

Text Similarity and Clustering

Text Summarization and Topic Models

1121AITA07

MBA, IM, NTPU (M5265) (Fall 2023)
Tue 2, 3, 4 (9:10-12:00) (B3F17)



<https://meet.google.com/miy-fbif-max>



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<https://web.ntpu.edu.tw/~myday>



Syllabus

Week Date Subject/Topics

- 1 2023/09/13 Introduction to Artificial Intelligence for Text Analytics
- 2 2023/09/20 Foundations of Text Analytics:
Natural Language Processing (NLP)
- 3 2023/09/27 Python for Natural Language Processing
- 4 2023/10/04 Natural Language Processing with Transformers
- 5 2023/10/11 Case Study on Artificial Intelligence for Text Analytics I
- 6 2023/10/18 Text Classification and Sentiment Analysis

Syllabus

Week Date Subject/Topics

7 2023/10/25 Multilingual Named Entity Recognition (NER)

8 2023/11/01 Midterm Project Report

9 2023/11/08 Text Similarity and Clustering

10 2023/11/15 Text Summarization and Topic Models

11 2023/11/22 Text Generation with Large Language Models (LLMs)

12 2023/11/29 Case Study on Artificial Intelligence for Text Analytics II

Syllabus

Week Date Subject/Topics

13 2023/12/06 Question Answering and Dialogue Systems

14 2023/12/13 Deep Learning, Generative AI, Transfer Learning,
Zero-Shot, and Few-Shot Learning for Text Analytics

15 2023/12/20 Final Project Report I

16 2023/12/27 Final Project Report II

17 2024/01/03 Self-learning

18 2024/01/10 Self-learning

Text Similarity

Text Clustering

Text Summarization

Topic Models

Outline

- **Text Similarity**
 - Analyzing and quantifying the likeness between text documents.
- **Text Clustering**
 - Grouping similar text documents using various algorithms.
- **Text Summarization**
 - Condensing text data into a shorter, coherent form.
- **Topic Models**
 - Identifying underlying themes or topics within text collections.

Text Similarity and Clustering

Text Similarity and Clustering

**Text Dataset
(Unsupervised)**

Text Pre-Processing

**Feature Extraction
(Vectorization) (TF-IDF)(Embedding)**

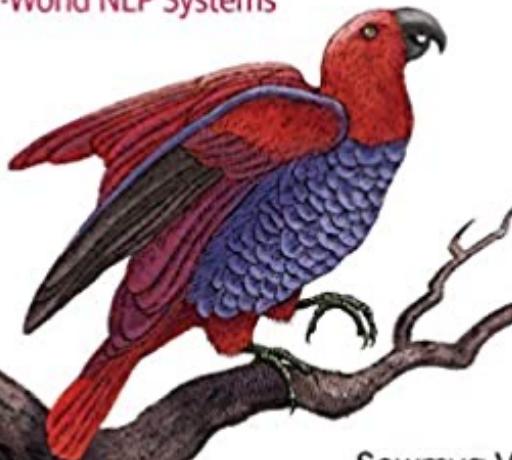
Text Similarity

Text Clustering

O'REILLY®

Practical Natural Language Processing

A Comprehensive Guide to Building
Real-World NLP Systems



Sowmya Vajjala,
Bodhisattwa Majumder,
Anuj Gupta & Harshit Surana

FOUNDATIONS

*Covered in
Chapters 1 to 3*



ML for NLP



NLP Pipelines



Data
Gathering



Multilingual
NLP



Text
Representation

CORE TASKS

*Covered in
Chapters 3 to 7*



Text
Classification



Information
Extraction



Conversational
Agents



Information
Retrieval



Question
Answering

GENERAL APPLICATIONS

*Covered in
Chapters 4 to 7*



Spam
Classification



Calendar Event
Extracton



Personal
Assistants



Search
Engines

JEOPARDY!

Jeopardy!

INDUSTRY SPECIFIC

*Covered in
Chapters 8 to 10*



Social Media
Analysis



Retail Data
Extracton



Health Records
Analysis



Financial
Analysis



Legal Entity
Extraction

AI PROJECT PLAYBOOK

*Covered in
Chapters 2 & 11*



Project
Processes



Best
Practices



Model
Iterations



MLOps



AI Teams
& Hiring

Text Similarity and Clustering

- How do we measure **similarity** between terms and documents?
- How can we use **distance measures** to find the most **relevant documents**?
- How can we build a **recommender system** from **text similarity**?
- How do we **group similar documents (document clustering)**?

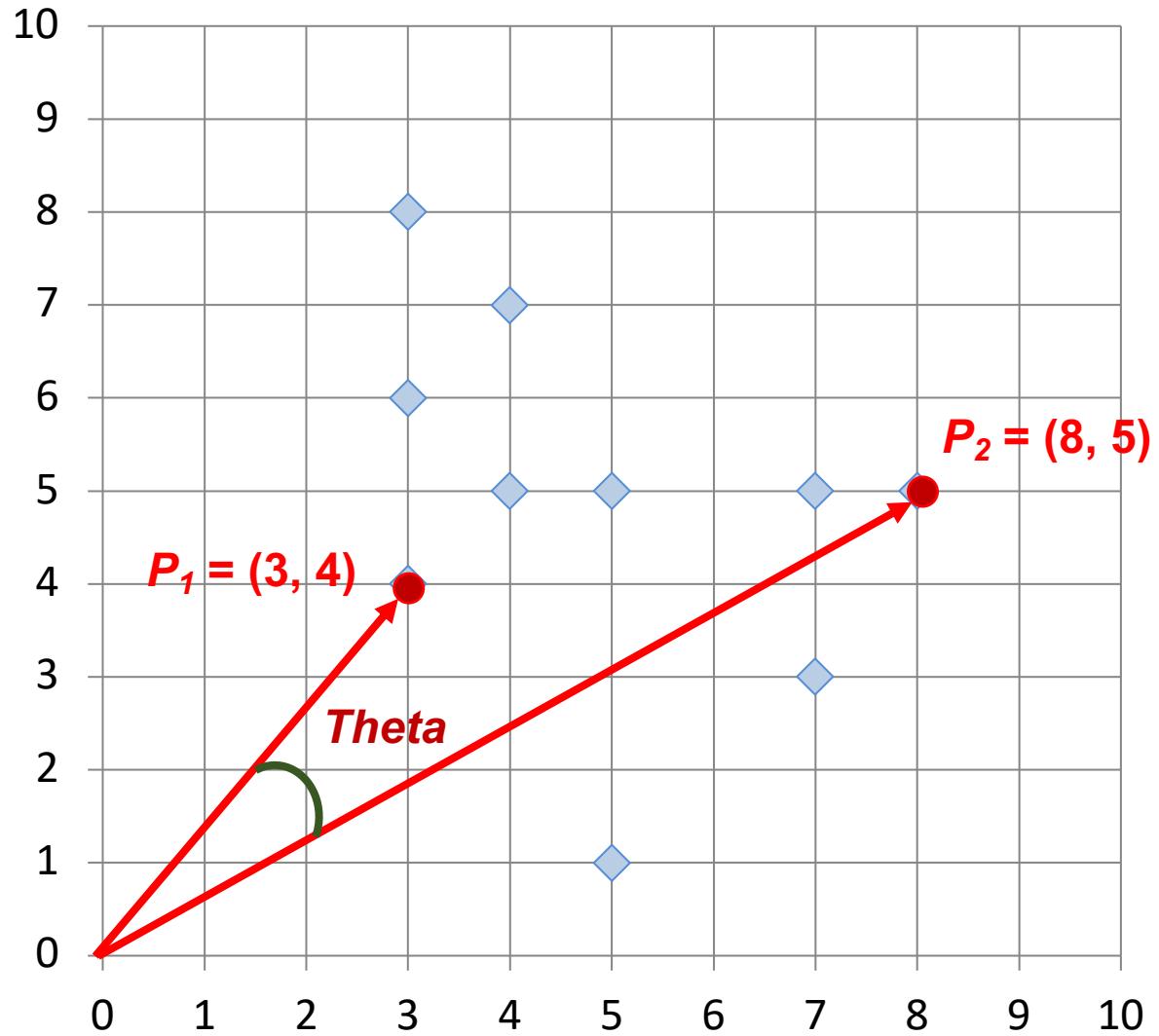
Text Similarity and Clustering

- **Information Retrieval (IR)**
- **Feature Engineering**
- **Similarity Measures**
- **Unsupervised Machine Learning Algorithms**

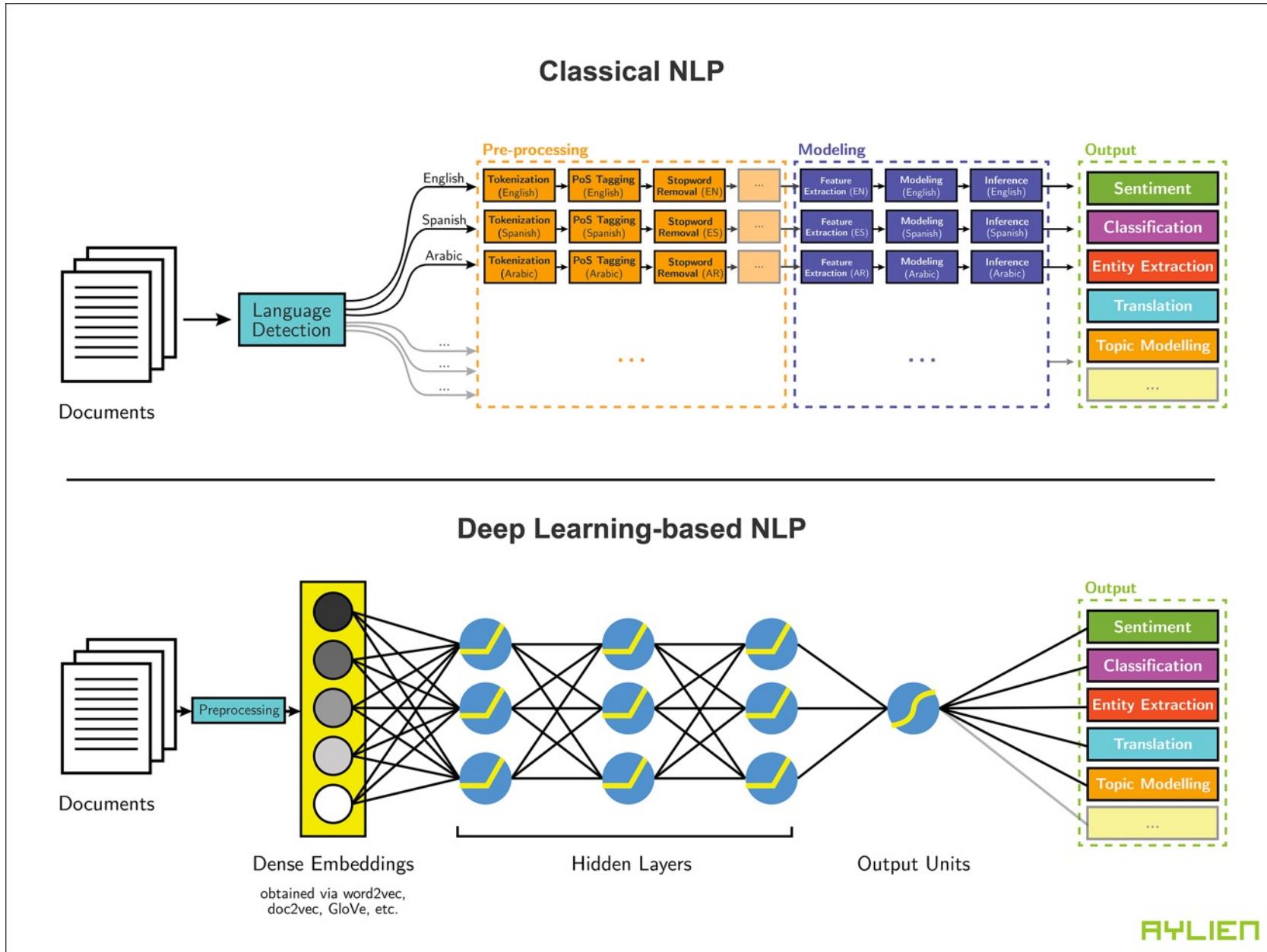
Text Similarity

- **Lexical similarity**
 - **Syntax, structure, and content of the documents**
- **Semantic similarity**
 - **Semantics, meaning, and context of the documents**

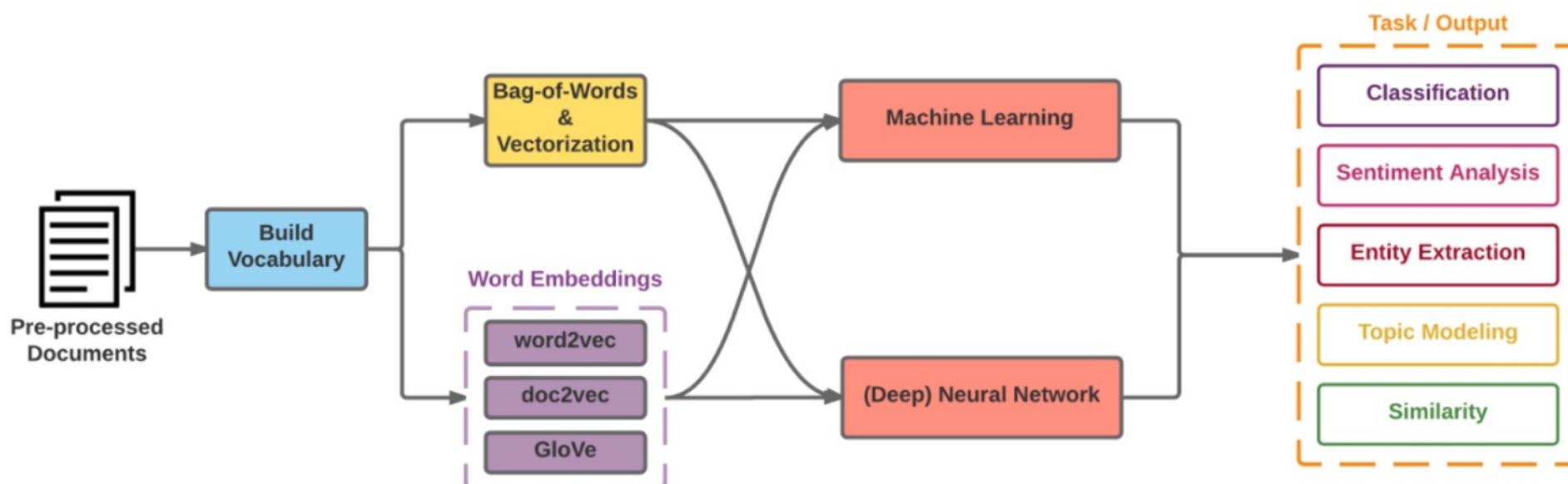
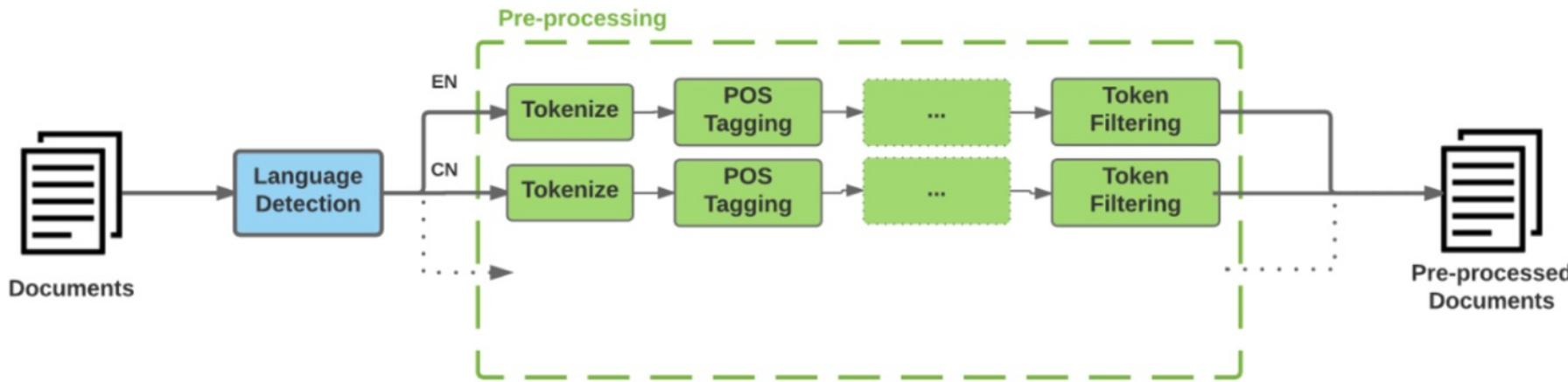
Cosine Similarity



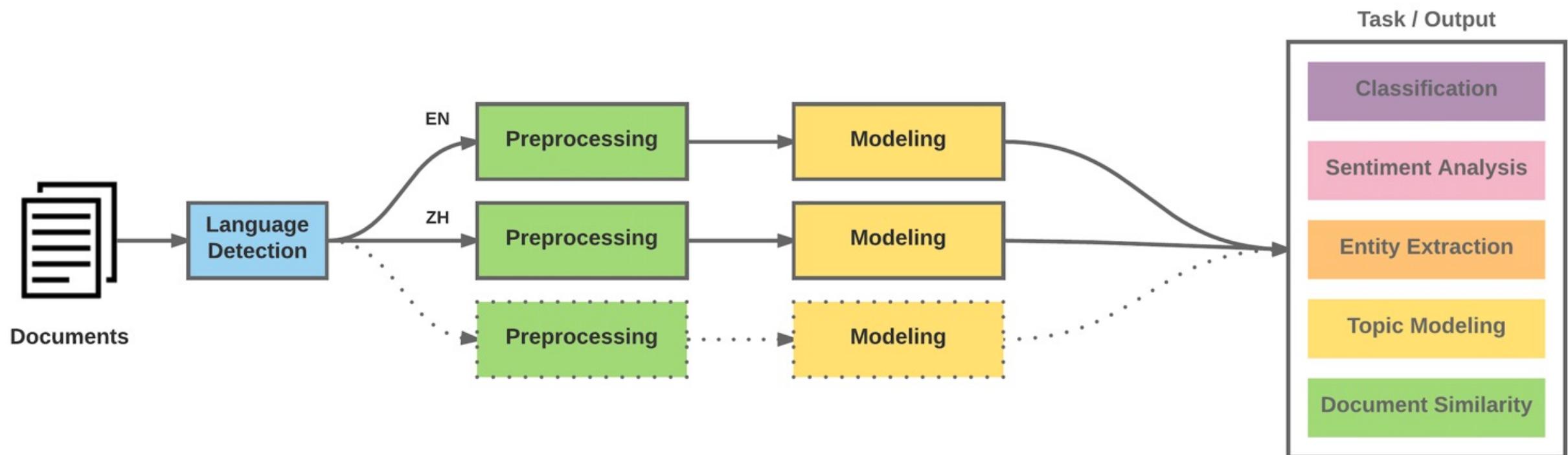
NLP



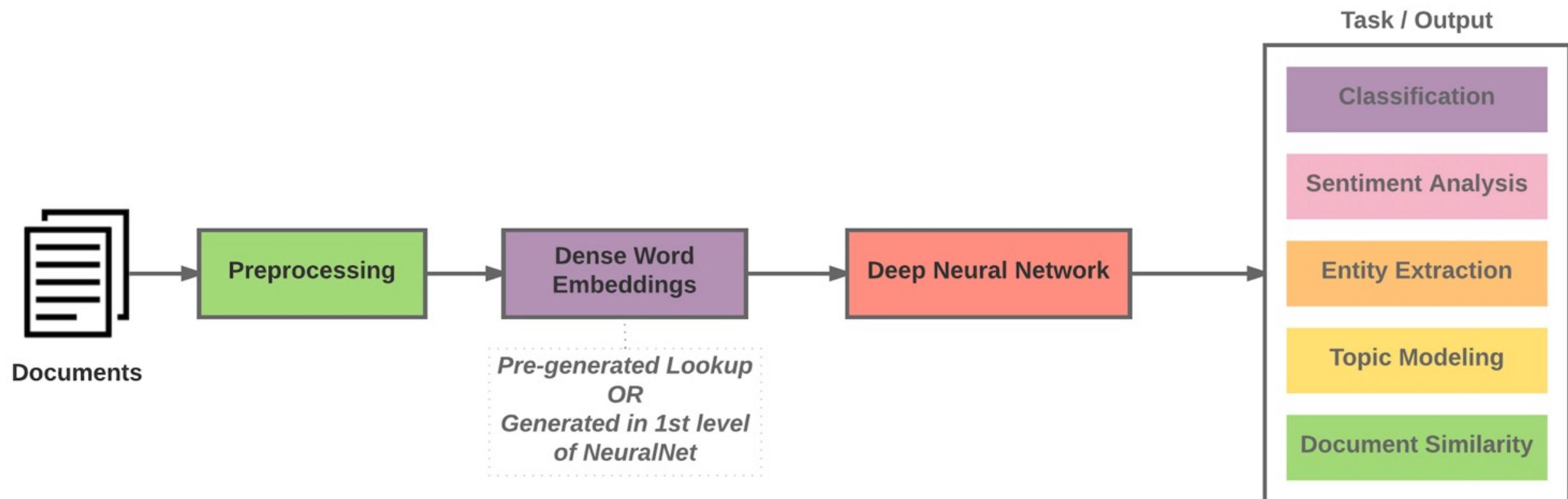
Modern NLP Pipeline



Modern NLP Pipeline



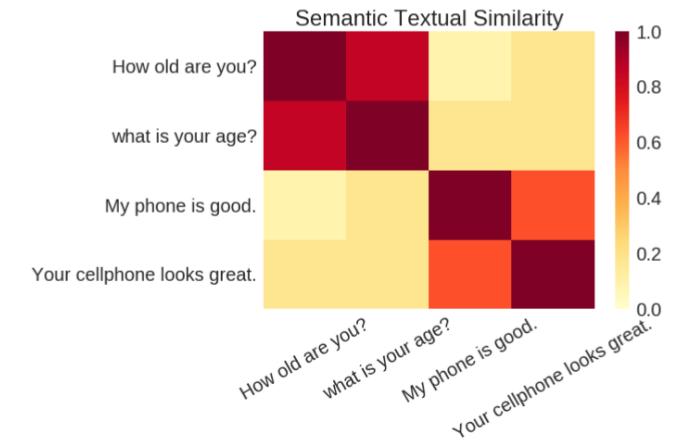
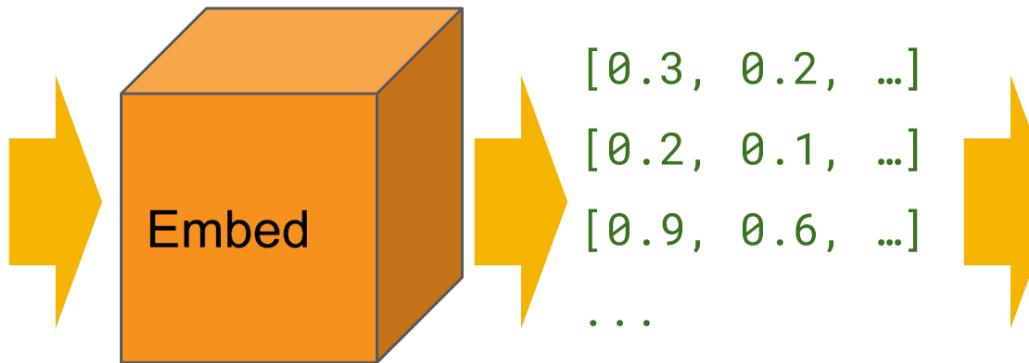
Deep Learning NLP



Text Similarity

Semantic Similarity

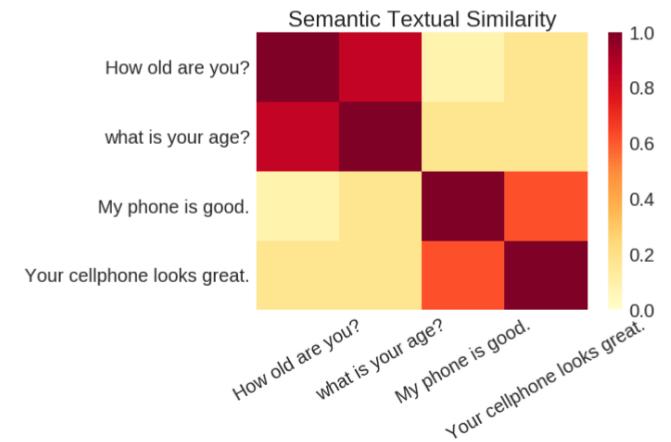
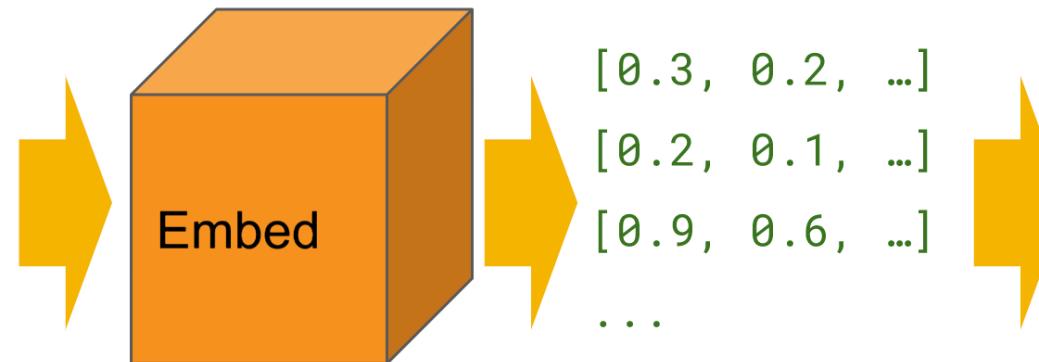
"How old are you?"
"What is your age?"
"My phone is good."
...



Text Similarity Text Classification

Semantic Similarity

"How old are you?"
"What is your age?"
"My phone is good."
...



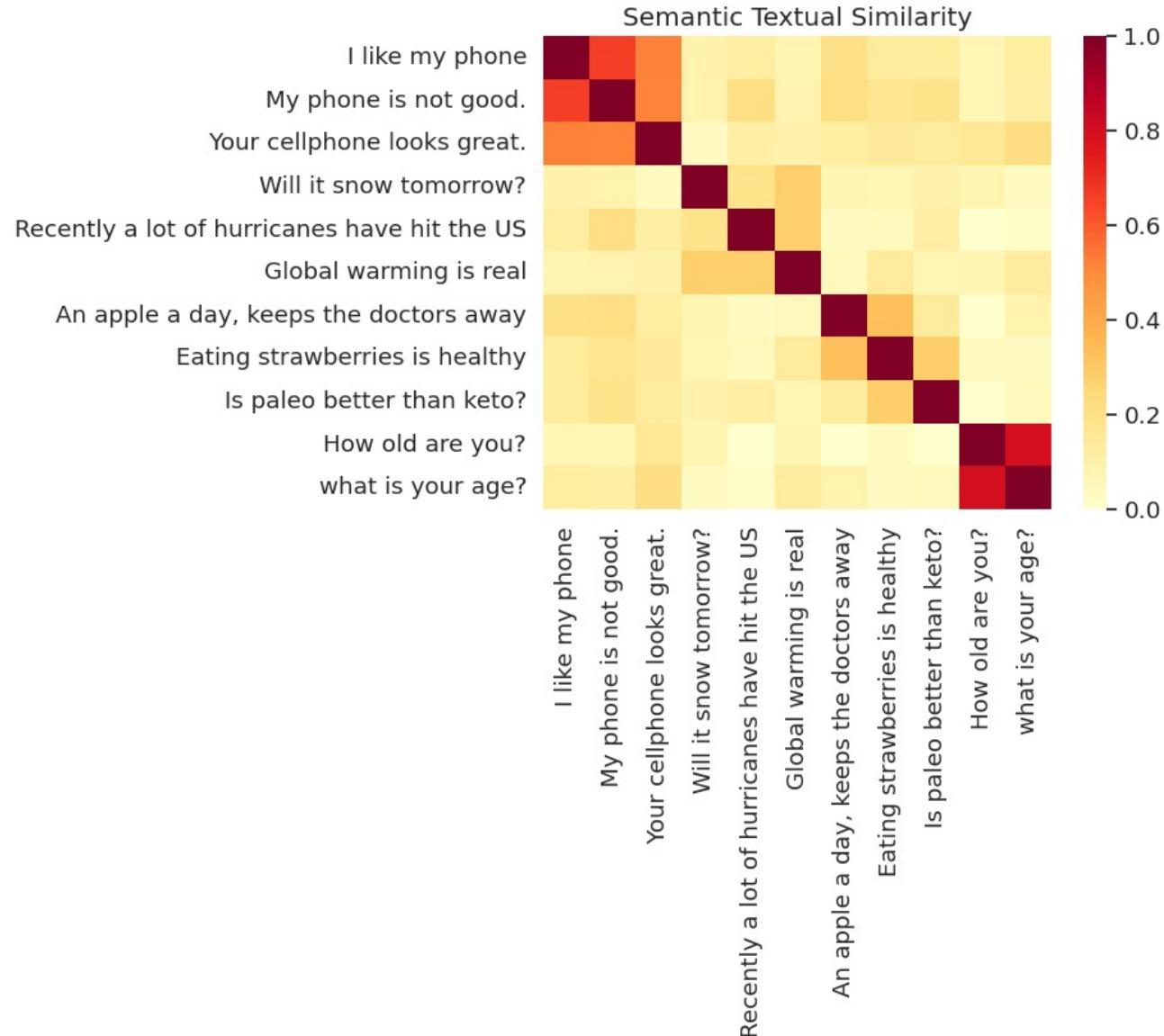
Classification

"How old are you?"
"What is your age?"
"My phone is good."
...

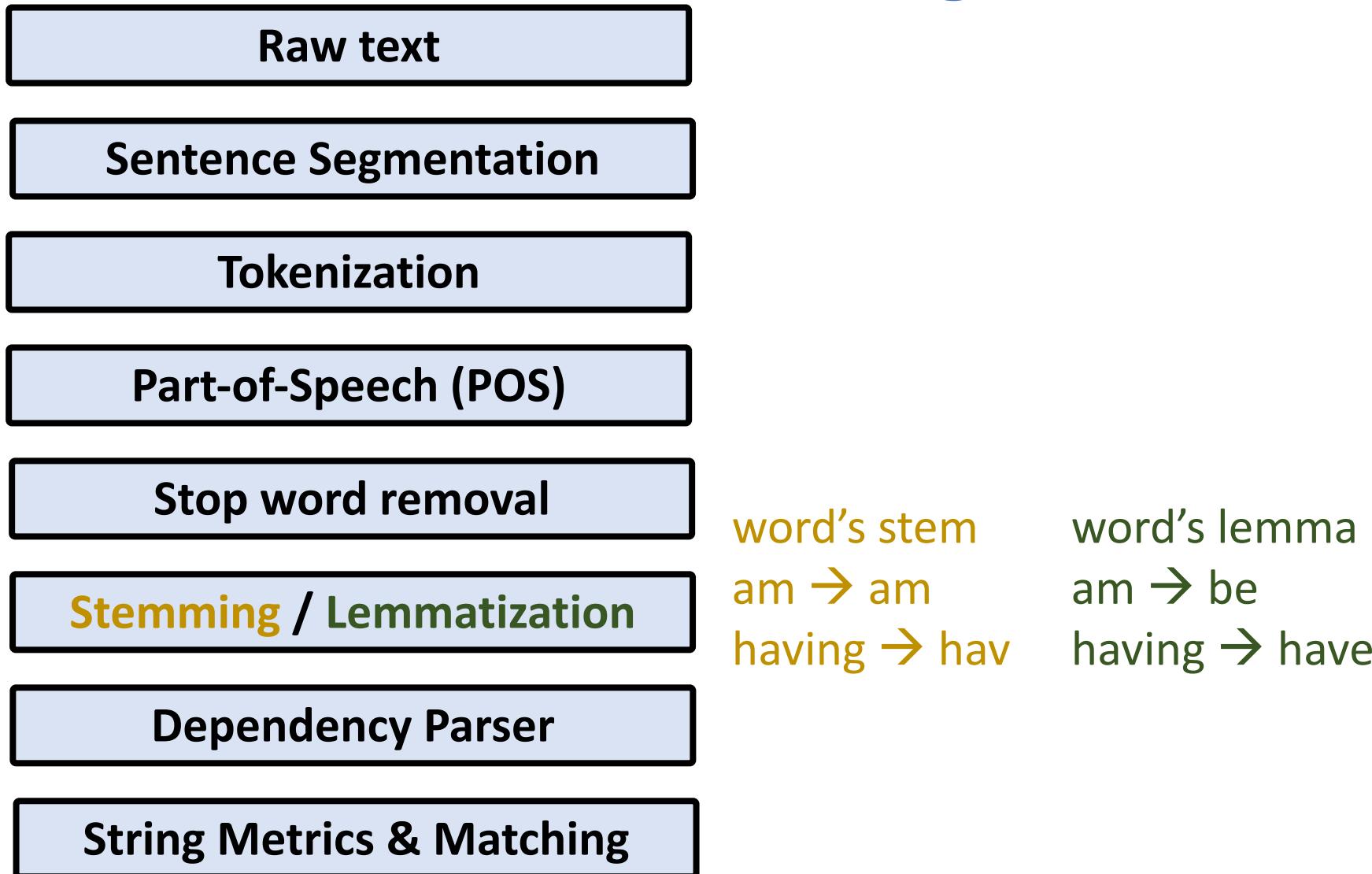


Confidence is a question
(96%) "How old are you?"
(98%) "What is your age?"
(7%) "My phone is good."
...

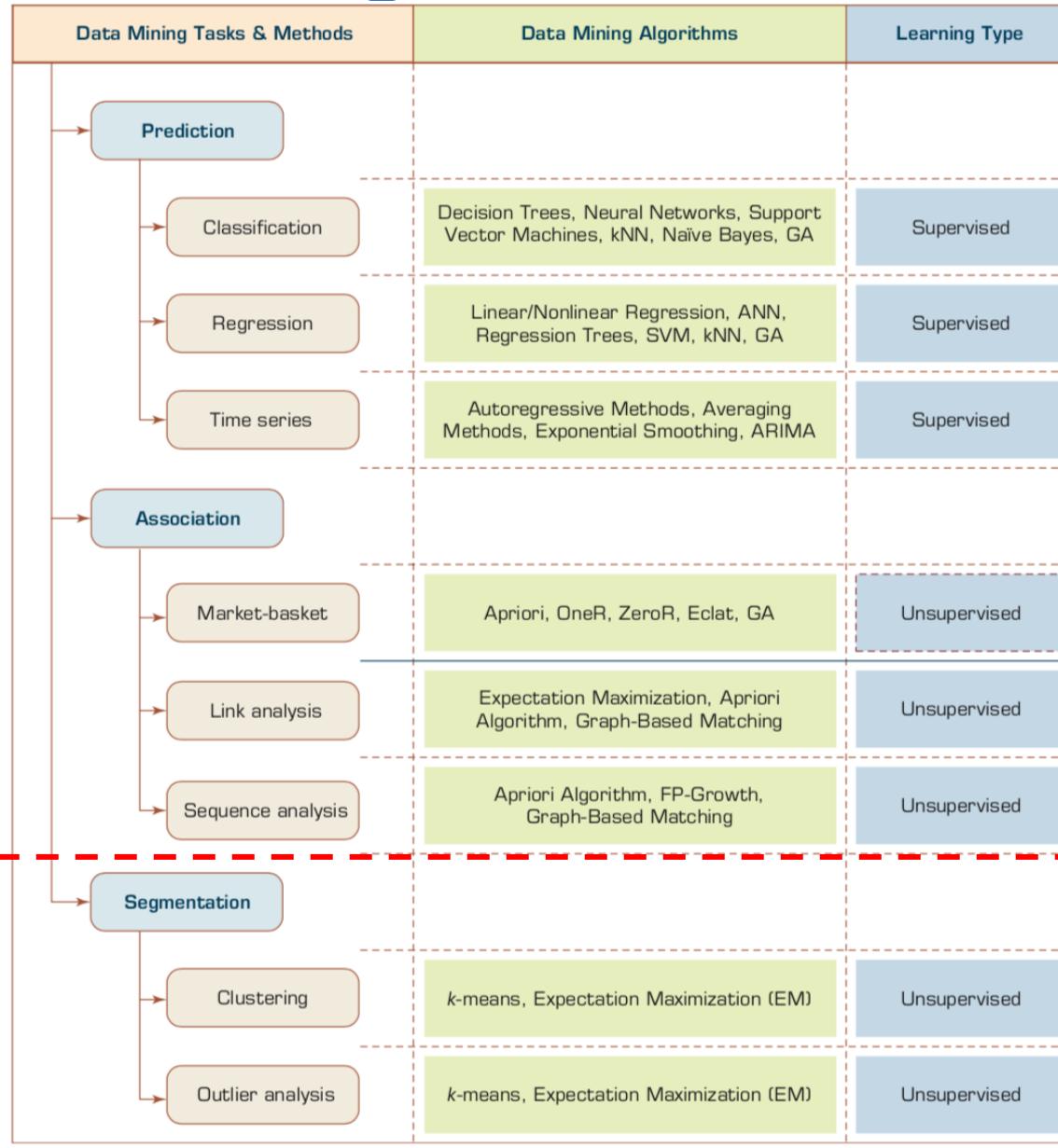
Semantic Textual Similarity



Natural Language Processing (NLP) and Text Mining



Data Mining Tasks & Methods



Example of Cluster Analysis

Point	P	P(x,y)
p01	a	(3, 4)
p02	b	(3, 6)
p03	c	(3, 8)
p04	d	(4, 5)
p05	e	(4, 7)
p06	f	(5, 1)
p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

K-Means Clustering

Point	P	P(x,y)	m1 distance	m2 distance	Cluster
p01	a	(3, 4)	1.95	3.78	Cluster1
p02	b	(3, 6)	0.69	4.51	Cluster1
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p04	d	(4, 5)	0.89	3.13	Cluster1
p05	e	(4, 7)	1.22	4.45	Cluster1
p06	f	(5, 1)	5.01	3.05	Cluster2
p07	g	(5, 5)	1.57	2.30	Cluster1
p08	h	(7, 3)	4.37	0.56	Cluster2
p09	i	(7, 5)	3.43	1.52	Cluster2
p10	j	(8, 5)	4.41	1.95	Cluster2

m1 (3.67, 5.83)

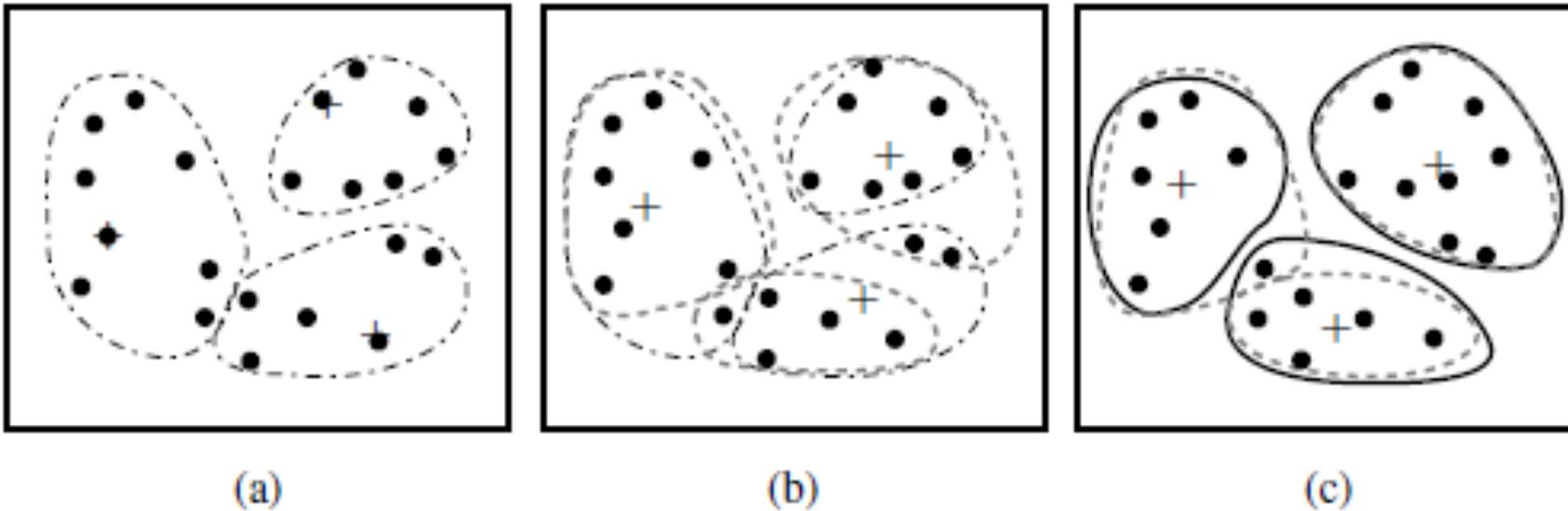
m2 (6.75, 3.50)

Cluster Analysis

Cluster Analysis

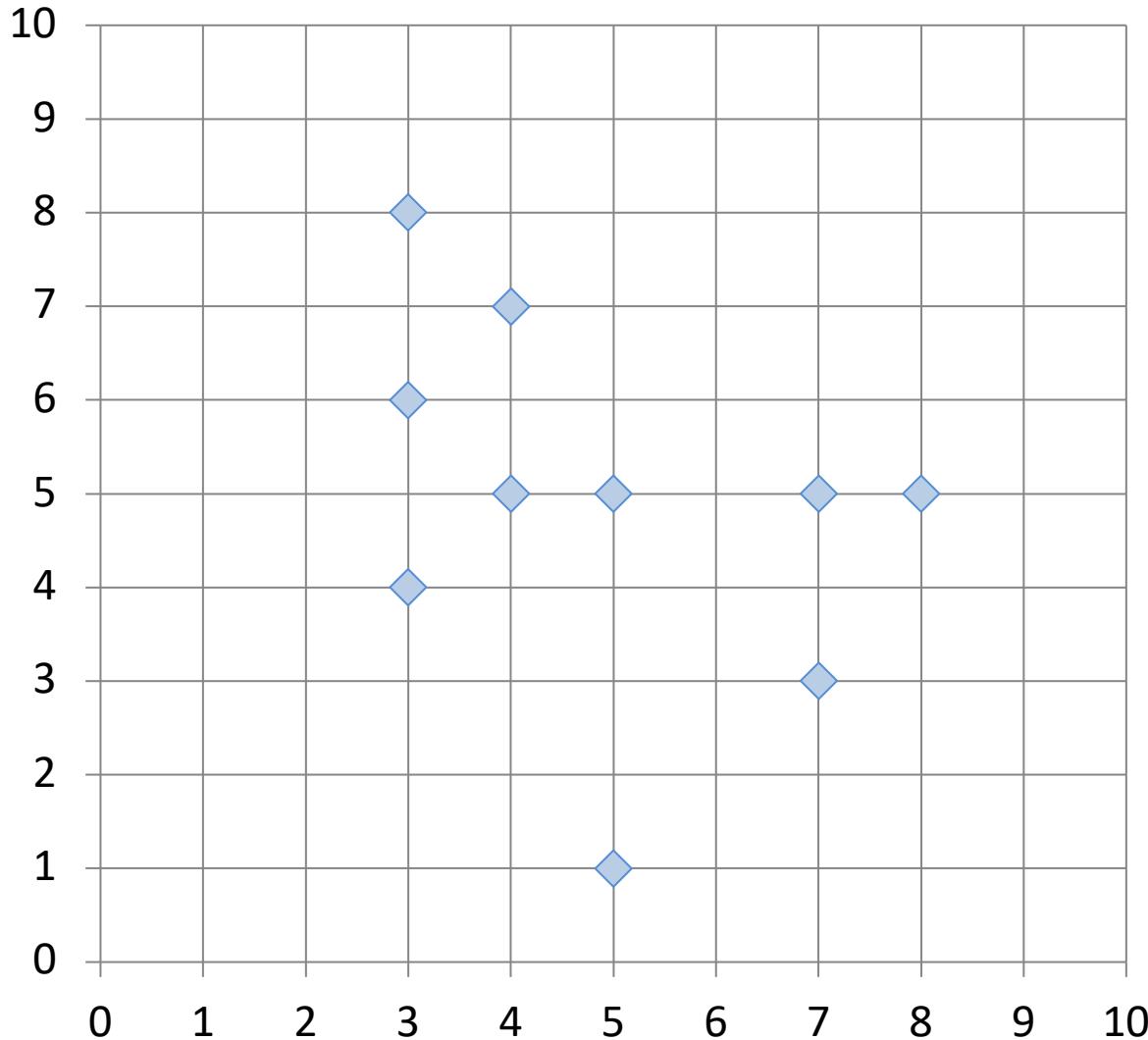
- Used for automatic identification of **natural groupings** of things
- Part of the machine-learning family
- Employ **unsupervised learning**
- Learns the clusters of things from past data, then assigns new instances
- There is not an output variable
- Also known as **segmentation**

Cluster Analysis



Clustering of a set of objects based on the *k-means method*.
(The mean of each cluster is marked by a “+”.)

Example of Cluster Analysis



Cluster Analysis for Data Mining

- **How many clusters?**
 - There is not a “truly optimal” way to calculate it
 - Heuristics are often used
 1. Look at the sparseness of clusters
 2. Number of clusters = $(n/2)^{1/2}$ (n: no of data points)
 3. Use Akaike information criterion (AIC)
 4. Use Bayesian information criterion (BIC)
- Most cluster analysis methods involve the use of a **distance measure** to calculate the closeness between pairs of items
 - Euclidian versus Manhattan (rectilinear) distance

***k*-Means Clustering Algorithm**

- k : pre-determined number of clusters
- Algorithm (**Step 0:** determine value of k)

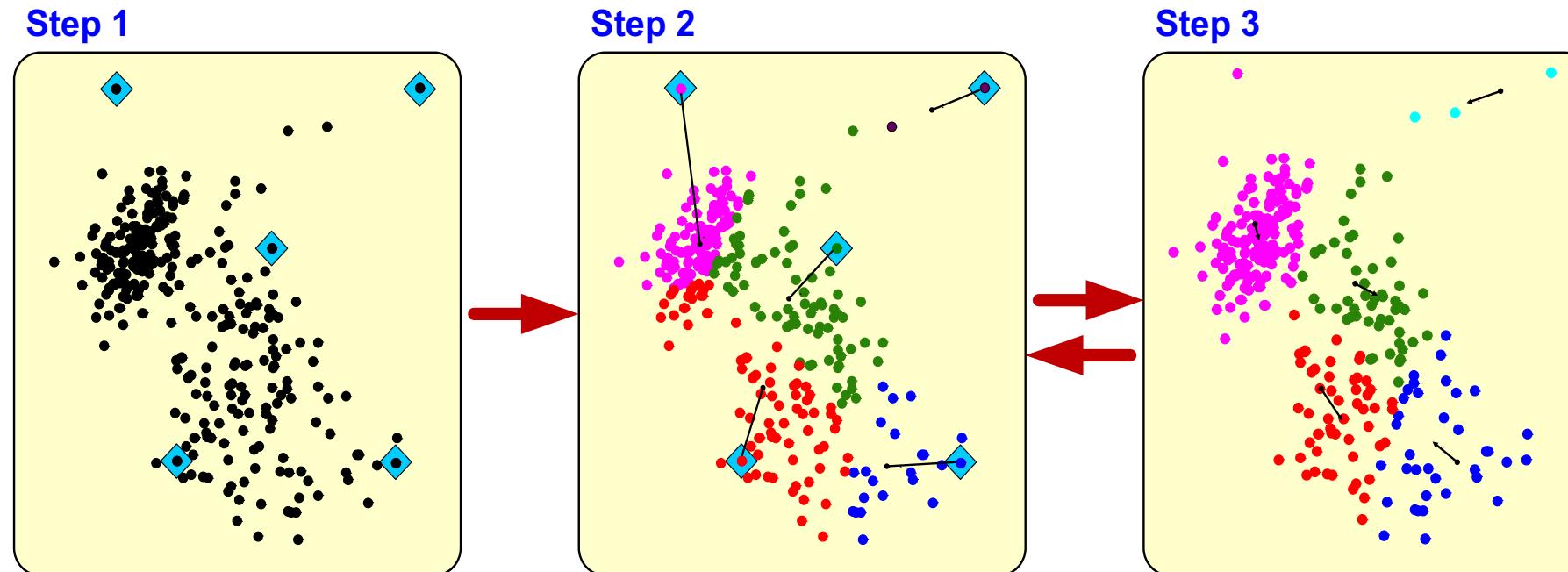
Step 1: Randomly generate k random points as initial cluster centers

Step 2: Assign each point to the nearest cluster center

Step 3: Re-compute the new cluster centers

Repetition step: Repeat steps 2 and 3 until some convergence criterion is met (usually that the assignment of points to clusters becomes stable)

Cluster Analysis for Data Mining - k -Means Clustering Algorithm



Similarity

Distance

Similarity and Dissimilarity Between Objects

- Distances are normally used to measure the similarity or dissimilarity between two data objects
- Some popular ones include: *Minkowski distance*:

$$d(i,j) = \sqrt[q]{(|x_{i1} - x_{j1}|^q + |x_{i2} - x_{j2}|^q + \dots + |x_{ip} - x_{jp}|^q)}$$

where $i = (x_{i1}, x_{i2}, \dots, x_{ip})$ and $j = (x_{j1}, x_{j2}, \dots, x_{jp})$ are two p -dimensional data objects, and q is a positive integer

- If $q = 1$, d is *Manhattan distance*

$$d(i,j) = |x_{i1} - x_{j1}| + |x_{i2} - x_{j2}| + \dots + |x_{ip} - x_{jp}|$$

Similarity and Dissimilarity Between Objects (Cont.)

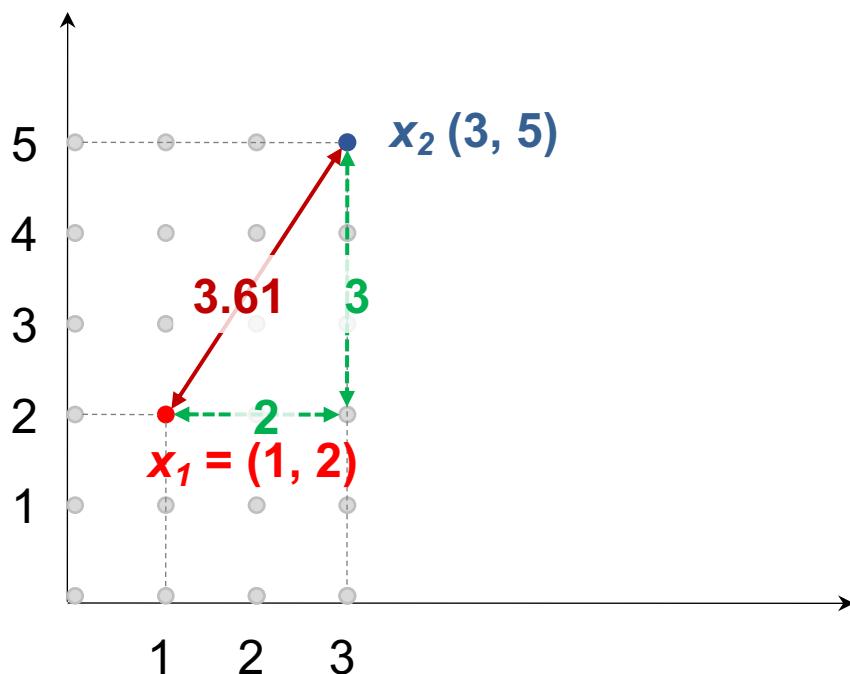
- If $q = 2$, d is **Euclidean distance**:

$$d(i,j) = \sqrt{(|x_{i_1} - x_{j_1}|^2 + |x_{i_2} - x_{j_2}|^2 + \dots + |x_{i_p} - x_{j_p}|^2)}$$

- **Properties**
 - $d(i,j) \geq 0$
 - $d(i,i) = 0$
 - $d(i,j) = d(j,i)$
 - $d(i,j) \leq d(i,k) + d(k,j)$
- **Also, one can use weighted distance, parametric Pearson product moment correlation, or other disimilarity measures**

Euclidean distance vs Manhattan distance

- Distance of two point $x_1 = (1, 2)$ and $x_2 (3, 5)$

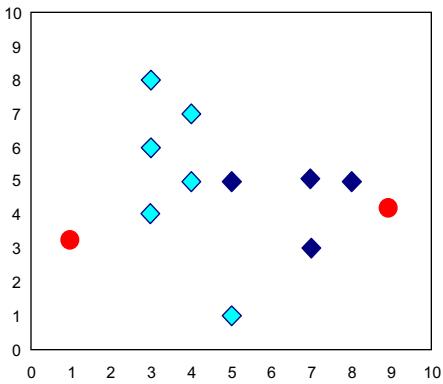


Euclidean distance:
 $= ((3-1)^2 + (5-2)^2)^{1/2}$
 $= (2^2 + 3^2)^{1/2}$
 $= (4 + 9)^{1/2}$
 $= (13)^{1/2}$
 $= 3.61$

Manhattan distance:
 $= (3-1) + (5-2)$
 $= 2 + 3$
 $= 5$

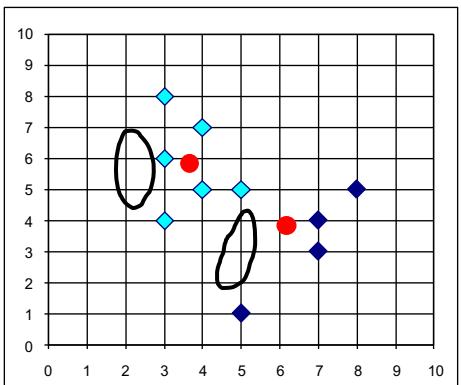
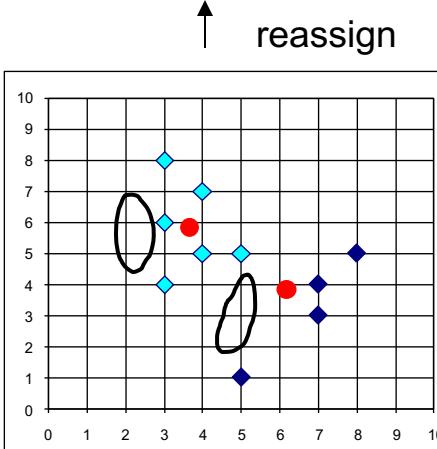
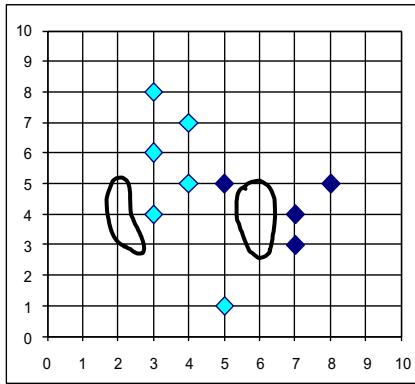
The *K*-Means Clustering Method

- Example



K=2
Arbitrarily choose K object as initial cluster center

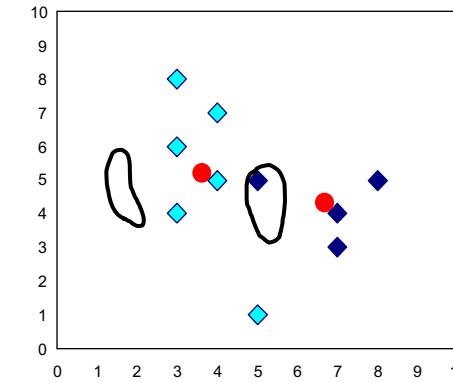
Assign each objects to most similar center



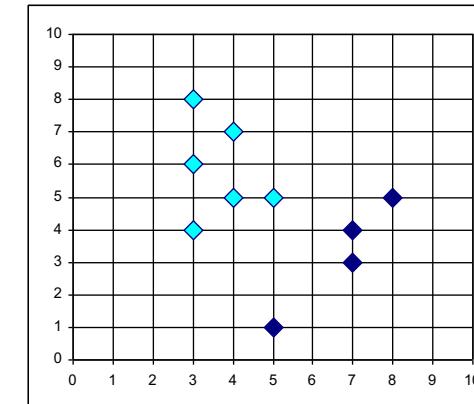
Update the cluster means

Update the cluster means

reassign



reassign



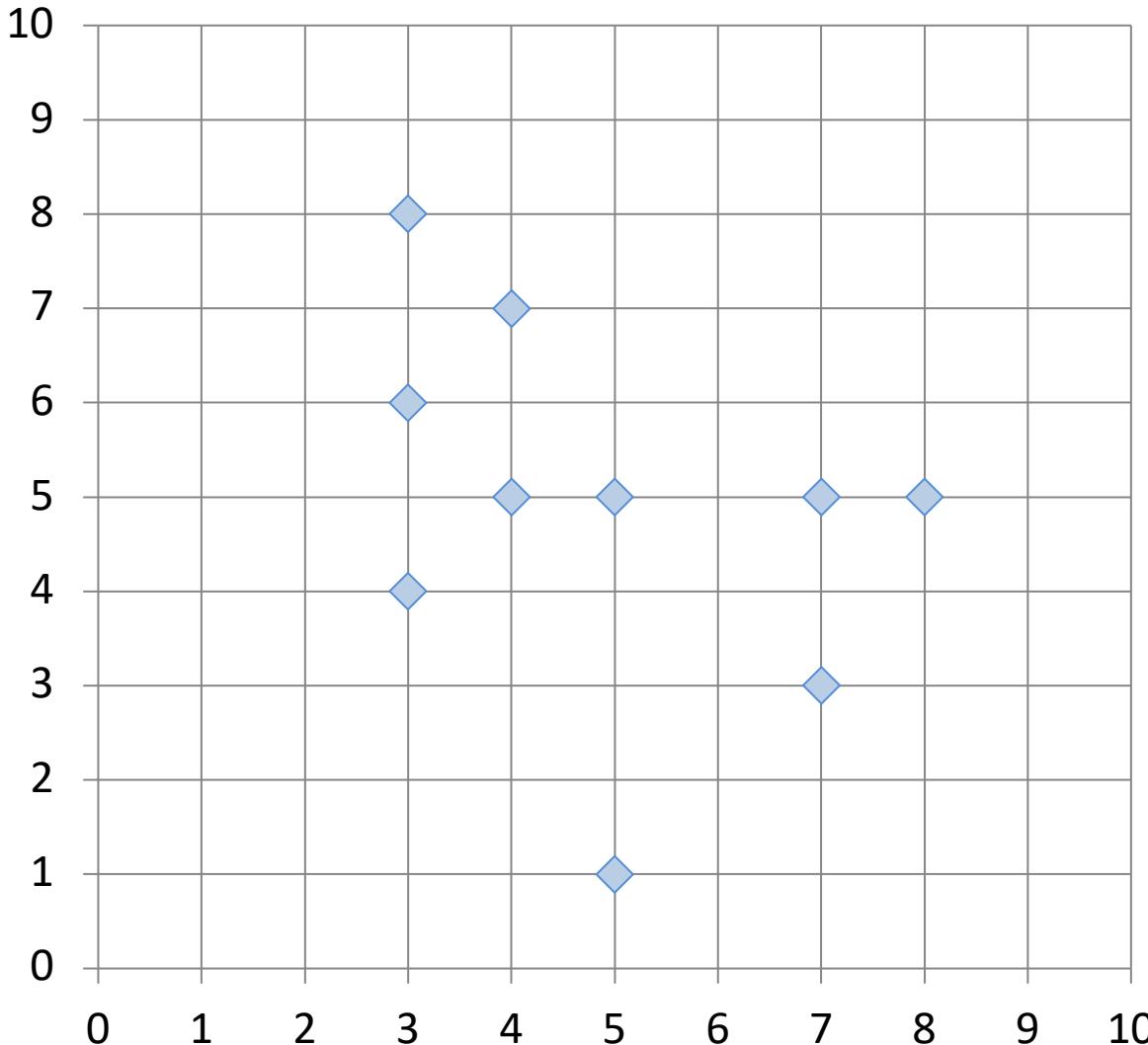
K-Means Clustering

Example of Cluster Analysis

Point	P	P(x,y)
p01	a	(3, 4)
p02	b	(3, 6)
p03	c	(3, 8)
p04	d	(4, 5)
p05	e	(4, 7)
p06	f	(5, 1)
p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

K-Means Clustering

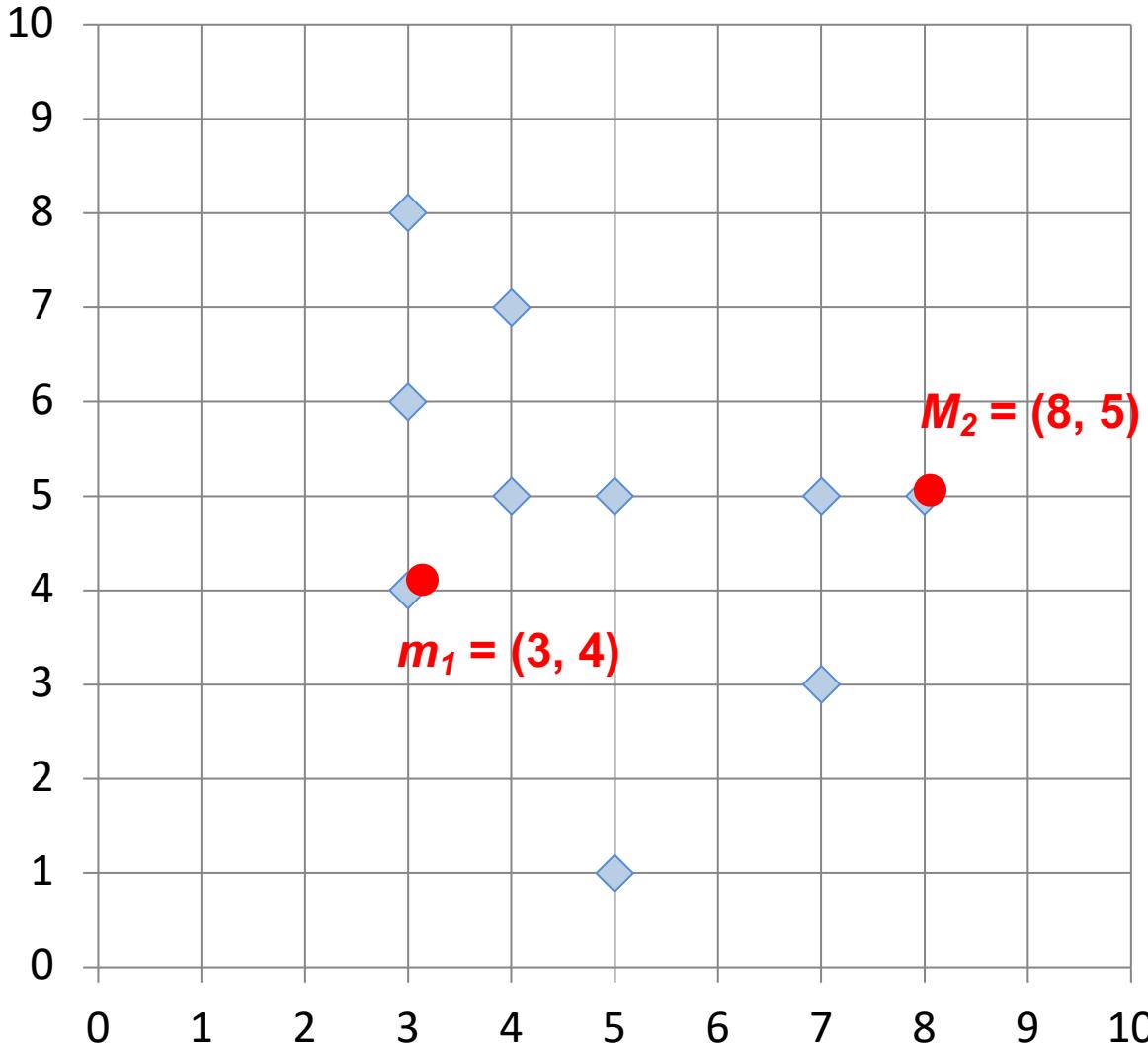
Step by Step



Point	P	P(x,y)
p01	a	(3, 4)
p02	b	(3, 6)
p03	c	(3, 8)
p04	d	(4, 5)
p05	e	(4, 7)
p06	f	(5, 1)
p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

K-Means Clustering

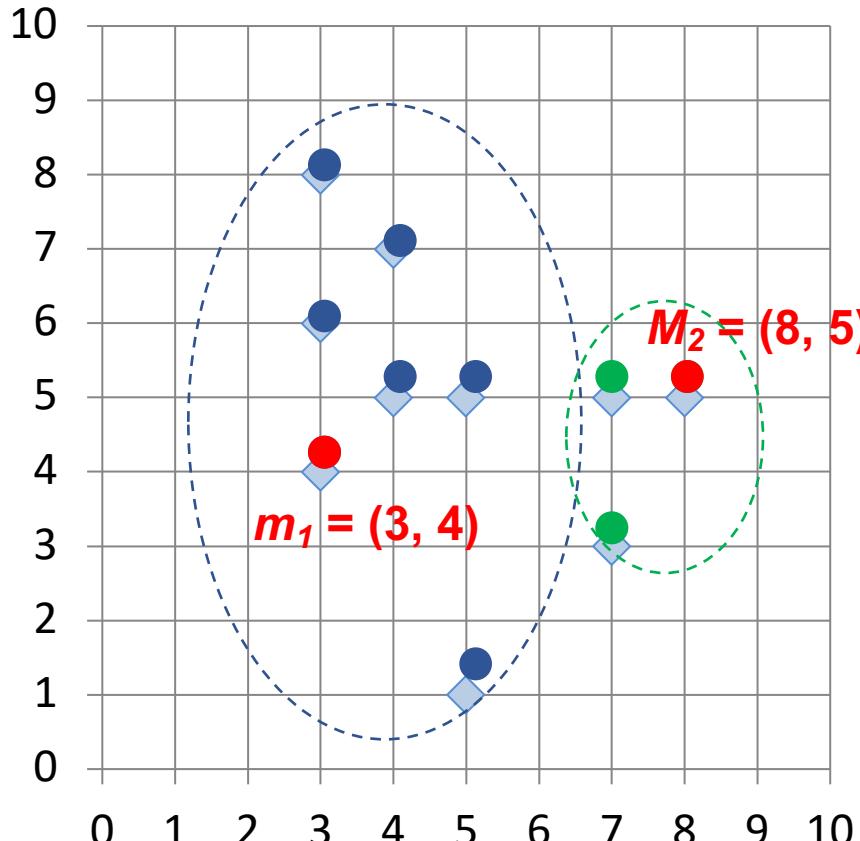
Step 1: K=2, Arbitrarily choose K object as initial cluster center



Initial m_1 (3, 4)
Initial m_2 (8, 5)

Step 2: Compute seed points as the centroids of the clusters of the current partition

Step 3: Assign each objects to most similar center



K-Means Clustering

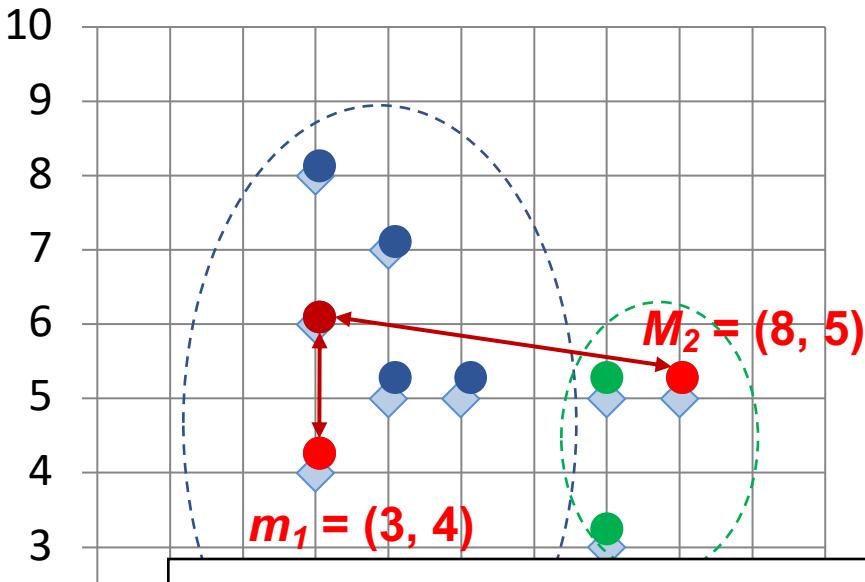
Initial $m_1 (3, 4)$

Initial $m_2 (8, 5)$

Point	P	P(x,y)	m1 distance	m2 distance	Cluster
p01	a	(3, 4)	0.00	5.10	Cluster1
p02	b	(3, 6)	2.00	5.10	Cluster1
p03	c	(3, 8)	4.00	5.83	Cluster1
p04	d	(4, 5)	1.41	4.00	Cluster1
p05	e	(4, 7)	3.16	4.47	Cluster1
p06	f	(5, 1)	3.61	5.00	Cluster1
p07	g	(5, 5)	2.24	3.00	Cluster1
p08	h	(7, 3)	4.12	2.24	Cluster2
p09	i	(7, 5)	4.12	1.00	Cluster2
p10	j	(8, 5)	5.10	0.00	Cluster2

Step 2: Compute seed points as the centroids of the clusters of the current partition

Step 3: Assign each objects to most similar center



K-1

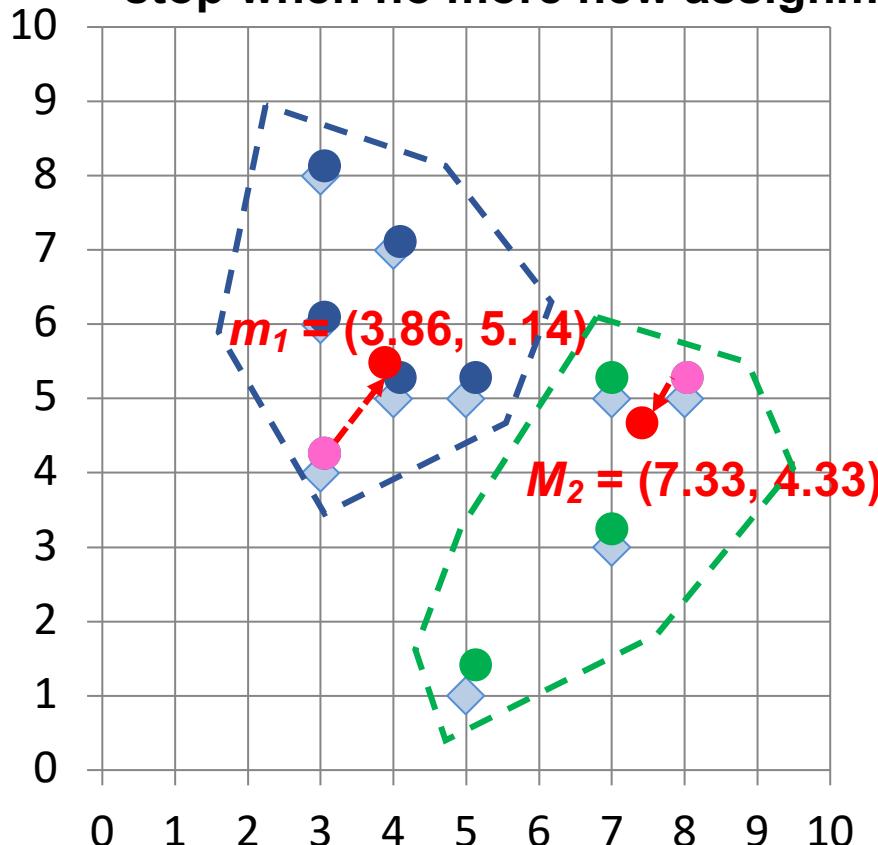
Euclidean distance
 $b(3,6) \leftrightarrow m1(3,4)$
 $= ((3-3)^2 + (4-6)^2)^{1/2}$
 $= (0^2 + (-2)^2)^{1/2}$
 $= (0 + 4)^{1/2}$
 $= (4)^{1/2}$
 $= 2.00$

Point	P	P(x,y)	m1 distance	m2 distance	Cluster
p01	a	(3, 4)	0.00	5.10	Cluster1
p02	b	(3, 6)	2.00	5.10	Cluster1
p03	c	(3, 8)	4.00	5.83	Cluster1
p04	d	(4, 5)	1.41	4.00	Cluster1
p05			Euclidean distance		
p06			$b(3,6) \leftrightarrow M_2(8,5)$		
p07			$= ((8-3)^2 + (5-6)^2)^{1/2}$		
p08			$= (5^2 + (-1)^2)^{1/2}$		Cluster2
p09			$= (25 + 1)^{1/2}$		Cluster2
p10			$= (26)^{1/2}$		Cluster2

Initial $m_1 (3, 4)$

Initial $m_2 (8, 5)$

**Step 4: Update the cluster means,
Repeat Step 2, 3,
stop when no more new assignment**

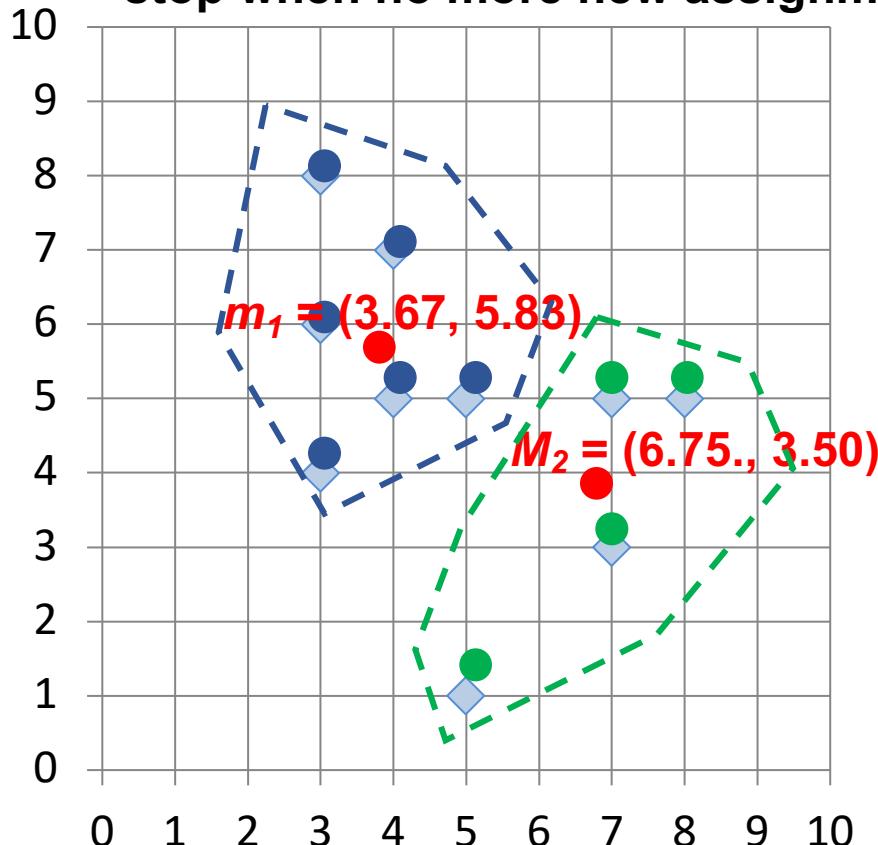


Point	P	P(x,y)	m_1 distance	m_2 distance	Cluster
p01	a	(3, 4)	1.43	4.34	Cluster1
p02	b	(3, 6)	1.22	4.64	Cluster1
p03	c	(3, 8)	2.99	5.68	Cluster1
p04	d	(4, 5)	0.20	3.40	Cluster1
p05	e	(4, 7)	1.87	4.27	Cluster1
p06	f	(5, 1)	4.29	4.06	Cluster2
p07	g	(5, 5)	1.15	2.42	Cluster1
p08	h	(7, 3)	3.80	1.37	Cluster2
p09	i	(7, 5)	3.14	0.75	Cluster2
p10	j	(8, 5)	4.14	0.95	Cluster2

$$\begin{aligned}m_1 &= (3.86, 5.14) \\m_2 &= (7.33, 4.33)\end{aligned}$$

K-Means Clustering

**Step 4: Update the cluster means,
Repeat Step 2, 3,
stop when no more new assignment**

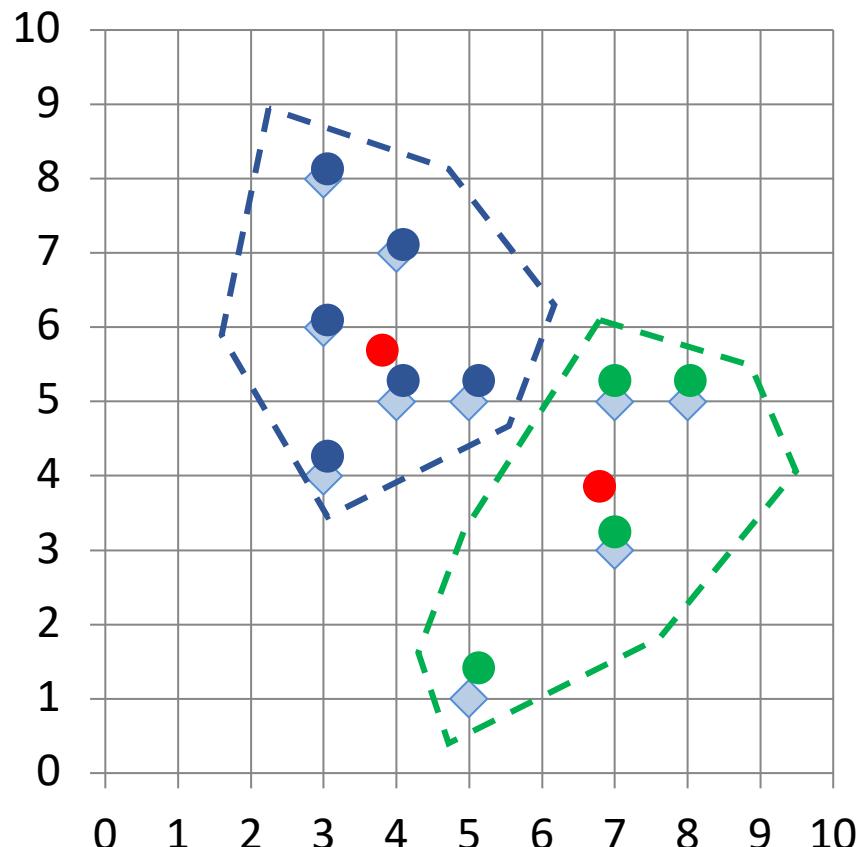


K-Means Clustering

Point	P	P(x,y)	m_1 distance	m_2 distance	Cluster
p01	a	(3, 4)	1.95	3.78	Cluster1
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p04	d	(4, 5)	0.89	3.13	Cluster1
p05	e	(4, 7)	1.22	4.45	Cluster1
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p07	g	(5, 5)	1.57	2.30	Cluster1
p08	h	(7, 3)	4.37	0.56	Cluster2
p09	i	(7, 5)	3.43	1.52	Cluster2
p10	j	(8, 5)	4.41	1.95	Cluster2

$$\begin{aligned}m_1 &= (3.67, 5.83) \\m_2 &= (6.75, 3.50)\end{aligned}$$

stop when no more new assignment

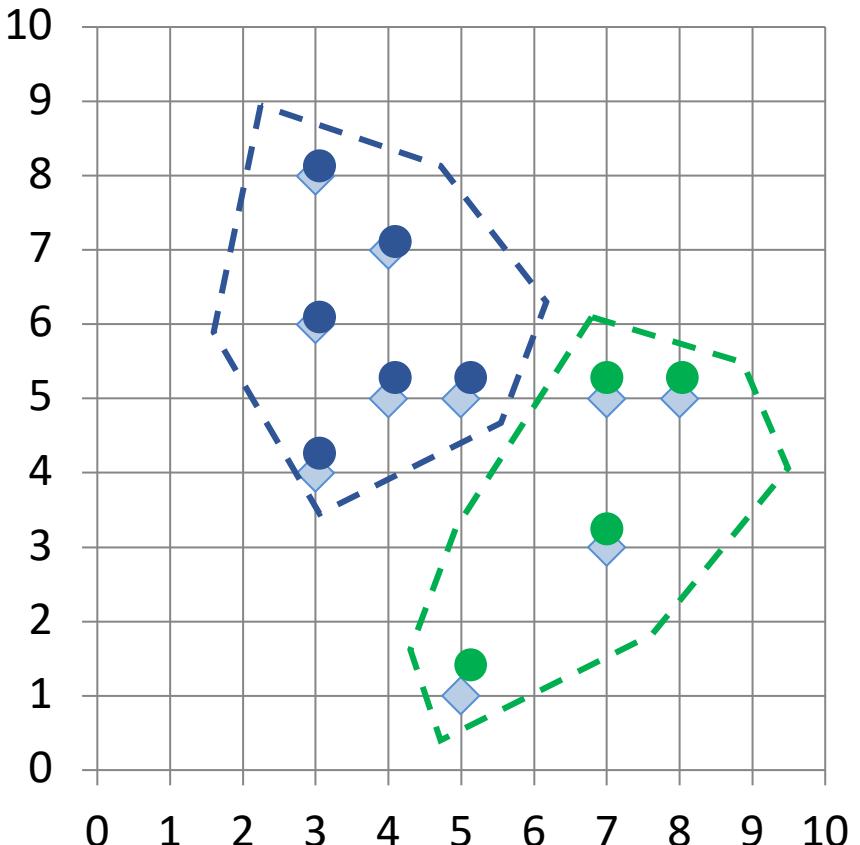


K-Means Clustering

$$\begin{aligned} m_1 & (3.67, 5.83) \\ m_2 & (6.75, 3.50) \end{aligned}$$

K-Means Clustering ($K=2$, two clusters)

stop when no more new assignment



Point	P	P(x,y)	m ₁ distance	m ₂ distance	Cluster
p01	a	(3, 4)	1.95	3.78	Cluster1
p02	b	(3, 6)	0.69	4.51	Cluster1
p03	c	(3, 8)	2.27	5.86	Cluster1
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$$m_1 \ (3.67, 5.83)$$

$$m_2 \ (6.75, 3.50)$$

K-Means Clustering

K-Means Clustering

Point	P	P(x,y)	m1 distance	m2 distance	Cluster
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p09	i	(7, 5)	3.43	1.52	Cluster2
p10	j	(8, 5)	4.41	1.95	Cluster2

m1 (3.67, 5.83)

m2 (6.75, 3.50)

gensim

The screenshot shows the official website for gensim. At the top left is a GitHub fork button labeled "Fork me on GitHub". To the right is the gensim logo, which includes a circular icon with "SS PIW 2.0" and a blue "gensim" title with the subtitle "topic modelling for humans". On the right side are two download buttons: a green one for "Download" from the Python Package Index, and a yellow one for "Direct install with: easy_install -U gensim". Below the main title is a navigation bar with links for Home, Tutorials, Install, Support, API, and About. The "Home" link is highlighted with a blue background. A large blue box at the bottom contains a Python code snippet demonstrating gensim's functionality:

```
>>> from gensim import corpora, models, similarities
>>>
>>> # Load corpus iterator from a Matrix Market file on disk.
>>> corpus = corpora.MmCorpus('/path/to/corpus.mm')
>>>
>>> # Initialize Latent Semantic Indexing with 200 dimensions.
>>> lsi = models.LsiModel(corpus, num_topics=200)
>>>
>>> # Convert another corpus to the Latent space and index it.
>>> index = similarities.MatrixSimilarity(lsi[another_corpus])
>>>
>>> # Compute similarity of a query vs. indexed documents
>>> sims = index[query]
```

To the right of the code box is a section titled "Gensim is a FREE Python library" with three bullet points:

- Scalable statistical semantics
- Analyze plain-text documents for semantic structure
- Retrieve semantically similar documents

spaCy

The screenshot shows the official spaCy website. At the top left is the spaCy logo. At the top right are links for HOME, USAGE, API, DEMOS, BLOG, and a user icon. The main title "Industrial-Strength Natural Language Processing" is prominently displayed in large white font against a blue background with a faint technical icon pattern. Below the title, it says "in Python". The page features three white callout boxes: "Fastest in the world", "Get things done", and "Deep learning", each containing descriptive text.

spaCy

HOME USAGE API DEMOS BLOG

Industrial-Strength Natural Language Processing

in Python

Fastest in the world

spaCy excels at large-scale information extraction tasks. It's written from the ground up in carefully memory-managed Cython. Independent research has confirmed that spaCy is the fastest in the world. If your application needs to process entire web dumps, spaCy is the library you want to be using.

Get things done

spaCy is designed to help you do real work — to build real products, or gather real insights. The library respects your time, and tries to avoid wasting it. It's easy to install, and its API is simple and productive. I like to think of spaCy as the Ruby on Rails of Natural Language Processing.

Deep learning

spaCy is the best way to prepare text for deep learning. It interoperates seamlessly with [TensorFlow](#), [Keras](#), [Scikit-Learn](#), [Gensim](#) and the rest of Python's awesome AI ecosystem. spaCy helps you connect the statistical models trained by these libraries to the rest of your application.

<https://spacy.io/>

Python in Google Colab (Python101)

<https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT>

The screenshot shows a Google Colab notebook interface. The title bar says 'python101.ipynb'. The left sidebar has a 'Table of contents' section with various sections like 'Build the model', 'Train the model', etc. A 'Text Similarity' section is currently selected. The main area shows a tree view with 'Text Similarity and Clustering' expanded, and 'Text Similarity' is also expanded. Below it, a bulleted list includes 'Spacy Vectors Similarity: <https://spacy.io/usage/vectors-similarity>'. The code editor contains several code snippets:

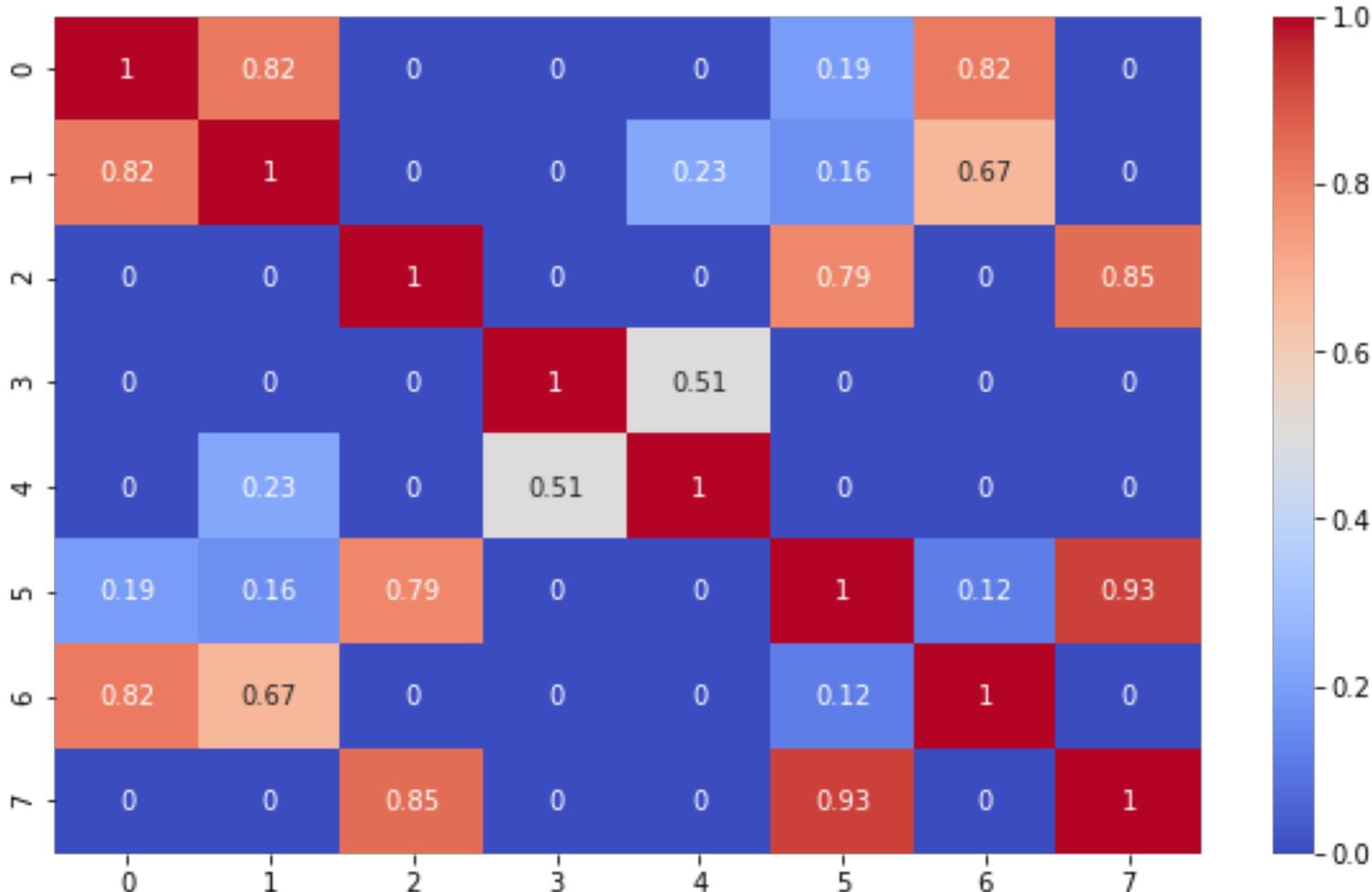
```
[1] 1 !python -m spacy download en_core_web_sm
[2] 1 !python -m spacy download en_core_web_lg
2 # Restart Runtime
[3] 1 import spacy
2 nlp = spacy.load("en_core_web_lg")
3 tokens = nlp("apple banana cat dog notaword")
4 for token in tokens:
5     print(token.text, token.has_vector, token.vector_norm, token.is_oov)
apple True 7.1346846 False
banana True 6.700014 False
cat True 6.6808186 False
dog True 7.0336733 False
notaword False 0.0 True
```

```
1 import spacy
2 nlp = spacy.load("en_core_web_lg")
3 doc1 = nlp("I like cat.")
4 doc2 = nlp("I like dog.")
5 doc1.similarity(doc2)
```

<https://tinyurl.com/aintpuppython101>

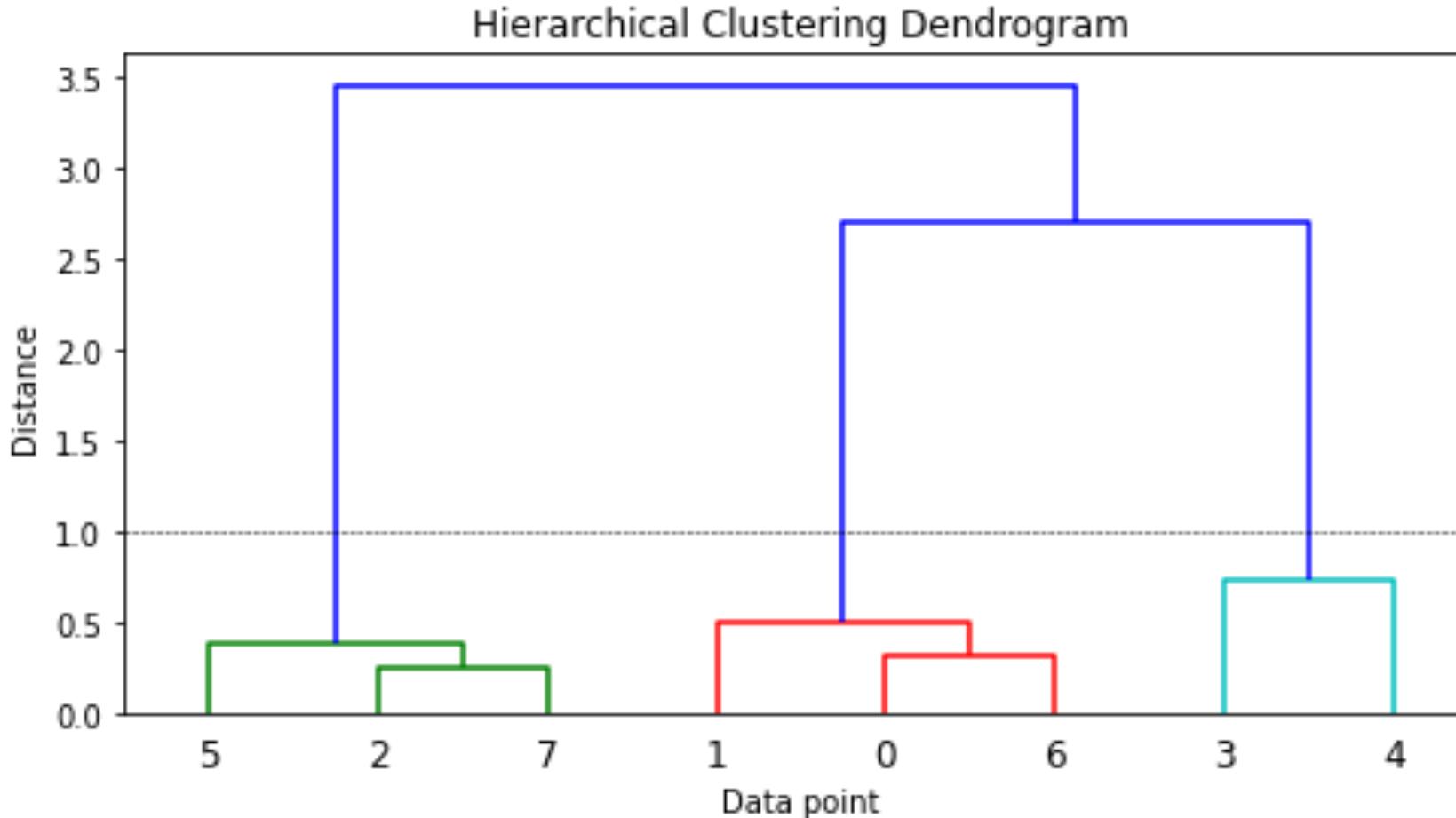
Python in Google Colab (Python101)

<https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT>



Python in Google Colab (Python101)

<https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT>



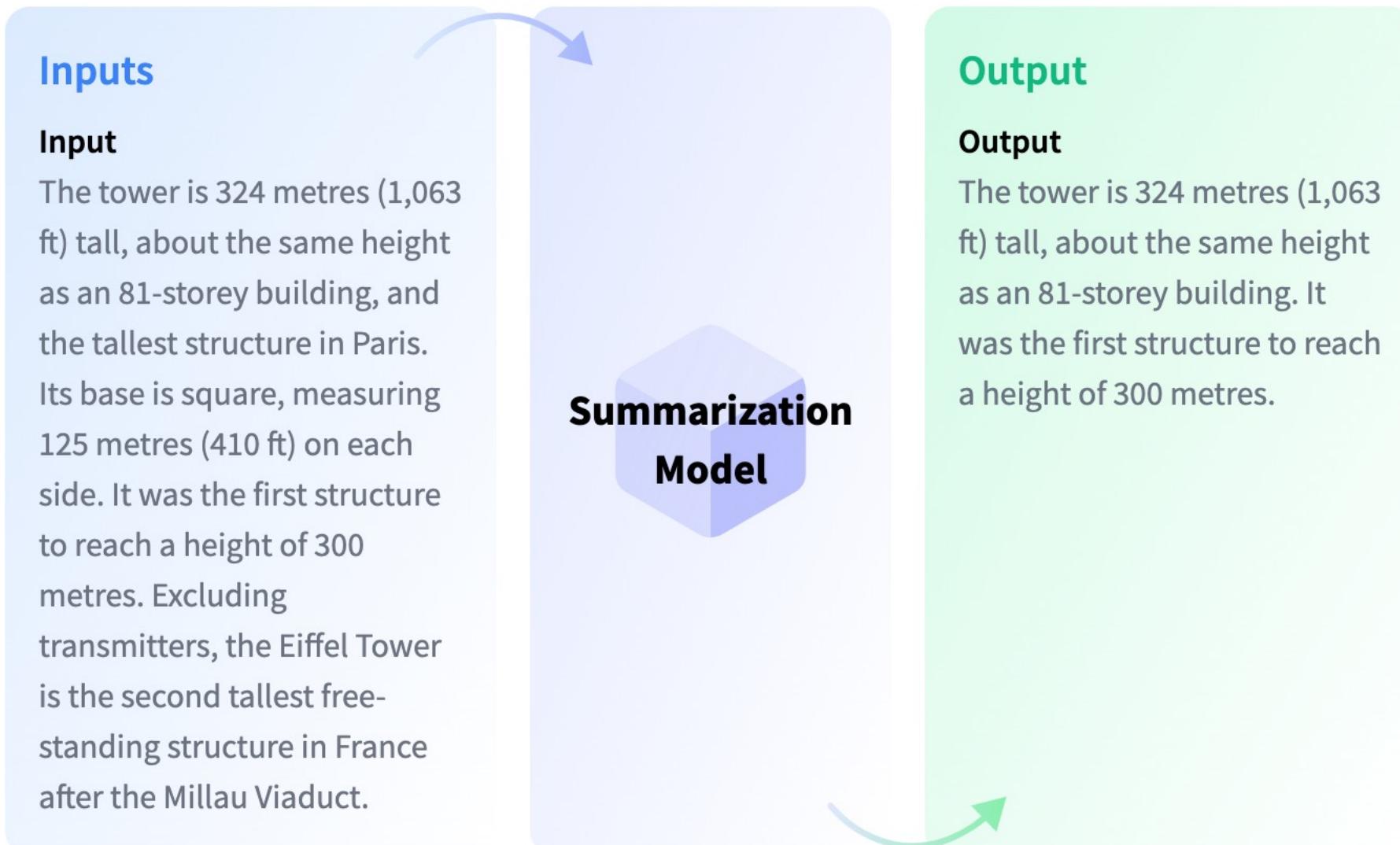
Text Summarization and Topic Models

Outline

- **Text Summarization**
 - **Extractive Text Summarization**
 - **Abstractive Text Summarization**
 - **PEGASUS: Abstractive Summarization**
- **Topic Models**
 - **Topic Modeling**
 - **Latent Dirichlet Allocation (LDA)**
 - **BERTopic**

Text Summarization

Text Summarization



Text Summarization

Summarization

Examples ▾

The tower is 324 metres (1,063 ft) tall, about the same height as an 81-storey building, and the tallest structure in Paris. Its base is square, measuring 125 metres (410 ft) on each side. During its construction, the Eiffel Tower surpassed the Washington Monument to become the tallest man-made structure in the world, a title it held for 41 years until the Chrysler Building in New York City was finished in 1930. It was the first structure to reach a height of 300 metres. Due to the addition of a broadcasting aerial at the top of the tower in 1957, it is now taller than the Chrysler Building by 5.2 metres (17 ft). Excluding transmitters, the Eiffel Tower is the second tallest free-standing structure in France after the Millau Viaduct.

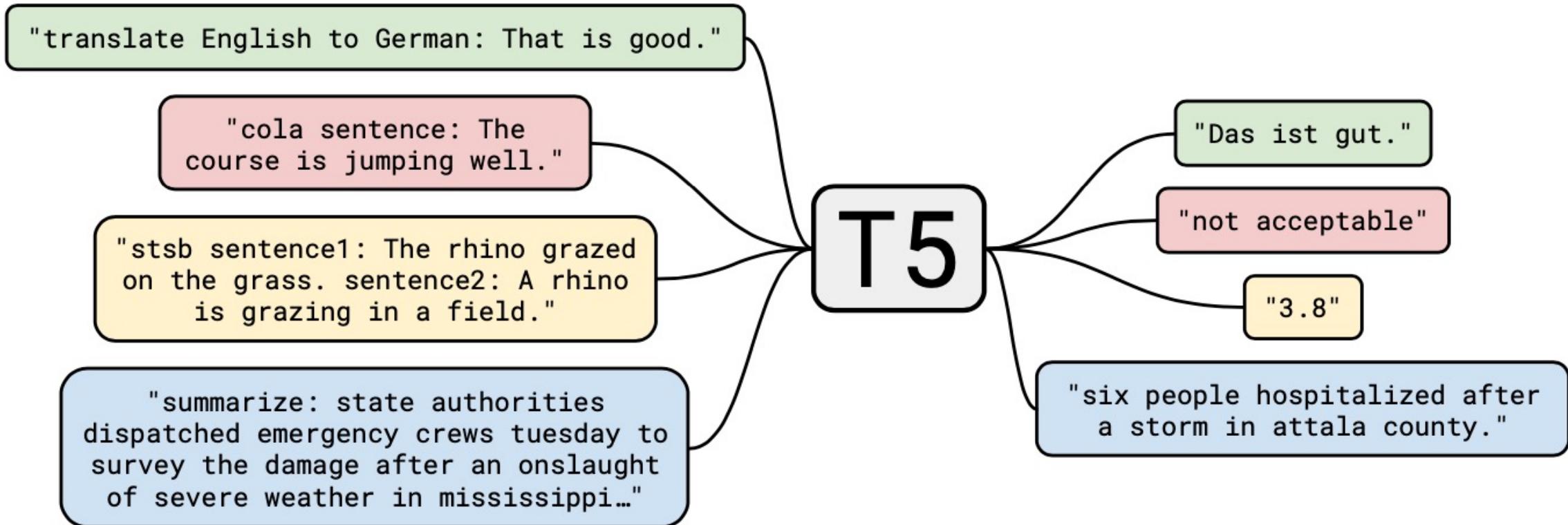
Compute

Computation time on cpu: cached

The tower is 324 metres (1,063 ft) tall, about the same height as an 81-storey building . It was the first structure to reach a height of 300 metres . It is now taller than the Chrysler Building in New York City by 5.2 metres (17 ft) Excluding transmitters, the Eiffel Tower is the second tallest free-standing structure in France .

T5

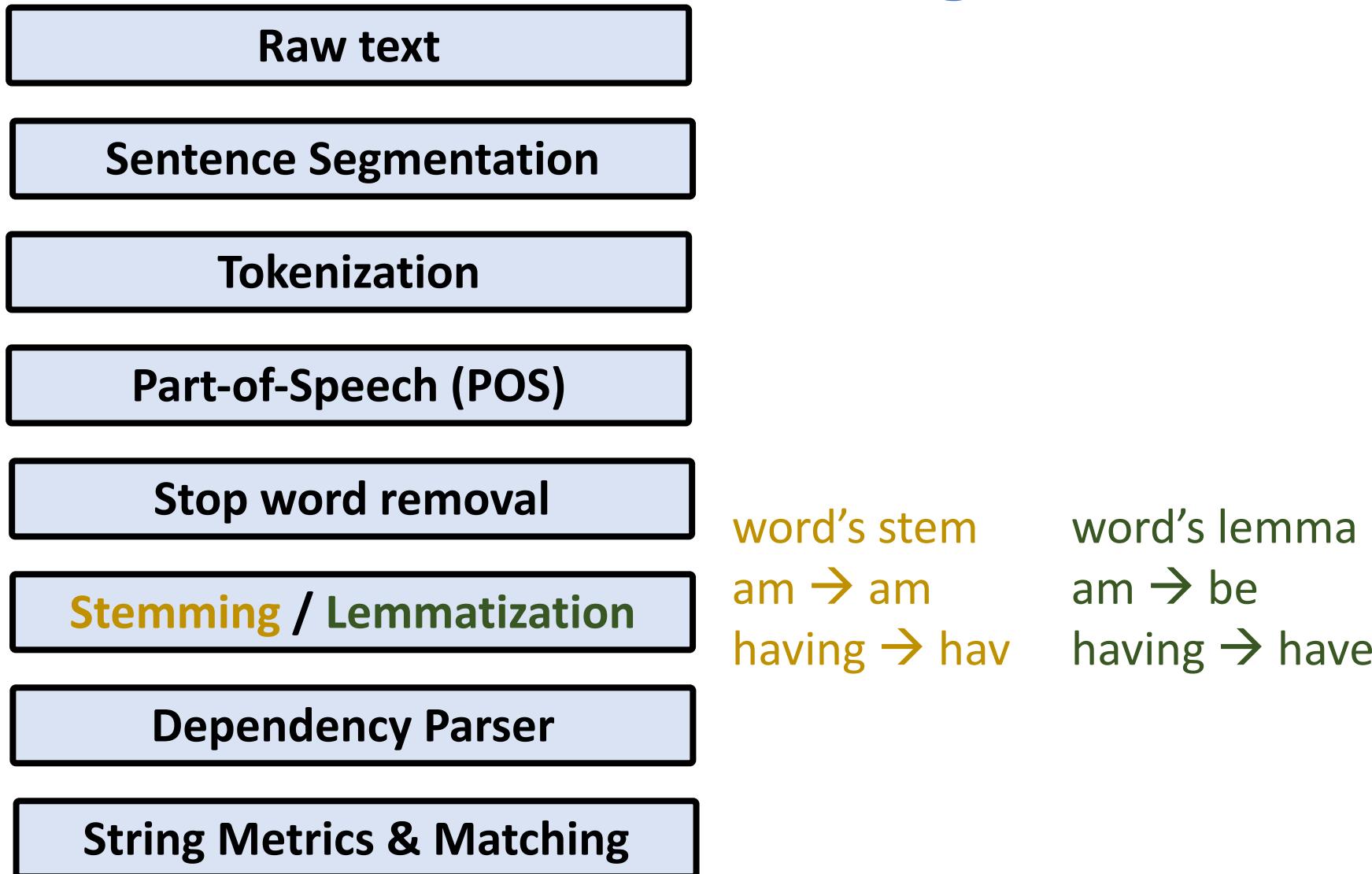
Text-to-Text Transfer Transformer



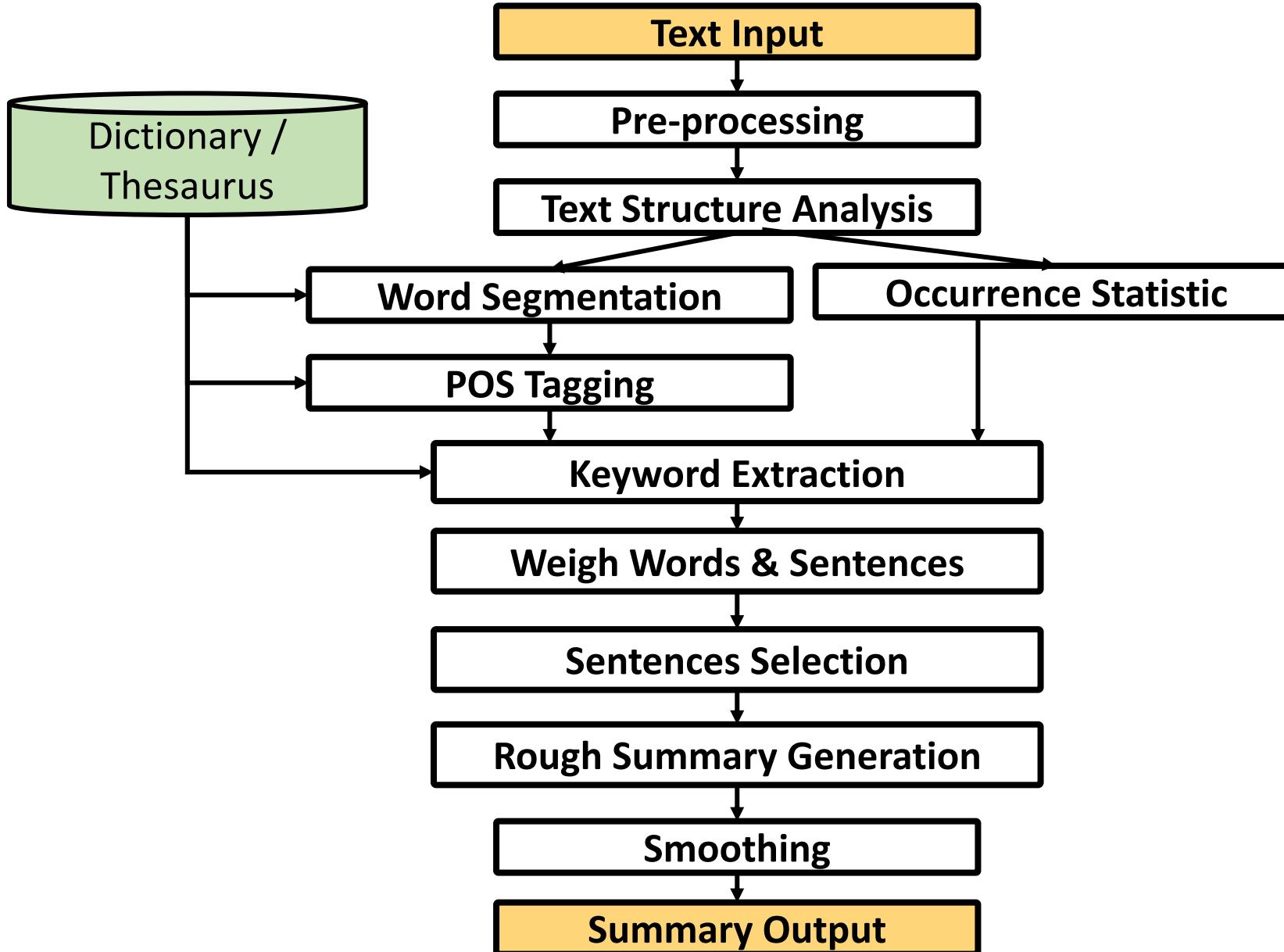
Text Summarization and Information Extraction

- Key-phrase extraction
 - extracting key influential phrases from the documents.
- Topic modeling
 - Extract various diverse concepts or topics present in the documents, retaining the major themes.
- Document summarization
 - Summarize entire text documents to provide a gist that retains the important parts of the whole corpus.

Natural Language Processing (NLP) and Text Mining

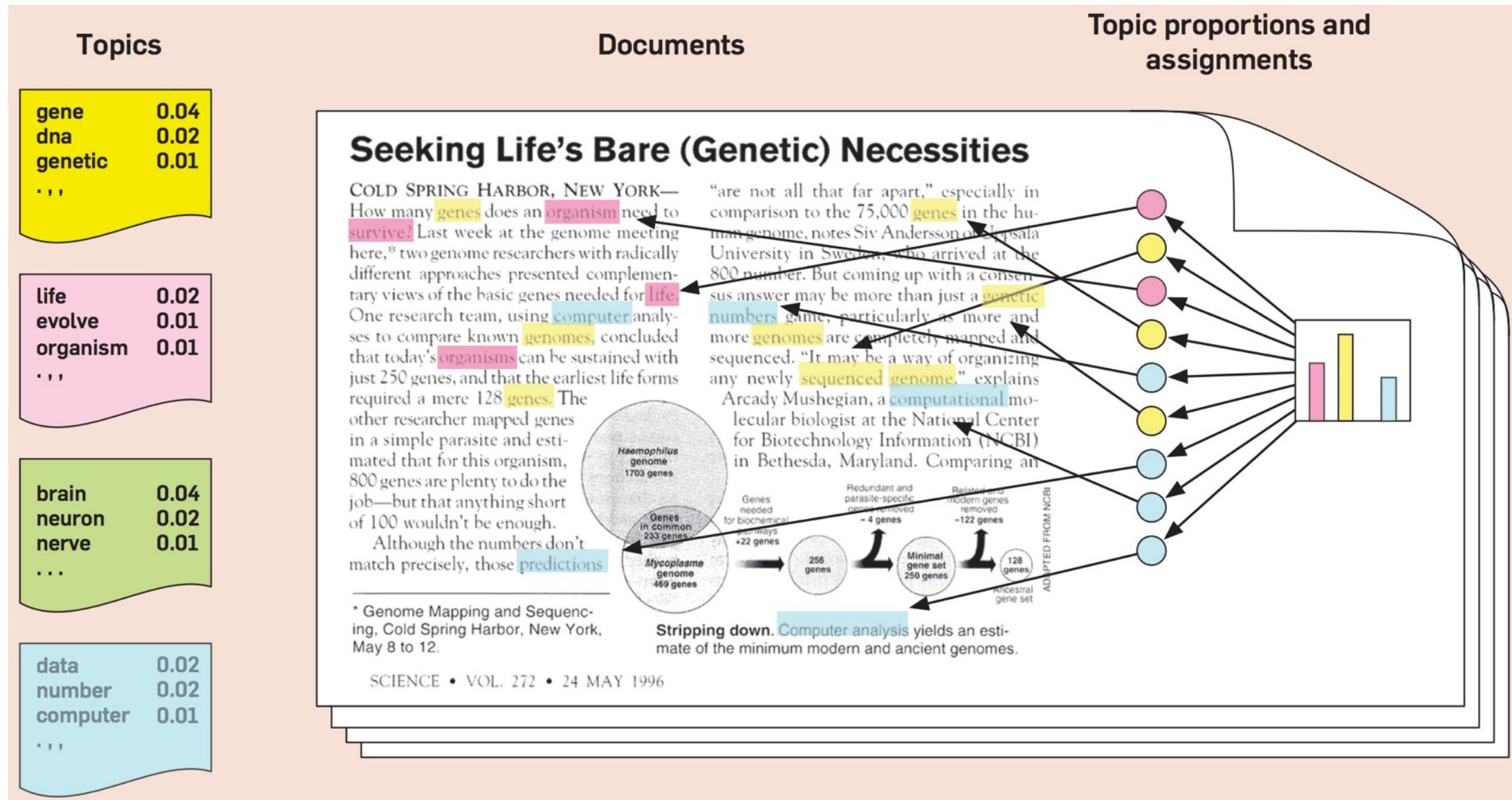


Text Summarization

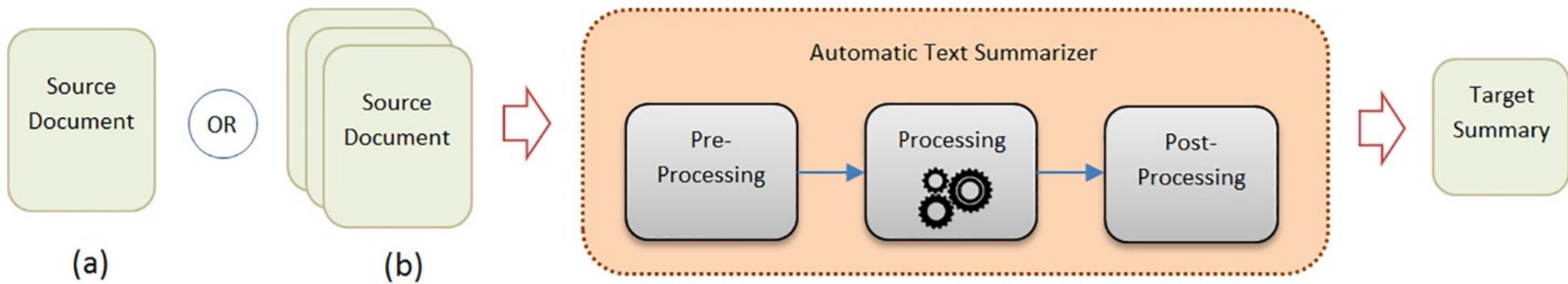


Source: Vishal Gupta and Gurpreet S. Lehal (2009), "A survey of text mining techniques and applications,"
Journal of emerging technologies in web intelligence, vol. 1, no. 1, pp. 60-76.

Topic Modeling

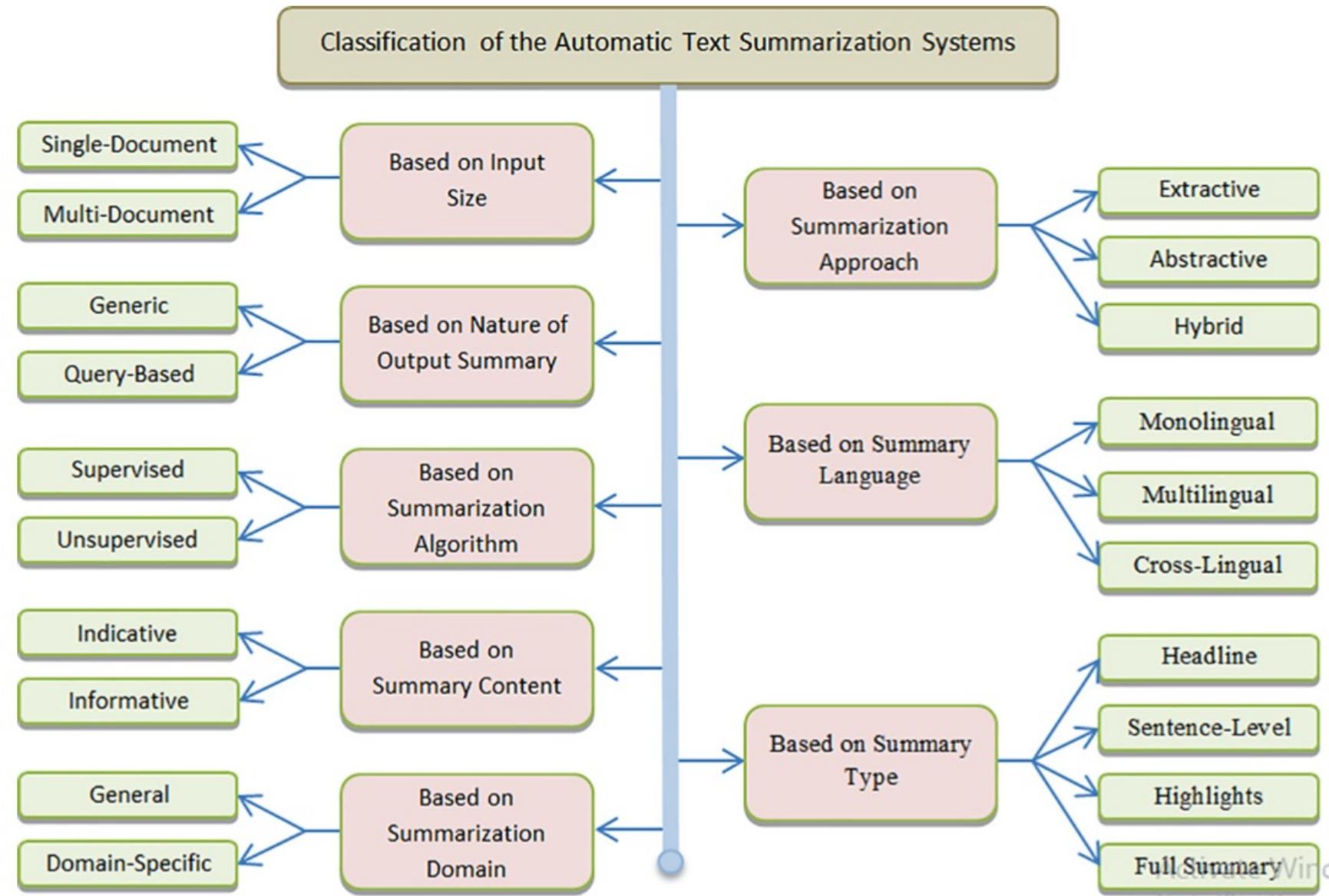


Automatic Text Summarization

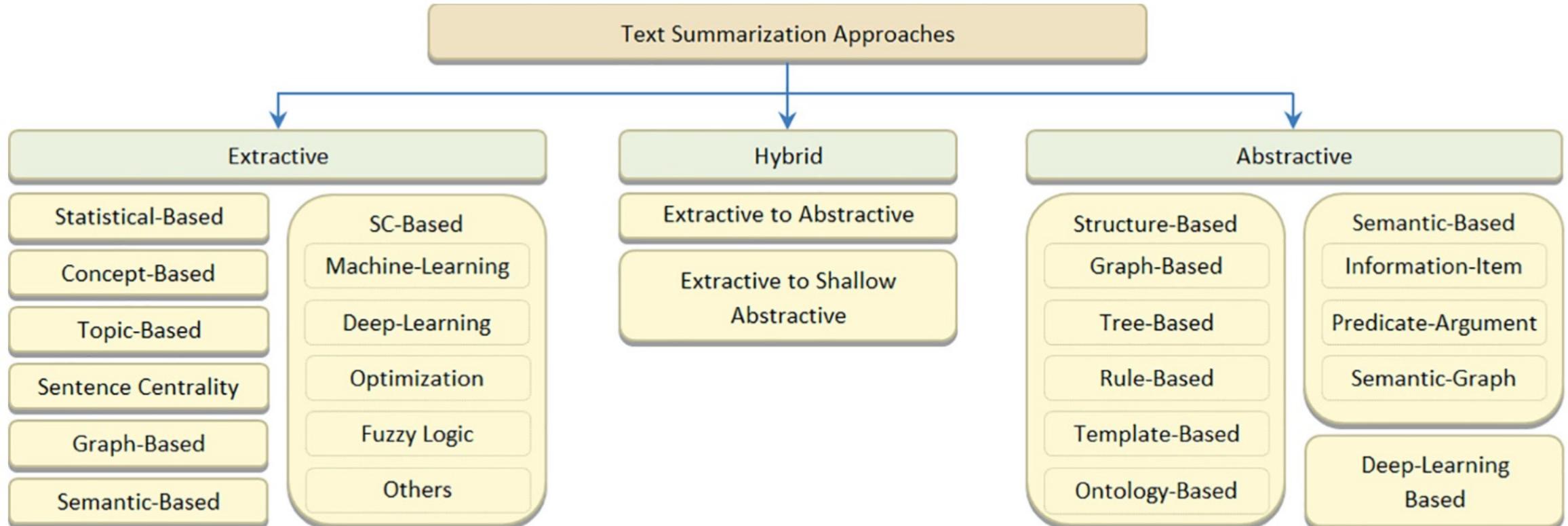


(a) Single-document or (b) Multi-document, automatic text summarizer

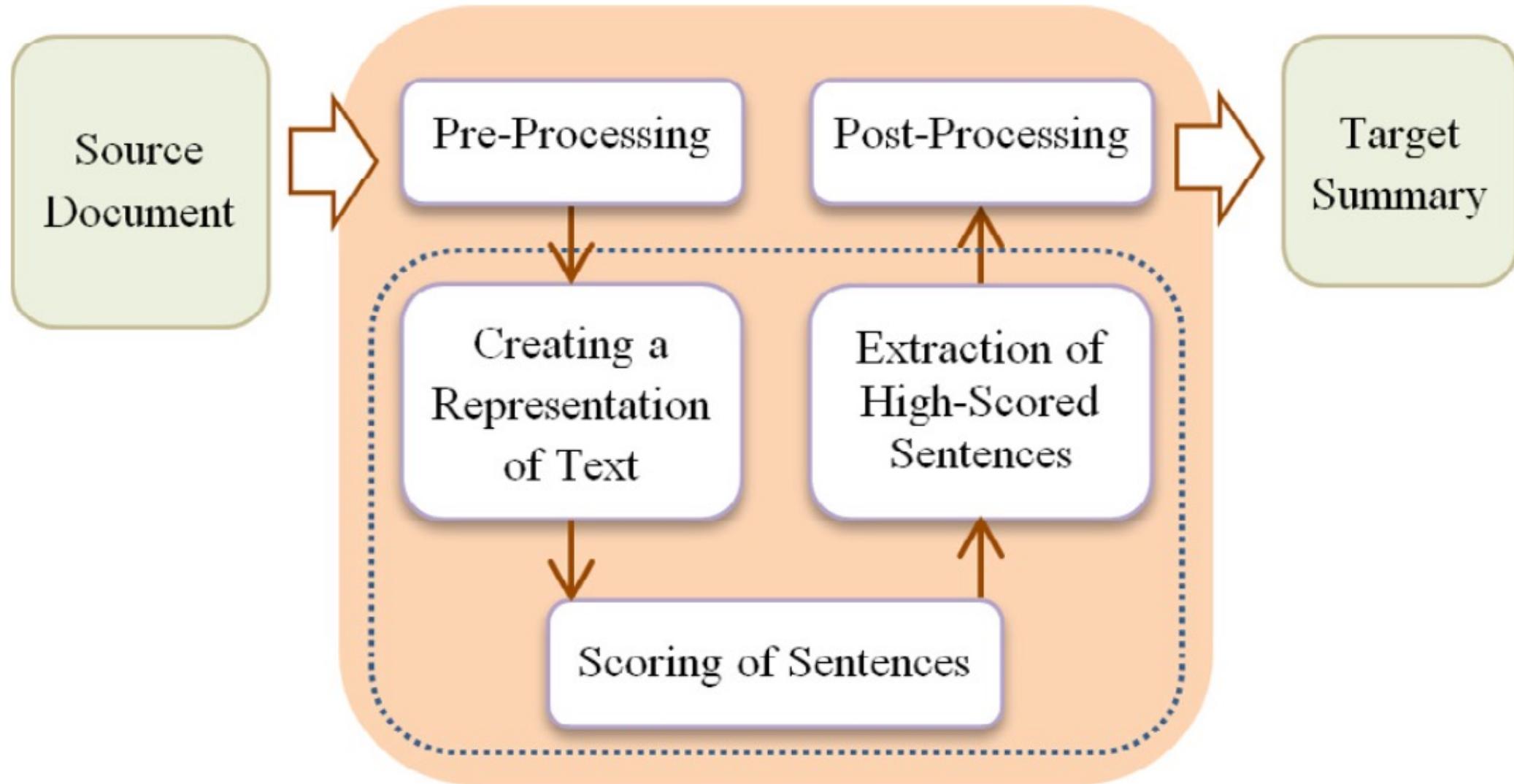
Classification of Automatic Text Summarization Systems



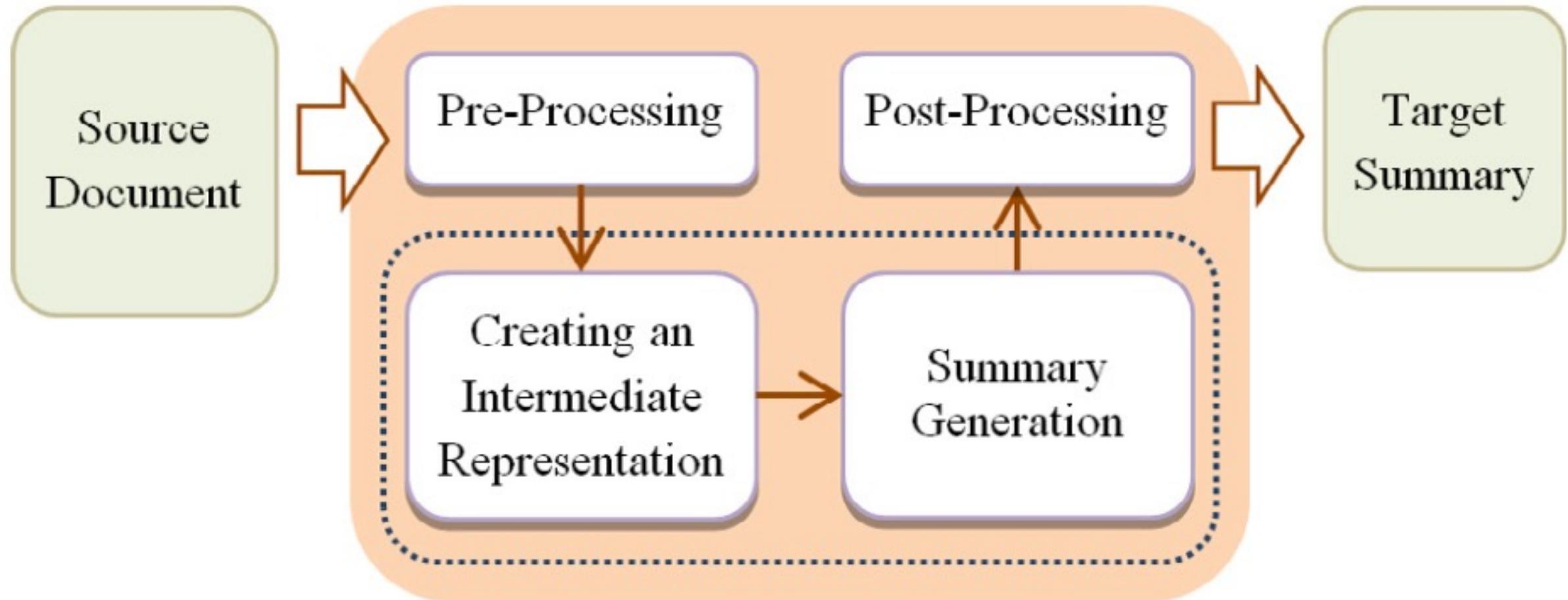
Automatic Text Summarization Approaches



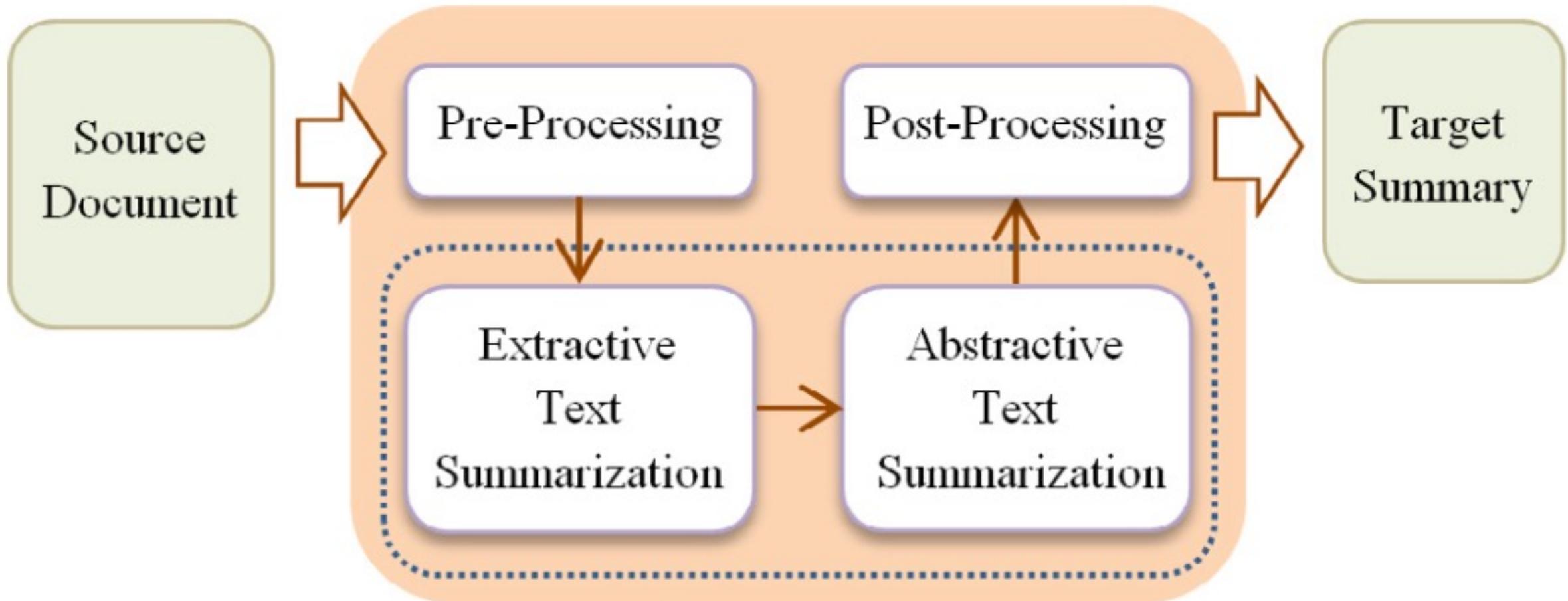
Extractive Text Summarization System



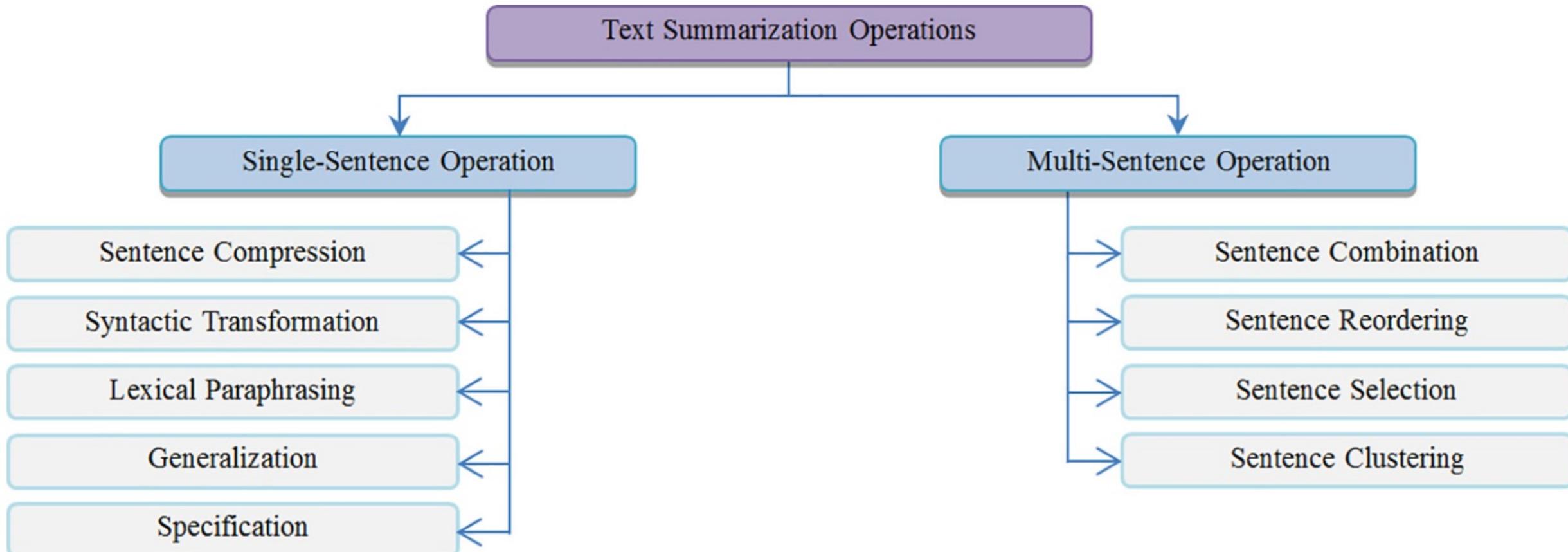
Abstractive Text Summarization System



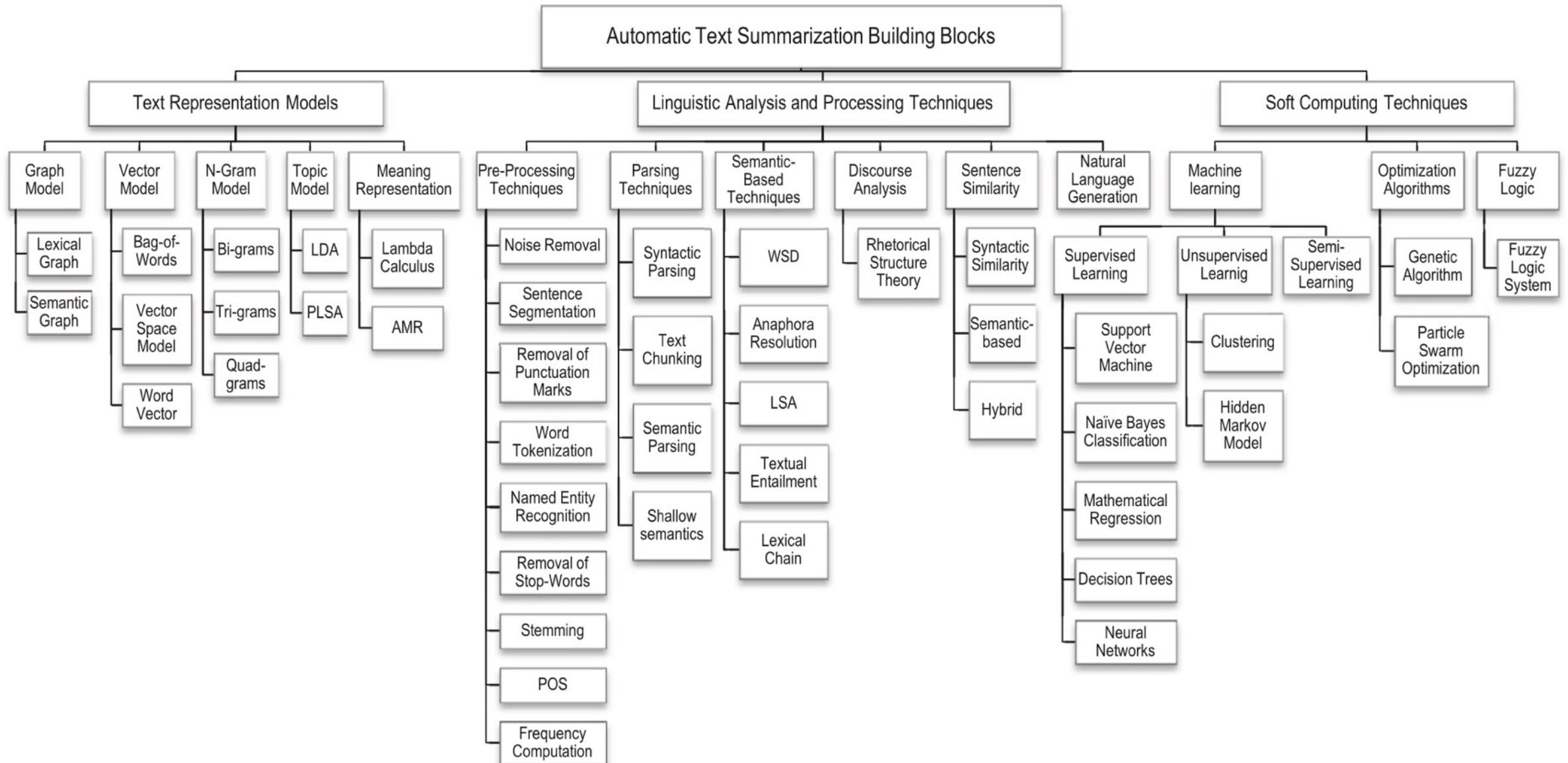
Hybrid Text Summarization System



Single-sentence and Multi-sentence Text Summarization Operations

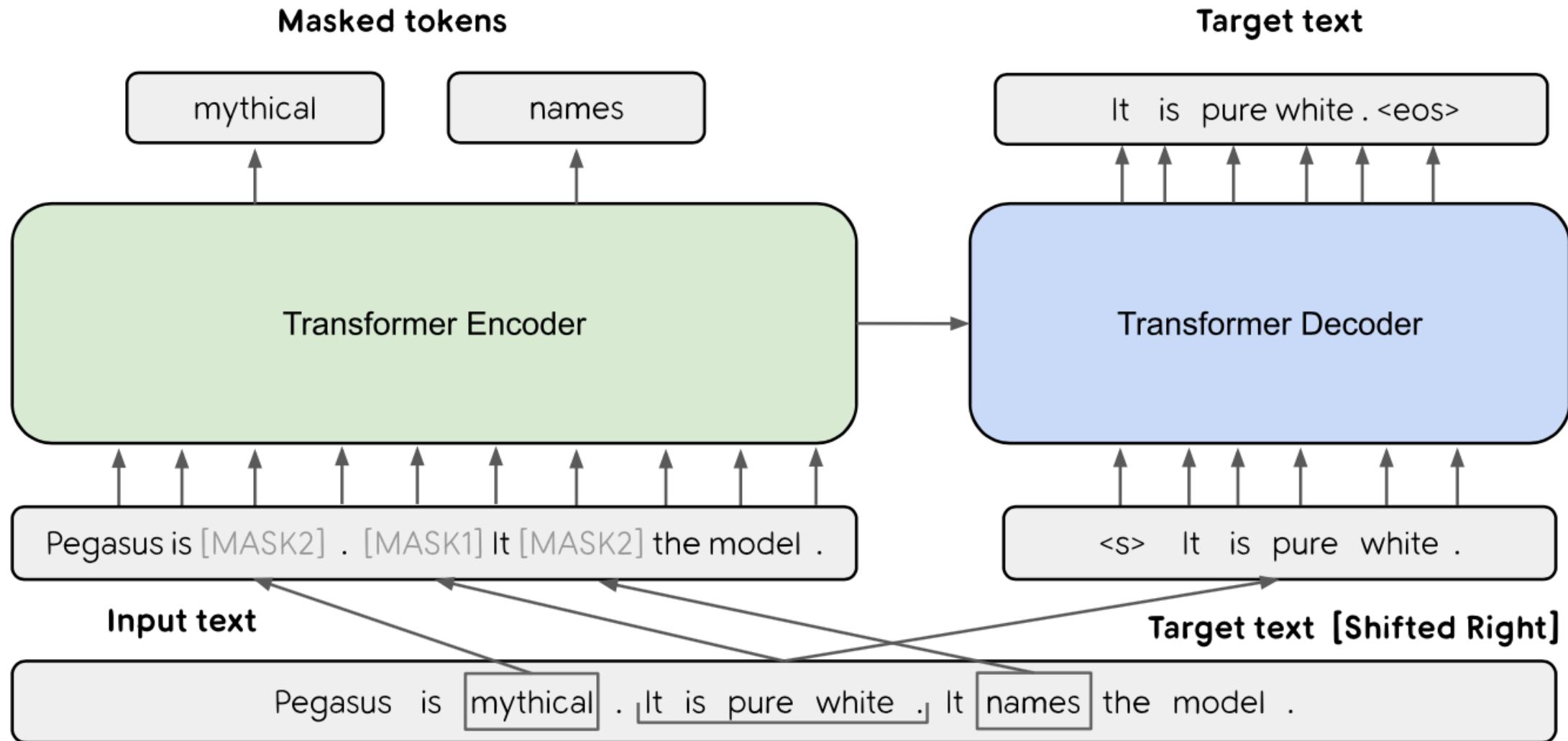


Automatic Text Summarization Building Blocks



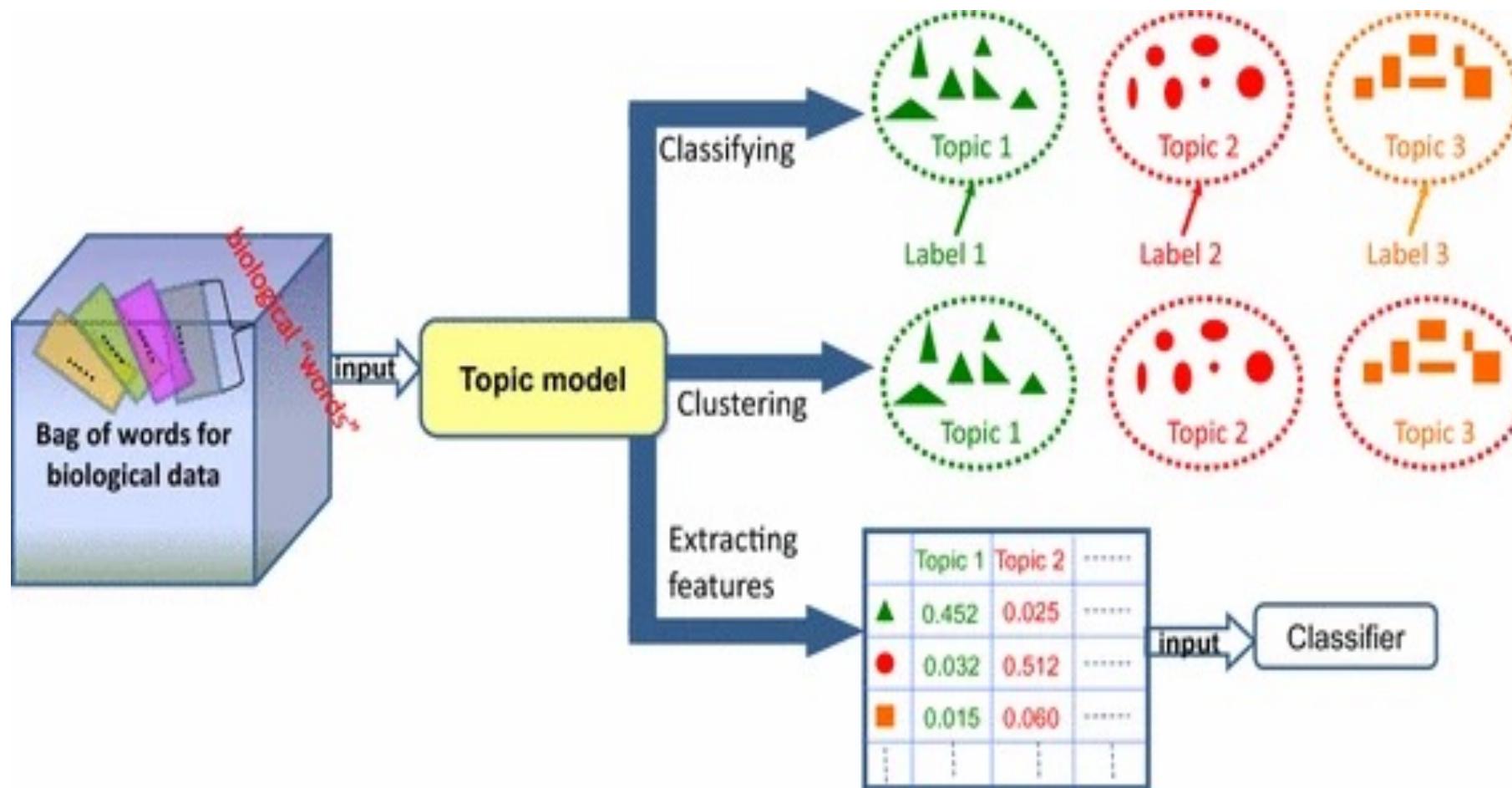
PEGASUS:

Pre-training with Extracted Gap-sentences for Abstractive Summarization

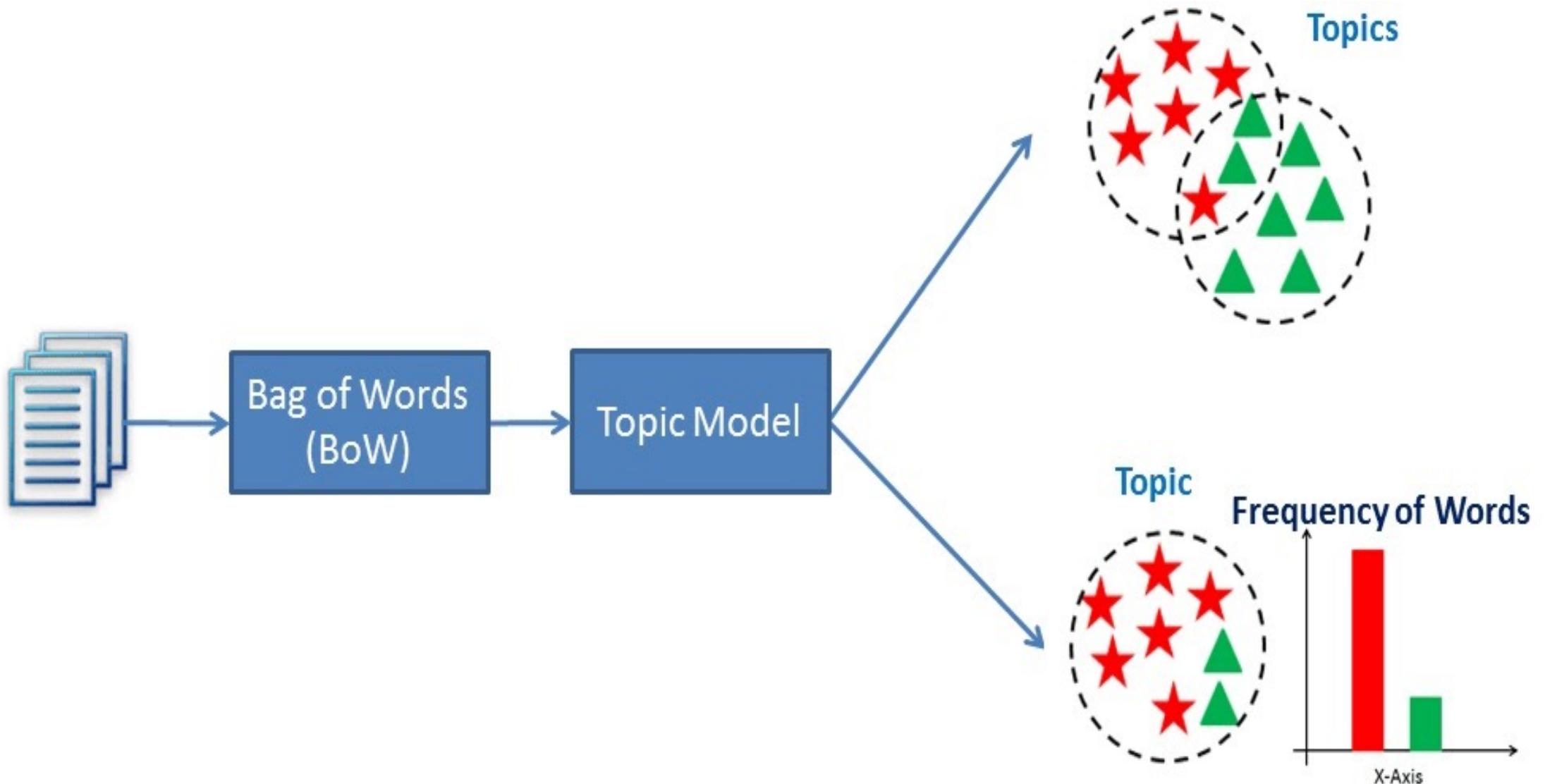


Topic Modeling

Topic Model in Bioinformatics



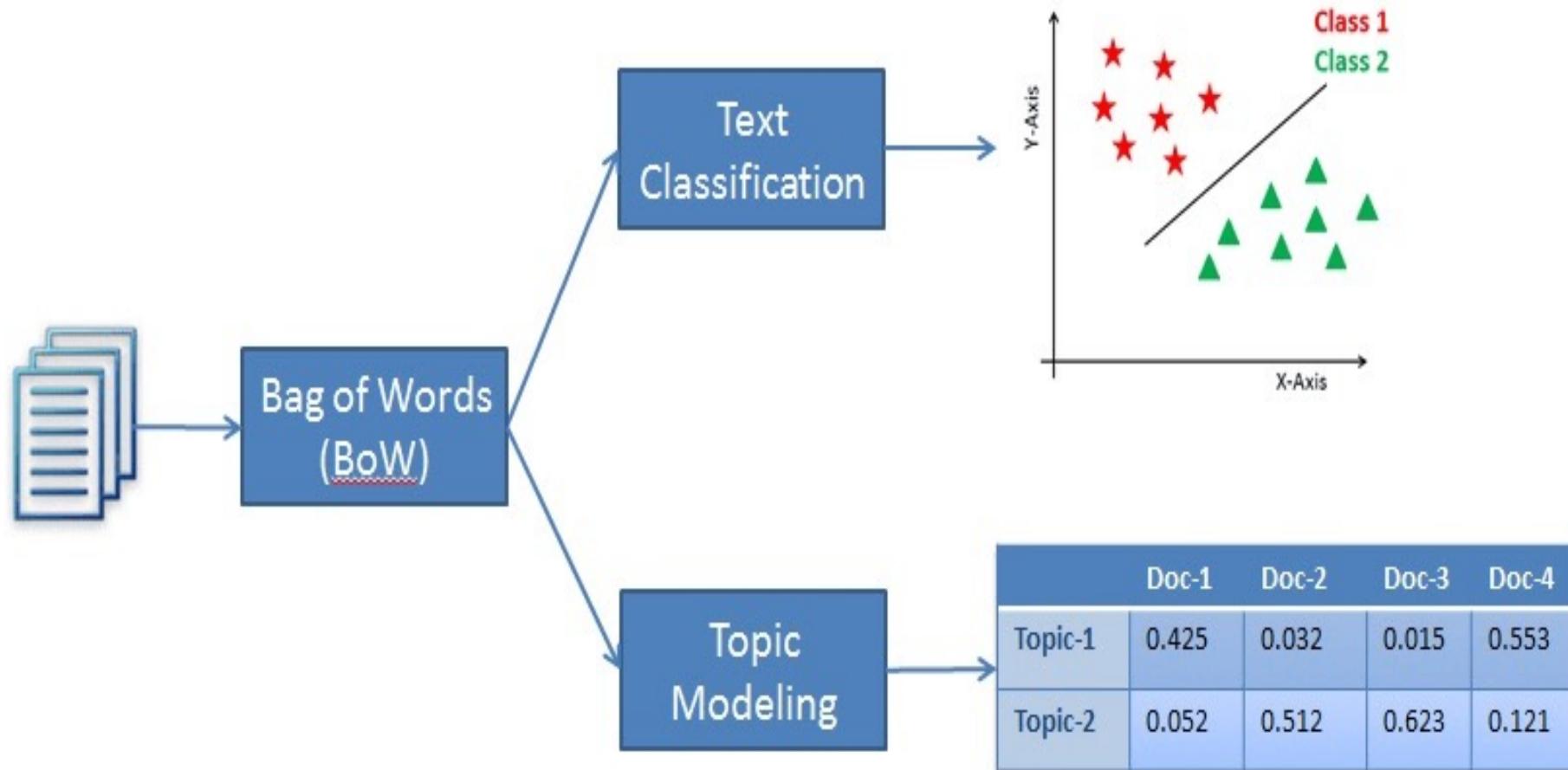
Topic Modeling



Topic Modeling (Unsupervised Learning)

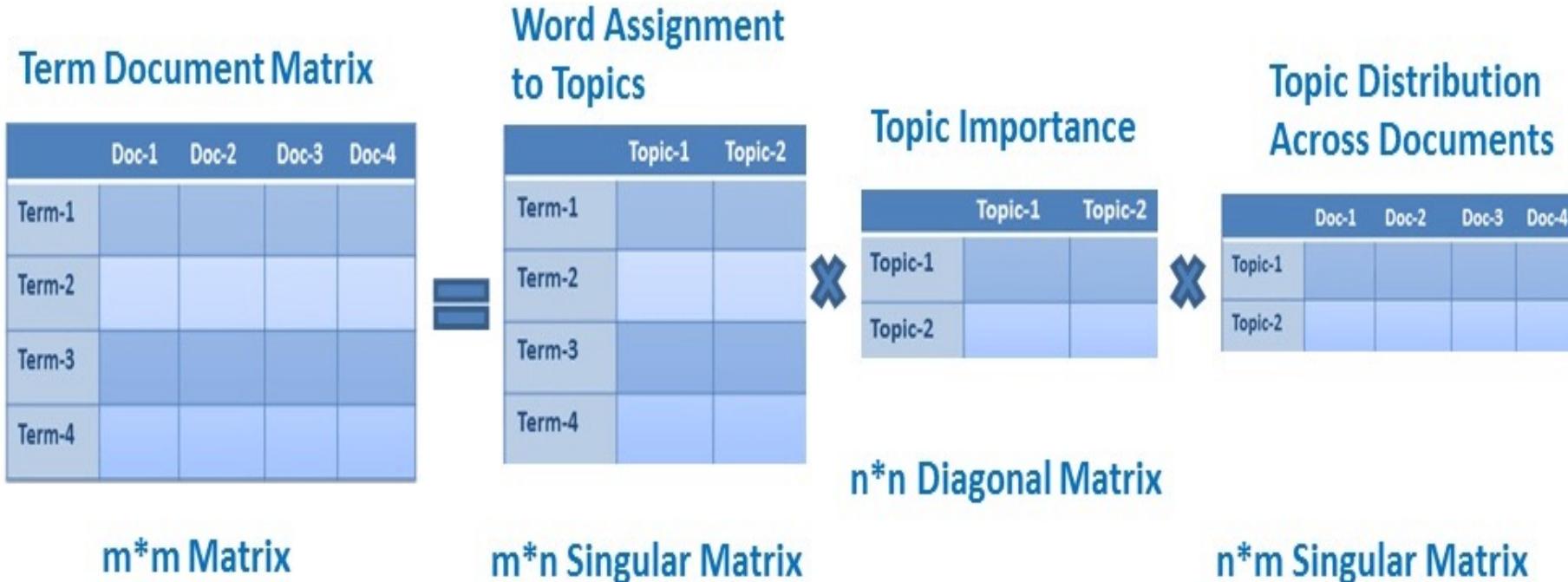
vs.

Text Classification (Supervised Learning)



Topic Modeling

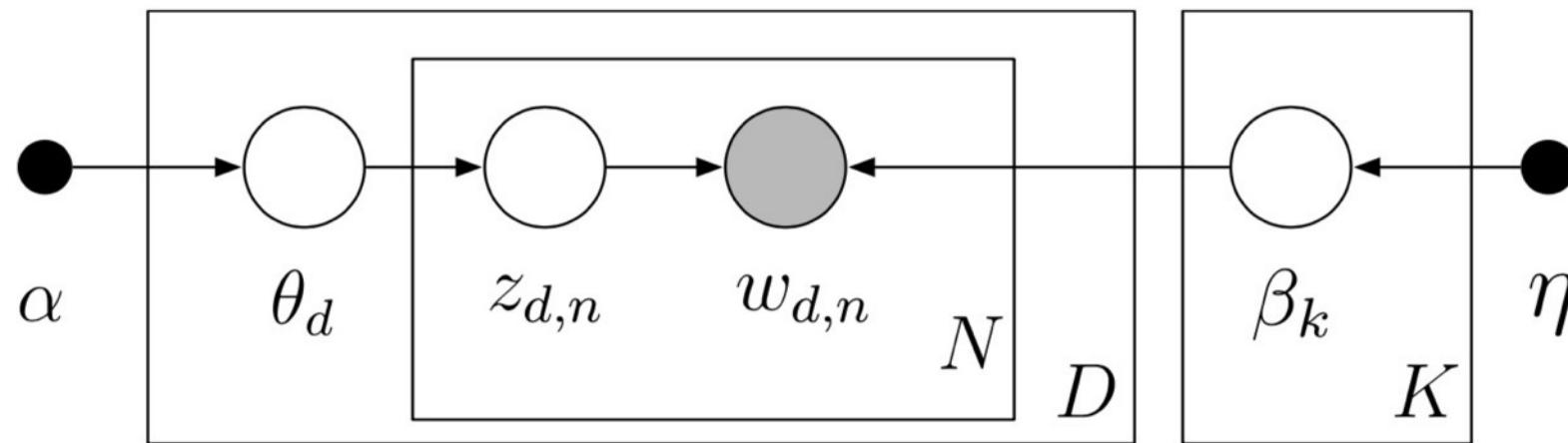
Term Document Matrix to Topic Distribution



Topic Modeling

Latent Dirichlet Allocation

(LDA)



D documents
 N words
 K topics

Latent Dirichlet Allocation (Blei et al., 2003)

Latent Dirichlet Allocation

David M. Blei

*Computer Science Division
University of California
Berkeley, CA 94720, USA*

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Andrew Y. Ng

*Computer Science Department
Stanford University
Stanford, CA 94305, USA*

ANG@CS.STANFORD.EDU

Michael I. Jordan

*Computer Science Division and Department of Statistics
University of California
Berkeley, CA 94720, USA*

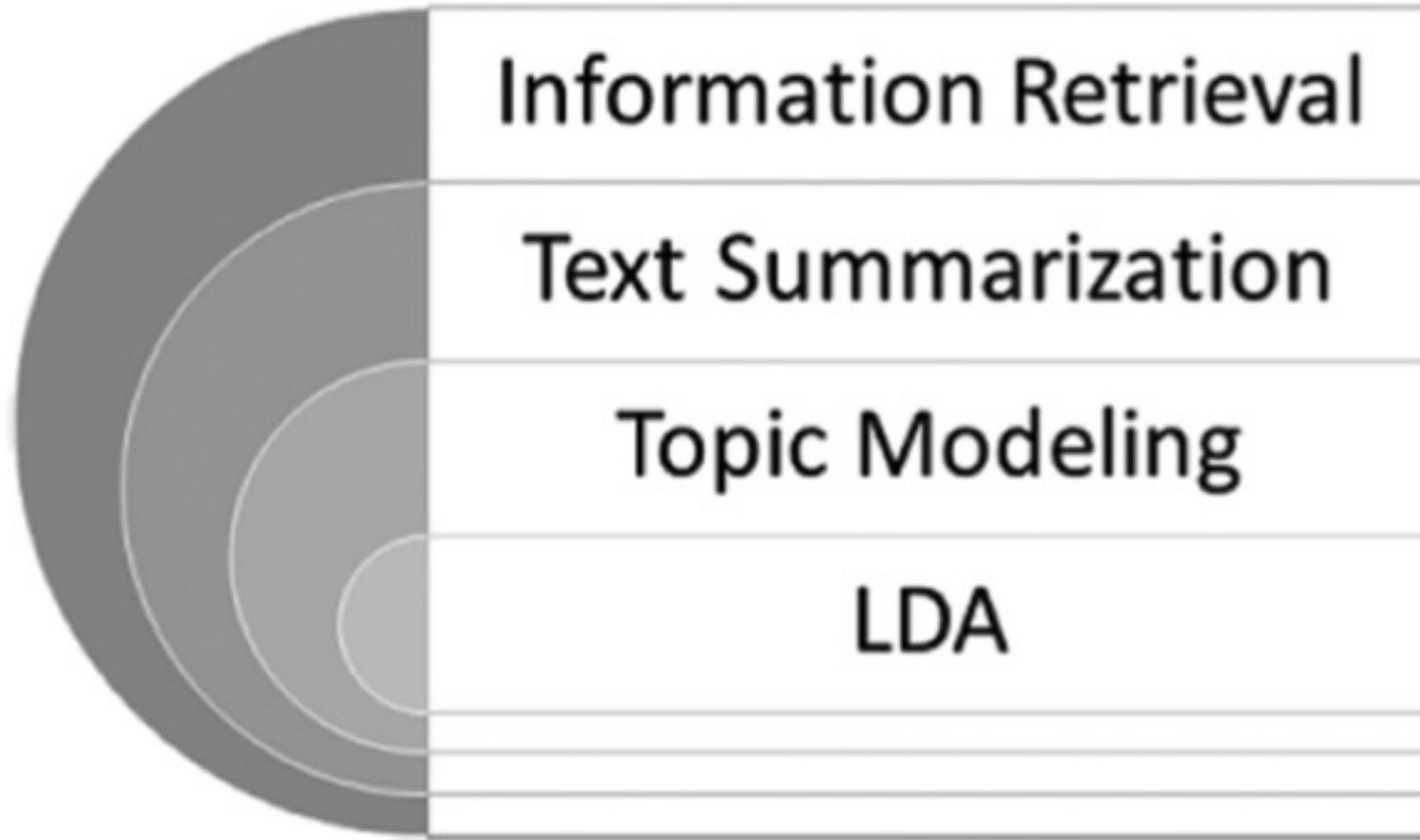
JORDAN@CS.BERKELEY.EDU

Editor: John Lafferty

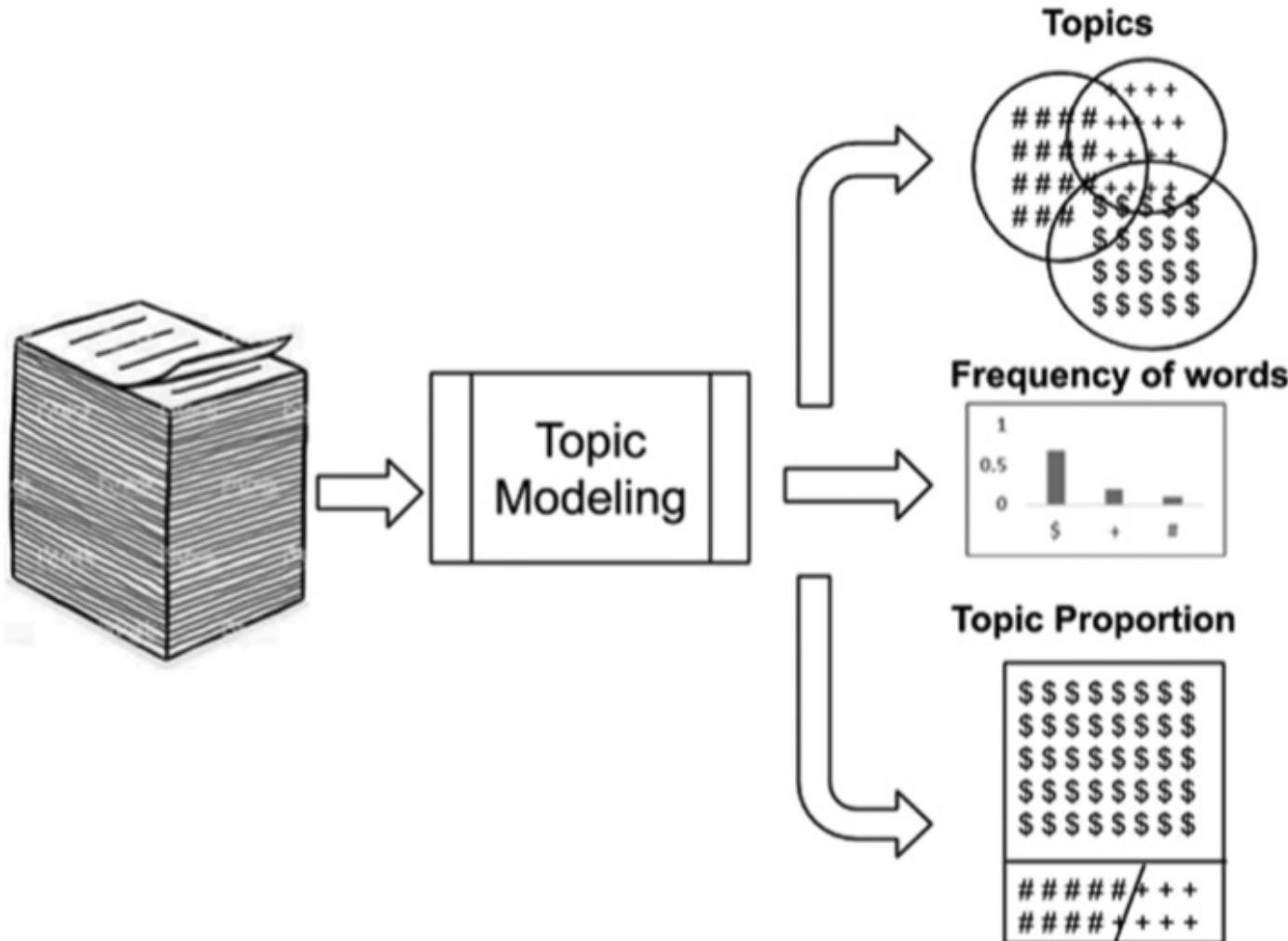
Abstract

We describe *latent Dirichlet allocation* (LDA), a generative probabilistic model for collections of discrete data such as text corpora. LDA is a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics. Each topic is, in turn, modeled as an infinite mixture over an underlying set of topic probabilities. In the context of text modeling, the topic probabilities provide an explicit representation of a document. We present efficient approximate inference techniques based on variational methods and an EM algorithm for empirical Bayes parameter estimation. We report results in document modeling, text classification, and collaborative filtering, comparing to a mixture of unigrams model and the probabilistic LSI model.

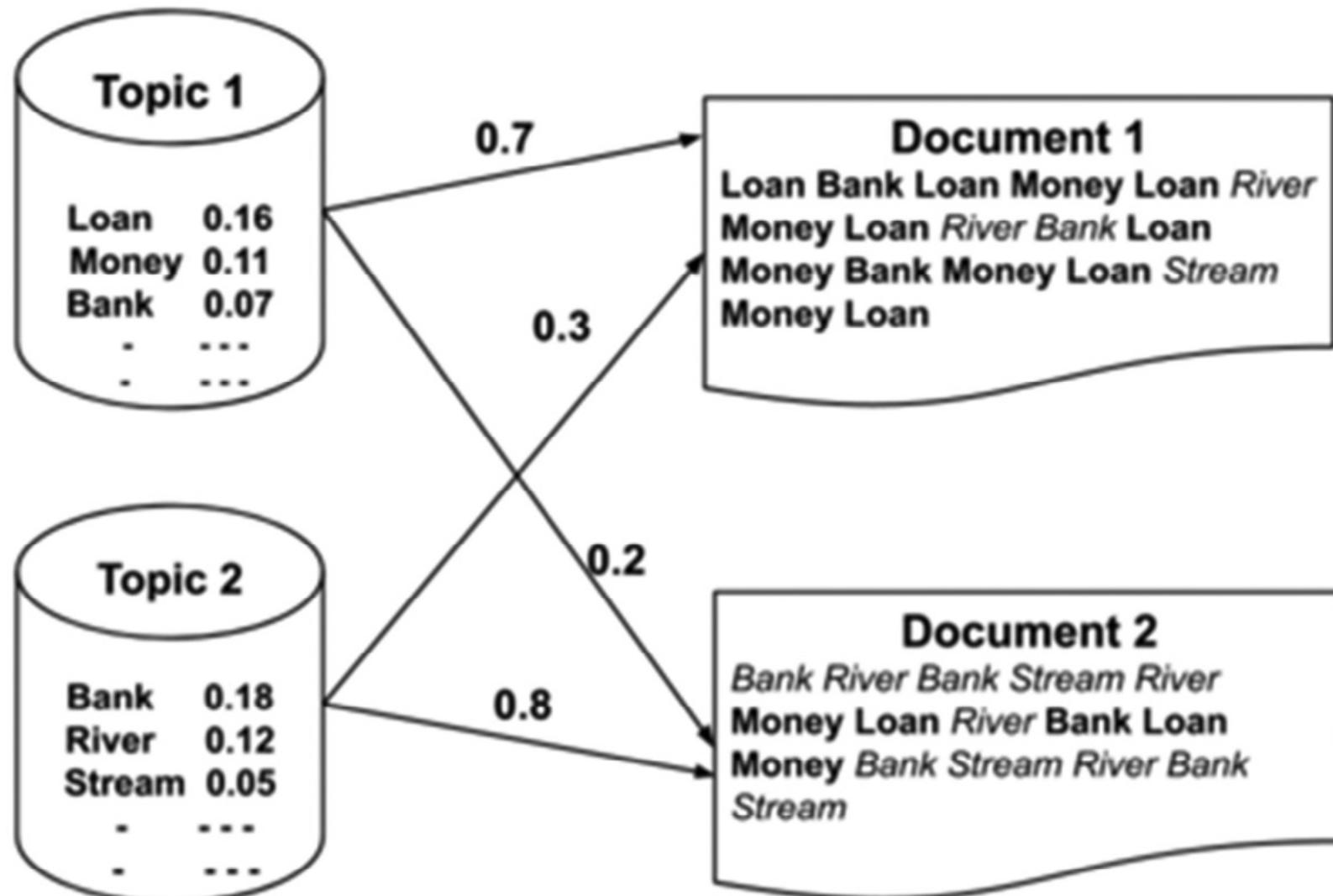
Topic Modeling Using Latent Dirichlet allocation (LDA)



Topic Modeling Technique



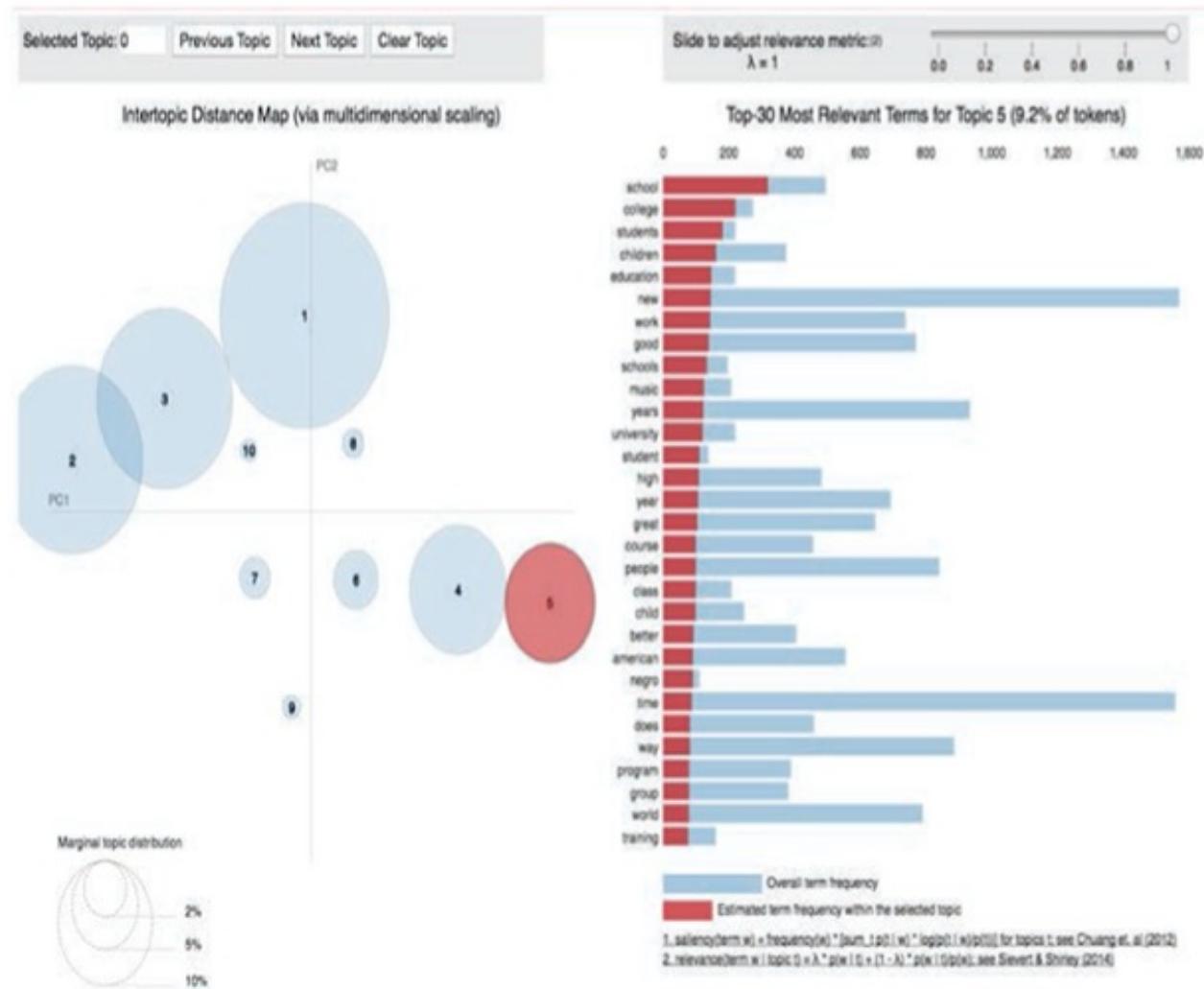
The Generative Process of Latent Dirichlet Allocation (LDA)



Topic Visualization as Word Clouds



LDAvis: Gensim Topic Model Visualization



BERTopic

Neural topic modeling with a class-based TF-IDF procedure



Maarten Grootendorst (2022). "BERTopic: Neural topic modeling with a class-based TF-IDF procedure." arXiv preprint arXiv:2203.05794 (2022).

<https://github.com/MaartenGr/BERTopic>

Topic Modeling

- **Latent Dirichlet Allocation (LDA)**
 - Versatile for large datasets.
- **BERTopic**
 - Advanced, contextual language understanding.
- **Non-Negative Matrix Factorization (NMF)**
 - Fast, effective clustering.
- **Latent Semantic Analysis (LSA)**
 - Latent Semantic Indexing (LSI), Efficient, initial data exploration.
- **Hierarchical Dirichlet Process (HDP)**
 - Adaptable, nonparametric approach.

gensim

The screenshot shows the official website for gensim. At the top left is a GitHub fork button labeled "Fork me on GitHub". To the right is the gensim logo, which includes a circular icon with "SS PIW 2.0" and the word "gensim" in large blue letters, followed by the tagline "topic modelling for humans". On the right side, there are two green buttons: "Download" (with a download arrow icon) and "Direct install with: easy_install -U gensim" (with a lightbulb icon). Below the main title, there is a navigation bar with tabs: Home (which is active), Tutorials, Install, Support, API, and About. A large blue section at the bottom contains Python code示例 and a summary of the library's features.

`>>> from gensim import corpora, models, similarities
>>>
>>> # Load corpus iterator from a Matrix Market file on disk.
>>> corpus = corpora.MmCorpus('/path/to/corpus.mm')
>>>
>>> # Initialize Latent Semantic Indexing with 200 dimensions.
>>> lsi = models.LsiModel(corpus, num_topics=200)
>>>
>>> # Convert another corpus to the Latent space and index it.
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>>> # Compute similarity of a query vs. indexed documents
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Gensim is a FREE Python library

- Scalable statistical semantics
- Analyze plain-text documents for semantic structure
- Retrieve semantically similar documents

spaCy

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- Fastest in the world**

spaCy excels at large-scale information extraction tasks. It's written from the ground up in carefully memory-managed Cython. Independent research has confirmed that spaCy is the fastest in the world. If your application needs to process entire web dumps, spaCy is the library you want to be using.
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spaCy is designed to help you do real work — to build real products, or gather real insights. The library respects your time, and tries to avoid wasting it. It's easy to install, and its API is simple and productive. I like to think of spaCy as the Ruby on Rails of Natural Language Processing.
- Deep learning**

spaCy is the best way to prepare text for deep learning. It interoperates seamlessly with [TensorFlow](#), [Keras](#), [Scikit-Learn](#), [Gensim](#) and the rest of Python's awesome AI ecosystem. spaCy helps you connect the statistical models trained by these libraries to the rest of your application.

<https://spacy.io/>

NLP Benchmark Datasets

Task	Dataset	Link
Machine Translation	WMT 2014 EN-DE WMT 2014 EN-FR	http://www-lium.univ-lemans.fr/~schwenk/csLM_joint_paper/
Text Summarization	CNN/DM Newsroom DUC Gigaword	https://cs.nyu.edu/~kcho/DMQA/ https://summar.es/ https://www-nplir.nist.gov/projects/duc/data.html https://catalog.ldc.upenn.edu/LDC2012T21
Reading Comprehension Question Answering Question Generation	ARC CliCR CNN/DM NewsQA RACE SQuAD Story Cloze Test NarrativeQA Quasar SearchQA	http://data.allenai.org/arc/ http://aclweb.org/anthology/N18-1140 https://cs.nyu.edu/~kcho/DMQA/ https://datasets.maluuba.com/NewsQA http://www.qizhexie.com/data/RACE_leaderboard https://rajpurkar.github.io/SQuAD-explorer/ http://aclweb.org/anthology/W17-0906.pdf https://github.com/deepmind/narrativeqa https://github.com/bdhingra/quasar https://github.com/nyu-dl/SearchQA
Semantic Parsing	AMR parsing ATIS (SQL Parsing) WikiSQL (SQL Parsing)	https://amr.isi.edu/index.html https://github.com/jkkummerfeld/text2sql-data/tree/master/data https://github.com/salesforce/WikiSQL
Sentiment Analysis	IMDB Reviews SST Yelp Reviews Subjectivity Dataset	http://ai.stanford.edu/~amaas/data/sentiment/ https://nlp.stanford.edu/sentiment/index.html https://www.yelp.com/dataset/challenge http://www.cs.cornell.edu/people/pabo/movie-review-data/
Text Classification	AG News DBpedia TREC 20 NewsGroup	http://www.di.unipi.it/~gulli/AG_corpus_of_news_articles.html https://wiki.dbpedia.org/Datasets https://trec.nist.gov/data.html http://qwone.com/~jason/20Newsgroups/
Natural Language Inference	SNLI Corpus MultiNLI SciTail	https://nlp.stanford.edu/projects/snli/ https://www.nyu.edu/projects/bowman/multinli/ http://data.allenai.org/scitail/
Semantic Role Labeling	Proposition Bank OneNotes	http://propbank.github.io/ https://catalog.ldc.upenn.edu/LDC2013T19

Source: Amirsina Torfi, Rouzbeh A. Shirvani, Yaser Keneshloo, Nader Tavvaf, and Edward A. Fox (2020).

"Natural Language Processing Advancements By Deep Learning: A Survey." arXiv preprint arXiv:2003.01200.

Hugging Face Tasks

Natural Language Processing



Text Classification

3345 models



Token Classification

1492 models



Question Answering

1140 models



Translation

1467 models



Summarization

323 models



Text Generation

3959 models



Fill-Mask

2453 models



Sentence Similarity

352 models

NLP with Transformers Github

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Code Issues Pull requests Actions Projects Wiki Security Insights

main 1 branch 0 tags Go to file Code

lewtn Merge pull request #21 from JingchaoZhang/patch-3 ... ae5b7c1 15 days ago 71 commits

.github/ISSUE_TEMPLATE Update issue templates 25 days ago

data Move dataset to data directory 4 months ago

images Add README last month

scripts Update issue templates 25 days ago

.gitignore Initial commit 4 months ago

01_introduction.ipynb Remove Colab badges & fastdoc refs 27 days ago

02_classification.ipynb Merge pull request #8 from nlp-with-transformers/remove-display-df 26 days ago

03_transformer-anatomy.ipynb [Transformers Anatomy] Remove cells with figure references 22 days ago

04_multilingual-ner.ipynb Merge pull request #8 from nlp-with-transformers/remove-display-df 26 days ago

05_text-generation.ipynb Merge pull request #8 from nlp-with-transformers/remove-display-df 26 days ago

About

Jupyter notebooks for the Natural Language Processing with Transformers book

[transformersbook.com/](#)

Readme Apache-2.0 License 1.1k stars 33 watching 170 forks

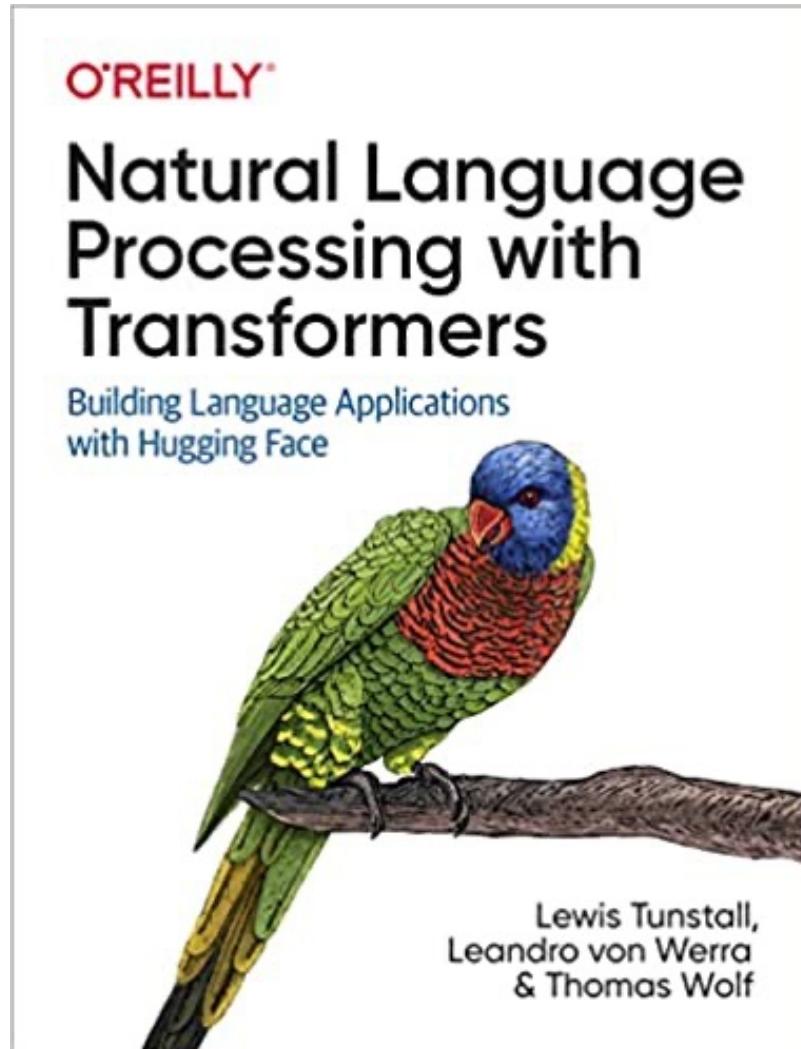
O'REILLY® Natural Language Processing with Transformers Building Language Applications with Hugging Face

Releases No releases published

Packages

<https://github.com/nlp-with-transformers/notebooks>

NLP with Transformers Github Notebooks



Running on a cloud platform

To run these notebooks on a cloud platform, just click on one of the badges in the table below:

Chapter	Colab	Kaggle	Gradient	Studio Lab
Introduction	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Text Classification	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Transformer Anatomy	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Multilingual Named Entity Recognition	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Text Generation	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Summarization	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Question Answering	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Making Transformers Efficient in Production	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Dealing with Few to No Labels	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Training Transformers from Scratch	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab
Future Directions	Open in Colab	Open in Kaggle	Run on Gradient	Open Studio Lab

Nowadays, the GPUs on Colab tend to be K80s (which have limited memory), so we recommend using [Kaggle](#), [Gradient](#), or [SageMaker Studio Lab](#). These platforms tend to provide more performant GPUs like P100s, all for free!

Python in Google Colab (Python101)

<https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT>

The screenshot shows a Google Colab notebook interface. The left sidebar contains a 'Table of contents' with several sections: 'Natural Language Processing with Transformers', 'Text Classification', 'Named Entity Recognition', 'Question Answering', 'Summarization', 'Translation', 'Text Generation', 'AI in Finance', 'Normative Finance and Financial Theories', 'Uncertainty and Risk', 'Expected Utility Theory (EUT)', 'Mean-Variance Portfolio Theory (MVPT)', 'Capital Asset Pricing Model (CAPM)', 'Arbitrage Pricing Theory (APT)', 'Data Driven Finance', 'Financial Econometrics and Regression', 'Data Availability', 'Normative Theories Revisited', and 'Mean-Variance Portfolio Theory'. The main area displays code snippets in a code editor:

- Natural Language Processing with Transformers**
 - Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
 - Github: <https://github.com/nlp-with-transformers/notebooks>
- Text Classification**
 - [1]

```
1 !git clone https://github.com/nlp-with-transformers/notebooks.git
2 %cd notebooks
3 from install import *
4 install_requirements()
```
 - [3]

```
1 from utils import *
2 setup_chapter()
```
 - [12]

```
1 text = """Dear Amazon, last week I ordered an Optimus Prime action figure \
2 from your online store in Germany. Unfortunately, when I opened the package, \
3 I discovered to my horror that I had been sent an action figure of Megatron \
4 instead! As a lifelong enemy of the Decepticons, I hope you can understand my \
5 dilemma. To resolve the issue, I demand an exchange of Megatron for the \
6 Optimus Prime figure I ordered. Enclosed are copies of my records concerning \
7 this purchase. I expect to hear from you soon. Sincerely, Bumblebee."""
    
```
 - [13]

```
1 from transformers import pipeline
2 classifier = pipeline("text-classification")
```
 - [14]

```
1 import pandas as pd
2 outputs = classifier(text)
3 pd.DataFrame(outputs)
```

<https://tinyurl.com/aintpuppython101>

Python in Google Colab (Python101)

<https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT>

The screenshot shows a Google Colab notebook interface. The left sidebar contains a 'Table of contents' with several sections under 'Text Classification with Transformers'. The main area displays code cells and their outputs.

Table of contents:

- Text Classification with Transformers
 - The Dataset
 - From Datasets to DataFrames
 - From Text to Tokens
 - Character Tokenization
 - Word Tokenization
 - Subword Tokenization
 - Tokenizing the Whole Dataset
 - Training a Text Classifier
 - Transformers as Feature Extractors
 - Extracting the last hidden states
 - Creating a feature matrix
 - Visualizing the training set
 - Training a simple classifier
 - Fine-Tuning Transformers
 - Loading a pretrained model
 - Defining the performance metrics
 - Training the model
 - Sidebar: Fine-Tuning with Keras
 - Error analysis
 - Saving and sharing the model

Main Content Area:

Text Classification with Transformers

- Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
- Github: <https://github.com/nlp-with-transformers/notebooks>

[10] 1 !nvidia-smi

[11] 1 # Uncomment and run this cell if you're on Colab or Kaggle
2 !git clone <https://github.com/nlp-with-transformers/notebooks.git>
3 %cd notebooks
4 from install import *
5 install_requirements()

[12] 1 # hide
2 from utils import *
3 setup_chapter()

The Dataset

[13] 1 from datasets import list_datasets
2 all_datasets = list_datasets()
3 print(f"There are {len(all_datasets)} datasets currently available on the Hub")
4 print(f"The first 10 are: {all_datasets[:10]}")

There are 3783 datasets currently available on the Hub
The first 10 are: ['acronym_identification', 'ade_corpus_v2', 'adversarial_qa',

<https://tinyurl.com/aintpuppython101>

Python in Google Colab (Python101)

<https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT>

The screenshot shows a Google Colab notebook titled "python101.ipynb". The notebook interface includes a toolbar at the top with icons for file operations, a search bar, and user settings. Below the toolbar is a sidebar with navigation icons for files, code, and text. The main content area displays a section titled "Multilingual Named Entity Recognition (NER)" with two bullet points:

- Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
- Github: <https://github.com/nlp-with-transformers/notebooks>

Below the text, there are two code cells. The first cell contains Python code for initializing a transformer pipeline for NER:

```
[ ] 1 #NER: https://huggingface.co/tasks/token-classification
2 !pip install transformers
3 from transformers import pipeline
4 classifier = pipeline("ner")
5 classifier("Hello I'm Omar and I live in Zürich.")
```

The second cell shows the output of the pipeline, which identifies entities in the input sentence:

```
▶ 1 from transformers import pipeline
2 classifier = pipeline("ner")
3 classifier("Hello I'm Omar and I live in Zürich.")

[] No model was supplied, defaulted to dbmdz/bert-large-cased-finetuned-conll03-english (https://huggingface.co/dbmdz/bert-large-cased-finetuned-conll03-english)
[{'end': 14,
 'entity': 'I-PER',
 'index': 5,
 'score': 0.99770516,
 'start': 10,
 'word': 'Omar'},
 {'end': 35,
 'entity': 'I-LOC',
 'index': 10,
 'score': 0.9968976,
 'start': 29,
 'word': 'Zürich'}]
```

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Python in Google Colab (Python101)

<https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT>

The screenshot shows a Google Colab notebook interface. The title bar says 'python101.ipynb'. The left sidebar has a 'Table of contents' section with various sections like 'Build the model', 'Train the model', etc. A 'Text Similarity' section is currently selected. The main area shows a tree view with 'Text Similarity and Clustering' expanded, and 'Text Similarity' is also expanded. Below it, a bulleted list includes 'Spacy Vectors Similarity: <https://spacy.io/usage/vectors-similarity>'. The code editor contains several code snippets:

```
[1] 1 !python -m spacy download en_core_web_sm
[2] 1 !python -m spacy download en_core_web_lg
2 # Restart Runtime
[3] 1 import spacy
2 nlp = spacy.load("en_core_web_lg")
3 tokens = nlp("apple banana cat dog notaword")
4 for token in tokens:
5     print(token.text, token.has_vector, token.vector_norm, token.is_oov)
apple True 7.1346846 False
banana True 6.700014 False
cat True 6.6808186 False
dog True 7.0336733 False
notaword False 0.0 True
```

At the bottom, there's another code block:

```
1 import spacy
2 nlp = spacy.load("en_core_web_lg")
3 doc1 = nlp("I like cat.")
4 doc2 = nlp("I like dog.")
5 doc1.similarity(doc2)
```

<https://tinyurl.com/aintpuppython101>

Python in Google Colab (Python101)

<https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT>

The screenshot shows a Google Colab interface with a Jupyter notebook titled "python101.ipynb". The left sidebar contains a "Table of contents" with the following sections:

- Build the model
- Train the model
- Evaluate the model
- Create a graph of accuracy and loss over time
- Text Classification: BBC News Articles
- Text Summarization and Topic Modeling
 - Text Summarization
 - Text Summarization with Gensim**
 - Summarization
- Topic Modeling
- Topic Modeling with Gensim LSI model
- Topic Modeling with Gensim LDA model
- Topic Modeling with Scikit-learn LDA and NMF
- Topic Modeling Visualization

The main area displays Python code for text summarization using Gensim. The code is as follows:

```
1 from pprint import pprint as print
2 from gensim.summarization import summarize

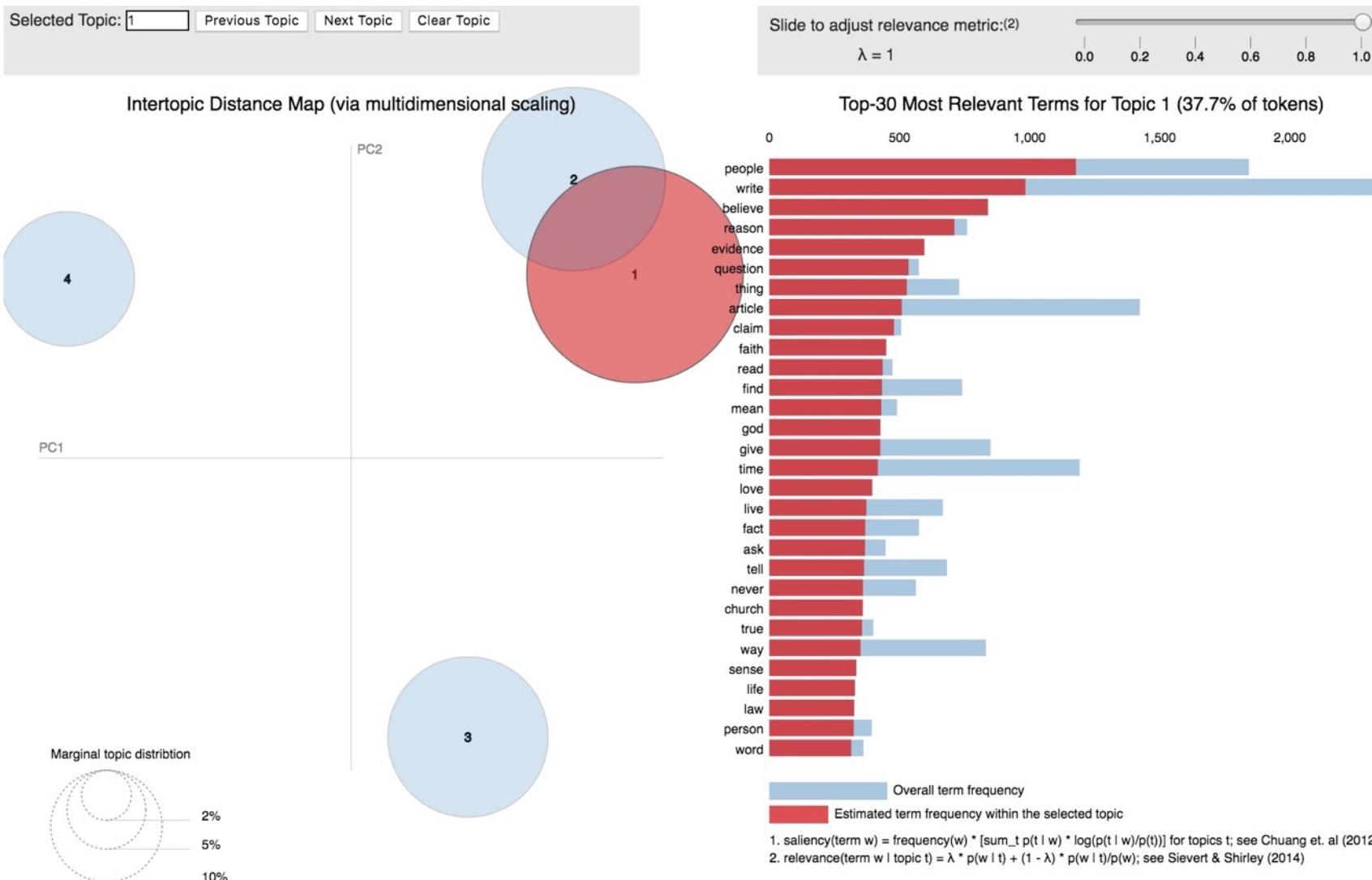
[ ] 1 text = (
2     "Thomas A. Anderson is a man living two lives. By day he is an "
3     "average computer programmer and by night a hacker known as "
4     "Neo. Neo has always questioned his reality, but the truth is "
5     "far beyond his imagination. Neo finds himself targeted by the "
6     "police when he is contacted by Morpheus, a legendary computer "
7     "hacker branded a terrorist by the government. Morpheus awakens "
8     "Neo to the real world, a ravaged wasteland where most of "
9     "humanity have been captured by a race of machines that live "
10    "off of the humans' body heat and electrochemical energy and "
11    "who imprison their minds within an artificial reality known as "
12    "the Matrix. As a rebel against the machines, Neo must return to "
13    "the Matrix and confront the agents: super-powerful computer "
14    "programs devoted to snuffing out Neo and the entire human "
15    "rebellion."
16 )
17 print(text)

⇒ ('Thomas A. Anderson is a man living two lives. By day he is an average '
 'computer programmer and by night a hacker known as Neo. Neo has always '
 'questioned his reality, but the truth is far beyond his imagination. Neo '
```

<https://tinyurl.com/aintpuppython101>

Python in Google Colab (Python101)

<https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT>



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Python in Google Colab (Python101)

<https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT>

The screenshot shows a Google Colab notebook titled "python101.ipynb". The notebook interface includes a toolbar at the top with icons for file operations, a search bar, and user settings. Below the toolbar is a code editor with two tabs: "+ Code" and "+ Text". The main content area displays a section titled "Text Summarization" with a list of sources and a code cell demonstrating text summarization using the Hugging Face Transformers library.

• Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
• Github: <https://github.com/nlp-with-transformers/notebooks>

```
1 #Source: https://huggingface.co/tasks/summarization
2 !pip install transformers
3 from transformers import pipeline
4 classifier = pipeline("summarization")
5 text = "Paris is the capital and most populous city of France, with an estimated population of 2,175,601 residents as of 2018, in an area of more than
6 classifier(text, max_length=30)

No model was supplied, defaulted to sshleifer/distilbart-cnn-12-6 (https://huggingface.co/sshleifer/distilbart-cnn-12-6)
Your min_length=56 must be inferior than your max_length=30.
[{'summary_text': ' Paris is the capital and most populous city of France, with an estimated population of 2,175,601 residents . The City of Paris'}]
```

```
1 #!pip install transformers
2 text = """Dear Amazon, last week I ordered an Optimus Prime action figure \
3 from your online store in Germany. Unfortunately, when I opened the package, \
4 I discovered to my horror that I had been sent an action figure of Megatron \
5 instead! As a lifelong enemy of the Decepticons, I hope you can understand my \
6 dilemma. To resolve the issue, I demand an exchange of Megatron for the \
7 Optimus Prime figure I ordered. Enclosed are copies of my records concerning \
8 this purchase. I expect to hear from you soon. Sincerely, Bumblebee."""
9 from transformers import pipeline
10 summarizer = pipeline("summarization")
11 outputs = summarizer(text, max_length=45, clean_up_tokenization_spaces=True)
12 print(outputs[0]['summary_text'])
```

<https://tinyurl.com/aintpuppython101>

Text Summarization

```
text = """Dear Amazon, last week I ordered an Optimus Prime action figure \
from your online store in Germany. Unfortunately, when I opened the package, \
I discovered to my horror that I had been sent an action figure of Megatron \
instead! As a lifelong enemy of the Decepticons, I hope you can understand my \
dilemma. To resolve the issue, I demand an exchange of Megatron for the \
Optimus Prime figure I ordered. Enclosed are copies of my records concerning \
this purchase. I expect to hear from you soon. Sincerely, Bumblebee."""
```

```
from transformers import pipeline
summarizer = pipeline("summarization")
outputs = summarizer(text, max_length=45, clean_up_tokenization_spaces=True)
print(outputs[0]['summary_text'])
```

Bumblebee ordered an Optimus Prime action figure from your online store in Germany. Unfortunately, when I opened the package, I discovered to my horror that I had been sent an action figure of Megatron instead.

Summary

- **Text Similarity**
 - Analyzing and quantifying the likeness between text documents.
- **Text Clustering**
 - Grouping similar text documents using various algorithms.
- **Text Summarization**
 - Condensing text data into a shorter, coherent form.
- **Topic Models**
 - Identifying underlying themes or topics within text collections.

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