Building Dialog Systems with Less Supervision

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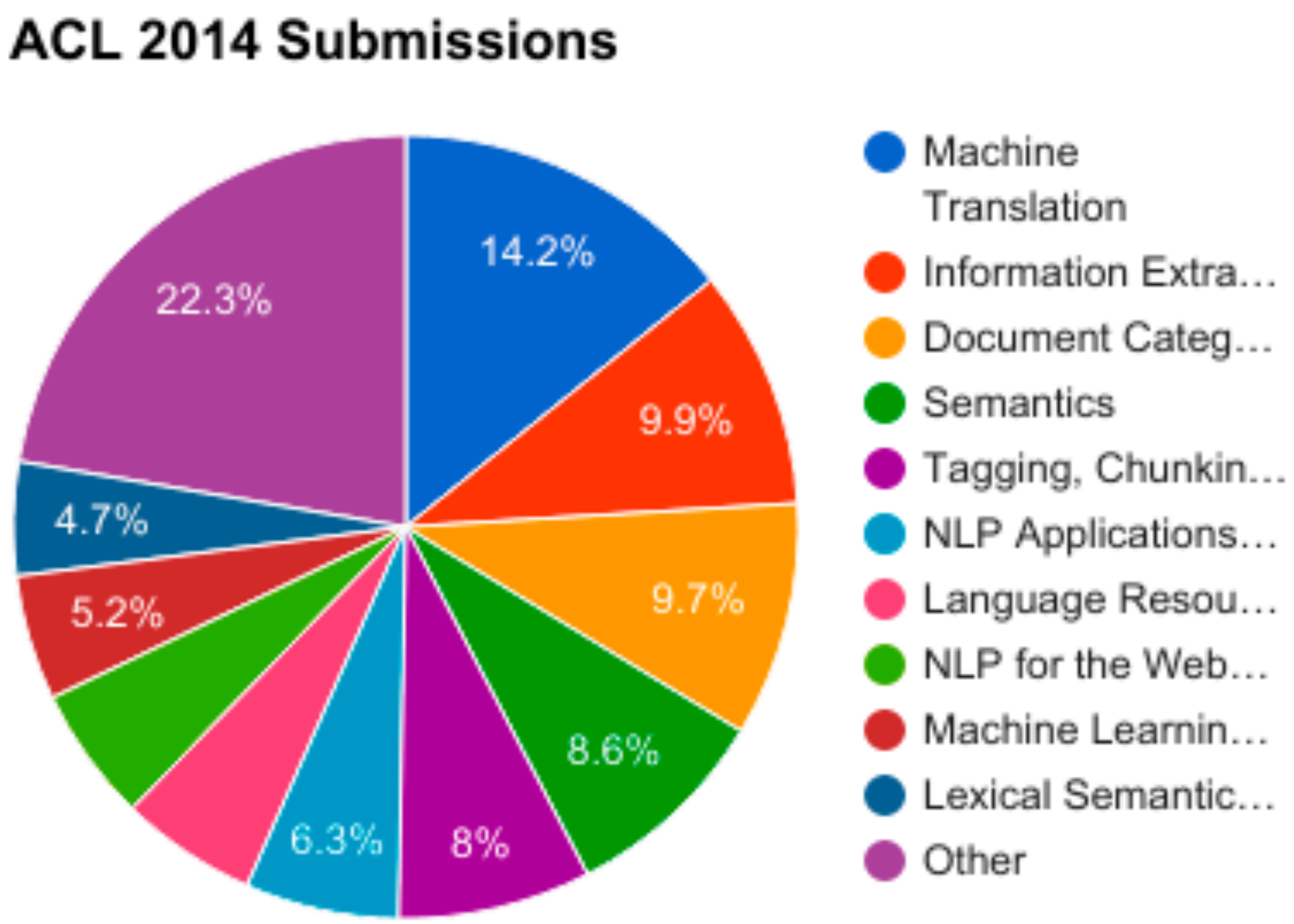
UC Davis


ACL 2014 Submissions
14.2%
9.9%
9.7%
8.6%
8%
6.3%
5.2%
4.7%
22.3%
Machine Translation
Information Extra…
Document Categ…
Semantics
Tagging, Chunkin…
NLP Applications…
Language Resou…
NLP for the Web…
Machine Learnin…
Lexical Semantic…
Other

ACL 2019

	Area	Long	Short	Total
1.	Information Extraction, Text Mining	156	93	249
2.	Machine Learning	148	73	221
3.	Machine Translation	102	105	207
4.	Dialogue and Interactive Systems	125	57	182
5.	Generation	97	58	155
6.	Question Answering	99	55	154
7.	Sentiment Analysis, Argument Mining	91	60	151
8.	Word-level Semantics	78	59	137
9.	Applications	65	72	137
10.	Resources and Evaluation	70	60	130
11.	Multidisciplinary, AC COI	70	44	114
12.	Sentence-level Semantics	70	42	112
13.	Tagging, Chunking, Syntax, Parsing	50	49	99
14.	Social Media	51	42	93
15.	Summarization	48	35	83
16.	Document Analysis	48	33	81
17.	Vision, Robotics Multimodal Grounding, Speech	56	23	79
18.	Multilinguality	43	32	75
19.	Textual Inference, Other Areas of Semantics	44	30	74
20.	Linguistic Theories, Cognitive, Psycholinguistics	39	21	60
21.	Discourse and Pragmatics	33	24	57
22.	Phonology, Morphology, Word Segmentation	26	18	44
	Total	**1609**	**1085**	**2694**

Lots of Real Dialog Applications!

Applicable in various areas, such as and entertainment, education and health care.

- Entertainment: Create targeted advertisement (Yu et al., IJCAI 2017, SLT 2016) Social chatbots (Amazon Alexa Prize, Cohn et al, SIGDIAL 2019)
- Education: Provide training (Yu et al., IWSDS 2016) and facilitate discussion on MOOCs
- Health care: Support therapy for depression (Yu et al., SEMDIAL 2013), aphasia and dementia, persuade people to perform physical exercise
- Customer Service: Provide information and perform actions (Shi&Yu ACL 2018, Zhang&Yu SIGDIAL 2018, Qian&Yu ACL 2019)
- Marketing: Persuade people to donate to charity (Wang et al., ACL 2019 best paper nomination), Anti-Scam (DARPA ASED)

Applicable in various platforms: virtual agents and robotics

- Virtual: Build characters for video games
- Robots: Service robots, e.g. direction giving (Yu et al., SIGDIAL 2015), nursing and rescuing

Dialog Research Challenges

- History or context tracking
- **Not enough data**
- Big variance across different dialog domains
- Difficult to evaluate: moving targets (human)!

Learning with Less Supervision

Reduce:

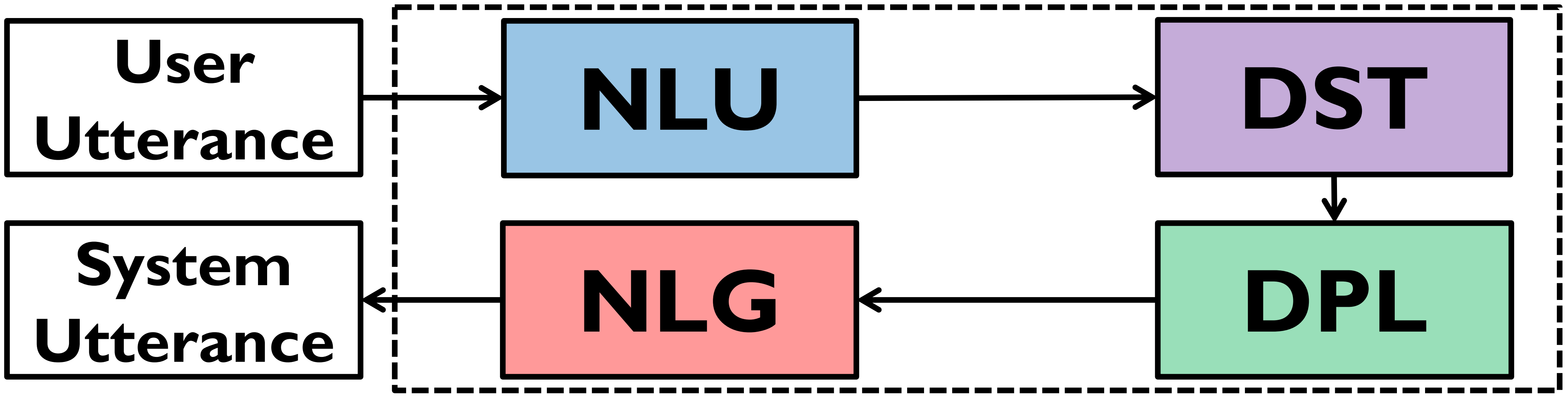
- Number of data points
- The level of details in labeling

$\Big\}$ Trade-off

- Number of **labeled** data points
  - Unsupervised dialog flow learning
  - One-shot learning using Meta learning

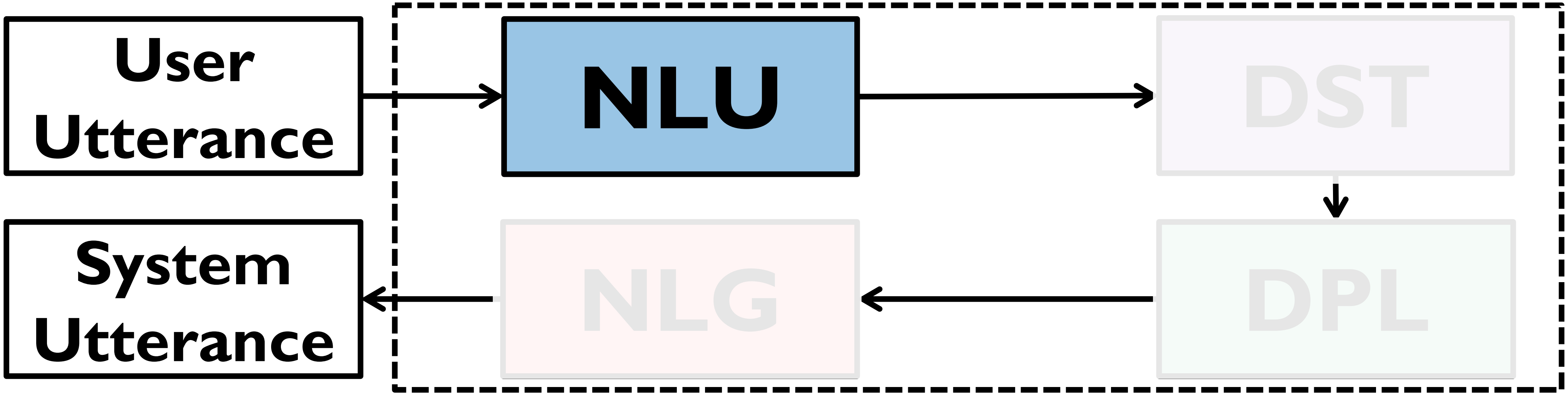
Dialog Basics: Modular Framework

A pipeline of different modules developed independently.



NLU: Natural Language Understanding

Problem: user utterance → a distributed semantic representation
Sub-Tasks: intent detection, slot filling
e.g. I **need** something that is in **east** part of the town → Inform: location=east
Solution: classification+sequence labeling or sequence generation



DST: Dialog State Tracking

Problem: NLU output of all turns/Raw dialog text → dialog state

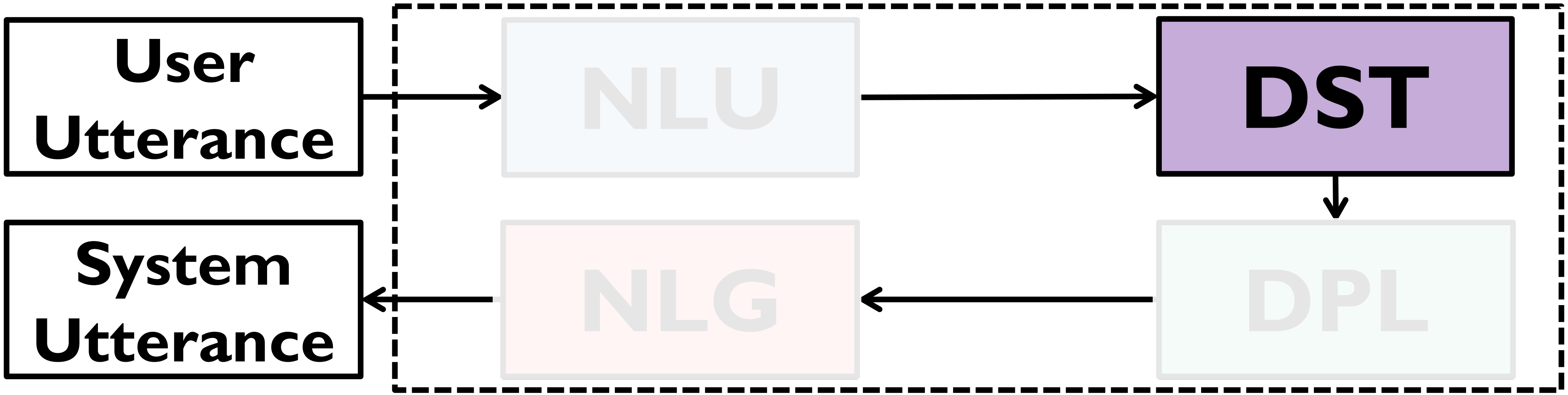
e.g. user: I am looking for a **moderate** price ranged Italian restaurant.

sys: De luca cucina and bar is a modern European restaurant in the **center**.

user: I need something that's in the **east** part of town

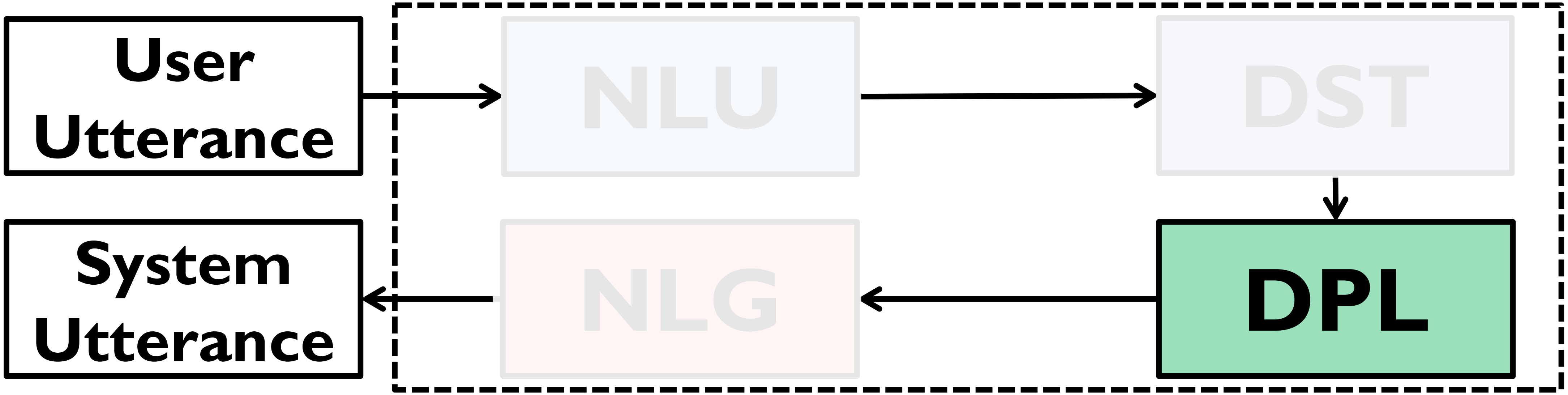
→ inform: price=moderate, location=east

Solution: Sequence classification or sequence generation



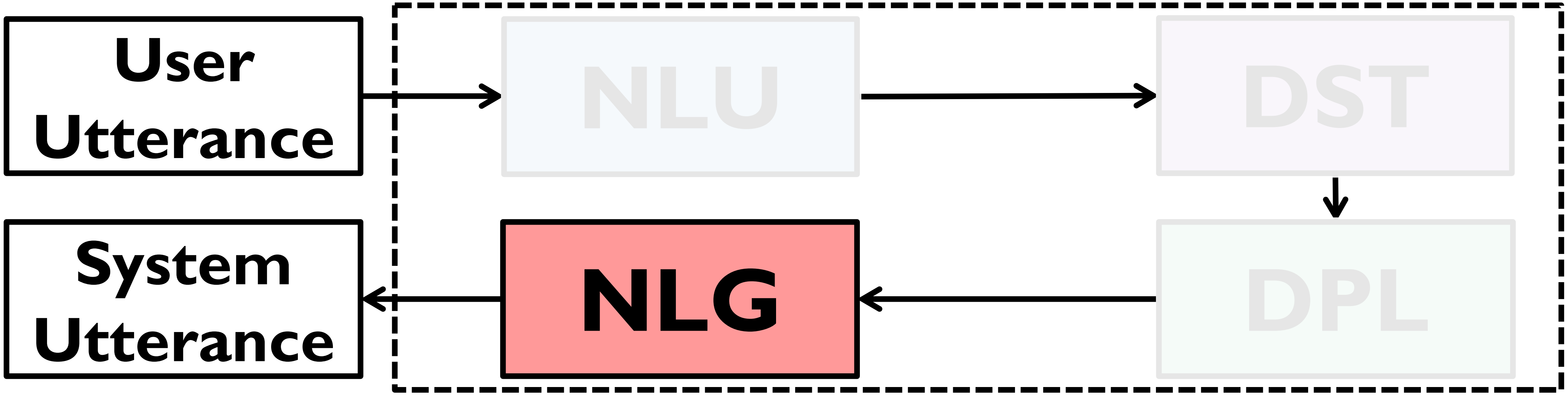
DPL: Dialog Policy Planning

Problem: dialog state → system action mean representation(intent + slot) /template
e.g. inform: price=moderate, location=east → provide: restaurant_name, price, address
Solution: supervised learning or reinforcement learning

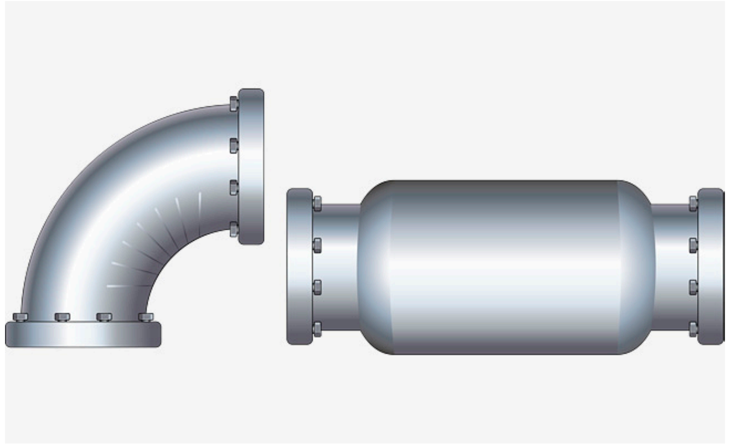


NLG: Natural Language Generation

Problem: System intent + slot → Natural system response
e.g. provide: restaurant_name, price, address → Curry prince is moderately priced and located at 452 newmarket road.
Solution: Sequence generation



Modular Framework Drawbacks

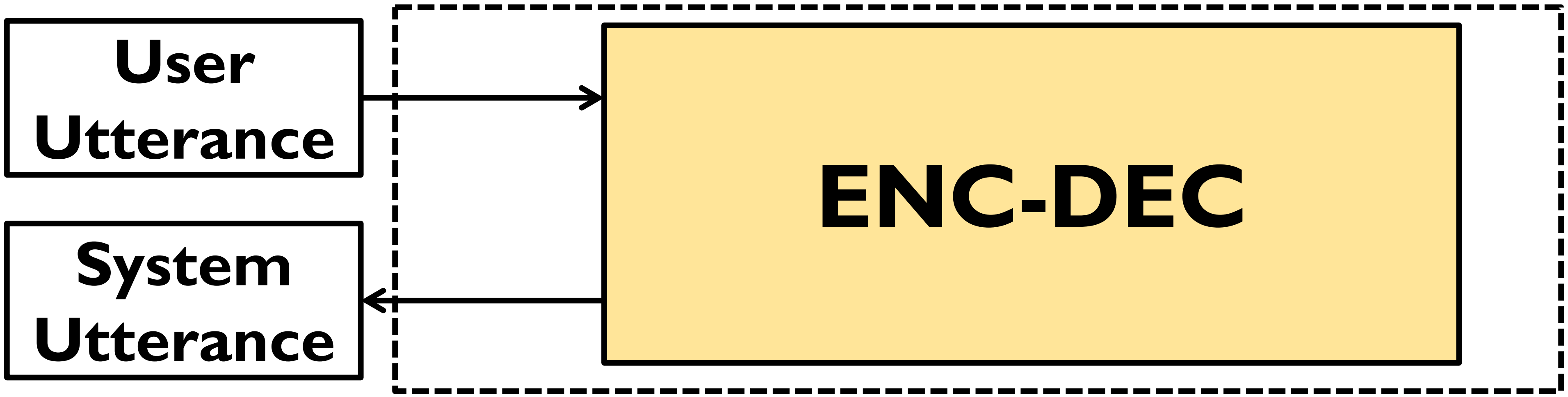


Difficult to update model

Heavy expert involvement

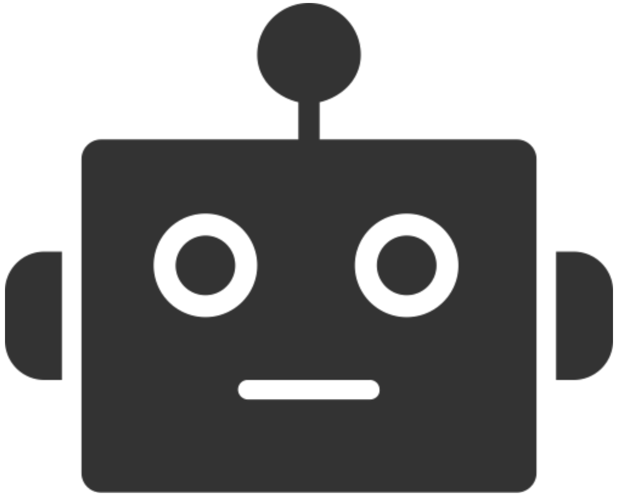
Heavy manual annotation involvement

End-to-End Framework



End-to-End Framework Drawbacks

Difficult To Perform Error Analysis

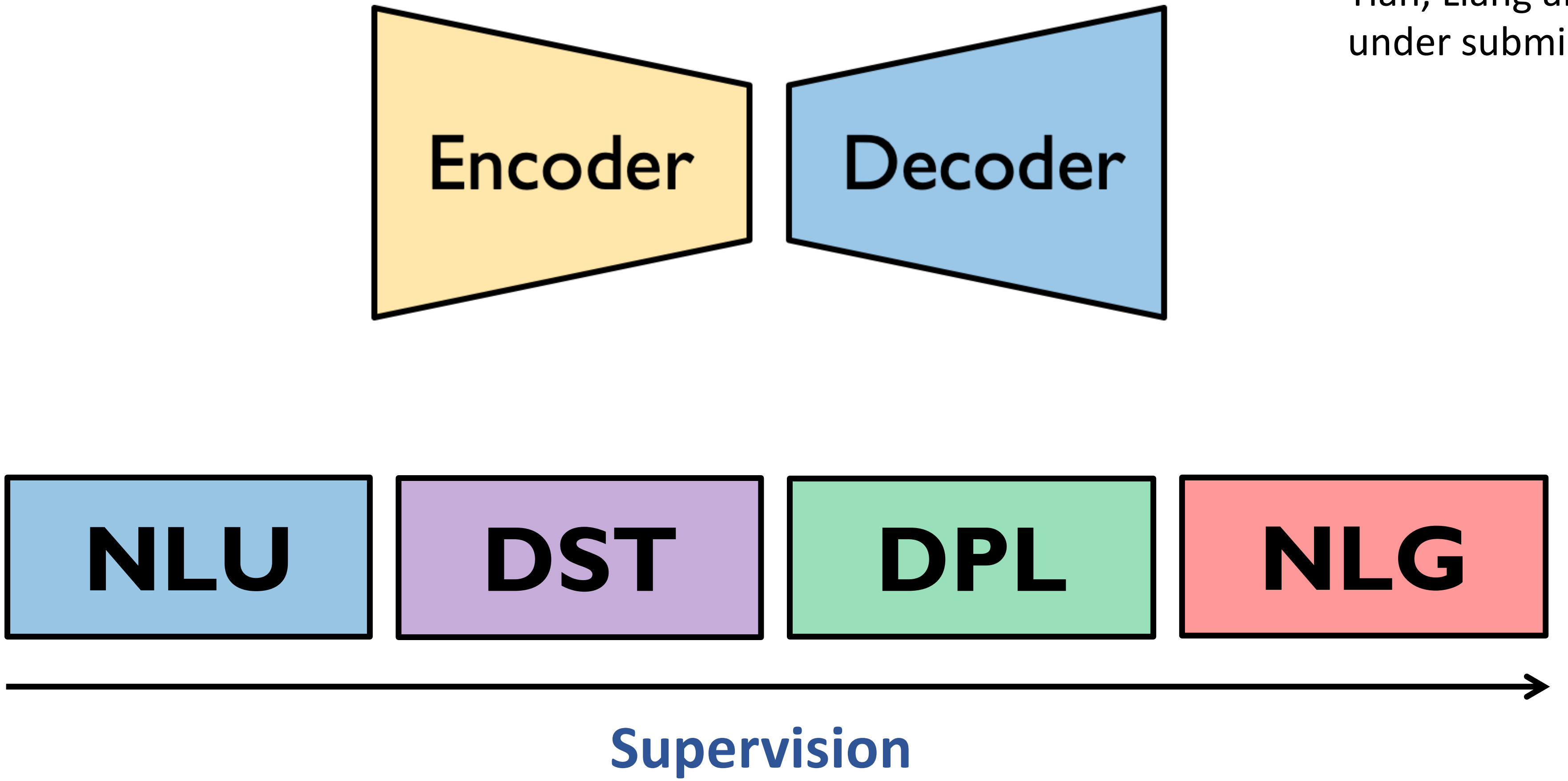


Simple Information Request Task

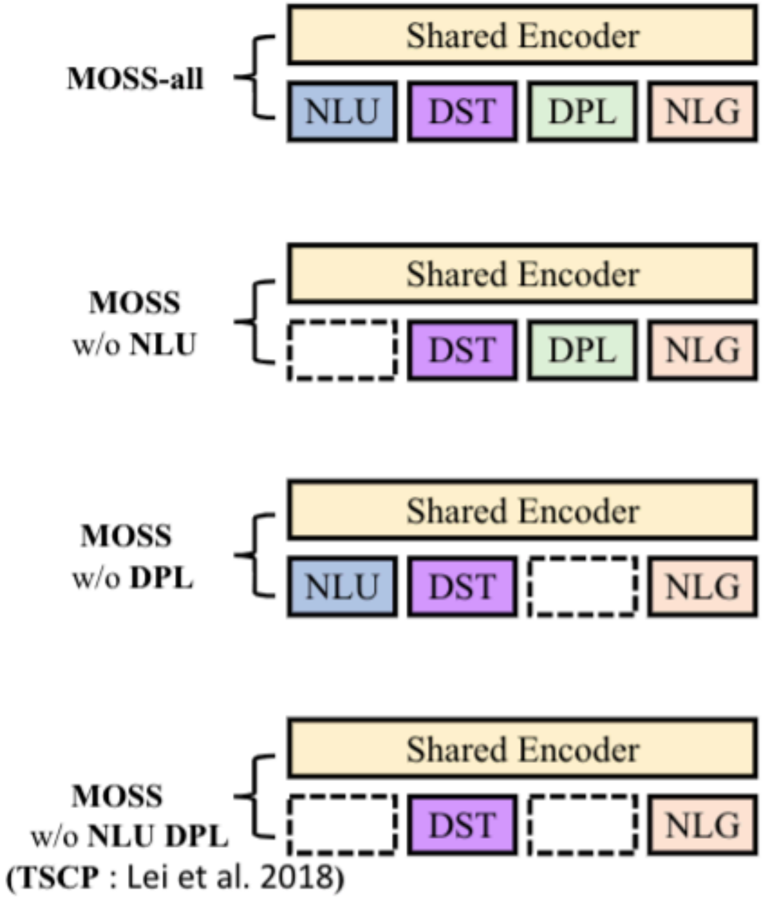
Thousands of Dialogs to Train

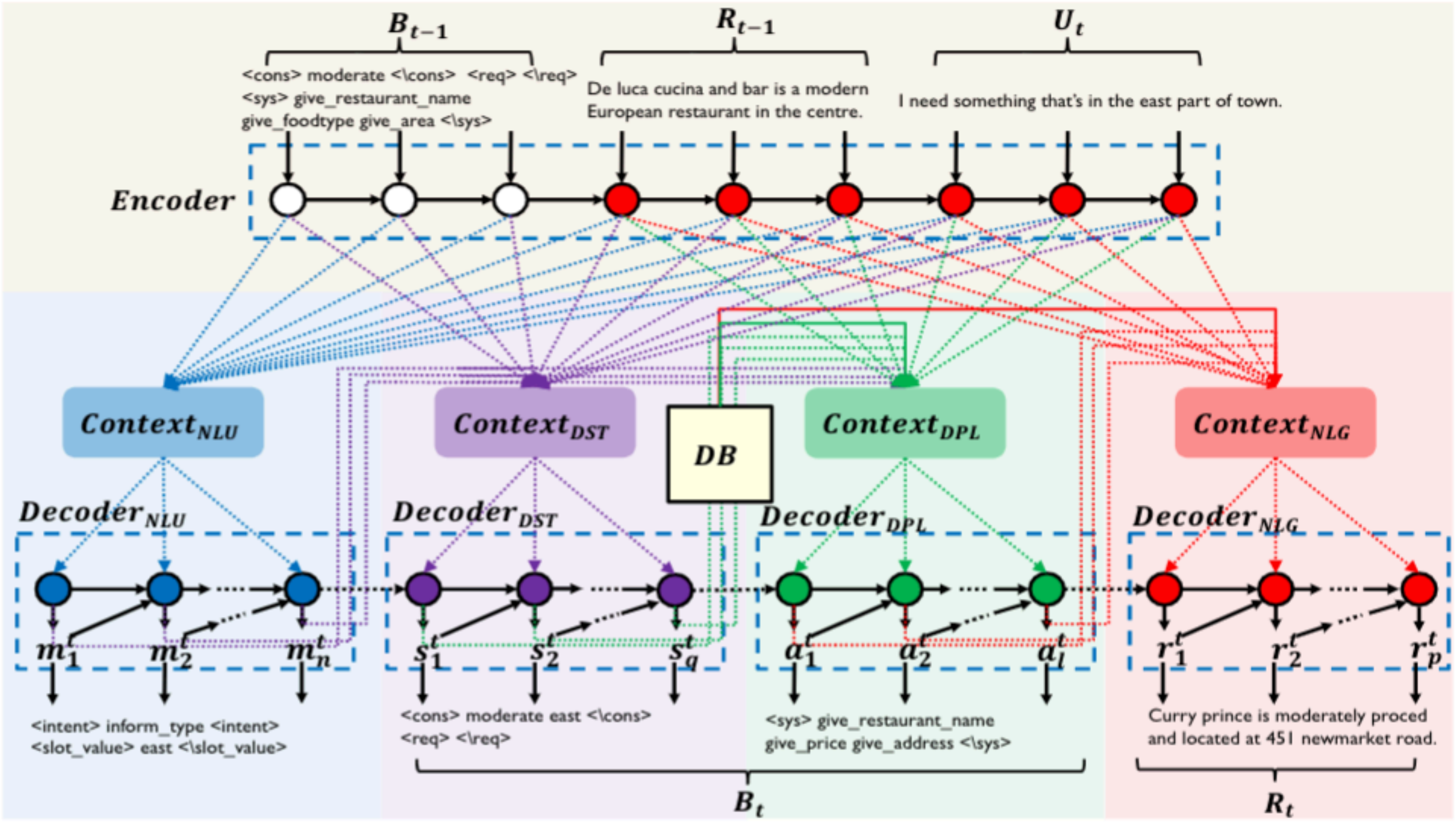
MOSS: End-end trainable framework with modular supervision

Tian, Liang and Yu
under submission

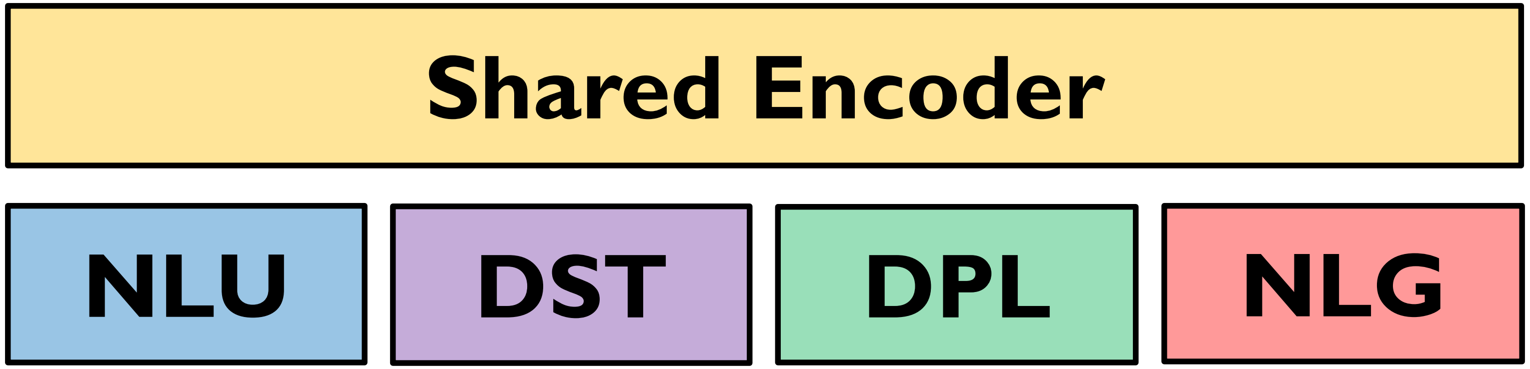


MOSS: Plug and Play Framework





MOSS-all: 1Encoder-4Decoder



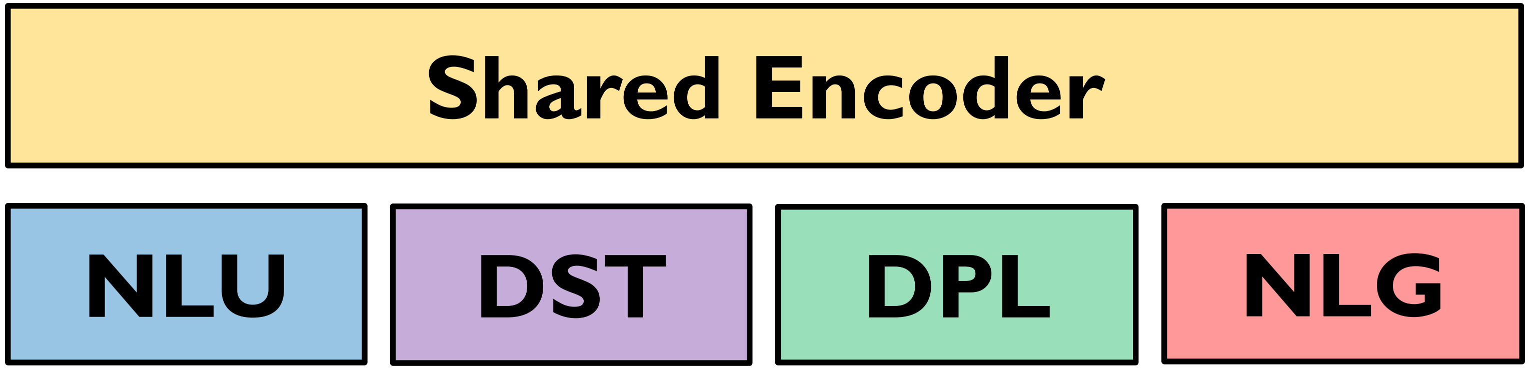
$$M_t = S2S_{NLU}(B_{t-1}, R_{t-1}, U_t)$$

$$S_t = S2S_{DST}(B_{t-1}, R_{t-1}, U_t | M_t)$$

$$A_t = S2S_{DPL}(B_{t-1}, R_{t-1}, U_t | M_t, S_t)$$

$$R_t = S2S_{NLG}(B_{t-1}, R_{t-1}, U_t | M_t, S_t, A_t)$$

Modular information is pass through hidden states



$$M_t = S2S_{NLU}(B_{t-1}, R_{t-1}, U_t)$$

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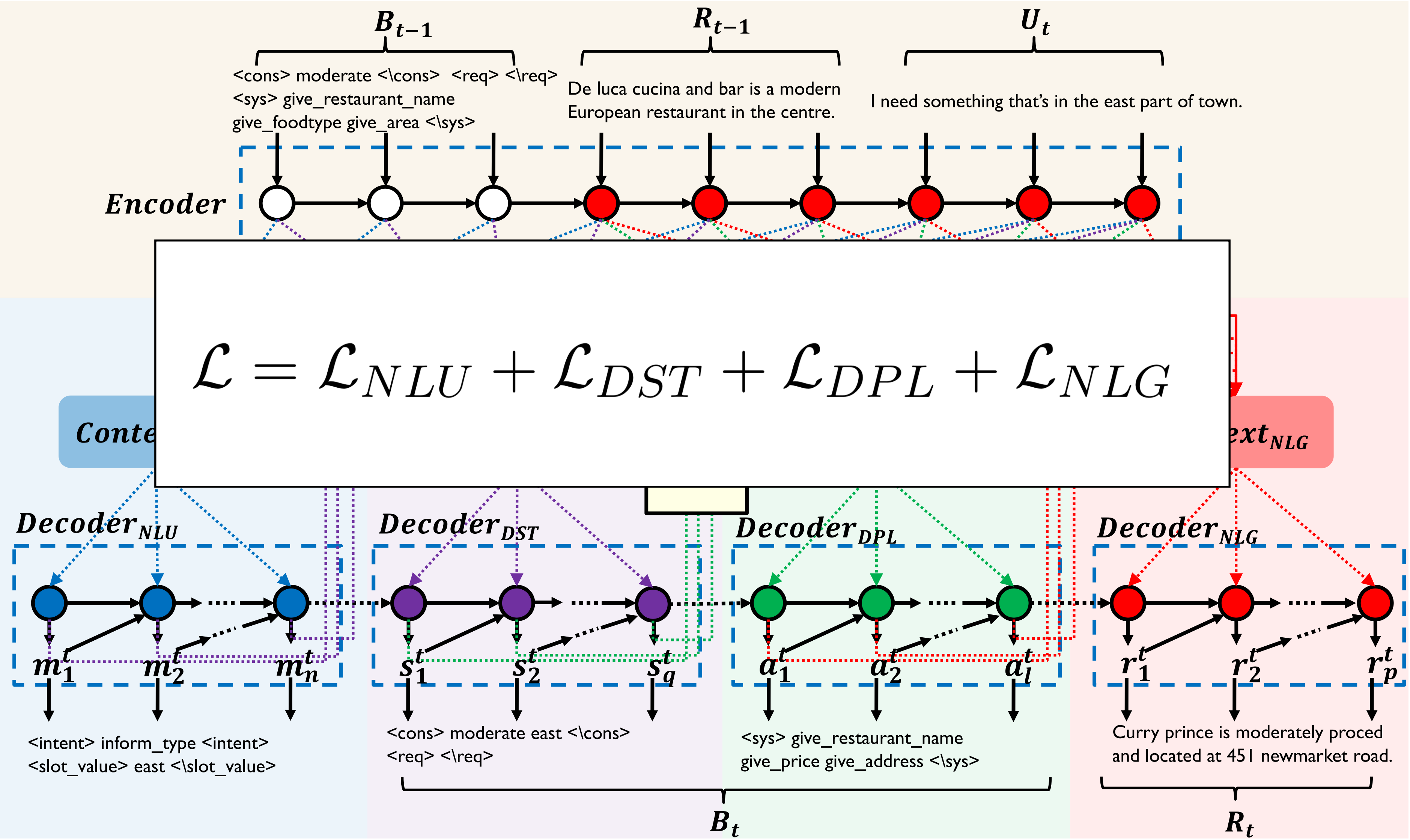
$$R_t = S2S_{NLG}(B_{t-1}, R_{t-1}, U_t | M_t, S_t, A_t)$$

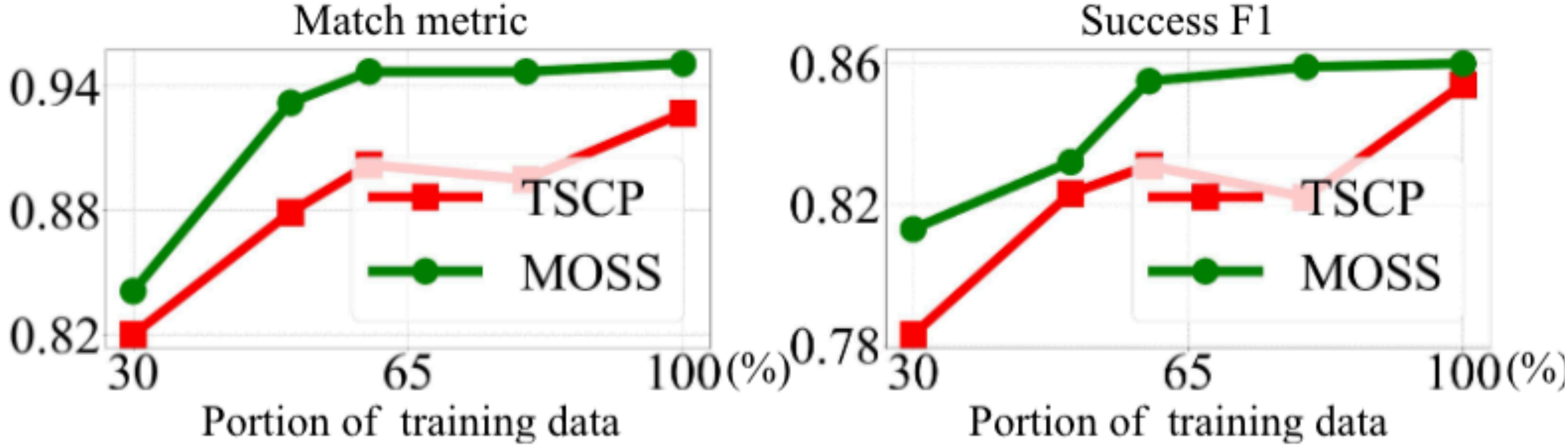
MOSS: Multitask Setting (plug and play)



$$\mathcal{L} = \mathcal{L}_{NLU} + \mathcal{L}_{DST} + \mathcal{L}_{DPL} + \mathcal{L}_{NLG}$$

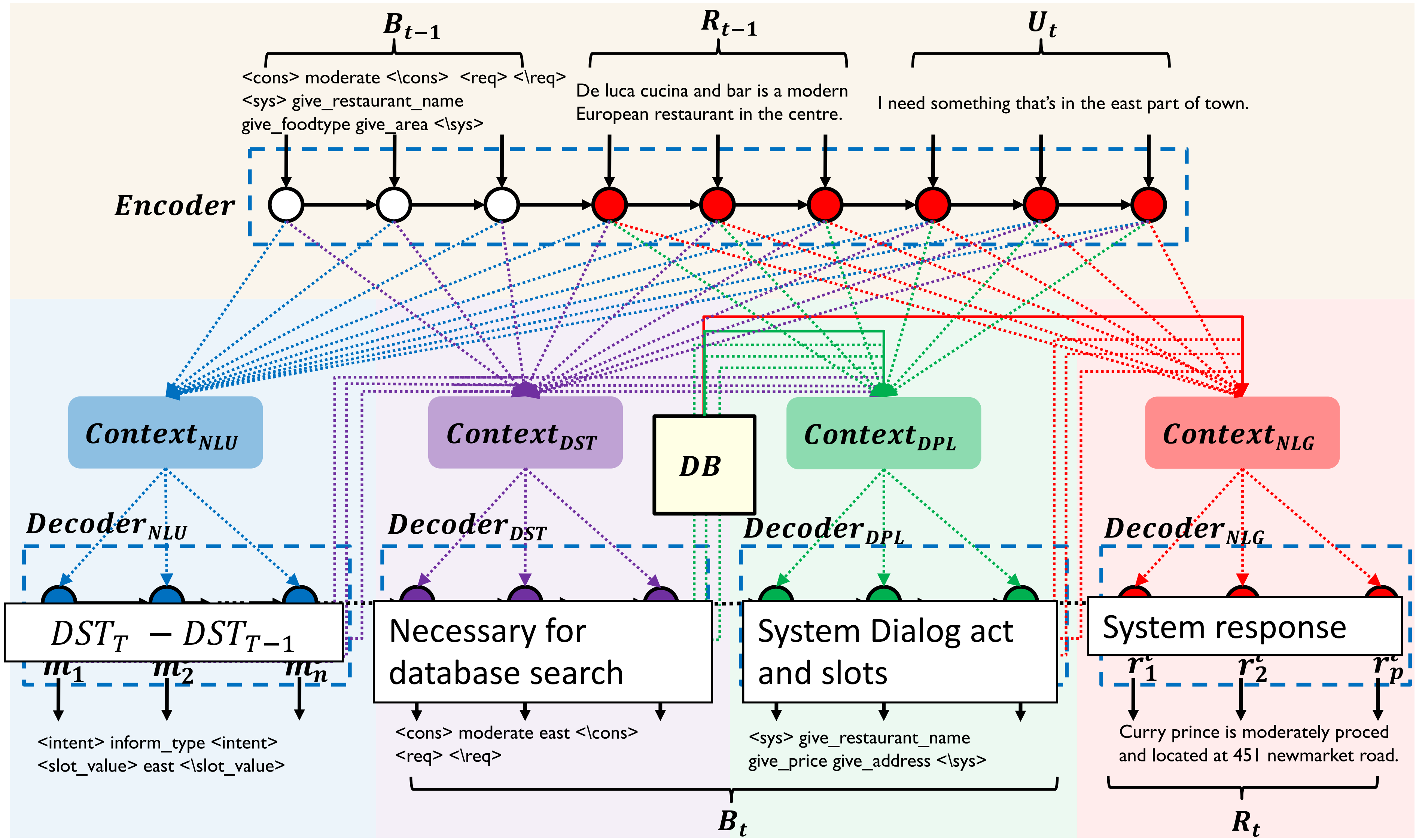
MOSS-all outperforms TSCP using only 60% data

CamRes676



Takeaway: More detailed annotation requires less training data

MOSS accepts data with partial annotation



MOSS performs well with data with mixed labels

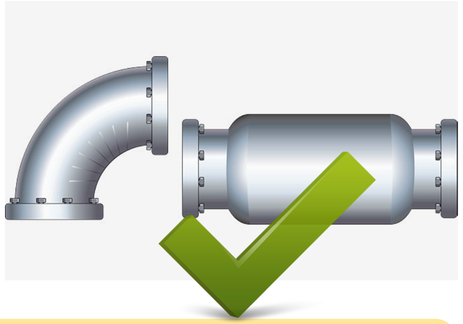
CamRes676

Model	Mat	Succ.F1	BLEU
KVRN	N/A	N/A	0.134
NDM	0.904	0.832	0.212
LIDM	0.912	0.840	0.246
TSCP	0.927	0.854	0.253
MOSS w/o DPL	0.932	0.856	0.251
MOSS w/o NLU	0.932	0.857	0.255
MOSS-all $\times$ 60%	0.947	0.857	0.202
MOSS$\times$ (60%all + 40%raw)	0.947	0.859	0.221
MOSS-all	**0.951**	**0.860**	**0.259**

MOSS-all is easier to perform error analysis

User:	I am looking for an expensive restaurant in the south
Ground truth system response:	Hi! We have Mexican, Italian, Indian and Chinese restaurants that fit the bill. Do you have any preferences?
MOSS response:	What type of food are you interested in south part of town? (system dialog act output: ask_food_type)
TSCP response:	Curry Garden is a expensive Indian restaurant in the south part of town.

MOSS’s Advantage



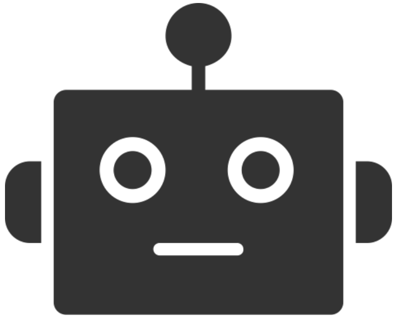
Difficult to update model

Heavy expert involvement

oice

My new talk:
Non-Collaborative Dialog Systems

Difficult To Perform Error Analysis



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Trade-off

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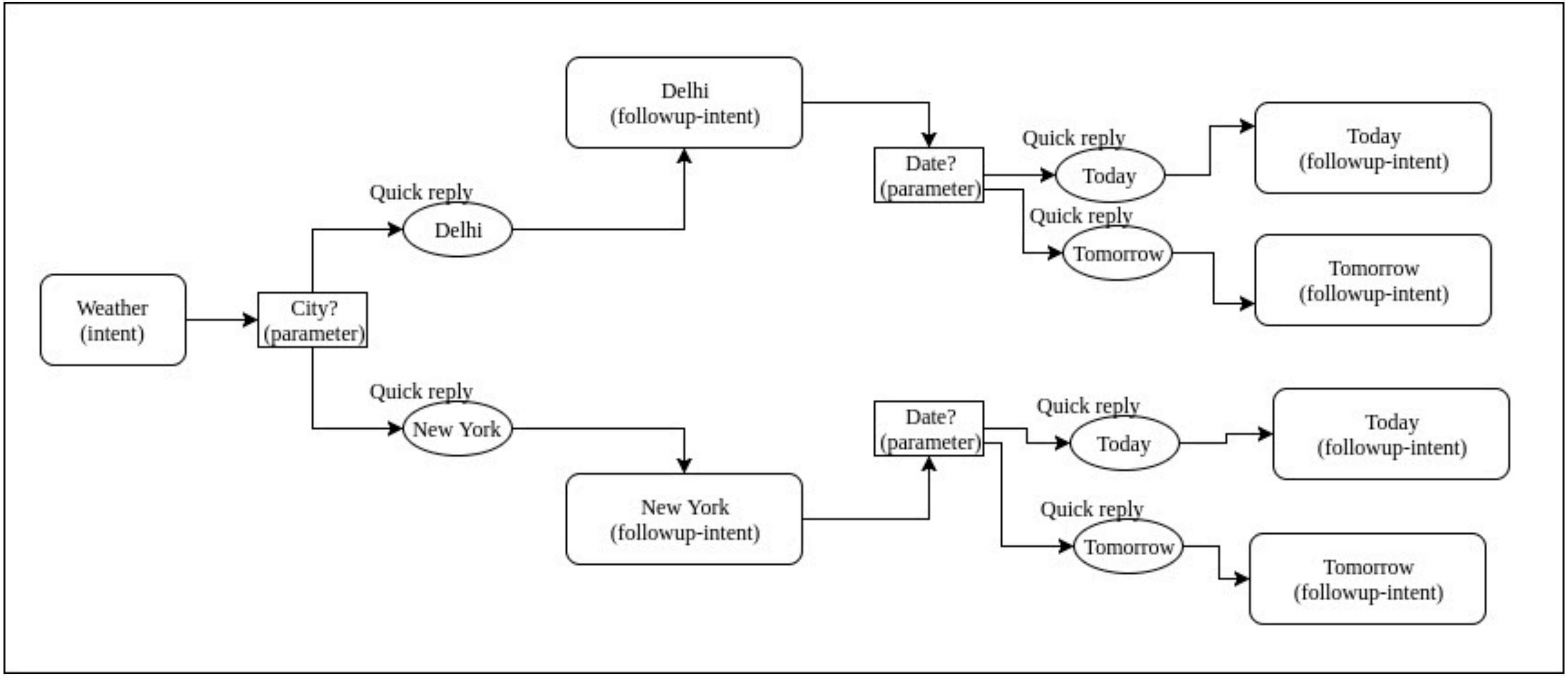
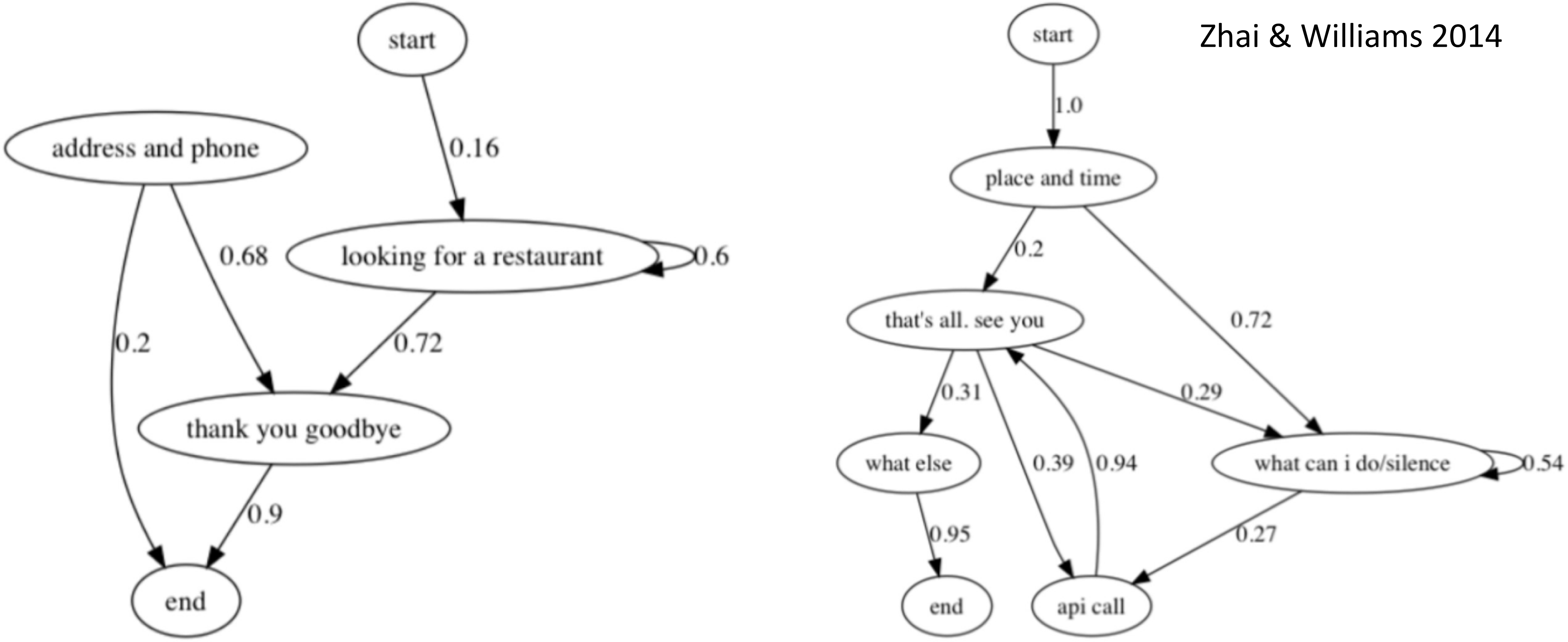
Dialog Manager: Industrial Dialog Flow



Unlabeled Conversations

Dialogue Structure learned by HMM

Zhai & Williams 2014



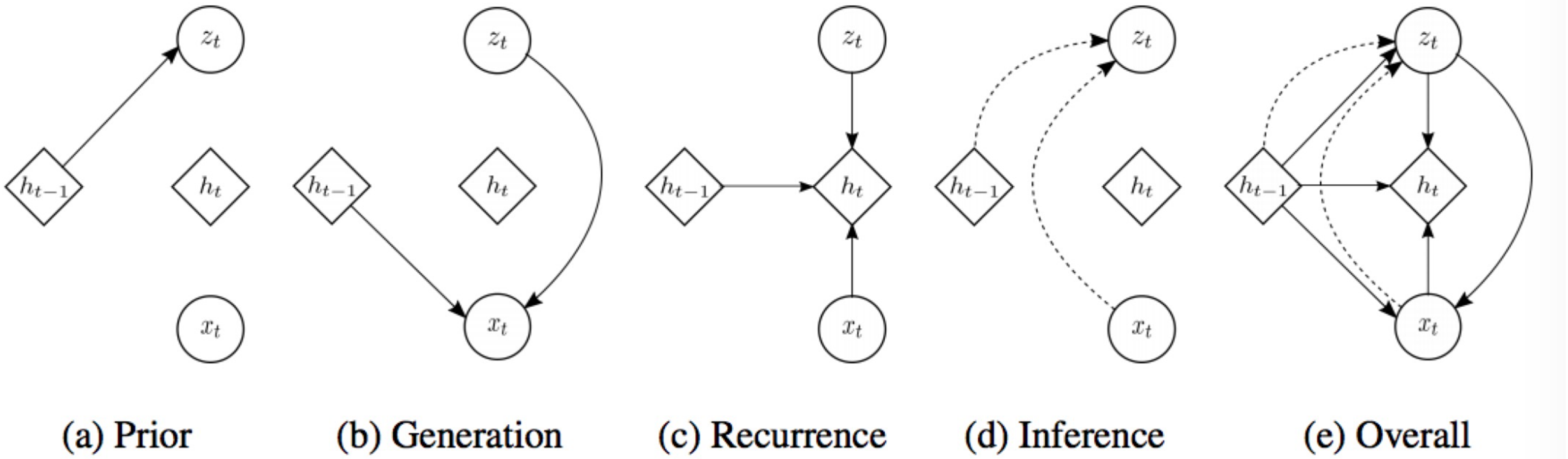
(a) HMM, restaurant data, 10 states

(b) HMM, weather data, 5 states

Figure 7: Dialog structures generated by HMM on different datasets.

Variational-RNN

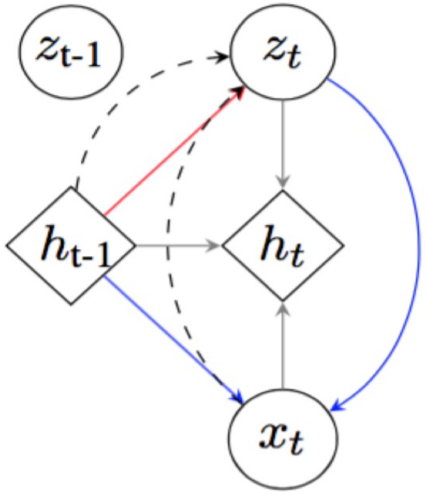
Shi et al., NAACL 2019



Variable	**Corresponding Interpretation in dialogue structure**
Xt: sequantial data	usr: “I want a <Chinese> restaurant” sys: “what <area> do you prefer?”
Zt: latent vector	latent state interpreted as <looking for a restaurant> **(<Z0, Z1, …, Zn>, transition prob <Zi, Zi+1>)** represents the dialogue structure
ht: hiddent vector in RNN	hidden representations

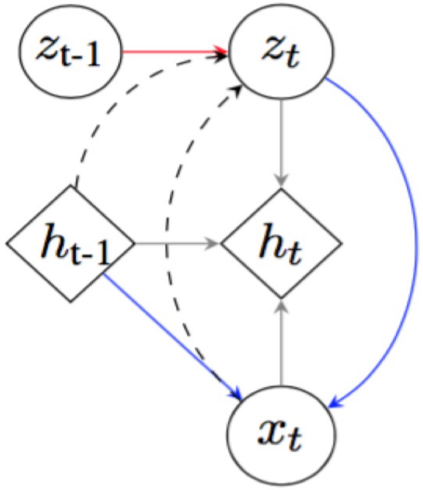
Discrete-Variational-RNN

Zt in VRNN: continuous → hard to interpret → discrete with Gumbel-Softmax



(a) Discrete-VRNN

Different in the prior!



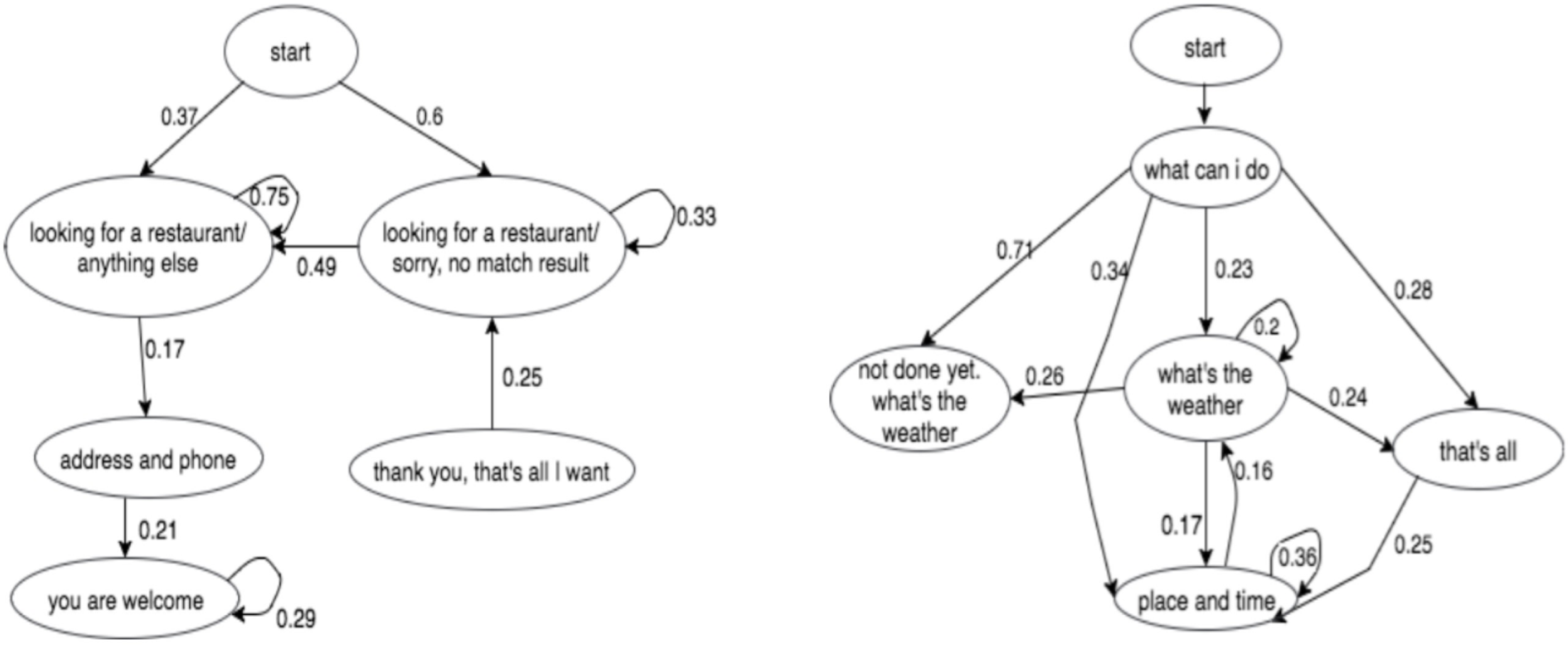
(b) Direct-Discrete-VRNN

+ penality on entity
→ NE-DD-VRNN

Transition prob <Zi, Zi+1>:
Frequency Count of predicted <Zi, Zi+1> tuple

Transition prob <Zi, Zi+1>:
These transition probabilities are model parameters in the prior, trained by minimizing the loss function.

Dialogue Structure by DD-VRNN



(a) DD-VRNN, restaurant data, 10 states

(b) DD-VRNN, weather data, 5 states

Figure 8: Dialog structures generated by DD-VRNN on different datasets.

Application in RL using Hybrid Code Network

Ppred from state1 to state2 from the RL model

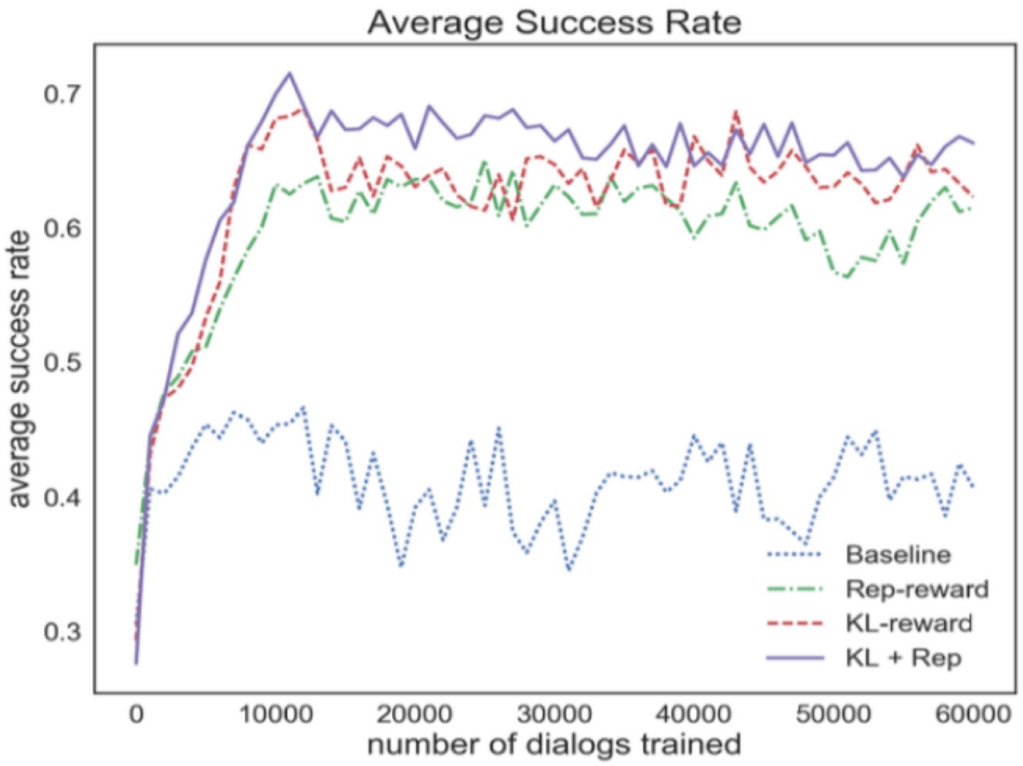
↕ **calculate KL divergence as the reward to force the RL model to be closer to the real distribution**

Ptrans from state1 to state2 from D-VRNN,
which summarizes the transition pattern in the real data

Algorithm 1 Reward function

if success **then**
  $R = 20$
else if failure **then**
  $R = -10$
else if repeated question **then**
  $R = f_{\text{reward}}(p_{\text{trans}}, p_{\text{pred}})$
else if each proceeding turn **then**
  $R = -1$
end if

$$f_{\text{reward}}(p_{\text{trans}}, p_{\text{pred}}) = \begin{cases} -1 & \text{Baseline} \\ -5 & \text{Rep-reward} \\ -\text{KL}(p_{\text{trans}}, p_{\text{pred}}) & \text{KL-reward} \\ -\text{KL}(p_{\text{trans}}, p_{\text{pred}}) - 2 & \text{KL+Rep} \end{cases} \tag{10}$$



Takeaway

Direct discrete variational RNN can discover dialog structure

Learned structure is helpful in understanding unlabeled dialogs

Learned structure is helpful in building RL based dialog systems

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Reduce:

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- The level of details in labeling

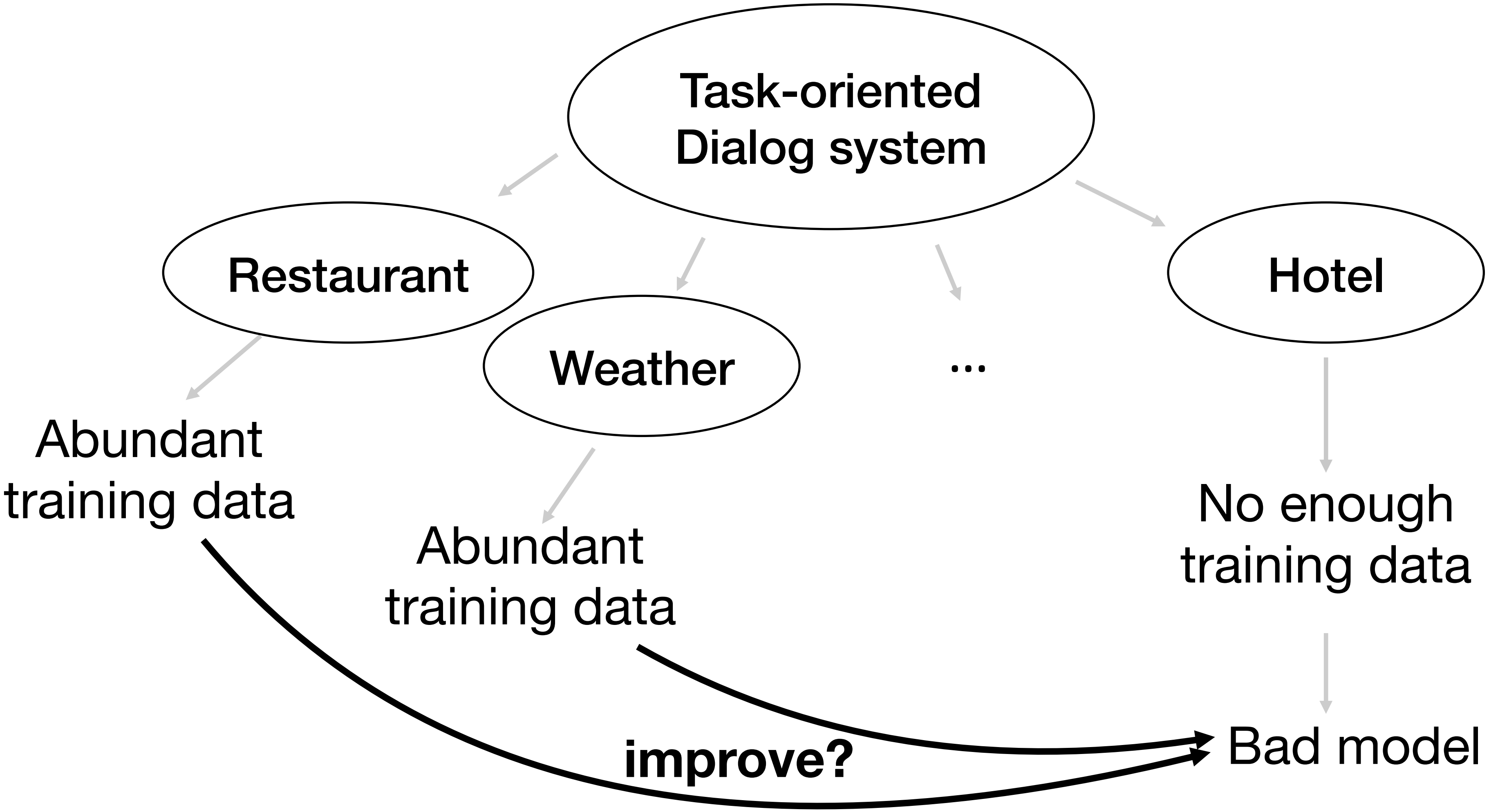
Trade-off

- Number of **labeled** data points
    - Unsupervised dialog flow learning
    - **One-shot learning using Meta learning**

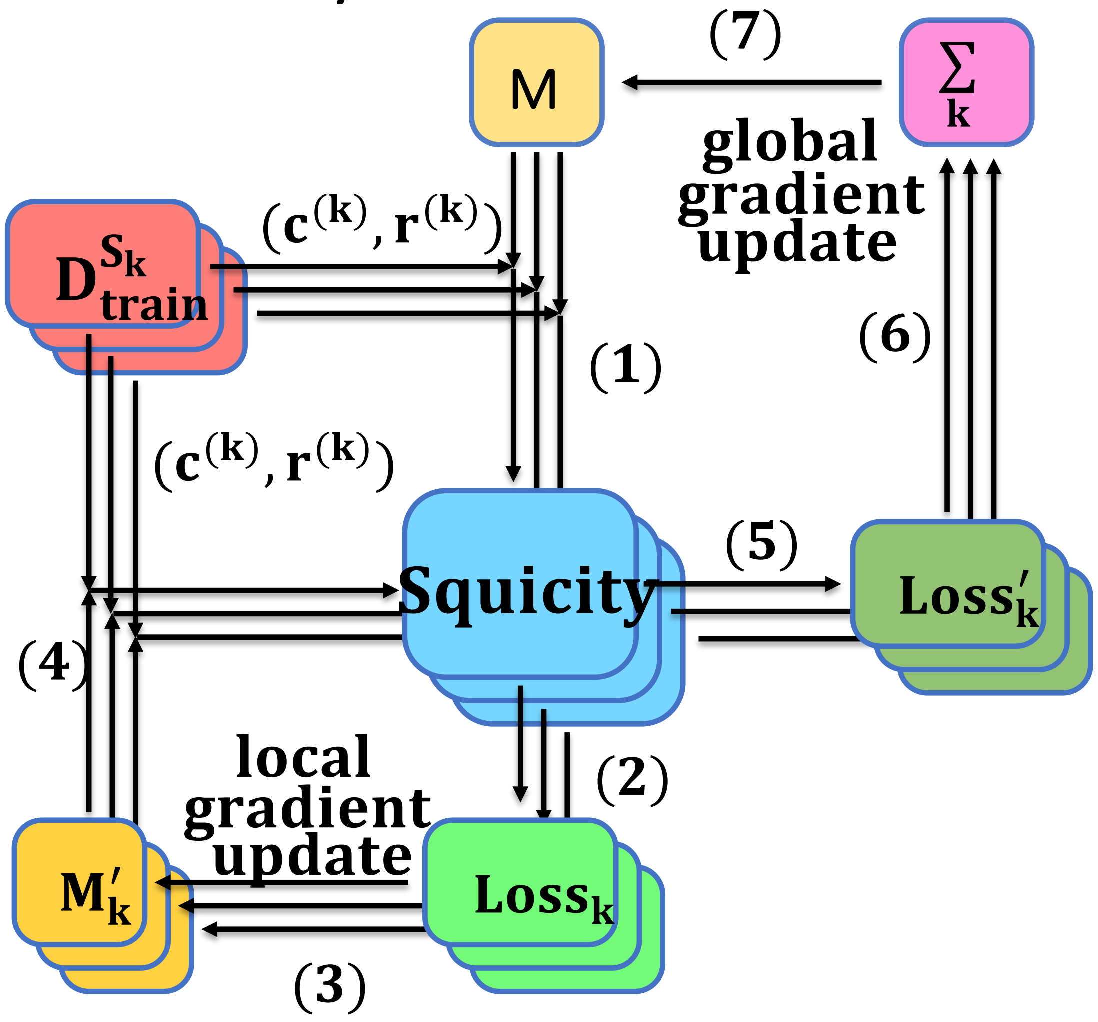
Too many skills !!!

Build a new skill without having enough data

Qian & Yu ACL 2019



Meta-learning to the rescue: leveraging a large number of close-by tasks.



Advancing dialog systems with less data by going beyond language

- Multi-task learning
- Unsupervised, semi-supervised learning
- Transfer learning

- Consider multimodal information, such as user sentiment
- Consider context information, such as user demographic and personality

Thanks!

- Questions?