Active Learning

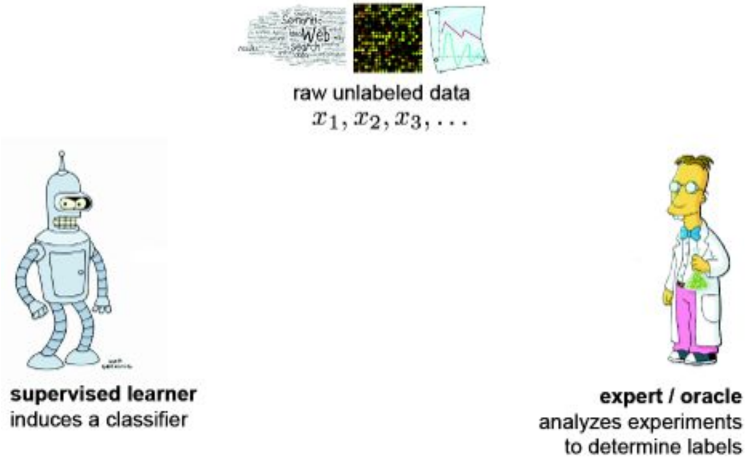
Digging into Data

April 21, 2014

COLLEGE OF INFORMATION STUDIES

Slides adapted from Piyush Rai

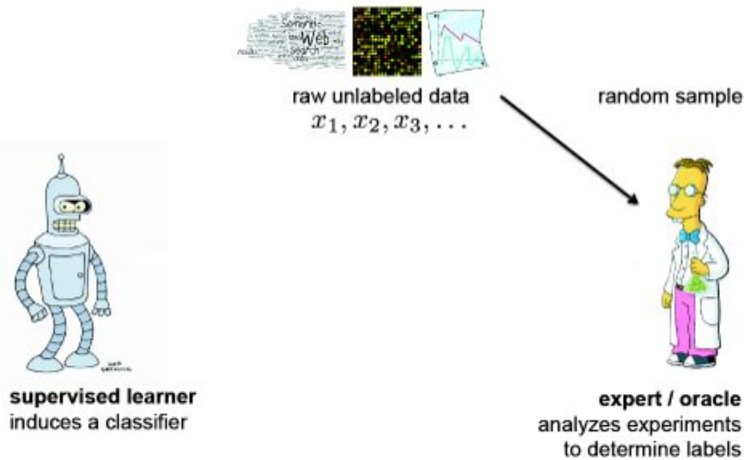
(Passive) Supervised Learning



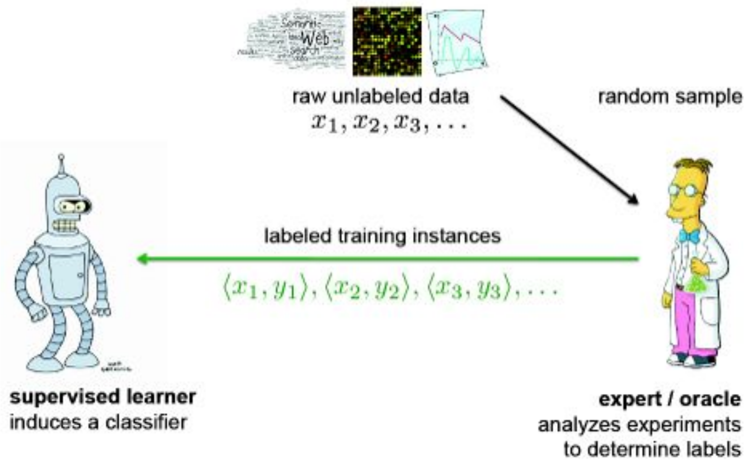
[1]

[1] Some figures from Burr Settles

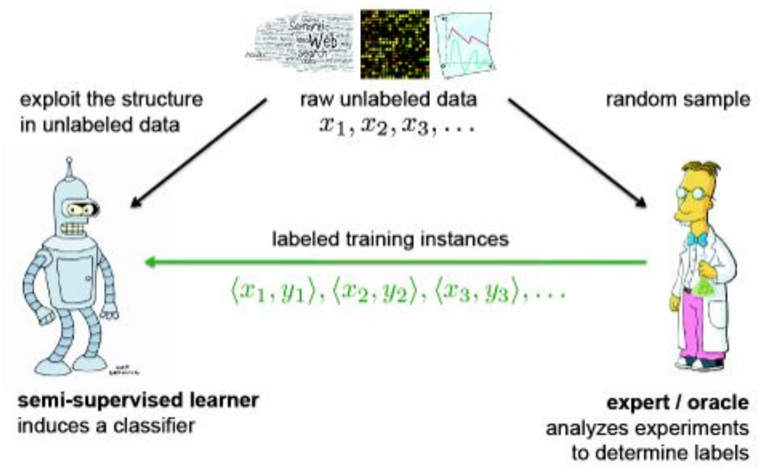
(Passive) Supervised Learning



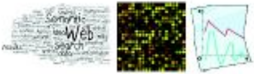
(Passive) Supervised Learning



Semi-supervised Learning

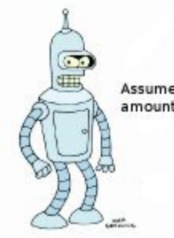


Active Learning



raw unlabeled data

$x_1, x_2, x_3, \ldots$

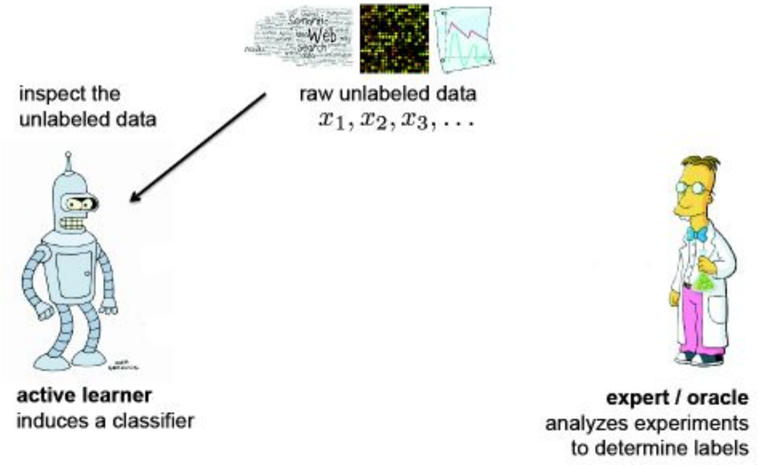


Assumes some small
amount of initial labeled training data

active learner
induces a classifier

expert / oracle
analyzes experiments
to determine labels

Active Learning



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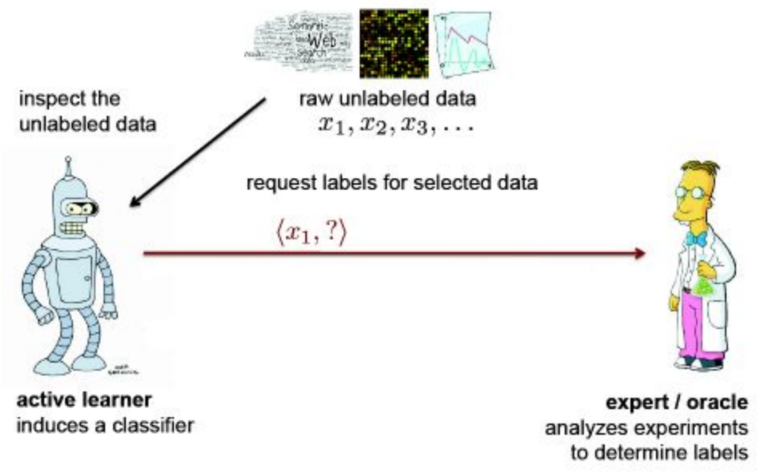

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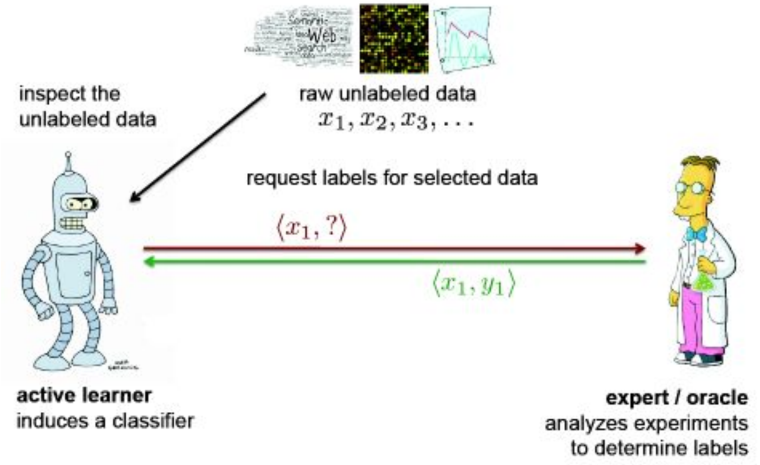

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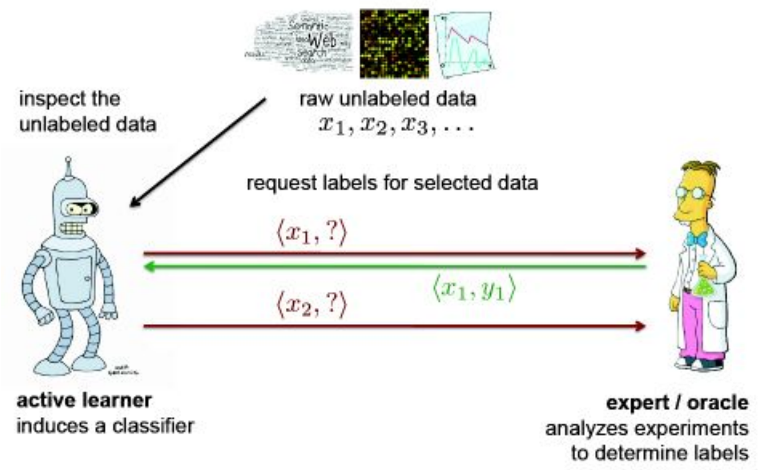

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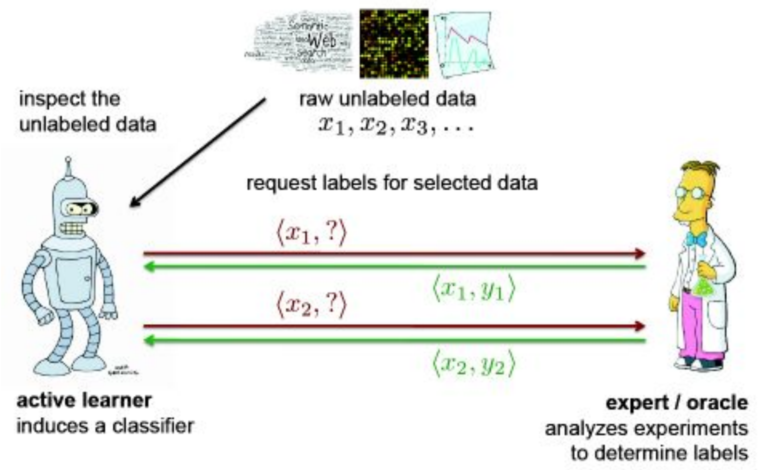
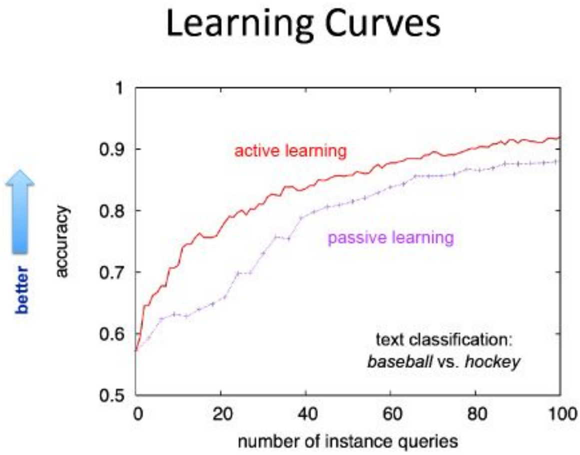


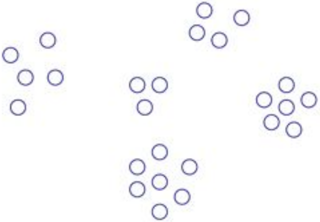
Active Learning vs Random Sampling

- Passive Learning curve: Randomly selects examples to get labels for
- Active Learning curve: Active learning selects examples to get labels for



A Naïve Approach

Suppose the unlabeled data looks like this.



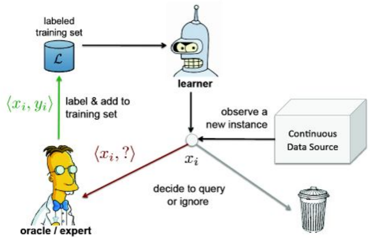
Then perhaps we just need five labels!

- Of course, thing could go wrong . . .

Types of Active Learning

Largely falls into one of these two types:

Stream-Based Active Learning



- Unlabeled example by example
- query its label or ignore it

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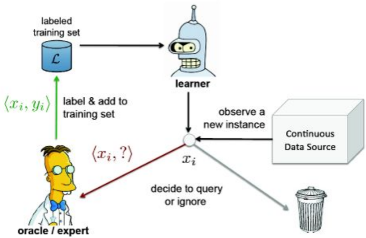

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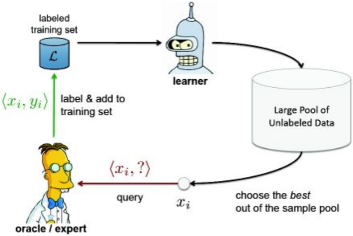
Pool-Based Active Learning



- Given: a large unlabeled pool of examples
- Rank examples in order of informativeness
- Query the labels for the most informative example(s)

How Active Learning Operates

- Active Learning proceeds in rounds
- Each round has a current model (learned using the labeled data seen so far)
- The current model is used to assess informativeness of unlabeled examples
  - . . . using one of the query selection strategies

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  - ...using one of the query selection strategies
  - The most informative example(s) is/are selected
  - The labels are obtained (by the labeling oracle)
  - The (now) labeled example(s) is/are included in the training data
  - The model is re-trained using the new training data

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- The process repeat until we have no budget left for getting labels

Query Selection Strategies

Any Active Learning algorithm requires a query selection strategy

Some examples:

- Uncertainty Sampling
- Query By Committee (QBC)
- Expected Model Change
- Expected Error Reduction
- Variance Reduction
- Density Weighted Methods

Uncertainty Sampling

- Select examples which the current model θ is the most uncertain about
- Various ways to measure uncertainty. For example:
  - Based on the distance from the hyperplane
  - Using the label probability $P_\theta(y|\vec{x})$ (for probabilistic models)

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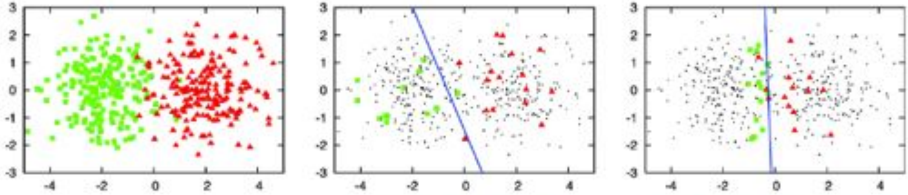
- Some typically used measures based on label probabilities:
  - **Least Confident:** $x^*_{LC} = \arg\max_x 1 - P_\theta(\hat{y}|x)$
    where $\hat{y}$ is the most probable label for x under the current model θ
  - **Smallest Margin:** $x^*_{SM} = \text{argmin}_x P_\theta(y_1|x) - P_\theta(y_2|x)$
    y_1, y_2 are the two most probable labels for x under the current model
  - **Label Entropy:** choose example whose label entropy is maximum

$$x^*_{LE} = \arg\max_x - \sum_i P_\theta(y_i|x) \log P_\theta(y_i|x)$$

where y_i ranges over all possible labels

Uncertainty Sampling

A simple illustration of uncertainty sampling based on the distance from the hyperplane (i.e., margin based)

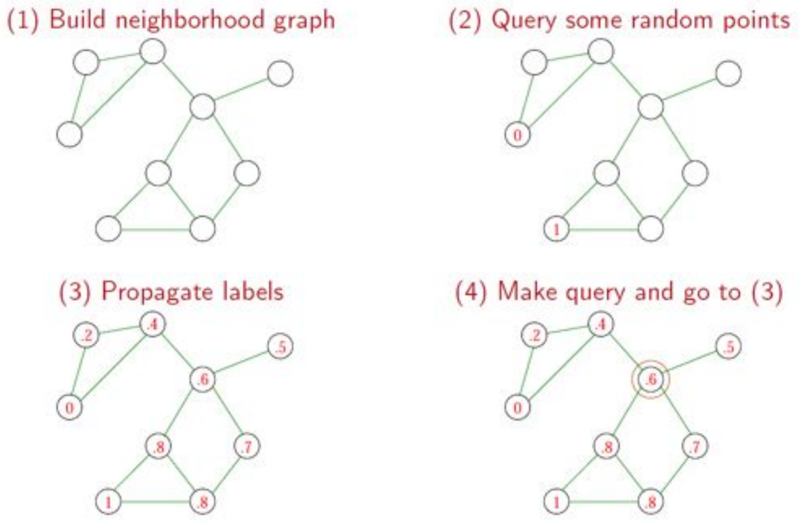


400 instances sampled from 2 class Gaussians

random sampling 30 labeled instances (accuracy=0.7)

uncertainty sampling 30 labeled instances (accuracy=0.9)

Uncertainty Sampling based on Label-Propagation



Query By Committee (QBC)

- QBC uses a committee of models $\mathscr{C} = \{\theta^{(1)}, \ldots, \theta^{(C)}\}$
- All models trained using the currently available labeled data $\mathscr{L}$
- How is the committee constructed? Some possible ways:
  - Sampling different models from the model distribution $P(\theta|\mathscr{L})$
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  - Using ensemble methods (bagging/boosting, etc.)
- All models vote their predictions on the unlabeled pool
- The example(s) with maximum disagreement is/are chosen for labeling
- One way of measuring disagreement is the Vote Entropy
  - Vote Entropy

$$x^*_{VE} = \arg\max_x - \sum_i \frac{V(y_i)}{C} \log \frac{V(y_i)}{C}$$

  y_i ranges over all possible labels, $V(y_i)$: number of votes received to label y_i

- Each model in the committee is re-trained after including the new example(s)

Effect of Outlier Examples

- Uncertainty Sampling or QBC may wrongly think an outlier to be an informative example
- Such examples won't really help (and can even be misleading)

- Other robust query selection methods exist to deal with outliers
- **Idea:** Instead of using the confidence of a model on an example, see how a labeled example affects the model itself (various ways to quantify this)
  - The example(s) that affects the model the most is probably the most informative

Other Query Selection Methods

- **Expected Model Change**
  - Select the example whose inclusion brings about the maximum change in the model (e.g., the gradient of the loss function w.r.t. the parameters)

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  - Select example that reduces the expected generalization error the most

$$R(x) = \sum_{u} \mathbb{E}_y \left[\mathbb{H}_{\theta + \langle x,y \rangle} \left[Y \mid u \right] \right] \quad (1)$$

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Consider all possible unlabeled instances

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Consider the possible labels of the point

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How uncertain is your model now given that information

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- **Variance Reduction**
  - Select example(s) that reduces the model variance by the most
- **Density Weighting**
  - Weight the informativeness of an example by its average similarity to the entire unlabeled pool of examples
  - An outlier will not get a substantial weight!

Concluding Thoughts...

- Active Learning: Label-efficient learning strategy
- Based on judging the informativeness of examples
- Several variants possible. E.g.,
  - Different examples having different labeling costs
  - Access to multiple labeling oracles (possibly noisy)
  - Active Learning on **features** instead of labels (e.g., if features are expensive)
- Being "actively" used in industry (IBM, Microsoft, Siemens, Google, etc.)
- Some questions worth thinking about (read the Active Learning survey)
  1. Can I reuse an actively labeled dataset to train a new different model?
  2. Sampling is biased. The actively labeled dataset doesn't reflect the **true** training/test data distribution. What could be the consequences? How could this be accounted for?

In class . . .

- Demo of active learning framework
- Discussion of when active learning might be appropriate
- Continue discussion of projects