Unit 8 – TF-IDF

CS 201 - Data Structures II
Spring 2022
Habib University

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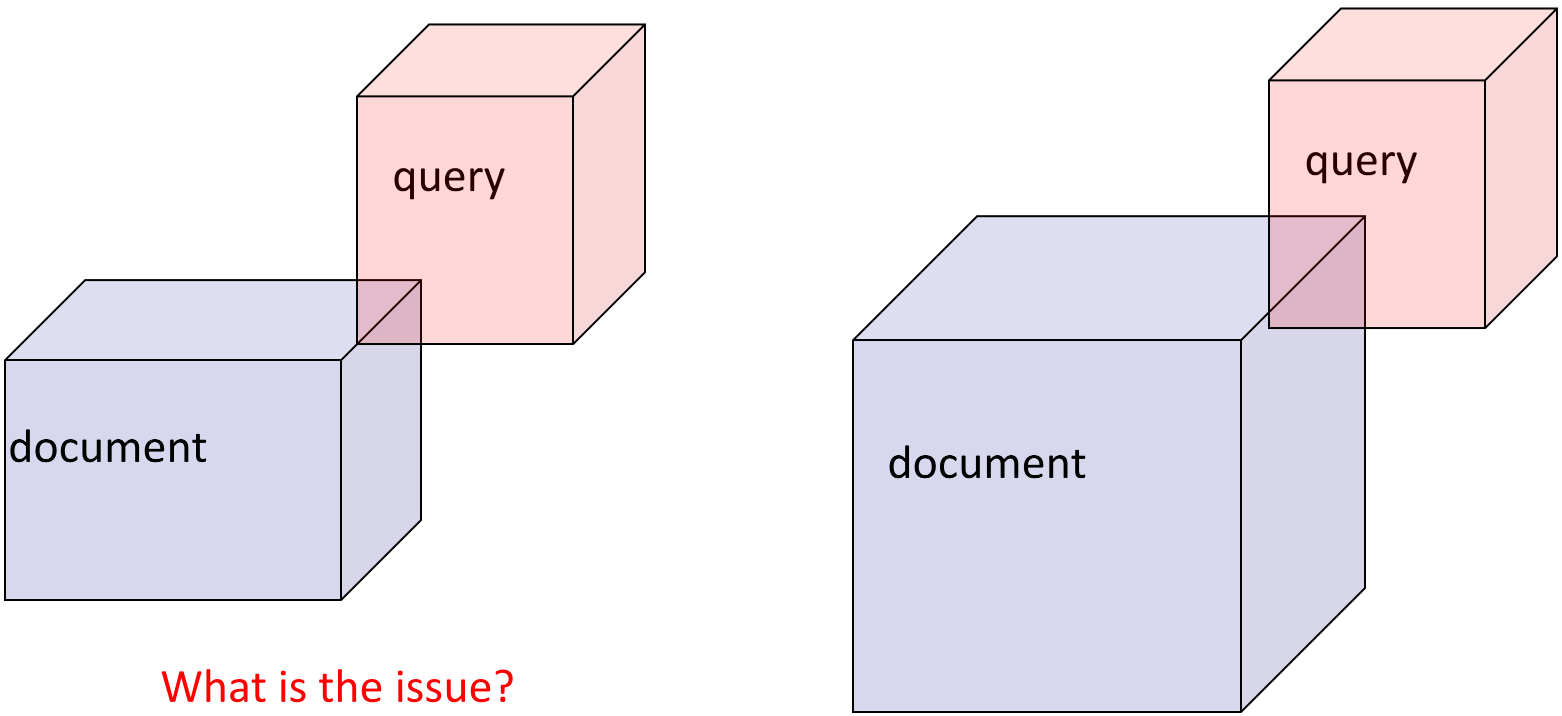
Bag of words

1. The sun is shining
2. The weather is sweet
3. The sun is shining and the weather is sweet

```
{'the': 5, 'shining': 2, 'weather': 6, 'sun': 3, 'is': 1, 'sweet': 4,
'and': 0}
```

```
[[0 1 1 1 0 1 0]
 [0 1 0 0 1 1 1]
 [1 2 1 1 1 2 1]]
```

Some things to be careful of…



What is the issue?

Need some notion of the length of a document

http://www.stanford.edu/class/cs276/handouts/lecture6-tfidf.ppt

Term Frequency

- In document d, the frequency represents the number of instances of a given word t.

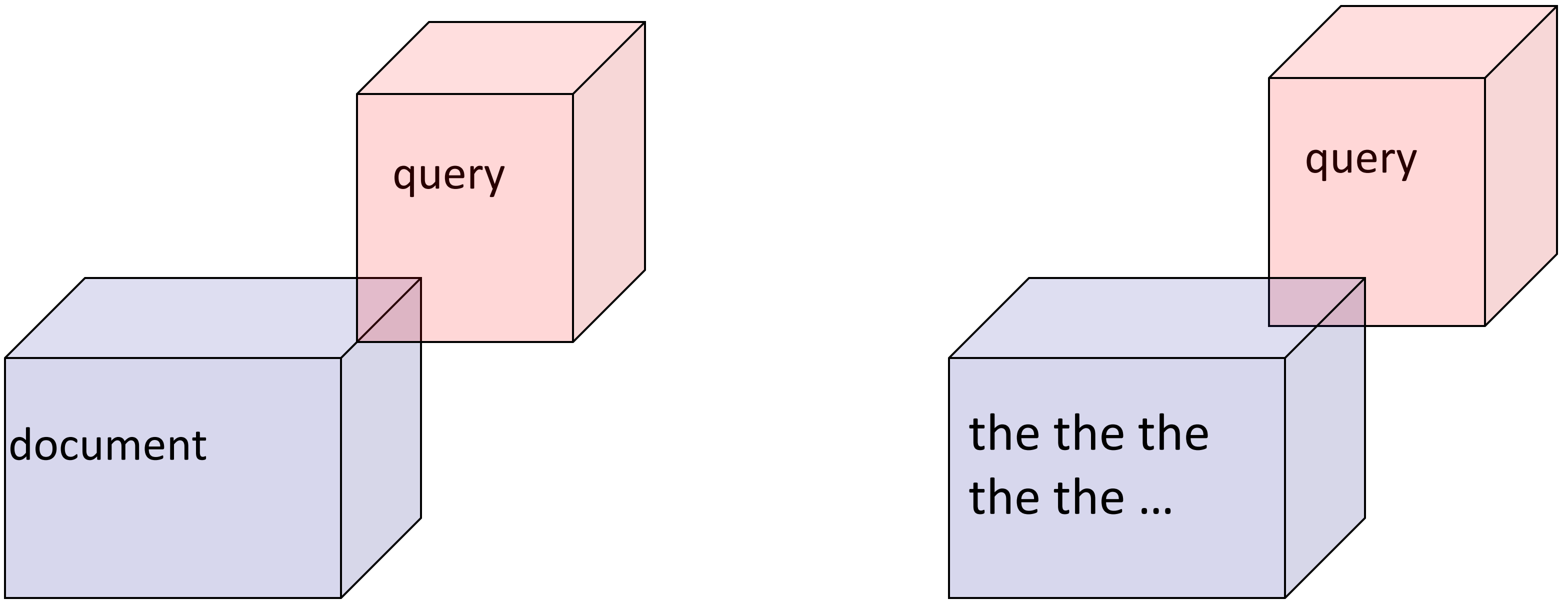
$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$

Pitfall with term frequency

Most frequent word on twitter in each state in the United States .

[Terrible Maps on Twitter: "The most popular word in each state https://t.co/LY7LewNohn" / Twitter]

Some things to be careful of…



Need some notion of the importance of words

http://www.stanford.edu/class/cs276/handouts/lecture6-tfidf.ppt

Term importance

- Rare terms are more informative than frequent terms
  - Recall stop words
- Consider a term in the query that is rare in the collection
- How to quantify rareness of a term?

Document frequency

- Terms that occur in many documents are weighted less, since overlapping with these terms is very likely
  - In the extreme case, take a word like the that occurs in EVERY document
- Terms that occur in only a few documents are weighted more

Inverse Document Frequency (IDF)

- Inverse Document Frequency (IDF)

$$idf_i = \log \frac{|D|}{|d : t_i \in d|}$$

  - Calculates how common a word is across documents. Most common terms are less significant.

TF-IDF

- **TF-IDF (term frequency-inverse document frequency)** is a statistical measure that evaluates how relevant a word is to a document in a collection of documents.

$$\text{tf-idf}_{i,j} = \text{tf}_{i,j} \times \text{idf}_i$$

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TF-IDF

1. `The sun is shining`
2. `The weather is sweet`
3. `The sun is shining and the weather is sweet`

```
{'the': 5, 'shining': 2, 'weather': 6, 'sun': 3, 'is': 1, 'sweet': 4,
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```

```
[[ 0.    0.43  0.56  0.56  0.    0.43  0.  ]
 [ 0.    0.43  0.    0.    0.56  0.43  0.56]
 [ 0.4   0.48  0.31  0.31  0.31  0.48  0.31]]
```

Interpreting TF-IDF

In other words, $\text{tf-idf}_{t,d}$ assigns to t a weight in document d that is:

- highest when t occurs many times within a small number of documents (thus lending high discriminating power to those documents);
- lower when the term occurs fewer times in a document, or occurs in many documents (thus offering a less pronounced relevance signal);
- lowest when the term occurs in virtually all documents.

Exercise

	Doc1	Doc2	Doc3
car	27	4	24
auto	3	33	0
insurance	0	33	29
best	14	0	17

- Compute TF-IDF score of each term in this corpus.

Cosine Similarity

$$\cos(\mathbf{a},\mathbf{b}) = \frac{\mathbf{a}\mathbf{b}}{\|\mathbf{a}\|\|\mathbf{b}\|} = \frac{\sum_{i=1}^{n}\mathbf{a}_i\mathbf{b}_i}{\sqrt{\sum_{i=1}^{n}(\mathbf{a}_i)^2}\sqrt{\sum_{i=1}^{n}(\mathbf{b}_i)^2}}$$

Example

An example is measuring the similarity between documents based on word counts:

Document	Advertising	Auto	Car	Detroit	Engine	Germany	Sales
a	5	88	123	43	35	0	36
b	71	125	42	76	0	27	88

$$a \cdot b = (5 \times 71) + (88 \times 125) + \cdots + (36 \times 88) = 22957$$

$$||a|| = \sqrt{5^2 + 88^2 + 123^2 + 43^2 + 35^2 + 0^2 + 36^2} = 165.13$$

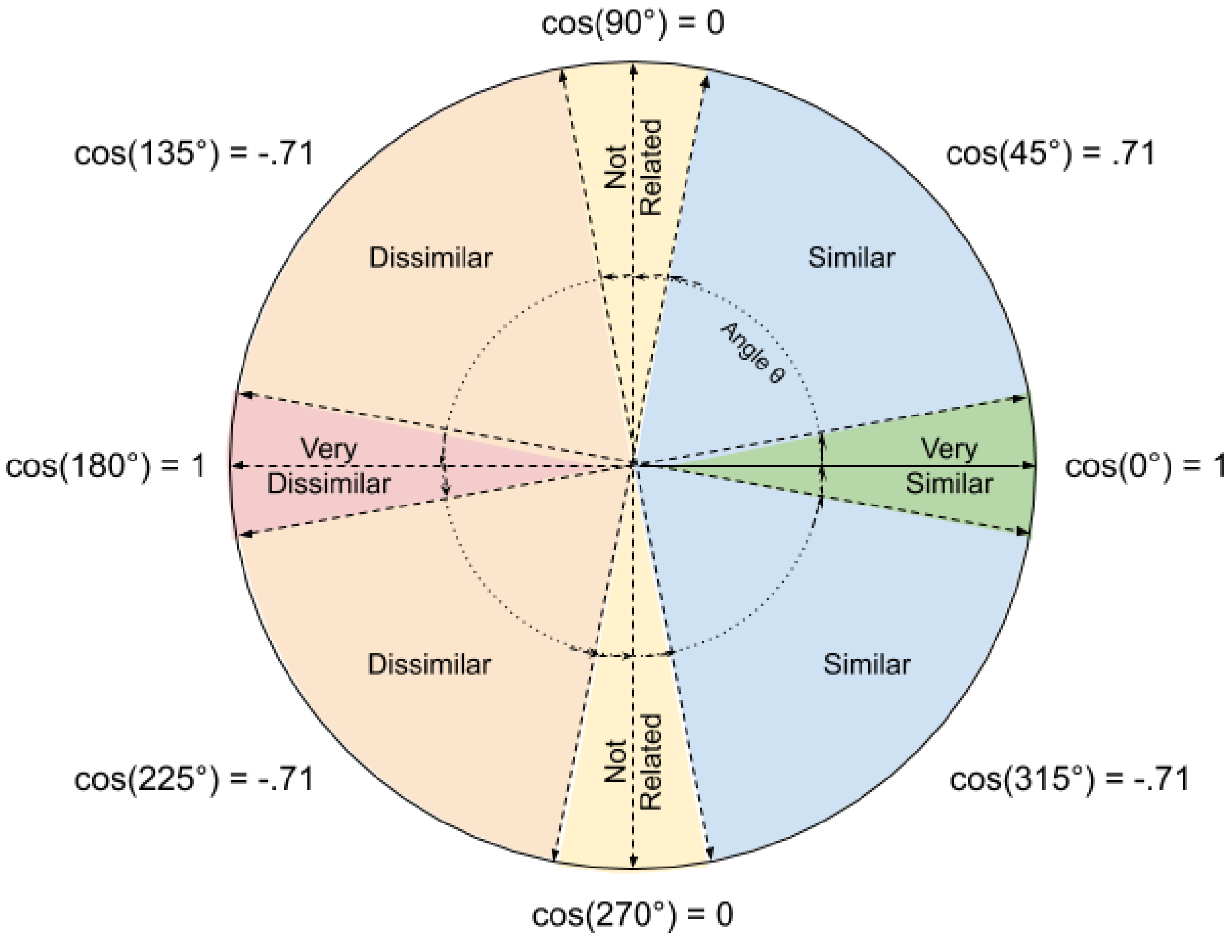
$$||b|| = \sqrt{71^2 + 125^2 + 42^2 + 76^2 + 0^2 + 27^2 + 88^2} = 191.52$$

$$||a||\;||b|| = 165.13 \times 191.52 = 31626$$

$$cosine\,similarity = cos\,\theta = \frac{a \cdot b}{||a||\;||b||} = \frac{22957}{31626} = .73$$

[Cosine Similarity — The Science of Machine Learning (ml-science.com)]

Interpreting Results



[Cosine Similarity — The Science of Machine Learning (ml-science.com)](ml-science.com)

The Three Documents and Similarity Metrics

Considering only the 3 words from the above documents: ‘sachin’, ‘dhoni’, ‘cricket’

Doc Sachin: Wiki page on Sachin Tendulkar
Dhoni - 10
Cricket - 50
Sachin - 200

Doc Dhoni: Wiki page on Dhoni
Dhoni - 400
Cricket - 100
Sachin - 20

Doc Dhoni_Small: Subsection of wiki on Dhoni
Dhoni - 10
Cricket - 5
Sachin - 1

Document - Term Matrix (Word Counts)

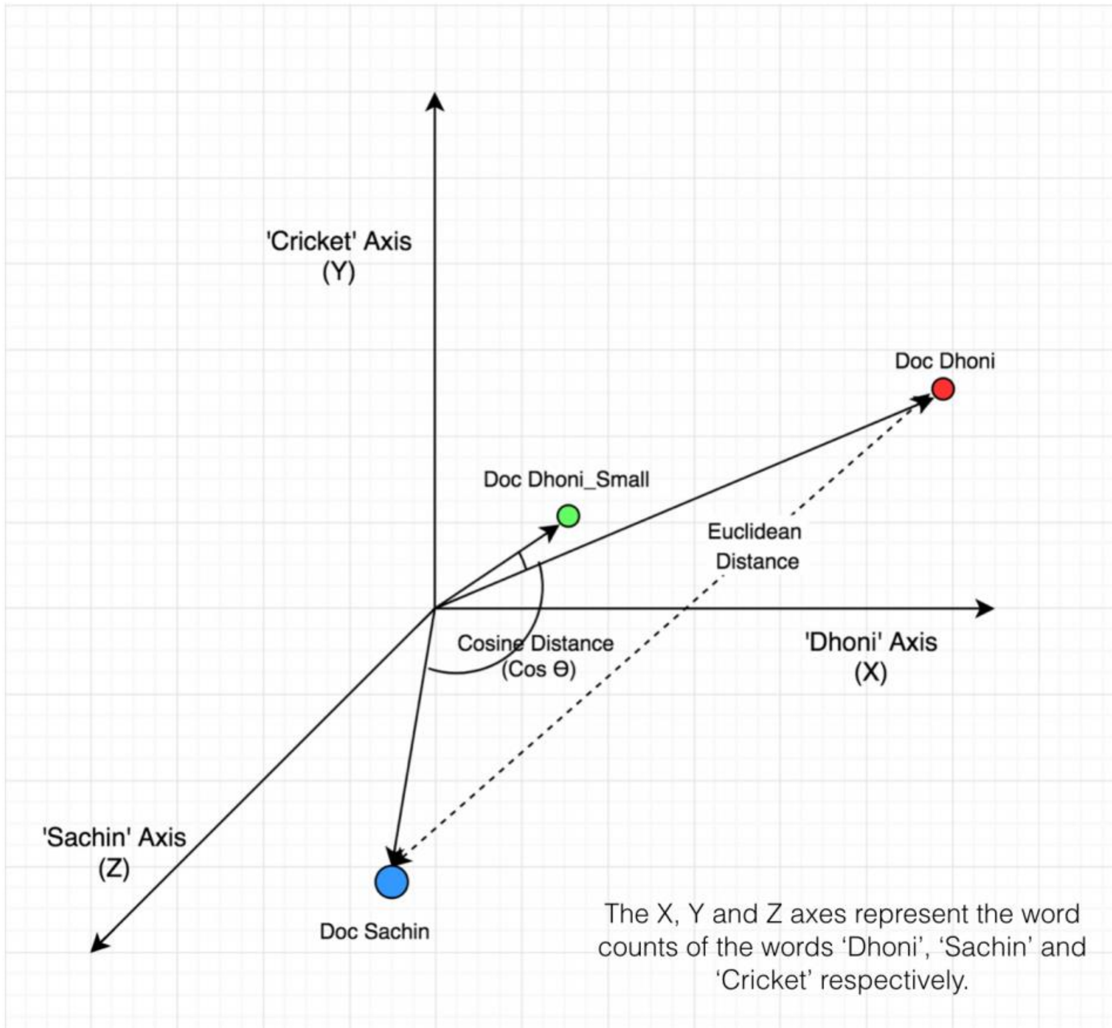
Word Counts	*“Dhoni”*	*“Cricket”*	*“Sachin”*
Doc Sachin	10	50	200
Doc Dhoni	400	100	20
Doc Dhoni_Small	10	5	1

Similarity Metrics

Similarity or Distance Metrics	*Total Common Words*	*Euclidean distance*	*Cosine Similarity*
Doc Sachin & *Doc Dhoni*	10 + 50 + 10 = **70**	432.4	0.15
Doc Dhoni & *Doc Dhoni_Small*	20 + 10 + 7 = **37**	204.0	0.23
Doc Sachin & *Doc Dhoni_Small*	10 + 10 + 7 = **27**	401.85	0.77

https://www.machinelearningplus.com/nlp/cosine-similarity/

Projection of Documents in 3D Space



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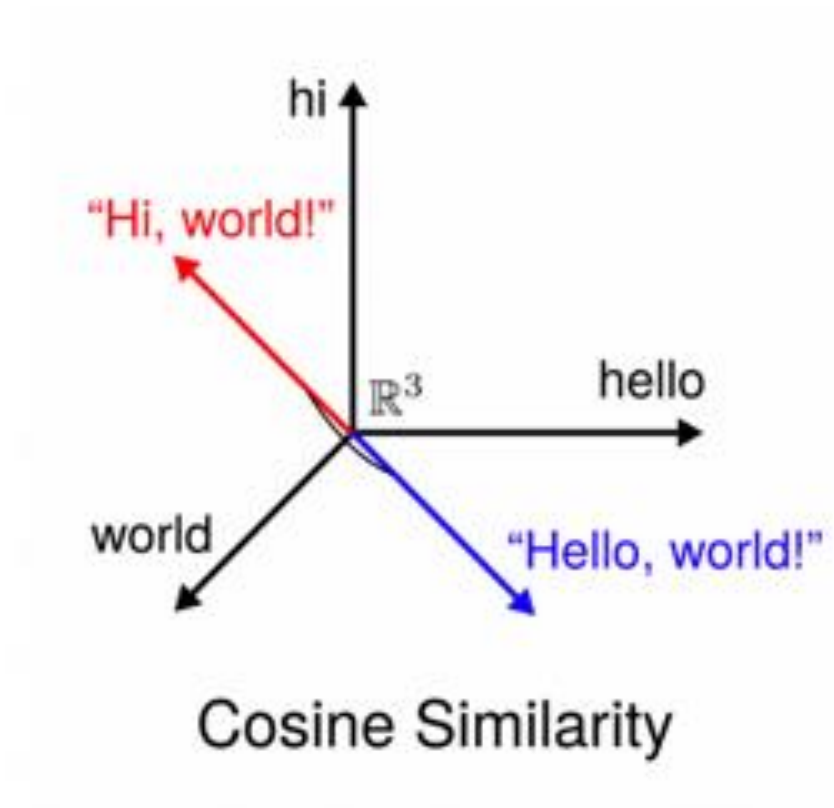
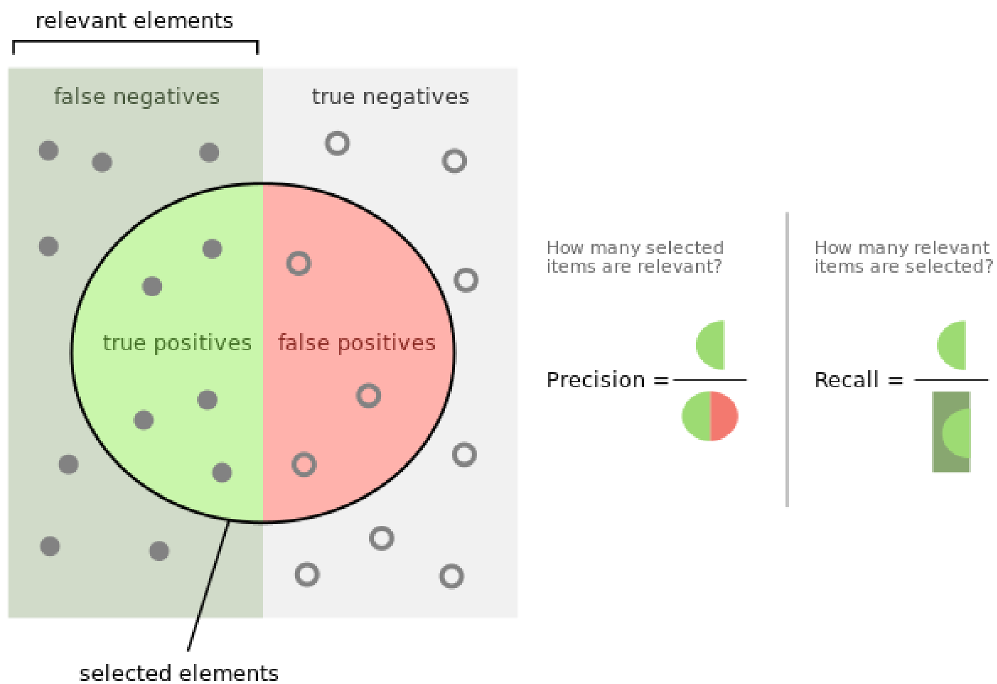
Projection of documents in 3D space



Precision vs Recall



https://en.wikipedia.org/wiki/Precision_and_recall

Thanks