CS 188: Artificial Intelligence
Fall 2007

Lecture 23: Naïve Bayes
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Machine Learning

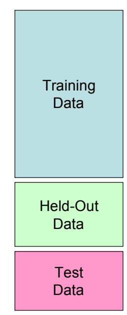
- Up till now: how to reason or make decisions using a model
- Machine learning: how to select a model on the basis of data / experience
  - Learning parameters (e.g. probabilities)
  - Learning structure (e.g. BN graphs)
  - Learning hidden concepts (e.g. clustering)

Classification

- In classification, we learn to predict labels (classes) for inputs
- 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!

Classification

- Data: labeled instances, e.g. emails marked spam/ham
  - Training set
  - Held out set
  - Test set
- Experimentation
  - Learn model parameters (probabilities) on training set
  - (Tune performance on held-out set)
  - Run a single test on the 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

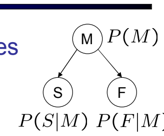
- One method of classification:
  - Features are observed variables
  - Y is the query variable
  - Use probabilistic inference to compute most likely Y

$$y = \text{argmax}_y \; P(y|f_1 \ldots f_n)$$

- You already know how to do this inference

Simple Classification

- Simple example: two binary features
  - This is a naïve Bayes model



$P(m|s,f)$ direct estimate

$$P(m|s,f) = \frac{P(s,f|m)P(m)}{P(s,f)}$$ Bayes estimate (no assumptions)

$$P(m|s,f) = \frac{P(s|m)P(f|m)P(m)}{P(s,f)}$$ Conditional independence

$$+ \begin{cases} P(m,s,f) = P(s|m)P(f|m)P(m) \\ P(\bar{m},s,f) = P(s|\bar{m})P(f|\bar{m})P(\bar{m}) \end{cases}$$

General Naïve Bayes

- A general *naive Bayes* model:

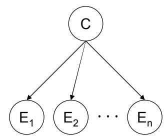
|C| x |E|^n parameters

$$P(\text{Cause}, \text{Effect}_1 \dots \text{Effect}_n) =$$

$$P(\text{Cause}) \prod_i P(\text{Effect}_i | \text{Cause})$$

|C| parameters

n x |E| x |C| 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

$$P(C, e_1 \dots e_n) =$$

$$\begin{bmatrix} P(c_1, e_1 \dots e_n) \\ P(c_2, e_1 \dots e_n) \\ \vdots \\ P(c_k, e_1 \dots e_n) \end{bmatrix} \Rightarrow \begin{bmatrix} P(c_1) \prod_i P(e_i|c_1) \\ P(c_2) \prod_i P(e_i|c_2) \\ \vdots \\ P(c_k) \prod_i P(e_i|c_k) \end{bmatrix}$$

+

  - Step 2: get probability of evidence

$$P(e_1 \dots e_n)$$

  - Step 3: renormalize

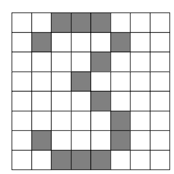
$$P(C|e_1 \dots e_n)$$

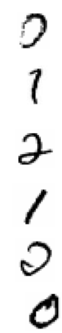
General Naïve Bayes

- What do we need in order to use naïve Bayes?
  - Inference (you know this part)
    - For fixed evidence, build P(C,e), that is, P(c,e) for each c
    - Sum out C to get P(e)
    - Divide to get P(C|e)
  - Estimates of local conditional probability tables
    - P(C), the prior over causes
    - P(E|C) for each evidence variable
    - These probabilities are collectively called the *parameters* of the model and denoted by $\boldsymbol{\theta}$
    - These typically come from observed 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>
  - Feature values are on / off based on whether intensity is more or less than 0.5
  - Input maps to feature vector, e.g.

 $\rightarrow \langle F_{0,0} = 0 \;\; F_{0,1} = 0 \;\; F_{0,2} = 1 \;\; F_{0,3} = 1 \;\; F_{0,4} = 0 \;\; \dots F_{15,15} = 0 \rangle$

- Naïve Bayes model:

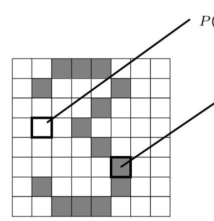
$$P(C, F_{0,0} \dots F_{15,15}) = P(C) \prod_{i,j} P(F_{i,j}|C)$$

- What do we need to learn?

Examples: CPTs

$P(C)$

1	0.1
2	0.1
3	0.1
4	0.1
5	0.1
6	0.1
7	0.1
8	0.1
9	0.1
0	0.1



$P(F_{3,1} = on|C)$

1	0.01
2	0.05
3	0.05
4	0.30
5	0.80
6	0.90
7	0.05
8	0.60
9	0.50
0	0.80

$P(F_{5,5} = on|C)$

1	0.05
2	0.01
3	0.90
4	0.80
5	0.90
6	0.90
7	0.25
8	0.85
9	0.60
0	0.80

Parameter Estimation

- Estimating distribution of random variables like X or X|Y
- *Empirically:* use training data
  - For each value x, look at the *empirical rate* of that value:

$$\hat{P}(x) = \frac{\text{count}(x)}{\text{total samples}}$$

r g g

$$\hat{P}(\text{r}) = 1/3$$

  - This estimate maximizes the *likelihood of the data*

$$L(x, \theta) = \prod_i P_\theta(x_i)$$

- *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

Dear Sir.

First, I must solicit your confidence in this transaction, this is by virture of its nature as being utterly confidencial 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, Iknow this is blatantly OT but I'm beginning to go insane. Had an old Dell Dimension XPS sitting in the corner and decided to put it to use, I know it was working pre being stuck in the corner, but when I plugged it in, hit the power nothing happened.

Naïve Bayes for Text

- Naïve Bayes:
  - Predict unknown cause (spam vs. ham)
  - Assume evidence (e.g. the words) to be independent
- Generative model

$$P(C, W_1 \ldots W_n) = P(C) \prod_i P(W_i|C)$$

Word at position i, not i^{th} word in the dictionary!

- Tied distributions and bag-of-words
  - Usually, each variable gets its own conditional probability distribution P(E|C)
  - In a bag-of-words model
    - Each position is identically distributed
    - All share the same distributions
    - Why make this assumption?

Example: Spam Filtering

- Model: $P(C, W_1 \ldots W_n) = P(C) \prod_i P(W_i|C)$
- What are the parameters?

$P(C)$

```
ham : 0.66
spam: 0.33
```

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

```
the :  0.0156
to  :  0.0153
and :  0.0115
of  :  0.0095
you :  0.0093
a   :  0.0086
with:  0.0080
from:  0.0075
...
```

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

```
the :  0.0210
to  :  0.0133
of  :  0.0119
2002:  0.0110
with:  0.0108
from:  0.0107
and :  0.0105
a   :  0.0100
...
```

- Where do these tables come from?

Spam Example

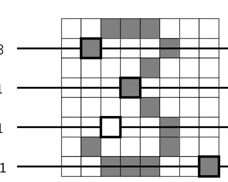
Word	P(w|spam)	P(w|ham)	Tot Spam	Tot Ham
(prior)	0.33333	0.66666	-1.1	-0.4

P(spam | w) = 98.9

Example: Overfitting

$P(\text{features}, C = 2)$ $P(\text{features}, C = 3)$

$P(\text{on}|C = 2) = 0.8$
$P(\text{on}|C = 2) = 0.1$
$P(\text{off}|C = 2) = 0.1$
$P(\text{on}|C = 2) = 0.01$



$P(\text{on}|C = 3) = 0.8$
$P(\text{on}|C = 3) = 0.9$
$P(\text{off}|C = 3) = 0.7$
$P(\text{on}|C = 3) = 0.0$

2 wins!!

Example: Spam Filtering

- Raw probabilities don't affect the posteriors; relative probabilities (odds ratios) do:

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

```
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!
  - 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?
  - 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: Smoothing

- Relative frequencies are the maximum likelihood estimates

$$\theta_{ML} = \arg\max_\theta P(\mathbf{X}|\theta) = \arg\max_\theta \prod_i P_\theta(X_i) \quad \Rightarrow \quad \hat{P}(x) = \frac{\text{count}(x)}{\text{total samples}}$$

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

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

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* (see cs281a)

Estimation: Laplace Smoothing

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

H H T

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

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

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

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

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

- Laplace for conditionals:
  - Smooth each condition independently:

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

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)

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

  - What if α is 0? 1?
- For even better ways to estimate parameters, as well as details of the math see cs281a, cs294

Real NB: Smoothing

- For real classification problems, smoothing is critical
- New odds ratios:

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

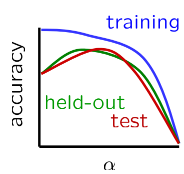
```
helvetica : 11.4
seems     : 10.8
group     : 10.2
ago       :  8.4
areas     :  8.3
...
```

```
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: the probabilities P(Y|X), P(Y)
  - Hyperparameters, like the amount of smoothing to do: k, α
- Where to learn?
  - Learn parameters from training data
  - Must tune hyperparameters on 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

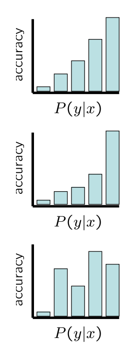
- First task: get a baseline
  - Baselines are very simple "straw man" procedures
  - Help determine how hard the task is
  - Help know what a "good" accuracy is
- Weak baseline: most frequent label classifier
  - Gives all test instances whatever label was most common in the training set
  - E.g. for spam filtering, might label everything as ham
  - Accuracy might be very high if the problem is skewed
- 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

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

  - 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?



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

- Bayes rule lets us do diagnostic queries with causal probabilities
- The naïve Bayes assumption makes all effects independent given the cause
- 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