THE UNIVERSITY *of* EDINBURGH

Text Technologies for Data Science

INFR11145

Ranked IR

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Pre-Lecture

- Lab 2 → Share results on Piazza
- CW1
  - Final part depends on this lecture (+ Lab3)
  - You can have your report ready from today
  - Test collection to be released in 2 weeks
  - Silence period !!!!
- Hint: Linear-merge
  - No need to implement. A simply intersection/union function shall do the job for your CW

Pre-Lecture

- Labs results:
  - We won’t provide the answers to the labs, but …
  - You already shared the answers and Piazza, and we acknowledged to be correct!
- Piazza discussions on Lab results
  - Amazing discussions are out there (e.g. Q)
  - Why results can be different?
    - Tokenisation is the key (how you handle special strings: numbers, urls, symbols … etc)
- For CW, take it easy, our automatic marker handle these *valid* simple variations

Pre-Lecture

- System speed
  - We won't punish on slow systems (unless extremely unnecessary slow, like process in over an hour)
  - Good system speed:
    - Preprocessing and indexing for the 1K docs: few secs
    - Loading index from desk before search: 1-5 secs
    - Processing query and getting results: < 1 sec
  - What if my system is much slower?
    - It is OK for now, but try to learn later some coding techniques to speed your processing (important for group project)
    - Think about: loops, regex, data structure (lists vs dic) … etc.
- Search: Load index & search (*index should be ready*)

Lecture Objectives

- Learn about Ranked IR
    - TFIDF
    - VSM
    - SMART notation

- Implement:
    - TFIDF

Boolean Retrieval

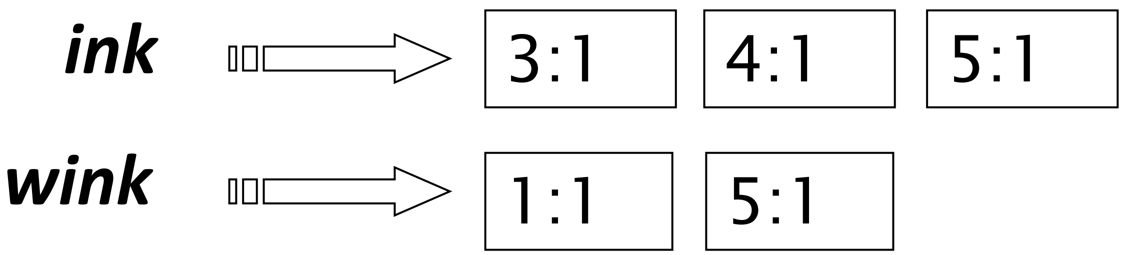
- Thus far, our queries have all been Boolean.
  - Documents either: “match” or “no match”.
- Good for expert users with precise understanding of their needs and the collection.
  - Patent search uses sophisticated sets of Boolean queries and check hundreds of search results
    (car OR vehicle) AND (motor OR engine) AND NOT (cooler)
- Not good for the majority of users.
  - Most incapable of writing Boolean queries.
  - Most don’t want to go through 1000s of results.
    - This is particularly true for web search
    - Question: What is the most unused web-search feature?

Ranked Retrieval

- Typical queries: free text queries
- Results are “ranked” with respect to a query
- Large result sets are not an issue
  - We just show the top k (≈ 10) results
  - We don’t overwhelm the user
- Criteria:
  - Top ranked documents are the most likely to satisfy user’s query
  - Score is based on how well documents match a query
    Score(*d*,*q*)

Old Example

- Find documents matching query {ink wink}
    1. Load inverted lists for each query word
    2. Merge two postings lists → **Linear merge**
- Apply function for matches
    - Boolean: exist / not exist = 0 or 1
    - <u>Ranked</u>: *f*(*tf*, *df*, *length*, ….) = 0 → 1



Matches

1: f(0,1)

3: f(1,0)

4: f(1,0)

5: f(1,1)

Function example: Jaccard coefficient

- a commonly used measure of overlap of two sets *A* and *B*
- $jaccard(A,B) = \frac{|A \cap B|}{|A \cup B|}$
- $jaccard(A,B) = 1 \rightarrow A = B$
- $jaccard(A,B) = 0 \rightarrow A \cap B = 0$
- Example:
  - D1 ∪ D2 = {he, likes, to, wink, and, drink}
  - D1 ∩ D2 = {he, likes, to, drink}
  - $jaccard(D1, D2) = \frac{4}{6} = 0.6667$

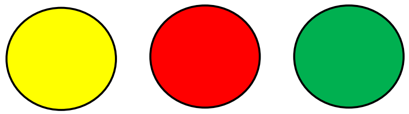
D1: He likes to wink, he likes to drink

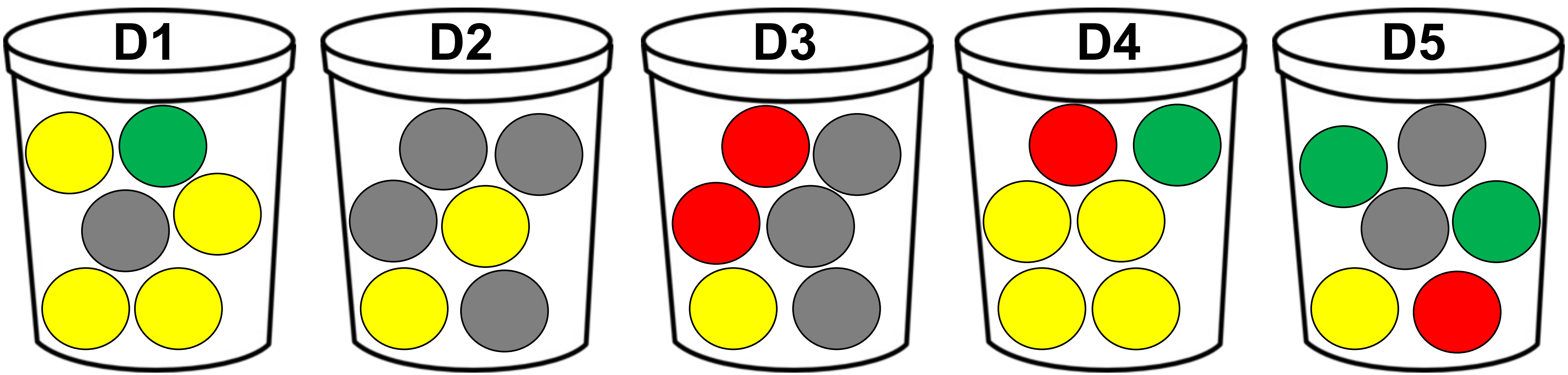
D2: He likes to drink, and drink, and drink

Jaccard coefficient: Issues

- Does not consider term frequency (how many times a term occurs in a document)
- It treats all terms equally!
  - How about rare terms in a collection?
    more informative than frequent terms.
  - *He likes to drink*, shall “to” == “drink”?
- Needs more sophisticated way of length normalization
  - |D1| = 3, |D2| = 1000!
  - D1 → Q, D2 → D

Should terms be treaded the same?

- Collection of 5 documents (balls = terms)
- Query 
- Which is the least relevant document?
- Which is the most relevant document?



TFIDF

- **TFIDF**:
  Term Frequency, Inverse Document Frequency
- ***tf(t,d)***:
  number of times term ***t*** appeared in document ***d***
  - As $tf(t,d)$ ↑↑ → importance of *t* in *d* ↑↑
  - Document about IR, contains "retrieval" more than others
- ***df(t)***:
  number of documents term ***t*** appeared in
  - As d$f(d)$ ↑↑ → importance if *t* in a collection ↓↓
    - "the" appears in many document → not important
    - "FT" is not important word in financial times articles

DF, CF, & IDF

- **DF ≠ CF** (collection frequency)
  - ***cf(t)*** = total number of occurrences of term ***t*** in a collection
  - ***df(t)*** ≤ ***N*** (***N***: number of documents in a collection)
  - ***cf(t)*** can be ≥ ***N***
- **DF** is more commonly used in IR than **CF**
  - **CF** is still used
- ***idf(t)***: inverse of ***df(t)***
  - As $\mathrm{i}df(t)$ ↑↑ → rare term → importance ↑↑
  - ***idf(t)*** → measure of the informativeness of *t*

DF vs CF

	he	drink	ink	likes	pink	think	wink
← **D1:** He likes to wink, he likes to drink	2	1	0	2	0	0	1
← **D2:** He likes to drink, and drink, and drink	1	3	0	1	0	0	0
← **D3:** The thing he likes to drink is ink	1	1	1	1	0	1	0
← **D4:** The ink he likes to drink is pink	1	1	1	1	1	0	0
← **D5:** He likes to wink, and drink pink ink	1	1	1	1	1	0	1
DF	5	5	3	5	2	1	2
CF	6	7	3	6	2	1	2

IDF: formula

$$idf(t) = log_{10}(\frac{N}{df(t)})$$

- Log scale used to dampen the effect of IDF
- Suppose *N* = 1 million →

term	*df(t)*	*idf(t)*
calpurnia	1	**6**
animal	100	**4**
sky	1,000	**3**
fly	10,000	**2**
under	100,000	**1**
the	1,000,000	**0**

TFIDF term weighting

- One the best known term weights schemes in IR
  - Increases with the number of occurrences within a document
  - Increases with the rarity of the term in the collection
- Combines TF and IDF to find the weight of terms

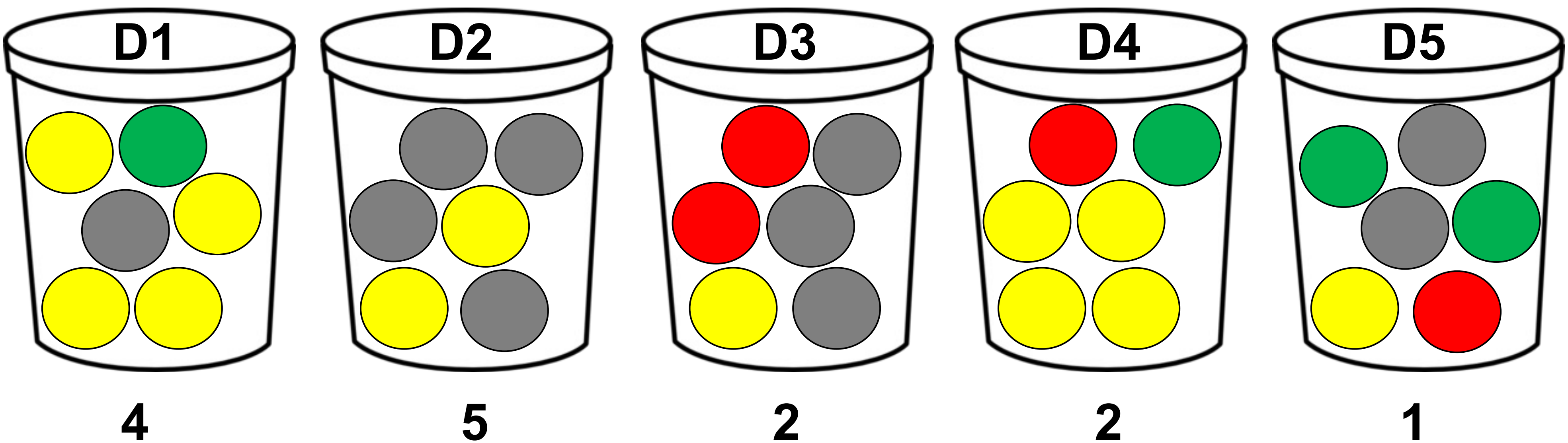
$$w_{t.d} = \left(1 + log_{10} tf(t,d)\right) \times log_{10}\left(\frac{N}{df(t)}\right)$$

- For a query *q* and document *d*, retrieval score *f(q,d)*:

$$Score(q,d) = \sum_{t \in q \cap d} w_{t.d}$$

Should terms be treaded the same?

- Collection of 5 documents (balls = terms)
- Query **the destructive storm**
- Which is the least relevant document?
- Which is the most relevant document?



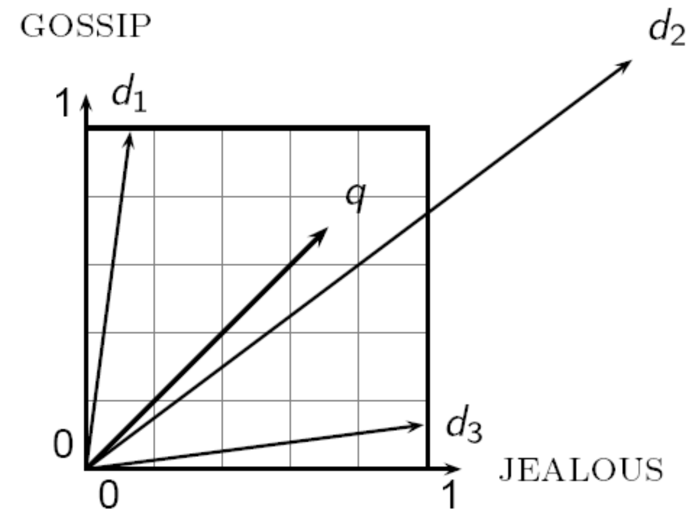
Document/Term vectors with tfidf

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	5.25	3.18	0	0	0	0.35
Brutus	1.21	6.1	0	1	0	0
Caesar	8.59	2.54	0	1.51	0.25	0
Calpurnia	0	1.54	0	0	0	0
Cleopatra	2.85	0	0	0	0	0
mercy	1.51	0	1.9	0.12	5.25	0.88
worser	1.37	0	0.11	4.15	0.25	1.95

→ Vector Space Model

Vector Space Model

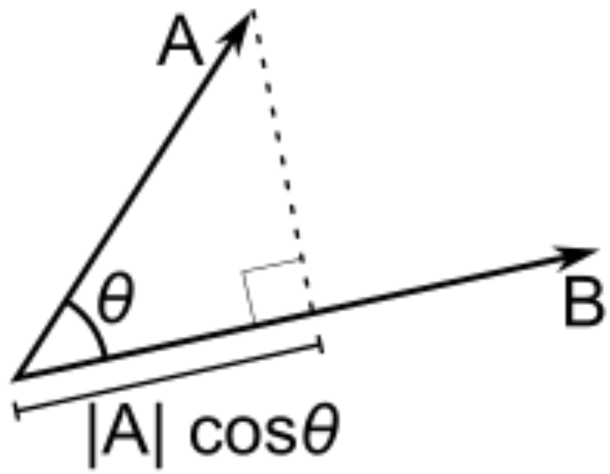
- Documents and Queries are presented as vectors
- Match (Q,D) = Distance between vectors
- Example: Q= Gossip Jealous
- Euclidean Distance?
  Distance between the endpoints of the two vectors



- Large for vectors of diff. lengths
- Take a document d and append it to itself. Call this document d′.
  - “Semantically” d and d′ have the same content
  - Euclidean distance can be quite large

Angle Instead of Distance

- The angle between the two documents is 0, corresponding to maximal similarity.
- Key idea: Rank documents according to angle with query.
  - Rank documents in increasing order of the angle with query
  - Rank documents in decreasing order of cosine (query, document)
- Cosine of angle = projection of one vector on the other



Length Normalization

- A vector can be normalized by dividing each of its components by its length – for this we use the L_2 norm:

$$\|\vec{x}\|_2 = \sqrt{\sum_i x_i^2}$$

- Dividing a vector by its L_2 norm makes it a unit (length) vector (on surface of unit hypersphere)
- Effect on the two documents d and d′ (d appended to itself) from earlier slide: they have identical vectors after length-normalization.
  - Long and short documents now have comparable weights

Example

- D1 = $\begin{bmatrix}1\\3\\2\end{bmatrix}$ ➔ $\left\|\overrightarrow{D1}\right\|_2 = \sqrt{1+9+4} = 3.74$
- D1$_{normalized}$ = $\begin{bmatrix}0.267\\0.802\\0.535\end{bmatrix}$
- D2 = $\begin{bmatrix}3\\9\\6\end{bmatrix}$ ➔ $\left\|\overrightarrow{D1}\right\|_2 = \sqrt{9+81+36} = 11.25$
- D2$_{normalized}$ = $\begin{bmatrix}0.267\\0.802\\0.535\end{bmatrix}$

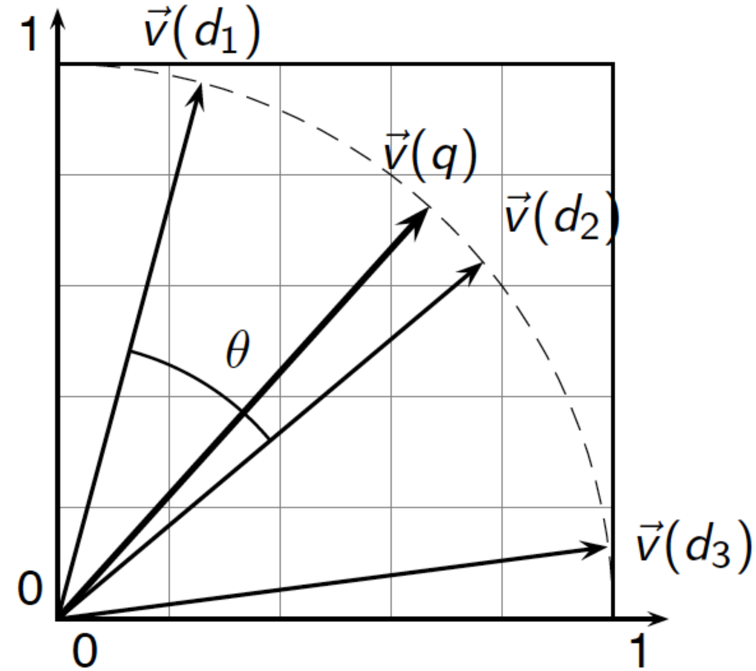
Cosine "Similarity" (Query, Document)

- $\vec{q}_i$ is the tf-idf weight of term i in the query
- $\vec{d}_i$ is the tf-idf weight of term i in the document
- For normalized vectors:

$$\cos(\vec{q}, \vec{d}) = \vec{q} \cdot \vec{d} = \sum_{i=1}^{|V|} q_i d_i$$

- For non-normalized vectors:

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



Algorithm

CosineScore(q)

float $Scores[N] = 0$
float $Length[N]$
for each query term t
do calculate $w_{t,q}$ and fetch postings list for t
    for each pair(d, $tf_{t,d}$) in postings list
    do $Scores[d] += w_{t,d} \times w_{t,q}$
Read the array $Length$
for each d
do $Scores[d] = Scores[d]/Length[d]$
return Top K components of $Scores[]$

TFIDF Variants

Term frequency		Document frequency		Normalization	
n (natural)	$\mathrm{tf}_{t,d}$	n (no)	1	n (none)	1
l (logarithm)	$1 + \log(\mathrm{tf}_{t,d})$	t (idf)	$\log \frac{N}{\mathrm{df}_t}$	c (cosine)	$\frac{1}{\sqrt{w_1^2+w_2^2+\ldots+w_M^2}}$
a (augmented)	$0.5 + \frac{0.5\times\mathrm{tf}_{t,d}}{\max_t(\mathrm{tf}_{t,d})}$	p (prob idf)	$\max\{0, \log \frac{N-\mathrm{df}_t}{\mathrm{df}_t}\}$	u (pivoted unique)	$1/u$
b (boolean)	$\begin{cases} 1 & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$			b (byte size)	$1/\mathit{CharLength}^{\alpha}$, $\alpha < 1$
L (log ave)	$\frac{1+\log(\mathrm{tf}_{t,d})}{1+\log(\mathrm{ave}_{t\in d}(\mathrm{tf}_{t,d}))}$				

- Many search engines allow for different weightings for queries vs. documents
- **SMART** Notation: use notation *ddd.qqq*, using the acronyms from the table
- A very standard weighting scheme is: *lnc.ltc*

For Lab and CW

Term frequency		Document frequency		Normalization	
n (natural)	$\mathrm{tf}_{t,d}$	n (no)	1	n (none)	1
l (logarithm)	$1+\log(\mathrm{tf}_{t,d})$	t (idf)	$\log\frac{N}{\mathrm{df}_t}$	c (cosine)	$\frac{1}{\sqrt{w_1^2+w_2^2+\ldots+w_M^2}}$
a (augmented)	$0.5+\frac{0.5\times\mathrm{tf}_{t,d}}{\max_t(\mathrm{tf}_{t,d})}$	p (prob idf)	$\max\{0,\log\frac{N-\mathrm{df}_t}{\mathrm{df}_t}\}$	u (pivoted unique)	$1/u$
b (boolean)	$\begin{cases}1 & \text{if } \mathrm{tf}_{t,d}>0\\ 0 & \text{otherwise}\end{cases}$			b (byte size)	$1/CharLength^{\alpha}$, $\alpha<1$
L (log ave)	$\frac{1+\log(\mathrm{tf}_{t,d})}{1+\log(\mathrm{ave}_{t\in d}(\mathrm{tf}_{t,d}))}$				

"OR" operator, then:

$$Score(q,d)=\sum_{t\in q\cap d}\big(1+log_{10}tf(t,d)\big)\times log_{10}\left(\frac{N}{df(t)}\right)$$

Summary of Steps:

- Represent the query as a weighted *tf-idf* vector
- Represent each document as a weighted *tf-idf* vector
- Compute the cosine similarity score for the query vector and each document vector
- Rank documents with respect to the query by score
- Return the top K (e.g., $K = 10$) to the user

Retrieval Output

- For a query q_1, the output would be a list of documents ranked according to the $score(q_1,d)$

- Possible output format:

```
1,   710,   0.9234
1,   213,   0.7678
1,   103,   0.6761
1,   13,    0.6556
1,   501,   0.4301
```

Query id

document id

score

Resources

- Text book 1: Intro to IR, Chapter 6.2 → 6.4
- Text book 2: IR in Practice, Chapter 7

- Lab 3