端到端任务导向对话生成的方法与挑战

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目录

- Introduction
- End2end dialogue generation

Coffee break 30min

- End-to-end task-oriented dialogue generation
- Conclusion&Outlook

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Part 1: Introduction

目录

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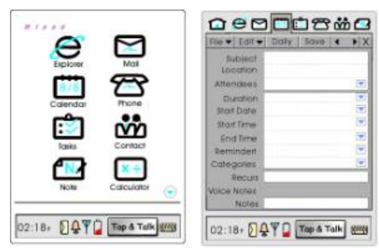
- 对话生成技术简介
- 从语言模型到对话生成
- 对话生成技术的研究热点
- 总结

Brief history of dialogue systems

Multi-modal systems
e.g., Microsoft MiPad, Pocket PC



TV Voice Search
e.g., Bing on Xbox

Virtual Personal Assistants

Task-specific argument extraction
(e.g., Nuance, SpeechWorks)
User: "I want to fly from Boston to New York next week."

2017

Early 2000s

IBM WATSON

Early 1990s

Intent Determination
(Nuance's Emily™, AT&T HMIHY)
User: "Uh…we want to move…we want to change our phone line from this house to another house"

DARPA
CALO Project

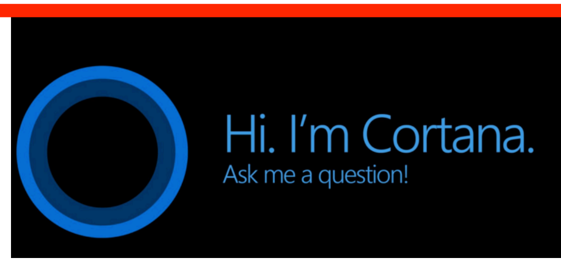
Keyword Spotting
(e.g., AT&T)
System: *"Please say collect, calling card, person, third number, or operator"*

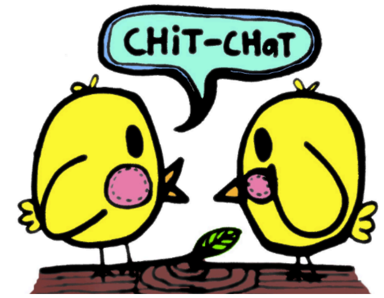
From Yun-Hung(Vivian) Chen

What is a dialogue system?

- The voice-driven personal assistant on your iPhone
- Perhaps the most visible & exciting application of NLU today
- A major breakthrough in artificial intelligence (AI)??
- The next generation of interaction design??

From Jiwei Li





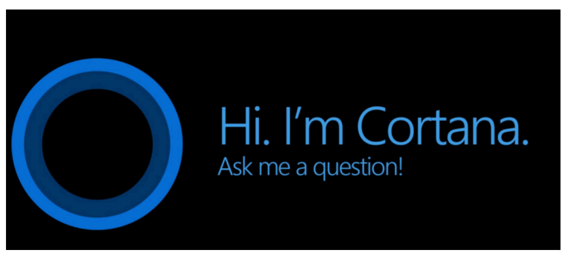
Dialogue systems

Task-oriented dialogue systems (Virtual assistant)

Chit-chat dialogue systems

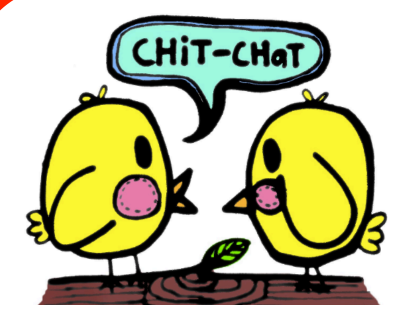
Types of dialogue systems

Task-oriented dialogue systems



Virtual assistants

Chit-chat dialogue systems



Xiao Ice

笨笨

… …

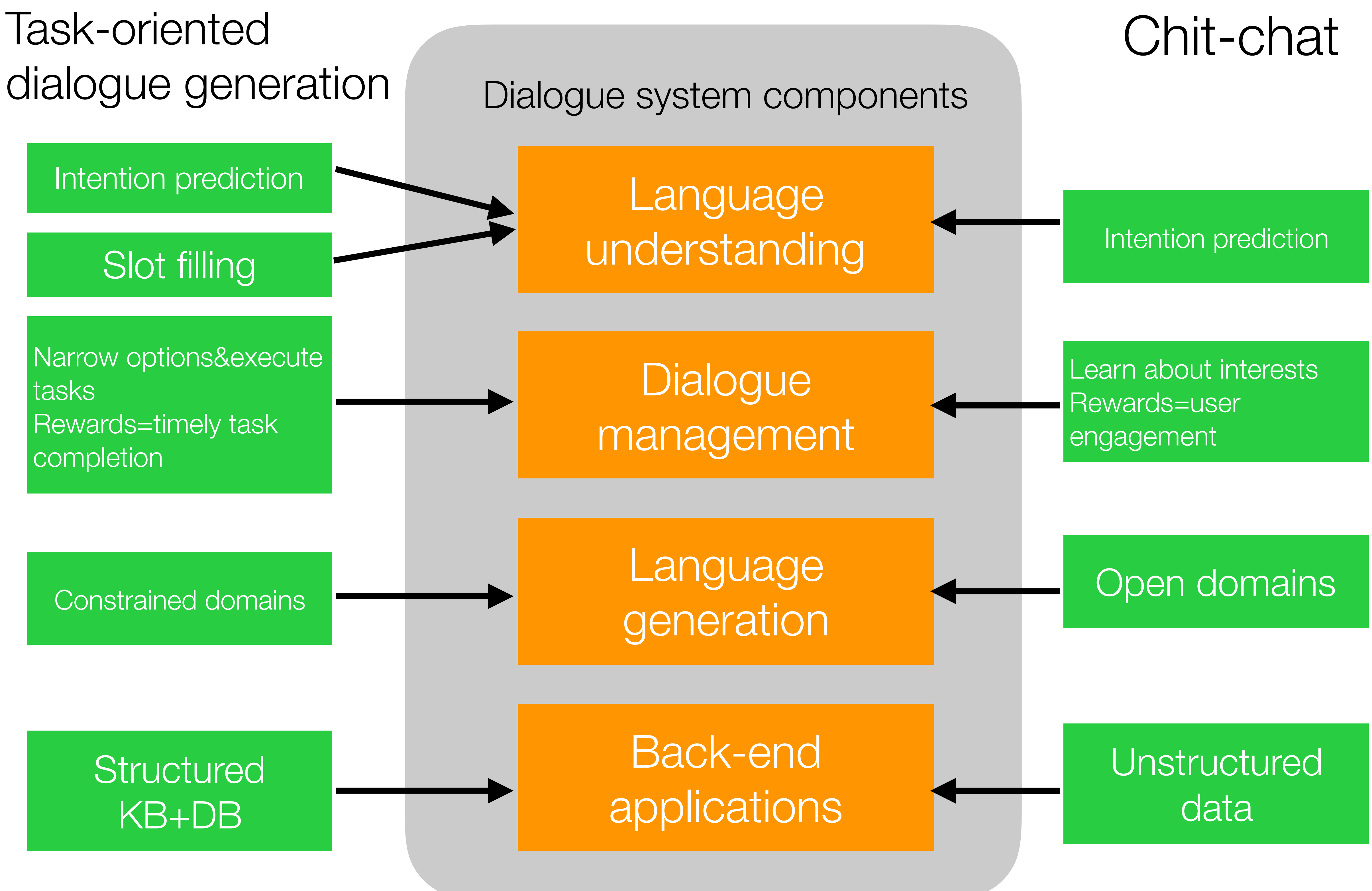
Types of dialogue systems

- Dialogue systems are receiving increasing attention in multiple applications.

- **Task oriented dialogue systems**
  - Used for hotel booking, navigation, restaurant reservation and etc.
  - Retrieve a specific entity from a domain-specific KB and provide cohesive response
  - Interact with KB

- **Non-task oriented dialogue systems**
  - Forum question answering, chit chatting and etc.
  - Provide informative and cohesive response
  - All the domain knowledge is embedded in raw corpus
  - Trained on mass corpus(up to millions of dialogue turns)

Issues vary for various paradigms



From Minlie Huang

Task-oriented dialogue systems

- Help users to accomplish some predefined goal/task
  - Hotel booking
  - Restaurant reservation

End-to-end method

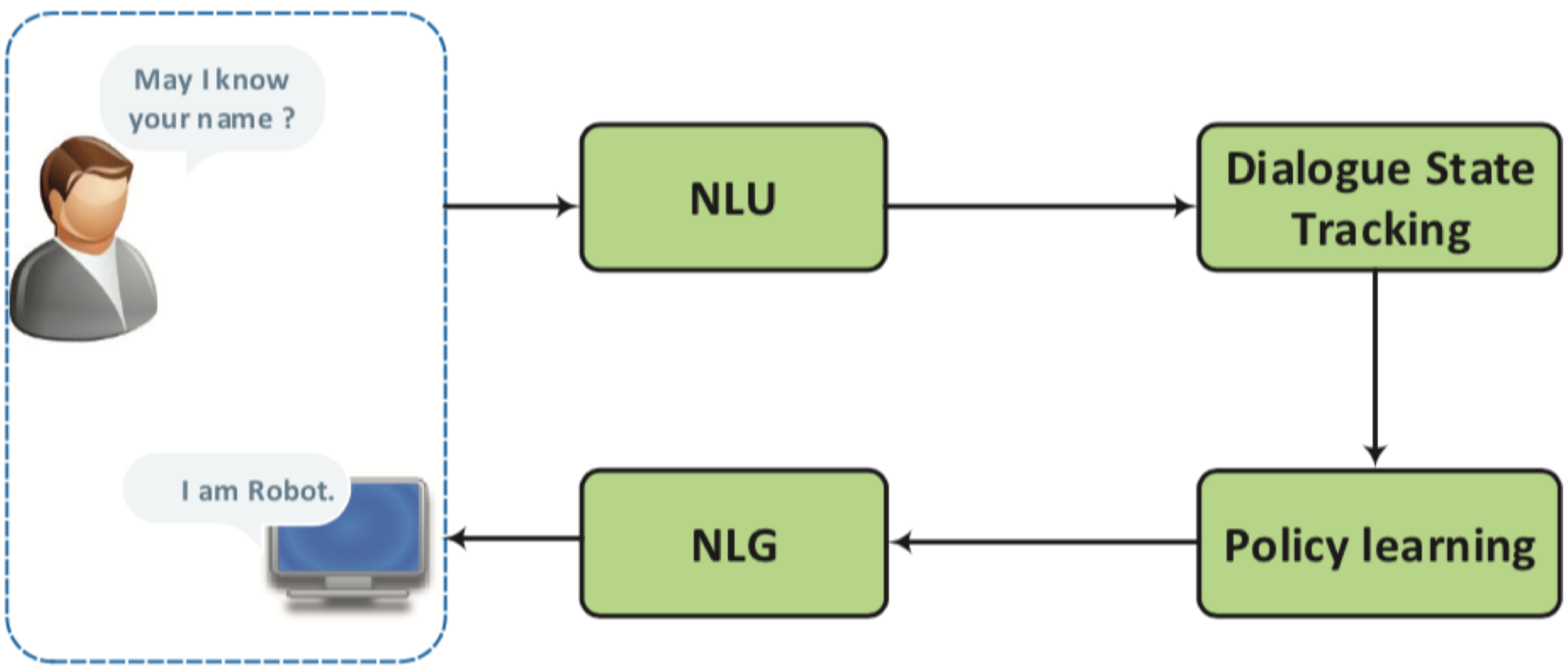
Pipeline method

$$\hat{Y} = \underset{Y}{argmax}\ P(Y|C, X)$$

- C ---context
- X ---current input
- Y ---desired output

Pipeline methods

- Understand user intention, update the dialogue state, select an appropriate system action, and finally transform it into a naturally-sounding response.



End-to-end dialogue methods

Pipeline methods have some problems

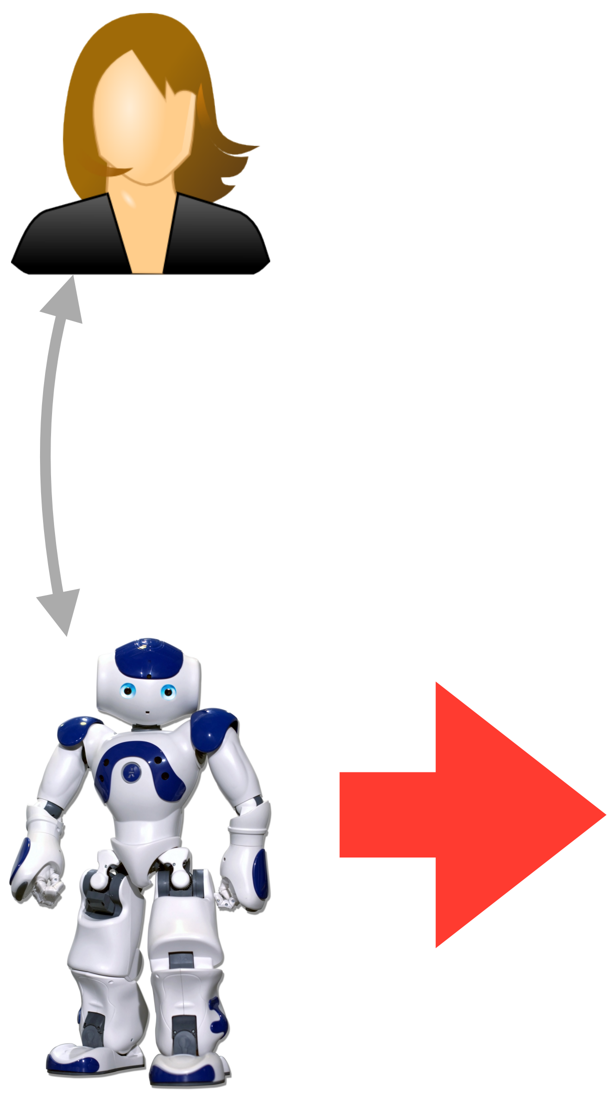
- Hard to propagate the supervision signal to each components
- Once the task is changed, all components need to be trained from the scratch.

Due to the recent development of end-to-end neural network models, there are many works trying to build end-to-end task oriented dialogue systems

End-to-end dialogue methods

- The development of end-to-end models are driven by neural network methods
  - Since all components are differentiable, the whole system becomes a larger differentiable system that can be optimized by back-propagation
- Supervised, semi-supervised, and reinforcement learning methods are utilized to build end-to-end models

Solutions for dialogue systems



- Retrieval-based dialogue systems
- Dialogue generation models

IR-based dialogue models

A big conversation corpus

A: How old are you
B: I am eight

A: What's your name ?
B: I am john

A: How do you like CS224n?
B: I cannot hate it more.

A: How do you like Jiwei ?
B: He's such a Jerk !!!!!

An new input :

What's your age ?

IR-based dialogue models

A big conversation corpus

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A: What's your name ?
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A: How do you like CS224n?
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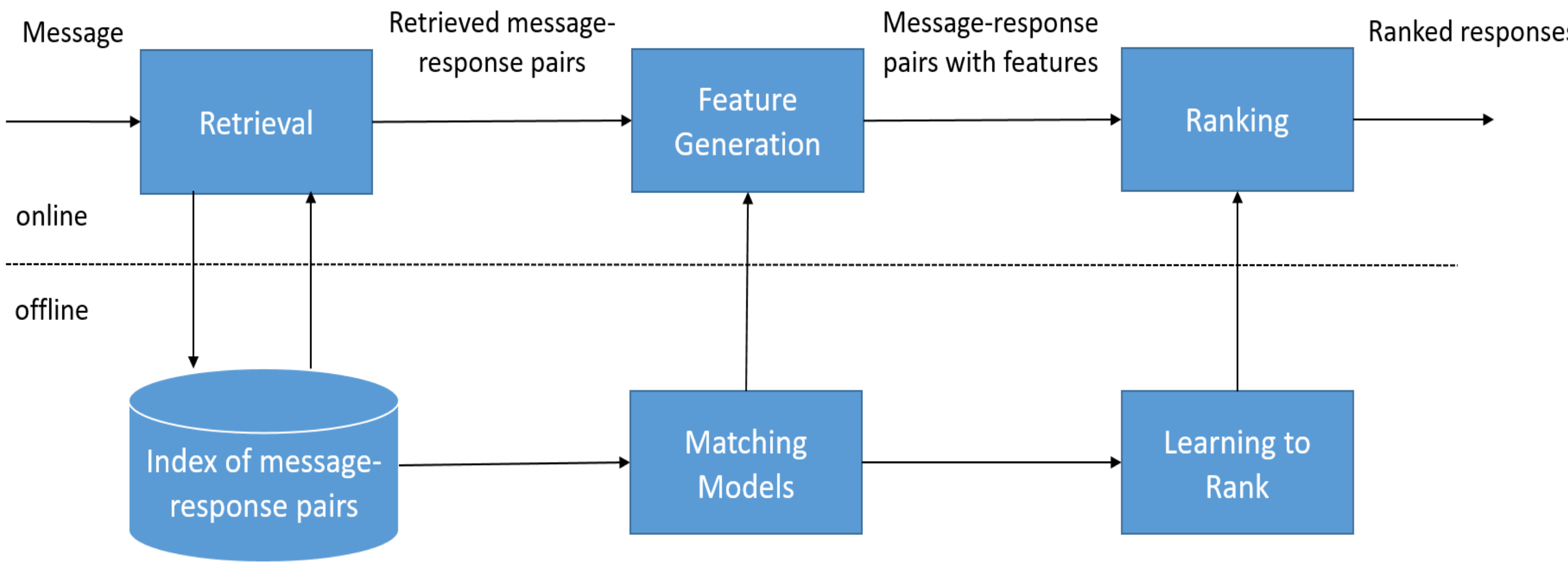
An new input :

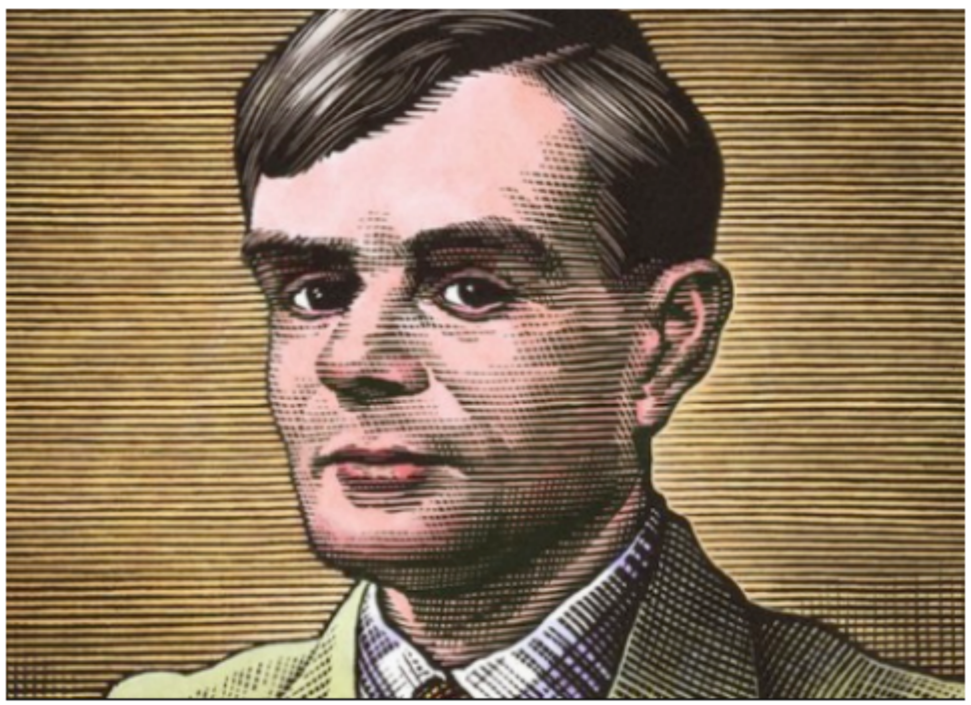
What's your age ?

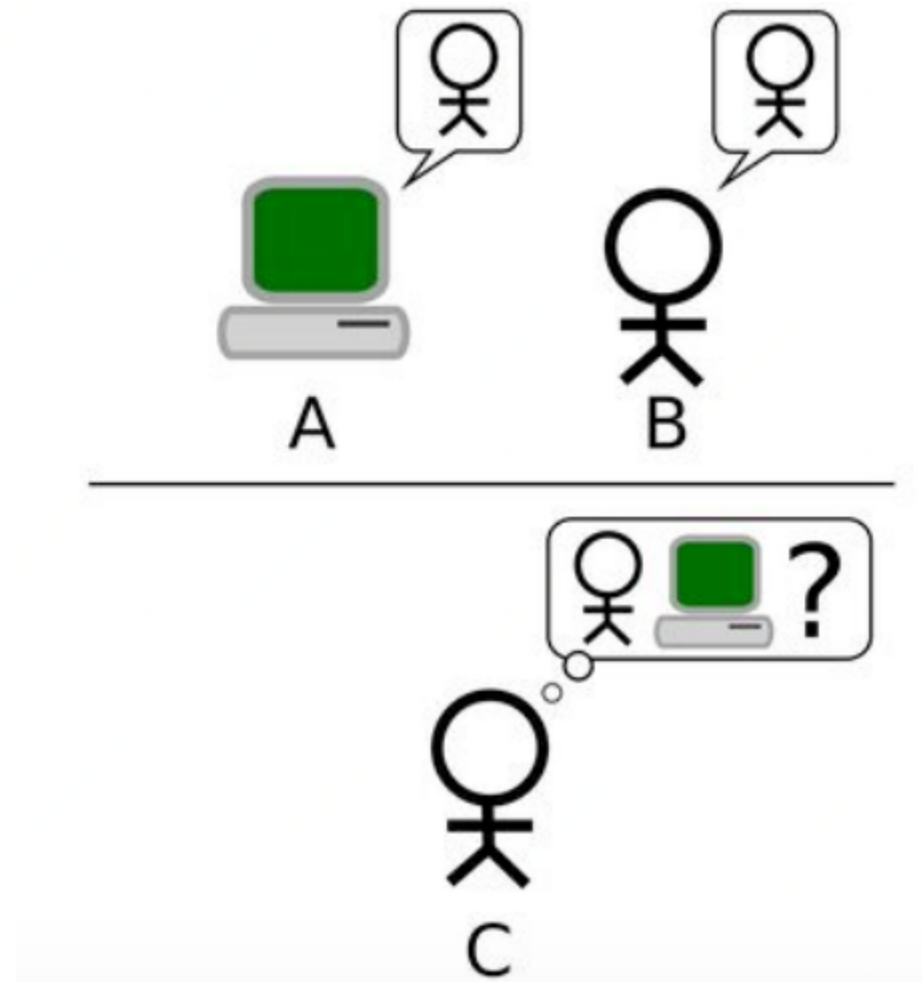
I am eight.

IR-based dialogue models



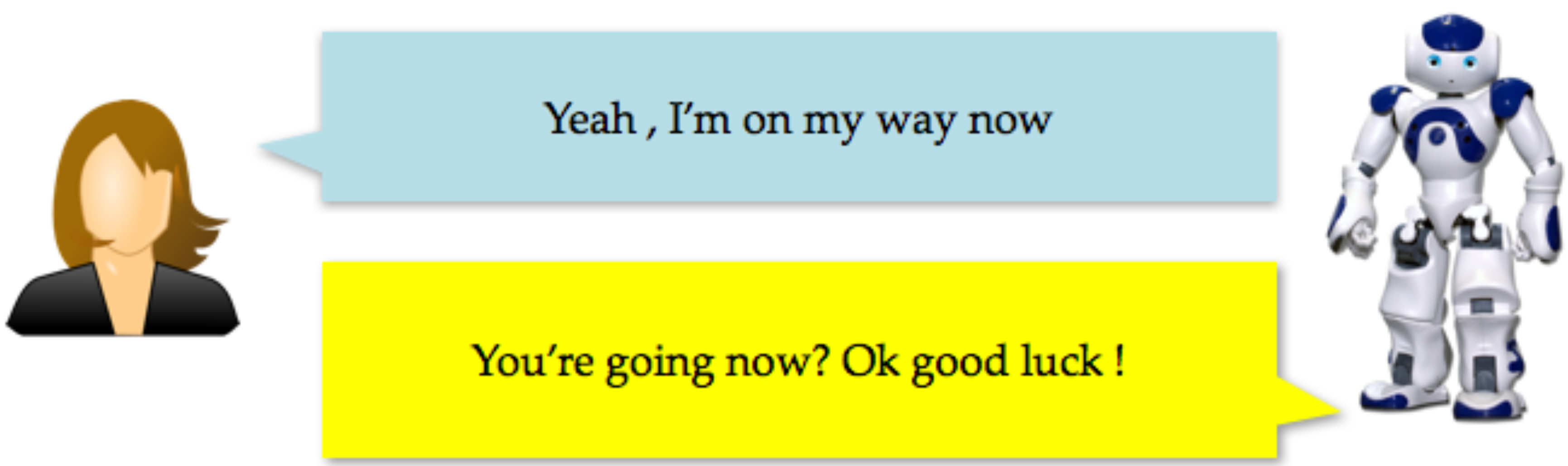
Dialogue generation 对话生成技术





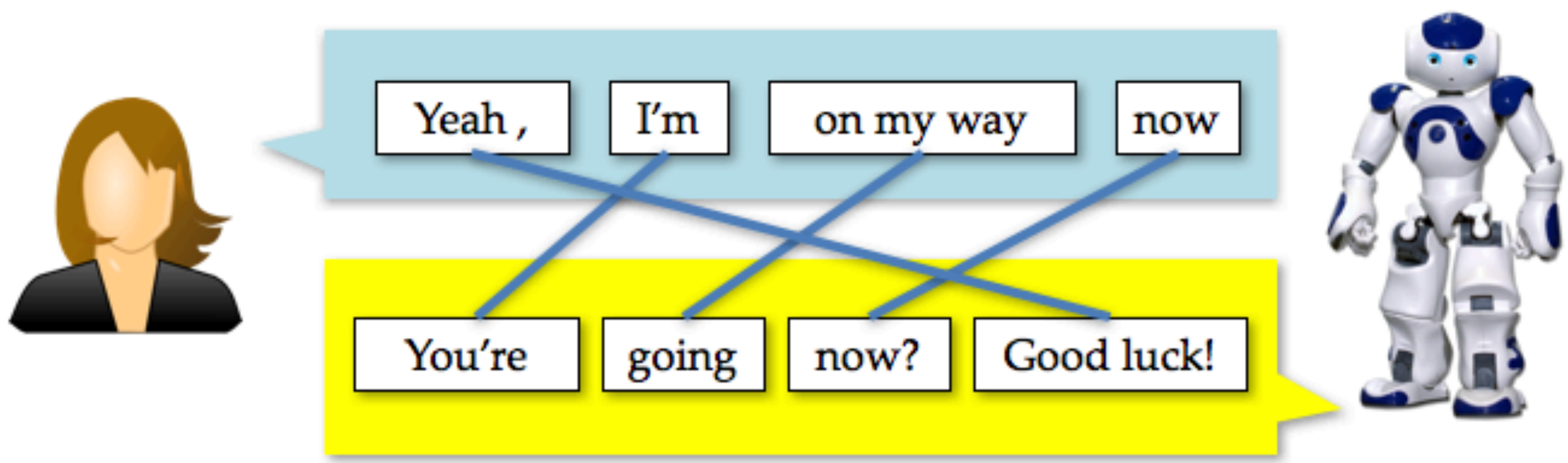
Illuminated from statistical machine translation

- Response Generation as Statistical Machine Translation (Ritter et al., 2010)



From Michel Galley

Dialogue generation vs. SMT

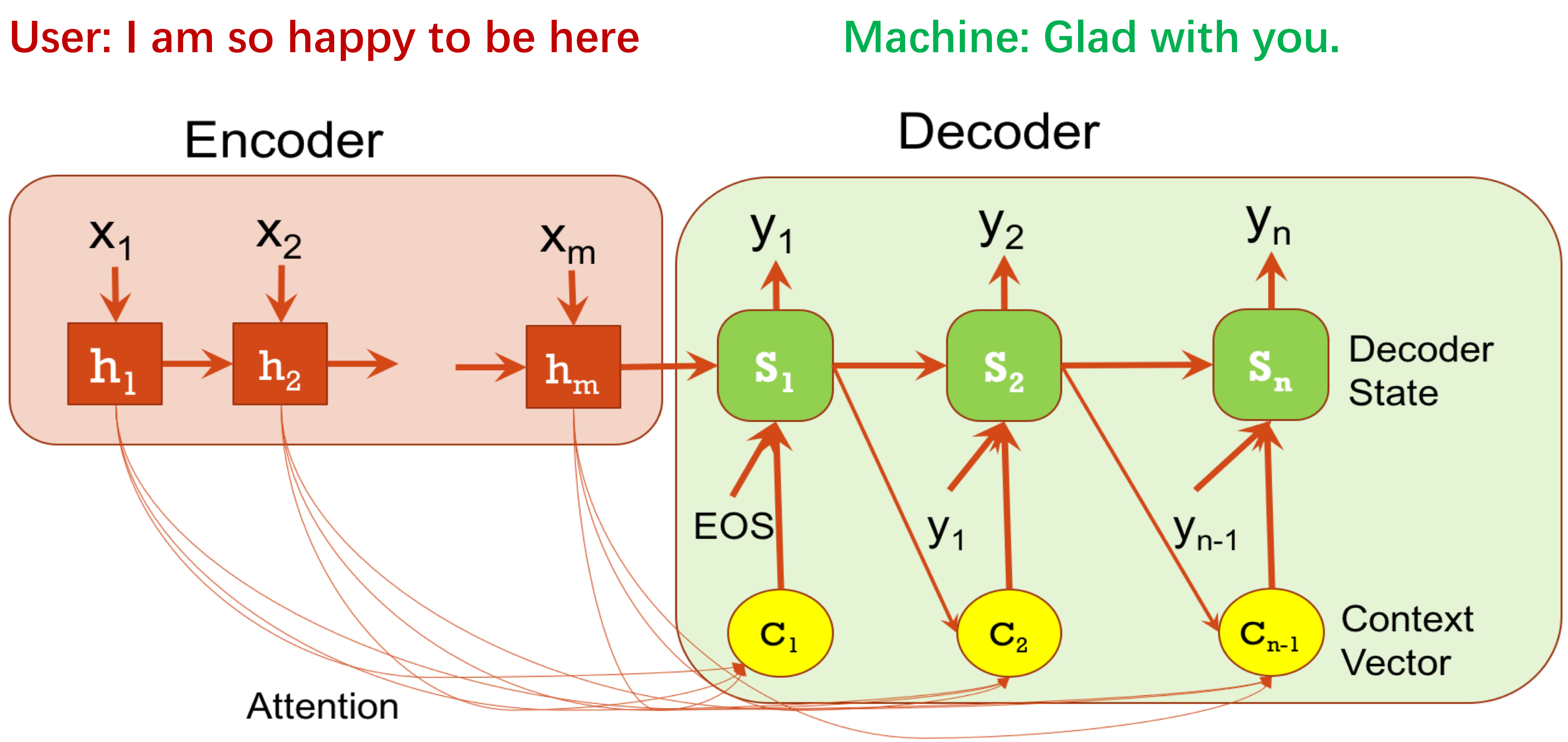


Exploit high-frequency patterns with phrase-based MT

"I am" → "you are"   "sick" → "get better"   "lovely!" → "thanks!"

From Michel Galley

Dialogue generation



Dialogue generation

- **Objective**: $\hat{Y} = \underset{Y \in V^N}{\operatorname{argmax}} \; P(Y|C, X)$
- **Decomposition**: $P(Y|C, X) = \prod_{t=1}^{M} P(y_t|y_{<t}, C, X)$
- **Recurrence function**: $s_t = f(s_{t-1}, y_{t-1}, C, X)$
- **Generation distribution**: $P(y_t|y_{<t}, C, X) = g(s_t)$
- Frameworks: **Seq2Seq, CVAE, GAN**

Sample results from Google's paper

Input	Response
what is moral ?	what empowered humanity
what is immoral ?	the fact that you have a child .
what is the purpose of existence ?	to find out what happens when we get to the planet earth .
what do you think about bill gates ?	He's a good man

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从语言模型到对话生成

- 语言模型
  - 给定一句话$\mathbf{e}$，由m个词组成：$w_1, w_2, \dots, w_m$。将这句话视为一个由m个词的序列
  - 语言模型评估这个词序列是一句话的可能性大小，即$P(\mathbf{e}) = P(w_1, w_2, \dots, w_m)$

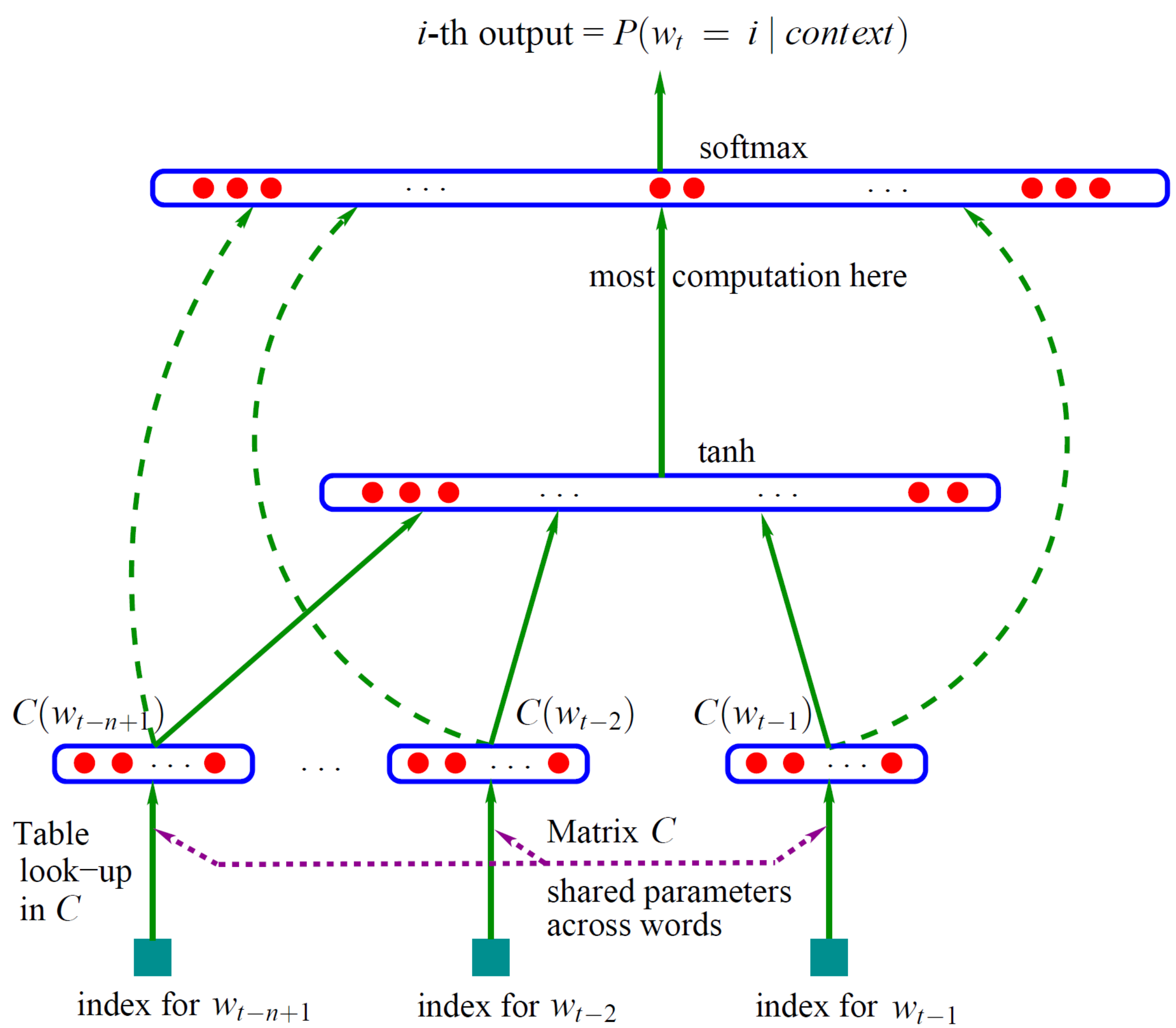
  - 如何计算这个词序列的概率呢？
  - 引入马尔科夫假设，假设每一个词$w_i (1 \le i \le m)$ 出现的概率将取决于前面$i-1$个词
  - $P(\mathbf{e}) = P(w_1, w_2, \dots, w_m) = p(w_1) * p(w_2|w_1) * p(w_3|w_1, w_2) * \cdots p(w_n|w_1, w_2, \dots, w_{m-1})$

  - 进一步地，如果假设任意一个词$p(w_i)$只取决于前面$n-1$个词，即得到$\boldsymbol{n}$**元语言模型**。$n = 3$时,
    $P(\mathbf{e}) = P(w_1, w_2, \dots, w_m)$
    $= p(w_1) * p(w_2|w_1) * p(w_3|w_1, w_2) * \cdots p(w_m|w_{m-2}, w_{m-1})$

从语言模型到对话生成

- 语言模型
  - 举个例子
  - P(我 爱 京东) = P(我，爱，京东)
  - = P(我) $*$ P(爱|我) $*$ P(京东|我，爱)

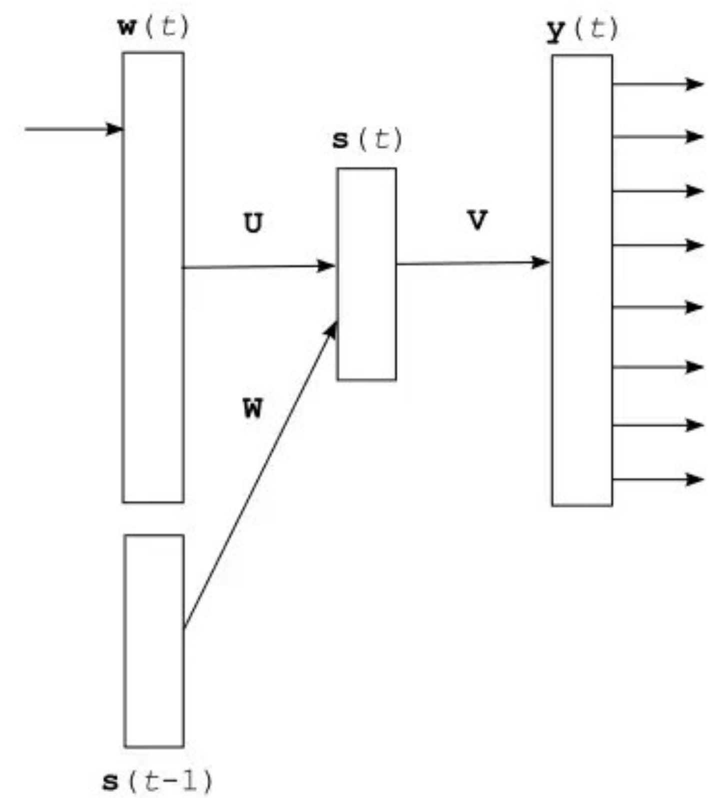
  - 怎么计算呢？
  - 神经网络建模语言模型
    - 前馈神经网络[Bengio et al, 2003]



从语言模型到对话生成

- 语言模型
  - 举个例子
  - P(我 爱 京东) = P(我，爱，京东)
  - $= P$(我) $*$ P(爱|我) $*$ P(京东|我，爱)

  - 怎么计算呢？
  - 神经网络建模语言模型
    - 前馈神经网络[Bengio et al, 2003]
    - 循环神经网络[Mikolov, 2013]



从语言模型到对话生成

- 条件化语言建模
  - $P(\mathbf{e}|\mathbf{c}) = P(\mathbf{e}) = p(w_1, w_2, \ldots, w_m|\mathbf{c})$
  - $= p(w_1|\mathbf{c}) * p(w_2|w_1, \mathbf{c}) * p(w_3|w_1, w_2, \mathbf{c}) * \cdots, p\left(w_n \middle| w_1, w_2, \ldots, w_{m,} \mathbf{c}\right)$
  - 应用实例：
    - **c**可以是某个词
    - **c**也可以是某个主题、情感
    - 总之，**c**可以是任何一个自定义的条件

- 序列到序列的语言建模
  - 典型应用（机器翻译）
  - $P(\mathbf{e}|\mathbf{f})$ 例如 $P(I\ love\ JD$ | 我 爱 京东)
    - 此处的**f**是源语言句子，**e**是目标语言句子。**f**等价于上面的条件
    - 为什么叫序列到序列的模型？
    - 如何将**f**转化成**c**?

从语言模型到对话生成

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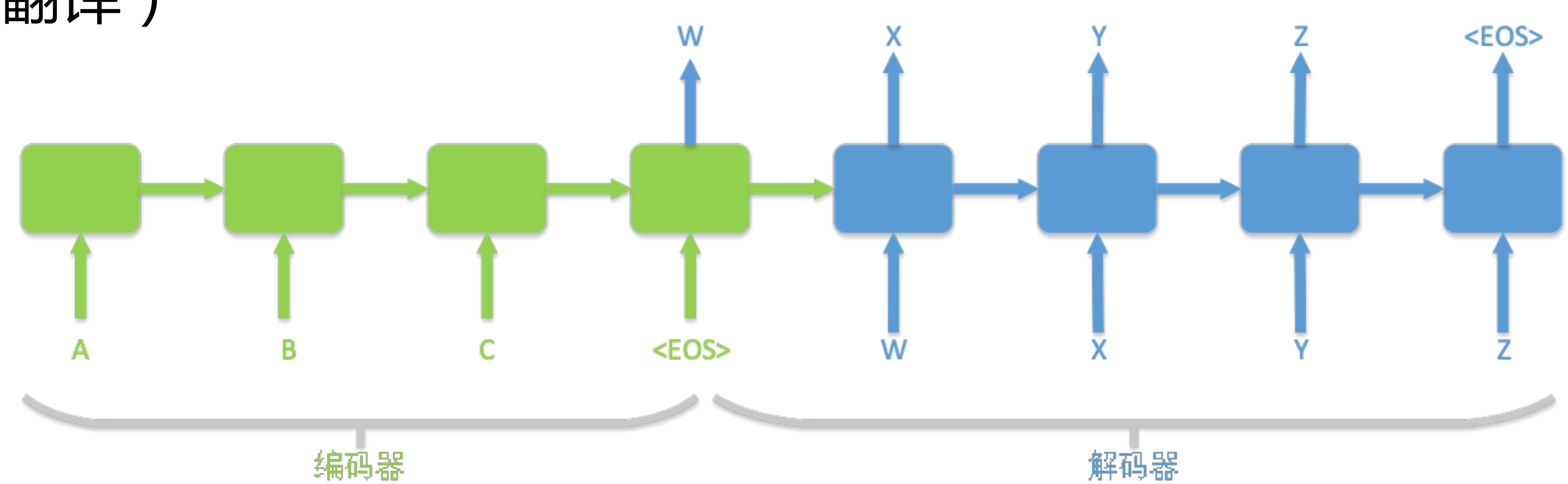
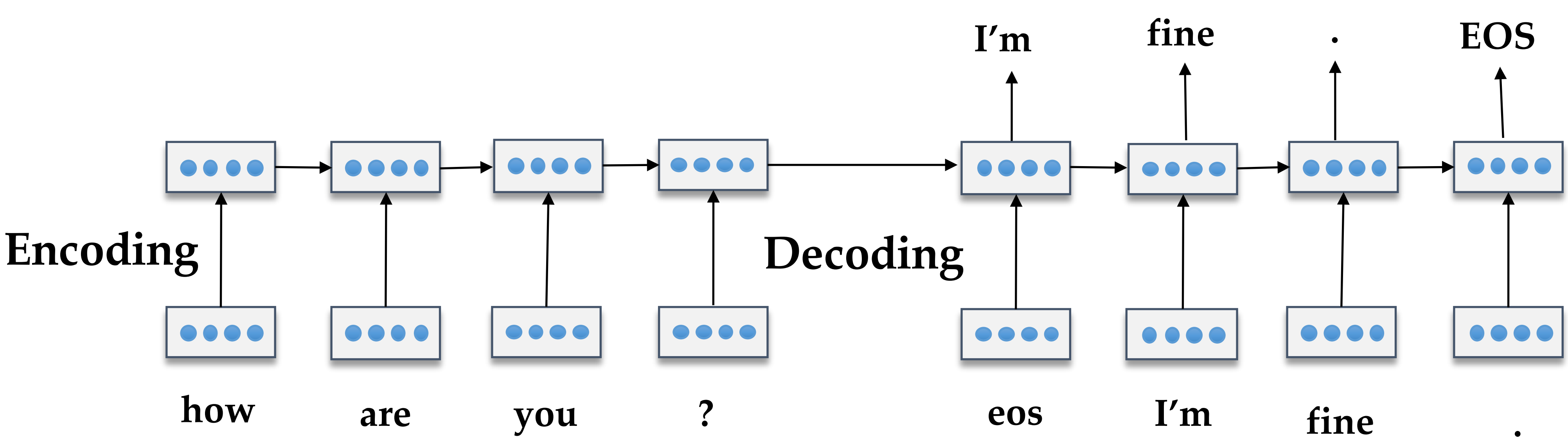
  - 典型应用（机器翻译）
  - $P(\mathbf{e}|\mathbf{f})$



Sequence-to-sequence models

$$\text{Loss} = -\log p(\text{target}|\text{source})$$

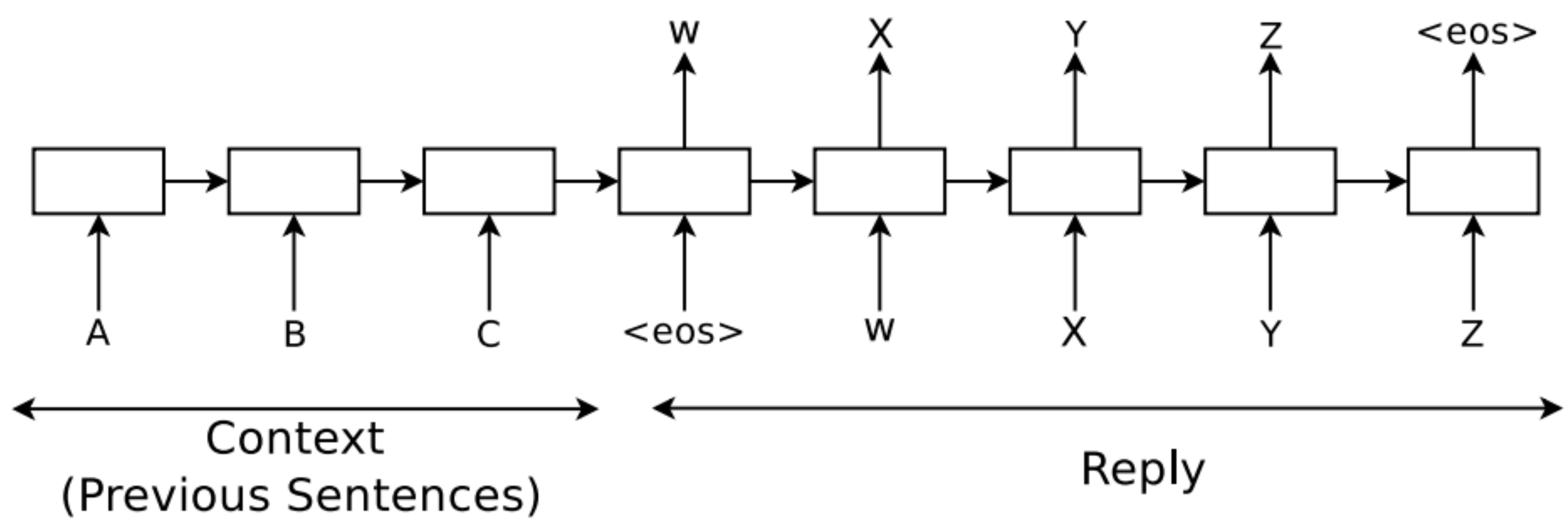
Source : Input Messages
Target : Responses



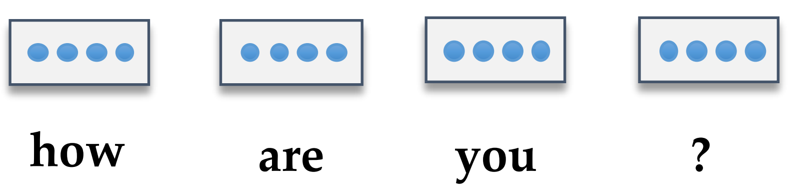
(Sutskever et al., 2014; Jean et al., 2014; Luong et al., 2015)

从语言模型到对话生成

- 对话生成
  - 序列到序列 (sequence-to-sequence) 的模型的应用之一
  - 给定一条消息$\mathbf{m}$，生成回复$\mathbf{r}$,记为$P(\mathbf{r}|\mathbf{m})$ 。
  - 举例：P (我叫机器人 | 你叫什么名字？)
  - 等价变种1



Sequence-to-sequence models for generation



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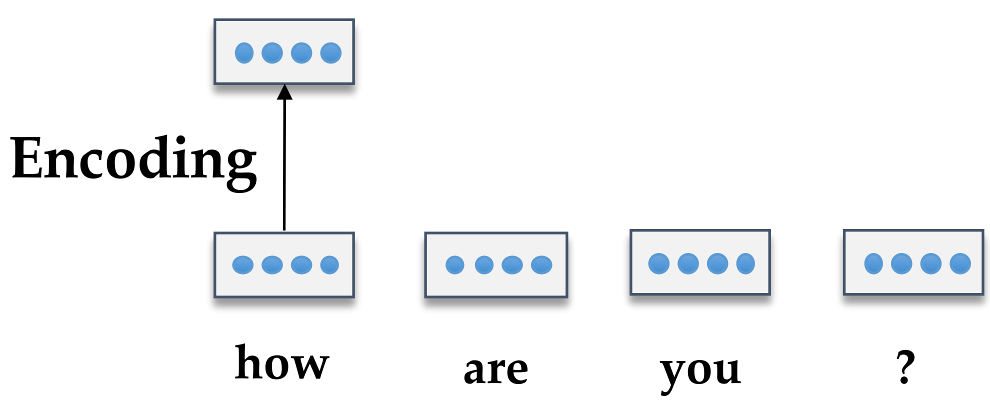

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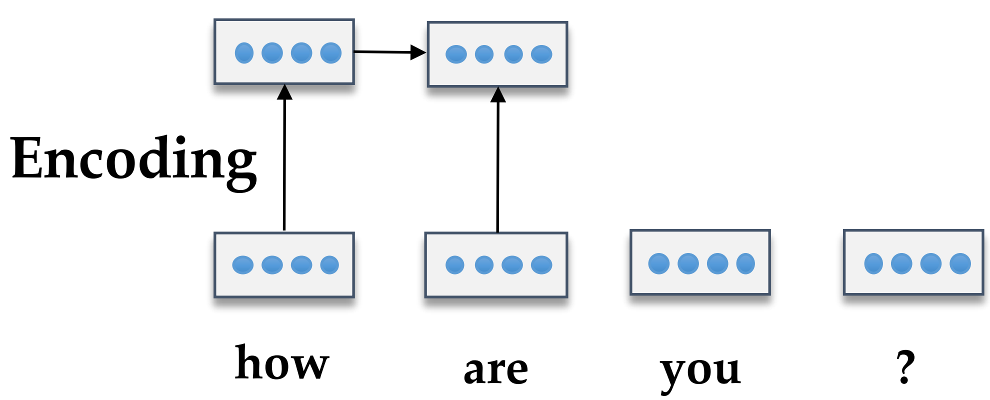

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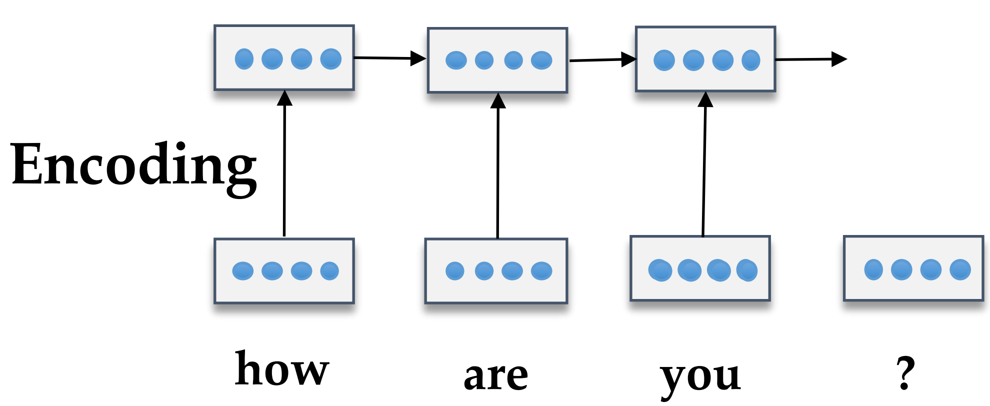

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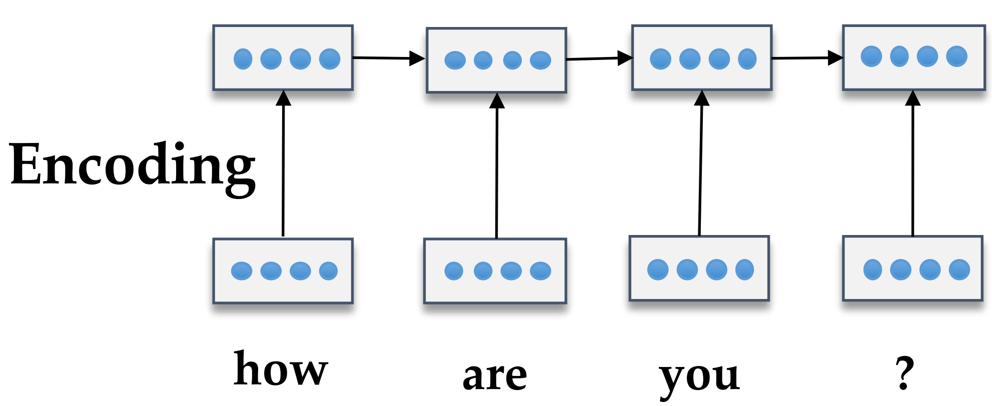

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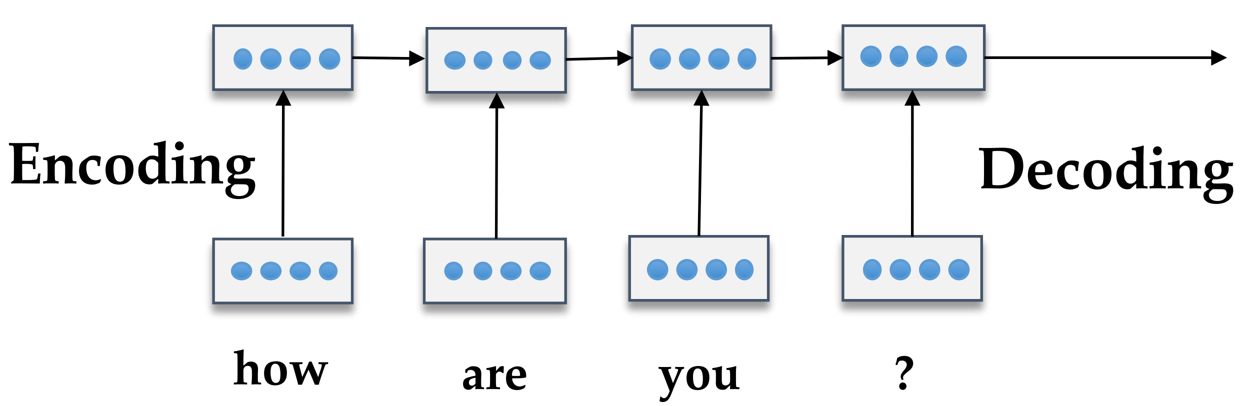

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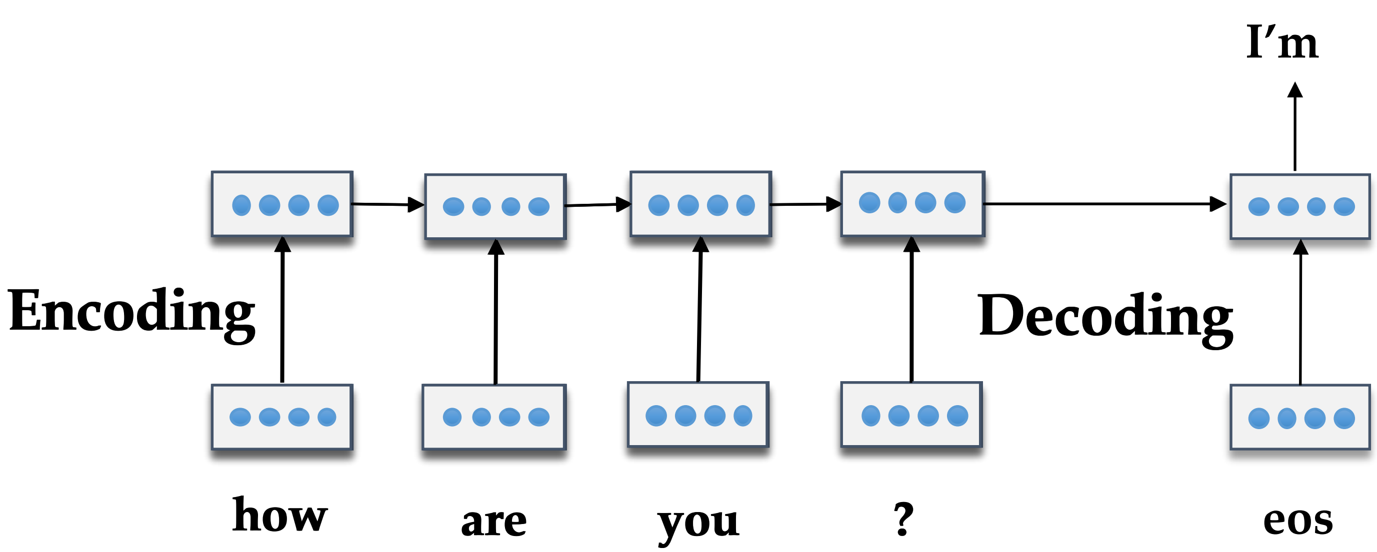

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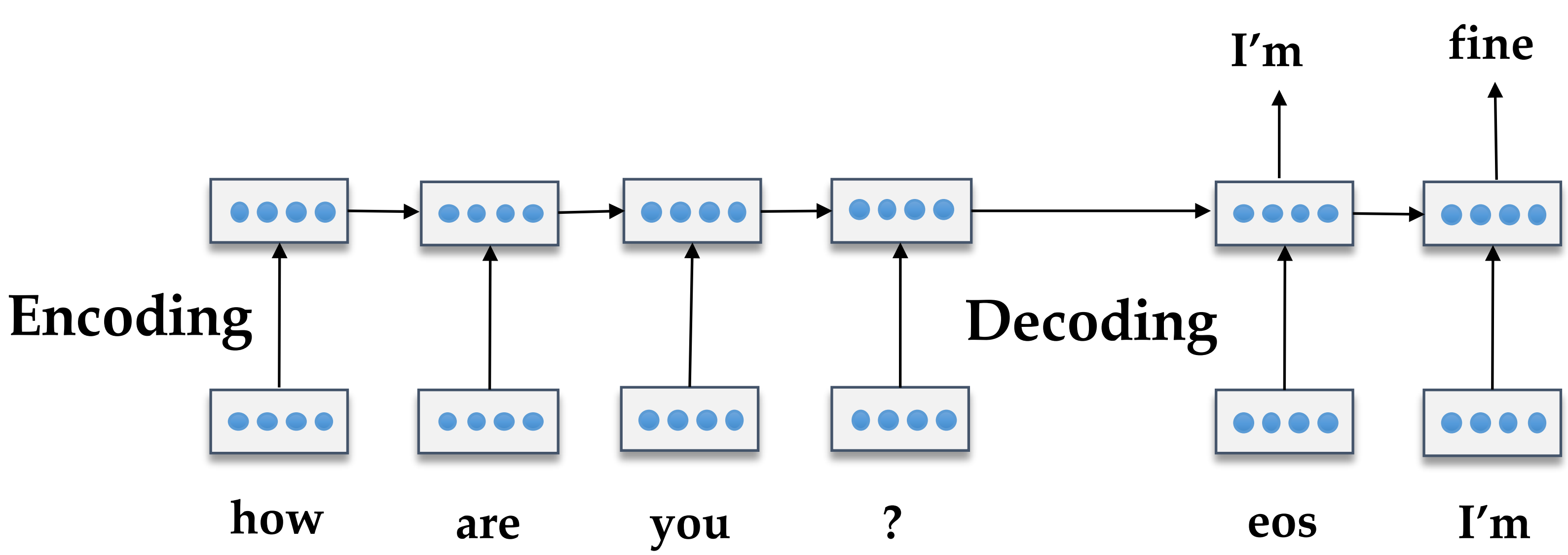

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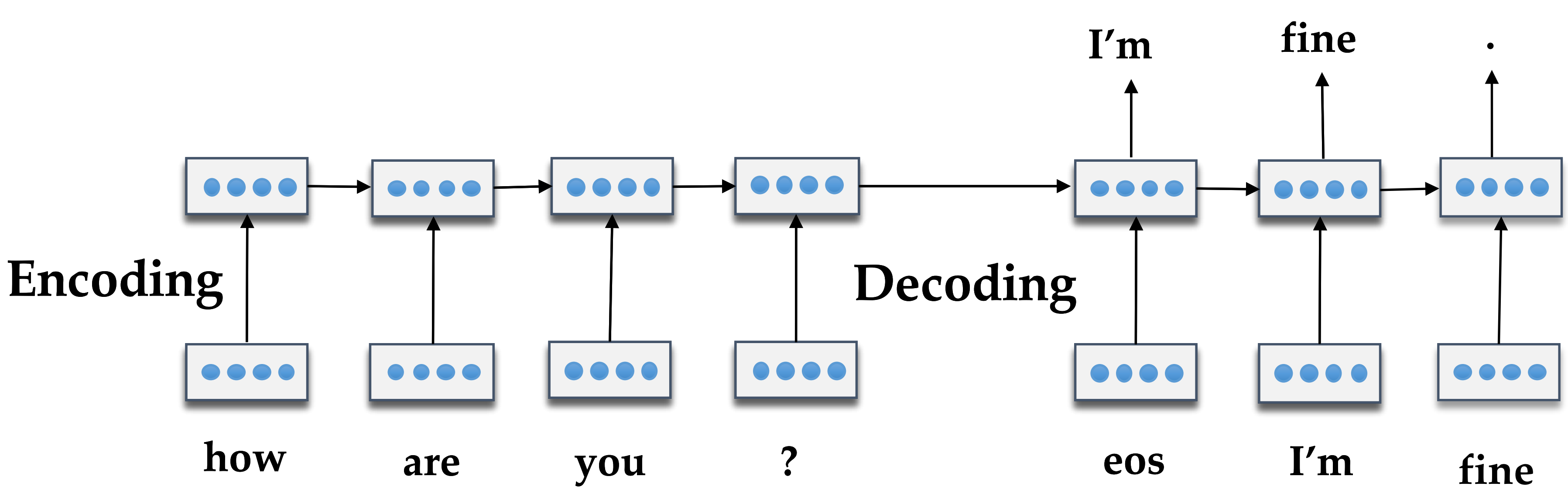

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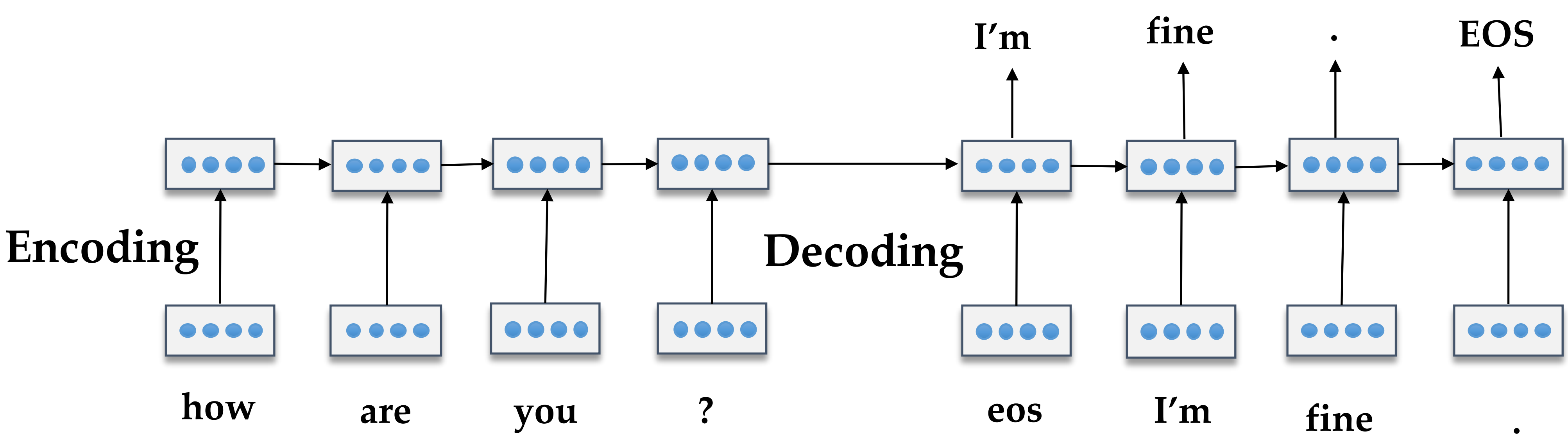

从语言模型到对话生成

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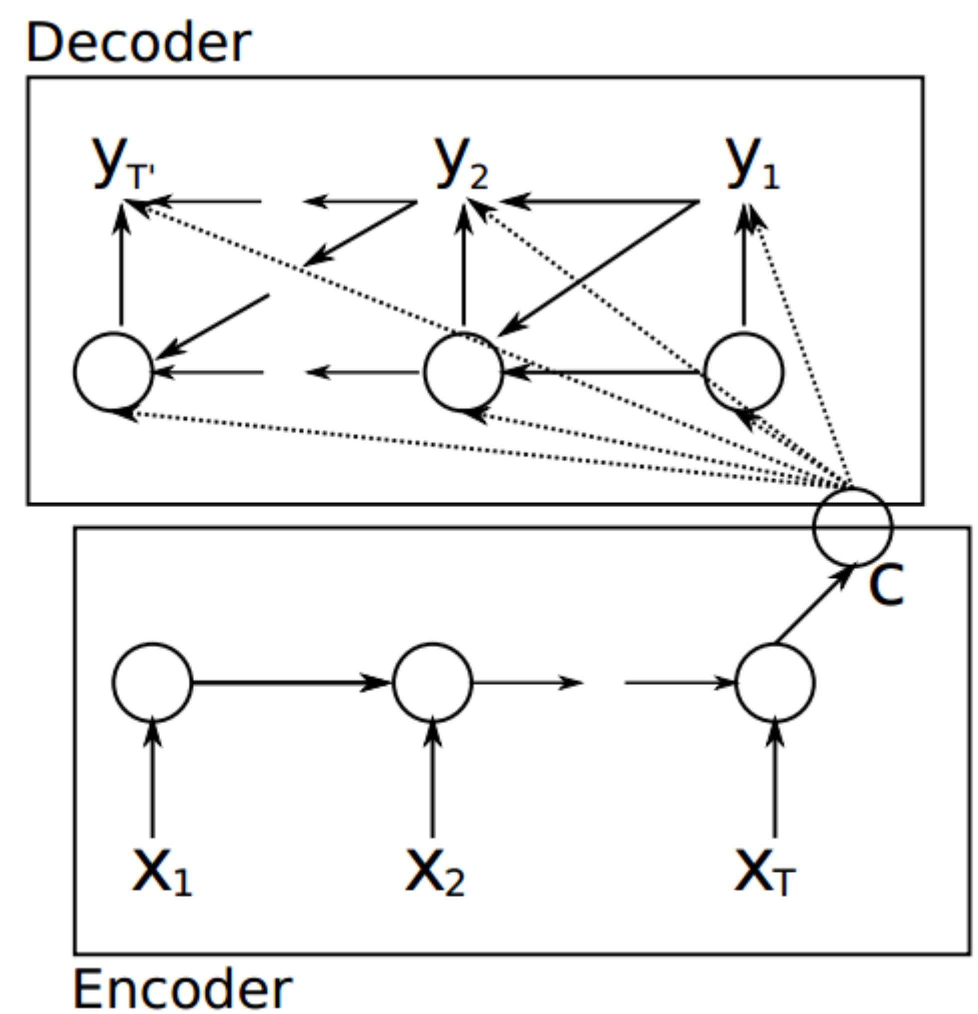
  - 等价变种2



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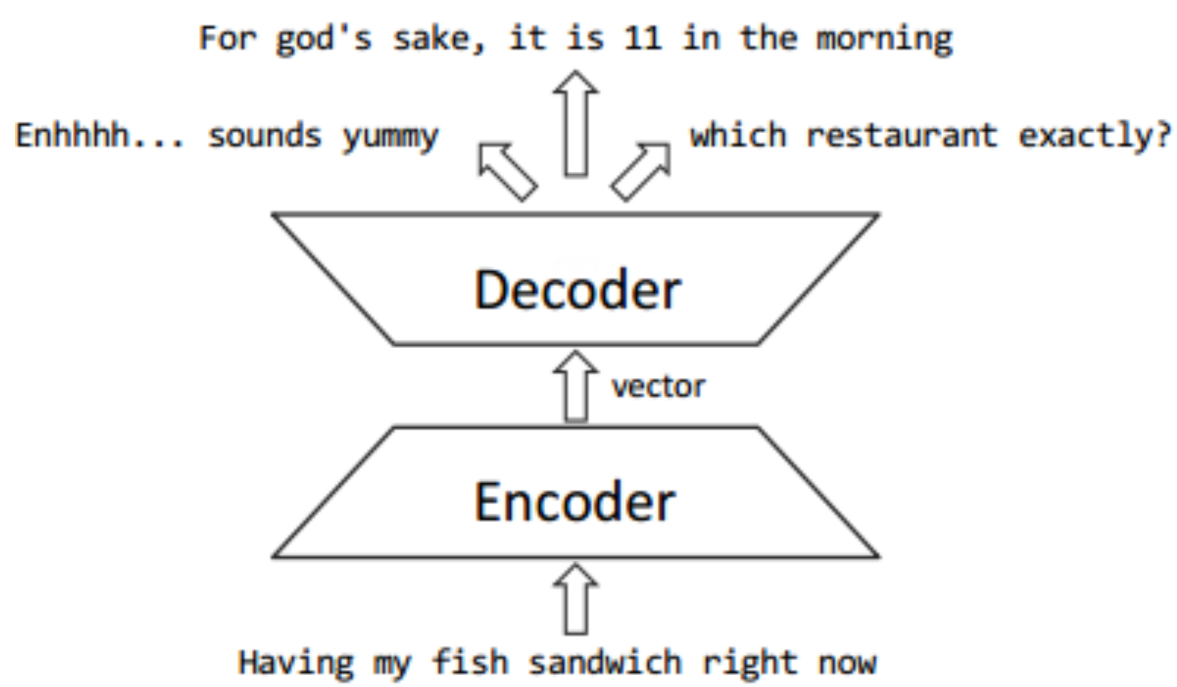
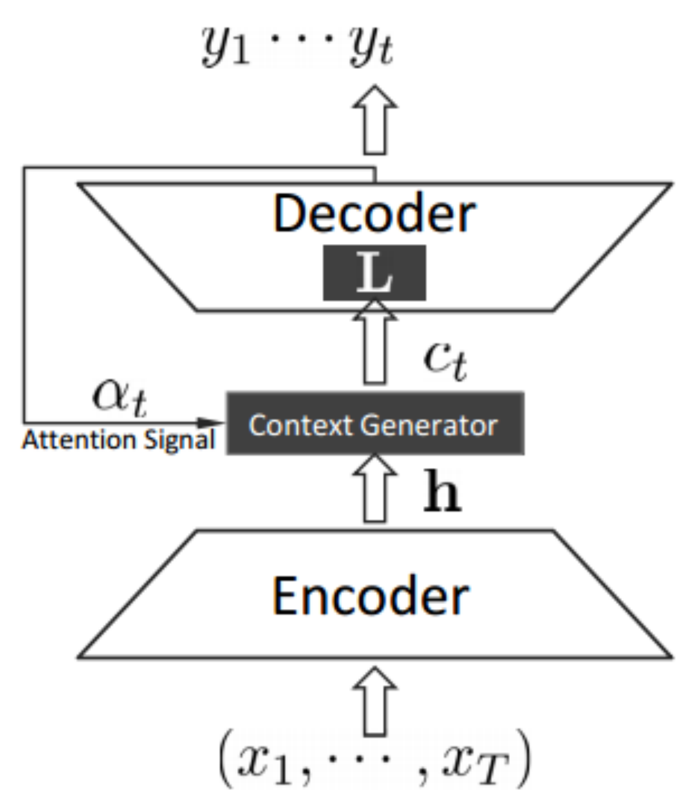
  - 等价变种3





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对话生成的研究热点

- Dialogue Context 对话文本使用方法
- Response Diversity 回复多样性
- Topic and Personality 主题与个性化
- Outside Knowledge Base 外部知识库
- Interactive Dialogue learning 交互式对话学习
- Evaluation 对话评估

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对话文本使用方法

- 问题描述：
  - 相对于单轮对话，多轮对话更是常态，如何更好地利用上文信息?
  - e.g., 今天看了《芳华》感觉怎么样? 这部电影非常精彩。。。

解决方案：
将所有对话历史变成embedding
如word embedding, phrase embedding

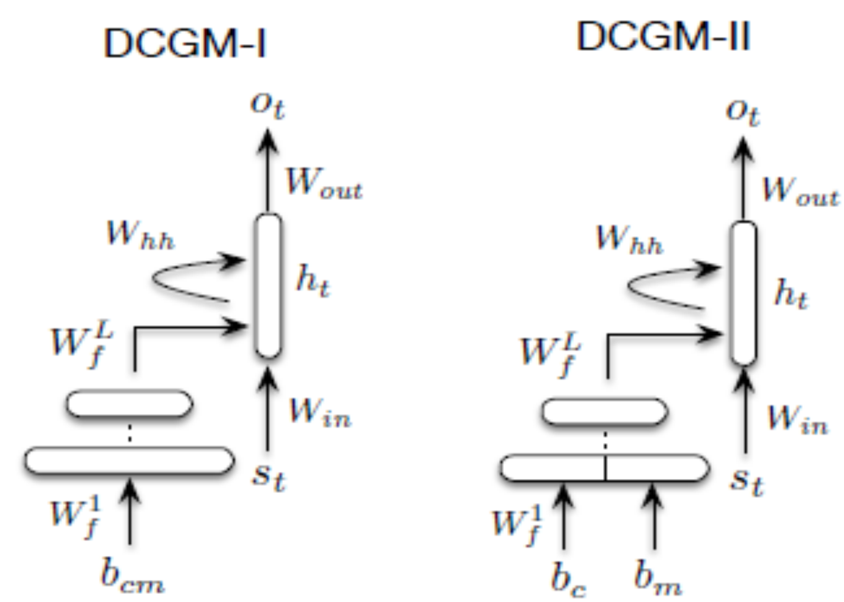
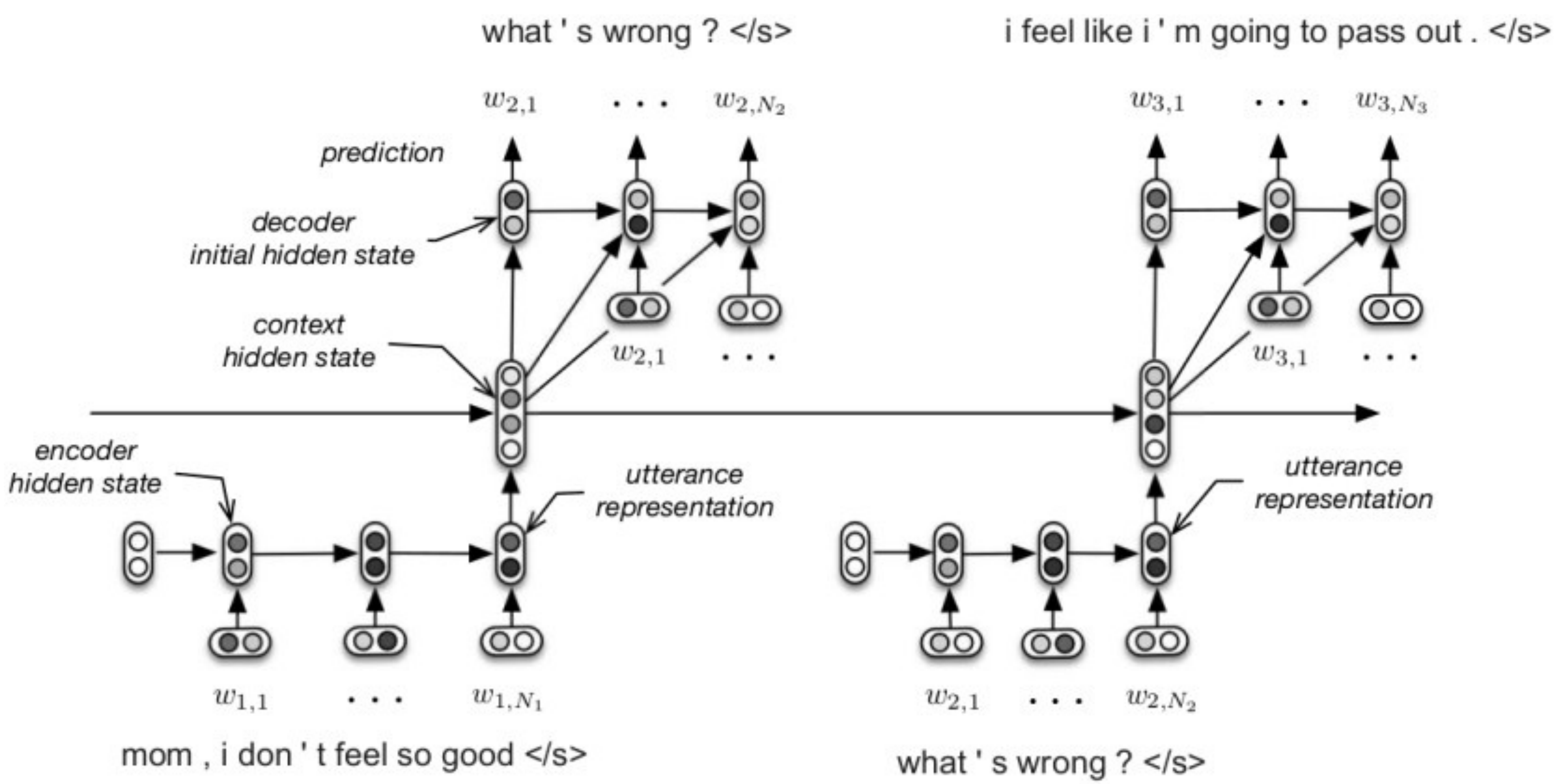


Figure 3: Compact representations of DCGM-I (left) and DCGM-II (right). The decoder RLM receives a bias from the context encoder. In DCGM-I, we encode the bag-of-words representation of both c and m in a single vector b_{cm}. In DCGM-II, we concatenate the representations b_c and b_m on the first layer to preserve order information.

Sordoni et al., A neural network approach to context-sensitive generation of conversational responses. NAACL 2015

对话文本使用方法



Serban et al., Building end-to-end dialogue systems using generative hierarchical neural network models, AAAI 2016

对话文本使用方法

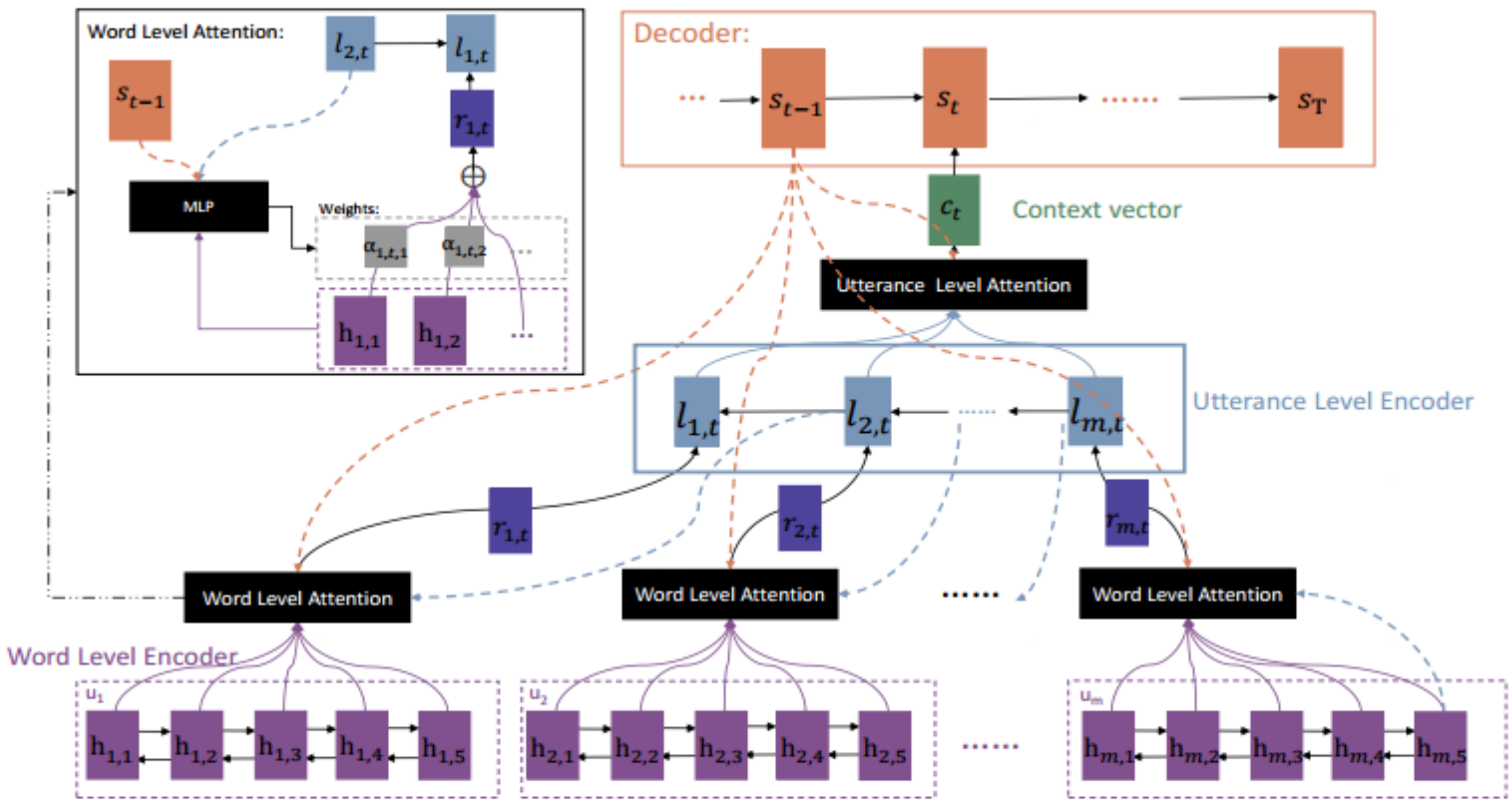


Figure 2: Hierarchical Recurrent Attention Network

Xing et al., Hierarchical recurrent attention network for response generation, AAAI 2018.

对话文本使用方法

- 问题描述：
  - 生成回复时，可能对话已经进行了多轮，如何更好地利用上文信息?
- 解决方案：
  - 将所有对话历史变成embedding，如word embedding, phrase embedding
  - 层次化网络，按对话轮数分层
  - 在层次化网络的基础上增加attention机制，以区分对话历史的轻重
  - 增加了历史信息后的效果
  - 生成的回复质量更好
  - 回复的更长、更有意义、更多样

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- Evaluation 对话评估

Response Diversity 回复多样性

- 问题描述：
    - 对话生成经常会产生无意义的，泛泛而谈（general & dull）的安全回复。比如，“哈哈”，“我不知道”
- 为什么？
    - 无意义的回复千篇一律，有价值的回复各式各样
    - 同样是基于序列到序列的模型，这也是对话生成比机器翻译难得多的重要原因所在
- 解决方案：
    - 改变目标函数
    - MLE $P(Y|X)$ VS $P(X|Y)$
      不仅衡量文本与回复之间的相关性，也考虑衡量回复与文本的相关性
    - 无意义的回复，可以用来应付千言万语
    - 有意义的回复，往往适用于特定的场景

Response Diversity 回复多样性

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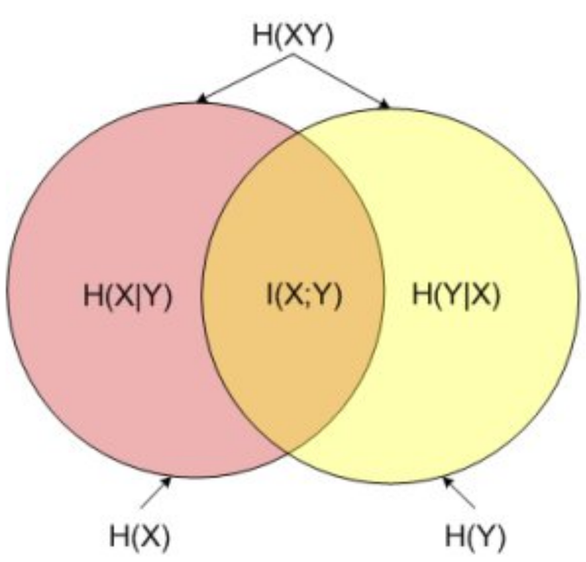
  - 对话生成经常会产生无意义的，泛泛而谈（general & dull）的安全回复比如，“哈哈”，“我不知道”
- 为什么?
  - 无意义的回复千篇一律，有价值的回复各式各样
- 解决方案：
  - 改变目标函数
  - 引入互信息(Mutual Information)

互信息可以用来衡量文本和回复的相互依存关系。无意义的回复与文本的相关性低。



I(X;Y)=H(X)-H(X|Y)

I(X;Y)=H(Y)-H(Y|X)

I(X;Y)=H(X)+H(Y)-H(XY)

Response Diversity 回复多样性

- 问题描述：
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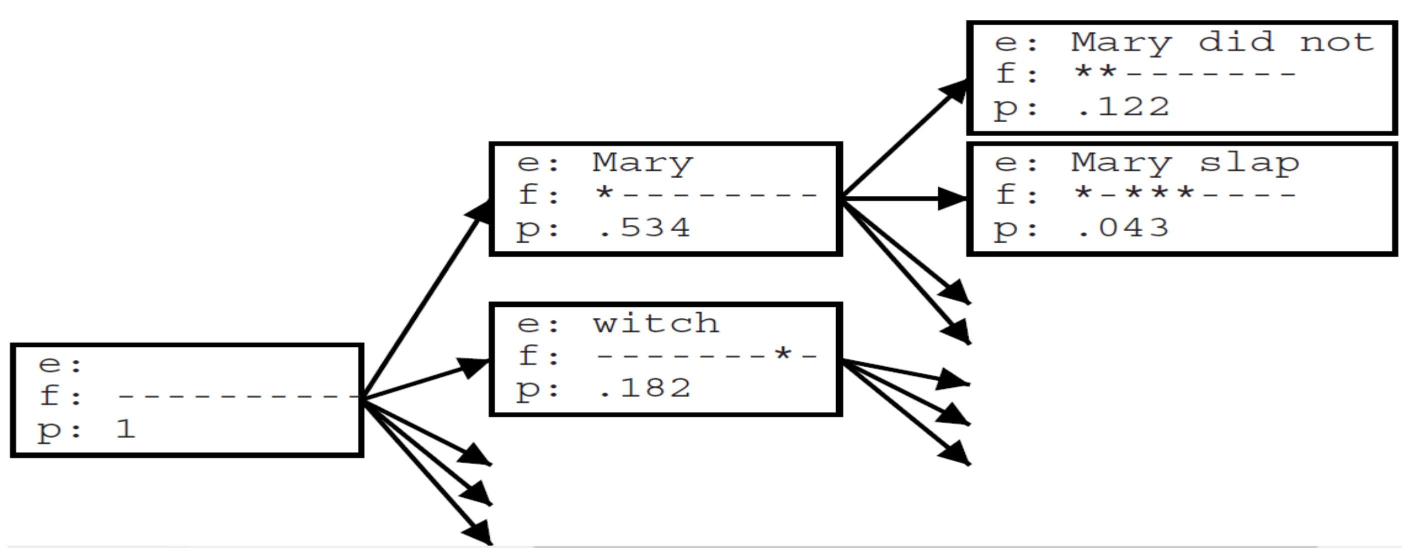
- 为什么?
  - 无意义的回复千篇一律，有价值的回复各式各样
- 解决方案：
  - 改变目标函数
  - 引入互信息(Mutual Information)
  - 引入引入逆文档频率（Inverse Document Frequency）
  - 改善解码过程-Beam-search 造成的冗余解码

Response Diversity 回复多样性

- Beam-search
  - 本质上类似于贪心算法，应用于解空间过大的情况，近似全局最优
  - 可以想象成一个规模巨大的树的搜索过程
  - 越是初始分数较高的候选，越有可能进入下一步search的环节
  - 而一味地对分数较高的候选进行search，实际上就损失了多样性
  - 简单地说，就是在树搜索的过程中，太关注深度而忽略了广度



Response Diversity 回复多样性

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- 为什么？
  - 无意义的回复千篇一律，有价值的回复各式各样
- 解决方案：
  - 改变目标函数
  - 改善解码过程-Beam-search 造成的冗余解码
  - 在候选的分数评估上，增加一个dissimilarity指标，越不相似的候选，分数越高
  - 增加随机性
  - 惩罚兄弟（sibling）
  - 采用全局特征重排序（re-ranking）
  - 生成时先预测关键词，如名词，再生成完整回复

对话文本使用方法

- 问题描述：
  - 对话生成经常会产生无意义的，泛泛而谈（general & dull）的安全回复比如，“哈哈”，“我不知道”
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  - 无意义的回复千篇一律，有价值的回复各式各样
- 解决方案：
  - 改变目标函数
  - 改善解码过程-Beam-search 造成的冗余解码
    - 本质上，都是在优先深度搜索的同时，兼顾广度搜索

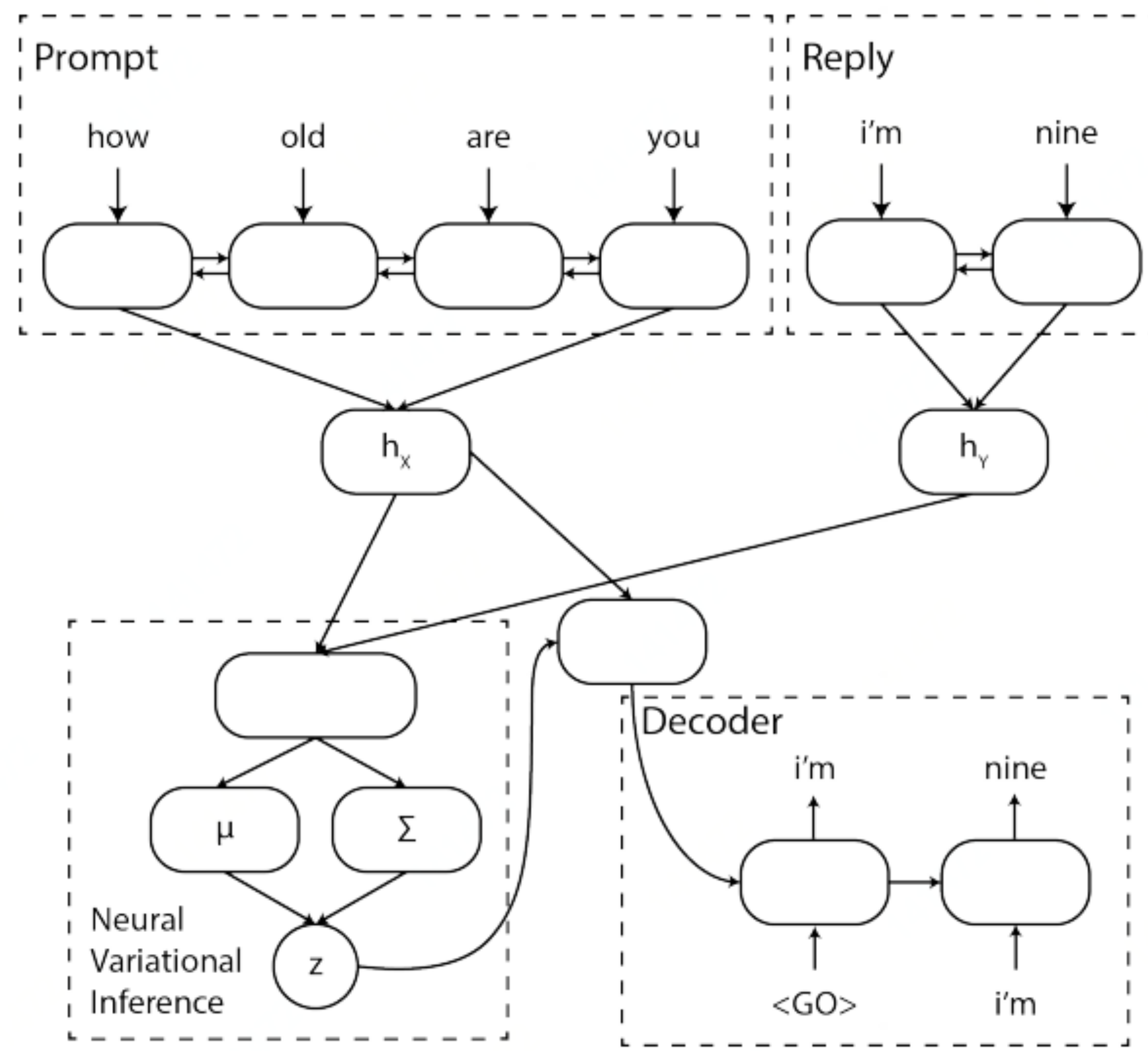
Multiresolution recurrent neural networks: An application to dialogue response generation.

对话文本使用方法

- 问题描述：
  - 对话生成经常会产生无意义的，泛泛而谈（general & dull）的安全回复比如，“哈哈”，“我不知道”
- 为什么？
  - 无意义的回复千篇一律，有价值的回复各式各样
- 解决方案：
  - 改变目标函数
  - 改善解码过程-Beam-search 造成的冗余解码
  - 引入随机隐变量（latent variable）
    - 建模文本和回复之间的通用隐含属性$P(Y|\mathbf{z}, X)$

对话文本使用方法

- 问题描述：
  - 对话生成经常会产生无意义的，泛泛而谈（general & dull）的安全回复比如，“哈哈”，“我不知道”
- 为什么?
  - 无意义的回复千篇一律，有价值的回复各式
- 解决方案：
  - 改变目标函数
  - 改善解码过程-Beam-search 造成的冗余解码
  - 引入随机隐变量（latent variable）
    - 在普通序列到序列网络中引入



Serban et al., Multi-resolution recurrent neural networks: An application to dialogue response generation, AAAI 2017.

对话文本使用方法

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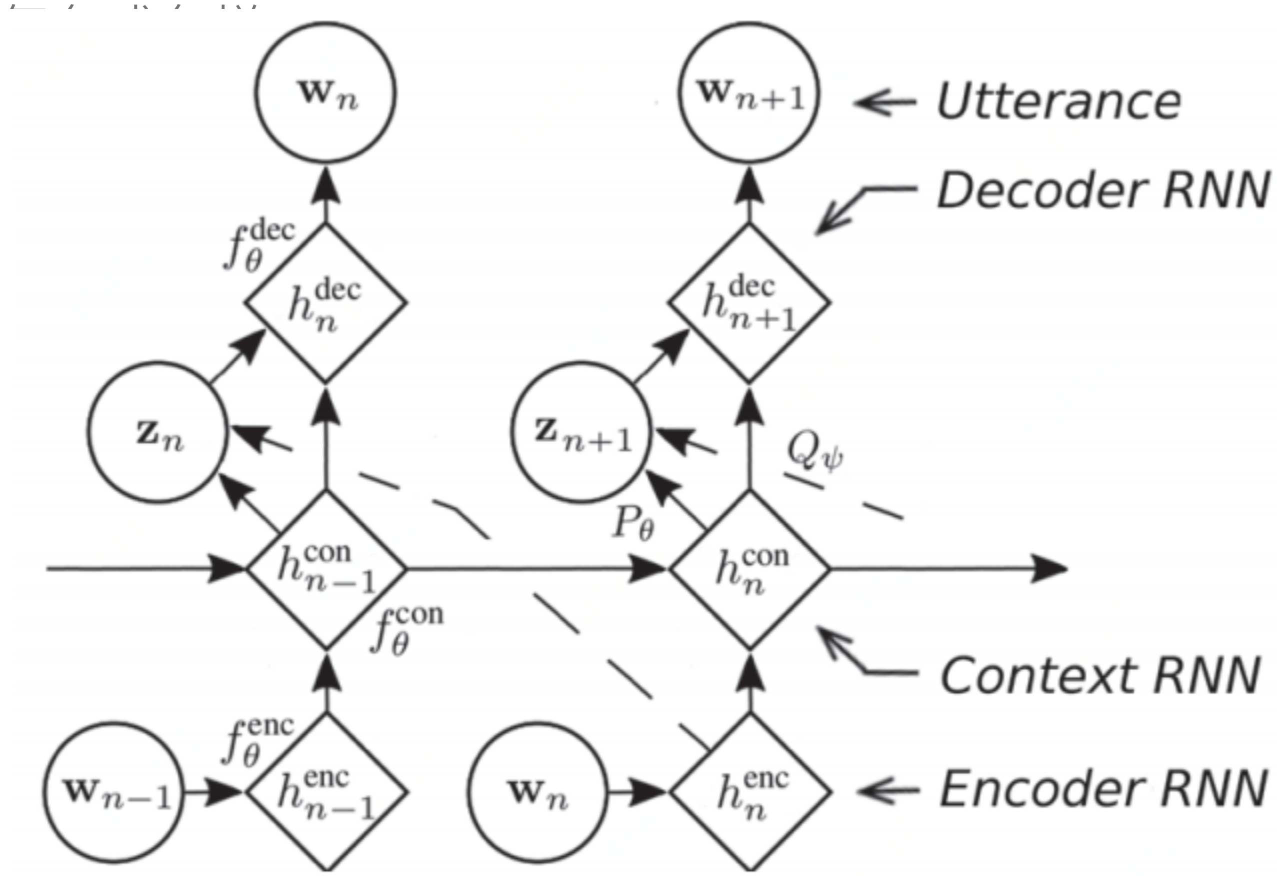
- 解决方案：
  - 改变目标函数
  - 改善解码过程-Beam-search 造成的
  - 引入随机隐变量（latent variable）
    - 在普通序列到序列网络中引入
    - 在层次化网络中引入



Serban et al., Multi-resolution recurrent neural networks: An application to dialogue response generation, AAAI 2017.

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- 解决方案：
  - 改变目标函数
  - 改善解码过程-Beam-search 造成的冗余解码
  - 引入随机隐变量（latent variable）
    - 在普通序列到序列网络中引入
    - 在层次化网络中引入
    - 学习隐变量序列
    - 基于显示属性，生成隐变量，增加可解释性

对话文本使用方法

- 问题描述：
  - 对话生成经常会产生无意义的，泛泛而谈（general & dull）的安全回复比如，“哈哈”，“我不知道”
- 为什么？
  - 无意义的回复千篇一律，有价值的回复各式各样
- 解决方案：
  - 改变目标函数-增加回复与与文本的相关性，减少泛回复
  - 改善解码过程-Beam-search 优先深度，兼顾广度
  - 引入随机隐变量（latent variable）-建模通用隐含属性，增加随机性

对话生成的研究热点

- Dialogue Context 对话文本使用方法
- Response Diversity 回复多样性
- Topic and Personality 主题与个性化
- Outside Knowledge Base 外部知识库
- Interactive Dialogue learning 交互式对话学习
- Evaluation 对话评估

Topic and Personality 主题与个性化

- 问题描述：
  - 如何学习对话的隐含属性，增加回复的多样性的同时，保证一致性?
  - 如何自定义生成的对话？使得对话更符合主题，更个性化?

什么是一致性？

什么是个性化？

- 今天看了《芳华》→感觉怎么样？→《妖猫传》非常精彩→。。。

Topic and Personality 主题与个性化

- 问题描述：
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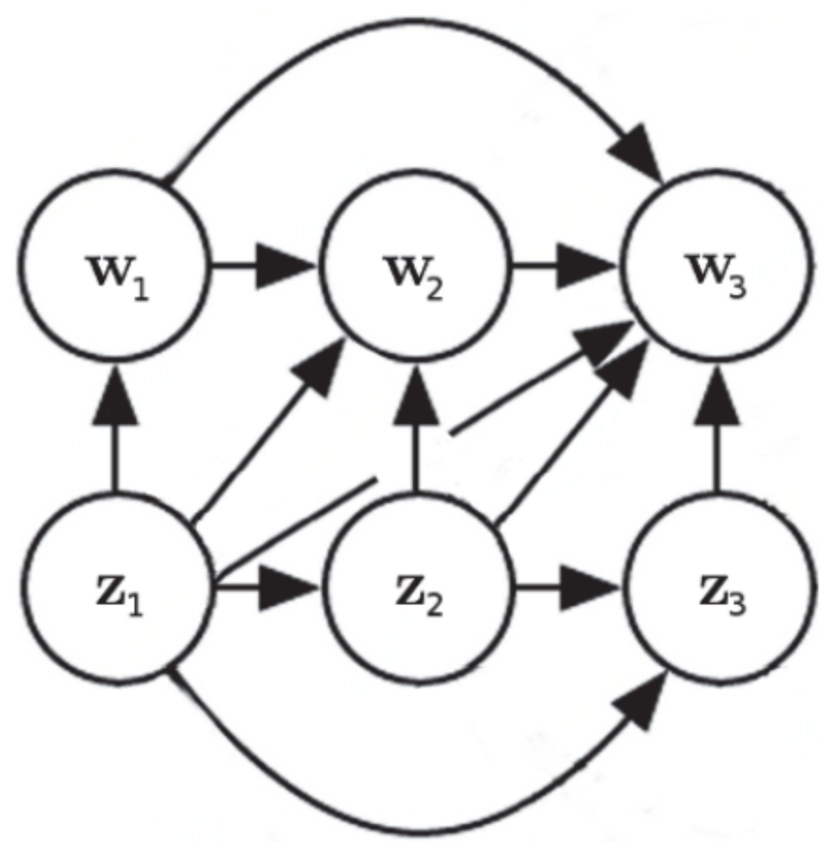
  - 如何自定义生成的对话？使得对话更符合主题，更个性化?
- 解决方案
  - 建模对话的主题

减少出现人家说东你说西
的概率

Topic and Personality 主题与个性化

- 问题描述：
    - 如何学习对话的隐含属性，增加回复的多样性的同时，保证一致性？
    - 如何自定义生成的对话？使得对话更符合主题，更个性化？
- 解决方案
    - 建模对话的主题
    - 学习浅表示序列



Topic and Personality 主题与个性化

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    - 如何学习对话的隐含属性，增加回复的多样性的同时，保证一致性?
    - 如何自定义生成的对话？使得对话更符合主题，更个性化?
- 解决方案
    - 建模对话的主题
    - 个性化

引入情感（emotion/sentiment）
引入人物简介（profile），也即自定义属性和属性值

Topic and Personality 主题与个性化

- 问题描述:
    - 如何学习对话的隐含属性，增加回复的多样性的同时，保证一致性?
    - 如何自定义生成的对话? 使得对话更符合主题，更个性化?
- 解决方案
    - 建模对话的主题
    - 个性化
        - 先用大规模语料预训练，再用个性化语料再训练（fine-tuning）
    - 简而言之，主题与个性化都是自定义的、可以为我们所理解和接受的属性

对话生成的研究热点

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- Outside Knowledge Base 外部知识库
- Interactive Dialogue learning 交互式对话学习
- Evaluation 对话评估

Outside Knowledge Base 外部知识库

- 问题描述：
  - 人在回复时是有背景知识的，但是模型没有。如何结合外部知识呢?
  - case: 今天看了《芳华》感觉怎么样? 我觉得黄轩演得挺好。。。

黄轩是谁？

Outside Knowledge Base 外部知识库

- 问题描述:
  - 人在回复时是有背景知识的，但是模型没有。如何结合外部知识呢?
- 解决方案
  - 结合Memory networks，将knowledge base表示成向量
    在生成回复的时候，采用copy-net的机制。每一个词的概率由生成概率和从knowledge base的拷贝概率相加而来

Outside Knowledge Base 外部知识库

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- **今天看了《芳华》→感觉怎么样？→我 觉得 黄轩 演得 挺好**

$P(\text{黄轩}|m,\text{我，觉得}) \propto p_{gen}(\text{黄轩}|m,\text{我，觉得})+p_{copy}(\text{黄轩}|m,\text{我，觉得})$

对话生成的研究热点

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Interactive Dialogue learning 交互式对话学习

- 问题描述：
- 让对话模型能够在与人交互的过程中学习，是终极目标之一。
- 目前有哪些方案呢?
- 解决方案
- 人工定义对话的效果，使之作为reward，然后使用policy gradient训练模型
  - Action：生成的回复
  - State：上一轮对话（消息，回复）
  - Policy：P*RL*(*r_i*+1_| *r_i* , *m_i*)
  - Reward:
    - 好不好回复 $r_1 = -\frac{1}{N_{\mathbb{S}}} \sum_{s \in \mathbb{S}} \frac{1}{N_s} \log p_{\text{seq2seq}}(s|a)$
    - 回复的有没有新内容 $r_2 = -\log \cos(h_{p_i}, h_{p_{i+1}}) = -\log \cos \frac{h_{p_i} \cdot h_{p_{i+1}}}{\|h_{p_i}\| \|h_{p_{i+1}}\|}$
    - 连贯性 $r_3 = \frac{1}{N_a} \log p_{\text{seq2seq}}(a|q_i, p_i) + \frac{1}{N_{q_i}} \log p^{\text{backward}}_{\text{seq2seq}}(q_i|a)$

一轮之后，话题还能不能聊的下去

这次说的和上次说的是否一样

Interactive Dialogue learning 交互式对话学习

- 问题描述：
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  - 目前有哪些方案呢?
- 解决方案
  - 人工定义对话的效果，使之作为reward，然后使用policy gradient训练模型
  - 让人在K个候选中选择1个最佳回复，训练模型选择最佳回复的能力

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Evaluation 对话评估

- 问题描述:
  - 如何评估生成回复的有效性?
- 解决方案
  - BLEU? METEOR? ROUGE? 词覆盖率指标
  - Embedding similarity 向量相似度指标
  - Automatic distinguish machine-generated texts from human-generated ones.

目录

- 对话生成技术简介
- 从语言模型到对话生成
- 对话生成技术的研究热点
- 总结

- 对话生成技术
    - 任务导向对话系统，闲聊对话
    - 模块化对话模型，端到端对话模型
    - 检索式对话，对话生成
- 从语言模型到对话生成
    - Seq2seq模型在生成中的应用
    - Seq2seq在对话生成中的变种应用
- 研究热点：对话文本使用方法，回复多样性，主题与个性化，外部知识库，交互式对话学习，对话评估

Part 2: 端到端对话生成技术

目录

- Background
- Challenges
- Several methods
- Conclusions

End-to-end dialogue systems

Dialogue systems

End-to-end method

Pipeline method

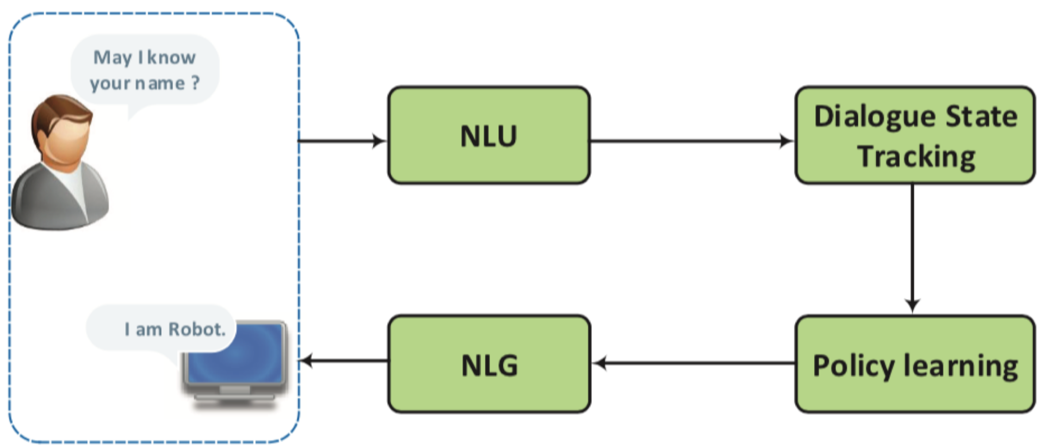
(Modular dialogue systems)

Traditional systems consist of modules

- Each module optimized with separate objective function

对话生成分类

- Pipeline dialogue generation
  - Understand user intention, update the dialogue state, select an appropriate system action, and finally transform it into a naturally-sounding response.



- End-to-end
  - A single model trained directly on conversational data
  - Uses a single objective function, usually maximum likelihood on next response

Ritter et al., 2011; Sordoni et al., 2015; Shang et al., 2015

Advantages of end2end dialogue generation

- Does not require feature engineering (only architecture engineering).
- Can be transferred to different domains.
- Does not require supervised data for each module

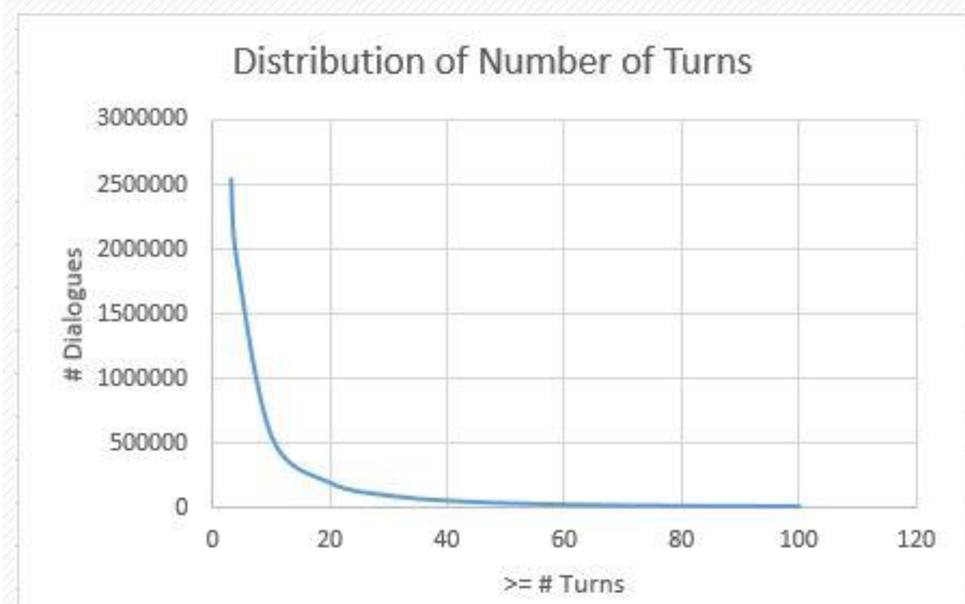
Challenges in end-to-end dialogue generation

- Datasets
- Generic responses
- Evaluation

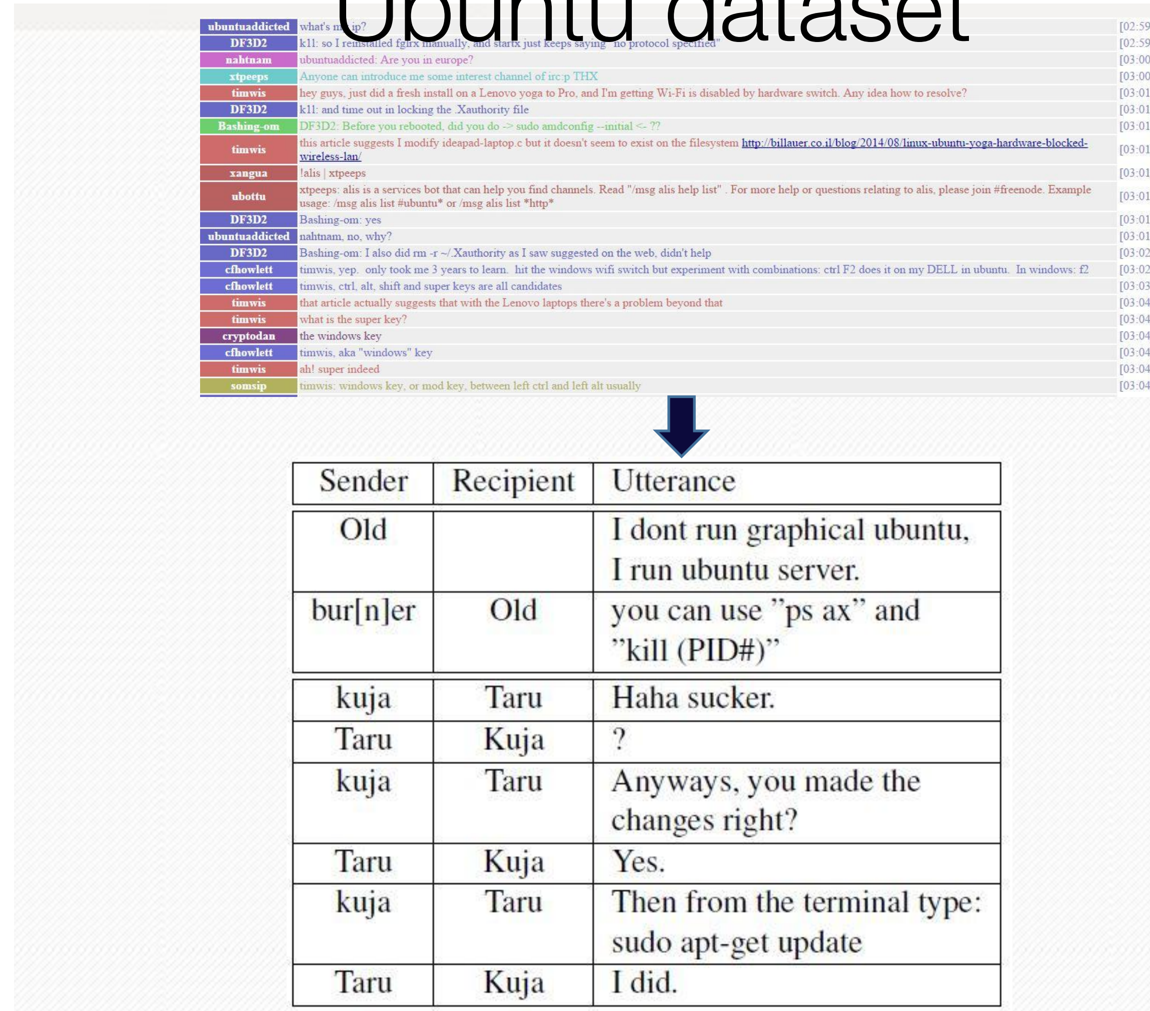
Challenges: Datasets

- Building general-purpose dialogue systems requires lots of data
- The best datasets are proprietary
- We need **large** (>500k dialogues), **open-source** datasets to make progress

- Large dataset of ~1 million tech support dialogues
- Scraped from Ubuntu IRC channel
- 2-person dialogues extracted from chat stream



Ubuntu dataset



Sender	Recipient	Utterance
Old		I dont run graphical ubuntu, I run ubuntu server.
bur[n]er	Old	you can use "ps ax" and "kill (PID#)"
kuja	Taru	Haha sucker.
Taru	Kuja	?
kuja	Taru	Anyways, you made the changes right?
Taru	Kuja	Yes.
kuja	Taru	Then from the terminal type: sudo apt-get update
Taru	Kuja	I did.

Lowe*, Pow*, Serban, Pineau. "The Ubuntu Dialogue Corpus: A Large Dataset for Research in Unstructured Multi-Turn Dialogue Systems." SIGDIAL, 2015.

Challenges: Datasets

- Building general-purpose dialogue systems requires lots of data
- The best datasets are proprietary
- We need **large** (>500k dialogues), **open-source** datasets to make progress

Other datasets

- Twitter Corpus, 850k Twitter dialogues (Ritter et al., 2011)
- Movie Dialog Dataset, 1 million Reddit dialogues (Dodge et al. 2016)

Challenges: generic responses

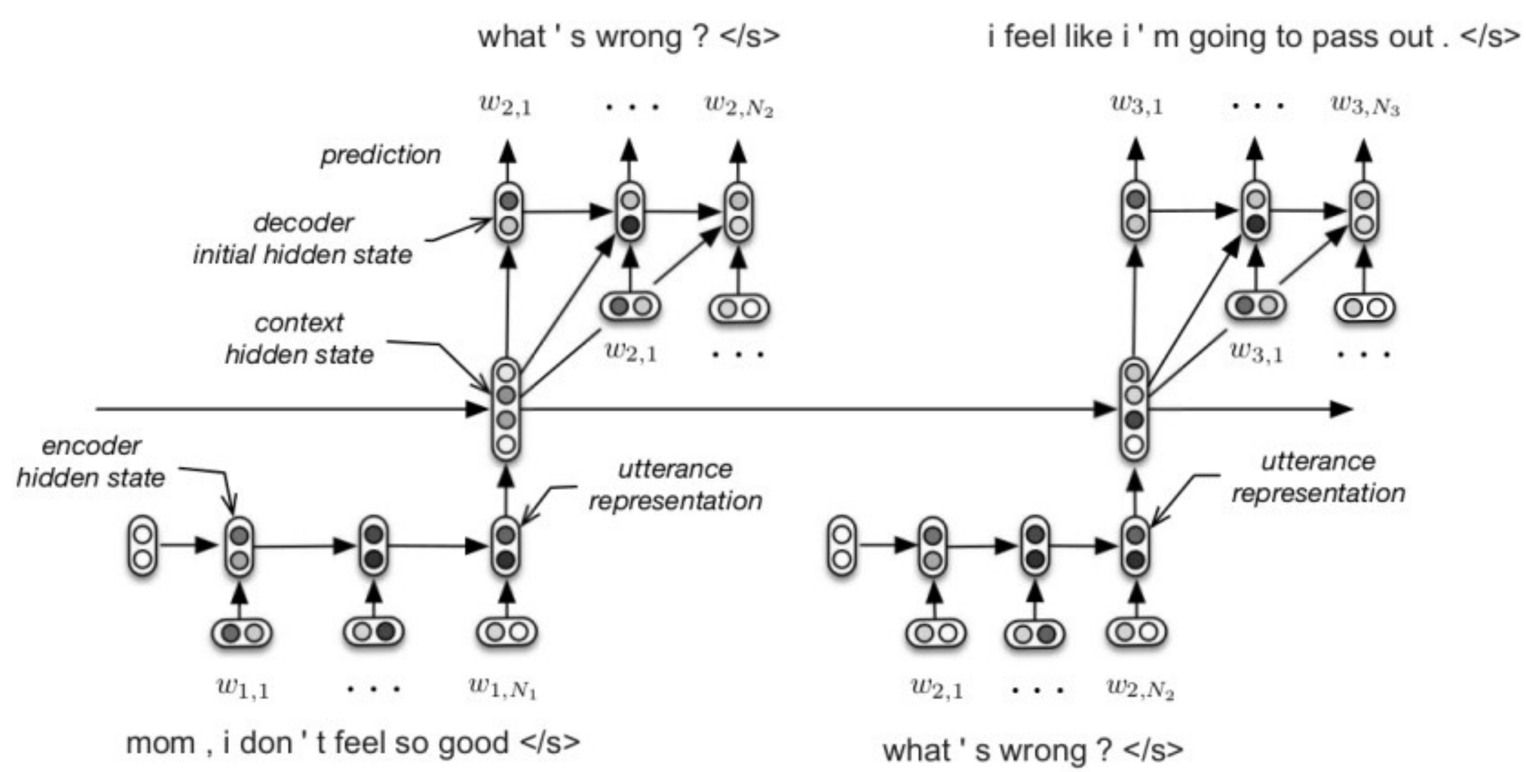
- Most models trained to predict most likely next utterance given context
- But some utterances are likely given any context!
- Neural models often generate "I don't know", or "I'm not sure" to most contexts

Input:	What are you doing?	
−0.86	I don't know.	–
−1.03	I don't know!	–
−1.06	Nothing.	–
−1.09	Get out of the way.	–
Input:	what is your name?	
−0.91	I don't know.	...
−0.92	I don't know!	–
−0.92	I don't know, sir.	–
−0.97	Oh, my god!	–
Input:	How old are you?	
−0.79	I don't know.	...
−1.06	I'm fine.	–
−1.17	I'm all right.	–
−1.17	I'm not sure.	–

(Li et al., 2016)

Sequence-to-sequence models

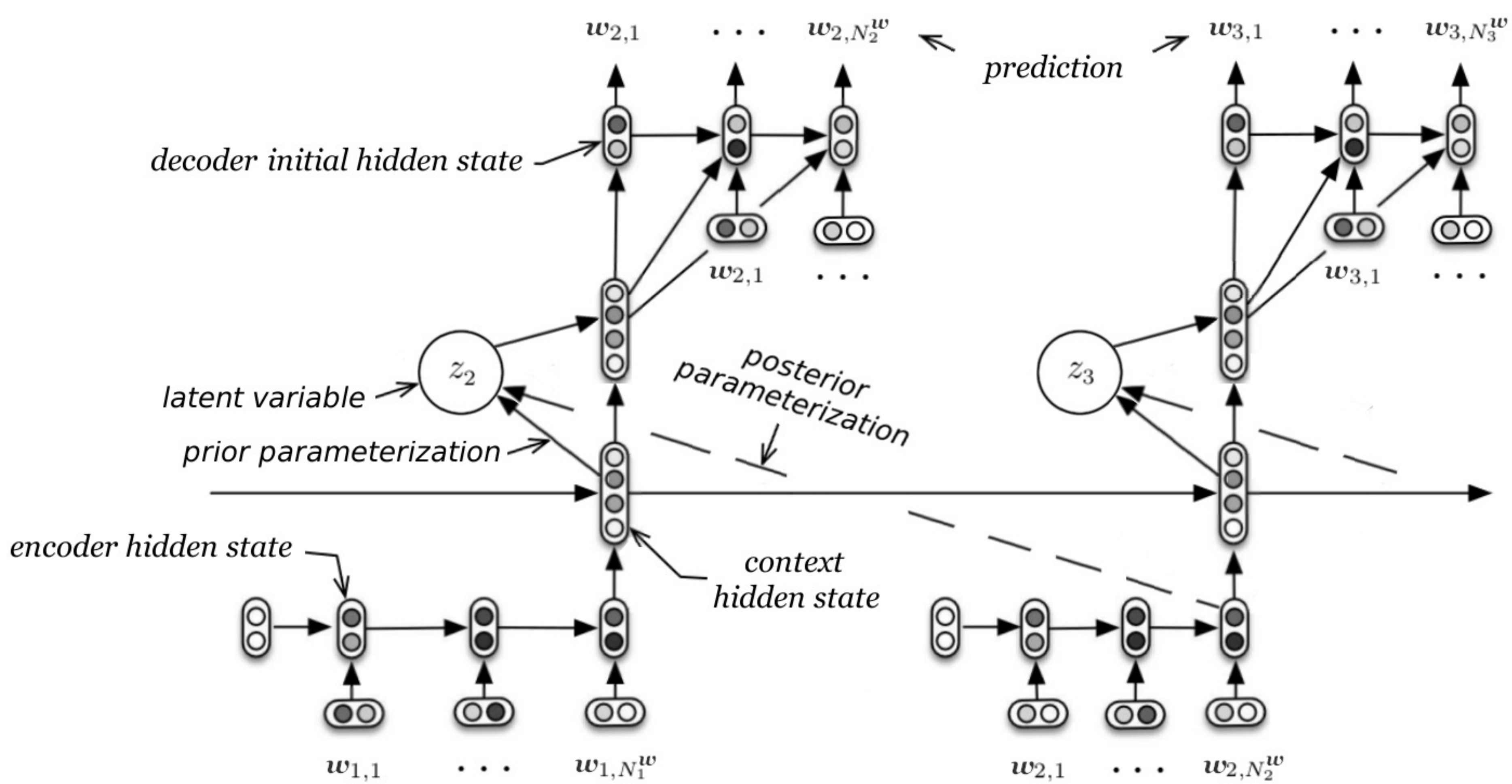
- Use RNN to encode text into fixed-length vector representation
- se another RNN to decode representation to text
- Can make this hierarchical



- Cho et al. “Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation.” EMNLP 2014.
- Serban, et al., “Building End-to-End Dialogue Systems using Generative Hierarchical Neural Network Models” AAAI, 2015.

Variational encoder-decoder (VHRED)

- Augment encoder-decoder with Gaussian latent variable
- Inspired by VAE (Kingma & Welling, 2014)
- When generating first sample latent variable, then use it to condition generation



Serban et al., “A hierarchical latent variable encoder-decoder model for generating dialogues” AAAI, 2017.

Variational encoder-decoder (VHRED)

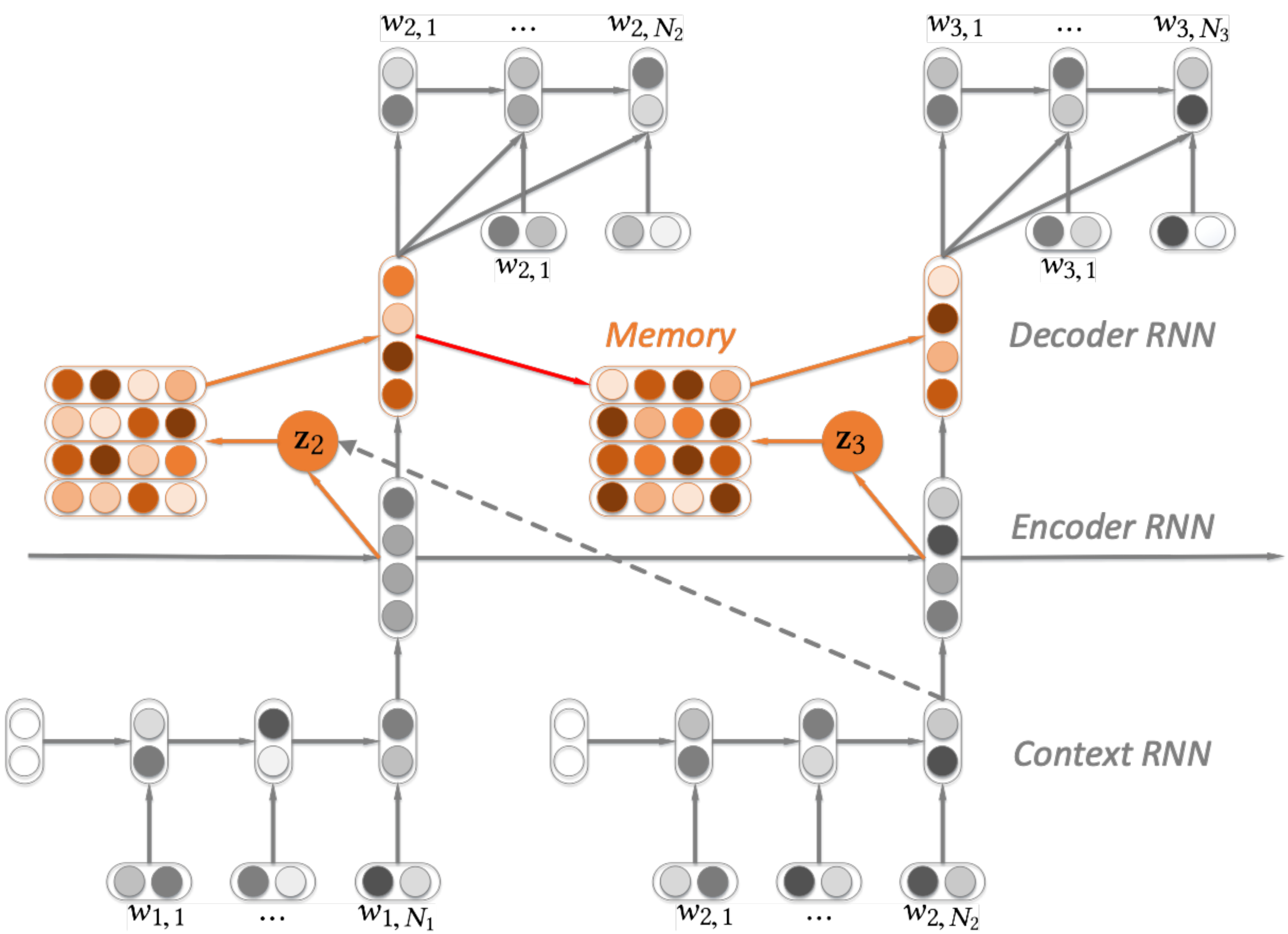
- VHRED generates longer responses with higher entropy
- Outperforms baselines in most experiments

Table 1: Wins, losses and ties (in %) of the VHRED model against the baselines based on the human study on Twitter (mean preferences $\pm$ 90% confidence intervals)

	Short Contexts			**Long Contexts**		
Opponent	**Wins**	**Losses**	**Ties**	**Wins**	**Losses**	**Ties**
VHRED vs LSTM	32.3 ± 2.4	$\mathbf{42.5 \pm 2.6}$	25.2 ± 2.3	$\mathbf{41.9 \pm 2.2}$	36.8 ± 2.2	21.3 ± 1.9
VHRED vs HRED	$\mathbf{42.0 \pm 2.8}$	31.9 ± 2.6	26.2 ± 2.5	$\mathbf{41.5 \pm 2.8}$	29.4 ± 2.6	29.1 ± 2.6
VHRED vs TF-IDF	$\mathbf{51.6 \pm 3.3}$	17.9 ± 2.5	30.4 ± 3.0	$\mathbf{47.9 \pm 3.4}$	11.7 ± 2.2	40.3 ± 3.4

Serban et al., “A hierarchical latent variable encoder-decoder model for generating dialogues” AAAI, 2017.

Hierarchical variational memory networks (HVMN)



- Hongshen Chen, et al., Hierarchical Variational Memory Network for Dialogue Generation. WWW, 2018

Variational Memory Reading

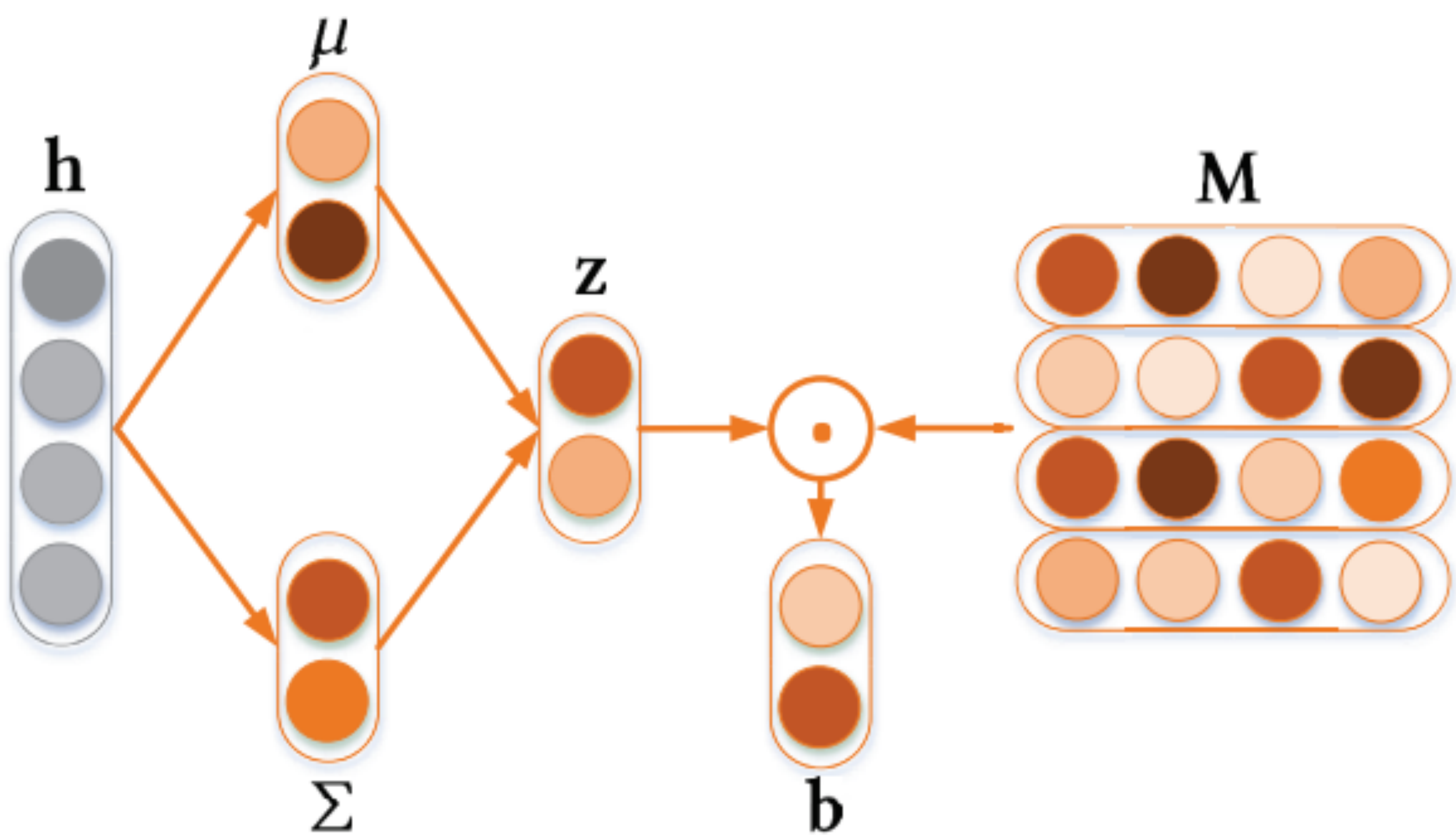


Figure 3: Variational memory reading mechanism.

- Hongshen Chen, et al., Hierarchical Variational Memory Network for Dialogue Generation. WWW, 2018

Variational Memory Updating

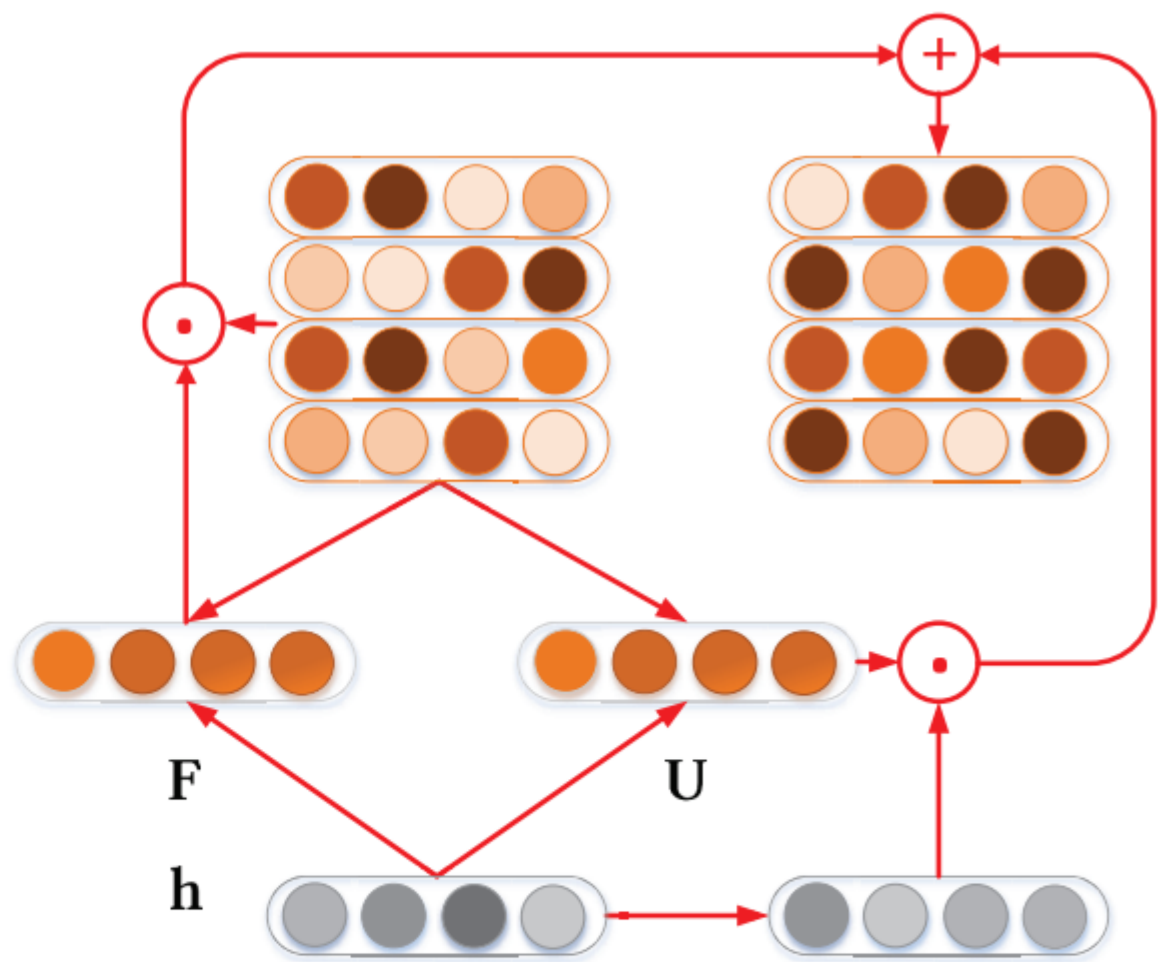


Figure 4: Variational memory updating mechanism.

- Hongshen Chen, et al., Hierarchical Variational Memory Network for Dialogue Generation. WWW, 2018

Challenges: evaluation metrics

- Automatic Evaluation Metrics
  - Embedding Similarity Based Metrics (Relativeness)
    - Embedding Average
    - Embedding Extrema
    - Embedding Greedy
  - Word Entropy (Informativeness)
    - $H_{w_n} = -p(w_n|w_{n-2}, w_{n-1})\log(p(w_n|w_{n-2}, w_{n-1}))$
- Human Evaluation
  - Appropriateness
  - Informativeness

实验结果

Model	Average	Greedy	Extrema	H(w)
Ubuntu				
SEQ2SEQ	0.215603	0.168833	0.126480	0.2638
HRED	0.541548	0.411681	0.319299	**0.3082**
VHRED	0.534103	0.402670	0.306242	0.2878
HVMN	**0.558392***	**0.422914***	**0.322032**	0.3002
Douban				
SEQ2SEQ	0.024255	0.002961	0.023805	1.2253
HRED	0.030904	0.003817	0.029889	1.5116
VHRED	0.042774	0.005147	0.041703	1.3671
HVMN	**0.053293**	**0.006507**	**0.051560**	**3.1042**
JD.com				
SEQ2SEQ	0.309752	0.204973	0.279654	0.3219
HRED	0.737606	0.500789	0.675900	0.3286
VHRED	0.609605	0.413422	0.558891	0.3473
HVMN	**0.752574***	**0.511170***	**0.691818**	**0.3555**

Table 3: Evaluations on embedding-based metrics. "*" denotes significantly better than VHRED with $p \leq 0.01$.

人工评测结果

两种指标： Appropriateness
Informativeness

Comparison	Appropriateness(%)	Informativeness(%)
HVMN *vs* SEQ2SEQ	77.07 : 22.93	84.46 : 15.54
HVMN *vs* HRED	48.52 : 51.48	58.41 : 41.59
VHRED *vs* HRED	44.57 : 55.43	52.91 : 47.09
HVMN *vs* VHRED	53.97 : 46.03	55.56 : 44.44

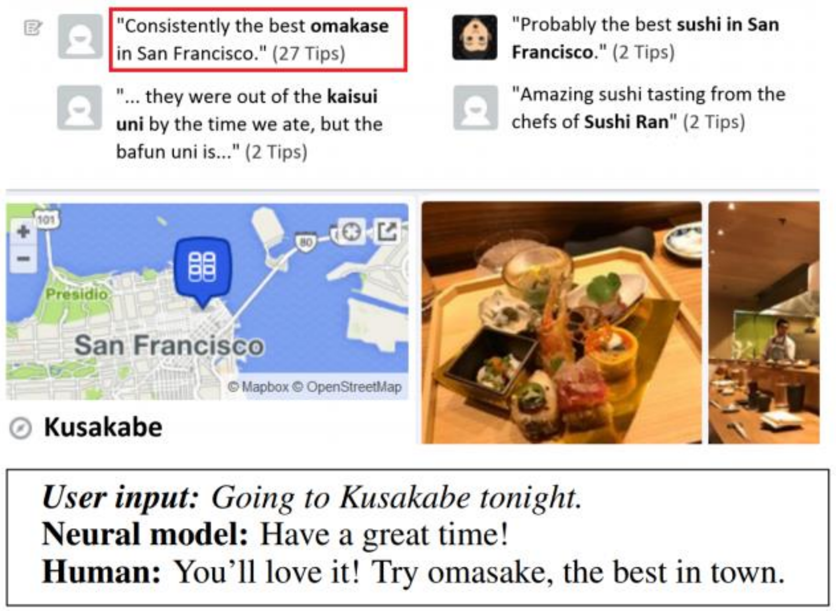
Table 4: Average differences on human evaluation.

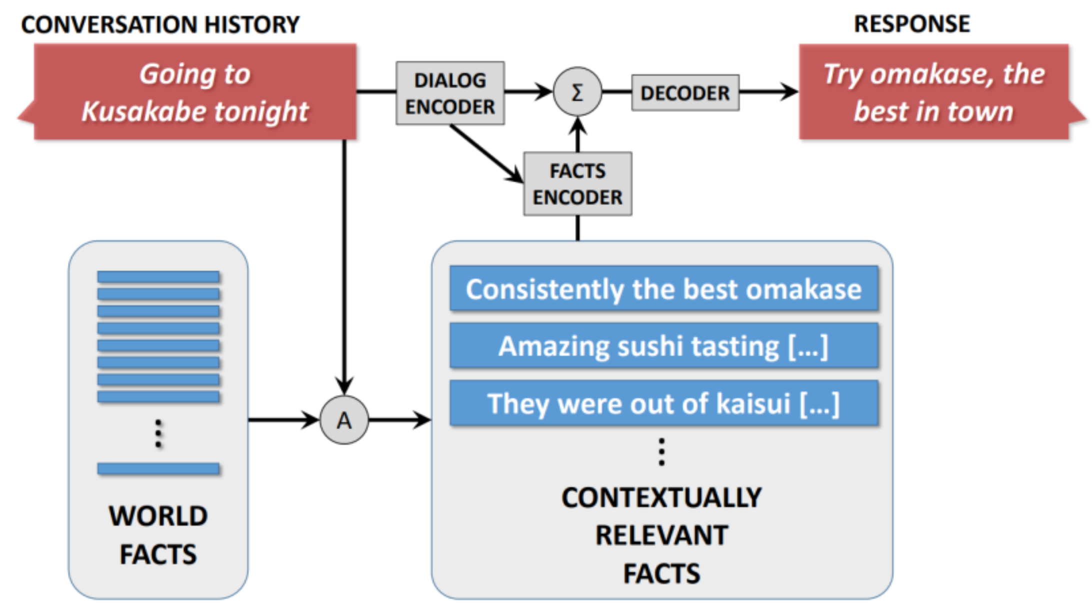
Case study of end2end dialogue models

Contexts	Response
hello , I'am using ubunutu 12.04 and have black screen It seems that I have graphical system X loggeed as root user , but not as my user . Can someone to end up my problem ? I have ubuntu 12.04 → are you logged on ? and do you have a text prompt ?	**HVMN**: yes , I can log in as root , but I am not able to log in as root **LSTM**: **unknown** **HRED**: yes **VHRED**: yes
hey what command would I use to extract a gz file tar . gz → in which part ? document , assignment , labs ? → sorry labs → wait a second, my connection gets slow connection → oh sorry , can you not see it ? do you know if I have to extract that . tar . gz → not yet finish :D skydrive was suck → lol its the only option I had , i could just send you my onenote linke → okey just for your link I get slower connections :D	**HVMN**: I am trying to get it to work , but I can't find it anywhere **LSTM**: ? **HRED**: yeah I know , but I have to go to bed , I have to go to bed :) **VHRED**: ok
I've been told that du doesn't count hidden files/directories size toward their parent directory size , yet in practice it seems du still does it → well read the manual . because it always did and always will ?	**HVMN**: that 's what I thought , but I don't think it 's possible to do that **LSTM**: ? **HRED**: I know , but I don't know how to do that , I just want to know if there is a way to do it **VHRED**: df -h returns nothing ?
Hello . I want to access a ubuntu desktop from windows 7 to know what the client is doing . How can i do that ? Hello . I want to access a ubuntu desktop from windows 7 to know what the client is doing . How can i do that ? → Try Teamviewer → I want to do without the knowledge of client	**HVMN** You'll need to set up a VNC server on the Ubuntu machine . **LSTM**: ? **HRED**: Sorry , I don't know how to do that . **VHRED**: Then I don't know , sorry .
Hi there , i'm doing an rsync on a server , ive just looked at it remotely and its showing as 3 occurrences of it running(via ps aux | grep rsync) is that normal ? → Do they all look exactly the same or is there any destingueal be difference → all look exactly the same : s whats that mean then ?	**HVMN** The rsync command will tell you if the rsync daemon is running . **LSTM**: **unknown** **HRED**: I don't know what you mean by " **un-known** " **VHRED**: grep " **unknown** . **unknown** "

Table 5: Ubuntu examples of different models. → denotes turn exchange.

Knowledge grounded neural models





A: **Looking forward to trying** *@pizzalibretto* **tonight! my expectations are high.**
B: **Get** *the rocco salad*. **Can you eat** *calamari*?

A: **Anyone in** *Chi* **have a** *dentist office* **they recommend? I'm never going back to** *[...]* **and would love a reco!**
B: **Really looved** *Ora* **in** *Wicker Park*.

A: **I'm at** *California Academy of Sciences*
B: **Make sure you catch** *the show* **at** *the Planetarium*. **Tickets are usually limited.**

A: **I'm at** *New Wave Cafe*.
B: **Try to get to** *Dmitri's* **for dinner. Their** *pan fried scallops* **and** *shrimp scampi* **are to die for.**

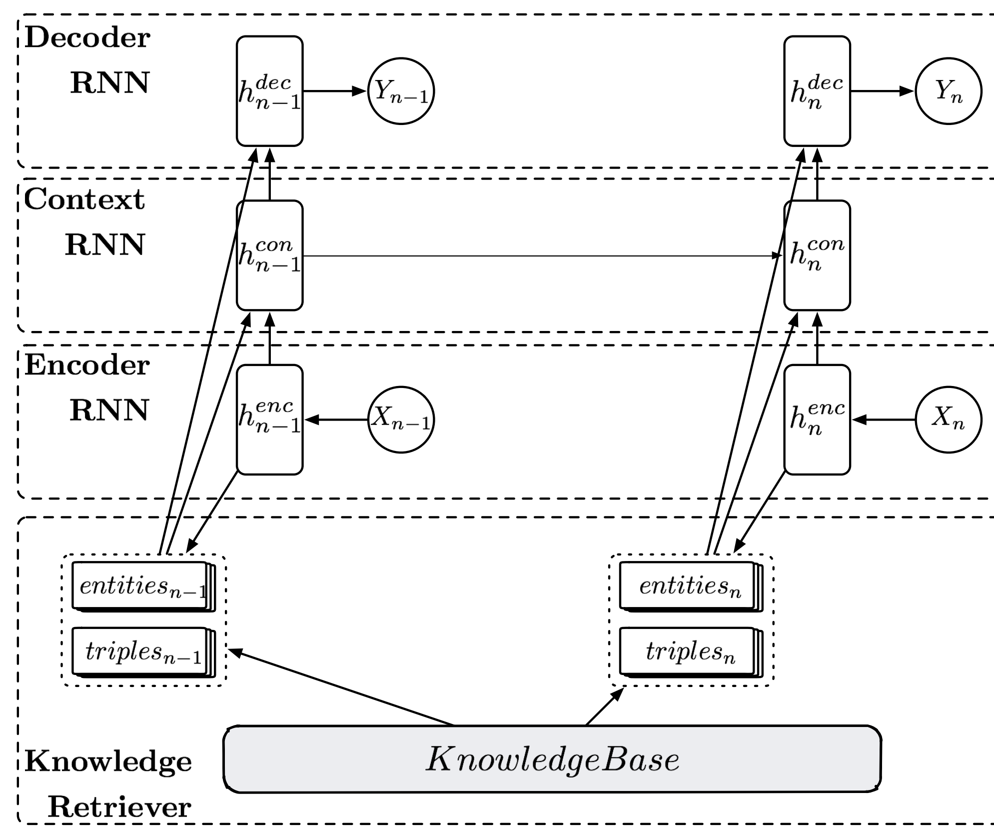
A: **I just bought:** *[...] 4.3-inch portable GPS navigator* **for my wife, shh, don't tell her.**
B: **I heard this brand** *loses battery power*.

Ghazvininejad et al., A Knowledge-Grounded Neural Conversation Model 2017

Knowledge diffusion for e2e dialogue generation

- A neural knowledge diffusion model (NKD) to introduce knowledge into dialogue generation

ID	Dialogue
1	A: Who is the director of the Titanic? 泰坦尼克号的导演是谁? B: James Cameron. 詹姆斯卡梅隆。
2	A: Titanic is my favorite film! 泰坦尼克号是我最爱的电影! B: The love inside it is so touching. 里面的爱情太感人了。
3	A: Is there anything like the Titanic? 有什么像泰坦尼克号一样的电影吗? B: I think the love story in film Waterloo Bridge is beautiful, too. 我觉得魂断蓝桥中的爱情故事也很美。
4	A: Is there anything like the Titanic? 有什么像泰坦尼克号一样的电影吗? B: Poseidon is also a classic marine film. 海神号也是一部经典的海难电影。



X_1 : *Who is the director of the Titanic?*

Y_1 : *James Cameron.*

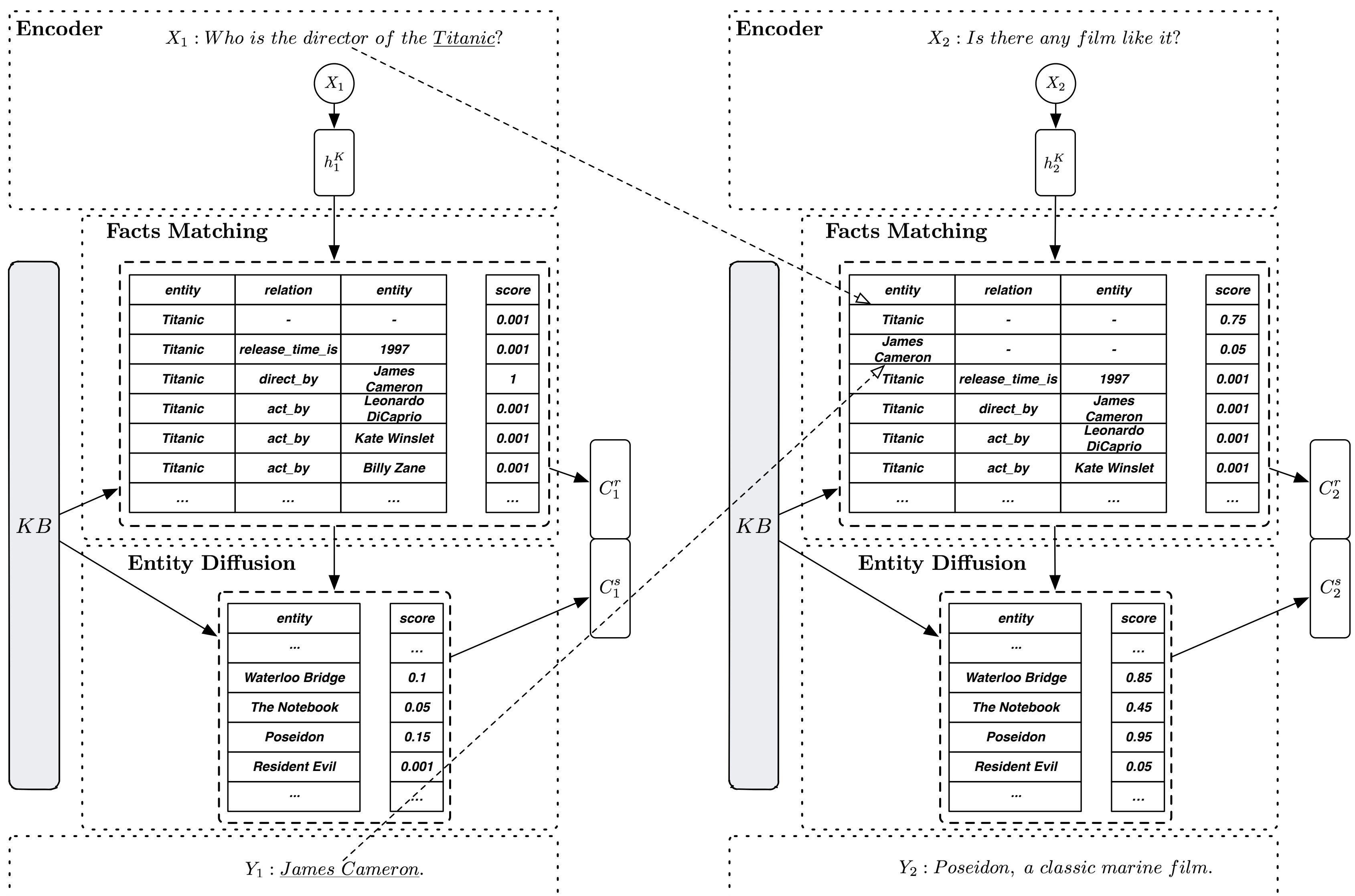
X_2 : *Is there any film like it?*

Y_2 : *Poseidon, a classic marine film.*

Liu et al.,Knowledge Diffusion for Neural Dialogue Generation, ACL 2018

Knowledge diffusion for e2e dialogue generation

- Knowledge Retriever:
  - Facts related to input utterance are extracted by fact
  - Sim diffusion.



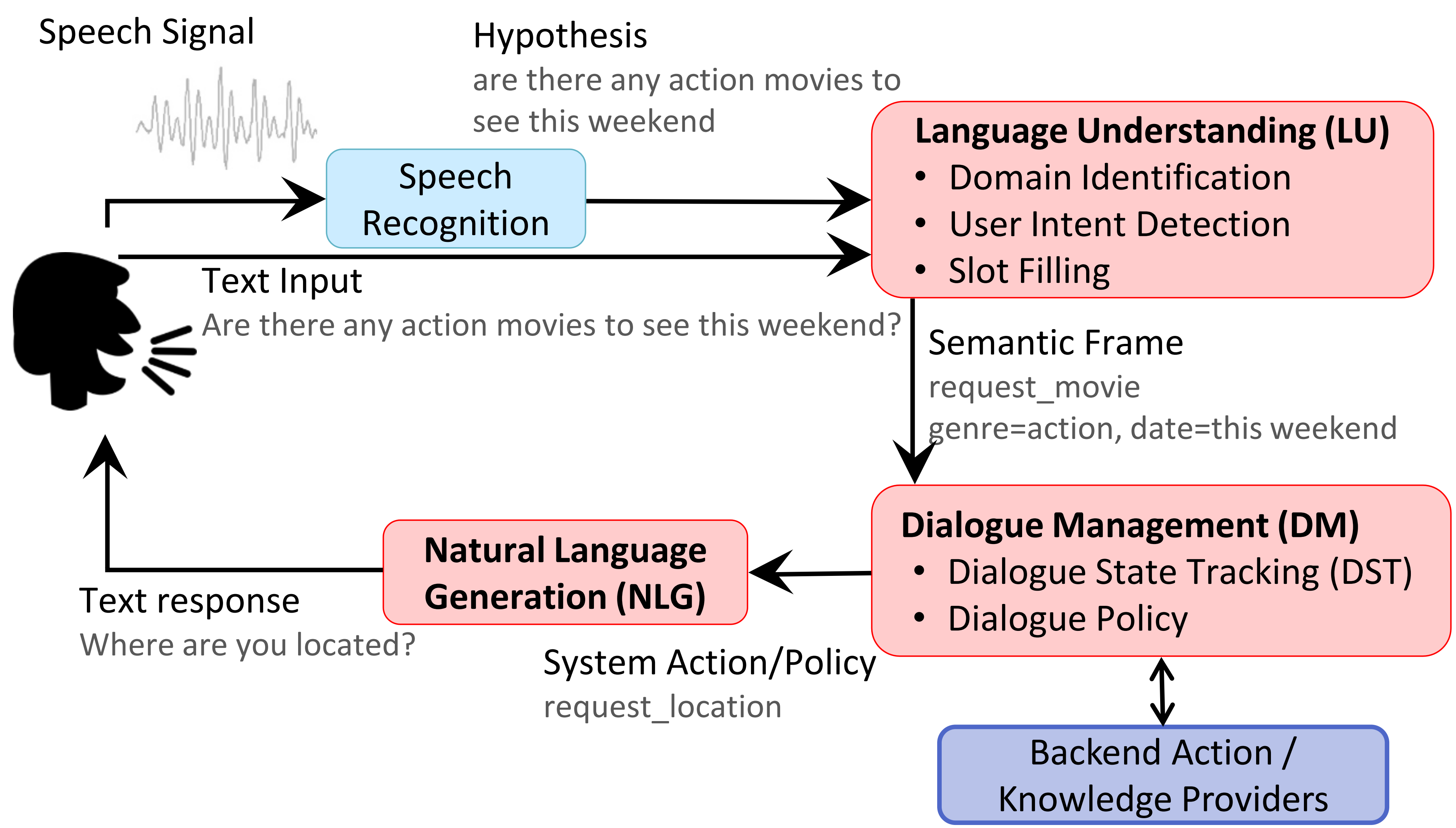
Liu et al.,Knowledge Diffusion for Neural Dialogue Generation, ACL 2018

Part 3: End-to-end task-oriented dialogue generation

目录

- Pipeline-based task-oriented dialogue generation
- End2End task-oriented dialogue generation
- Related real-world applications
- Future work

Task-oriented dialogue generation



Young et al, Phone-level pronunciation scoring and assessment for interactive language learning 2000

Pipeline-based dialogue generation

- Natural language understanding (NLU)

Domain/Intent classification

- Mainly viewed as an utterance classification task
  - Given a collection of utterances u_i with labels c_i, D= $\{(u_1,c_1),\ldots,(u_n,c_n)\}$ where $c_i \in C$, train a model to estimate labels for new utterances u_k.

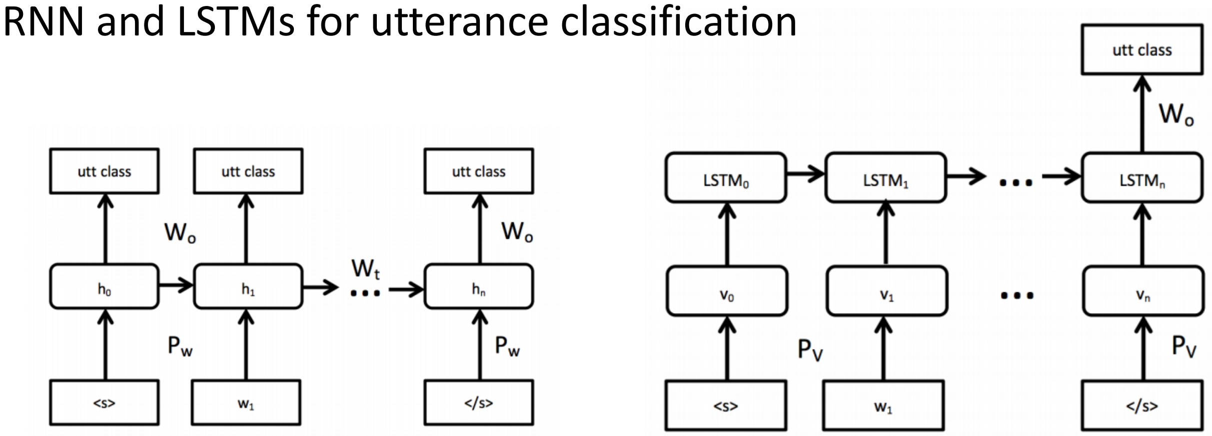
Deep belief nets (DBN)

- Unsupervised training of weights
- Fine-tuning by back-propagation
- Compared to MaxEnt, SVM, and boosting

Deep convex networks (DCN)

- Simple classifiers are stacked to learn complex functions
- Feature selection of salient n-grams
- Extension to kernel-DCN

RNN and LSTMs for utterance classification



Intent decision after reading all words performs better

Sarikaya et al., 2011,Tur et al., 2012, Deng et al., 2012, Ravuri&Stolcke, 2015

Slot filling

Considered as a sequence tagging task

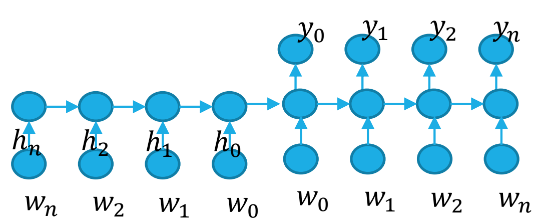
Given a collection tagged word sequences, $S=\{((w_{1,1},w_{1,2},\ldots,\ w_{1,n1}),\ (t_{1,1},t_{1,2},\ldots,t_{1,n1})),\ ((w_{2,1},w_{2,2},\ldots,w_{2,n2}),\ (t_{2,1},t_{2,2},\ldots,t_{2,n2}))\ \ldots\}$ where $t_i \in M$, the goal is to estimate tags for a new word sequence.

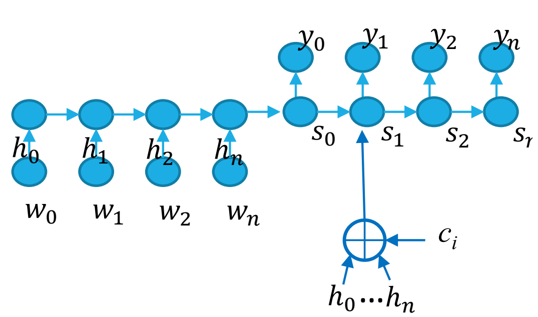
flights from Boston to New York today

	flights	from	Boston	to	New	York	today
Entity Tag	O	O	B-city	O	B-city	I-city	O
Slot Tag	O	O	B-dept	O	B-arrival	I-arrival	B-date

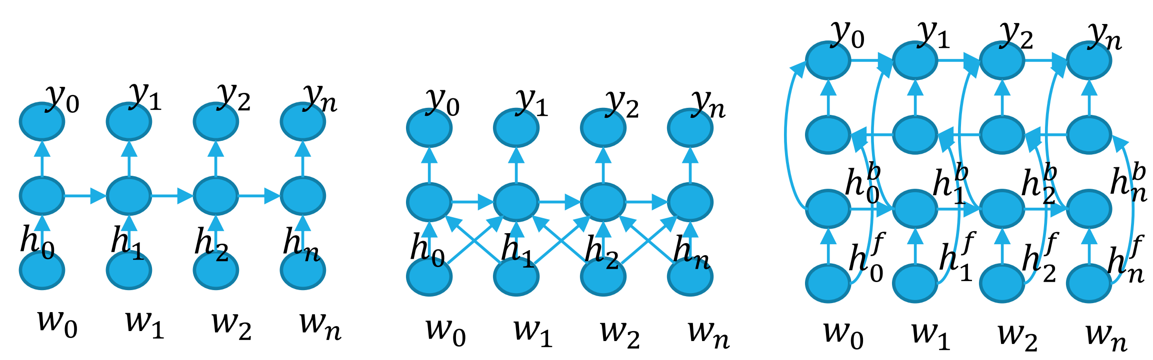
Recurrent neural networks for slot filling

- Encoder-decoder networks
  - Leverages sentence level information
- Attention-based encoder-decoder
  - Use of attention (as in MT) in the encoder-decoder network
  - Attention is estimated using a feed-forward network with input: h_t and s_t at time t





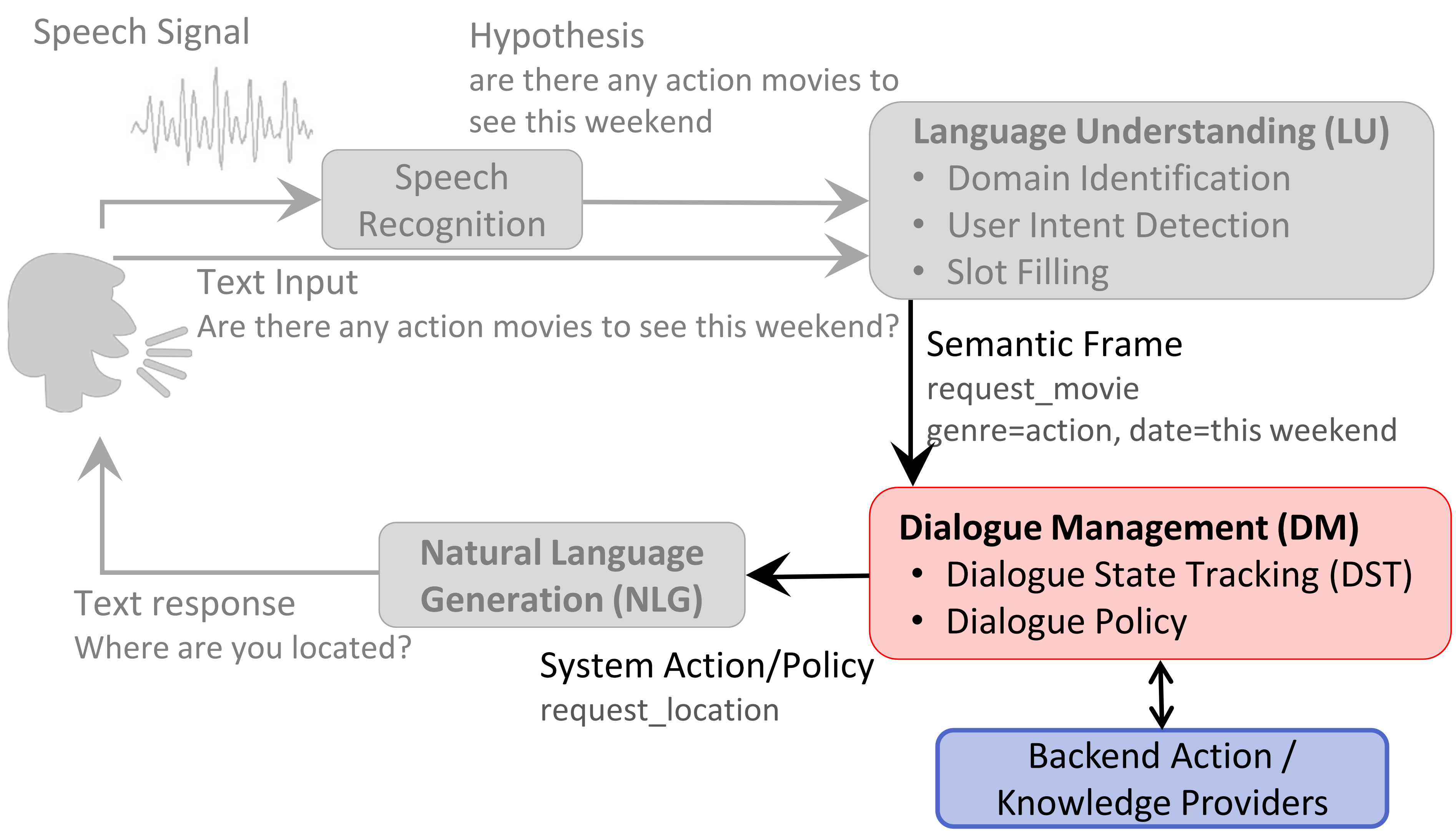
- RNNs with LSTM cells
- Input, sliding window of n-grams
- Bi-directional LSTMs



(a) LSTM (b) LSTM-LA (c) bLSTM

Yao et al., 2013, Mesnil et al., 2015, Kurata et al., 2016, Simonnet et al., 2015

Dialogue management



State tracking

- A dialogue state refers to representation of user's intention up to current dialogue turn

- In task-oriented dialogue systems, dialogue state tracking is necessary since it is utilized for KB search
- Example training data for explicit dialogue states

User: Please find a moderately priced Italian restaurant

Slot	Value
Price	Moderate
Food type	Italian

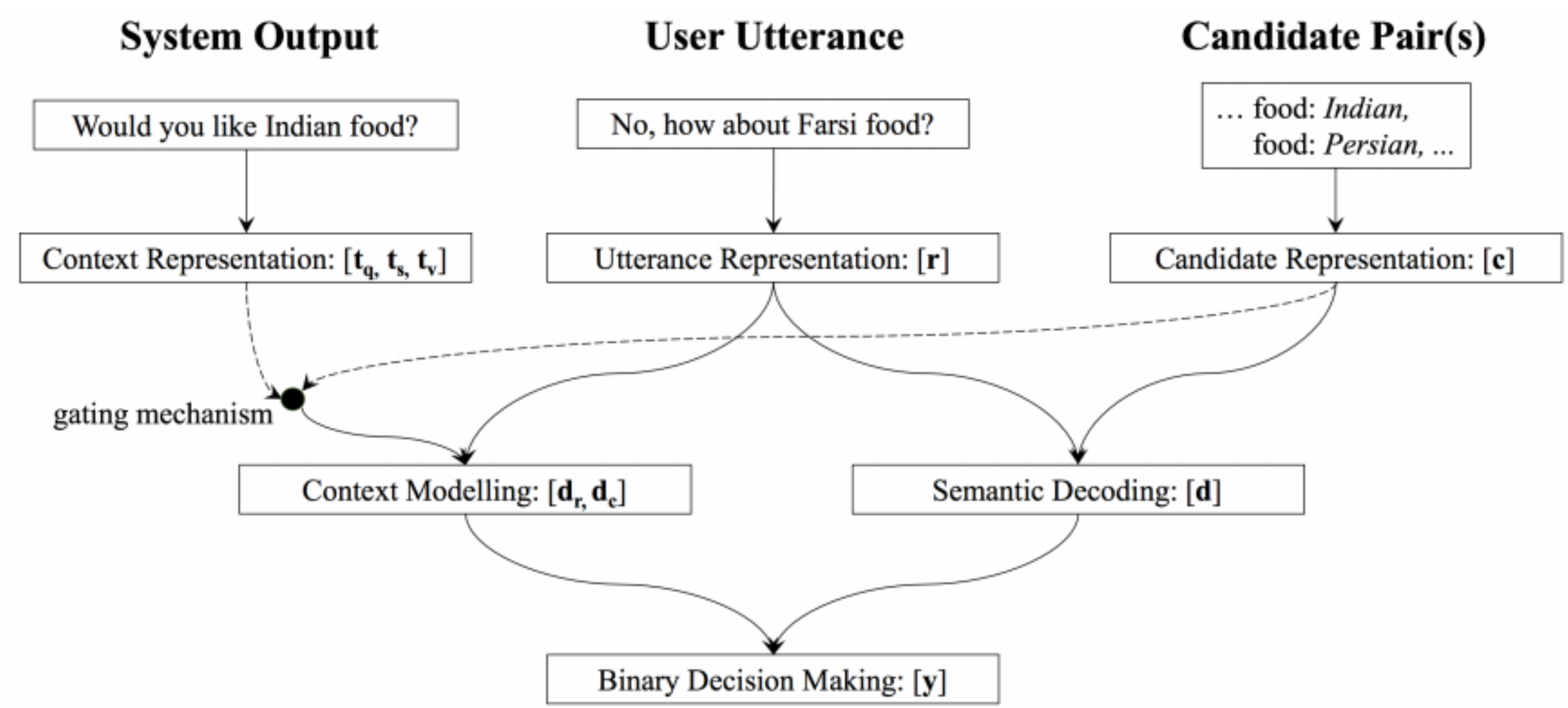
- In non-task oriented dialogue systems, dialogue state tracking is helpful to generate context-aware and coherent responses
- Hardly have annotated data
- Usually implemented implicitly or with latent variables

Dialogue state tracking challenge (DSTC)

Challenge	Type	Domain	Data Provider	Main Theme
DSTC1	Human-Machine	Bus Route	CMU	Evaluation Metrics
DSTC2	Human-Machine	Restaurant	U. Cambridge	User Goal Changes
DSTC3	Human-Machine	Tourist Information	U. Cambridge	Domain Adaptation
DSTC4	Human-Human	Tourist Information	I2R	Human Conversation
DSTC5	Human-Human	Tourist Information	I2R	Language Adaptation

Williams et al., 2013, Henderson et al. 2014, Henderson et al. 2014, Kim et al. 2016, Kim et al. 2016

Neural belief tracker



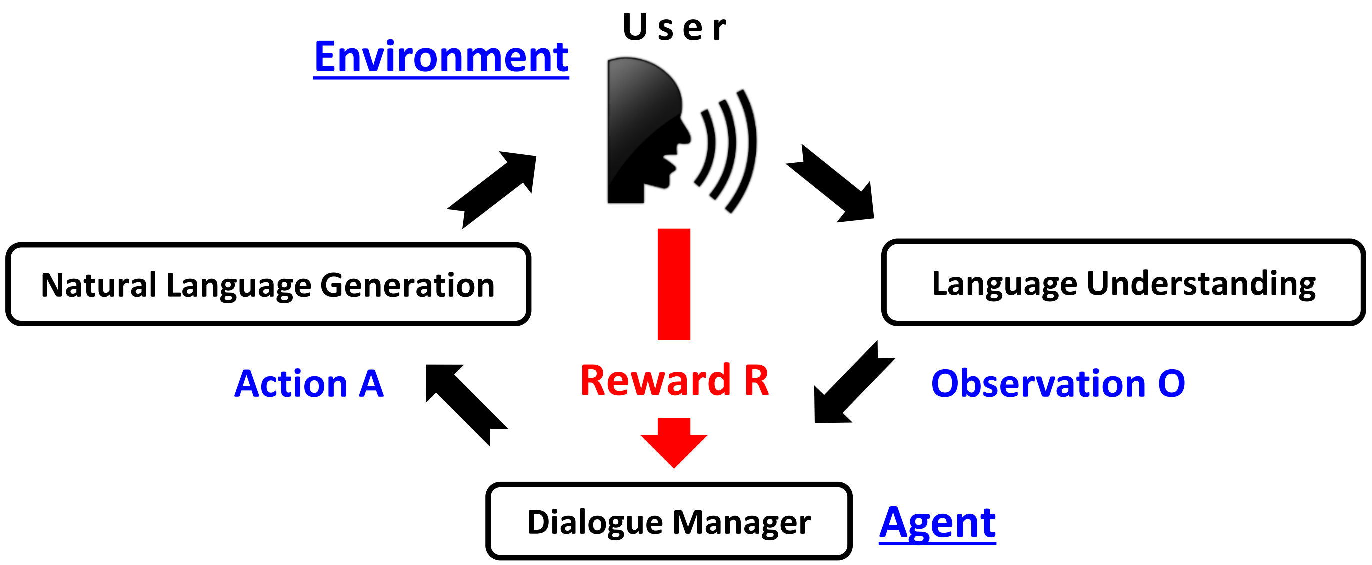
Mrkšić et al., Neural Belief Tracker: Data-Driven Dialogue State Tracking, ACL 2017

Dialogue policy learning

- Inform(location="The forbidden city")
  - "The nearest one is at The forbidden city"
- Request(location)
  - "Where is your home?"
- Confirm(type="Chinese")
  - "Did you want Chinese food?"

Reinforcement learning in policy learning

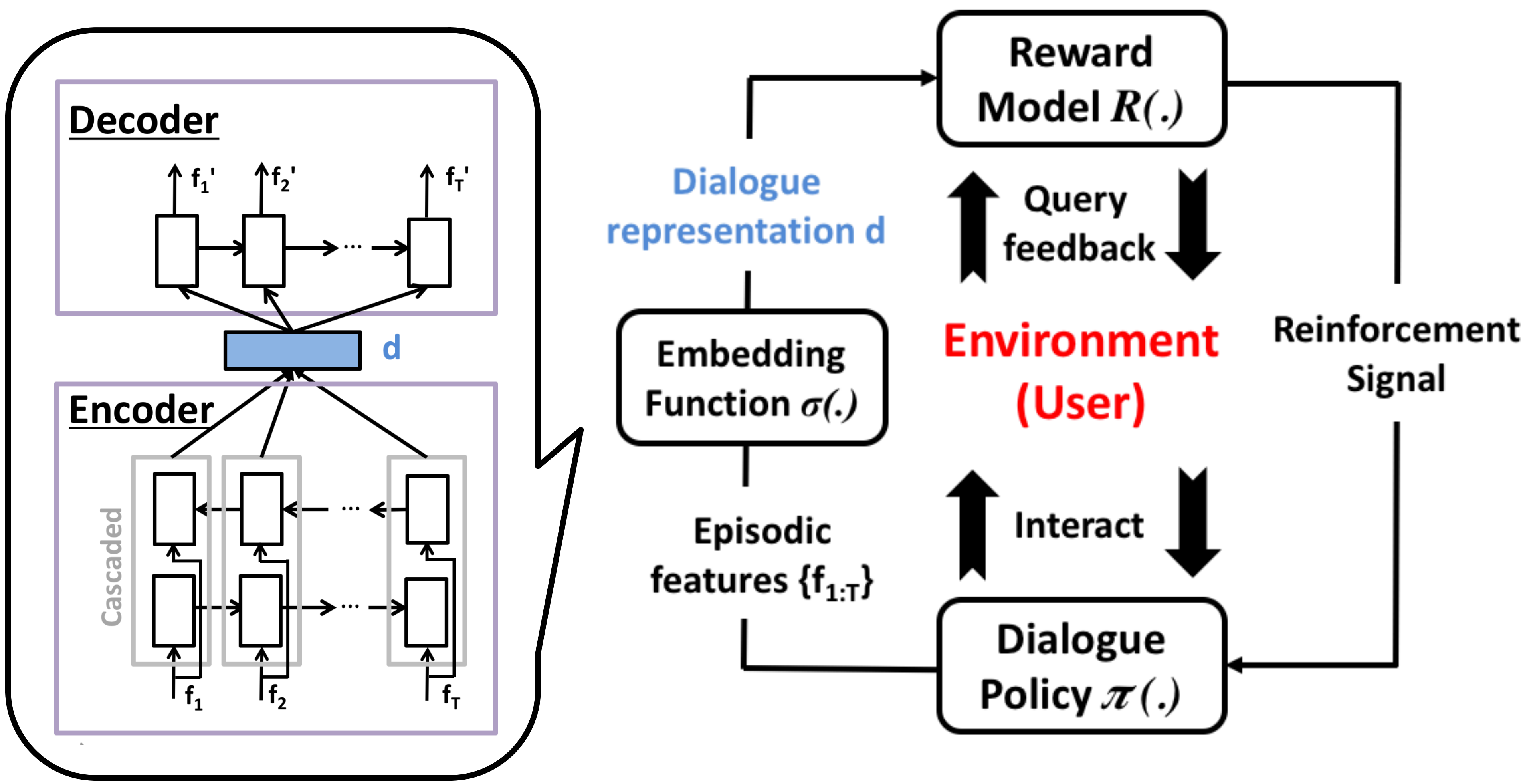
- Select the best action that can maximize the future reward.



- Dialogue is a special RL task
  - Human involves in interaction and rating (evaluation) of a dialogue
  - Fully human-in-the-loop framework
- Rating: correctness, appropriateness, and adequacy

Interactions with users

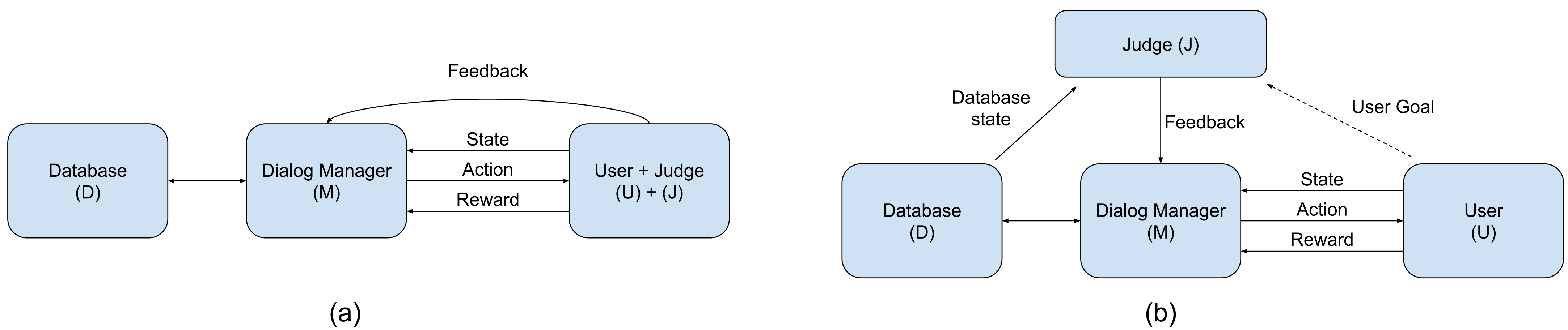
- Provide a external feedback to the dialogue manager



Su et al., On-line Active Reward Learning for Policy Optimisation in Spoken Dialogue Systems, 2016

Interactive reinforcement learning for dialogue management

- Using the feedback to directly shape the policy enables a dialogue manager to learn new interactions faster compared to interpreting the feedback as a reward value.

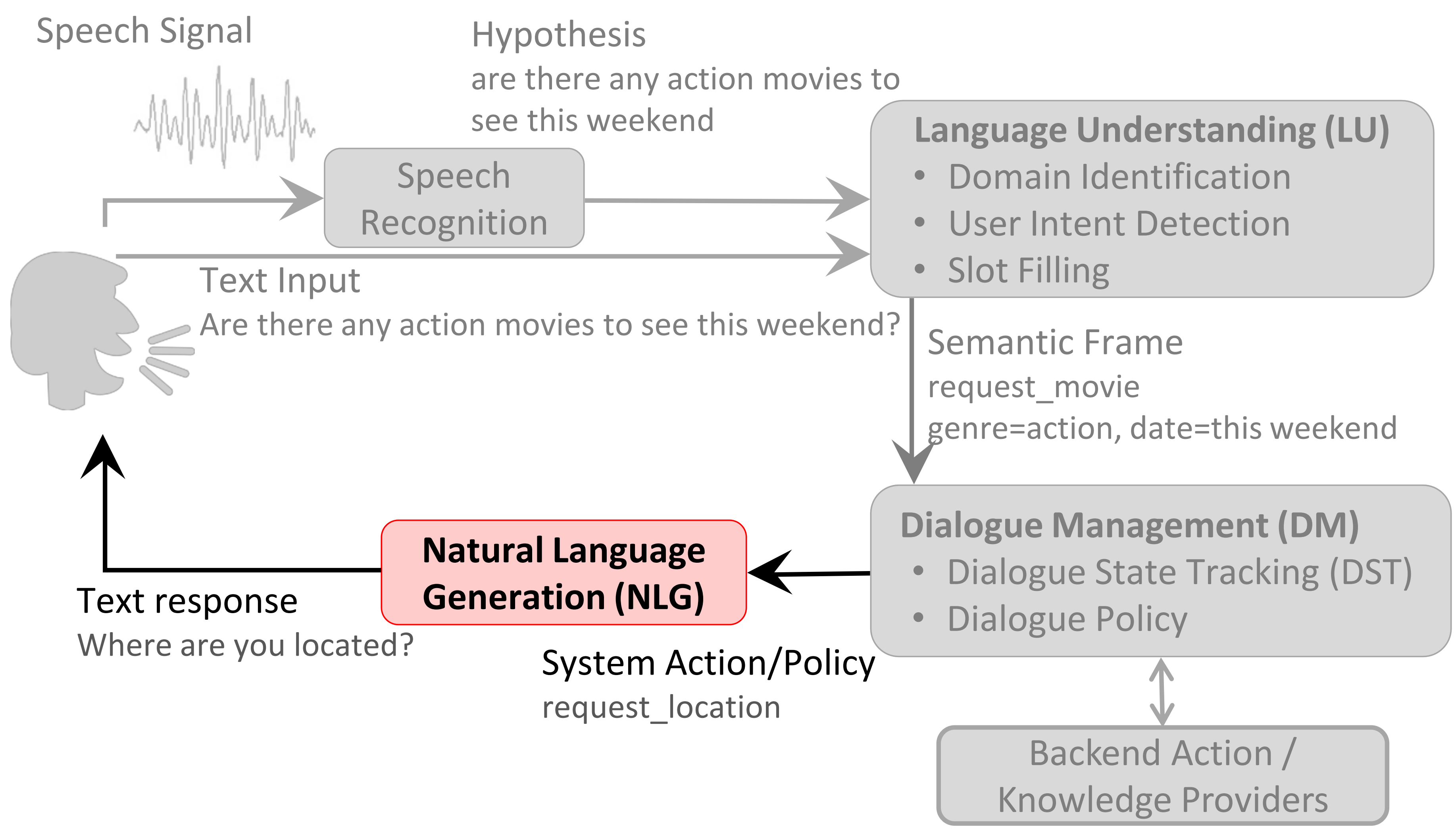


Interactive RL for training a dialogue manager.

- (a) The user provides a feedback signal to the dialogue manager.
- (b) A third agent, J, observes the interactions and provides feedback to the dialogue manager.

Shah et al., Interactive reinforcement learning for task-oriented dialogue management, 2016

Natural language generation



Goal: generate natural language or GUI given the selected dialogue action for interactions

目录

- Pipeline-based task-oriented dialogue generation
- End2End task-oriented dialogue generation
- Related real-world applications
- Future work

Traditional Pipeline Designs

- Intent classifier
  - Booking restaurants, flights, etc.
- Belief tracker
- Policy maker
- Dialogue generator

Problems of Traditional Pipeline Designs

- Complex belief trackers
- Fragility
- Templated response

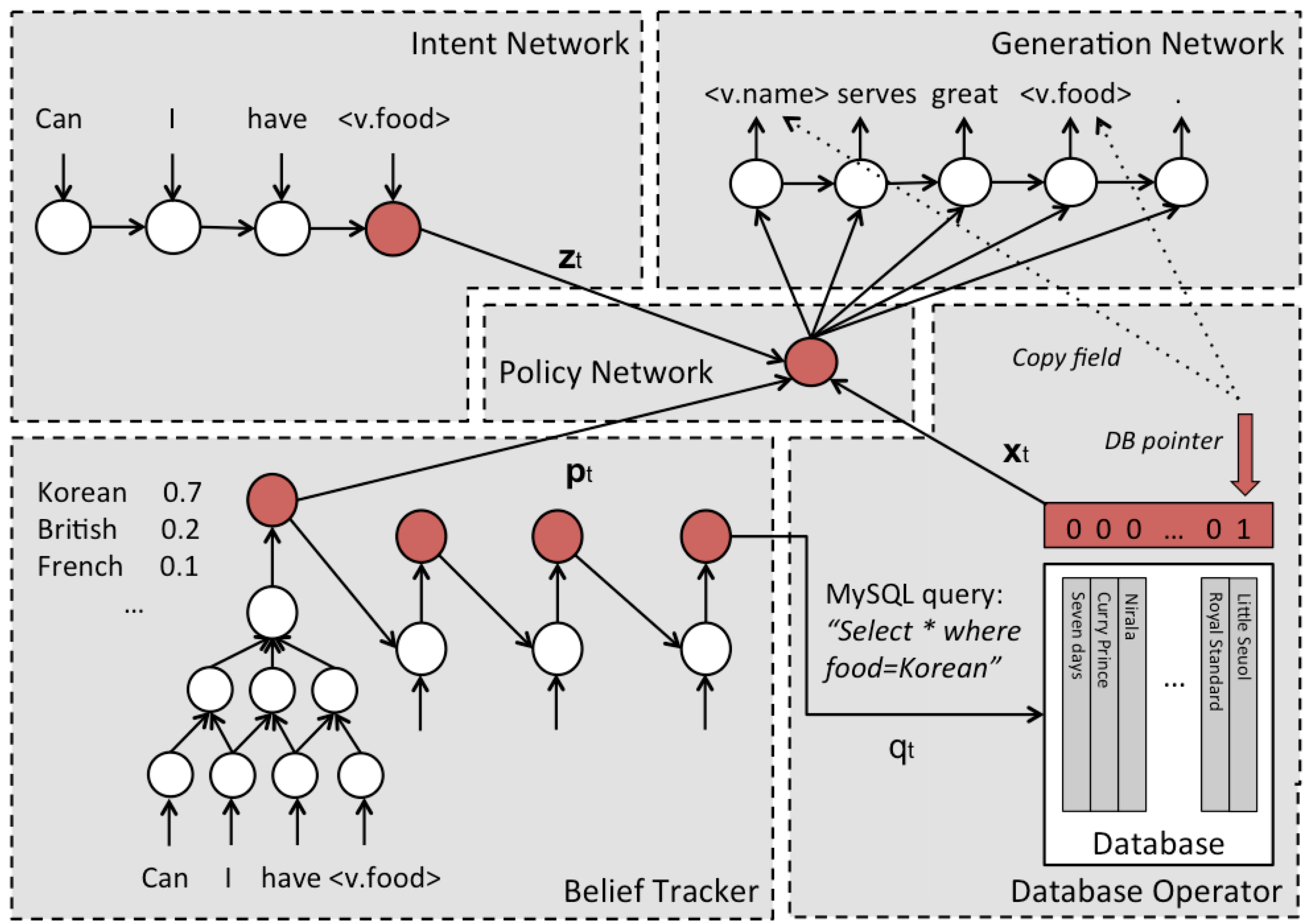
An End-to-end Solution

- Intent classifier
- Booking restaurants etc.
- Belief tracker
- Policy maker
- Response generator

An End-to-end Trainable Dialogue System (NDM) (Wen et al., 2017b)

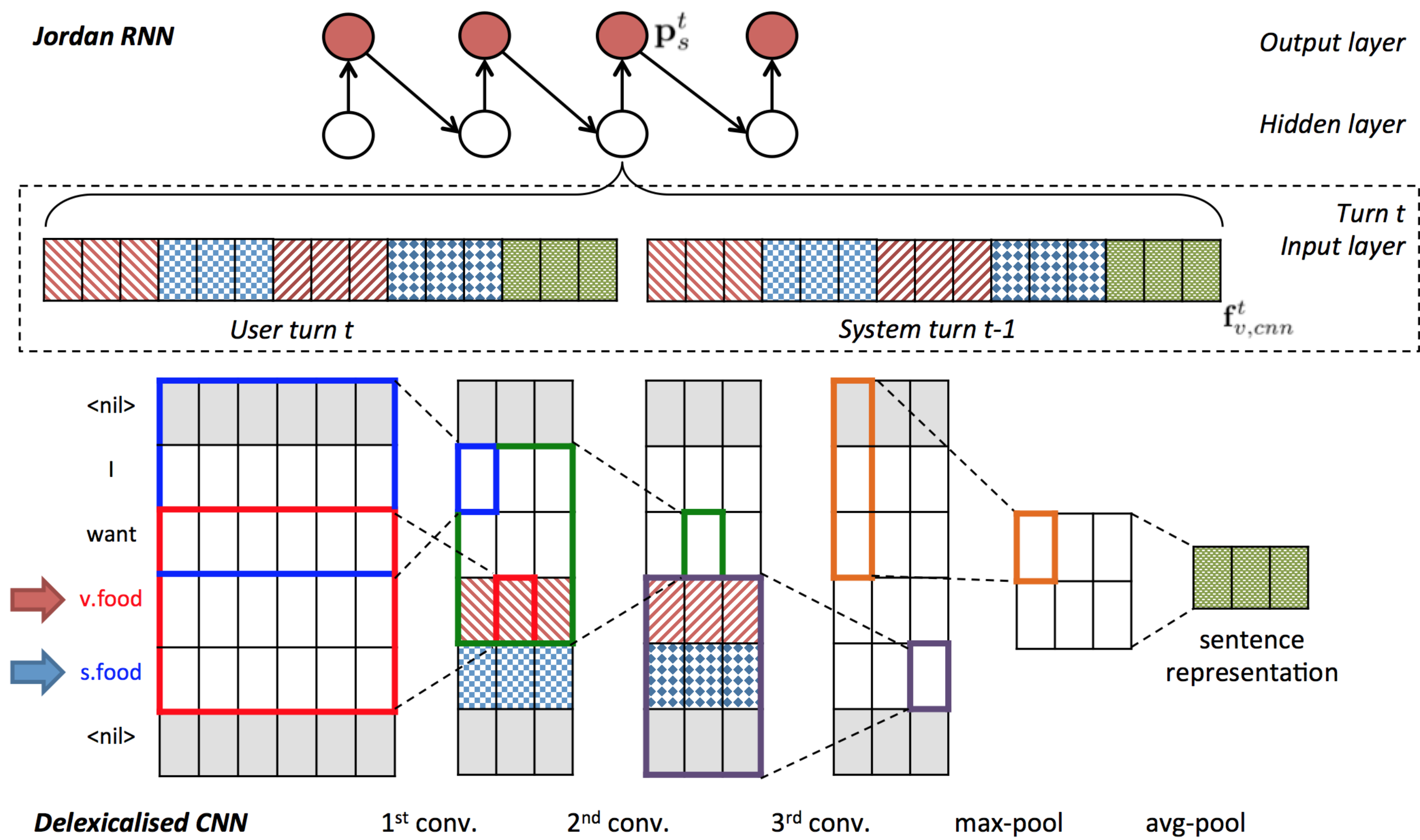
Wen, et al., A network-based end-to-end trainable task-oriented dialogue system. EACL .

Neural dialogue manager



Wen, et al., A network-based end-to-end trainable task-oriented dialogue system. EACL .

Tied Jordan-type RNN belief tracker

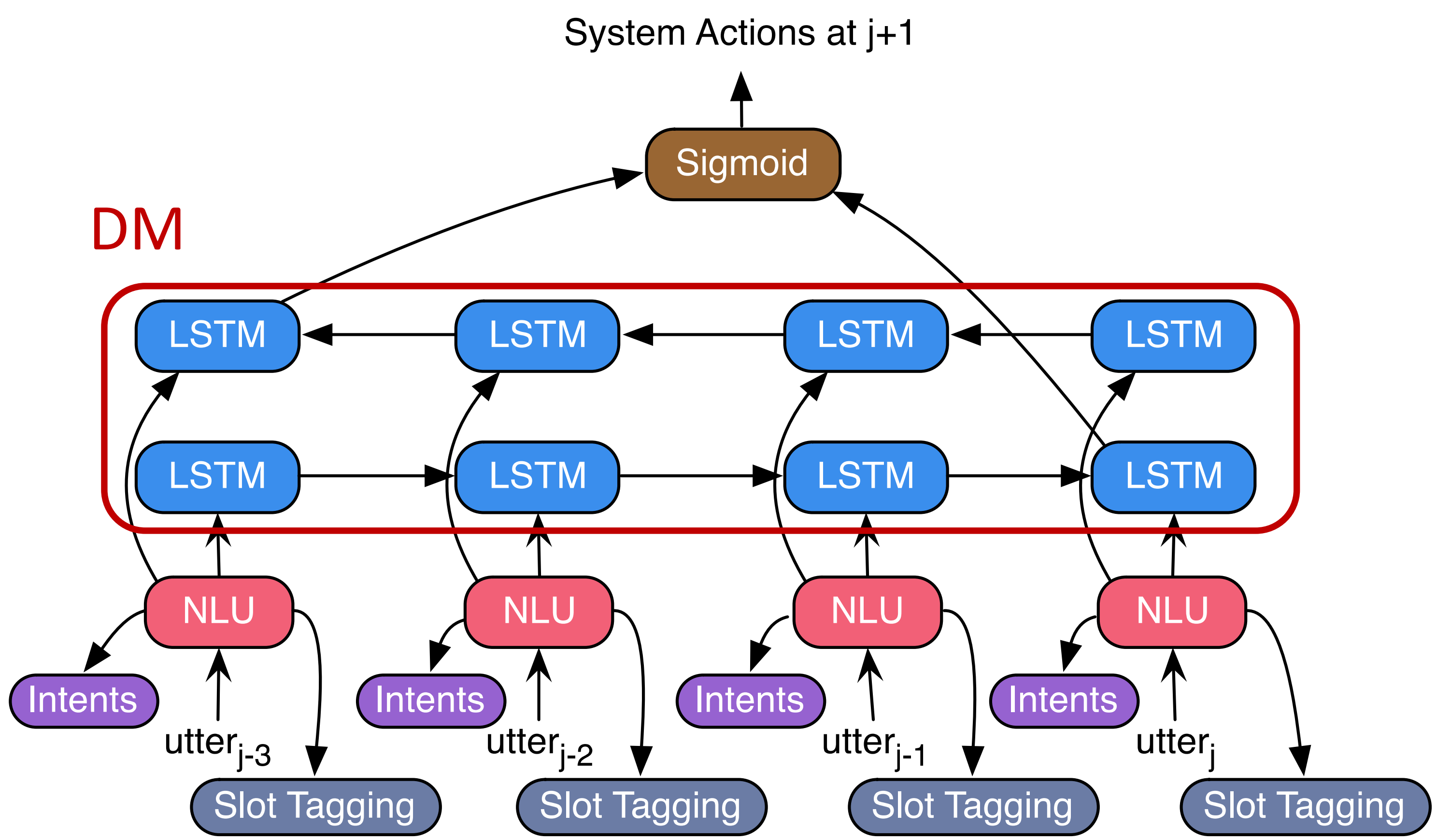


Tied Jordan-type RNN belief tracker with delexicalised CNN feature extractor.

Wen, et al., A network-based end-to-end trainable task-oriented dialogue system. EACL .

End-to-end model joint NLU and DM

- Errors from dialogue manager can be propagated to NLU for regularization+robustness

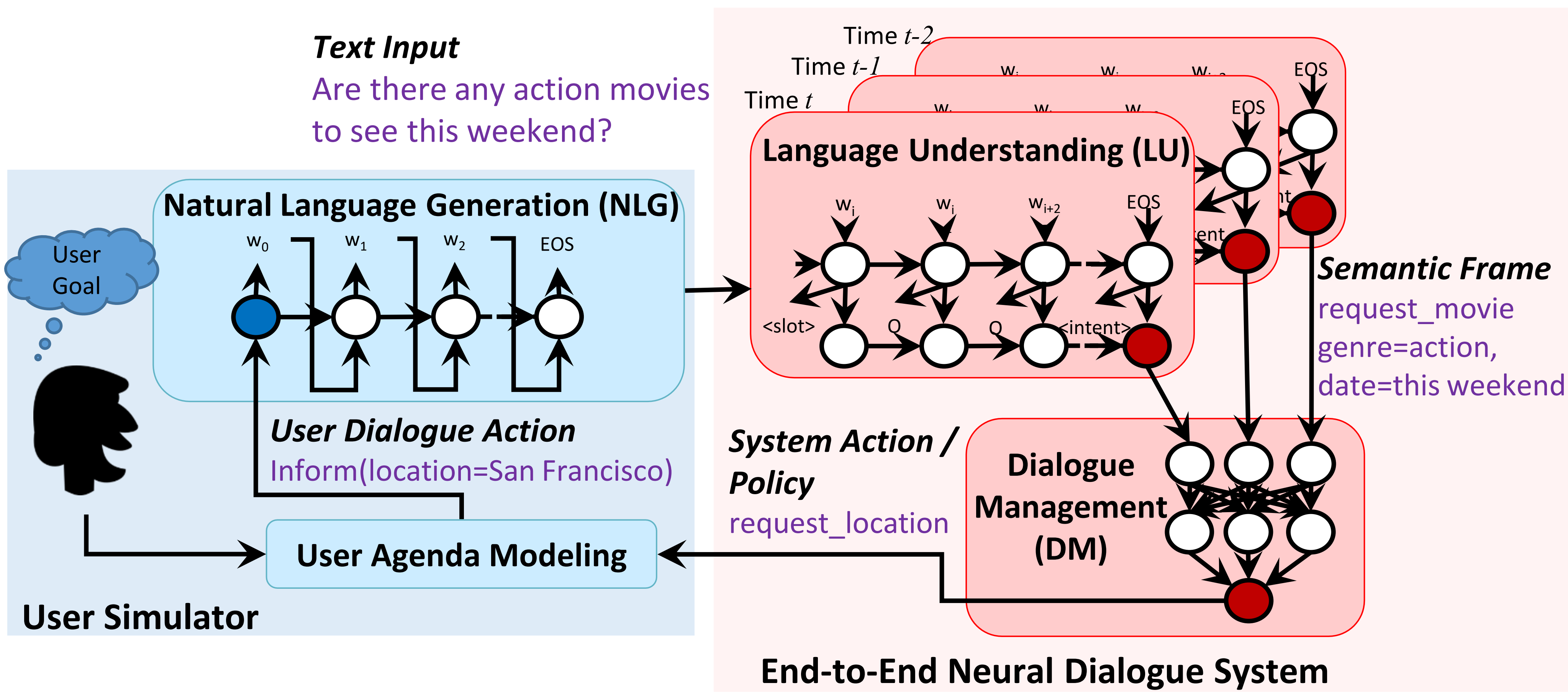


Both DM and NLU performance (frame accuracy) is improved

Yang et al., End-to-End Joint Learning of Natural Language Understanding and Dialogue Manager, ICASSP 2017

End-to-end task completion Bot

- Supervised learning for each component and reinforcement learning for end-to-end training the neural dialogue system



Li et al., End-to-End Task-Completion Neural Dialogue Systems, IJCNLP 2017

End-to-end task completion Bot

User goal: two tickets for “the witch” tomorrow 9h30 at regal meridian 16, Seattle

The system is capable to learn how to efficiently interact with users for task completion

Rule-based Agent

User: What is the start time for 10 cloverfield lane?
Agent: What movie are you interested in?
User: I want to watch at 10 cloverfield lane.
Agent: What time would you like to see it?
User: What time is it playing tomorrow? I need 3 tickets.
Agent: What city you would like?
User: I do not care.
Agent: What date would you like to watch it?
User: I want to set it up tomorrow.
Agent: Which theater would you like?
User: Which theater is available?
Agent: How many tickets do you need?
User: I want 3 tickets please!
Agent: Okay, I have booked 3 tickets for 10 cloverfield lane tomorrow.
User: Thank you.
Agent: Thank you.

Failure: Agent does not answer all the questions (starttime, theater) from user.

RL Agent

User: Which theater can I book 3 tickets for 10 cloverfield lane?
Agent: What time would you like to see it?
User: Which theater and start time are available tomorrow?
Agent: 11:45am is available.
User: Which theater is available?
Agent: regal la live stadium 14 is available.
User: Could you help me to book the tickets?
Agent: Okay - I was able to book 3 tickets for you to see 10 cloverfield lane at regal la live stadium 14 at 11:45am tomorrow.
User:Thank you.
Agent: Thank you.

Success

Li et al., End-to-End Task-Completion Neural Dialogue Systems, IJCNLP 2017

Some problems still remains…

- Complex belief trackers
    - Pre-trained Belief Tracker
- Fragility
- Templated response

Sequicity: Simplifying Task-oriented Dialogue Systems with Single Sequence-to-Sequence Architectures (ACL 2018)

Wenqiang Lei, Xisen Jin, Zhaochun Ren, Xiangnan He, Min-Yen Kan, Dawei Yin

Complex BeliefTracker in NDM

- Informable slots

Food style	Price range	Open hour	…
Chinese food	Expensive	Before 11:00 pm	…
Japanese food	Cheap	…	…
French food	…	…	…
…	…	…	…
…	…	…	…

- Requestable slots

Requiring address?	Requiring phone	Requiring name?	…
Yes	Yes	Yes	…
No	No	Know	…

Sequicity solution

- Belief span
  - <Inf>Italian;Cheap</Inf> <Req>Address</Req>

Turn	Dialogue
$User_1$	Can I have some Italian food please?
$Machine_1$	<Inf> Italian </Inf><Req> </Req> What price range are you looking for?
$User_2$	I want cheap ones.
$Machine_2$	<Inf> Italian ; cheap </Inf> <Req></Req> NAME_SLOT is a cheap restaurant serving western food
$User_3$	Tell me the address and the phone number please .
$Machine_3$	<Inf> Italian ; cheap </Inf> <Req>address ; phone</Req> The address is ADDRESS_SLOT and the phone number is PHONE_SLOT

Sequicity solution

- Belief span
  - <Inf>Italian;Cheap</Inf> <Req>Address</Req>

Turn	Dialogue
$User_1$	Can I have some Italian food please?
$Machine_1$	<Inf> Italian </Inf><Req> </Req> What price range are you looking for?
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Sequicity solution

Belief span
—<Inf>Italian;Cheap</Inf>
<Req>Address; Phone</Req>

Turn	Dialogue
$User_1$	Can I have some Italian food please?
$Machine_1$	<Inf> Italian </Inf><Req> </Req> What price range are you looking for?
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Sequicity solution

Belief span

— <Inf>Italian;Cheap</Inf>
<Req>Address; Phone</Req>

Notation

- B_t: belief span
- U_t: user utterance
- R_t: machine response

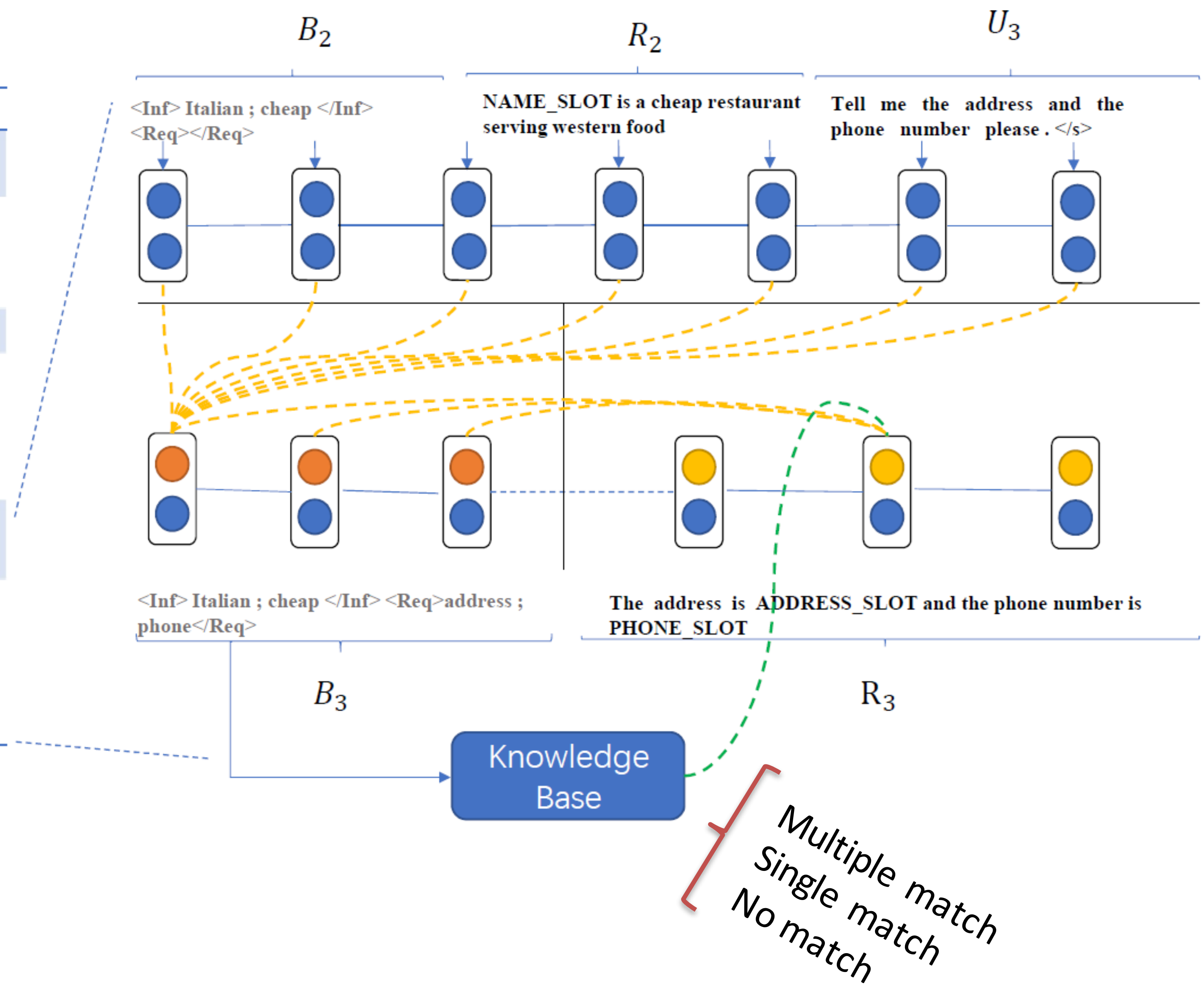
Source sequence

Target sequence

Turn	Dialogue
User$_1$	Can I have some Italian food please?
Machine$_1$	<Inf> Italian </Inf><Req> </Req> What price range are you looking for?
User$_2$	I want cheap ones.
Machine$_2$	<Inf> Italian ; cheap </Inf> <Req></Req> NAME_SLOT is a cheap restaurant serving western food
User$_3$	Tell me the address and the phone number please .
Machine$_3$	<Inf> Italian ; cheap </Inf> <Req>address ; phone</Req> The address is ADDRESS_SLOT and the phone number is PHONE_SLOT

Sequicity illustration

Turn	Dialogue
User$_1$	Can I have some Italian food please?
Mach ine$_1$	<Inf> Italian </Inf><Req> </Req> What price range are you looking for?
User$_2$	I want cheap ones.
Mach ine$_2$	<Inf> Italian ; cheap </Inf> <Req></Req> NAME_SLOT is a cheap restaurant serving western food
User$_3$	Tell me the address and the phone number please .
Mach ine$_3$	<Inf> Italian ; cheap </Inf> <Req>address ; phone</Req> The address is ADDRESS_SLOT and the phone number is PHONE_SLOT



Optimization

- Joint log-likelihood
  - Short coming: treating each word equally
  - E.g., The closest Italian restaurant is at <addr_slot>
- Reinforcement learning
  - Action: decoding a word
  - State: hidden vectors generated by RNNs
  - Reward: decoding a correct placeholder +1, decoding each word -0.1

Experiments: datasets

Dataset	Cam676
Size	Train:408 / Test: 136 / Dev: 136
Domains	restaurant reservation
Slot types	price, food style etc.
Distinct slot values	99

Dataset	KVRET		
Size	Train:2425 / Test: 302 / Dev: 302		
Domains	calendar	weather info.	POI
Slot types	date, etc.	location, etc.	poi, etc.
Distinct slot values	79	65	140

Experimental results

	CamRes676					KVRET				
	Mat.	BLEU	Succ. F_1	$Time_{full}$	$Time_{N.B.}$	Mat.	BLEU	Succ. F_1	$Time_{full}$	$Time_{N.B.}$
(1) NDM	0.904	0.212	0.832	91.9 min	8.6 min	0.724	0.186	0.741	285.5 min	29.3 min
(2) NDM + Att + SS	0.904	0.240	0.836	93.7 min	10.4 min	0.724	0.188	0.745	289.7 min	33.5 min
(3) LIDM	0.912	0.246	0.840	97.7 min	14.4 min	0.721	0.173	0.762	312.8 min	56.6 min
(4) KVRN	N/A	0.134	N/A	21.4 min	–	0.459	0.184	0.540	46.9 min	–
(5) TSCP	**0.927**	**0.253**	**0.854**	7.3 min	–	**0.845**	**0.219**	**0.811**	25.5 min	–
(6) Att-RNN	0.851	0.248	0.774	7.2 min	–	0.805	0.208	0.801	23.0 min	–
(7) TSCP\\k_t	**0.927**	0.232	0.835	7.2 min	–	**0.845**	0.168	0.759	25.3 min	–
(8) TSCP\\RL	**0.927**	0.234	0.834	**4.1** min	–	**0.845**	0.191	0.774	**17.5** min	–
(9) TSCP\\B_t	0.888	0.197	0.809	22.9 min	–	0.628	0.182	0.755	42.7 min	–

Table 2: Model performance on CamRes676 and KVRET. This table is split into two parts: competitors on the upper side and our ablation study on the bottom side. **Mat.** and **Succ. F1** are for match rate and success F1 respectively. $\mathbf{Time_{full}}$ column reports training time till converge. For NDM, NDM+Att+SS and LIDM, we also calculate the training time for the rest parts except for the belief tracker ($\mathbf{Time_{N.B.}}$).

Time expenses on BeliefTrackers

	CamRes676					KVRET				
	Mat.	BLEU	Succ. F_1	$Time_{full}$	$Time_{N.B.}$	Mat.	BLEU	Succ. F_1	$Time_{full}$	$Time_{N.B.}$
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RL helps with BLEU and Succ. F1

	CamRes676					KVRET				
	Mat.	BLEU	Succ. F_1	$Time_{full}$	$Time_{N.B.}$	Mat.	BLEU	Succ. F_1	$Time_{full}$	$Time_{N.B.}$
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Removing CopyNets

	CamRes676					KVRET				
	Mat.	BLEU	Succ. F_1	$Time_{full}$	$Time_{N.B.}$	Mat.	BLEU	Succ. F_1	$Time_{full}$	$Time_{N.B.}$
(1) NDM	0.904	0.212	0.832	91.9 min	8.6 min	0.724	0.186	0.741	285.5 min	29.3 min
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Discussions: OOV experiments

- Synthesized OOV data:
    - I would like some **Chinese** food. I would like some **Chinese_unk** food.

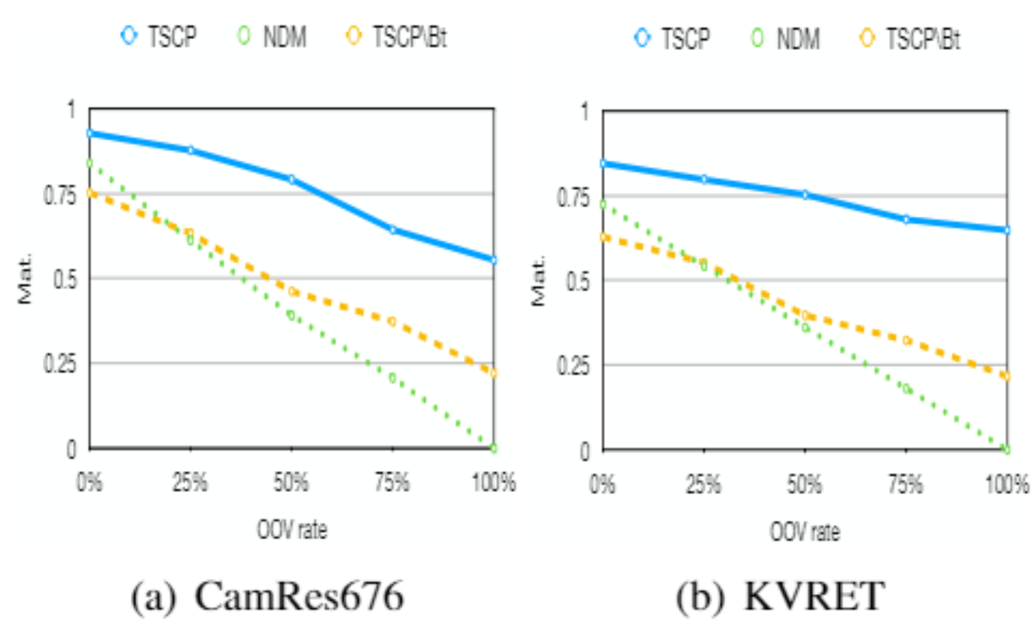


Figure 2: OOV tests. 0% OOV rate means no OOV instance while 100% OOV rate means all instances are changed to be OOV.

Discussions: Parameter Scales

Dataset	Cam676		
Size	Train:408 / Test: 136 / Dev: 136		
Domains	restaurant reservation		
Slot types	price, food style etc.		
Distinct slot values	99		
Dataset	KVRET		
Size	Train:2425 / Test: 302 / Dev: 302		
Domains	calendar	weather info.	POI
Slot types	date, etc.	location, etc.	poi, etc.
Distinct slot values	79	65	140

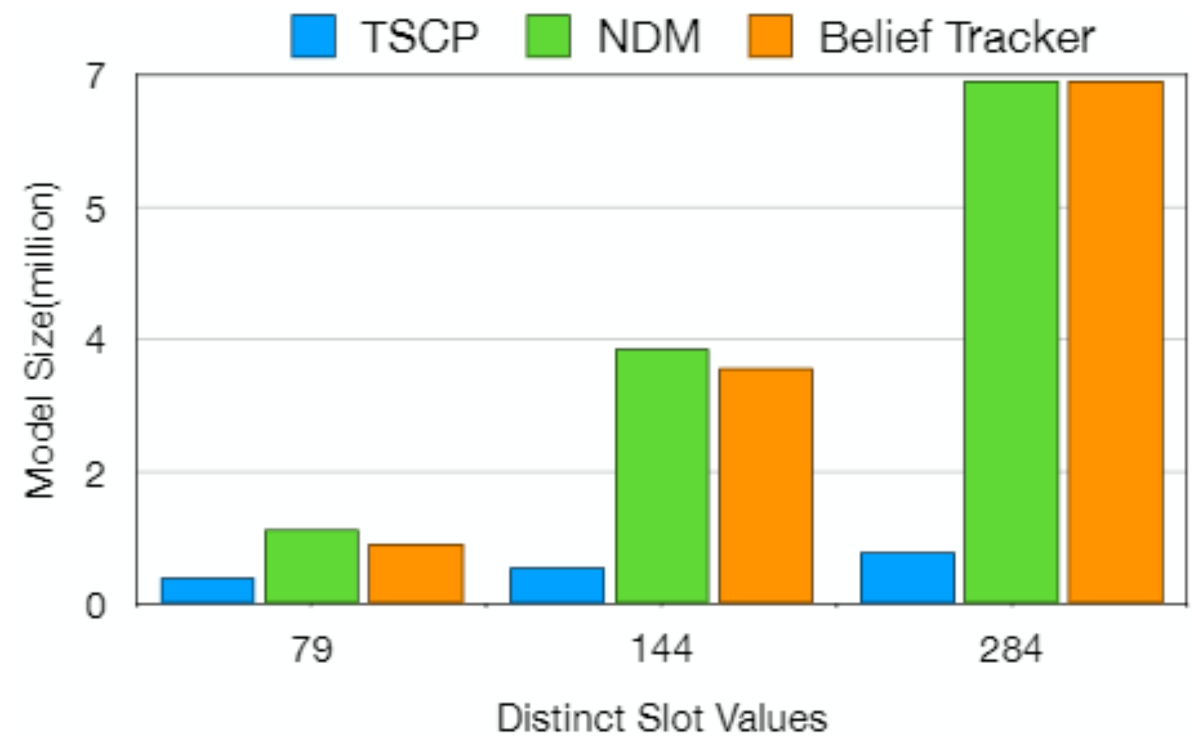


Figure 3: Model size sensitivity with respect to KVRET. Distinct slot values of 79, 144, 284 correspond to the number of slots in KVRET's *calendar*, *calendar* + *weather info.*, and all 3 domains.

Explicit state tracking with semi-supervision for neural dialogue generation (CIKM 2018)

Xisen Jin, Wenqiang Lei, Zhaochun Ren, Hongshen Chen, Shangsong Liang, Dawei Yin

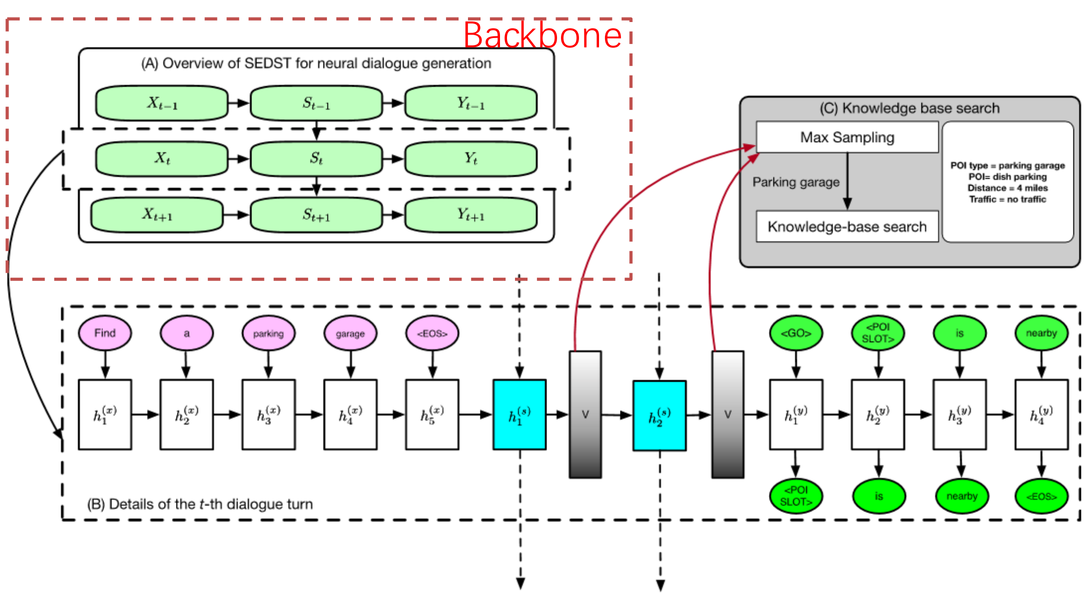
Semi-supervised explicit state tracking framework

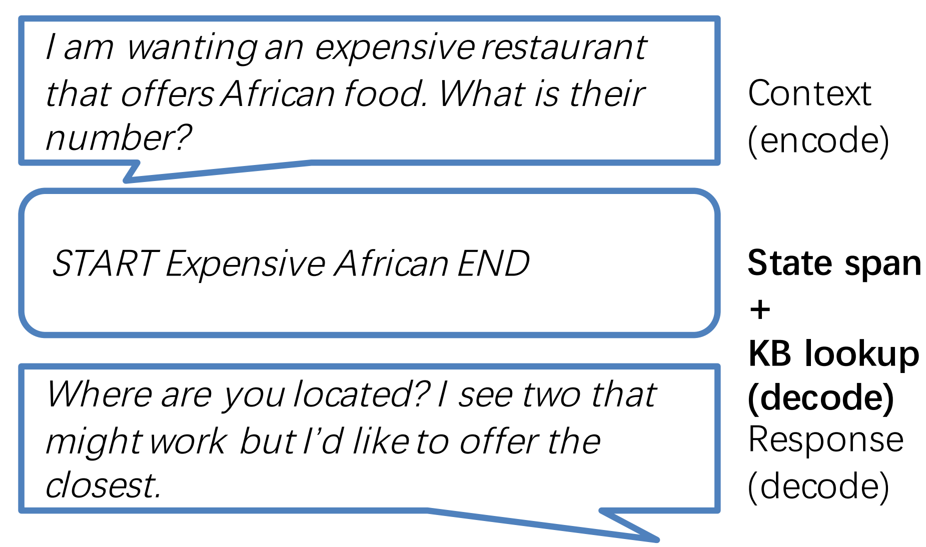
- Current issue
  - Task oriented dialogue systems
    - Expensive state labeling
  - Non task oriented dialogue systems
    - Almost impossible state labeling
    - Implicit dialogue states are not capable for distinguishing similar concepts or entities(e.g. product names) in QA / transactional domain
    - Implicit dialogue states have poor interpretability

- SEDST – semi-supervised explicit state tracking framework
- Goal: Semi-supervised / Unsupervised explicit state tracking for task& non-task oriented dialogue systems

Backbone of CopyFlow network

- Copyflow network
  - Input encoder
  - State span decoder
    - Decode dialogue states sequentially (Lei et al. 2018)
    - E.g: <inf> Italian <sep> moderate </inf>
  - Response decoder





Procedure of encoding and decoding in a dialogue turn

Model architecture — CopyFlow network

- Attention GRU encoder decoder
  - More details in the paper
- A "copyflow" from s to t:
  - Definition: Incorporating copying mechanism from *s* to *t*.
  - The probability of decoding a word is the sum of generation and copying probability
  - Generation probability $p_j^g = \frac{1}{Z} e^{w_3 h_j^{(y)}}$
  - Copying probability
    - "Hard" copy (Gu et al. 2016) $p^{c(X)}(y_j) = \begin{cases} \frac{1}{Z}\sum_{i:w_{x_i}=y_j} e^{\psi(w_{x_i})}, y_j \in X \\ 0, otherwise \end{cases}$
    - "Soft" copy (proposed) $p^{c(X)}(y_j) = \frac{1}{Z}\sum_{i=1}^{|X|} p_i(w_{x_i} = y_j) e^{\psi(w_{x_i})}$

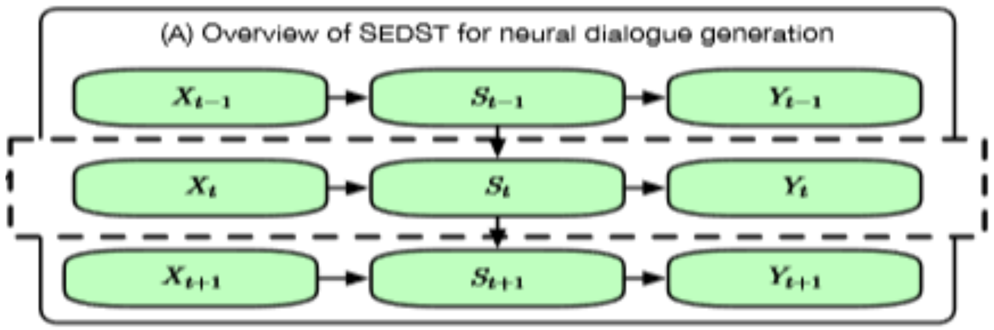
$w_{x_i} = y_j$: enable copying if the word exists in *s*
$\psi(w_{x_i})$: score of copying the i-th positional word

$p_u(w_{x_i} = y_j)$: the probability that the i-th word in source sequence is yj

Model architecture — CopyFlow network

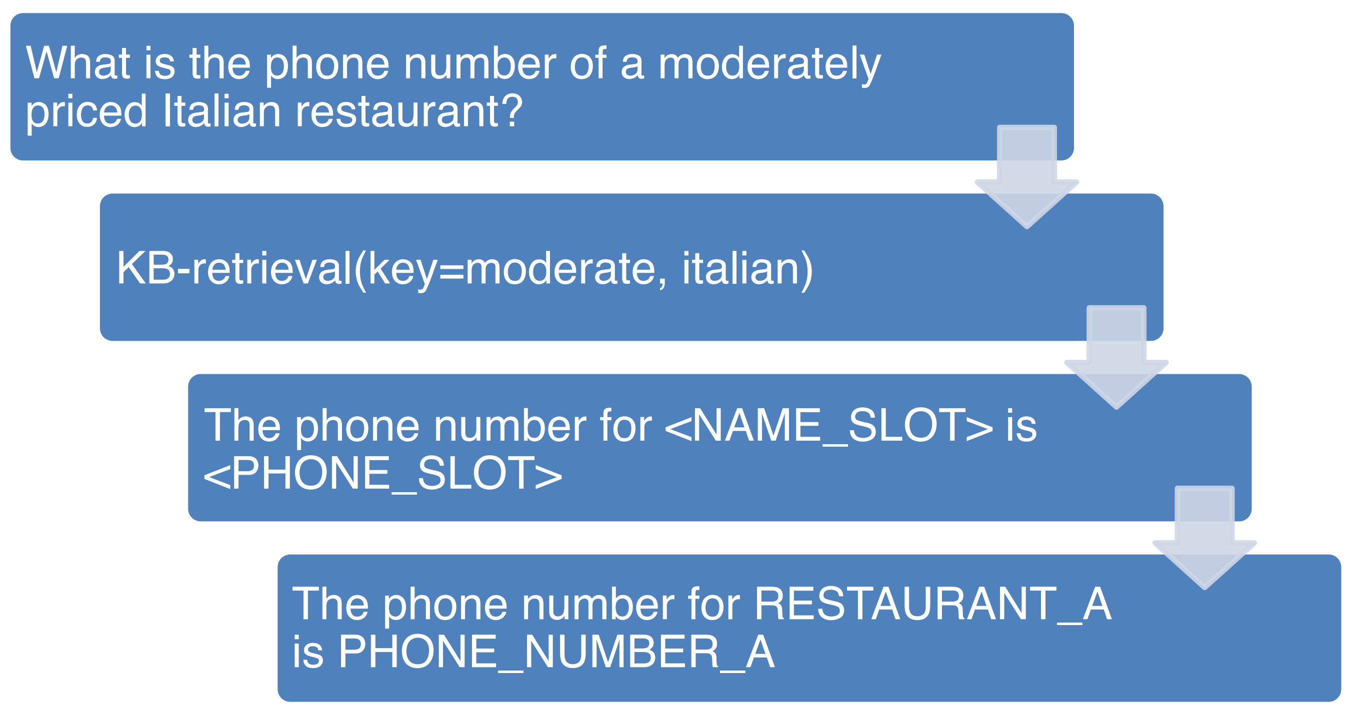
- Inspired from the pattern that repeating of keywords could indicate dialogue states
- Co-occurrence may span over dialogue turns – keywords should be “copied” over dialogue turns
- From {previous responses, current inputs} to current state spans & From current state spans to current responses
  - Enables the model to “cache” keywords in state spans
  - Also possible to generate new words in state spans to further copy
- From previous state spans to current state spans
- The model learns to store information at state spans in the form of explicit word sequences

Role	Utterance
User	*I am wanting an expensive restaurant that offers African food. What is their number?*
Agent	*Where are you located? I see two that might work but I’d like to offer the closest.*
User	*I do not care about the area of town.*
Agent	*Bedouin is an expensive African restaurant in the city centre.*



Knowledge-base search

- We follow the setting of Sequicity (Lei et al. 2018)
- The state spans are decoded without keyword and the queries are performed to all fields in a KB
- Entity type information can be obtained with a separate classifier or pre-defined table
- The retrieved results are utilized to fill in the placeholders in generated responses



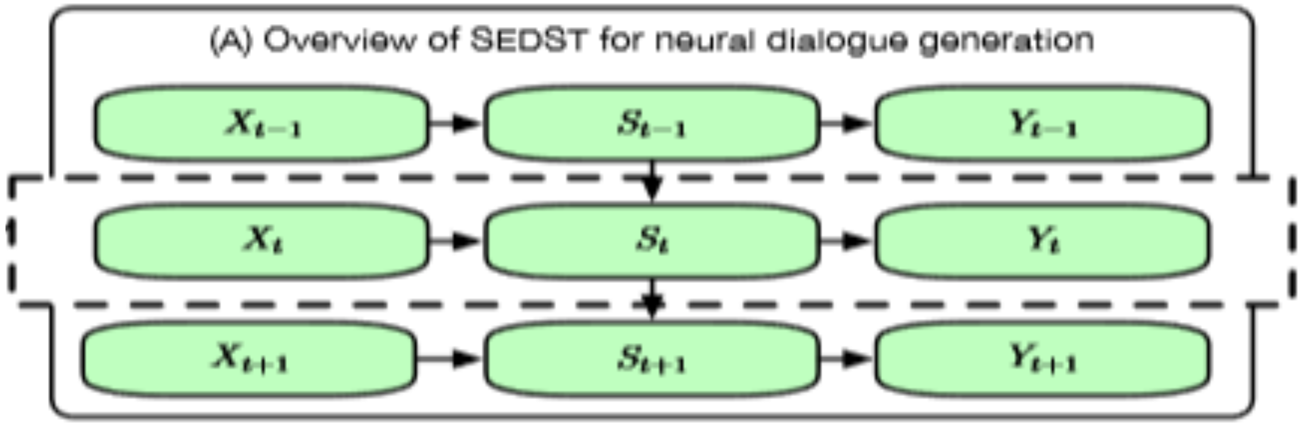
Training — posterior regularization

- The training can be unstable without it
- Probabilistic interpretation of above-mentioned model
  - State span: $P_\Theta(S_t|R_{t-1}, S_{t-1}, U_t) = \Pi_i \mathbf{p}(s_t^{(i)}|s_t^{(<i)}, R_{t-1}, S_{t-1}, U_t)$.
  - Response generation: $P(R_t|R_{t-1}, U_t, S_t)$

- Additionally train a (helper) posterior network

$$Q_\Phi(S_t|S_{t-1}, R_{t-1}, U_t, R_t) = \Pi_i \mathbf{q}(s_t^{(i)}|s_t^{(<i)}, R_{t-1}, S_{t-1}, U_t, R_t)$$

Inputs for this model



Training — posterior regularization

- Learning objective in semi-supervised scenarios for task-oriented datasets

$$\mathcal{L}_1 = -\sum^{\mathcal{A}\cup\mathcal{U}} log[P(R_t|R_{t-1}, U_t, S_t)]$$ Response generation loss

$$-\sum^{\mathcal{A}} log[P_\Theta(S_t|R_{t-1}, U_t, S_{t-1})Q_\Phi(S_t|R_{t-1}, U_t, S_{t-1}, R_t)]$$ Prior & Posterior state span generation loss

$$+\lambda \sum^{\mathcal{U}} \sum_{i=1}^{N} KL(\mathbf{q}_i||\mathbf{p}_i),$$ Regularization loss

- Interpretation:
  - Given limited data, the posterior network learns better than the prior network, since it is exposed to more inputs
  - The output of the prior network is forced to be close to that of the posterior network – “weak supervision”

Training — posterior regularization

- Learning objective in unsupervised scenarios
- Have no annotated dialogue state data to train on for both prior and posterior network

- Method: Adjust the input and output of the posterior network as an auto-encoder
  - Learn to reconstruct the encoder input $R_{t-1}U_tR_t$ at its decoder
  - The model learns to cache keywords in $R_{t-1}U_tR_t$ into S_t

Training — posterior regularization

- Learning objective in unsupervised scenarios

$$
\begin{aligned}
\mathcal{L}_2 = &-\sum^{\mathcal{U}} log[P(R_t|R_{t-1}, U_t, S_t)] && \text{Response generation loss} \\
&-\sum^{\mathcal{U}} log[Q_\Phi(R_{t-1}, U_t, R_t|\hat{S}_t)] && \text{Reconstruction loss} \\
&+\lambda \sum^{\mathcal{U}} \sum_{i=1}^{N} KL(\mathbf{q}_i||\mathbf{p}_i)\,. && \text{Regularization loss}
\end{aligned}
$$

- Interpretation:
  - The posterior network learns compacted representation of _R_t−1__U_t__R_t_ with a learning objective of autoencoder
  - Although the prior network can explore a generation strategy of the state span, it is regularized towards the posterior network.

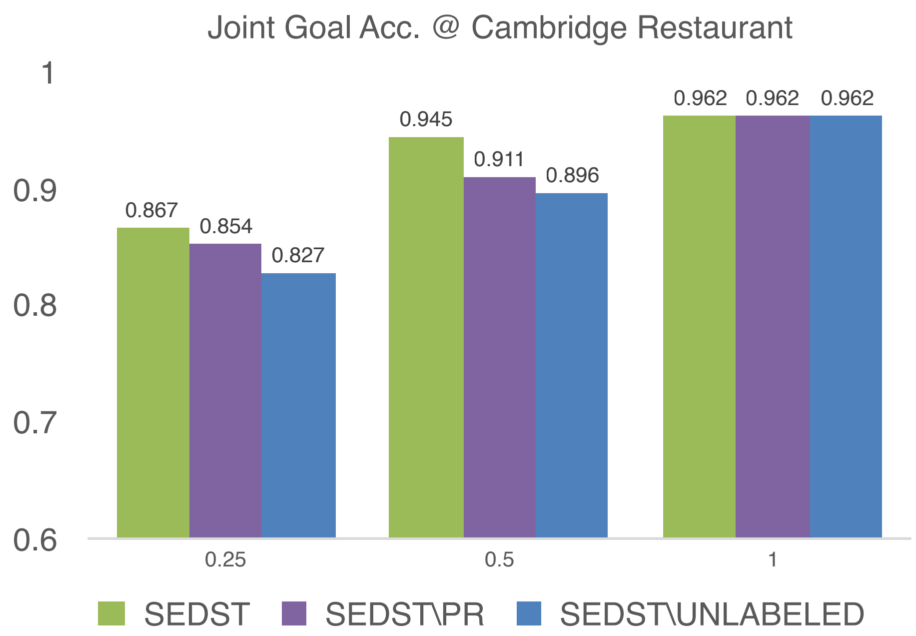
Experiments

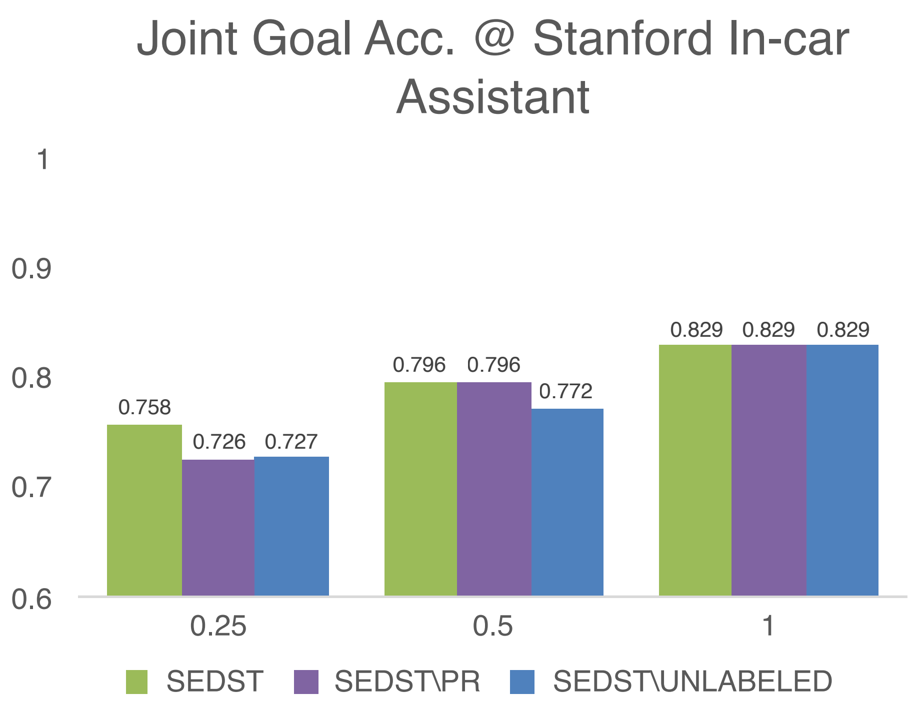
- Task-oriented Dataset
  - Cambridge Restaurant Reservation dataset(676 dialogues)
  - Stanford In-Car Assistant dataset(3029 dialogues)

- Non-task oriented Dataset
  - Ubuntu Dialogue corpus(487337 dialogues)
  - JD.com Customer Service corpus (425005 dialogues)
- Research Questions
  - What is the overall performance of our model SEDST
  - How much does unlabeled data help dialogue state tracking on task-oriented dialogues?
  - Is our explicit state tracker helpful for non-task oriented response generation?
  - Does posterior regularization helps?
  - Can SEDST generate interpretable state spans?

Results — Task-oriented dialogue generation

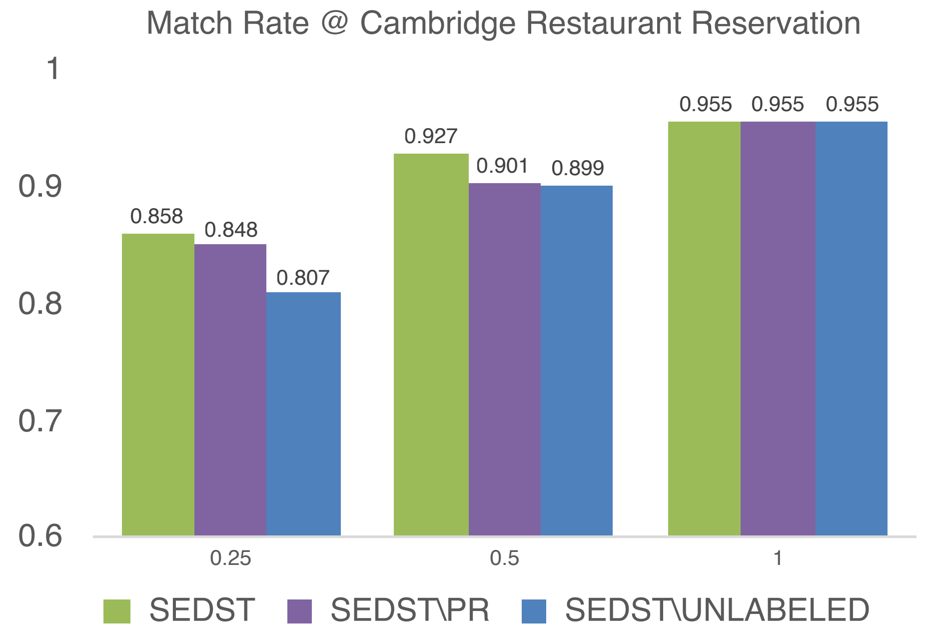
- Comparisons: SEDST, SEDST\PR(without posterior-regularization), SEDST\UNLABELED(only trained on labeled data)
- Metric 1: Joint Goal Accuracy(whether all the constraints are correct in a turn)

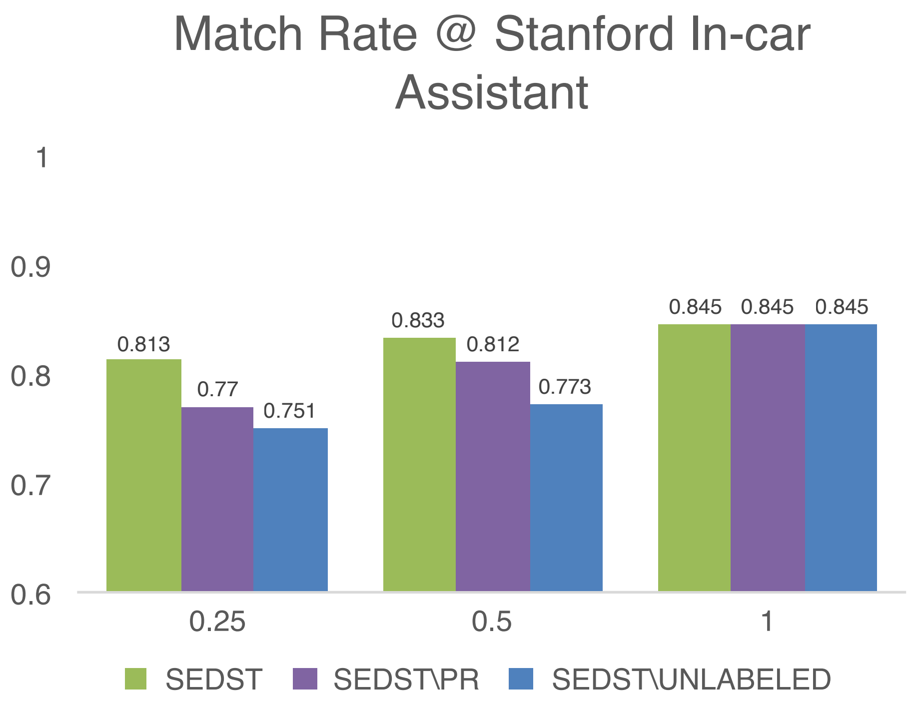




Results — Task-oriented dialogue generation

- Metric 2: Final Entity Match Rate(whether the state span in the final turn is correct)
- SEDST outperforms SEDST\UNLABELED: SEDST could utilize unlabeled data for learning
- SEDST outperforms SEDST\PR: Posterior regularization is effective





Results — Non-task-oriented dialogue generation

- Metric for response generation: Embedding Based Metrics
  - Embedding Average
  - Embedding Greedy
  - Embedding Extrema
- Specifically, our model outperforms VHRED and HVMN, which employs continuous latent variables for state tracking

Model	Emb. Average	Emb. Greedy	Emb. Extrema
SEQ2SEQ	0.216	0.169	0.126
HRED	0.542	0.412	0.319
VHRED	0.534	0.403	0.306
HVMN	0.558	0.423	0.322
DAWnet	0.530	0.390	0.333
SEDST\PR	0.586	0.438	0.330
SEDST	**0.609**	**0.451**	**0.337**

Model	Emb. Average	Emb. Greedy	Emb. Extrema
SEQ2SEQ	0.425	0.479	0.264
HRED	0.549	0.587	**0.406**
VHRED	0.576	0.593	0.392
HVMN	0.564	0.596	0.405
DAWnet	0.579	0.574	0.375
SEDST\PR	0.575	0.602	0.373
SEDST	**0.585**	**0.607**	0.392

Part 5: Summary and outlook

Challenges

- Human-machine interfaces is a hot topic but several components must be integrated
- Most of state-of-the-art methods are based on Deep NNs
- Fast domain adaptation with scare data + re-use of rules
- Data collection&analysis from unstructured data
- Complex-cascade systems requires high accuracy

Summary

- Brief introduction about dialogue systems
- Introduce recent NN-based methods for dialogue generation
- Main components of task-oriented dialogue generation
- Each component in pipeline dialogue generation
- Recent work on end-to-end task-oriented dialogue generation

Future work

- 快速轻巧地开启模型的训练
- 更加深刻地理解对话的内容
- 隐私保护

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- My previous colleagues in data science lab @ JD.com

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  - Wenqiang Lei (NUS), Xinsen Jin (FDU), Shuman Zhao (CAS), Shen Gao (PKU)

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- 2.Xisen Jin, Wenqiang Lei, Zhaochun Ren, Hongshen Chen, Shangsong Liang, Yihong Zhao, and Dawei Yin. Explicit State Tracking with Semi-Supervision for Neural Dialogue Generation. In CIKM`18, Turin, Italy, 2018.
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Available codes&datasets released with our work

- JD dialogue dataset

  https://github.com/chenhongshen/HVMN

- Dataset for Neural-Knowledge-Diffusion

  https://github.com/liushuman/neural-knowledge-diffusion

- Product-aware question-answering service in JD

  https://github.com/gsh199449/productqa

- Sequicity dialogue generation

  https://github.com/WING-NUS/sequicity

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谢谢！

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