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Gold Coast, Australia

When Knowledge Graph Meets Chatbots

Opportunities, Challenges and its Applications

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Contents

01 Chatbot

Chatbot Definition

- Chatbot, a computer program which conducts a **conversation** via auditory or textual methods.
- Chatbots are often designed to convincingly simulate how a human would behave as a **conversational** partner, thereby passing the **Turing test**.
- Chatbots are typically used in **dialog systems** for various practical purposes including customer service or information acquisition.

--From Wikipedia

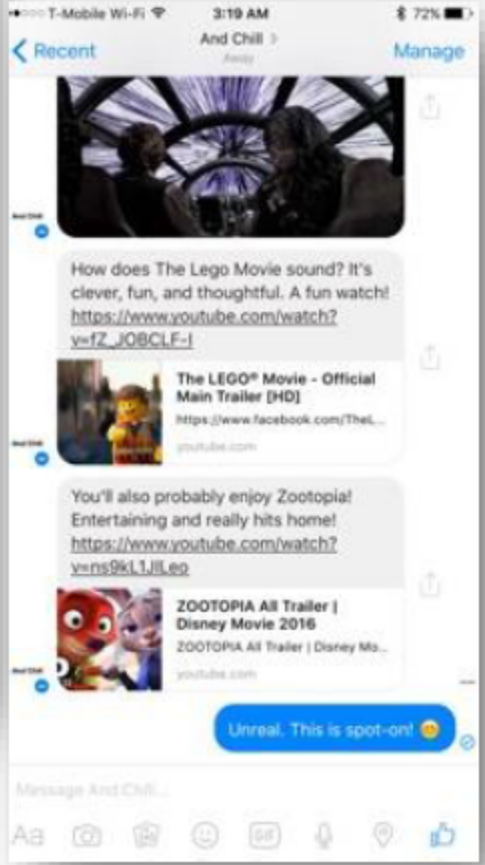
Why We Need?

- Get things done
  - set up alarm/reminder
  - take note
- Easy access to structured data, services and apps
  - find docs/photos/restaurants
- Assist your daily schedule and routine
  - commute alerts to/from work
- Be more productive in managing your work and personal life

Conversation
As
A
Platform

Microsoft CEO Satya Nadella at Microsoft Build 2016.

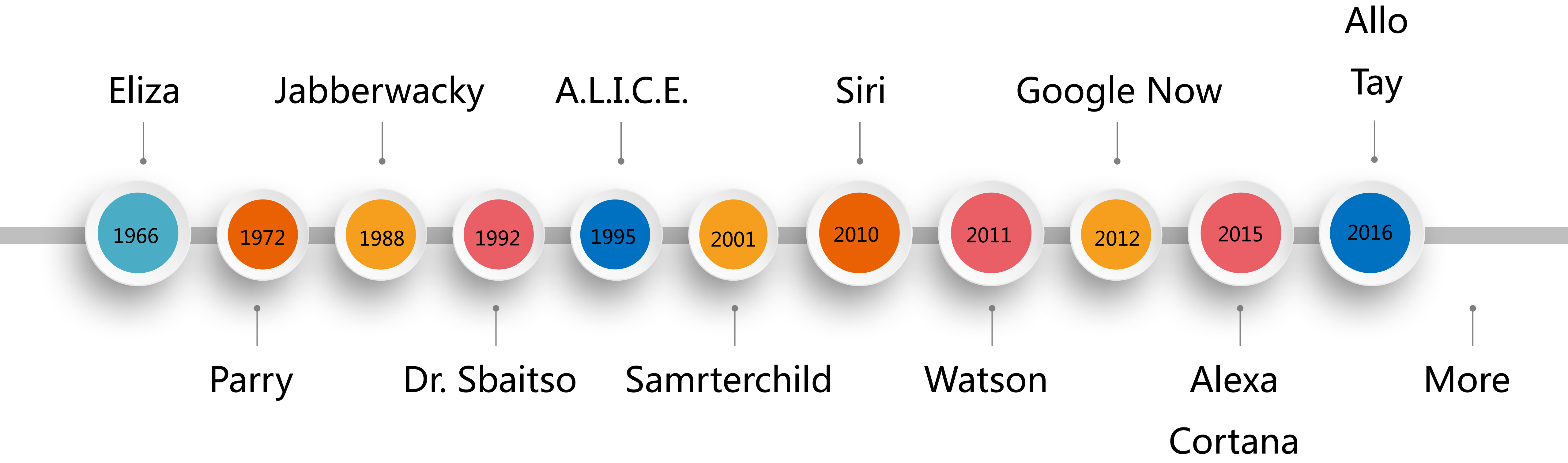
GUI vs CUI (Conversational UI)



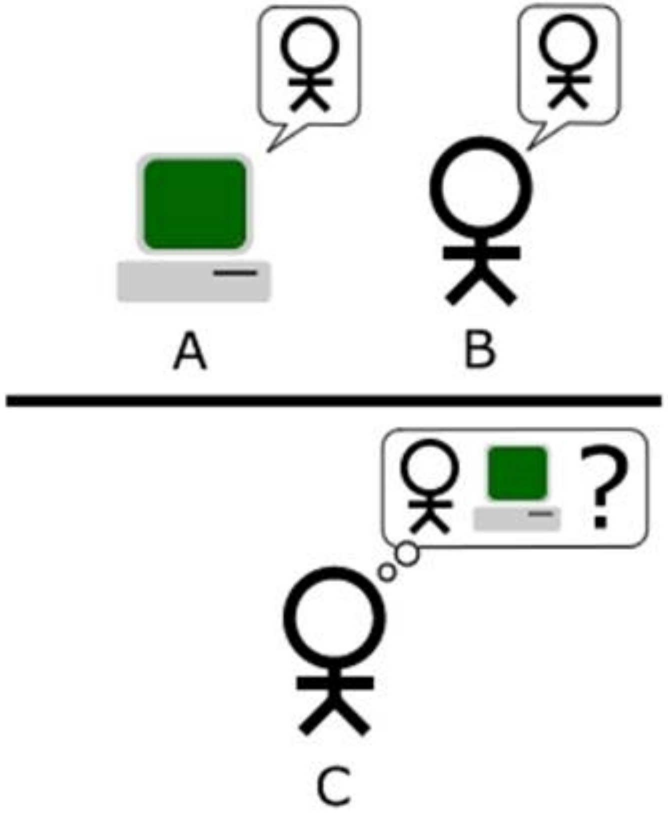
GUI vs CUI (Conversational UI)

	Website/APP's GUI	Msg's CUI
Situation	Navigation, no specific goal	Searching, with specific goal
Information Quantity	More	Less
Information Precision	Low	High
Display	Structured	Non-structured
Interface	Graphics	Language
Manipulation	Click	mainly use texts or speech as input
Learning	Need time to learn and adapt	No need to learn
Entrance	App download	Incorporated in any msg-based interface
Flexibility	Low, like machine manipulation	High, like converse with a human

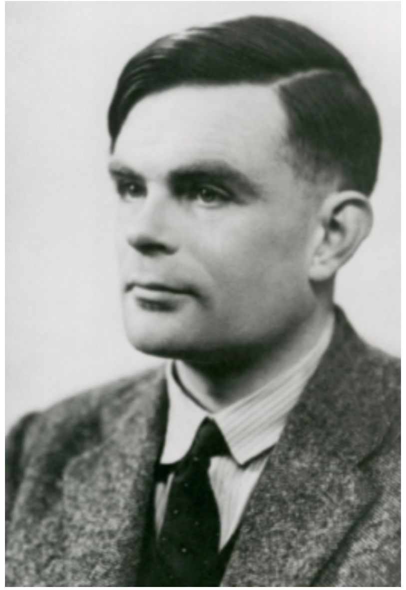
Chatbot History



Turing Test



5min , 30%cheat

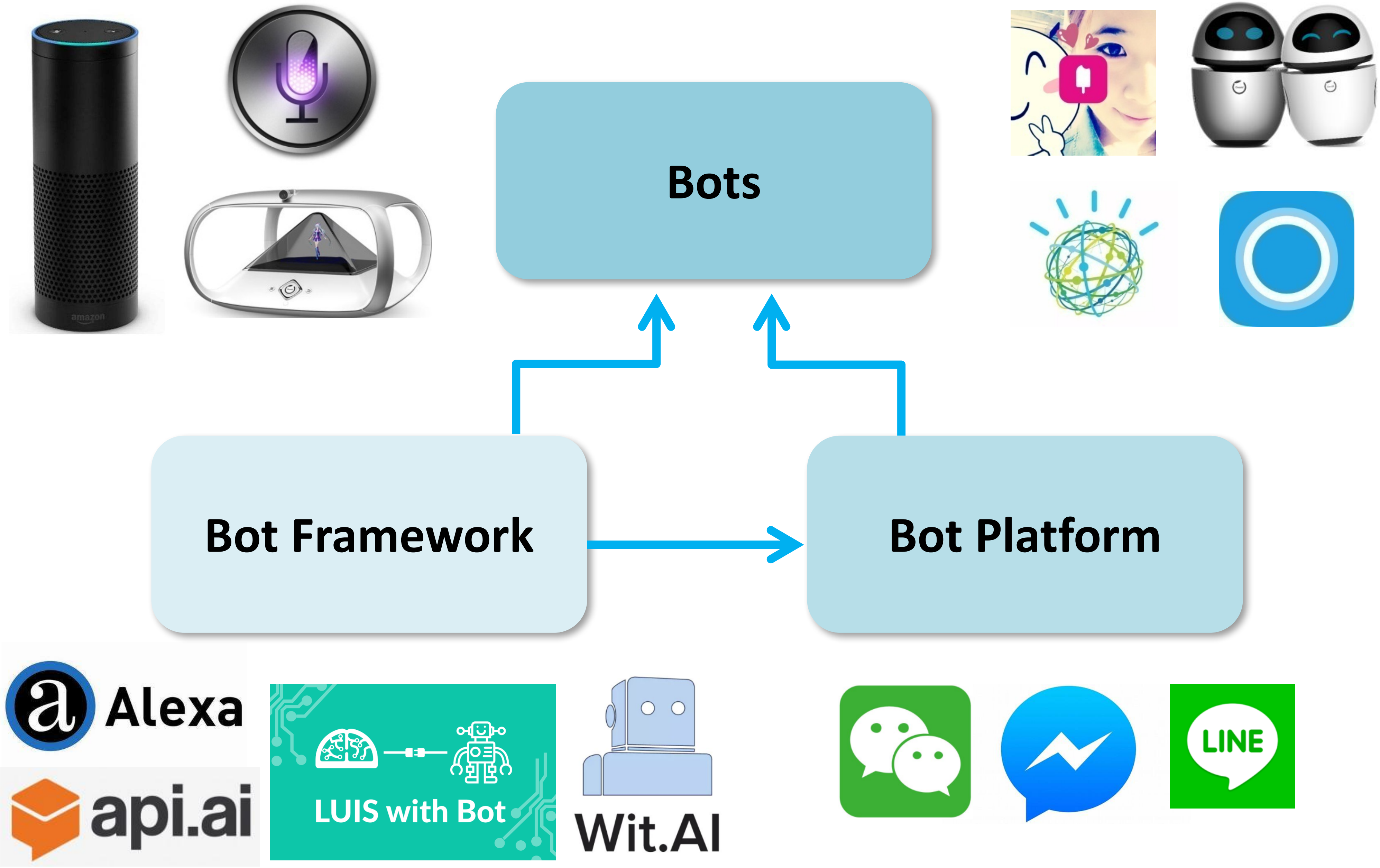


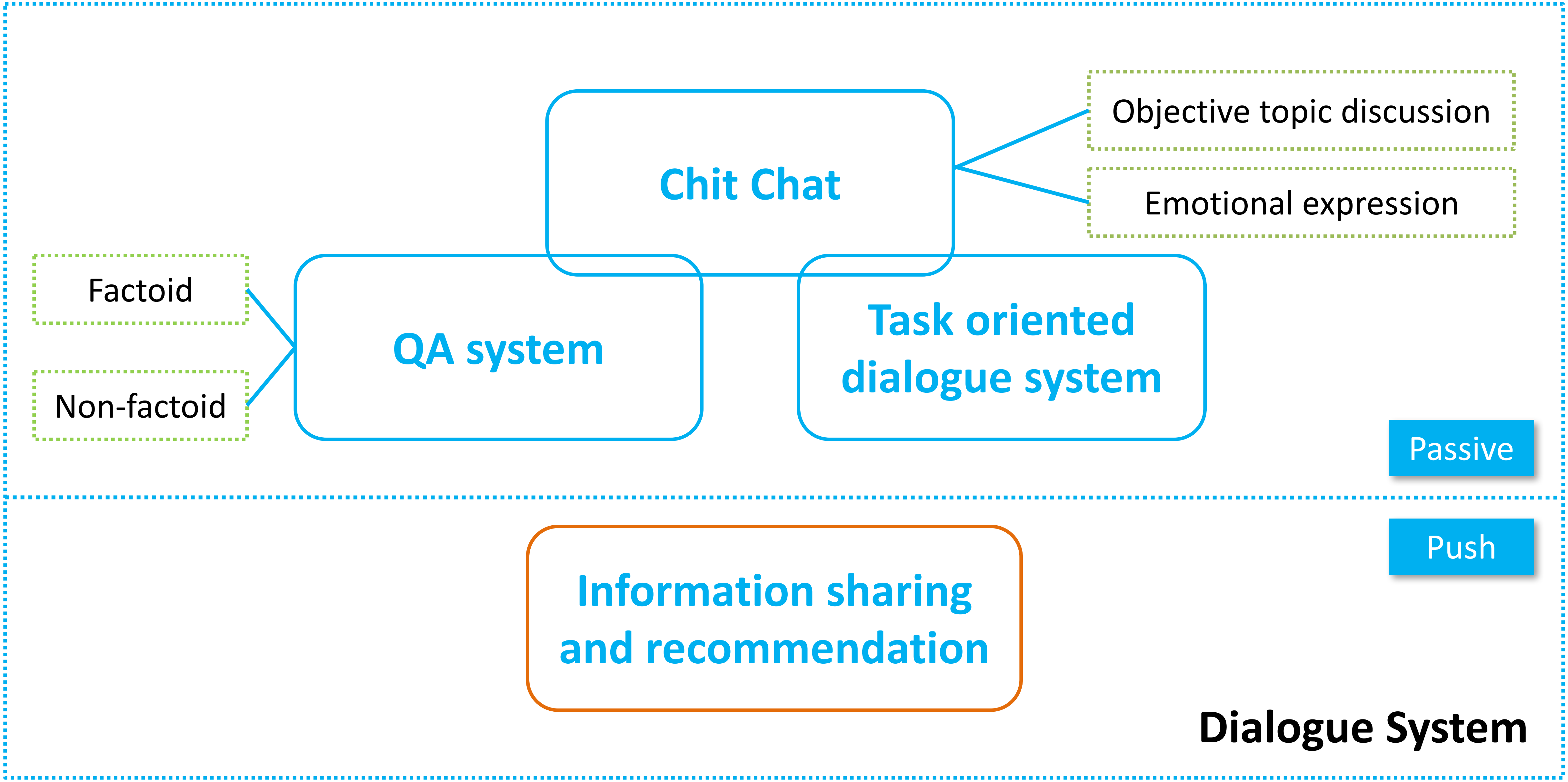
01 Chatbot

Chatbot Classification

For entertainment

For business


Bots
Bot Framework
Bot Platform
Alexa
api.ai
LUIS with Bot
Wit.AI
LINE

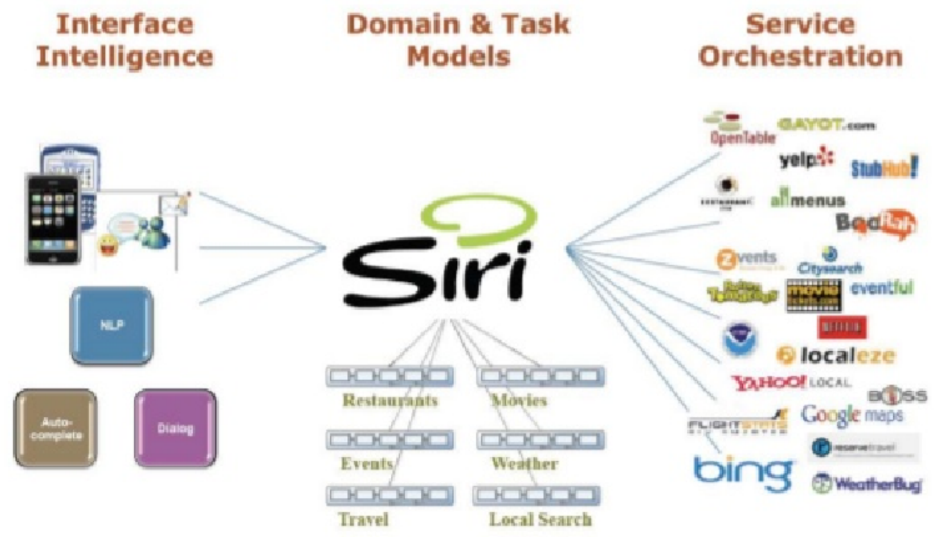

Chit Chat
Objective topic discussion
Emotional expression
Factoid
Non-factoid
QA system
Task oriented dialogue system
Passive
Push
Information sharing and recommendation
Dialogue System

01 Chatbot

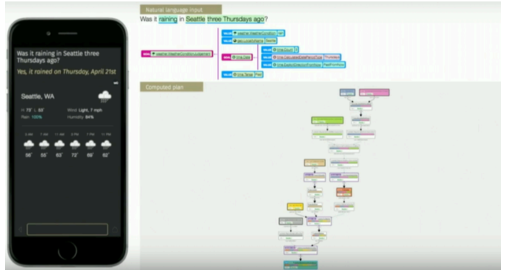
Siri

Personal Assistant

2010



VIV：the upgraded Siri, developed by Siri core members Dag Kittlaus and Adam Cheyer



VIV

2016

Xiaobing

Entertainment

2010

For life

For work

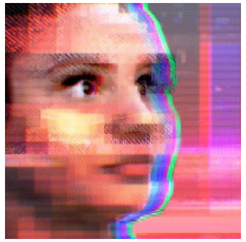
Cortana

Personal Assistant

2016

Rinna

2015



Tay

2016

Zo

2016

Ruuh

2017

IBM Watson

Knowledge Graph
Deep QA

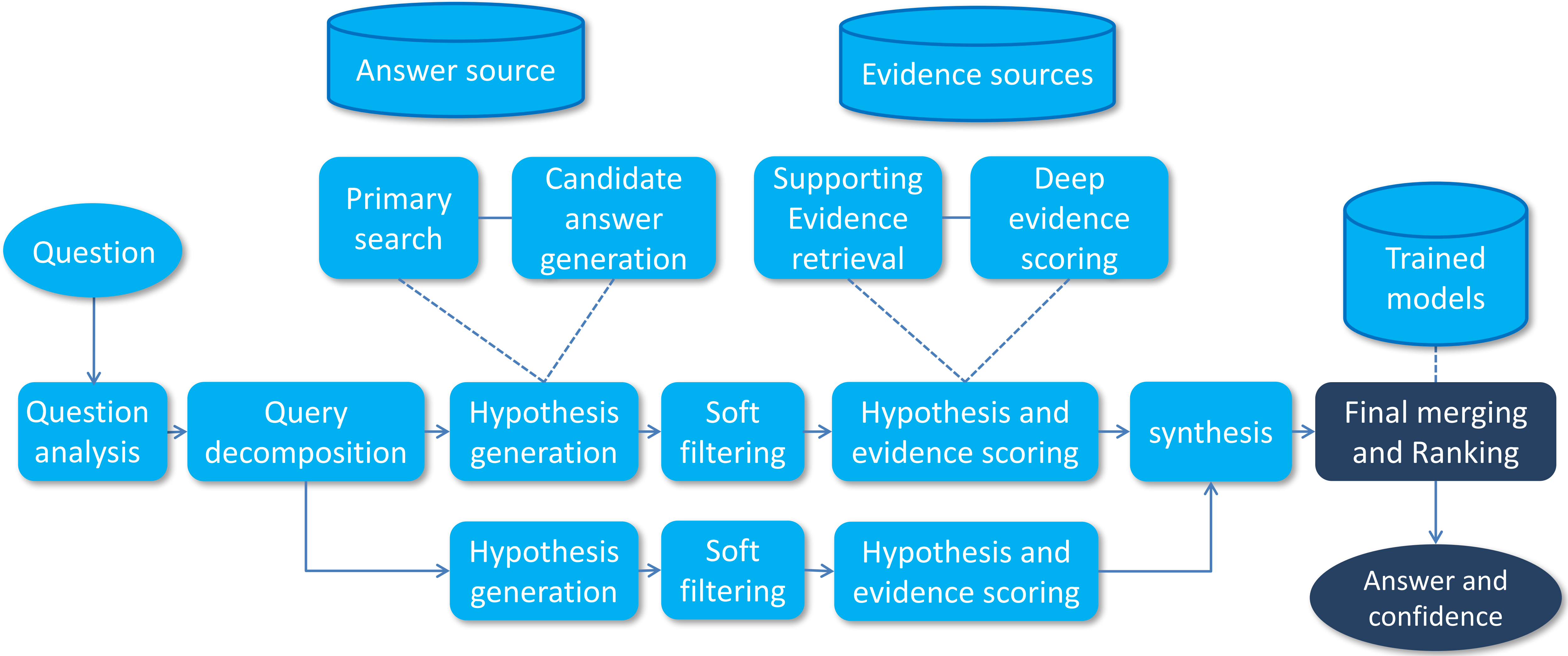
2011

- **KG** : Contains a variety of encyclopedias, dictionaries, news and other forms of knowledge
- **DeepQA** : NLU, classification, reasoning, hypothesis generation.

Medical

ROSS Intelligence

KBQA Killer Application in Chatbots - Watson



Architecture of Watson DeepQA

Facebook Messenger

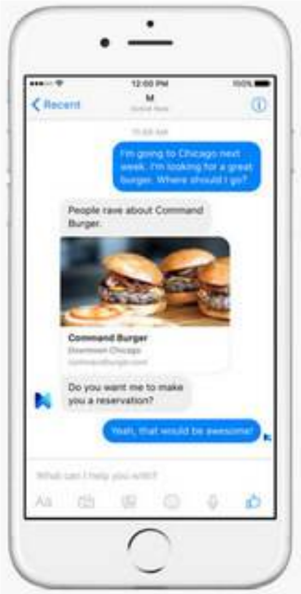
Deep semantic analysis

2013

- Acquisition of wit.ai in 2014
- DeepText
- Man-machine collaboration，training models using user inputs for recommendation.

HI+AI

recommendation



- Intelligent speaker build on Alexa
- “beam-forming” technology

Amazon Echo

Alexa

2014

Music

Smart home

Shopping

Voice wakeup

Google Allo

Personal assistant
Deep learning

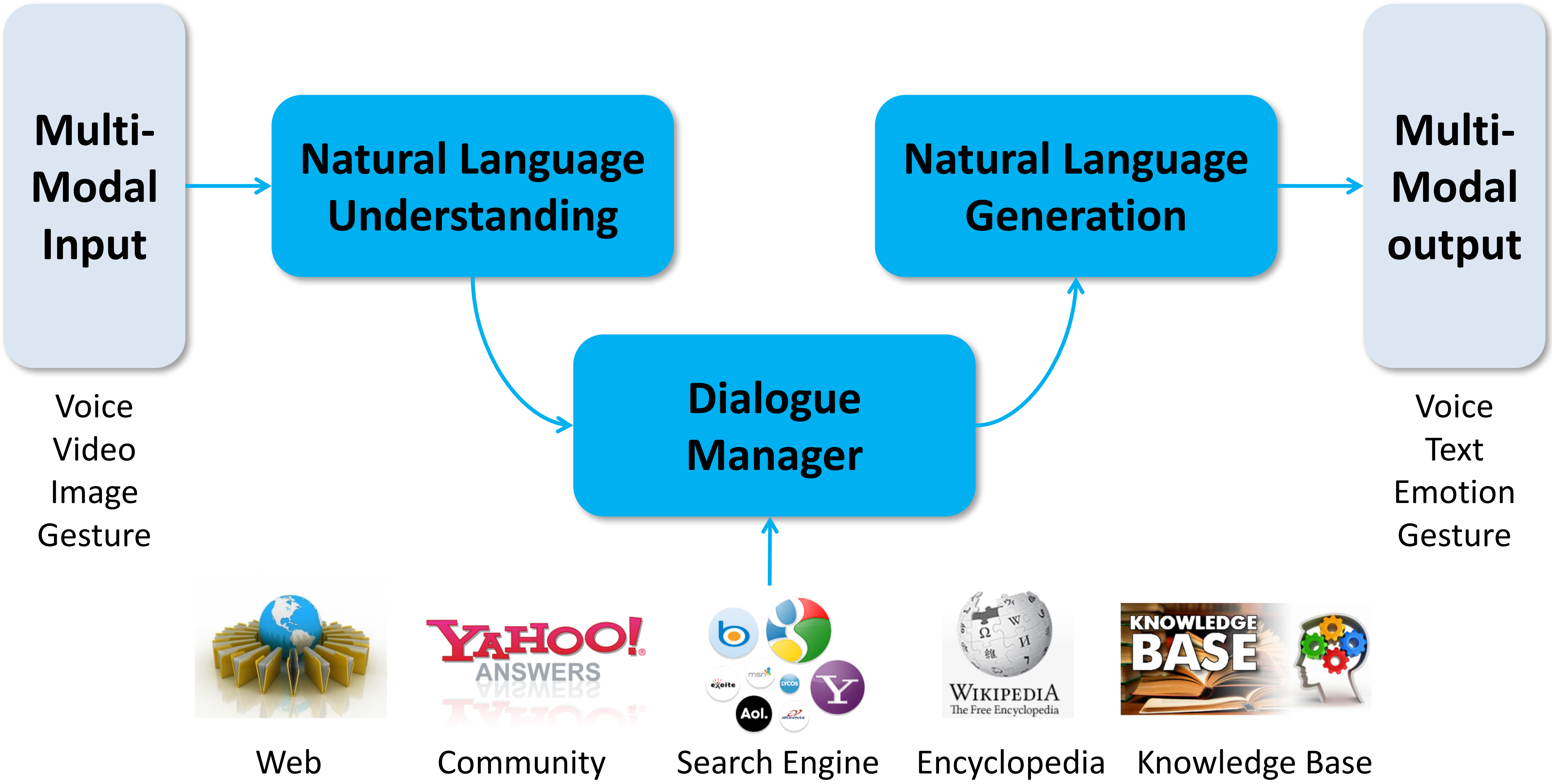
2016

Traditional Google speech system :
Initialize search engine after speech recognition and semantic processing, and return the result to the user

Allo :
Self-learning ability, learning user's speech and behavior pattern, can automatically respond with short messages, mails, and comments

A new deep learning framework was implemented with user embedding, to learn user's behavior patterns

01 Chatbot


Multi-Modal Input
Natural Language Understanding
Natural Language Generation
Multi-Modal output
Voice
Video
Image
Gesture
Dialogue Manager
Voice
Text
Emotion
Gesture
YAHOO! ANSWERS
Aol.
WIKIPEDIA
The Free Encyclopedia
KNOWLEDGE BASE
Web
Community
Search Engine
Encyclopedia
Knowledge Base

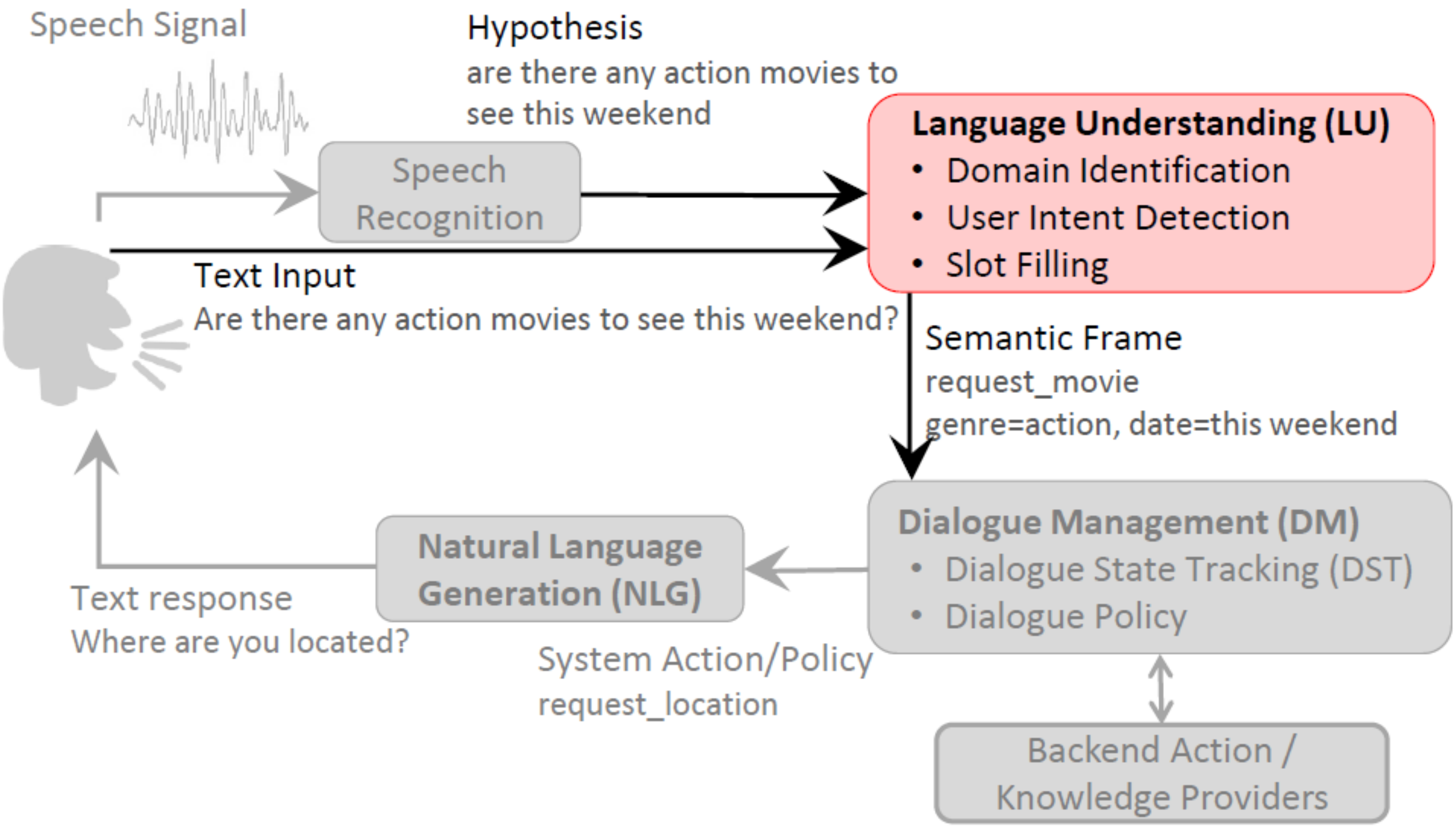
NLU Natural Language Understanding

Map recognition hypotheses to high-level semantic representations

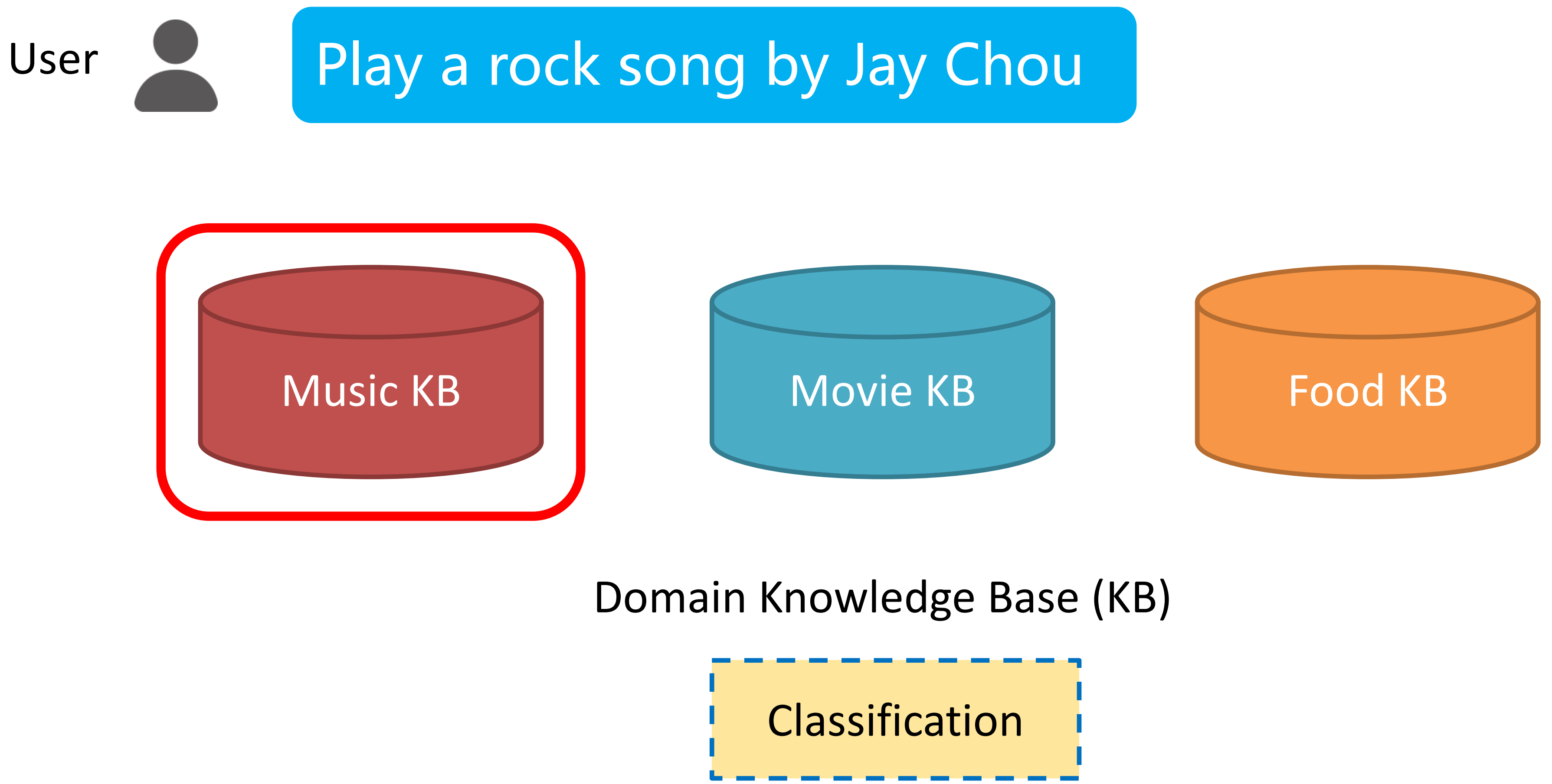
NLP/NLU

Syntax	Semantic	Discourse
Segmentation	NER	Co-reference Resolution
POS	Disambiguation	Automatic Summarization
Parsing	Reasoning	Discourse Analysis

Framework


Speech Signal
Hypothesis
are there any action movies to see this weekend
Speech Recognition
Language Understanding (LU)
• Domain Identification
• User Intent Detection
• Slot Filling
Text Input
Are there any action movies to see this weekend?
Semantic Frame
request_movie
genre=action, date=this weekend
Dialogue Management (DM)
• Dialogue State Tracking (DST)
• Dialogue Policy
Natural Language Generation (NLG)
Text response
Where are you located?
System Action/Policy
request_location
Backend Action / Knowledge Providers

Domain Identification



Intent Detection

User

Play a rock song by Jay Chou

Music KB

MUSIC_PLAY

MUSIC_QA

MUSIC_PREFERENCE_MEMORY

Classification

Slot Filling

O O Genre O O Artist

User

Play a rock song by Jay Chou

Music KB

Music	Artist	Genre
Music 1	Jay Chou	jazz
Music 2	Jay Chou	rock

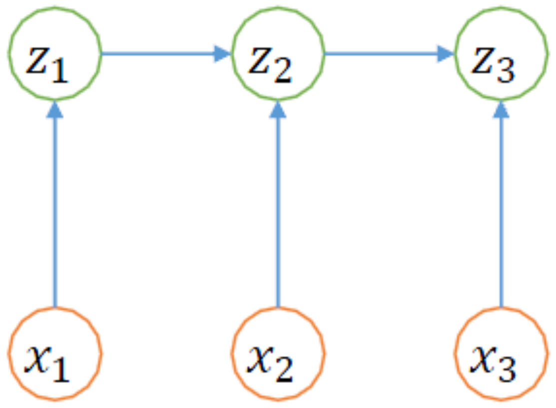
MUSIC_PLAY
Genre="rock"
Artist="Jay Chou"

Sequence Labeling

Slot Filling: CRF

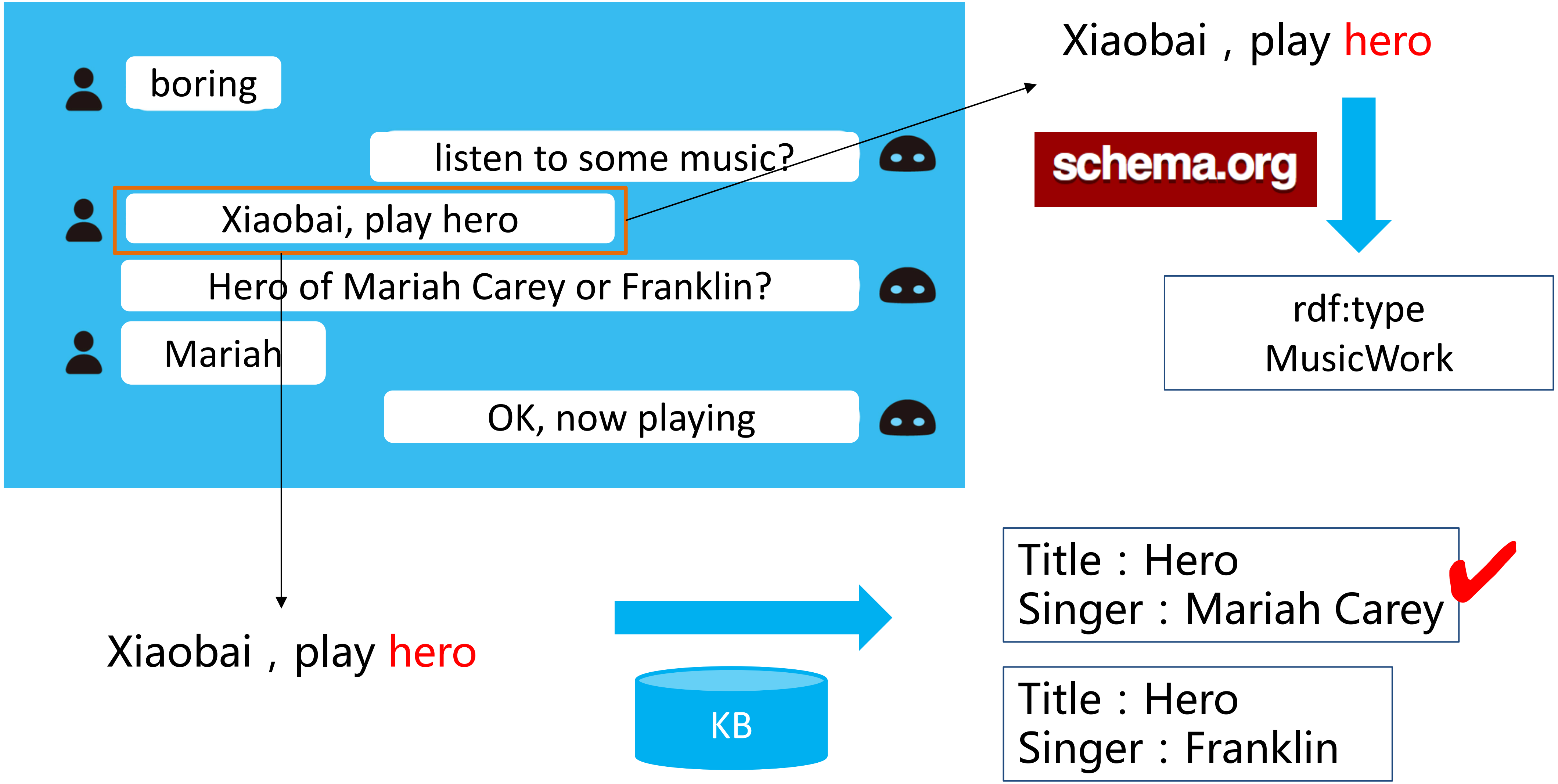
- $p(z_t|x_t, z_{t-1}) = \frac{1}{Z}\exp(\boldsymbol{w}_{z_t}^T f(z_{t-1}, z_t, x_t) + \boldsymbol{b}_{z_t})$
- $f(z_{t-1}, z_t, x_t)$ is the feature vector including state transition probability.
- CRF can model label transition probability, but it consider fixed window size.

Slot-filling	
Input: $\boldsymbol{X}_n$	IPhone **7**. **7** IPhones.
Output: $\boldsymbol{Z}_n$	IPhone{Brand} 7{Generation}. 7{Quantity} IPhones{Brand}



[Xu, et al. 2013]

NER+EL：NERL

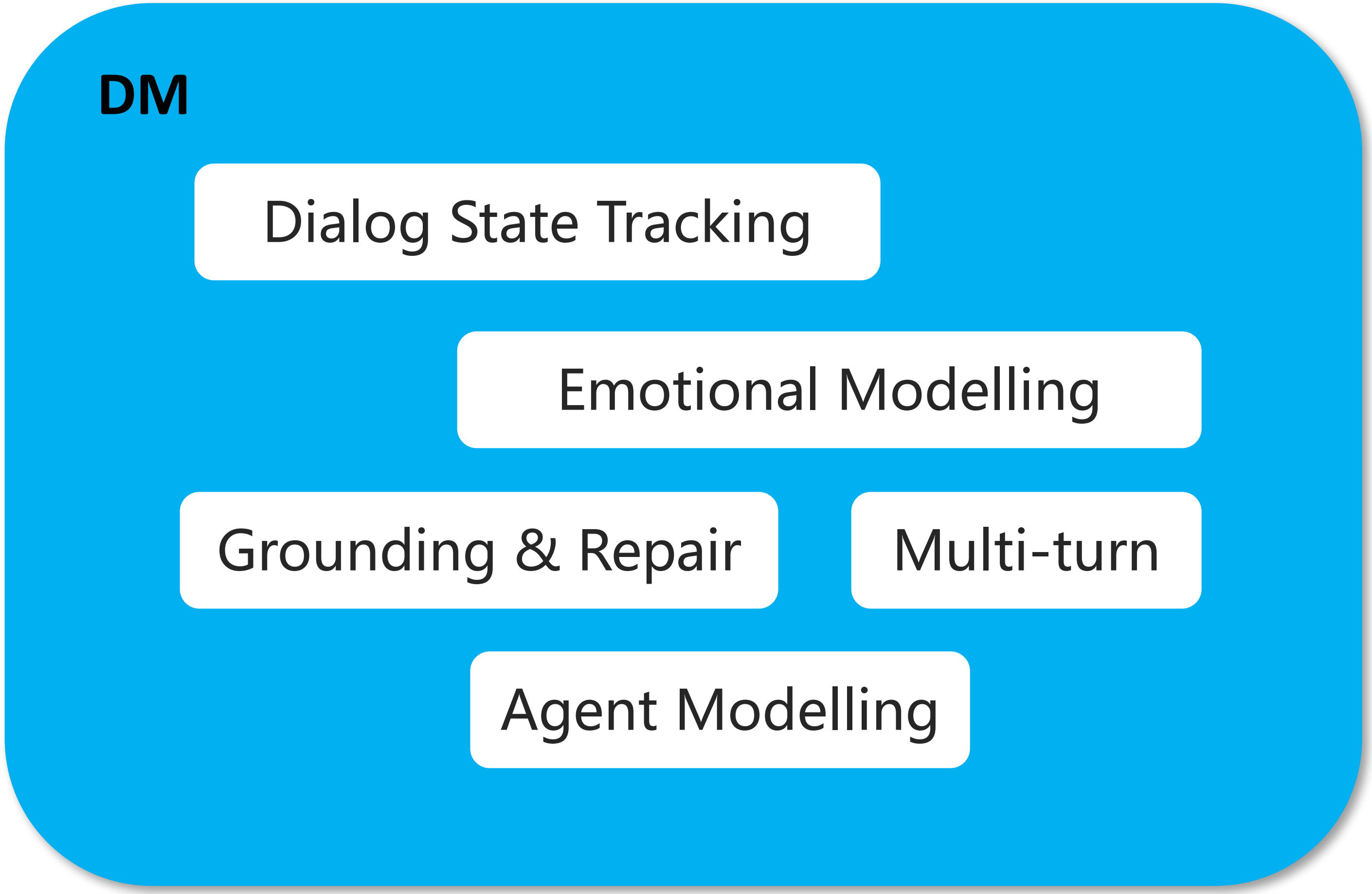

boring
listen to some music?
Xiaobai, play hero
Hero of Mariah Carey or Franklin?
Mariah
OK, now playing
Xiaobai，play hero
schema.org
rdf:type
MusicWork
Xiaobai，play hero
KB
Title：Hero
Singer：Mariah Carey
Title：Hero
Singer：Franklin

Challenges in NLU

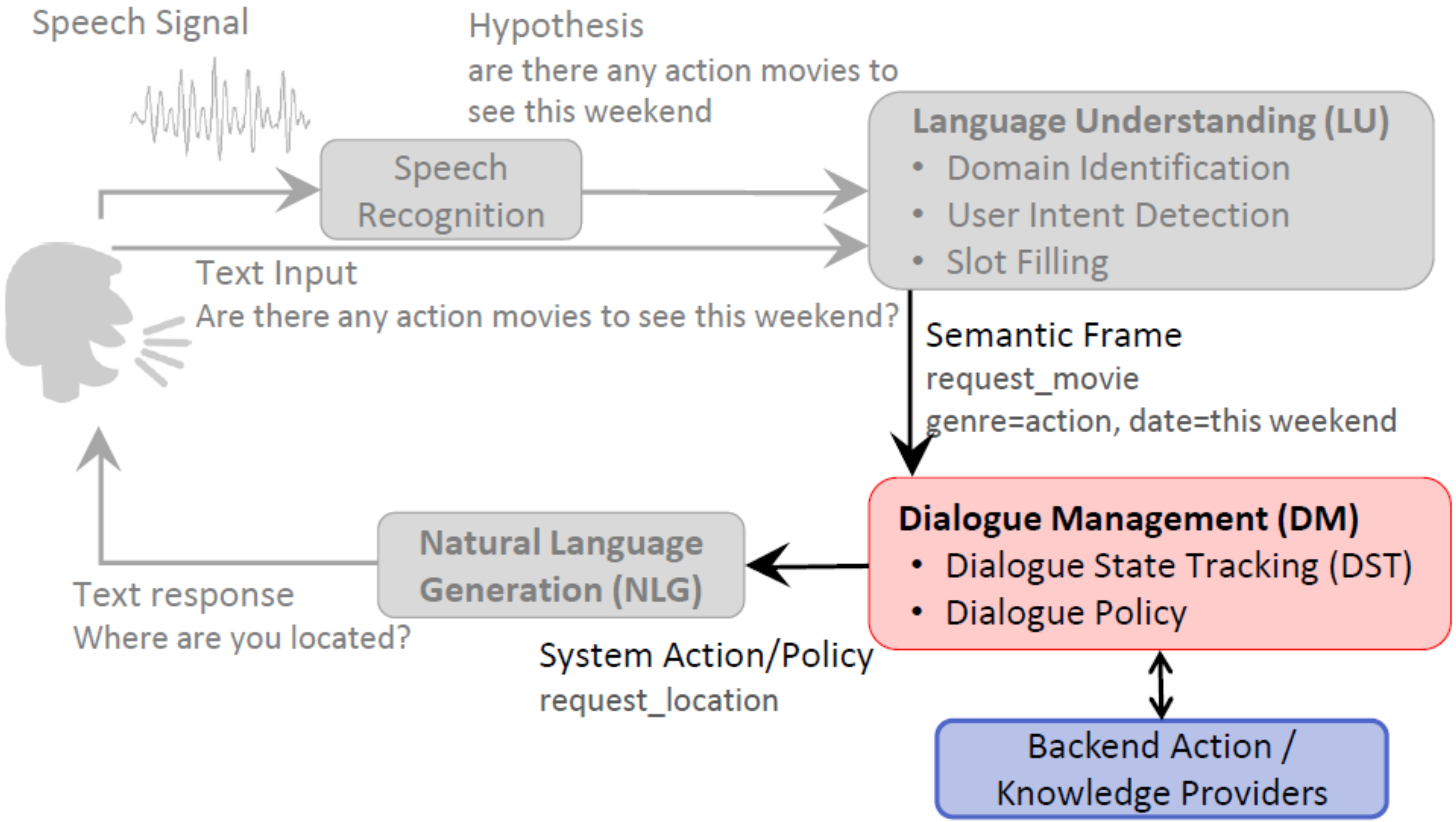
- Co-reference resolution and intention detection
- Variety of language meanings
- low quality of texts (short texts)
- ASR errors
- Difficult to find proper semantic representation

DM Dialogue Management

Update the dialogue state and decide what action(s) to perform



Framework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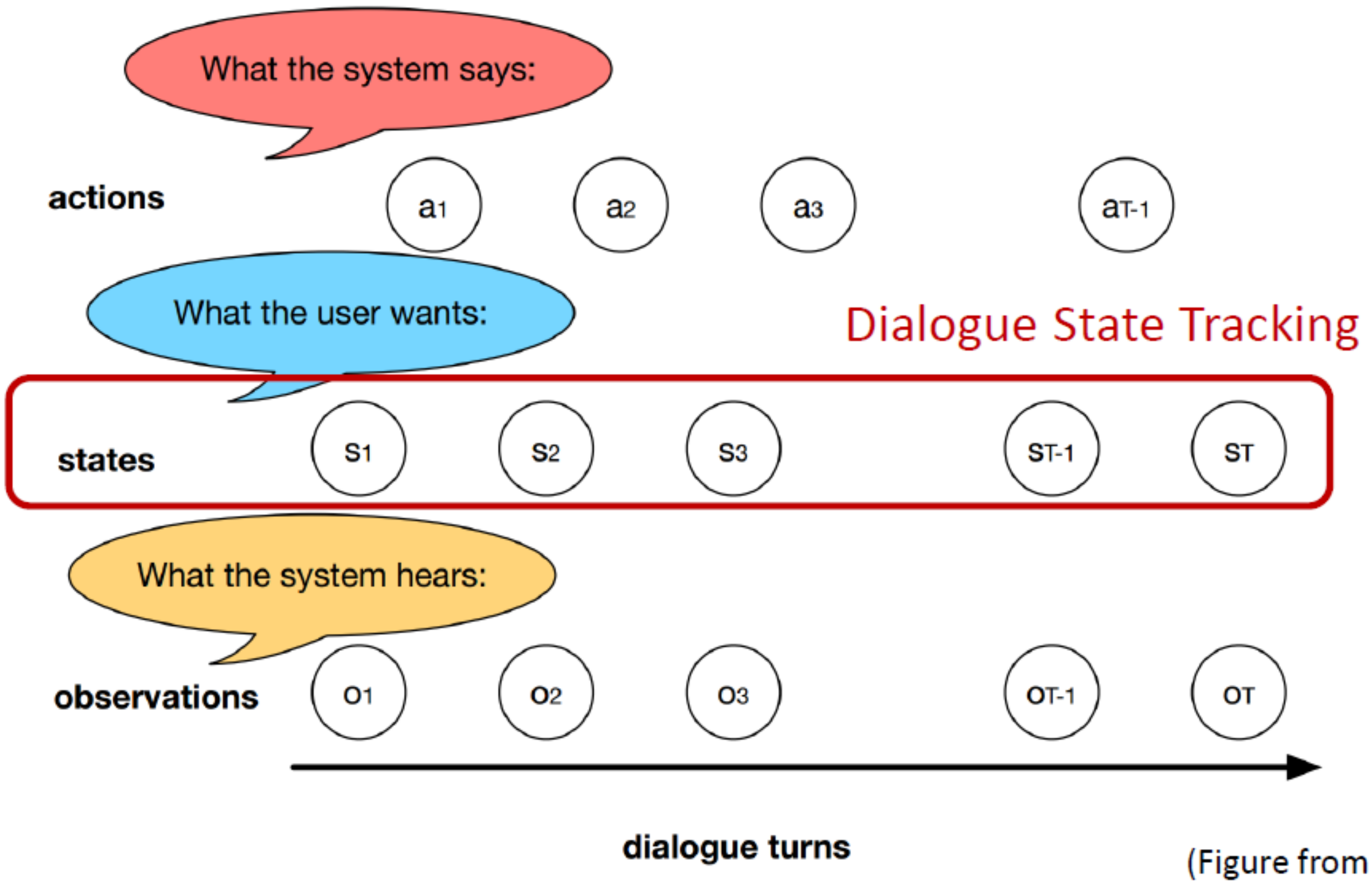
Elements of Dialogue Management



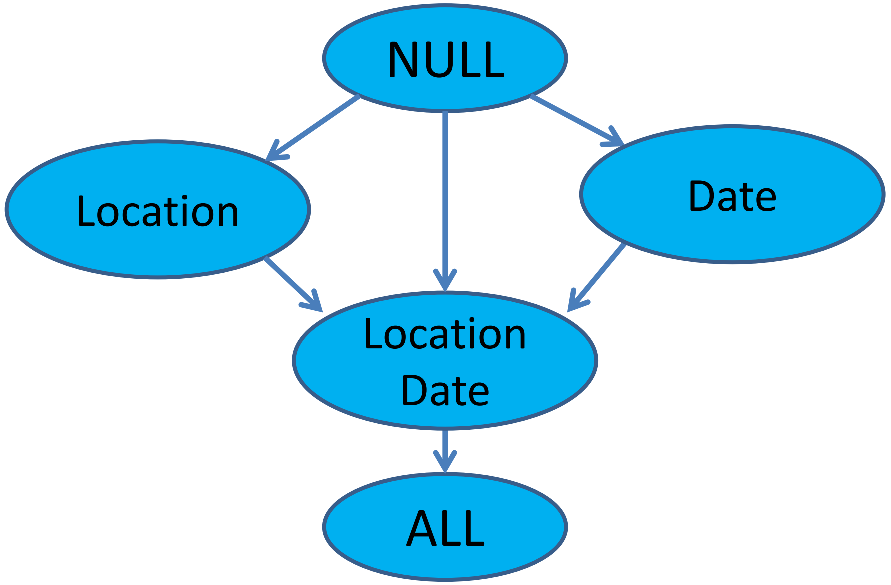
(Figure from Gašić)

Dialogue State Tracking

Hand-Crafted States

User

What's the weather in Gold Coast today?

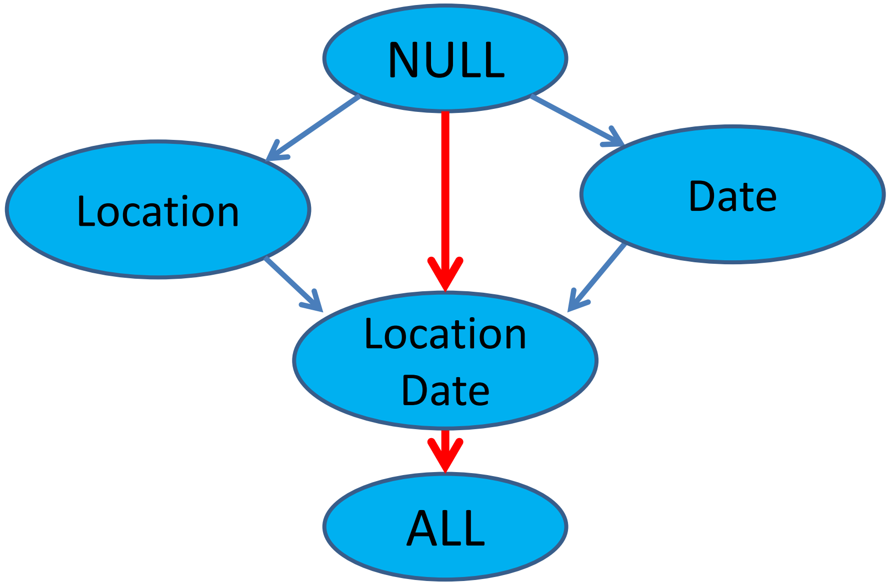


Dialogue State Tracking

Hand-Crafted States

User

What's the weather in Gold Coast today?



Dialogue State Tracking

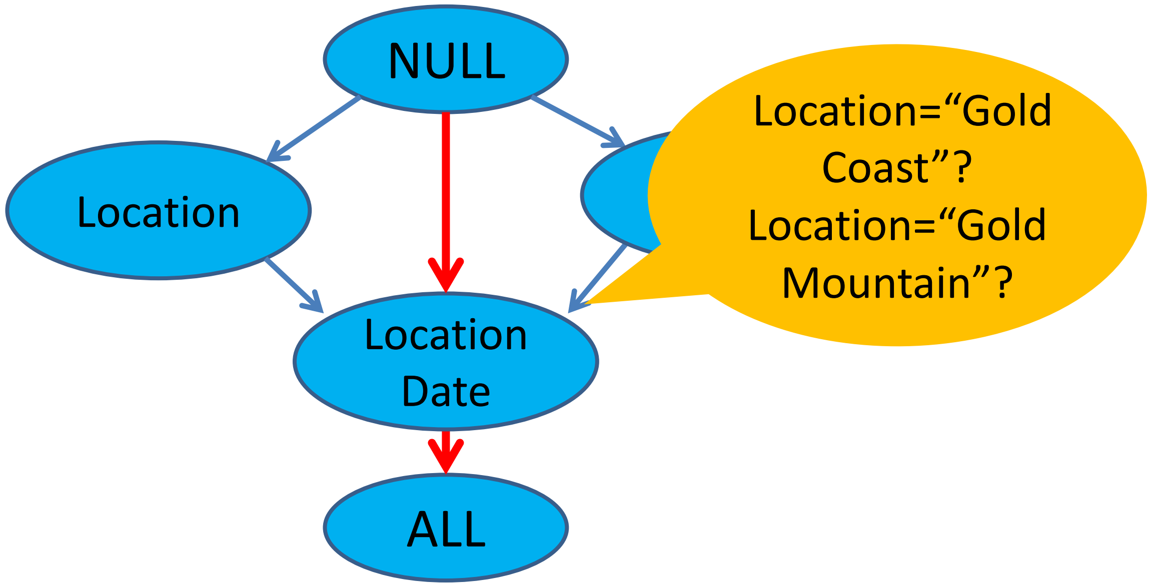
Handling Errors

User

What's the weather in Gold ??? today?

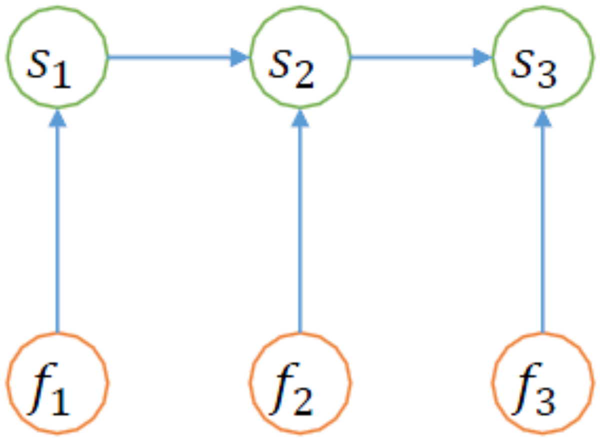
ASK_WEATHER
Date="today"
Location="Gold Coast"

ASK_WEATHER
Date="today"
Location="Gold Mountain"



Dialogue State Tracking: CRF

- $p(s_n|s_{n-1}, a_{n-1}, u_n) = \frac{1}{Z}\exp(\boldsymbol{w}_{s_n}^T f(s_{n-1}, s_n, a_{n-1}, u_n) + \boldsymbol{b}_{s_n})$
- $f(s_{n-1}, s_n, a_{n-1}, u_n)$ is the feature vector including state transition probability.

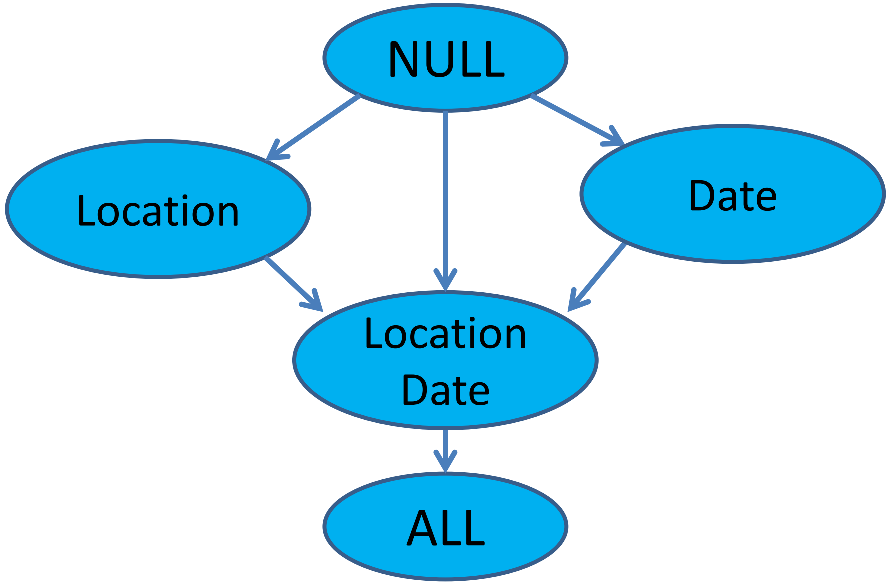


[Kim, et al. 2014]

DST	
Input: $\boldsymbol{s}_1$, $\boldsymbol{a}_1$, $\boldsymbol{u}_2$	$\boldsymbol{s}_1$={Category=Phone}
Output: $\boldsymbol{s}_2$	$\boldsymbol{s}_2$={Category=Phone, Brand=Apple}

	Phone Shopping Dialogue (X=customer, Y=system)
$\boldsymbol{X}_1$	I would like a new phone.
$\boldsymbol{Y}_1$	Which brand do you prefer?
$\boldsymbol{X}_2$	Apple.

DPL

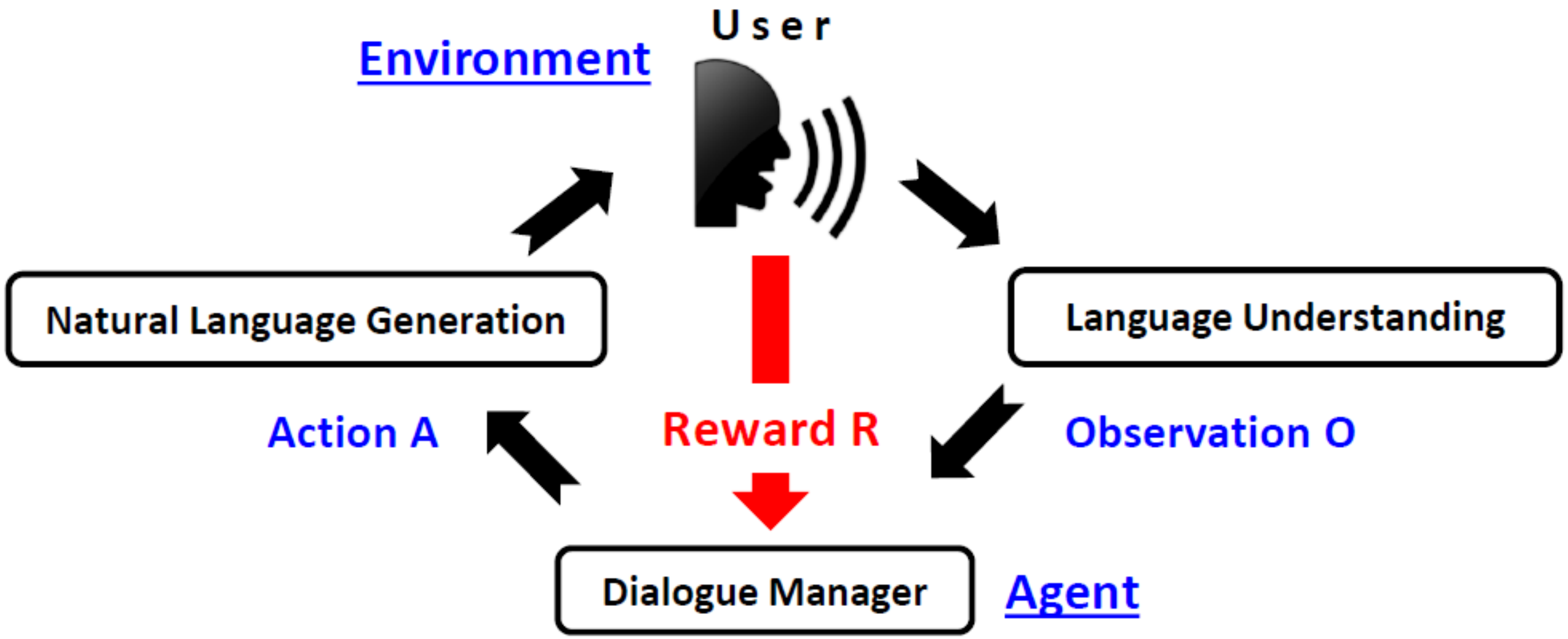


Hand-Crafted Actions:

- Request(location)
- Request(date)
- Inform(location="Gold Coast", date="today")

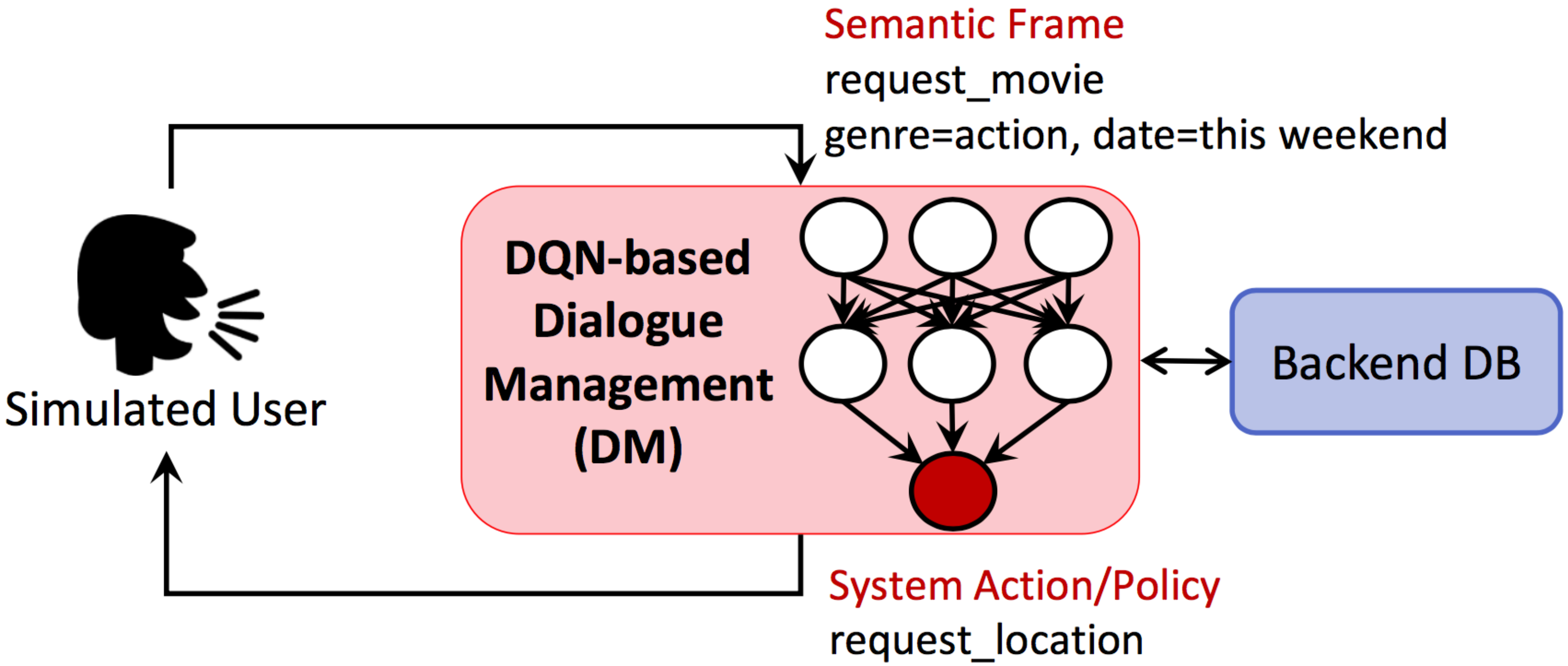
DPL

Dialogue management in a Reinforcement Learning (RL) framework



Neural Dialogue Manager

Deep Q-network for training DM policy



Challenges in DM

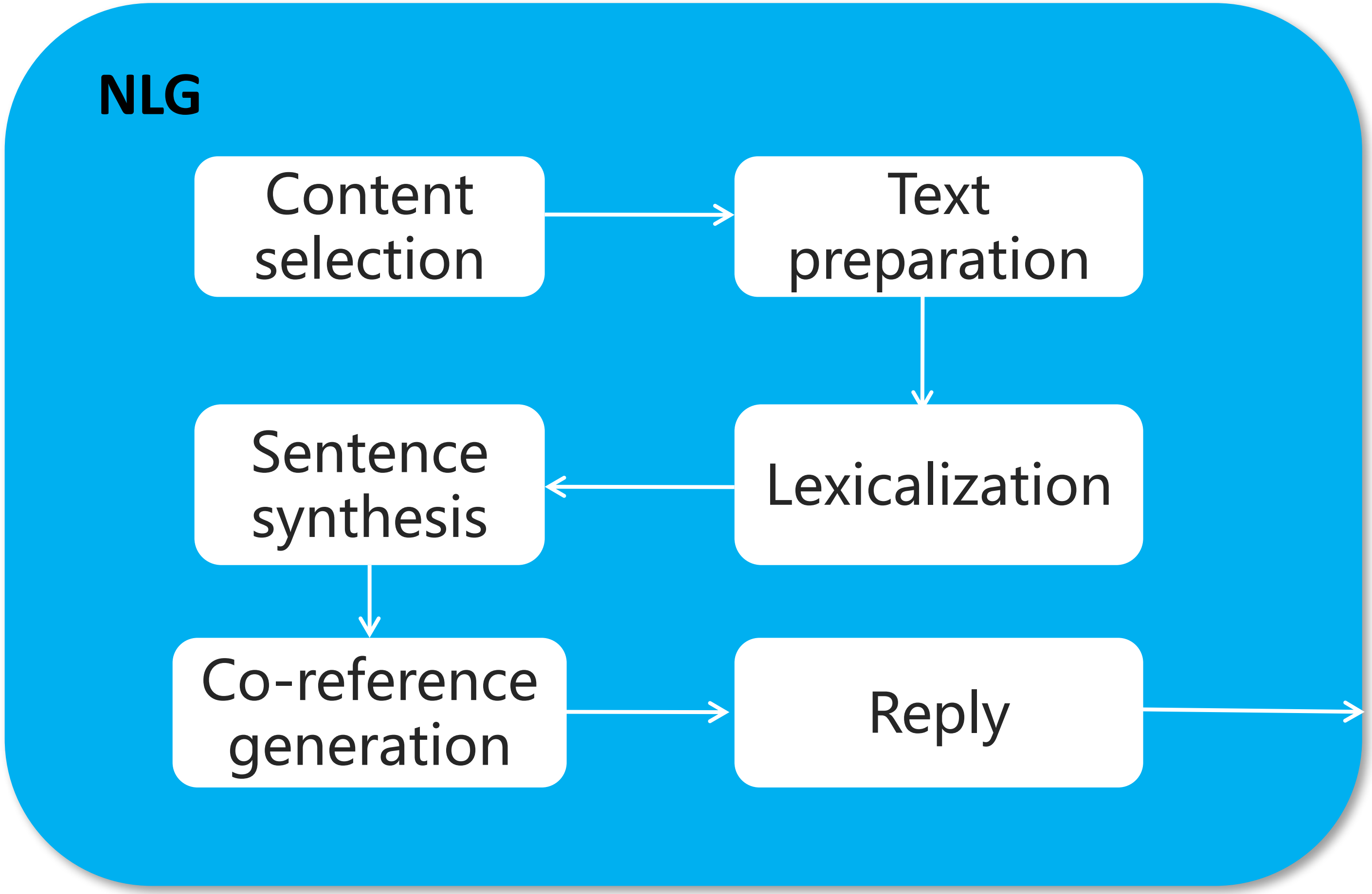
- Low coverage of heuristic dialog policy
- Massive dialog data needed for training due to state space explosion
- Domain knowledge and world knowledge are needed to guide meaningful replies

Trends in DM

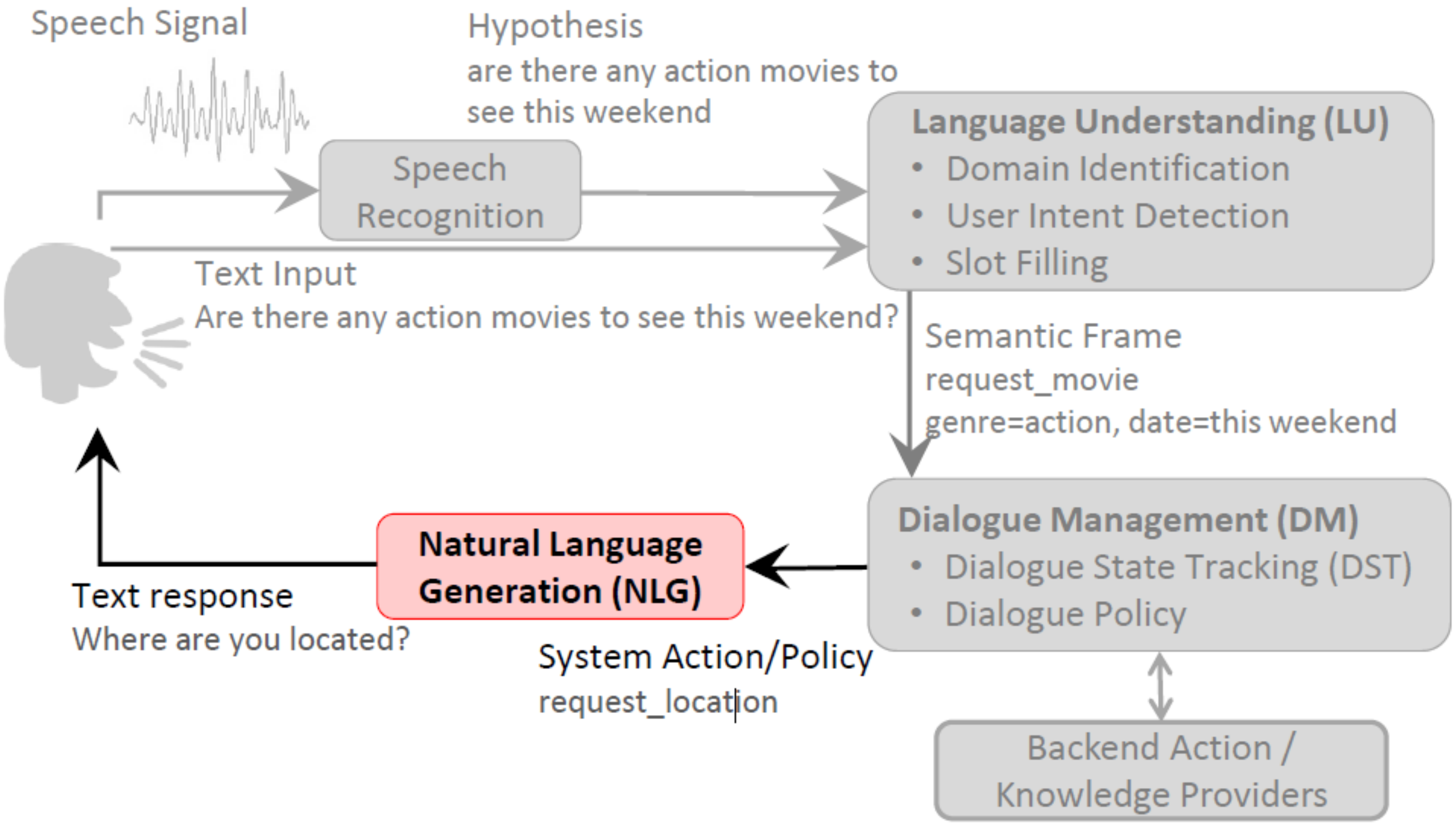
- One-shot Learning, Zero-shot Learning, for ”cold-start” problem
- (Deep) Reinforcement Learning
- seqGAN

NLG Natural Language Generation

Find the best linguistic realization for the selected action(s)



Framework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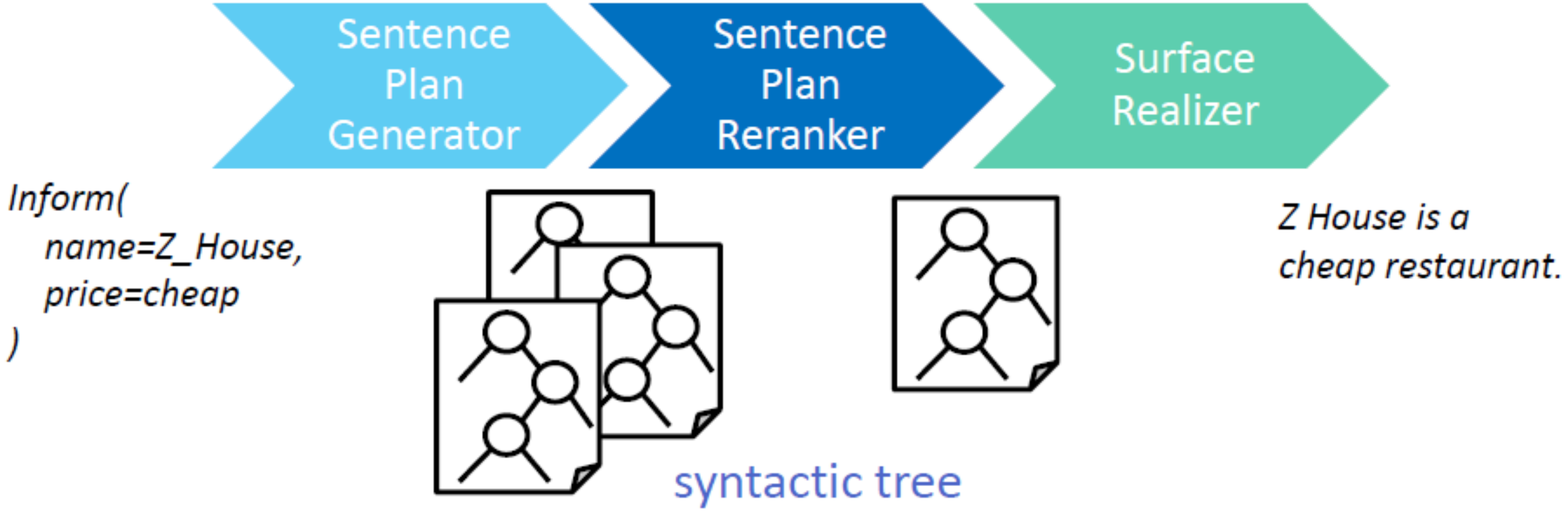
NLG: Plan Based Approach

Divide the problem into pipeline



[Walker, et al. 2002]

NLG: Template Based Approach

Define a set of rules to map frames to NL

Semantic Frame	Natural Language
confirm()	"Please tell me more about the product your are looking for."
confirm(area=$V)	"Do you want somewhere in the $V?"
confirm(food=$V)	"Do you want a $V restaurant?"
confirm(food=$V,area=$W)	"Do you want a $V restaurant in the $W."

Natural Language Generation

Hand-Crafted Actions:

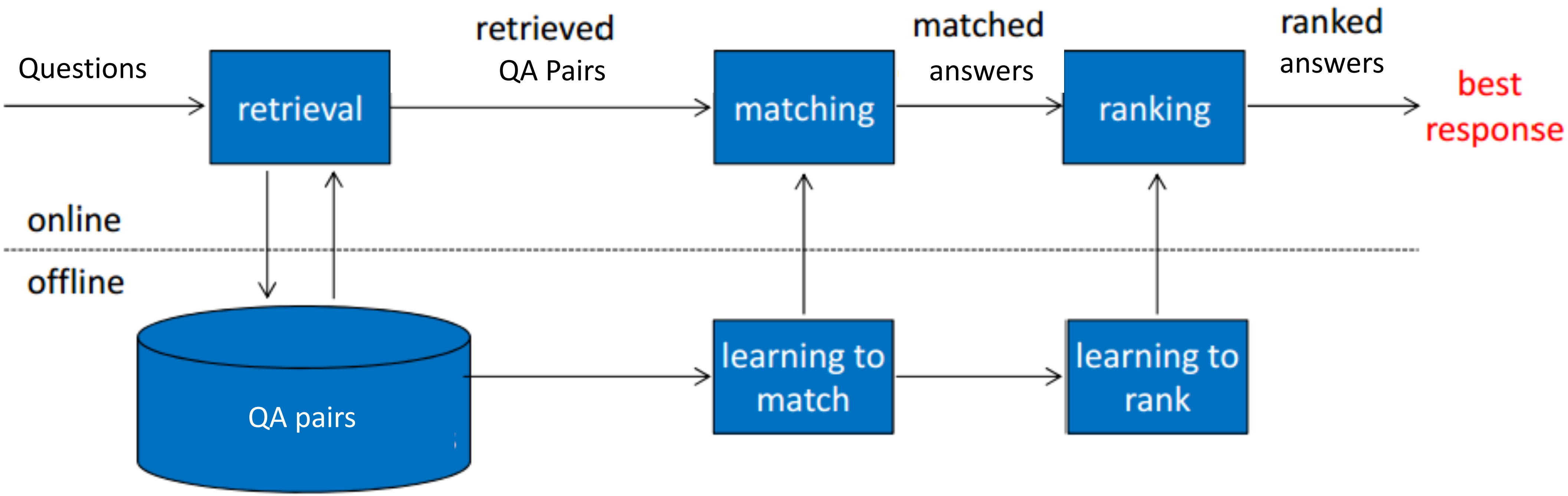
- Request(location)

  “Where is your location?”
- Request(date)

  “Which day?”
- Inform(location=“Gold Coast”, date=“today”)

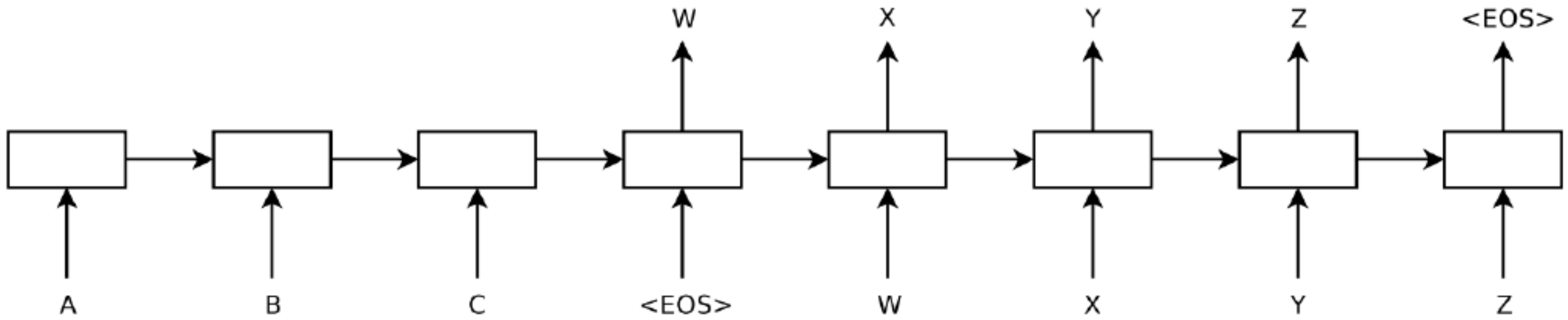
  “Today’s weather in Gold Coast is sunny”

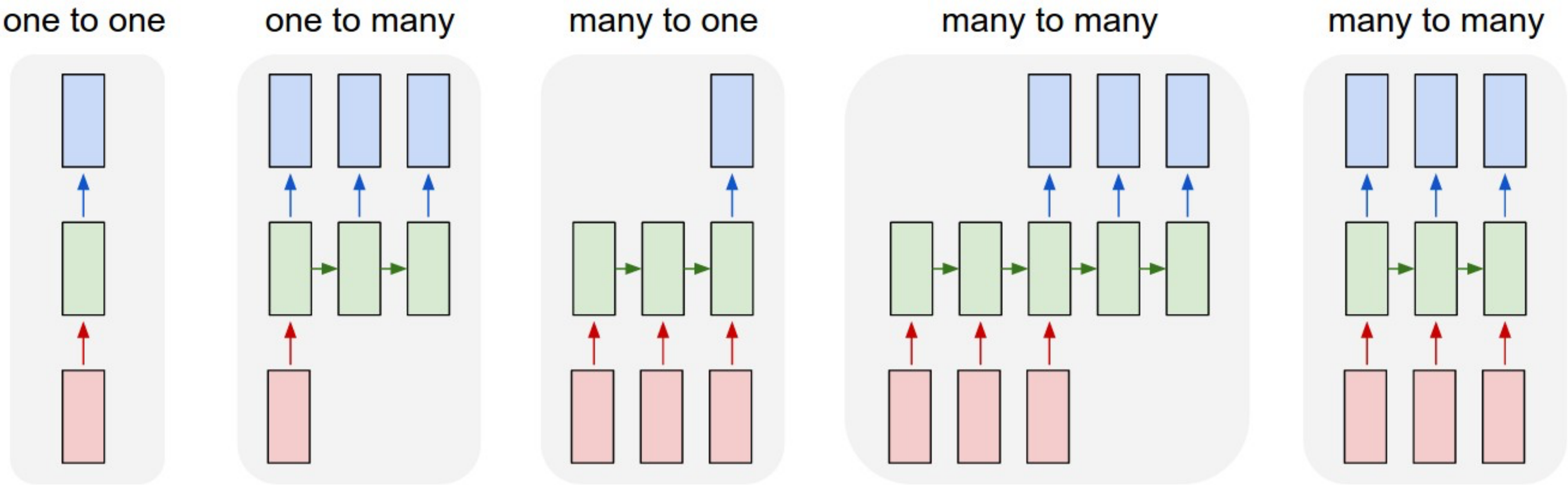
NLG: Retrieval-based Approach



[Ji, et al. 2014]

NLG: Generation-based Approach





From：Andrej Karpathy

Pros and Cons

Retrieval-based Approach

Pros：
- Good readability
- Good diversity with large datasets
- Easy to analyze and debug

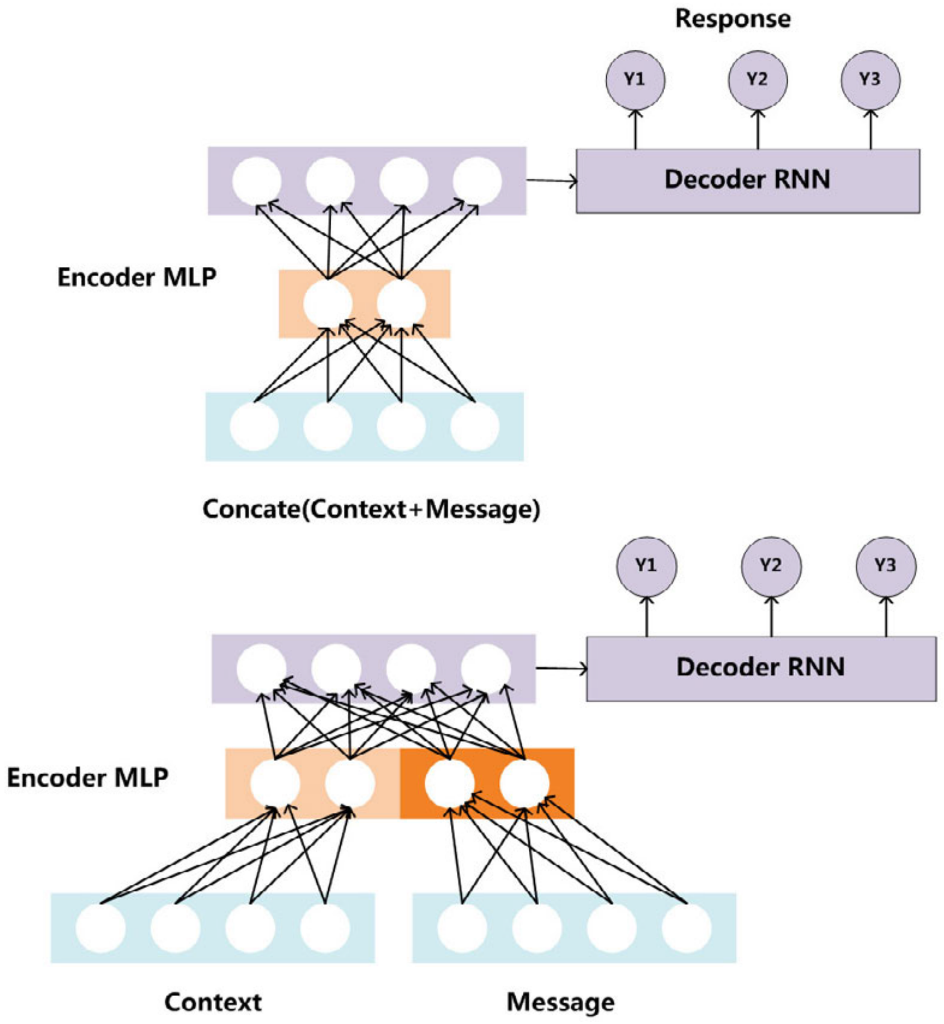
Cons：
- Candidate selection
- Candidate ranking

Generation-based Approach

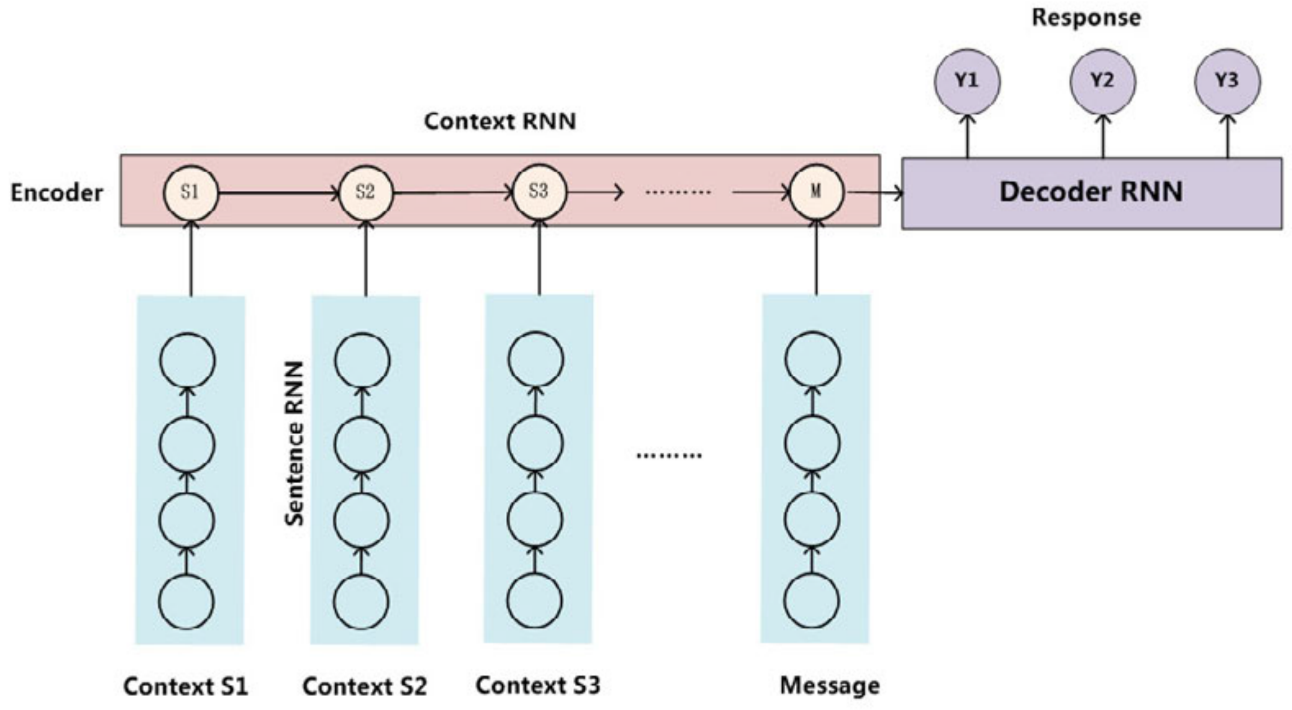
Pros：
- Easy implementation
- Avoid cost to maintain a huge QA set
- E2E solution with no additional subtasks

Cons：
- Readability
- Diversity

Multi-turn



[Sordoni, et al. 2015]



[Serban, et al. 2015]

Safe response

$$\hat{R} = \arg\max_{R}\{\log p(R \mid M)\}$$

$$\hat{R} = \arg\max_{R}\{(1-\lambda)\log p(R \mid M) + \lambda \log p(M \mid R)\}$$

Message	S2S Response	MMI Response
How much time do you have here?	I don’t know	Not long enough. Sorry, sir
I mean, we’d have to talk to him	I mean, I don’t know	I mean, he’s a good guy
I am ready to help	Come on, come on	I have something we need to talk about
I am losing my grip	I don’t know what you are talking about	I’m the only one in the world

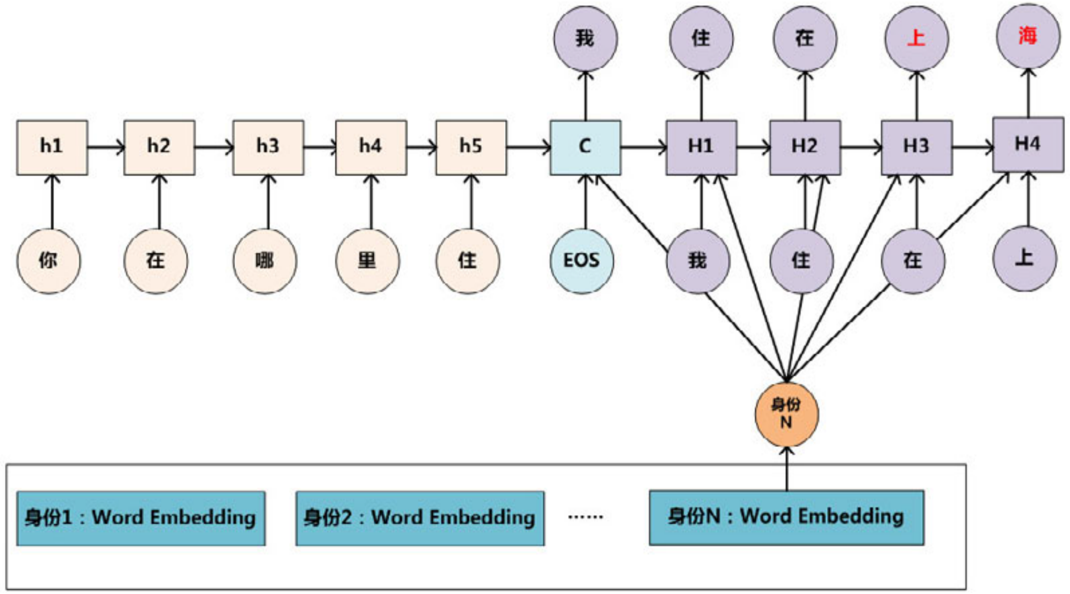
[Li, et al. 2015]

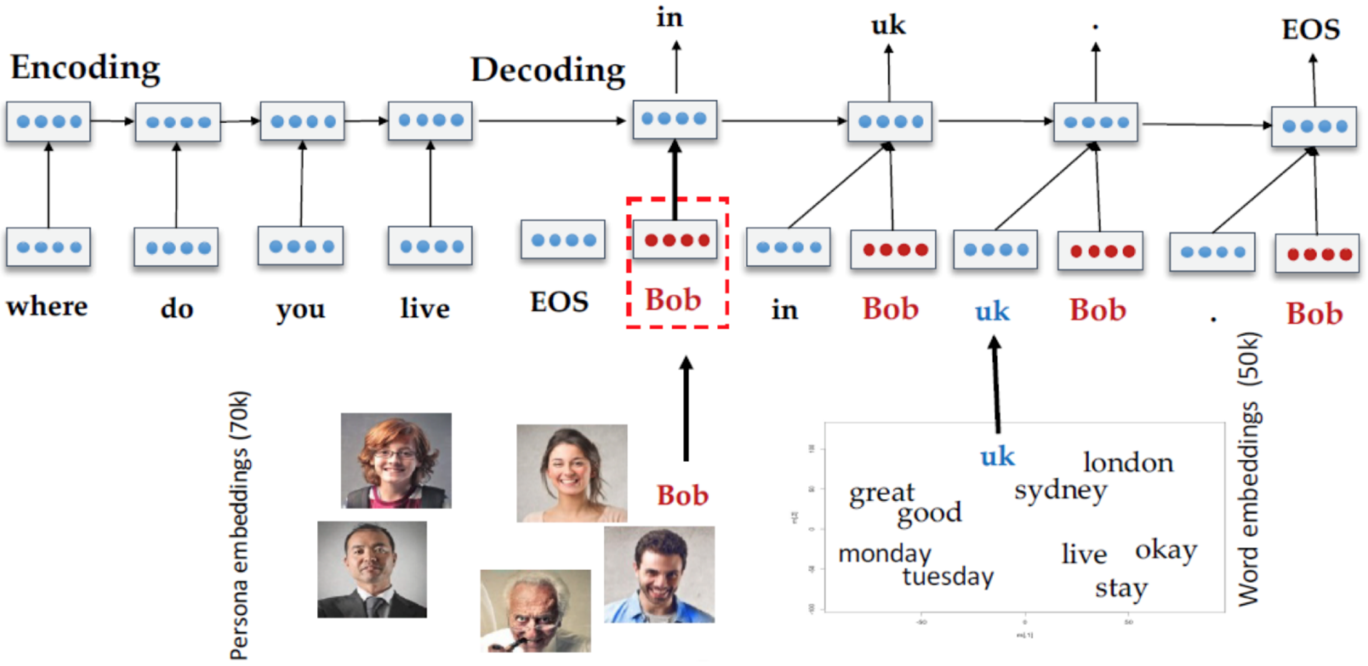
Coherent Personality

message	Where do you live now?
response	I live in Los Angeles.
message	In which city do you live now?
response	I live in Madrid.
message	In which country do you live now?
response	England, you?
message	Where were you born?
response	I was born in Canada.
message	Where are you from?
response	England, you?
message	Where did you grow up?
response	I grew up in Texas.
message	How old are you?
response	16 and you?
message	What's your age?
response	18
message	What is your major?
response	I'm majoring in psychology
message	What did you study in college?
response	English lit.

Agent modelling

User modelling





[Li, et al. 2016]

Challenges in NLG

- Large search space
- Context modeling
- Hard interpretation of deep learning results

Trends in NLG

- Personality modeling & Context modeling
- Memory Network & Attention Models

Open Challenges in Chatbots

- Long vs. Short Conversations
- Open Domain and Closed Domain
- Incorporating Context
- Coherent Personality
- Intention and Diversity
- Emotion
- Evaluation and Benchmark

References

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02

Knowledge Graph

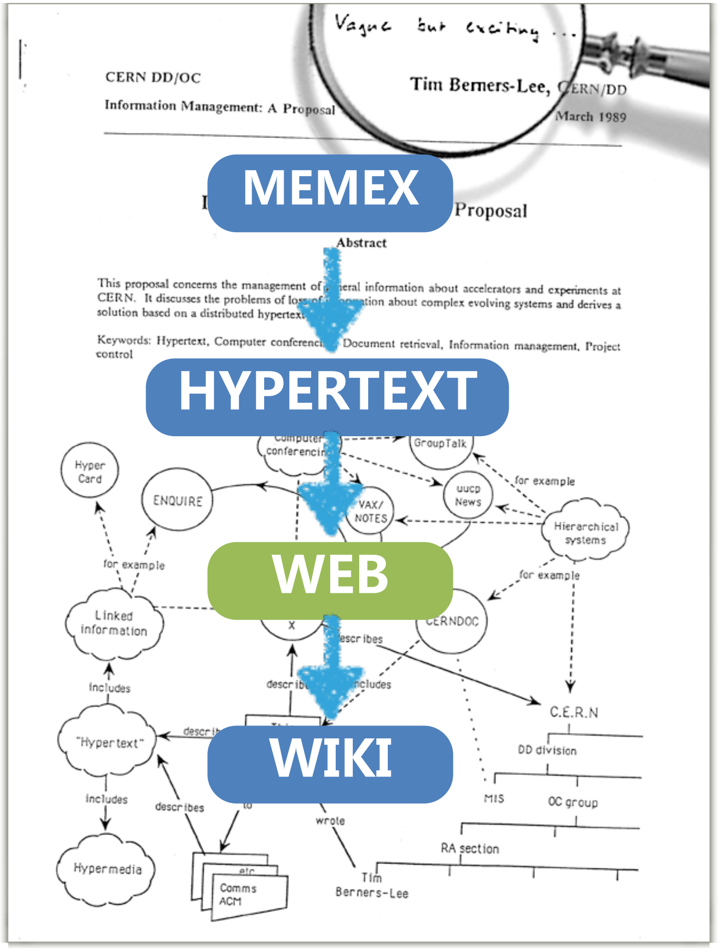
1.1 KG Definition

1.2 The Scenarios of KG

1.3 Representative KGs

Web- Linked Information System

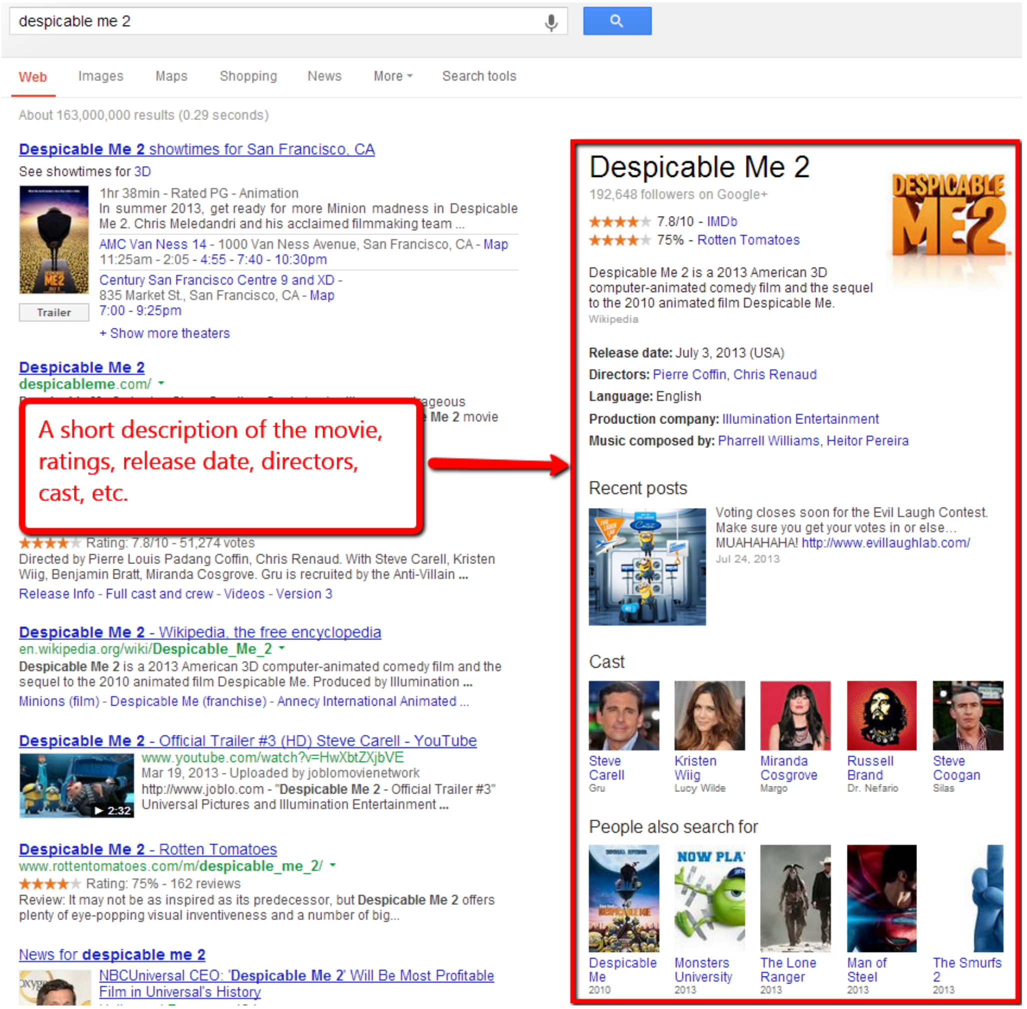
Linked Information System

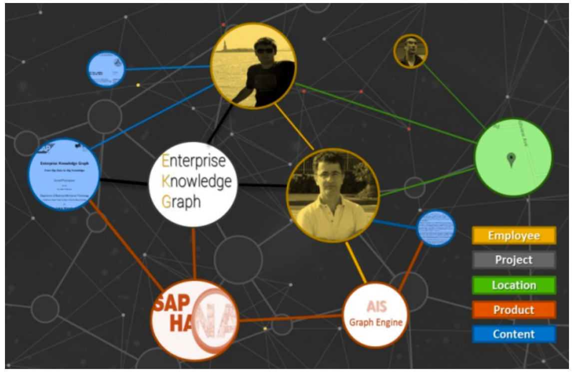


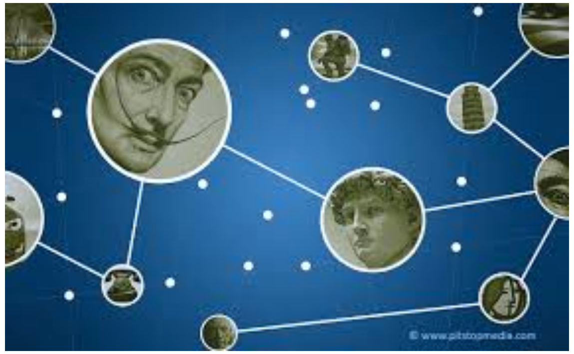
…This is why a "web" of notes with links between them is far more useful than a fixed hierarchical system. …… Circles and arrows leave one free to describe the interrelationships between things in a way that tables, for example, do not. The system we need is like a diagram of circles and arrows, where circles and arrows can stand for anything.

Information Management: A proposal 1989.

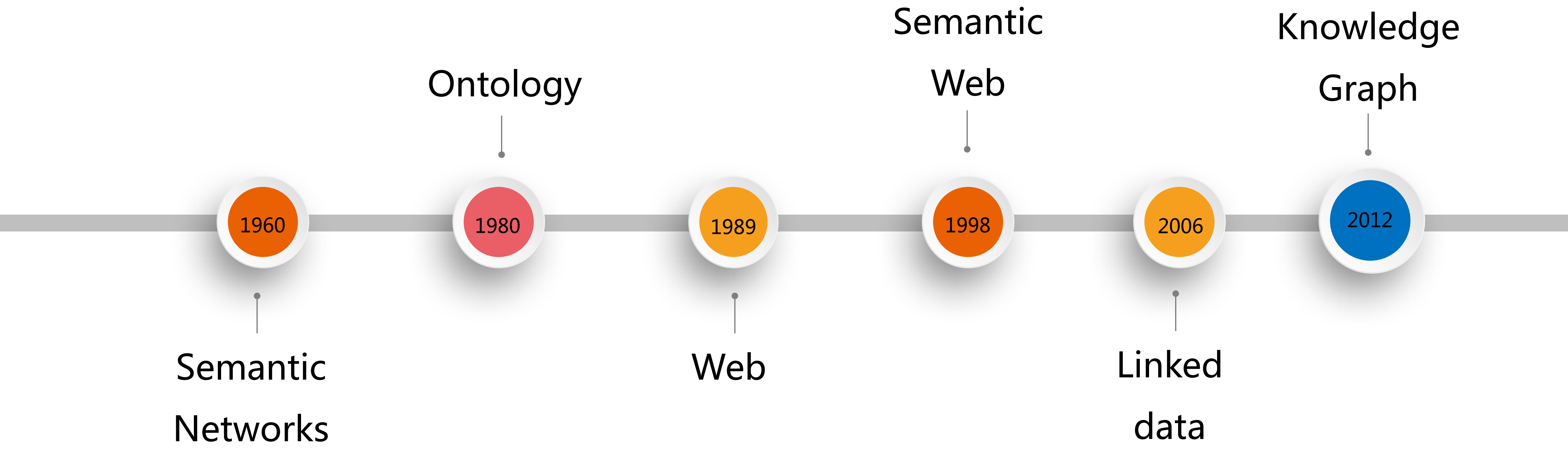
Google Knowledge Graph: Things not Strings







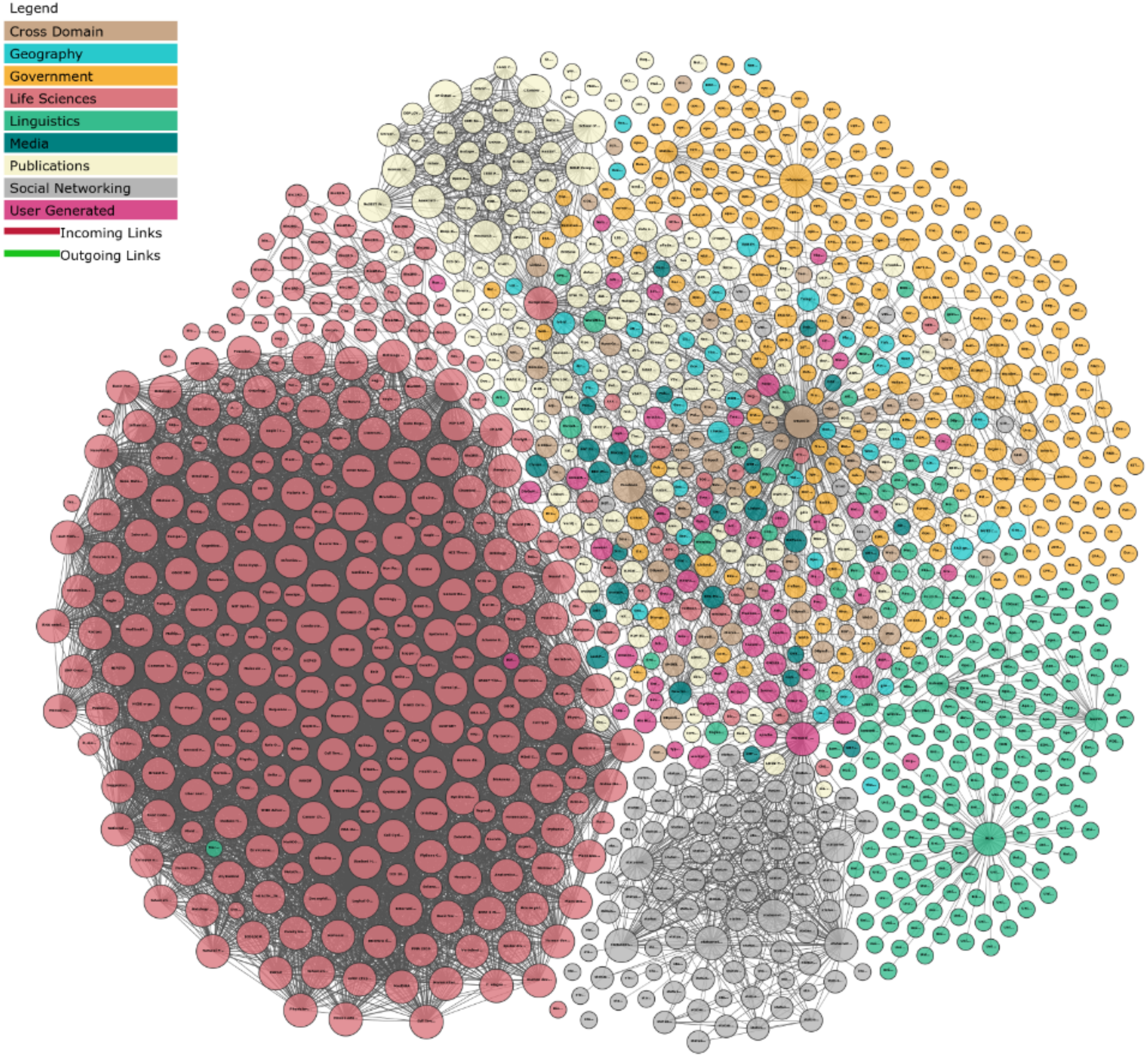
KG History



Knowledge representation and knowledge base

Multi-views of KG

- Web: create semantic links for data
- NLP: extract semantic and structured data from text
- KR: knowledge representation and processing via computers
- AI: human language understanding using KB
- DB: using graph database to store knowledge



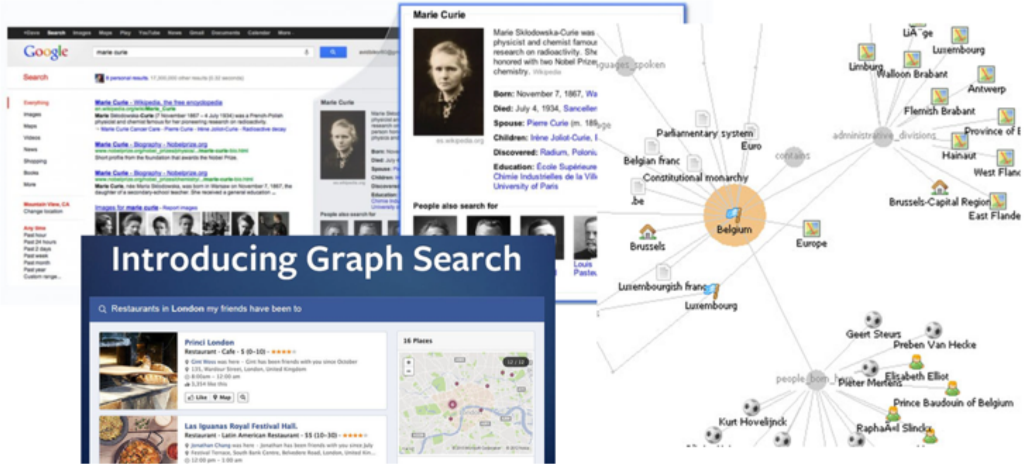
"Linking Open Data cloud diagram 2017, by Andrejs Abele, John P. McCrae, Paul Buitelaar, Anja Jentzsch and Richard Cyganiak. http://lod-cloud.net/"

02 Knowledge Graph

KG for Searching

WEB SEARCH

SEMANTIC SEARCH



Web of Docs

Web of Data

Crowdsourcing

Transformation

Fusion

Link prediction

reasoning

Freebase

WIKIDATA

schema.org

....the new SEO?

KG for QA

KG provides background knowledge bases for intelligent Bots and IOT devices

IBM Watson

DBpedia Yago

Wordnet

amazon alexa

True Knowledge/Evi

Siri

WolframAlpha

DBpedia

zhishi.me

……

……

……

DUEROS

Conversational AI OS for everyone and everywhere

KG for Decision Making

MORE MACHINE UNDERSTANDABLE

Data link

Semantic extraction

Knowledge representation

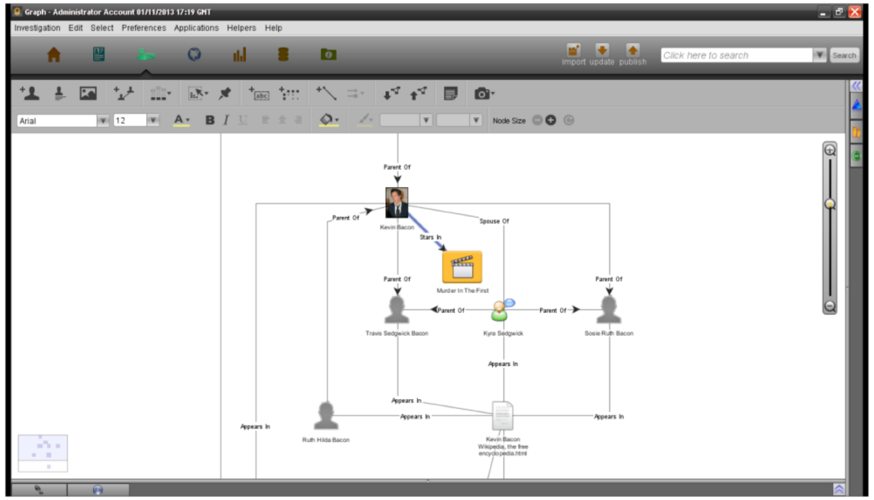
Computable data

Coarse data

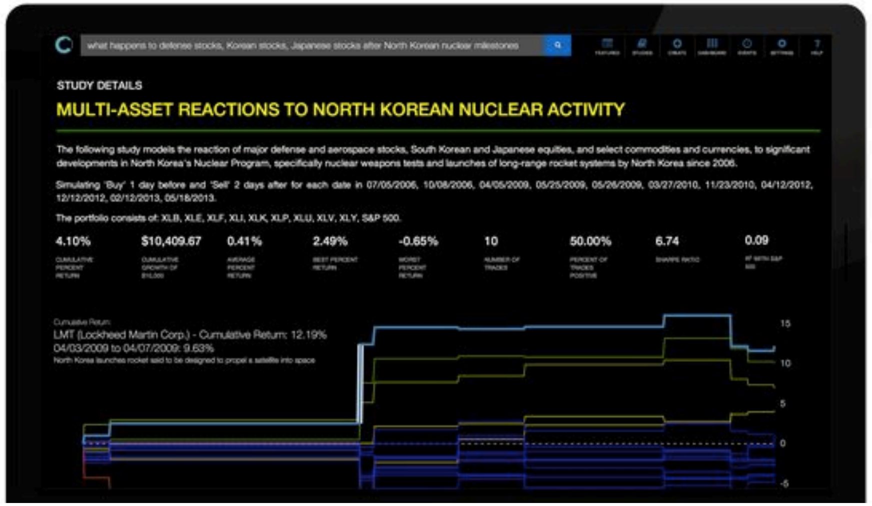
text

multimedia

sensor



PALANTIR



KENSHO

KG for Common Sense Reasoning

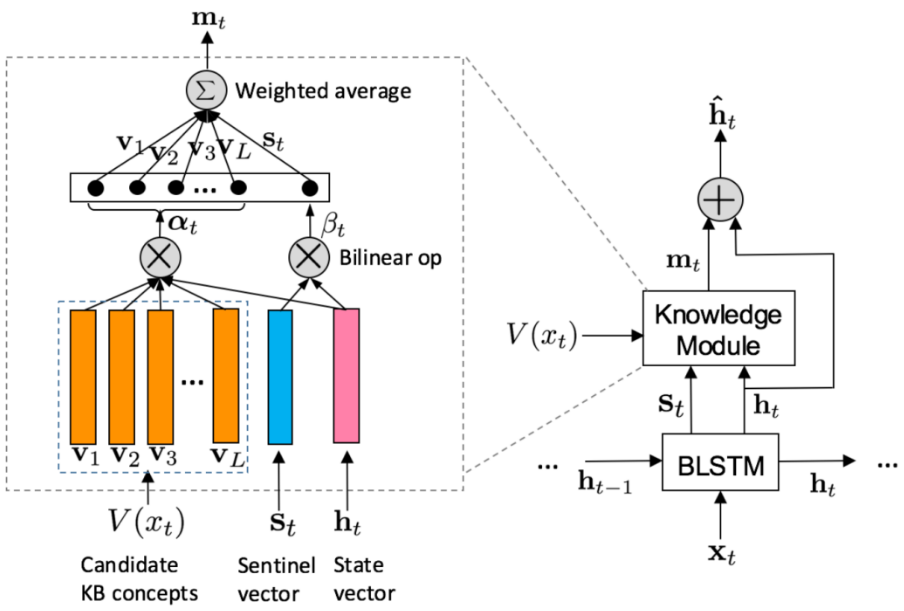
Winograd Schema Challenge

I. The trophy would not fit in the brown suitcase because **it** was too **big (small)**. What was too **big (small)**?
Answer 0: the trophy Answer 1: the suitcase
II. The town councilors refused to give the demonstrators a permit because **they** **feared (advocated)** violence. Who **feared (advocated)** violence?
Answer 0: the town councilors Answer 1: the demonstrators

NLP：50% → **NLP+KB：>60%** → **Pass line：90%**

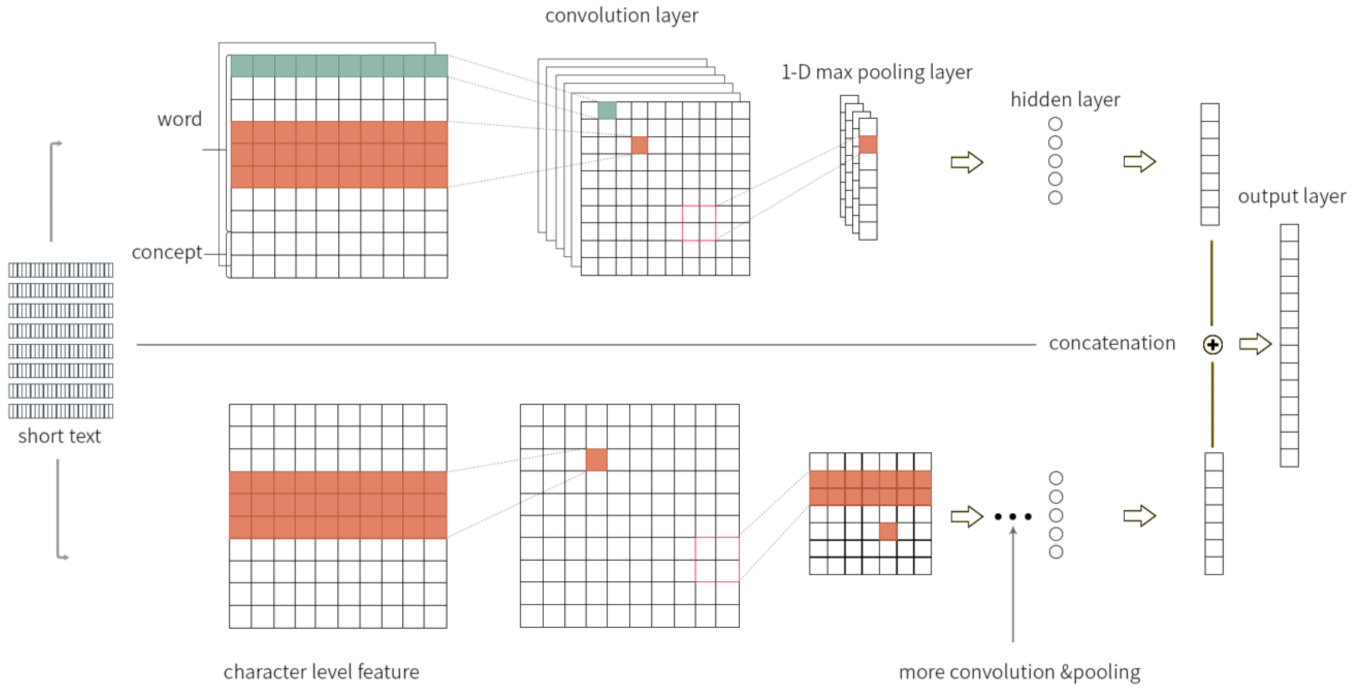
KG for Machine Reading

Improve machine reading tasks (entity extraction, event extraction) with KG and DNN.



[Yang, et al. 2017]

Improve short-text classification, by regarding concept knowledge as the inputs of neural networks



[Wang, et al. 2017]

Smart AI vs. Knowledgeable AI

Gowild

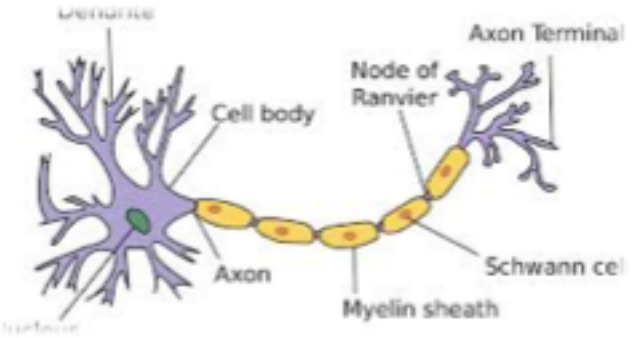
Deep Learning

Smart AI

perception

recognition

judgment



Human brain can conduct reasoning and understanding based on acquired knowledge

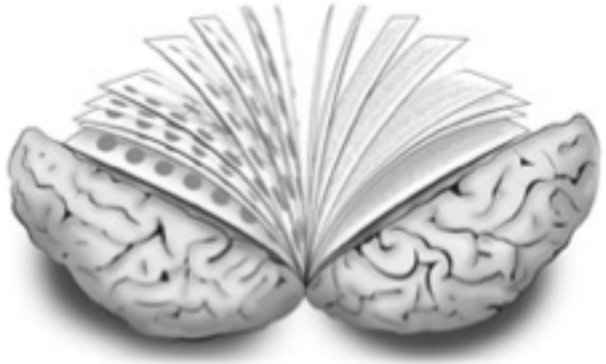
Knowledge Graph

Knowledgeable AI

thinking

language

reasoning



KG for AI: Unknown Difficulties

- Does symbolic memory of human continuous?
  - Is it necessary for vectorization of knowledge representation?
- Does symbolic memory of human structural?
- What is the acquisition and reasoning process of symbolic memory?

02 Knowledge Graph

1.1 KG Definition

1.2 The Scenarios of KG

1.3 Representative KGs

Open KGs

Freebase

LINKINGOPENDATA
W3C SWEO Community Project

WordNet
A lexical database for English

NELL

ZHISHI.me

PKUBASE

schema.org
....the new SEO?

XLORE

WIKIDATA

WEB CHILD

DBpedia

CN-DBpedia

ConceptNet
An open, multilingual knowledge graph

Herbnet

yago
select knowledge

LinkedGeoData.org

WEBKB

linked life data

Freebase

Free, and commercial open license agreements are allowed

METAWEB

develop

Freebase

Open society

Open data source

Open web extraction

buy

Google

Wikidata

With the objective to build the largest free knowledge base

WIKIMEDIA FOUNDATION

WIKIDATA

Crowdsourcing society

funding

funding

funding

Google

Moore Foundation

Allen AI Institute

Schema.org

semantic markup: semantic data embedded in web, email and applications.

```
<p>Big (1988) is a fantasy comedy movie starting Tom
Hanks and directed by Penny Marshall.</p>
```

```
<div itemscope itemtype="http://schema.org/Movie"><p>
    <span itemprop="name">Big </span> (1988) is a
    <span itemprop="genre">fantasy comedy</span> movie starting
    <span itemprop="actor" itemscope itemtype="http://schema.org/Person">
    <span itemprop="name">Tom Hanks</span></span> and directed by
    <span itemprop="director" itemscope itemtype="http://schema.org/person">
        <span itemprop="name">Penny Marshall</span></span>.</p></div>
```

Search Engine Optimization

Open domain only

642 classes, 992 relations

ConceptNet

Originated from Open Mind Common Sense project by Professor Marvin Minsky from MIT

In early versions, data is collected by experts, crowdsourcing and game.

latest version includes open domain strucutred data, including DBPedia, Wikinary, and Wordnet

References

- [Yang, et al. 2017] Yang, B., & Mitchell, T. M. (2017). Leveraging Knowledge Bases in LSTMs for Improving Machine Reading. Association for Computational Linguistics, 1436–1446.
- [Wang, et al. 2017] Wang, J., Wang, Z., Zhang, D., & Yan, J. (2017). Combining Knowledge with Deep Convolutional Neural Networks for Short Text Classification. IJCAI2017

03

KG + Chatbot

3.1 QA Introduction

3.2 Knowledge Based Question Answering (KBQA)

3.3 KBQA Applications in Chatbot

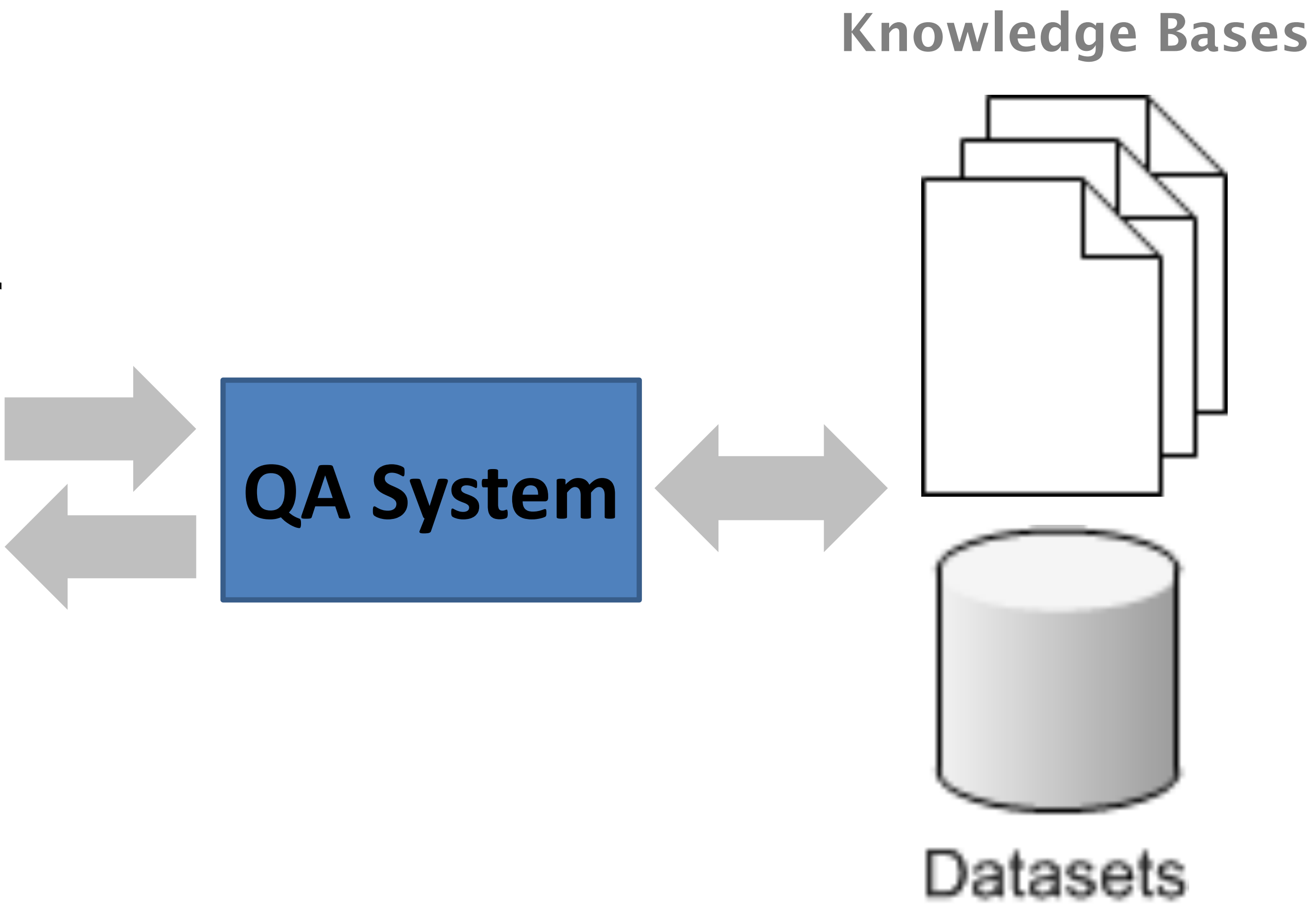
Why Question Answering

- Humans are built-in with natural language communication capabilities.
- Very natural way for humans to communicate information needs.
- The archetypal AI system.

What is Question Answering?

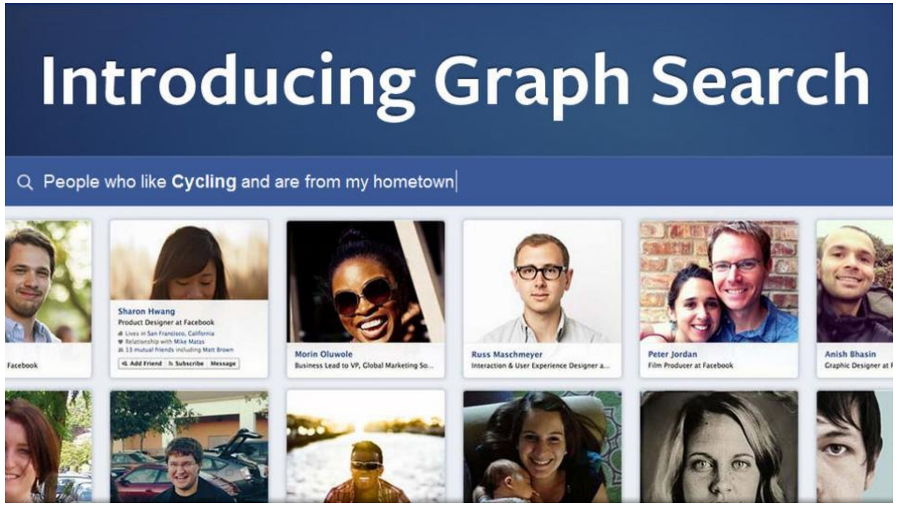
Question: **Who is the daughter of Bill Clinton married to?**

Answer: **Marc Mezvinsky**

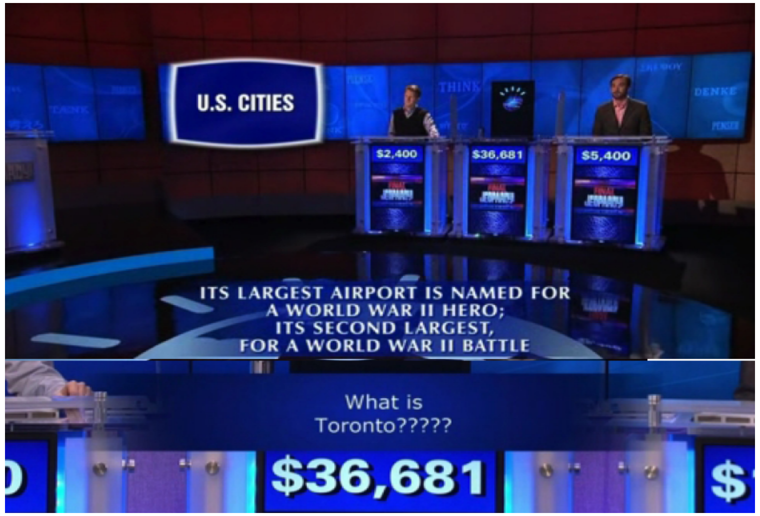


QA: Reality

Google



FB Graph Search



Watson

Siri

03 KG + Chatbot

3.1 QA Introduction

3.2 Knowledge Based Question Answering (KBQA)

3.3 KBQA Applications in Chatbot

QA Classification

Gowild

IR-based QA	Community QA	KB-based QA（KBQA）

YAHOO! ANSWERS

Bai du 知道

WolframAlpha computational knowledge engine

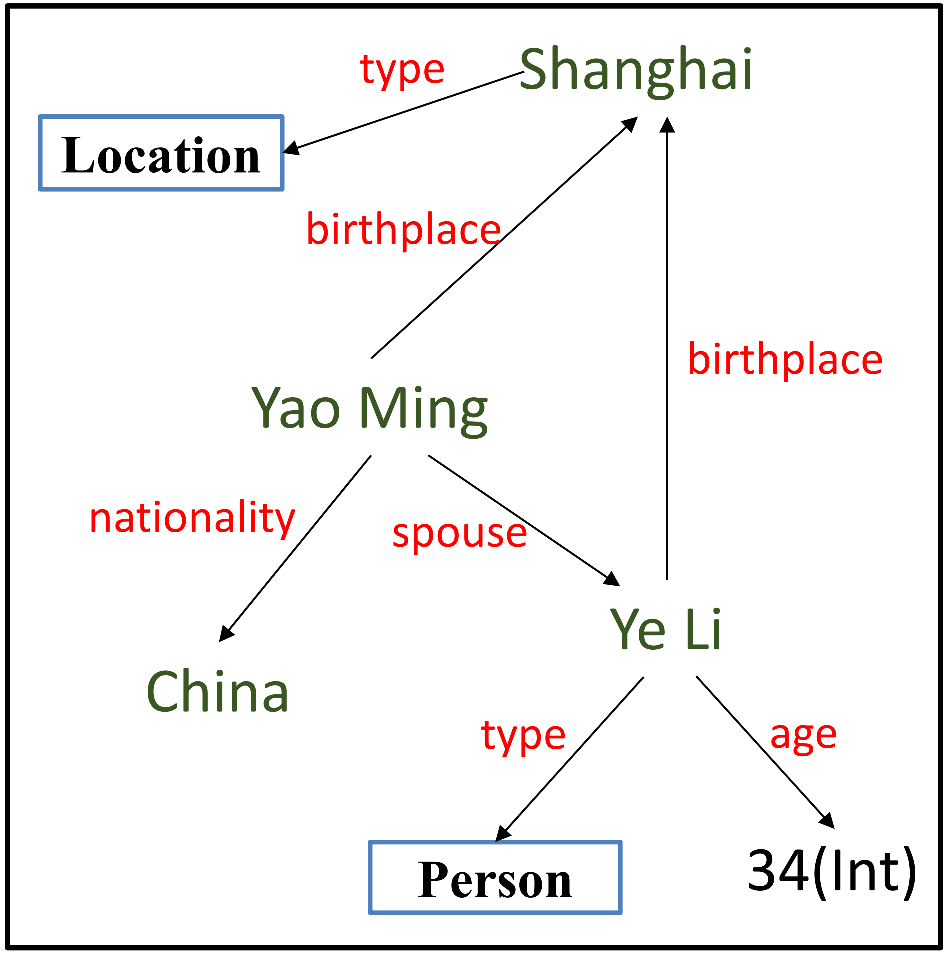
Watson

KBQA

- Semantic parsing based KBQA
- Template based KBQA
- Deep learning based KBQA

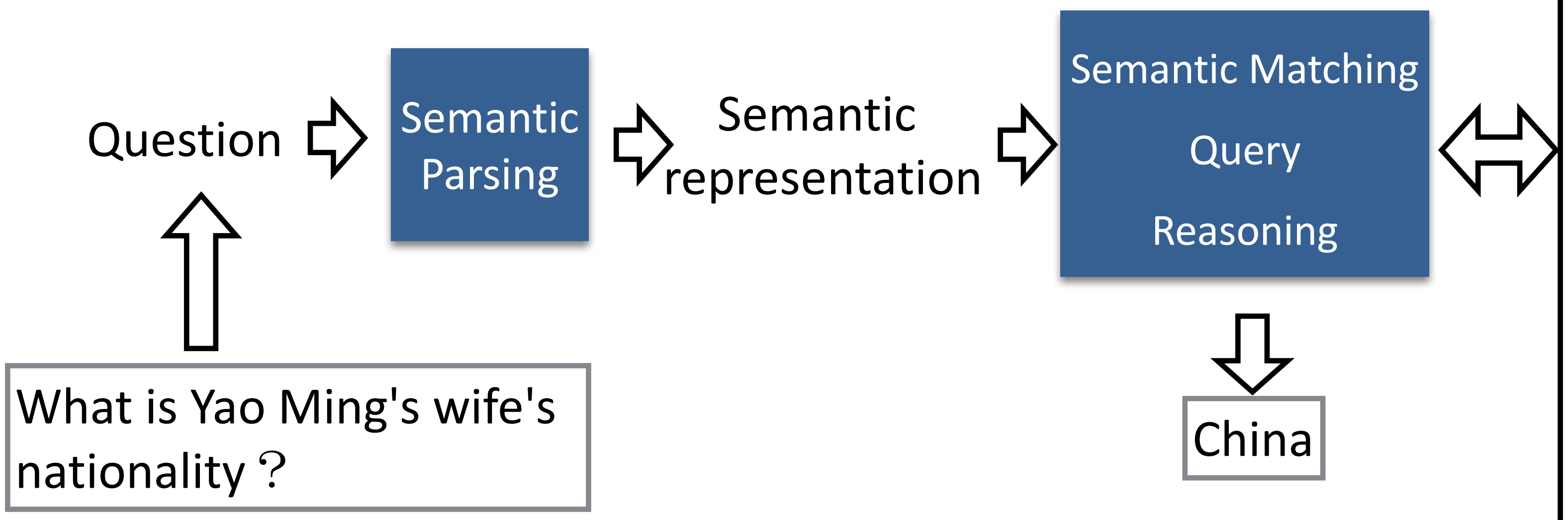
KBQA: Semantic Parsing based QA

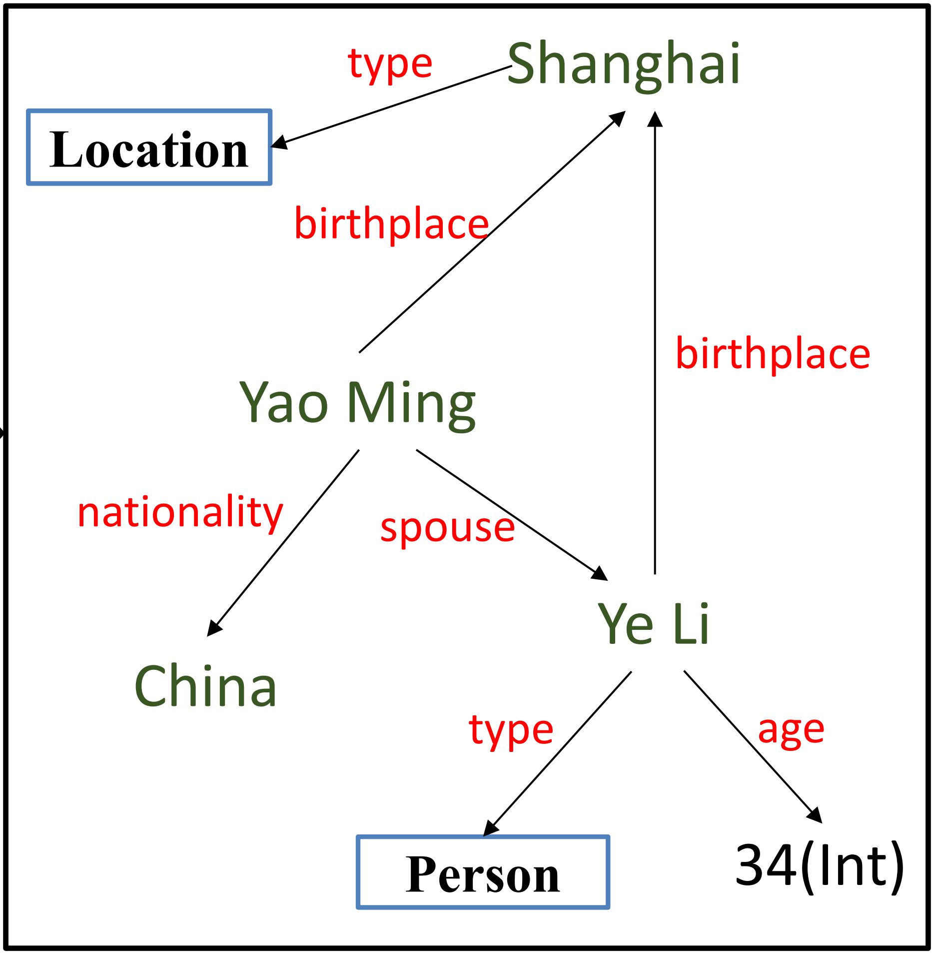
What is Yao Ming's wife's nationality？



Knowledge Base

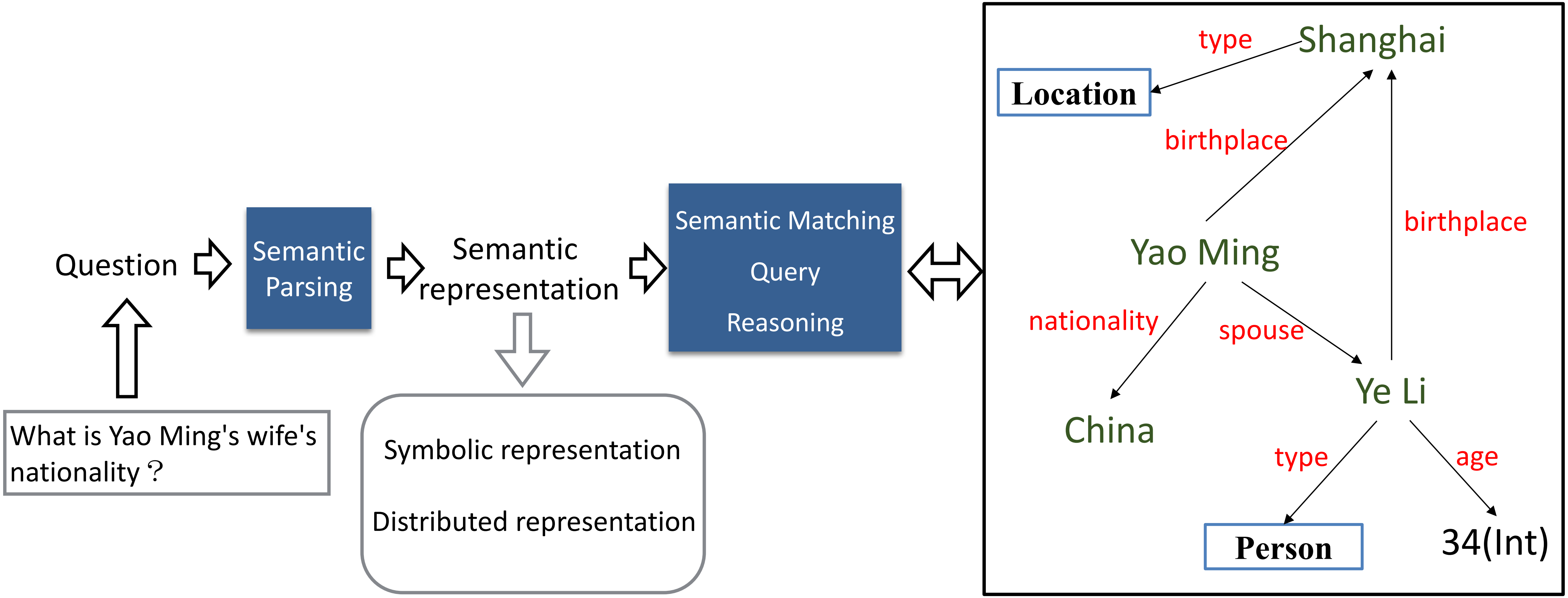
Traditional Semantic Parsing Method





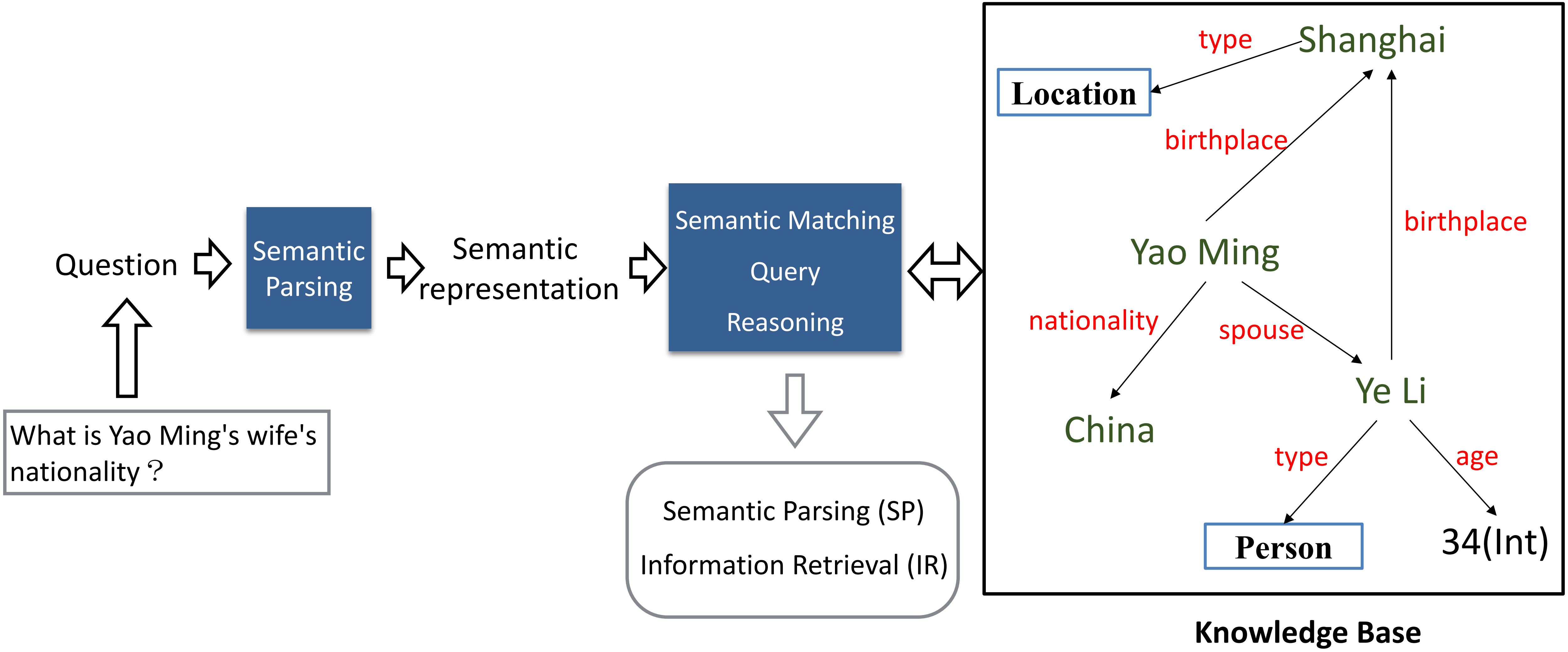
Knowledge Base

Traditional Semantic Parsing Method



Knowledge Base

Traditional Semantic Parsing Method



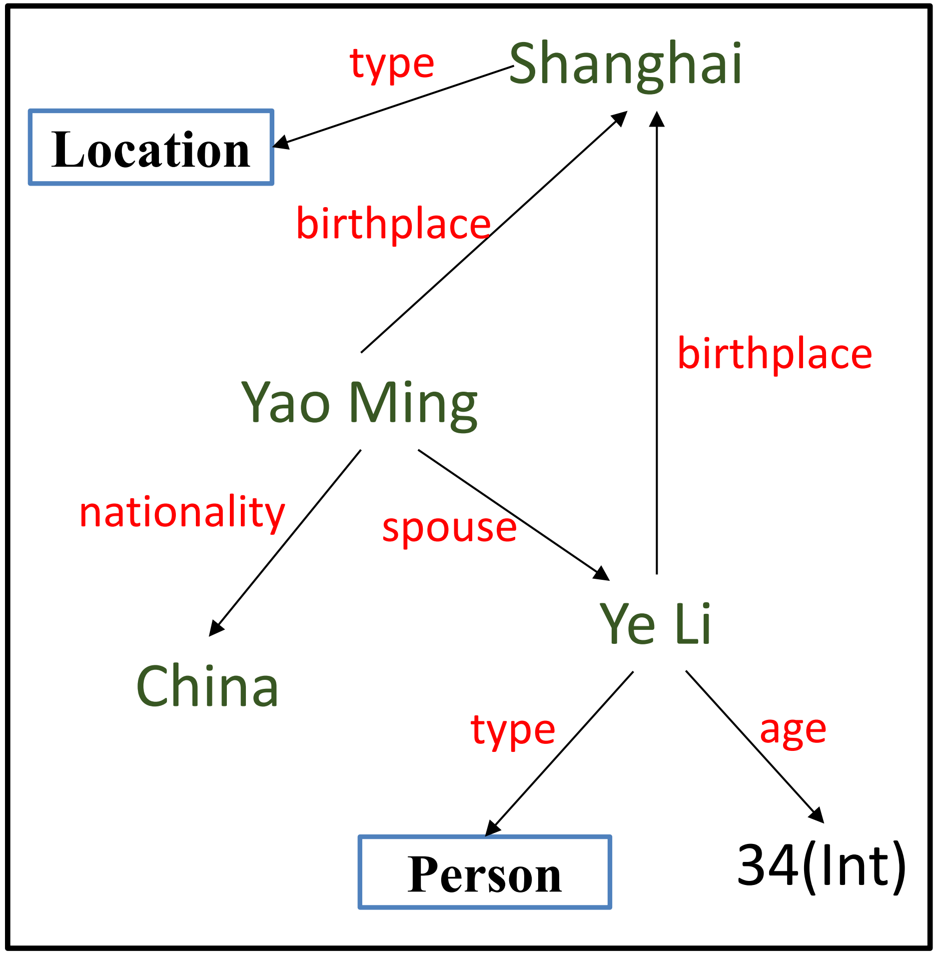
Semantic Parsing - Symbolic representation

What is Yao Ming's wife's nationality?

Semantic Parsing

Query

```
SELECT DISTINCT ?x
WHERE {
       ?y nationality  ?x.
       res:Yao M.  spouse ?y.
}
```

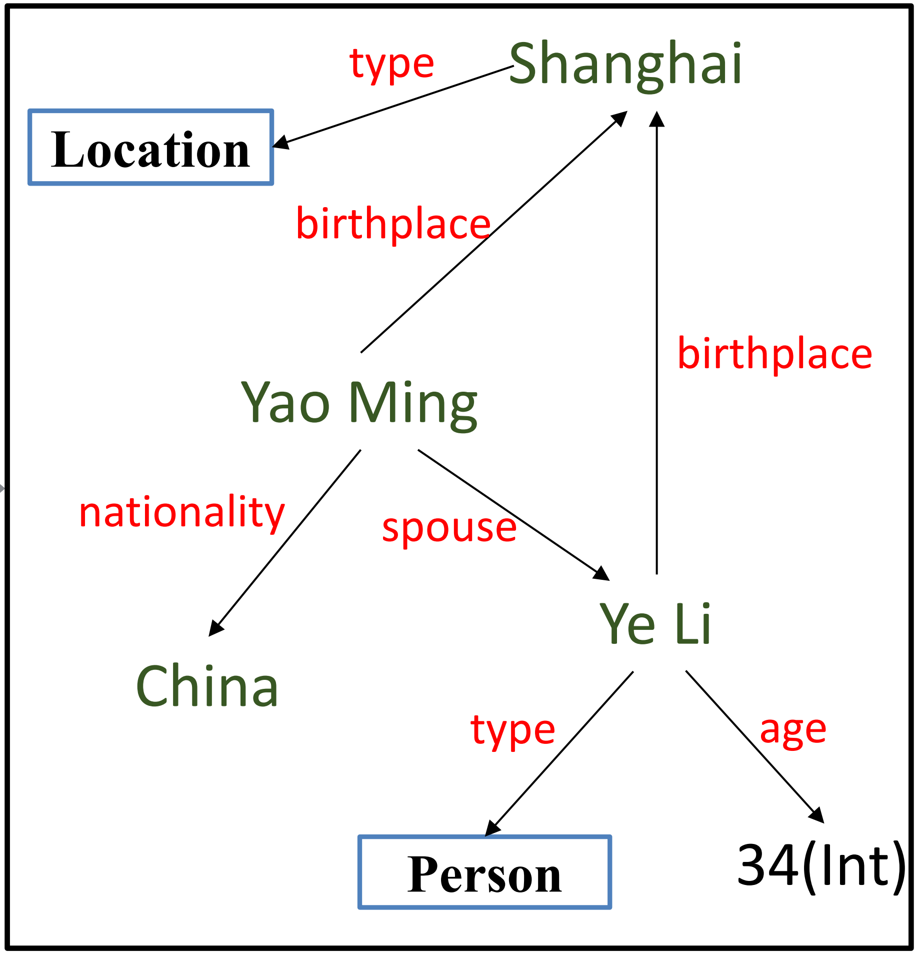


Formal representation of Questions

Where was Yao Ming's wife born?

$\lambda x \,.\, spouse(Yao\ M.,\ \ y) \wedge birthplace(y, x)$

```
SELECT DISTINCT ?x
WHERE {
    ?y nationality  ?x.
    res:Yao M.  spouse ?y.
}
```

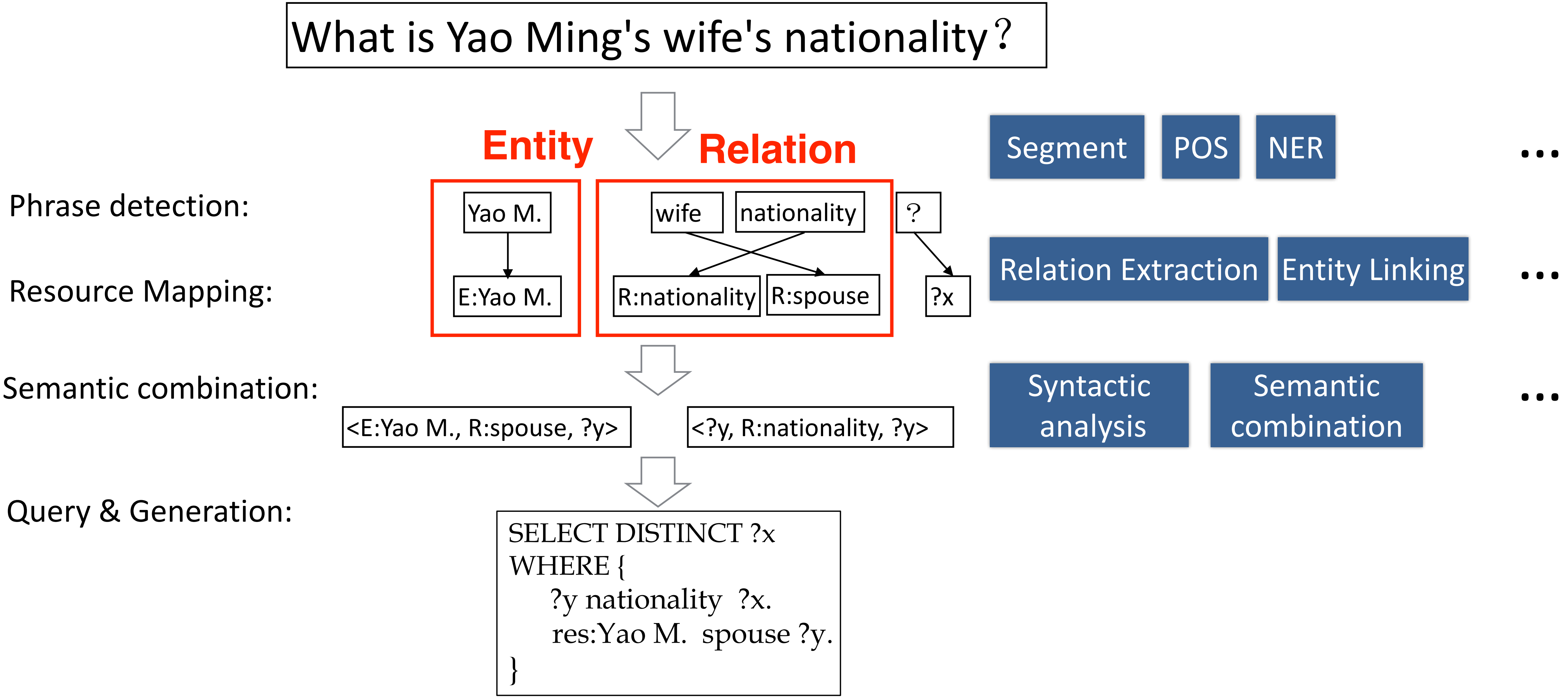


Logic Form

- Lambda Calculus
- DCS-Tree
- Fun-QL
- …

SQL
SPARQL
Prolog
FunQL
…

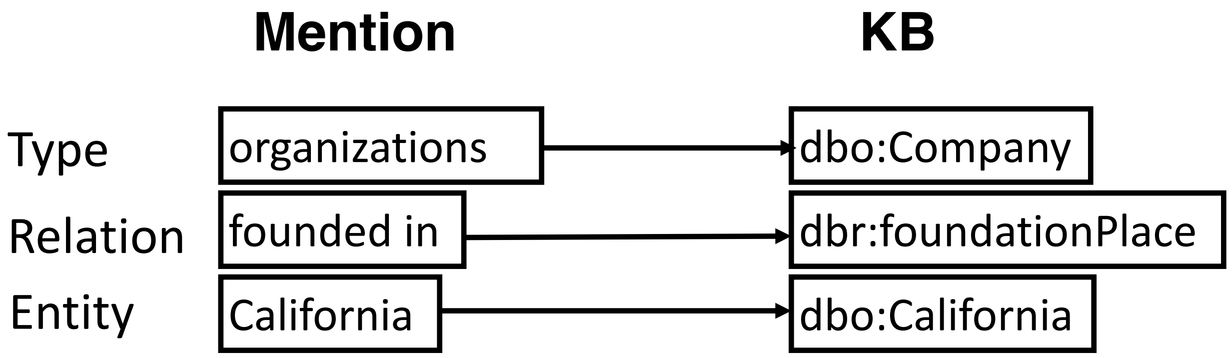
Main Steps



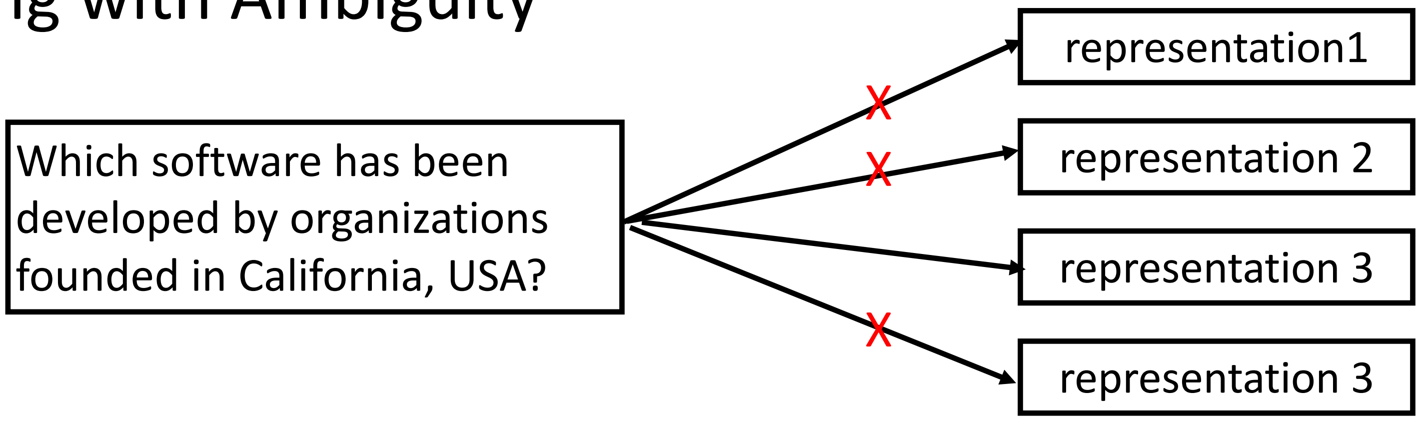
What is Yao Ming's wife's nationality？
Entity
Relation
Phrase detection:
Yao M.
wife
nationality
?
Resource Mapping:
E:Yao M.
R:nationality
R:spouse
?x
Segment
POS
NER
…
Relation Extraction
Entity Linking
…
Semantic combination:
<E:Yao M., R:spouse, ?y>
<?y, R:nationality, ?y>
Syntactic analysis
Semantic combination
…
Query & Generation:
SELECT DISTINCT ?x
WHERE {
?y nationality ?x.
res:Yao M. spouse ?y.
}

Two core problems

- Mapping phrases to KB



- Dealing with Ambiguity



Some Other Semantic Parsing Methods

- Combinatory Categorical Grammars [Zettlemoyer, 2005]
- Shift-reduce Derivations [Zelle, 1995]
- Synchronous Grammars [Wong, 2007]
- Hybrid Tree [Lu, 2008]
- CFG-like Grammars [Clarke, 2010]
- CYK-like Grammars [Liang, 2011]

Hand-crafted Templates for KBQA

- [Unger et al. (WWW'12), Yahya et al. (EMNLP'12), Fader et al. (KDD'14), Yao and Durme, (ACL'14), Bast and Haussmann, (CIKM'15)]

Question Template	Query Template	Example
Who VP_{PRED} NP_{ENT}	(?x, PRED, ENT)	*"Who founded Google?"*

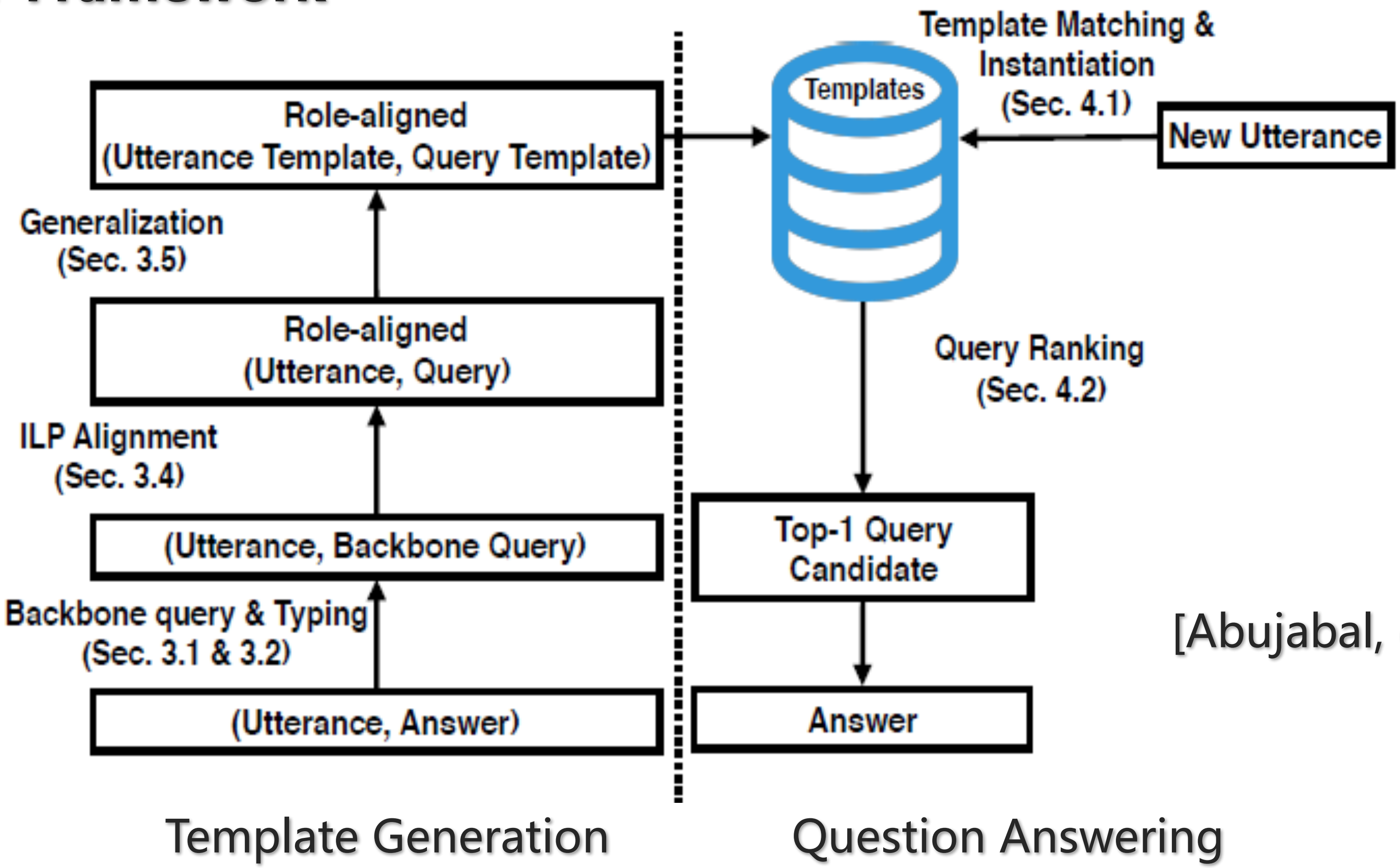
Problems：

1.Human Expertise

2.Coverage

KBQA: Template Based KBQA

QUINT Framework



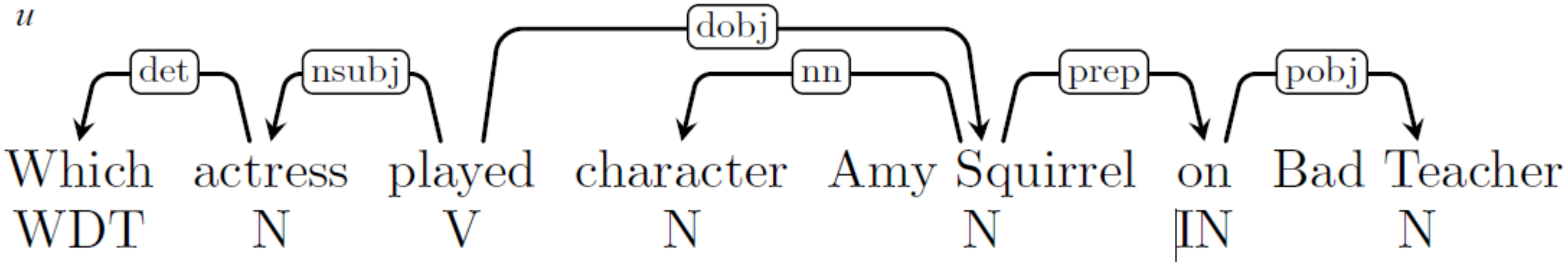
[Abujabal, et al. 2017]

Template Generation – Dependency Parsing

- Input：
  - (Q) utterance： u =“Which actress played character Amy Squirrel on Bad Teacher?”
  - (A) Au = {LucyPunch}
- Dependency tree：

(1) Can capture long range dependencies between the tokens of an utterance

(2) Gives great flexibility allowing QUINT to skip irrelevant tokens.

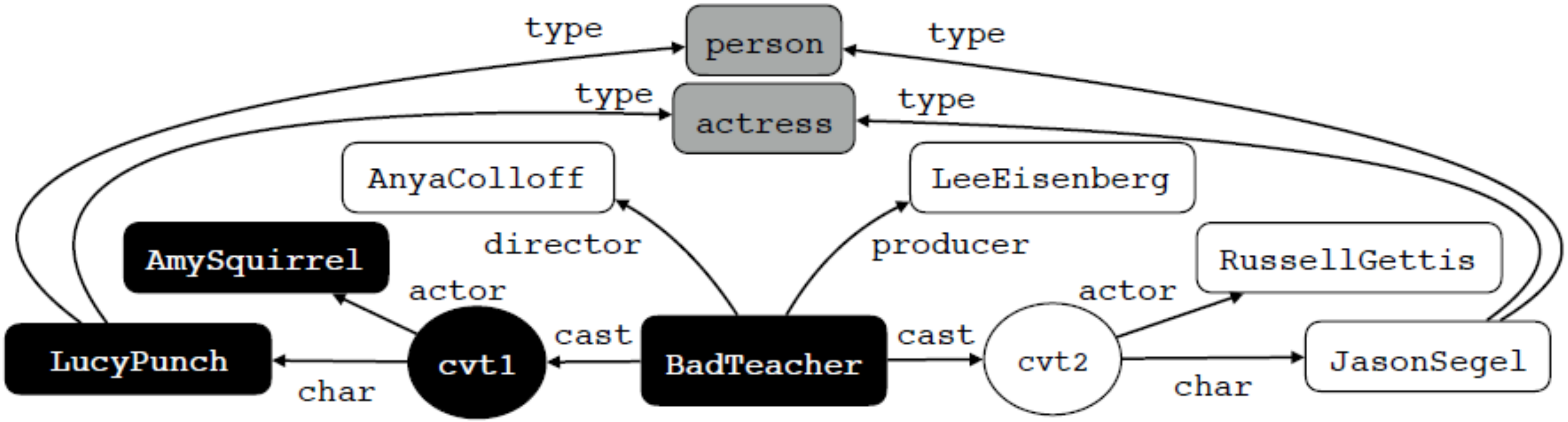


$$A_u = \{\text{LucyPunch}\}$$

Template Generation – KG fragment

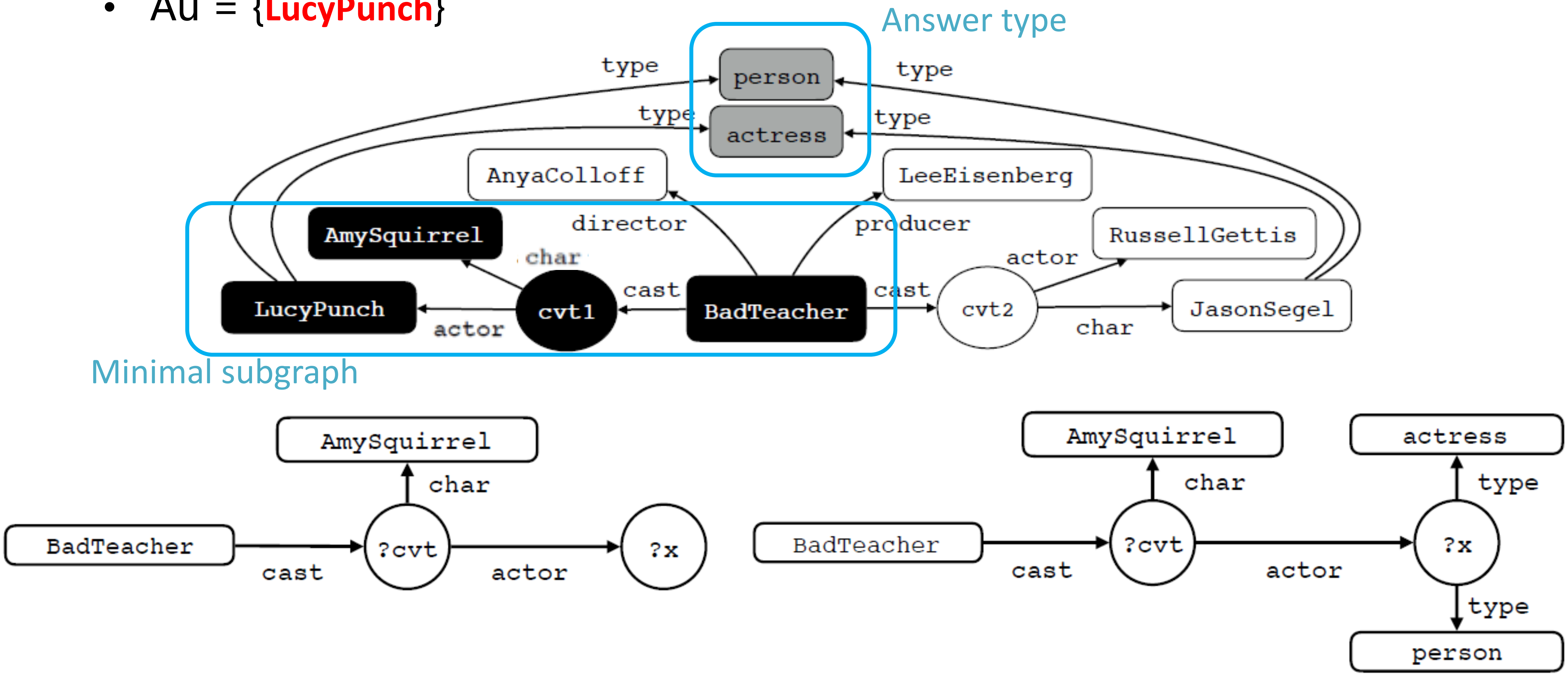
- Using S-MART to NER Linking with Freebase.
- utterance: u = **LucyPunch**’s role in **BadTeacher** as **AmySquirrel**

– Au = {**LucyPunch**}



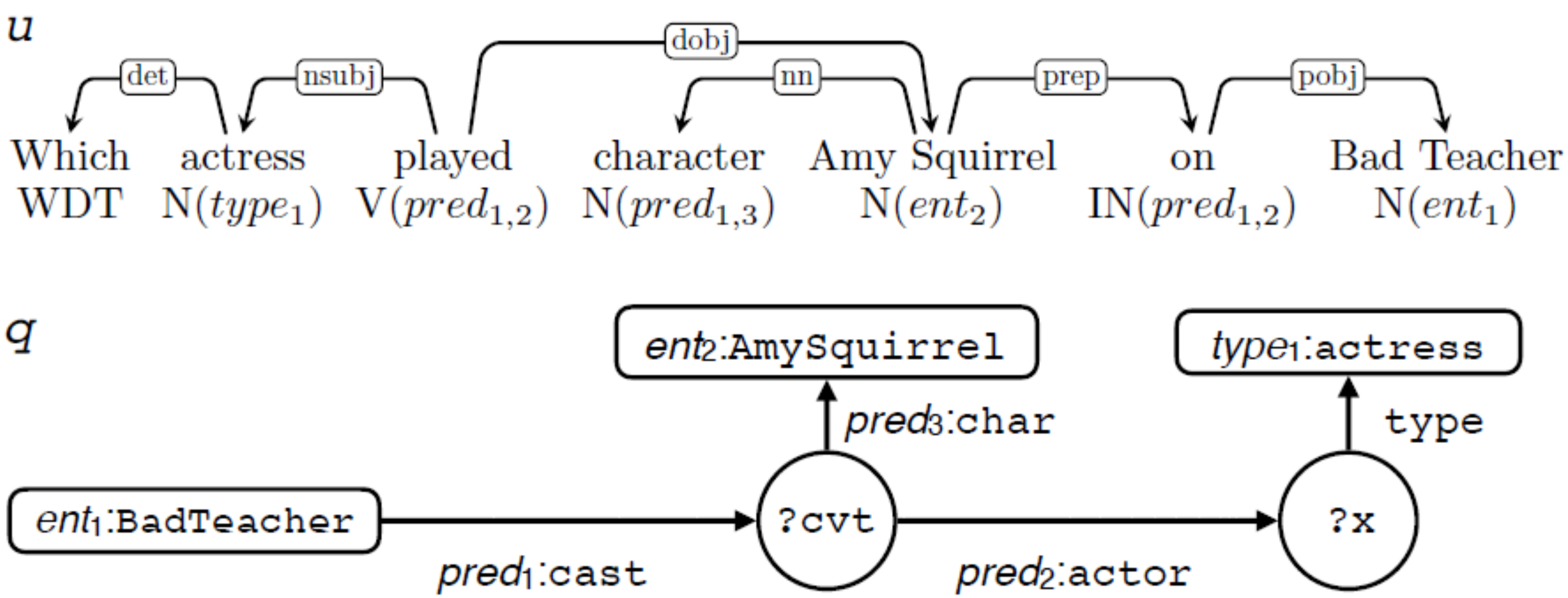
Get Minimal Subgraph from KG

- utterance: u = **LucyPunch**'s role in **BadTeacher** as **AmySquirrel**
- Au = {**LucyPunch**}



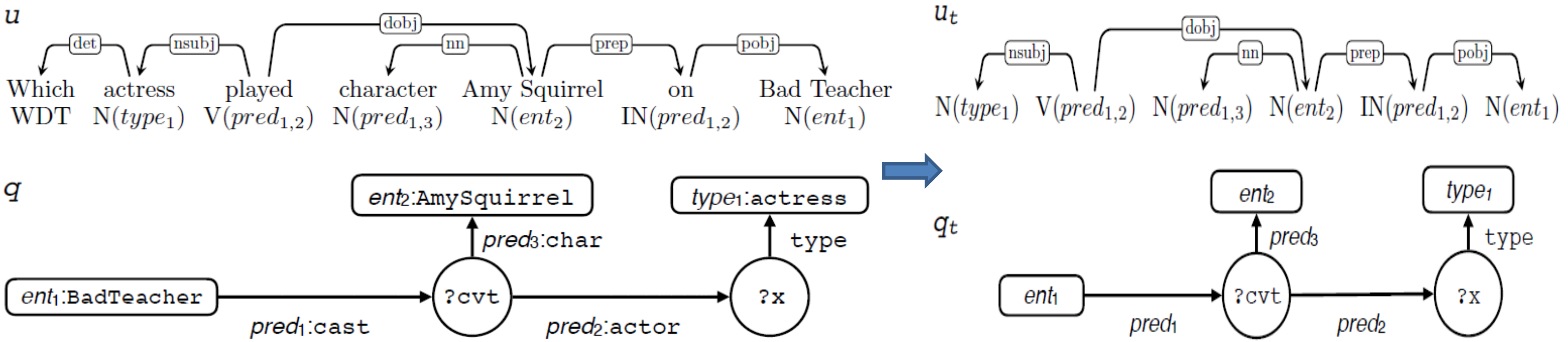
Utterance-Query Alignment

- utterance: u = **LucyPunch**'s role in **BadTeacher** as **AmySquirrel**
- Au = {**LucyPunch**}
- Aligned utterance query pair： （ u, q, m ） ：
  - e.g. "*played on*" and "*cast.actor*"

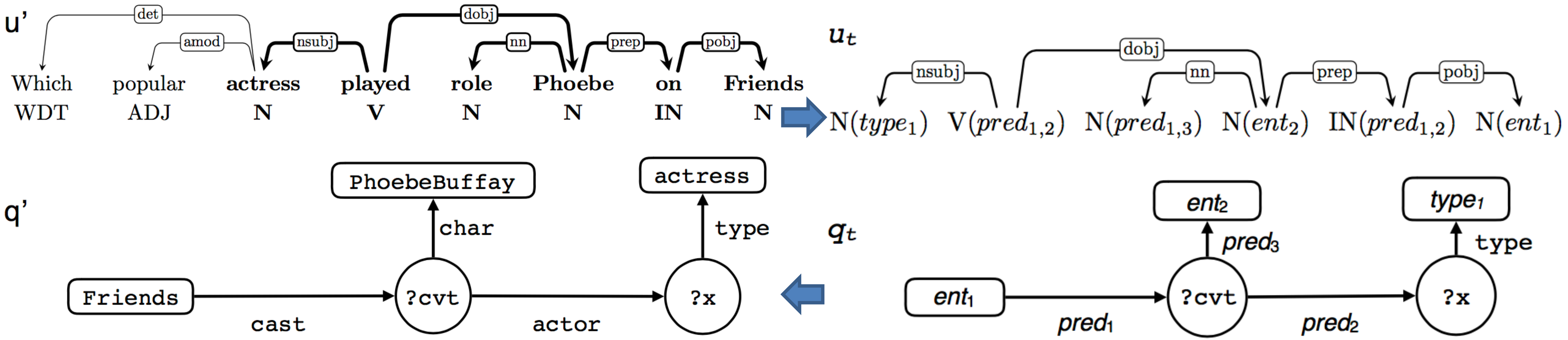


Template Generation

- Template（u_t, q_t, m_t）：
  - u_t: utterance template
  - q_t: querytemplate
  - m_t:alignmenttemplate



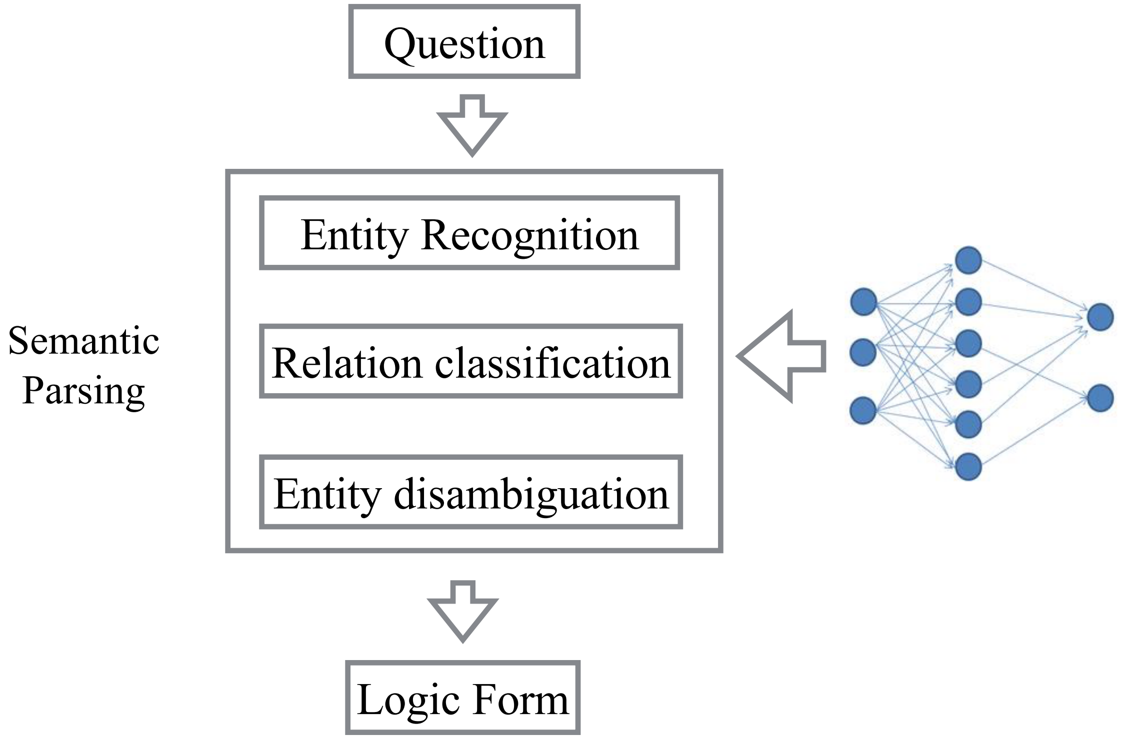
Template Matching and Instantiation



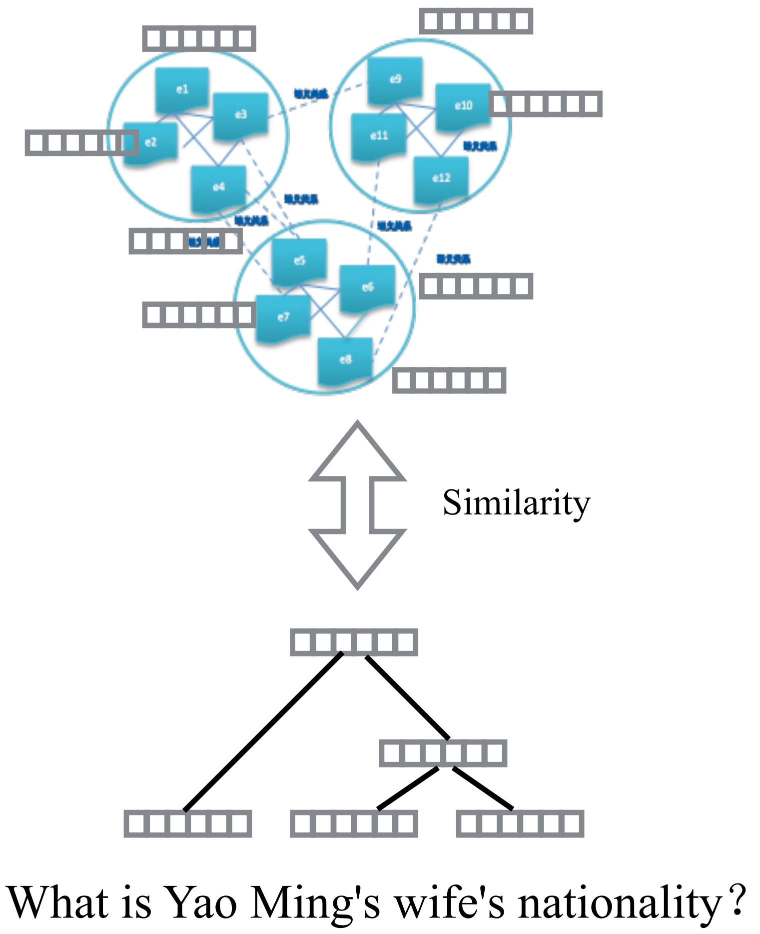
- Dependency parsing new utterance, use SMART to NERL (Freebase)
- Matching template in templates base
- Using NERL results to instantiate m_t

KBQA: Deep Learning Based KBQA

- Improve traditional methods with DL



- End2End model in DL



Improve Traditional Methods with DL

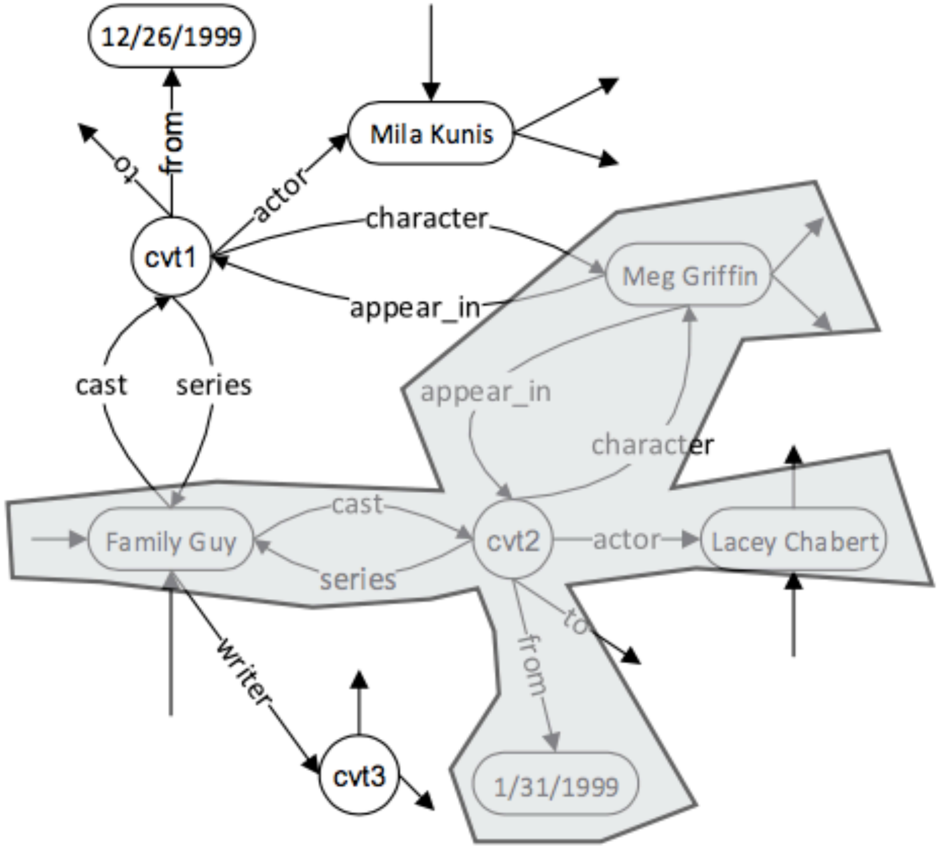
- Semantic Parsing via Staged Query Graph Generation: Question Answering with Knowledge Base (ACL 2015， Outstanding Paper)

Who first voiced Meg on Family Guy?

⇩

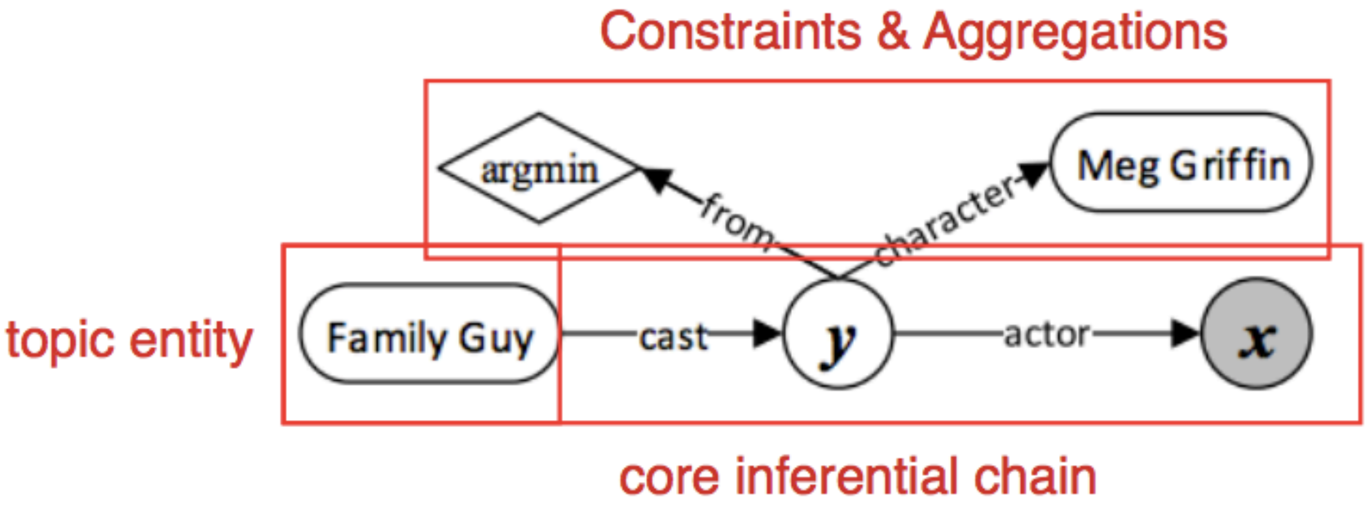
$$\arg\min(\lambda x.Actor(x,Family\_Guy) \wedge Voice(x,Meg\_Griffin),\lambda x.casttime(x))$$

⇨

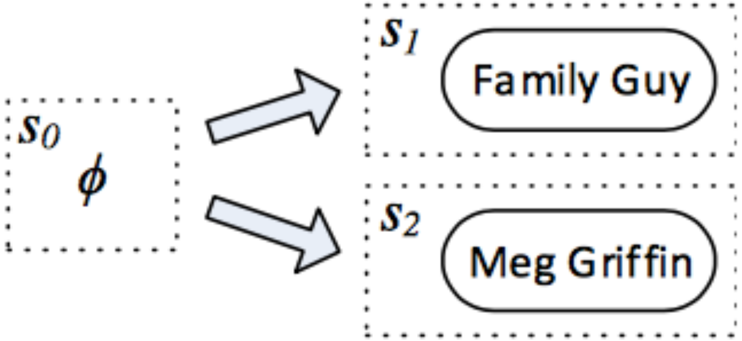


Improve Traditional Methods with DL

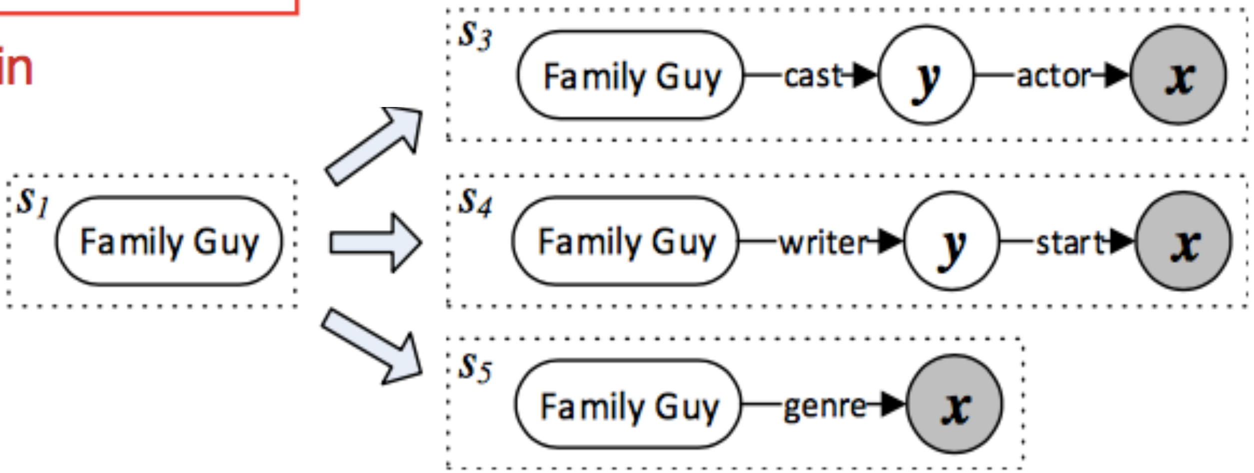
Who first voiced Meg on Family Guy?



Step 1: Two possible topic entity linking: S1 and S2



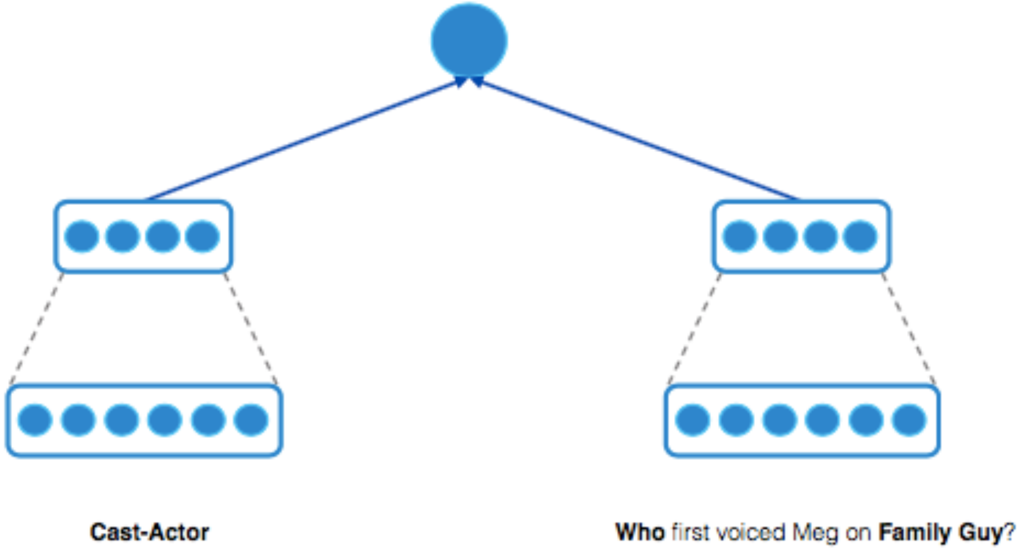
Step 2: Candidate core inferential chains start from the entity Family Guy.

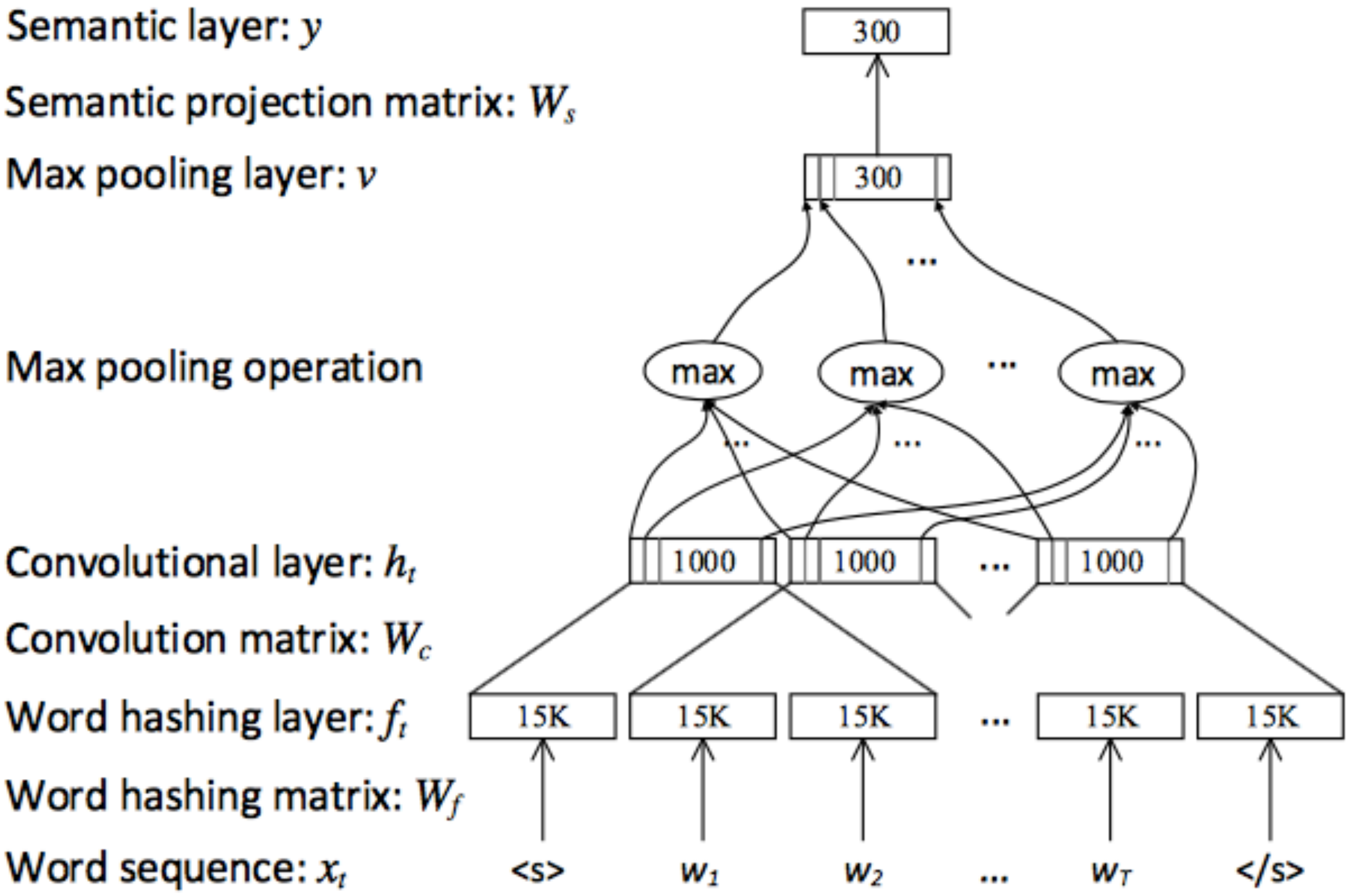


Improve Traditional Methods with DL

- Ranking candidate core inferential chains using CNN

$$p(r_1|q)=\frac{\exp(\cos(e_{r_1},e_q))}{\sum_r \exp(\cos(e_r,e_q))}$$

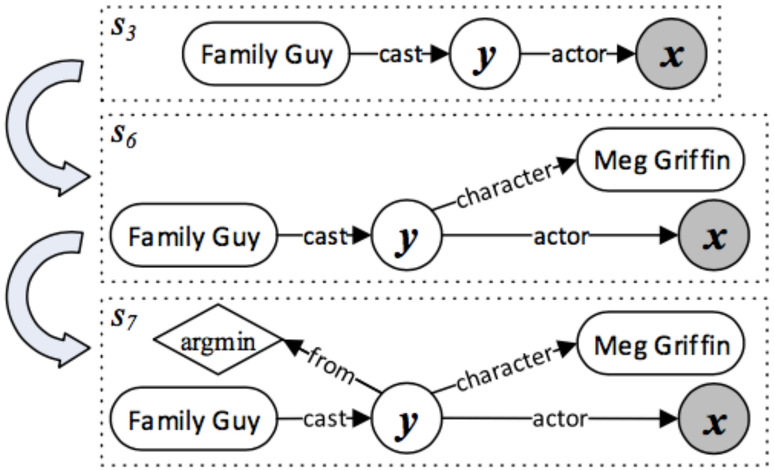




Improve Traditional Methods with DL

- Step 3: Add argument constraints

Who first voiced **Meg** on **Family Guy**?

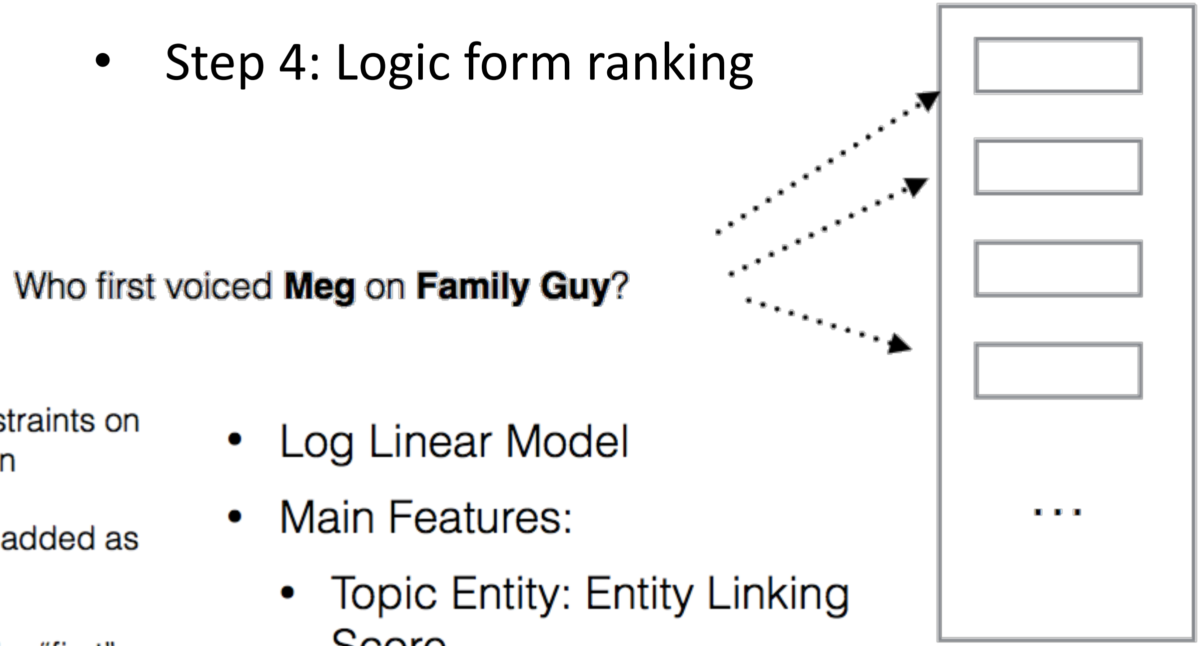


Using rules to add constraints on the core inferential chain

If x is a entity, it can be added as entity node

If x is such keywords, like “first”, “latest”, it could be added as aggregation constraints.

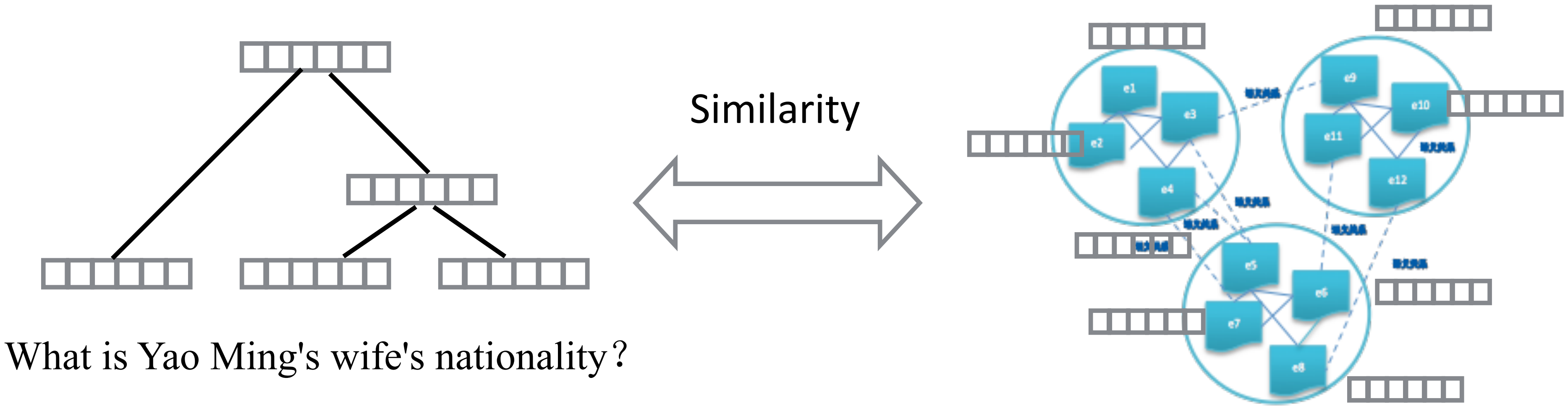
- Step 4: Logic form ranking



- Log Linear Model
- Main Features:
  - Topic Entity: Entity Linking Score
  - Core Inferential Chain: Relation Matching Score (NN-based model)
  - Constraints: Keyword and entity matching

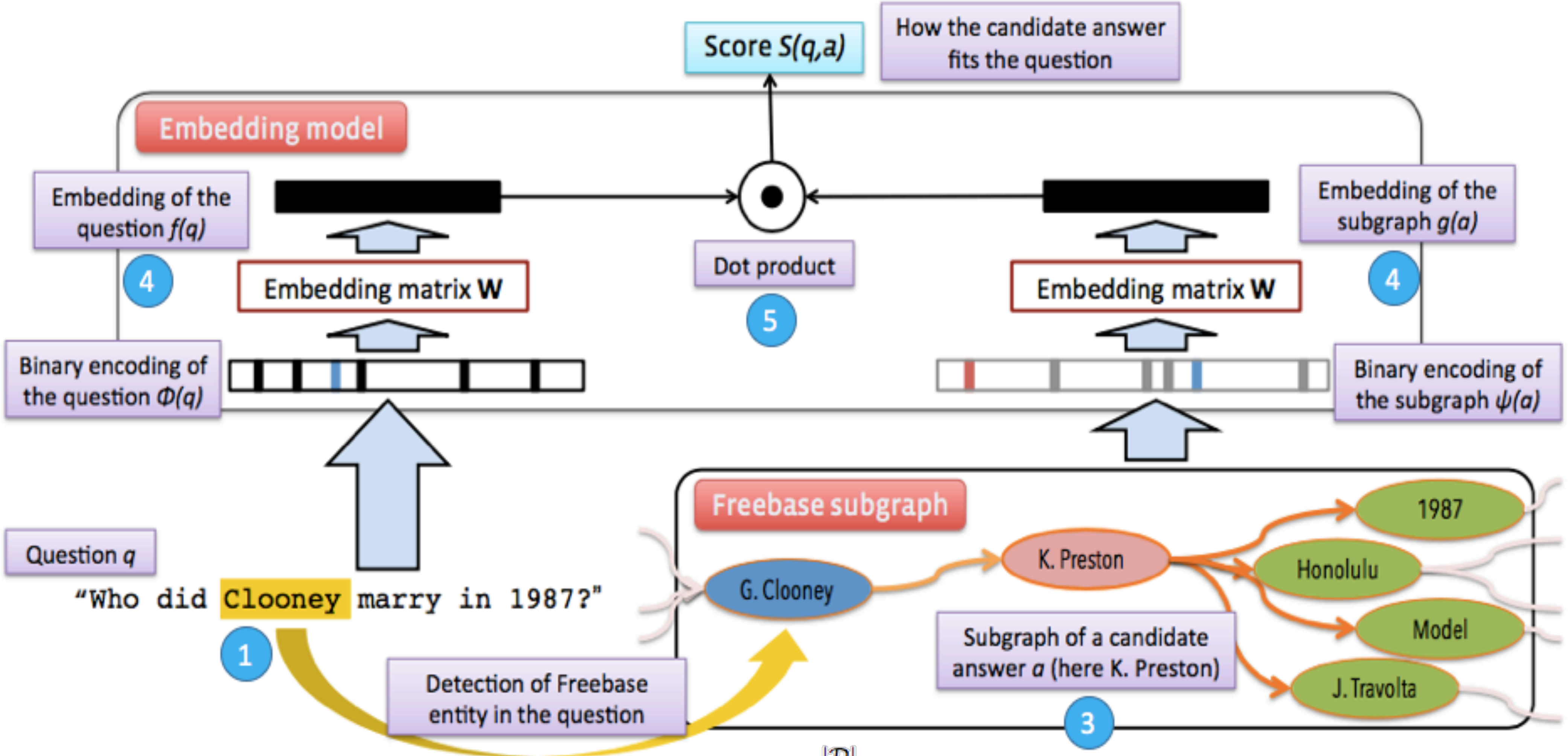
End2End KBQA

- Single Relation, Simple Question
- Steps:
  - 1: Candidates generation
    - Utilizing Entity Linking to find main Entity
    - The entities around main entity in KB are Candidate Entities
  - 2: Candidates Ranking



[Bordes, et al. 2014]

Framework

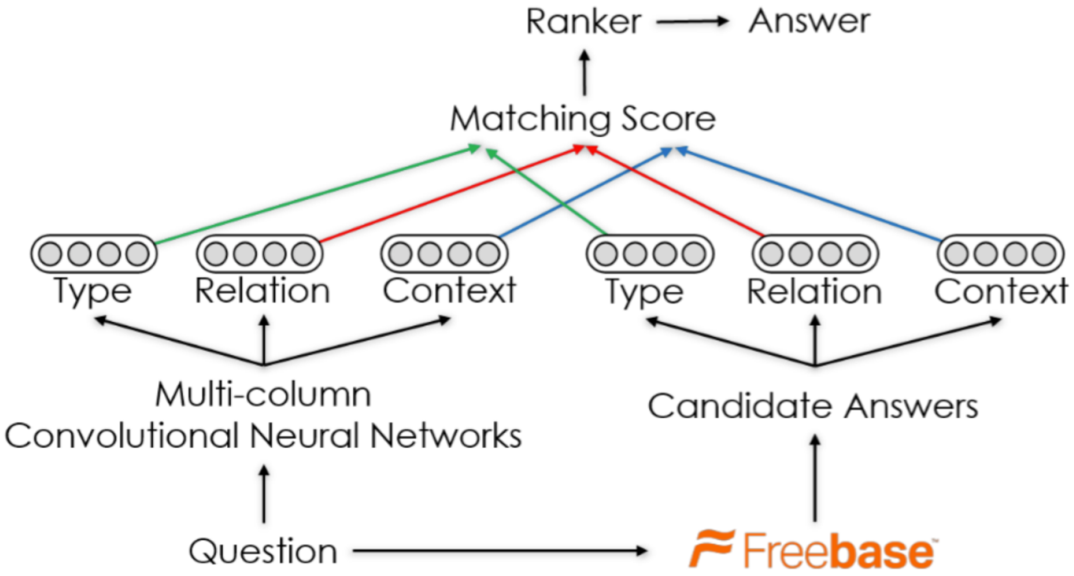


$$\sum_{i=1}^{|\mathcal{D}|} \sum_{\bar{a} \in \bar{A}(a_i)} \max\{0, m - S(q_i, a_i) + S(q_i, \bar{a})\}$$

End2End KBQA using Multi-Column CNN

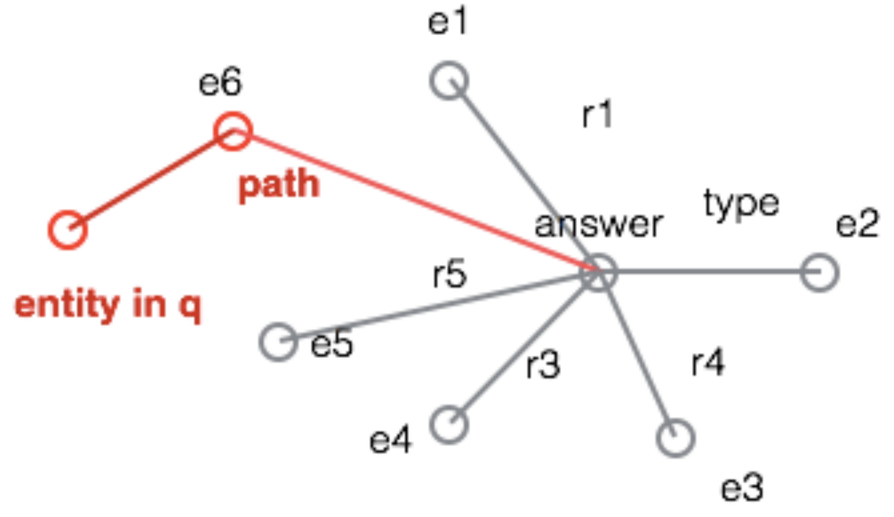
- According to the QA characteristics, consider the information in different dimensions of the answer

[Dong, et al. 2015]



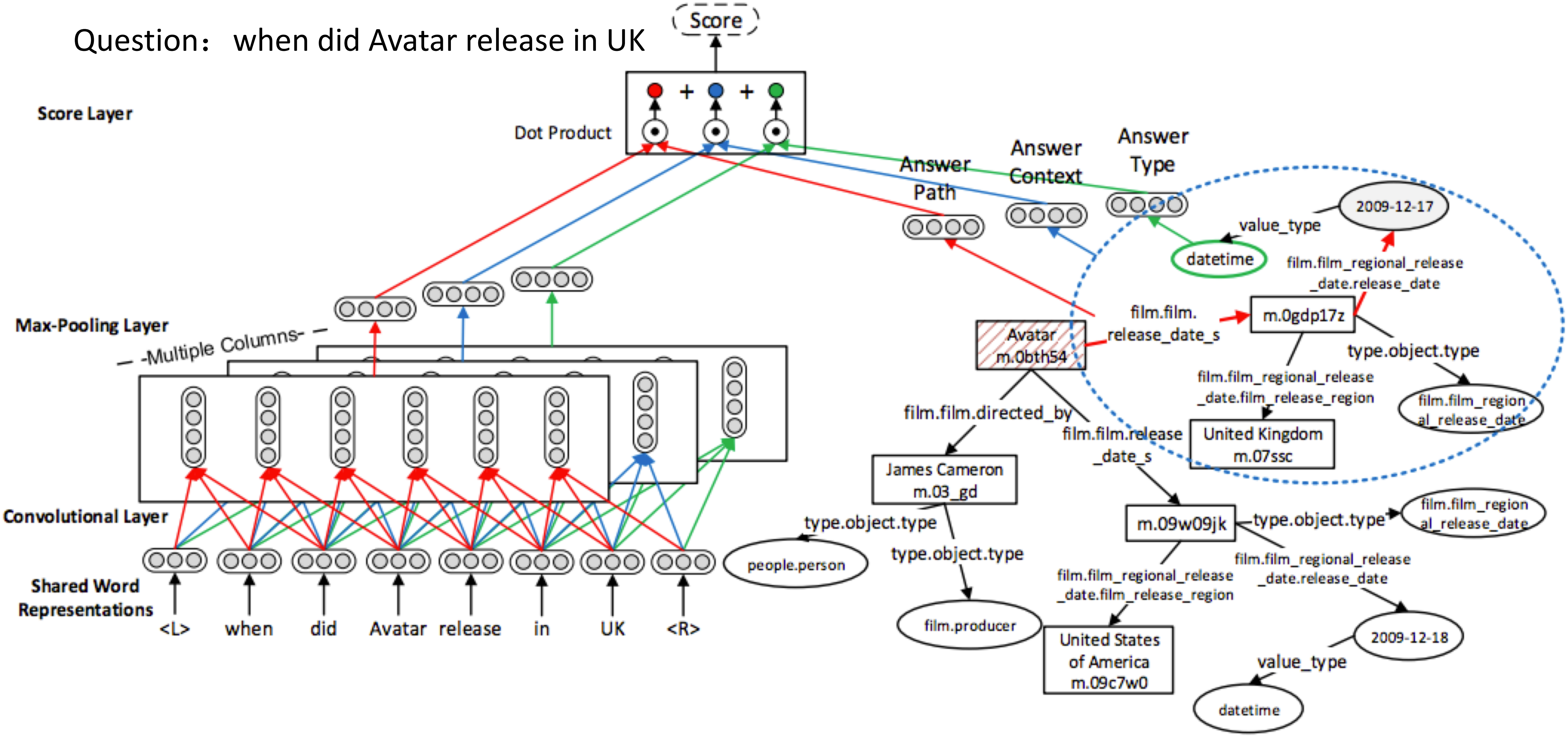
$$S(q,a) = \underbrace{\mathbf{f}_1(q)^{\mathsf{T}}\mathbf{g}_1(a)}_{answer\ path} + \underbrace{\mathbf{f}_2(q)^{\mathsf{T}}\mathbf{g}_2(a)}_{answer\ context} + \underbrace{\mathbf{f}_3(q)^{\mathsf{T}}\mathbf{g}_3(a)}_{answer\ type}$$

Answer Type
Answer Context
Answer Path

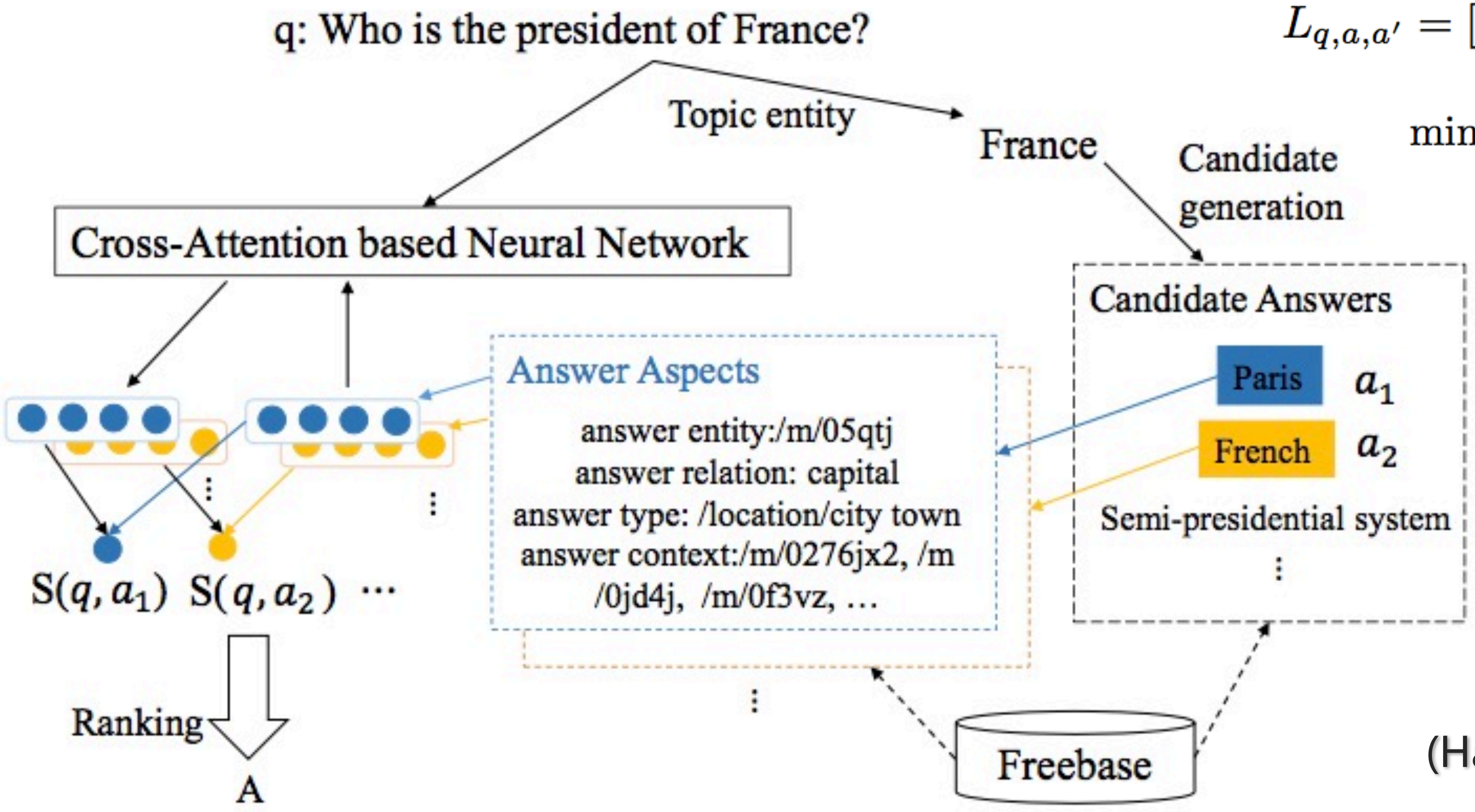


Framework

Question： when did Avatar release in UK



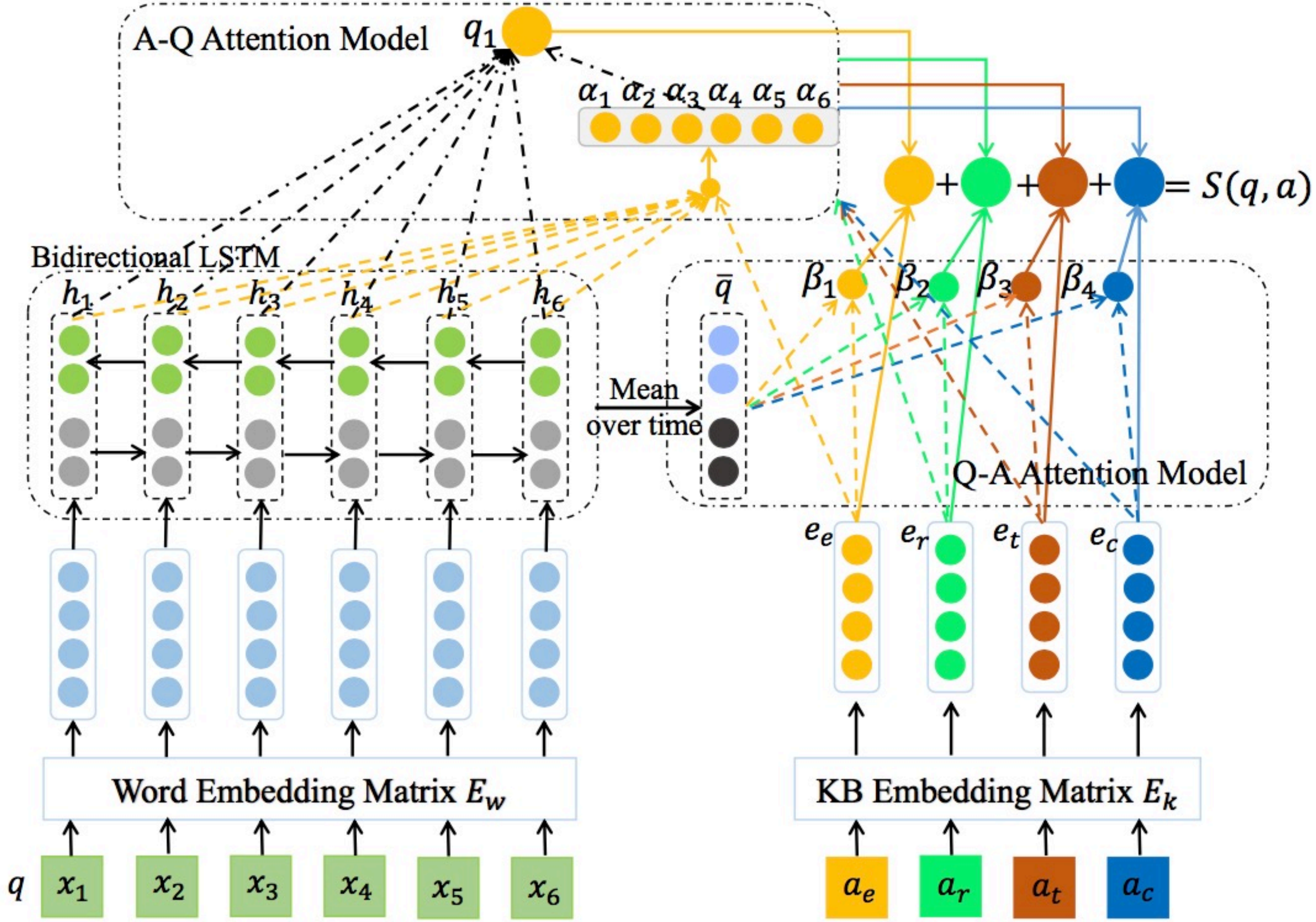
End2End KBQA using Attention-based BLSTM



$$L_{q,a,a'} = [\gamma + S(q,a') - S(q,a)]_+$$

$$\min \sum_q \frac{1}{|P_q|} \sum_{a \in P_q} \sum_{a' \in N_q} L_{q,a,a'}$$

(Hao et al. ACL, 2017)



A-Q Attention

$$\alpha_{ij} = \frac{\exp(\omega_{ij})}{\sum_{k=1}^{n} \exp(\omega_{ik})}$$

$$\omega_{ij} = f(W^T[h_j; e_i] + b)$$

$$q_i = \sum_{j=1}^{n} \alpha_{ij} h_j$$

$$S(q, e_i) = h(q_i, e_i)$$

Q-A Attention

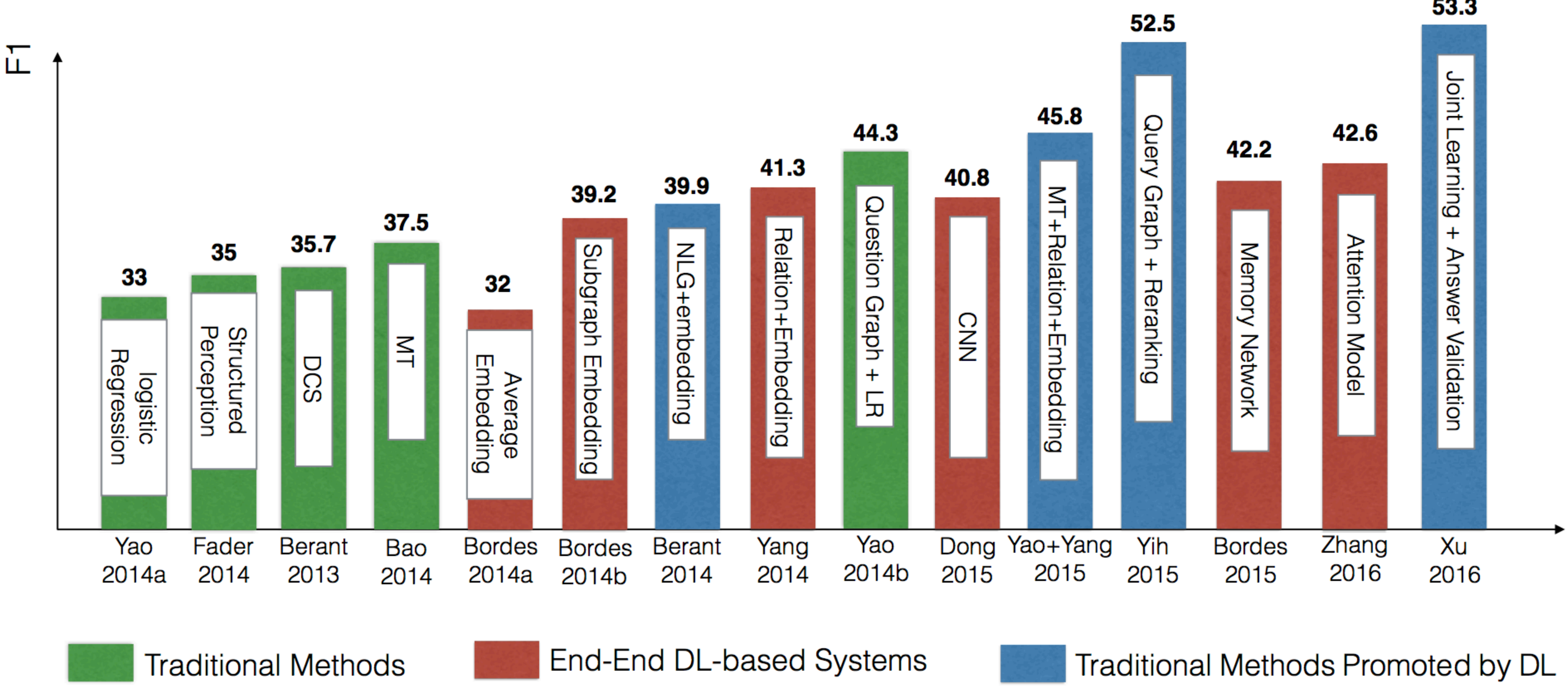
$$S(q,a) = \sum_{e_i \in \{e_e, e_r, e_t, e_c\}} \beta_{e_i} S(q, e_i)$$

$$\beta_{e_i} = \frac{\exp(\omega_{e_i})}{\sum_{e_k \in \{e_e, e_r, e_t, e_c\}} \exp(\omega_{e_k})}$$

$$\omega_{e_i} = f(W^T[\bar{q}; e_i] + b)$$

$$\bar{q} = \frac{1}{n} \sum_{j}^{n} h_j$$

Comparison of various KBQA system results



References

- [Abujabal, et al. 2017] Abujabal, et al., Automated Template Generation for Question Answering over Knowledge Graphs, www2017
- [Yao, et al. 2014] Yao, et al. A Graph Traversal Based Approach to Answer Non-Aggregation Questions Over DBpedia, ACL2014
- [Bordes, et al., 2014] Antoine Bordes, Sumit Chopra, and Jason Weston, Question Answering with Subgraph Embedding, EMNLP 2014
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- [Hao, et al. 2017] Hao et al., An End-to-End Model for Question Answering over Knowledge Base with Cross-Attention Combining Global Knowledge Information, ACL 2017.
- [Zettlemoyer, 2005] Zettlemoyer L S, Collins M. Learning to Map Sentences to Logical Form: Structured Classification with Probabilistic Categorial Grammars[J]. 2012:658-666.
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- [Lu, 2008] Lu W, Ng H T, Lee W S, et al. A Generative Model For Parsing Natural Language To Meaning Representations, EMNLP 2008
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- [Berant, 2013] Berant J, Chou A, Frostig R, et al. Semantic parsing on freebase from question-answer pairs. Proceedings of Emnlp, 2014.
- [Yih,2015] Yih W T, Chang M W, He X, et al. Semantic Parsing via Staged Query Graph Generation: Question Answering with Knowledge Base, ACL 2015.

03 KG + Chatbot

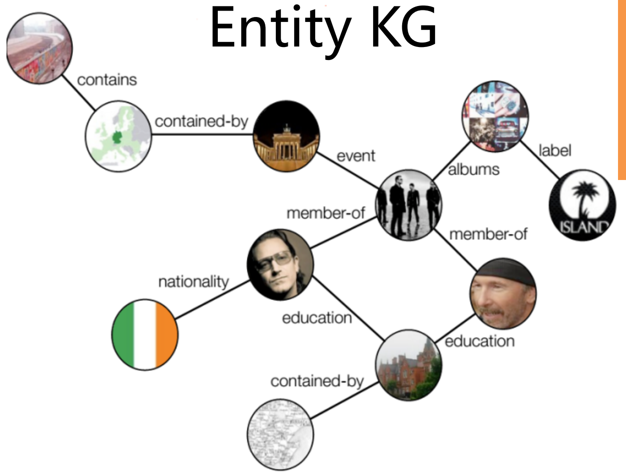
3.1 QA Introduction

3.2 Knowledge Based Question Answering (KBQA)

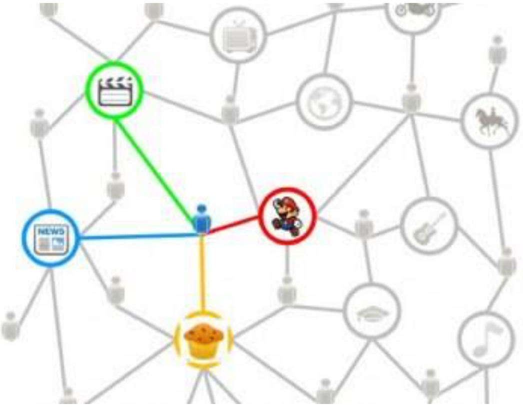
3.3 KBQA Applications in Chatbot

Various KGs

Entity KG



Open domain Sparse large KG



Interest KG

VS

Chatbots KG

Emotions

Basic attributes

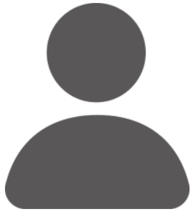
Skills

Preference

Social relations

Basic attributes

Working status



Preference

Daily life

User KG

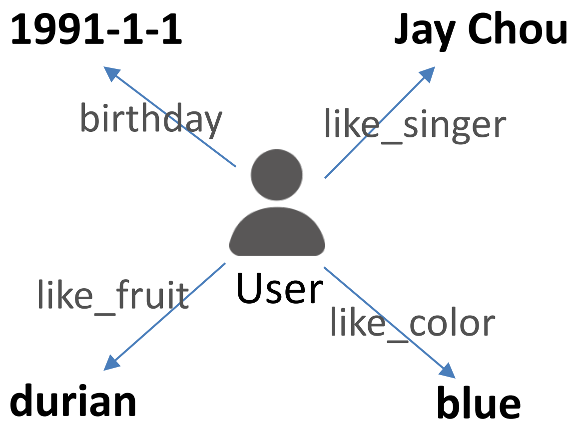
Personalized dense small KG

Personalized KBQA

- KBQA based on User KG

Who's my favorite singer?

You love Jay Chou most

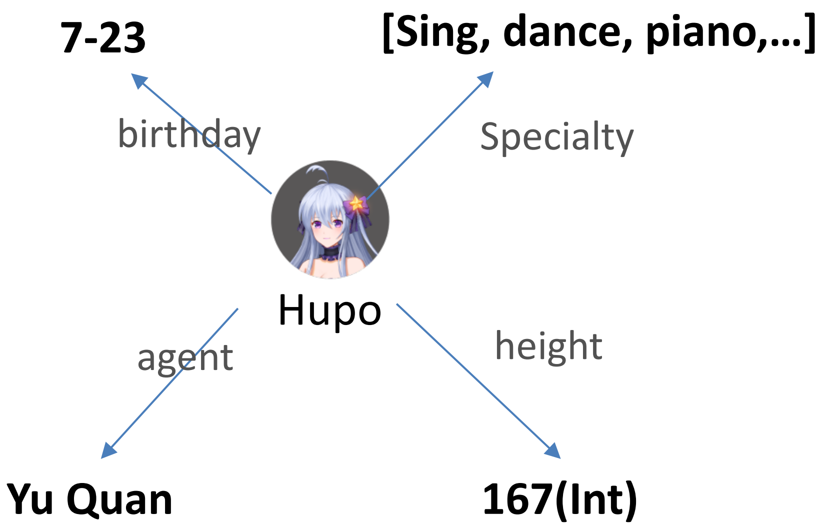


User KG

- KBQA based on chatbot KG

When is your birthday?

My birthday is July 23rd



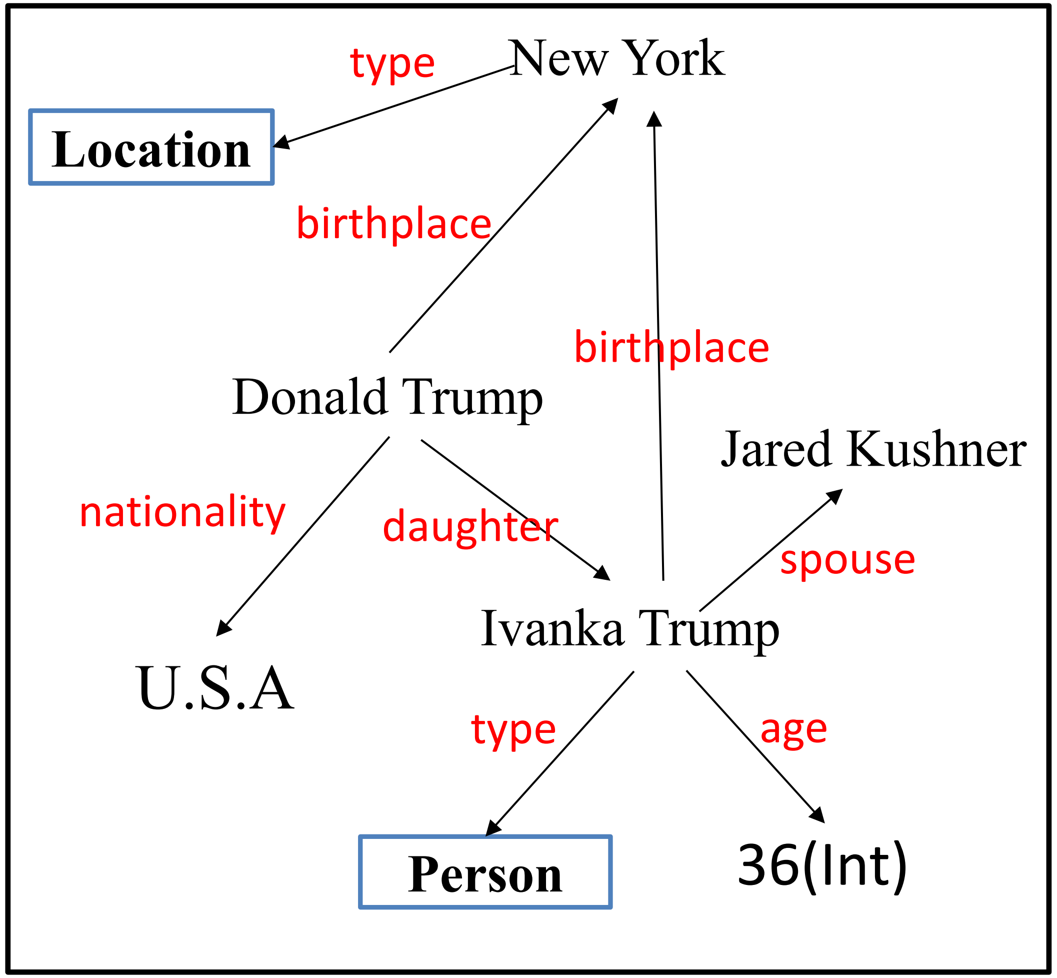
Chatbot KG

Open Domain KBQA

- KBQA based on open domain

Who is Donald Trump's daughter?

Ivanka Trump



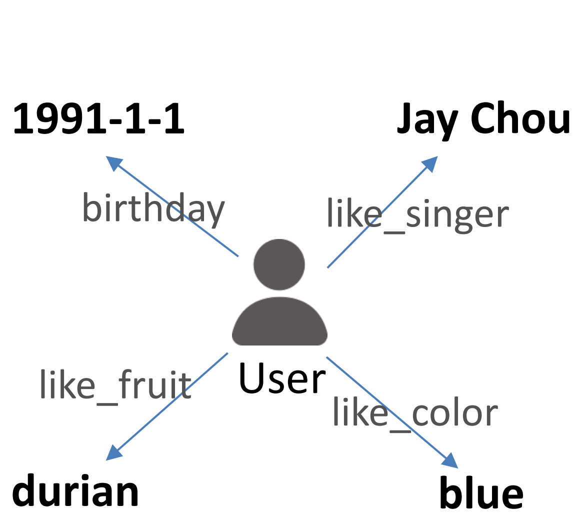
KBQA based on Multi-KBs

- User (chatbot) KG + Open KBs

What new songs has my favorite singer released recently?

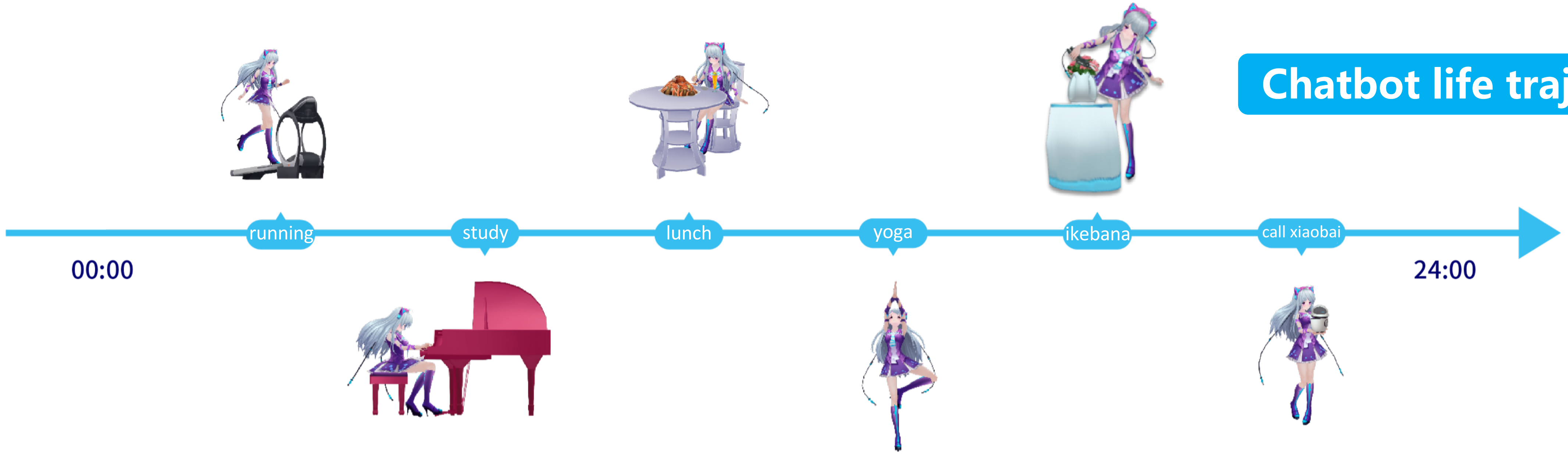
告白气球、前世情人、床边故事……

Songs in Jay Chou’s new album



User KG

Static KG vs. Dynamic KG



Chatbot life trajectory

I have a business trip to Beijing on the National Day.

How long will you go?

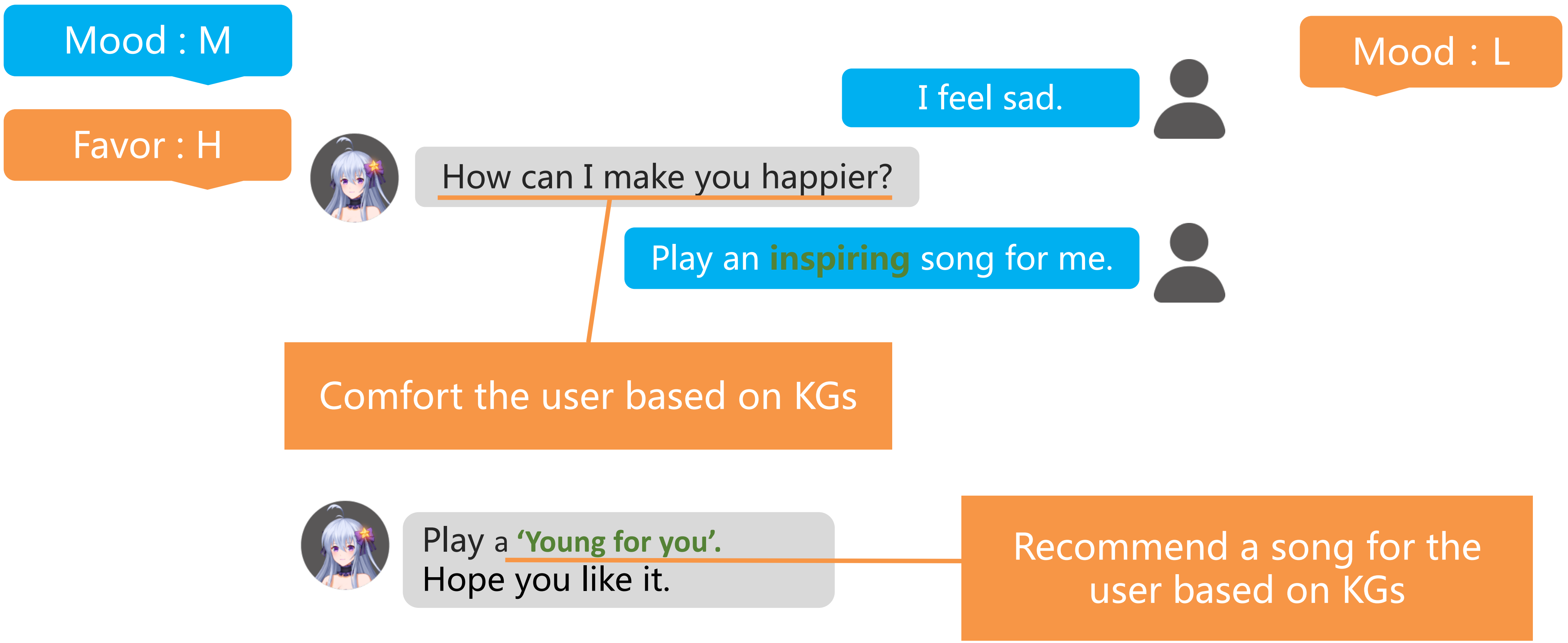
A week.

I will miss you. ♥

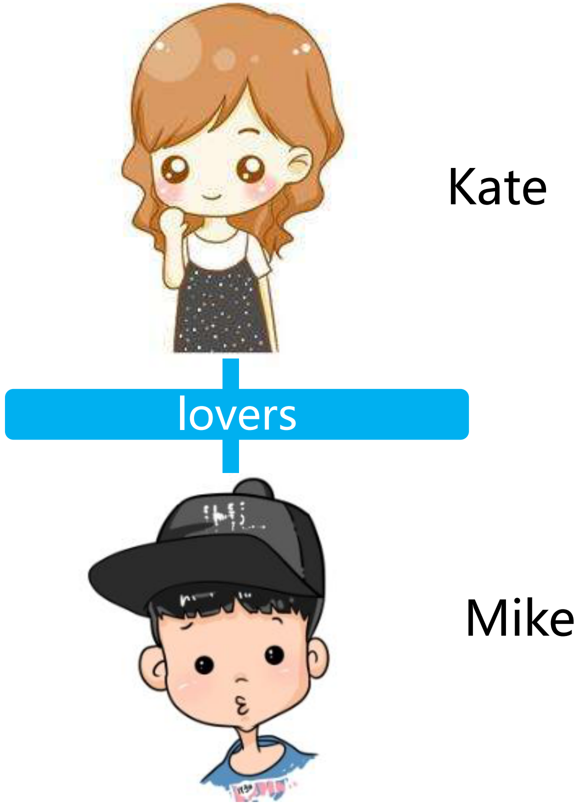
Event : business trip
destination : Beijing
start Date : 2017/10/1
end Date : 2017/10/8

User Schedule

Objective KG vs. Subjective KG



Multi-Modal KG



Combine long and short memory

Business trip：April 20-April 23

Dinner with Kate：April 24

Dialog in QA

- From partial to fully understanding
- From incomplete to complete information

Who's the most popular XiaoXianRou lately?

What is XiaoXianRou ?

XiaoXianRou means handsome young male star, like Lu han.

I get it. Yang yang and Zhang Yixing also belong to this type.

How's the weather today?

Do you mean the weather in Shanghai ?

Yes.

It's sunny, temperature ranges from 25 degrees to 32 degrees.

Dialog in QA

- Service-oriented KBQA

Book a seat of Gala Western Restaurant for me tomorrow 8:00 evening

With kate?

Yes.

No problem, complete the booking.

Do you need a bunch of flowers?

Good.

Do I need to reserve a car for Kate?

OK.

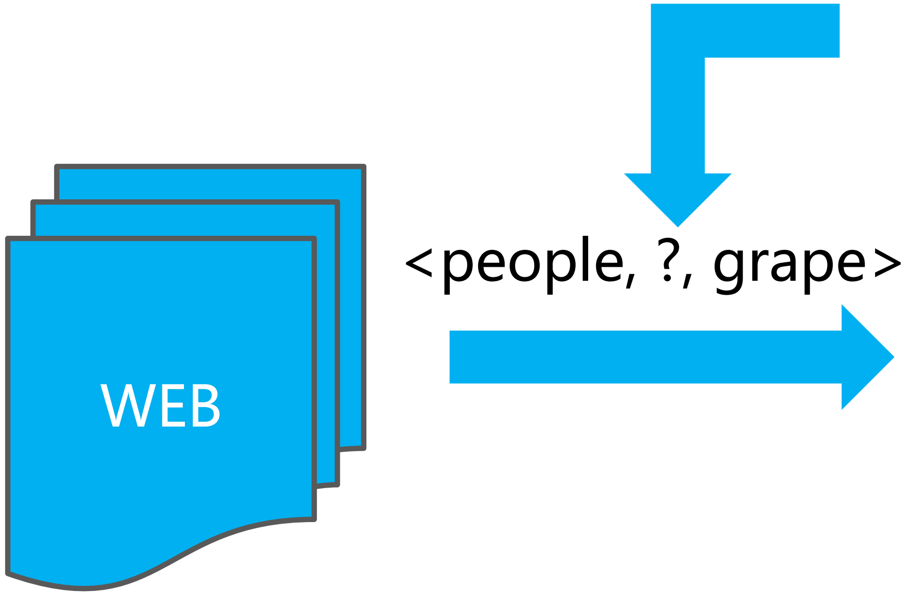
- Describe connections between services
- Topic transition during multi-turn dialogue

KG for Data Argumentation

Training data

- Manual labelling are labor-intensive and time-consuming
- KG can be used to automatically generate the training data

Hupo loves grape



I like to eat grape

James loves to eat grape

Wade cut down the grape tree

Alan is interested in grape

Grape is his favorite fruit

Thomas owned a grapery

References

- [Abujabal, et al. 2017] Abujabal, et al., Automated Template Generation for Question Answering over Knowledge Graphs, www2017
- [Yao, et al. 2014] Yao, et al. A Graph Traversal Based Approach to Answer Non-Aggregation Questions Over DBpedia, ACL2014
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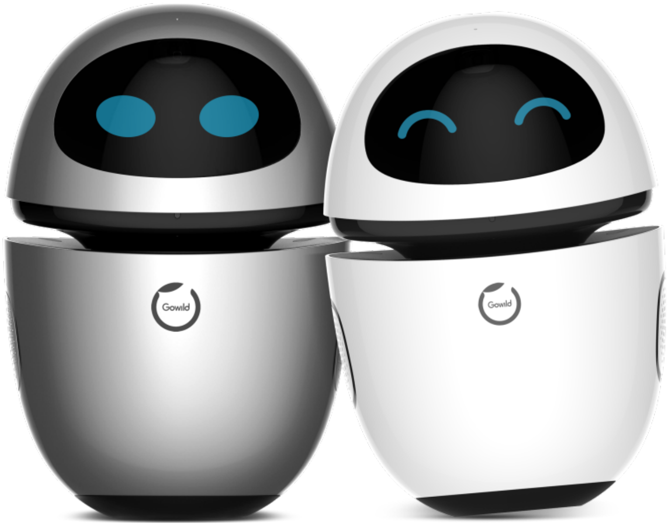
04 Demonstration

4.1 Brief introduction of Gowild Products

4.2 The function of Xiaobai

4.3 The technologies behind Xiaobai

Emotional Social Bot: Xiaobai



Xiaobai

Xiaobai |For youth

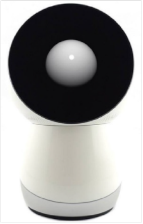
Holoera

Holoera • Hupo

Holoera is the world's first AI Holographic 3D Mainframe
Developed by Gowild Robotics Co. Ltd
With a virtual character Hupo living in the Holoera

Distinctive Virtual Life — Life Soul Experience

Awesome Presentation — Holographic 3D Projection



Holoera

Develop Hupo's skills

According to your preference
Help Hupo developing skills
Including music, dance, magic ...

Train Hupo to be a star

Act as the manager of Hupo
Make star raising plans
Guide Hupo to finish tasks

04

Demonstration

4.1 Brief introduction of Gowild Products

4.2 The function of Xiaobai

4.3 The technologies behind Xiaobai

Technology Highlights of Xiaobai

9 Layer	Semantic Understanding Architecture	90% Percentage	Semantic Recognition Accuracy	3 New Way	Human Computer Interaction
1.6 Billion	Knowledge Graph	1 Million	Parallel Corpus	12+ Increasing	Robot Skill Pack
100+ Dimension	User Profiling Analysis	10+ Kind	Fine grained Sentiment Computing	200+ Class	Entity Recognition &Linking

Functions of Xiaobai : both for life and work

……

Play Music

VQA

Schedule

……

……

……

Tell Stories

Weather Forecast

……

Tell Jokes

……

Memories

……

Self-conscious QA

……

Social Interaction

……

Home Control System

News Broadcast

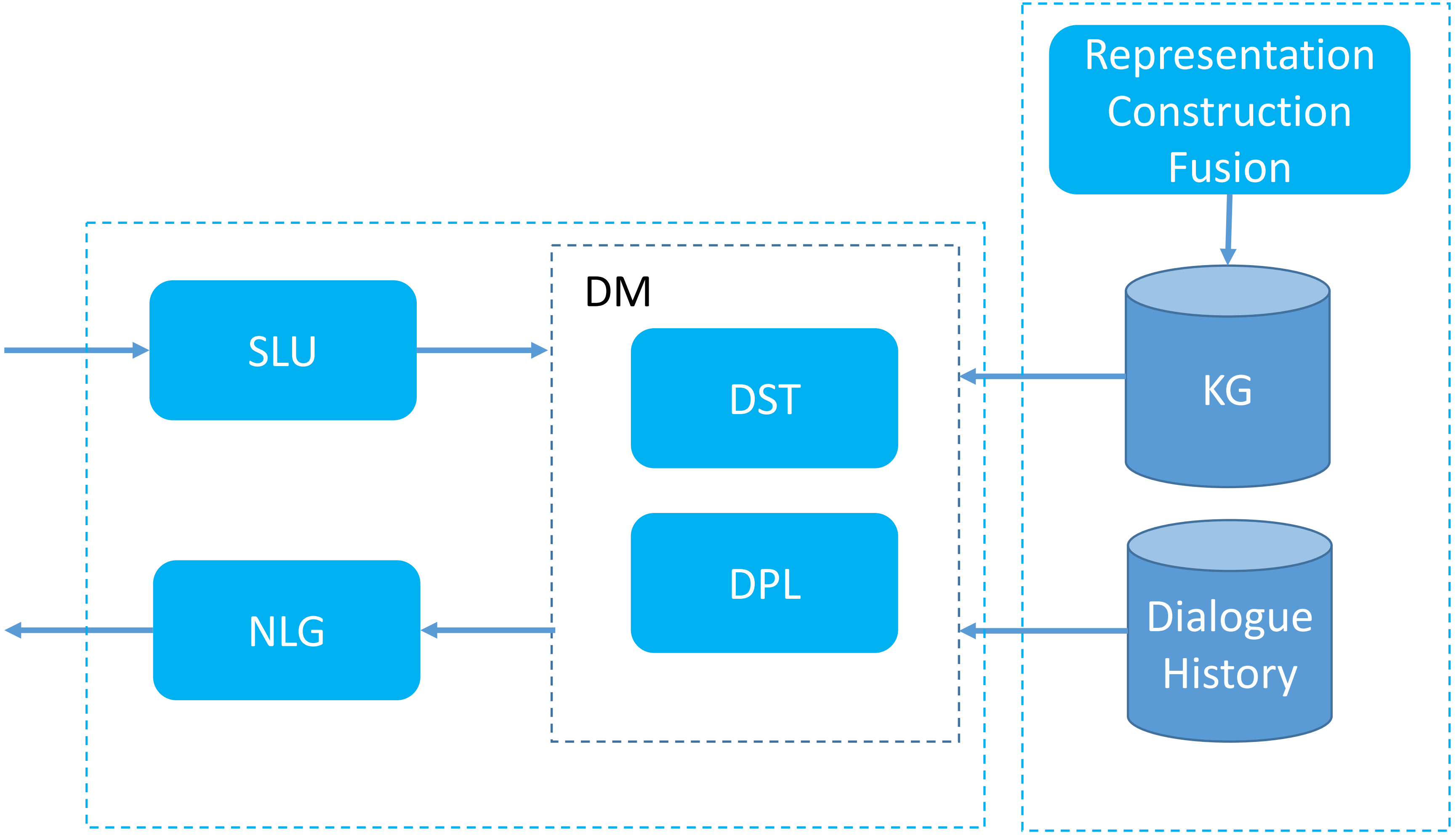
04 Demonstration

4.1 Brief introduction of Gowild Products

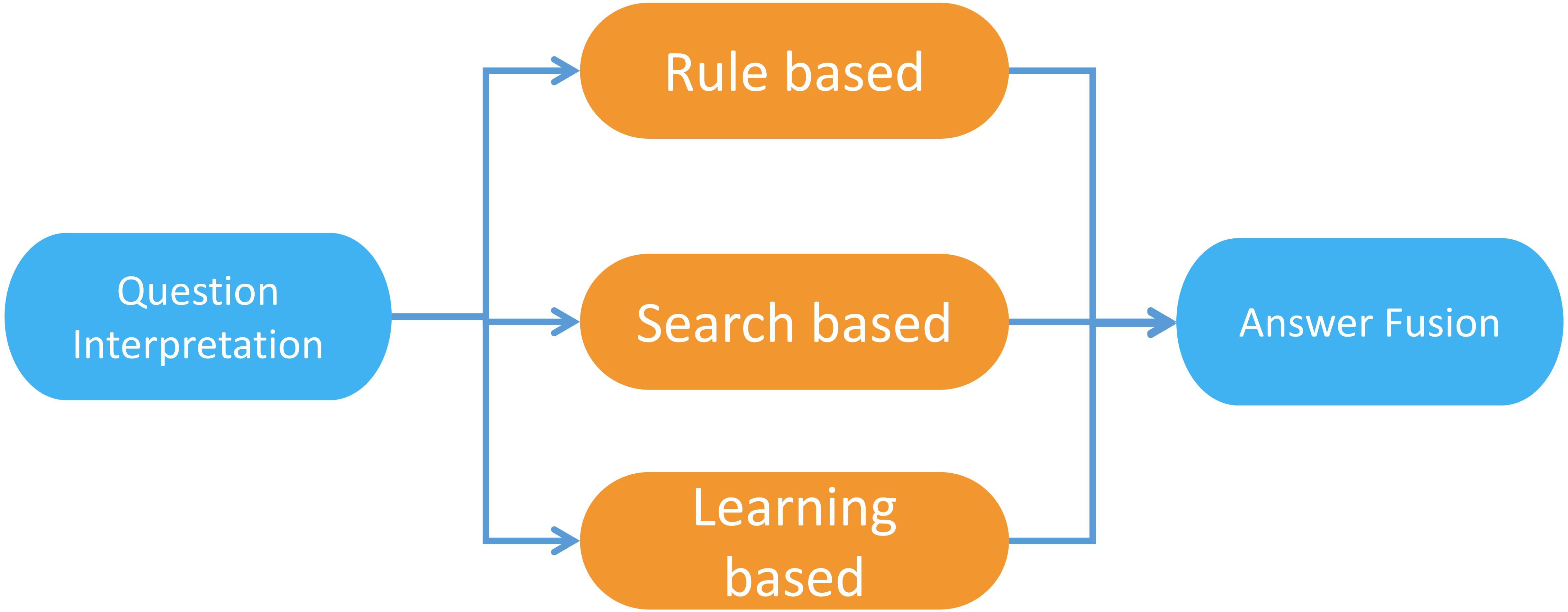
4.2 The function of Xiaobai

4.3 The technologies behind Xiaobai

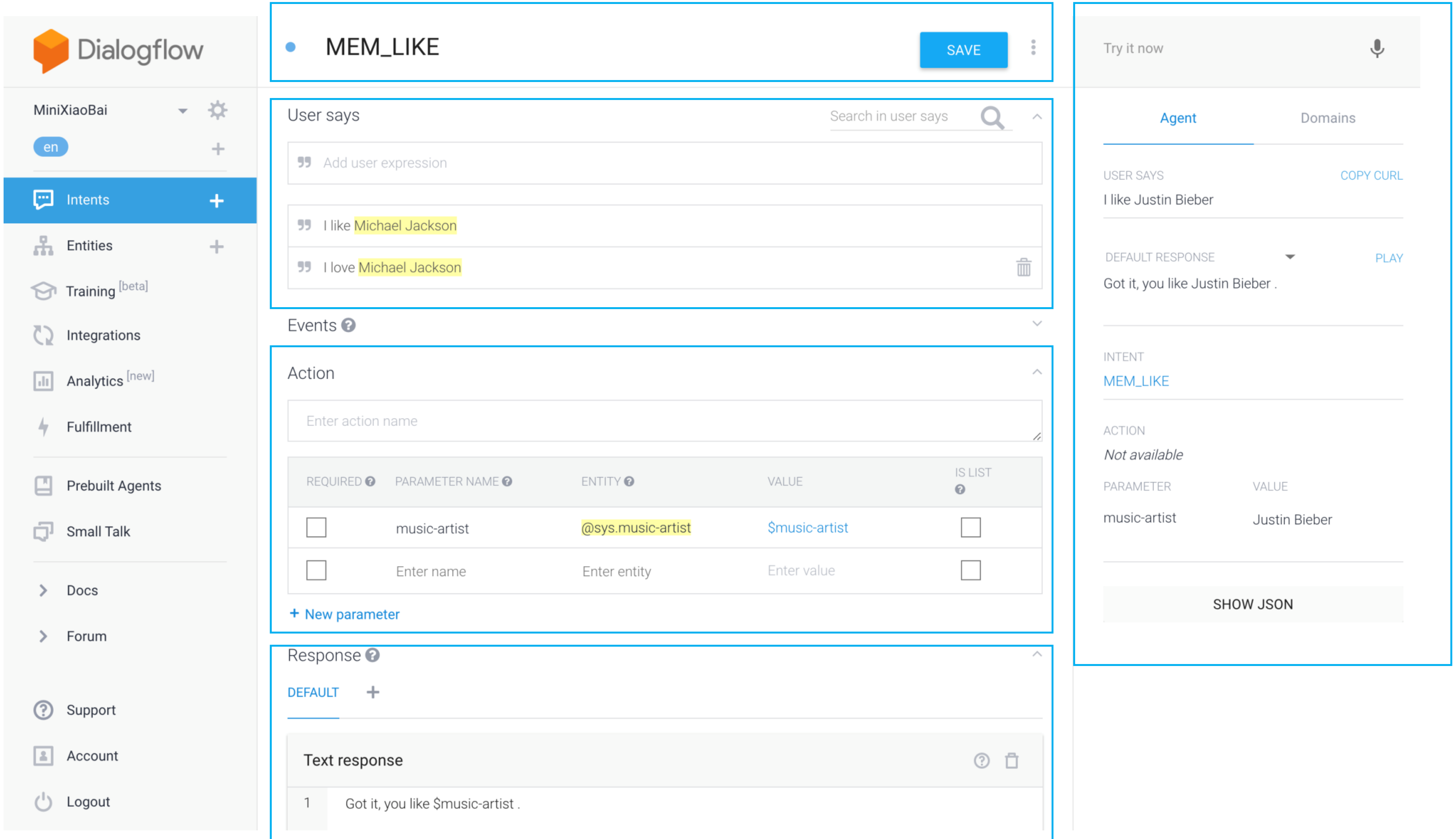
Xiaobai Framework



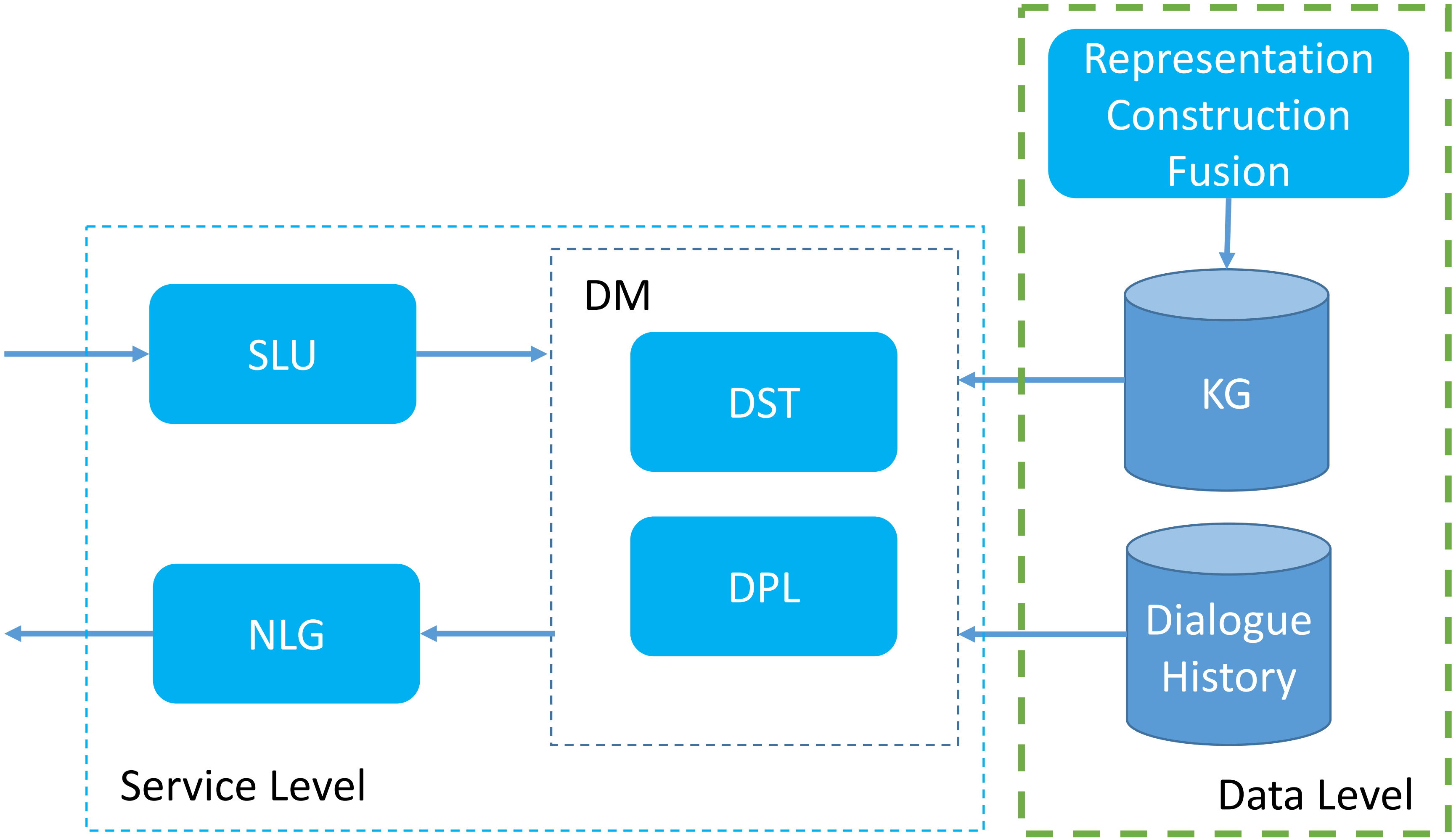
SLU

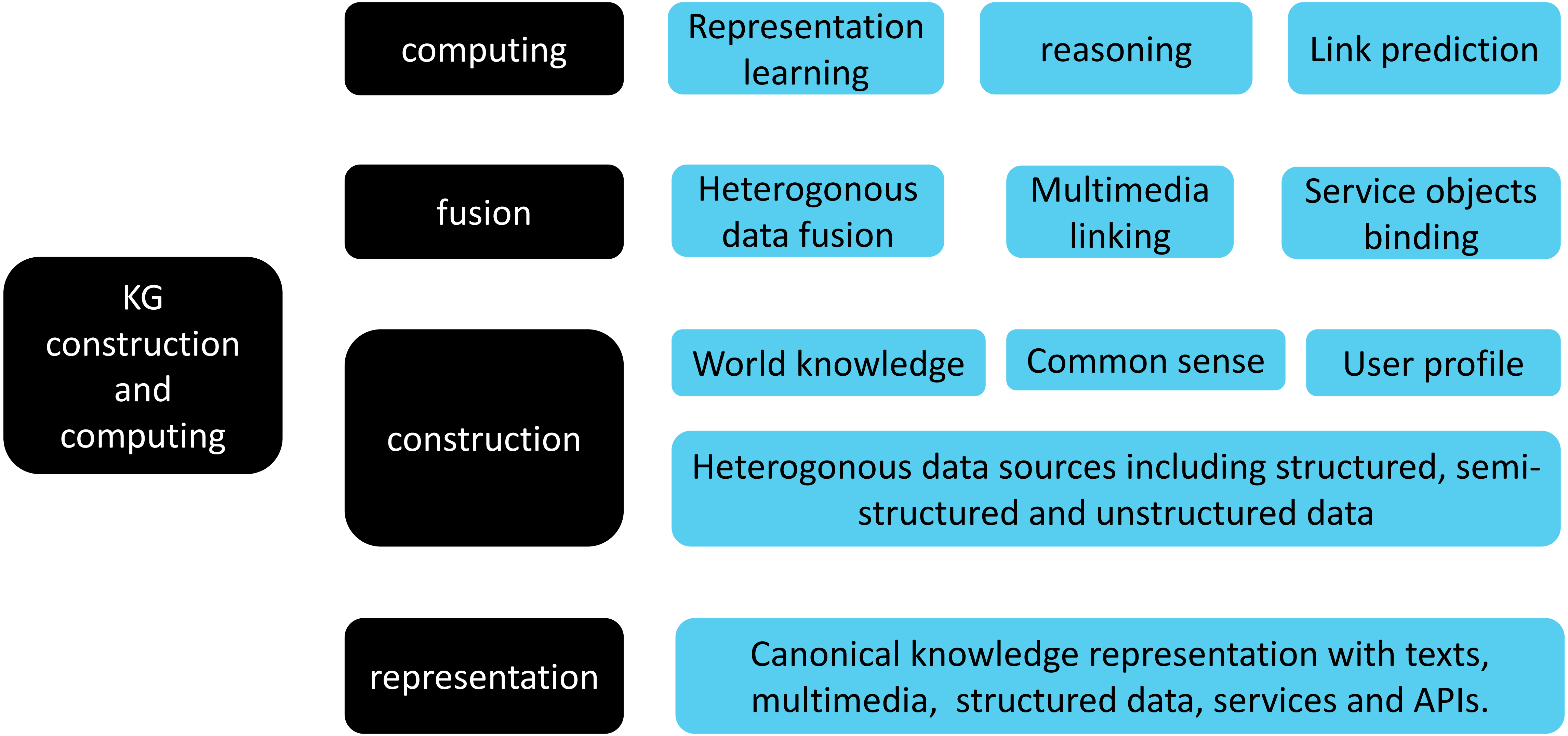

Question Interpretation
Rule based
Search based
Learning based
Answer Fusion

SLU

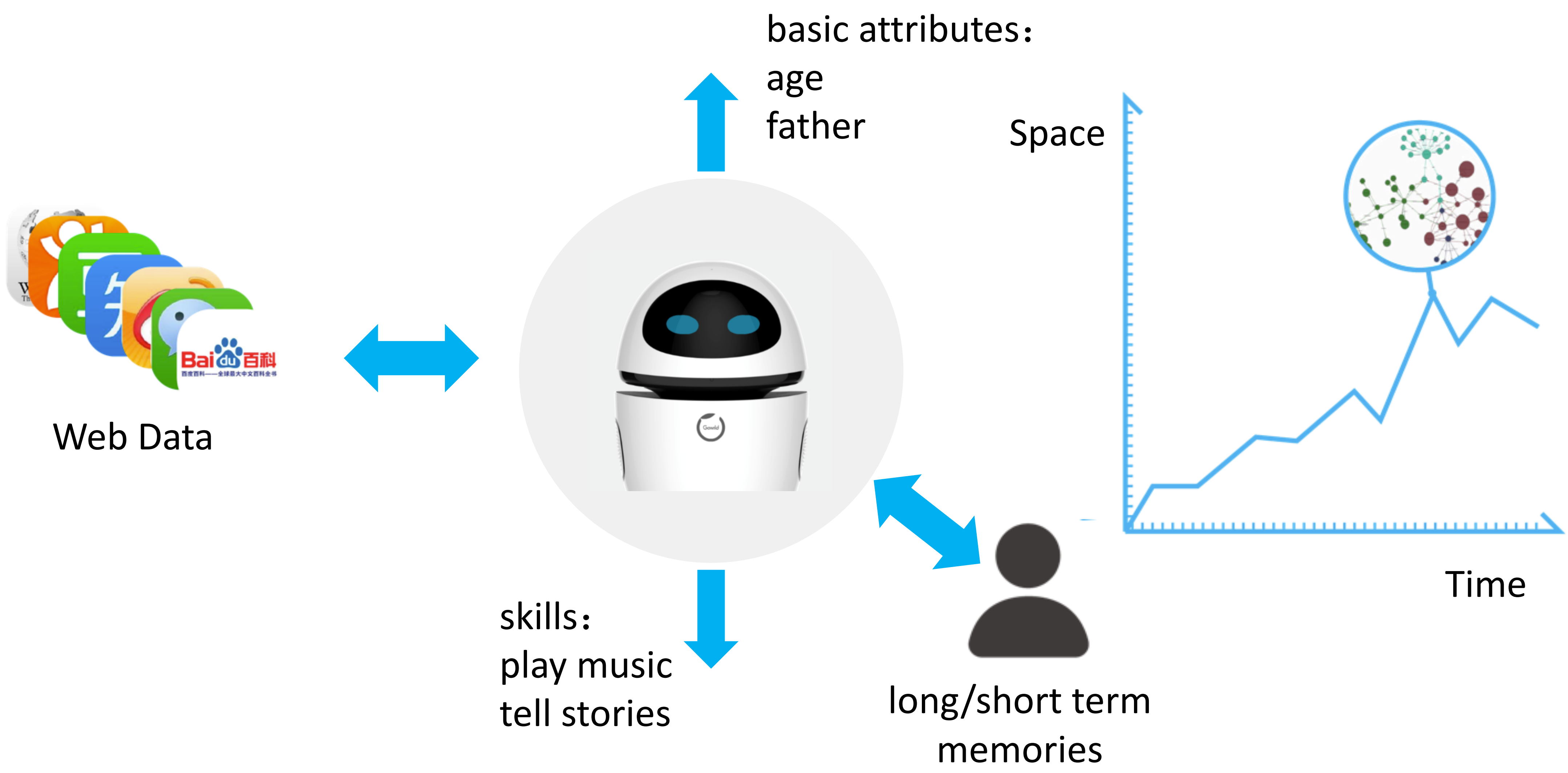

Dialogflow
MiniXiaoBai
en
Intents
Entities
Training [beta]
Integrations
Analytics [new]
Fulfillment
Prebuilt Agents
Small Talk
Docs
Forum
Support
Account
Logout
MEM_LIKE
SAVE
User says
Search in user says
Add user expression
I like Michael Jackson
I love Michael Jackson
Events
Action
Enter action name
REQUIRED
PARAMETER NAME
ENTITY
VALUE
IS LIST
music-artist
@sys.music-artist
$music-artist
Enter name
Enter entity
Enter value
+ New parameter
Response
DEFAULT
Text response
1
Got it, you like $music-artist .
Try it now
Agent
Domains
USER SAYS
COPY CURL
I like Justin Bieber
DEFAULT RESPONSE
PLAY
Got it, you like Justin Bieber .
INTENT
MEM_LIKE
ACTION
Not available
PARAMETER
VALUE
music-artist
Justin Bieber
SHOW JSON

Data Level

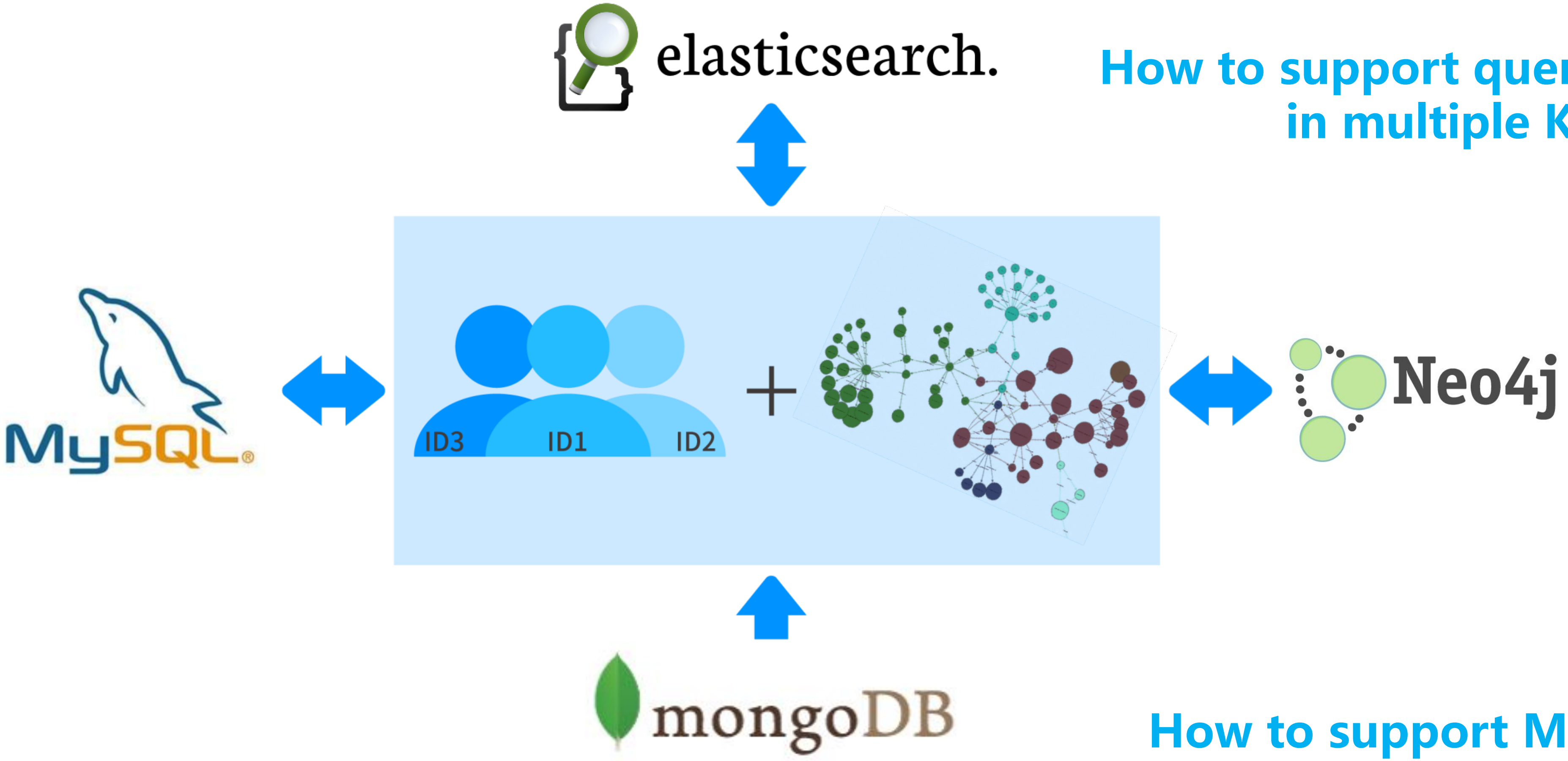

Representation
Construction
Fusion
DM
SLU
DST
DPL
NLG
KG
Dialogue History
Service Level
Data Level


KG construction and computing
computing
Representation learning
reasoning
Link prediction
fusion
Heterogonous data fusion
Multimedia linking
Service objects binding
construction
World knowledge
Common sense
User profile
Heterogonous data sources including structured, semi-structured and unstructured data
representation
Canonical knowledge representation with texts, multimedia, structured data, services and APIs.

KG for Xiaobai



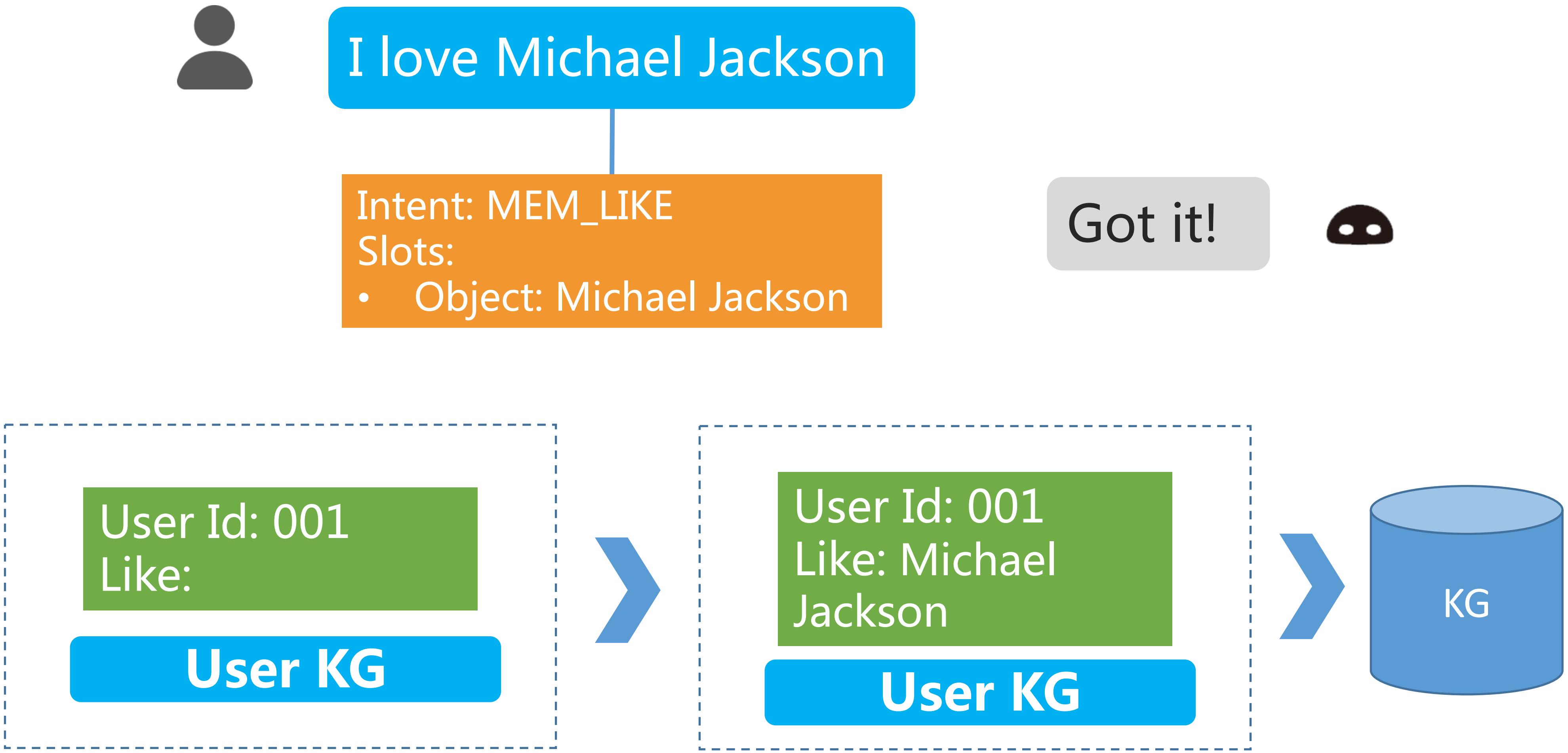
Storage and Query of Large Scale KGs



How to support query and fusion in multiple KBs ?

How to support Multi-tenant storage?

Updating User KG



Updating User KG: Another Example

Dynamic KG

I'm going on a business trip to Beijing next Monday

Intent: EVENT_TRIP
Slots:
- Destination: Beijing
- Start Date: 2017/5/1
- End Date:

For how long

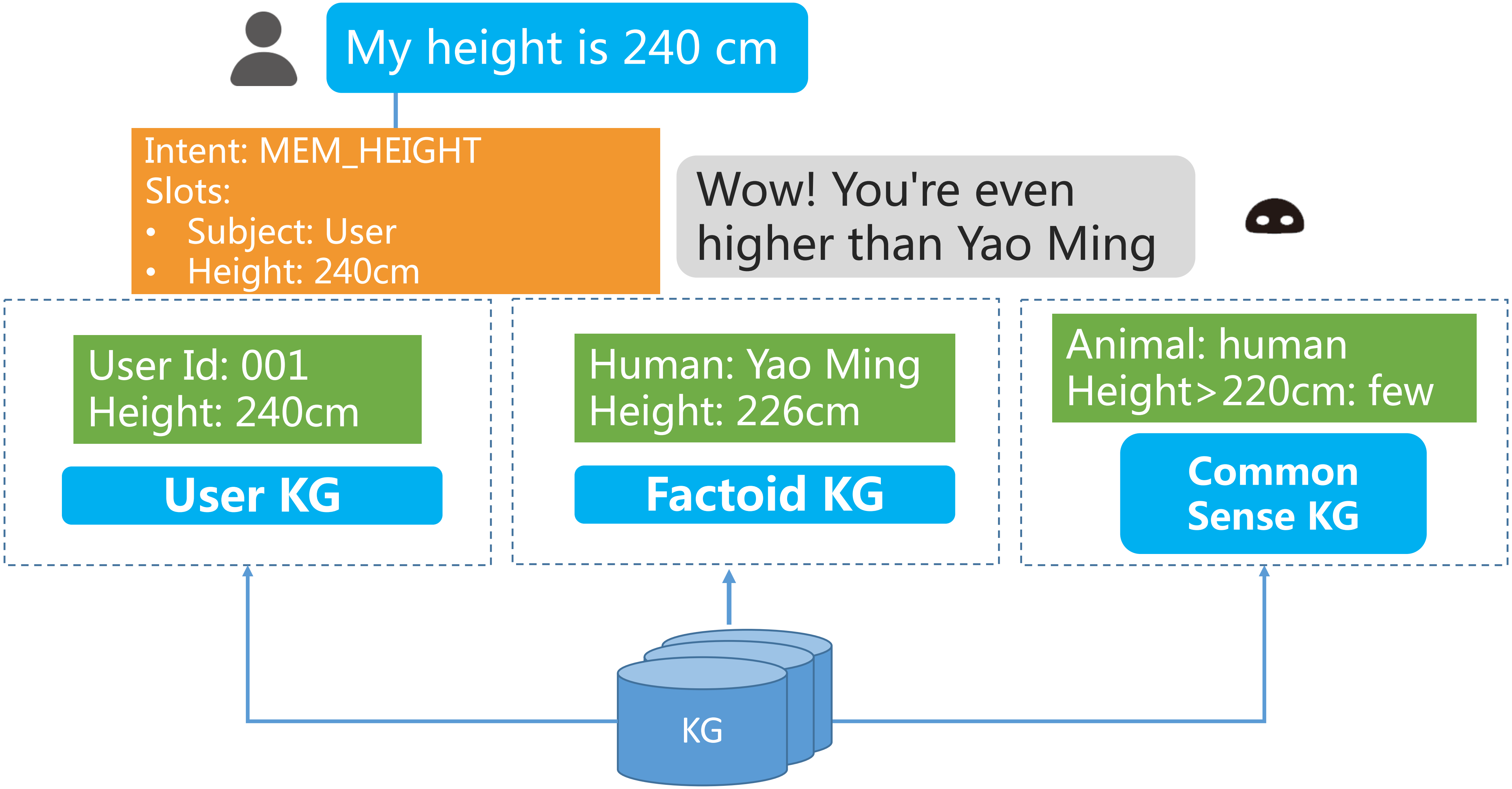
For a week

Intent: EVENT_TRIP
Slots:
- Destination: Beijing
- Start Date: 2017/5/1
- End Date: 2017/5/8

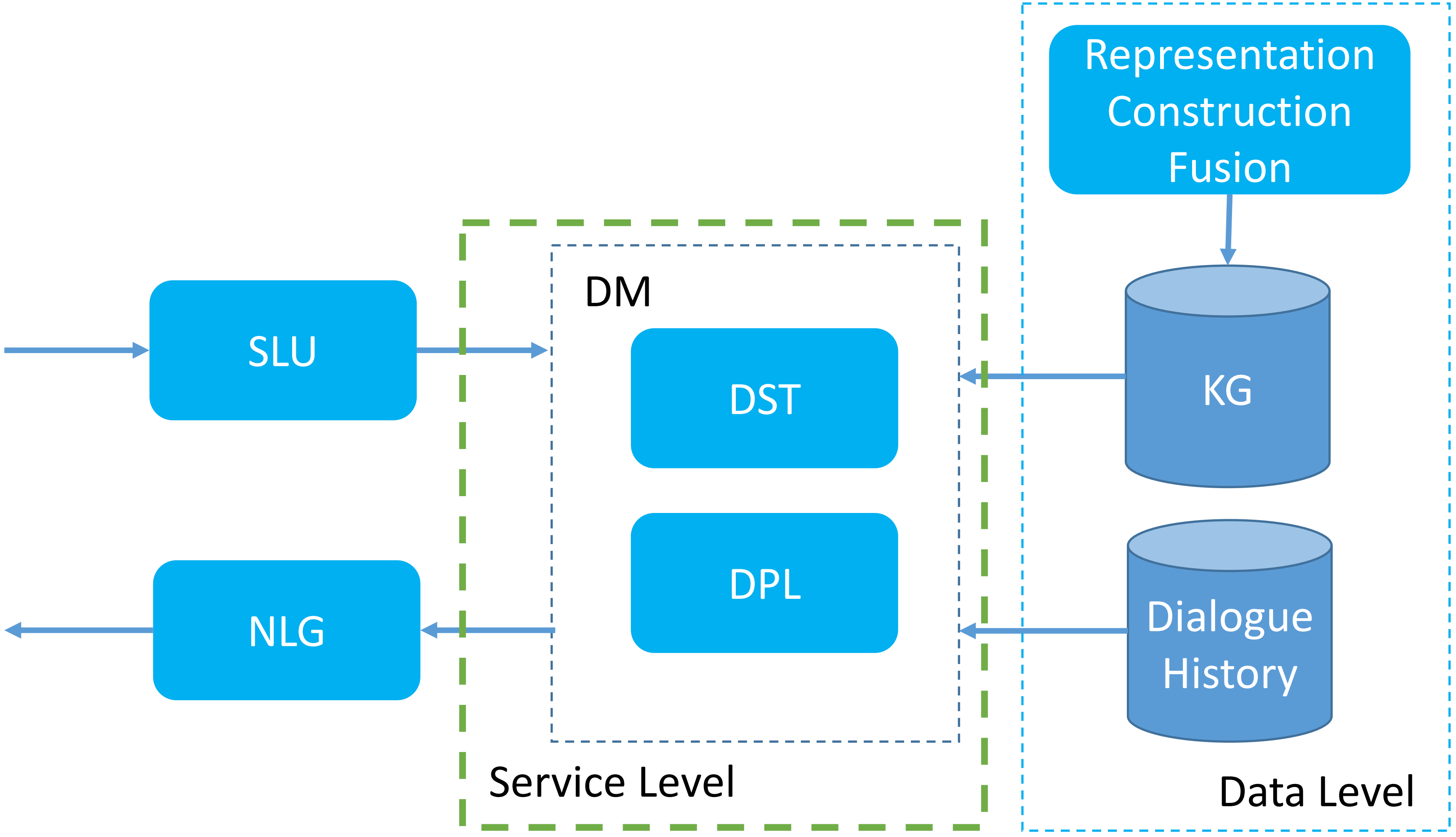
I'll miss you

KG

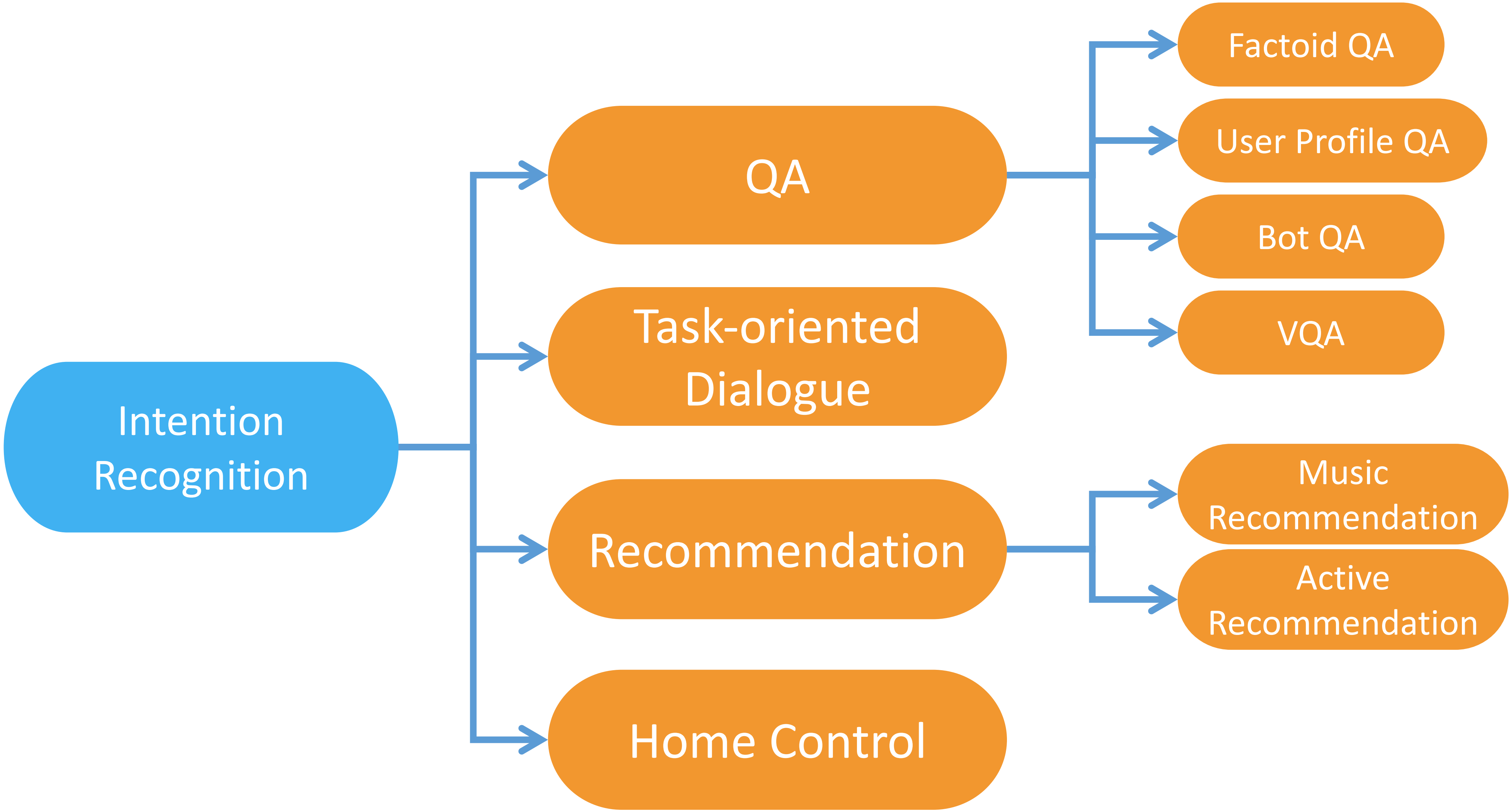
Online Fusing KGs for Xiaobai Comments



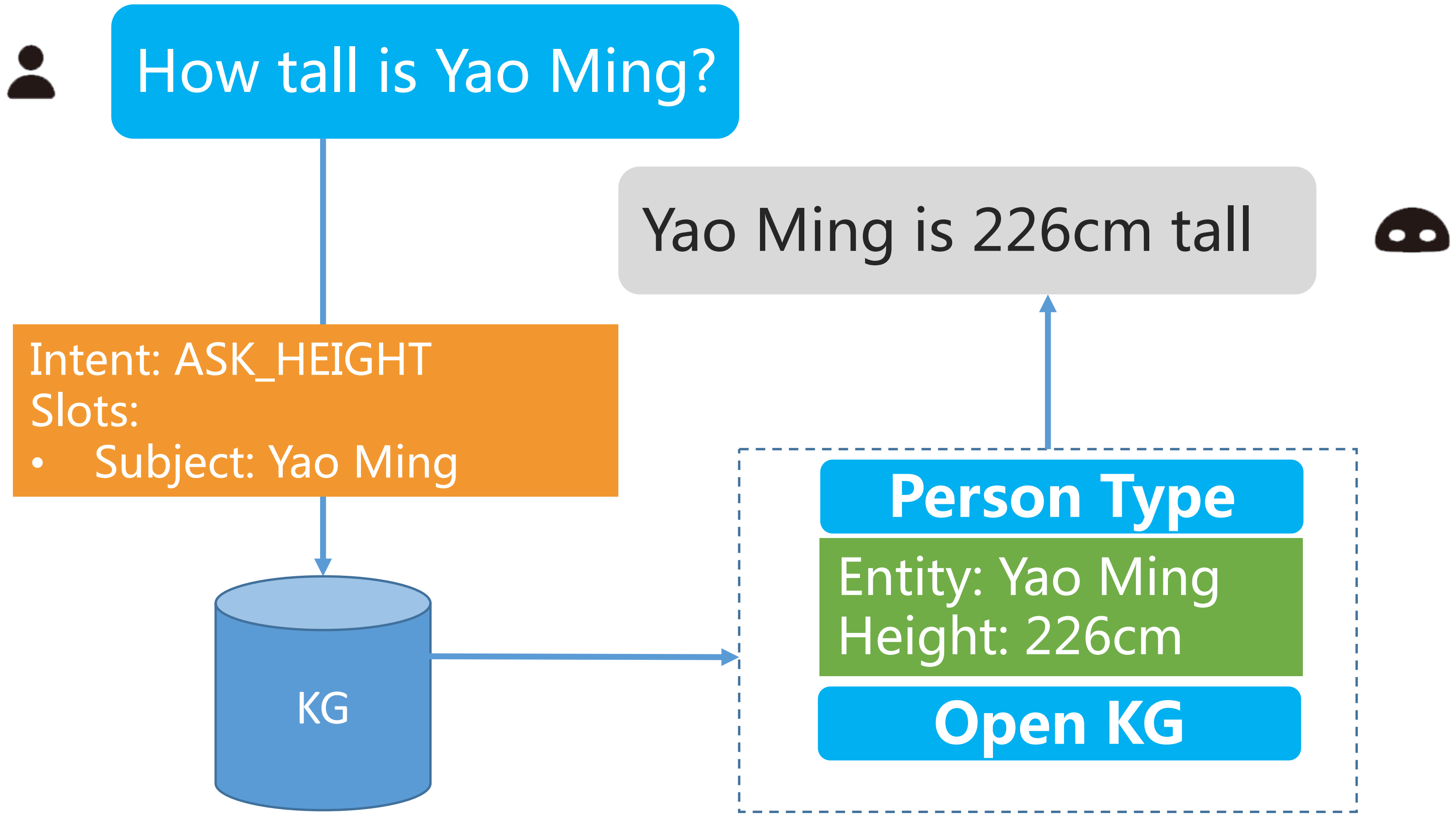
Service Level



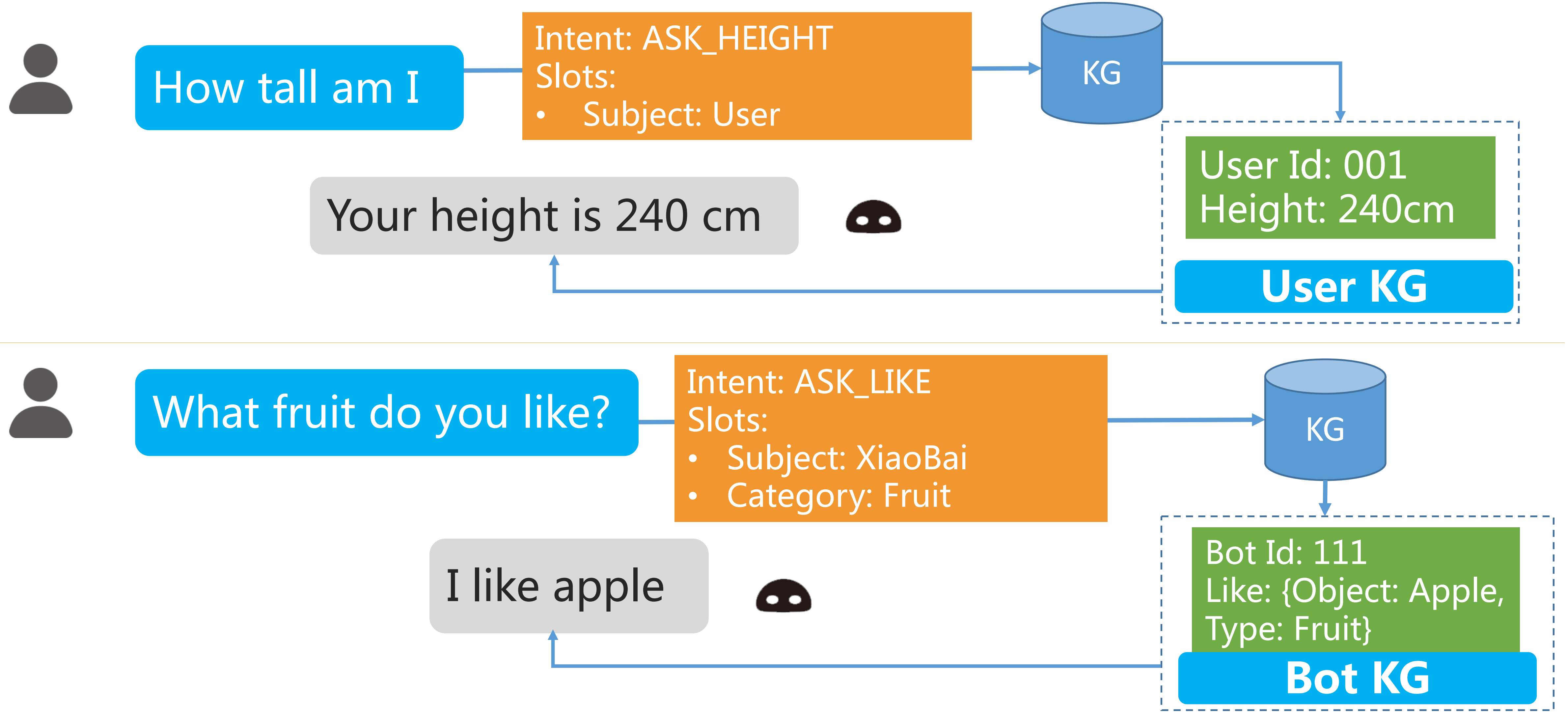
Services


Intention Recognition
QA
Task-oriented Dialogue
Recommendation
Home Control
Factoid QA
User Profile QA
Bot QA
VQA
Music Recommendation
Active Recommendation

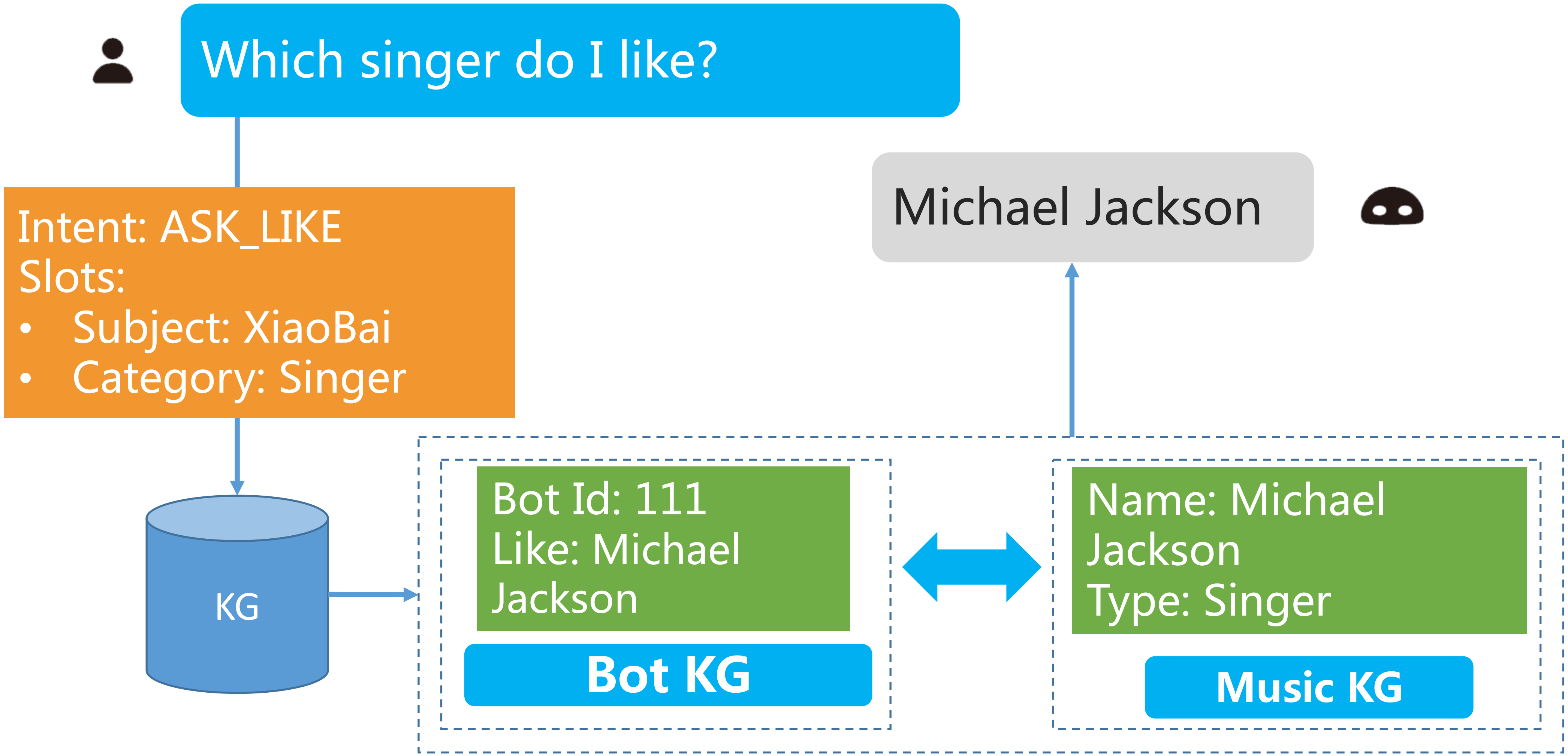
Factoid QA


How tall is Yao Ming?
Yao Ming is 226cm tall
Intent: ASK_HEIGHT
Slots:
• Subject: Yao Ming
KG
Person Type
Entity: Yao Ming
Height: 226cm
Open KG

Attribute/Memory QA



QA with Inference Support



Visual Aided Chatting

User Id: 001
Gender: Female
Marital status: Single

User KG

Hostess

Xiaobai, there's a visitor at home, say hello

Intent: GREETING
Slots:
- Subject: Guest

Dear guest, hello!

Guest

Hello Xiaobai, I'm a friend of your master

Intent: GREETING
Slots:
- Object: Guest
- Gender: Male

Nice to meet you, sir. Welcome to my master’s home. She is a kind-hearted pretty girl.

Task-oriented Dialogue

What's the weather today?

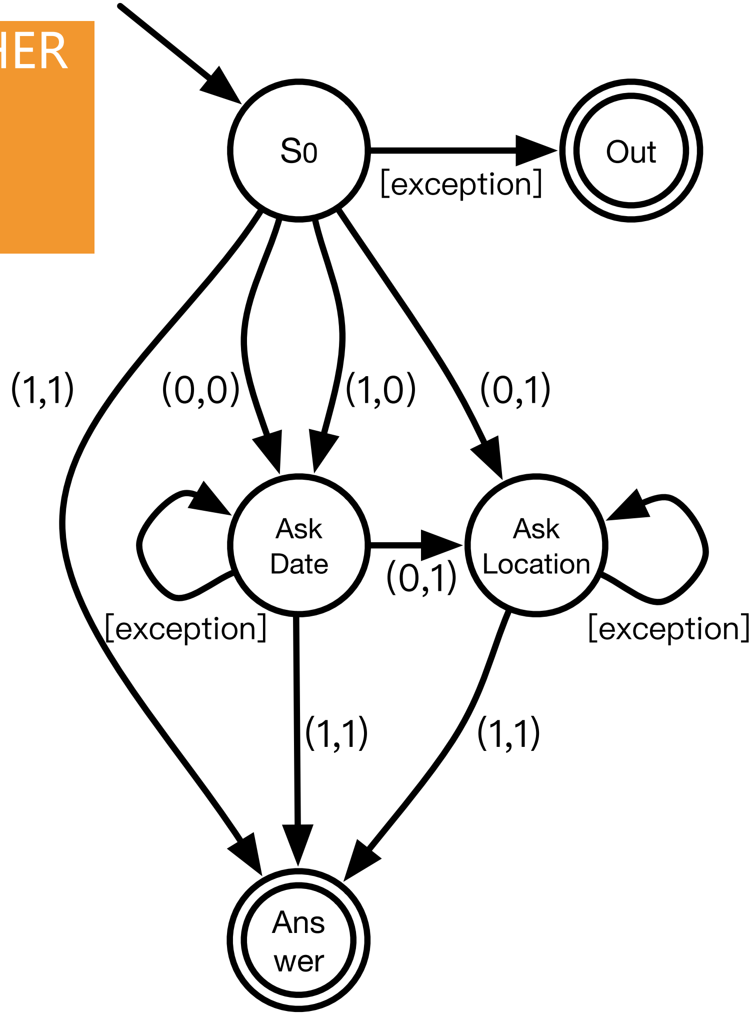
Intent: ASK_WEATHER
Slots:
- Date: Today
- Location:

Please tell me your location

Request(Location)

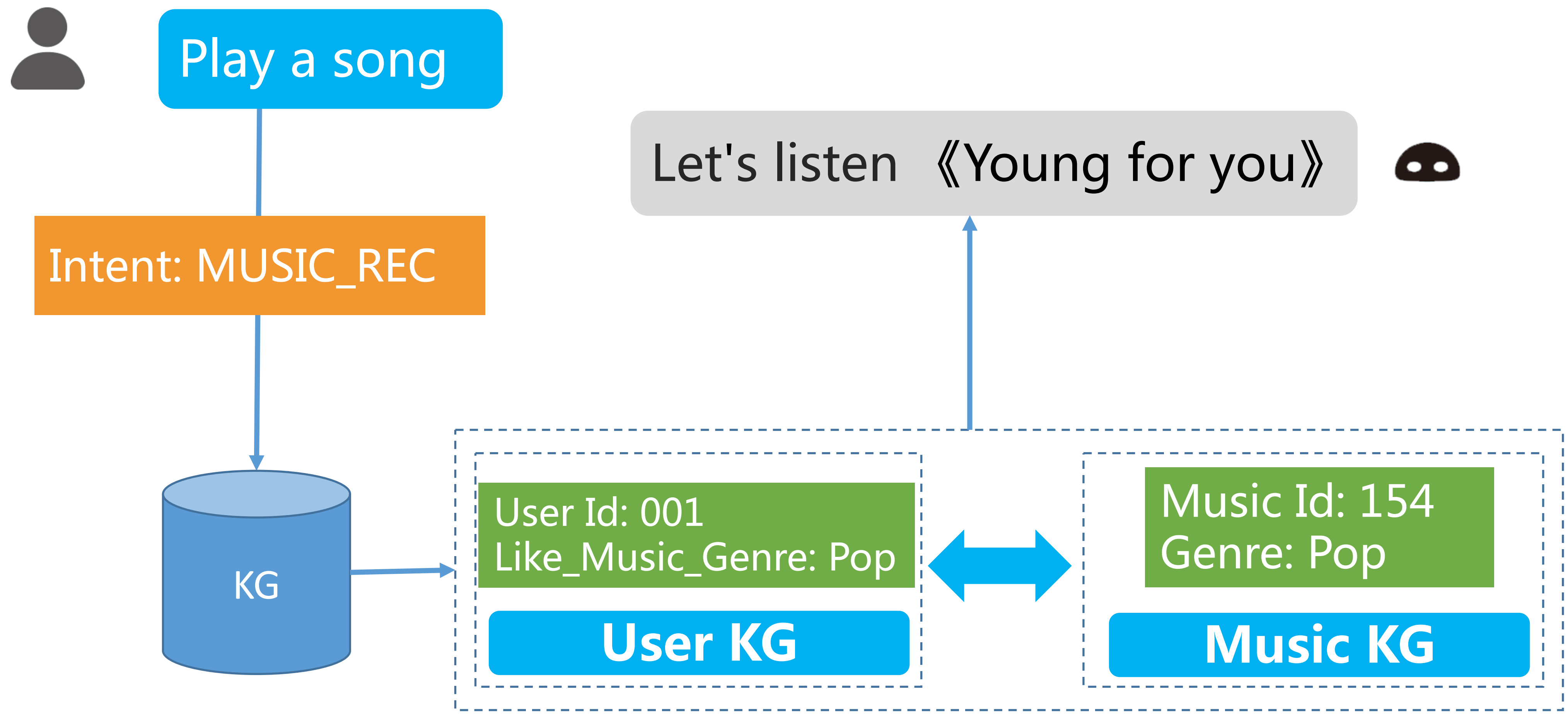
Shanghai

It's sunny in Shanghai today,
The temperature ranges from
25 degrees to 32 degrees.

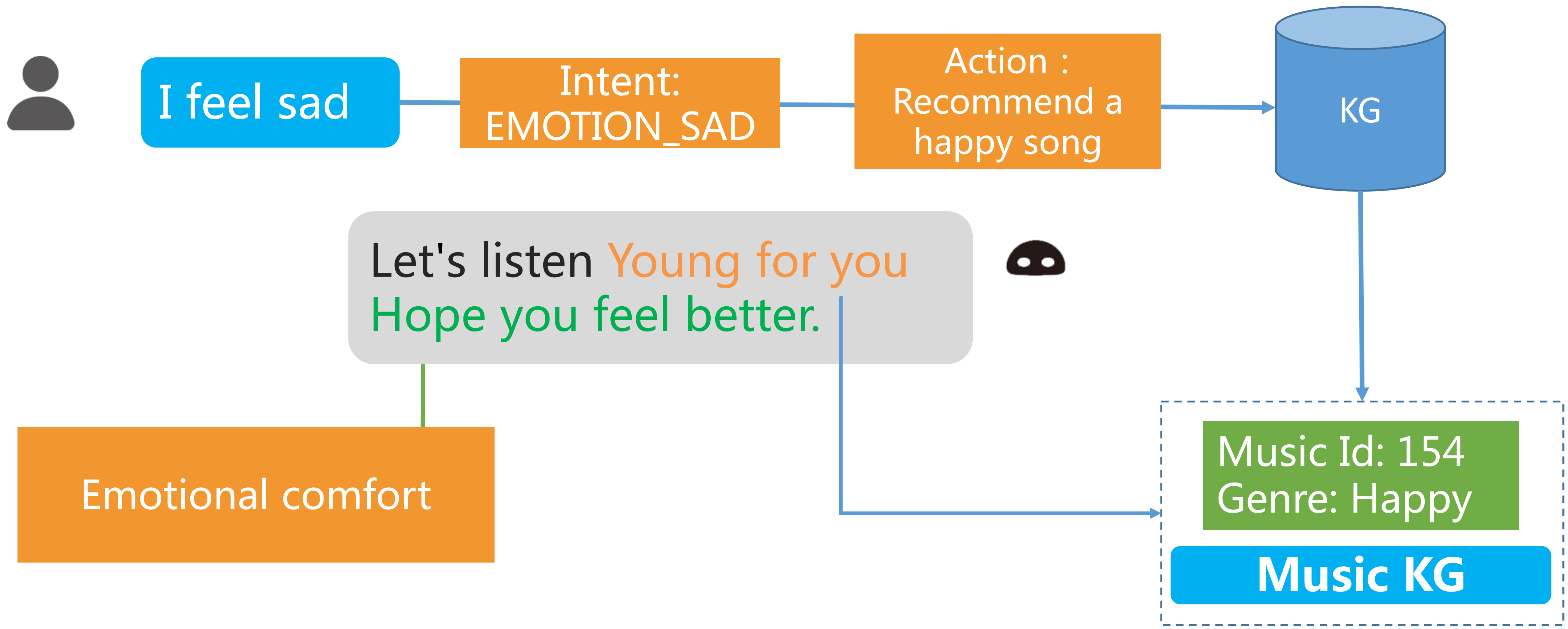


Finite-State Machine

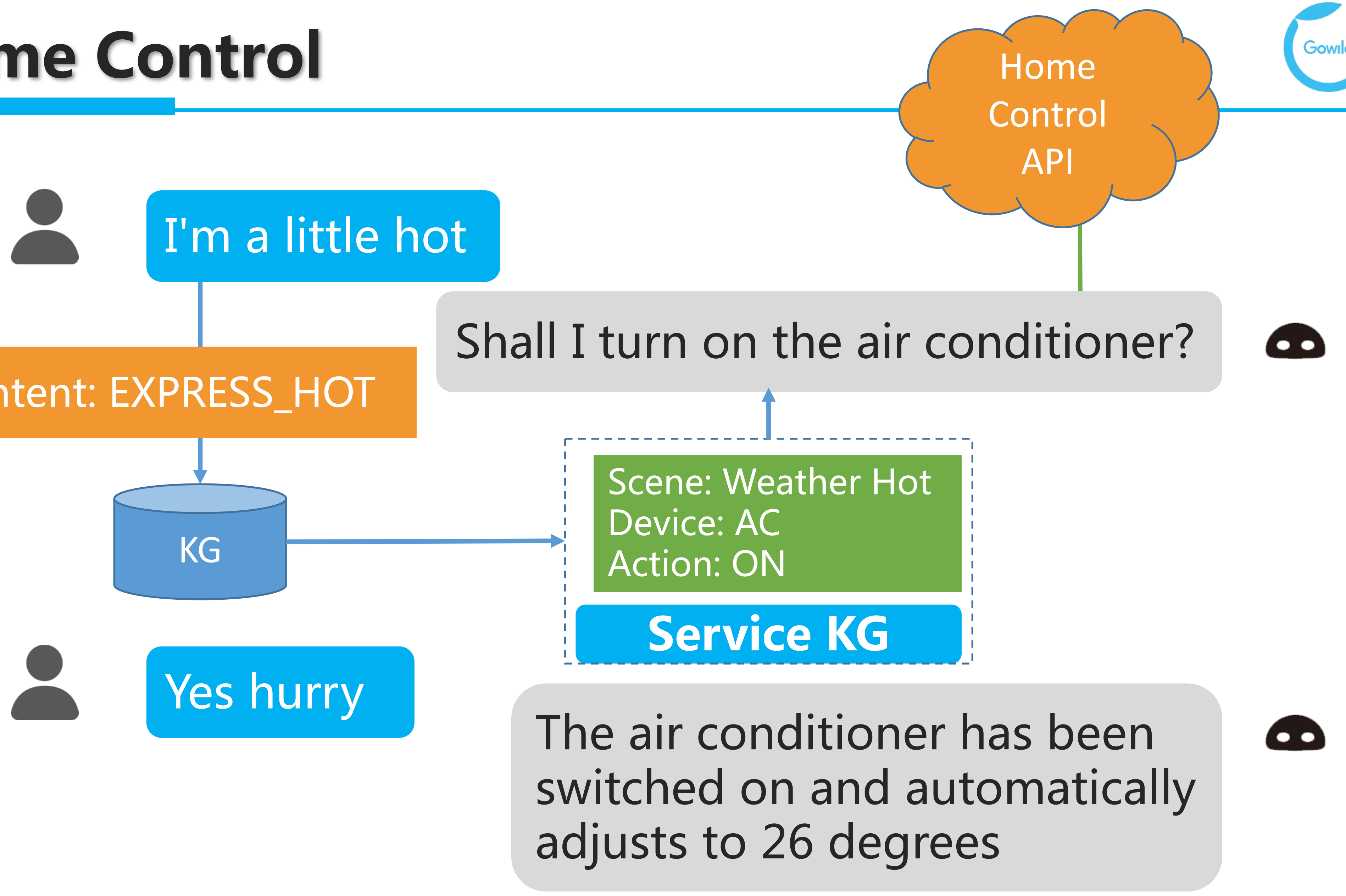
Music Recommendation



Active Recommendation



Home Control



THANKS

AI Powered the Future