Machine Learning

- Up until now: how to reason in a model and how to make optimal decisions

- Machine learning: how to acquire a model on the basis of data / experience
  - Learning parameters (e.g. probabilities)
  - Learning structure (e.g. BN graphs)
  - Learning hidden concepts (e.g. clustering)

This slide deck courtesy of Dan Klein at UC Berkeley

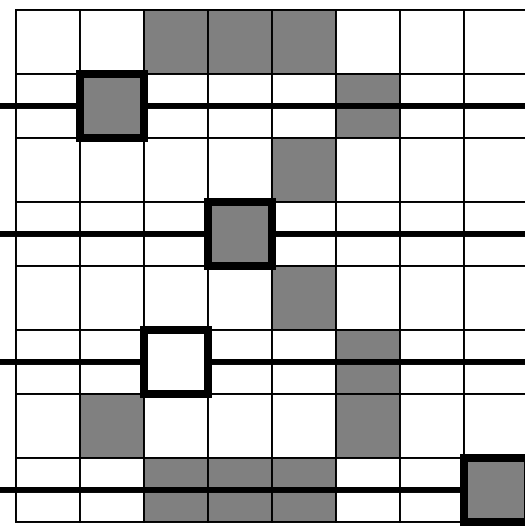
Example: Overfitting

$P(\text{features}, C=2)$

$P(\text{features}, C=3)$

$P(C=2) = 0.1$

$P(C=3) = 0.1$



$P(\text{on}|C=2) = 0.8$ — $P(\text{on}|C=3) = 0.8$

$P(\text{on}|C=2) = 0.1$ — $P(\text{on}|C=3) = 0.9$

$P(\text{off}|C=2) = 0.1$ — $P(\text{off}|C=3) = 0.7$

$P(\text{on}|C=2) = 0.01$ — $P(\text{on}|C=3) = 0.0$

2 wins!!

Example: Overfitting

- Posteriors determined by *relative* probabilities (odds ratios):

$$\frac{P(W|\text{ham})}{P(W|\text{spam})} \qquad \frac{P(W|\text{spam})}{P(W|\text{ham})}$$

```
south-west  :  inf
nation      :  inf
morally     :  inf
nicely      :  inf
extent      :  inf
seriously   :  inf
...
```

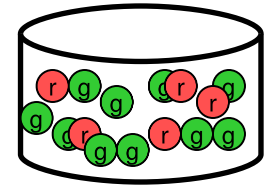
```
screens     :  inf
minute      :  inf
guaranteed  :  inf
$205.00     :  inf
delivery    :  inf
signature   :  inf
...
```

What went wrong here?

Generalization and Overfitting

- Relative frequency parameters will overfit the training data!
  - Just because we never saw a 3 with pixel (15,15) on during training doesn't mean we won't see it at test time
  - Unlikely that every occurrence of "minute" is 100% spam
  - Unlikely that every occurrence of "seriously" is 100% ham
  - What about all the words that don't occur in the training set at all?
  - In general, we can't go around giving unseen events zero probability
- As an extreme case, imagine using the entire email as the only feature
  - Would get the training data perfect (if deterministic labeling)
  - Wouldn't *generalize* at all
  - Just making the bag-of-words assumption gives us some generalization, but isn't enough
- To generalize better: we need to smooth or regularize the estimates

Estimation: Smoothing



- Maximum likelihood estimates:

$$P_{\mathsf{ML}}(x) = \frac{\mathsf{count}(x)}{\mathsf{total\ samples}}$$

$$P_{\mathsf{ML}}(\mathsf{r}) = 1/3$$

- Problems with maximum likelihood estimates:
  - If I flip a coin once, and it's heads, what's the estimate for P(heads)?
  - What if I flip 10 times with 8 heads?
  - What if I flip 10M times with 8M heads?

- Basic idea:
  - We have some prior expectation about parameters (here, the probability of heads)
  - Given little evidence, we should skew towards our prior
  - Given a lot of evidence, we should listen to the data

Estimation: Smoothing

- Relative frequencies are the maximum likelihood estimates

$$\theta_{ML} = \arg\max_{\theta} P(\mathbf{X}|\theta) = \arg\max_{\theta} \prod_i P_{\theta}(X_i)$$

$$\Rightarrow \quad P_{\mathsf{ML}}(x) = \frac{\mathsf{count}(x)}{\mathsf{total\ samples}}$$

- In Bayesian statistics, we think of the parameters as just another random variable, with its own distribution

$$\theta_{MAP} = \arg\max_{\theta} P(\theta|\mathbf{X}) = \arg\max_{\theta} P(\mathbf{X}|\theta)P(\theta)/P(\mathbf{X}) = \arg\max_{\theta} P(\mathbf{X}|\theta)P(\theta)$$

$$\Rightarrow$$

????

Estimation: Laplace Smoothing

- Laplace's estimate:
  - Pretend you saw every outcome once more than you actually did

H H T

$$P_{LAP}(x) = \frac{c(x)+1}{\sum_x [c(x)+1]}$$

$$= \frac{c(x)+1}{N+|X|}$$

$$P_{ML}(X) =$$

$$P_{LAP}(X) =$$

  - Can derive this as a MAP estimate with *Dirichlet priors*

Estimation: Laplace Smoothing

- Laplace's estimate (extended):
  - Pretend you saw every outcome k extra times

$$P_{LAP,k}(x) = \frac{c(x) + k}{N + k|X|}$$

  - What's Laplace with k = 0?
  - k is the strength of the prior

- Laplace for conditionals:
  - Smooth each condition independently:

$$P_{LAP,k}(x|y) = \frac{c(x, y) + k}{c(y) + k|X|}$$

H H T

$$P_{LAP,0}(X) =$$

$$P_{LAP,1}(X) =$$

$$P_{LAP,100}(X) =$$

Estimation: Linear Interpolation

- In practice, Laplace often performs poorly for P(X|Y):
  - When |X| is very large
  - When |Y| is very large

- Another option: linear interpolation
  - Also get P(X) from the data
  - Make sure the estimate of P(X|Y) isn't too different from P(X)

$$P_{LIN}(x|y) = \alpha \widehat{P}(x|y) + (1.0 - \alpha)\widehat{P}(x)$$

  - What if α is 0? 1?

Better: Linear Interpolation

- Linear interpolation for conditional likelihoods
  - **Idea**: the conditional probability of a feature x given a label y should be close to the marginal probability of x
  - **Example**: A rare word like "interpolation" should be similarly rare in both ham and spam (a priori)
  - **Procedure**: Collect relative frequency estimates of both conditional and marginal, then average

$$P_{ML}(x|y) = \frac{\text{count}(x, y)}{\text{count}(\cdot, y)} \qquad P_{ML}(x) = \frac{\text{count}(x)}{\text{count}(\cdot)}$$

$$P_{LIN}(x|y) = (1 - \alpha)P_{ML}(x|y) + (\alpha)P_{ML}(x)$$

  - **Effect**: Features have odds ratios closer to 1

Real NB: Smoothing

- Odds ratios without smoothing:

$$\frac{P(W|\text{ham})}{P(W|\text{spam})}$$

```
south-west  : inf
nation      : inf
morally     : inf
nicely      : inf
extent      : inf
...
```

$$\frac{P(W|\text{spam})}{P(W|\text{ham})}$$

```
screens     : inf
minute      : inf
guaranteed  : inf
$205.00     : inf
delivery    : inf
...
```

Real NB: Smoothing

- Odds ratios after smoothing:

$$\frac{P(W|\text{ham})}{P(W|\text{spam})}$$

helvetica	:	11.4
seems	:	10.8
group	:	10.2
ago	:	8.4
areas	:	8.3
...		

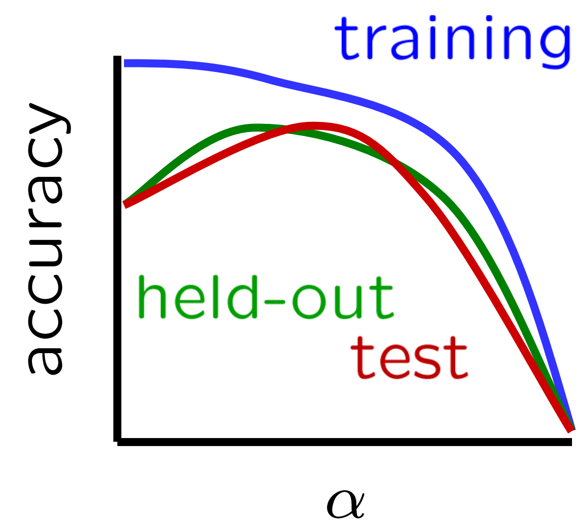
$$\frac{P(W|\text{spam})}{P(W|\text{ham})}$$

verdana	:	28.8
Credit	:	28.4
ORDER	:	27.2
<FONT>	:	26.9
money	:	26.5
...		

Do these make more sense?

Tuning on Held-Out Data

- Now we've got two kinds of unknowns
  - Parameters: $P(F_i|Y)$ and $P(Y)$
  - Hyperparameters, like the amount of smoothing to do: k, α
- Where to learn which unknowns
  - Learn parameters from training set
  - Can't tune hyperparameters on training data (why?)
  - For each possible value of the hyperparameters, train and test on the held-out data
  - Choose the best value and do a final test on the test data



Proportion of $P_{ML}(x)$ in $P(x|y)$

Baselines

- First task when classifying: get a baseline
  - Baselines are very simple “straw man” procedures
  - Help determine how hard the task is
  - Help know what a “good” accuracy is

- Weak baseline: most frequent label classifier
  - Gives all test instances whatever label was most common in the training set
  - E.g. for spam filtering, might label everything as spam
  - Accuracy might be very high if the problem is skewed

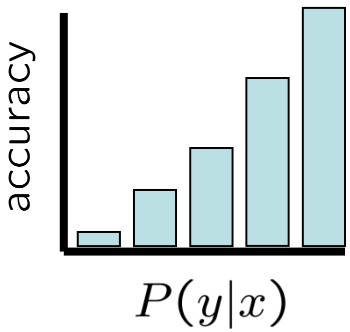
- When conducting real research, we usually use previous work as a (strong) baseline

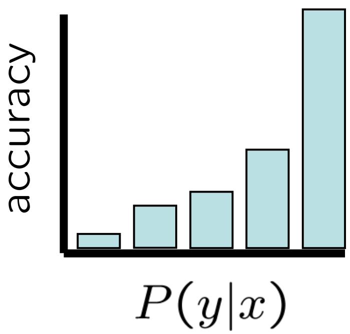
Confidences from a Classifier

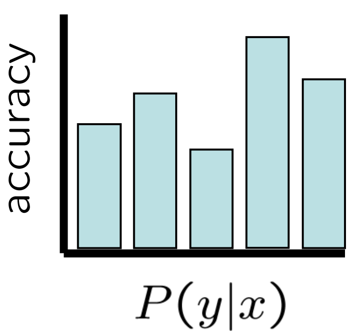
- The confidence of a classifier:
  - Posterior of the most likely label

$$\text{confidence}(x) = \max_y P(y|x)$$

  - Represents how sure the classifier is of the classification
  - Any probabilistic model will have confidences
  - No guarantee confidence is correct
- Calibration
  - Strong calibration: confidence predicts accuracy rate
  - Weak calibration: higher confidences mean higher accuracy
  - What's the value of calibration?

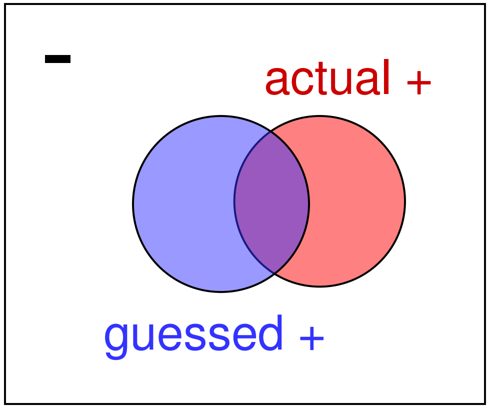






Precision vs. Recall

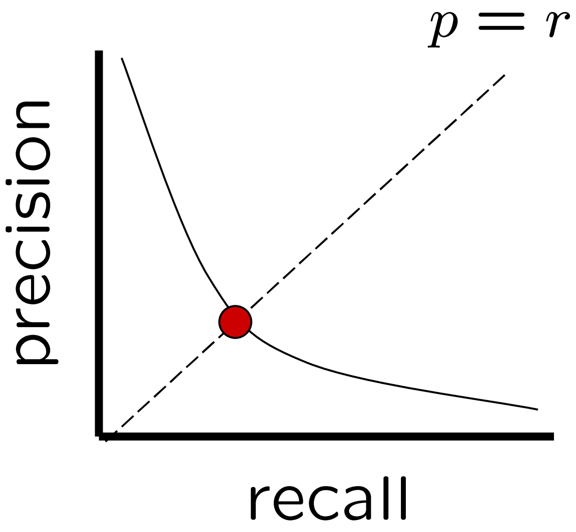
- Let's say we want to classify web pages as homepages or not
  - In a test set of 1K pages, there are 3 homepages
  - Our classifier says they are all non-homepages
  - 99.7 accuracy!
  - Need new measures for rare positive events



- Precision: fraction of guessed positives which were actually positive
- Recall: fraction of actual positives which were guessed as positive
- Say we guess 5 homepages, of which 2 were actually homepages
  - Precision: 2 correct / 5 guessed = 0.4
  - Recall: 2 correct / 3 true = 0.67
- Which is more important in customer support email automation?
- Which is more important in airport face recognition?

Precision vs. Recall

- Precision/recall tradeoff
  - Often, you can trade off precision and recall
  - Only works well with weakly calibrated classifiers



- To summarize the tradeoff:
  - Break-even point: precision value when p = r
  - F-measure: harmonic mean of p and r:

$$F_1 = \frac{2}{1/p + 1/r}$$

Naïve Bayes Summary

- Bayes rule lets us do diagnostic queries with causal probabilities
- The naïve Bayes assumption takes all features to be independent given the class label
- We can build classifiers out of a naïve Bayes model using training data
- Smoothing estimates is important in real systems
- Confidences are useful when the classifier is calibrated

Example Errors

Dear GlobalSCAPE Customer,

GlobalSCAPE has partnered with ScanSoft to offer you the latest version of OmniPage Pro, for just $99.99* - the regular list price is $499! The most common question we've received about this offer is - Is this genuine? We would like to assure you that this offer is authorized by ScanSoft, is genuine and valid. You can get the . . .

. . . To receive your $30 Amazon.com promotional certificate, click through to

http://www.amazon.com/apparel

and see the prominent link for the $30 offer. All details are there. We hope you enjoyed receiving this message. However, if you'd rather not receive future e-mails announcing new store launches, please click . . .

What to Do About Errors

- Problem: there's still spam in your inbox
- Need more features – words aren't enough!
  - Have you emailed the sender before?
  - Have 1K other people just gotten the same email?
  - Is the sending information consistent?
  - Is the email in ALL CAPS?
  - Do inline URLs point where they say they point?
  - Does the email address you by (your) name?
- Naïve Bayes models can incorporate a variety of features, but tend to do best in homogeneous cases (e.g. all features are word occurrences)

Features

- A feature is a function that signals a property of the input
  - **Naïve Bayes**: features are random variables & each value has conditional probabilities given the label.
  - **Most classifiers**: features are real-valued functions
  - **Common special cases**:
    - Indicator features take values 0 and 1 (or -1 and 1)
    - Count features return non-negative integers
- Features are anything you can think of for which you can write code to evaluate on an input
  - Many are cheap, but some are expensive to compute
  - Can even be the output of another classifier or model
  - Domain knowledge goes here!

Feature Extractors

- Features: anything you can compute about the input
- A feature extractor maps inputs to feature vectors

```
Dear Sir.

First, I must
solicit your
confidence in
this
transaction,
this is by
virtue of its
nature as being
utterly
confidencial and
top secret. …
```

```
W=dear       :  1
W=sir        :  1
W=this       :  2
...
W=wish       :  0
...
MISSPELLED   :  2
YOUR_NAME    :  1
ALL_CAPS     :  0
NUM_URLS     :  0
...
```

- Many classifiers take feature vectors as inputs
- Feature vectors usually very sparse, use sparse encodings (i.e. only represent non-zero keys)

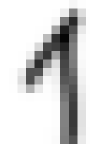
Generative vs. Discriminative

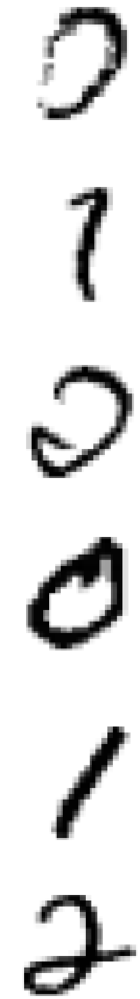
- Generative classifiers:
  - E.g. naïve Bayes
  - A causal model with evidence variables
  - Query model for causes given evidence

- Discriminative classifiers:
  - No causal model, no Bayes rule, often no probabilities at all!
  - Try to predict the label Y directly from X
  - Robust, accurate with varied features
  - Loosely: mistake driven rather than model driven

Nearest-Neighbor Classification

- Nearest neighbor for digits:
  - Take new image
  - Compare to all training images
  - Assign based on closest example





- Encoding: image is vector of intensities:

 $= \langle 0.0 \;\; 0.0 \;\; 0.3 \;\; 0.8 \;\; 0.7 \;\; 0.1 \ldots 0.0 \rangle$

- What's the similarity function?
  - Dot product of two images vectors?

$$\text{sim}(x, y) = x \cdot y = \sum_i x_i y_i$$

  - Usually normalize vectors so ||x|| = 1
  - min = 0 (when?), max = 1 (when?)