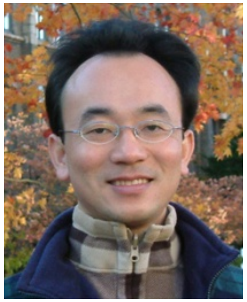
Tamkang Universit
淡江大學

文字探勘
(Text Mining)

文字探勘課程介紹
(Course Orientation on Text Mining)

1082TM01
MBA, BDABI, TKU (E3611) (8480) (Spring 2020)
Mon, 7, 8, 9 (14:10-17:00) (B206)

Chichang Jou
周清江
Associate Professor
副教授
cjou@mail.tku.edu.tw



Min-Yuh Day
戴敏育
Associate Professor
副教授
myday@mail.tku.edu.tw

Dept. of Information Management, Tamkang University
淡江大學 資訊管理學系

2020-03-02

文字探勘

(Text Mining)

淡江大學108學年度第2學期
課程教學計畫表
Spring 2020 (2020.02 - 2020.06)

- 課程名稱：文字探勘 (Text Mining)
- 授課教師：周清江 (Chichang Jou)，
  戴敏育 (Min-Yuh Day)
- 開課系級：大數據碩士學程 (TLXDM)
  Master’s Program in Big Data Analytics and Business Intelligence
- 開課資料：選修 單學期 3 學分 (3 Credits, Elective)
- 上課時間：週一 7, 8, 9 (Mon 14:10-17:00)
- 上課教室： B206 (淡江大學淡水校園)

淡江大學大數據所系(所)教育目標

- 培育學生具研究大數據的能力。
- 培育學生具大數據程式設計的能力。

淡江大學大數據所 系(所)核心能力

- A. 具研究大數據分析理論的能力。 (比重：40.00)
- B. 具大數據分析的能力。 (比重：40.00)
- C. 具整合各領域之知識的能力。 (比重：20.00)

課程簡介

- 本課程介紹文字探勘基本概念與研究議題。
- 課程內容包括
  - 文字探勘的基礎：自然語言處理 (NLP)、
  - Python自然語言處理、
  - 處理和理解文本、
  - 文本表達特徵工程、
  - 文本分類、
  - 文本摘要和主題模型、
  - 文本相似度和分群、
  - 語意分析與命名實體識別 (NER)、
  - 情感分析、
  - 深度學習和通用句子嵌入模型、
  - 問答系統與對話系統、
  - 和文字探勘個案研究。

Course Introduction

- This course introduces the fundamental concepts and research issues of Text Mining.
- Topics include
  - Foundations of Text Mining: Natural Language Processing (NLP),
  - Python for NLP,
  - Processing and Understanding Text,
  - Feature Engineering for Text Representation,
  - Text Classification,
  - Text Summarization and Topic Models,
  - Text Similarity and Clustering,
  - Semantic Analysis and Named Entity Recognition,
  - Sentiment Analysis,
  - The Promise of Deep Learning and Universal Sentence-Embedding Models,
  - Question Answering and Dialogue Systems,
  - and Case Study on Text Mining.

課程目標
(Objective)

- 瞭解及應用文字探勘基本概念與研究議題。
  Understand and apply the fundamental concepts and research issues of Text Mining.

- 進行文字探勘相關之資訊管理研究。
  Conduct information systems research in the context of Text Mining.

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
1	2020/03/02	文字探勘課程介紹 (Course Orientation on Text Mining)
2	2020/03/09	文字探勘基礎：自然語言處理 (Foundations of Text Mining: Natural Language Processing; NLP)
3	2020/03/16	Python自然語言處理 (Python for Natural Language Processing)
4	2020/03/23	處理和理解文本 (Processing and Understanding Text)
5	2020/03/30	文本表達特徵工程 (Feature Engineering for Text Representation)
6	2020/04/06	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	2020/04/13	文本分類 (Text Classification)
8	2020/04/20	文本摘要和主題模型 (Text Summarization and Topic Models)
9	2020/04/27	期中報告 (Midterm Project Report)
10	2020/05/04	文本相似度和分群 (Text Similarity and Clustering)
11	2020/05/11	語意分析和命名實體識別 (Semantic Analysis and Named Entity Recognition; NER)
12	2020/05/18	情感分析 (Sentiment Analysis)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
13	2020/05/25	人工智慧文本分析個案研究 II (Case Study on Artificial Intelligence for Text Analytics II)
14	2020/06/01	深度學習和通用句子嵌入模型 (Deep Learning and Universal Sentence-Embedding Models)
15	2020/06/08	問答系統與對話系統 (Question Answering and Dialogue Systems)
16	2020/06/15	期末報告 I (Final Project Presentation I)
17	2020/06/22	期末報告 II (Final Project Presentation II)
18	2020/06/29	教師彈性補充教學

教學方法與評量方法

- 教學方法
  - 講述、討論、發表、實作
- 評量方法
  - 討論、實作、報告

教材課本

- 教材課本
  - 講義 (Slides)
  - 文字探勘相關個案與論文 (Cases and Papers related to Text Mining)

參考書籍 (References)

1. Dipanjan Sarkar (2019), Text Analytics with Python: A Practitioner’s Guide to Natural Language Processing, Second Edition. APress.
2. Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018), Applied Text Analysis with Python: Enabling Language-Aware Data Products with Machine Learning, O’Reilly.
3. Charu C. Aggarwal (2018), Machine Learning for Text, Springer.
4. Gabe Ignatow and Rada F. Mihalcea (2017), An Introduction to Text Mining: Research Design, Data Collection, and Analysis, SAGE Publications.

作業與學期成績計算方式

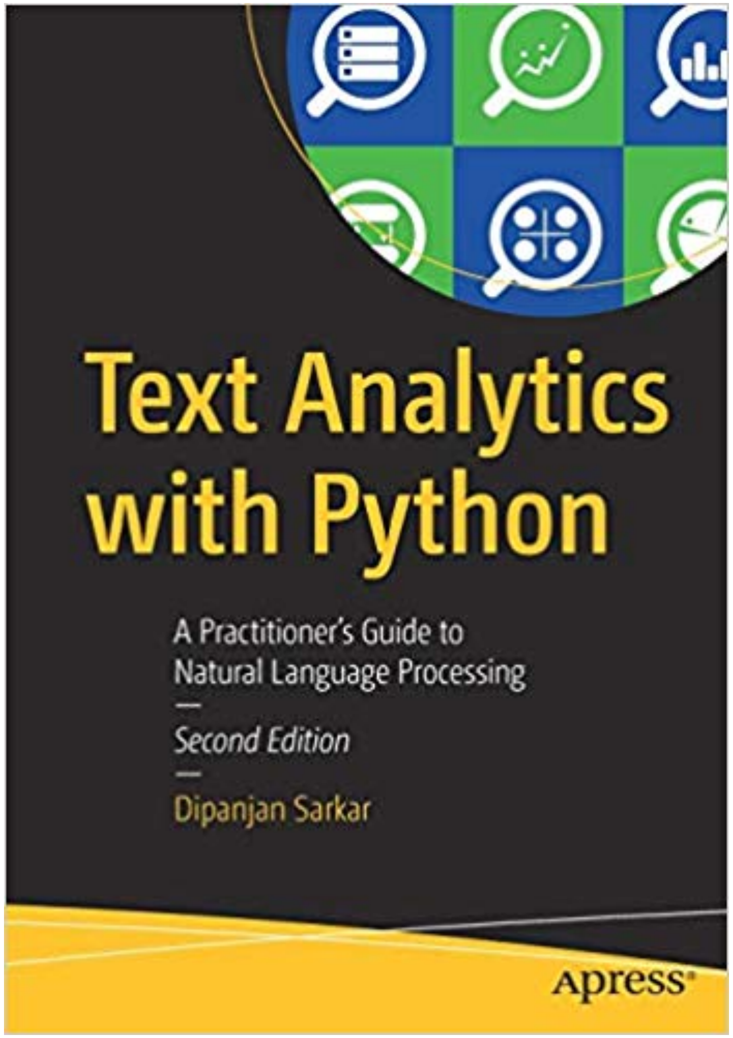
- 作業篇數
  - 3篇
- 學期成績計算方式
  - ☑期中評量：30 ％
  - ☑期末評量：30 ％
  - ☑其他（課堂參與及報告討論表現）：40 ％

Dipanjan Sarkar (2019),

Text Analytics with Python:

A Practitioner’s Guide to Natural Language Processing,

Second Edition. APress.


Text Analytics with Python
A Practitioner’s Guide to Natural Language Processing
Second Edition
Dipanjan Sarkar
apress

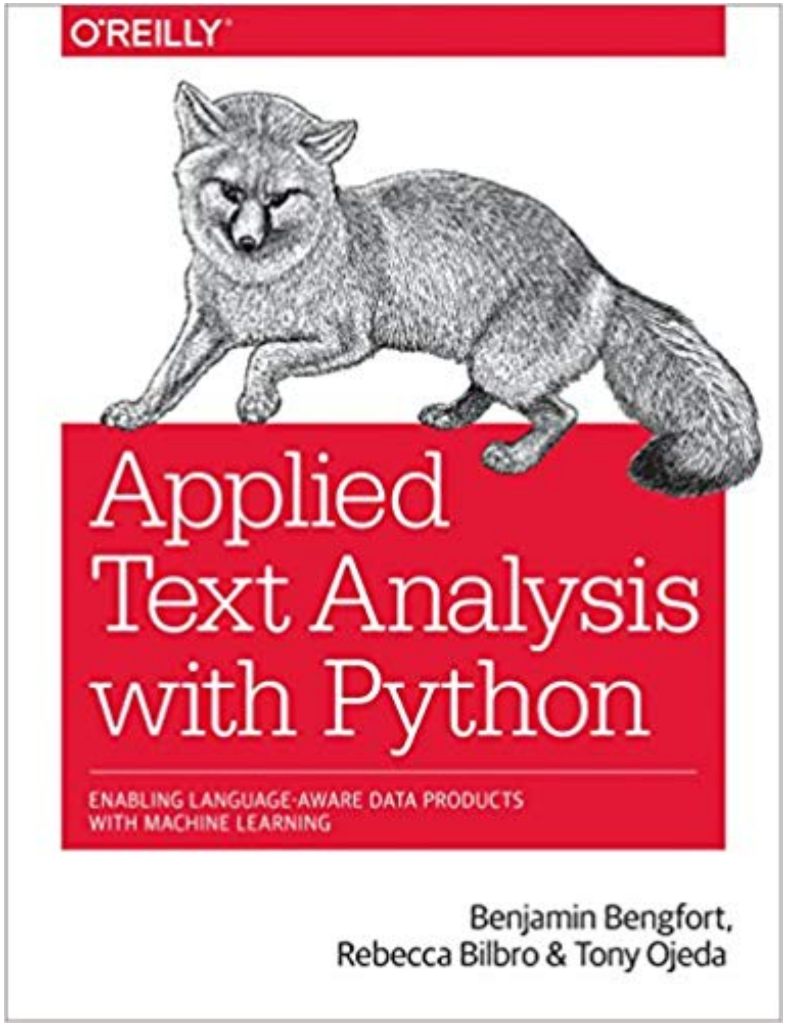
Source: https://www.amazon.com/Text-Analytics-Python-Practitioners-Processing/dp/1484243536

Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018),

Applied Text Analysis with Python:

Enabling Language-Aware Data Products with Machine Learning,

O'Reilly.



O'REILLY

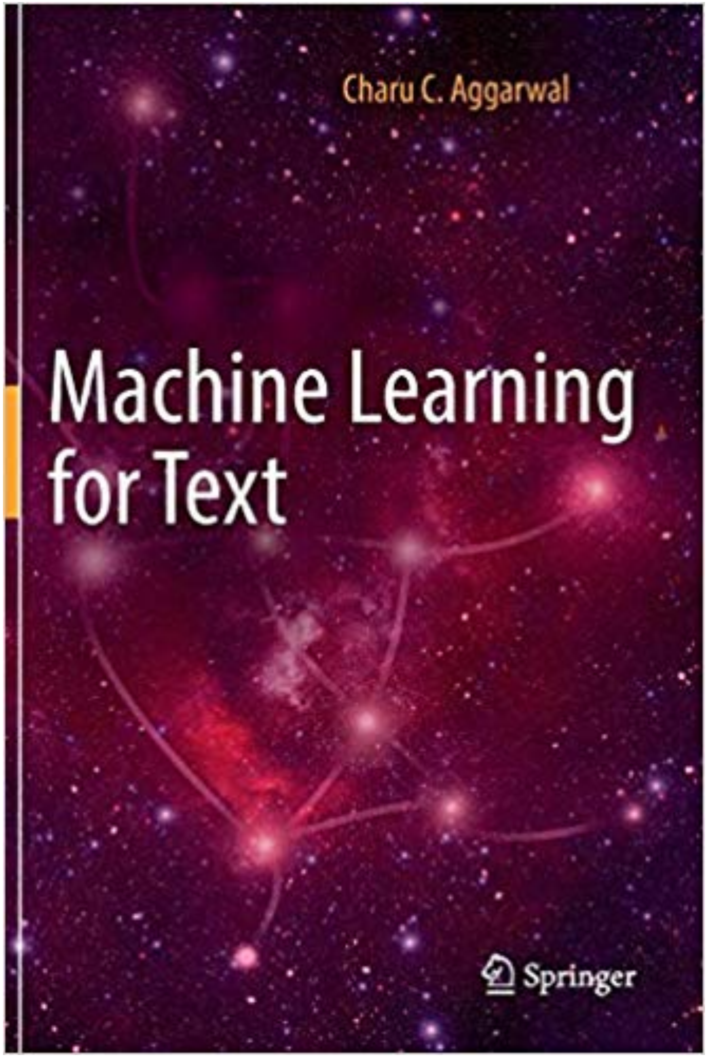
Applied Text Analysis with Python

ENABLING LANGUAGE-AWARE DATA PRODUCTS WITH MACHINE LEARNING

Benjamin Bengfort,
Rebecca Bilbro & Tony Ojeda

Source: https://www.amazon.com/Applied-Text-Analysis-Python-Language-Aware/dp/1491963042

Charu C. Aggarwal (2018),
Machine Learning for Text,
Springer



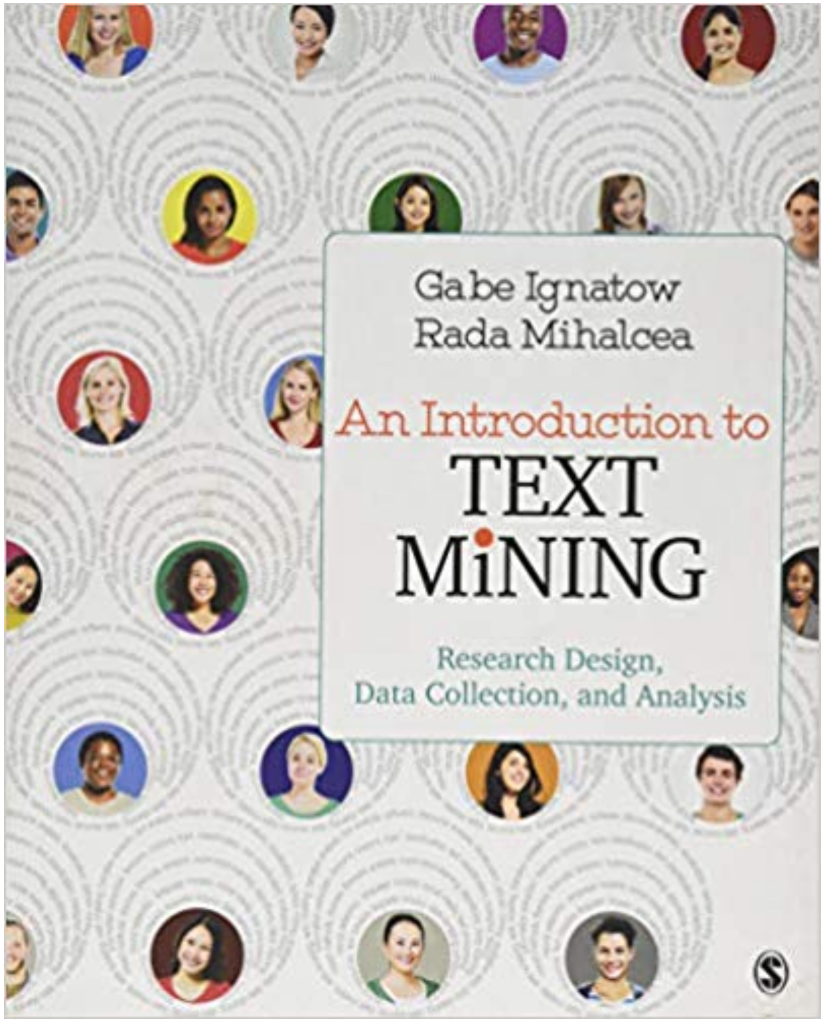
Source: https://www.amazon.com/Machine-Learning-Text-Charu-Aggarwal/dp/3319735306

Gabe Ignatow and Rada F. Mihalcea (2017),

An Introduction to Text Mining:

Research Design, Data Collection, and Analysis,

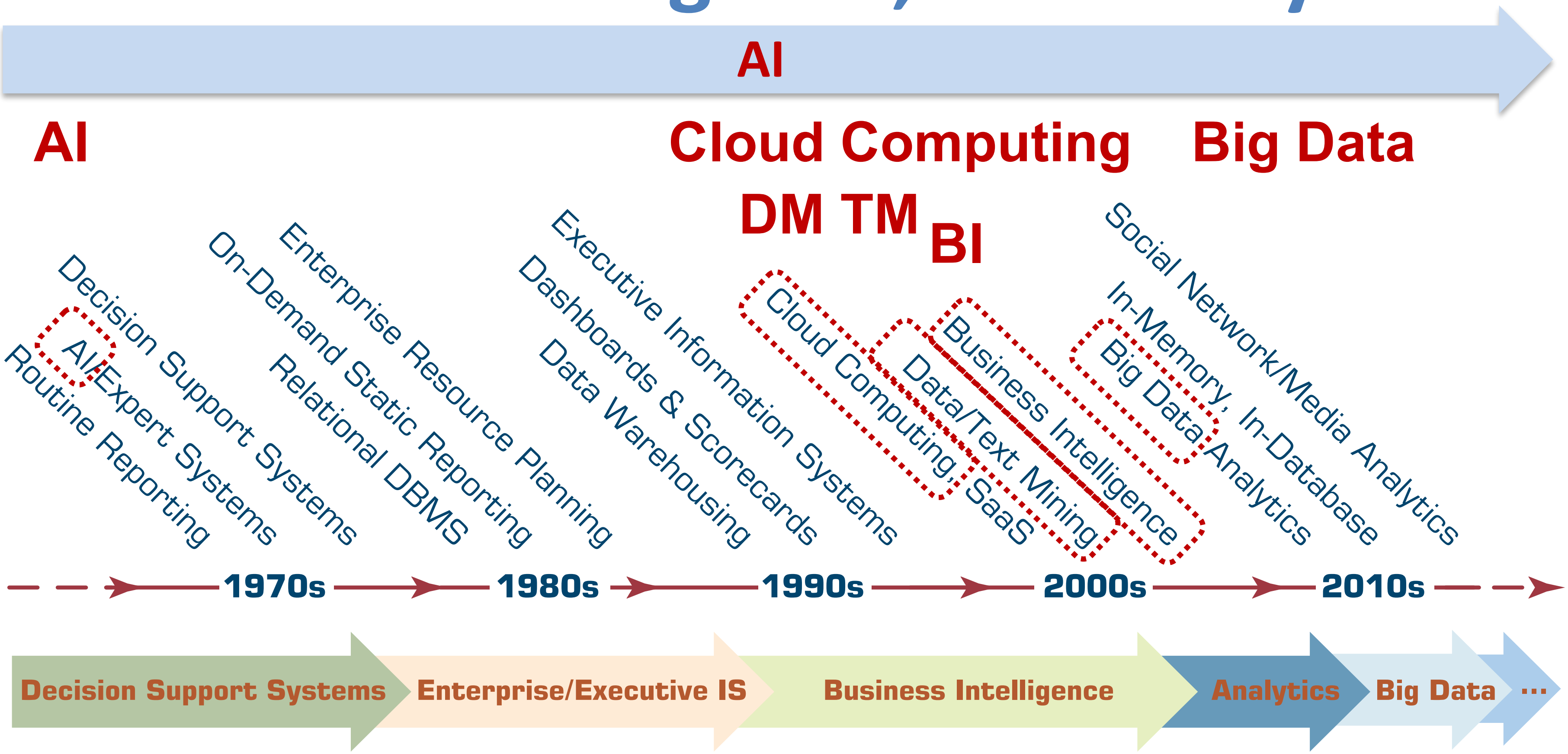
SAGE Publications.



Source: https://www.amazon.com/Introduction-Text-Mining-Research-Collection/dp/1506337007

AI, Big Data, Cloud Computing

Evolution of Decision Support, Business Intelligence, and Analytics



AI

AI

Cloud Computing

Big Data

DM TM

BI

Routine Reporting

AI/Expert Systems

Decision Support Systems

Relational DBMS

On-Demand Static Reporting

Enterprise Resource Planning

Data Warehousing

Dashboards & Scorecards

Executive Information Systems

Cloud Computing, SaaS

Data/Text Mining

Business Intelligence

Big Data Analytics

In-Memory, In-Database

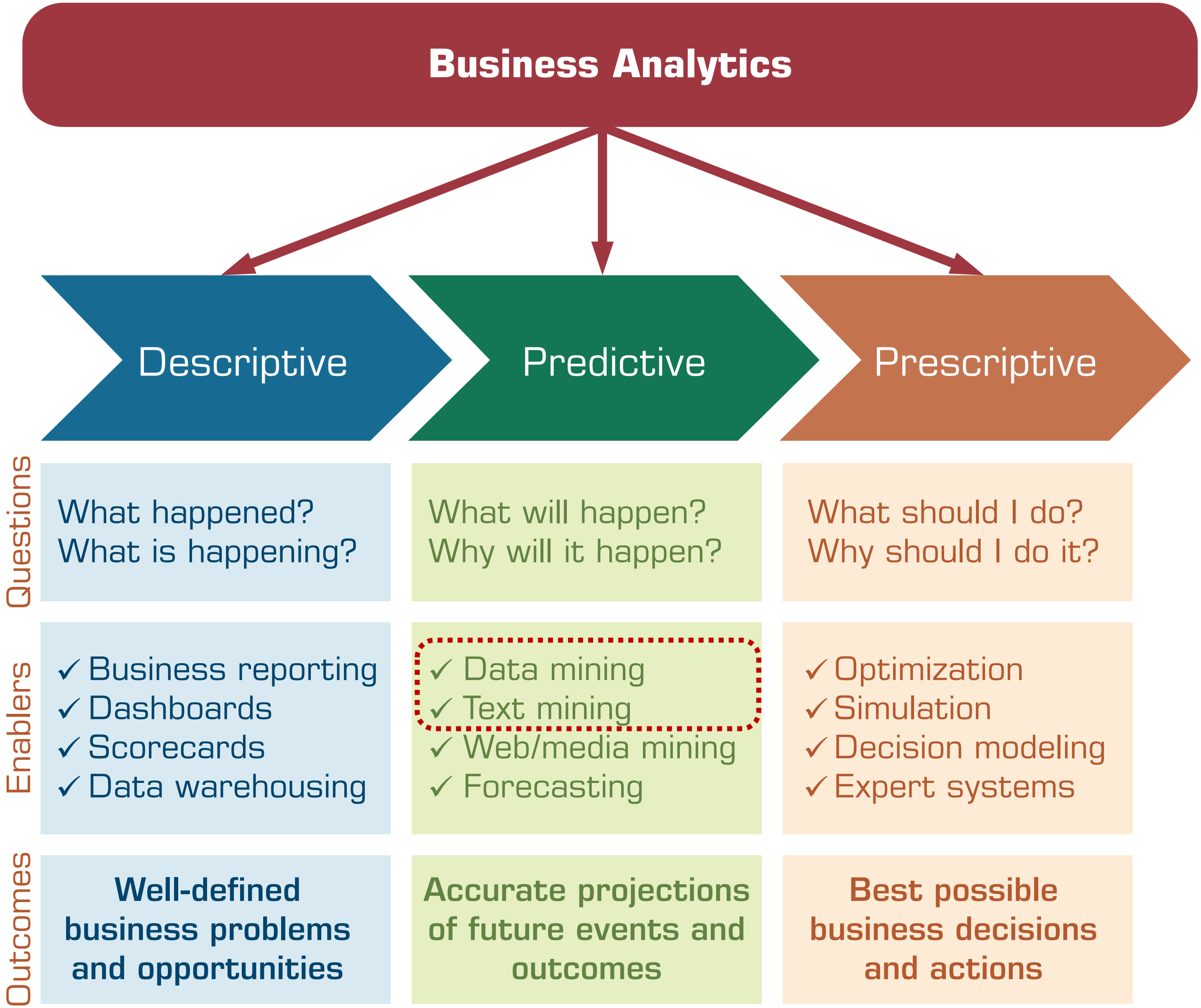
Social Network/Media Analytics

1970s → 1980s → 1990s → 2000s → 2010s

Decision Support Systems → Enterprise/Executive IS → Business Intelligence → Analytics → Big Data → …

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

Three Types of Analytics

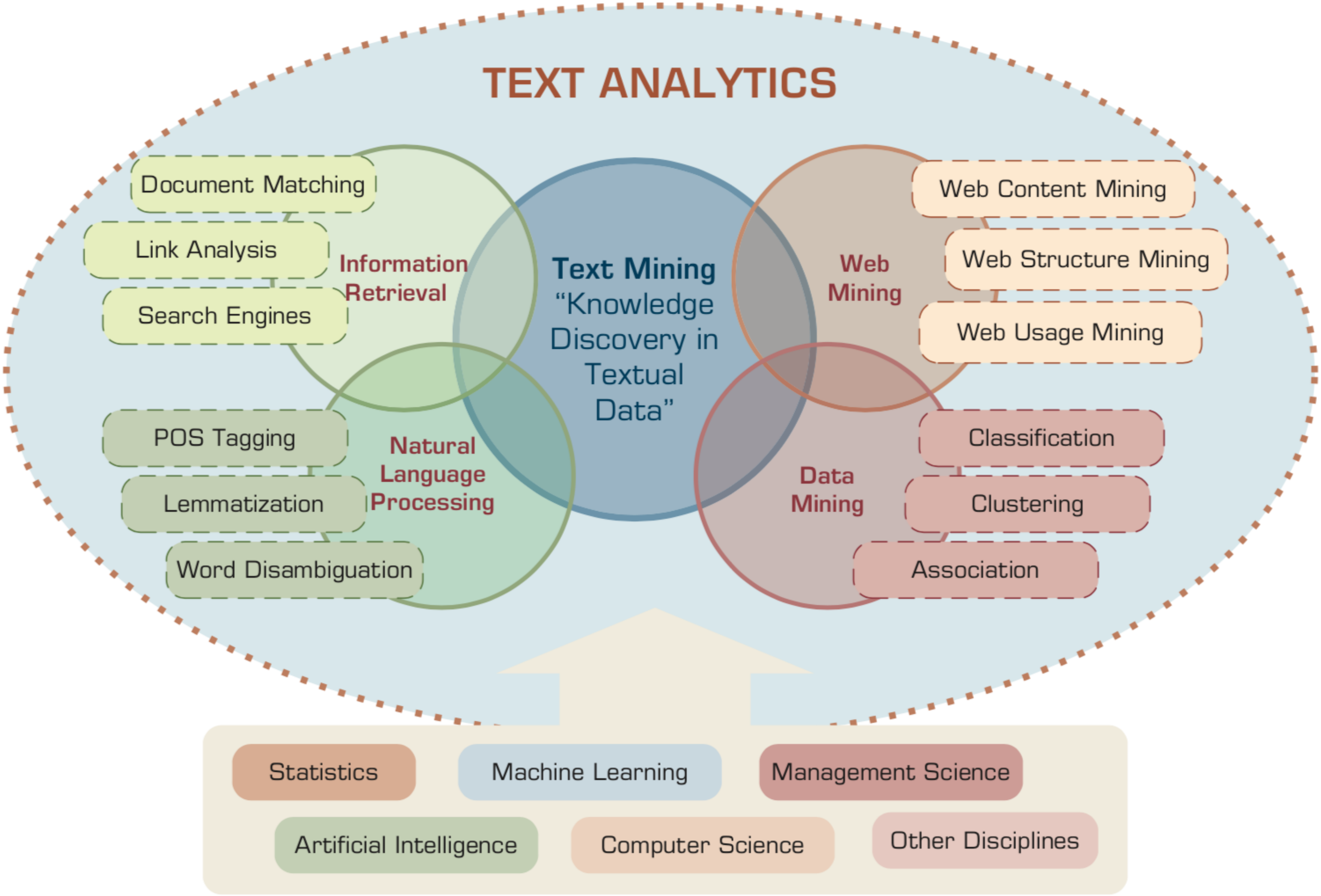


Business Analytics

	Descriptive	Predictive	Prescriptive
Questions	What happened? What is happening?	What will happen? Why will it happen?	What should I do? Why should I do it?
Enablers	✓ Business reporting ✓ Dashboards ✓ Scorecards ✓ Data warehousing	✓ Data mining ✓ Text mining ✓ Web/media mining ✓ Forecasting	✓ Optimization ✓ Simulation ✓ Decision modeling ✓ Expert systems
Outcomes	**Well-defined business problems and opportunities**	**Accurate projections of future events and outcomes**	**Best possible business decisions and actions**

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

Text Analytics and Text Mining



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

Text Analytics

- **Text Analytics** =
  Information Retrieval +
  Information Extraction +
  Data Mining +
  Web Mining
- **Text Analytics** =
  Information Retrieval +
  Text Mining

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

Text mining

- Text Data Mining
- Knowledge Discovery in Textual Databases

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

Application Areas of Text Mining

- Information extraction
- Topic tracking
- Summarization
- Categorization
- Clustering
- Concept linking
- Question answering

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

Natural Language Processing (NLP)

- Natural language processing (NLP) is an important component of text mining and is a subfield of artificial intelligence and computational linguistics.

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

Natural Language Processing (NLP)

- Part-of-speech tagging
- Text segmentation
- Word sense disambiguation
- Syntactic ambiguity
- Imperfect or irregular input
- Speech acts

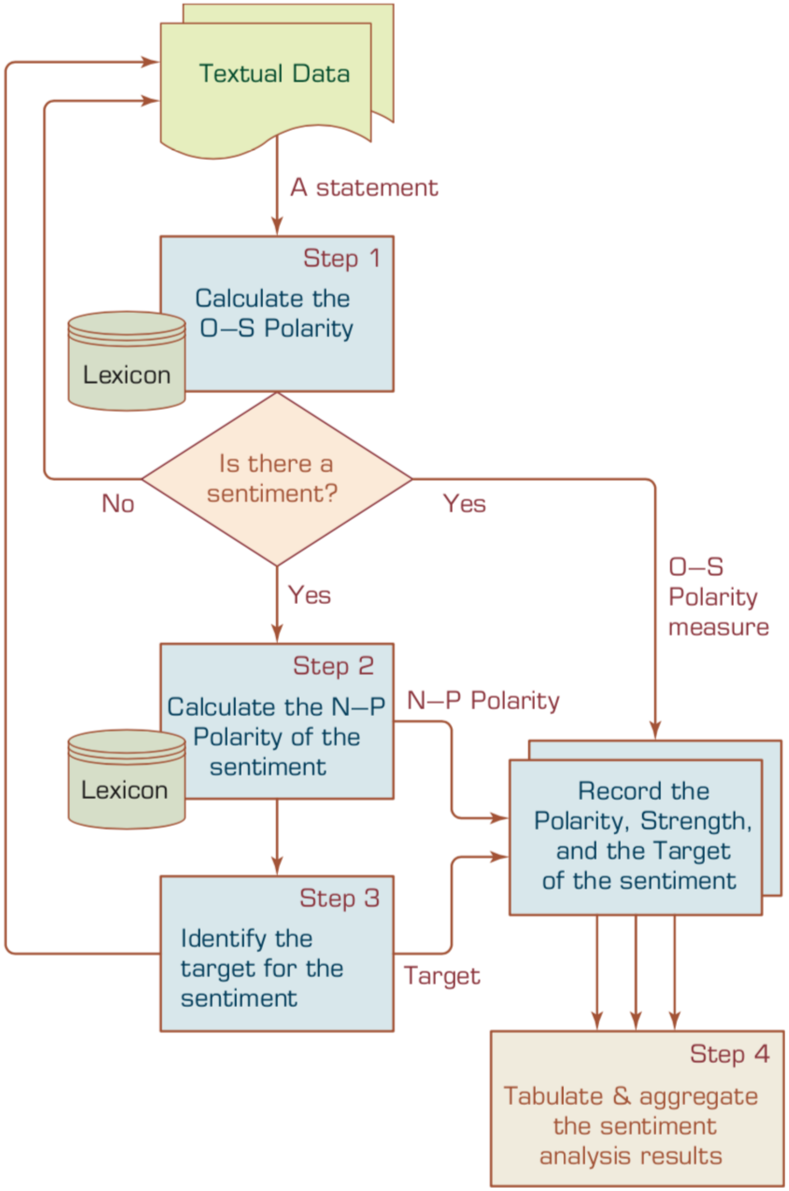
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

NLP Tasks

- Question answering
- Automatic summarization
- Natural language generation
- Natural language understanding
- Machine translation
- Foreign language reading
- Foreign language writing.
- Speech recognition
- Text-to-speech
- Text proofing
- Optical character recognition

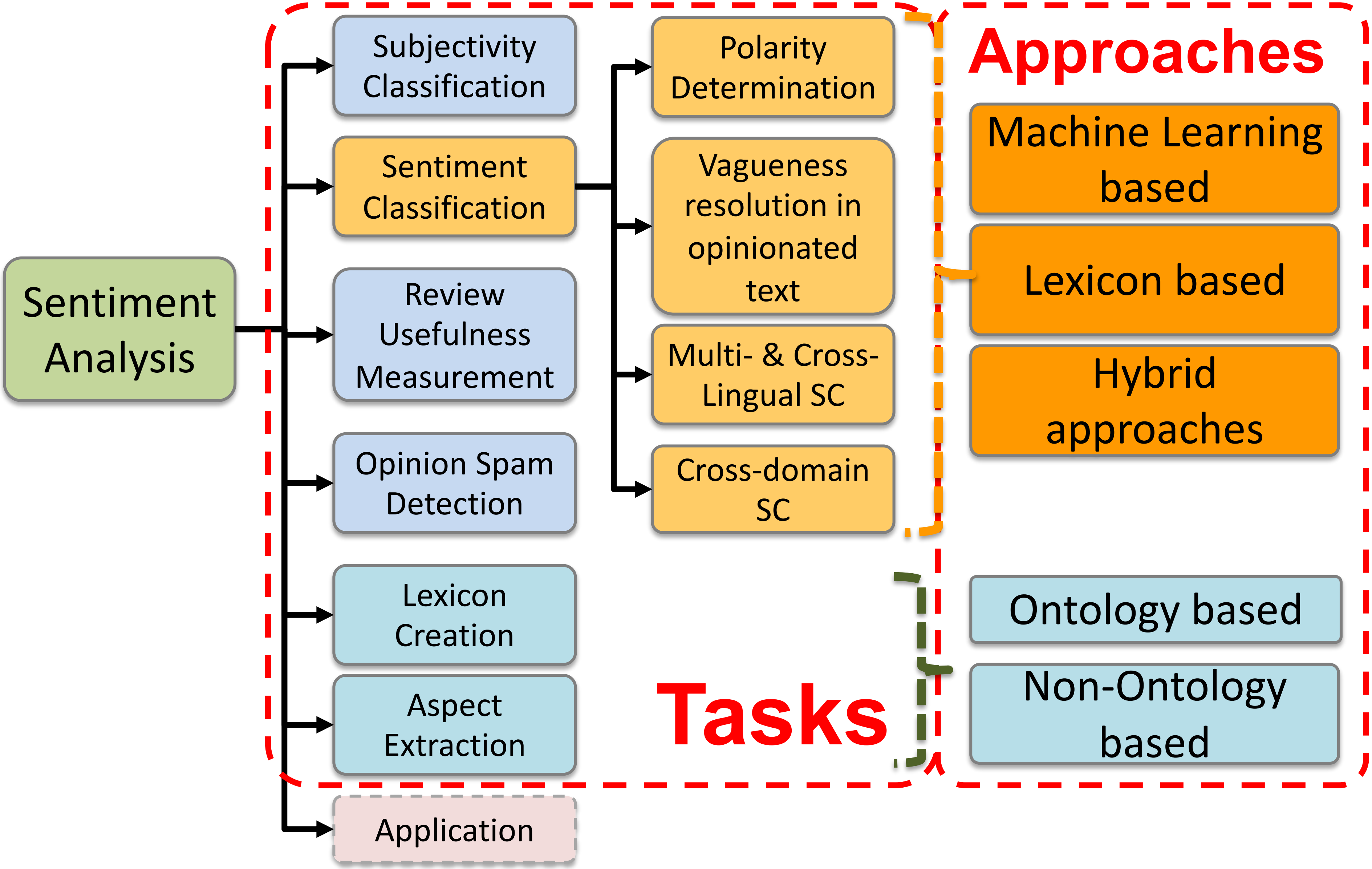
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

A Multistep Process to Sentiment Analysis


Textual Data
A statement
Step 1
Calculate the O–S Polarity
Lexicon
Is there a sentiment?
No
Yes
Yes
O–S Polarity measure
Step 2
Calculate the N–P Polarity of the sentiment
Lexicon
N–P Polarity
Record the Polarity, Strength, and the Target of the sentiment
Step 3
Identify the target for the sentiment
Target
Step 4
Tabulate & aggregate the sentiment analysis results

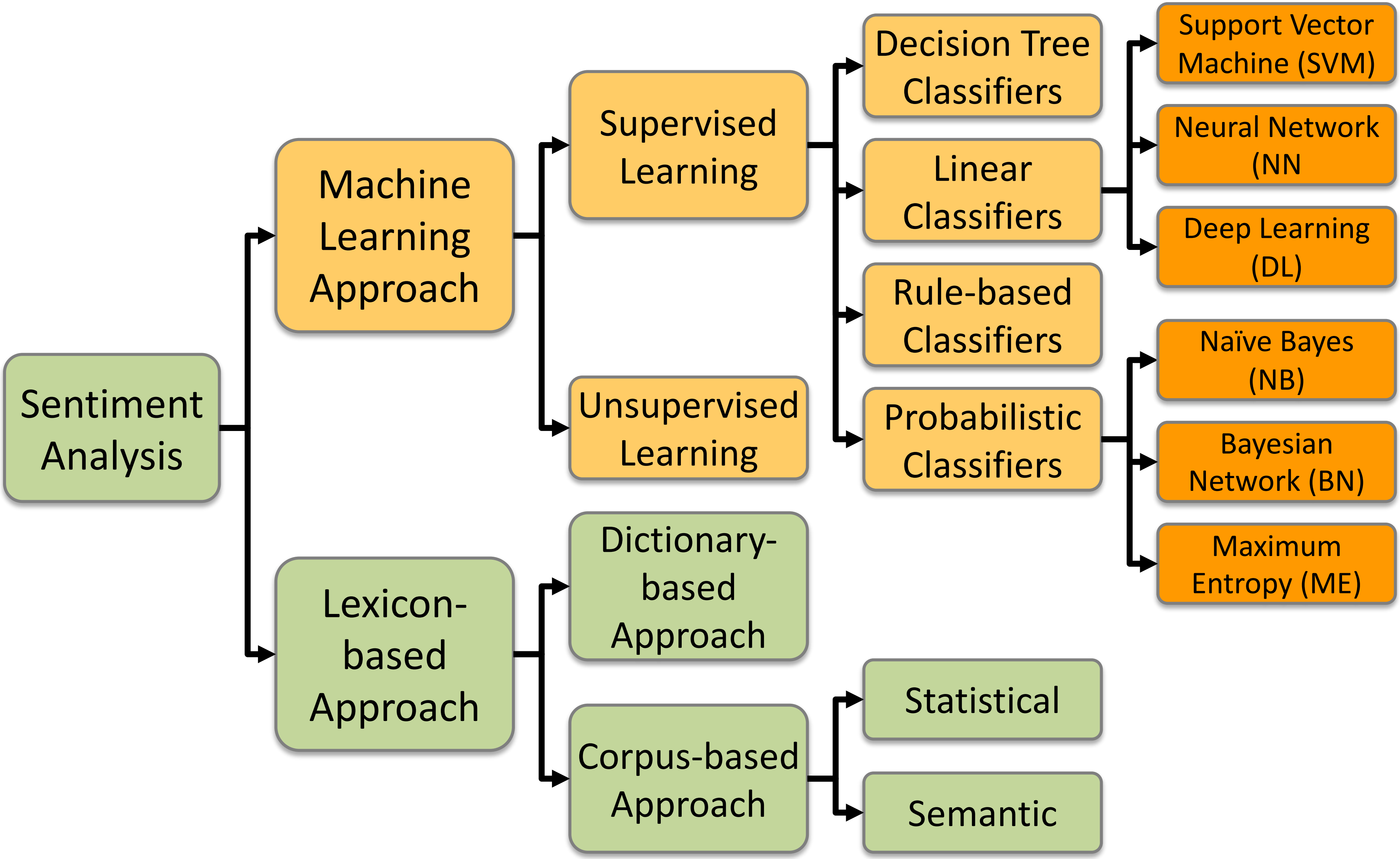
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Sentiment Analysis



Source: Kumar Ravi and Vadlamani Ravi (2015), "A survey on opinion mining and sentiment analysis: tasks, approaches and applications." Knowledge-Based Systems, 89, pp.14-46.

Sentiment Classification Techniques



Source: Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.

Example of Opinion: review segment on iPhone

“I bought an iPhone a few days ago.

It was such a nice phone.

The touch screen was really cool.

The voice quality was clear too.

However, my mother was mad with me as I did not tell her before I bought it.

She also thought the phone was too expensive, and wanted me to return it to the shop. … ”

Source: Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” Springer, 2nd Edition,

Example of Opinion: review segment on iPhone

“(1) I bought an iPhone a few days ago.

(2) It was such a **nice** phone.

(3) The touch screen was really **cool**.

(4) The voice quality was **clear** too.

(5) However, my mother was mad with me as I did not tell her before I bought it.

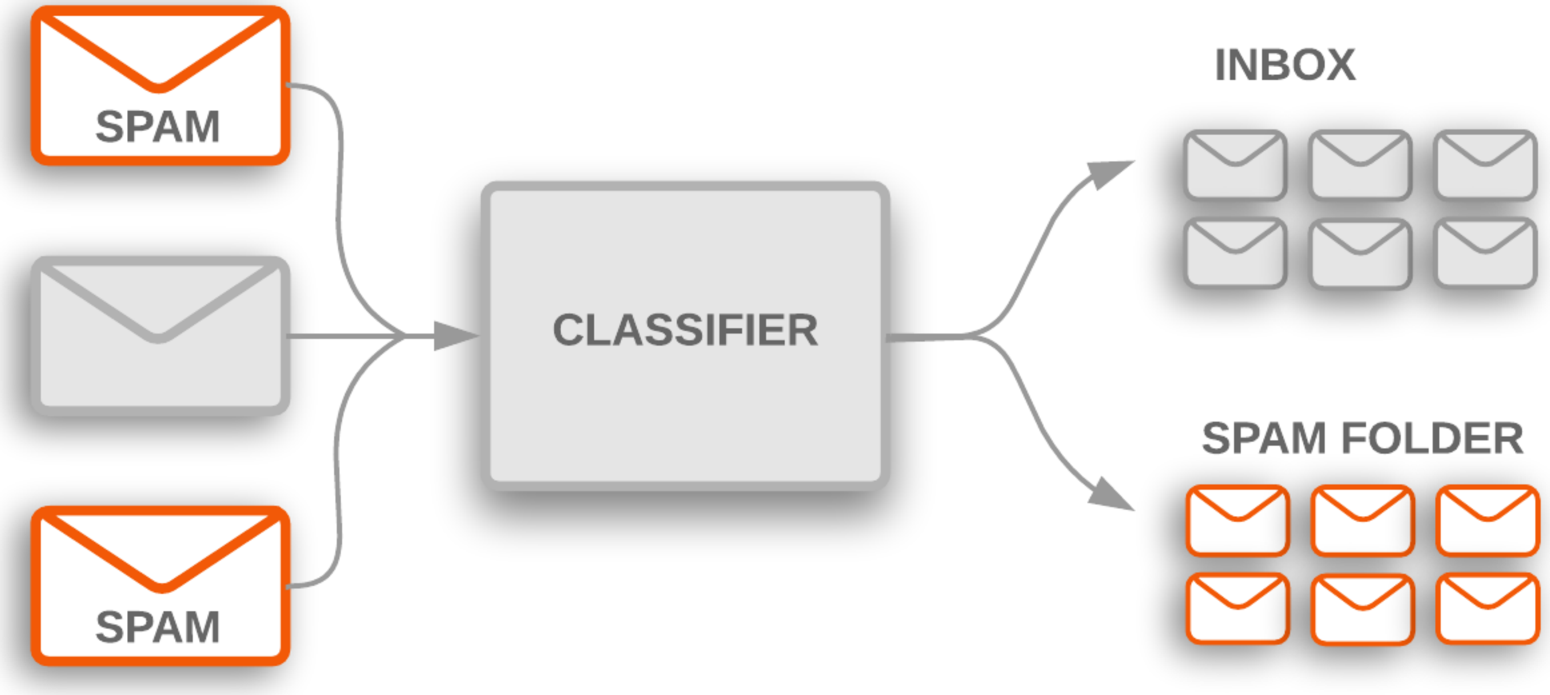
(6) She also thought the phone was too **expensive**, and wanted me to return it to the shop. … ”

☺ **+Positive Opinion**

☹ **-Negative Opinion**

Source: Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” Springer, 2nd Edition,

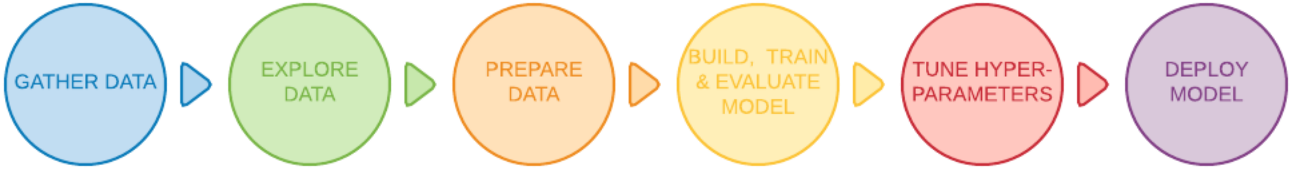
Text Classification



Source: https://developers.google.com/machine-learning/guides/text-classification/

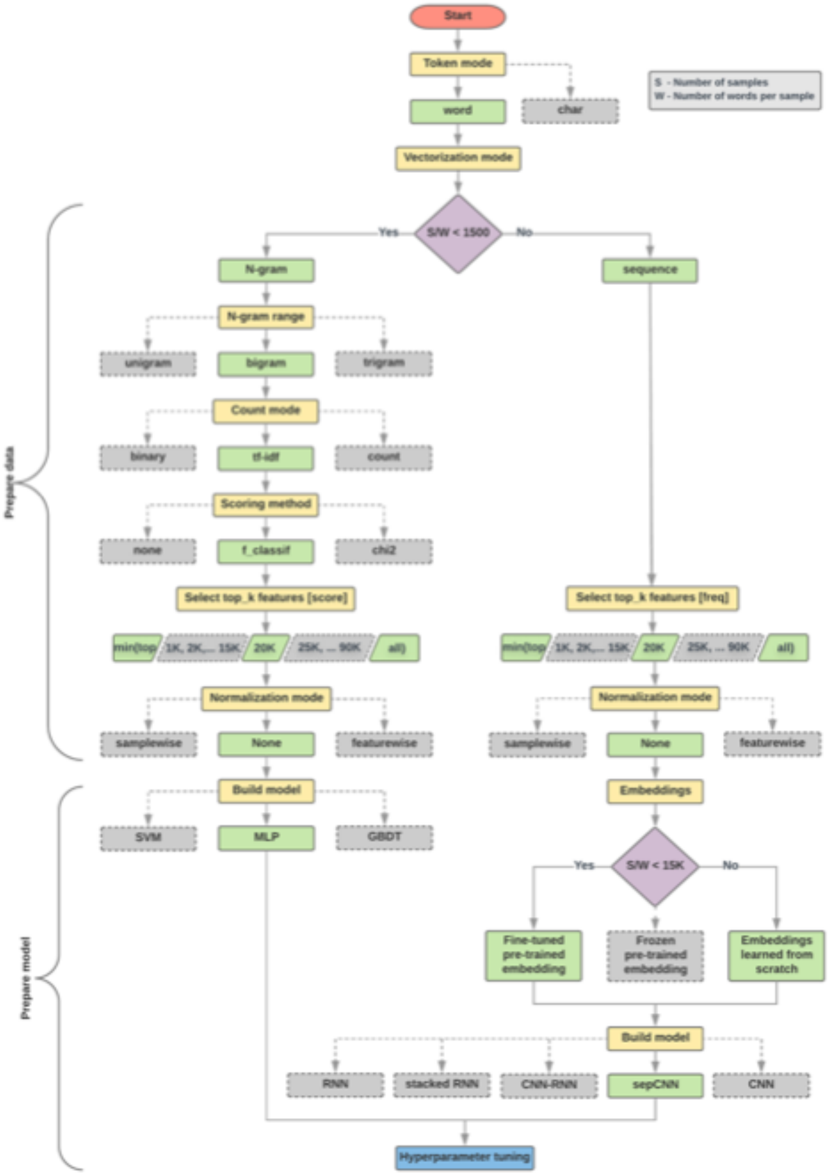
Text Classification Workflow

- Step 1: Gather Data
- Step 2: Explore Your Data
- Step 2.5: Choose a Model*
- Step 3: Prepare Your Data
- Step 4: Build, Train, and Evaluate Your Model
- Step 5: Tune Hyperparameters
- Step 6: Deploy Your Model



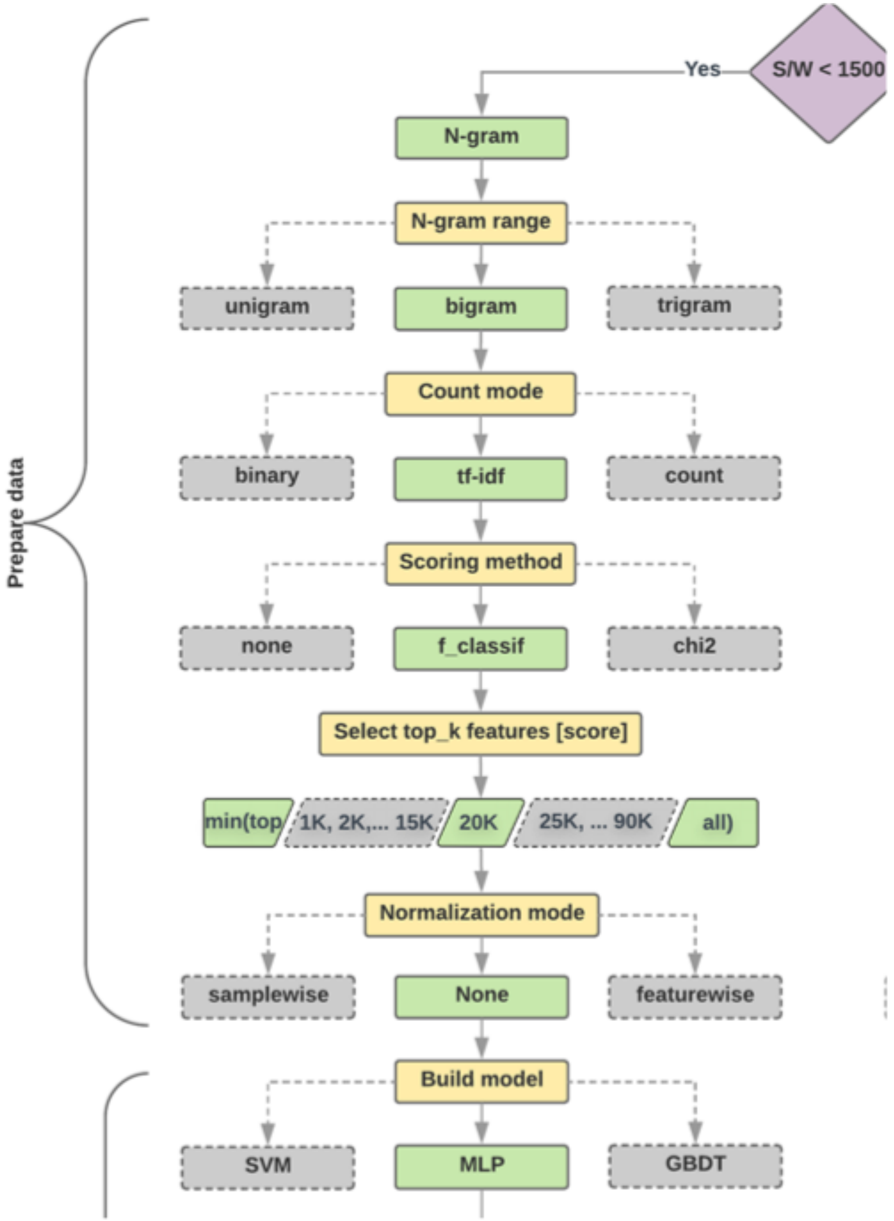
Source: https://developers.google.com/machine-learning/guides/text-classification/

Text Classification Flowchart



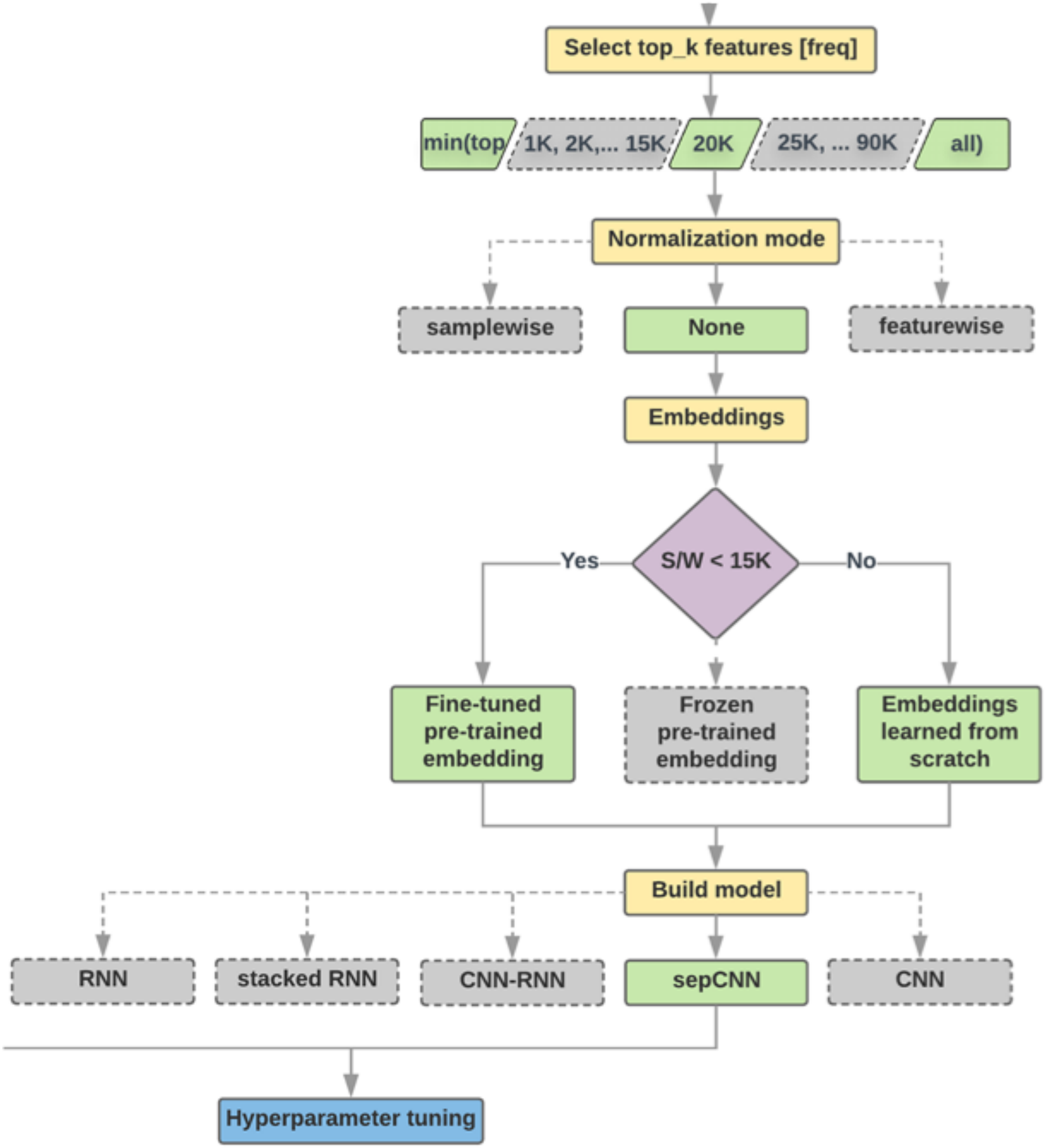
Source: https://developers.google.com/machine-learning/guides/text-classification/step-2-5

Text Classification S/W<1500: N-gram



Source: https://developers.google.com/machine-learning/guides/text-classification/step-2-5

Text Classification S/W>=1500: Sequence

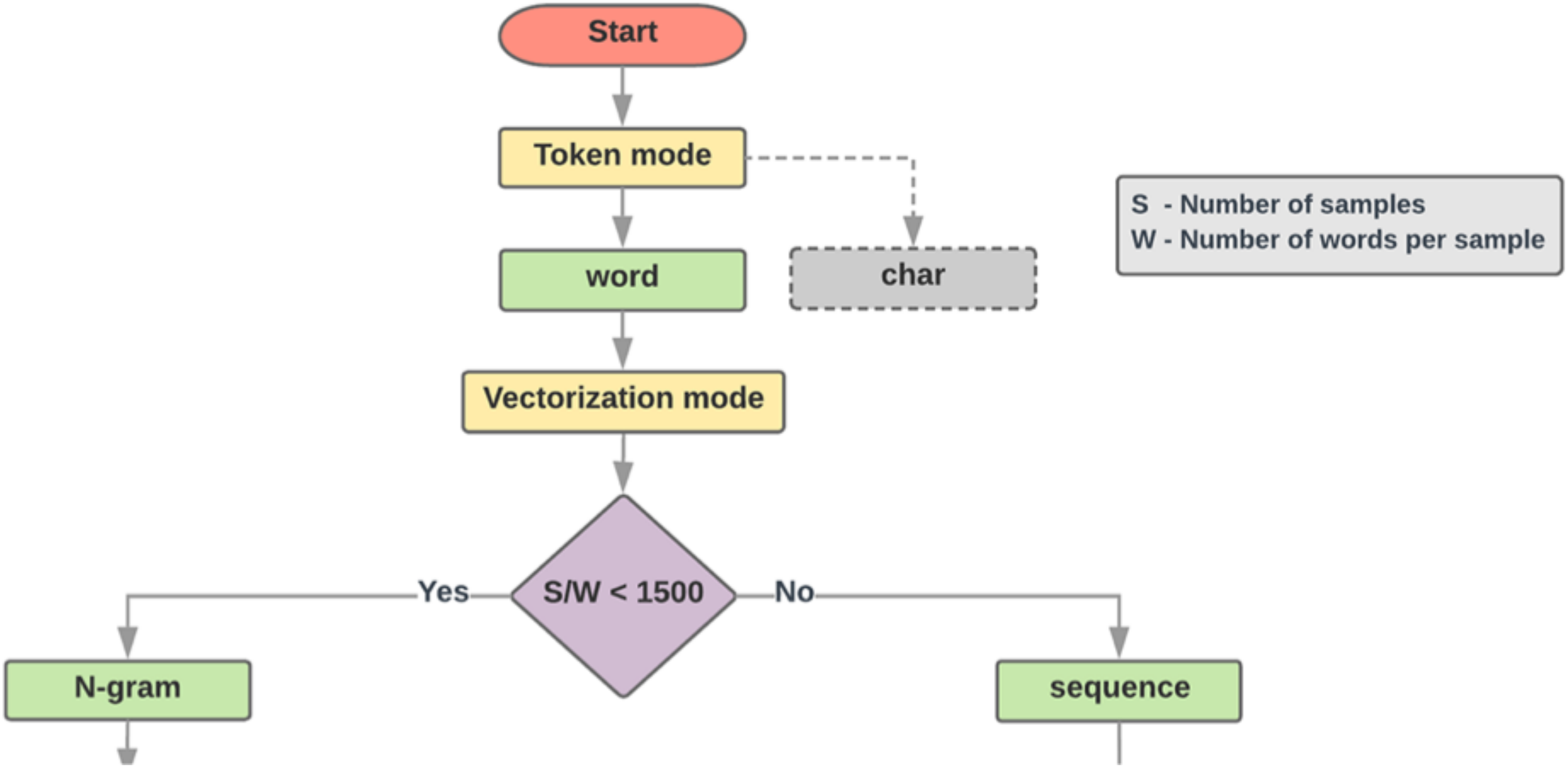


Source: https://developers.google.com/machine-learning/guides/text-classification/step-2-5

Step 2.5: Choose a Model

Samples/Words < 1500

150,000/100 = 1500



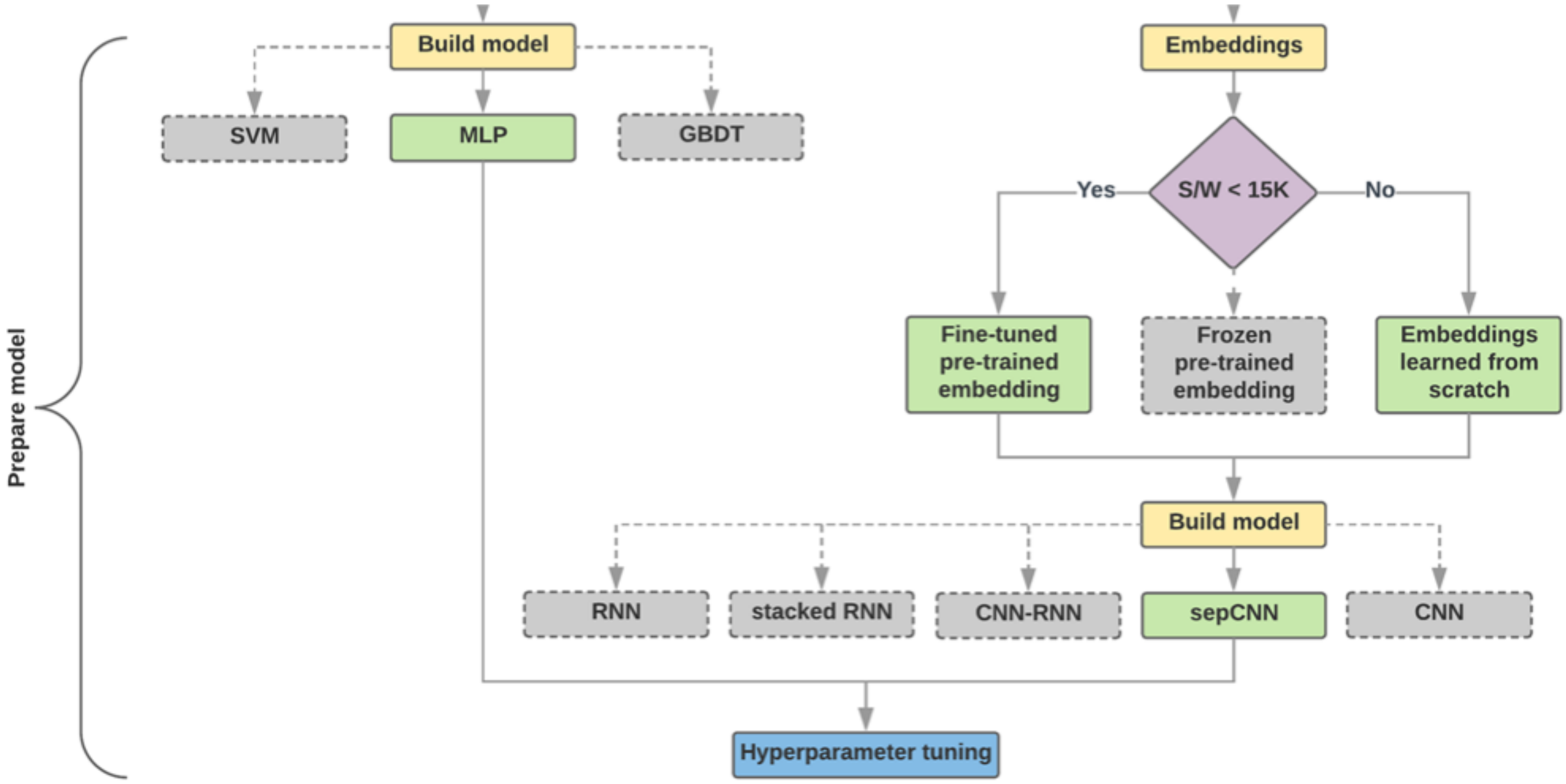
IMDb review dataset,
the samples/words-per-sample ratio is ~ 144

Source: https://developers.google.com/machine-learning/guides/text-classification/step-2-5

Step 2.5: Choose a Model

Samples/Words < 15,000

1,500,000/100 = 15,000



Source: https://developers.google.com/machine-learning/guides/text-classification/step-2-5

Step 3: Prepare Your Data

```
Texts:
T1: ’The mouse ran up the clock'
T2: ’The mouse ran down’

Token Index:
{'the': 1, 'mouse’: 2, 'ran': 3, 'up': 4, 'clock': 5, 'down': 6,}.
   NOTE: 'the' occurs most frequently,
          so the index value of 1 is assigned to it.
          Some libraries reserve index 0 for unknown tokens,
          as is the case here.

Sequence of token indexes:
T1: ‘The mouse ran up the clock’ =
      [1,  2,   3, 4,  1,  5]
T1: ’The mouse ran down’ =
      [1,   2,   3,  6]
```

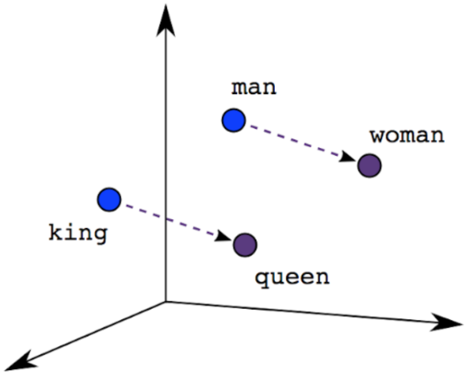
Source: https://developers.google.com/machine-learning/guides/text-classification/step-3

One-hot encoding

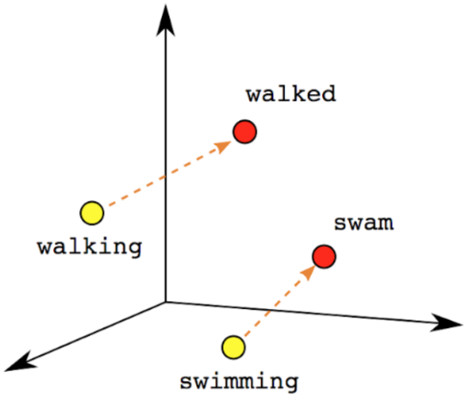
```
                 'The mouse ran up the clock’ =

The       1      [ [0, 1, 0, 0, 0, 0, 0],
mouse     2        [0, 0, 1, 0, 0, 0, 0],
ran       3        [0, 0, 0, 1, 0, 0, 0],
up        4        [0, 0, 0, 0, 1, 0, 0],
the       1        [0, 1, 0, 0, 0, 0, 0],
clock     5        [0, 0, 0, 0, 0, 1, 0] ]

                   [0, 1, 2, 3, 4, 5, 6]
```

Source: https://developers.google.com/machine-learning/guides/text-classification/step-3

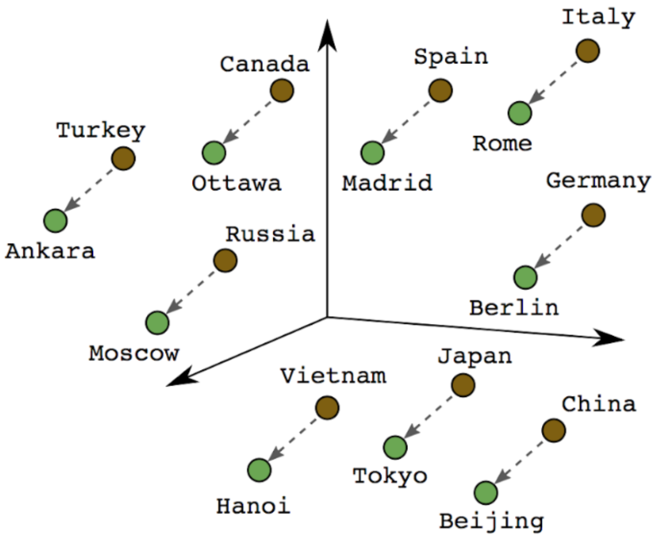
Word embeddings



Male-Female



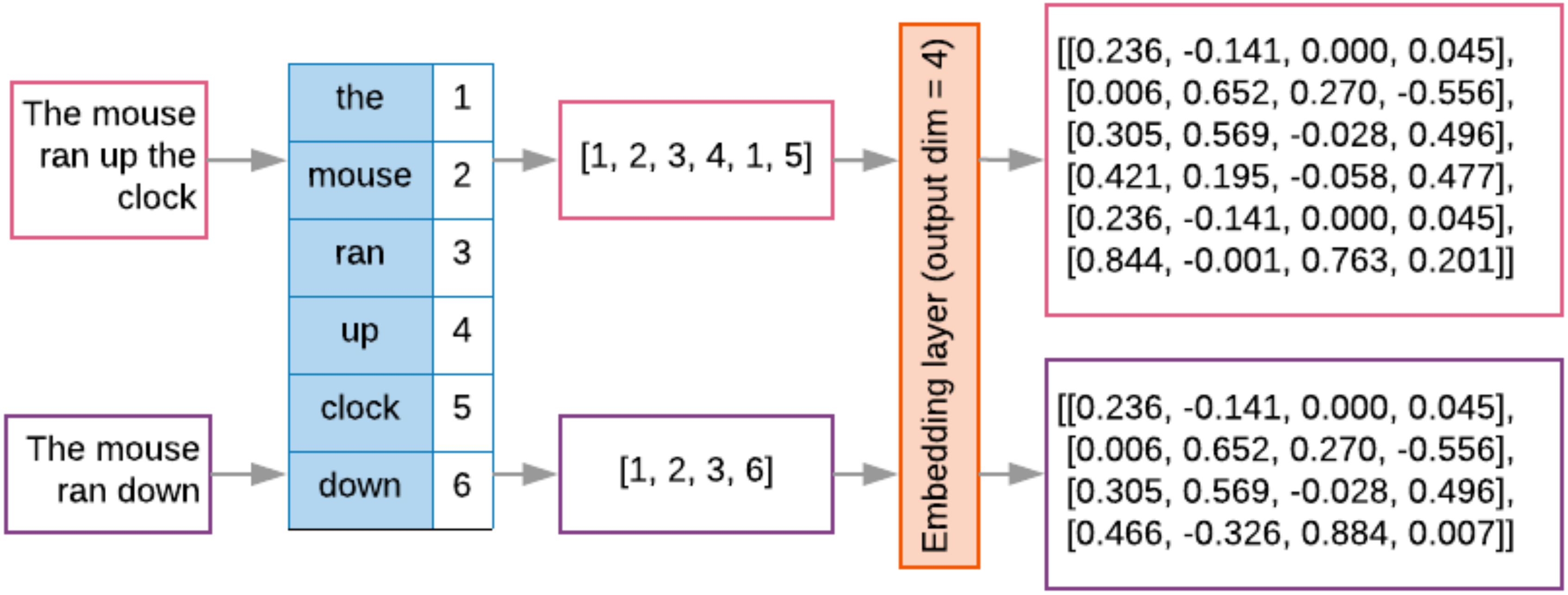
Verb Tense



Country-Capital

Source: https://developers.google.com/machine-learning/guides/text-classification/step-3

Word embeddings



The mouse ran up the clock

The mouse ran down

the	1
mouse	2
ran	3
up	4
clock	5
down	6

[1, 2, 3, 4, 1, 5]

[1, 2, 3, 6]

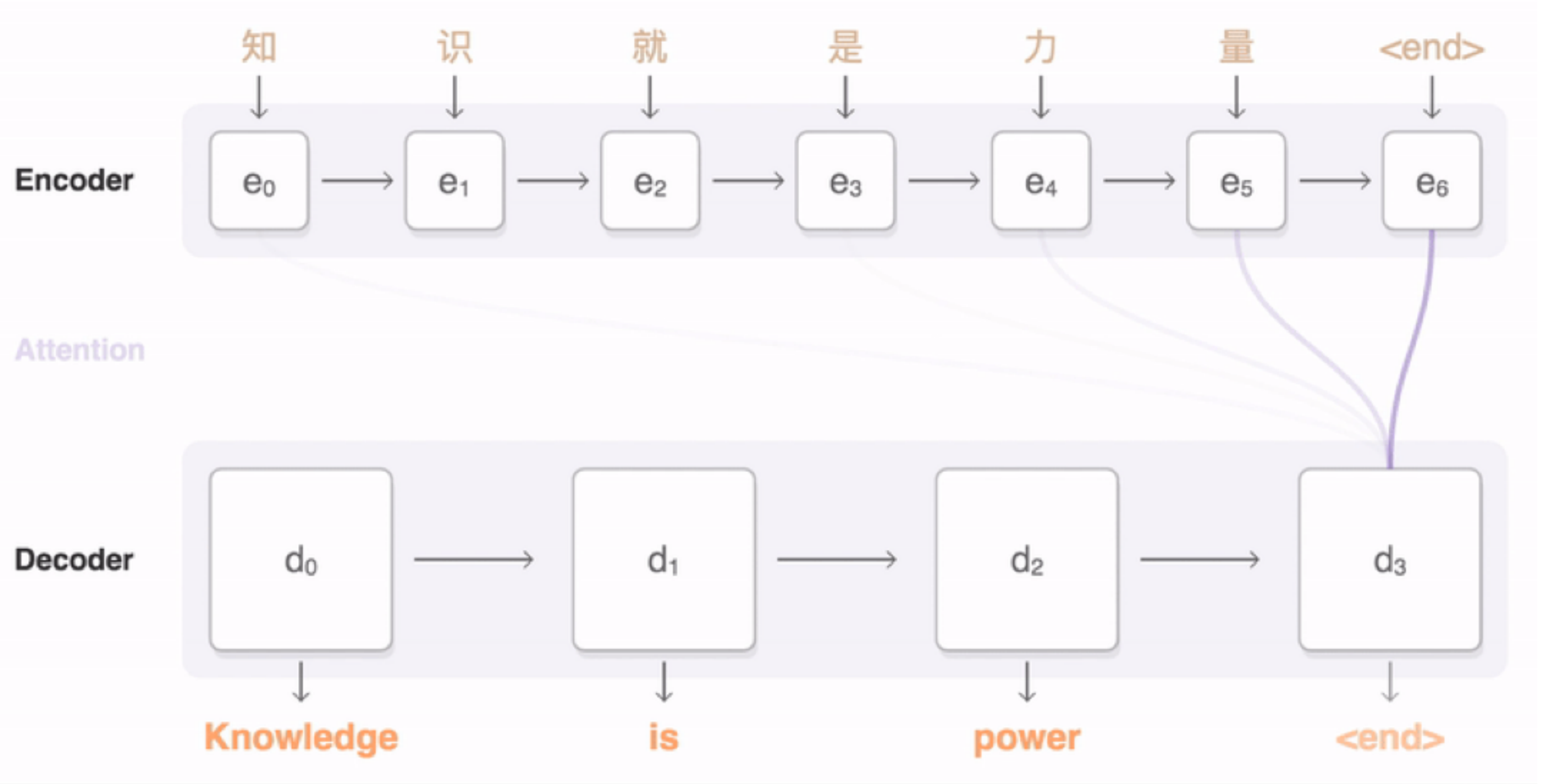
Embedding layer (output dim = 4)

```
[[0.236, -0.141, 0.000, 0.045],
 [0.006, 0.652, 0.270, -0.556],
 [0.305, 0.569, -0.028, 0.496],
 [0.421, 0.195, -0.058, 0.477],
 [0.236, -0.141, 0.000, 0.045],
 [0.844, -0.001, 0.763, 0.201]]
```

```
[[0.236, -0.141, 0.000, 0.045],
 [0.006, 0.652, 0.270, -0.556],
 [0.305, 0.569, -0.028, 0.496],
 [0.466, -0.326, 0.884, 0.007]]
```

Source: https://developers.google.com/machine-learning/guides/text-classification/step-3

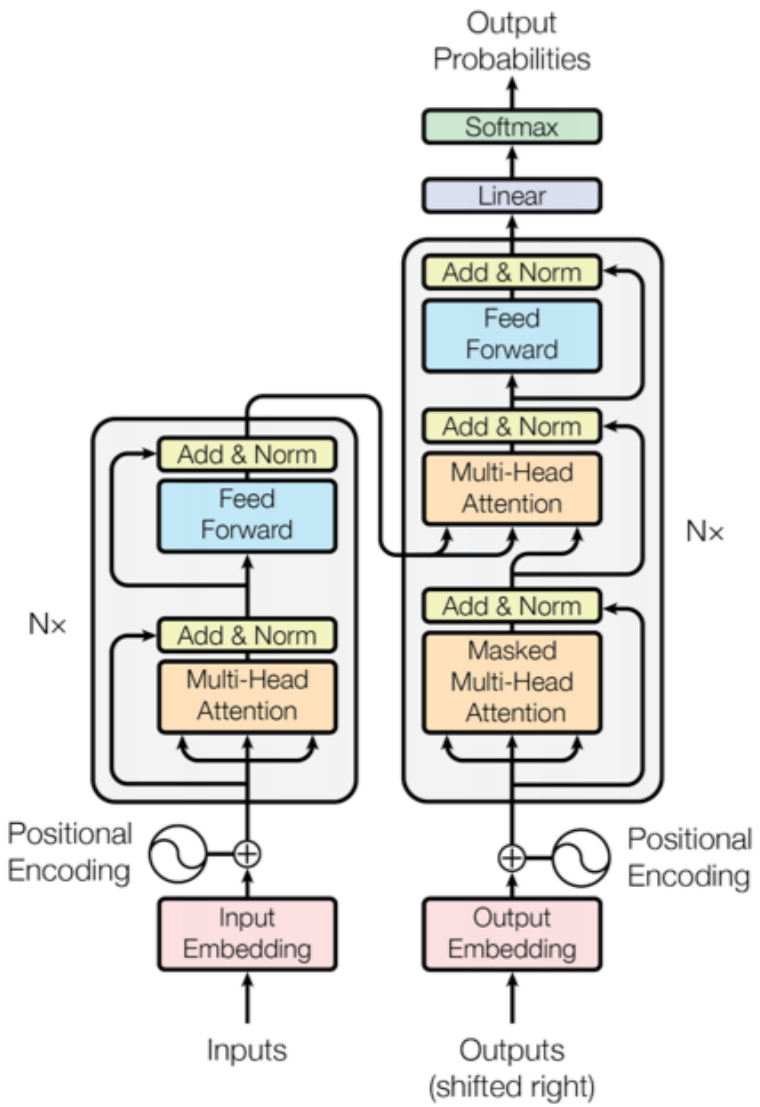
Sequence to Sequence (Seq2Seq)



Source: https://google.github.io/seq2seq/

Transformer (Attention is All You Need)

(Vaswani et al., 2017)

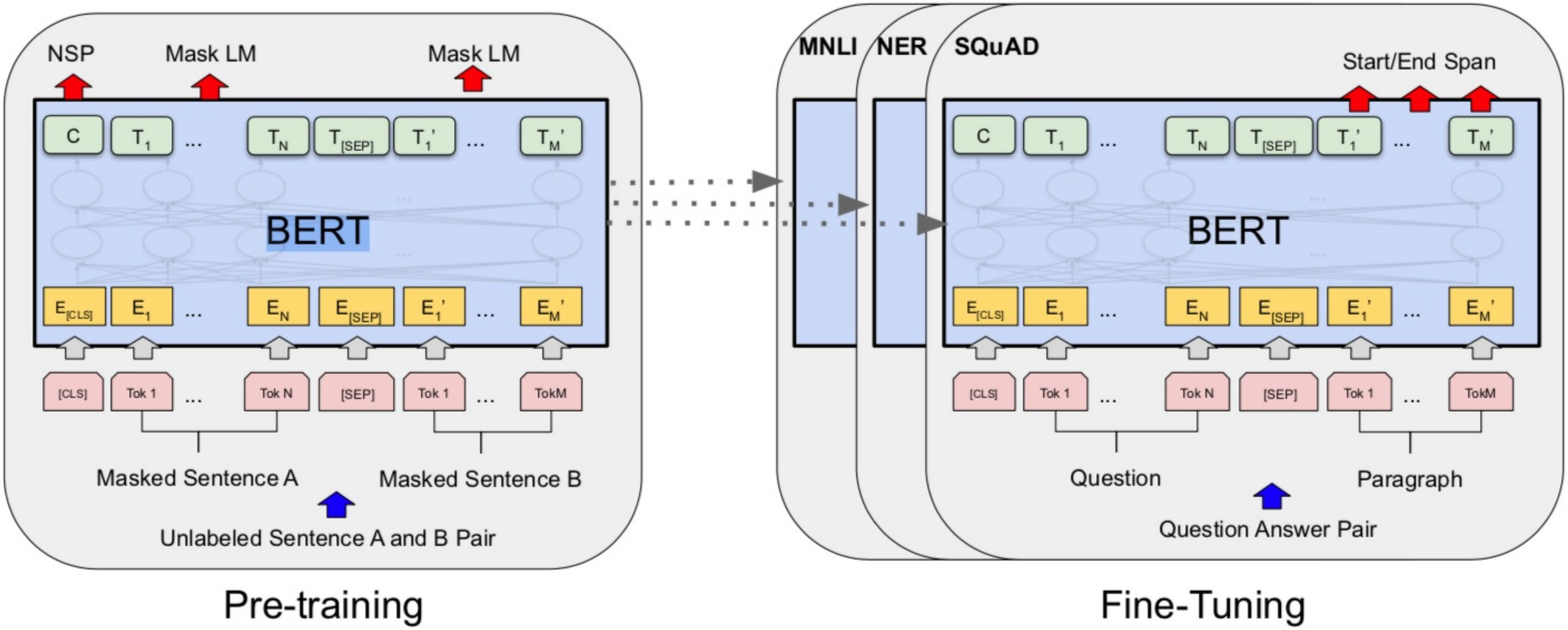


Source: Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." In *Advances in neural information processing systems*, pp. 5998-6008. 2017.

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT (Bidirectional Encoder Representations from Transformers)

Overall pre-training and fine-tuning procedures for BERT

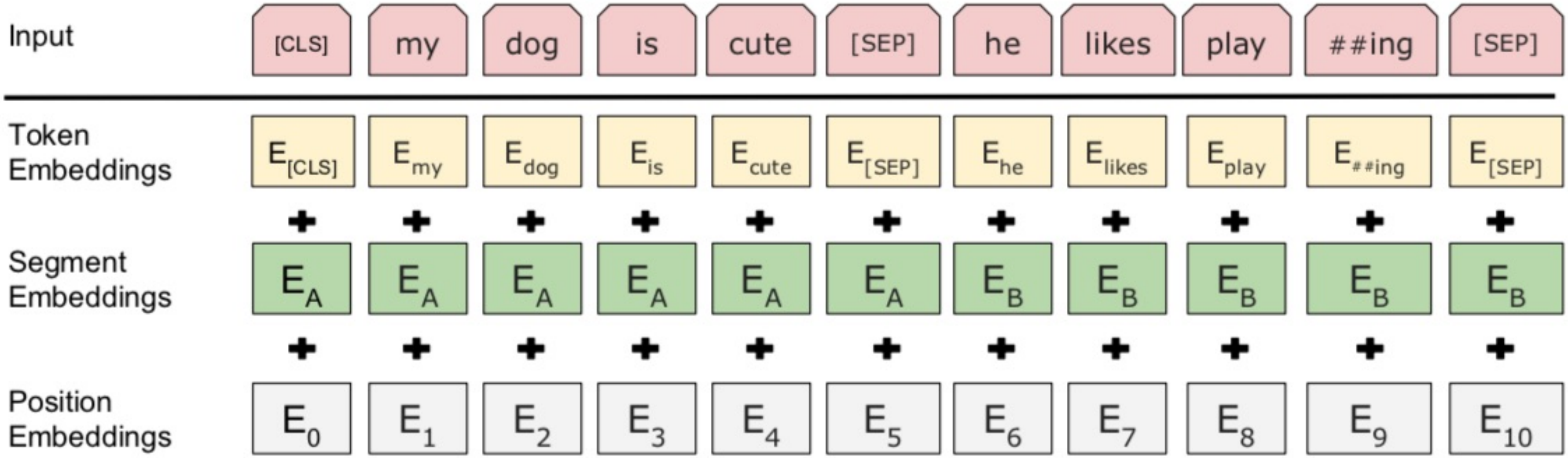


Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT (Bidirectional Encoder Representations from Transformers)

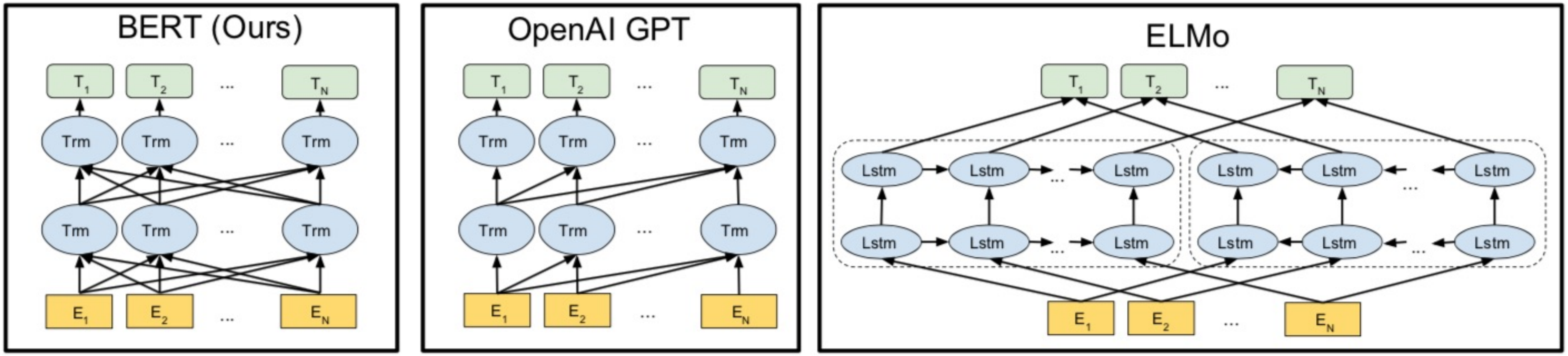
BERT input representation



Input	[CLS]	my	dog	is	cute	[SEP]	he	likes	play	##ing	[SEP]
Token Embeddings	$E_{[CLS]}$	E_{my}	E_{dog}	E_{is}	E_{cute}	$E_{[SEP]}$	E_{he}	E_{likes}	E_{play}	$E_{\#\#ing}$	$E_{[SEP]}$
	+	+	+	+	+	+	+	+	+	+	+
Segment Embeddings	E_A	E_A	E_A	E_A	E_A	E_A	E_B	E_B	E_B	E_B	E_B
	+	+	+	+	+	+	+	+	+	+	+
Position Embeddings	E_0	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}

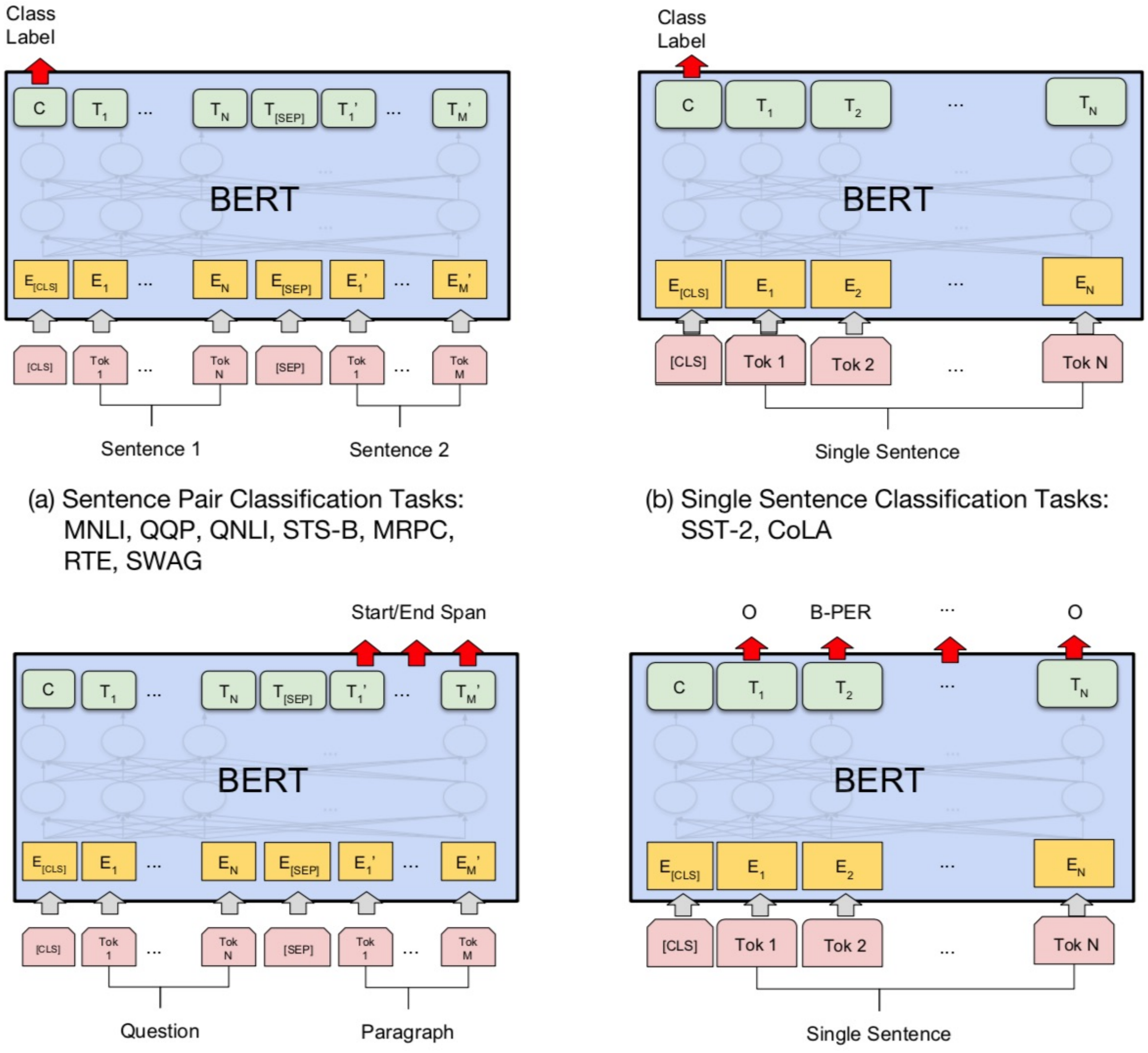
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

BERT, OpenAI GPT, ELMo



Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

Fine-tuning BERT on Different Tasks



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

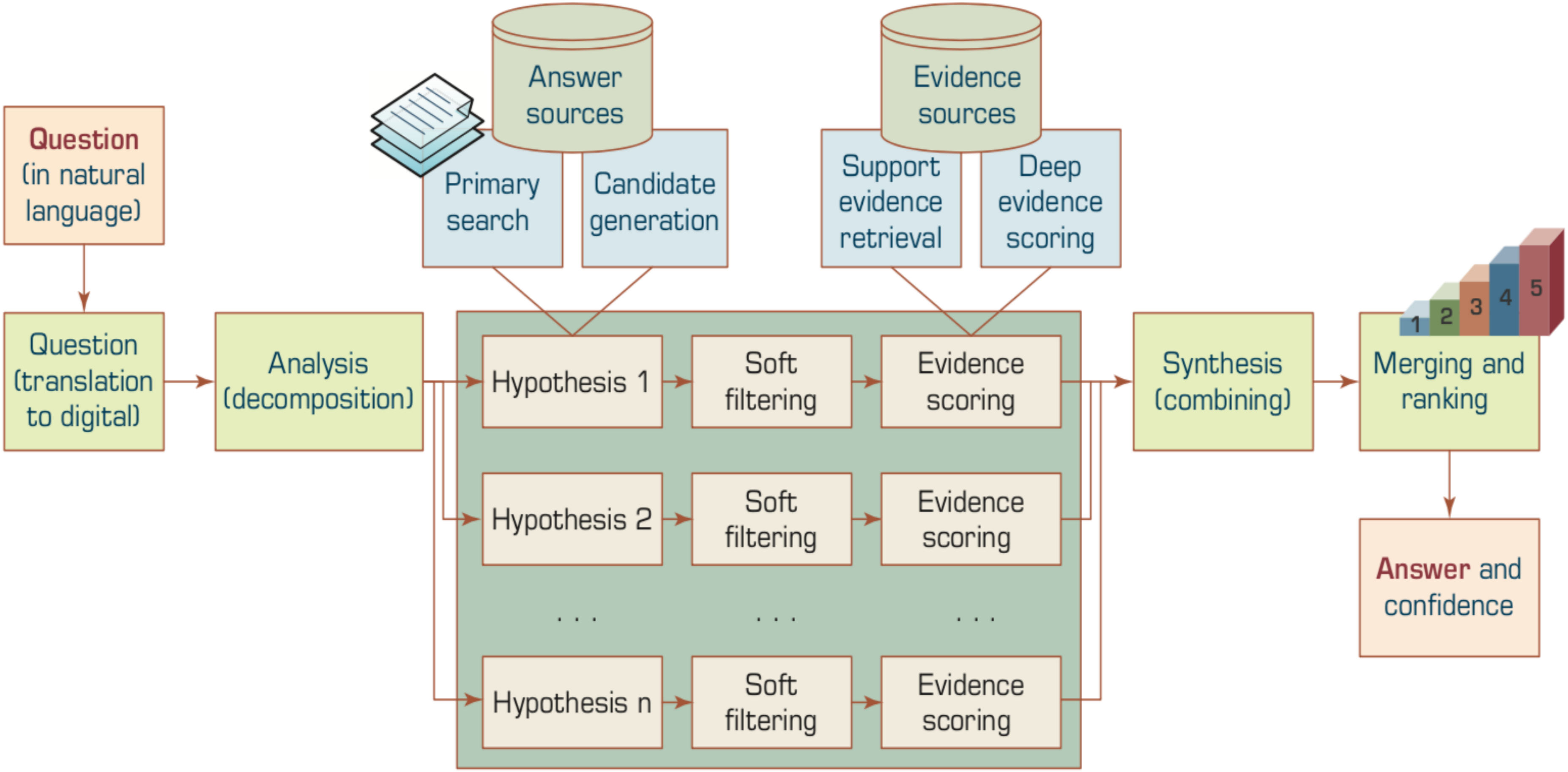
(b) Single Sentence Classification Tasks: SST-2, CoLA

(c) Question Answering Tasks: SQuAD v1.1

(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

A High-Level Depiction of DeepQA Architecture

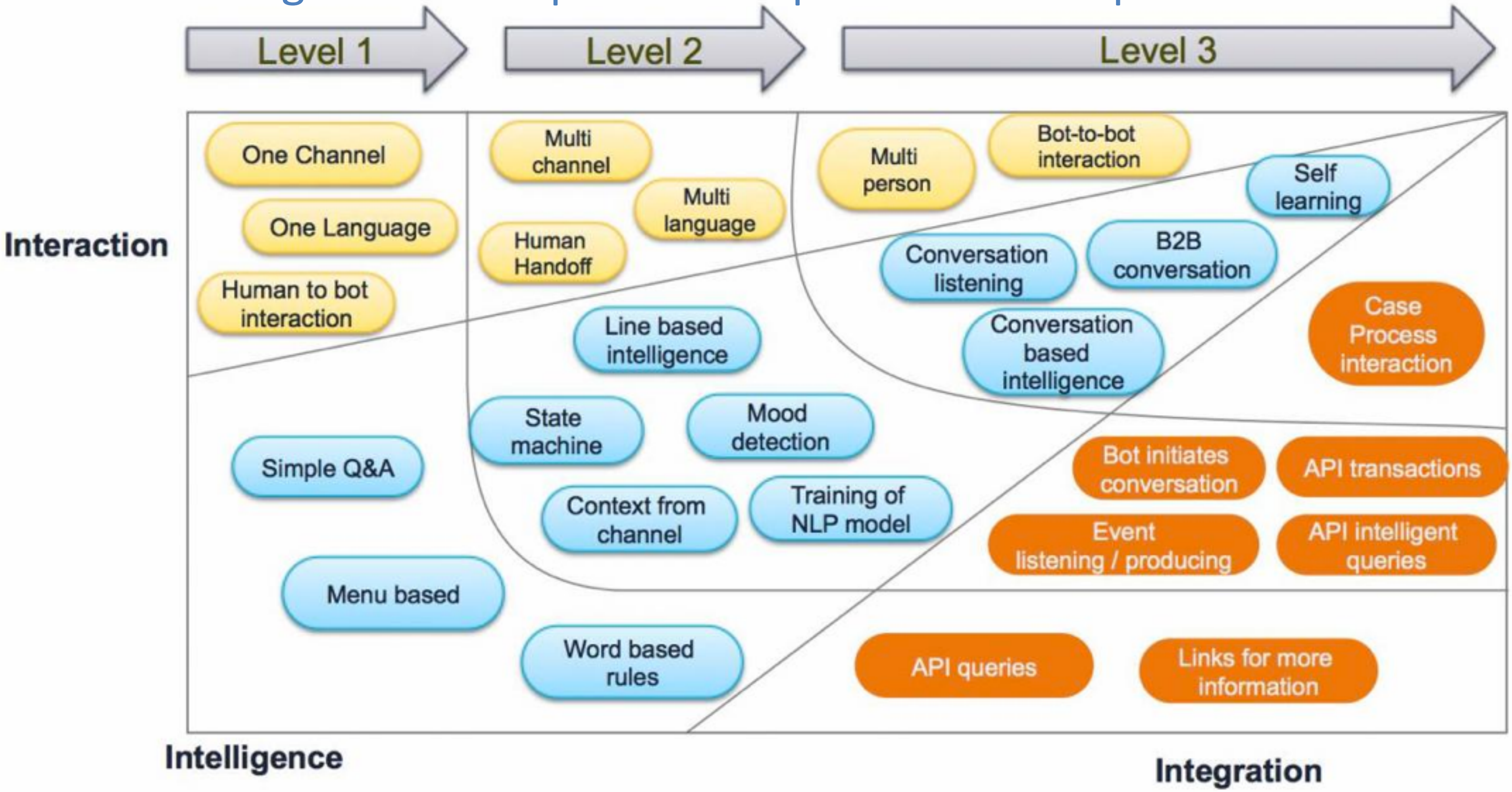


Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Chatbots

Bot Maturity Model

Customers want to have simpler means to interact with businesses and get faster response to a question or complaint.

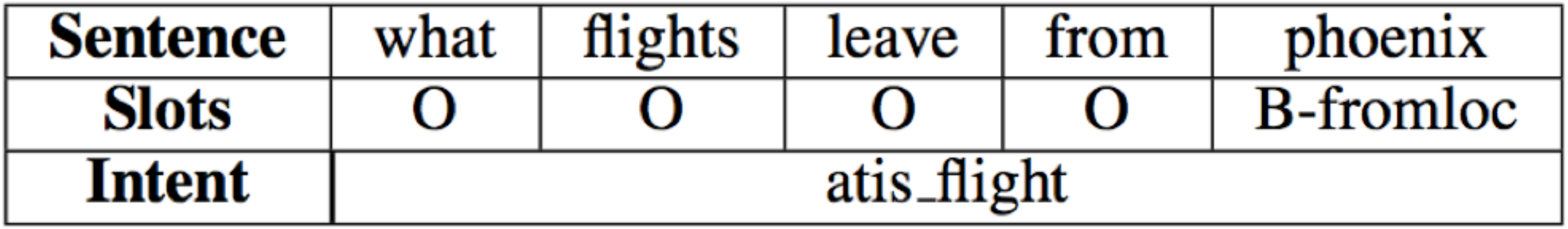


Source: https://www.capgemini.com/2017/04/how-can-chatbots-meet-expectations-introducing-the-bot-maturity/

Dialogue on Airline Travel Information System (ATIS)

The ATIS (Airline Travel Information System) Dataset

https://www.kaggle.com/siddhadev/atis-dataset-from-ms-cntk



Sentence	what	flights	leave	from	phoenix
Slots	O	O	O	O	B-fromloc
Intent	atis_flight				

Training samples: 4978
Testing samples: 893
Vocab size: 943
Slot count: 129
Intent count: 26

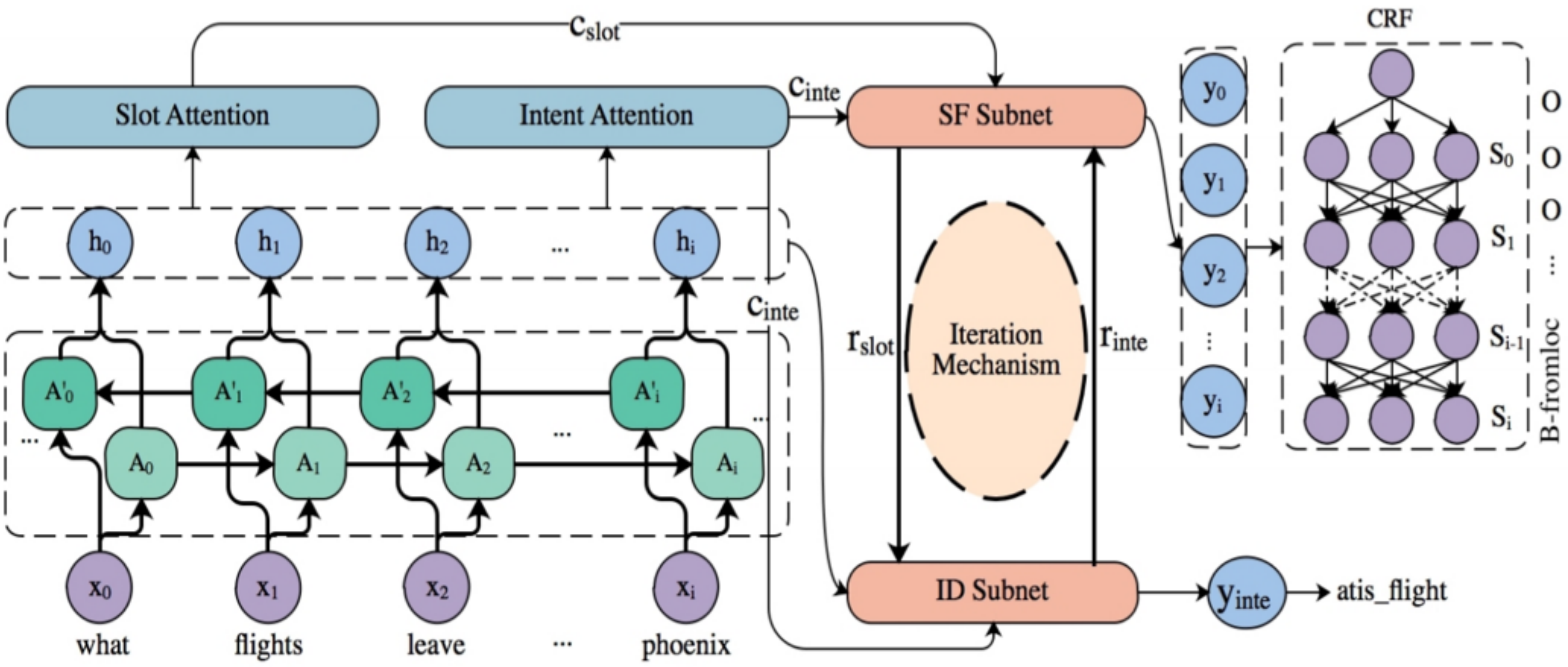
Source: Haihong, E., Peiqing Niu, Zhongfu Chen, and Meina Song. "A novel bi-directional interrelated model for joint intent detection and slot filling." In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pp. 5467-5471. 2019.

SF-ID Network (E et al., 2019)

Slot Filling (SF)

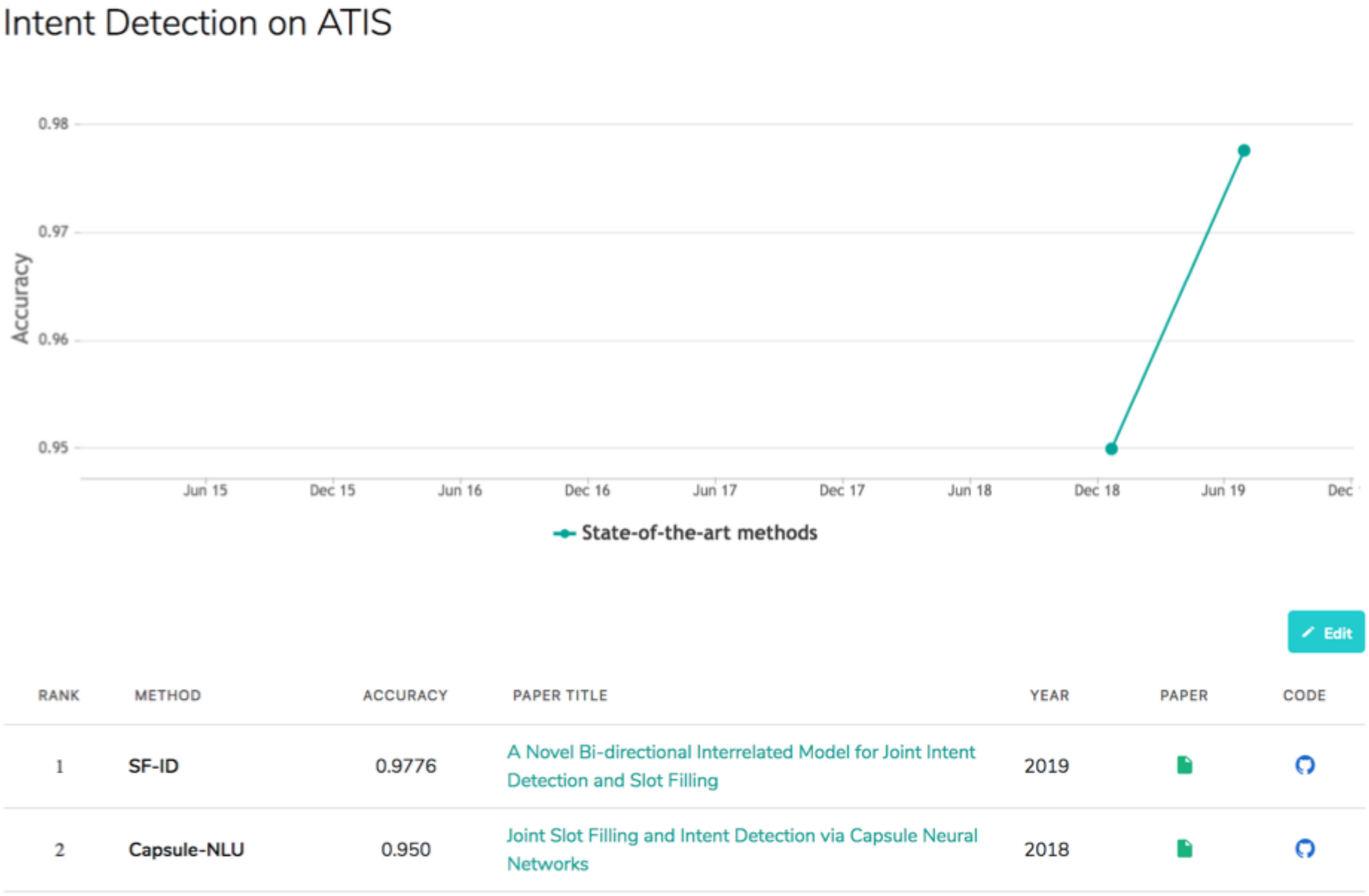
Intent Detection (ID)

A Novel Bi-directional Interrelated Model for Joint Intent Detection and Slot Filling



Source: Haihong, E., Peiqing Niu, Zhongfu Chen, and Meina Song. "A novel bi-directional interrelated model for joint intent detection and slot filling." In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pp. 5467-5471. 2019.

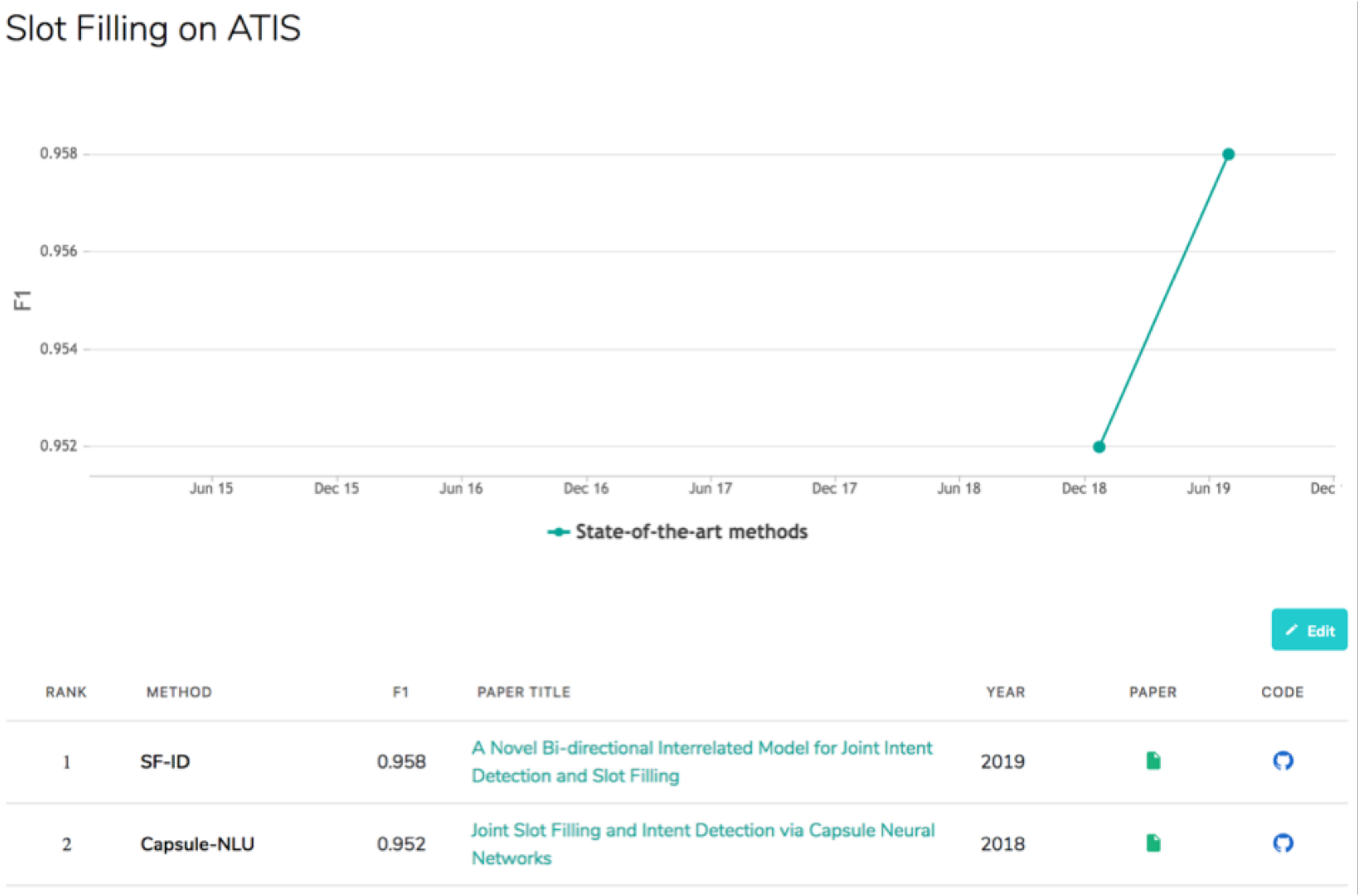
Intent Detection on ATIS State-of-the-art



RANK	METHOD	ACCURACY	PAPER TITLE	YEAR	PAPER	CODE
1	**SF-ID**	0.9776	A Novel Bi-directional Interrelated Model for Joint Intent Detection and Slot Filling	2019	📄	◯
2	**Capsule-NLU**	0.950	Joint Slot Filling and Intent Detection via Capsule Neural Networks	2018	📄	◯

Source: https://paperswithcode.com/sota/intent-detection-on-atis

Slot Filling on ATIS State-of-the-art



RANK	METHOD	F1	PAPER TITLE	YEAR	PAPER	CODE
1	**SF-ID**	0.958	A Novel Bi-directional Interrelated Model for Joint Intent Detection and Slot Filling	2019	📄	◯
2	**Capsule-NLU**	0.952	Joint Slot Filling and Intent Detection via Capsule Neural Networks	2018	📄	◯

Source: https://paperswithcode.com/sota/slot-filling-on-atis

Restaurants Dialogue Datasets

- MIT Restaurant Corpus
  - https://groups.csail.mit.edu/sls/downloads/restaurant/
- CamRest676
  (Cambridge restaurant dialogue domain dataset)
  - https://www.repository.cam.ac.uk/handle/1810/260970
- DSTC2 (Dialog State Tracking Challenge 2 & 3)
  - http://camdial.org/~mh521/dstc/

任務型對話系統

The Evaluation of Chinese Human-Computer Dialogue Technology, SMP2019-ECDT

- 自然語言理解
  Natural Language Understanding (NLU)
- 對話管理
  Dialog Management (DM)
- 自然語言生成
  Natural Language Generation (NLG)

Source: http://conference.cipsc.org.cn/smp2019/evaluation.html
https://github.com/OnionWang/SMP2019-ECDT-NLU

Summary

- This course introduces the fundamental concepts and research issues of Text Mining.
- Topics include
  - Foundations of Text Mining: Natural Language Processing (NLP),
  - Python for NLP,
  - Processing and Understanding Text,
  - Feature Engineering for Text Representation,
  - Text Classification,
  - Text Summarization and Topic Models,
  - Text Similarity and Clustering,
  - Semantic Analysis and Named Entity Recognition,
  - Sentiment Analysis,
  - The Promise of Deep Learning and Universal Sentence-Embedding Models,
  - Question Answering and Dialogue Systems,
  - and Case Study on Text Mining.

文字探勘 (Text Mining)

Contact Information

Chichang Jou

周清江

Associate Professor

副教授

cjou@mail.tku.edu.tw

Min-Yuh Day

戴敏育

Associate Professor

副教授

myday@mail.tku.edu.tw

淡江大學 資訊管理學系

Department of Information Management, Tamkang University