Conversational Commerce and Intelligent Chatbots for Fintech

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Wed 7, 8, 9 (15:10-18:00) (B8F40)

https://web.ntpu.edu.tw/~myday
2020-12-30
<table>
<thead>
<tr>
<th>週次 (Week)</th>
<th>日期 (Date)</th>
<th>內容 (Subject/Topics)</th>
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<tbody>
<tr>
<td>1</td>
<td>2020/09/16</td>
<td>大數據分析介紹 (Introduction to Big Data Analysis)</td>
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<td>2</td>
<td>2020/09/23</td>
<td>AI人工智慧與大數據分析 (AI and Big Data Analysis)</td>
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<td>3</td>
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<td>Python 大數據分析基礎 (Foundations of Big Data Analysis in Python)</td>
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<td>2020/10/07</td>
<td>數位沙盒第一堂課：數位沙盒服務平台簡介 (Digital Sandbox Lesson 1: Introduction to FintechSpace Digital Sandbox)</td>
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<td>2020/10/14</td>
<td>數位沙盒第二堂課：工程師操作說明與實作教學 (Digital Sandbox Lesson 2: Hands-on Practices)</td>
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<td>Python Pandas 大數據量化分析 (Quantitative Big Data Analysis with Pandas in Python)</td>
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<tr>
<td>週次 (Week)</td>
<td>日期 (Date)</td>
<td>內容 (Subject/Topics)</td>
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<tr>
<td>7 2020/10/28</td>
<td>Python Scikit-Learn</td>
<td>機器學習 I (Machine Learning with Scikit-Learn in Python I)</td>
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<td>8 2020/11/04</td>
<td>數位沙盒第三堂課：學生小組討論實作與成果發表</td>
<td>(Digital Sandbox Lesson 3: Learning Teams Hands-on Project Discussion and Project Presentation)</td>
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<tr>
<td>9 2020/11/11</td>
<td>期中報告</td>
<td>(Midterm Project Report)</td>
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<td>10 2020/11/18</td>
<td>Python Scikit-Learn</td>
<td>機器學習 II (Machine Learning with Scikit-Learn in Python II)</td>
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<tr>
<td>12 2020/12/02</td>
<td>大數據分析個案研究</td>
<td>(Case Study on Big Data Analysis)</td>
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</tbody>
</table>
週次 (Week) 日期 (Date) 內容 (Subject/Topics)

13 2020/12/09  TensorFlow 深度學習金融大數據分析 II
(Deep Learning for Finance Big Data Analysis with TensorFlow II)

14 2020/12/16  TensorFlow 深度學習金融大數據分析 III
(Deep Learning for Finance Big Data Analysis with TensorFlow III)

15 2020/12/23  AI 機器人理財顧問
(Artificial Intelligence for Robo-Advisors)

16 2020/12/30  金融科技智慧型交談機器人
(Conversational Commerce and Intelligent Chatbots for Fintech)

17 2021/01/06  期末報告 I (Final Project Report I)

18 2021/01/13  期末報告 II (Final Project Report I)
Conversational Commerce and Intelligent Chatbots for Fintech
Conversational Commerce
From E-Commerce to Conversational Commerce: Chatbots and Virtual Assistants

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

Server-side

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

Hotel Chatbot

**BookHotel**

- I’d like to book a hotel
- Sure, which city?
  - New York City
- What date are you leaving?
  - November 30th, 2016
- Are you sure you want to book the hotel in NYC?
  - Yes
- Thank you. The reservation went through successfully.

**Intent Detection**
- **Intents**
  - An intent performs an action in response to natural language user input

**Slot Filling**
- **Utterances**
  - Spoken or typed phrases that invoke your intent

- **Slots**
  - Slots are input data required to fulfill the intent

- **Fulfillment**
  - Fulfillment mechanism for your intent

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

- 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

1. **Tell me about savings**
   - A penny saved is a penny earned.

2. **Do you want me to turn on my auto-save feature?**
   - Yes.

3. **Awesome! What are you saving for this time?**

4. **New Ride**

5. **How much do you want to save?**
   - $9,500

6. **Ok, how soon do you want this new ride?**
   - 6 months.

7. **Alright! I've checked your spending habits and I'll transfer a few dollars into this account every week.**

8. **OK if I send you updates every once in a while to let you know how you're doing?**

Mastercard Makes Commerce More Conversational

Chatbot
Dialogue System
Intelligent Agent
Chatbot

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

Overall Architecture of Intelligent Chatbot

Can machines think?

(Alan Turing, 1950)

Chatbot

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

Chatbot Conversation Framework

![Diagram showing the chatbot conversation framework with quadrants for open and closed domain conversations, as well as retrieval-based and generative-based responses.]

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.

AI Dialogue
System
Dialogue Subtasks

**Dialogue Generation**
- Dialogue Generation
  - 9 leaderboards
  - 35 papers with code

**Dialogue State Tracking**
- Dialogue State Tracking
  - 2 leaderboards
  - 30 papers with code

**Visual Dialog**
- Visual Dialog
  - 3 leaderboards
  - 28 papers with code

**Task-Oriented Dialogue Systems**
- Task-Oriented Dialogue Systems
  - 20 papers with code

**Goal-Oriented Dialog**
- Goal-Oriented Dialog
  - 15 papers with code

**Short-Text Conversation**
- Short-Text Conversation
  - 6 papers with code
  - 5 papers with code
  - 3 papers with code

**Dialogue Management**
- Dialogue Management
  - 10 papers with code

**Dialogue Understanding**
- Dialogue Understanding
  - 6 papers with code

**Goal-Oriented Dialogue Systems**
- Goal-Oriented Dialogue Systems
  - 3 papers with code

**Task-Completion Dialogue Policy Learning**
- Task-Completion Dialogue Policy Learning
  - 2 papers with code

Source: https://paperswithcode.com/area/natural-language-processing/dialogue
IMTKU Textual Entailment System for Recognizing Inference in Text at NTCIR-9 RITE

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Tamkang University, Taiwan

Min-Yuh Day
myday@mail.tku.edu.tw

Chun Tu

NTCIR-9 Workshop, December 6-9, 2011, Tokyo, Japan
IMTKU Textual Entailment System for Recognizing Inference in Text at NTCIR-10 RITE-2

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Chun Tu
Hou-Cheng Vong
Shih-Wei Wu
Shih-Jhen Huang

myday@mail.tku.edu.tw

NTCIR-10 Conference, June 18-21, 2013, Tokyo, Japan
IMTKU Textual Entailment System for Recognizing Inference in Text at NTCIR-11 RITE-VAL 2014

Tamkang University

Min-Yuh Day
Ya-Jung Wang
Che-Wei Hsu
En-Chun Tu

Huai-Wen Hsu
Yu-An Lin
Shang-Yu Wu
Yu-Hsuan Tai
Cheng-Chia Tsai

NTCIR-11 Conference, December 8-12, 2014, Tokyo, Japan
2016 IMTKU Question Answering System for World History Exams at NTCIR-12 QA Lab2

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NTCIR-12 Conference, June 7-10, 2016, Tokyo, Japan
IMTKU Question Answering System for World History Exams at NTCIR-13 QALab-3

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Tamkang University, Taiwan

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

NTCIR-13 Conference, December 5-8, 2017, Tokyo, Japan
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

myday@mail.tku.edu.tw
**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)

<table>
<thead>
<tr>
<th>Run</th>
<th>Mean RSNOD</th>
<th>Run</th>
<th>Mean NMD</th>
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<tbody>
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<td>0.1918</td>
<td>IMTKU-run2</td>
<td>0.1254</td>
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<tr>
<td>IMTKU-run1</td>
<td>0.1964</td>
<td>IMTKU-run0</td>
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<td>IMTKU-run0</td>
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<td>IMTKU-run1</td>
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<td>TUA1-run2</td>
<td>0.1310</td>
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<td>0.2053</td>
<td>TUA1-run0</td>
<td>0.1322</td>
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<tr>
<td>NKUST-run1</td>
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<td>NKUST-run1</td>
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<tr>
<td>BL-lstm</td>
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<td>BL-popularity</td>
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<td>WUST-run0</td>
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<td>BL-uniform</td>
<td>0.2811</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

IMTKU System Architecture for NTCIR-13 QALab-3

Question Analysis

Document Retrieval

Answer Extraction

Answer Generation

Answer (XML)

Question (XML)

JA&EN Translator

Stanford CoreNLP

Wikipedia

Word Embedding Wiki Word2Vec

Complex Essay

Simple Essay

True-or-False

Factoid

Slot-Filling

Unique

NTCIR-13 Conference, December 5-8, 2017, Tokyo, Japan
System Architecture of Intelligent Dialogue and Question Answering System

User Question Input

- Dialogue Intention Detection
  - RNN
  - LSTM
  - GRU

- AIML Dialogue Engine
  - AIML KB

- Real Time Dialogue API
  - Cloud Resource

System Response Generator

Question Analysis

- Document Retrieval
  - Deep Learning
  - TensorFlow
  - IR
  - Dialogue KB

- Answer Extraction
  - Python
  - NLTK

Answer Generation

Answer Validation

Answer
IMTKU Emotional Dialogue
System Architecture

1. Retrieval-Based Model

2. Generation-Based Model

3. Emotion Classification Model

4. Response Ranking
The system architecture of IMTKU retrieval-based model for NTCIR-14 STC-3

Retrieval-Based Model

- Post
- Word Segmentation
- Keyword Boolean Query
- Solr Matching
- Building Index
- Corpus
- Distinct Result Data
- Emotion Matching
- Word2Vec Similarity Ranking
- Emotion Classification
- Retrieval-Based Response
The system architecture of IMTKU generation-based model for NTCIR-14 STC-3

**Generation-Based Model**

1. **Training Data**
2. **Building Word Index**
3. **Word Embedding**
4. **Training Data Seq2seq model**
5. **Post**
6. **Word Segmentation**
7. **Short Text Emotion Classifier**
8. **Trained Model**
9. **Emotion Matching**
10. **Word2Vec Similarity Ranking**
11. **Generation-Based Response**

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

Emotion Classification Model

Corpus → Emotion Classification → Training Dataset → MLP LSTM BiLSTM → Emotion Classification Model → Emotion Prediction

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

Response Ranking

1. STC3 Corpus
2. Chinese Segmentation using Jieba
3. Stop Words Removal
4. Word2Vec
5. 1.2 million data (300 dimensions)
6. Vector of Corpus
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**

<table>
<thead>
<tr>
<th></th>
<th>Japanese</th>
<th>Chinese</th>
<th>English</th>
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</thead>
<tbody>
<tr>
<td><strong>NTCIR-12 STC-1</strong>&lt;br&gt;22 active participants</td>
<td>Twitter, Retrieval</td>
<td>Weibo, Retrieval</td>
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<td><strong>NTCIR-13 STC-2</strong>&lt;br&gt;27 active participants</td>
<td>Yahoo! News, Retrieval+ Generation</td>
<td>Weibo, Retrieval+ Generation</td>
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<tr>
<td><strong>NTCIR-14 STC-3</strong></td>
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<td></td>
</tr>
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</table>

**Chinese Emotional Conversation Generation (CECG) subtask**

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

**Weibo, Generation for given emotion categories**

**Weibo+English translations, distribution estimation for subjective annotations**

**Single-turn, Non task-oriented**

**Multi-turn, task-oriented (helpdesk)**

Source: [https://waseda.app.box.com/v/STC3atNTCIR-14](https://waseda.app.box.com/v/STC3atNTCIR-14)
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.

General AI agents with platforms
Developer access available now or announced

Source: https://www.oreilly.com/ideas/infographic-the-bot-platform-ecosystem
How to Build Chatbots

Chatbot Frameworks and AI Services

• Bot Frameworks
  – Botkit
  – Microsoft Bot Framework
  – Rasa NLU

• AI Services
  – Wit.ai
  – api.ai
  – LUIS.ai
  – IBM Watson

# Chatbot Frameworks

## Comparison Table of Most Prominent Bot Frameworks

<table>
<thead>
<tr>
<th>Feature</th>
<th>Botkit</th>
<th>Microsoft Bot Framework</th>
<th>RASA NLU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built-in integration with messaging platforms</td>
<td>✔️</td>
<td>✔️</td>
<td>✗</td>
</tr>
<tr>
<td>NLP support</td>
<td>✗ but possible to integrate with middlewares</td>
<td>✗ but have close bonds with LUIS.ai</td>
<td>✔️</td>
</tr>
<tr>
<td>Out-of-box bots ready to be deployed</td>
<td>✔️</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>Programming Language</td>
<td>JavaScript (Node)</td>
<td>JavaScript (Node), C#</td>
<td>Python</td>
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</tbody>
</table>

## Comparison of Most Prominent AI Services

<table>
<thead>
<tr>
<th></th>
<th>wit.ai</th>
<th>api.ai</th>
<th>LUIS.ai</th>
<th>IBM Watson</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Free of charge</strong></td>
<td>✓</td>
<td><img src="https://example.com/check-mark" alt="Check" /> but has paid enterprise version</td>
<td><img src="https://example.com/check-mark" alt="Check" /> it is in beta and has transaction limits</td>
<td>30 days trial then priced for enterprise use</td>
</tr>
<tr>
<td><strong>Text and Speech processing</strong></td>
<td>✓</td>
<td><img src="https://example.com/check-mark" alt="Check" /></td>
<td><img src="https://example.com/check-mark" alt="Check" /> with use of Cortana</td>
<td><img src="https://example.com/check-mark" alt="Check" /></td>
</tr>
<tr>
<td><strong>Machine Learning Modeling</strong></td>
<td>✓</td>
<td><img src="https://example.com/check-mark" alt="Check" /></td>
<td><img src="https://example.com/check-mark" alt="Check" /></td>
<td><img src="https://example.com/check-mark" alt="Check" /></td>
</tr>
<tr>
<td><strong>Support for Intents, Entities, Actions</strong></td>
<td><img src="https://example.com/check-mark" alt="Check" /> Intents used as trait entities, actions are combined operations</td>
<td><img src="https://example.com/check-mark" alt="Check" /> Intents is the main prediction mechanism. Domains of entities, intents and actions</td>
<td><img src="https://example.com/check-mark" alt="Check" /></td>
<td><img src="https://example.com/check-mark" alt="Check" /></td>
</tr>
<tr>
<td><strong>Pre-build entities for easy parsing of numbers, temperature, date, etc.</strong></td>
<td><img src="https://example.com/check-mark" alt="Check" /></td>
<td><img src="https://example.com/check-mark" alt="Check" /></td>
<td><img src="https://example.com/check-mark" alt="Check" /></td>
<td><img src="https://example.com/check-mark" alt="Check" /></td>
</tr>
<tr>
<td><strong>Integration to messaging platforms</strong></td>
<td><img src="https://example.com/not-check-mark" alt="Not Check" /> web service API</td>
<td><img src="https://example.com/check-mark" alt="Check" /> also has facility for deploying to heroku. Paid environment</td>
<td><img src="https://example.com/check-mark" alt="Check" /> integrated to Azure</td>
<td><img src="https://example.com/check-mark" alt="Check" /> possible via API</td>
</tr>
<tr>
<td><strong>Support of SDKs</strong></td>
<td><img src="https://example.com/check-mark" alt="Check" /> includes SDKs for Python, Node.js, Rust, C, Ruby, iOS, Android, Windows Phone</td>
<td><img src="https://example.com/check-mark" alt="Check" /> C#, Xamarin, Python, Node.js, iOS, Android, Windows Phone</td>
<td><img src="https://example.com/check-mark" alt="Check" /> enables building with Web Service API, Microsoft Bot Framework integration</td>
<td>Proprietary language “AlchemyLanguage”</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Input</th>
<th>[CLS]</th>
<th>my</th>
<th>dog</th>
<th>is</th>
<th>cute</th>
<th>[SEP]</th>
<th>he</th>
<th>likes</th>
<th>play</th>
<th>#ing</th>
<th>[SEP]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(E_{[CLS]})</td>
<td>(E_{my})</td>
<td>(E_{dog})</td>
<td>(E_{is})</td>
<td>(E_{cute})</td>
<td>(E_{[SEP]})</td>
<td>(E_{he})</td>
<td>(E_{likes})</td>
<td>(E_{play})</td>
<td>(E_{#ing})</td>
<td>(E_{[SEP]})</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Token Embeddings</th>
</tr>
</thead>
<tbody>
<tr>
<td>(E_{[CLS]}) + (E_{my}) + (E_{dog}) + (E_{is}) + (E_{cute}) + (E_{[SEP]}) + (E_{he}) + (E_{likes}) + (E_{play}) + (E_{#ing}) + (E_{[SEP]})</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Segment Embeddings</th>
</tr>
</thead>
<tbody>
<tr>
<td>(E_A) + (E_A) + (E_A) + (E_A) + (E_A) + (E_A) + (E_B) + (E_B) + (E_B) + (E_B) + (E_B)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Position Embeddings</th>
</tr>
</thead>
<tbody>
<tr>
<td>(E_0) + (E_1) + (E_2) + (E_3) + (E_4) + (E_5) + (E_6) + (E_7) + (E_8) + (E_9) + (E_{10})</td>
</tr>
</tbody>
</table>

BERT, OpenAI GPT, ELMo

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

Fine-tuning BERT on Question Answering (QA)

(c) Question Answering Tasks: SQuAD v1.1

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

Fine-tuning BERT on Dialogue Slot Filling (SF)

Pre-trained Language Model (PLM)

Semi-supervised Sequence Learning
context2Vec
Pre-trained seq2seq

ULMFiT
ELMo
Transformer
Bidirectional LM

GPT
GPT-2
Larger model
More data
Defense
Grover

BERT

Multi-lingual
Cross-lingual
Multi-task
Generation

XLM
UDify
MT-DNN
MASS
UniLM
MT-DNN
SpanBERT
RoBERTa
XLNet

ERNIE (Tsinghua)
KnowBert

VideoBERT
CBT
ViLBERT
VisualBERT
B2T2
Unicoder-VL
LXMERT
VL-BERT
UNITER

By Xiaozhi Wang & Zhengyan Zhang @THUNLP

Source: https://github.com/thunlp/PLMpapers
Turing Natural Language Generation (T-NLG)

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

Question Answering (QA)

SQuAD

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.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Model</th>
<th>EM</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Human Performance Stanford University (Rajpurkar &amp; Jia et al. ‘18)</td>
<td>86.831</td>
<td>89.452</td>
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<tr>
<td>2</td>
<td>SA-Net on Albert (ensemble) QIANXIN</td>
<td>90.724</td>
<td>93.011</td>
</tr>
<tr>
<td>3</td>
<td>SA-Net-V2 (ensemble) QIANXIN</td>
<td>90.679</td>
<td>92.948</td>
</tr>
<tr>
<td>4</td>
<td>Retro-Reader (ensemble)</td>
<td>90.578</td>
<td>92.978</td>
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</tbody>
</table>

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?

**graupeal**

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
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]
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
Super Bowl 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.

https://en.wikipedia.org/wiki/Super_Bowl_50
Dialogue on Airline Travel Information System (ATIS)
The ATIS (Airline Travel Information System) Dataset


<table>
<thead>
<tr>
<th>Sentence</th>
<th>what</th>
<th>flights</th>
<th>leave</th>
<th>from</th>
<th>phoenix</th>
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</thead>
<tbody>
<tr>
<td>Slots</td>
<td>O</td>
<td>O</td>
<td>O</td>
<td>O</td>
<td>B-fromloc</td>
</tr>
<tr>
<td>Intent</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>atis_flight</td>
</tr>
</tbody>
</table>

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

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

# Intent Detection on ATIS

## State-of-the-art

### Intent Detection on ATIS

![Graph showing accuracy over time for ATIS intent detection.](https://paperswithcode.com/sota/intent-detection-on-atis)

<table>
<thead>
<tr>
<th>RANK</th>
<th>METHOD</th>
<th>ACCURACY</th>
<th>PAPER TITLE</th>
<th>YEAR</th>
<th>PAPER</th>
<th>CODE</th>
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<td>0.9776</td>
<td>A Novel Bi-directional Interrelated Model for Joint Intent Detection and Slot Filling</td>
<td>2019</td>
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<td>2</td>
<td>Capsule-NLU</td>
<td>0.950</td>
<td>Joint Slot Filling and Intent Detection via Capsule Neural Networks</td>
<td>2018</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: [https://paperswithcode.com/sota/intent-detection-on-atis](https://paperswithcode.com/sota/intent-detection-on-atis)
Slot Filling on ATIS

State-of-the-art

Slot Filling on ATIS

---

<table>
<thead>
<tr>
<th>RANK</th>
<th>METHOD</th>
<th>F1</th>
<th>PAPER TITLE</th>
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<th>PAPER</th>
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<td>Capsule-NLU</td>
<td>0.952</td>
<td>Joint Slot Filling and Intent Detection via Capsule Neural Networks</td>
<td>2018</td>
<td></td>
<td></td>
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</tbody>
</table>

Source: [https://paperswithcode.com/sota/slot-filling-on-atis](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>
<thead>
<tr>
<th>MultiWOZ</th>
<th>CrossWOZ</th>
</tr>
</thead>
<tbody>
<tr>
<td>usr: I’m looking for a college type attraction.</td>
<td>usr: 你好，可以帮我推荐一个评分是4.5分以上的景点吗？</td>
</tr>
<tr>
<td>...</td>
<td>Hello, could you recommend an attraction with a rating of 4.5 or higher?</td>
</tr>
<tr>
<td>usr: I would like to visit in town centre please.</td>
<td>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。</td>
</tr>
<tr>
<td>...</td>
<td>Tiananmen, Gui Street, and Beijing Happy Valley are very nice places.</td>
</tr>
<tr>
<td>usr: Can you find an Indian restaurant for me that is also in the town centre?</td>
<td>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？</td>
</tr>
<tr>
<td></td>
<td>I like Beijing Happy Valley. What hotels are around this attraction?</td>
</tr>
<tr>
<td></td>
<td>sys: 那可多了，有A酒店, B酒店, C酒店。</td>
</tr>
<tr>
<td></td>
<td>那可多了，有A酒店, B酒店, C酒店。</td>
</tr>
<tr>
<td></td>
<td>There are many, such as hotel A, hotel B, and hotel C.</td>
</tr>
<tr>
<td></td>
<td>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？</td>
</tr>
<tr>
<td></td>
<td>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>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Type</th>
<th>Single-domain goal</th>
<th>Multi-domain goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset</td>
<td>DSTC2</td>
<td>WOZ 2.0</td>
</tr>
<tr>
<td>Language</td>
<td>EN</td>
<td>EN</td>
</tr>
<tr>
<td>Speakers</td>
<td>H2M</td>
<td>H2H</td>
</tr>
<tr>
<td># Domains</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td># Dialogues</td>
<td>1,612</td>
<td>600</td>
</tr>
<tr>
<td># Turns</td>
<td>23,354</td>
<td>4,472</td>
</tr>
<tr>
<td>Avg. domains</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Avg. turns</td>
<td>14.5</td>
<td>7.5</td>
</tr>
<tr>
<td># Slots</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td># Values</td>
<td>212</td>
<td>99</td>
</tr>
</tbody>
</table>

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


• 自然语言理解
Natural Language Understanding (NLU)

• 對話管理
Dialog Management (DM)

• 自然語言生成
Natural Language Generation (NLG)

Python in Google Colab (Python101)

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

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- Named Entity Recognition (NER)
  - NER with CRF
  - NER with CRF and RandomizedSearchCV
- Sentiment Analysis
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    - 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

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 pre-trained 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 representation 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 computed similarly with the vector T.
4. Fine-tune BERT and learn S and T along the way.

References:

- BERT
- SQuAD

https://tinyurl.com/aintpupython101
Python in Google Colab (Python101)

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

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  - 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

Layer (type)       | Output Shape       | Param # | Connected to
------------------|--------------------|---------|----------------------
input_1 (InputLayer) | [(None, 384)]     | 0       | input_2[0][0]
input_3 (InputLayer) | [(None, 384)]     | 0       | input_3[0][0]
input_2 (InputLayer) | [(None, 384)]     | 0       | input_2[0][0]
tf_bert_model (TFBertModel) | [(None, 384, 768), | 109482240 | input_1[0][0]
  (109482240)
start_logit (Dense) | (None, 384, 1)    | 768     | tf_bert_model[0][0]
end_logit (Dense)   | (None, 384, 1)    | 768     | tf_bert_model[0][0]
flattend (Flatten)   | (None, 384)       | 0       | start_logit[0][0]
flattend (Flatten)   | (None, 384)       | 0       | end_logit[0][0]
activation_7 (Activation) | (None, 384)     | 0       | flattend[0][0]
activation_8 (Activation) | (None, 384)     | 0       | flattend_1[0][0]
Python in Google Colab (Python101)

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

Dialogue Systems

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:

```python
>>> 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/aintpupython101
Python in Google Colab (Python101)

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

https://tinyurl.com/aintpupython101
Python in Google Colab (Python101)

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

```
# Naive NLU 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)
```

https://tinyurl.com/aintpupython101
## NLP Benchmark Datasets

<table>
<thead>
<tr>
<th>Task</th>
<th>Dataset</th>
<th>Link</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WMT 2014 EN-FR</td>
<td></td>
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<tr>
<td>Text Summarization</td>
<td>CNN/DM</td>
<td><a href="https://cs.nyu.edu/~kcho/DMQA/">https://cs.nyu.edu/~kcho/DMQA/</a></td>
</tr>
<tr>
<td></td>
<td>Newsroom</td>
<td><a href="https://summarie.es/">https://summarie.es/</a></td>
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<tr>
<td></td>
<td>Gigaword</td>
<td><a href="https://catalog.ldc.upenn.edu/LDC2012T21">https://catalog.ldc.upenn.edu/LDC2012T21</a></td>
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<tr>
<td>Reading Comprehension</td>
<td>ARC</td>
<td><a href="http://data.allenai.org/arc/">http://data.allenai.org/arc/</a></td>
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<tr>
<td>Question Answering</td>
<td>CliCR</td>
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<td>RACE</td>
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<td>SQuAD</td>
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<td>SearchQA</td>
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<tr>
<td>Semantic Parsing</td>
<td>AMR parsing</td>
<td><a href="https://amr.isi.edu/index.html">https://amr.isi.edu/index.html</a></td>
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Summary

• Conversational Commerce
• Intelligent Chatbots for Fintech
• Task Oriented Dialogue System
References

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- Olivier Grisel (2020), Transformers (BERT fine-tuning): Joint Intent Classification and Slot Filling, https://m2dsupdslclass.github.io/lectures-labs/