11: Machine Learning System Design

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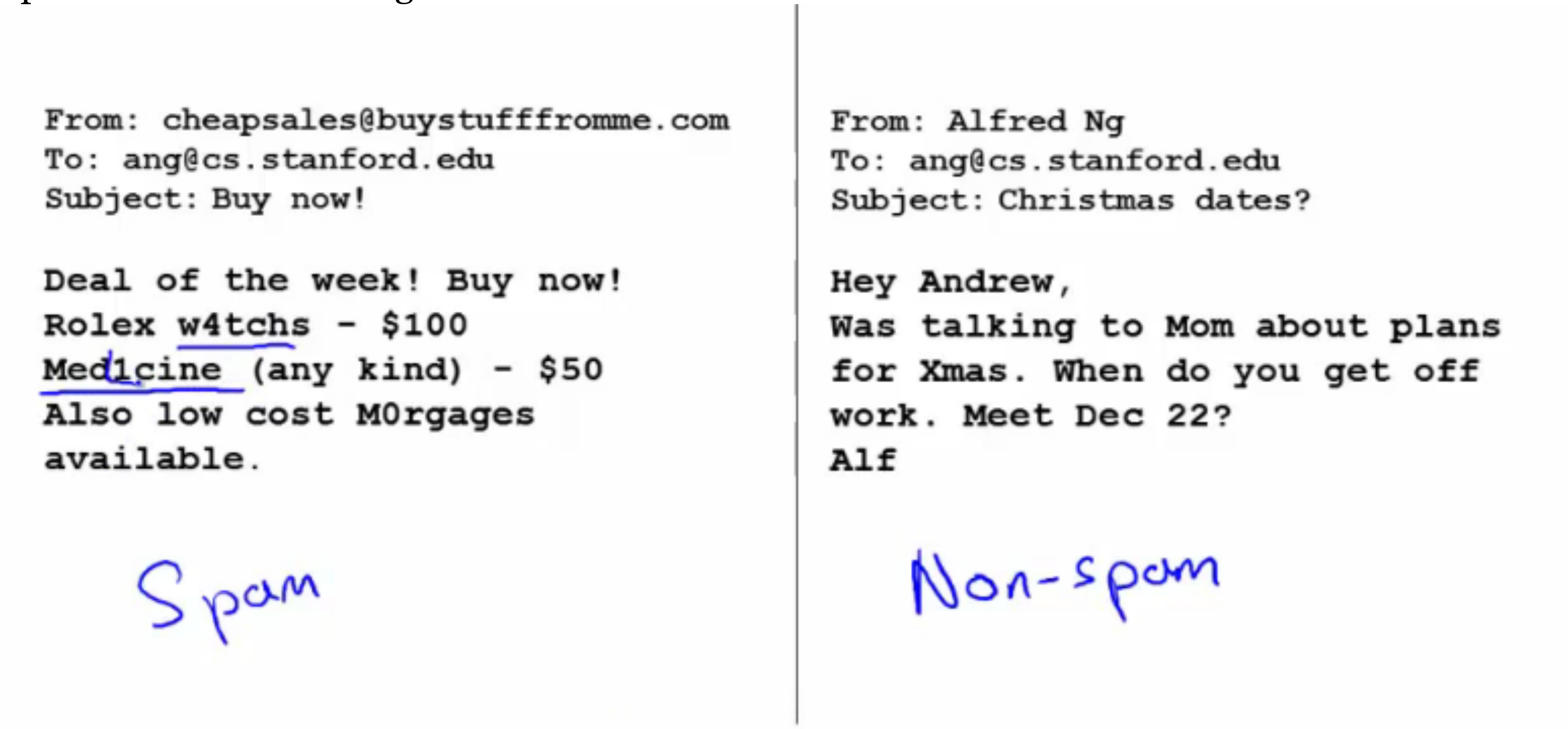
Machine learning systems design

- In this section we'll touch on how to put together a system
- Previous sections have looked at a wide range of different issues in significant focus
- This section is less mathematical, but material will be very useful non-the-less
    - Consider the system approach
    - You can understand all the algorithms, but if you don't understand how to make them work in a complete system that's no good!

Prioritizing what to work on - spam classification example

- The idea of prioritizing what to work on is perhaps the most important skill programmers typically need to develop
    - It's so easy to have many ideas you want to work on, and as a result do none of them well, because doing one well is harder than doing six superficially
        - So you need to make sure you complete projects
        - Get something "shipped" - even if it doesn't have all the bells and whistles, that final 20% getting it ready is often the toughest
        - If you only release when you're totally happy you rarely get practice doing that final 20%
    - So, back to machine learning...
- Building a spam classifier
- Spam is email advertising



From: cheapsales@buystufffromme.com
To: ang@cs.stanford.edu
Subject: Buy now!

Deal of the week! Buy now!
Rolex w4tchs - $100
Med1cine (any kind) - $50
Also low cost M0rgages
available.

Spam

From: Alfred Ng
To: ang@cs.stanford.edu
Subject: Christmas dates?

Hey Andrew,
Was talking to Mom about plans
for Xmas. When do you get off
work. Meet Dec 22?
Alf

Non-spam

- What kind of features might we define
    - Spam (1)
        - Misspelled word
    - Not spam (0)
        - Real content
- How do we build a classifier to distinguish between the two
    - Feature representation

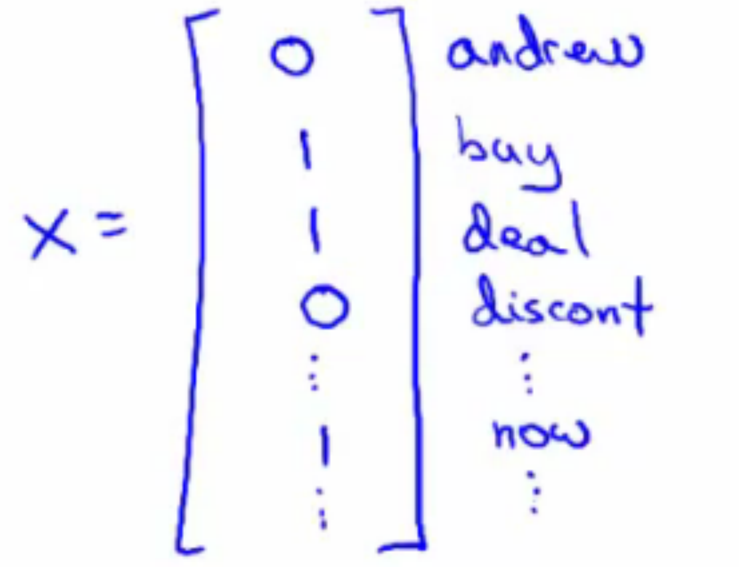
        - How do represent x (features of the email)?
            - y = spam (1) or not spam (0)

One approach - choosing your own features

- Chose 100 words which are indicative of an email being spam or not spam
    - Spam --> e.g. buy, discount, deal
    - Non spam --> Andrew, now
    - All these words go into one long vector

- Encode this into a **reference vector**
    - See which words appear in a message

- Define a feature vector x
    - Which is 0 or 1 if a word corresponding word in the reference vector is present or not
        - This is a bitmap of the word content of your email
    - i.e. don't recount if a word appears more than once



    - In practice its more common to have a training set and pick the most frequently n words, where n is 10 000 to 50 000
        - So here you're not specifically choosing your own features, but you are choosing *how* you select them from the training set data

What's the best use of your time to improve system accuracy?

- Natural inclination is to collect lots of data
    - Honey pot anti-spam projects try and get fake email addresses into spammers' hands, collect loads of spam
    - This doesn't always help though
- Develop sophisticated features based on email routing information (contained in email header)
    - Spammers often try and obscure origins of email
    - Send through unusual routes
- Develop sophisticated features for message body analysis
    - Discount == discounts?
    - DEAL == deal?
- Develop sophisticated algorithm to detect misspelling
    - Spammers use misspelled word to get around detection systems

- Often a research group **randomly focus on one option**
    - May not be the most fruitful way to spend your time
    - If you brainstorm a set of options this is **really good**
        - Very tempting to just try something

Error analysis

- When faced with a ML problem lots of ideas of how to improve a problem

    - Talk about error analysis - how to better make decisions
- If you're building a machine learning system often good to start by building a simple algorithm which you can implement quickly
    - Spend at most 24 hours developing an initially bootstrapped algorithm
        - Implement and test on cross validation data
    - Plot learning curves to decide if more data, features etc will help algorithmic optimization
        - Hard to tell in advance what is important
        - Learning curves really help with this
        - Way of avoiding **premature optimization**
            - We should let evidence guide decision making regarding development trajectory
    - **Error analysis**
        - Manually examine the samples (in cross validation set) that your algorithm made errors on
        - See if you can work out why
            - Systematic patterns - help design new features to avoid these shortcomings
        - e.g.
            - Built a spam classifier with 500 examples in CV set
                - Here, error rate is high - gets 100 wrong
            - Manually look at 100 and categorize them depending on features
                - e.g. type of email
            - Looking at those email
                - May find **most common type** of spam emails are pharmacy emails, phishing emails
                    - See which type is most common - focus your work on those ones
                - What **features would have helped** classify them correctly
                    - e.g. deliberate misspelling
                    - Unusual email routing
                    - Unusual punctuation
                    - May fine some "spammer technique" is causing a lot of your misses
                        - Guide a way around it
    - Importance of **numerical evaluation**
        - Have a way of numerically evaluated the algorithm
        - If you're developing an algorithm, it's really good to have some performance calculation which gives a single real number to tell you how well its doing
        - e.g.
            - Say were deciding if we should treat a set of similar words as the same word
            - This is done by stemming in NLP (e.g. "Porter stemmer" looks at the etymological stem of a word)
            - This may make your algorithm better or worse
                - Also worth consider weighting error (false positive vs. false negative)
                    - e.g. is a false positive really bad, or is it worth have a few of one to improve performance a lot
            - Can use numerical evaluation to compare the changes
                - See if a change improves an algorithm or not
        - A single real number may be hard/complicated to compute
            - But makes it much easier to evaluate how changes impact your algorithm
    - You should do error analysis on the cross validation set instead of the test set

Error metrics for skewed analysis

- Once case where it's hard to come up with good error metric - skewed classes
- Example
    - Cancer classification

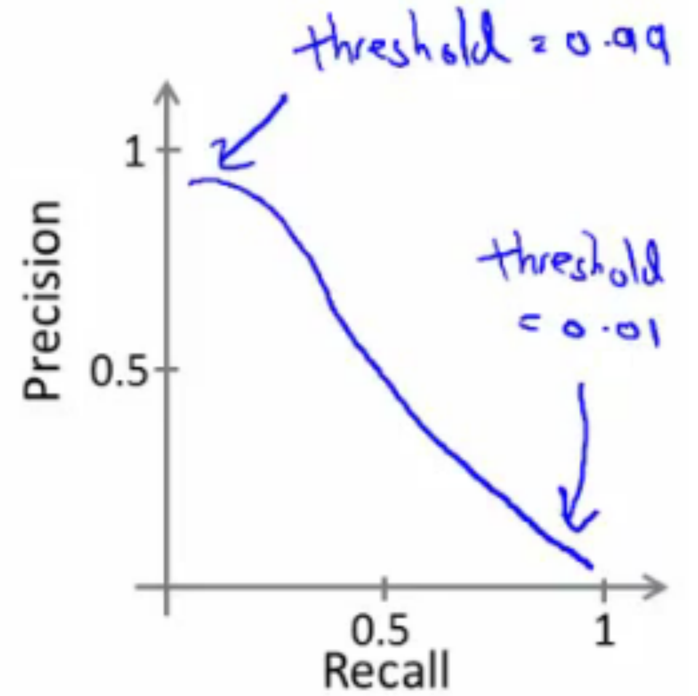
        - Train logistic regression model $h_\theta(x)$ where
            - Cancer means y = 1
            - Otherwise y = 0
        - Test classifier on test set
            - Get 1% error
                - So this looks pretty good..
            - But only 0.5% have cancer
                - Now, 1% error looks very bad!
    - So when one number of examples is very small this is an example of skewed classes
        - LOTS more of one class than another
        - So standard error metrics aren't so good
- Another example
    - Algorithm has 99.2% accuracy
    - Make a change, now get 99.5% accuracy
        - Does this really represent an improvement to the algorithm?
    - Did we do something useful, or did we just create something which predicts y = 0 more often
        - Get very low error, but classifier is still not great

Precision and recall

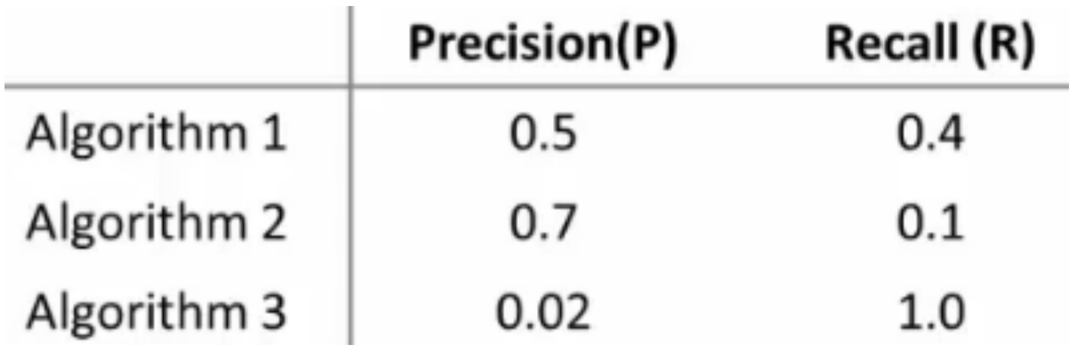
- Two new metrics - **precision** and **recall**
    - Both give a value between 0 and 1
    - Evaluating classifier on a test set
    - For a test set, the actual class is 1 or 0
    - Algorithm predicts some value for class, predicting a value for each example in the test set
        - Considering this, classification can be
            - True positive (we guessed 1, it was 1)
            - False positive (we guessed 1, it was 0)
            - True negative (we guessed 0, it was 0)
            - False negative (we guessed 0, it was 1)
    - **Precision**
        - *How often does our algorithm cause a false alarm?*
        - Of all patients we predicted have cancer, what fraction of them *actually* have cancer
            - = true positives / # predicted positive
            - = true positives / (true positive + false positive)
        - High precision is good (i.e. closer to 1)
            - You want a big number, because you want false positive to be as close to 0 as possible
    - **Recall**
        - *How sensitive is our algorithm?*
        - Of all patients in set that actually have cancer, what fraction did we correctly detect
            - = true positives / # actual positives
            - = true positive / (true positive + false negative)
        - High recall is good (i.e. closer to 1)
            - You want a big number, because you want false negative to be as close to 0 as possible
    - By computing precision and recall get a better sense of how an algorithm is doing
        - This can't really be gamed
        - Means we're much more sure that an algorithm is good
    - Typically we say the presence of a rare class is what we're trying to determine (e.g. positive (1) is the existence of the rare thing)

Trading off precision and recall

- For many applications we want to control the trade-off between precision and recall
- Example
  - Trained a logistic regression classifier
    - Predict 1 if $h_\theta(x)$ >= 0.5
    - Predict 0 if $h_\theta(x)$ < 0.5
  - This classifier may give some value for precision and some value for recall
  - Predict 1 only if very confident
    - One way to do this modify the algorithm we could modify the prediction threshold
      - Predict 1 if $h_\theta(x)$ >= 0.8
      - Predict 0 if $h_\theta(x)$ < 0.2
    - Now we can be more confident a 1 is a true positive
    - But classifier has lower recall - predict y = 1 for a smaller number of patients
      - Risk of false negatives
  - Another example - avoid false negatives
    - This is probably worse for the cancer example
      - Now we may set to a lower threshold
        - Predict 1 if $h_\theta(x)$ >= 0.3
          - Predict 0 if $h_\theta(x)$ < 0.7
      - i.e. 30% chance they have cancer
      - So now we have have a higher recall, but lower precision
        - Risk of false positives, because we're less discriminating in deciding what means the person has cancer
- This threshold defines the trade-off
  - We can show this graphically by plotting precision vs. recall



  - This curve can take many different shapes depending on classifier details
  - Is there a way to automatically chose the threshold
    - Or, if we have a few algorithms, how do we compare different algorithms or parameter sets?



	Precision(P)	Recall (R)
Algorithm 1	0.5	0.4
Algorithm 2	0.7	0.1
Algorithm 3	0.02	1.0

  - How do we decide which of these algorithms is best?
    - We spoke previously about using a single real number evaluation metric
    - By switching to precision/recall we have two numbers
    - Now comparison becomes harder
      - Better to have just one number
    - How can we convert P & R into one number?
      - One option is the average - (P + R)/2

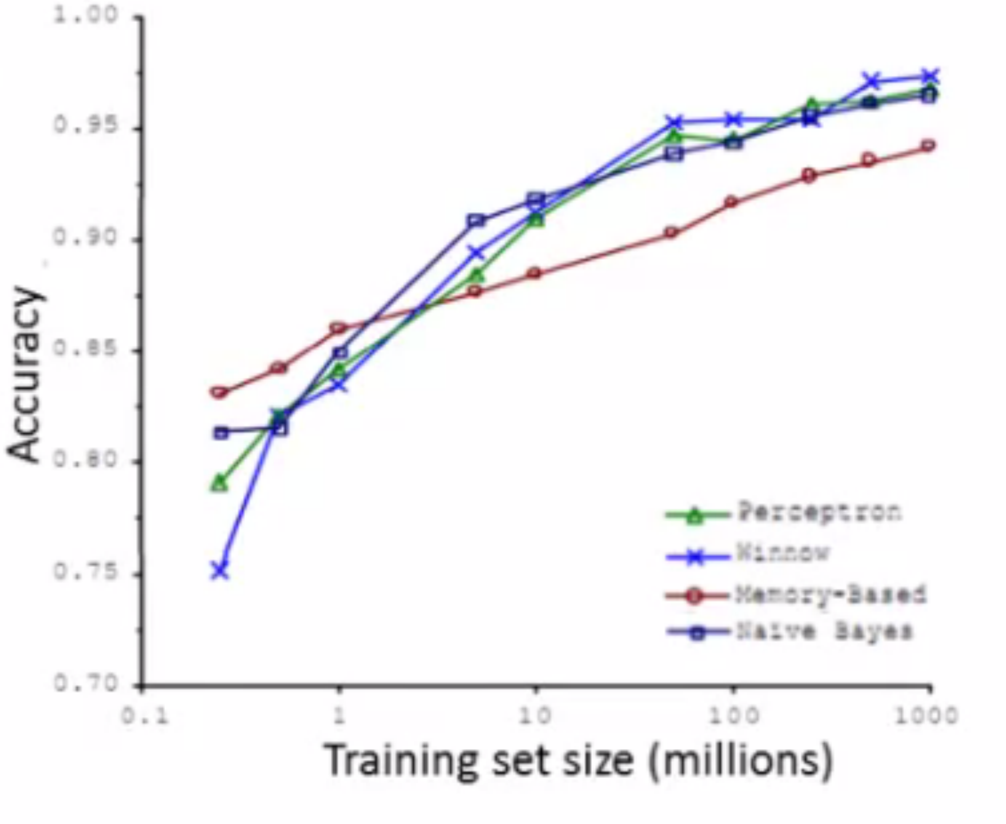
        - This is not such a good solution
          - Means if we have a classifier which predicts y = 1 all the time you get a high recall and low precision
          - Similarly, if we predict Y rarely get high precision and low recall
          - So averages here would be 0.45, 0.4 and 0.51
            - 0.51 is best, despite having a recall of 1 - i.e. predict y=1 for everything
        - So average isn't great
      - **F_1Score (fscore)**
        - = 2 * (PR/ [P + R])
        - Fscore is like taking the average of precision and recall giving a higher weight to the lower value
      - Many formulas for computing comparable precision/accuracy values
        - If P = 0 or R = 0 the Fscore = 0
        - If P = 1 and R = 1 then Fscore = 1
        - The remaining values lie between 0 and 1
- Threshold offers a way to control trade-off between precision and recall
- Fscore gives a single real number evaluation metric
  - If you're trying to automatically set the threshold, one way is to try a range of threshold values and evaluate them on your cross validation set
    - Then pick the threshold which gives the best fscore.

Data for machine learning

- Now switch tracks and look at how much data to train on
- On early videos caution on just blindly getting more data
  - Turns out under certain conditions getting more data is a very effective way to improve performance

Designing a high accuracy learning system

- There have been studies of using different algorithms on data
  - Data - confusing words (e.g. two, to or too)
  - Algorithms
    - Perceptron (logistic regression)
    - Winnow
      - Like logistic regression
      - Used less now
    - Memory based
      - Used less now
      - Talk about this later
    - Naive Bayes
      - Cover later
  - Varied training set size and tried algorithms on a range of sizes



  - What can we conclude
    - Algorithms give remarkably similar performance
    - As training set sizes increases accuracy increases
    - Take an algorithm, give it more data, should beat a "better" one with less data
    - Shows that
      - Algorithm choice is pretty similar
      - More data helps

- When is this true and when is it not?
  - If we can correctly assume that features x have enough information to predict y accurately, then more data will probably help
    - A useful test to determine if this is true can be, "given x, can a human expert predict y?"
  - So lets say we use a learning algorithm with many parameters such as logistic regression or linear regression with many features, or neural networks with many hidden features
    - These are powerful learning algorithms with many parameters which can fit complex functions
      - Such algorithms are low bias algorithms
        - Little systemic bias in their description - flexible
    - Use a small training set
      - Training error should be small
    - Use a very large training set
      - If the training set error is close to the test set error
      - Unlikely to over fit with our complex algorithms
      - So the test set error should also be small
  - Another way to think about this is we want our algorithm to have low bias and low variance
    - Low bias --> use complex algorithm
    - Low variance --> use large training set