Announcements

- W4 out, due next week Monday
- P4 out, due next week Friday
- Mid-semester survey

Announcements II

- Course contest
  - Regular tournaments. Instructions have been posted!
  - First week extra credit for top 20, next week top 10, then top 5, then top 3.
  - First nightly tournament: tentatively Monday night

P4: Ghostbusters 2.0

- Plot: Pacman’s grandfather, Grandpac, learned to hunt ghosts for sport.
- He was blinded by his power, but could hear the ghosts’ banging and clanging.
- Transition Model: All ghosts move randomly, but are sometimes biased
- Emission Model: Pacman knows a “noisy” distance to each ghost

Today

- Dynamic Bayes Nets (DBNs)
  - [sometimes called temporal Bayes nets]
- Demos:
  - Localization
  - Simultaneous Localization And Mapping (SLAM)
- Start machine learning

Dynamic Bayes Nets (DBNs)

- We want to track multiple variables over time, using multiple sources of evidence
- Idea: Repeat a fixed Bayes net structure at each time
- Variables from time \( t \) can condition on those from \( t-1 \)
- Discrete valued dynamic Bayes nets are also HMMs
Exact Inference in DBNs

- Variable elimination applies to dynamic Bayes nets
- Procedure: "unroll" the network for $T$ time steps, then eliminate variables until $P(X_T|E_{1:T})$ is computed
- Online belief updates: Eliminate all variables from the previous time step; store factors for current time only

DBN Particle Filters

- A particle is a complete sample for a time step
- Initialize: Generate prior samples for the $t=1$ Bayes net
  - Example particle: $G_1^a = (3, 3), G_1^b = (5, 3)$
- Elapse time: Sample a successor for each particle
  - Example successor: $G_2^a = (2, 3), G_2^b = (6, 3)$
- Observe: Weight each entire sample by the likelihood of the evidence conditioned on the sample
  - Likelihood: $P(E_1^a|G_1^a) \times P(E_1^b|G_1^b)$
- Resample: Select prior samples (tuples of values) in proportion to their likelihood

Trick I to Improve Particle Filtering Performance: Low Variance Resampling

- Advantages:
  - More systematic coverage of space of samples
  - If all samples have same importance weight, no samples are lost
  - Lower computational complexity

Trick II to Improve Particle Filtering Performance: Regularization

- If no or little noise in transitions model, all particles will start to coincide
  → regularization: introduce additional (artificial) noise into the transition model

SLAM

- SLAM = Simultaneous Localization And Mapping
  - We do not know the map or our location
  - Our belief state is over maps and positions!
  - Main techniques: Kalman filtering (Gaussian HMMs) and particle methods
  - [DEMOS]
Robot Localization

- In robot localization:
  - We know the map, but not the robot’s position
  - Observations may be vectors of range finder readings
  - State space and readings are typically continuous (works basically like a very fine grid) and so we cannot store \( B(X) \)
  - Particle filtering is a main technique

[Demos]

Global-floor

SLAM

- SLAM = Simultaneous Localization And Mapping
  - We do not know the map or our location
  - State consists of position AND map!
  - Main techniques: Kalman filtering (Gaussian HMMs) and particle methods

Further readings

- We are done with Part II Probabilistic Reasoning
- To learn more (beyond scope of 188):
  - Koller and Friedman, Probabilistic Graphical Models (CS281A)
  - Thrun, Burgard and Fox, Probabilistic Robotics (CS287)

Particle Filter Example

- 3 particles
- map of particle 1
- map of particle 2
- map of particle 3

SLAM

- DEMOS
  - fastslam.avi, visionSlam_heliOffice.wmv

Part III: 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)
Machine Learning Today

- An ML Example: Parameter Estimation
  - Maximum likelihood
  - Smoothing
- Applications
- Main concepts
- Naïve Bayes

Parameter Estimation

- Estimating the distribution of a random variable
- Elicitation: ask a human (why is this hard?)
- Empirical: use training data (learning!)
  - E.g., for each outcome \( x \), look at the empirical rate of that value:
    \[
    P_{ML}(x) = \frac{\text{count}(x)}{\text{total samples}}
    \]
  - This is the estimate that maximizes the likelihood of the data
    \[
    L(x, \theta) = \prod_i P_{\theta}(x_i)
    \]
- Issue: overfitting. E.g., what if only observed 1 jelly bean?

Estimation: Smoothing

- Relative frequencies are the maximum likelihood estimates
  
  \[
  \hat{g}_{ML} = \arg \max_{\theta} P(X|\theta) = \arg \max_{\theta} \prod_i P_{\theta}(X_i) = \frac{\text{count}(x)}{\text{total samples}}
  \]
- In Bayesian statistics, we think of the parameters as just another random variable, with its own distribution
  
  \[
  \hat{g}_{MAP} = \arg \max_{\theta} P(\theta|X) = \arg \max_{\theta} P(X|\theta)P(\theta)/P(X)
  \]

Estimation: Laplace Smoothing

- Laplace’s estimate:
  - Pretend you saw every outcome once more than you actually did
    \[
    P_{LAP}(x) = \frac{c(x) + 1}{N + |X|}
    \]
  - Can derive this as a MAP estimate with Dirichlet priors (see cs281a)

Example: Spam Filter

- Input: email
- Output: spam/ham
- Setup:
  - Get a large collection of example emails, each labeled “spam” or “ham”
  - Note: someone has to hand label all this data
  - Want to learn to predict labels of new, future emails
- Features: The attributes used to make the ham / spam decision
  - Words: FREE!
  - Text Patterns: $dd, CAPS
  - Non-text: SenderInContacts
  - …

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**Example Email:**

Dear Sir,

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

…

TO BE REMOVED FROM FUTURE MAILINGS. SIMPLY REPLY TO THIS MESSAGE AND PUT "REMOVE" IN THE SUBJECT.

99 MILLION EMAIL ADDRESSES FOR ONLY $99

Ok, I know this is blatantly OT but I’m beginning to go insane. Had an old Dell Dimension 3DF sitting in the corner and decided to put it to use. I know it was working fine being stuck in the corner, but when I plugged it in, the power nothing happened.
Example: Digit Recognition

- Input: images / pixel grids
- Output: a digit 0-9
- Setup:
  - Get a large collection of example images, each labeled with a digit
  - Note: someone has to hand label all this data!
  - Want to learn to predict labels of new, future digit images
- Features: The attributes used to make the digit decision
  - Pixels: (i,j)=ON
  - Shape Patterns: NumComponents, AspectRatio, NumLoops
  - ...

Other Classification Tasks

- In classification, we predict labels $y$ (classes) for inputs $x$
- Examples:
  - Spam detection (input: document, classes: spam / ham)
  - OCR (input: images, classes: characters)
  - Medical diagnosis (input: symptoms, classes: diseases)
  - Automatic essay grader (input: document, classes: grades)
  - Fraud detection (input: account activity, classes: fraud / no fraud)
  - Customer service email routing
  - ... many more
- Classification is an important commercial technology!

Important Concepts

- Data: labeled instances, e.g. emails marked spam/ham
  - Training set
  - Held out set
  - Test set
- Features: attribute-value pairs which characterize each $x$
- Experimentation cycle
  - Learn parameters (e.g. model probabilities) on training set
  - Tune hyperparameters on held-out set
  - Compute accuracy of test set
  - Very important: never "peek" at the test set!
- Evaluation
  - Accuracy: fraction of instances predicted correctly
- Overfitting and generalization
  - Want a classifier which does well on test data
  - Overfitting: fitting the training data very closely, but not generalizing well
  - We’ll investigate overfitting and generalization formally in a few lectures

Bayes Nets for Classification

- One method of classification:
  - Use a probabilistic model!
  - Features are observed random variables $F_i$
  - $Y$ is the query variable
  - Use probabilistic inference to compute most likely $Y$
    \[ y = \arg \max_y P(y | f_1 \ldots f_n) \]
  - You already know how to do this inference

Simple Classification

- Simple example: two binary features
  \[ P(m | s, f) \]

General Naïve Bayes

- A general naïve Bayes model:
  \[ P(Y, F_1 \ldots F_n) = \prod_i P(F_i | Y) \]
  \[ |Y| \text{ parameters} \quad n \times |F| \times |Y| \text{ parameters} \]
- We only specify how each feature depends on the class
- Total number of parameters is linear in $n$
Inference for Naïve Bayes

- Goal: compute posterior over causes
  - Step 1: get joint probability of causes and evidence
    \[ P(Y; f_1 \ldots f_n) = \frac{P(y_1; f_1 \ldots f_n)}{P(y_2; f_1 \ldots f_n)} \frac{P(y_3; f_1 \ldots f_n)}{P(y_4; f_1 \ldots f_n)} \]
  - Step 2: get probability of evidence
  - Step 3: renormalize

General Naïve Bayes

- What do we need in order to use naïve Bayes?
  - Inference (you know this part)
  - Estimates of local conditional probability tables
    - P(Y), the prior over labels
    - P(F_i|Y) for each feature (evidence variable)
    - These probabilities are collectively called the parameters of the model and denoted by \( \theta \)
    - Up until now, we assumed these appeared by magic, but...
    - ...they typically come from training data: we’ll look at this now

A Digit Recognizer

- Input: pixel grids
- Output: a digit 0-9

Naïve Bayes for Digits

- Simple version:
  - One feature F_{ij} for each grid position \( <i,j> \)
  - Possible feature values are on / off, based on whether intensity is more or less than 0.5 in underlying image
  - Each input maps to a feature vector, e.g.
    \[ \begin{array}{cccc}
      0 & 0.01 & 0 & 0.01 \\
      0.05 & 0.05 & 0.05 & 0.05 \\
      0.30 & 0.30 & 0.30 & 0.30 \\
      0.60 & 0.60 & 0.60 & 0.60 \\
      0.90 & 0.90 & 0.90 & 0.90 \\
      0.00 & 0.00 & 0.00 & 0.00 \\
      0.25 & 0.25 & 0.25 & 0.25 \\
      0.50 & 0.50 & 0.50 & 0.50 \\
      0.80 & 0.80 & 0.80 & 0.80 \\
      0.00 & 0.00 & 0.00 & 0.00 \\
    \end{array} \]
  - Naïve Bayes model:
    \[ P(Y|F_{0,0} \ldots F_{15,15}) \propto P(Y) \prod_{i,j} P(F_{i,j}|Y) \]
  - What do we need to learn?

Examples: CPTs

- Estimating distribution of random variables like X or X | Y
- Empirically: use training data
  - For each outcome x, look at the empirical rate of that value:
    \[ P_{\text{MLE}}(x) = \frac{\text{count}(x)}{\text{total samples}} \]
  - This is the estimate that maximizes the likelihood of the data
    \[ L(x, \theta) = \prod_i P_F(x_i) \]
- Elicitation: ask a human!
  - Usually need domain experts, and sophisticated ways of eliciting probabilities (e.g. betting games)
  - Trouble calibrating
A Spam Filter

- Naïve Bayes spam filter
- Data:
  - Collection of emails, labeled spam or ham
  - Note: someone has to hand label all this data!
  - Split into training, held-out, test sets
- Classifiers
  - Learn on the training set
  - (Tune it on a held-out set)
  - Test it on new emails

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Naïve Bayes for Text

- Bag-of-Words Naïve Bayes:
  - Predict unknown class label (spam vs. ham)
  - Assume evidence features (e.g. the words) are independent
- Generative model
  \[ P(Y, W_1 \ldots W_n) = P(Y) \prod_i P(W_i|Y) \]
- Tied distributions and bag-of-words
  - Usually, each variable gets its own conditional probability distribution \( P(F|Y) \)
  - In a bag-of-words model
    - Each position is identically distributed
    - All positions share the same conditional probs \( P(W|C) \)
- Why make this assumption?

Example: Spam Filtering

- Model:
  \[ P(Y, W_1 \ldots W_n) = P(Y) \prod_i P(W_i|Y) \]
- What are the parameters?
  - \( P(Y) \)
  - \( P(W|spam) \)
  - \( P(W|ham) \)

\[
\begin{array}{c|c|c|c}
| Word | P(w|spam) & P(w|ham) & Total Spam \# \times \% & Total Ham \# \times \% \\
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>the</td>
<td>0.0156</td>
<td>0.0210</td>
<td>-11.8</td>
<td>-8.9</td>
</tr>
<tr>
<td>to</td>
<td>0.0153</td>
<td>0.0133</td>
<td>-19.1</td>
<td>-16.0</td>
</tr>
<tr>
<td>of</td>
<td>0.0095</td>
<td>0.0119</td>
<td>-23.8</td>
<td>-21.8</td>
</tr>
<tr>
<td>you</td>
<td>0.0093</td>
<td>0.0100</td>
<td>-30.9</td>
<td>-28.9</td>
</tr>
<tr>
<td>a</td>
<td>0.0086</td>
<td>0.0084</td>
<td>-35.1</td>
<td>-33.2</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>the</td>
<td>0.0210</td>
<td>0.0133</td>
<td>-35.1</td>
<td>-33.2</td>
</tr>
<tr>
<td>to</td>
<td>0.0133</td>
<td>0.0100</td>
<td>-35.1</td>
<td>-33.2</td>
</tr>
<tr>
<td>of</td>
<td>0.0119</td>
<td>0.0100</td>
<td>-35.1</td>
<td>-33.2</td>
</tr>
<tr>
<td>you</td>
<td>0.0100</td>
<td>0.0084</td>
<td>-35.1</td>
<td>-33.2</td>
</tr>
<tr>
<td>a</td>
<td>0.0084</td>
<td>0.0086</td>
<td>-35.1</td>
<td>-33.2</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>ham</td>
<td>0.66</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>spam</td>
<td>0.33</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
\end{array}
\]

Where do these tables come from?

Example: Overfitting

- Posterior probabilities (odds ratios):
  \[
  P(W|ham) \quad P(W|spam)
\]
  - southwest : 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.
  - 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

- 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: Laplace Smoothing

- Laplace’s estimate:
  - Pretend you saw every outcome once more than you actually did.
  - Can derive this as a MAP estimate with Dirichlet priors (see cs281a).

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).

Estimation: Laplace Smoothing (extended):

- Laplace’s estimate:
  - Pretend you saw every outcome once more than you actually did.
  - What’s Laplace with k = 0?
  - k is the strength of the prior.
- Laplace for conditionals:
  - Smooth each condition
  - What if α is 0? 1?

For even better ways to estimate parameters, as well as details of the math see cs281a, cs288.
Real NB: Smoothing

- For real classification problems, smoothing is critical
- New odds ratios:
  \[
  \frac{P(W|\text{ham})}{P(W|\text{spam})}, \quad \frac{P(W|\text{spam})}{P(W|\text{ham})}
  \]
  helvetica : 11.4  
  seems     : 10.8  
  group     : 10.2  
  area       :  8.4  
  areas      :  8.3  
  ...        
  verdana    : 28.8  
  Credit     : 28.4  
  ORDER      : 27.2  
  <FIND>     : 26.9  
  ...        
  ...        
  Do these make more sense?

Tuning on Held-Out Data

- Now we’ve got two kinds of unknowns:
  - Parameters: the probabilities \(P(Y|X), P(Y)\)
  - Hyperparameters, like the amount of smoothing to do \(k, \alpha\)
- Where to learn?
  - Learn parameters from training data
  - Must tune hyperparameters on a different
    data
- Why?
  - For each 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

Baselines

- First step: 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 ham
  - Accuracy might be very high if the problem is skewed
    - E.g., calling everything “ham” gets 66%, so a classifier that gets 
      70% isn’t very good...
  - For real research, usually use previous work as a (strong) baseline

Confidences from a Classifier

- The confidence of a probabilistic classifier:
  - Posterior over the top 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
  - Weak calibration: higher confidences mean 
    higher accuracy
  - Strong calibration: confidence predicts 
    accuracy rate
  - 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?
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 . . .

Errors, and What to Do

- Examples of 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?

- 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?

- Can add these information sources as new variables in the NB model
- Next class we’ll talk about classifiers which let you easily add arbitrary features more easily

Summary Naïve Bayes Classifier

- 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
- Classifier confidences are useful, when you can get them