Matching Functions

LIS466 - Information Retrieval

Week 5

Models, Classification & Clustering

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- Next Time
  - Ranking documents - Blended

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  - Ford Motor Company announces new Lincoln Mercury
  - president AND lincoln AND NOT (automobile OR car)

Example

- *Let's experiment using different online search engines*

Vector Space Model

- Started in the 1960s, 70; simple, intuitive, less common now
- A document D is represented by a number of index terms
  - Di = (di1, di2, ... din)
  - Create term/document matrix

$$Cos(D_i Q) = \frac{\sum_{j=1}^{t} d_{ij} \bullet q_j}{\sqrt{\sum_{j=1}^{t} d_{ij}^{\,2} \cdot \sum_{j=1}^{t} q_j^{\,2}}}$$

Vector Space Model - weighting

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- The normalized count of the term occurrences in a document ... where tfik is the term frequency weight of term k in document Di, and fik is the number of occurrences of term k in the document

$$tf_{ik} = \frac{f_{ik}}{\sum_{j=1}^{t} f_{ik}}$$

$$idf_k = \log N/n_k$$

VM term weighting

$$d_{ik} = \frac{(\log(f_{ik}) + 1) \cdot \log(N / n_k)}{\sqrt{\sum_{k=1}^{t} [(\log(f_{ik}) + 1.0) \cdot \log(N / n_k)]^2}}$$

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- Implicit assumption that terms in query are in the document and that they're good indicators of relevance
- Modify queries (relevance feedback) creates a kind of baseline of the optimal query, the average vector representing the relevant documents and average vector of non-relevant documents.
  - Rocchio algorithm, 1971

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- *Assumption that documents have* some *degree, or probability, of association to queries.*
- *Often treated as a classification issue: classify something as relevant or as not relevant ...*
- *And then the conditions under which it's relevant....*

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- *A document D is relevant if* P(R | D) > P(NR | D), *where* P(R|D) *is a conditional probability representing the probability of relevance given the representation of that document, and* P(NR|D) *is the conditional probability of non-relevance.*

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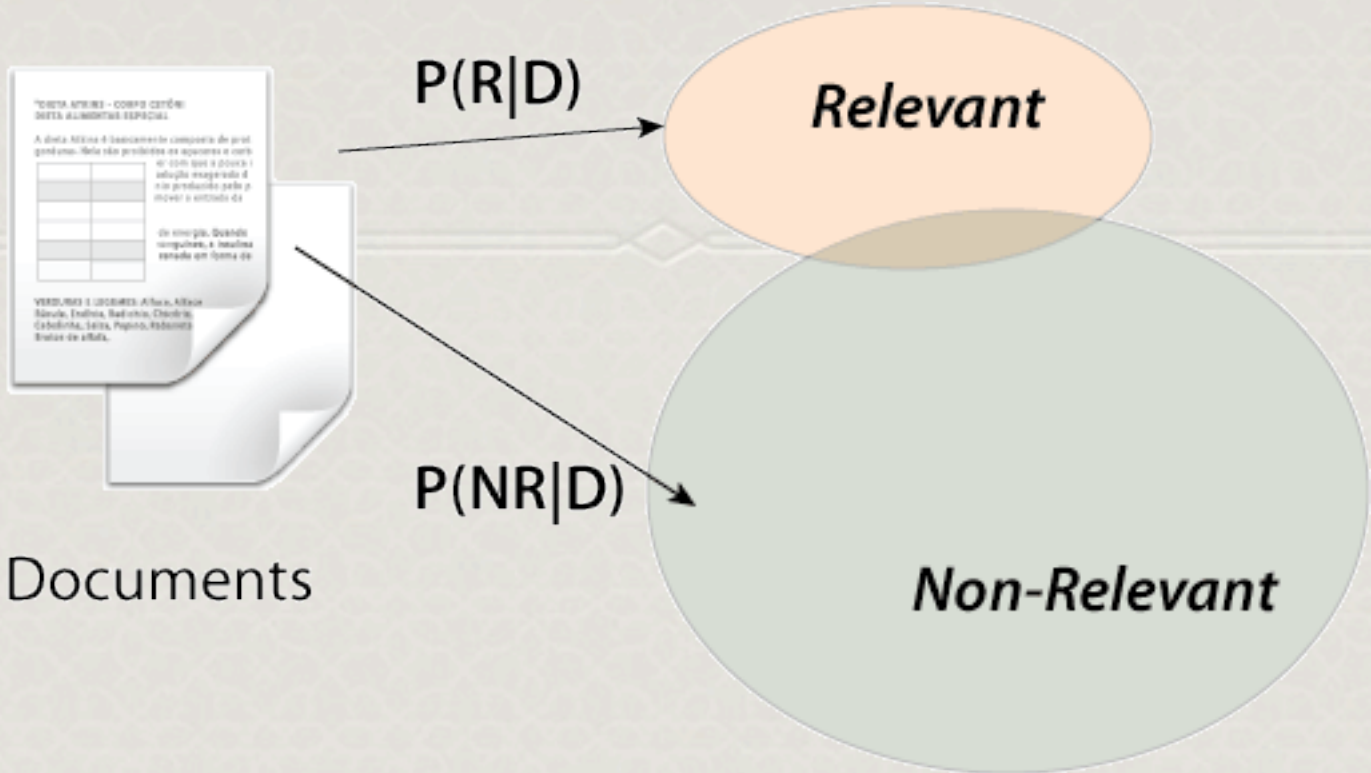
- *Aka Bayes Decision Rules (or here a Bayes classifier)*



So, how to calculate the relevant documents?

"Likelihood ratio"

- P(R|D) = P(D|R)P(R) / P(D)
  - *(Skipping all the other formula & variants)*
- *Contingency Table*

	Relevant	Non-Rel	Total
di=1	ri	ni - ri	ni
di=0	R-ri	N-ni-R+ri	N-ri
Total	R	N-R	N

BM25

- TREC - set of retrieval experiments
- BM25 - used in commercial search engines

$$\sum_{i \in Q} \log \frac{(r_i + 0.5)/(R - r_i + 0.5)}{(n_i - r_i + 0.5)/(N - n_i - R + r_i + 0.5)} \bullet \frac{(k_i + 1) f_i}{K + f_i} \cdot \frac{(k_2 + 1) qf_i}{k_2 + qf_i}$$

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- *bi-gram (predicting based on previous term; tri-gram...)*

Query Likelihood Ranking

- *Rank documents by the probability that the query text could be generated by the document language model ... In other words, we calculate the probability that we could pull the query words out of the "bucket" of words representing the document.*

Relevance Models & Pseudo-Relevance Feedback

- *Emphasis on the representation of* the topic.
- *Using Relevance to affect the probability ranking ...*
  - P(w|R)logP(w|D)
  - *P = probability*
  - w|R = *weight given some Relevance input*
  - w|D = *weight given some Document*

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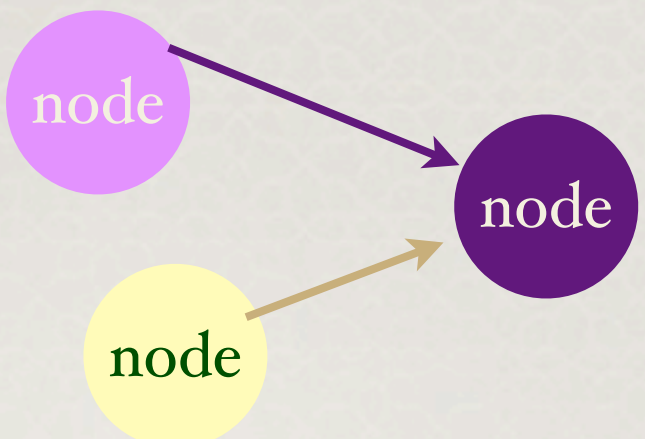


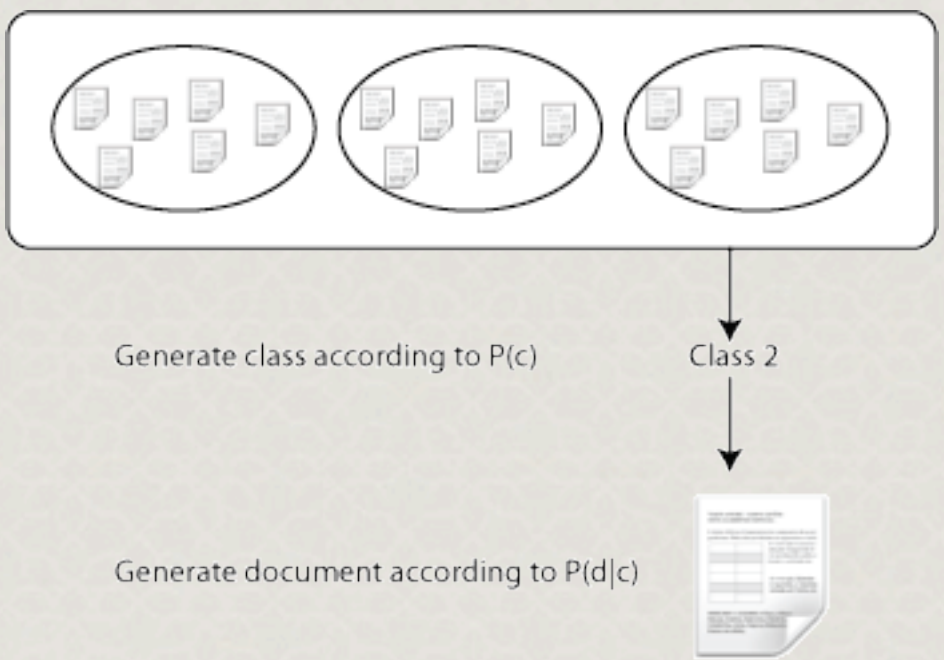
Inference network with 3 nodes

Humans or Machine?!

- Machine Learning
- Train the software to classify new documents based on evidence from a training set.
  - Two classes (those that are + relevant and those that are - not)
  - Part of data mining
  - Visualization, too.
  - Be aware of "overtraining" the system.

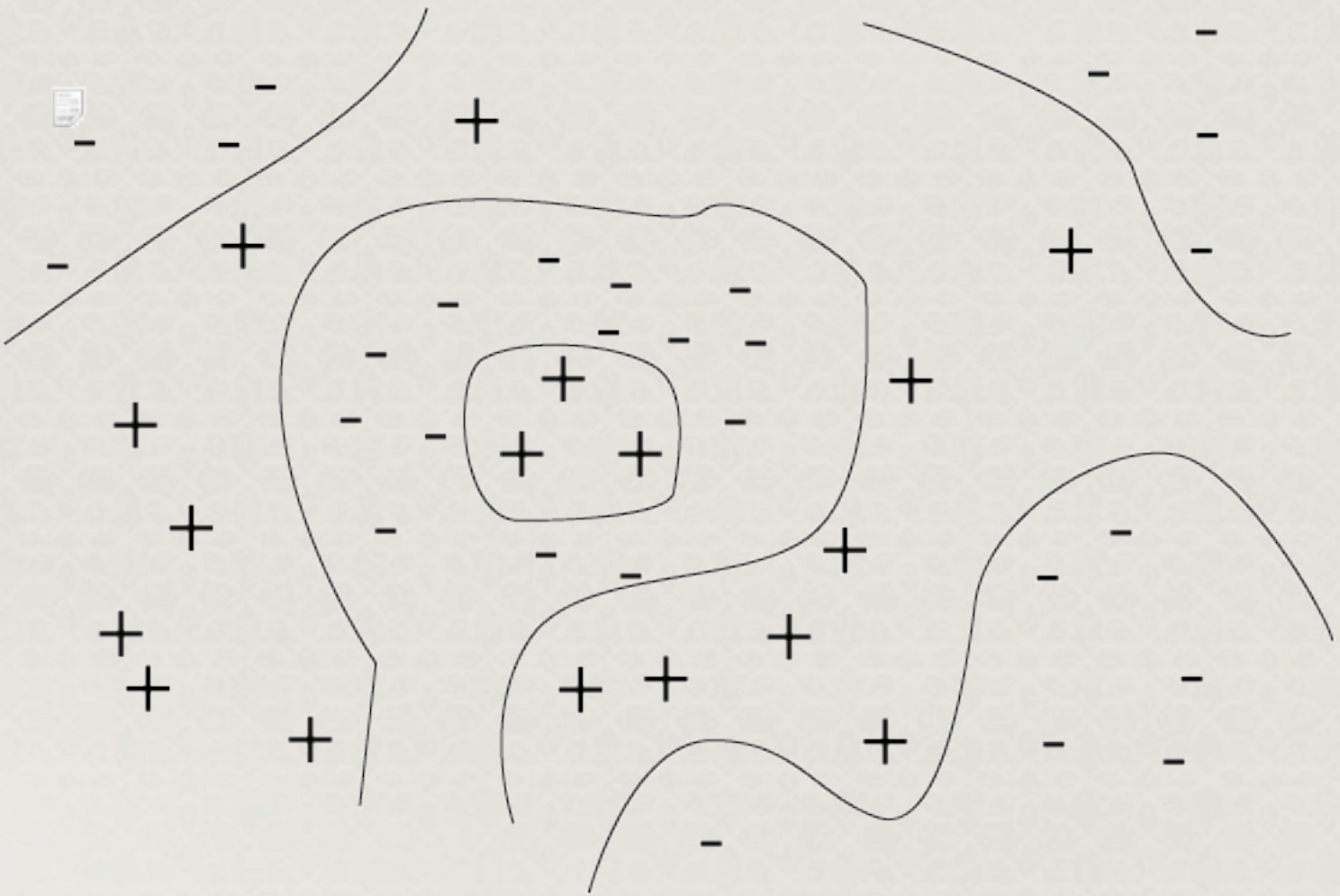
Clustering

- *Too many to mention but here are some examples.*



Nearest neighbor clustering

+ = relevant



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- SIGIR, D-Lib, *other journals*

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  - Would be useful for searching?
  - Other features or values?

Project - MARC example

- *Follow this link to see more about MARC - what parts should we extract?*
- *http://www.loc.gov/marc/bibliographic/examples.html*
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