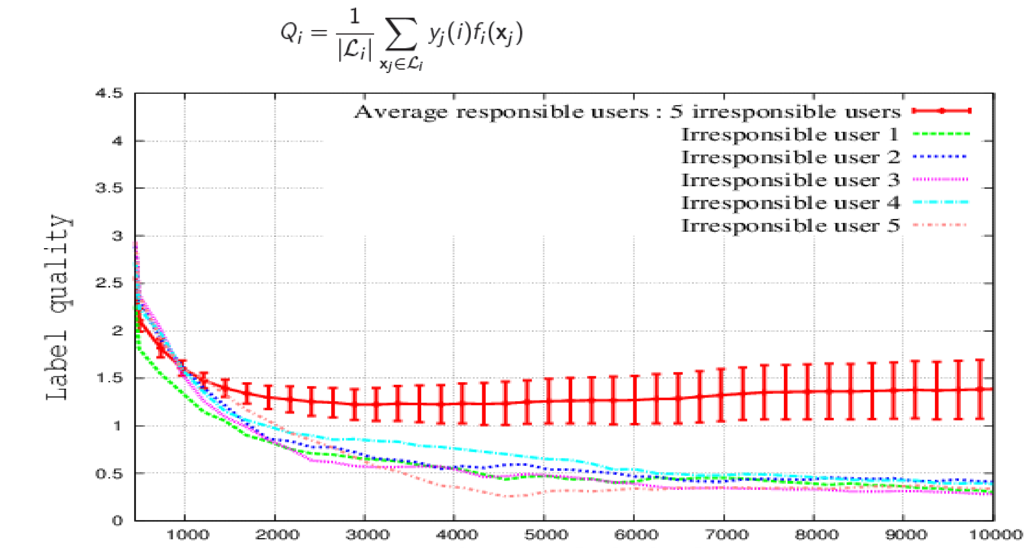
$$\mathbf{x}_i^* = \arg\min_{\mathbf{x}_k\in\mathcal{U}_i}\mathcal{A}_i(\mathbf{x}_k)$$
$$\mathcal{A}_i(\mathbf{x}_k) = |f_i(\mathbf{x}_k)|$$
$$f_i(\mathbf{x}_k) = \sum_{\mathbf{x}_j\in\mathcal{D}_i}\alpha_{ij}\mathbf{k}(\mathbf{x}_j,\mathbf{x}_k)$$



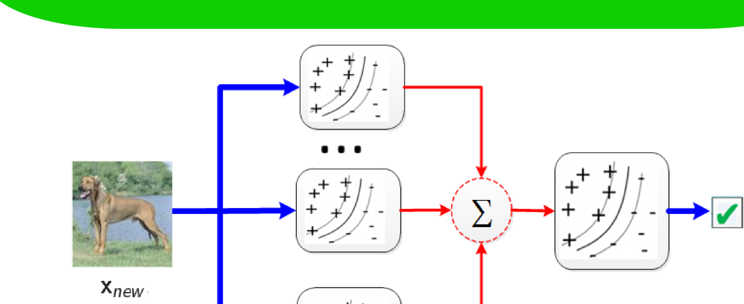
Label quality control

Label quality is defined to indicate if labeler i is conflicting with other labelers.

$$Q_i = \frac{1}{|\mathcal{L}_i|}\sum_{\mathbf{x}_j\in\mathcal{L}_i} y_j(i) f_i(\mathbf{x}_j)$$



Kernel machine ensemble

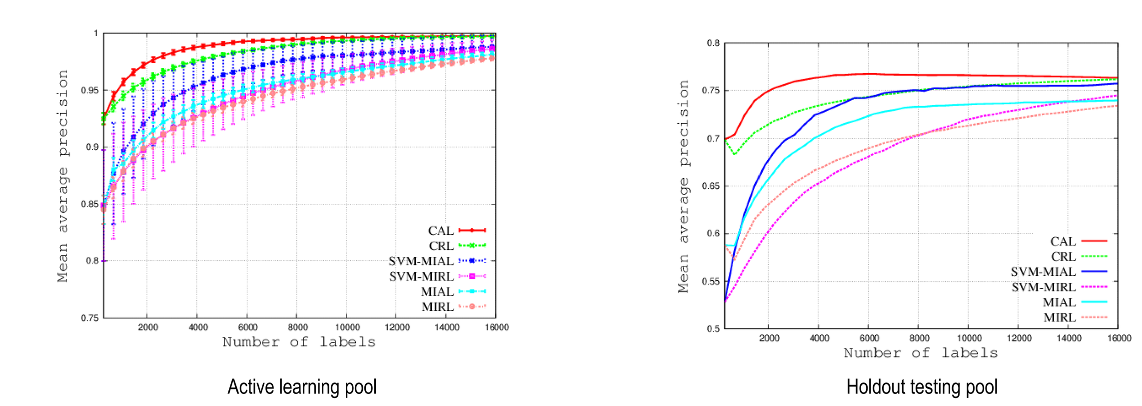


To classify a new data sample $\mathbf{x}_{new}$
1). Identify the nearest neighbor $\mathcal{N}(\mathbf{x}_{new})$ of $\mathbf{x}_{new}$ in $\mathcal{D}$.
2). Final prediction score

$$f(\mathbf{x}_{new}) = \sum_{\mathcal{N}(\mathbf{x}_{new})\in\mathcal{D}_i} f_i(\mathbf{x}_{new})$$

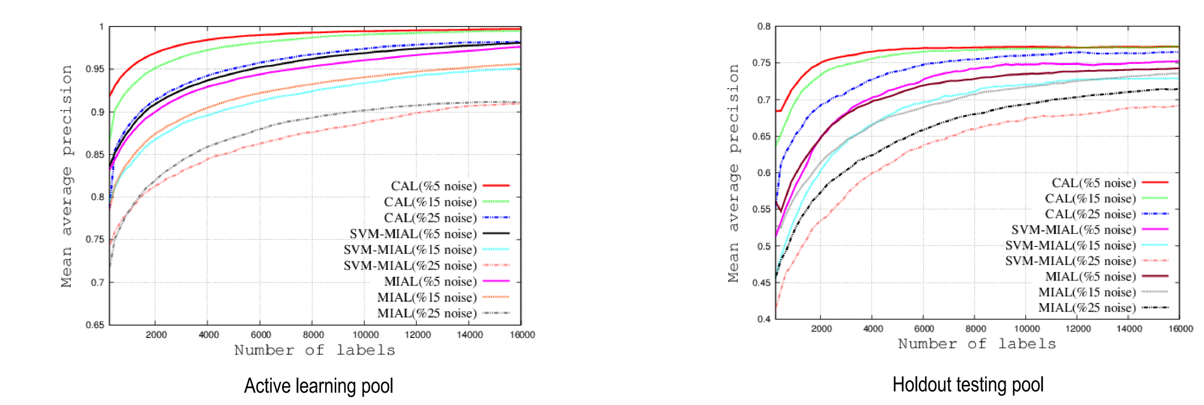
Simulated experiments

Simulated experiment result 1: (with noise-free labels)



Our CAL leads the improvement.

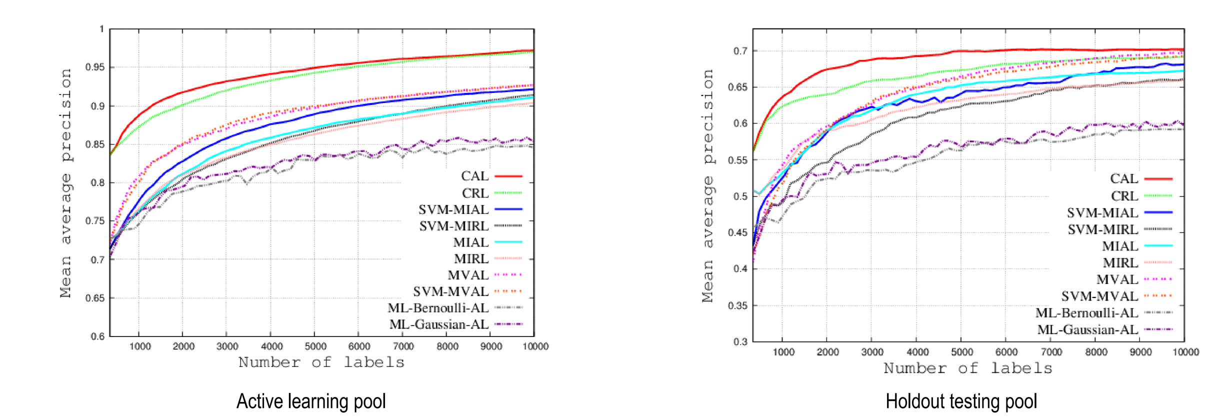
Simulated experiment result 2: (with different noise level labels)



At all noise level, our CAL achieves the highest mean average precision in both active learning and holdout testing pool.

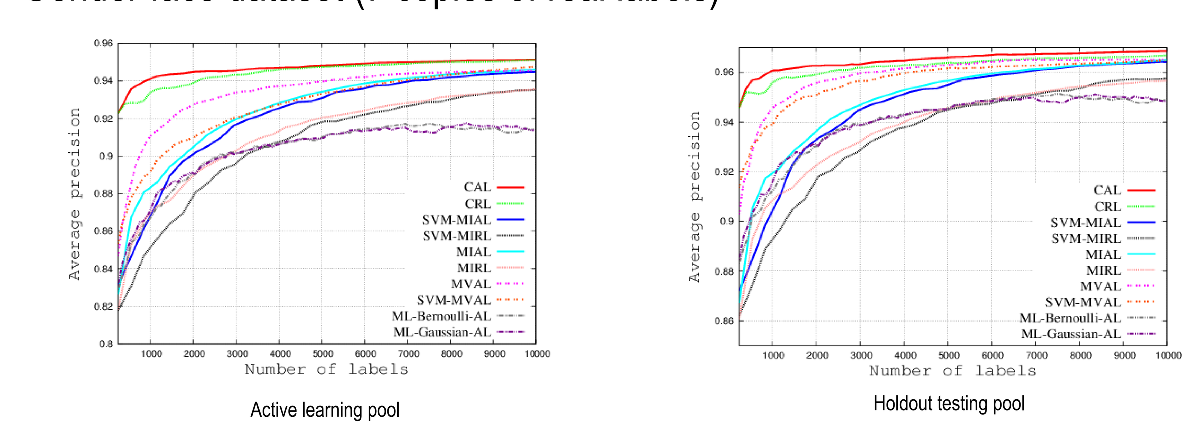
Experiments with real labels

ImageNet dataset (5 copies of real labels on 5 categories)



Our CAL outperforms the other 9 baselines.

Gender face dataset (7 copies of real labels)



Our CAL still outperforms the other 9 baselines.

Conclusion

We present a collaborative active learning framework to support multiple labelers to collaboratively label a set of images to learn an ensemble kernel machine classifier.

As verified by our experiments, our approach enables more efficient model learning from multiple labelers, is robust to label noise and irresponsible labelers, and can readily detect irresponsible labelers online.