Task-Oriented Dialog Systems that Consider Multiple Appropriate Responses under the Same Context

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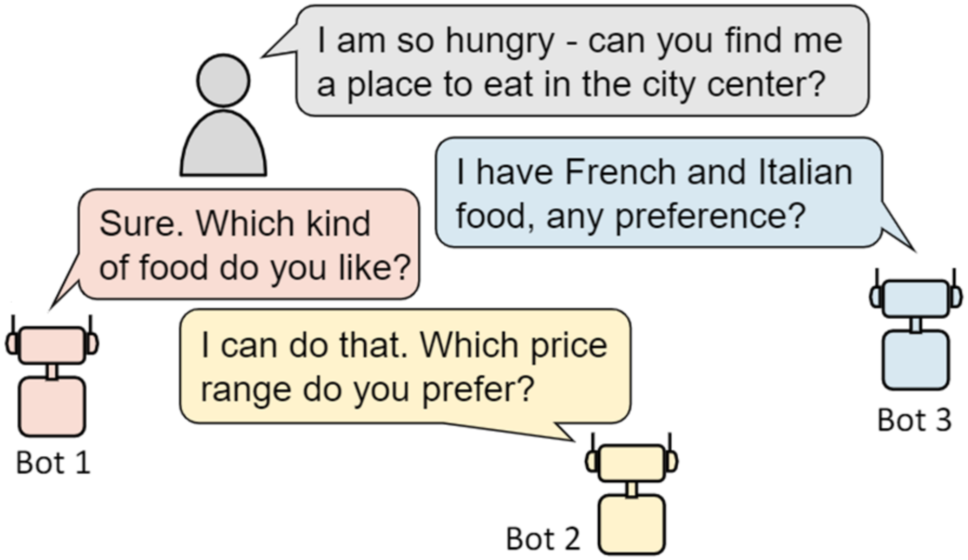
Outline

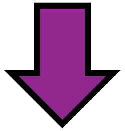
- Problem
  - One-to-Many Problem in Task-Oriented Dialogs
  - Difficulty: Data Bias in Collected Dialog Datasets
- Proposed Method
  - Framework: Multi-Action Data Augmentation (MADA)
  - Model: Domain Aware Multi-Decoder Network (DAMD)
- Experiments
- Conclusion & Future Work

One-to-Many Problem in Task-Oriented Dialogs

- Multiple responses can be appropriate for the same dialog context.



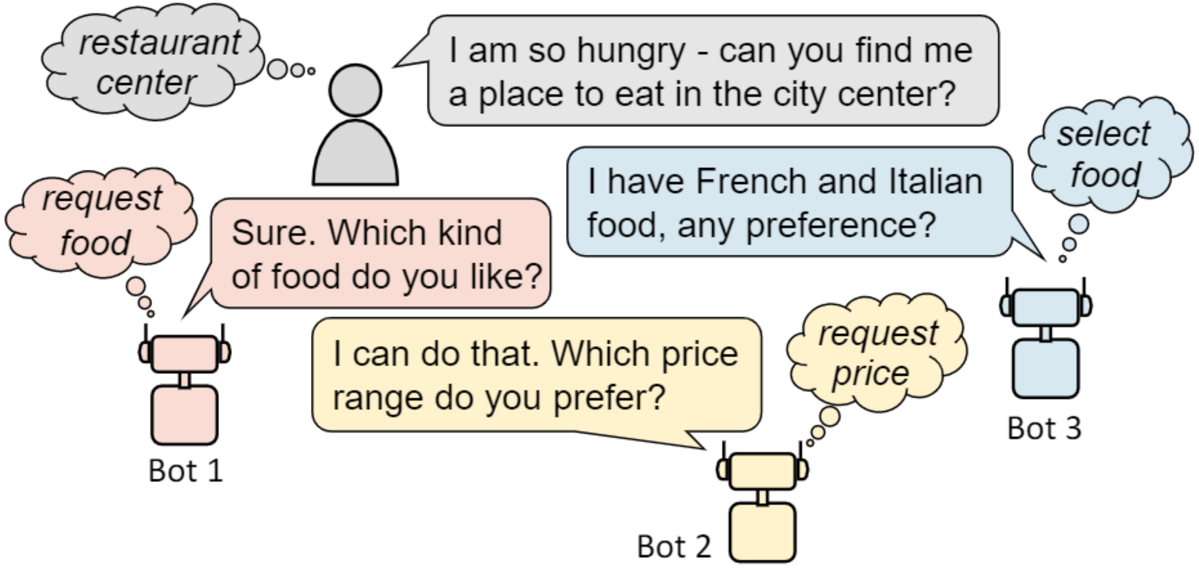
Dialog Context



Multiple Appropriate System Responses

One-to-Many Problem in Task-Oriented Dialogs

- Results from the one-to-many mapping in dialog policy.



Dialog State

domain=restaurant

price=? food=? area=?

Multiple Valid System Actions

restaurant-request-food

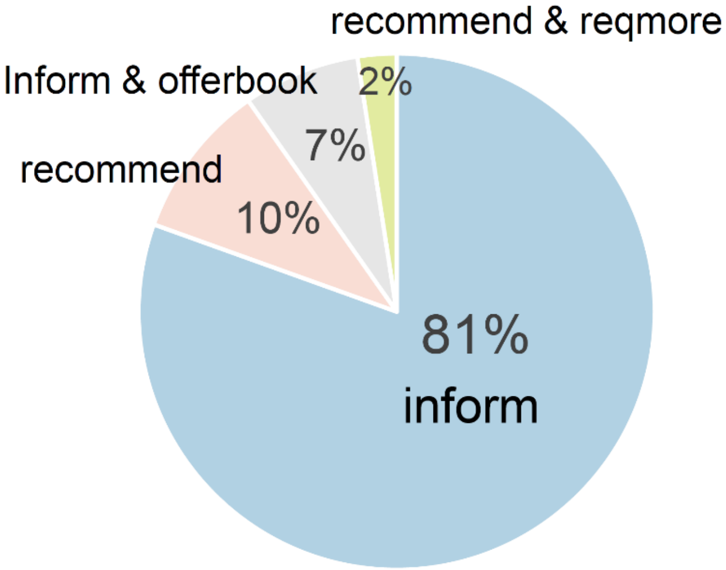
restaurant-request-price

…

(domain-act-slot)

Difficulty: Data Bias in Collected Dialog Datasets

- Only provide a single reference
- Unbalanced action distribution



....

User: By the way, I also need internet service.

Domain	hotel	**User Action**	inform
Belief State	area=west, price=any, wifi=yes		
Database Search Results	match # : 3		

System:

inform	I find a hotel for you. The name is …
recommend	I'd like to recommend [name] hotel …
inform & offerbook	[name] hotel is … Would you like to book it?
recommend & reqmore	I recommend … What else could I help?

[1] Budzianowski P, Wen T H, Tseng B H, et al. Multiwoz-a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling[C]. EMNLP 2018.

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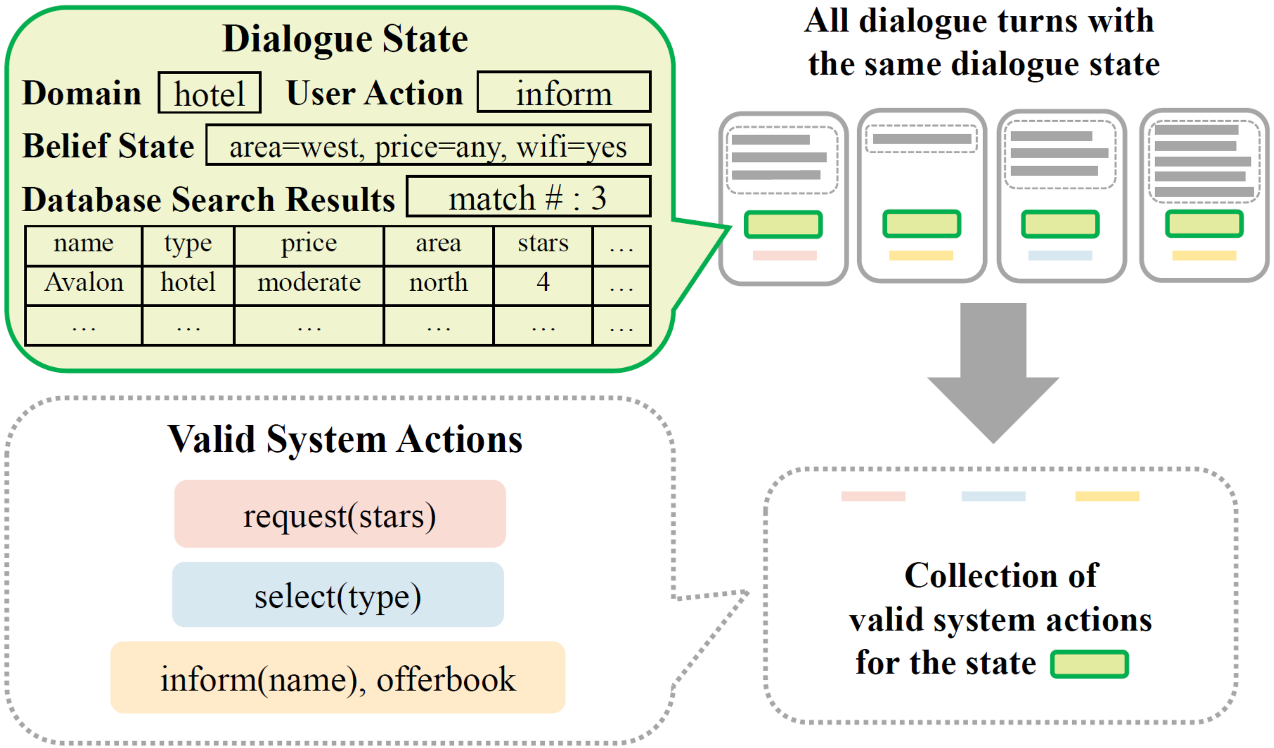
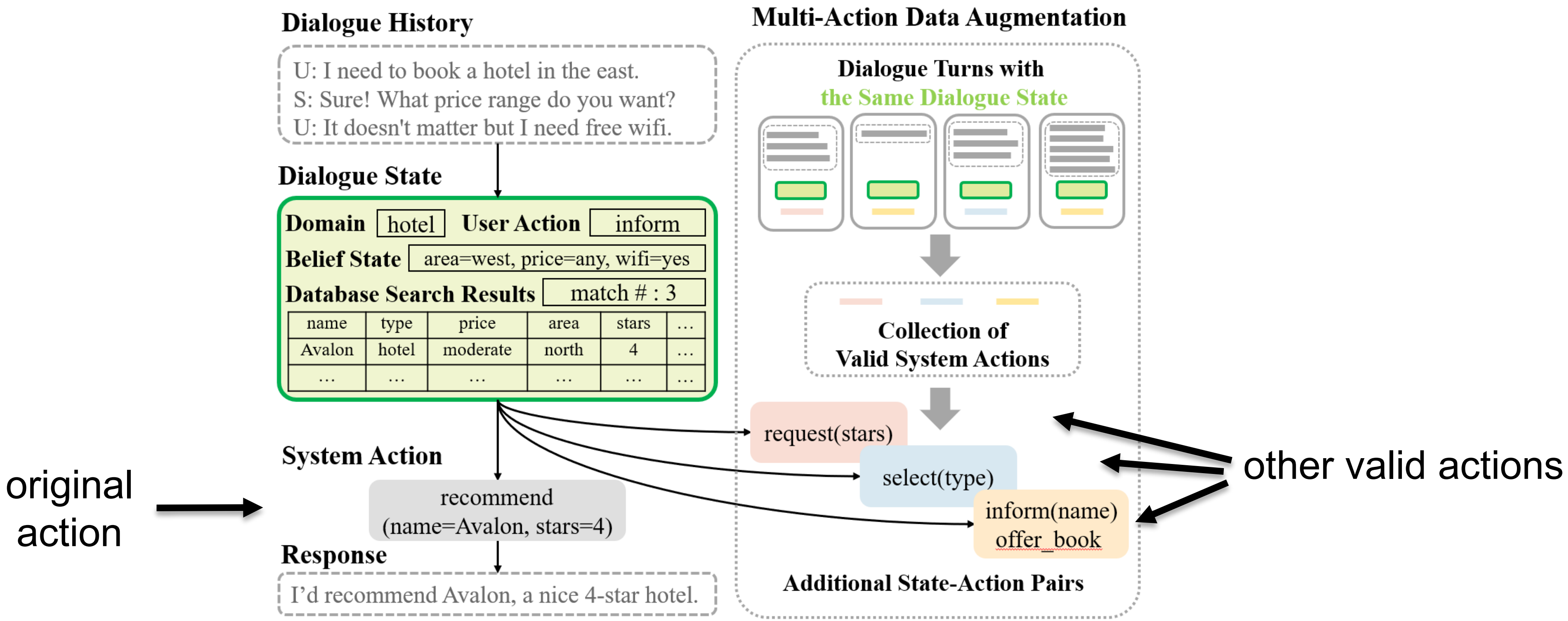
Framework: Multi-Action Data Augmentation (MADA)

- Before training: collect all the valid system actions for each dialog state



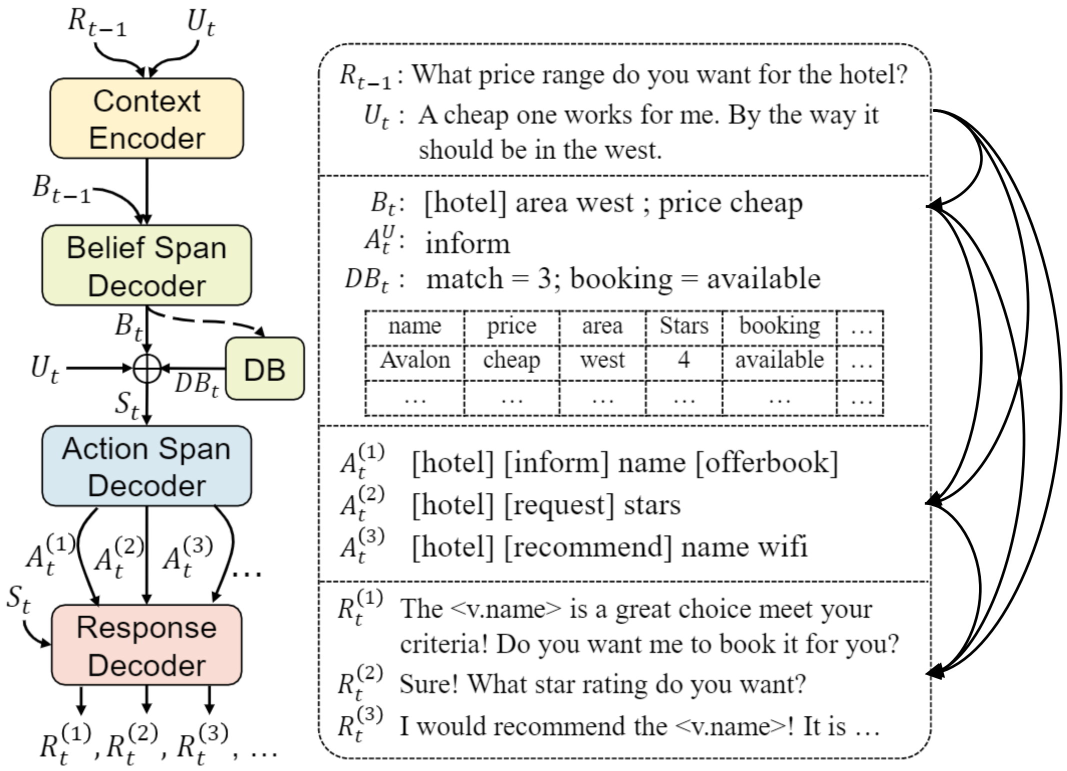
Framework: Multi-Action Data Augmentation (MADA)

- During training: use all the valid state-action pairs as additional data for policy learning



Model: Domain Aware Multi-Decoder Network (DAMD)

- DAMD: an end-to-end model for multi-domain response generation which can take full advantage of the proposed MADA framework.



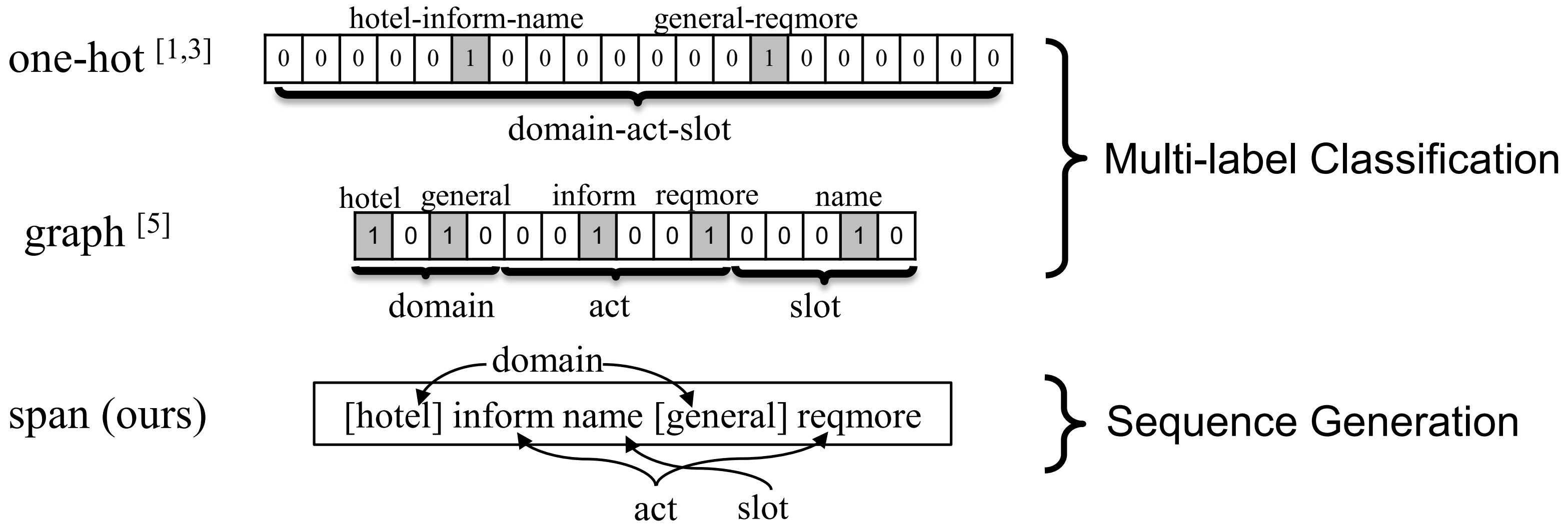
Hierarchal
Seq2Seq Learning
+
Copy Mechanism[2]

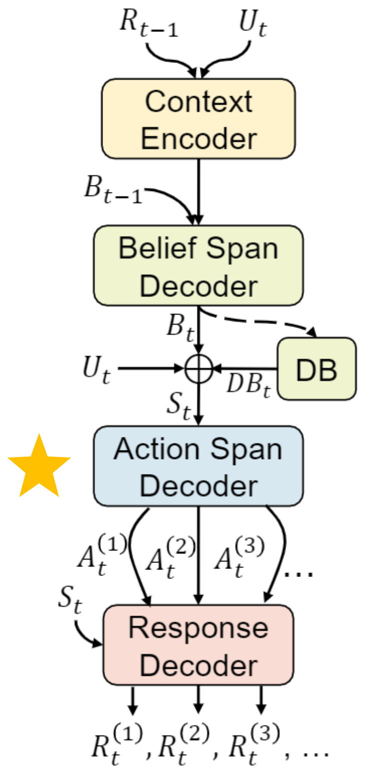
Compared to Sequicity[3]:
(1) Generalize to multi-domain settings
(2) Add the system action span decoder

[3] Lei W, Jin X, Kan M Y, et al. Sequicity: Simplifying task-oriented dialogue systems with single sequence-to-sequence architectures[C]. ACL 2018.

Text Span Based System Action Modeling

- Low space complexity and high representation ability.
- Enable the use of diverse decoding techniques[6,7,8] to generate system actions with higher diversity.





Outline

- Problem
  - The One-to-Many Property in Human Conversations
  - Difficulty: Data Bias in Collected Dialog Datasets
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- **Experiments**
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Experiments - MultiWOZ Dataset

- Human-human task-oriented dialogs
- 7 domains: restaurant, hotel, attraction, train, taxi, police, hospital
- Multiple domains in a single dialog
- Large scale
- Complex ontology

Metric	DSTC2	SFX	WOZ2.0	FRAMES	KVRET	M2M	MultiWOZ
# Dialogues	1,612	1,006	600	1,369	2,425	1,500	**8,438**
Total # turns	23,354	12,396	4,472	19,986	12,732	14,796	**115,424**
Total # tokens	199,431	108,975	50,264	251,867	102,077	121,977	**1,520,970**
Avg. turns per dialogue	14.49	12.32	7.45	**14.60**	5.25	9.86	13.68
Avg. tokens per turn	8.54	8.79	11.24	12.60	8.02	8.24	**13.18**
Total unique tokens	986	1,473	2,142	12,043	2,842	1,008	**24,071**
# Slots	8	14	4	**61**	13	14	25
# Values	212	1847	99	3871	1363	138	**4510**

[3] Budzianowski P, Wen T H, Tseng B H, et al. Multiwoz-a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling[C]. EMNLP 2018.

Experiments - Multiple Response Generation

- Automatic evaluation of generated actions
- Human evaluation of generated responses
- Generating system responses with:
  - high policy-level diversity
  - good appropriateness

Model	Diversity	App	Good%	OK%	Invalid%
DAMD	3.12	2.50	56.5%	**37.4%**	6.1%
DAMD (+)	**3.65**	**2.53**	**63.0%**	27.1%	9.9%
HDSA (+)	2.14	2.47	57.5%	32.5%	**10.0%**

* (+) denotes applying our data augmentation method.
* HDSA[5] is the previous SOTA model.

Human evaluation details:
(1) Each model generates 5 responses.
(2) Score the appropriateness (good/ok/invalid) for each of the response.
(3) Score a diversity score (1-5) of the 5 responses generated by each model.

Model & Decoding Scheme	Action # w/o	Action # w/	Slot # w/o	Slot # w/
Single-Action Baselines				
DAMD + greedy	**1.00**	**1.00**	1.95	**2.51**
HDSA + fixed threshold	**1.00**	**1.00**	2.07	**2.40**
5-Action Generation				
DAMD + beam search	2.67	**2.87**	3.36	**4.39**
DAMD + diverse beam search	2.68	**2.88**	3.41	**4.50**
DAMD + top-k sampling	3.08	**3.43**	3.61	**4.91**
DAMD + top-p sampling	3.08	**3.40**	3.79	**5.20**
HDSA + sampled threshold	1.32	**1.50**	3.08	**3.31**
10-Action Generation				
DAMD + beam search	3.06	**3.39**	4.06	**5.29**
DAMD + diverse beam search	3.05	**3.39**	4.05	**5.31**
DAMD + top-k sampling	3.59	**4.12**	4.21	**5.77**
DAMD + top-p sampling	3.53	**4.02**	4.41	**6.17**
HDSA + sampled threshold	1.54	**1.83**	3.42	**3.92**

Experiments - Model Comparison and Ablation Study

- SOTA results on the MultiWOZ context-to-response generation benchmark.

Metrics

Inform: entity match rate
Success: entity match + answer all the requests
Combined Score: 0.5*(inform+success)+BLEU

Different accesses to ground-truth information

Model	Belief State Type	System Action Type	System Action Form	Inform (%)	Success (%)	BLEU	Combined Score
1. Seq2Seq + Attention (Budzianowski et al. 2018)	oracle	-	-	71.3	61.0	**18.9**	85.1
2. Seq2Seq + Copy	oracle	-	-	86.2	**72.0**	15.7	94.8
3. MD-Sequicity	oracle	-	-	**86.6**	71.6	16.8	**95.9**
4. SFN + RL (Mehri et al. 2019)	oracle	generated	one-hot	82.7	72.1	16.3	93.7
5. HDSA (Chen et al. 2019)	oracle	generated	graph	82.9	68.9	**23.6**	99.5
★ 6. DAMD	oracle	generated	span	**89.5**	75.8	18.3	100.9
★ 7. DAMD + multi-action data augmentation	oracle	generated	span	89.2	**77.9**	18.6	**102.2**
8. SFN + RL (Mehri et al. 2019)	oracle	oracle	one-hot	-	-	29.0	106.0
9. HDSA (Chen et al. 2019)	oracle	oracle	graph	87.9	78.0	**30.4**	113.4
★ 10. DAMD + multi-action data augmentation	oracle	oracle	span	**95.4**	**87.2**	27.3	**118.5**
11. SFN + RL (Mehri et al. 2019)	generated	generated	one-hot	73.8	58.6	**16.9**	83.0
★ 12. DAMD + multi-action data augmentation	generated	generated	span	**76.3**	**60.4**	16.6	**85.0**

Conclusion & Future Work

- Proposed MADA, an effective data augmentation framework for diverse policy learning.
- Experimentally justified that our MADA results in generating responses with better diversity and appropriateness.
- Proposed DAMD, a new state-of-the-art model on MultiWOZ response generation benchmark, which can take full advantage of our data augmentation framework.

What's Next

- Build diverse and comprehensive user models.
- Apply to RL-based policy learning methods for higher exploration efficiency.

Reference

- [1] Budzianowski P, Wen T H, Tseng B H, et al. Multiwoz-a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling[C]. EMNLP 2018.
- [2] Gu J, Lu Z, Li H, et al. Incorporating Copying Mechanism in Sequence-to-Sequence Learning[C]. ACL 2016.
- [3] Lei W, Jin X, Kan M Y, et al. Sequicity: Simplifying task-oriented dialogue systems with single sequence-to-sequence architectures[C]. ACL 2018.
- [4] Mehri S, Srinivasan T, Eskenazi M. Structured fusion networks for dialog[J]. arXiv preprint 2019.
- [5] Chen W, Chen J, Qin P, et al. Semantically Conditioned Dialog Response Generation via Hierarchical Disentangled Self-Attention[J]. arXiv 2019.
- [6] Li J, Monroe W, Jurafsky D. A simple, fast diverse decoding algorithm for neural generation[J]. arXiv 2016.
- [7] Fan A, Lewis M, Dauphin Y. Hierarchical Neural Story Generation[C]. ACL 2018.
- [8] Holtzman A, Buys J, Forbes M, et al. The curious case of neural text degeneration[J]. arXiv 2019.

Thank you!

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Paper: https://arxiv.org/abs/1911.10484

Code: https://github.com/594zyc/damd-multiwoz