Machine Learning Coms-4771

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(partially based on Yann LeCun's and Sam Roweis's slides; see links at the web page)

Logistics

- The course web page is
  `http://hunch.net/~coms-4771`
- If you have a question, email
  `beygel@us.ibm.com`
  or post it at
  `http://coms-4771.blogspot.com/`
- Do interrupt and ask questions during the class.
- The web page has notes on probability theory and statistics (if you need to refresh your memory)

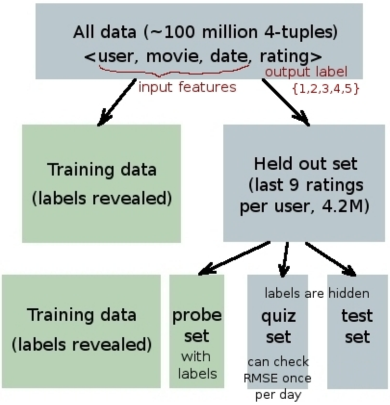
What is Machine Learning?

www.netflixprize.com

- In October 2006, Netflix announced a \$1M problem:

  Predict the rating a given user would assign to a given movie (based on 100 million past user-movie ratings).
- 10% improvement = \$1M
- 2500 teams; annual progress prize of \$50K went to KorBell from AT&T Labs (8.43%)

Netflix Problem Setup



- Success is measured by the root mean squared error (RMSE) on the test set:

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2},$$

where y_i and $\hat{y}_i$ are the actual and predicted movie ratings.

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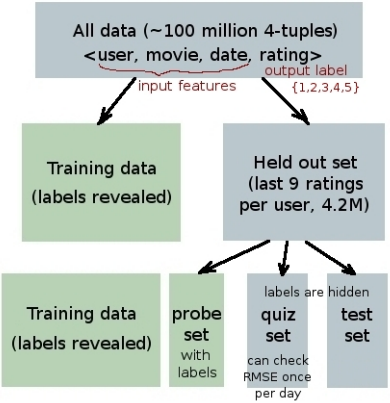

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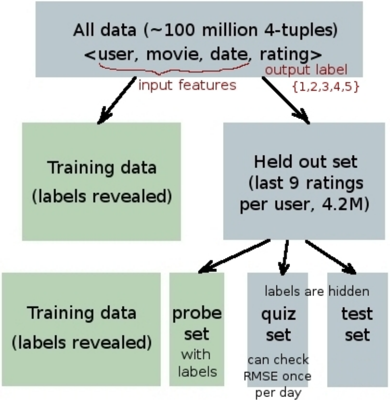

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  where y_i and $\hat{y}_i$ are the actual and predicted movie ratings.
- Q: What's the role of the probe set?
- Q: Why are there both quiz and test sets?
- We have a well defined task. How would you go about solving it?

What is Machine Learning?

- We want robust, intelligent behavior. Hand-programming a solution directly is not going to work. The world is too complex.
- Learning approach = programming by example: Get the machine to program itself by showing it examples of the behavior we want. Learning is about improving performance through experience.
  - Learning is data driven. It can examine much larger amounts of data than you can.
  - Labeling examples is perhaps the easiest way to express knowledge.
  - Learning is general purpose—algorithm reuse!
- In reality, we specify a space of possible solutions, and let the machine find a good solution in this space.

Learning Problems, Structure of Learning Machines

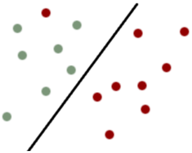
- Learning problem = (unknown) distribution of inputs and outputs D + (typically known) loss function L.
- Hypothesis space H = Space of functions mapping inputs to outputs (H is often indexed by a set of parameters the algorithm can tune to create different solutions)
- Learning algorithm searches (or prunes or tunes parameters in) H to find a hypothesis minimizing the expected L on D, based on a limited set of input-output examples.

The hardest part is deciding how to represent inputs/outputs and how to select appropriate L and H.

How do we incorporate prior information?

Supervised Learning

Given a set of labeled examples, predict outputs of future unlabeled examples.



Classification: Feature space X, discrete set of labels Y (categories). Find a decision boundary between the categories in Y.

Loss function: $\ell(y, y') = \mathbf{1}(y \neq y')$ (zero-one loss)

Distribution D over $X \times Y$. Find a classifier $h : X \to Y$ minimizing the expected loss on D given by $\mathbf{Pr}_{(x,y)\sim D}[h(x) \neq y] = \mathbf{E}_{(x,y)\sim D}\, \ell(y, h(x))$.

Regression ("curve fitting" or "function approximation"): $Y = \mathbb{R}$

Loss function: $\ell_{sq}(y, y') = (y - y')^2$ (squared loss)

Learn a continuous mapping $f : X \to \mathbb{R}$ minimizing $\mathbf{E}_{(x,y)\sim D}\, \ell_{sq}(y, f(x))$.

Training vs. Testing

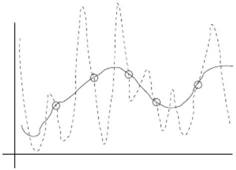
- Training (empirical) error: the average loss on the training data
- Test error: the average loss on the test data
- Ideally we want to minimize the test error, but we can't evaluate it! (Most of the time we don't even know future inputs.)
- Do we want to minimize the training error instead?

Training vs. Testing

- Training (empirical) error: the average loss on the training data
- Test error: the average loss on the test data
- Ideally we want to minimize the test error, but we can't evaluate it! (Most of the time we don't even know future inputs.)
- Do we want to minimize the training error instead?
- NO. Consider an algorithm that memorizes training examples. If a test example is in the training set, produce the memorized output. Otherwise, choose a random output.
- We are overfitting: Training error is 0. Test error is HUGE.
- Learning is not Memorization. We want to generalize from training examples to predict well on previously unseen examples.

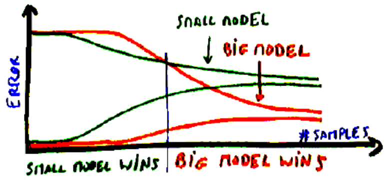
Inductive Bias

- There should be some hope that the data is predictive.
- No Free Lunch Theorems: an unbiased learner can never generalize. Inductive bias = set of assumptions that favor some predictors over others.



- Ways of incorporating bias: assumptions on the data distribution (test data is drawn from the same distribution as the training data, examples are independent), choice of the hypothesis class
- Examples: Occam's Razor (choose the simplest consistent hypothesis), maximum margin (attempt to maximize the width of the boundary), nearest neighbors (guess the label based on closest training examples).

Choosing Hypothesis Space



- The number of training examples for which the training error and test error start converging = "capacity" of the learning machine.
- Can we bound the expected loss as a function of the empirical loss, the capacity of the family of functions, and the size of the training set? (Yes, sometimes.)
- Problem: if the class is too rich, there is a risk of overfitting the data. If the class if too simple, there is a risk of not being able to approximate the data well.

Q: How to choose the hypothesis space so that it is large enough to contain a solution to your problem, yet small enough to ensure generalization from the training sets you have?

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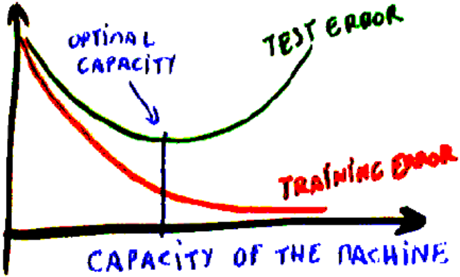


For each training set size, there is an optimal capacity for the machine.

Choosing the Loss Function

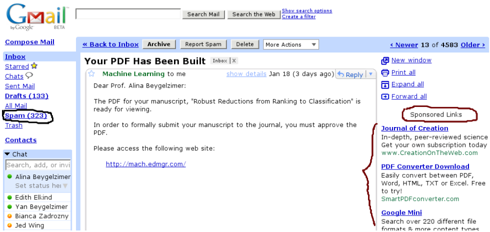
- L quantifies what it means to do well/poorly on the task
- Tradeoff: L captures what we actually want to minimize vs. L is computationally easy to optimize.
- Loss function semantics:
  - Optimizing squared loss means predicting the conditional mean $\mathbf{E}_{(x,y)\sim D}(y \mid x)$.
  - Optimizing the absolute loss $|y - y'|$ means predicting the conditional median.
- Good rule: start with what you want and try to derive a loss.

Other Types of Learning

- Unsupervised learning: given only inputs, automatically discover structure (clustering, outlier detection, embedding in low-dimensional manifold, compression). Not so well defined.
- Semi-supervised learning: labels are expensive, unlabeled data is cheap. Use the unlabeled data to help you learn.
- Active learning: ask for labels on unlabeled examples of your choice, direct the learning process.
- Reinforcement learning: learn how to act in a way that maximizes your expected reward; your actions change the distribution of future inputs.

Some Applications of Machine Learning

- Handwritten character recongition, speech recognition, speaker verification, object detection, tracking objects in videos
- Search, targeted ads, recommendation systems, spam filtering, auctions



- Credit card fraud, insurance premium prediction, product pricing, stock market analysis (Wall Street uses a lot of machine learning)
- Medical diagnosis and prognosis, fMRI analysis
- Game playing (adaptive opponents)
- Robotics, adaptive decision making under uncertainty