Building Robust Text Processing Pipelines

Maryam Jahanshahi Ph.D.

Achtung!

The focus of this talk will **not** be about text analysis in R

Corpus Processing

spaCy

Language Modeling

gensim

TensorFlow

Stack Considerations

- Actively developed libraries
- Industrial-strength NLP:
  - Parallel processing of large datasets
  - Prototype to Production
  - Effective memory management

Design Considerations

- Maintainability
- Reproducibility
- Environments

A Day in the Life of an NLP Project

Textual Resources for Text Analysis and NLP

Applied Text Analysis with Python by Benjamin Bengfort, Rebecca Bilbro & Tony Ojeda

Natural Language Processing with Python by Steven Bird, Ewan Klein & Edward Loper

Speech and Language Processing by Dan Jurafsky & James Martin

Foundations of Statistical Natural Language Processing by Chris Manning & Hinrich Schutze

Text Mining with R by Julia Silge & David Robinson

A Day in the Life of an NLP Project

- Data Ingestion
- Data Organization
- Data Preprocessing
- Data Exploration
- Model Building

Corpus: A collection of documents

Document: Unprocessed string, typically associated with structured data

'Amanda didn't start the fire'

Segment: Processed string (i.e. sentence, paragraph etc.)

('fire', NN)

Token: Processed single data point

Designing Data Preprocessors

Clean up	**Goal:** Remove inconsistency between otherwise similar data points
Segmentation	**Goal:** Split text chunks into data points (i.e. the unit of analysis or evaluation)
Normalization	**Goal:** Put data points on an equal footing

Designing Data Preprocessors

Clean up

Segmentation

Normalization

General Considerations

- What is the unit or data structure of analysis? (Tokens vs sentences vs paragraphs vs docs)
- Can the cleanup aid segmentation?

Specific Considerations

- What is the role of punctuation?
- What role do hyphenated words play?
- Will parsing emojis or emoticons be helpful?

Functions in a typical clean up script

HTML/XML	** **Amanda didn\u0027t start the fire!** **	Python: **`Beautiful Soup`** R: **`xml2?`**
Unicode	Amanda didn**\u0027**t start the fire!	Python: **`regex`** R: **`utf8`**
Contractions	Amanda did**n't** start the fire!	Python: **`spaCy`** R: **`textclean`**
Punctuation	Amanda did not start the fire**!**	Python: **`spaCy`** R: **`textclean`**
Tokenization	Amanda did not start the fire	Python: **`spaCy`** R: **`tokenizers`**

Functions in a typical clean up script

The order of operations is important

HTML/XML	** **Amanda didn\u0027t start the fire!** **	Python: **`Beautiful Soup`** R: **`xml2?`**
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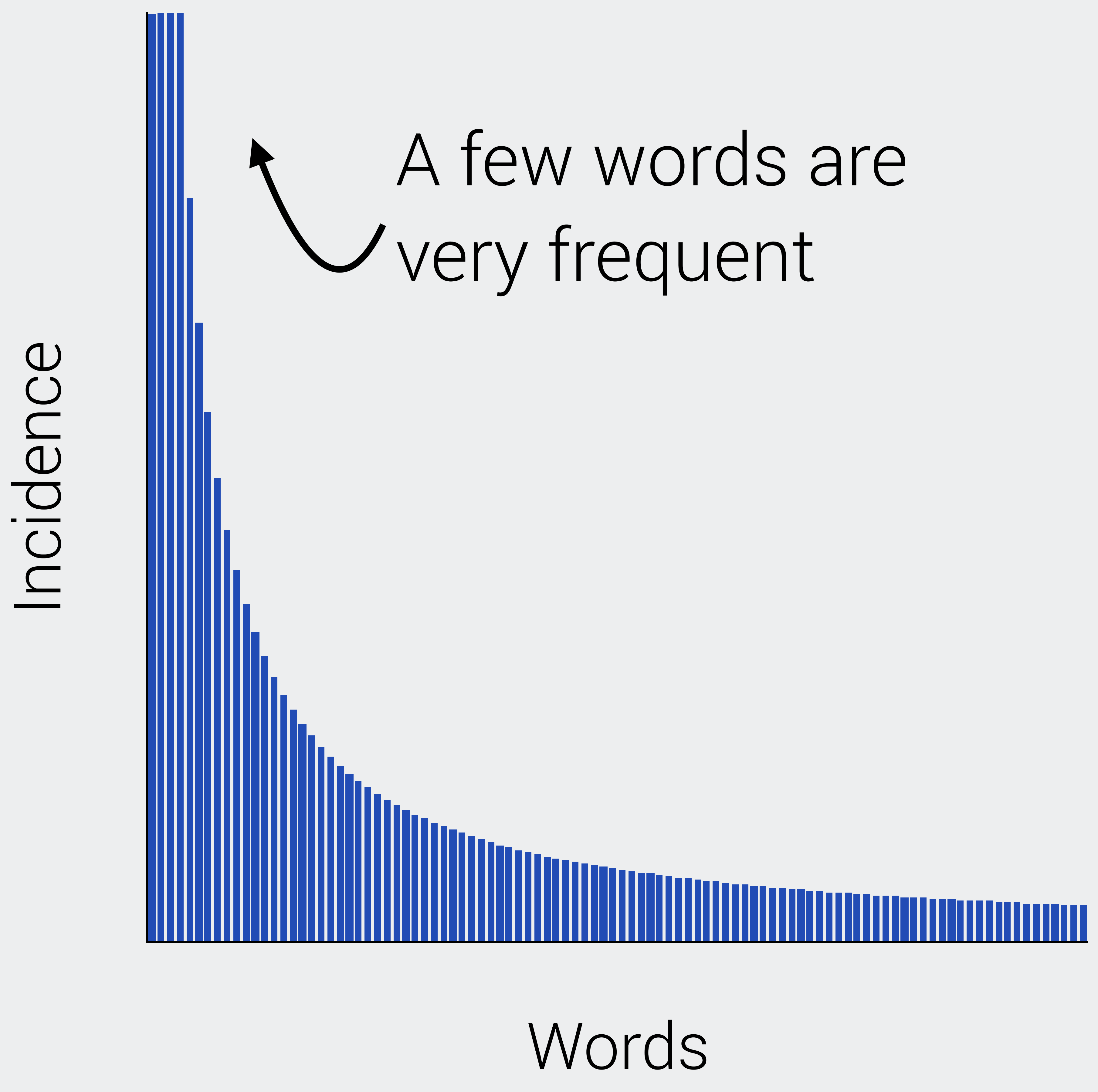
Word incidence is rarely distributed normally



- **Stop words**: Removing most frequent words.
    - Standard list with most NLP libraries
    - Make your own artisanal list

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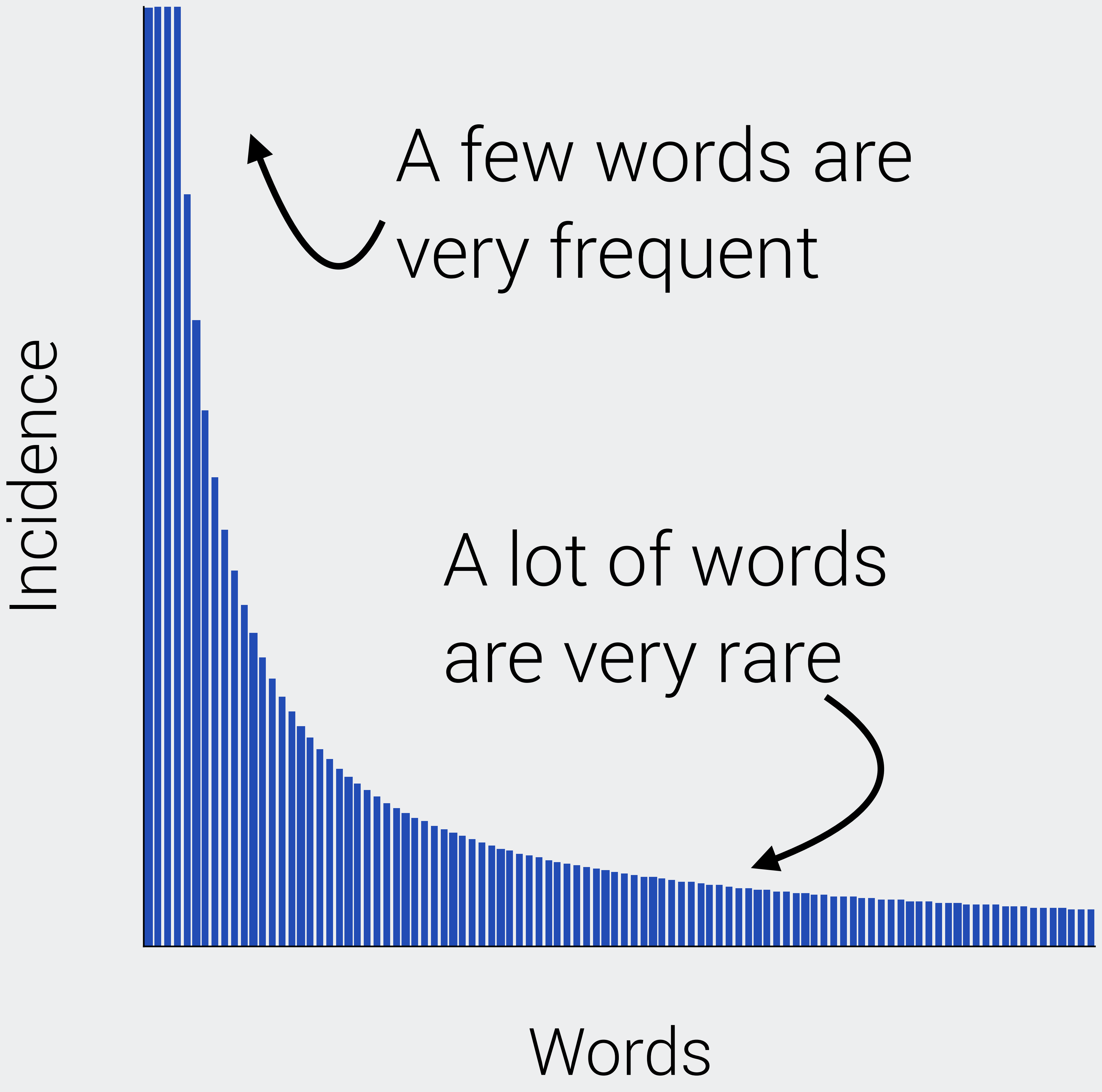

- **Stop words**: Removing most frequent words.
  - Standard list with most NLP libraries
  - Make your own artisanal list
- **Changing cases**:
  - Standard is to convert to lower case
  - Casing may matter for you (e.g. IT vs it)
- **Process numbers**:
  - Standard is to remove all numbers
  - Convert into words via **`inflect`** library in Python and **`textclean`** package in R
- **Correct spelling**:
- **Stem or lemmatize words**: Lemmatization is std

Best Practices in Data Organization

```
corpus
|_README.md
|_raw
  |_01.txt
  |_02.txt
  |_03.txt
  |_metadata.json
|_processed
  |_processed.json
  |_metadata.json
|_scripts
```

Processed documents:
Save down processed documents either as JSON objects or in a document database (NoSQL)

Metadata:
Define what has been processed and when in metadata:
- Files
- Words
- Unique Tokens
- Date of latest preprocessing

Advanced Best Practices in Data Organization

Create a corpus reading module:

- Define which files should be loaded and how those files should be loaded.
  - Store these as parameters in README.
  - Regex for file names / formats [**`\w\.txt+`**]
  - Can include a filter list for restricting files

```
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```
import json

def project_reader(self):
    return json.load(self.open(“README”))
```

Feature Extraction

Bag of Words representation vectorizes through word counts

	amanda	baby	did	doo	fire	not	shark	start	the
Amanda didn’t start the fire	1	0	1	0	1	1	0	1	1
Baby shark, doo doo doo doo doo doo	0	1	0	6	0	0	1	0	0

Feature Extraction

Bag of Words representation vectorizes through word counts

Amanda didn't start the fire

	amanda	baby	did	doo	fire	not	shark	start	the
Bag of Words	1	0	1	0	1	1	0	1	1
- stop words	1	0	0	0	1	0	0	1	0
+ normalization	0.3	0	0	0	0.3	0	0	0.3	0

Feature Extraction

One Hot Encoding and TFIDF normalize token frequencies

Baby shark, doo doo doo doo doo doo

	amanda	baby	did	doo	fire	not	shark	start	the
Bag of Words	0	1	0	6	0	0	1	0	0
One Hot Encoding	0	1	0	1	0	0	1	0	0
TFIDF	0	0.05	0	0.4	0	0	0.2	0	0

Feature Extraction

Transforming text data into numeric features

Non-distributed			Distributed
One Hot Encoding	Bag of Words	TF-IDF	Embeddings
Stop word removal?	Stop word removal	No need for stop word removal	Stop word removal?
None	Document-level normalization	Corpus and document-level normalization	Context and corpus-level normalization

Word embeddings capture semantic similarities

Statistical modeling through software (e.g. SPSS) or programming language (e.g. **Python**)

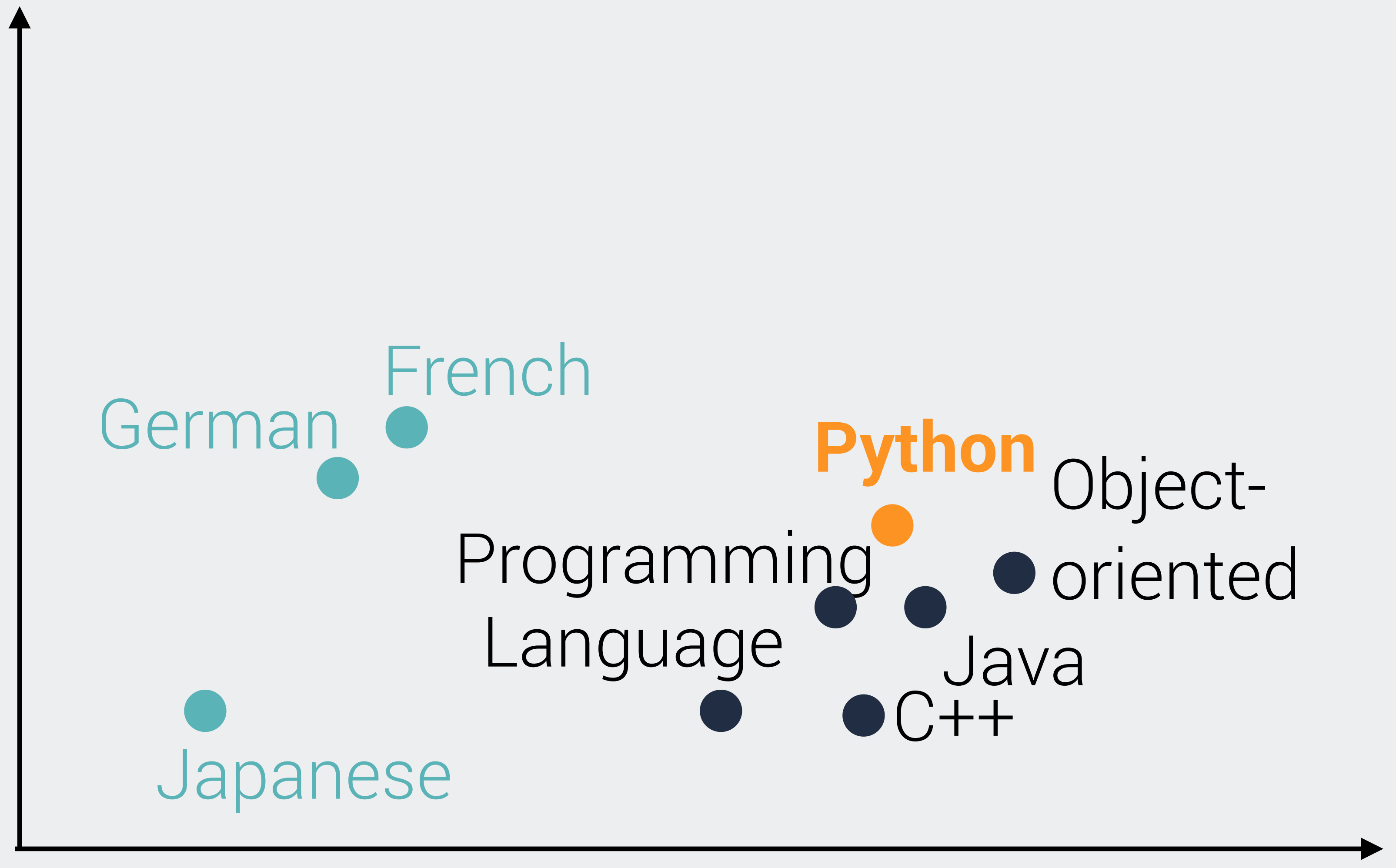
Context **Word**

Experience in **Python**, Java or other object-oriented programming languages

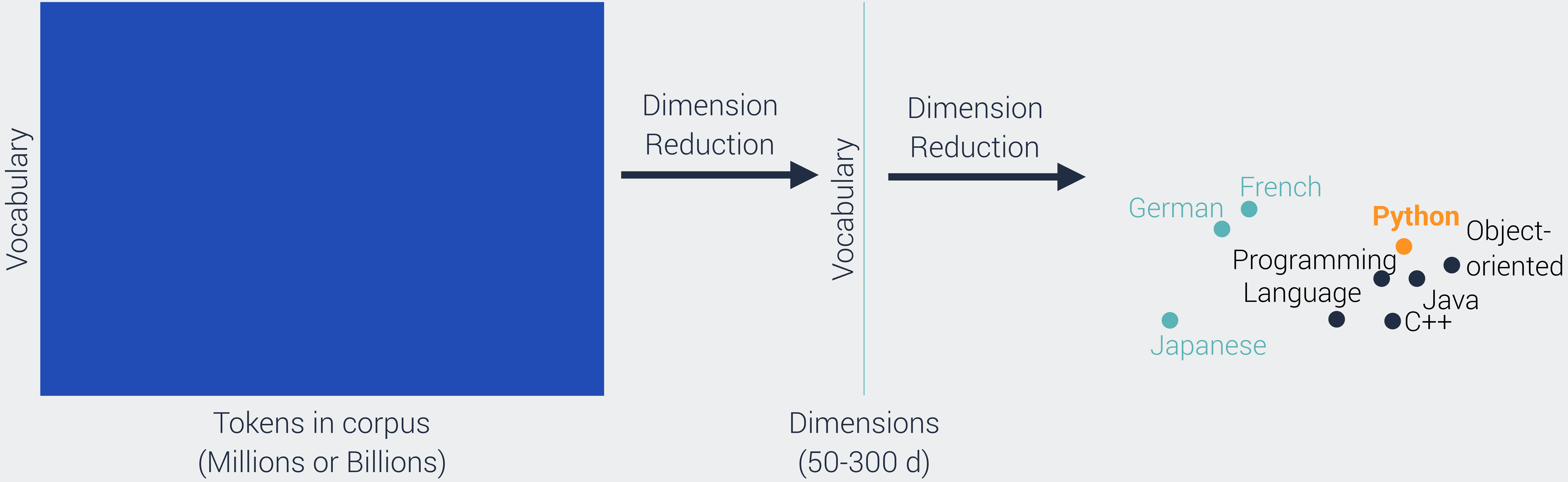
Context **Word** **Context**

Proficiency programming in **Python**, Java or C++.

Context **Word** **Context**



A simplified representation of word vectors



A simplified representation of word vectors

	Proficiency	programming	Python	Java	C++	⋮	Experience	Python	Java	object-oriented	programming	languages
proficiency	1	0	0	0	0		0	0	0	0	0	0
programming	0	1	0	0	0		0	0	0	0	1	0
python	0	0	1	0	0		0	1	0	0	0	0
java	0	0	0	1	0		0	0	1	0	0	0
c++	0	0	0	0	1		0	0	0	0	0	0
experience	0	0	0	0	0		1	0	0	0	0	0
object-oriented	0	0	0	0	0		0	0	0	1	0	0
languages	0	0	0	0	0		0	0	0	0	0	1

Dimension Reduction

	qualification	**data science**	**translation**	⋮
proficiency	**0.8**	0.1	0.3	...
programming	0.2	**0.7**	0.1	...
python	0.1	**0.9**	-0.2	...
java	-0.1	**0.6**	0.1	...
c++	-0.2	0.4	-0.1	...
experience	**1.0**	0.3	0.4	...
object-oriented	-0.3	0.3	-0.2	...
languages	0.4	0.1	**0.9**	...

Feature Extraction

Transforming text data into numeric features

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Stop word removal?	Stop word removal	No need for stop word removal	Stop word removal?
None	Document-level normalization	Corpus and document-level normalization	Context and corpus-level normalization
All tokens are equidistant			Distance ∝ token similarity
High dimensionality, extremely sparse			Lower dimensionality

Document categorization

Extracting semantic structure from numeric features

Topic Modeling	Document Classification
What are the topics that occur in a collection of documents?	Which class does document X belong to?
Unsupervised Dimension Reduction (LDA / LSA)	Supervised ML Algorithms Regex (Standard or Artisanal)
Every document is a mixture of topics	Every document belongs to a single class
Every topic is a mixture of words	The presence or absence of a subset of words impacts the classification

Thank you R Ladies!

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