SDS Exam 2 Notes

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1. 7 - Kappa

1.1. Inter-Rater Reliability

- Dialogue Act Classification
    - can be straightforward, i.e. question, declaration, apology
    - can be subject to interpretation
        - yeah, right - agreement or sarcasm?
        - what!? - question, exclamation, or reaction?
    - **solution** - test how well two people agree on given dialogue acts
        - **inter-rater reliability**
- **inter-rater reliability** - degree of agreement between raters where raters work independently of each other
    - application - *validation* of rating protocols
- useful when rating protocols are ambiguous
    - applying dialogue act tags
    - codes from thematic analysis
    - judging the quality of something

1.2. Agreement Calculations

- **agreement** - probability that you and your partner selected the same tag for an item on the list
    - $agreement = \frac{count(item\ rated\ the\ same)}{count(item)}$
- **observed vs. expected agreement** - determine what agreement was likely due to chance
    - **observed agreement** - probability that items were rated the same
      $P(items\ rated\ the\ same)$
    - **expected agreement** - sum over all ratings

        - $P(item\ rated\ by\ both\ as\ X)$
        - $= P(judge\ 1\ rated\ X \cap judge\ 2\ rated\ X)$
    - if judges rated independently
        - $P(judge\ 1\ rated\ X) * P(judge\ 2\ rated\ X)$
- example
    - rate 20 items good or bad
    - rater 1 rated 1 item bad rest good
    - rater 2 rated 2 items bad rest good
    - all the bad rates, the other rater rated that item as good
    - observed agreement = 17 / 20 = 0.85
    - expected agreement - make table where entry is the count that the rater rated items that class out of all items

	Rater 1	Rater 2
Bad	0.05	0.10
Good	0.95	0.90

    - bad = 0.05 x 0.10 = 0.005
    - good = 0.95 x 0.90 = 0.855
    - total = 0.855 + 0.005

1.3. Cohen's Kappa

- measures the degree to which two raters' agreement exceeds chance
    - $k = \frac{O-E}{1-E}$
- O is observed agreement, E expected agreement
- from previous example

    - O = 0 + 0.85 = 0.85
    - E = (0.05 x 0.1) + (0.95 x 0.9) = 0.86
    - k = (0.85 - 0.86) / (1 - 0.86) = -0.071, poor agreement
- kappa ranges from -1 to 1
    - k > 0 indicates agreement better than chance
        - k = 1 perfect agreement
    - k < 0 indicates agreement worse than chance
        - k = -1 perfect disagreement and 50% expected agreement
    - applicable when data are *nominal* and *unordered*
Score	Interpretation
< 0	poor
0 - 0.2	slight
0.2 - 0.4	fair
0.41 - 0.6	moderate
0.61 - 0.8	substantial
0.81 - 1	almost perfect
- example

Rater 2

		B	G	Meh	
Rater 1	B	5	1	0	6
	G	1	9	1	11
	Meh	1	1	1	3
		7	11	2	

Rater 2

		B	G	Meh	
Rater 1	B	.25	.05	0	.3
	G	.05	.45	.05	.55
	Meh	.05	.05	.05	.15
		.35	.55	.1	

    - O = 0.25 + 0.45 + 0.05 = 0.75

- E = (0.3 x 0.35) + (0.55 x 0.55) + (0.15 x 0.1) = 0.4225
- k = (0.75 - 0.4225) / (1 - 0.4225) = 0.57, moderate agreement

1.4. Applications

- dialogue act classification
  - define a set of dialogue tags and detailed descriptions for each one
  - train secondary annotators on how to use your tagging scheme
  - calculate kappa on subset of data (generally around 20%)
  - if kappa is too low, retrain and repeat
  - standard practices for corpus-based research
    - one or more annotators tag entire corpus split across each annotator
    - kappa computed on double-tagged portion of corpus, around 20%
    - kappa of around 0.8 is generally acceptable for dialogue act tags
      - lower kappas are acceptable depending on the task
      - tagging uncertainty, disengagement, etc

1.5. Weighted Kappa

- **weighted kappa** - accounts for degree of disagreement
- useful when ratings are ordered
  - i.e. disagreement between good and bad should have more weight than disagreement between good and meh
- consists of **3 matrices**
  - observed agreement matrix
  - expected agreement matrix
  - weight matrix
- **observed agreement matrix** - same as the contingency matrix = X
- **expected agreement matrix** - probabilities for each pair of ratings = M
  - $m_{ij} = \frac{(rater\ 1's\ i\ ratings) \times (rater\ 2's\ j\ ratings)}{total\ data\ points}$
- **weight matrix** - each cell in the contingency matrix = W
  - matrix diagonal is zero, no penalty for agreement
  - other weights determined by distance between ratings
    - good/meh and meh/bad = 1, good/bad = 2
- $k = 1 - \frac{\sum \sum w_{ij} x_{ij}}{\sum \sum w_{ij} m_{ij}}$
  - sum of products of weight and observed agreement matrices divided by sum of products of weight and expected agreement matrices

1.6. Other Inter-Rater Reliability Methods

- **Fleiss' kappa** - multiple raters, ordinal data

    - alternative - average pairwise Cohen's kappa
- **Pearson's correlation coefficient and Spearman's rank correlation coefficient** - used for continuous data
- **Krippendorff's alpha** - generalizable to multiple raters and data types
- **Cronbach's alpha** - validating psychometric test items

2. 8 - Dialogue System Evaluation

2.1. Dialogue Evaluation

- things we can measure about how well a dialogue went
    - user satisfaction
    - learning
    - task completion
    - how long they stayed with it
- outcomes
    - tell us how well a dialogue went
    - can be represented numerically in some way and then predicted based on what happened within the dialogues themselves
    - you need to keep records of what happened in the dialogues themselves

2.2. PARADISE Framework

- used to evaluate dialogue systems
- *performance* of a dialogue system is affected by both:
    - *what* gets accomplished by the user and the dialogue agent and
    - *how* it gets accomplished
- maximize user satisfaction
    - maximize task success
    - minimize costs
        - efficiency measures
        - qualitative measures
- regress against user satisfaction
    - questionnaire to assign each dialogue a user satisfaction rating - *dependent* measure
    - cost and success factors - *independent* measures
    - use regression to train weights for each factor

2.3. Experimental Procedures

- subjects given specific tasks
- spoken dialogues recorded

- cost factors, states, dialogue acts automatically logged
- ASR accuracy, barge-in hand-labeled
- users specify task solution via web page
- users complete user satisfaction survey of some kind
- use **multiple linear regression** to model user satisfaction as a function of task success and costs
    - test for significant predictive factors

2.4. Success Metric

- could we use the success metric to drive automatic learning?
- methods for automatically evaluating system performance
- way of obtaining training data for further system development
- can we find intrinsic evaluation metrics that correlate with extrinsic results?

3. 9 - Basic Text Processing

3.1. Regular Expressions

- formal language for specifying text strings
- process based on fixing two kinds of errors
    - matching strings that we should not have matched (there, then, other)
        - *false positives*
    - not matching things that we should have matched (the)
        - *false negatives*
- sophisticated sequences of regular expressions are often the first model for any text processing
    - therefore play a large role
- for many hard tasks, use machine learning classifiers
    - but regular expressions are used as features in the classifiers
    - can be very useful in capturing generalizations

3.2. Word Tokenization

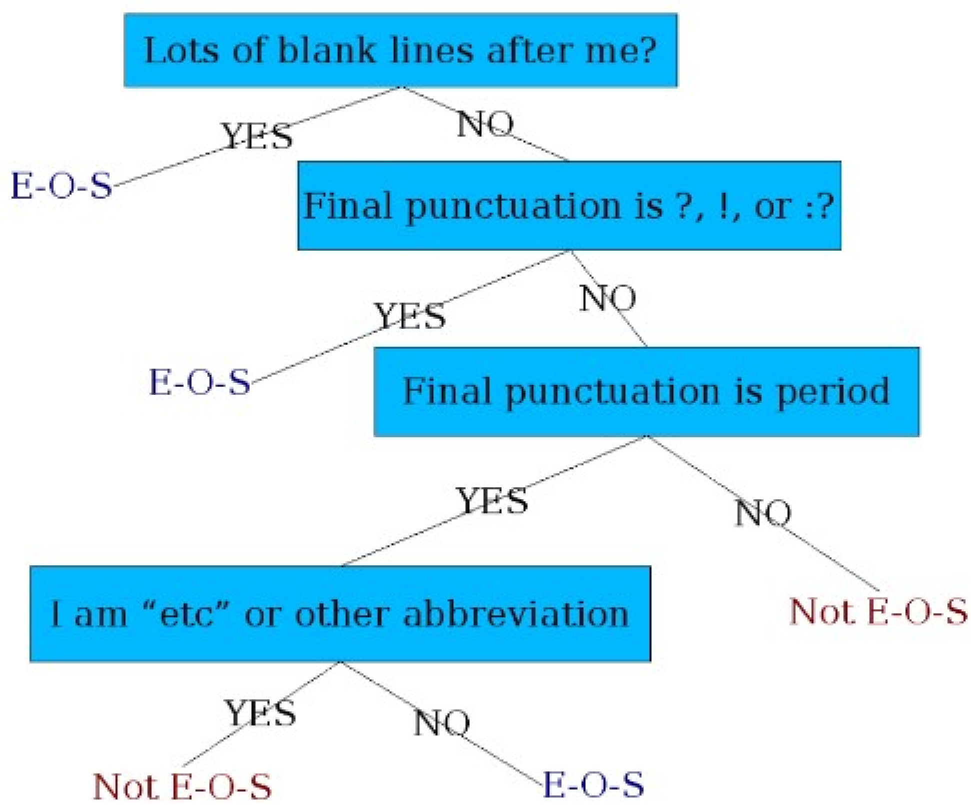
- **text normalization**
    1. segmenting/tokenizing words in running text
    2. normalizing word formats
    3. segmenting sentences in running text
- can be hard to determine how many words are in an utterance
    - "I do uh main- mainly business data processing" - fragments, filled pauses
    - "Suess's cat in the hat is different from other cats!"
        - lemma - same stem, part of speech, rough worse sense
            - cat and cats = same lemma

        - wordform - the full inflected surface form
            - cat and cats = different wordforms
        - "they lay back on the San Francisco grass and looked at the stars and their"
            - **type** - an element of the vocabulary
            - **token** - an instance of that type in running text
            - 15 tokens, 13 types
- issues in tokenization
    - "Finland's capital" -> Finland, Finlands, Finland's?
    - "what're, I'm, isn't" -> what are, I am, is not
    - "Hewlett-Packard" -> Hewlett Packard?
    - "state-of-the-art" -> state of the art?
    - "Lowercase" -> lower-case, lowercase, lower case?
    - "San Francisco" -> one token or two?
    - "m.p.h., PhD." -> ??
- **normalization** - break words down to their equivalence classes of terms
    - information retrieval - indexed text and query terms must have same form, i.e. match U.S.A and USA as the same
    - implicitly define equivalence classes of terms
        - i.e. deleting periods in a term
    - *alternative* - asymmetric expansion
        - enter: window, search: window, windows
        - enter: windows, search: Windows, windows, window
        - enter: Windows, search: Windows
    - potentially more powerful, but less efficient
- **case folding** - reduce all letters to lower case
    - users tend to use lower case
    - possible exception - upper case in mid-sentence?
        - i.e. General Motors, Fed vs fed, SAIL vs sail
    - for sentiment analysis, MT, information extraction, case is helpful
        - US vs us is important
- **lemmatization** - reduce inflections or variant forms to base form
    - am, are, is -> be
    - car, cars, car's, cars' -> car
    - the boy's cars are different colors -> the boy car be different color
    - have to find correct dictionary headword form
    - machine translation
- **morphology**
    - **morphemes** - small meaningful units that make up words
    - *stems* - core meaning-bearing units
    - *affixes* - bits and pieces that adhere to stems
        - often with grammatical functions

- **stemming** - crude chopping of affixes
    - goal is to reduce terms to their stems in information retrieval
    - language dependent
    - automate, automatic, automation all reduced to automat
    - **Porter's algorithm** - most common English stemmer
    - only strip -ing if there is a verb
        - walking -> walk
        - sing -> sing

3.3. Sentence Segmentation and Decision Trees

- **sentence segmentation** - meaning of punctuation
    - !, ? are relatively unambiguous
    - . is quite ambiguous
        - sentence boundary
        - abbreviations (Dr., Inc, etc)
        - numbers (.02, 4.3)
    - build a binary classifier
        - looks at a .
        - decides end of sentence or not end of sentence
        - *classifiers* - hand-written rules, regular expressions, or machine learning
- use a **decision tree** to determine if a word is end-of-sentence



    - more sophisticated decision tree features
        - word with period - upper, lower, caps, number
- implementing decision trees
    - decision tree is just an *if else* statement
    - interesting research is choosing the features
    - setting up the structure is often too hard to do by hand
        - hand building only possible for very simple features, domains
            - for numeric features, it's too hard to pick each threshold
        - instead, structure usually learned by machine learning from a training corpus
    - think of the questions in a decision tree as *features* that could be exploited by any kind of classifier
        - logistic regression
        - SVM
        - neural nets, etc

3.4. Minimum Edit Distance

- **minimum edit distance** - minimum number of editing operations between to strings to transform one into the other
- **editing operations** - insert, delete, substitution
- example
    - ```
      I N T E * N T I O N
      | | | | | | | | | |
      * E X E C U T I O N
      d s s   i s
      ```
    - strings need to be *aligned*
    - if each operation has cost of 1, distance between the two is 5
    - if substitutions cost 2, distance between them is 8
- other uses in NLP
    - evaluating machine translation and speech recognition
    - named entity extraction and entity co-reference
- finding min edit distance
    - search for path (sequence of edits) from the start string to the final string
    - *initial state* - word we are transforming
    - *operators* - insert, delete, substitute
    - *goal state* - word we are trying to get to
    - *path cost* - what we want to minimize, the number of edits
    - space of all edit sequences is huge
        - cannot afford to navigate naively
        - lots of distinct paths wind up at the same state, therefore we don't have to keep track
      ```

of all of them, just the *shortest path* to each of those revised states

- **dynamic programming** - solving problems by combining solutions to subproblems
  - use it for a tabular computation of D(n, m)
  - *bottom-up* - we compute D(i, j) for small i, j, and compute larger D(i, j) based on previously computed smaller values
- Levenshtein
  - initialization - D(i, 0) = i, D(0, j) = j
  - recurrence relation

    For each i = 1…M

    For each j = 1…N

    $$D(i,j) = \min \begin{cases} D(i-1,j) + 1 \\ D(i,j-1) + 1 \\ D(i-1,j-1) + \begin{cases} 2; & \text{if } X(i) \neq Y(j) \\ 0; & \text{if } X(i) = Y(j) \end{cases} \end{cases}$$
  - termination - D(N, M) is distance
  - create an edit distance table
- computing alignments
  - edit distance isn't sufficient
  - often need to *align* each character of the two strings to each other
  - do this by keeping a **backtrace**
    - every time we enter a cell, remember where we came from
  - when we reach the end, trace back the path from the upper right corner to read off the alignment
  - do this through the table
    - label each part of the path with a symbol
    - left = insertion
    - down = deletion
    - diagonal = substitution
  - an optimal alignment is composed of optimal subalignments
  - honestly just look at the slides for these looking at the tables and them transitioning makes it a lot easier to understand
  - **performance**
    - *time* - O(nm)
    - *space* - O(nm)
    - *backtrace* - O(n+m)
- **weighted edit distance** - add weights to the computation
  - *spell correction* - some letters are more likely to be mistyped than others
  - *biology* - certain kinds of deletions or insertions are more likely than others
- alignments in 2 fields
  - **NLP** - generally talk about *distance* (minimized) and *weights*
  - **Computational Biology** - generally talk about *similarity* (maximized) and *scores*
- Needleman-Wunsch - start at top left corner for edit table instead of bottom left

- variant of basic algorithm - might be ok to have unlimited number of gaps in the beginning and end
    - if so, we do not want to penalize gaps at the ends
- Smith-Waterman algorithm
    - ignore badly aligned regions
    - modify Needleman-Wunsch
    - want to have local alignment

4. 10 - Language Modeling

4.1. Probabilistic Language Models

- **goal** - assign a probability to a sentence
    - *machine translation* - P(high winds tonight) > P(large winds tonight)
    - *spell correction* - the office is about fifteen minuets from my house
        - P(about fifteen minutes from) > P(about fifteen minuets from)
    - *speech recognition* - P(I saw a van) >> P(eyes awe of an)
    - summarization, question-answering, etc
    - $P(W) = P(w_1, w_2, w_3, w_4, w_5)$
- **related task** - probability of an upcoming word
    - $P(w_5 | w_1, w_2, w_3, w_4)$
- **language model (LM)** - model that computes either of the two formulas
    - also called *grammar*
- how do we compute P(W)?
    - rely on **Chain Rule of Probability**

4.2. Chain Rule

- definitions of conditional probabilities
    - $P(B|A) = \frac{P(A,B)}{P(A)}$
    - $P(A, B) = P(A)P(B|A)$
- **general equation**
    - $P(x_1, x_2, x_3, ..., x_n) = P(x_1)P(x_2|x_1)P(x_3|x_1, x_2)...P(x_n|x_1, ..., x_{n-1})$

4.3. Applied Chain Rule

- **applied** to *joint probability of words* in a sentence
    - $P(w_1 w_2 ... w_n) = \Pi i \; P(w_i | w_1 w_2 ... w_{i-1})$
    - sidenote: latex sucks so if you see Πi that means i is the bound, not multiplying the rest of the stuff by i

- example: P("its water is so transparent")
  - $= P(its) \times P(water|its) \times P(so|its\ water\ is) \times P(transparent|its\ water\ is\ so)$
- **naive estimation** - count and divide
  - $P(the|its\ water\ is\ so\ transparent\ that) = \frac{Count(its\ water\ is\ so\ transparent\ that\ the)}{Count(its\ water\ is\ so\ transparent\ that)}$
  - but there are *way too many* possible sentences
  - never see enough data for estimating

4.4. Markov Assumption

- *simplify* assumption
- approximate each component in the product
  - $P(w_i|w_1 w_2 ... w_{i-1} \approx P(w_i|w_{i-k} ... w_{i-1})$
- **unigram model** - simplest case
  - $P(w_1 w_2 ... w_n) \approx \Pi i\ P(w_i)$
- **bigram model** - condition on the previous word
  - $P(w_i|w_1 w_2 ... w_{i-1}) \approx P(w_i|w_{i-1})$
- **n-gram models** - can extend to trigrams, 4-grams, etc
  - in general this is an *insufficient model of language* because language has **long-distance dependencies**
    - words that have meaning tied with another part of the sentence may be many many words separated
  - we can often get away with n-gram models though

4.5. Estimating Bigram Probabilities

- **maximum likelihood estimate**
  - count abbreviated to c in following formulas
  - $P(w_i|w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$
- example:
  - I am Sam. Sam I am. I do not like green eggs and ham.
  - P(Sam | am) = 1/2
  - P(am | I) = 2/3
  - P(do | I) = 1/3
- **raw bigram count table** - (row, column) is count of times that row column appears in the given sentences
  - to get probabilities, normalize by the unigrams
  - see HW4
- **practical issues** - we do everything in log space
  - avoid *underflow*
  - adding is faster than multiplying

    - $\log(p_1 \times p_2 \times p_3 \times p_4) = \log p_1 + \log p_2 + \log p_3 + \log p_4$

4.6. Evaluation

- does our language model prefer *good* sentences to *bad* ones?
- assign higher probability to *real* or *frequently observed* sentences than *ungrammatical* or *rarely observed* sentences
- train parameters of the model on a **training set**
- test the model's performance on data it has not seen
    - **test set** - unseen dataset that is different from the training set, totally unused
    - **evaluation metric** - how well the model does on the test set
- training on the **test set**
    - cannot allow test sentences in the training set
    - assign it an artificially high probability when we set it in the test set
    - training on the test set is bas science and violates the honor code
- **extrinsic** evaluation of **n-gram models** - best evaluation for comparing models A and B
    - put each model in a task, such as spelling corrector, speech recognizer, MT system, etc
    - run the task, get an *accuracy* for A and for B
        - how many misspelled words corrected properly
        - how many words translated correctly
        - etc
    - compare accuracy for A and B
    - **difficulty** - time-consuming, can take days or weeks
- **intrinsic** evaluation - **perplexity**
    - bad approximation, unless test data looks just like the training data
    - generally only useful in *pilot experiments*
    - helpful to think about though

4.7. Perplexity

- **Shannon Game** - how well can we predict the next word?
    - unigrams are terrible at this due to only calculating the probability of a word, not with context in sentence
    - a better model of text is one which assigns a higher probability to the word that actually occurs
- **best language model** is one that best predicts an unseen test set, so it gives the highest P(sentence)
- **perplexity** - inverse probability of the test set, *normalized* by the number of words
- **!!!** minimizing perplexity is the same as maximizing probability **!!!**
- equations (I hope we don't need to memorize these...)

Chain rule:

$$\mathrm{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_1 \ldots w_{i-1})}}$$

For bigrams:

$$\mathrm{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_{i-1})}}$$

- perplexity as a **branching factor**
  - example: sentence consists of random digits
    - perplexity of the sentence according to a model that assigns P=1/10 to each digit?
    - $PP(W) = P(w_1 w_2 ... w_N)^{-\frac{1}{N}}$

      $PP(W) = (\frac{1}{10}^N)^{-\frac{1}{N}} = \frac{1}{10}^{-1} = 10$
- lower perplexity = *better model*

4.8. Generalization

- **Shannon Visualization Method**
  - choose a random bigram (<s>, w) according to its probability
  - now choose a random bigram (w, x) according to its probability
  - and so on until we choose </s>
  - then string the words together
- **perils of overfitting** - N-grams only work well for word prediction if the test corpus looks like the training corpus
  - in reality, it often does not
  - need to train robust models that *generalize*
  - one kind of generalization - **zeros**
    - things that do not ever occur in the training set, but occur in the test set

4.9. Zeros

- training set:
  - ...denied the allegations
  - ...denied the reports
  - ...denied the claims
  - ...denied the request
- test set:
  - ...denied the offer
  - ...denied the loan

- P("offer" | denied the) = 0
- **zero probability bigrams** - bigrams with zero probability that means we will assign 0 probability to the test set
    - and thus we cannot compute perplexity, we cannot divide by 0

4.10. Laplace Add-One Smoothing

- **smoothing intuition** - when we have sparse statistics, steal probability mass to generalize better
- **Laplace Add-One smoothing** - pretend we saw each word one more time than we did
    - add one to all counts
    - traditional MLE estimate: $P_{MLE}(w_i|w_{i-1}) = \frac{c(w_{i-1},w_i)}{c(w_{i-1})}$
    - Add-1 estimate: $P_{Add-1}(w_i|w_{i-1}) = \frac{c(w_{i-1},w_i)+1}{c(w_{i-1})+V}$
- **maximum likelihood estimates (MLE)** - maximizes the likelihood of the training set T given the model M based on some parameter of a model M from a training set T
    - example: suppose word "bagel" occurs 400 times in a corpus of a million words
        - probability that a random word from some other text will be "bagel"?
        - MLE estimate = 400/1,000,000 = 0.0004
    - may be a bad estimate for some other corpus
        - but it is the *estimate* that makes it *most likely* that "bagel" will occur 400 times in a million word corpus
- Add-1 is a *blunt instrument*, so it is not used for N-grams
- used to smooth other NLP models for text classification and in domains where the number of zeros is not huge

5. 11 - Naive Bayes

5.1. 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

5.2. 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

5.3. 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**

5.4. Learning

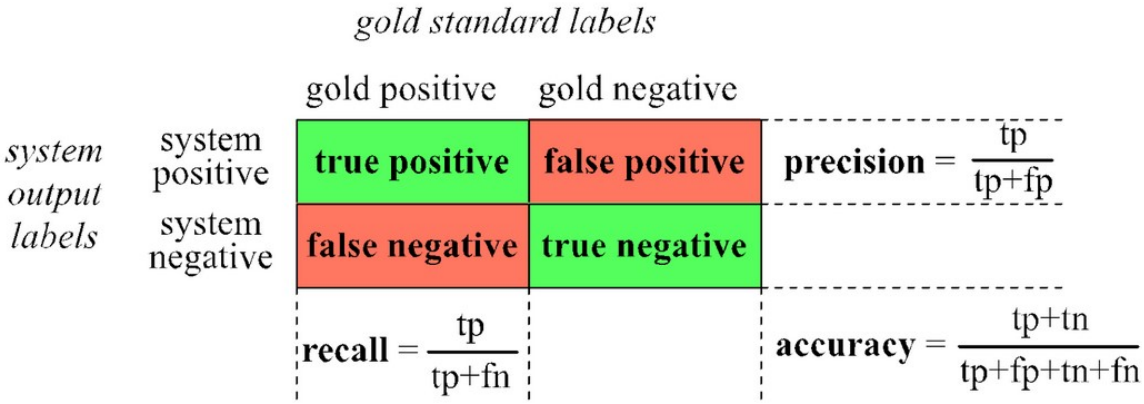
- *first attempt* - use MLE with the frequencies in the data
    - $P(w_i|c_j) = \frac{count(w_i, c_j)}{\Sigma(w \in V)\ count(w, c_j)}$

    - 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

5.5. 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)

5.6. 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 ($\beta = 1$)
        - $F_1 = \frac{2PR}{P+R}$

5.7. 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

5.8. 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

6. 12 - Vector Semantics

6.1. Word Meaning

- in N-gram or text classification methods, words are just strings
    - not very satisfactory
- from **lexical semantics**, the linguistic study of word meaning
- **sense/concept** - meaning component of a word
- lemmas can be **polysemous** - have multiple senses

6.2. Word Relation

- **synonyms** - words that have the same meaning in some or all contexts
    - there are probably no examples of perfect synonymy, even if many aspects of meaning are identical
        - still may differ bassed on politeness, slang, register, genre, etc
- **similarity** - words with similar meanings

    - not synonyms, but *sharing some* element of meaning
- **word relatedness/association** - relation of words in any way, such as via a semantic frame or field
    - coffee, tea are similar
    - coffee, cup are related, but not similar
- **semantic field** - words that
    - cover a particular *semantic domain*
    - bear *structured relations* with each other
    - hospitals - surgeon, scalpel, nurse, hospital
    - restaurants - waiter, menu, plate, food, chef
    - houses - door, roof, kitchen, family, bed
- **antonymy** - senses that are opposite with respect to only one feature of meaning
    - otherwise they are very similar
    - dark/light, short/long, fast/slow, rise/fall, hot/cold, etc
    - more formally, *anyonymy* can
        - define a binary opposition or be at opposite ends of a scale (i.e. long/short, fast/slow)
        - be *reversives* (i.e. rise/fall, up/down)
- **connotation** - words have affective meanings
    - positive or negative
    - can be *subtle*
    - evaluation is the sentiment
    - words seem to vary along **3 affective dimensions**
        - **valence** - the pleasantness of the stimulus
        - **arousal** - the intensity of emotion provoked by the stimulus
        - **dominance** - the degree of control exerted by the stimulus
- *summary so far*
    - concepts or word senses have a complex many-to-many association with words
    - have relations with each other

6.3. Vector Semantics

- **vector semantics** - model in language processing
- define words by their **usage** - defined by their environments (words around them)
- if A and B have almost identical environments we say that they are **synonyms**
- **idea 1** - define meaning by *linguistic distribution*
    - distribution in language use = neighboring words or grammatical environments
- **idea 2** - define meaning as a *point in space*
    - 3 affective dimensions for a word
    - connotation of a word is a vector in 3-space
    - each word is a **vector**
    - similar words are *nearby in semantic space*
    - build this space *automatically* by seeing which words are nearby in text

- define meaning of a word as a **vector**
  - called an **embedding** because it is embedded into a space
  - standard way to represent meaning in NLP
  - fine-grained model of meaning for similarity
- **but why vectors?**
  - consider *sentiment analysis*
    - with **words** a feature is a word identity
      - feature 5: "the previous word was "terrible"" requires *exact same word* to be in training and test
    - with **embeddings** feature is a *word vector*
      - "the previous word was vector [35, 22, 17...]
      - now in the test set we might see a similar vector [34, 21, 14...]
      - we can generalize to *similar but unseen* words
- 2 kinds of embeddings
  - **tf-idf**
    - information retrieval workhorse
    - common baseline model
    - *sparse* vectors
    - words are represented by the *counts* of nearby words
  - **word2vec**
    - *dense* vectors
    - representation is created by training a classifier to *predict* whether a word is likely to appear nearby
- now we are computing with meaning representations instead of string representations

6.4. Words and Vectors

- **term-document matrix** - each document is represented by a vector of words
  -

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

  - can visualize with a graph where one word is x axis and another is y
- vectors are the basis of *information retrieval*
  - in previous matrix, vectors are similar for the two comedies, but comedies are different than the other two
    - comedies have more fools and wit and fewer battles
- words can be vectors too

-

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

    - battle is the kind of word that occurs in Julius Caesar and Henry V
    - fool is the kind of word that occurs in comedies, especially Twelfth Night
- **word-word/term-context matrix** - two words are similar in meaning if their context vectors are similar
    - more commonly used
    -

	aardvark	...	computer	data	result	pie	sugar	...
cherry	0	...	2	8	9	442	25	...
strawberry	0	...	0	0	1	60	19	...
digital	0	...	1670	1683	85	5	4	...
information	0	...	3325	3982	378	5	13	...

    - if context is a document, cells represent the number of times both the words appeared in the same document

6.5. Computing Word Similarity

- dot product between two vectors is a scalar
    - $dot\ product(v, w) = v \cdot w = v_1 w_1 + v_2 w_2 + ... + v_N w_N$
- dot product tends to be high when the two vectors have large values in the same dimensions
- dot product can thus be a useful *similarity metric* between two vectors
- **problem** with raw dot-product
    - favors long vectors
    - higher if a vector is longer (has higher values in many dimensions)
    - **vector length** - $|v| = \sqrt{\Sigma(i = 1 : N)\ v_i^2}$
    - frequent words (of, the, you) have long vectors, since they occur many times with other words
    - therefore, dot product *overly favors frequent words*
- **alternative** - use cosine for computing word similarity
    - $\frac{a \cdot b}{|a|\ |b|} = \cos\theta$
    - -1 = vectors point in opposite directions
    - +1 = vectors point in the same directions
    -
        - = vectors are orthogonal (perpendicular, form 90 degrees)
    - but since raw frequency values are non-negative, the cosine for term-term matrix vectors range from 0-1

6.6. TF-IDF

- raw frequency is a *bad representation*

- co-occurrence matrices we have seen represent each cell by word frequencies
    - frequency is clearly useful, if sugar appears a lot near apricot, that is useful information
    - but overly frequent words like the, it, or they are not very informative about the context
    - how can we balance these two conflicting constraints?
- **solutions for word weighting**
    - **tf-idf** - turn-frequency-inverse document frequency (tf-idf) for word t in document d
        - $w_{t,d} = tf_{t,d} \times idf_t$
        - words like the or it have very low idf
    - **pointwise mutual information (PMI)** - see if words like good appear more often with great than we would expect by chance
        - $PMI(w_1, w_2) = \log \frac{p(w_1,w_2)}{p(w_1)p(w_2)}$
- **turn frequency (tf)** - $tf_{t,d} = count(t, d)$
    - instead of using raw count, we can squash it a bit: $tf_{t,d} = \log base10\ (count(t,d) + 1)$
- **document frequency (df)**
    - df_t is the number of documents t occurs in
    - this is *not collection frequency* - total count across all documents
- **inverse document frequency (idf)**
    - $idf_t = \log base10\ (\frac{N}{df_t})$, N is the total number of documents in the collection
- **document** - can be anything, often call each paragraph a document
- **final tf-idf weighted value** for a word
    - $w_{t,d} = tf_{t,d} \times idf_t$

6.7. Sparse vs. Dense Vectors

- tf-idf or PMI vectors are
    - *long* - length |V| = 20,000 to 50,000
    - *sparse* - most elements are 0
- **alternative** - learn vectors which are
    - *short* - length 50 to 1,000
    - *dense* - most elements are non-zero
- why **dense vectors**?
    - short vectors may be *easier* to use as *features* in ML - fewer weights to tune
    - dense vectors may *generalize* better than explicit counts
    - dense vectors may do better at capturing synonymy
        - car and automobile are synonyms, but are distinct dimensions
        - a word with car as a neighbor and a word with automobile as a neighbor should be similar, but are not
    - **in practice, they work better**
- common methods for getting *short dense vectors*
    - "neural language model" inspired models - word2vec, GloVe
    - singular value decomposition (SVD) - special case is Latent Semantic Analysis (LSA)

    - alternatives to these static embeddings
        - contextual embeddings (ELMo, BERT)
        - compute distinct embeddings for a word in its context
        - separate embeddings for each token of a word

6.8. Word2vec

- popular embedding method
- very fast to train
- code available on the web provided by Google
- **idea** - *predict* rather than *count*
- provides various options, such as skip-gram or continuous bag of words (CBOW)
    - we will use skip-gram
- instead of *counting* how often each word w occurs near apricot, train a **classifier** on a **binary prediction** task
    - is w likely to show up near apricot?
    - don't actually care about this task, but we will take the learned classifier weights as the *word embeddings*
- **big idea** - **self supervision**
    - a word c that occurs near apricot in the corpus acts as the gold correct answer for supervised learning
    - no need for human labels
- **approach** - predict if candidate word c is a *neighbor*
    1. treat the target word t and a neighboring context word c as **positive examples**
    2. randomly sample other words in the lexicon to get **negative examples**
    3. use *logistic regression* to train a classifier to distinguish those two cases
    4. use the learned weights as the embeddings
- **skip-gram training data** - assume a +/- 2 word window, given training sentence
    - 

    - target is apricot, google slides didn't make it go under right word -_-
    - **goal** - train a classifier that is given a candidate (word, context) pair and assigns each pair a probability
        - $P(+|w,c), P(-|w,c) = 1 - P(+|w,c)$
- **similarity** is computed from dot product
    - two vectors are *similar* if they have a high dot product
    - cosine is just a *normalized* dot product
    - $similarity(w,c) \propto w \cdot c$
        - similarity is proportional to the dot product
    - have to normalize to get a probability, cosine is not a probability either

- use the sigmoid from *logistic regression*
    - and there is where I don't think we went over anything more