

Information Retrieval

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Lecture 8, Tuesday December 12nd, 2017
(Vector Space Model)

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Overview of this lecture

■ Organizational

- Your experiences with ES7 Web app, part 2
- Demo of some web apps

■ Contents

- Encoding last part of L7
- Vector Space Model (VSM) documents as vectors
- ES8: re-implement your code from ES2 using the VSM, and re-evaluate benchmark

■ Summary / excerpts

- Again, many of you liked this **a lot**
- Less work than ES6
- Most time spent on encoding issues (harder in C++), perfecting the design (optional), or playing Gorillas
- "After 5 hours, we still haven't tried all gravitation settings"
- "The last sub-task was hard to implement, because we think it is morally wrong to remove these easter eggs"
- "Fit of rage, because index building takes so long (Java)"

■ Demos

- Many of you produced some really nice web apps

Let's look at a small selection together

(and maybe a few more next week)

- Let us also appreciate the easter (or rather xmas) eggs that were hidden in wikidata-entities-with-surprises.tsv and emerged for (not only) these queries:

the mätrix, nirwana, gorilas, harlem, mikrosöft, snow,
turn around, asteroids

■ Motivation

- For this lecture, it will be useful to represent documents as **vectors** ... here is our running example for today:

	D ₁	D ₂	D ₃	D ₄	D ₅	D ₆
internet	1	1	0	1	0	0
web	1	0	1	1	0	0
surfing	1	1	1	2	1	1
beach	0	0	0	1	1	1

- Each row corresponds to a word, each column to a document
- Non-zero entries: score for that word in that document

In the lecture, we use tf scores ... for ES8, use BM25 scores

■ Terminology

- Often referred to as the **Vector Space Model (VSM)**
- In the VSM, words are traditionally referred to as **terms**
- Putting the vectors from all documents from a given corpus side by side gives us the so-called **term-document matrix**

	D ₁	D ₂	D ₃	D ₄	D ₅	D ₆
internet	1	1	0	1	0	0
web	1	0	1	1	0	0
surfing	1	1	1	2	1	1
beach	0	0	0	1	1	1

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■ Retrieval

$Q = \text{web surfing}$

- A query can also be represented as a vector ... we take **1** for a term used in the query, and **0** for all other terms
- We measure the relevance of a document to the query by taking the **dot product** of the two vectors

Note: this is exactly the same score as in Lecture 2

	D_1	D_2	D_3	D_4	D_5	D_6	Q
internet	1	1	0	1	0	0	0
web	1	0	1	1	0	0	1
surfing	1	1	1	2	1	1	1
beach	0	0	0	1	1	1	0

dot
product

$D_i \cdot Q$

2 1 2 3 1 1

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A 4×6

1×6

■ Algebra

$$\underbrace{(0, 1, 1, 0)}_{q^T \quad 1 \times 4} \cdot \underbrace{\begin{pmatrix} 1 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 2 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{pmatrix}}_{A \quad 4 \times 6} = (2, 1, 2, 3, 1, 1)$$

- More formally, let us write A for the term-document matrix and q for the query vector
- Then the matrix-vector product $q^T \cdot A$ gives us a vector with the relevance scores of all the documents

Let us implement this together now

	D_1	D_2	D_3	D_4	D_5	D_6	Q
internet	1	1	0	1	0	0	0
web	1	0	1	1	0	0	1
surfing	1	1	1	2	1	1	1
beach	0	0	0	1	1	1	0

A

q

■ Basic linear algebra in Python

- For standard linear algebra, we can use **numpy**

```
sudo apt-get install python3-numpy
```

```
import numpy
```

```
A = numpy.array([[1, 1, 0, 1, 0, 0], ...])
```

```
q = numpy.array([0, 1, 1, 0])
```

```
scores = q.dot(A)
```

```
print(scores)
```

Use **numpy.array** and **dot** for multiplication, not *****

q is a row vector above = q^T from the previous slide

- See the code from the lecture for more example usage

■ Sparse matrices

- Most entries in a term-document matrix are **zero**

Storing all entries explicitly is infeasible for large matrices

- Sparse-matrix representation: store only the non-zero entries (together with their row and column index)

$(1, 0, 0), (1, 0, 1), (1, 0, 3), \dots, (2, 2, 3), \dots$

		0	1	2	3	4	5
		D ₁	D ₂	D ₃	D ₄	D ₅	D ₆
0	internet	1	1	0	1	0	0
1	web	1	0	1	1	0	0
2	surfing	1	1	1	2	1	1
3	beach	0	0	0	1	1	1

■ Sparse matrices

- Two principle ways to store the list of non-zero values

row-major: store row by row (sort by row index first)

column-major: store col by col (sort by col index first)

- Note: the sparse row-major representation of a term-document matrix is equivalent to an **inverted index**

(1, 0, 0), (1, 0, 1), (1, 0, 3) ids of docs containing term 0

(1, 1, 0), (1, 1, 2), (1, 1, 3) ids of docs containing term 1

(1, 2, 0), (1, 2, 1), (1, 2, 2) ... ids of docs containing term 2

(1, 3, 3), (1, 3, 4), (1, 3, 5) ids of docs containing term 3

(non-zero score, row index = term id, col index = doc id)

■ Normalization

- The idf part from BM25 or tf.idf can be seen as a **normalization** of the term document matrix:
multiply each row by a certain factor (the idf)
- Another typical normalization for matrices is such that the rows or columns have norm 1

L1-norm: sum of the absolutes of the entries

L2-norm: sum of the squares of the entries

For ES8, play around with different normalizations of the TD matrix and see whether it improves the results

■ Sparse matrices in Python

- Not included in numpy, we have to use **scipy**

```
sudo apt-get install python3-scipy
```

```
import scipy.sparse
```

```
nz_vals = [1, 1, 1, 1, 1, 1, ...]
```

```
row_inds = [0, 0, 0, 1, 1, 1, ...]
```

```
col_inds = [0, 1, 3, 0, 2, 3, ...]
```

```
A = scipy.sparse.csr_matrix((nz_vals, (row_inds, col_inds)))
```

```
q = scipy.sparse.csr_matrix([0, 1, 1, 0])
```

```
scores = q.dot(A)
```

```
print(scores)
```

"csr" stands for "compressed sparse row"

References

- Textbook

Section 6.3: The vector space model for scoring

- Linear algebra in Python

- <http://www.numpy.org>
- <http://www.scipy.org>
- You find a Python numpy/scipy cheat sheet on the **wiki**