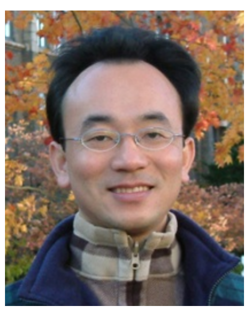
國立臺北護理健康大學
National Taipei University of Nursing and Health Sciences

Tamkang University
淡江大學

問答系統與對話系統 (Question Answering and Dialogue Systems)

Time: 2020/06/19 (Fri) (9:10 -12:00)
Place: 國立臺北護理健康大學 (台北市明德路365號) G210
Host: 祝國忠 院長 (健康科技學院院長)



Min-Yuh Day
戴敏育
Associate Professor
副教授
Dept. of Information Management, Tamkang University
淡江大學 資訊管理學系
http://mail. tku.edu.tw/myday/

2020-06-19

Topics

1. **自然語言處理核心技術與文字探勘**
   (Core Technologies of Natural Language Processing and Text Mining)
2. **人工智慧文本分析基礎與應用**
   (Artificial Intelligence for Text Analytics: Foundations and Applications)
3. **文本表達特徵工程**
   (Feature Engineering for Text Representation)
4. **語意分析和命名實體識別**
   (Semantic Analysis and Named Entity Recognition; NER)
5. **深度學習和通用句子嵌入模型**
   (Deep Learning and Universal Sentence-Embedding Models)
6. **問答系統與對話系統**
   (Question Answering and Dialogue Systems)

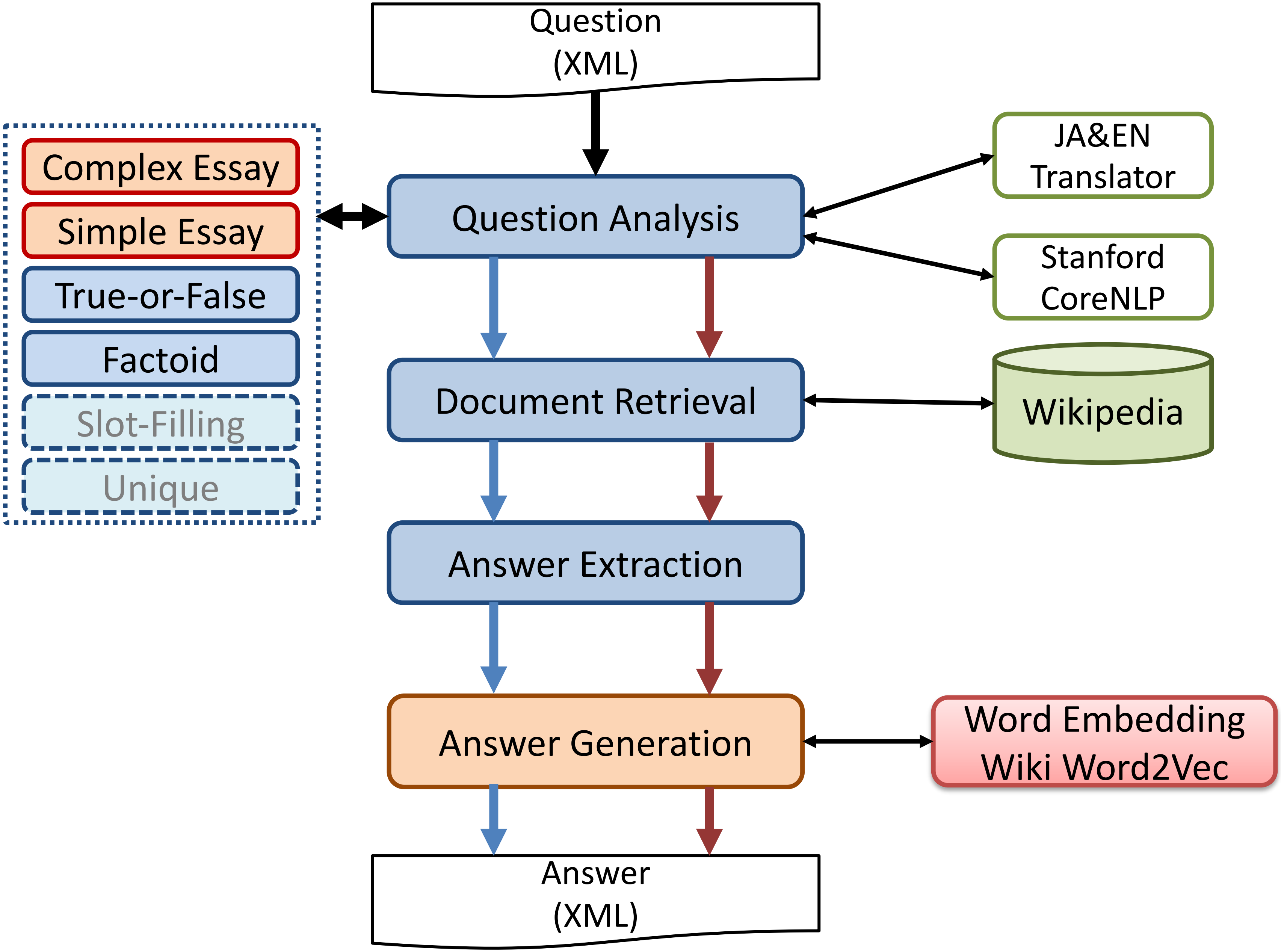
Question Answering and Dialogue Systems

Outline

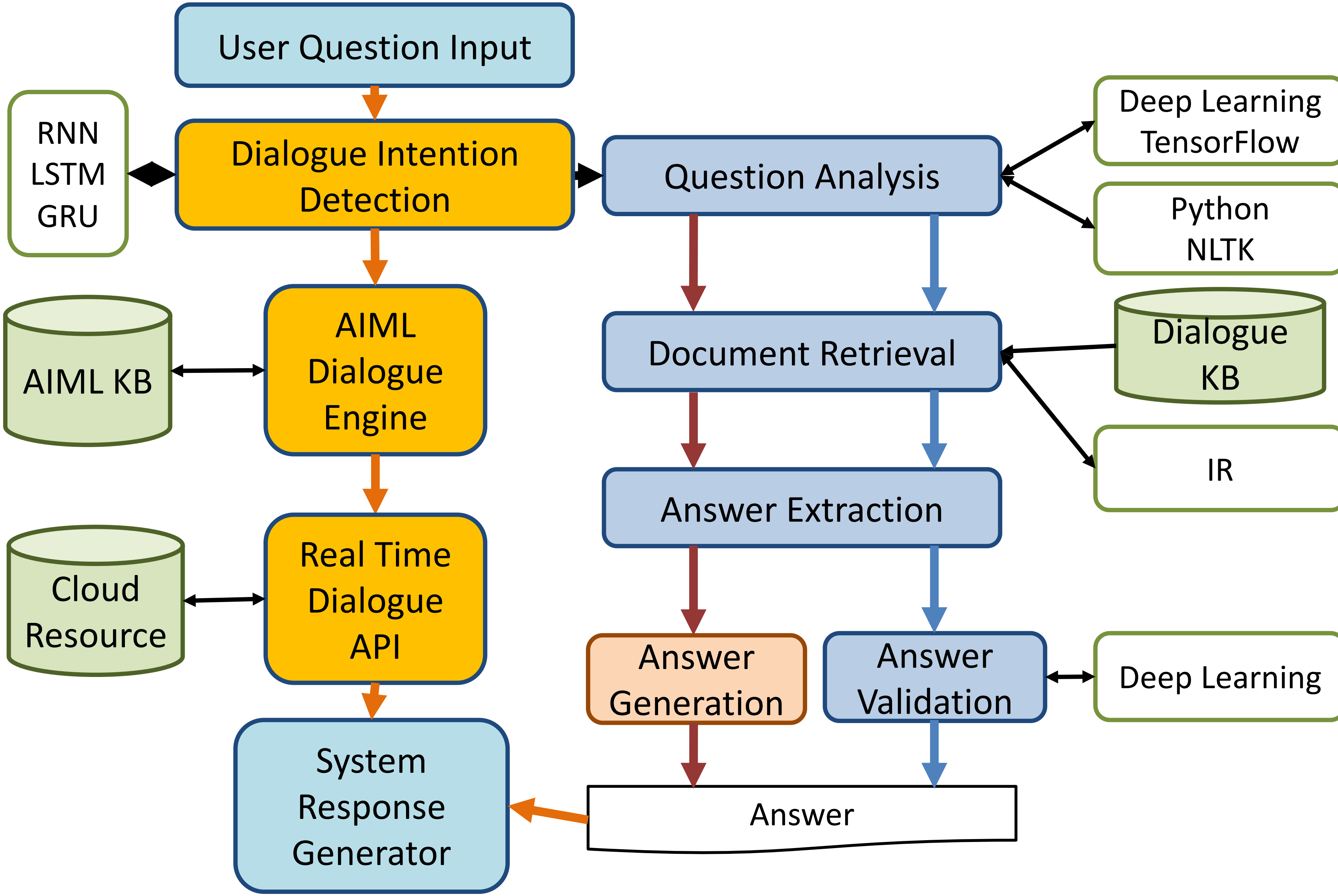
- Question Answering

- Dialogue Systems

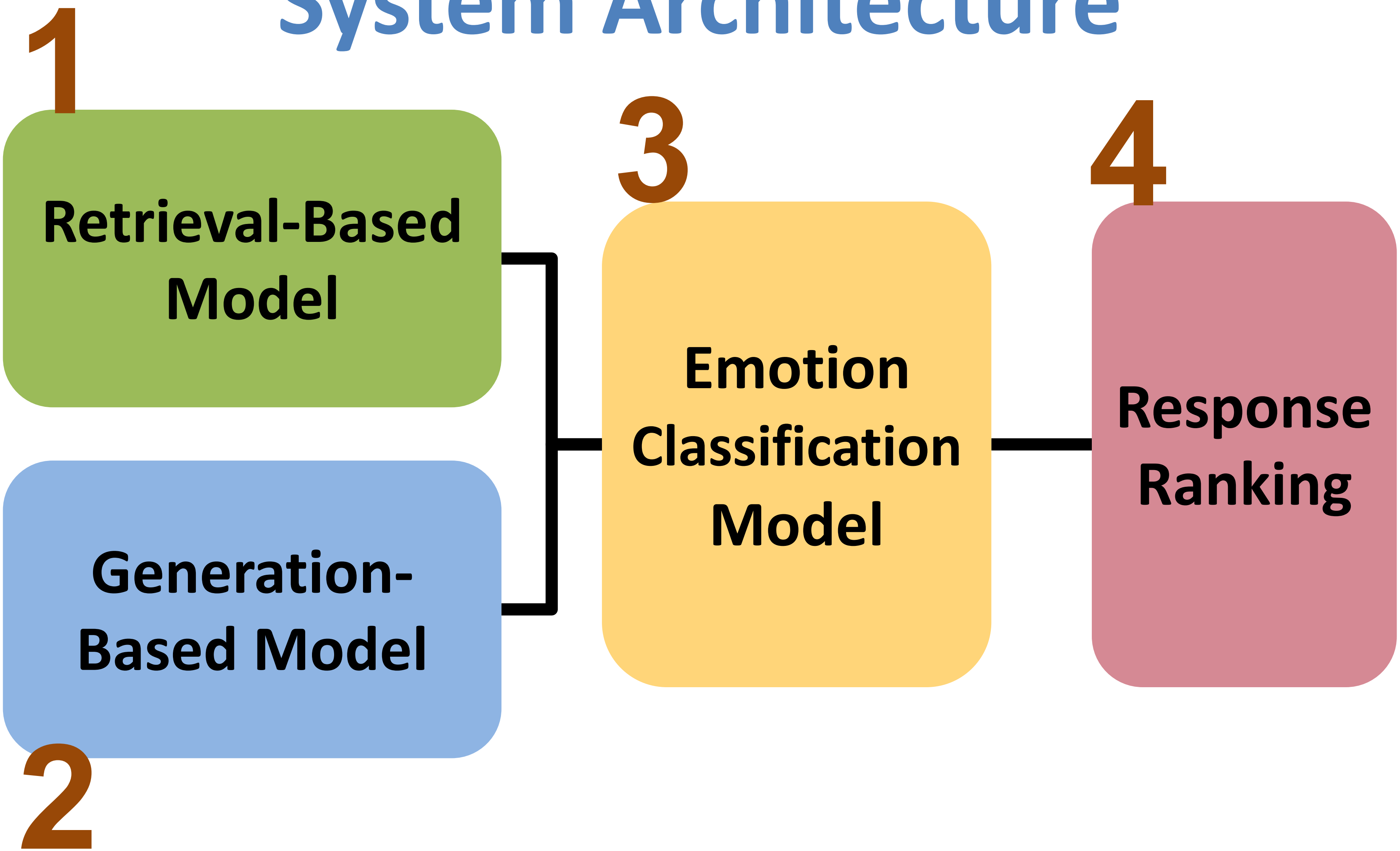
IMTKU System Architecture for NTCIR-13 QALab-3



System Architecture of Intelligent Dialogue and Question Answering System

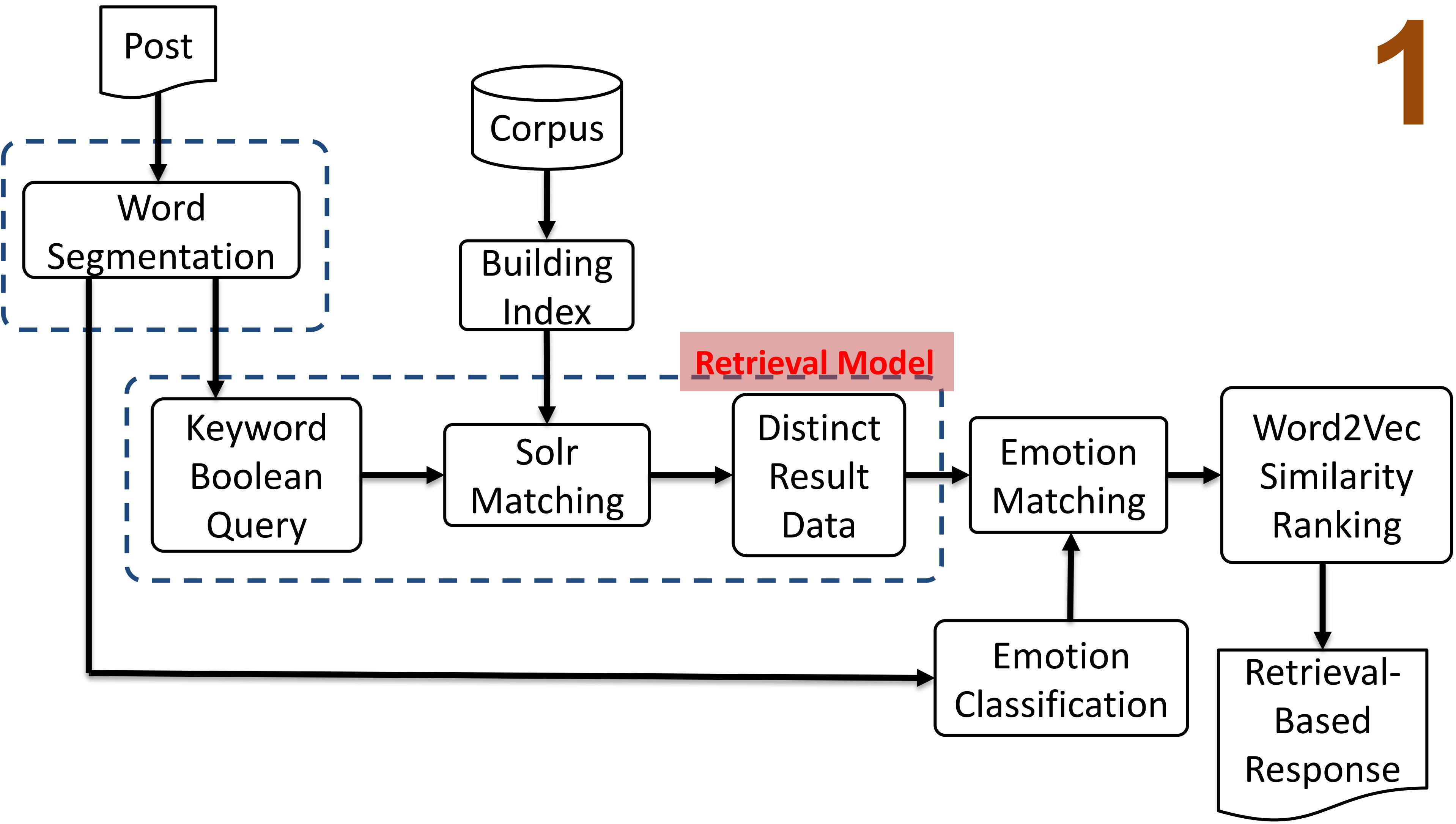


IMTKU Emotional Dialogue System Architecture



The system architecture of IMTKU retrieval-based model for NTCIR-14 STC-3

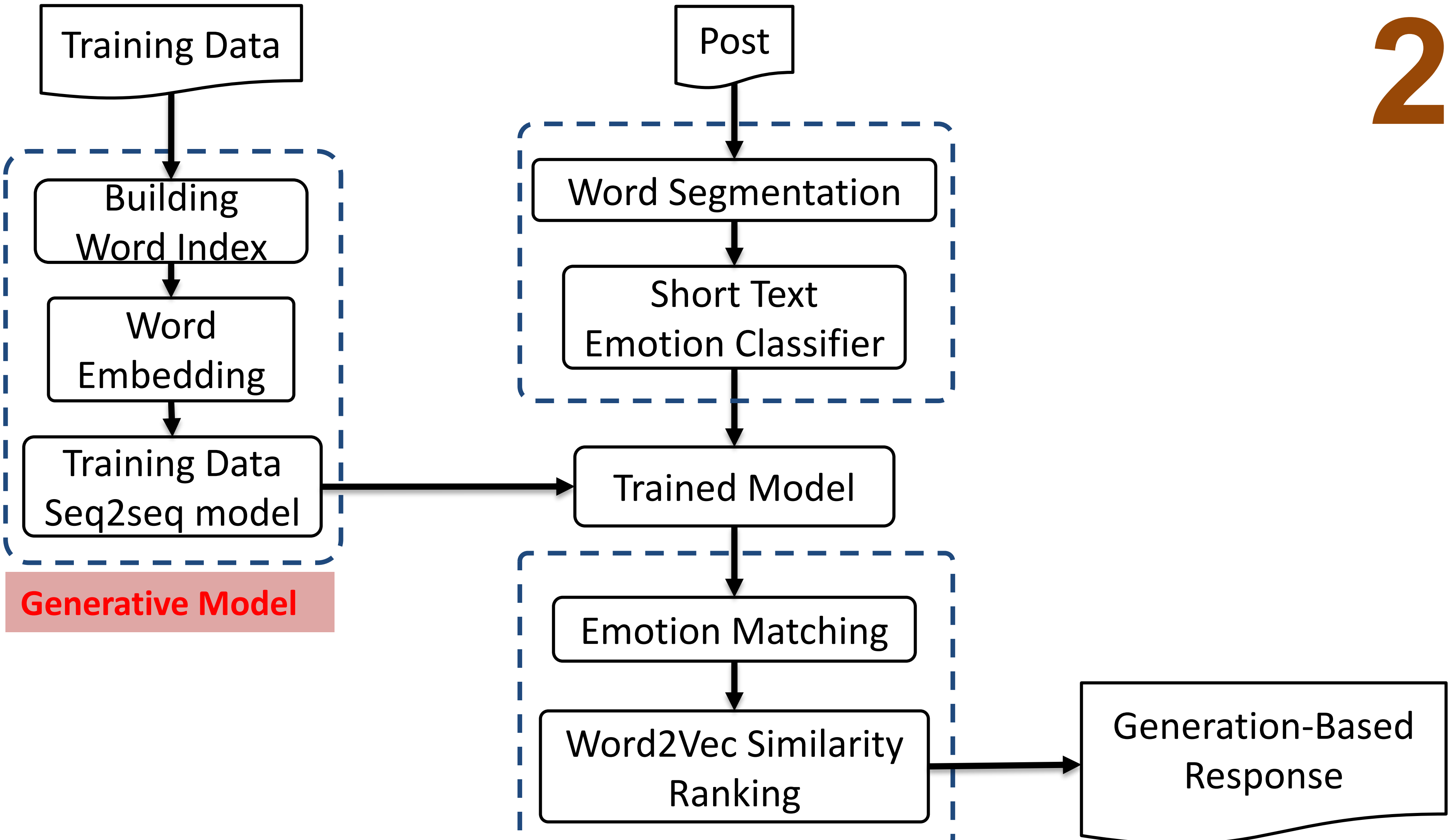
Retrieval-Based Model



The system architecture of IMTKU generation-based model for NTCIR-14 STC-3

Generation-Based Model

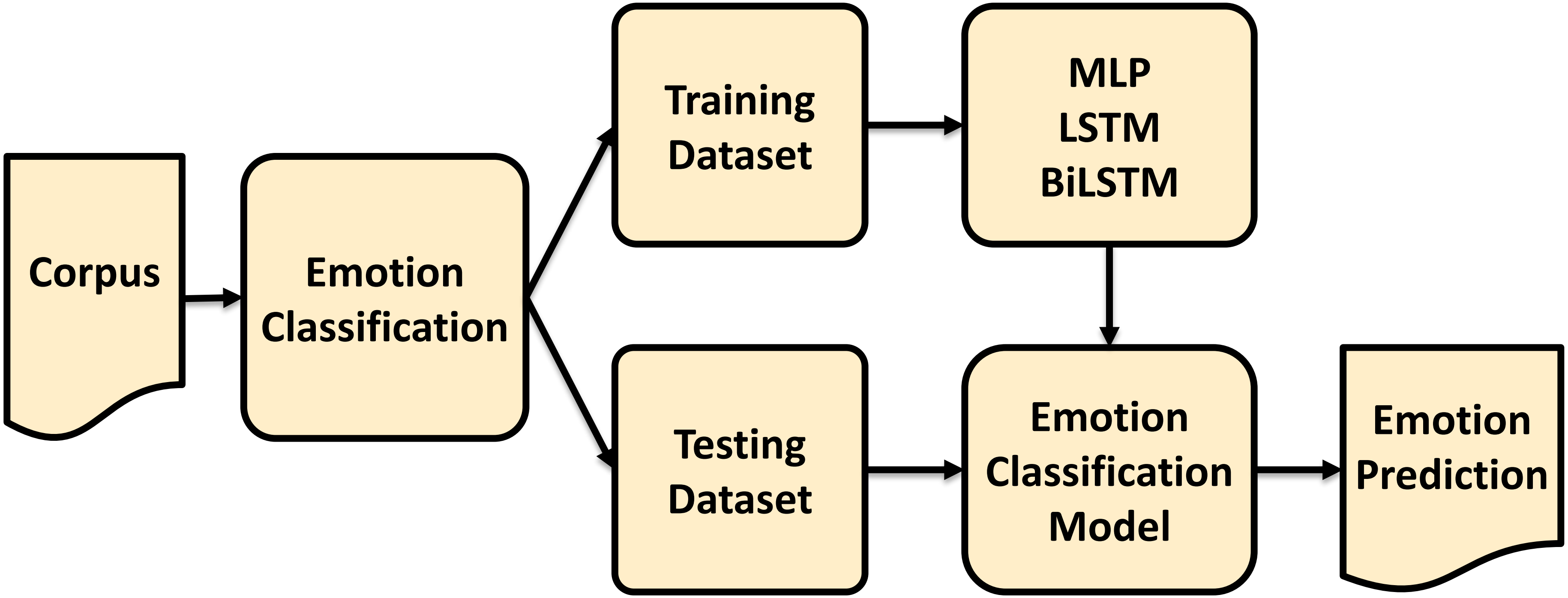
2



The system architecture of IMTKU emotion classification model for NTCIR-14 STC-3

Emotion Classification Model

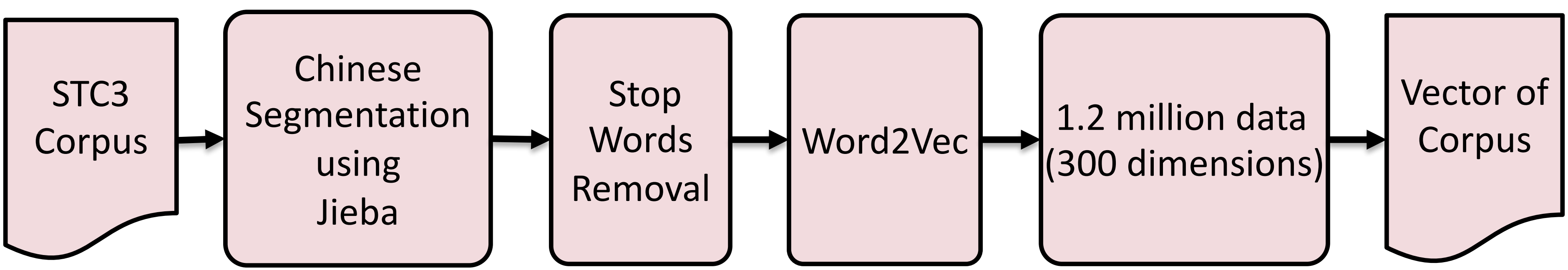
3



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

Response Ranking

4



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

Source: http://coai.cs.tsinghua.edu.cn/hml/challenge.html

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

	Japanese	Chinese	English
NTCIR-12 STC-1 22 active participants	Twitter, Retrieval	Weibo, Retrieval	
NTCIR-13 STC-2 27 active participants	Yahoo! News, Retrieval+ Generation	Weibo, Retrieval+ Generation	
NTCIR-14 STC-3		Weibo, Generation for given emotion categories	
		Weibo+English translations, distribution estimation for subjective annotations	

Chinese Emotional Conversation Generation (CECG) subtask

Dialogue Quality (DQ) and Nugget Detection (ND) subtasks

Single-turn, Non task-oriented

Multi-turn, task-oriented (helpdesk)

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

Chatbots: Evolution of UI/UX

Paradigm	*mid - 80s* PC	*mid - 90s* Web	*mid - 00s* Smartphone	*mid - 10s* Messaging
				
Platform *Examples*	Desktop *DOS, Windows, Mac OS*	Browser *Mosaic, Explorer, Chrome*	Mobile OS *iOS, Android*	Messaging Apps *WhatsApp, Messenger, Slack*
Applications *Examples*	Clients *Excel, PPT, Lotus*	Website *Yahoo, Amazon*	Apps *Angry Birds, Instagram*	Bots *Weather, Travel*
UI/UX	Native Screens	Web Pages	Native Mobile Screens	Message
S/w Dev	Client-side	Server-side	Client-side	Server-side

Source: https://bbvaopen4u.com/en/actualidad/want-know-how-build-conversational-chatbot-here-are-some-tools

AI Dialogue System

Dialogue Subtasks

Browse > Natural Language Processing > Dialogue

Dialogue subtasks

Dialogue Generation

Dialogue Generation

9 leaderboards

35 papers with code

Dialogue State Tracking

2 leaderboards

30 papers with code

Visual Dialog

3 leaderboards

28 papers with code

Task-Oriented Dialogue Systems

Task-Oriented Dialogue Systems

20 papers with code

Goal-Oriented Dialog

15 papers with code

Dialogue Management

10 papers with code

Dialogue Understanding

6 papers with code

Short-Text Conversation

Short-Text Conversation

5 papers with code

Goal-Oriented Dialogue Systems

3 papers with code

Task-Completion Dialogue Policy Learning

2 papers with code

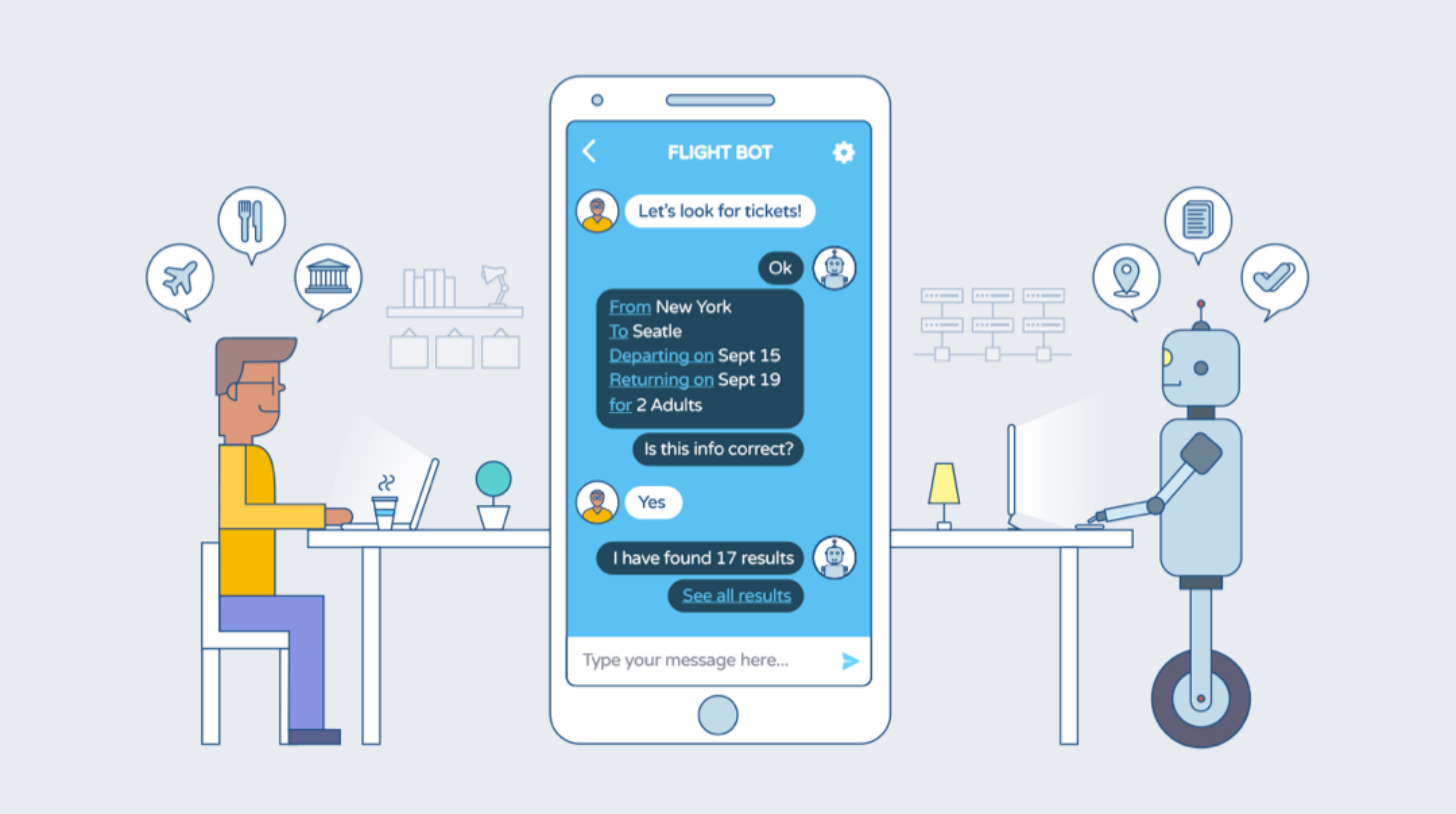
Source: https://paperswithcode.com/area/natural-language-processing/dialogue

Chatbot

Dialogue System

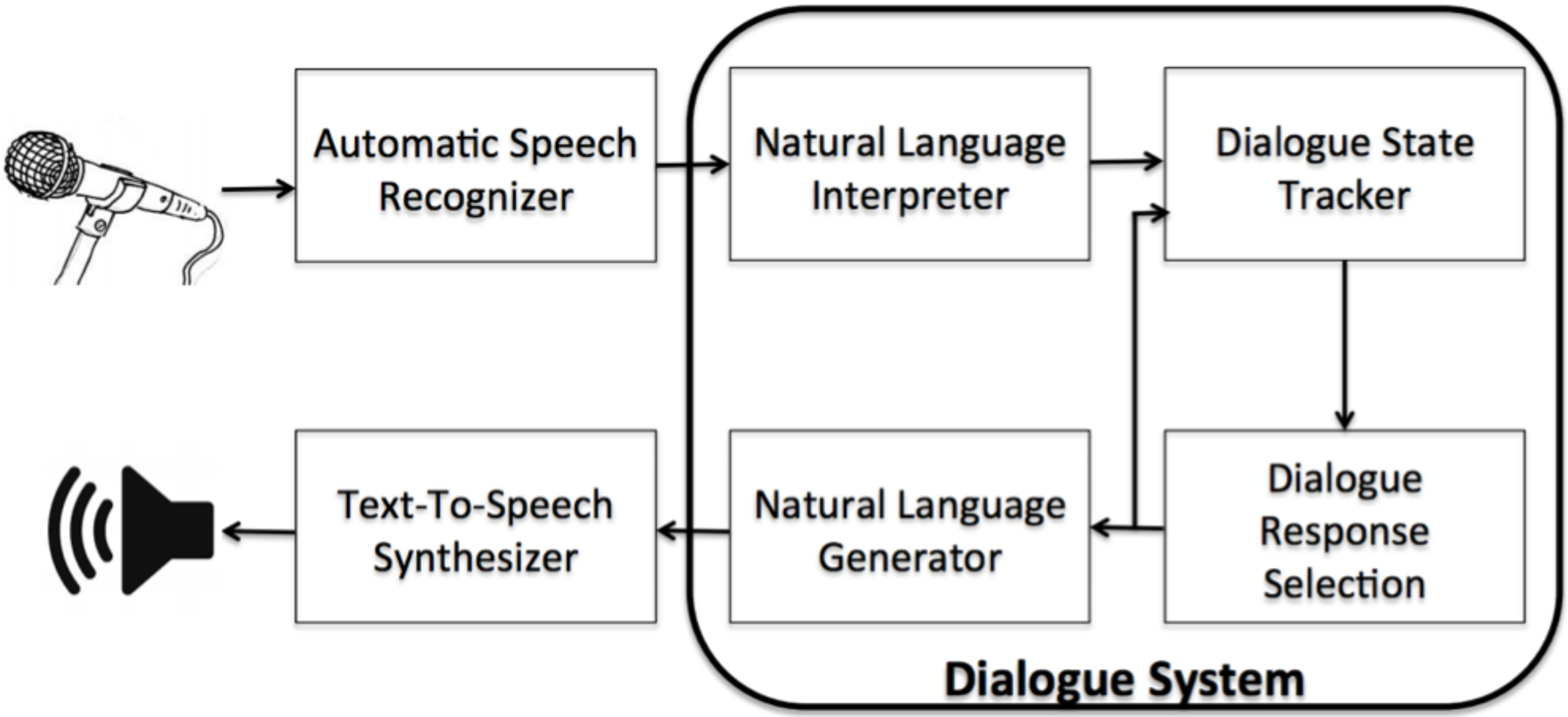
Intelligent Agent

Chatbot



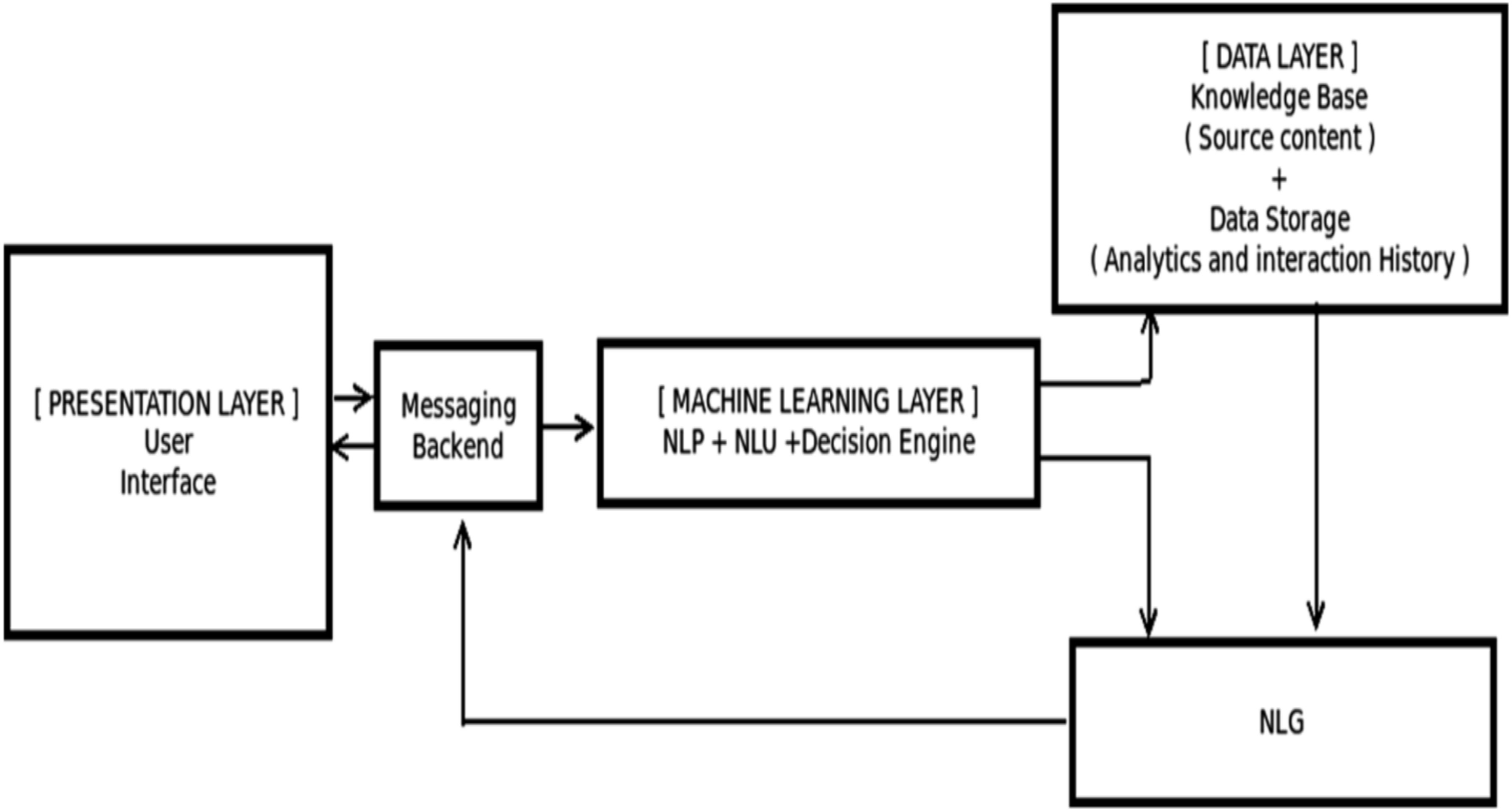
Source: https://www.mdsdecoded.com/blog/the-rise-of-chatbots/

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.

Can machines think?

(Alan Turing ,1950)

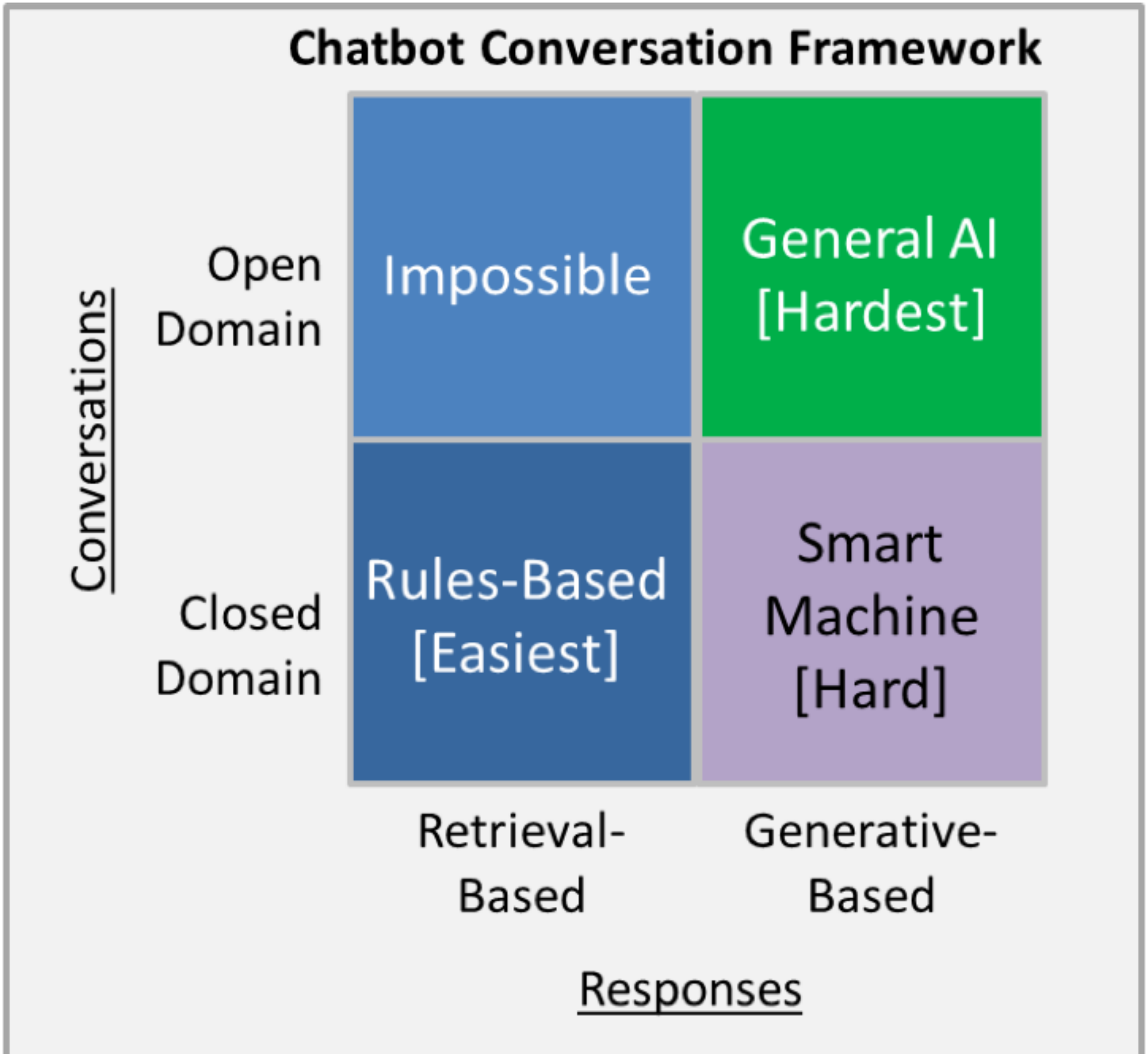
Source: Cahn, Jack. "CHATBOT: Architecture, Design, & Development." PhD diss., University of Pennsylvania, 2017.

Chatbot

“online human-computer dialog system with natural language.”

Source: Cahn, Jack. "CHATBOT: Architecture, Design, & Development." PhD diss., University of Pennsylvania, 2017.

Chatbot Conversation Framework

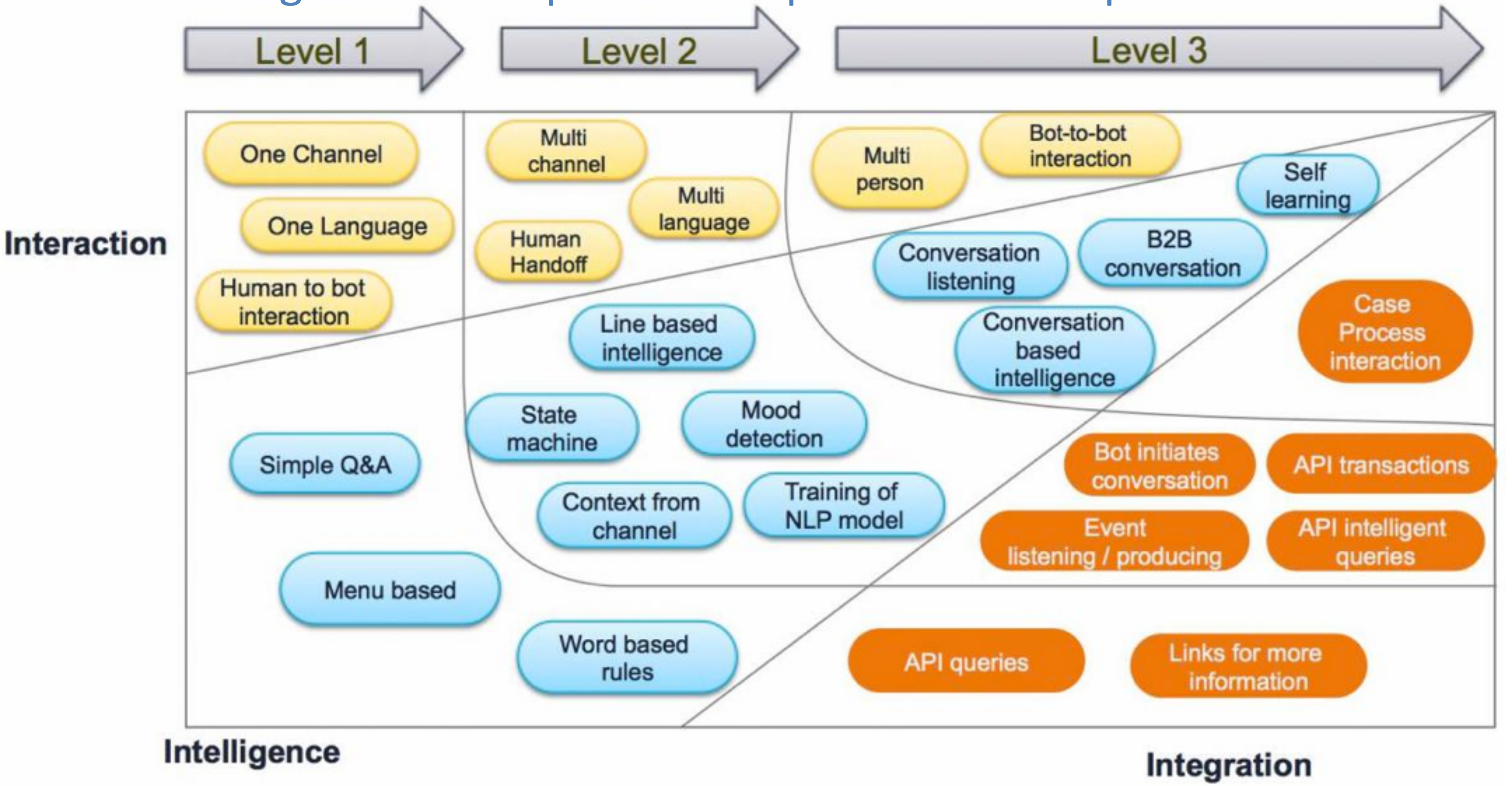


Source: https://chatbotslife.com/ultimate-guide-to-leveraging-nlp-machine-learning-for-you-chatbot-531ff2dd870c

Chatbots

Bot Maturity Model

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

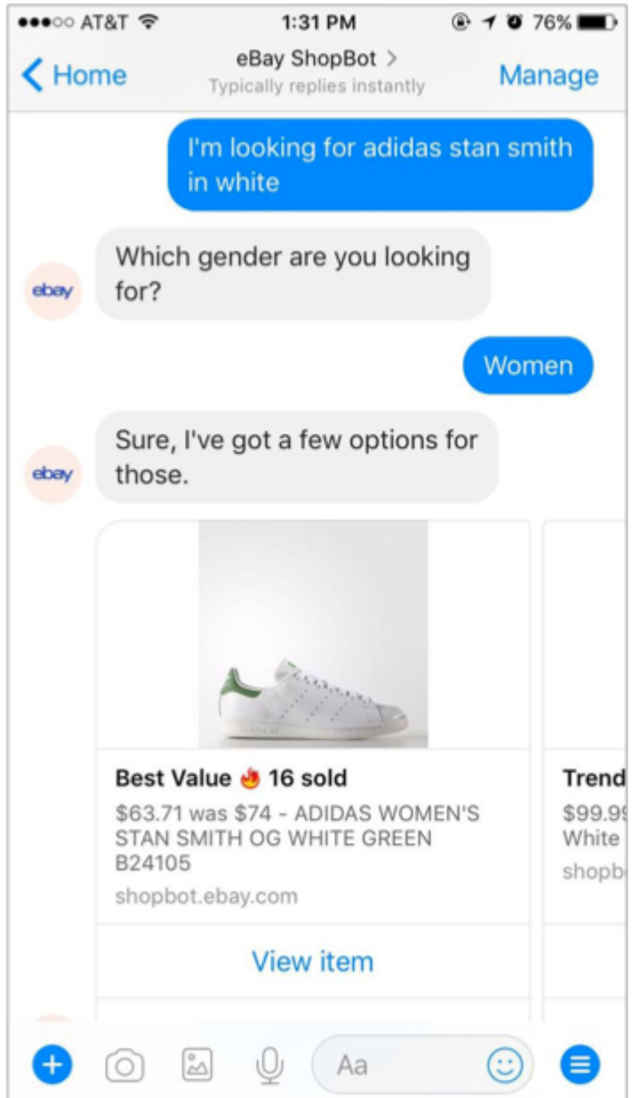


Source: https://www.capgemini.com/2017/04/how-can-chatbots-meet-expectations-introducing-the-bot-maturity/

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

Source: http://www.guided-selling.org/from-e-commerce-to-conversational-commerce/

Conversational Commerce: eBay AI Chatbots



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

Hotel Chatbot

Intents
An intent performs an action in response to natural language user input

Intent Detection

Utterances
Spoken or typed phrases that invoke your intent

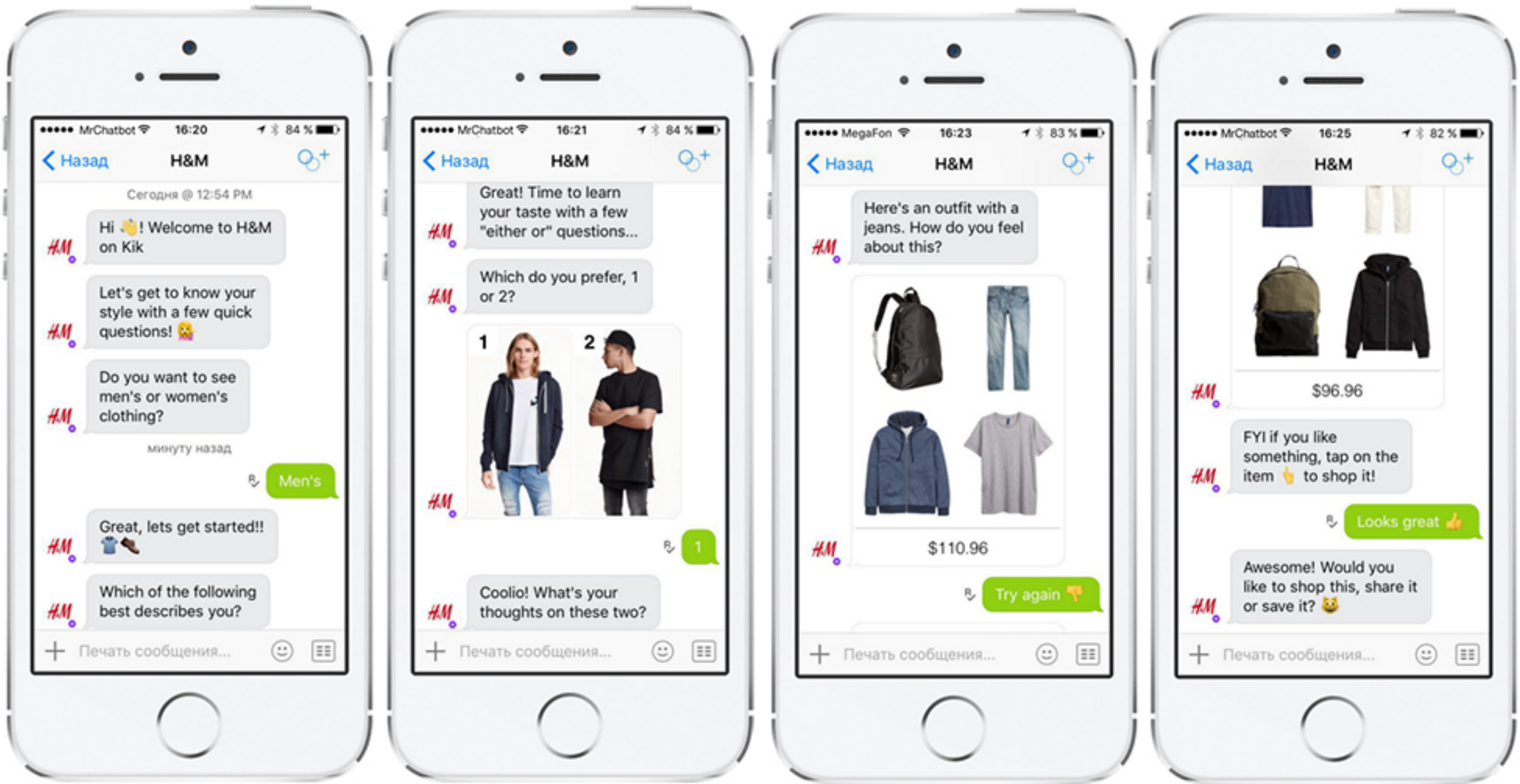
Slots
Slots are input data required to fulfill the intent

Slot Filling

Fulfillment
Fulfillment mechanism for your intent

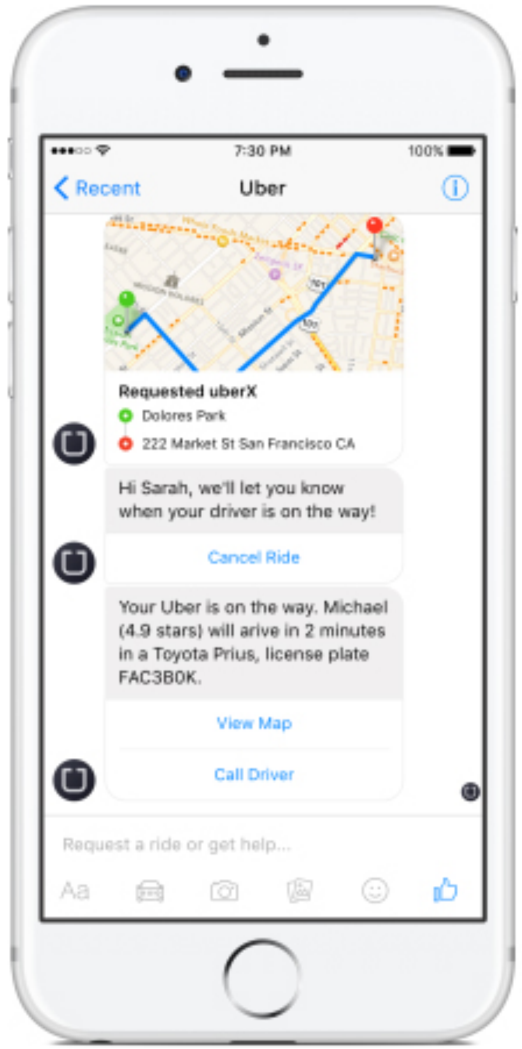
Source: https://sdtimes.com/amazon/guest-view-capitalize-amazon-lex-available-general-public/

H&M's Chatbot on Kik



Source: http://www.guided-selling.org/from-e-commerce-to-conversational-commerce/

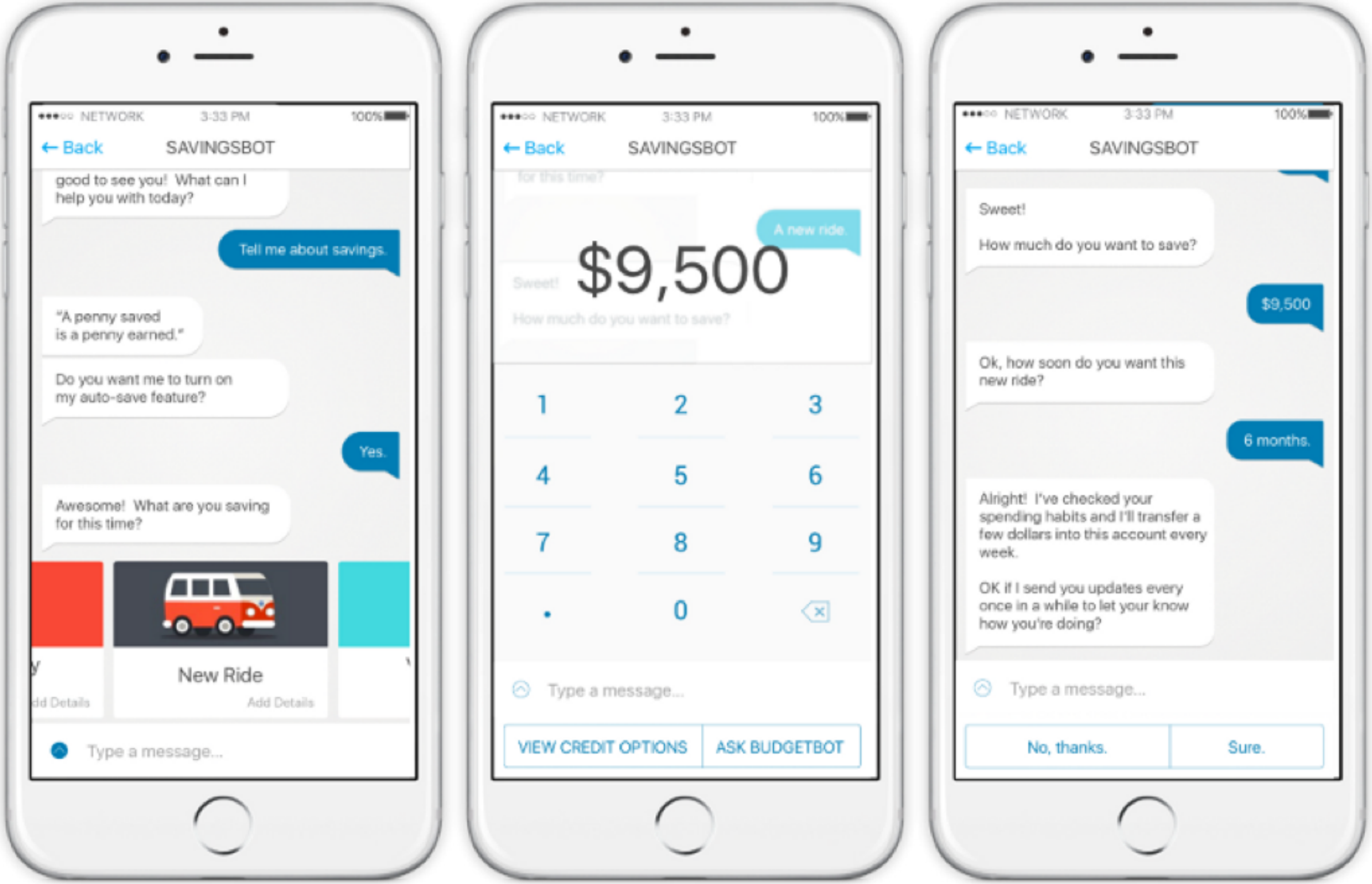
Uber's Chatbot on Facebook's Messenger



Uber's chatbot on Facebook's messenger
- one main benefit: it loads much faster than the Uber app

Source: http://www.guided-selling.org/from-e-commerce-to-conversational-commerce/

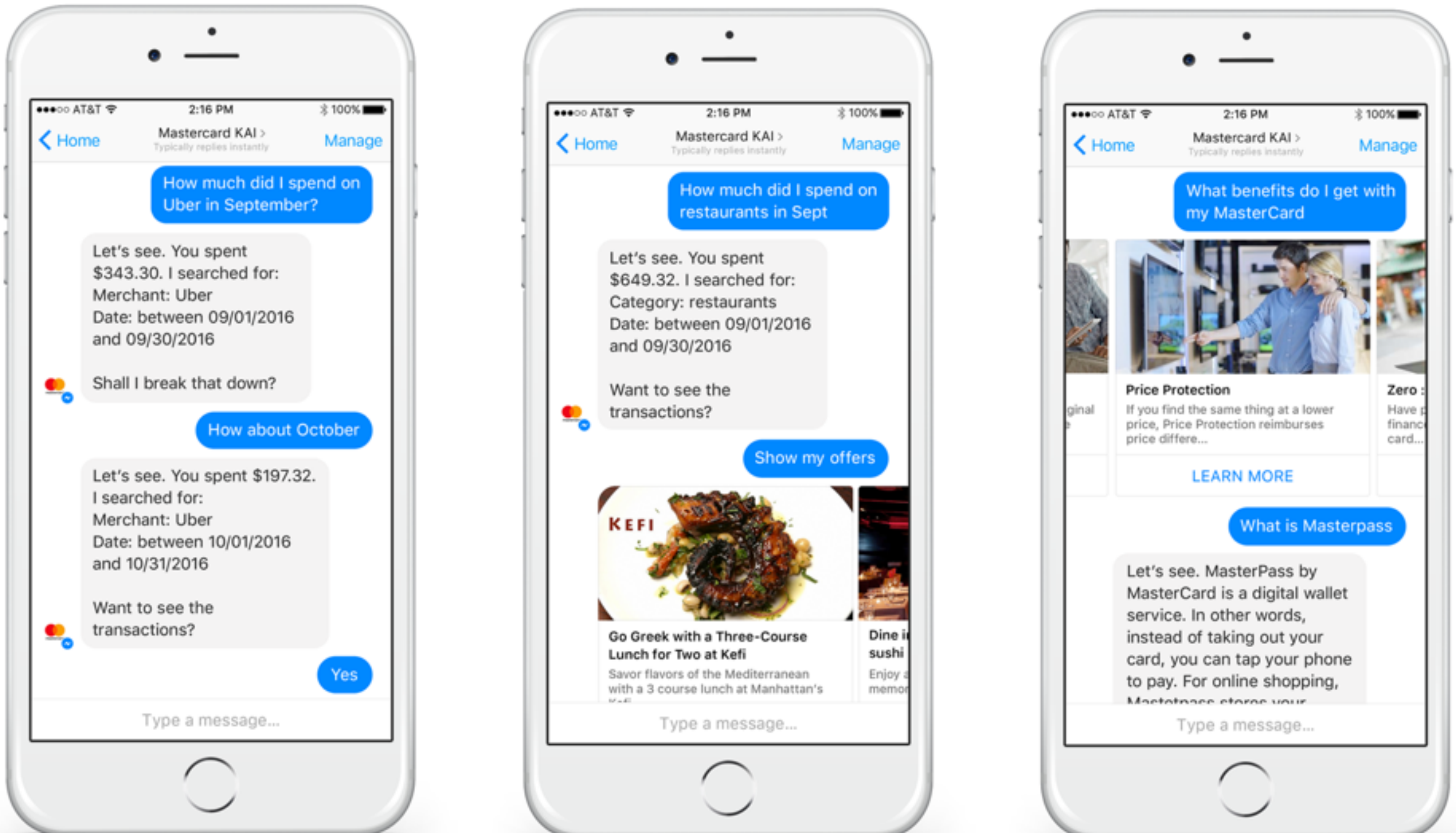
Savings Bot



Source: https://chatbotsmagazine.com/artificial-intelligence-ai-and-fintech-part-1-7cae1e67dc13

Mastercard Makes Commerce More Conversational

mastercard



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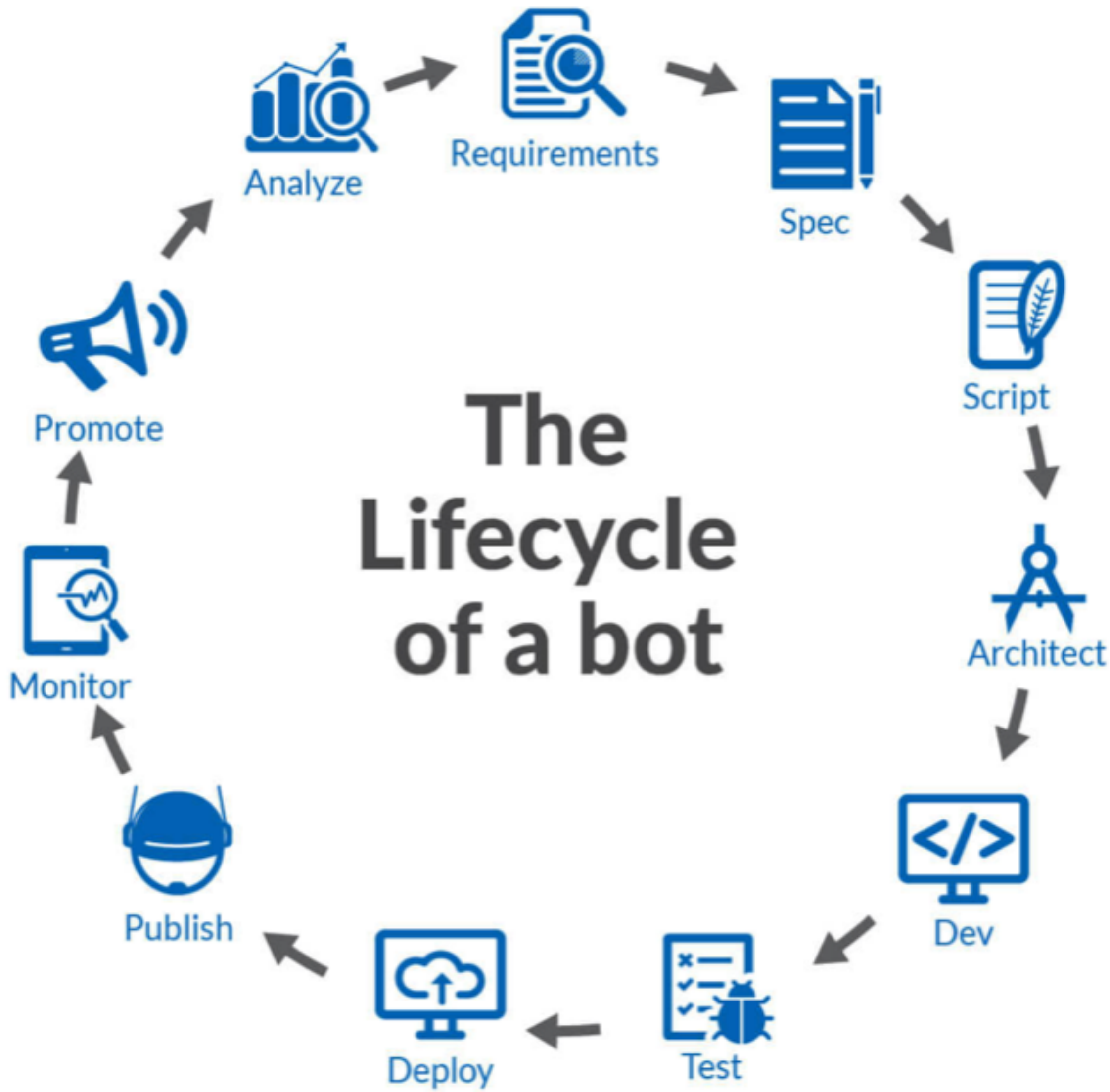
kasisto

Source: https://newsroom.mastercard.com/press-releases/mastercard-makes-commerce-more-conversational-with-launch-of-chatbots-for-banks-and-merchants/

Bot Life Cycle and Platform Ecosystem

The Bot Lifecycle



Source: https://chatbotsmagazine.com/the-bot-lifecycle-1ff357430db7

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.

Source: https://www.oreilly.com/ideas/infographic-the-bot-platform-ecosystem

Bot frameworks and deployment platforms

Wit.ai
Facebook

BotKit
Howdy

Chatfuel

Automat

Bot Framework
Microsoft

Api.ai
Google

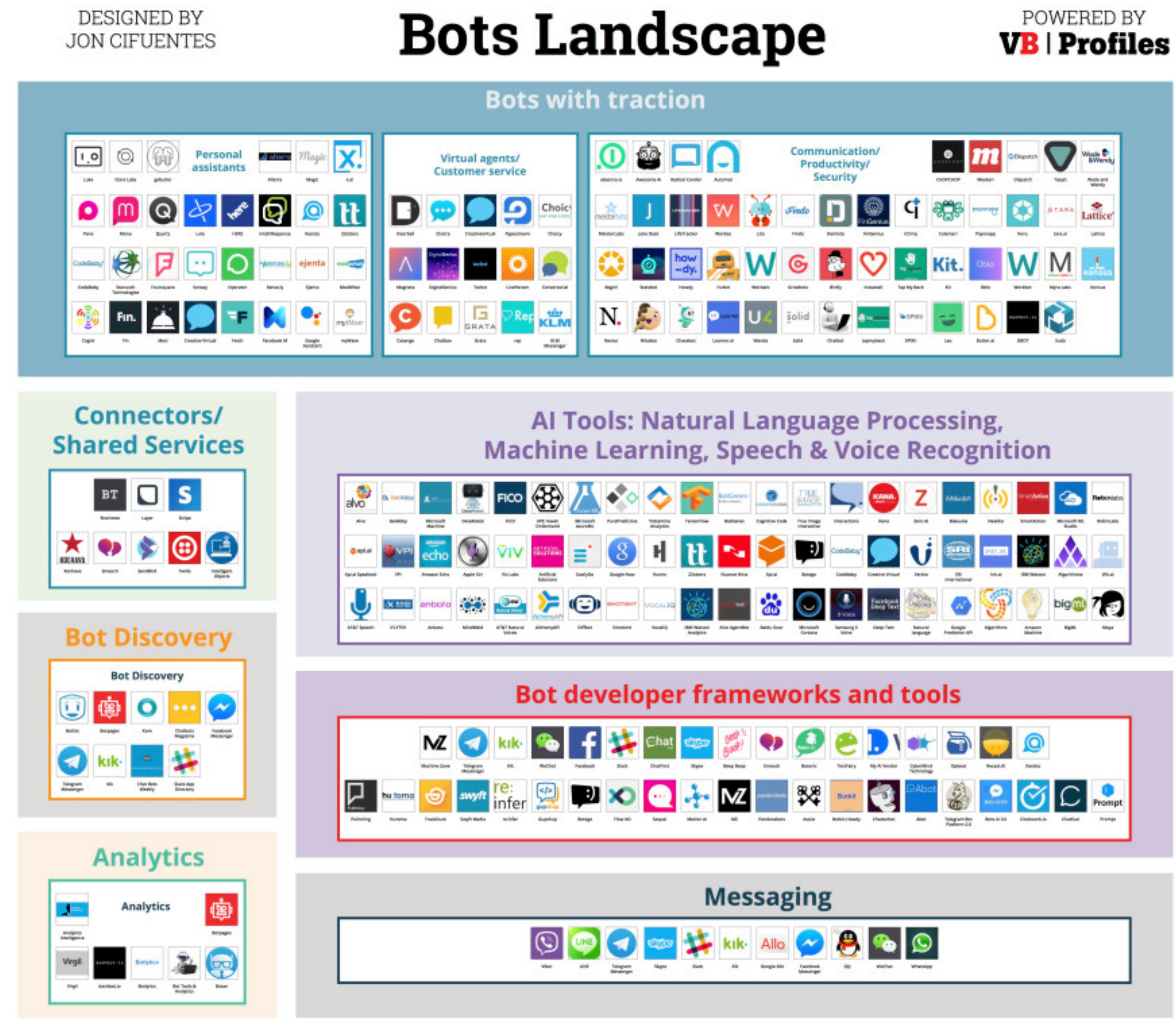
Pandorabots

MindMeld

Gupshup

Sequel

Source: https://www.oreilly.com/ideas/infographic-the-bot-platform-ecosystem



Source: https://venturebeat.com/2016/08/11/introducing-the-bots-landscape-170-companies-4-billion-in-funding-thousands-of-bots/

RECAST.AI

Messenger Bot Landscape

May 2017

Food

The Wine Pairer, Plum, Pescetarian Kitchen, Hungry, Foodie, Fitmeal, Entrée, Chatobook, Make My Sushi, Voome

Communication

Tangowork, Typeform, Anony, Tarjimly, Refugio, Rescue, Messenger Match, Sensay, LangLearnBot, Chat Club, Lingio Translate, Decodemoji, U-Report Global, Twiggo

Utilities

Poncho, Calcbot, Smokey, DotCom, Server Monitoring, English Dictionary, Youtube Search, Idea Bot, QRobot, Instant Translator

Personal

M, Assist, Operator, Uber, Swelly, AskVoila, Ikea Build, Selectionnist, Bud Light Bot, Ask Gary Vee, Gidi, Visabot

Design

ColoretoBot, Connie Digital, AWWWARDS, Mr. Norman, Graphic Design, SnapBot

Analytics

SISENSE, Stockflare, PageInsights, DAM, BuzzLogger, Trading Bot

News

CNN, TIA, Digg, WSJ, Reddit Bot, Al Jazeera, Hacker News, Wired, The Guardian, France Info, Chatbots Mag, VentureBeat

Travel

Grindbase, KLM, British Airways, Space Explorer, AustrianAirlines, SnapTravel, Skyscanner, Kayak, Ticketbot, Rapido

Entertainment

Spotify, Kim Kardashian, La Bringue, 50 Cent, L'oquillo Fiel, Lindsay Lohan, Maroon 5, MTV News, Axwell Λ Ingrosso, RedBull TV, SantaBot, Star Wars Bot, Citron, Pokébot

Developer Tools

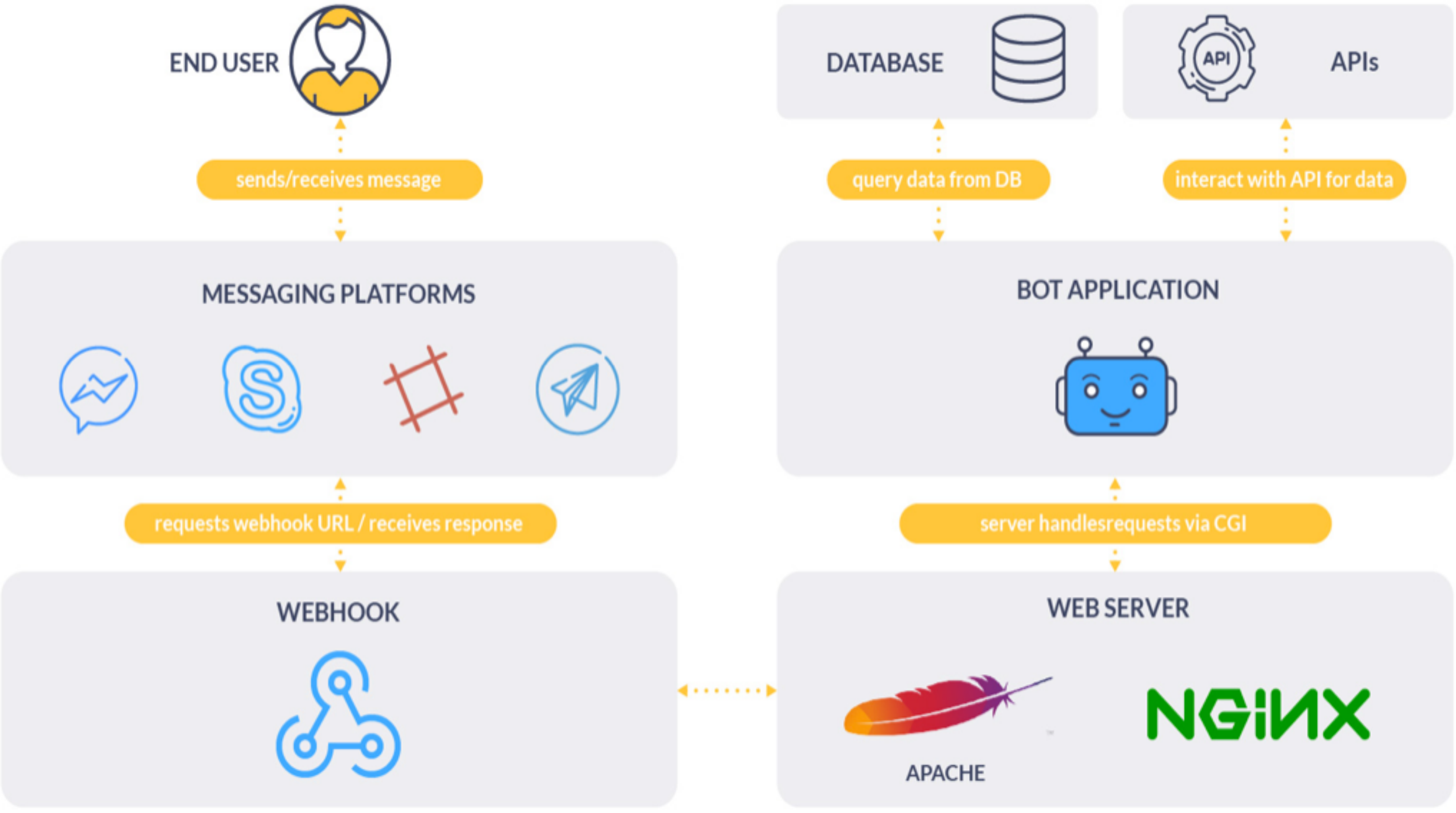
HackerOne, Wiredelta, Robbie, Zilly

Education

Genius, Kimchi, MemoryzerBot, Ainstein

Source: https://medium.com/@RecastAI/2017-messenger-bot-landscape-a-public-spreadsheet-gathering-1000-messenger-bots-f017fdb1448a /

How to Build Chatbots



Source: Igor Bobriakov (2018), https://activewizards.com/blog/a-comparative-analysis-of-chatbots-apis/

Chatbot Frameworks and AI Services

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

Source: Igor Bobriakov (2018), https://activewizards.com/blog/a-comparative-analysis-of-chatbots-apis/

Chatbot Frameworks

Comparison Table of Most Prominent Bot Frameworks

	Botkit	Microsoft Bot Framework	RASA NLU
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	✓	✗	✗
Programming Language	JavaScript (Node)	JavaScript (Node), C#	Python

Created by ActiveWizards

Source: Igor Bobriakov (2018), https://activewizards.com/blog/a-comparative-analysis-of-chatbots-apis/

Comparison of Most Prominent AI Services

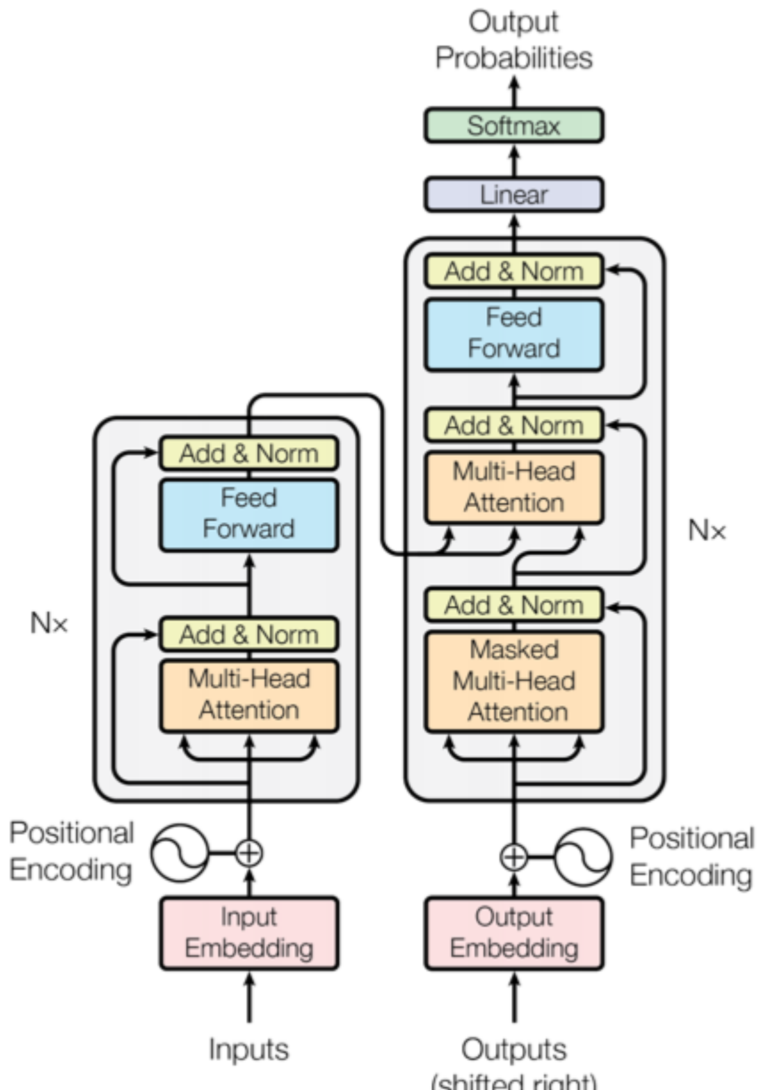
	wit.ai	api.ai	LUIS.ai	IBM Watson
Free of charge	✓	✓ but has paid enterprise version	✓ it is in beta and has transaction limits	**30 days trial** then priced for enterprise use
Text and Speech processing	✓	✓	✓ with use of Cortana	✓
Machine Learning Modeling	✓	✓	✓	✓
Support for Intents, Entities, Actions	✓ 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.	✓	✓	✓	✓
Integration to messaging platforms	✗ web service API	✓ also has facility for deploying to heroku. Paid environment	✓ integrated to Azure	✓ 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

Source: Igor Bobriakov (2018), https://activewizards.com/blog/a-comparative-analysis-of-chatbots-apis/

Transformer (Attention is All You Need)

(Vaswani et al., 2017)

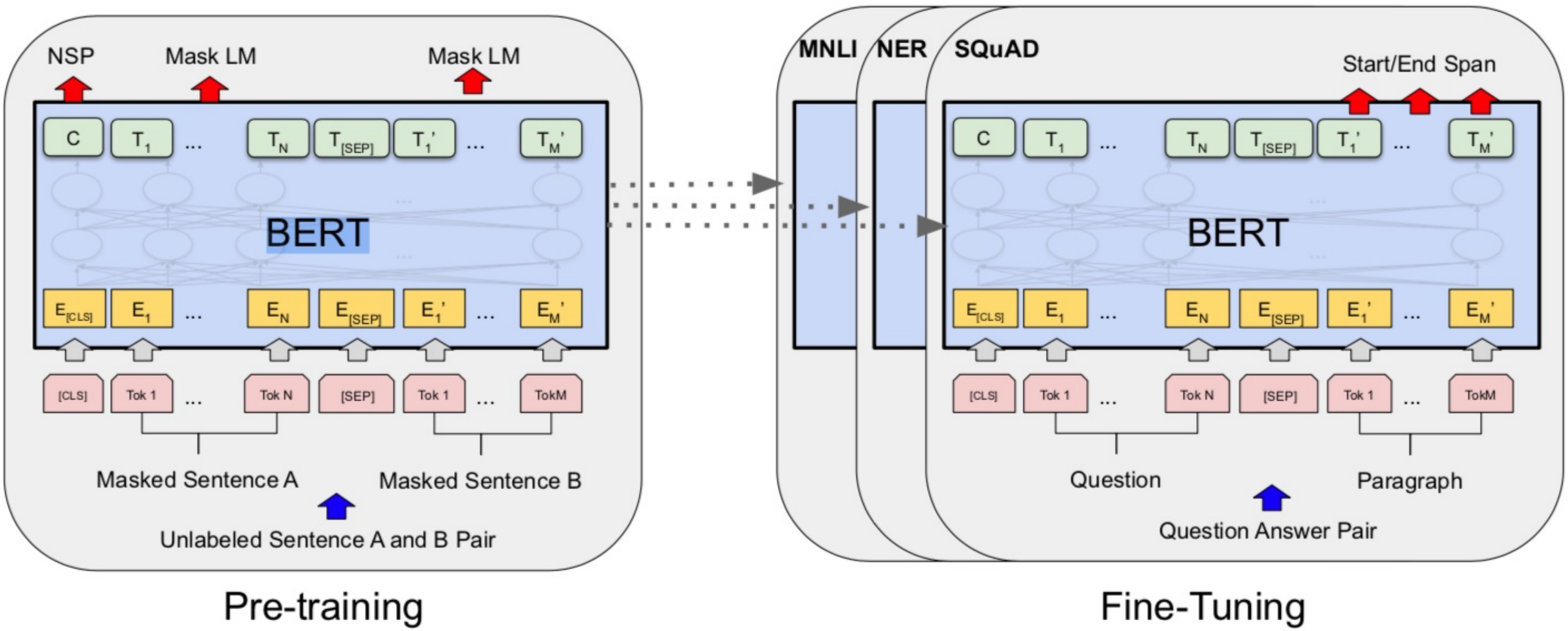


Source: Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." In *Advances in neural information processing systems*, pp. 5998-6008. 2017.

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

BERT (Bidirectional Encoder Representations from Transformers)

Overall pre-training and fine-tuning procedures for BERT

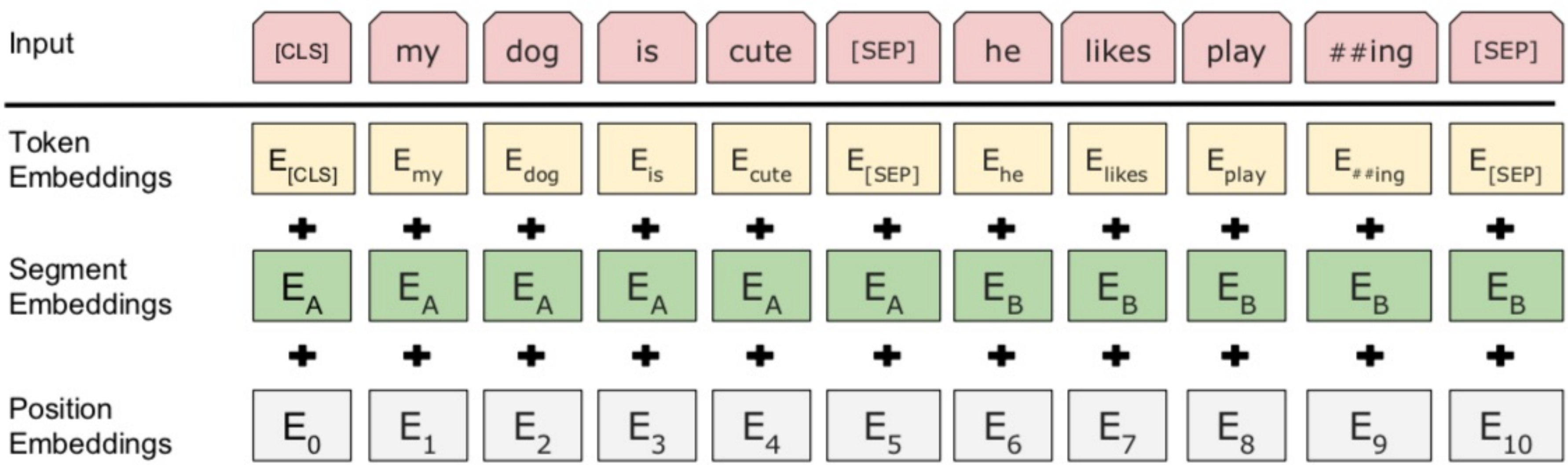


Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

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

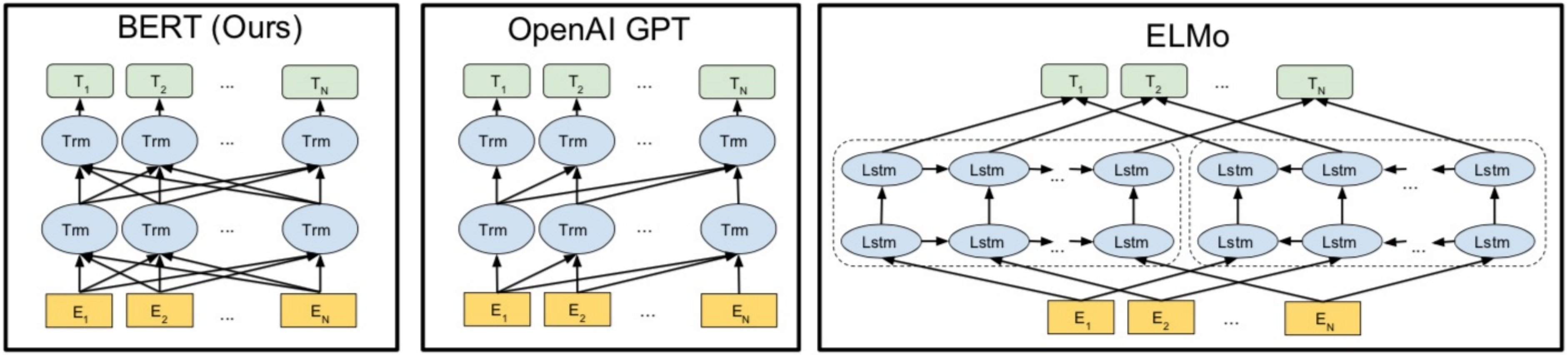
BERT (Bidirectional Encoder Representations from Transformers)

BERT input representation



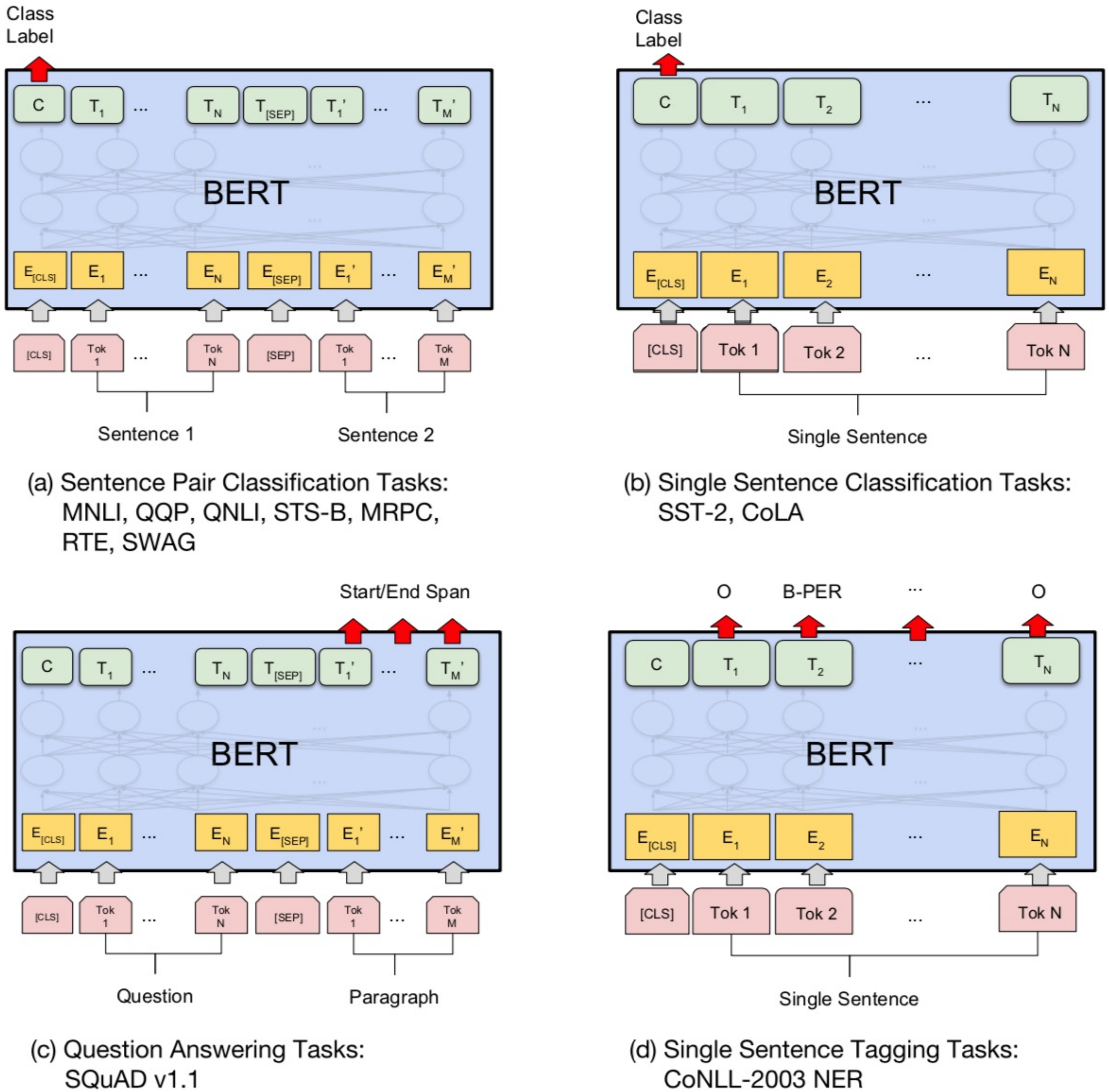
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

BERT, OpenAI GPT, ELMo



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

Fine-tuning BERT on Different Tasks



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

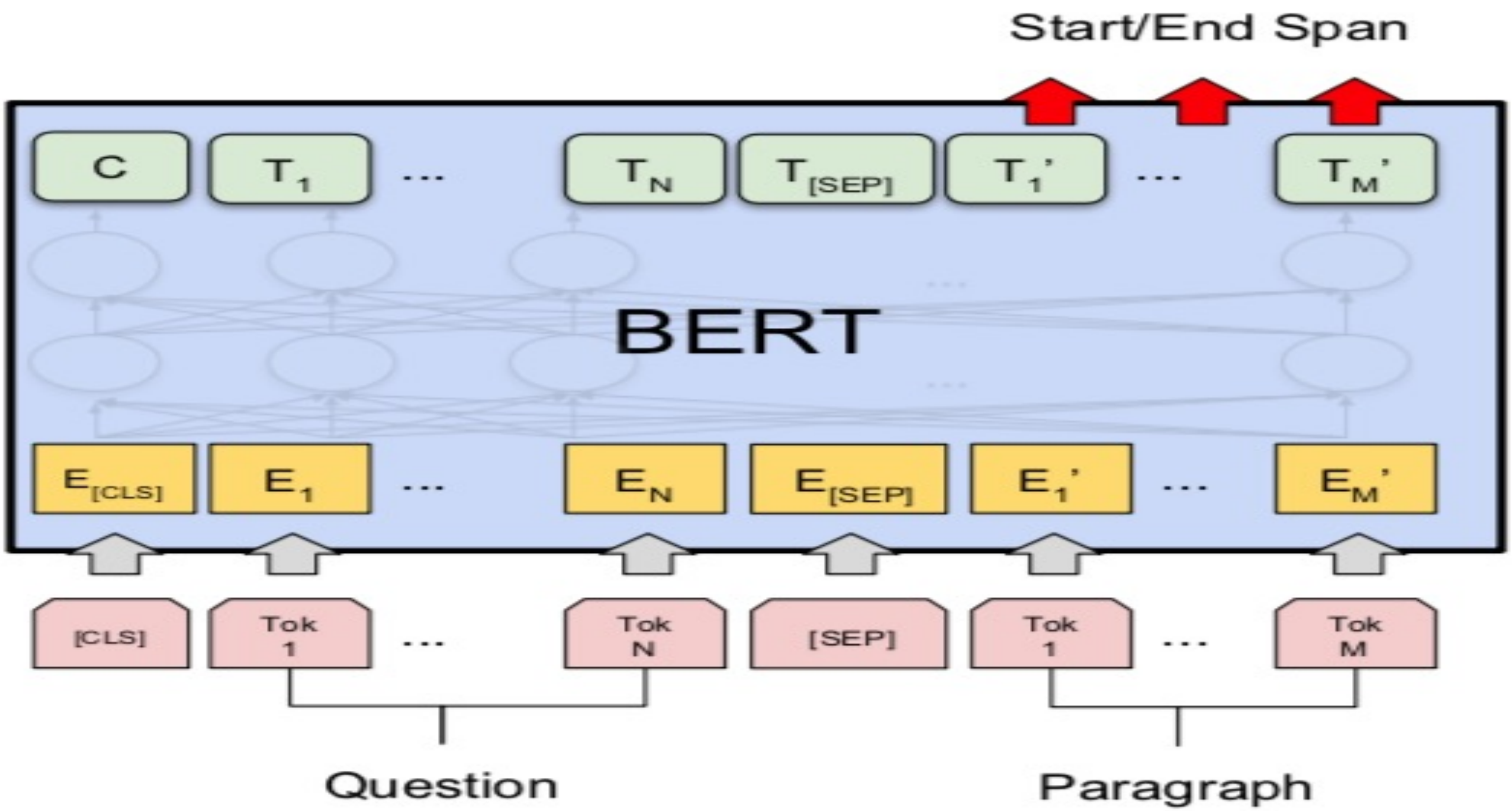
(b) Single Sentence Classification Tasks: SST-2, CoLA

(c) Question Answering Tasks: SQuAD v1.1

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

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

Fine-tuning BERT on Question Answering (QA)

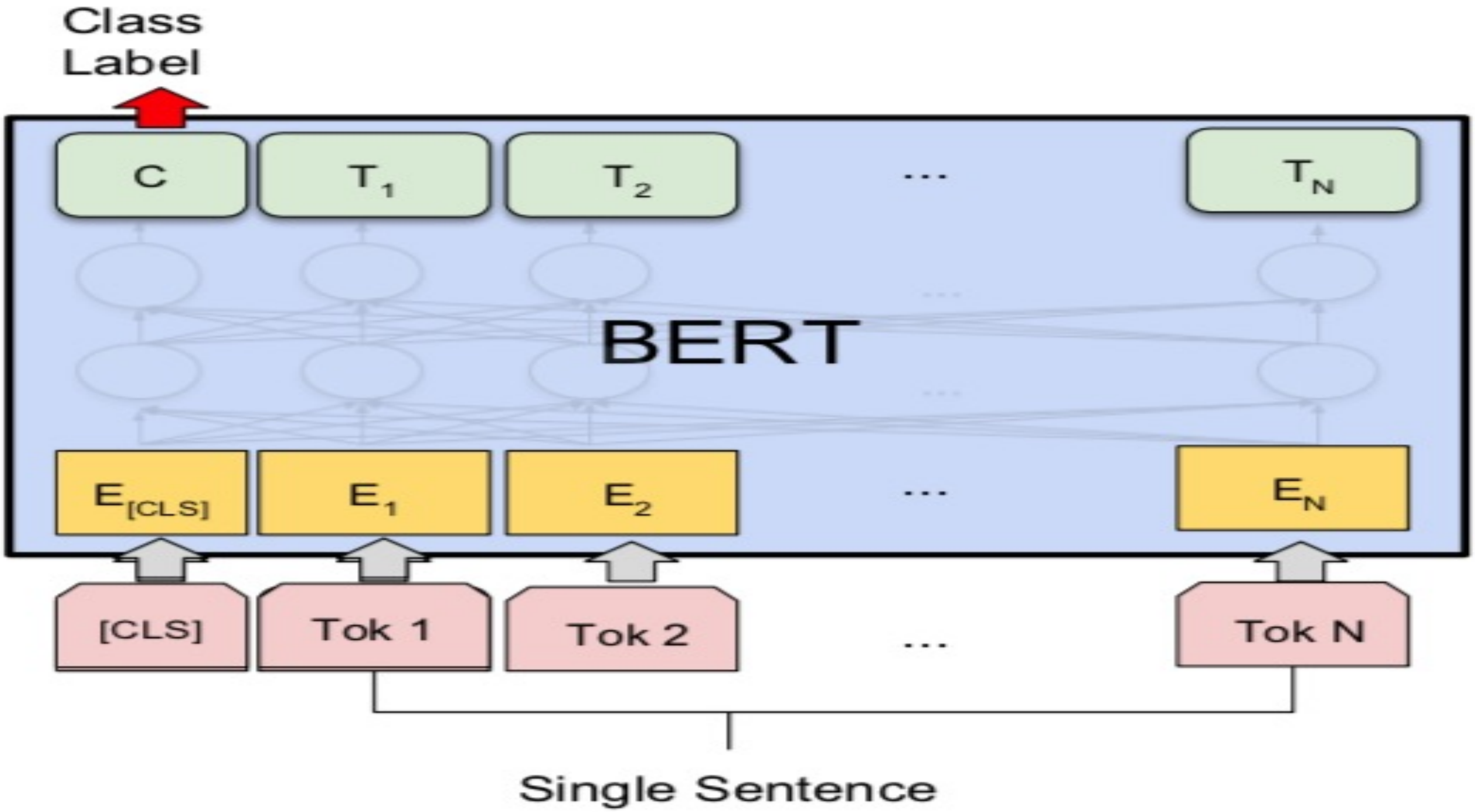


(c) Question Answering Tasks: SQuAD v1.1

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.

Fine-tuning BERT on Dialogue

Intent Detection (ID; Classification)

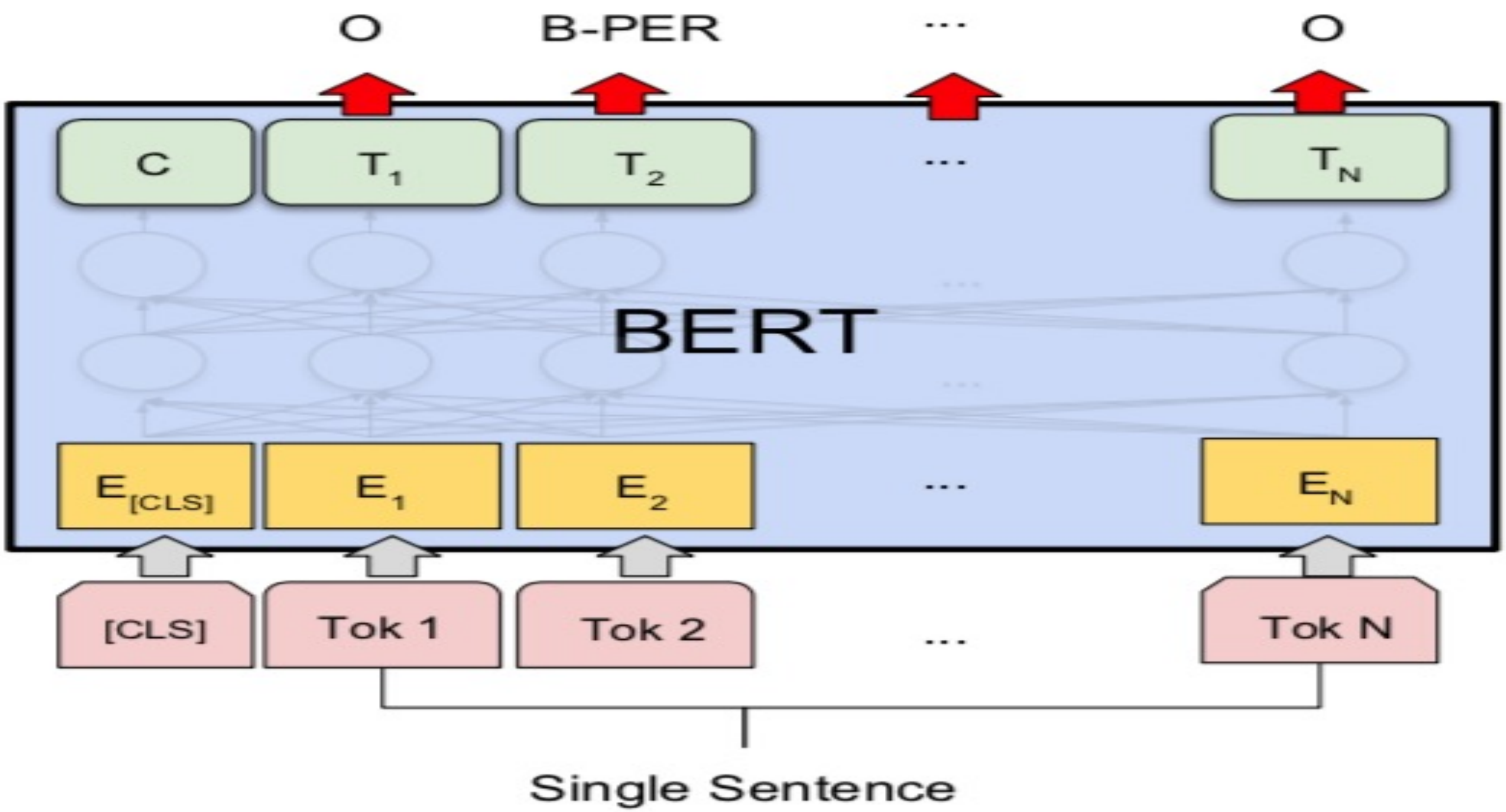


(b) Single Sentence Classification Tasks: SST-2, CoLA

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

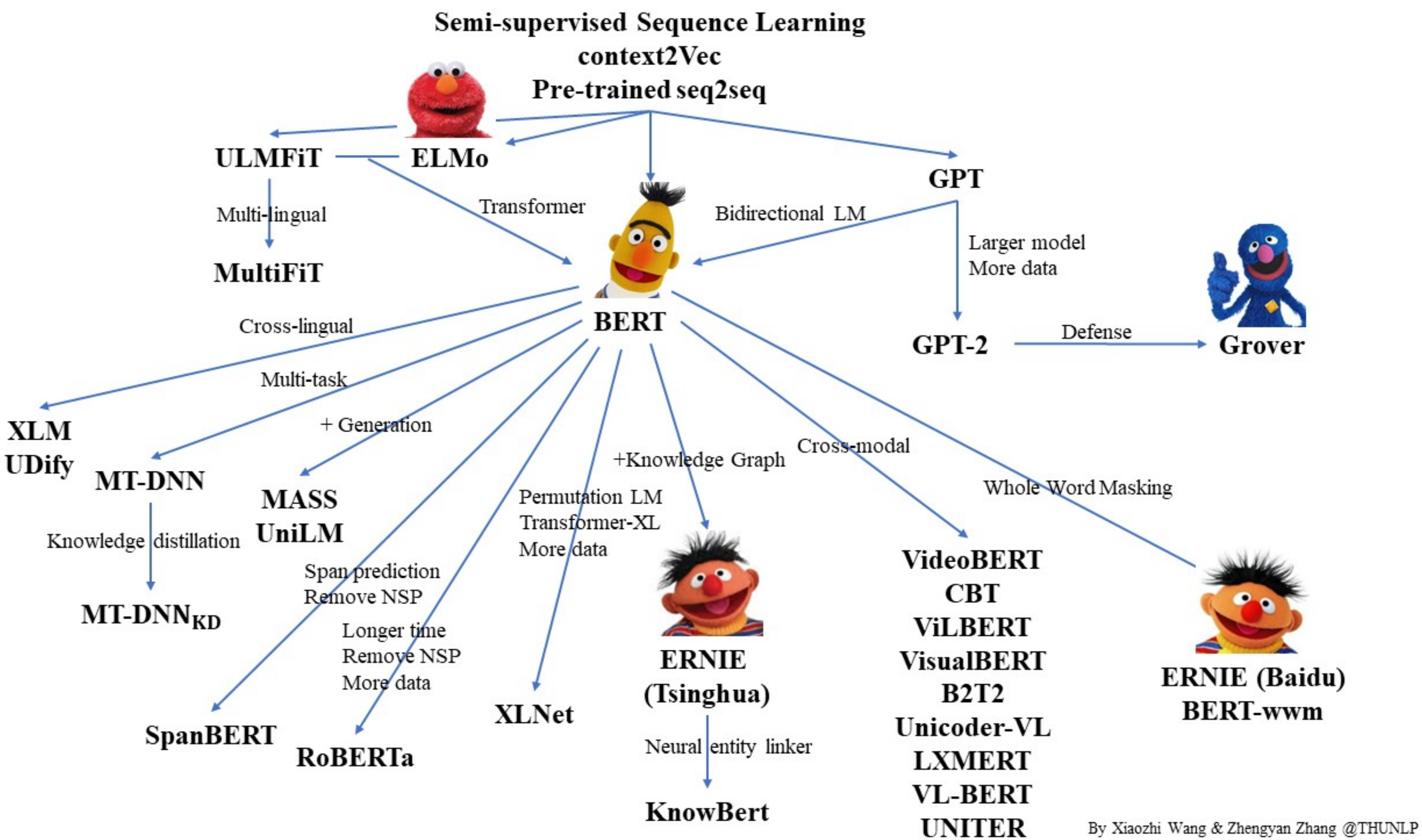
Slot Filling (SF)



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

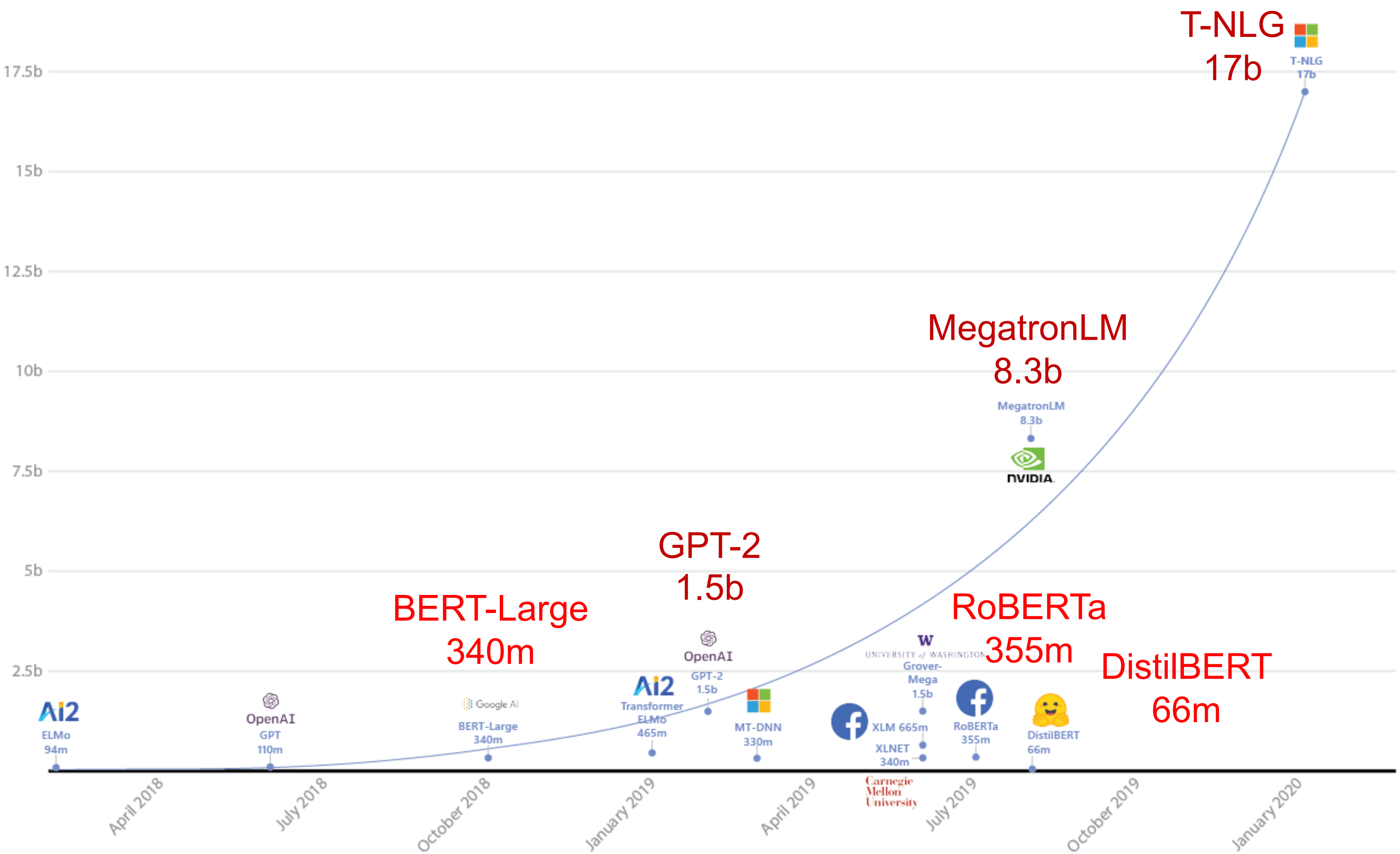
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

Pre-trained Language Model (PLM)



Source: https://github.com/thunlp/PLMpapers

Turing Natural Language Generation (T-NLG)



Source: https://www.microsoft.com/en-us/research/blog/turing-nlg-a-17-billion-parameter-language-model-by-microsoft/

Transformers

Transformers

State-of-the-art Natural Language Processing for TensorFlow 2.0 and PyTorch

- Transformers
  - pytorch-transformers
  - pytorch-pretrained-bert
- provides state-of-the-art general-purpose architectures
  - (BERT, GPT-2, RoBERTa, XLM, DistilBert, XLNet, CTRL...)
  - for Natural Language Understanding (NLU) and
    Natural Language Generation (NLG)
    with over 32+ pretrained models
    in 100+ languages
    and deep interoperability between
    TensorFlow 2.0 and
    PyTorch.

Source: https://github.com/huggingface/transformers

Transfer Learning in Natural Language Processing

Source: Sebastian Ruder, Matthew E. Peters, Swabha Swayamdipta, and Thomas Wolf (2019), "Transfer learning in natural language processing." In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Tutorials, pp. 15-18.

NLP Benchmark Datasets

Task	Dataset	Link
Machine Translation	WMT 2014 EN-DE WMT 2014 EN-FR	http://www-lium.univ-lemans.fr/~schwenk/cslm_joint_paper/
Text Summarization	CNN/DM Newsroom DUC Gigaword	https://cs.nyu.edu/~kcho/DMQA/ https://summari.es/ https://www-nlpir.nist.gov/projects/duc/data.html https://catalog.ldc.upenn.edu/LDC2012T21
Reading Comprehension Question Answering Question Generation	ARC CliCR CNN/DM NewsQA RACE SQuAD Story Cloze Test NarativeQA Quasar SearchQA	http://data.allenai.org/arc/ http://aclweb.org/anthology/N18-1140 https://cs.nyu.edu/~kcho/DMQA/ https://datasets.maluuba.com/NewsQA http://www.qizhexie.com/data/RACE_leaderboard https://rajpurkar.github.io/SQuAD-explorer/ http://aclweb.org/anthology/W17-0906.pdf https://github.com/deepmind/narrativeqa https://github.com/bdhingra/quasar https://github.com/nyu-dl/SearchQA
Semantic Parsing	AMR parsing ATIS (SQL Parsing) WikiSQL (SQL Parsing)	https://amr.isi.edu/index.html https://github.com/jkkummerfeld/text2sql-data/tree/master/data https://github.com/salesforce/WikiSQL
Sentiment Analysis	IMDB Reviews SST Yelp Reviews Subjectivity Dataset	http://ai.stanford.edu/~amaas/data/sentiment/ https://nlp.stanford.edu/sentiment/index.html https://www.yelp.com/dataset/challenge http://www.cs.cornell.edu/people/pabo/movie-review-data/
Text Classification	AG News DBpedia TREC 20 NewsGroup	http://www.di.unipi.it/~gulli/AG_corpus_of_news_articles.html https://wiki.dbpedia.org/Datasets https://trec.nist.gov/data.html http://qwone.com/~jason/20Newsgroups/
Natural Language Inference	SNLI Corpus MultiNLI SciTail	https://nlp.stanford.edu/projects/snli/ https://www.nyu.edu/projects/bowman/multinli/ http://data.allenai.org/scitail/
Semantic Role Labeling	Proposition Bank OneNotes	http://propbank.github.io/ https://catalog.ldc.upenn.edu/LDC2013T19

Source: Amirsina Torfi, Rouzbeh A. Shirvani, Yaser Keneshloo, Nader Tavvaf, and Edward A. Fox (2020).
"Natural Language Processing Advancements By Deep Learning: A Survey." arXiv preprint arXiv:2003.01200.

Question Answering (QA)

SQuAD

Stanford **Q**uestion **A**nswering **D**ataset

SQuAD

SQuAD | Home | Explore 2.0 | Explore 1.1

SQuAD2.0

The Stanford Question Answering Dataset

What is SQuAD?

Stanford **Q**uestion **A**nswering **D**ataset (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

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

SQuAD (Question Answering)

Super Bowl 50

From Wikipedia, the free encyclopedia

"2016 Super Bowl" redirects here. For the Super Bowl that was played at the completion of the 2016 season, see Super Bowl LI.
"SB 50" redirects here. For the California transit-density bill, see California Senate Bill 50.

Super Bowl 50 was an American football game to determine the champion of the National Football League (NFL) for the 2015 season. The American Football Conference (AFC) champion Denver Broncos defeated the National Football Conference (NFC) champion Carolina Panthers, 24–10. The game was played on February 7, 2016, at Levi's Stadium in Santa Clara, California, in the San Francisco Bay Area. As this was the 50th Super Bowl game, the league emphasized the "golden anniversary" with various gold-themed initiatives during the 2015 season, as well as suspending the tradition of naming each Super Bowl game with Roman numerals (under which the game would have been known as "Super Bowl L"), so the logo could prominently feature the Arabic numerals 5 and 0.[5][6]

The Panthers finished the regular season with a 15–1 record, racking up the league's top offense, and quarterback Cam Newton was named the NFL Most Valuable Player (MVP). They defeated the Arizona Cardinals 49–15 in the NFC Championship Game and advanced to their second Super Bowl appearance since the franchise began playing in 1995. The Broncos finished the regular season with a 12–4 record, bolstered by having the league's top defense. The Broncos defeated the defending Super Bowl champion New England Patriots 20–18 in the AFC Championship Game joining the Patriots, Dallas Cowboys, and Pittsburgh Steelers as one of four teams that have made eight appearances in the Super Bowl. This record would later be broken the next season, in 2017, when the Patriots advanced to their ninth Super Bowl appearance in Super Bowl LI.

Super Bowl 50

Carolina Panthers (1) (NFC) (15–1) — **10** — **Head coach: Ron Rivera**

Denver Broncos (1) (AFC) (12–4) — **24** — **Head coach: Gary Kubiak**

	1	2	3	4	Total
CAR	0	7	0	3	10

https://en.wikipedia.org/wiki/Super_Bowl_50

Dialogue

on

Airline Travel Information System (ATIS)

The ATIS (Airline Travel Information System) Dataset

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

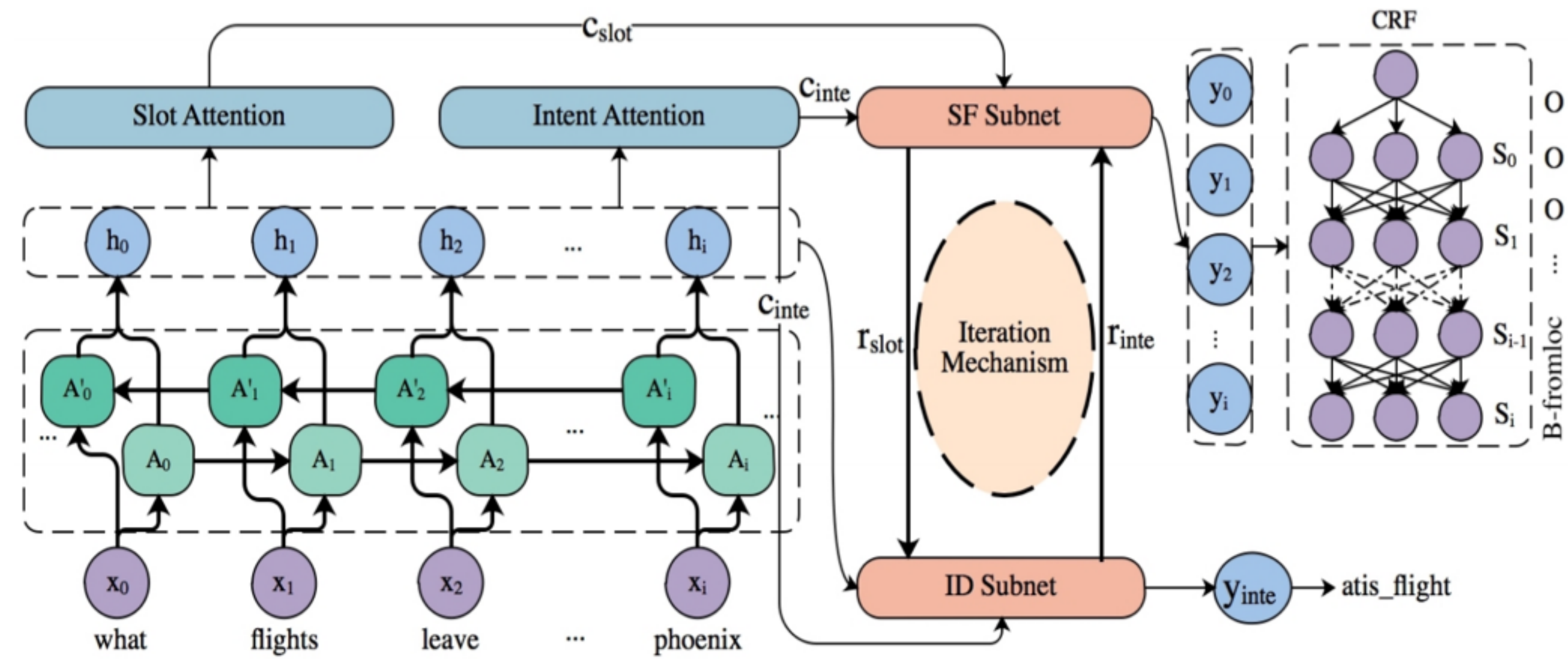
Sentence	what	flights	leave	from	phoenix
Slots	O	O	O	O	B-fromloc
Intent	atis_flight				

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

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

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

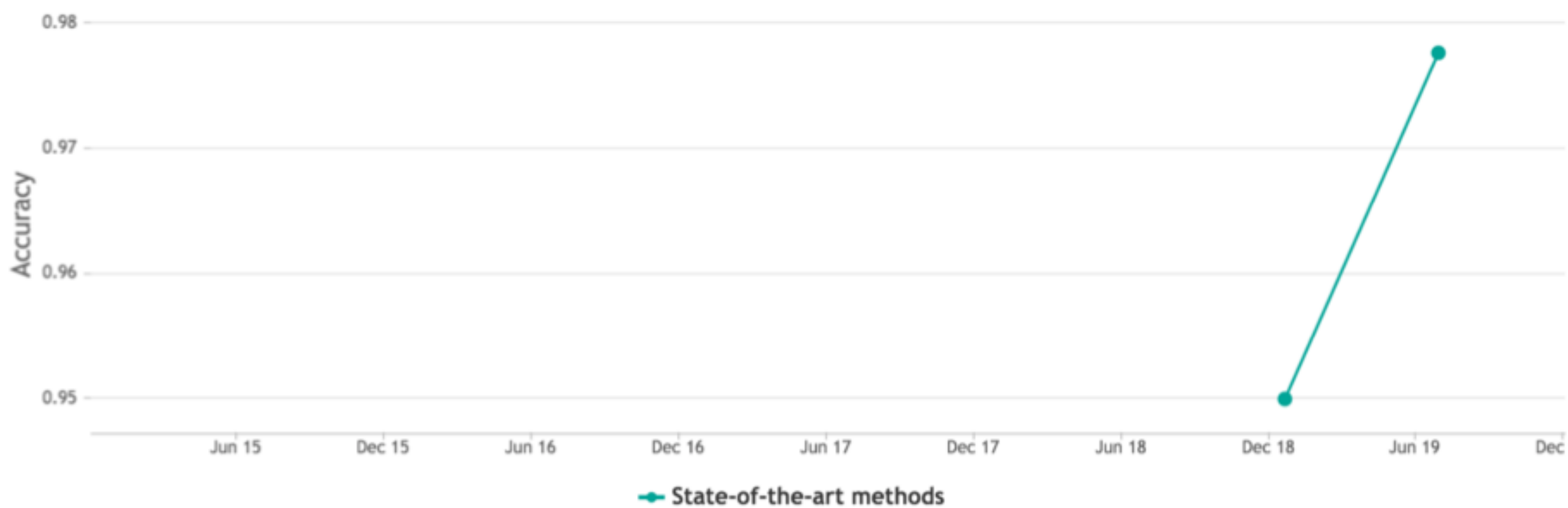
A Novel Bi-directional Interrelated Model for Joint Intent Detection and Slot Filling



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

Intent Detection on ATIS State-of-the-art

Intent Detection on ATIS

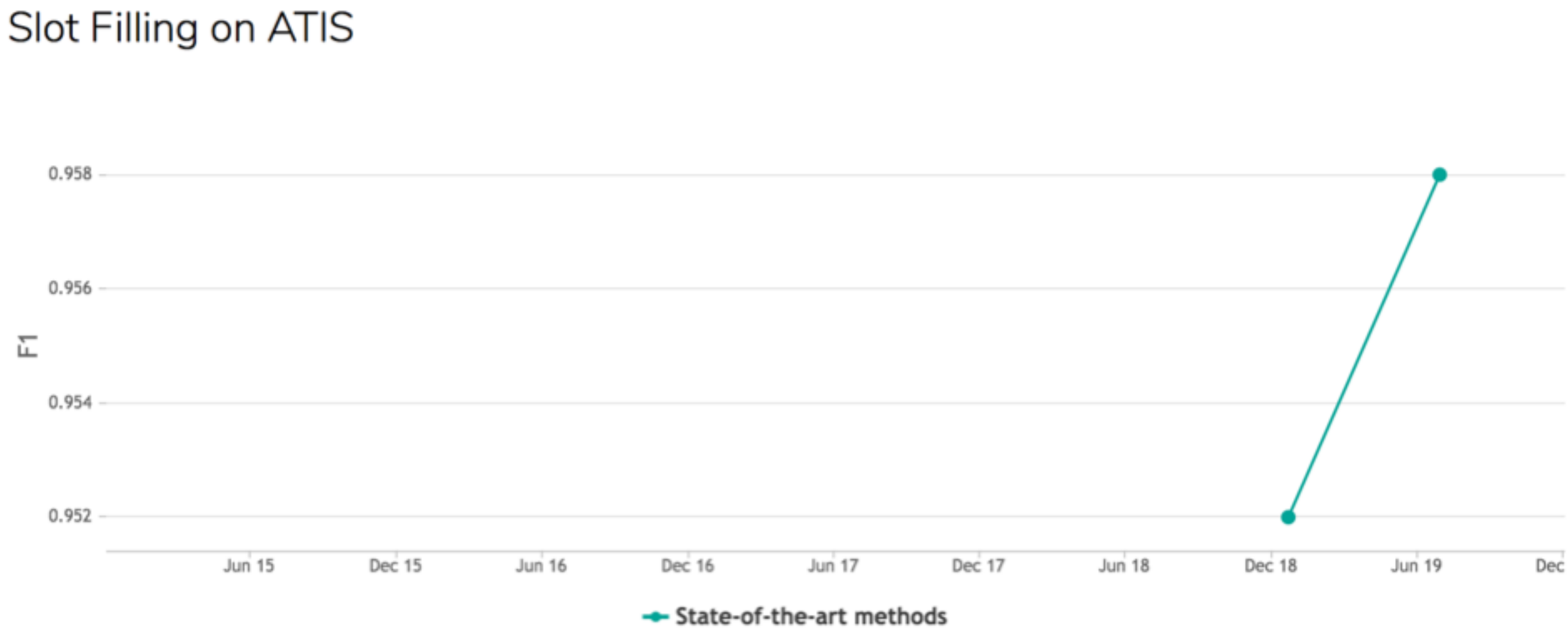


Edit

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		
2	Capsule-NLU	0.950	Joint Slot Filling and Intent Detection via Capsule Neural Networks	2018		

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

Slot Filling on ATIS State-of-the-art



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		
2	Capsule-NLU	0.952	Joint Slot Filling and Intent Detection via Capsule Neural Networks	2018		

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

Restaurants Dialogue Datasets

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

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

<table>
<tr><th>MultiWOZ</th><th>CrossWOZ</th></tr>
<tr><td>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?</td><td rowspan="3">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?</td></tr>
<tr><th>Schema</th></tr>
<tr><td>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.</td></tr>
</table>

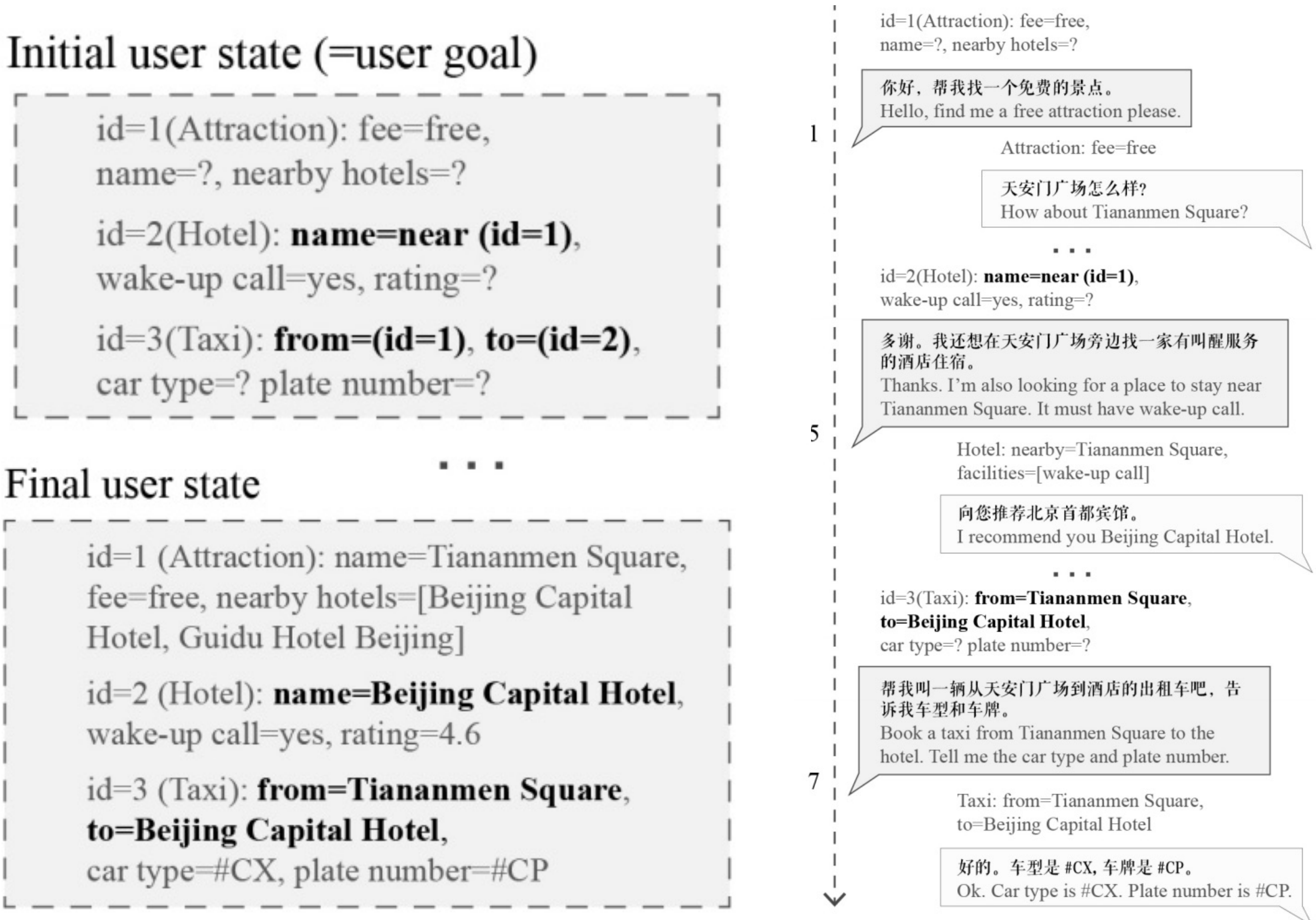
Source: Zhu, Qi, Kaili Huang, Zheng Zhang, Xiaoyan Zhu, and Minlie Huang. "Crosswoz: A large-scale chinese cross-domain task-oriented dialogue dataset." arXiv preprint arXiv:2002.11893 (2020).

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



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).

任務型對話系統
The Evaluation of Chinese Human-Computer Dialogue Technology, SMP2019-ECDT

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

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

Python in Google Colab (Python101)

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

python101.ipynb

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Question Answering and Dialogue Systems

Question Answering (QA)

BERT for Question Answering

Source: Apoorv Nandan (2020), BERT (from HuggingFace Transformers) for Text Extraction, https://keras.io/examples/nlp/text_extraction_with_bert/

Description: Fine tune pretrained BERT from HuggingFace Transformers on SQuAD.

Introduction

This demonstration uses SQuAD (Stanford Question-Answering Dataset). In SQuAD, an input consists of a question, and a paragraph for context. The goal is to find the span of text in the paragraph that answers the question. We evaluate our performance on this data with the "Exact Match" metric, which measures the percentage of predictions that exactly match any one of the ground-truth answers.

We fine-tune a BERT model to perform this task as follows:

1. Feed the context and the question as inputs to BERT.
2. Take two vectors S and T with dimensions equal to that of hidden states in BERT.
3. Compute the probability of each token being the start and end of the answer span. The probability of a token being the start of the answer is given by a dot product between S and the representatio of the token in the last layer of BERT, followed by a softmax over all tokens. The probability of a token being the end of the answer is compute similarly with the vector T.
4. Fine-tune BERT and learn S and T along the way.

References:

- BERT
- SQuAD

https://tinyurl.com/imtkupython101

Python in Google Colab (Python101)

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

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Downloading: 100% 433/433 [00:29<00:00, 14.5B/s]

Downloading: 100% 536M/536M [00:29<00:00, 18.3MB/s]

```
Model: "model"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_1 (InputLayer)            [(None, 384)]        0
__________________________________________________________________________________________________
input_3 (InputLayer)            [(None, 384)]        0
__________________________________________________________________________________________________
input_2 (InputLayer)            [(None, 384)]        0
__________________________________________________________________________________________________
tf_bert_model (TFBertModel)     ((None, 384, 768), ( 109482240   input_1[0][0]
__________________________________________________________________________________________________
start_logit (Dense)             (None, 384, 1)       768         tf_bert_model[0][0]
__________________________________________________________________________________________________
end_logit (Dense)               (None, 384, 1)       768         tf_bert_model[0][0]
__________________________________________________________________________________________________
flatten (Flatten)               (None, 384)          0           start_logit[0][0]
__________________________________________________________________________________________________
flatten_1 (Flatten)             (None, 384)          0           end_logit[0][0]
__________________________________________________________________________________________________
activation_7 (Activation)       (None, 384)          0           flatten[0][0]
__________________________________________________________________________________________________
activation_8 (Activation)       (None, 384)          0           flatten_1[0][0]
==================================================================================================
Total params: 109,483,776
Trainable params: 109,483,776
Non-trainable params: 0
__________________________________________________________________________________________________
CPU times: user 20.8 s, sys: 7.75 s, total: 28.5 s
Wall time: 1min 42s
```

https://tinyurl.com/imtkupython101

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Section

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Dialogue Systems

```
[ ]
#Source: Olivier Grisel (2020), Transformers (BERT fine-tuning): Joint Intent Classification and S
#https://github.com/m2dsupsdlclass/lectures-labs/blob/master/labs/06_deep_nlp/Transformers_Joint_I
```

Joint Intent Classification and Slot Filling with Transformers

The goal of this notebook is to fine-tune a pretrained transformer-based neural network model to convert a user query expressed in English into a representation that is structured enough to be processed by an automated service.

Here is an example of interpretation computed by such a Natural Language Understanding system:

```
>>> nlu("Book a table for two at Le Ritz for Friday night",
        tokenizer, joint_model, intent_names, slot_names)
```

```
{
    'intent': 'BookRestaurant',
    'slots': {
        'party_size_number': 'two',
        'restaurant_name': 'Le Ritz',
        'timeRange': 'Friday night'
    }
}
```

Intent classification is a simple sequence classification problem. The trick is to treat the structured knowledge extraction part ("Slot Filling") as token-level classification problem using BIO-annotations:

https://tinyurl.com/imtkupython101

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

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- RandomizedSearchCV
- Sentiment Analysis
  - Sentiment Analysis - Unsupervised Lexical
  - Sentiment Analysis - Supervised Machine Learning
  - Sentiment Analysis - Supervised Deep Learning Models
  - Sentiment Analysis - Advanced Deep Learning
- Deep Learning and Universal Sentence-Embedding Models
  - Universal Sentence Encoder (USE)
  - Universal Sentence Encoder Multilingual (USEM)
- Question Answering and Dialogue Systems
  - Question Answering (QA)
    - BERT for Question Answering
  - Dialogue Systems
    - **Joint Intent Classification and Slot Filling with Transformers**
- Data Visualization

\+ Code + Text RAM Disk Editing

```python
def show_predictions(text, tokenizer, model, intent_names, slot_names):
    inputs = tf.constant(tokenizer.encode(text))[None, :]  # batch_size = 1
    outputs = model(inputs)
    slot_logits, intent_logits = outputs
    slot_ids = slot_logits.numpy().argmax(axis=-1)[0, 1:-1]
    intent_id = intent_logits.numpy().argmax(axis=-1)[0]
    print("Text:", text)
    print("Intent:", intent_names[intent_id])
    print("Slots:")
    for token, slot_id in zip(tokenizer.tokenize(text), slot_ids):
        print(f"{token:>10} : {slot_names[slot_id]}")

show_predictions("Book a table for two at Le Ritz for Friday night!",
                 tokenizer, joint_model, intent_names, slot_names)
```

```
Text: Book a table for two at Le Ritz for Friday night!
Intent: BookRestaurant
Slots:
      Book : O
         a : O
     table : O
       for : O
       two : B-party_size_number
        at : O
        Le : B-restaurant_name
         R : I-restaurant_name
     ##itz : I-restaurant_name
       for : O
    Friday : B-timeRange
     night : O
         ! : O
```

https://tinyurl.com/imtkupython101

Python in Google Colab (Python101)

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

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```python
            # Naive BIO: handling: treat B- and I- the same...
            new_slot_name = current_word_slot_name[2:]
            if active_slot_name is None:
                active_slot_words.append(word)
                active_slot_name = new_slot_name
            elif new_slot_name == active_slot_name:
                active_slot_words.append(word)
            else:
                collected_slots[active_slot_name] = " ".join(active_slot_words)
                active_slot_words = [word]
                active_slot_name = new_slot_name
    if active_slot_name:
        collected_slots[active_slot_name] = " ".join(active_slot_words)
    info["slots"] = collected_slots
    return info

def nlu(text, tokenizer, model, intent_names, slot_names):
    inputs = tf.constant(tokenizer.encode(text))[None, :]  # batch_size = 1
    outputs = model(inputs)
    slot_logits, intent_logits = outputs
    slot_ids = slot_logits.numpy().argmax(axis=-1)[0, 1:-1]
    intent_id = intent_logits.numpy().argmax(axis=-1)[0]

    return decode_predictions(text, tokenizer, intent_names, slot_names,
                              intent_id, slot_ids)

nlu("Book a table for two at Le Ritz for Friday night",
    tokenizer, joint_model, intent_names, slot_names)
```

```
{'intent': 'BookRestaurant',
 'slots': {'party_size_number': 'two',
  'restaurant_name': 'Le Ritz',
  'timeRange': 'Friday night'}}
```

https://tinyurl.com/imtkupython101

NLP Benchmark Datasets

Task	Dataset	Link
Machine Translation	WMT 2014 EN-DE WMT 2014 EN-FR	http://www-lium.univ-lemans.fr/~schwenk/cslm_joint_paper/
Text Summarization	CNN/DM Newsroom DUC Gigaword	https://cs.nyu.edu/~kcho/DMQA/ https://summari.es/ https://www-nlpir.nist.gov/projects/duc/data.html https://catalog.ldc.upenn.edu/LDC2012T21
Reading Comprehension Question Answering Question Generation	ARC CliCR CNN/DM NewsQA RACE SQuAD Story Cloze Test NarativeQA Quasar SearchQA	http://data.allenai.org/arc/ http://aclweb.org/anthology/N18-1140 https://cs.nyu.edu/~kcho/DMQA/ https://datasets.maluuba.com/NewsQA http://www.qizhexie.com/data/RACE_leaderboard https://rajpurkar.github.io/SQuAD-explorer/ http://aclweb.org/anthology/W17-0906.pdf https://github.com/deepmind/narrativeqa https://github.com/bdhingra/quasar https://github.com/nyu-dl/SearchQA
Semantic Parsing	AMR parsing ATIS (SQL Parsing) WikiSQL (SQL Parsing)	https://amr.isi.edu/index.html https://github.com/jkkummerfeld/text2sql-data/tree/master/data https://github.com/salesforce/WikiSQL
Sentiment Analysis	IMDB Reviews SST Yelp Reviews Subjectivity Dataset	http://ai.stanford.edu/~amaas/data/sentiment/ https://nlp.stanford.edu/sentiment/index.html https://www.yelp.com/dataset/challenge http://www.cs.cornell.edu/people/pabo/movie-review-data/
Text Classification	AG News DBpedia TREC 20 NewsGroup	http://www.di.unipi.it/~gulli/AG_corpus_of_news_articles.html https://wiki.dbpedia.org/Datasets https://trec.nist.gov/data.html http://qwone.com/~jason/20Newsgroups/
Natural Language Inference	SNLI Corpus MultiNLI SciTail	https://nlp.stanford.edu/projects/snli/ https://www.nyu.edu/projects/bowman/multinli/ http://data.allenai.org/scitail/
Semantic Role Labeling	Proposition Bank OneNotes	http://propbank.github.io/ https://catalog.ldc.upenn.edu/LDC2013T19

Source: Amirsina Torfi, Rouzbeh A. Shirvani, Yaser Keneshloo, Nader Tavvaf, and Edward A. Fox (2020). "Natural Language Processing Advancements By Deep Learning: A Survey." arXiv preprint arXiv:2003.01200.

Summary

- Question Answering
- Dialogue Systems

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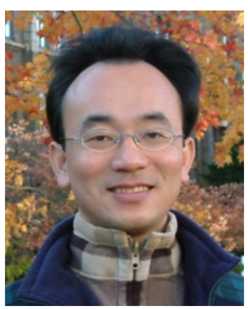
國立臺北護理健康大學
National Taipei University of Nursing and Health Sciences

Q & A

Tamkang University
淡江大學

問答系統與對話系統 (Question Answering and Dialogue Systems)

Time: 2020/06/19 (Fri) (9:10 -12:00)
Place: 國立臺北護理健康大學 (台北市明德路365號) G210
Host: 祝國忠 院長 (健康科技學院院長)



Min-Yuh Day
戴敏育
Associate Professor
副教授
Dept. of Information Management, Tamkang University
淡江大學 資訊管理學系
http://mail. tku.edu.tw/myday/

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