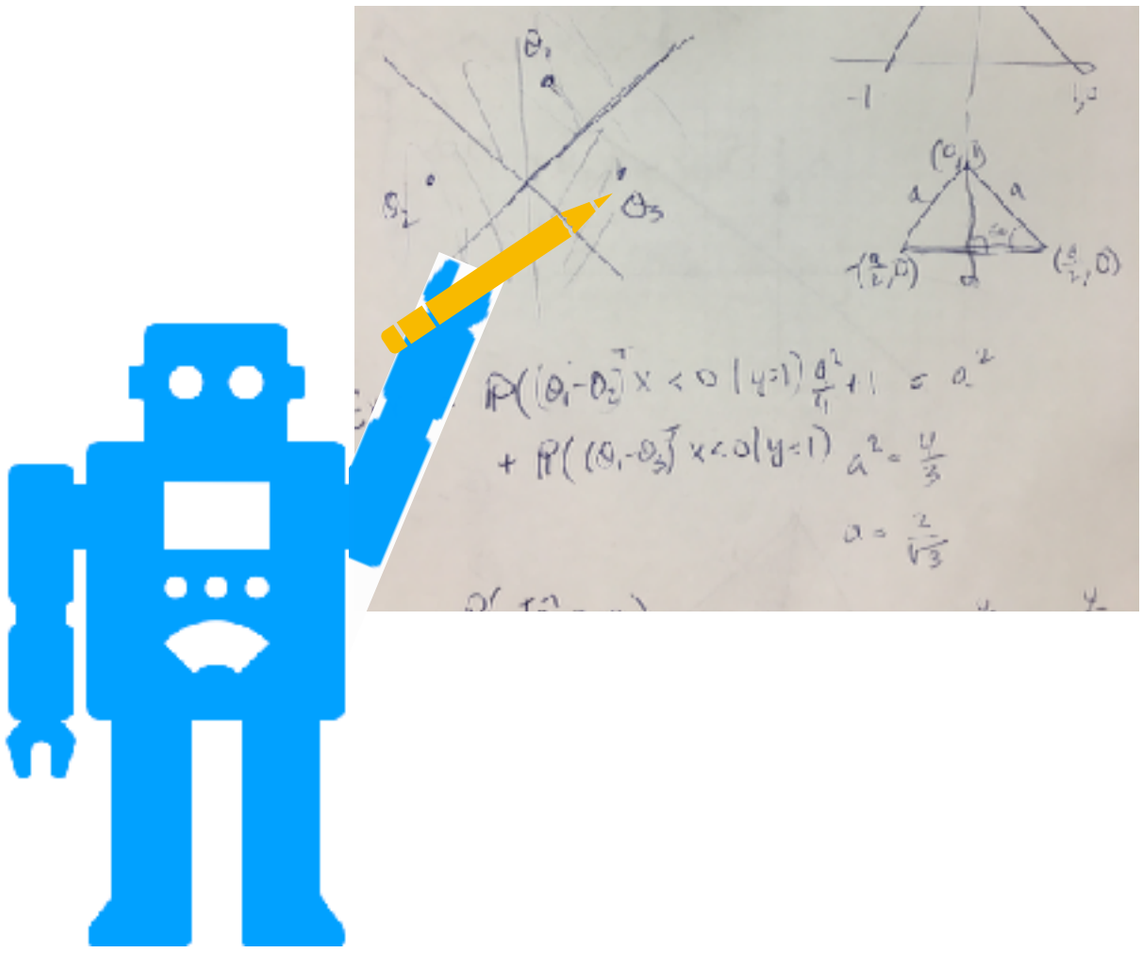
Introduction to Theory of Active Machine Learning



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ICML | 2019

Thirty-sixth International Conference on Machine Learning

Tutorial Outline

Part 1: Introduction to Active Learning (Rob)

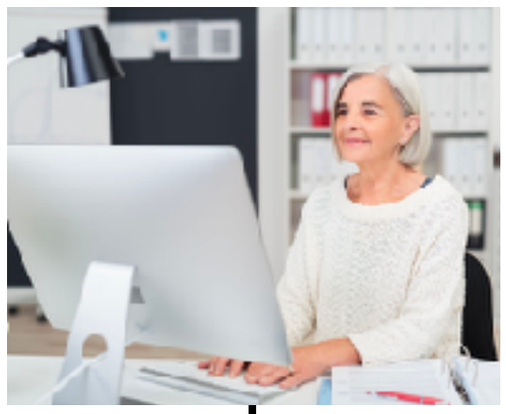
Part 2: Theory of Active Learning (Steve)

Part 3: Advanced Topics and Open Problems (Steve)

Part 4: Nonparametric Active Learning (Rob)

slides: http://nowak.ece.wisc.edu/ActiveML.html

Conventional (Passive) Machine Learning



unlabeled raw data

human labeling

labeled data

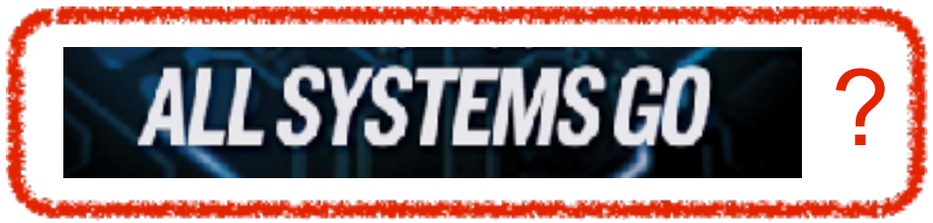
machine learning

predictive model

dog

boat

⋮



theguardian

Computers now better than humans at recognising and sorting images

millions of labeled images
1000's of human hours

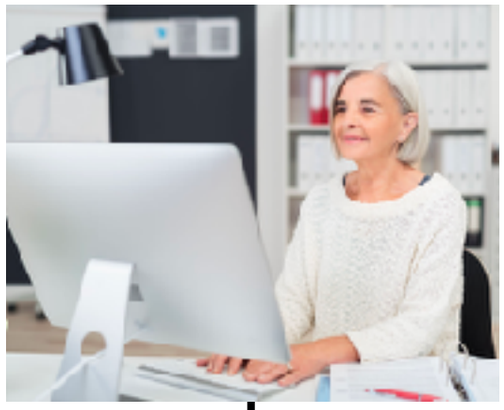
QUARTZ

Google says its new AI-powered translation tool scores nearly identically to human translators

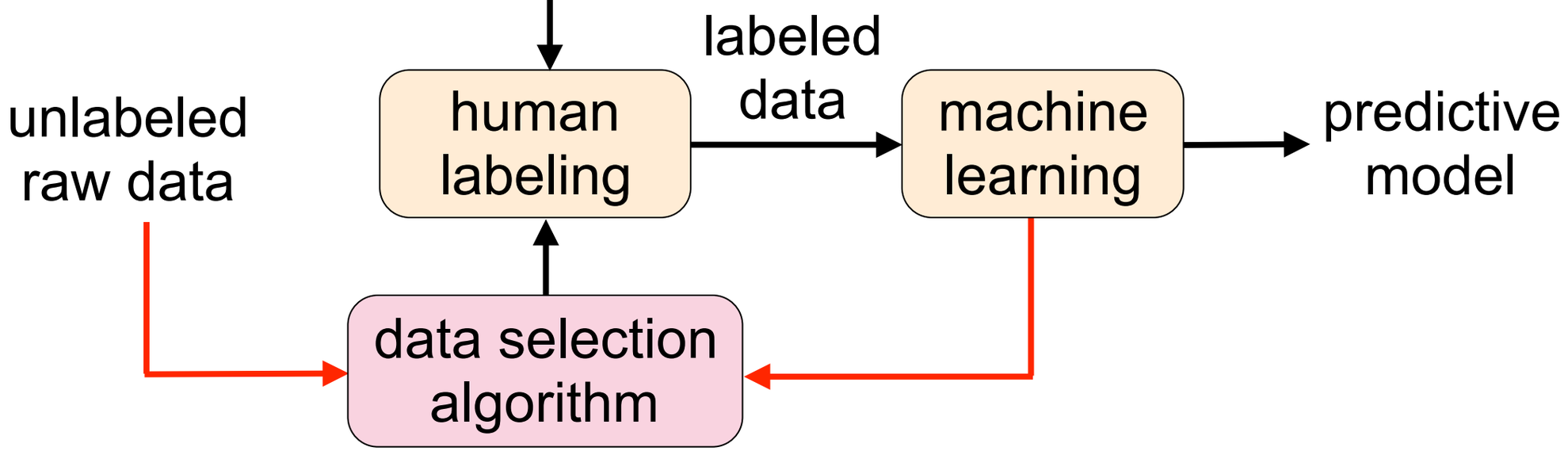
trained on more texts than a human could read in a lifetime

Can we train machines with less labeled data and less human supervision?

Active Machine Learning



Goal: machine automatically and adaptively selects most informative data for labeling



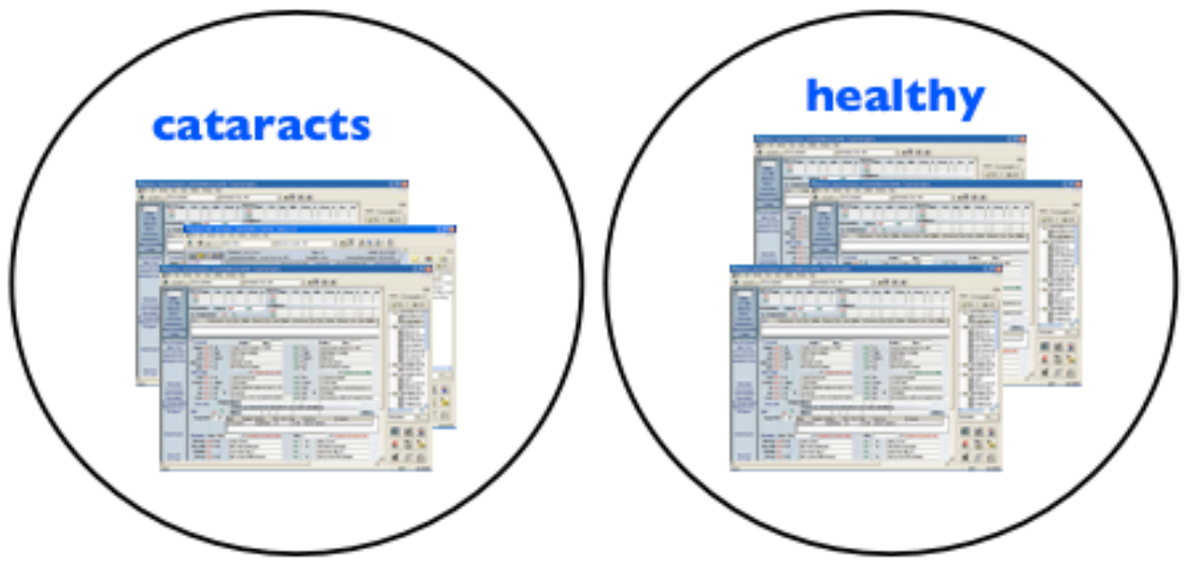
Motivating Application

unlabeled electronic
health records (EHRs)

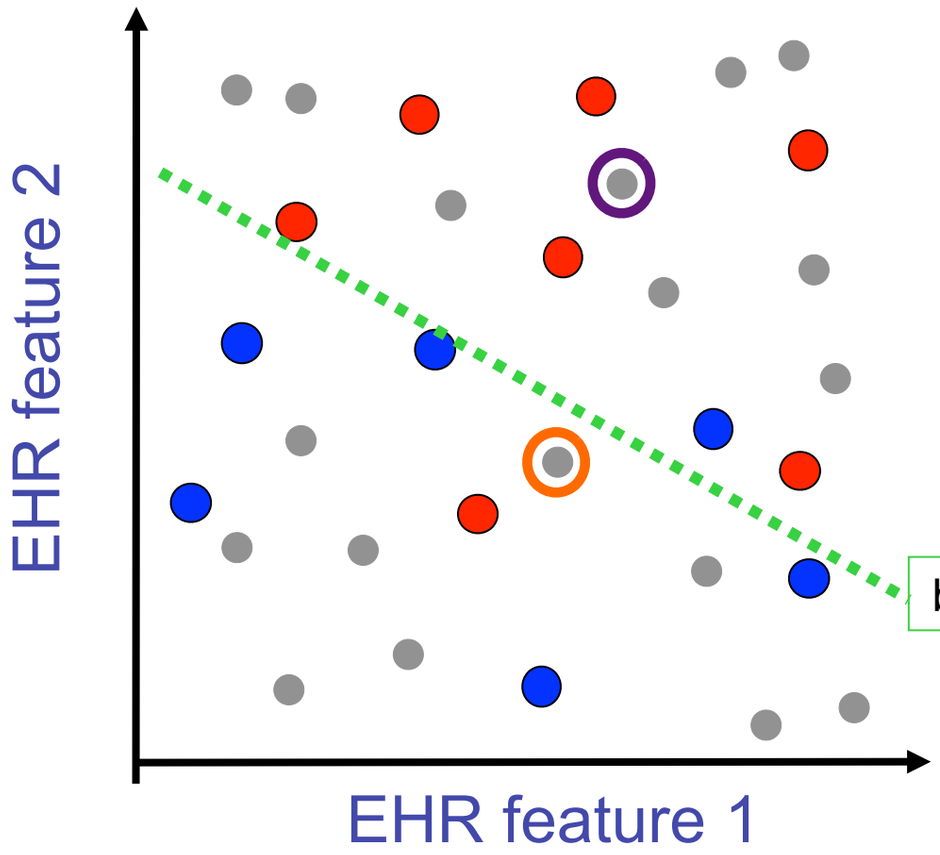
human experts

provides labels to machine learner
(several minutes / EHR)

prediction rule
that can be applied
to unlabeled EHRs

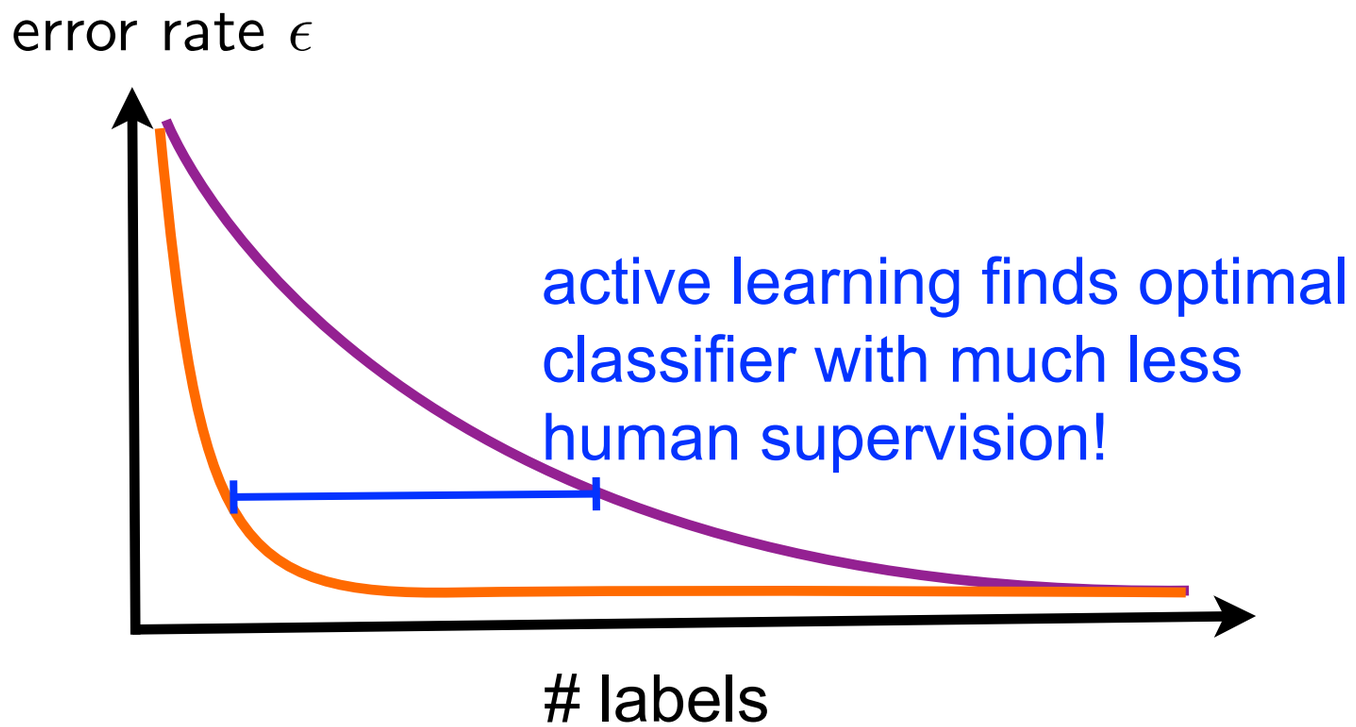


Active Learning

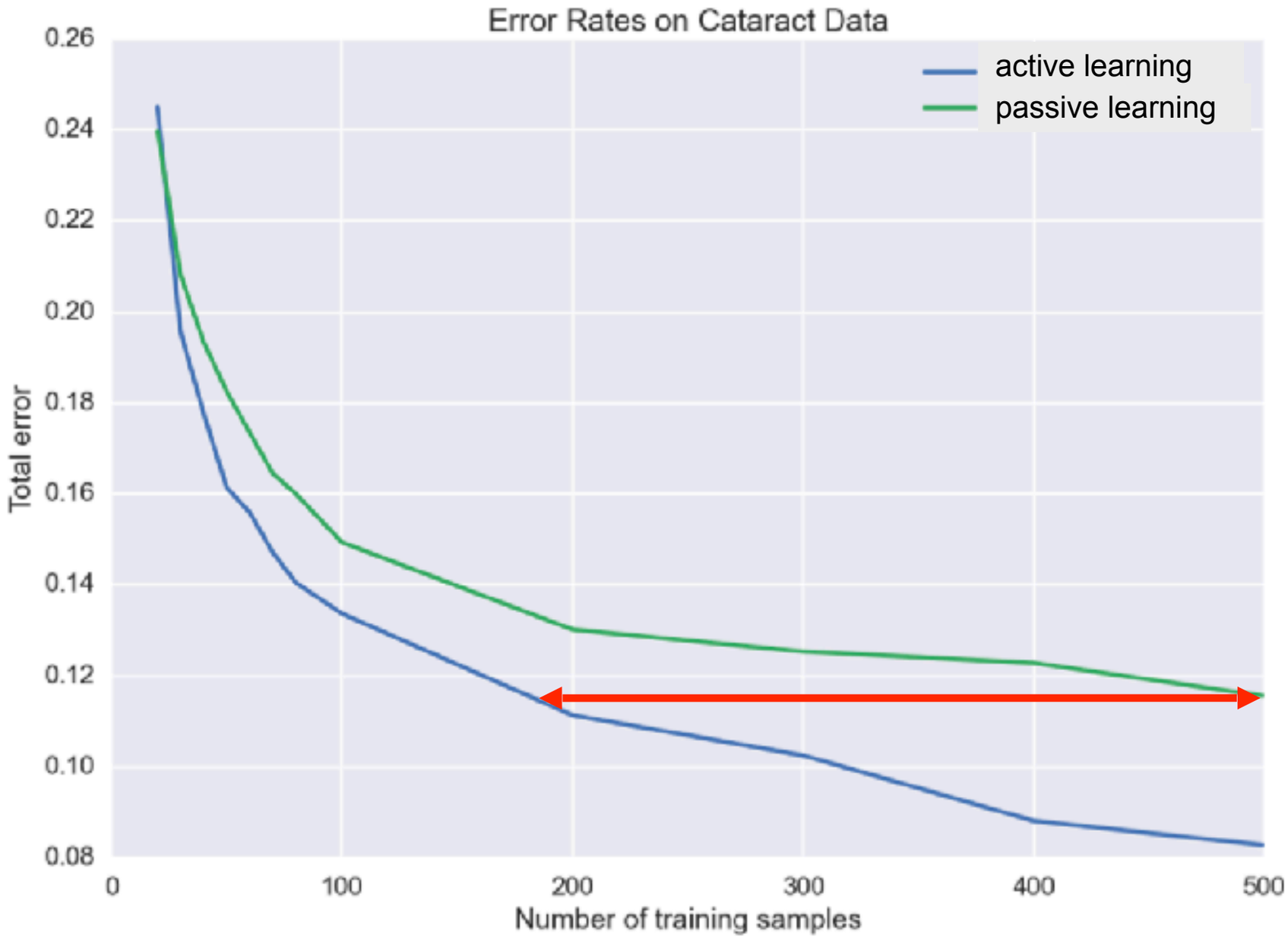


Non-adaptive strategy: Label a random sample

Active strategy: Label a sample near best decision boundary based on labels seen so far



Active Logistic Regression



11000 patient records
- 8000 positive
- 3000 negative

6182 Numerical Features
- icd9 codes
- lab tests
- patient data

Classification task:
cataracts or healthy

less than half as many labeled examples needed by active learning

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NEXT

ASK BETTER QUESTIONS.

GET BETTER RESULTS.

FASTER. AUTOMATED.

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UNIVERSITY OF WISCONSIN-MADISON

DEPARTMENT OF
Computer Sciences
UNIVERSITY OF WISCONSIN-MADISON

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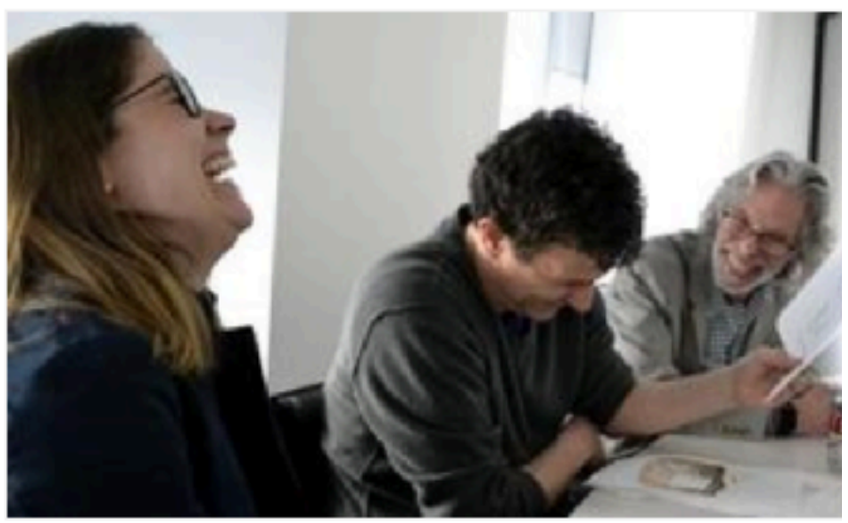
LEAD | DISCOVER | DEVELOP | DELIVER

Active learning to optimize crowdsourcing and rating in New Yorker Cartoon Caption Contest

digg



BY DOING THE EXACT OPPOSITE

How New Yorker Cartoons Could Teach Computers To Be Funny

3 diggs CNET Technology

With the help of computer scientists from the University of Wisconsin at Madison, The New Yorker for the first time is using crowdsourcing algorithms to uncover the best captions.

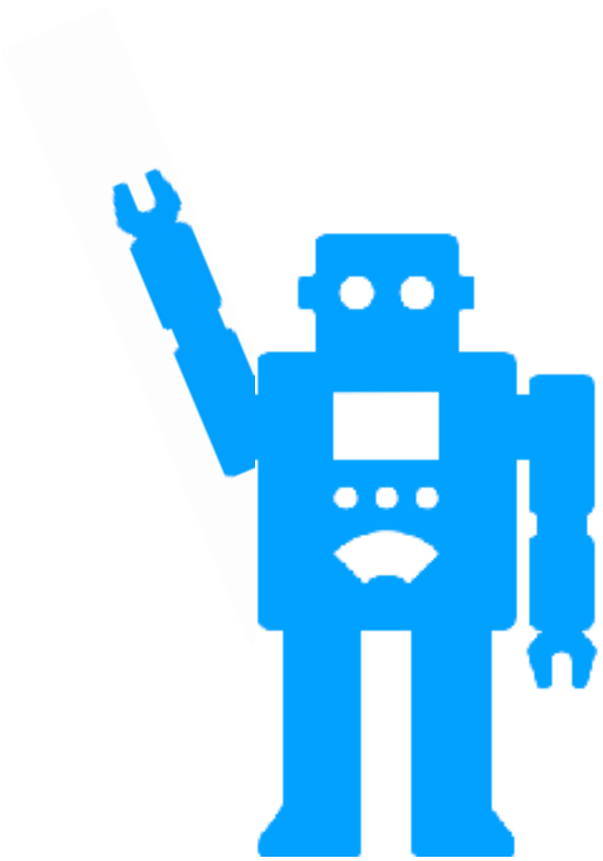
3

Actively learning user's beer preferences

BeerMapper℠

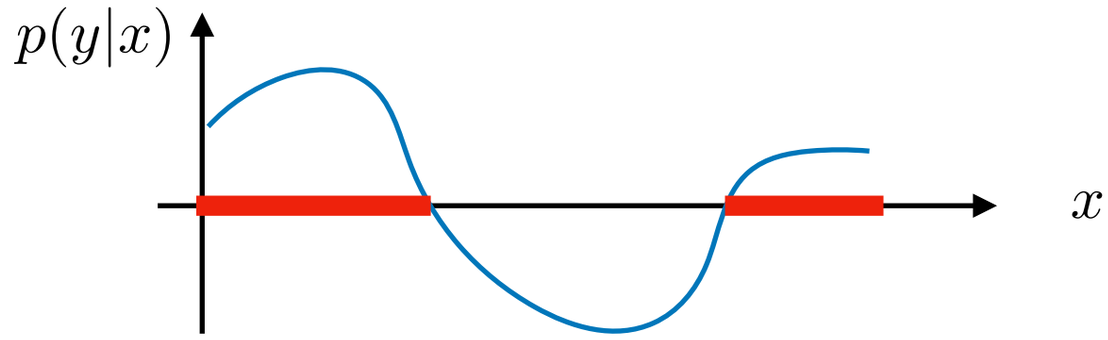
Home Contact About FAQs

Principles of Active Learning

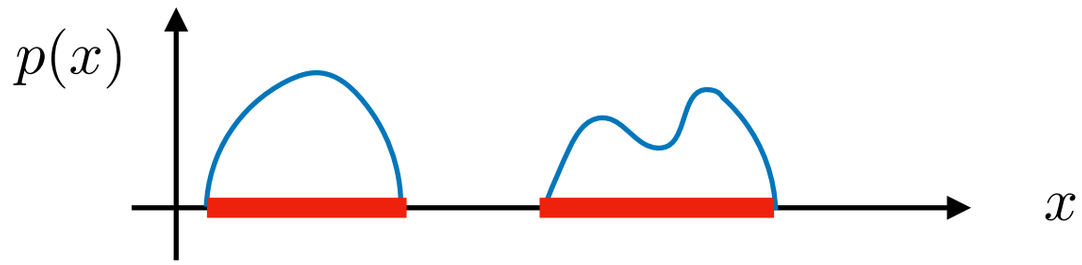


What and Where Information

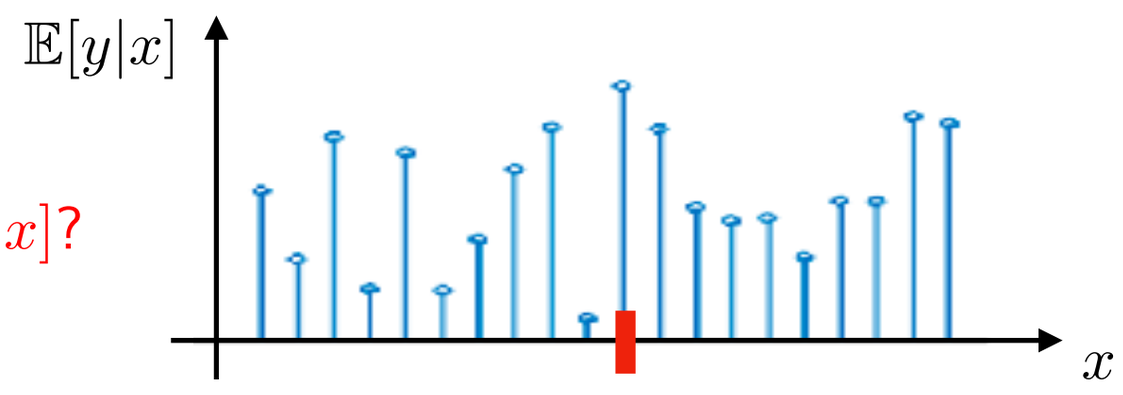
Density estimation: What is $p(y|x)$?
Classification: Where is $p(y|x) > 0$?



Density estimation: What is $p(x)$?
Clustering: Where is $p(x) > \epsilon$?



Function estimation: What is $\mathbb{E}[y|x]$?
Bandit optimization: Where is $\max_x \mathbb{E}[y|x]$?



Active learning is more efficient than passive learning for localized "where" information

Meta-Algorithm for Active Learning

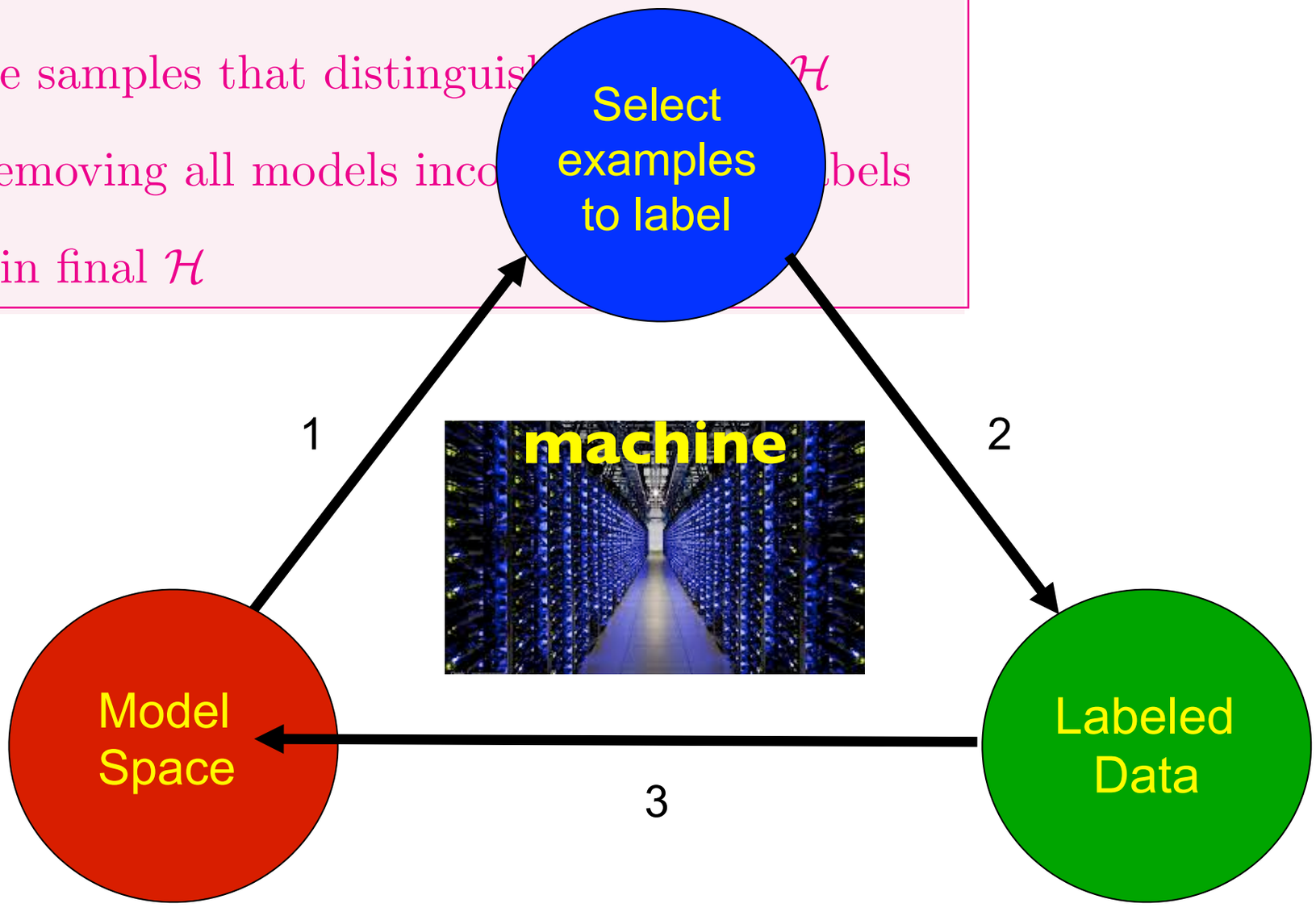
Version-Space (VS) Active Learning

initialize VS: $\mathcal{H}$ = all models/hypotheses

while (*stopping-criterion*) not met

1. **sample** at random from available dataset
2. **label** only those samples that distinguis $\mathcal{H}$
3. **reduce** $\mathcal{H}$ by removing all models inco bels

output: best model in final $\mathcal{H}$



Learning a 1-D Classifier

binary search quickly finds **decision boundary**

$$\text{passive}: \text{err} \sim n^{-1}$$

$$\text{active}: \text{err} \sim 2^{-n}$$

Vapnik-Chervonenkis (VC) Theory

Given training data $\{(x_j, y_j)\}_{j=1}^n$, learn a function f to predict y from x

Consider a possibly infinite set of hypotheses $\mathcal{F}$ with *finite VC dimension* d and for each $f \in \mathcal{F}$ define the risk (error rate):

$$R(f) \;:=\; \mathbb{P}(f(x) \neq y)$$

error rate on training data:

$$\widehat{R}(f) \;=\; \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}\Big(f(x_i) \neq y_i\Big)$$

"empirical risk"

VC bound:

$$\sup_{f \in \mathcal{F}} |R(f) - \widehat{R}(f)| \;\leq\; 6\sqrt{\frac{d \log(n/\delta)}{n}}$$

w.p. $\geq\; 1 - \delta$

Empirical Risk Minimization (ERM)

Goal: select hypothesis with true error rate within $\epsilon > 0$ of $\min_{f \in \mathcal{F}} R(f)$

$$f^* = \arg\min_{f \in \mathcal{F}} R(f) \quad \text{true risk minimizer}$$

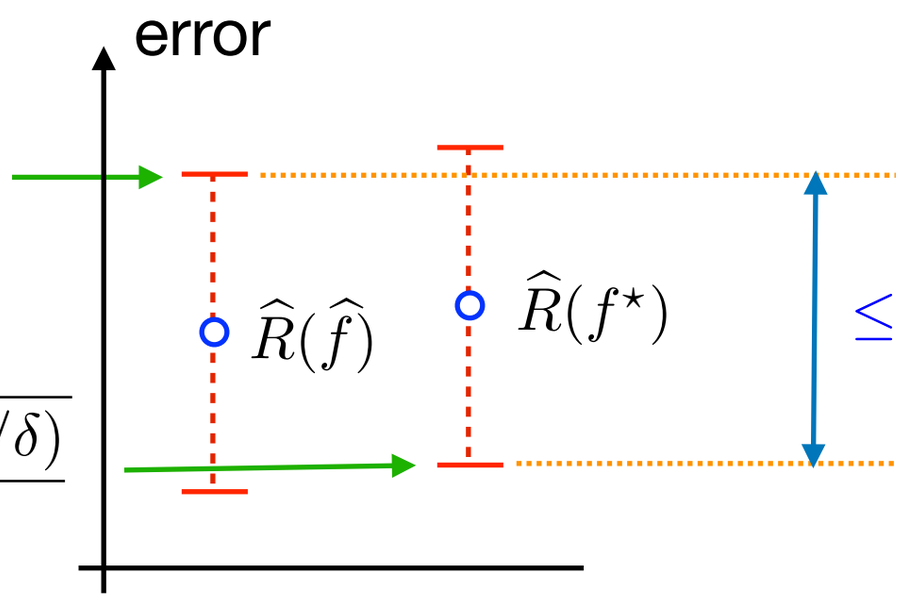
$$\widehat{f} = \arg\min_{f \in \mathcal{F}} \widehat{R}(f) \quad \text{empirical risk minimizer}$$

$\widehat{f}$ minimizes empirical risk:

$$\widehat{R}(\widehat{f}) \leq \widehat{R}(f^*)$$

$$R(\widehat{f}) \leq \widehat{R}(\widehat{f}) + 6\sqrt{\frac{d\log(n/\delta)}{n}}$$

$$R(f^*) \geq \widehat{R}(f^*) - 6\sqrt{\frac{d\log(n/\delta)}{n}}$$

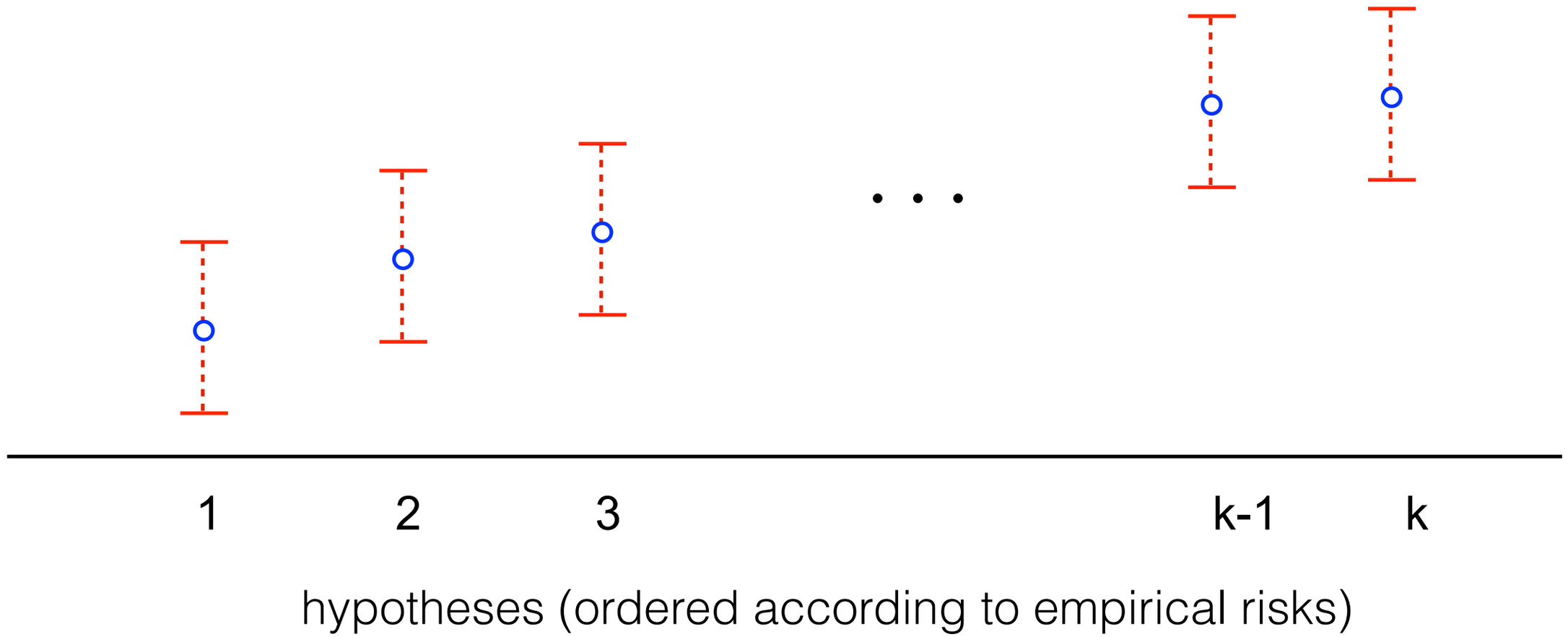


$$\leq \quad 12\sqrt{\frac{d\log(n/\delta)}{n}}$$

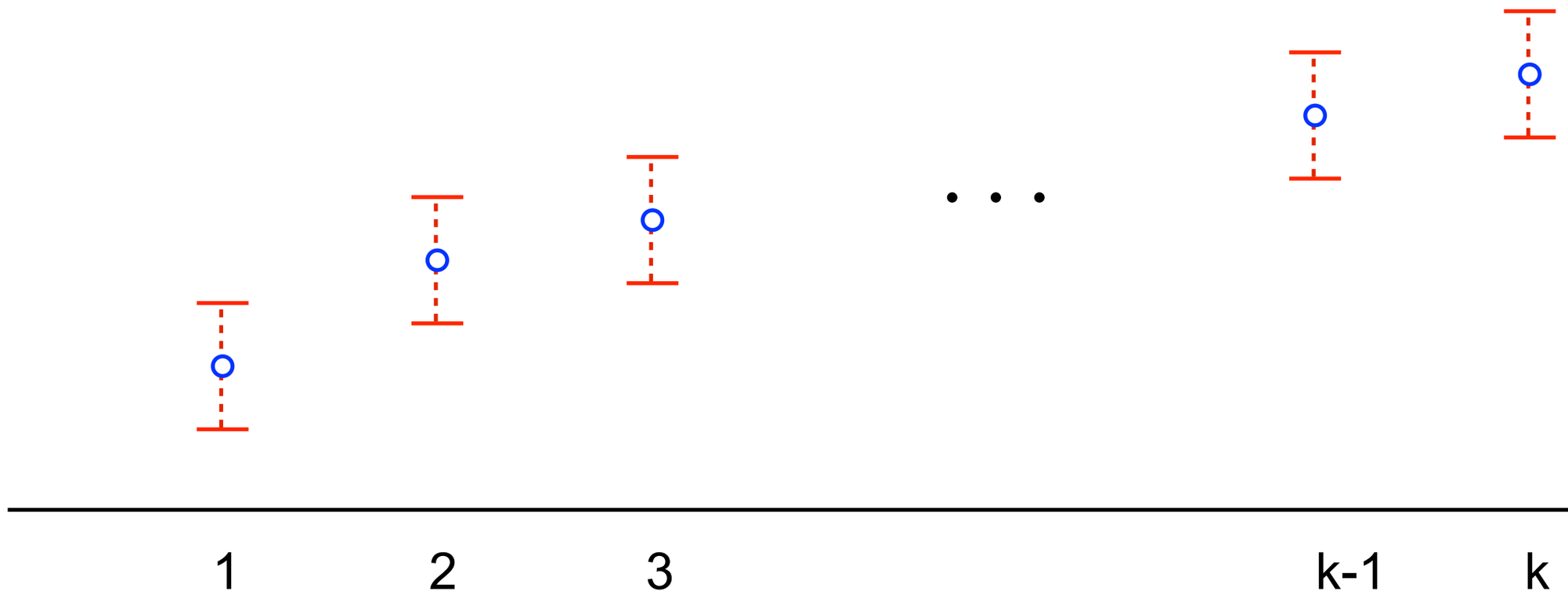
sufficient number of training examples:

$$12\sqrt{\frac{d\log(n/\delta)}{n}} \leq \epsilon \quad \Rightarrow \quad n = \widetilde{O}\Big(\frac{d\log(1/\delta)}{\epsilon^2}\Big)$$

Empirical Risks and Confidence Intervals

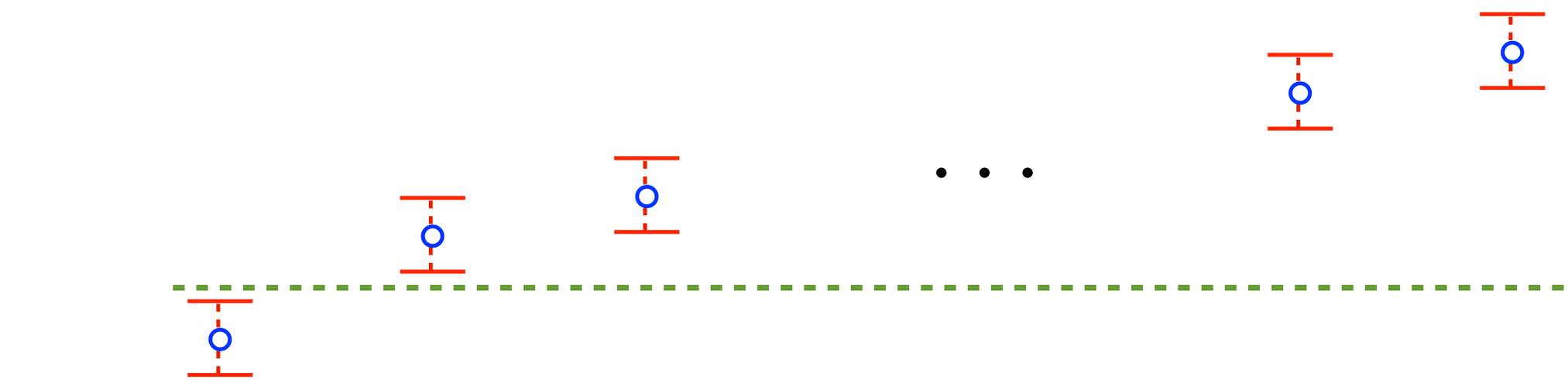


Empirical Risks and Confidence Intervals



more training data $\Rightarrow$ smaller confidence intervals

Empirical Risks and Confidence Intervals

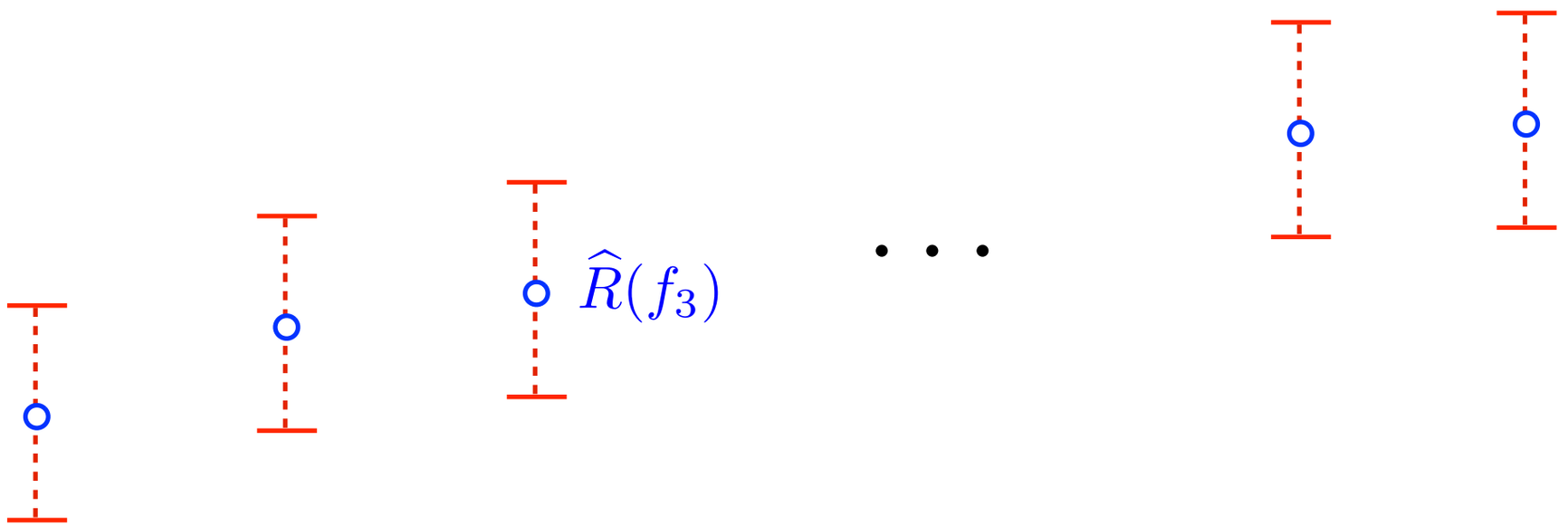


1 2 3 k-1 k

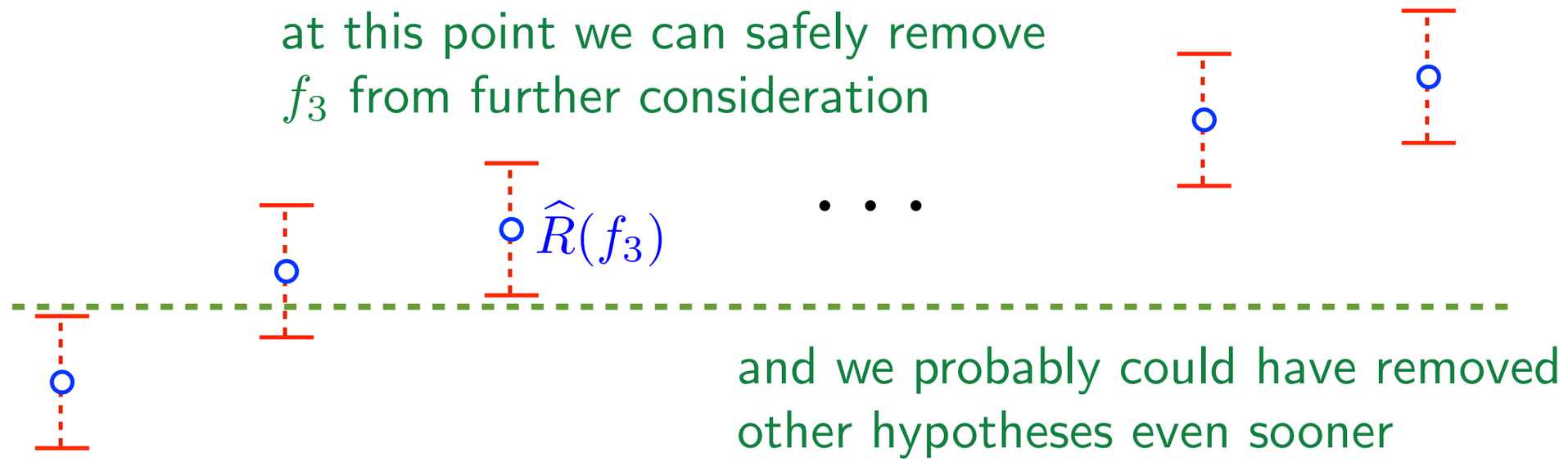
hypotheses (ordered according to empirical risks)

more training data $\Rightarrow$ smaller confidence intervals

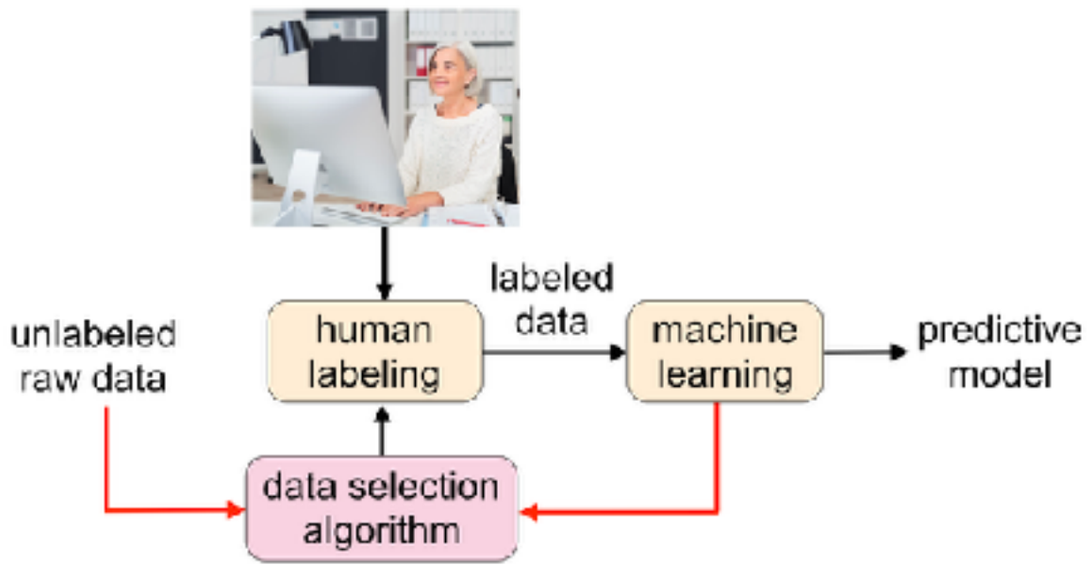
ERM is Wasting Labeled Examples



ERM is Wasting Labeled Examples

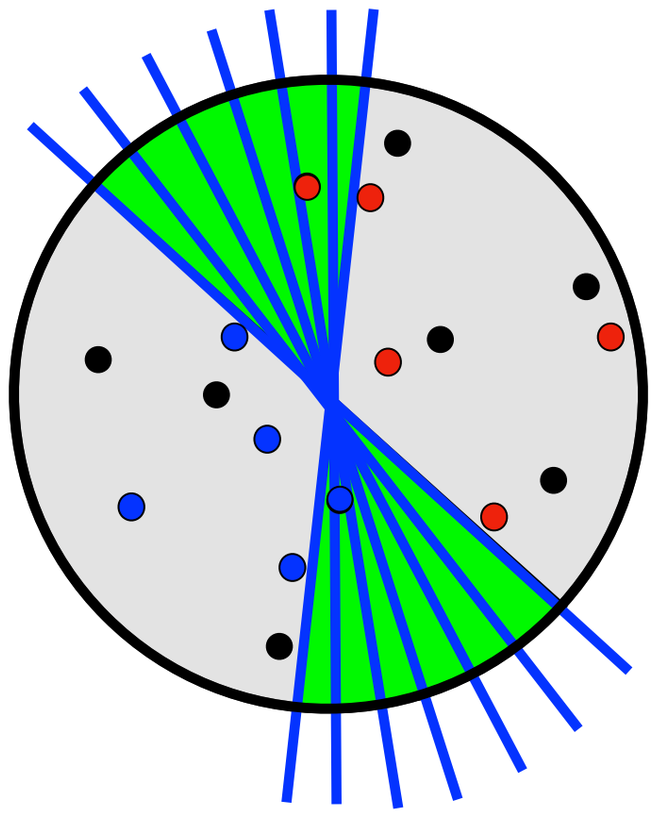


only require labels for examples that hypotheses 1 and 2 label differently (i.e., examples where they *disagree*)



Disagreement-Based Active Learning

consider points uniform on unit ball and
linear classifiers passing through origin



only label points in the
region of disagreement $\mathfrak{D}$

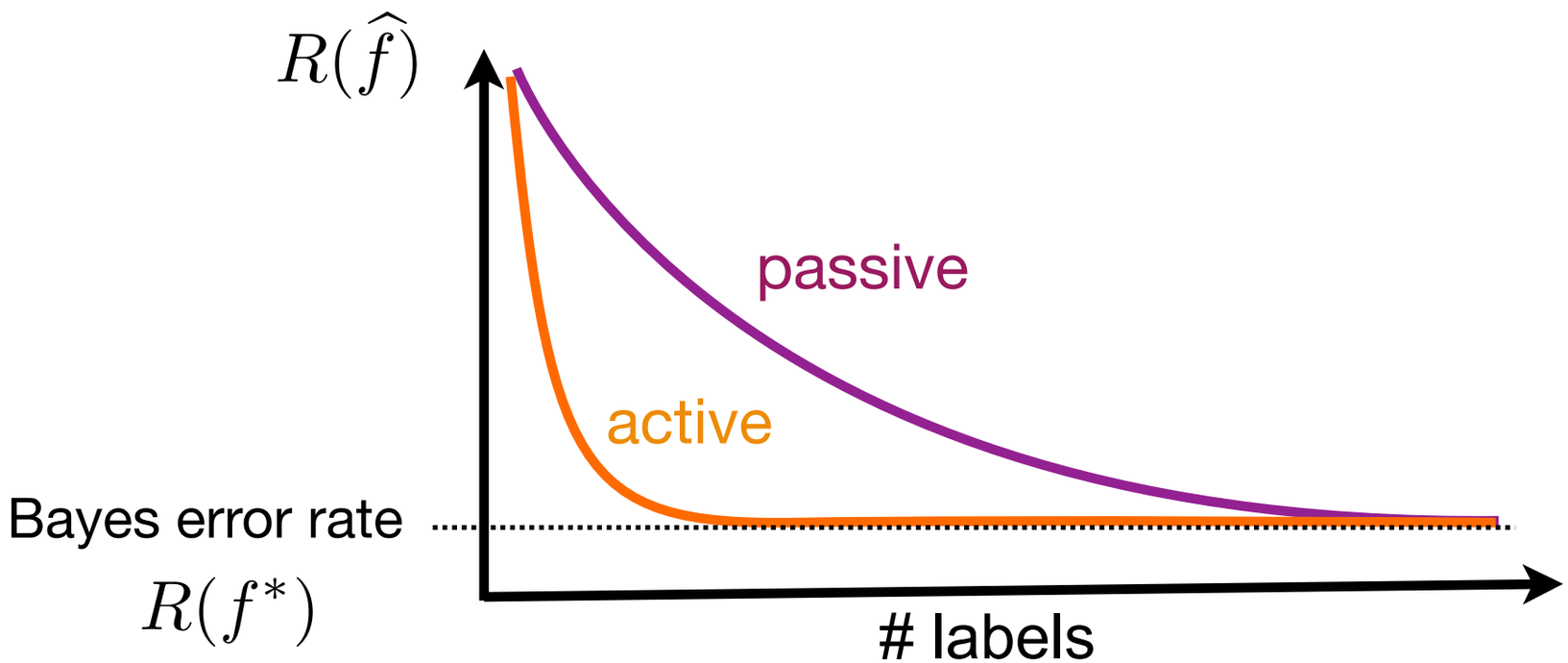
Active Binary Classification

Assuming optimal Bayes classifer f^* in VC class with dimension d and "nice" distributions (e.g., bounded label noise)

$$\epsilon \quad = \quad R(\widehat{f}) - R(f^*)$$

passive $\quad \epsilon \quad \sim \quad \frac{d}{n}$ parametric rate

active $\quad \epsilon \quad \sim \quad \exp\left(-c\,\frac{n}{d}\right)$ exponential speed-up



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Recommended Reading (Foundations of Active Learning)

Settles, Burr. "Active learning." *Synthesis Lectures on Artificial Intelligence and Machine Learning* 6.1 (2012): 1-114.

Dasgupta, Sanjoy. "Two faces of active learning." *Theoretical computer science* 412.19 (2011): 1767-1781.

Cohn, David, Les Atlas, and Richard Ladner. "Improving generalization with active learning." *Machine learning* 15.2 (1994): 201-221.

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Nowak, Robert D. "The geometry of generalized binary search." *IEEE Transactions on Information Theory* 57, no. 12 (2011): 7893-7906.

Hanneke, Steve. "Theory of active learning." *Foundations and Trends in Machine Learning* 7, no. 2-3 (2014).