UNSUPERVISED LEARNING AND MODELING OF KNOWLEDGE AND INTENT FOR SPOKEN DIALOGUE SYSTEMS

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OUTLINE

Introduction

Semantic Decoding

- Ontology Induction
- Knowledge Graph Propagation
- Matrix Factorization
- Experiments

Future Work

Conclusions

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Introduction

Semantic Decoding [ACL-IJCNLP'15]

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A POPULAR ROBOT - BAYMAX

Big Hero 6 -- Video content owned and licensed by Disney Entertainment, Marvel Entertainment, LLC, etc

A POPULAR ROBOT - BAYMAX

Baymax is capable of maintaining a good **spoken dialogue system** and **learning** new knowledge for better **understanding** and **interacting** with people.

The goal is to automate learning and understanding procedures in system development.

SPOKEN DIALOGUE SYSTEM (SDS)

Spoken dialogue systems are the intelligent agents that are able to help users finish tasks more efficiently via speech interactions.

Spoken dialogue systems are being incorporated into various devices (smart-phones, smart TVs, in-car navigating system, etc).

Apple's Siri

Microsoft's Cortana

Microsoft's XBOX Kinect

Amazon's Echo

Samsung's SMART TV

Google Now

https://www.apple.com/ios/siri/
http://www.windowsphone.com/en-us/how-to/wp8/cortana/meet-cortana
http://www.xbox.com/en-US/
http://www.amazon.com/oc/echo/
http://www.samsung.com/us/experience/smart-tv/
https://www.google.com/landing/now/

LARGE SMART DEVICE POPULATION

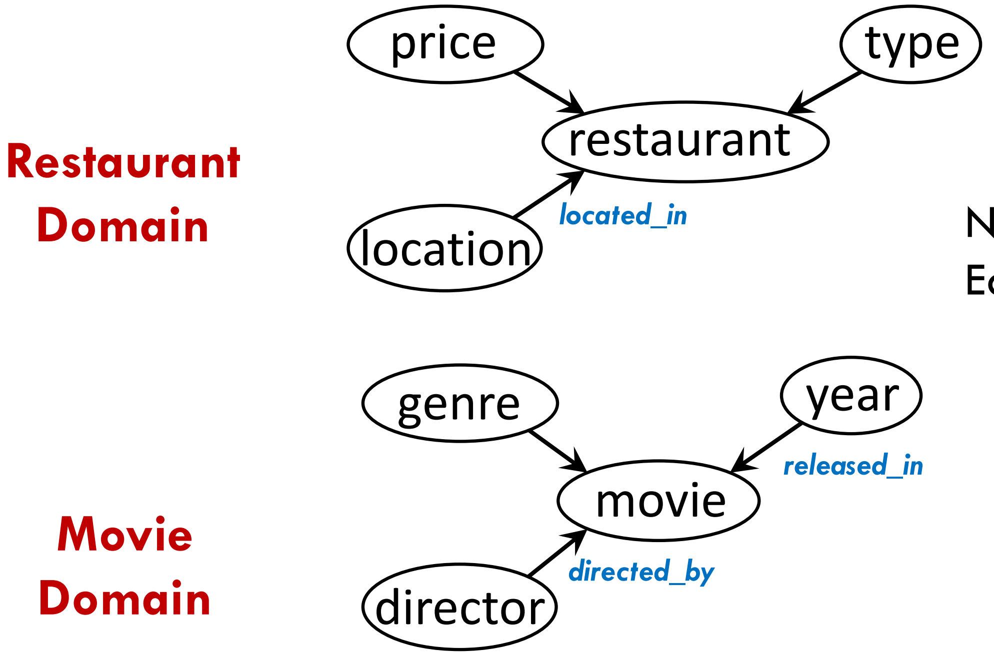
The number of global smartphone users will surpass 2 billion in 2016.

As of 2012, there are 1.1 billion automobiles on the earth.

The more **natural** and **convenient** input of the devices evolves towards speech

KNOWLEDGE REPRESENTATION/ONTOLOGY

Traditional SDSs require **manual annotations** for **specific domains** to represent domain knowledge.

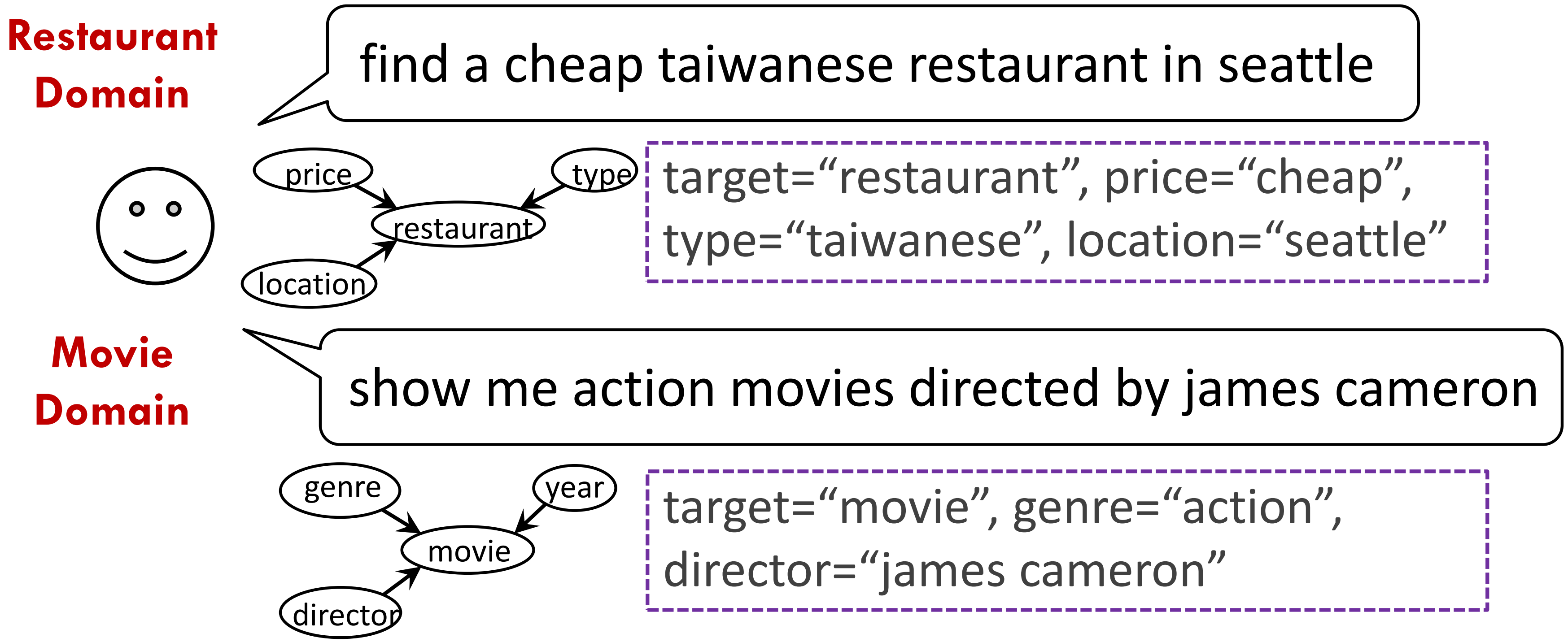


Node: semantic concept/slot

Edge: relation between concepts

UTTERANCE SEMANTIC REPRESENTATION

A spoken language understanding (SLU) component requires the domain ontology to decode utterances into semantic forms, which contain **core content (a set of slots and slot-fillers)** of the utterance.



CHALLENGES FOR SDS

An SDS in a new domain requires

1) A hand-crafted domain ontology
2) Utterances labelled with semantic representations
3) An SLU component for mapping utterances into semantic representations

With increasing spoken interactions, building domain ontologies and annotating utterances cost a lot so that the data does not scale up.

The goal is to enable an SDS to automatically learn this knowledge so that open domain requests can be handled.

INTERACTION EXAMPLE

User

find an inexpensive eating place for taiwanese food

Intelligent Agent

Inexpensive Taiwanese eating places include Din Tai Fung, Boiling Point, etc. What do you want to choose? I can help you go there.

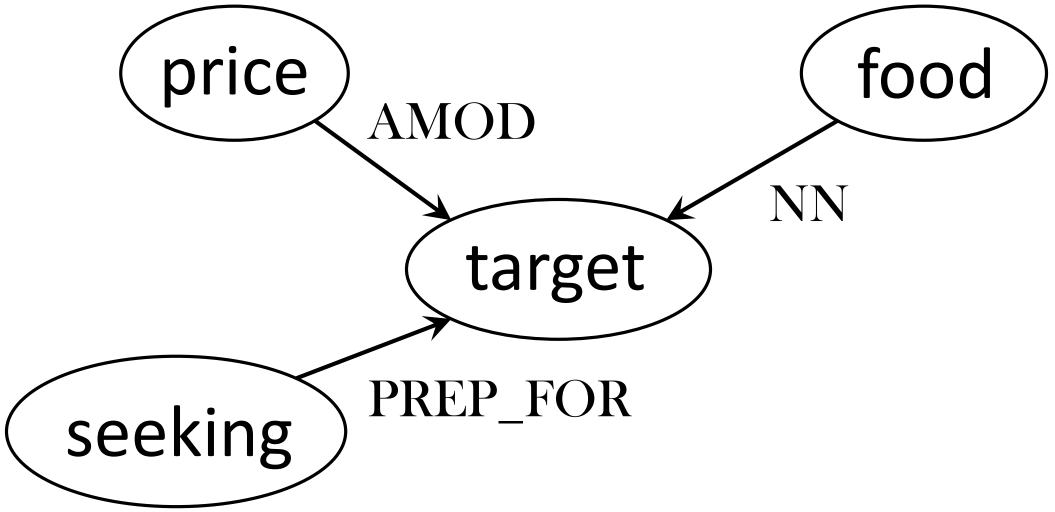
Q: How does a dialogue system process this request?

SDS PROCESS – AVAILABLE DOMAIN ONTOLOGY

User

find an inexpensive eating place for taiwanese food

Intelligent Agent



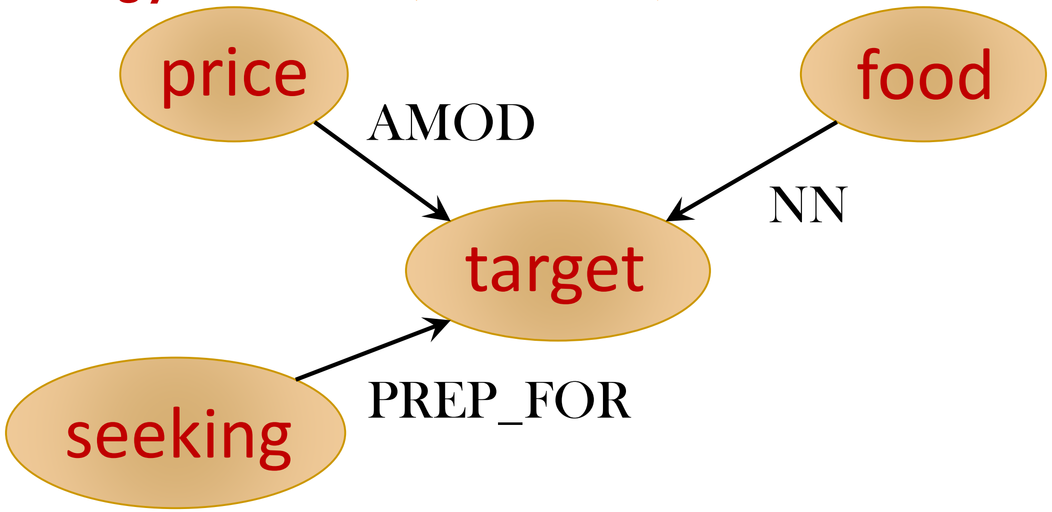
Organized Domain Knowledge

SDS PROCESS – AVAILABLE DOMAIN ONTOLOGY

User

find an inexpensive eating place for taiwanese food

Ontology Induction *(semantic slot)*



Organized Domain Knowledge

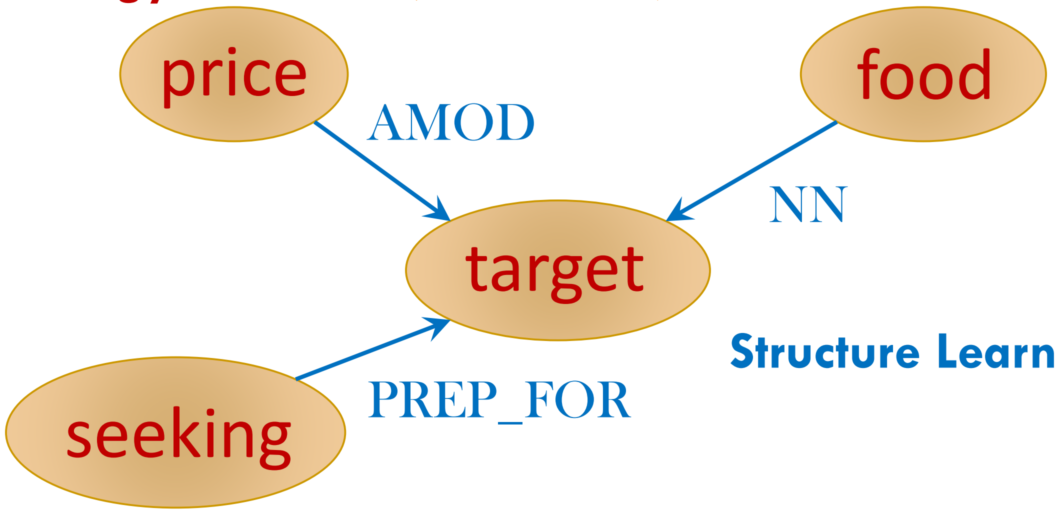
Intelligent Agent

SDS PROCESS – AVAILABLE DOMAIN ONTOLOGY

User

find an inexpensive eating place for taiwanese food

Ontology Induction *(semantic slot)*



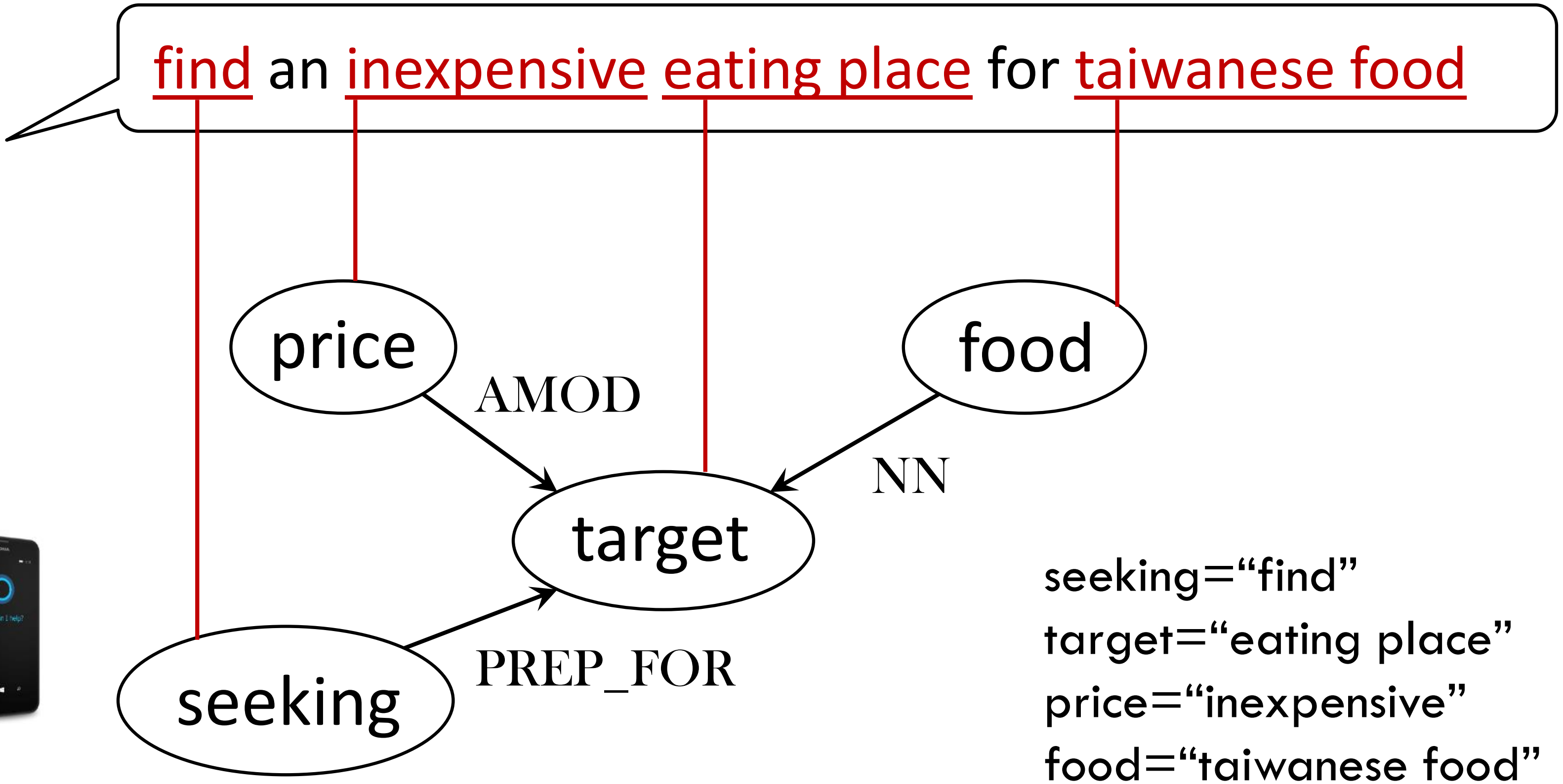
Structure Learning *(inter-slot relation)*

Intelligent Agent

Organized Domain Knowledge

SDS PROCESS – SPOKEN LANGUAGE UNDERSTANDING (SLU)

User



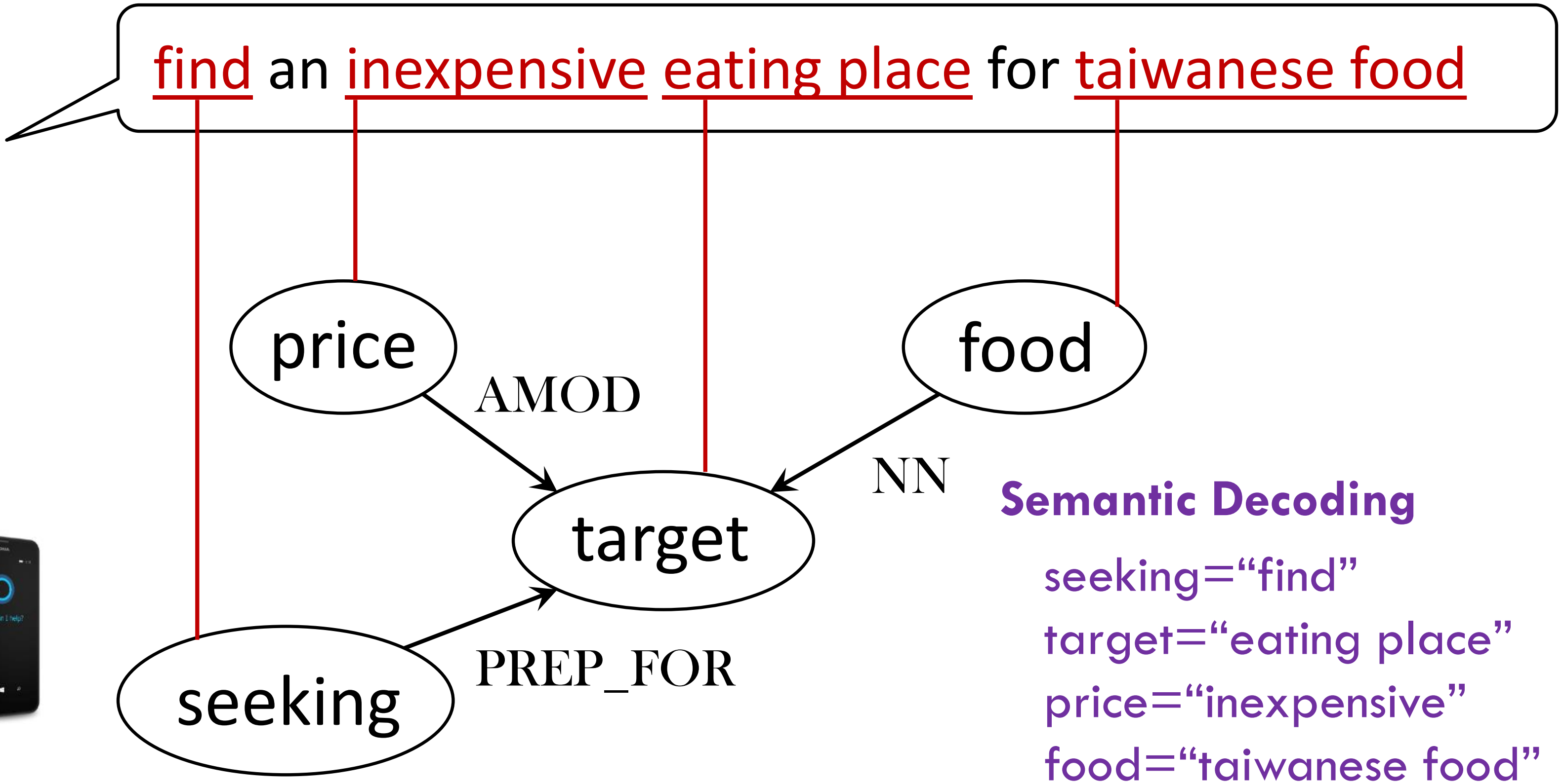
Intelligent Agent

seeking="find"
target="eating place"
price="inexpensive"
food="taiwanese food"

SDS PROCESS – SPOKEN LANGUAGE UNDERSTANDING (SLU)

User

Intelligent Agent

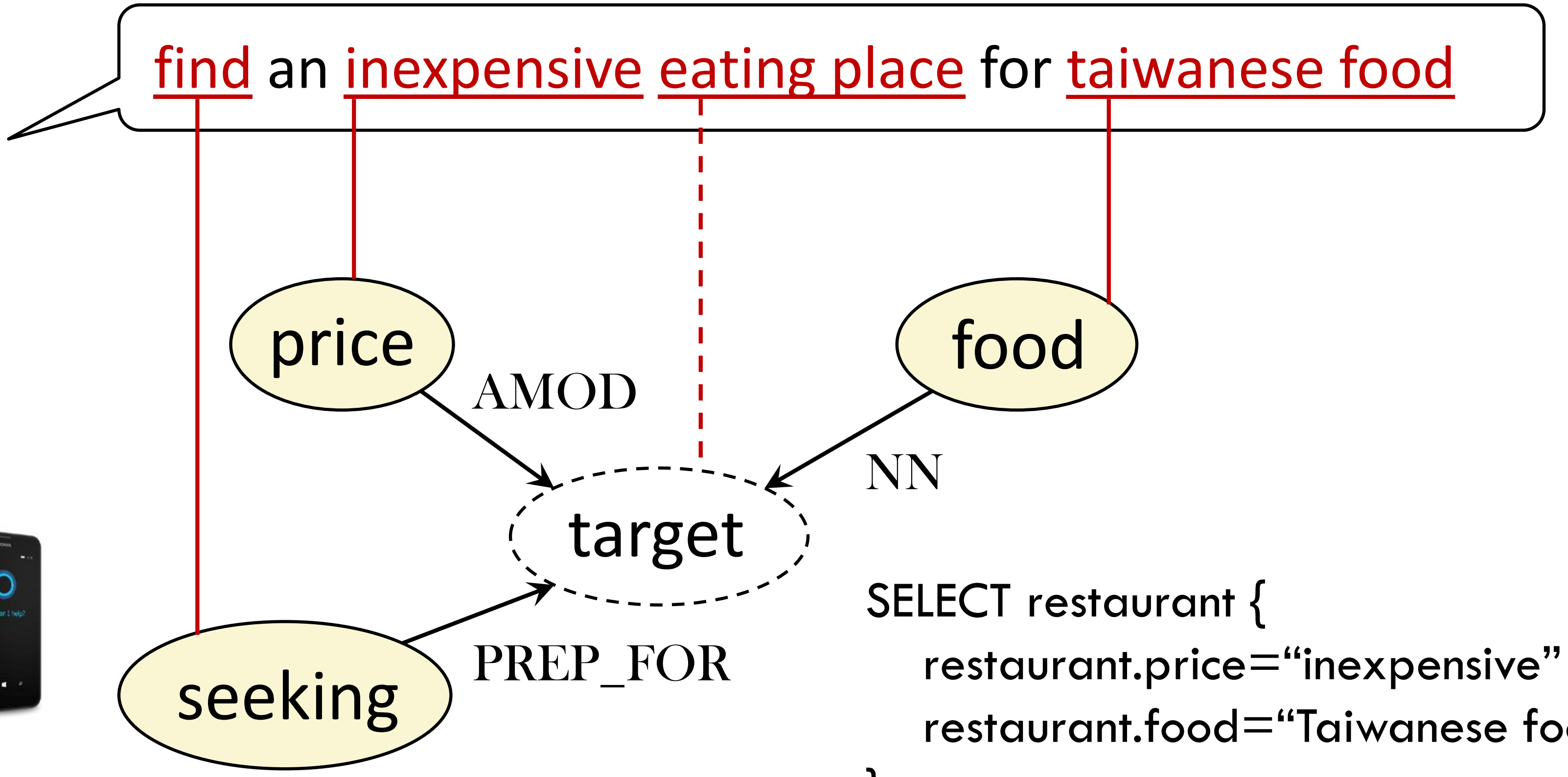


Semantic Decoding

seeking="find"
target="eating place"
price="inexpensive"
food="taiwanese food"

SDS PROCESS – DIALOGUE MANAGEMENT (DM)

User



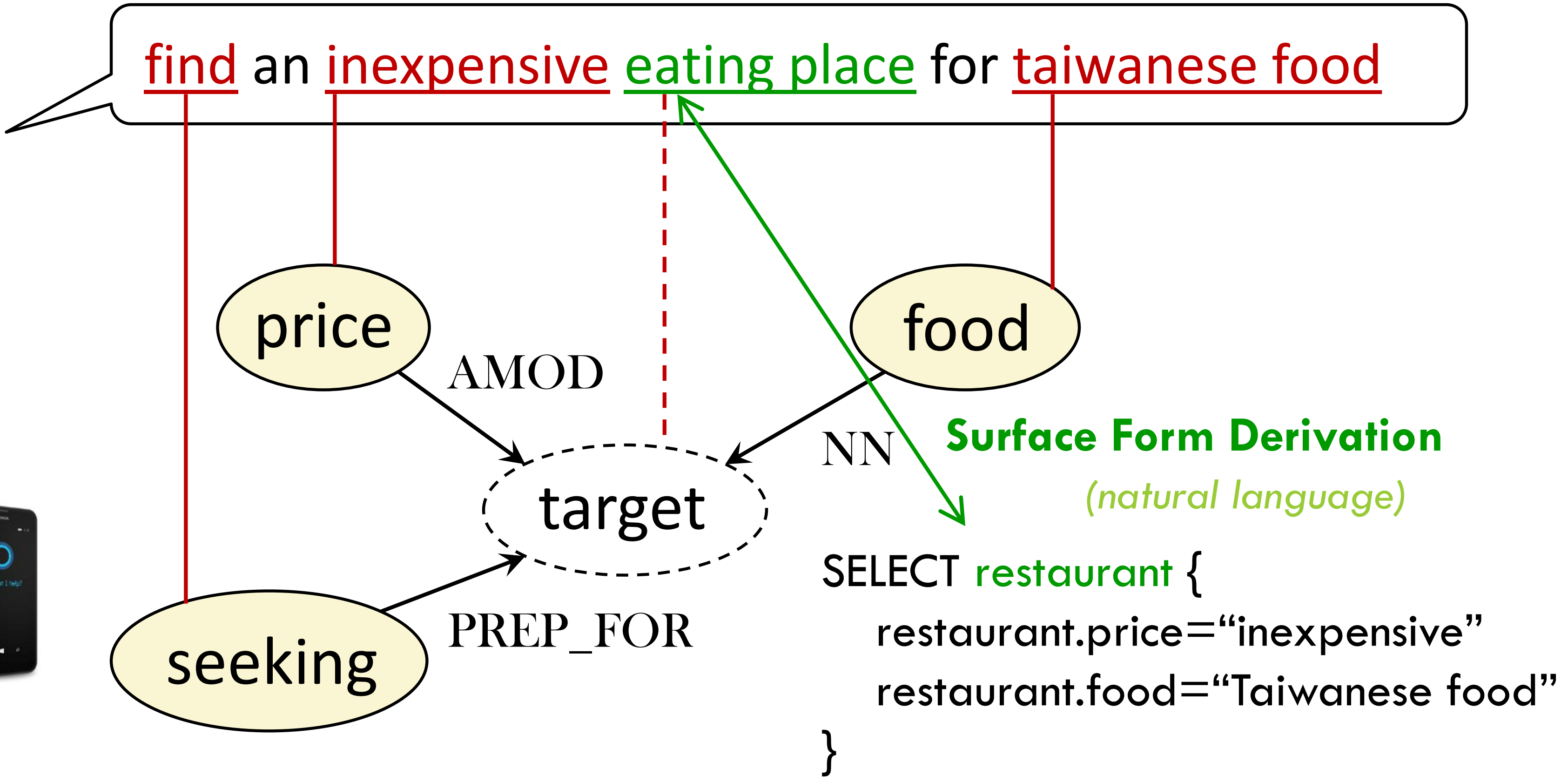
Intelligent Agent

```
SELECT restaurant {
    restaurant.price="inexpensive"
    restaurant.food="Taiwanese food"
}
```

SDS PROCESS – DIALOGUE MANAGEMENT (DM)

User

Intelligent Agent



SDS PROCESS – DIALOGUE MANAGEMENT (DM)

User

find an inexpensive eating place for taiwanese food

Intelligent Agent

SELECT restaurant {
    restaurant.price="inexpensive"
    restaurant.food="Taiwanese food"
}

Predicted behavior: navigation

Din Tai Fung
Boiling Point
:
:

SDS PROCESS – DIALOGUE MANAGEMENT (DM)

User

find an inexpensive eating place for taiwanese food

```
SELECT restaurant {
    restaurant.price="inexpensive"
    restaurant.food="Taiwanese food"
}
```

Din Tai Fung
Boiling Point
:
:

Predicted behavior: navigation

Behavior Prediction

Intelligent Agent

SDS PROCESS – NATURAL LANGUAGE GENERATION (NLG)

User

find an inexpensive eating place for taiwanese food

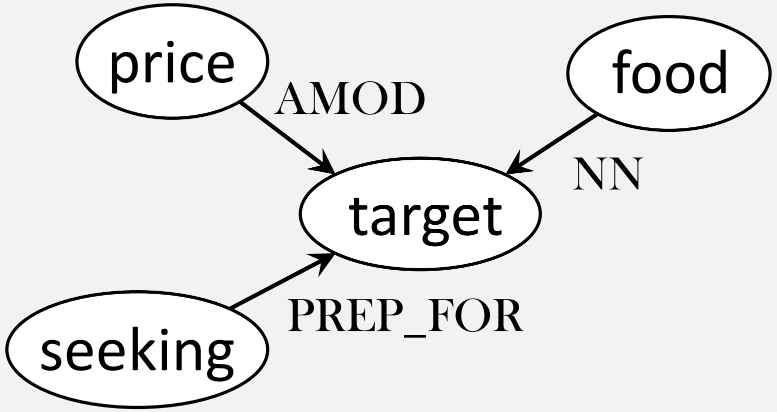
Inexpensive Taiwanese eating places include Din Tai Fung, Boiling Point, etc. What do you want to choose? I can help you go there. (navigation)

Intelligent Agent

GOALS

User

find an inexpensive eating place for taiwanese food




```
SELECT restaurant {
    restaurant.price="inexpensive"
    restaurant.food="taiwanese food"
}
```

Predicted behavior: navigation

Required Domain-Specific Information

FIVE GOALS

User

find an inexpensive eating place for taiwanese food

1. Ontology Induction *(semantic slot)*

price, food, target, seeking

price $\xrightarrow{\text{AMOD}}$ target

food $\xrightarrow{\text{NN}}$ target

seeking $\xrightarrow{\text{PREP\_FOR}}$ target

2. Structure Learning *(inter-slot relation)*

Required Domain-Specific Information

3. Surface Form Derivation *(natural language)*

SELECT restaurant {
  restaurant.price="inexpensive"
  restaurant.food="taiwanese food"
}

4. Semantic Decoding

Predicted behavior: navigation

5. Behavior Prediction

FIVE GOALS

User

find an inexpensive eating place for taiwanese food

1. Ontology Induction *(semantic slot)*

2. Structure Learning *(inter-slot relation)*

3. Surface Form Derivation *(natural language)*

4. Semantic Decoding

5. Behavior Prediction

FIVE GOALS

User

find an inexpensive eating place for taiwanese food

1. Ontology Induction
2. Structure Learning
3. Surface Form Derivation

Knowledge Acquisition

4. Semantic Decoding
5. Behavior Prediction

SLU Modeling

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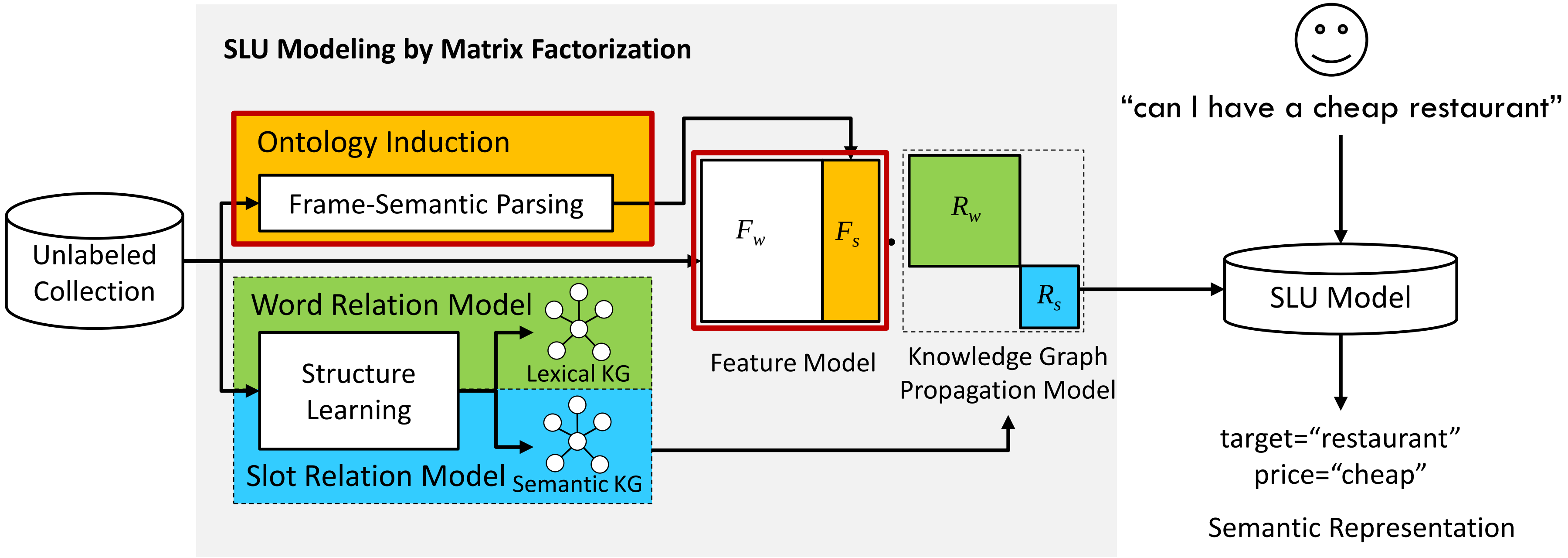
SEMANTIC DECODING

Input: user utterances

Output: the domain-specific semantic concepts included in each individual utterance



Y.-N. Chen et al., "Matrix Factorization with Knowledge Graph Propagation for Unsupervised Spoken Language Understanding," (to appear) in *Proc. of ACL-IJCNLP*, 2015.

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PROBABILISTIC FRAME-SEMANTIC PARSING

FrameNet [Baker et al., 1998]

- a linguistically semantic resource, based on the frame-semantics theory
- "low fat milk" → "milk" evokes the "food" frame;
  "low fat" fills the descriptor frame element

SEMAFOR [Das et al., 2014]

- a state-of-the-art frame-semantics parser, trained on manually annotated FrameNet sentences

Baker et al., " The berkeley framenet project," in Proc. of International Conference on Computational linguistics, 1998.
Das et al., " Frame-semantic parsing," in Proc. of Computational Linguistics, 2014.

FRAME-SEMANTIC PARSING FOR UTTERANCES

Good!

Good!

?

can i have a cheap restaurant

Frame: capability
FT LU: can FE LU: i

Frame: expensiveness
FT LU: cheap

Frame: locale by use
FT/FE LU: restaurant

FT: Frame Target; FE: Frame Element; LU: Lexical Unit

1st Issue: adapting ***generic*** frames to ***domain-specific*** settings for SDSs

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Input: user utterances

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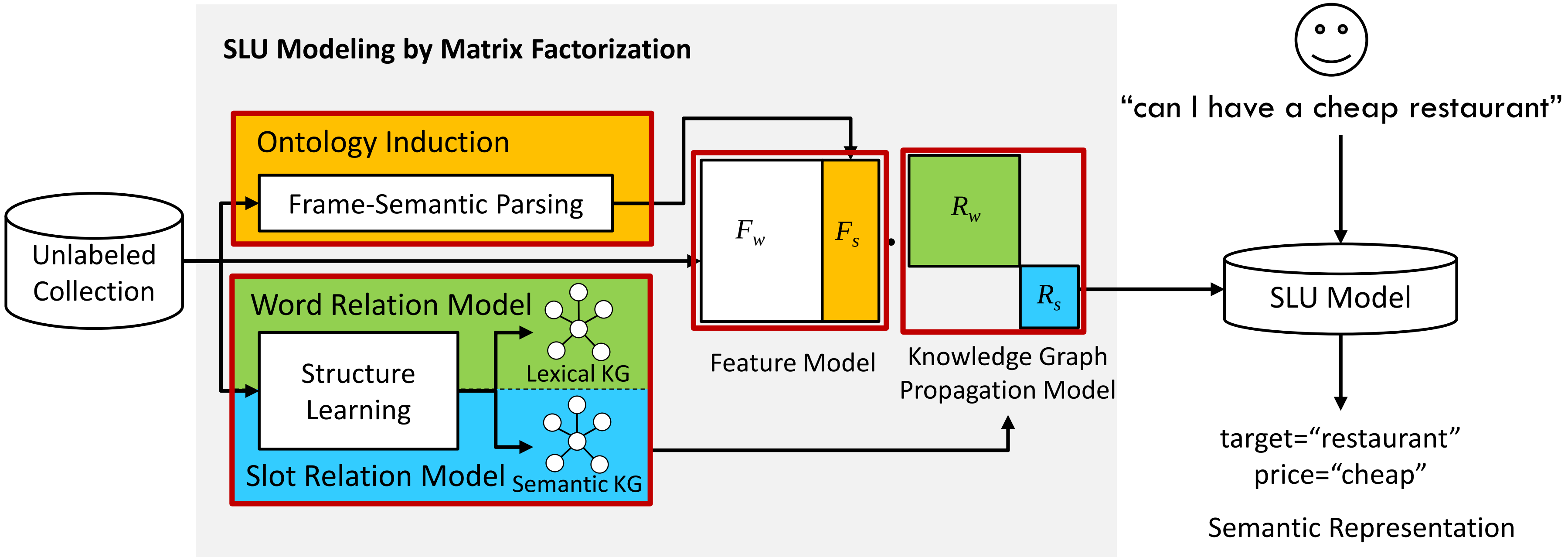

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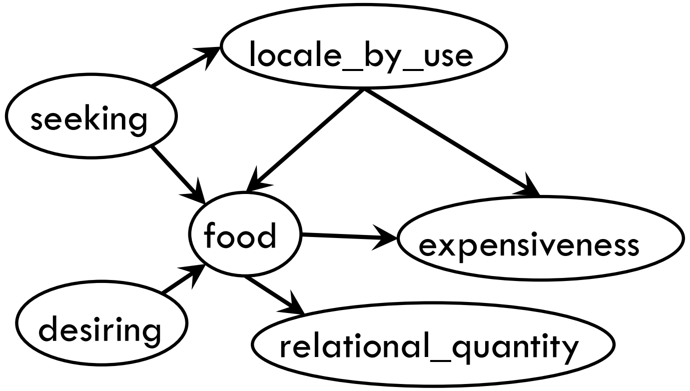
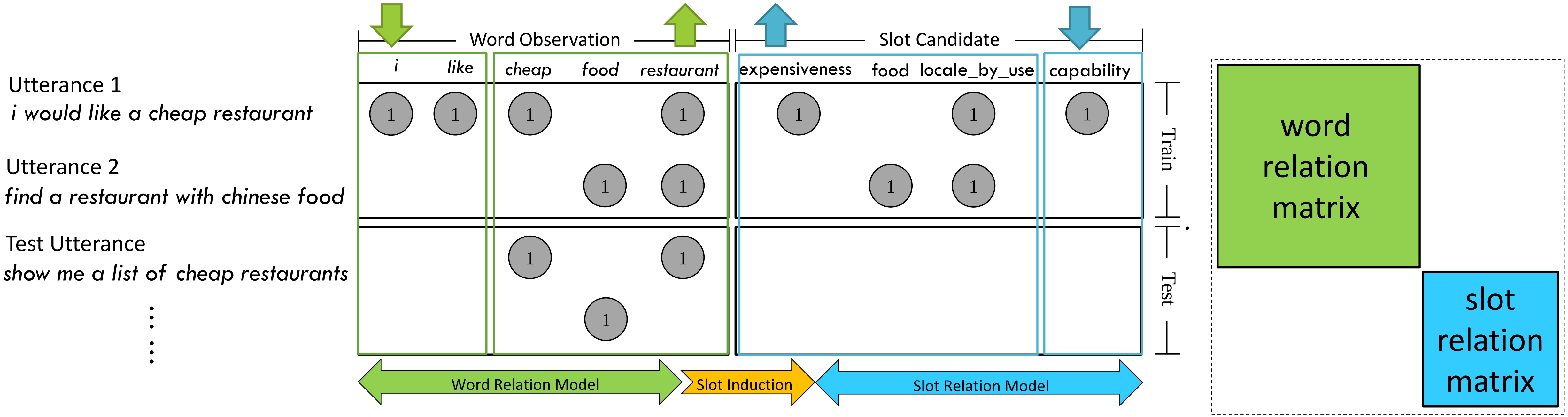
1ST ISSUE: HOW TO ADAPT GENERIC SLOTS TO DOMAIN-SPECIFIC?

KNOWLEDGE GRAPH PROPAGATION MODEL

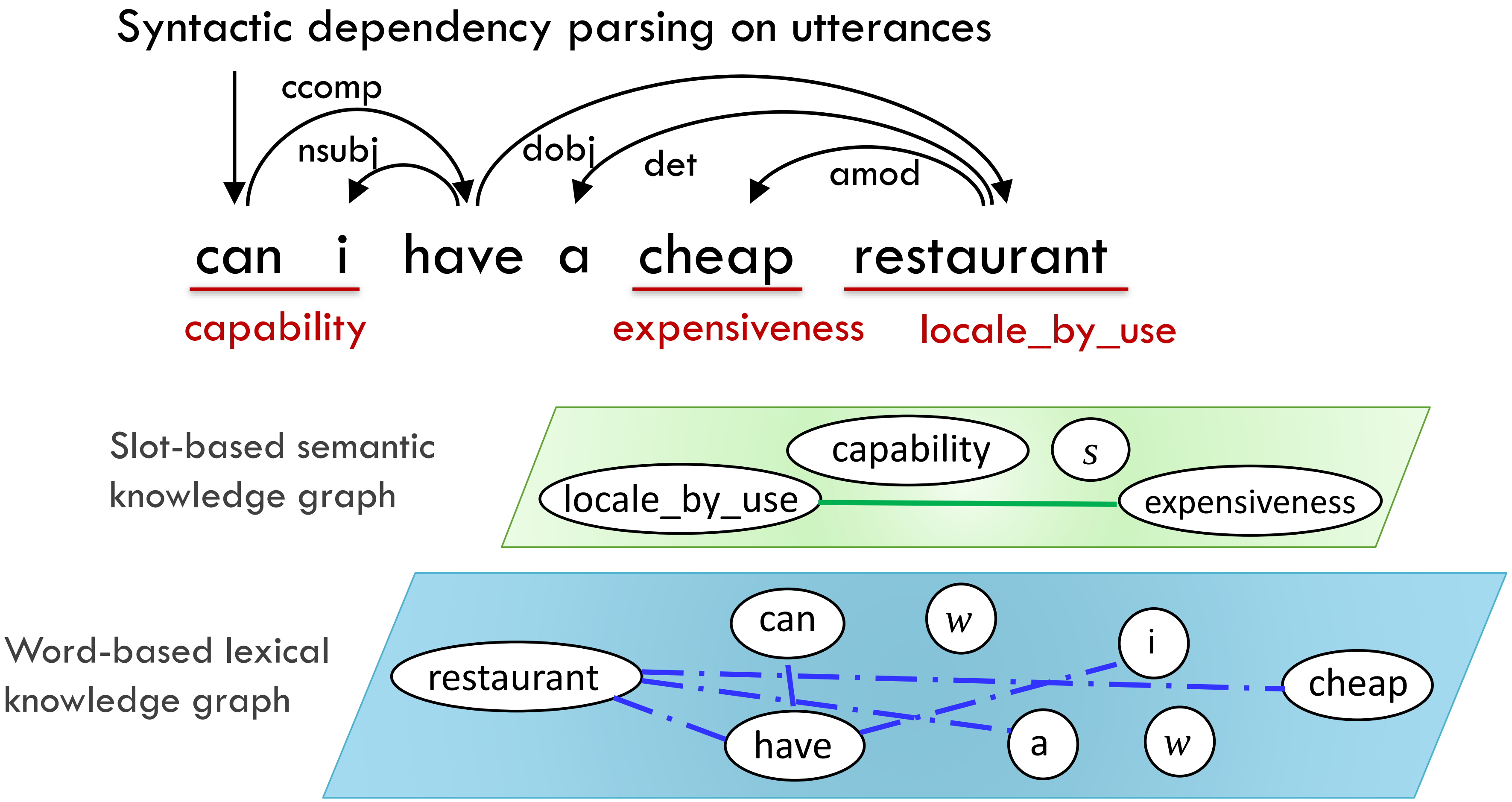


Assumption: The domain-specific words/slots have more dependency to each other.



The relation matrices allow each node propagate the scores to its neighbor in the knowledge graph, so that the domain-specific words/slots have higher scores during training.

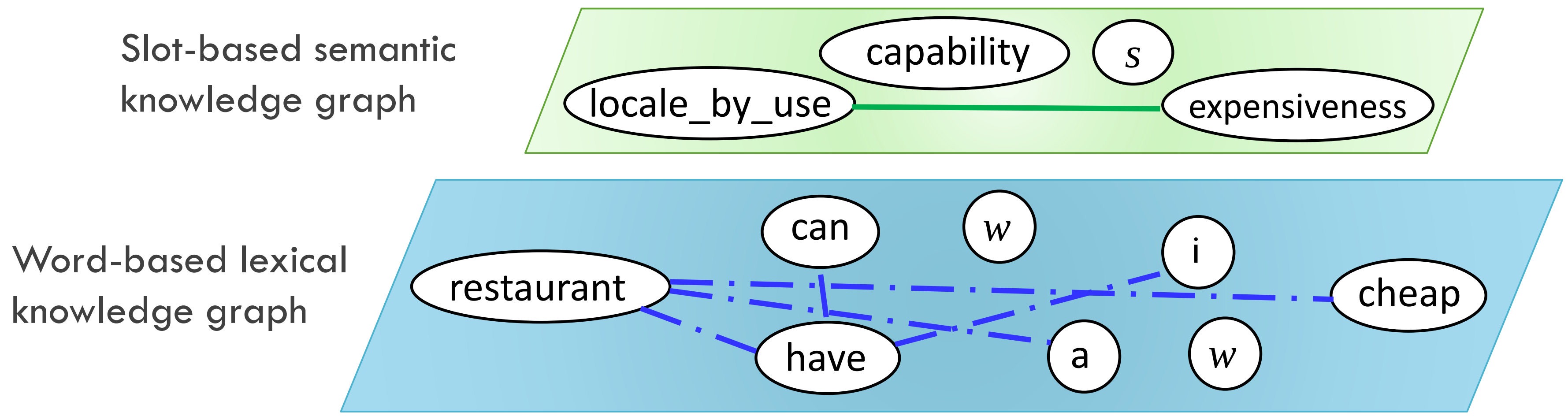
KNOWLEDGE GRAPH CONSTRUCTION



KNOWLEDGE GRAPH CONSTRUCTION

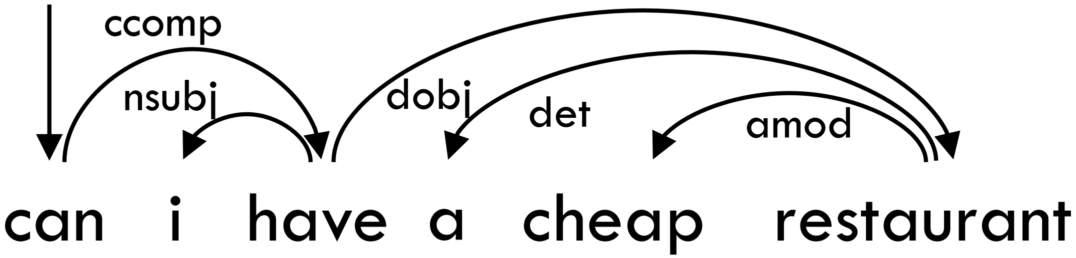
The edge between a node pair is weighted as relation importance for build the matrix

How to decide the weights to represent relation importance?



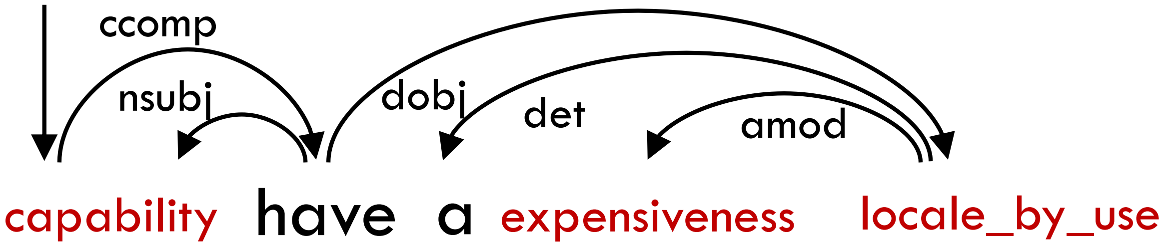
WEIGHT MEASUREMENT BY EMBEDDINGS

Dependency-based word embeddings



$$\text{can} = [0.8 \quad \ldots \quad 0.24]$$
$$\text{have} = [0.3 \quad \ldots \quad 0.21]$$
$$\vdots$$

Dependency-based slot embeddings



$$\text{expensiveness} = [0.12 \quad \ldots \quad 0.7]$$
$$\text{capability} = [0.3 \quad \ldots \quad 0.6]$$
$$\vdots$$

Levy and Goldberg, " Dependency-Based Word Embeddings," in *Proc. of ACL*, 2014.

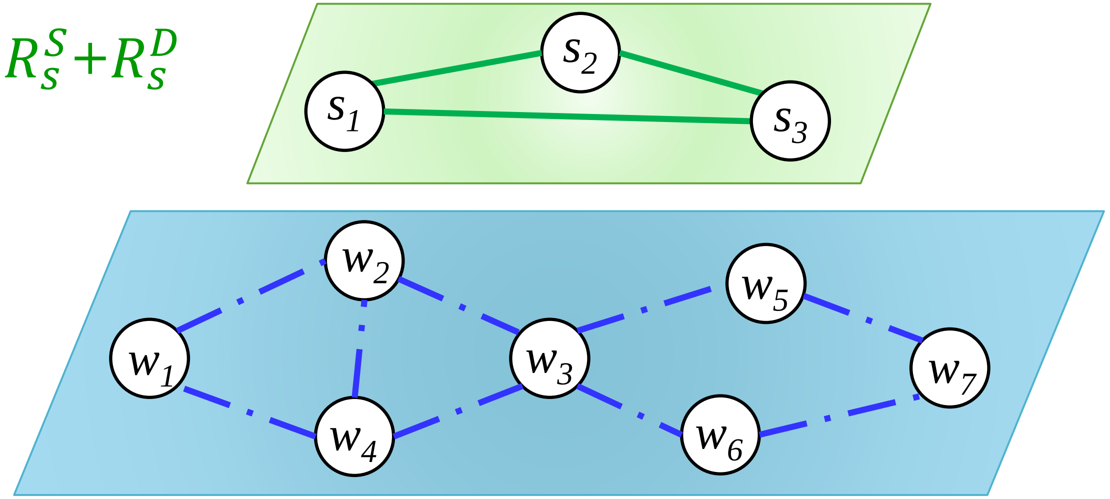
WEIGHT MEASUREMENT BY EMBEDDINGS

Compute edge weights to represent relation importance

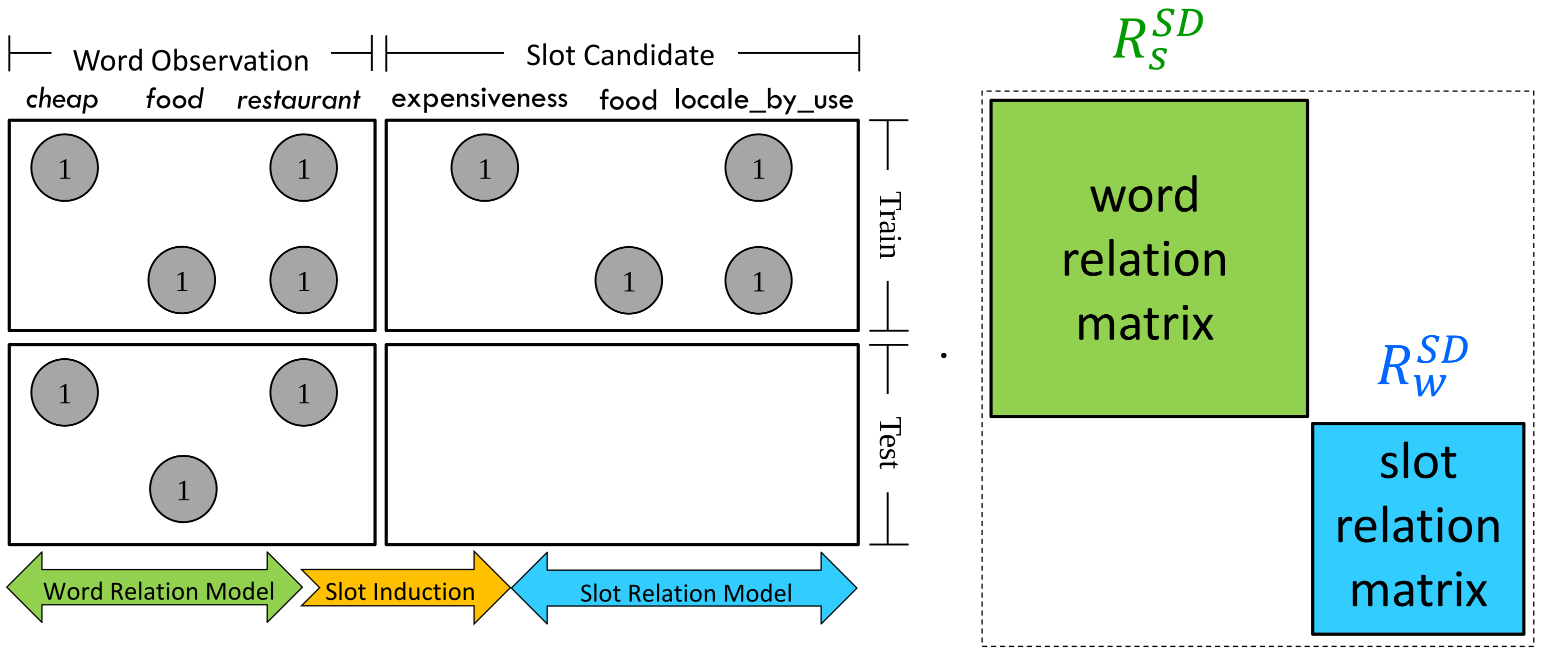
- Slot-to-slot semantic relation R_s^S: similarity between slot embeddings
- Slot-to-slot dependency relation R_s^D: dependency score between slot embeddings
- Word-to-word semantic relation R_w^S: similarity between word embeddings
- Word-to-word dependency relation R_w^D: dependency score between word embeddings

$R_s^{SD} = R_s^S + R_s^D$

$R_w^{SD} = R_w^S + R_w^D$



KNOWLEDGE GRAPH PROPAGATION MODEL



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- **Matrix Factorization (for 2nd issue)**
- Experiments

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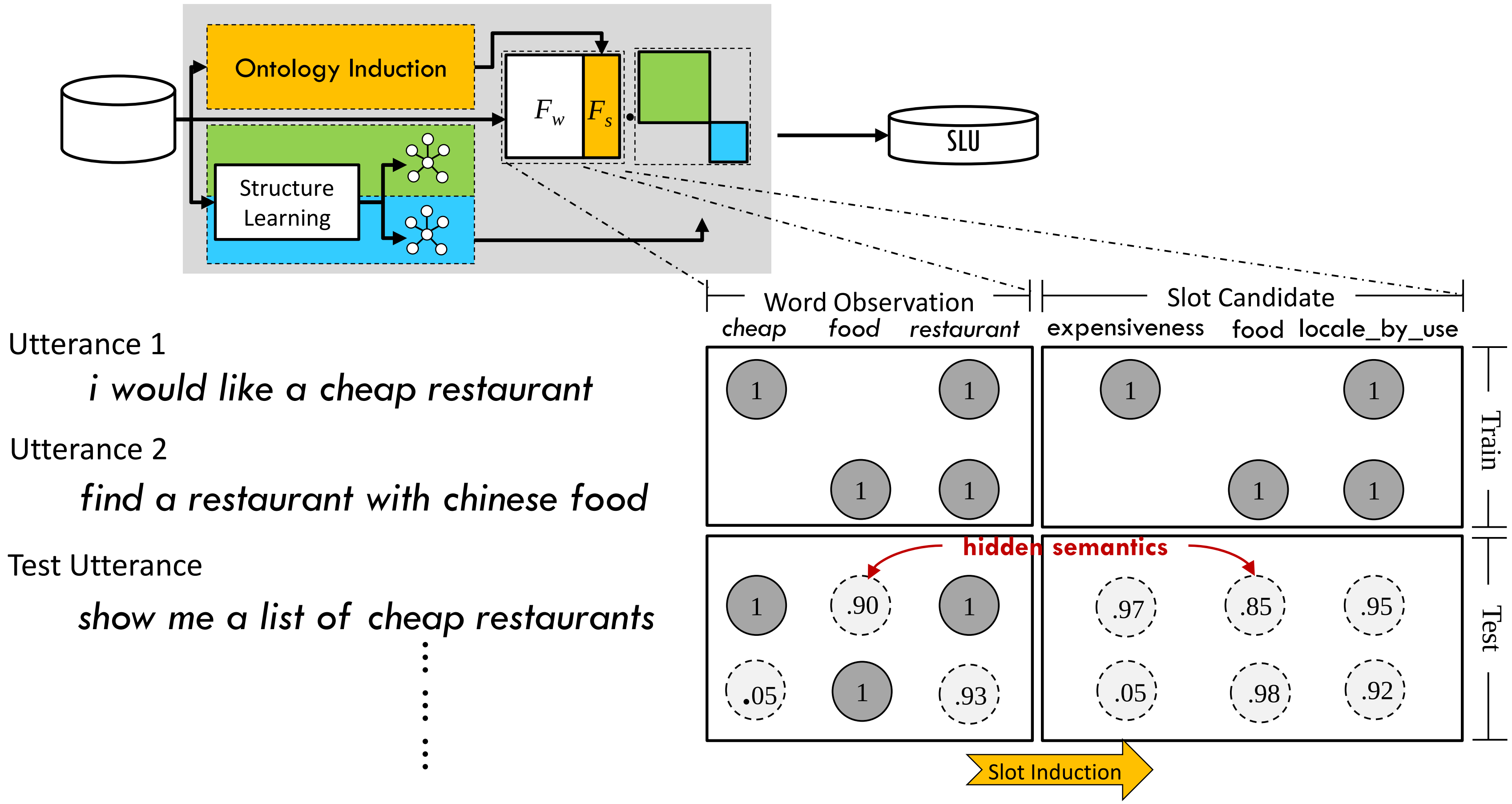
MATRIX FACTORIZATION (MF)

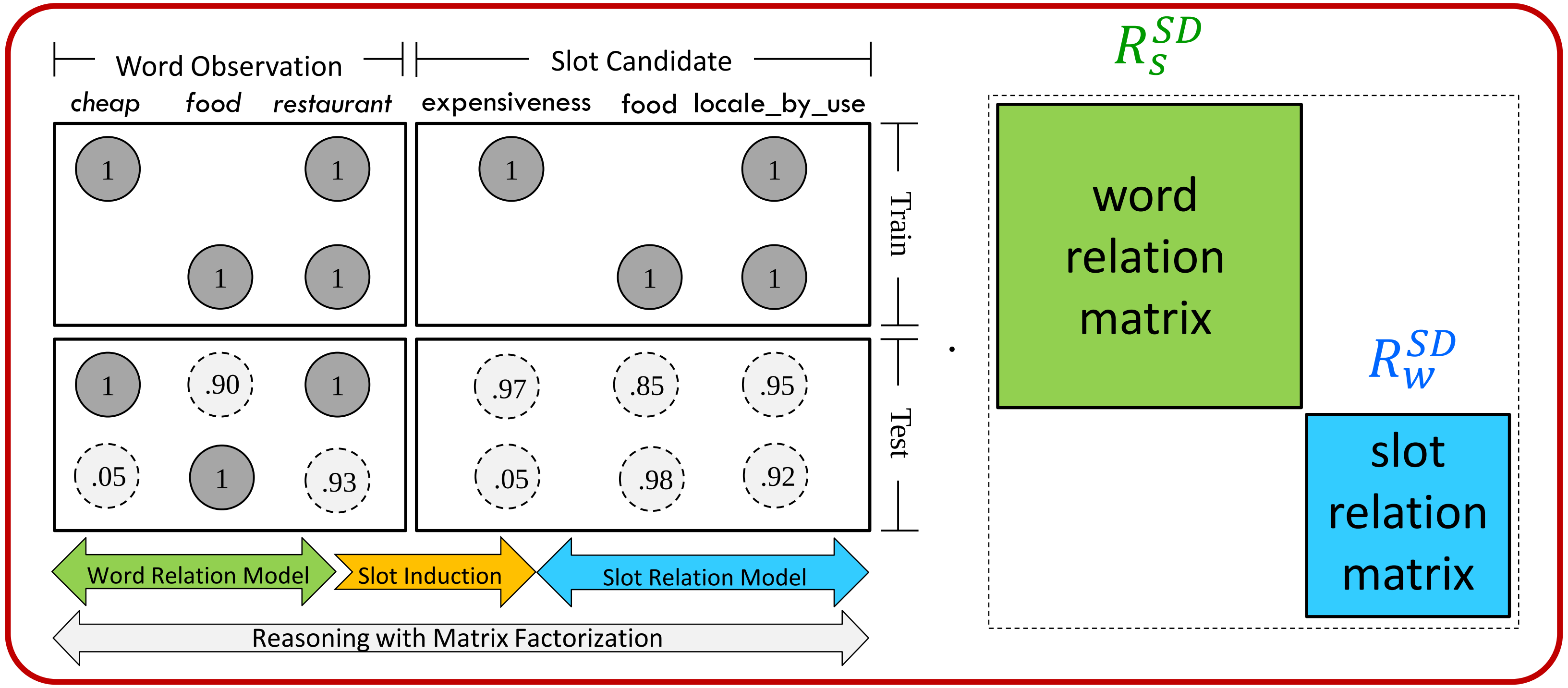
FEATURE MODEL



2nd Issue: hidden semantics cannot be observed but may benefit the understanding performance

2ND ISSUE: HOW TO LEARN THE IMPLICIT SEMANTICS?

MATRIX FACTORIZATION (MF)

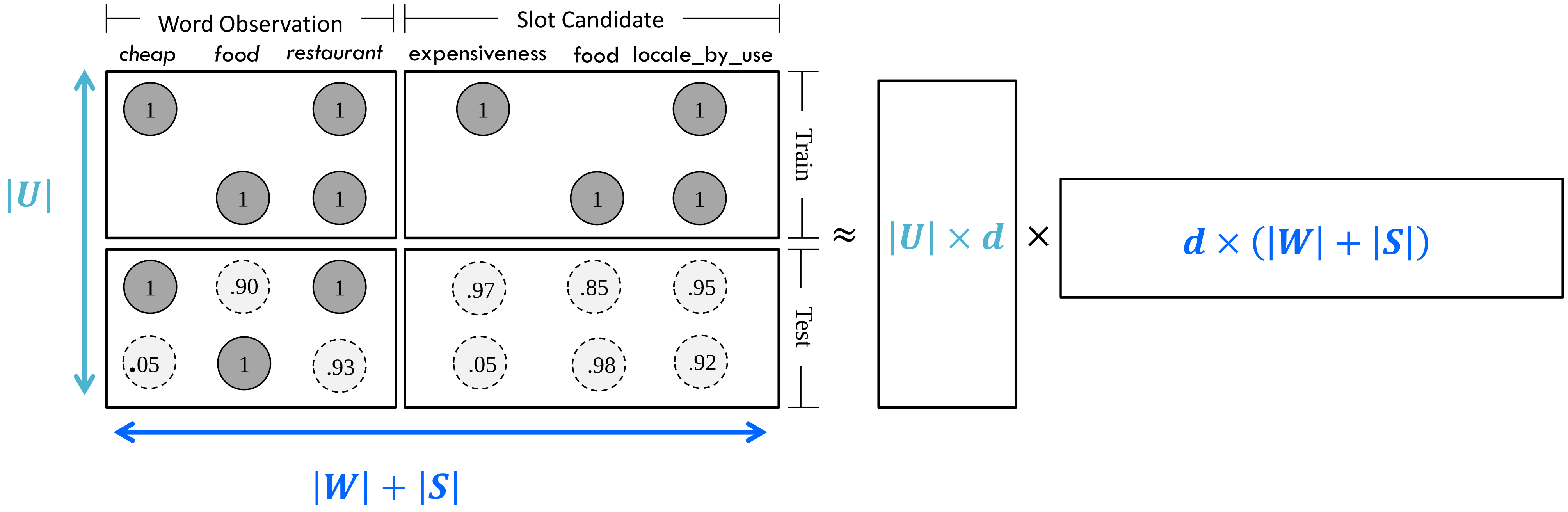


The MF method completes a partially-missing matrix based on the latent semantics by decomposing it into product of two matrices.

MATRIX FACTORIZATION (MF)

The decomposed matrices represent latent semantics for utterances and words/slots respectively

The product of two matrices fills the probability of hidden semantics



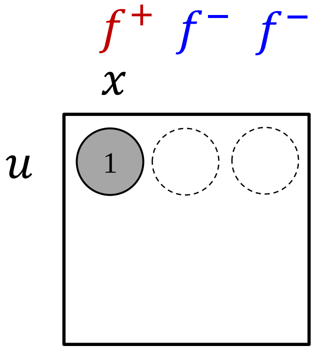
BAYESIAN PERSONALIZED RANKING FOR MF

Model implicit feedback

- not treat unobserved facts as negative samples (true or false)
- give observed facts higher scores than unobserved facts

$$\begin{aligned} f^+ &= \langle u, x^+ \rangle \\ f^- &= \langle u, x^- \rangle \end{aligned} \Rightarrow p(f^+) > p(f^-)$$

$$p(M_{u,x} = 1 \mid \theta_{u,x}) = \sigma(\theta_{u,x}) = \frac{1}{1 + \exp\left(-\theta_{u,x}\right)}$$



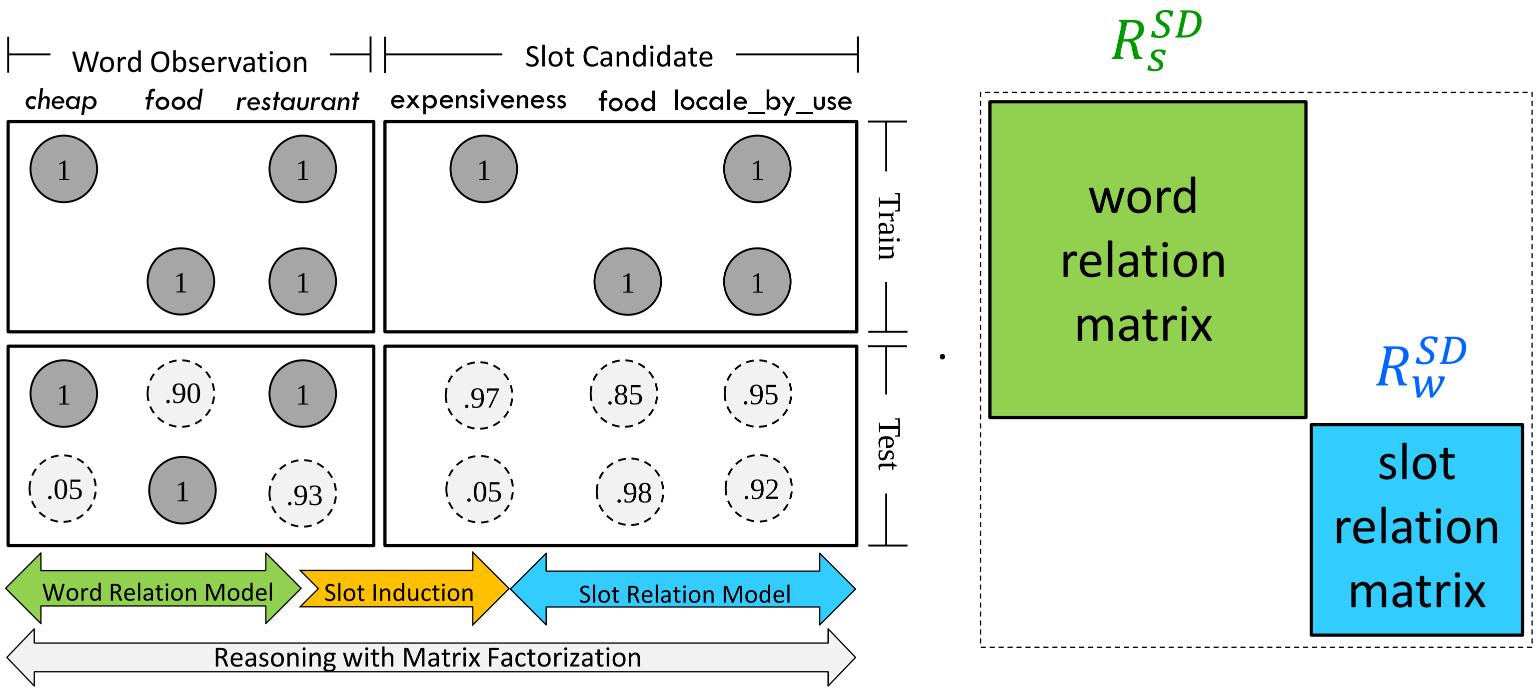
Objective:

$$\sum_{f^+ \in \mathcal{O}} \sum_{f^- \notin \mathcal{O}} \ln \sigma(\theta_{f^+} - \theta_{f^-})$$

The objective is to learn a set of well-ranked semantic slots per utterance.

2ND ISSUE: HOW TO LEARN THE IMPLICIT SEMANTICS?

MATRIX FACTORIZATION (MF)



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- **Experiments**

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EXPERIMENTAL SETUP

Dataset

- Cambridge University SLU corpus [Henderson, 2012]
  - Restaurant recommendation in an in-car setting in Cambridge
    - WER = 37%
    - vocabulary size = 1868
    - 2,166 dialogues
    - 15,453 utterances
    - dialogue slot: addr, area, food, name, phone, postcode, price range, task, type

locale by use, building	type
food, origin	food
speak on topic	addr
seeking, desiring, locating	task
commerce scenario, expensiveness, range	price range
part orientational, direction, locale, part inner outer	area
contacting	phone
sending	postcode

The mapping table between induced and reference slots

Henderson et al., "Discriminative spoken language understanding using word confusion networks," in Proc. of SLT, 2012.

EXPERIMENT 1: QUALITY OF SEMANTICS ESTIMATION

Metric: Mean Average Precision (MAP) of all estimated slot probabilities for each utterance

<table>
<tr><th colspan="2" rowspan="2">Approach</th><th colspan="2">ASR</th><th colspan="2">Manual</th></tr>
<tr><th>w/o</th><th>w/ Explicit</th><th>w/o</th><th>w/ Explicit</th></tr>
<tr><td rowspan="2">Explicit</td><td>Support Vector Machine</td><td colspan="2">32.5</td><td colspan="2">36.6</td></tr>
<tr><td>Multinomial Logistic Regression</td><td colspan="2">34.0</td><td colspan="2">38.8</td></tr>
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<tr><td rowspan="4">Implicit</td><td rowspan="2">Baseline</td><td>Random</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Majority</td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="2">MF</td><td>Feature Model</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Feature Model +
Knowledge Graph Propagation</td><td></td><td></td><td></td><td></td></tr>
</table>

Modeling Implicit Semantics

EXPERIMENT 1: QUALITY OF SEMANTICS ESTIMATION

Metric: Mean Average Precision (MAP) of all estimated slot probabilities for each utterance

Modeling Implicit Semantics

Approach			ASR		Manual	
			w/o	w/ Explicit	w/o	w/ Explicit
Explicit	Support Vector Machine		32.5		36.6	
Explicit	Multinomial Logistic Regression		34.0		38.8	
Implicit	Baseline	Random	3.4		2.6	
Implicit	Baseline	Majority	15.4		16.4	
Implicit	MF	Feature Model	24.2		22.6	
Implicit	MF	Feature Model + Knowledge Graph Propagation	**40.5*** (+19.1%)		**52.1*** (+34.3%)	

EXPERIMENT 1: QUALITY OF SEMANTICS ESTIMATION

Metric: Mean Average Precision (MAP) of all estimated slot probabilities for each utterance

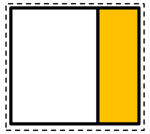
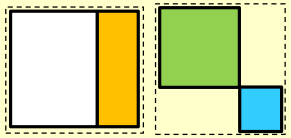
Modeling Implicit Semantics

Approach			ASR		Manual	
			w/o	w/ Explicit	w/o	w/ Explicit
Explicit	Support Vector Machine		32.5		36.6	
Explicit	Multinomial Logistic Regression		34.0		38.8	
Implicit	Baseline	Random	3.4	22.5	2.6	25.1
Implicit	Baseline	Majority	15.4	32.9	16.4	38.4
Implicit	MF	Feature Model	24.2	37.6*	22.6	45.3*
Implicit	MF	Feature Model + Knowledge Graph Propagation	**40.5*** (+19.1%)	**43.5*** (+27.9%)	**52.1*** (+34.3%)	**53.4*** (+37.6%)

The MF approach effectively models hidden semantics to improve SLU.

Adding a knowledge graph propagation model further improves the results.

EXPERIMENT 2: EFFECTIVENESS OF RELATIONS

Approach			ASR	Manual
Feature Model 			37.6	45.3
Feature + Knowledge Graph Propagation 	Semantic	$\begin{bmatrix} R_w^S & 0 \\ 0 & R_s^S \end{bmatrix}$	41.4*	51.6*
	Dependency	$\begin{bmatrix} R_w^D & 0 \\ 0 & R_s^D \end{bmatrix}$	41.6*	49.0*
	Word	$\begin{bmatrix} R_w^{SD} & 0 \\ 0 & 0 \end{bmatrix}$	39.2*	45.2
	Slot	$\begin{bmatrix} 0 & 0 \\ 0 & R_s^{SD} \end{bmatrix}$	42.1*	49.9*
	Both	$\begin{bmatrix} R_w^{SD} & 0 \\ 0 & R_s^{SD} \end{bmatrix}$		

All types of relations are useful to infer hidden semantics.

EXPERIMENT 2: EFFECTIVENESS OF RELATIONS

Approach			ASR	Manual
Feature Model			37.6	45.3
Feature + Knowledge Graph Propagation	Semantic	$\begin{bmatrix} R_w^S & 0 \\ 0 & R_s^S \end{bmatrix}$	41.4*	51.6*
	Dependency	$\begin{bmatrix} R_w^D & 0 \\ 0 & R_s^D \end{bmatrix}$	41.6*	49.0*
	Word	$\begin{bmatrix} R_w^{SD} & 0 \\ 0 & 0 \end{bmatrix}$	39.2*	45.2
	Slot	$\begin{bmatrix} 0 & 0 \\ 0 & R_s^{SD} \end{bmatrix}$	42.1*	49.9*
	Both	$\begin{bmatrix} R_w^{SD} & 0 \\ 0 & R_s^{SD} \end{bmatrix}$	**43.5*** **(+15.7%)**	**53.4*** **(+17.9%)**

All types of relations are useful to infer hidden semantics.

Combining different relations further improves the performance.

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- Ontology Induction
- Knowledge Graph Propagation
- Bayesian Personalized Ranking for Matrix Factorization
- Experiments

Future Work

Conclusions

LOW- AND HIGH-LEVEL UNDERSTANDING

Semantic concepts for individual utterances do not consider high-level semantics (user intents)

The follow-up behaviors are observable and usually correspond to user intents

"can i have a cheap restaurant"

↓

SLU Component

↓

price="*cheap*"
target="*restaurant*"

behavior=*navigation*

"i plan to dine in din tai fung tonight"

↓

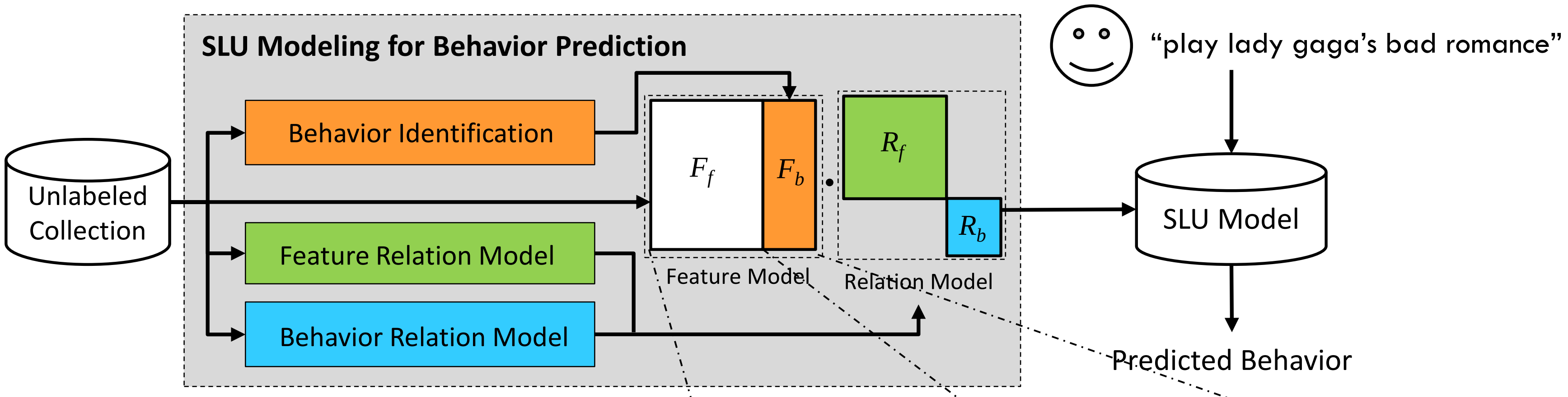
SLU Component

↓

restaurant="*din tai fung*"
time="*tonight*"

behavior=*reservation*

BEHAVIOR PREDICTION



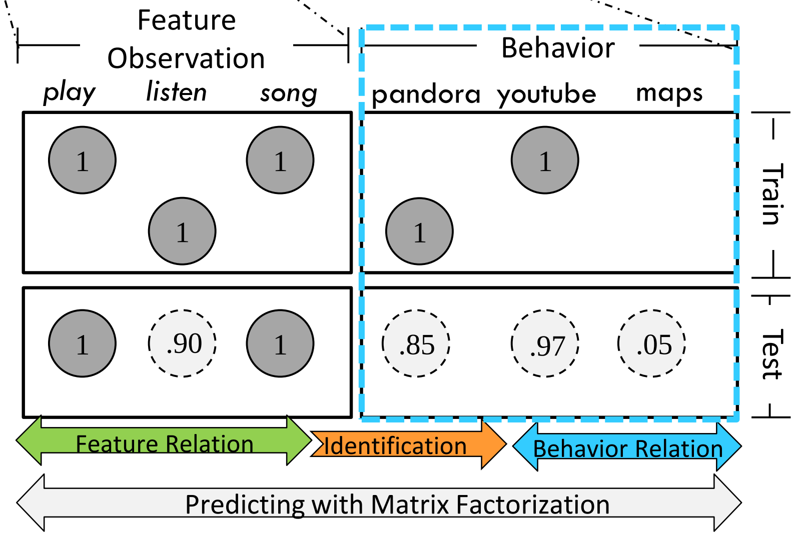
Utterance 1

play lady gaga's song bad romance

Utterance 2

i'd like to listen to lady gaga's bad romance

⋮



OUTLINE

Introduction

Semantic Decoding [ACL-IJCNLP'15]

- Ontology Induction
- Knowledge Graph Propagation
- Bayesian Personalized Ranking for Matrix Factorization
- Experiments

Future Work

Conclusions

CONCLUSIONS

The ontology induction and knowledge graph construction enable systems to automatically acquire open domain knowledge.

The MF technique for SLU modeling provides a principle model that is able to unify the automatically acquired knowledge, and then allows systems to consider implicit semantics for better understanding.

- Better semantic representations for individual utterances
- Better follow-up behavior prediction

The work shows the feasibility and the potential of improving *generalization*, *maintenance*, *efficiency*, and *scalability* of SDSs.

Q & A

Thanks for your attentions!!

CAMBRIDGE UNIVERSITY SLU CORPUS

hi i'd like a restaurant in the cheap price range in the centre part of town	type=restaurant, pricerange=cheap, area=centre
um i'd like chinese food please	food=chinese
how much is the main cost	pricerange
okay and uh what's the address	addr
great uh and if i wanted to uh go to an italian restaurant instead	food=italian, type=restaurant
italian please	food=italian
what's the address	addr
i would like a cheap chinese restaurant	pricerange=cheap, food=chinese, type=restaurant
something in the riverside	area=centre

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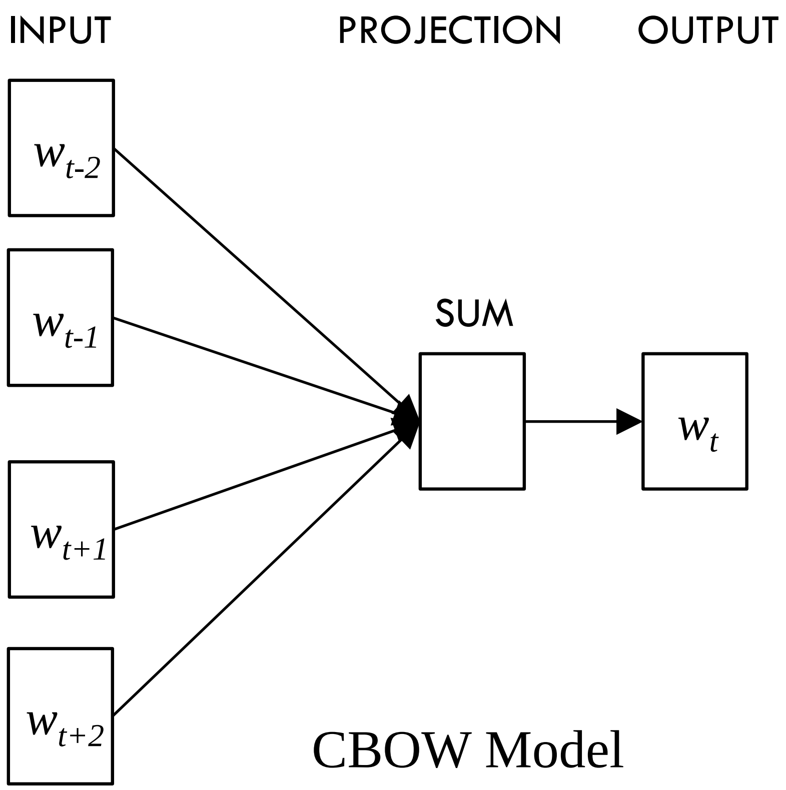
WORD EMBEDDINGS



CBOW Model

Training Process

- Each word w is associated with a vector
- The contexts within the window size c are considered as the training data D
- Objective function:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq i\leq c, i\neq 0}\log p(w_t \mid w_{t+i})$$

Mikolov et al., " Efficient Estimation of Word Representations in Vector Space," in *Proc. of ICLR*, 2013.
Mikolov et al., " Distributed Representations of Words and Phrases and their Compositionality," in *Proc. of NIPS*, 2013.
Mikolov et al., " Linguistic Regularities in Continuous Space Word Representations," in *Proc. of NAACL-HLT*, 2013.

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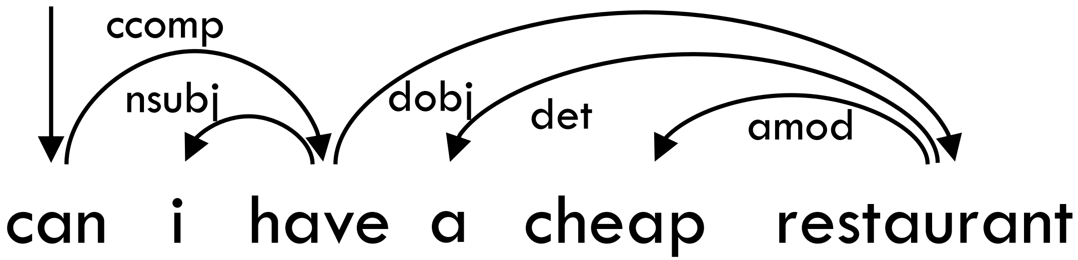
DEPENDENCY-BASED EMBEDDINGS

Word & Context Extraction



Word	Contexts
can	have/ccomp
i	have/nsub^{-1}
have	can/ccomp^{-1}, i/nsubj, restaurant/dobj
a	restaurant/det^{-1}
cheap	restaurant/amod^{-1}
restaurant	have/dobj^{-1}, a/det, cheap/amod

Levy and Goldberg, " Dependency-Based Word Embeddings," in *Proc. of ACL*, 2014.

DEPENDENCY-BASED EMBEDDINGS

Training Process

- Each word w is associated with a vector v_w and each context c is represented as a vector v_c
- Learn vector representations for both words and contexts such that the dot product $v_w \cdot v_c$ associated with good word-context pairs belonging to the training data D is maximized
- Objective function:

$$\arg\max_{v_w, v_c} \sum_{(w,c)\in D} \log \frac{1}{1+\exp(-v_c \cdot v_w)}$$

Levy and Goldberg, " Dependency-Based Word Embeddings," in *Proc. of ACL*, 2014.

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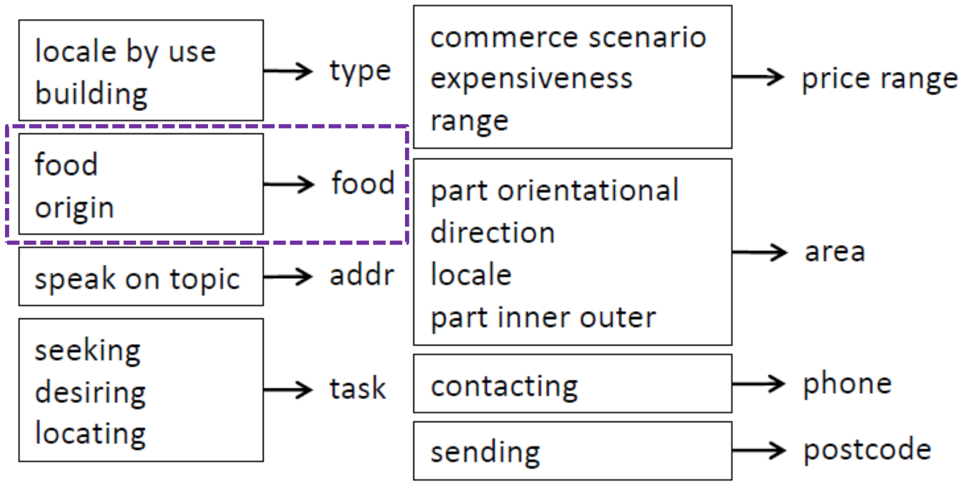
SLOT MAPPING TABLE

Create the mapping if slot fillers of the induced slot are included by the reference slot

	induced slots		reference slot
	origin	**food**	**food**
u_1	asian	:	asian
u_2	:	beer	beer
:	:	:	:
u_k	japan	:	japan
:	:	:	:
u_n	:	noodle	noodle



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SEMAFOR PERFORMANCE

The SEMAFOR evaluation

Table 5
Frame identification results on both the SemEval 2007 data set and the FrameNet 1.5 release. Precision, recall, and F_1 were evaluated under exact and partial frame matching; see Section 3.3. **Bold** indicates best results on the SemEval 2007 data, which are also statistically significant with respect to the baseline ($p < 0.05$).

FRAME IDENTIFICATION (§5.2)		exact matching *P*	exact matching *R*	exact matching F_1	partial matching *P*	partial matching *R*	partial matching F_1
SemEval 2007 Data	gold targets	60.21	60.21	60.21	74.21	74.21	74.21
	automatic targets (§4)	**69.75**	**54.91**	**61.44**	**77.51**	**61.03**	**68.29**
	J&N'07 targets	65.34	49.91	56.59	74.30	56.74	64.34
	Baseline: J&N'07	*66.22*	*50.57*	*57.34*	*73.86*	*56.41*	*63.97*
FrameNet 1.5 Release	gold targets	82.97	82.97	82.97	90.51	90.51	90.51
	– unsupported features	80.30	80.30	80.30	88.91	88.91	88.91
	& – latent variable	75.54	75.54	75.54	85.92	85.92	85.92

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