11 - Naive Bayes

Text Classification

- **input** - a document d and a fixed set of classes $C = \{c_1, c_2, ..., c_j\}$
- **output** - a predicted class $c \in C$
- *classification methods* - **hand-coded rules**
    - rules based on combinations of words or other features
    - accuracy can be high, if rules carefully refined by expert
    - but building and maintaining these rules is *expensive*
- *classification *methods* - **supervised machine learning**
    - **input** - a document d, a fixed set of classes $C = \{c_1, c_2, ..., c_j\}$, and a training set of m hand-labeled documents $(d_1, c_1), ..., (d_m, c_m)$
    - **output** - a learned classifier $\gamma : d \Rightarrow c$
    - any kind of classifier
        - naive bayes
        - logistic regression
        - neural networks
        - k-nearest neighbors
        - etc

Naive Bayes Classifier

- **intuition for Naive Bayes** - simple classification method based on Bayes rule
    - relies on very simple representation of document, *bag of words*
- **Bayes' Rule** - for a document d and a class c, $P(c|d) = \frac{P(d|c)P(c)}{P(d)}$
- **Naive Bayes Classifier**
    - MAP = most likely class
    - $c_{MAP} = \arg\max{(c \in C)} P(c|d)$
    - using Bayes' Rule, can simplify to
    - $c_{MAP} = \arg\max{(c \in C)} P(d|c)P(c)$
    - where $P(d|c)$ is the *likelihood* and $P(c)$ is the *prior*
    - d can be represented as features $x_1, ..., x_n$
    - $O(|X|^n \times |C|)$ parameters
        - could only be estimated if a very, very large number of training examples was available
        - we can just count the relative frequencies in a corpus

Multinomial Naive Bayes

- **independence assumptions** - $P(x_1, x_2, ..., x_n|c)$
- **bag of words assumption** - assume position does not matter
- **conditional independence** - assume the feature probabilities $P(x_i|c_j)} are independent given the class c
  - $P(x_1, x_2, ..., x_n|c) = P(x_1|c) \times P(x_2|c) \times P(x_3|c) \times ... \times P(x_n|c)$
- $c_{NB} = \arg\max\,(c \in C)\;\Pi(x \in X)\;P(x|c)$
- **problem** with multiplying lots of probabilities
  - can result in floating point underflow
  - *solution* - use logs since multiplications become additions
  - taking log does not change the ranking of classes
  - linear model - max of a sum of weights, so it is a linear function of the inputs
- Naive Bayes is a **linear classifier**

Learning

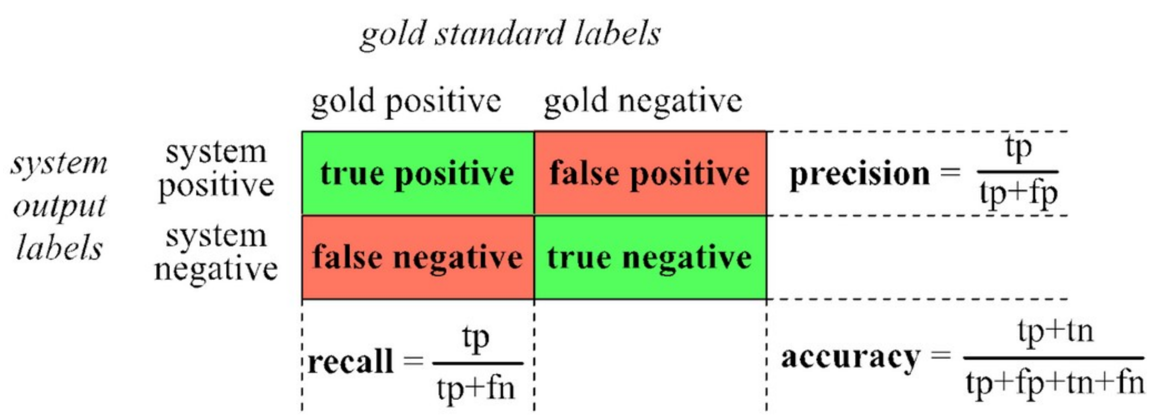
- *first attempt* - use MLE with the frequencies in the data
  - $P(w_i|c_j) = \frac{count(w_i, c_j)}{\Sigma(w \in V)\;count(w, c_j)}$
  - fraction of times word w_i appears among all words in documents of topic c_j
  - create *mega-document* for topic j by concatenating all docs in this topic
    - use frequency of w in mega-document
  - **problem** - what if we have seen no training documents with a word classified in a class?
    - we will get 0
    - cannot condition away zero probabilities no matter what
    - **solution** - Laplace Add-1 smoothing, same idea as with Markov assumptions, add one to all counts
- **unknown words** - what do we do with them that appear in the test data but not in the training data or vocabulary?
  - **ignore them** - remove from test document, pretend they were not there
    - do not include any probability for them at all
  - building an unknown word model does not help, knowing which class has more unknown words is *not generally helpful*
- **stop words** - very frequent words like "the" and "a"
  - some systems ignore them
    - but usually does not help
  - sort vocabulary by word frequency in a training set
  - call the top 10 or 50 words the *stopword list*
  - remove all stop words from both training and test sets, as if they were never there to begin with

Relationship to Language Modeling

- **generative model of NB** - graph of the words that are classified to a specific class
- NB classifiers can use any sort of *feature*
    - i.e. URL, email address, dictionaries, network features
    - we use **only** word features
    - we use **all** of the words in the text, not a subset
    - then NB has an *important similarity* to language modeling
- **each class = a unigram language model**
    - assigning each word: $P(word|c)$
    - assigning each sentence: $P(s|c) = \Pi \ P(word|c)$
    - example: each word and their probability it is positive class
        - I = 0.1, love = 0.1, this = 0.05, fun = 0.01, film = 0.1
        - P(sentence | positive) = 0.1 x 0.1 x 0.05 x 0.01 x 0.1 = 0.0000005
    - example: using positive class from previous and given new negative class, which one assigns the higher probability to sentence?
        - negative: I = 0.2, love = 0.001, this = 0.01, fun = 0.005, film = 0.1
        - P(sentence | negative) = 10^{-9}
        - P(sentence | positive) > P(sentence | negative)

Naive Bayes Evaluation

- **2 by 2 confusion matrix**



- **accuracy** - do not use as the evaluation metric
    - useless, does not return what we are looking for
    - can get amazing accuracy for very dumb labeling that is not very representative of the data as a whole
    - use *precision* and *recall* instead
- **precision** - percent of items the system detected (i.e. items the system labeled as positive) that are positive (according to human gold labels)
    - $precision = \frac{true\ positives}{true\ positives + false\ positives}$
- **recall** - percent of items actually present in the input that were correctly identified by the system
    - $recall = \frac{true\ positives}{true\ positives + false\ negatives}$

- precision and recall, not accuracy, emphasize **true positives** - finding the things that we are supposed to be looking for
- **combined measure F** - a single number that combines both *precision* and *recall*
    - $$F_\beta = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$$
    - almost always use balanced F_1 ($\beta = 1$)
        - $F_1 = \frac{2PR}{P+R}$

Cross-Validation

- **devsets** - development test sets
- train on training set, tune on devset, report on test set
    - avoids *overfitting* - tuning to the test set
    - more conservative estimate of performance
    - **paradox** - want as much data as possible for training and as much for dev, so how do you split it?
- **cross-validation** - multiple splits
    - pool results over splits, compute pooled dev performance

Harms in Classification

- can have biases in classifiers that perpetuate negative stereotypes against a certain group of people, etc
    - or censorship of discussion about a group of people
- **causes of harms**
    - problems in the training data, ML systems known to amplify biases in their training data
    - problems in the human labels
    - problems in the resources used (like lexicons)
    - problems in the model architecture (like what the model is trained to optimize)
- **mitigation** of these harms is an *open research area*
- **model cards** - for each algorithm you release, document:
    - training algorithms and parameters
    - training data sources, motivation, and preprocessing
    - evaluation data sources, motivation, and preprocessing
    - intended use and users
    - model performance across different demographic or other groups and environmental situations