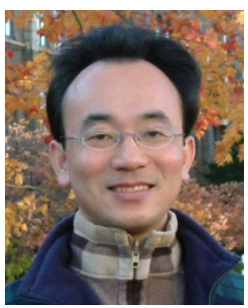
Tamkang Universit
淡江大學

人工智慧文本分析
(Artificial Intelligence for Text Analytics)

文本相似度和分群
(Text Similarity and Clustering)

1082AITA08
MBA, IMTKU (M2455) (8410) (Spring 2020)
Wed 8, 9 (15:10-17:00) (B605)



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2020-05-06

課程大綱 (Syllabus)

週次 (Week) 日期 (Date) 內容 (Subject/Topics)

1 2020/03/04 人工智慧文本分析課程介紹
(Course Orientation on Artificial Intelligence for Text Analytics)

2 2020/03/11 文本分析的基礎：自然語言處理
(Foundations of Text Analytics: Natural Language Processing; NLP)

3 2020/03/18 Python自然語言處理
(Python for Natural Language Processing)

4 2020/03/25 處理和理解文本
(Processing and Understanding Text)

5 2020/04/01 文本表達特徵工程
(Feature Engineering for Text Representation)

6 2020/04/08 人工智慧文本分析個案研究 I
(Case Study on Artificial Intelligence for Text Analytics I)

課程大綱 (Syllabus)

週次 (Week)　日期 (Date)　內容 (Subject/Topics)

7　2020/04/15　文本分類 (Text Classification)

8　2020/04/22　文本摘要和主題模型
(Text Summarization and Topic Models)

9　2020/04/29　期中報告 (Midterm Project Report)

10　2020/05/06　文本相似度和分群 (Text Similarity and Clustering)

11　2020/05/13　語意分析和命名實體識別
(Semantic Analysis and Named Entity Recognition; NER)

12　2020/05/20　情感分析 (Sentiment Analysis)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
13	2020/05/27	人工智慧文本分析個案研究 II (Case Study on Artificial Intelligence for Text Analytics II)
14	2020/06/03	深度學習和通用句子嵌入模型 (Deep Learning and Universal Sentence-Embedding Models)
15	2020/06/10	問答系統與對話系統 (Question Answering and Dialogue Systems)
16	2020/06/17	期末報告 I (Final Project Presentation I)
17	2020/06/24	期末報告 II (Final Project Presentation II)
18	2020/07/01	教師彈性補充教學

Outline

- Text Similarity
- Text Clustering
  - Cluster Analysis
  - K-Means Clustering

Text Similarity and Clustering

Text Similarity and Clustering

Text Dataset (Unsupervised)

Text Pre-Processing

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

Text Similarity

Text Clustering

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**)?

Source: Dipanjan Sarkar (2019), Text Analytics with Python: A Practitioner's Guide to Natural Language Processing, Second Edition. APress.

Text Similarity and Clustering

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

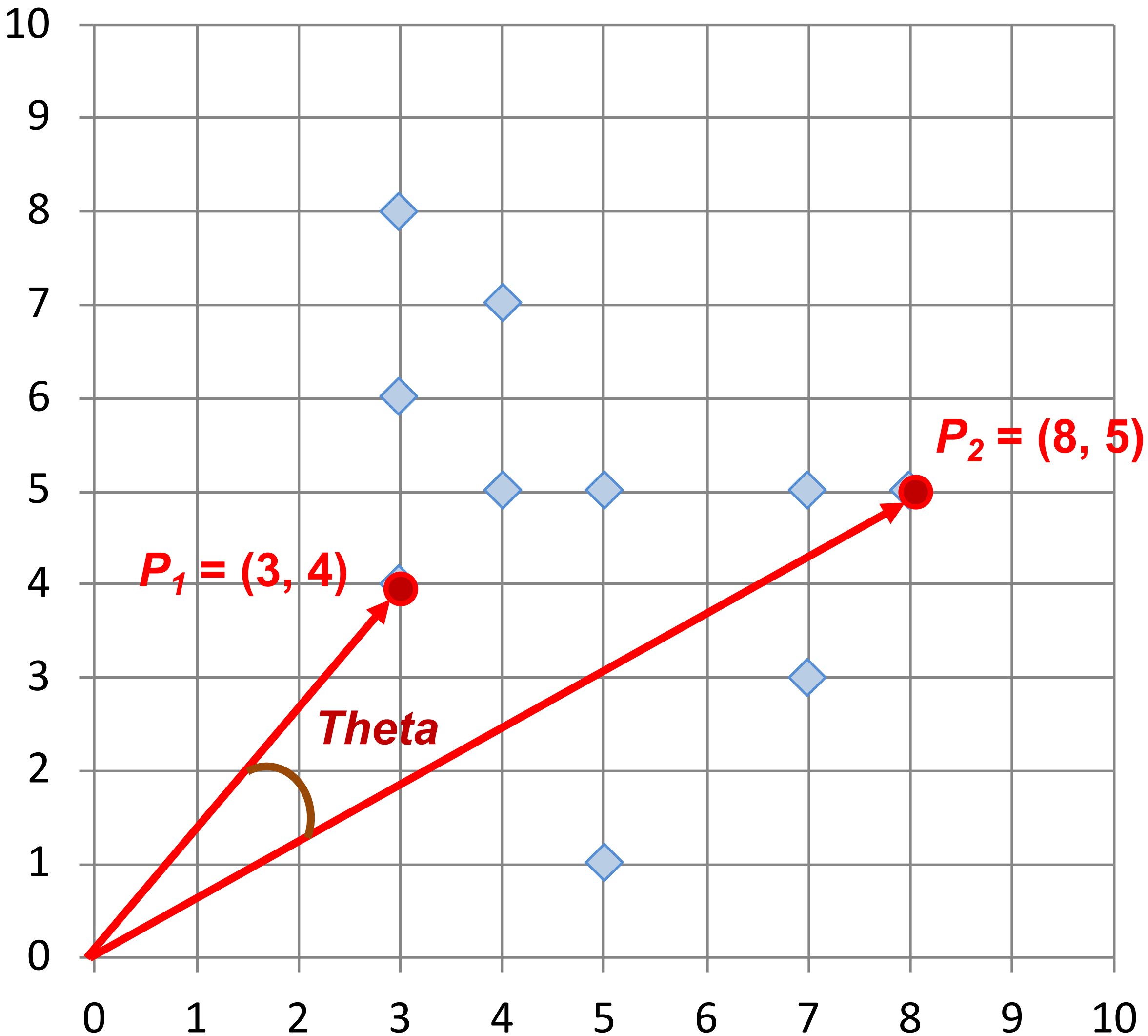
Source: Dipanjan Sarkar (2019), Text Analytics with Python: A Practitioner's Guide to Natural Language Processing, Second Edition. APress.

Text Similarity

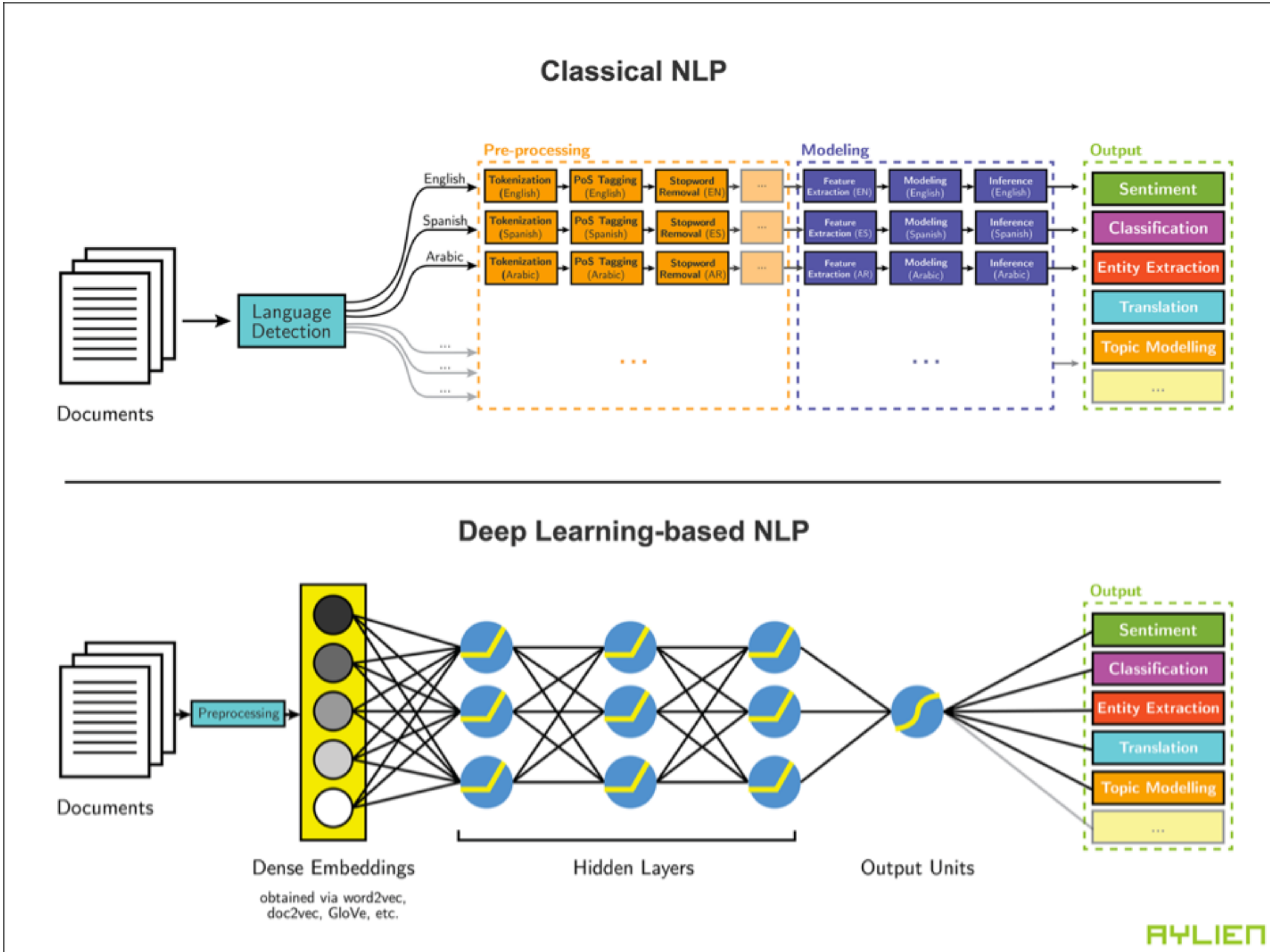
- Lexical similarity
  - Syntax, structure, and content of the documents
- Semantic similarity
  - Semantics, meaning, and context of the documents

Source: Dipanjan Sarkar (2019), Text Analytics with Python: A Practitioner's Guide to Natural Language Processing, Second Edition. APress.

Cosine Similarity

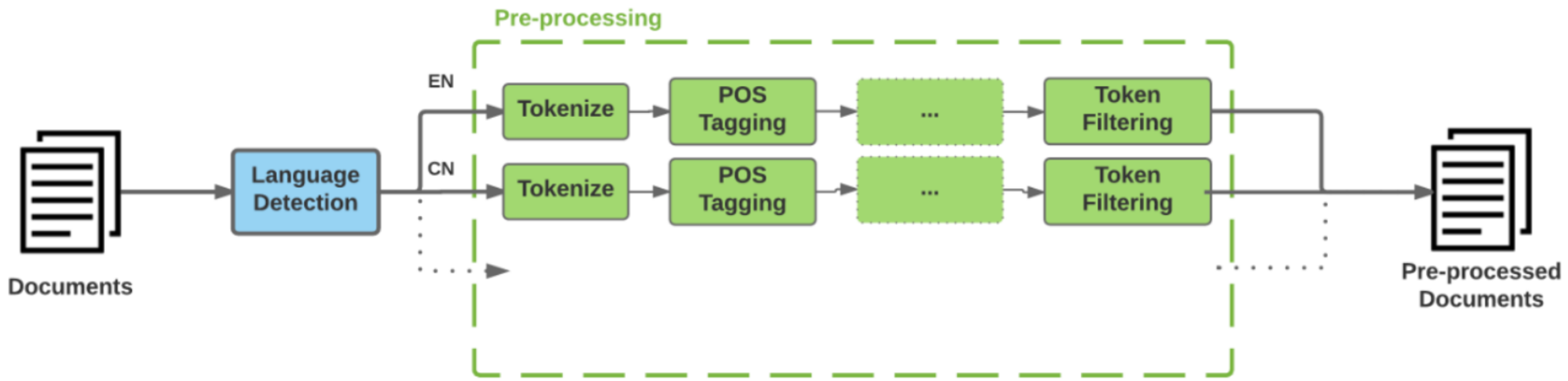


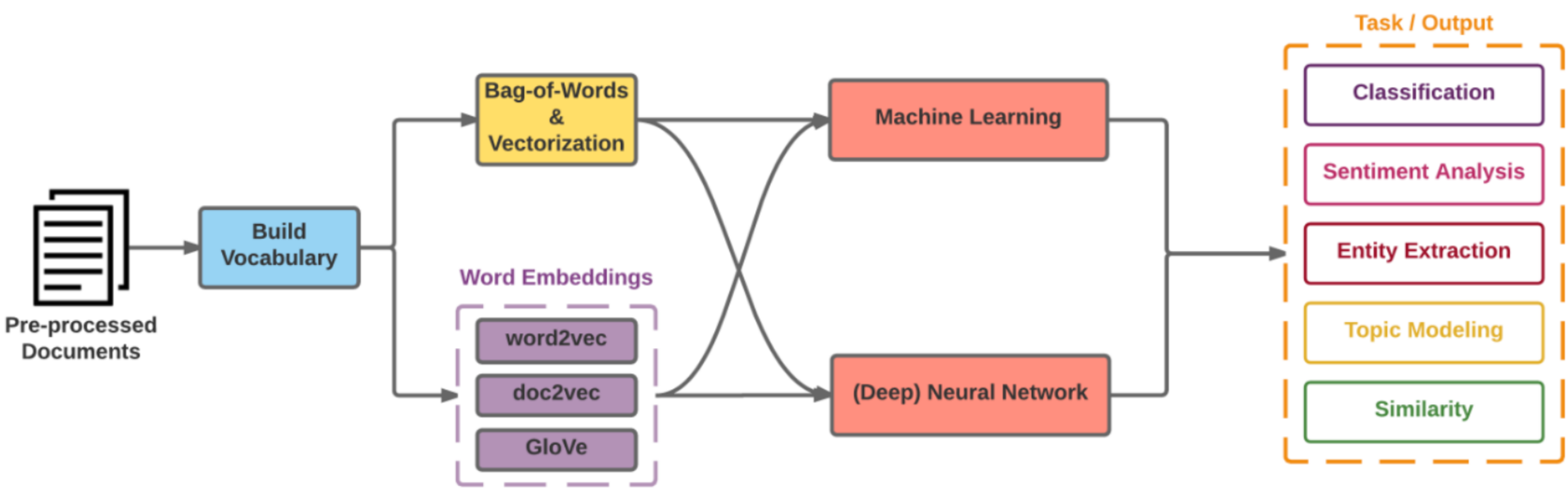
NLP



Source: http://blog.aylien.com/leveraging-deep-learning-for-multilingual/

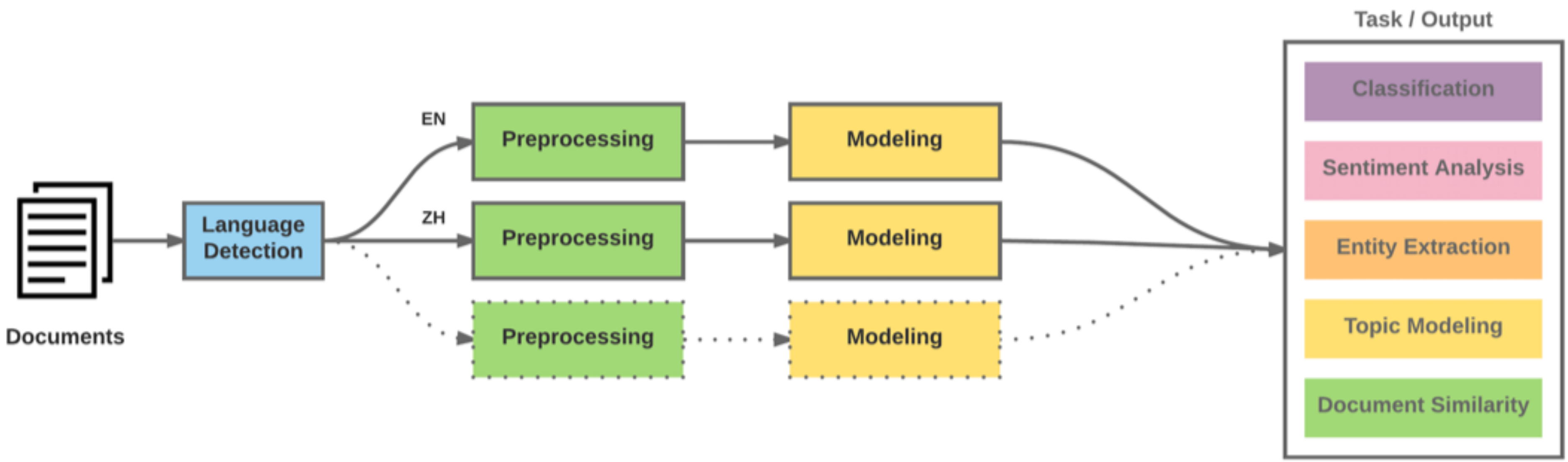
Modern NLP Pipeline





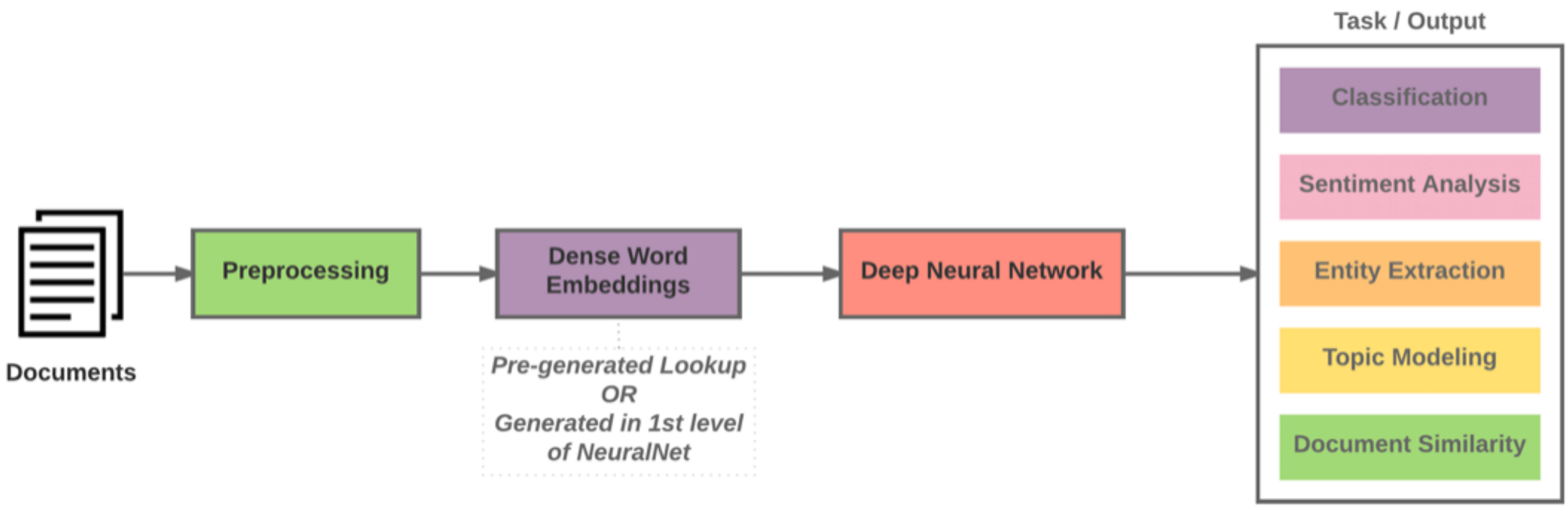
Source: https://github.com/fortiema/talks/blob/master/opendata2016sh/pragmatic-nlp-opendata2016sh.pdf

Modern NLP Pipeline



Source: http://mattfortier.me/2017/01/31/nlp-intro-pt-1-overview/

Deep Learning NLP



Source: http://mattfortier.me/2017/01/31/nlp-intro-pt-1-overview/

Natural Language Processing (NLP) and Text Mining

- Raw text
- Sentence Segmentation
- Tokenization
- Part-of-Speech (POS)
- Stop word removal
- Stemming / Lemmatization
- Dependency Parser
- String Metrics & Matching

word's stem	word's lemma
am → am	am → be
having → hav	having → have

Source: Nitin Hardeniya (2015), NLTK Essentials, Packt Publishing; Florian Leitner (2015), Text mining - from Bayes rule to dependency parsing

Data Mining Tasks & Methods

Data Mining Tasks & Methods	Data Mining Algorithms	Learning Type
Prediction		
Classification	Decision Trees, Neural Networks, Support Vector Machines, kNN, Naïve Bayes, GA	Supervised
Regression	Linear/Nonlinear Regression, ANN, Regression Trees, SVM, kNN, GA	Supervised
Time series	Autoregressive Methods, Averaging Methods, Exponential Smoothing, ARIMA	Supervised
Association		
Market-basket	Apriori, OneR, ZeroR, Eclat, GA	Unsupervised
Link analysis	Expectation Maximization, Apriori Algorithm, Graph-Based Matching	Unsupervised
Sequence analysis	Apriori Algorithm, FP-Growth, Graph-Based Matching	Unsupervised
Segmentation		
Clustering	*k*-means, Expectation Maximization (EM)	Unsupervised
Outlier analysis	*k*-means, Expectation Maximization (EM)	Unsupervised

Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

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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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)

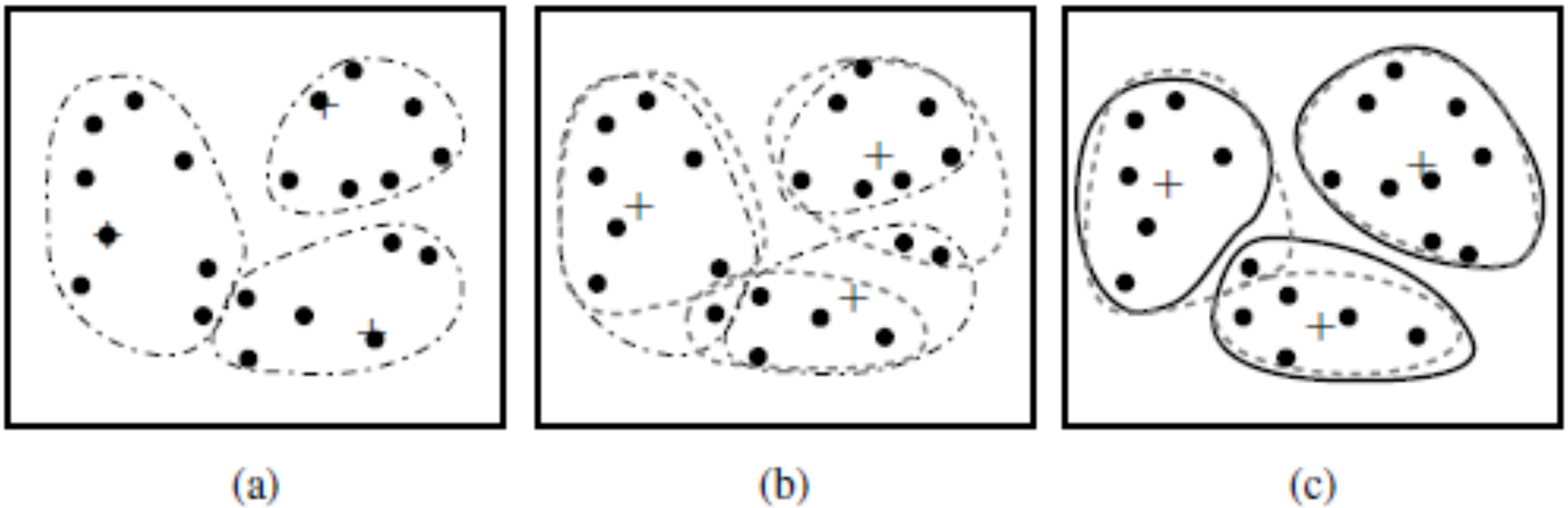
Cluster Analysis

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

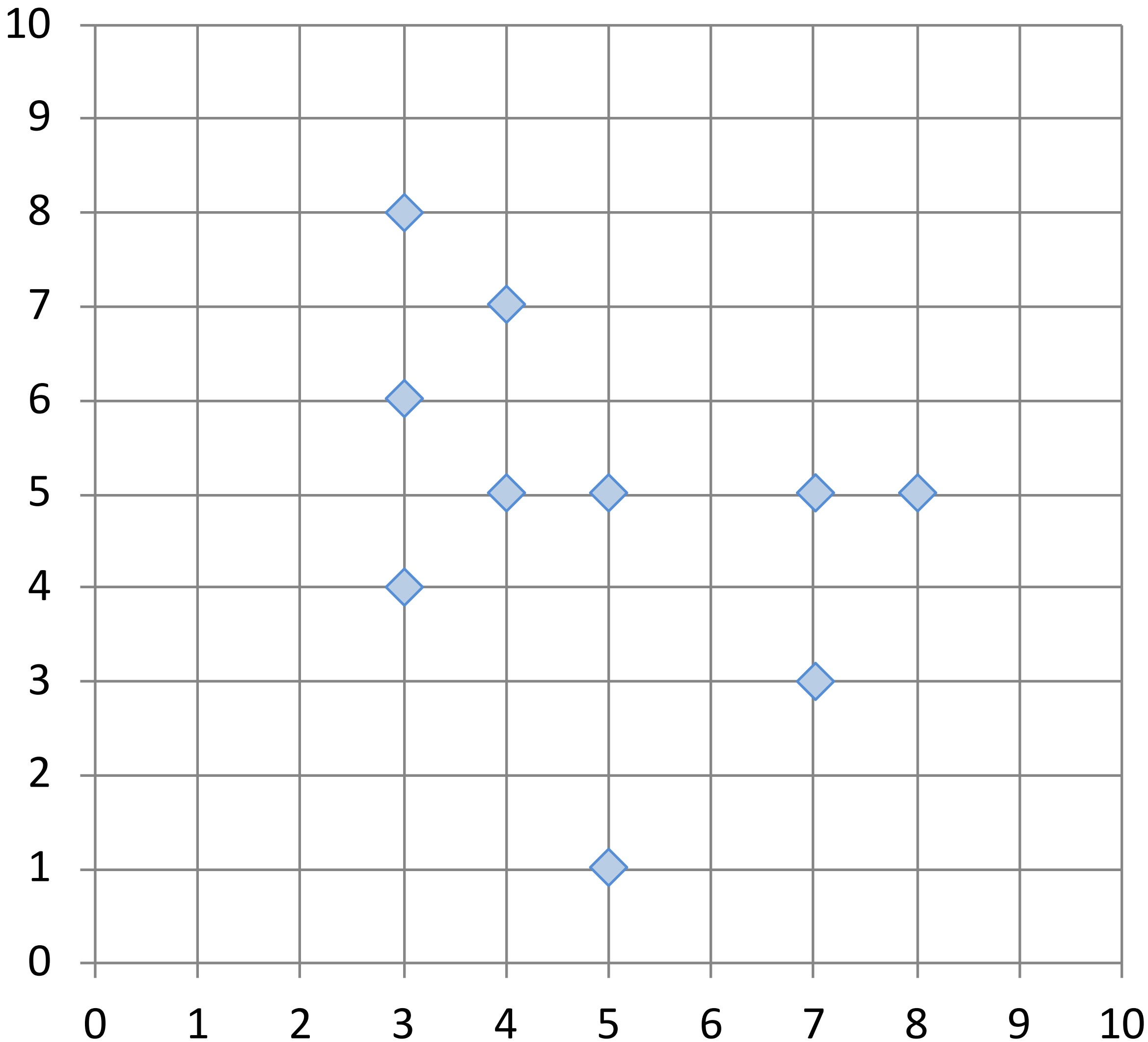
Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

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



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p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

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

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

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

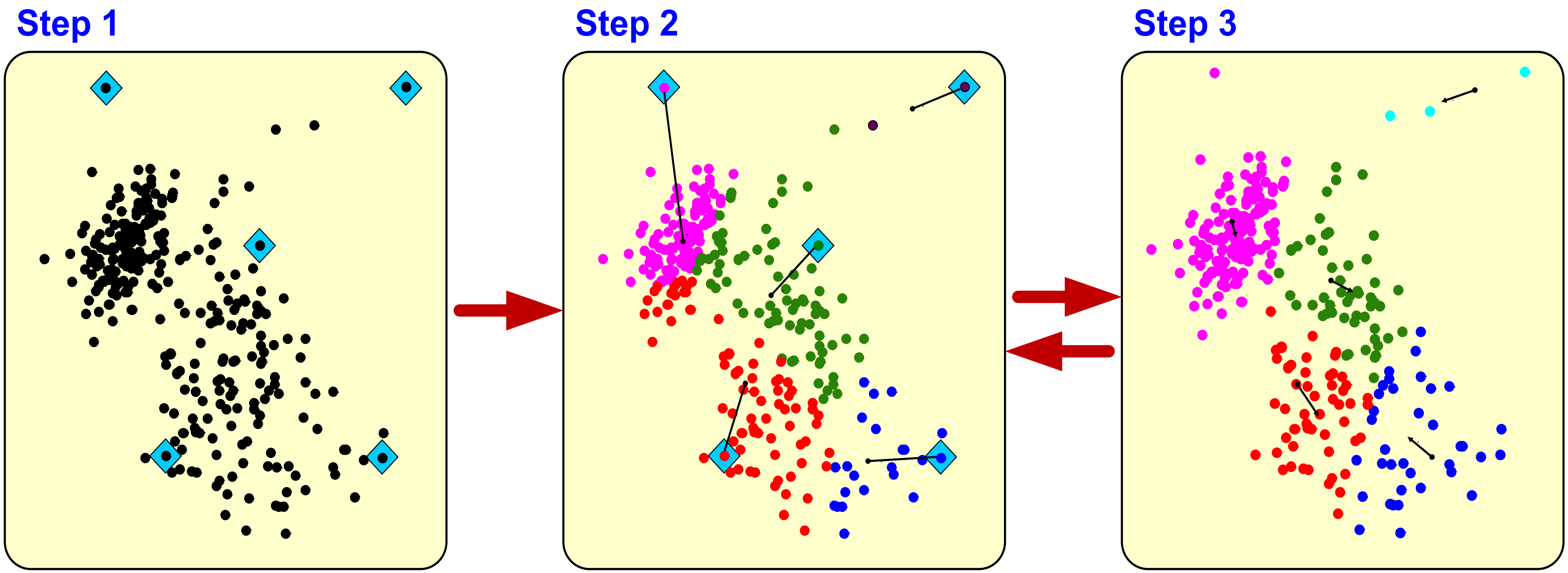
Step 2: Assign each point to the nearest cluster center

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)

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

Cluster Analysis for Data Mining - *k*-Means Clustering Algorithm



Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

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*:

$$d(i,j) = \sqrt[q]{(|x_{i_1} - x_{j_1}|^q + |x_{i_2} - x_{j_2}|^q + ... + |x_{i_p} - x_{j_p}|^q)}$$

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

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

$$d(i,j) = |x_{i_1} - x_{j_1}| + |x_{i_2} - x_{j_2}| + ... + |x_{i_p} - x_{j_p}|$$

Source: Han & Kamber (2006)

Similarity and Dissimilarity Between Objects (Cont.)

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

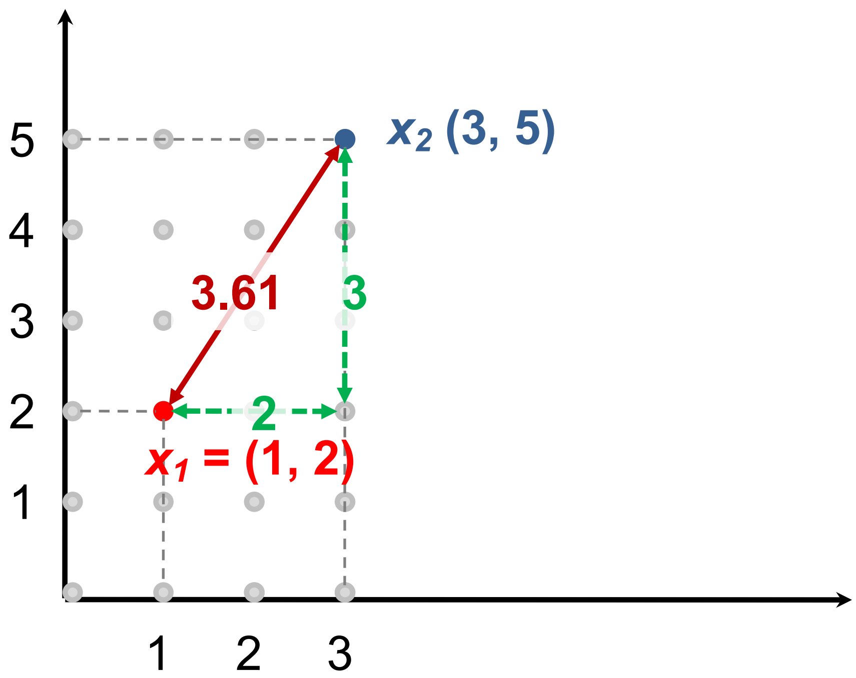
$$d(i,j)=\sqrt{(|x_{i_1}-x_{j_1}|^2+|x_{i_2}-x_{j_2}|^2+...+|x_{i_p}-x_{j_p}|^2)}$$

  - 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

Source: Han & Kamber (2006)

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:

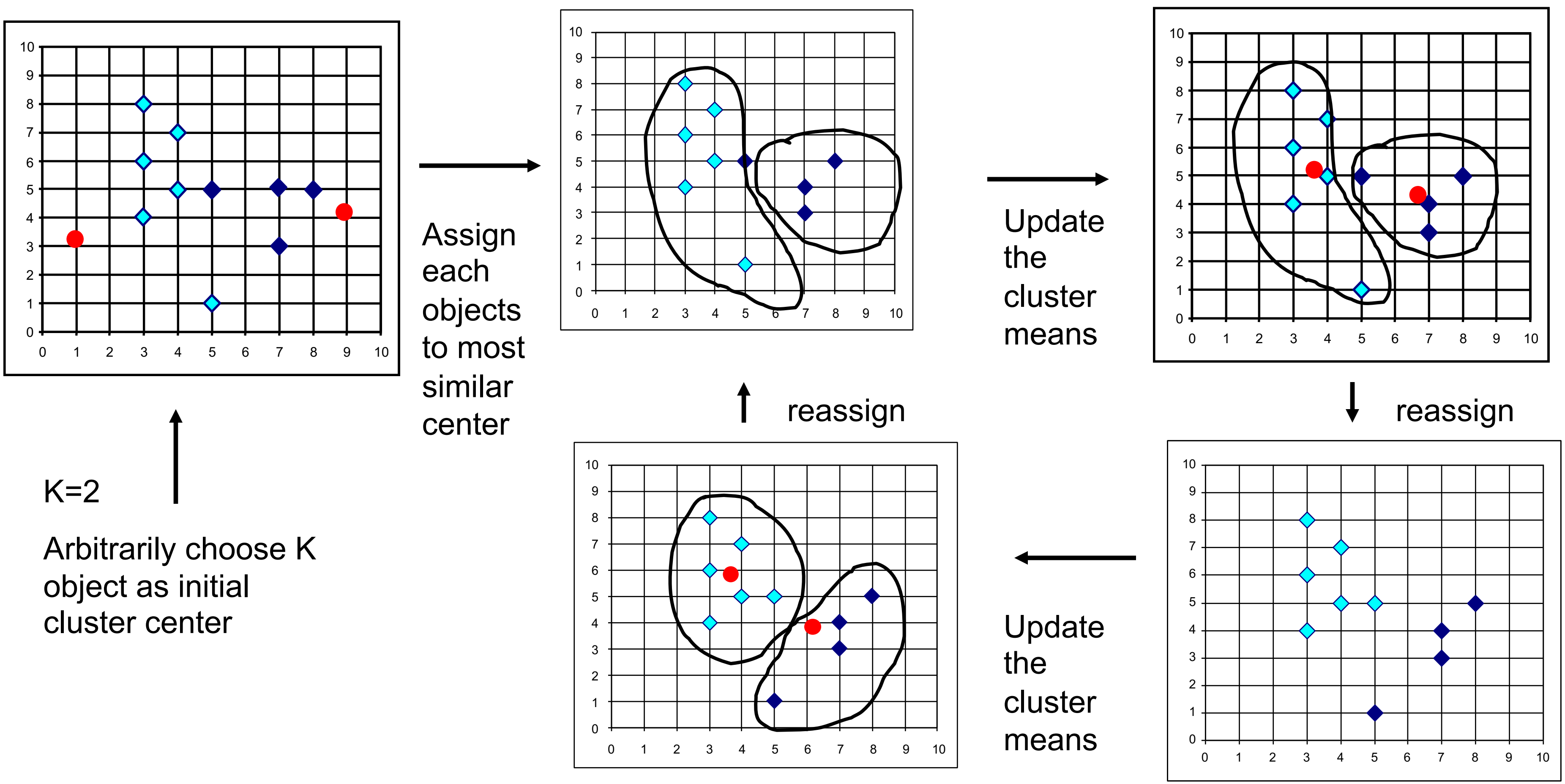
$= (3-1) + (5-2)$

$= 2 + 3$

$= 5$

The *K-Means* Clustering Method

- Example



Source: Han & Kamber (2006)

K-Means Clustering

Example of Cluster Analysis

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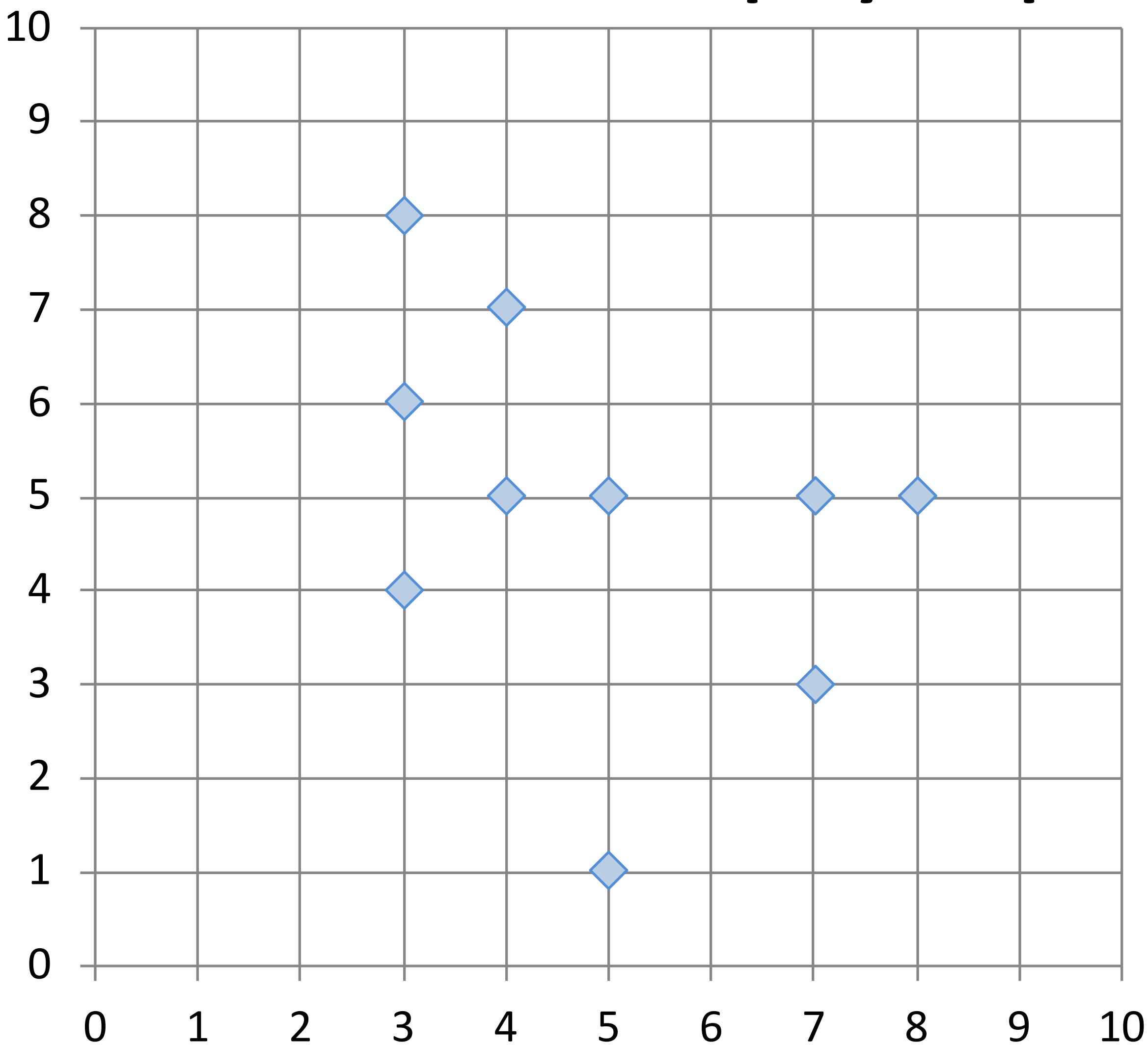
p02	b	(3, 6)
p03	c	(3, 8)
p04	d	(4, 5)
p05	e	(4, 7)
p06	f	(5, 1)
p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

K-Means Clustering

Step by Step



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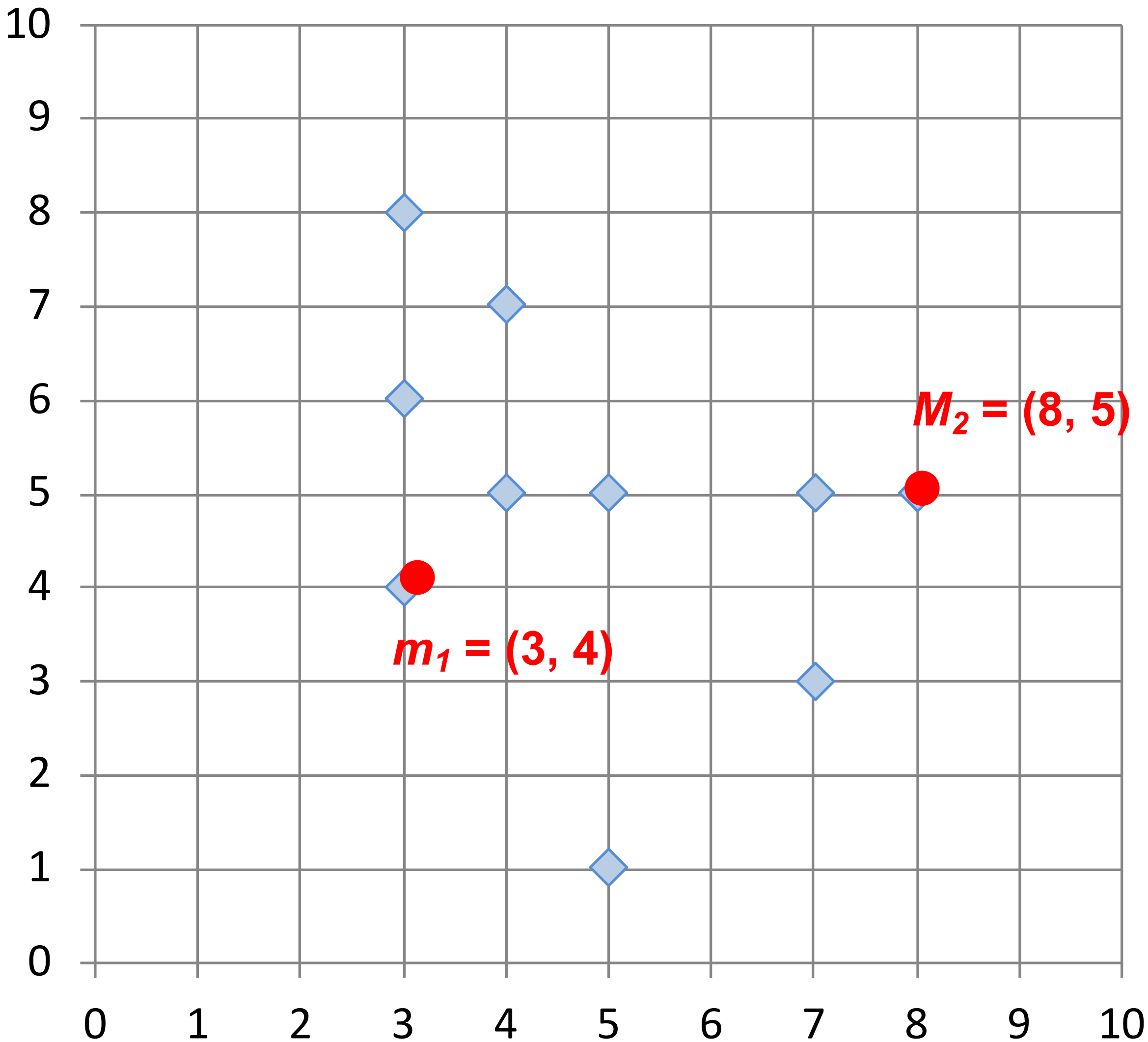
p05	e	(4, 7)
p06	f	(5, 1)
p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)

K-Means Clustering

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



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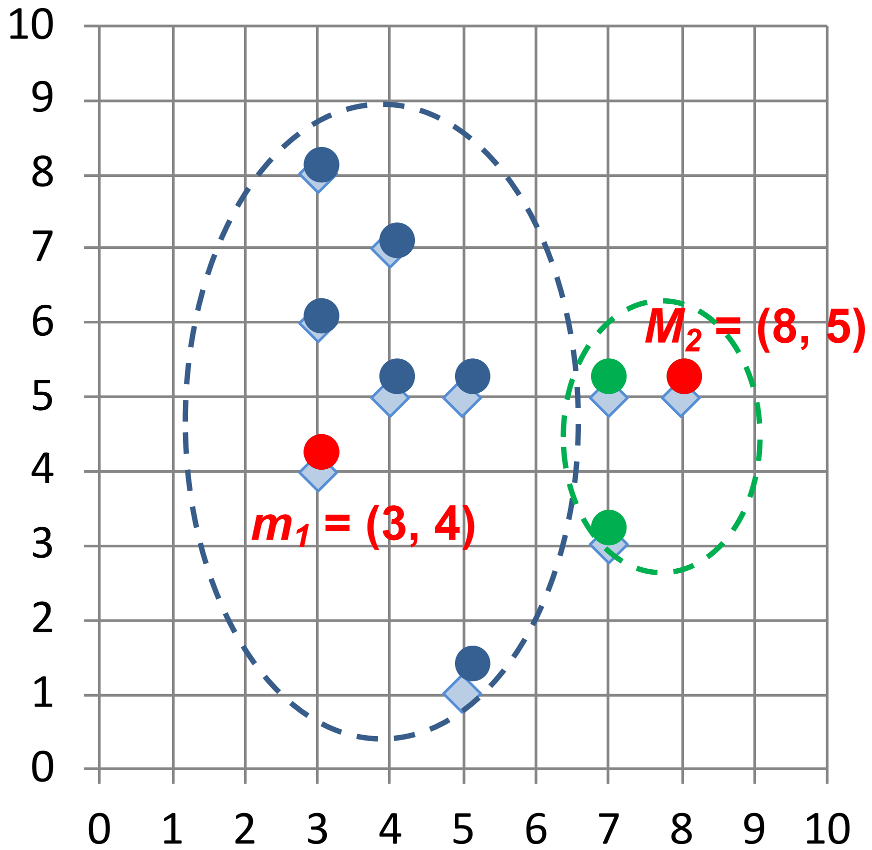
p02	b	(3, 6)
p03	c	(3, 8)
p04	d	(4, 5)
p05	e	(4, 7)
p06	f	(5, 1)
p07	g	(5, 5)
p08	h	(7, 3)
p09	i	(7, 5)
p10	j	(8, 5)
Initial	m1	(3, 4)
Initial	m2	(8, 5)

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

Step 3: Assign each objects to most similar center



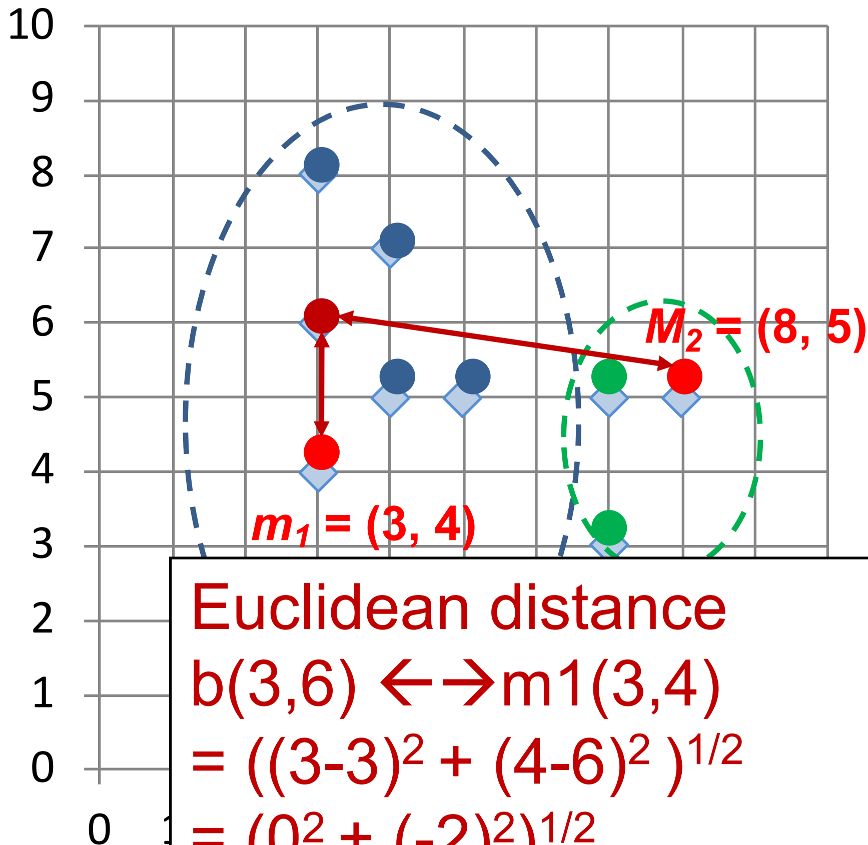
Point	P	P(x,y)	m1 distance	m2 distance	Cluster
p01	a	(3, 4)	0.00	5.10	Cluster1
p02	b	(3, 6)	2.00	5.10	Cluster1
p03	c	(3, 8)	4.00	5.83	Cluster1
p04	d	(4, 5)	1.41	4.00	Cluster1
p05	e	(4, 7)	3.16	4.47	Cluster1
p06	f	(5, 1)	3.61	5.00	Cluster1
p07	g	(5, 5)	2.24	3.00	Cluster1
p08	h	(7, 3)	4.12	2.24	Cluster2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

Initial	m1	(3, 4)
Initial	m2	(8, 5)

***K-Means* Clustering**

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

Step 3: Assign each objects to most similar center



Euclidean distance

b(3,6) ←→ m1(3,4)

$= ((3-3)^2 + (4-6)^2)^{1/2}$

$= (0^2 + (-2)^2)^{1/2}$

$= (0 + 4)^{1/2}$

$= (4)^{1/2}$

$= 2.00$

K-I

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					ster1
p06					ster1
p07					ster1
p08					ster2
p09					ster2
p10					ster2

Euclidean distance

b(3,6) ←→ m2(8,5)

$= ((8-3)^2 + (5-6)^2)^{1/2}$

$= (5^2 + (-1)^2)^{1/2}$

$= (25 + 1)^{1/2}$

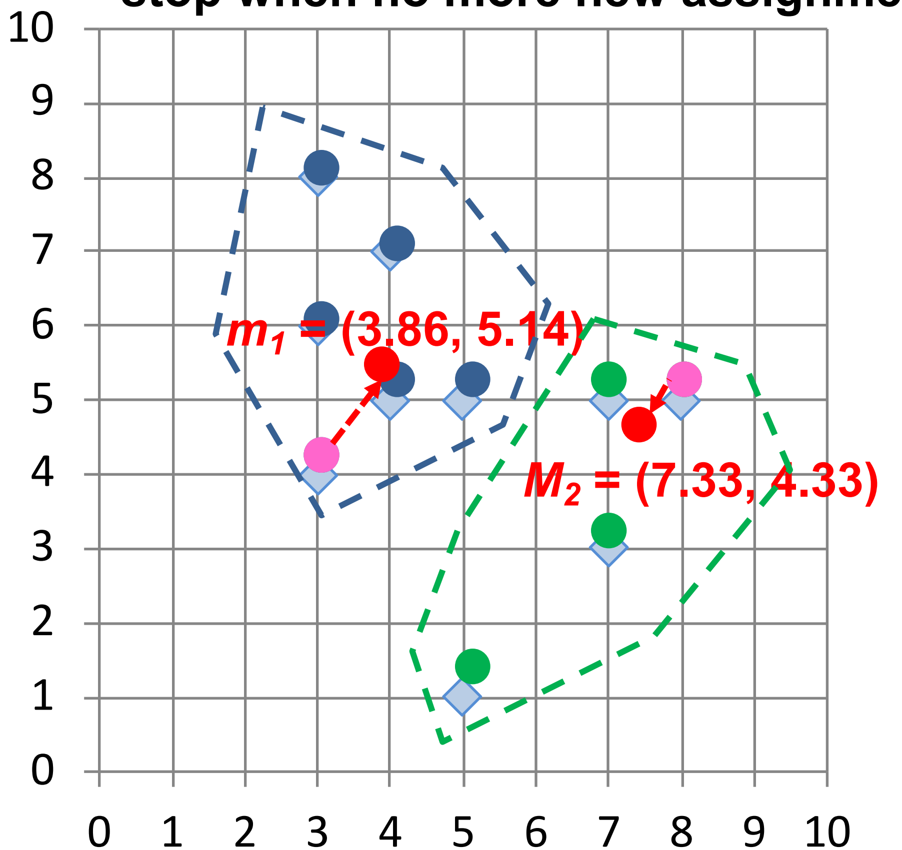
$= (26)^{1/2}$

$= 5.10$

Initial m1 (3, 4)

Initial m2 (8, 5)

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



Point	P	P(x,y)	m1 distance	m2 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

m1 (3.86, 5.14)
m2 (7.33, 4.33)

K-Means Clustering

Step 4: Update the cluster means,
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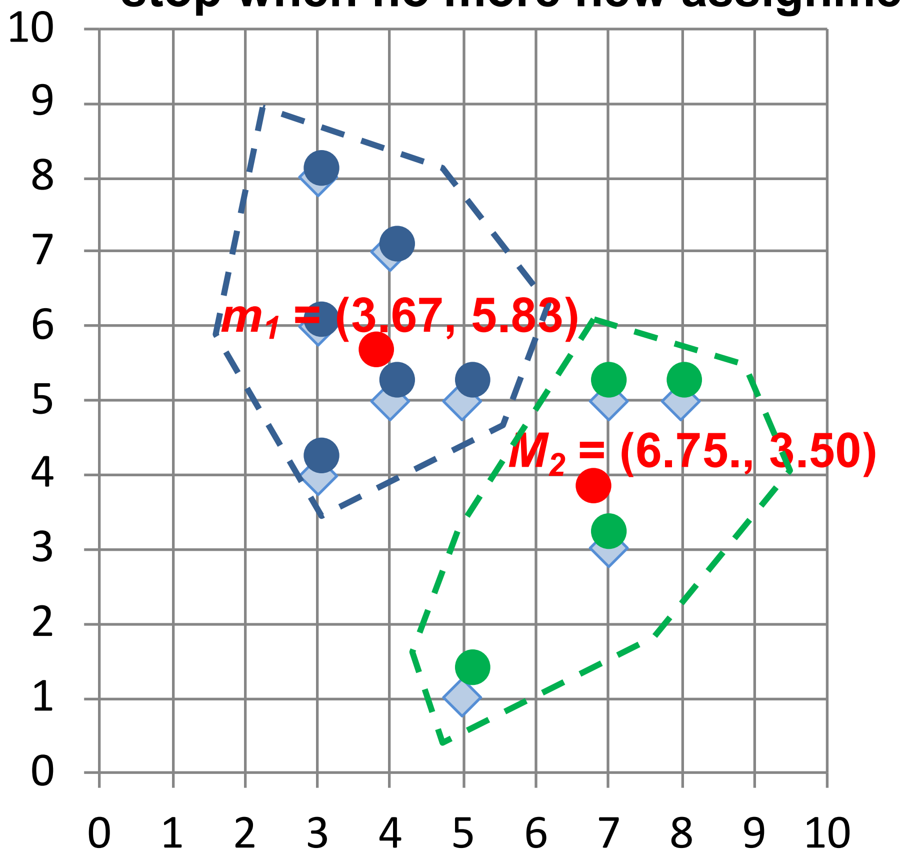

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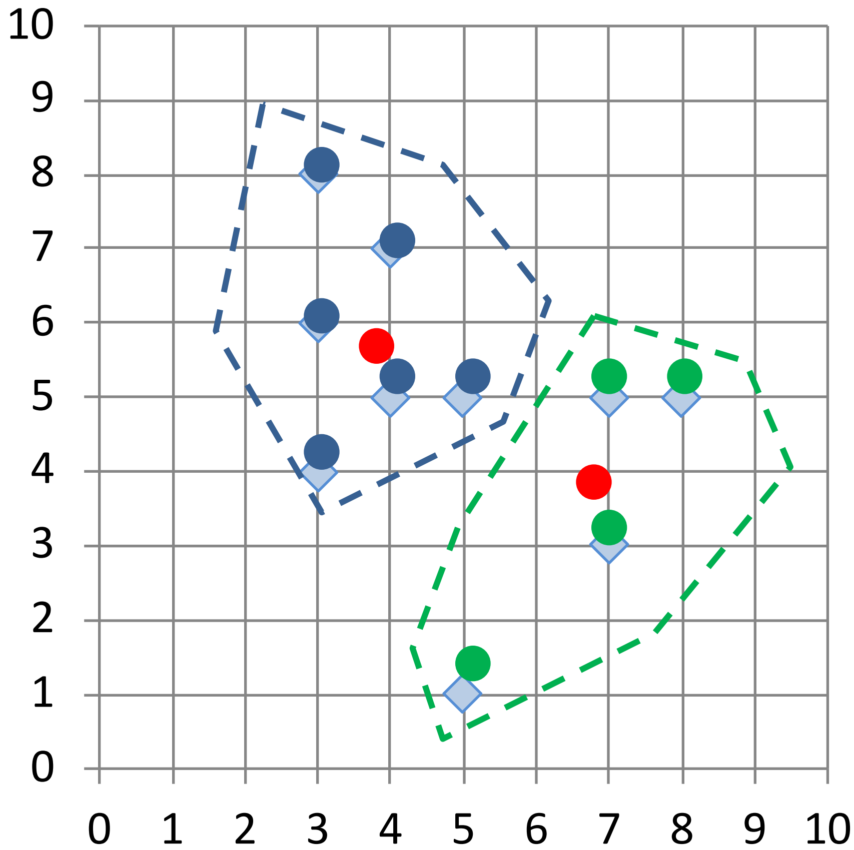
p04	d	(4, 5)	0.89	3.13	Cluster1
p05	e	(4, 7)	1.22	4.45	Cluster1
p06	f	(5, 1)	5.01	3.05	Cluster2
p07	g	(5, 5)	1.57	2.30	Cluster1
p08	h	(7, 3)	4.37	0.56	Cluster2
p09	i	(7, 5)	3.43	1.52	Cluster2
p10	j	(8, 5)	4.41	1.95	Cluster2

m1 (3.67, 5.83)
m2 (6.75, 3.50)

K-Means Clustering

stop when no more new assignment



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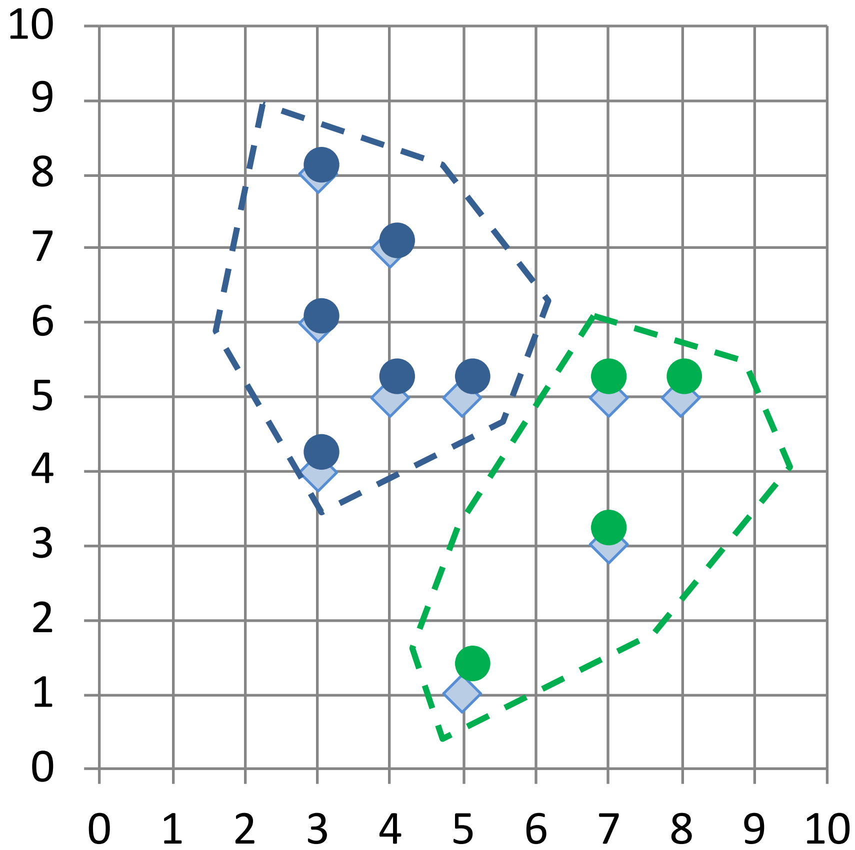
m1 (3.67, 5.83)

m2 (6.75, 3.50)

K-Means Clustering

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

stop when no more new assignment



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K-Means Clustering

m1 (3.67, 5.83)

m2 (6.75, 3.50)

K-Means Clustering

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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)

gensim

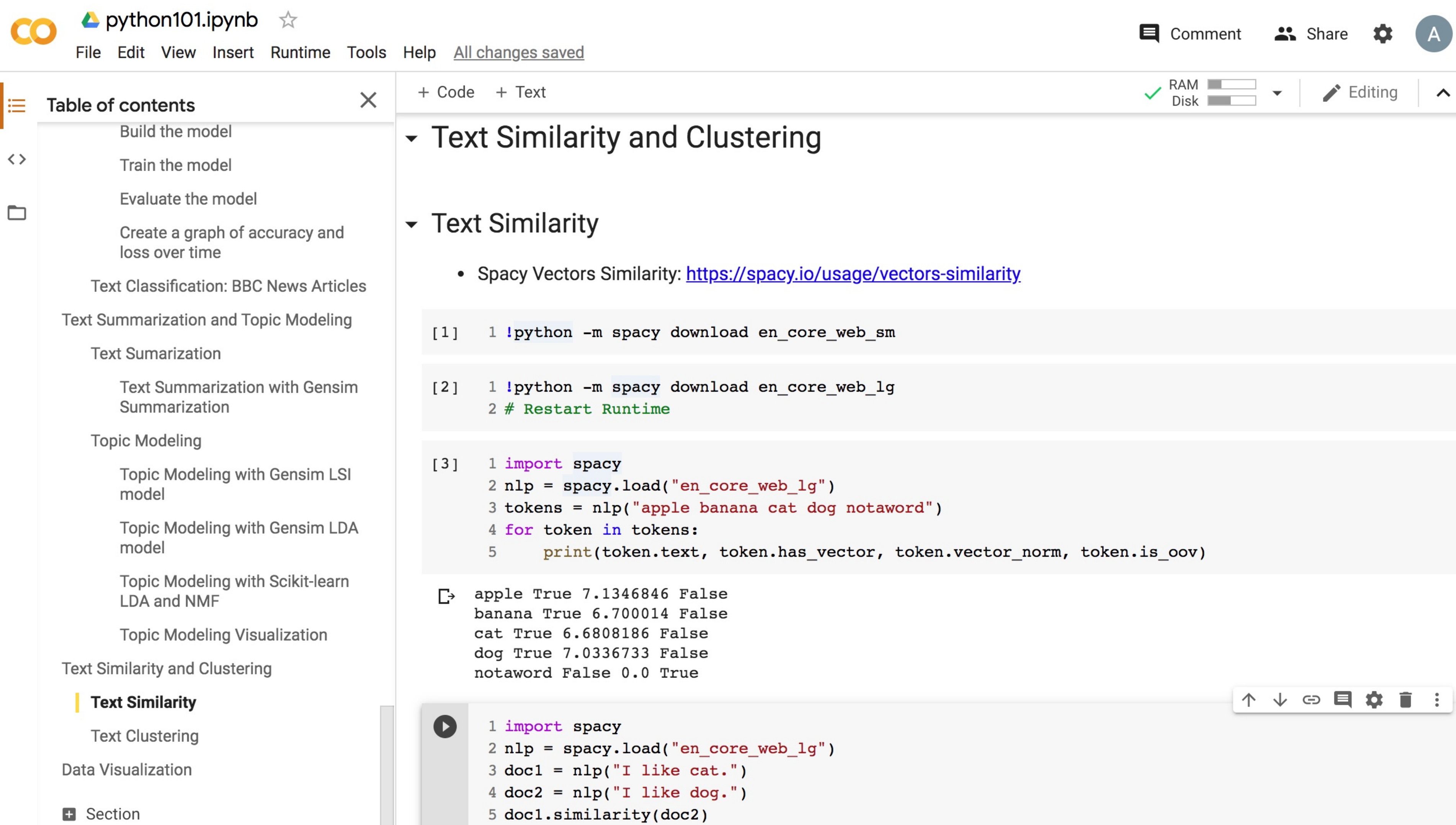
https://radimrehurek.com/gensim/

spaCy

https://spacy.io/

Python in Google Colab (Python101)

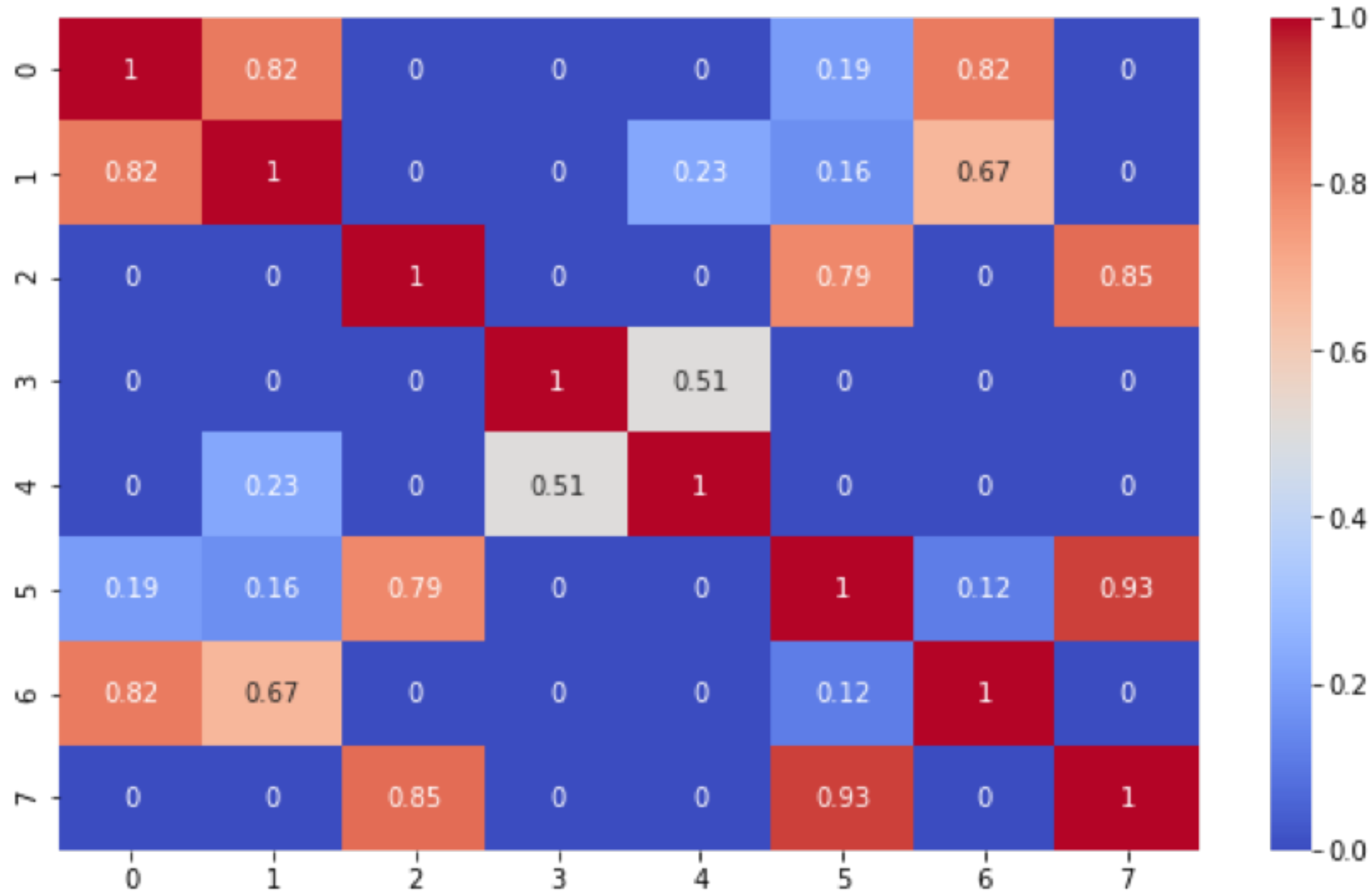
https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT



https://tinyurl.com/imtkupython101

Python in Google Colab (Python101)

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



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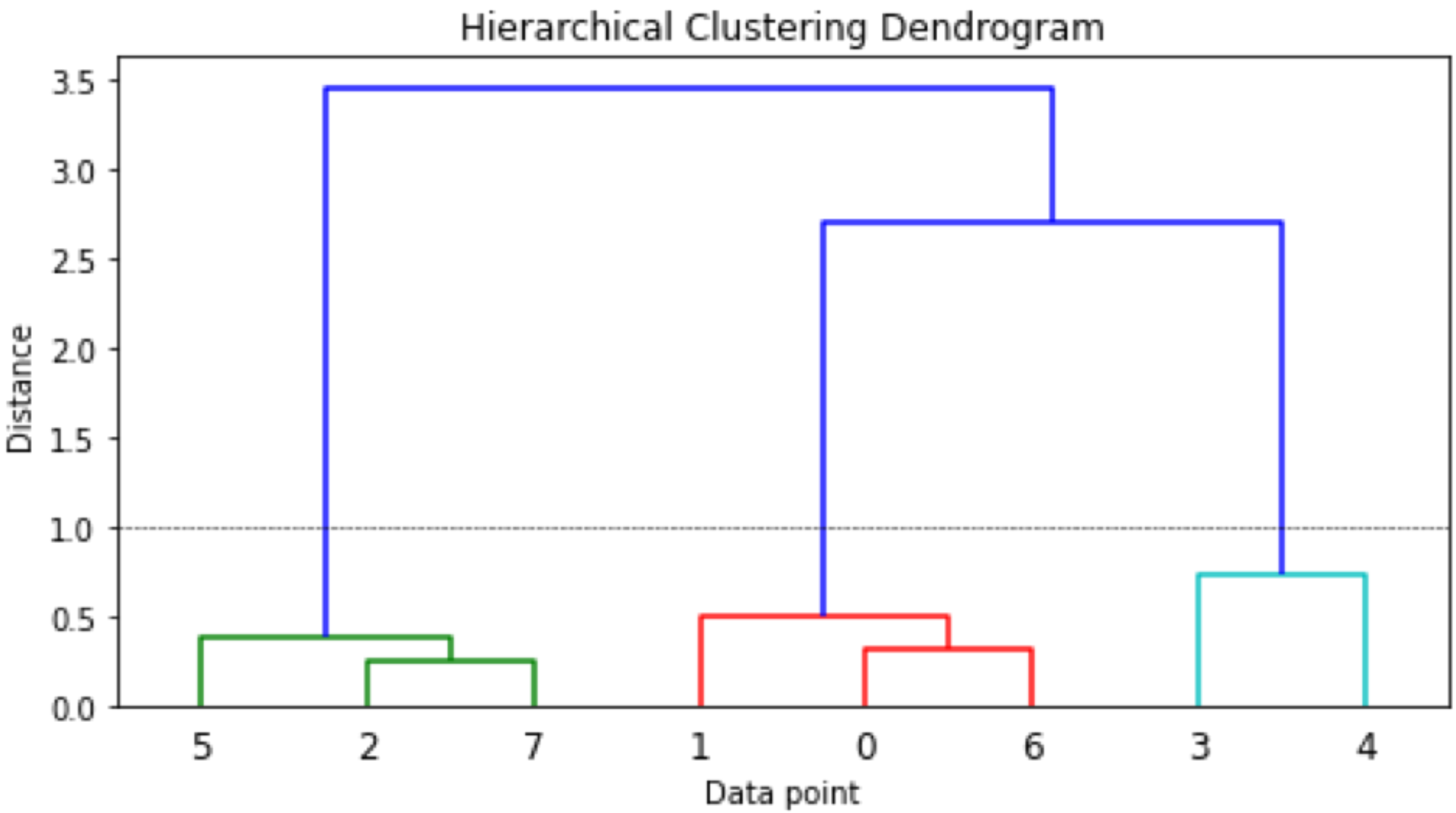

https://tinyurl.com/imtkupython101

Summary

- Text Similarity
- Text Clustering
  - Cluster Analysis
  - K-Means Clustering

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  https://www.oreilly.com/library/view/applied-text-analysis/9781491963036/
- Min-Yuh Day (2020), Python 101, https://tinyurl.com/imtkupython101