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第七节课:对话系统从原理到应用

具体领域案例 强化学习 工业界bots

本节内容

- □ 订餐机器人案例研究
- □对话系统的强化学习
- □ Api.ai为例看工业界chatbot

参考文献

- □ 订餐机器人案例研究
 - A network-based end-to-end trainable task-oriented dialogue system (2016)
- □ 对话系统的强化学习
 - Interactive reinforcement learning for task-oriented dialogue management (2016)
 - Deep Reinforcement Learning for Dialogue Generation (2016)
 - Deal or No Deal? End-to-end learning for negotiation dialogues (2017)
- □ 工业界的chatbot



综合多个module的Ent-to-End模型

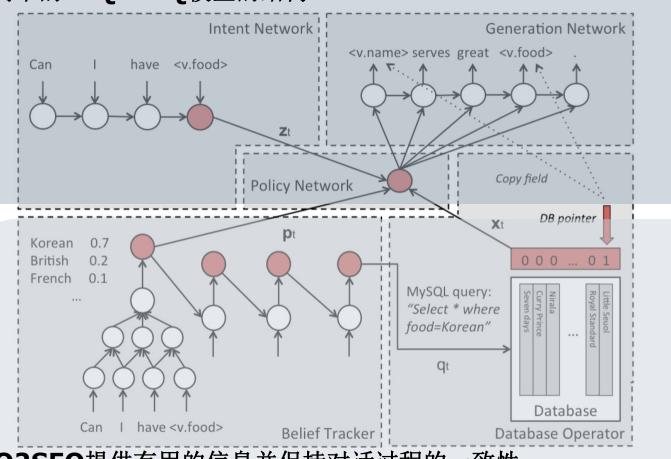
订餐机器人案例



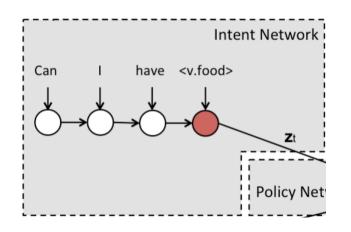
- ☐ A network-based end-to-end trainable taskoriented dialogue system (2016)
 - 关键词: Ent-to-end, sequence-to-sequence mapping, policy, goal, Wizard-of-Oz framework, multi-module
 - 模型; 数据; 效果

Seq2seq模型在封闭领域应用

类似于简单的SEQ2SEQ模型的结构



为SEQ2SEQ提供有用的信息并保持对话过程的一致性



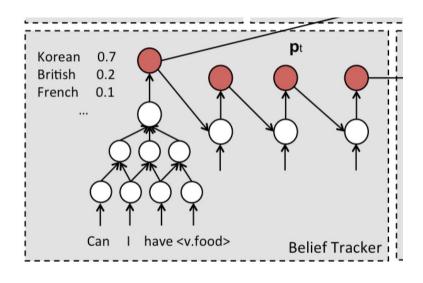
模型接受用户的输入序列(input sequence), 转化为两个内部表示

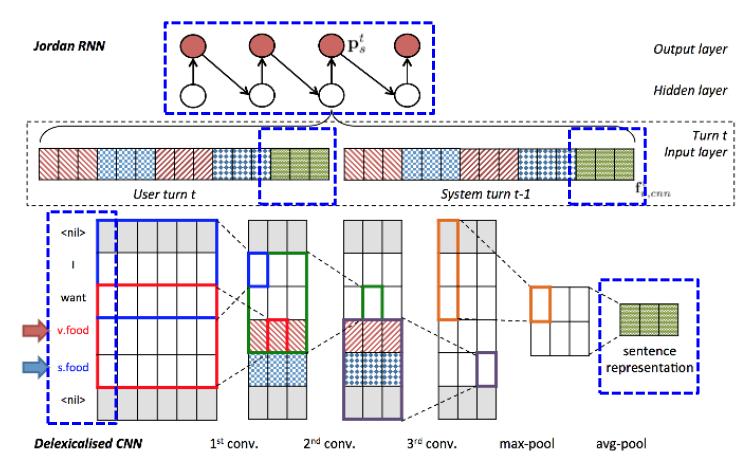
1. 由intent network生成的表示用户意图的分布式表达(distributed representation)

Intent network可以类比成seq2seq 模型里面的encoder

模型接受用户的输入序列(input sequence), 转化为两个内部表示

- 1. 由intent network生成的表示用户意图的分布式表达(distributed representation)
- 2. 由一组belief trackers生成一个slot-value pair的概率分布,叫做(belief state)





Belief tracker (也叫Dialogue State tracker)

的实现细节 😡



对话系统中的belief tracker

- □ Belief tracker 是对话 系统的一个核心部分 ,用来记录对话过程 中用户的目标信息
- ☐ (One of the core components of modern spoken dialogue systems is the belief tracker, which estimates the user's goal at every step of the dialogue.——neural belief tracker: data driven dialogue state tracking 2016)

User: I'm looking for a <u>cheaper</u> restaurant inform(price=cheap)

System: Sure. What kind - and where?
User: Thai food, somewhere downtown
inform(price=cheap, food=Thai,
area=centre)

System: The House serves cheap Thai food **User:** Where is it?

inform(price=cheap, food=Thai,
area=centre); request(address)

System: The House is at 106 Regent Street



对话系统中的belief tracker

- □ 对话系统有一个domain ontology,表示系统能够处理 的用户意图的集合
- □ Domain ontology 定义一系列 slot,和每个slot可以包含的数值/选项
- □ 系统需要从对话记录(包含 用户输入和系统的回复)中 发现并记录
 - 1. 用户的目标和信息 (goal, informable slots)
 - 2. 用户的对搜索结果的问题(requests)

User: I'm looking for a <u>cheaper</u> restaurant inform (price=cheap)

System: Sure. What kind - and where?
User: Thai food, somewhere downtown
inform(price=cheap, food=Thai,
area=centre)

System: The House serves cheap Thai food

User: Where is it?

inform(price=cheap, food=Thai,
area=centre); request(address)

System: The House is at 106 Regent Street



对话系统中的belief tracker

FOOD=CHEAP: [affordable, budget, low-cost, low-priced, inexpensive, cheaper, economic, ...]

RATING=HIGH: [best, high-rated, highly rated, top-rated, cool, chic, popular, trendy, ...]

AREA = CENTRE: [center, downtown, central, city centre, midtown, town centre, ...]

一个使用semantic dictionary做 delexicalization 的例子,一些意义相 似的词语被转化为一个标准形式

也可以使用表示semantic similarity的词向量参数简介达到这样的效果

User: I'm looking for a <u>cheaper</u> restaurant inform (price=cheap)

System: Sure. What kind - and-where?
User: Thai food, somewhere downtown inform (price=cheap, food=Thai, area = centre)

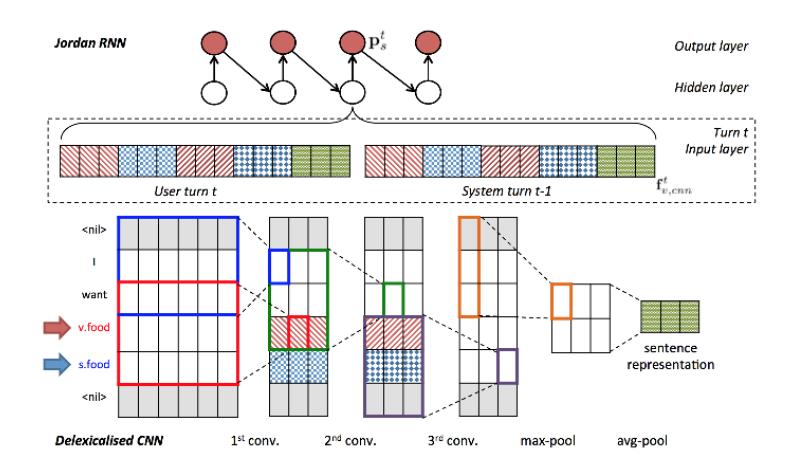
System: The House serves cheap Thai food

User: Where is it?

inform(price=cheap, food=Thai,
area=centre); request(address)

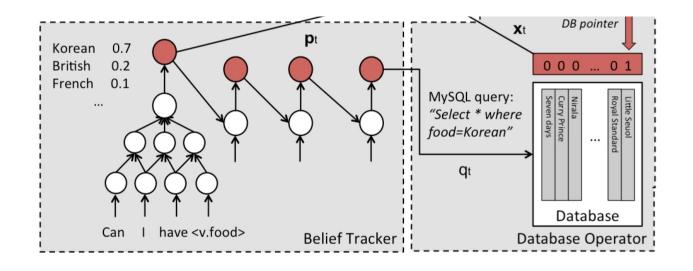
System: The House is at 106 Regent Street



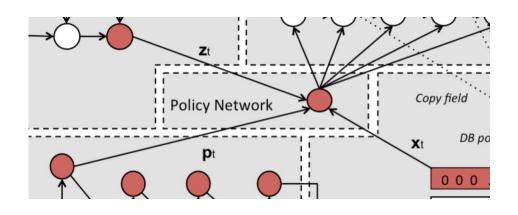


Belief tracker(也叫Dialogue State tracker)的实现细节

基于belief tracker的输出,产生query,在数据库中寻找对应的条目

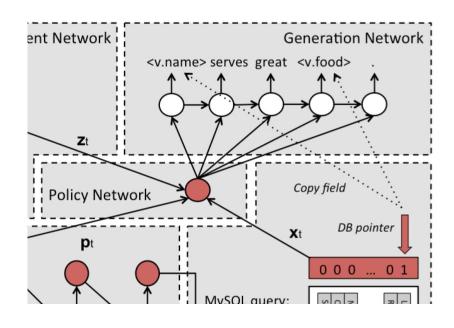


将intent network, belief tracker, DB query综合起来生成输出状态



$$o_t = \tanh(W_{zo}\mathbf{z}_t + W_{po}\mathbf{p}_t + W_{xo}\mathbf{x}_t)$$

 $\mathbf{p}_t = [p_{s1}^t, p_{s2}^t \dots p_{sK}^t]$ 综合所有的slot-value pair



RNN decoder生成最终回复

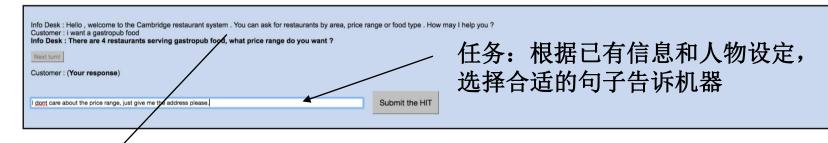
数据收集流程

- □ 使用统计方法构建聊天系统的最大瓶颈之一 是收集合适的数据
- □ 使用奥兹巫师实验的方式搜集数据
 - 在人机交互领域,一个奥兹巫师实验是一个研究实验,在这个实验中,受试者与一个计算机系统进行交互,这个系统被认为是自主的,但实际上是由一个看不见的人类操作或部分操作的。

数据收集流程

任务: 你想要寻找一个酒吧类餐厅, 不关心价格范围, 需要知道地址

Task 02004: You are looking for and it should serve gastropub food. You don't care about the price range. You want to know the address.



已有信息:

•Wizard: 你好,欢迎来到剑桥餐馆系统,你可以根据地址,价格和食物种 类询问餐馆

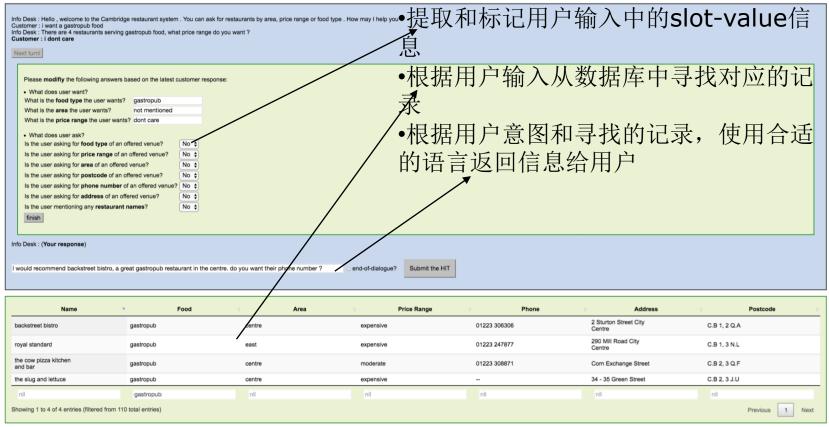
•User: 我想找一家酒吧类餐厅

•Wizard: 有四家酒吧类餐厅,请问你选择什么价格范围的餐厅?



数据收集流程

假装你是机器(wizard),



模型效果

Human : Restaurant in any area that serves Vietnamese food

Machine : thanh binh serves vietnamese food type, is there anything else i can help you with?

Human : What is the phone number and post code

Machine: the number is 01223 362456 and the area code is c.b 3, 0 a.f. is there anything else i can do for you?

Human : Good bye

Machine : thank you for using the cambridge restaurant system .

Human : i am looking for moderately priced halal food

Machine: i am sorry, there are no halal restaurants in the moderate price range, would you like something else?

Human : how about european food

Machine : galleria serves european food type and is in the moderate price range .

Human : address and postcode

Machine : the address is 33 bridge street and the area code is c.b 2, 1 u.w. is there anything else i can help you with today?

Human : thanks

Machine : galleria is a european restaurant in the moderate price range . would you like their phone ?

Human : thank you

Machine : thank you for using the cambridge restaurant system . good bye

Human : Hi, I'm hungry for some Indonesian food

Machine : i am sorry, there are no indonesian restaurants. would you like a different food?

Human : Oh no. How about Indian?

Machine : there are 9 restaurants serving indian types of food . do you have a preference on side of town?

Human : East side please

Machine : sitar tandoori is a indian restaurant in the east side of town . would you like their information?

Human : Yes, the address and phone number please

Machine : sitar tandoori is located at 43 high street cherry hinton cherry hinton and their phone number is 01223 249955 .

Human : Okay, thank you Machine : thank you, goodbye.

目标导向的模型训练方法

强化学习



强化学习概述

- ☐ Agent interacting with a dynamic environment with the objective of maximizing a long term reward
 - 强化学习(Reinforcement Learning, RL) 关注目标导向 (goal-directed learning) 的学习和决策问题.
 - 强化学习中, agent 通过(states, actions 和rewards) 和环境交流从中学习知识.
 - □ agent 通过 policy 从 state 出发寻找 actions
 - 强化学习中, agent 试图优化长期目标(long-term goal), 而 rewards 的反馈通常有延迟.

强化学习概述

- □强化学习使用目标导向的(agents),获取环境的状态,作出决定(action),影响环境
- □ 强化学习中的探索-开发 (exploration-exploitation dilemma) 过程
 - 在学习初期, agent 对环境有很多不确定,侧重使用探索(exploration) 方式作出不确定性比较大的决策
 - 在学习后期, agent 侧重使用开发(exploitation)作 出认为当前最好的决策

强化学习概述

□例子

- 围棋软件:了解棋盘局面(state),作出符合围棋规则的决策(action),期望最终赢得比赛(reward),每一步的决策选项相对较小,轮数相对较大
- 聊天系统:了解用户意图和总结当下语境(state),给出有质量的回复(action),期望尽快给出用户想要的信息,避免无用或者错误回复,使得用户满意(reward);每一步的决策选项相对较大,轮数相对较小

Dialogue turns	Dialogue acts
User: Suggest an Indian restaurant for dinner.	intent(find_restaurant),
	inform(cuisine=Indian, meal=dinner)
System: Which area are you interested in?	request(location)
User: Near Mountain View.	inform(location=Mountain View)
System: Sakoon and Shiva's are good	select(restaurant_name=Sakoon,
choices in Mountain View.	restaurant_name=Shiva's)
User: What is the price range for Sakoon?	request(price_range,
	restaurant_name=Sakoon)
System: Sakoon is in the moderate price range.	inform(price_range=moderate,
	restaurant_name=Sakoon)
User: Thanks, that works for me.	thank_you()

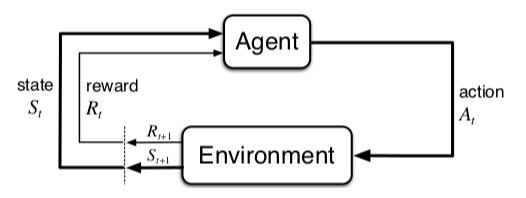
- \square Markov Decision Process: $\{S, A, P, R, \gamma\}$
 - {state, action, policy, reward, discount factor}

Dialogue turns	Dialogue acts
User: Suggest an Indian restaurant for dinner.	intent(find_restaurant),
	inform(cuisine=Indian, meal=dinner)
System: Which area are you interested in?	request(location)
User: Near Mountain View.	inform(location=Mountain View)
System: Sakoon and Shiva's are good	select(restaurant_name=Sakoon,
choices in Mountain View.	restaurant_name=Shiva's)
Heart What is the price range for Salzaen?	request(price_range,
User: What is the price range for Sakoon?	restaurant_name=Sakoon)
System: Sakoon is in the moderate price range.	inform(price_range=moderate,
	restaurant_name=Sakoon)
User: Thanks, that works for me.	thank_you()

- □ 环境状态通常使用{用户动机, slot-value pair}等特征表示

Dialogue turns	Dialogue acts
User: Suggest an Indian restaurant for dinner.	<pre>intent(find_restaurant), inform(cuisine=Indian, meal=dinner)</pre>
System: Which area are you interested in?	request(location)
User: Near Mountain View.	inform(location=Mountain View)
System: Sakoon and Shiva's are good	select(restaurant_name=Sakoon,
choices in Mountain View.	restaurant_name=Shiva's)
User: What is the price range for Sakoon?	request(price_range,
	restaurant_name=Sakoon)
System: Sakoon is in the moderate price range.	inform(price_range=moderate,
	restaurant_name=Sakoon)
User: Thanks, that works for me.	thank_you()

- □ 在找餐館的环境下, agent 的action通常有提供信息, 询问slot-value等
 - 例: request(location), select(...)



目标:寻找一个policy π_{θ} : $S \to P(A)$, 最大化期望的 reward: "cumulative reward agent receives in the long

run 《 Richard S. Sutton, Andrew G. Barto. Reinforcement Learning - An Introduction》

- $J_t(\theta) = E[R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \cdots]$
- 当前(时间t)的决策会**长期**地影响将来的进程
- 一段时间以后才便于更准确地估计当下的决策会有什么 样的**长期**后果 即 rewards 的反馈通堂有**延迟**



强化学习的chatbot上的应用案例

- □ 拟合数据 (观察到的实际回复) 训练模型
 - 目标函数和人类对话的目的不符
 - 数据有限,安全回复
- □ 强化学习
 - 设计+优化 和人类对话目的更相近的长期目标

一个开放领域的强化学习应用

- □ Deep Reinforcement Learning for Dialogue Generation (2016)
- □ 通过强化学习手段,鼓励两个互相聊天的 agents产生高质量的对话

设计一个强化学习问题

- 四 强化学习模型: 两个使用seq2seq模型的 agents 对话
 - State: [p_i, q_i] , 一轮对话
 - Policy: $P(p_{i+1}|p_i,q_i)$, 使用seq2seq模型,包含需要学习的参数
 - Action: agent产生的回复
 - Goal: 两个使用seq2seq模型的agent的对话接近有意义的 人类对话

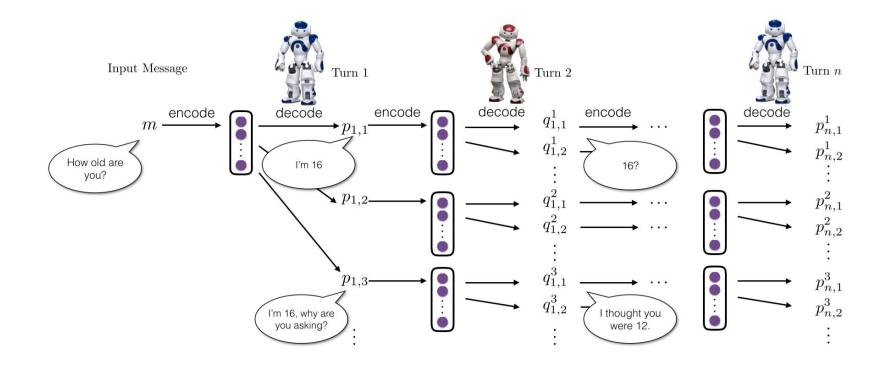
设计一个强化学习问题

- 四 强化学习模型: 两个使用seq2seq模型的agents 对话
 - State: [p_i, q_i] , 一轮对话
 - Policy: $P(p_{i+1}|p_i,q_i)$,使用seq2seq模型,包含需要学习的参数
 - Action: agent产生的回复
 - Reward:
 - □ Ease of answering: 如果本回复导致对方更倾向于回复"不知道", "不清楚"等表示难以继续交流下去的意思, 扣分
 - □ Information flow:如果这一轮的回复和上一轮本agent的回复非常相似,扣分
 - □ Semantic coherence:如果(1)给定上一轮对话(state),本 轮回复的概率比较大(传统的SEQ2SEQ里面的cond. prob),且(2)从本轮回复能比较容易地反推出上一轮对话的信息,加分

强化学习过程

- □ 模型(policy)初始化: 基于优化likelihood的 seq2seq模型
- □ 模型 simulation:
 - 两个agent聊天产生聊天样本数据集
 - 每个样本是多轮对话
 - 通过优化样本的reward更新模型(policy)的参数,使模型产生更好的对话效果

强化学习过程



强化学习效果

Input Message	Mutual Information Model	RL
How old are you?	I'm 16.	I'm 16, why are you asking?
What's your full name?	I have no idea.	What's yours?
I don't want to go home tonight.	Really ?	Why?
Do you have any feelings for me?	I don't know what you are talking about.	I don 't want to hurt your feelings.
How much time do you have here?	Not long enough. Sorry, sir.	Ten seconds.
Shall we get started?	Of course!	Yes. We 've got a lot of work to do here.
Do you play football?	No, i don't	Yes. I love football!
We'd have to talk to him.	I mean, he's a good guy	About what ?
How come you never say it?	Because I don't want to hurt you.	I don't think it's a good idea to say it.

Model	# of simulated turns
SEQ2SEQ	2.68
mutual information	3.40
RL	4.48

一个封闭领域的强化学习应用

- □ Deal or no deal? End-to-end learning for negotiation dialogues (2017-06)
- □在一个人工生成的商议任务数据集上,训练 两个chatbot互相聊天谈判
 - 拟合导向的模型(最大化对话数据概率的模型)
 - 目标导向的模型 (优化bot收益的模型)

人工产生的 bot-bot 聊天数据

Divide these objects between you and another Turker. Try hard to get as many points as you can!

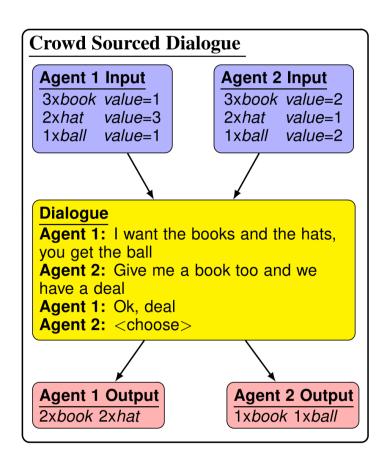
Send a message now, or enter the agreed deal!

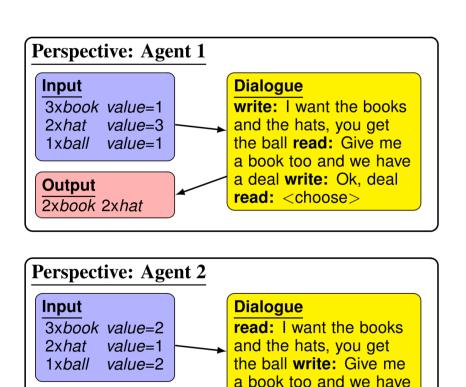


- □ 两个users (bots)协商瓜分一部分物品
 - 对每个user (bot),所有物品 的价值总和是10
 - 每个物品在不同的user(bot) 那里可以有不同的价值
 - 有些物品对于两个users(bots) 都有价值(竞争关系)
 - 每个物品至少对于一个 user(bot) 是有价值的 (>0)
- □ 目标/收益
 - 最大化自身的收益
 - 需要保证对方也同意



人工产生的 bot-bot 聊天数据





每段对话分成两个样本,分别对应两个Bot视角的对话记录



a deal read: Ok, deal

write: <choose>

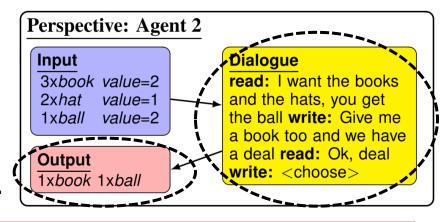
Output

1xbook 1xball

Baseline: likelihood model

□ 输入数据

- 物品信息g: $[c_1, v_1, c_2, v_2, c_3, v_3]$, 三类物品各自的数量和价值
- 讨论结果o: [n₁₁, n₁₂, n₁₃, n₂₁, n₂₂, n₂₃],每个物品 每个bot各自挑选多少
- 对话记录x: [x_0 , ... x_T], 自己和对方Bot的话
- □ 目标函数
 - 拟合对话和商议结果



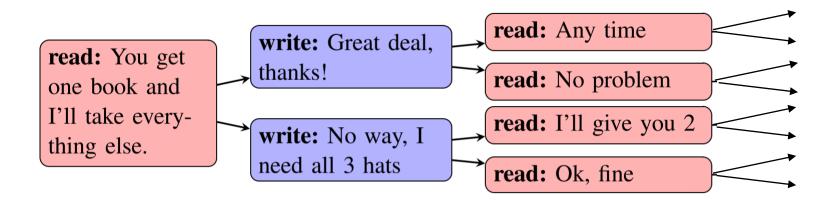


e.g.

Baseline: likelihood model

- □ Likehihood 模型的问题在于目标函数和实际目标不符:
 - Likelihood模型: 拟合对话数据
 - 实际目标:最大化用户的收益

- □ 首先训练likelihood model初始化模型参数
- □ 使用强化学习根据衡量标准(收益) finetune 模型



☐ Reward:

- r^A : 在这句话结束协商的话, 收益会是多少
- 考虑到长期收益:

$$R(\mathbf{x}_t) = \sum_{\mathbf{x}_t \in X^A} \gamma^{(T-t)} (\gamma^A(o) - \mu)$$

	vs. LIKELIHOOD			vs. Human				
Model	Score	Score	%	% Pareto	Score	Score	%	% Pareto
Model	(all)	(agreed)	Agreed	Optimal	(all)	(agreed)	Agreed	Optimal
LIKELIHOOD	5.4 vs. 5.5	6.2 vs. 6.2	87.9	49.6	4.7 vs. 5.8	6.2 vs. 7.6	76.5	66.2
RL	7.1 vs. 4.2	7.9 vs. 4.7	89.9	58.6	4.3 vs. 5.0	6.4 vs. 7.5	67.3	69.1
ROLLOUTS	7.3 vs. 5.1	7.9 vs. 5.5	92.9	63.7	5.2 vs. 5.4	7.1 vs. 7.4	72.1	78.3
RL+ROLLOUTS	8.3 vs. 4.2	8.8 vs. 4.5	94.4	74.8	4.6 vs. 4.2	8.0 vs. 7.1	57.2	82.4

Model	Valid PPL	Test PPL	Test Avg. Rank
LIKELIHOOD	5.62	5.47	521.8
RL	6.03	5.86	517.6
ROLLOUTS	-	-	844.1
RL+ROLLOUTS	-	-	859.8

Input			
Human	man 3x book value=2 3x hat value=1 1x ball value=		
RL+ROLLOUTS	3 3xbook value=1 3xhat value=2 1xball value=1		
Human	I'd like the books and the hats.		
RL+ROLLOUTS	I will take the books and hats		
Human	I really need the books and at least one other object.		
RL+ROLLOUTS	Ok, you can have one book and one ball		
Human	If I can have all the books, I can leave you the rest.		
RL+ROLLOUTS	Deal		
Output		Reward	
RL+ROLLOUTS	3xhat 1xball	7/10	
Human	3x book	6/10	

Figure 6: Example of model compromising.

Input			
RL+ROLLOUTS	LOUTS 4xbook value=0 2xhat value=5 1xball value=0		
Human	4xbook value=1 2xhat value=2 1xball value=2		
RL+ROLLOUTS	You can have the ball if I can have everything else.		
Human	No can't do that the ball is not going to give me anything		
RL+ROLLOUTS	I need the hats and you can have the rest		
Human	Deal		
RL+ROLLOUTS	Great! Thank you!		
Output		Reward	
RL+ROLLOUTS	2x hat	10/10	
Human	4xbook 1xball	6/10	

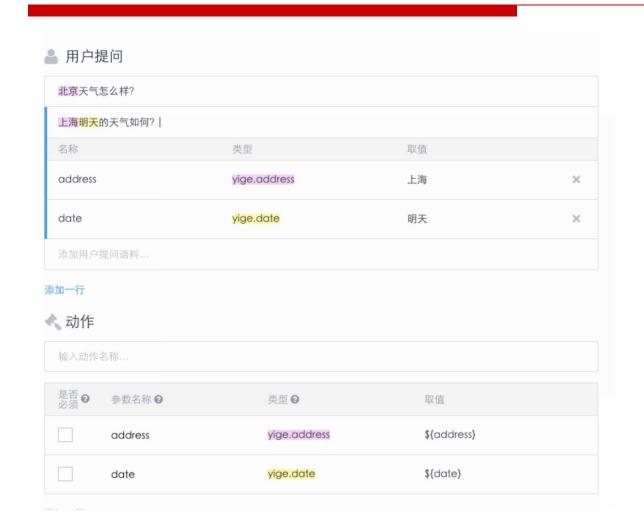
Figure 7: Dialogue in which the model's initial interest in the valueless books allows it to compromise while achieving a maximum score.

工业界的CHATBOT



Api.ai和'一个'ai的典型工作流程

- "一个"AI遵循的流程和Api.ai类似,接收到用户的输入后,流程如下
- □一个AI首先识别用户输入中的词库和用户场景。词库和场景的识别并不是独立的,相同的词在不同的场景下可能属于不同的词库类型。在场景识别时也会考虑到场景设定的状态是否存在。如果某场景设定的输入状态不是都存在,则不会把用户输入识别为此场景。
- □查看动作中需要的必须参数(slog-value)是否都已获得取值。如果存在必须参数还没有获得取值,就触发设定好的提示语作为机器人回复,要求用户输入对应的参数取值。参数的取值不仅可以来自于此次用户输入中的词库,也可以来自于输入状态中的变量。对于非必须参数,可以为他们设定默认值。
- □只有所有必须参数都已收集到取值,此场景才能完成,场景设定的AI回复才会作为回复返回给用户。到这里此场景就完成了,用户之后的输入就会触发新的循环。



API.AI演示

疑问

□问题答疑: http://www.xxwenda.com/

■可邀请老师或者其他人回答问题

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