# COM6115: Text Processing

# Information Retrieval: retrieval models — ranked retrieval methods

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#### Overview

- Definition of the information retrieval problem
- Approaches to document indexing
  - manual approaches
  - automatic approaches
- Automated retrieval models
  - boolean model
  - ranked retrieval methods (e.g. vector space model)
- Term manipulation:
  - stemming, stopwords, term weighting
- Web Search Ranking
- Evaluation

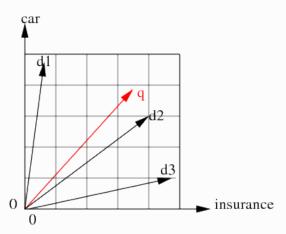
#### The Vector Space model

- Documents are also represented as "bags of words":
  - "John is quicker than Mary" = "Mary is quicker than John"
- Documents are points in high-dimensional vector space
  - ♦ each term in index is a dimension → sparse vectors
  - ♦ values are frequencies of terms in documents, or variants of frequency
- Queries are also represented as vectors (for terms that exist in index)
- Approach
  - Select document(s) with highest document-query similarity
  - Document-query similarity is a model for relevance (ranking)
  - $\diamond$  With ranking, the number of returned documents is less relevant  $\to$  users start at the top and stop when satisfied

## The Vector Space model (contd)

#### 2 dimensions:

Query: car insurance



### The Vector Space Model (contd)

Approach: compare vector of query against vector of each document
to rank documents according to their similarity to the query

	$Term_1$	$Term_2$	$Term_3$	 $Term_n$
$Doc_1$	9	0	1	 0
Doc <sub>2</sub> Doc <sub>3</sub>	0	1	0	 10
$Doc_3$	0	1	0	 2
$Doc_{N}$	4	7	0	 5
Q	0	1	0	 1

#### How to measure similarity between vectors?

Each document and the query are represented as a vector of n values:

$$\vec{d^i} = (d_1^i, d_2^i, \dots, d_n^i), \qquad \vec{q} = (q_1, q_2, \dots, q_n)$$

• Many metrics of similarity between 2 vectors, e.g.: Euclidean

$$\sqrt{\sum_{k=1}^n (q_k - d_k)^2}$$

E.g.: Distance between:

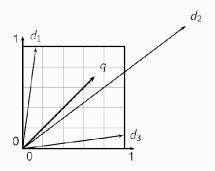
$$\begin{array}{l} \textit{Doc}_1 \text{ and } Q = \sqrt{(9-0)^2 + (0-1)^2 + (1-0)^2 + (0-1)^2} = \sqrt{84} = 9.15 \\ \textit{Doc}_2 \text{ and } Q = \sqrt{(0-0)^2 + (1-1)^2 + (0-0)^2 + (10-1)^2} = \sqrt{81} = 9 \\ \textit{Doc}_3 \text{ and } Q = \sqrt{(0-0)^2 + (1-1)^2 + (0-0)^2 + (2-1)^2} = \sqrt{1} = 1 \end{array}$$

Doc 3 is the closest (shortest distance)

### How to measure similarity between vectors? (contd)

#### Is it a good idea?

- distance is large for vectors of different lengths, even if by only one term (e.g. Doc<sub>2</sub> and Q)
- means frequency of terms given too much impact



## How to measure similarity between vectors? (contd)

• Better similarity metric, used in *vector-space* model: cosine of the angle between two vectors  $\vec{x}$  and  $\vec{y}$ :

$$cos(\vec{x}, \vec{y}) = \frac{\vec{x} \cdot \vec{y}}{|\vec{x}||\vec{y}|} = \frac{\sum_{i=1}^{n} x_{i} y_{i}}{\sqrt{\sum_{i=1}^{n} x_{i}^{2}} \sqrt{\sum_{i=1}^{n} y_{i}^{2}}}$$

- It can be interpreted as the normalised correlation coefficient:
  - i.e. it computes how well the  $x_i$  and  $y_i$  correlate, and then divides by the length of the vectors, to scale for their magnitude
    - $\diamond$  The vector  $\vec{x}$  is normalised by dividing its components by its length:

$$|\vec{x}| = \sqrt{\sum_{i=1}^{n} x_i^2}$$

## How to measure similarity between vectors? (contd)

- The cosine value ranges from:
  - ♦ 1, for vectors pointing in the same direction, to
  - 0, for orthogonal vectors, to
  - ⋄ -1, for vectors pointing in opposite directions
- Specialising the equation to comparing a query q and document d:

$$sim(\vec{q}, \vec{d}) = cos(\vec{q}, \vec{d}) = \frac{\sum_{i=1}^{n} q_i d_i}{\sqrt{\sum_{i=1}^{n} q_i^2} \sqrt{\sum_{i=1}^{n} d_i^2}}$$

i.e. computes how well occurrences of each term i correlate in query and document, then scales for the magnitude of the overall vectors