Artificial Intelligence for Text Analytics



Question Answering and Dialogue Systems

1102AITA09 MBA, IM, NTPU (M5026) (Spring 2022) Tue 2, 3, 4 (9:10-12:00) (B8F40)







Min-Yuh Day, Ph.D, Associate Professor

Institute of Information Management, National Taipei University

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



Syllabus



Week Date Subject/Topics

- 1 2022/02/22 Introduction to Artificial Intelligence for Text Analytics
- 2 2022/03/01 Foundations of Text Analytics:
 Natural Language Processing (NLP)
- 3 2022/03/08 Python for Natural Language Processing
- 4 2022/03/15 Natural Language Processing with Transformers
- 5 2022/03/22 Case Study on Artificial Intelligence for Text Analytics I
- 6 2022/03/29 Text Classification and Sentiment Analysis

Syllabus



Week Date Subject/Topics

- 7 2022/04/05 Tomb-Sweeping Day (Holiday, No Classes)
- 8 2022/04/12 Midterm Project Report
- 9 2022/04/19 Multilingual Named Entity Recognition (NER),
 Text Similarity and Clustering
- 10 2022/04/26 Text Summarization and Topic Models
- 11 2022/05/03 Text Generation
- 12 2022/05/10 Case Study on Artificial Intelligence for Text Analytics II

Syllabus



Week Date Subject/Topics

- 13 2022/05/17 Question Answering and Dialogue Systems
- 14 2022/05/24 Deep Learning, Transfer Learning,
 Zero-Shot, and Few-Shot Learning for Text Analytics
- 15 2022/05/31 Final Project Report I
- 16 2022/06/07 Final Project Report II
- 17 2022/06/14 Self-learning
- 18 2022/06/21 Self-learning

Question Answering and Dialogue Systems

Outline

- Question Answering
- Dialogue Systems
- Task Oriented Dialogue System

Inputs

Question

Which name is also used to describe the Amazon rainforest in English?

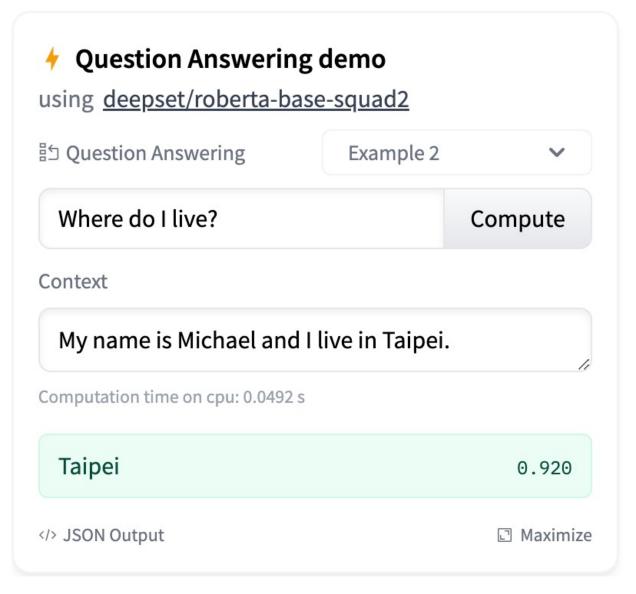
Context

The Amazon rainforest, also known in English as Amazonia or the Amazon Jungle Question
Answering
Model

Output

Answer

Amazonia



```
!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}
```

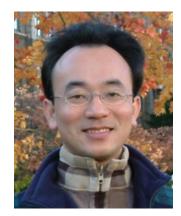
```
from transformers import pipeline
qamodel = pipeline("question-answering", model ='deepset/roberta-base-squad2')
question = "Where do I live?"
context = "My name is Michael and I live in Taipei."
output = qamodel(question = question, context = context)
print(output['answer'])
```

Taipei



IMTKU Textual Entailment System for Recognizing Inference in Text at NTCIR-9 RITE

Department of Information Management Tamkang University, Taiwan



Min-Yuh Day



Chun Tu

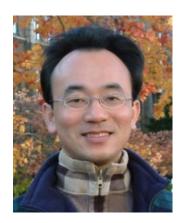
myday@mail.tku.edu.tw

NTCIR-9 Workshop, December 6-9, 2011, Tokyo, Japan



IMTKU Textual Entailment System for Recognizing Inference in Text at NTCIR-10 RITE-2

Department of Information Management Tamkang University, Taiwan



Min-Yuh Day



Chun Tu



Hou-Cheng Vong



Shih-Wei Wu



Shih-Jhen Huang

myday@mail.tku.edu.tw

IMTKU Textual Entailment System for Recognizing Inference in Text at NTCIR-11 RITE-VAL

Tamkang University

2014











Ya-Jung Wang



Che-Wei Hsu



En-Chun Tu



Huai-Wen Hsu



Yu-An Lin



Shang-Yu Wu



Yu-Hsuan Tai



Cheng-Chia Tsai





IMTKU Question Answering System for World History Exams at NTCIR-12 QA Lab2

Department of Information Management Tamkang University, Taiwan

Sagacity Technology



















Min-Yuh Day Cheng-Chia Tsai Wei-Chun Chung Hsiu-Yuan Chang

Tzu-Jui Sun

Yuan-Jie Tsai

Cheng-Hung Lee



Yu-Ming Guo



Yue-Da Lin



Wei-Ming Chen



Yun-Da Tsai



Cheng-Jhih Han







Yi-Jing Lin Yi-Heng Chiang Ching-Yuan Chien

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IMTKU Question Answering System for World History Exams at NTCIR-13 QALab-3

Department of Information Management Tamkang University, Taiwan



Min-Yuh Day



Chao-Yu Chen



Wanchu Huang



Shi-Ya Zheng



I-Hsuan Huang



Tz-Rung Chen



Min-Chun Kuo



Yue-Da Lin



Yi-Jing Lin

myday@mail.tku.edu.tw





IMTKU Emotional Dialogue System for Short Text Conversation at NTCIR-14 STC-3 (CECG) Task

Department of Information Management Tamkang University, Taiwan



Min-Yuh Day



Chi-Sheng Hung



Yi-Jun Xie



Jhih-Yi Chen



Yu-Ling Kuo



Jian-Ting Lin





IMTKU Multi-Turn Dialogue System Evaluation at the NTCIR-15 DialEval-1 **Dialogue Quality and Nugget Detection**

¹ Zeals Co., Ltd. Tokyo, Japan ² Information Management, Tamkang University, Taiwan ³ Information Management, National Taipei University, Taiwan

















Mike Tian-Jian Jiang¹

Zhao-Xian Gu²

Cheng-Jhe Chiang²

Yueh-Chia Wu² Yu-Chen Huang² Cheng-Han Chiu² Sheng-Ru Shaw²

2020 NTCIR-15 Dialogue Evaluation (DialEval-1) Task Dialogue Quality (DQ) and Nugget Detection (ND) Chinese Dialogue Quality (S-score) Results (Zeng et al., 2020)

Run	Mean RSNOD	Run	Mean NMD
IMTKU-run2	0.1918	IMTKU-run2	0.1254
IMTKU-run1	0.1964	IMTKU-run0	0.1284
IMTKU-run0	0.1977	IMTKU-run1	0.1290
TUA1-run2	0.2024	TUA1-run2	0.1310
TUA1-run0	0.2053	TUA1-run0	0.1322
NKUST-run1	0.2057	NKUST-run1	0.1363
BL-lstm	0.2088	TUA1-run1	0.1397
WUST-run0	0.2131	BL-popularity	0.1442
RSLNV-run0	0.2141	BL-lstm	0.1455
BL-popularity	0.2288	RSLNV-run0	0.1483
TUA1-run1	0.2302	WUST-run0	0.1540
NKUST-run0	0.2653	NKUST-run0	0.2289
BL-uniform	0.2811	BL-uniform	0.2497

Transformer-based Fine-tuning Techniques Models Selection FinNum-2 DialEval-1 **BERT Discriminative Transfer Fine-tuning** Learning **RoBERTa One-cycle Policy Optimization XLM-RoBERTa Tokenization Tricks Pre-trained Models**

Source: Jiang, Mike Tian-Jian, Shih-Hung Wu, Yi-Kun Chen, Zhao-Xian Gu, Cheng-Jhe Chiang, Yueh-Chia Wu, Yu-Chen Huang, Cheng-Han Chiu, Sheng-Ru Shaw, and Min-Yuh Day (2020). "Fine-tuning techniques and data augmentation on transformer-based models for conversational texts and noisy user-generated content." In 2020 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), pp. 919-925. IEEE, 2020.



Short Text Conversation Task
(STC-3)
Chinese Emotional
Conversation Generation
(CECG) Subtask

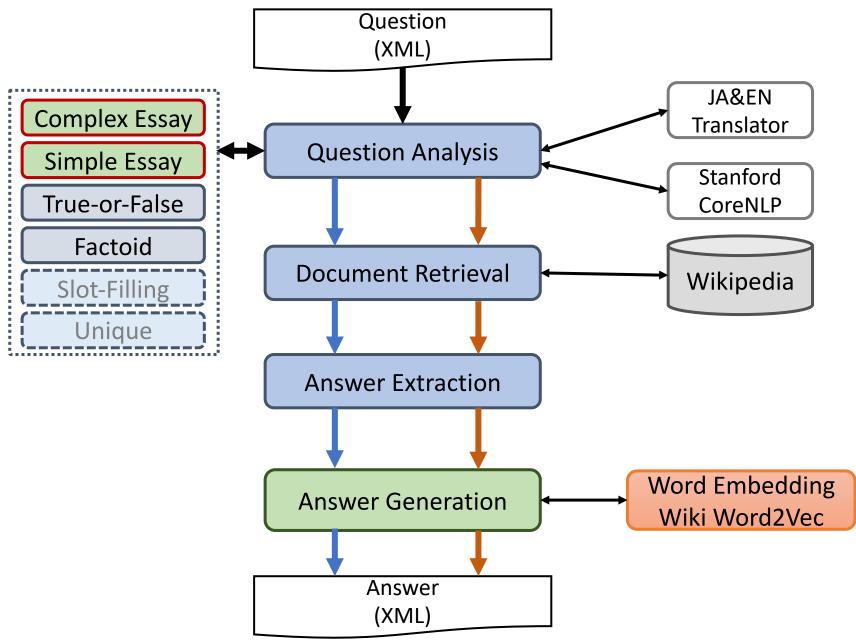
NTCIR Short Text Conversation STC-1, STC-2, STC-3

			Japanese	Chinese	English		
	NT	CIR-12 STC-1 22 active participants	Twitter, Retrieval	Weibo, Retrieval			Single-turn,
	NT	CIR-13 STC-2 27 active participants	Yahoo! News, Retrieval+ Generation	Weibo, Retrieval+ Generation			Non task-oriented
	Chinese Emotional Conversation Generation (CECG) subtask Dialogue Quality (DQ) and Nugget Detection (ND) subtasks		Weibo, Generation for given emotion				
			Weibo+English translations, distribution estimation for subjective annotations		H	Multi-turn, task-oriented (helpdesk)	

Source: https://waseda.app.box.com/v/STC3atNTCIR-14

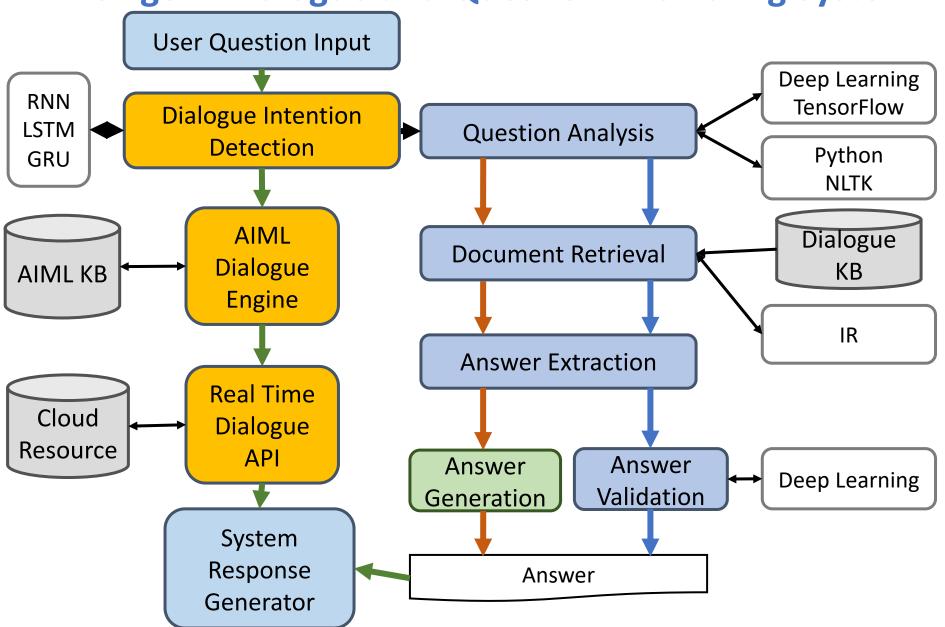
IMTKU System Architecture for NTCIR-13 QALab-3





System Architecture of

Intelligent Dialogue and Question Answering System





IMTKU Emotional Dialogue System Architecture

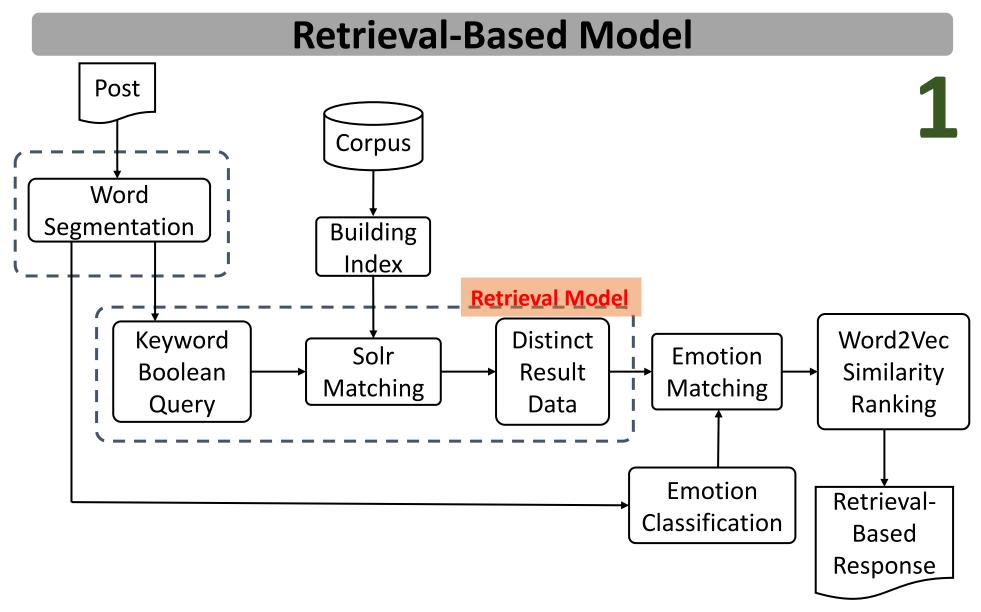
Retrieval-Based Model **Emotion** Response Classification **Ranking** Model **Generation-Based Model**

2

The system architecture of



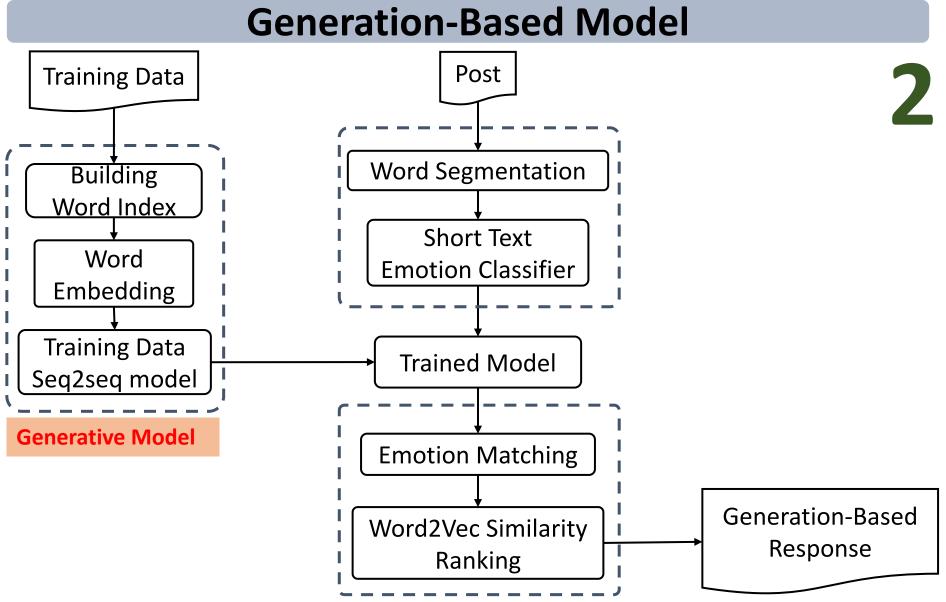
IMTKU retrieval-based model for NTCIR-14 STC-3



The system architecture of



IMTKU generation-based model for NTCIR-14 STC-3

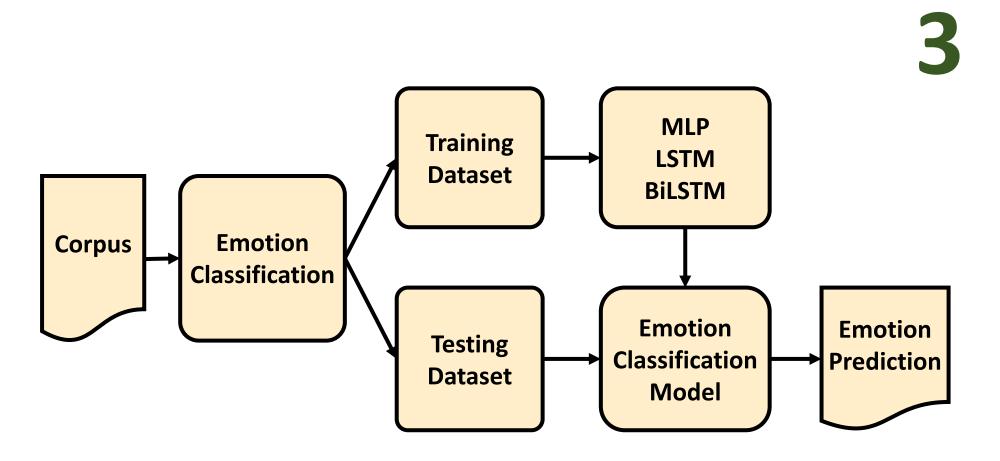


The system architecture of



IMTKU emotion classification model for NTCIR-14 STC-3

Emotion Classification Model

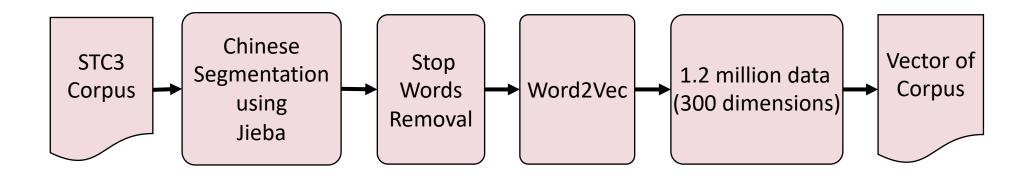


The system architecture of IMTKU Response Ranking for NTCIR-14 STC-3



Response Ranking

4



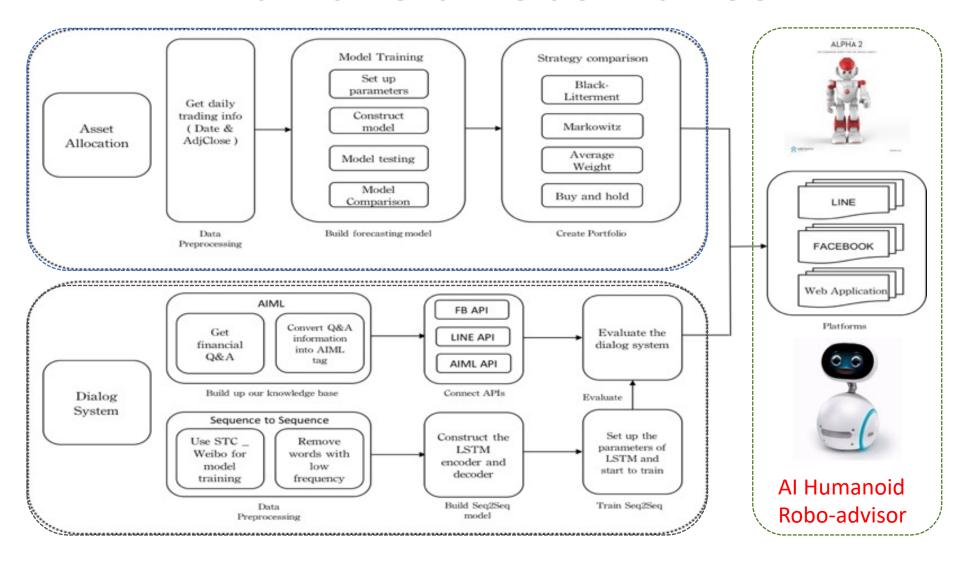
Al Humanoid Robo-Advisor

Al Humanoid Robo-Advisor

for Multi-channel Conversational Commerce

Multichannel Al Portfolio **Platforms Asset Allocation** Web LINE Facebook **Al Conversation** Humanoid **Dialog System** Robot

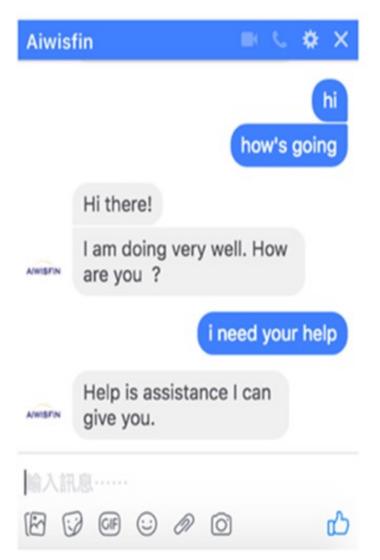
System Architecture of Al Humanoid Robo-Advisor



Conversational Model

(LINE, FB Messenger)





Conversational Robo-Advisor Multichannel UI/UX Robots



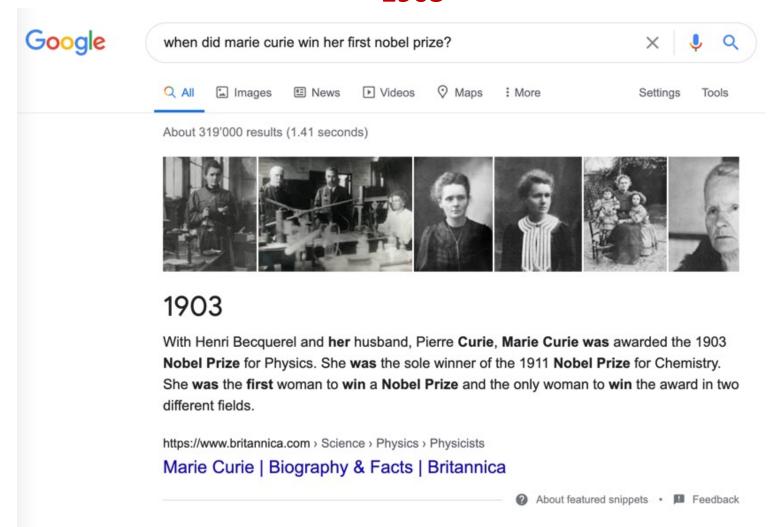
ALPHA 2





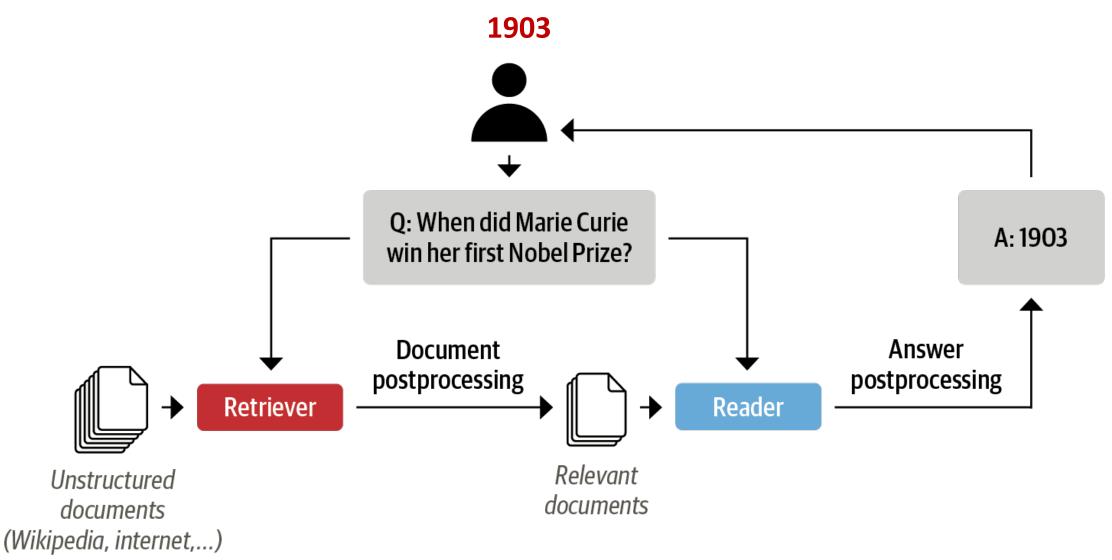


When did Marie Curie win her first Nobel Prize? 1903

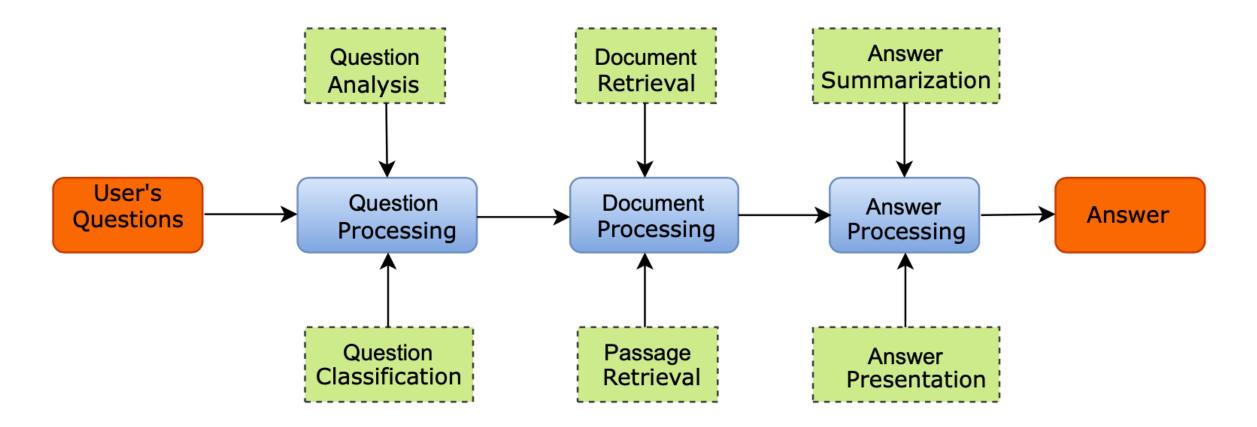


The Retriever-Reader Architecture for Modern QA Systems

When did Marie Curie win her first Nobel Prize?

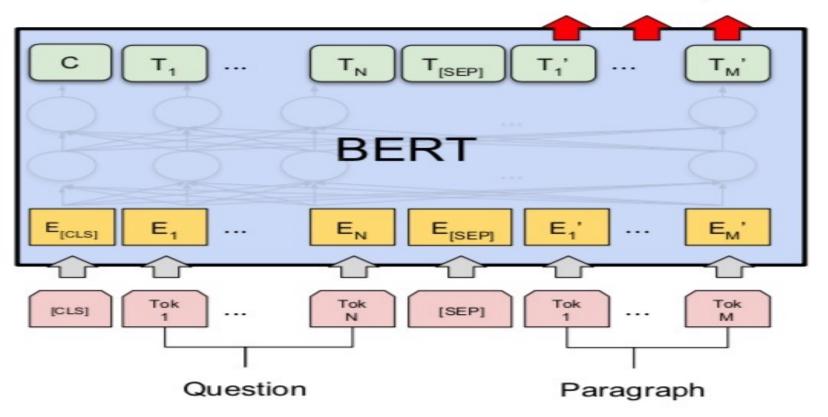


Question Answering System (QAS)



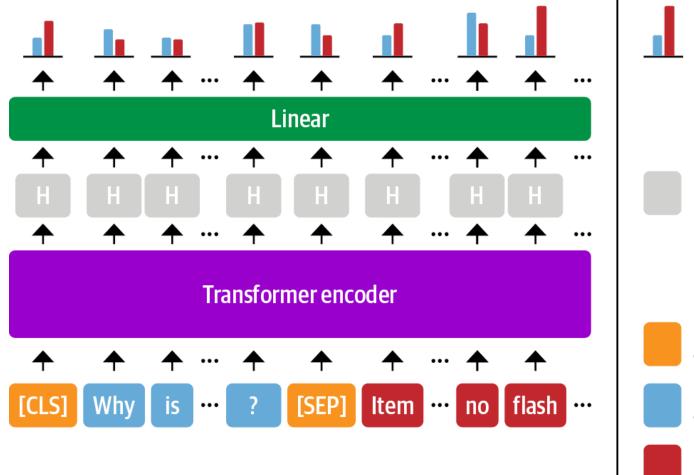
Fine-tuning BERT on Question Answering (QA)

Start/End Span



(c) Question Answering Tasks: SQuAD v1.1

The span classification head for QA tasks



Start and end logits

Hidden states

Special tokens Question tokens

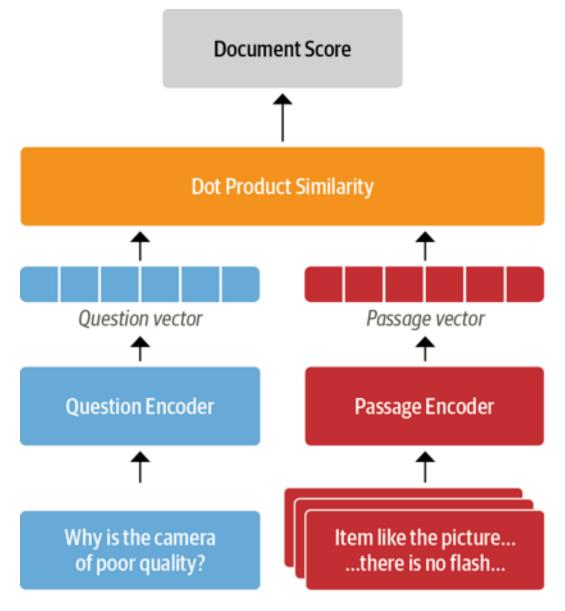
Context tokens

Question answering

Multiple question-context pairs

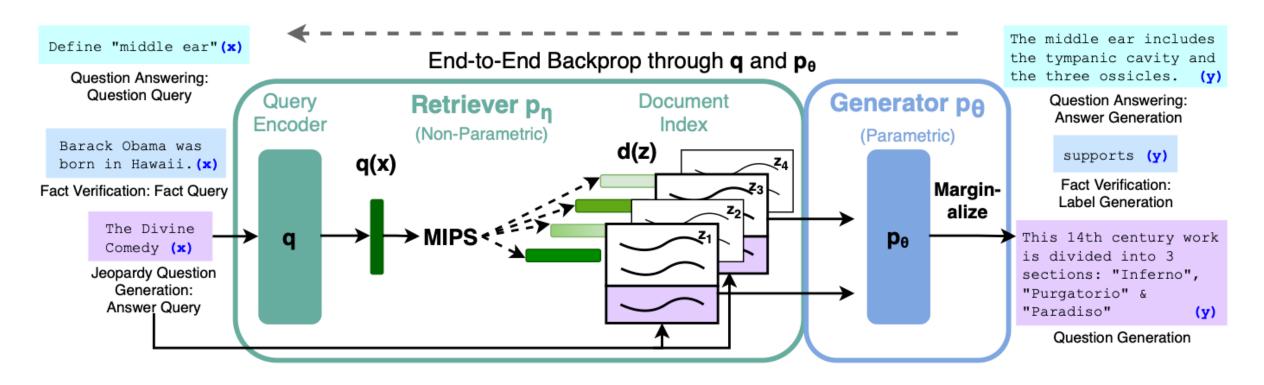
Why is the camera of poor quality? Item like the picture, fast deliver 3 days well packed, good quality for the price. The camera is decent (as phone cameras go). There is no flash though... [SEP] Stride Why is the camera of poor quality? Item like the picture, fast deliver 3 days well packed, good quality for the price. The camera is decent (as phone cameras go). There is no flash though...

Dense Passage Retrieval (DPR)

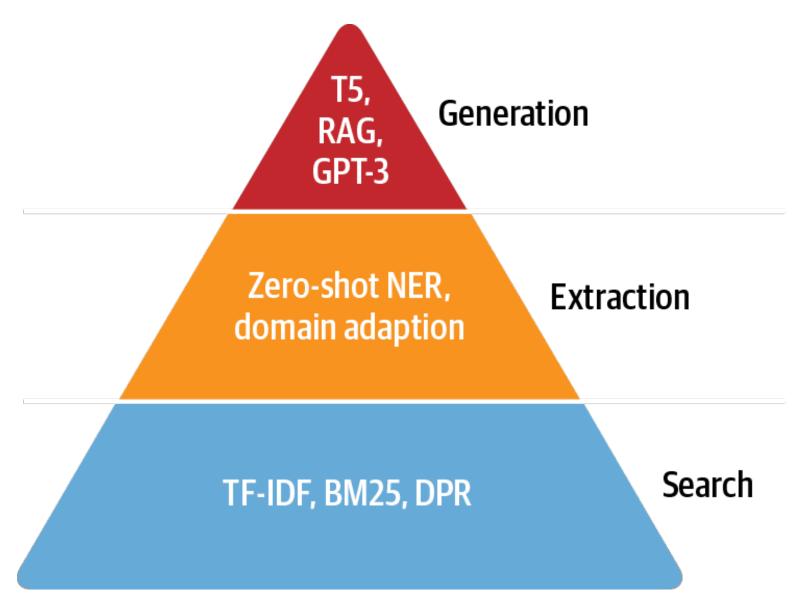


Going Beyond Extractive QA Retrieval-Augmented Generation (RAG)

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

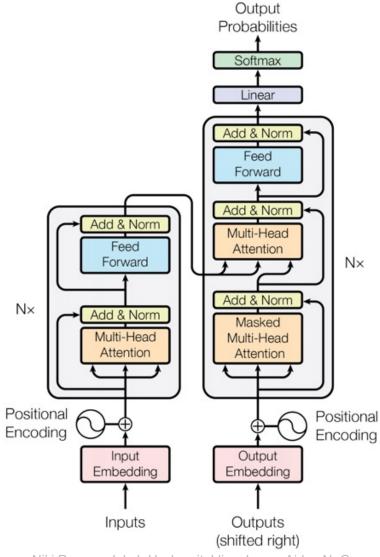


The QA Hierarchy of Needs



Transformer (Attention is All You Need)

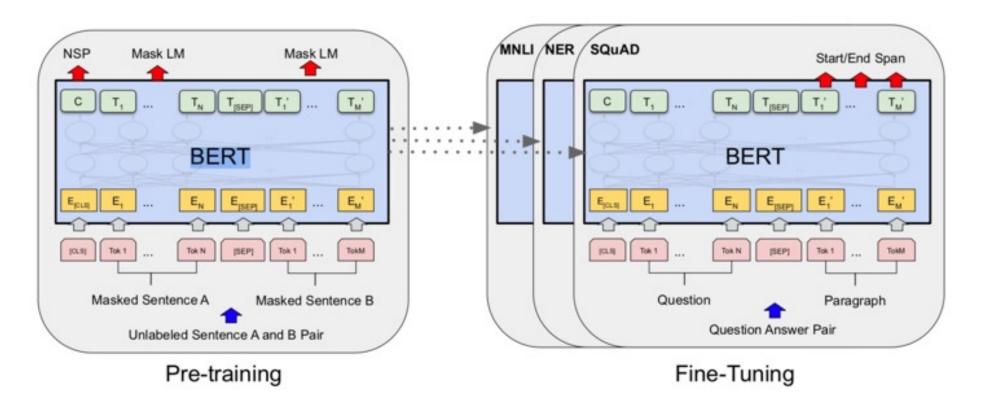
(Vaswani et al., 2017)



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

BERT (Bidirectional Encoder Representations from Transformers)

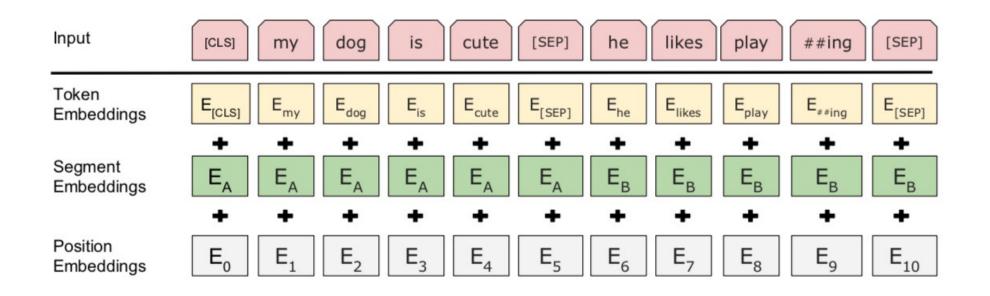
Overall pre-training and fine-tuning procedures for BERT



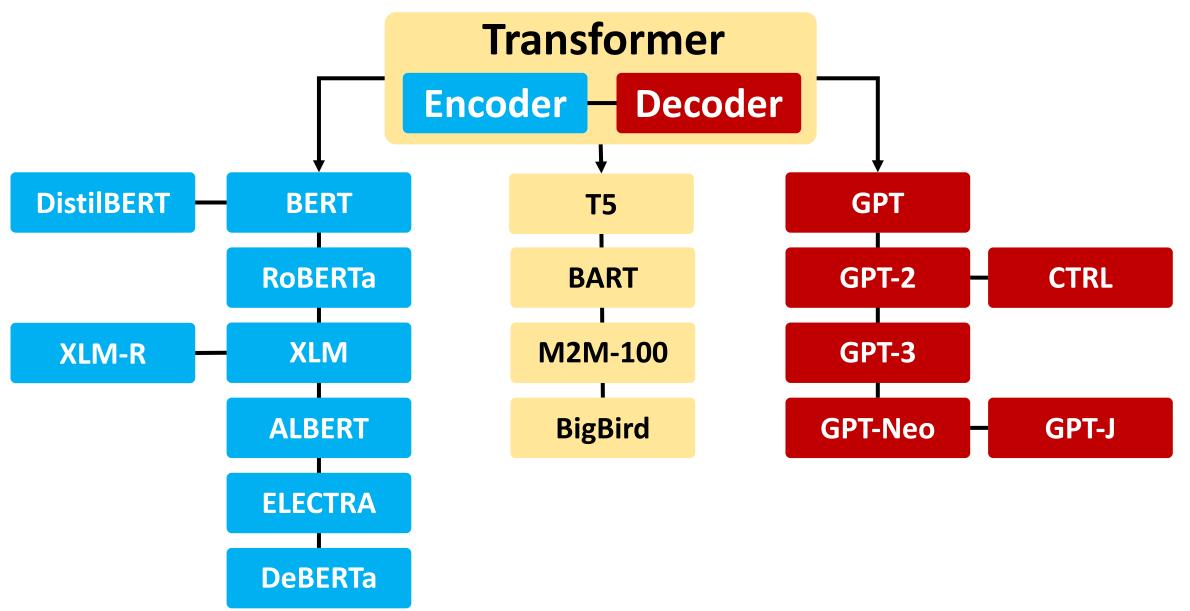
BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT (Bidirectional Encoder Representations from Transformers)

BERT input representation

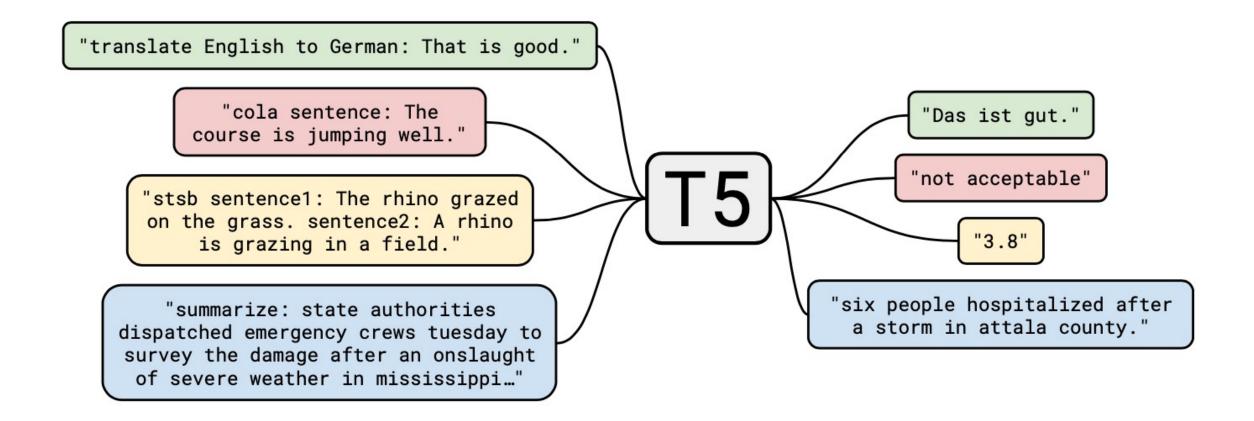


Transformer Models

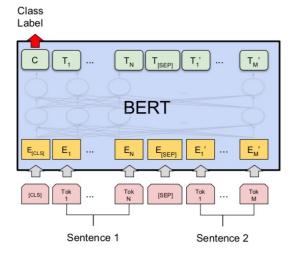


T5

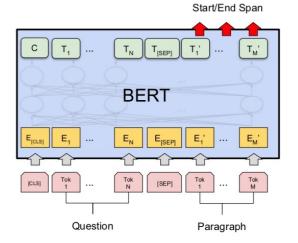
Text-to-Text Transfer Transformer



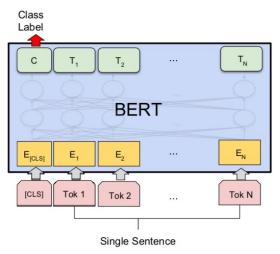
Fine-tuning BERT on Different Tasks



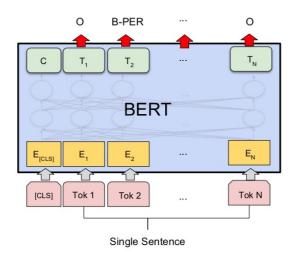
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



(c) Question Answering Tasks: SQuAD v1.1



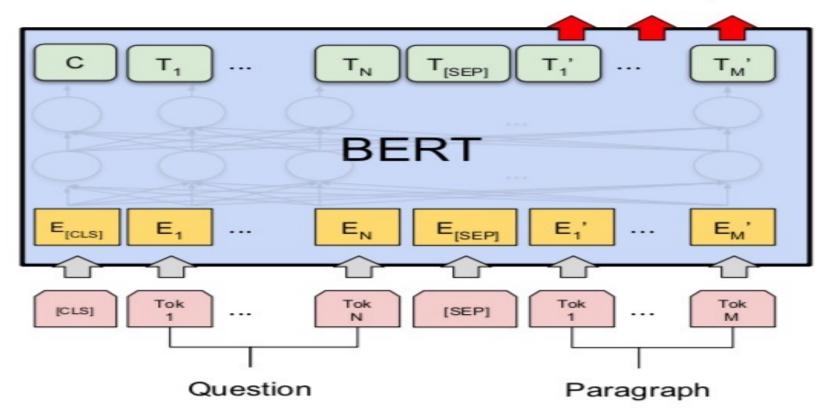
(b) Single Sentence Classification Tasks: SST-2, CoLA



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

Fine-tuning BERT on Question Answering (QA)

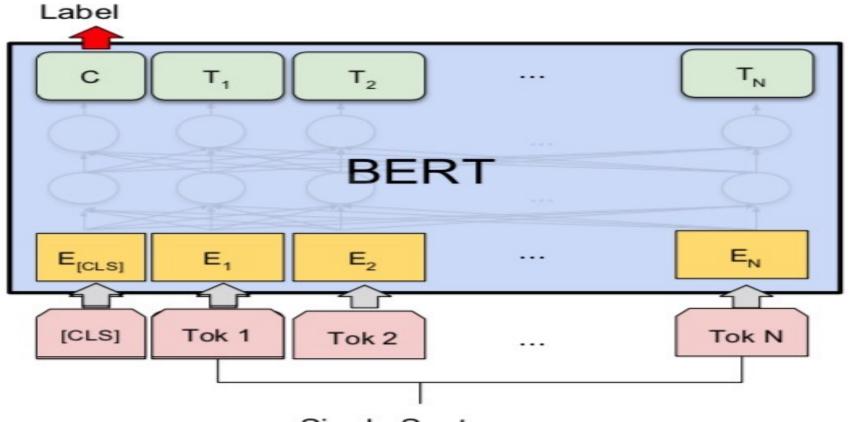
Start/End Span



(c) Question Answering Tasks: SQuAD v1.1

Fine-tuning BERT on Dialogue Intent Detection (ID; Classification)

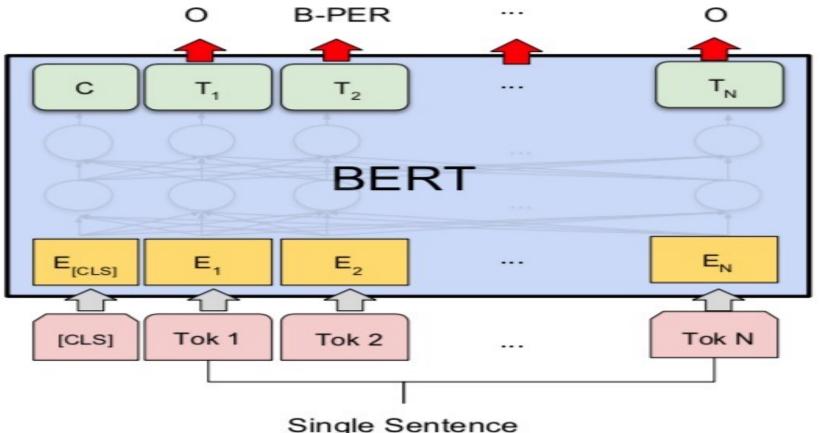
Class



Single Sentence

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

Fine-tuning BERT on Dialogue Slot Filling (SF)



Single Sentence

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

Question Answering (QA) SQuAD

Stanford Question Answering Dataset



SQuAD Home Explore 2.0 Explore 1.1

SQuAD2.0

The Stanford Question Answering Dataset

What is SQuAD?

Stanford Question Answering Dataset (SQuAD) is a reading comprehension dataset, consisting of questions posed by crowdworkers on a set of Wikipedia articles, where the answer to every question is a segment of text, or *span*, from the corresponding reading passage, or the question might be unanswerable.

SQuAD2.0 combines the 100,000 questions in SQuAD1.1 with over 50,000 unanswerable questions written adversarially by crowdworkers to look similar to answerable ones. To do well on SQuAD2.0, systems must not only answer questions when possible, but also determine when no answer is supported by the paragraph and abstain from answering.

Leaderboard

SQuAD2.0 tests the ability of a system to not only answer reading comprehension questions, but also abstain when presented with a question that cannot be answered based on the provided paragraph.

Rank	Model	EM	F1
	Human Performance Stanford University (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Apr 06, 2020	SA-Net on Albert (ensemble) QIANXIN	90.724	93.011
2 May 05, 2020	SA-Net-V2 (ensemble) QIANXIN	90.679	92.948
2	Retro-Reader (ensemble)	90.578	92.978



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-ga.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

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. 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]

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?

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

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

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

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?

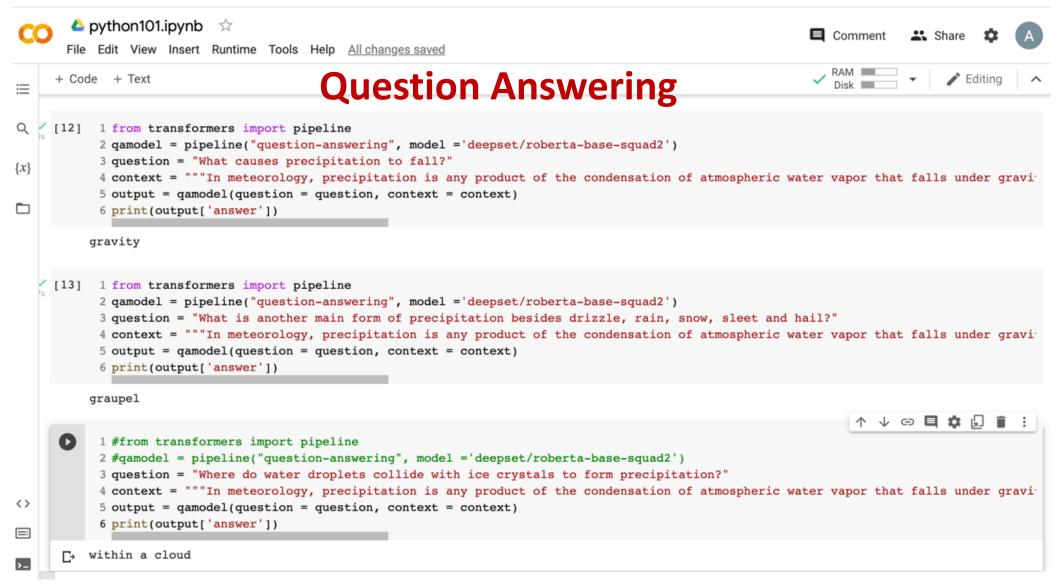
A: graupel

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



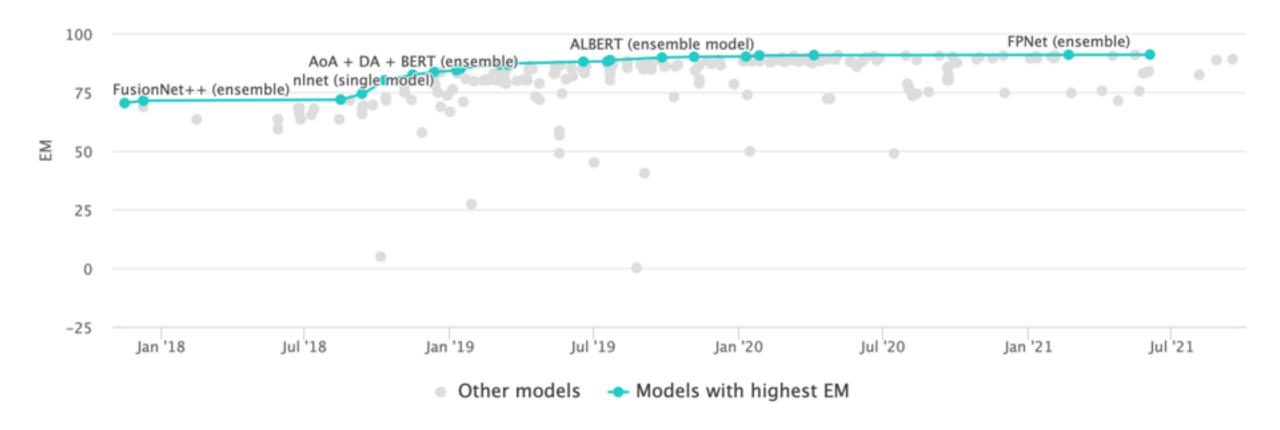
Question Answering

```
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

Question Answering on SQuAD2.0

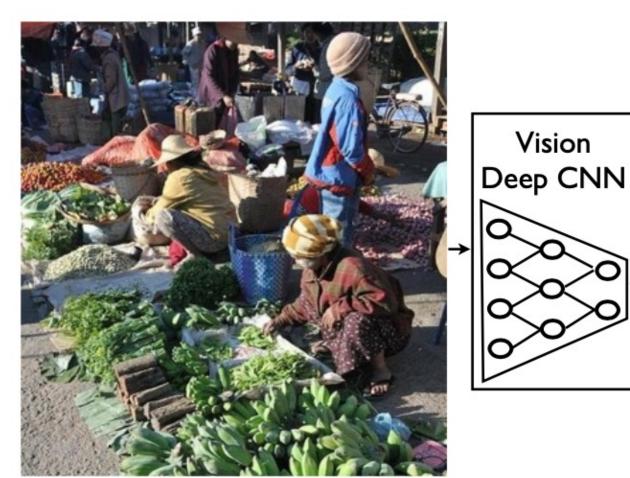
SQuAD 2.0 benchmark (Papers with Code)



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

Neural Image Captioning (NIC)

image-to-text description generation



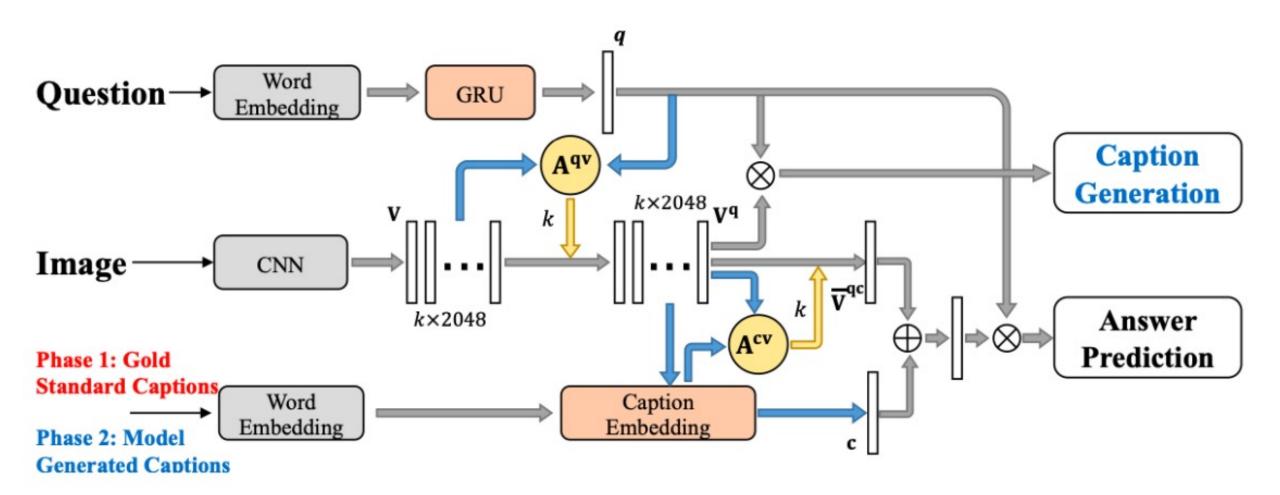
Vision Language
Deep CNN Generating
RNN

A group of people shopping at an outdoor market.

There are many vegetables at the fruit stand.

Visual Question Answering

Neural caption generation is employed to aid answer prediction



Dialogue Systems

Conversational Commerce

Chatbot Dialogue System Intelligent Agent

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 1 benchmark

20 papers with code



Dialogue Management

12 papers with code



Dialogue Understanding

11 benchmarks

12 benchmarks

13 benchmarks

14 benchmarks

15 benchmarks

16 benchmarks

17 benchmarks

18 benchmarks

8 papers with code



Dialogue Act Classification

2 benchmarks

8 papers with code

Short-Text Conversation

Short-Text Conversation

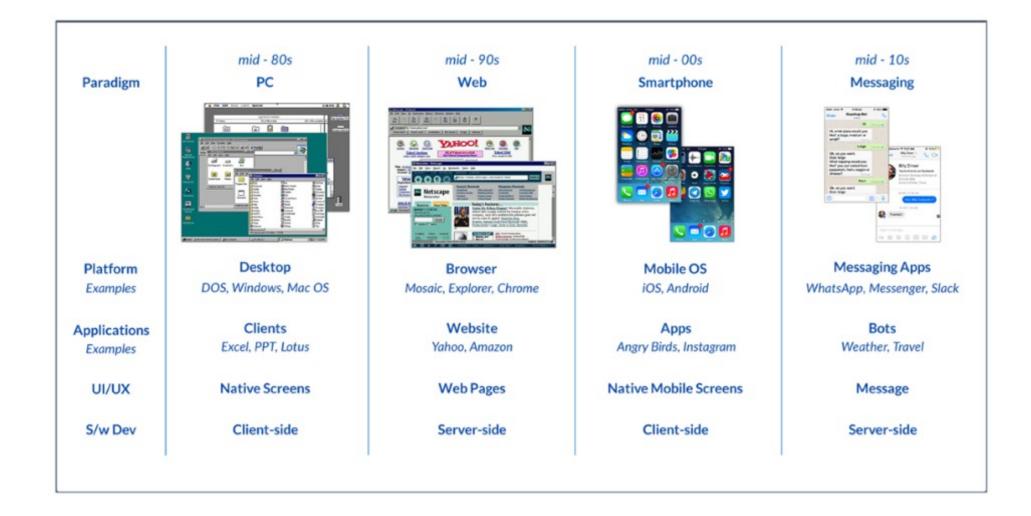
7 papers with code



Goal-Oriented Dialogue Systems

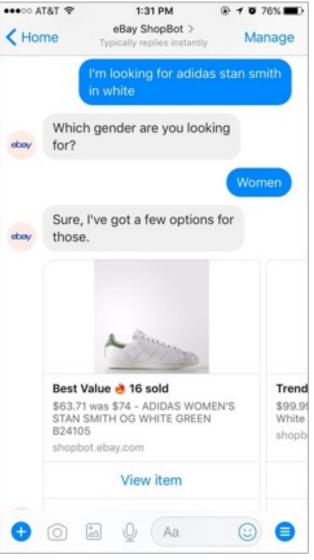
7 papers with code

Chatbots: Evolution of UI/UX

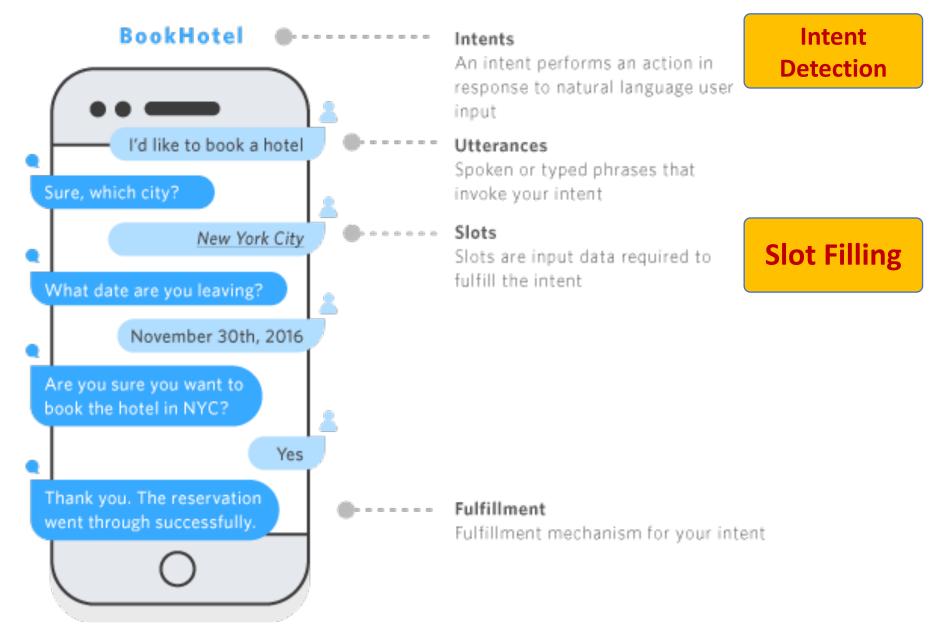


From **E-Commerce** to **Conversational Commerce:** Chatbots and **Virtual Assistants**

Conversational Commerce: eBay AI Chatbots

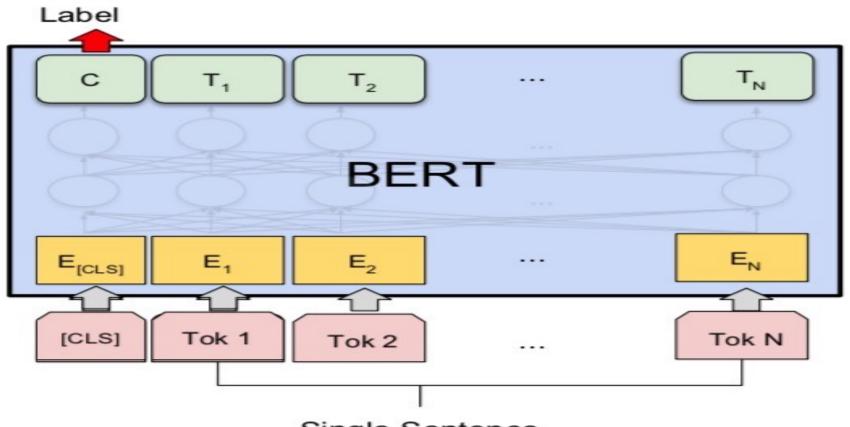


Hotel Chatbot



Fine-tuning BERT on Dialogue Intent Detection (ID; Classification)

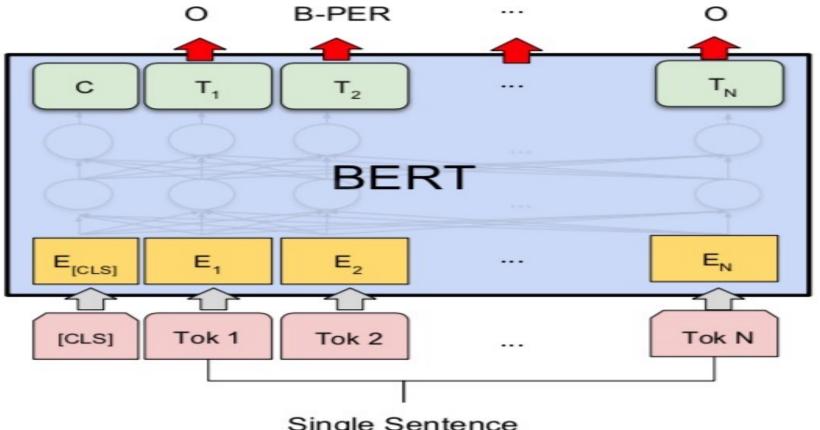
Class



Single Sentence

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

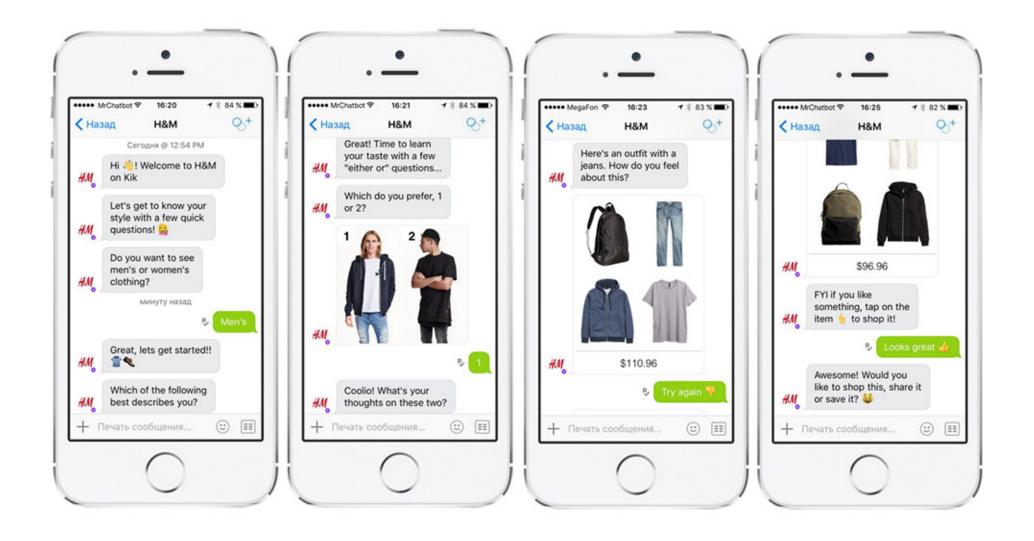
Fine-tuning BERT on Dialogue Slot Filling (SF)



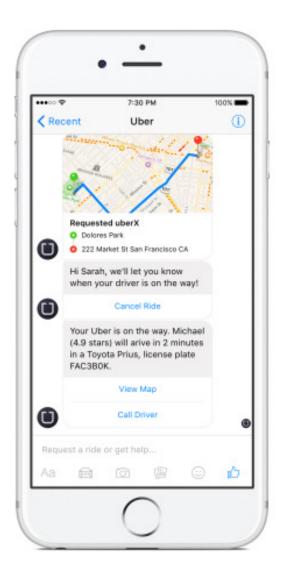
Single Sentence

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

H&M's Chatbot on Kik



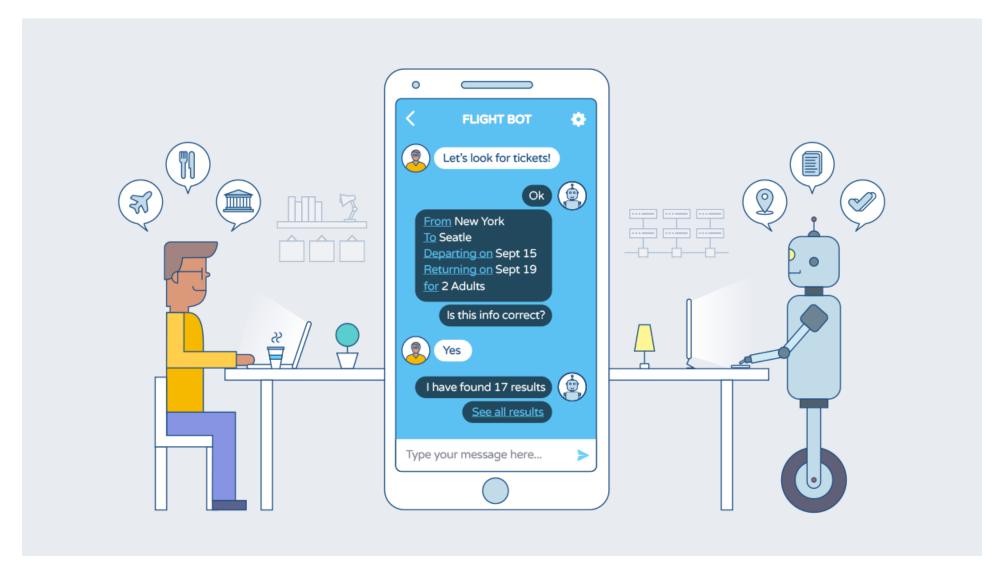
Uber's Chatbot on Facebook's Messenger



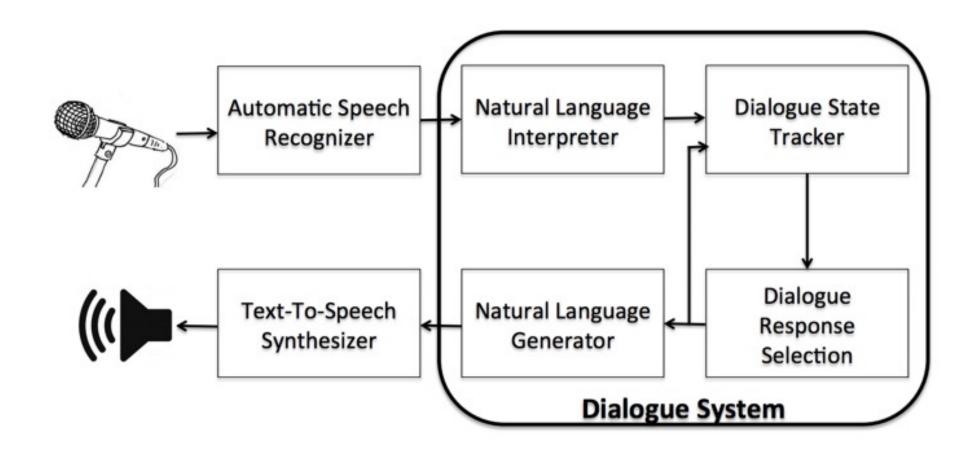
Uber's chatbot on Facebook's messenger

- one main benefit: it loads much faster than the Uber app

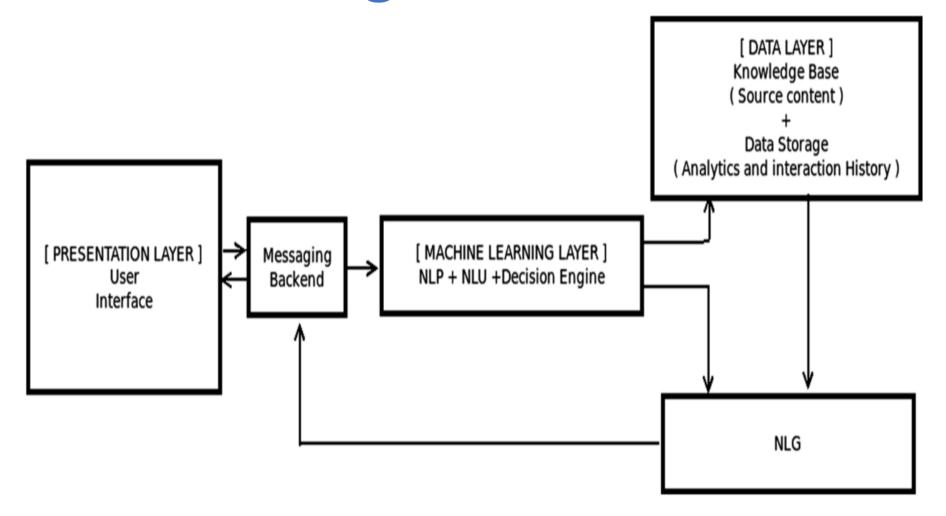
Chatbot



Dialogue System



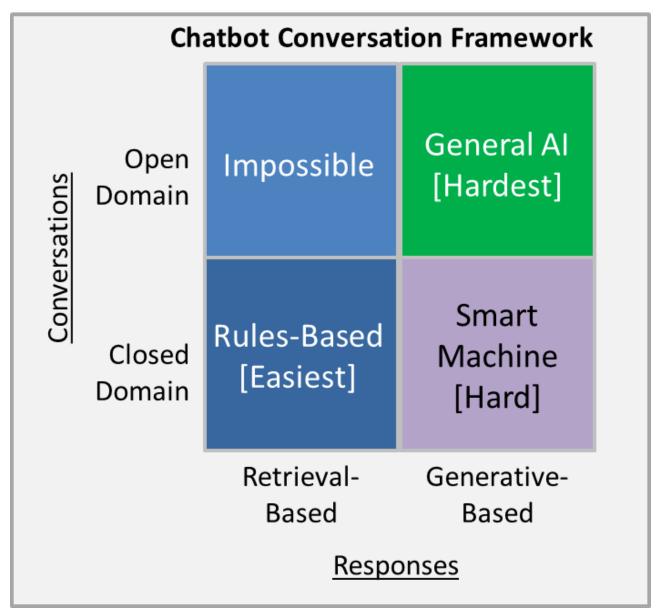
Overall Architecture of Intelligent Chatbot



Can machines think? (1950, Alan Turing)

Chatbot "online human-computer dialog system with natural language."

Chatbot Conversation Framework

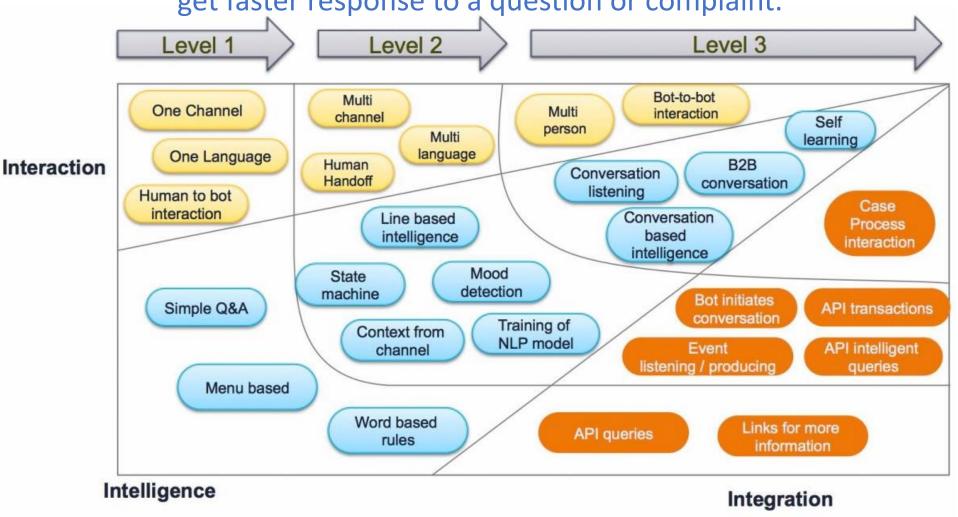


Chatbots

Bot Maturity Model

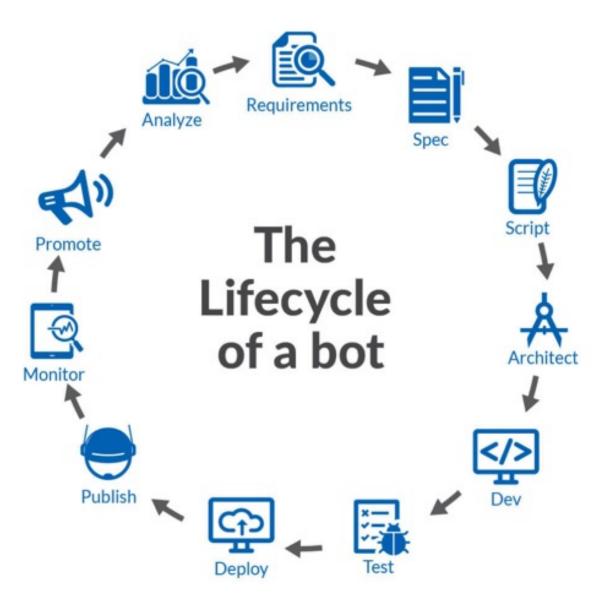
Customers want to have simpler means to interact with businesses and

get faster response to a question or complaint.



Bot Life Cycle and Platform Ecosystem

The Bot Lifecycle



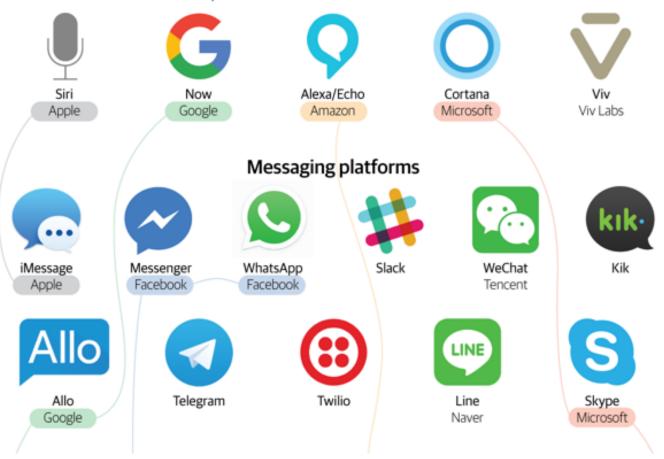
The bot platform ecosystem

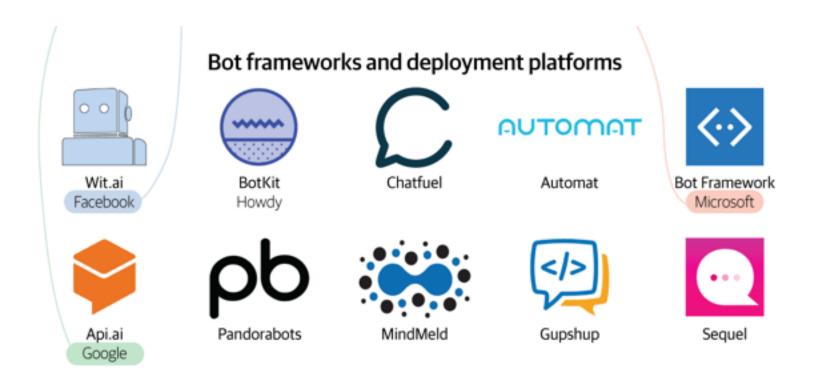
and the emerging giants

Nearly every large software company has announced some sort of bot strategy in the last year. Here's a look at a handful of leading platforms that developers might use to send messages, interpret natural language, and deploy bots, with the emerging bot-ecosystem giants highlighted.

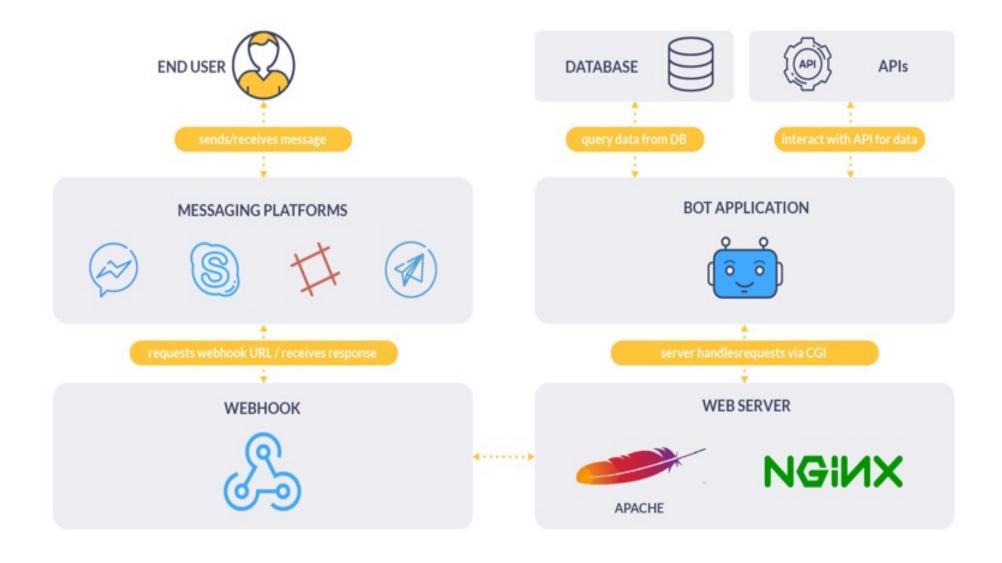
General AI agents with platforms

Developer access available now or announced





How to Build Chatbots



Chatbot Frameworks and Al Services

- Bot Frameworks
 - Botkit
 - Microsoft Bot Framework
 - Rasa NLU
- Al Services
 - Wit.ai
 - api.ai
 - LUIS.ai
 - IBM Watson

Chatbot Frameworks

Comparison Table of Most Prominent Bot Frameworks

	Botkit	Microsoft Bot Framework	RASA
Built-in integration with messaging platforms		⊗	⊗
NLP support	but possible to integrate with middlewares	but have close bonds with LUIS.ai	⊗
Out-of-box bots ready to be deployed	\odot	⊗	⊗
Programming Language	JavaScript (Node)	JavaScript (Node), C#	Python
			Created by ActiveWizards

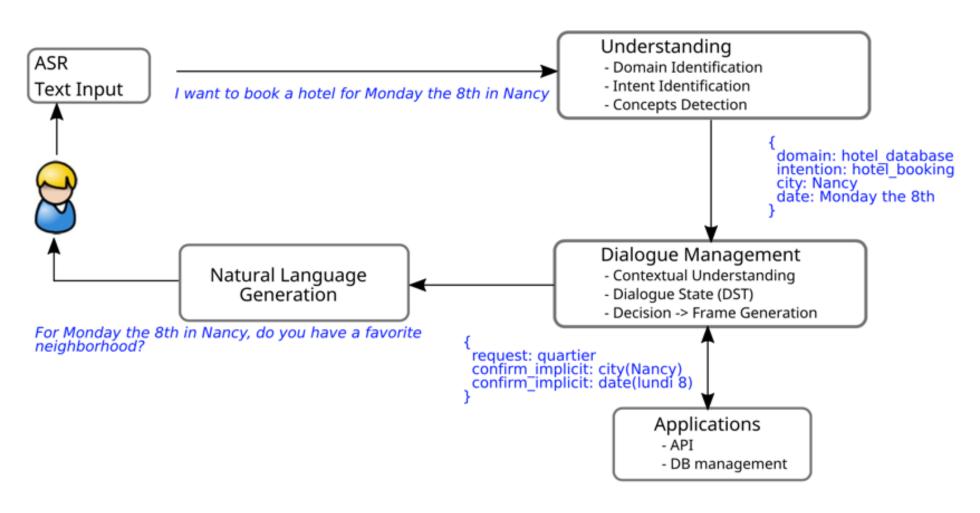
Comparison of Most Prominent Al Services

	wit.ai	api.ai	LUIS.ai	IBM Watson		
Free of charge	⊘	but has paid enterprise version	it is in beta and has transaction limits	30 days trial then priced for enterprise use		
Text and Speech processing	\otimes	⊘		⊗		
Machine Learning Modeling	⊗	⊘	⊗	⊗		
Support for Intents, Entities, Actions	Intents used as trait entities, actions are combined operations	Intents is the main prediction mechanism. Domains of entities, intents and actions	⊗	⊘		
Pre-build entities for easy parsing of numbers, temperature, date, etc.	⊗	⊗	⊗	\otimes		
Integration to messaging platforms	⊗ web service API	also has facility for deploying to heroku. Paid environment		⊘ possible via API		
Support of SDKs	includes SDKs for Python, Node.js, Rust, C, Ruby, iOS, Android, Windows Phone	⊘ C#, Xamarin, Python, Node.js, iOS, Android, Windows Phone	enables building with Web Service API, Microsoft Bot Framework integration	Proprietary language "AlchemyLanguage"		
Created by ActiveWizards						

Task-Oriented Dialogue System

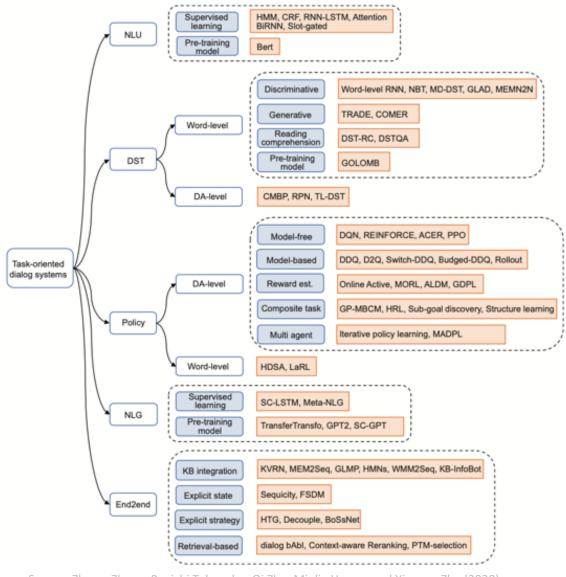
Task-Oriented Dialogue System

(Deriu et al., 2021)



Task-Oriented Dialogue Systems

(Zhang et al., 2020)



Dialog State Tracker (DST)

	Dialog state tracker inputs				Dialog state tracker outpu	its
System action/ user response	ASR outp	out	SLU output		State	Score
How can I help you? welcome()	Cheap restaurant	0.6	inform(price=cheap)	0.5	price=cheap	
	Restaurant	0.2	inform(food=italian)	0.3	food=Italian	
An Italian restaurant	Italian	0.1			food=italian,price=cheap	l
					[none]	
What price did you want?	East Area	0.5	inform(area=east)	0.6	price=cheap	
request(price)	Italian	0.3	inform(food=italian)	0.3	food=Italian	
Uh, Italian	Yeah	0.1	affirm()	0.2	food=italian,price=cheap	
					area=east	
					food=italian, area=east	
					price=cheap, area=east	
				foo	d=italian,price=cheap,area=east	
					[none]	

Dialogue Acts

(Young et al., 2010)

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

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()

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	О	О	О	О	B-fromloc
Intent	atis_flight				

Training samples: 4978

Testing samples: 893

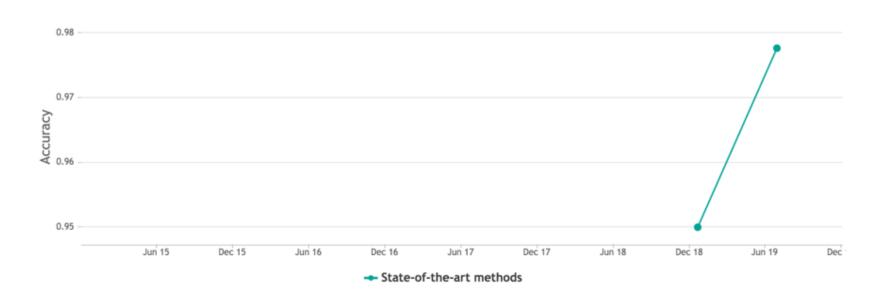
Vocab size: 943

Slot count: 129

Intent count: 26

Intent Detection on ATIS State-of-the-art

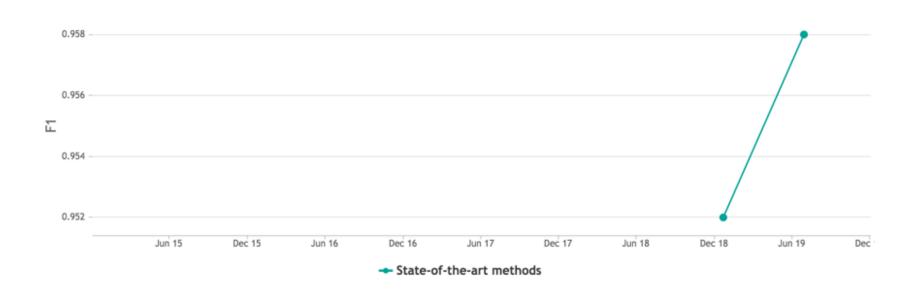
Intent Detection on ATIS



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

Slot Filling on ATIS State-of-the-art

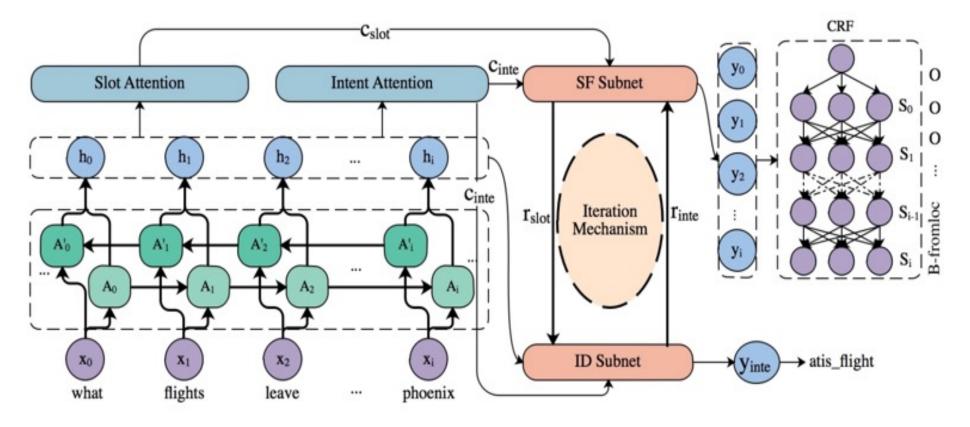
Slot Filling on ATIS



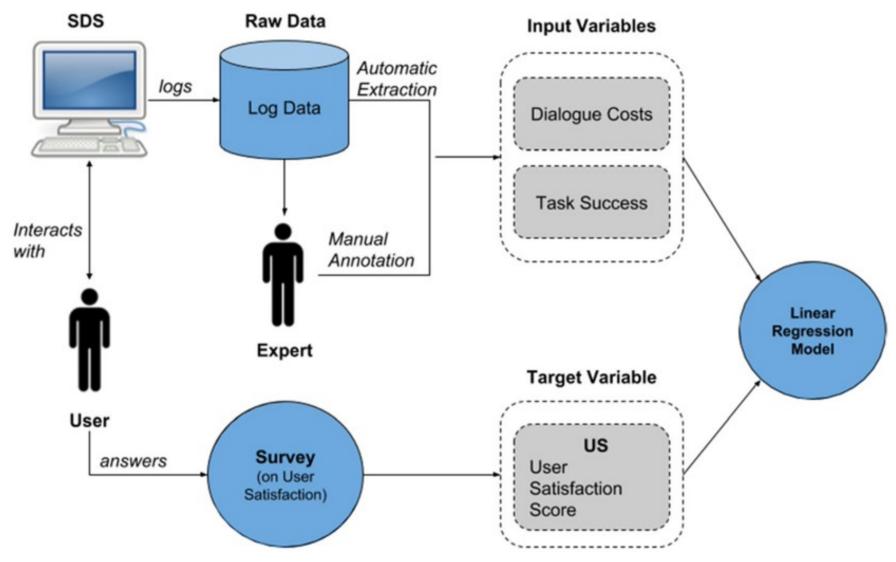
						✓ Edit
RANK	METHOD	F1	PAPER TITLE	YEAR	PAPER	CODE
1	SF-ID	0.958	A Novel Bi-directional Interrelated Model for Joint Intent Detection and Slot Filling	2019	•	0
2	Capsule-NLU	0.952	Joint Slot Filling and Intent Detection via Capsule Neural Networks	2018	•	0

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

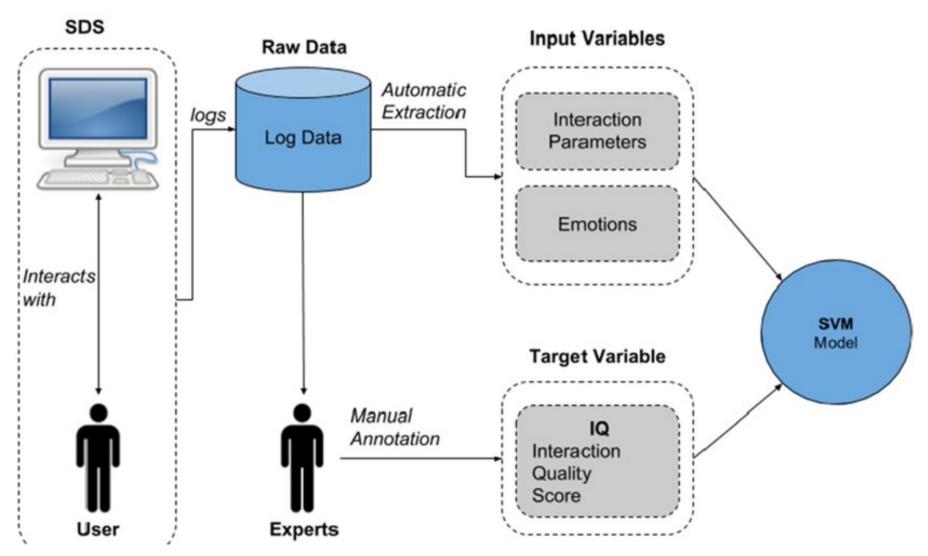


PARAdigm for Dialog System Evaluation PARADISE Framework (Walker et al. 1997)



Interaction Quality procedure

(Schmitt and Ultes, 2015)



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)

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: 你好,可以帮我推荐一个评分是4.5分以上的景点吗?				
usr: I would like to visit in town centre please.	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 <u>北京欢乐谷</u> 都是很不错的地方呢。				
	Tiananmen, Gui Street, and Beijing Happy Valley are very nice places.				
usr: Can you find an Indian restaurant for me	usr: 我喜欢 <u>北京欢乐谷</u> ,你知道这个景点周边的酒店都是什么吗?				
that is also in the town centre?	I like Beijing Happy Valley. What hotels are around this attraction?				
Schema	sys: 那可多了,有A酒店, B酒店, C酒店。				
usr: I want a hotel in San Diego and I want to	There are many, such as hotel A, hotel B, and hotel C.				
check out on Thursday next week.	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?				
usr: I need a one way flight to go there.	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?				

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	Н2Н	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

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
```

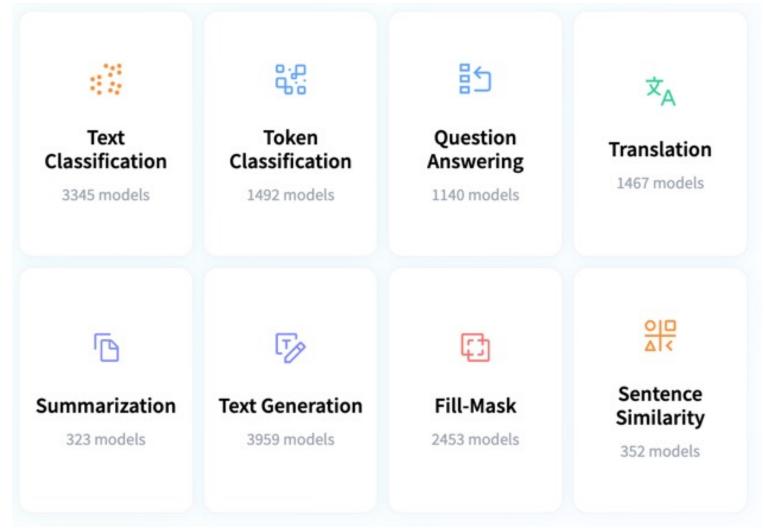


An example dialog from the test set for MultiWOZ

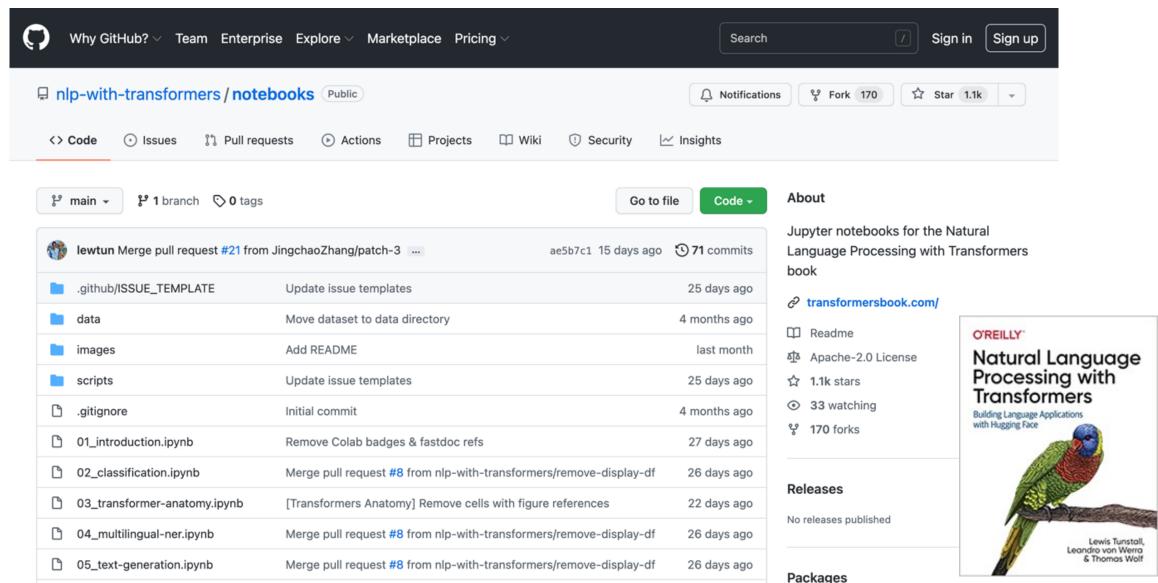
(en→zh) sub-task

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。	MATE (HIT MAY HAVE HAVE)		
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。	PK/1. {~175. U~7KMP}		
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。	山及地: 业川山入任佰加平實脈唱}		
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!			

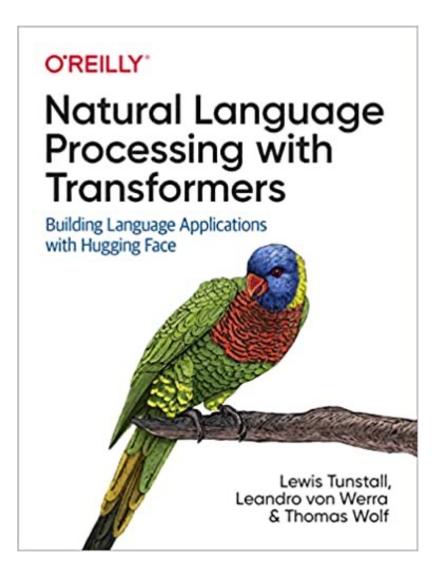
Hugging Face Tasks Natural Language Processing



NLP with Transformers Github



NLP with Transformers Github Notebooks

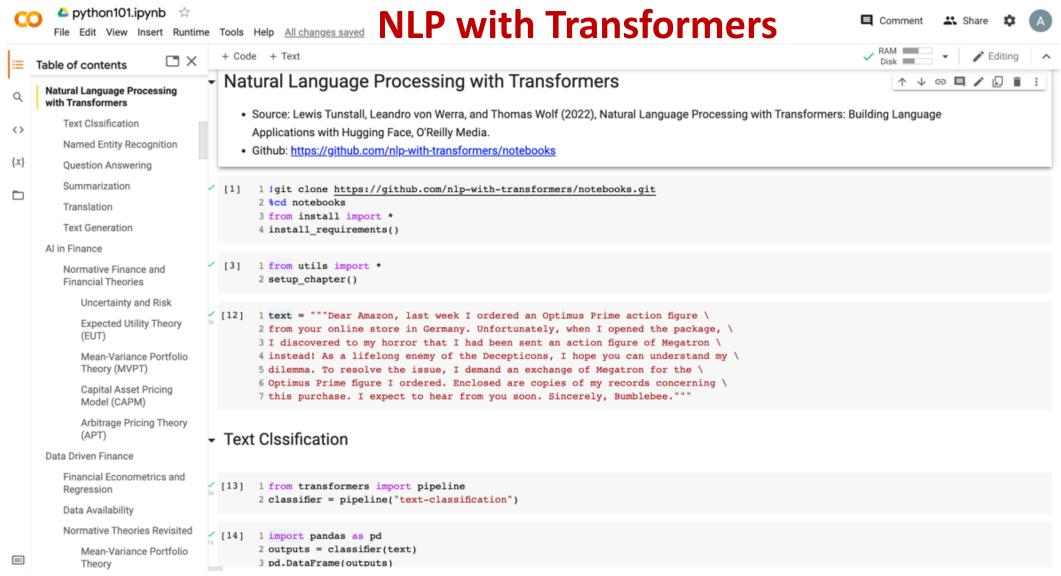


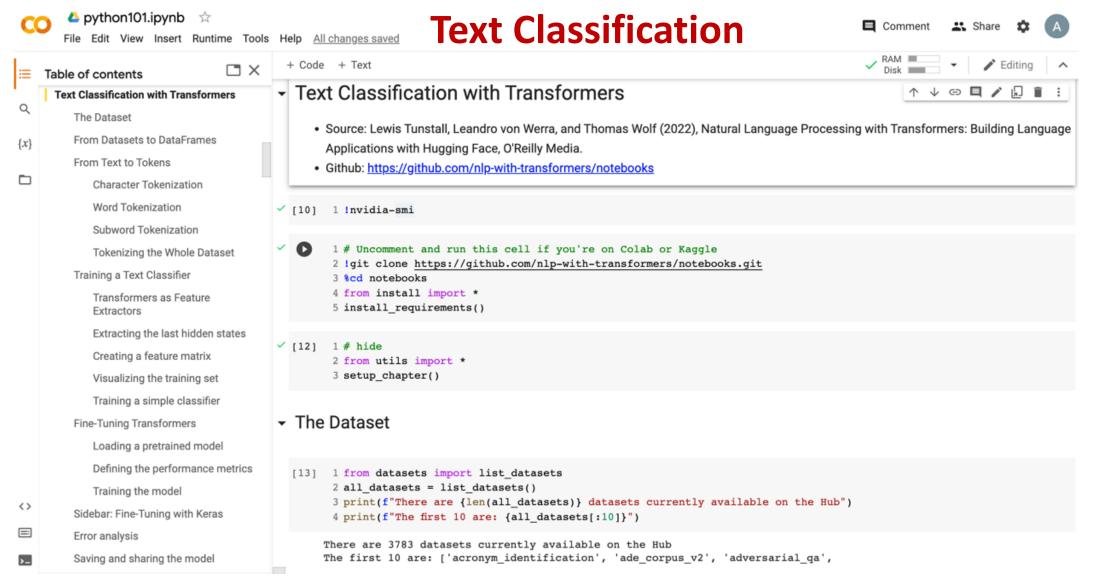
Running on a cloud platform

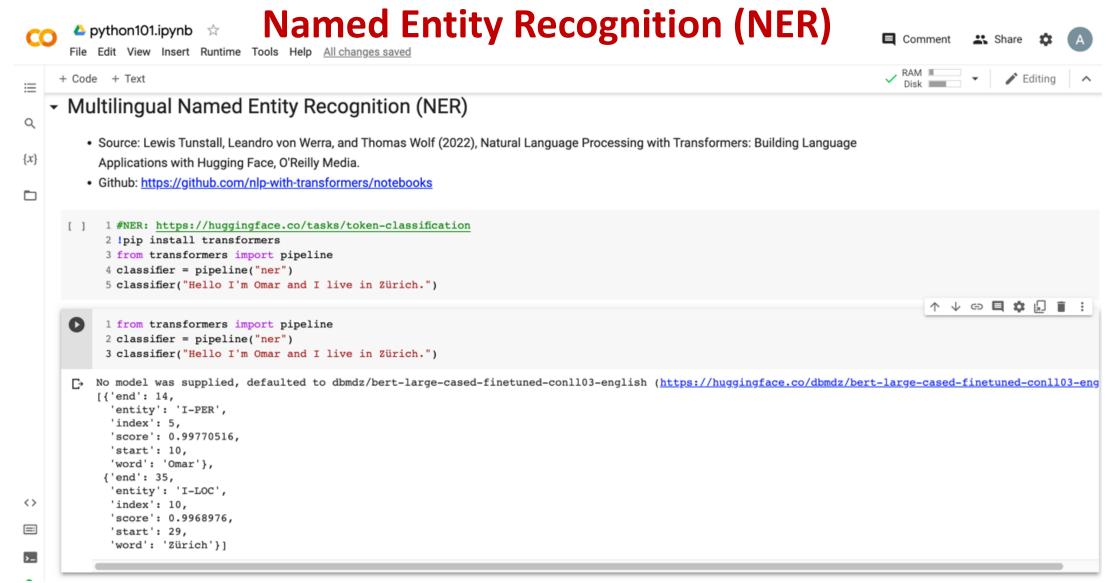
To run these notebooks on a cloud platform, just click on one of the badges in the table below:

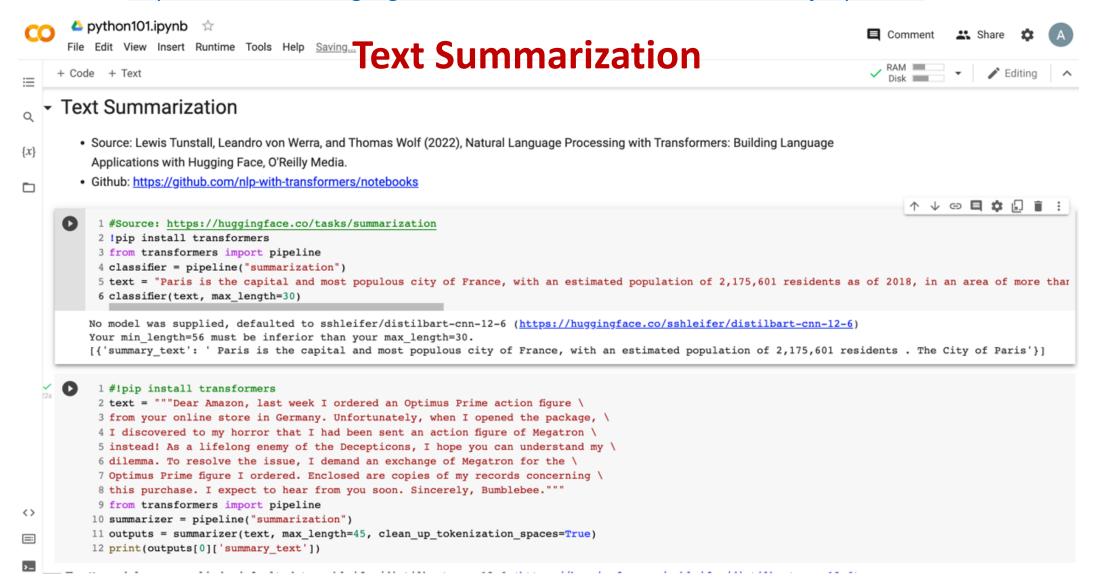
Chapter	Colab	Kaggle	Gradient	Studio Lab
Introduction	Open in Colab	k Open in Kaggle	Run on Gradient	۩ Open Studio Lab
Text Classification	Open in Colab	k Open in Kaggle	Run on Gradient	۩ Open Studio Lab
Transformer Anatomy	Open in Colab	k Open in Kaggle	Run on Gradient	۩ Open Studio Lab
Multilingual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

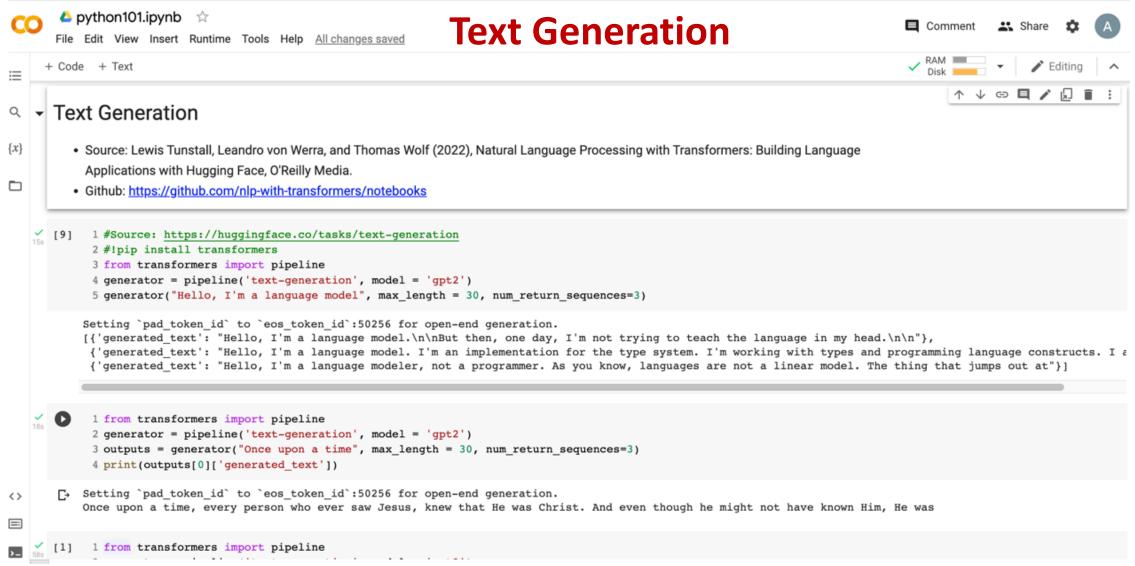
Nowadays, the GPUs on Colab tend to be K80s (which have limited memory), so we recommend using Kaggle, Gradient, or SageMaker Studio Lab. These platforms tend to provide more performant GPUs like P100s, all for free!

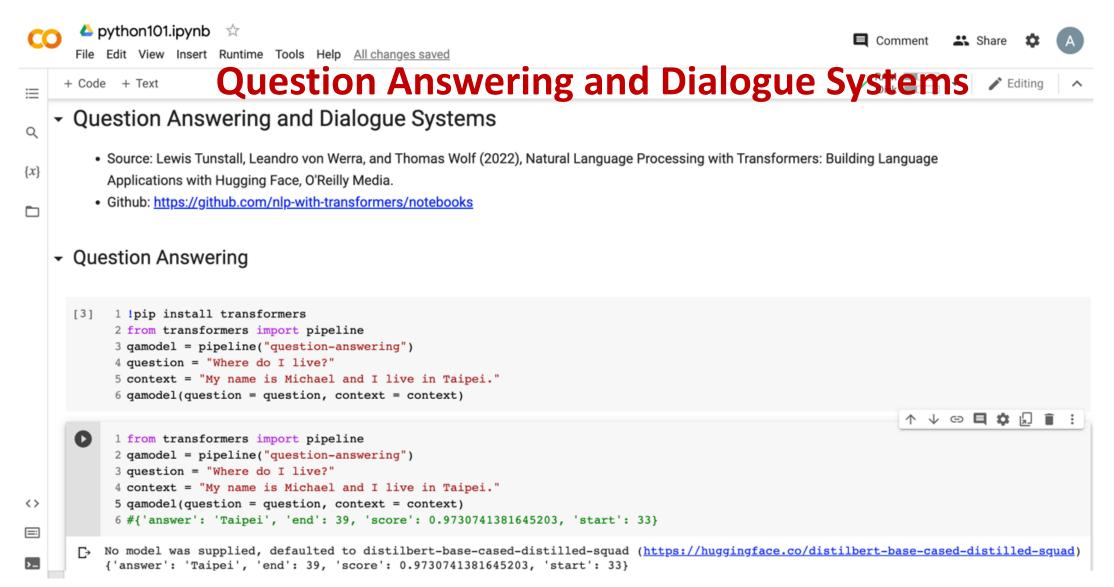


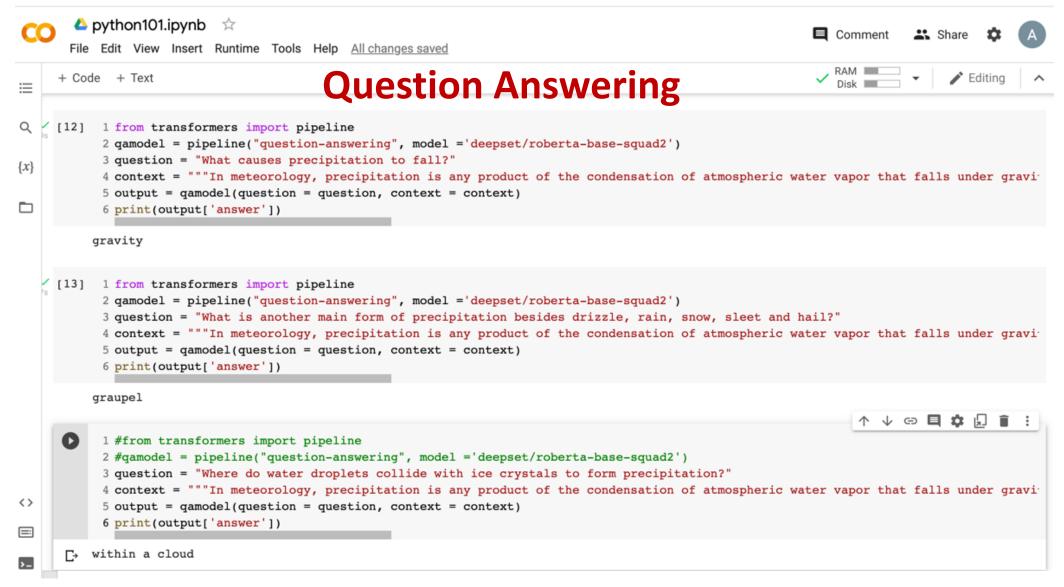


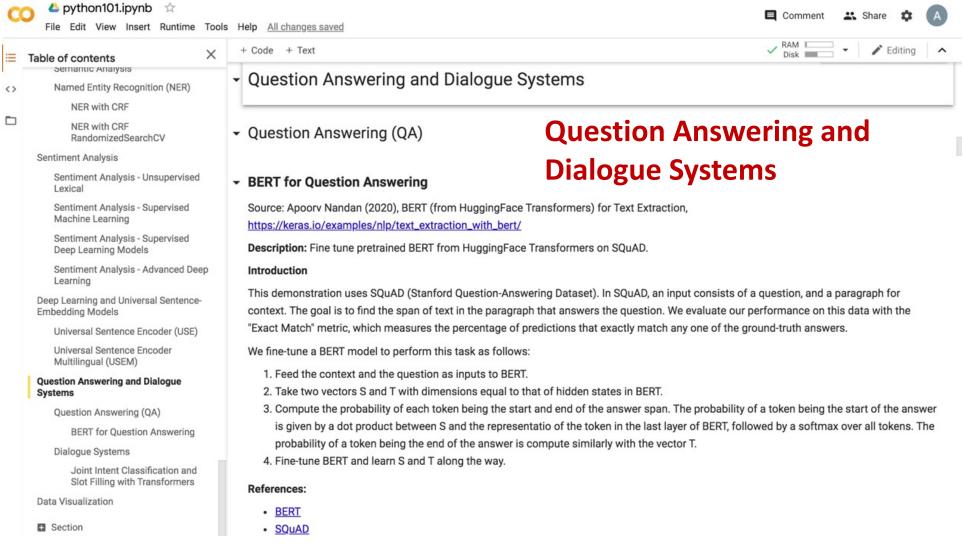


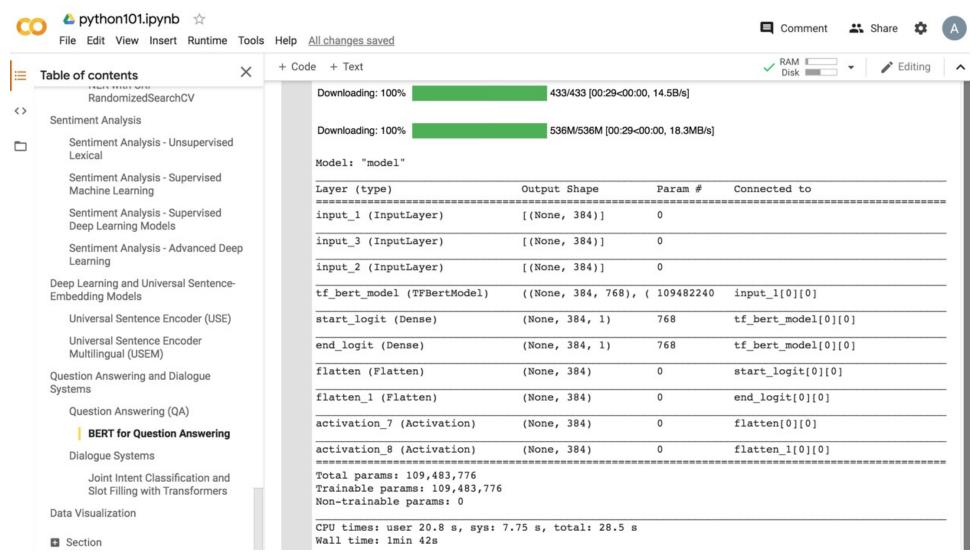


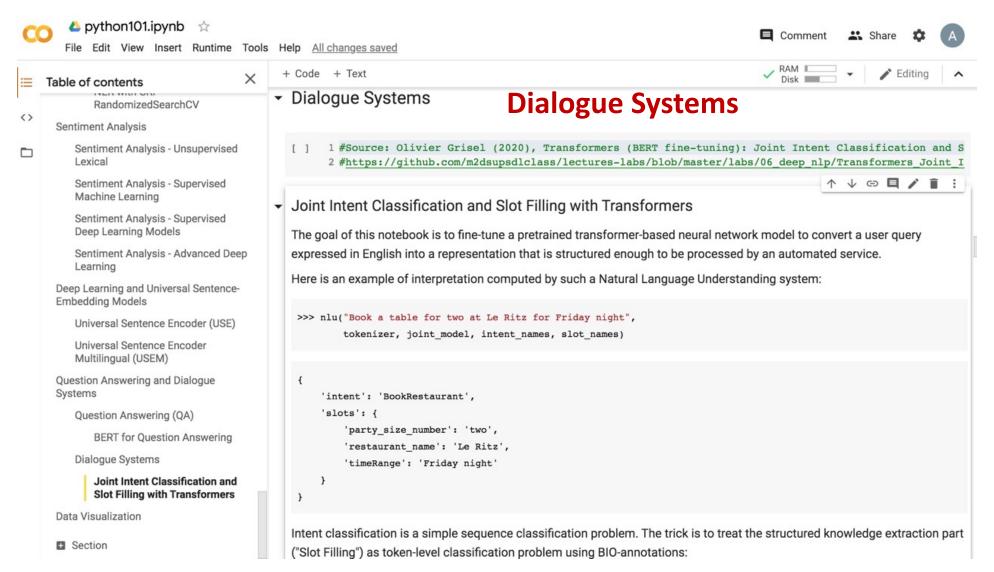


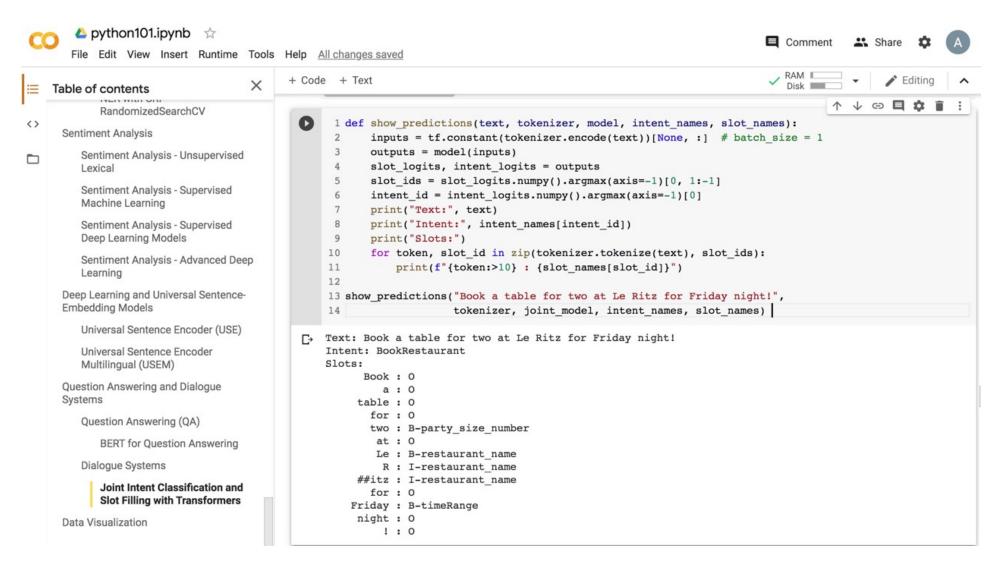


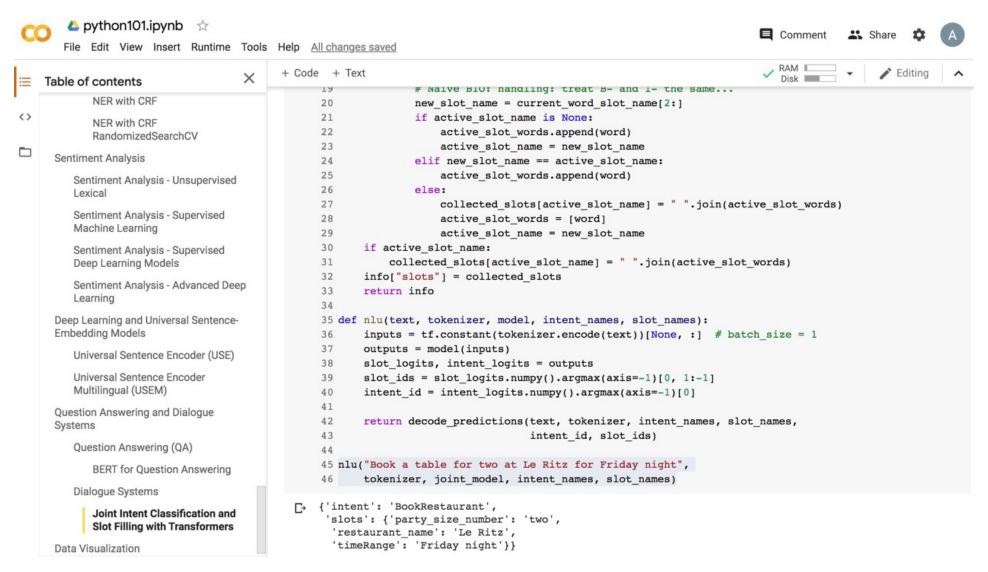












Question Answering

```
!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

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

Summary

- Question Answering
- Dialogue Systems
- Task Oriented Dialogue System

References

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