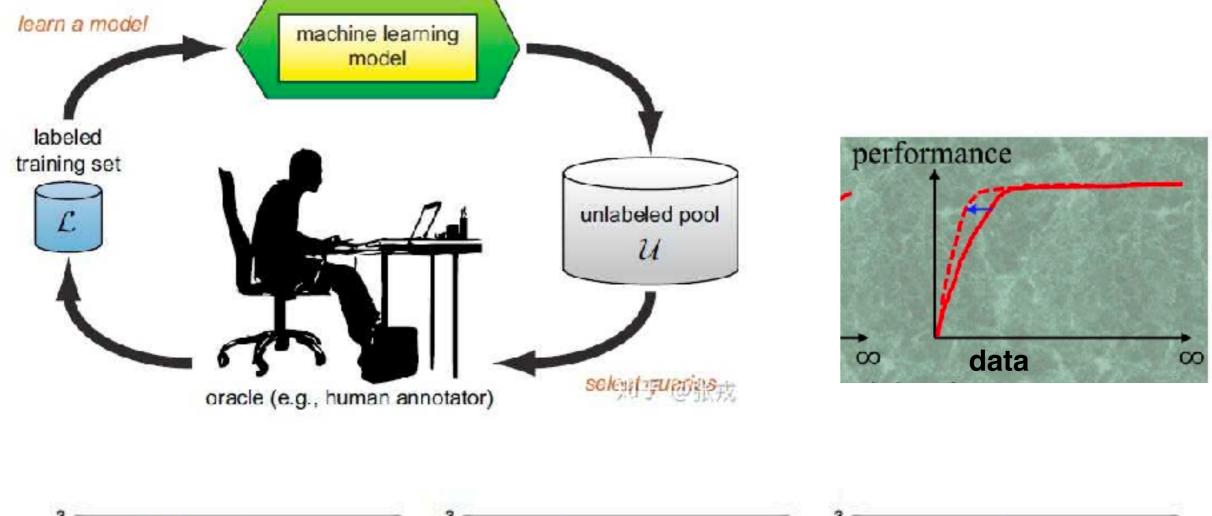
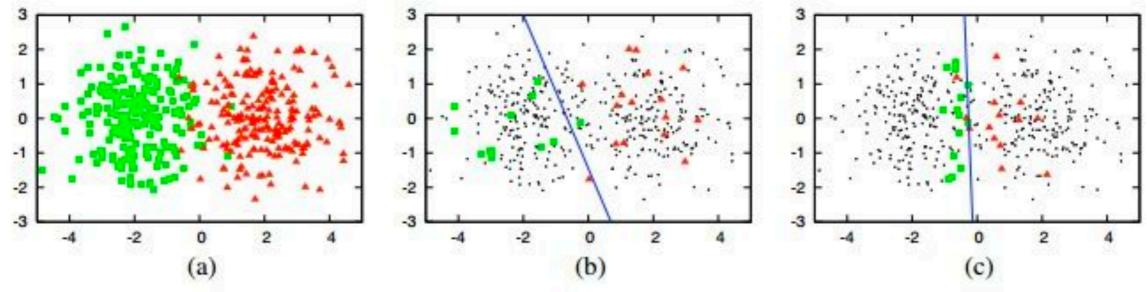
Survey of Active Learning







- membership query synthesis: learner请求标注任何未标注样本,包括 learner<u>自身随机生成</u>的样本
- **stream-based**:基于某种query strategy依次检验样本究竟是否需要标注;
- pool-based: 每次根据query strategy排序整个数据集,确定一批未标注样本

Fine-tuning Convolutional Neural Networks for Biomedical Image Analysis: Actively and Incrementally **CVPR 2017**

Continuous fine-tuning

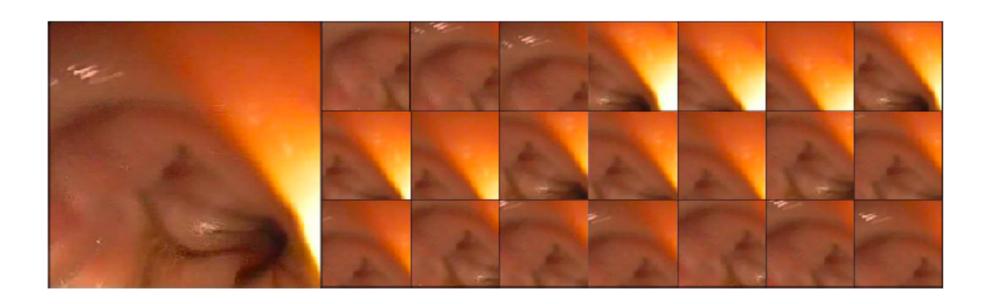
Start from AlexNet pre-trained on ImageNet, fine-tune with enlarged dataset.

Active candidate selection (query strategy)

Entropy and diversity.

Handling noisy label via majority selection

Data augmentation generate hard samples. Use top 1/4 confident part



Classification uncertainty

Inconsistency among patches

Entropy

Diversity

$$e_i^j = -\sum_{k=1}^{|Y|} p_i^{j,k} \log p_i^{j,k}$$

$$d_i(j, l) = \sum_{k=1}^{|Y|} (p_i^{j,k} - p_i^{l,k}) log \frac{p_i^{j,k}}{p_i^{l,k}}$$

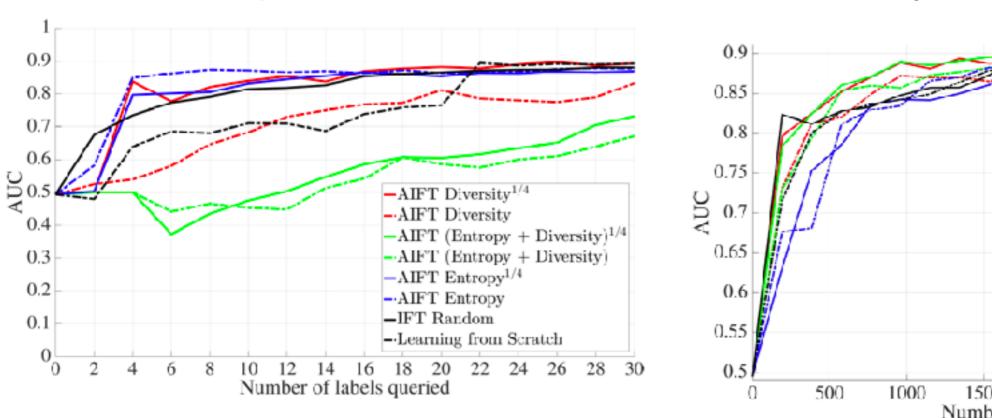
Prediction Patt	ern	Example	Entropy	Entropy ^{1/4}	Diversity	Diversity ^{1/4}	(Entropy+ Diversity)	(Entropy+ Diversity) ^{1/4}
#	A 1 Prob	{0.4 0.4 0.4 0.5 0.5 0.5 0.5 0.5 0.5 0.6 0.6}	7.52	2.02	4.38	0.00	11.90	2.02
#	B 1 Prob	{0.0 0.1 0.2 0.3 0.4 0.4 0.6 0.7 0.8 1.0 1.0}	4.57	0.83	1237.21	20.79	1241.77	21.62
el #	C 1 Prob	{0.0 0.0 0.0 0.1 0.1 0.9 0.9 1.0 1.0 1.0 1.0}	1.30	0.00	2816.66	0.00	2817.96	0.00
#	D 1 Prob	{0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.1 0.1 0.1 0.1}	1.30	0.00	189.54	0.00	190.84	0.00
#1	E 1 Prob	{0.9 0.9 0.9 0.9 1.0 1.0 1.0 1.0 1.0 1.0 1.0}	1.30	0.00	189.54	0.00	190.84	0.00
#	F 1 Prob	{0.0 0.0 0.1 0.1 0.1 0.1 0.2 0.2 0.3 0.9 1.0}	3.24	0.33	1076.87	13.54	1080.11	13.86
#	G Prob	{0.0 0.1 0.7 0.8 0.8 0.9 0.9 0.9 0.9 1.0 1.0}	3.24	0.33	1076.87	13.54	1080.11	13.86

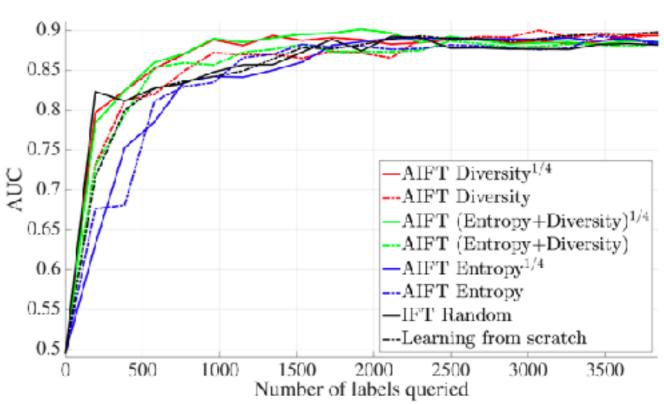
noisy labe

Binary Classification

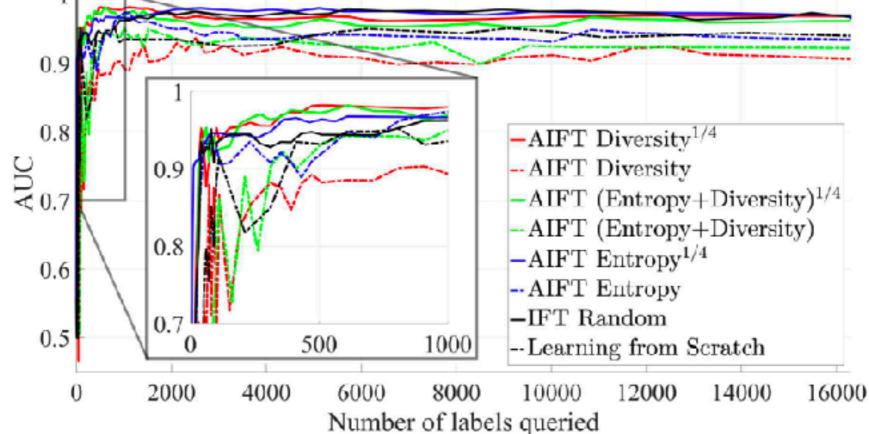


Pulmonary Embolism(肺栓塞) Detection



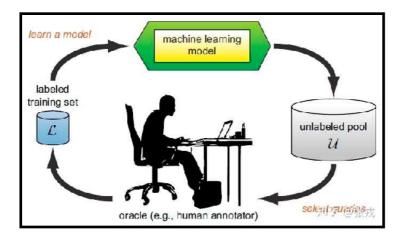


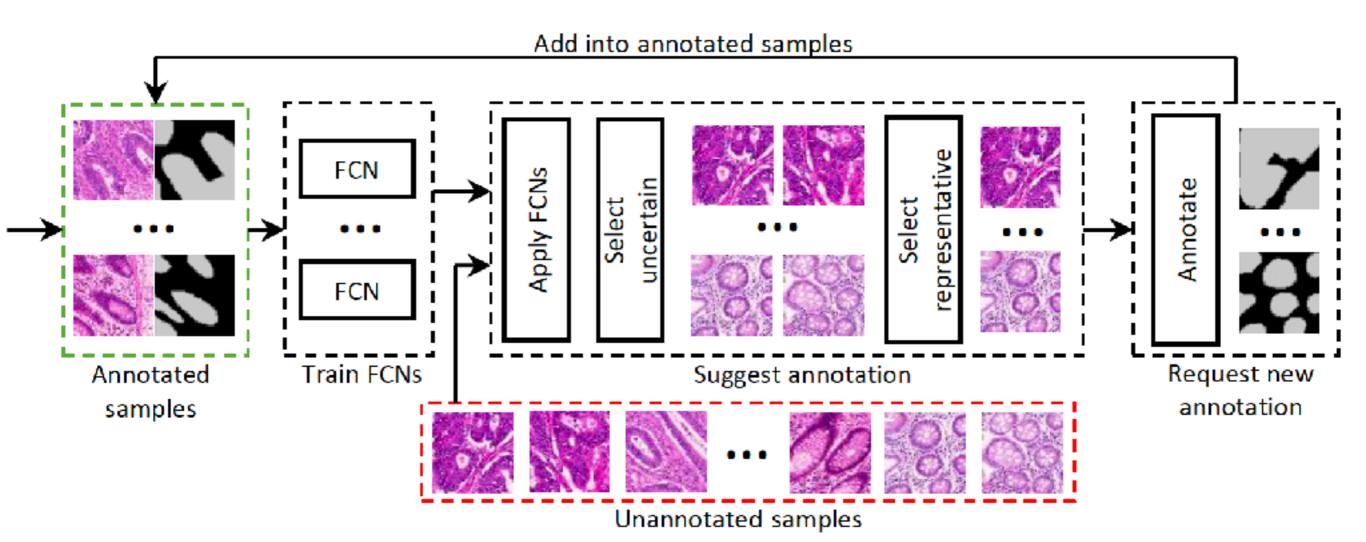




Suggestive Annotation: A Deep Active Learning Framework for Biomedical Image Segmentation

MICCAI 2017



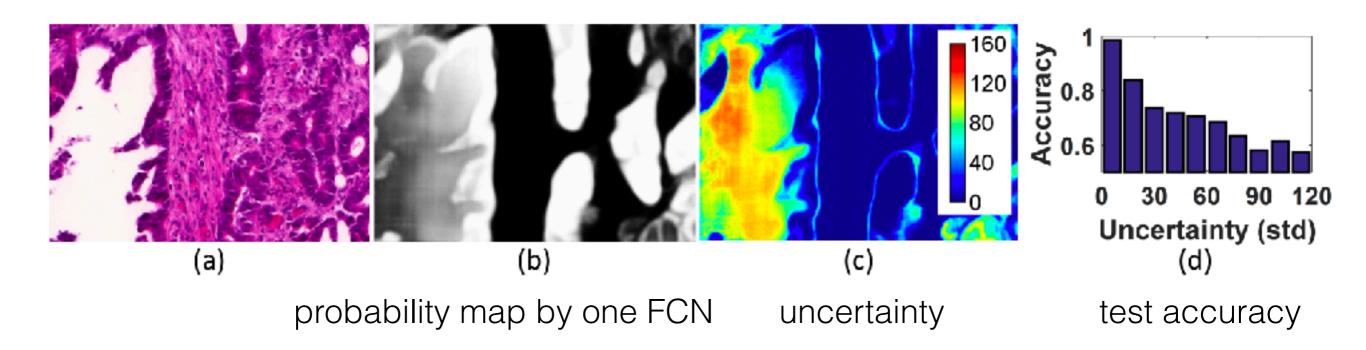


A new FCN for active learning

achieve state-of-the-art performance when all training data is used, while still able to produce reasonable results when very little training data is available.

Query strategy 1: Uncertainty

Bootstrapping: train a set of models while restricting each of them to use a subset of the training data (generated by sampling with replacement) and calculate the variance (disagreement) among these models.



Query strategy 2: Similarity

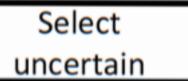
Select representative subset: deep learning models tend to be uncertainfor similar types of instances

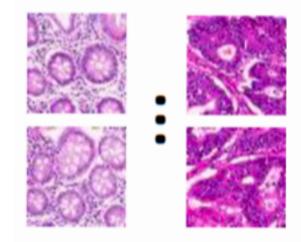
$$sim(I_i, I_j) = cosine_similarity(I_i^c, I_j^c)$$

$$f(S_a, I_x) = \max_{I_i \in S_a} sim(I_i, I_x)$$

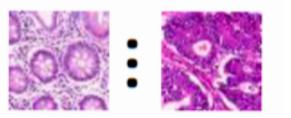
find
$$S_a$$
 that maximize $F(\mathcal{S}_a, \mathcal{S}_u) = \sum_{I_i \in \mathcal{S}_u} f(\mathcal{S}_a, I_j)$

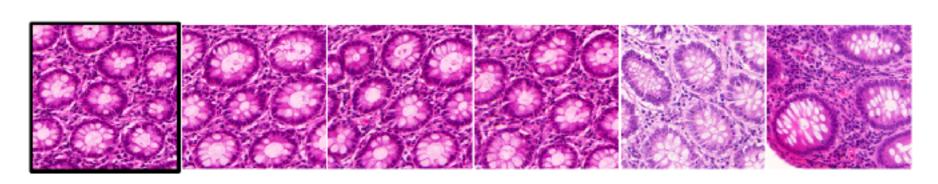
maximum set cover problem





Select representative

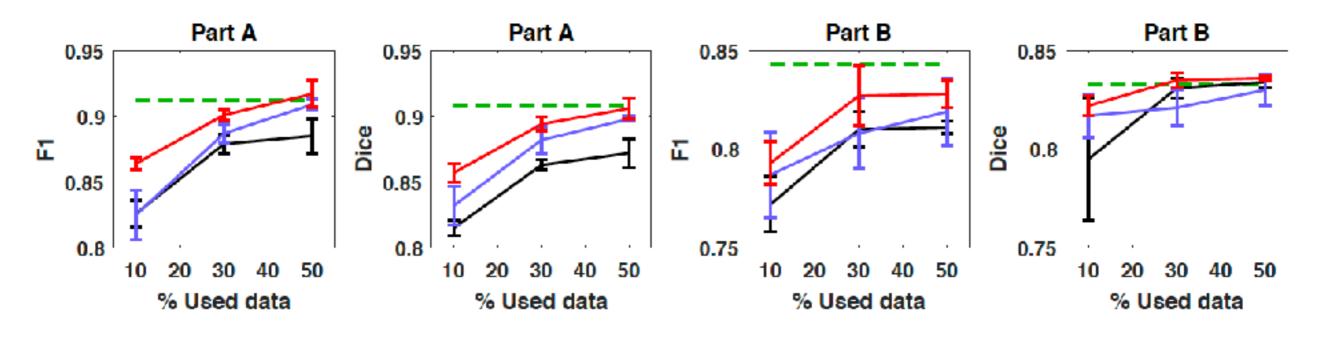




similar instance measured

Method	Mean IU	F1 score
Uncertainty 50%	0.858	0.849
Our method 50%	0.875	0.871
Our method full	0.879	0.874

lymph node ultrasound image segmentation



gland segmentation

Query strategy

Uncertainty-based

Samples that are difficult for the classier to correctly classify

- mutual information Bayesian active learning for classication and preference learning.
- distance between samples and the decision boundary
- information entropy and risk expectation
- · dropout layers Deep bayesian active learning with image data.
- auxiliary loss prediction module

 Learning loss for active learning.
- combine GAN and VAE Dual Adversarial Network for Deep Active Learning

Representation-based

the most representative samples of the entire dataset