Lecture 2
Retrieval Models
Part 1

Reference:

James Allan, University of Massachusetts Amherst
Pandu Nayak and Prabhakar Raghavan, Stanford University
Partially modified by Qingcai Chen, HIT Shenzhen

What is a retrieval model?

- Retrieval models (检索模型) can describe the computational process of IR
  - e.g. how documents are ranked
  - Note that how documents or indexes (索引) are *stored* is implementation
- Retrieval models can attempt to describe the human process
  - e.g. the information need, interaction
- Retrieval variables
  - queries (查询), documents (文档), terms (术语), relevance judgments (相关性判别), users, information needs, …
- Retrieval models have an explicit or implicit definition of relevance (相关度)

Models we’ll consider

- Boolean (布尔模型) (exact match)
- Statistical language models (统计语言模型)
- Vector space(向量空间）
- Latent Semantic Indexing （潜层语义分析）
- Inference network
- Classic probabilistic approaches（经典概率模型）
- Other models exist
  - Topological
  - Generalized vector space
  - Logic-based

in this lecture

Exact vs. Best Match

- Exact-match (精确匹配)
  - (例: “哈工大” ≠ “哈尔滨工业大学”, “哈工程” ≠ “哈尔滨工业大学”)
  - query specifies precise retrieval criteria
  - every document either matches or fails to match query
  - result is a set of documents
  - Unordered in pure exact match
- Best-match (最佳匹配)
  - (例: “哈工大” ≈” 哈尔滨工业大学”, 相似度80%, “哈工程” ≈” 哈尔滨工业大学”, 相似度50%)
  - Query describes good or “best” matching document
  - Every document matches query to some degree
  - Result is *ranked list* of documents
- Popular approaches often provide some of each
  - E.g., some type of ranking of result set
  - E.g., best-match query language that incorporates exact-match operators

(Unranked) Boolean retrieval

- Boolean model
  - is most common exact-match model
  - queries are logic expressions with document features as operands
  - In pure Boolean model, retrieved documents are not ranked
  - Most implementations provide some sort of ranking
  - query formulation difficult for novice users (新用户)
- Boolean queries (布尔查询)
  - Used by Boolean model
  - and in other models (Boolean query ≠ Boolean model)
- “Pure” Boolean operators
  - AND, OR, AND-NOT
- Most systems have proximity operators (邻接算子)
- Most systems support simple regular expressions (正则表达式) as search terms to match spelling variants

Unstructured data for Boolean retrieval

- Example:
  - Information needs: Which plays of Shakespeare contain the words Brutus AND Caesar but NOT Calpurnia?
  - 注:Brutus布鲁图 (85-42B.C.,罗马政治家,暗杀恺撒者之一)
    Calpurnia 是Julius Caesar的第三任，也是最后一位妻子

- One could *grep* (a command in Linux system) all of Shakespeare's plays for Brutus and Caesar, then strip out lines containing Calpurnia?
- Why is that not the answer?
  - Slow (for large corpora)
  - NOT Calpurnia is non-trivial
  - Other operations (e.g., find the word Romans near countrymen) not feasible

- What's the solution for such problem?

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Document Representation: Term-document incidence

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	1	1	0	0	0	1
Brutus	1	1	0	1	0	0
Caesar	1	1	0	1	1	1
Calpurnia	0	1	0	0	0	0
Cleopatra	1	0	0	0	0	0
mercy	1	0	1	1	1	1
worser	1	0	1	1	1	0

Brutus *AND* ***Caesar*** *BUT NOT* ***Calpurnia***

1 if play contains word, 0 otherwise

Incidence vectors（关联向量）

- So we have a 0/1 vector for each term.
- To answer query: take the vectors for ***Brutus, Caesar*** and ***Calpurnia*** (complemented) ➔ bitwise *AND*.

Proximity operators

- Proximity operators
  - Phrases - “two fish”
  - Same sentence “tiger /s photo”
    - To force order to be honored, “tiger +s photo”
  - Same paragraph - “southchina tiger” /p “photo”
    - Similarly, +p forces order
  - Word proximity “southchina /5 tiger” or “southchina +5 tiger”

Features to Note about Queries

- Queries are developed incrementally
  - Change query until reasonable number of documents retrieved
    - “language models”
    - “language models” /s statistical
    - “language models” /s stat!
    - (“language models” /s stat!) % toolkit
    - (“language models” /s stat!) % (toolkit HMM)
  - implicit relevance feedback
- Queries are complex
  - proximity operators used very frequently
  - implicit OR used for synonyms
  - NOT (%) is rare
- Queries are long (av. 9-10 words)
  - not typical Internet queries (1-2 words)

Boolean query languages still used

- Many users prefer Boolean
  - Especially professional searchers
  - “Control”
  - Understandability
- For some queries or collections, Boolean often works better (e.g., using AND on the Web)
- Boolean and free text find different documents
  - Need retrieval models that support both
  - “Extended Boolean”
    - vector space
    - Probabilistic inference network
- Need interfaces that provide good cognitive models (认知模型) for ranking (排序)

Models we'll consider

- *Boolean (exact match)*
- Statistical language models

Example: Small document

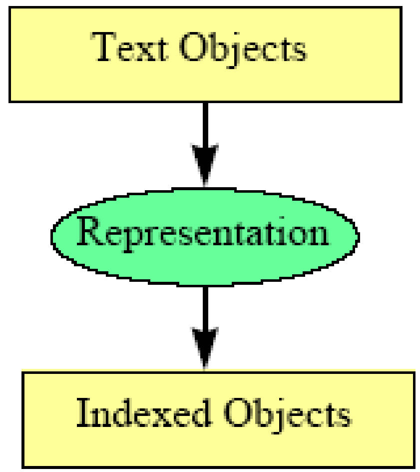
$$D = \begin{cases} \text{One fish, two fish, red fish, blue fish.} \\ \text{Black fish, blue fish, old fish, new fish.} \end{cases}$$

So we know that document D is more likely to talk about "fish" rather than "egg"!

Statistical language model: basic idea

Queries are used to describe the topic of user's needs.

- Document comes from a topic
- Topic (unseen) describes how words appear in documents on the topic
- Use document to guess what the topic looks like
  - Words common in document are common in topic
  - Words not in document much less likely
- Assign probability to words based on document
  - $P(w|Topic) \approx P(w|D) = tf(w,D) / len(D)$
- Index estimated topics



What is a Language Model?

- Probability distribution over strings of text
  - how likely is a given string (observation) in a given “language”
  - for example, consider probability for the following four strings

p_1 = P(“a quick brown dog”)

p_2 = P(“dog quick a brown”)

p_3 = P(“ 狗 brown dog”)

p_4 = P(“棕色狗”)

- … depends on what “language” we are modeling
  - In English: p1 > p2 > p3 > p4
  - In most of IR, assume that p1 == p2
  - for some applications we will want p3 to be highly probable, when?

A quick review of probabilistic

- Independence
  - If events w_1 and w_2 are independent then
    - $P(w_1 \text{ AND } w_2) = P(w_1) \cdot P(w_2)$

$$P(q_1, \ldots, q_t | D) = \prod_{i=1}^{t} P(q_i | D)$$

- Bayes' rule

$$P(B|A) = \frac{P(A|B) \cdot P(B)}{P(A)}$$

Language Modeling Notation

- Convenient to make explicit what we are modeling:
    - M … “language” we are trying to model
    - *s* … observation (string of tokens from some vocabulary)
    - P(*s*|M) … probability of observing “*s*” in language M
- M can be thought of as a “source” or a generator
  - a mechanism that can spit out strings that are legal in the language
    - E.g. “人活着就要吃东西” is a legal sentence in Chinese,
    - But “活着人东西吃” is not (generally) a sentence in Chinese (not include some novels or on Internet)
  - P(*s*|M) … probability of getting “s” during random sampling from M

Language Modeling for IR

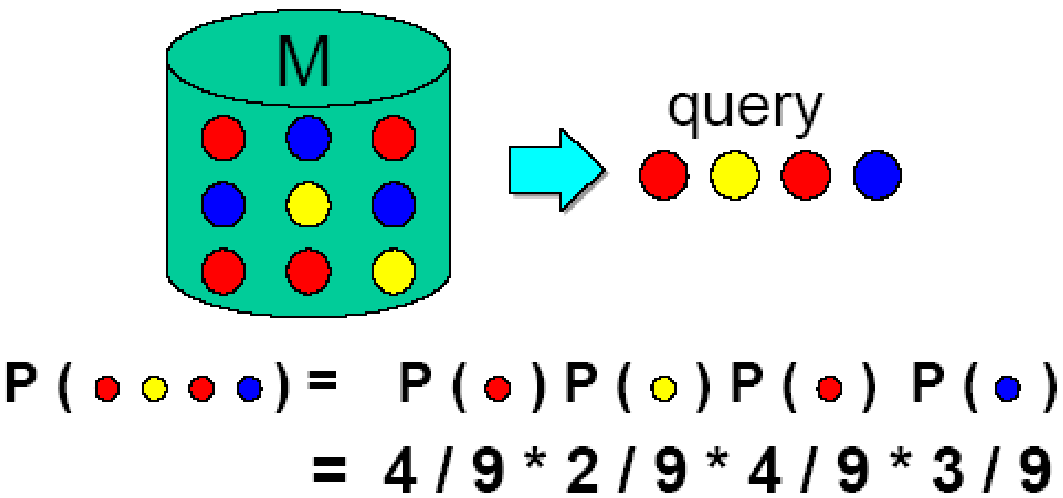
- Every document in a collection defines a "language"
  - consider all possible sentences (strings) that author could have written down when creating some given document
  - some are perhaps more likely to occur than others
    - subject to topic, writing style, language …
  - $P(s|M_D)$ … probability that author would write down string "s"
    - think of writing a billion variations of a document and counting how many time we get "s"
- Now suppose "Q" is the user's query
  - what is the probability that author would write down "Q" ? *
- Rank documents D in the collection by $P(Q|M_D)$ [1]
  - probability of observing "Q" during random sampling from the language model of document D

Major issues in applying LMs

- Which kind of language model should we use?
  - Unigram or higher-order models?
- How can we estimate model parameters
  - Basic models
  - Translation models
  - non-parametric models
- How can we use the model for ranking?
  - Query-likelihood
  - Document-likelihood
  - Divergence (差异) of query and document models

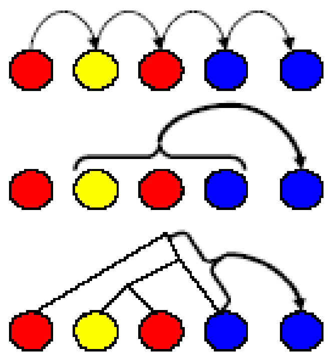
Unigram Language Models

- words are “sampled” independently of each other
  - Metaphor (一个比喻): randomly pulling words from an urn (缸) (with replacement)
  - joint probability decomposes into a product of each element
  - estimation of probabilities: simple counting



Higher-order Models

- Unigram model assumes word independence
  - cannot capture surface form: P(“brown dog”) == P(“dog brown”)
- *Higher-order models
  - n-gram: condition on preceding words:
  - cache: condition on a window (cache):
  - grammar: condition on parse tree



- Are they useful?*
  - no improvements from n-gram, grammar-based models
  - some research on cache-like models (passages, etc.)
  - parameter estimation is prohibitively expensive

Ranking with Language Models

- Standard approach: **query-likelihood (查询的似然排序)**
  - estimate a language model M_D for every document D in the collection
    - (assume that we know how to do this)
  - rank docs by the probability of “generating” the query

$$P(q_1 \ldots q_k \mid M_D) = \prod_{i=1}^{k} P(q_i \mid M_D)$$

- Example:
- Q = “人民 创造”
- D1 = “在 漫长 的 历史 进程 中 中国 人民 辛勤 劳动 不懈 探索 勇于 创造 中国 人民 热爱 和平 ”
- D2= “中国 人民 勇于 创造”
-
-
-

Example (Cont'd)

D_1 = { This one, I think, is called a Yink.
He likes to wink, he likes to drink.

D_2 = { He likes to drink, and drink, and drink.
The thing he likes to drink is ink.

D_3 = { The ink he likes to drink is pink.
He links to wink and drink pink ink.

Query "drink"
- $P(drink|D_1) = 1/16$
- $P(drink|D_2) = 4/16$
- $P(drink|D_3) = 2/16$

Query "wink drink"
- $P(Q|D_1) = 0.004$
- $P(Q|D_2) = 0$
- $P(Q|D_3) = 1/16 \cdot 2/16 = 0.008$

Query "pink ink"
- $P(Q|D_1) = 0 \cdot 0 = 0$
- $P(Q|D_2) = 0 \cdot 1/16 = 0$
- $P(Q|D_3) = 2/16 \cdot 2/16 = 0.016$

Ranking with Query Likelihood

- Drawbacks:
  - no notion of relevance in the model: everything is random sampling
  - user feedback / query expansion not part of the model*
    - examples of relevant documents cannot help us improve the language model M_D
    - the only option is augmenting the original query Q with extra terms
    - however, we could make use of sample queries for which D is relevant
  - does not directly allow weighted or structured queries

Ranking: Document-likelihood (文档似然)

- Flip(翻转) the direction of the query-likelihood approach
  - estimate a language model M_Q for the query Q
  - rank docs D by the likelihood of being a random sample from M_Q
  - M_Q expected to “predict” a typical relevant document

$$P(D \mid M_Q) = \prod_{w \in D} P(w \mid M_Q)$$

- Problems:
  - different doc lengths, probabilities not comparable
  - favors documents that contain frequent (low content) words
  - consider “ideal” (highest-ranked) document for a given query*:
  - $$\max_D \prod_{w \in D} P(w \mid M_Q) = \max_{w \in D} P(w \mid M_Q)^n$$

Ranking: Likelihood Ratio

- Try to fix document likelihood: [8]
  - Bayes' likelihood that M_q was the source, given that we observed D

$$P(M_Q \mid D) = \frac{P(M_Q)P(D \mid M_Q)}{P(D)} \approx \frac{c\prod_{w \in D} P(w \mid M_Q)}{\prod_{w \in D} P(w \mid GE)}$$

  - related to Probability Ranking Principle: P(D|R) / P (D|N)
  - allows relevance feedback, query expansion, etc.
  - can benefit from complex estimation of the query model M_Q
- Cons:
  - does not provide for modeling on the document side
  - "ideal" doc: $$\max_D \prod_{w \in D} \frac{P(w \mid M_Q)}{P(w \mid GE)} = \max_{w \in D} \frac{P(w \mid M_Q)^n}{P(w \mid GE)^n}$$

Ranking by Model Comparison

- Combine advantages of two ranking methods
  - estimate a model of both the query M_Q and the document M_D
  - directly compare similarity of the two models
  - natural measure of similarity is cross-entropy (others exist):

$$H(M_Q \,||\, M_D) = -\sum_{w} P(w|M_Q) \log P(w|M_D)$$

  - number of bits we would need to "encode" M_Q using M_D
  - equivalent to Kullback-Leiblar divergence: $H(M_Q \,||\, M_D) - H(M_Q \,||\, M_Q)$
  - equivalent to query-likelihood if M_Q is simply counts of words in Q
- Cross-entropy is not symmetric: use $H(M_Q \,||\, M_D)$
  - reverse works consistently worse, favors different document [9]
  - use reverse if ranking multiple queries w.r.t. one document

Summary of LM choices

- Use Unigram models
  - no consistent benefit from using higher order models
  - estimation is much more complex (e.g. bi-gram from a 3-word query)
- Use Model Comparison for ranking
  - allows feedback, expansion, etc. through estimation of M_Q and M_D
  - use $H(M_Q \| M_D)$ for ranking multiple documents against a query
- Estimation of M_Q and M_D is a crucial step
  - very significant impact on performance (more than other choices)
  - key to cross-language, cross-media and other applications

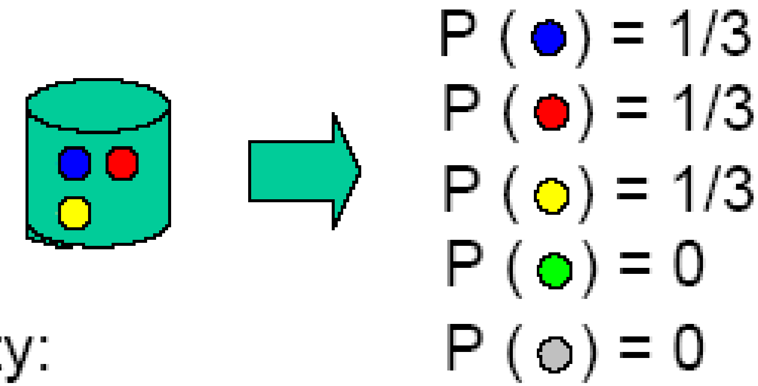
Estimation

- Want to estimate M_Q and/or M_D from Q and/or D
- General problem:
  - given a string of text S (= Q or D), estimate its language model M_S
  - S is commonly assumed to be an i.i.d. random sample from M_S
    - Independent and identically distributed
- Basic Language Models:
  - maximum-likelihood estimator and the zero frequency problem
  - discounting techniques:
    - Laplace correction, Lindstone correction, absolute discounting, leave-one-out discounting, Good-Turing method
  - interpolation/back-off techniques:
    - Jelinek-Mercer smoothing, Dirichlet smoothing, Witten-Bell smoothing, Zhai-Lafferty two-stage smoothing, interpolation vs. back-off techniques
  - Bayesian estimation

Maximum-likelihood

- count relative frequencies of words in S

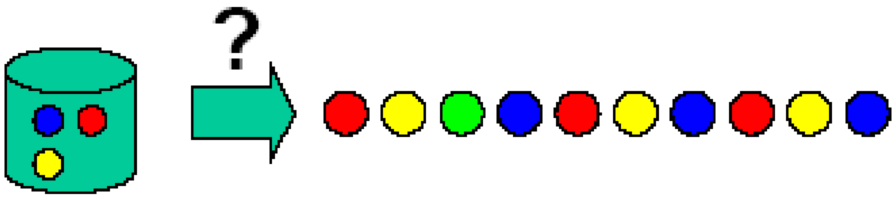
$$P_{ml}(w|M_S) = \#(w,S) / |S|$$



- maximum-likelihood property:
  - assigns highest possible likelihood to the observation
- unbiased estimator:
  - if we repeat estimation an infinite number of times with different starting points S, we will get correct probabilities (on average)
  - this is not very useful…

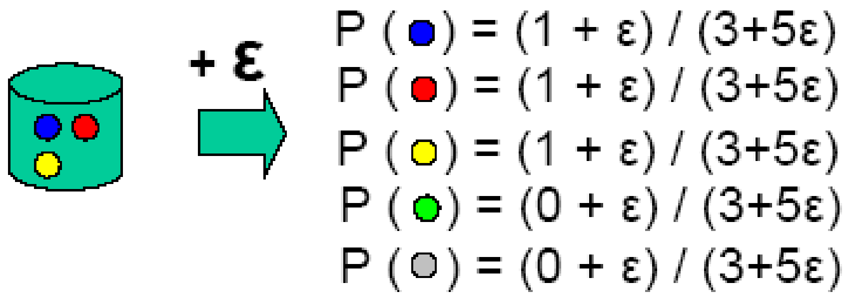
The Zero-frequency Problem

- Suppose some event not in our observation S
  - Model will assign zero probability to that event
  - And to any set of events involving the unseen event
- Happens very frequently with language
- It is incorrect to infer zero probabilities
  - especially when creating a model from short samples



Discounting Methods (折扣法)[6]

- Laplace correction:
  - add 1 to every count, normalize
  - problematic for large vocabularies
- Lindstone correction:
  - add a small constant ***ε*** to every count, re-normalize



- Absolute Discounting
  - subtract a constant ***ε***, re-distribute the probability mass

Basic Models: Summary

- Goal: estimate a model M from a sample text S
- Use maximum-likelihood estimator
  - count the number of times each word occurs in S, divide by length
- Smoothing to avoid zero frequencies
  - discounting methods: add or subtract a constant, redistribute mass
  - better: interpolate with background probability of a word
  - smoothing has a role similar to IDF in classical models
- Smoothing parameters is very important
  - Dirichlet works well for short queries (need to tune the parameter)
  - Jelinek-Mercer works well for longer queries (also needs tuning)
  - Lots of other ideas being worked on

Homework 2

Back Up (Self-study)

*Discounting methods (cont.)

- Held-out estimation
  - Assume $P(w_1|M)=P(w_2|M)$ if w_1 and w_2 have same frequency
  - Divide data into training and held-out sections
  - In training data, count N_r, the number of words occurring *r* times
  - In held-out data, count T_r, the number of times those words occur
    - Doesn't matter how often they actually occur in held-out data
  - $r^* = T_r/N_r$ is adjusted count (equals *r* if training matches held-out)
  - Use r^*/N as estimate for words that occur *r* times
- Deleted estimation (cross-validation)
  - Same idea, but break data into *K* sections
    - Use each in turn as held-out data, to calculate $T_r(k)$ and $N_r(k)$
  - Estimate for words that occur *r* times is average of each

$$r^* = \frac{\frac{1}{K}\sum_{i=1}^{K} T_r(k)}{\frac{1}{K}\sum_{i=1}^{K} N_r(k)} = \frac{\sum_{i=1}^{K} T_r(k)}{\sum_{i=1}^{K} N_r(k)}$$

Discounting Methods (cont.)

- Good-Turing estimation
  - From previous, $P(w|M) = r^* / N$ if word *w* occurs *r* times in sample
  - In Good-Turing, steal total probability mass from next most frequent word

$$TPM(r+1) = N_{r+1} \cdot \frac{r+1}{N}$$

$$\boxed{\begin{aligned} P(w_r|M) &= TPM(r+1)/N_r \\ &= \frac{N_{r+1}}{N_r} \cdot \frac{r+1}{N} \end{aligned}}$$

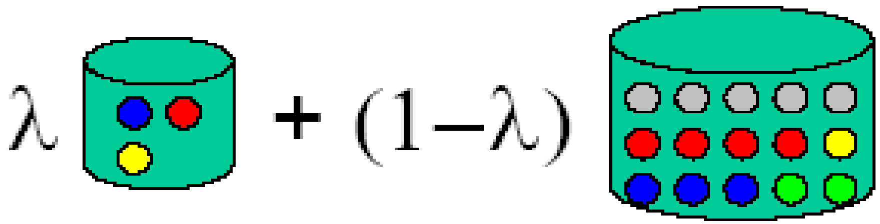
  - What good does this do?
  - Provides probability mass for words that occur r=0 times
    - Take what's leftover from r>0 to ensure adds to one
- Cleaning up Good-Turing estimation
  - What happens if there are no words that occur *r* times for some *r* ?
    - Makes estimate very unreliable for large values of *r*
  - Need to use expected count $E(N_r)$ and $E(N_{r+1})$
    - Regression to smooth out counts
    - Simply use maximum-likelihood probabilities r/N

$$\frac{E(N_{r+1})}{E(N_r)} \cdot \frac{r+1}{N}$$

  - Can also be derived from leaving out a single word at a time (K=|D|)
    - Called "leave one out" discounting

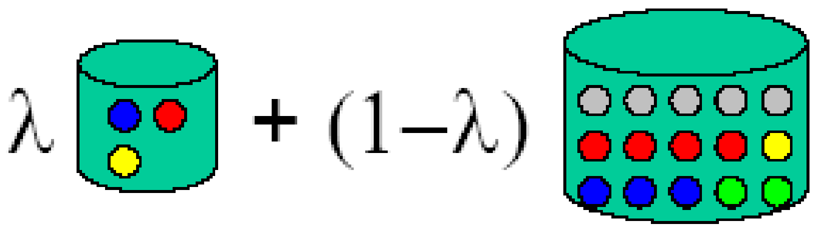
Interpolation Methods [6,7]

- Problem with all discounting methods:
  - discounting treats unseen words equally (add or subtract ε)
  - some words are more frequent than others
- Idea: use background probabilities
  - "interpolate" ML estimates with General English expectations (computed as relative frequency of a word in a large collection)
  - reflects expected frequency of events
- 2-state HMM analogy



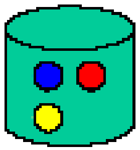
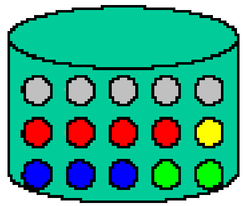
“Jelinek-Mercer” Smoothing

- Correctly setting λ is very important
- Start simple:
  - set λ to be a constant, independent of document, query
- Tune to optimize retrieval performance
  - optimal value of λ varies with different databases, query sets, etc.



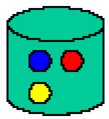
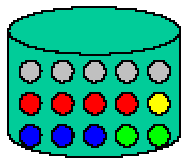
"Dirichlet" Smoothing

- Problem with Jelinek-Mercer:
  - longer documents provide better estimates
  - could get by with less smoothing
- Make smoothing depend on sample size
- Here N is length of sample and μ is a constant

$\underbrace{N / (N + \mu)}_{\lambda}$  + $\underbrace{\mu / (N + \mu)}_{(1-\lambda)}$ 

“Witten-Bell” Smoothing

- A step further:
  - condition smoothing on “redundancy” of the example
  - long, redundant example requires little smoothing
  - short, sparse example requires a lot of smoothing
- Derived by considering the proportion of new events as we walk through example
  - N is total number of events
  - V is number of unique events

$\underbrace{N / (N + V)}_{\lambda}$  + $\underbrace{V / (N + V)}_{(1-\lambda)}$ 

Interpolation vs. back-off

- Two possible approaches to smoothing
- Interpolation:
  - Adjust probabilities for all events, both seen and unseen
- Back-off:
  - Adjust probabilities only for unseen events
  - Leave non-zero probabilities as they are
  - Rescale everything to sum to one:
    - rescales “seen” probabilities by a constant
- Interpolation tends to work better
  - And has a cleaner probabilistic interpretation (HMM, mixture)

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