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Beyond Conditional LM:
Neural Network Language Generation for Dialogue Systems

Heriot Watt University Seminar, 24/05/2016

Tsung-Hsien (Shawn) Wen and Steve Young

Outline

- Intro
- Multi-domain Neural NLG
- Neural Dialogue System
- Conclusion

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- **Intro**
- Multi-domain Neural NLG
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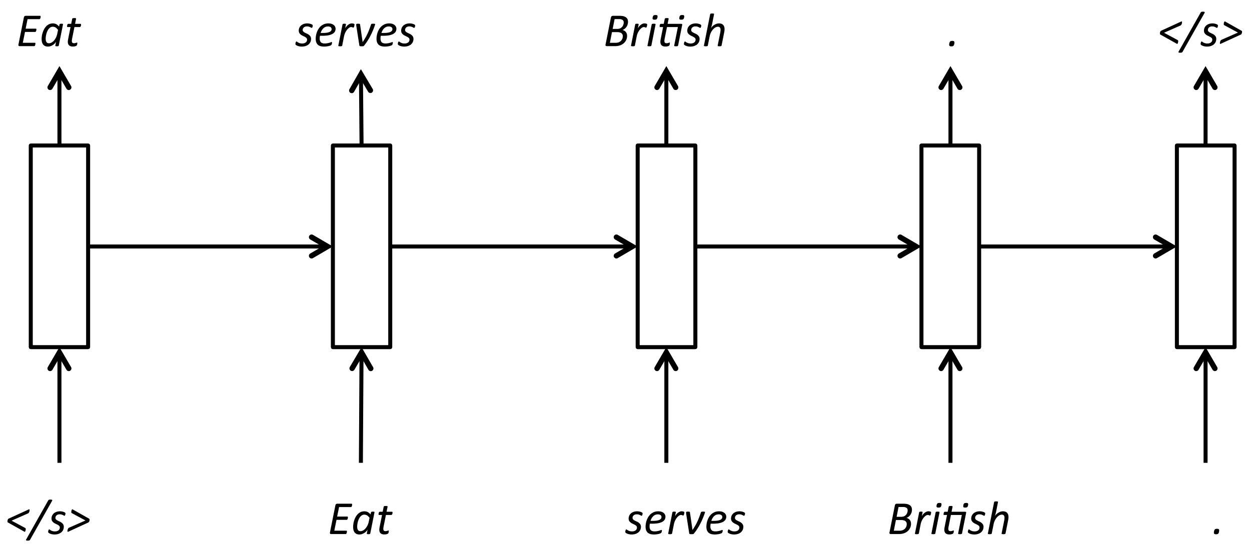
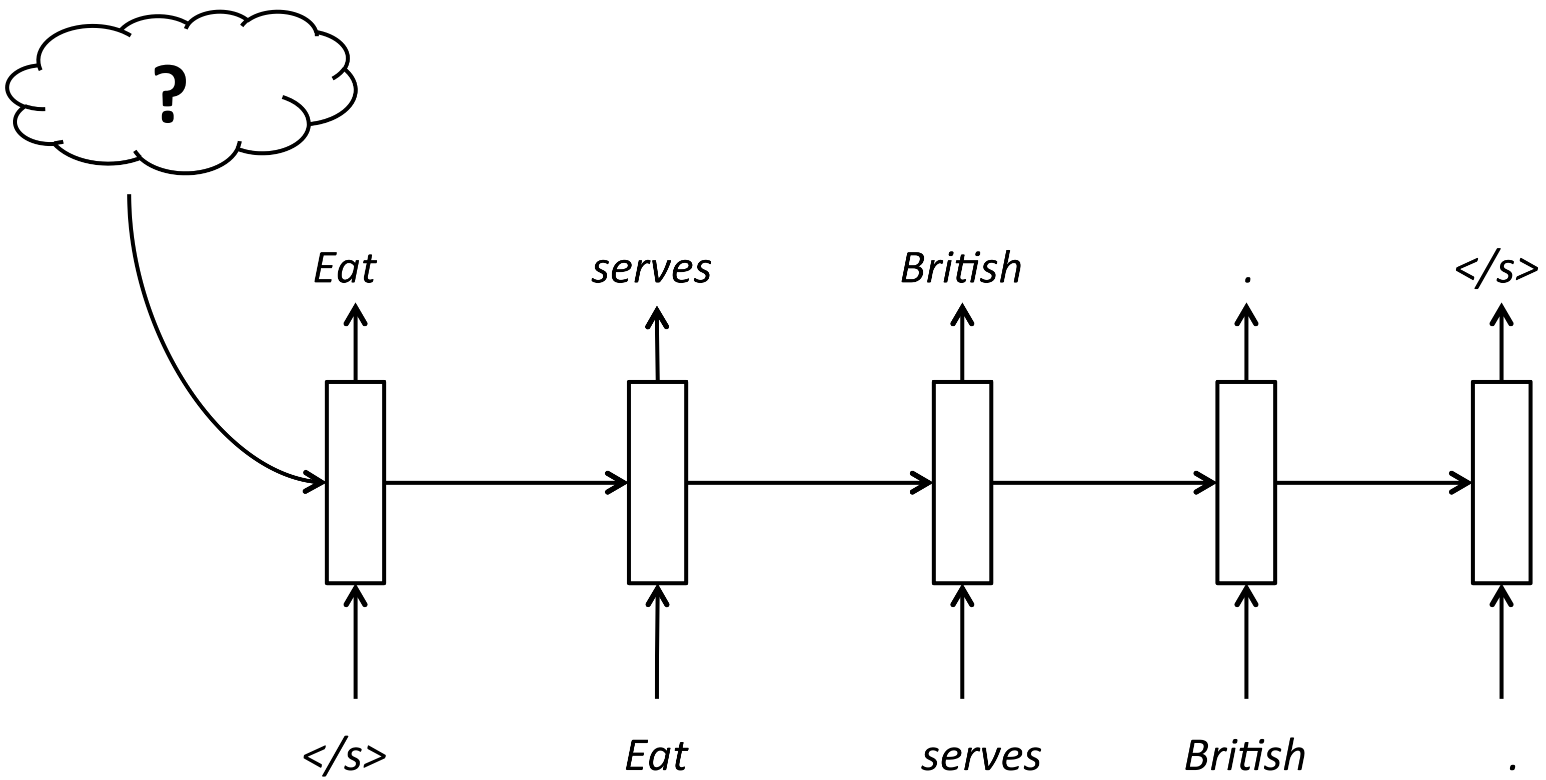
RNN Language Modeling

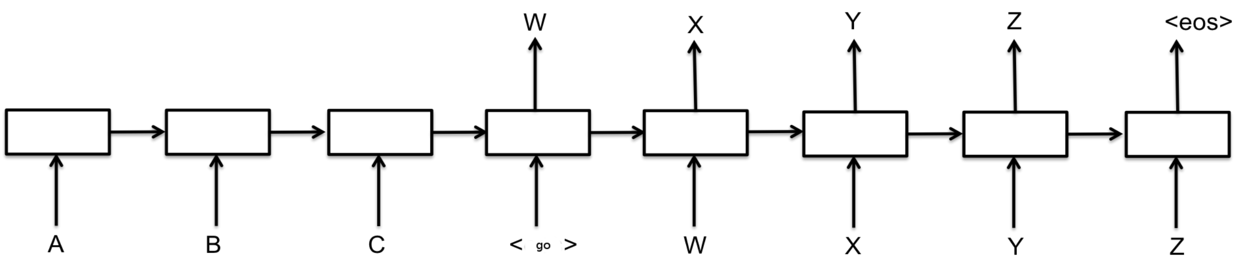


RNNLM (Mikolov et al, 2010)

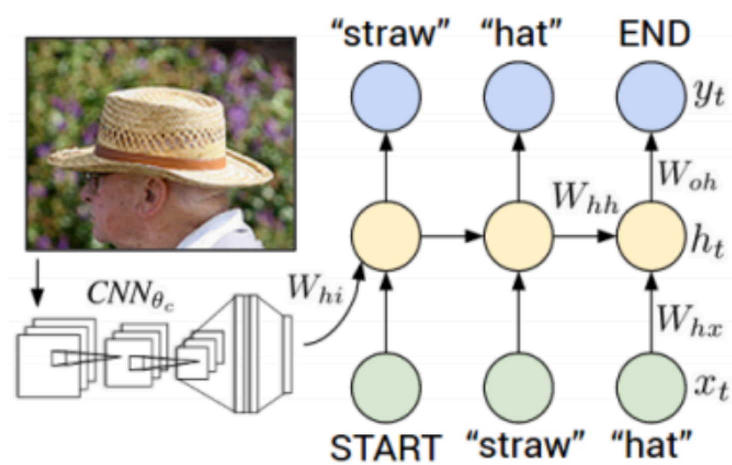
Conditional RNN LM



Many things could be a condition LM



Sutskever et al, 2014



Karpathy et al, 2015

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- **Multi-domain Neural NLG**
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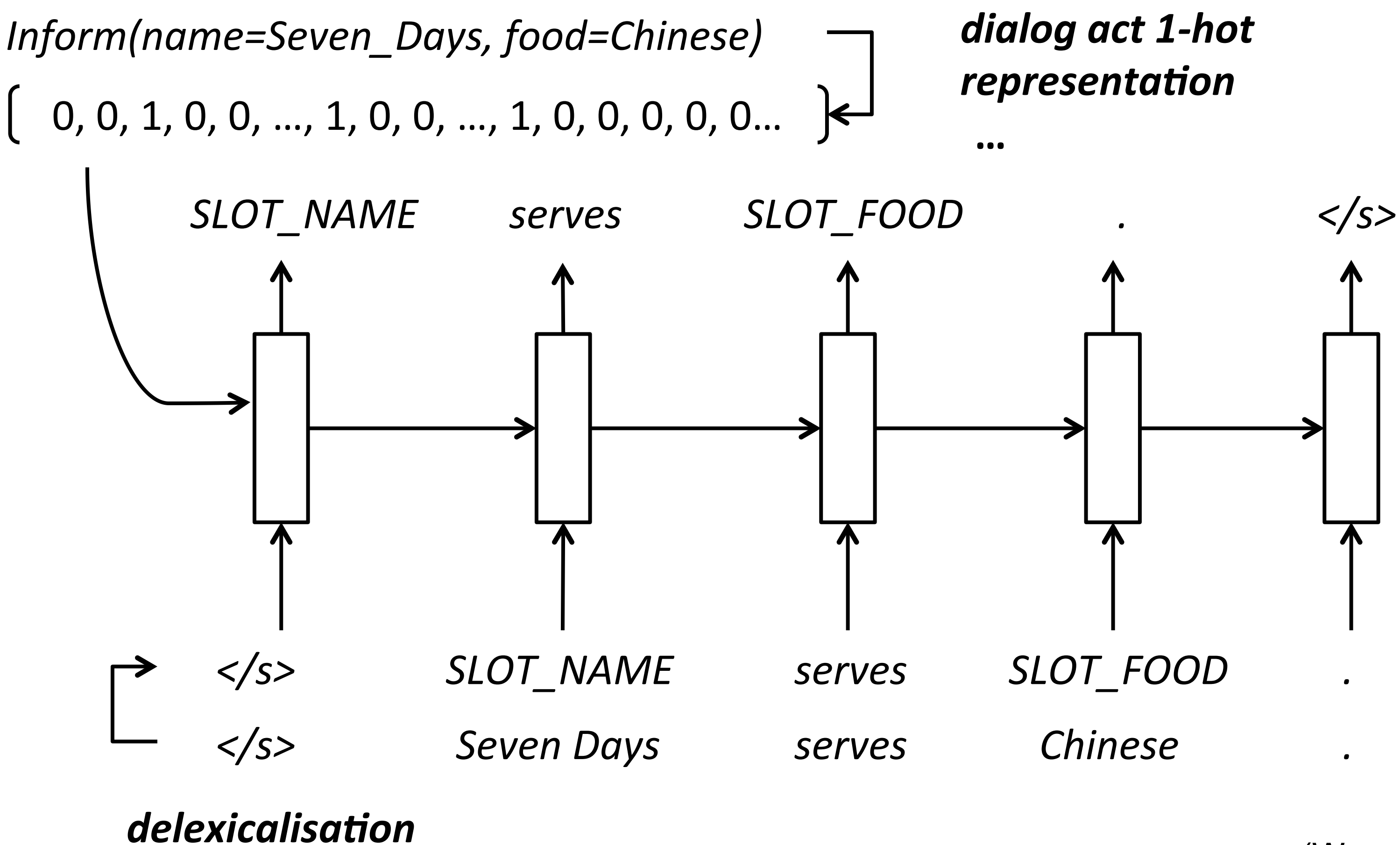
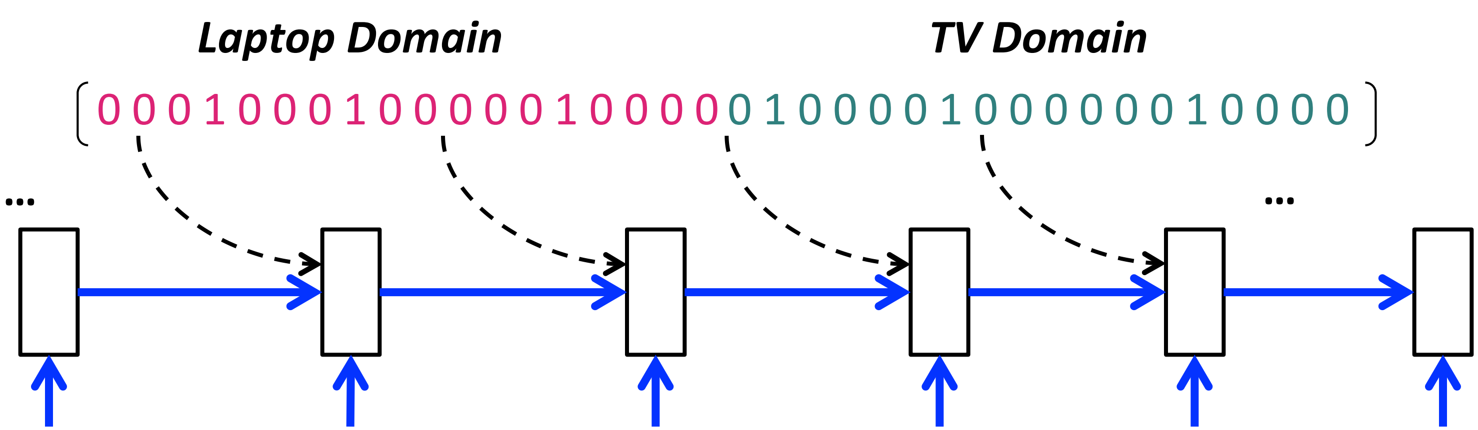
Neural NLG



(Wen et al, 2015)

Domain Adaptation

- Adaptation for NN?
  - Continue to train the model on adaptation dataset
- Parameters are shared on LM part of the network
  - But not for the DA weights
  - New slot-value pairs can only be learned from scratch



Data counterfeiting

- Produce pseudo target domain data by replacing source domain slot-values pairs with target domains slot-value pairs.
- Procedure:

An example realisation in laptop (source) domain:

Zeus 19 is a heavy laptop with a 500GB memory

delexicalisation

<NAME-value> is a <WEIGHT-value> <TYPE-value> with a <MEMEORY-value> <MEMORY-slot>

counterfeiting

<NAME-value> is a <FAMILY-value> <TYPE-value> with a <SCREEN-value> <SCREEN-slot>

A possible realisation in TV (target) domain:

Apollo 73 is a U76 television with a 29-inch screen

Data counterfeiting

- Choice of target domain slots?
  - The realisation should be similar to the source one.
  - Simple case: based on their functional class.
    - Informable, requestable, and binary slots.
  - Example:

	Laptop	**Television**
Informable	family, price_range, battery_rating,…	family, price_range, screen_size_range,…
Requestable	price, memory,…	price, resolution,…
Binary	is_for_business	has_usb_port

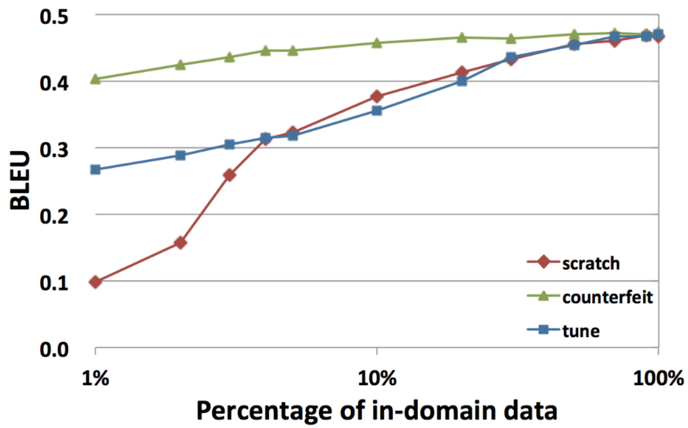
Laptop/TV dataset

- A more difficult dataset than restaurant/hotel
  - Permutate all possible DAs, ~13K/7K
  - Only a few example utterances for each DA

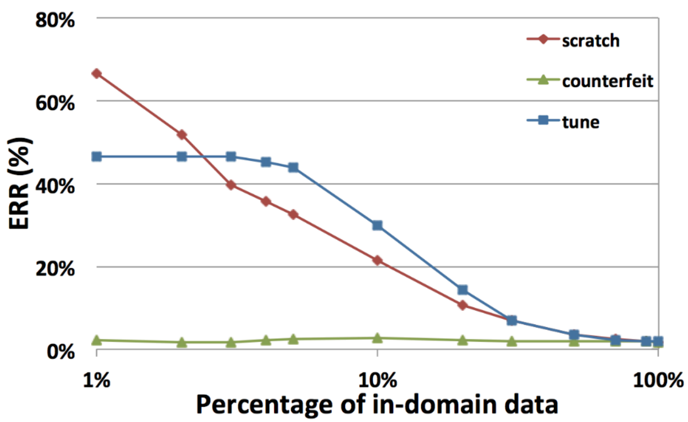
	Laptop	Television
informable slots	family, *pricerange, batteryrating, driverange, weightrange, **isforbusinesscomputing**	family, *pricerange, screensizerange, ecorating, hdmiport, **hasusbport**
requestable slots	*name, *type, *price, warranty, battery, design, dimension, utility, weight, platform, memory, drive, processor	*name, *type, *price, resolution, powerconsumption, accessories, color, screensize, audio
act type	*inform, *inform_only_match, *inform_on_match, inform_all, *inform_count, inform_no_info, *recommend, compare, *select, suggest, *confirm, *request, *request_more, *goodbye	

bold=binary slots, *=overlap with SF Restaurant and Hotel domains, all *informable slots* can take ”dontcare” value

Data counterfeiting - Results



(a) BLEU score curve

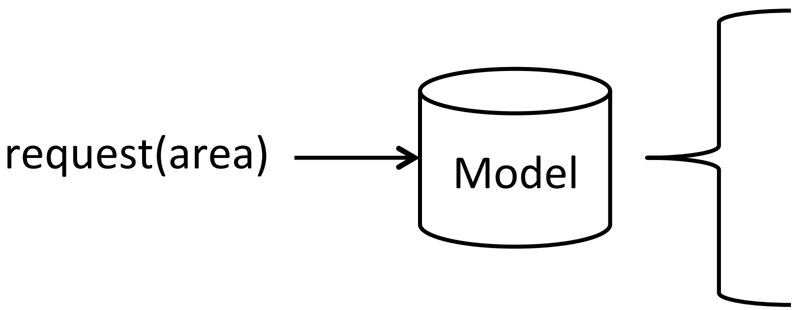


(b) Slot error rate curve

Laptop to TV

Discriminative Training

- Explore model capacity and correct it.



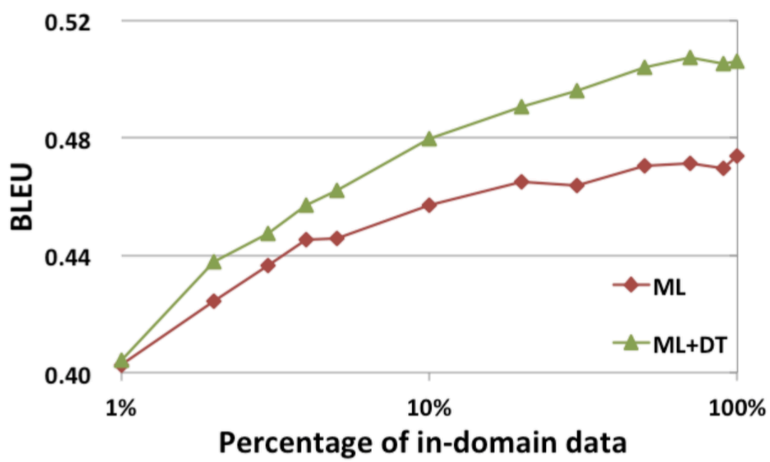
candidates	*score*
What area do you want?	0.9
What food type do you want?	0.2
Do you want north area?	0.1
Do you have any area in mind?	0.8
What part of town do you want?	1.0

- DT cost function:

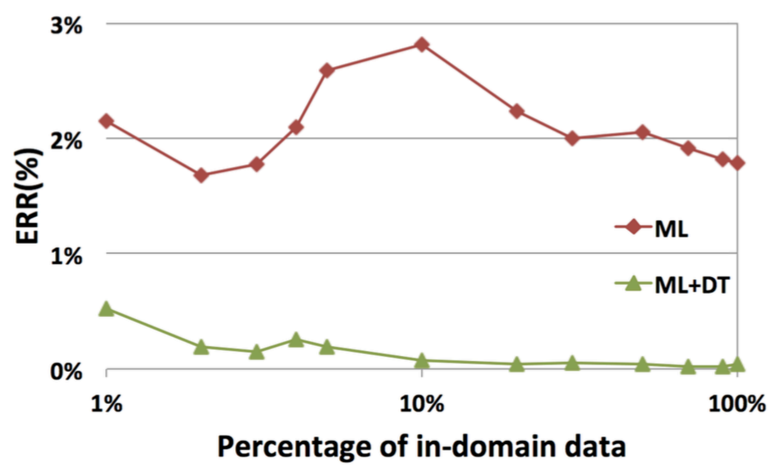
$$F(\theta) = -\mathbb{E}[L(\theta)]$$
$$= - \sum_{\Omega \in Gen(d_i)} p_\theta(\Omega | d_i) L(\Omega, \Omega_i)$$

Ω: candidate sentence
Ωi: reference sentence
di: dialogue act
L(.): scoring function

Discriminative Training - Results



(a) Effect of DT on BLEU



(b) Effect of DT on slot error rate

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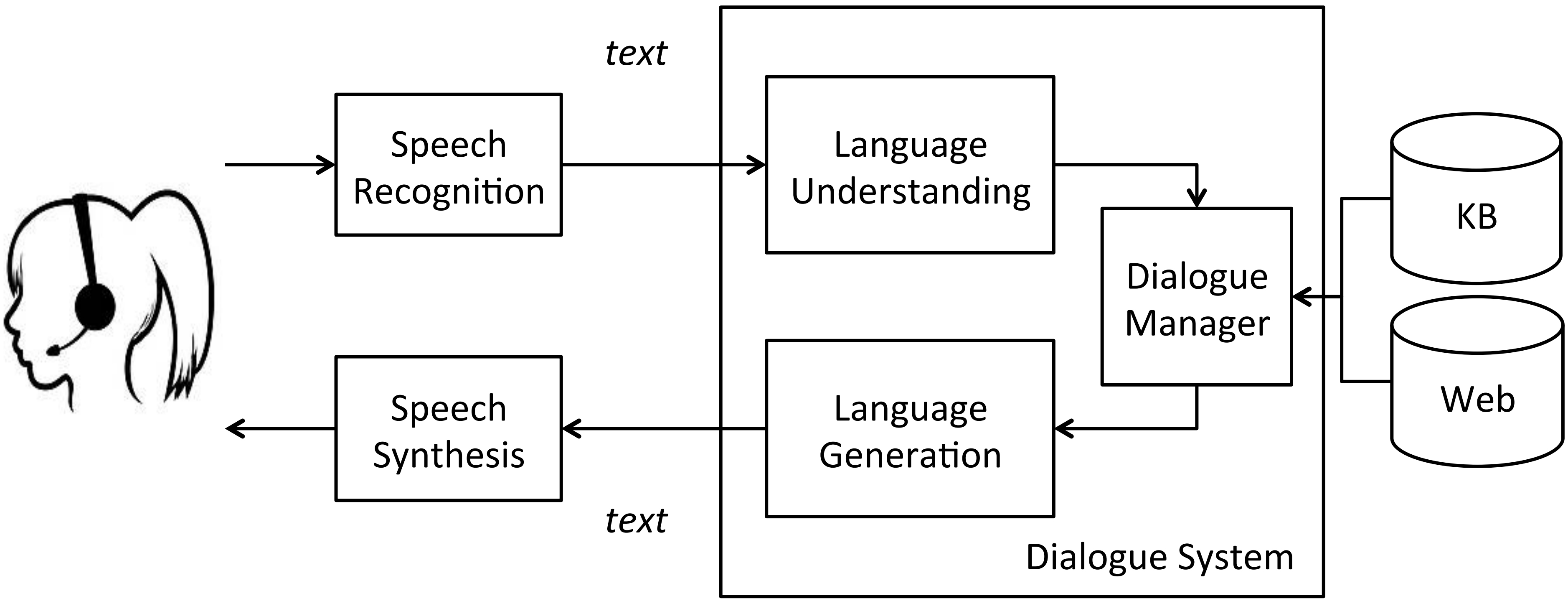
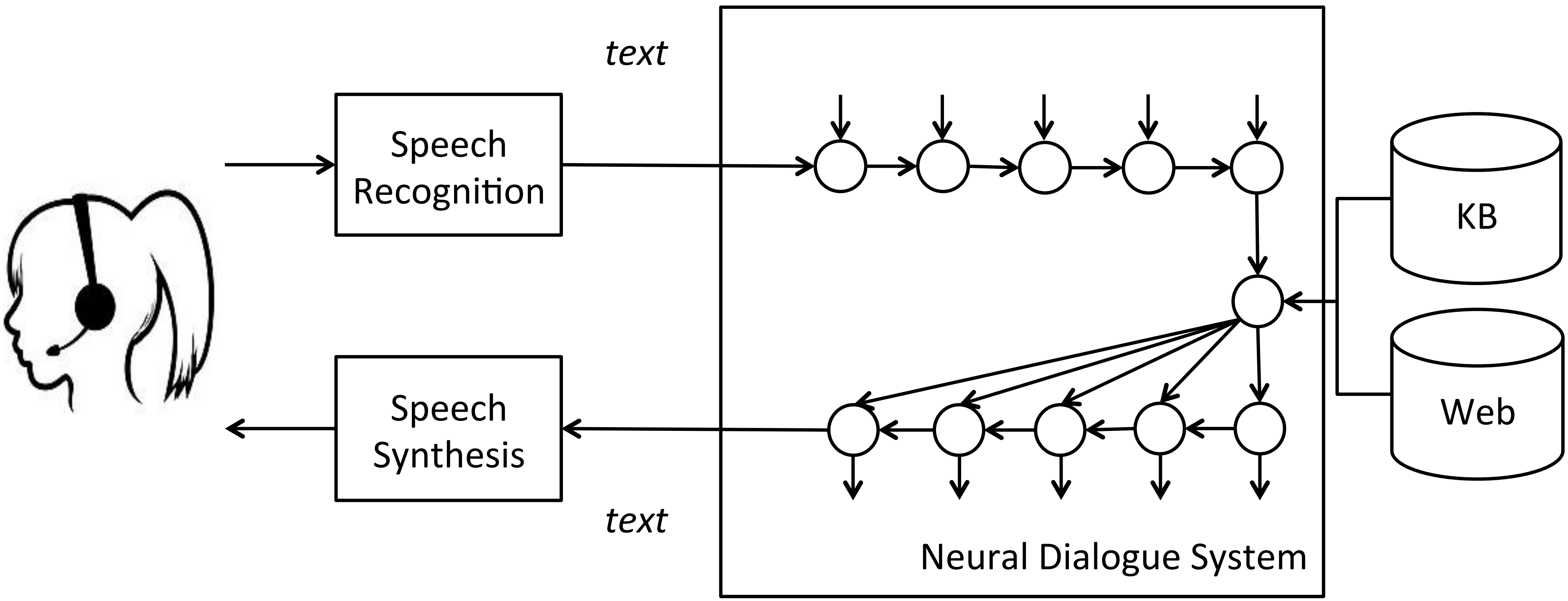
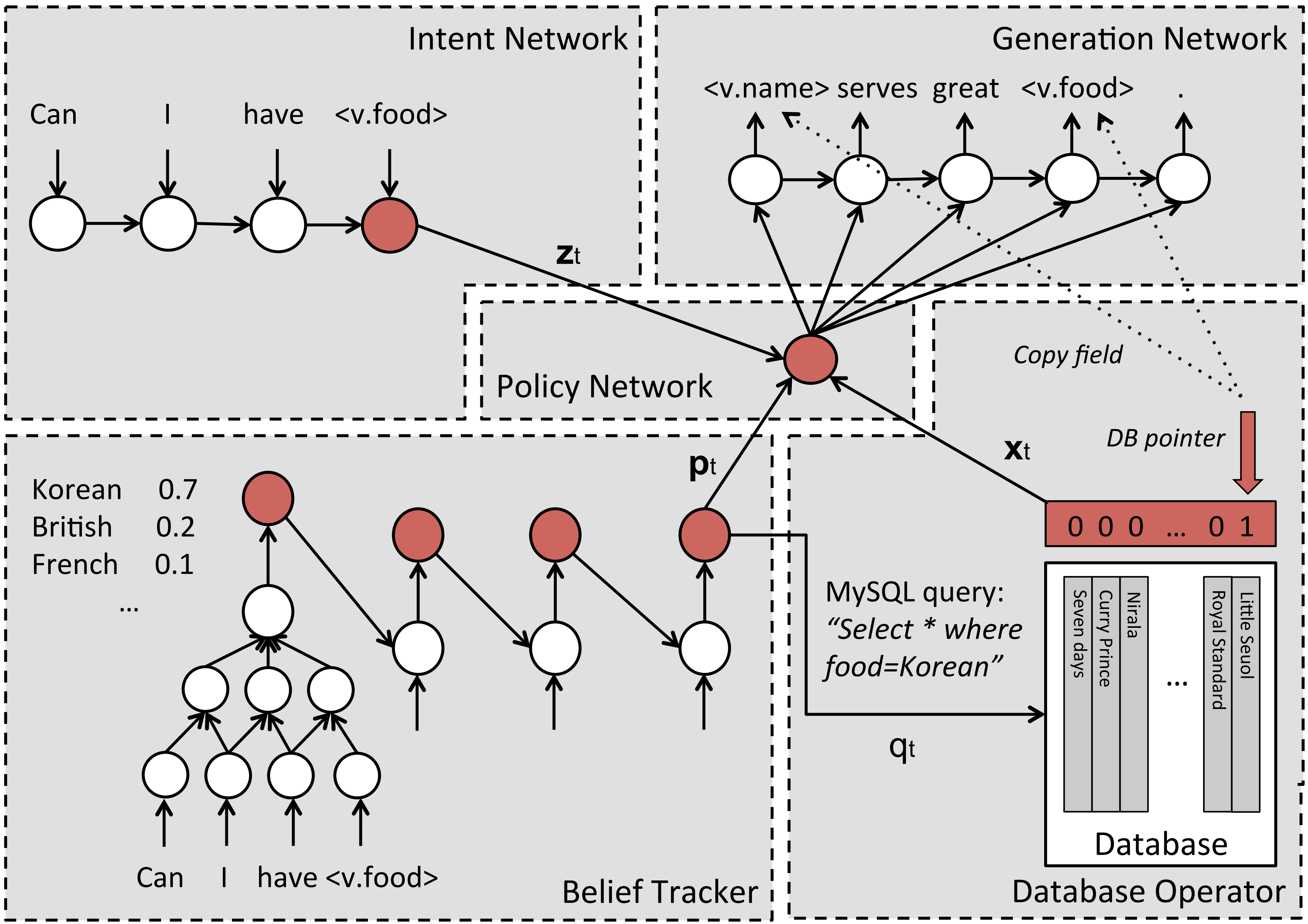
Traditional Dialogue Systems

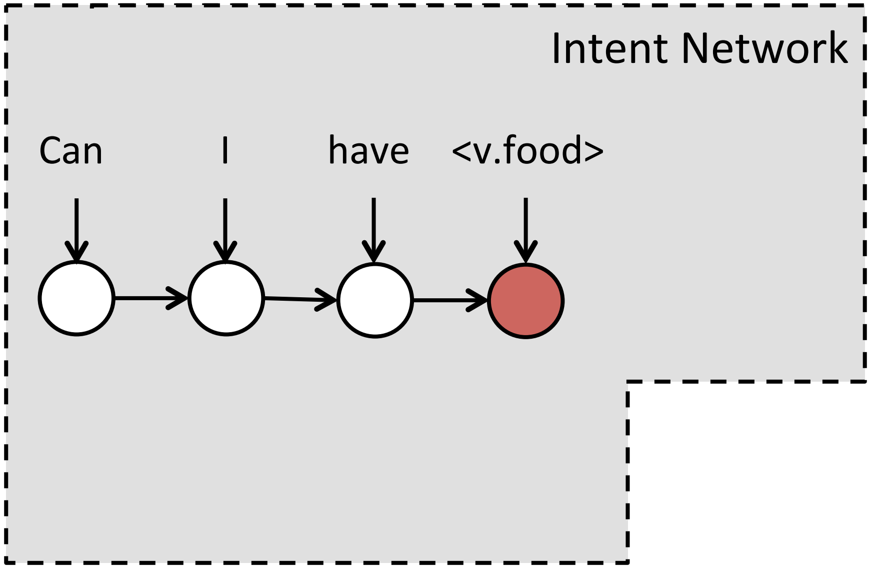


Neural Dialogue Systems





Intent Network
Can
I
have
<v.food>
zt
Generation Network
<v.name> serves great <v.food> .
Policy Network
Copy field
DB pointer
xt
pt
Korean 0.7
British 0.2
French 0.1
...
0 0 0 ... 0 1
MySQL query:
"Select * where food=Korean"
qt
Seven days
Curry Prince
Nirala
...
Royal Standard
Little Seuol
Database
Can I have <v.food>
Belief Tracker
Database Operator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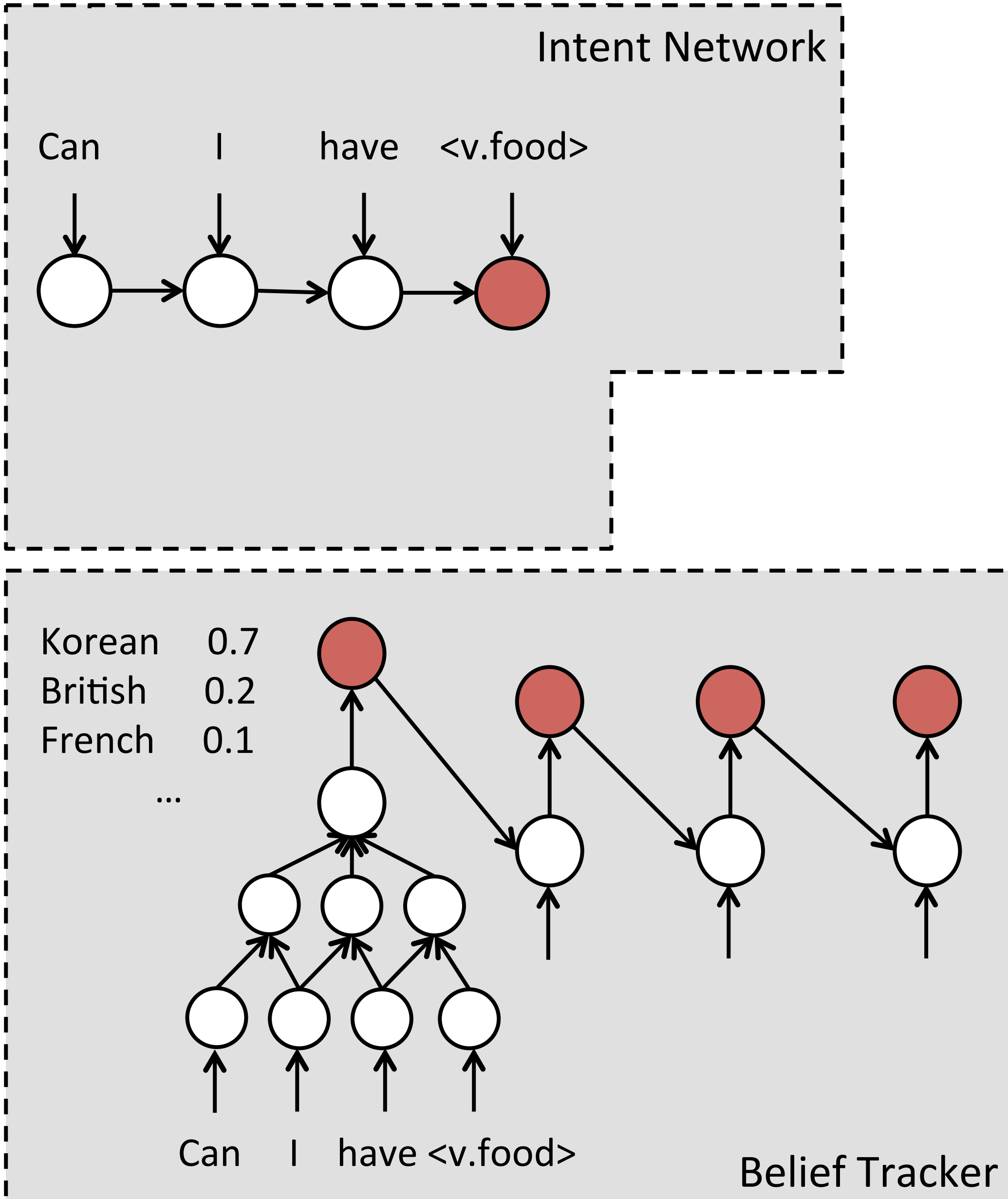

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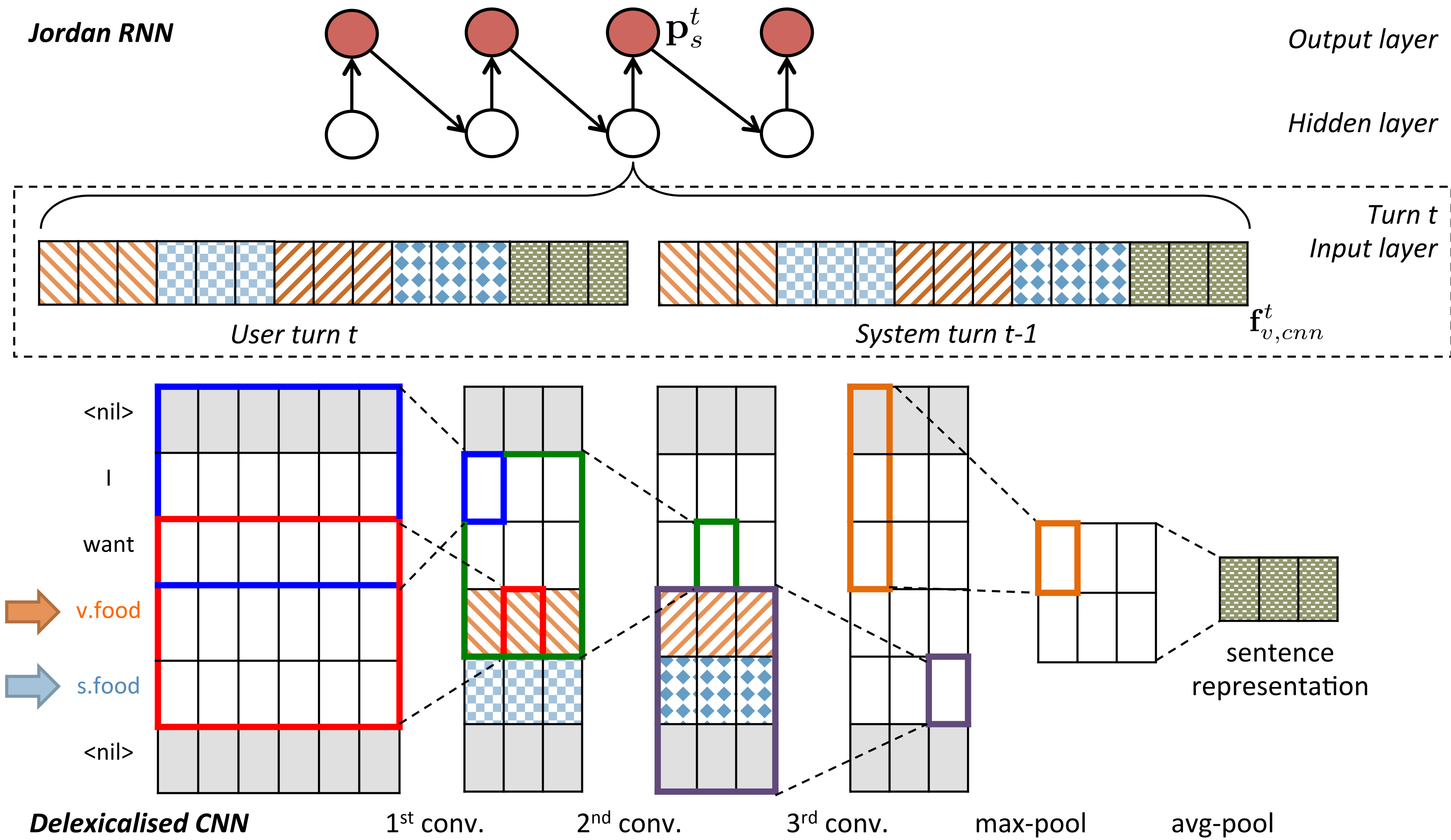
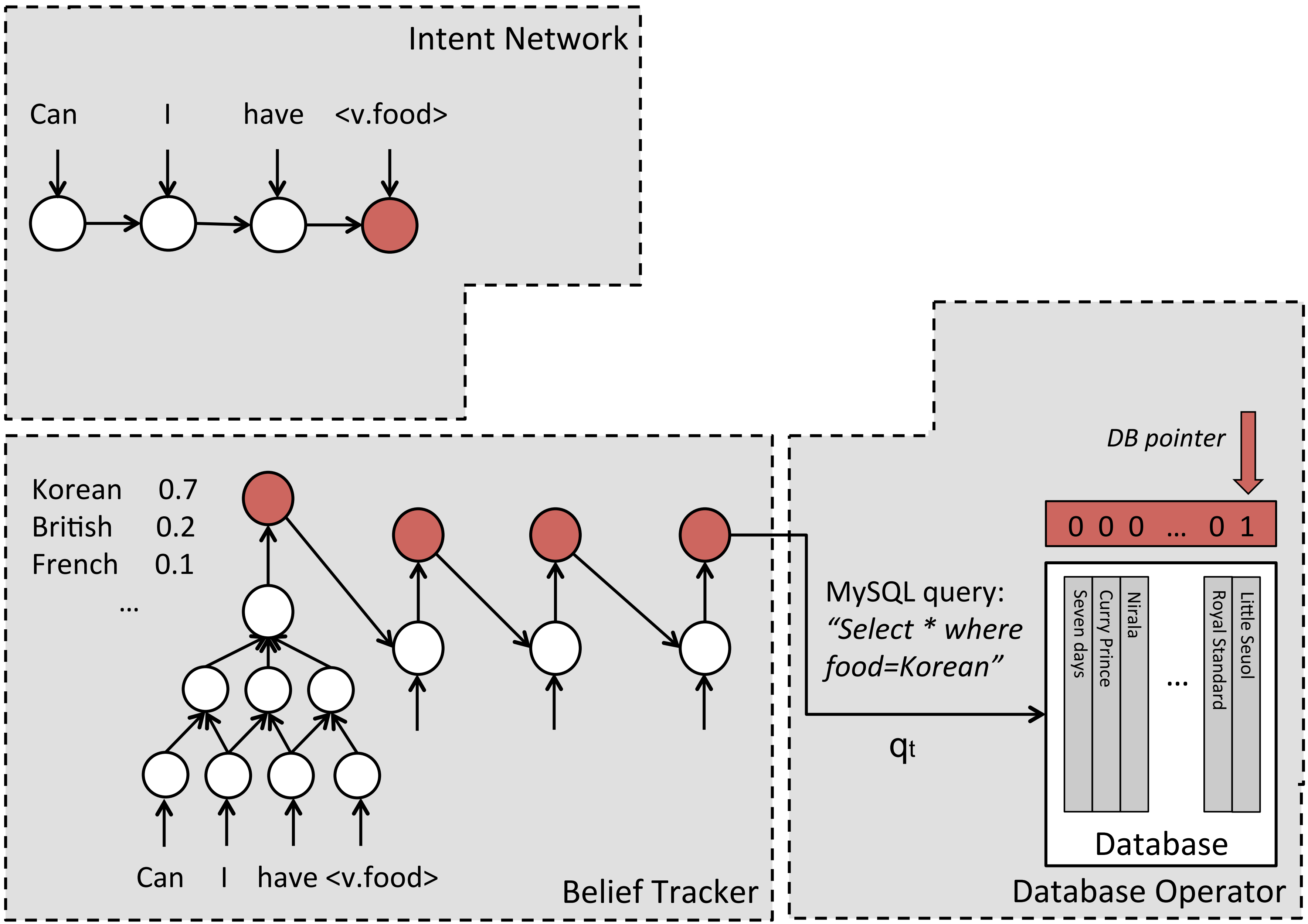
Belief Tracker

Jordan RNN-CNN belief trackers





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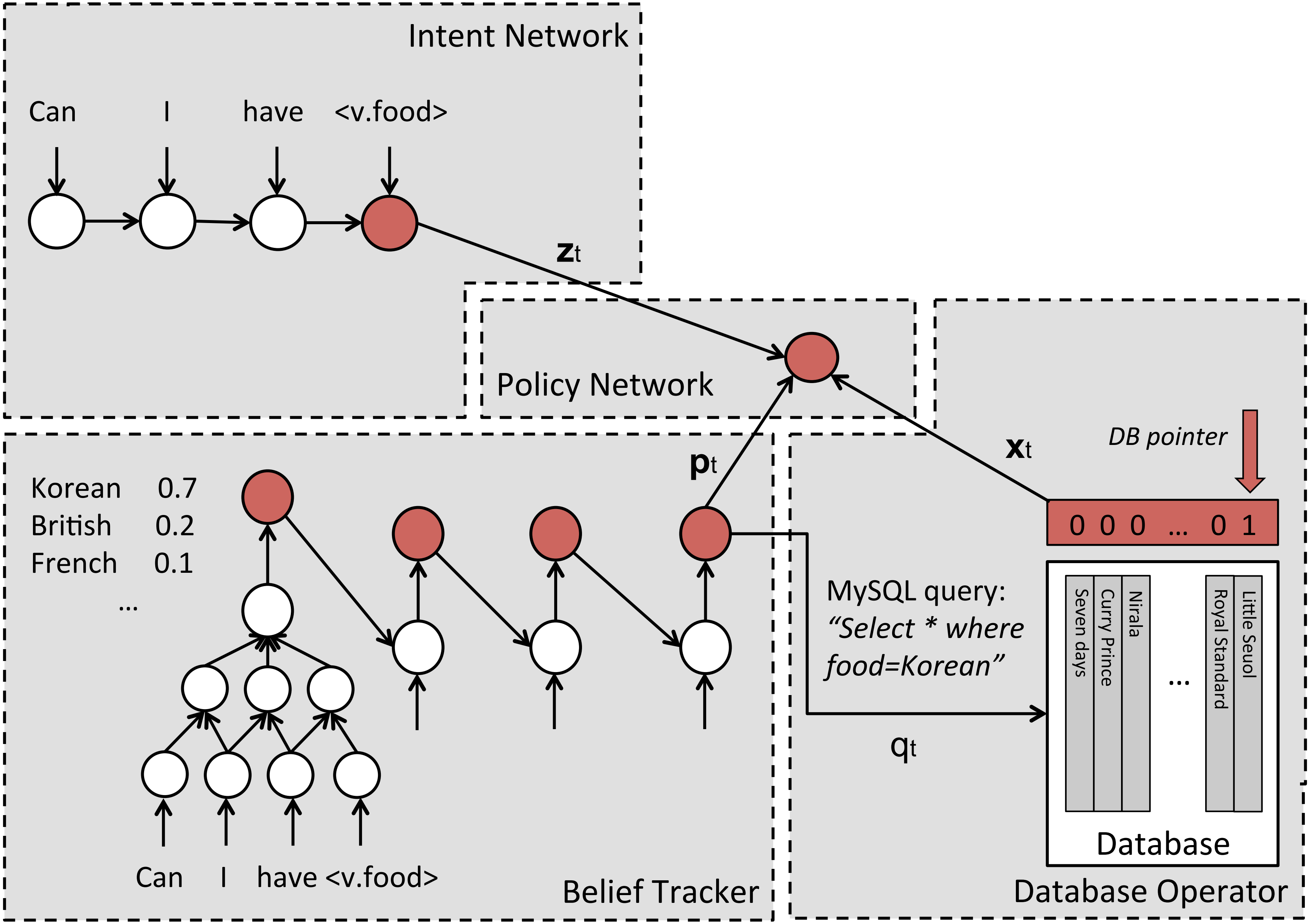

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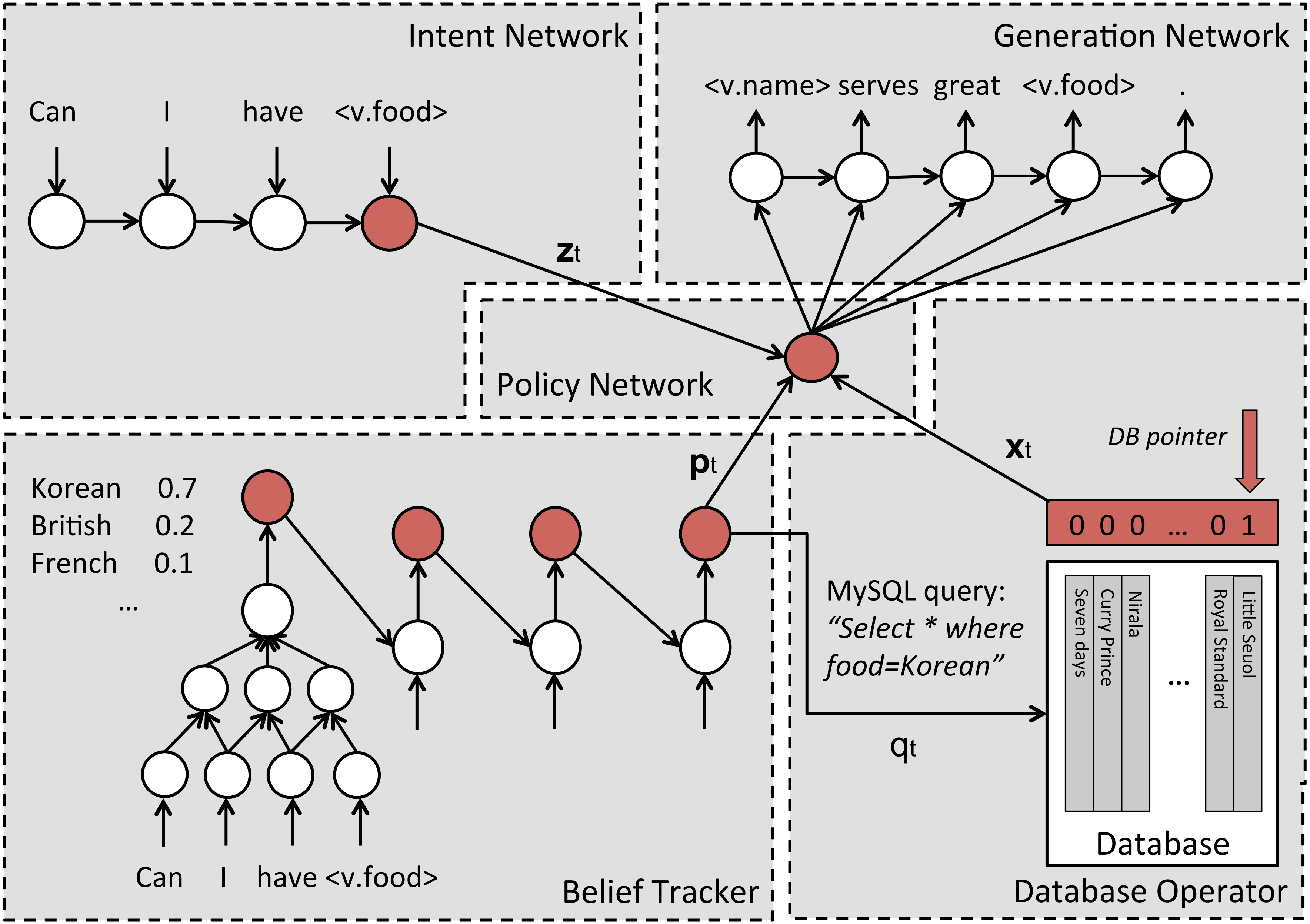

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DB pointer
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MySQL query:
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Seven days
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...
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Database
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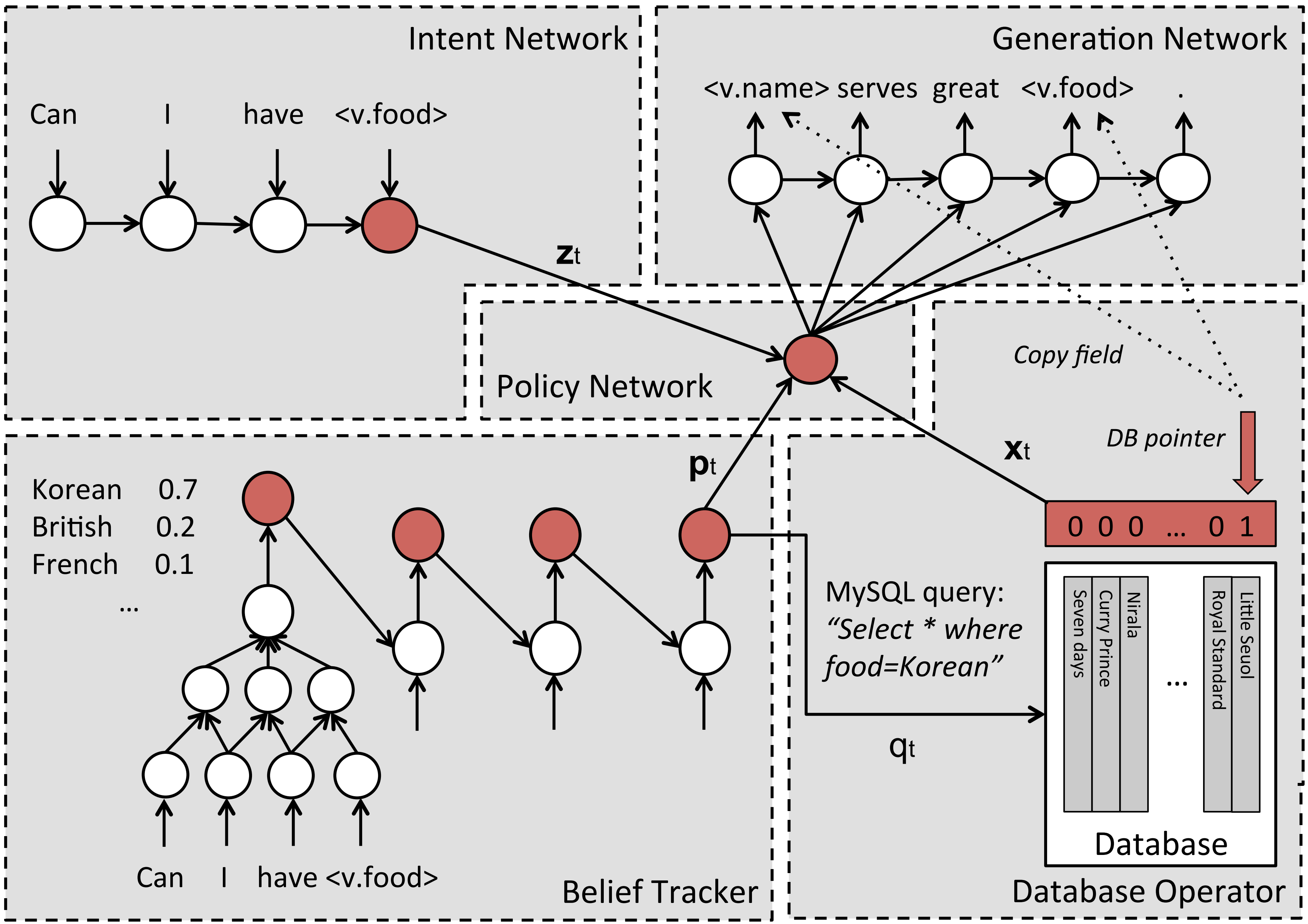

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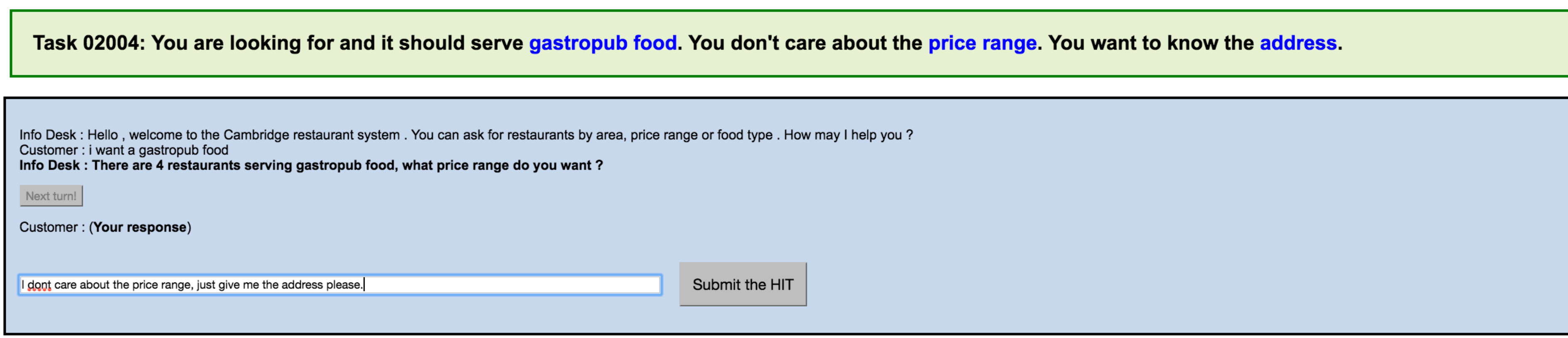
Wizard of Oz Data Collection

- Online parallel version of WOZ on MTurk
  - Randomly hire a worker to be user/wizard.
  - Ask them to enter an appropriate response for one turn (following some instructions).
  - Repeat the process until all dialogues are finished.
- Example user page



Wizard of Oz Data Collection

- Example wizard page

Info Desk : Hello , welcome to the Cambridge restaurant system . You can ask for restaurants by area, price range or food type . How may I help you ?
Customer : i want a gastropub food
Info Desk : There are 4 restaurants serving gastropub food, what price range do you want ?
Customer : i dont care

Next turn!

Please **modifiy** the following answers based on the latest customer response:

- What does user want?

What is the **food type** the user wants? gastropub
What is the **area** the user wants? not mentioned
What is the **price range** the user wants? dont care

- What does user ask?

Is the user asking for **food type** of an offered venue? No
Is the user asking for **price range** of an offered venue? No
Is the user asking for **area** of an offered venue? No
Is the user asking for **postcode** of an offered venue? No
Is the user asking for **phone number** of an offered venue? No
Is the user asking for **address** of an offered venue? No
Is the user mentioning any **restaurant names**? No

finish

Info Desk : (**Your response**)

I would recommend backstreet bistro, a great gastropub restaurant in the centre. do you want their phone number ?   end-of-dialogue?   Submit the HIT

Name	Food	Area	Price Range	Phone	Address	Postcode
backstreet bistro	gastropub	centre	expensive	01223 306306	2 Sturton Street City Centre	C.B 1, 2 Q.A
royal standard	gastropub	east	expensive	01223 247877	290 Mill Road City Centre	C.B 1, 3 N.L
the cow pizza kitchen and bar	gastropub	centre	moderate	01223 308871	Corn Exchange Street	C.B 2, 3 Q.F
the slug and lettuce	gastropub	centre	expensive	--	34 - 35 Green Street	C.B 2, 3 J.U
nil	gastropub	nil	nil	nil	nil	nil

Showing 1 to 4 of 4 entries (filtered from 110 total entries)

Previous 1 Next

Data Statistics

- Ontology:
  - Cambridge restaurant domain, 99 venues.
  - 3 informable slots, 6 requestable slots

- Dataset
  - 676 dialogues, ~2750 turns
  - 3000 HITS, takes 3 days, costs ~400 USD
  - Data cleaning takes 2-3 days for one person

Experiments

- Experimental details
  - Train/valid/test: 3/1/1
  - SGD, l2 regularisation, early stopping, gradient clip=1
  - Hidden size = 50, Vocab size: ~500
- Two stage training:
  - Training trackers with label cross entropy
  - Training other parts with response cross entropy
- Decoding
  - Beam search w/ beam width 10
  - Decode with average word likelihood

Human evaluation

Quality assessment

Metric	N2N
Success	98%
Comprehension	4.11
Naturalness	4.05
# of dialogues:	245

System Comparison

Metric	N2N	Modular	Tie
Subj. Success	96.95%	95.12%	-
Avg. # of Turn	3.95	4.54	-
Comparisons(%)			
Naturalness	46.95*	25.61	27.44
Comprehension	45.12*	21.95	32.93
Preference	50.00*	24.39	25.61
Performance	43.90*	25.61	30.49

* $p < 0.005$, # of comparisons: 164

Example dialogues

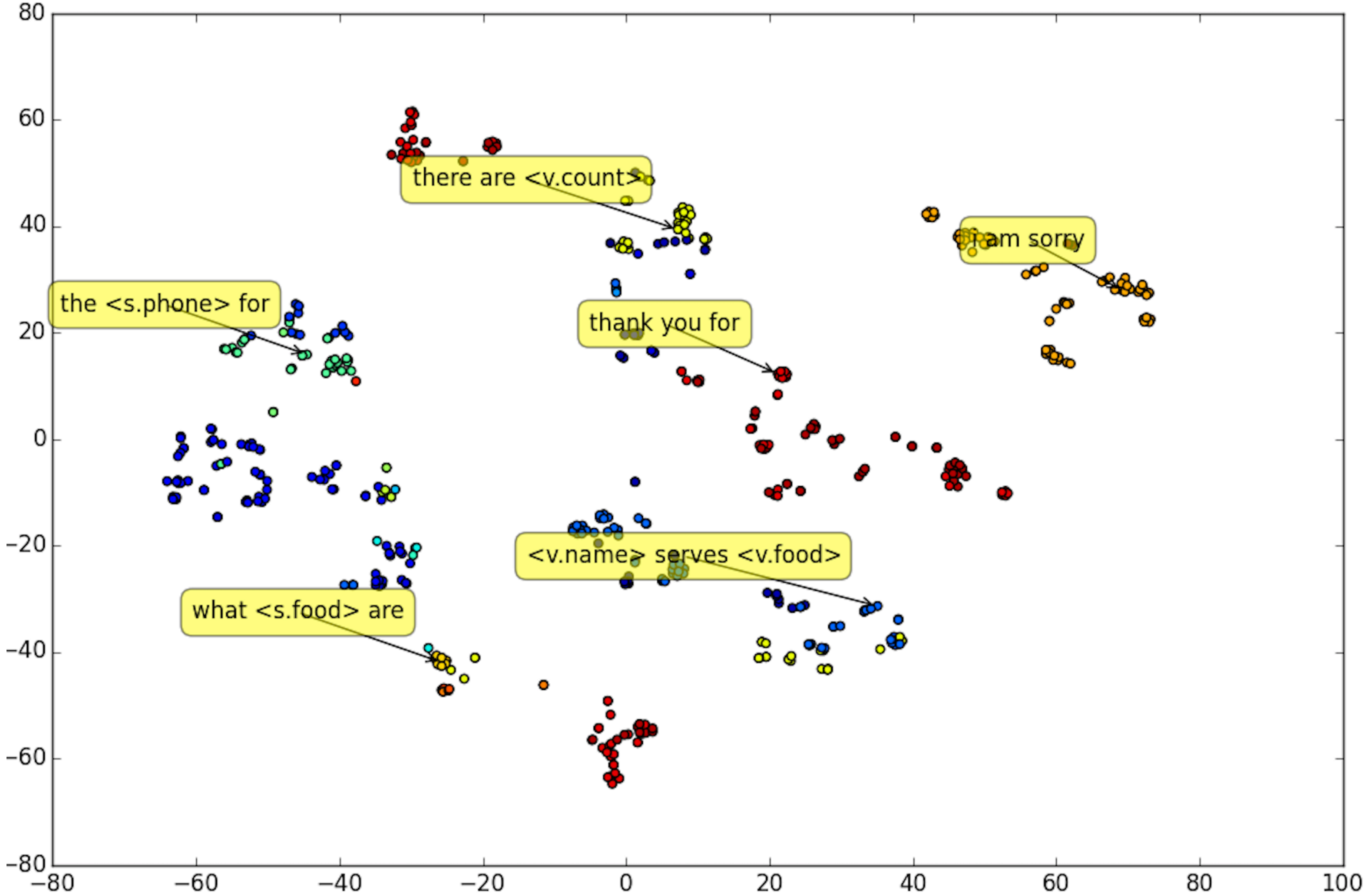
Human	: Restaurant in any area that serves Vietnamese food
Machine	: thanh binh serves vietnamese food type , is there anything else i can help you with ?
Human	: What is the phone number and post code
Machine	: the number is 01223 362456 and the area code is c.b 3, 0 a.f . is there anything else i can do for you ?
Human	: Good bye
Machine	: thank you for using the cambridge restaurant system .

Human	: 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 .

Example dialogues

Human	: hello
Machine	: what cuisine would you like ?
Human	: afghan
Machine	: i am sorry , there are no afghan restaurants . would you like something else ?
Human	: korean
Machine	: little seoul serves korean food , it is located at 108 regent street city centre .
Human	: is it expensive?
Machine	: little seoul serves korean food and is in the expensive price range .
Human	: what area is that
Machine	: little seoul is located in the centre area of town . would you like their number ?
Human	: yes
Machine	: the telephone number is 01223 308681 . is there anything else i can help you with today ?
Human	: no goodbye
Machine	: thank you for using the cambridge restaurant system , goodbye .

Visualising action embeddings



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Conclusion

- NN-based conditional LM is widely applied.
  - Generation based on dialogue act representation.
  - Generation based on the entire dialogue context.

- Achieve domain extension by data counterfeiting and discriminative training.

- Develop an end-to-end task oriented dialogue system by collecting WOZ data and JUST training it!

Papers

- Tsung-Hsien Wen, Milica Gasic , Nikola Mrksic, Pei-Hao Su, David Vandyke, and Steve Young. Semantically Conditioned LSTM-based Natural Language Generation for Spoken Dialogue Systems. In *Proceedings of EMNLP 2015*.
- Tsung-Hsien Wen, Milica Gasic, Nikola Mrksic, Lina M.R. Barahona, Pei-Hao Su, David Vandyke, and Steve Young. Muti-domain Neural Language Generation for Spoken Dialogue Systems*. In Proceedings of NAACL-HLT* 2016.
- Tsung-Hsien Wen, David Vandyke, Nikola Mrksic, Milica Gasic, Lina M.R. Barahona, Pei-Hao Su, Stefan Ultes, and Steve Young. A Network-based End-to-End Trainable Task-oriented Dialogue System. *arXiv preprint: 1604.04562* 2016.

Selected References

- Tomas Mikolov, Martin Karafit, Lukas Burget, Jan Cernocky, and Sanjeev Khudanpur. Recurrent neural network based language model. *In Proceedings on InterSpeech* 2010.
- Sepp Hochreiter and Jurgen Schmidhuber. Long short-term memory. *Neural Computation* 1997.
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- Andrej Karpathy and Li Fei-Fei. Deep Visual-Semantic Alignments for Generating Image Descriptions. *In Proceedings of CVPR* 2015.

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Thank you! Questions?

Tsung-Hsien Wen is supported by a studentship funded by Toshiba Research Europe Ltd, Cambridge Research Laboratory

SC-LSTM

- **Original LSTM cell**

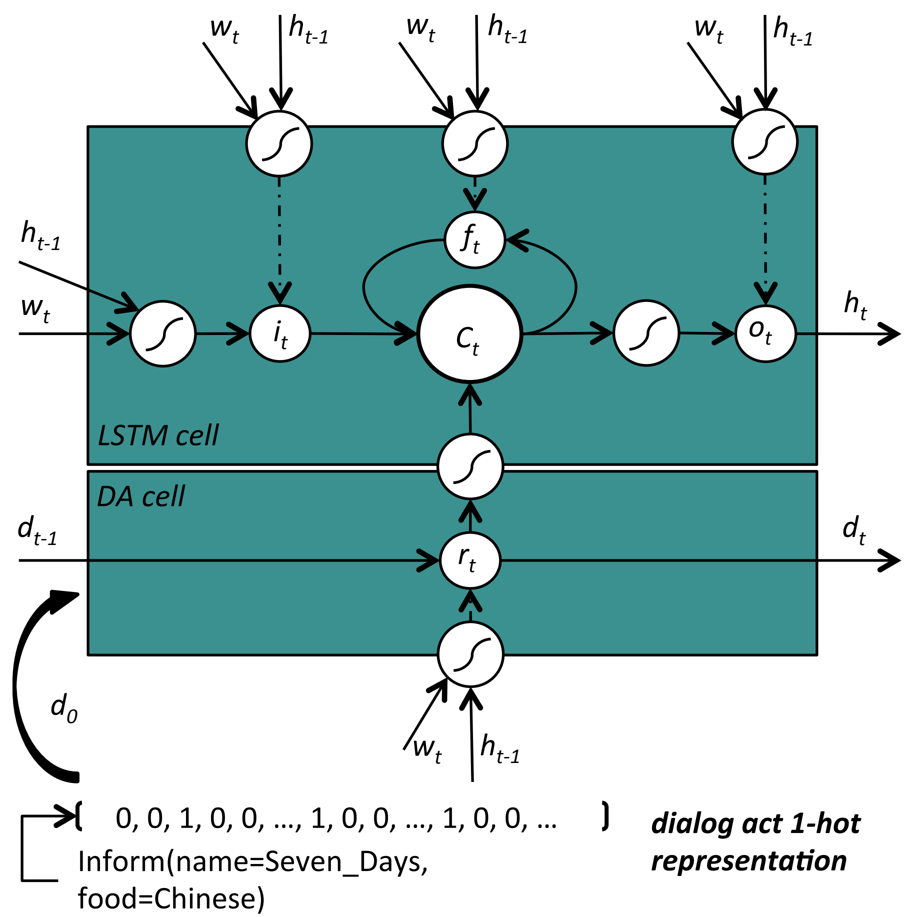
$$\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{w}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$$
$$\mathbf{f}_t = \sigma(\mathbf{W}_{wf}\mathbf{w}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1})$$
$$\mathbf{o}_t = \sigma(\mathbf{W}_{wo}\mathbf{w}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1})$$
$$\hat{\mathbf{c}}_t = \tanh(\mathbf{W}_{wc}\mathbf{w}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1})$$
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{c}}_t$$
$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

- **DA cell**

$$\mathbf{r}_t = \sigma(\mathbf{W}_{wr}\mathbf{w}_t + \mathbf{W}_{hr}\mathbf{h}_{t-1})$$
$$\mathbf{d}_t = \mathbf{r}_t \odot \mathbf{d}_{t-1}$$

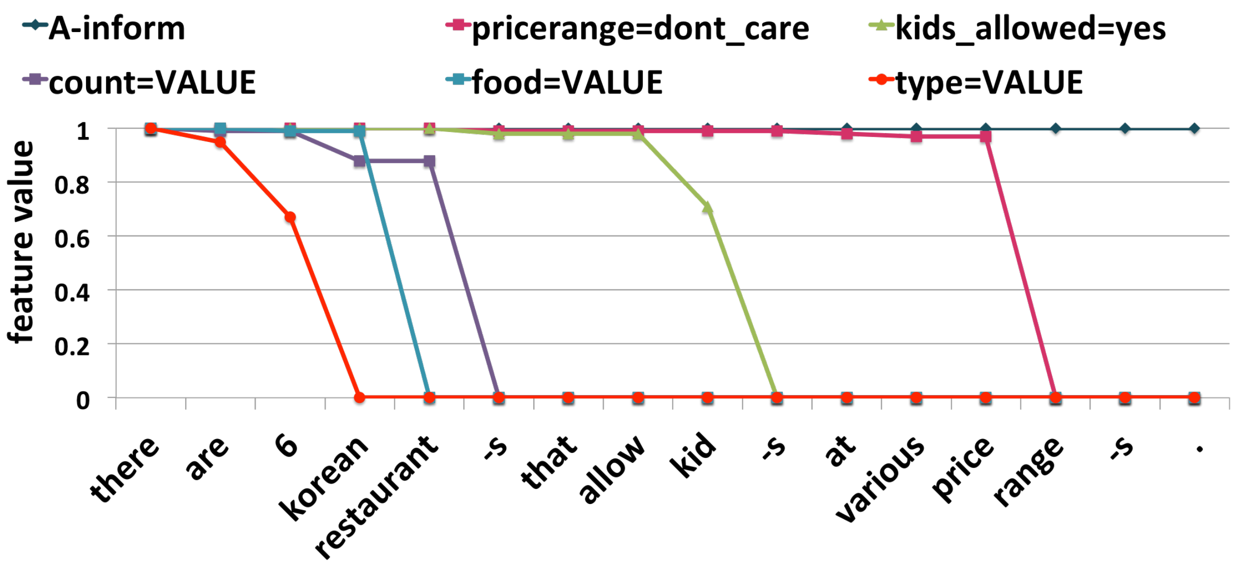
- **Modify Ct**

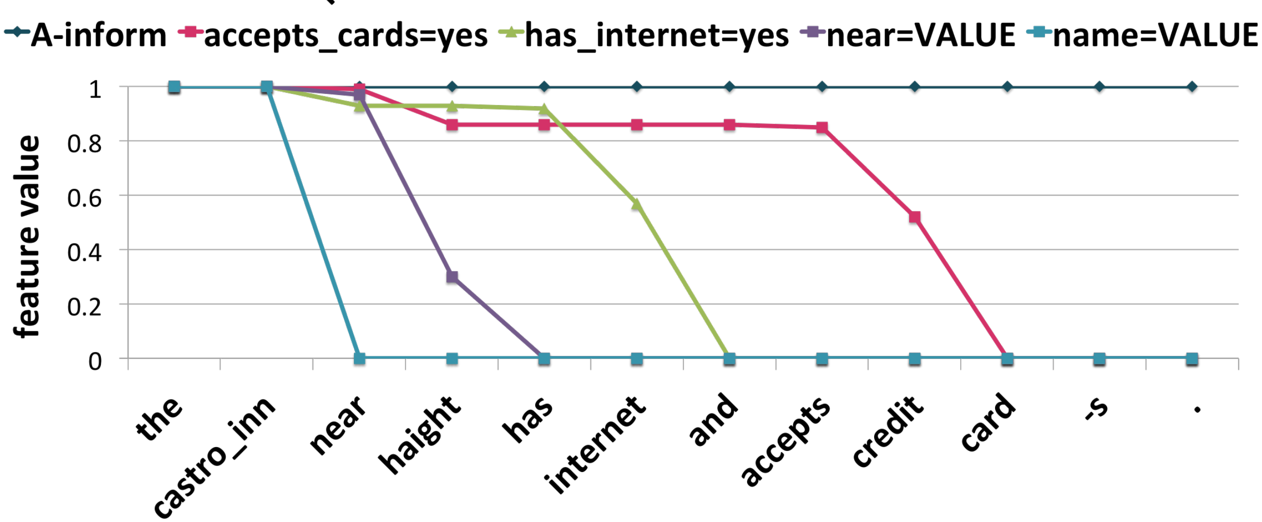
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{c}}_t + \tanh(\mathbf{W}_{dc}\mathbf{d}_t)$$



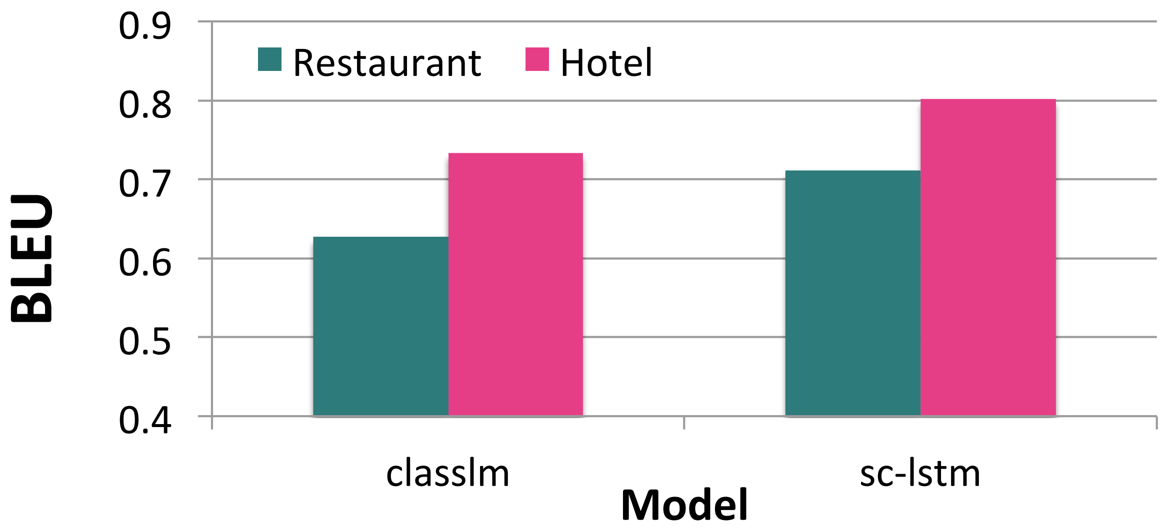
(Hochreiter and Schmidhuber, 1997)

Visualization





Results



Human Evaluation

Method	Informativeness	Naturalness
sc-lstm	**2.59**	2.50
classlm	2.46^{**}	2.45

$^{*}p < 0.05$ $^{**}p < 0.005$

Human Evaluation

Method	TV to Laptop Info.	TV to Laptop Nat.	laptop to TV Info.	laptop to TV Nat.
scrALL	2.64	2.37	2.54	2.36
DT-10%	**2.52****	**2.25****	**2.51**	2.19**
ML-10%	2.51**	2.22**	2.45**	**2.22****
scr-10%	2.24**	2.03**	2.00**	1.92**

* $p < 0.05$, ** $p < 0.005$

- scrALL : train from scratch with 100% ID data.
- scr-10% : train from scratch with 10% ID data.
- ML-10% : data counterfeiting + ML training on 10% ID data.
- DT-10% : data counterfeiting + DT training on 10% ID data.