



UNIVERSITY OF
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Deep Learning for Natural Language Generation & End-to-End Dialogue Modeling

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Dialogue Systems Group

Part I: NLG Overview

- Basic concepts and techniques in DL for NLG
- Recent progress of DL in NLG-related topics

- ⊙ Mapping MR(meaning representation) -> NL

- ⊙ inform(name=Seven_Days, food=Chinese)

- ⊙ Seven Days is a nice Chinese restaurant.

- ⊙ Evaluation

- ⊙ Automatic metrics such as BLEU [Papineni et al, 2002]

| Correlation | Adequacy | Fluency |
|-------------|----------|---------|
| BLEU | 0.388 | -0.492 |

[Stent et al, 2005]

- ⊙ Human Evaluation

Template-based NLG

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- ⦿ Define a set of rules to map MR to NL
 - ⦿ Pros: simple, error-free, easy to control
 - ⦿ Cons: time consuming, scalability

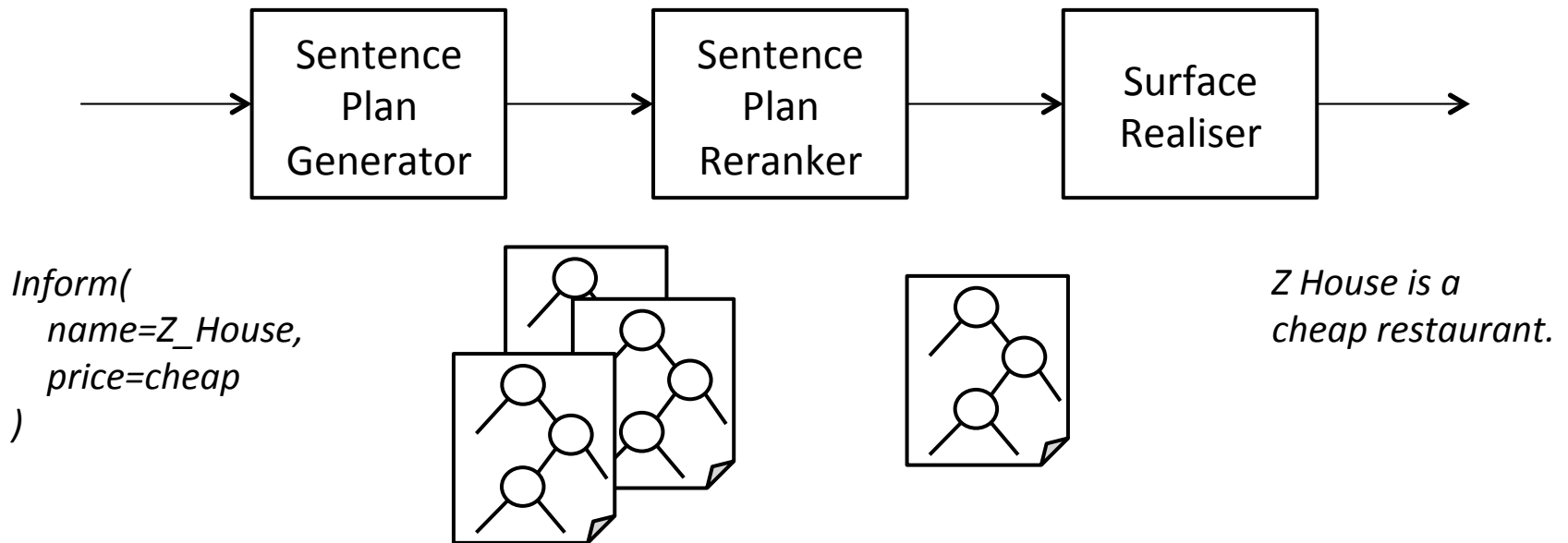
```
confirm()           "Please tell me more about the product your are looking for."  
confirm(area=$V)    "Do you want somewhere in the $V?"  
confirm(food=$V)    "Do you want a $V restaurant?"  
confirm(food=$V,area=$W) "Do you want a $V restaurant in the $W."
```

...

Trainable Generator [*Walker et al 2002*]

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- ⊙ Divide the problem into pipeline



- ⊙ Focus on applying ML to sentence plan reranker.

Follow-up works

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- ⊙ Statistical sentence plan generator [*Stent et al 2009*]
- ⊙ Statistical surface realisers [*Dethlefs et al 2013, Cuayáhuitl et al 2014, ...*]
- ⊙ Learn from unaligned data [Dusek and Jurcicek 2015]
- ⊙ Pros: can model complex linguistic structures
- ⊙ Cons: heavily engineered, require domain knowledge

Sequential NLG models

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- ⊙ Class-based LM [*Oh and Rudnicky, 2000*]

- ⊙ Class-based Language Modeling

$$P(W|\mathbf{u}) = \prod_t P(w_t | w_0, w_1, \dots, w_{t-1}, \mathbf{u})$$

- ⊙ Decoding

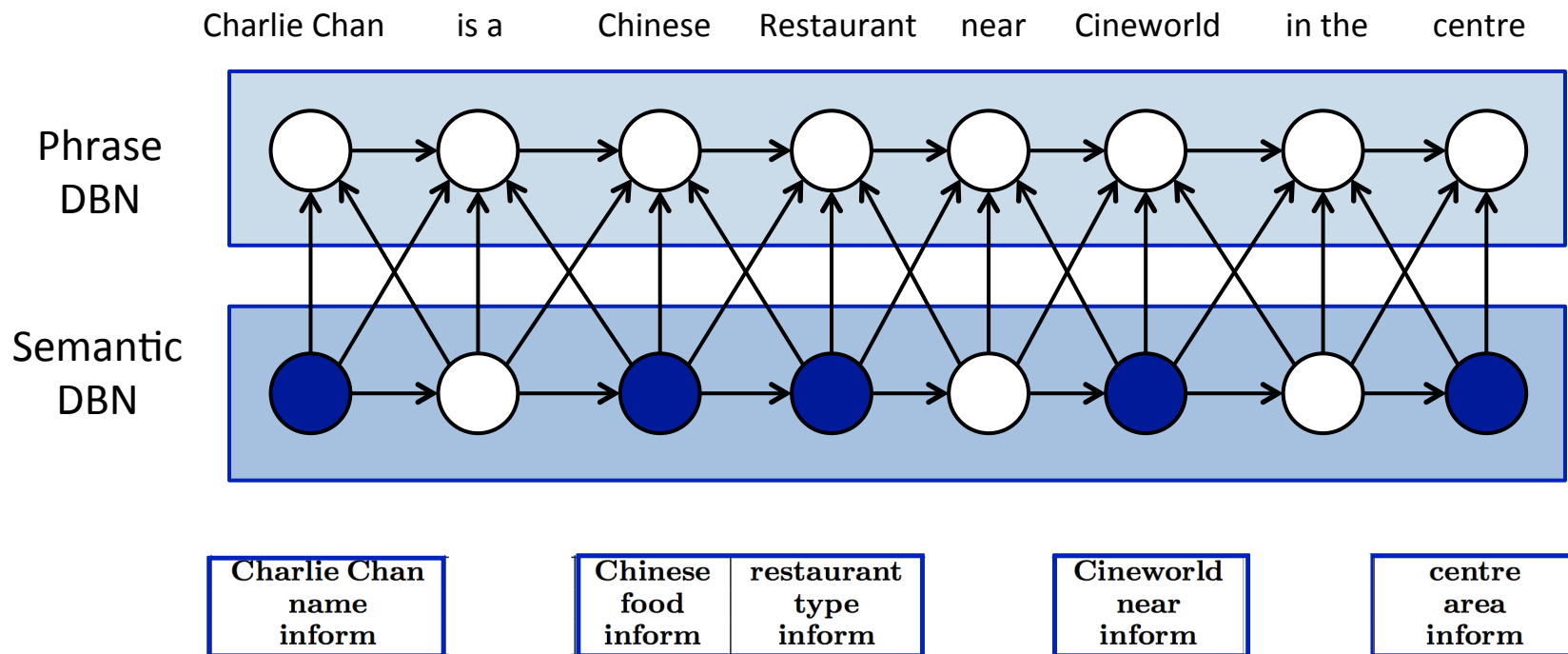
$$W^* = \operatorname{argmax}_W P(W|\mathbf{u})$$

- ⊙ Pros: easy to implement/understand, simple rules
 - ⊙ Cons: computationally inefficient

Sequential NLG models

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Phrase-based NLG using DBN [Mairesse et al, 2010]



Inform(type= restaurant, name=Charlie Chan,
food=chinese, near=Cineworld, area=centre)

Sequential NLG models

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- Phrase-based NLG using DBN [*Mairesse et al, 2010*]
- Pros: efficient, good performance
- Cons: require semantic alignments

| r_t | s_t | h_t | l_t |
|----------------------|--------------------------|------------|--------------|
| <S> | START | START | START |
| <i>The Rice Boat</i> | inform(name(X)) | X | inform(name) |
| <i>is a</i> | inform | inform | EMPTY |
| <i>restaurant</i> | inform(type(restaurant)) | restaurant | inform(type) |
| <i>in the</i> | inform(area) | area | inform |
| <i>riverside</i> | inform(area(riverside)) | riverside | inform(area) |
| <i>area</i> | inform(area) | area | inform |
| <i>that</i> | inform | inform | EMPTY |
| <i>serves</i> | inform(food) | food | inform |
| <i>French</i> | inform(food(French)) | French | inform(food) |
| <i>food</i> | inform(food) | food | inform |
| </S> | END | END | END |

Q & A

Neural Networks

NN basics

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⊙ Artificial Neuron

$$h_i = \sigma\left(\sum_j \omega_{ij} x_j + b_i\right)$$

Diagram illustrating the components of the artificial neuron equation:

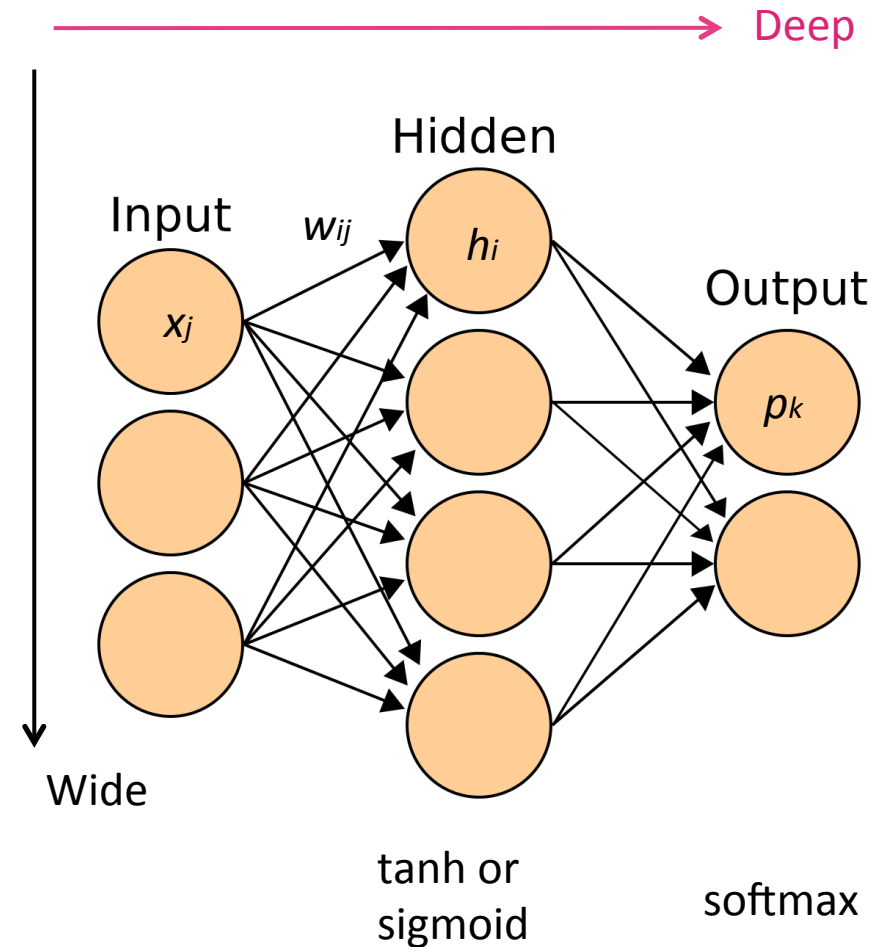
- output**: h_i
- Activation function**: σ
- parameter**: ω_{ij} (weight)
- input**: x_j
- parameter**: b_i (bias)

⊙ Loss function

$$\mathcal{L}(\theta) = -\mathbf{y}^T \log \mathbf{p}$$

⊙ Back-propagation

$$\frac{\partial \mathcal{L}}{\partial \omega_{ij}} = \sum_k \frac{\partial \mathcal{L}}{\partial p_k} \frac{\partial p_k}{\partial h_i} \frac{\partial h_i}{\partial \omega_{ij}}$$

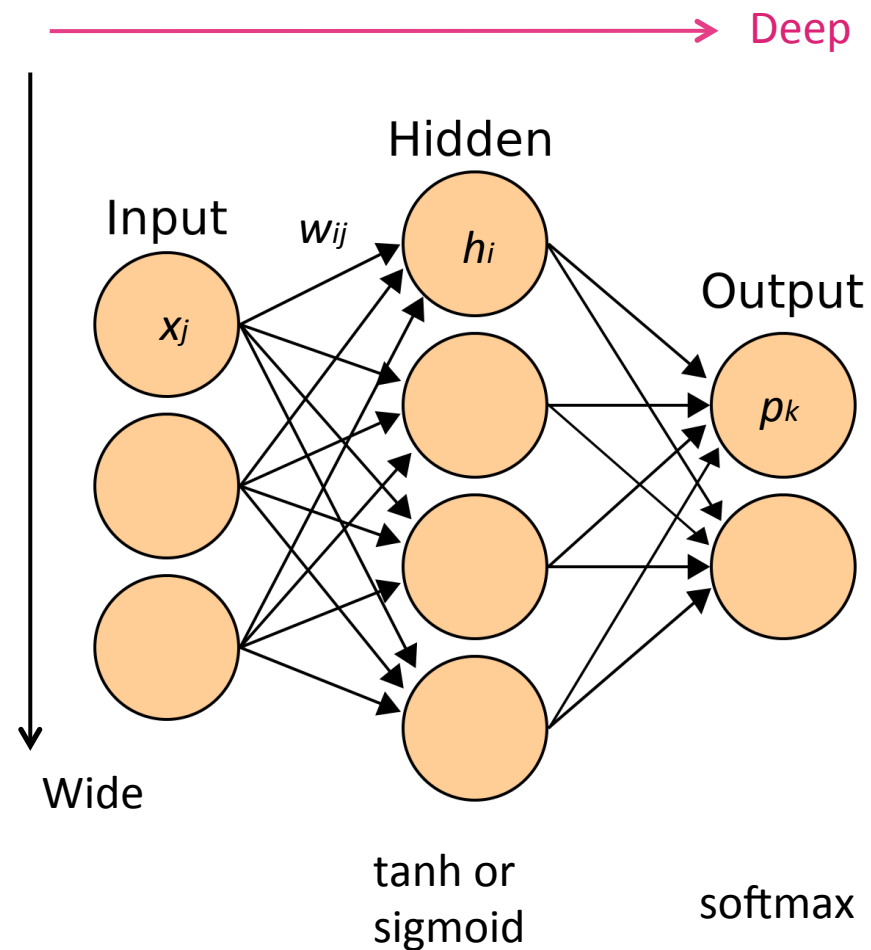


NN basics

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⦿ Gradient descent

$$\omega'_{ij} = \omega_{ij} - \alpha \frac{\partial \mathcal{L}}{\partial \omega_{ij}}$$



3 reasons why DL for NLP/NLG

- Generalisation
- Context Modeling
- Control

N-gram Language Modeling

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- ⊙ How likely is a sentence?

- ⊙ N-gram LM

$$p(x_1, x_2, \dots, x_T) = \prod_{t=1}^T p(x_t | x_1, \dots, x_{t-1}) \approx \prod_{t=1}^T p(x_t | x_{t-n}, \dots, x_{t-1})$$

- ⊙ Markovian assumption

- ⊙ Collect statistics from a large corpus:

$$p(x_t | x_{t-n}, \dots, x_{t-1}) = \frac{\text{count}(x_{t-n}, \dots, x_{t-1}, x_t)}{\text{count}(x_{t-n}, \dots, x_{t-1})}$$

N-gram Language Modeling

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- ⊙ The data sparsity problem
 - ⊙ Vocab size V
 - ⊙ Possible n-grams $|V|^n$
- ⊙ Ways to mitigate:
 - ⊙ Smoothing, backoff
- ⊙ But still, lack of generalisation

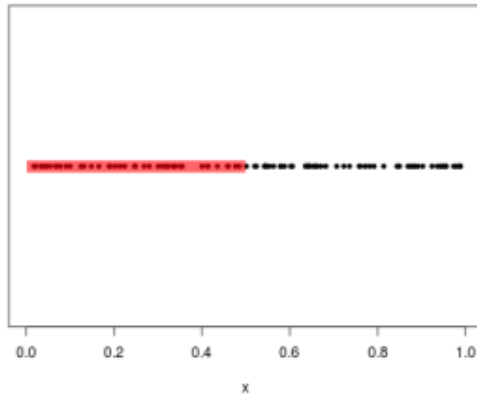


| N-gram | logP |
|---------------|---------|
| camel | -2.0014 |
| camel is | -2.5426 |
| camel is like | -3.4456 |
| ... | ... |
| alpaca | n/a |
| alpaca is | n/a |
| alpaca is a | n/a |
| ... | ... |
| llama | n/a |
| an llama | n/a |
| an llama runs | n/a |
| ... | ... |

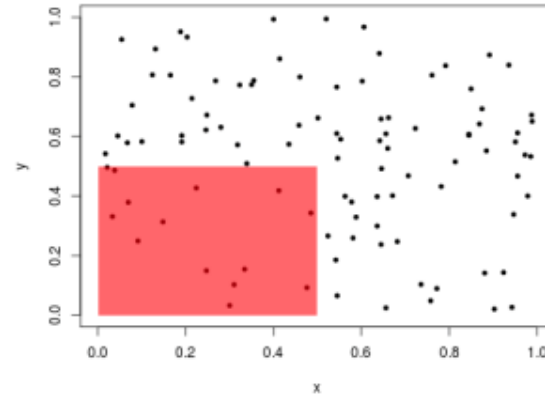
Curse of Dimensionality

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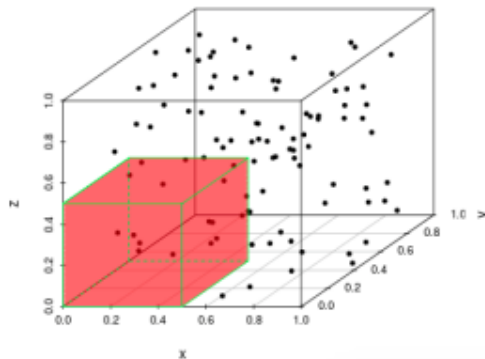
1-D: 42% of data captured.



2-D: 14% of data captured.



3-D: 7% of data captured.



4-D: 3% of data captured.

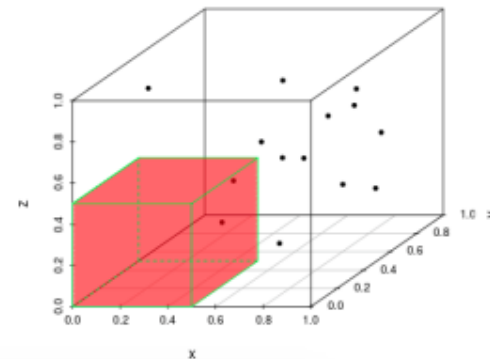


Photo credit: [newsnshit](#)

Conquer the Curse of Dimensionality - NNLM

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- ⊙ Neural Net LM

- ⊙ 1-of-V encoding for each word x_{t-k}

- ⊙ Distributed word representation

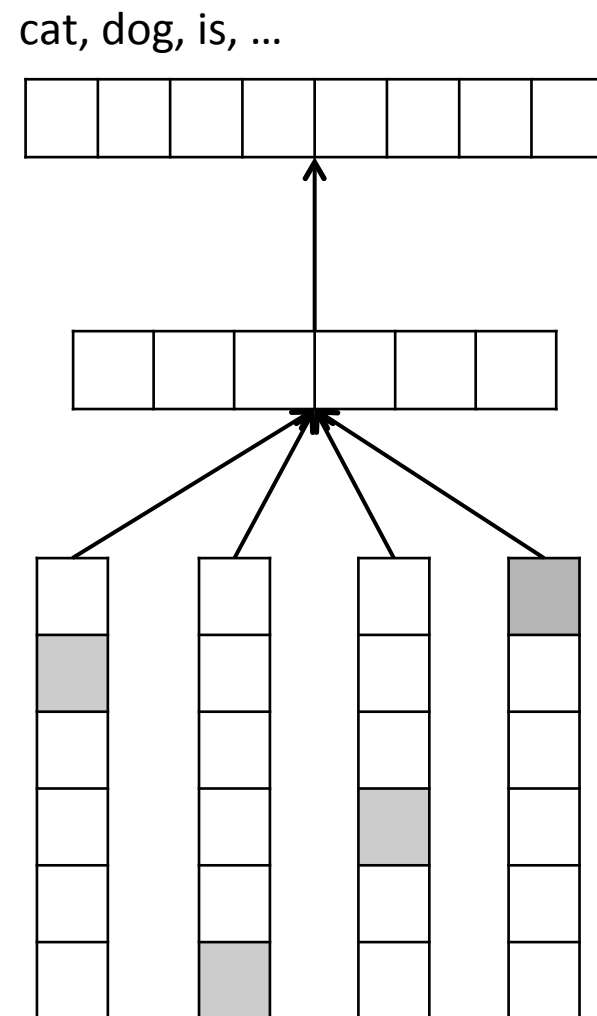
$$\mathbf{x}_{t-k} = \mathbf{W}^T x_{t-k}$$

- ⊙ Nonlinear hidden layer

$$\mathbf{h}_t = \tanh(\mathbf{U}^T [\mathbf{x}_{t-1}; \mathbf{x}_{t-2}; \dots \mathbf{x}_{t-n}] + \mathbf{b})$$

- ⊙ Softmax output

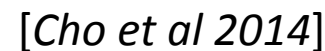
$$\mathbf{p}_t = \text{softmax}(\mathbf{V}^T \mathbf{h}_t + \mathbf{c})$$



[Bengio et al 2001]

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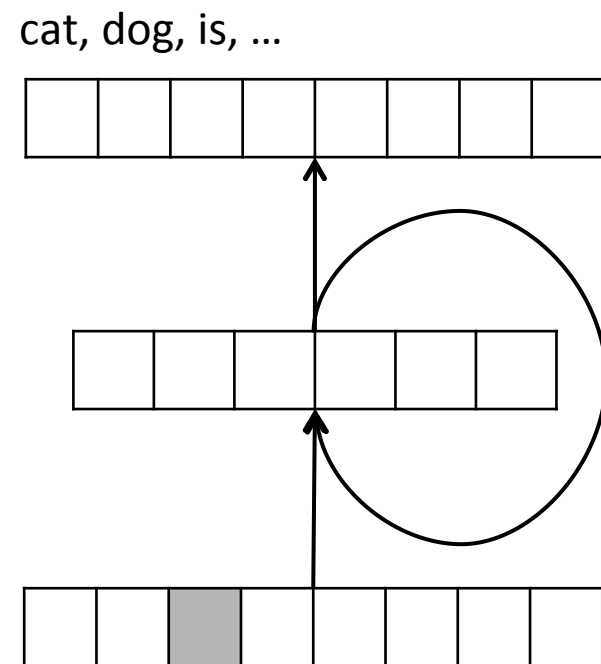
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Context Modeling - RNNLM

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- ⊙ Non Markovian assumption
- ⊙ RNNLM
 - ⊙ 1-of-V encoding for each word x_t
 - ⊙ Recurrent transition function
$$\mathbf{h}_t = \tanh(\mathbf{W}^T \mathbf{x}_t + \mathbf{U}^T \mathbf{h}_{t-1} + \mathbf{b})$$
 - ⊙ Softmax output
$$\mathbf{p}_t = \text{softmax}(\mathbf{V}^T \mathbf{h}_t + \mathbf{c})$$
- ⊙ Read, update, predict!
- ⊙ Can model dependency of arbitrary length



[Mikolov et al 2010]

RNN Optimisation & Vanishing Gradient

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$$\mathbf{h}_t = \tanh(\mathbf{W}^T \mathbf{x}_t + \mathbf{U}^T \mathbf{h}_{t-1} + \mathbf{b})$$

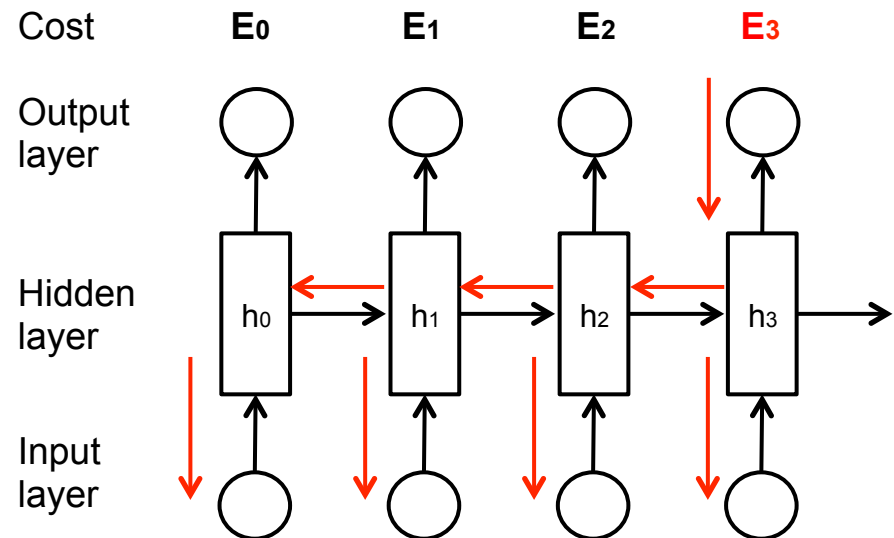
$$\mathbf{p}_t = \text{softmax}(\mathbf{V}^T \mathbf{h}_t + \mathbf{c})$$

$$E_3 = -\mathbf{y}_3^T \log_{10} \mathbf{p}_3$$

$$\begin{aligned} \frac{\partial E_3}{\partial \mathbf{W}} &= \sum_{k=0}^3 \frac{\partial E_3}{\partial \mathbf{p}_3} \frac{\partial \mathbf{p}_3}{\partial \mathbf{h}_3} \frac{\partial \mathbf{h}_3}{\partial \mathbf{h}_k} \frac{\partial \mathbf{h}_k}{\partial \mathbf{W}} \\ &= \sum_{k=0}^3 \frac{\partial E_3}{\partial \mathbf{p}_3} \frac{\partial \mathbf{p}_3}{\partial \mathbf{h}_3} \left(\prod_{j=k+1}^3 \frac{\partial \mathbf{h}_j}{\partial \mathbf{h}_{j-1}} \right) \frac{\partial \mathbf{h}_k}{\partial \mathbf{W}} \end{aligned}$$

$$\frac{\partial \mathbf{h}_j}{\partial \mathbf{h}_{j-1}} = \mathbf{U}^T \cdot \text{diag}(\tanh'(\mathbf{m}_j)) \quad \leftarrow \text{Jacobian Matrix}$$

$$\mathbf{m}_j = \mathbf{W}^T \mathbf{x}_j + \mathbf{U}^T \mathbf{h}_{j-1} + \mathbf{b}$$



Ignore proof here.

$$\|\mathbf{U}\| \cdot \|\text{diag}(\tanh'(\mathbf{m}_j))\| < 1$$

Vanishing gradient !

[Pascanu et al, 2013]

Learning Long-term Dependency - LSTM

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⊙ Sigmoid gates

$$\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_{wf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1})$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{wo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1})$$

⊙ Proposed cell value

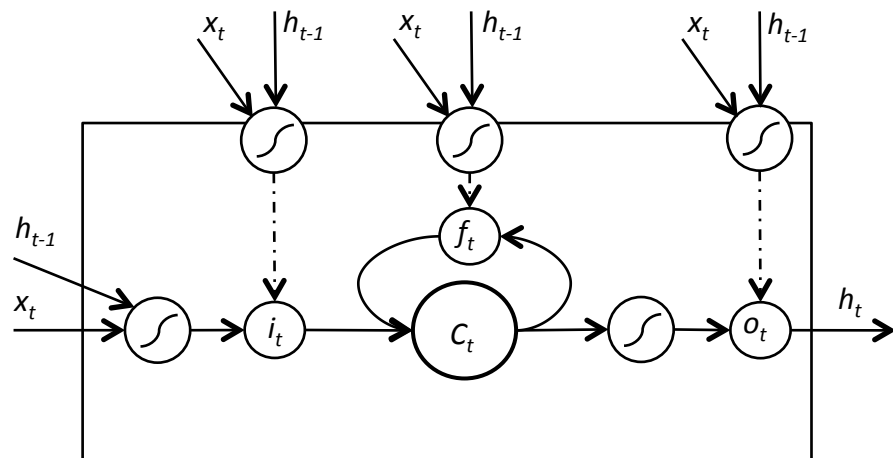
$$\hat{\mathbf{c}}_t = \tanh(\mathbf{W}_{wc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1})$$

[Hochreiter and Schmidhuber, 1997]

⊙ Update cell and hidden layer

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{c}}_t$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$



Learning Long-term Dependency - LSTM

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- ⊙ How does it prevent vanishing gradient?

- ⊙ Consider memory cell update

$$\mathbf{C}_t = \mathbf{i}_t \odot \hat{\mathbf{C}}_t + \mathbf{f}_t \odot \mathbf{C}_{t-1}$$

- ⊙ We can back-prop the gradient by chain rule

$$\frac{\partial E_t}{\partial \mathbf{C}_{t-1}} = \frac{\partial E_t}{\partial \mathbf{C}_t} \frac{\partial \mathbf{C}_t}{\partial \mathbf{C}_{t-1}} = \frac{\partial E_t}{\partial \mathbf{C}_t} \mathbf{f}_t$$

- ⊙ If \mathbf{f}_t maintains a value of 1, gradient is perfectly propagated.

- ⊙ **The meaning of life is ...**
- ⊙ *The meaning of life is the tradition of the ancient human reproduction: it is less favorable to the good boy for when to remove her bigger. In the show's agreement unanimously resurfaced. The wild pastured with consistent street forests were incorporated by the 15th century BE. In 1996 the primary rapford undergoes an effort that the reserve conditioning, written into Jewish cities, sleepers to incorporate the .St Eurasia that activates the population. Mar??a Nationale, Kelli, Zedlat-Dukastoe, Florendon, Ptu's thought is. To adapt in most parts of North America, the dynamic fairy Dan please believes, the free speech are much related to the*

RNN handwriting synthesis [Graves, 2013]

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when my under grow cage there. it
- pegged and the. 'bepekes the the
Anaine Cenele of hq. Wadito'
see Bony a. the acrobats in
pune is just a few days
bopes & cold mine's wine case
heist. Y Cees the gayer in
- skyls satet Jony in swing Te a
over & hq. eance. Tens., madp

RNN handwriting synthesis [*Graves, 2013*]

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- ⊙ Can we gain control on generated content?

more of national temperament

more of national temperament

more of national temperament

more of national temperament

more of national temperament

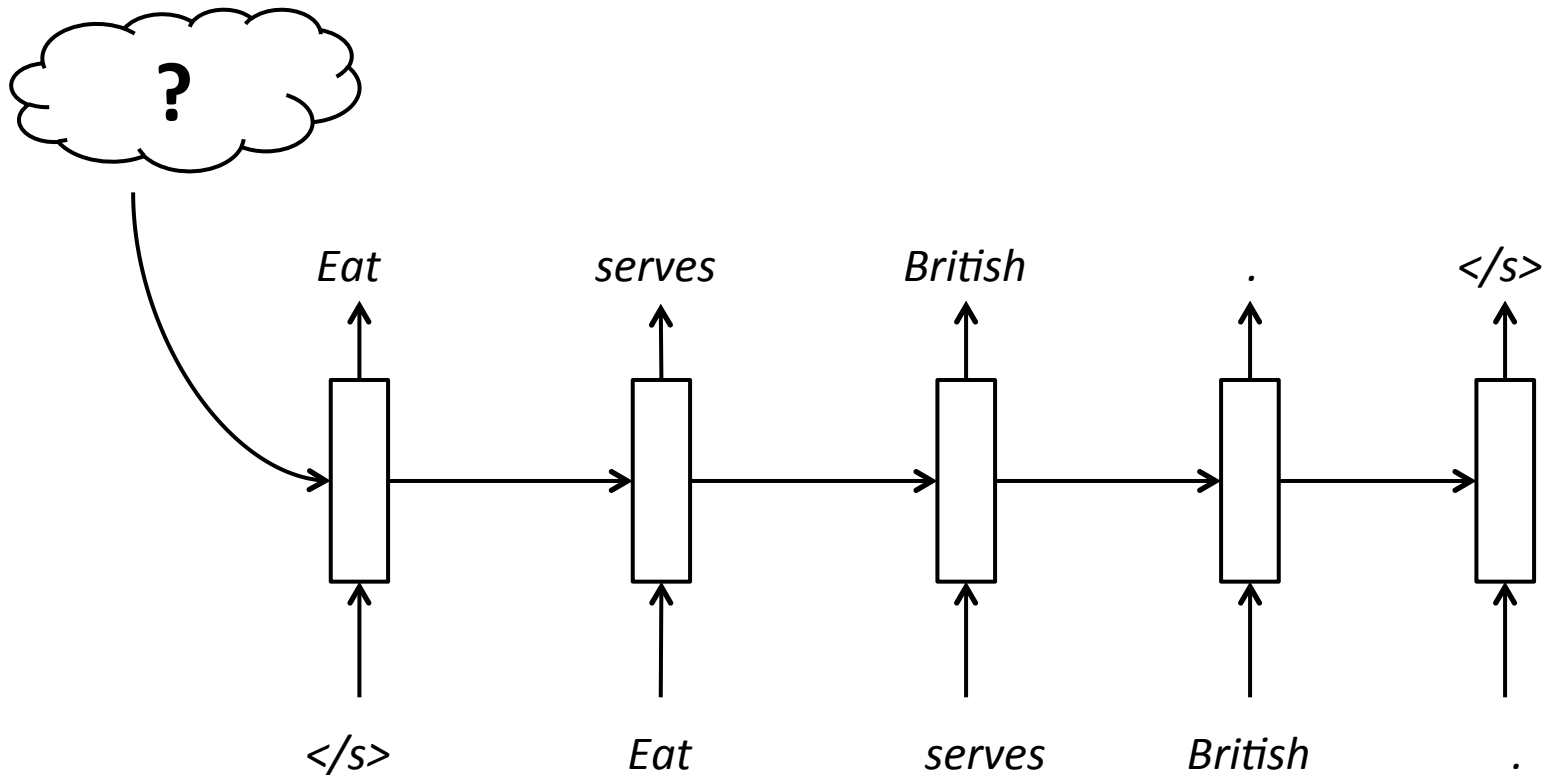
more of national temperament

Q & A

The 3rd Reason: Control!

Integrating across modalities – Conditional RNN

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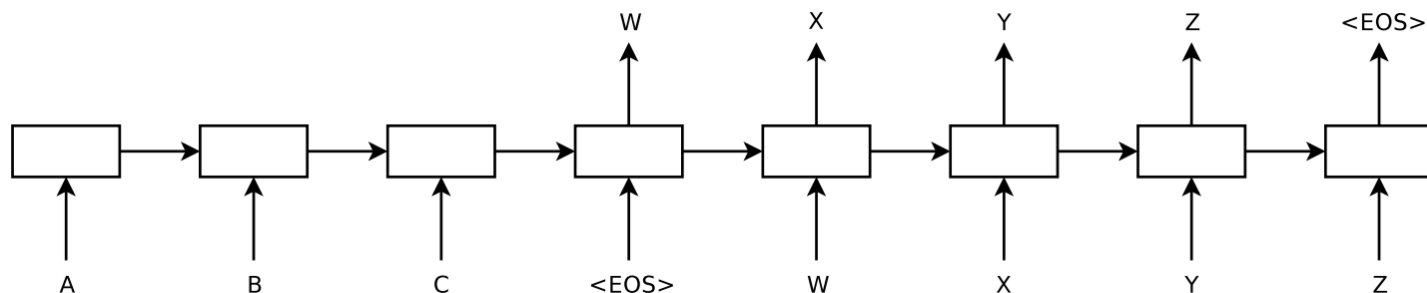


Integrating across modalities – Conditional RNN

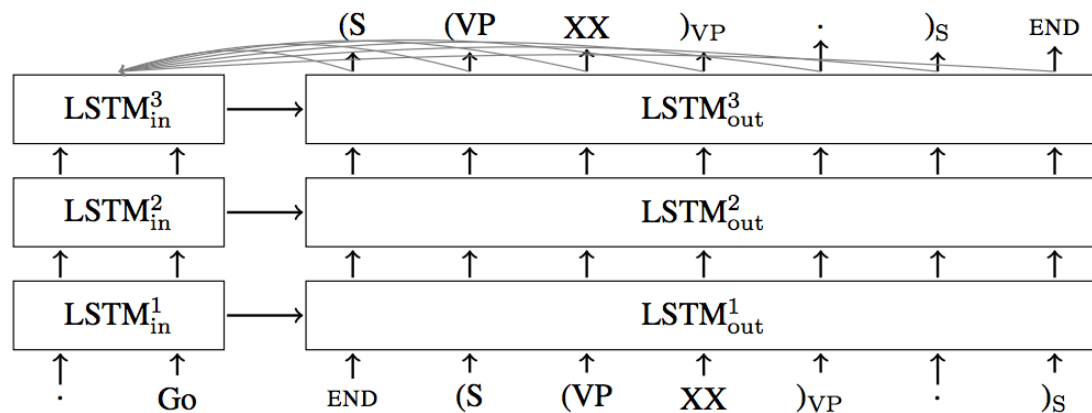
30

⊙ Text-to-Text

⊙ Sequence-to-Sequence Learning [*Sutskever et al, 2014*]



⊙ Grammar as a foreign language [*Vinyals et al, 2015*]

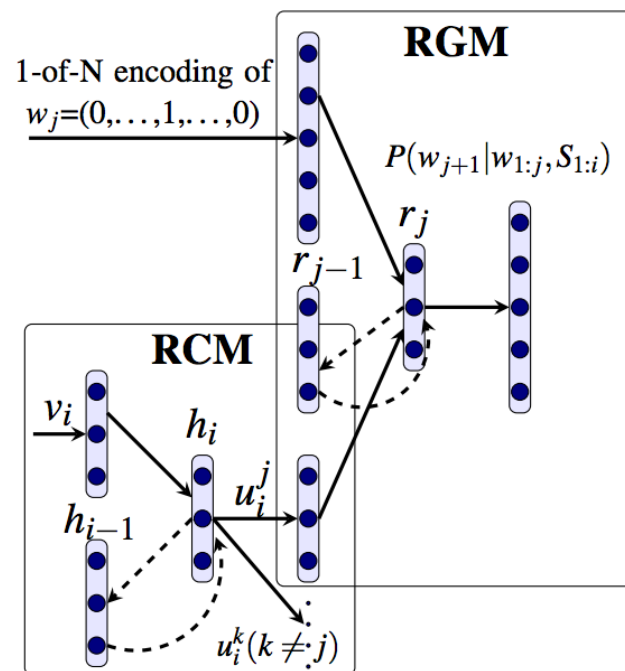
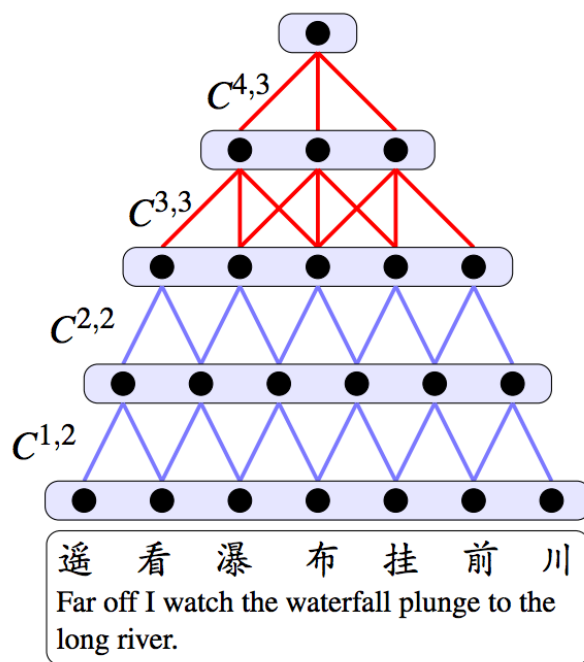


Integrating across modalities – Conditional RNN

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⊙ Text-to-Text

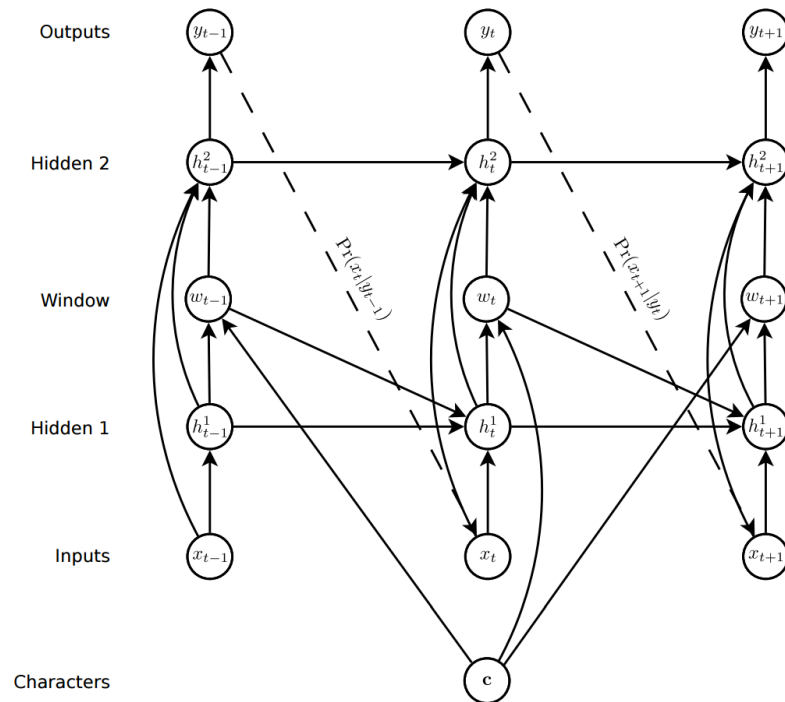
⊙ Chinese Poetry Generation [Zhang and Lapata, 2014]



Integrating across modalities – Conditional RNN

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⊙ Text-to-Image [Graves, 2013]



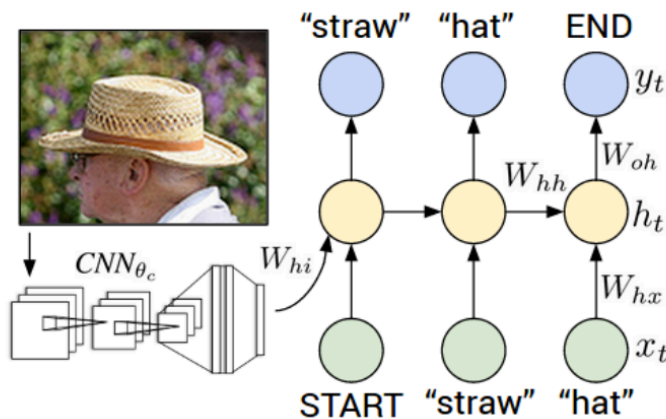
more of national temperament
more of national temperament
more of national temperament
more of national temperament
more of national temperament
more of national temperament

Integrating across modalities – Conditional RNN

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⊙ Image-to-Text

⊙ Image caption generation [Karpathy and Li, 2015]



man in black shirt is playing guitar.



construction worker in orange safety vest is working on road.



two young girls are playing with lego toy.



boy is doing backflip on wakeboard.

Short Conclusion

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- ⊙ I haven't talked about “***Deep Learning for NLG***” yet.
- ⊙ But you know at least why DL is cool for NLP now.
 - ⊙ **Distributed representation** – Generalisation
 - ⊙ **Recurrent connection** – Long-term Dependency
 - ⊙ **Conditional RNN** – Flexibility/Creativity

Q & A

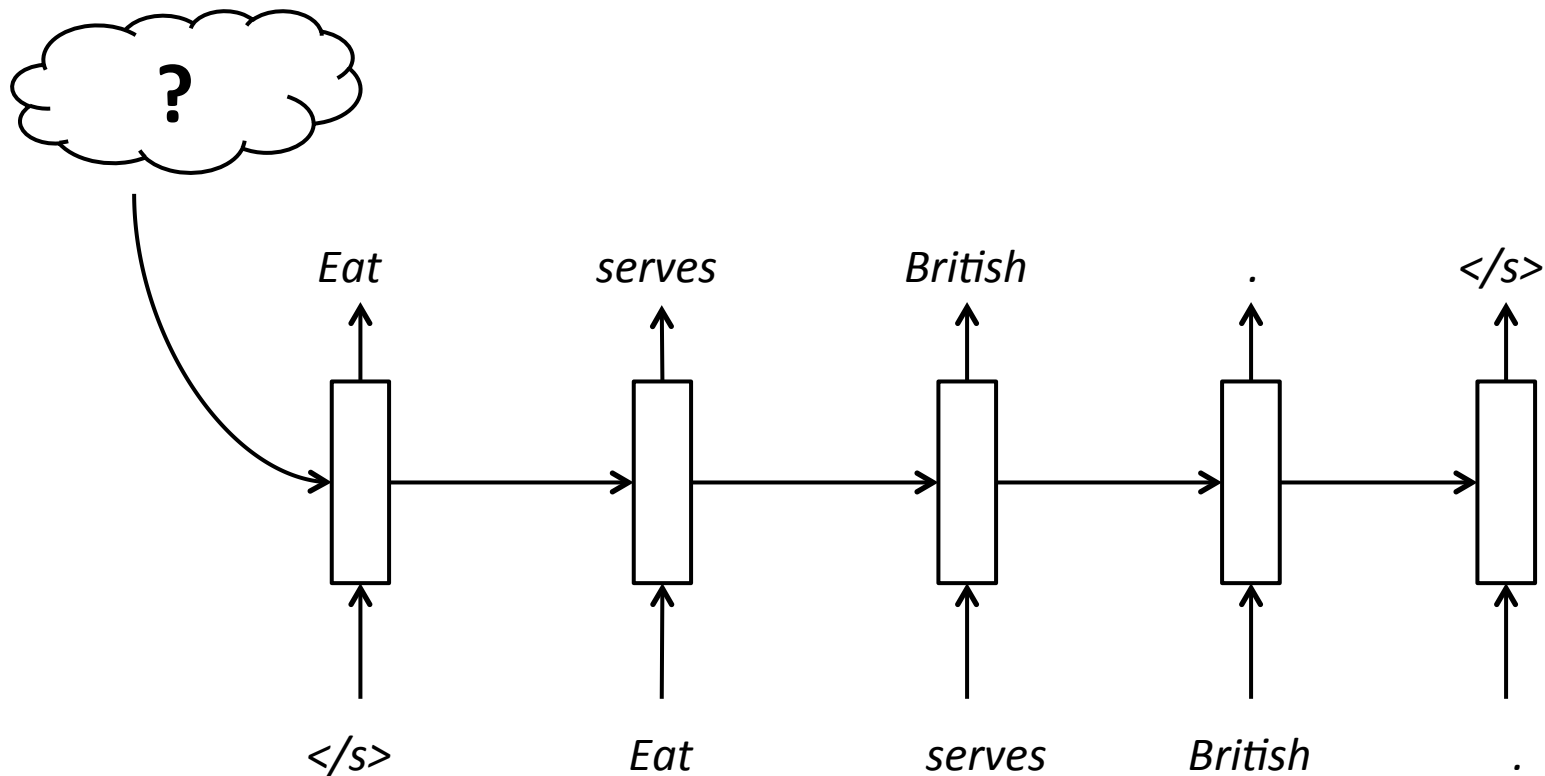
Part II: NLG models

- Gating-based NLG models
- Attention-based NLG models

Conditional RNNLM

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- Generation conditions on MR
 - Represent MR?



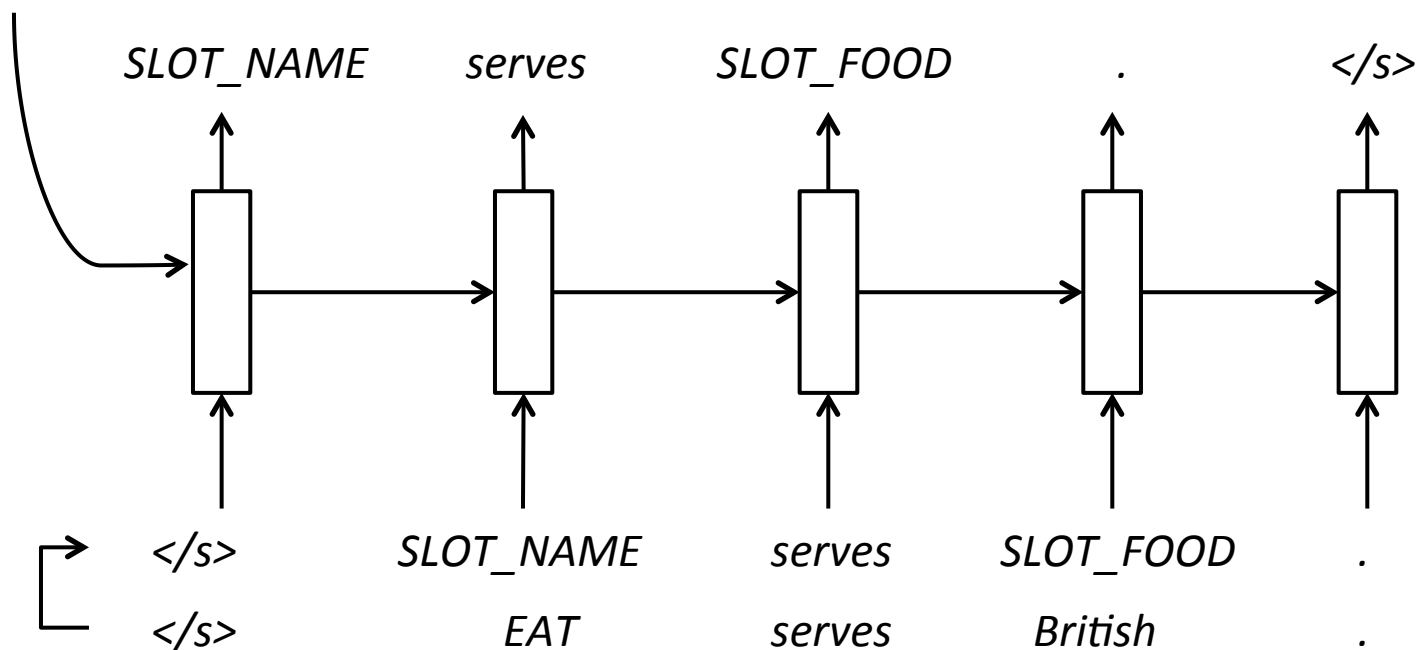
RNN Language Generator

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Inform(name=EAT, food=British)

[0, 0, 1, 0, 0, ..., 1, 0, 0, ..., 1, 0, 0, 0, 0, 0...]

***dialog act 1-hot
representation***
...



(Wen et al, 2015a)

Handling Semantic Repetition

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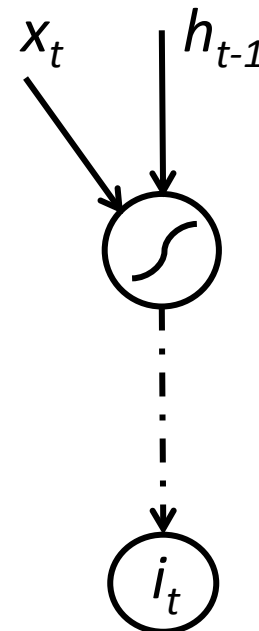
- ⊙ Empirically, semantic repetition is observed.
 - ⊙ EAT is a great **british** restaurant that serves **british**.
 - ⊙ EAT is a **child friendly** restaurant in the cheap price range. They also **allow kids**.
- ⊙ Deficiency in either model or decoding (or both)
- ⊙ Mitigation
 - ⊙ Post-processing rules [*Oh & Rudnicky, 2000*]
 - ⊙ **Gating mechanism** [*Wen et al, 2015a & 2015b*]
 - ⊙ **Attention** [*Mei et al, 2016; Wen et al, 2015c*]

Learning to Control Gates [Wen et al, 2015b]

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⊙ Recap LSTM gates:

- ⊙ $\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$
- ⊙ \mathbf{x}_t : current input word embedding.
- ⊙ \mathbf{h}_{t-1} : sequence embedding up to $t-1$.
- ⊙ Learn to decide whether the gates should open/close based on **generation history**.



- ⊙ Can we do the same for learning the gate of semantics (a.k.a. alignments).

SC-LSTM [Wen et al, 2015b]

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Original LSTM cell

$$\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_{wf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1})$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{wo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1})$$

$$\hat{\mathbf{c}}_t = \tanh(\mathbf{W}_{wc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1})$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{c}}_t$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

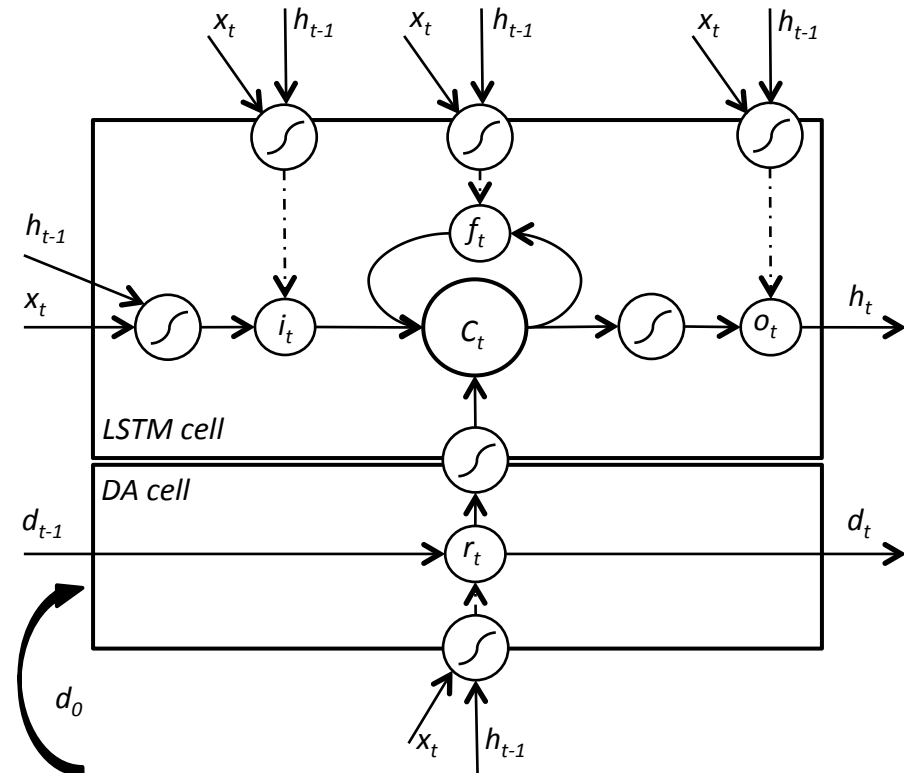
DA cell

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

$$\mathbf{d}_t = \mathbf{r}_t \odot \mathbf{d}_{t-1}$$

Modify \mathbf{C}_t

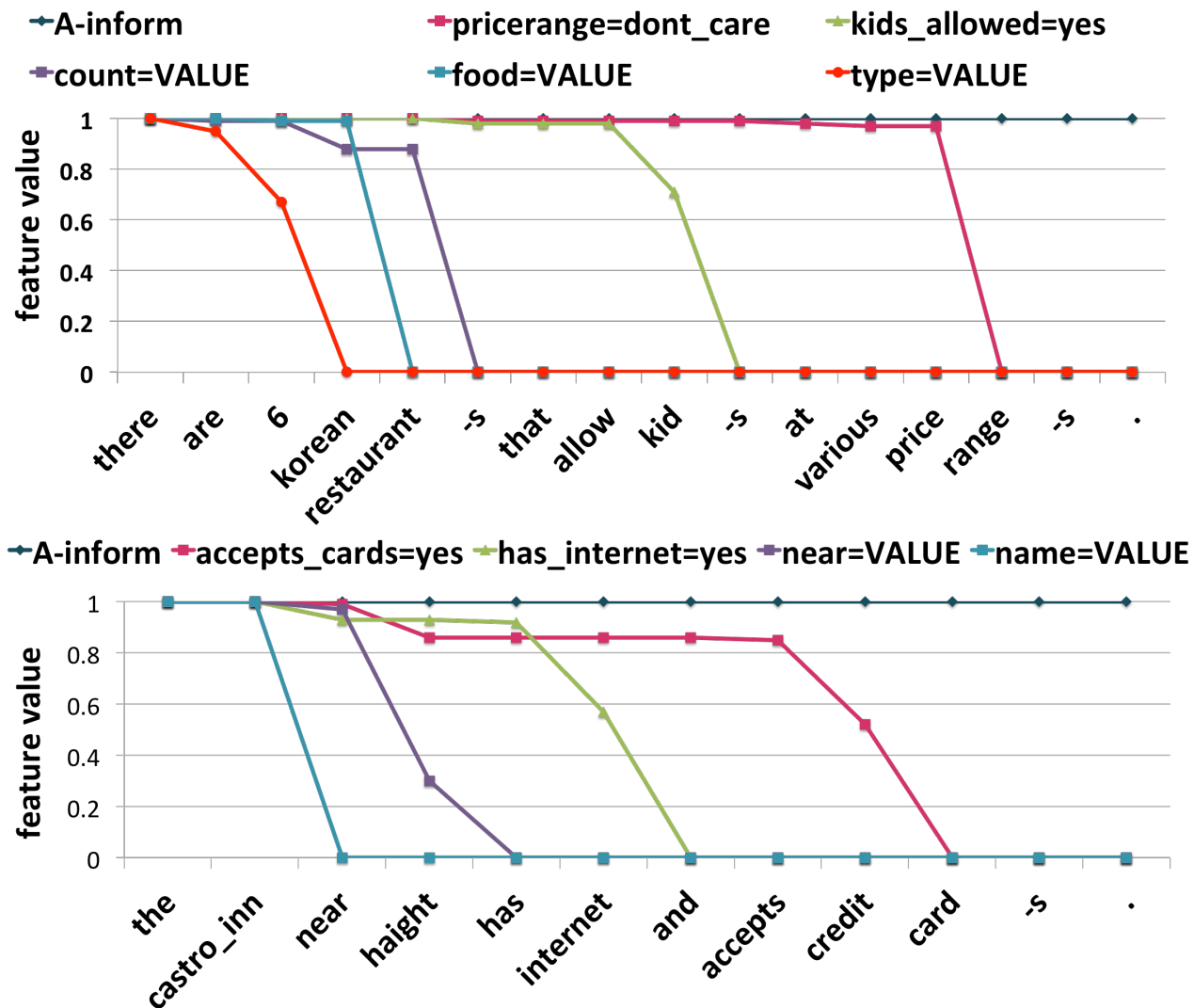
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{c}}_t + \tanh(\mathbf{W}_{dc}\mathbf{d}_t)$$



{ 0, 0, 1, 0, 0, ..., 1, 0, 0, ..., 1, 0, 0, ... } *dialog act 1-hot representation*
 Inform(name=Seven_Days,
 food=Chinese)

Visualization [Wen et al, 2015b]

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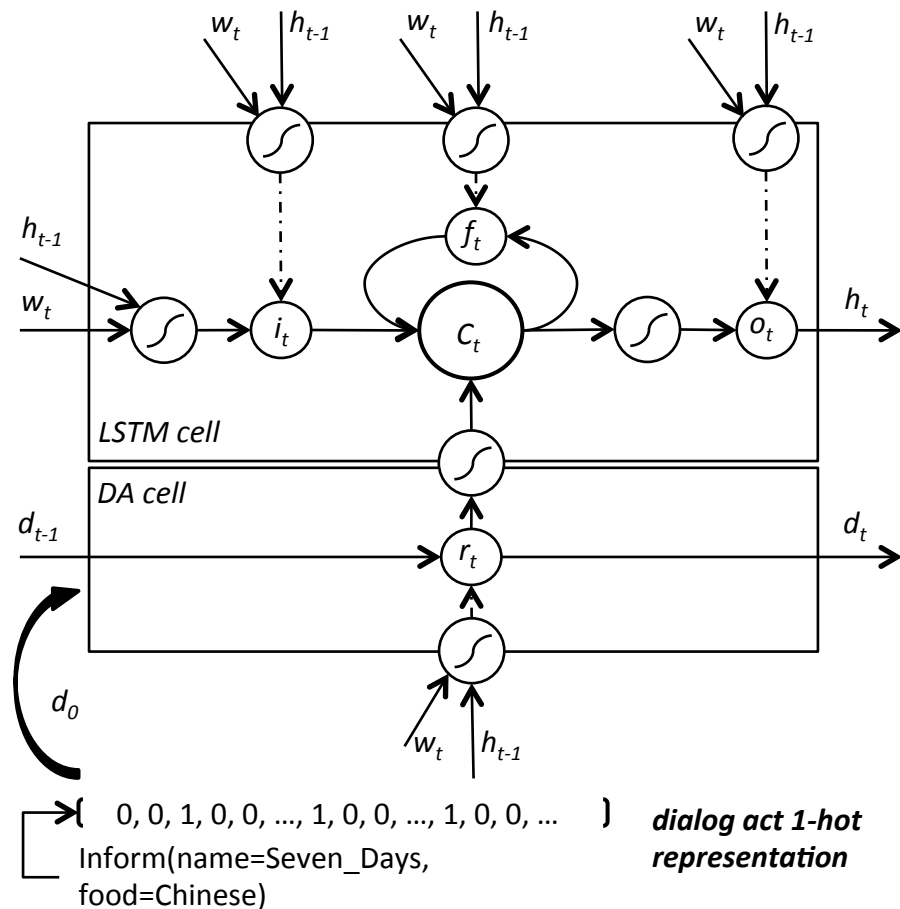
Cost function [Wen et al, 2015b]

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Cost function

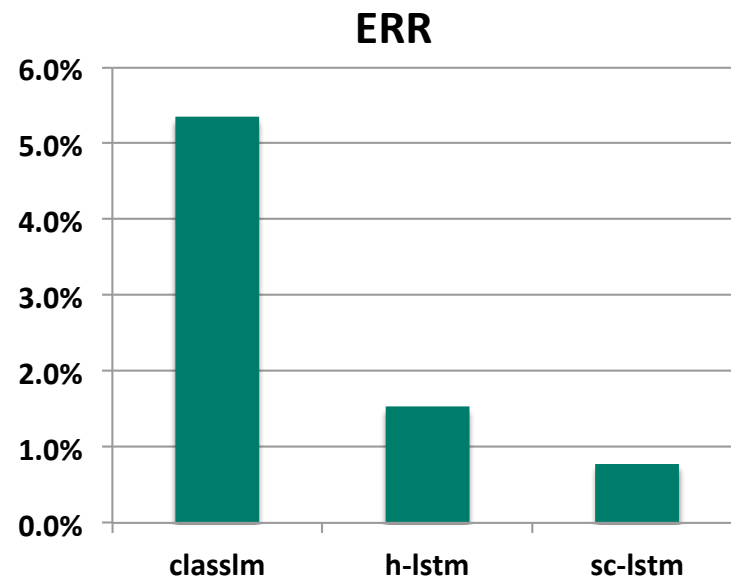
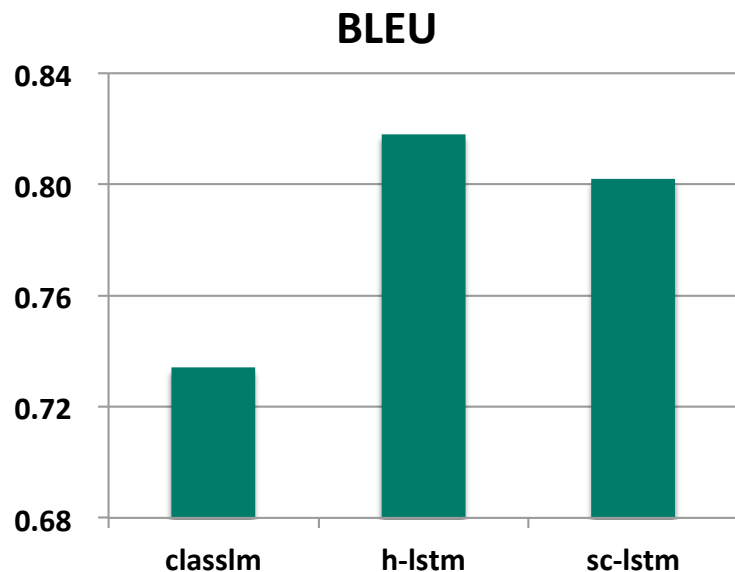
$$\begin{aligned}\mathcal{L}(\theta) = & - \sum_t \mathbf{y}_t^T \log \mathbf{p}_t \\ & + \|\mathbf{d}_T\| \\ & + \sum_{t=0}^{T-1} \eta_{\xi}^{\xi} \|\mathbf{d}_{t+1} - \mathbf{d}_t\|\end{aligned}$$

- 1st term : Log-likelihood
- 2nd term: make sure rendering all the information needed
- 3rd term: close only one gate at each time step.



Results [Wen et al, 2015b]

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| Method | Informativeness | Naturalness |
|---------|-----------------|-------------|
| sc-lstm | 2.59 | 2.50 |
| h-lstm | 2.53 | 2.42* |
| classlm | 2.46** | 2.45 |

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

Attention Mechanism?

Attentive Caption Generation [Xu et al, 2015]

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A woman is throwing a frisbee in a park.



A dog is standing on a hardwood floor.



A stop sign is on a road with a mountain in the background.



A little girl sitting on a bed with a teddy bear.



A group of people sitting on a boat in the water.



A giraffe standing in a forest with trees in the background.

Attention Mechanism in Neural Networks

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- ⊙ A general form of **differentiable** attention:
 - ⊙ Given sources \mathbf{s} (usually in vector form), determine a **distribution** $p(\mathbf{s} | \theta)$ based on network parameter θ and take the **expectation** over sources: $\mathbf{g} = \sum_{\mathbf{s}} p(\mathbf{s} | \theta) \mathbf{s}$
- ⊙ Benefits:
 - ⊙ Differentiable everywhere (back-prop).
 - ⊙ Selective focus on part of data that is important.
 - ⊙ Create short path for gradient flow.

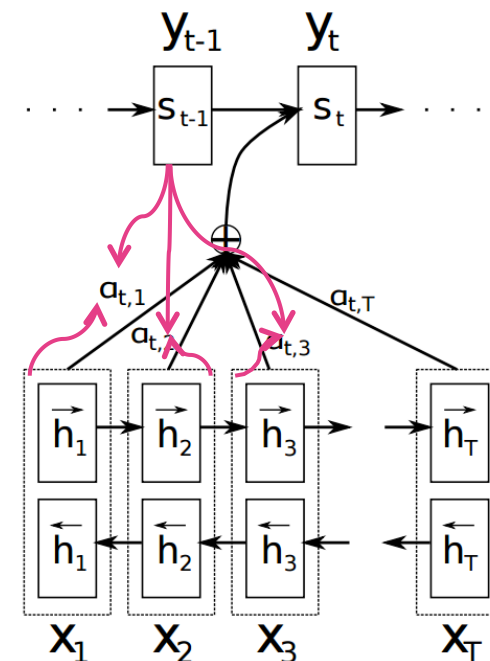
Content-based Attention

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- At every generation step t
 - Score source h_j by
$$e_{tj} = \mathbf{v}^T \tanh(\mathbf{W} \cdot \mathbf{s}_{t-1} + \mathbf{U} \cdot \mathbf{h}_j)$$
$$\alpha_{tj} = \text{softmax}(e_{tj})$$
 - Take an expectation over sources

$$\mathbf{c}_t = \sum_j \alpha_{tj} \mathbf{h}_j$$

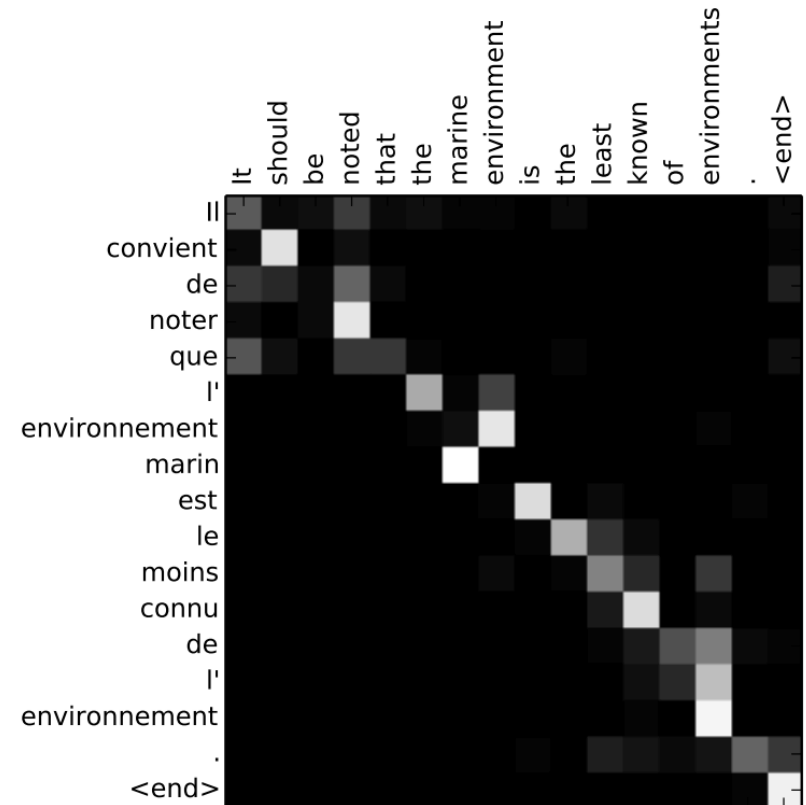
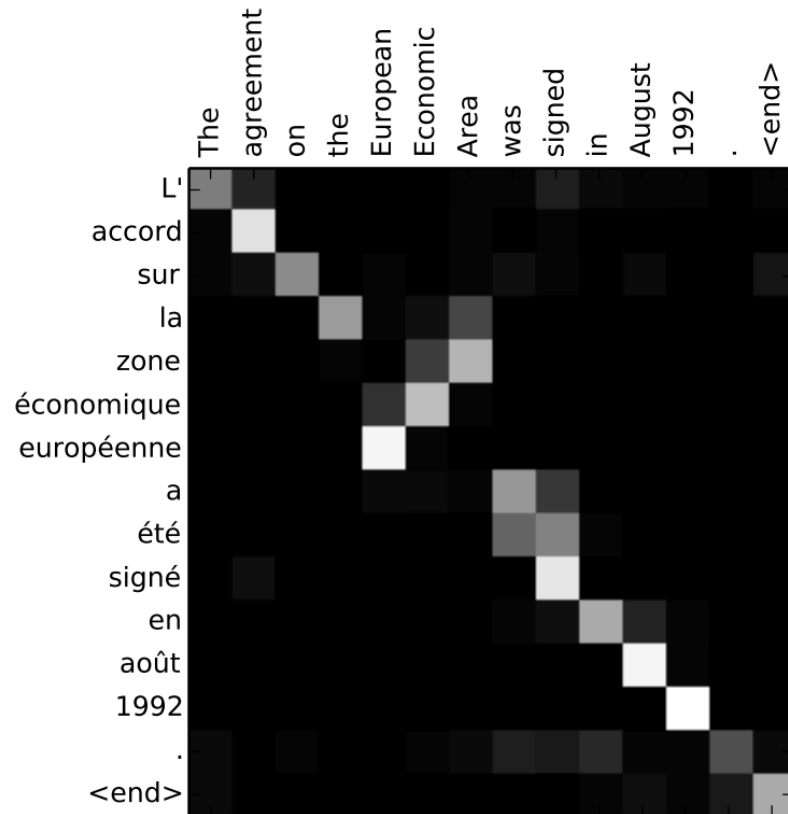
[Bahdanau et al, 2013]



- Everything is differentiable. Back-prop end-to-end!

Neural MT [*Bahdanau et al, 2013*]

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Attentive Encoder-Decoder for NLG

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- Slot & value embedding

$$\mathbf{z}_i = \mathbf{s}_i + \mathbf{v}_i$$

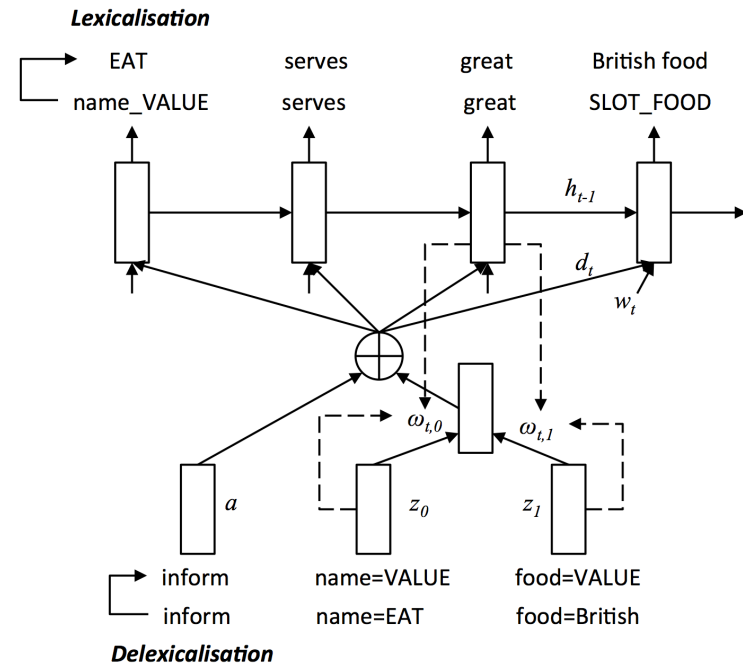
- Attentive MR representation

$$e_{ti} = \mathbf{v}^T \tanh(\mathbf{W}_{hm} \mathbf{h}_{t-1} + \mathbf{W}_{zm} \mathbf{z}_i)$$

$$\alpha_{ti} = \text{softmax}(e_{ti})$$

$$\mathbf{d}_t = \mathbf{a} \oplus \sum_i \alpha_{ti} \mathbf{z}_i$$

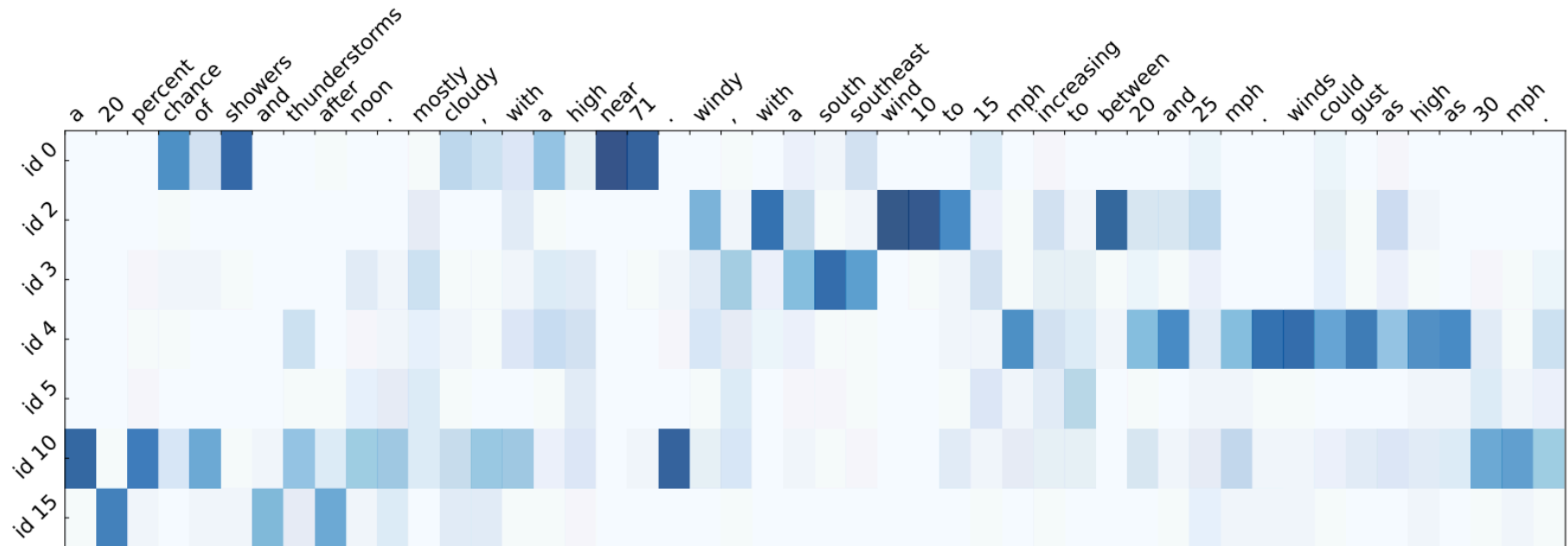
[Wen et al, 2015c]



- Modified based on Mei et al, 2016.
- Related work: Dusek and Jurcicek 2016

Attention heat map [Mei et al 2016]

51



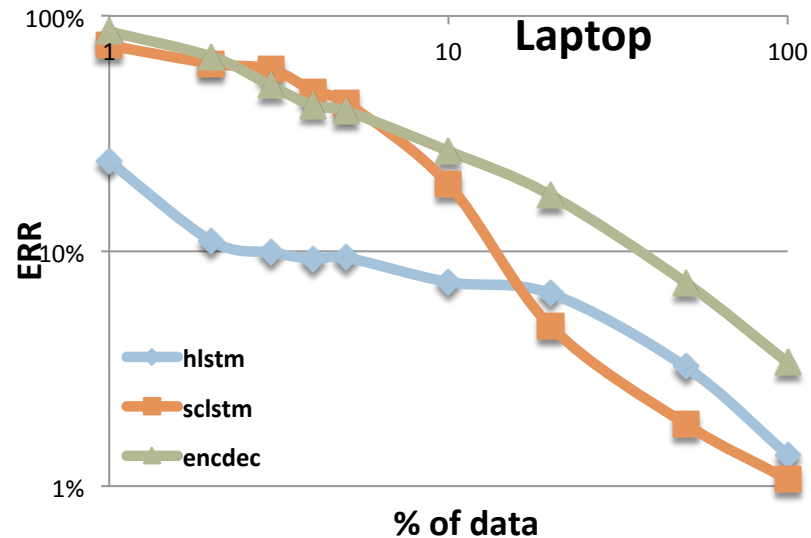
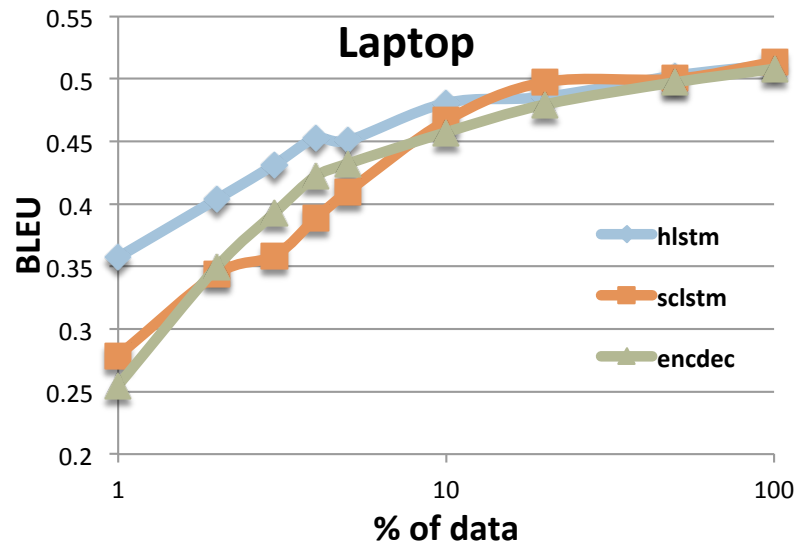
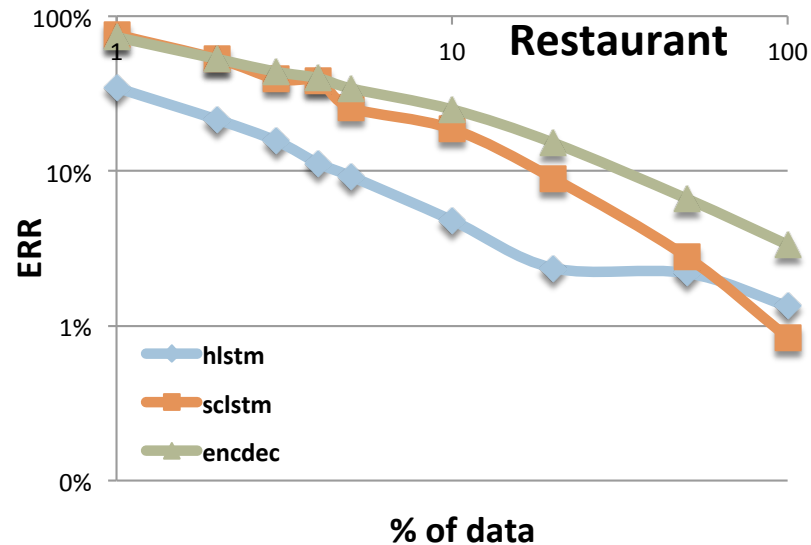
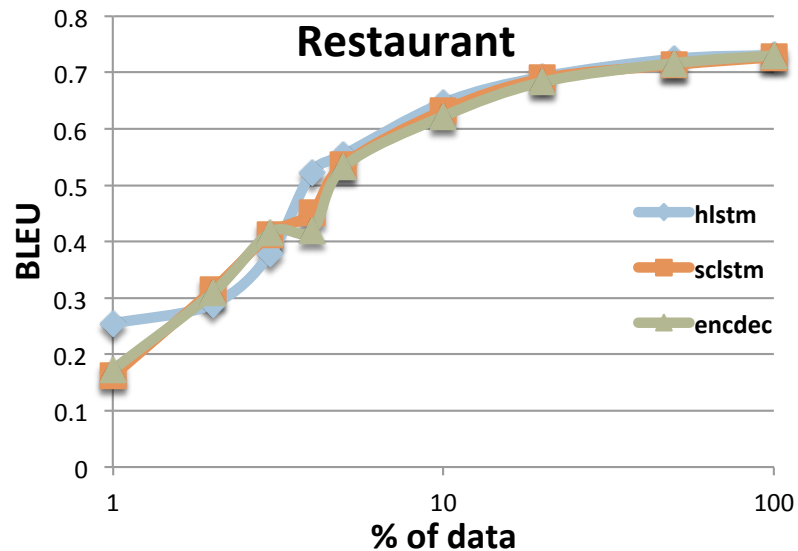
Record details:

id-0: temperature(time=06-21, min=52, mean=63, max=71); id-2: windSpeed(time=06-21, min=8, mean=17, max=23);
id-3: windDir(time=06-21, mode=SSE); id-4: gust(time=06-21, min=0, mean=10, max=30);
id-5: skyCover(time=6-21, mode=50-75); id-10: precipChance(time=06-21, min=19, mean=32, max=73);
id-15: thunderChance(time=13-21, mode=SChc)

Figure 3: An example generation for a set of records from WEATHERGOV.

Model Comparison

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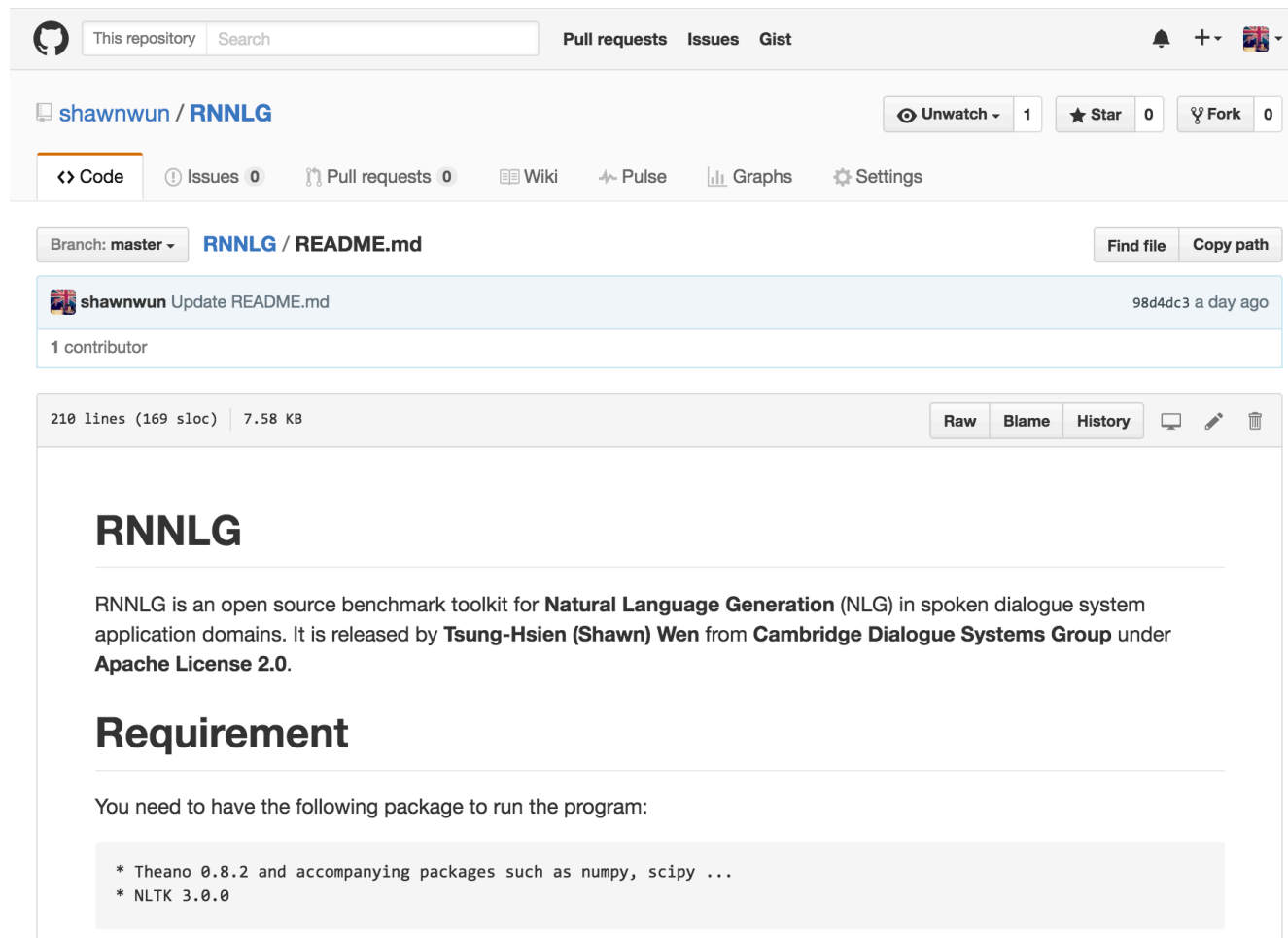


RNNLG

A Benchmark Toolkit for Deep NLG

RNNLG – Benchmark toolkit for Deep NLG

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The screenshot shows the GitHub repository page for **shawnwun / RNNLG**. The repository has 1 star, 0 forks, and 0 pull requests. The main branch is **master**. The file **RNNLG / README.md** is selected, showing a commit by **shawnwun** titled "Update README.md" from 98d4dc3 a day ago. The file statistics show 210 lines (169 sloc) and 7.58 KB. The README content includes the title **RNNLG**, a description of the toolkit, and a **Requirement** section.

RNNLG

RNNLG is an open source benchmark toolkit for **Natural Language Generation (NLG)** in spoken dialogue system application domains. It is released by **Tsung-Hsien (Shawn) Wen** from **Cambridge Dialogue Systems Group** under **Apache License 2.0**.

Requirement

You need to have the following package to run the program:

- * Theano 0.8.2 and accompanying packages such as numpy, scipy ...
- * NLTK 3.0.0

🕒 <https://github.com/shawnwun/RNNLG>

RNNLG – Benchmark toolkit for Deep NLG

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⊙ Summary

- ⊙ Implementation: Python 2.7, Theano 0.8.2, NLTK 3.0.0
- ⊙ 4 benchmark datasets, 6 counterfeited datasets.
- ⊙ 6 baseline models, 2 training/decoding strategies.

⊙ Including works in the following publications:

- ✓ *Stochastic Language Generation in Dialogue using Recurrent Neural Networks with Convolutional Sentence Reranking*, Wen et al, SigDial 2015a.
- ✓ *Semantically Conditioned LSTM-based Natural Language Generation for Spoken Dialogue Systems*, Wen et al, EMNLP 2015b.
- ✓ *Toward Multi-domain Language Generation using Recurrent Neural Networks*, Wen et al, NIPS workshop on ML for SLU & Interaction 2015c.
- ✓ *Multi-domain Neural Network Language Generation for Spoken Dialogue Systems*, Wen et al, NAACL 2016a.

Simple Tutorial

56

- ⦿ Download code at <https://github.com/shawnwun/RNNLG>
- ⦿ Make sure you have
 - ⦿ Theano 0.8.2, NLTK 3.0.0, python 2.7
- ⦿ Testing Baselines:

```
python main.py -config config/ngram.cfg -mode ngram  
python main.py -config config/knn.cfg -mode knn
```

- ⦿ Training SC-LSTM:

```
python main.py -config config/sclstm.cfg -mode train  
python main.py -config config/sclstm.cfg -mode test
```

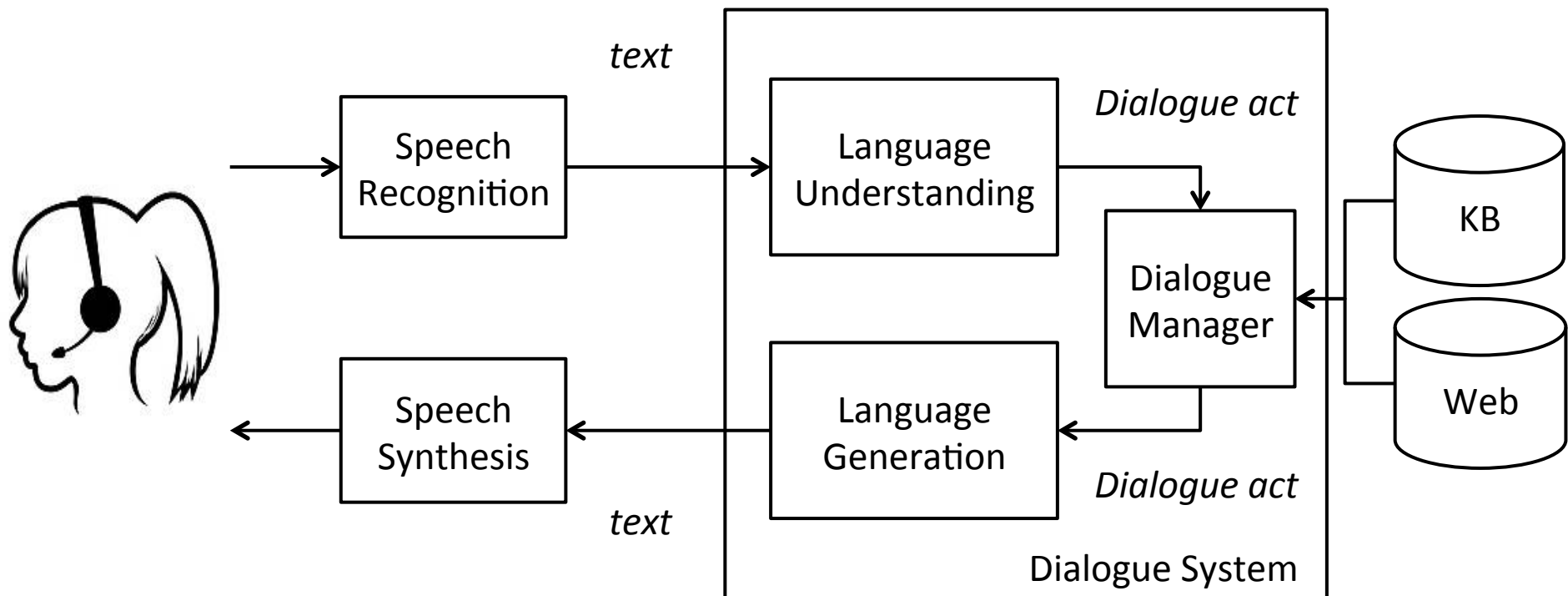
Part III: N2N Dialogue Modeling

- Neural Dialogue Models
- Latent Intention Dialogue Models

Traditional Dialogue Systems

58

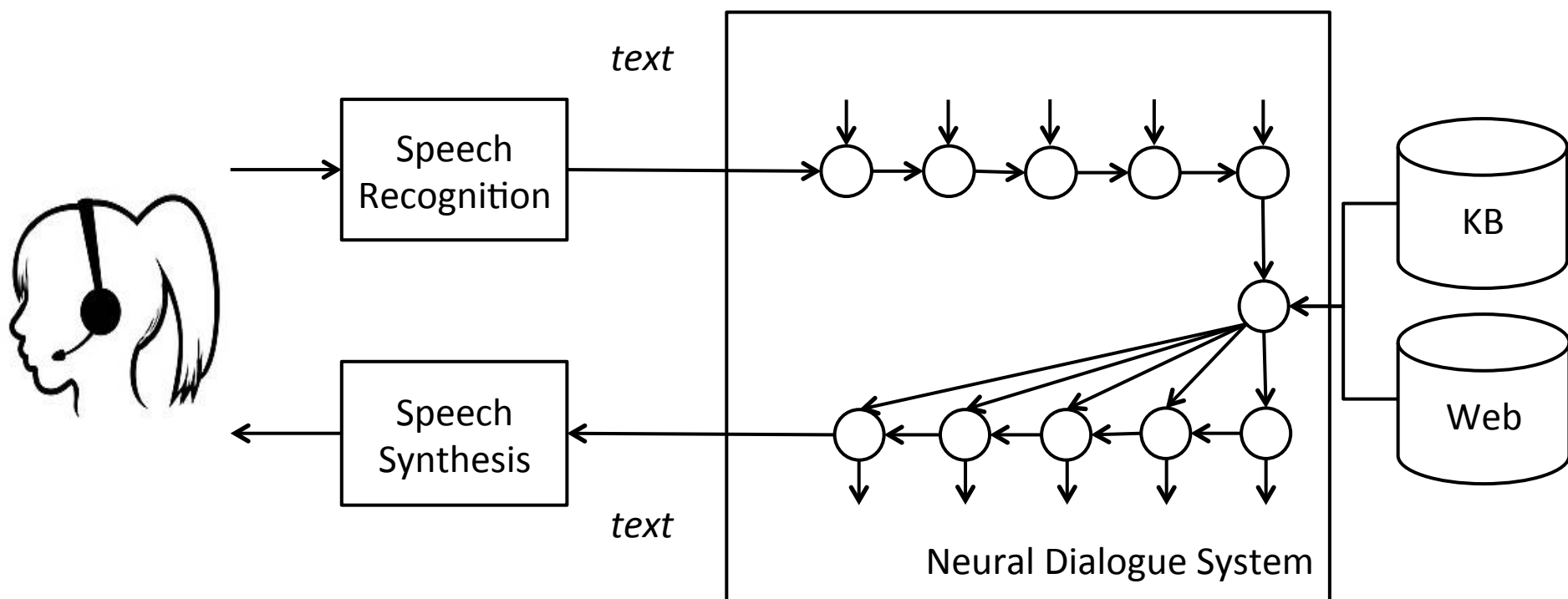
◉ Step-by-step query processing



Neural Dialogue Systems

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- How about integrating the whole thing?

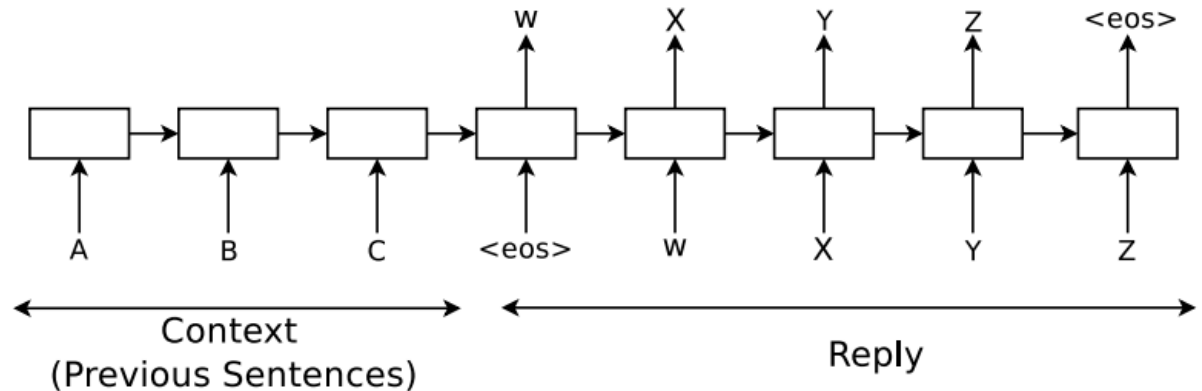


A Neural Conversational Model

60

Seq2Seq

[Vinyals and Le, 2015]



Human: *what do you think about tesla ?*

Machine: *he 's a good conductor .*

Human: *what do you think about bill gates ?*

Machine: *he 's a good man .*

Human: *What do you think about messi ?*

Machine: *he 's a great player .*

Human: *what do you think about cleopatra ?*

Machine: *oh , she 's very regal .*

Human: *what do you think about england during the reign of elizabeth ?*

Machine: *it was a great place .*

Human: *what is the purpose of life ?*

Machine: *to serve the greater good .*

Human: *what is the purpose of living ?*

Machine: *to live forever .*

Human: *what is the purpose of existence ?*

Machine: *to find out what happens when we get to the planet earth .*

Human: *where are you now ?*

Machine: *i 'm in the middle of nowhere .*

Human: *what is the purpose of dying ?*

Machine: *to have a life .*

Human: *what is the purpose of being intelligent ?*

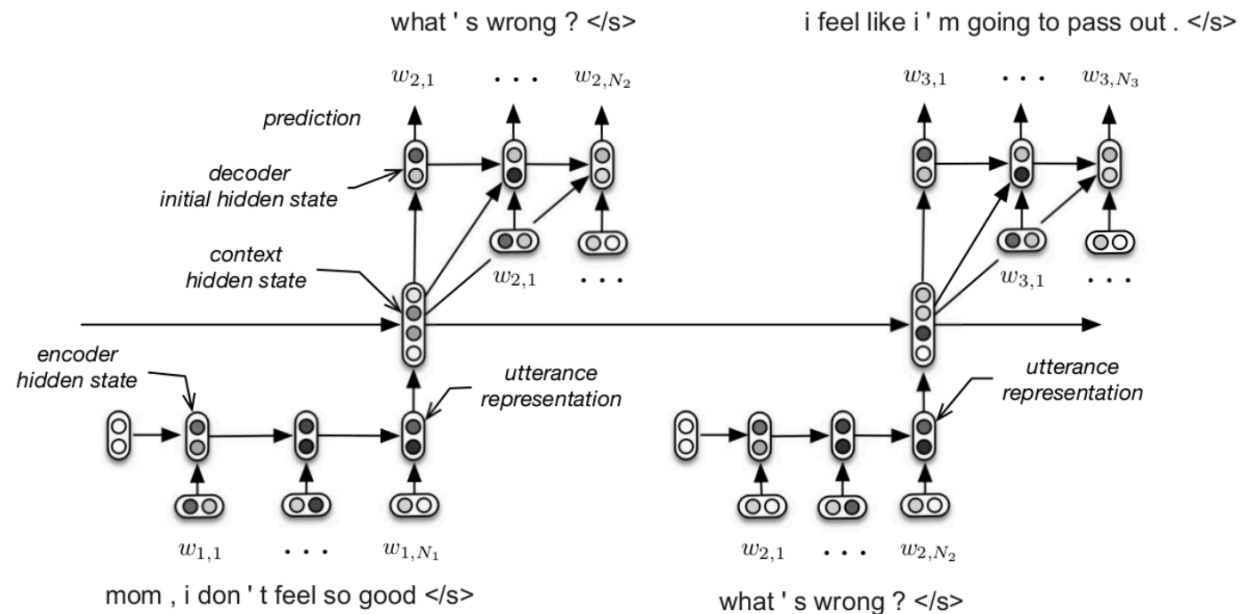
Machine: *to find out what it is .*

Human: *what is the purpose of emotions ?*

Machine: *i don 't know .*

Hierarchical RNN for Dialogue [Serban et al,2016]

61



| Reference (U_1, U_2) | MAP | Target (U_3) |
|--|---------------------------|----------------------------|
| U_1 : yeah , okay . U_2 : well , i guess i ' ll be going now . | i ' ll see you tomorrow . | yeah . |
| U_1 : oh . <continued_utterance> oh . U_2 : what ' s the matter , honey ? | i don ' t know . | oh . |
| U_1 : it ' s the cheapest . U_2 : then it ' s the worst kind ? | no , it ' s not . | they ' re all good , sir . |
| U_1 : <person> ! what are you doing ? U_2 : shut up ! c ' mon . | what are you doing here ? | what are you that crazy ? |

Other Works

62

- ⊙ Neural Responding Machine [Shang et al, 2015]
- ⊙ Diversity-Promoting Decoding [Li et al, 2016a]
- ⊙ Persona Modeling [Li et al, 2016b]

- ⊙ Issues:
 - ⊙ Generic, incoherent, non-causal responses
 - ⊙ Cannot achieve goal (no goal)
 - ⊙ Does NOT ground conversation on knowledge.
 - ⊙ Evaluation

- ⊙ Chatbot/Open domain dialogue with grounding is a FALSE proposition.

Neural Dialogue Model

A Knowledge-Grounded Neural Conversational Model

Neural Dialogue Model

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Can I have Korean

Little Seoul serves great Korean .

→ tracker parameters (pre-trained)> discrete operations → generator parameters

Neural Dialogue Model

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Can I have <v.food>

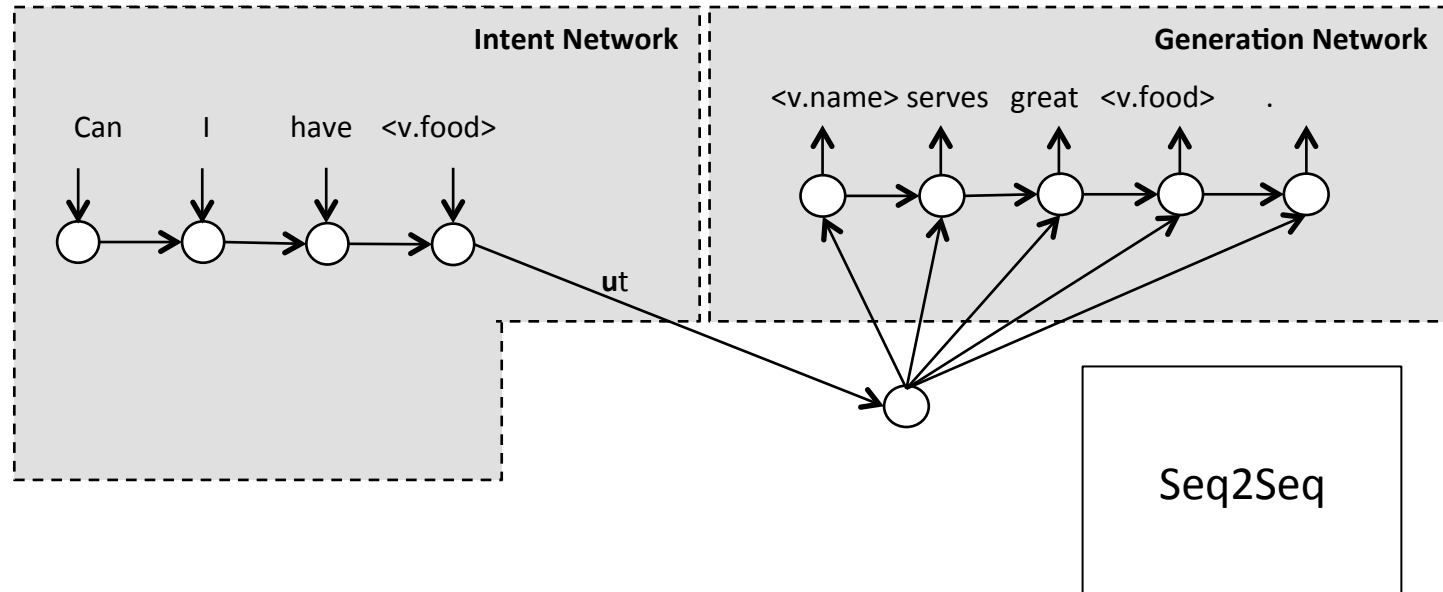
<v.name> serves great <v.food> .

Delexicalisation

→ tracker parameters (pre-trained)> discrete operations → generator parameters

Neural Dialogue Model

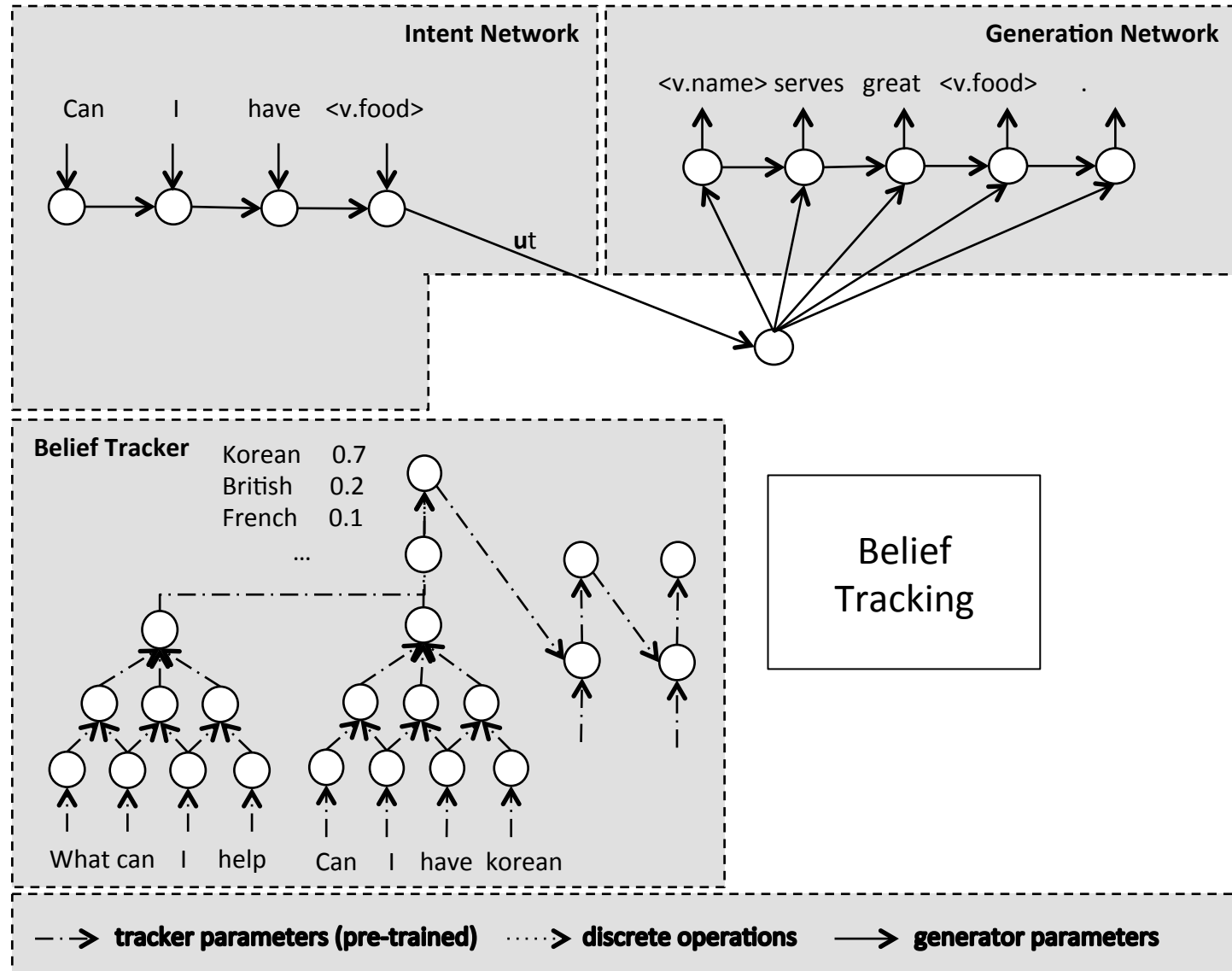
66



—→ tracker parameters (pre-trained) > discrete operations —→ generator parameters

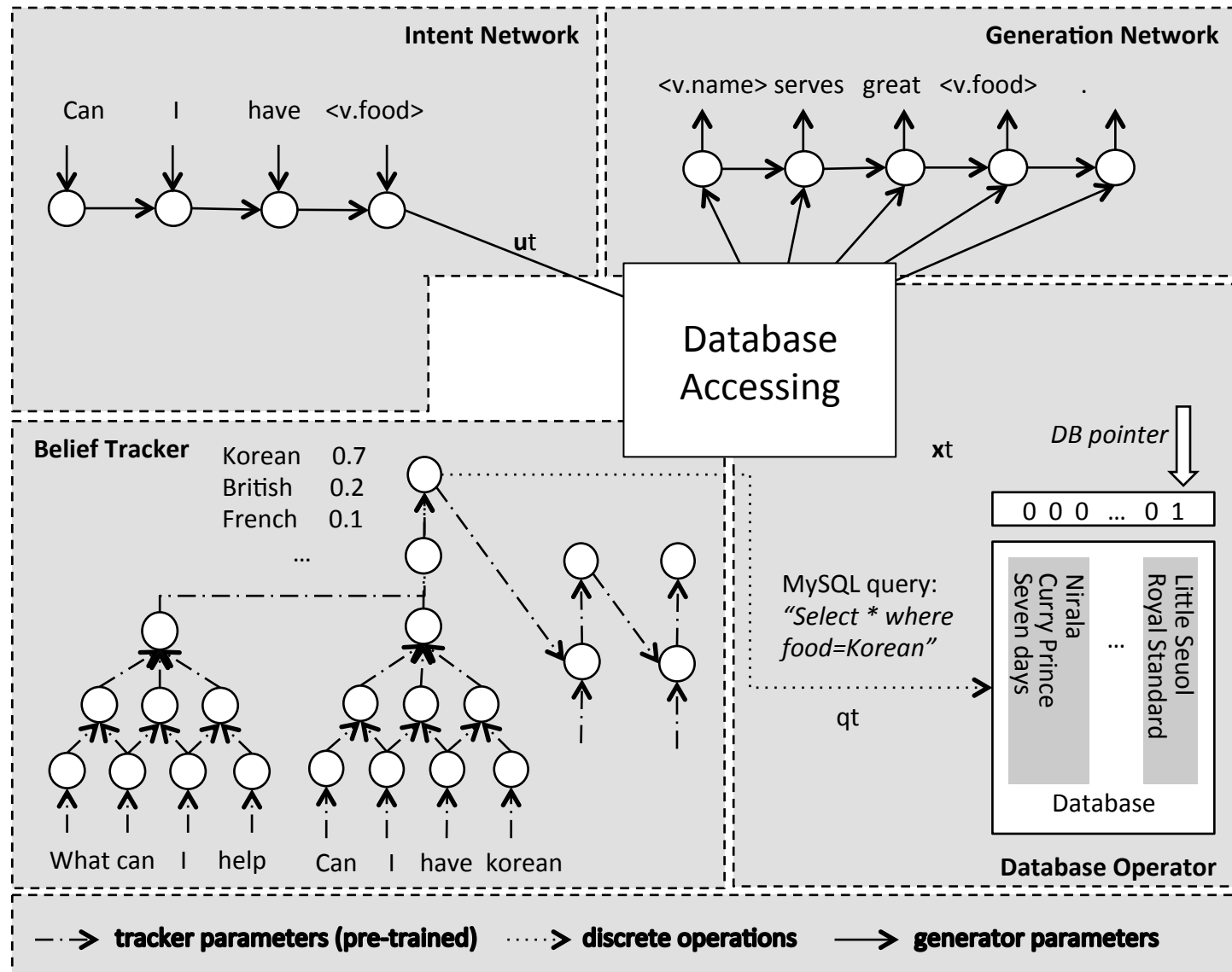
Neural Dialogue Model

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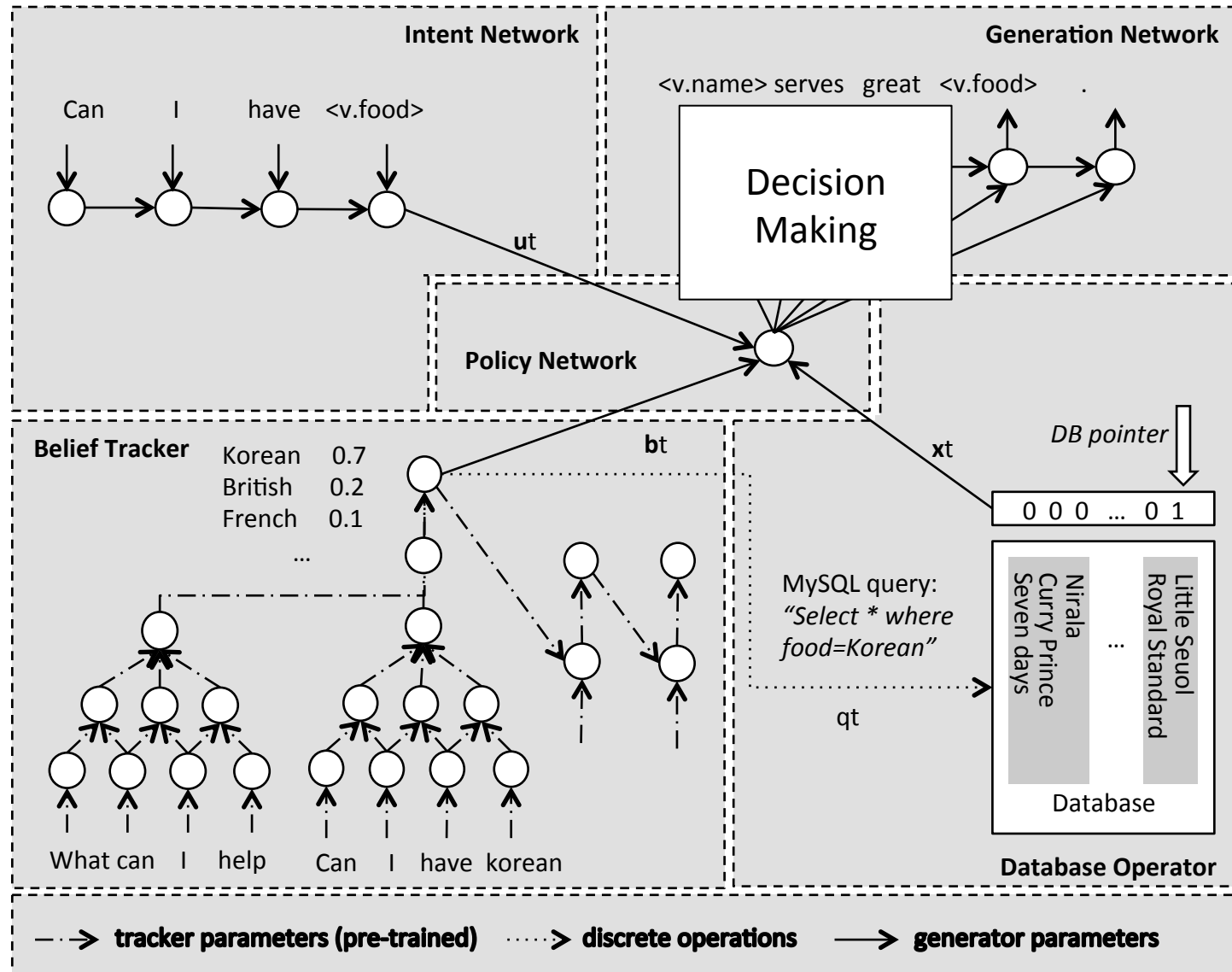
Neural Dialogue Model

68



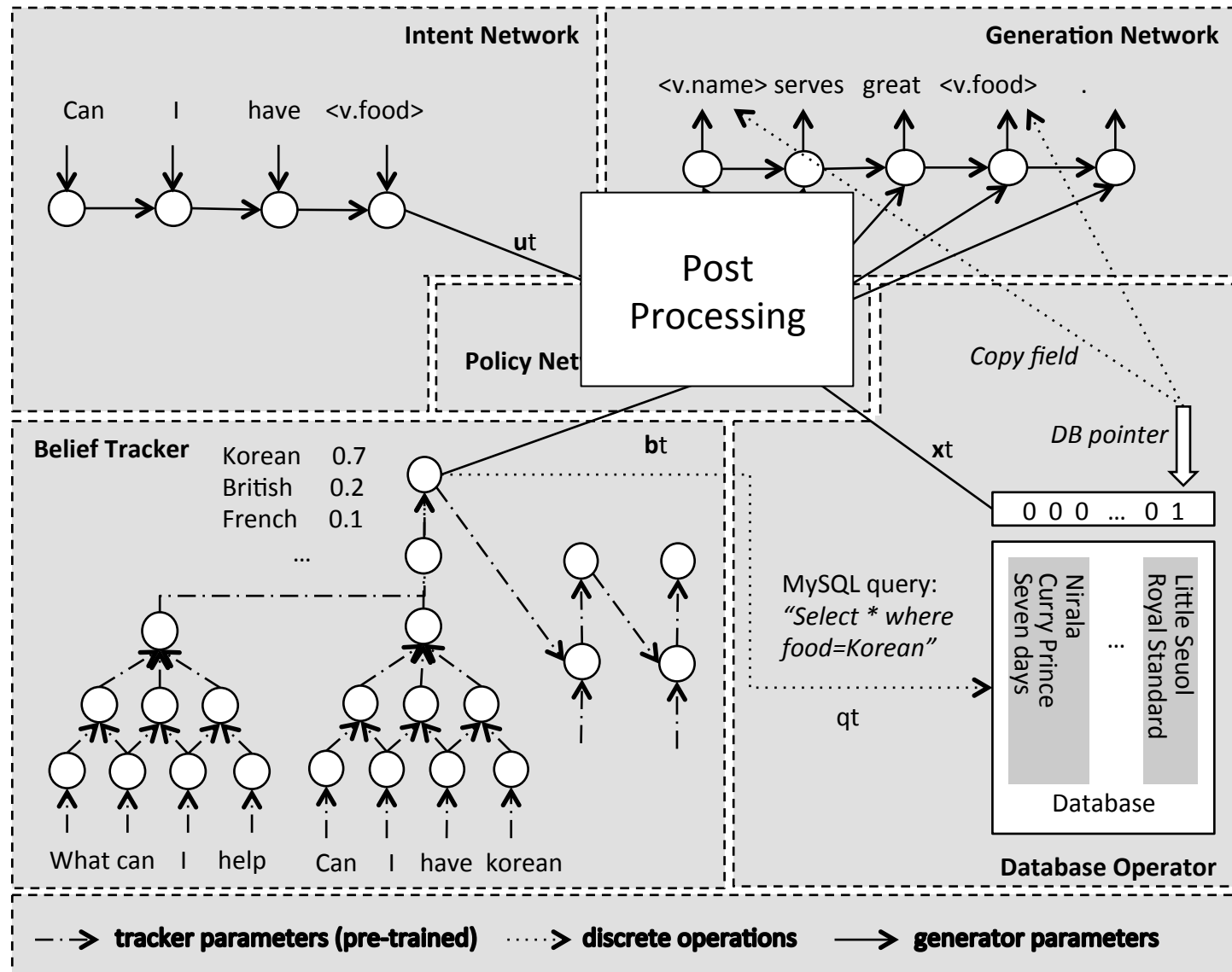
Neural Dialogue Model

69



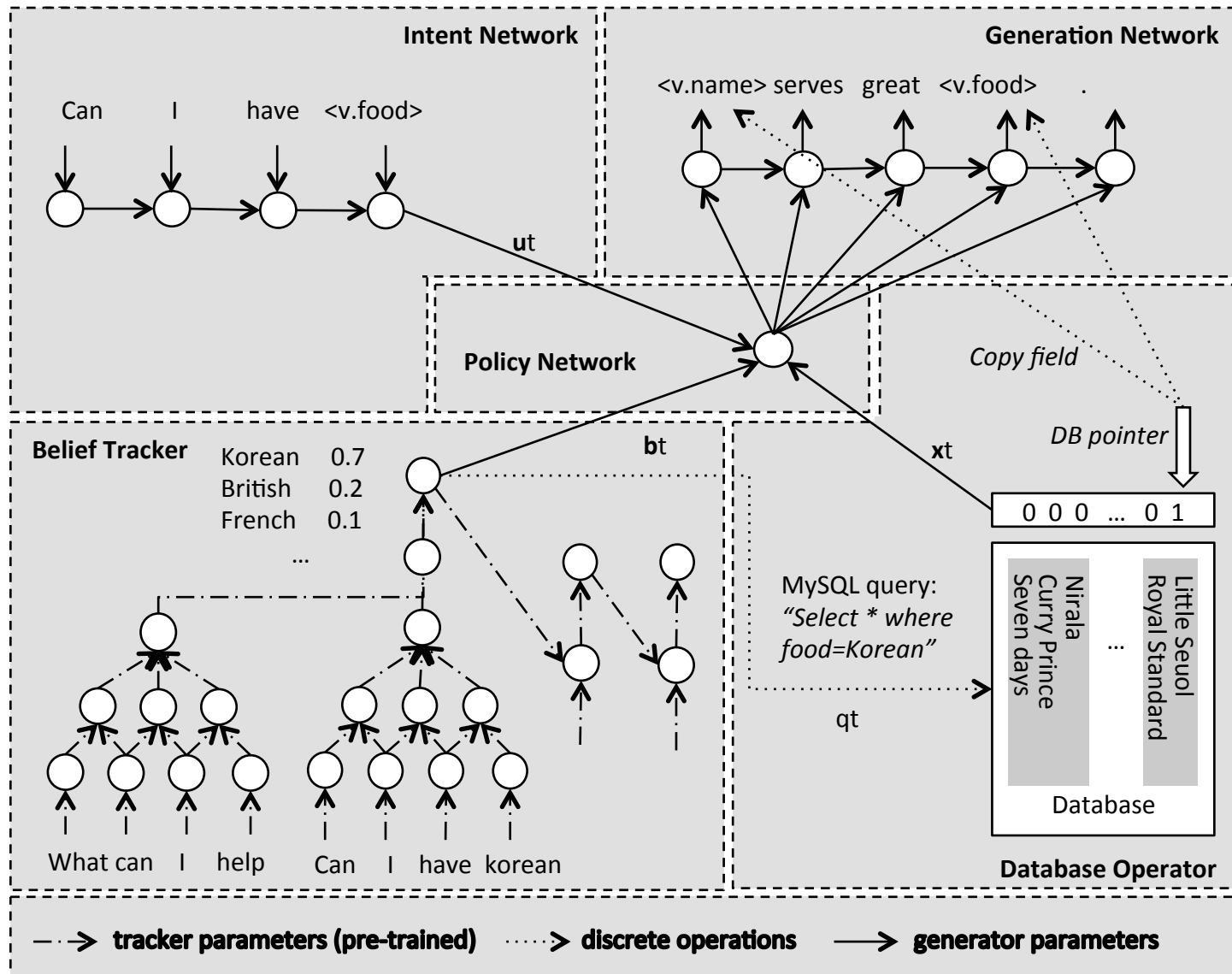
Neural Dialogue Model

70



Neural Dialogue Model

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Task: CamRest676 dataset

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- ⦿ Cambridge restaurant dialogue domain.
- ⦿ In-domain human-human conversation.
- ⦿ Users can look for restaurant with particular **food type**, **price range**, and **area**, and ask for **phone number**, **address** and **postcode**.
- ⦿ Including coarse slot-value labels per turn.
- ⦿ Evaluation:
 - ⦿ *Dialogue success
 - ⦿ BLEU

Hi, I want a cheap Korean restaurant.

*What **area** are you looking for ?*

Somewhere in the north.

Little Seoul is nice one in the north.

*What is the **phone number**?*

*Its phone number is **01223456789**.*

Thank you very much, good bye.

Thank you for using the system.

What user wants?

| | |
|-------|--------|
| Food | Korean |
| Price | Cheap |
| Area | North |

<https://www.repository.cam.ac.uk/handle/1810/260970>

- ⊙ Ontology:
 - ⊙ Cambridge restaurant domain, 99 venues.
 - ⊙ 3 informable slots: area, price range, food type
 - ⊙ 3 requestable slots: address, phone, postcode

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

Response Generation Task

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| Model | Match (%) | Success (%) | BLEU |
|---------------------------------|-----------|-------------|--------|
| Seq2Seq [Sutskever et al, 2014] | - | - | 0.1718 |
| HRED [Serban et al, 2015] | - | - | 0.1861 |
| Our full model | 86.34 | 75.16 | 0.2313 |
| Our full model + attention | 90.88 | 80.02 | 0.2388 |

Human evaluation

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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

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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 .

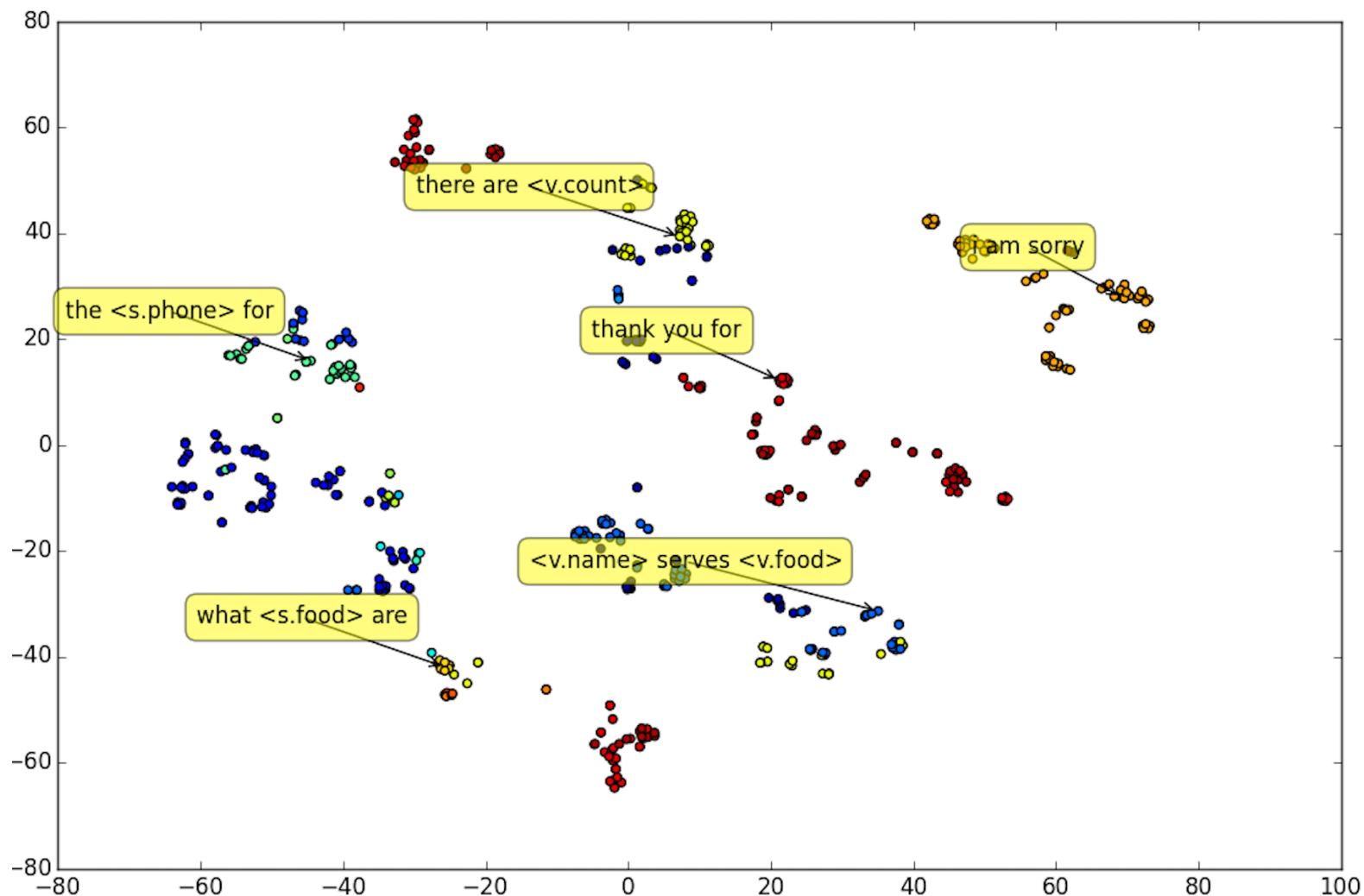
Example dialogues

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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 embedding

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Short Conclusion

79

- ⊙ Benefits of DL in complex NLP systems
 - ⊙ **Distributed representation** – “AGAIN” Generalisation
 - ⊙ **Recurrent connection** – Learning “RAW” inputs
 - ⊙ **Conditional RNN** – “MULTIMODAL” sources
- ⊙ DL allows us to build complex NLP learning systems like never before.
- ⊙ It is impractical to learn EVERYTHING from scratch
 - ⊙ Figure out what should be (shouldn't) learned.

Q & A

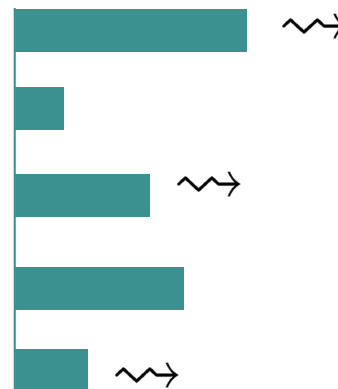
Latent Intention Dialogue Models

Inferring interpretable intentions w/ latent variable models!

Motivation – Intention Variation

82

- ⊙ Query: **What do you do?**
- ⊙ Valid responses for a **SWE**:
 - ⊙ *I'm a programmer.*
 - ⊙ *I build features for Gmail.*
 - ⊙ *Do you want to make a guess?*
 - ⊙ *I don't want to tell you.*
 - ⊙ *You can ask Sophie.*



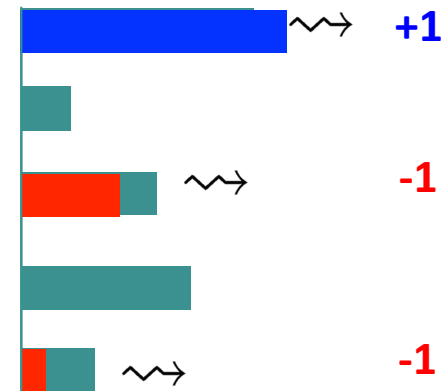
- ⊙ Intention is a probability distribution!
- ⊙ Sampling as the decision-making!

Motivation – An Unified Learning Framework

83

- ⊙ Discrete latent variable as a latent POLICY!

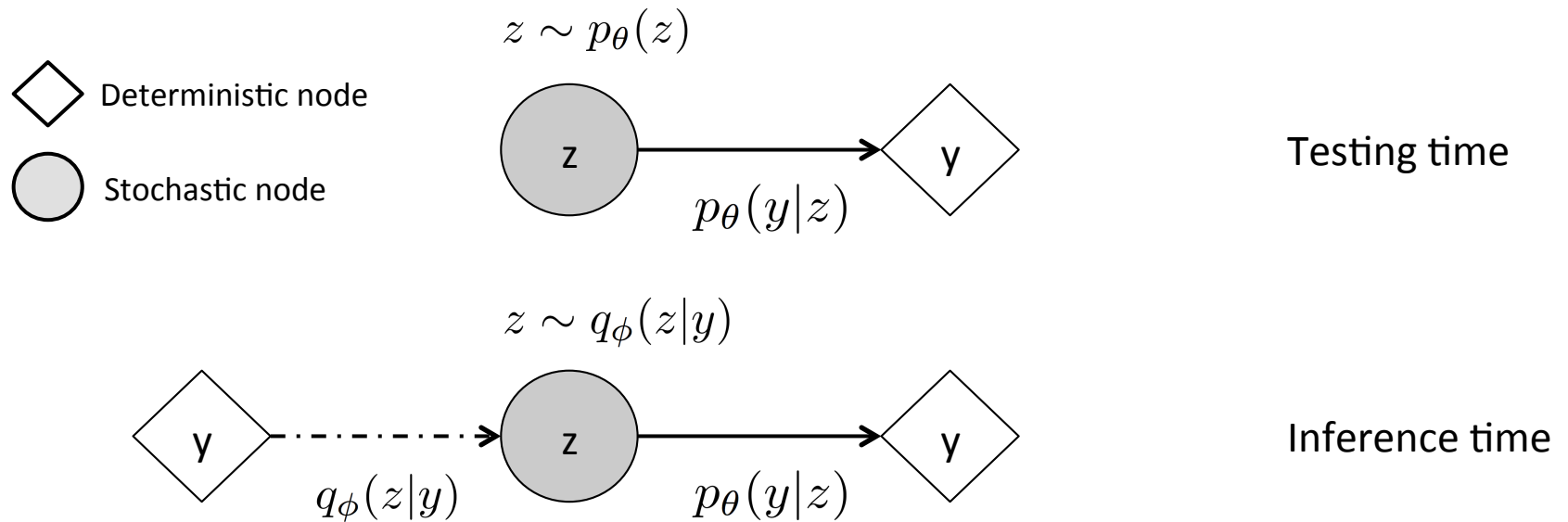
- ⊙ *I'm a programmer.*
- ⊙ *I build features for Gmail.*
- ⊙ *Do you want to make a guess?*
- ⊙ *I don't want to tell you.*
- ⊙ *You can ask Sophie.*



- ⊙ Discrete latent variable as an interface for RL.
- ⊙ Decompose learning of language and decision-making, but still, learn in an end-to-end fashion!
- ⊙ An unified framework for SL, RL, and UL!

Variational Autoencoder (VAE)

84



$$\log p_\theta(y) = \log \sum_z p_\theta(y|z) p_\theta(z)$$

Variational Autoencoder (VAE)

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VAE for Summarisation

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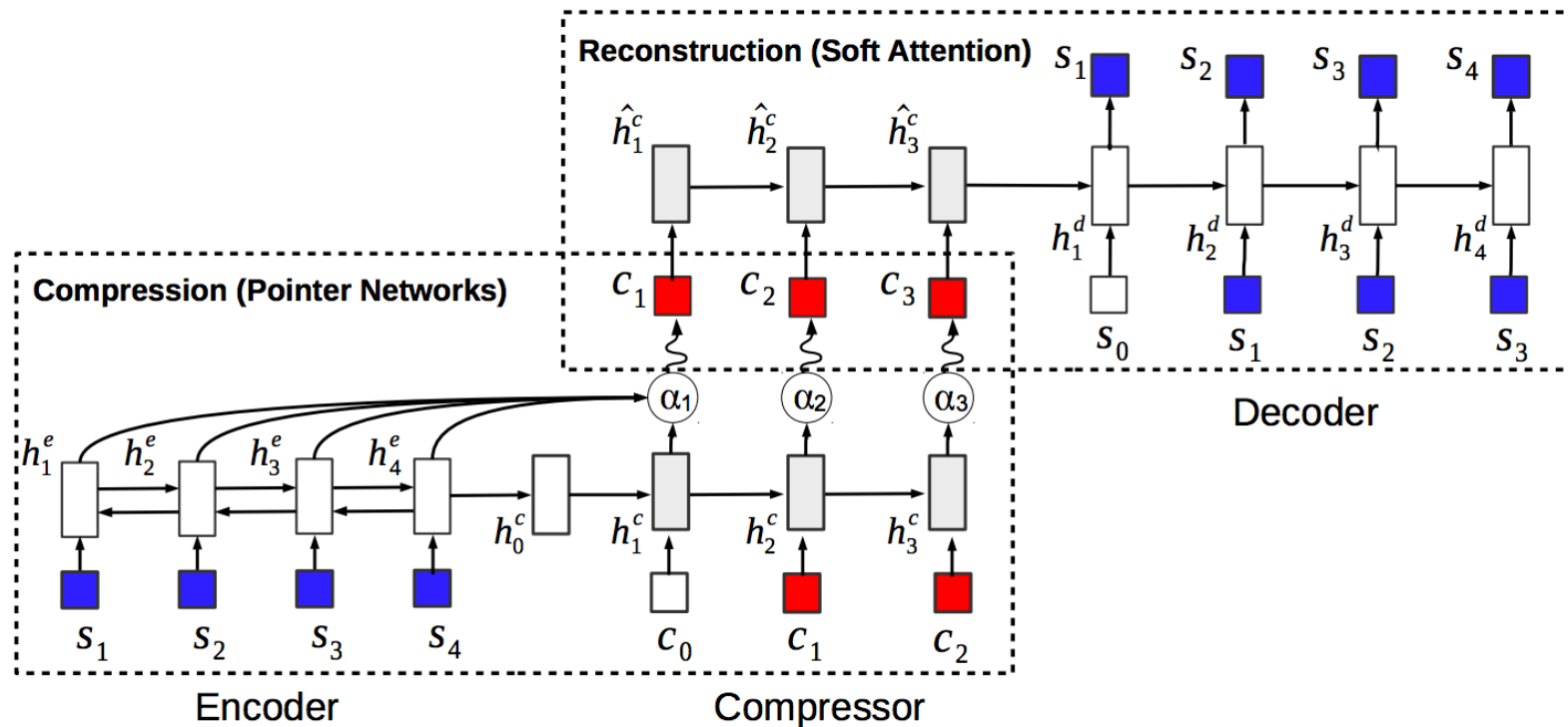
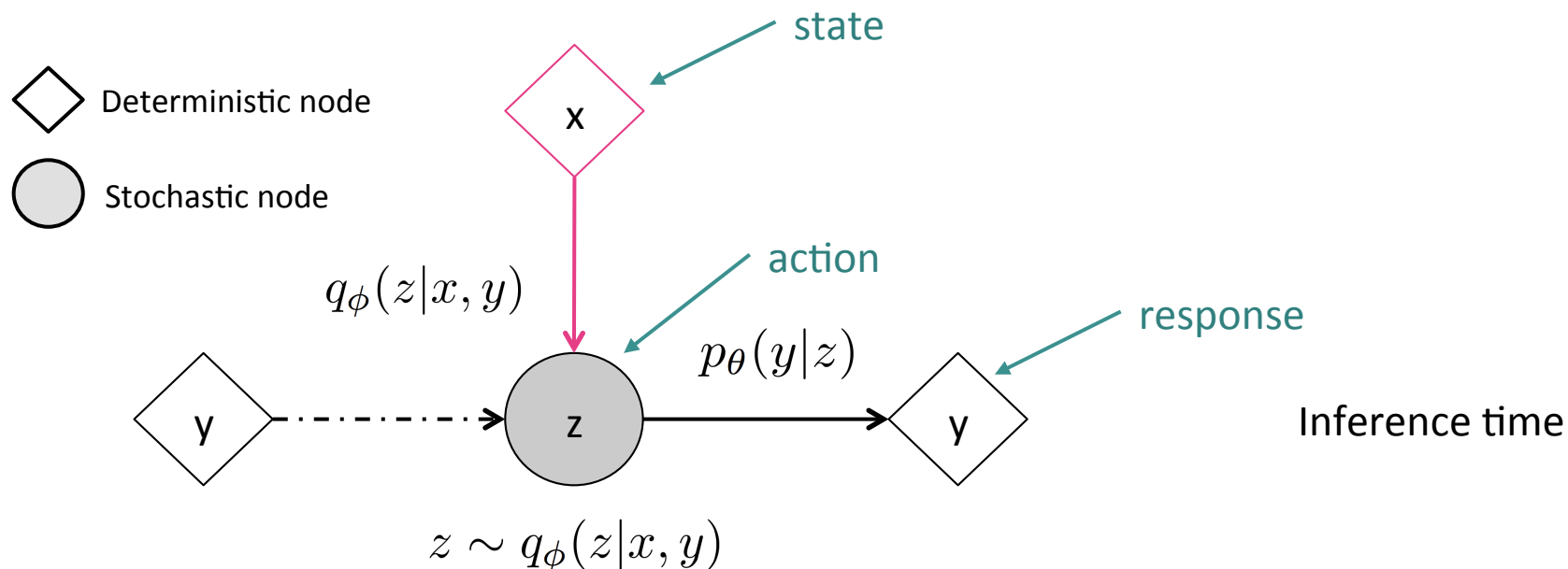


Figure 1: Auto-encoding Sentence Compression Model

Dialogue as a Conditional VAE

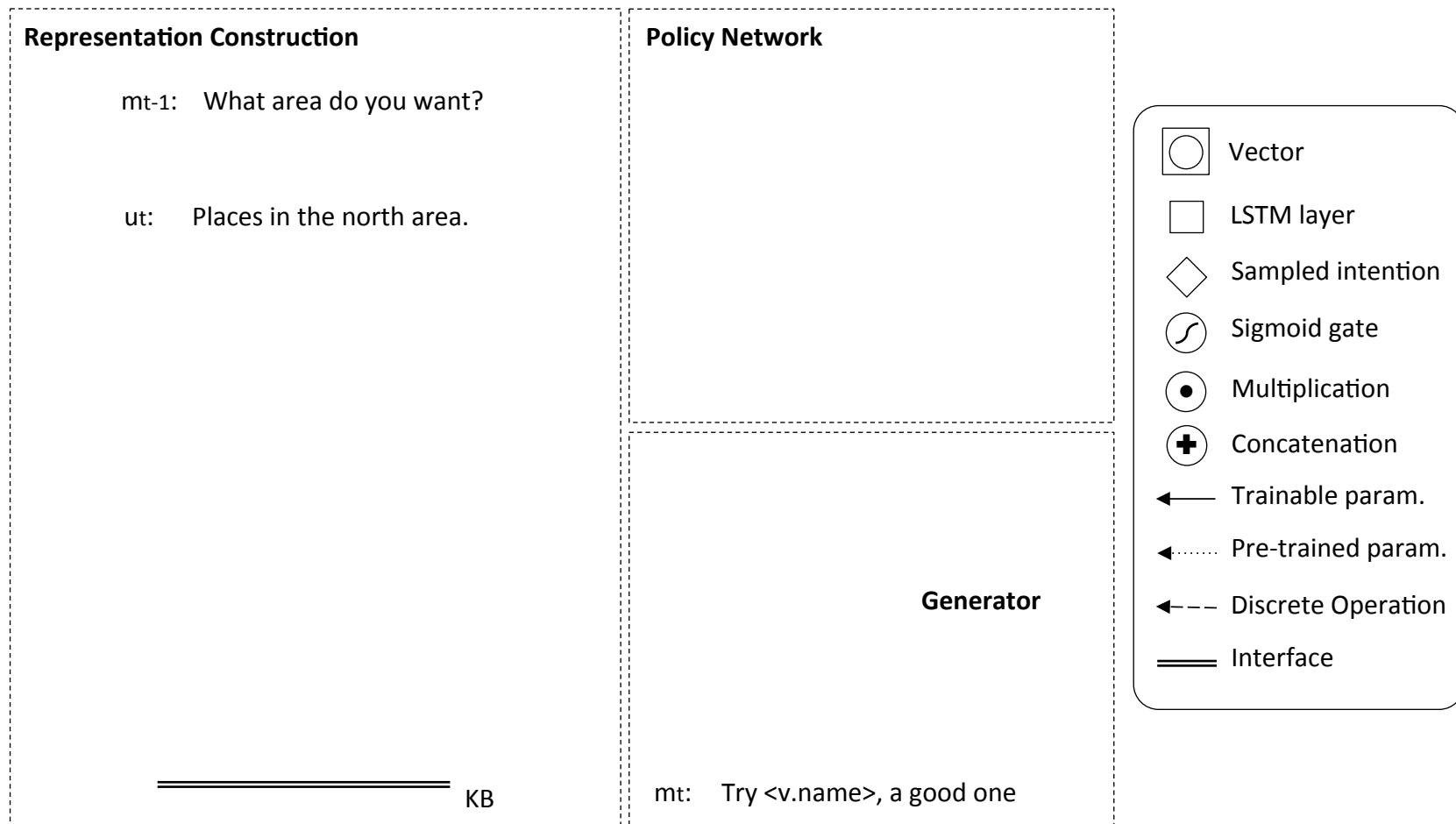
87



$$\begin{aligned}\log p_\theta(y|x) &= \log \sum_z p_\theta(y|z)p_\theta(z|x) \\ &\geq \mathbb{E}_{q_\phi(z|x, y)} [\log p_\theta(y|z)] - D_{KL}(q_\phi(z|x, y) || p_\theta(z|x)) \\ &= \mathcal{L}(\theta, \phi)\end{aligned}$$

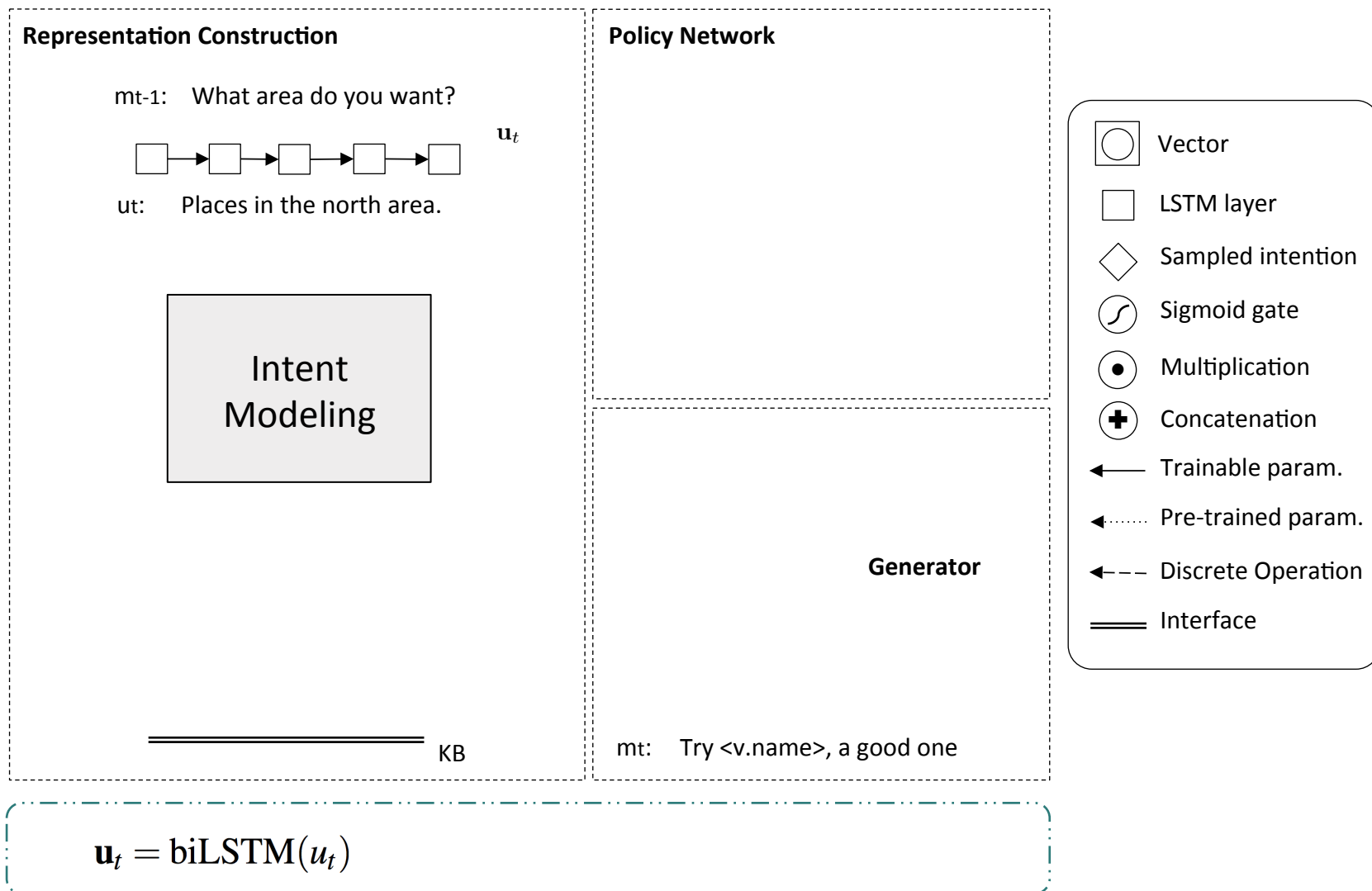
Latent Intention Dialogue Models

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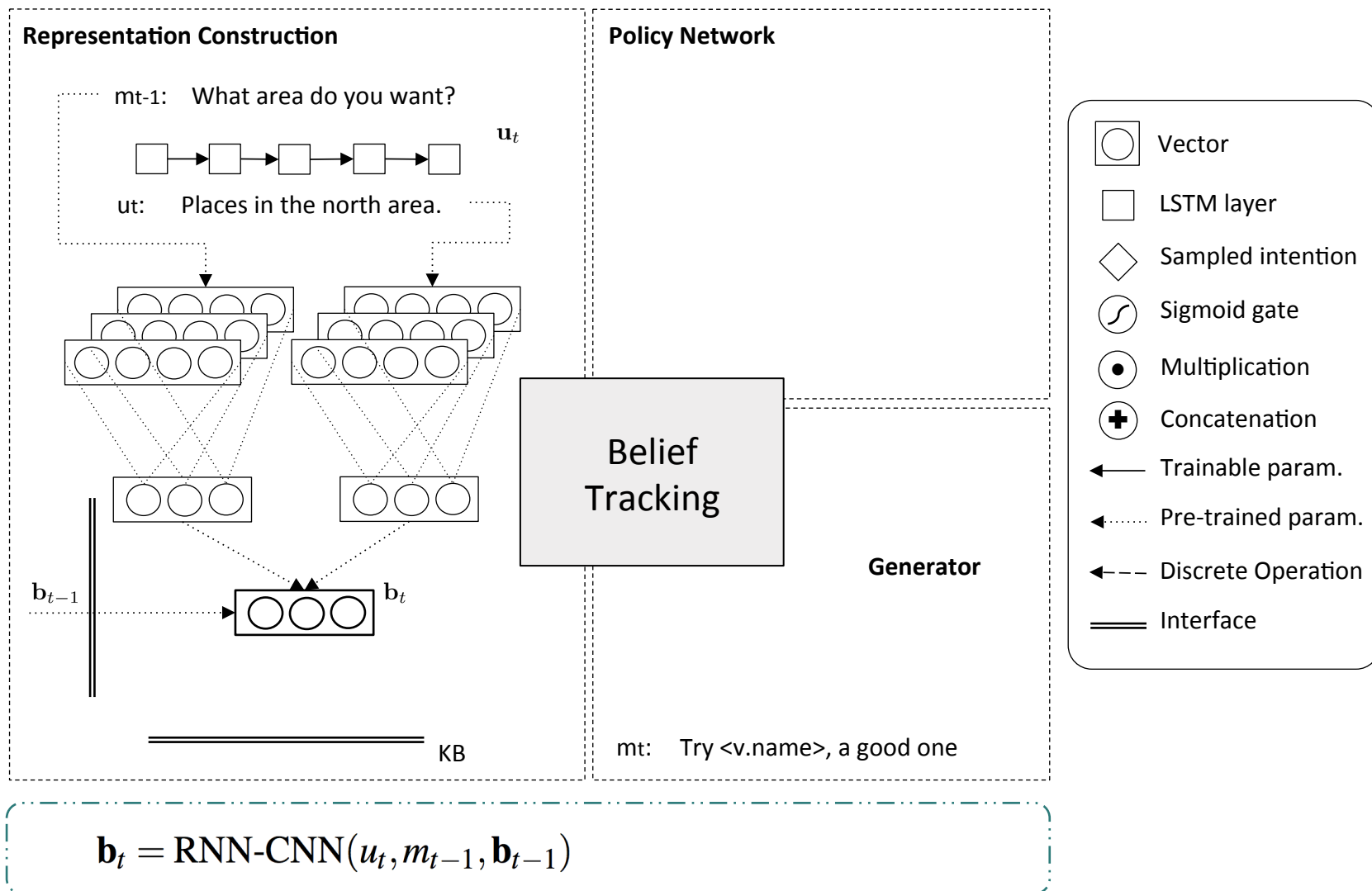
Latent Intention Dialogue Models

89



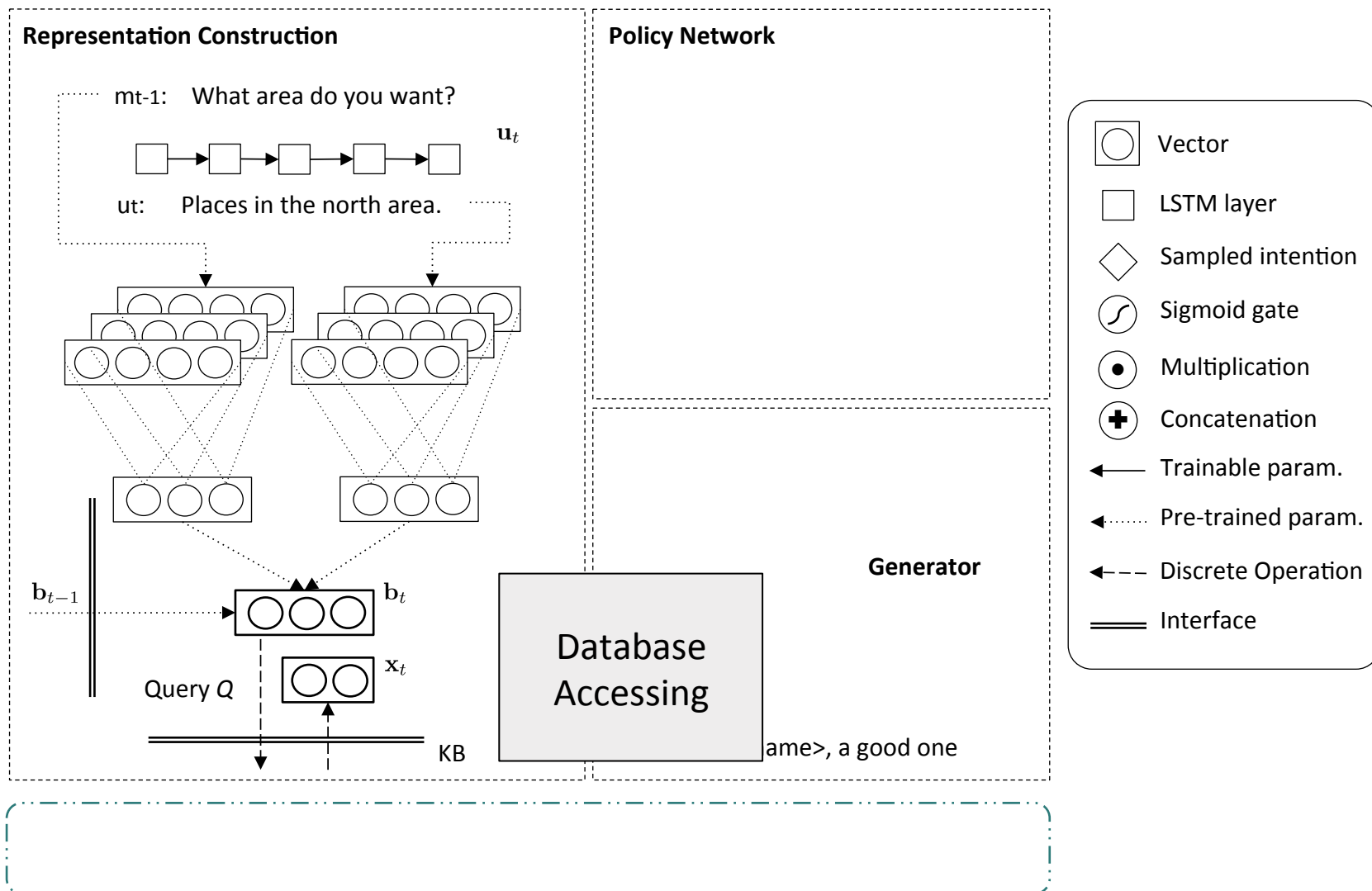
Latent Intention Dialogue Models

90



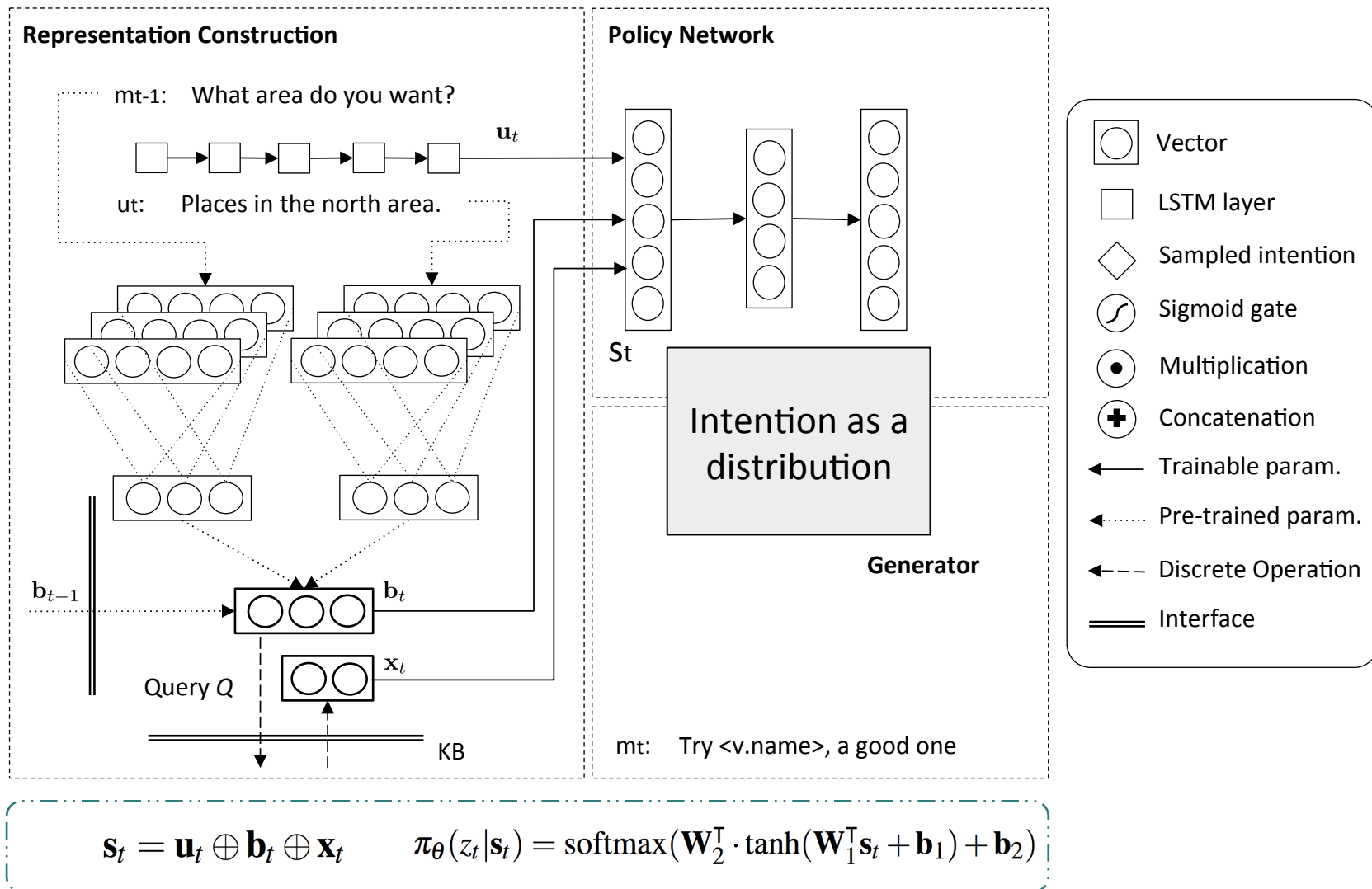
Latent Intention Dialogue Models

91



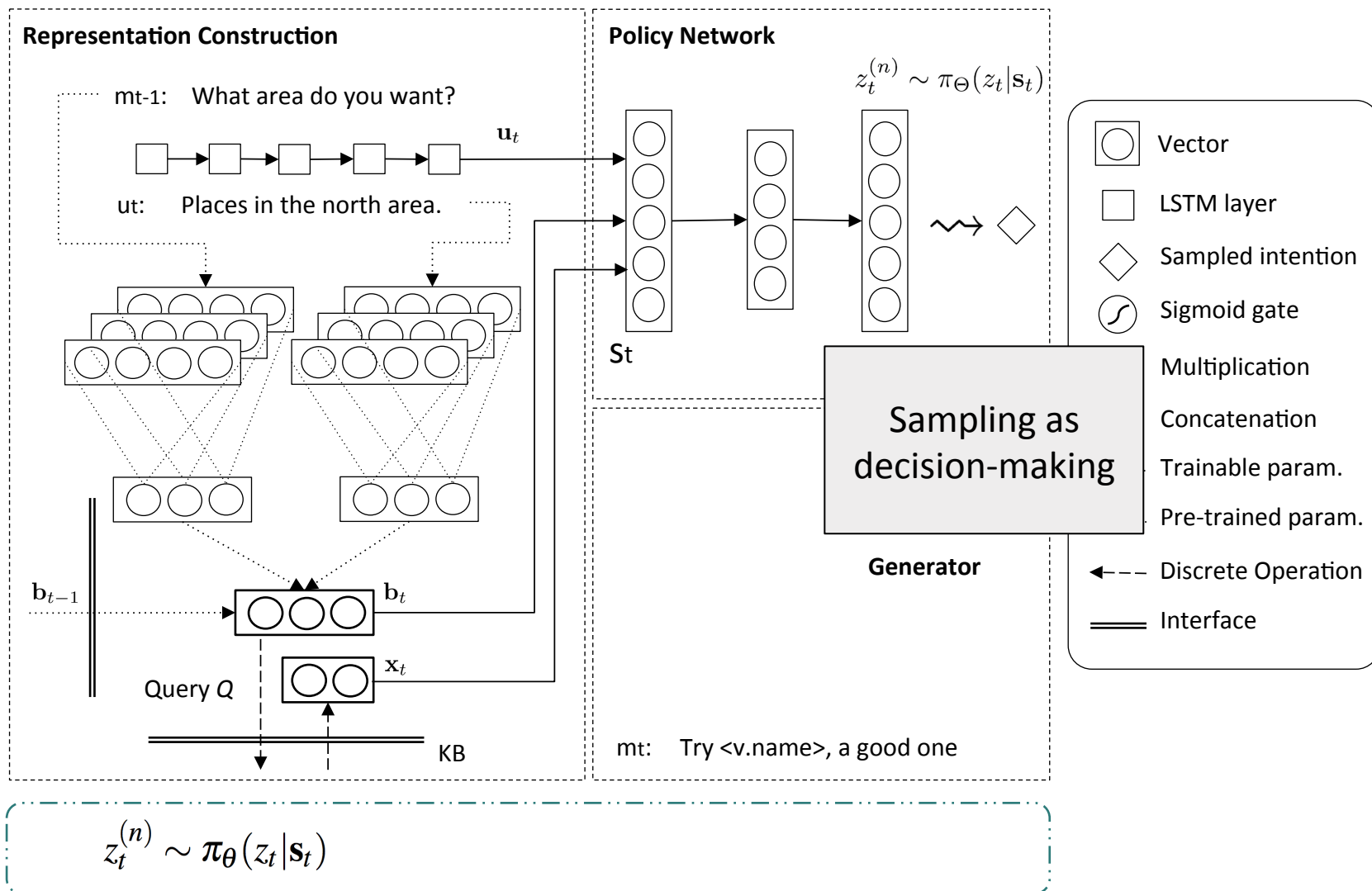
Latent Intention Dialogue Models

92



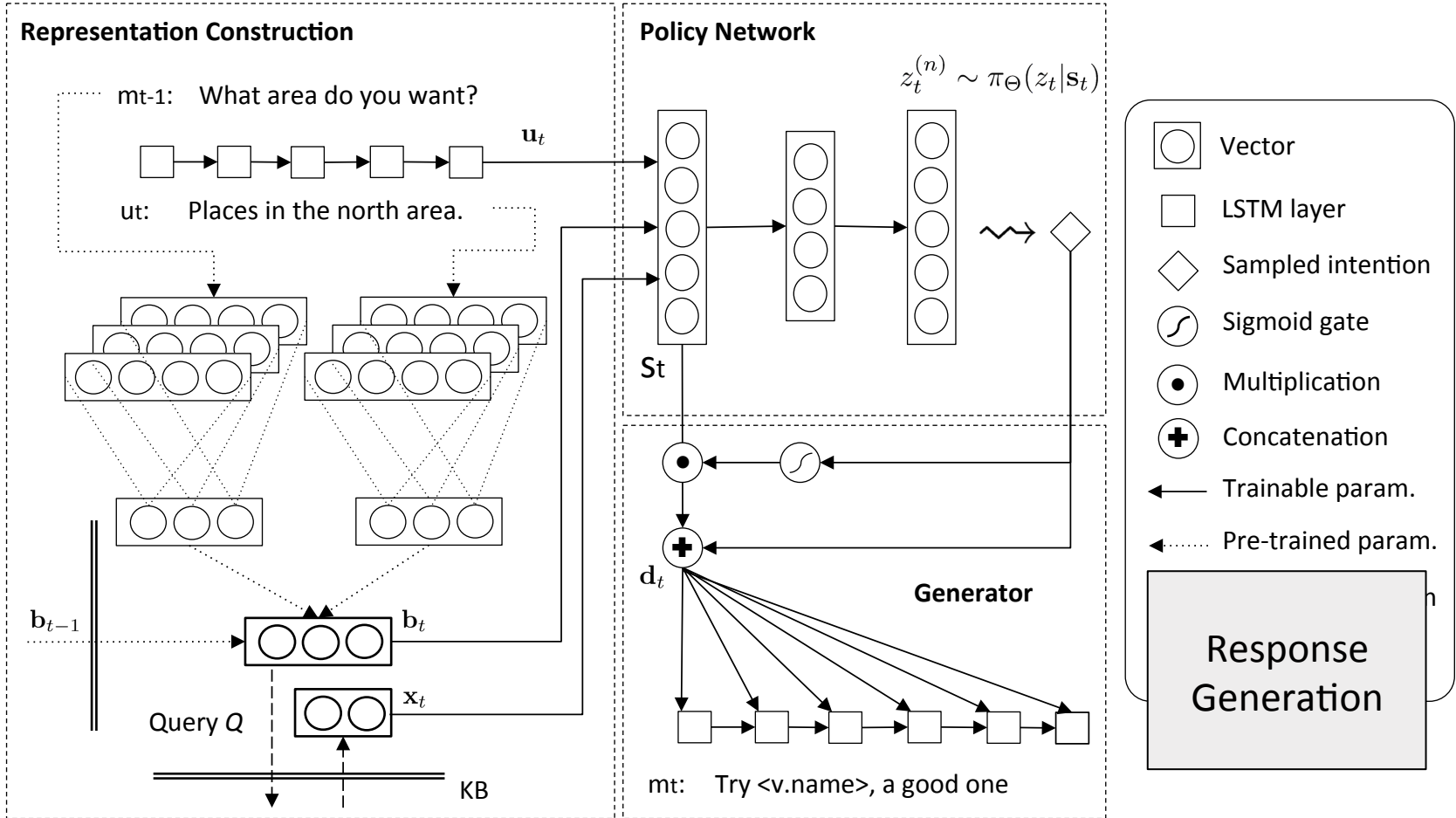
Latent Intention Dialogue Models

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Latent Intention Dialogue Models

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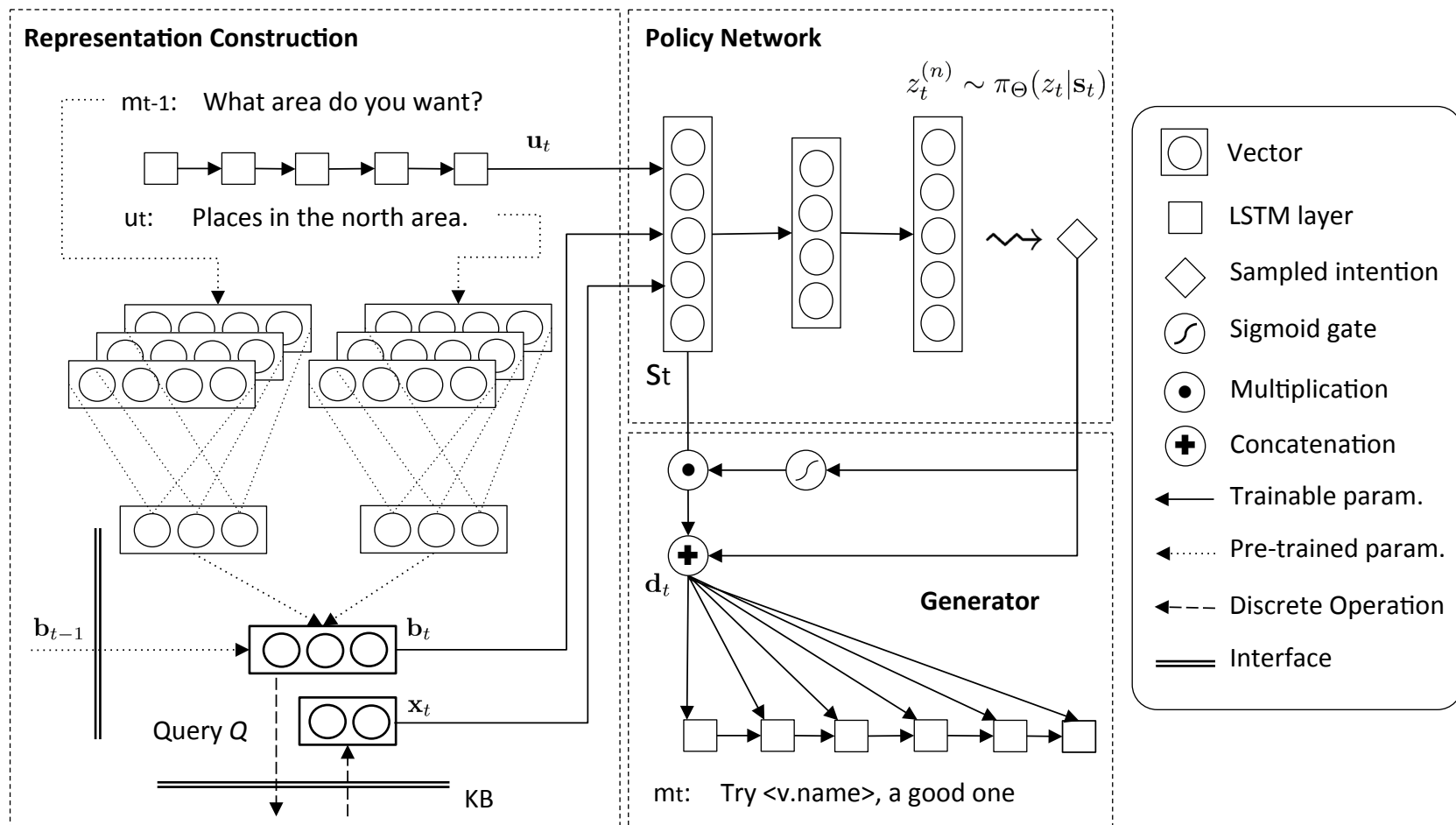


$$\mathbf{d}_t = \mathbf{W}_4^T \mathbf{z}_t \oplus [\text{sigmoid}(\mathbf{W}_3^T \mathbf{z}_t + \mathbf{b}_3) \cdot \mathbf{W}_5^T \mathbf{s}_t]$$

$$p_{\theta}(m_t | \mathbf{s}_t, \mathbf{z}_t) = \prod_j p(w_{j+1}^t | w_j^t, \mathbf{h}_{j-1}^t, \mathbf{d}_t)$$

Latent Intention Dialogue Models

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$$p_{\theta}(m_t|s_t) = \sum_{z_t} p_{\theta}(m_t|z_t, s_t) \pi_{\theta}(z_t|s_t)$$

Reinforcement Learning

96

- ⊙ Policy gradient based RL can be directly applied:

$$\frac{\partial \mathcal{J}}{\partial \theta'} \approx \frac{1}{N} \sum_n r_t^{(n)} \frac{\partial \log \pi_{\theta}(z_t^{(n)} | \mathbf{s}_t)}{\partial \theta'}$$

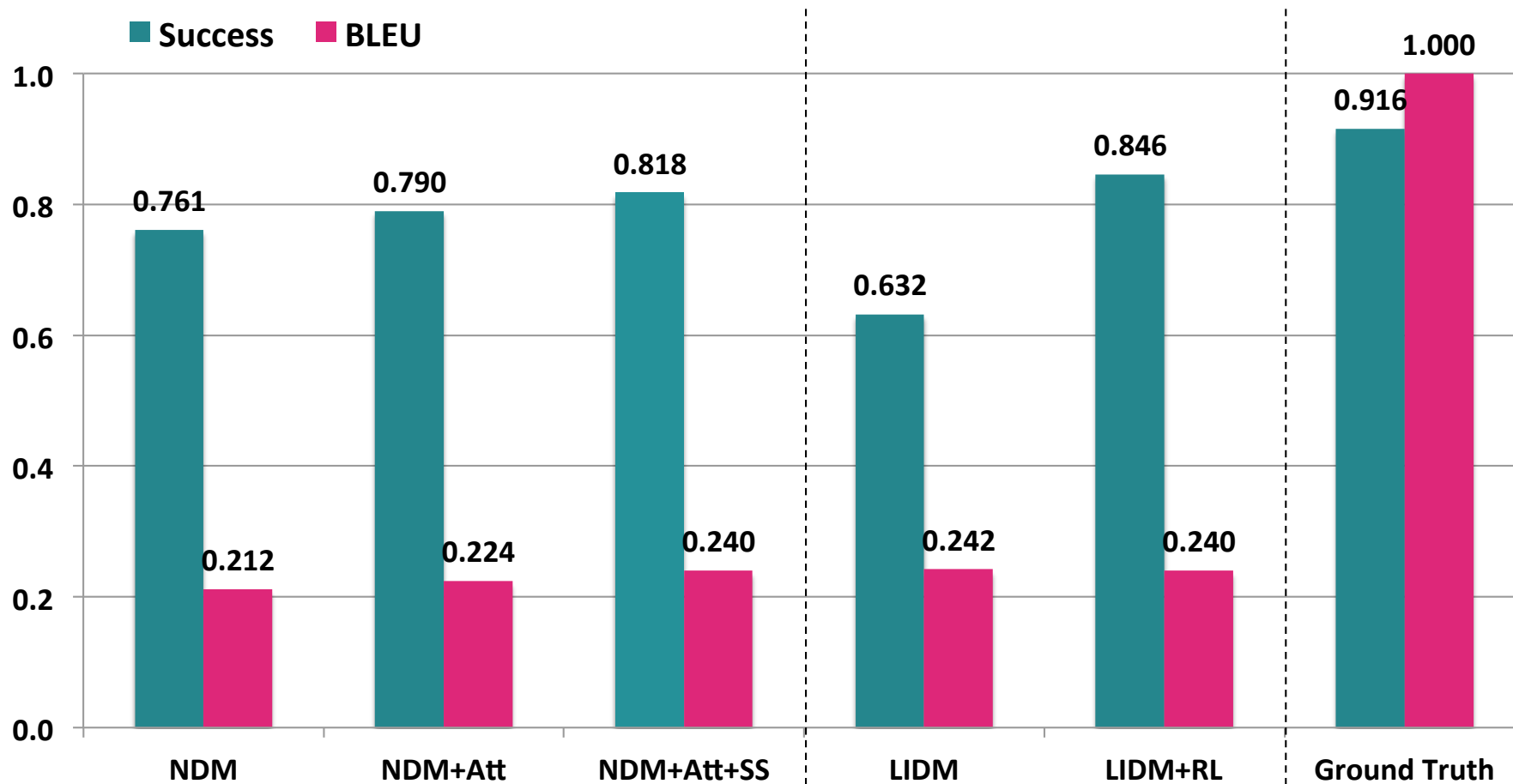
- ⊙ A simple corpus-based RL setting is applied,
 - ⊙ Swap each ground truth with a model candidate m_t
 - ⊙ Receive reward r_t as defined below,

$$r_t = \eta \cdot \text{sBLEU}(m_t, \hat{m}_t) + \begin{cases} 1 & m_t \text{ improves} \\ -1 & m_t \text{ degrades} \\ 0 & \text{otherwise} \end{cases}$$

- ⊙ Update model parameters

Corpus-based Result

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Human Evaluation

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| Metrics | NDM | LIDM | LIDM+RL |
|---------------|-------|-------|---------|
| Success | 91.5% | 92.0% | 93.0% |
| Comprehension | 4.21 | 4.40* | 4.40 |
| Naturalness | 4.08 | 4.29* | 4.28* |
| # of Turns | 4.45 | 4.54 | 4.29 |

* $p < 0.05$

- ⊙ Subjectively, LIDM performs indistinguishably from the others -> discrepancy due to a **biased preference toward greedy policy** in corpus-based evaluation.
- ⊙ LIDMs can produce more natural dialogues than NDM.

An Example Dialogue of LIDM

99

Human : Hi, I'm hungry for some Indonesian

Machine: (0 0.71) **i am sorry , there are no indonesian restaurants in the area . would you like something else ?**
(46 0.19) there are no restaurants serving indonesian kind of food .
(34 0.07) what location would you like ?

Human : Oh no. How about Indian?

Machine: (0 0.59) there are 9 restaurants in the east side of town . would you like their address ?
(30 0.15) curry prince serves indian cuisine .
(34 0.10) **what area would you like ?**

Human : East side please

Machine: (0 0.62) **curry prince is a indian restaurant in the east side of town . would you like their telephone number ?**
(84 0.19) curry prince is an indian restaurant in the east of town and the number is 01223 566388 .
(81 0.08) curry prince serves indian type of cuisine and is located in the east part of town .

Human : yes , the address and phone number please

Machine: (3 0.46) the address is 451 newmarket road fen ditton and the phone is 01223 566388 .
(11 0.16) **the address for curry prince is 451 newmarket road fen ditton and the phone number is 01223 566388 .**
(0 0.15) curry prince is located at 451 newmarket road fen ditton and their phone is 01223 566388 . is there anything else i can help you with ?

Human : Okay, thank you goodbye

Machine: (0 0.57) thank you , goodbye .
(2 0.13) goodbye .
(1 0.11) **you are welcome . goodbye .**
(6 0.10) thank you for using the cambridge restaurant system . goodbye .

Table 4. A sample dialogue from the LIDM, I=100 model, one exchange per block. Each latent intention is shown by a tuple (index, probability), followed by a decoded response. The sample dialogue was produced by following the responses highlighted in bold.

Example Dialogues of LIDM+RL

100

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

Machine: (0 0.61) **i am sorry , there are no indonesian restaurants in the area . would you like something else ?**
(46 0.17) no restaurants in the part of town .
(34 0.14) what part of town would you like ?

Human : Oh no. How about Indian?

Machine: (93 0.51) **the gandhi is located at 72 regent street city centre and their telephone number is 01223 353942 .**
(72 0.21) the gandhi serves indian kind of food and is in the centre of town and is in the cheap price range .
(12 0.12) the gandhi is a indian restaurant in the centre location and is in the cheap price range .

Human : Okay, thank you goodbye

Machine: (6 0.28) **thank you for using the cambridge restaurant system . goodbye .**
(1 0.24) you are welcome . goodbye .
(85 0.19) is there anything else i can help you with ?

Human : hey can i have some chinese cuisines in the centre ? and a cheap one please

Machine: (15 0.42) golden house is located at 12 lensfield road city centre and their number is 01842 753771 .
(5 0.38) **golden house is located at 12 lensfield road city centre and the number is 01842 753771 . is there ...**
(93 0.10) golden house is located at 12 lensfield road city centre and their phone is 01842 753771 .

Human : that is all

Machine: (6 0.57) **thank you for using the cambridge restaurant system . goodbye .**
(1 0.20) you are welcome . goodbye .
(17 0.11) have a nice day !

Table 5. Two sample dialogues from the LIDM+RL, I=100 model, one exchange per block. Comparing to Table 4, the RL agent demonstrates a much greedier behavior toward task success. This can be seen in *block 2* & *block 4* in which the agent provides the address and phone number even before the user asks.

NNDIAL

A Toolkit for Goal-Oriented Neural Dialogue Models

NNDIAL – A Tool for Neural Dialogue Models

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The screenshot shows the GitHub repository page for NNDIAL by shawnwun. The repository has 5 watches, 3 stars, and 0 forks. It includes tabs for Code, Issues (0), Pull requests (0), Projects (0), Wiki, Settings, and Insights. The description states it is an open source toolkit for building end-to-end trainable task-oriented dialogue models, released by Tsung-Hsien (Shawn) Wen from Cambridge Dialogue Systems Group under Apache License 2.0. It lists several topics: machine-learning, dialogue-systems, dialogue-generation, dialogues, dialogue, dialogue-agents, dialogue-manager, machine-learning-library, natural-language-processing, and natural-language-generation. The repository statistics show 10 commits, 1 branch, 0 releases, and 1 contributor. At the bottom, there is a table of files and folders.

| File/Folder | Description | Last Commit |
|-------------|-------------------------|-------------|
| api | 1st version for release | a day ago |
| config | 1st version for release | a day ago |
| data | 1st version for release | a day ago |
| db | 1st version for release | a day ago |
| emb | 1st version for release | a day ago |
| loader | 1st version for release | a day ago |

🕒 <https://github.com/shawnwun/NNDIAL>

NNDIAL – A Tool for Neural Dialogue Models

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◎ Summary

- ◎ Implementation: Python 2.7, Theano 0.8.2, NLTK 3.0.0
- ◎ Including CamRest676 WoZ dataset
- ◎ 2 Models: NDM (w/ attention) and LIDM

◎ Including works in the following publications:

- ✓ *A Network-based End-to-End Trainable Task-oriented Dialogue System*, Wen et al, EACL, 2017.
- ✓ *Latent Intention Dialogue Models*, Wen et al, ICML 2017.
- ✓ *Conditional Generation and Snapshot Learning in Neural Dialogue Systems*, Wen et al, EMNLP, 2016.

Toolkit Navigation

Part IV: Conclusion & Challenge

Conclusion & Challenge

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- ⊙ The three pillars of DL for NLG/NLP
 - ⊙ **Distributed representation** – Generalisation.
 - ⊙ **Recurrent connection** – Long-term Dependency.
 - ⊙ **Conditional RNN** – Flexibility/Creativity.
- ⊙ The last one is the key to many interesting applications in DL today.

Conclusion & Challenge

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- ⊙ Useful techniques in DL for NLG
 - ⊙ Learnable gates
 - ⊙ Attention mechanism
- ⊙ Challenges for Deep NLG
 - ⊙ Generating longer/complex sentences.
 - ⊙ Generating coherent narratives.
 - ⊙ Employing latent syntactic structures?

Conclusion & Challenge

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- ⊙ DL offers flexible learning models for dialogue
 - ⊙ LSTM for response decoding.
 - ⊙ CNN for language understanding.
 - ⊙ MLP for any arbitrary input-output mappings.
 - ⊙ Discrete latent variable as a latent policy.
- ⊙ Dialogue MUST be grounded!
- ⊙ Chatbot/Open-domain dialogue without grounding is a FALSE proposition. Like ELIZA in 50 years ago.
- ⊙ NDM & LIDM show a promising step forward.

Conclusion & Challenge

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- ⊙ Challenges for End-to-End Dialogue Modeling
 - ⊙ From a produce development perspective
 - ⊙ How to gain access to in-domain dialogue corpora?
 - ⊙ How to scale systems across different domains?
 - ⊙ How to gain control over system behaviors?
 - ⊙ From an AI perspective
 - ⊙ What is the internal semantic representation?
 - ⊙ How to learn from conversational cues in interactions?
 - ⊙ How to acquire new knowledge?

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