National Taipei University

Foundations of Text Analytics: Natural Language Processing (NLP)

1121AITA02
MBA, IM, NTPU (M5265) (Fall 2023)
Tue 2, 3, 4 (9:10-12:00) (B3F17)

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

aws educate Cloud Ambassador 2020 Cohort
aws academy Accredited Educator
aws certified Cloud Practitioner
aws certified Solutions Architect Associate

Min-Yuh Day, Ph.D,
Associate Professor
Institute of Information Management, National Taipei University
https://web.ntpu.edu.tw/~myday

2023-09-20

Syllabus

国立臺北大學
National Taipei University

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

Foundations of Text Analytics: Natural Language Processing (NLP)

Outline

- Text Analytics and Text Mining
- Natural Language Processing (NLP)

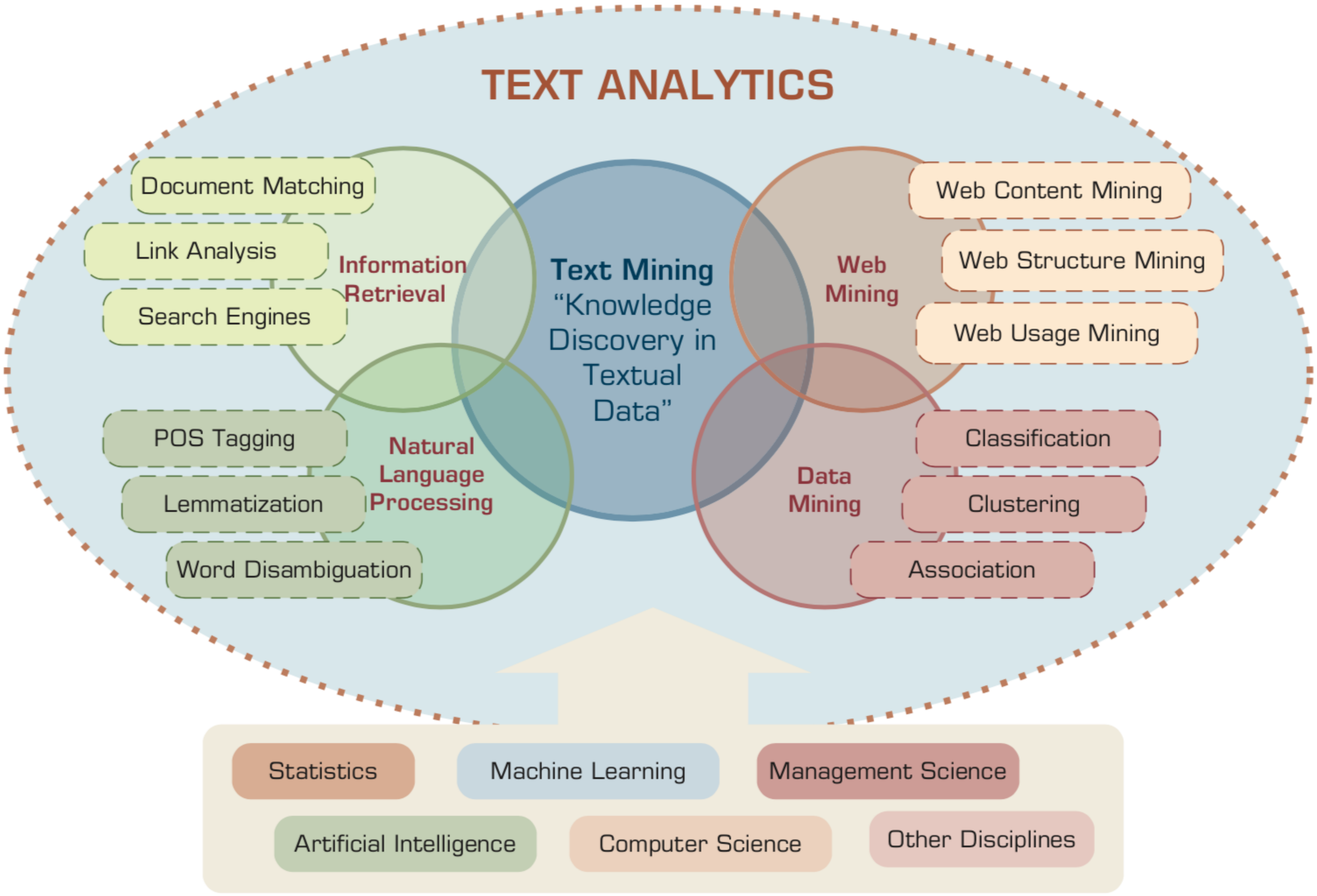
Artificial Intelligence (AI)

Text Analytics (TA)

Text Mining
(TM)

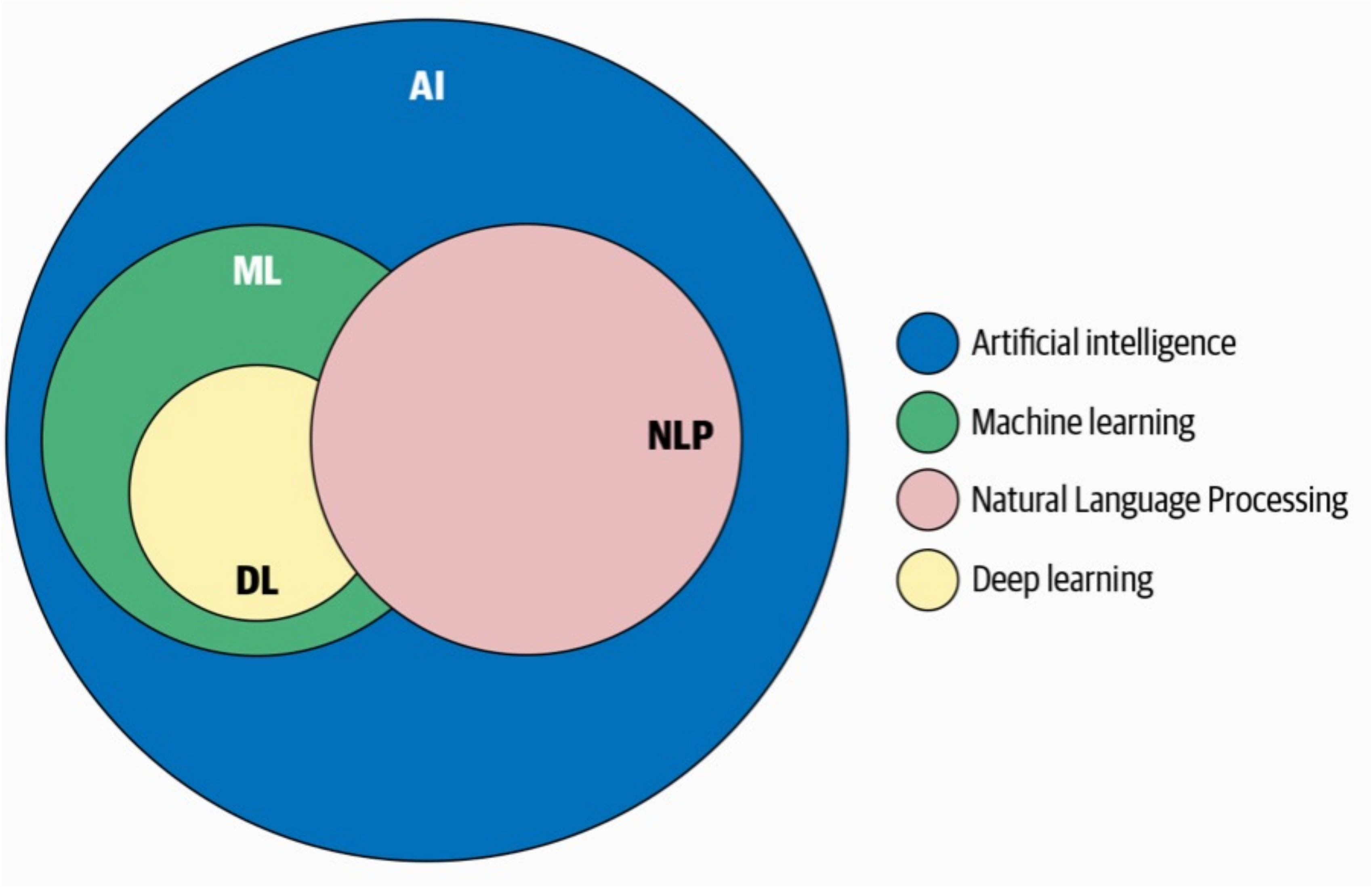
Natural Language Processing (NLP)

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

AI, NLP, ML, DL

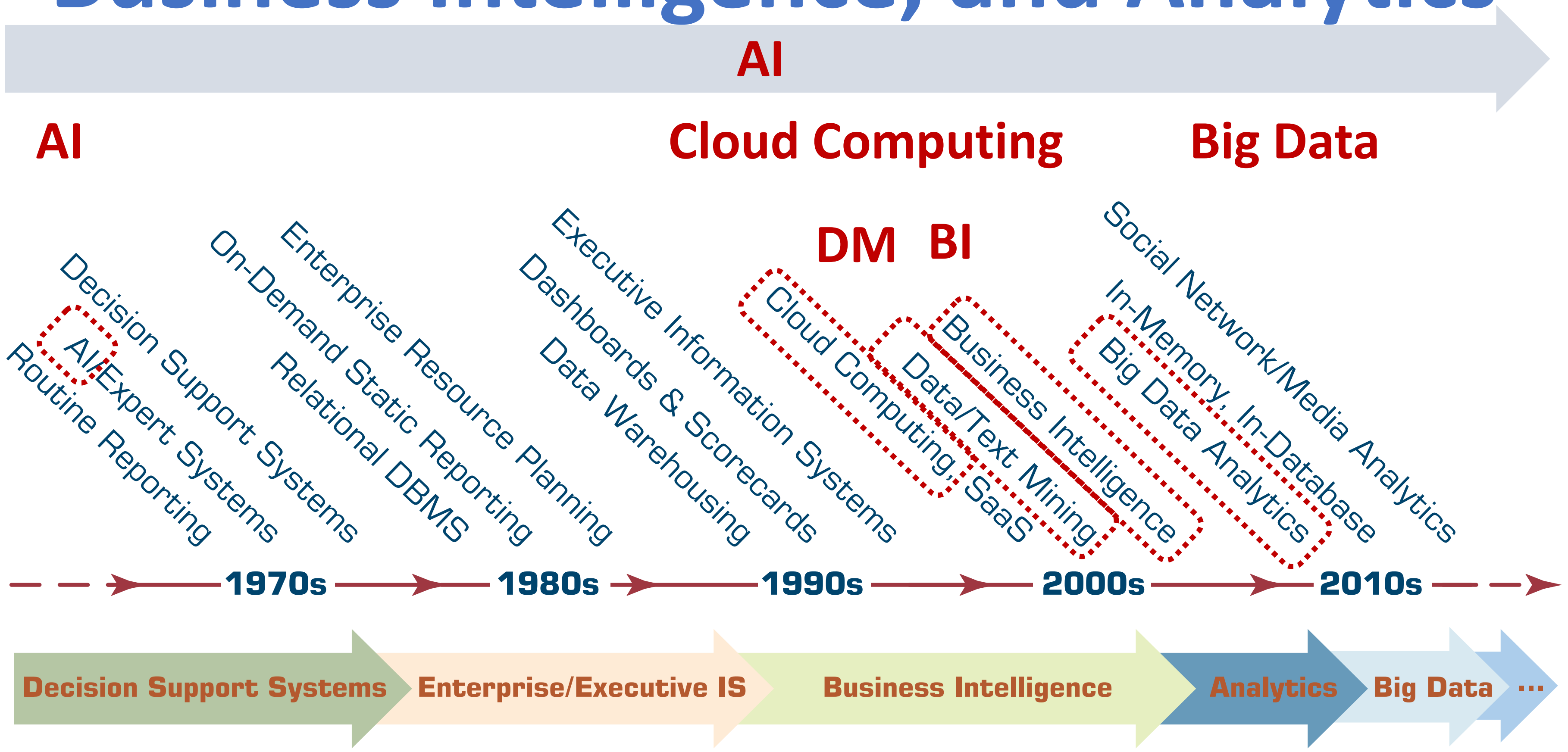


Source: Sowmya Vajjala, Bodhisattwa Majumder, Anuj Gupta (2020), Practical Natural Language Processing: A Comprehensive Guide to Building Real-World NLP Systems, O'Reilly Media.

Artificial Intelligence (AI)

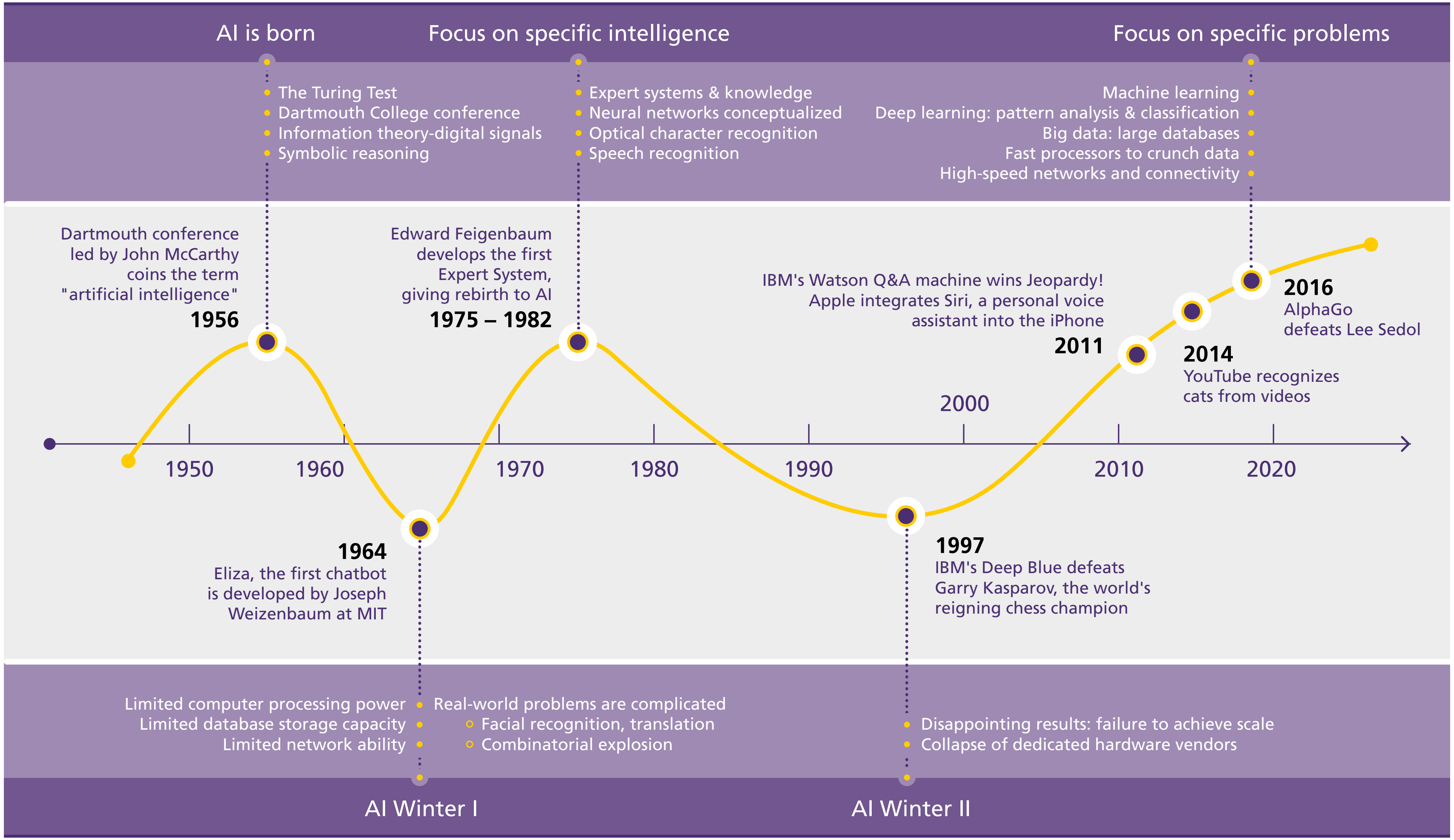
AI, Big Data, Cloud Computing

Evolution of Decision Support, Business Intelligence, and Analytics



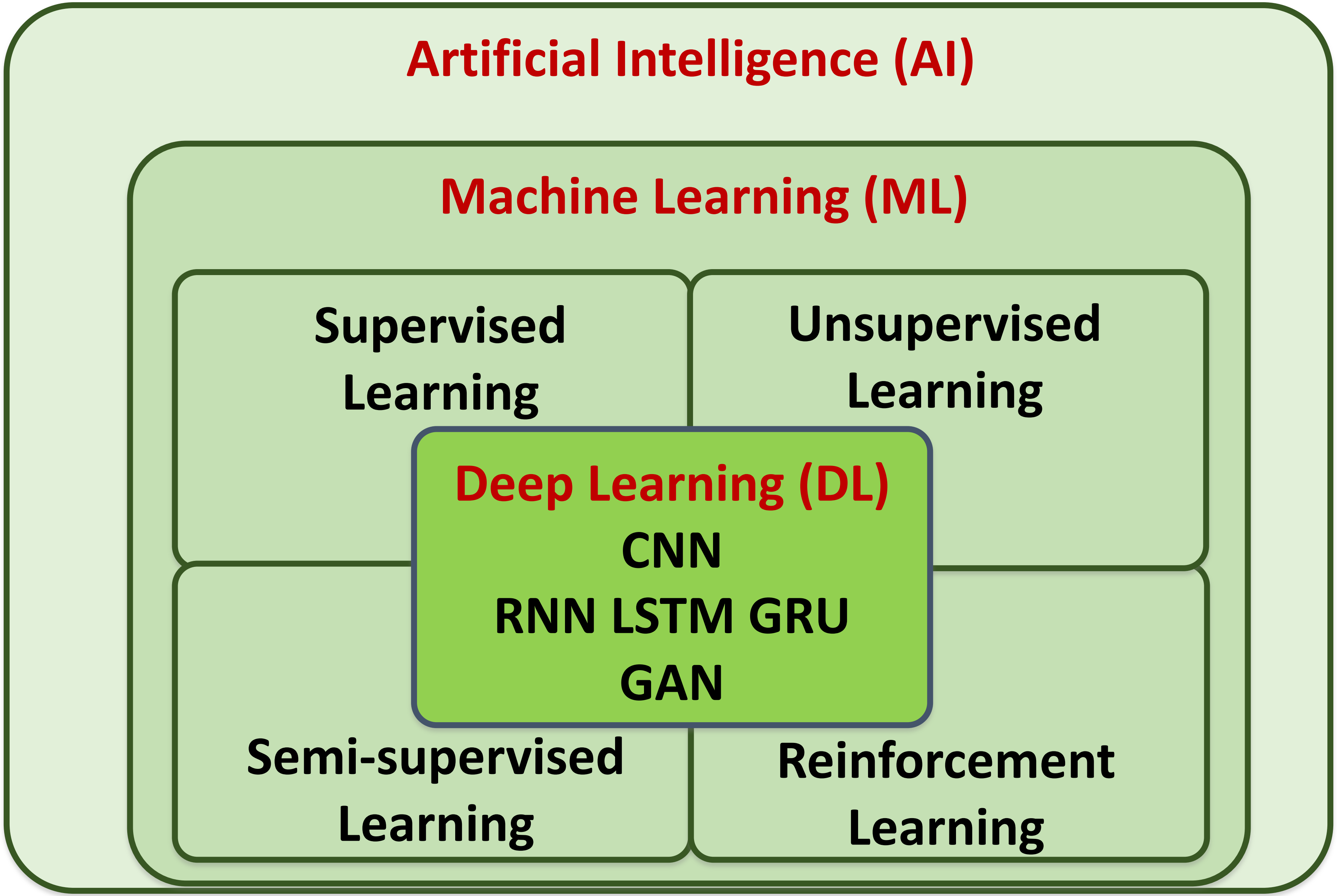
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

The Rise of AI



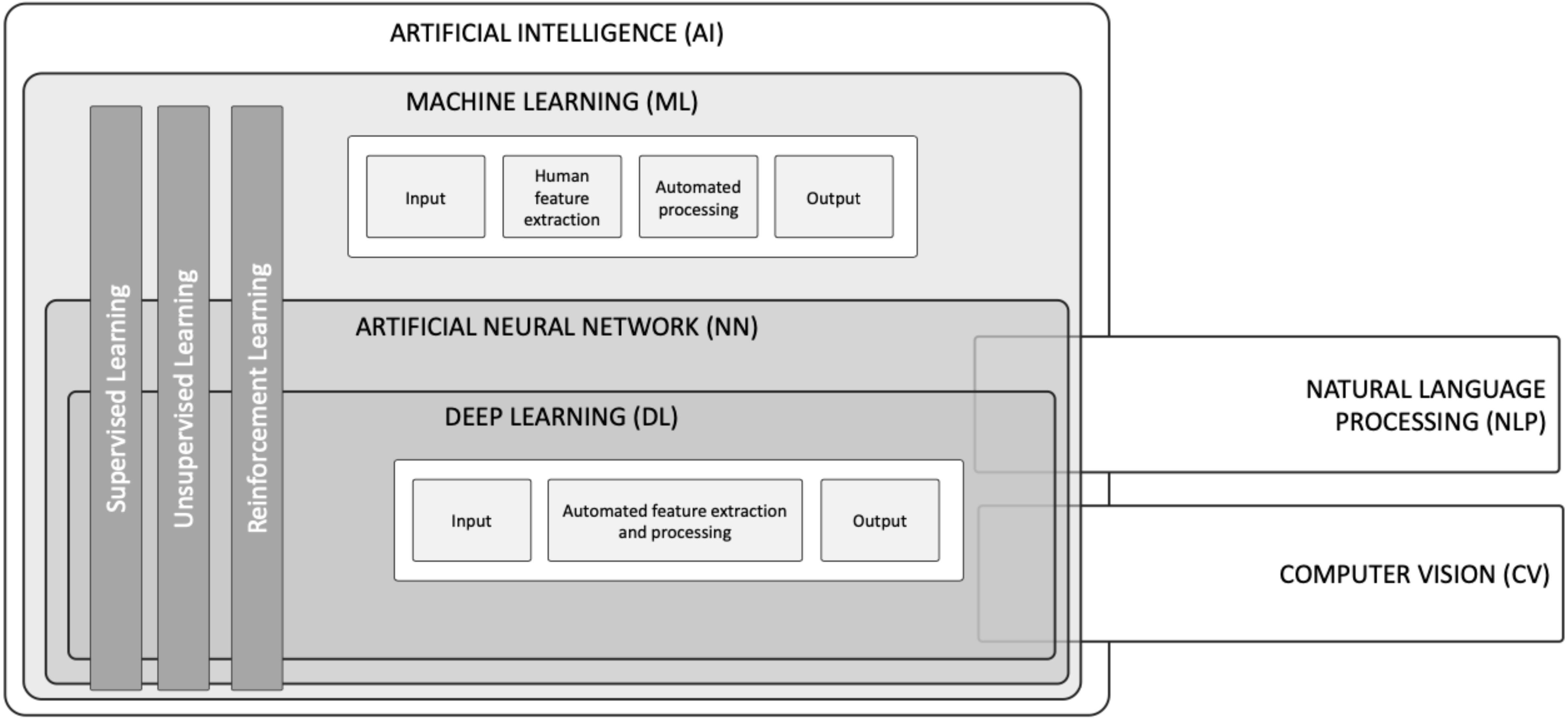
Source: DHL (2018), Artificial Intelligence in Logistics, http://www.globalhha.com/doclib/data/upload/doc_con/5e50c53c5bf67.pdf/

AI, ML, DL



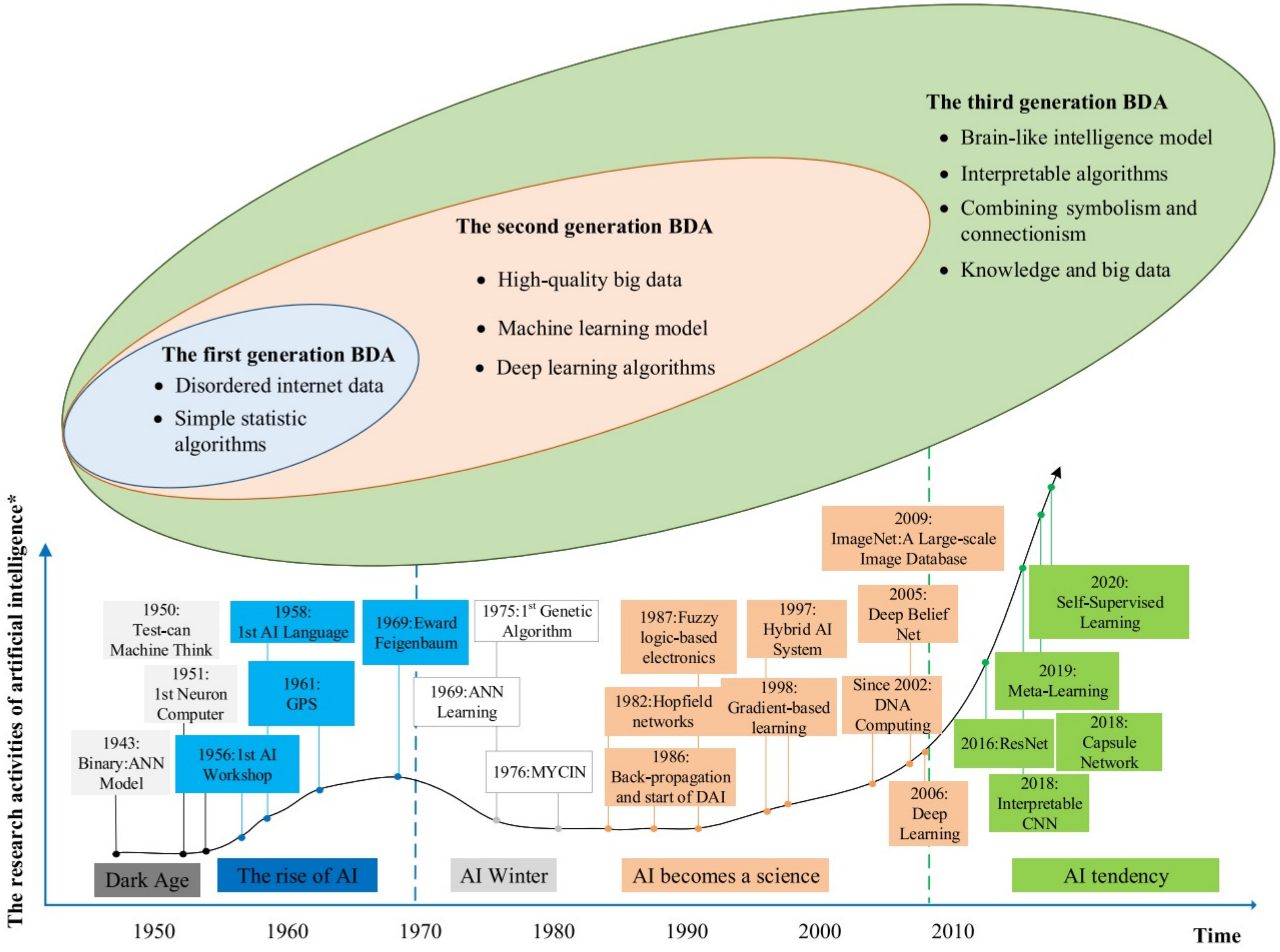
Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/deep_learning.html

AI, ML, NN, DL



Source: Schoormann, T., Strobel, G., Möller, F., Petrik, D., & Zschech, P. (2023).
Artificial Intelligence for Sustainability—A Systematic Review of Information Systems Literature. Communications of the Association for Information Systems, 52(1), 8.

AI and Big Data Analytics (BDA)



Source: Wang, Junliang, Chuqiao Xu, Jie Zhang, and Ray Zhong (2022). "Big data analytics for intelligent manufacturing systems: A review." Journal of Manufacturing Systems 62 (2022): 738-752.

Definition of Artificial Intelligence (A.I.)

Artificial Intelligence

“… the science and

engineering

of

making

intelligent machines”

(John McCarthy, 1955)

Source: https://digitalintelligencetoday.com/artificial-intelligence-defined-useful-list-of-popular-definitions-from-business-and-science/

Artificial Intelligence

"... technology that thinks and acts like humans"

Source: https://digitalintelligencetoday.com/artificial-intelligence-defined-useful-list-of-popular-definitions-from-business-and-science/

Artificial Intelligence

"… intelligence exhibited by machines or software"

Source: https://digitalintelligencetoday.com/artificial-intelligence-defined-useful-list-of-popular-definitions-from-business-and-science/

4 Approaches of AI

Thinking Humanly	Thinking Rationally
Acting Humanly	Acting Rationally

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

4 Approaches of AI

2. Thinking Humanly: The Cognitive Modeling Approach	3. Thinking Rationally: The “Laws of Thought” Approach
1. Acting Humanly: The Turing Test Approach (1950)	4. Acting Rationally: The Rational Agent Approach

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

AI Acting Humanly: The Turing Test Approach
(Alan Turing, 1950)

- Knowledge Representation
- Automated Reasoning
- Machine Learning (ML)
  - Deep Learning (DL)
- Computer Vision (Image, Video)
- Natural Language Processing (NLP)
- Robotics

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

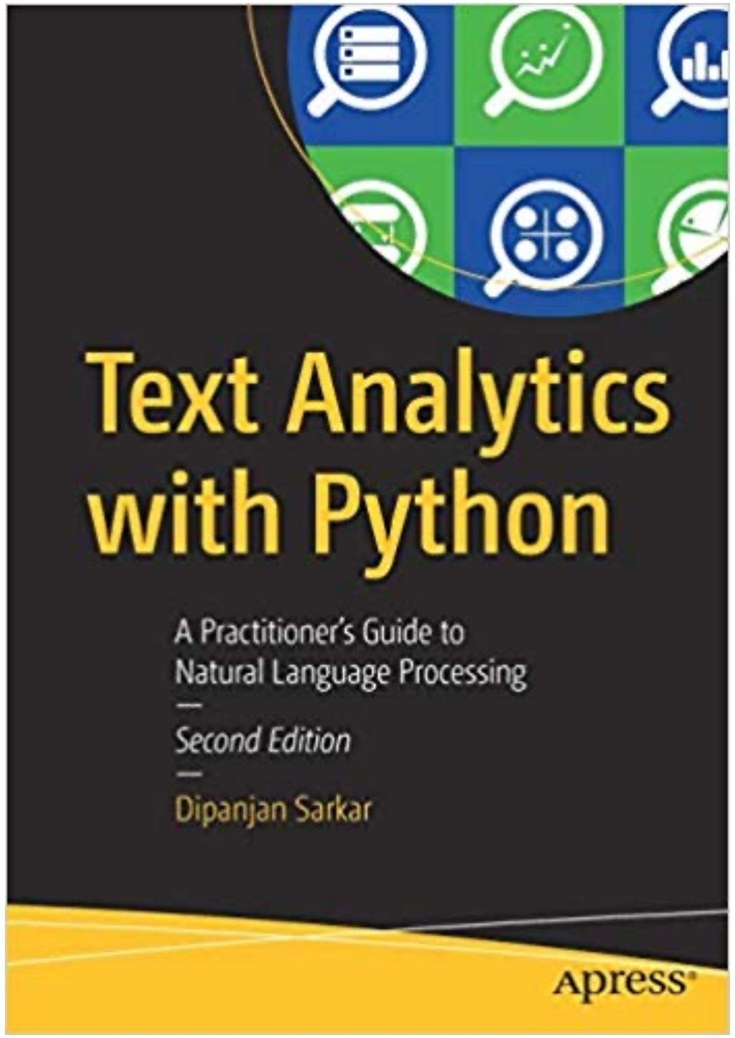
Text Analytics and Text Mining

Dipanjan Sarkar (2019),

Text Analytics with Python:

A Practitioner's Guide to Natural Language Processing,

Second Edition. APress.



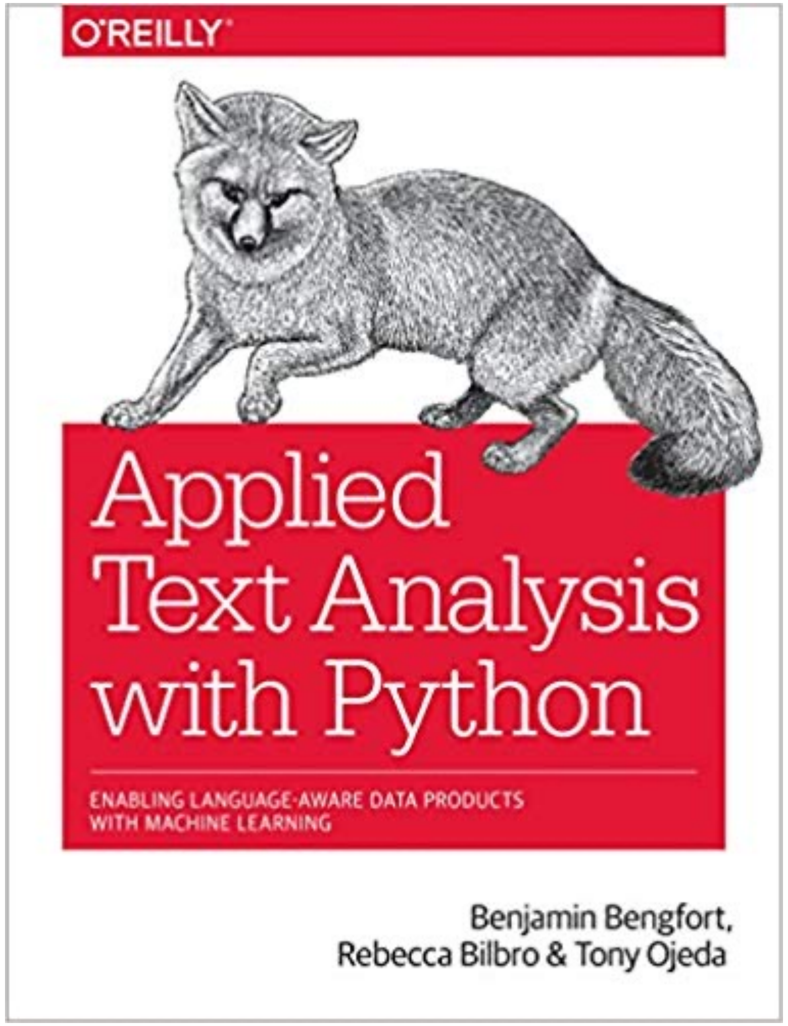
Source: https://www.amazon.com/Text-Analytics-Python-Practitioners-Processing/dp/1484243536

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

Applied Text Analysis with Python:

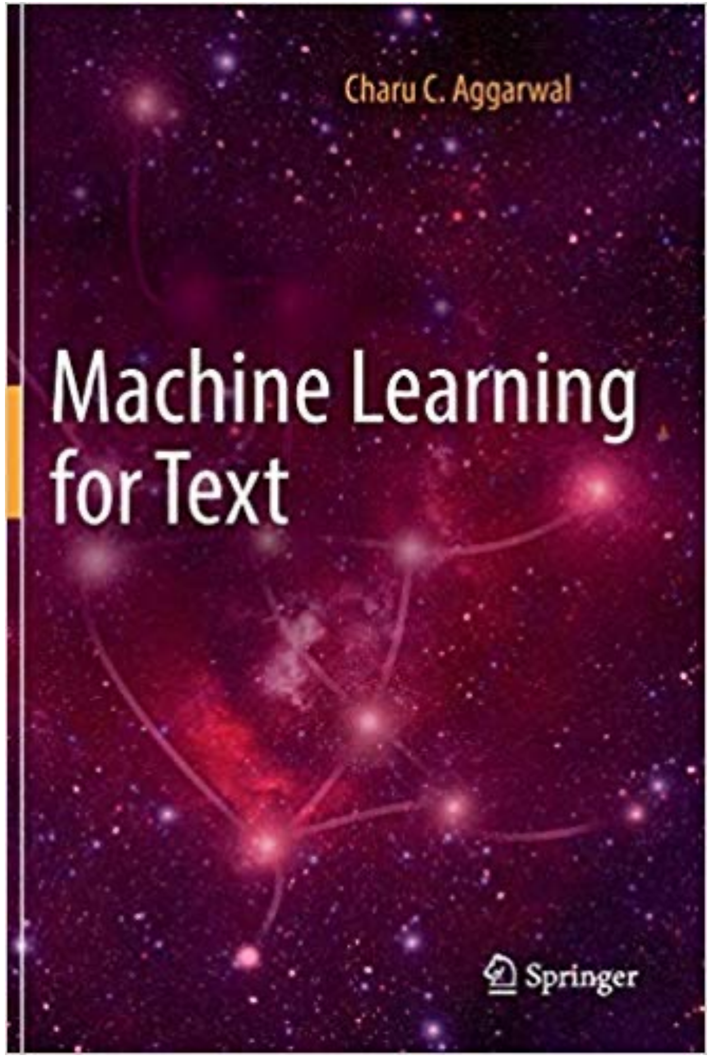
Enabling Language-Aware Data Products with Machine Learning,

O'Reilly.



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

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



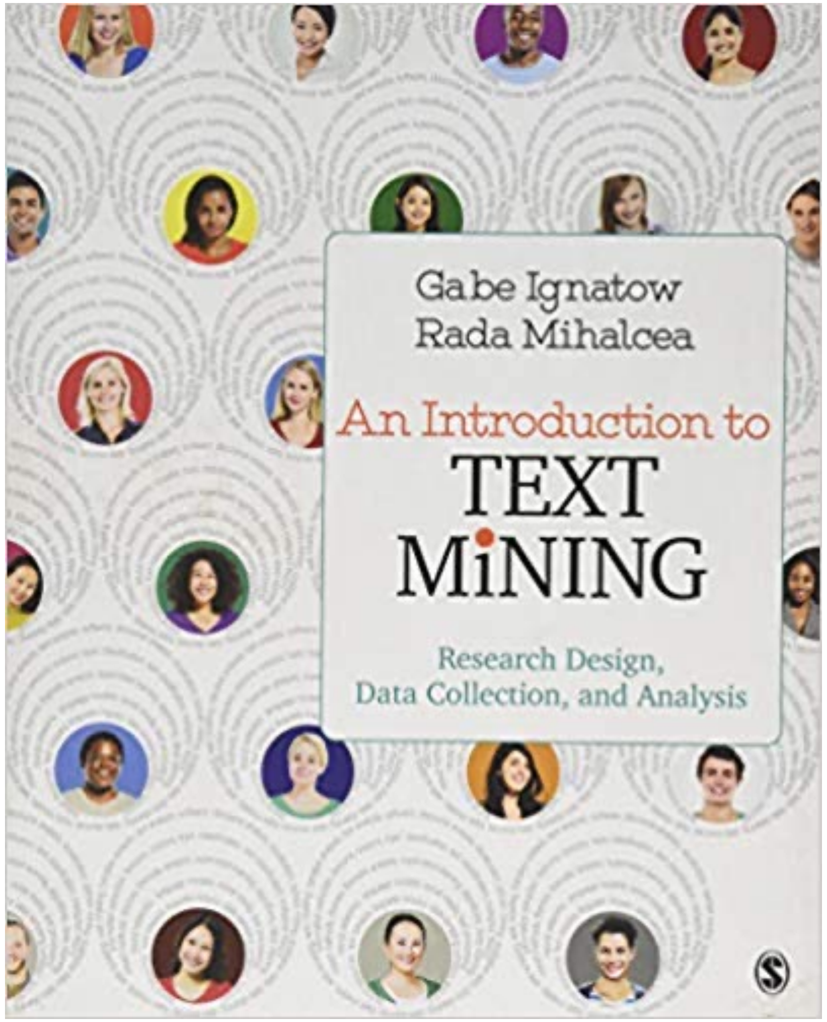
Source: https://www.amazon.com/Machine-Learning-Text-Charu-Aggarwal/dp/3319735306

Gabe Ignatow and Rada F. Mihalcea (2017),

An Introduction to Text Mining:

Research Design, Data Collection, and Analysis,

SAGE Publications.



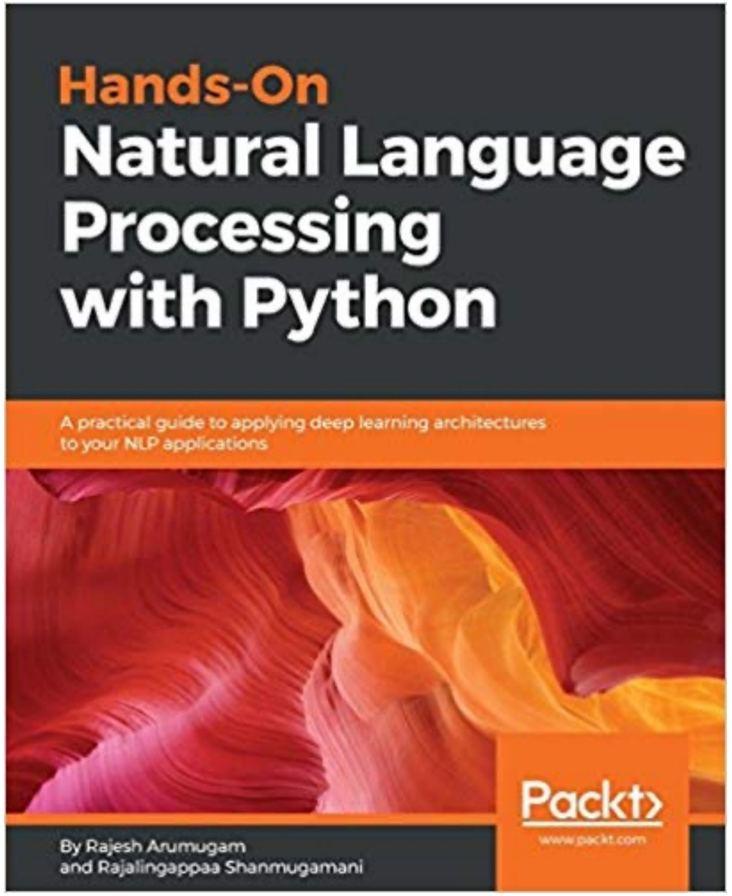
Source: https://www.amazon.com/Introduction-Text-Mining-Research-Collection/dp/1506337007

Rajesh Arumugam (2018),

Hands-On Natural Language Processing with Python:

A practical guide to applying deep learning architectures to your NLP applications,

Packt



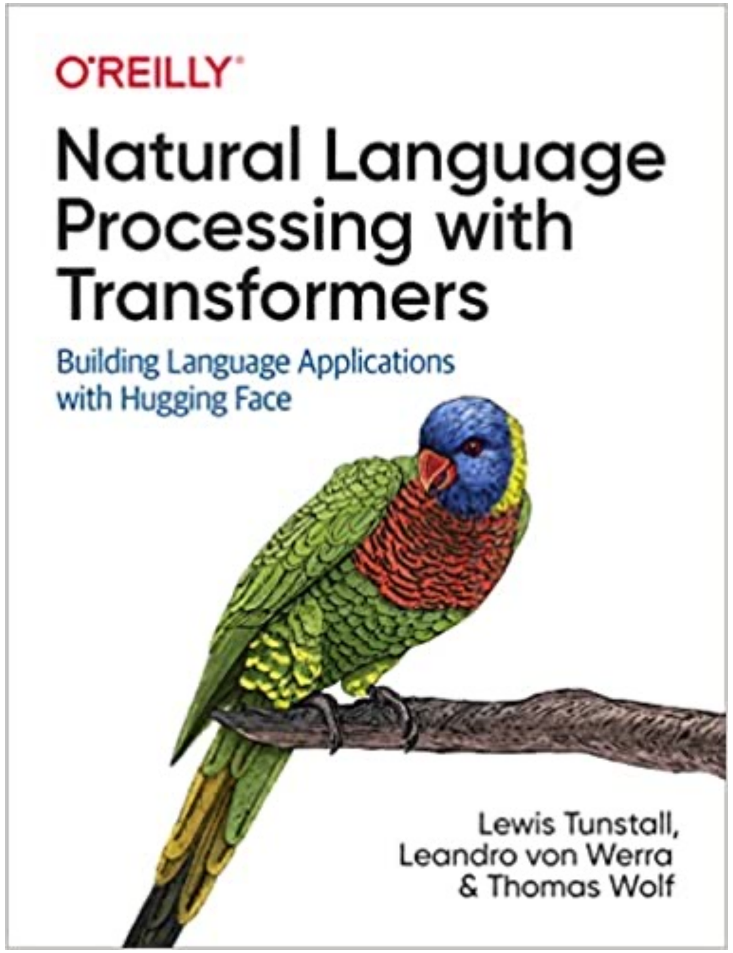
https://www.amazon.com/Hands-Natural-Language-Processing-Python/dp/178913949X

Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022),

Natural Language Processing with Transformers:

Building Language Applications with Hugging Face,

O'Reilly Media.



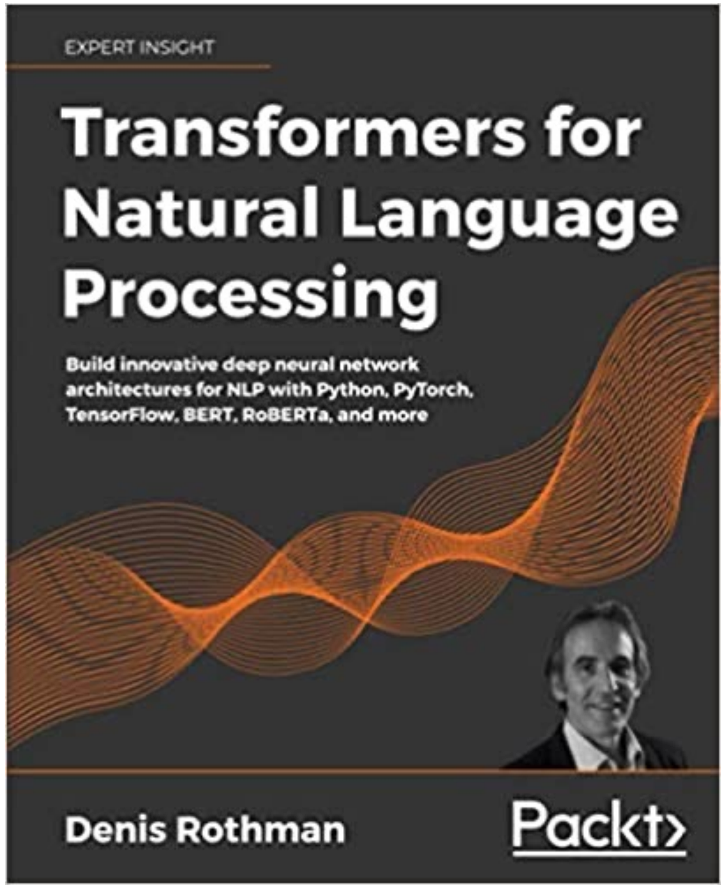
Source: https://www.amazon.com/Natural-Language-Processing-Transformers-Applications/dp/1098103246

Denis Rothman (2021),

Transformers for Natural Language Processing:

Build innovative deep neural network architectures for NLP with Python, PyTorch, TensorFlow, BERT, RoBERTa, and more,

Packt Publishing.



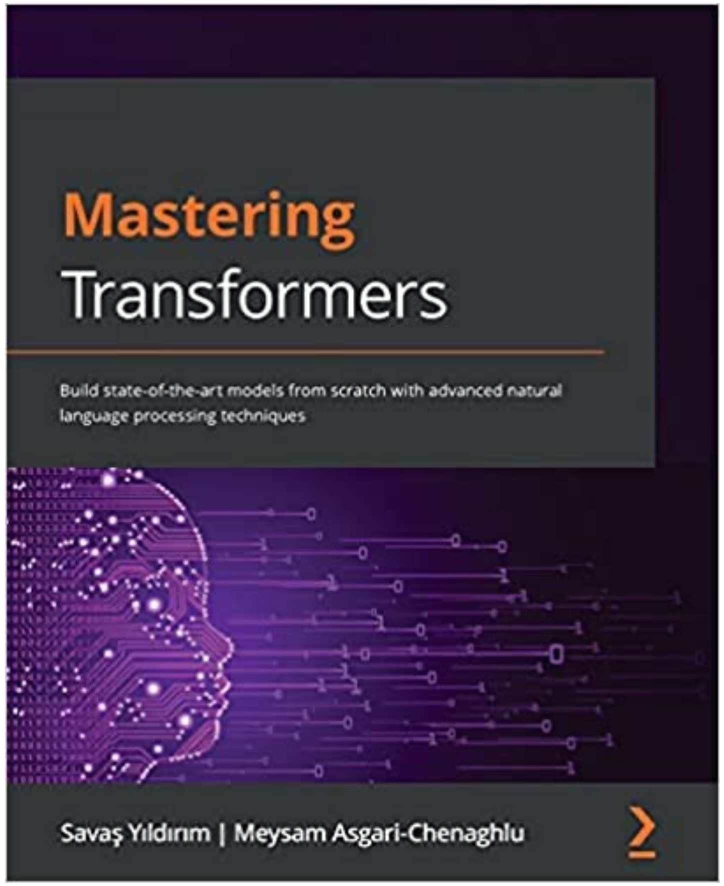
Source: https://www.amazon.com/Transformers-Natural-Language-Processing-architectures/dp/1800565798

Savaş Yıldırım and Meysam Asgari-Chenaghlu (2021),

Mastering Transformers:

Build state-of-the-art models from scratch with advanced natural language processing techniques,

Packt Publishing.



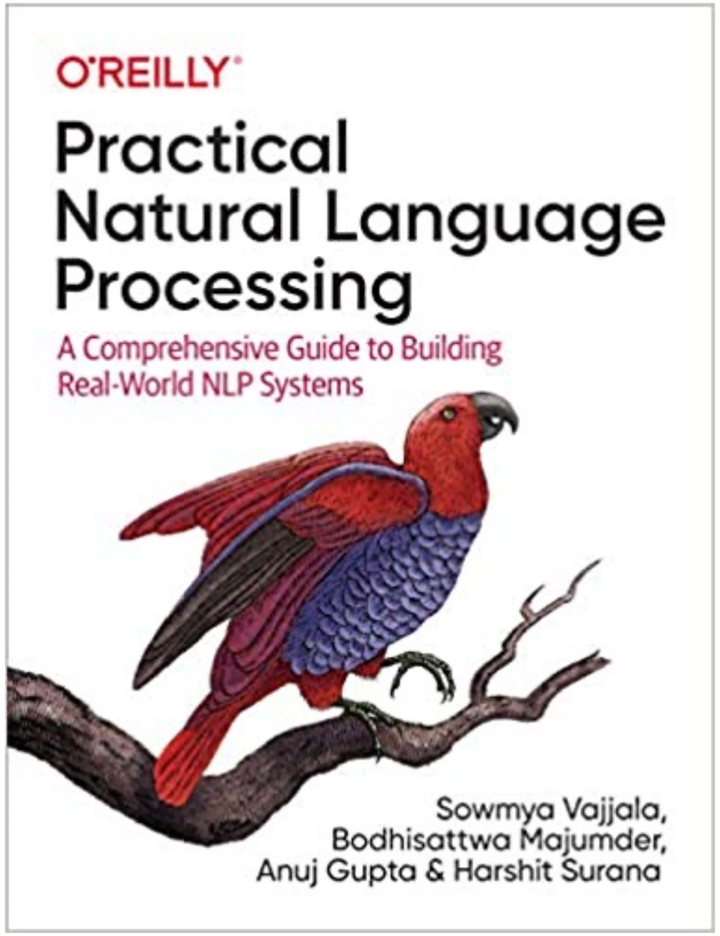
Source: https://www.amazon.com/Mastering-Transformers-state-art-processing/dp/1801077657/

Sowmya Vajjala, Bodhisattwa Majumder, Anuj Gupta (2020),

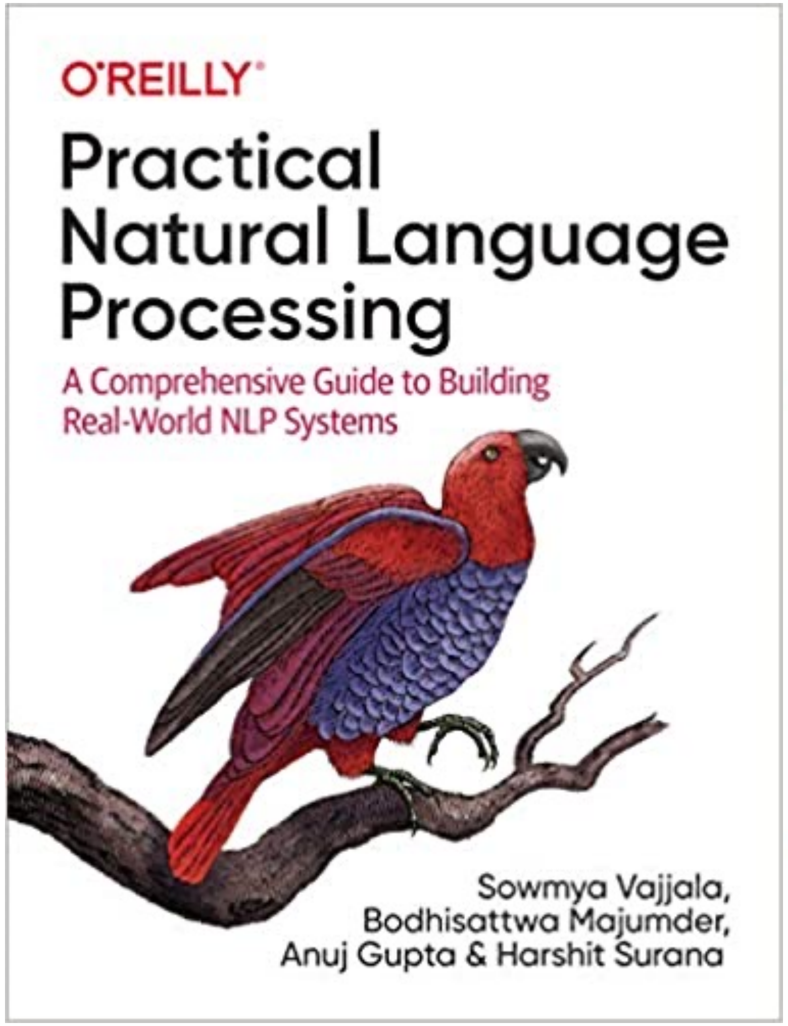
Practical Natural Language Processing:

A Comprehensive Guide to Building Real-World NLP Systems,

O'Reilly Media.



Source: https://www.amazon.com/Practical-Natural-Language-Processing-Pragmatic/dp/1492054054



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!
INDUSTRY SPECIFIC *Covered in Chapters 8 to 10*	Social Media Analysis	Retail Data Extraction	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

Source: Sowmya Vajjala, Bodhisattwa Majumder, Anuj Gupta (2020), Practical Natural Language Processing: A Comprehensive Guide to Building Real-World NLP Systems, O'Reilly Media.

Source: https://www.amazon.com/Practical-Natural-Language-Processing-Pragmatic/dp/1492054054

Text Analytics (TA)

Text Analytics

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

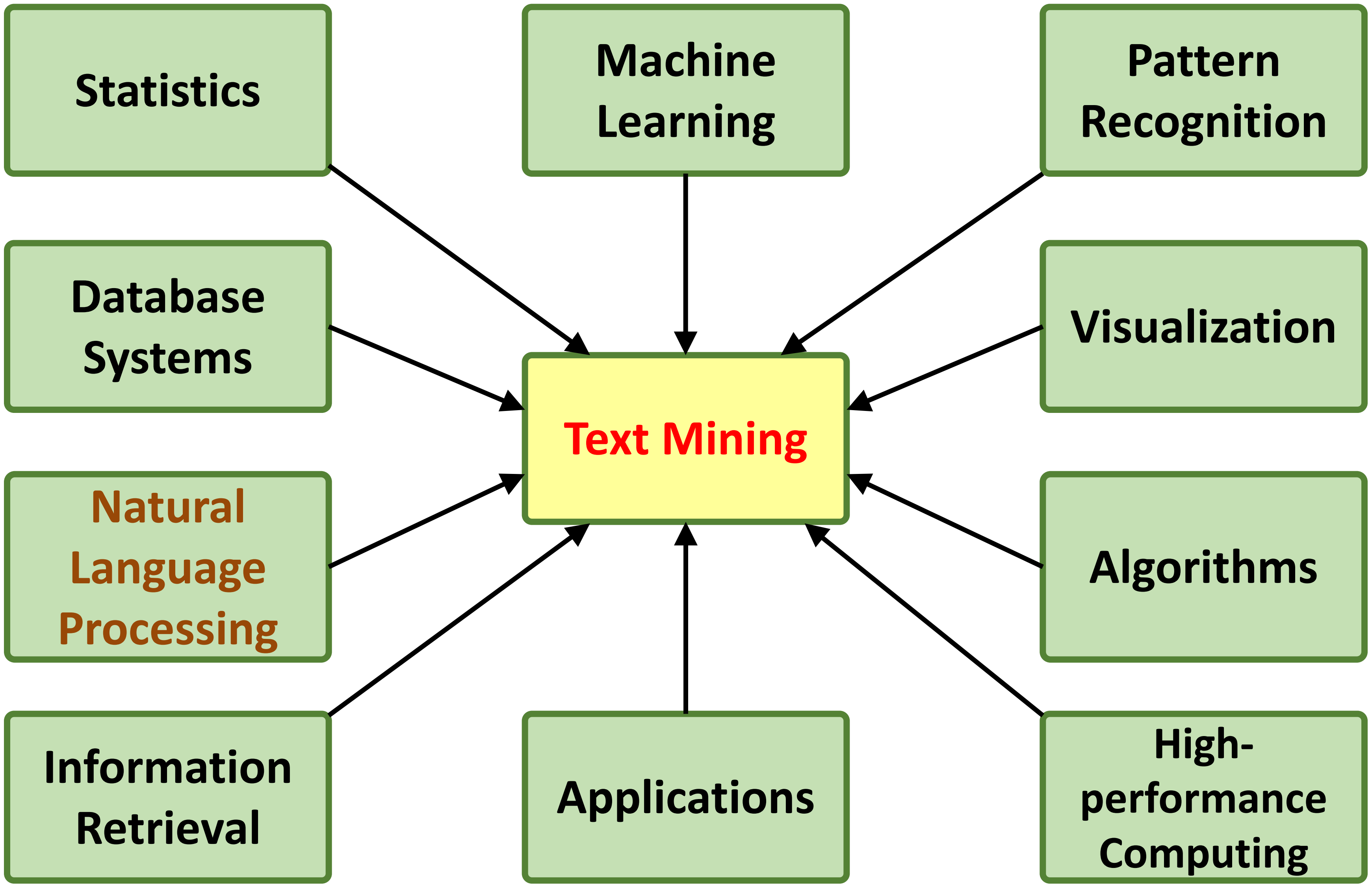
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

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

Text Mining Technologies



Adapted from: Jiawei Han and Micheline Kamber (2011), Data Mining: Concepts and Techniques, Third Edition, Elsevier

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

Emotions

Love	Anger
Joy	Sadness
Surprise	Fear

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.

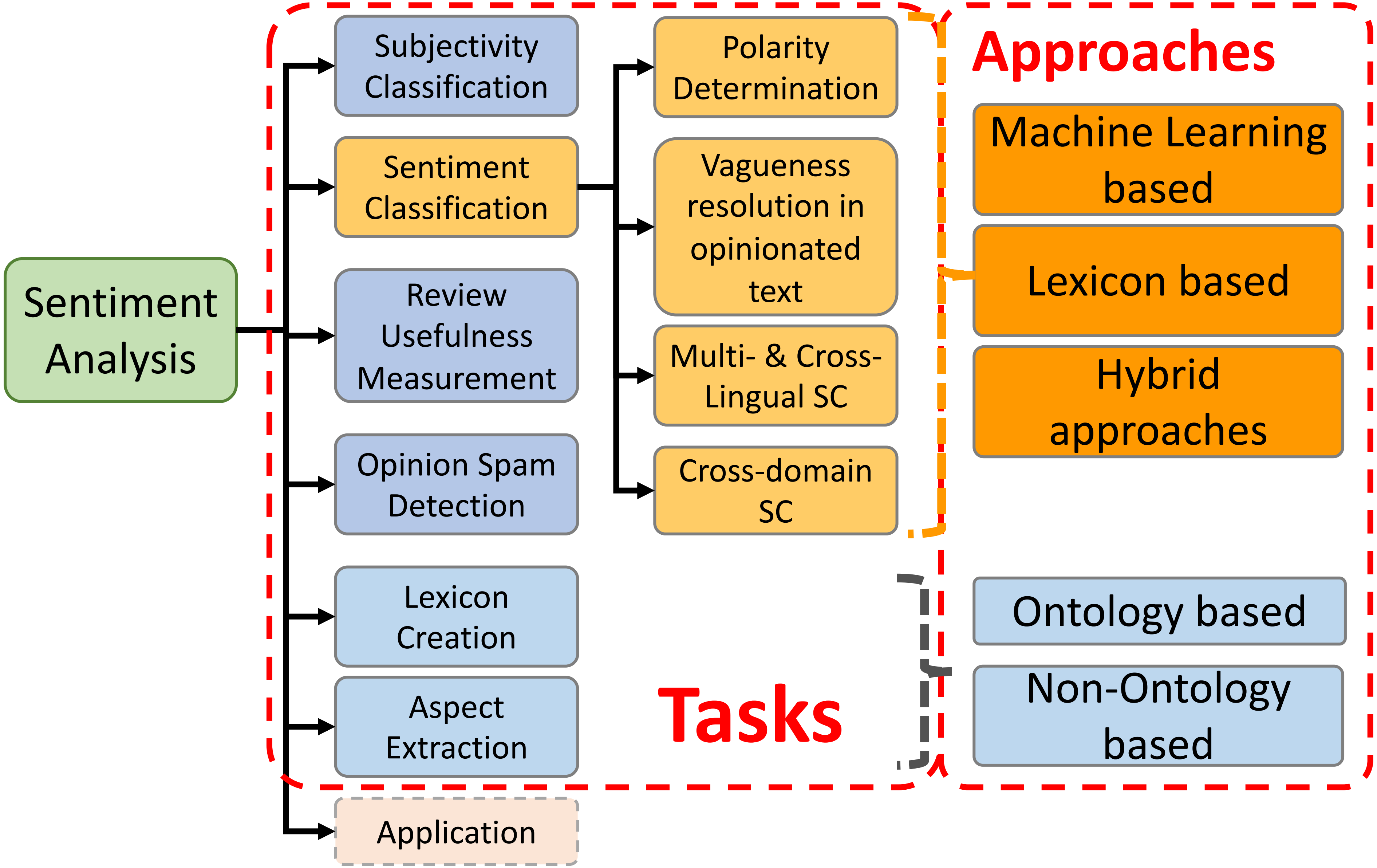
(6) She also thought the phone was too expensive, and wanted me to return it to the shop. … "

+Positive Opinion

-Negative Opinion

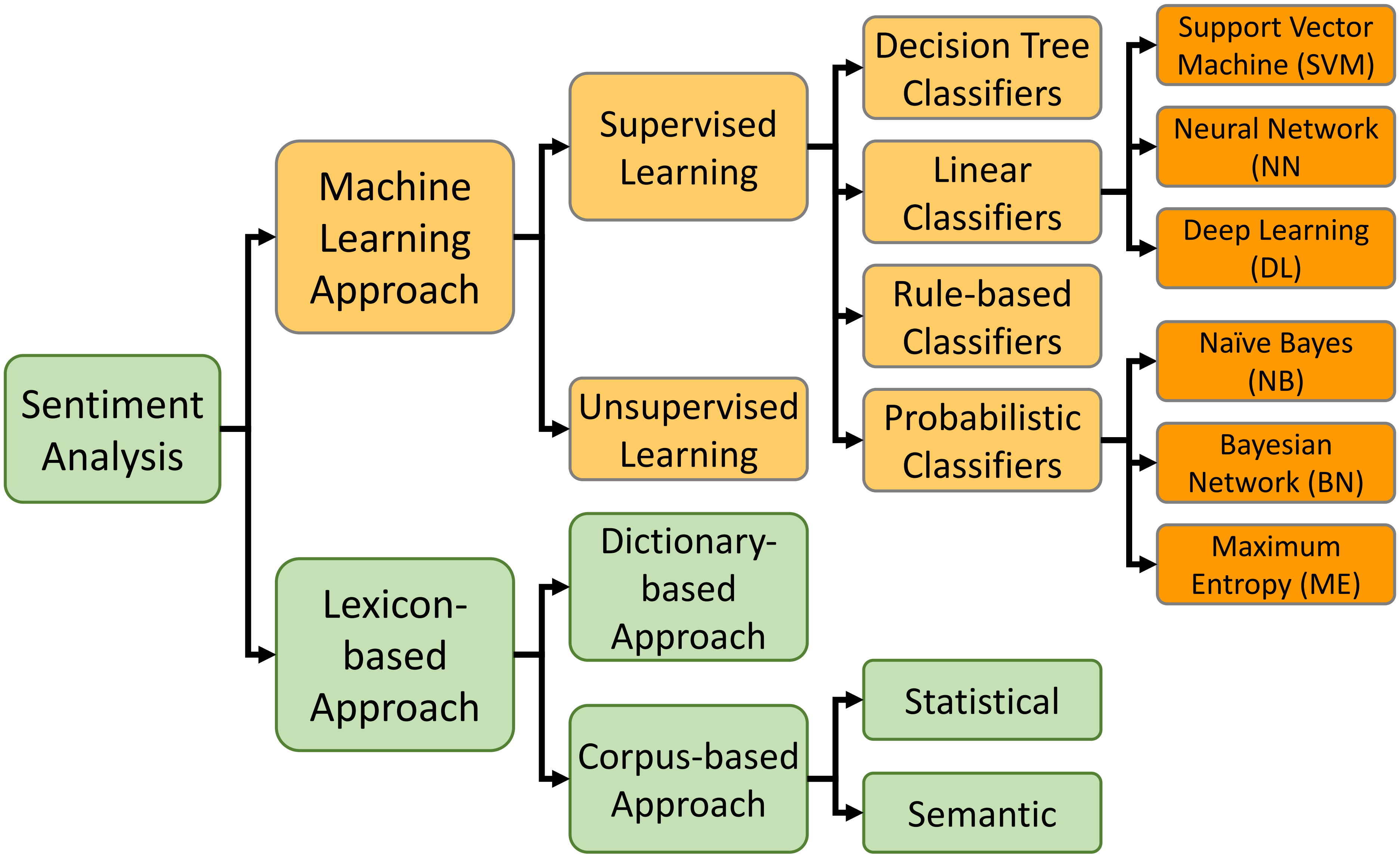
Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

Sentiment Analysis



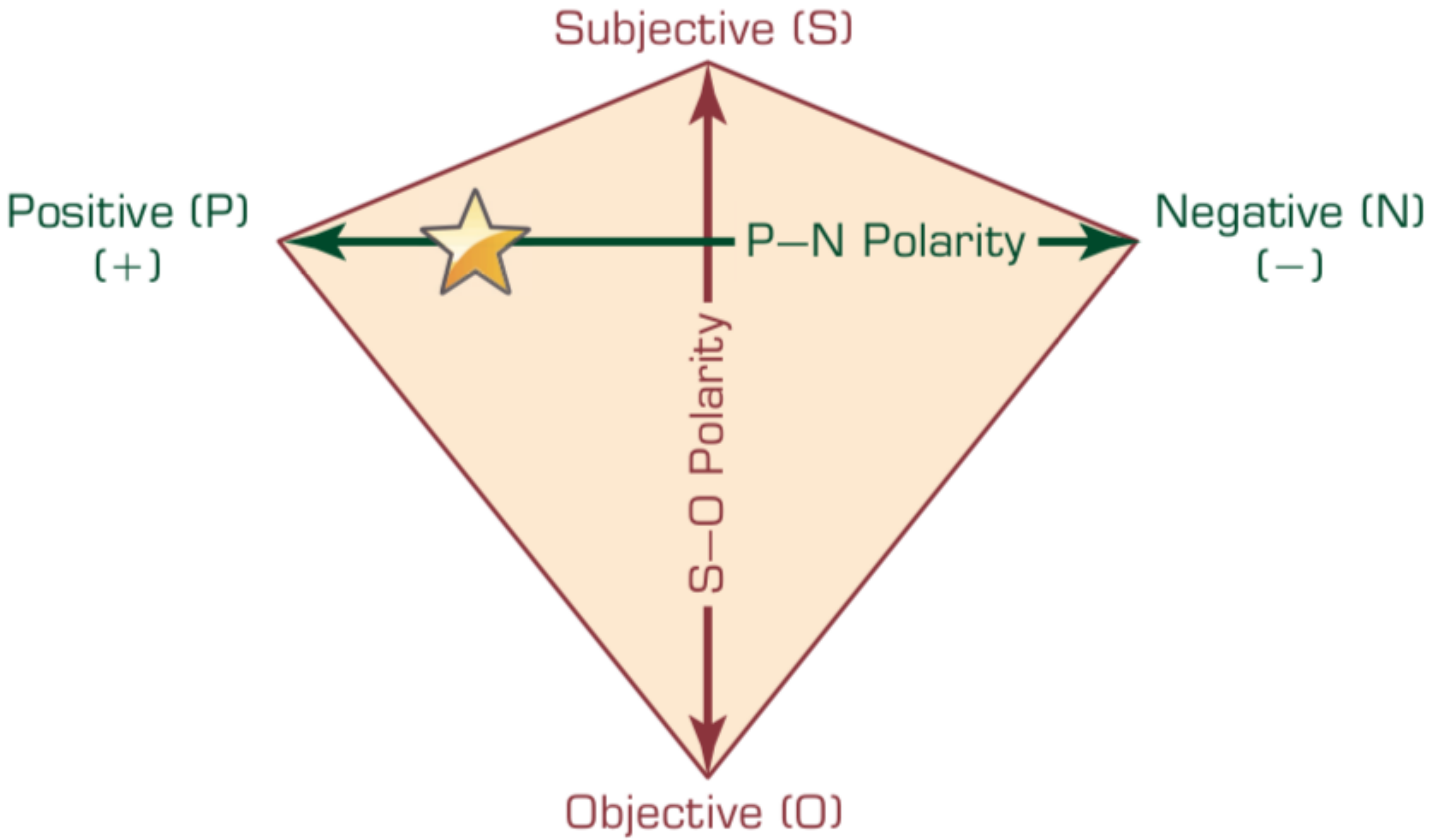
Source: Kumar Ravi and Vadlamani Ravi (2015), "A survey on opinion mining and sentiment analysis: tasks, approaches and applications." Knowledge-Based Systems, 89, pp.14-46.

Sentiment Classification Techniques



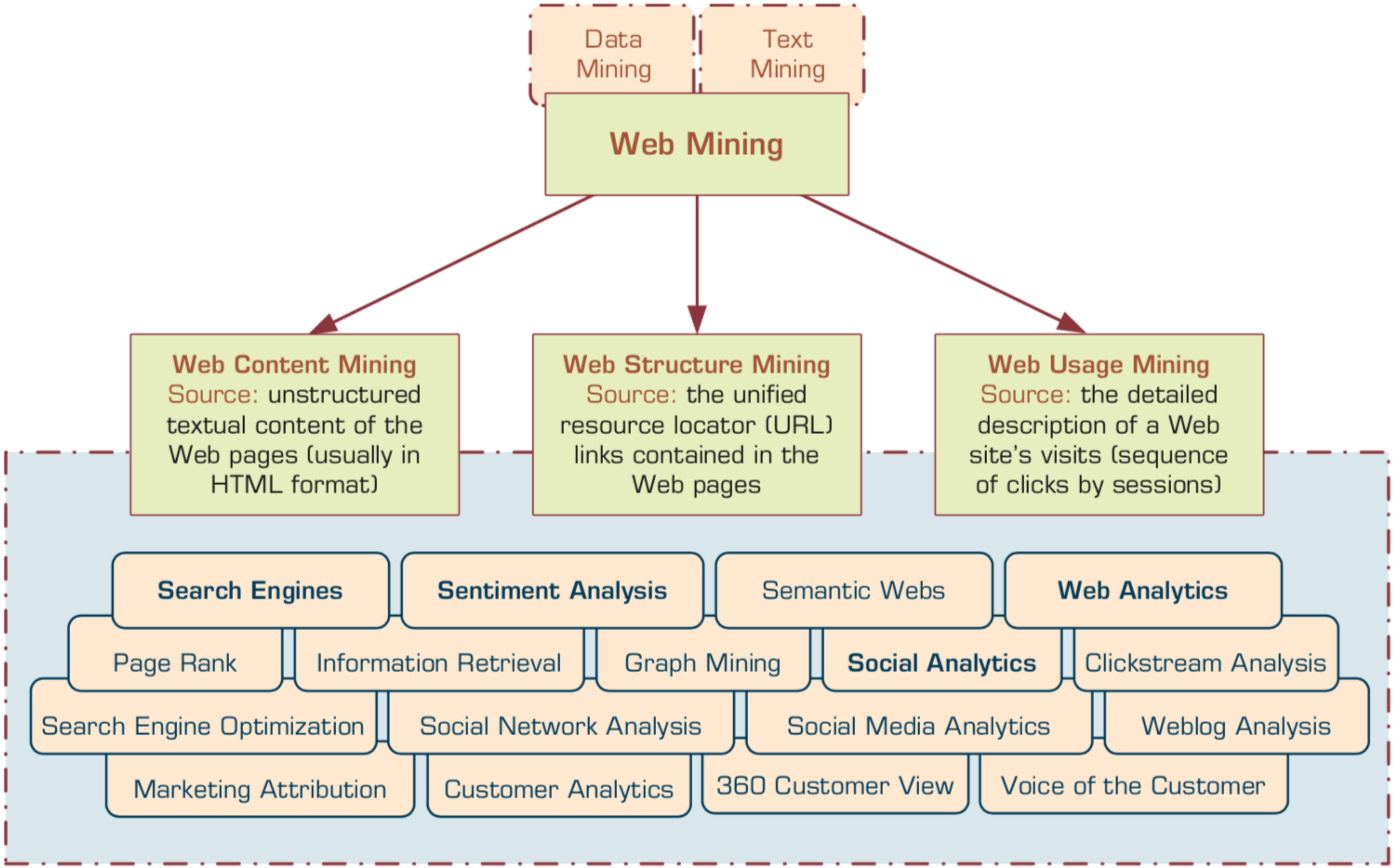
Source: Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.

P–N Polarity and S–O Polarity Relationship



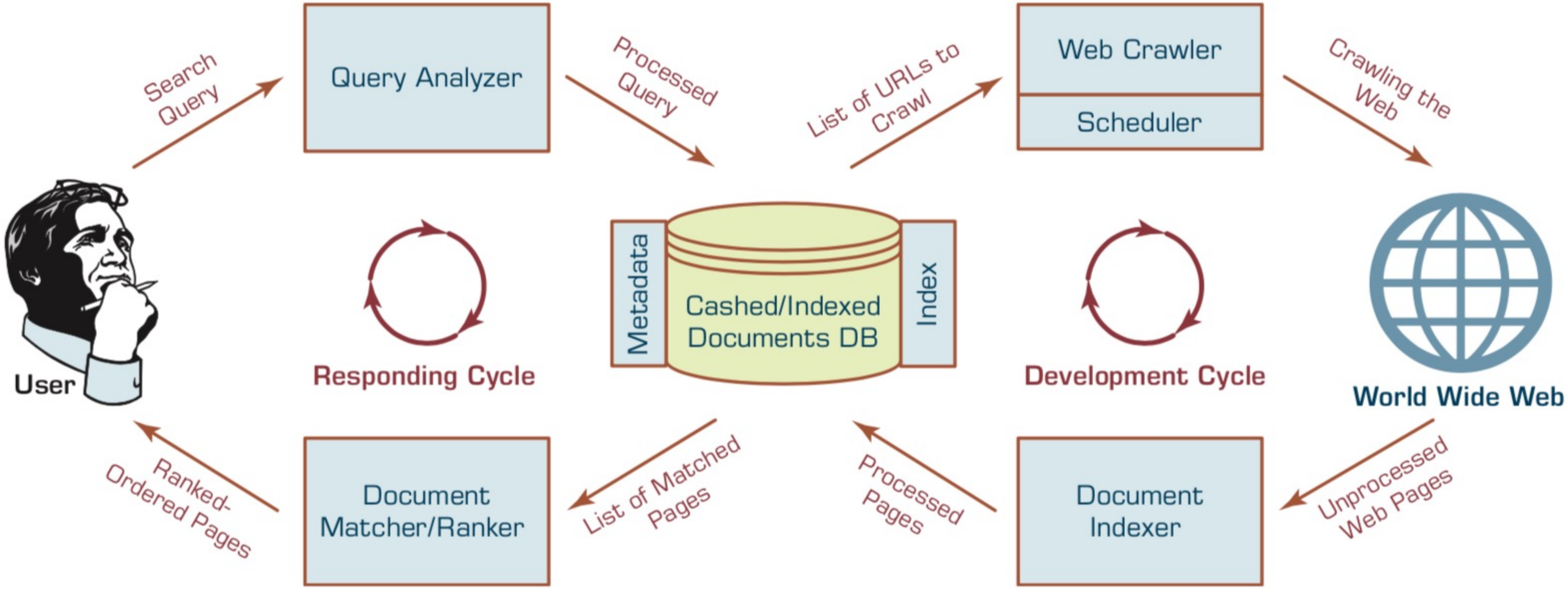
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Taxonomy of Web Mining



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

Structure of a Typical Internet Search Engine



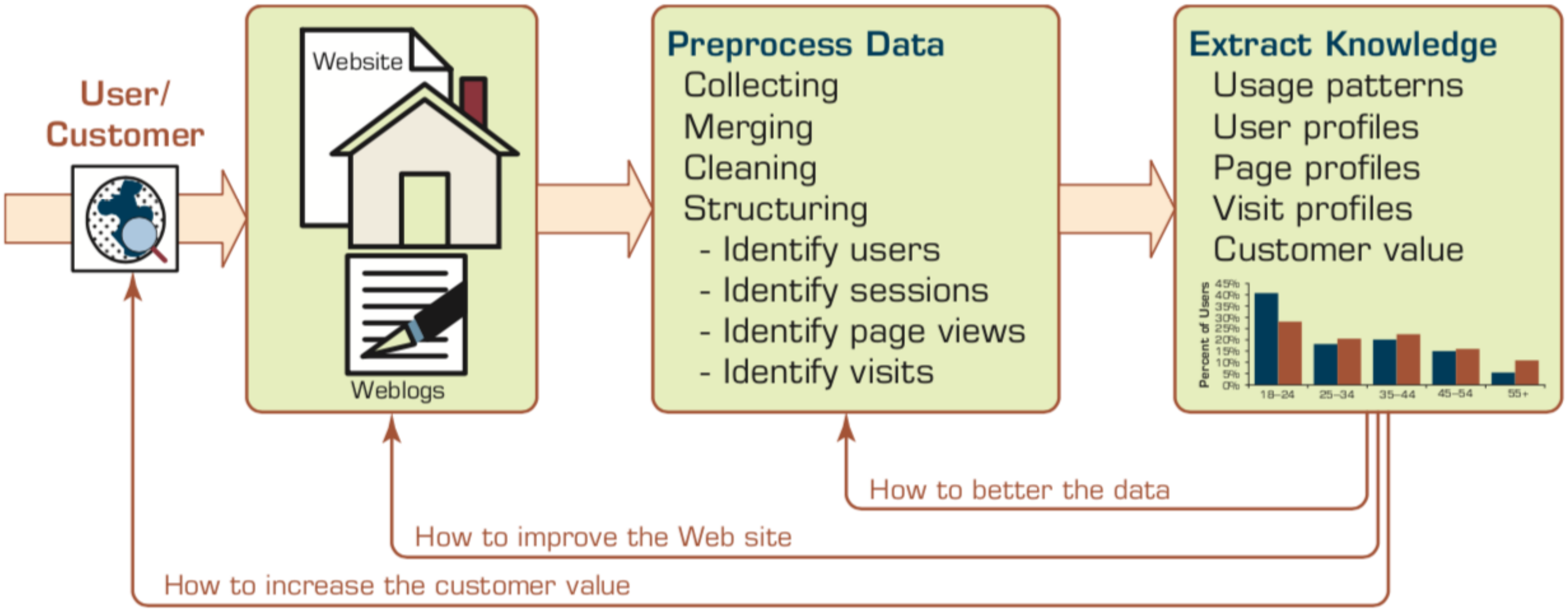
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Web Usage Mining (Web Analytics)

- **Web usage mining (Web analytics) is the extraction of useful information from data generated through Web page visits and transactions.**
- **Clickstream Analysis**

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

Extraction of Knowledge from Web Usage Data



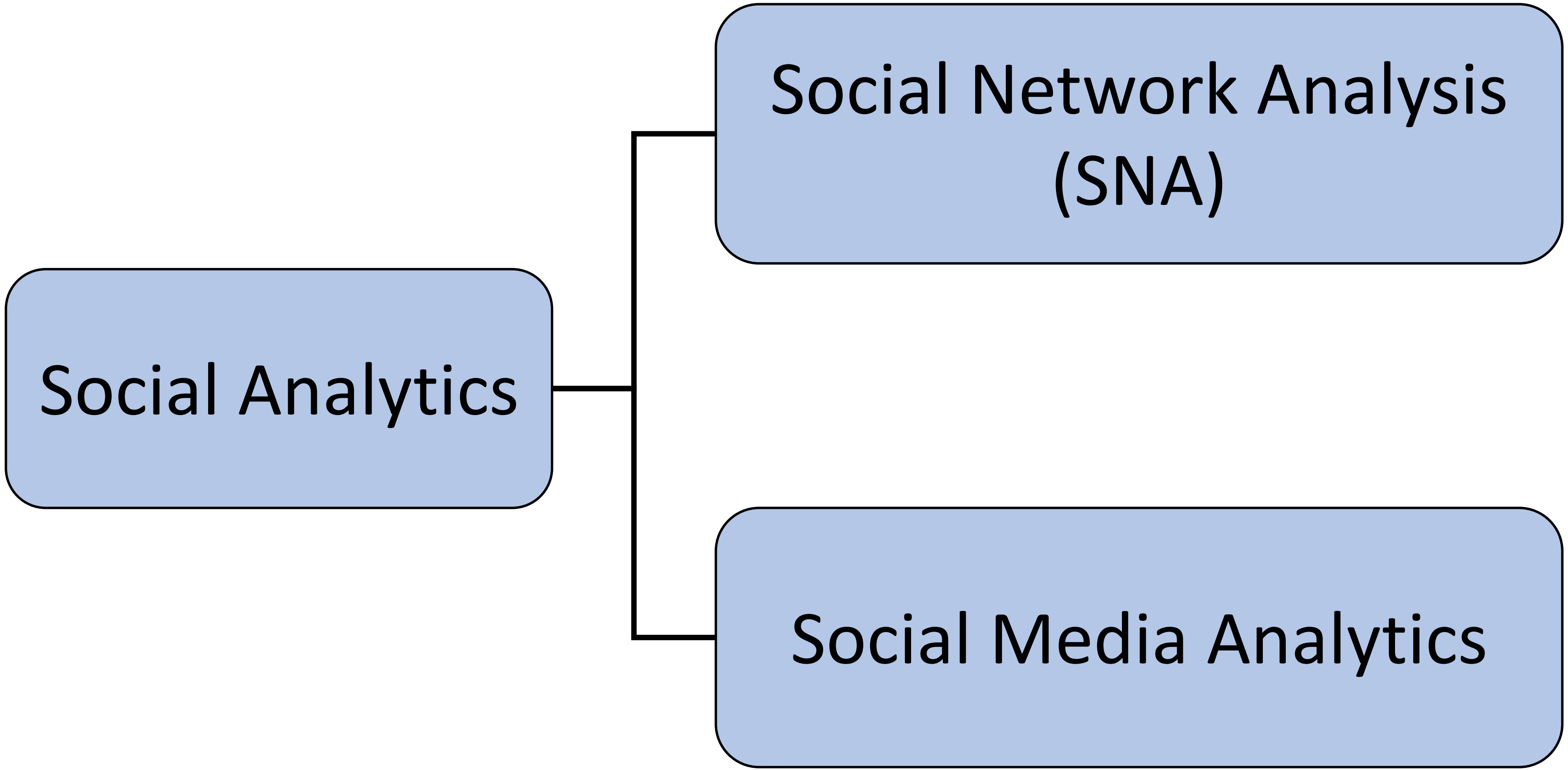
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Social Analytics

- **Social analytics is defined as monitoring, analyzing, measuring and interpreting digital interactions and relationships of people, topics, ideas and content.**

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

Branches of Social Analytics



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

Text Mining Technologies

Text Mining
(TM)

Natural Language Processing
(NLP)

Text mining

Text Data Mining

Intelligent Text Analysis

Knowledge-Discovery in Text (KDT)

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.

Text Mining
(text data mining)

the process of
deriving
high-quality information
from text

http://en.wikipedia.org/wiki/Text_mining

Text Mining:

the process of extracting interesting and non-trivial information and knowledge from unstructured text.

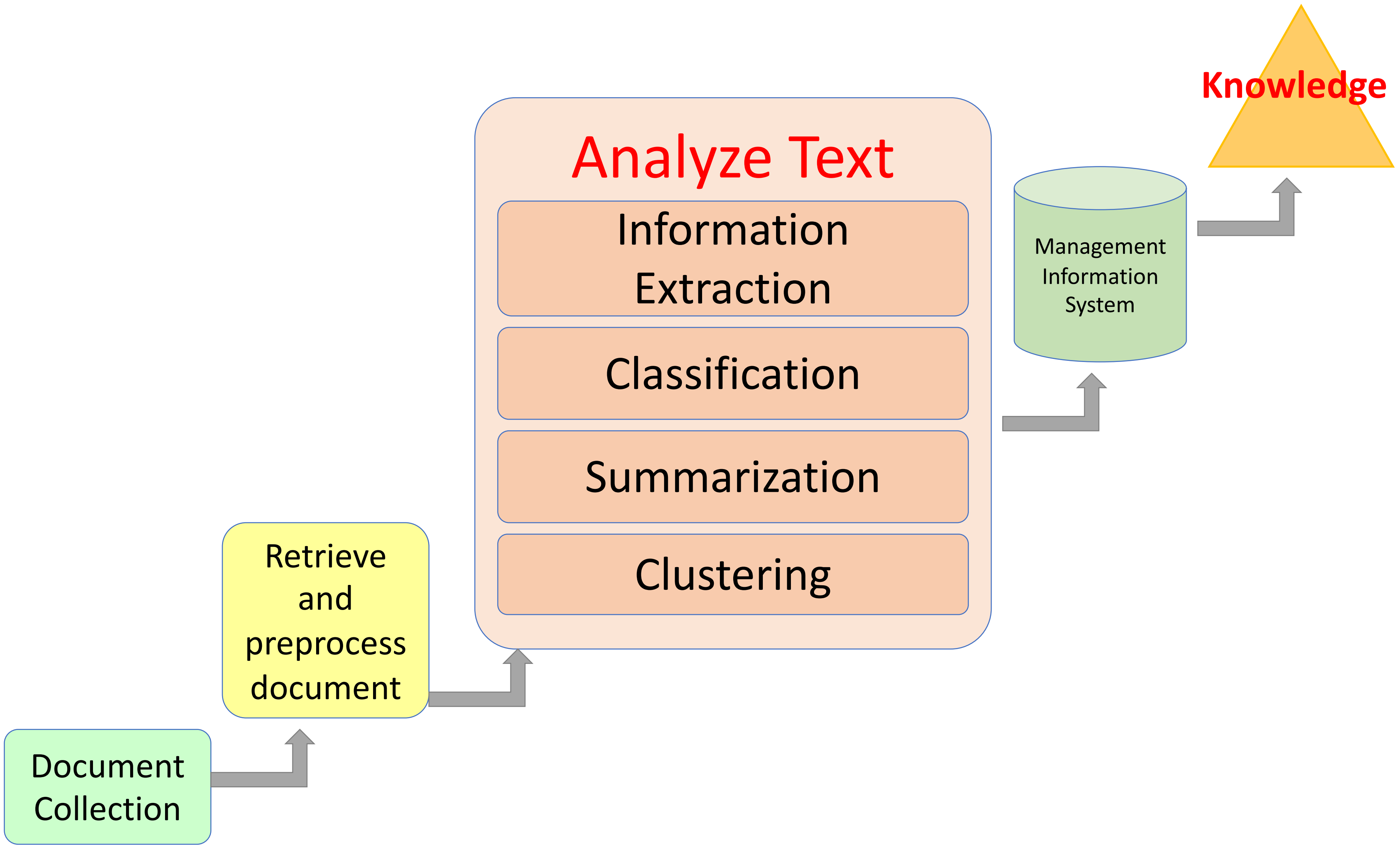
Source: Vishal Gupta and Gurpreet S. Lehal (2009), "A survey of text mining techniques and applications," Journal of emerging technologies in web intelligence, vol. 1, no. 1, pp. 60-76.

Text Mining:

discovery by computer of new, previously unknown information, by automatically extracting information from different written resources.

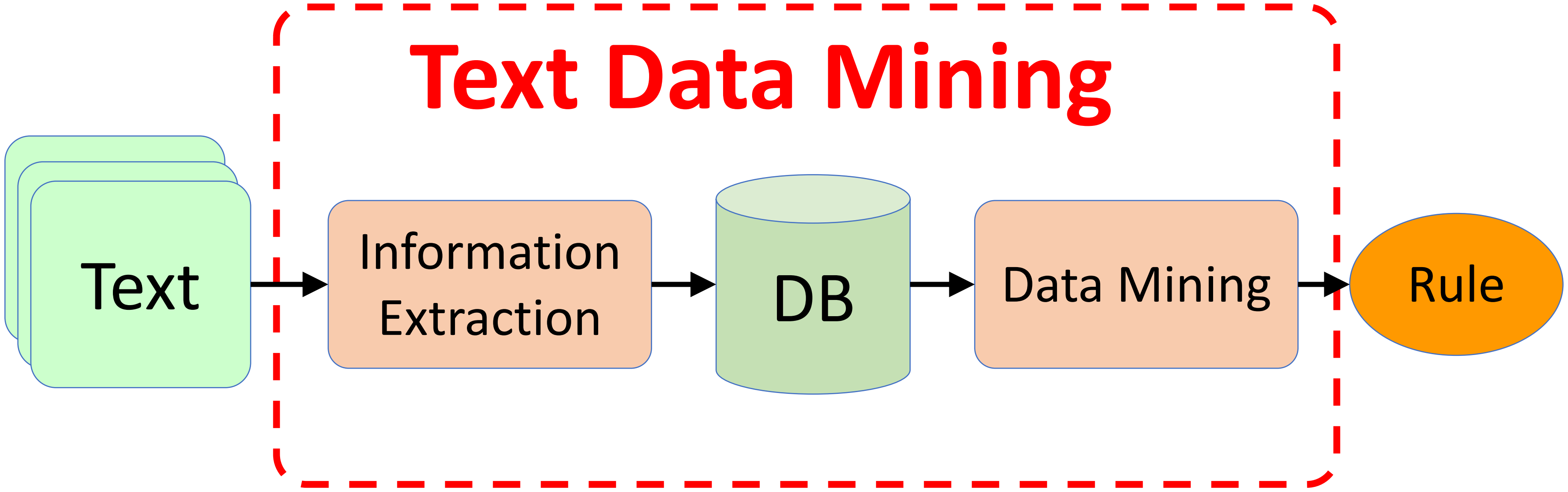
Source: Vishal Gupta and Gurpreet S. Lehal (2009), "A survey of text mining techniques and applications," Journal of emerging technologies in web intelligence, vol. 1, no. 1, pp. 60-76.

An example of Text Mining



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.

Overview of Information Extraction based Text Mining Framework



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.

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

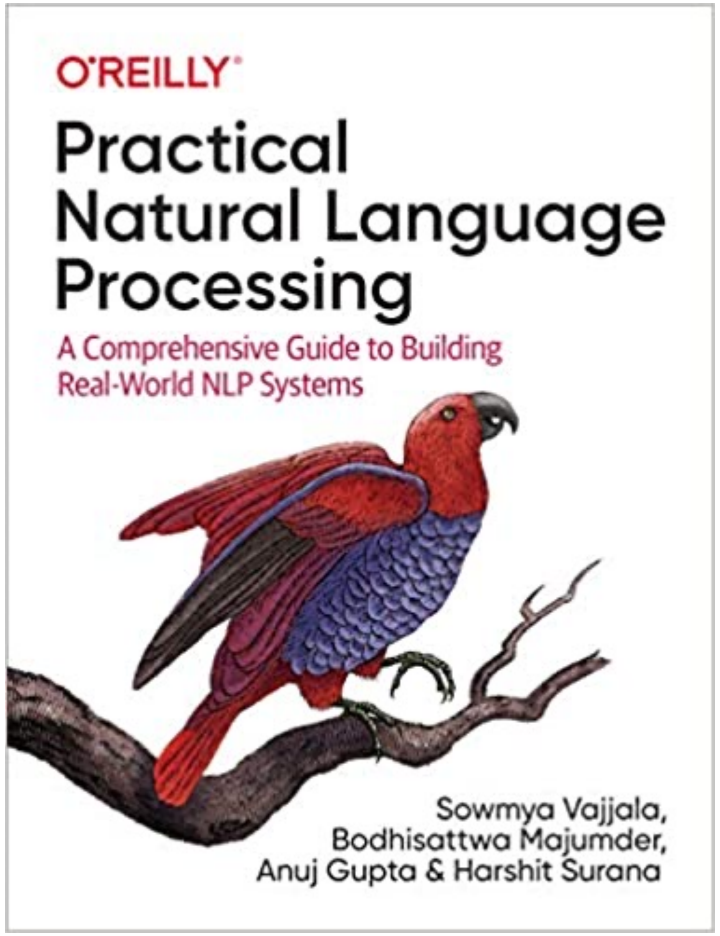
Natural Language Processing (NLP) and Text Mining

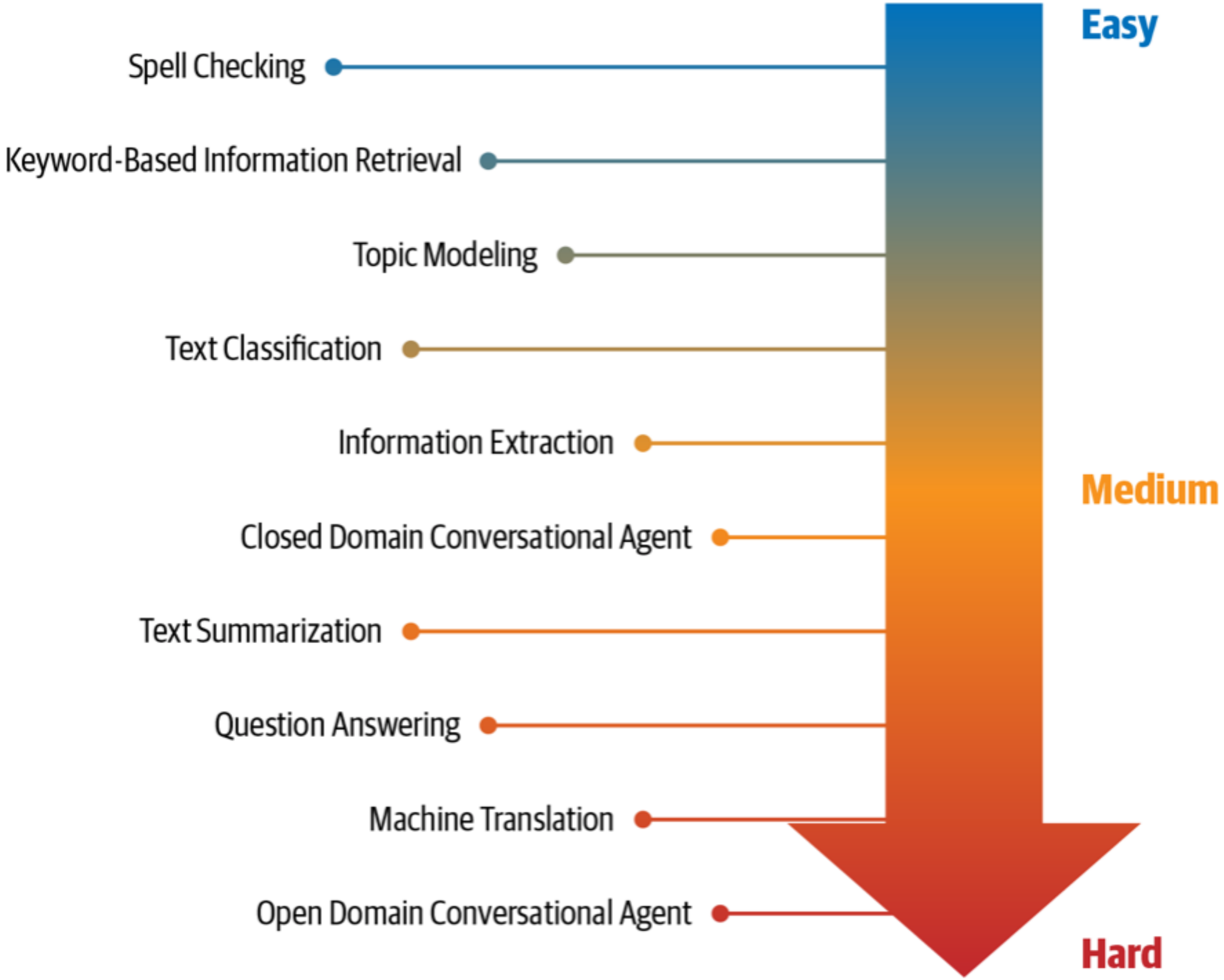
- Raw text
- Sentence Segmentation
- Tokenization
- Part-of-Speech (POS)
- Stop word removal
- Stemming / Lemmatization
- Dependency Parser
- String Metrics & Matching

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

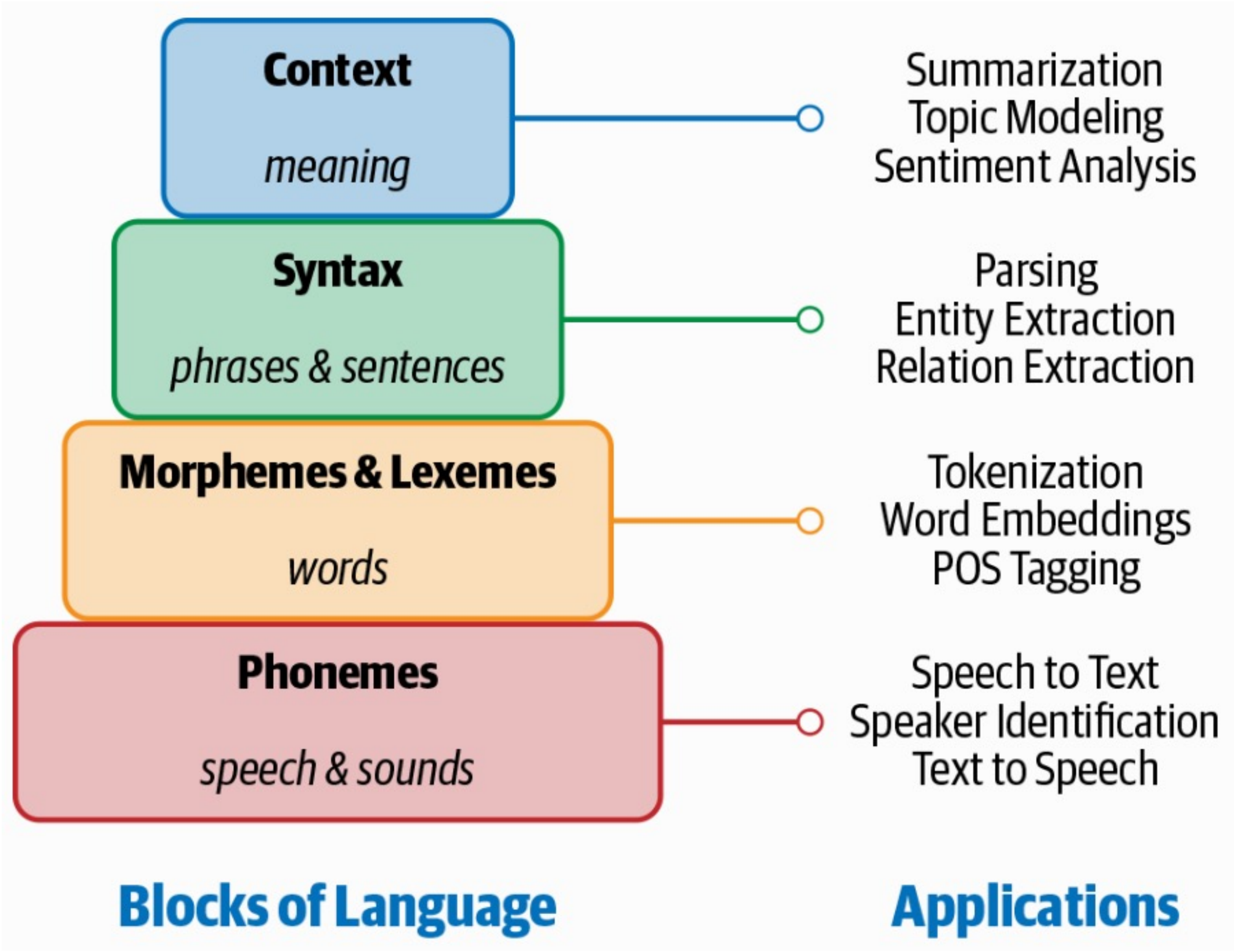
NLP Tasks





Source: Sowmya Vajjala, Bodhisattwa Majumder, Anuj Gupta (2020), Practical Natural Language Processing: A Comprehensive Guide to Building Real-World NLP Systems, O'Reilly Media.

Building Blocks of Language and Applications



Source: Sowmya Vajjala, Bodhisattwa Majumder, Anuj Gupta (2020), Practical Natural Language Processing: A Comprehensive Guide to Building Real-World NLP Systems, O'Reilly Media.

Morpheme Examples

unbreakable
un + break + able

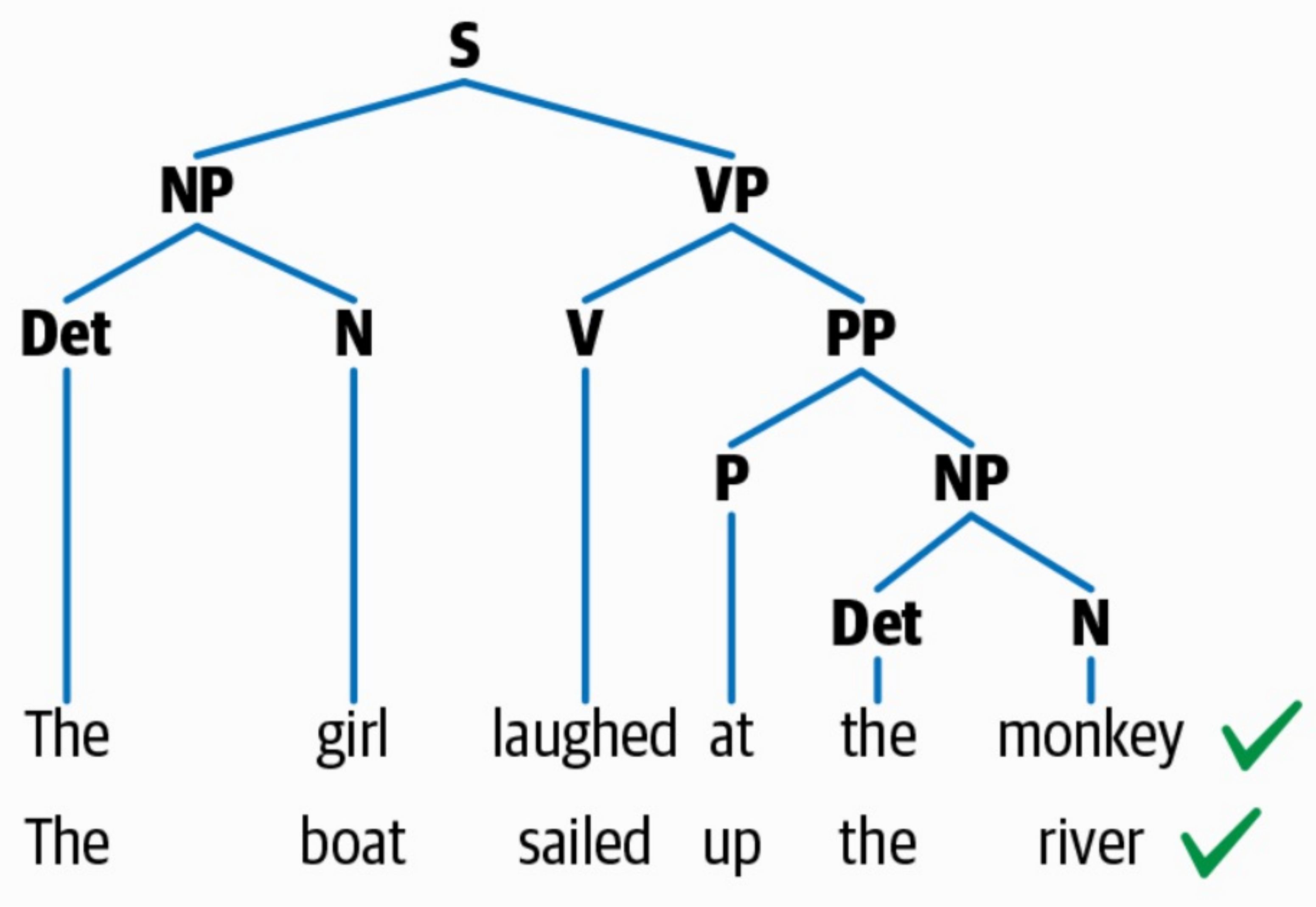
cats
cat + s

tumbling
tumble + ing

unreliability
un + rely + able + ity

Source: Sowmya Vajjala, Bodhisattwa Majumder, Anuj Gupta (2020), Practical Natural Language Processing: A Comprehensive Guide to Building Real-World NLP Systems, O'Reilly Media.

Syntactic Structure



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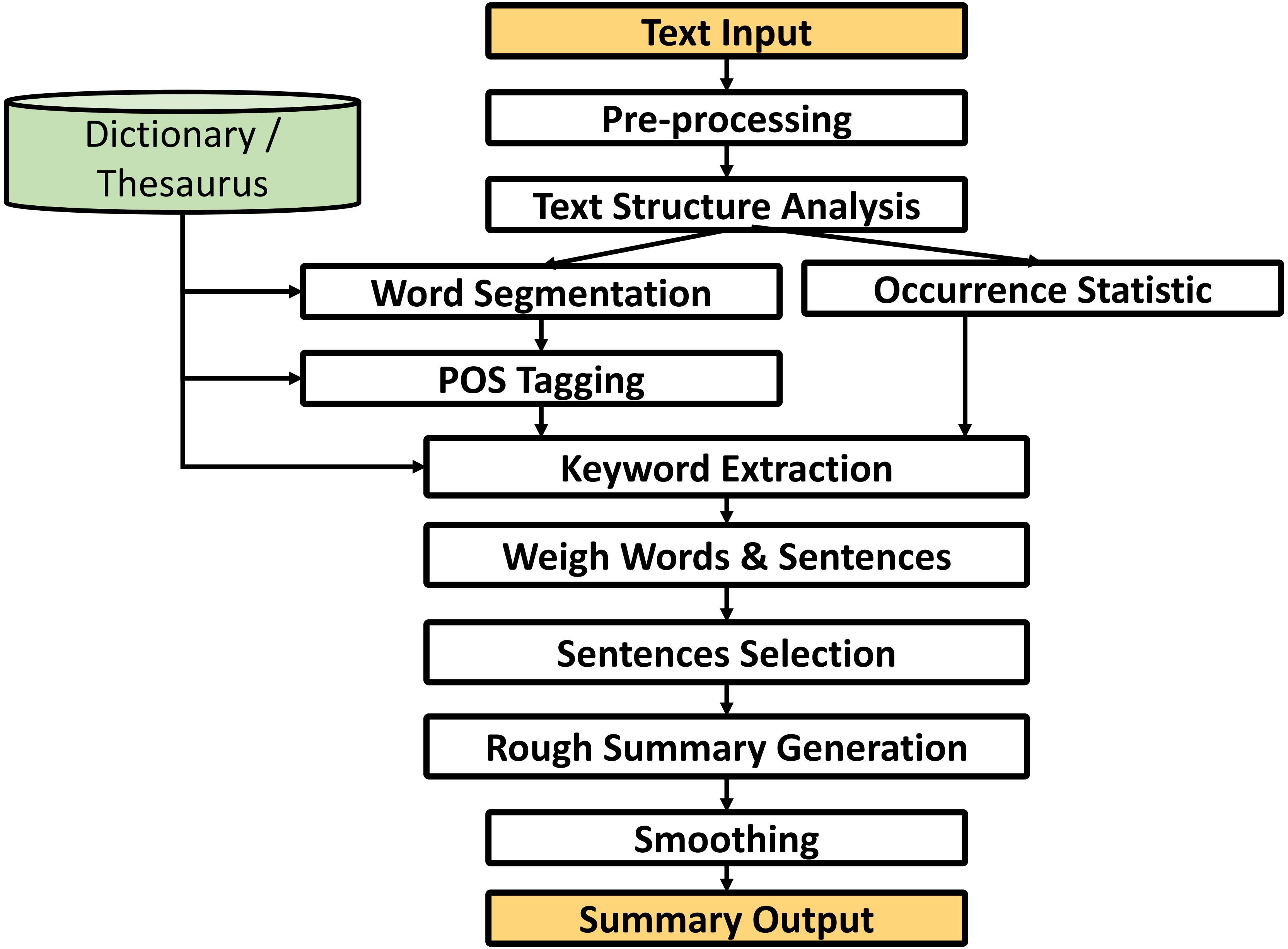
Text Summarization



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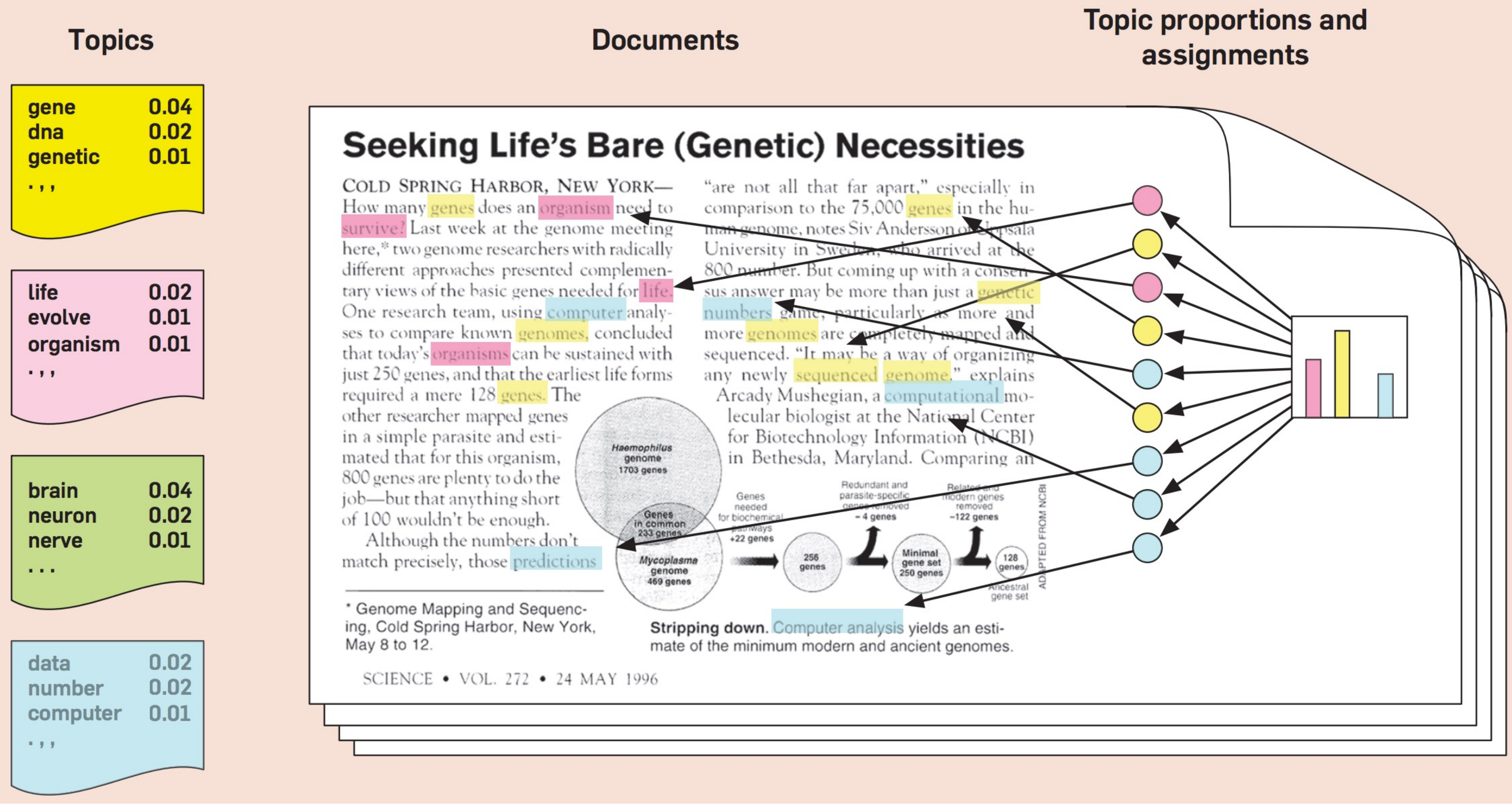
Topic Modeling



Natural Language Processing (NLP)

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

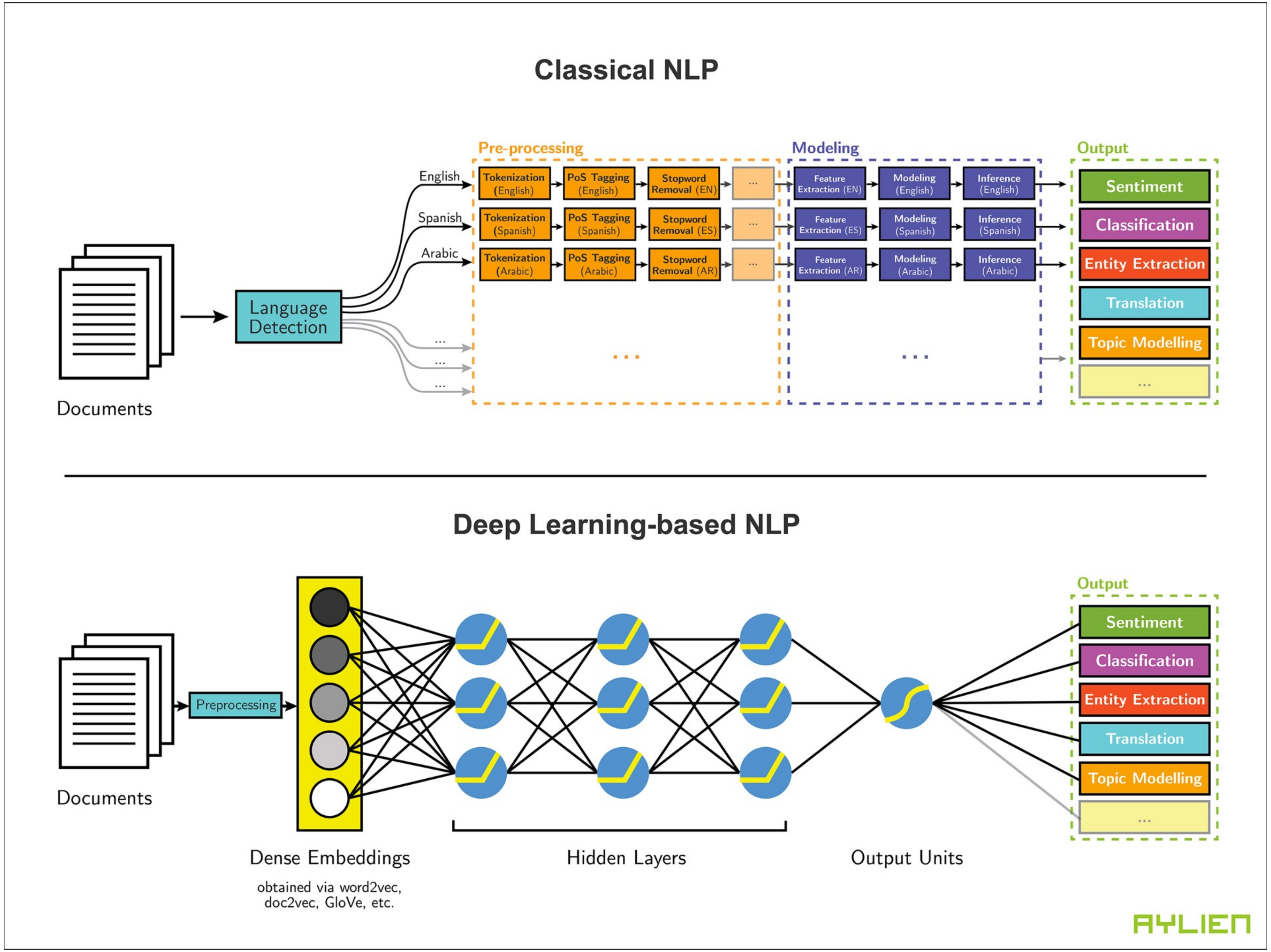
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

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

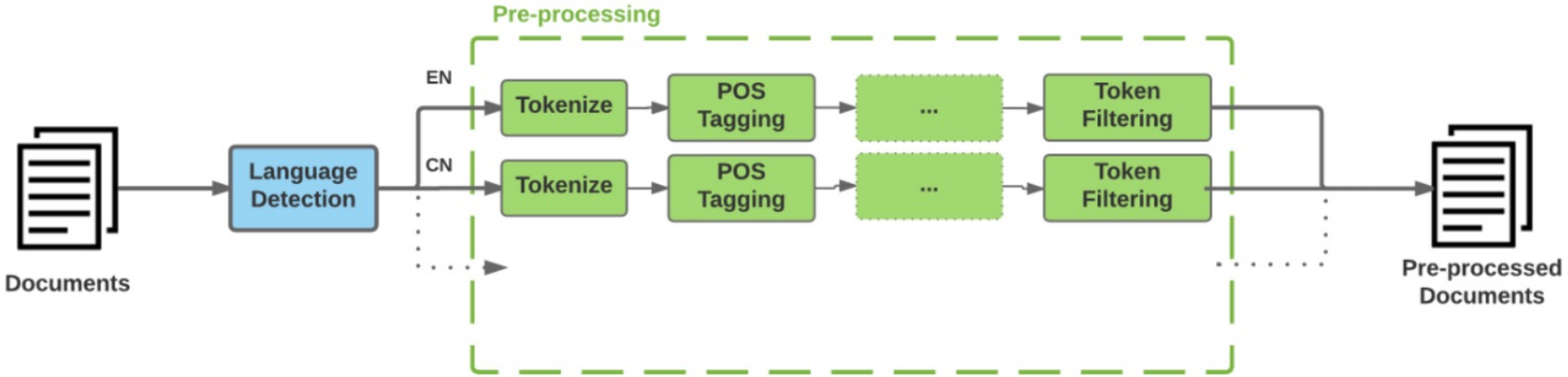
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

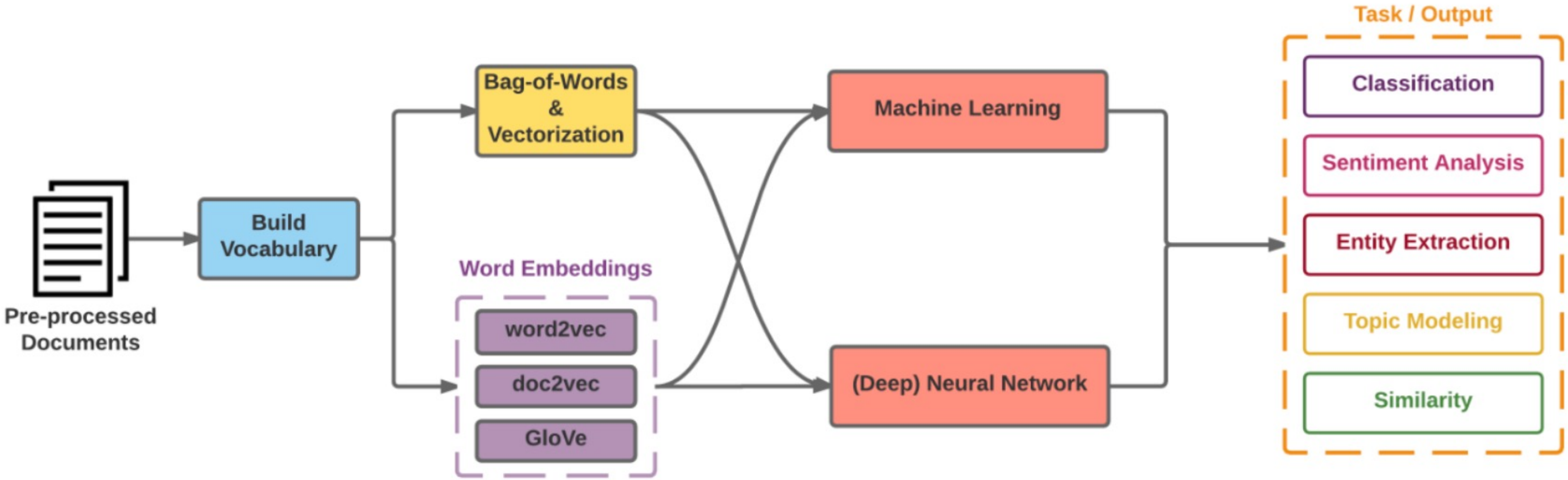
NLP



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

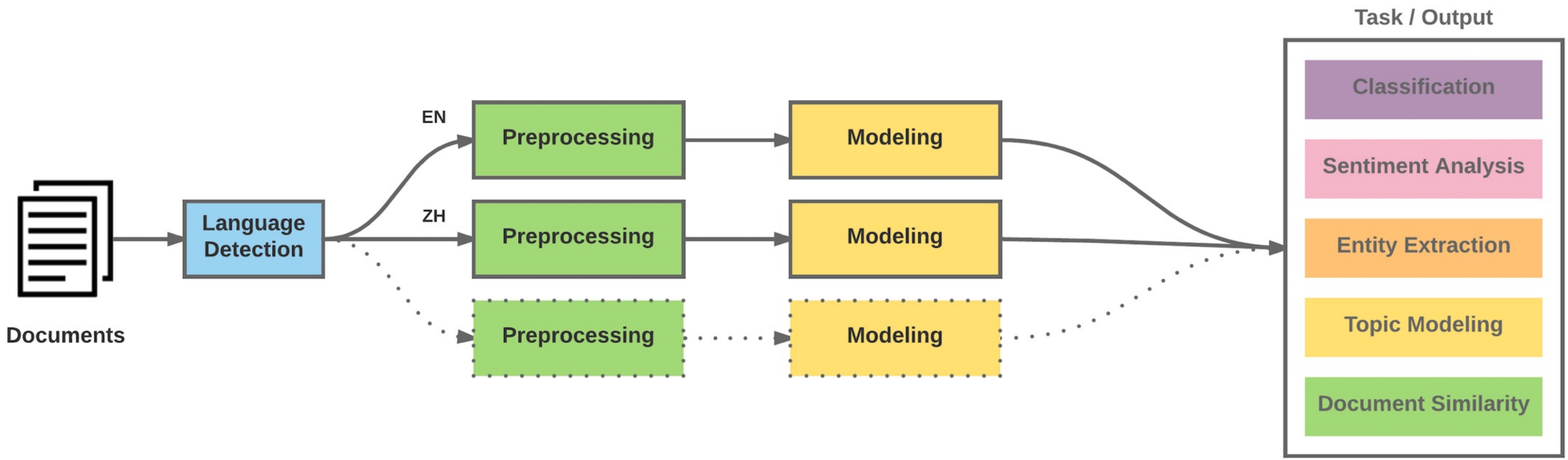
Modern NLP Pipeline





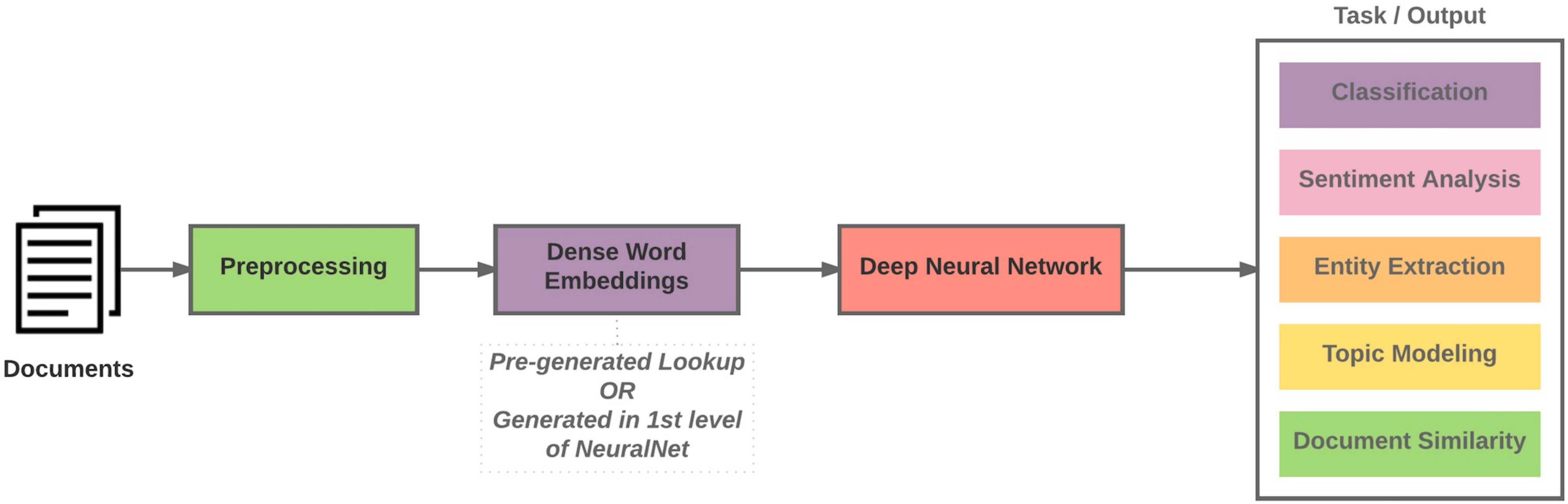
Source: https://github.com/fortiema/talks/blob/master/opendata2016sh/pragmatic-nlp-opendata2016sh.pdf

Modern NLP Pipeline



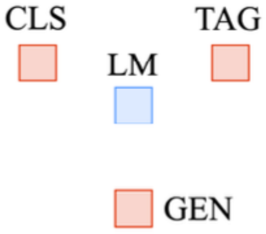
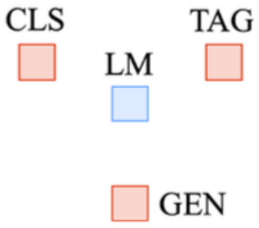
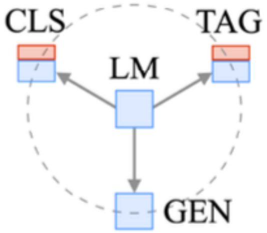
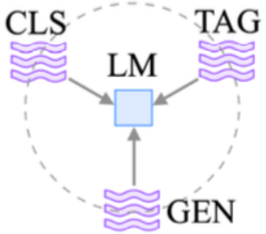
Source: http://mattfortier.me/2017/01/31/nlp-intro-pt-1-overview/

Deep Learning NLP



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

Four Paradigms in NLP

Paradigm	Engineering	Task Relation
a. Fully Supervised Learning (Non-Neural Network)	Feature (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	
d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	

Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

Text Data for NLP
Representations of Words

```
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

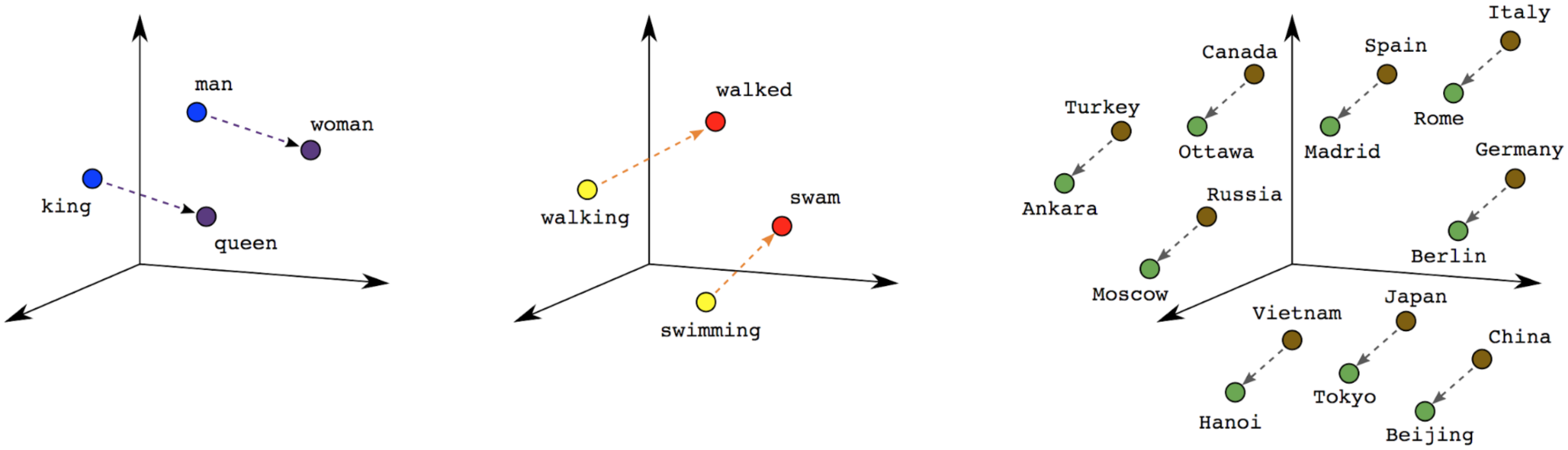
```
'The mouse ran up the clock' =

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

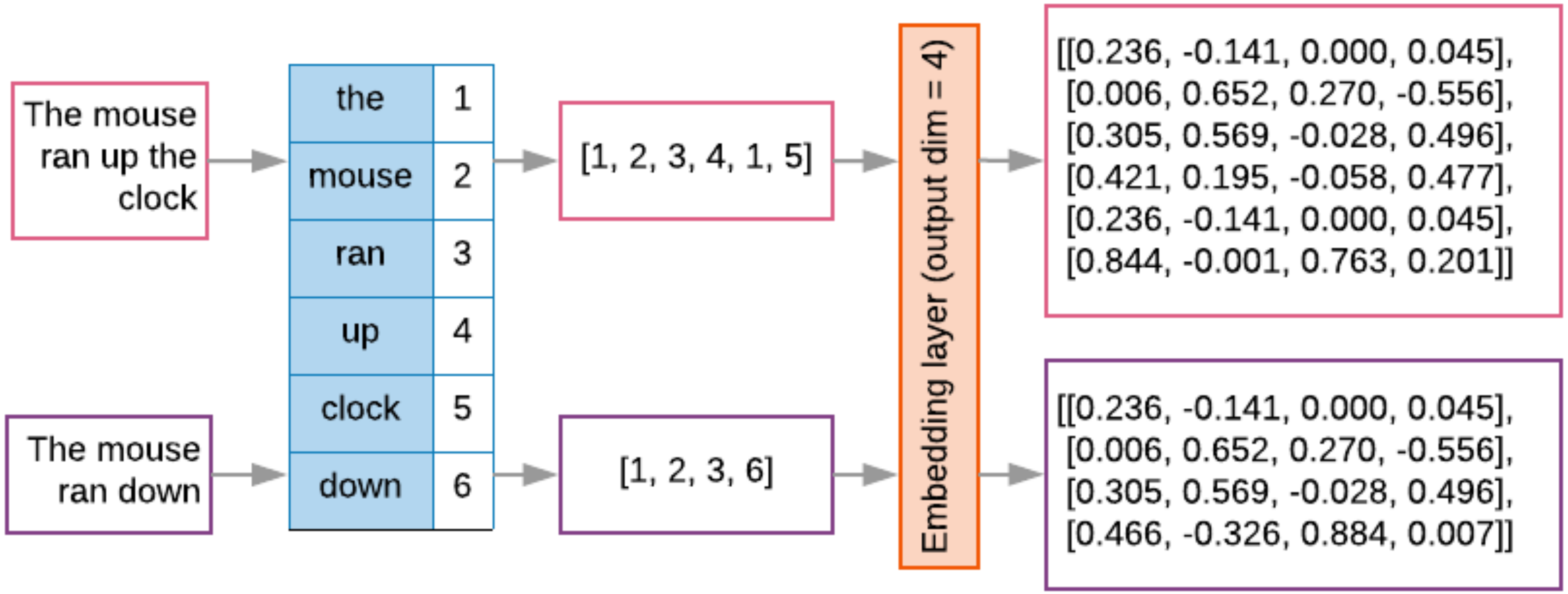
Word embeddings



Male-Female Verb Tense Country-Capital

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

Word embeddings



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

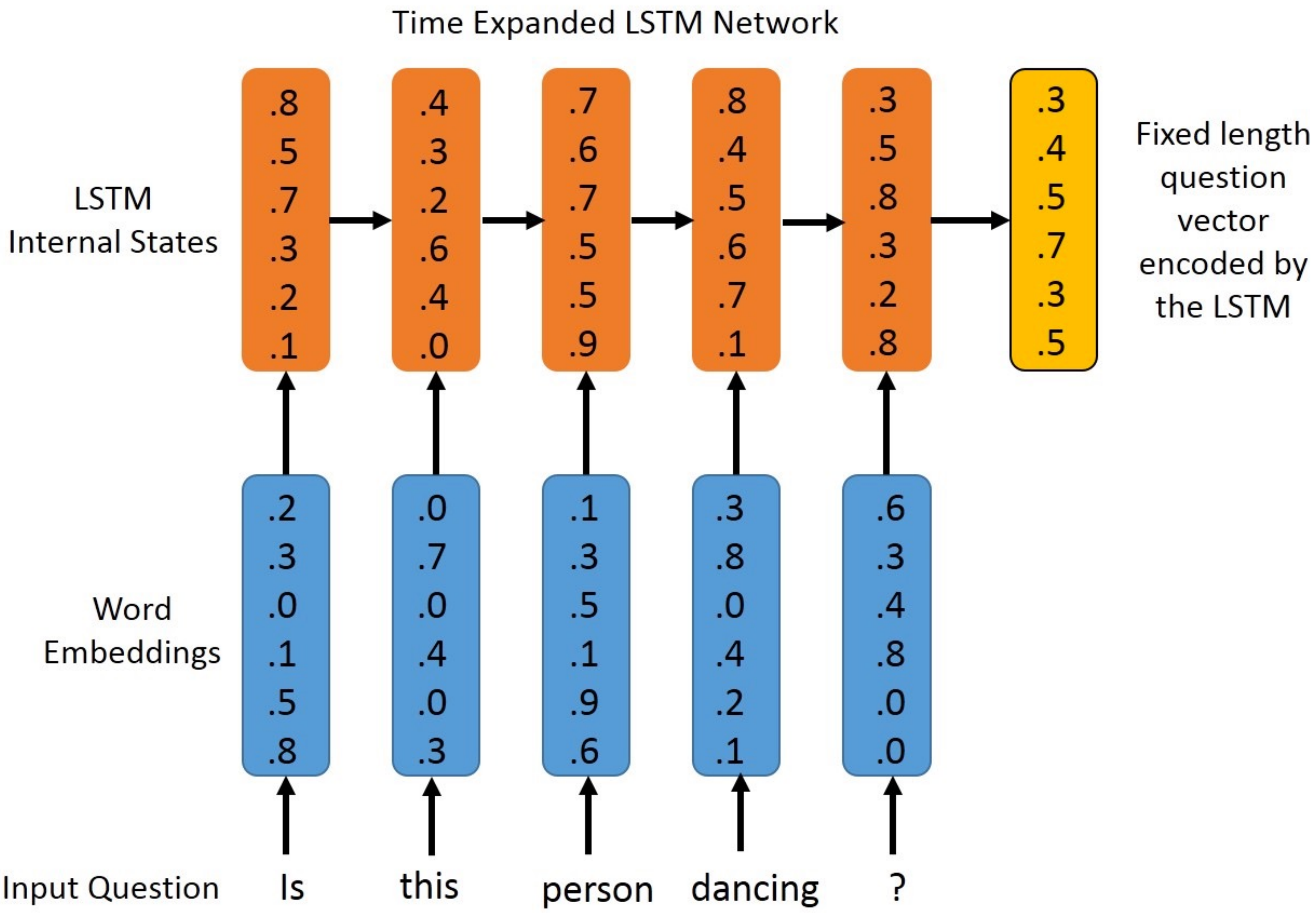
Vector Representations of Words

Word Embeddings

Word2Vec

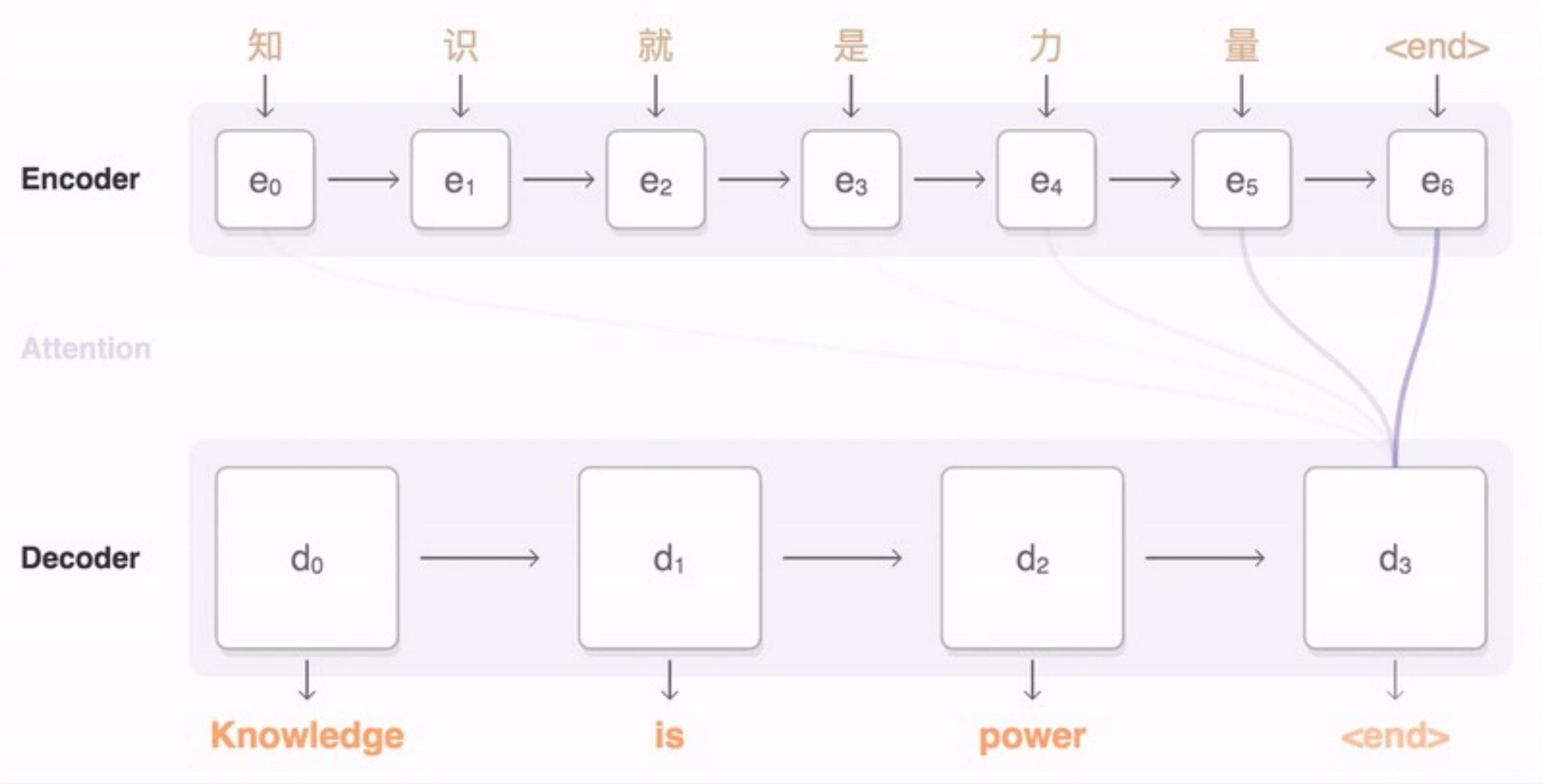
GloVe

Word Embeddings in LSTM RNN



Source: https://avisingh599.github.io/deeplearning/visual-qa/

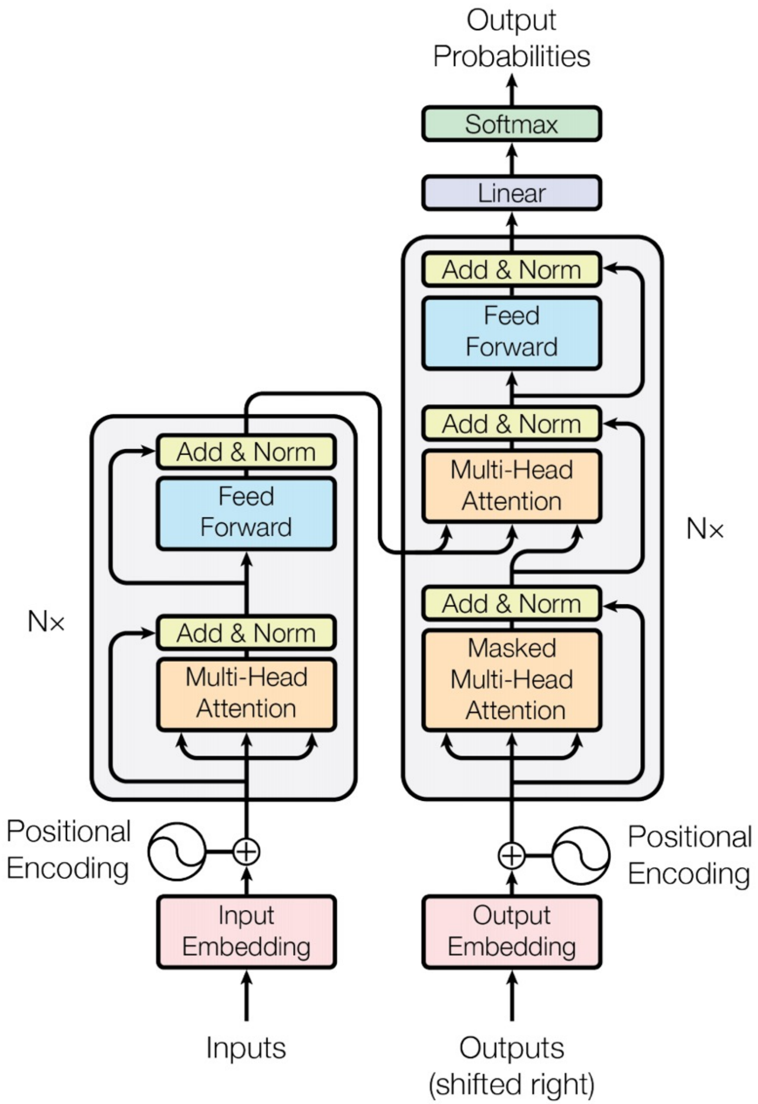
Sequence to Sequence (Seq2Seq)



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

Transformer (Attention is All You Need)

(Vaswani et al., 2017)

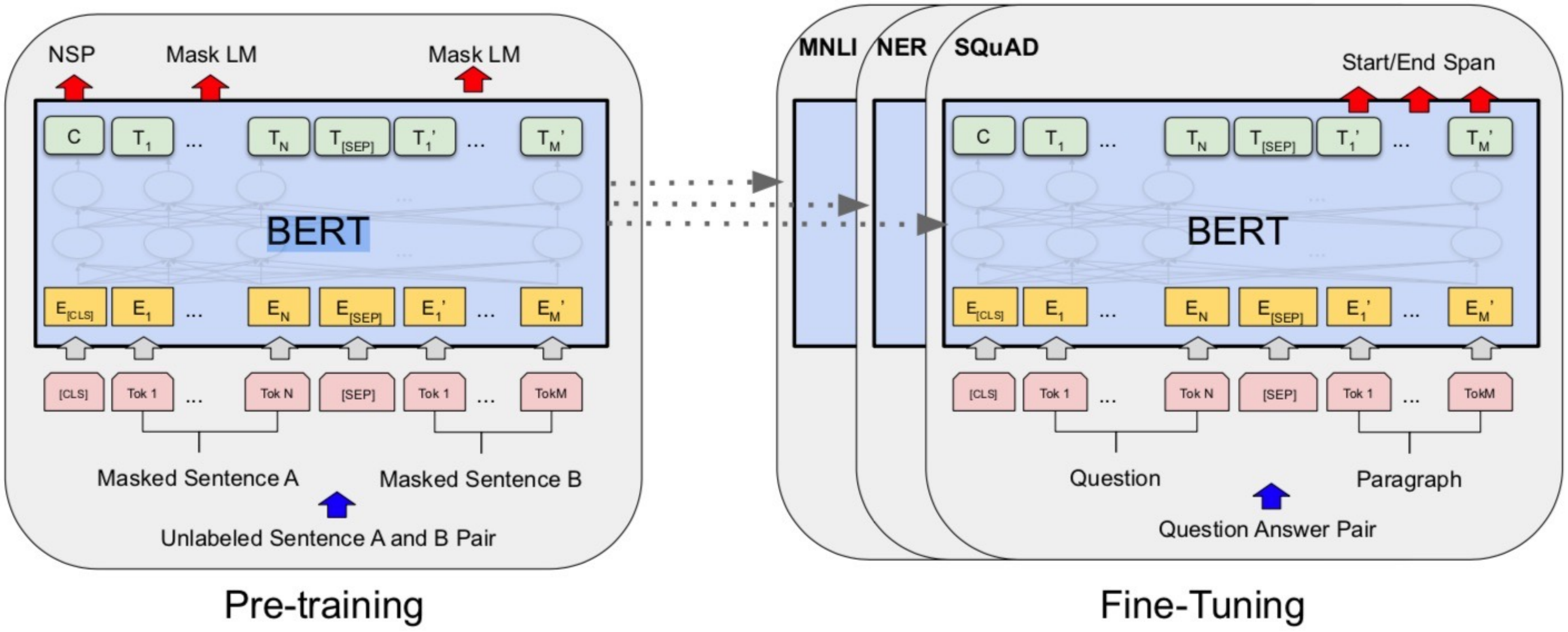


Source: Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." In *Advances in neural information processing systems*, pp. 5998-6008. 2017.

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

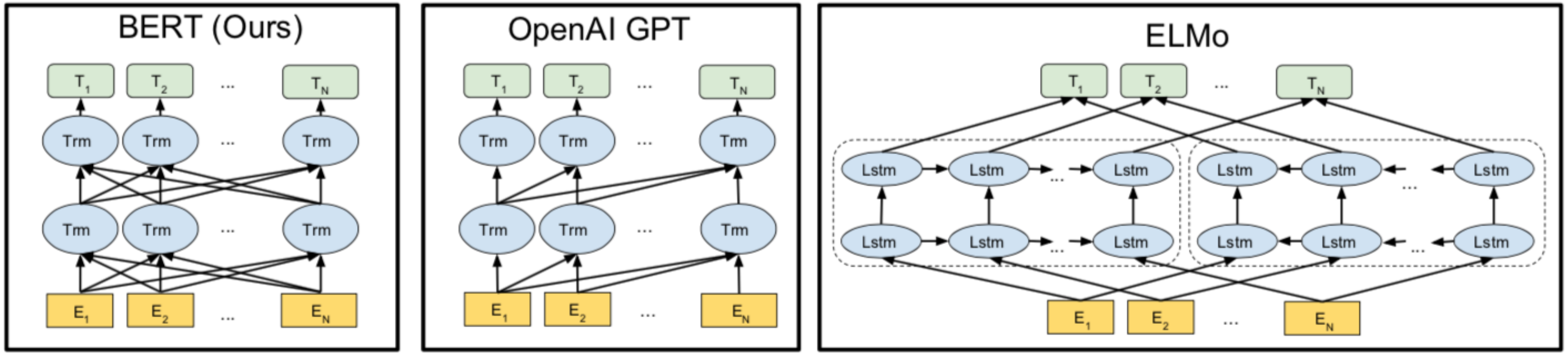
BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin   Ming-Wei Chang   Kenton Lee   Kristina Toutanova
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

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

Bidirectional Encoder Representations from Transformers



Pre-training model architectures

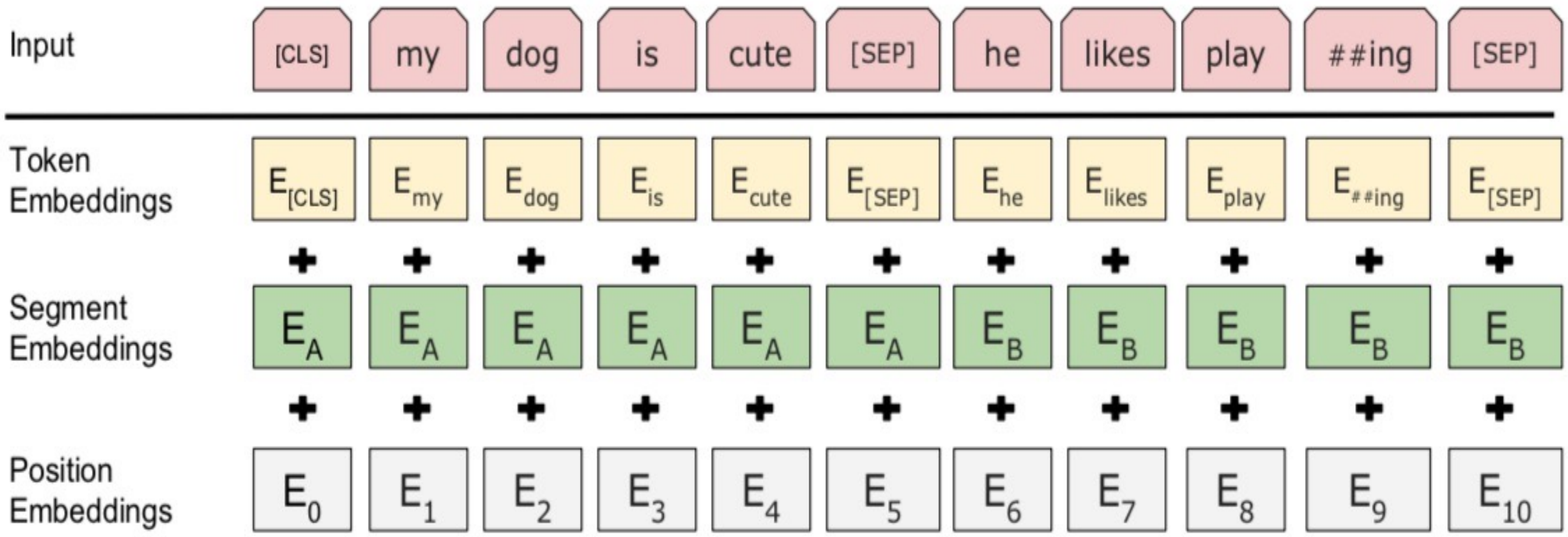
BERT uses a bidirectional Transformer.
OpenAI GPT uses a left-to-right Transformer.
ELMo uses the concatenation of independently trained left-to-right and right- to-left LSTM to generate features for downstream tasks.
Among three, only BERT representations are jointly conditioned on both left and right context in all layers.

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)

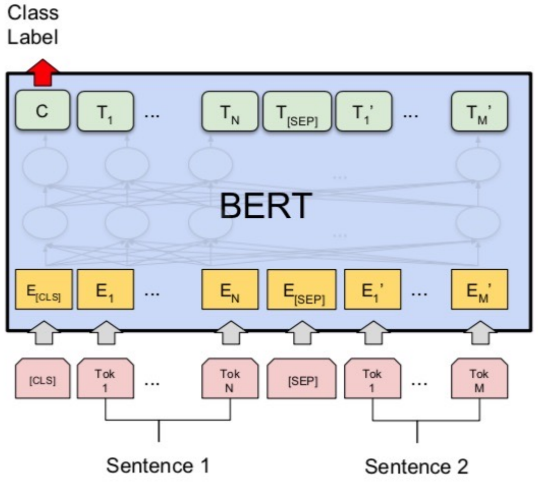
BERT input representation



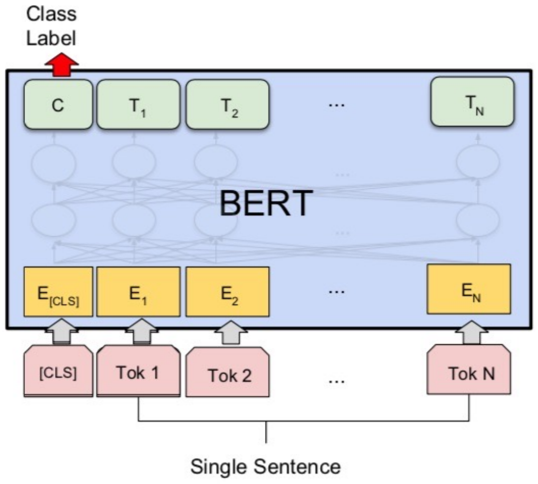
The input embeddings is the sum of the token embeddings, the segmentation embeddings and the position embeddings.

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.

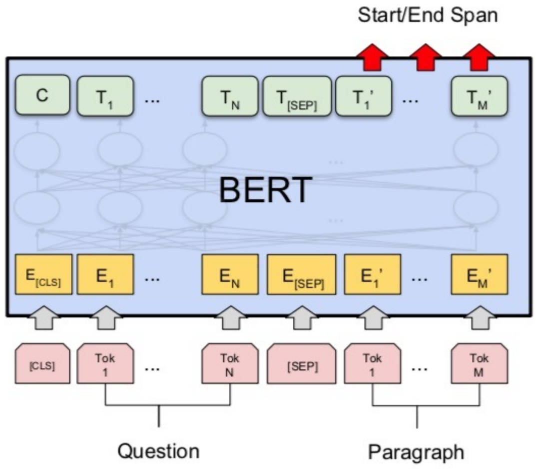
Fine-tuning BERT on NLP Tasks



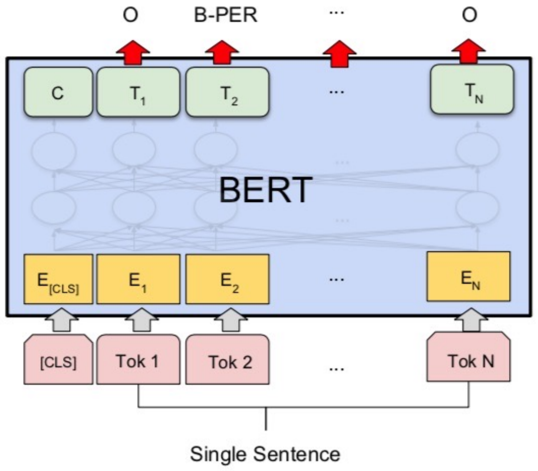
(a) Sentence Pair Classification Tasks:
MNLI, QQP, QNLI, STS-B, MRPC,
RTE, SWAG



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



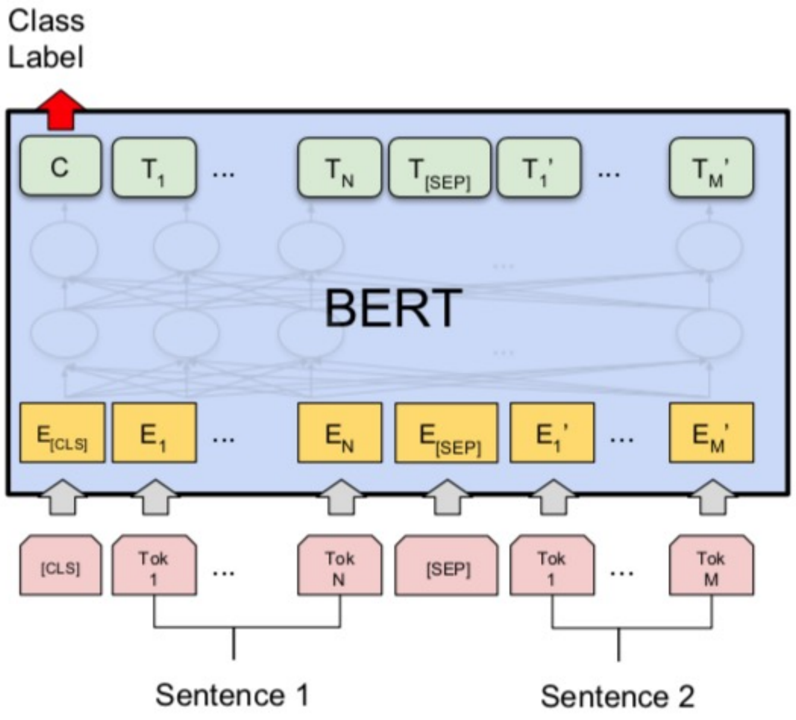
(c) Question Answering Tasks:
SQuAD v1.1



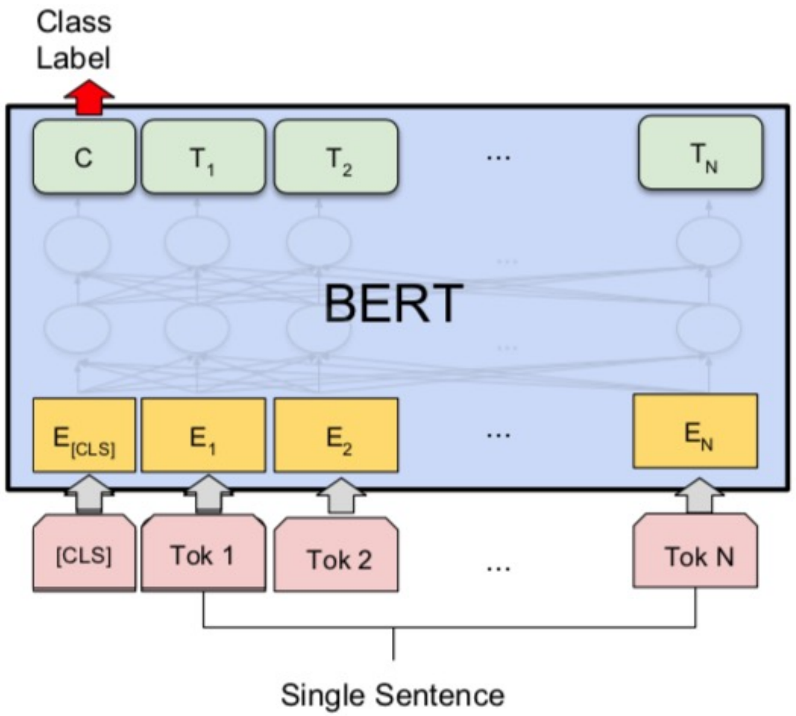
(d) Single Sentence Tagging Tasks:
CoNLL-2003 NER

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

BERT Sequence-level tasks



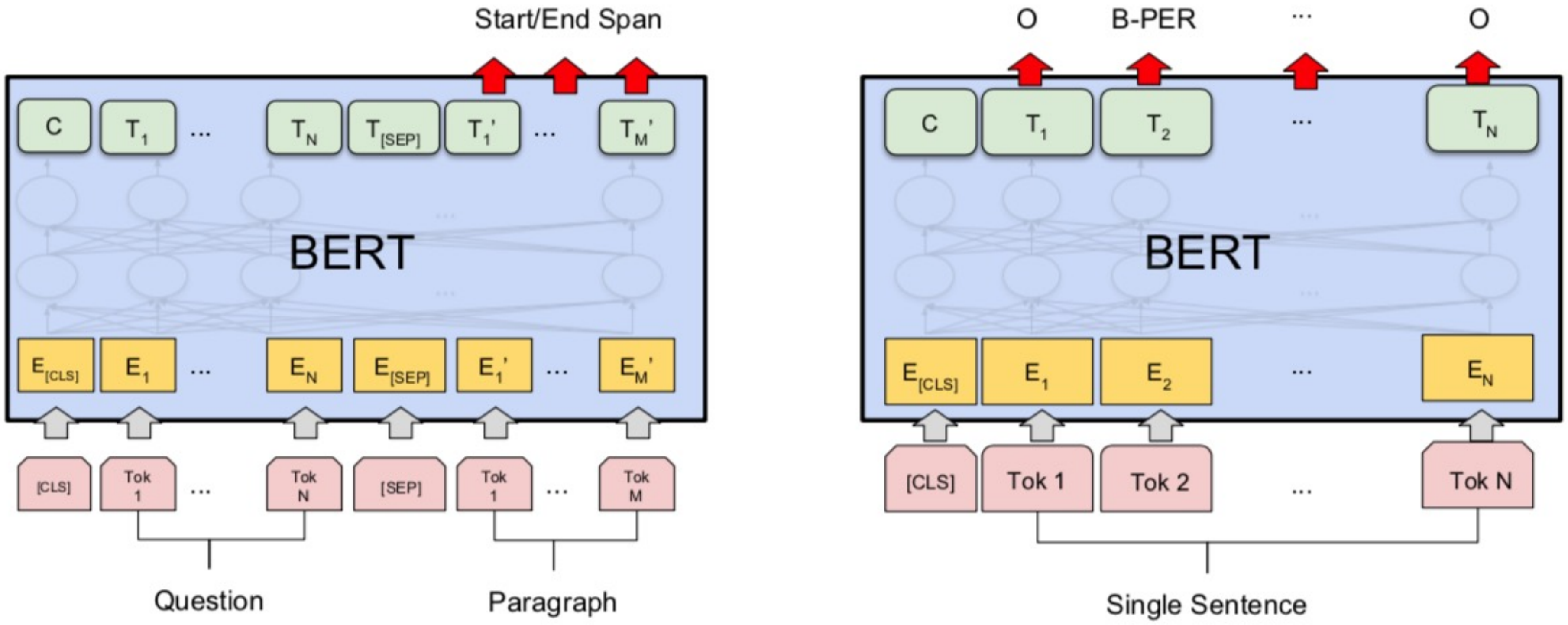
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



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

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 Token-level tasks



(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

General Language Understanding Evaluation (GLUE) benchmark

GLUE Test results

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

MNLI: Multi-Genre Natural Language Inference
QQP: Quora Question Pairs
QNLI: Question Natural Language Inference
SST-2: The Stanford Sentiment Treebank
CoLA: The Corpus of Linguistic Acceptability
STS-B:The Semantic Textual Similarity Benchmark
MRPC: Microsoft Research Paraphrase Corpus
RTE: Recognizing Textual Entailment

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

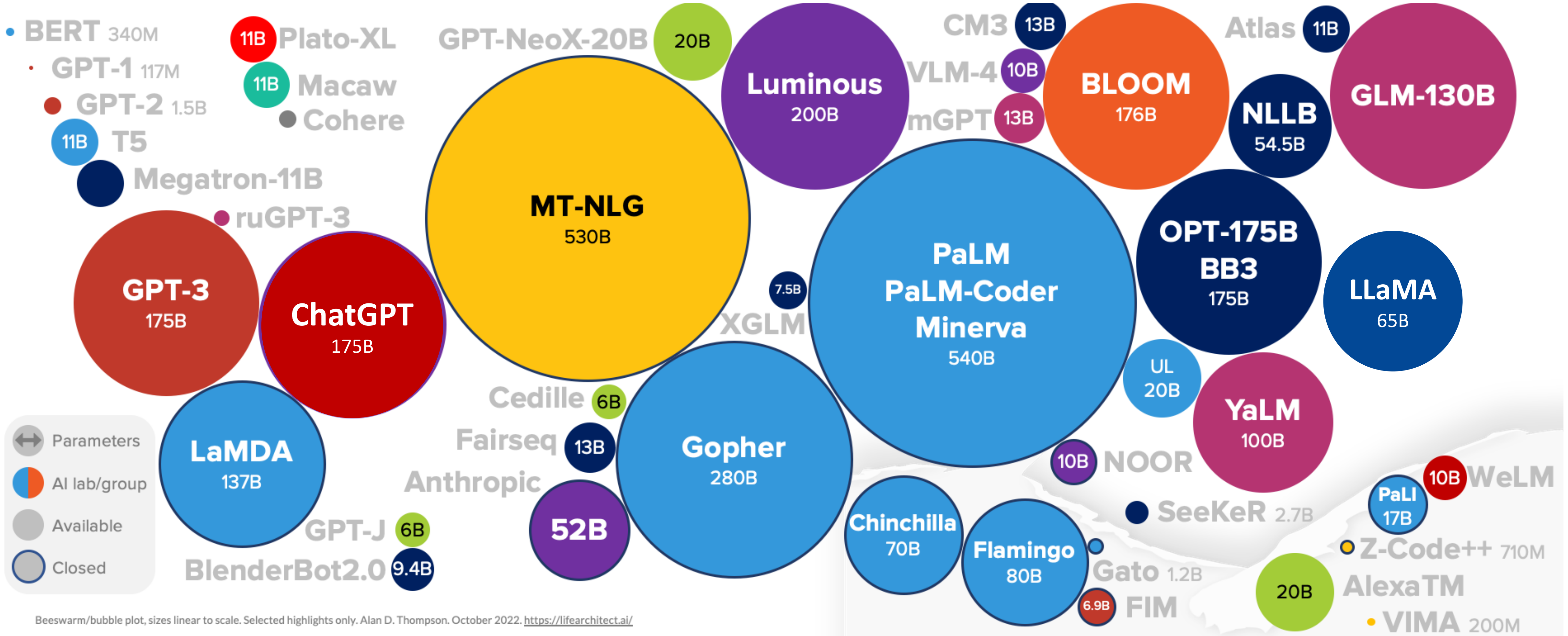
ChatGPT

Large Language Models (LLMs)

Foundation Models

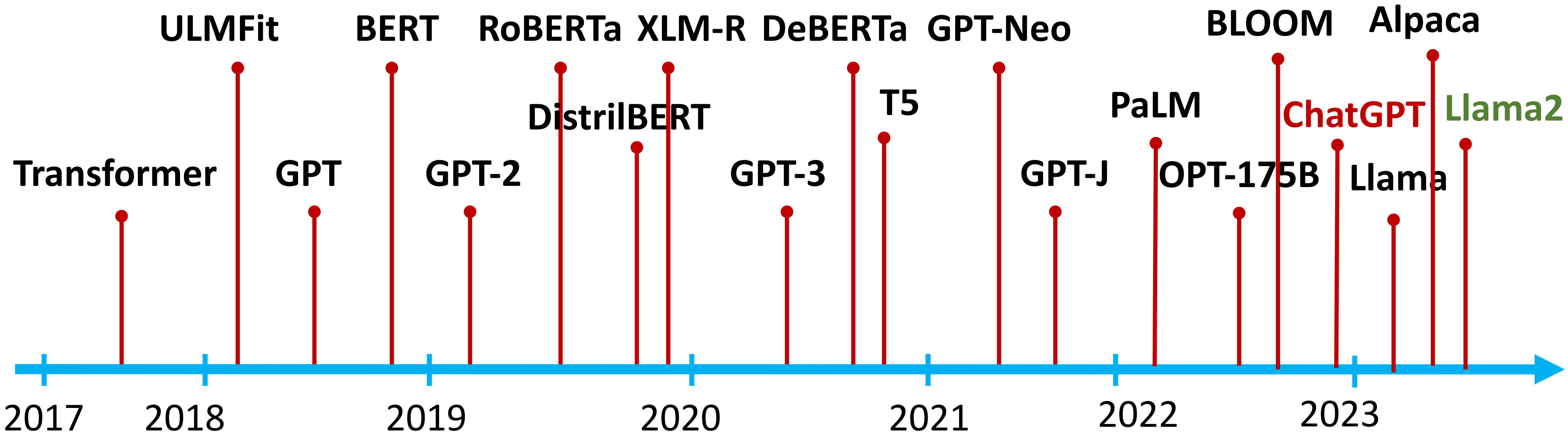
Large Language Models (LLM)

(GPT-3, ChatGPT, PaLM, BLOOM, OPT-175B, LLaMA)



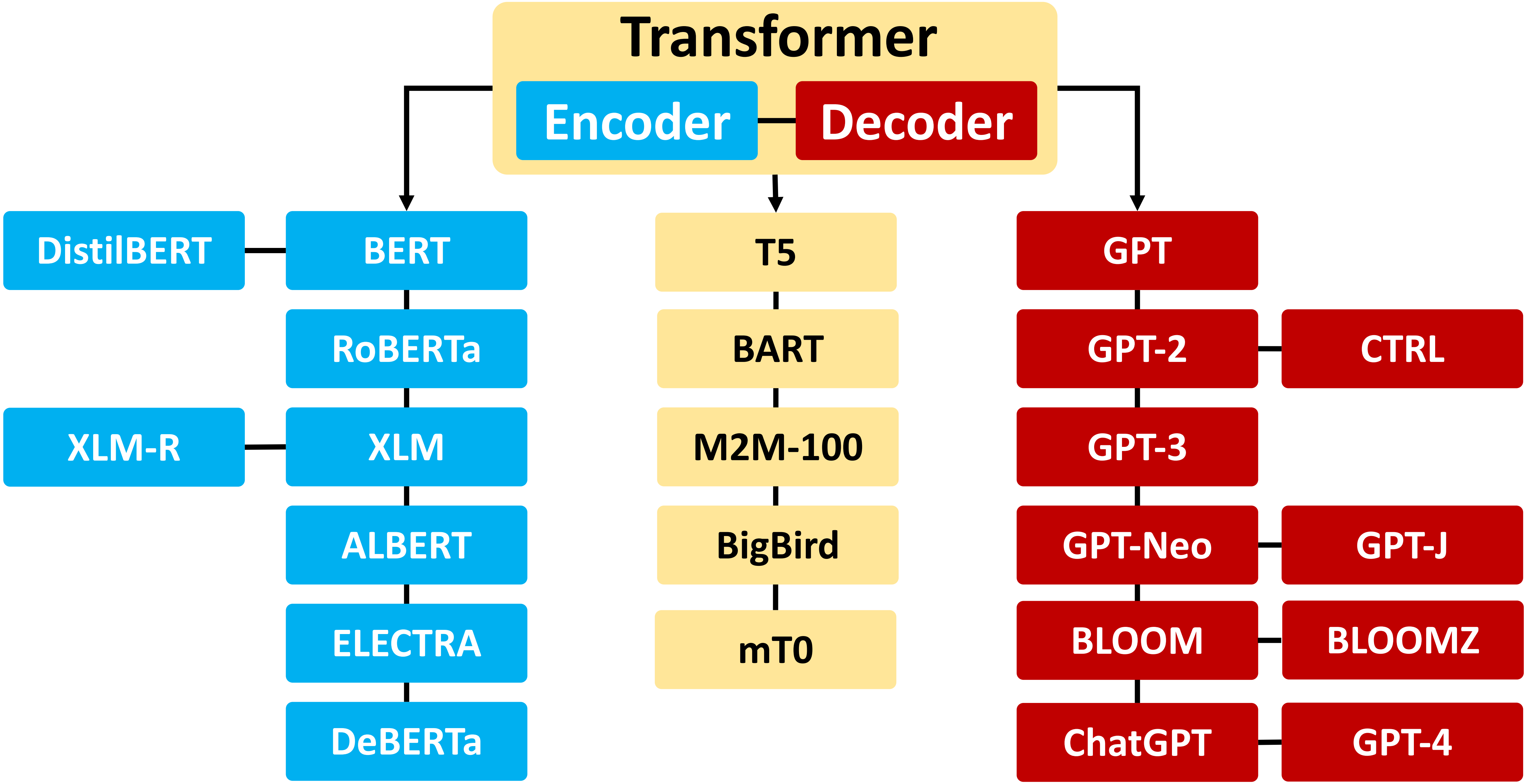
Source: https://lifearchitect.ai/models/

The Transformers Timeline



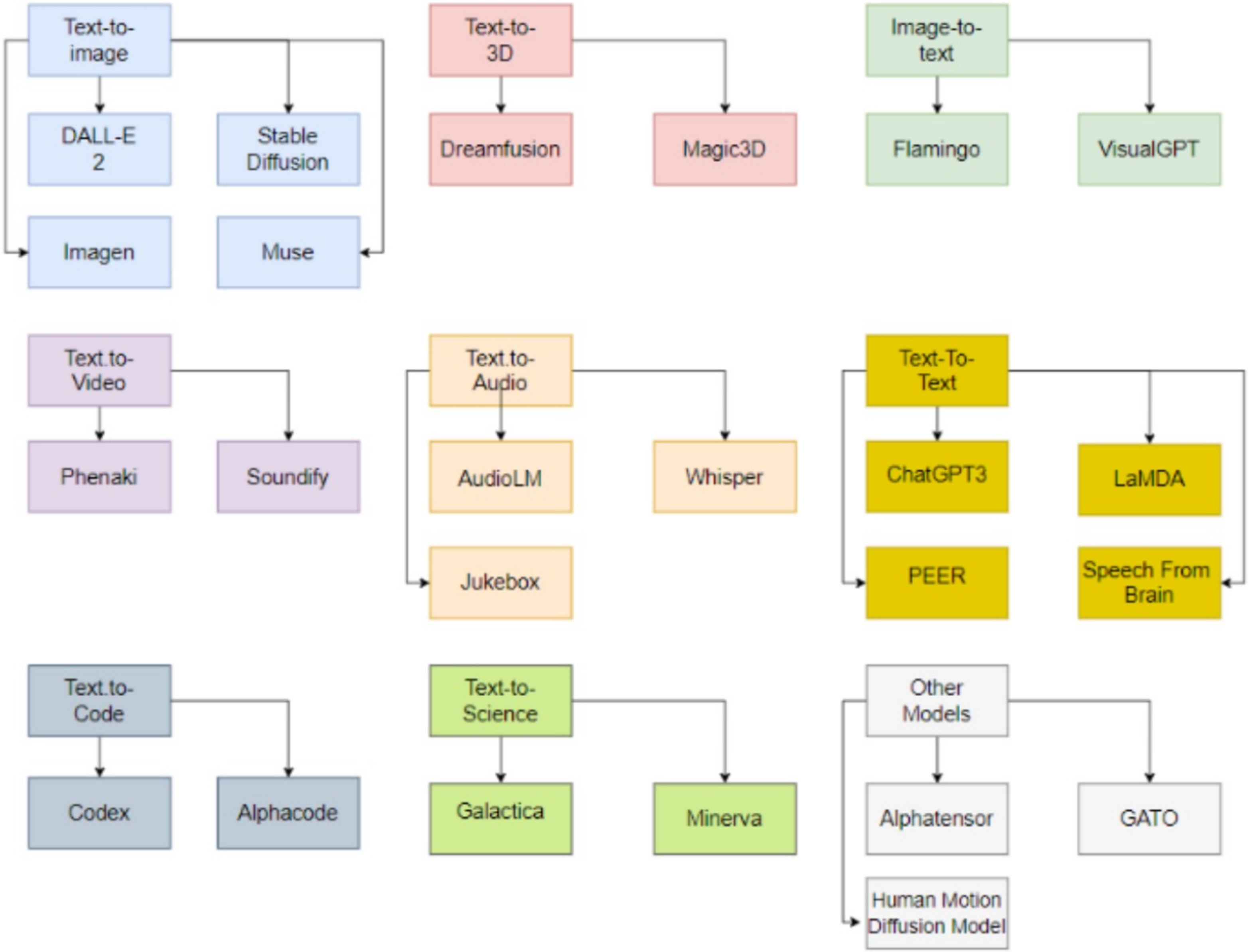
Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.

Transformer Models



Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.

Generative AI Models

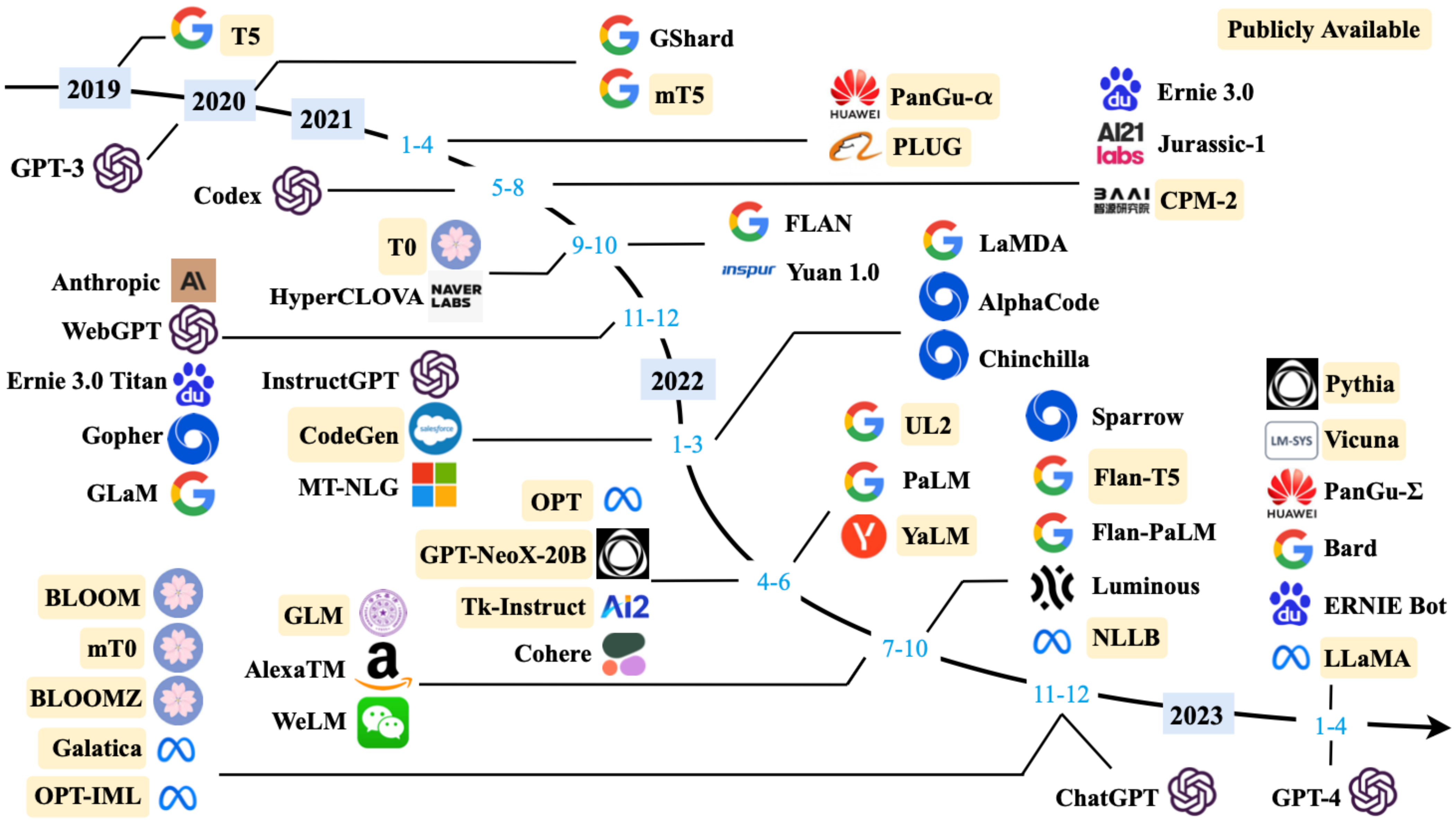


ChatGPT is not all you need

Attention is all you need

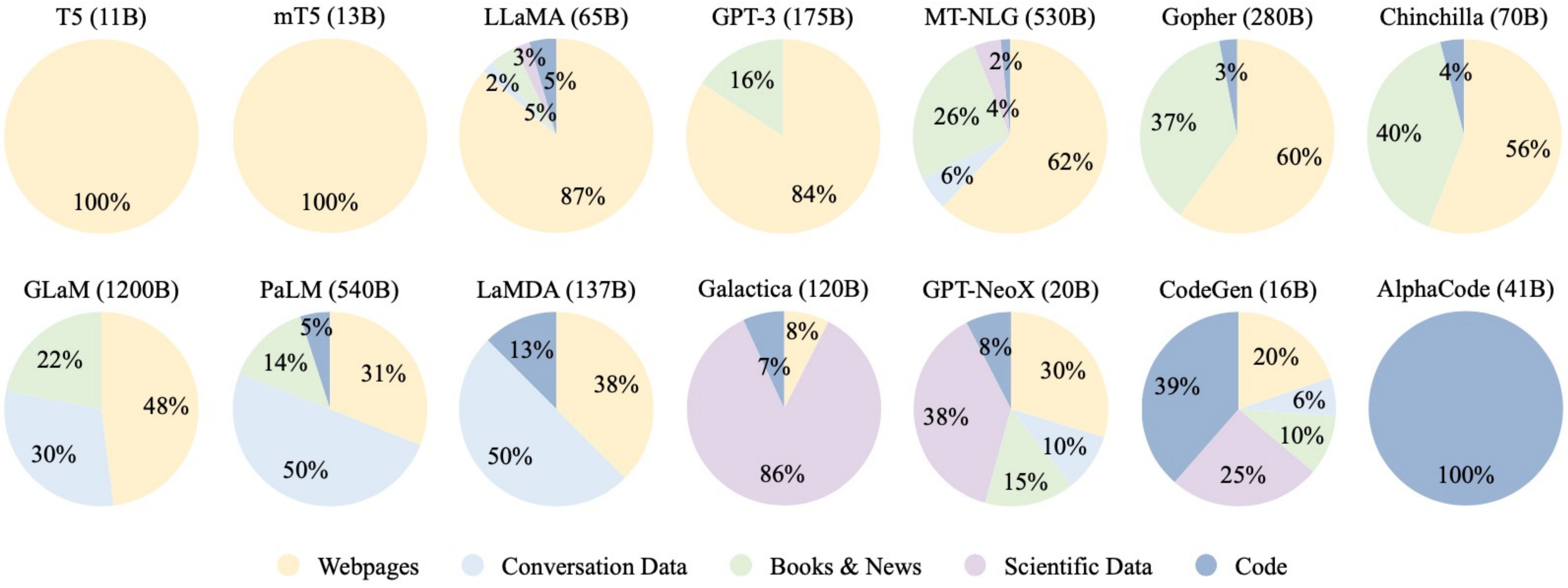
Source: Gozalo-Brizuela, Roberto, and Eduardo C. Garrido-Merchan (2023). "ChatGPT is not all you need. A State of the Art Review of large Generative AI models." arXiv preprint arXiv:2301.04655 (2023).

Large Language Models (LLMs) (larger than 10B)



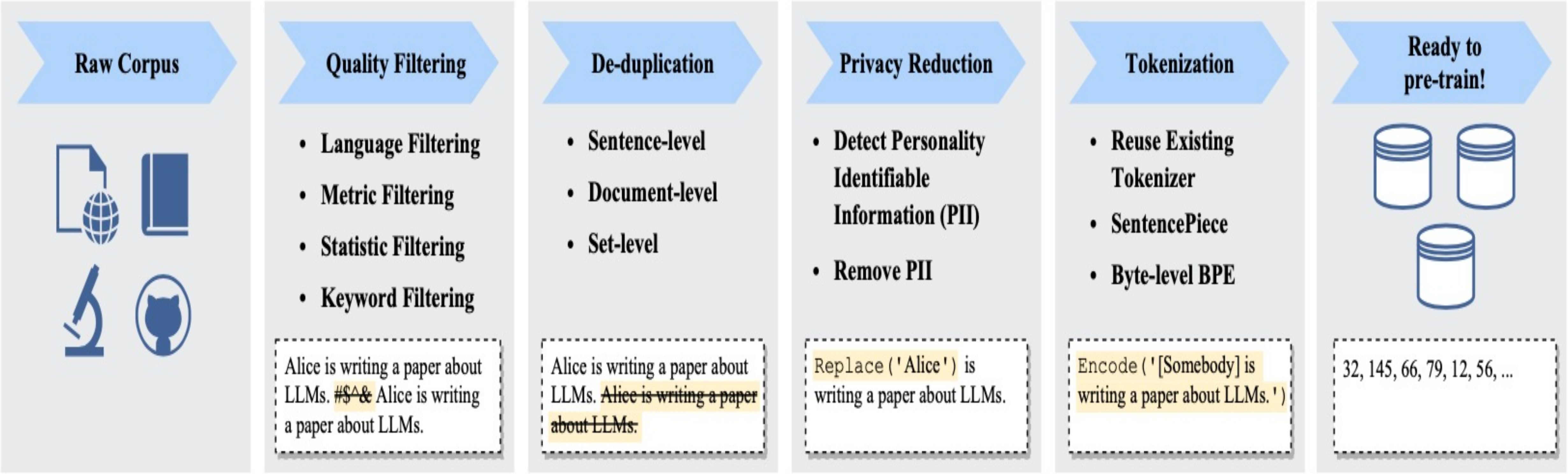
Source: Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min et al. (2023) "A Survey of Large Language Models." arXiv preprint arXiv:2303.18223.

Ratios of various data sources in the pre-training data for existing LLMs



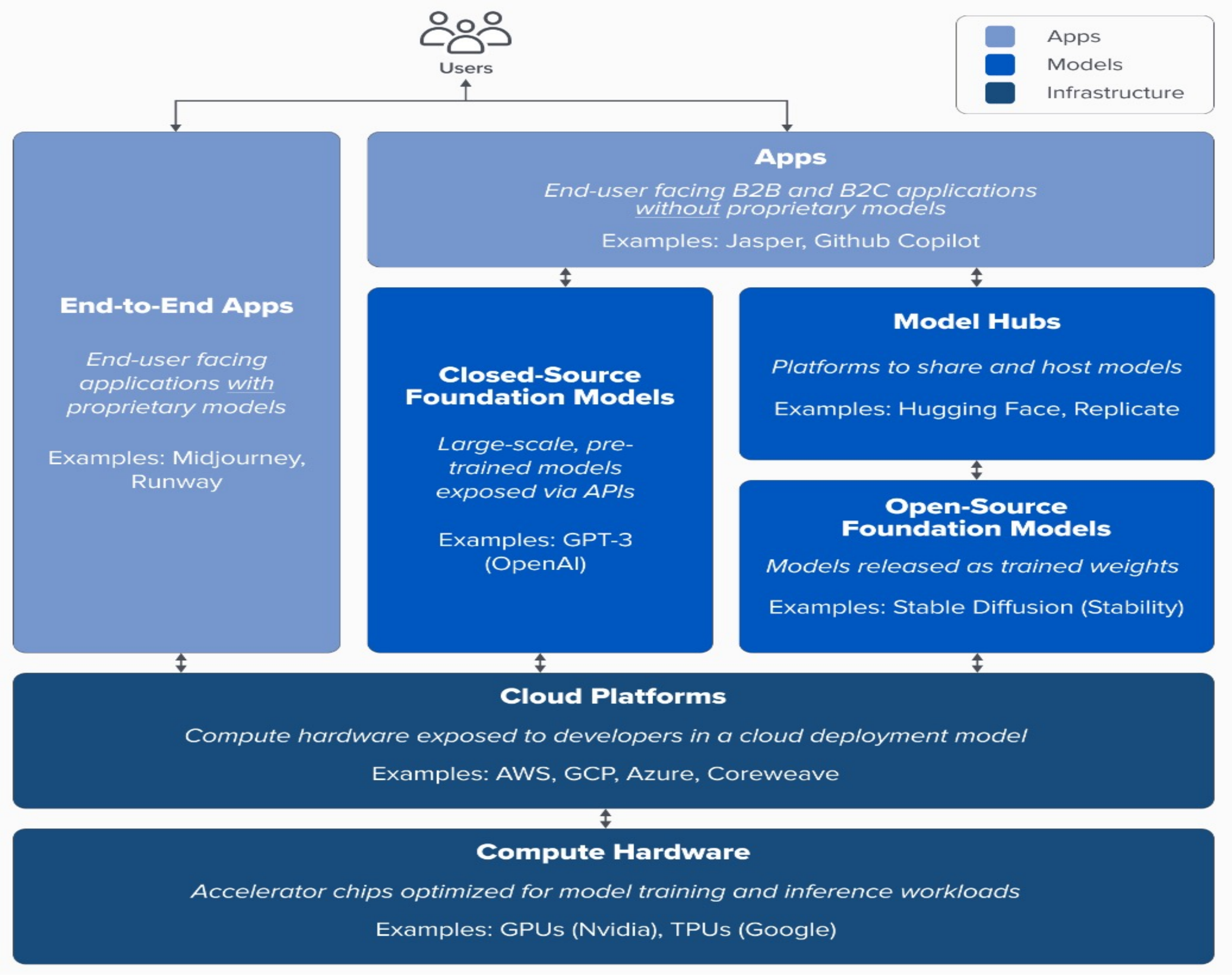
Source: Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min et al. (2023) "A Survey of Large Language Models." arXiv preprint arXiv:2303.18223.

Typical Data Preprocessing Pipeline for Pre-training Large Language Models (LLMs)



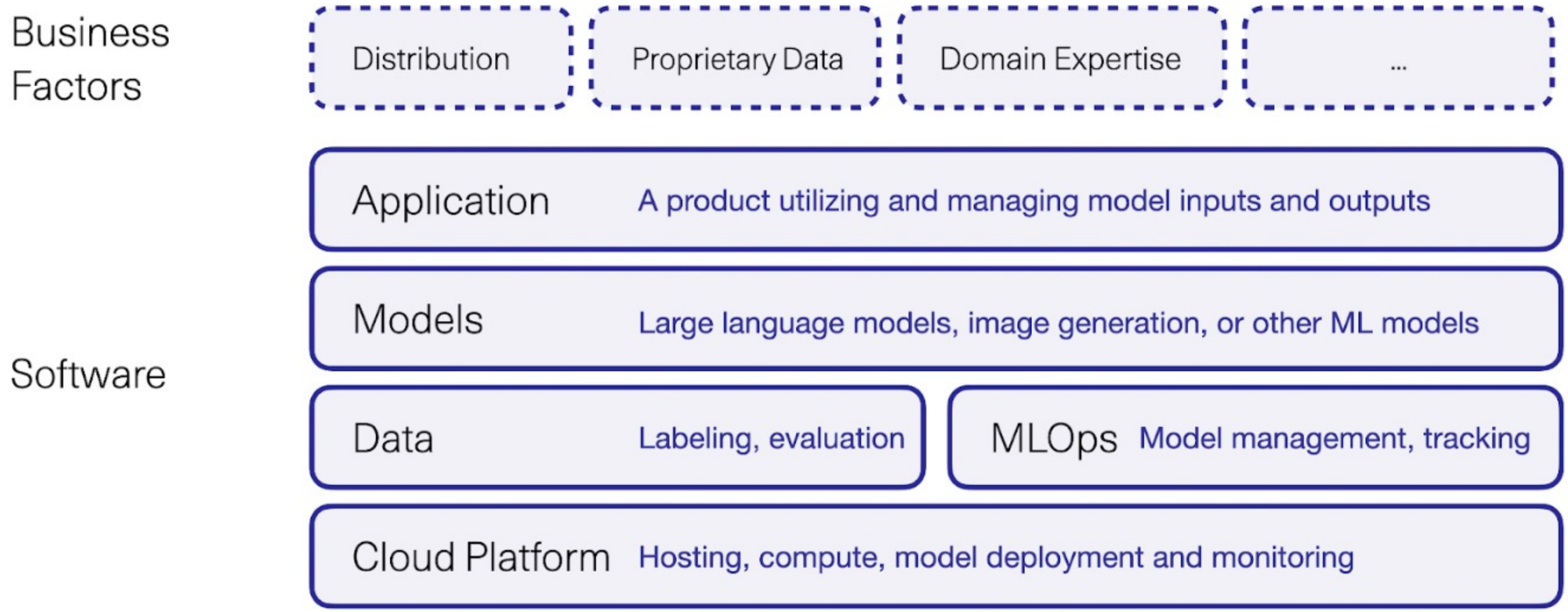
Source: Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min et al. (2023) "A Survey of Large Language Models." arXiv preprint arXiv:2303.18223.

Generative AI Tech Stack



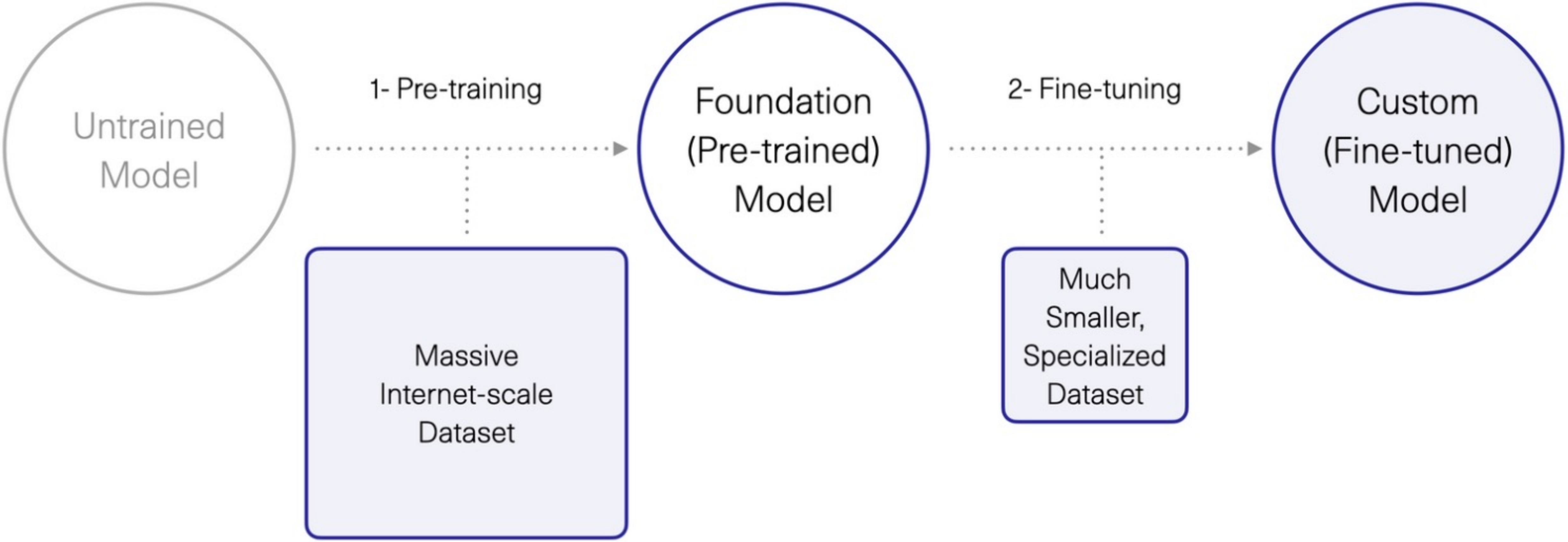
Source: Matt Bornstein, Guido Appenzeller, and Martin Casado (2023), Who Owns the Generative AI Platform?, https://a16z.com/2023/01/19/who-owns-the-generative-ai-platform/

Generative AI Software and Business Factors



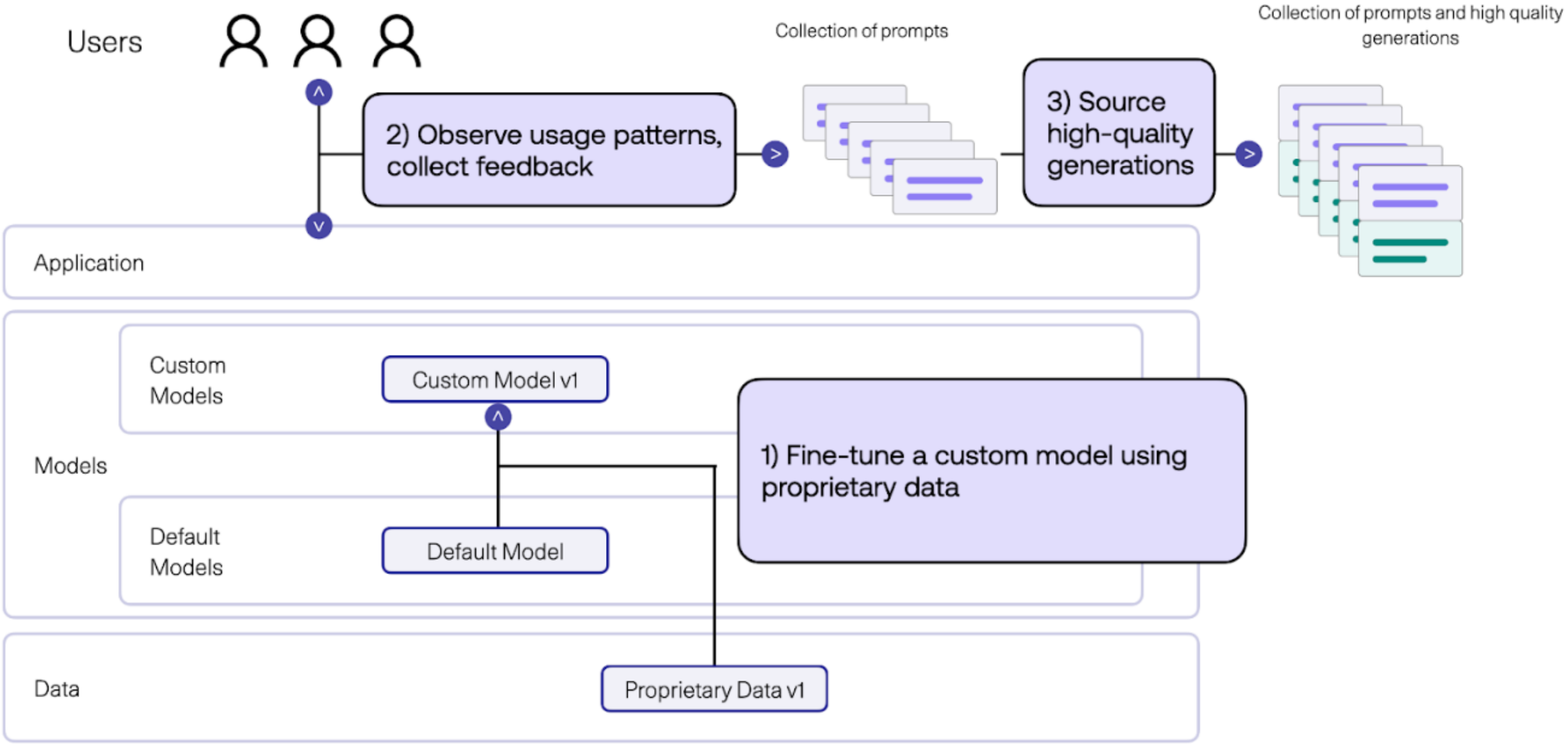
Source: Jay Alammar (2023), AI is Eating The World, https://txt.cohere.com/ai-is-eating-the-world/

Generative AI
1. Pre-training Foundation (Pre-trained) Model
2. Fine-turning Custom (Fine-tuned) Model



Source: Jay Alammar (2023), AI is Eating The World, https://txt.cohere.com/ai-is-eating-the-world/

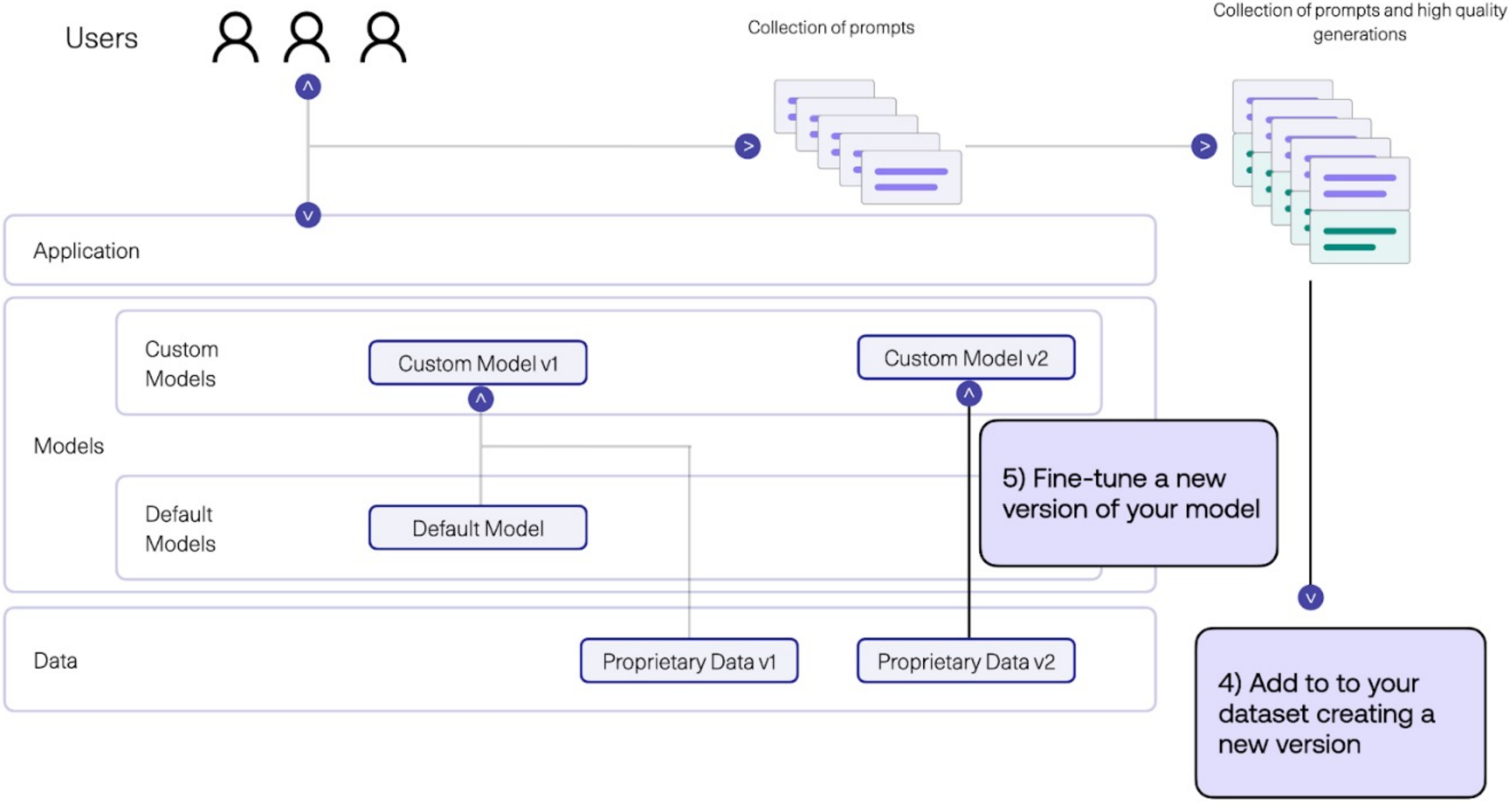
Generative AI
Fine-tune Custom Models using Proprietary Data



Source: Jay Alammar (2023), AI is Eating The World, https://txt.cohere.com/ai-is-eating-the-world/

Generative AI

Fine-tune Custom Models using Proprietary Data



Source: Jay Alammar (2023), AI is Eating The World, https://txt.cohere.com/ai-is-eating-the-world/

Meta **Llama-2 70B:** Best Open Source and Commercial LLM (Llama-2, Falcon, MPT)

Benchmark (Higher is better)	MPT (7B)	Falcon (7B)	Llama-2 (7B)	Llama-2 (13B)	MPT (30B)	Falcon (40B)	Llama-1 (65B)	Llama-2 (70B)
MMLU	26.8	26.2	45.3	54.8	46.9	55.4	63.4	68.9
TriviaQA	59.6	56.8	68.9	77.2	71.3	78.6	84.5	85.0
Natural Questions	17.8	18.1	22.7	28.0	23.0	29.5	31.0	33.0
GSM8K	6.8	6.8	14.6	28.7	15.2	19.6	50.9	56.8
HumanEval	18.3	N/A	12.8	18.3	25.0	N/A	23.7	29.9
AGIEval (English tasks only)	23.5	21.2	29.3	39.1	33.8	37.0	47.6	54.2
BoolQ	75.0	67.5	77.4	81.7	79.0	83.1	85.3	85.0

Llama 2 outperforms other open source language models on many external benchmarks, including reasoning, coding, proficiency, and knowledge tests.

Source: https://ai.meta.com/llama/

Llama-2: Comparison to closed-source models (GPT-3.5, GPT-4, PaLM) on academic benchmarks

Benchmark (shots)	GPT-3.5	GPT-4	PaLM	PaLM-2-L	Llama 2
MMLU (5-shot)	70.0	**86.4**	69.3	78.3	68.9
TriviaQA (1-shot)	–	–	81.4	**86.1**	85.0
Natural Questions (1-shot)	–	–	29.3	**37.5**	33.0
GSM8K (8-shot)	57.1	**92.0**	56.5	80.7	56.8
HumanEval (0-shot)	48.1	**67.0**	26.2	–	29.9
BIG-Bench Hard (3-shot)	–	–	52.3	**65.7**	51.2

Results for GPT-3.5 and GPT-4 are from OpenAI (2023).
Results for the PaLM model are from Chowdhery et al. (2022).
Results for the PaLM-2-L are from Anil et al. (2023).

Source: Touvron, Hugo, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov et al. (2023) "Llama 2: Open Foundation and Fine-Tuned Chat Models." arXiv preprint arXiv:2307.09288 (2023).

Llama 2: Open Foundation and Fine-Tuned Chat Models

:2307.09288v2 [cs.CL] 19 Jul 2023

LLAMA 2: Open Foundation and Fine-Tuned Chat Models

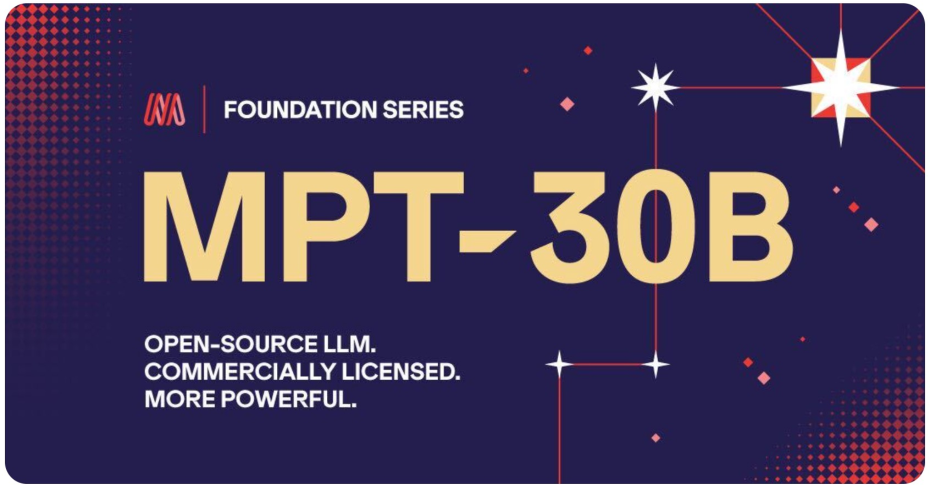
Hugo Touvron* Louis Martin† Kevin Stone†
Peter Albert Amjad Almahairi Yasmine Babaei Nikolay Bashlykov Soumya Batra
Prajjwal Bhargava Shruti Bhosale Dan Bikel Lukas Blecher Cristian Canton Ferrer Moya Chen
Guillem Cucurull David Esiobu Jude Fernandes Jeremy Fu Wenyin Fu Brian Fuller
Cynthia Gao Vedanuj Goswami Naman Goyal Anthony Hartshorn Saghar Hosseini Rui Hou
Hakan Inan Marcin Kardas Viktor Kerkez Madian Khabsa Isabel Kloumann Artem Korenev
Punit Singh Koura Marie-Anne Lachaux Thibaut Lavril Jenya Lee Diana Liskovich
Yinghai Lu Yuning Mao Xavier Martinet Todor Mihaylov Pushkar Mishra
Igor Molybog Yixin Nie Andrew Poulton Jeremy Reizenstein Rashi Rungta Kalyan Saladi
Alan Schelten Ruan Silva Eric Michael Smith Ranjan Subramanian Xiaoqing Ellen Tan Binh Tang
Ross Taylor Adina Williams Jian Xiang Kuan Puxin Xu Zheng Yan Iliyan Zarov Yuchen Zhang
Angela Fan Melanie Kambadur Sharan Narang Aurelien Rodriguez Robert Stojnic
Sergey Edunov Thomas Scialom*

GenAI, Meta

Abstract

In this work, we develop and release Llama 2, a collection of pretrained and fine-tuned large language models (LLMs) ranging in scale from 7 billion to 70 billion parameters. Our fine-tuned LLMs, called LLAMA 2-CHAT, are optimized for dialogue use cases. Our models outperform open-source chat models on most benchmarks we tested, and based on our human evaluations for helpfulness and safety, may be a suitable substitute for closed-source models. We provide a detailed description of our approach to fine-tuning and safety improvements of LLAMA 2-CHAT in order to enable the community to build on our work and contribute to the responsible development of LLMs.

Source: Touvron, Hugo, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov et al. (2023) "Llama 2: Open Foundation and Fine-Tuned Chat Models." arXiv preprint arXiv:2307.09288 (2023).

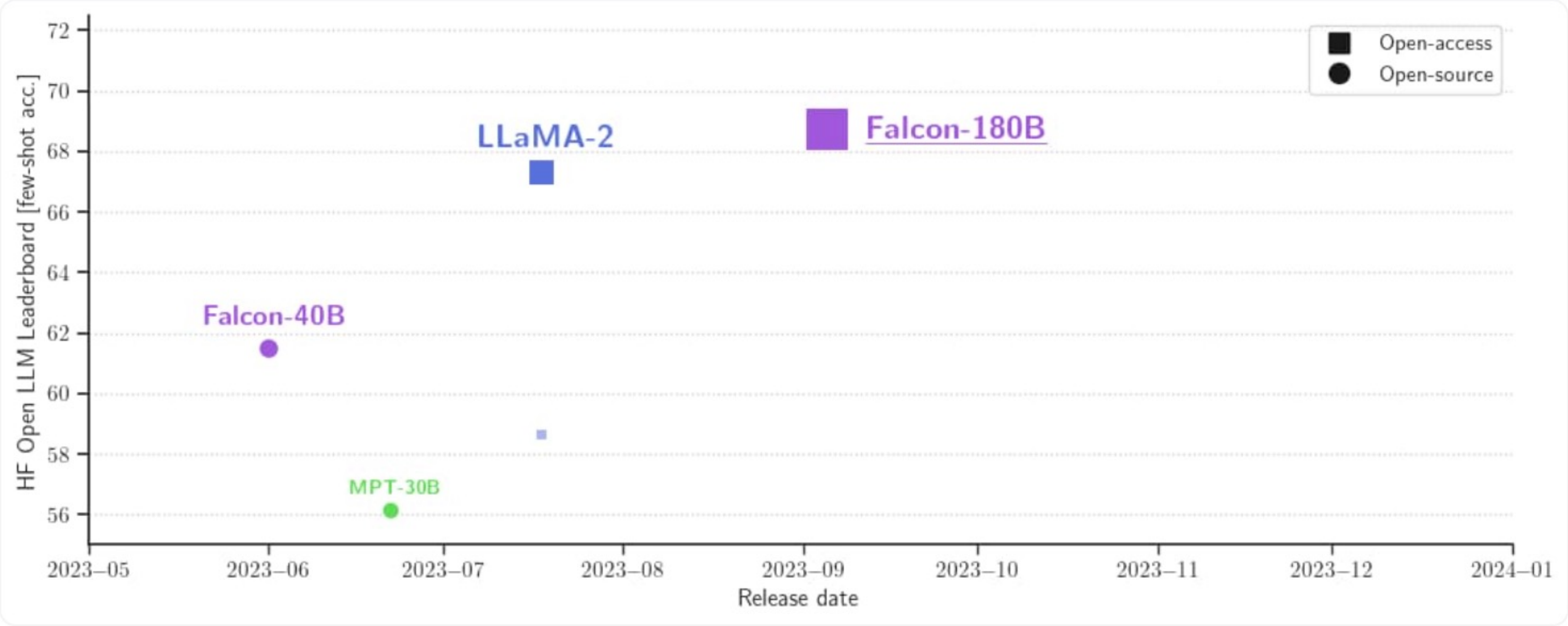


MPT-30B, MPT-7B
LLaMa-30B, LLaMa-7B

Model Purpose	Model Series	Model	Sequence Length	Accuracy (Pass@1)	Externally Reported Pass@1 & [Source]
General Purpose	MPT	MPT-30B	1024	25.00%	N/A
		MPT-30B Chat	1024	37.20%	N/A
		MPT-30B Instruct	1024	26.20%	N/A
		MPT-7B	1024	15.90%	N/A
		MPT-7B Instruct	1024	16.50%	N/A
	LLaMa	LLaMa-7B	1024	10.10%	10.5% [1]
		LLaMa-13B	1024	16.50%	15.8% [1]
		LLaMa-30B	1024	20.10%	21.7% [1]
	Falcon	Falcon-40B	1024	1.2%* (did not generate code)	N/A
		Falcon-40B Instruct	1024	0.6%* (did not generate code)	18.9% [2]

Source: https://www.mosaicml.com/blog/mpt-30b

Falcon 180B



Source: https://huggingface.co/blog/falcon-180b

Falcon 180B, LLaMA 65B, MPT 30B

Model	Size	Leaderboard score	Commercial use or license	Pretraining length
Falcon	180B	68.74	🟠	3,500B
Llama 2	70B	67.35	🟠	2,000B
LLaMA	65B	64.23	🔴	1,400B
Falcon	40B	61.48	🟢	1,000B
MPT	30B	56.15	🟢	1,000B

Source: https://huggingface.co/blog/falcon-180b

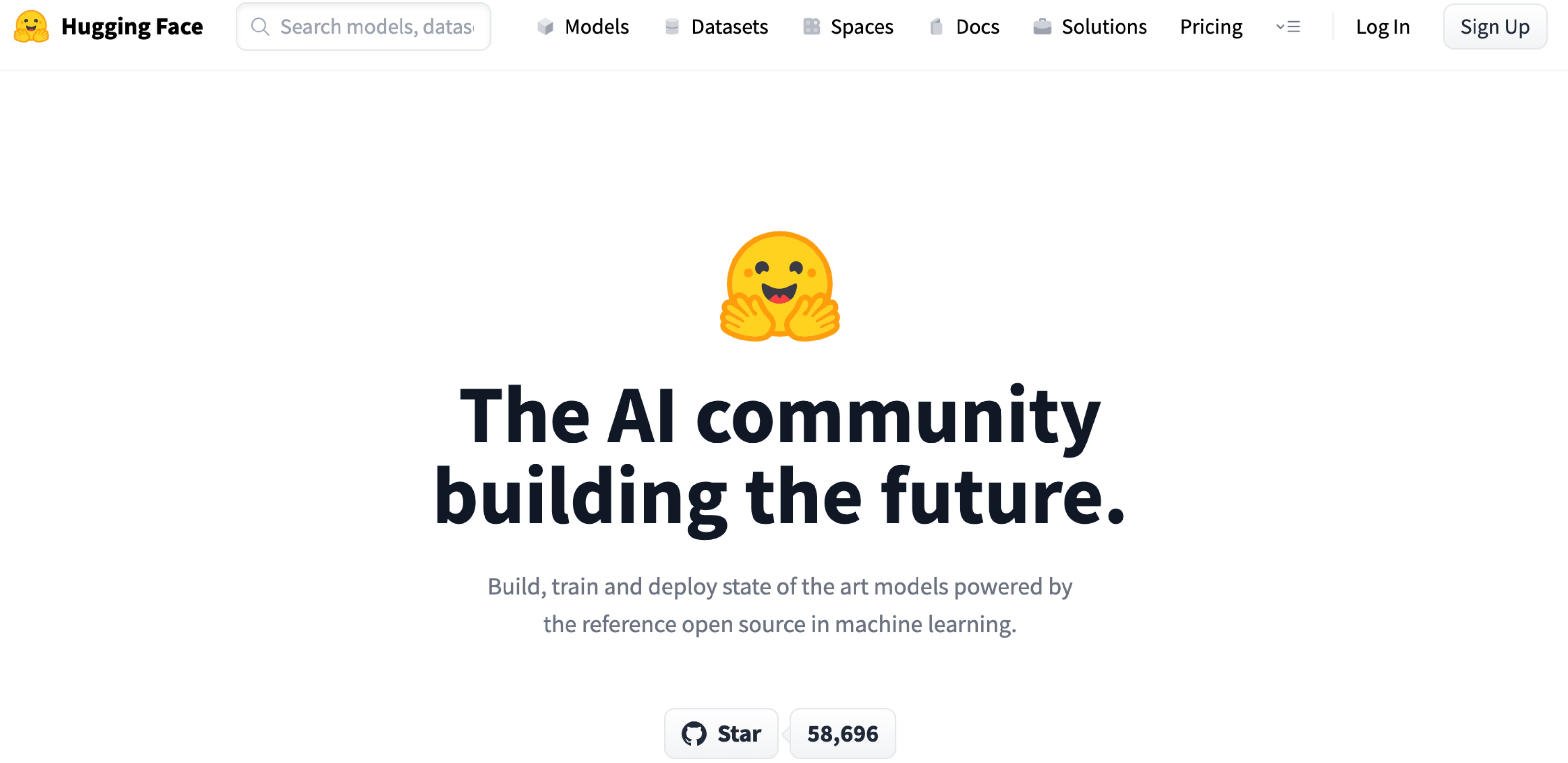
Falcon 180B
Hardware requirements

NVIDIA A100 80 GB: $16,135

	Type	Kind	Memory	Example
Falcon 180B	Training	Full fine-tuning	5120GB	8x 8x A100 80GB
Falcon 180B	Training	LoRA with ZeRO-3	1280GB	2x 8x A100 80GB
Falcon 180B	Training	QLoRA	160GB	2x A100 80GB
Falcon 180B	Inference	BF16/FP16	640GB	8x A100 80GB
Falcon 180B	Inference	GPTQ/int4	320GB	8x A100 40GB

Source: https://huggingface.co/blog/falcon-180b

Hugging Face



https://huggingface.co/

Hugging Face Transformers

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Transformers

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GET STARTED

- Transformers
- Quick tour
- Installation
- Philosophy
- Glossary

USING 🤗 TRANSFORMERS

- Summary of the tasks
- Summary of the models
- Preprocessing data
- Fine-tuning a pretrained model
- Distributed training with 🤗 Accelerate

🤗 Transformers

State-of-the-art Machine Learning for Jax, Pytorch and TensorFlow

🤗 Transformers (formerly known as *pytorch-transformers* and *pytorch-pretrained-bert*) provides thousands of pretrained models to perform tasks on different modalities such as text, vision, and audio.

These models can applied on:

- 📝 Text, for tasks like text classification, information extraction, question answering, summarization, translation, text generation, in over 100 languages.
- 🖼️ Images, for tasks like image classification, object detection, and segmentation.
- 🗣️ Audio, for tasks like speech recognition and audio classification.

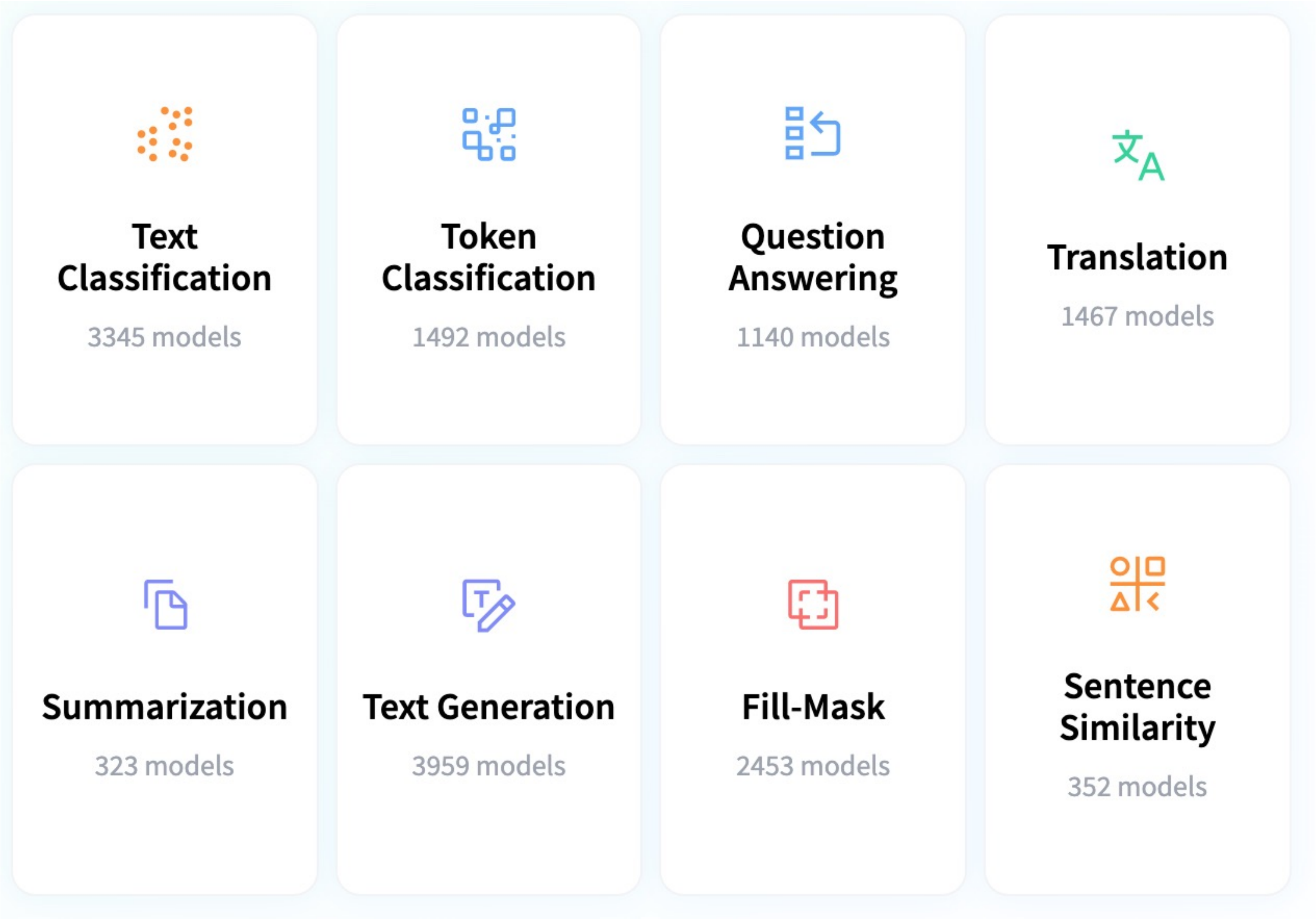
Transformer models can also perform tasks on **several modalities combined**, such as table question answering, optical character recognition, information extraction from scanned documents, video classification, and visual question answering.

🤗 Transformers

- If you are looking for custom support from the Hugging Face team
- Features
- Contents
  - Supported models
  - Supported frameworks

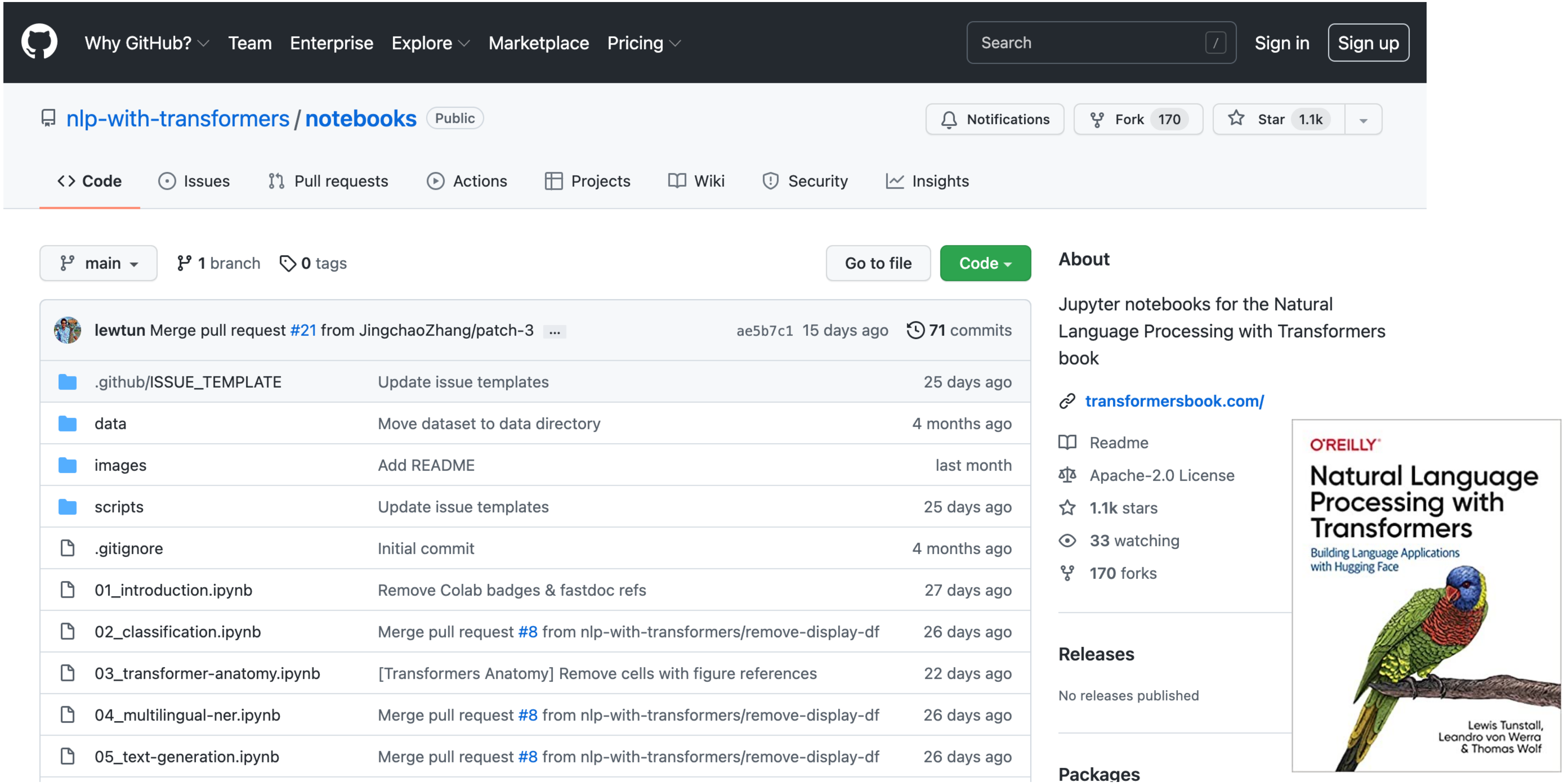
https://huggingface.co/docs/transformers/index

Hugging Face Tasks
Natural Language Processing



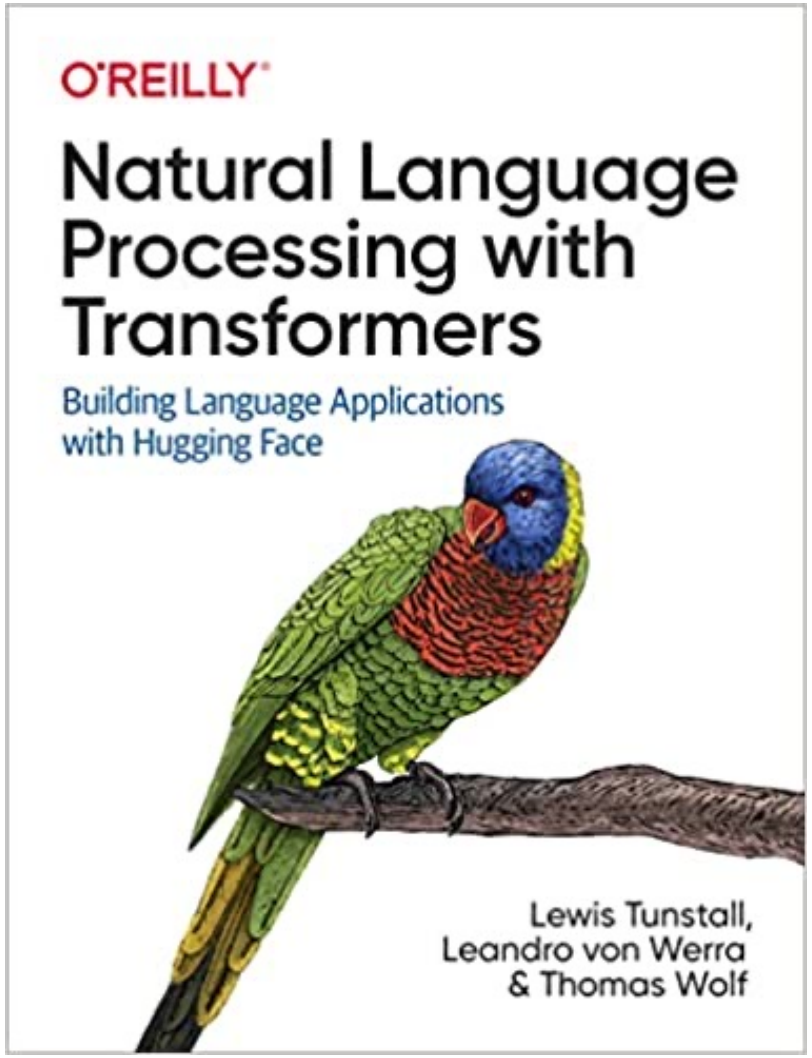
https://huggingface.co/tasks

NLP with Transformers Github



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!

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

NLP with Transformers

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

```
from utils import *
setup_chapter()
```

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

Text Classification

```
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."""
```

Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.
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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
classifier = pipeline("text-classification")
```

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

	label	score
0	NEGATIVE	0.901546

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

Text Classification

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from transformers import pipeline
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https://github.com/nlp-with-transformers/notebooks

Named Entity Recognition

```
ner_tagger = pipeline("ner", aggregation_strategy="simple")
outputs = ner_tagger(text)
pd.DataFrame(outputs)
```

	entity_group	score	word	start	end
0	ORG	0.879010	Amazon	5	11
1	MISC	0.990859	Optimus Prime	36	49
2	LOC	0.999755	Germany	90	97
3	MISC	0.556570	Mega	208	212
4	PER	0.590256	##tron	212	216
5	ORG	0.669692	Decept	253	259
6	MISC	0.498349	##icons	259	264
7	MISC	0.775362	Megatron	350	358
8	MISC	0.987854	Optimus Prime	367	380
9	PER	0.812096	Bumblebee	502	511

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

Question Answering

```
reader = pipeline("question-answering")
question = "What does the customer want?"
outputs = reader(question=question, context=text)
pd.DataFrame([outputs])
```

	score	start	end	answer
0	0.631292	335	358	an exchange of Megatron

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

Summarization

```
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.
```

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

Translation

```python
translator = pipeline("translation_en_to_de",
                      model="Helsinki-NLP/opus-mt-en-de")
outputs = translator(text, clean_up_tokenization_spaces=True, min_length=100)
print(outputs[0]['translation_text'])
```

Sehr geehrter Amazon, letzte Woche habe ich eine Optimus Prime Action Figur aus Ihrem Online-Shop in Deutschland bestellt. Leider, als ich das Paket öffnete, entdeckte ich zu meinem Entsetzen, dass ich stattdessen eine Action Figur von Megatron geschickt worden war! Als lebenslanger Feind der Decepticons, Ich hoffe, Sie können mein Dilemma verstehen. Um das Problem zu lösen, Ich fordere einen Austausch von Megatron für die Optimus Prime Figur habe ich bestellt. Anbei sind Kopien meiner Aufzeichnungen über diesen Kauf. Ich erwarte, bald von Ihnen zu hören. Aufrichtig, Bumblebee.

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

Text Generation

```
from transformers import set_seed
set_seed(42) # Set the seed to get reproducible results
```

```
generator = pipeline("text-generation")
response = "Dear Bumblebee, I am sorry to hear that your order was mixed up."
prompt = text + "\n\nCustomer service response:\n" + response
outputs = generator(prompt, max_length=200)
print(outputs[0]['generated_text'])
```

```
Customer service response:
Dear Bumblebee, I am sorry to hear that your order was mixed up. The
order was completely mislabeled, which is very common in our online
store, but I can appreciate it because it was my understanding from this
site and our customer service of the previous day that your order was
not made correct in our mind and that we are in a process of resolving
this matter. We can assure you that your order
```

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

Text Generation

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.

Customer service response:
Dear Bumblebee, I am sorry to hear that your order was mixed up. The order was completely mislabeled, which is very common in our online store, but I can appreciate it because it was my understanding from this site and our customer service of the previous day that your order was not made correct in our mind and that we are in a process of resolving this matter. We can assure you that your order

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

Question Answering

```
!pip install transformers
from transformers import pipeline
qamodel = pipeline("question-answering")
question = "Where do I live?"
context = "My name is Michael and I live in Taipei."
qamodel(question = question, context = context)
```

```
{'answer': 'Taipei', 'end': 39, 'score': 0.9730741381645203, 'start': 33}
```

https://tinyurl.com/aintpupython101

Question Answering

```
from transformers import pipeline
qamodel = pipeline("question-answering", model ='deepset/roberta-base-squad2')
question = "Where do I live?"
context = "My name is Michael and I live in Taipei."
output = qamodel(question = question, context = context)
print(output['answer’])
```

```
Taipei
```

https://tinyurl.com/aintpupython101

Python in Google Colab (Python101)

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

python101.ipynb

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Table of contents

+ Code + Text Connect Editing


```python
text = "Steve Jobs and Steve Wozniak incorporated Apple Computer on January 3, 1977, in Cupertino, California."
doc = nlp(text)
displacy.render(doc, style="ent", jupyter=True)
```

Steve Jobs PERSON and Steve Wozniak PERSON incorporated Apple Computer ORG on January 3, 1977 DATE , in Cupertino GPE , California GPE .

```python
import spacy
nlp = spacy.load("en_core_web_sm")
doc = nlp("Stanford University is located in California. It is a great university.")
import pandas as pd
cols = ("text", "lemma", "pos", "tag", "pos_explain", "stopword")
rows = []
for t in doc:
    row = [t.text, t.lemma_, t.pos_, t.tag_,spacy.explain(t.pos_), t.is_stop]
    rows.append(row)
df = pd.DataFrame(rows, columns=cols)
df
```

	text	lemma	pos	tag	pos_explain	stopword
0	Stanford	Stanford	PROPN	NNP	proper noun	False
1	University	University	PROPN	NNP	proper noun	False
2	is	be	VERB	VBZ	verb	True
3	located	locate	VERB	VBN	verb	False
4	in	in	ADP	IN	adposition	True
5	California	California	PROPN	NNP	proper noun	False
6	.	.	PUNCT	.	punctuation	False
7	It	-PRON-	PRON	PRP	pronoun	True

https://tinyurl.com/aintpupython101

Python in Google Colab (Python101)

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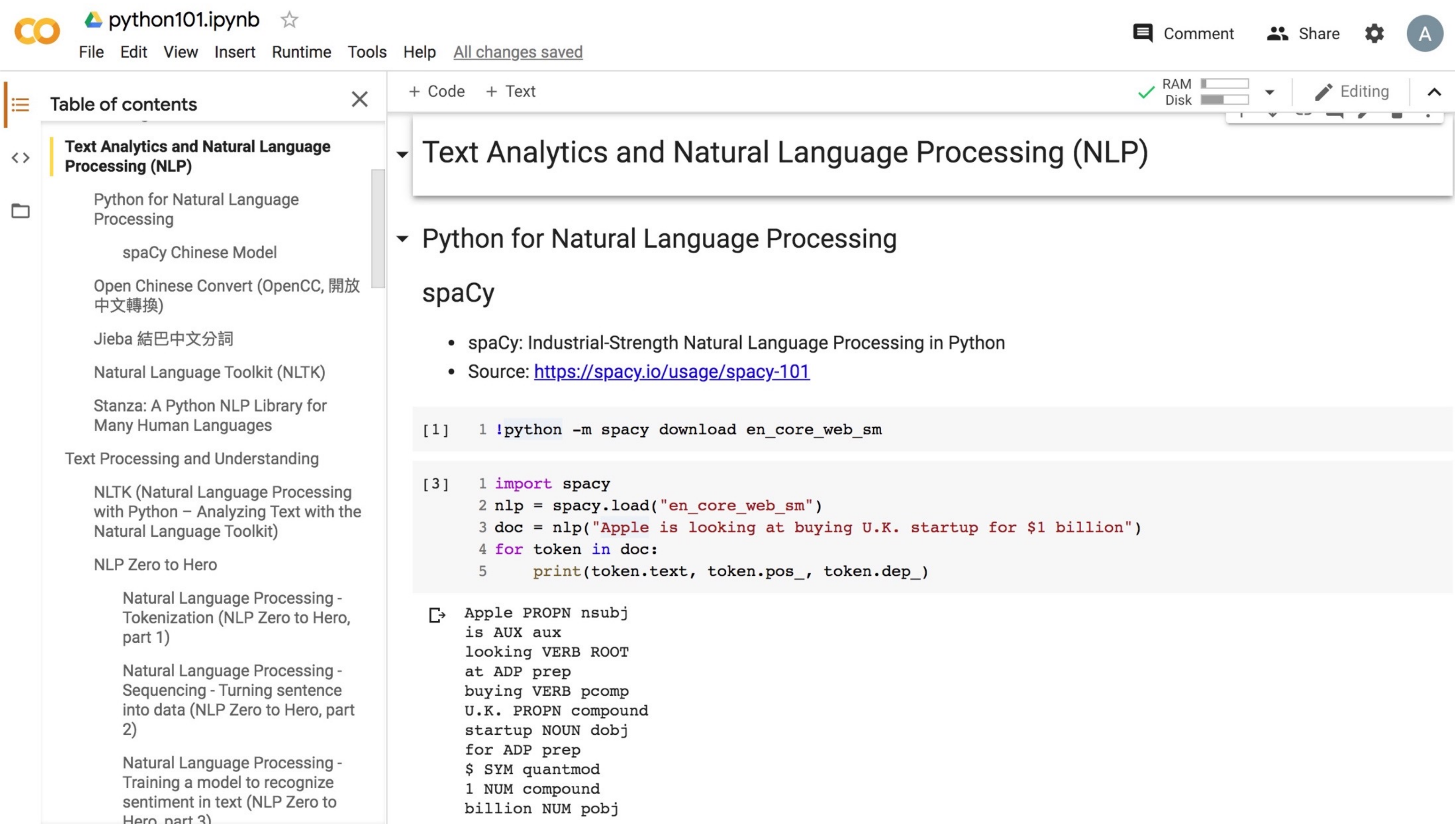

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python101.ipynb

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```python
import spacy
nlp = spacy.load("en_core_web_sm")
doc = nlp("Apple is looking at buying U.K. startup for $1 billion")
import pandas as pd
cols = ("text", "lemma", "POS", "explain", "stopword")
rows = []
for t in doc:
    row = [t.text, t.lemma_, t.pos_, spacy.explain(t.pos_), t.is_stop]
    rows.append(row)
df = pd.DataFrame(rows, columns=cols)
df
```

	text	lemma	POS	explain	stopword
0	Apple	Apple	PROPN	proper noun	False
1	is	be	VERB	verb	True
2	looking	look	VERB	verb	False
3	at	at	ADP	adposition	True
4	buying	buy	VERB	verb	False
5	U.K.	U.K.	PROPN	proper noun	False
6	startup	startup	NOUN	noun	False
7	for	for	ADP	adposition	True
8	$	$	SYM	symbol	False
9	1	1	NUM	numeral	False
10	billion	billion	NUM	numeral	False

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

python101.ipynb

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+ Code + Text

```python
import spacy
nlp = spacy.load("en_core_web_sm")
doc = nlp("Stanford University is located in California. It is a great university.")
import pandas as pd
cols = ("text", "lemma", "POS", "explain", "stopword")
rows = []
for t in doc:
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```

	text	lemma	POS	explain	stopword
0	Stanford	Stanford	PROPN	proper noun	False
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3	located	locate	VERB	verb	False
4	in	in	ADP	adposition	True
5	California	California	PROPN	proper noun	False
6	.	.	PUNCT	punctuation	False
7	It	-PRON-	PRON	pronoun	True
8	is	be	VERB	verb	True
9	a	a	DET	determiner	True
10	great	great	ADJ	adjective	False
11	university	university	NOUN	noun	False
12	.	.	PUNCT	punctuation	False

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+ Code + Text

```
[ ]
import spacy
nlp = spacy.load("en_core_web_sm")
text = "Stanford University is located in California. It is a great university."
doc = nlp(text)
for ent in doc.ents:
    print(ent.text, ent.label_)
```

```
Stanford University ORG
California GPE
```

```
[ ]
from spacy import displacy
text = "Stanford University is located in California. It is a great university."
doc = nlp(text)
displacy.render(doc, style="ent", jupyter=True)
```

Stanford University ORG is located in California GPE . It is a great university.

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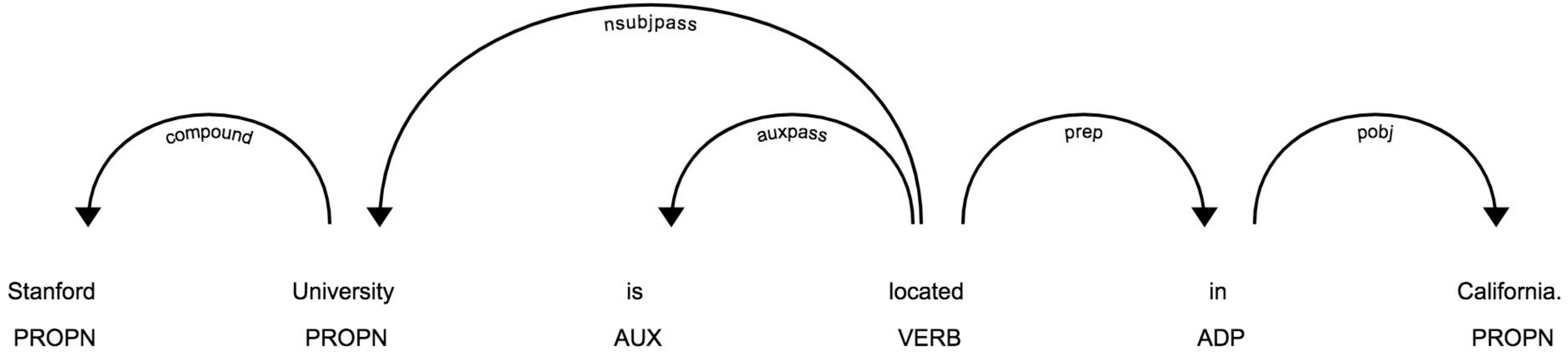
https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT

```
from spacy import displacy
text = "Stanford University is located in California. It is a great university."
doc = nlp(text)
displacy.render(doc, style="ent", jupyter=True)
displacy.render(doc, style="dep", jupyter=True)
```

Stanford University **ORG** is located in California **GPE** . It is a great university.



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4	in	in	ADP	IN	adposition	True
5	California	California	PROPN	NNP	proper noun	False
6	.	.	PUNCT	.	punctuation	False
7	It	-PRON-	PRON	PRP	pronoun	True

https://tinyurl.com/aintpupython101

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://summari.es/ https://www-nlpir.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 NarativeQA 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.

Summary

- Text Analytics and Text Mining
- Natural Language Processing (NLP)

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