Artificial Intelligence for Text Analytics

NTPU
國立臺北大學
National Taipei University

Question Answering and Dialogue Systems

1121AITA09
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

2023-12-06

Syllabus

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

Syllabus

Week	Date	Subject/Topics
7	2023/10/25	Multilingual Named Entity Recognition (NER)
8	2023/11/01	Midterm Project Report
9	2023/11/08	Text Similarity and Clustering
10	2023/11/15	Text Summarization and Topic Models
11	2023/11/22	Text Generation with Large Language Models (LLMs)
12	2023/11/29	Case Study on Artificial Intelligence for Text Analytics II

Syllabus

Week	Date	Subject/Topics
13	2023/12/06	Question Answering and Dialogue Systems
14	2023/12/13	Deep Learning, Generative AI, Transfer Learning, Zero-Shot, and Few-Shot Learning for Text Analytics
15	2023/12/20	Final Project Report I
16	2023/12/27	Final Project Report II
17	2024/01/03	Self-learning
18	2024/01/10	Self-learning

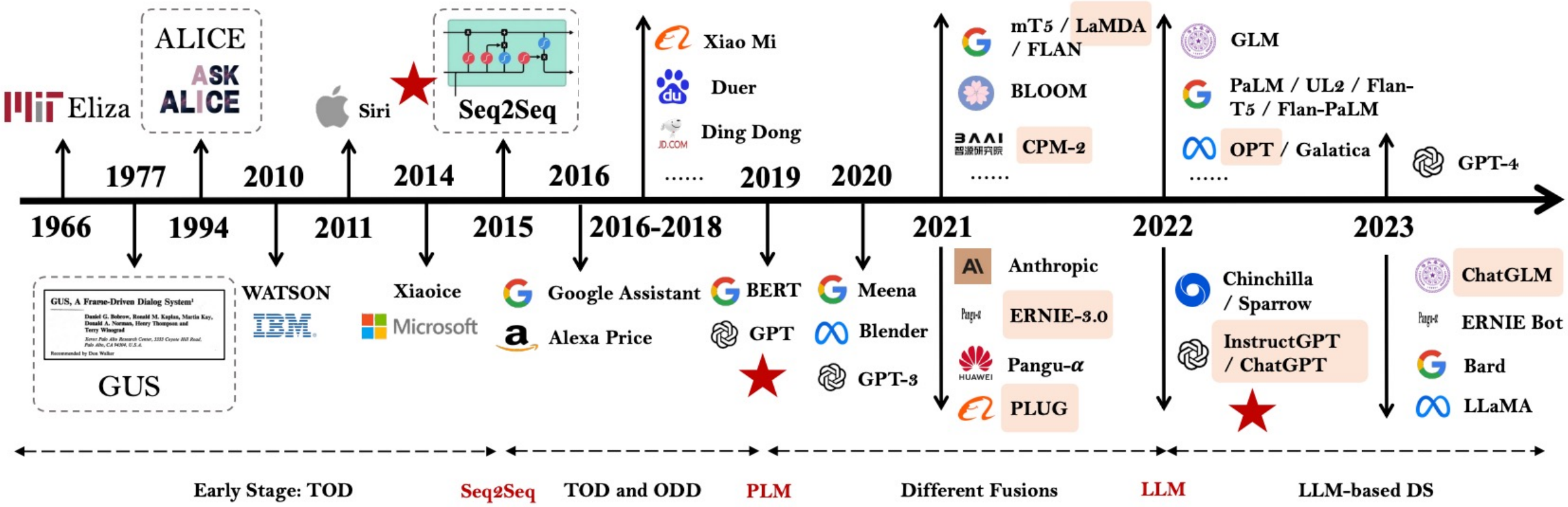
Question Answering and Dialogue Systems

Outline

- Question Answering
- Dialogue Systems
  - Task Oriented Dialogue (TOD) System
- Task-Oriented Dialogue System (TDS)
- Conversational Dialogue System (CDS)
- Question Answering Dialogue System (QADS)

The Development of LM-based Dialogue Systems

1) Early Stage (1966 - 2015)
2) The Independent Development of TOD and ODD (2015 - 2019)
3) Fusions of Dialogue Systems (2019 - 2022)
4) LLM-based DS (2022 - Now)



Task-oriented DS (TOD), Open-domain DS (ODD)

Source: Wang, Hongru, Lingzhi Wang, Yiming Du, Liang Chen, Jingyan Zhou, Yufei Wang, and Kam-Fai Wong. "A Survey of the Evolution of Language Model-Based Dialogue Systems." arXiv preprint arXiv:2311.16789 (2023).

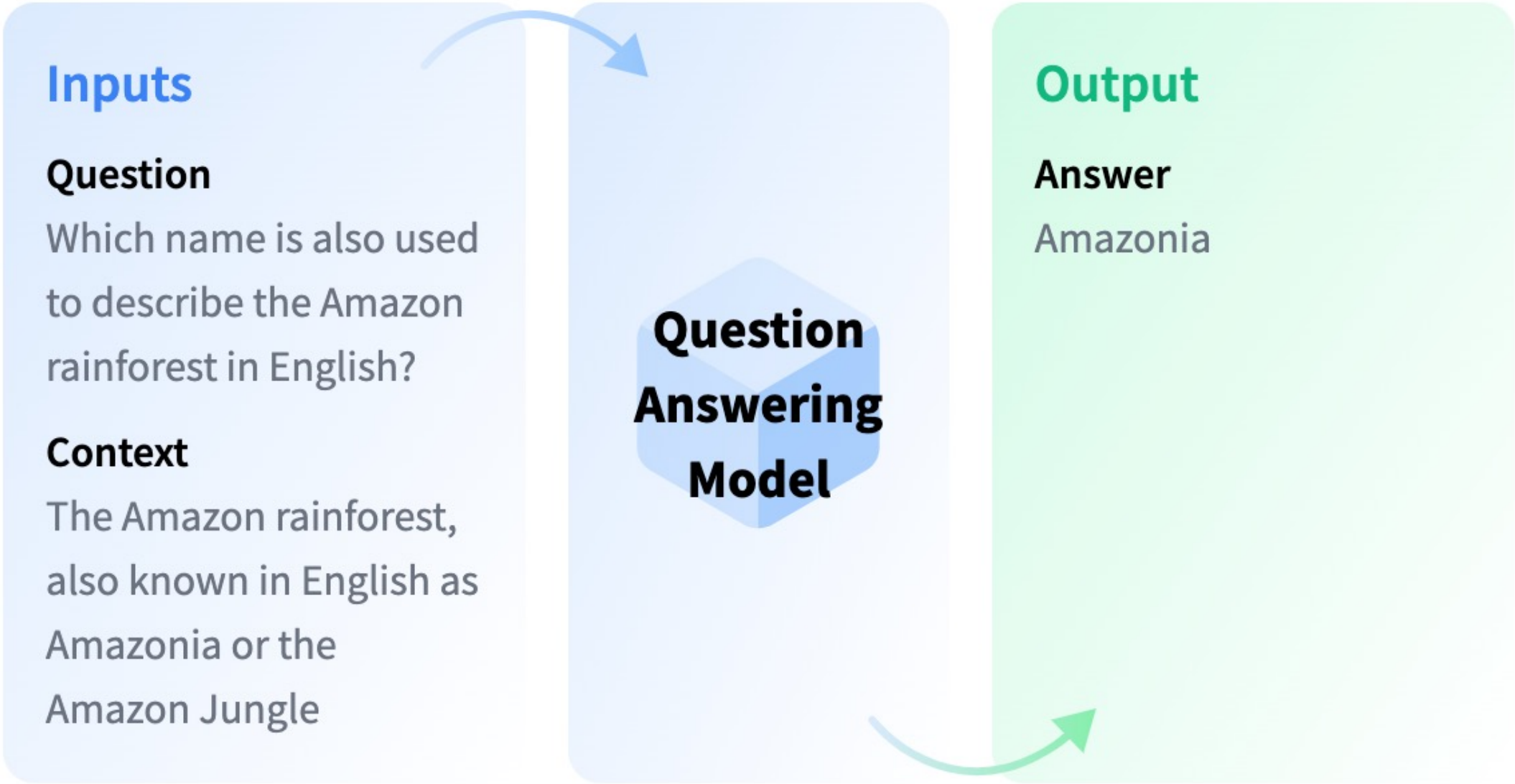
Dialogue System

Different types of dialogues in Task-oriented DS (TOD) and Open-domain DS (ODD)

Types of DS	**Types of Dialogues**	**User message** (*U*)	**System response** (*S*)	**External knowledge** (*K*)
Task-oriented DS (TOD)	Task-oriented	I need to find a nice restaurant in Madrid that serves expensive Thai food	There is a restaurant called Bangkok City located at 9 Red Ave.	Restaurant database
Open-domain DS (ODD)	Social Chit-Chat	How are you going ?	I am good. And you?	-
	KG Chit-Chat	I like watching action movies	Here are some action movies from various eras and styles that you might enjoy: *Inception*, *The Avengers*	Movie KG
	Question Answering	Do you know which team wins the 2022 World Cup?	The Argentina team	Wikipedia

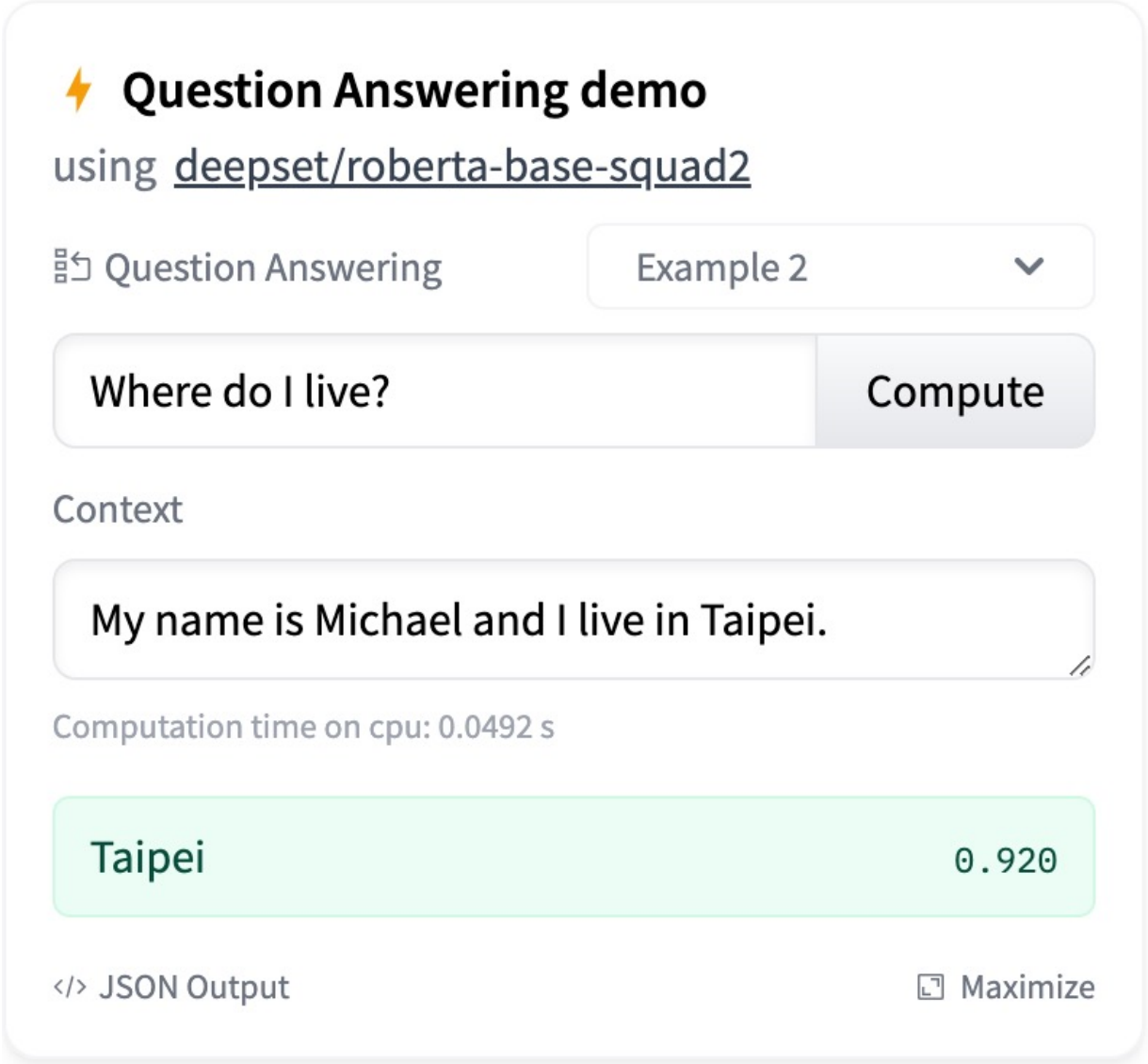
Source: Wang, Hongru, Lingzhi Wang, Yiming Du, Liang Chen, Jingyan Zhou, Yufei Wang, and Kam-Fai Wong. "A Survey of the Evolution of Language Model-Based Dialogue Systems." arXiv preprint arXiv:2311.16789 (2023).

Question Answering



https://huggingface.co/tasks/question-answering

Question Answering



https://huggingface.co/tasks/question-answering

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
```

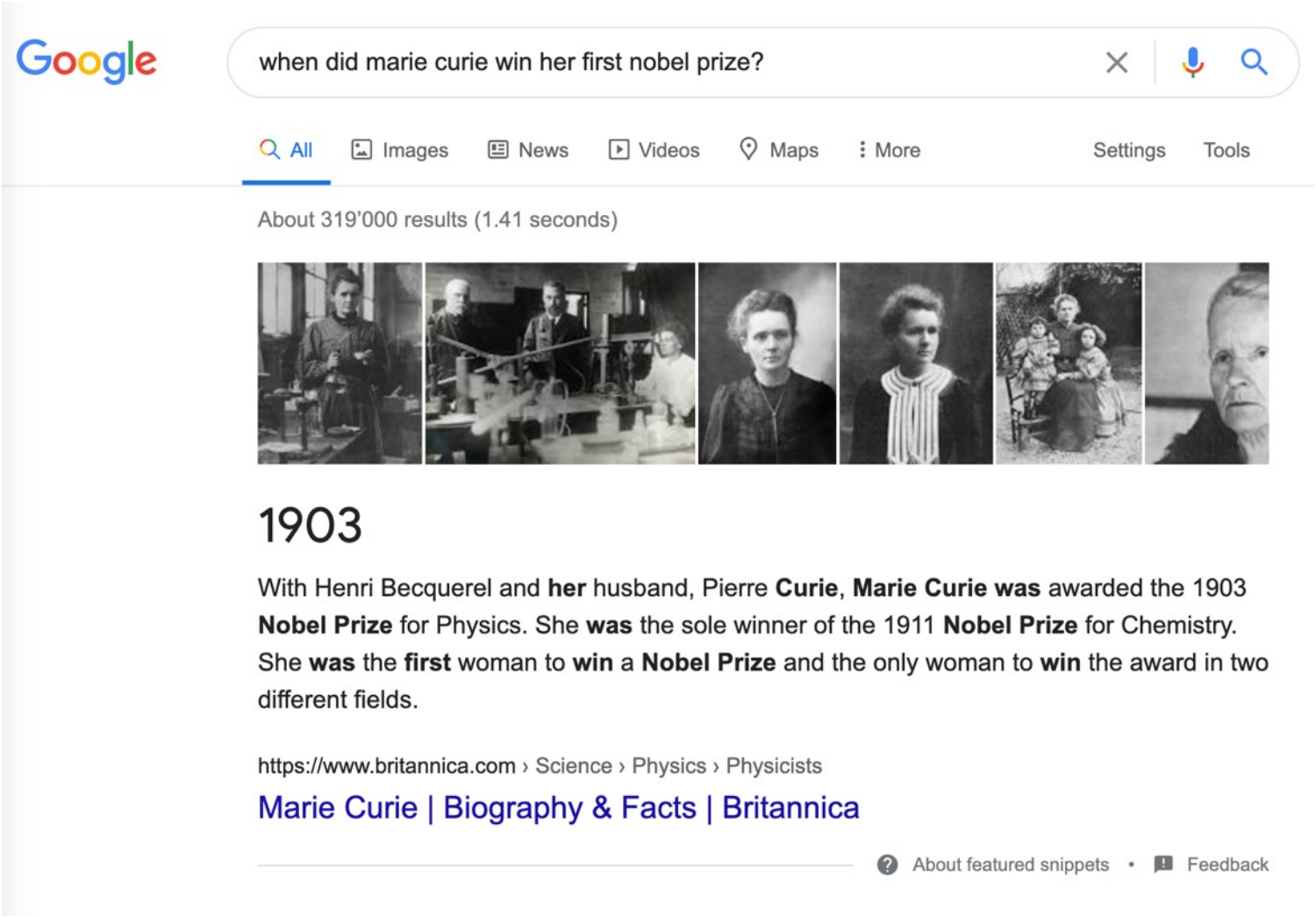
https://tinyurl.com/aintpupython101

Question Answering

Question Answering

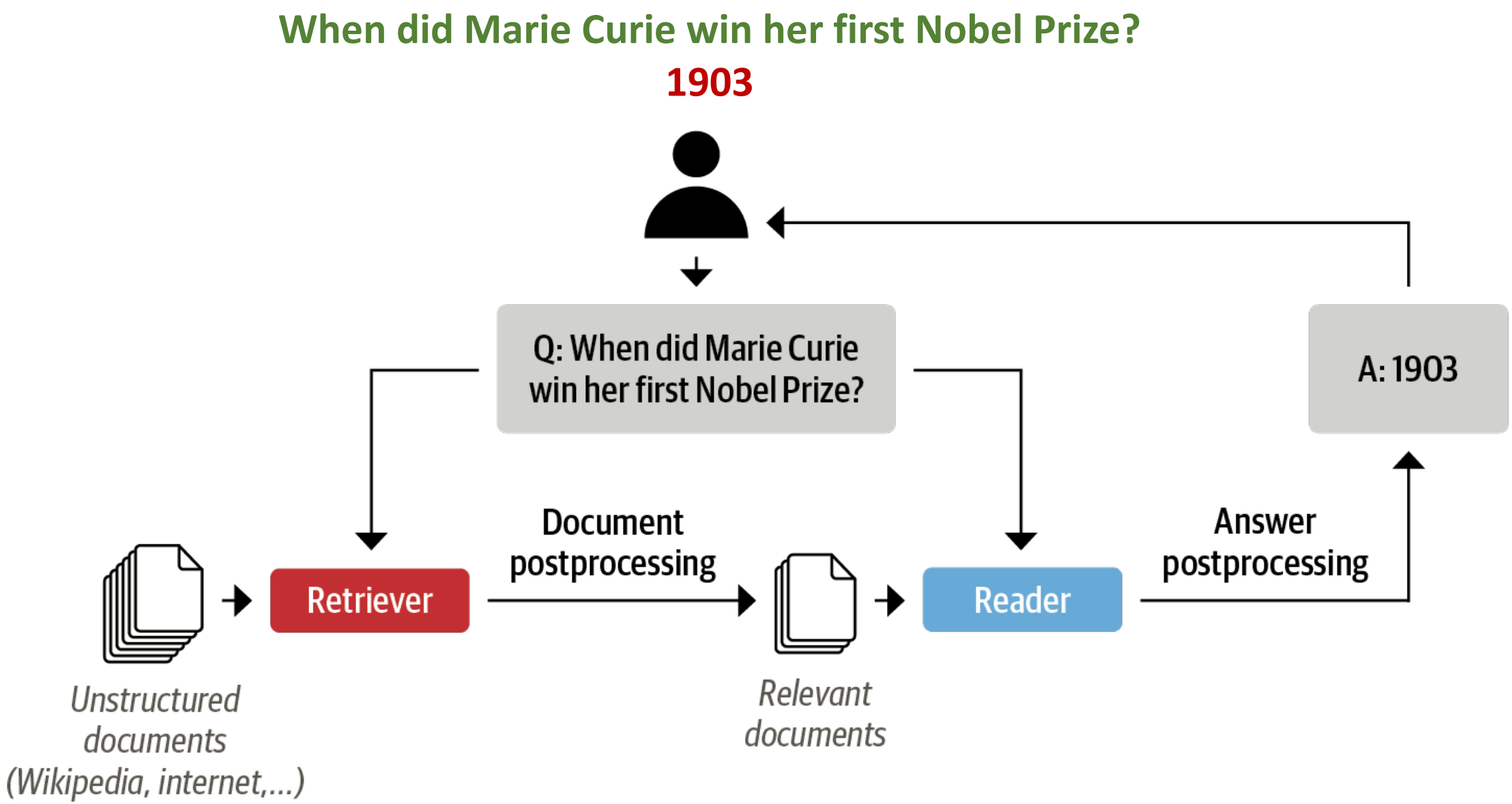
When did Marie Curie win her first Nobel Prize?

1903



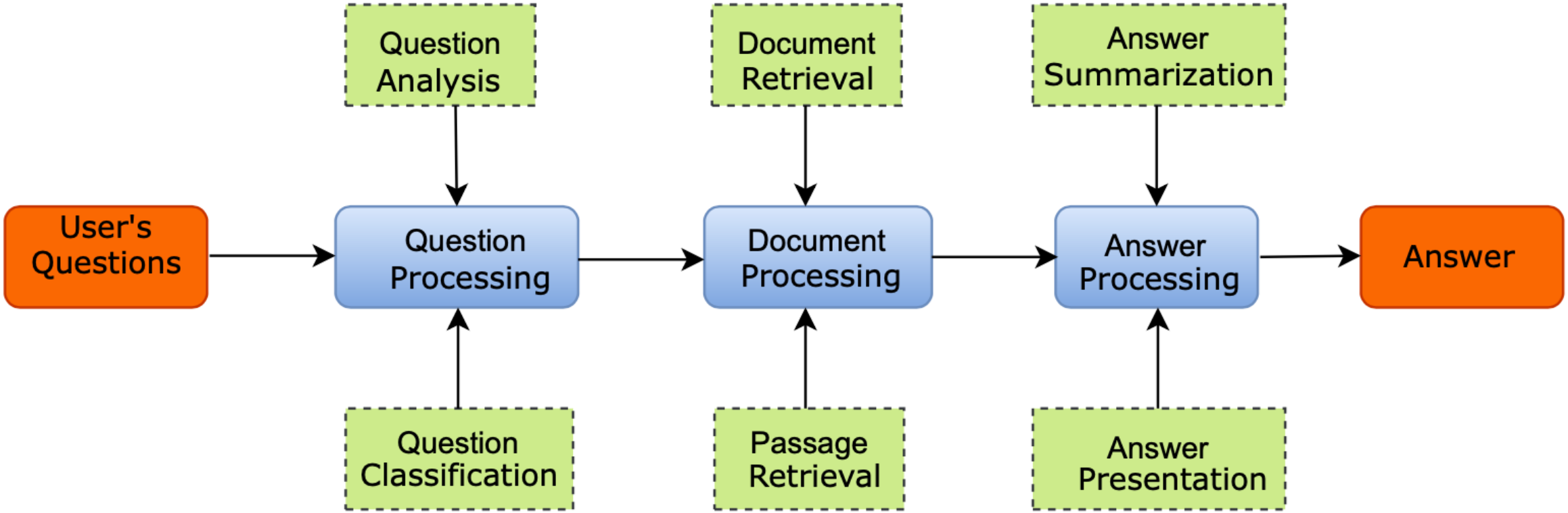
Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.

The Retriever-Reader Architecture for Modern QA Systems



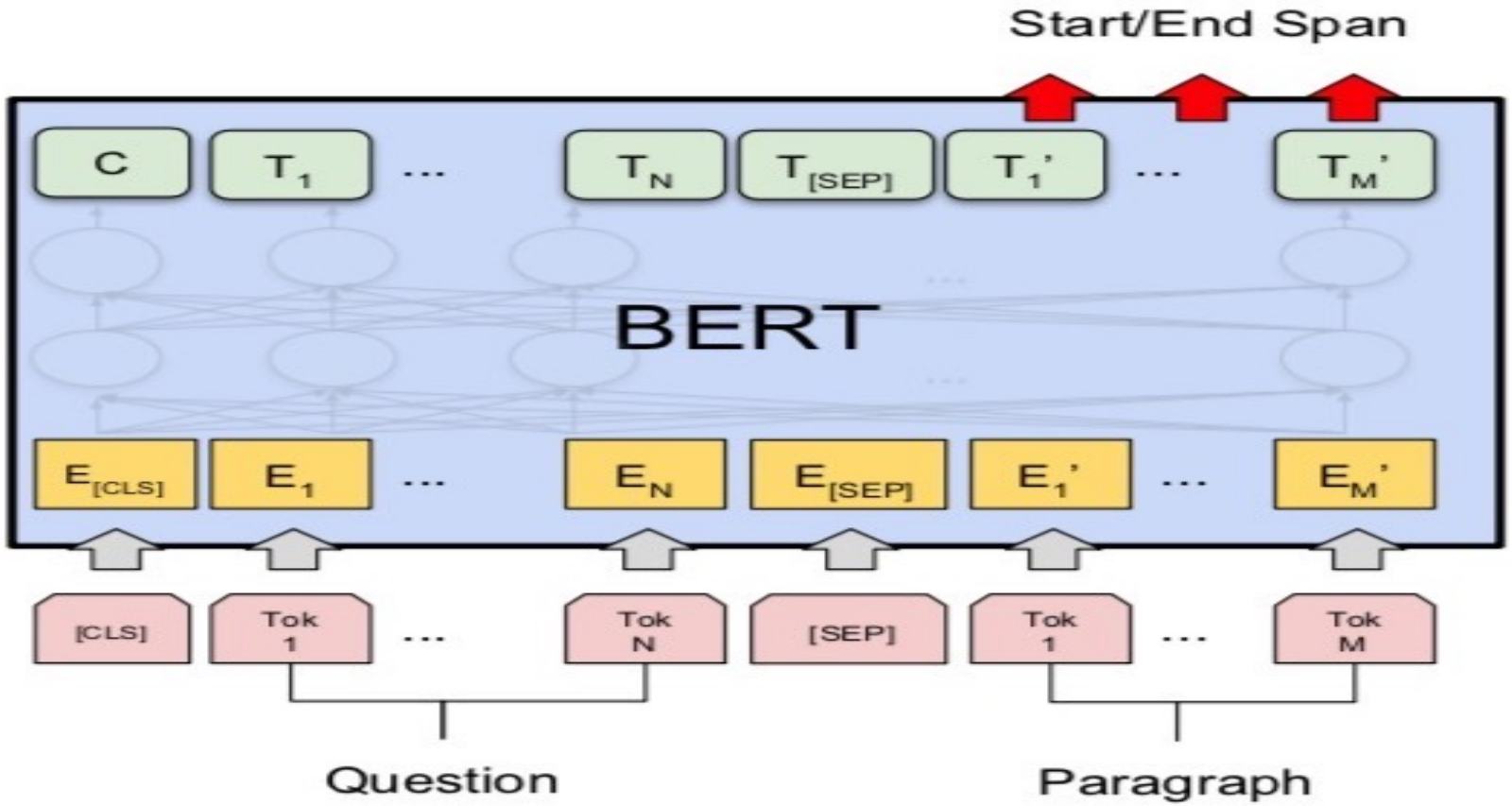
Source: Lewis Tunstall, Leandro von Werra, and Thomas Wolf (2022), Natural Language Processing with Transformers: Building Language Applications with Hugging Face, O'Reilly Media.

Question Answering System (QAS)



Source: Mutabazi, Emmanuel, Jianjun Ni, Guangyi Tang, and Weidong Cao (2021) "A review on medical textual question answering systems based on deep learning approaches." Applied Sciences 11, no. 12 (2021): 5456.

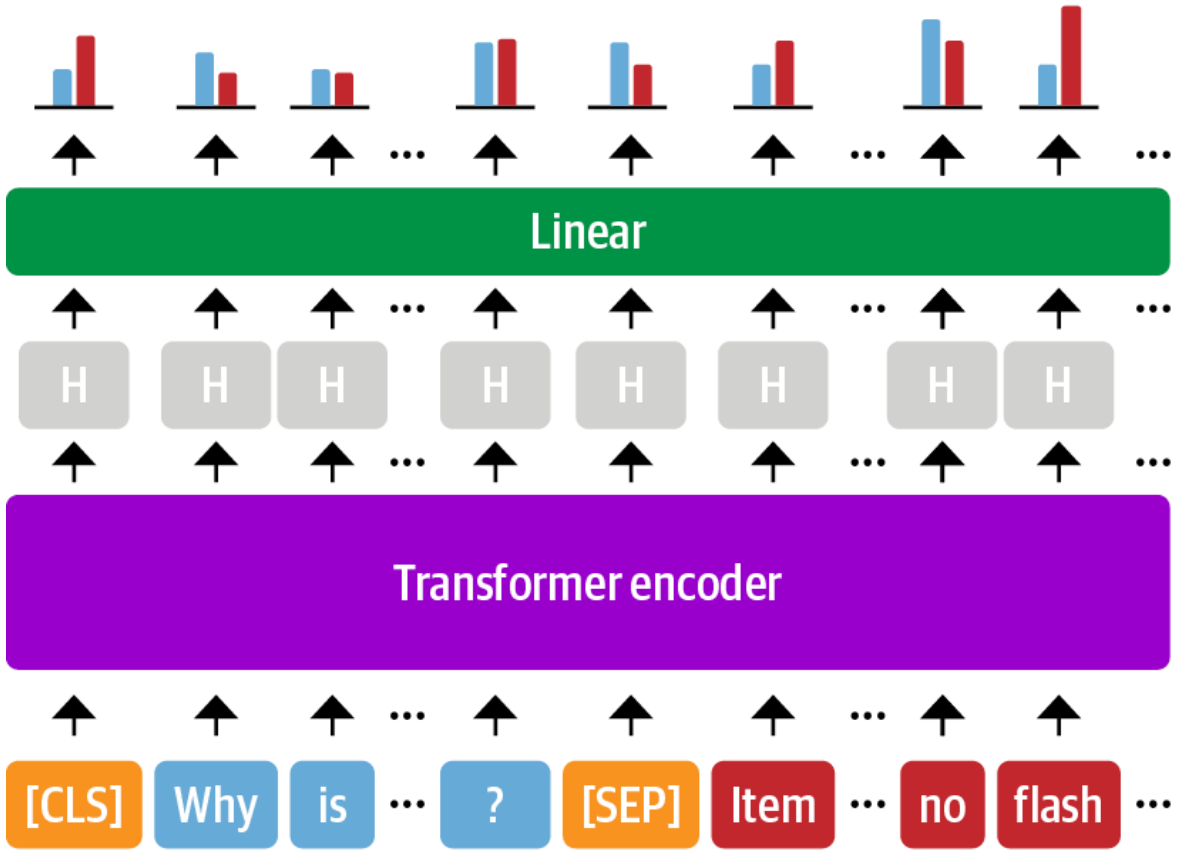
Fine-tuning BERT on Question Answering (QA)



(c) Question Answering Tasks: SQuAD v1.1

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.

The span classification head for QA tasks



Question answering

Start and end logits

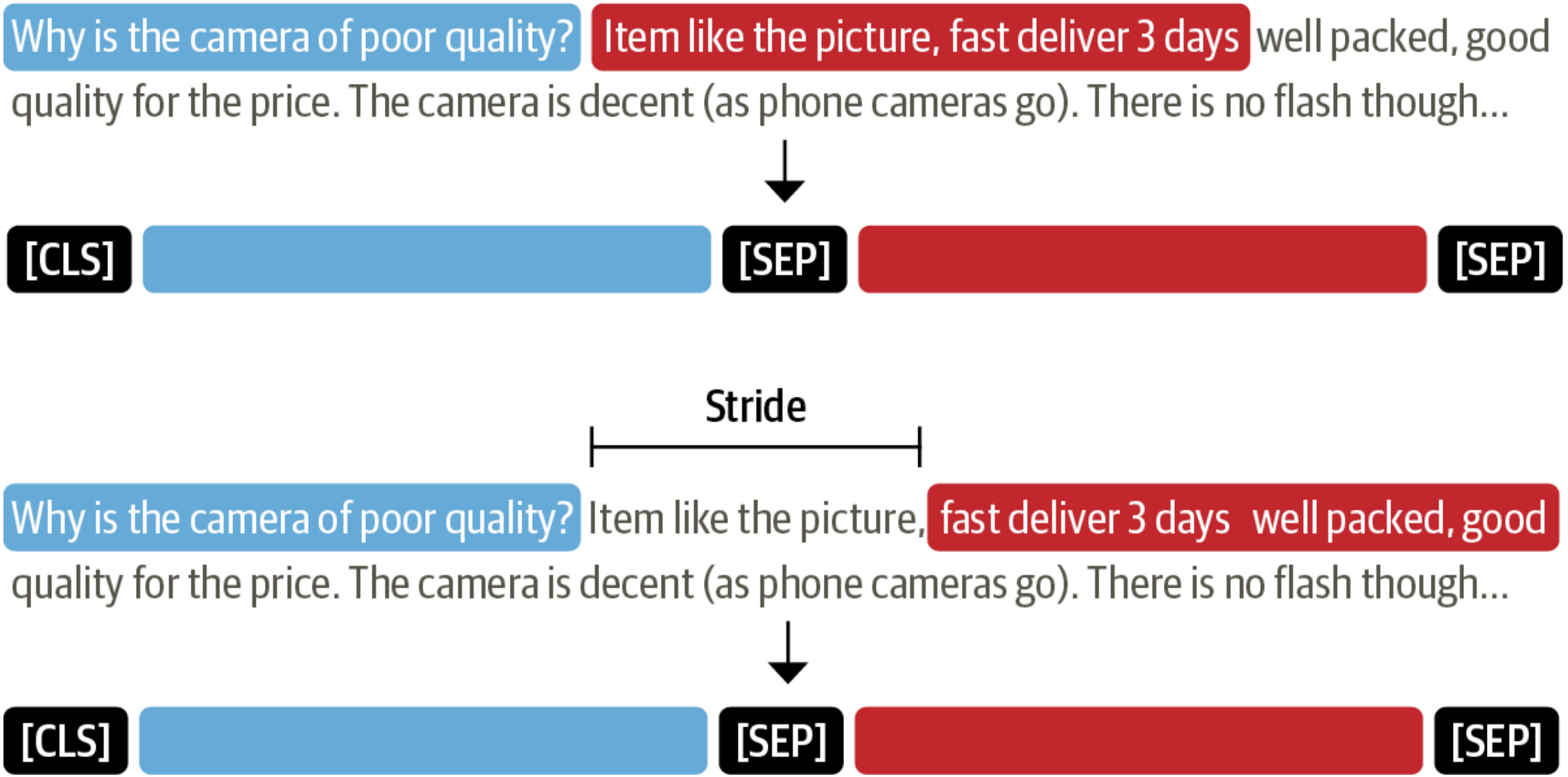
Hidden states

Special tokens

Question tokens

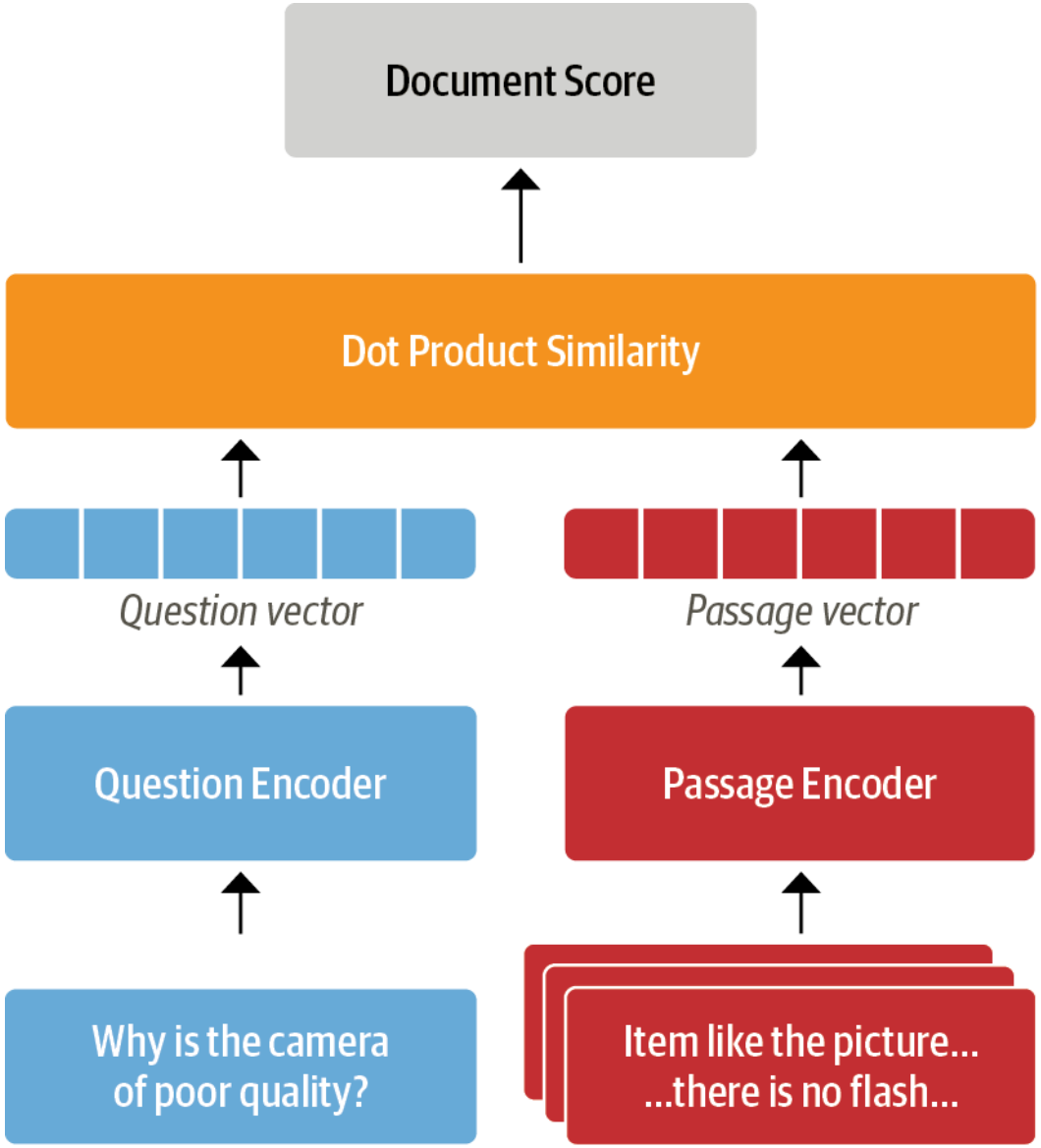
Context tokens

Multiple question-context pairs



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

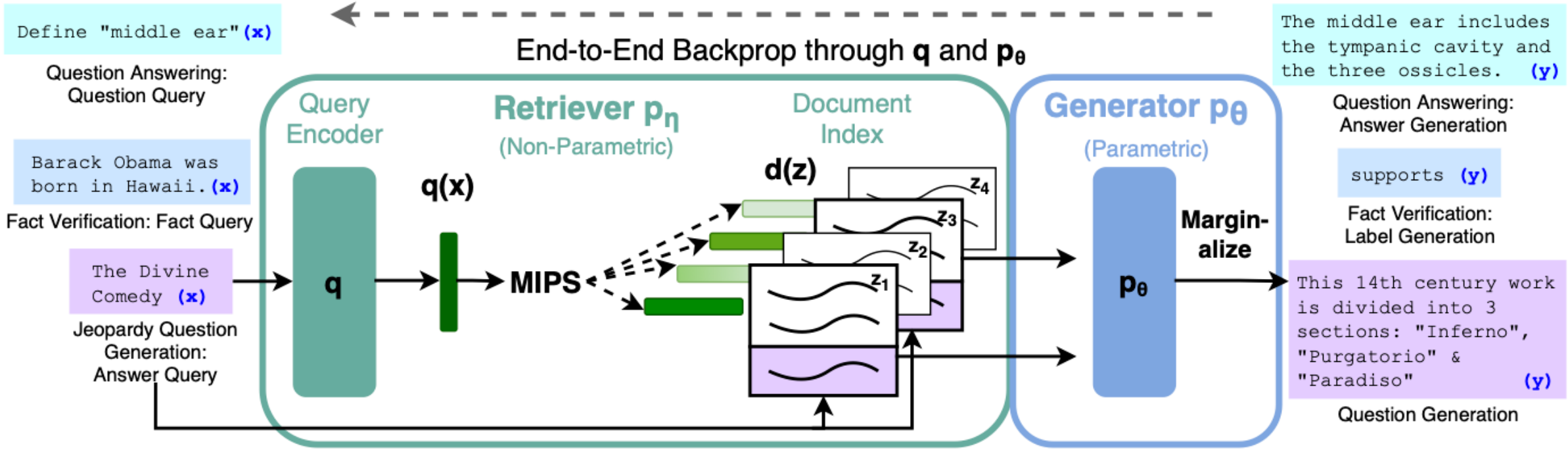
Dense Passage Retrieval (DPR)



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

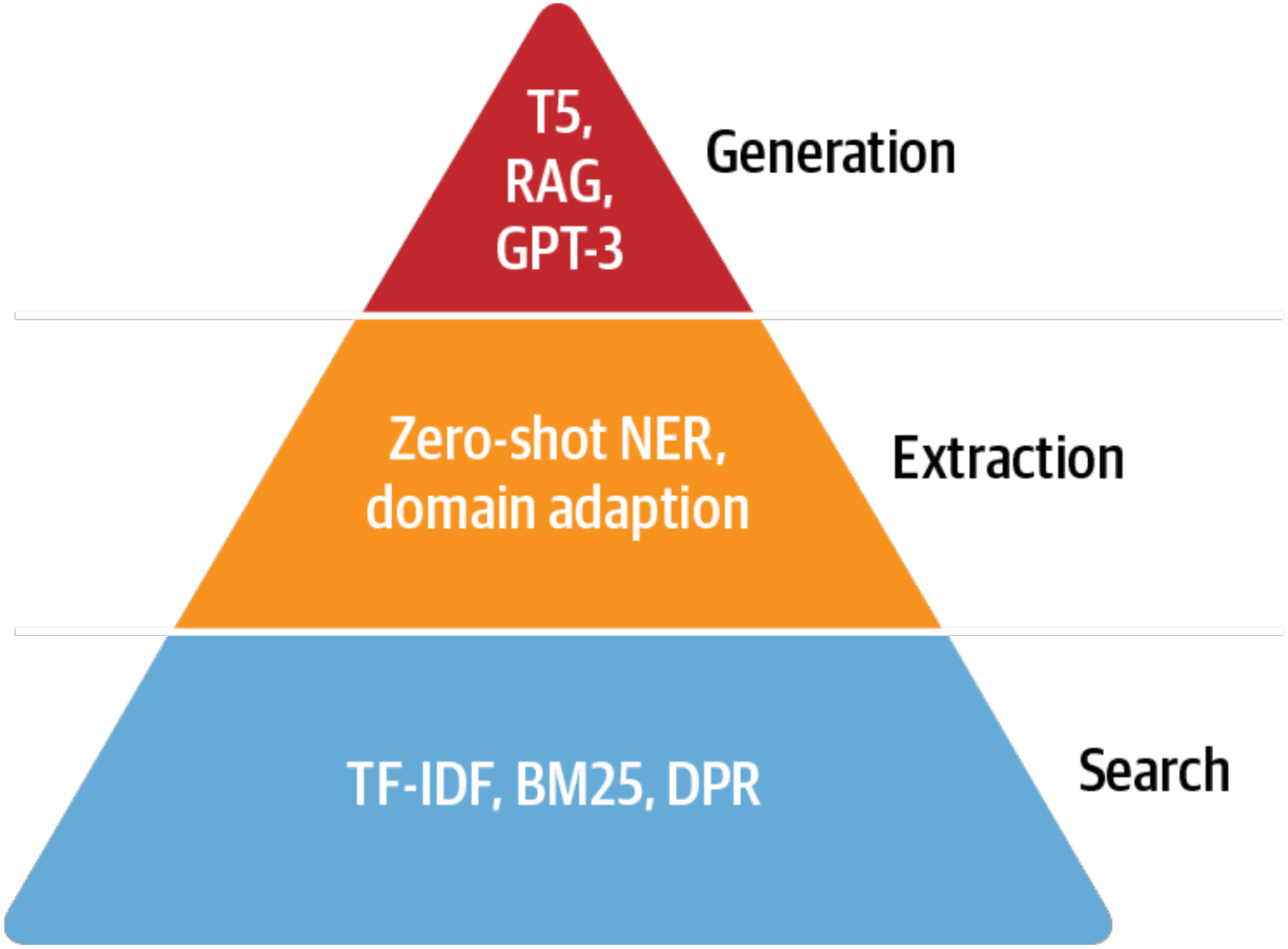
Going Beyond Extractive QA
Retrieval-Augmented Generation (RAG)

The RAG architecture for fine-tuning a retriever and generator end-to-end



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

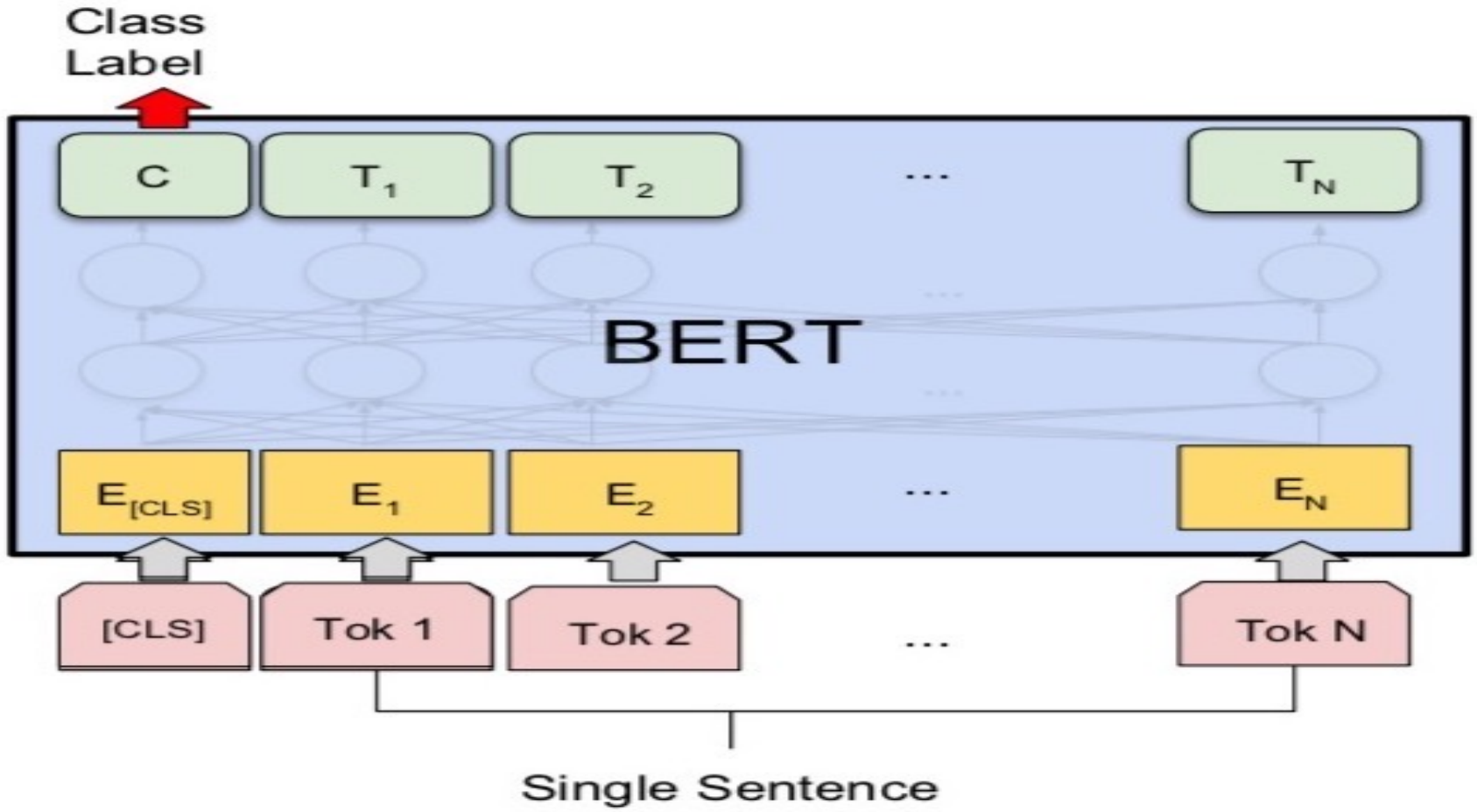
The QA Hierarchy of Needs



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

Fine-tuning BERT on Dialogue

Intent Detection (ID; Classification)

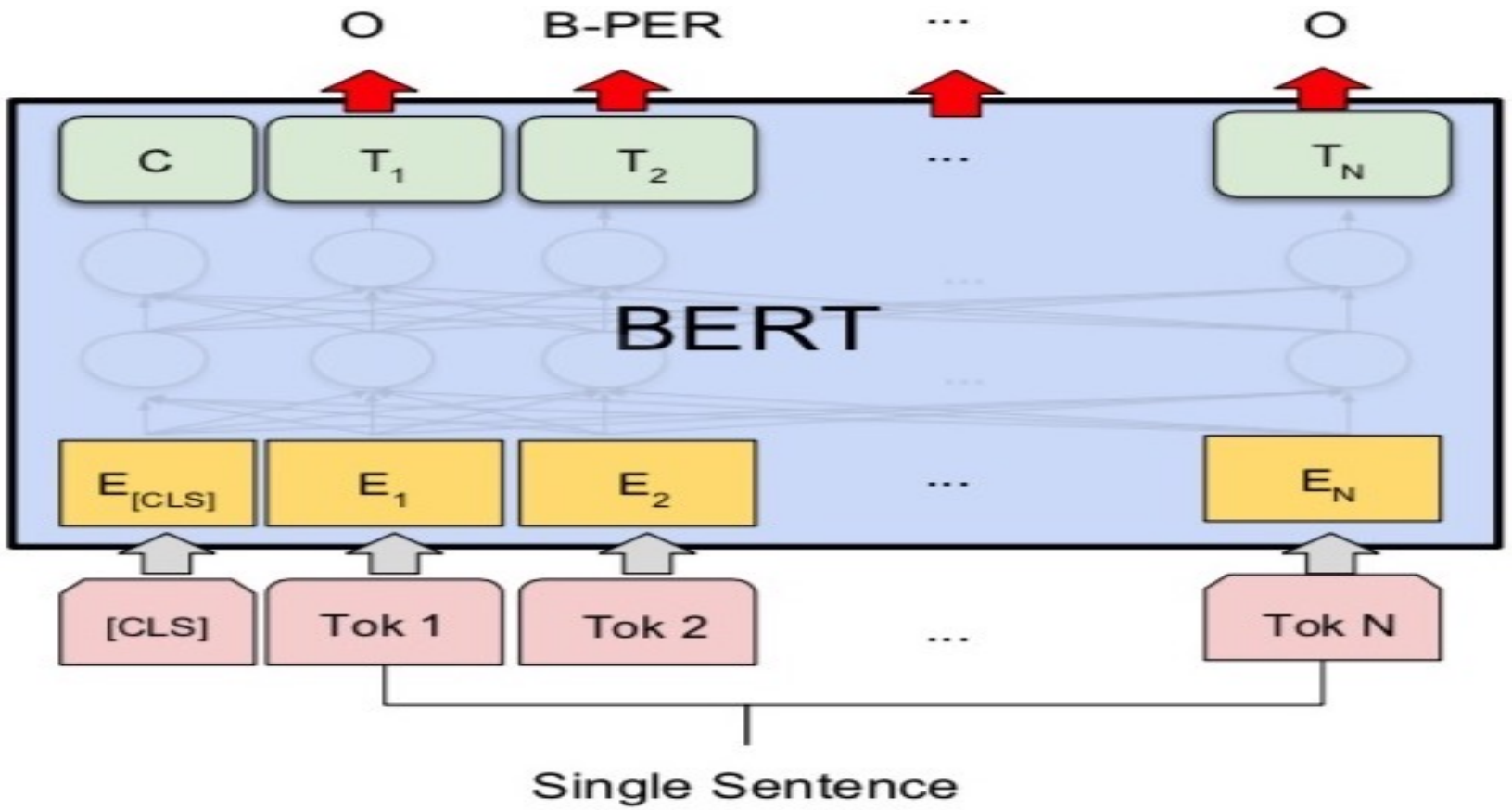


(b) Single Sentence Classification Tasks: SST-2, CoLA

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.

Fine-tuning BERT on Dialogue

Slot Filling (SF)



(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.

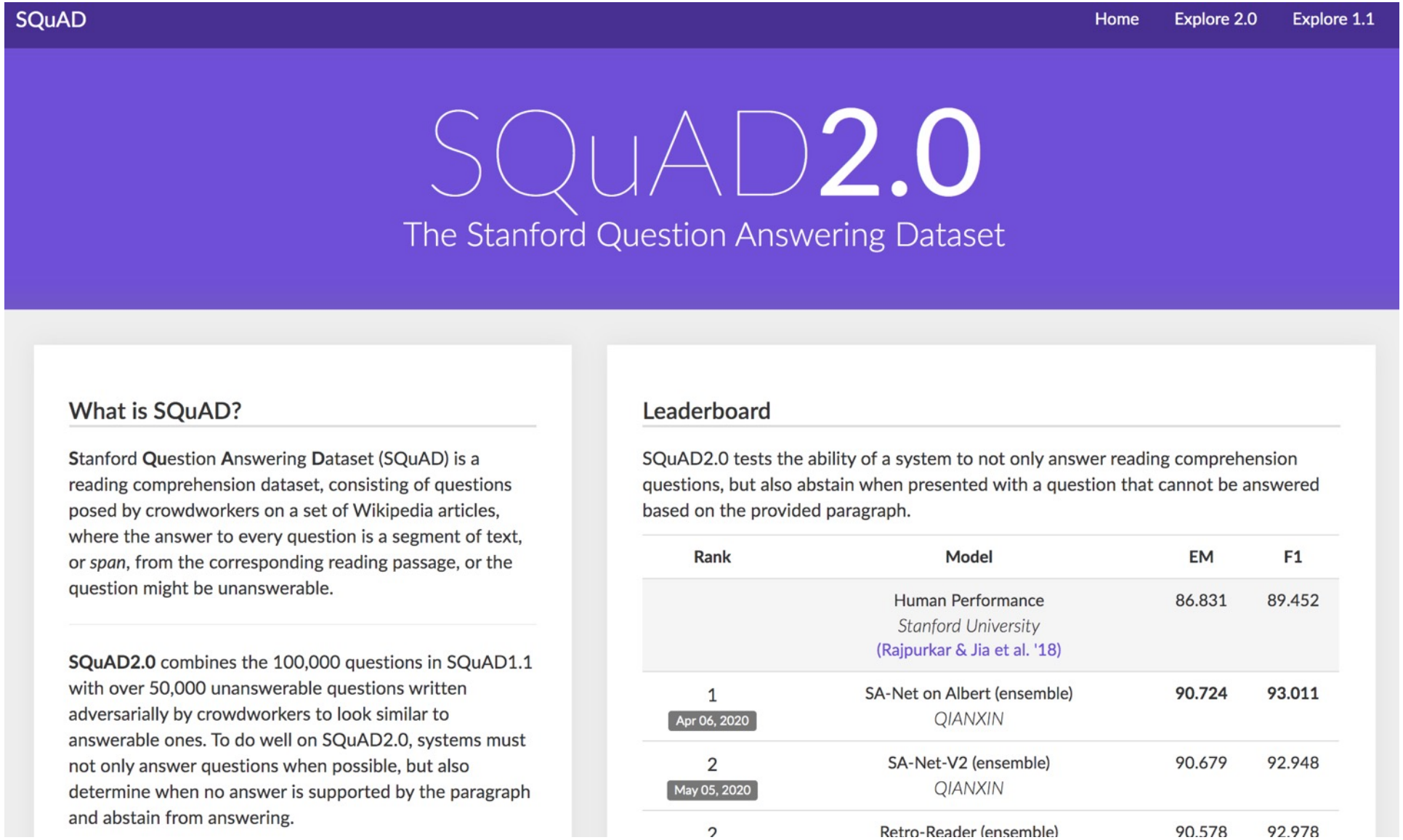
Question Answering

(QA)

SQuAD

Stanford **Qu**estion **A**nswering **D**ataset

SQuAD



https://rajpurkar.github.io/SQuAD-explorer/

SQuAD

SQuAD: 100,000+ Questions for Machine Comprehension of Text

Pranav Rajpurkar and **Jian Zhang** and **Konstantin Lopyrev** and **Percy Liang**
{pranavsr,zjian,klopyrev,pliang}@cs.stanford.edu
Computer Science Department
Stanford University

Abstract

We present the Stanford Question Answering Dataset (SQuAD), a new reading comprehension dataset consisting of 100,000+ questions posed by crowdworkers on a set of Wikipedia articles, where the answer to each question is a segment of text from the corresponding reading passage. We analyze the dataset to understand the types of reasoning required to answer the questions, leaning heavily on dependency and constituency trees. We build a strong logistic regression model, which achieves an F1 score of 51.0%, a significant improvement over a simple baseline (20%). However, human performance (86.8%) is much higher, indicating that the dataset presents a good challenge problem for future research. The dataset is freely available at https://stanford-qa.com.

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called "showers".

What causes precipitation to fall?
gravity

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?
graupel

Where do water droplets collide with ice crystals to form precipitation?
within a cloud

Figure 1: Question-answer pairs for a sample passage in the

Source: Rajpurkar, Pranav, Jian Zhang, Konstantin Lopyrev, and Percy Liang.
"Squad: 100,000+ questions for machine comprehension of text." arXiv preprint arXiv:1606.05250 (2016).

SQuAD (Question Answering)

Q: What causes precipitation to fall?

Precipitation

From Wikipedia, the free encyclopedia

For other uses, see Precipitation (disambiguation).

In meteorology, **precipitation** is any product of the condensation of atmospheric water vapor that falls under gravity from clouds.[2] The main forms of precipitation include drizzle, rain, sleet, snow, ice pellets, graupel and hail. Precipitation occurs when a portion of the atmosphere becomes saturated with water vapor (reaching 100% relative humidity), so that the water condenses and "precipitates". Thus, fog and mist are not precipitation but suspensions, because the water vapor does not condense sufficiently to precipitate. Two processes, possibly acting together, can lead to air becoming saturated: cooling the air or adding water vapor to the air. Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called "showers."[3]

https://en.wikipedia.org/wiki/Precipitation

SQuAD (Question Answering)

Paragraph

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called "showers".

Q: What causes precipitation to fall?

SQuAD (Question Answering)

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called "showers".

Q: What causes precipitation to fall?

A: gravity

SQuAD (Question Answering)

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called "showers".

Q: What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?

A: graupel

SQuAD (Question Answering)

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called "showers".

Q: Where do water droplets collide with ice crystals to form precipitation?

A: within a cloud

SQuAD (Question Answering)

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called "showers".

Q: What causes precipitation to fall?

A: gravity

Q: What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?

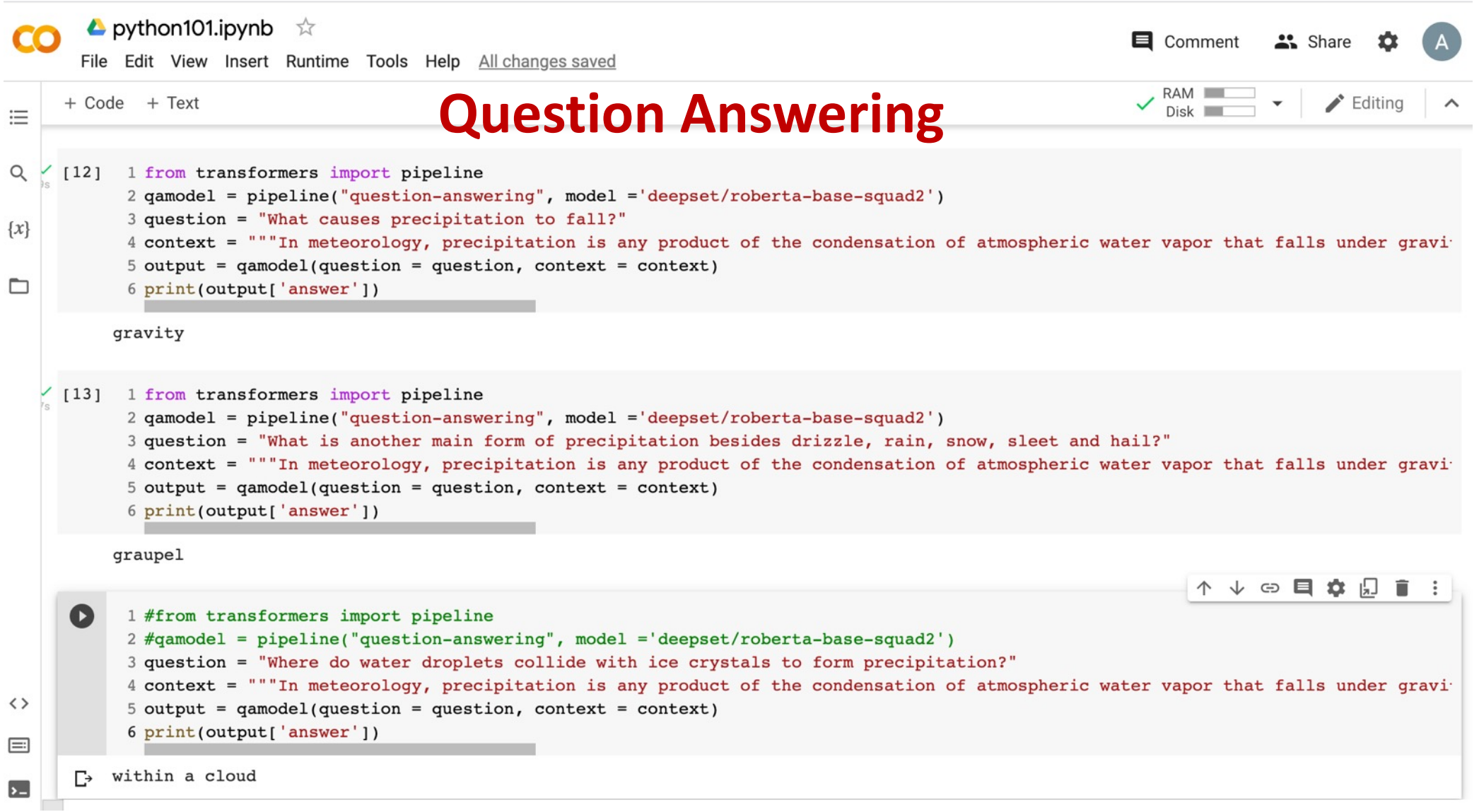
A: graupel

Q: Where do water droplets collide with ice crystals to form precipitation?

A: within a cloud

Python in Google Colab (Python101)

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



https://tinyurl.com/aintpupython101

Question Answering

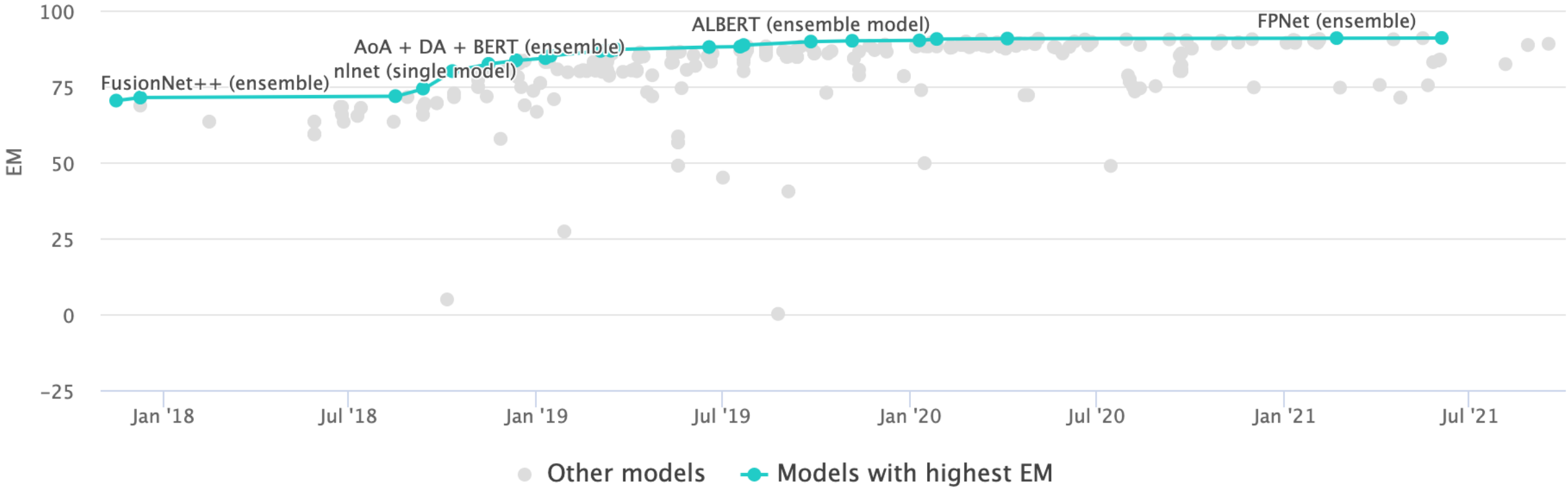
```
from transformers import pipeline
qamodel = pipeline("question-answering", model ='deepset/roberta-base-squad2')
question = "What causes precipitation to fall?"
context = """In meteorology, precipitation is any product of
the condensation of atmospheric water vapor that falls under
gravity. The main forms of precipitation include drizzle,
rain, sleet, snow, graupel and hail... Precipitation forms as
smaller droplets coalesce via collision with other rain drops
or ice crystals within a cloud. Short, intense periods of
rain in scattered locations are called "showers"."""
output = qamodel(question = question, context = context)
print(output['answer'])
```

```
gravity
```

https://tinyurl.com/aintpupython101

Question Answering on SQuAD2.0

SQuAD 2.0 benchmark (Papers with Code)

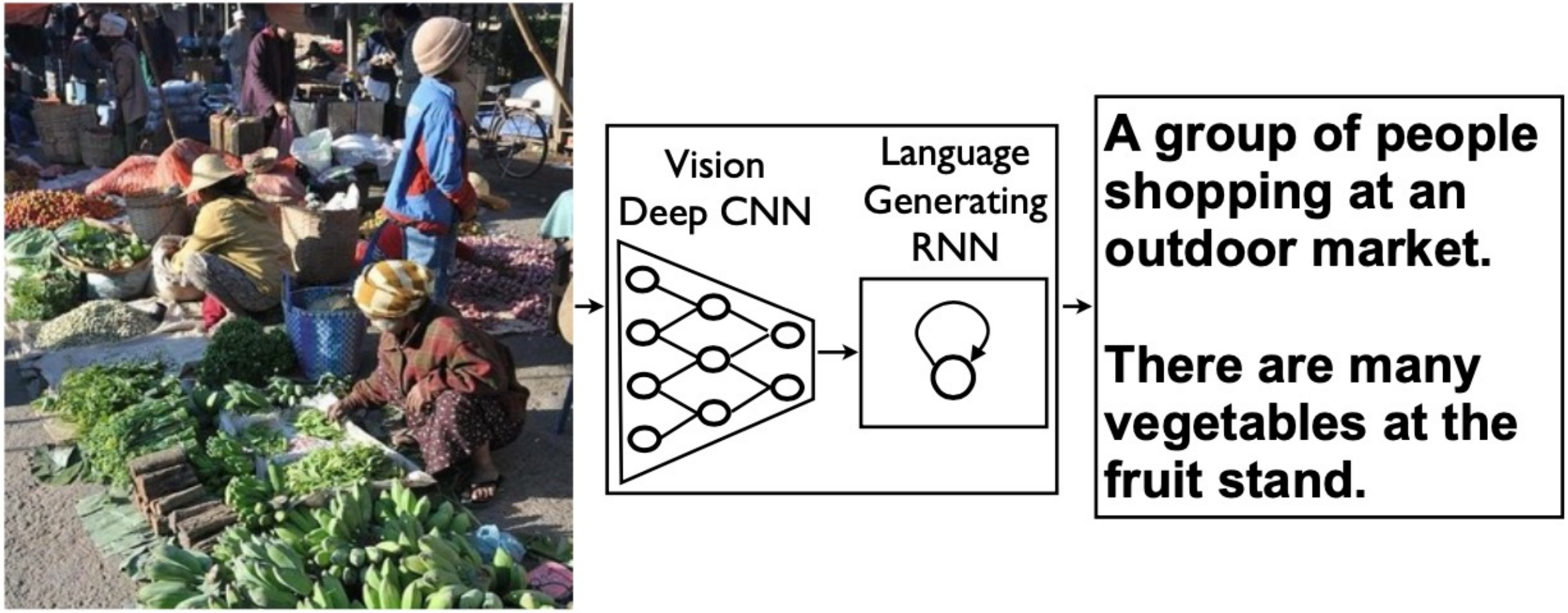


https://paperswithcode.com/sota/question-answering-on-squad20

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

Neural Image Captioning (NIC)

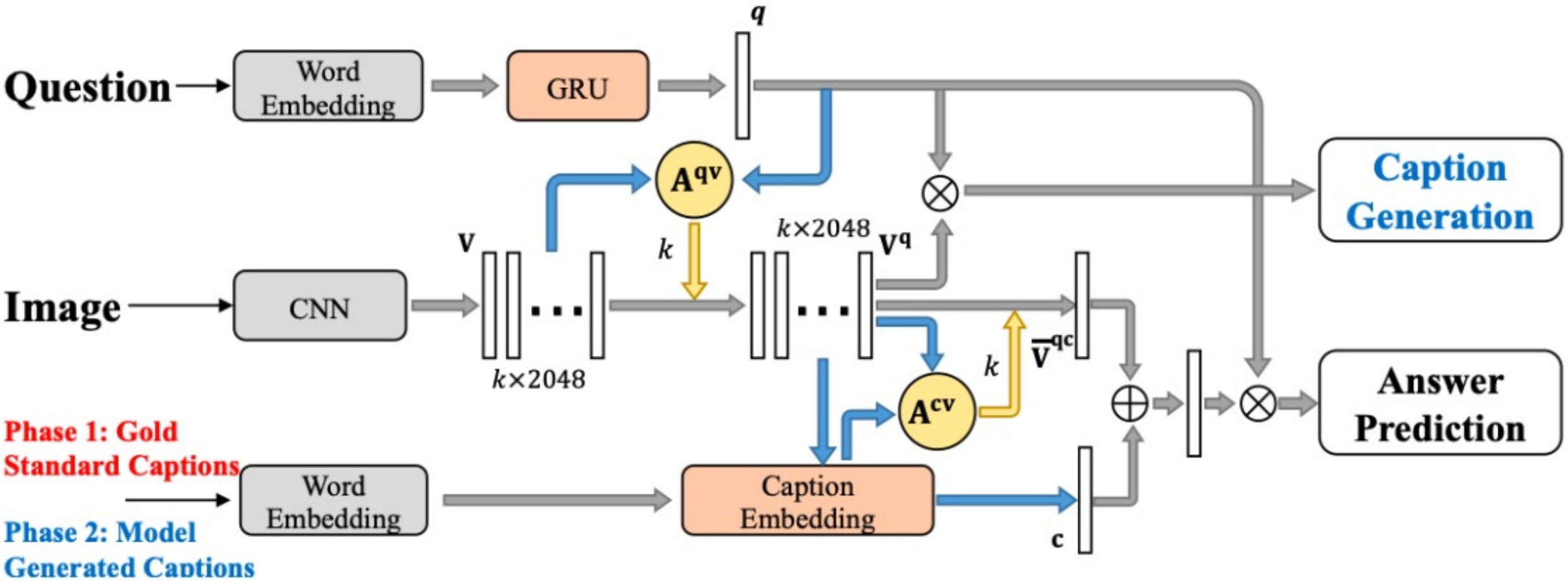
image-to-text description generation



Source: Erkut Erdem, Menekse Kuyu, Semih Yagcioglu, Anette Frank, Letitia Parcalabescu, Barbara Plank, Andrii Babii et al (2022). "Neural Natural Language Generation: A Survey on Multilinguality, Multimodality, Controllability and Learning." Journal of Artificial Intelligence Research 73 (2022): 1131-1207.

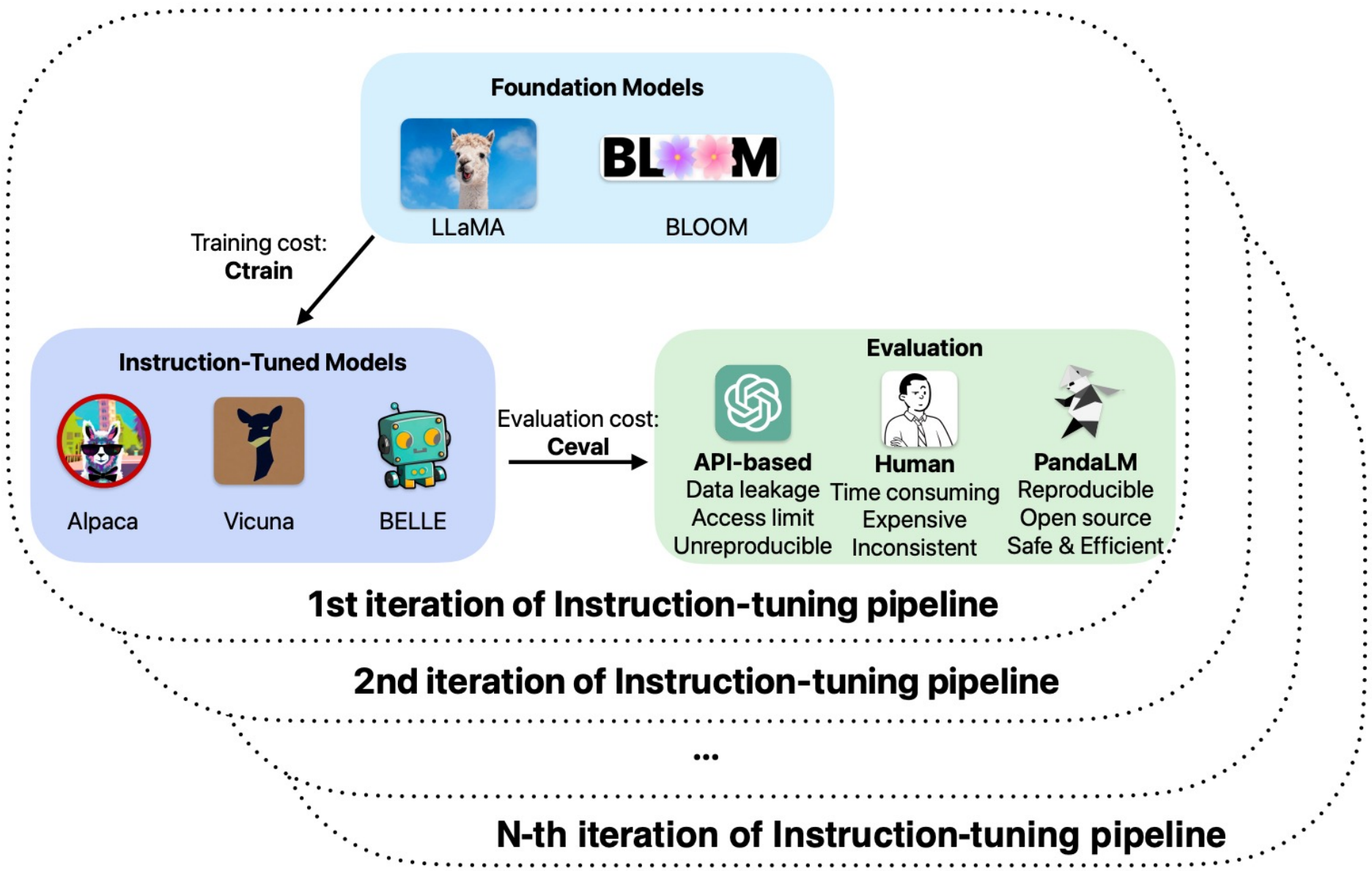
Visual Question Answering

Neural caption generation is employed to aid answer prediction



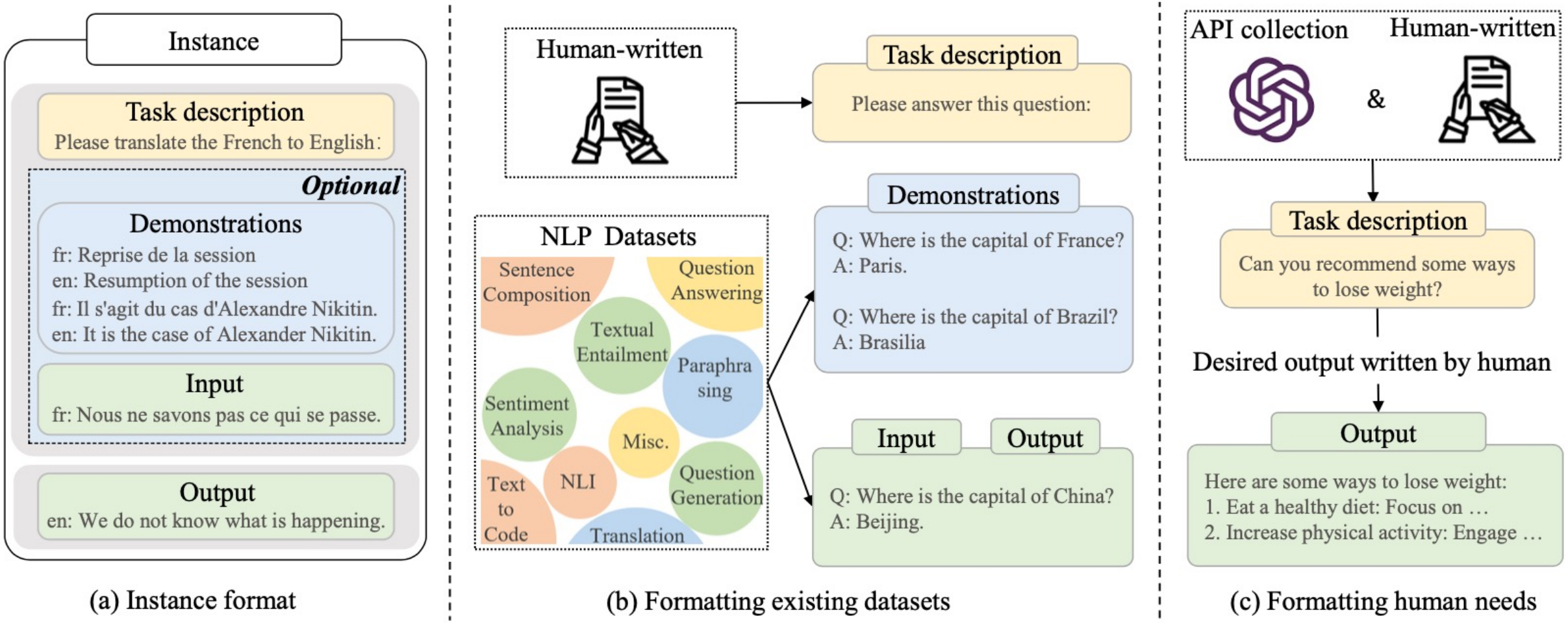
Source: Erkut Erdem, Menekse Kuyu, Semih Yagcioglu, Anette Frank, Letitia Parcalabescu, Barbara Plank, Andrii Babii et al (2022). "Neural Natural Language Generation: A Survey on Multilinguality, Multimodality, Controllability and Learning." Journal of Artificial Intelligence Research 73 (2022): 1131-1207.

Pipeline of Instruction Tuning LLMs



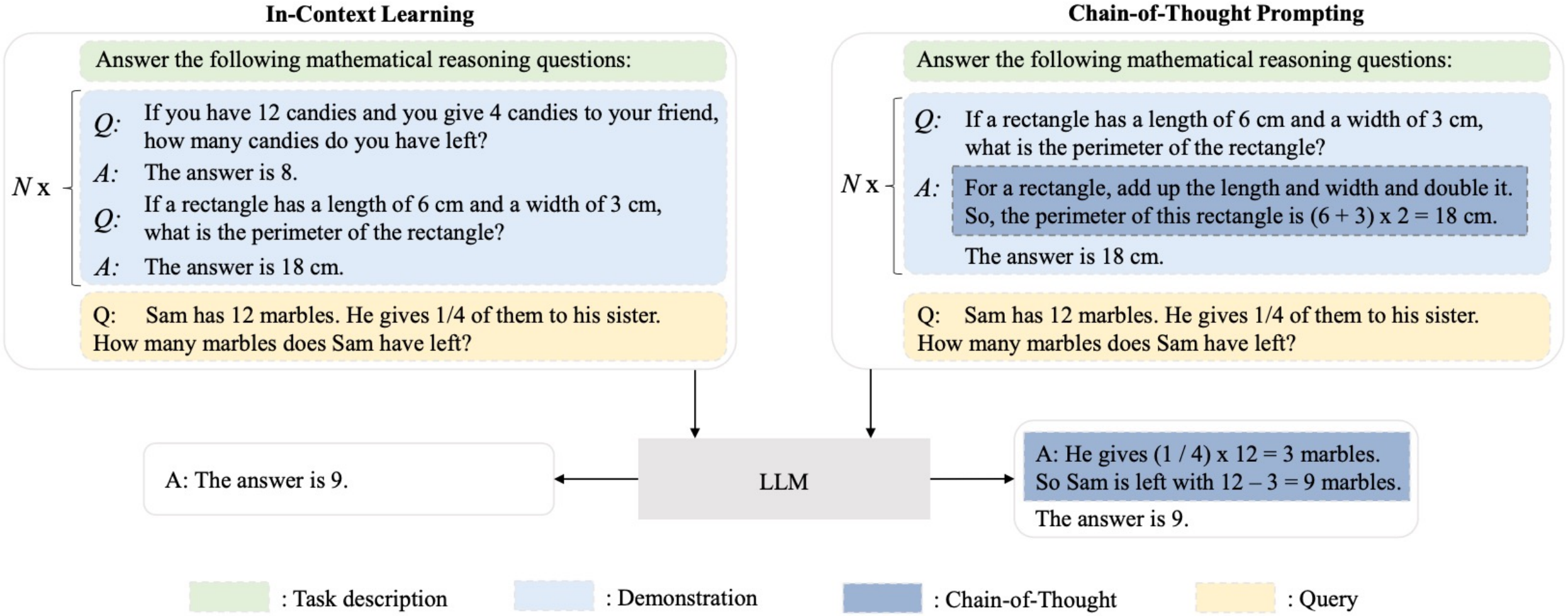
Source: Wang, Yidong, Zhuohao Yu, Zhengran Zeng, Linyi Yang, Cunxiang Wang, Hao Chen, Chaoya Jiang et al. "PandaLM: An Automatic Evaluation Benchmark for LLM Instruction Tuning Optimization." arXiv preprint arXiv:2306.05087 (2023).

Instance Formatting and Two Different Methods for Constructing the Instruction-formatted Instances



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.

In-context Learning (ICL) and Chain-of-thought (CoT) Prompting

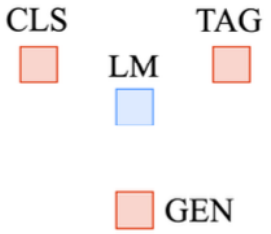
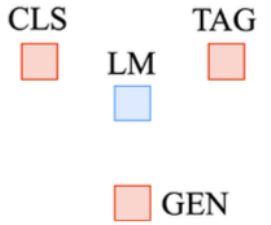
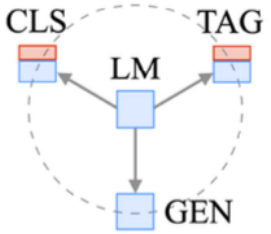
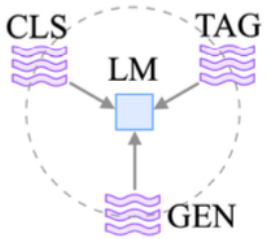


Source: Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min et al. (2023) "A Survey of Large Language Models." arXiv preprint arXiv:2303.18223.

Pre-train, Prompt, and Predict: Prompting Methods in Natural Language Processing (LLMs)

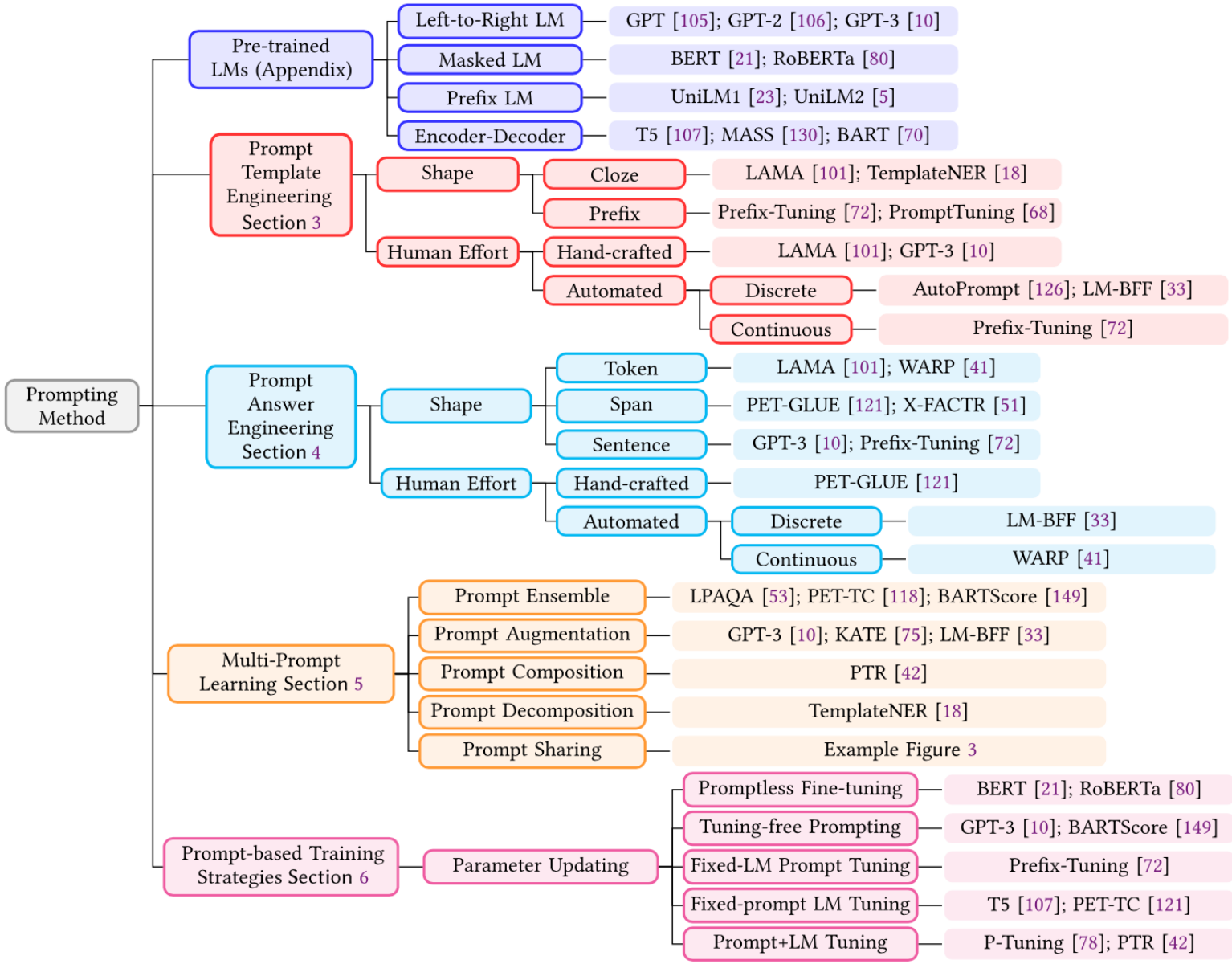
Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

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)	

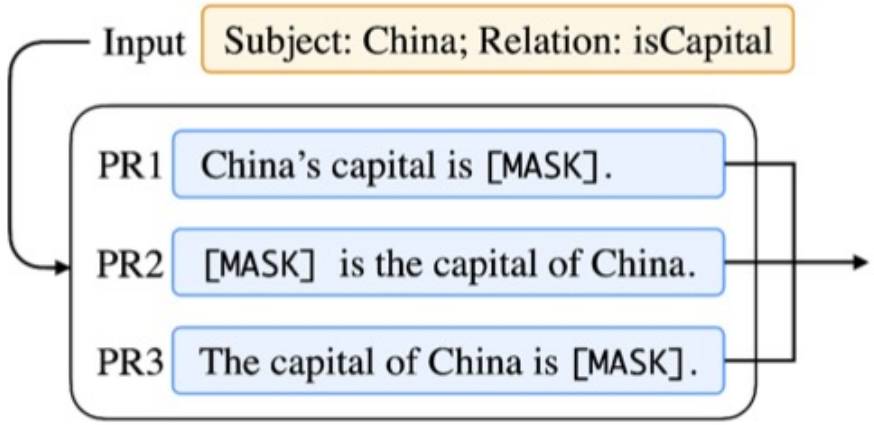
Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

Typology of Prompting Methods

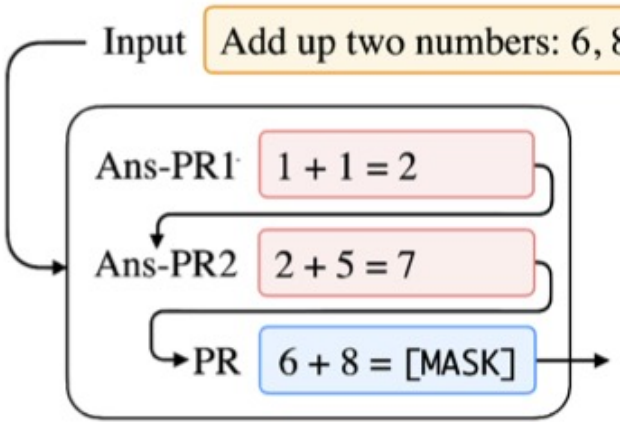


Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

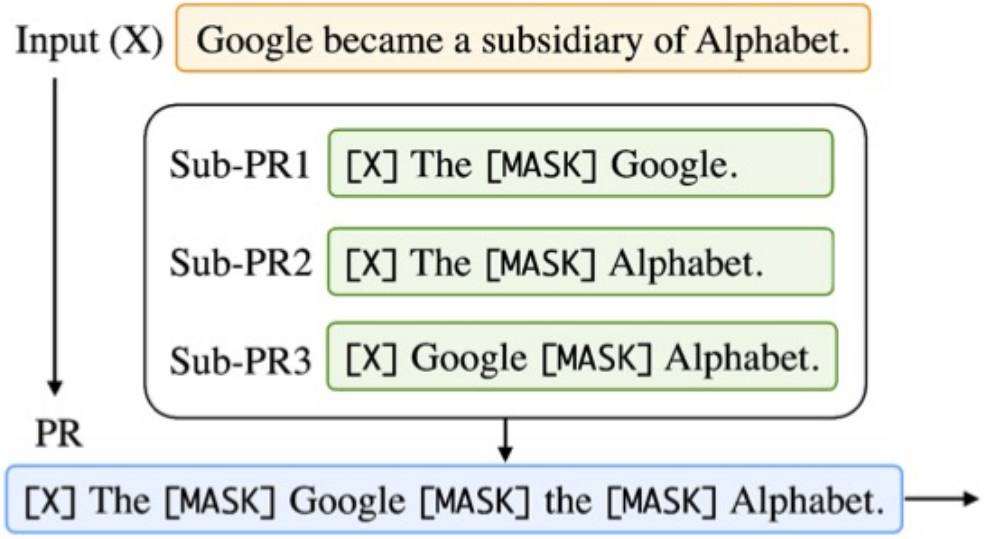
Different Multi-Prompt Learning Strategies



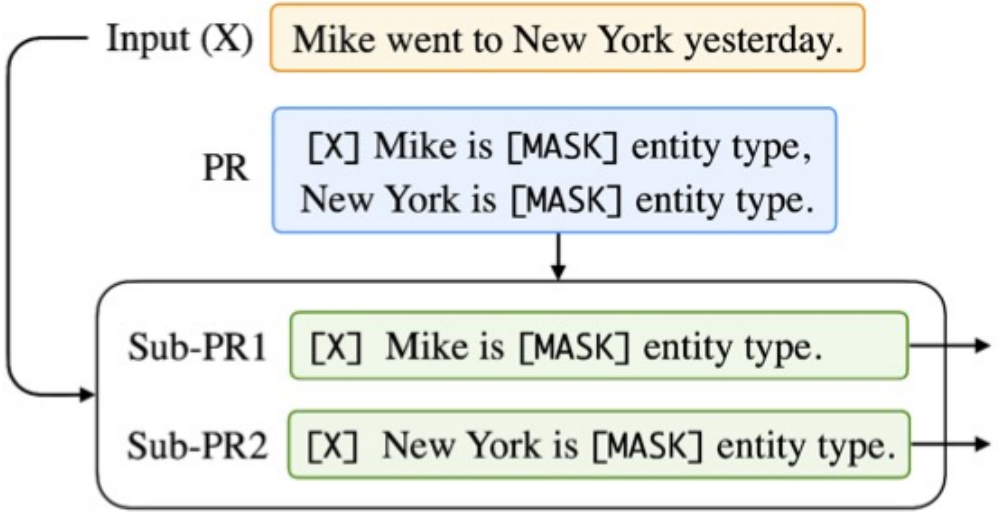
(a) Prompt Ensembling.



(b) Prompt Augmentation.



(c) Prompt Composition.



(d) Prompt Decomposition.

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.

Examples of Input, Template, and Answer for Different Tasks

Type	Task Example	Input ([X])	Template	Answer ([Z])
Text Classification	Sentiment	I love this movie.	[X] The movie is [Z].	great fantastic ...
	Topics	He prompted the LM.	[X] The text is about [Z].	sports science ...
	Intention	What is taxi fare to Denver?	[X] The question is about [Z].	quantity city ...
Text-span Classification	Aspect Sentiment	Poor service but good food.	[X] What about service? [Z].	Bad Terrible ...
Text-pair Classification	Natural Language Inference	[X1]: An old man with ... [X2]: A man walks ...	[X1]? [Z], [X2]	Yes No ...
Tagging	Named Entity Recognition	[X1]: Mike went to Paris. [X2]: Paris	[X1][X2] is a [Z] entity.	organization location ...
Text Generation	Summarization	Las Vegas police ...	[X] TL;DR: [Z]	The victim ... A woman ... ...
	Translation	Je vous aime.	French: [X] English: [Z]	I love you. I fancy you. ...
Regression	Textual Similarity	[X1]: A man is smoking. [X2]: A man is skating.	[X1] [Z], [X2]	Yes No ...

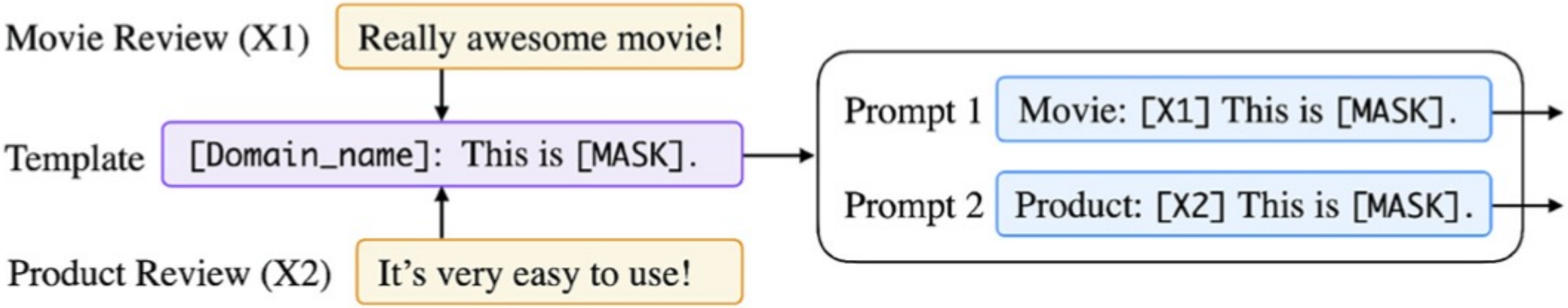
Source: Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. (2023) "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

Characteristics of Different Tuning Strategies

Strategy	LM Params	Prompt Params		Example
		Additional	Tuned	
Promptless Fine-tuning	Tuned	–		ELMo [97], BERT [20], BART [69]
Tuning-free Prompting	Frozen	✗	✗	GPT-3 [9], AutoPrompt [125], LAMA [100]
Fixed-LM Prompt Tuning	Frozen	✓	Tuned	Prefix-Tuning [71], Prompt-Tuning [67]
Fixed-prompt LM Tuning	Tuned	✗	✗	PET-TC [117], PET-Gen [118], LM-BFF [32]
Prompt+LM Fine-tuning	Tuned	✓	Tuned	PADA [5], P-Tuning [77], PTR [41]

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.

Multi-prompt Learning for Multi-task, Multi-domain, or Multi-lingual Learning



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.

GPT Prompt Engineering for Question Answering

- **Find the answer to the question from the given context.**
- **When the question cannot be answered with the given context, say "unanswerable".**
- **Just say the answer without repeating the question.**
- **Context: {context}**
- **Question:{question}**
- **Answer:**

Prompts and QA Inference For FLAN T5 Question Answering

- **Prompts and QA Inference For FLAN T5, we follow [41] and use the following prompt:**
- **Context: {context}\nQuestion: {question}\nAnswer:**

- **Context: {context}**
- **Question: {question}**
- **Answer:**

Prompt Engineering

- **Prompts For FLAN models**
  - Longpre, S., Hou, L., Vu, T., Webson, A., Chung, H. W., Tay, Y., ... & Roberts, A. (2023). The flan collection: Designing data and methods for effective instruction tuning. *arXiv preprint arXiv:2301.13688*.
- **MNLI, NLI-FEVER, VitaminC:**
  - **"Premise: {premise}\n\nHypothesis: {hypothesis}\n\nDoes the premise entail the hypothesis?\n\nA yes\nB it is not possible to tell\nC no"**
- **ANLI:**
  - **"{context}\n\nBased on the paragraph above can we conclude that\"{hypothesis}\"?\n\nA Yes\nB It's impossible to say\nC No"**
- **SNLI:**
  - **"If \"{premise}\", does this mean that \"{hypothesis}\"?\n\nA yes\nB it is not possible to tell\nC no"**

Dialogue Systems

Fine-tuning LLM for Dialogue System

Reinforcement Learning from Human Feedback (RLHF)

ChatGPT: Optimizing Language Models for Dialogue

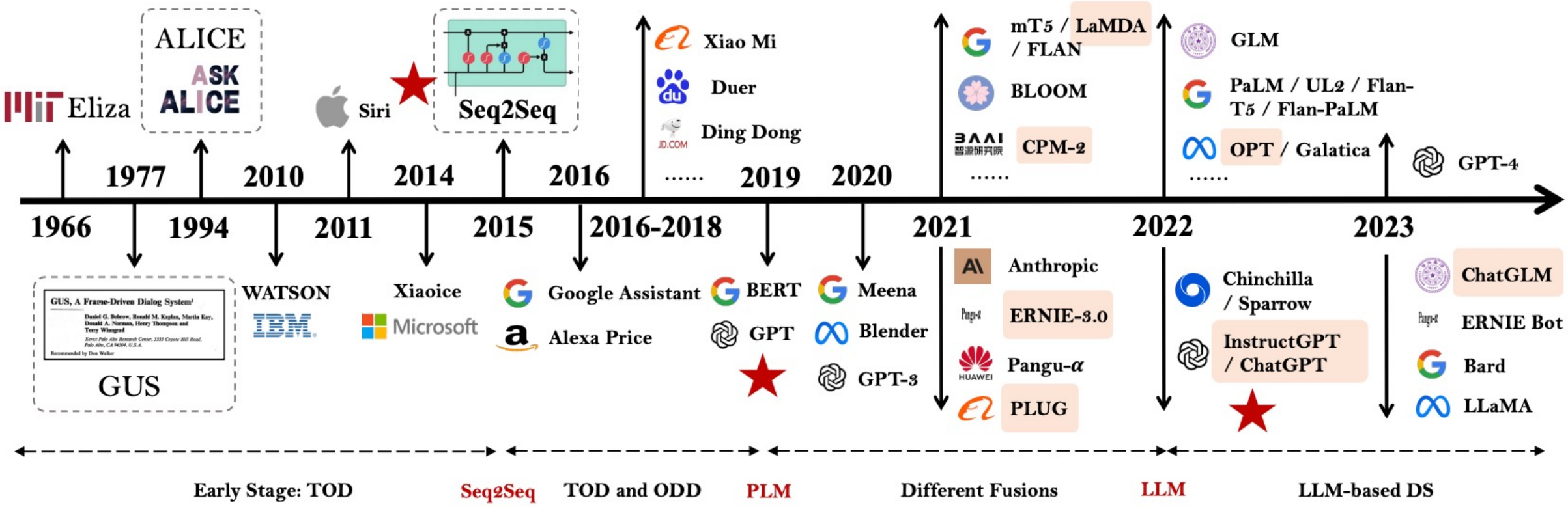
Chatbot

Dialogue System

Intelligent Agent

The Development of LM-based Dialogue Systems

1) Early Stage (1966 - 2015)
2) The Independent Development of TOD and ODD (2015 - 2019)
3) Fusions of Dialogue Systems (2019 - 2022)
4) LLM-based DS (2022 - Now)



Task-oriented DS (TOD), Open-domain DS (ODD)

Source: Wang, Hongru, Lingzhi Wang, Yiming Du, Liang Chen, Jingyan Zhou, Yufei Wang, and Kam-Fai Wong. "A Survey of the Evolution of Language Model-Based Dialogue Systems." arXiv preprint arXiv:2311.16789 (2023).

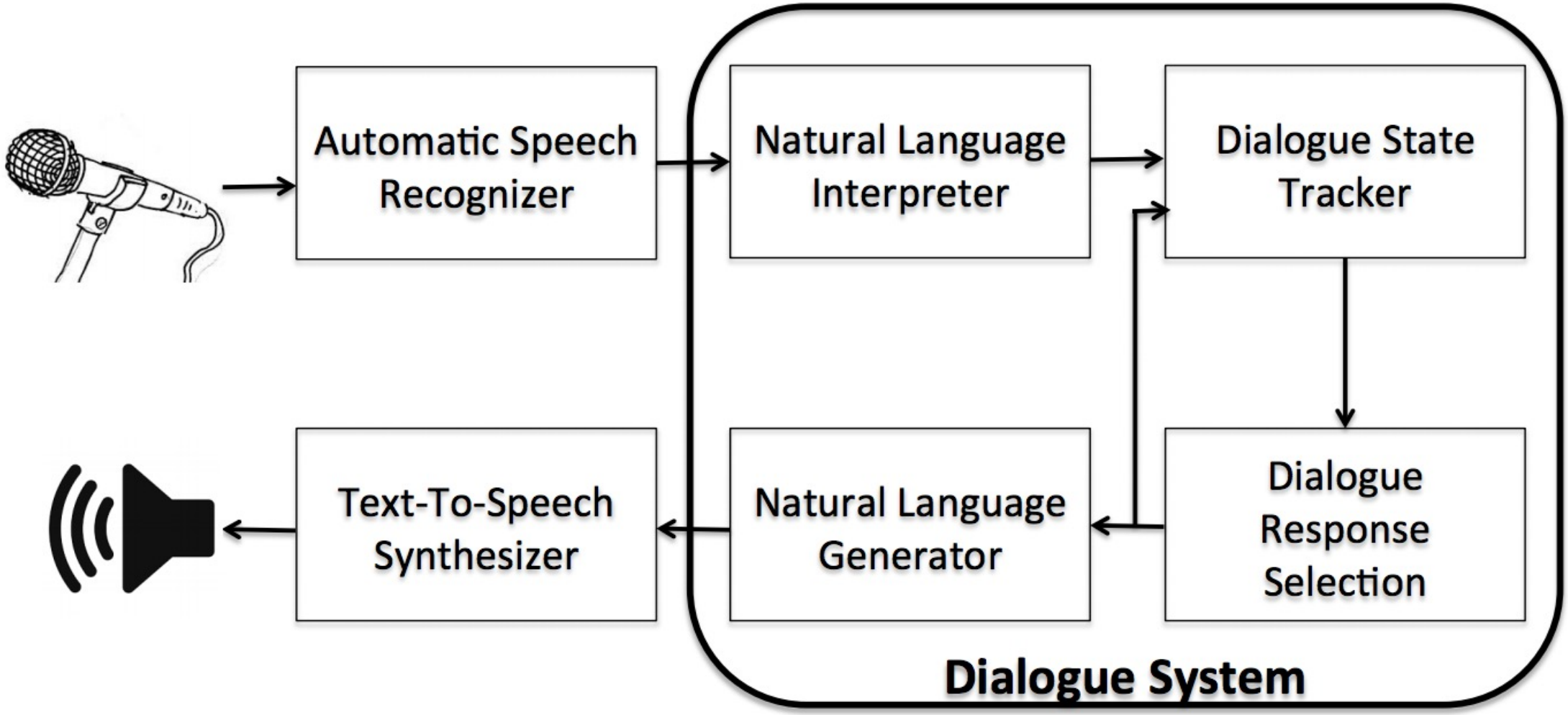
Dialogue System

Different types of dialogues in Task-oriented DS (TOD) and Open-domain DS (ODD)

Types of DS	**Types of Dialogues**	**User message** (*U*)	**System response** (*S*)	**External knowledge** (*K*)
Task-oriented DS (TOD)	Task-oriented	I need to find a nice restaurant in Madrid that serves expensive Thai food	There is a restaurant called Bangkok City located at 9 Red Ave.	Restaurant database
Open-domain DS (ODD)	Social Chit-Chat	How are you going ?	I am good. And you?	-
	KG Chit-Chat	I like watching action movies	Here are some action movies from various eras and styles that you might enjoy: *Inception*, *The Avengers*	Movie KG
	Question Answering	Do you know which team wins the 2022 World Cup?	The Argentina team	Wikipedia

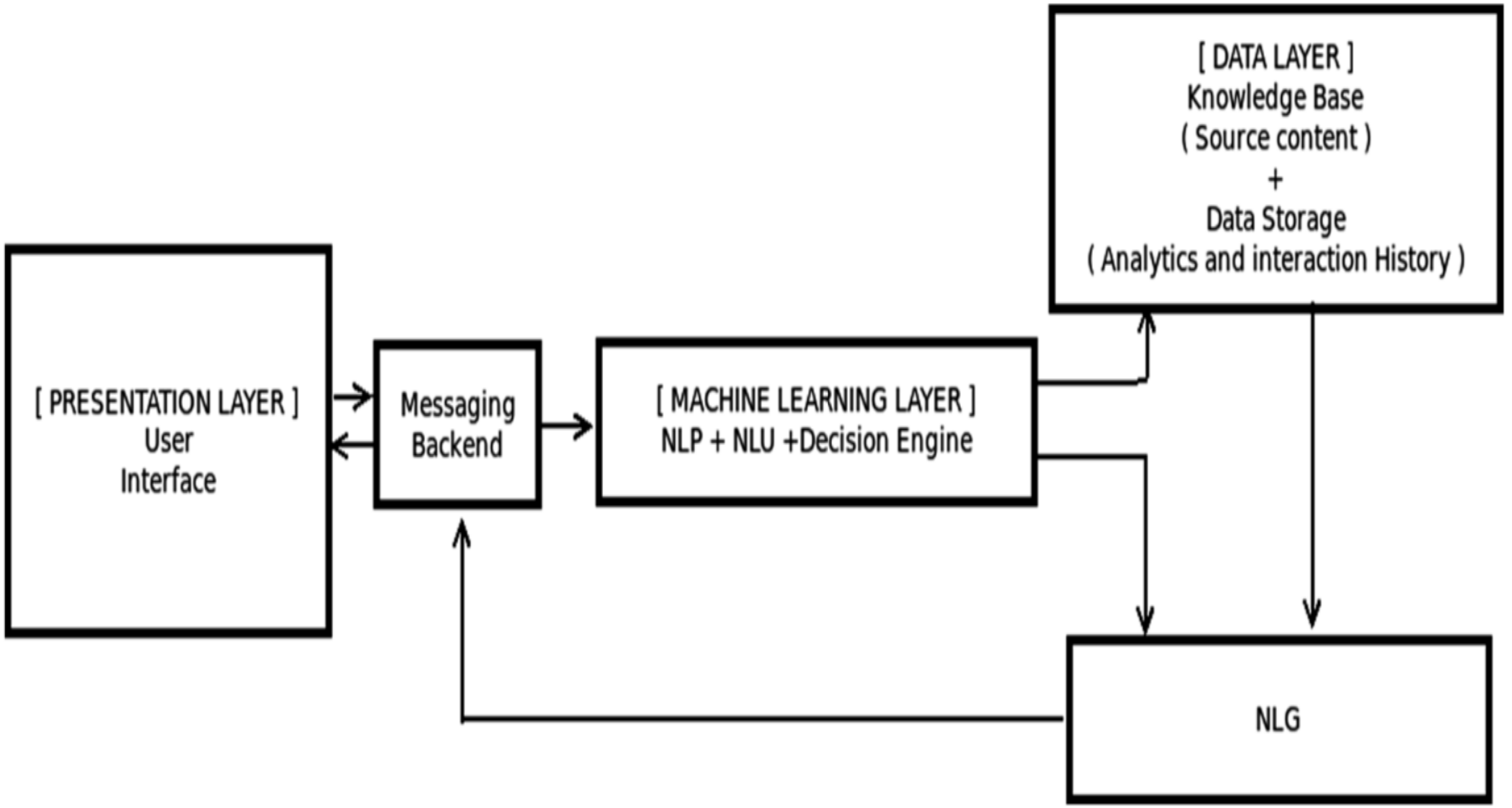
Source: Wang, Hongru, Lingzhi Wang, Yiming Du, Liang Chen, Jingyan Zhou, Yufei Wang, and Kam-Fai Wong. "A Survey of the Evolution of Language Model-Based Dialogue Systems." arXiv preprint arXiv:2311.16789 (2023).

Dialogue System



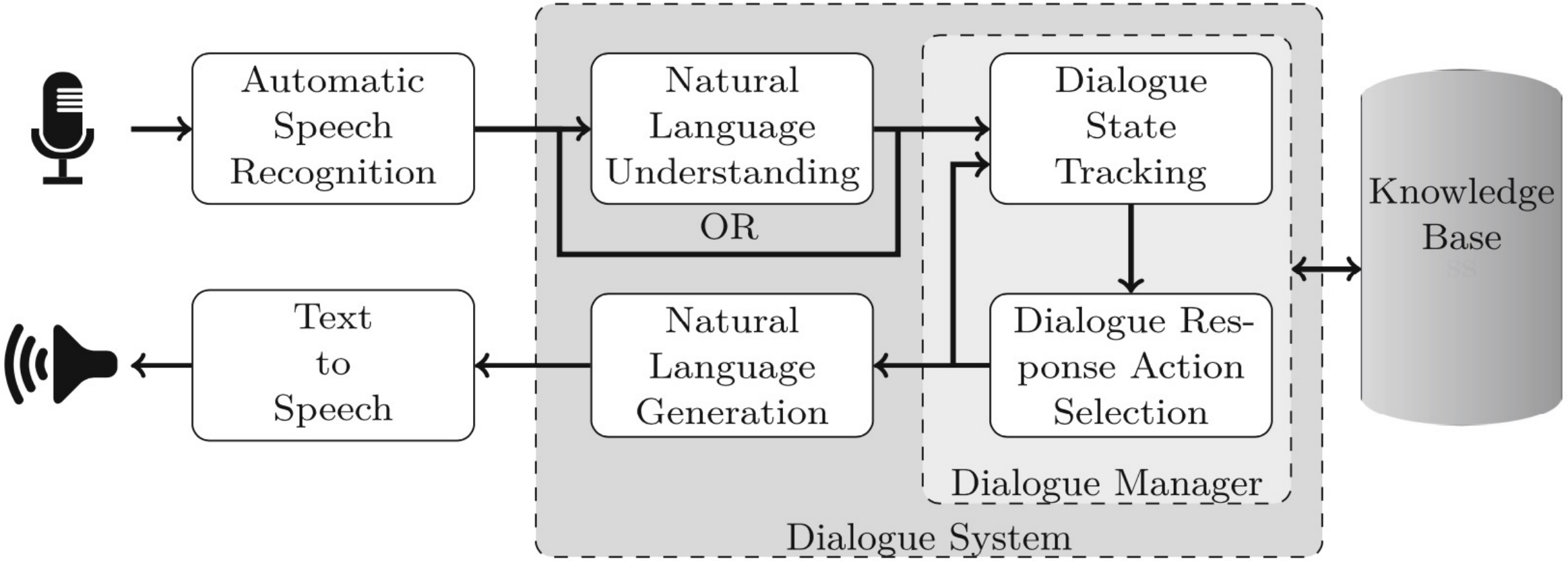
Source: Serban, I. V., Lowe, R., Charlin, L., & Pineau, J. (2015). A survey of available corpora for building data-driven dialogue systems. *arXiv preprint arXiv:1512.05742*.

Overall Architecture of Intelligent Chatbot



Source: Borah, Bhriguraj, Dhrubajyoti Pathak, Priyankoo Sarmah, Bidisha Som, and Sukumar Nandi. "Survey of Textbased Chatbot in Perspective of Recent Technologies." In International Conference on Computational Intelligence, Communications, and Business Analytics, pp. 84-96. Springer, Singapore, 2018.

Modular Speech-based Dialogue System



Source: Kath, Hannes, Bengt Lüers, Thiago S. Gouvêa, and Daniel Sonntag. "Lost in Dialogue: A Review and Categorisation of Current Dialogue System Approaches and Technical Solutions." In German Conference on Artificial Intelligence (Künstliche Intelligenz), pp. 98-113. Cham: Springer Nature Switzerland, 2023.

Categories of Dialogue Systems:

Task-Oriented Dialogue System (TDS)

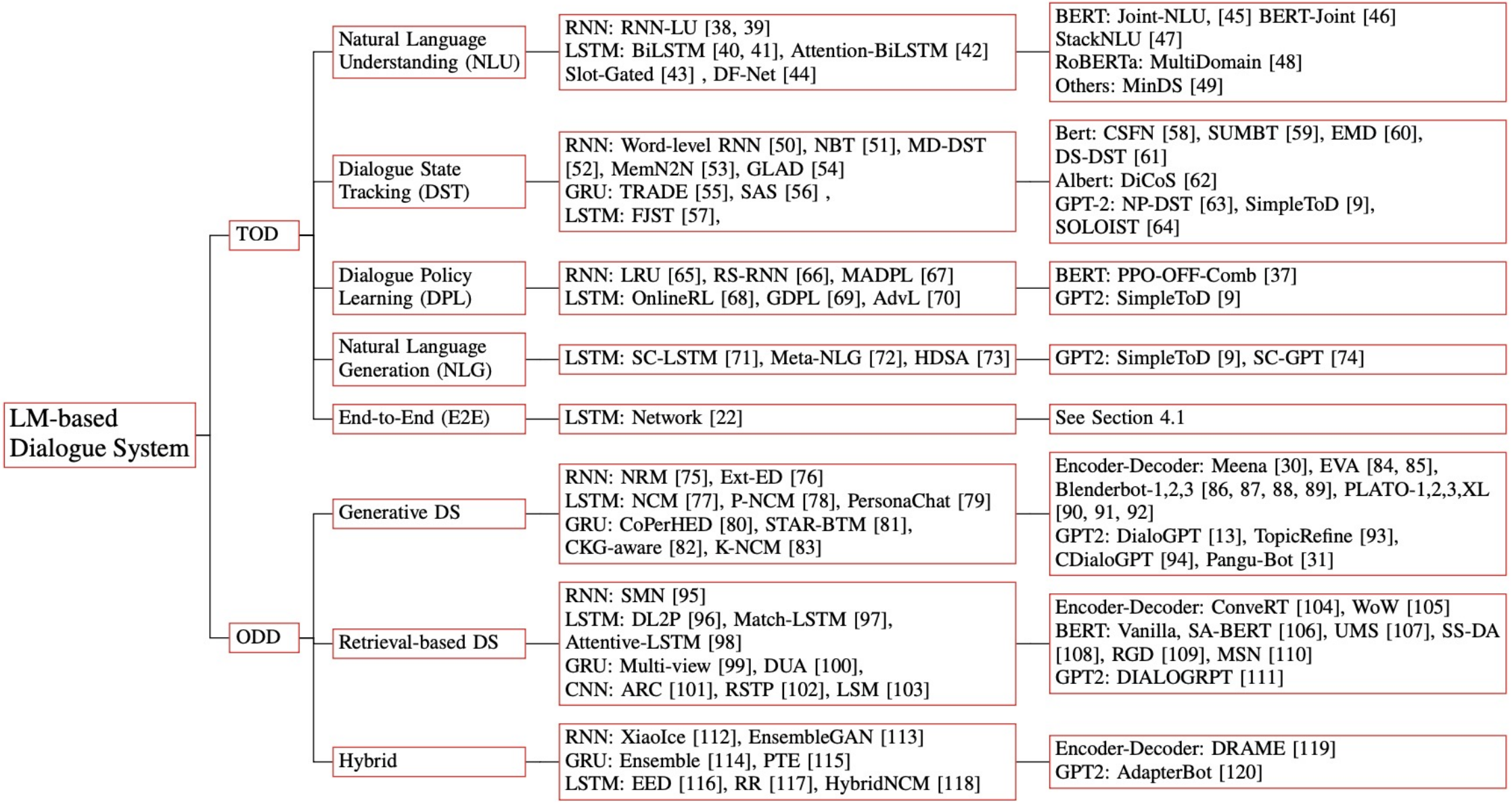
Conversational Dialogue System (CDS)

Question Answering Dialogue System (QADS)

Objective	Modality	Domain	Architecture	Model
TDS	text/speech/multi	single/multi	modular	rule/statistical/neural
CDS	text/speech/multi	open	end-to-end	neural
QADS	text	multi/open	modular/end-to-end	rule/statistical/neural

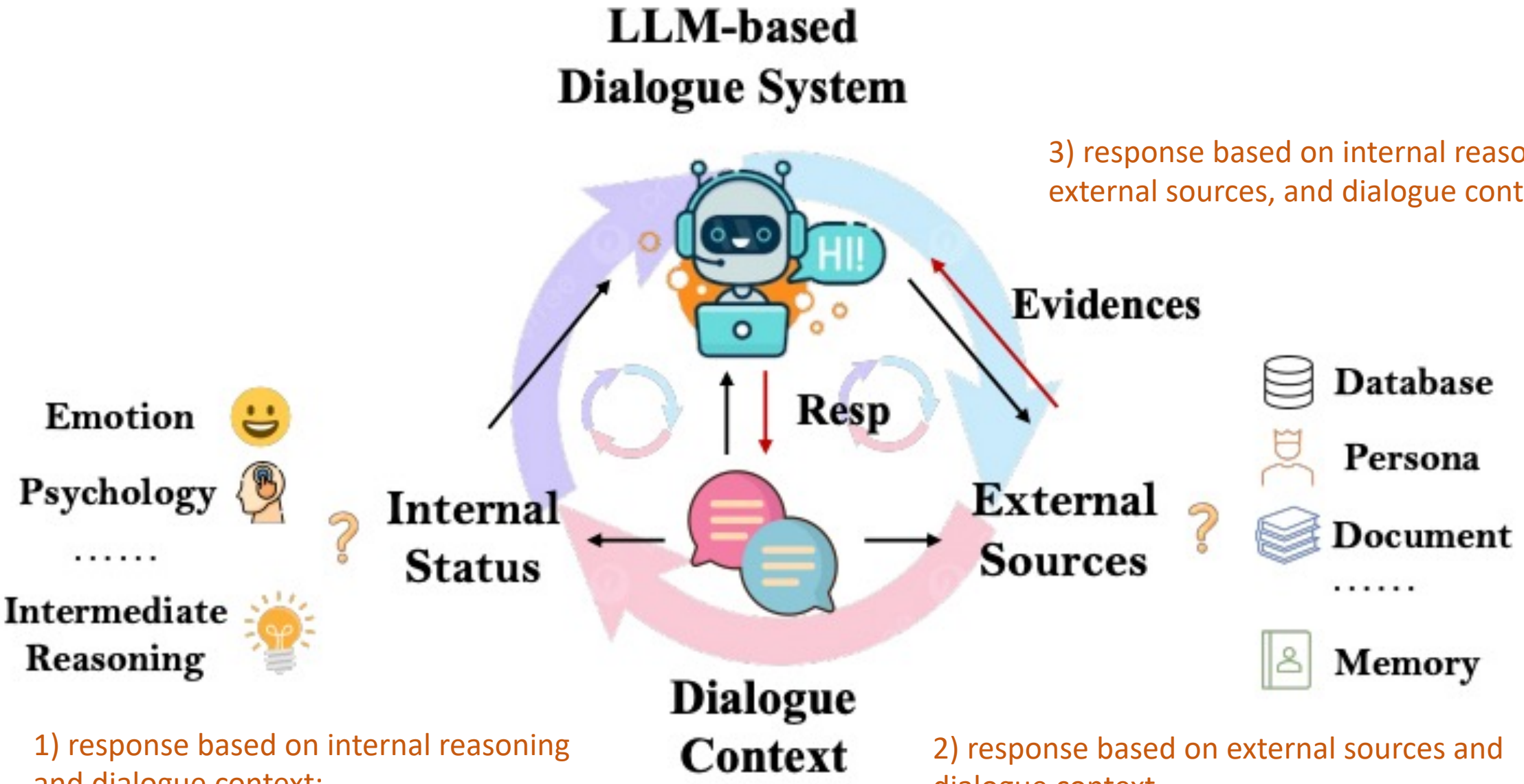
Source: Kath, Hannes, Bengt Lüers, Thiago S. Gouvêa, and Daniel Sonntag. "Lost in Dialogue: A Review and Categorisation of Current Dialogue System Approaches and Technical Solutions." In German Conference on Artificial Intelligence (Künstliche Intelligenz), pp. 98-113. Cham: Springer Nature Switzerland, 2023.

Taxonomy of LM-based Dialogue System



Source: Wang, Hongru, Lingzhi Wang, Yiming Du, Liang Chen, Jingyan Zhou, Yufei Wang, and Kam-Fai Wong. "A Survey of the Evolution of Language Model-Based Dialogue Systems." arXiv preprint arXiv:2311.16789 (2023).

LLM-based Dialogue System



3) response based on internal reasoning, external sources, and dialogue context

1) response based on internal reasoning and dialogue context;

2) response based on external sources and dialogue context

Source: Wang, Hongru, Lingzhi Wang, Yiming Du, Liang Chen, Jingyan Zhou, Yufei Wang, and Kam-Fai Wong. "A Survey of the Evolution of Language Model-Based Dialogue Systems." arXiv preprint arXiv:2311.16789 (2023).

Dialogue Subtasks

Browse SoTA > Natural Language Processing > Dialogue

Dialogue subtasks

Dialogue Generation

Dialogue Generation

9 benchmarks

78 papers with code

Dialogue State Tracking

2 benchmarks

51 papers with code

Task-Oriented Dialogue Systems

Task-Oriented Dialogue Systems

2 benchmarks

48 papers with code

Visual Dialog

8 benchmarks

37 papers with code

Goal-Oriented Dialog

1 benchmark

20 papers with code

Dialogue Management

12 papers with code

Dialogue Understanding

11 benchmarks

8 papers with code

Dialogue Act Classification

2 benchmarks

8 papers with code

Short-Text Conversation

Short-Text Conversation

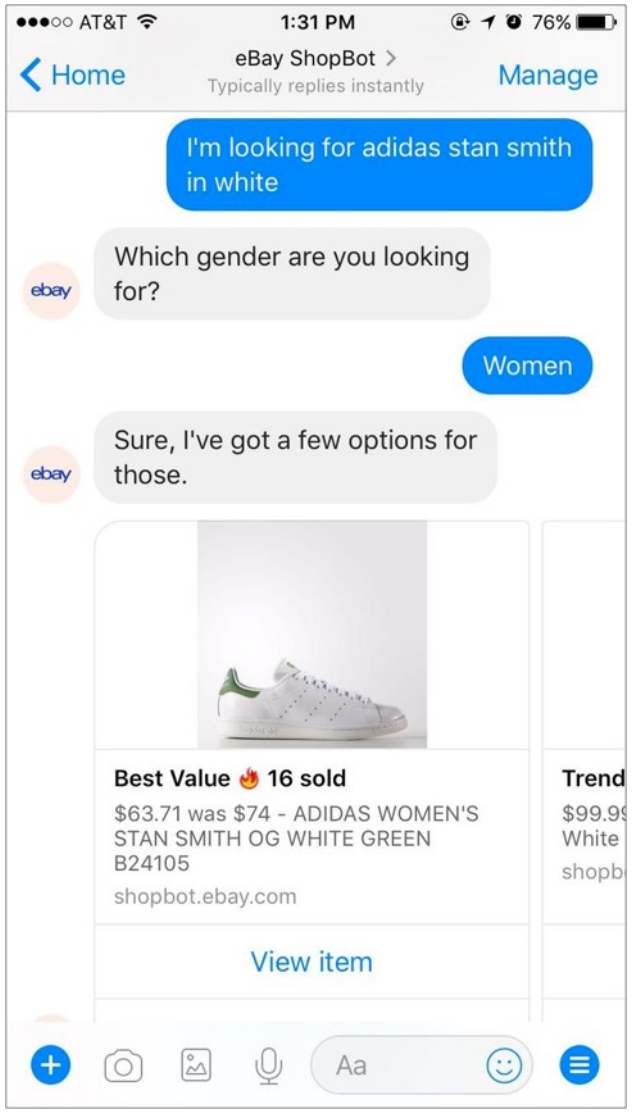
7 papers with code

Goal-Oriented Dialogue Systems

7 papers with code

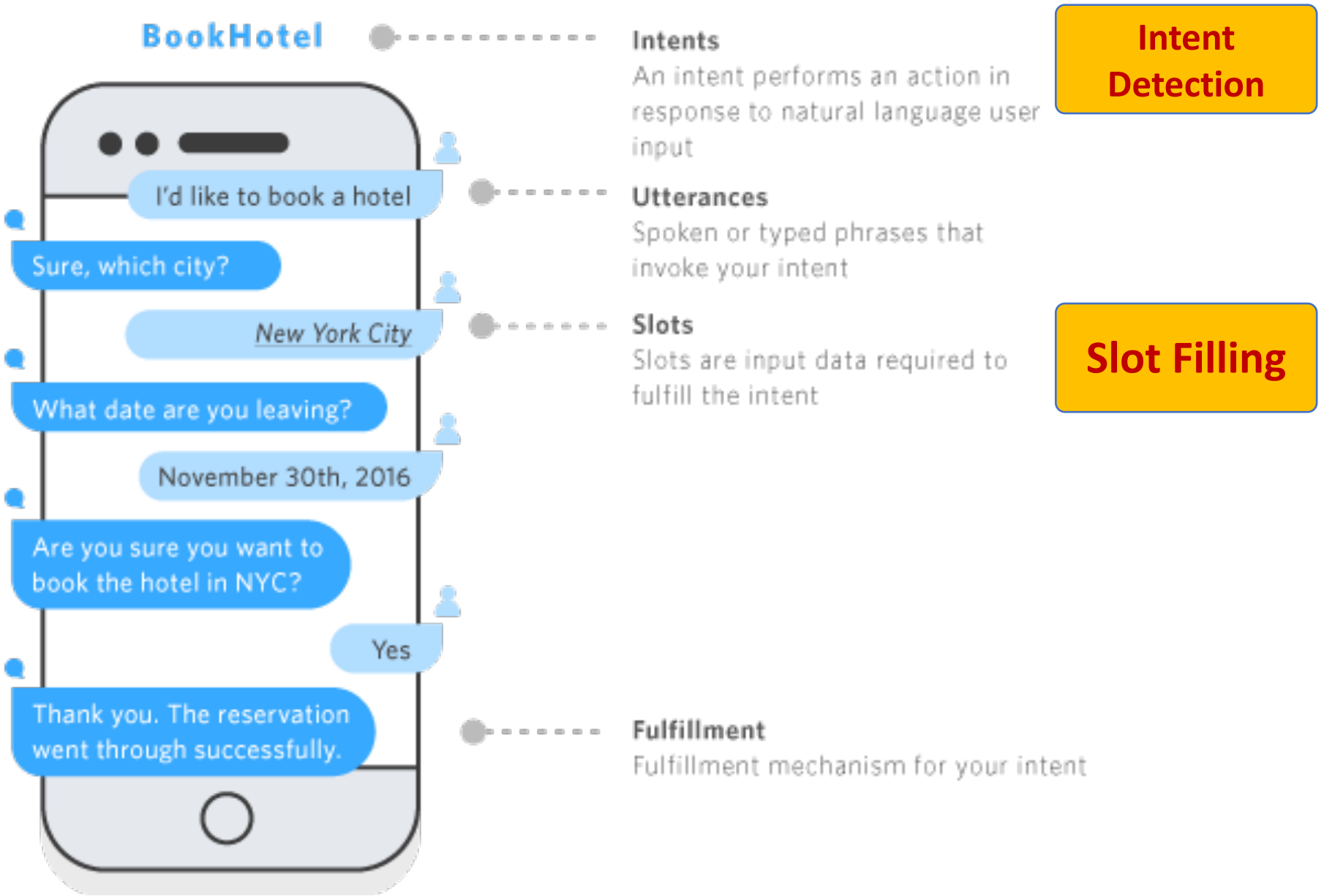
Source: https://paperswithcode.com/area/natural-language-processing/dialogue

Conversational Commerce: eBay AI Chatbots



Source: https://www.forbes.com/sites/rachelarthur/2017/07/19/conversational-commerce-ebay-ai-chatbot/

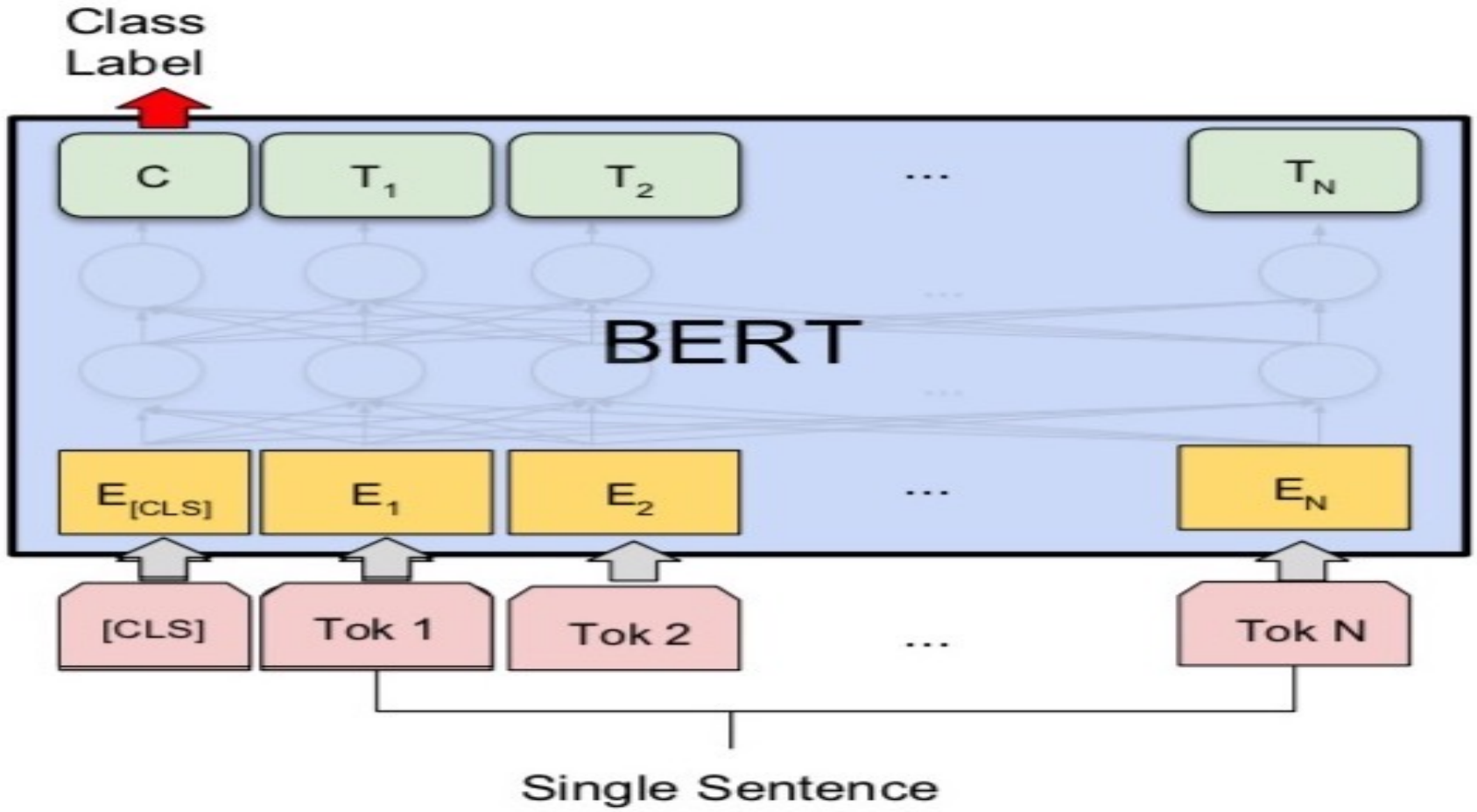
Hotel Chatbot



Source: https://sdtimes.com/amazon/guest-view-capitalize-amazon-lex-available-general-public/

Fine-tuning BERT on Dialogue

Intent Detection (ID; Classification)

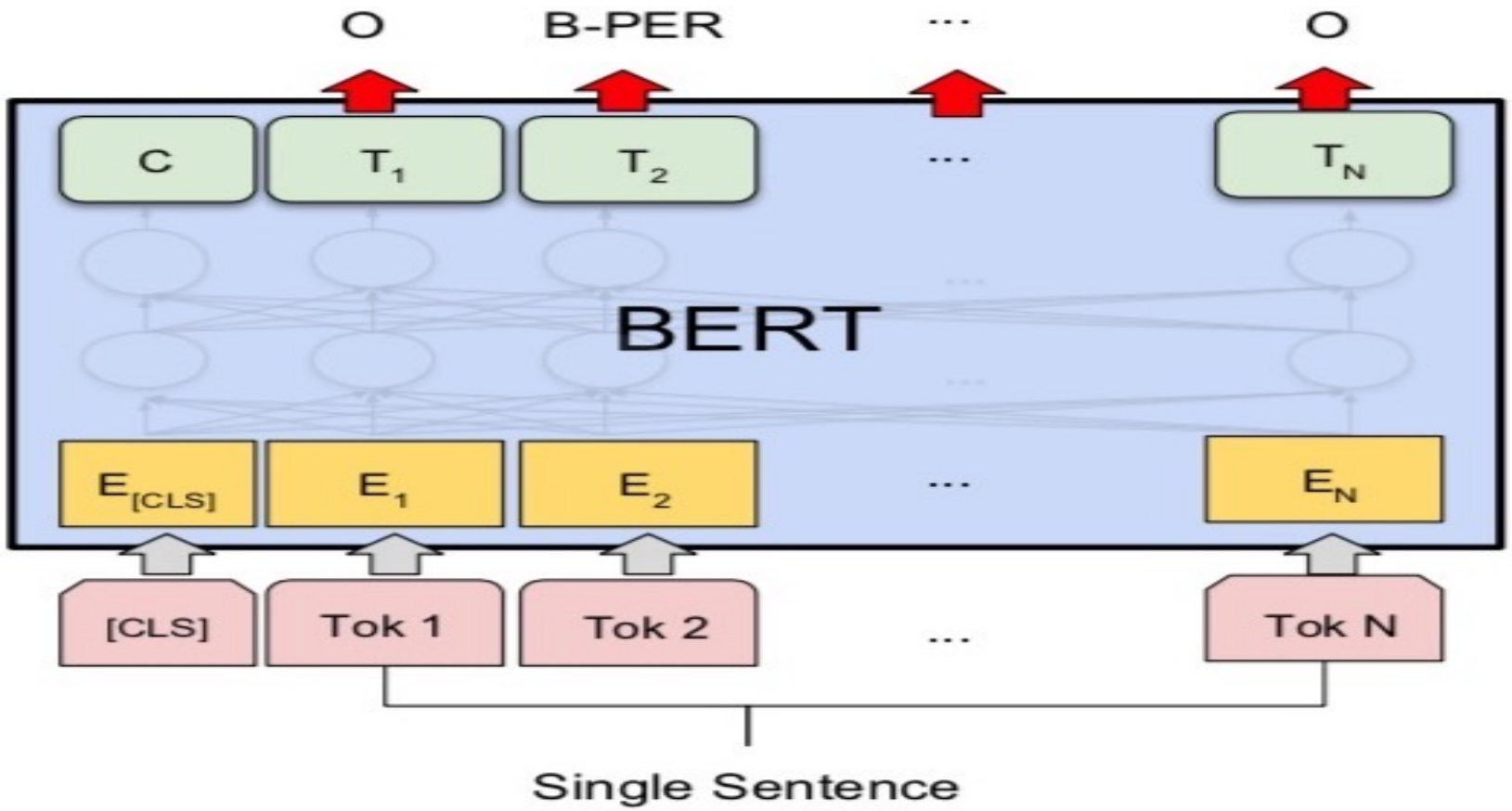


(b) Single Sentence Classification Tasks: SST-2, CoLA

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.

Fine-tuning BERT on Dialogue

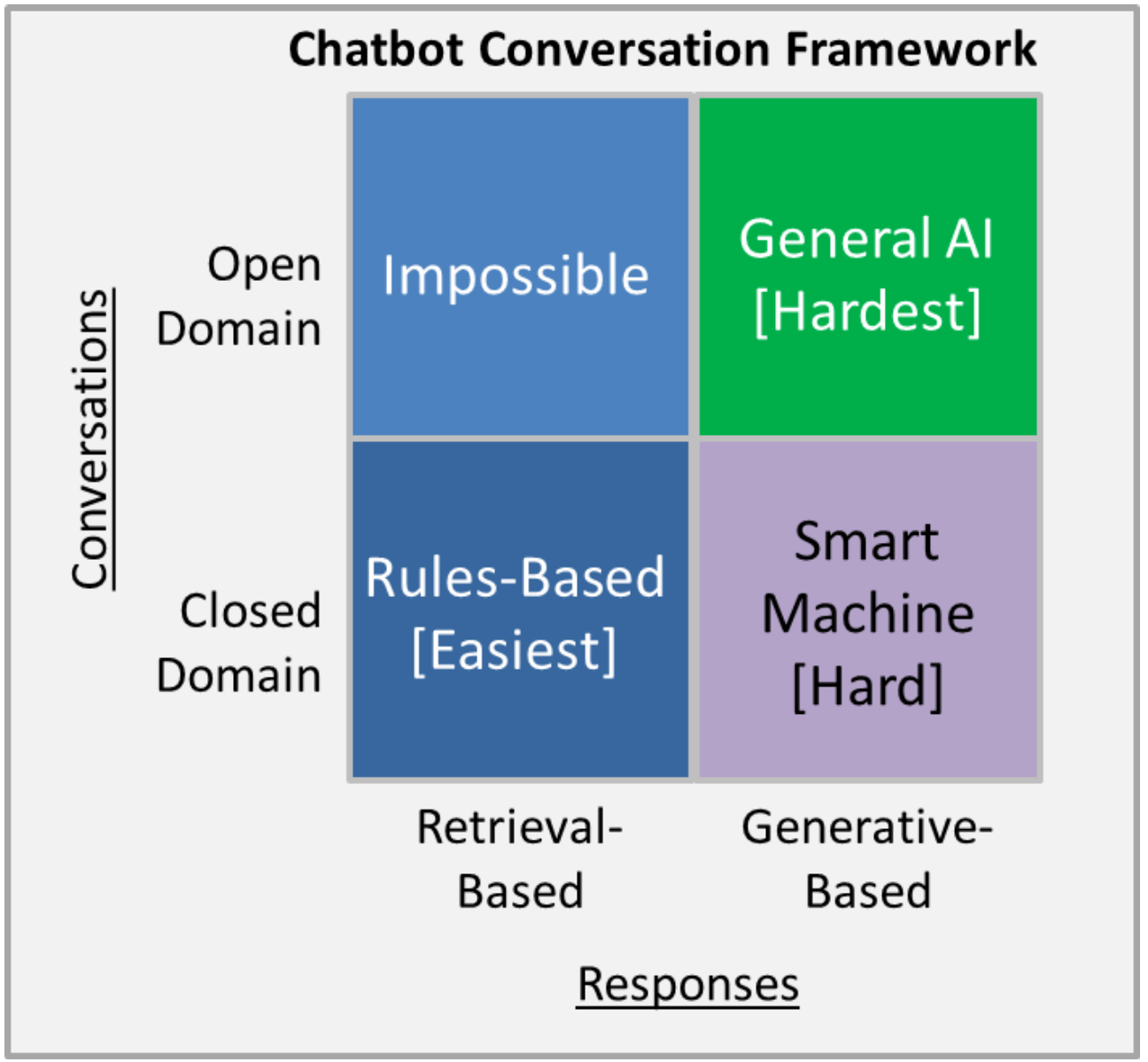
Slot Filling (SF)



(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.

Chatbot Conversation Framework

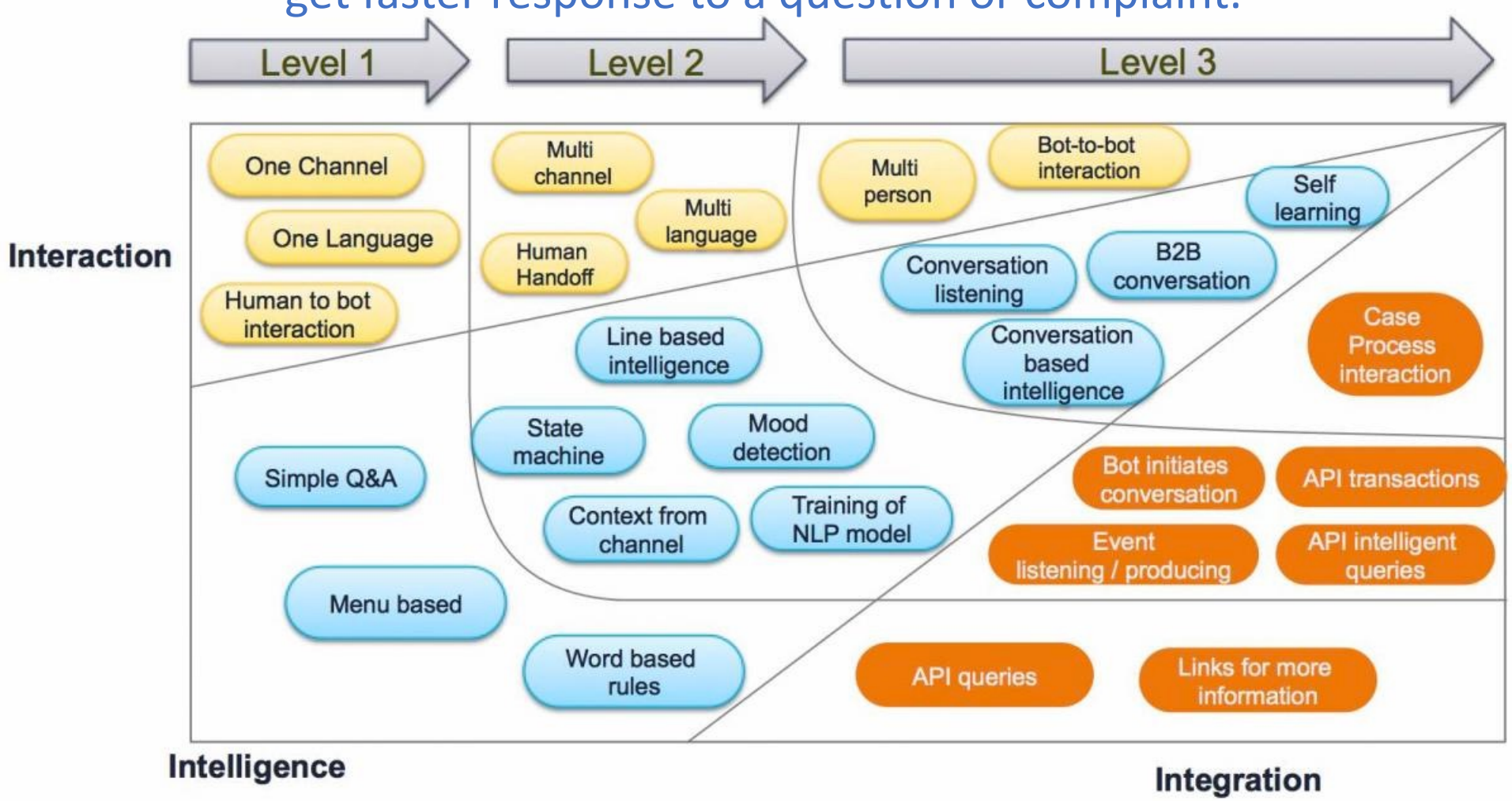


Source: https://chatbotslife.com/ultimate-guide-to-leveraging-nlp-machine-learning-for-you-chatbot-531ff2dd870c

Chatbots

Bot Maturity Model

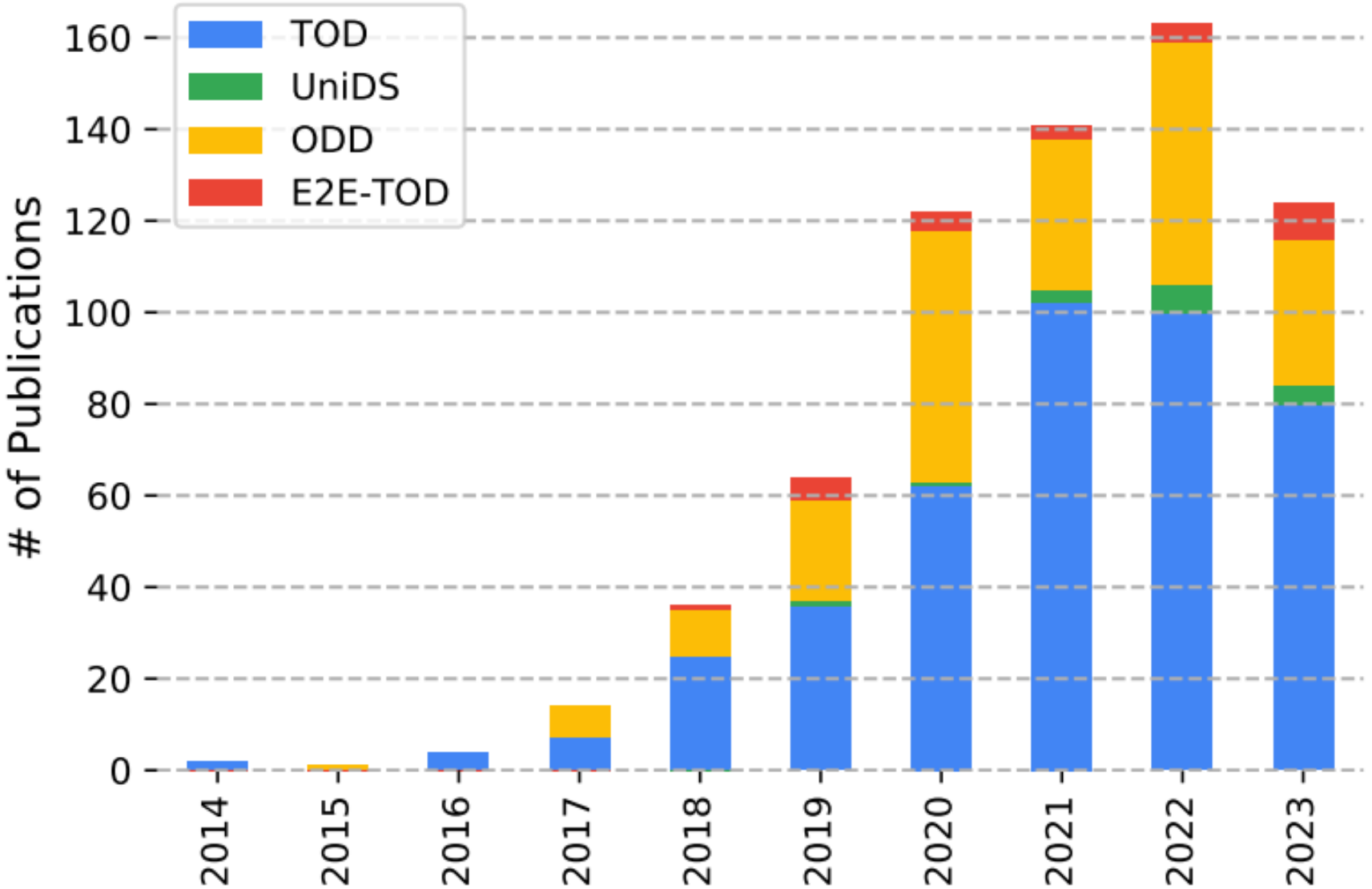
Customers want to have simpler means to interact with businesses and get faster response to a question or complaint.



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

LM-based Dialogue Systems

The number of publication at ACL Anthology conferences of different research directions in LM-based dialogue systems



Source: Wang, Hongru, Lingzhi Wang, Yiming Du, Liang Chen, Jingyan Zhou, Yufei Wang, and Kam-Fai Wong. "A Survey of the Evolution of Language Model-Based Dialogue Systems." arXiv preprint arXiv:2311.16789 (2023).

End-to-End (E2E) Task-oriented Dialogue System

Model	Year	Base Model	NLU	DST	DPL	NLG	Add Tasks*	Add Data	Evaluation Dataset
NN [22]	2017	LSTM, RNN, CNN	✓	✓	✓	✓	✗	✗	Wizard-of-Oz Data
MOSS [154]	2019	GRU	✓	✓	✓	✓	✗	✗	CamRest676, LaptopNetwork
MinTL [161]	2020	T5, BART		✓		✓	✗	✗	MultiWOZ 2.0
SimpleTOD [162]	2020	GPT2		✓	✓	✓	✗	✗	MultiWOZ 2.0
SOLOIST [64]	2021	GPT2		✓		✓	Cont	✓	CamRest676, MultiWOZ 2.0
UBAR [163]	2021	DistilGPT2		✓	✓	✓	✗	✗	MultiWOZ 2.0, 2.1
MTTOD [164]	2021	T5		✓		✓	SP	✗	MultiWOZ 2.0, 2.1
AuGPT [159]	2021	GPT2		✓		✓	BC, SAC, IC	✓	MultiWOZ 2.0, 2.1
GALAXY [156]	2022	UniLM			✓	✓	RS, CR	✓	In-Car, MultiWOZ 2.0, 2.1
PPTOD [155]	2022	T5	✓	✓	✓	✓	✗	✓	MultiWOZ 2.0 2.1
OPERA [160]	2022	T5				✓	QA	✗	OB-MultiWOZ
SPACE-3 [157]	2022	UniLM	✓		✓	✓	MLM,SRM	✓	MultiWOZ, CamRest676, In-Car

Source: Wang, Hongru, Lingzhi Wang, Yiming Du, Liang Chen, Jingyan Zhou, Yufei Wang, and Kam-Fai Wong. "A Survey of the Evolution of Language Model-Based Dialogue Systems." arXiv preprint arXiv:2311.16789 (2023).

High-level of fusion between TOD and ODD

Task-oriented DS (TOD)
Open-domain DS (ODD)

Model	Task	Type of ODD	Knowledge sources			Training method
			Database	Web	PLMs	
Q-TOD [135]	TOD	✗	✓	✗	✗	End-to-end
Internet-Augmented [88]	ODD	KG Chit-Chat	✗	✓	✗	End-to-end
UniDS [134], FusedChat [170] SalesBot [168]	TOD + ODD	Chit-Chat	✓	✗	✗	End-to-end
HyKnow [173], KETOD [169]	TOD + ODD	KG Chit-Chat	✓	✓	✗	End-to-end
GODEL [153]	TOD + ODD	Question Answering, KG Chit-Chat	✓	✓	✗	End-to-end
DuClarifyDial [8]	TOD + ODD	Chit-Chat, Question Answering, KG Chit-Chat	✓	✓	✗	End-to-end
MDS [174]	TOD + ODD	Question Answering	✓	✓	✗	End-to-end
OPERA [160]	TOD + ODD	Question Answering	✓	✓	✓	End-to-end
DialogStudio [133]	TOD + ODD	Dial-Sum, NLU, Conv-Rec, KG Chit-Chat	✓	✓	✗	End-to-end

Source: Wang, Hongru, Lingzhi Wang, Yiming Du, Liang Chen, Jingyan Zhou, Yufei Wang, and Kam-Fai Wong. "A Survey of the Evolution of Language Model-Based Dialogue Systems." arXiv preprint arXiv:2311.16789 (2023).

Dialogue Models based on Large Language Models

Dialogue Models	Release Date	Base Model	# of Params	Window size	Trainig Tokens	Language Preference	Source Type
BlenderBot3[89]	Aug, 2022	OPT	3B/30B/175B	✗	180B	EN	Open
ChatGPT	Dec, 2022	GPT3.5 [176]	175B	4k/16k	✗	EN	Closed
Bing Chat	Feb, 2023	GPT4 [177]	✗	8k/32k	✗	EN	Closed
LLaMA-Chat [35]	Feb, 2023	LLaMA	7B/13B/33B/65B	2k	1.4T	EN	Open
Alpaca [178]	Mar, 2023	LLaMA	7B	2k	1.4T	EN	Open
Vicuna [179]	Mar, 2023	LLaMA	7B/13B	2k	1.4T	EN	Open
ChatGLM [180]	Mar, 2023	GLM	6B/12B	2k	1T	CN	Open
Slack	Mar, 2023	Claude	✗	200k	2.0T	EN	Closed
Bard	Mar, 2023	PALM	540B	✗	✗	EN	Closed
Falcon-Chat [181]	Jun, 2023	Falcon	7.5B/40B/180B	2k	1.5T/1T/3.5T	EN	Open
MPT-Chat [182]	Jun, 2023	MPT	7B/30B	8k	1T	EN	Closed
InternLM-Chat [183]	Jun, 2023	InternLM	7B/20B	8k	2.3T	CN	Open
Baichuan-Chat [184],	Jun, 2023	Baichuan	7B/13B/53B	4k	1.2T	CN	Open (7B/13B)
ChatGLM2 [180]	Jun, 2023	GLM	6B/12B	32k	1T	CN	Open
LLaMA2-Chat [185]	Jul, 2023	LLaMA2	7B/13B/34B/70B	4k	2.0T	EN	Open
Atom-Chat	Aug, 2023	LLaMA2	7B/13B	4k	1.0T	CN	Open
Qwen-Chat [186]	Aug, 2023	QWen	7B/14B	8k	2.4T	CN	Open
Baichuan2-Chat [184]	Sep, 2023	Baichuan2	7B/13B	4k	2.6T	CN	Open
ChatGLM3	Oct, 2023	GLM	6B	32k	/	CN	Open

Source: Wang, Hongru, Lingzhi Wang, Yiming Du, Liang Chen, Jingyan Zhou, Yufei Wang, and Kam-Fai Wong. "A Survey of the Evolution of Language Model-Based Dialogue Systems." arXiv preprint arXiv:2311.16789 (2023).

Dialogue System

Objective	Modality	Domain	Architecture	Model
TDS	text/speech/multi	single/multi	modular	rule/statistical/neural
CDS	text/speech/multi	open	end-to-end	neural
QADS	text	multi/open	modular/end-to-end	rule/statistical/neural

Source: Kath, Hannes, Bengt Lüers, Thiago S. Gouvêa, and Daniel Sonntag. "Lost in Dialogue: A Review and Categorisation of Current Dialogue System Approaches and Technical Solutions." In German Conference on Artificial Intelligence (Künstliche Intelligenz), pp. 98-113. Cham: Springer Nature Switzerland, 2023.

Dialogue System

Extracted information for the example sentence
show restaurant at New York tomorrow
by the module natural language understanding

Sentence	show	restaurant	at	New	York	tomorrow
Slots	O	O	O	B-desti	I-desti	B-date
Intent	Find Restaurant					
Category	Order					

Source: Kath, Hannes, Bengt Lüers, Thiago S. Gouvêa, and Daniel Sonntag. "Lost in Dialogue: A Review and Categorisation of Current Dialogue System Approaches and Technical Solutions." In German Conference on Artificial Intelligence (Künstliche Intelligenz), pp. 98-113. Cham: Springer Nature Switzerland, 2023.

Dialogue System

Selected intelligent virtual assistants, commercial frameworks and research dialogue systems categorised by objective, modality, domain, architecture and model

		Objective			Modality			Domain			Architecture		Model				
	System name	Task-oriented	Conversational	Question Answering	Text	Speech	Multi-modal	Single	Multi	Open	Modular	End-to-end	Rule-based	Statistical	Neural	Open source	Specifications
Intelligent Virtual Assistants	Amazon Alexa[a]	●	-	-	●	●	-	-	●	-	-	●	●	●	●	-	
	Bixby[b]	●	-	-	●	●	-	-	●	-	x	x	●	●	●	-	
	Cortana [48]	●	-	-	●	●	-	-	●	-	●	-	●	●	●	-	
	Google Assistant[c]	●	-	-	●	●	-	-	●	-	x	x	●	●	●	-	
	Siri[d]	●	-	-	●	●	-	-	●	-	x	x	●	●	●	-	
	XiaoIce [79]	-	●	-	●	●	-	-	-	●	●	-	●	-	●	-	Emotional module, Chinese
Commercial Frameworks	Cerence Studio[e]	●	-	-	●	●	-	-	●	-	●	-	-	●	●	-	
	Conversational AI[f]	●	-	-	●	●	-	-	●	-	-	●	x	x	x	-	
	Dialogflow[g]	●	-	-	●	●	-	-	●	-	-	●	●	-	●	-	
	Dragon[h]	-	-	-	-	●	-	-	●	●	x	x	-	-	●	-	ASR (dictation software)
	LUIS[i]	●	-	-	●	●	-	-	●	-	x	x	-	-	●	-	
	Nuance Mix[j]	●	-	●	●	●	-	-	●	●	●	-	●	-	●	-	
	Rasa[k]	●	-	-	●	-	-	-	●	-	●	-	-	●	●	●	NLU&DM, also research system
	SemVox [3]	●	-	-	-	●	●	-	●	-	●	-	x	x	x	-	also IVA
	Watson Assistant[l]	●	-	●	●	●	-	-	●	-	●	-	-	-	●	-	

Source: Kath, Hannes, Bengt Lüers, Thiago S. Gouvêa, and Daniel Sonntag. "Lost in Dialogue: A Review and Categorisation of Current Dialogue System Approaches and Technical Solutions." In German Conference on Artificial Intelligence (Künstliche Intelligenz), pp. 98-113. Cham: Springer Nature Switzerland, 2023.

Dialogue System

Selected intelligent virtual assistants, commercial frameworks and research dialogue systems categorised by objective, modality, domain, architecture and model

		Objective			Modality			Domain			Architecture		Model				
	System name	Task-oriented	Conversational	Question Answering	Text	Speech	Multi-modal	Single	Multi	Open	Modular	End-to-end	Rule-based	Statistical	Neural	Open source	Specifications
Research Dialogue Systems	DenSPI [52]	-	-	●	●	-	-	-	-	●	-	●	-	-	●	●	
	DrQA [4]	-	-	●	●	-	-	-	-	●	●	-	●	-	●	●	
	R^3 [65]	-	-	●	●	-	-	-	-	●	●	-	-	-	●	●	
	SmartWeb [56]	-	-	●	●	●	●	-	●	-	●	-	●	-	-	●	
	ELIZA [67]	-	●	-	●	-	-	-	-	●	●	-	●	-	-	●	First dialogue system (1966)
	ConvLab [27]	●	-	-	●	-	-	-	●	-	●	●	-	-	●	●	GUI included
	DialogOS [23]	●	-	-	-	●	-	-	●	-	●	-	●	-	-	●	GUI included
	Nemo [25]	●	●	●	-	●	-	-	-	●	●	-	-	-	●	●	
	ParlAI [40]	●	●	●	●	-	●	-	-	●	-	●	-	-	●	●	
	Plato [47]	●	-	-	●	-	-	-	●	-	●	●	●	●	-	●	Speech interface integrable
	PyDial [61]	●	-	-	●	●	-	-	●	-	●	-	-	●	-	●	
	ReTiCo [38,39]	●	-	-	●	●	-	-	●	-	●	-	-	●	●	●	DM based on Rasa
	Siam-dp [42]	●	-	●	-	●	●	-	●	-	●	-	●	-	-	●	

Source: Kath, Hannes, Bengt Lüers, Thiago S. Gouvêa, and Daniel Sonntag. "Lost in Dialogue: A Review and Categorisation of Current Dialogue System Approaches and Technical Solutions." In German Conference on Artificial Intelligence (Künstliche Intelligenz), pp. 98-113. Cham: Springer Nature Switzerland, 2023.

Properties relevant for implementation of research dialogue systems

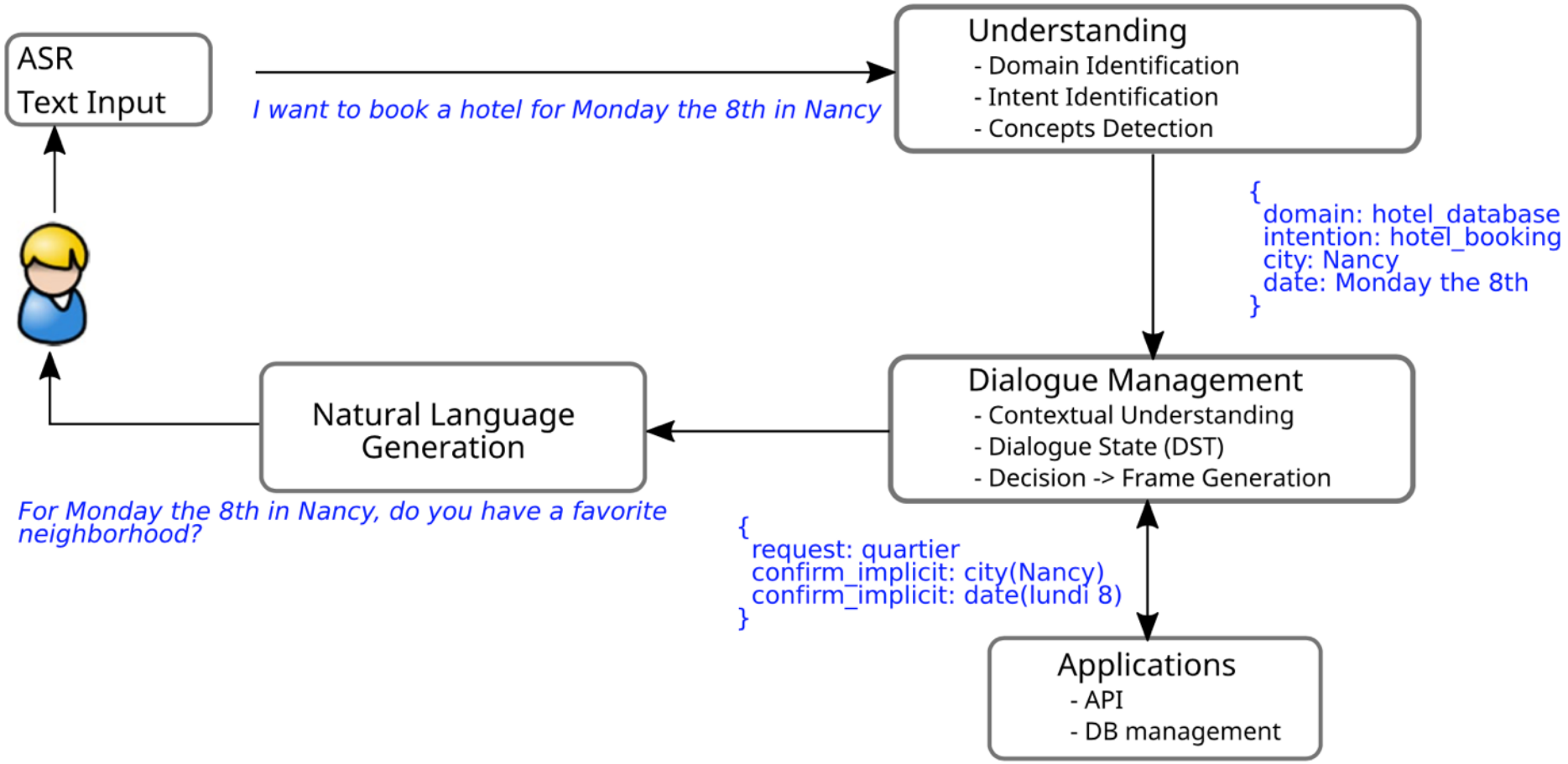
System	Application Framework	Code Availability	Programming Language	Windows	MacOS	Linux	Tutorial	Demonstration	Last Activity (Releases, Commits, Issues)	Purpose
DenSPI	• -	•	Python	•	•	•	-	•	06/2022	Real-time, Wikipedia-based
DrQA	• -	•	Python	-	•	•	-	•	11/2022	Machine reading at scale
R^3	• -	•	Lua, Python	•	•	•	-	-	04/2018	Reinforcement learning
SmartWeb	• -	-	Java	•	•	•	-	-	2014	Multi-modal access to Web
ELIZA	• •	•	Python	•	•	•	-	•	1966	Simulate interlocutors
ConvLab	- •	•	Python	-	•	•	•	-	04/2023	Reusable experimental setup
DialogOS	- •	•	Java	•	•	•	-	-	12/2022	Student projects
Nemo	- •	•	Python	•	•	•	•	-	04/2023	Reuse code and models
ParlAI	- •	•	Python	-	•	•	•	•	04/2023	Share, train and test systems
Plato	- •	•	Python	•	•	•	•	-	09/2020	Multi-agent setting
PyDial	- •	•	HTML	•	•	•	•	•	04/2022	Research on modules
ReTiCo	- •	•	Python	•	•	•	-	-	04/2023	Real time, incremental
Siam-dp	- •	•	Java	•	•	•	-	-	02/2017	Multi-modal development

Source: Kath, Hannes, Bengt Lüers, Thiago S. Gouvêa, and Daniel Sonntag. "Lost in Dialogue: A Review and Categorisation of Current Dialogue System Approaches and Technical Solutions." In German Conference on Artificial Intelligence (Künstliche Intelligenz), pp. 98-113. Cham: Springer Nature Switzerland, 2023.

Task-Oriented Dialogue System

Task-Oriented Dialogue System

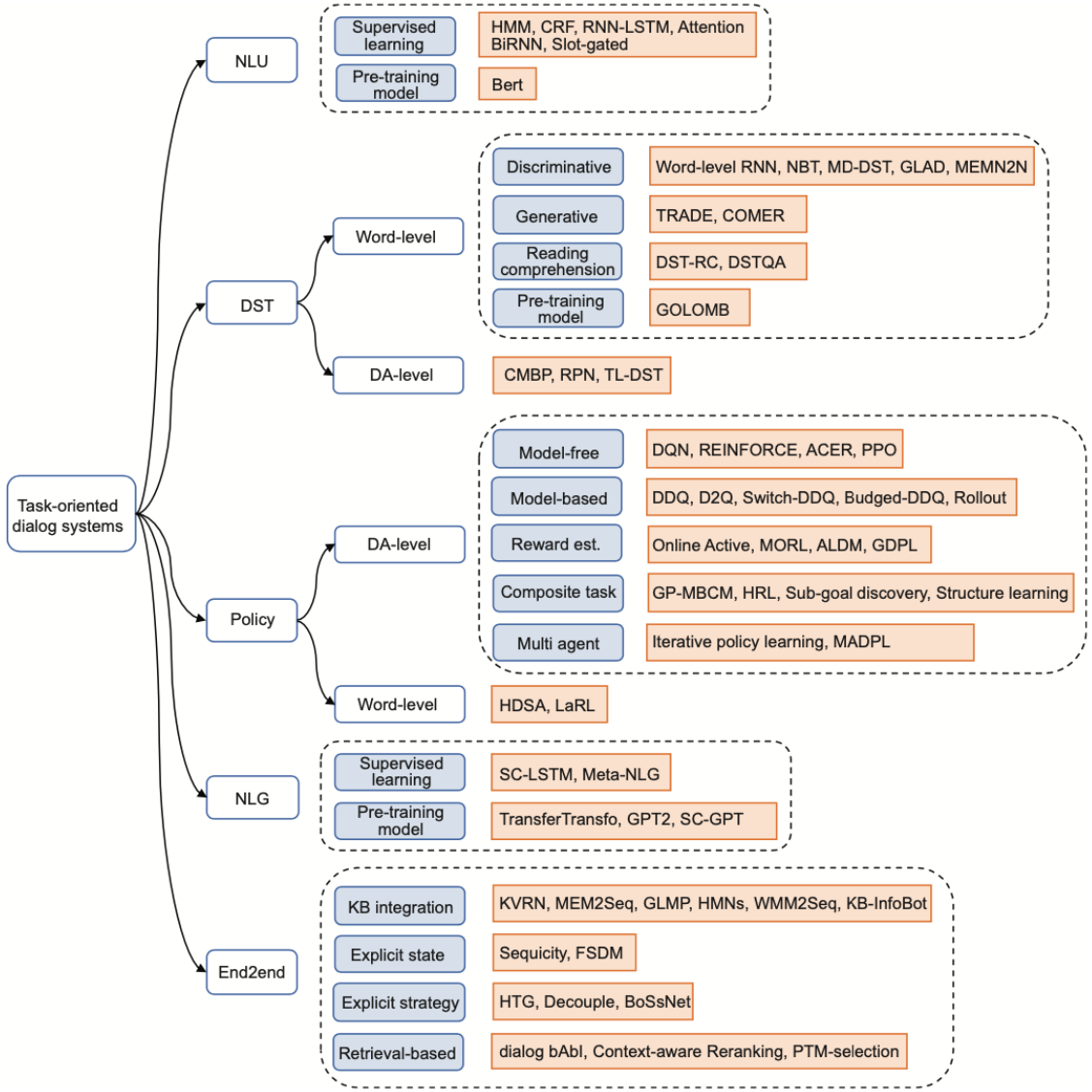
(Deriu et al., 2021)



Source: Deriu, Jan, Alvaro Rodrigo, Arantxa Otegi, Guillermo Echegoyen, Sophie Rosset, Eneko Agirre, and Mark Cieliebak (2021). "Survey on evaluation methods for dialogue systems." Artificial Intelligence Review 54, no. 1 (2021): 755-810.

Task-Oriented Dialogue Systems

(Zhang et al., 2020)



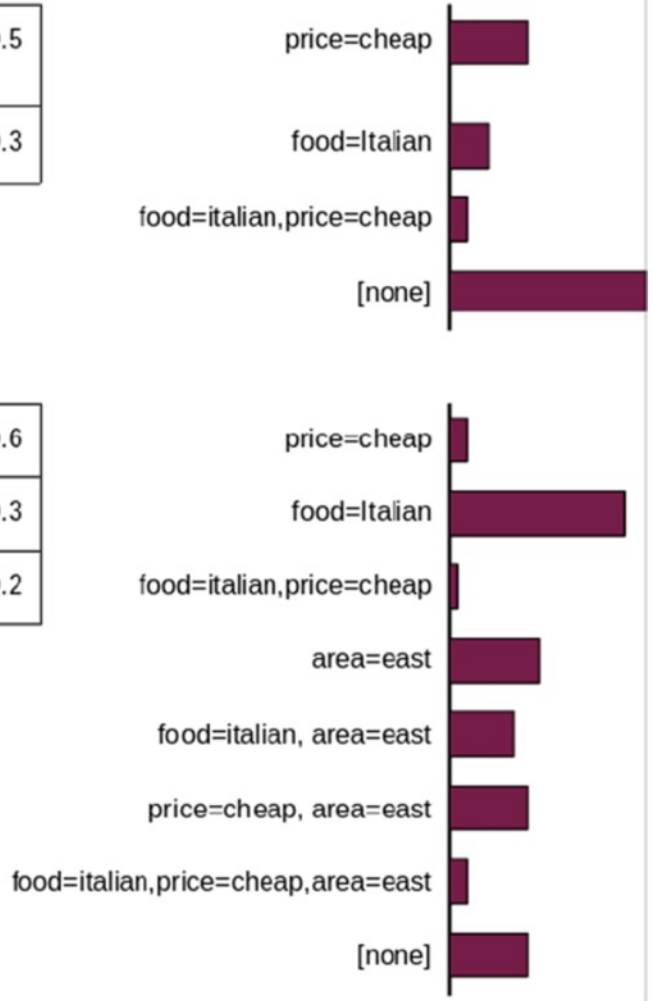
Source: Zhang, Zheng, Ryuichi Takanobu, Qi Zhu, Minlie Huang, and Xiaoyan Zhu (2020). "Recent advances and challenges in task-oriented dialog systems." Science China Technological Sciences (2020): 1-17.

Dialog State Tracker (DST)

Dialog state tracker inputs

System action/ user response	ASR output		SLU output	
How can I help you? *welcome()*	Cheap restaurant	0.6	inform(price=cheap)	0.5
	Restaurant	0.2	inform(food=italian)	0.3
An Italian restaurant	Italian	0.1		
What price did you want? *request(price)*	East Area	0.5	inform(area=east)	0.6
	Italian	0.3	inform(food=italian)	0.3
Uh, Italian	Yeah	0.1	affirm()	0.2

Dialog state tracker outputs



Source: Deriu, Jan, Alvaro Rodrigo, Arantxa Otegi, Guillermo Echegoyen, Sophie Rosset, Eneko Agirre, and Mark Cieliebak (2021). "Survey on evaluation methods for dialogue systems." Artificial Intelligence Review 54, no. 1 (2021): 755-810.

Dialogue Acts

(Young et al., 2010)

Dialogue act	Description
hello($a = x, b = y, \ldots$)	Open a dialogue and give info $a = x, b = y, \ldots$
inform($a = x, b = y, \ldots$)	Give information $a = x, b = y, \ldots$
request($a, b = x, \ldots$)	Request value for a given $b = x, \ldots$
reqalts($a = x, \ldots$)	Request alternative with $a = x, \ldots$
confirm($a = x, b = y, \ldots$)	Explicitly confirm $a = x, b = y, \ldots$
confreq($a = x, \ldots, d$)	Implicitly confirm $a = x, \ldots$ and request value of d
select($a = x, a = y$)	Select either $a = x$ or $a = y$
affirm($a = x, b = y$)	Affirm and give further info $a = x, b = y, \ldots$
negate($a = x$)	Negate and give corrected value $a = x$
deny($a = x$)	Deny that $a = x$
bye()	Close a dialogue

Source: Deriu, Jan, Alvaro Rodrigo, Arantxa Otegi, Guillermo Echegoyen, Sophie Rosset, Eneko Agirre, and Mark Cieliebak (2021). "Survey on evaluation methods for dialogue systems." Artificial Intelligence Review 54, no. 1 (2021): 755-810.

Sample Dialogue Acts

Utterance	Dialogue Act
U: Hi, I am looking for somewhere to eat	hello(task = find,type=restaurant)
S: You are looking for a restaurant. What type of food?	confreq(type = restaurant,food)
U: I'd like an Italian somewhere near the museum.	inform(food = Italian,near=museum)
S: Roma is a nice Italian restaurant near the museum.	inform(name = "Roma", type = restaurant, food = Italian, near = museum)
U: Is it reasonably priced?	confirm(pricerange = moderate)
S: Yes, Roma is in the moderate price range.	affirm(name = "Roma", pricerange = moderate)
U: What is the phone number?	request(phone)
S: The number of Roma is 385456.	inform(name = "Roma", phone = "385456")
U: Ok, thank you goodbye.	bye()

Source: Deriu, Jan, Alvaro Rodrigo, Arantxa Otegi, Guillermo Echegoyen, Sophie Rosset, Eneko Agirre, and Mark Cieliebak (2021). "Survey on evaluation methods for dialogue systems." Artificial Intelligence Review 54, no. 1 (2021): 755-810.

Dialogue on Airline Travel Information System (ATIS)

The ATIS (Airline Travel Information System) Dataset

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

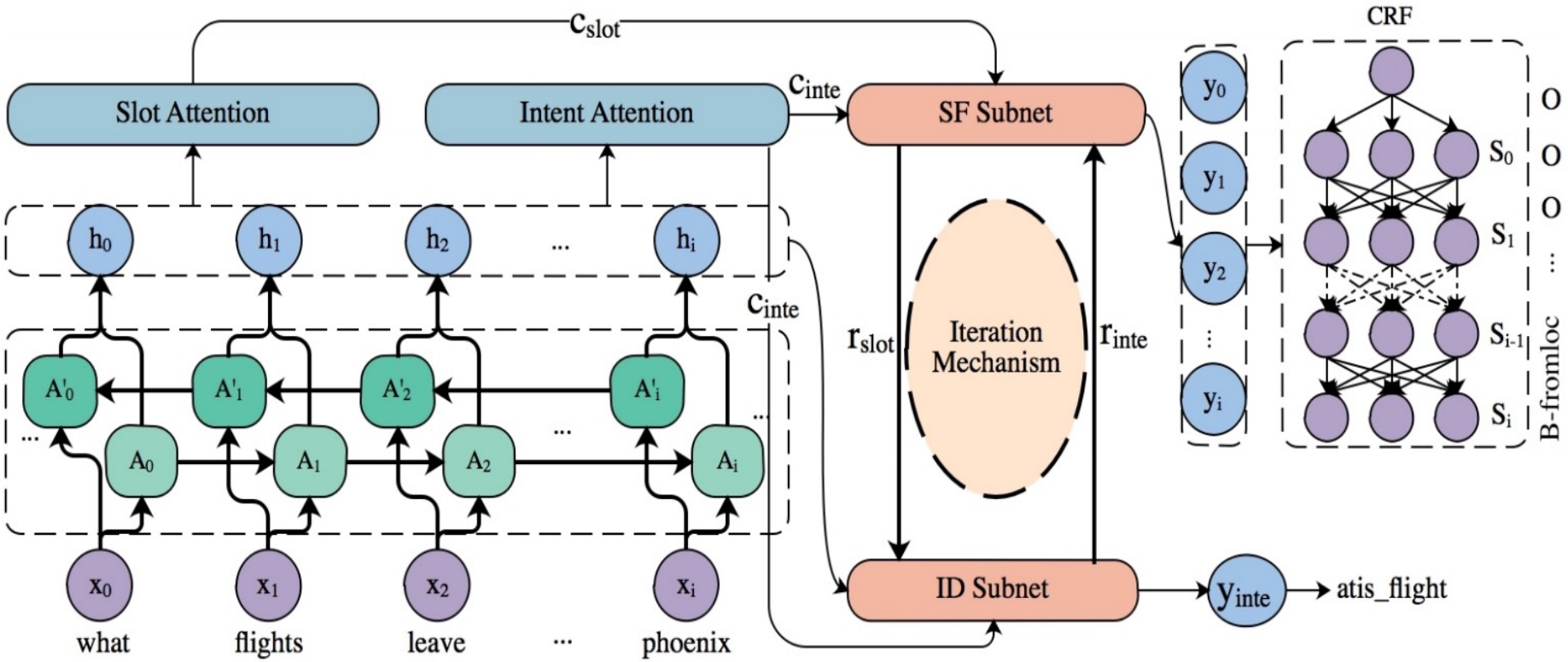
Sentence	what	flights	leave	from	phoenix
Slots	O	O	O	O	B-fromloc
Intent	atis_flight				

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.

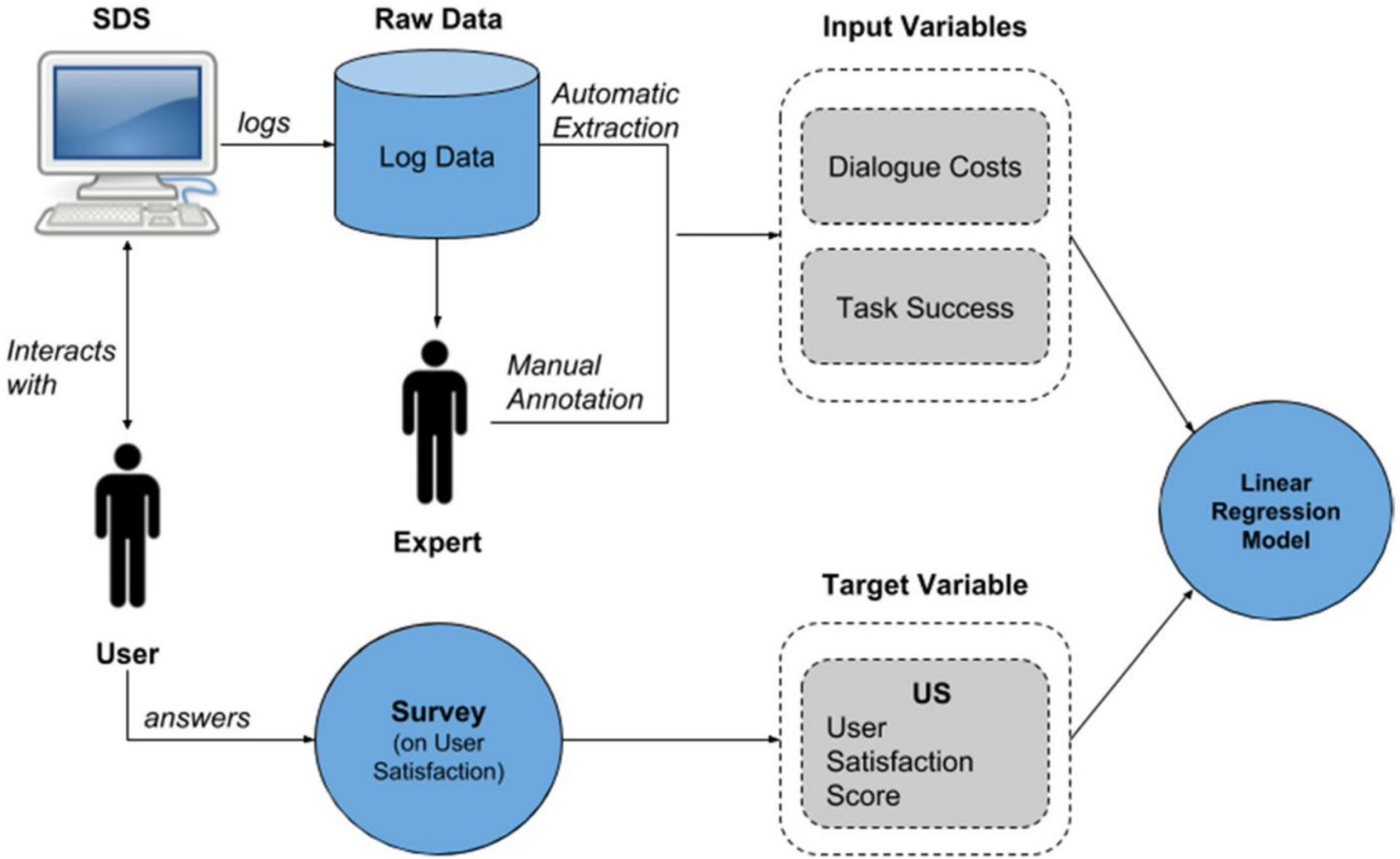
SF-ID Network (E et al., 2019)
Slot Filling (SF)
Intent Detection (ID)

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.

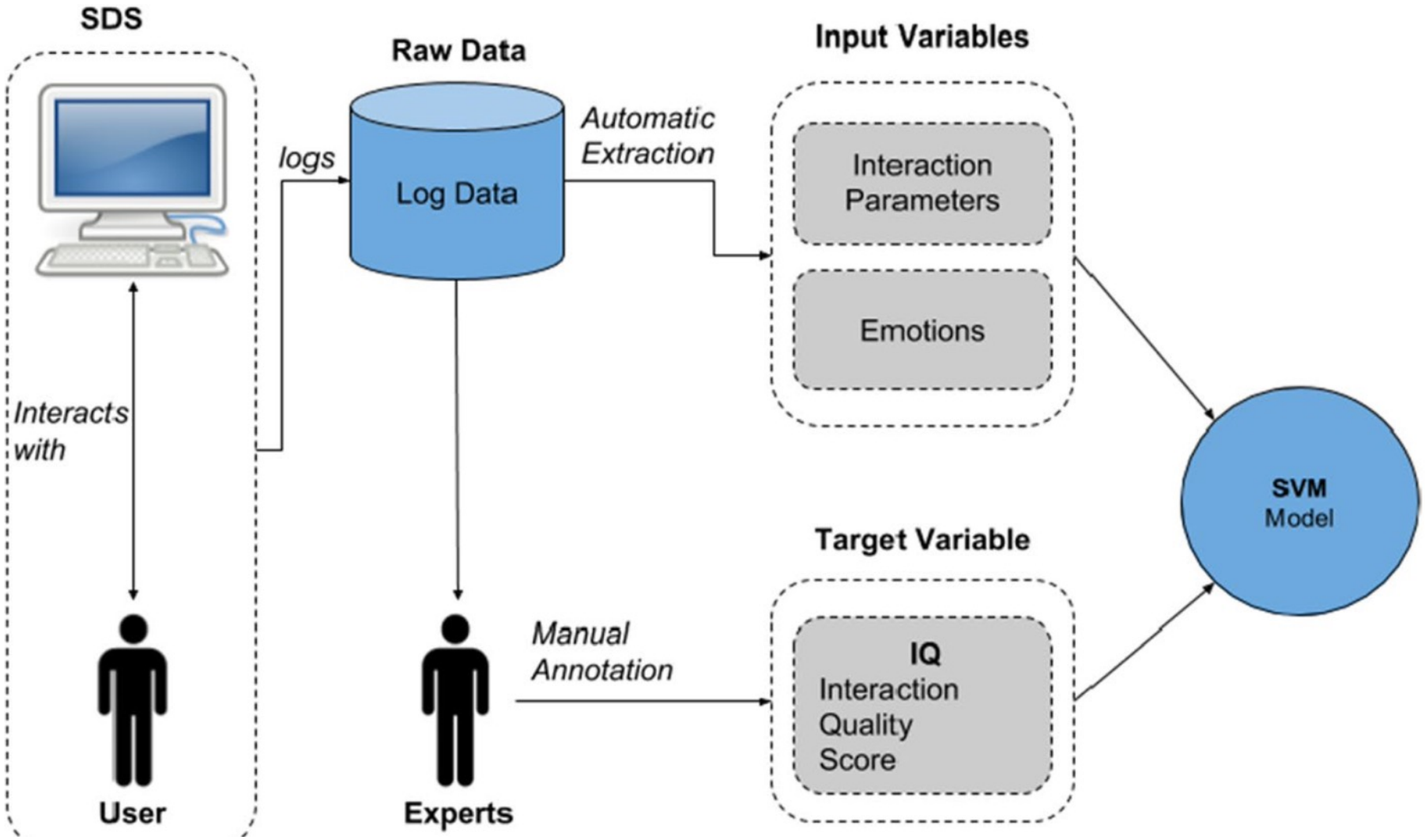
PARAdigm for Dialog System Evaluation
PARADISE Framework (Walker et al. 1997)



Source: Deriu, Jan, Alvaro Rodrigo, Arantxa Otegi, Guillermo Echegoyen, Sophie Rosset, Eneko Agirre, and Mark Cieliebak (2021). "Survey on evaluation methods for dialogue systems." Artificial Intelligence Review 54, no. 1 (2021): 755-810.

Interaction Quality procedure

(Schmitt and Ultes, 2015)



Source: Deriu, Jan, Alvaro Rodrigo, Arantxa Otegi, Guillermo Echegoyen, Sophie Rosset, Eneko Agirre, and Mark Cieliebak (2021). "Survey on evaluation methods for dialogue systems." Artificial Intelligence Review 54, no. 1 (2021): 755-810.

Datasets for task-oriented dialogue systems

Name	Topics	# dialogues	Reference
DSTC1	Bus schedules	15,000	(Williams et al. 2013)
DSTC2	Restaurants	3000	(Henderson et al. 2014)
DSTC3	Tourist information	2265	(Henderson et al. 2013a)
DSTC4 & DSTC5	Tourist information	35	(Kim et al. 2016)
DSTC6	Restaurant reservation	–	(Perez et al. 2017)
DSTC7 (Flex Data)	Student guiding	500	(Gunasekara et al. 2019)
DSTC8 (MetaLWOz)	47 domains	37,884	(Lee et al. 2019)
DSTC8 (Schema-Guided)	20 domains	22,825	(Rastogi et al. 2019)
MultiWOZ	Tourist information	10,438	(Budzianowski et al. 2018)
Taskmaster-1	6 domains	13,215	(Byrne et al. 2019)
MultiDoGo	6 domains	86,698	(Peskov et al. 2019)

Source: Deriu, Jan, Alvaro Rodrigo, Arantxa Otegi, Guillermo Echegoyen, Sophie Rosset, Eneko Agirre, and Mark Cieliebak (2021). "Survey on evaluation methods for dialogue systems." Artificial Intelligence Review 54, no. 1 (2021): 755-810.

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/

CrossWOZ:
A Large-Scale Chinese Cross-Domain Task-Oriented Dialogue Dataset

MultiWOZ	CrossWOZ
usr: I'm looking for a college type attraction. ... usr: I would like to visit in town centre please. ... usr: Can you find an Indian restaurant for me that is **also in the town centre**?	usr: 你好，可以帮我推荐一个评分是4.5分以上的景点吗? Hello, could you recommend an attraction with a rating of 4.5 or higher? sys: 天安门城楼，簋街小吃和北京欢乐谷都是很不错的地方呢。 Tiananmen, Gui Street, and Beijing Happy Valley are very nice places. usr: 我喜欢北京欢乐谷，你知道这个景点周边的酒店都是什么吗? I like Beijing Happy Valley. What hotels are around this attraction? sys: 那可多了，有A酒店, B酒店, C酒店。 There are many, such as hotel A, hotel B, and hotel C. usr: 太好了，我正打算在**景点附近**找个酒店住宿呢，知道哪家评分是4分以上，提供叫醒服务的不? Great! I am planning to find a hotel to stay **near the attraction**. Which one has a rating of 4 or higher and offers wake-up call service?
Schema	
usr: I want a hotel in San Diego and I want to check out on Thursday next week. ... usr: I need a one way flight to **go there**.	

Source: Zhu, Qi, Kaili Huang, Zheng Zhang, Xiaoyan Zhu, and Minlie Huang. "Crosswoz: A large-scale chinese cross-domain task-oriented dialogue dataset." arXiv preprint arXiv:2002.11893 (2020).

CrossWOZ:
A Large-Scale Chinese Cross-Domain Task-Oriented Dialogue Dataset

Type	Single-domain goal					Multi-domain goal		
Dataset	DSTC2	WOZ 2.0	Frames	KVRET	M2M	MultiWOZ	Schema	**CrossWOZ**
Language	EN	EN	EN	EN	EN	EN	EN	**CN**
Speakers	H2M	H2H	H2H	H2H	M2M	H2H	M2M	**H2H**
# Domains	1	1	1	3	2	7	16	**5**
# Dialogues	1,612	600	1,369	2,425	1,500	8,438	16,142	**5,012**
# Turns	23,354	4,472	19,986	12,732	14,796	115,424	329,964	**84,692**
Avg. domains	1	1	1	1	1	1.80	1.84	**3.24**
Avg. turns	14.5	7.5	14.6	5.3	9.9	13.7	20.4	**16.9**
# Slots	8	4	61	13	14	25	214	**72**
# Values	212	99	3,871	1363	138	4,510	14,139	**7,871**

Source: Zhu, Qi, Kaili Huang, Zheng Zhang, Xiaoyan Zhu, and Minlie Huang. "Crosswoz: A large-scale chinese cross-domain task-oriented dialogue dataset." arXiv preprint arXiv:2002.11893 (2020).

Task-Oriented Dialogue

Initial user state (=user goal)

id=1(Attraction): fee=free, name=?, nearby hotels=?

id=2(Hotel): **name=near (id=1)**, wake-up call=yes, rating=?

id=3(Taxi): **from=(id=1)**, **to=(id=2)**, car type=? plate number=?

. . .

Final user state

id=1 (Attraction): name=Tiananmen Square, fee=free, nearby hotels=[Beijing Capital Hotel, Guidu Hotel Beijing]

id=2 (Hotel): **name=Beijing Capital Hotel**, wake-up call=yes, rating=4.6

id=3 (Taxi): **from=Tiananmen Square**, **to=Beijing Capital Hotel**, car type=#CX, plate number=#CP

Source: Zhu, Qi, Kaili Huang, Zheng Zhang, Xiaoyan Zhu, and Minlie Huang. "Crosswoz: A large-scale chinese cross-domain task-oriented dialogue dataset." arXiv preprint arXiv:2002.11893 (2020).

An example dialog from the test set for MultiWOZ (en→zh) sub-task

Speaker	Utterance	Dialog State Update
User	Hello! I am looking for a local guesthouse in the centre. 你好！我在市中心找一家本地宾馆。	hotel: {area: centre, type: guesthouse} 旅馆: {区域: 中心, 类型: 宾馆}
System	OK. I am glad to recommend Alexander Bed and Breakfast to you. 好的。这边很高兴向您推荐亚历山大住宿加早餐旅馆。	
User	Where is it? 它在哪里?	hotel: {name: alexander bed and breakfast} 旅馆: {名称: 亚历山大住宿加早餐旅馆}
System	It is at 56 Saint Barnabas Road. 圣巴纳巴斯路56号。	
User	I also wish to have a meal in a local European restaurant in the centre. 我还想在市中心的一家本地欧洲餐厅吃饭。	restaurant: {food: european, area: centre} 餐厅: {食物: 欧洲的, 区域: 中心}
System	You can choose Eraina. 您可以选择伊莱娜。	
User	Please give me its address. 那请给我它的地址。	restaurant: {name: eraina} 餐厅: {名称: 伊莱娜}
System	It is in Free School Lane City Centre. 市中心自由校园巷。	
User	Ok. I'll go there. I need to book a taxi from Alexander Bed and Breakfast to Eraina after 07:00. 好。那我去那里。我还要预订一辆7:00时从亚历山大住宿加早餐旅馆到伊莱娜的出租车。	taxi: {leaveAt: 07:00, destination: eraina, departure: alexander bed and breakfast} 出租车: {出发时间: 07:00, 目的地: 伊莱娜, 出发地: 亚历山大住宿加早餐旅馆}
System	Well. I find a yellow Skoda. 好的。是一辆黄色的斯柯达。	
User	How about its phone number? 它的电话号码是多少?	No update
System	It is 78519675253. 78519675253。	
User	Thank you for your help. Bye! 谢谢你帮忙。再见！	No update
System	A pleasure. Bye bye! 我很乐意。再见！	

Reinforcement Learning from Human Feedback (RLHF)

ChatGPT: Optimizing Language Models for Dialogue

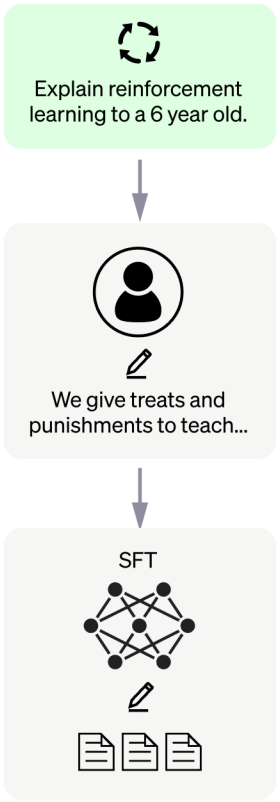
Step 1

Collect demonstration data and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3.5 with supervised learning.



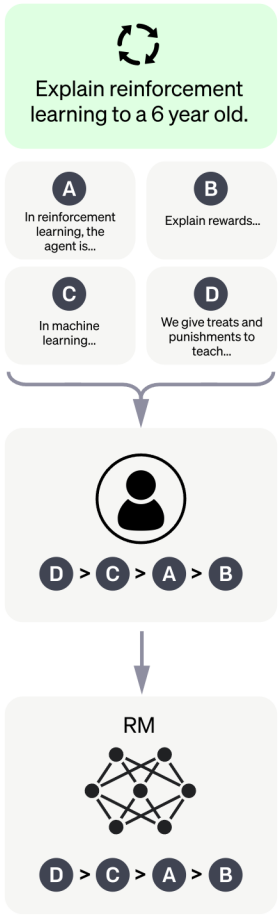
Step 2

Collect comparison data and train a reward model.

A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.



Step 3

Optimize a policy against the reward model using the PPO reinforcement learning algorithm.

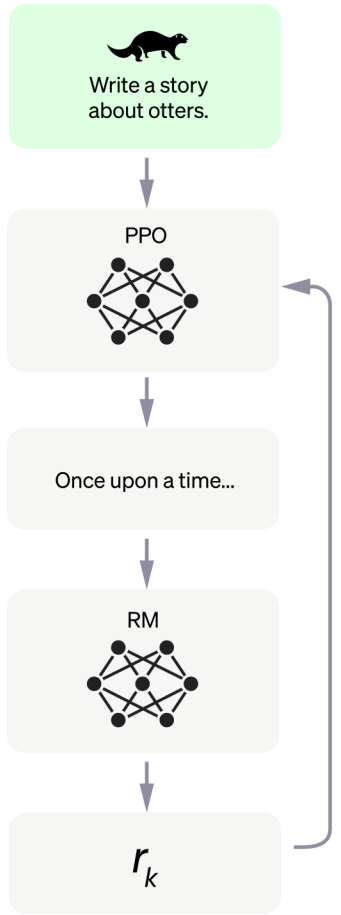
A new prompt is sampled from the dataset.

The PPO model is initialized from the supervised policy.

The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.



Source: https://openai.com/blog/chatgpt/

Training language models to follow instructions with human feedback

InstructGPT and GPT 3.5

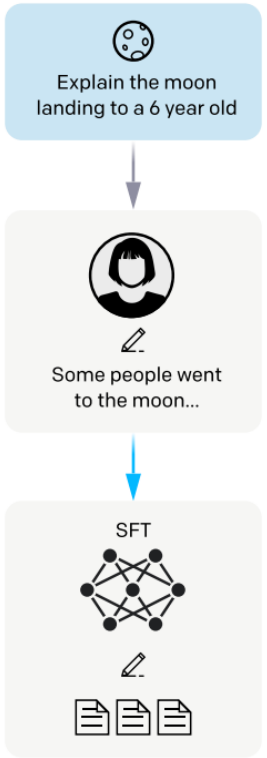
Step 1

Collect demonstration data, and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3 with supervised learning.



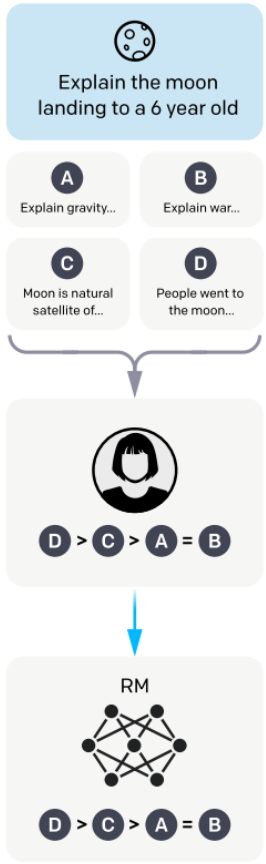
Step 2

Collect comparison data, and train a reward model.

A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.



Step 3

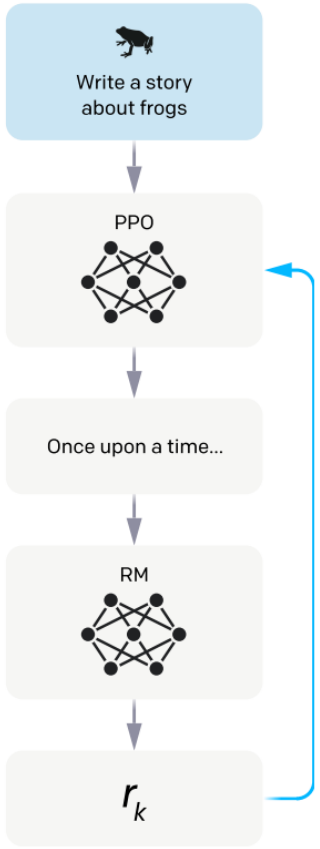
Optimize a policy against the reward model using reinforcement learning.

A new prompt is sampled from the dataset.

The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.



Source: Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C. L., Mishkin, P., ... & Lowe, R. (2022). Training language models to follow instructions with human feedback. arXiv preprint arXiv:2203.02155.

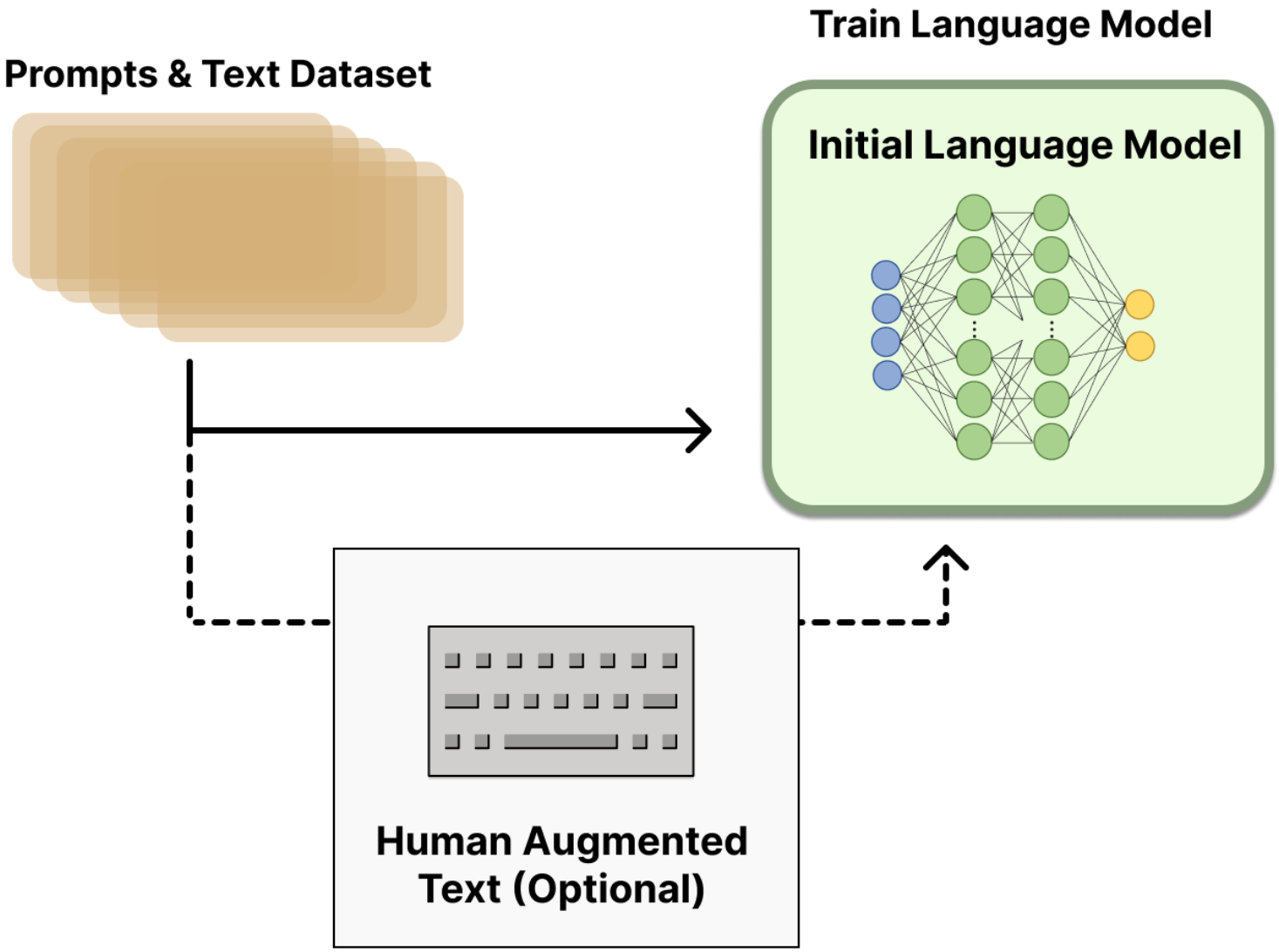
Reinforcement Learning from Human Feedback (RLHF)

1. Pretraining a Language Model (LM)
2. Gathering Data and Training a Reward Model
3. Fine-tuning the LM with Reinforcement Learning

Source: https://huggingface.co/blog/rlhf

Reinforcement Learning from Human Feedback (RLHF)

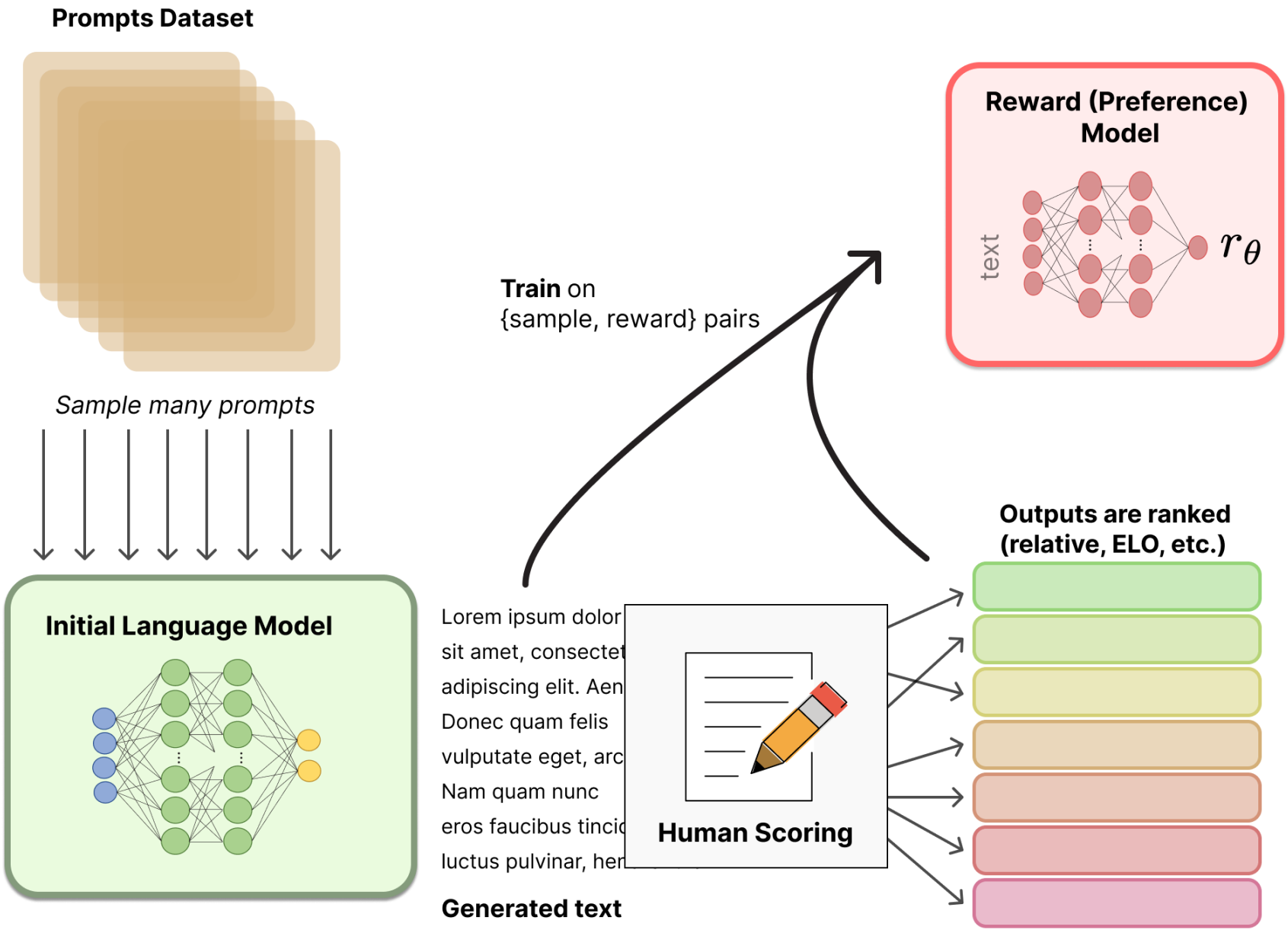
Step 1. Pretraining a Language Model (LM)



Source: https://huggingface.co/blog/rlhf

Reinforcement Learning from Human Feedback (RLHF)

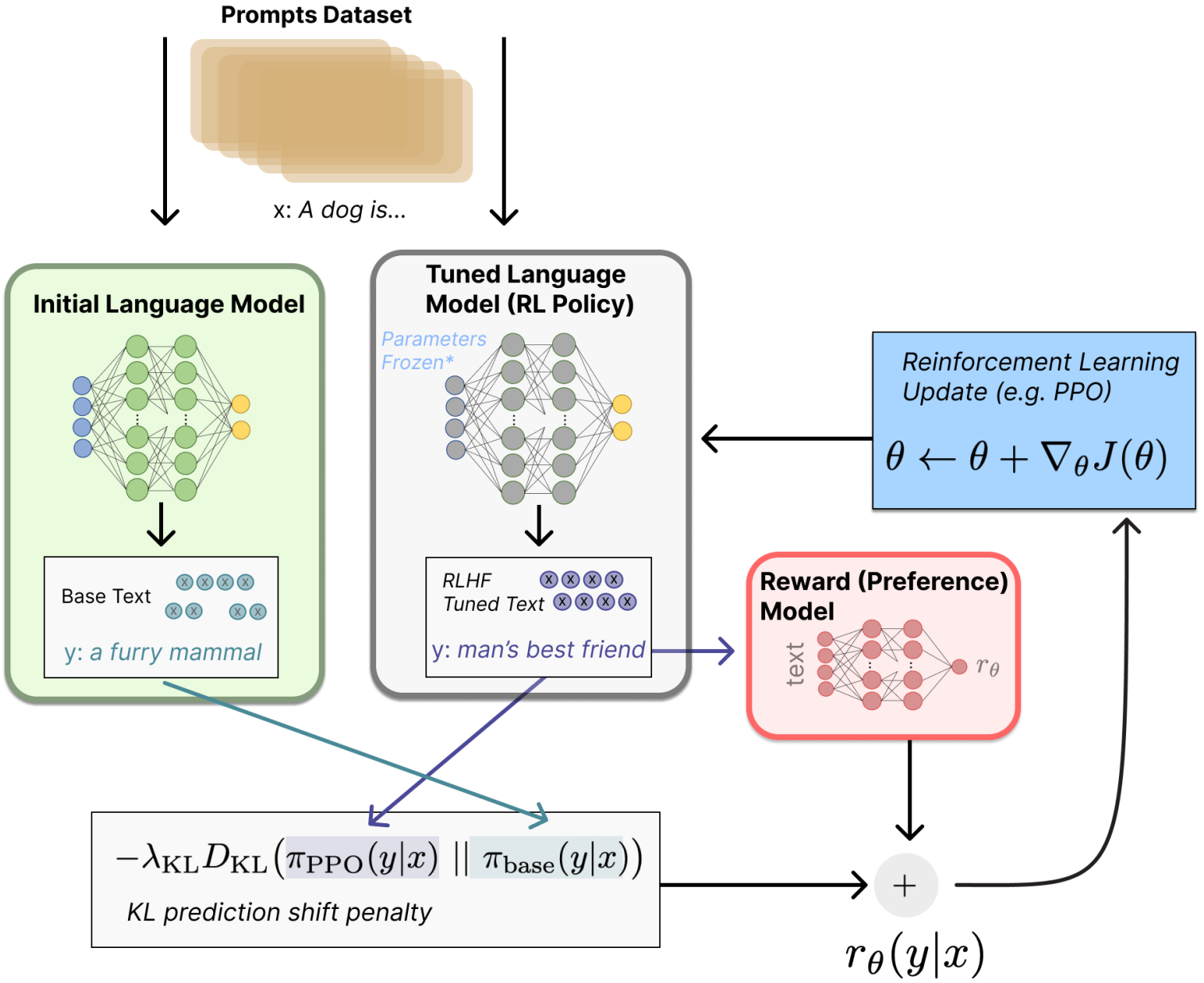
Step 2. Gathering Data and Training a Reward Model



Source: https://huggingface.co/blog/rlhf

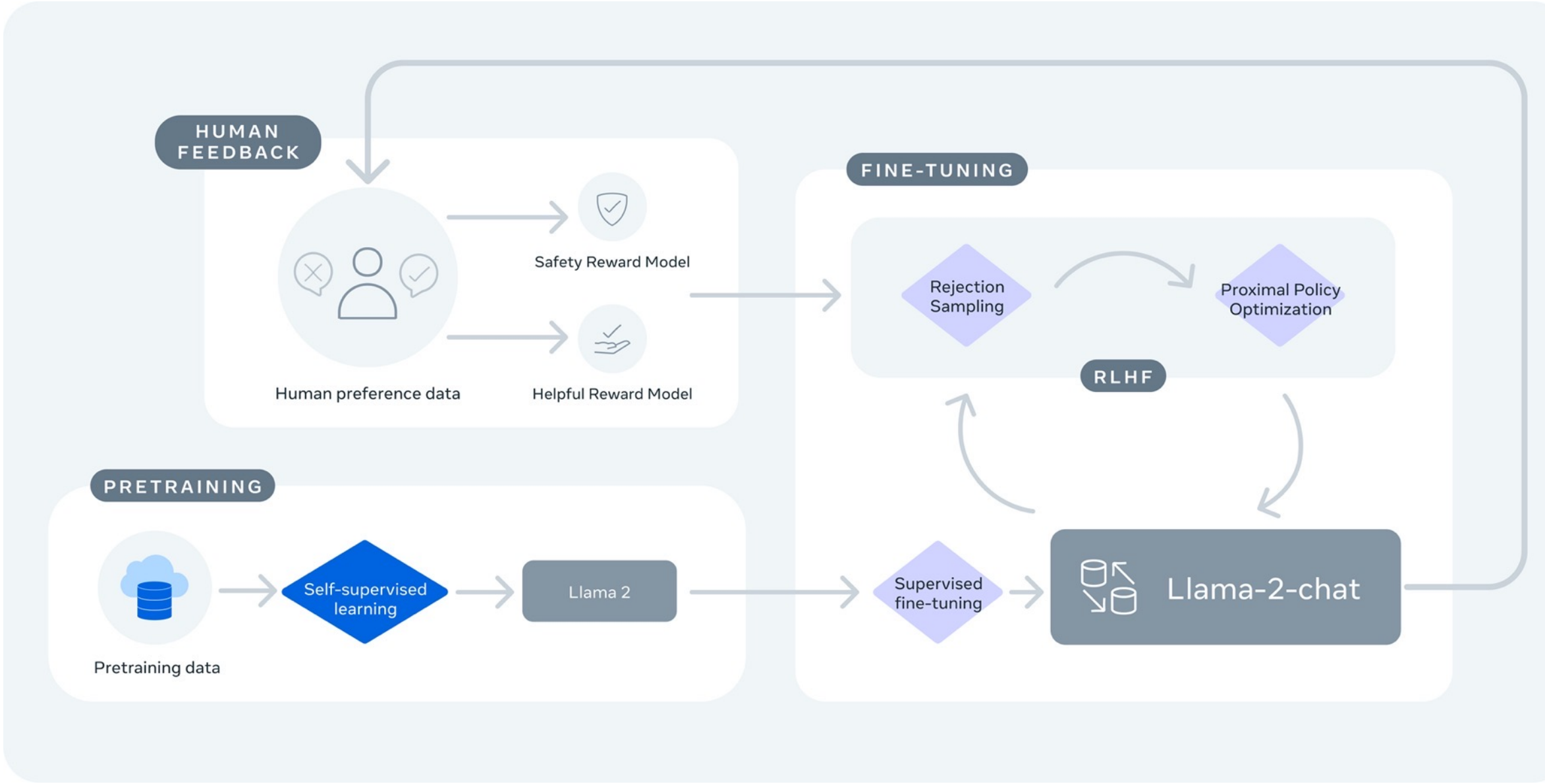
Reinforcement Learning from Human Feedback (RLHF)

Step 3. Fine-tuning the LM with Reinforcement Learning



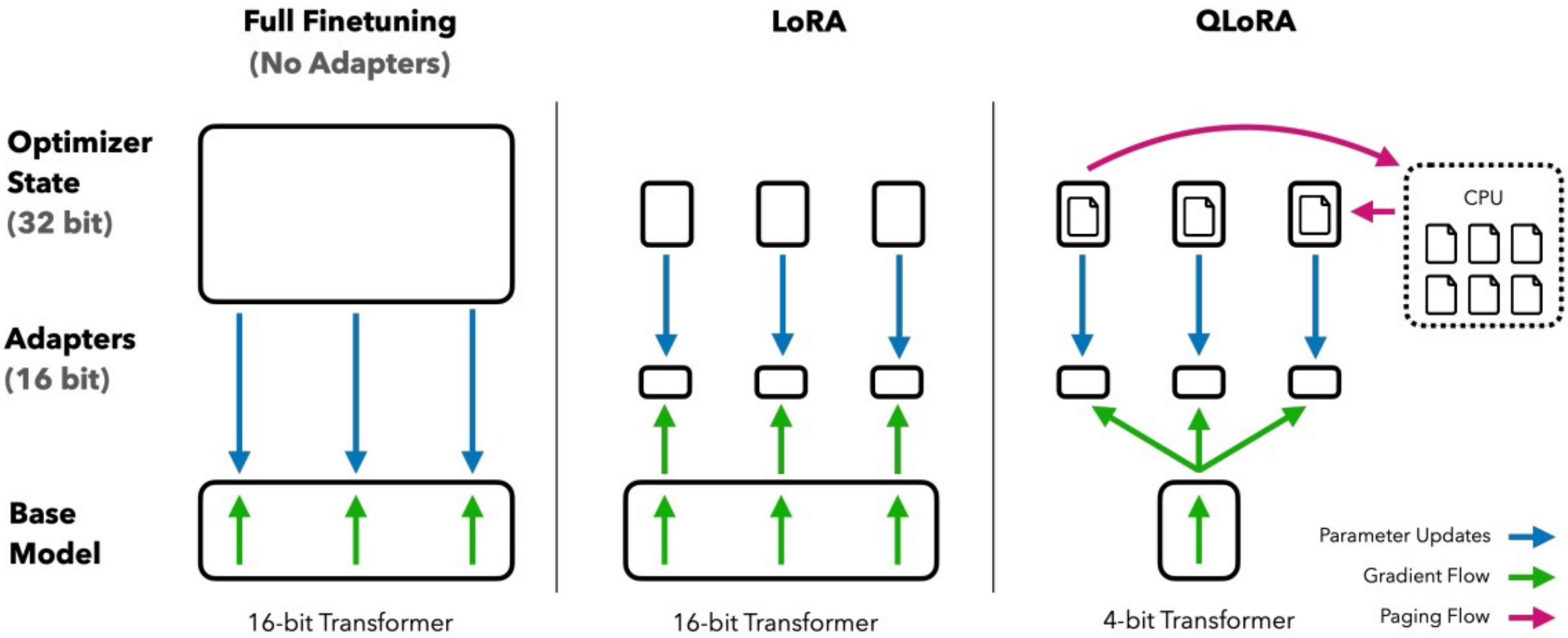
Source: https://huggingface.co/blog/rlhf

Llama-2-chat uses RLHF to ensure safety and helpfulness



Source: https://ai.meta.com/resources/models-and-libraries/llama/

QLoRA: Efficient Finetuning of Quantized LLMs



Source: Dettmers, Tim, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. "QLoRA: Efficient Finetuning of Quantized LLMs." arXiv preprint arXiv:2305.14314 (2023).

QLoRA: Efficient Finetuning of Quantized LLMs

QLoRA reduces the average memory requirements of finetuning a **65B** parameter model from >780GB of **GPU memory** to **<48GB**

Model	Size	Elo
GPT-4	-	1348 ± 1
Guanaco 65B	41 GB	1022 ± 1
Guanaco 33B	21 GB	992 ± 1
Vicuna 13B	26 GB	974 ± 1
ChatGPT	-	966 ± 1
Guanaco 13B	10 GB	916 ± 1
Bard	-	902 ± 1
Guanaco 7B	6 GB	879 ± 1

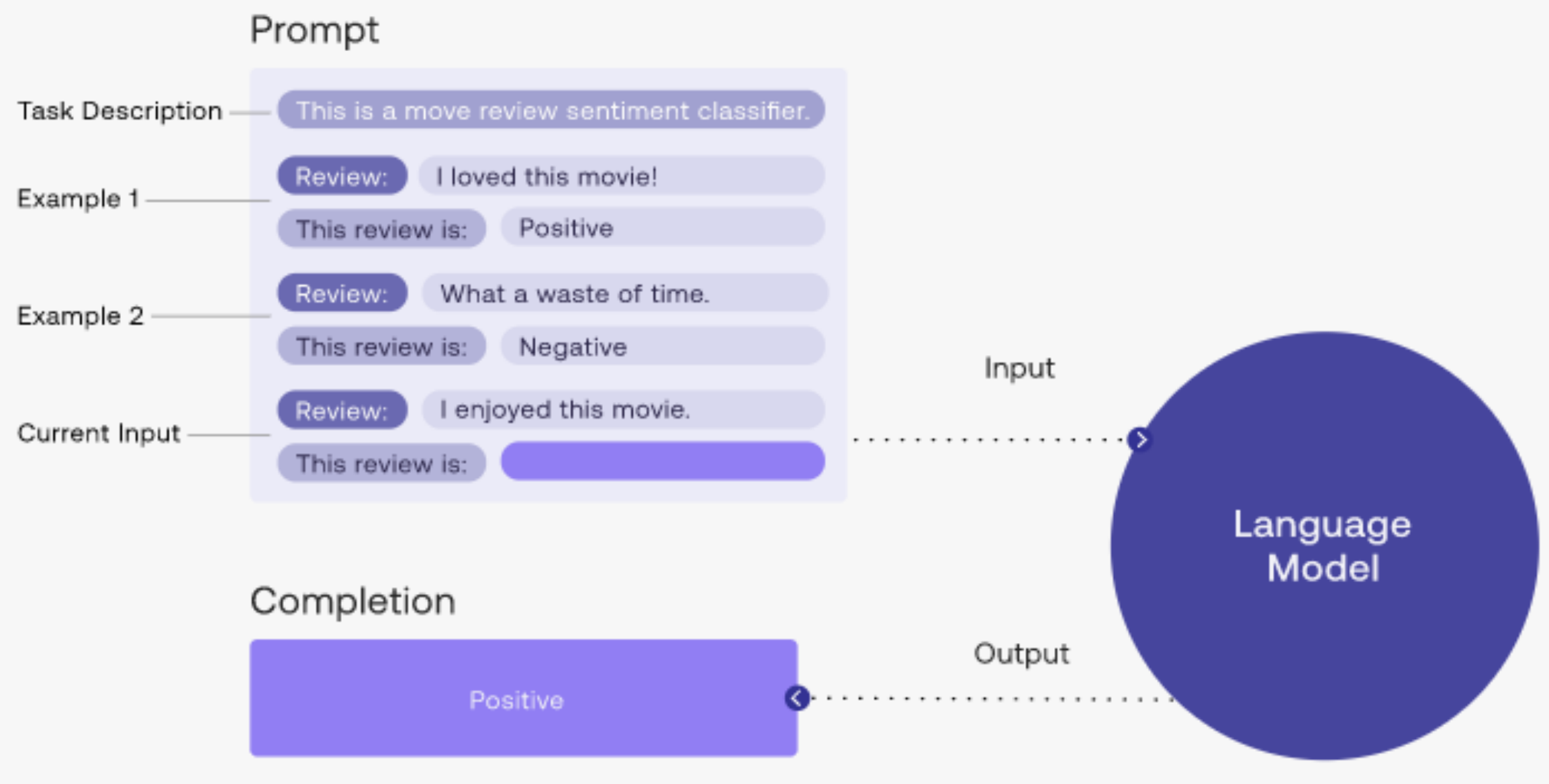
Source: Dettmers, Tim, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. "QLoRA: Efficient Finetuning of Quantized LLMs." arXiv preprint arXiv:2305.14314 (2023).

QLoRA: Efficient Finetuning of Quantized LLMs

Model / Dataset	Params	Model bits	Memory	ChatGPT vs Sys	Sys vs ChatGPT	Mean	95% CI
GPT-4	-	-	-	119.4%	110.1%	**114.5%**	2.6%
Bard	-	-	-	93.2%	96.4%	94.8%	4.1%
Guanaco	65B	4-bit	41 GB	96.7%	101.9%	**99.3%**	4.4%
Alpaca	65B	4-bit	41 GB	63.0%	77.9%	70.7%	4.3%
FLAN v2	65B	4-bit	41 GB	37.0%	59.6%	48.4%	4.6%
Guanaco	33B	4-bit	21 GB	96.5%	99.2%	**97.8%**	4.4%
Open Assistant	33B	16-bit	66 GB	91.2%	98.7%	94.9%	4.5%
Alpaca	33B	4-bit	21 GB	67.2%	79.7%	73.6%	4.2%
FLAN v2	33B	4-bit	21 GB	26.3%	49.7%	38.0%	3.9%
Vicuna	13B	16-bit	26 GB	91.2%	98.7%	**94.9%**	4.5%
Guanaco	13B	4-bit	10 GB	87.3%	93.4%	90.4%	5.2%
Alpaca	13B	4-bit	10 GB	63.8%	76.7%	69.4%	4.2%
HH-RLHF	13B	4-bit	10 GB	55.5%	69.1%	62.5%	4.7%
Unnatural Instr.	13B	4-bit	10 GB	50.6%	69.8%	60.5%	4.2%
Chip2	13B	4-bit	10 GB	49.2%	69.3%	59.5%	4.7%
Longform	13B	4-bit	10 GB	44.9%	62.0%	53.6%	5.2%
Self-Instruct	13B	4-bit	10 GB	38.0%	60.5%	49.1%	4.6%
FLAN v2	13B	4-bit	10 GB	32.4%	61.2%	47.0%	3.6%
Guanaco	7B	4-bit	5 GB	84.1%	89.8%	**87.0%**	5.4%
Alpaca	7B	4-bit	5 GB	57.3%	71.2%	64.4%	5.0%
FLAN v2	7B	4-bit	5 GB	33.3%	56.1%	44.8%	4.0%

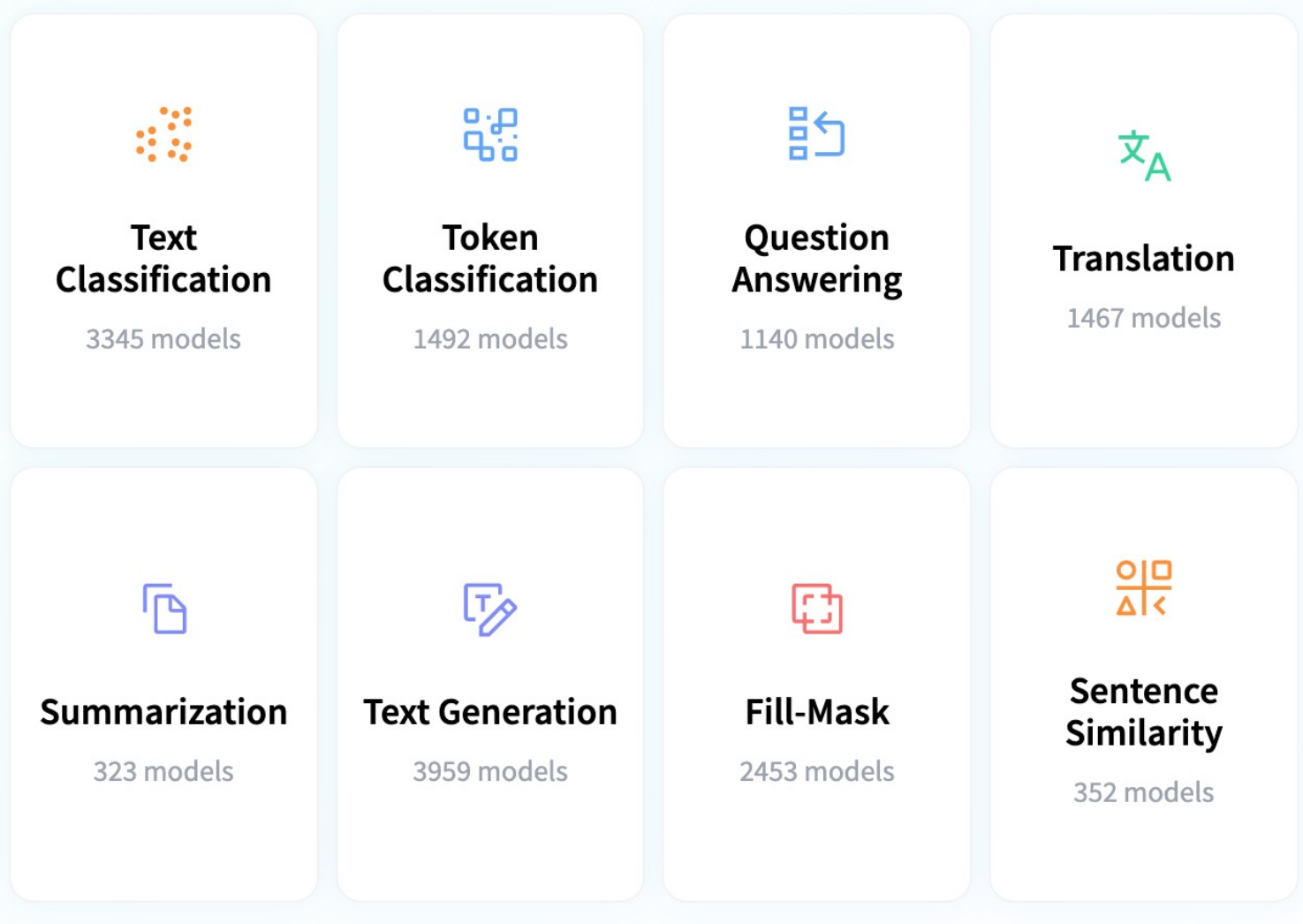
Source: Dettmers, Tim, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. "QLoRA: Efficient Finetuning of Quantized LLMs." arXiv preprint arXiv:2305.14314 (2023).

Prompt Engineering with ChatGPT for NLP



Source: https://www.predera.com/blog/prompt-engineering-for-nlp-tasks

Hugging Face Tasks
Natural Language Processing



https://huggingface.co/tasks

NLP with Transformers Github

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Code Issues Pull requests Actions Projects Wiki Security Insights

main 1 branch 0 tags Go to file Code

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

.github/ISSUE_TEMPLATE	Update issue templates	25 days ago
data	Move dataset to data directory	4 months ago
images	Add README	last month
scripts	Update issue templates	25 days ago
.gitignore	Initial commit	4 months ago
01_introduction.ipynb	Remove Colab badges & fastdoc refs	27 days ago
02_classification.ipynb	Merge pull request #8 from nlp-with-transformers/remove-display-df	26 days ago
03_transformer-anatomy.ipynb	[Transformers Anatomy] Remove cells with figure references	22 days ago
04_multilingual-ner.ipynb	Merge pull request #8 from nlp-with-transformers/remove-display-df	26 days ago
05_text-generation.ipynb	Merge pull request #8 from nlp-with-transformers/remove-display-df	26 days ago

About

Jupyter notebooks for the Natural Language Processing with Transformers book

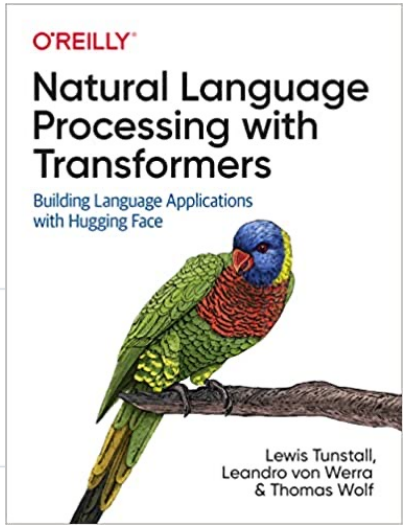
transformersbook.com/

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

Releases

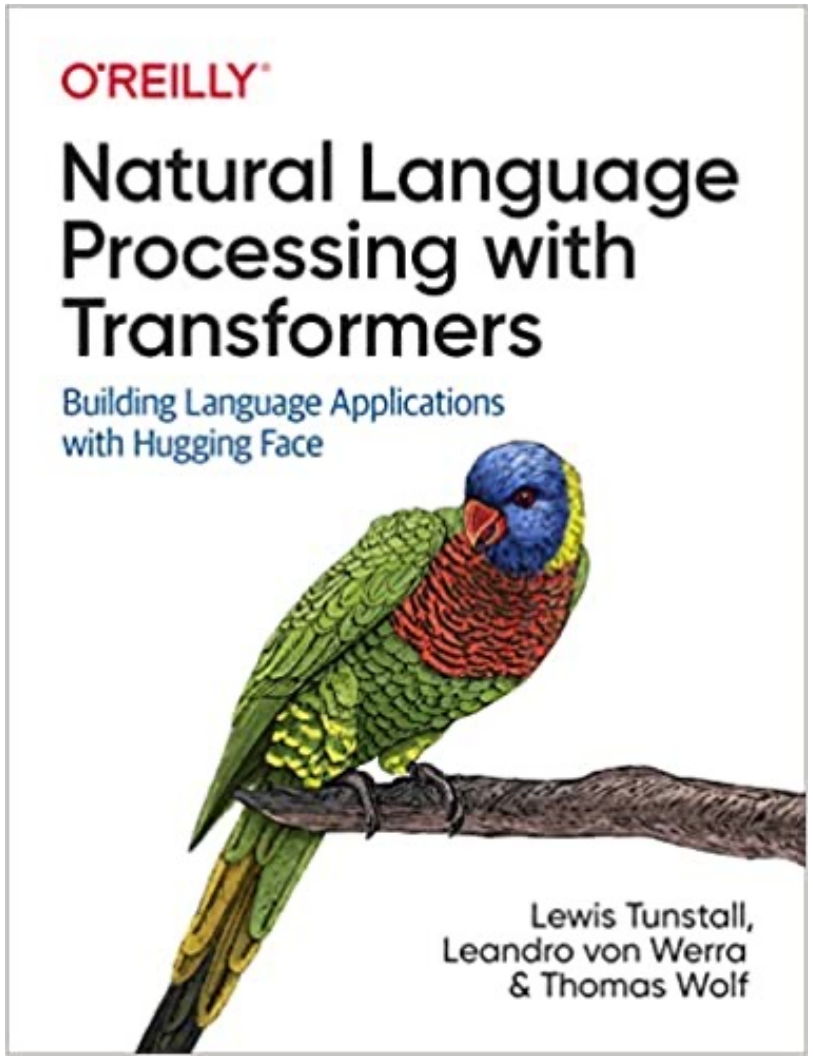
No releases published

Packages



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

NLP with Transformers Github Notebooks



Running on a cloud platform

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

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

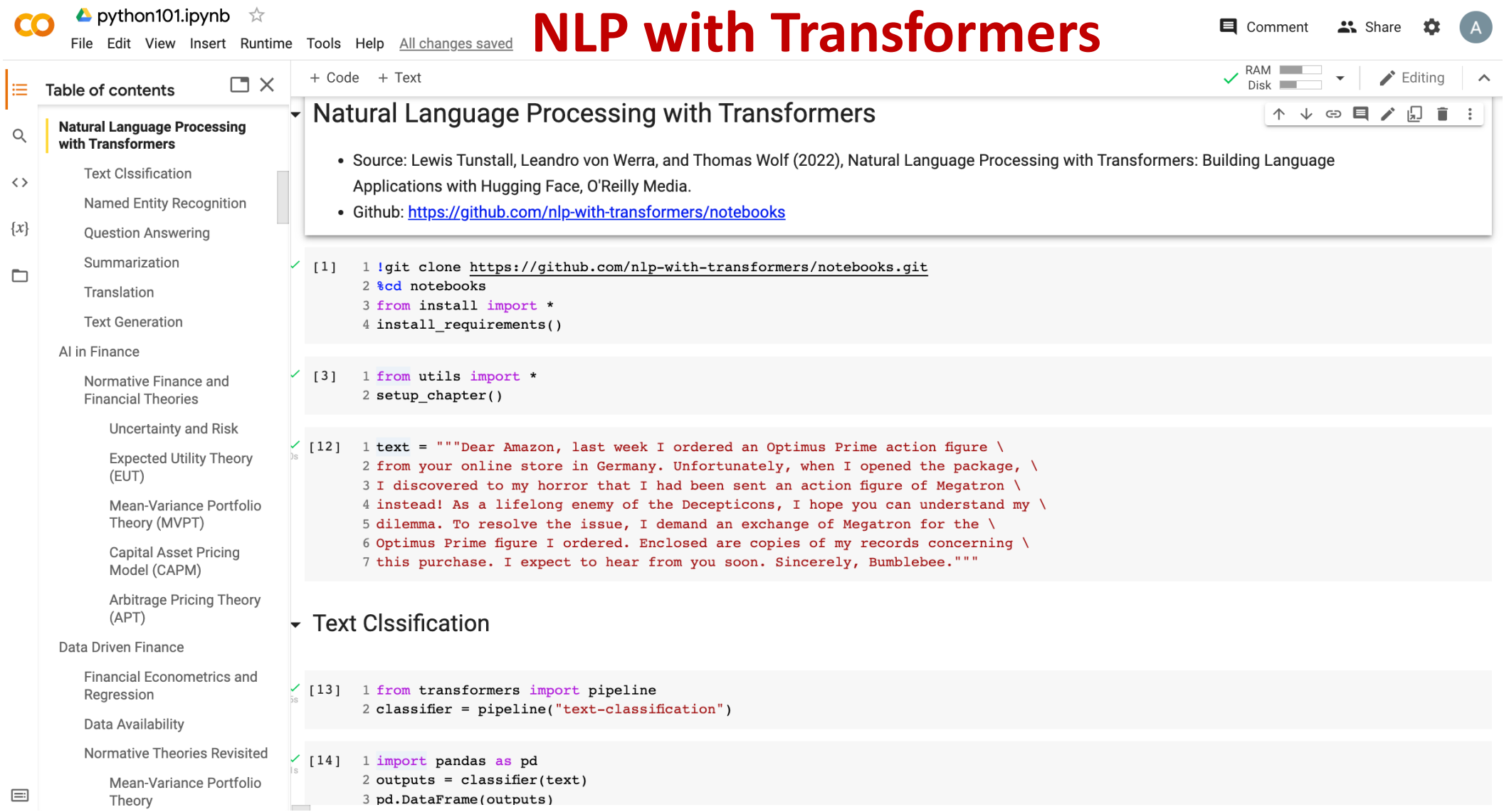
Nowadays, the GPUs on Colab tend to be K80s (which have limited memory), so we recommend using Kaggle, Gradient, or SageMaker Studio Lab. These platforms tend to provide more performant GPUs like P100s, all for free!

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

Python in Google Colab (Python101)

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

NLP with Transformers



https://tinyurl.com/aintpupython101

Python in Google Colab (Python101)

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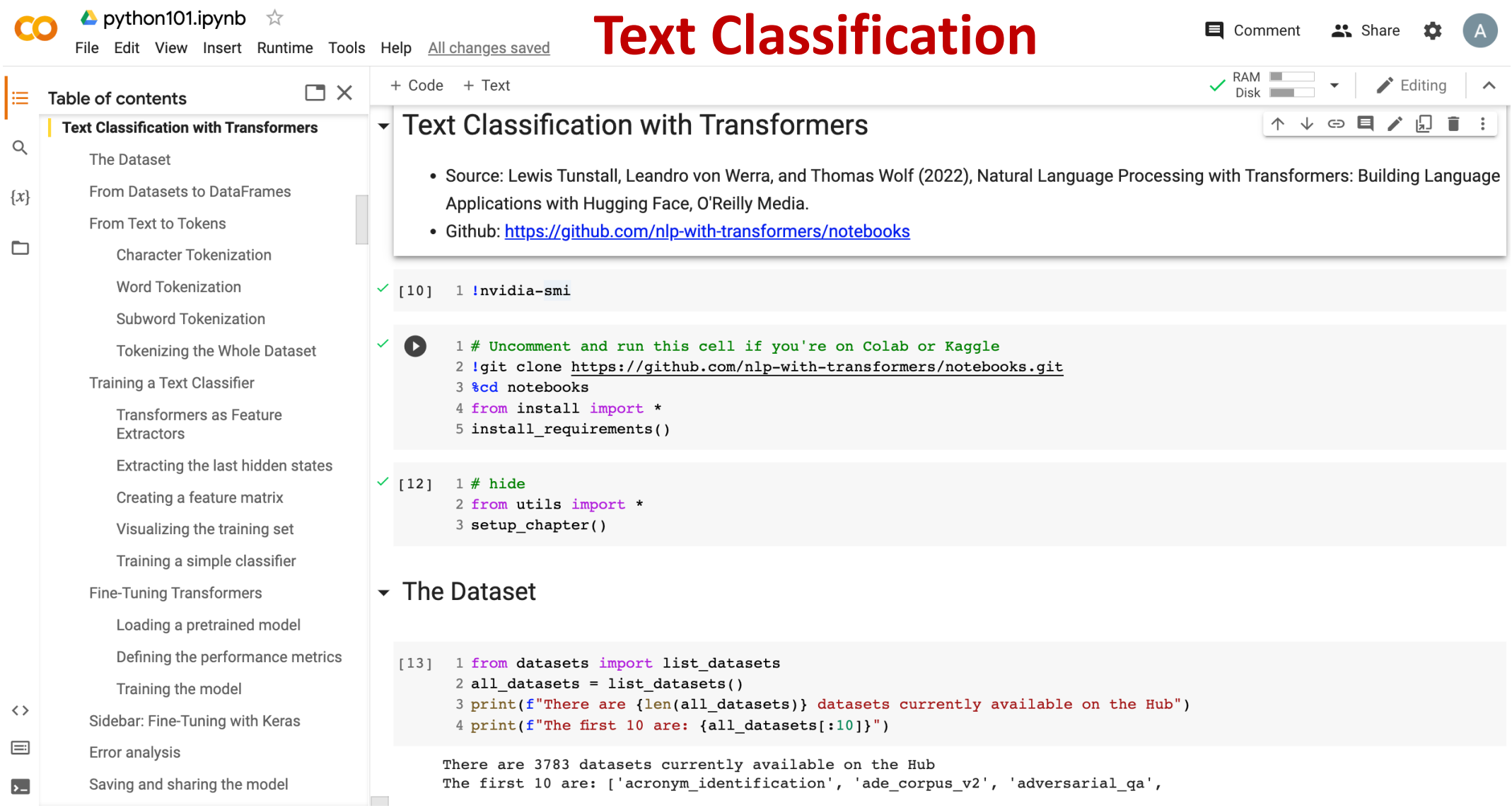

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Python in Google Colab (Python101)

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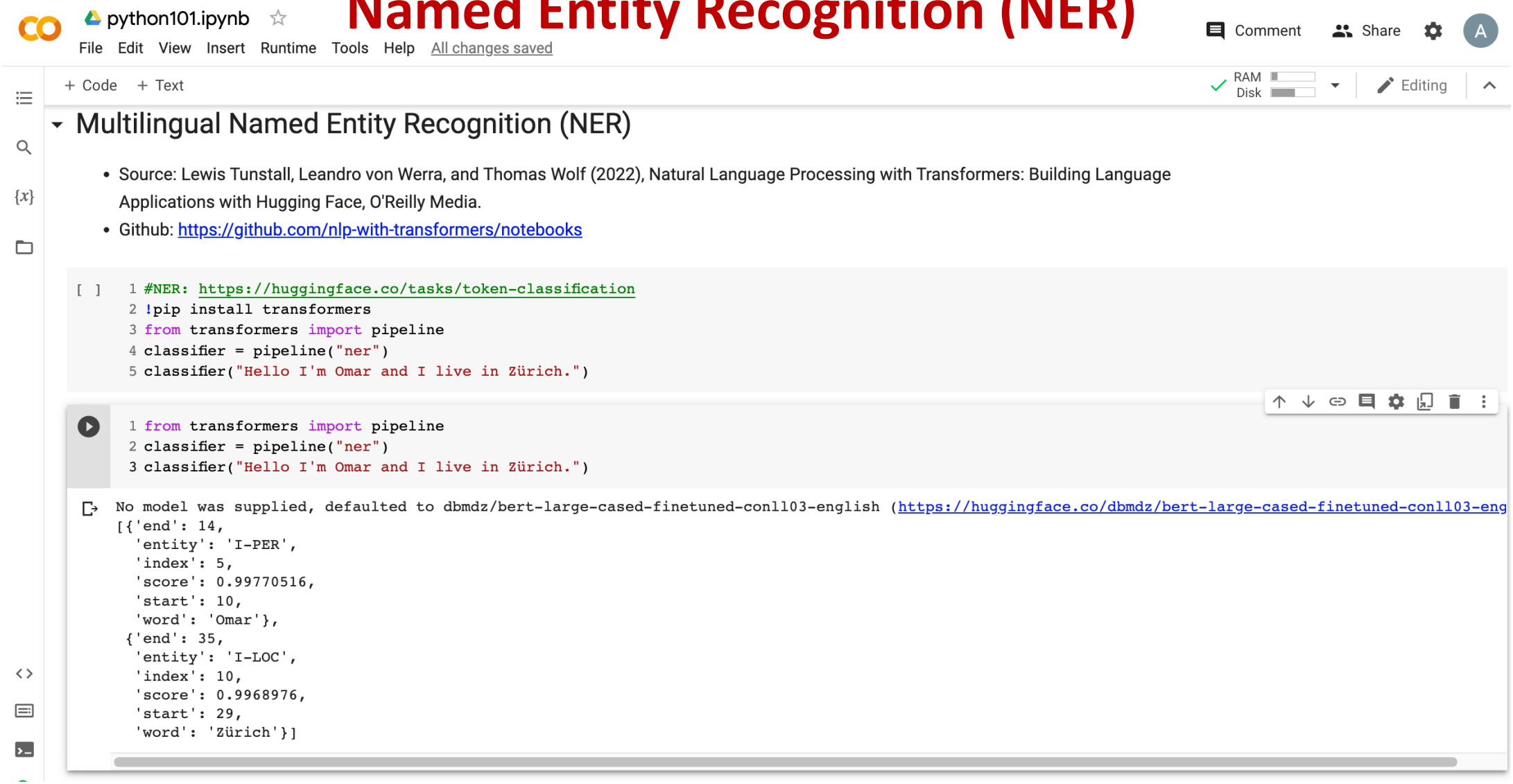
Named Entity Recognition (NER)



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Python in Google Colab (Python101)

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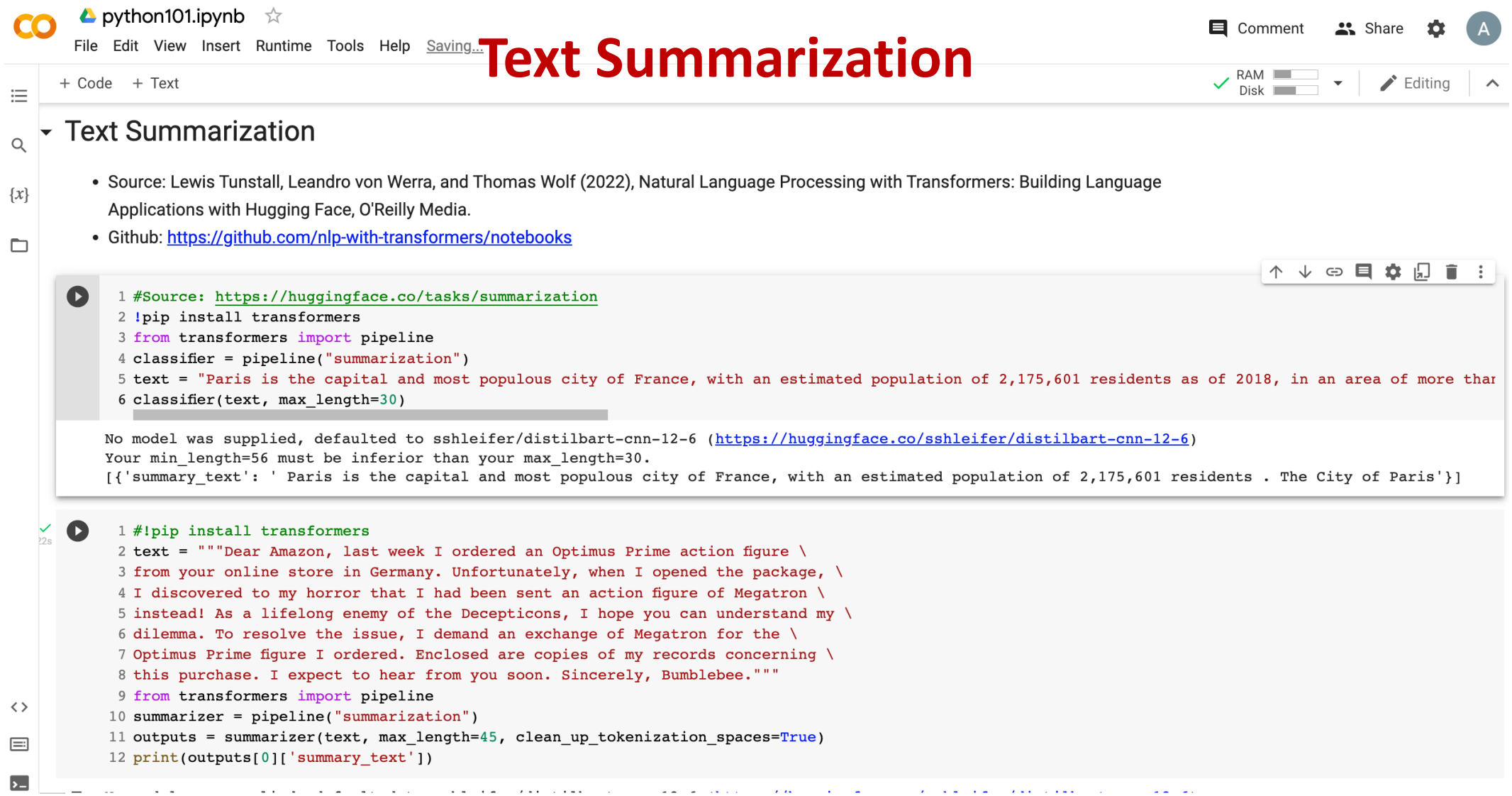

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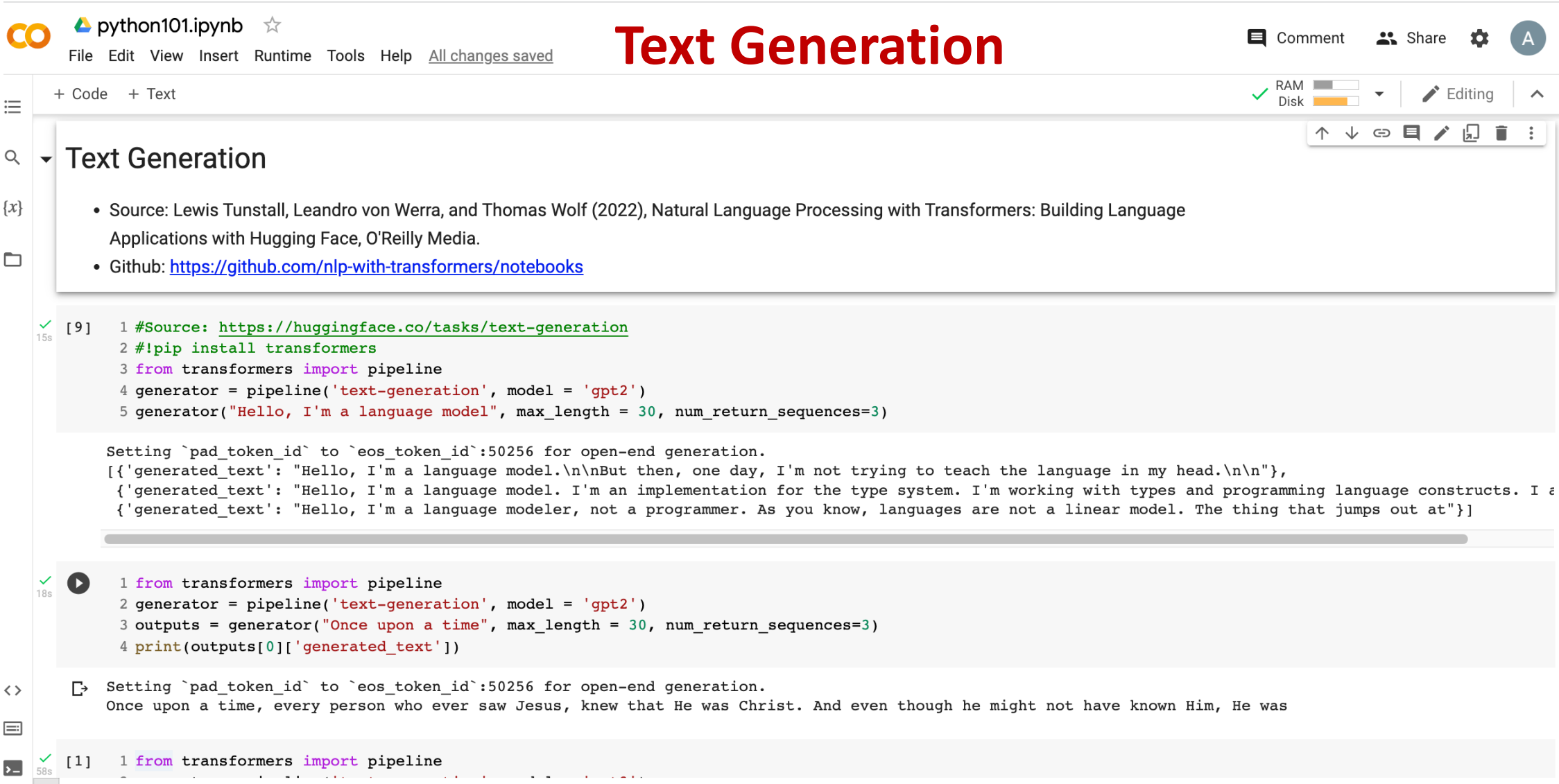

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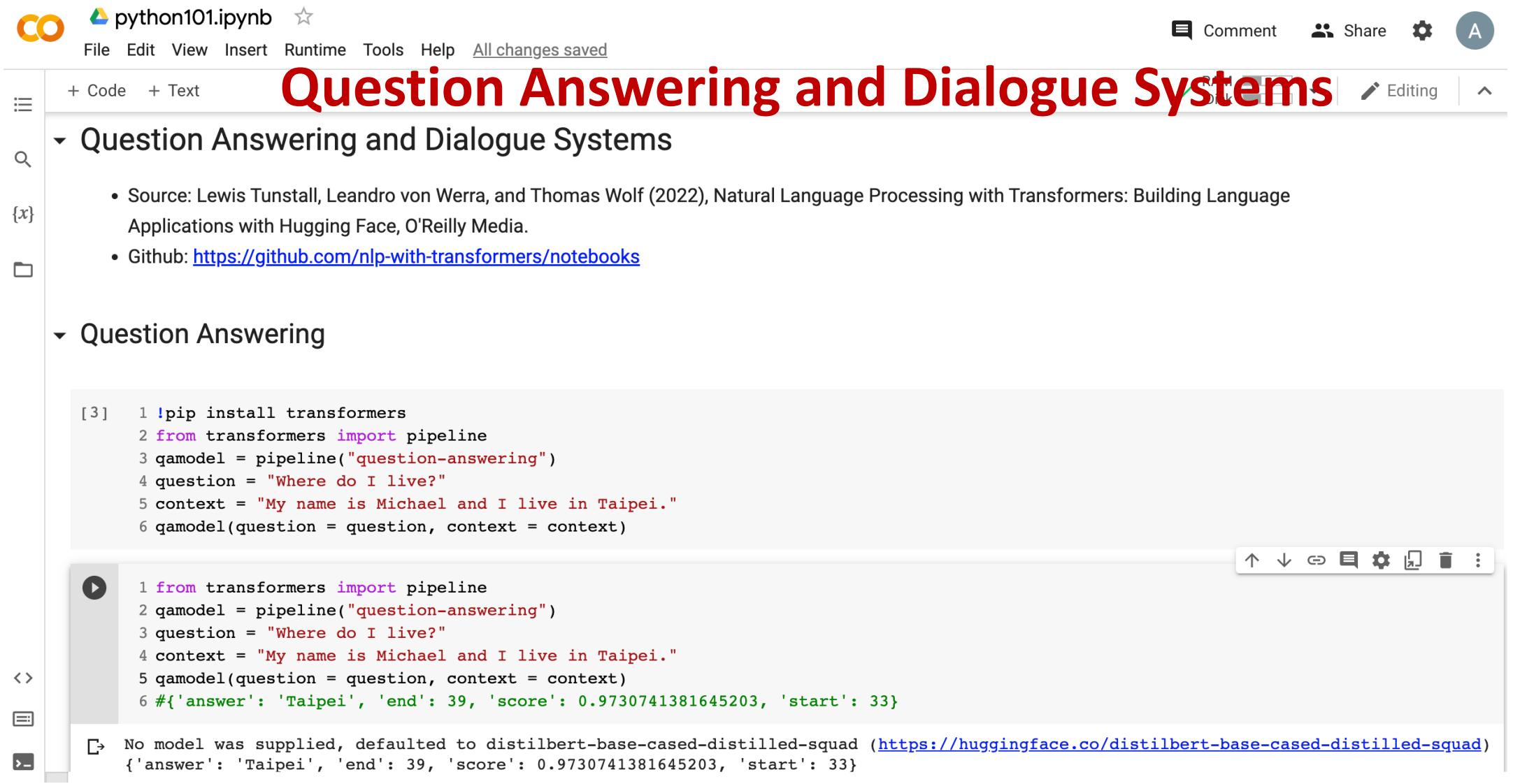

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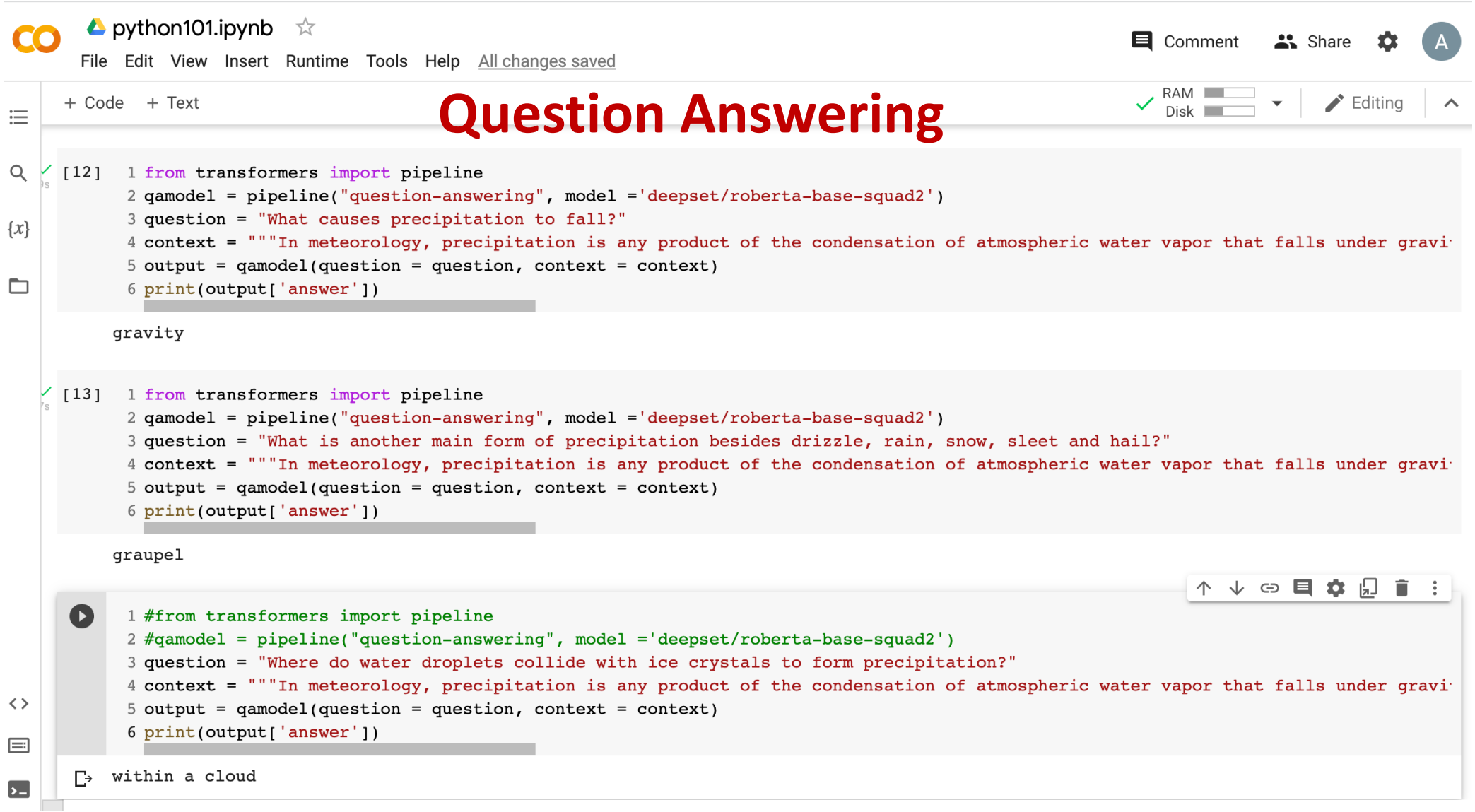

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Python in Google Colab (Python101)

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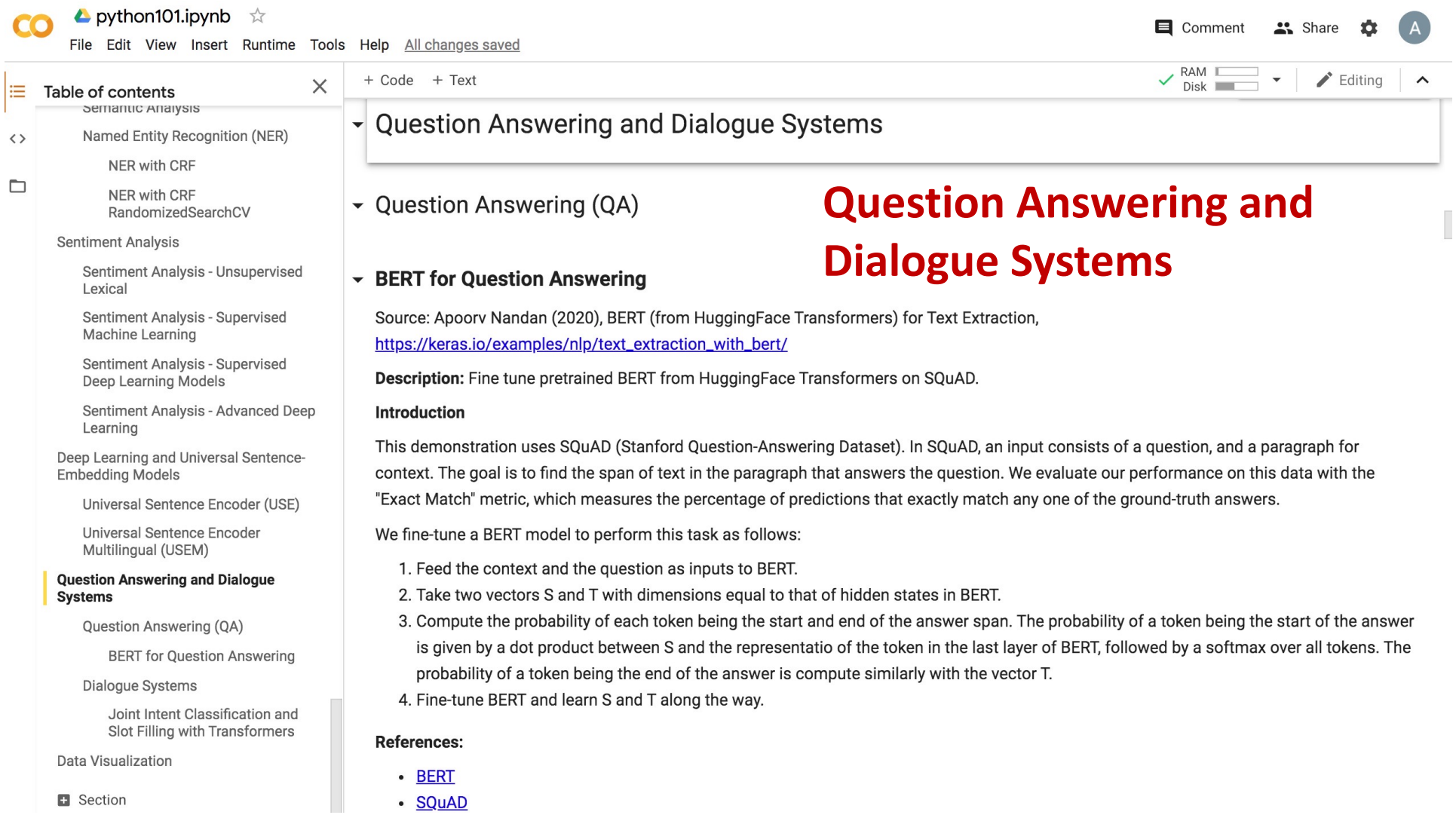

Question Answering and Dialogue Systems

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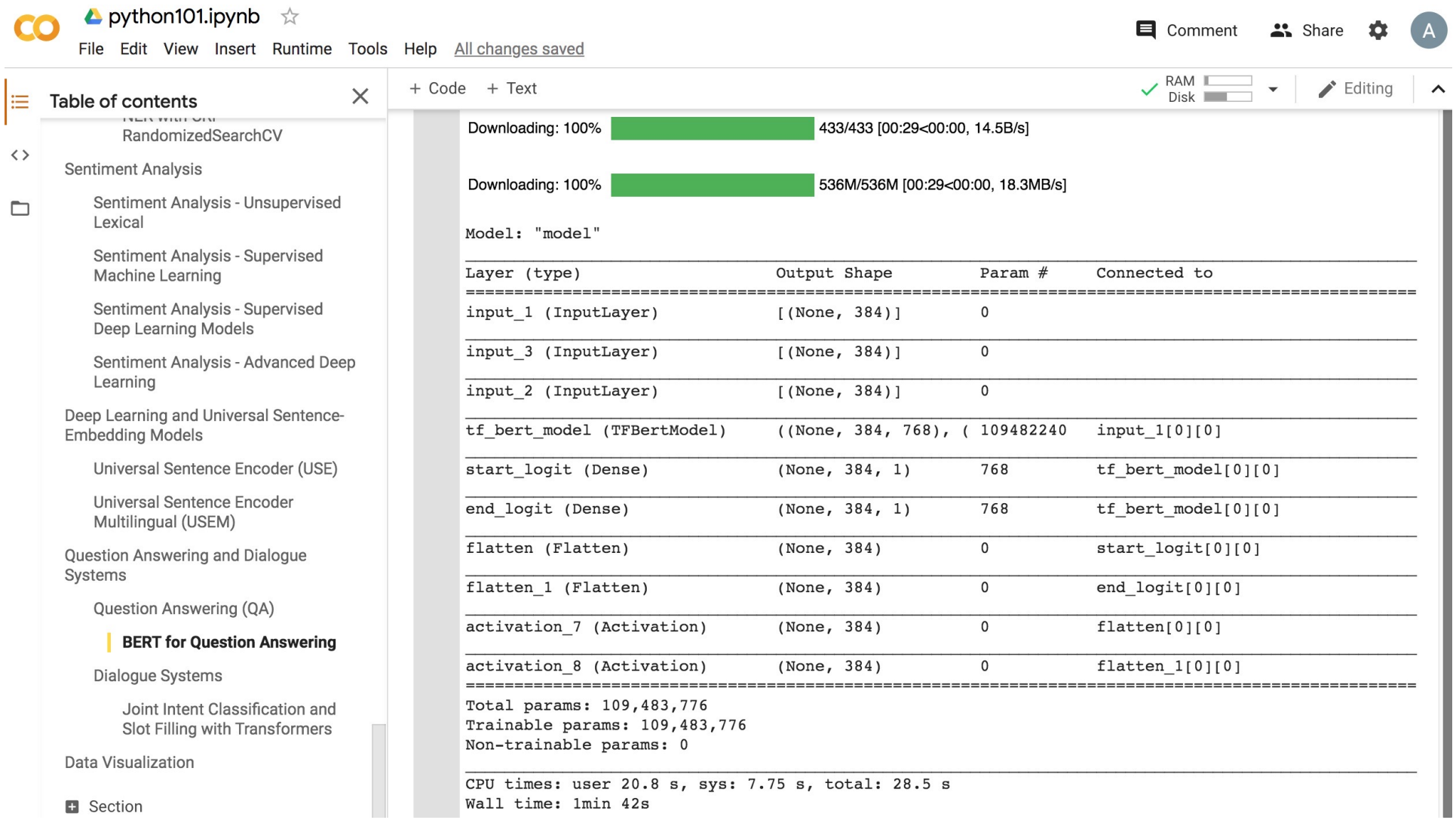

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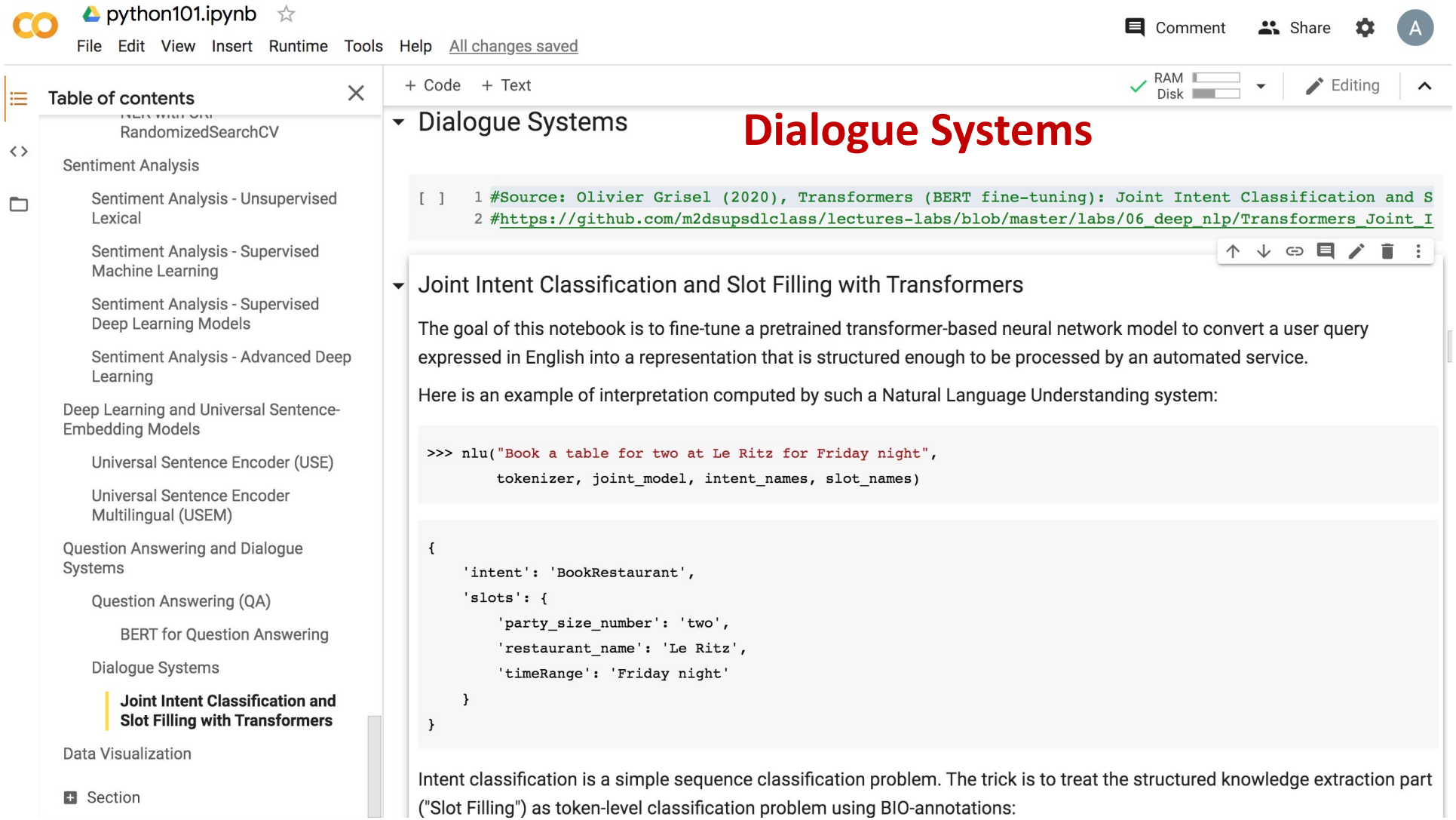

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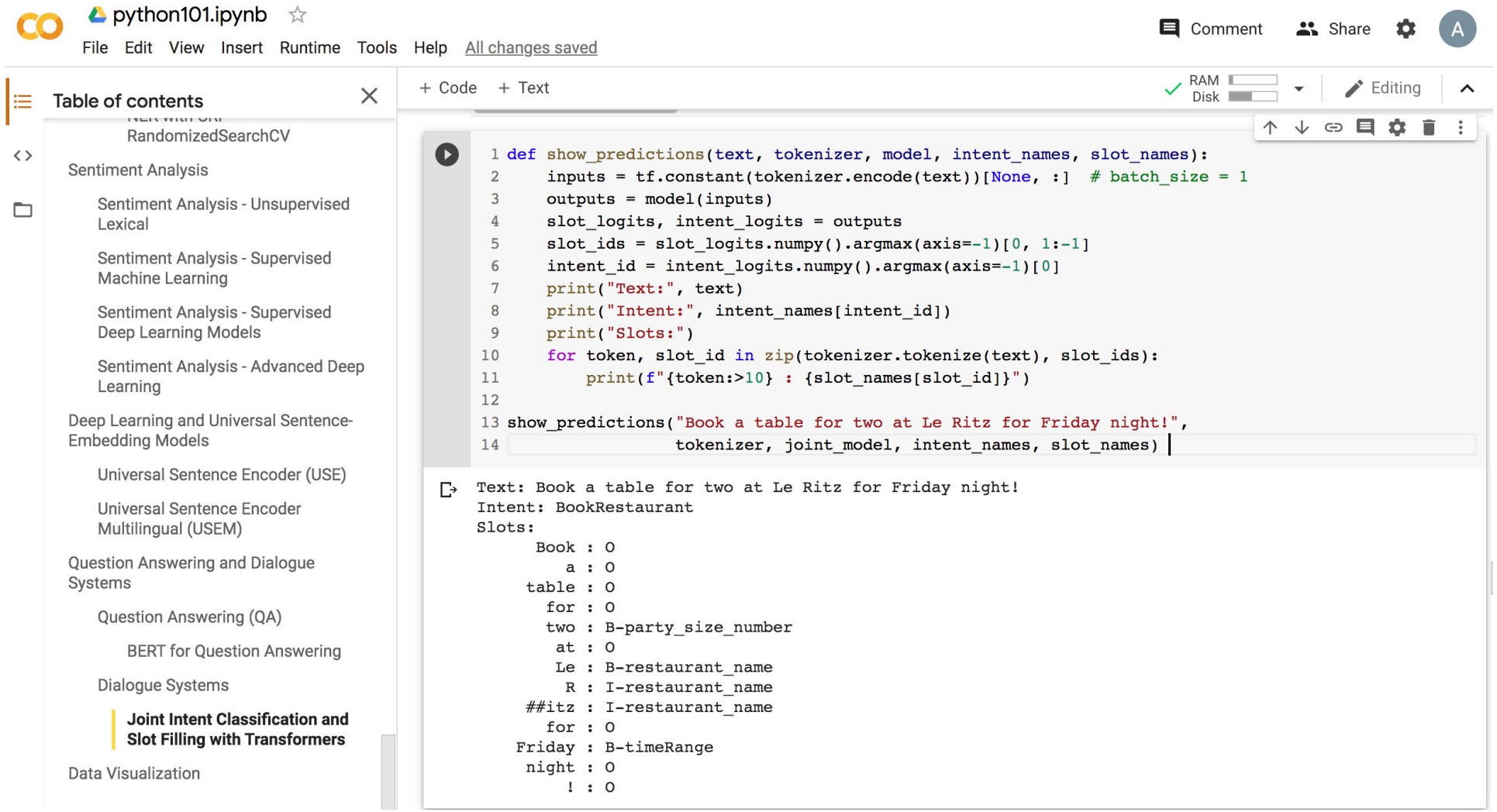

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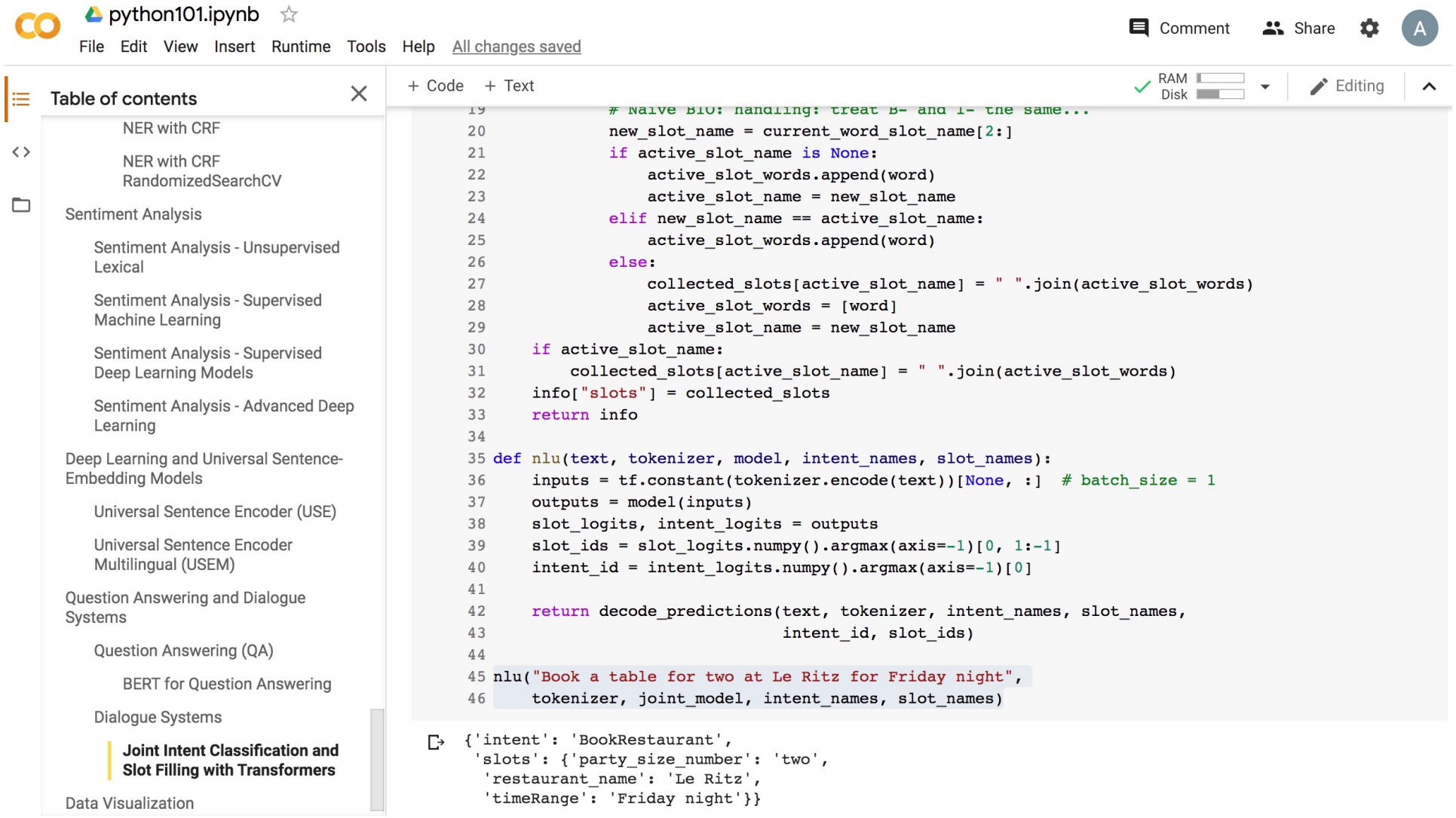

https://tinyurl.com/aintpupython101

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.
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."""
```

```
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

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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.
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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.
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```

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

https://tinyurl.com/aintpupython101

Translation

```
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.
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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

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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}
```

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

Text Generation with LLM (zephyr-7b-beta)

```
# Install transformers from source - only needed for versions <= v4.34
!pip install git+https://github.com/huggingface/transformers.git
!pip install accelerate
```

https://huggingface.co/HuggingFaceH4/zephyr-7b-beta

Text Generation with LLM (zephyr-7b-beta)

```
import torch
from transformers import pipeline

pipe = pipeline("text-generation",
model="HuggingFaceH4/zephyr-7b-beta",
torch_dtype=torch.bfloat16,
device_map="auto")
```

https://huggingface.co/HuggingFaceH4/zephyr-7b-beta

Text Generation with LLM (zephyr-7b-beta)

```
# We use the tokenizer's chat template to format each message - see https://huggingface.co/docs/transformers/main/en/chat_templating
messages = [
            {
            "role": "system",
            "content": "You are a friendly chatbot who always responds in the style of a pirate",
            },
            {"role": "user", "content": "How many helicopters can a human eat in one sitting?"},
            ]
prompt = pipe.tokenizer.apply_chat_template(messages, tokenize=False, add_generation_prompt=True)

outputs = pipe(prompt, max_new_tokens=256, do_sample=True, temperature=0.7, top_k=50, top_p=0.95)
print(outputs[0]["generated_text"])
```

https://huggingface.co/HuggingFaceH4/zephyr-7b-beta

Text Generation with LLM (zephyr-7b-beta)

```
import torch
from transformers import pipeline

pipe = pipeline("text-generation", model="HuggingFaceH4/zephyr-7b-beta",
torch_dtype=torch.bfloat16, device_map="auto")

# We use the tokenizer's chat template to format each message - see
https://huggingface.co/docs/transformers/main/en/chat_templating
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https://huggingface.co/HuggingFaceH4/zephyr-7b-beta

Summary

- Question Answering
- Dialogue Systems
  - Task Oriented Dialogue (TOD) System
- Task-Oriented Dialogue System (TDS)
- Conversational Dialogue System (CDS)
- Question Answering Dialogue System (QADS)

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