

# Big Data Computing

Master's Degree in Computer Science

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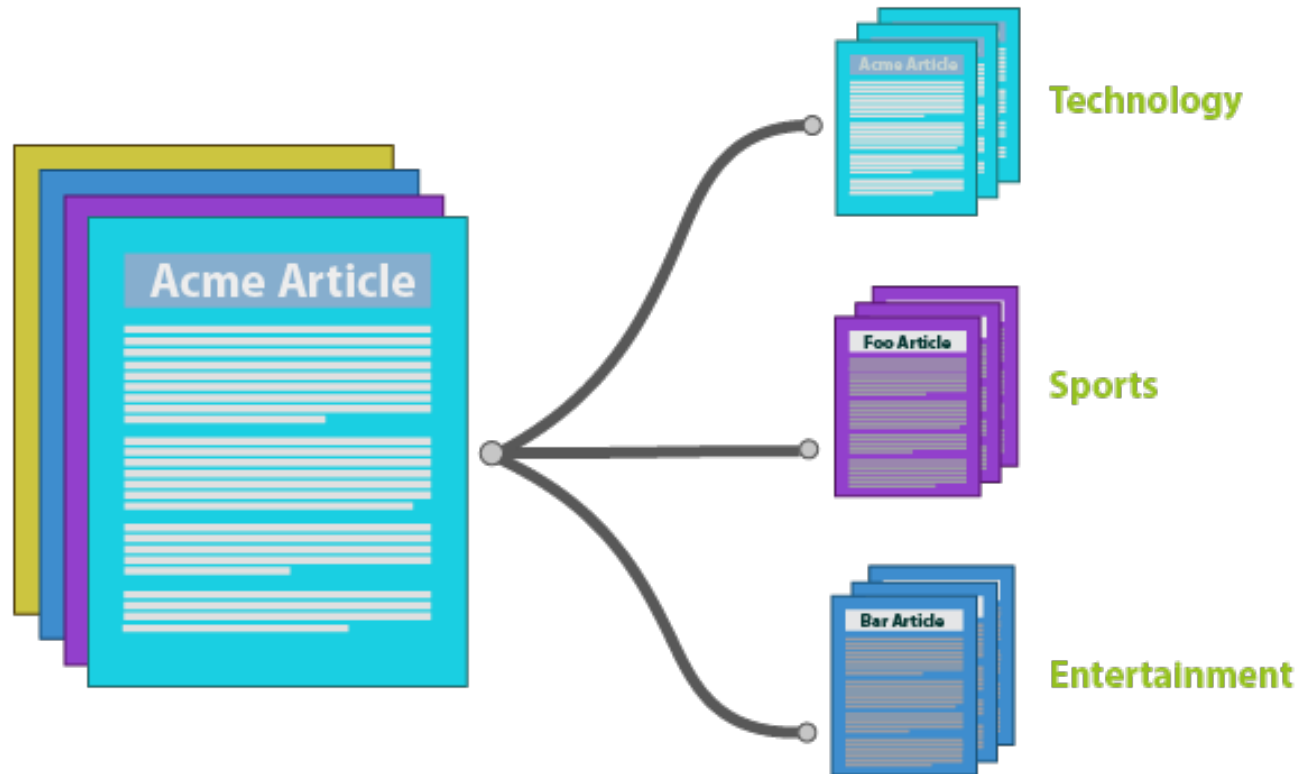
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# Our Running Example: Document Clustering



source: <https://towardsdatascience.com/applying-machine-learning-to-classify-an-unsupervised-text-document-e7bb6265f52>

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  - Measuring document similarity (in the space of words)

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- **Key Issues:**
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## NOTE

A dual problem is topic clustering, where topics (i.e., set of words co-occurring in many documents) are clustered within the space of documents

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  - As a **bag-of- $n$ -grams** (i.e., the more general case of bag-of-words)
  - More advanced representations derived from Neural Language Models (e.g., word2vec)
- The choice of document representation affects the similarity measure

# Document Representation: Set of Words

doc 1

John likes to  
watch movies.  
Mary likes  
movies too.

doc 2

Mary also likes  
to watch  
football games.

# Document Representation: Set of Words

doc 1

John likes to  
watch movies.  
Mary likes  
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{John, likes, to, watch, movies, Mary, too}

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Mary also likes  
to watch  
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{Mary, also, likes, to, watch, football, games}

# Document Representation: Bag-of-Words

We keep **multiplicity**

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# Document Representation: Bag-of-Words

We keep **multiplicity**

doc 1

John likes to  
watch movies.  
Mary likes  
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```
{  
John:1, likes:2, to:1, watch:1,  
movies:2, Mary:1, too:1  
}
```

doc 2

Mary also likes  
to watch  
football games.

```
{  
Mary:1, also:1, likes:1, to:1,  
watch:1, football:1, games:1  
}
```

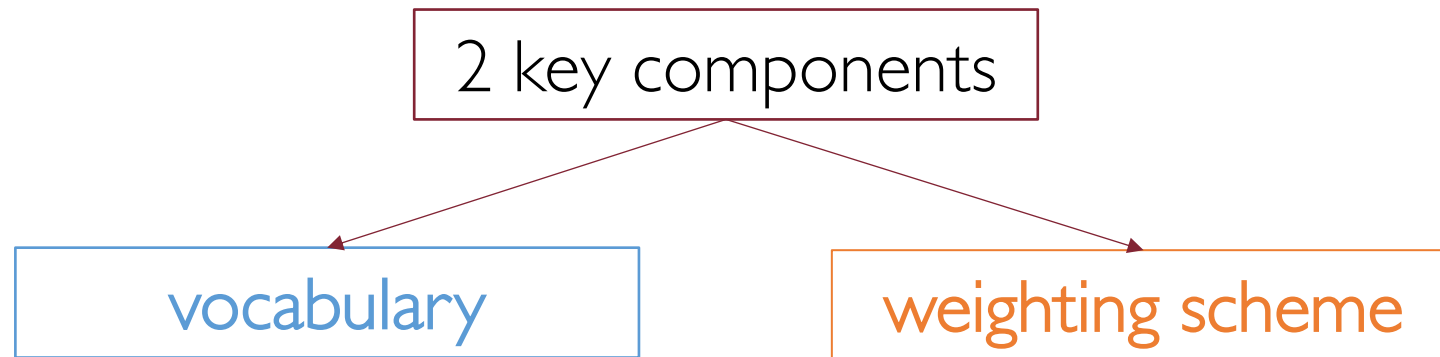


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# Bag-of-Words: Vocabulary

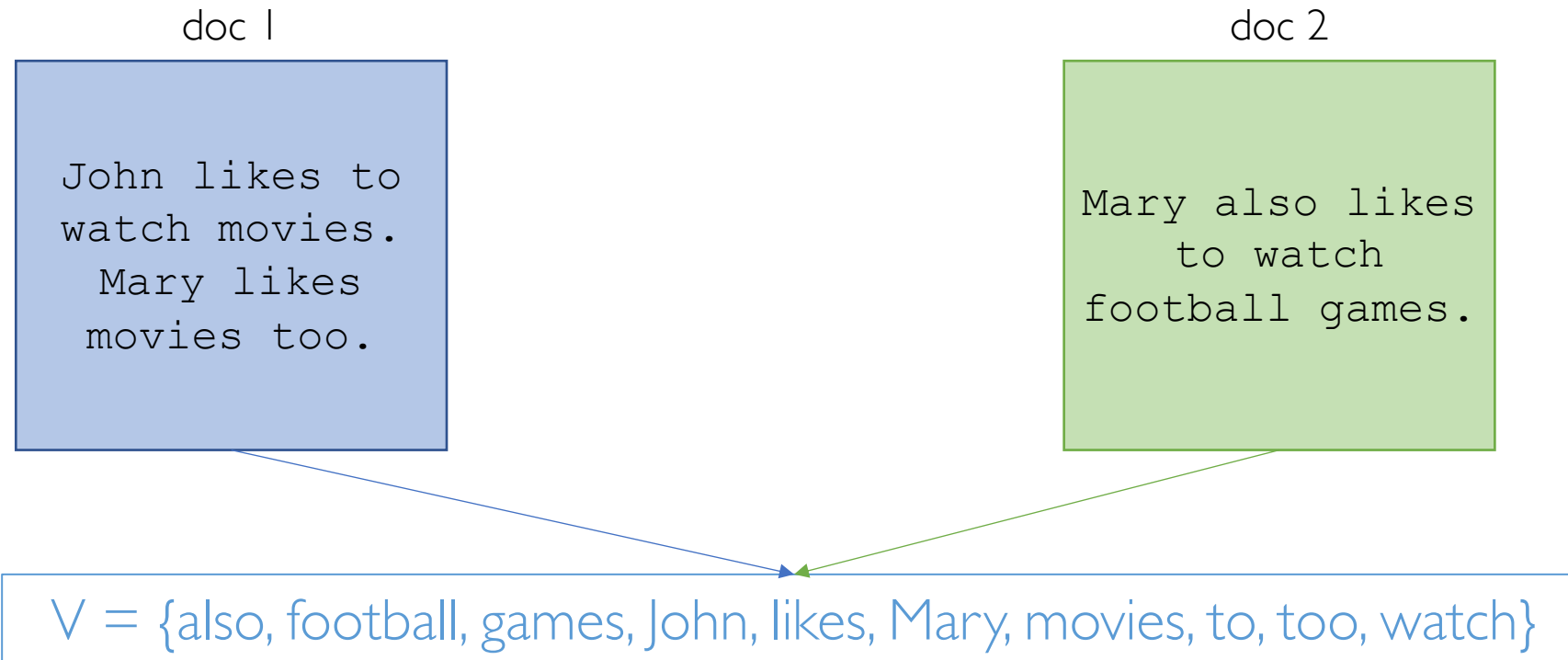
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# Bag-of-Words: Weighting Scheme

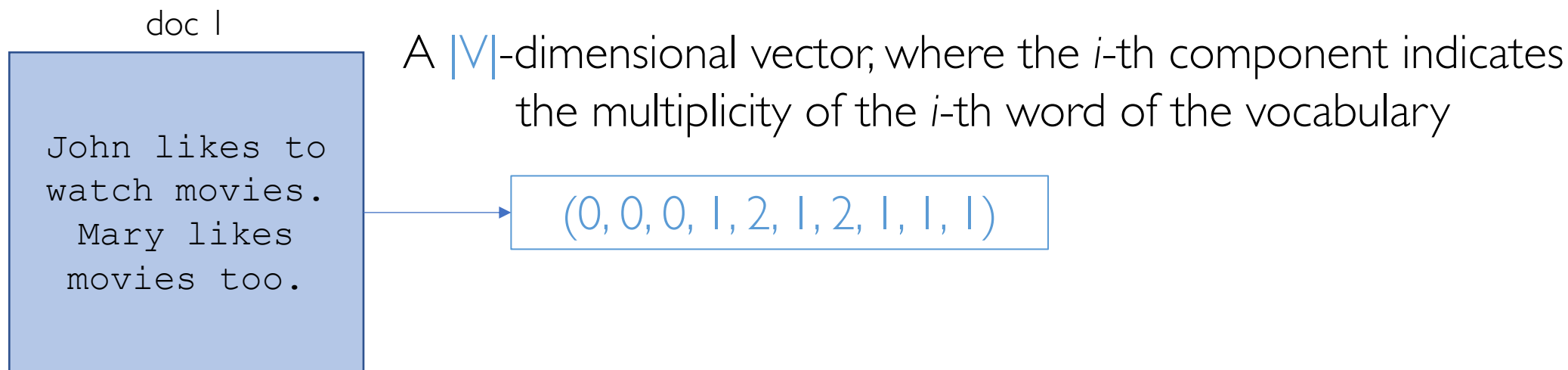
doc 1

John likes to  
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A  $|V|$ -dimensional vector, where the  $i$ -th component indicates the multiplicity of the  $i$ -th word of the vocabulary

$V = \{\text{also, football, games, John, likes, Mary, movies, to, too, watch}\}$

# Bag-of-Words: Weighting Scheme



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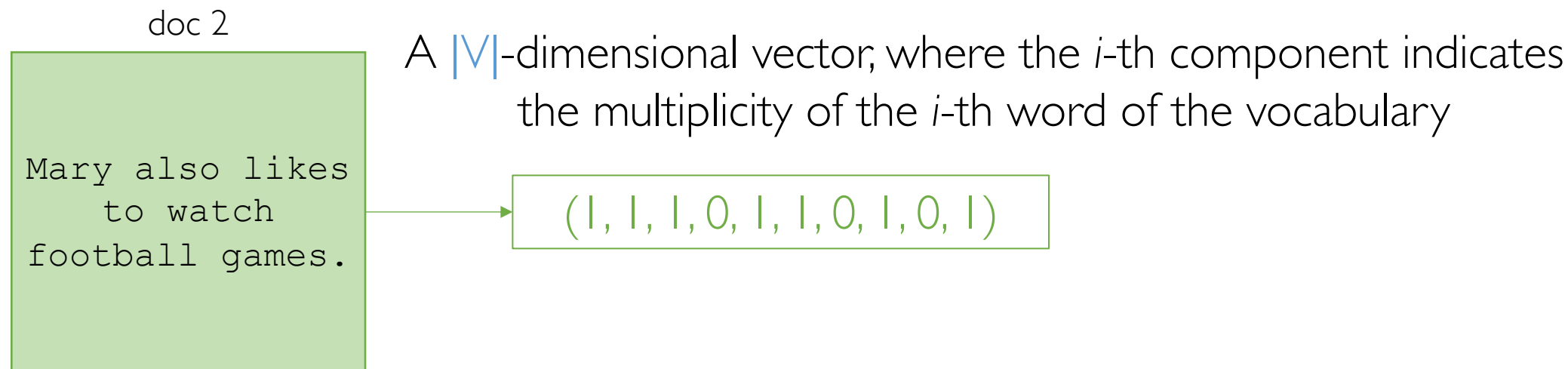
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# Bag-of-Words: A Formal Perspective

$D = \{d_1, \dots, d_N\}$  = collection of  $N$  documents

$V = \{w_1, \dots, w_{|V|}\}$  = **vocabulary** of  $|V|$  words extracted from  $D$

$\mathbf{d}_i = (f(w_1, i), \dots, f(w_{|V|}, i))$  =  $|V|$ -dimensional vector representing  $d_i$

$f : V \times D \mapsto \mathbb{R}$  is a function that maps each word of a document to a real value (**weighting scheme**)

# Bag-of-Words: A Formal Perspective

One-Hot (binary) weighting scheme

$$f(w_j, i) = \begin{cases} 1 & \text{if } w_j \text{ appears in } d_i \\ 0 & \text{otherwise} \end{cases}$$

# Bag-of-Words: A Formal Perspective

Term-Frequency weighting scheme

$$f(w_j, i) = tf(w_j, i)$$

$tf$  computes the number of times word  $w_j$  occurs in document  $d_i$

# Bag-of-Words: A Formal Perspective

TF-IDF weighting scheme

$$f(w_j, i) = tf(w_j, i) * idf(w_j)$$

$$idf(w_j) = \log \left( \frac{N}{1 + n_j} \right)$$

$n_j$  is the number of documents in  $D$  containing the word  $w_j$

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TF-IDF weighting scheme

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Any idea why?

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- 2 main limitations of BoW model:
  - High dimensionality → sparseness
  - No sequential information nor semantics included → unigram model

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- 2 main limitations of BoW model:
  - High dimensionality → sparseness
  - No sequential information nor semantics included → unigram model
- Possible improvements:
  - Use  $n$ -grams rather than unigrams to capture sequentiality between consecutive words (i.e., context)
  - Even better, use so-called Neural Language Models like word2vec

# Document Representation: Bag-of- $n$ -grams

Example: bigrams ( $n=2$ )

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# Document Representation: Bag-of- $n$ -grams

Example: bigrams ( $n=2$ )

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John likes to  
watch movies.  
Mary likes  
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{"John likes", "likes to", "to watch",  
"watch movies", "Mary likes",  
"likes movies", "movies too"}

doc 2

Mary also likes  
to watch  
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{"Mary also", "also likes", "likes to",  
"to watch", "watch football", "football games"}

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- Depending on those, several similarity measures can be used
- For example, if documents are represented as:
  - set of words → Jaccard coefficient
  - one-hot bag-of-words → Euclidean distance
  - tf or tf-idf bag-of-words → Cosine similarity