Tamkang University

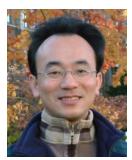






# Practices of Business Intelligence AI交談機器人與對話式商務 (AI Chatbots and Conversational Commerce)

1071BI12 MI4 (M2084) (2888) Wed, 7, 8 (14:10-16:00) (B217)



<u>Min-Yuh Day</u> <u>戴敏育</u> Assistant Professor

專任助理教授

Dept. of Information Management, Tamkang University

淡江大學 資訊管理學系



http://mail. tku.edu.tw/myday/ 2018-12-19

# 課程大綱 (Syllabus)

- 週次(Week) 日期(Date) 內容(Subject/Topics)
- 1 2018/09/12 商業智慧實務課程介紹 (Course Orientation for Practices of Business Intelligence)
- 2 2018/09/19 商業智慧、分析與資料科學 (Business Intelligence, Analytics, and Data Science)
- 3 2018/09/26 人工智慧、大數據與雲端運算 (ABC: AI, Big Data, and Cloud Computing)
- 4 2018/10/03 描述性分析I:數據的性質、統計模型與可視化 (Descriptive Analytics I: Nature of Data, Statistical Modeling, and Visualization)
- 5 2018/10/10 國慶紀念日(放假一天)(National Day)(Day off)
- 6 2018/10/17 描述性分析II:商業智慧與資料倉儲 (Descriptive Analytics II: Business Intelligence and Data Warehousing)

# 課程大綱 (Syllabus)

週次(Week) 日期(Date) 內容(Subject/Topics)

7 2018/10/24 預測性分析I:資料探勘流程、方法與演算法 (Predictive Analytics I: Data Mining Process,

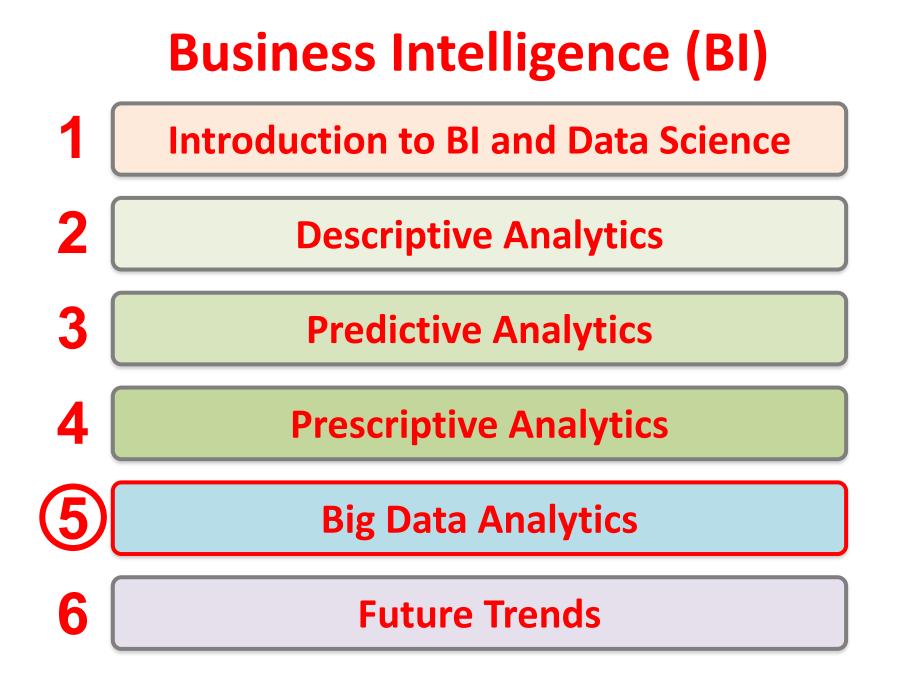
Methods, and Algorithms)

- 8 2018/10/31 預測性分析II:文本、網路與社群媒體分析 (Predictive Analytics II: Text, Web, and Social Media Analytics)
- 9 2018/11/07 期中報告 (Midterm Project Report)
- 10 2018/11/14 期中考試 (Midterm Exam)
- 11 2018/11/21 處方性分析:最佳化與模擬 (Prescriptive Analytics: Optimization and Simulation)

12 2018/11/28 社會網絡分析 (Social Network Analysis)

# 課程大綱 (Syllabus)

- 週次(Week) 日期(Date) 內容(Subject/Topics)
- 13 2018/12/05 機器學習與深度學習 (Machine Learning and Deep Learning)
- 14 2018/12/12 自然語言處理 (Natural Language Processing)
- 15 2018/12/19 AI交談機器人與對話式商務 (AI Chatbots and Conversational Commerce)
- 16 2018/12/26 商業分析的未來趨勢、隱私與管理考量 (Future Trends, Privacy and Managerial Considerations in Analytics)
- 17 2019/01/02 期末報告 (Final Project Presentation)
- 18 2019/01/09 期末考試 (Final Exam)



# **Al Chatbots** and Conversational

# Commerce

# Outline

- AI Chatbots
- Conversational Commerce
- Bot Platform Ecosystem



# and Cognitive Computing

Source: http://research.ibm.com/cognitive-computing/

# **Artificial Intelligence (A.I.) Timeline**

### A.I. TIMELINE









1997

**DEEP BLUE** 

Deep Blue, a chess-



### 1950

### **TURING TEST** Computer scientist Alan Turing proposes a intelligence' is coined test for machine intelligence. If a machine can trick humans into thinking it is human, then it has intelligence

### 1955 A.I. BORN

Term 'artificial by computer scientist, John McCarthy to describe "the science and engineering of making intelligent machines"

ODD

and clean homes

### 1964

Pioneering chatbot developed by Joseph Weizenbaum at MIT with humans

### 1966 **A.I.**

### WINTER

playing computer from Many false starts and dead-ends leave A.I. out champion Garry Kasparov

### 1998

Cynthia Breazeal at MIT introduces KISmet, an IBM defeats world chess emotionally intelligent robot insofar as it detects and responds to people's feelings

First industrial robot, Unimate, goes to work at GM replacing assembly line

1961

UNIMATE

### The 'first electronic person' from Stanford,

Shakey is a generalpurpose mobile robot that reasons about its own actions

🔅 AlphaGo

### 1999

### AIBO

Sony launches first consumer robot pet dog autonomous robotic AiBO (Al robot) with skills and personality that develop over time

### 2002

Apple integrates Siri, an intelligent virtual vacuum cleaner from assistant with a voice iRobot learns to navigate interface, into the iPhone 4S

2011



### WATSON

IBM's question answering computer Watson wins first place on popular \$1M prize television guiz show

### 2014

Eugene is human

Eugene Goostman, a chatbot passes the Turing Test with a third of judges believing

### 2014

Amazon launches Alexa, Microsoft's chatbot Tay an intelligent virtual assistant with a voice interface that completes inflammatory and shopping tasks offensive racist

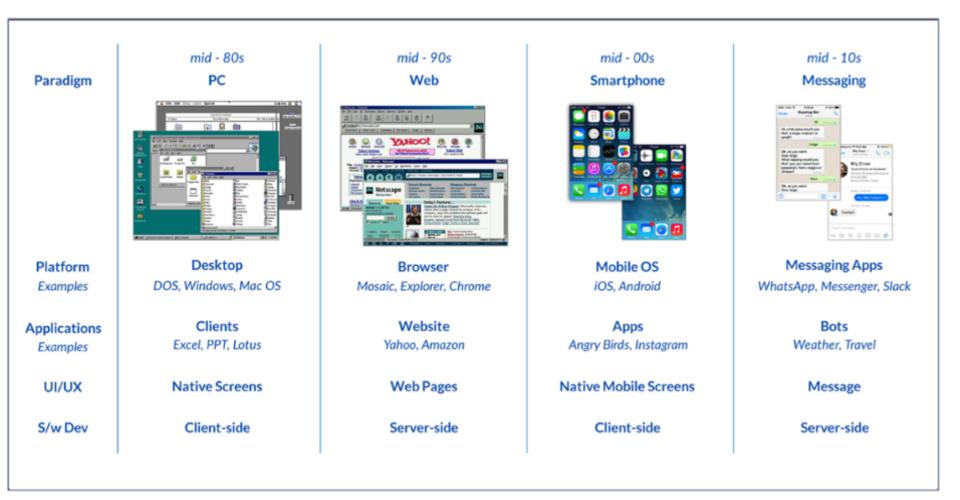
### 2016

goes roque on social media making

### 2017 **ALPHAGO**

Google's A.I. AlphaGo beats world champion Ke Jie in the complex board game of Go, notable for its vast number (2<sup>170</sup>) of possible positions

# **Chatbots: Evolution of UI/UX**



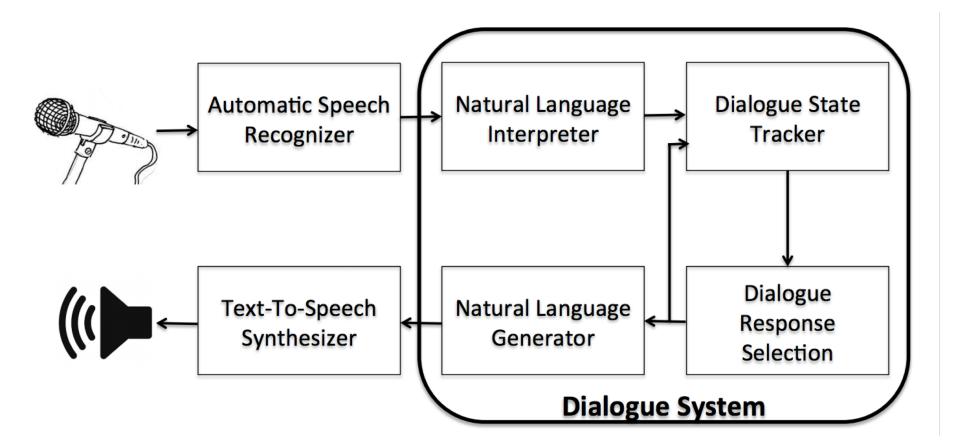
# **Al Chatbot for** Conversational Commerce

# Chatbot **Dialogue System** Intelligent Agent

# Chatbot



# **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.



# machines

# think?

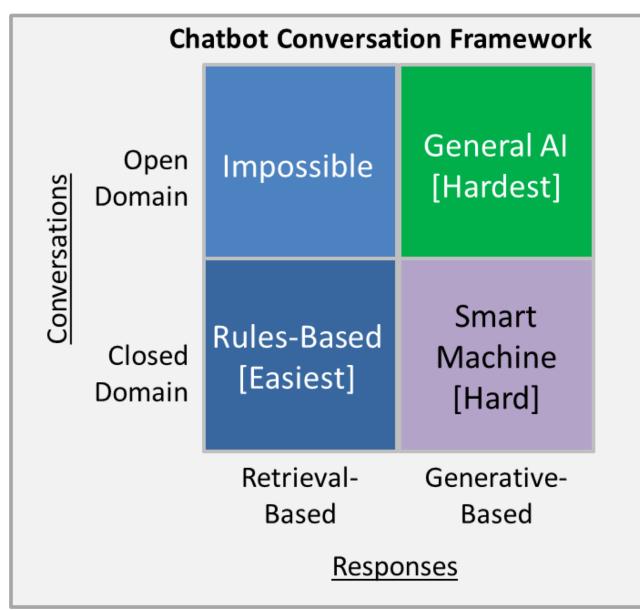
# (Alan Turing ,1950)

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**



# Conversational Commerce

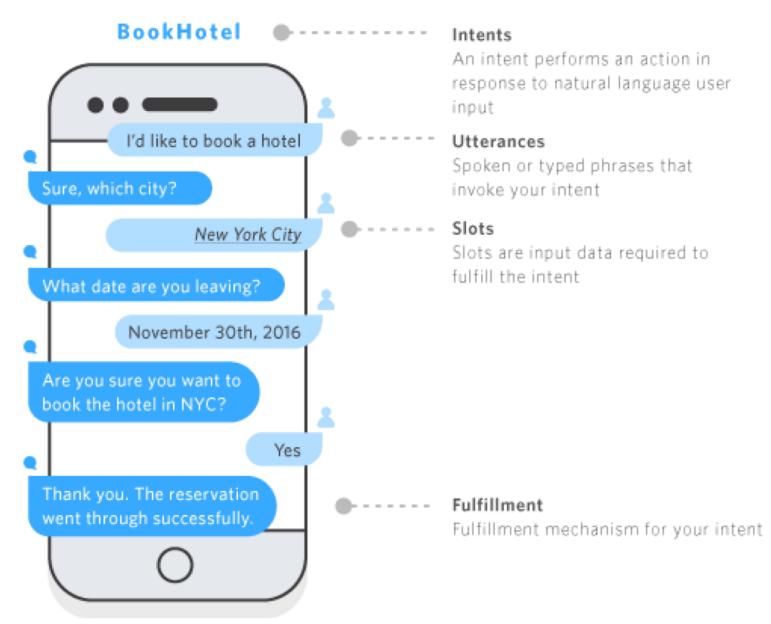
# From **E-Commerce** to **Conversational Commerce: Chatbots** and **Virtual Assistants**

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

# Conversational Commerce: eBay AI Chatbots

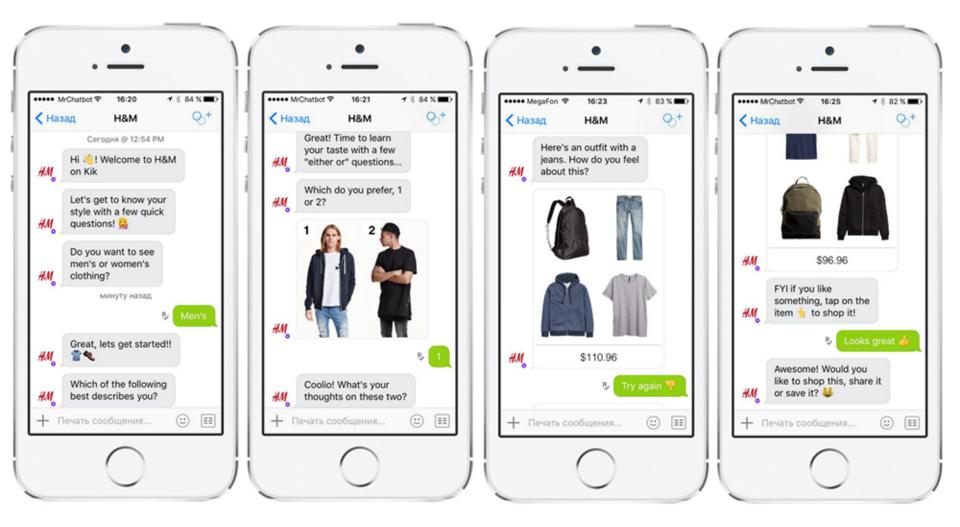
•••• A	T&T 穼 1:31 PM 🕑 🕇 🏵	76% 🔳	
< Hor	me eBay ShopBot > Ma Typically replies instantly	Manage	
	I'm looking for adidas stan sn in white	hith	
ebay	Which gender are you looking for?		
	Won	nen	
ebay	Sure, I've got a few options for those.		
	Best Value 🔌 16 sold	Trend	
	\$63.71 was \$74 - ADIDAS WOMEN'S STAN SMITH OG WHITE GREEN B24105 shopbot.ebay.com	\$99.99 White shopb	
	View item		
Ð		•	

# **Hotel Chatbot**

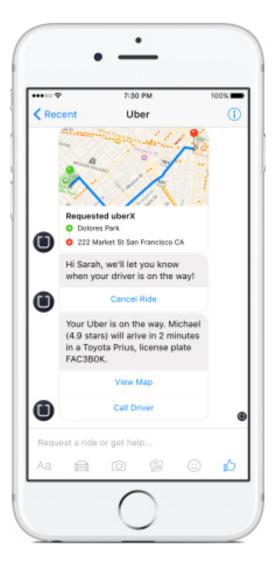


Source: https://sdtimes.com/amazon/guest-view-capitalize-amazon-lex-available-general-public/

# H&M's Chatbot on Kik



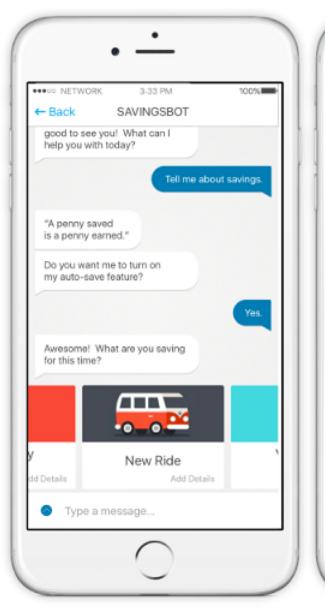
### **Uber's Chatbot on Facebook's Messenger**



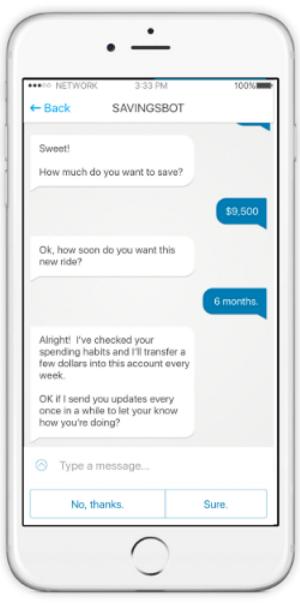
### Uber's chatbot on Facebook's messenger - one main benefit: it loads much faster than the Uber app

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

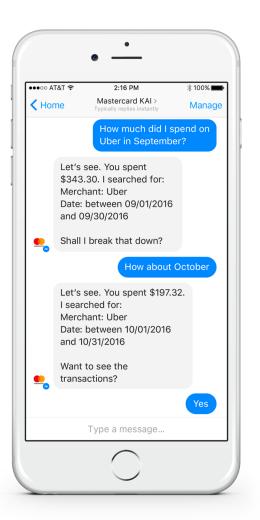
# **Savings Bot**



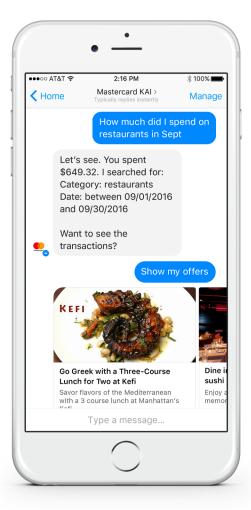
3:33 PM AVINGSBOT	100%
9,50	0
2	3
5	6
8	9
0	×
age	
TIONS ASK	BUDGETBOT
	xvant to save? 2 5 8 0 age



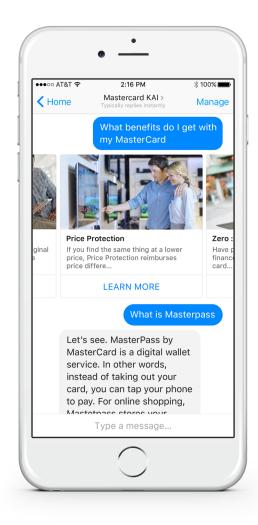
### **Mastercard Makes Commerce More Conversational**







POWERED BY



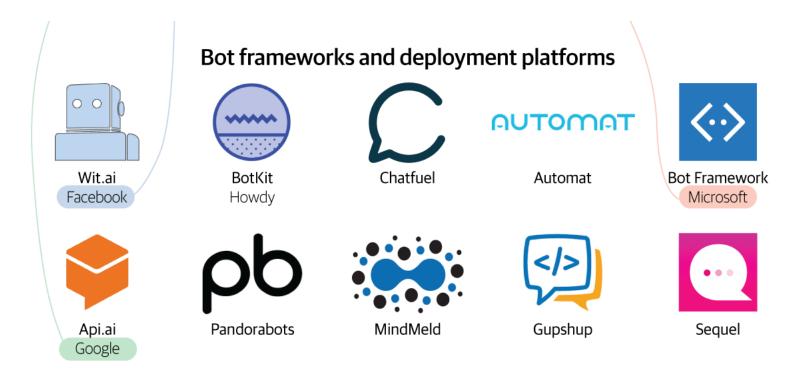
Bot Platform Ecosystem

# 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.



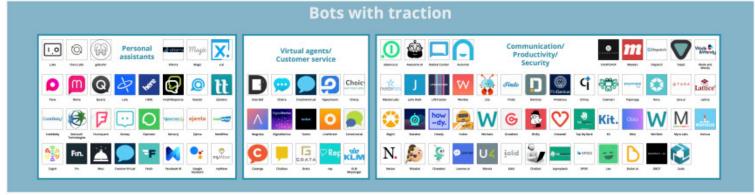
Source: https://www.oreilly.com/ideas/infographic-the-bot-platform-ecosystem



DESIGNED BY JON CIFUENTES

### **Bots Landscape**





### Connectors/ Shared Services



### **Bot Discovery**



Analytics

Analytics

.....

ġ

AI Tools: Natural Language Processing, Machine Learning, Speech & Voice Recognition

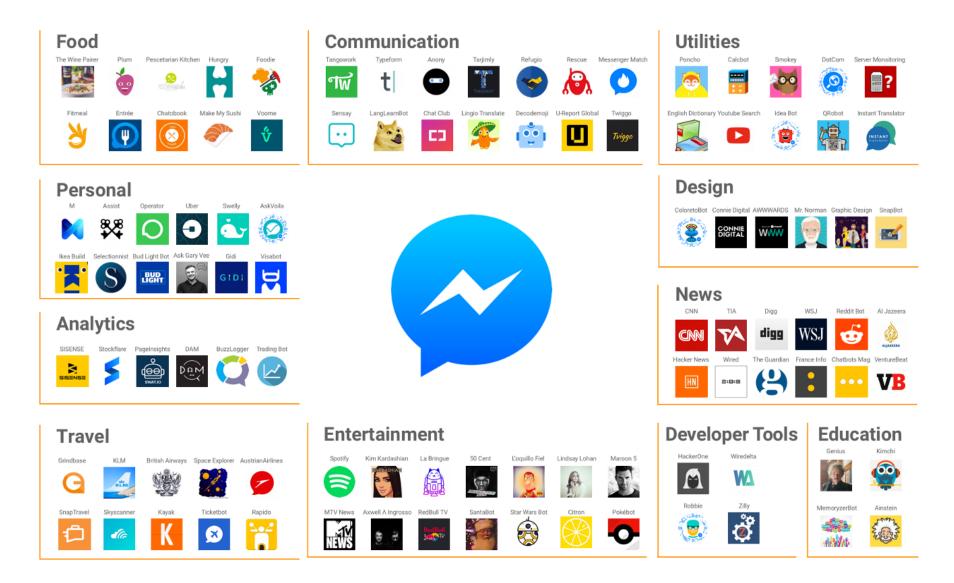






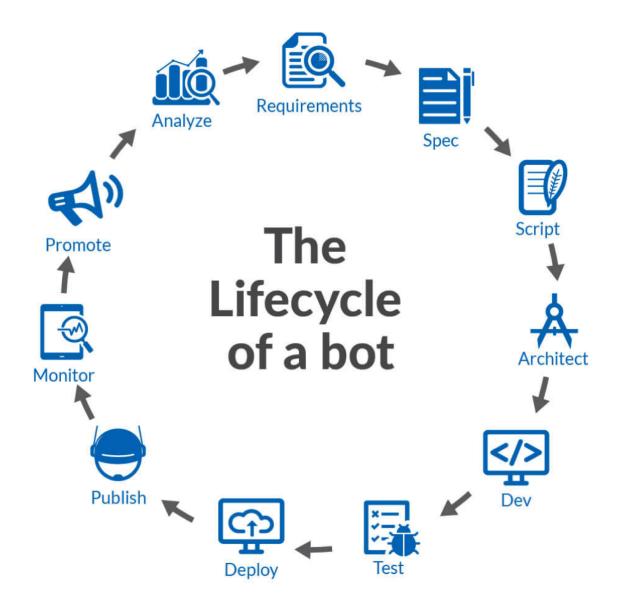
### 🕁 RECAST.AL Messenger Bot Landscape

### May 2017



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

# **The Bot Lifecycle**

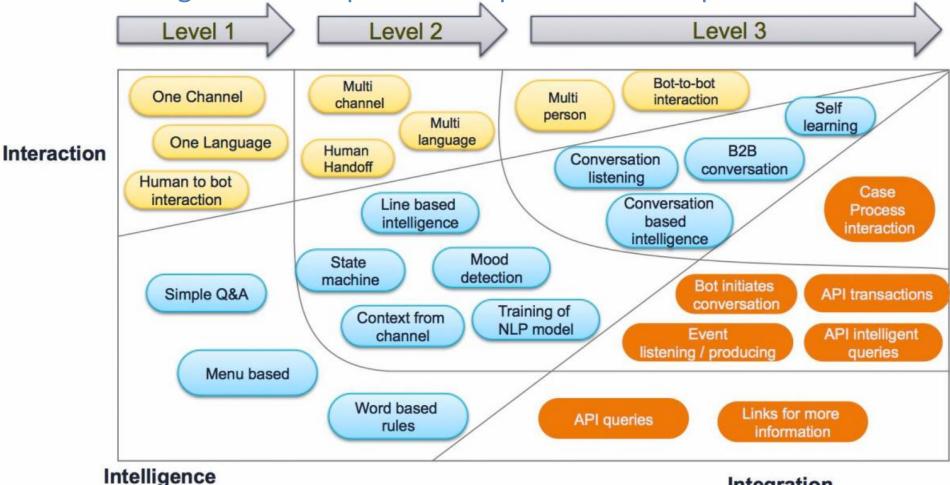


# **Chatbots**

# **Bot Maturity Model**

Customers want to have simpler means to interact with businesses and

get faster response to a question or complaint.



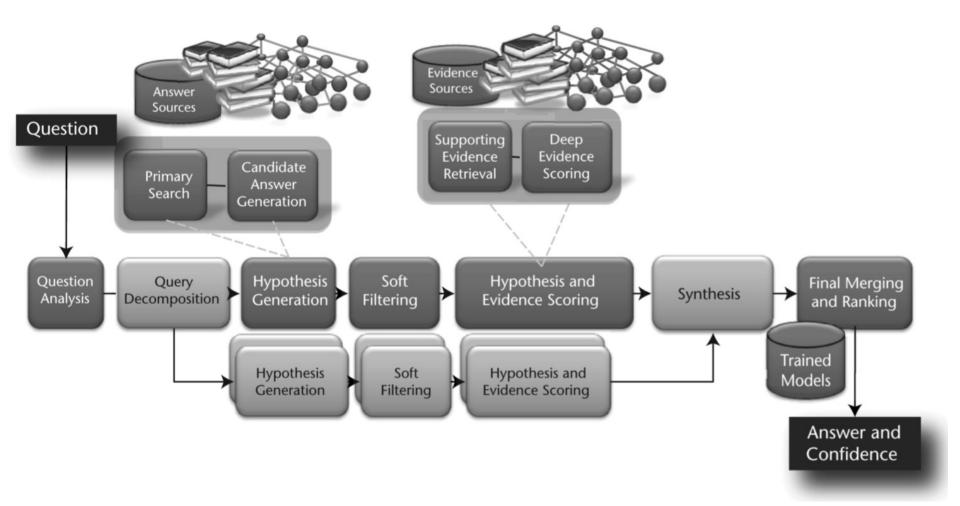
### Source: https://www.capgemini.com/2017/04/how-can-chatbots-meet-expectations-introducing-the-bot-maturity/

Integration

# **Chatbot Architectures**

- Information Retrieval based Bot (IR-Bot)
- Task Oriented Bot (Task-Bot)
- Chitchat-Bot (Chatbot)

## Watson DeepQA Architecture



Source: Ferrucci, David, Eric Brown, Jennifer Chu-Carroll, James Fan, David Gondek, Aditya A. Kalyanpur, Adam Lally et al. "Building Watson: An overview of the DeepQA project." *AI magazine* 31, no. 3 (2010): 59-79.

## **ALICE and AIML**

ARTIFICIAL INTELLIGENCE FOUNDATION PROMOTING THE DEVELOPMENT AND ADOPTION OF ALICE AND AIML FREE SOFTWARE A.L.I.C.E Silver Edition DAVE E.S.L. bot C.L.A.U.D.I.O Personality Test Free Live Chat with the award winning A. I. chat robot A. L. I. C. E.				
Get Started	AIML: Artificial Intelligence Markup Language	Subscription Bots		
Chat with A.L.I.C.E.	AIML (Artificial Intelligence Markup Language) is an XML-compliant language that's easy to learn, and makes it possible for you to begin customizing an Alicebot or creating one from scratch within minutes.	A.L.I.C.E. Silver Edition DAVE E.S.L. Bot		
Chat with Fake Kirk	The most important units of AIML are:	CLAUDIO Personality Test		
What is AIML? Foundation Bot Directory Bot Industry Survey AIML Overview	<ul> <li><aiml>: the tag that begins and ends an AIML document</aiml></li> <li><category>: the tag that marks a "unit of knowledge" in an Alicebot's knowledge base</category></li> <li><pattern>: used to contain a simple pattern that matches what a user may say or type to an Alicebot</pattern></li> </ul>	×		
Software	<ul> <li><template>: contains the response to a user input</template></li> </ul>	Build native		
Downloads Bot Hosting AIML Sets AIML 1.1 Specification AIML 2.0 Working Draft Documentation Superbot - New! Links ESL Books Film and TV	There are also 20 or so additional more tags often found in AIML files, and it's possible to create your own so-called "custom predicates". Right now, a beginner's guide to AIML can be found in the AIML Primer. The free A.L.I.C.E. AIML includes a knowledge base of approximately 41,000 categories. Here's an example of one of them: <category> <pattern>WHAT ARE YOU</pattern> <template>  Ke &gt;</template></category>	Build native iOS, Android, and Windows apps in C#		
Recent Press Popular Culture	(The opening and closing <aiml> tags are not shown here, because this is an excerpt from the middle of a document.)</aiml>			
Web Ontologies ALICE and A.I. History Scholarly Research and Teaching Site Info alicebot.org Rank: 257,092	Everything between <category> and </category> is you guessed it a category. A category can have one pattern and one template. (It can also contain a <that> tag, but we won't get into that here.) The pattern shown will match <i>only</i> the exact phrase "what are you" (capitalization is ignored). But it's possible that this category may be invoked by another category, using the <srai> tag (not shown) and the principle of <b>reductionism</b>. In any case, if this category is called, it will produce the response "I am the latest result in artificial intelligence" shown above. In</srai></that>	C#		
Links in: 638	addition, it will do something else interesting. Using the <think> tag, which causes Alicebot to perform whatever it contains but hide the result from the user, the Alicebot engine will set the "topic" in its memory to "Me". This allows any categories elsewhere with an</think>			

### AIML

### (Artificial Intelligence Markup Language)

<category>

<pattern>HELLO</pattern>

<template>Hi, I am a robot</template>

</category>

### AIML

### (Artificial Intelligence Markup Language)

- <aiml>
  - the tag that begins and ends an AIML document
- <category>
  - the tag that marks a "unit of knowledge" in an Alicebot's knowledge base
- <pattern>
  - used to contain a simple pattern that matches
     what a user may say or type to an Alicebot
- <template>
  - contains the response to a user input

### AIML

### (Artificial Intelligence Markup Language)

<category>

<pattern>WHAT ARE YOU</pattern>

<template>

- <think><set name="topic">Me</set></think>
- I am the latest result in artificial intelligence,
- which can reproduce the capabilities of the human brain
- with greater speed and accuracy.
- </template>

</category>

### **Deep Learning for Dialogues**

# Intent Classification Intent LSTM

# LSTM (Long-Short Term Memory) GRU (Gated Recurrent Unit)

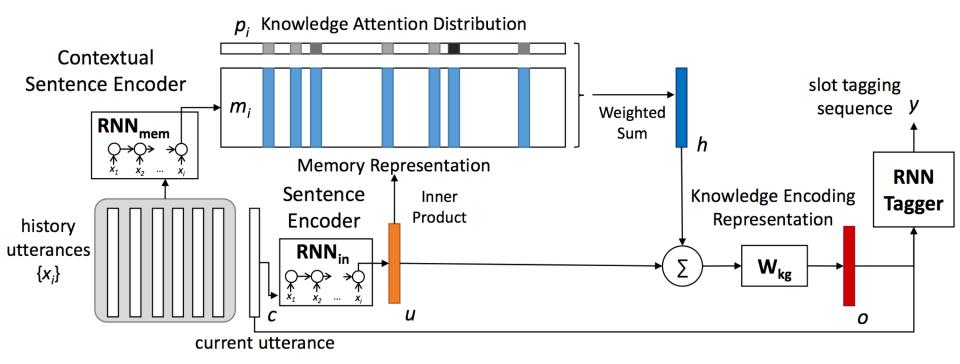
Source: Hakkani-Tür, Dilek, Gokhan Tur, Asli Celikyilmaz, Yun-Nung Chen, Jianfeng Gao, Li Deng, and Ye-Yi Wang. "Multi-domain joint semantic frame parsing using bi-directional RNN-LSTM." In *Proceedings of The 17th Annual Meeting of the International Speech Communication Association*. 2016.

## **Dialogue Utterance**

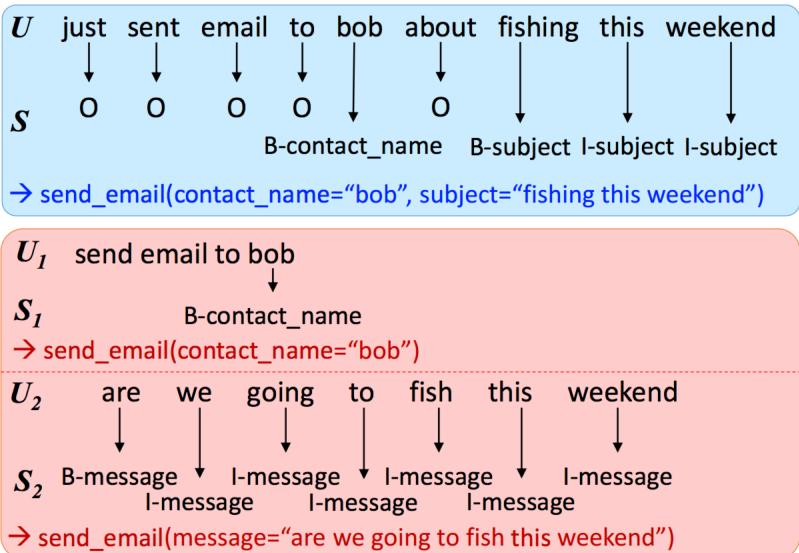
W find comedies recent james by cameron S **B-dir** I-dir **B**-date **B**-genre  $\mathbf{O}$ movies D find\_movie

An example utterance with annotations of semantic slots in IOB format (S), domain (D), and intent (I), B-dir and I-dir denote the director name.

# End-to-end Memory Network Model for Multi-turn SLU

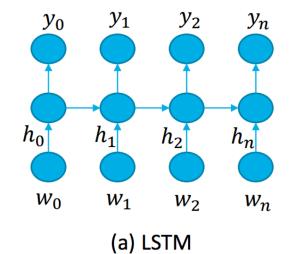


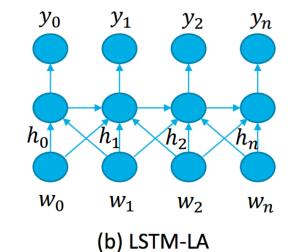
- **D** communication
- I send\_email

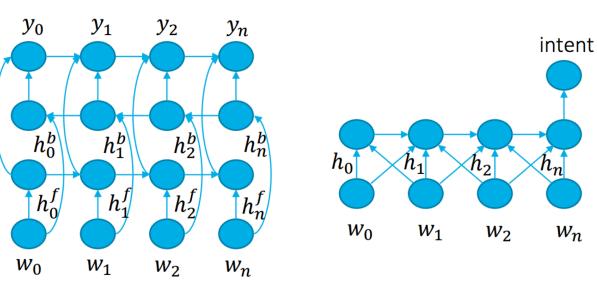


Source: Chen, Yun-Nung, Dilek Hakkani-Tür, Gokhan Tur, Jianfeng Gao, and Li Deng. "End-to-end memory networks with knowledge carryover for multi-turn spoken language understanding." In *Proceedings of Interspeech*. 2016.

### **Deep Learning for SLU** (Spoken Language Understanding)





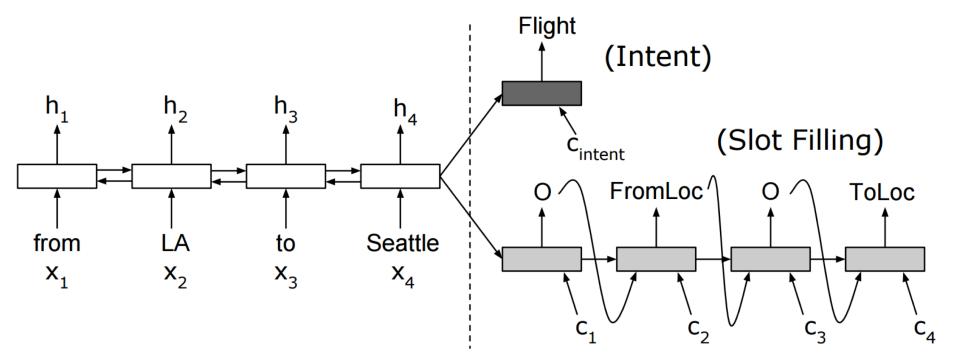


(c) bLSTM-LA

#### (b) Intent LSTM

Source: Hakkani-Tür, Dilek, Gokhan Tur, Asli Celikyilmaz, Yun-Nung Chen, Jianfeng Gao, Li Deng, and Ye-Yi Wang. "Multi-domain joint semantic frame parsing using bi-directional RNN-LSTM." In Proceedings of The 17th Annual Meeting of the International Speech Communication Association. 2016.

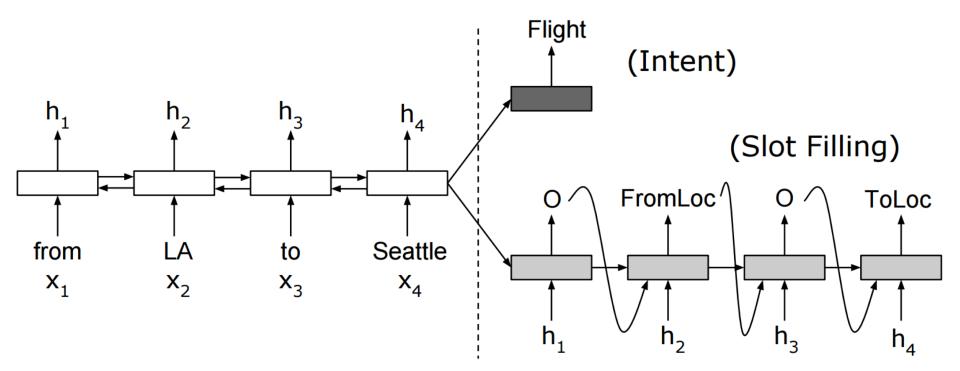
# Encoder-decoder model for joint intent detection and slot filling



### (a) with no aligned inputs.

Source: Liu, Bing, and Ian Lane. "Attention-Based Recurrent Neural Network Models for Joint Intent Detection and Slot Filling." arXiv preprint arXiv:1609.01454 (2016).

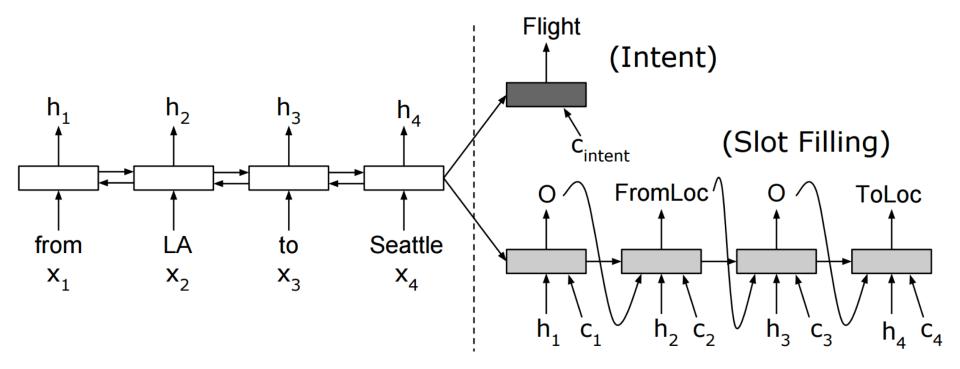
# Encoder-decoder model for joint intent detection and slot filling



### (b) with aligned inputs.

Source: Liu, Bing, and Ian Lane. "Attention-Based Recurrent Neural Network Models for Joint Intent Detection and Slot Filling." arXiv preprint arXiv:1609.01454 (2016).

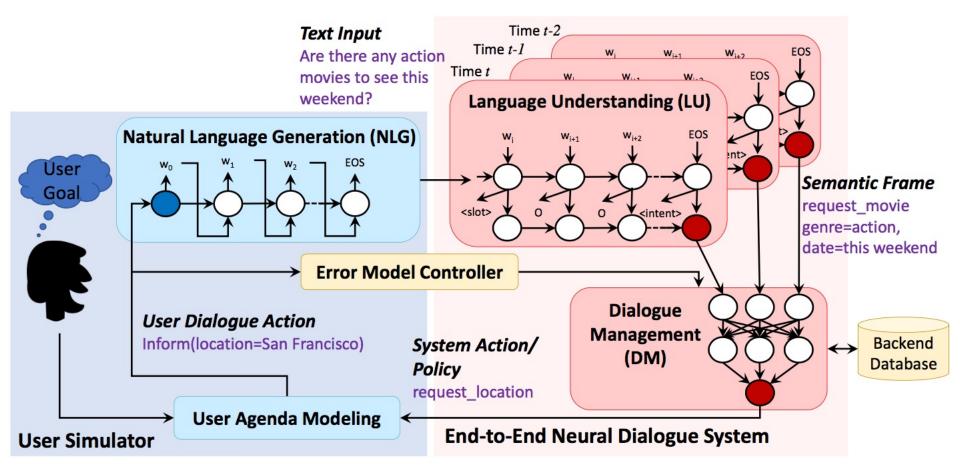
# Encoder-decoder model for joint intent detection and slot filling



#### (c) with aligned inputs and attention

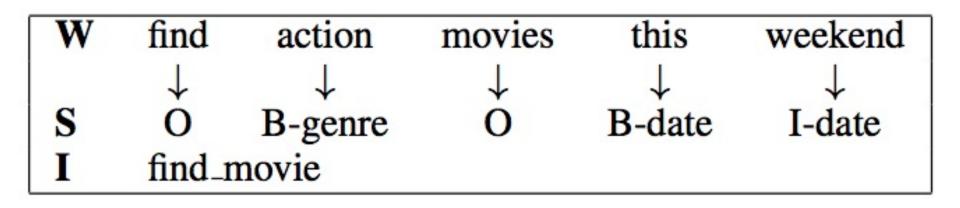
Source: Liu, Bing, and Ian Lane. "Attention-Based Recurrent Neural Network Models for Joint Intent Detection and Slot Filling." arXiv preprint arXiv:1609.01454 (2016).

# End-to-End Task-Completion Neural Dialogue Systems



#### Reinforcement learning is used to train all components in an end-to-end fashion

# Slot Intent



# Slot Intent

Annotations					
Intent	request, inform, deny, confirm_question, confirm_answer, greeting, closing, not_sure, multiple_choice, thanks, welcome				
Slot	actor, actress, city, closing, critic_rating, date, description, distanceconstraints, greeting, implicit_value, movie_series, moviename, mpaa_rating, numberofpeople, numberofkids, taskcomplete, other, price, seating, starttime, state, theater, theater_chain, video_format, zip, result, ticket, mc_list				

# Sample dialogues generated by rule-based and RL agents

#### **Rule-based agent**

User: Can I get some tickets for zoolander 2? Agent: What movie are you interested in? User: I want to watch zoolander 2. Agent: What time would you like to see it? User: I want to watch at 9:25 pm. Agent: What city you would like? User: I want to watch at seattle. Agent: What date would you like to watch it? User: I want to set it up tomorrow. Agent: Which theater would you like? User: I want to watch at regal meridian 16. Agent: How many tickets do you need? User: I want 2 tickets please! Agent: Great - I was able to purchase 2 tickets for you to see zoolander 2 tomorrow at regal meridian 16 theater in seattle at 9:25 pm.

User: Thank you.

Agent: Thank you.

#### Success

### Sample dialogues generated by rule-based and RL agents RL agent

User: Can I get tickets for zoolander 2 tomorrow?

Agent: Which city would you like?

User: I want to watch at seattle.

Agent: How many tickets do you need?

User: I want 2 tickets please!

Agent: 9:25 pm is available.

User: I want to watch at regal meridian 16.

Agent: Great - I was able to purchase 2 tickets for you to see zoolander 2 tomorrow at regal meridian 16 theater in seattle at 9:25 pm.

User: Thank you.

Agent: Thank you.

Source: Li, Xuijun, Yun-Nung Chen, Lihong Li, and Jianfeng Gao. "End-to-end task-completion neural dialogue systems." arXiv preprint arXiv:1703.01008 (2017).

```
Sample dialogues generated
by rule-based and RL agents
    New episode, user goal:
       "request_slots": {
         "ticket": "UNK"
       "inform_slots": {
         "city": "seattle",
        "numberofpeople": "2",
         "theater": "regal meridian 16",
         "starttime": "9:25 pm",
         "date": "tomorrow",
         "moviename": "zoolander 2"
```

# A Deep Reinforcement Learning Chatbot

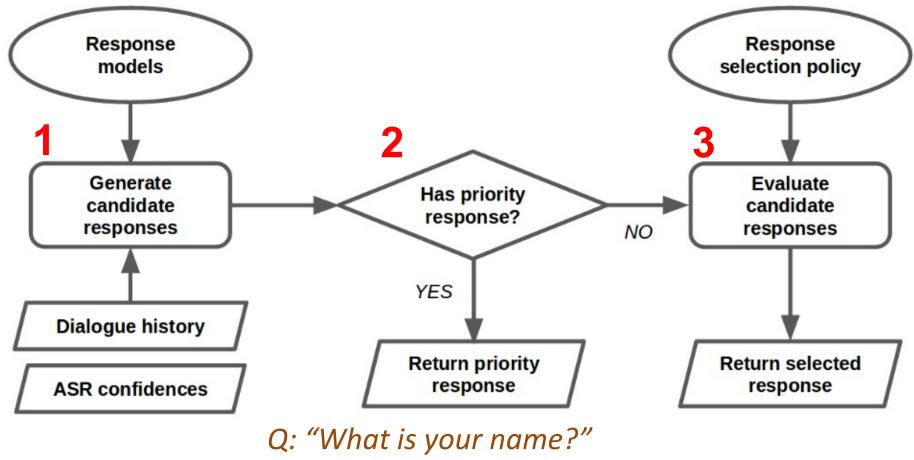
Iulian V. Serban, Chinnadhurai Sankar, Mathieu
 Germain, Saizheng Zhang, Zhouhan Lin, Sandeep
 Subramanian, Taesup Kim, Michael Pieper, Sarath
 Chandar, Nan Rosemary Ke, Sai Mudumba, Alexandre
 de Brebisson Jose M. R. Sotelo, Dendi Suhubdy,
 Vincent Michalski, Alexandre Nguyen, Joelle Pineau
 and Yoshua Bengio

### Montreal Institute for Learning Algorithms, Montreal, Quebec, Canada

# **A Deep Reinforcement Learning** Chatbot **MILABOT:** Chatbot developed by the **Montreal Institute for Learning Algorithms (MILA)** for the **Amazon Alexa Prize competition**

Source: Serban, Iulian V., Chinnadhurai Sankar, Mathieu Germain, Saizheng Zhang, Zhouhan Lin, Sandeep Subramanian, Taesup Kim et al. "A Deep Reinforcement Learning Chatbot." *arXiv preprint arXiv:1709.02349* (2017).

# MILABOT Dialogue manager control flow

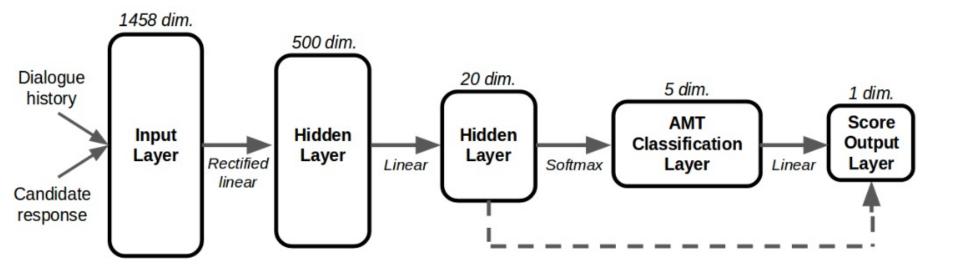


R: "I am an Alexa Prize Socialbo"

Source: Serban, Iulian V., Chinnadhurai Sankar, Mathieu Germain, Saizheng Zhang, Zhouhan Lin, Sandeep Subramanian, Taesup Kim et al. "A Deep Reinforcement Learning Chatbot." *arXiv preprint arXiv:1709.02349* (2017).

Dialogue	Dialogue		
SYSTEM: Hi. This is an Alexa Prize			
socialbot.	USER: Let's talk about movies.		
USER: Hi	SYSTEM: What's your favorite movie?		
SYSTEM: Do you have pets?	USER: star wars movie		
USER: Yes, I have two rabbits.			
Candidate Responses	Candidate Responses		
BoWEscapePlan: I don't have an answer for	BoWEscapePlan: I don't have an answer for this.		
this.	BoWFactGenerator: Here's an interesting fact. The		
BoWFactGenerator: Did you know that male	international telephone dialing code for Antarctica is 672.		
rabbits are called bucks, females are does?	GRUQuestionGenerator: how about your New York City?		
GRUQuestionGenerator: How about the	Initiatorbot: How was your day?		
American family of it?	LSTMClassifierMSMarco: A third Anthology film will		
Initiatorbot: Do you believe in love at first	be released in 2020.		
sight?	DualEncoderRedditNews: Now whisper it to me, one		
LSTMClassifierMSMarco: Mar 23, 2017 Two	more time bby.		
Parts: Learning What to Feed Your Rabbit	DualEncoderRedditPolitics: hahaha on mobile this ain't		
Learning How to	even close. I wish I could show you but this looks awful		
DualEncoderRedditNews: bye doggie	I'm sorry man.		
DualEncoderRedditPolitics: Who's edger u shboys?	Alicebot: What did you like about the robots in that movie?		
Alicebot: Hurrah! Two is a good number	Elizabot: How does that make you feel?		
of rabbits.	Evi: Star Wars movie a movie in the Star Wars series.		
Elizabot: OK, but can you elaborate a bit?	VHREDRedditMovies: Oh please. Please. Pleeeease. Let		
VHREDRedditMovies: Hmm. Nope, never	this happen.		
heard of it.	VHREDSubtitles: What?		
VHREDSubtitles: Would you like to see	HelpResponse: I would really like to talk about news,		
them?	politics or movies.		
HelpResponse: I would really like to talk			
about news, politics or movies.			

# MILABOT Computational graph for scoring model



### model selection policies based on both action-value function and stochastic policy parametrizations

Source: Serban, Iulian V., Chinnadhurai Sankar, Mathieu Germain, Saizheng Zhang, Zhouhan Lin, Sandeep Subramanian, Taesup Kim et al. "A Deep Reinforcement Learning Chatbot." *arXiv preprint arXiv:1709.02349* (2017).

# Facebook Al Research : bAbl Project

- The (20) QA bAbl tasks
- The (6) dialog bAbI tasks
- The Children's Book Test
- The Movie Dialog dataset
- The WikiMovies dataset
- The Dialog-based Language Learning dataset
- The SimpleQuestions dataset

1 Mary moved to the bathroom. 2 John went to the hallway. 3 Where is Mary? bathroom 1 4 Daniel went back to the hallway. 5 Sandra moved to the garden. 6 Where is Daniel? hallway 4 7 John moved to the office. 8 Sandra journeyed to the bathroom. 9 Where is Daniel? hallway 4 10 Mary moved to the hallway. 11 Daniel travelled to the office. 12 Where is Daniel? office 11 13 John went back to the garden. 14 John moved to the bedroom. 15 Where is Sandra? bathroom 8 1 Sandra travelled to the office. 2 Sandra went to the bathroom. 3 Where is Sandra? bathroom 2

#### Task 1: Single Supporting Fact

Mary went to the bathroom. John moved to the hallway. Mary travelled to the office. Where is Mary? A:office

#### **Task 3: Three Supporting Facts**

John picked up the apple. John went to the office. John went to the kitchen. John dropped the apple. Where was the apple before the kitchen? A:office

#### **Task 5: Three Argument Relations**

Mary gave the cake to Fred. Fred gave the cake to Bill. Jeff was given the milk by Bill. Who gave the cake to Fred? A: Mary Who did Fred give the cake to? A: Bill

#### Task 2: Two Supporting Facts

John is in the playground. John picked up the football. Bob went to the kitchen. Where is the football? A:playground

#### **Task 4: Two Argument Relations**

The office is north of the bedroom. The bedroom is north of the bathroom. The kitchen is west of the garden. What is north of the bedroom? A: office What is the bedroom north of? A: bathroom

#### Task 6: Yes/No Questions

John moved to the playground. Daniel went to the bathroom. John went back to the hallway. Is John in the playground? A:no Is Daniel in the bathroom? A:yes

Source: Weston, Jason, Antoine Bordes, Sumit Chopra, Alexander M. Rush, Bart van Merriënboer, Armand Joulin, and Tomas Mikolov. "Towards Al-complete question answering: A set of prerequisite toy tasks." *arXiv preprint arXiv:1502.05698* (2015).

Task 7: Counting	Task 8: Lists/Sets		
Daniel picked up the football.	Daniel picks up the football.		
Daniel dropped the football.	Daniel drops the newspaper.		
Daniel got the milk.	Daniel picks up the milk.		
Daniel took the apple.	John took the apple.		
How many objects is Daniel holding? A: two	What is Daniel holding? milk, football		
Task 9: Simple Negation	Task 10: Indefinite Knowledge		
Sandra travelled to the office.	John is either in the classroom or the playground.		
Fred is no longer in the office.	Sandra is in the garden.		
Is Fred in the office? A:no	Is John in the classroom? A:maybe		
Is Sandra in the office? A:yes	Is John in the office? A:no		
Task 11: Basic Coreference	Task 12: Conjunction		
Daniel was in the kitchen.			
Then he went to the studio.	Mary and Jeff went to the kitchen.		
Sandra was in the office.	Then Jeff went to the park. Where is Mary? A: kitchen		
Where is Daniel? A:studio	Where is Jeff? A: park		
Where is Damer / A.studio	where is Jell? A. park		
Task 13: Compound Coreference	Task 14: Time Reasoning		
Daniel and Sandra journeyed to the office.	In the afternoon Julie went to the park.		
Then they went to the garden.	Yesterday Julie was at school.		
Sandra and John travelled to the kitchen.	Julie went to the cinema this evening.		
After that they moved to the hallway.	Where did Julie go after the park? A:cinema		
Where is Daniel? A: garden	Where was Julie before the park? A:school		

Source: Weston, Jason, Antoine Bordes, Sumit Chopra, Alexander M. Rush, Bart van Merriënboer, Armand Joulin, and Tomas Mikolov. "Towards Al-complete question answering: A set of prerequisite toy tasks." *arXiv preprint arXiv:1502.05698* (2015).

Task 15: Basic Deduction Sheep are afraid of wolves. Cats are afraid of dogs. Mice are afraid of cats. Gertrude is a sheep. What is Gertrude afraid of? A:wolves

Task 17: Positional Reasoning The triangle is to the right of the blue square. The red square is on top of the blue square. The red sphere is to the right of the blue square. Is the red sphere to the right of the blue square? A:yes Is the red square to the left of the triangle? A:yes

#### Task 19: Path Finding

The kitchen is north of the hallway. The bathroom is west of the bedroom. The den is east of the hallway. The office is south of the bedroom. How do you go from den to kitchen? A: west, north How do you go from office to bathroom? A: north, west Task 16: Basic Induction Lily is a swan. Lily is white. Bernhard is green. Greg is a swan. What color is Greg? A:white

Task 18: Size Reasoning The football fits in the suitcase. The suitcase fits in the cupboard. The box is smaller than the football. Will the box fit in the suitcase? A:yes Will the cupboard fit in the box? A:no

Task 20: Agent's Motivations John is hungry. John goes to the kitchen. John grabbed the apple there. Daniel is hungry. Where does Daniel go? A:kitchen Why did John go to the kitchen? A:hungry

Source: Weston, Jason, Antoine Bordes, Sumit Chopra, Alexander M. Rush, Bart van Merriënboer, Armand Joulin, and Tomas Mikolov. "Towards Al-complete question answering: A set of prerequisite toy tasks." *arXiv preprint arXiv:1502.05698* (2015).

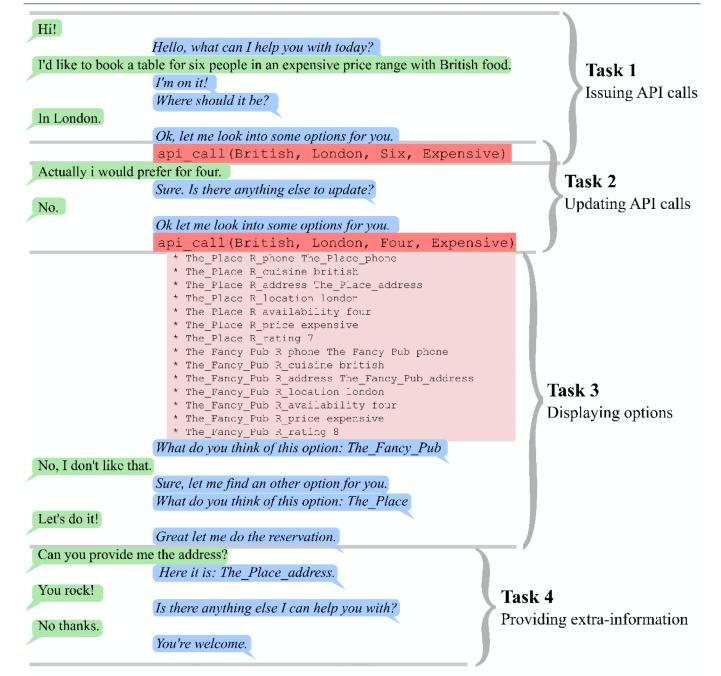
# Learning End-to-End Goal-Oriented Dialog

### Facebook bAbl Dialogue Datasets

1 hi hello what can i help you with today

2 can you make a restaurant reservation with italian cuisine for six people in a cheap price range i'm on it

- 3 <SILENCE> where should it be
- 4 rome please ok let me look into some options for you
- 5 <SILENCE> api\_call italian rome six cheap



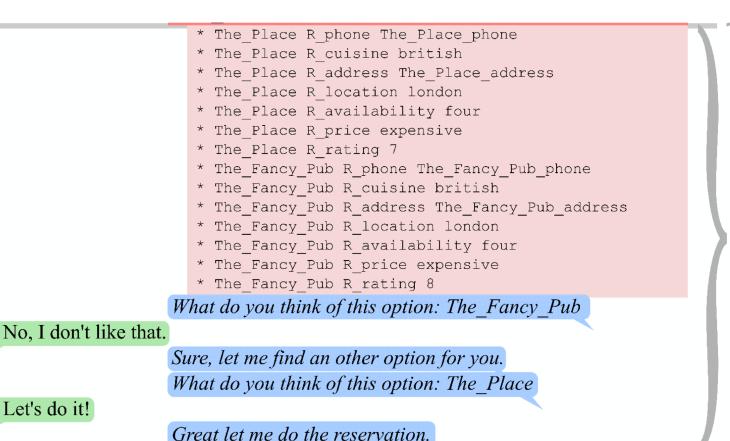
#### Task 5 Conducting full dialogs

Source: Bordes, Antoine, and Jason Weston. "Learning End-to-End Goal-Oriented Dialog." arXiv preprint arXiv:1605.07683 (2016).

## The Dialog bAbl Tasks



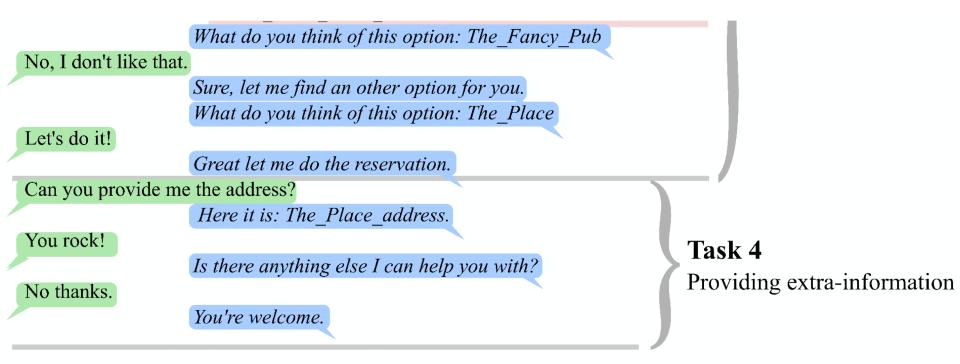
## The Dialog bAbl Tasks



Let's do it!

Task 3 **Displaying options** 

## The Dialog bAbl Tasks



Task 5 Conducting full dialogs

Short Text Conversation **(STC)** 



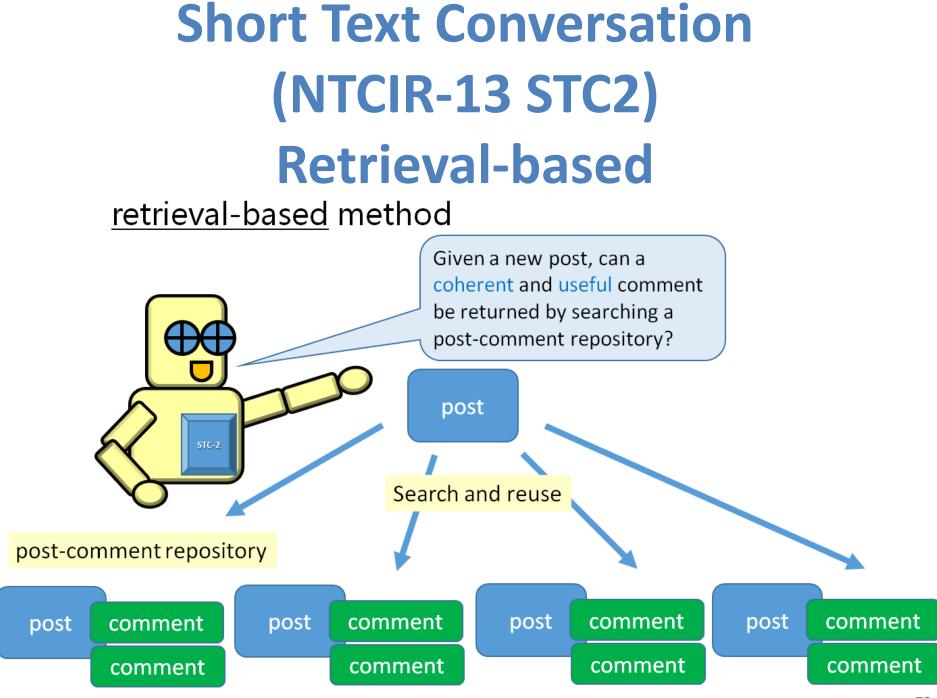
# Short Text Conversation Task (STC-3) Chinese Emotional Conversation Generation (CECG) Subtask

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

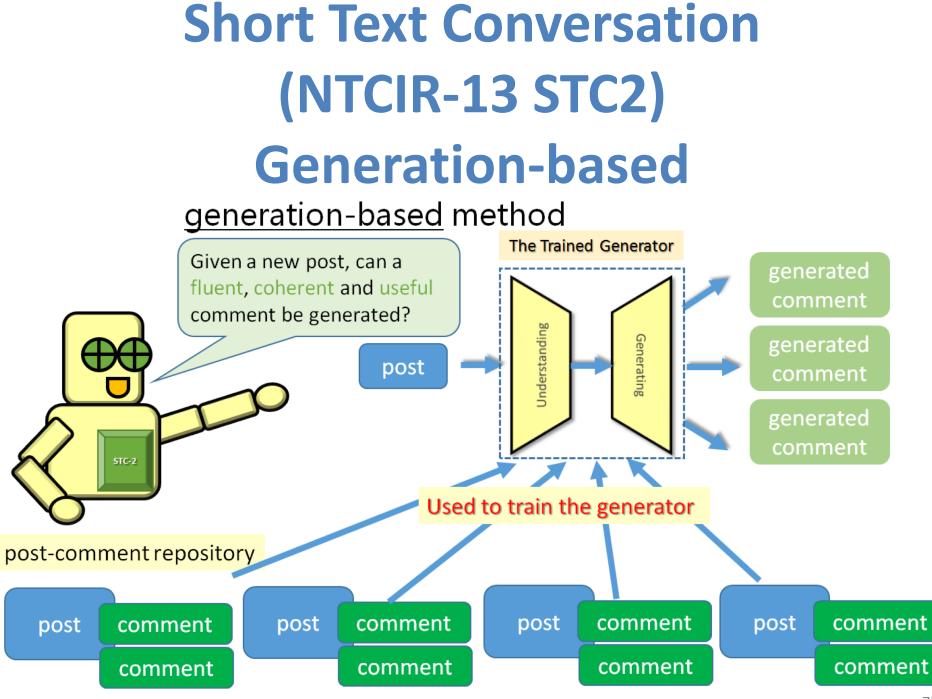
# NTCIR Short Text Conversation STC-1, STC-2, STC-3

		Japanese	Chinese	English	
	NTCIR-12 STC-1 22 active participants	Twitter, Retrieval	Weibo, Retrieval		Single-turn,
	NTCIR-13 STC-2 27 active participants	Yahoo! News, Retrieval+ Generation	Weibo, Retrieval+ Generation		Non task-oriented
	NTCIR-14 STC-3 Chinese Emotion Generation (C		IOI given		
Dialogue Quality (DQ) and Nugget		categories Weibo+English translations,		Multi-turn, task-oriented (helpdesk)	
	Detection (N		distribution estimation for subjective annotations		

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



Source: http://ntcirstc.noahlab.com.hk/STC2/stc-cn.htm



Source: http://ntcirstc.noahlab.com.hk/STC2/stc-cn.htm

## Short Text Conversation (STC-3)

- Emotional Conversation Generation
- Dialogue Quality
- Nugget Detection subtasks using Chinese and English dialogue data

## NTCIR-14 Short Text Conversation Task (STC-3)

- Three new subtasks
  - Chinese Emotional Conversation Generation (CECG)
  - Dialogue Quality (DQ) (for Chinese and English)
  - Nugget Detection (ND) (for Chinese and English)

## Given post: 爱狗还会做饭的男人,最帅了!

The man who cooks and loves dogs is very handsome!

Response	Chinese / Translated English	Emotion Class	Coherence and Fluency	Emotion Consistency	Label
Response 1	会做饭的男人是很帅的啊。	喜欢	Yes	Yes	2
	The man who cooks is handsome.	Like			
Response 2	哈哈,我也觉得。	喜欢	Yes	No	1
	Haha, I feel the same way.	Like			
Response 3	这是哪部电影里的?	厌恶	No	Yes	0
	Which movie is this from?	Disgust			
Response 4	哈哈,你也是。	喜欢	No	No	0
	Haha, the same to you.	Like			
Response 5	我爱你会。	厌恶	No	Yes	0
	I love you, will you.	Disgust			
Response 6	这是同主义同的道!	厌恶	No	No	0
	This is the same way of the same doctrine!	Disgust			

Source: http://coai.cs.tsinghua.edu.cn/hml/challenge/evaluation\_metric/

## NLPCC Emotion Classification Challenge 6 classes (64%)

- 0: Other
- 1: Like
- 2: Sadness
- 3: Disgust
- 4: Anger
- 5: Happiness

#### Chinese Emotional Conversation Generation (CECG)

<b>Post</b> (Given)	Emotion Category (Given)	Response (to be generated)
爱狗还会做饭的男人,最帅了!	喜欢	会做饭的男人是很帅的啊。
The man who cooks and loves dogs is very handsome!	Like	The man who cooks is handsome.
爸爸,明天是六一啦,带我出去玩吧!	喜欢	好,一定带。
Daddy, tomorrow is June 1th Children's Day. Please take me out to play!	Like	Yes, of course.
被特别在乎的人忽略,会很难过,而装做不在乎,会更难	悲伤	因为在乎,所以在乎。
过。	Sadness	I am concerned with it, because I care
It's sad to be ignored by someone that you really care, and it's harder to pretend that you don't care.		about it.
冰天雪地的哈尔滨!你要冻死我咋地?!?!	喜欢	注意保暖,小心别感冒!
Harbin is in the snow! Are you going to freeze me to death?!?!	Like	Keep warm. Watch out for getting cold!
本来想学一把沧桑,结果令我更忧伤。	悲伤	这是一个悲伤的故事。
I wanted to learn the vicissitudes of life, but I became sadder.	Sadness	It a sad story.
今天一整天都在海边训练。虽然很累,但还是很开心的!	快乐	是的呢,开心!
I have been training at the seaside all day. Though very tired, I still very happy!	Happiness	Yeah, happy!

Source: http://coai.cs.tsinghua.edu.cn/hml/challenge/task\_definition/

#### Chinese Emotional Conversation Generation (CECG) Dataset

- 1,110,000 Weibo post-response pairs
  - [[post,post\_label],[response,response\_label]], [[post,post\_label],[response,response\_label]],...].

#### Fluency judgement on responses with repetitive words

Response	Fluency
悲哀,悲哀,悲哀。	Yes
飘逸,飘逸,飘逸!	Yes
好可爱,好可爱!	Yes
哈哈哈,当然啦	Yes
疯了。疯了。全疯了	Yes
对的对的对的对的对的对的对的对的对的对的对的	No
我骗骗骗骗我骗你信不信不信不信我反正信了	No
中国的教育教育教育教育教育教育教育教育教育教育教育教育教育教育教育教育教育教育教育	No
矮贱贱贱贱贱贱贱,你爱你,我也不爱你了	No
不关我事不关我事不关我事不关我事不关我事!	No

Source: Huang, Minlie, Zuoxian Ye, and Hao Zhou. "Overview of the NLPCC 2017 Shared Task: Emotion Generation Challenge." In *National CCF Conference on Natural Language Processing and Chinese Computing (NLPCC)*, pp. 926-936. Springer, Cham, 2017.

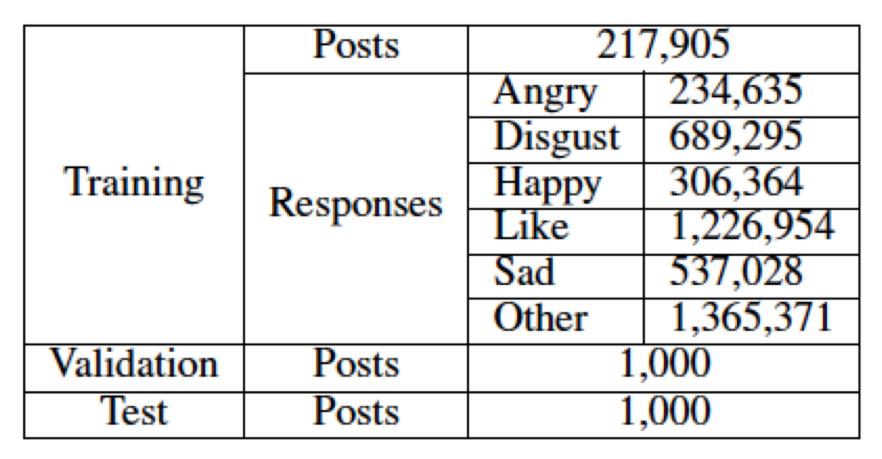
## Sample responses generated by Seq2Seq and ECM (Emotional Chatting Machine)

Post	Model		Response(Original)	Response(Translated)
	Sec	12Seq	承诺,就是一个骗子说给一个傻子听的。	A promise is what a cheater says to a fool.
承诺,就是一个骗子说给		Like	承诺是一个专一的傻子	Promise is a single-minded fool
一个傻子听的。		Нарру	我就是一个 <mark>开心</mark> 的傻子	I'm just a happy fool
A promise is what a cheater says to a fool.	ECM	Sad	我就是一个 <mark>悲伤</mark> 的傻子	I am a <mark>sad</mark> fool
says to a 1001.		Disgust	一个骗子说给一个傻子听	A cheater says to a fool
		Angry	不管你信不信,反正我信了!	Whatever you believe or not, I trust in it!
	Seq2Seq		知道真相的我眼泪掉下来。	After knowing the truth, I burst into tears.
	限泪笑下来 tth, I laughed ECM	Like	太可爱了,太可爱了!	Too lovely, it's too lovely.
知道真相的我眼泪笑下来 Knowing the truth, I laughed		Нарру	笑得我眼泪都出来了。	I can't help laugh myself to tears.
myself to tears		Sad	知道真相的我 <mark>眼泪</mark> 掉下来。	After knowing the truth, I burst into tears.
		Disgust	这是真的还是假的?	Is this true?
		Angry	什么意思?没看懂。	What do you mean? I don't understand.

## Sample responses generated by Seq2Seq and ECM (Emotional Chatting Machine)

Post	Model		Response(Original)
	Sec	12Seq	承诺,就是一个骗子说给一个傻子听的。
承诺,就是一个骗子说给		Like	承诺是一个专一的傻子
一个傻子听的。		Нарру	我就是一个 <mark>开心</mark> 的傻子
A promise is what a cheater	ECM	Sad	我就是一个 <mark>悲伤</mark> 的傻子
says to a fool.		Disgust	一个骗子说给一个傻子听
		Angry	不管你信不信,反正我信了!

#### Emotional Short Text Conversation (ESTC) Dataset

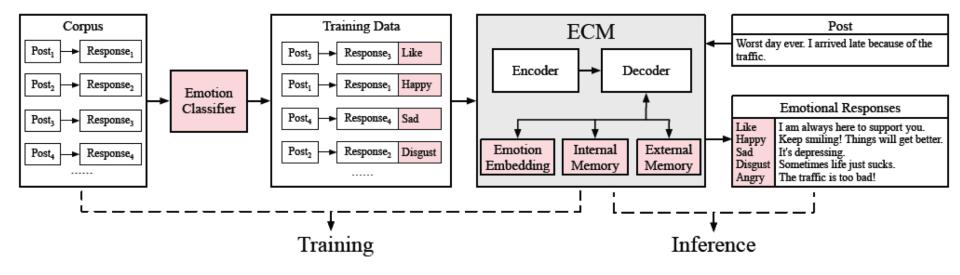


#### Conversations

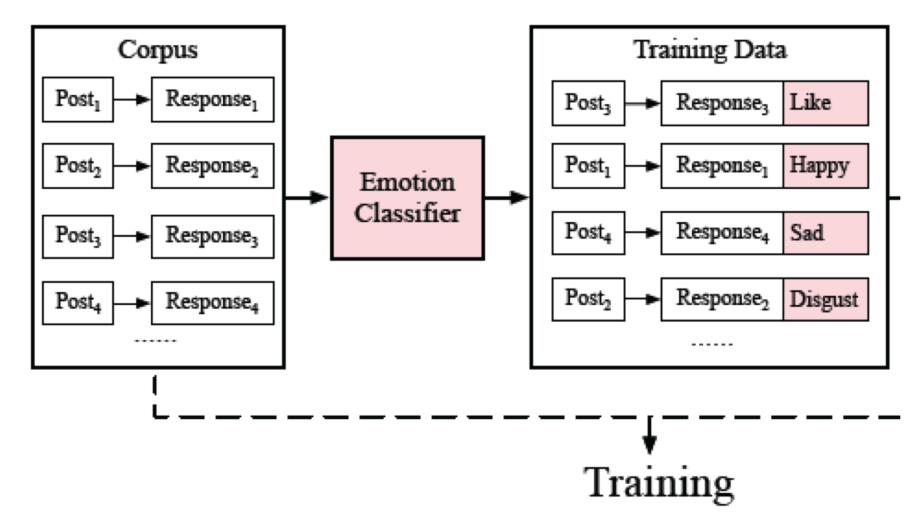
## with/without considering emotion Emotional Chatting Machine (ECM)

- User: Worst day ever. I arrived late because of the traffic.
  - 1. Basic Seq2Seq: You were late.
  - 2. ECM (Like): I am always here to support you.
  - 3. ECM (Happy): Keep smiling! Things will get better.
  - 4. ECM (Sad): It's depressing.
  - 5. ECM (Disgust): Sometimes life just sucks.
  - 6. ECM (Angry): The traffic is too bad!

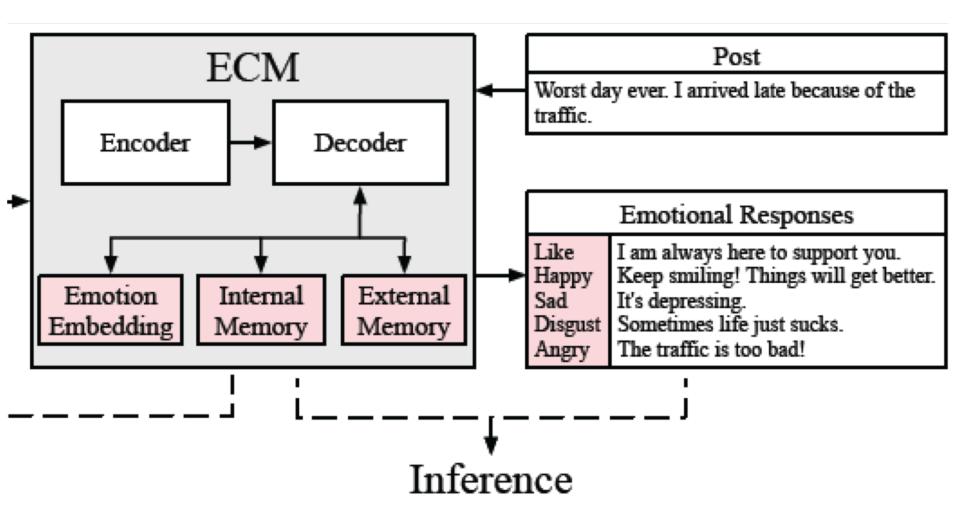
## **Overview of Emotional Chatting Machine (ECM)**



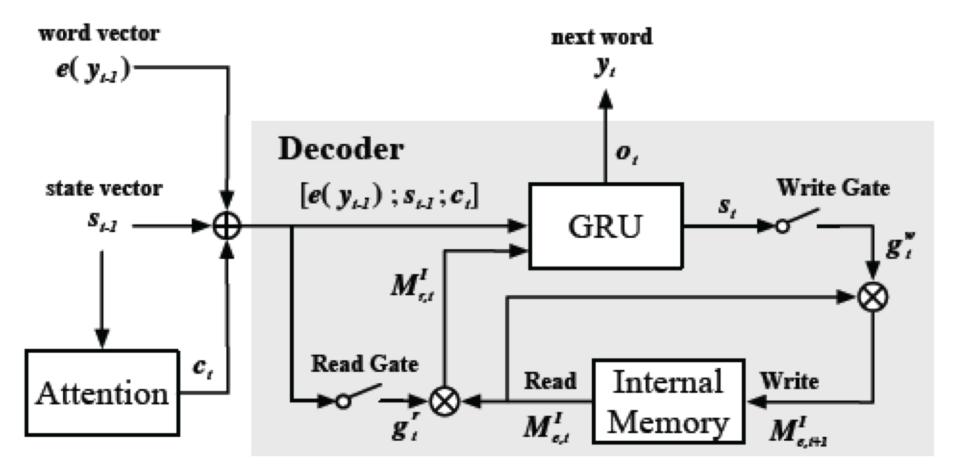
## **Overview of Emotional Chatting Machine (ECM)**



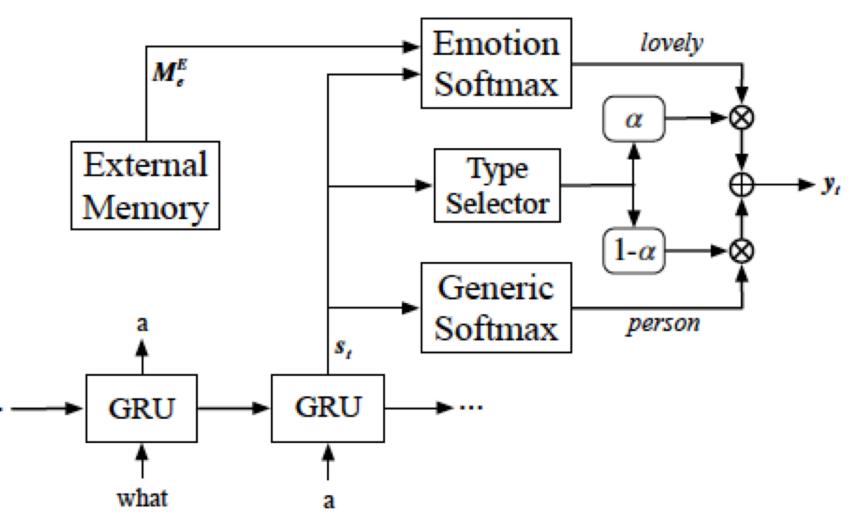
## **Overview of Emotional Chatting Machine (ECM)**



## Data flow of the decoder with an internal memory



## Data flow of the decoder with an external memory



## Sample responses generated by Seq2Seq and ECM (Emotional Chatting Machine)

Post	Model		Response(Original)
	Sec	q2Seq	知道真相的我眼泪掉下来。
		Like	太可爱了,太可爱了!
知道真相的我眼泪笑下来 Knowing the truth, I laughed		Нарру	笑得我眼泪都出来了。
myself to tears	ECM	Sad	知道真相的我 <mark>眼泪</mark> 掉下来。
		Disgust	这是真的还是假的?
		Angry	什么意思?没看懂。

#### Chinese Emotional Conversation Generation (CECG) Evaluation Metric

- Emotion Consistency
  - whether the emotion class of a generated response is the same as the pre-specified class.
- Coherence
  - whether the response is appropriate in terms of both logically coherent and topic relevant content.
- Fluency
  - whether the response is fluent in grammar and acceptable as a natural language response.

Source: <u>http://coai.cs.tsinghua.edu.cn/hml/challenge/evaluation\_metric/</u>

Chinese Emotional Conversation Generation (CECG) Evaluation Metric IF Coherence and Fluency IF Emotion Consistency

LABEL 2

LABEL 1

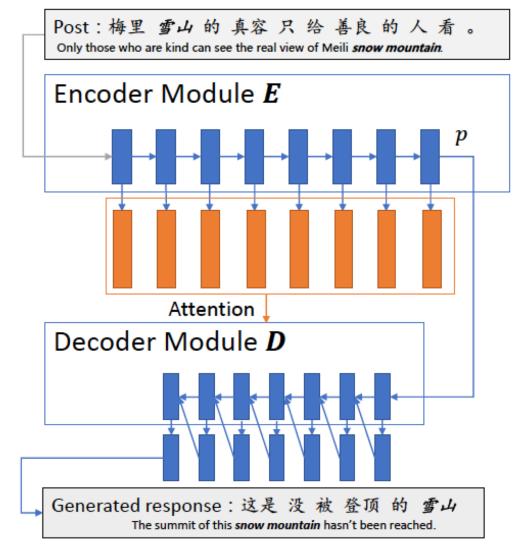
ELSE

LABEL O

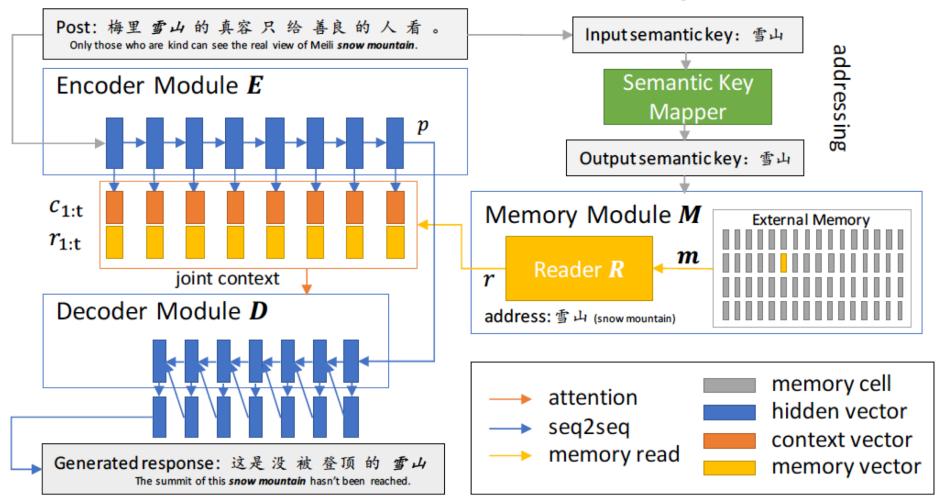
ELSE

Source: http://coai.cs.tsinghua.edu.cn/hml/challenge/evaluation\_metric/

#### Sequence-to-sequence Learning with Attention for Generation-based STC



#### General Framework of Controllable Short-Text-Conversation Generation with External Memory



#### **Controllable Short Text Conversation Examples**

D. (	李娜太牛了!中	国第一个世界网球大满贯冠军!
Post	Li Na is great!	China's first World Tennis Grand Slam champion!
	李娜是世界冠	¥!
NRM	Li Na is the wo	orld champion!
MrRNN	李娜加油,加油	
WITKININ	Come on, Li N	a. Come on!
	Key-Word	Response
	世界	李娜是世界上最棒的!
ESED	world	Li Na is the best in the world!
LOLD	中国	李娜是中国的骄傲!
	China	Li Na is the pride of China!
	网球	中国网球公开赛,加油!
	tennis	China Tennis Open, come on!
Post	感人器官捐献)	广告,请感谢那些给你第二次生命的人.
rost	A touching org	an donation advertisement, please thank those who gave you a second life.
NRM	给我第二次生命	命的人。
INKINI		es me a second life.
MrRNN	感谢每一个人!	
MILKININ	Thanks for even	ryone!
	Key-Word	Response
	生命	感谢生命给予的一切!
	life	Thanks for everything given by life!
ESED	器官	感谢那些器官捐赠者。
LOED	organ	Thanks for those organ donors.
	广告	很感人的广告!
	advertisement	A very touching advertisement!

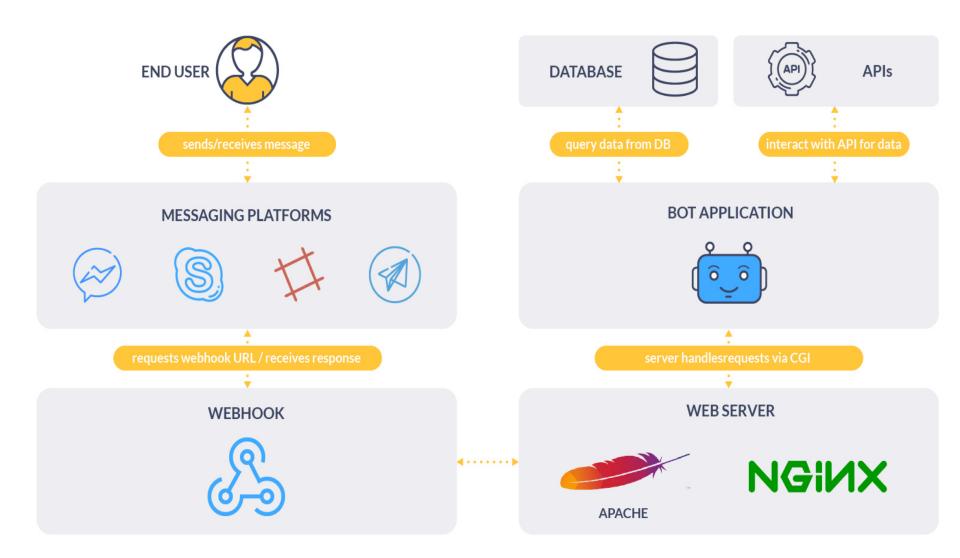
#### **Comments Generated Using Different Semantic key Mapping Methods**

Post	美好的社会。	立该由善良的人组成。
POSt	A good socie	ety should be composed of people of kindness.
Mapping-Method	Key-Word	Response
Identity Mapper	善良	善良是一种信仰。
Identity Mapper	kindness	Kindness is a belief.
Synonym	友善	善良是一种美德。
Synonym	friendliness	Kindness is a virtue.
Antonym	丑恶	没有丑恶的社会,更可怕。
Antonym	evil	A society without evils is more terrifying.
Embedding	乐观	乐观是一种生活态度。
Enlocading	optimism	Optimism is an attitude of life.
	真	真的吗?
Common-Reply	really	Really?
common-reply	对	对的,对的。
	right	Right, right.
	人	每个人都有善良的一面。
Random	person	Every person has a side of kindness.
	中国	中国的贫富差距太大了。
	China	The gap between the wealthy and the poor in China is too big.

#### Generated Responses of Knowledge Introduction by External Memory

Post	你最喜欢那	
rost	What is you	r favorite constellation?
	Key-Word	Response
	摩羯座	我最喜欢摩羯座。
Semantic-Key	Capricorn	I love Capricorn.
Semantic-Key	射手座	我是射手座,我喜欢。
	Sagittarius	I am a Sagittarius and I like it.
Dest	今天周杰伦	的电影,太好看了。
Post		movie is so nice today.
	Key-Word	Response
Semantic-Key	歌	杰伦的歌也很好听。
	song	Jay Chou's songs are nice too.
Dest	梵高的画,很	と漂亮。
Post	Van Gogh's	paintings are very beautiful.
	Key-Word	Response
	向日葵	梵高笔下的向日葵。
Semantic-Key	sunflower	The Sunflower by Van Gogh.
Semanue-Key	荷兰	梵高的画,很漂亮。
	Holland	Van Gogh's paintings are very beautiful.

#### **How to Build Chatbots**



### Chatbot Frameworks and AI Services

- Bot Frameworks
  - Botkit
  - Microsoft Bot Framework
  - Rasa NLU
- Al 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	
Built-in integration with messaging platforms	$\oslash$	$\odot$	۲
NLP support	(X) but possible to integrate with middlewares	(X) but have close bonds with LUIS.ai	$\bigotimes$
Out-of-box bots ready to be deployed	$\odot$	$\otimes$	$\otimes$
Programming Language	JavaScript (Node)	JavaScript (Node), C#	Python
			Created by ActiveWizards

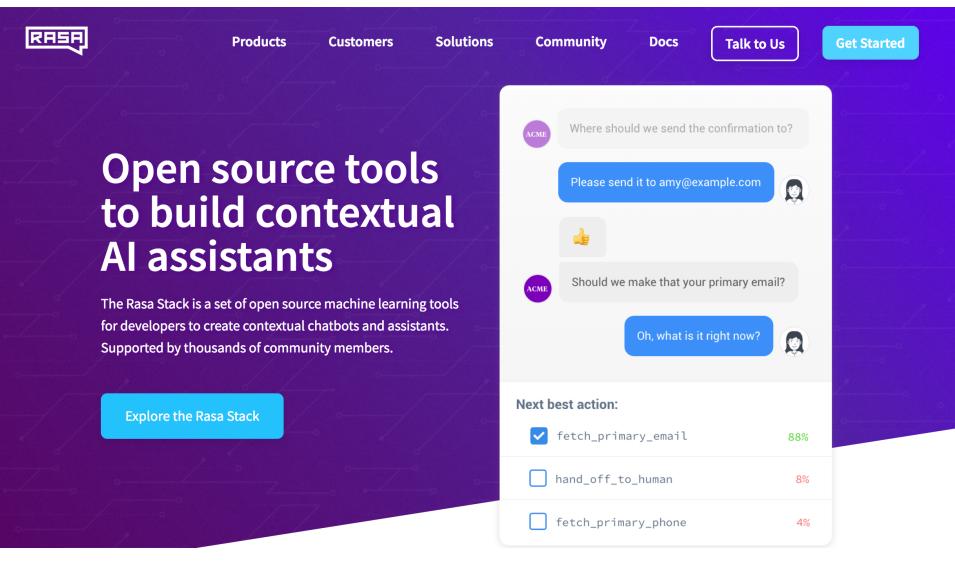
#### Comparison of Most Prominent Al Services

	wit.ai	api.ai	LUIS.ai	IBM Watson		
Free of charge	$\odot$	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	${ \bigcirc }$	$\odot$	⊘ with use of Cortana	$\odot$		
Machine Learning Modeling	$\odot$	$\odot$	$\odot$	$\odot$		
Support for Intents, Entities, Actions	S Intents used as trait entities, actions are combined operations	⊘ Intents is the main prediction mechanism. Domains of entities, intents and actions	$\bigotimes$	$\bigcirc$		
Pre-build entities for easy parsing of numbers, temperature, date, etc.	${ \bigcirc }$	$\odot$	${ \bigcirc }$	${ \bigcirc }$		
Integration to messaging platforms	() web service API	So 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 ÁctiveWizards						

# Rasa

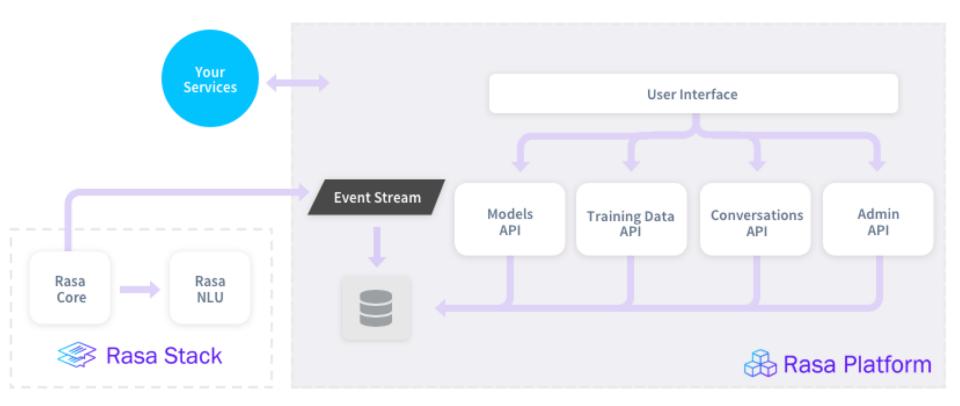
## **Conversational Al**

#### **Rasa: Conversational Al**



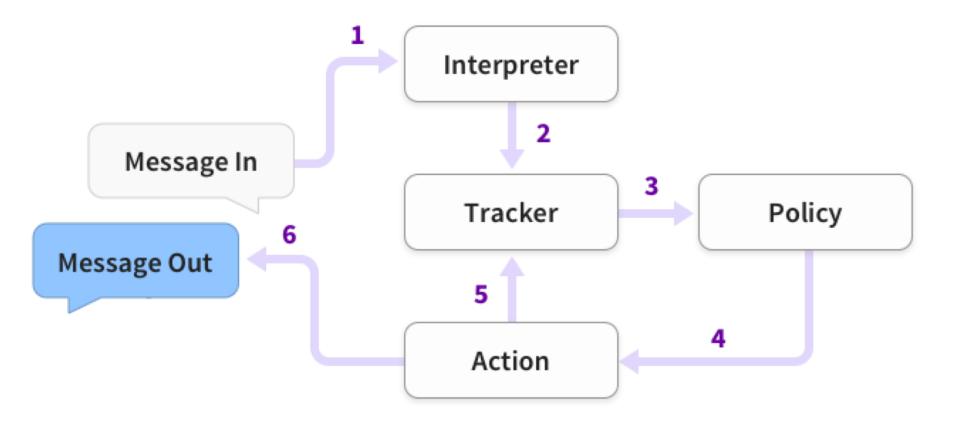
#### https://rasa.com/

#### Rasa Platform Rasa Stack

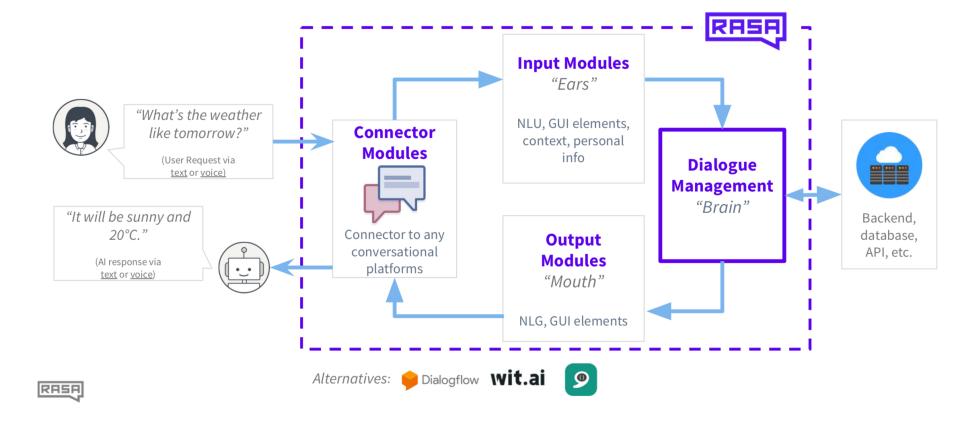


https://rasa.com/

#### **Rasa Core High-Level Architecture**

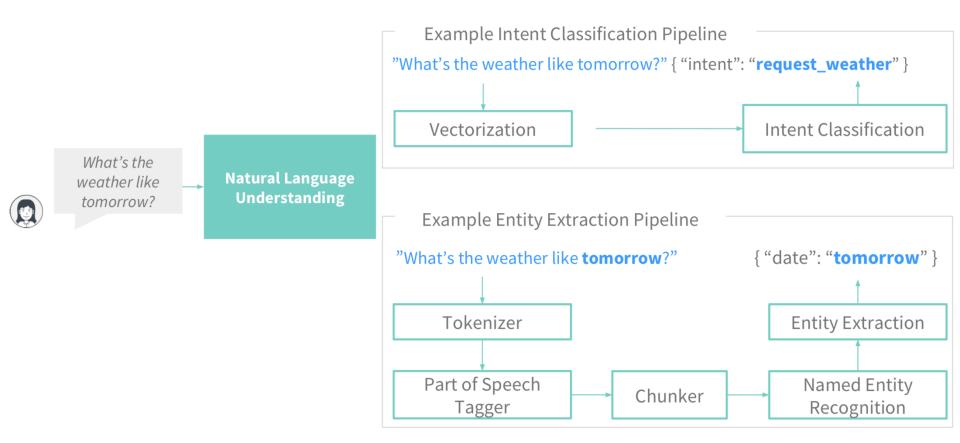


## Rasa the OSS to build conversational software with ML

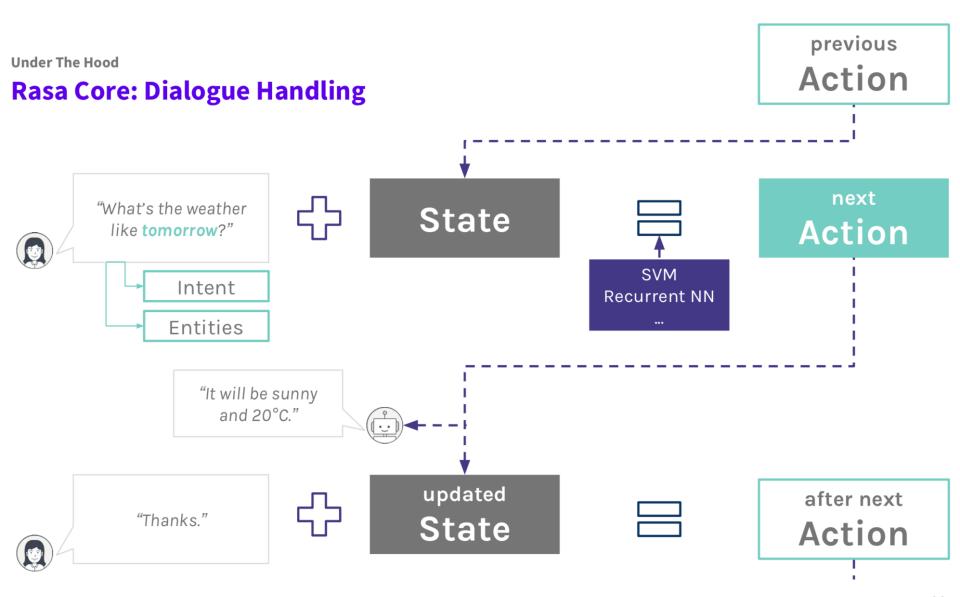


#### https://github.com/RasaHQ/rasa-workshop-pydata-berlin

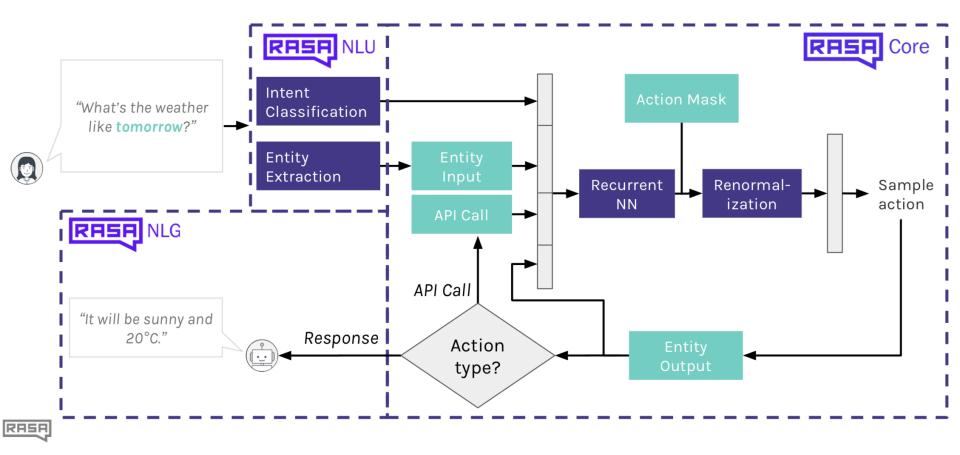
## Rasa NLU: Natural Language Understanding



#### **Rasa Core: Dialogue Handling**

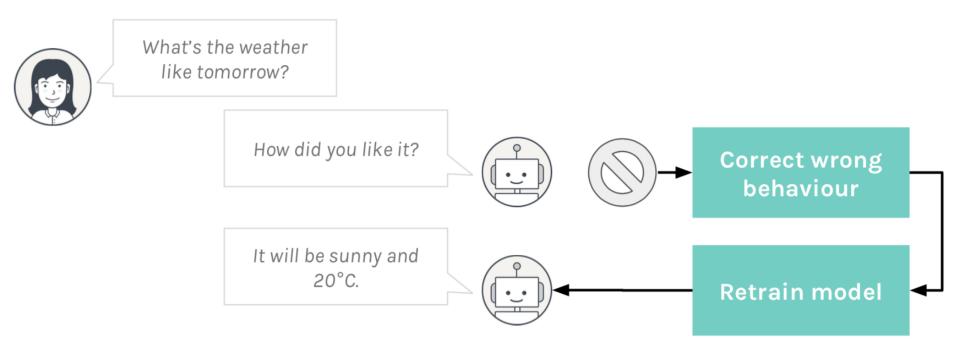


#### **Rasa Core: Dialogue Handling**



#### **Rasa Core: Dialogue Training**

Issue: How to get started? → Online Learning



#### Dialogflow

#### Dialogflow

Overview Case studies

Blog Pricing

Docs

Support

Q Search

Go to console

#### Build natural and rich conversational experiences

Give users new ways to interact with your product by building engaging voice and text-based conversational interfaces, such as voice apps and chatbots, powered by AI. Connect with users on your website, mobile app, the Google Assistant, Amazon Alexa, Facebook Messenger, and other popular platforms and devices.



#### Sign up for free

#### Powered by Google's machine learning

Dialogflow incorporates Google's machine learning expertise and products such as Google Cloud Speech-to-Text.

#### Built on Google infrastructure

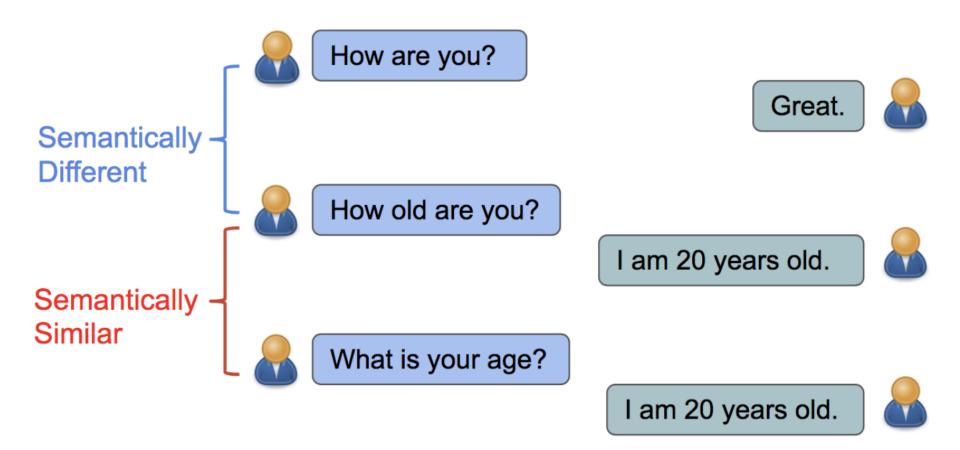
Dialogflow is backed by Google and runs on Google Cloud Platform, letting you scale to hundreds of millions of users.

#### Optimized for the Google Assistant

Dialogflow is the most widely used tool to build Actions for more than 400M+ Google Assistant devices.

#### https://dialogflow.com/

#### Learning Semantic Textual Similarity from Conversations



Source: Yinfei Yang, Steve Yuan, Daniel Cer, Sheng-yi Kong, Noah Constant, Petr Pilar, Heming Ge, Yun-Hsuan Sung, Brian Strope, and Ray Kurzweil (2018). "Learning Semantic Textual Similarity from Conversations." arXiv preprint arXiv:1804.07754.

#### **TF-Hub Modules** Sentence Embedding Universal Sentence Encoder

$\equiv$ TensorFlow Hub	Q	USER GUIDE
Text	Text embedding	
Embedding	universal-sentence-encoder By Google	
Image	Text embedding DAN English	
Classification Feature Vector	Encoder of greater-than-word length text trained on a variety of data.	
Generator	universal-sentence-encoder-large By Google	
Other	Text embedding Transformer English	
Video	Encoder of greater-than-word length text trained on a variety of data.	
Classification		
Publishers	elmo By Google Text embedding 1 Billion Word Benchmark ELMo English	
Google DeepMind	Embeddings from a language model trained on the 1 Billion Word Benchmark.	
	View more text embeddings	
	Image feature vectors	
	imagenet/inception_v3/feature_vector By Google	

Image feature vector ImageNet (ILSVRC-2012-CLS) Inception V3 Feature vectors of images with Inception V3 trained on ImageNet (ILSVRC-2012-CLS).

#### https://tfhub.dev/

#### Semantic Similarity with TF-Hub University Sentence Encoder

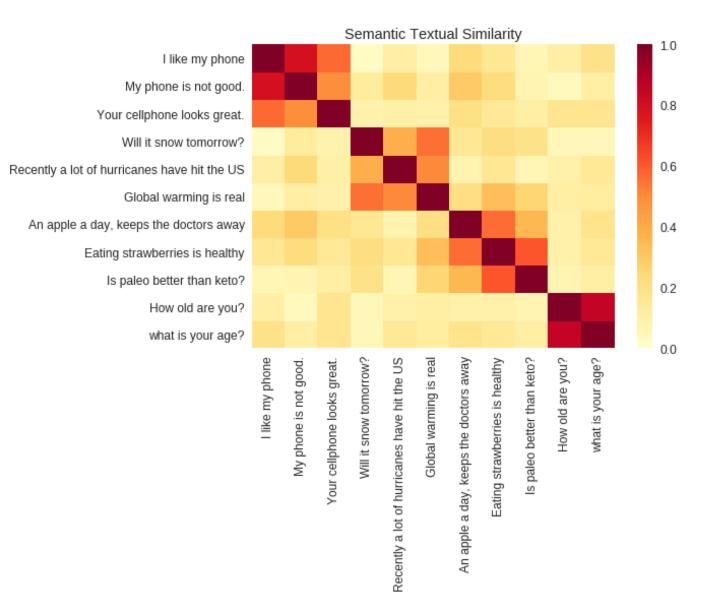
20	Semantic Similarity with TF-Hub Universal Encoder 🗟		G) SHARE	A
	CODE      TEXT     ↑ CELL     COPY TO DRIVE     CONNECT	•	EDITING	^
•	Copyright 2018 The TensorFlow Hub Authors. Licensed under the Apache License, Version 2.0 (the "License");			
	↔ 1 cells hidden			
·	Universal Sentence Encoder			
	This notebook illustrates how to access the Universal Sentence Encoder and use it for sentence similarity and sentence classification tasks.			
	The Universal Sentence Encoder makes getting sentence level embeddings as easy as it has historically been to lookup the embeddings for individual words. The sentence embeddings can then be trivially used to compute sentence level meaning similarity as well as to enable better performance on downstream classification tasks using less supervised training data.			
•	Getting Started			
	This spation sets up the applying the appages to the Universal Sentence Encoder on TE Hub and provides examples of applying the appender to words, contences			

This section sets up the environment for access to the Universal Sentence Encoder on TF Hub and provides examples of applying the encoder to words, sentences, and paragraphs.

1 # Install the latest Tensorflow version.
2 Ipip3 install --quiet "tensorflow>=1.7"
3 # Install TF-Hub.
4 Ipip3 install --quiet tensorflow-hub
5 Ipip3 install --quiet seaborn

114

#### **Semantic Textual Similarity**



115

## anaGo Sequence Labeling (NER)

#### anaGo is a Python library for sequence labeling(NER, PoS Tagging,...), implemented in Keras.

anaGo can solve sequence labeling tasks such as named entity recognition (NER), part-of-speech tagging (POS tagging), semantic role labeling (SRL) and so on. Unlike traditional sequence labeling solver, anaGo don't need to define any language dependent features. Thus, we can easily use anaGo for any languages.

As an example of anaGo, the following image shows named entity recognition in English:

#### anaGo Demo

anaGo

	President Obama is speaking at the White House	
ſ	PER LOC ORG MISC	
	President Obama is speaking at the White House	

#### https://github.com/Hironsan/anago

#### GRAM-CNN BioNER

- GRAM-CNN is a novel end-to-end approach for biomedical NER tasks. To automatically label a word, this method uses the local information around the word. Therefore, the GRAM-CNN method doesn't require any specific knowledge or feature engineering and can be theoretically applied to all existing NER problems.
- The GRAM-CNN approach was evaluated on three well-known biomedical datasets containing different BioNER entities. It obtained an F1-score of 87.38% on the Biocreative II dataset, 86.65% on the NCBI dataset, and 72.57% on the JNLPBA dataset. Those results put GRAM-CNN in the lead of the biological NER methods.
- Pre-trained embedding are from:
  - https://github.com/cambridgeltl/BioNLP-2016

Source: Zhu, Qile, Xiaolin Li, Ana Conesa, and Cécile Pereira. "GRAM-CNN: a deep learning approach with local context for named entity recognition in biomedical text." Bioinformatics 34, no. 9 (2017): 1547-1554. <u>https://github.com/valdersoul/GRAM-CNN</u>

## Summary

- AI Chatbots
- Conversational Commerce
- Bot Platform Ecosystem

#### References

- Yun-Nung Chen, Dilek Hakkani-Tür, Gokhan Tur, Jianfeng Gao, and Li Deng (2016), "End-to-end memory networks with knowledge carryover for multi-turn spoken language understanding." In Proceedings of Interspeech.
- Hakkani-Tür, Dilek, Gokhan Tur, Asli Celikyilmaz, Yun-Nung Chen, Jianfeng Gao, Li Deng, and Ye-Yi Wang. "Multi-domain joint semantic frame parsing using bi-directional RNN-LSTM." In Proceedings of The 17th Annual Meeting of the International Speech Communication Association. 2016.
- Jeongkyu Shin (2016), Building AI Chat bot with Python 3 and TensorFlow, PyCon APAC 2016.
- Ankit Kumar, Ozan Irsoy, Jonathan Su, James Bradbury, Robert English, Brian Pierce, Peter Ondruska, Ishaan Gulrajani, and Richard Socher (2015). "Ask me anything: Dynamic memory networks for natural language processing." arXiv preprint arXiv:1506.07285.
- Antoine Bordes and Jason Weston (2016), "Learning End-to-End Goal-Oriented Dialog." arXiv preprint arXiv:1605.07683.
- Jason Weston, Antoine Bordes, Sumit Chopra, Alexander M. Rush, Bart van Merriënboer, Armand Joulin, and Tomas Mikolov (2015), "Towards AI-complete question answering: A set of prerequisite toy tasks." arXiv preprint arXiv:1502.05698.
- Iulian V. Serban, Chinnadhurai Sankar, Mathieu Germain, Saizheng Zhang, Zhouhan Lin, Sandeep Subramanian, Taesup Kim et al (2017). "A Deep Reinforcement Learning Chatbot." arXiv preprint arXiv:1709.02349.
- Xuijun Li, Yun-Nung Chen, Lihong Li, and Jianfeng Gao (2017), "End-to-end task-completion neural dialogue systems." arXiv preprint arXiv:1703.01008.
- Jack Cahn (2017), "CHATBOT: Architecture, Design, & Development." PhD diss., University of Pennsylvania.
- Ferrucci, David, Eric Brown, Jennifer Chu-Carroll, James Fan, David Gondek, Aditya A. Kalyanpur, Adam Lally et al.(2010) ". Building Watson: An overview of the DeepQA project" AI magazine 31, no. 3 (2010): 59-79.
- Kato, Makoto P., and Yiqun Liu (2017), "Overview of NTCIR-13." In Proceedings of the 13th NTCIR Conference. 2017.
- Huang, Minlie, Zuoxian Ye, and Hao Zhou (2017). "Overview of the NLPCC 2017 Shared Task: Emotion Generation Challenge." In National CCF Conference on Natural Language Processing and Chinese Computing (NLPCC), pp. 926-936. Springer, Cham, 2017.
- Zhou, Hao, Minlie Huang, Tianyang Zhang, Xiaoyan Zhu, and Bing Liu. (2017) "Emotional chatting machine: emotional conversation generation with internal and external memory." arXiv preprint arXiv:1704.01074.
- Yu, Kai, Zijian Zhao, Xueyang Wu, Hongtao Lin, and Xuan Liu. (2018)"Rich Short Text Conversation Using Semantic Key Controlled Sequence Generation." IEEE/ACM Transactions on Audio, Speech, and Language Processing.
- Justina Petraityte (2018), Deprecating the state machine: building conversational AI with the Rasa stack, PyData Berlin 2018.
- Yinfei Yang, Steve Yuan, Daniel Cer, Sheng-yi Kong, Noah Constant, Petr Pilar, Heming Ge, Yun-Hsuan Sung, Brian Strope, and Ray Kurzweil (2018). "Learning Semantic Textual Similarity from Conversations." arXiv preprint arXiv:1804.07754.