

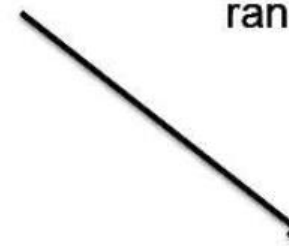
# Active Learning

# (Passive) Supervised Learning



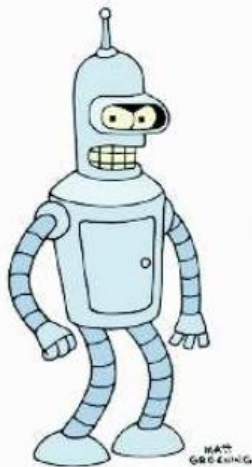
raw unlabeled data  
 $x_1, x_2, x_3, \dots$

random sample



labeled training instances

$\langle x_1, y_1 \rangle, \langle x_2, y_2 \rangle, \langle x_3, y_3 \rangle, \dots$

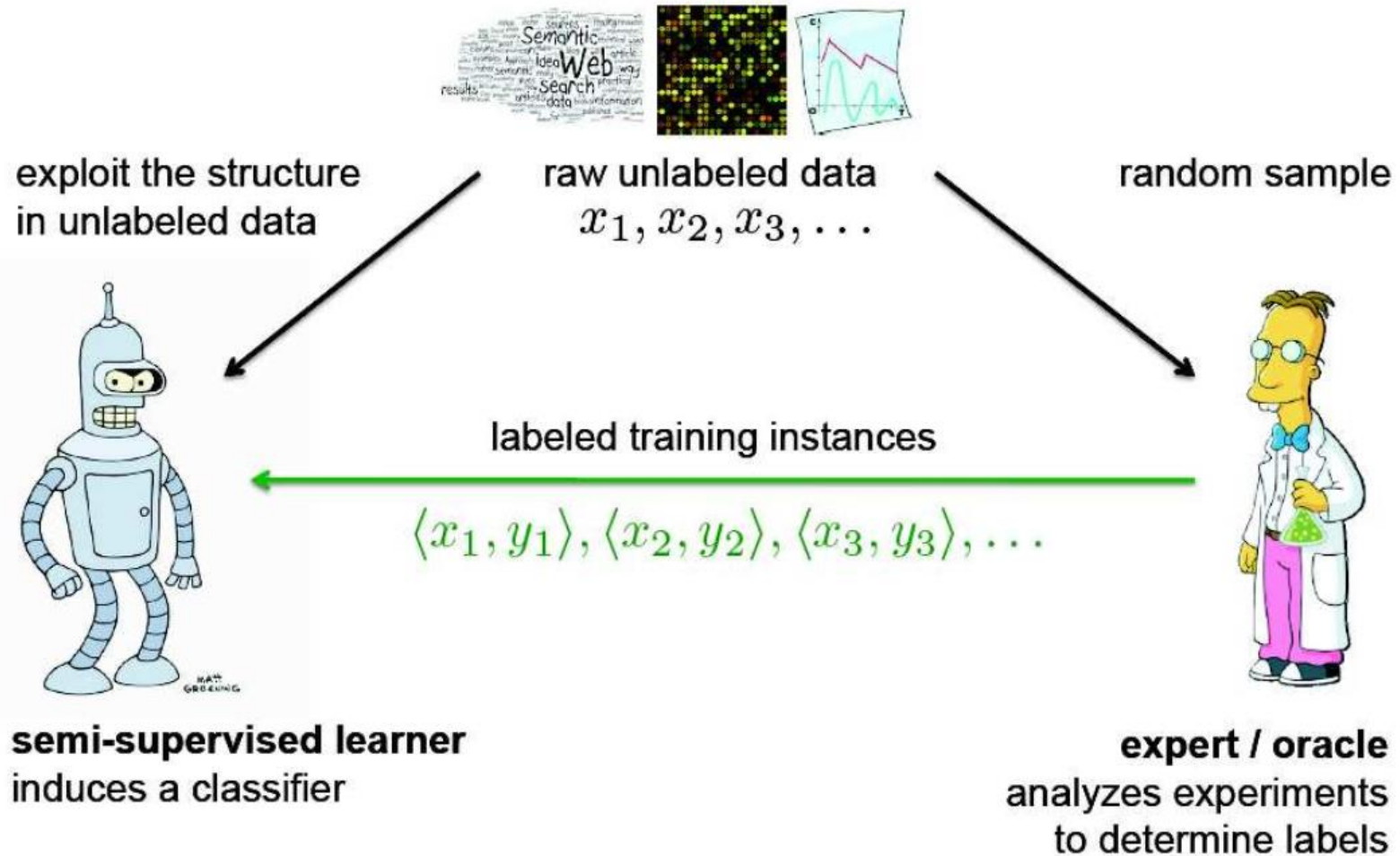


**supervised learner**  
induces a classifier



**expert / oracle**  
analyzes experiments  
to determine labels

# Semi-Supervised Learning

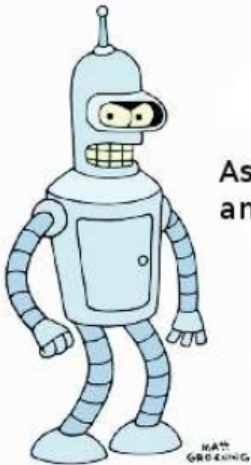


# Active Learning



raw unlabeled data

$x_1, x_2, x_3, \dots$



Assumes some small  
amount of initial labeled training data

**active learner**  
induces a classifier



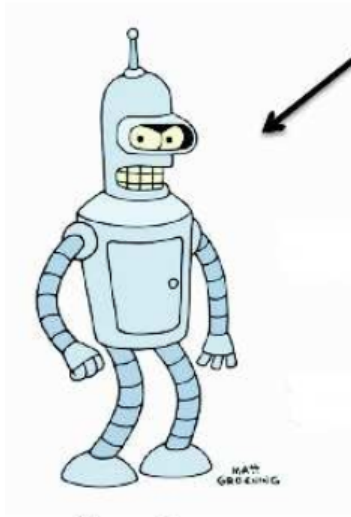
**expert / oracle**  
analyzes experiments  
to determine labels

# Active Learning



inspect the  
unlabeled data

raw unlabeled data  
 $x_1, x_2, x_3, \dots$



**active learner**  
induces a classifier



**expert / oracle**  
analyzes experiments  
to determine labels

# Active Learning

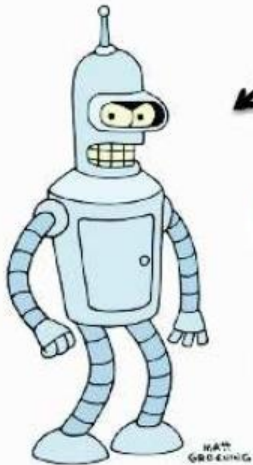


inspect the  
unlabeled data

raw unlabeled data  
 $x_1, x_2, x_3, \dots$

request labels for selected data

$\langle x_1, ? \rangle$



**active learner**  
induces a classifier



**expert / oracle**  
analyzes experiments  
to determine labels

# Active Learning



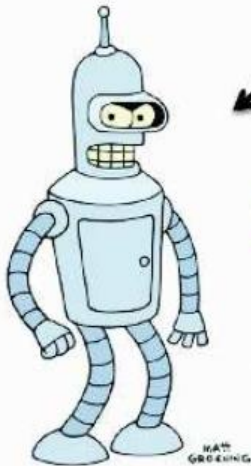
inspect the  
unlabeled data

raw unlabeled data  
 $x_1, x_2, x_3, \dots$

request labels for selected data

$\langle x_1, ? \rangle$

$\langle x_1, y_1 \rangle$



**active learner**  
induces a classifier



**expert / oracle**  
analyzes experiments  
to determine labels



# Active Learning



inspect the  
unlabeled data

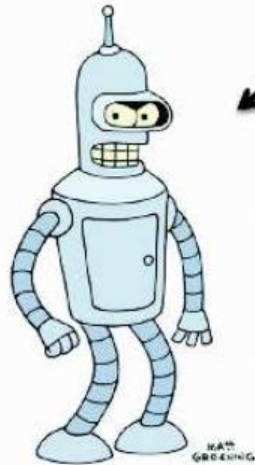
raw unlabeled data  
 $x_1, x_2, x_3, \dots$

request labels for selected data

$\langle x_1, ? \rangle$

$\langle x_2, ? \rangle$

$\langle x_1, y_1 \rangle$



**active learner**  
induces a classifier



**expert / oracle**  
analyzes experiments  
to determine labels



# Active Learning



inspect the  
unlabeled data

raw unlabeled data  
 $x_1, x_2, x_3, \dots$

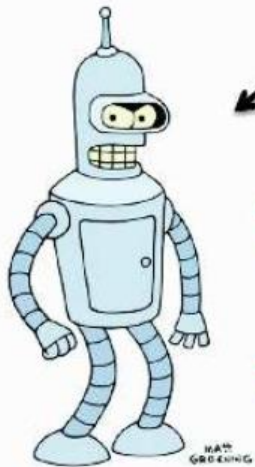
request labels for selected data

$\langle x_1, ? \rangle$

$\langle x_2, ? \rangle$

$\langle x_1, y_1 \rangle$

$\langle x_2, y_2 \rangle$



**active learner**  
induces a classifier



**expert / oracle**  
analyzes experiments  
to determine labels

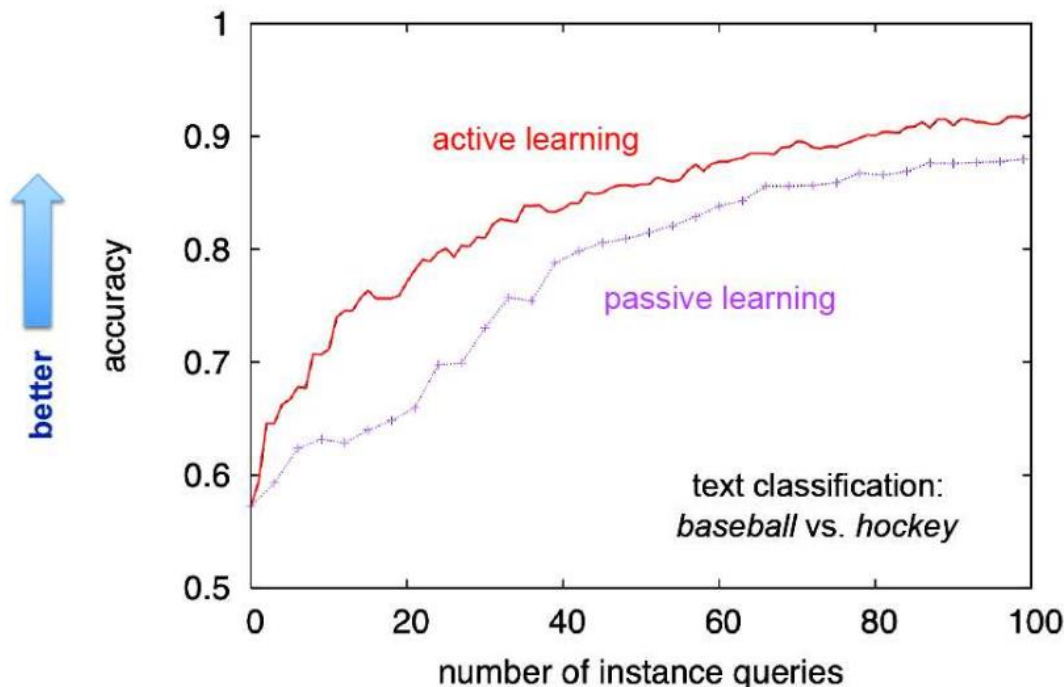
# Active Learning vs Random Sampling

- **Passive learning curve**

- ▶ Randomly selects examples to get labels for

- **Active learning curve**

- ▶ Active learning selects examples to get labels for

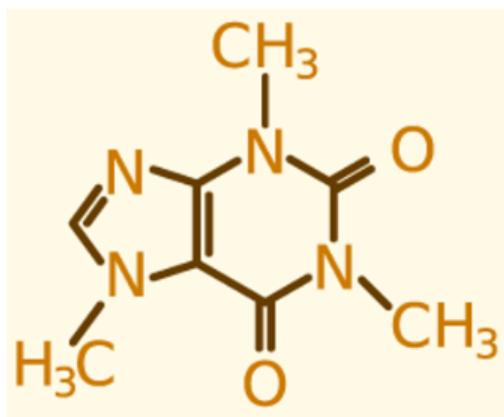


# Motivation

- **Why do we need active learning?**
  - ▶ Supervised learning can solve all our problems, right?
  - ▶ Yes, if we have enough labeled data (input-output pairs)
  - ▶ But Labeling is expensive
  - ▶ We want to learn a highly-accurate function with few labeled examples
  - ▶ Intelligently select the examples for which we want to get labels for (unlabeled data is plentiful and cheap)

# Active Learning Example: Drug Design

Goal: find compounds which bind to a particular target

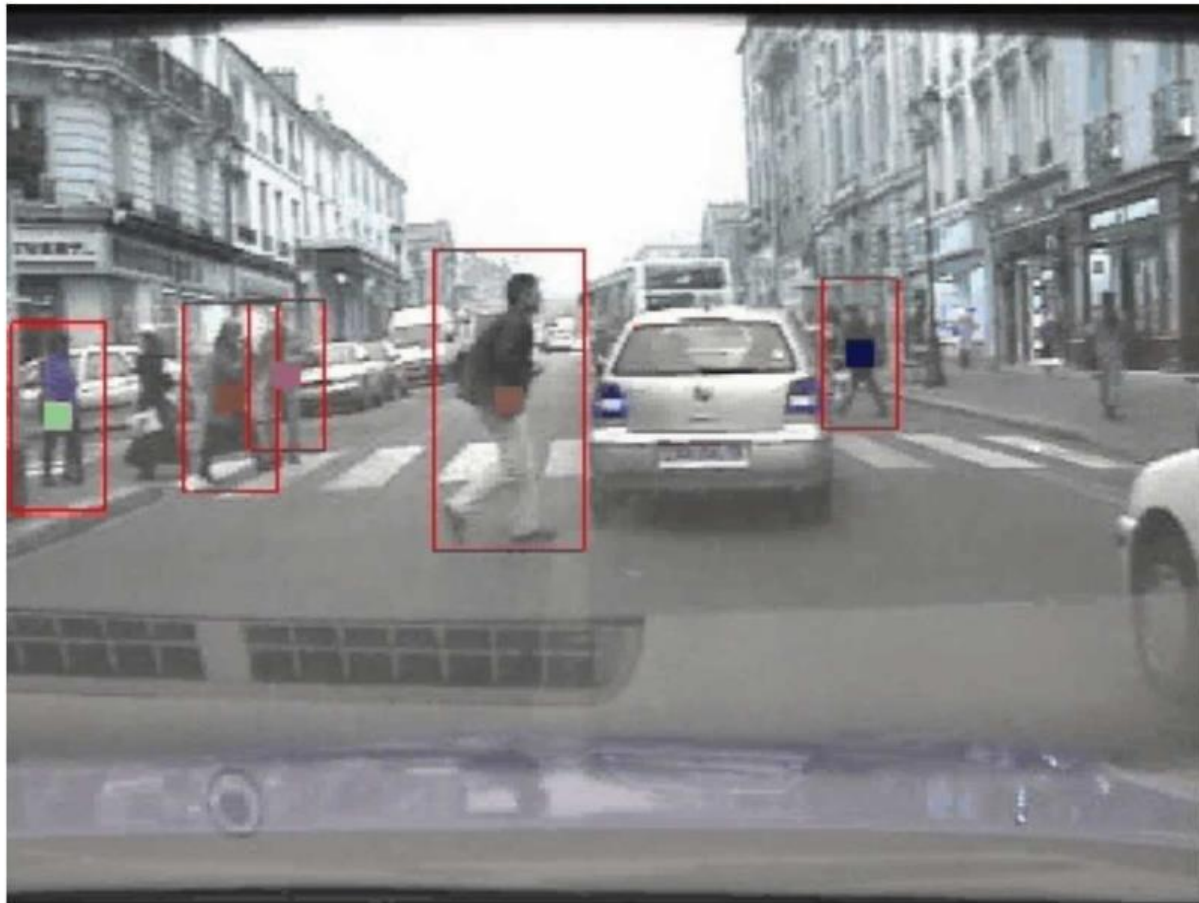


Large collection of compounds, from:

- ▶ vendor catalogs
- ▶ corporate collections
- ▶ combinatorial chemistry

unlabeled point     $\equiv$     description of chemical compound  
label     $\equiv$     *active* (binds to target) vs. *inactive*  
getting a label     $\equiv$     chemistry experiment

# Active Learning Example: Pedestrian detection



# Who uses Active Learning?



Sentiment analysis for blogs; Noisy relabeling  
– *Prem Melville*



Biomedical NLP & IR; Computer-aided diagnosis  
– *Balaji Krishnapuram*

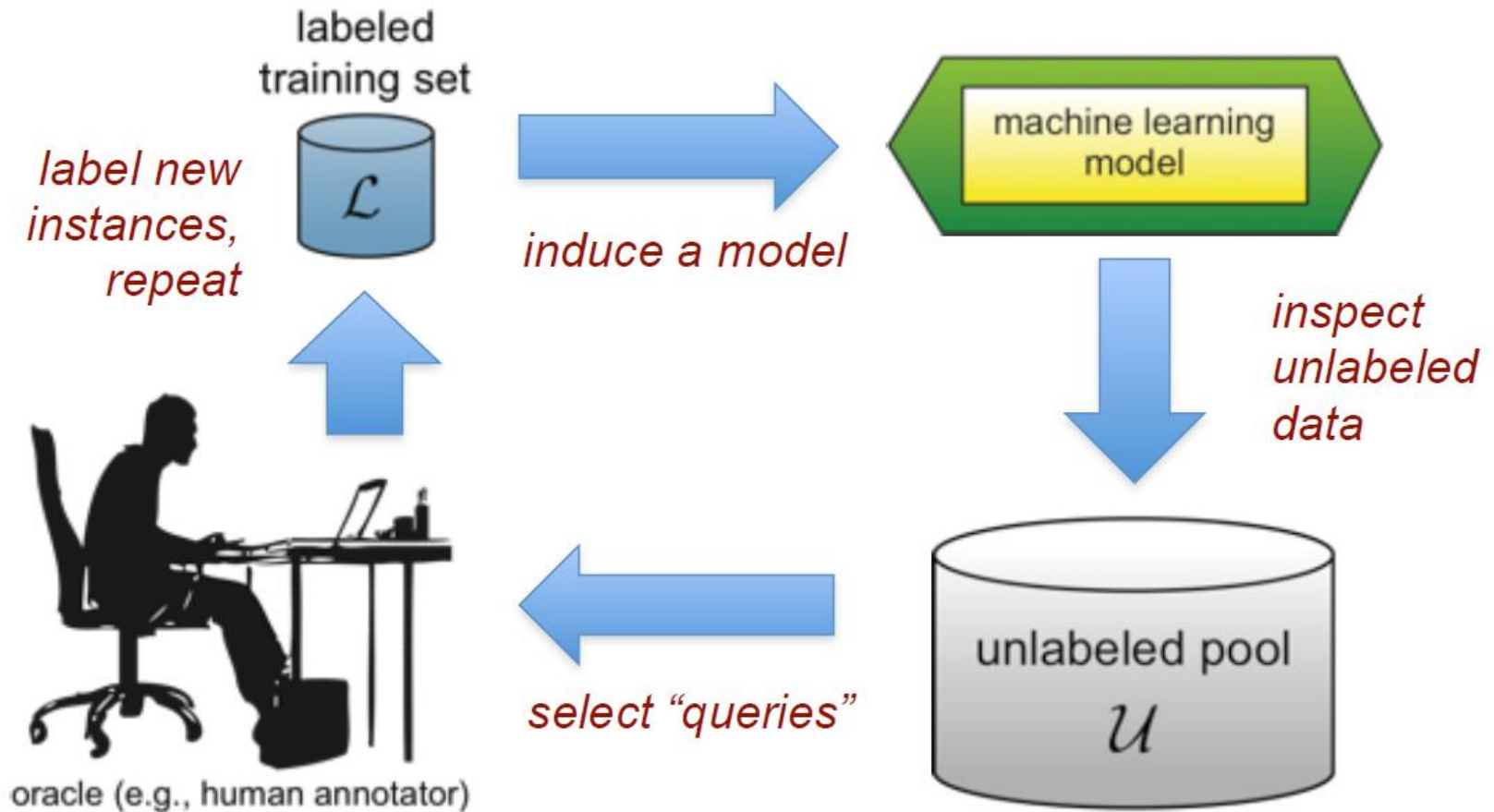


MS Outlook voicemail plug-in [Kapoor et al., IJCAI'07];  
“A variety of prototypes that are in use throughout the company.” – *Eric Horvitz*



“While I can confirm that we're using active learning in earnest on many problem areas... I really can't provide any more details than that. Sorry to be so opaque!”  
– *David Cohn*

# Pool based Active Learning





# Query Selection Strategies

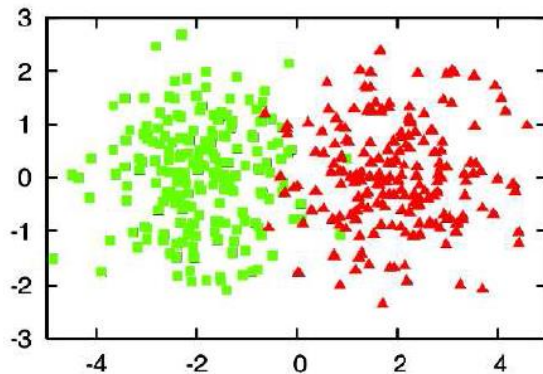
- Any active learning algorithm requires a query selection strategy.
- Some examples
  - ▲ Uncertainty Sampling
  - ▲ Query By Committee (QBC)
  - ▲ Expected Model Change
  - ▲ Expected Error Reduction
  - ▲ Variance Reduction
  - ▲ Density Weighted Methods

# Uncertainty Sampling

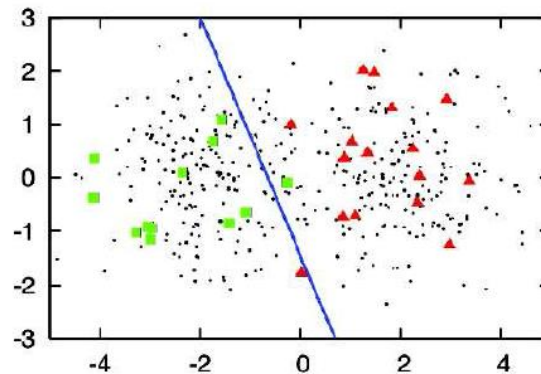
- Select examples which the current model is most uncertain about
- Many ways to measure uncertainty
  - ▲ Based on distance from the hyperplane
  - ▲ Using the probability distribution over labels  $P(y|x)$  for probabilistic models
- Some examples based on label probabilities
  - ▲ **Least Confident**, where confidence is defined as  $1 - \text{probability of highest scoring label}$
  - ▲ **Smallest Margin**, where margin is defined as the difference between the probabilities of the first and second best labels

# Uncertainty Sampling: Illustration

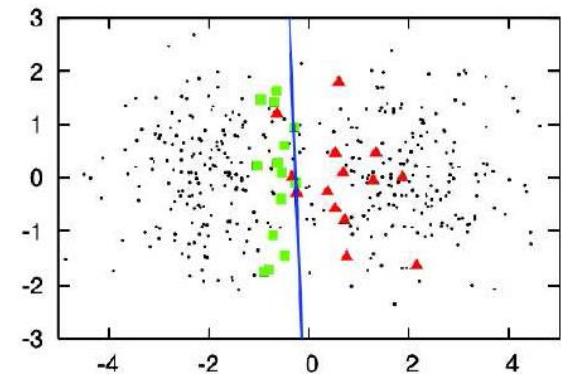
- Example: uncertainty sampling based on the distance from hyperplane (i.e., margin based)



400 instances sampled  
from 2 class Gaussians



random sampling  
30 labeled instances  
(accuracy=0.7)



uncertainty sampling  
30 labeled instances  
(accuracy=0.9)

# Query By Committee (QBC)

- QBC uses a committee of models (say  $h_1, h_2, \dots, h_k$ )
- All models are trained using the currently available labeled data  $L$
- How is the committee constructed?
  - ▲ Ensemble methods (e.g., bagging, boosting)
- All models vote their predictions on the unlabeled pool
- The example(s) with maximum disagreement is(are) chosen for labeling
  - ▲ simple disagreement rate
  - ▲ Entropy over the vote distribution over all labels
- Each model in the committee is re-trained with new examples

# Summary and Outlook

- Active learning is a **label-efficient** learning strategy
- Intelligently selects the examples based on their informativeness
- Other variants
  - ▶ Different examples having different labeling costs
  - ▶ Access to multiple labeling oracles varying in labeling cost and accuracy
  - ▶ Active learning on features instead of labels
- Further Reading
  - ▶ Active learning survey from Burr Settles
  - ▶ <http://burrsettles.com/pub/settles.activelearning.pdf>