西湖大學
WESTLAKE UNIVERSITY

Dialogue State Induction Using Neural Latent Variable Models

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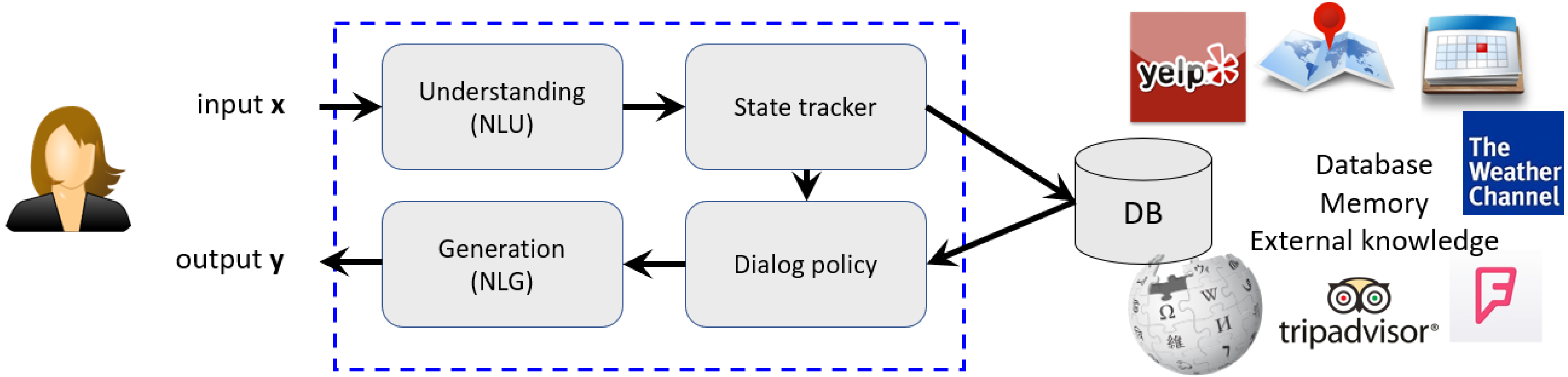
Motivation

What is a task-oriented dialogue system?

Assist user in solving a task



Typical modular architecture

Pic from: Gao J, Galley M, Li L. Neural approaches to conversational AI[C]//The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval. 2018: 1371-1374.

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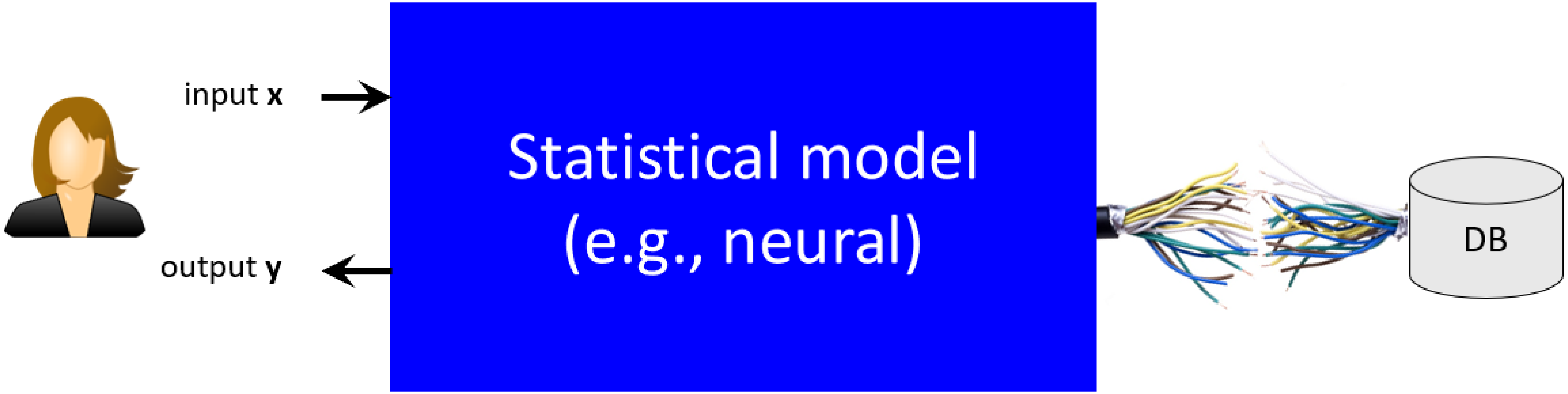

End-to-end architecture

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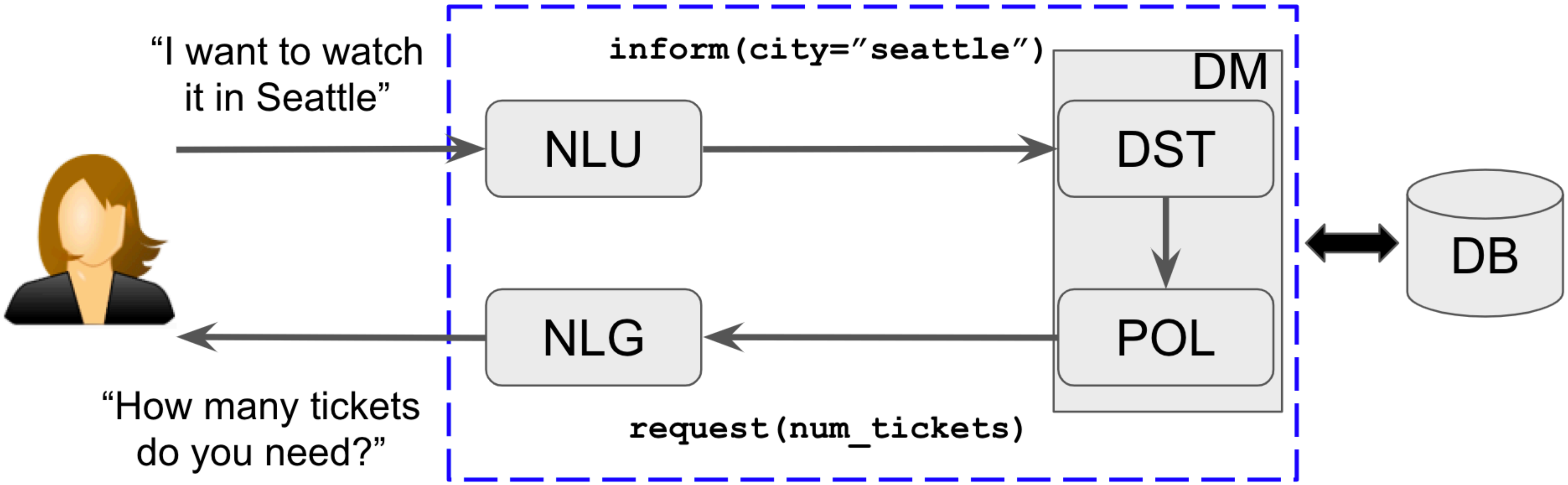

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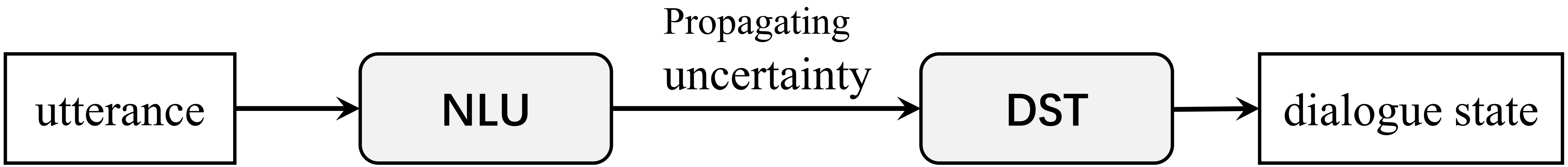
Dialogue State Tracking

Traditional DST:



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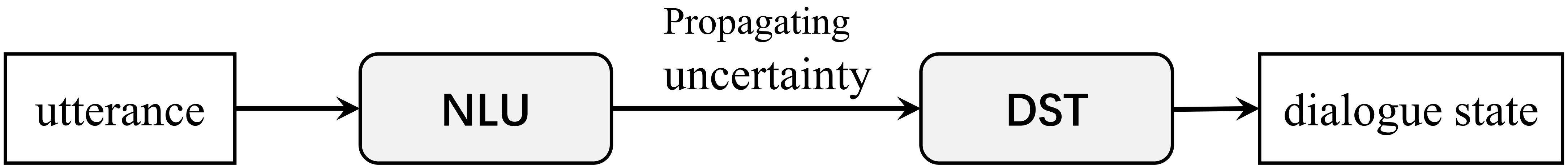

End-to-end DST:

CHAPTER 1

What is the problem?

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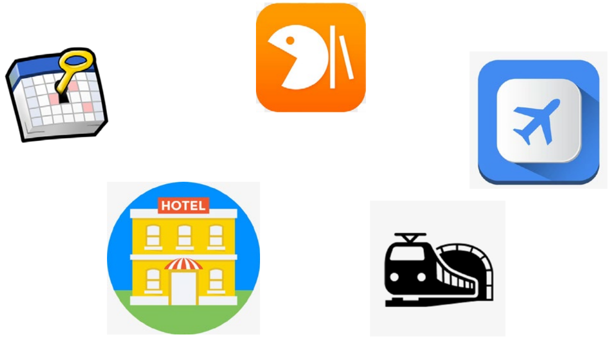
Successful in narrow domains with large annotated datasets



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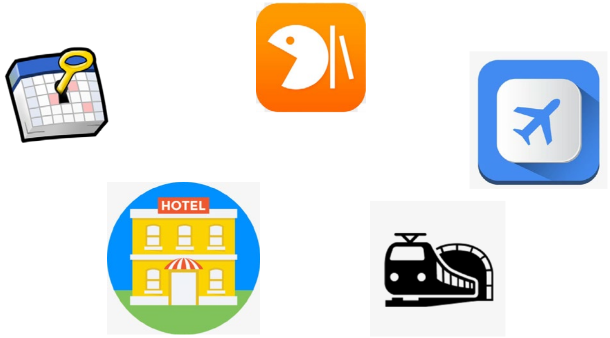

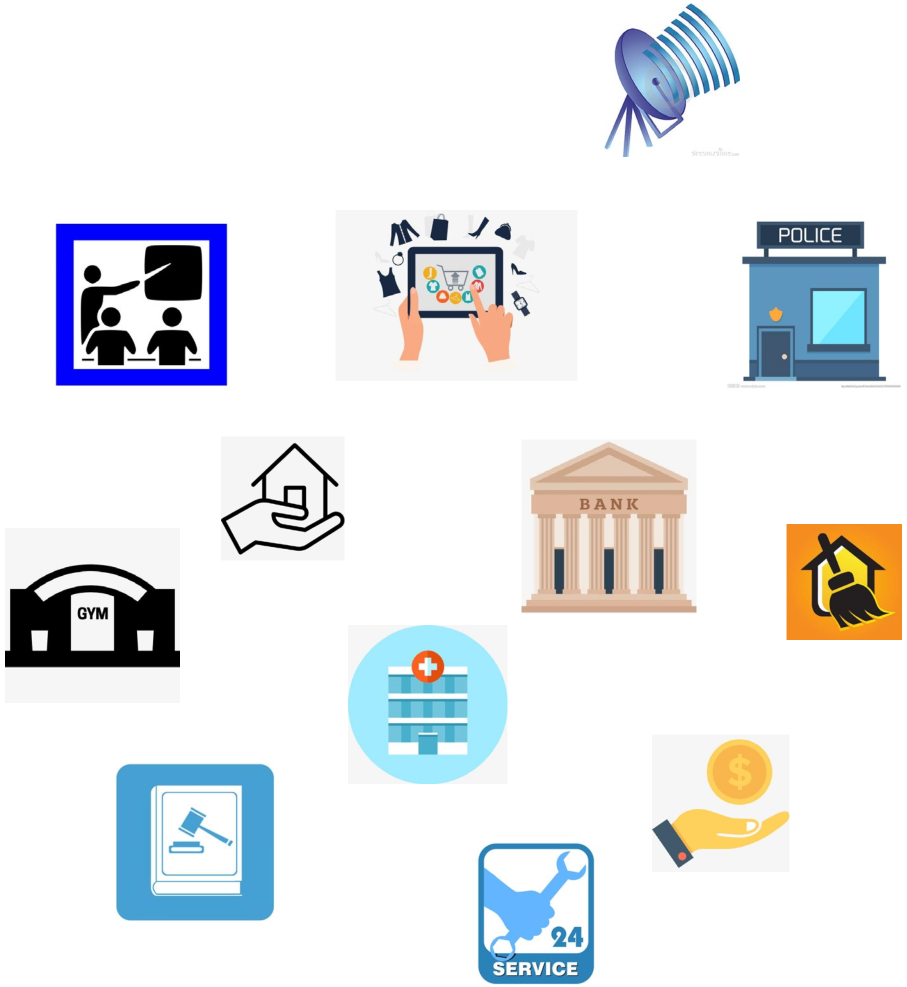

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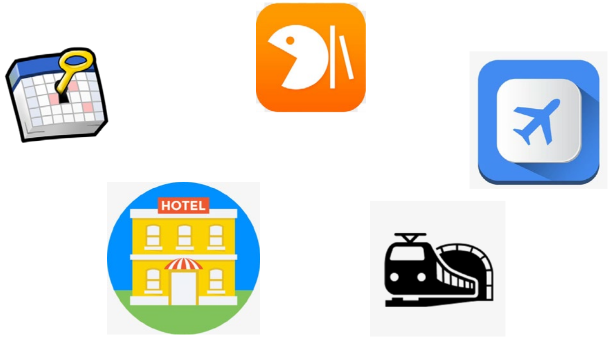

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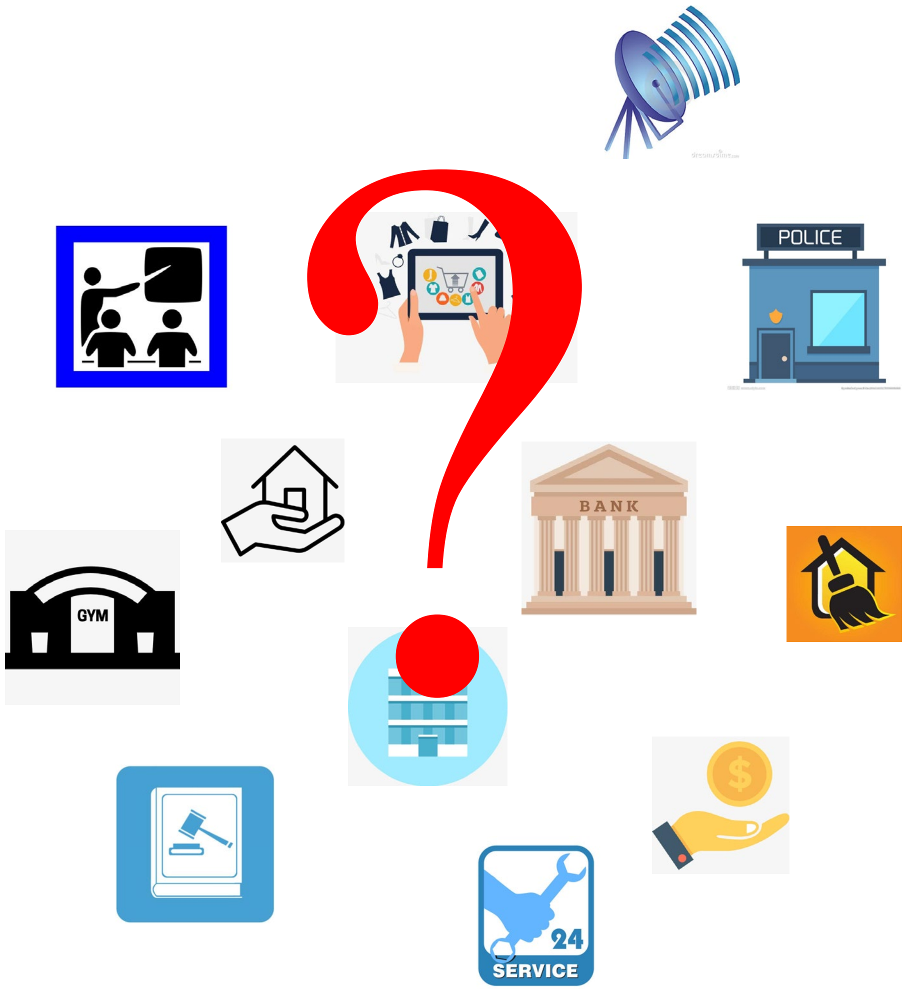
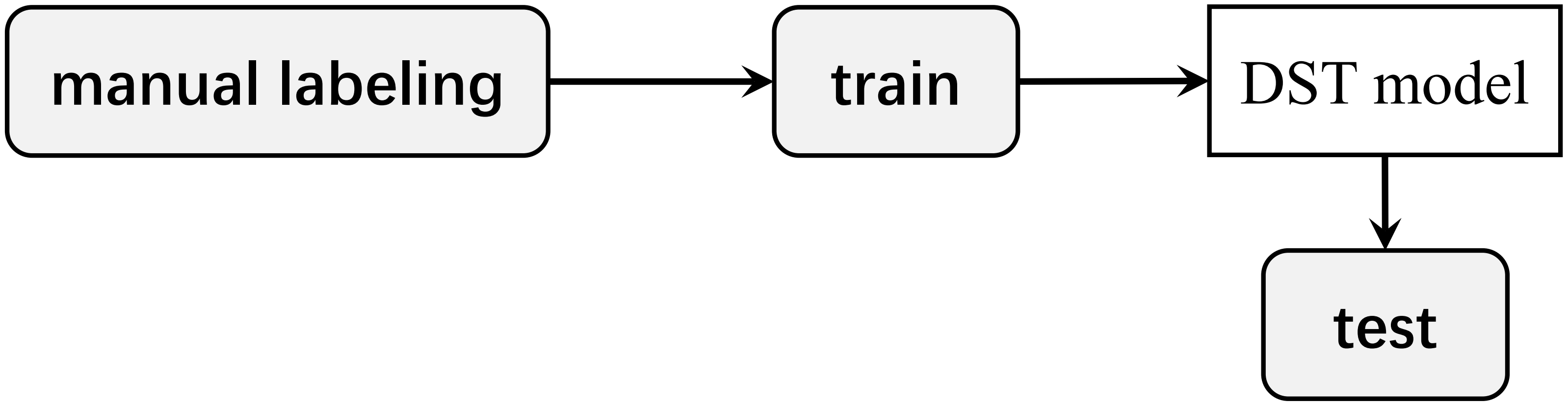


Limitation of DST

DST paradigm:



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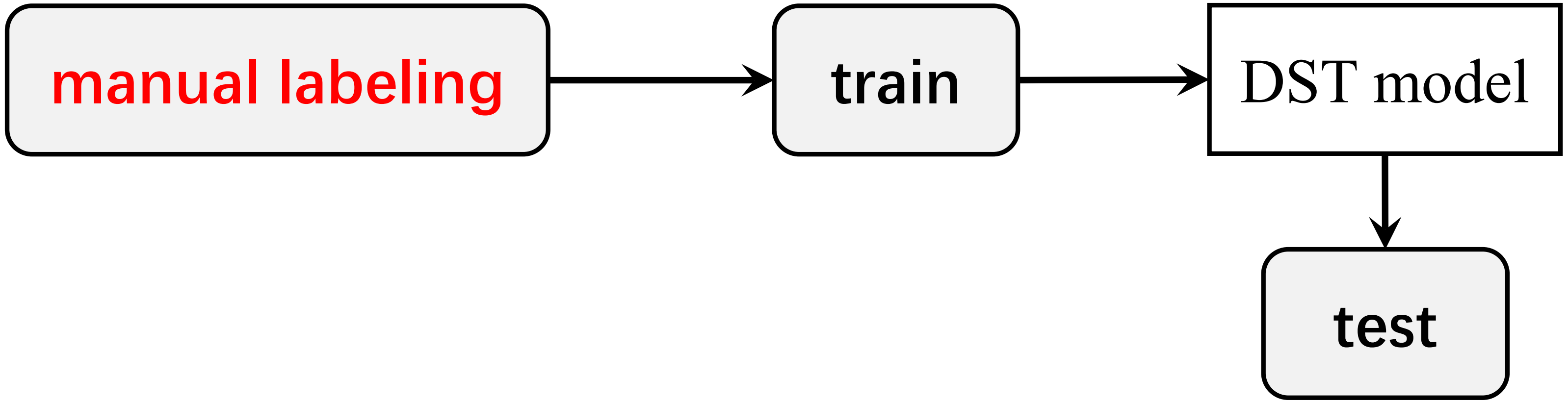

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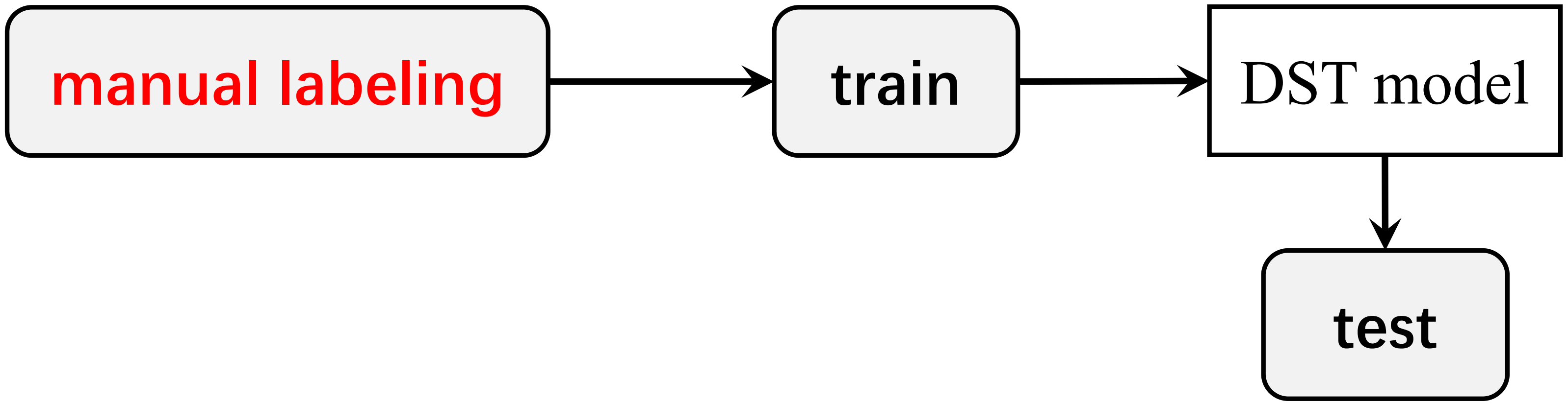

Limitations:

- Costly and slow: 8438 dialogues with 1249 workers in MultiWOZ 2.0 dataset

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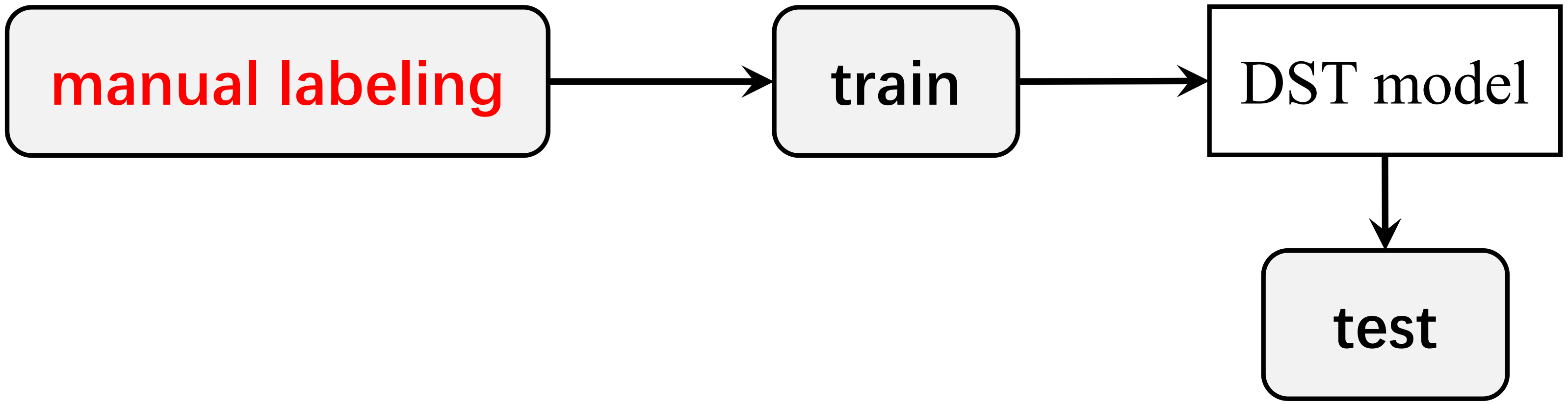

Limitations:

- Costly and slow: 8438 dialogues with 1249 workers in MultiWOZ 2.0 dataset

- Error-prone:

	Annotation errors
MultiWOZ 2.0	around 40% [Eric et al., 2019]
MultiWOZ 2.1	over 30% [Zhang et al., 2019]

[Eric et al., 2019] Mihail Eric, Rahul Goel, Shachi Paul, Abhishek Sethi, Sanchit Agarwal, Shuyag Gao, and Dilek Hakkani-Tur. Multiwoz 2.1: Multi-domain dialogue state corrections and state tracking baselines. arXiv, 2019.
[Zhang et al., 2019] Jian-Guo Zhang, Kazuma Hashimoto, Chien-Sheng Wu, Yao Wan, Philip S Yu, Richard Socher, and Caiming Xiong. Find or classify? dual strategy for slot-value predictions on multi-domain dialog state tracking. arXiv, 2019.

CHAPTER 1

Limitation of DST

DST paradigm: manual labeling → train → DST model → test

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now updated to → MultiWOZ 2.2

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Definition:

What is given?

A set of customer service records without annotation.

User: I want an expensive restaurant that serves Turkish food.
System: Anatolia serves Turkish food.
User: What is the area?

Dialogue State Induction (DSI)

Definition:

What is given?

A set of customer service records without annotation.

What is the target?

Automatically discover information that the user is looking for at each turn.

User: I want an expensive restaurant that serves Turkish food.
System: Anatolia serves Turkish food.
User: What is the area?

→ `inform(price=expensive, food=Turkish)`

→ `inform(price=expensive, food=Turkish); request(area)`

Dialogue State Induction vs DST

Dialogue State Induction vs DST

User: I want an expensive restaurant that serves Turkish food.

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Dialogue State Induction vs DST

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Ontology(optional):
price: [cheap, expensive, moderate, ...]
food: [Turkish, Italian, polish, ...]
area: [south, north, center, ...]

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DSI VS zero-shot DST

Zero-shot DST: support unseen domains (services)

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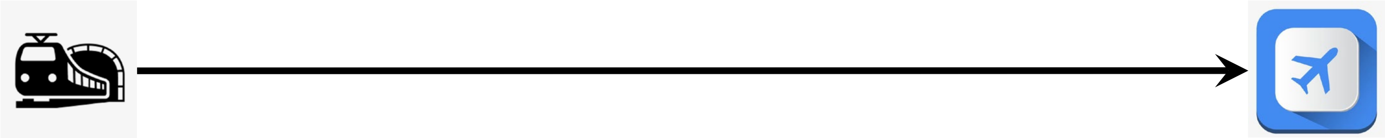
Zero-shot DST: support unseen domains (services)

Motivation: Different domains (services) with similar schemas

DSI VS zero-shot DST

Zero-shot DST: support unseen domains (services)

Motivation: Different domains (services) with similar schemas



service_name: "Trains"	**Service**
name: "from"	**Slots**
name: "to"	

service_name: "trains"	**Service**
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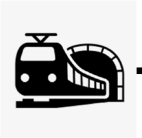
name: "destination"	

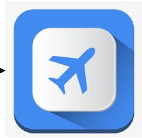
DSI VS zero-shot DST

Zero-shot DST: support unseen domains (services)

Motivation: Different domains (services) with similar schemas



slots along with their natural language description



service_name: "Trains" description: "Service to find train journeys between cities"	**Service**
name: "from" description: "Starting city for train journey"	**Slots**
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service_name: "trains" description: "Search for cheap trains across multiple providers"	**Service**
name: "origin" description: "City of origin for the train"	**Slots**
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Example from the SGD dataset [Rastogi et al., 2019].

[Rastogi et al., 2019]Rastogi A, Zang X, Sunkara S, et al. Towards scalable multi-domain conversational agents: The schema-guided dialogue dataset[J]. arXiv preprint arXiv:1909.05855, 2019.

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Zero-shot DST Limitations:

DSI VS zero-shot DST

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- High qualified (consistent) human annotation

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consistency

Zero-shot DST Limitations:

- High qualified (consistent) human annotation
- Transfer to distant domain (service)

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consistency

service_name: "Financial" **Service**
description: “Search for financial products across multiple providers"

name: “deposit_rate" **Slots**
description: "the standard for calculating deposit interest"

name: "loan_rate"
description: "the interest rate that banks charge to borrowers"

Zero-shot DST Limitations:

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DSI VS zero-shot DST

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Zero-shot DST Limitations:

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DSI features:

- Release human burden
- Data-driven: automatically discover

CHAPTER 2

Method

How we solve DSI?

Two steps:

Utterance: I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

How we solve DSI?

Two steps:

- Candidates (values) extraction (POS tag, NER, coreference)

Utterance: I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

train, Chicago, Dallas, Wednesday

How we solve DSI?

Two steps:

- Candidates (values) extraction (POS tag, NER, coreference)
- Slot assignment: two neural latent variable models (*DSI-base* and *DSI-GM*)

Utterance: I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

↓

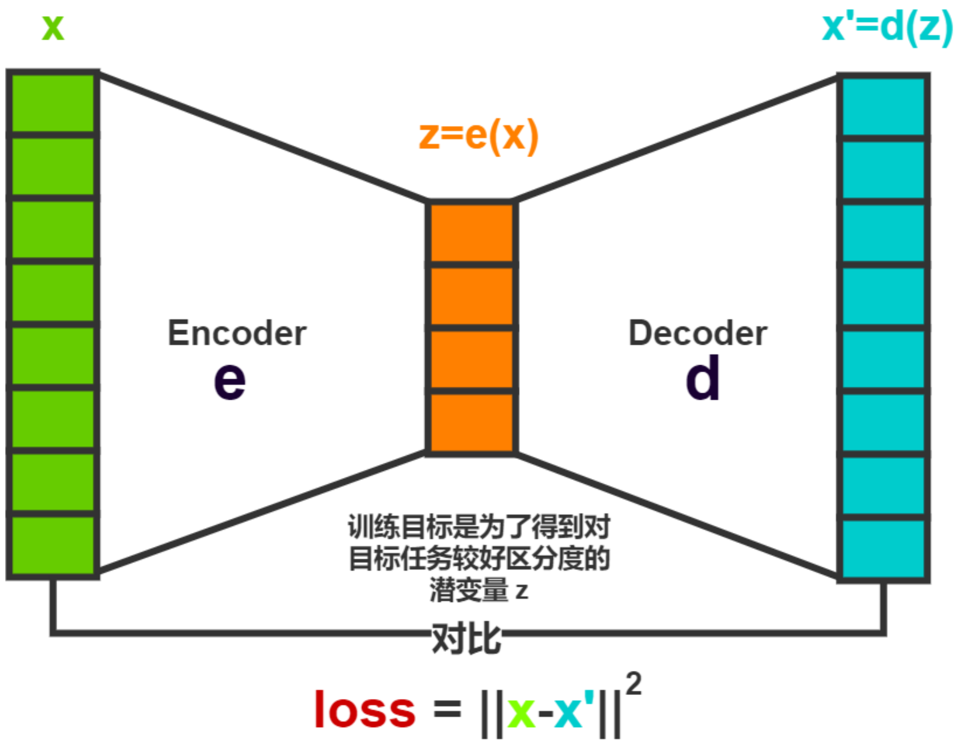
train, Chicago, Dallas, Wednesday

↓

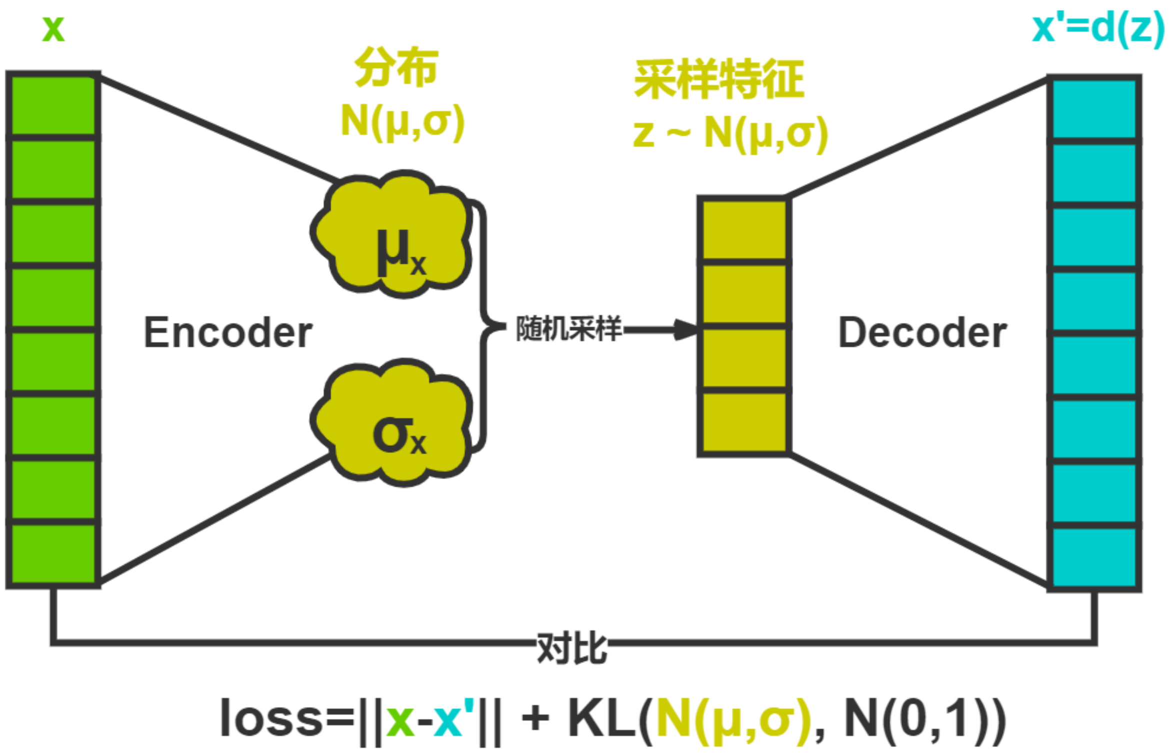
~~train=None~~

```
Inform{train-departure=Chicago,
train-destination=Dallas,
train-leave at=Wednesday}
```

What is VAE?



AutoEncoder



Variational AutoEncoder

Pics from https://www.jianshu.com/p/ffd493e10751

Model: generative *DSI-base*

I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

Model: generative *DSI-base*

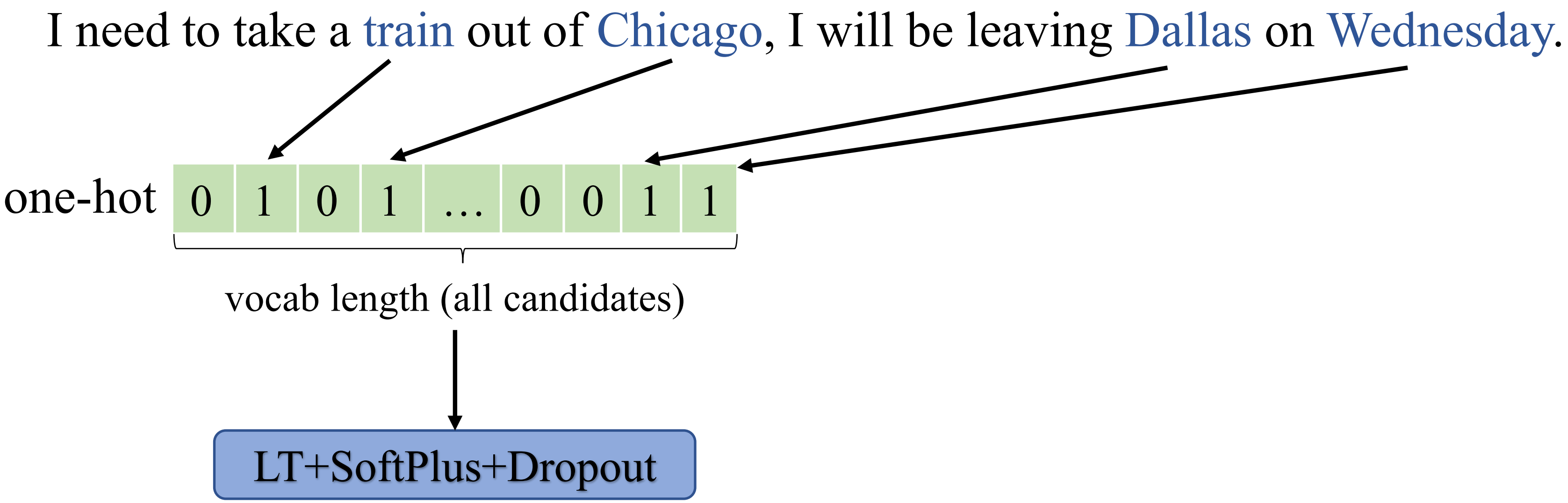
I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

one-hot

0	1	0	1	…	0	0	1	1

vocab length (all candidates)

Model: generative *DSI-base*



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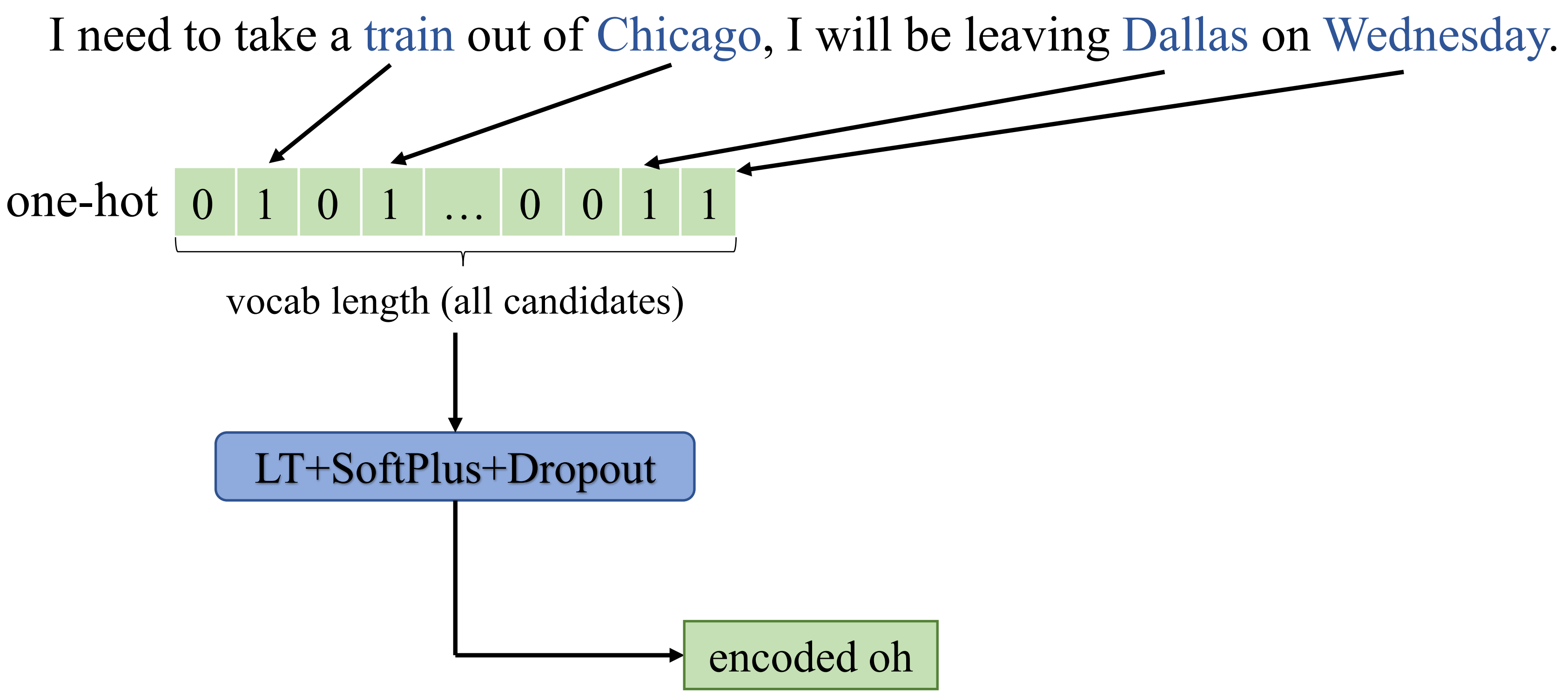

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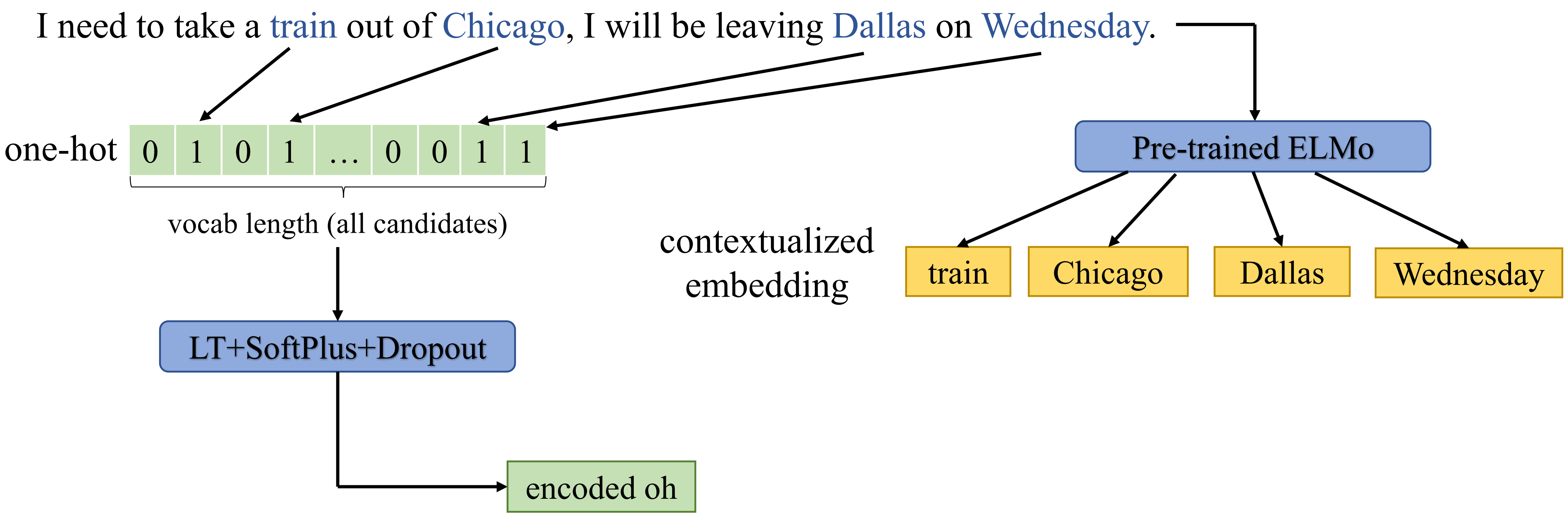

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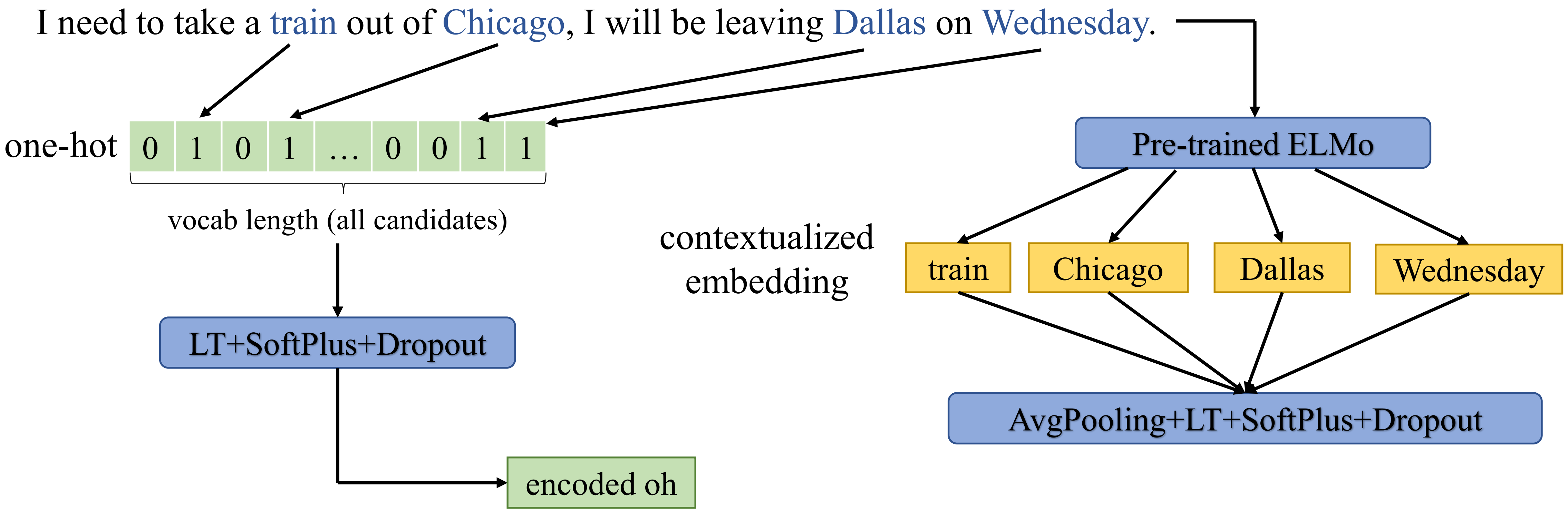

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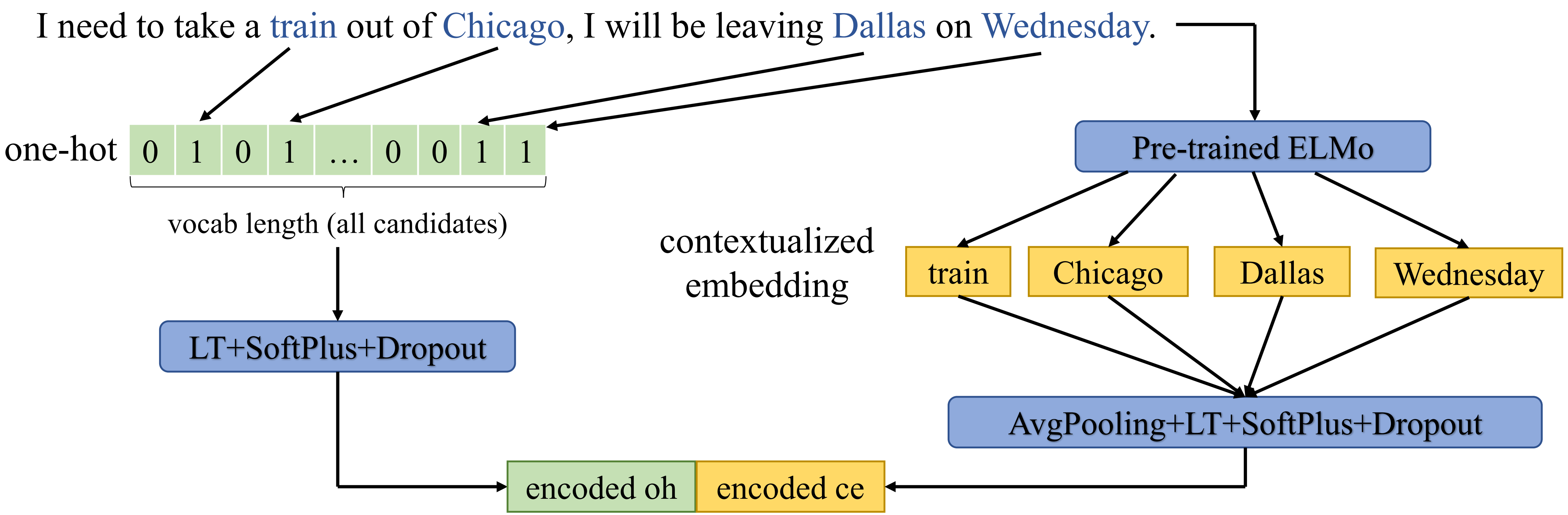

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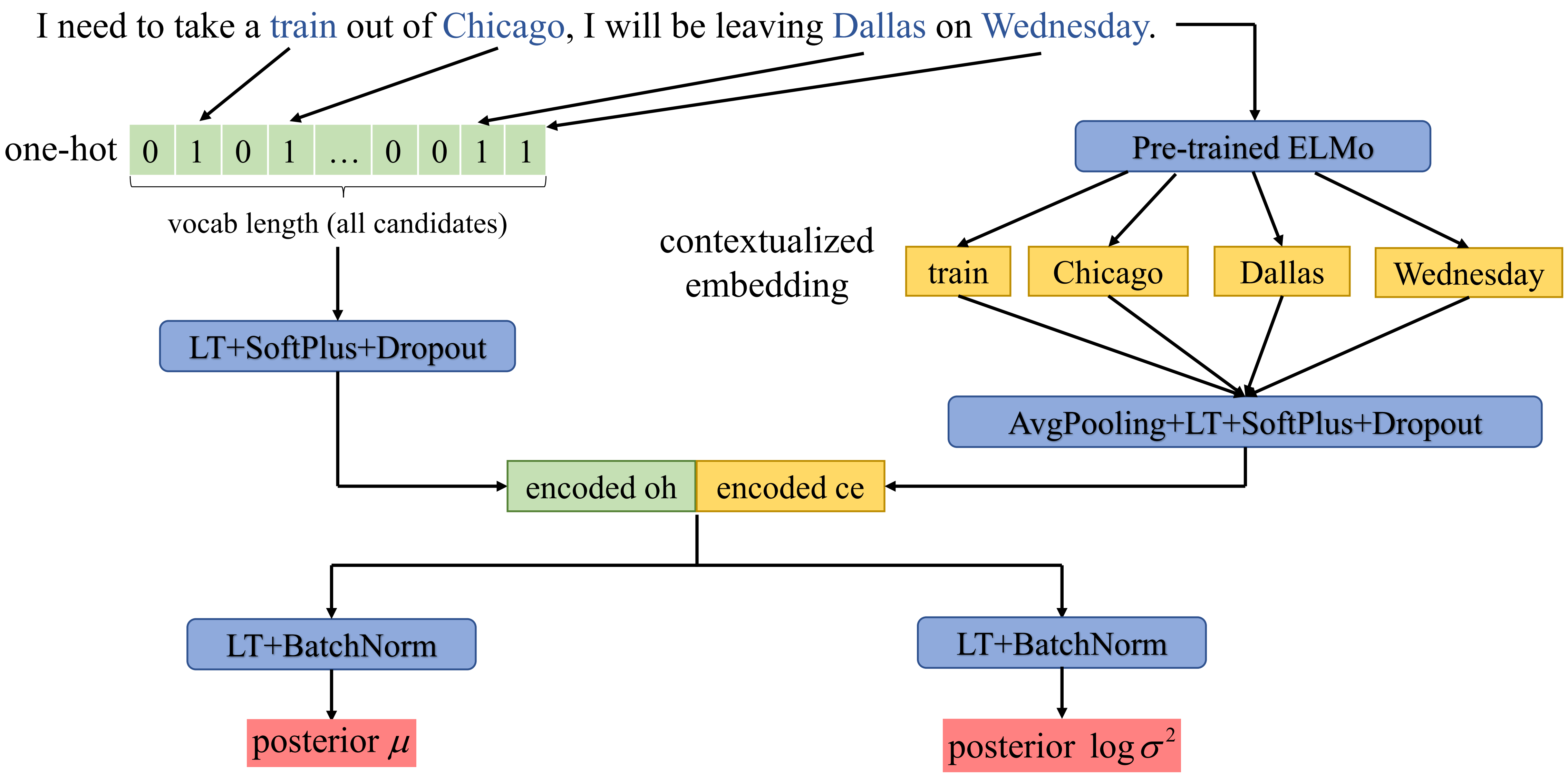

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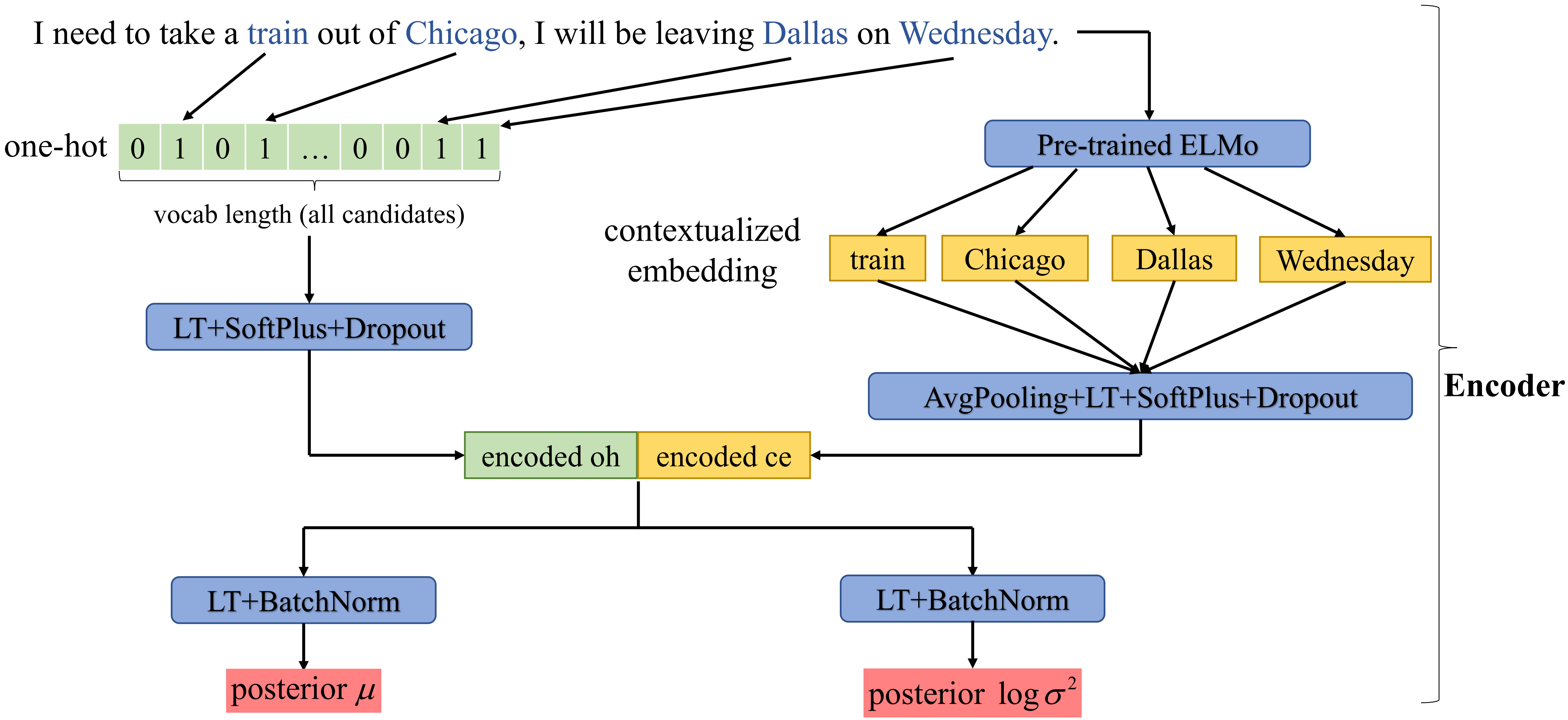


Model: generative *DSI-base*

posterior μ

posterior $\log \sigma^2$

Model: generative *DSI-base*

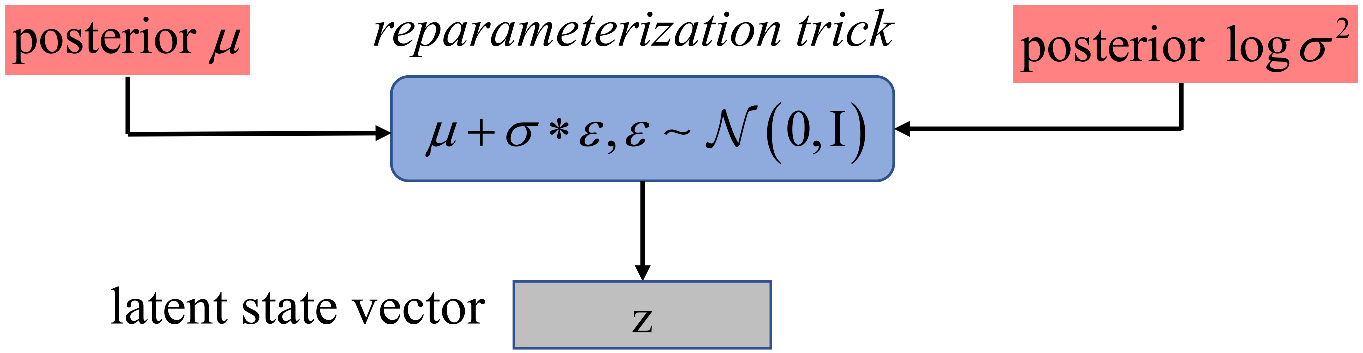
posterior μ

reparameterization trick

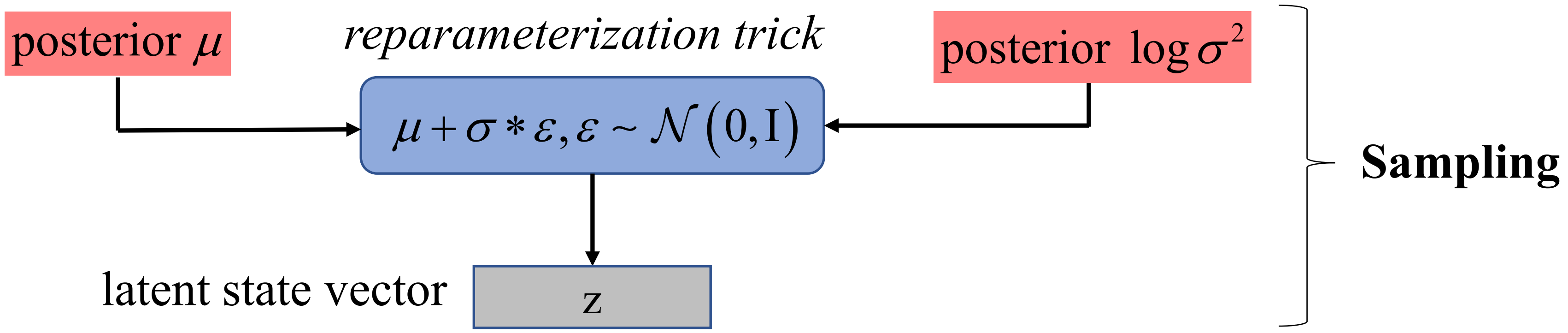
$$\mu + \sigma * \varepsilon, \varepsilon \sim \mathcal{N}(0, \mathrm{I})$$

posterior $\log \sigma^2$

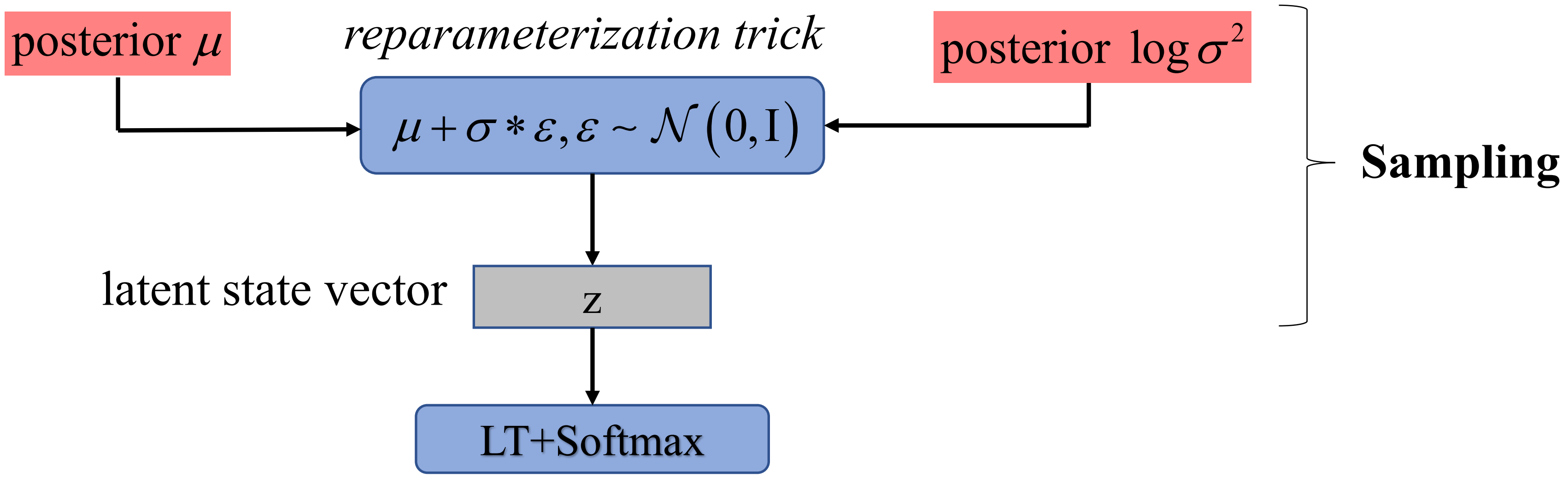
Model: generative *DSI-base*



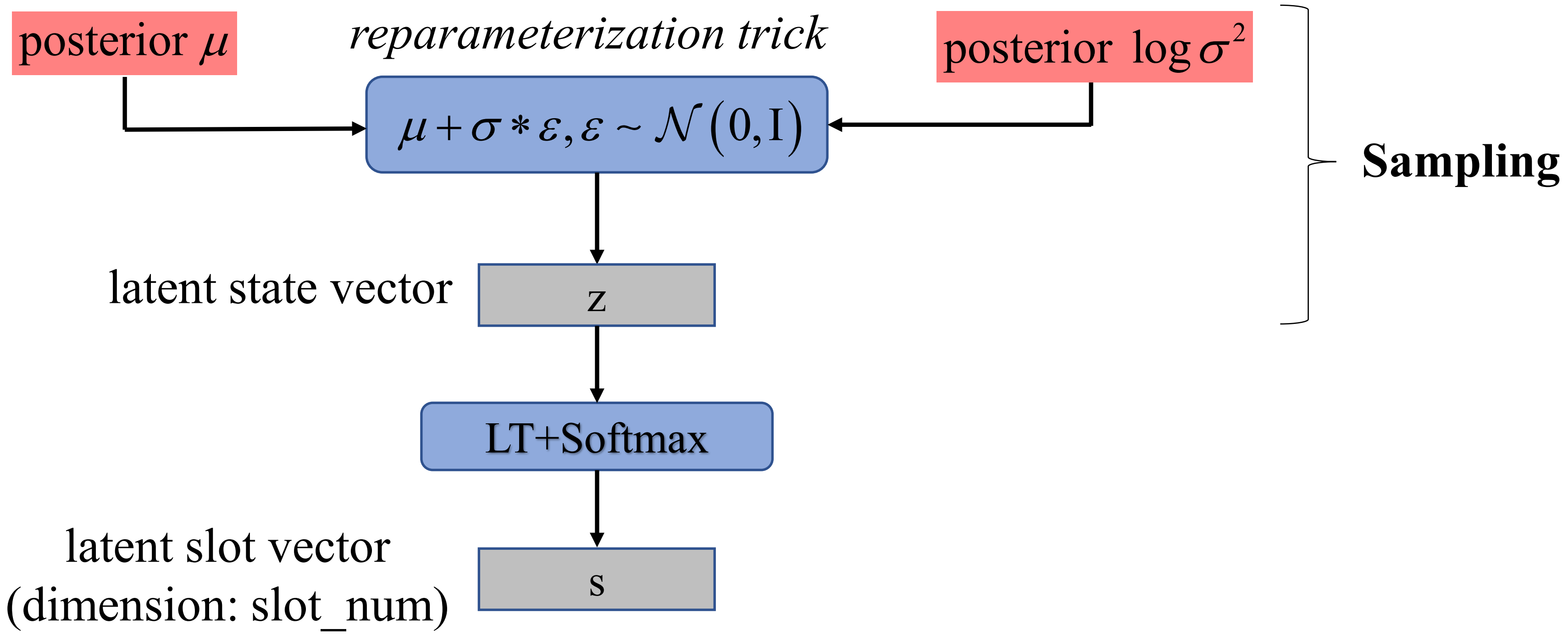
Model: generative *DSI-base*



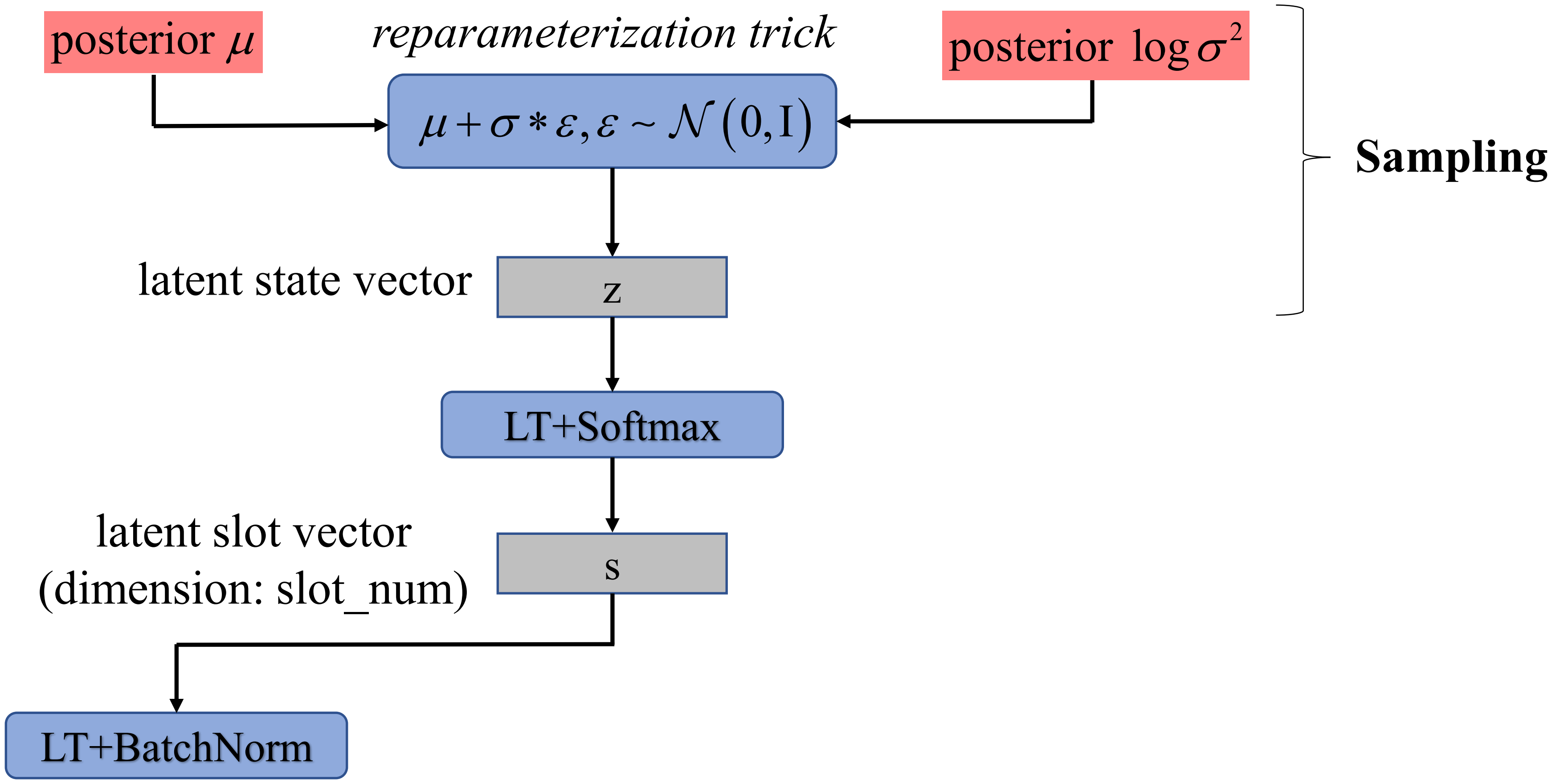
Model: generative *DSI-base*



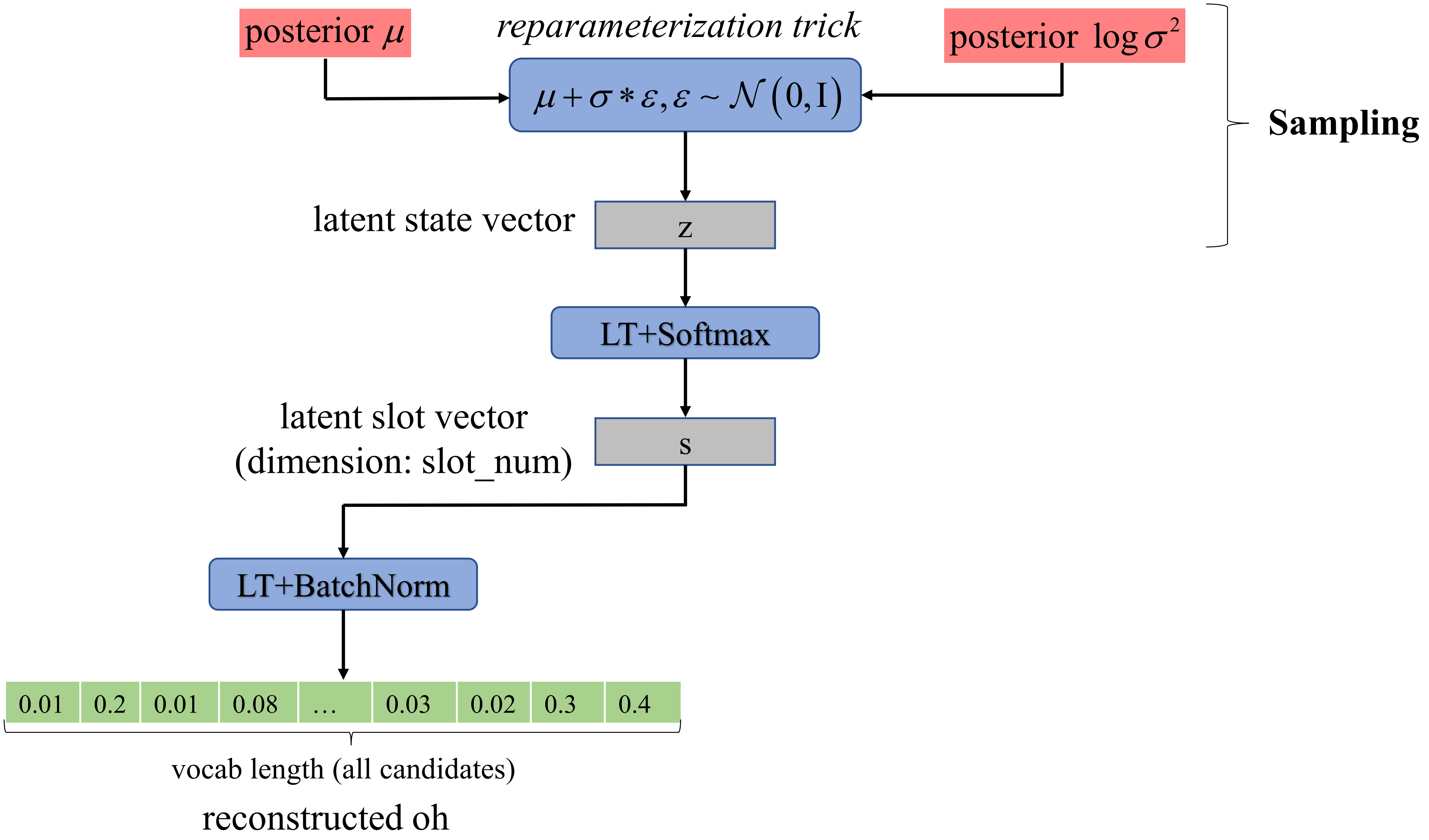
Model: generative *DSI-base*



Model: generative *DSI-base*



Model: generative *DSI-base*



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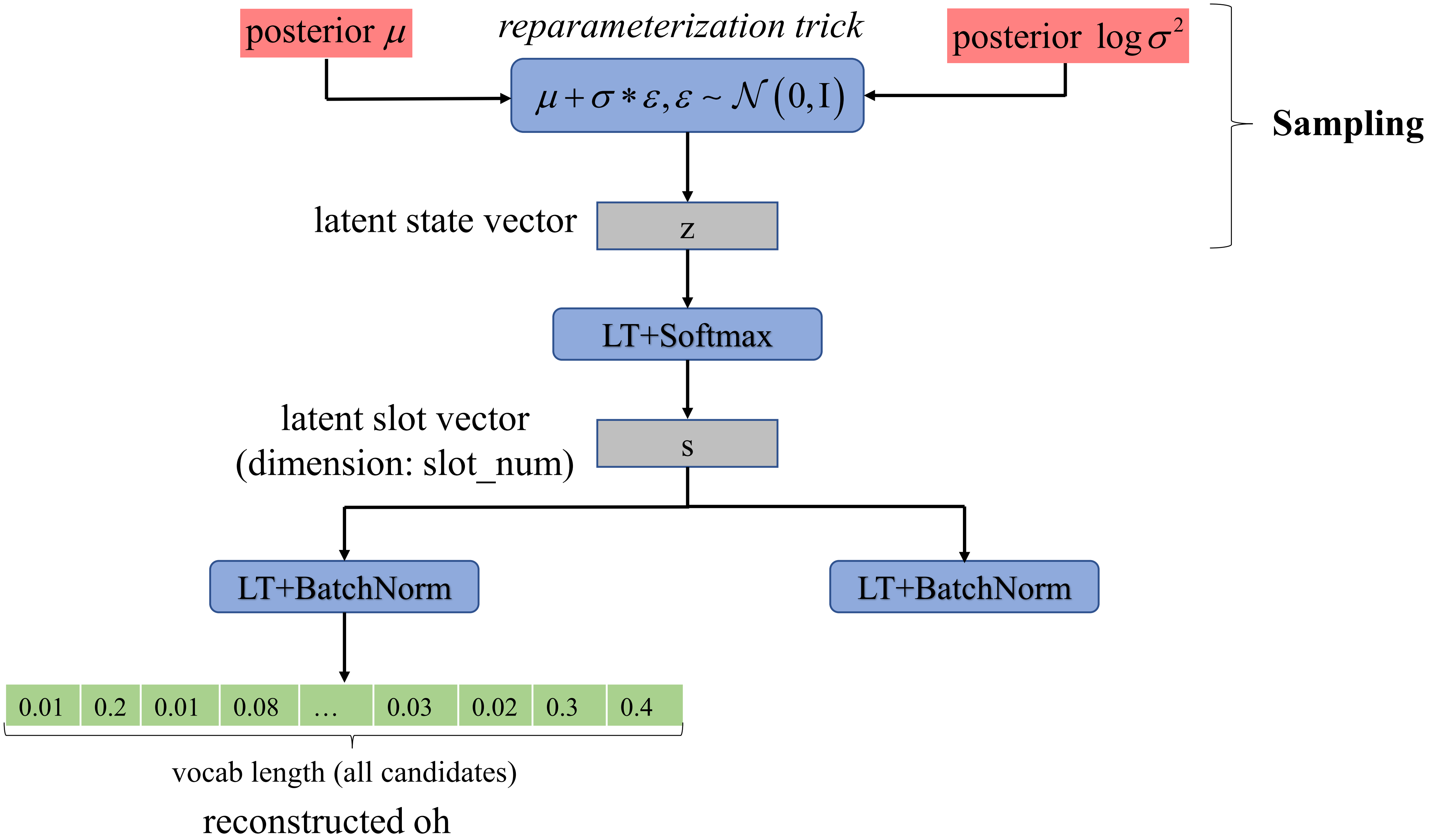

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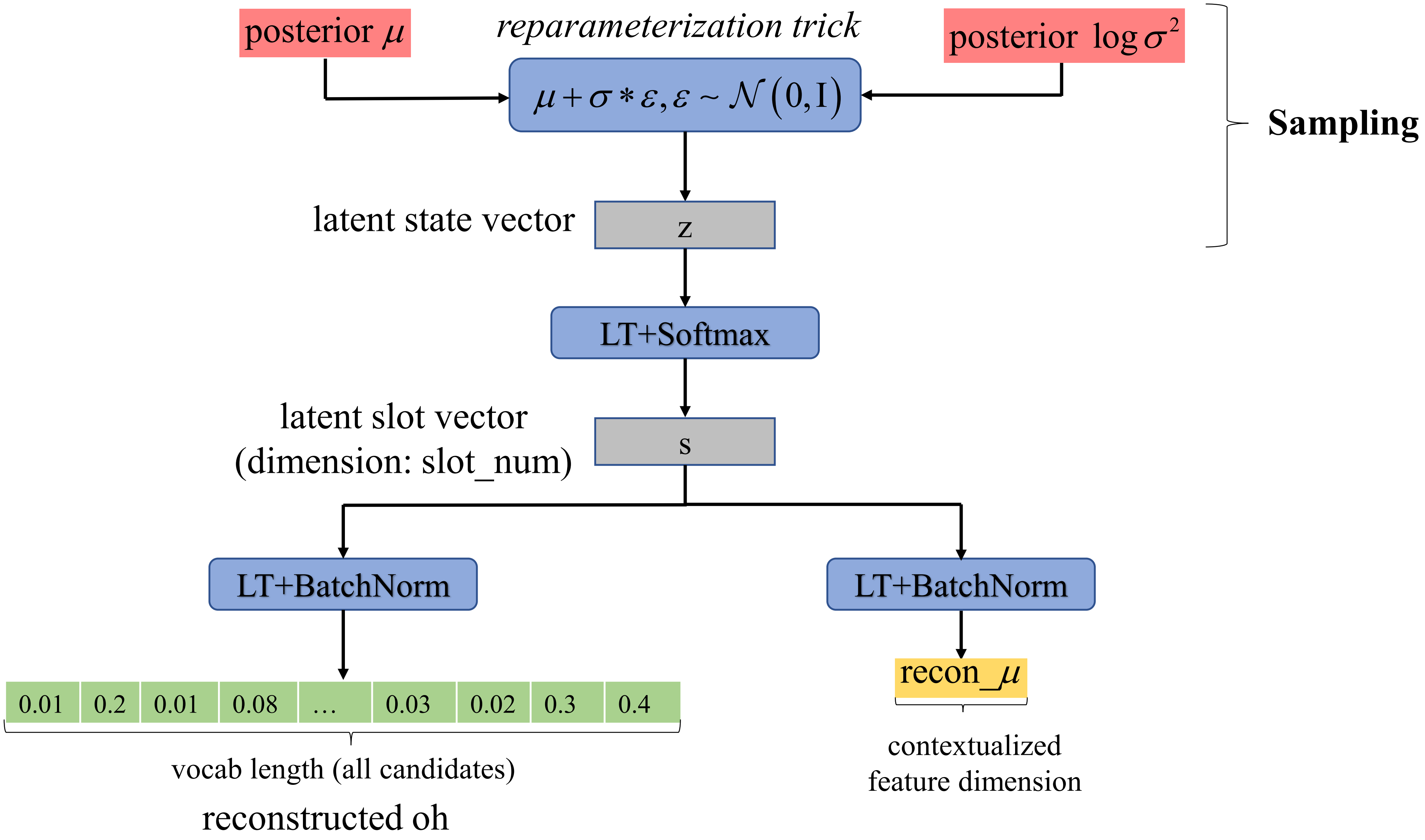
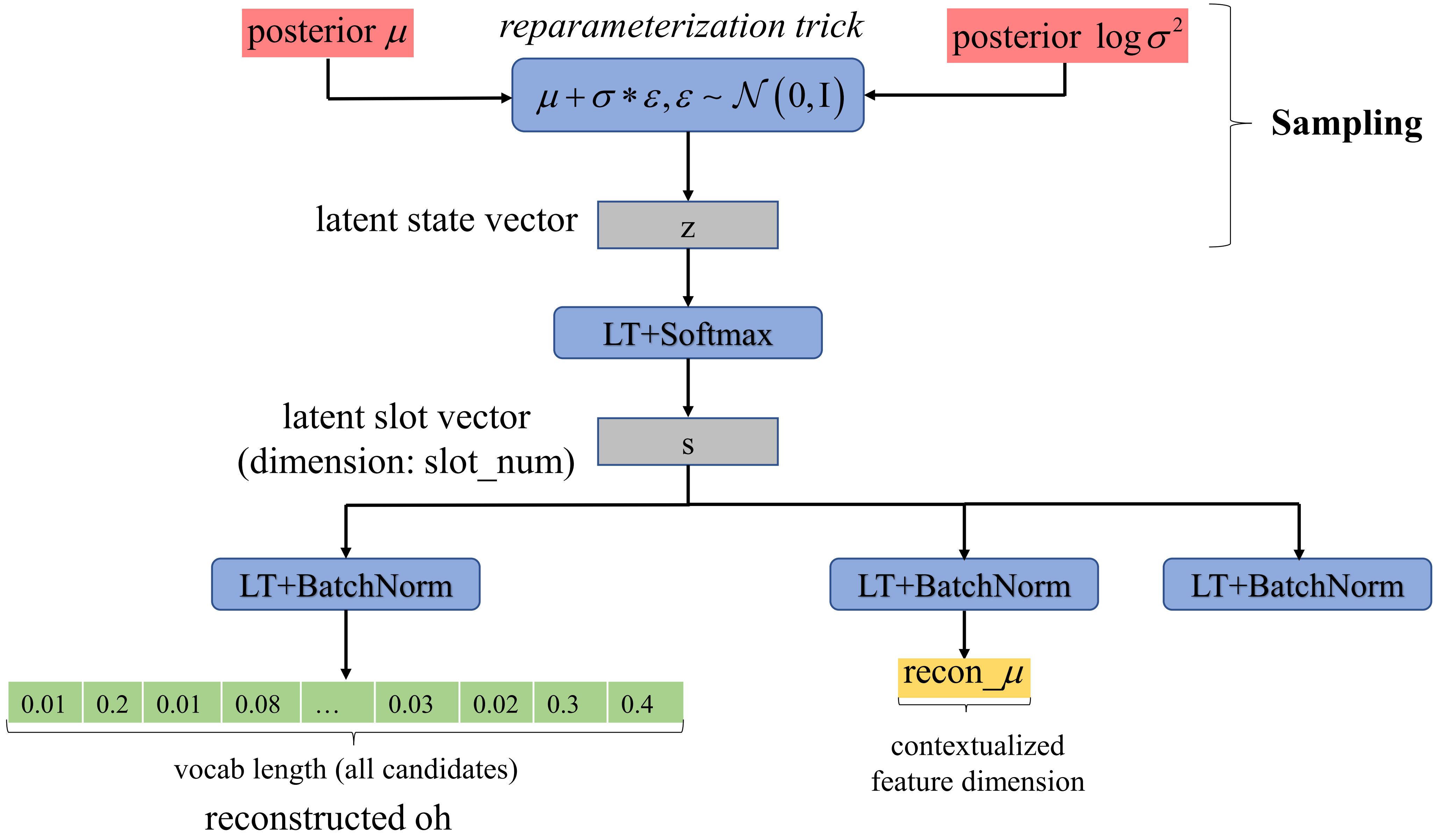
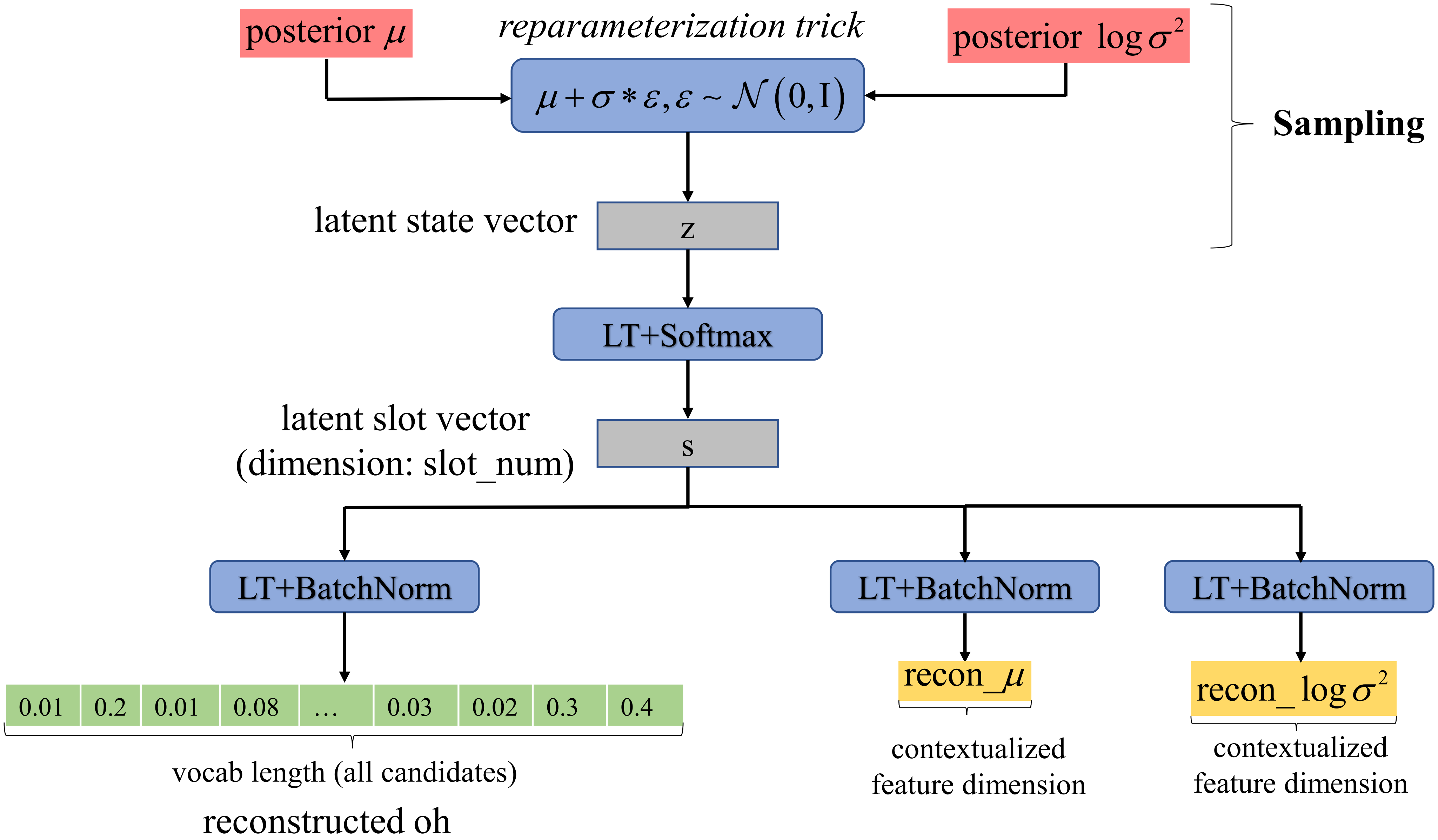


Model: generative *DSI-base*



Model: generative *DSI-base*



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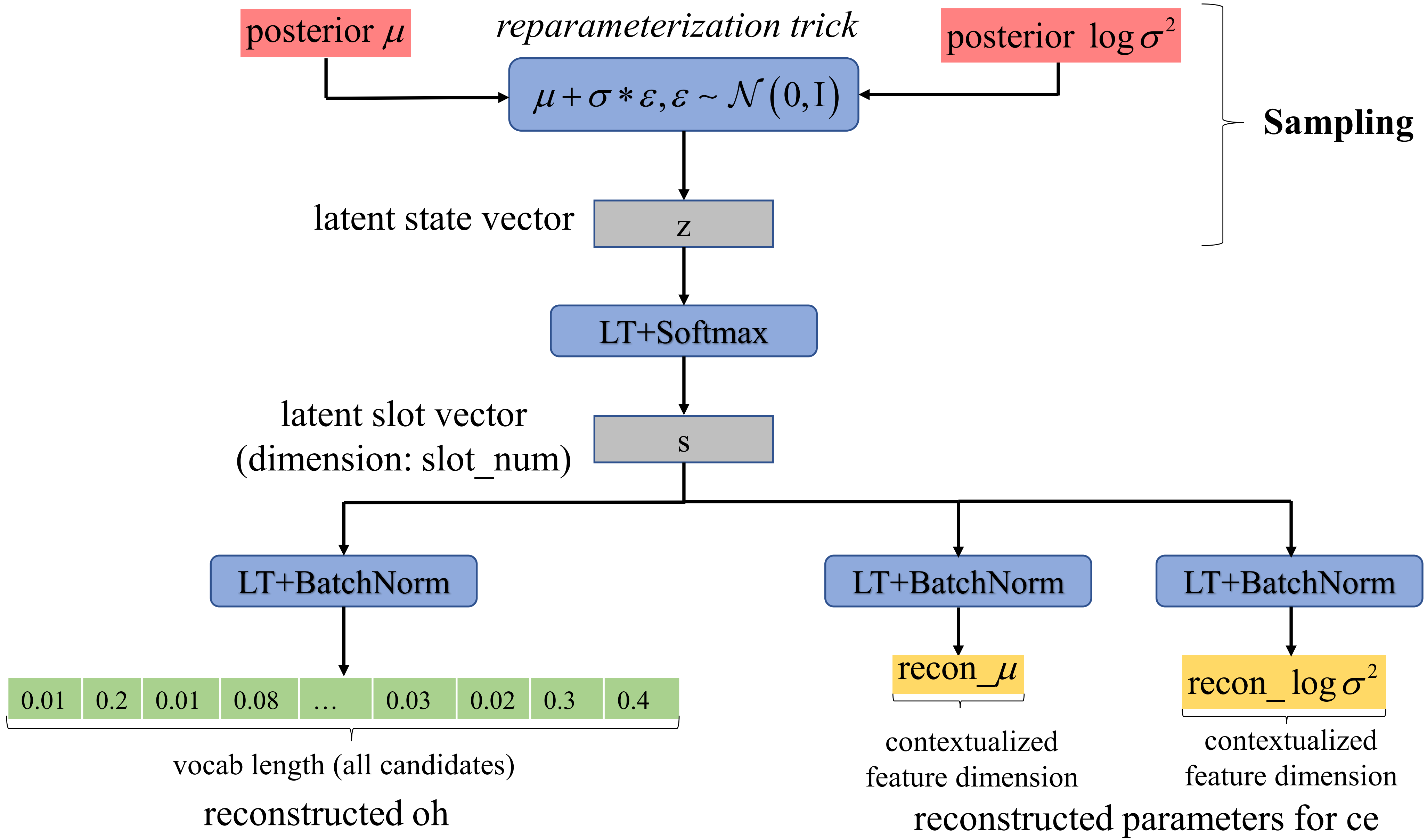
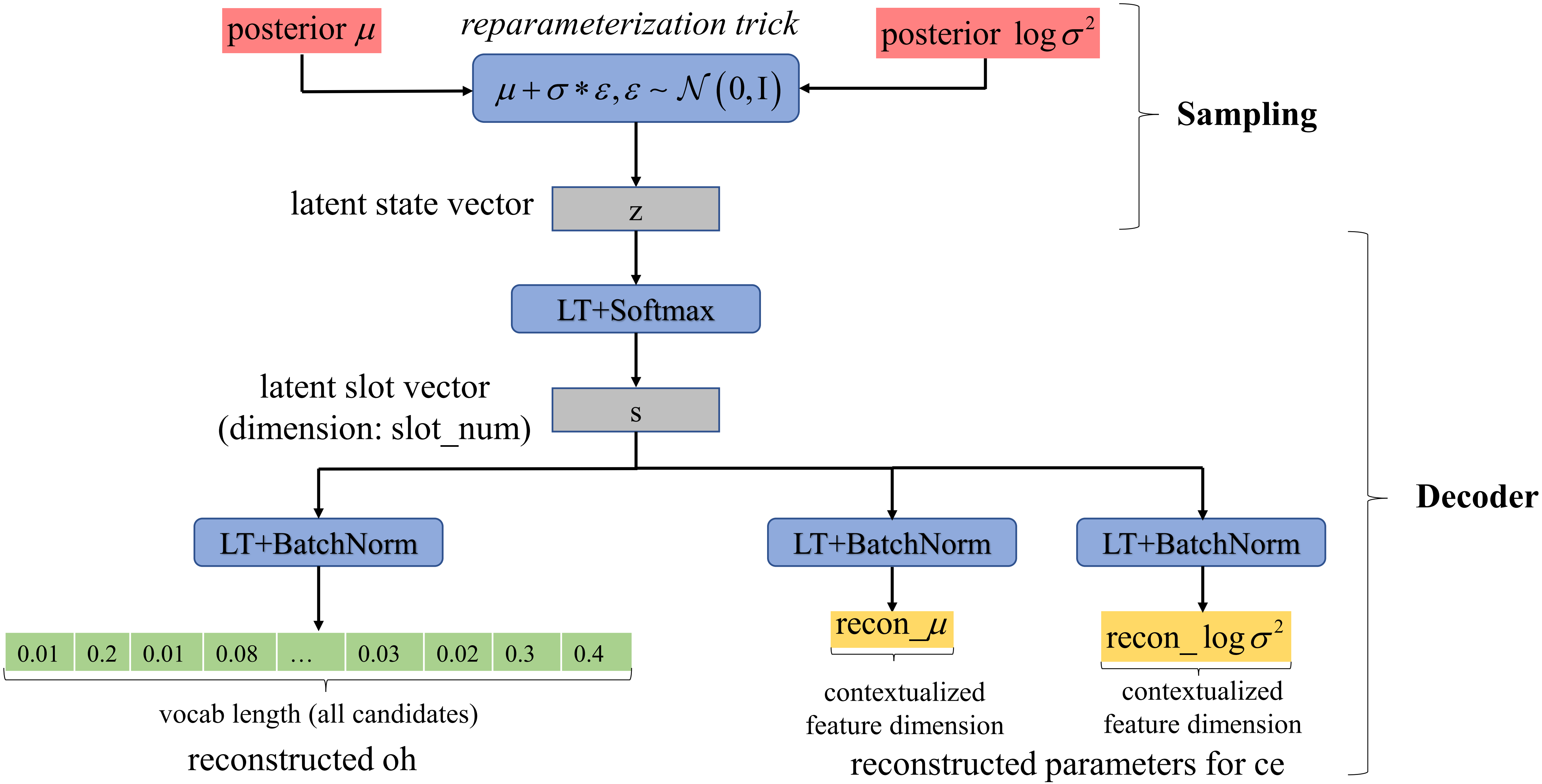


Model: generative *DSI-base*



Loss

0.01	0.2	0.01	0.08	…	0.03	0.02	0.3	0.4	reconstructed oh
0	1	0	1	…	0	0	1	1	oh

$\underbrace{\qquad\qquad\qquad}_{\text{vocab length (all candidates)}}$

reconstructed oh, oh $\}$ Cross Entropy Loss

Loss

0.01	0.2	0.01	0.08	…	0.03	0.02	0.3	0.4
0	1	0	1	…	0	0	1	1

vocab length (all candidates)

reconstructed oh

oh

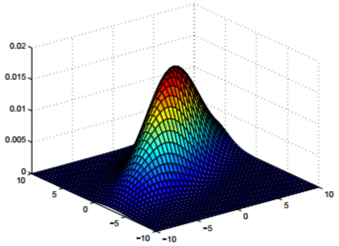
Cross Entropy Loss

$\underbrace{\text{recon}\_\mu}_{\text{contextualized feature dimension}}$

contextualized feature dimension

$\underbrace{\text{recon}\_\log\sigma^2}_{\text{contextualized feature dimension}}$

contextualized feature dimension



Multivariate Gaussian Distribution

0.01	0.2	0.01	0.08	…	0.03	0.02	0.3	0.4
0	1	0	1	…	0	0	1	1

reconstructed oh

oh

Cross Entropy Loss

vocab length (all candidates)

$\underbrace{\text{recon}\_\mu}_{\text{contextualized feature dimension}}$

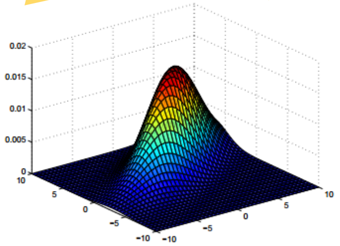
$\underbrace{\text{recon}\_\log\sigma^2}_{\text{contextualized feature dimension}}$

train

Chicago

Dallas

Wednesday



Multivariate Gaussian Distribution

0.01	0.2	0.01	0.08	…	0.03	0.02	0.3	0.4	reconstructed oh
0	1	0	1	…	0	0	1	1	oh

vocab length (all candidates)

Cross Entropy Loss

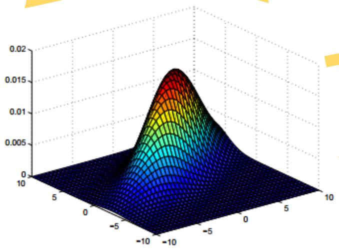
recon_μ

contextualized feature dimension

recon_ $\log\sigma^2$

contextualized feature dimension

train | Chicago | Dallas | Wednesday



Multivariate Gaussian Distribution

-dist.log_prob(ce[train])

-dist.log_prob(ce[Chicago])

-dist.log_prob(ce[Dallas])

-dist.log_prob(ce[Wednesday])

Pic from https://www.datalearner.com/blog/1051485590815771

Loss

0.01	0.2	0.01	0.08	…	0.03	0.02	0.3	0.4	reconstructed oh
0	1	0	1	…	0	0	1	1	oh

vocab length (all candidates)

Cross Entropy Loss

$\underbrace{\text{recon\_}\mu}_{\text{contextualized feature dimension}}$

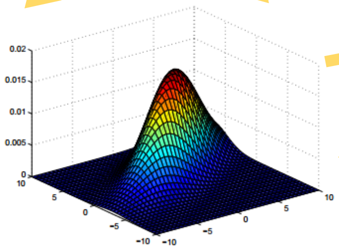
$\underbrace{\text{recon\_}\log\sigma^2}_{\text{contextualized feature dimension}}$

train

Chicago

Dallas

Wednesday



Multivariate Gaussian Distribution

-dist.log_prob(ce[train])

-dist.log_prob(ce[Chicago])

-dist.log_prob(ce[Dallas])

-dist.log_prob(ce[Wednesday])

sum

Pic from https://www.datalearner.com/blog/1051485590815771

Loss

0.01	0.2	0.01	0.08	…	0.03	0.02	0.3	0.4	reconstructed oh
0	1	0	1	…	0	0	1	1	oh

vocab length (all candidates)

Cross Entropy Loss

$\underbrace{\text{recon\_}\mu}_{}$

contextualized feature dimension

$\underbrace{\text{recon\_}\log\sigma^2}_{}$

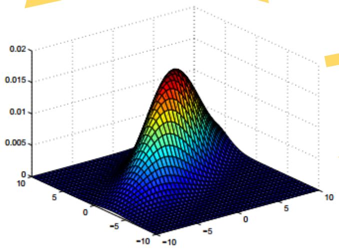
contextualized feature dimension

train

Chicago

Dallas

Wednesday



Multivariate Gaussian Distribution

-dist.log_prob(ce[train])

-dist.log_prob(ce[Chicago])

-dist.log_prob(ce[Dallas])

-dist.log_prob(ce[Wednesday])

sum

reconstruction term

Pic from https://www.datalearner.com/blog/1051485590815771

Loss

0.01	0.2	0.01	0.08	…	0.03	0.02	0.3	0.4	reconstructed oh
0	1	0	1	…	0	0	1	1	oh

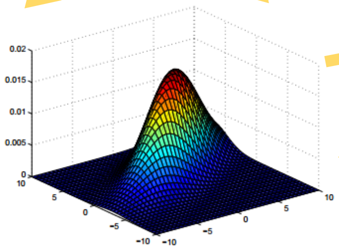
vocab length (all candidates)

Cross Entropy Loss

$\underbrace{\text{recon\_}\mu}_{\text{contextualized feature dimension}}$

$\underbrace{\text{recon\_}\log\sigma^2}_{\text{contextualized feature dimension}}$

train Chicago Dallas Wednesday



Multivariate Gaussian Distribution

-dist.log_prob(ce[train])

-dist.log_prob(ce[Chicago])

-dist.log_prob(ce[Dallas])

-dist.log_prob(ce[Wednesday])

sum

reconstruction term

KL Divergence between posterior and prior: $KL(\mathcal{N}(\mu,\sigma),\mathcal{N}(0,1))$

Pic from https://www.datalearner.com/blog/1051485590815771

Loss

0.01	0.2	0.01	0.08	…	0.03	0.02	0.3	0.4
0	1	0	1	…	0	0	1	1

reconstructed oh

oh

Cross Entropy Loss

vocab length (all candidates)

recon_μ

contextualized feature dimension

recon_ $\log\sigma^2$

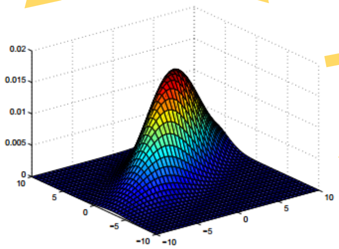
contextualized feature dimension

train

Chicago

Dallas

Wednesday



Multivariate Gaussian Distribution

-dist.log_prob(ce[train])

-dist.log_prob(ce[Chicago])

-dist.log_prob(ce[Dallas])

-dist.log_prob(ce[Wednesday])

sum

reconstruction term

KL Divergence between posterior and prior: $KL(\mathcal{N}(\mu,\sigma),\mathcal{N}(0,1))$

regularization term

Pic from https://www.datalearner.com/blog/1051485590815771

DSI-base inference

I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

CHAPTER 2 **DSI-base inference**

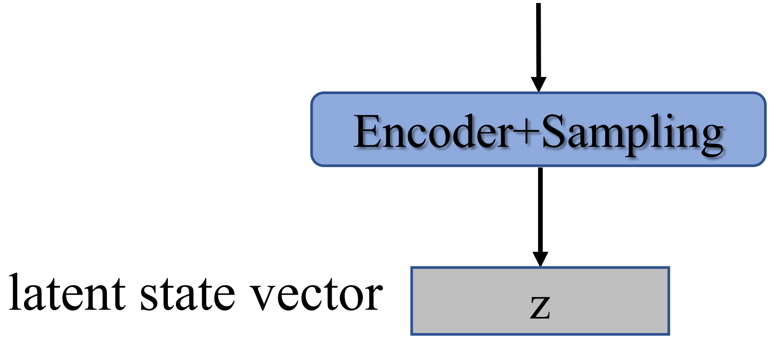
I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

↓

Encoder+Sampling

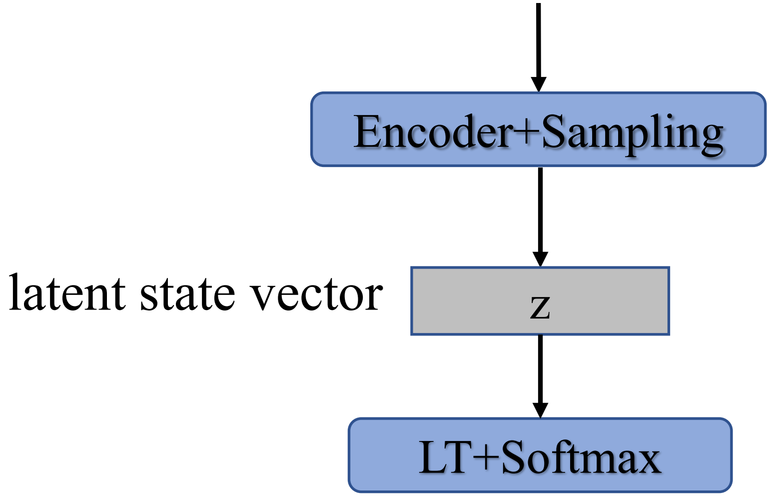
DSI-base inference

I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.



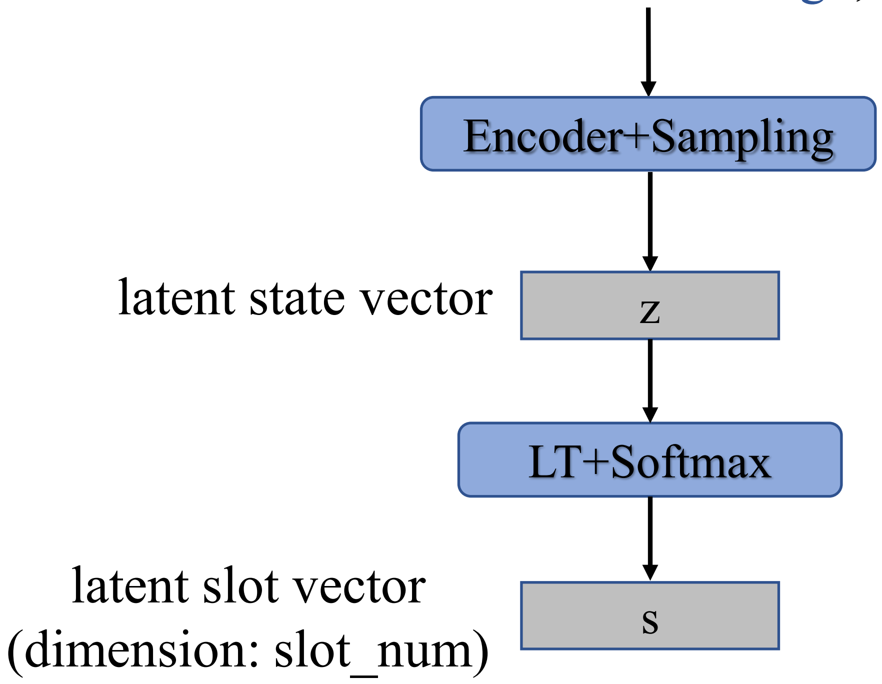
DSI-base inference

I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.



DSI-base inference

I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

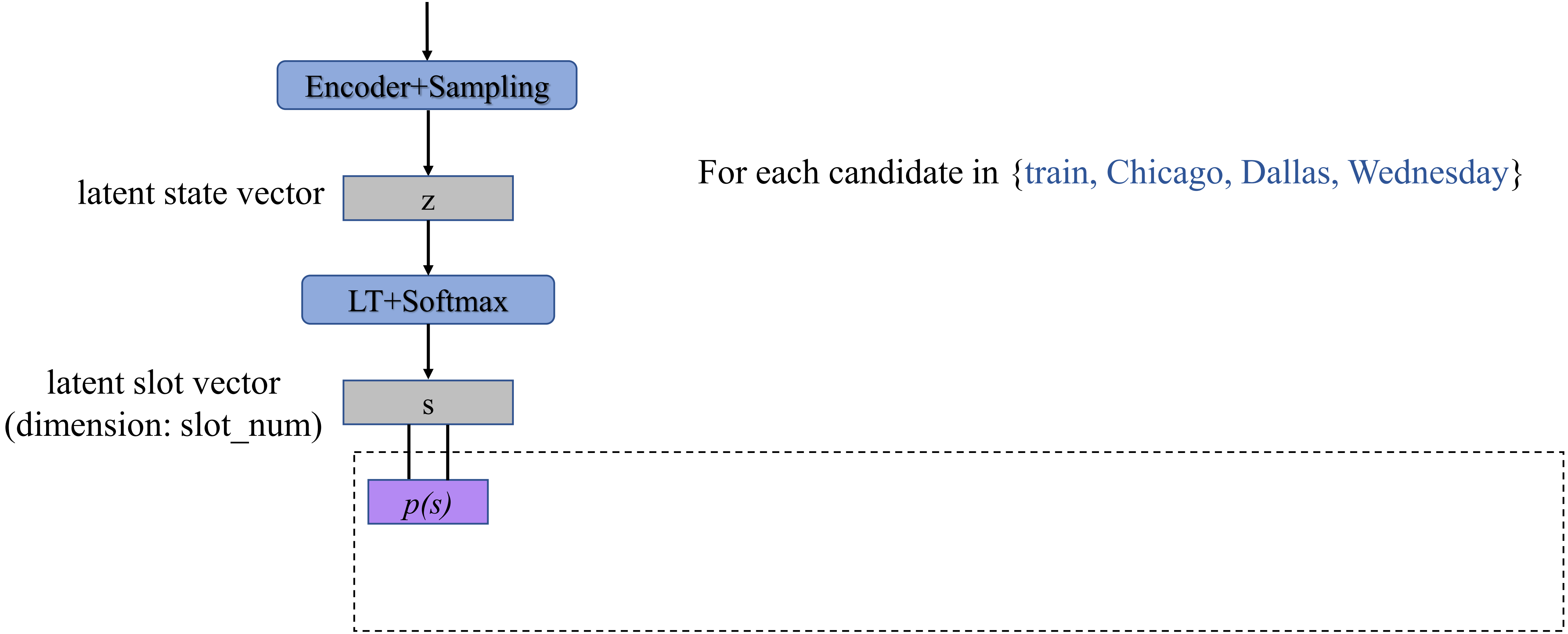


DSI-base inference

I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

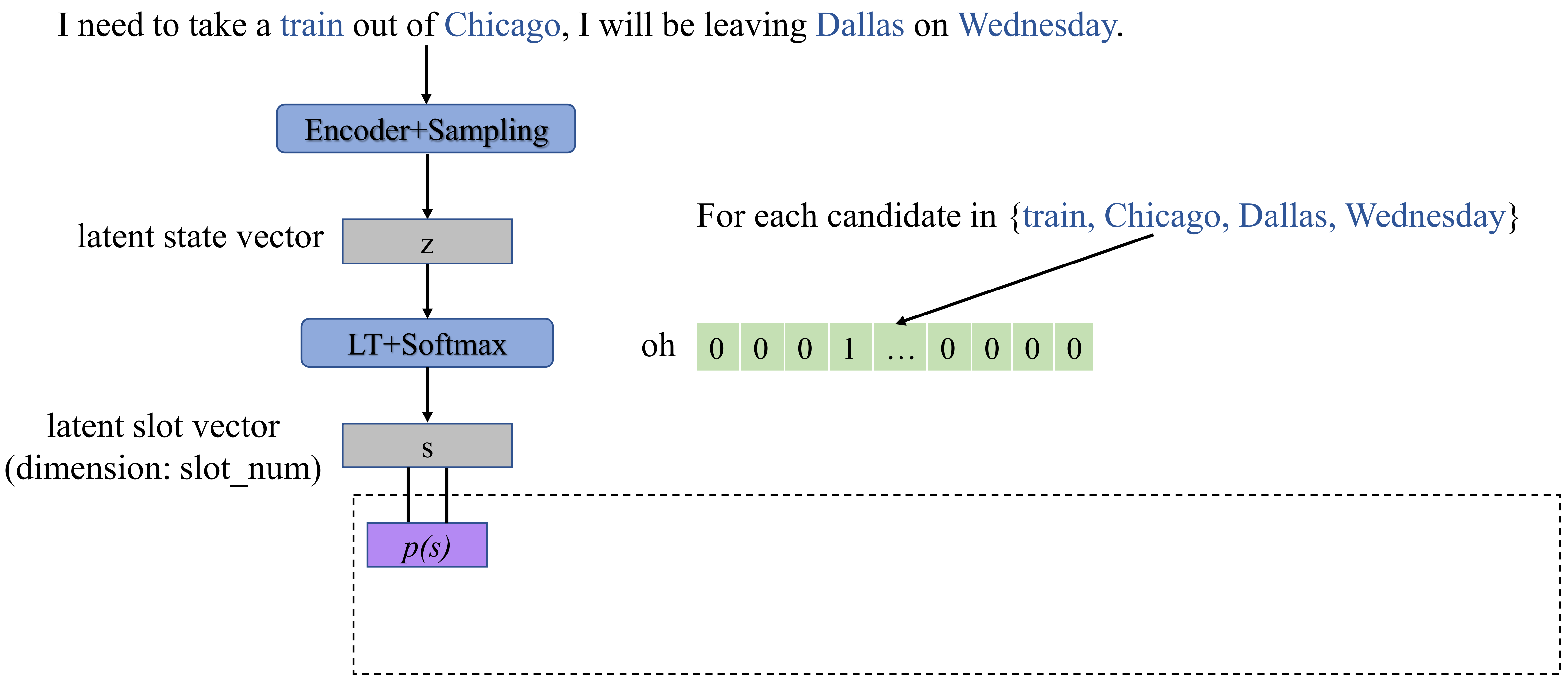
DSI-base inference

I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

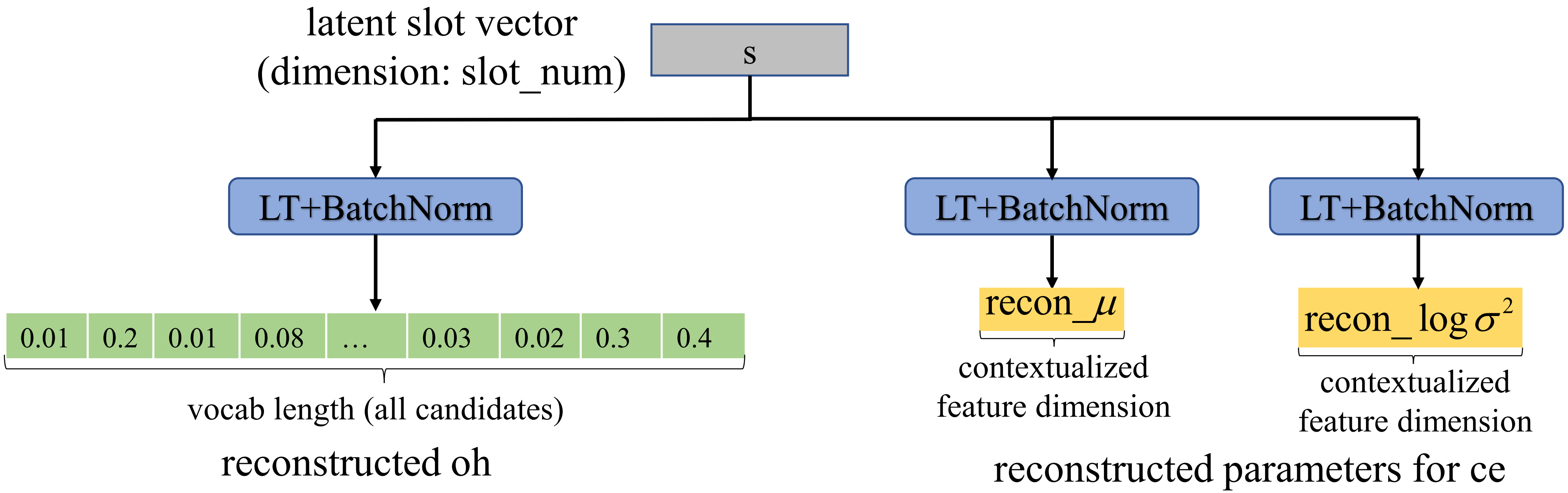


For each candidate in {train, Chicago, Dallas, Wednesday}

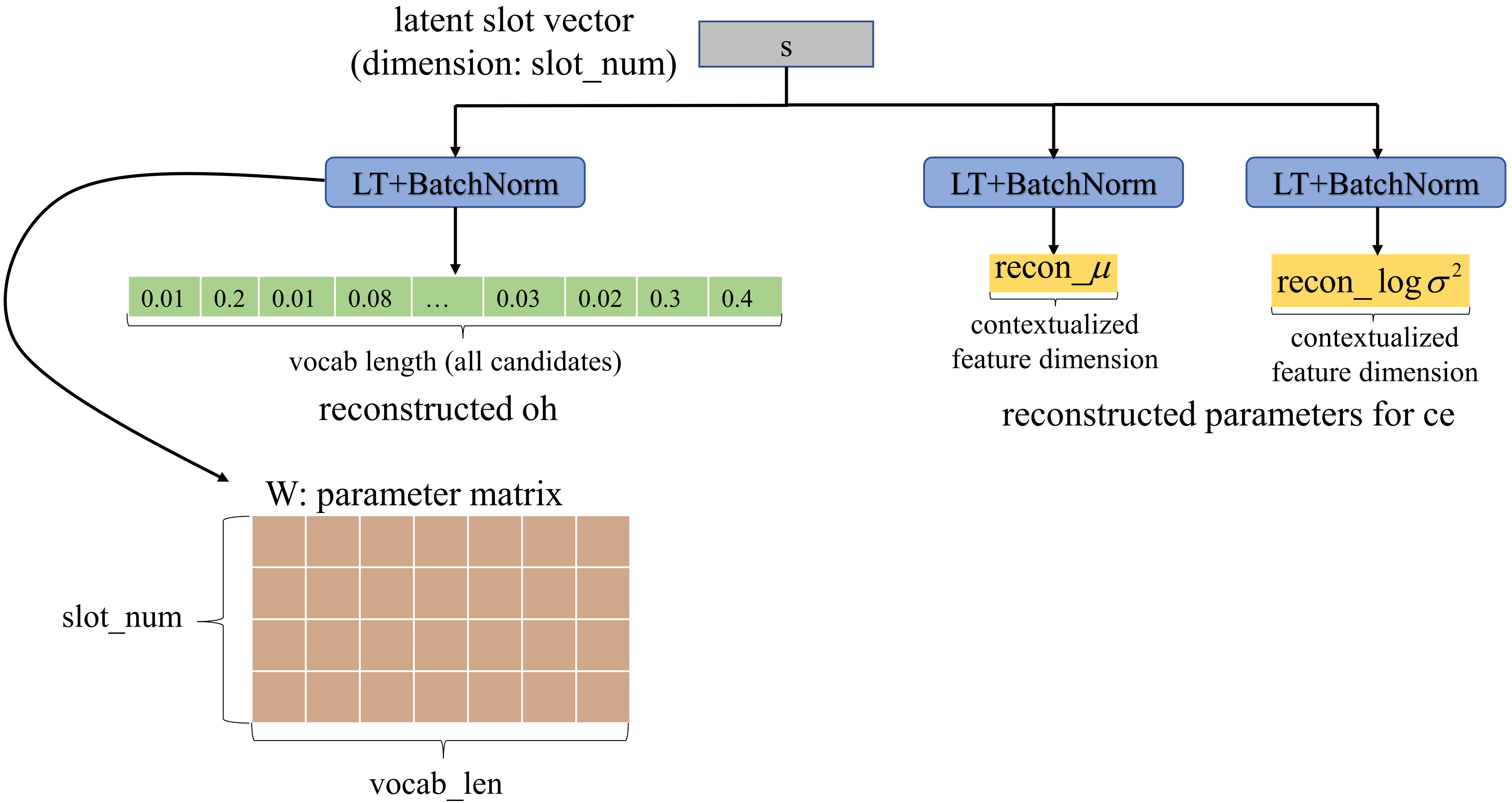
DSI-base inference



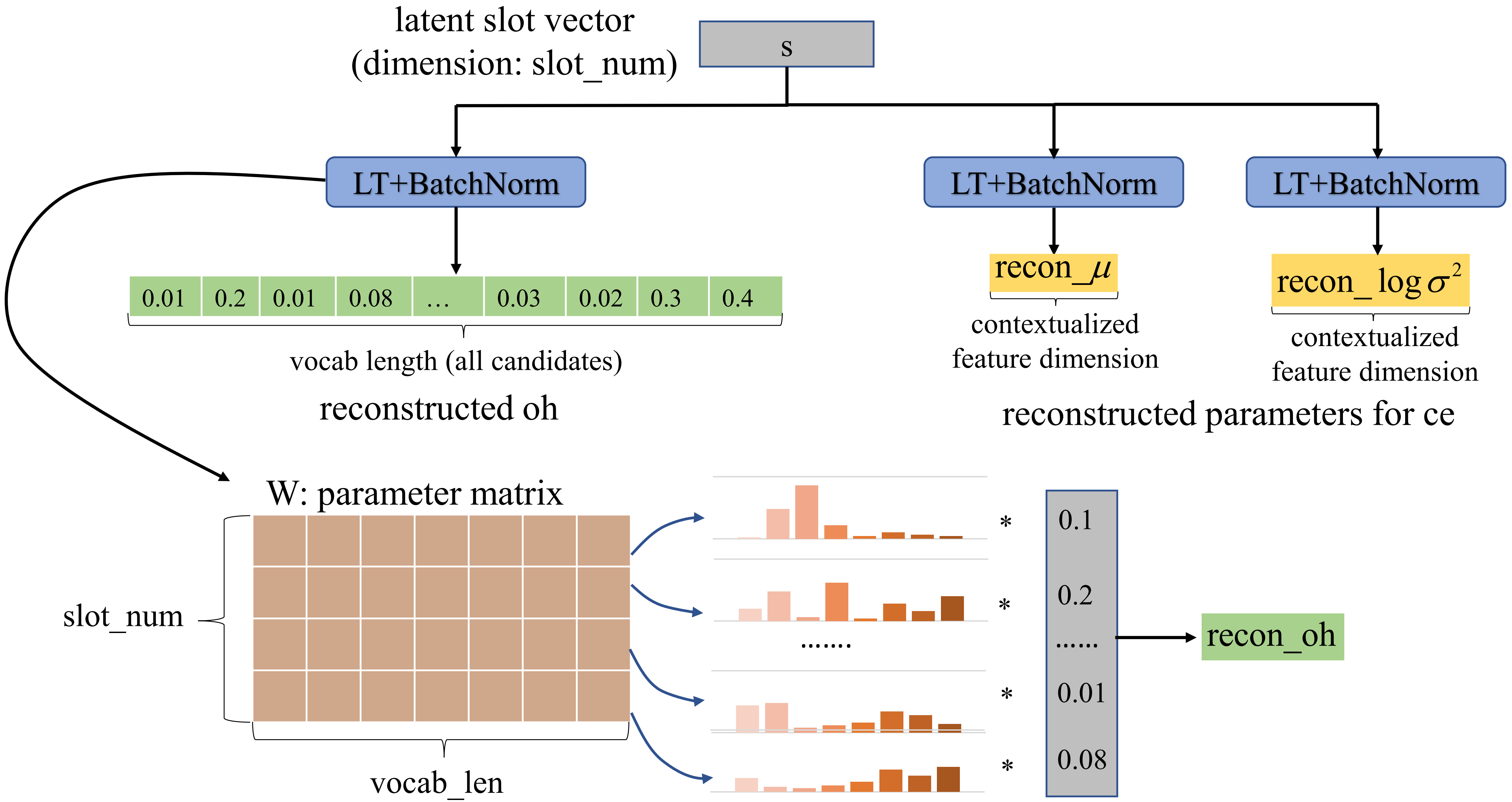
DSI-base inference



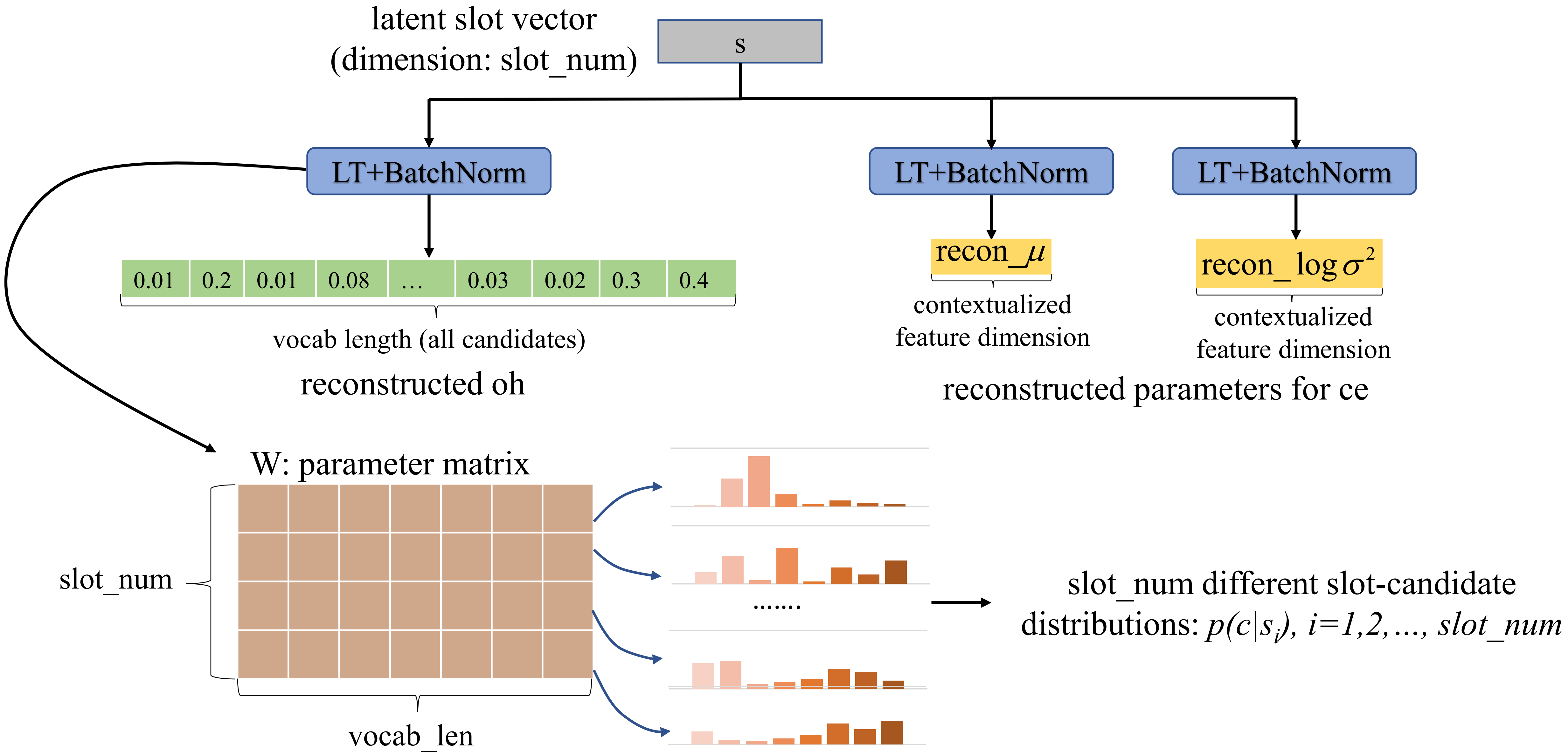
DSI-base inference



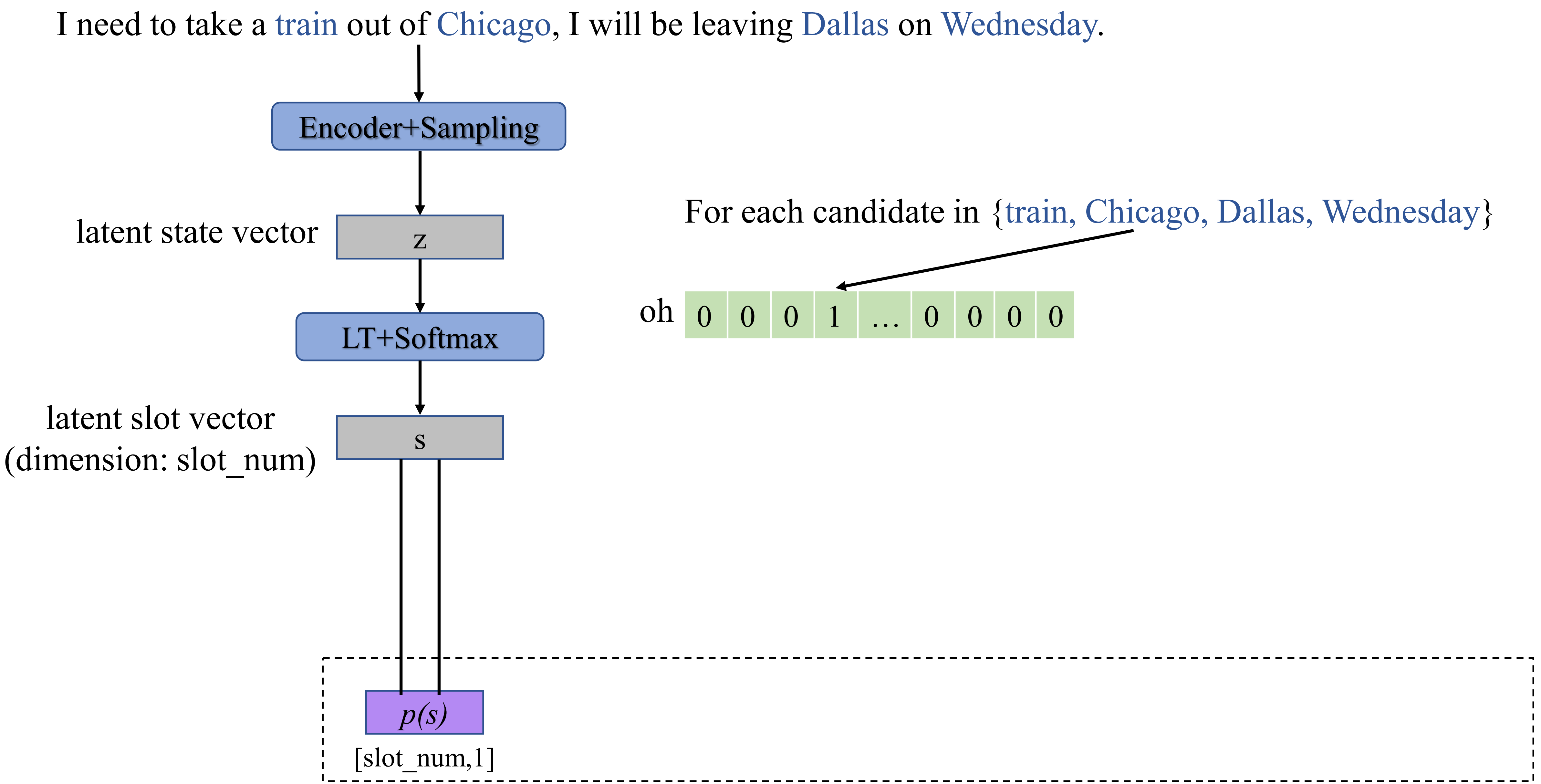
DSI-base inference



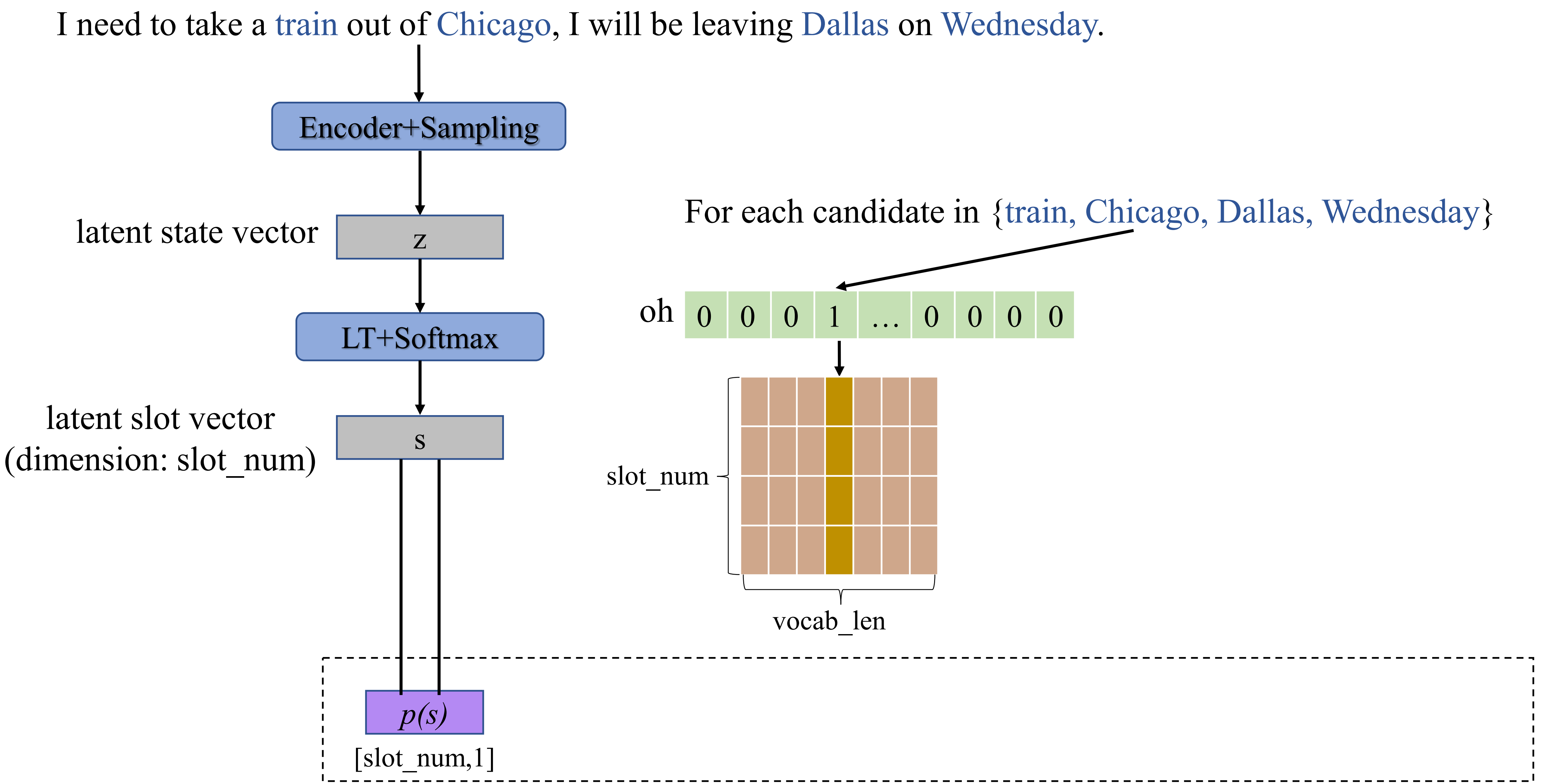
DSI-base inference



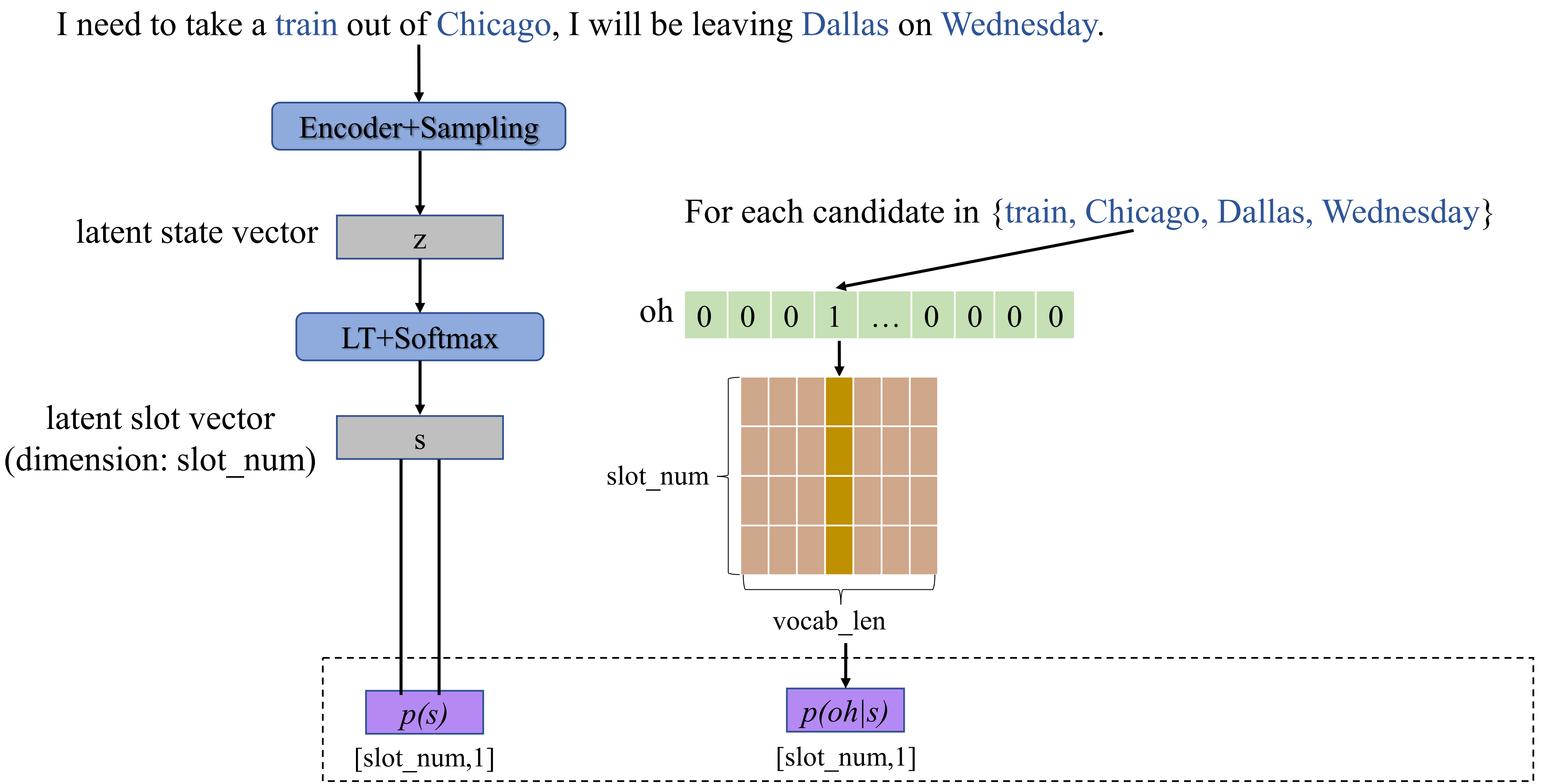
DSI-base inference



DSI-base inference



DSI-base inference



DSI-base inference

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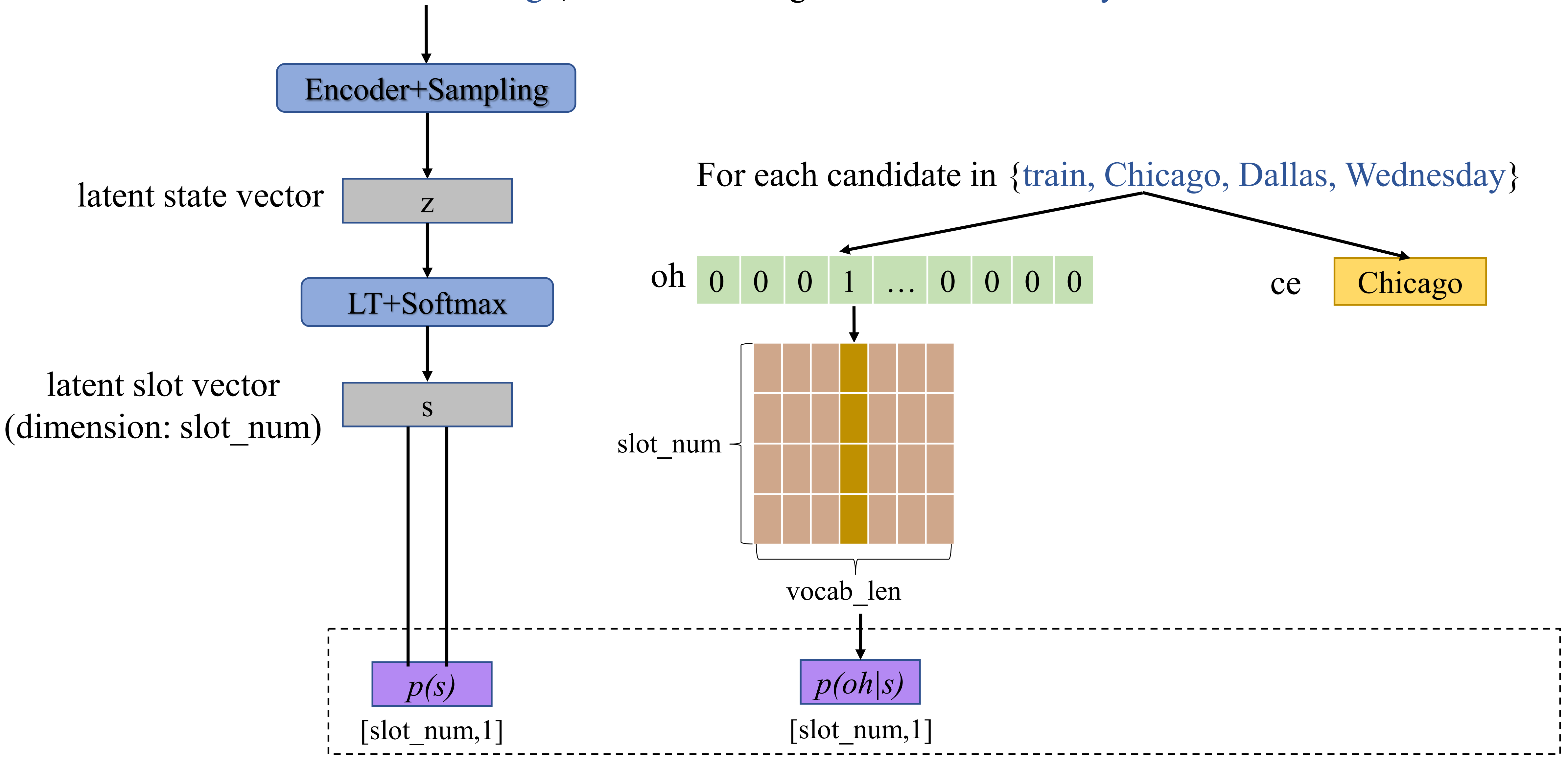
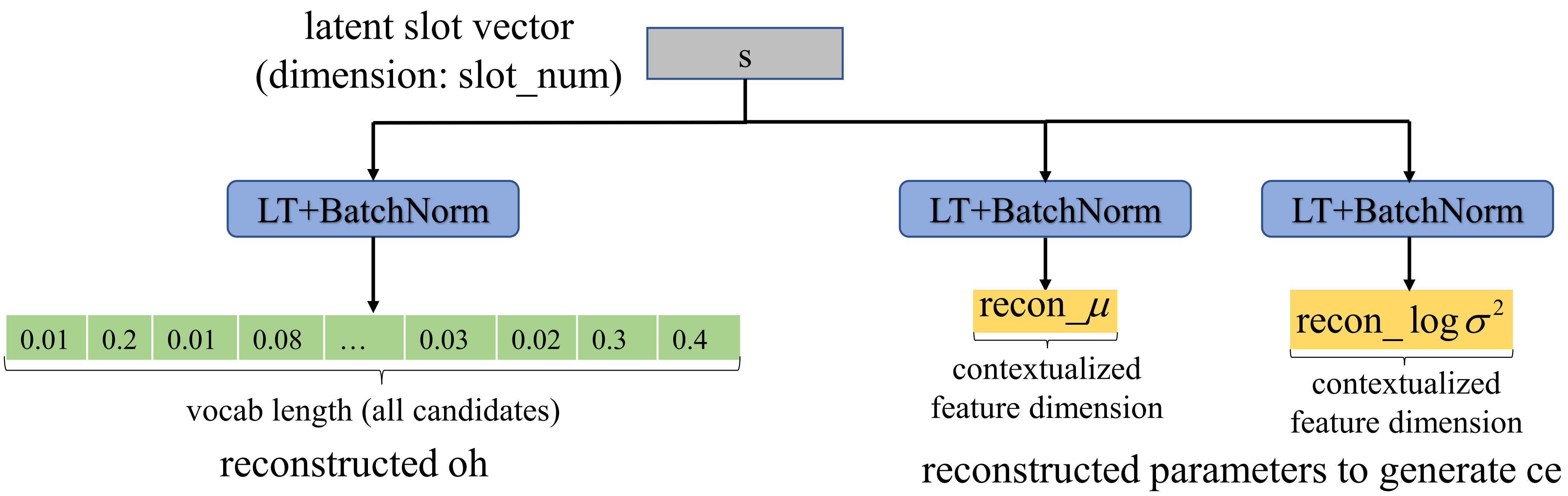


DSI-base inference



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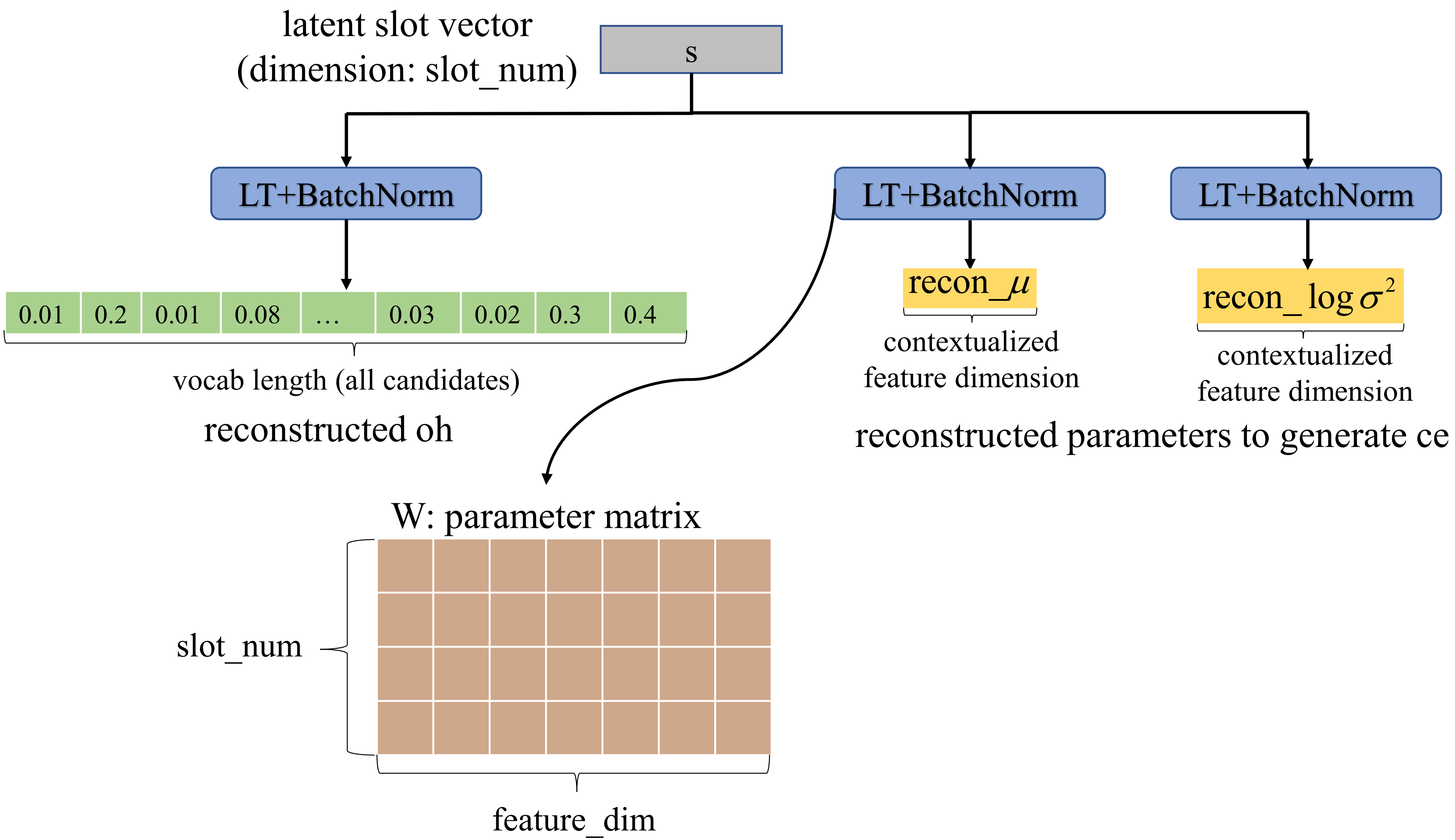

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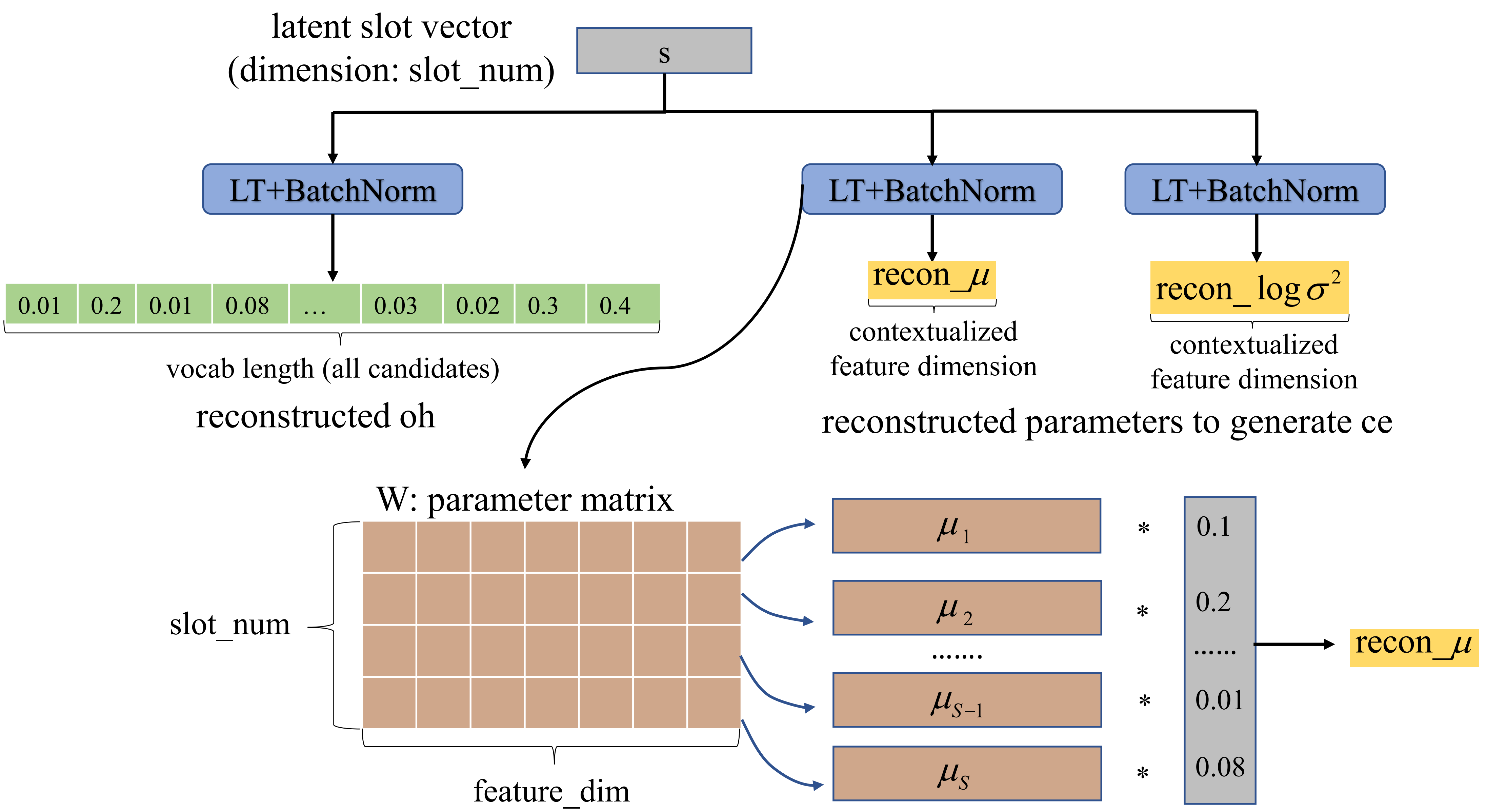
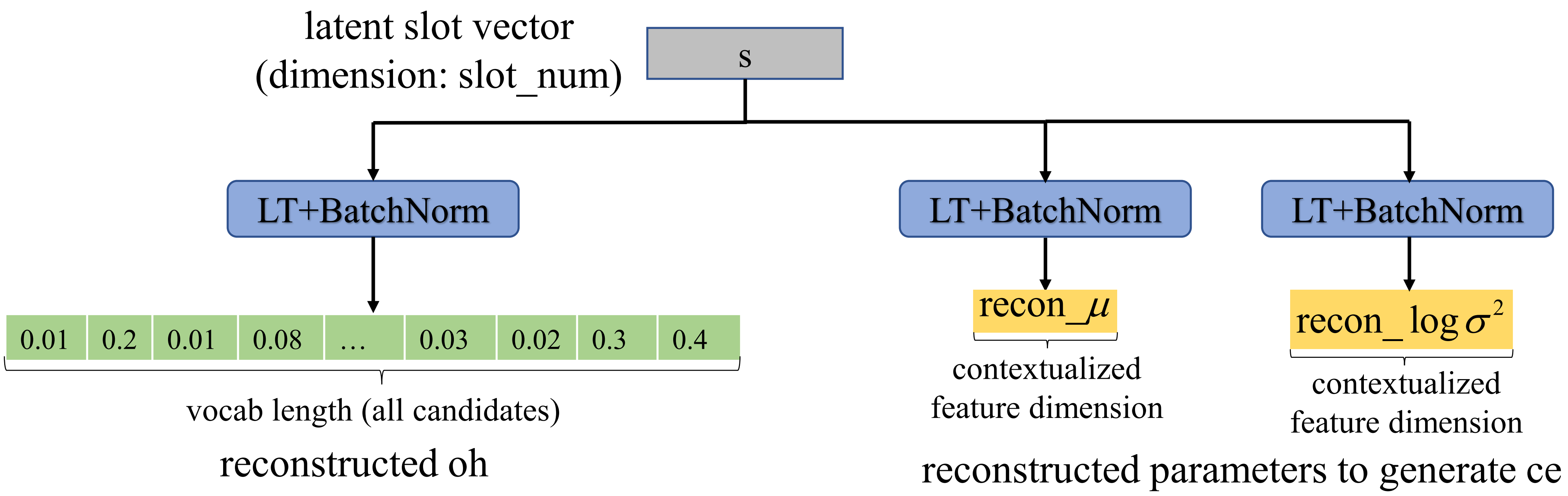
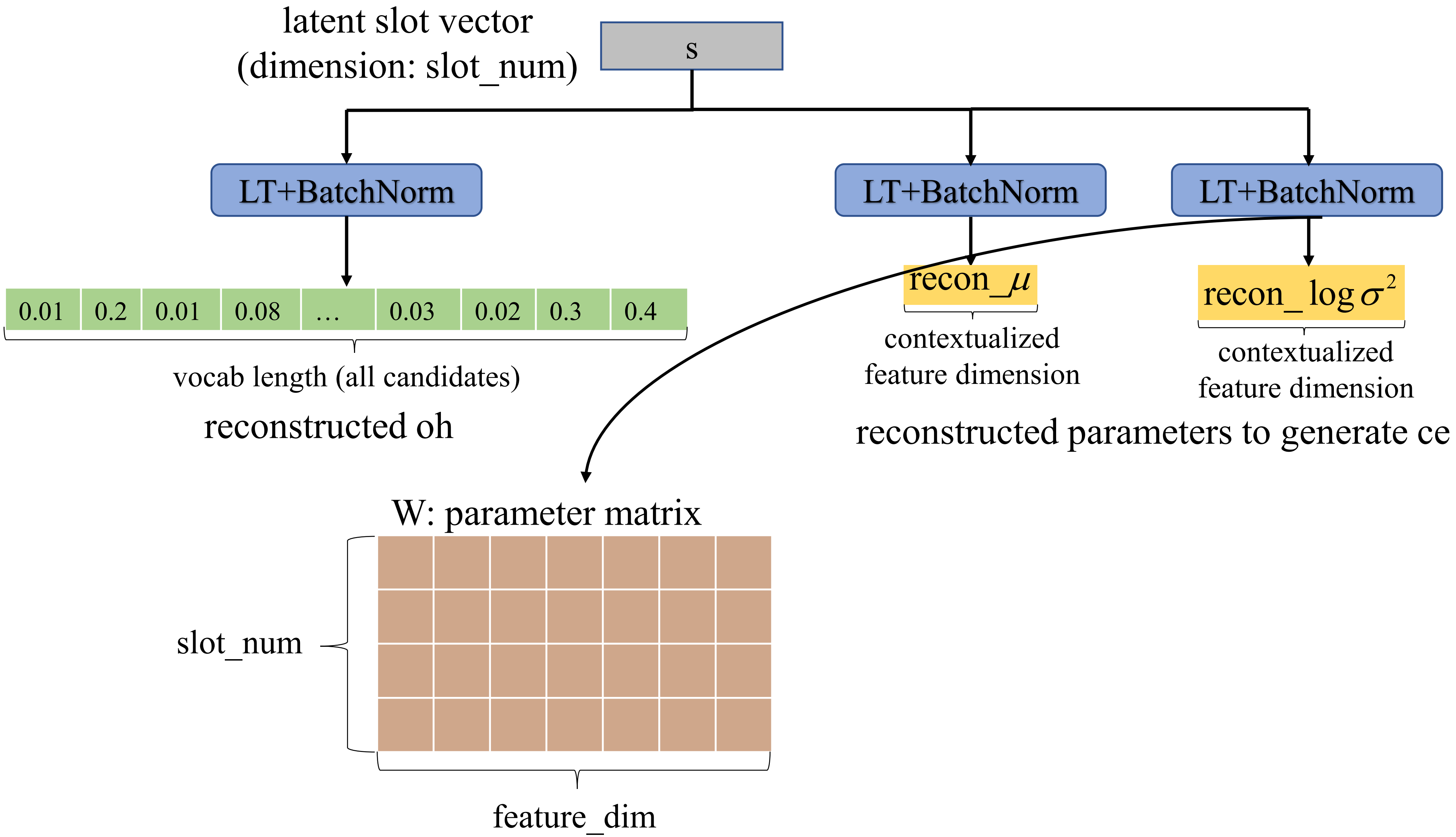


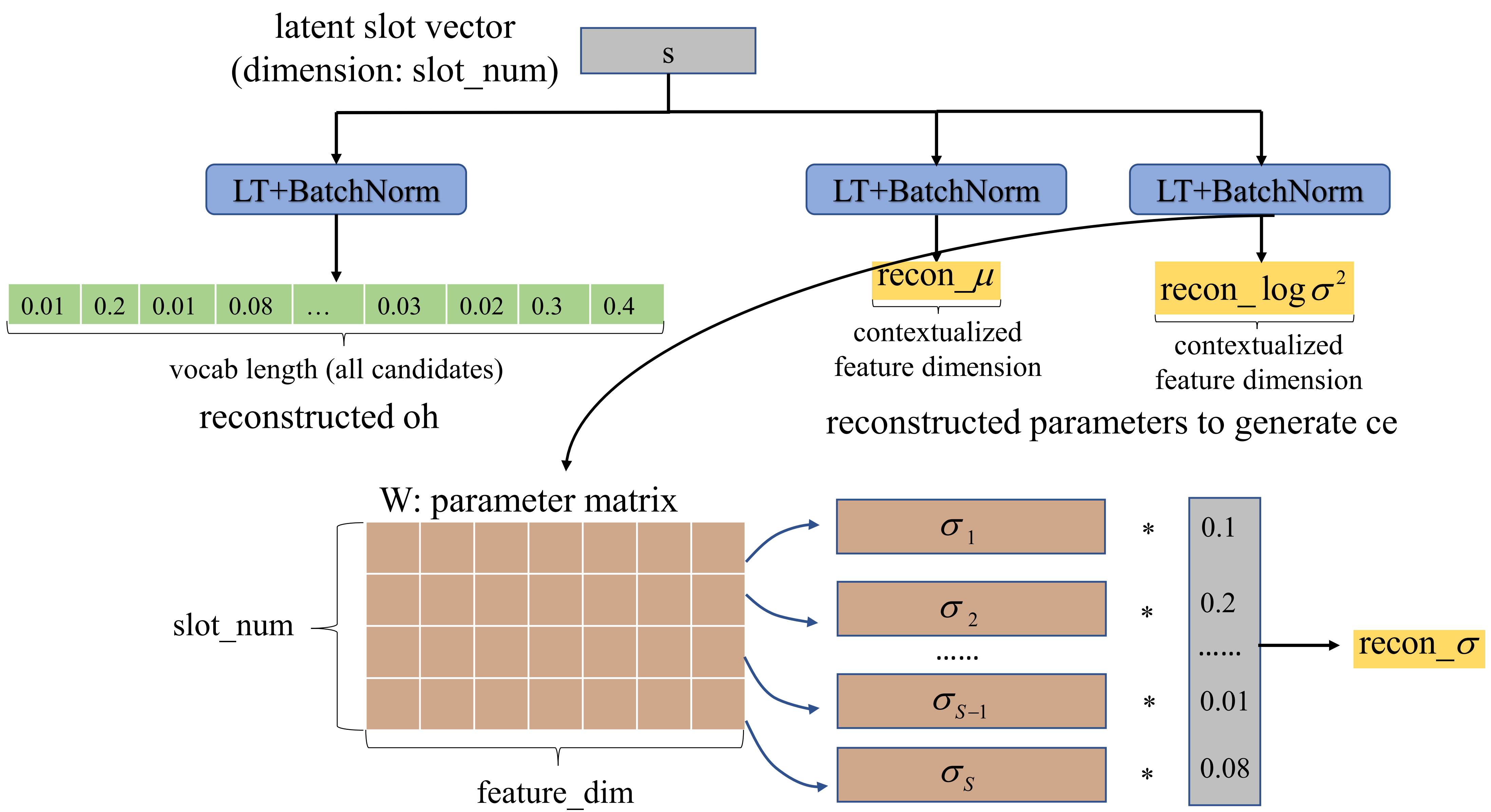
Model: *DSI-base* inference



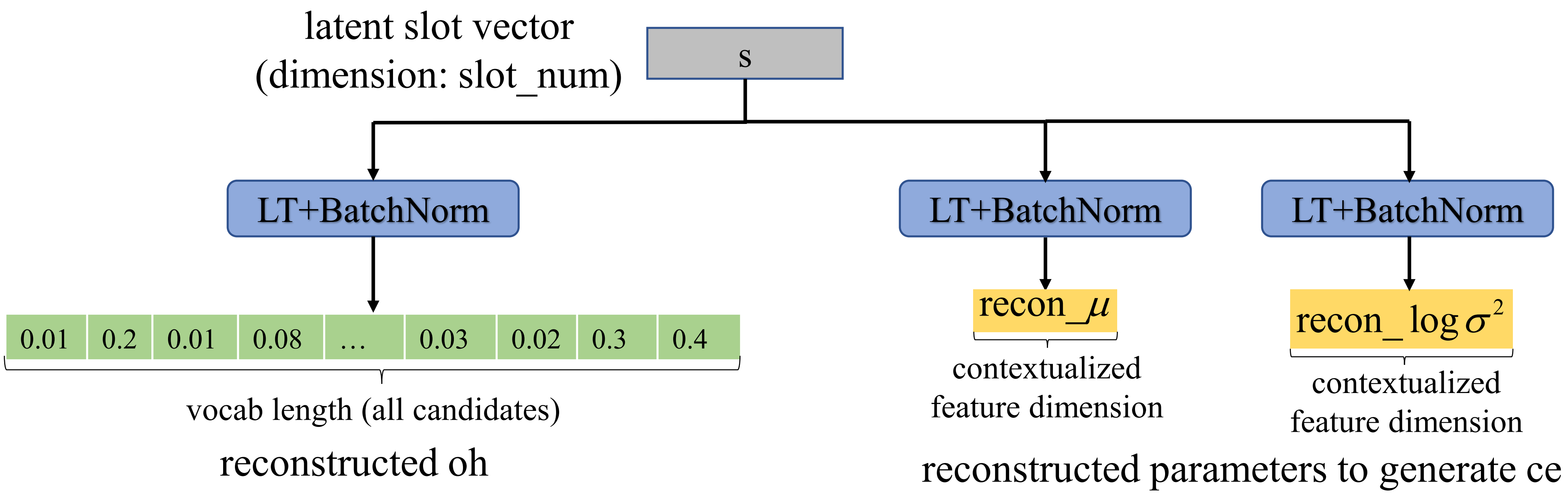
Model: *DSI-base* inference



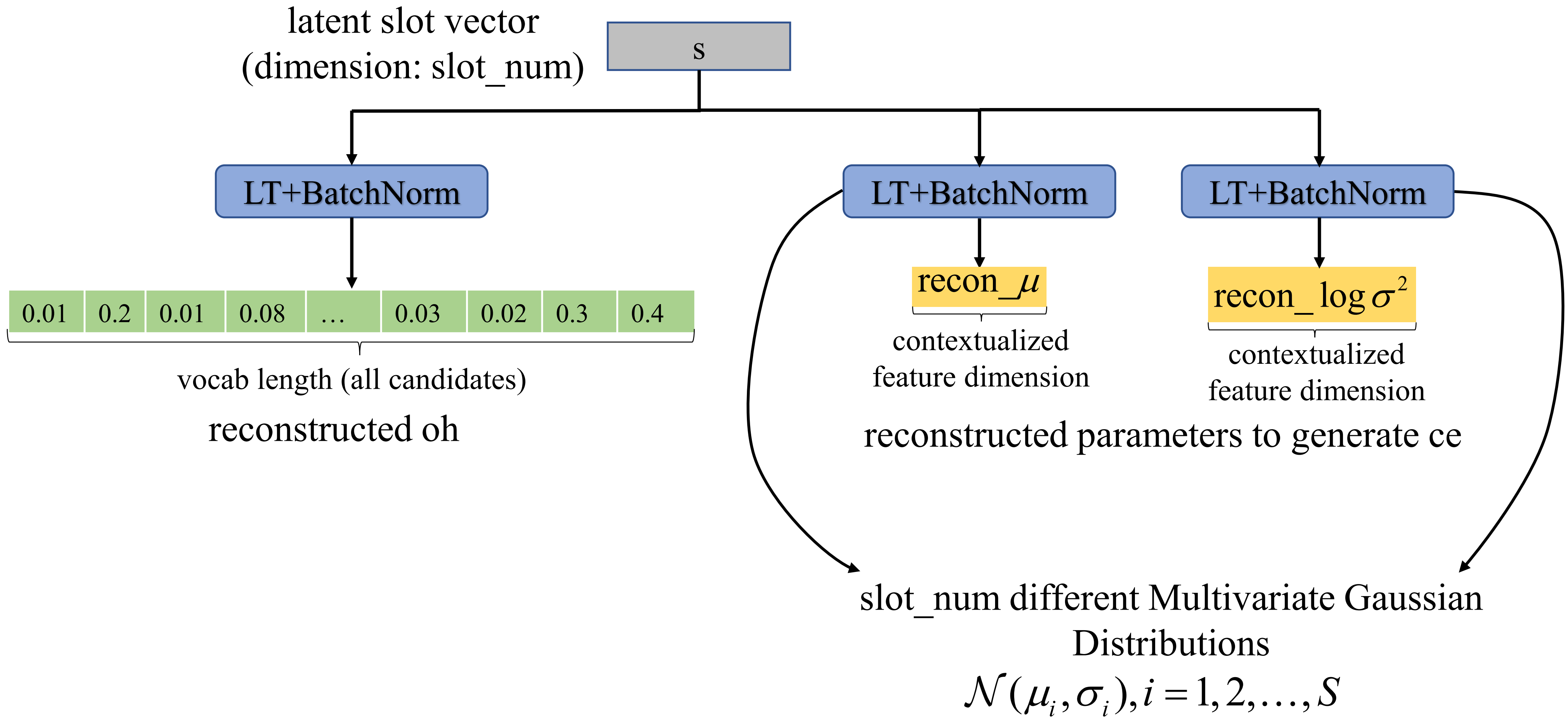
Model: *DSI-base* inference



DSI-base inference



DSI-base inference



Multivariate Gaussian probability density

$\underbrace{\mu}_{\text{contextualized feature dimension}}$

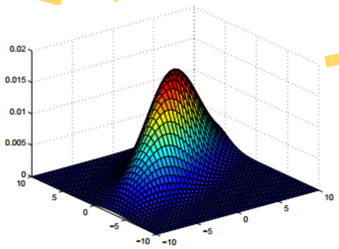
$\underbrace{\sigma}_{\text{contextualized feature dimension}}$

train

Chicago

Dallas

Wednesday



Multivariate Gaussian Distribution

-dist.log_prob(ce[train])

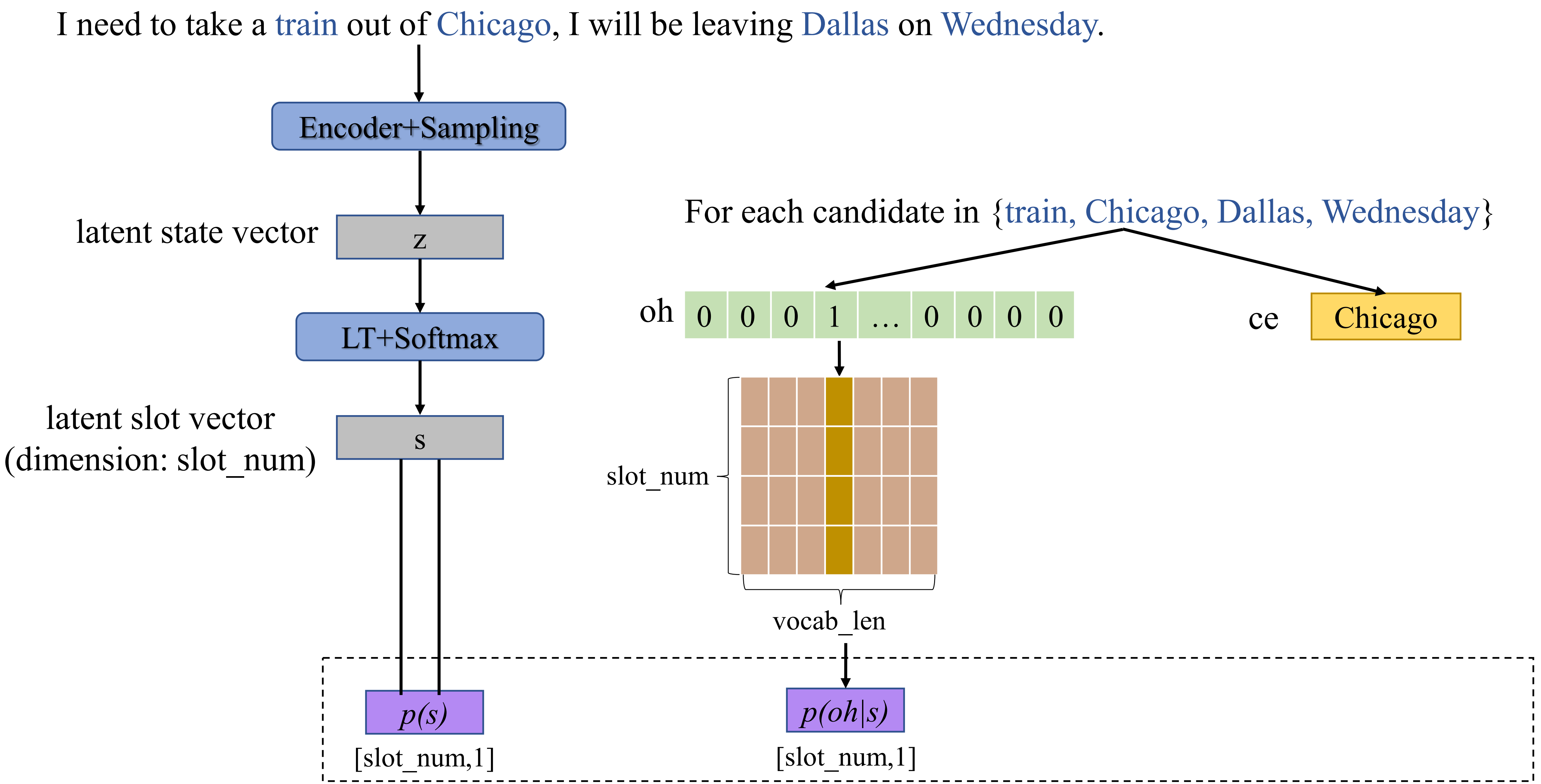
-dist.log_prob(ce[Chicago])

-dist.log_prob(ce[Dallas])

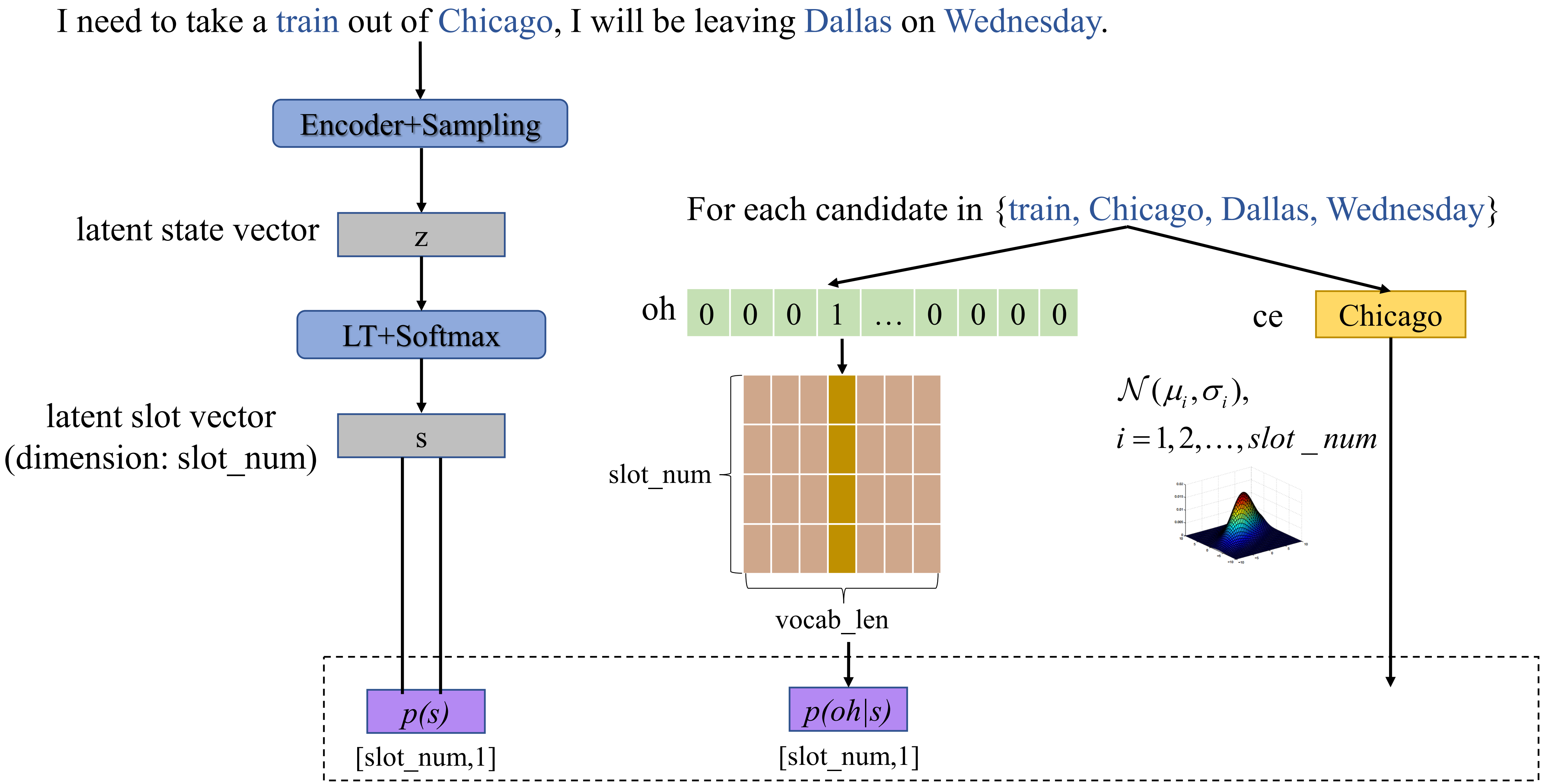
-dist.log_prob(ce[Wednesday])

Pic from https://www.datalearner.com/blog/1051485590815771

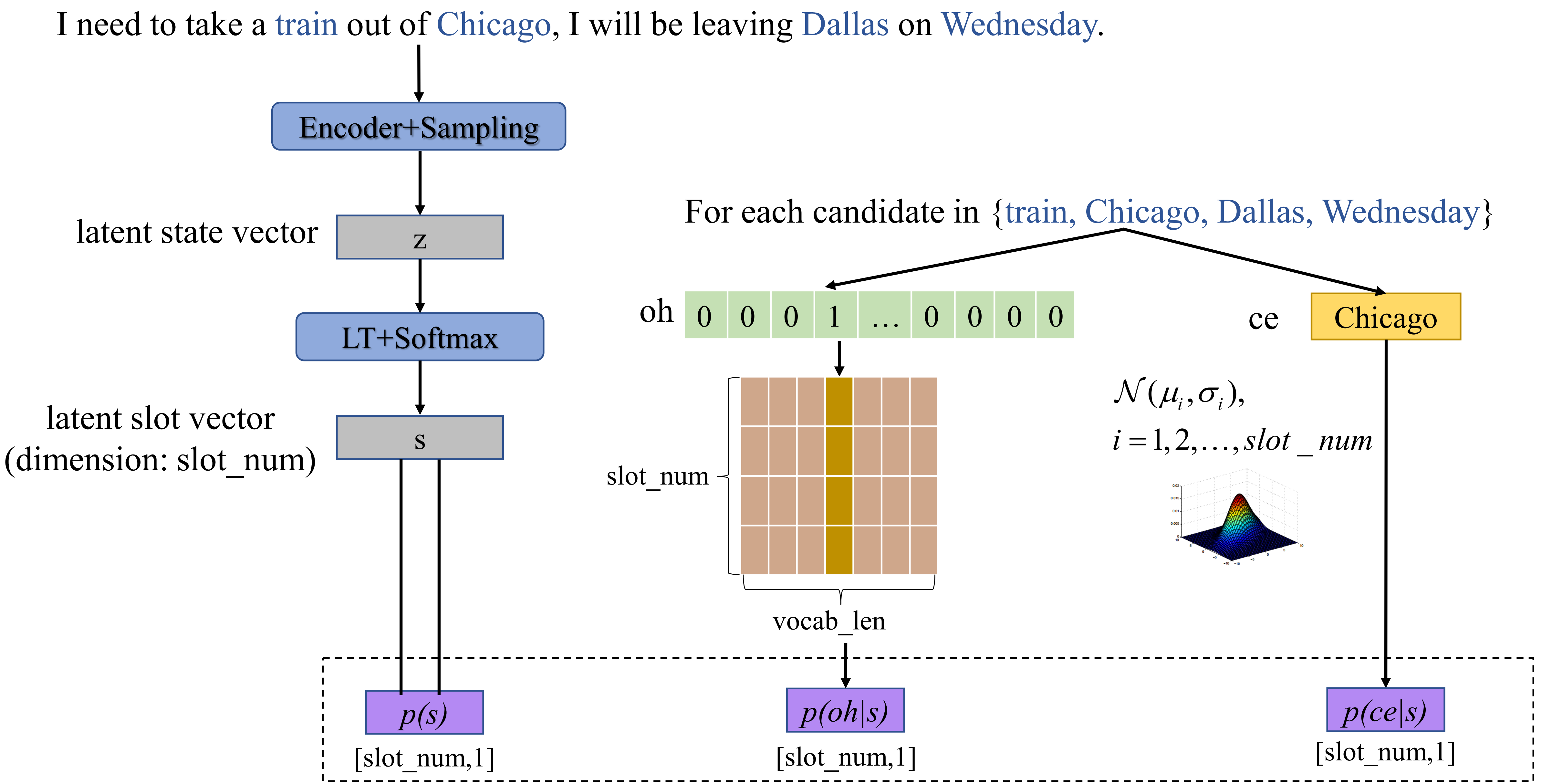
DSI-base inference



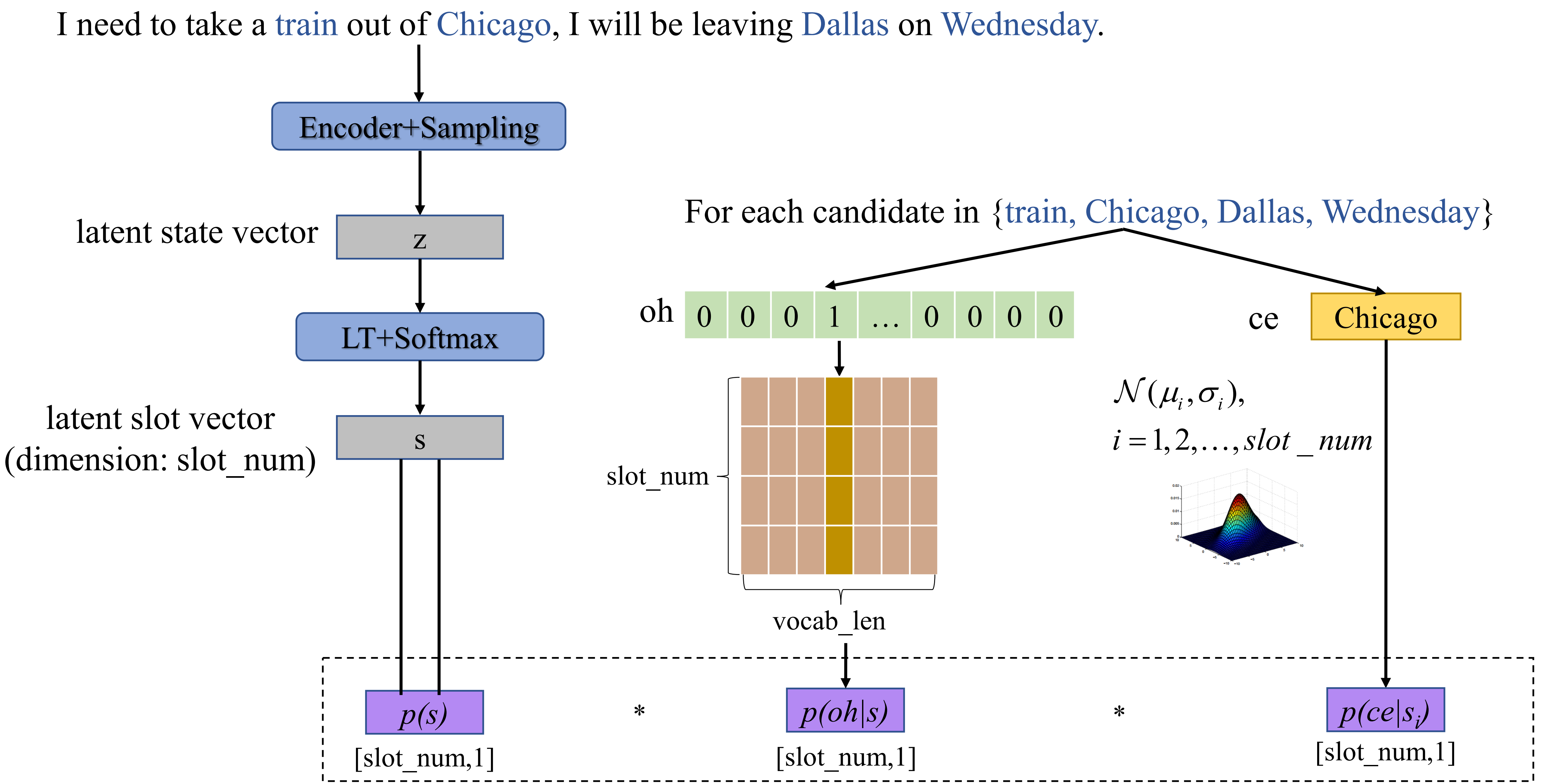
DSI-base inference



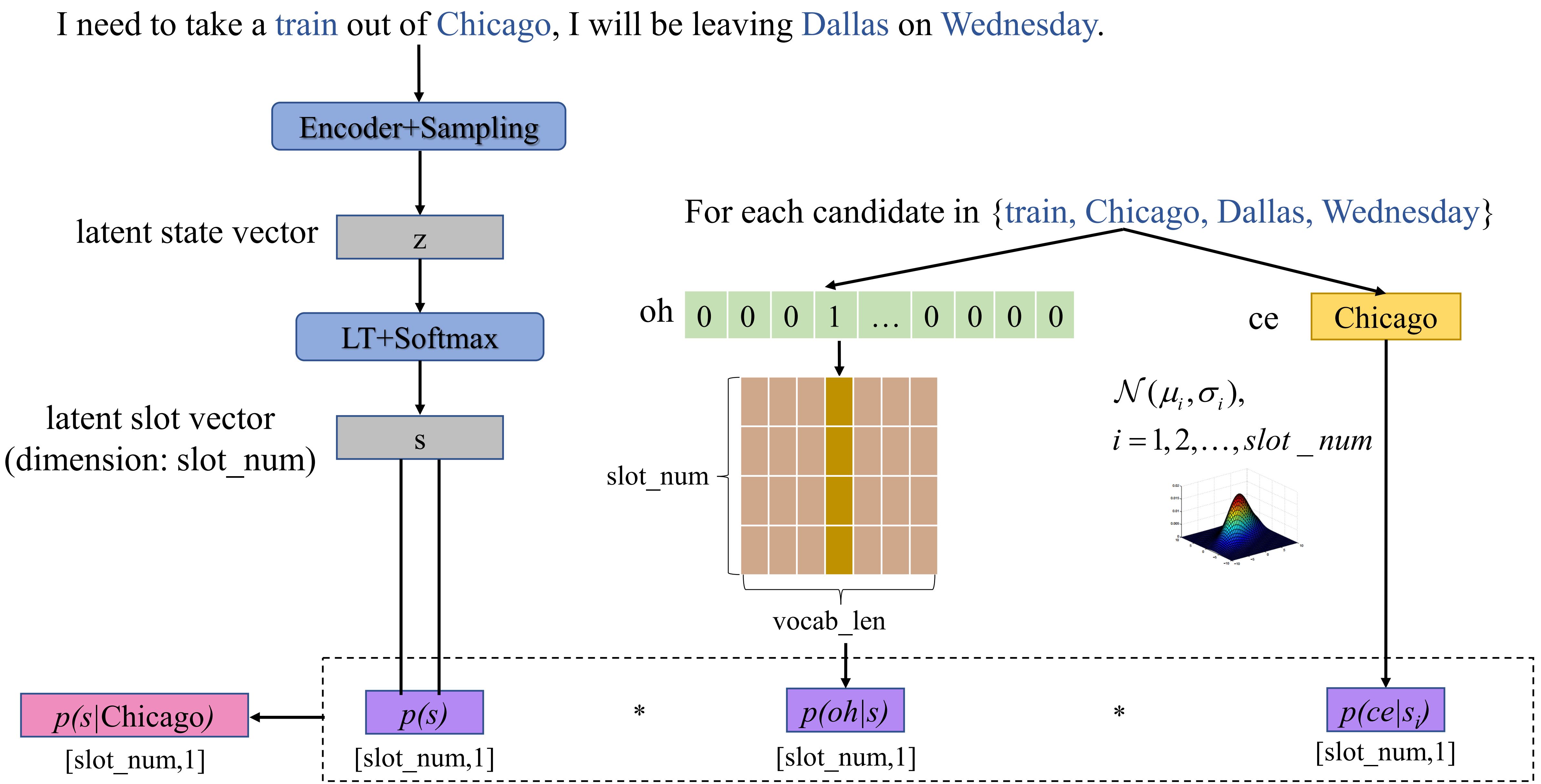
DSI-base inference



DSI-base inference

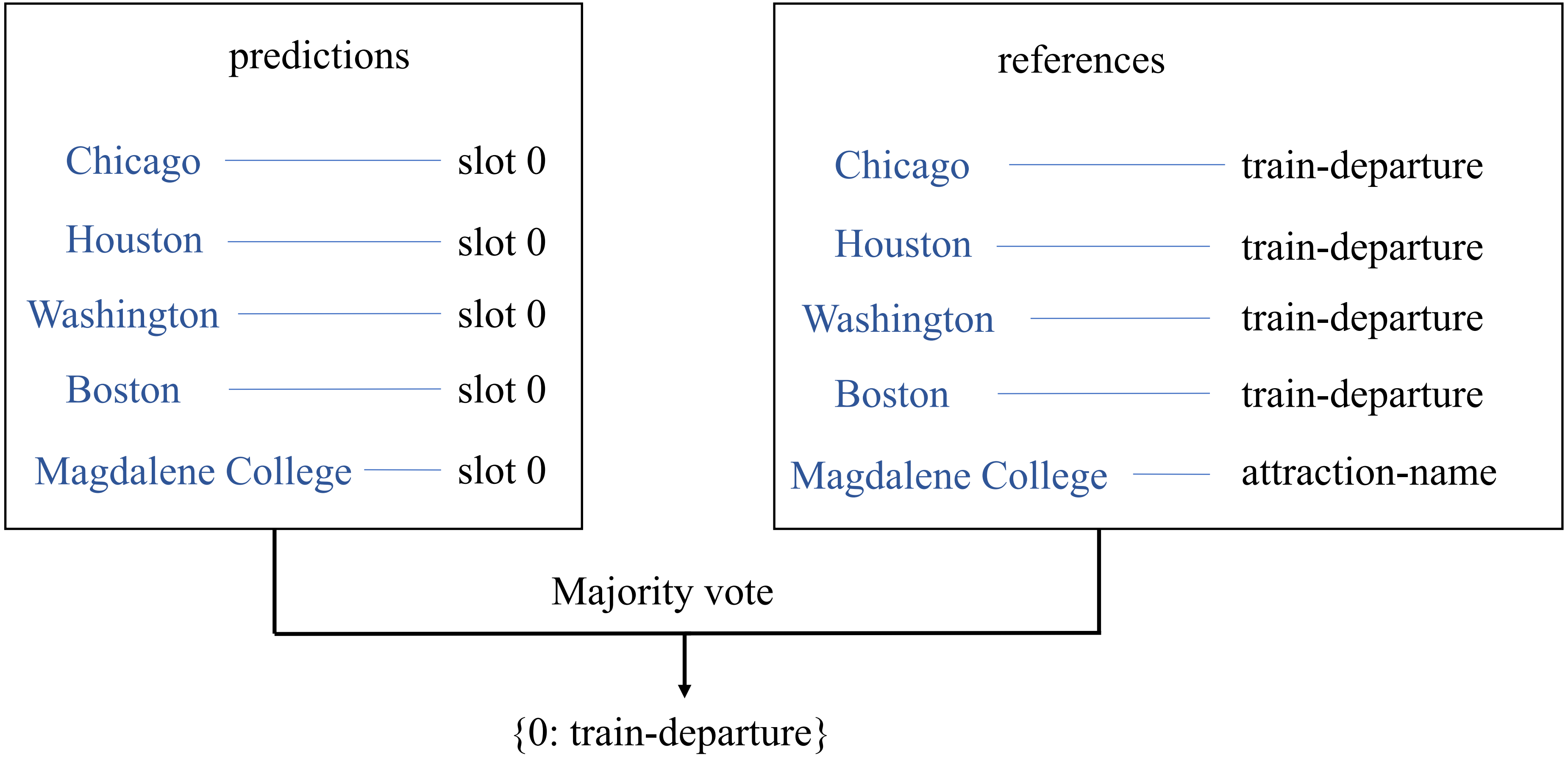


DSI-base inference



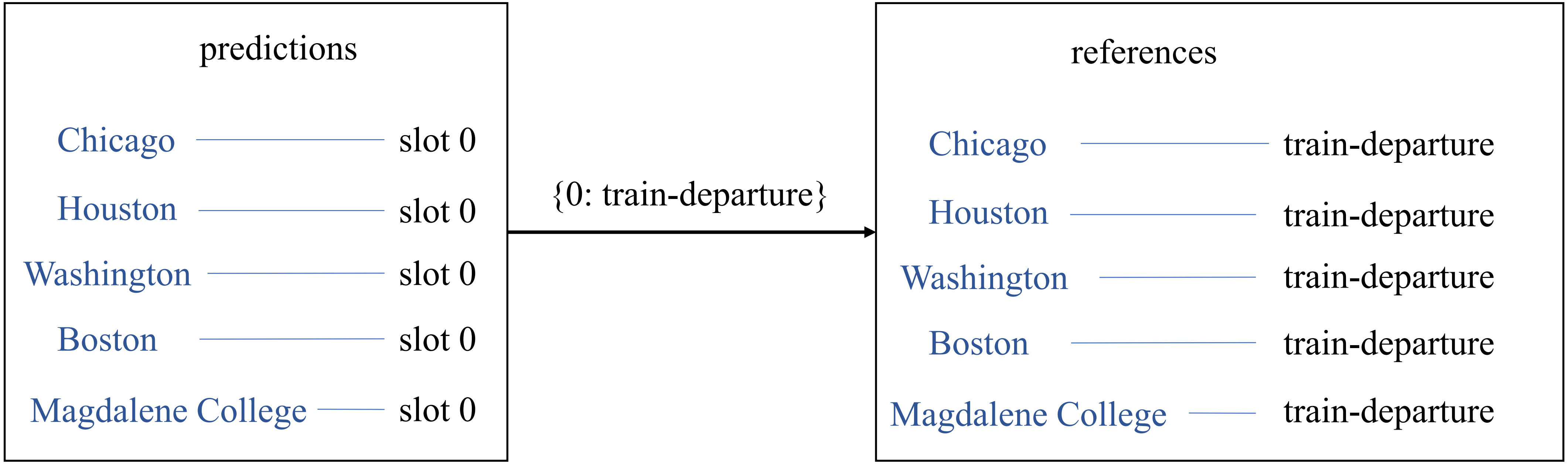
Post-processing: slot mapping

Mapping from slot indexes to labels?



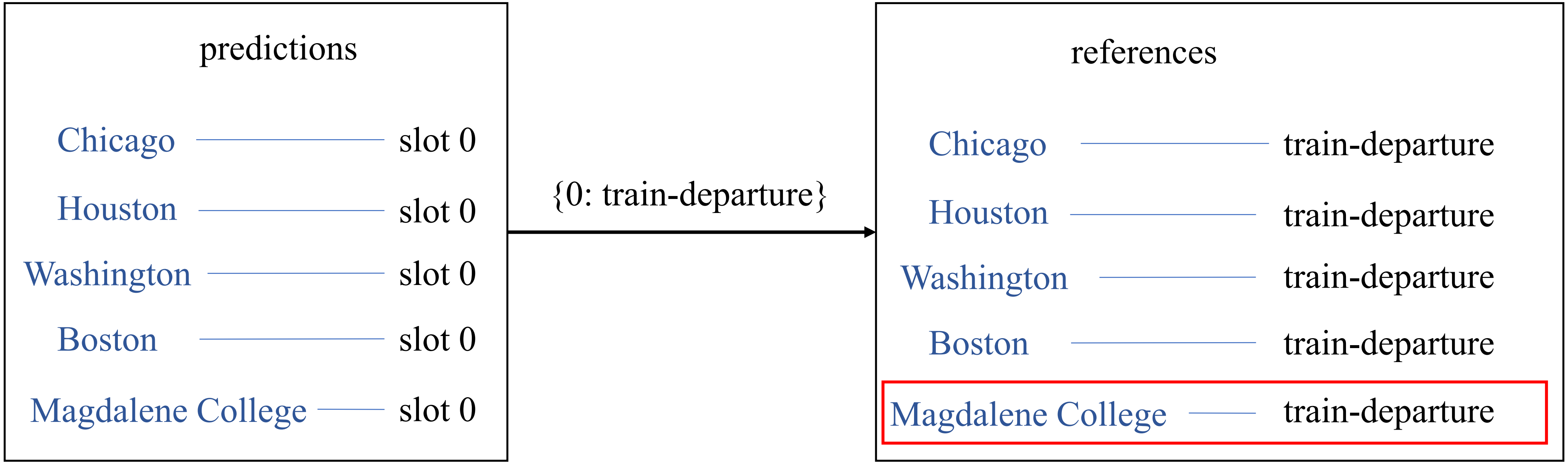
Post-processing: slot mapping

Mapping from slot indexes to labels?

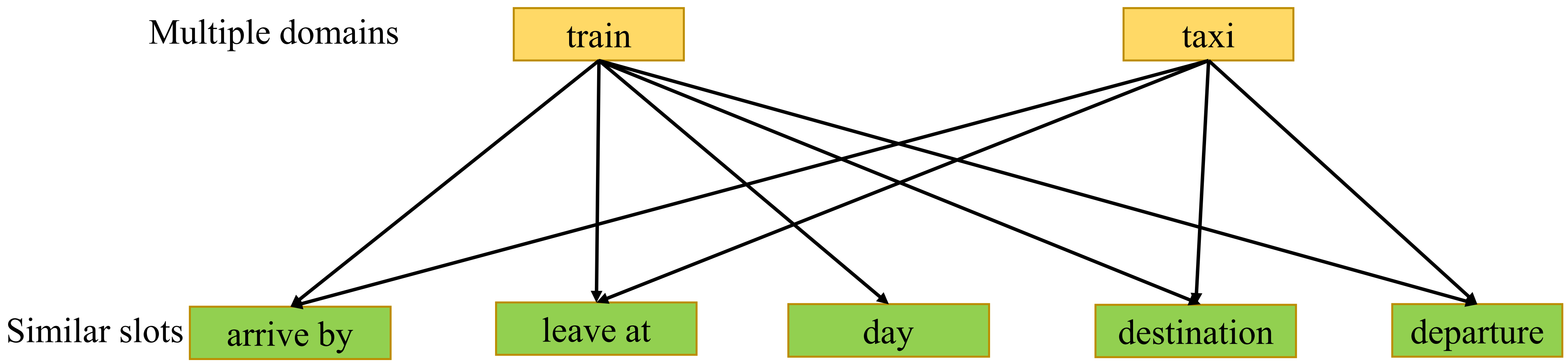


Post-processing: slot mapping

Mapping from slot indexes to labels?



What is the problem with *DSI-base*?



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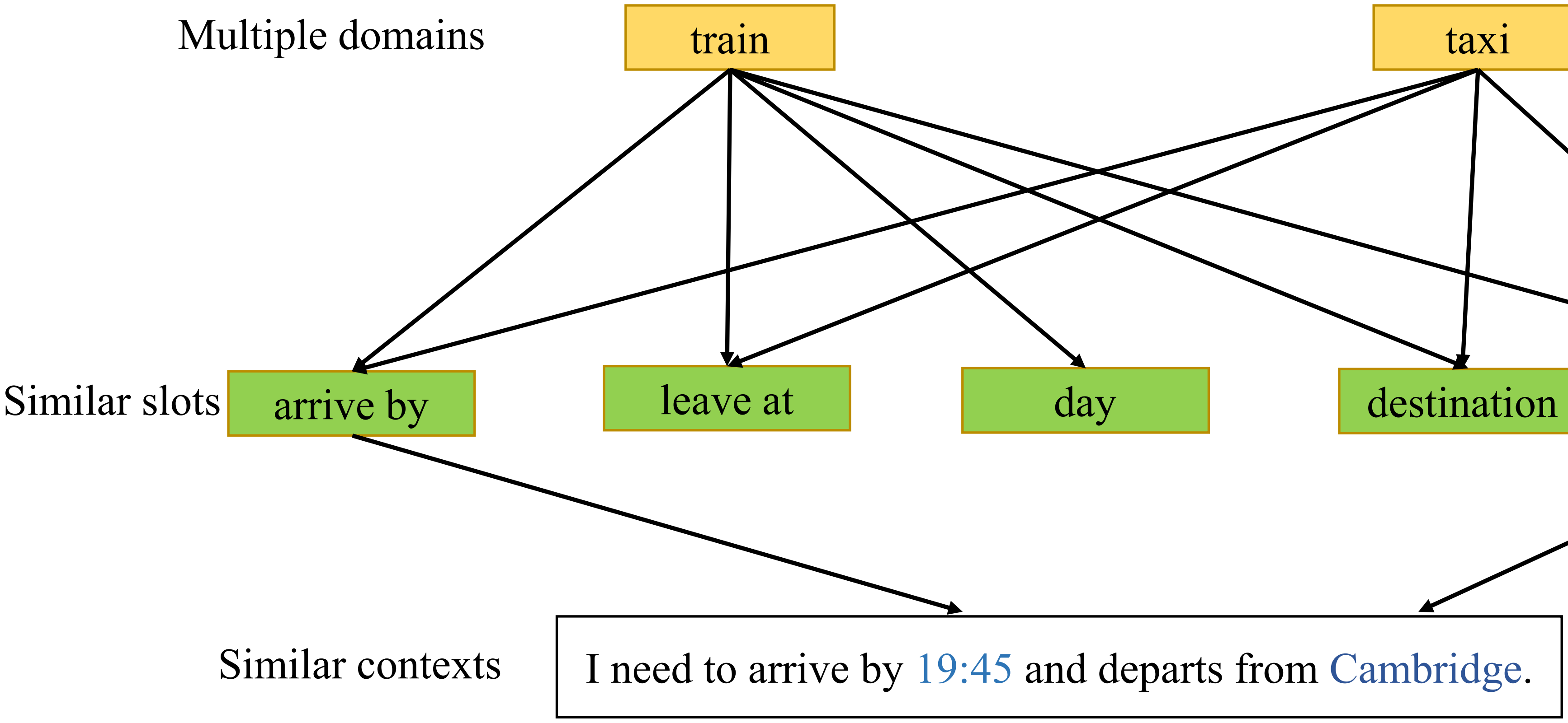
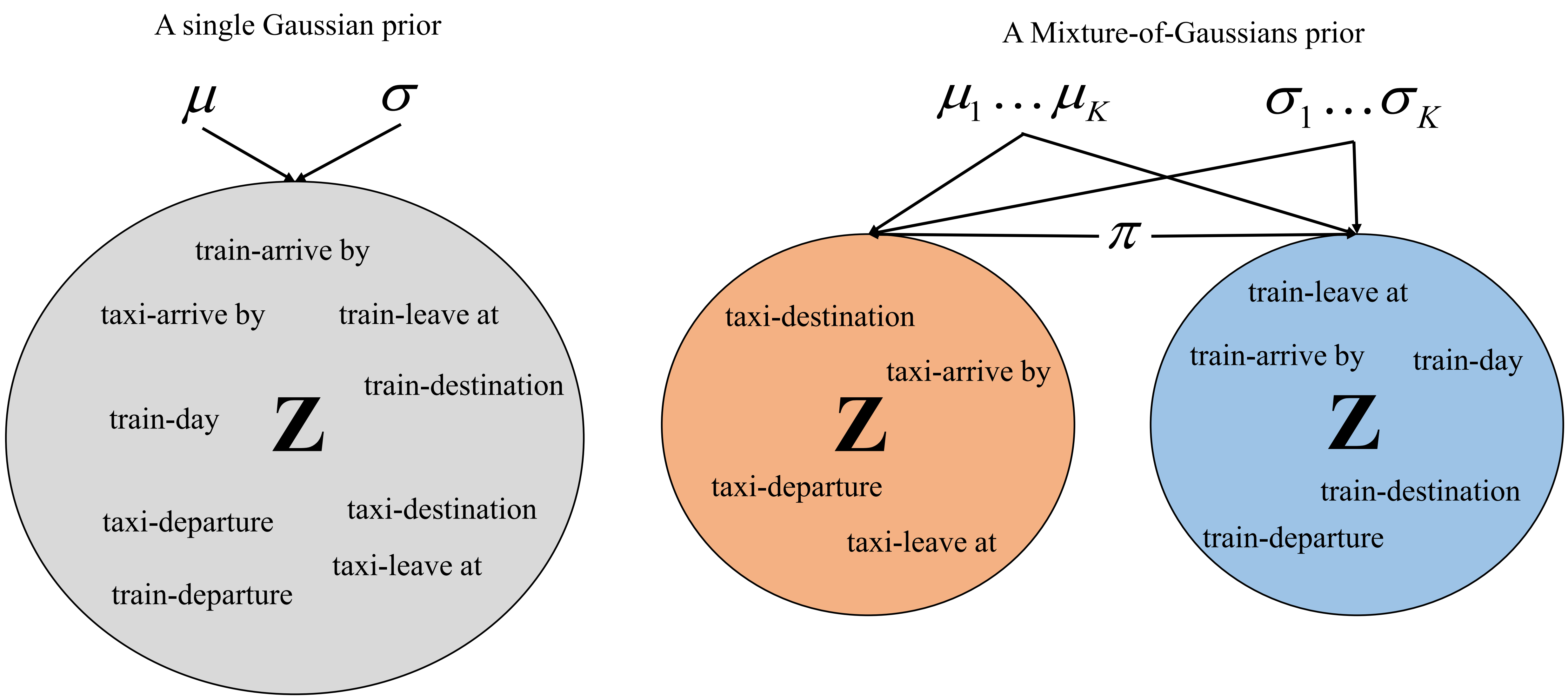


How does *DSI-GM* work?



How does *DSI-GM* work?

I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

How does *DSI-GM* work?

I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

DSI-base

How does *DSI-GM* work?

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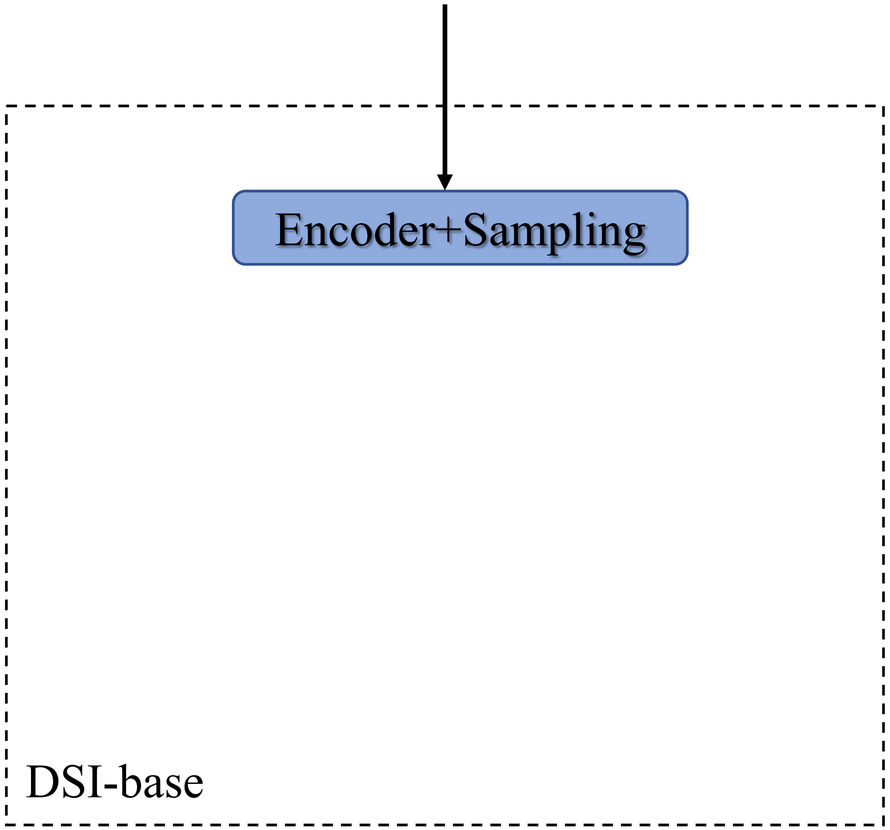

How does *DSI-GM* work?

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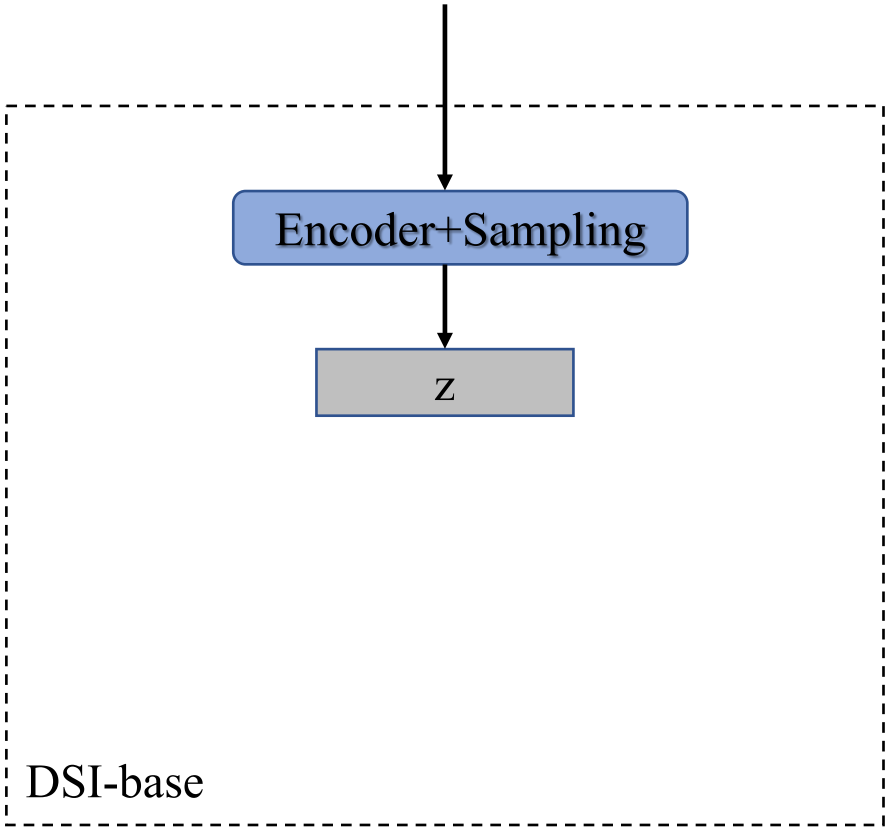

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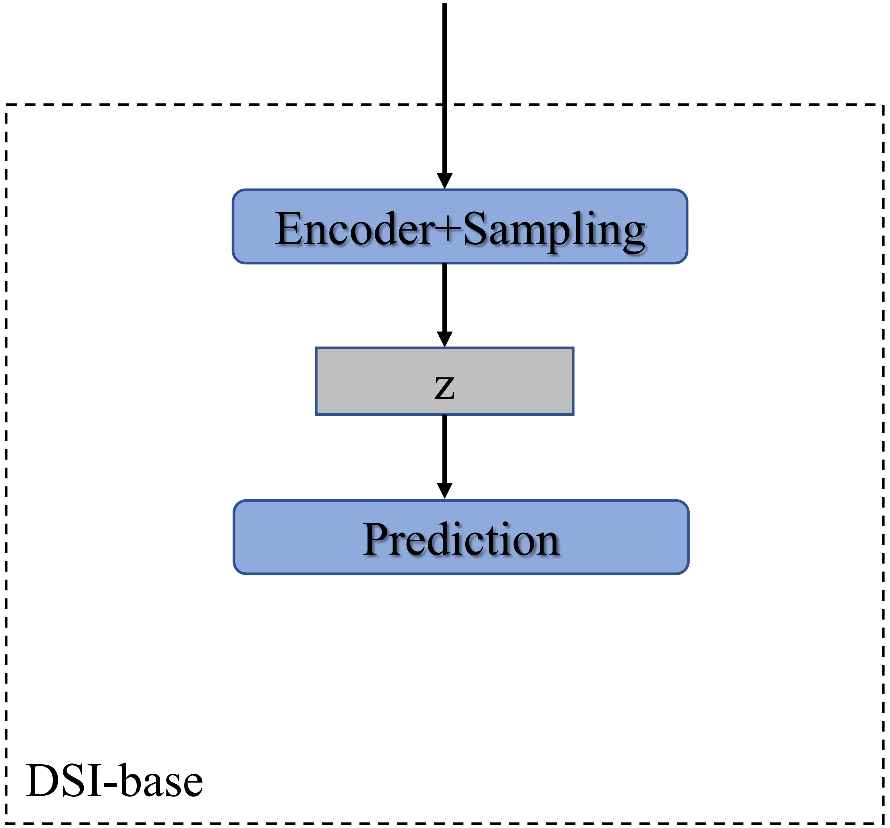
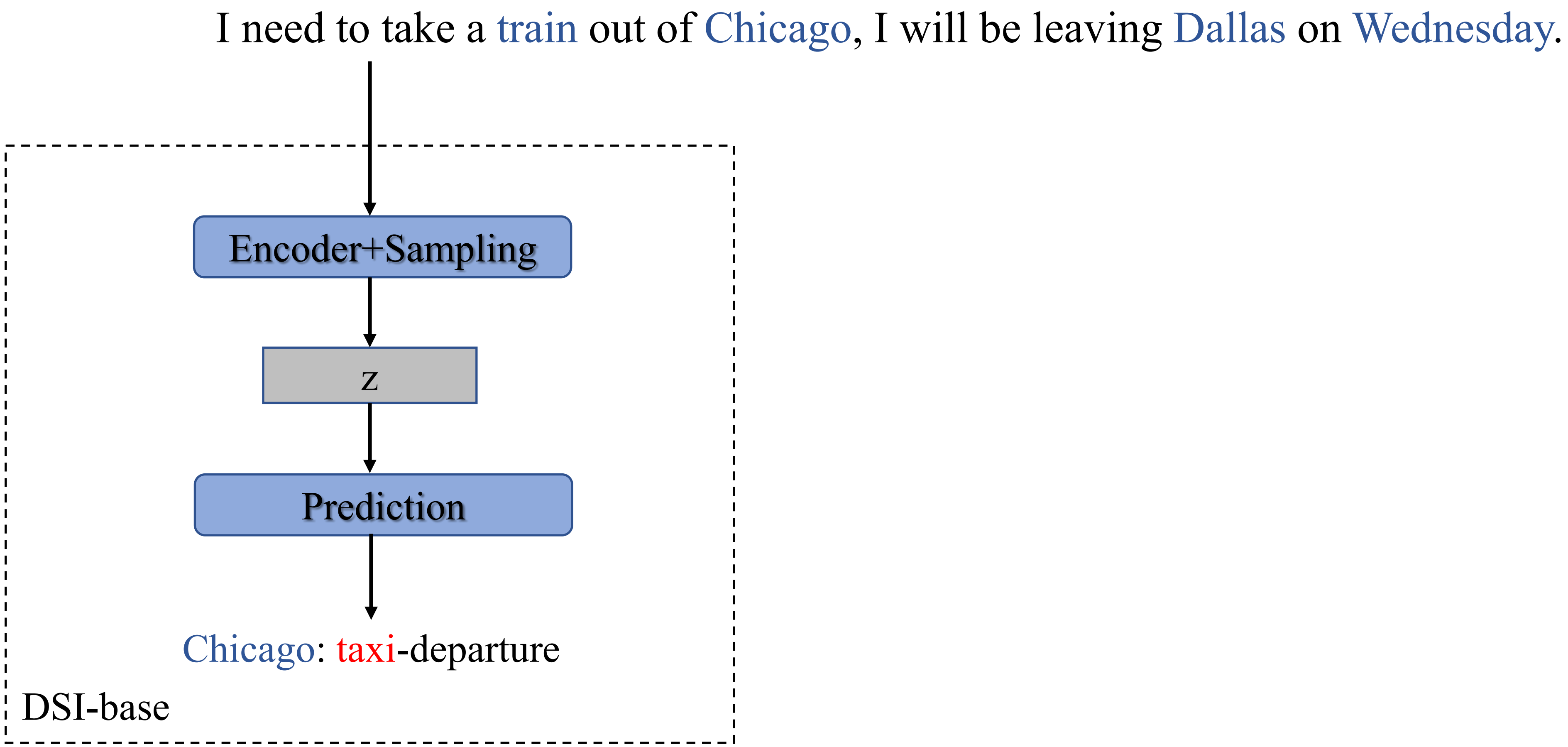


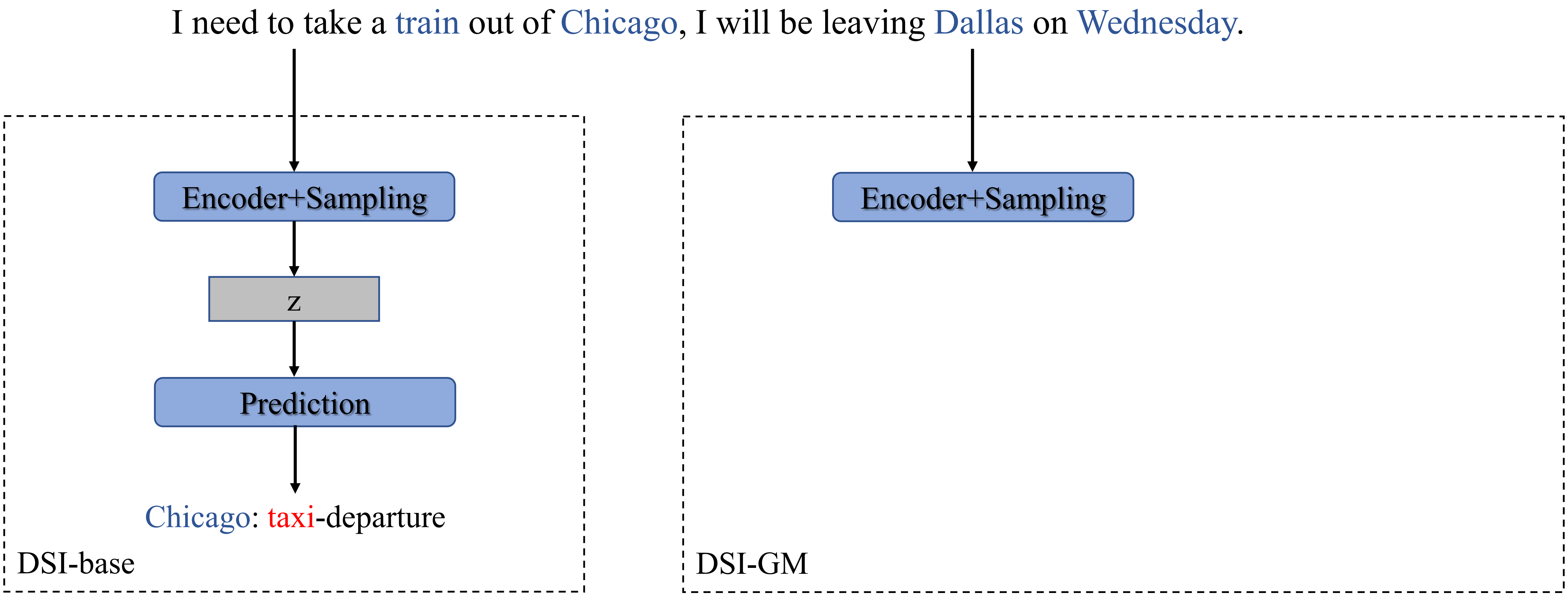
How does *DSI-GM* work?



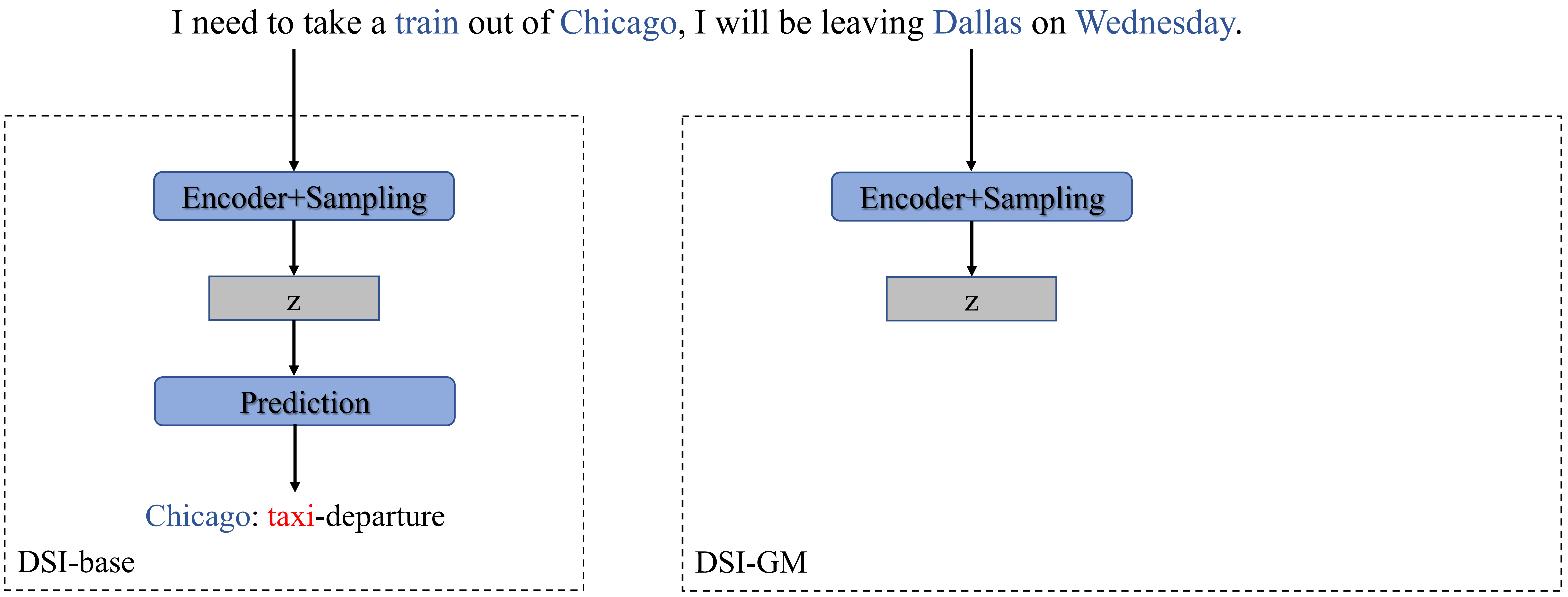
How does *DSI-GM* work?

I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

How does *DSI-GM* work?



How does *DSI-GM* work?



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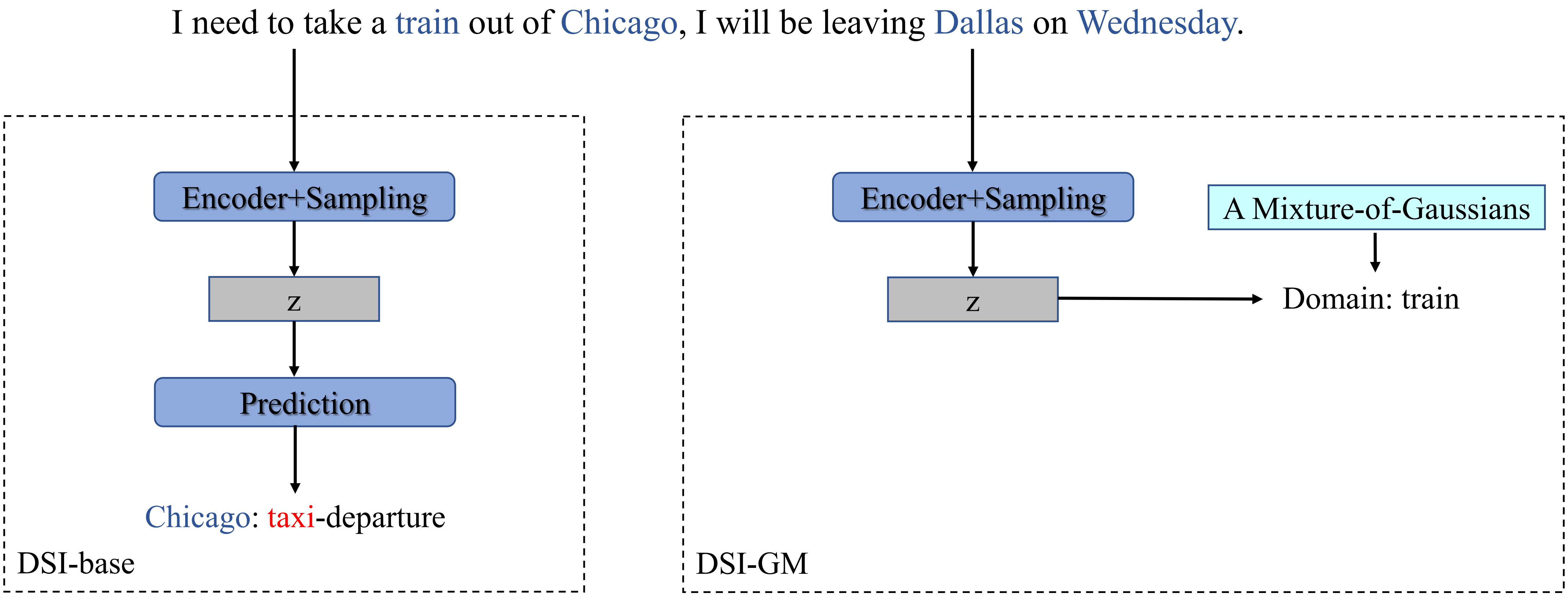
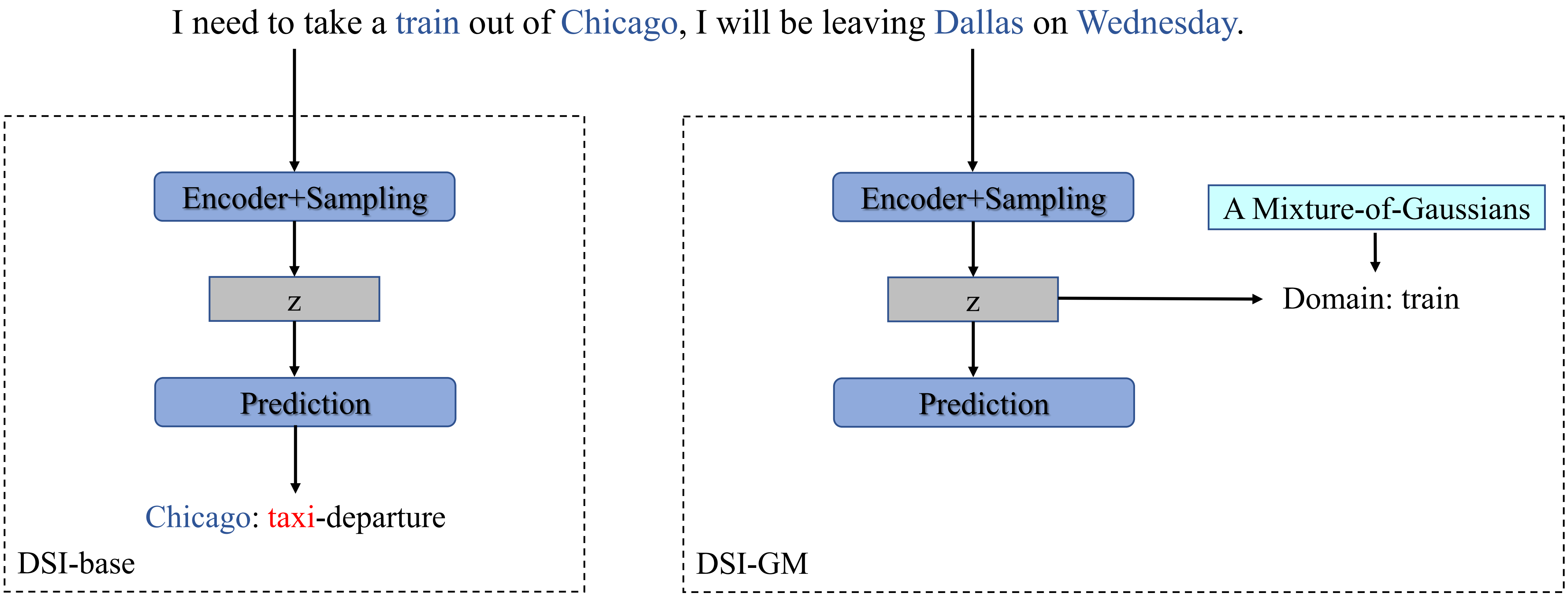
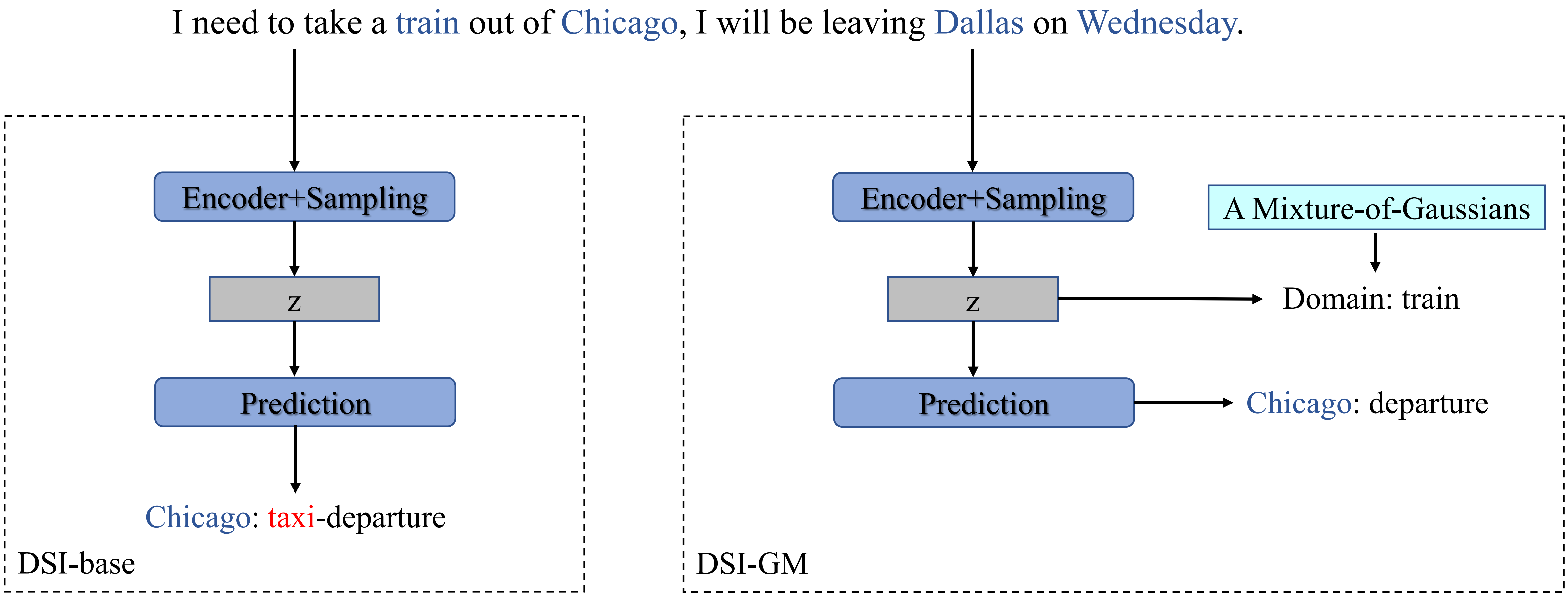


How does *DSI-GM* work?



How does *DSI-GM* work?



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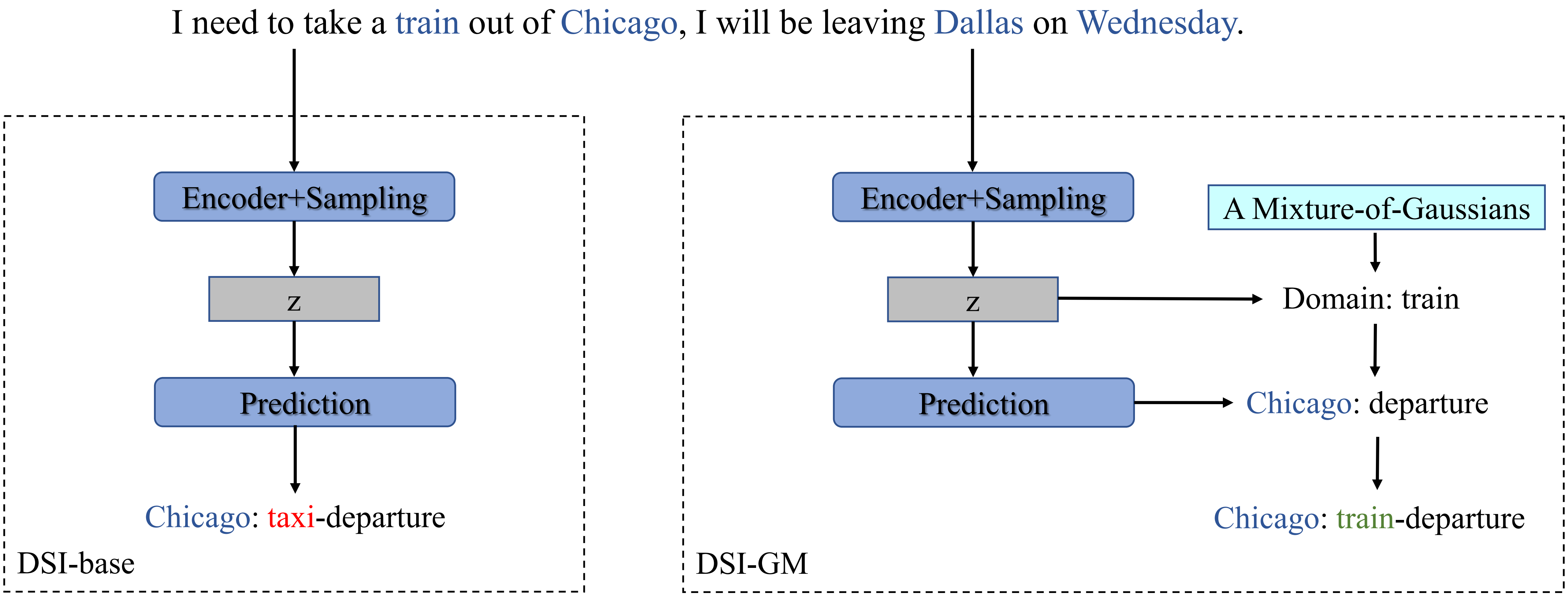

CHAPTER 3

Experiments

DSI results

Models	MultiWOZ 2.1								SGD							
	Turn level				Joint level				Turn level				Joint level			
	Precision	Recall	F1	Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1	Accuracy
Random	1.49	1.51	1.49	1.39	0.21	0.28	0.23	0.02	0.94	0.95	0.94	0.92	0.05	0.08	0.06	0.02
DSI-base	38.8	37.7	37.3	25.7	33.9	32.1	32.1	2.3	27.0	26.0	26.0	21.1	13.9	17.5	14.5	2.3
DSI-GM	52.5	39.3	49.6	36.1	49.2	43.2	44.8	5.0	34.7	33.4	33.5	27.5	19.0	22.9	19.5	3.1

Table 1: Overall results of DSI.

DSI results

Models	MultiWOZ 2.1								SGD							
	Turn level				Joint level				Turn level				Joint level			
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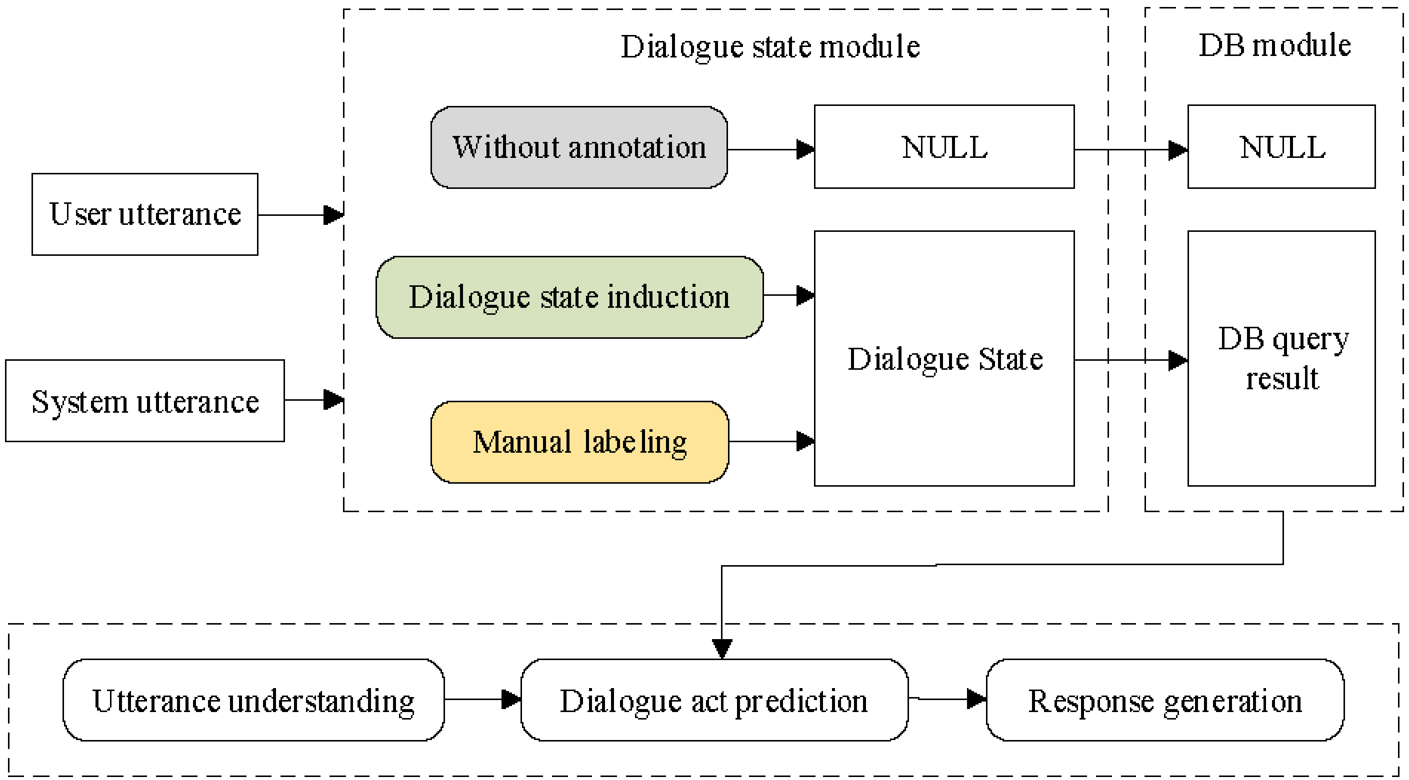
DSI-GM	52.5	39.3	49.6	36.1	49.2	43.2	44.8	5.0	34.7	33.4	33.5	27.5	19.0	22.9	19.5	3.1

Table 1: Overall results of DSI.

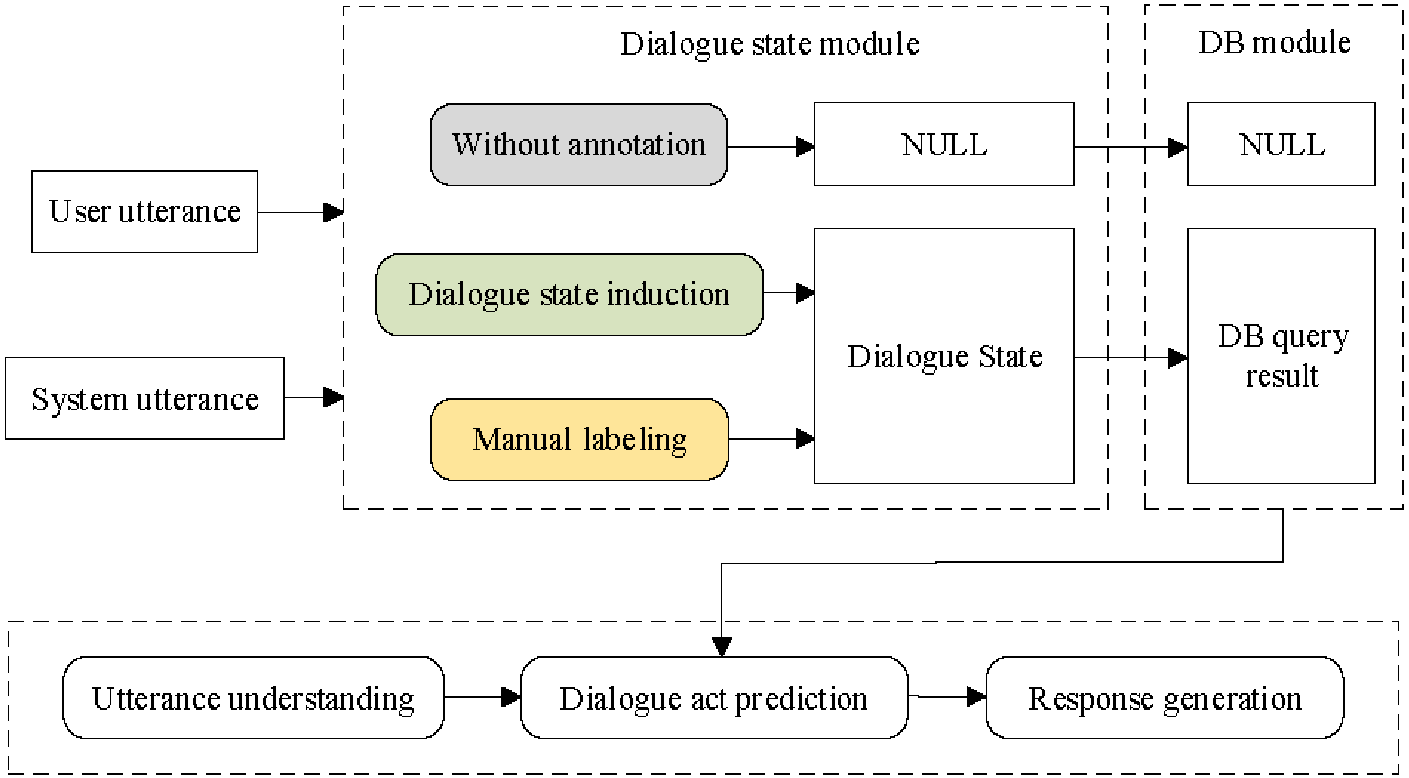
DSI-Based Response Generation

DSI-Based Response Generation



[Chen et al., 2019] Wenhu Chen, Jianshu Chen, Pengda Qin, Xifeng Yan, and William Yang Wang. Semantically conditioned dialog response generation via hierarchical disentangled self-attention. In ACL, 2019.

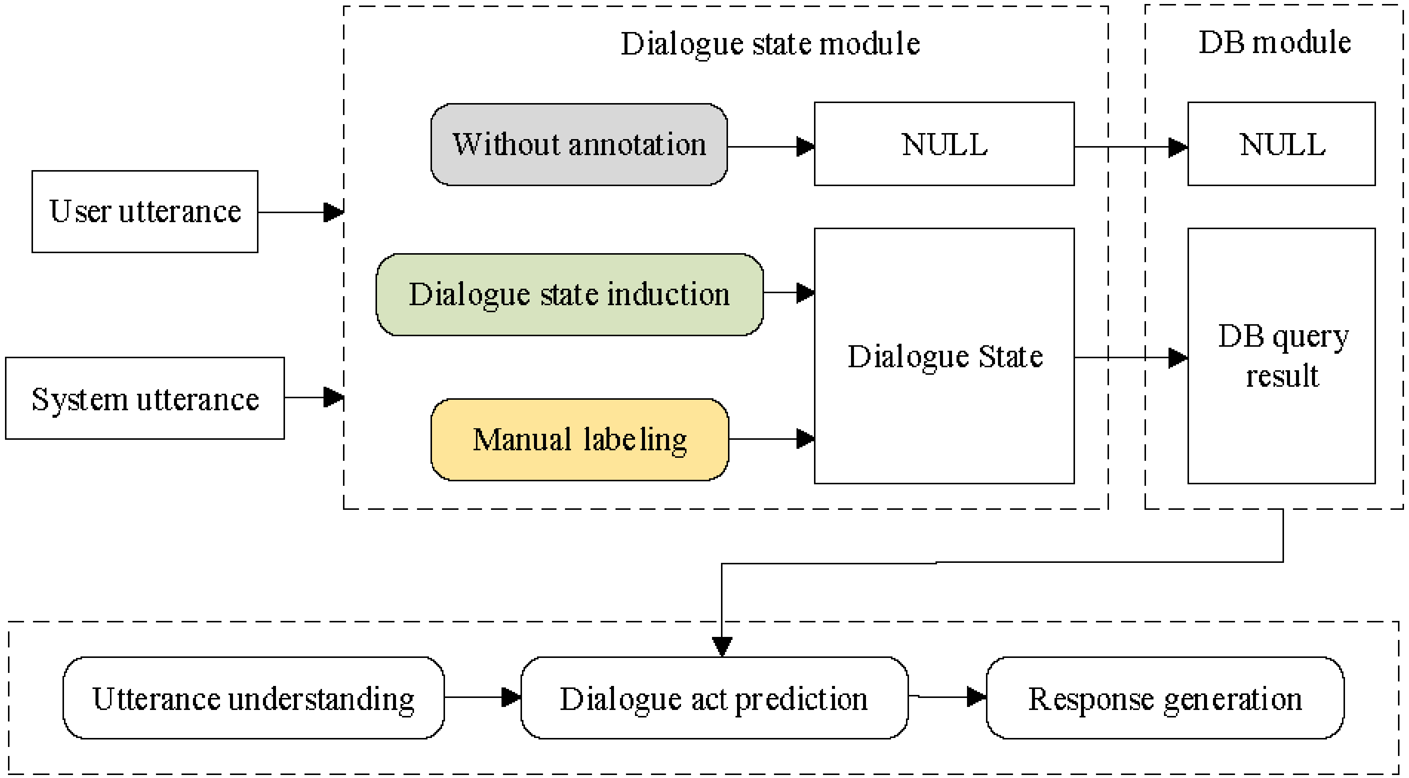
DSI-Based Response Generation



Dialogue State	Dialog Act Prediction			Delexicalized	
	Precision	Recall	F1	BLEU	Entity F1
None	71.0	67.4	69.1	18.7	54.6
DSI-GM	72.0	70.5	71.2	20.8	56.5
Manual labeling	75.6	73.0	74.2	21.6	61.3

[Chen et al., 2019] Wenhu Chen, Jianshu Chen, Pengda Qin, Xifeng Yan, and William Yang Wang. Semantically conditioned dialog response generation via hierarchical disentangled self-attention. In ACL, 2019.

DSI-Based Response Generation



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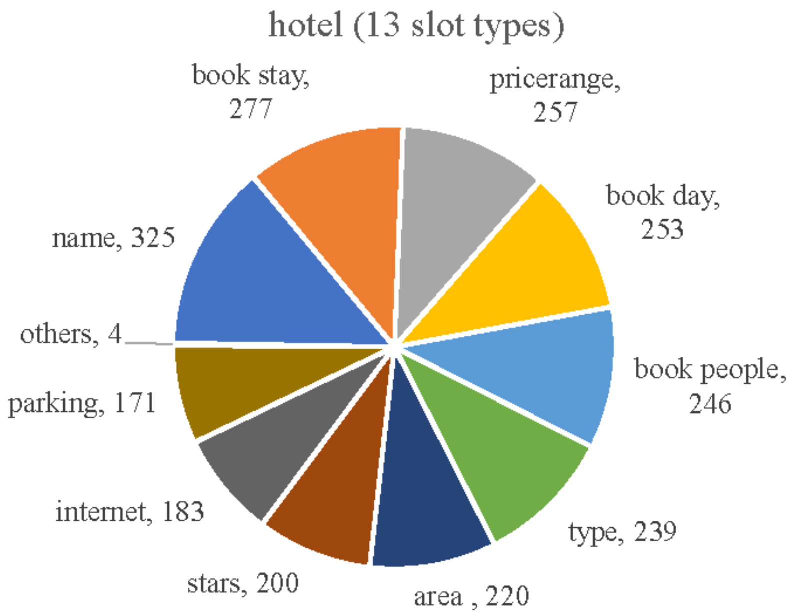
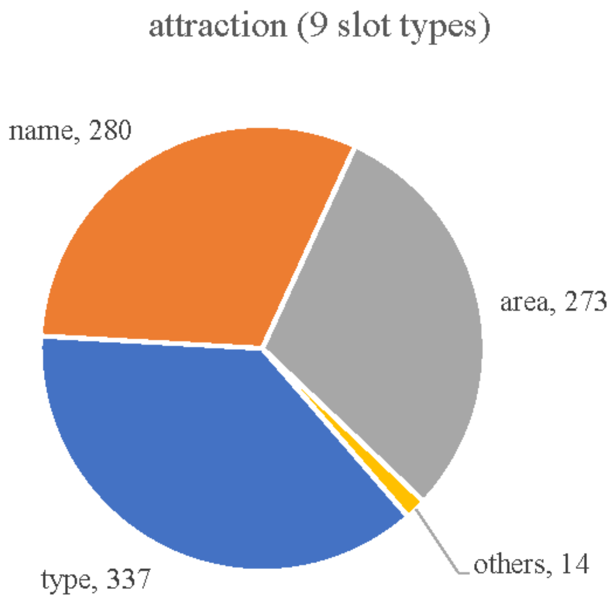
Analysis

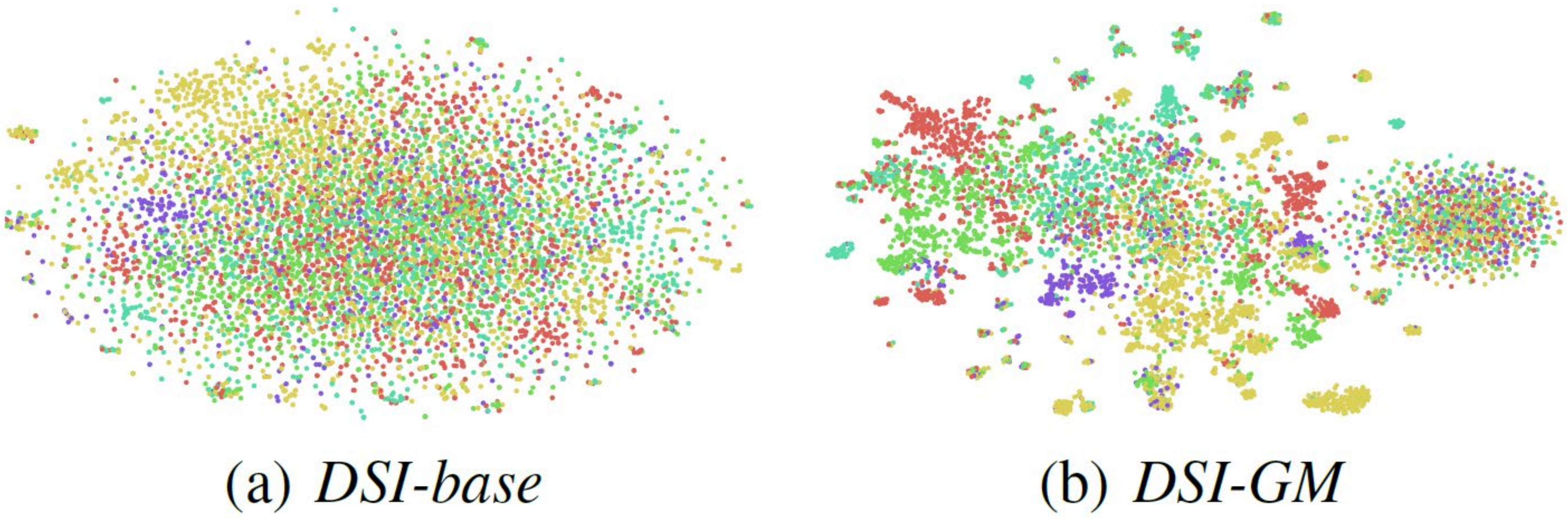
	attraction	hotel	restaurant	taxi	train
DSI-base	27.9	21.7	26.1	30.7	26.0
DSI-GM	40.3	31.4	35.6	39.9	36.8

Table 4: Turn goal accuracy per domain.





Analysis



Domain level comparison of the latent representation z.

CHAPTER 4

Conclusion

Conclusion

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- Dialogue state induction: a novel task to automatically identify dialogue states
- *DSI-base/DSI-GM*: two neural generative models with latent variables
- Challenging and promising: unsupervised setting is very practical
- IJCAI review: this problem is important and interesting, this area should attract more attention. This work has great potential of motivating follow-up research.

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THANK YOU

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minqingkai@westlake.edu.cn

Paper:
https://www.ijcai.org/Proceedings/2020/0532.pdf

GitHub:
https://github.com/taolusi/dialogue-state-induction

paper

GitHub