

Recent Progress on Active Learning

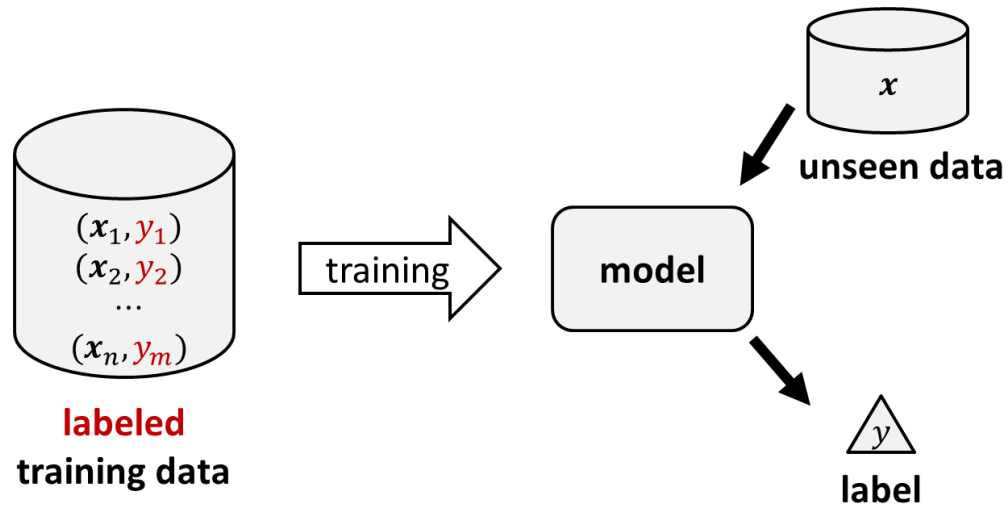
Sheng-Jun Huang (黄圣君)

Nanjing University of Aeronautics and Astronautics



2018-4-22 @Valse

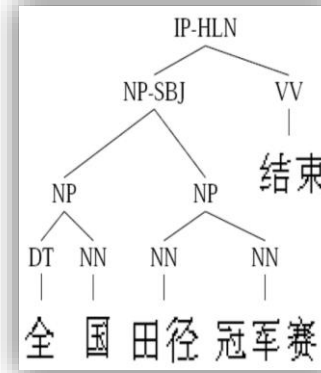
Learning with Fewer Labeled Data



$$R(h) \leq R_{\text{emp}}(h) + \sqrt{\frac{\ln |\mathcal{H}| + \ln \frac{2}{\delta}}{2m}}$$

Labeled data is **important** but **expensive**

→ Can we learn with fewer labeled data?



2 years for 4000 sentences
in Penn Chinese Treebank

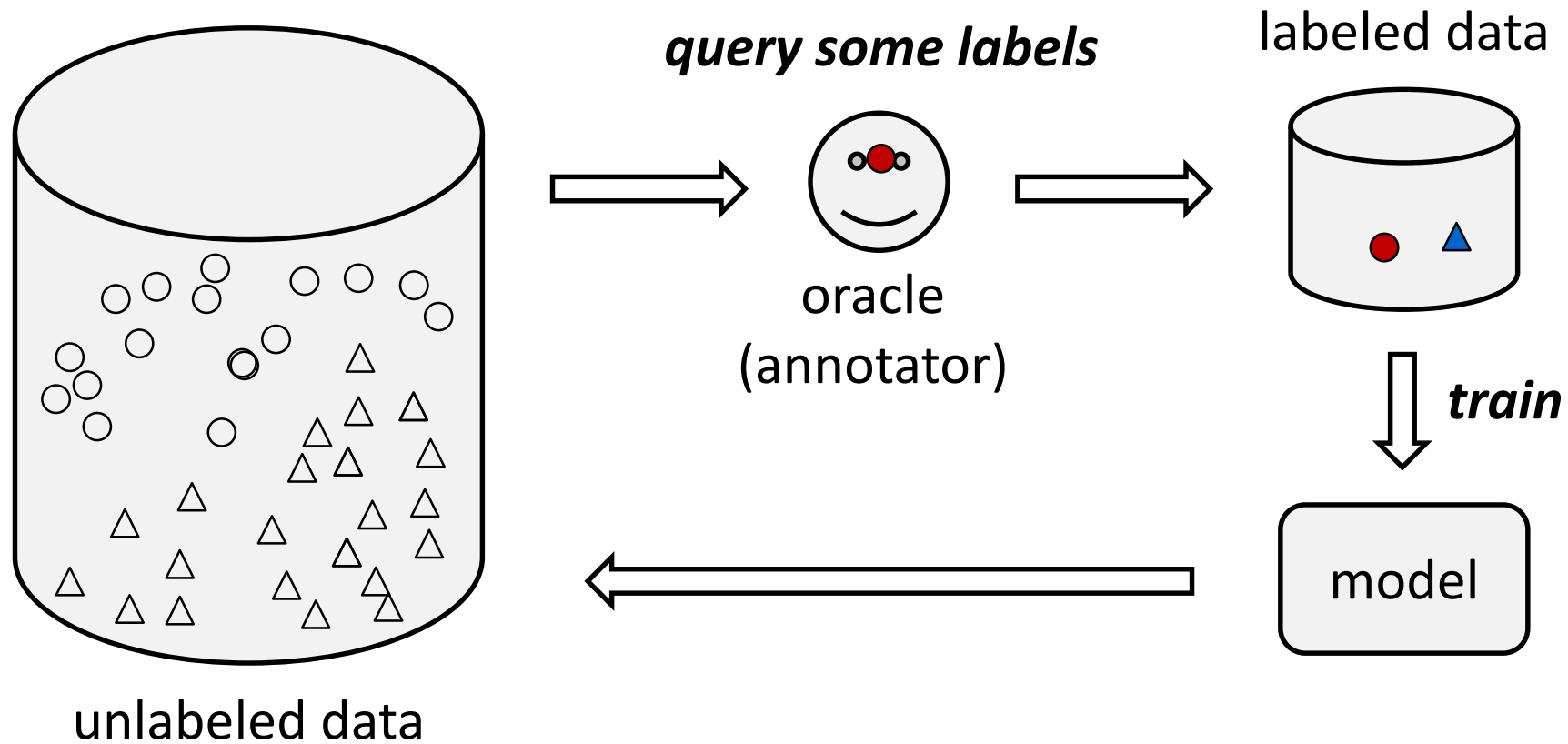
time consuming



only experts can provide
accurate annotations

high expertise

Active Learning

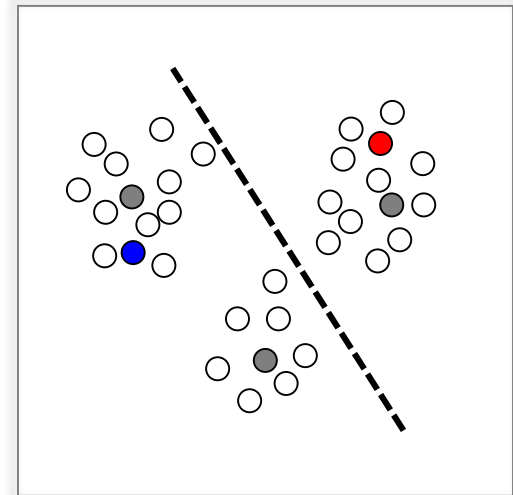
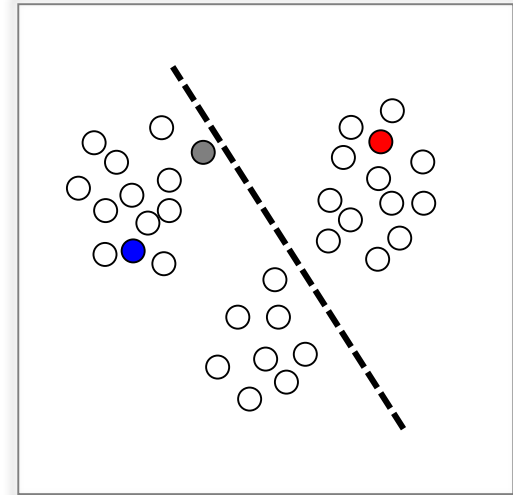
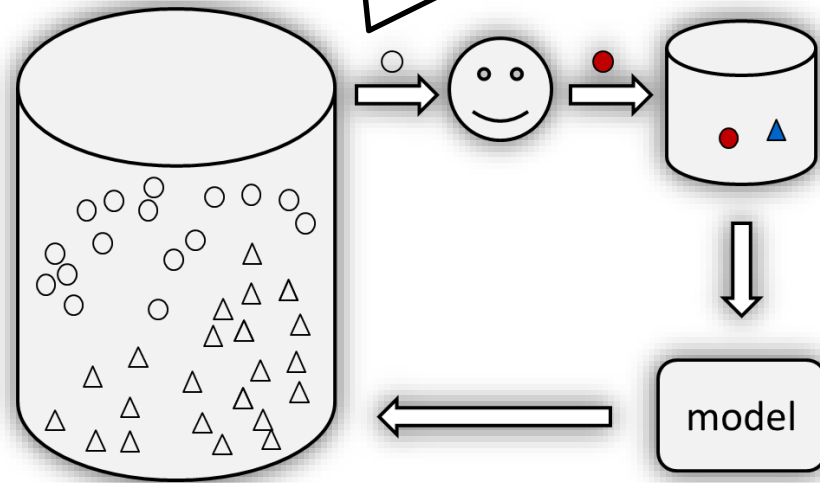


Goal: train an effective model with least labeling cost

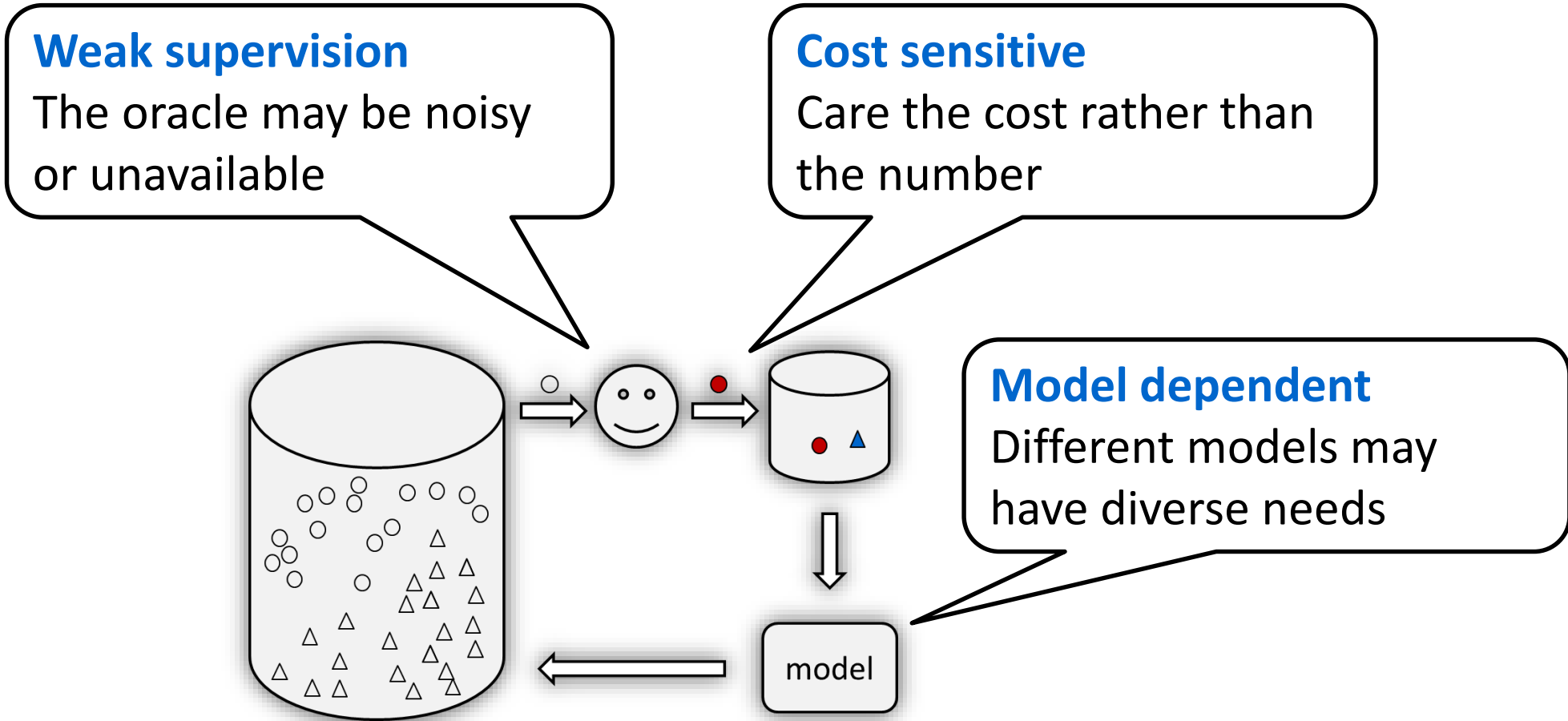
Active Learning

Which instance to select?

- Informative instances
- Representative instances
- Informative & representative instances

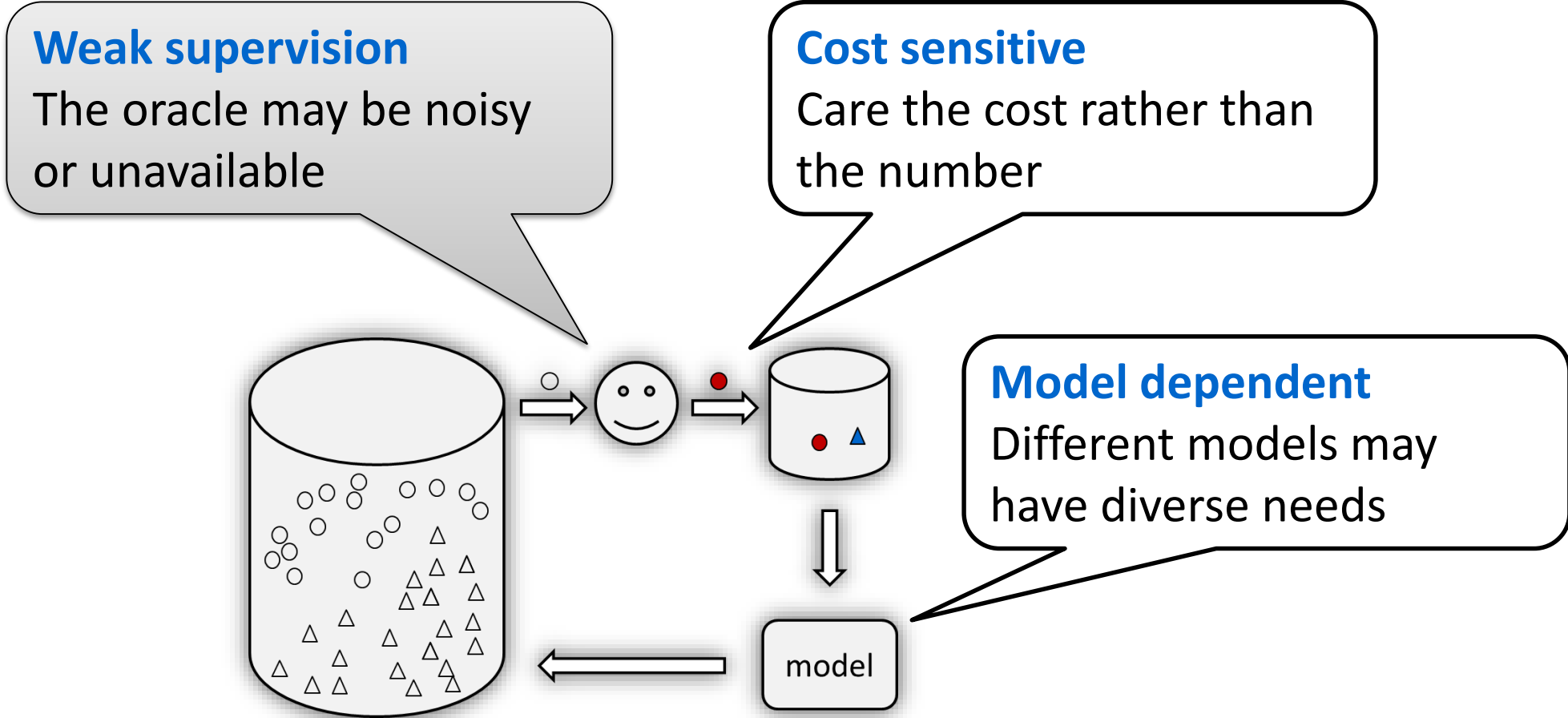


Recent Progress



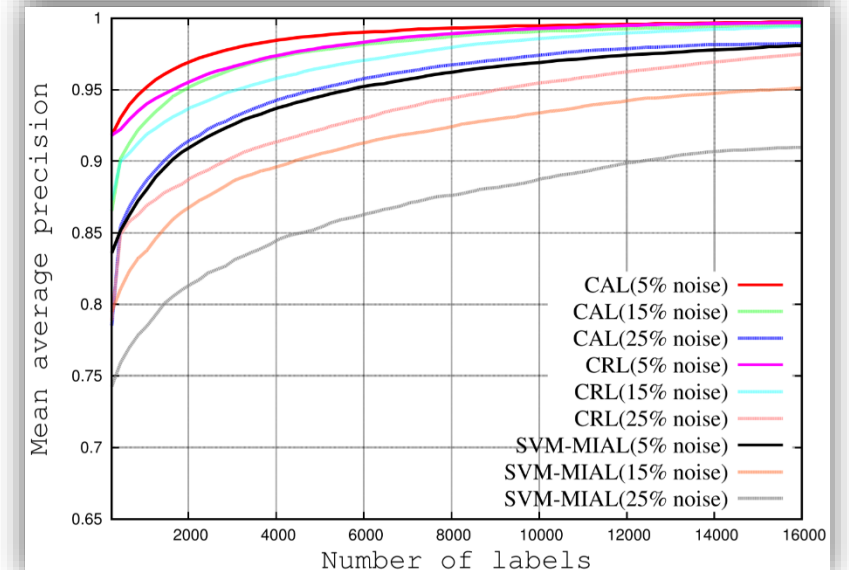
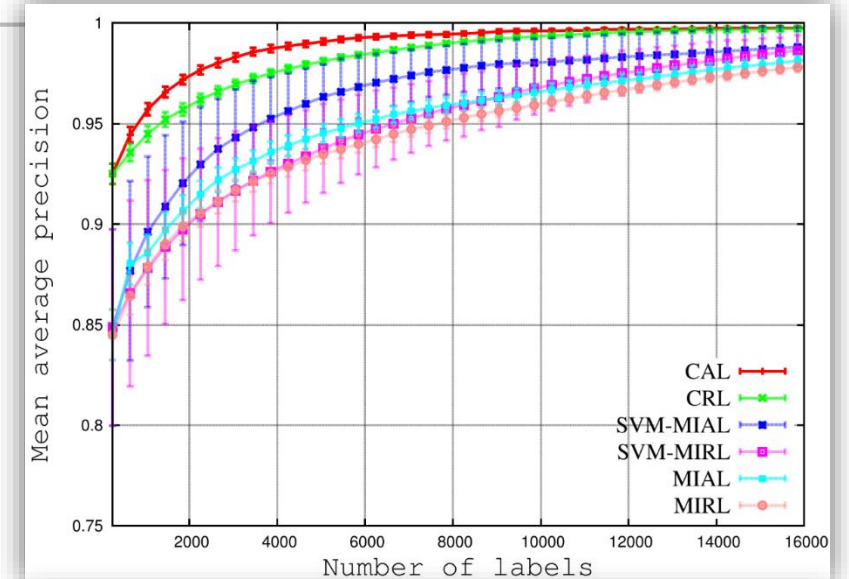
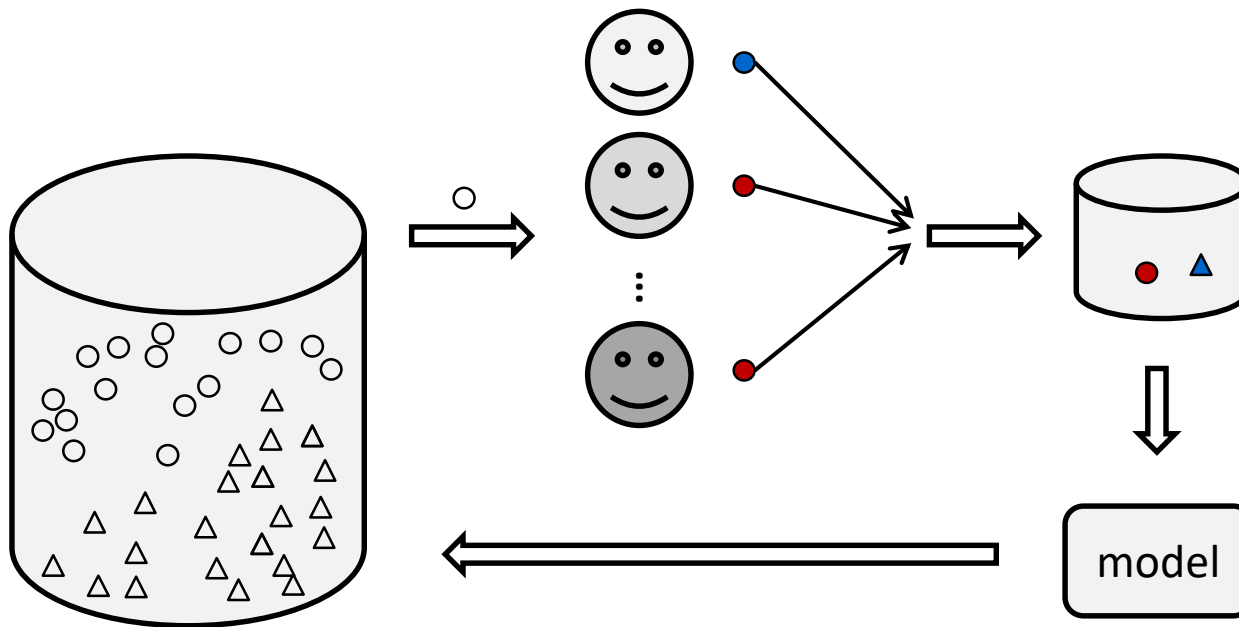
More Practical and More Systematic

Recent Progress



Active learning with Weak Supervision

- Collaborative labeling from crowds
 - Labeler quality estimation
 - Ensemble kernel machine classifier
 - Robust to label noise



Active learning with Weak Supervision

- Pairwise comparison from noisy labelers
 - Leverage both types of oracles
 - Lower querying complexity under different noise conditions

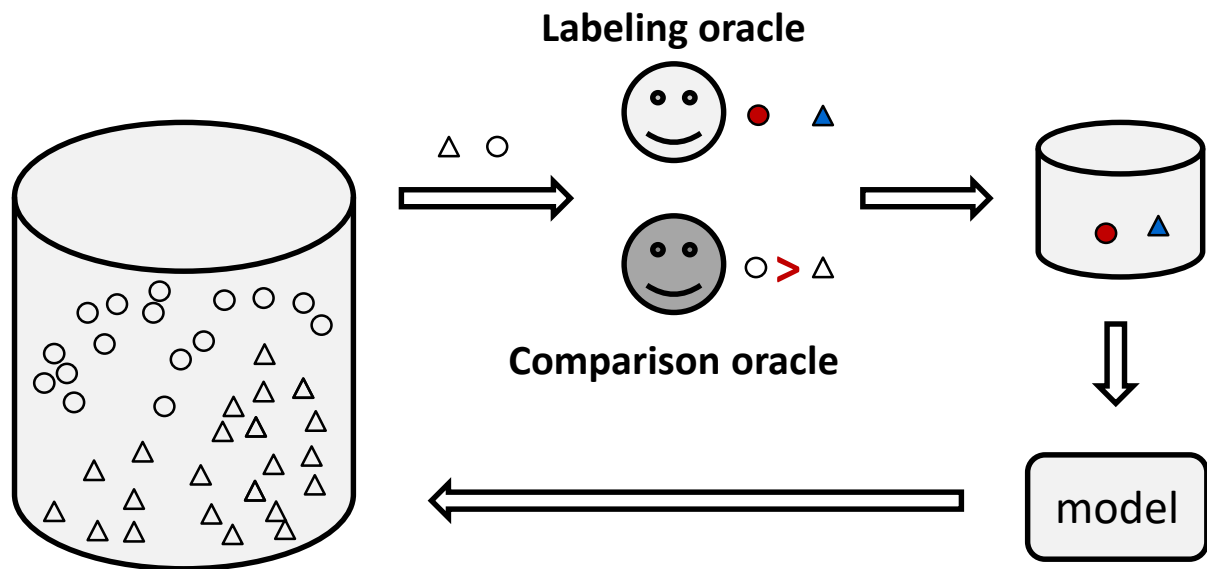
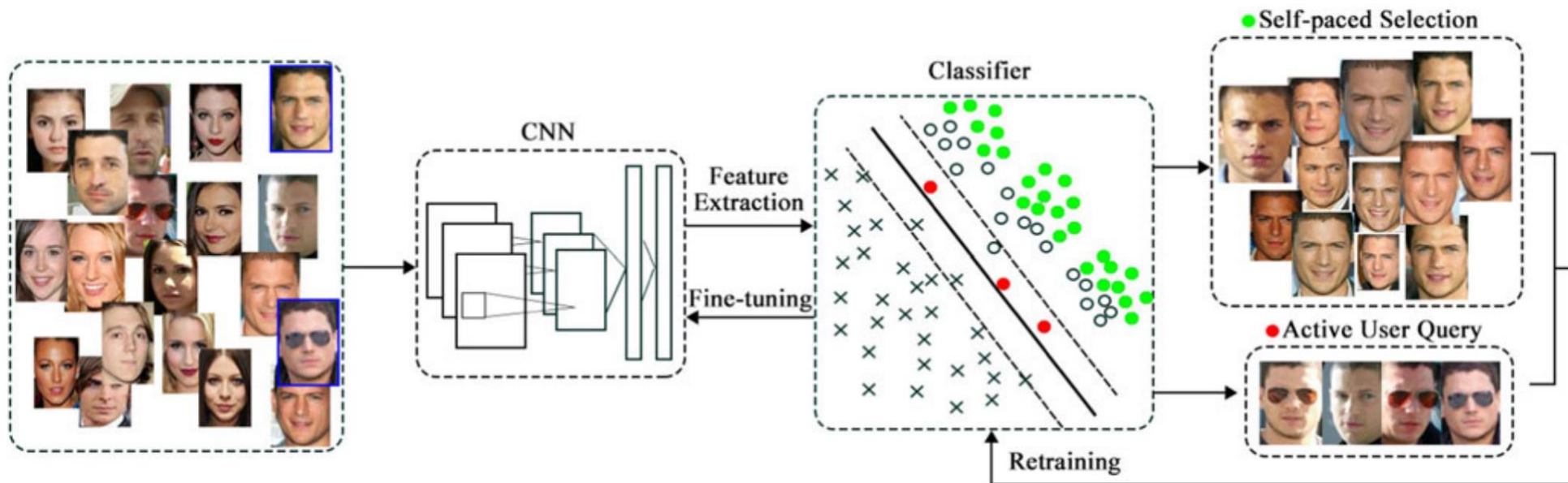
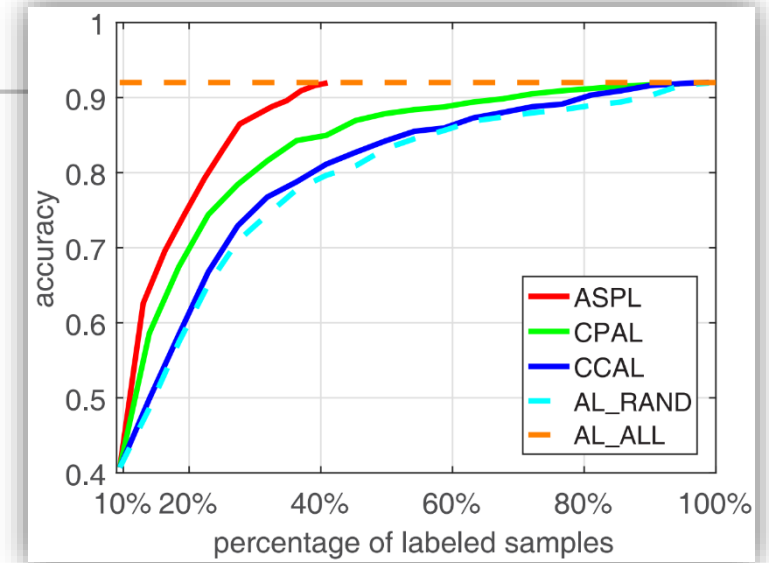


Table 2: Comparison of various methods for learning of halfspaces (Omit

Label Noise	Work	# Label	# Query
Massart	[8]	$\tilde{O}(d)$	$\tilde{O}(d)$
Massart	[5]	$\text{poly}(d)$	$\text{poly}(d)$
Massart	Ours	$\tilde{O}(1)$	$\tilde{O}(d)$
Tsybakov (κ)	[19]	$\tilde{O}\left(\left(\frac{1}{\varepsilon}\right)^{2\kappa-2} d\theta\right)$	$\tilde{O}\left(\left(\frac{1}{\varepsilon}\right)^{2\kappa-2} d\theta\right)$
Tsybakov (κ)	Ours	$\tilde{O}\left(\left(\frac{1}{\varepsilon}\right)^{2\kappa-2}\right)$	$\tilde{O}\left(\left(\frac{1}{\varepsilon}\right)^{2\kappa-2} + d\right)$
Adversarial ($\nu = \mathcal{O}(\varepsilon)$)	[34]	$\tilde{O}(d)$	$\tilde{O}(d)$
Adversarial ($\nu = \mathcal{O}(\varepsilon)$)	[6]	$\tilde{O}(d^2)$	$\tilde{O}(d^2)$
Adversarial ($\nu = \mathcal{O}(\varepsilon)$)	Ours	$\tilde{O}(1)$	$\tilde{O}(d)$

Active learning with Weak Supervision

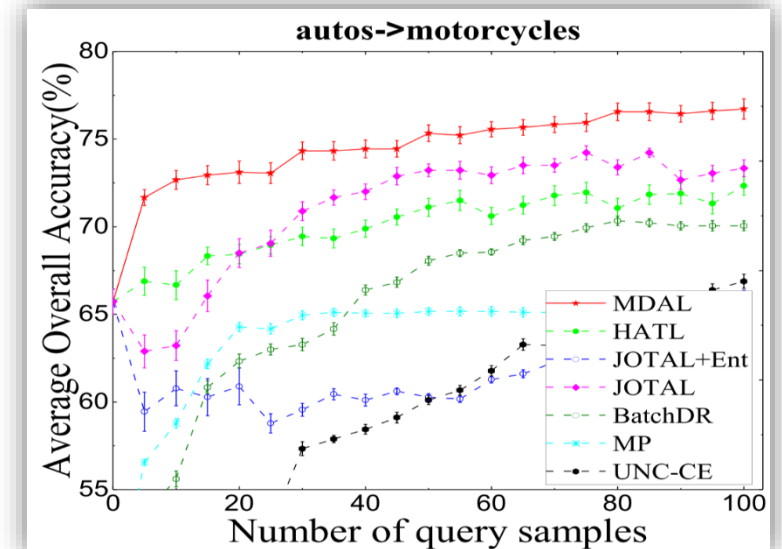
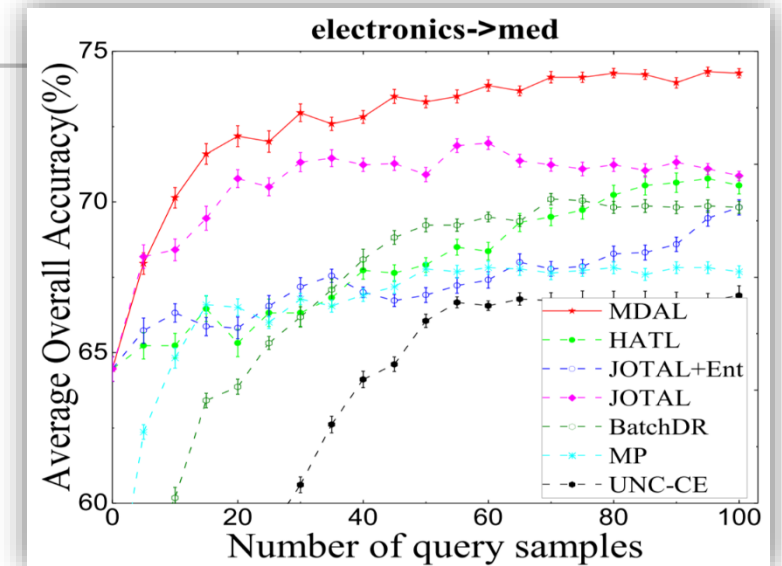
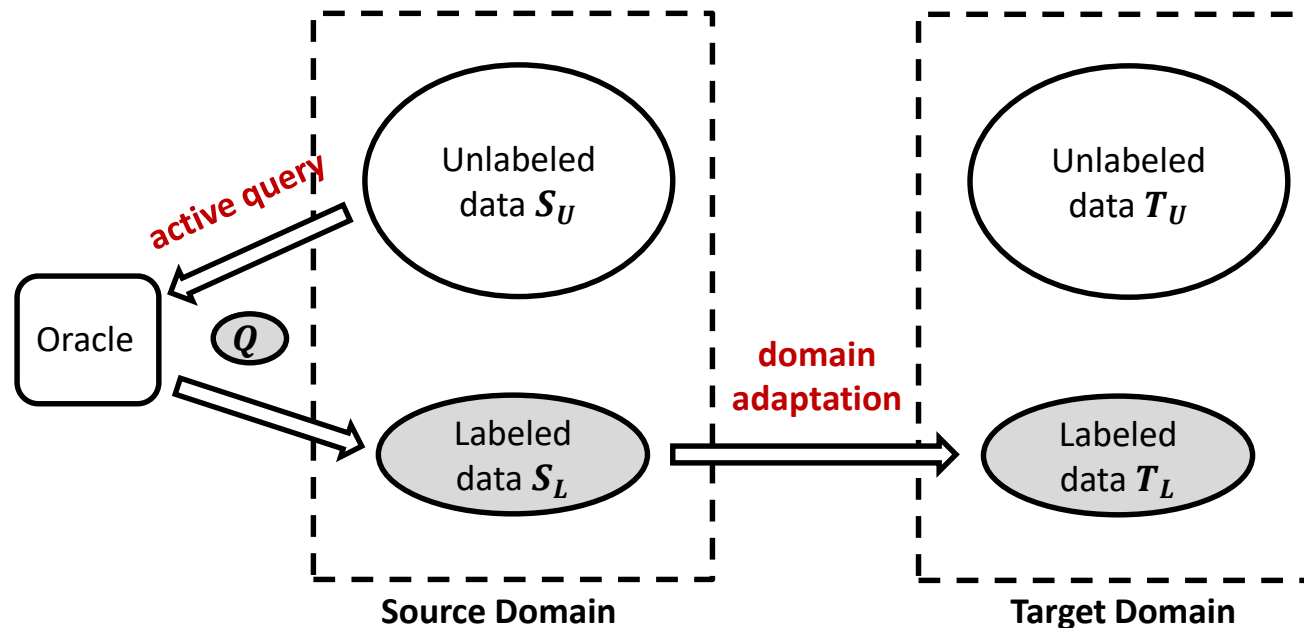
- Self-paced active learning
 - Self-annotation for high-confident instances
 - Oracle annotation for low-confident instances



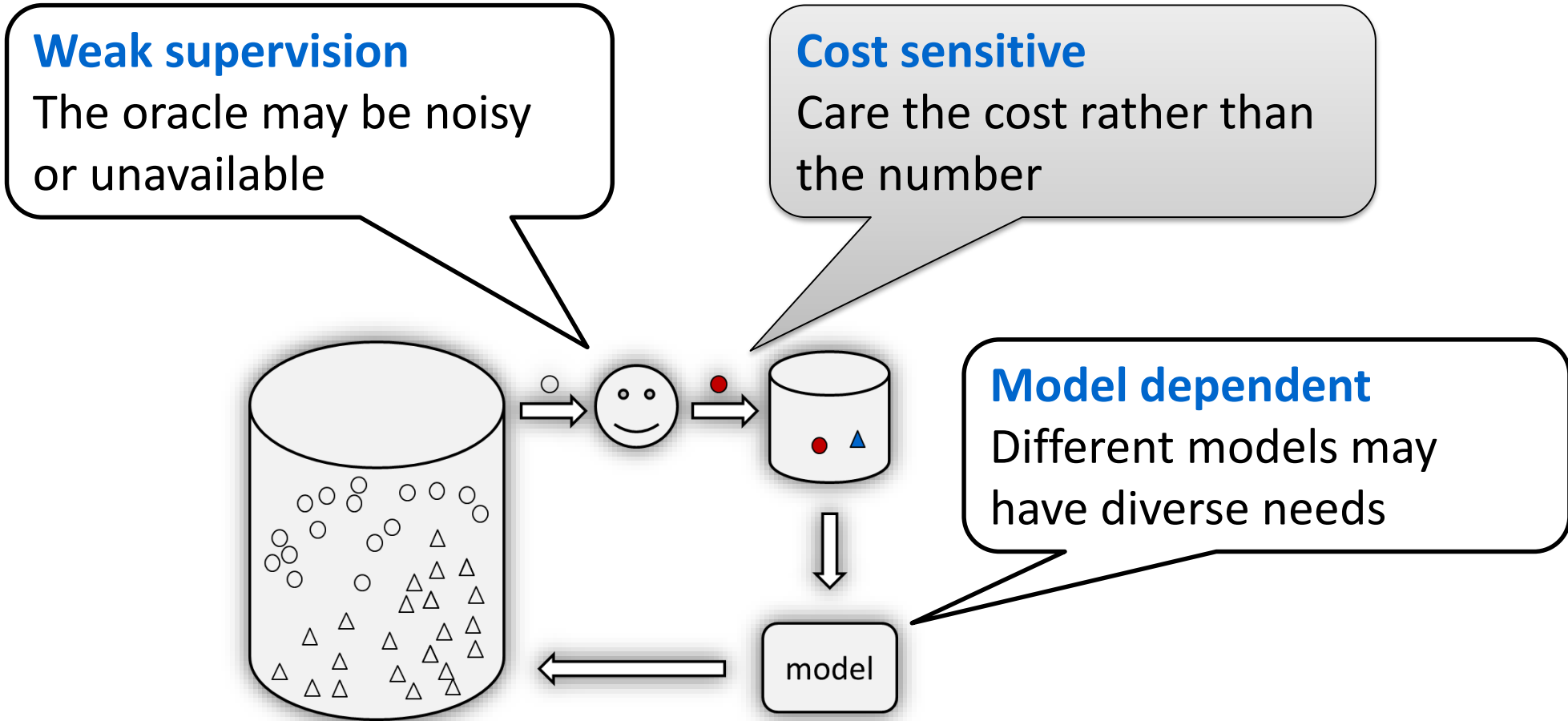
Lin et al. Active Self-Paced Learning for Cost-Effective and Progressive Face Identification. PAMI 2018.

Active learning with Weak Supervision

- Active query from source domains
 - Oracle is not available in the target domain
 - Insufficient labeled data in all domains

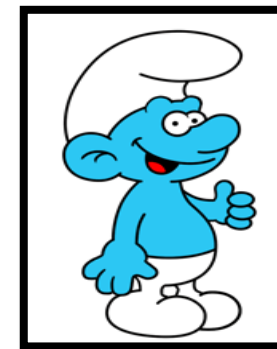
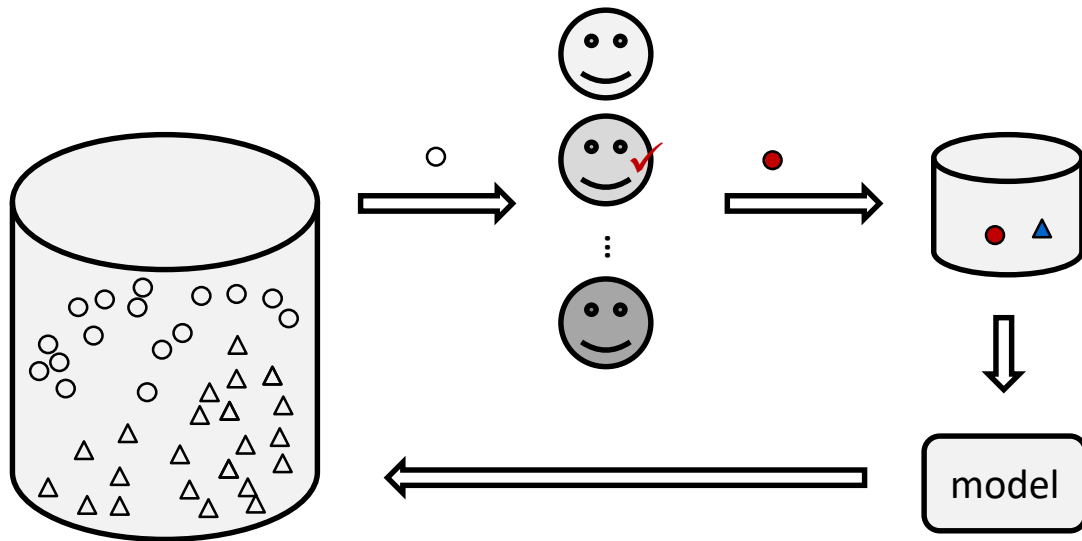
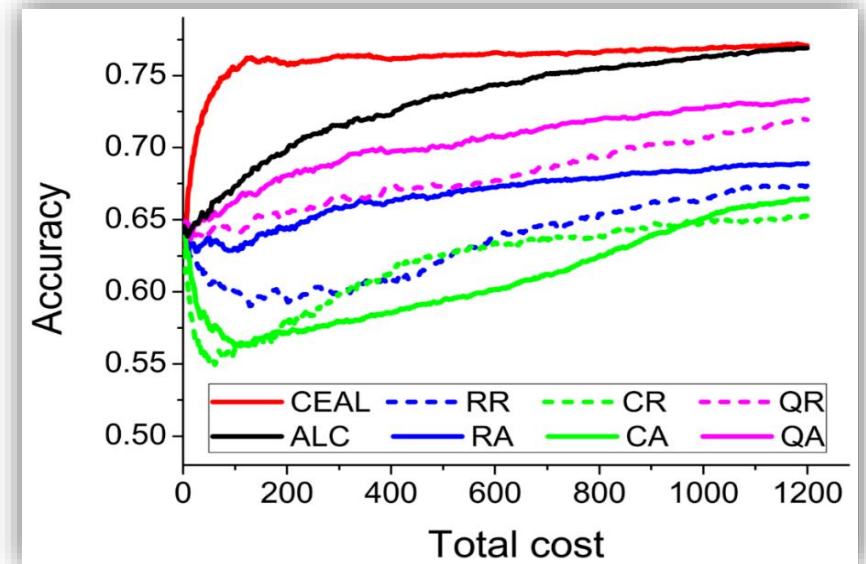


Recent Progress

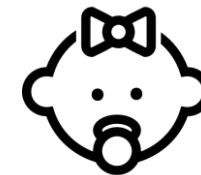


Cost-Sensitive Active Learning

- Oracles are cost-sensitive
 - Different oracles have diverse prices
 - Selecting both instance and oracle
 - Accurate yet cheap annotations



Who is this ?



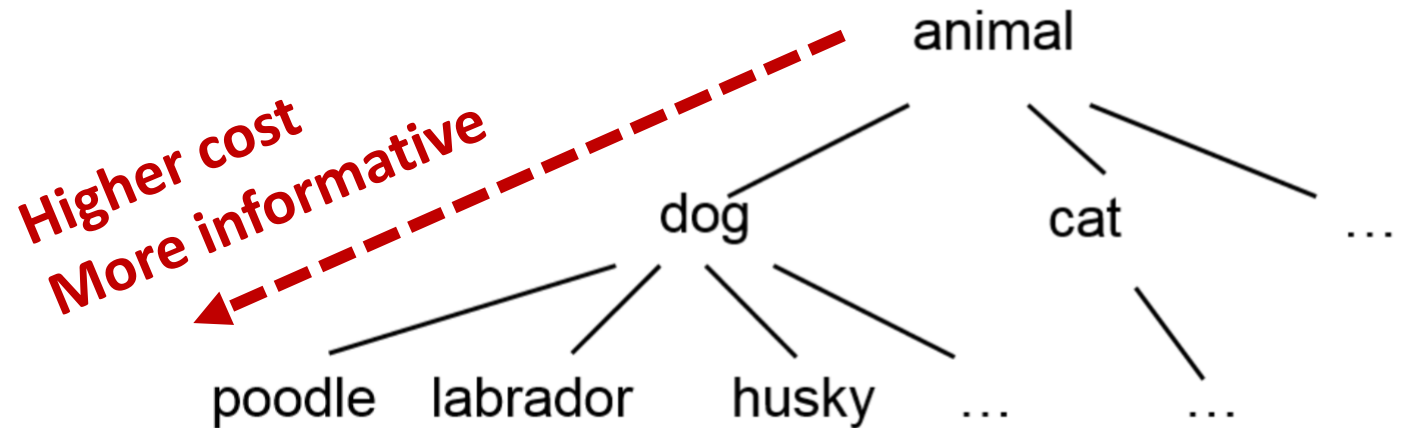
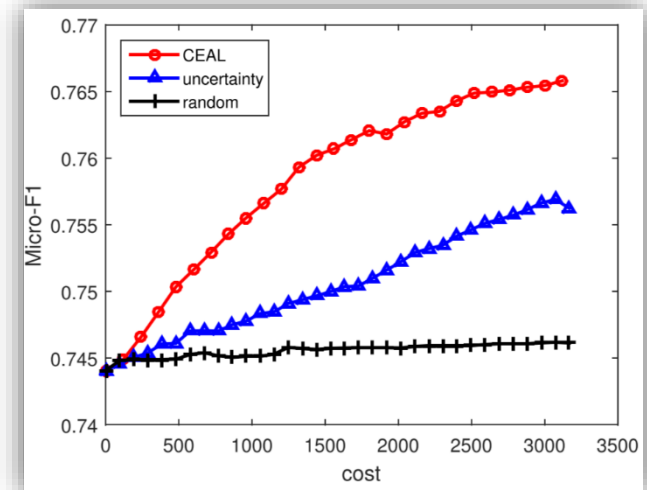
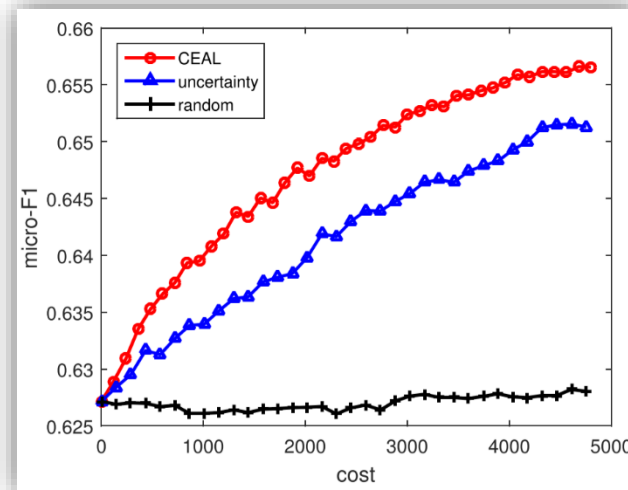
- Low overall quality
- Low price
- Expert for this query



- High overall quality
- High price
- Less familiar with it

Cost-Sensitive Active Learning

- Labels are cost-sensitive
 - Labels have hierarchies
 - Bi-objective optimization to balance the cost and information

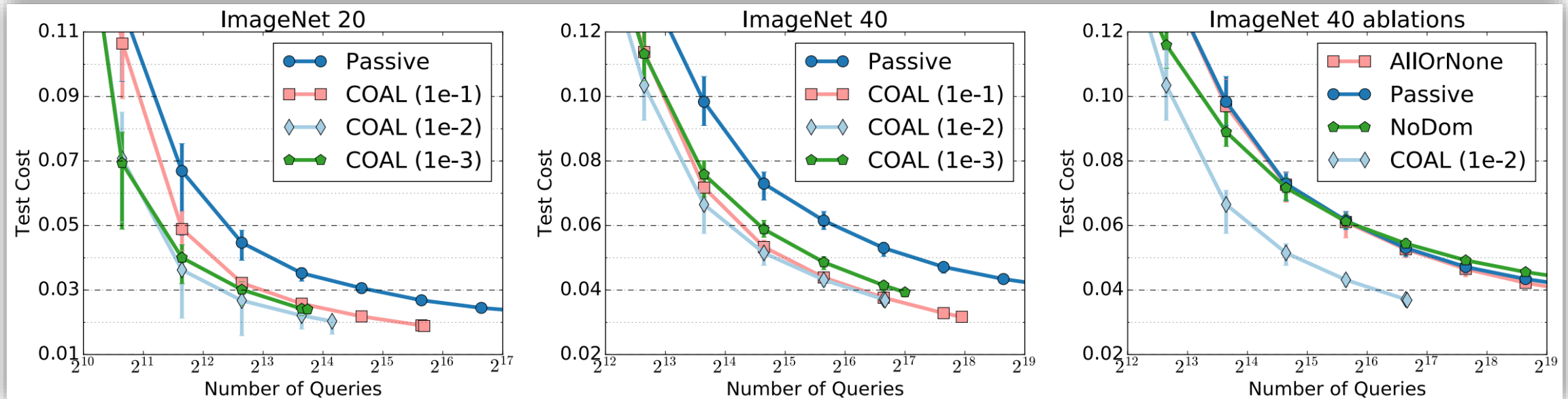


Cost-Sensitive Active Learning

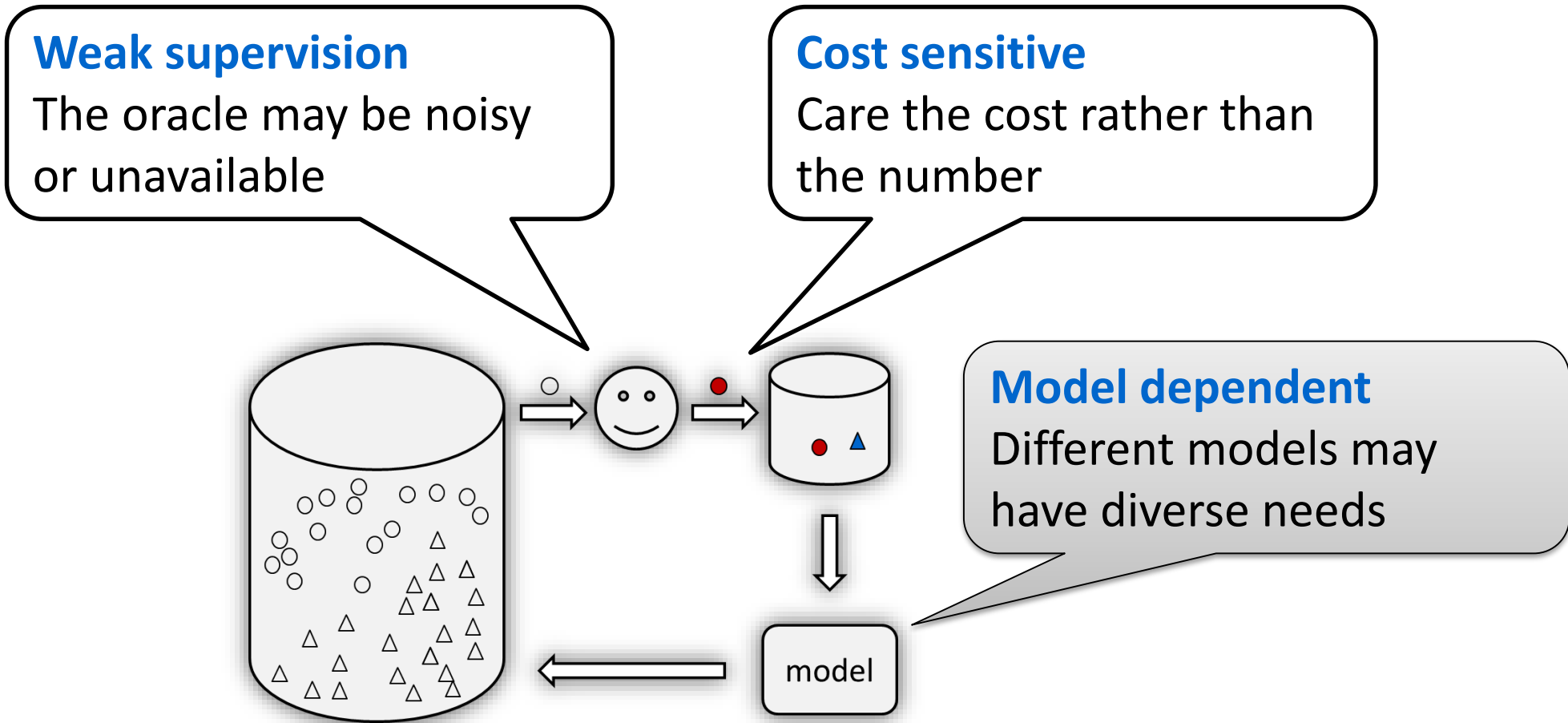
- Learning task is cost-sensitive
 - Query the cost of predicting a specific label
 - Guarantee a polynomial improvement on label complexity for low noise case

Theorem 6. Assume the Massart noise condition holds. With probability at least $1 - 2\delta$ the label complexity of the algorithm over n examples is at most,

$$L_1 = \mathcal{O} \left(\frac{25^{1/\beta}}{\tau^2} (n^\beta K \log(n) \nu_n \theta_1 + \log(1/\delta)) \right)$$
$$L_2 = \mathcal{O} \left(\frac{25^{1/\beta} K}{\tau^2} (n^\beta \log(n) \nu_n [K\theta_1 + \theta_2] + \log(1/\delta)) \right)$$

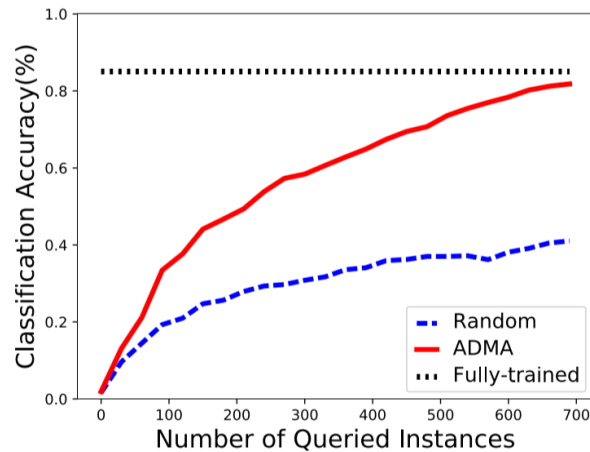
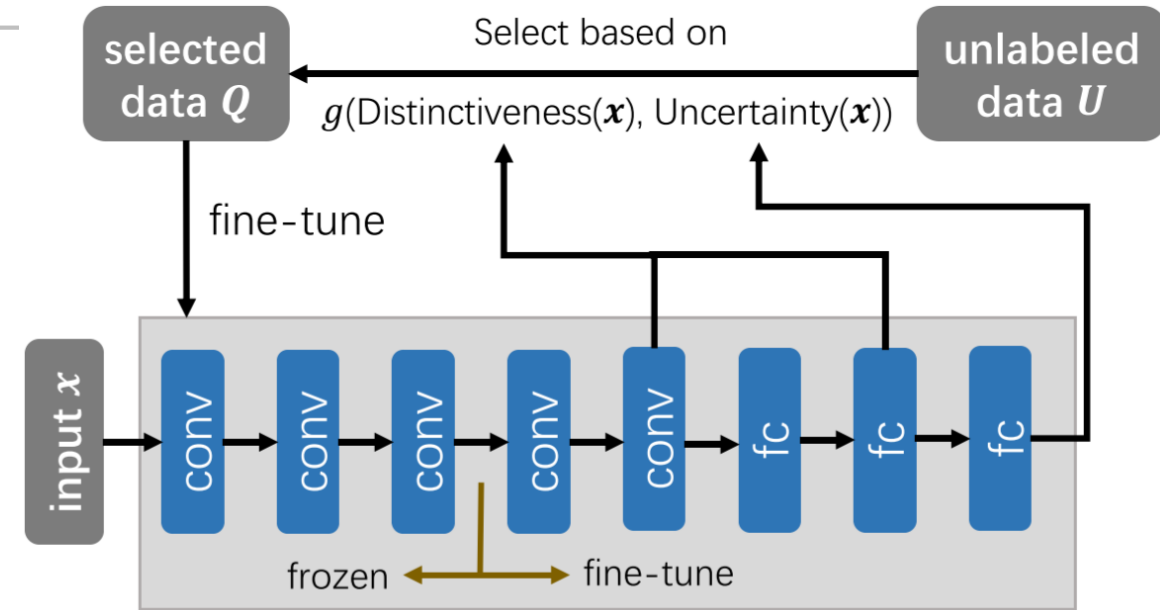


Recent Progress

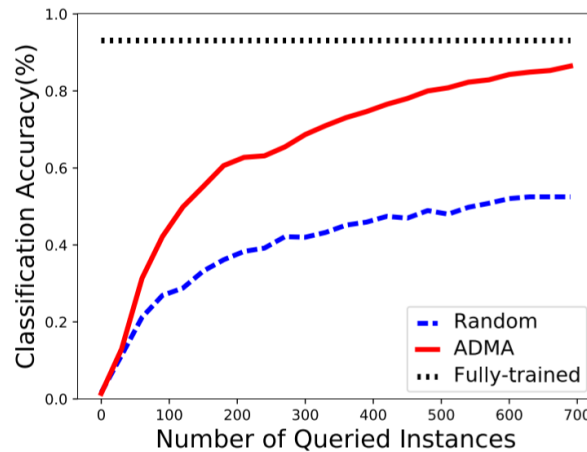


Active Learning with Deep Models

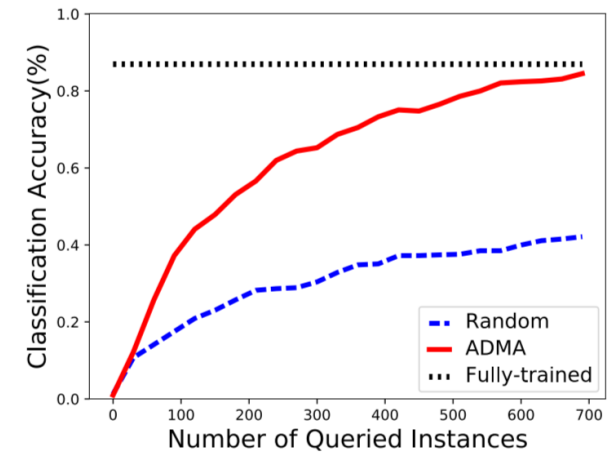
- Active model adaptation
 - A novel criterion “distinctiveness”
 - Reuse of pre-trained models
 - Less training data



(d) AlexNet + Indoor



(e) VGG-16 + Indoor

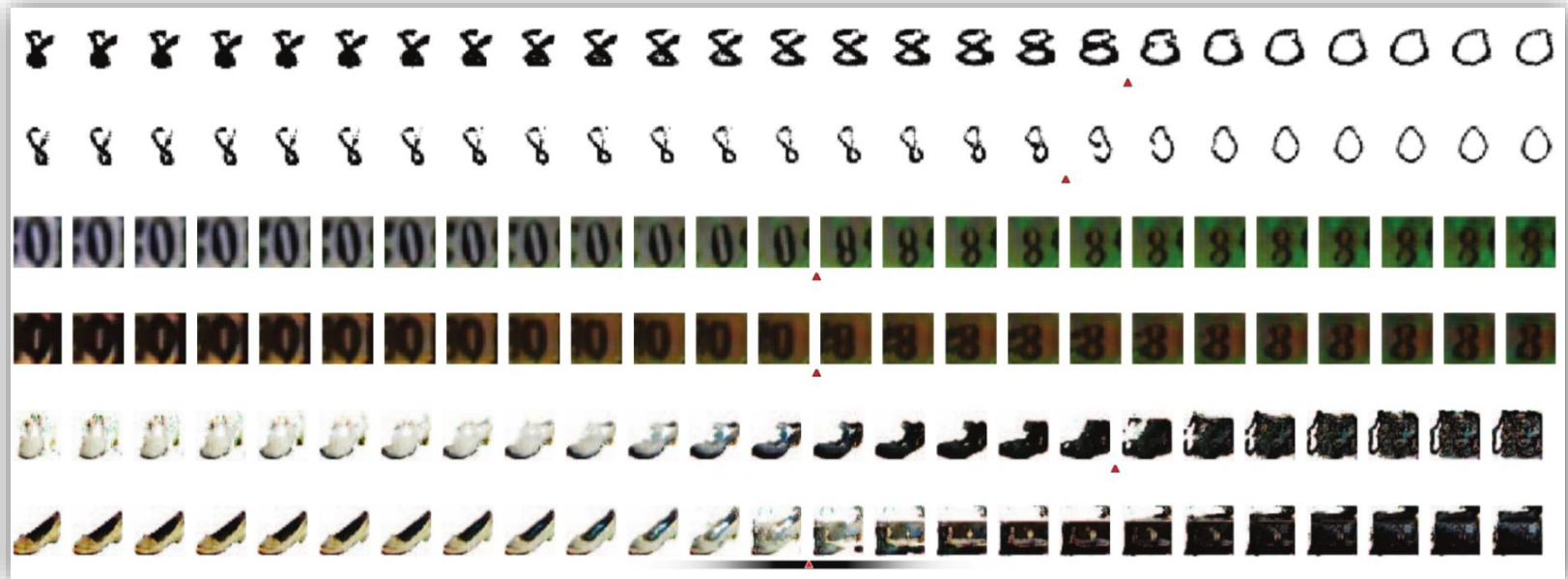
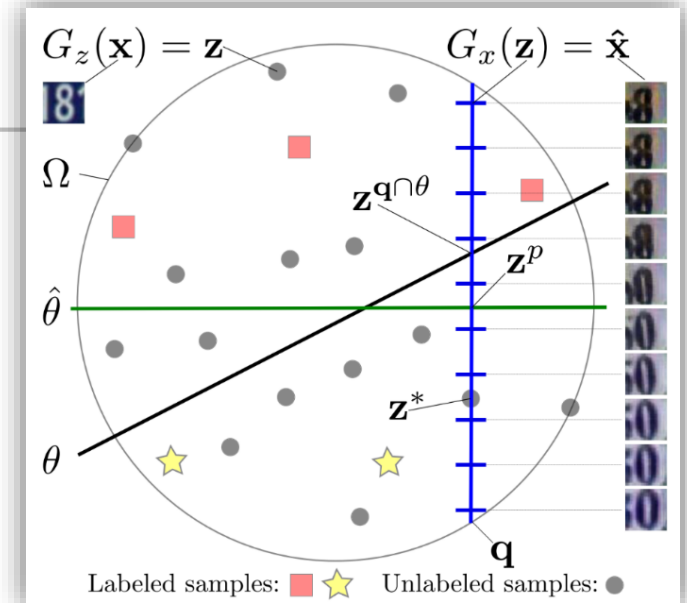
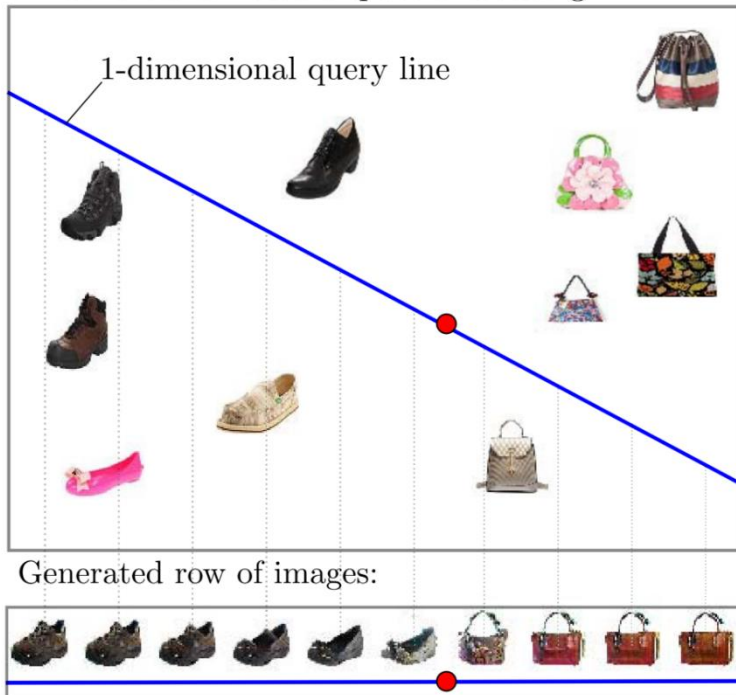


(f) ResNet-18 + Indoor

Active Learning with Deep Models

- Active annotation with deep generative models
 - Deep generative model to create novel instances
 - Oracle directly annotates the decision boundary

K -dimensional feature space embedding:



Huijser et al. Active Decision Boundary Annotation with Deep Generative Models. ICCV 2017.

Active Learning for Various Applications

- Human Pose Estimation [Liu & Ferrari ICCV'17]
- Face Identification [Lin et al. PAMI'18]
- Semantic Role Labeling [Wang et al. IJCAI'17]
- Biomedical Image Analysis [Zhou et al. CVPR'17]
- Quadcopter Control [Andersson et al. AAI'17]
- Sentiment Analysis [Wu et al. ACL'17]
- Recommendation [Zhao et al. AIJ'17]
- Surveying [Lewenberg et al. AAI'17]
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Thank You !

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