国际人工智能会议
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FORCE: A Framework Of Rule-based Conversational REcommender System

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Motivation

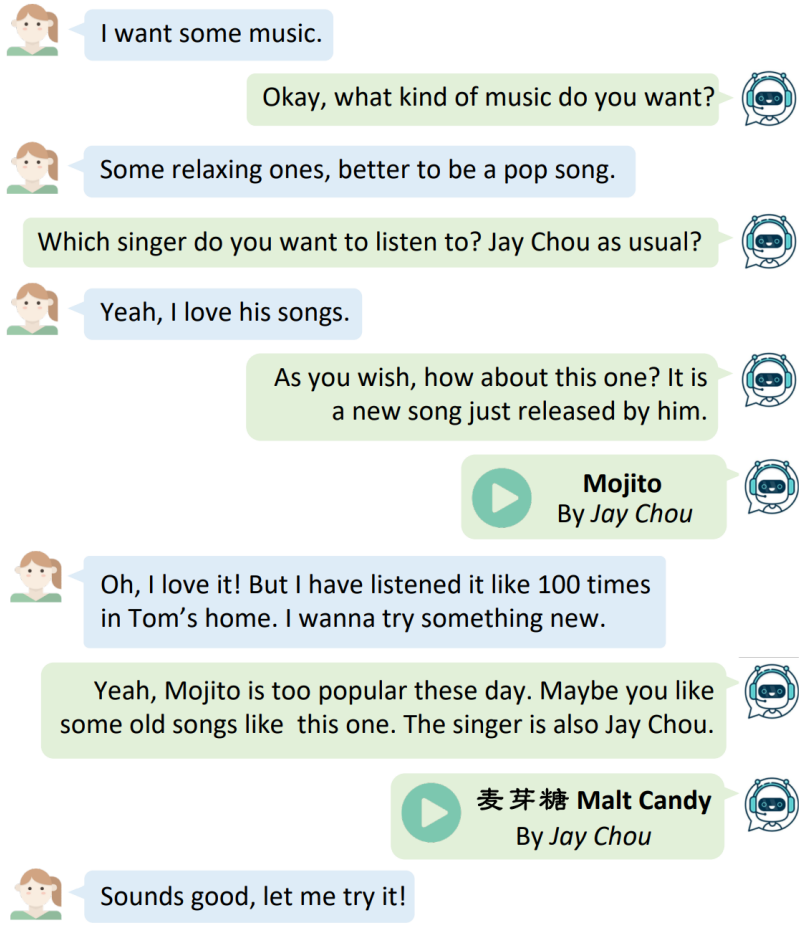
System Demo

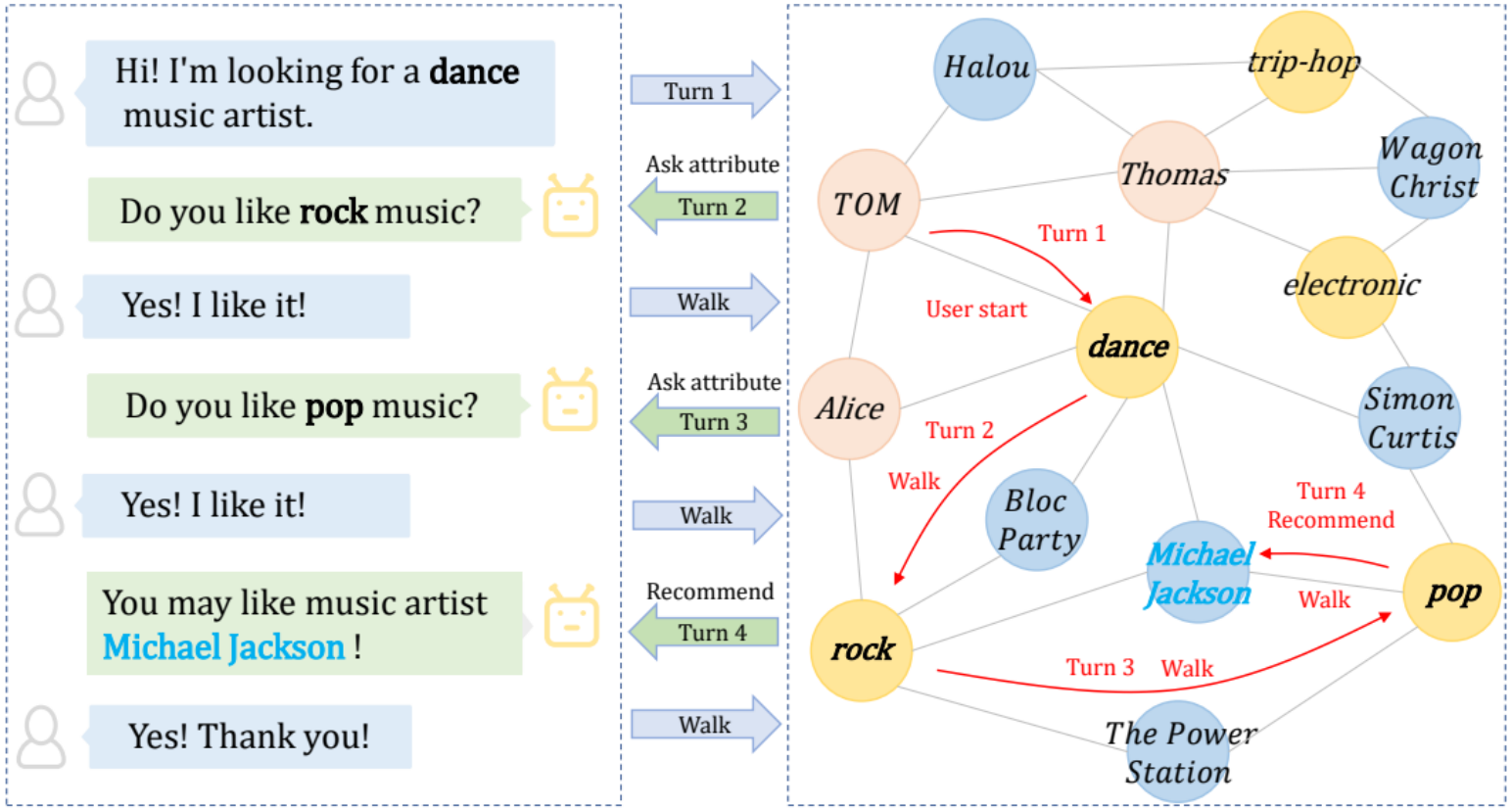
System introduction

Dataset and Experiment

Summary

Background





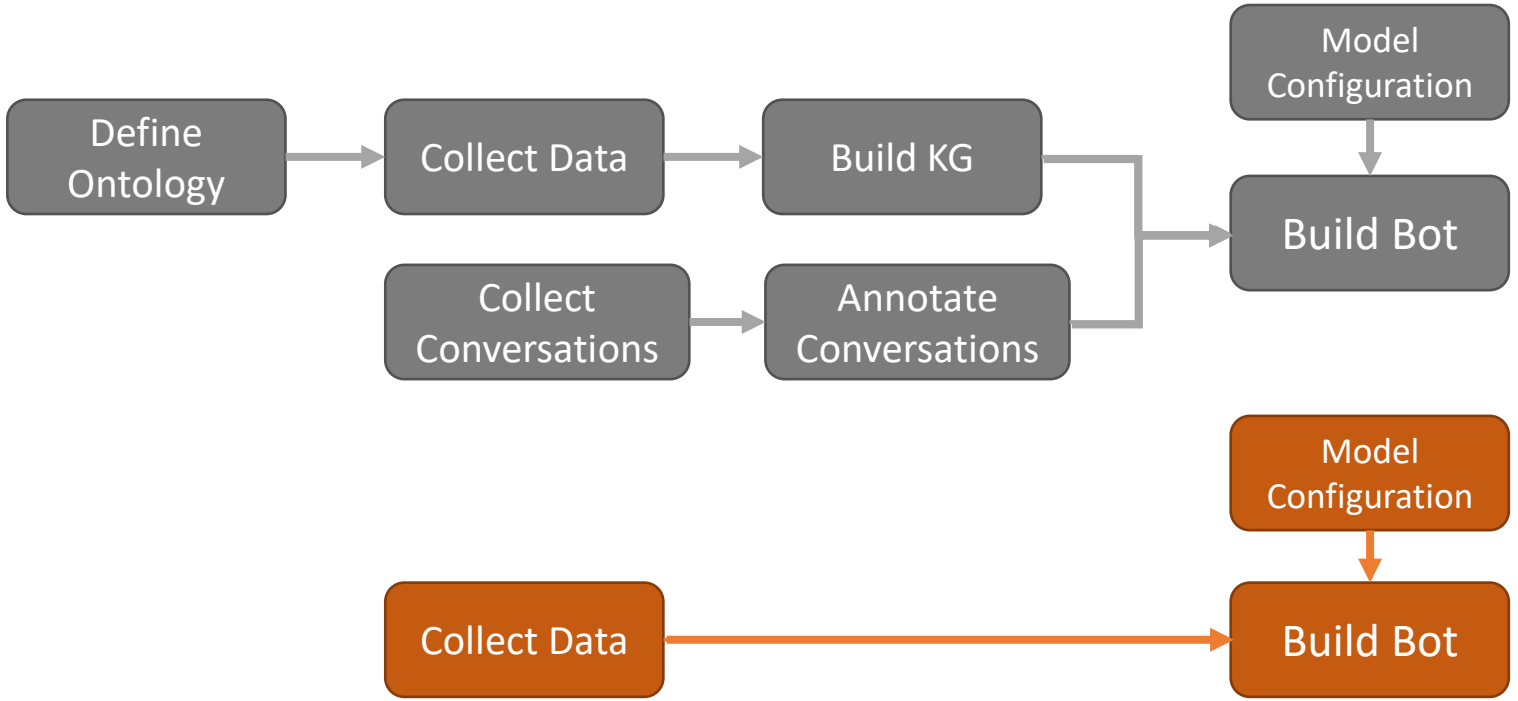
Gao, Chongming, et al. "Advances and challenges in conversational recommender systems: A survey."

Motivation

- Why Conversational ?
  - Capture users' real-time feedback through interaction and then make better recommendation.

- Why FORCE ?
  1. Deep learning methods require plenty of annotated data for each domain.
  2. Unbearable time and financial cost for industrial products.
     - Imagine building a shopping guider bot in e-commerce field.
  3. Need a low-cost and interpretable approach.
     - Data + Configuration = CRS Bot

Motivation



Major practices to build CRS Bot

Build CRS Bot with FORCE

- FORCE: a low-cost and interpretable approach.
  - Data + Configuration = CRS Bot

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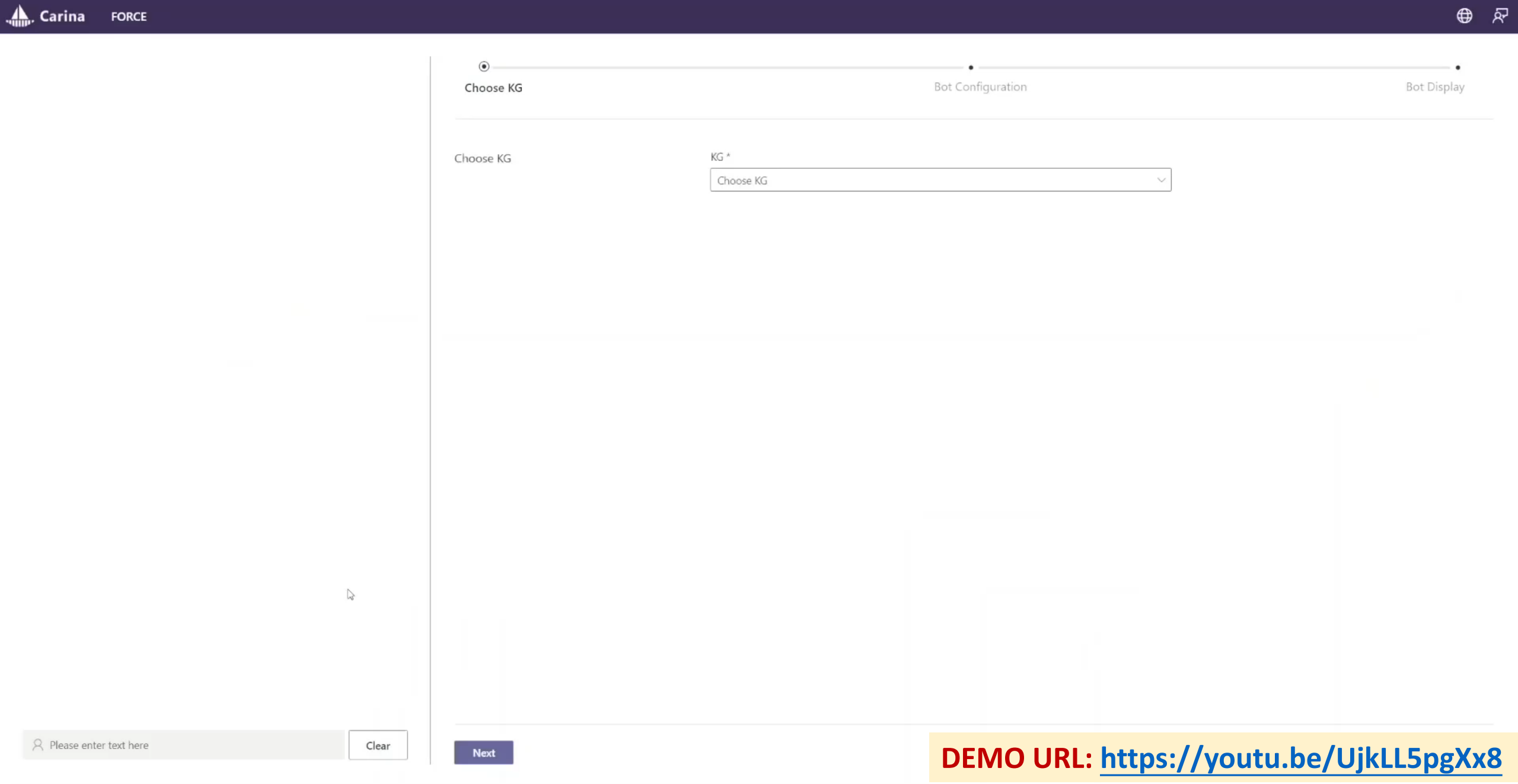

Here is the initial view of the FORCE live demo

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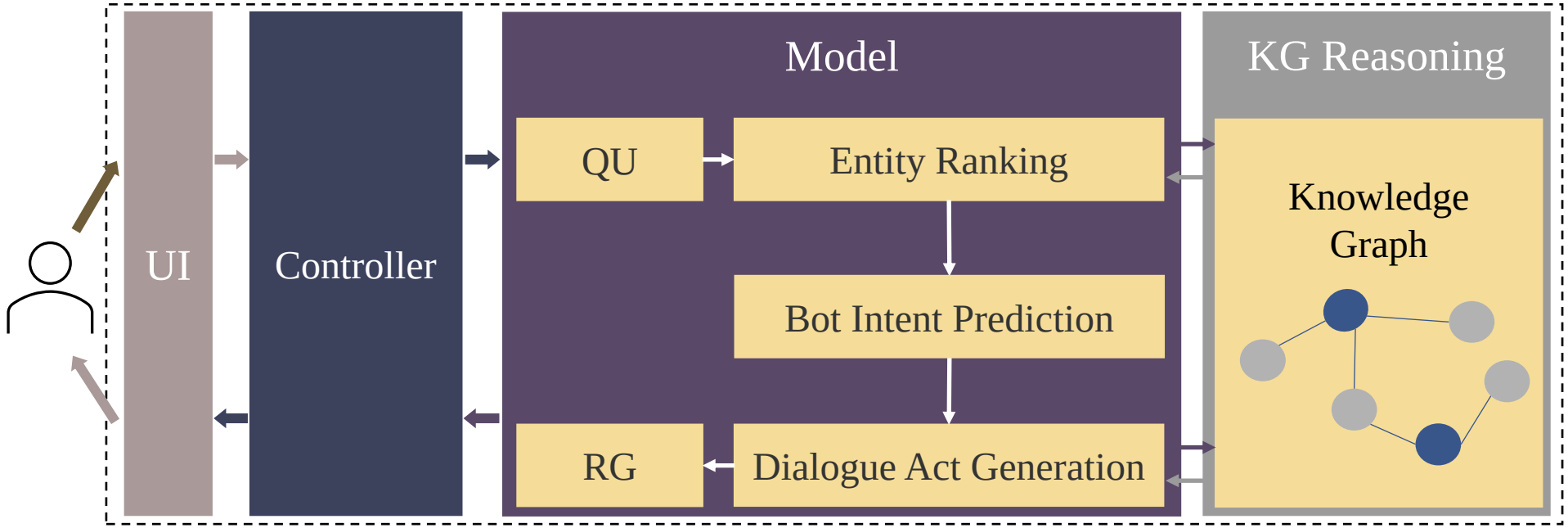
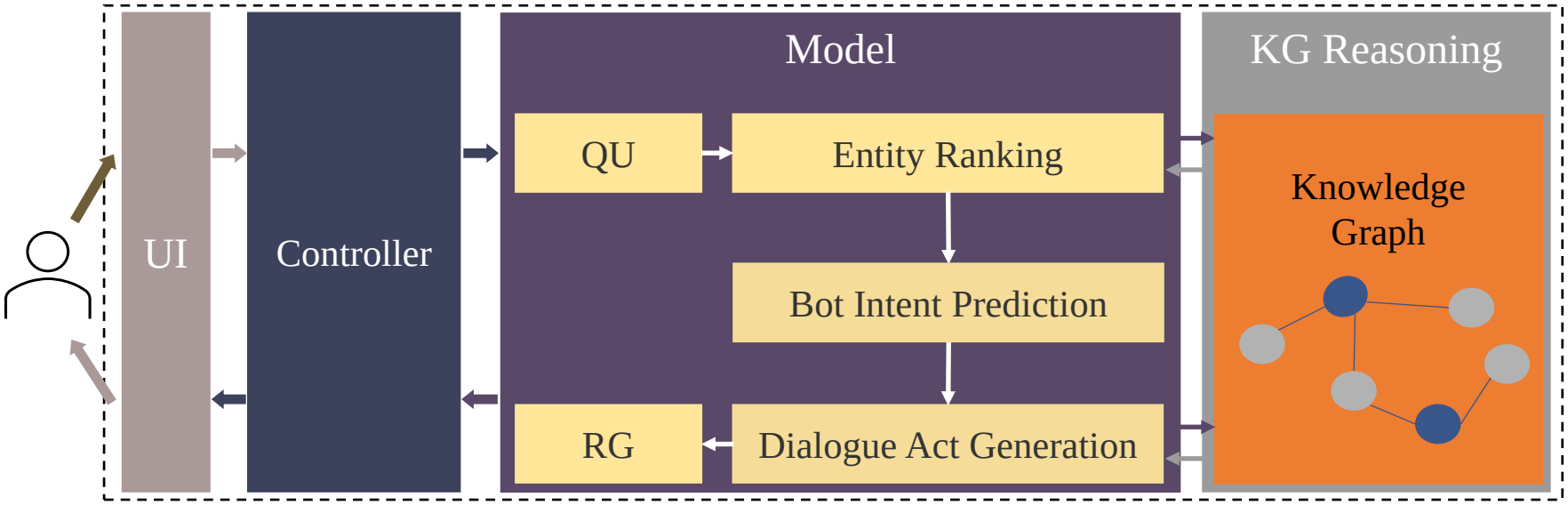
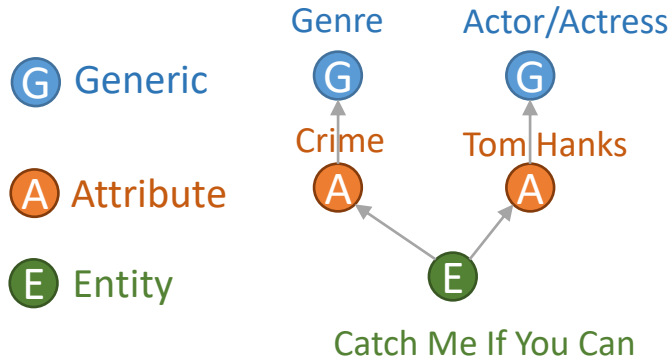
System Overview



Knowledge Graph Reasoning



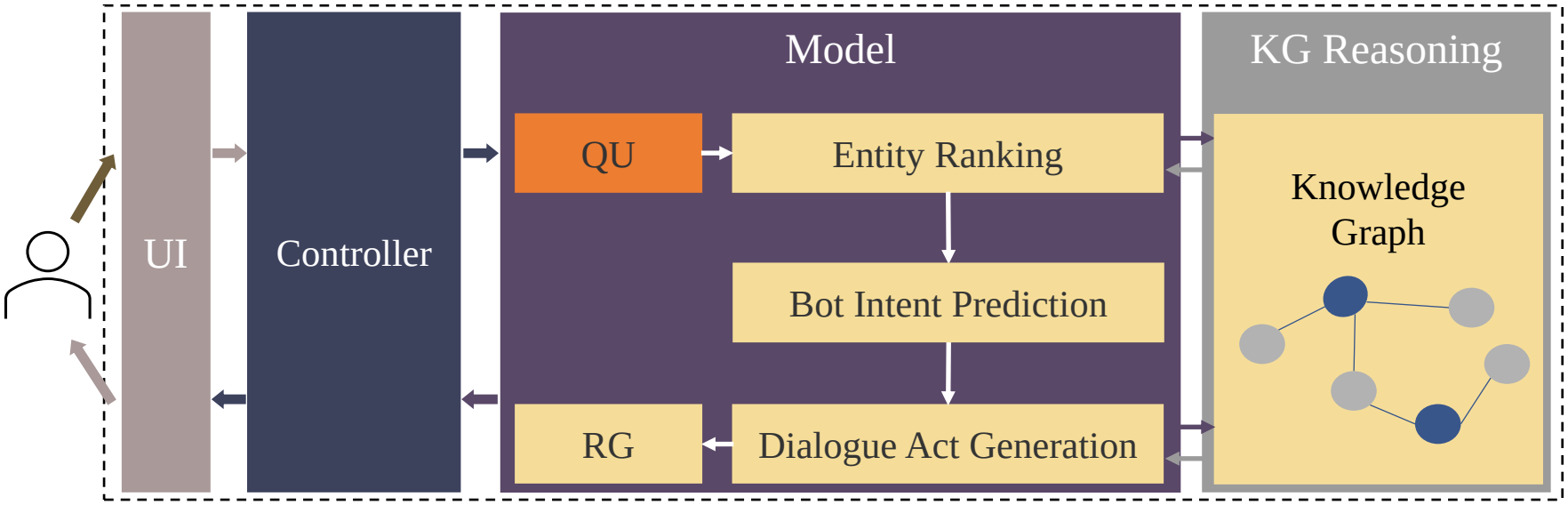


Main Functionality:

- Get entity/attribute/generic nodes
- Get attribute nodes of an entity
- Get attribute nodes under a generic class
- Get entity nodes containing an attribute
- Get neighbor entity nodes of an entity

[1] Ma, Wenchang, et al. "Bridging the Gap between Conversational Reasoning and Interactive Recommendation."

Query Understanding



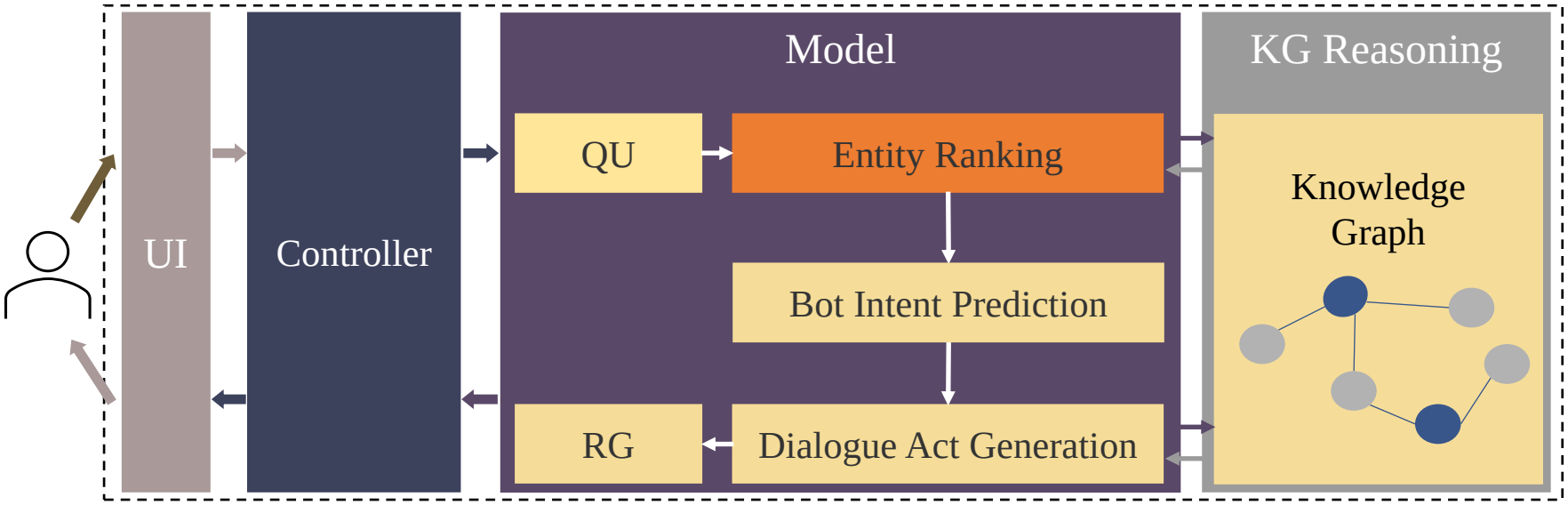

```
13 references | qigan, 69 days ago | 1 author, 5 changes
public class SemanticFrame
{
    27 references | qigan, 93 days ago | 1 author, 1 change
    public UserIntent Intent { get; set; }

    3 references | qigan, 93 days ago | 1 author, 1 change
    public List<UserSlot> Slots { get; set; }
}
```

```
36 references | qigan, 88 days ago | 1 author, 4 changes
public enum UserIntent
{
    None = 0,
    ProvideSlot = 1,
    AcceptRecommend = 2,
    RejectRecommend = 3,
    Chat = 4
}
```

Query Understanding Configuration

```
"recommendAcceptWords": [
    "good",
    "yes",
    "like",
    "thanks",
    "thank you"
],
"recommendRejectWords": [
    "no",
    "dislike"
],
"queryConfirmWords": [
    "yes"
],
"queryDenyWords": [
    "no"
],
```

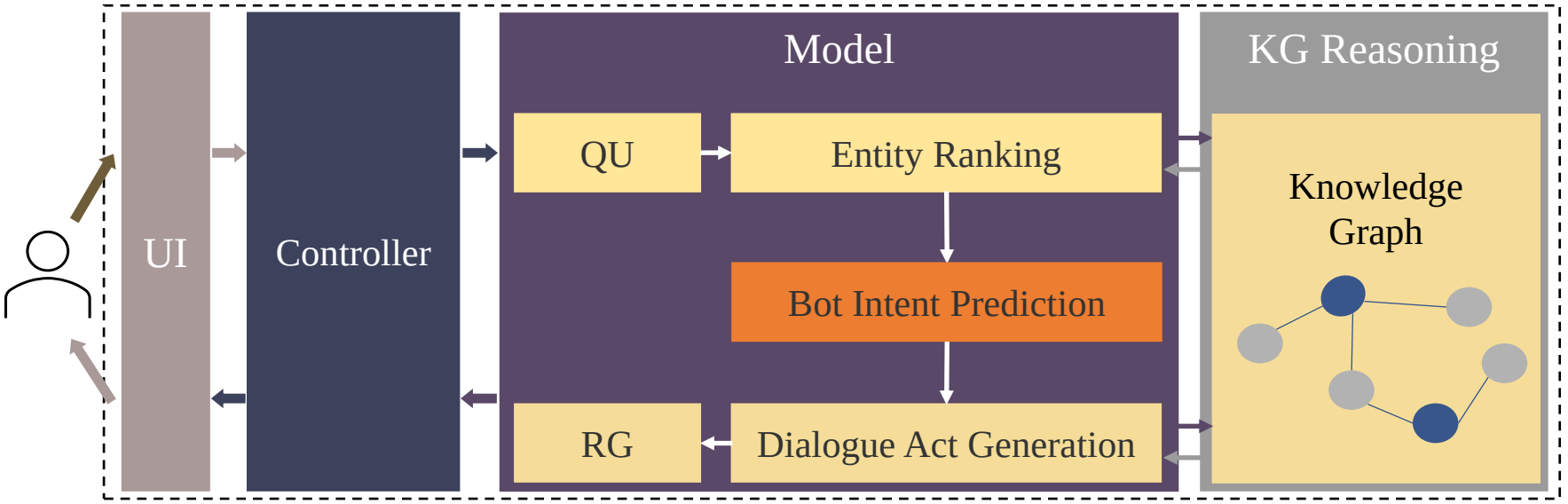
Entity Ranking



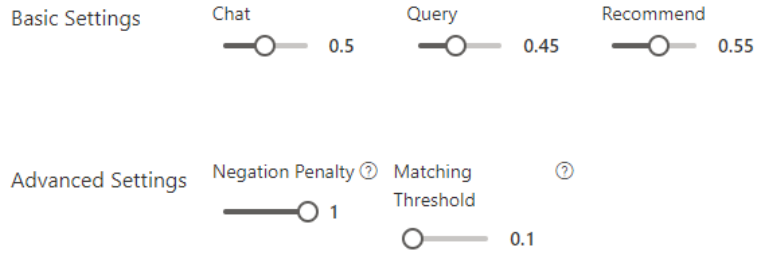
Positive score to an entity:
1. Attributes preferred by user
2. Share attributes with mentioned entity

Negative score to an entity:
1. Attributes denied by user
2. Entity already mentioned by user
3. Entity already mentioned by bot

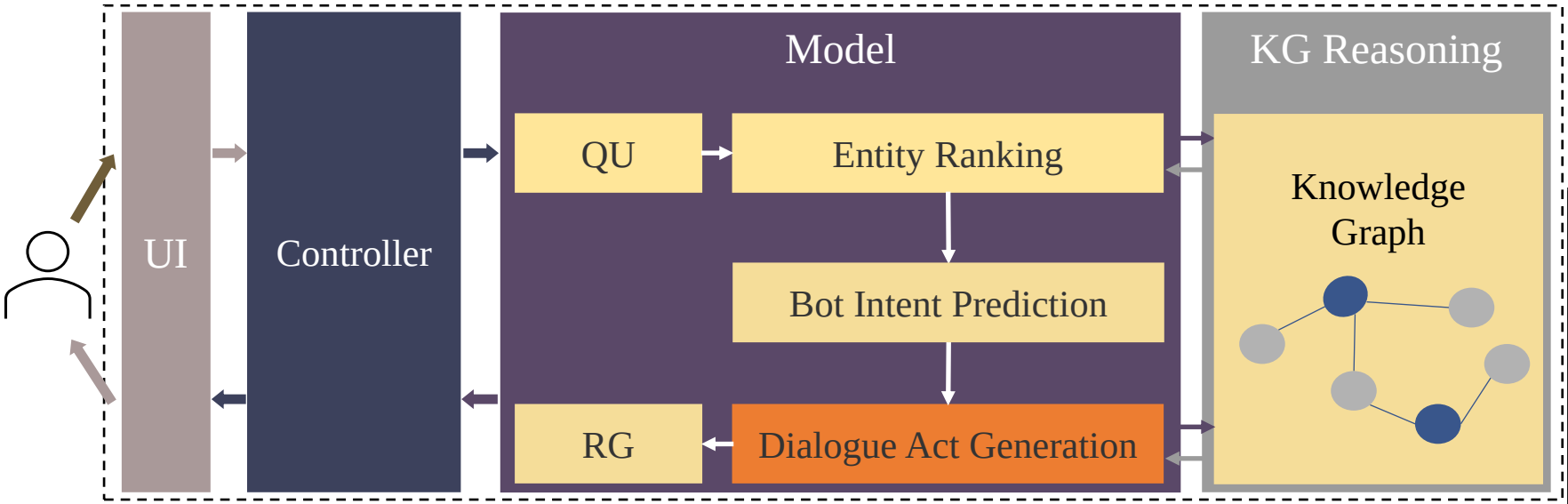
Bot Intent Prediction




```
99+ references | qigan, 109 days ago | 1 author, 2 changes
public enum BotIntent
{
    None = 0,
    Recommend = 1,
    Query = 2,
    Chat = 3
}
```



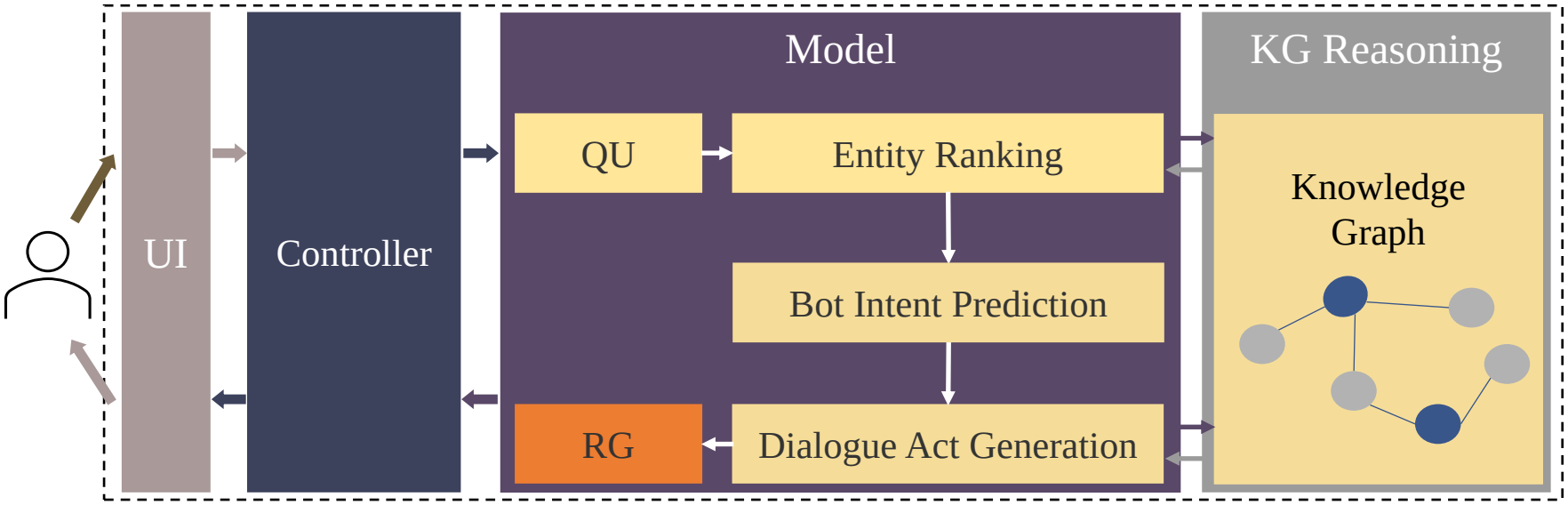
Dialogue Act Generation




```
33 references | qigan, 109 days ago | 1 author, 3 changes
public class DialogAct
{
    15 references | qigan, 114 days ago | 1 author, 1 change
    public BotIntent BotIntent { get; set; }
    21 references | qigan, 109 days ago | 1 author, 2 changes
    public List<DialogActNode> CoreNodes { get; set; }
}
```

```
15 references | Qiang Gan, 44 days ago | 2 authors, 2 changes
public class DialogActNode
{
    6 references | qigan, 109 days ago | 1 author, 1 change
    public NodeType Type { get; set; }
    15 references | qigan, 109 days ago | 1 author, 1 change
    public string Value { get; set; }
    11 references | qigan, 109 days ago | 1 author, 1 change
    public HashSet<string> Neighbors { get; set; }
}

87 references | qigan, 114 days ago | 1 author, 1 change
public enum NodeType
{
    Entity = 0,
    Attribute = 1,
    Generic = 2
}
```

Response Generation



Response Generation Configuration

```
{
  "queryTemplates": {
    "director": [
      "Which director's movies do you like ? E.g. {attributes}"
    ],
    "genre": [
      "What kind of movie do you like ? Such as {attributes}"
    ],
    "actor": [
      "Are there any actors or actresses that you like ? E.g. {attributes}"
    ],
    "subject": [
      "Do you have preference on the movie subject ? E.g. {attributes}"
    ],
    "time": [
      "What's the release time of movies do you prefer ? E.g. {attributes}"
    ]
  },
  "recommendTemplates": [
    "You can try {entity}, it's a {genre} movie starred by {actor} and directed by {director}."
```

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Dataset and Experiment

Dataset	Domain	Language	Dialogues	Turns	Knowledge Graph		
					Nodes	Edges	Entities
M-RD	Movie	English	54	324	2667	8908	246
DX	Medical	Chinese	527	1408	47	109	5

Movie domain

- We sample dialogues from ReDial dataset [1] to form the M-RD (Mini-ReDial)
- Sampling rule: 5-7 turn conversations with all Chat/Query/Recommend intent.

Medical domain

- We reprocess a dataset on medical diagnosis named DX [2].

[1] Li, Raymond, et al. "Towards deep conversational recommendations."
[2] Xu, Lin, et al. "End-to-end knowledge-routed relational dialogue system for automatic diagnosis."

Dataset and Experiment

Movie

Method	Bot Intent Prediction	Entity Recommendation		
	Accuracy (%)	R@1 (%)	R@10 (%)	R@50 (%)
Random (cold-start)	33.33	0.41	4.1	20.3
Ours	67.28	4.37	16.50	50.97

Table 2: Results on the movie dataset M-RD.

Medical

Method	Bot Intent Prediction	Entity Recommendation		
	Accuracy (%)	R@1 (%)	R@2 (%)	R@3 (%)
Random (cold-start)	33.33	20.0	40.0	60.0
Ours	66.34	79.51	92.98	97.15

Table 3: Results on the medical diagnosis dataset DX.

[1] Ma, Wenchang, et al. "Bridging the Gap between Conversational Reasoning and Interactive Recommendation."

- CR-Walker on ReDial Precision: 67.8%, Entity Recall: 3.1%(R@1) / 15.5%(R@10) / 36.5%(R@50)

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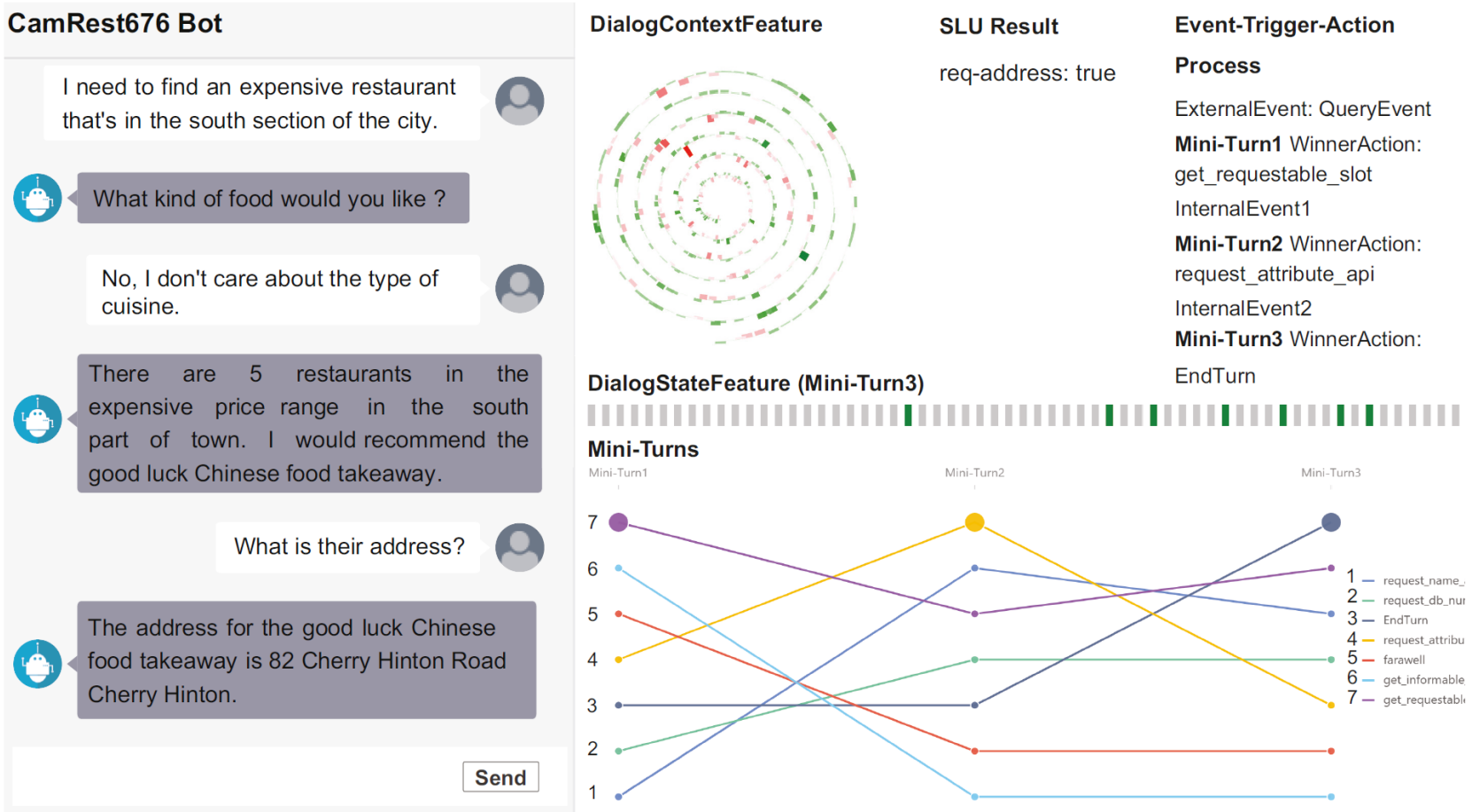
- We introduce FORCE, a framework to support developers in constructing cold-start CRS bots with good interpretability.
- We evaluate FORCE on two datasets in different languages and domains, which verified its effectiveness and usability.
- CRS bots by FORCE can be used as a conversation collection tool. Developers can fine-tune each module later with deep learning models.

How to bridge the gap between **academic research** and **industrial applications** ?

Integrating Pre-trained Model into Rule-based Dialogue Management (AAAI-2021 DEMO)



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THANKS

2022.01.08

may the FORCE be with you