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

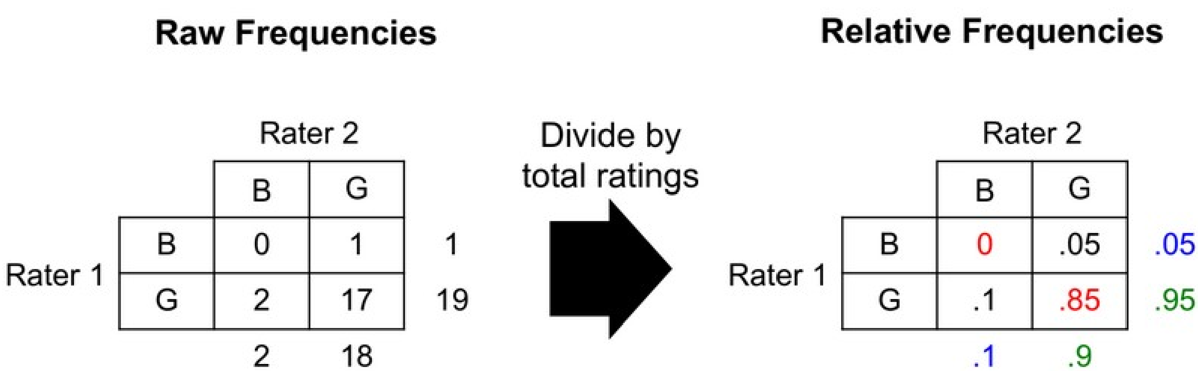
	Rater 1	Rater 2

	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

Score	Interpretation
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

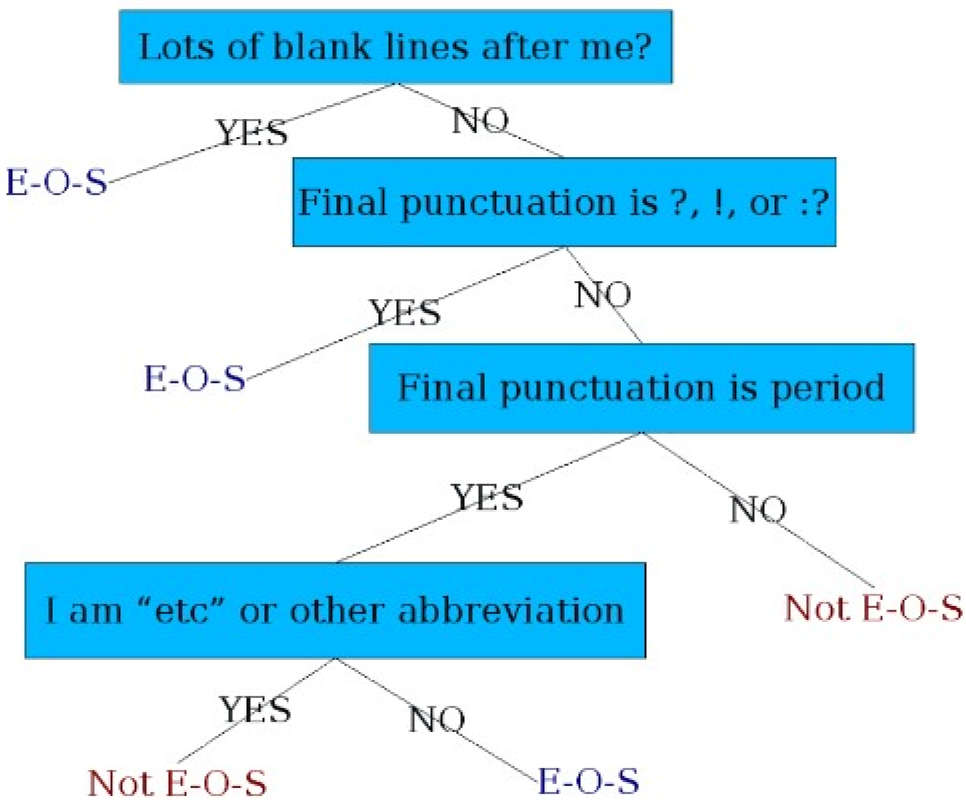
- **text normalization**
    1. segmenting/tokenizing words in running text
    2. normalizing word formats
    3. segmenting sentences in running text
- can be hard to determine how many words are in an utterance
    - "I do uh main- mainly business data processing" - fragments, filled pauses
    - "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
      ```

- $$D(i,j) = \min \begin{cases} D(i-1,j) + 1 \\ D(i,j-1) + 1 \\ D(i-1,j-1) + \begin{cases} 2; & \text{if } X(i) \neq Y(j) \\ 0; & \text{if } X(i) = Y(j) \end{cases} \end{cases}$$

  ```
  For each  i = 1…M
        For each  j = 1…N
  ```
  - 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
    - $P(w_1w_2...w_n) = \Pi i \ P(w_i|w_1w_2...w_{i-1})$
    - 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:

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

    For bigrams:

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

- 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