Unsupervised and Unstructured Machine Learning

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Midterm Review

Start
Stop
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Please fill this out

- https://forms.gle/VuHJUjtzLrrr1TNY8

Text Mining

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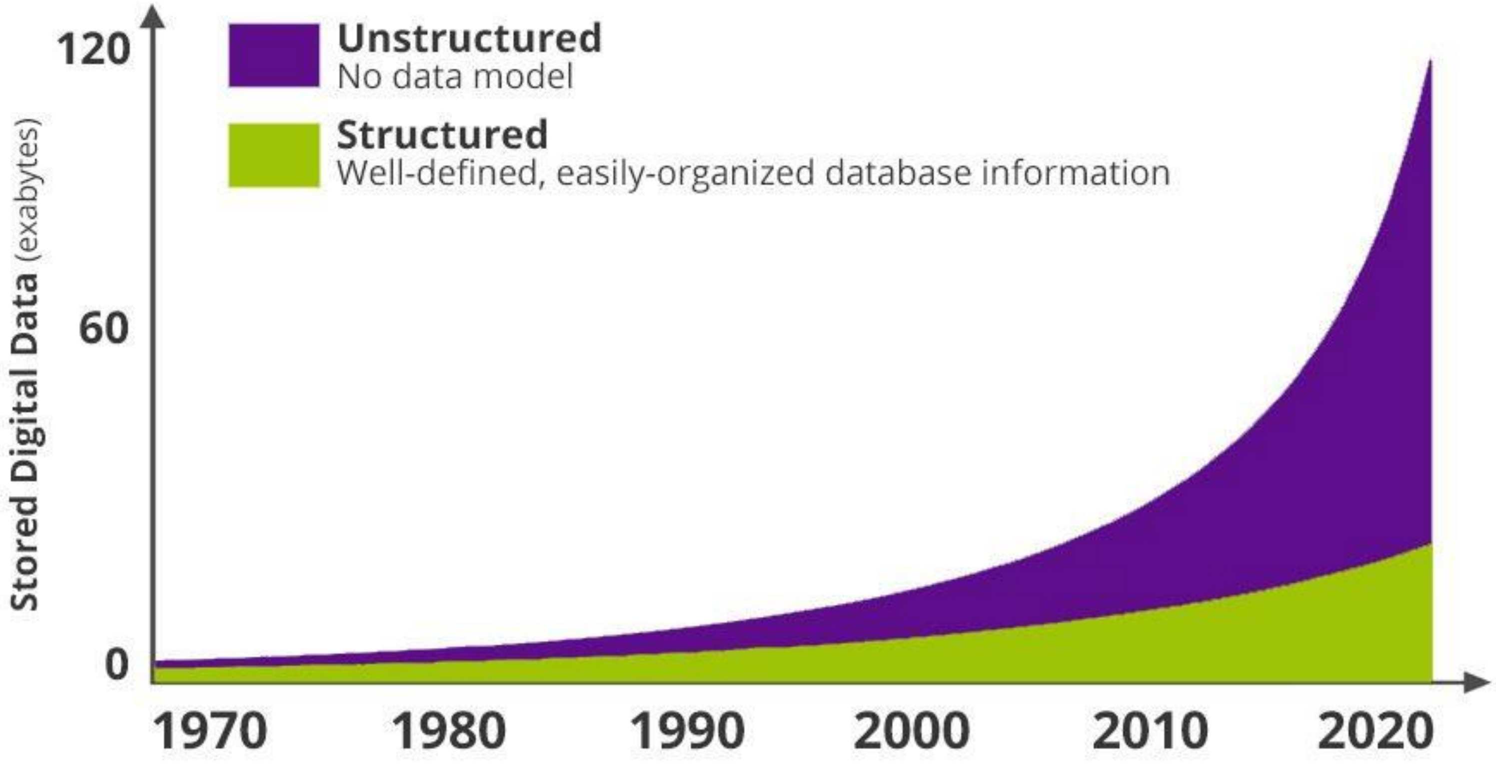
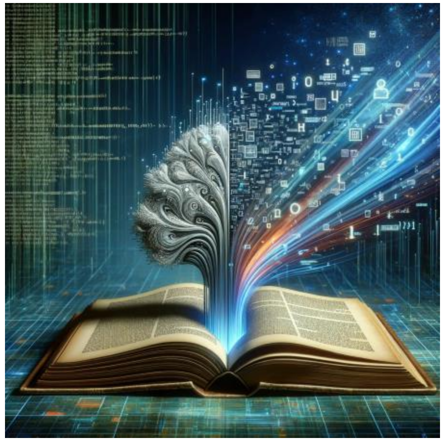
Most Data is No Longer Structured…



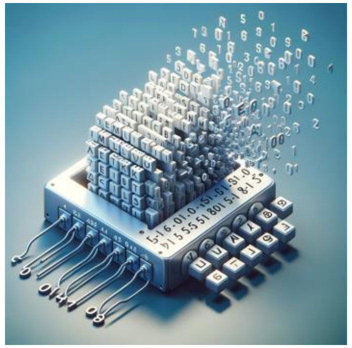
https://www.komprise.com/

What can we do with this data?



- Text classification
- Text generation
- Text summarization
- Music recommendation
- Image categorization
- ….

Text Mining



Unstructured Text → Data Cleaning → Text Representation / Feature Extraction → Text modeling (SL and UL) → Information

Collecting Unstructured Data

- How can we extract this data?
  - Datasets found publicly (UCI, Kaggle, Common Crawl, Wikimedia Downloads, etc.).
  - Using APIs (e.g., twitter API, News API).
  - Web scrapping (e.g., BeautifulSoup, Selenium)
  - Own private data.

Data Cleaning with *Regex*

- Just like structured/tabular data, we generally need to clean up the text to make it more useful.
  - Examples: case-sensitivity, punctuation, etc.

- *Regex* is used for finding string matches and formatting text:
  - Playground: https://www.w3schools.com/python/python_regex.asp
  - Cheat sheet: https://www.debuggex.com/cheatsheet/regex/python

How to Represent Text?

- Computers do not understand text…
- We need to represent text in a language they understand… numbers!

- Simple proposals (we are just brainstorming here):
  - Each sentence is represented in terms of the words it contains…
    - This is called *Tokenization.*
  - Each word is represented by a number…
    - This is called *Vectorization*.

Tokenization: Some Terminology

- ***Document:*** A body of text (e.g., a tweet, a pdf, an article, etc.).
- ***A token:*** The building block of a document.
  - Examples: character-level, word-level, …
- ***A separator:*** Special tokens that split a document into tokens.
  - Examples: punctuation, spaces,
- Demo

Need for Advanced Text Pre-Processing

- Some tokens may occur too frequently in any text without contributing much to its meaning. These are called *stop words* and are generally removed.

- Other issues:
  - ***Stemming:*** big, bigger, biggest
  - ***Lemmatization:*** drive drove driven
  - ***Homonyms:*** bank (river or money?)
  - ***Synonym:*** Yes, sure.

- We will come back to all of this later…

Syntax vs. Semantics

- Notice that:
  - Different tokens might have the same meaning (e.g., like, enjoy)
  - The same token might have different meanings (is *like* something, to *like* something)
- **So, while tokens represent syntax, we really care about meaning/semantics.**
- In many cases, you can only get the meaning through **context** (i.e., the token's place with respect to other tokens.)
- We will come back to all of this later…

Text Modeling

- Once text data is in the proper representation (i.e., tokenized and vectorized), we can apply the methods we have learned so far:
  - Unsupervised ML (e.g., dimensionality reduction, clustering, etc.).
  - Supervised ML (e.g., classification, translation, etc.).

Text Vectorization

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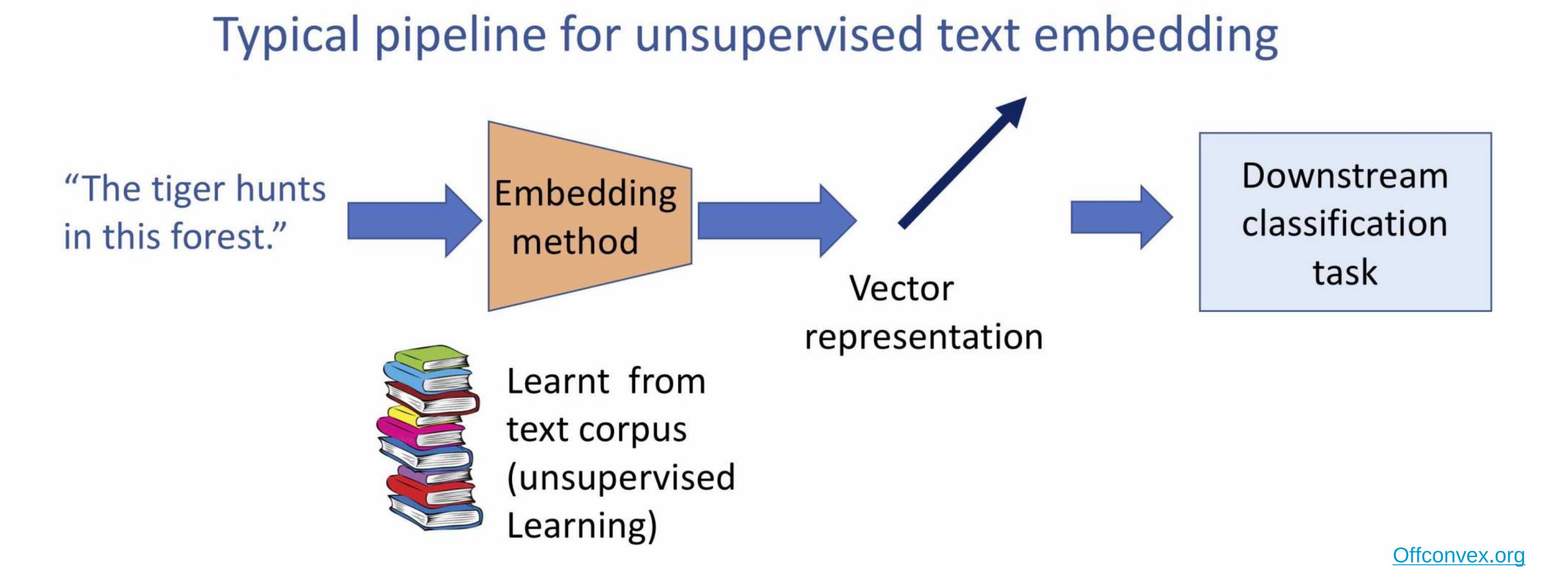
Vectorization: Text as Numbers



Offconvex.org

How Would You Represent a Document?

- Let's start simple. We could represent a document simply *as a collection of tokens*.
  - Vectorization by document (not token).

- This approach is called ***Bag of Words (BoW).***

- **Demo**

Sentence	hockey	fun	i	like	golf
I like golf!			1	1	1
I like hockey.	1		1	1	
Hockey and golf are fun!	1	1			1

Bag of Words (BoW)

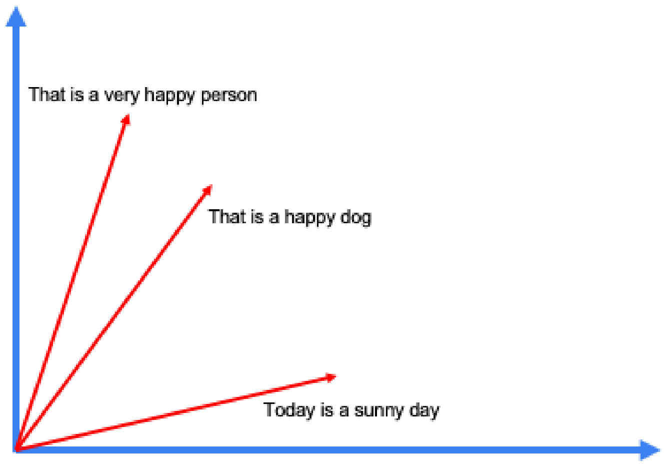
- **Cons:**
  - Disregards word order!
  - Number of features can be exhaustive.
  - **Frequency bias.**
    - (e.g., If the word “space” appears in a children’s book, it carries more significance than when it appears in an article about galaxies.
- **Pros:**
  - Simple to implement

	I	hate	love	golf	soccer
I hate golf and love soccer	1	1	1	1	1
I hate soccer and love golf	1	1	1	1	1

Document Similarity

- How do we measure if two documents are similar?
  - We need a metric like Euclidean distance.
  - But… What if documents have different lengths?

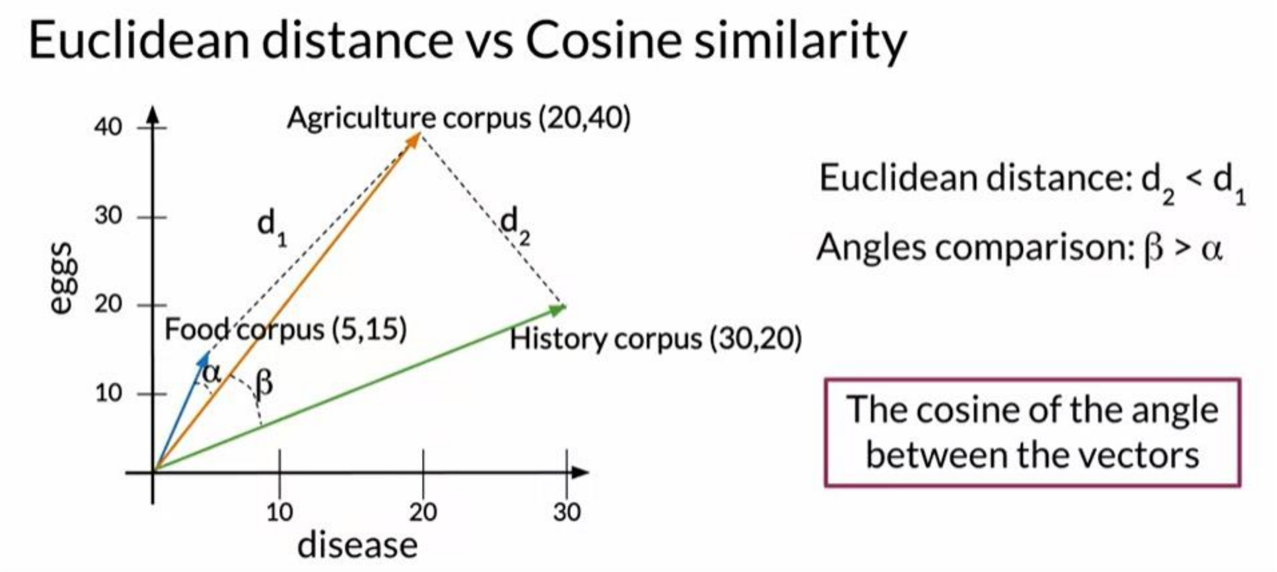
- We need a metric that is robust to differences in document size…
  - Enter *Cosine Similarity.*



https://mlops.community

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}},$$

Document Similarity



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medium.com

Solving for Frequency Bias: TF-IDF

- Term Frequency – Inverse Document Frequency

- Instead of simply counting the <u>absolute</u> number of occurrences, how about we *<u>adjust in terms of token presence across documents</u>*?

TF-IDF

Term x within document y

$tf_{x,y}$ = frequency of x in y

df_x = number of documents containing x

N = total number of documents

$$w_{x,y} = tf_{x,y}$$

Portion of documents the token appears in

BoW frequency

Solving for Frequency Bias: TF-IDF

- The more commonly a word exists across documents the less important it is!
- What happens when a term (i.e., token) appears in all documents?
- **Demo**

$$w_{x,y} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right)$$

Context Matters...

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So far…

- We calculated a score for each <u>*individual*</u> token (e.g., the frequency of the word in BoW).

- Have our methods captured context so far?
  - Context has so far been captured as *"the collection of words that appear together in a document"*, <u>regardless of order.</u>

Can We Do Better?

- Tokens that are immediately next to each other are generally more related to each other.
- Can we apply this concept at the tokenization level?

I love cookies and hate chocolate

1-gram → {I, love, cookies, and, hate, chocolate}

2-gram → {I love, love cookies, cookies and, and hate, hate chocolate)

n-grams

- An *n*-gram is a sequence of n items (i.e., tokens).
- *n* refers to the context size.
- The larger *n* is, the more context a token captures.
- What happens to the number of possible tokens as *n* increases?
- What happens to the vector representation as *n* increases?

How Much Context Is Needed?

- A large *n* captures more context, but it's more restrictive in terms of finding matches.
- A small *n* captures less context. but a token is more likely to be matched in other documents.
- Maybe we can include both? Any draw backs?
- **Demo**

Meaning: The Illusive Goal…

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Where Does Meaning Come From?

I went to the branch and deposited some money.

I went to the bank and deposited some money.

I went to the ATM and deposited some money.

> Words which frequently appear in **similar contexts** have **similar meaning**.

Lena-voita

Representing Meaning as a Vector

- So, why don't we construct vector representations such that words that appear in the same context have similar vectors.
  - embeddings = vector representation = features = latent space.
  - v_1 and v_2 are similar $\Rightarrow || v_1 - v_2 || \approx 0$

- Example from images.

Word Embeddings

- Represent each word as a vector of some pre-defined size/dimensionality.
- You can visualize these embeddings using PCA or t-SNE.

- Some interesting properties will appear:
  - Demo 1 (directionality)
  - Demo 2 (semantics)

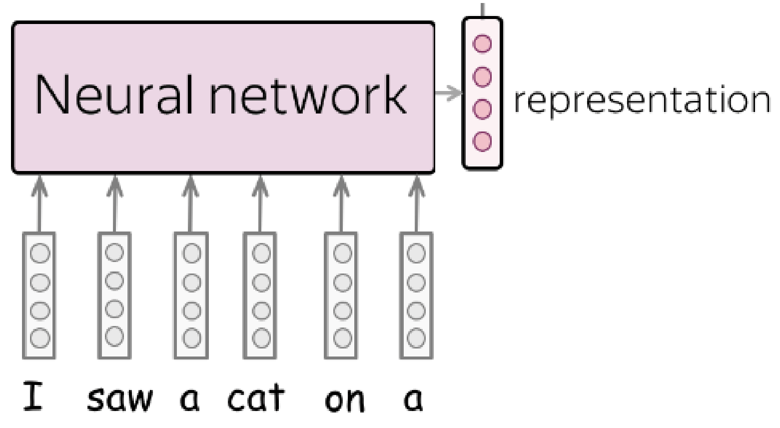
How are such embeddings constructed?

- For each token, start with a randomly initialized vector.
- From your training text, construct a table showing which tokens co-occur and which don't.
- For words that co-occur, push the vectors towards each other.
- For words that don't, push them away from each other.

- Examples of word embeddings:
  - *Word2Vec*
  - *GloVe*

Something is still missing…

- Well, now we have word embeddings…
  - But, how do we get sentence embeddings?!
- We need to somehow aggregate the word embeddings.
  - There are many ways to do this…
  - The most basic one is taking the average embedding.
  - Another way is to take the TF-DIF weighted averaging.
  - Or…. Using a Neural Net. Welcome to Deep Learning!



So, what's the big deal?

[Demo (Predict the next word)]

Demo

Language Modeling

- A playground for predicting the next word:

https://pair.withgoogle.com/explorables/fill-in-the-blank/