Dialogue State Induction Using Neural Latent Variable Models

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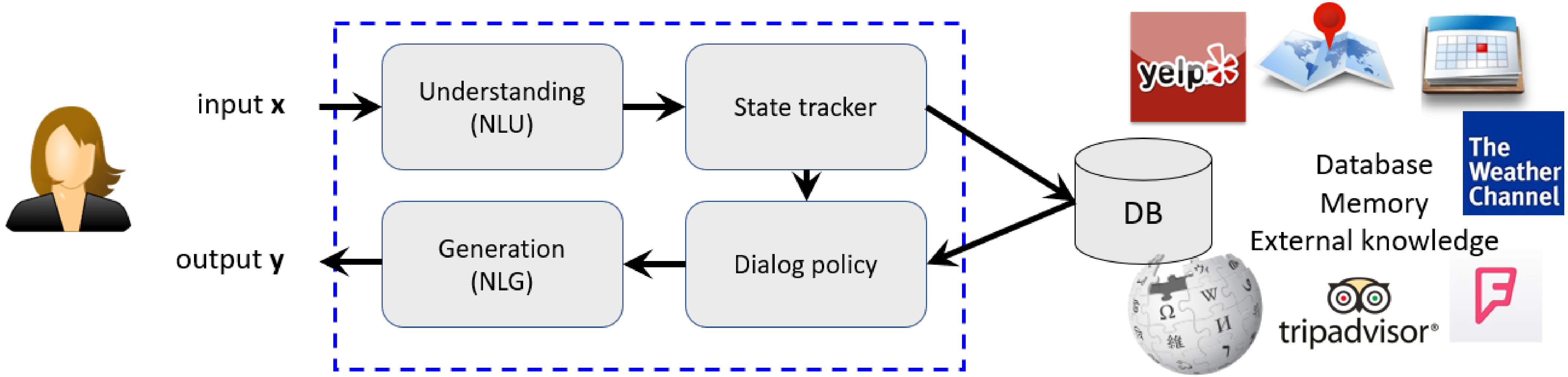
CHAPTER 1

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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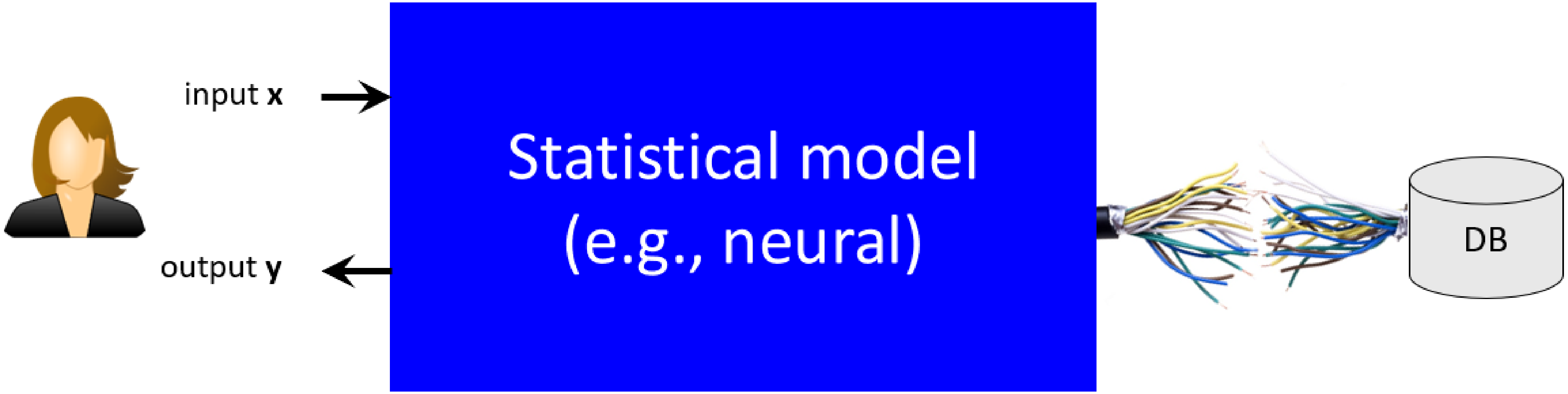

End-to-end architecture

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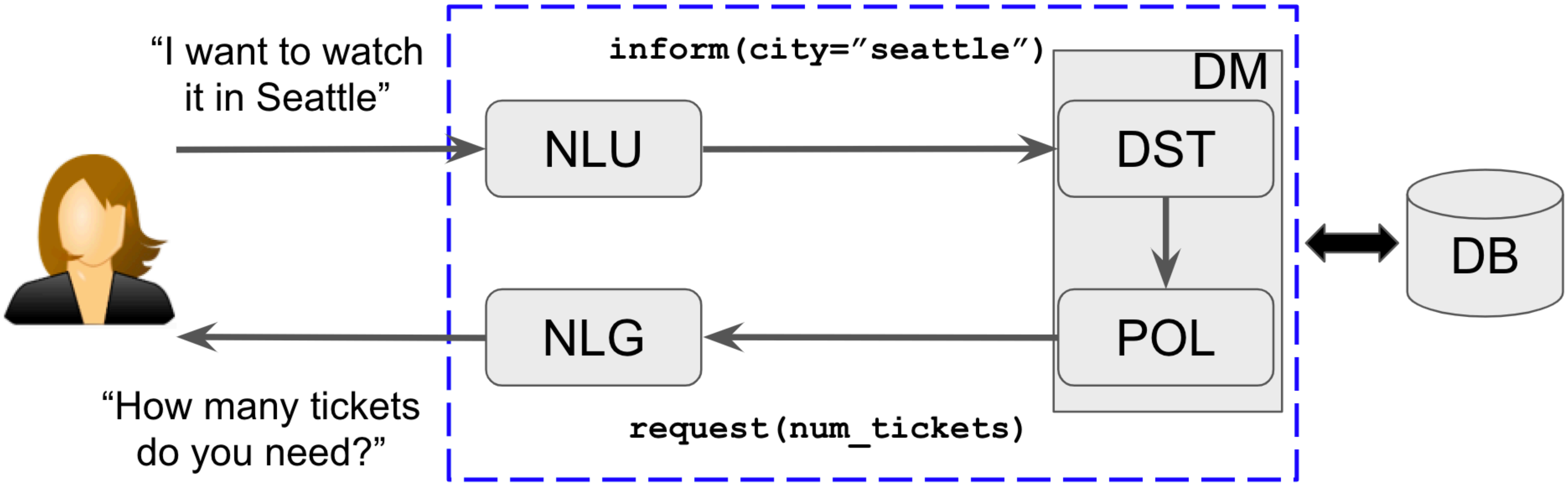

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The dialogue state represents what the user is looking for at the current turn of the conversation.

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Current DST scenarios

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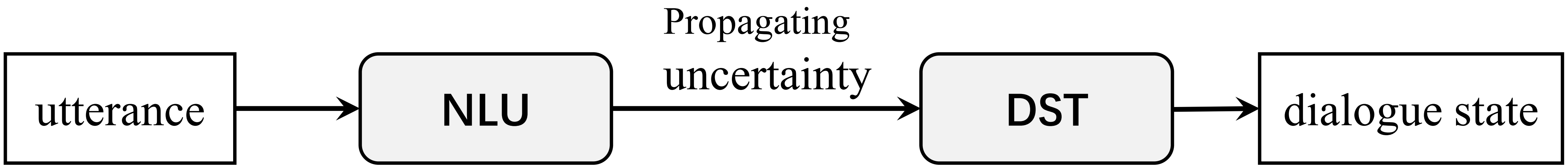

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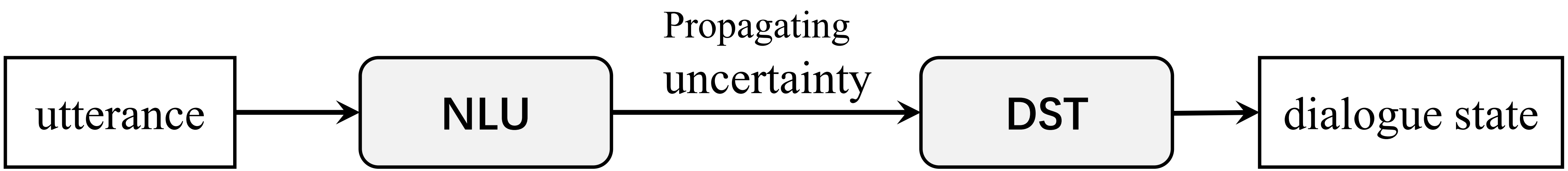

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manual labeling → corpus → **train** → DST model → **test**

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- 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.
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now updated to → MultiWOZ 2.2

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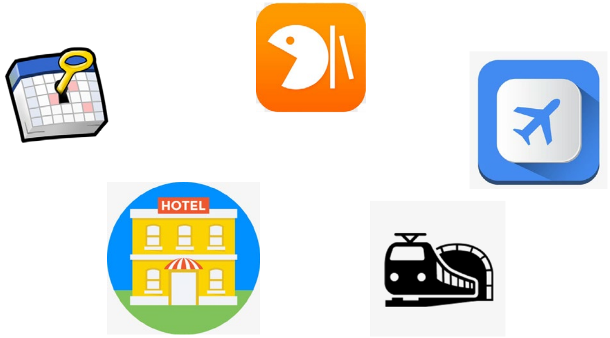
Successful in narrow domains with large annotated datasets



CHAPTER 1

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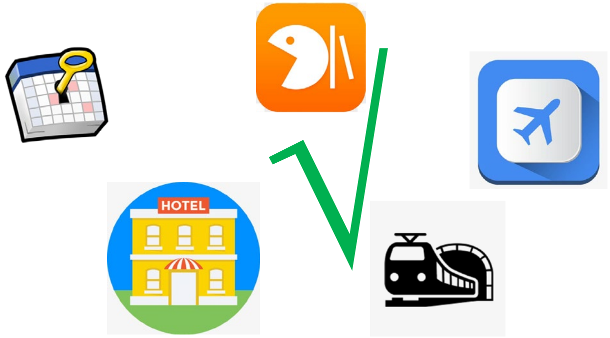

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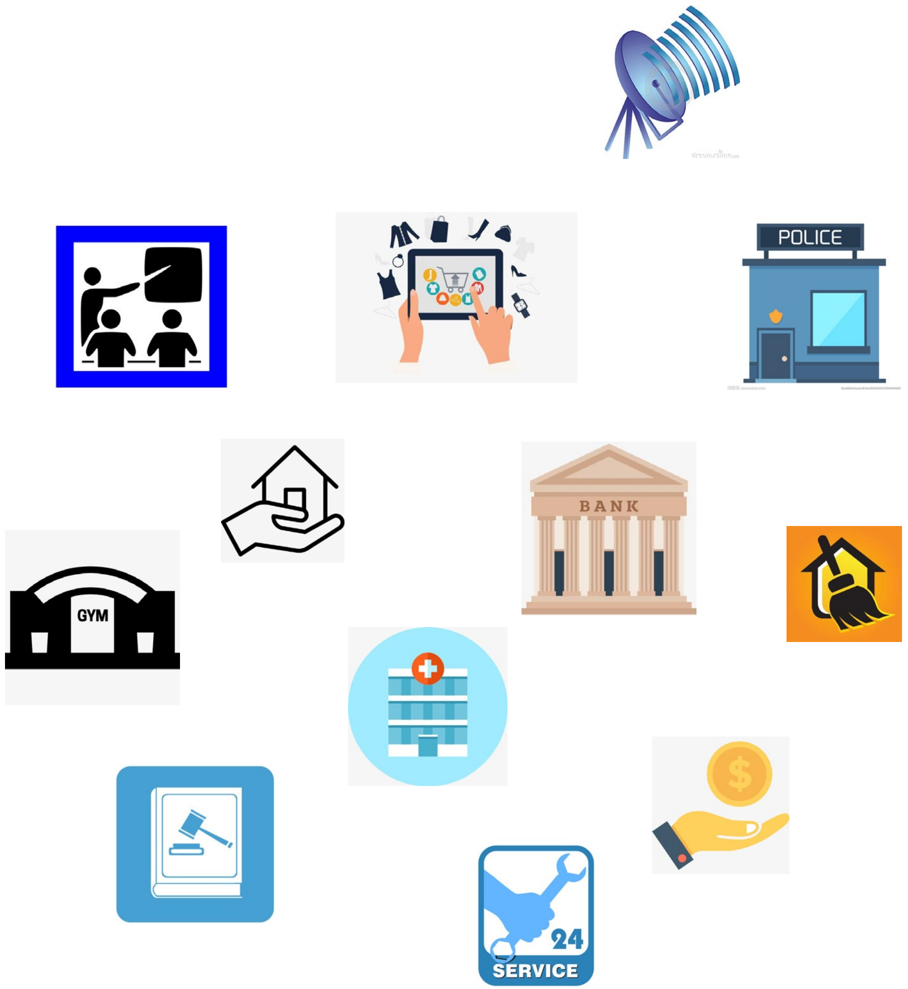

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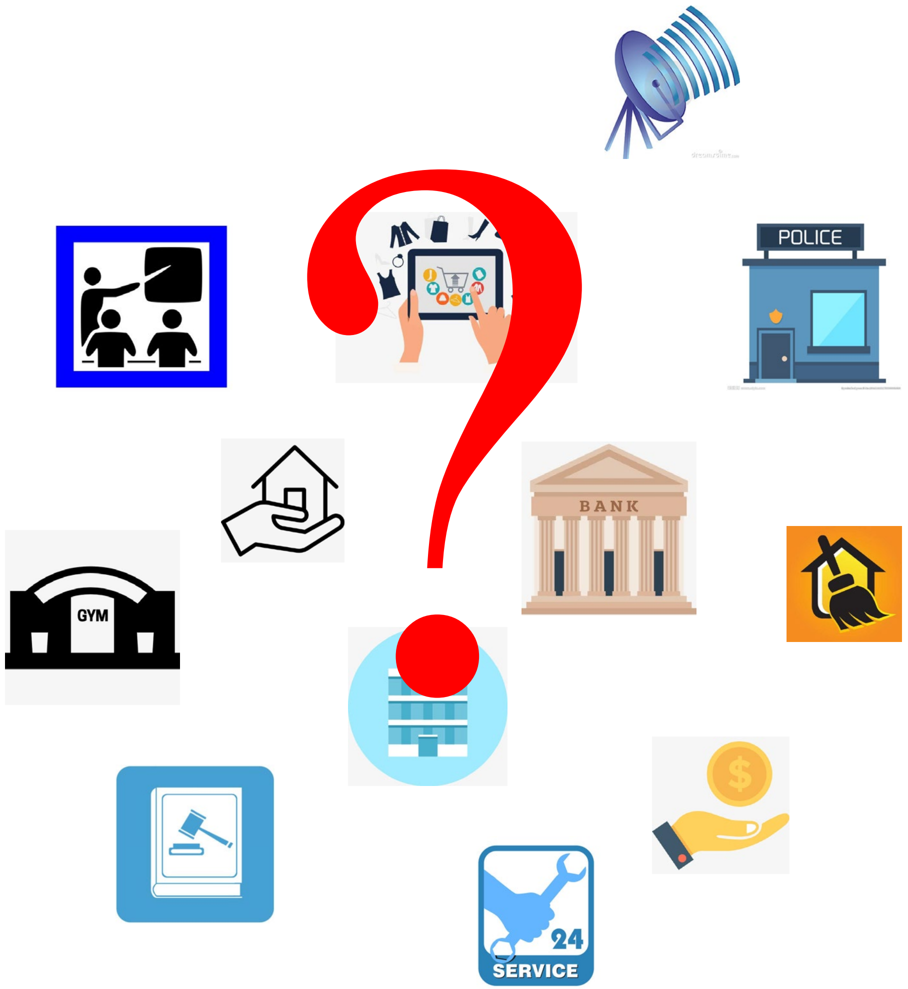

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Definition:

What is given?

A set of customer service records without annotation.

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

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DSI

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DSI VS zero-shot DST

Zero-shot DST: support unseen domains (services)

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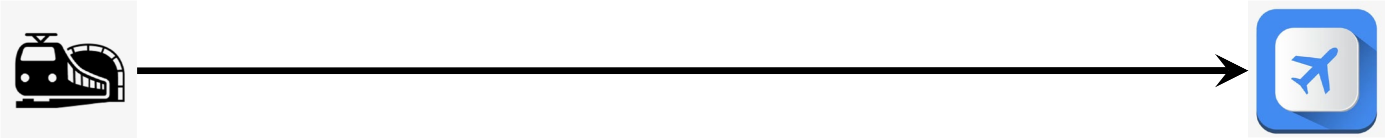
Motivation: Different domains (services) with similar schemas

DSI VS zero-shot DST

Zero-shot DST: support unseen domains (services)

Motivation: Different domains (services) with similar schemas



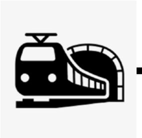
service_name: "Trains"	**Service**
name: "from"	**Slots**
name: "to"	

service_name: “Flights"	**Service**
name: "origin"	**Slots**
name: "destination"	

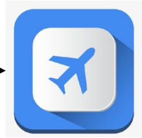
DSI VS zero-shot DST

Zero-shot DST: support unseen domains (services)

Motivation: Different domains (services) with similar schemas



slots along with their natural language description



Service service_name: "Trains" description: “Service to find train journeys between cities"	**Service** service_name: “Flights" description: "Search for cheap flights across multiple providers"
Slots name: "from" description: “Starting city for train journey"	**Slots** name: "origin" description: “City of origin for the flight"
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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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- High qualified (consistent) human annotation
- Transfer to distant domain (service)

DSI VS zero-shot DST

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description: "Ending city for the train journey"

consistency

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

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

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

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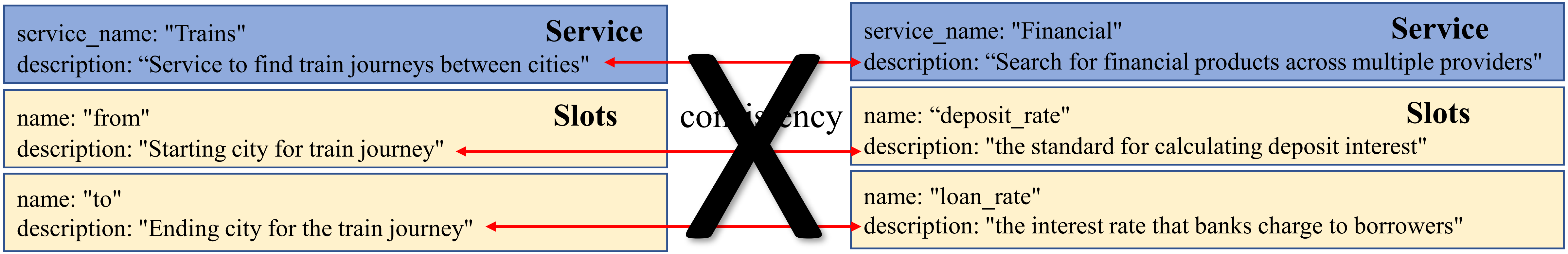

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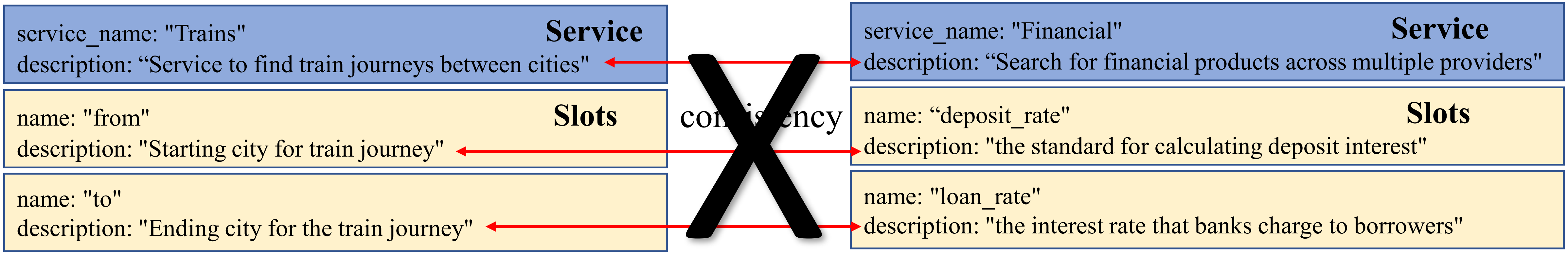

Zero-shot DST Limitations:

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DSI features:

- Release human burden
- Data-driven: automatically discover

CHAPTER 2

Method

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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*)

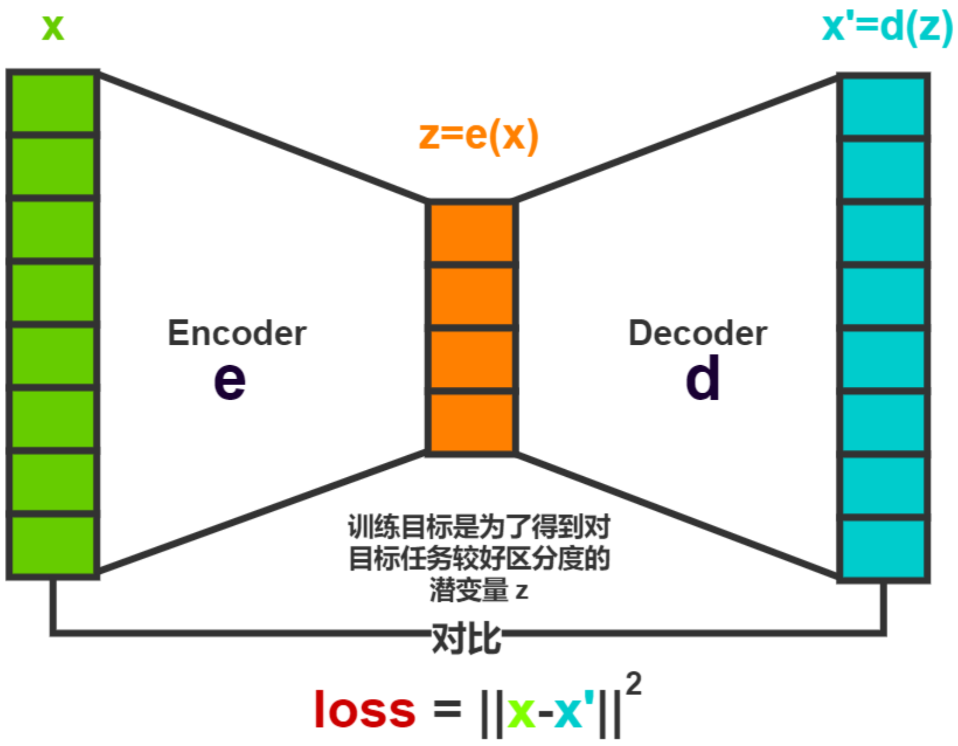
Utterance: I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

train, Chicago, Dallas, Wednesday

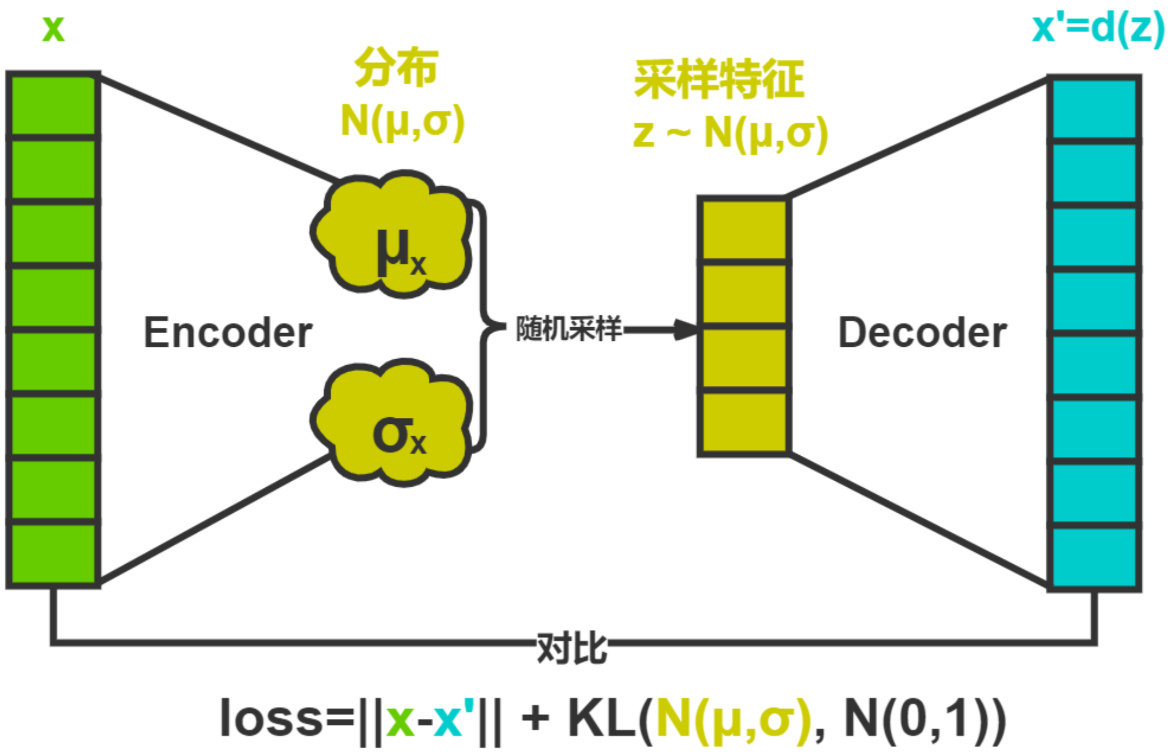
```
Inform{train-departure=Chicago,
train-destination=Dallas,
train-leave at=Wednesday}
```

~~train=None~~

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.

$\left.\vphantom{\begin{matrix}a\\b\\c\\d\\e\\f\end{matrix}}\right\}$ **Encoder**

Model: generative *DSI-base*

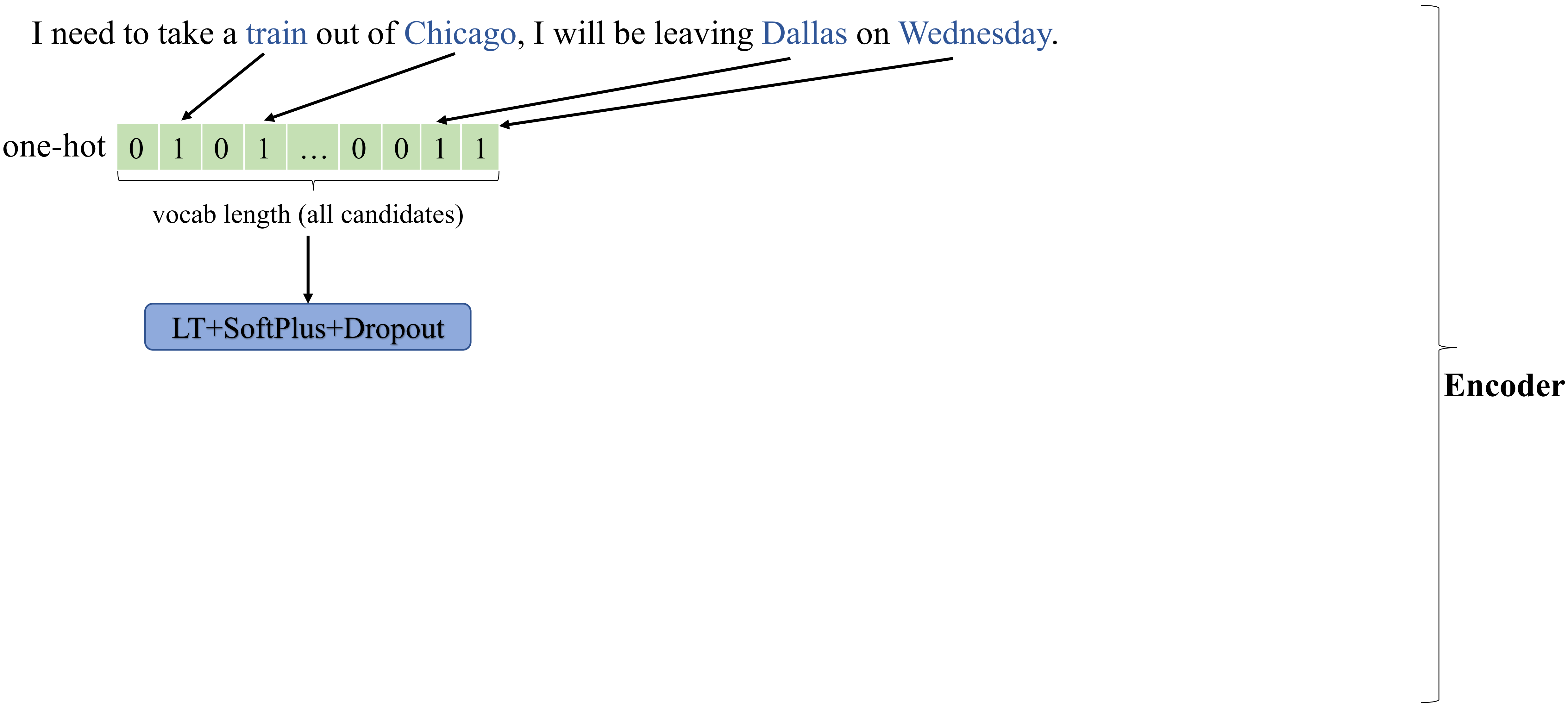
I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

one-hot									
	0	1	0	1	…	0	0	1	1

vocab length (all candidates)

Encoder

Model: generative *DSI-base*



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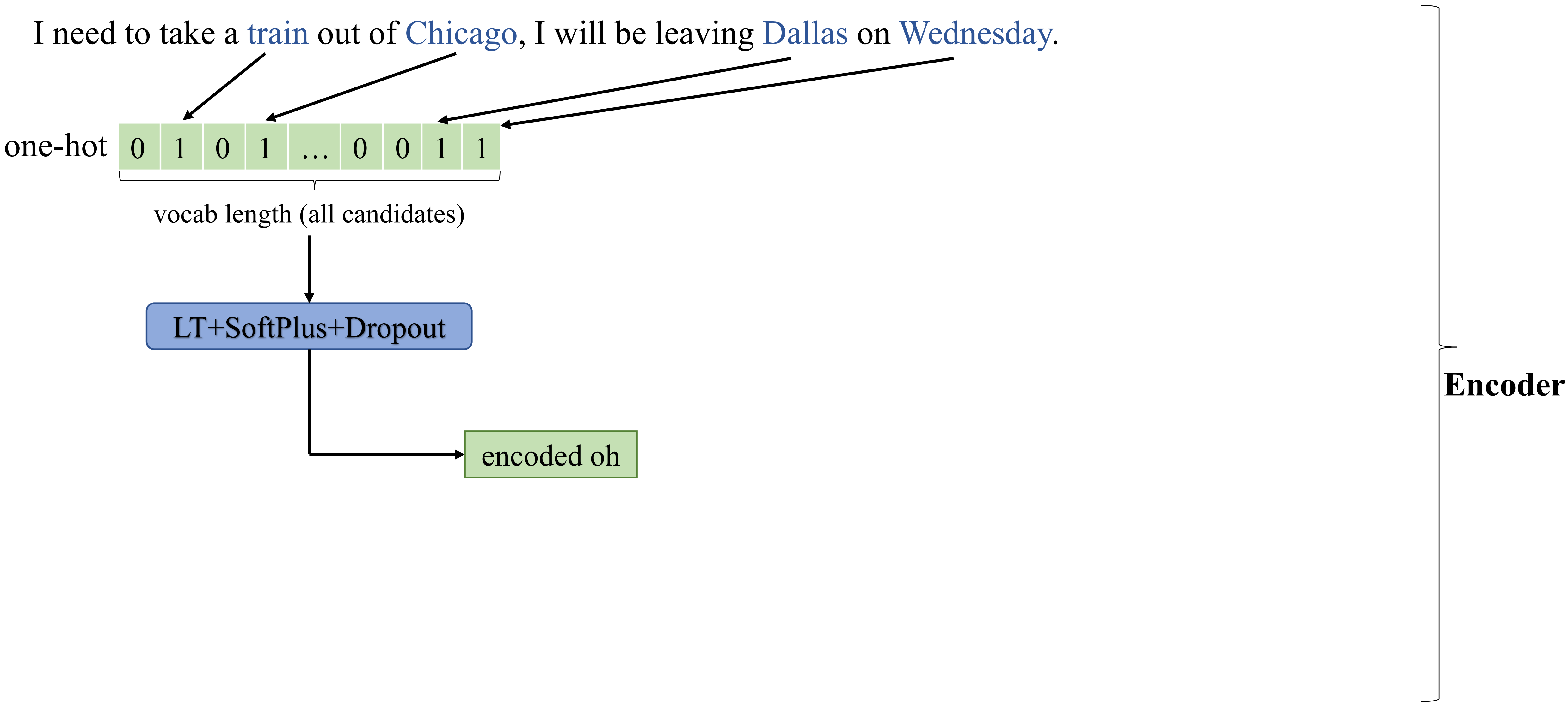

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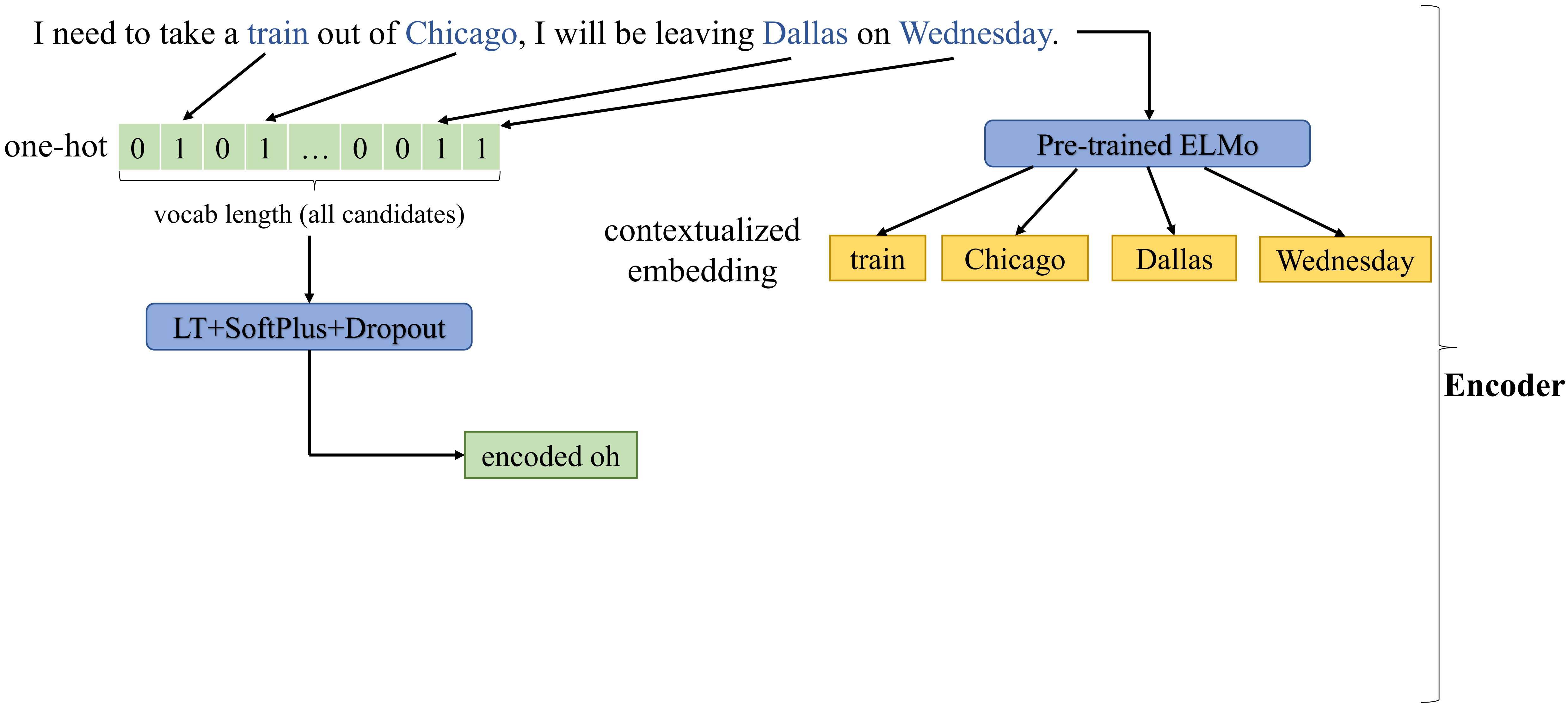

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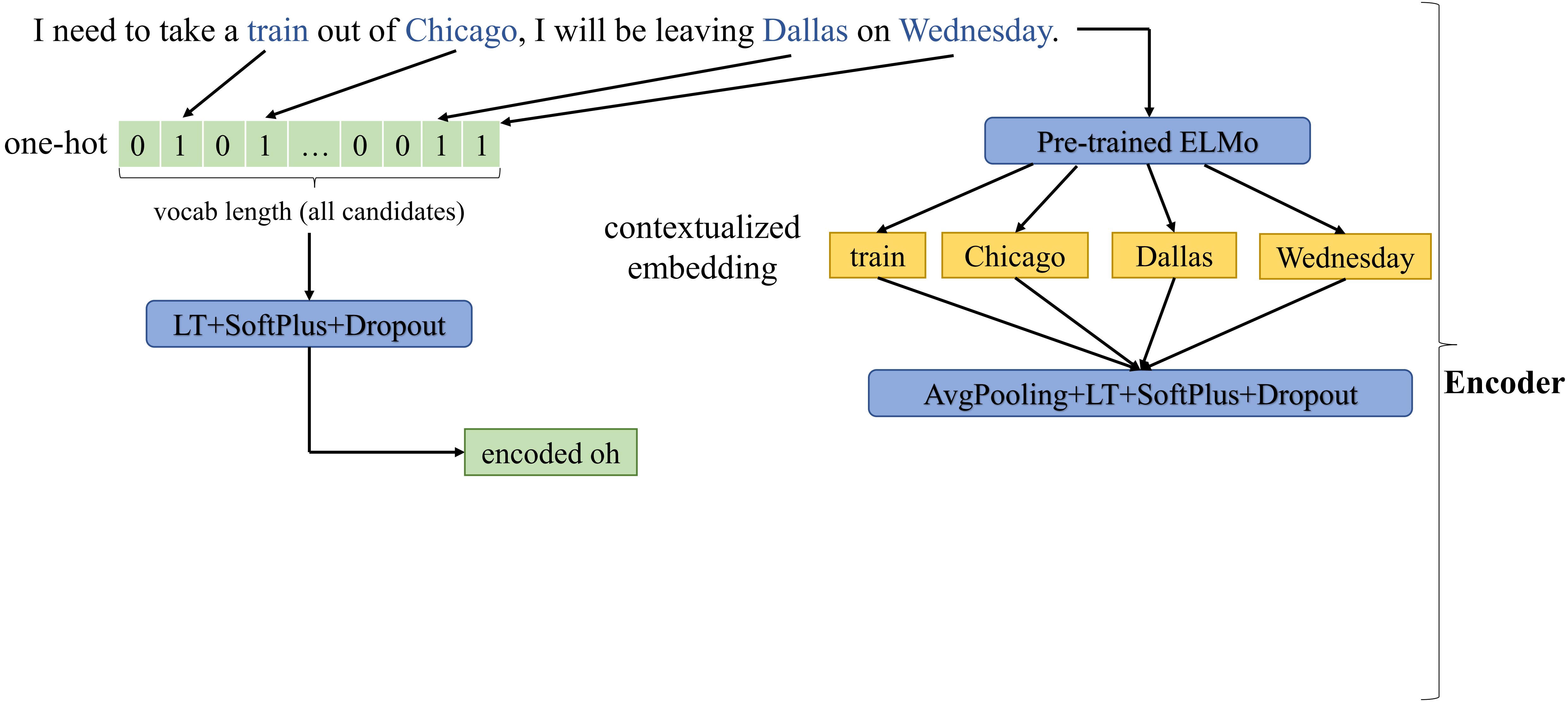

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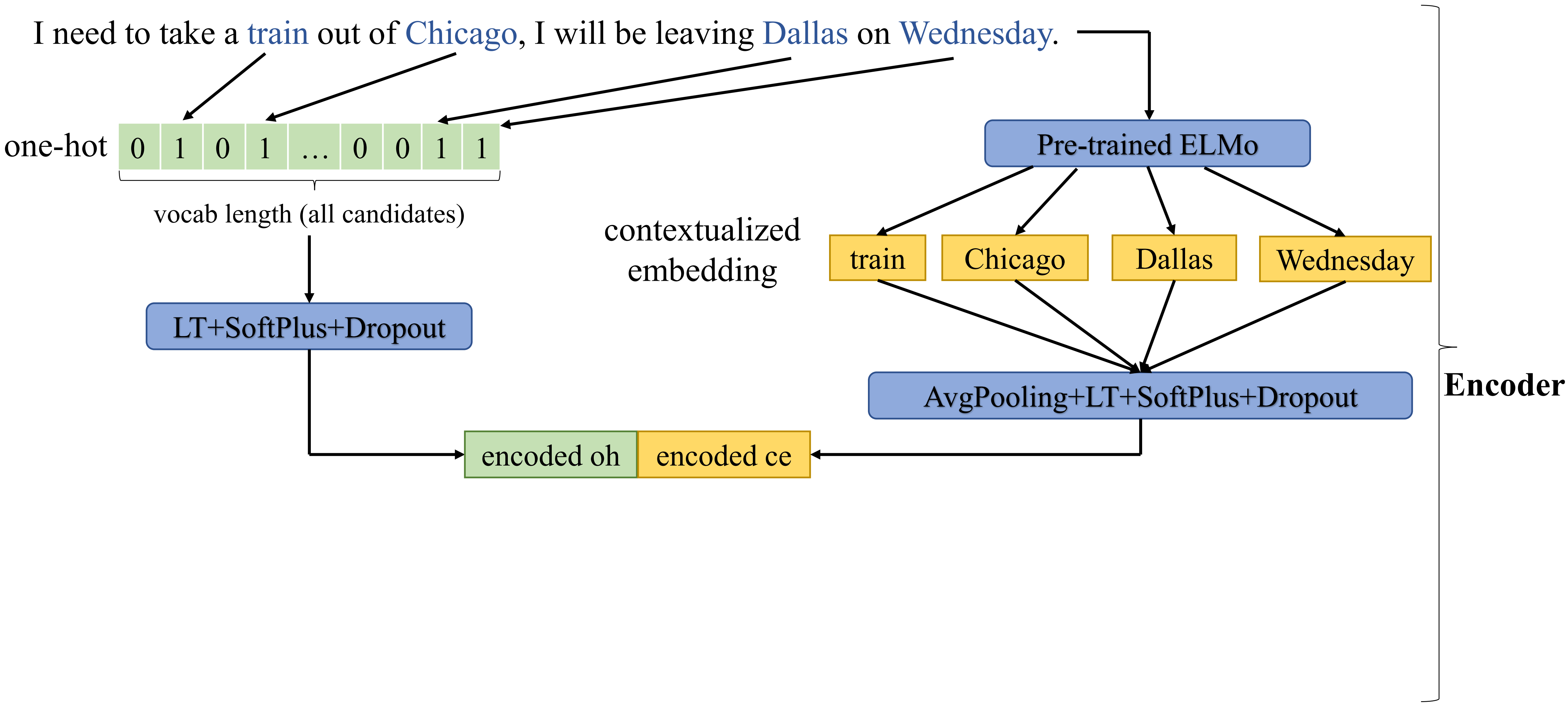

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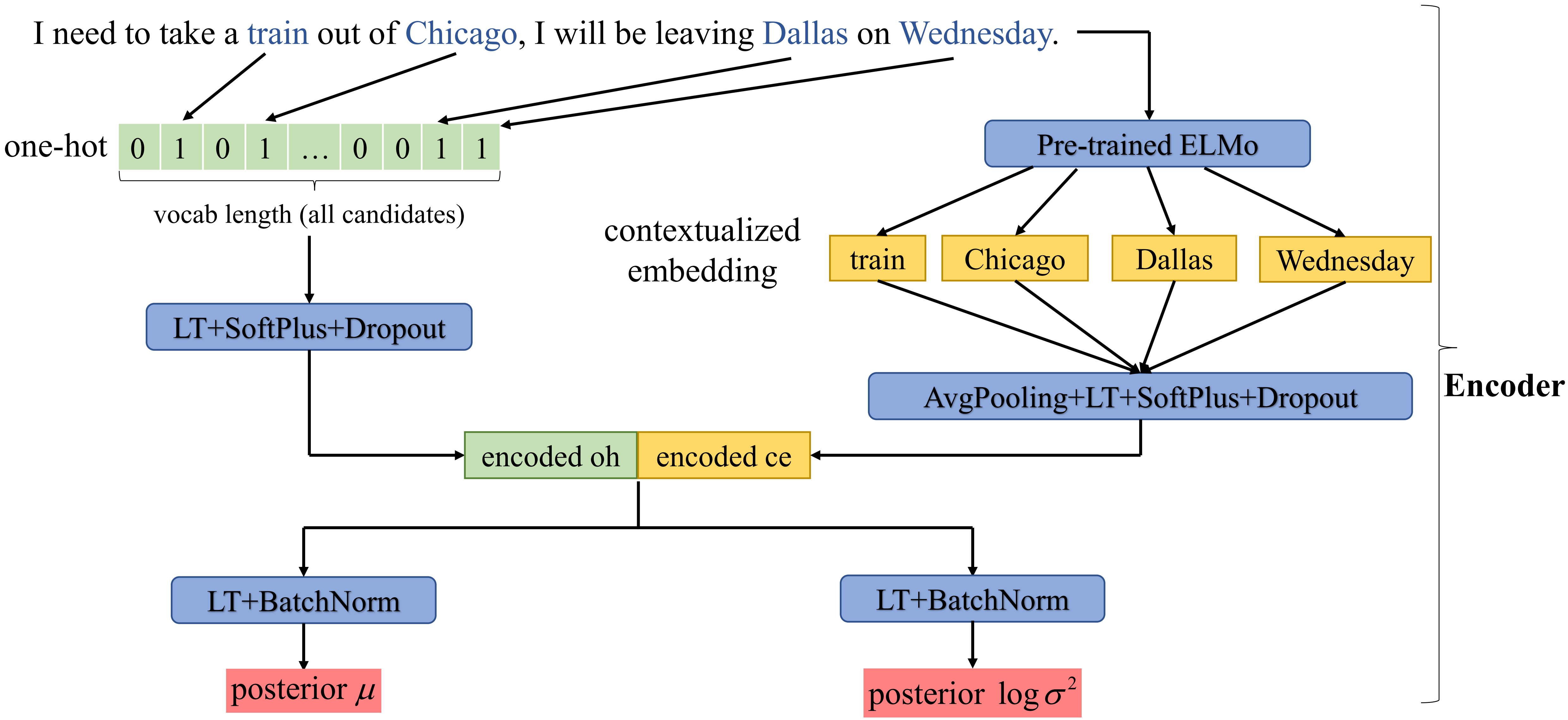


Model: generative *DSI-base*

posterior μ

posterior $\log \sigma^2$

Model: generative *DSI-base*

posterior μ

posterior $\log \sigma^2$

Sampling

Model: generative *DSI-base*

posterior μ

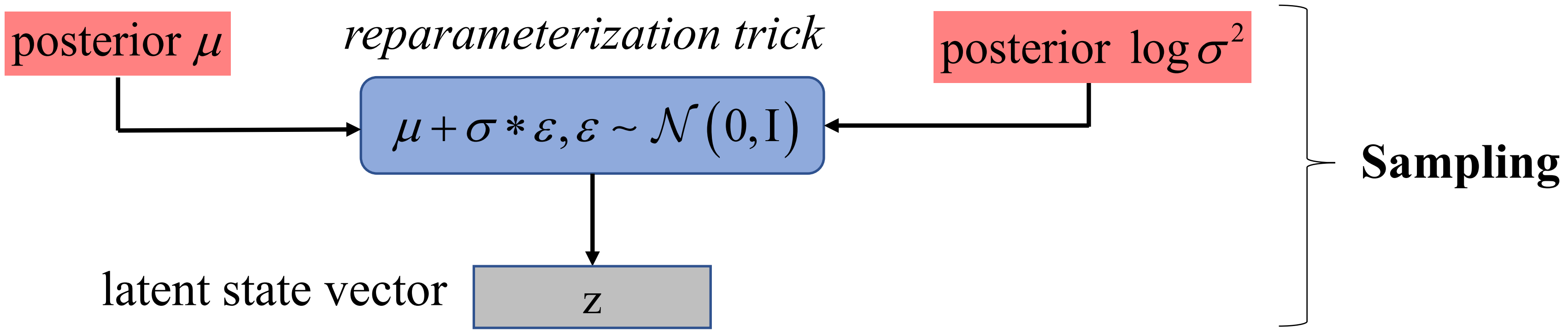
reparameterization trick

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

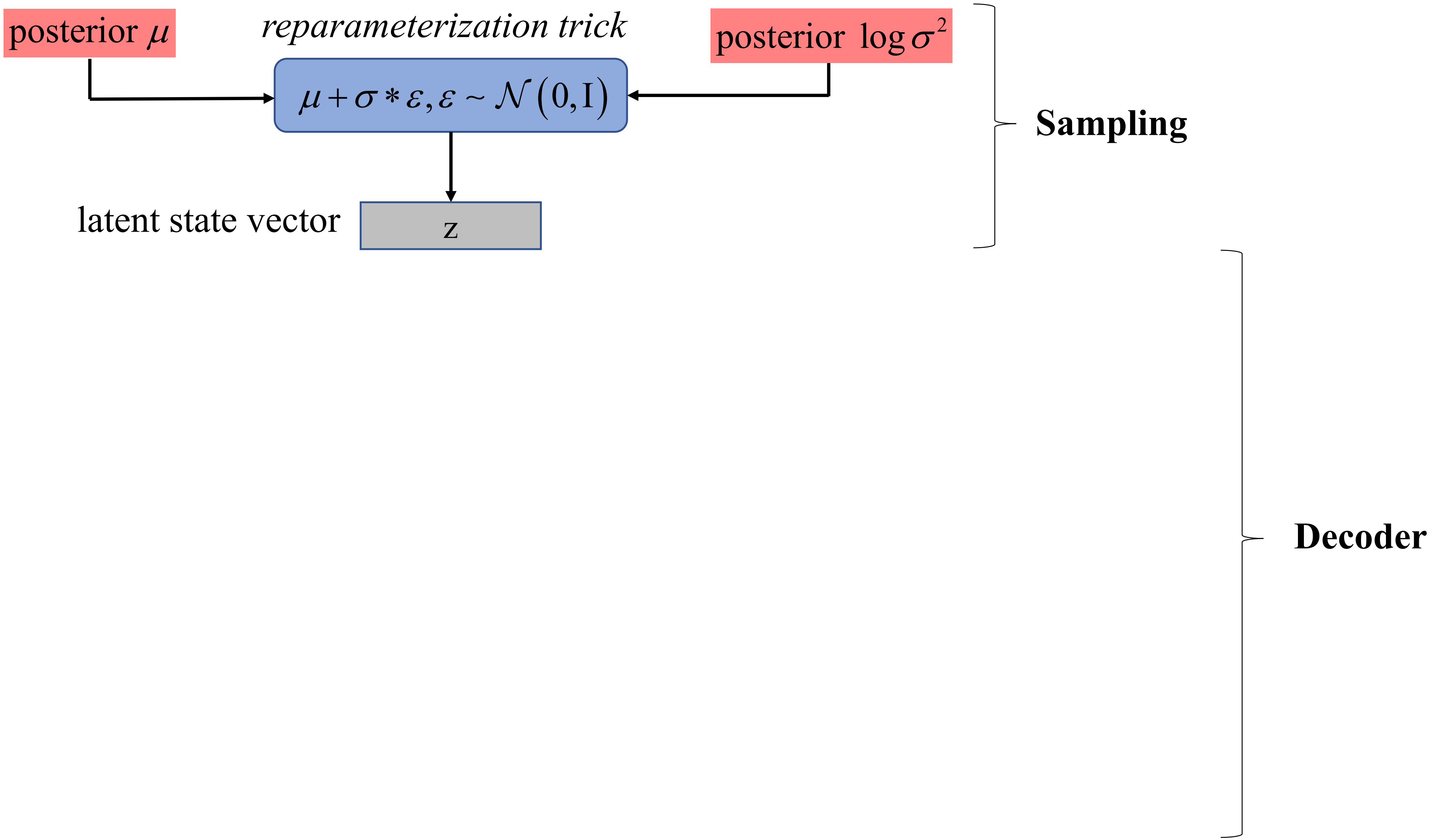
posterior $\log \sigma^2$

Sampling

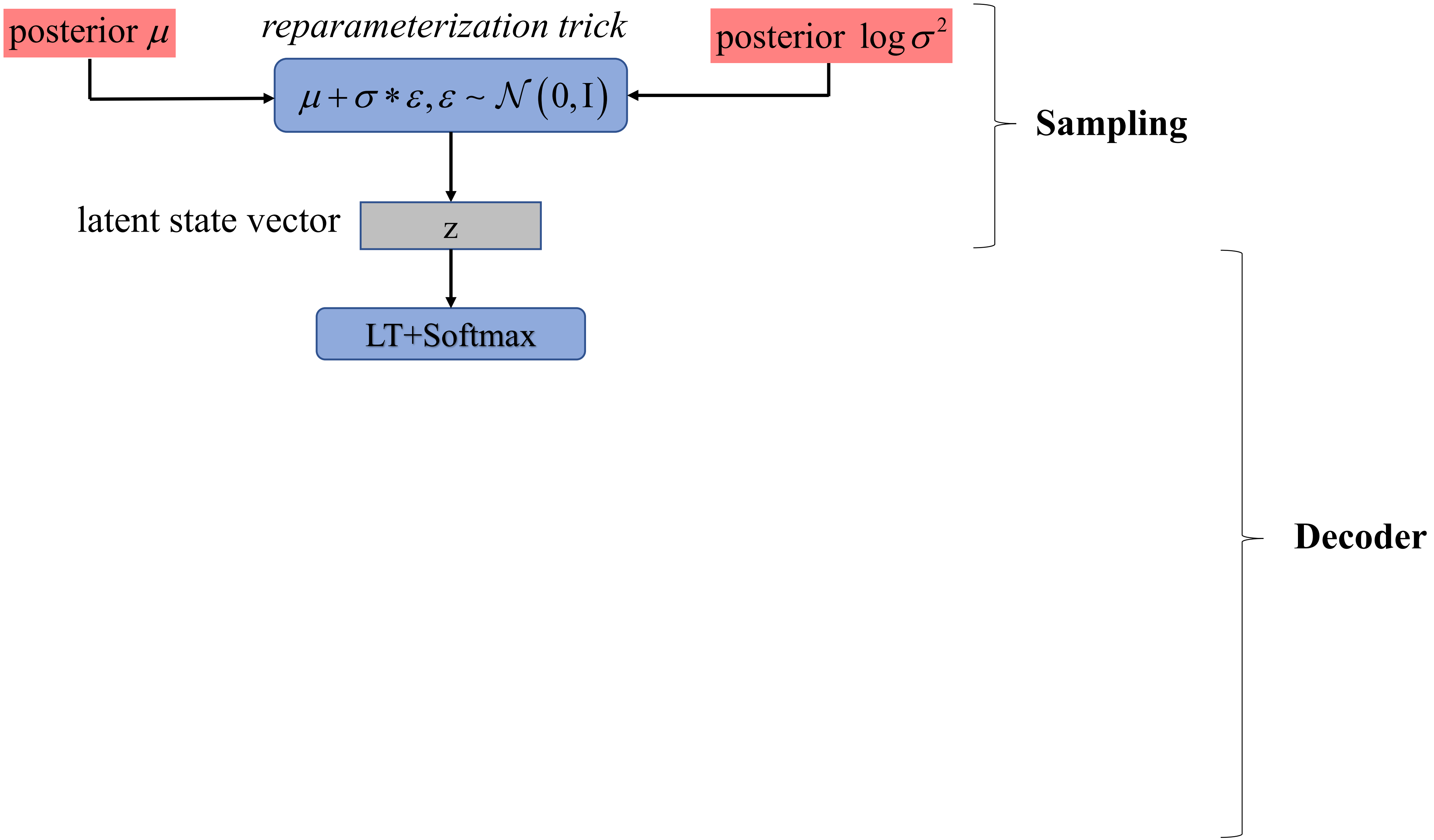
Model: generative *DSI-base*



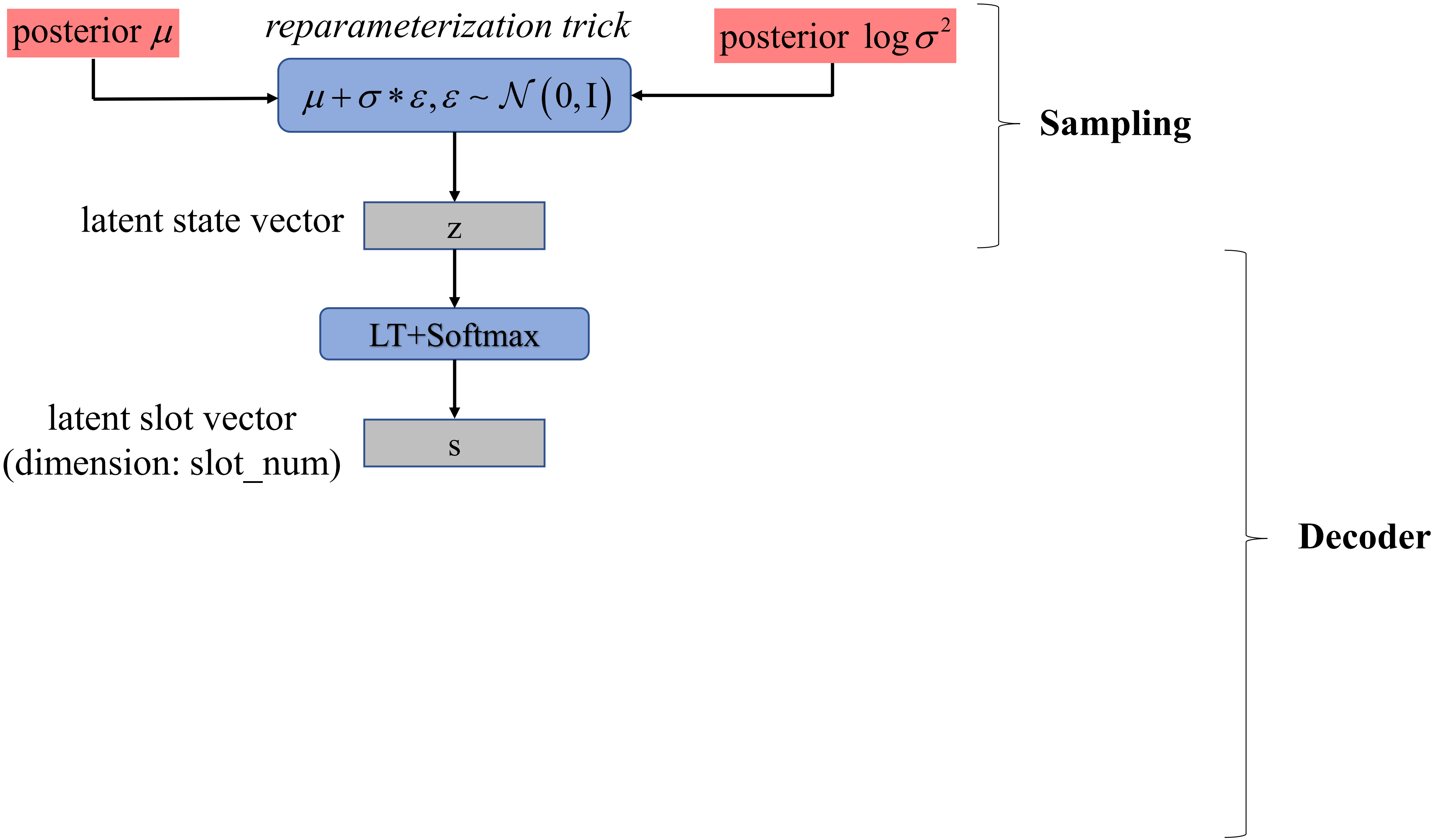
Model: generative *DSI-base*



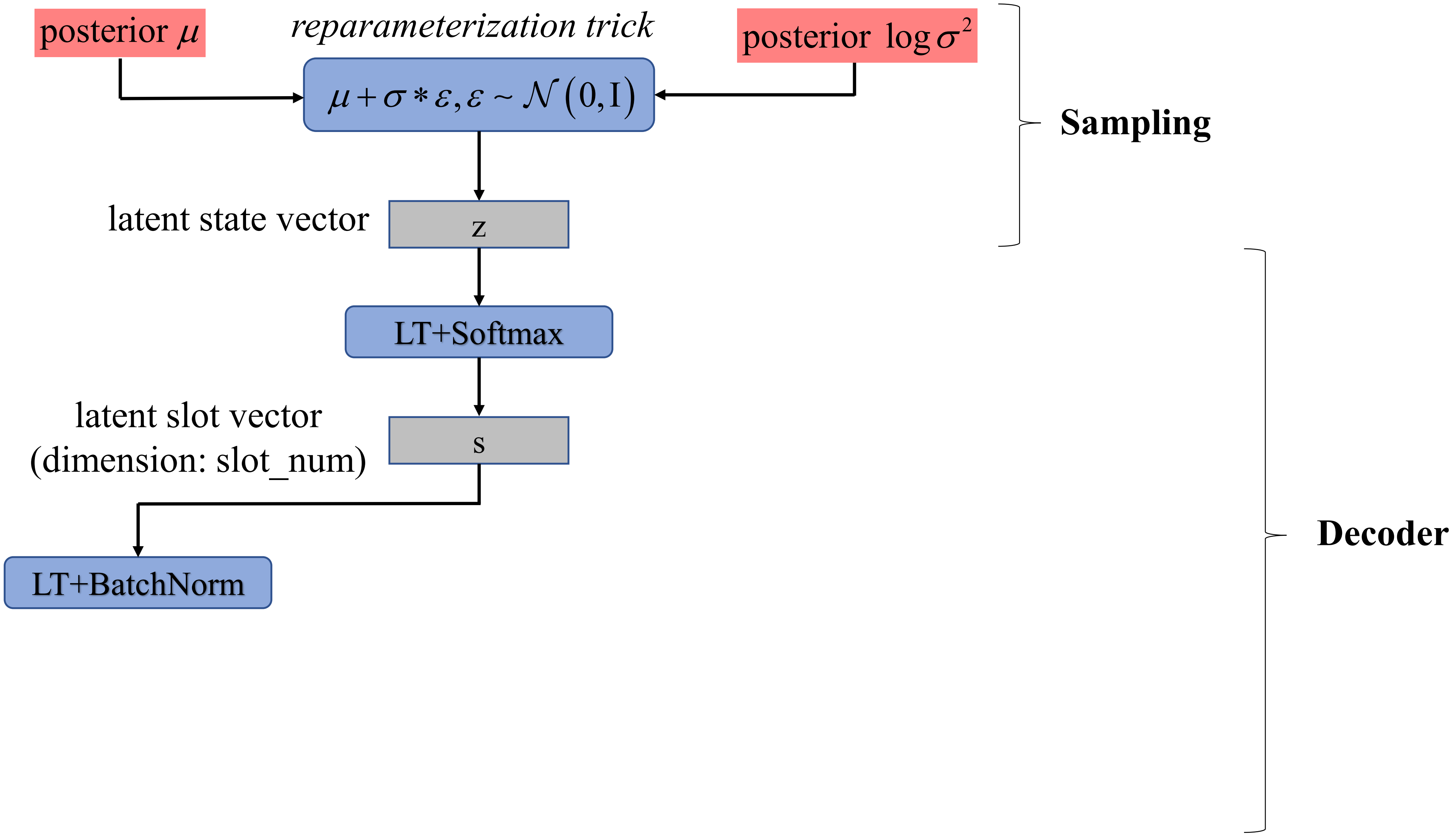
Model: generative *DSI-base*



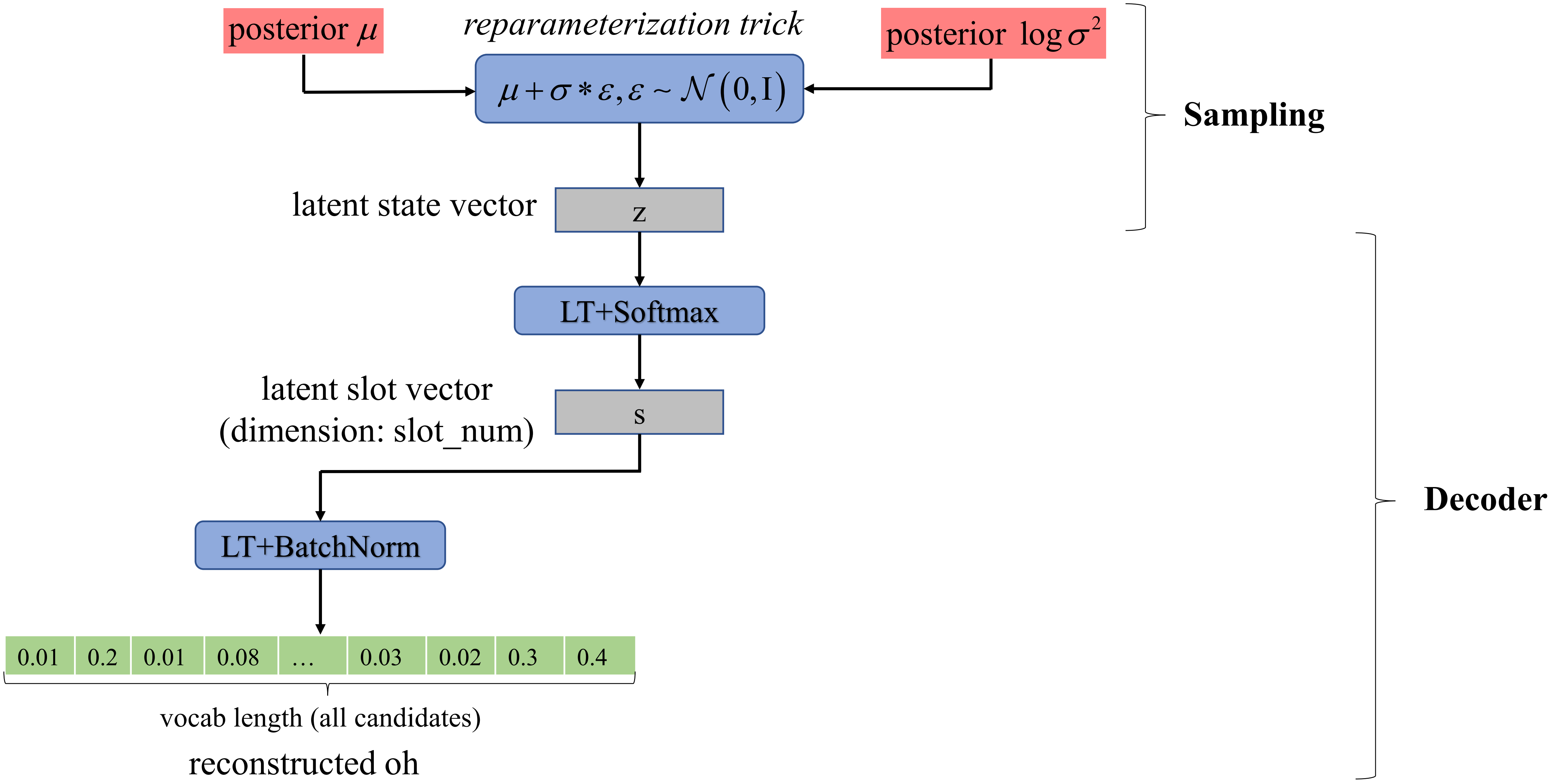
Model: generative *DSI-base*



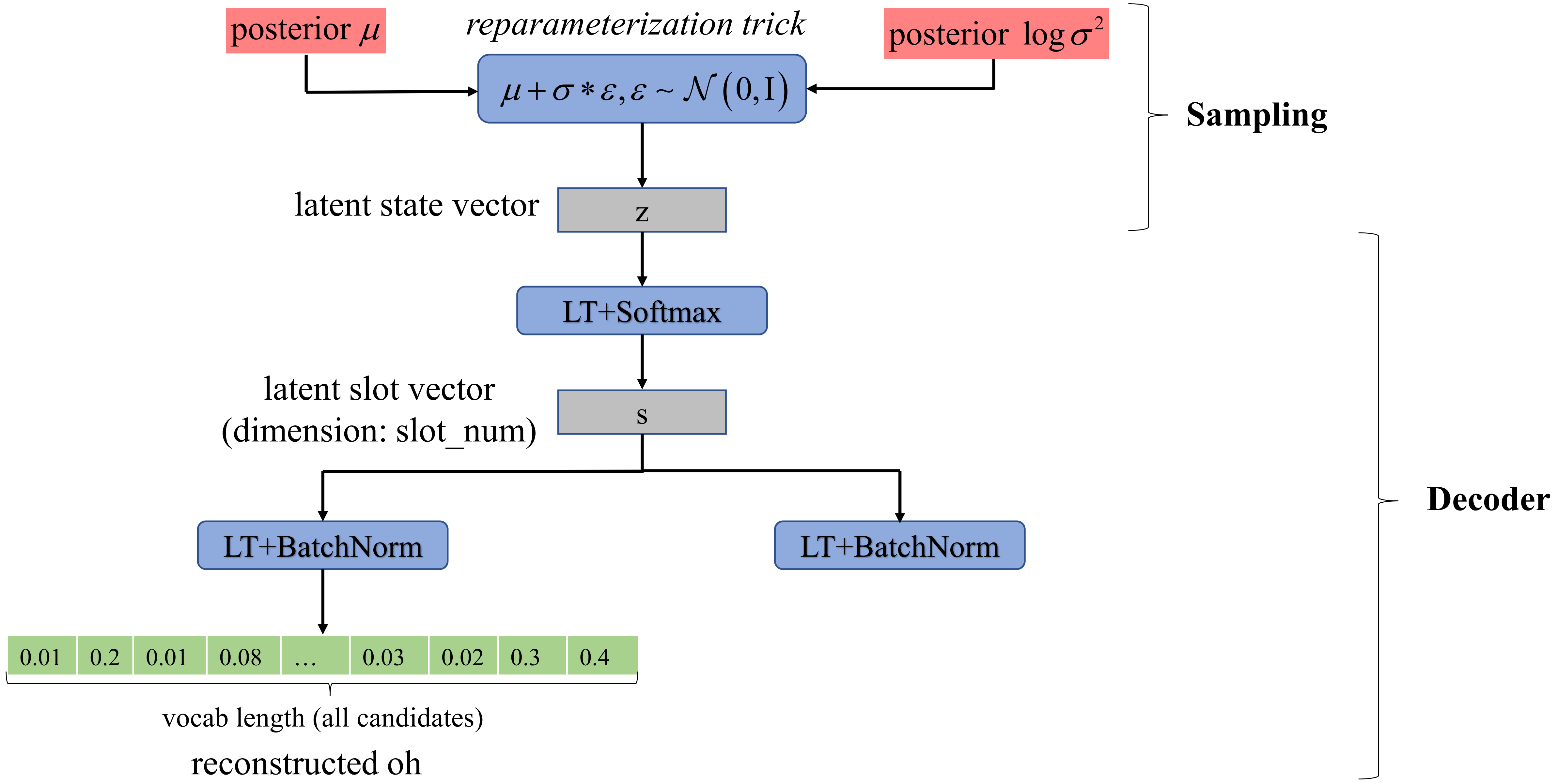
Model: generative *DSI-base*



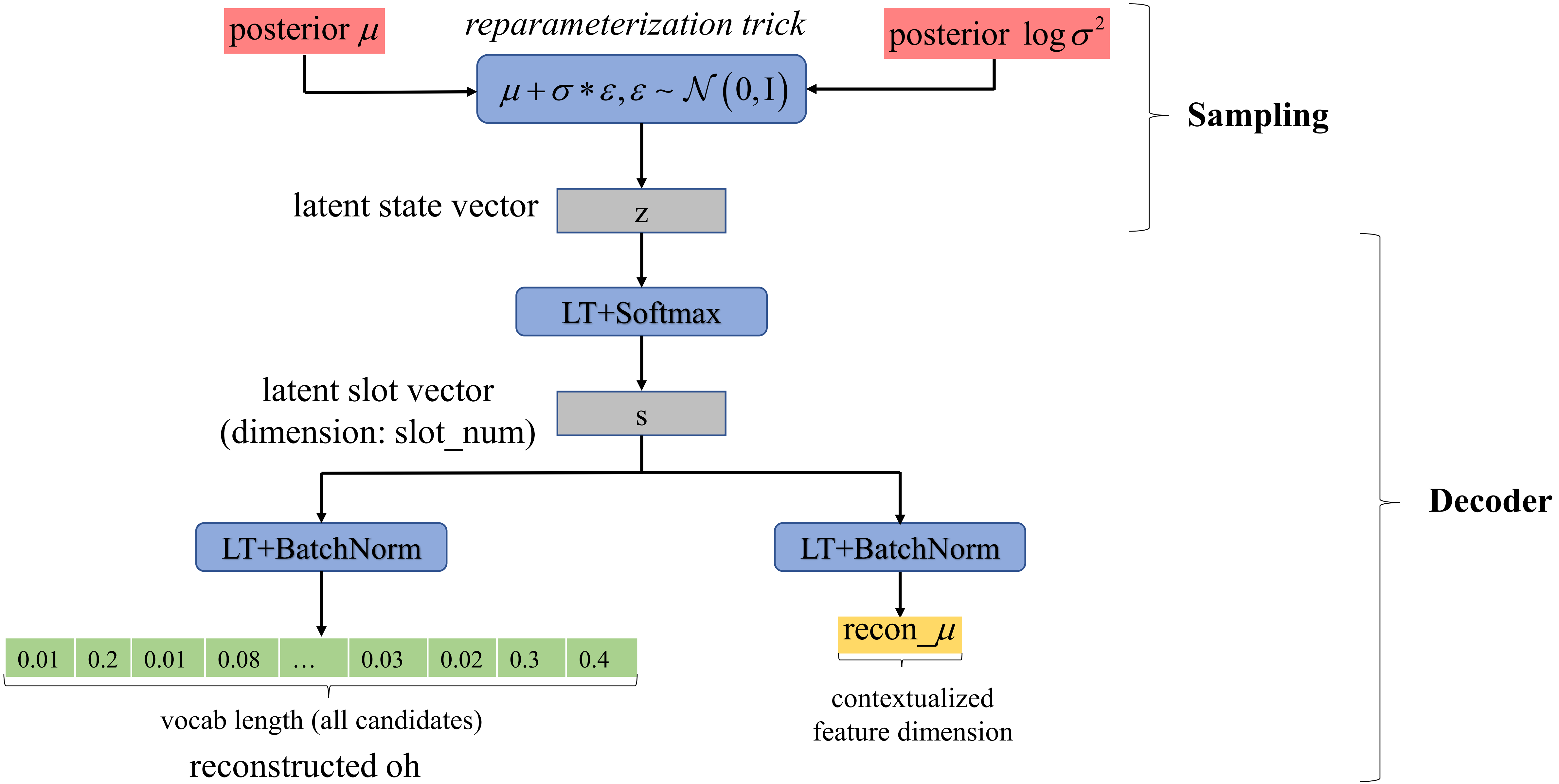
Model: generative *DSI-base*



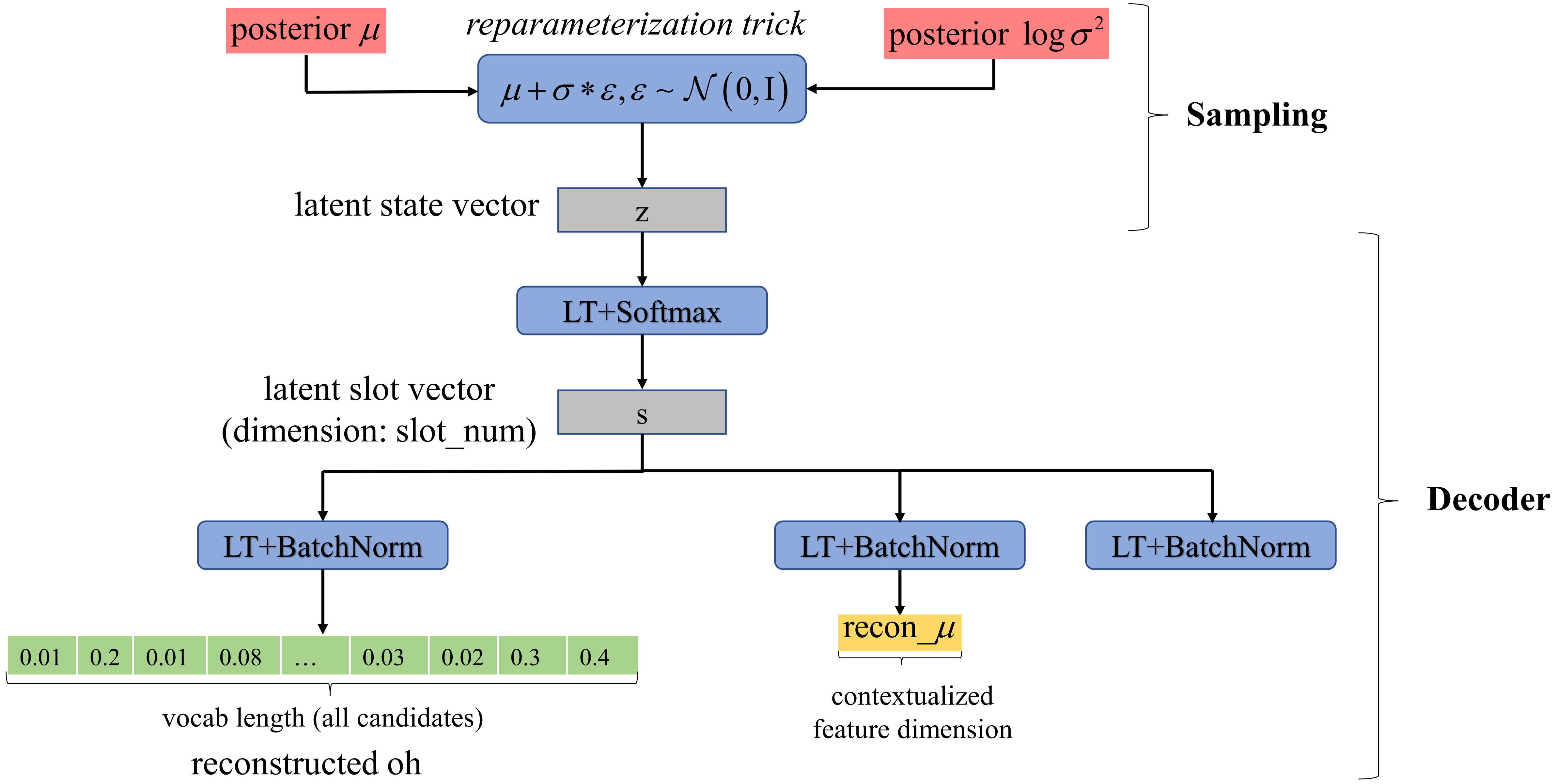
Model: generative *DSI-base*



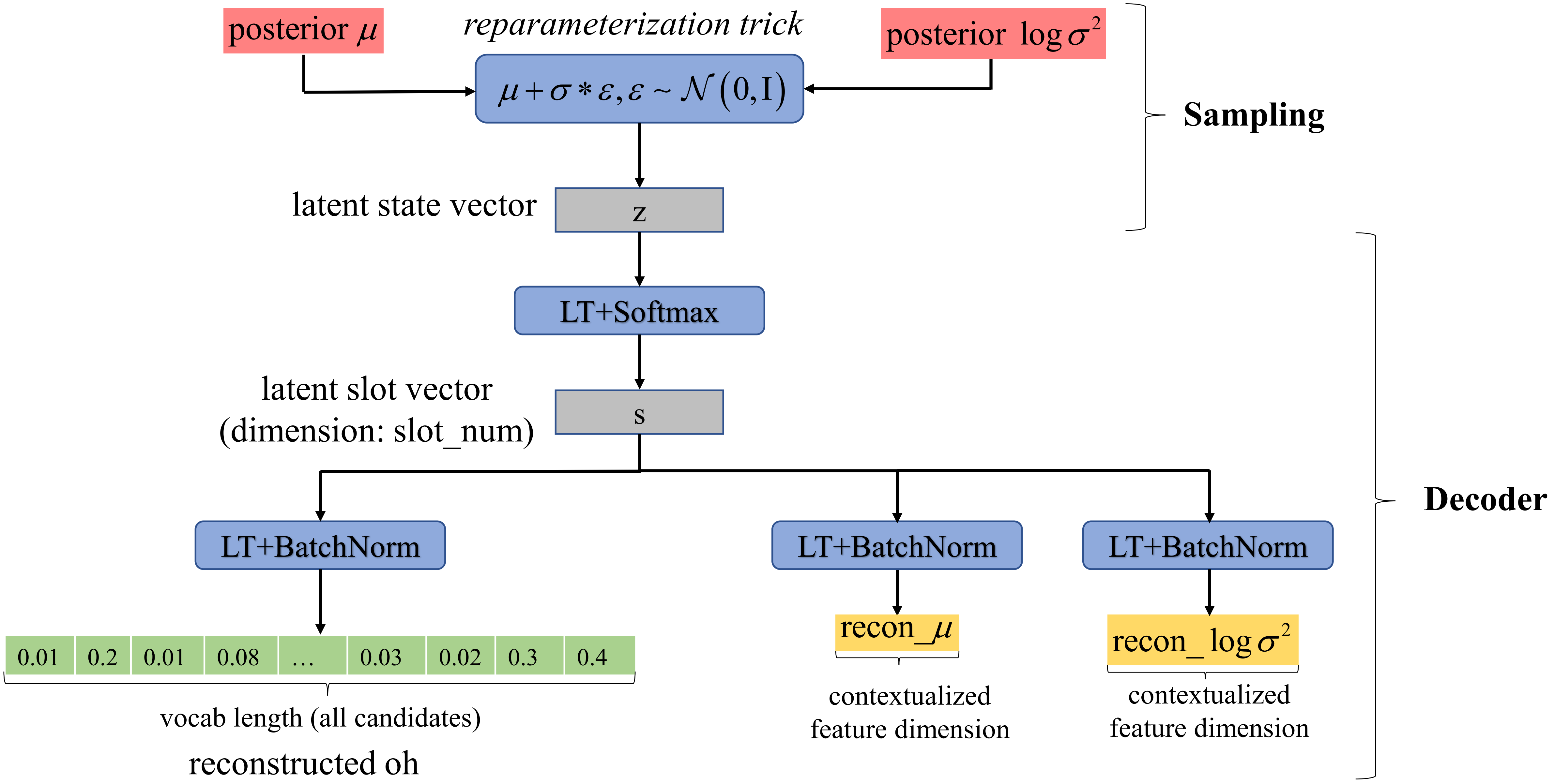
Model: generative *DSI-base*



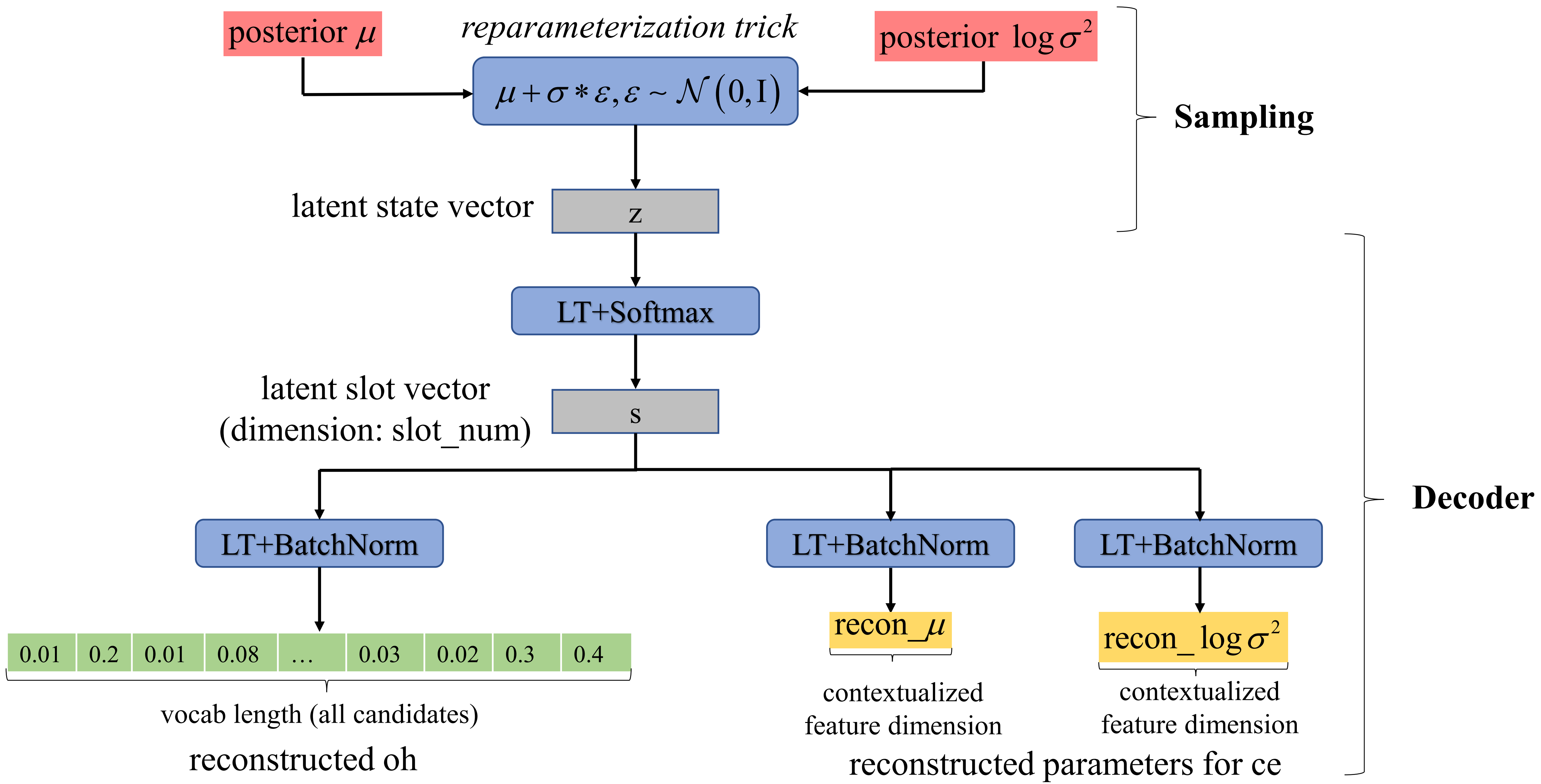
Model: generative *DSI-base*



Model: generative *DSI-base*



Model: generative *DSI-base*



reconstruction term

regularization term

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

reconstruction term

regularization term

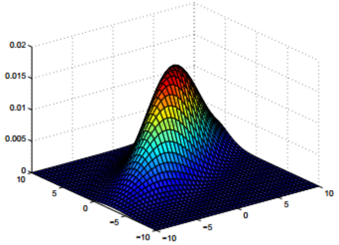
0.01	0.2	0.01	0.08	…	0.03	0.02	0.3	0.4	reconstructed oh
0	1	0	1	…	0	0	1	1	oh

vocab length (all candidates)

Cross Entropy Loss

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

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



Multivariate Gaussian Distribution

reconstruction term

regularization term

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

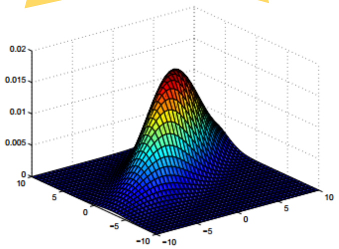
train | Chicago | Dallas | Wednesday

recon_μ

contextualized feature dimension

recon_ $\log\sigma^2$

contextualized feature dimension



Multivariate Gaussian Distribution

reconstruction term

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Loss

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vocab length (all candidates)

reconstructed oh

oh

Cross Entropy Loss

train

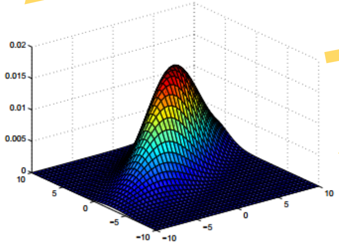
Chicago

Dallas

Wednesday

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

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



Multivariate Gaussian Distribution

-dist.log_prob(ce[train])

-dist.log_prob(ce[Chicago])

-dist.log_prob(ce[Dallas])

-dist.log_prob(ce[Wednesday])

reconstruction term

regularization 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

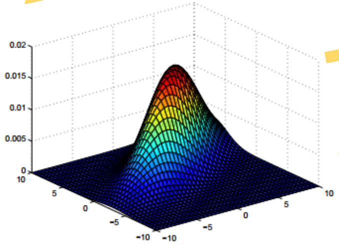
recon_μ

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

regularization term

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

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

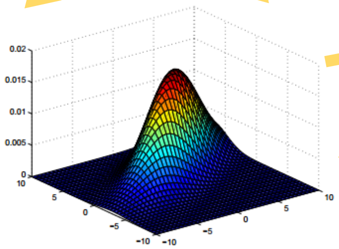
recon_μ

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])

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.

DSI-base inference

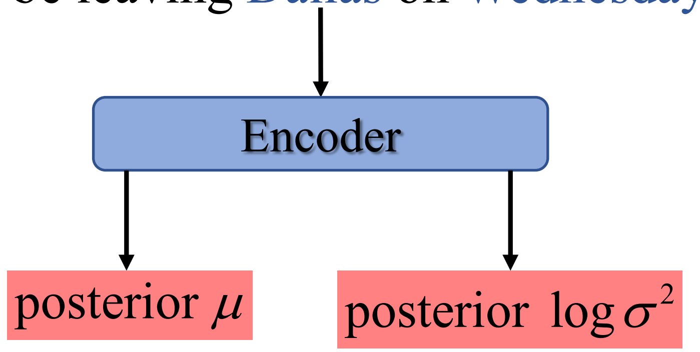
I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.

↓

Encoder

DSI-base inference

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



DSI-base inference

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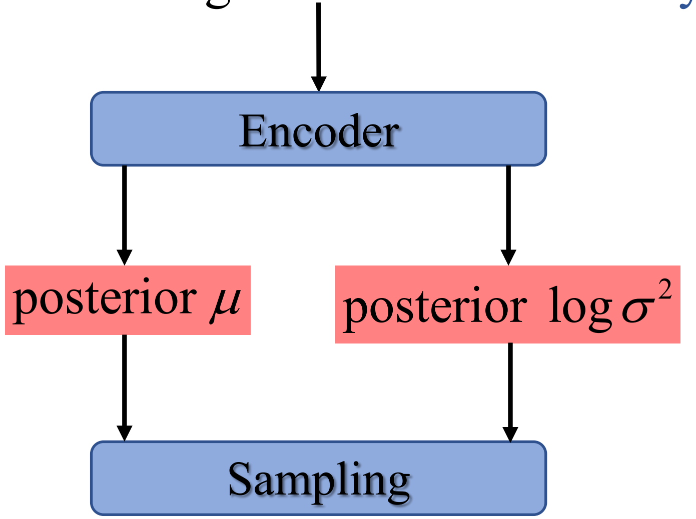
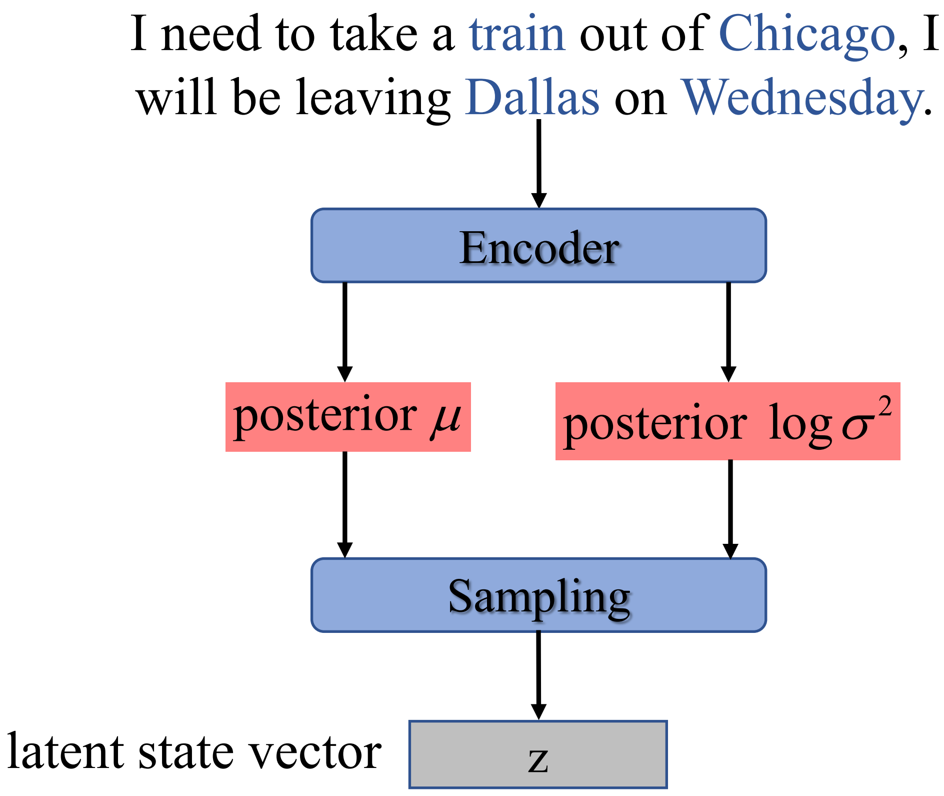
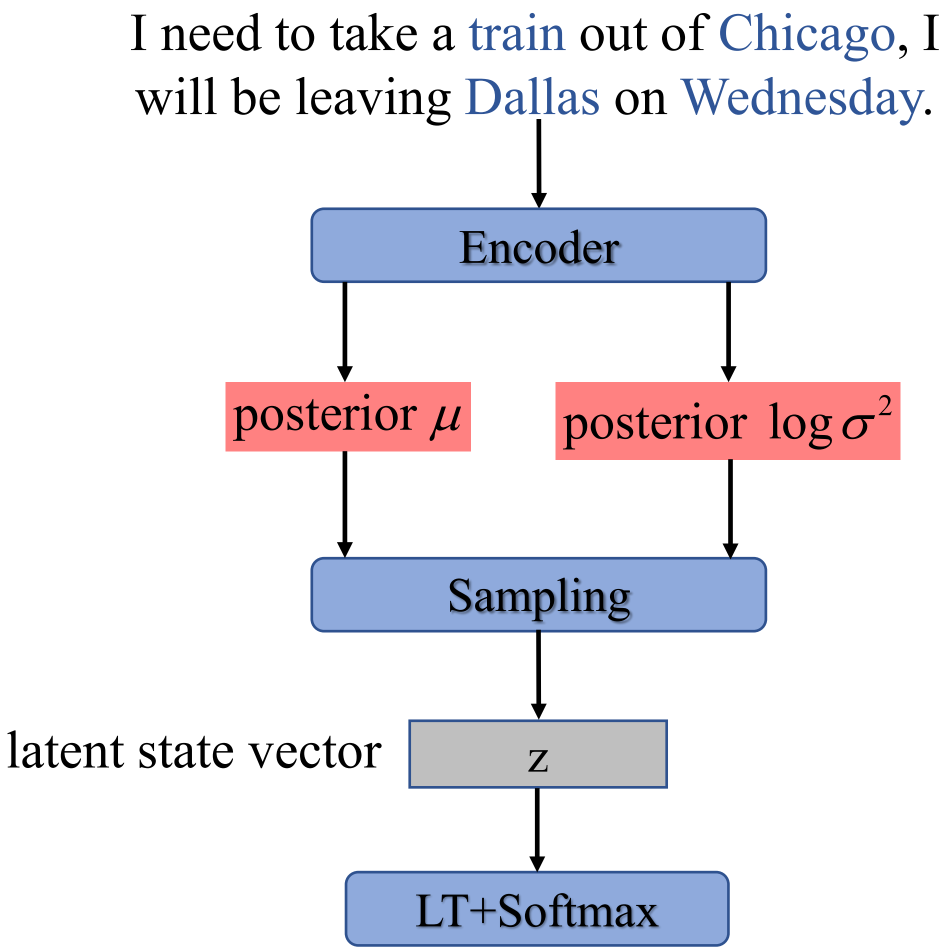


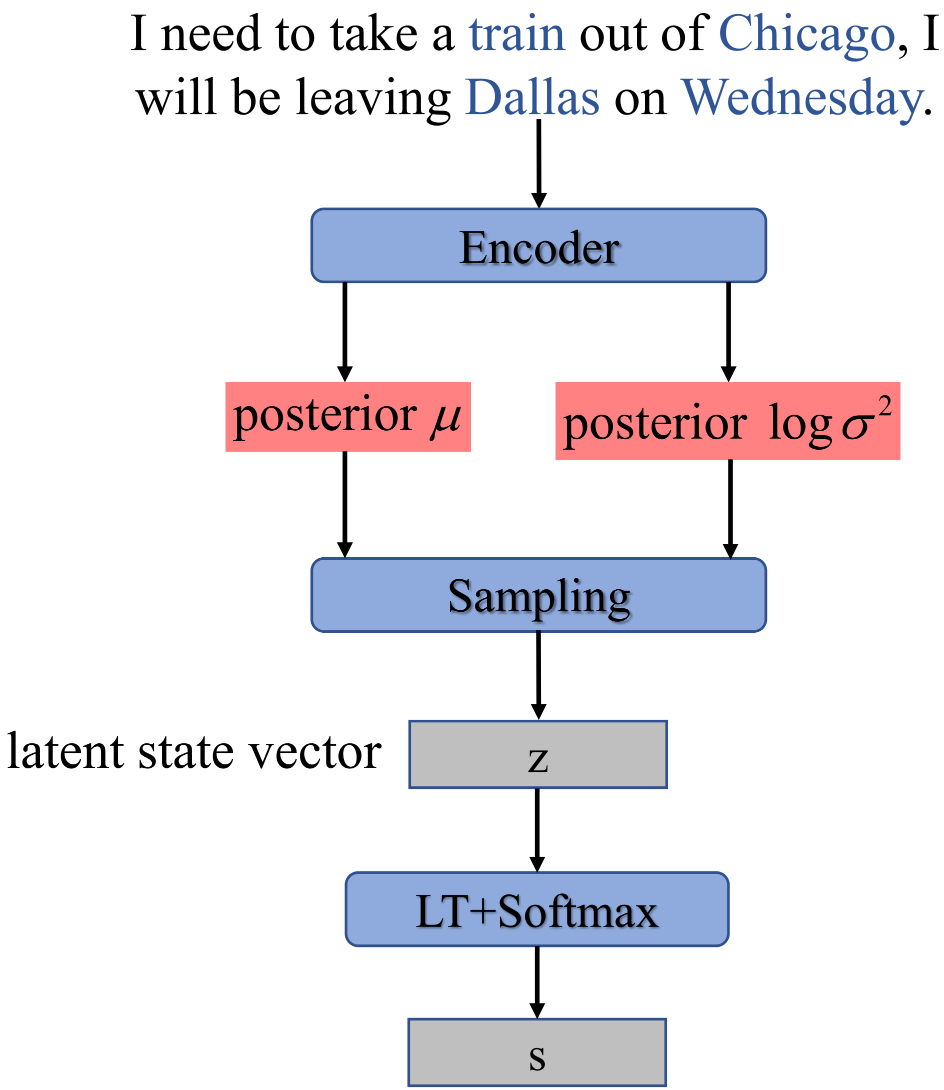
DSI-base inference



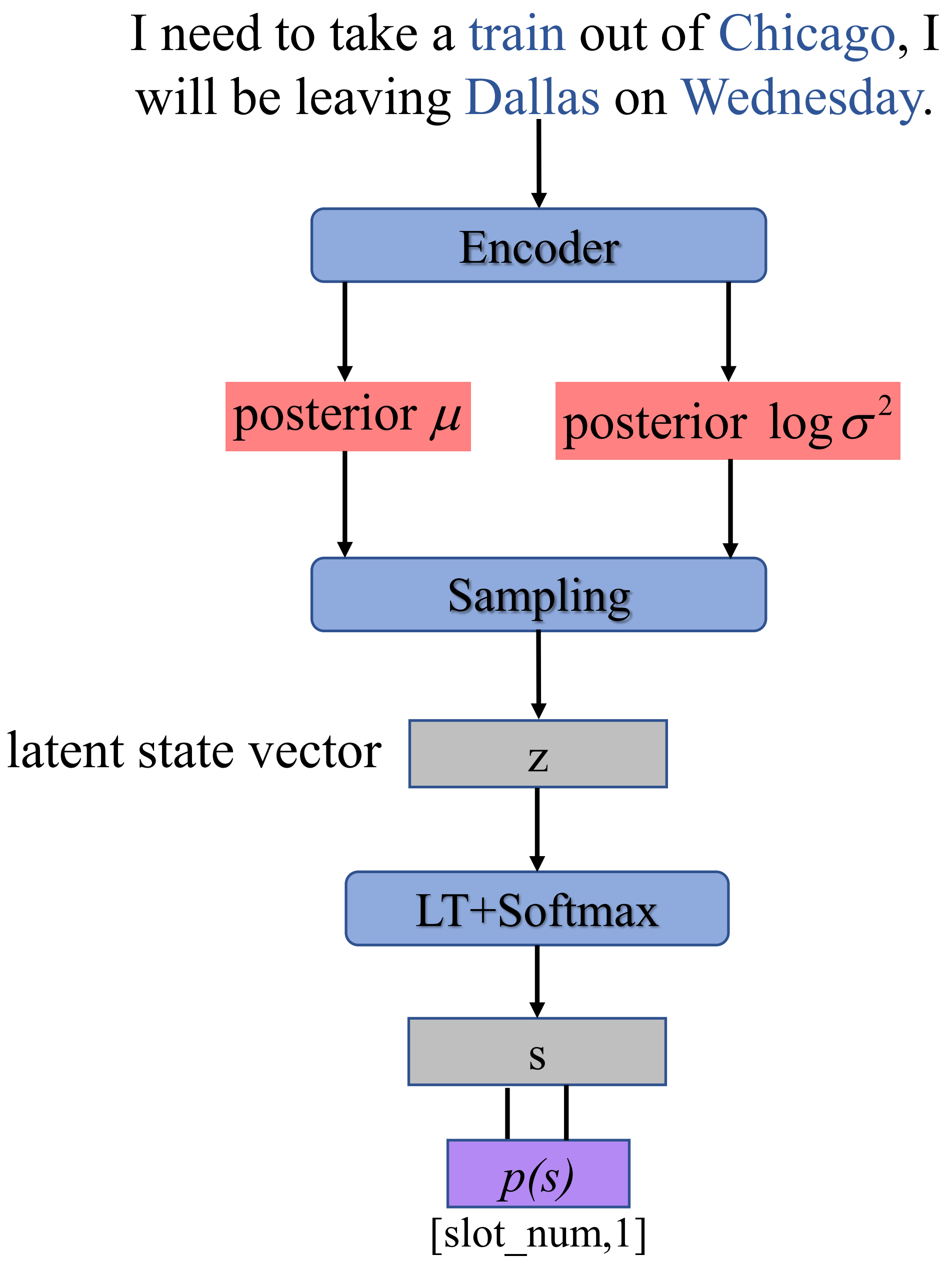
DSI-base inference



DSI-base inference

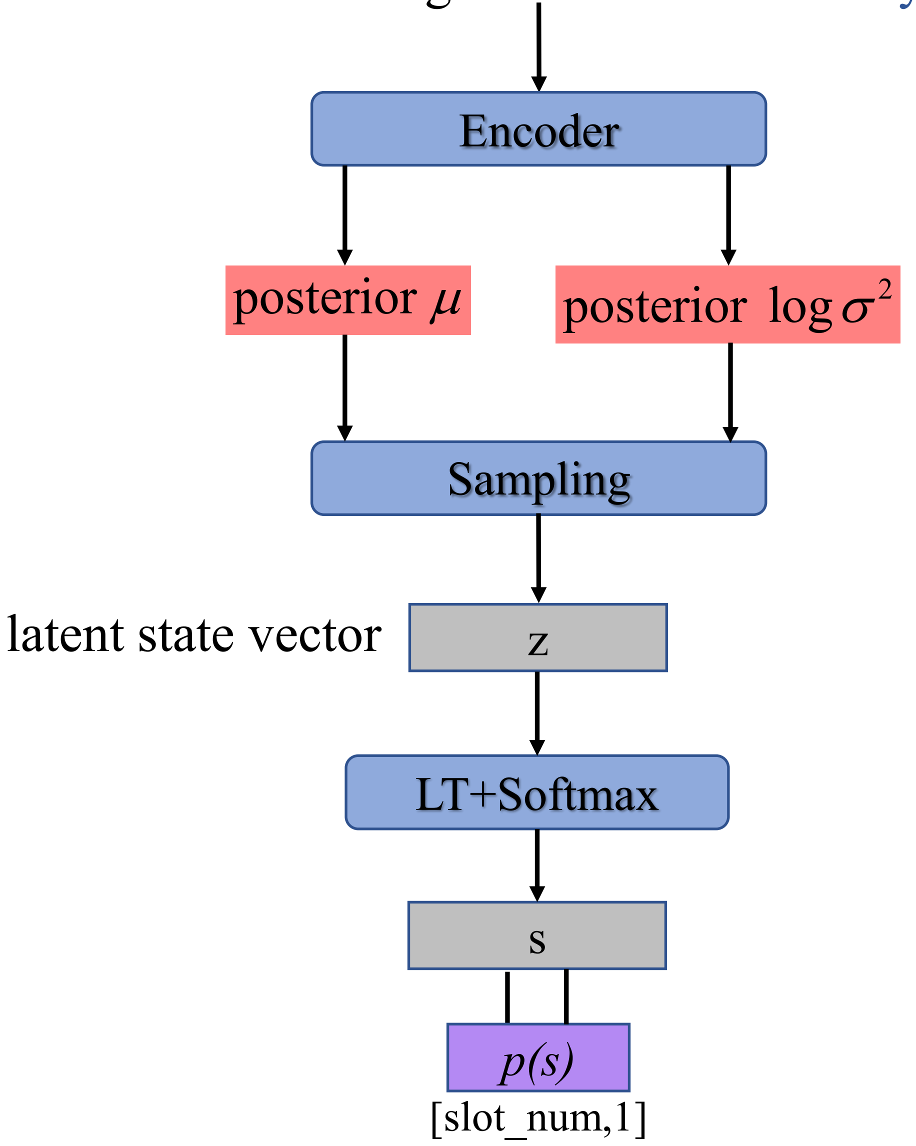


DSI-base inference



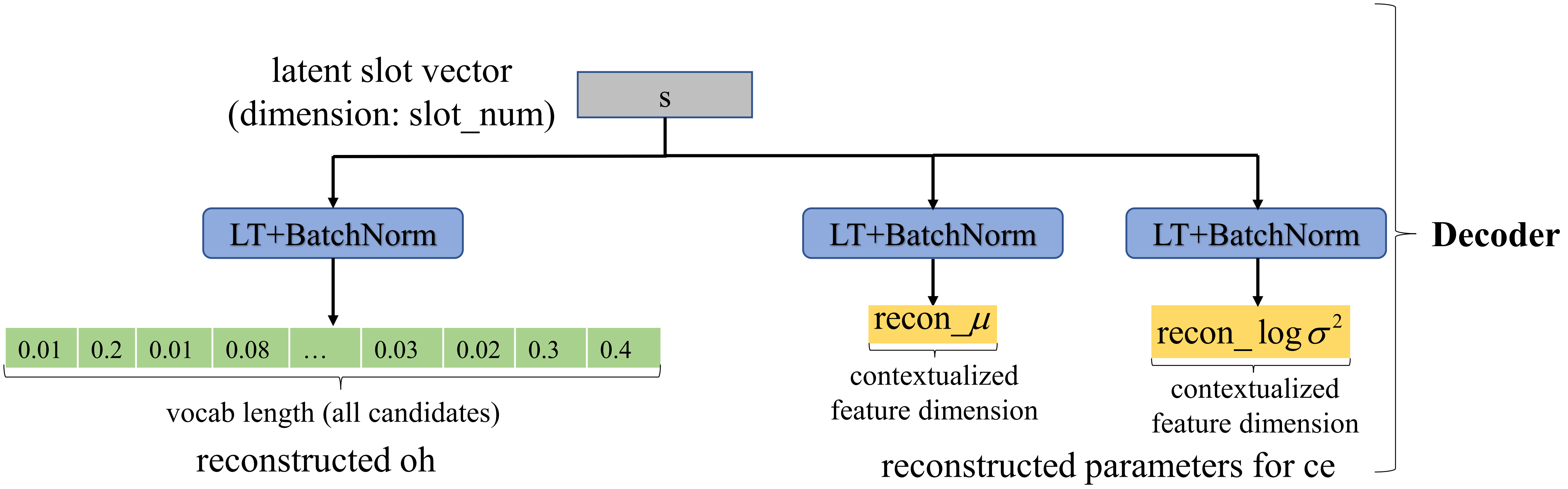
DSI-base inference

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

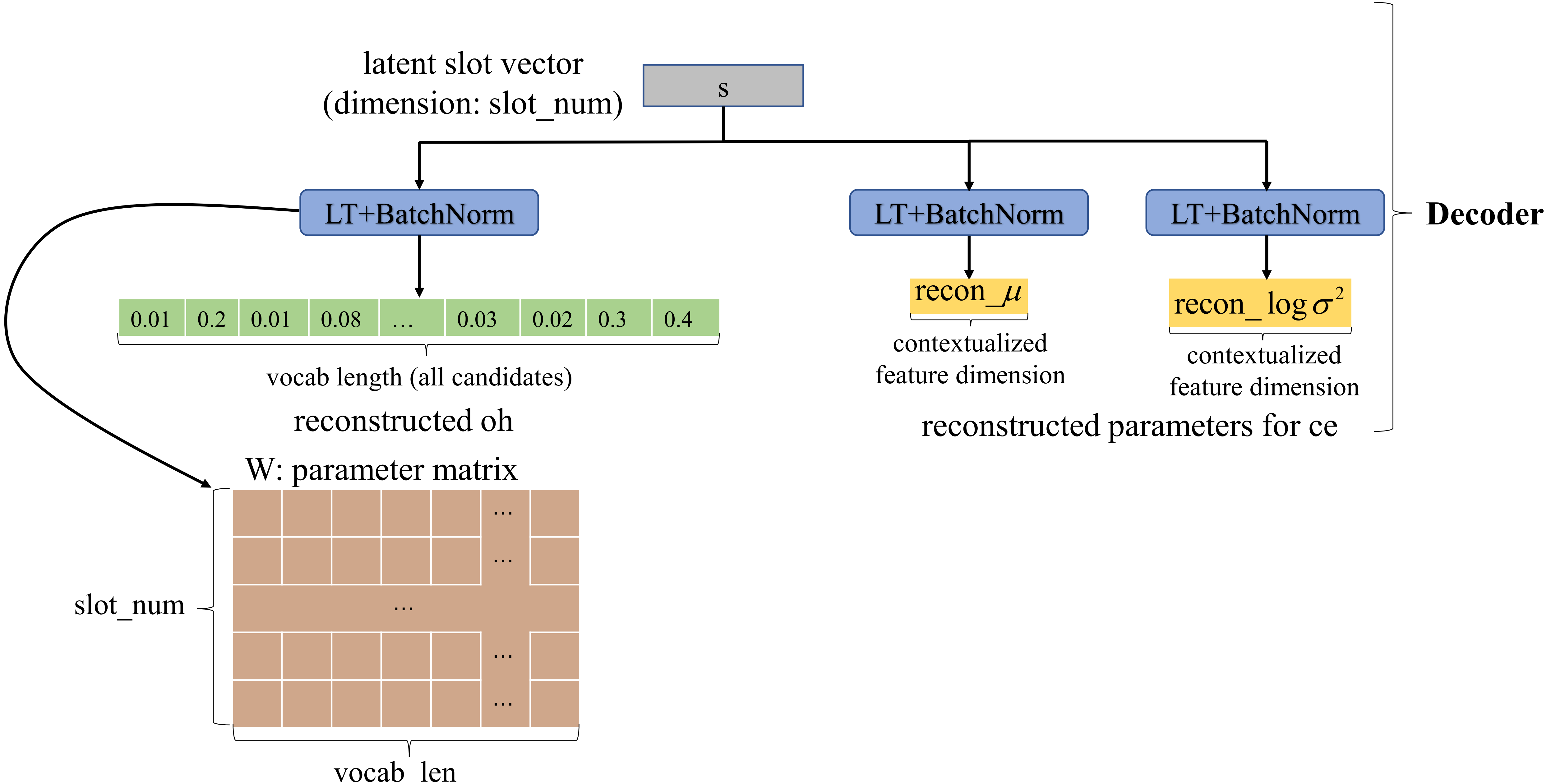


For each candidate in {train, Chicago, Dallas, Wednesday}

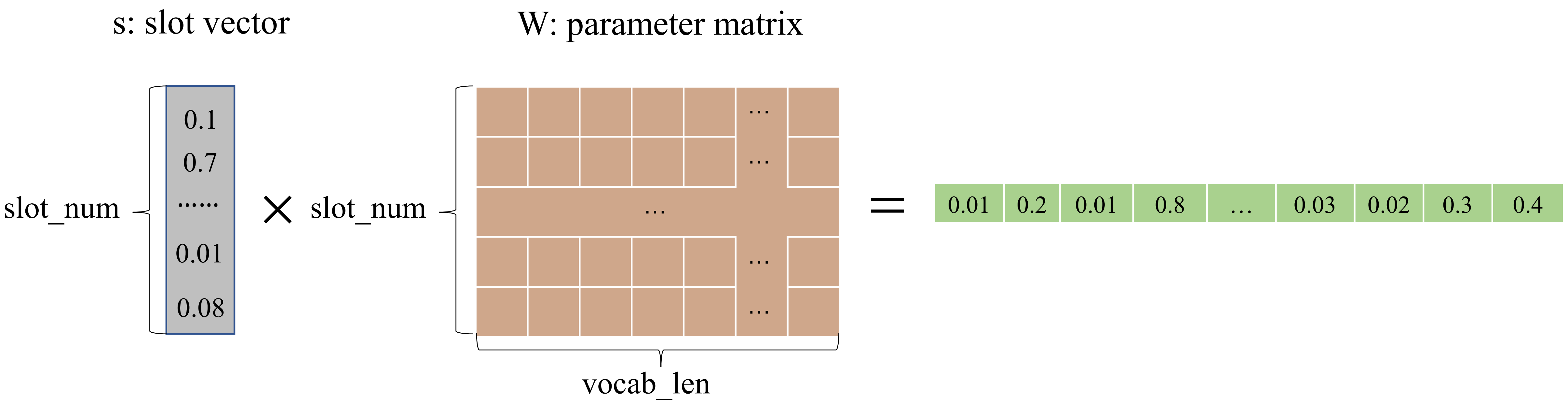
What does the model learn ?



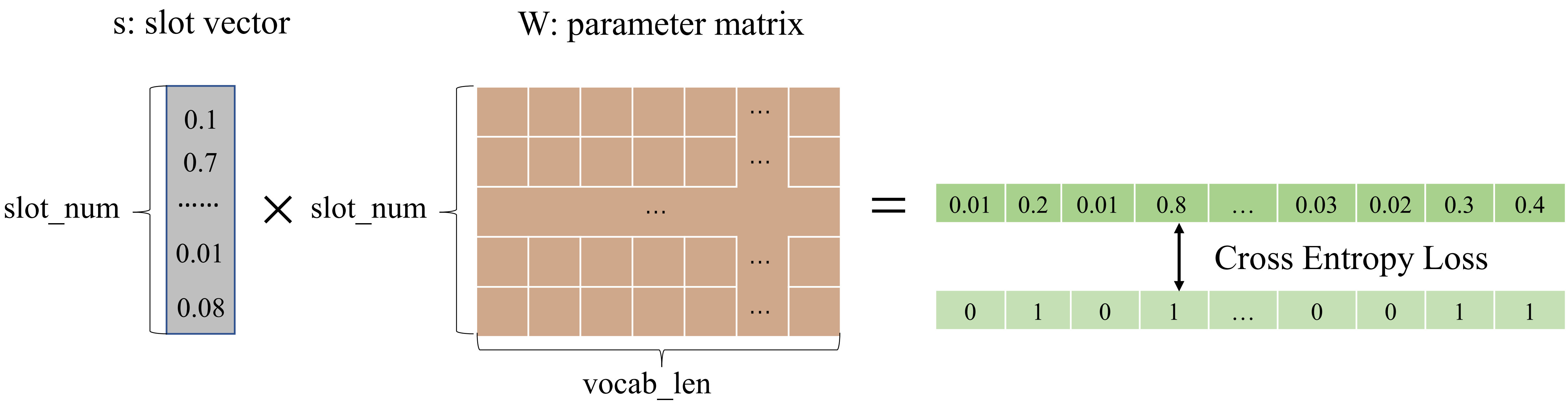
What does the model learn ?



What does the model learn ?



What does the model learn ?



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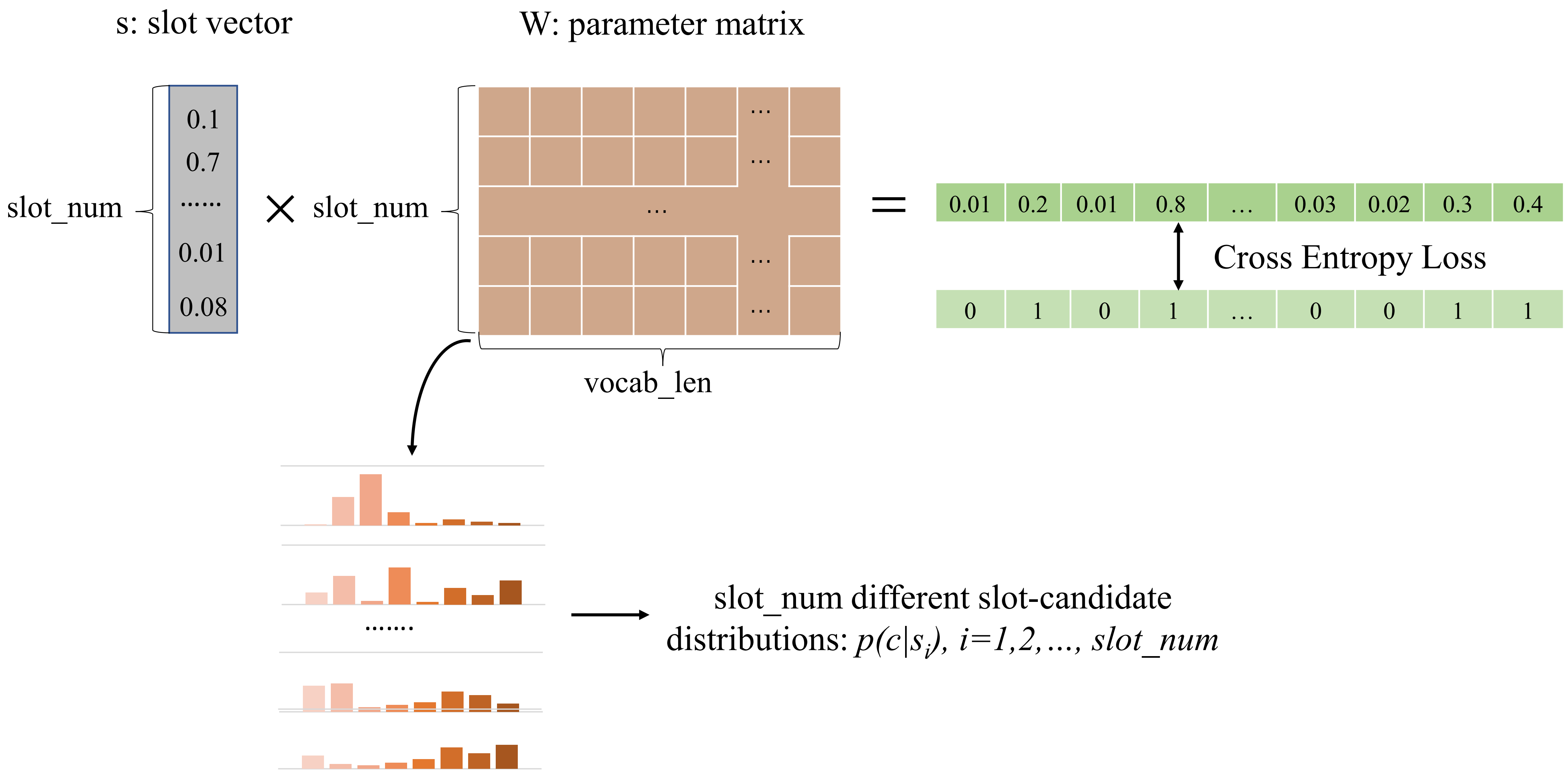
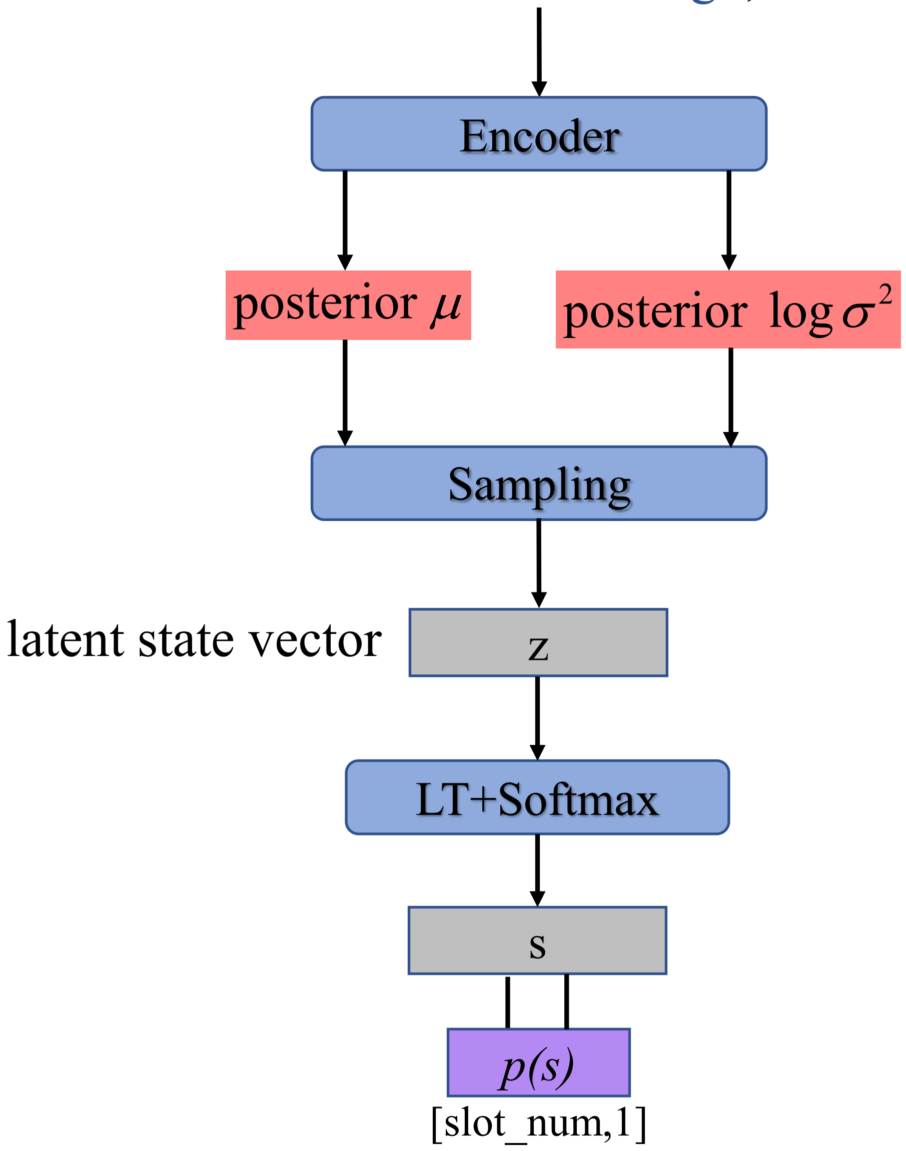


DSI-base inference

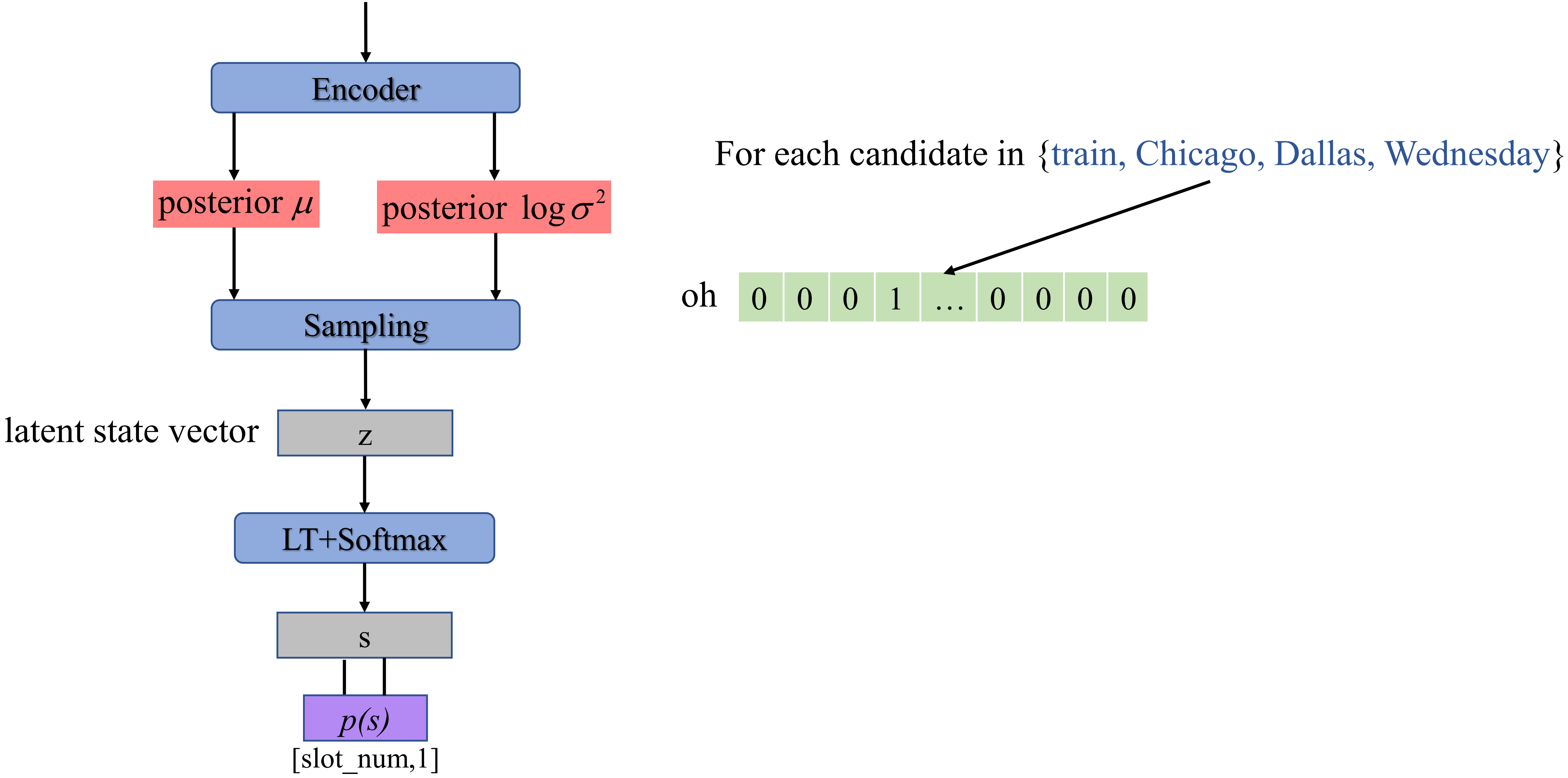
I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.



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

DSI-base inference

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



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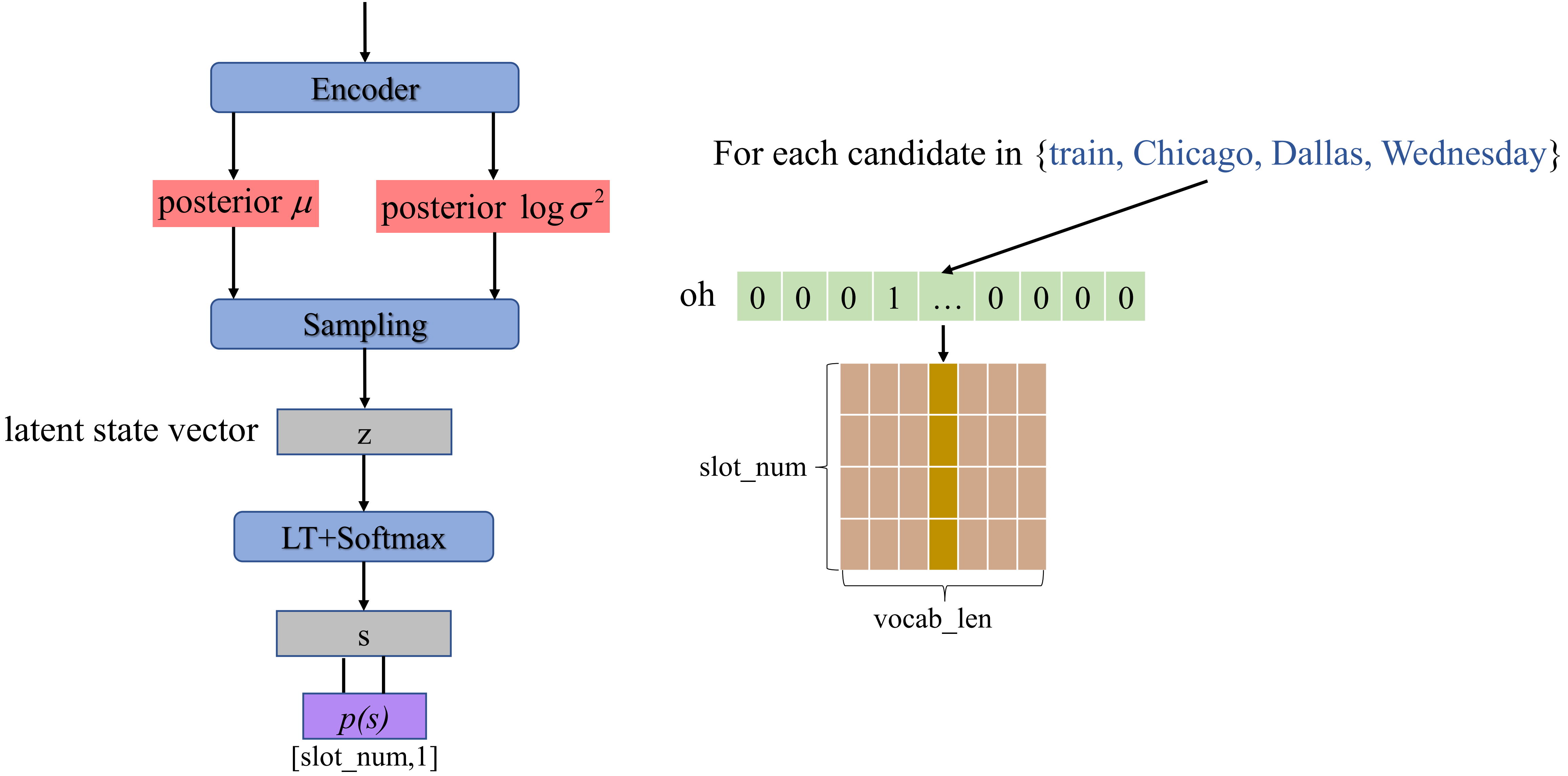

DSI-base inference

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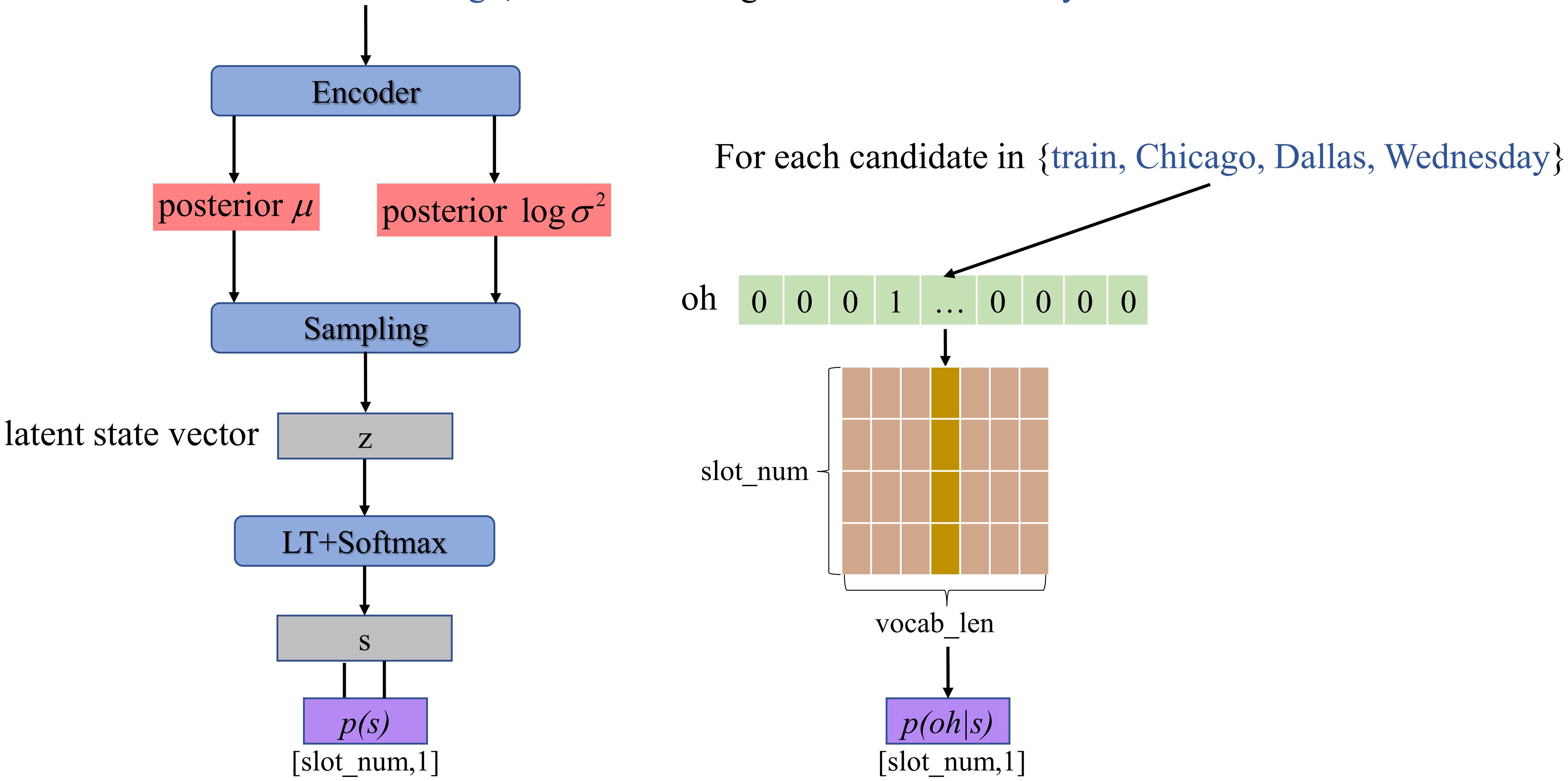
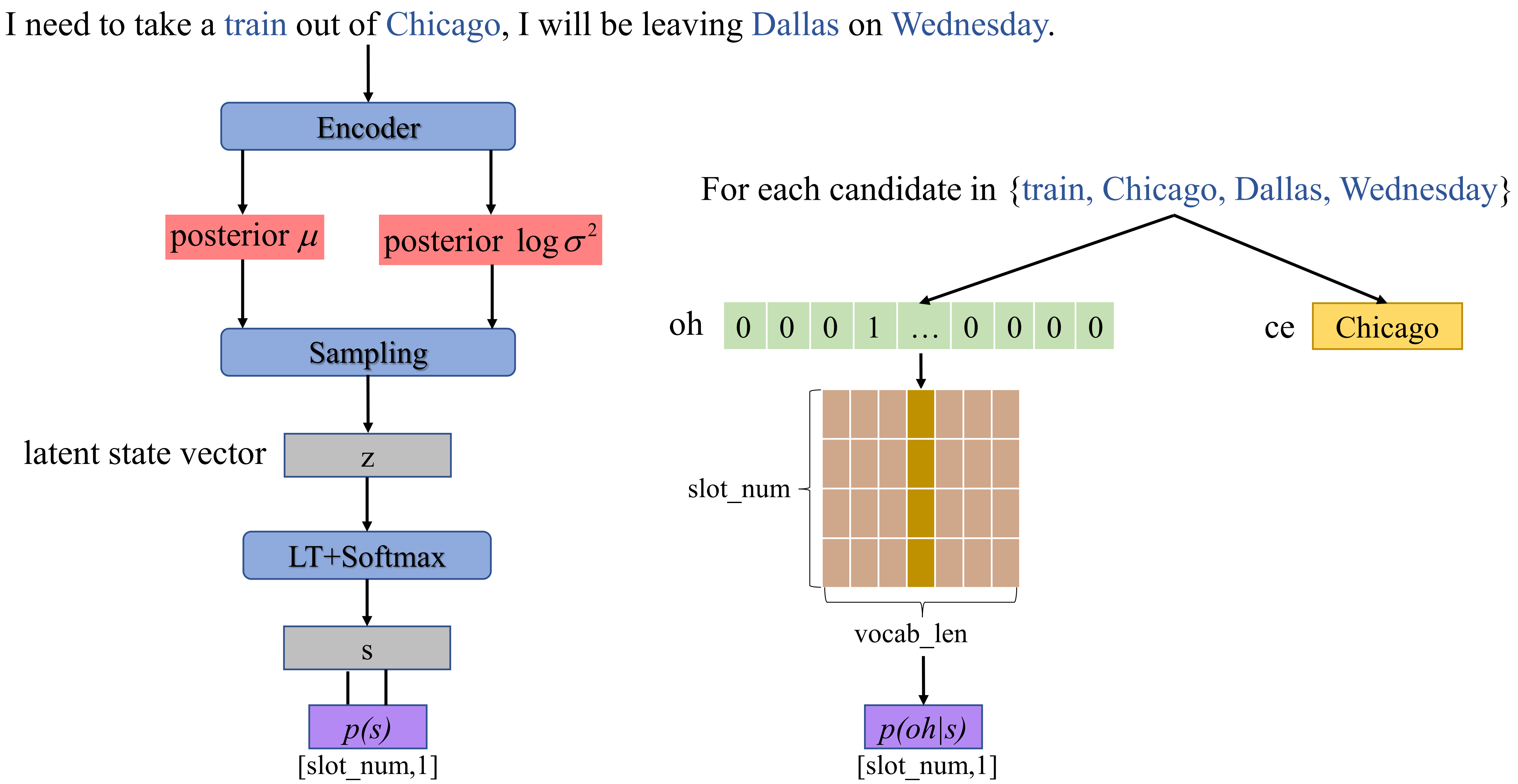
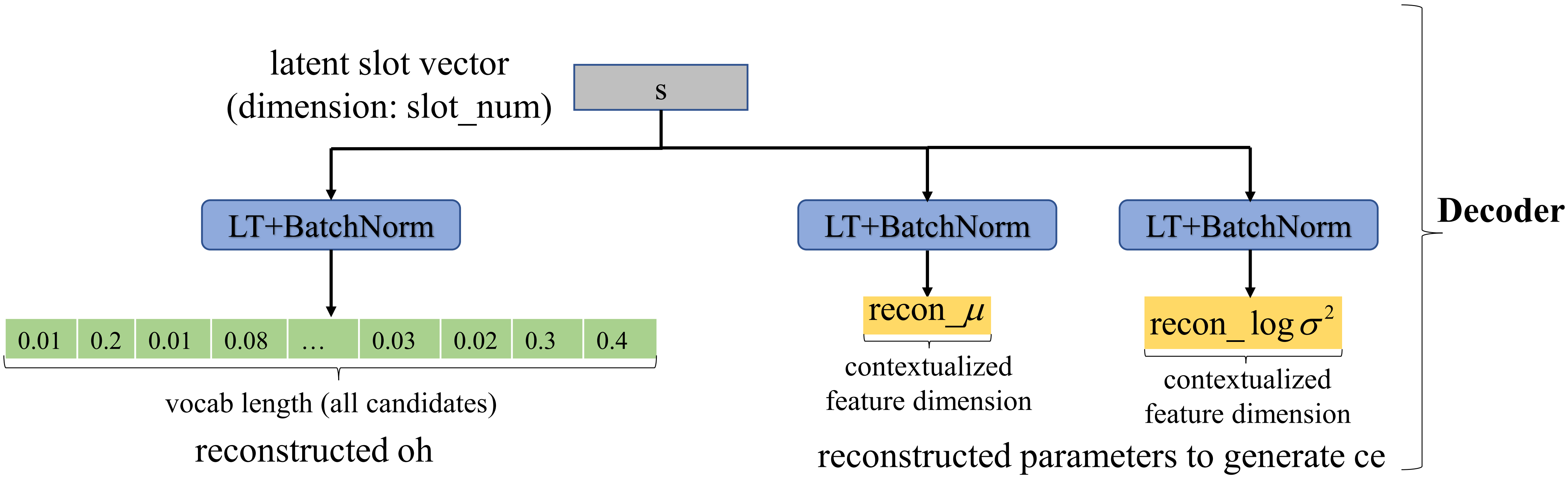


DSI-base inference

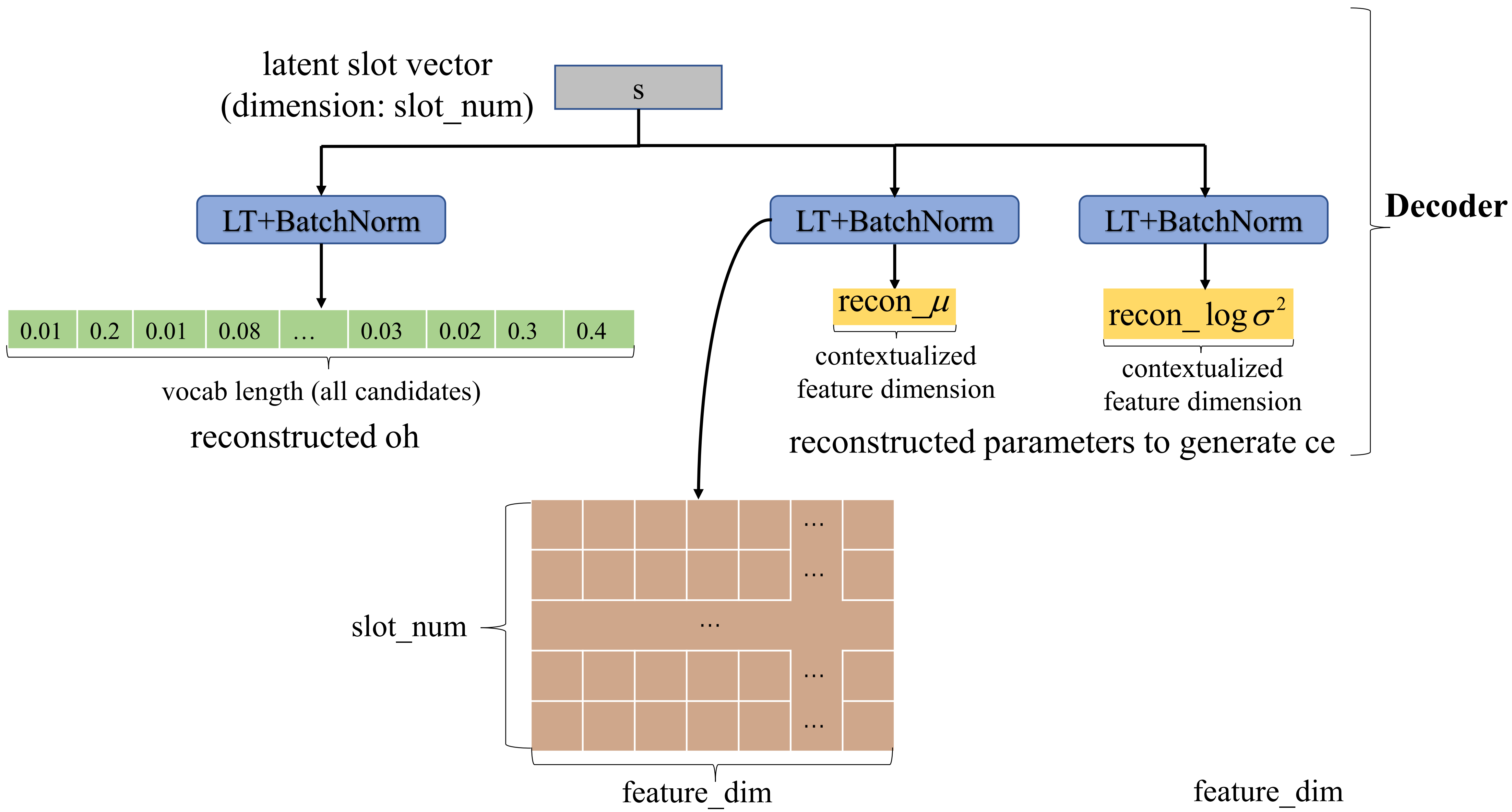


DSI-base inference

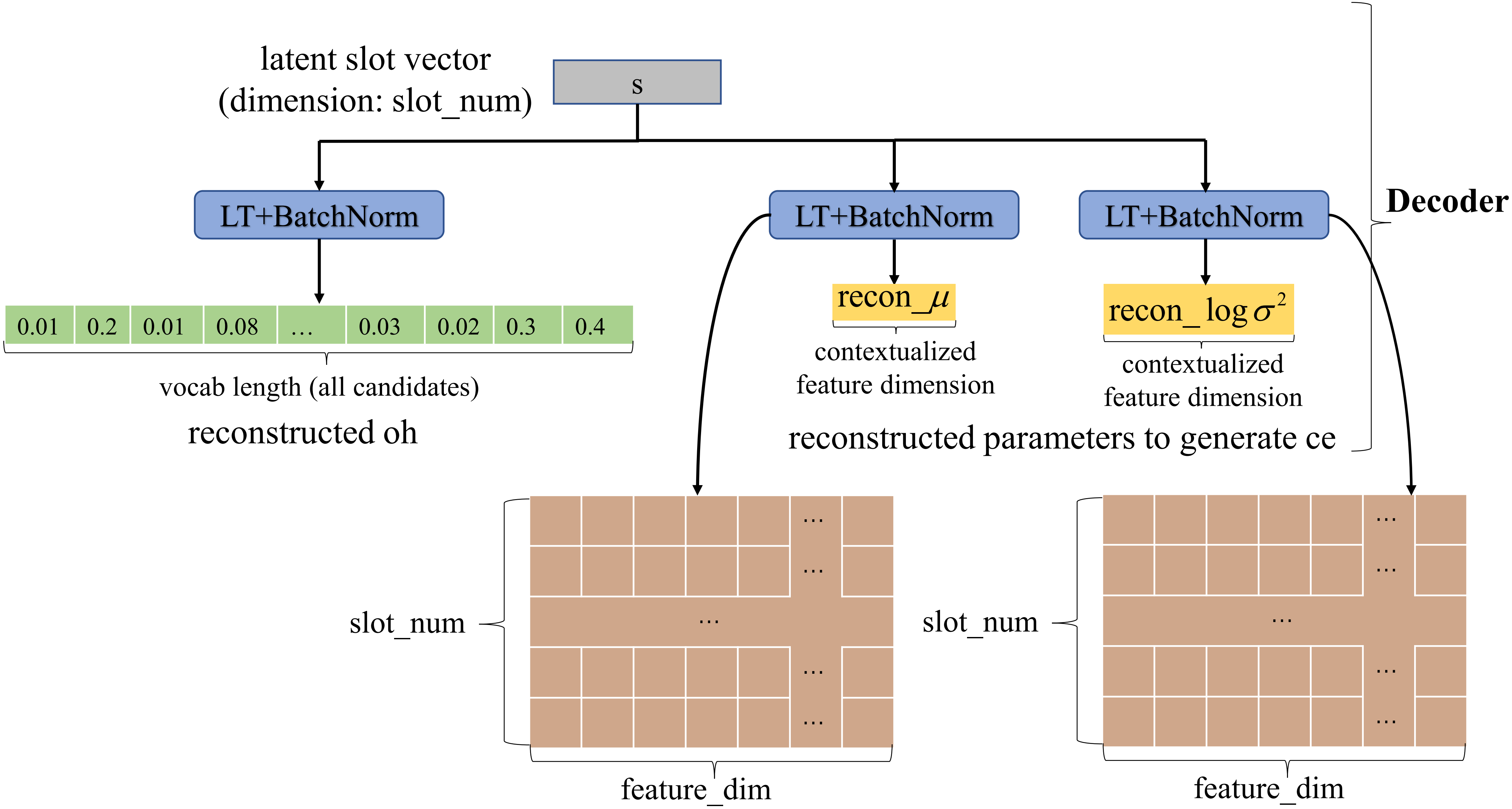


feature_dim

DSI-base inference



DSI-base inference



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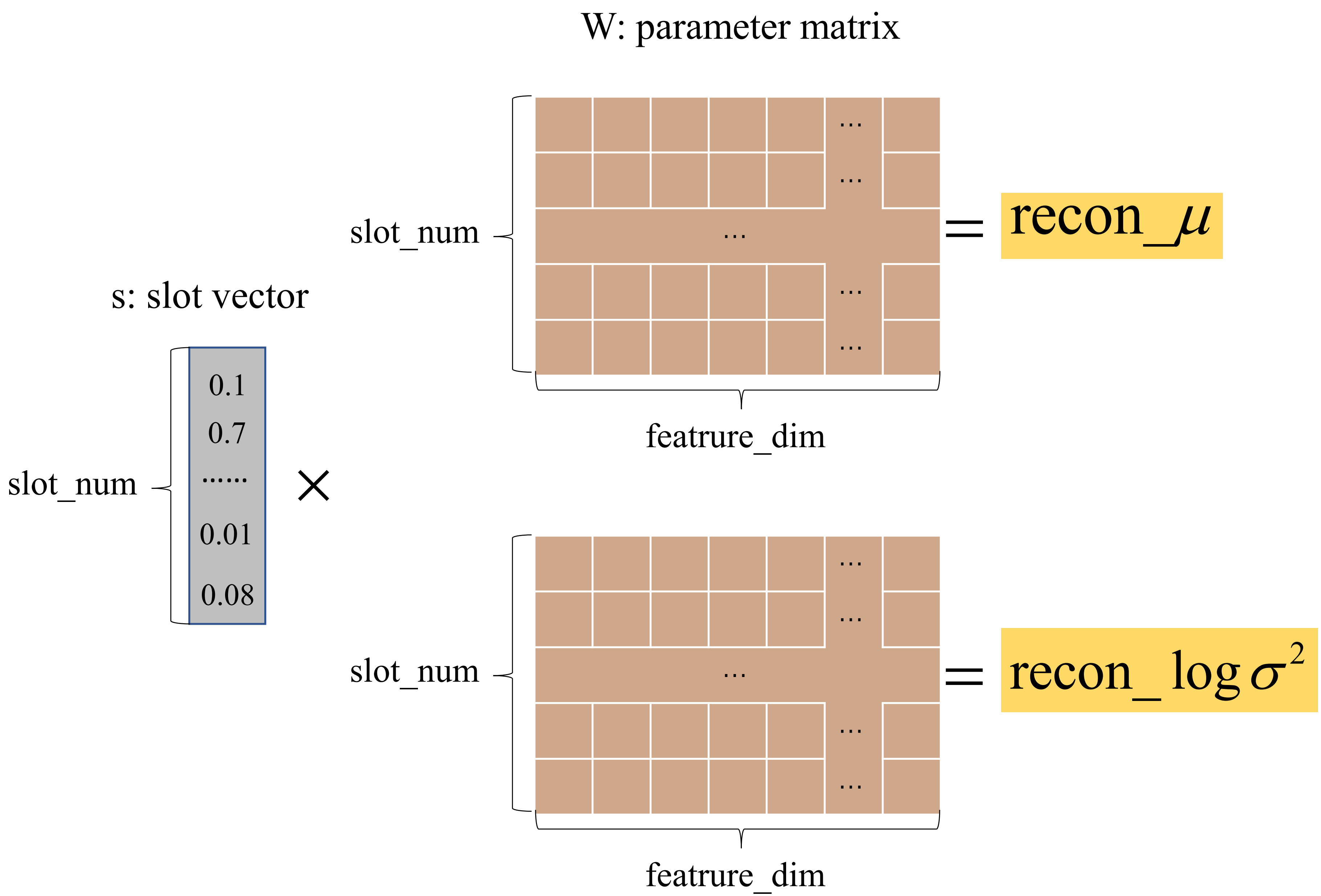

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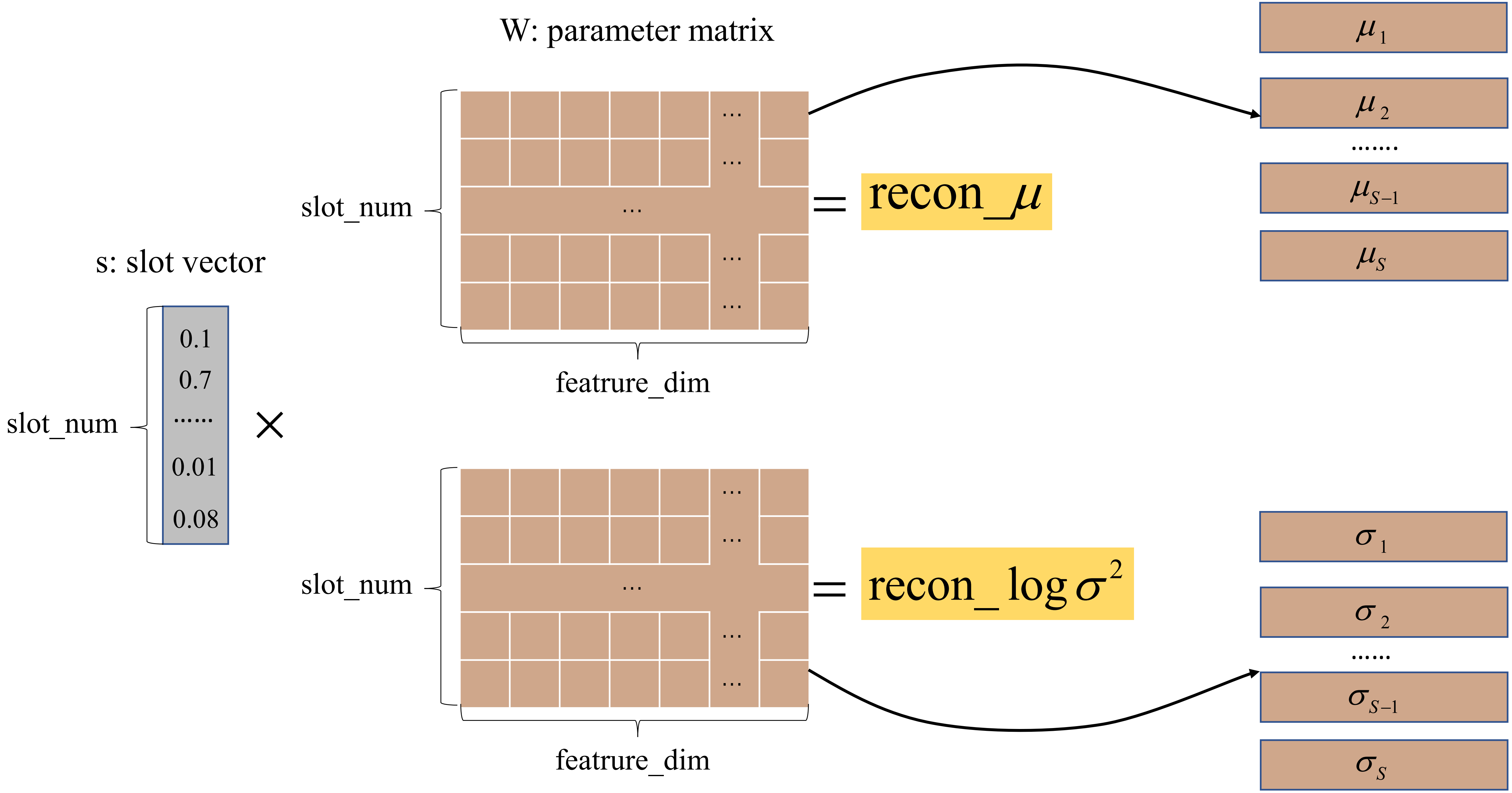

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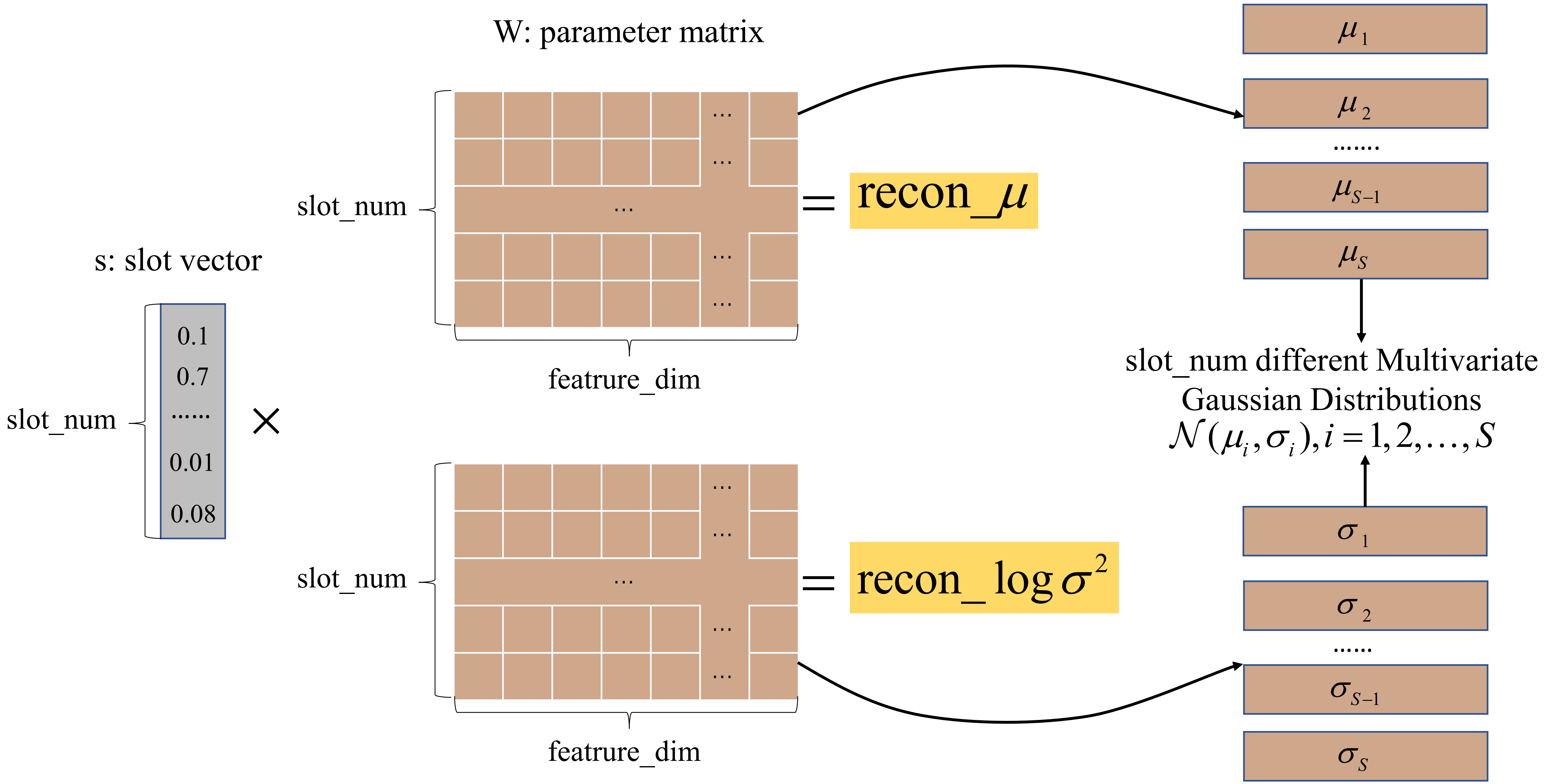
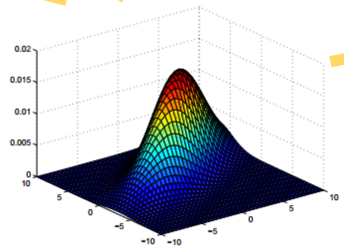


Multivariate Gaussian probability density

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

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

train Chicago Dallas Wednesday



Multivariate Gaussian Distribution

-dist.log_prob(ce[train])

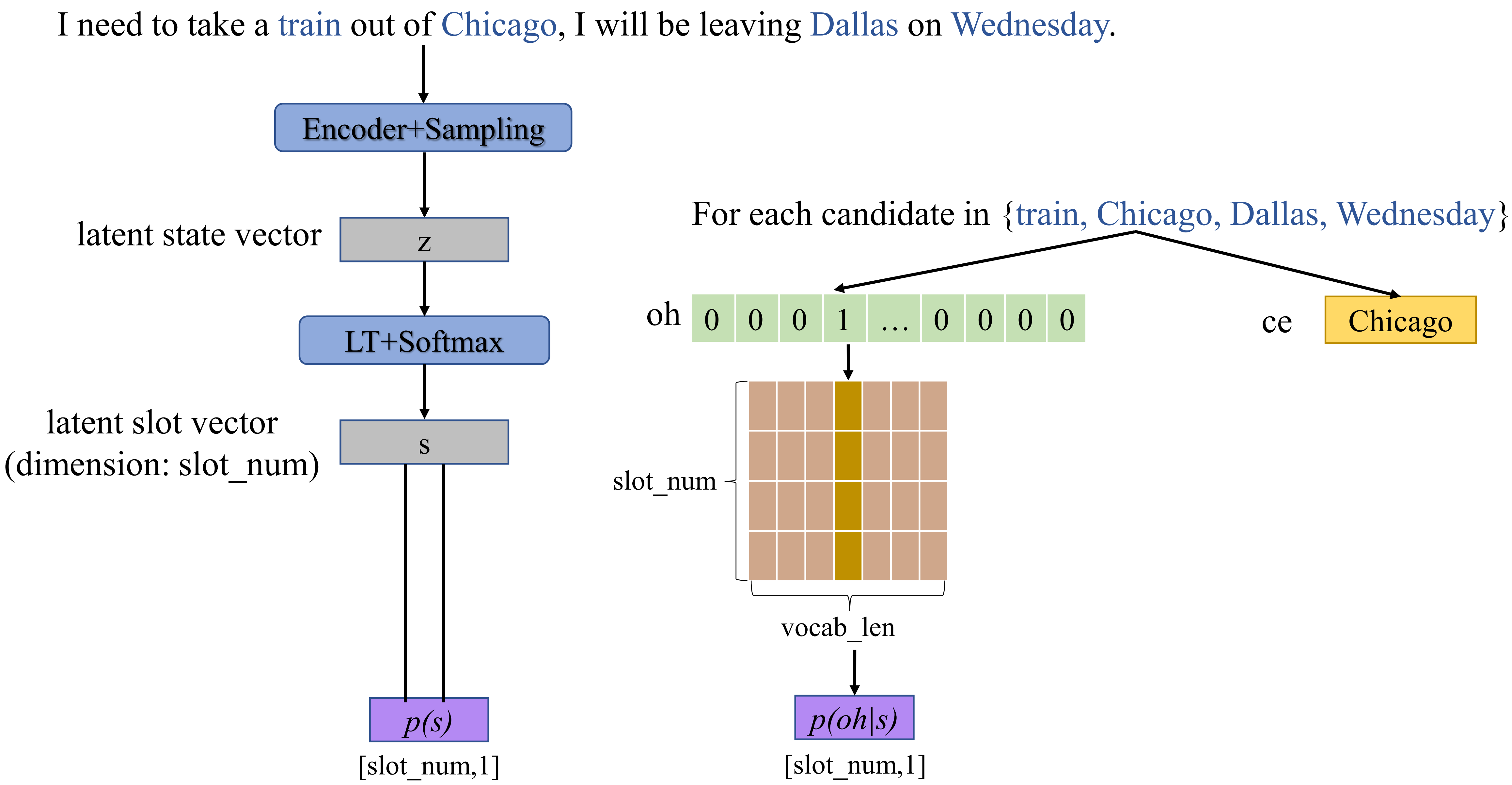
-dist.log_prob(ce[Chicago])

-dist.log_prob(ce[Dallas])

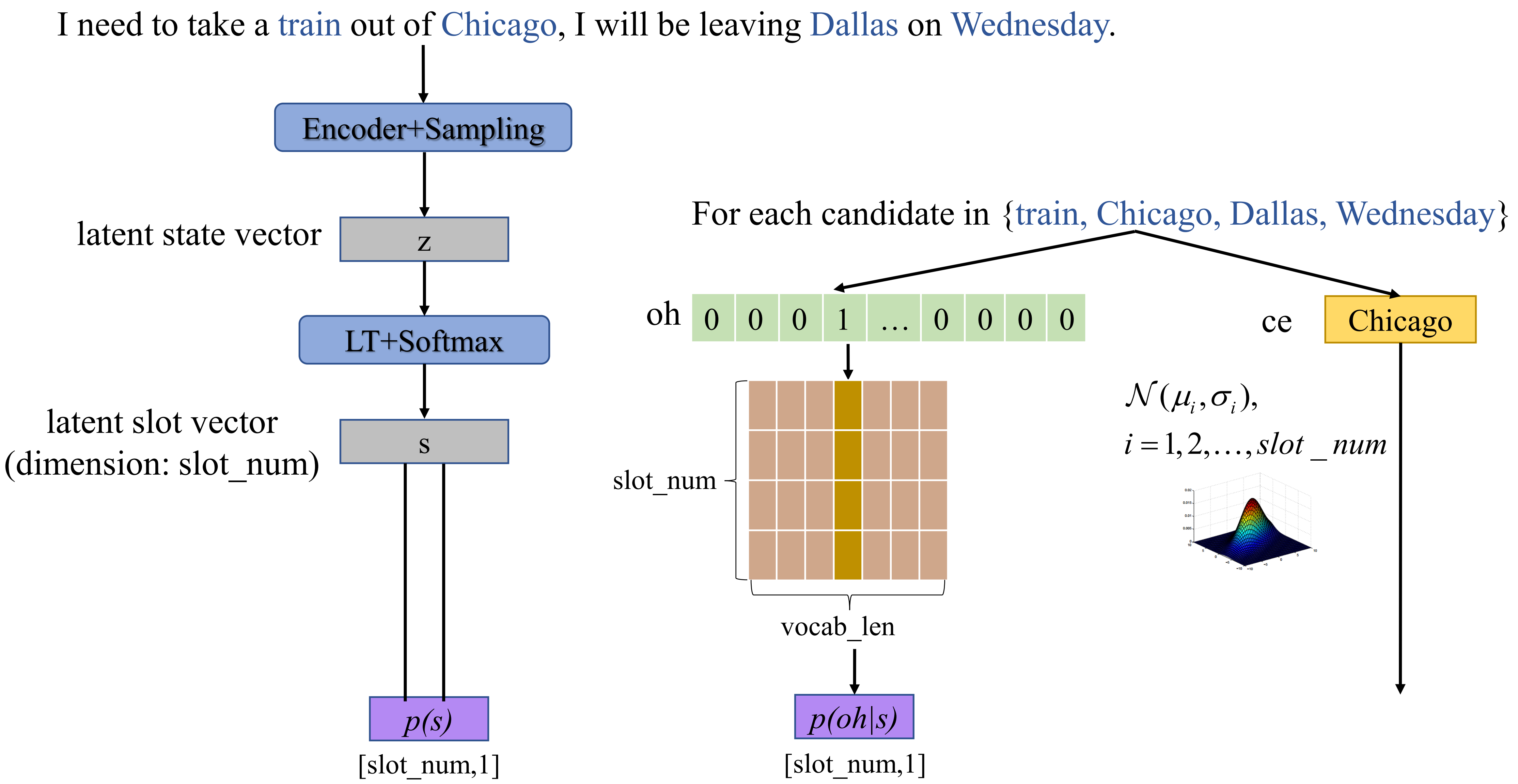
-dist.log_prob(ce[Wednesday])

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

DSI-base inference



DSI-base inference



DSI-base inference

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

Encoder+Sampling

latent state vector: z

LT+Softmax

latent slot vector (dimension: slot_num): s

$p(s)$

[slot_num,1]

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

oh: 0 0 0 1 … 0 0 0 0

slot_num

vocab_len

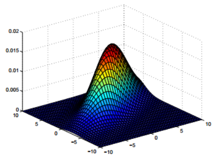
$p(oh|s)$

[slot_num,1]

ce: Chicago

$\mathcal{N}(\mu_i, \sigma_i)$,

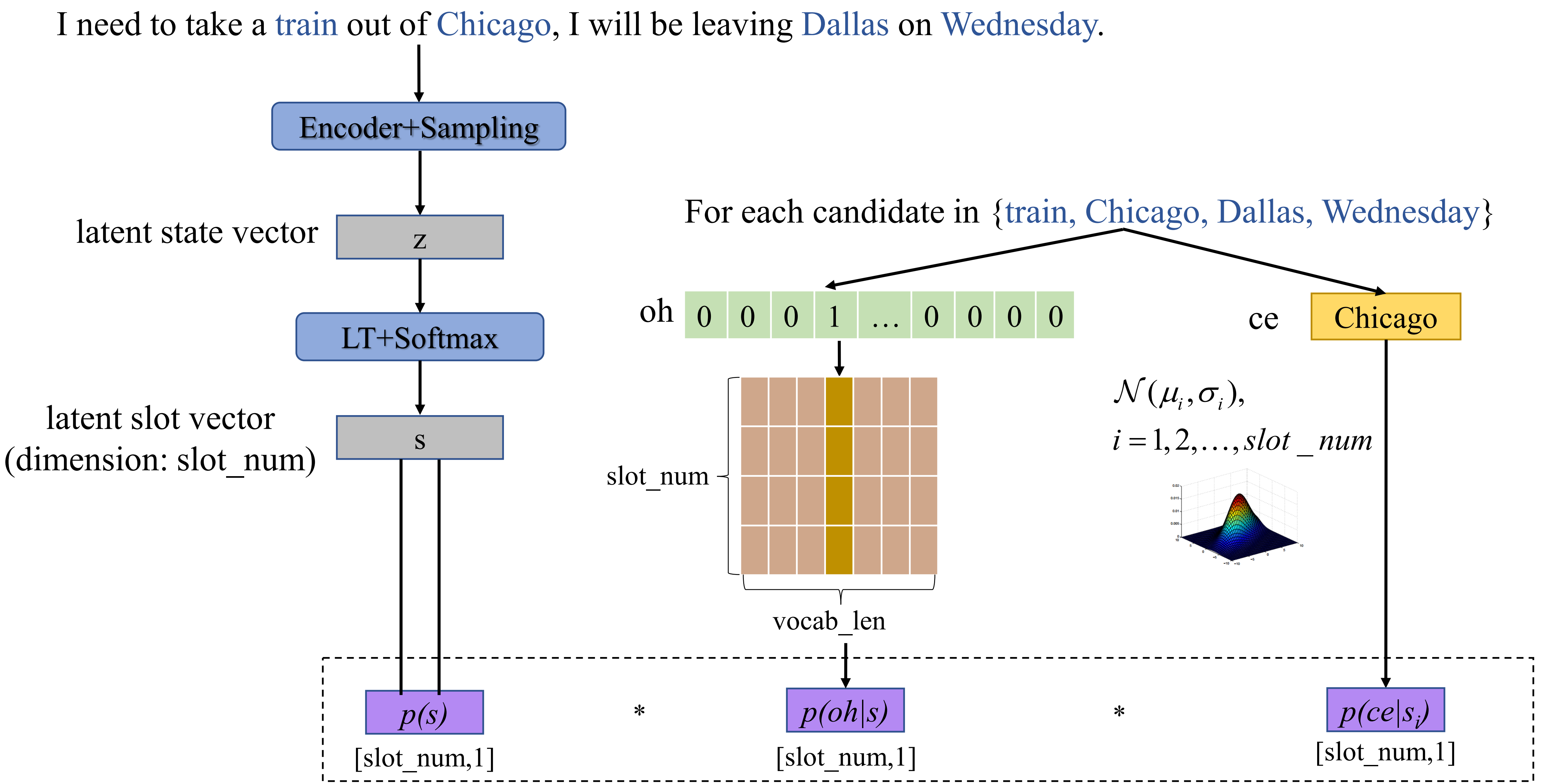
$i = 1, 2, \ldots, slot\_num$



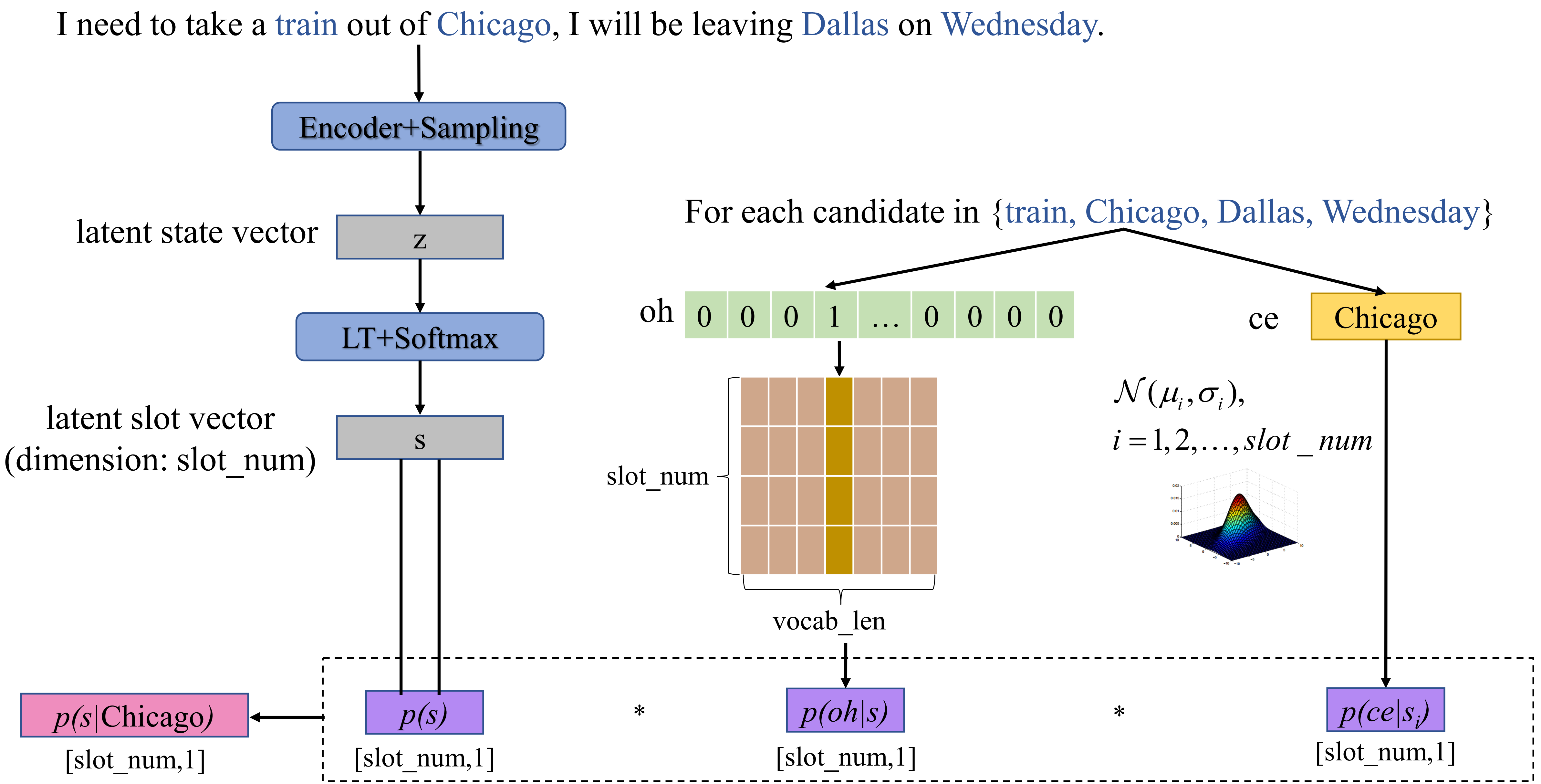
$p(ce|s)$

[slot_num,1]

DSI-base inference

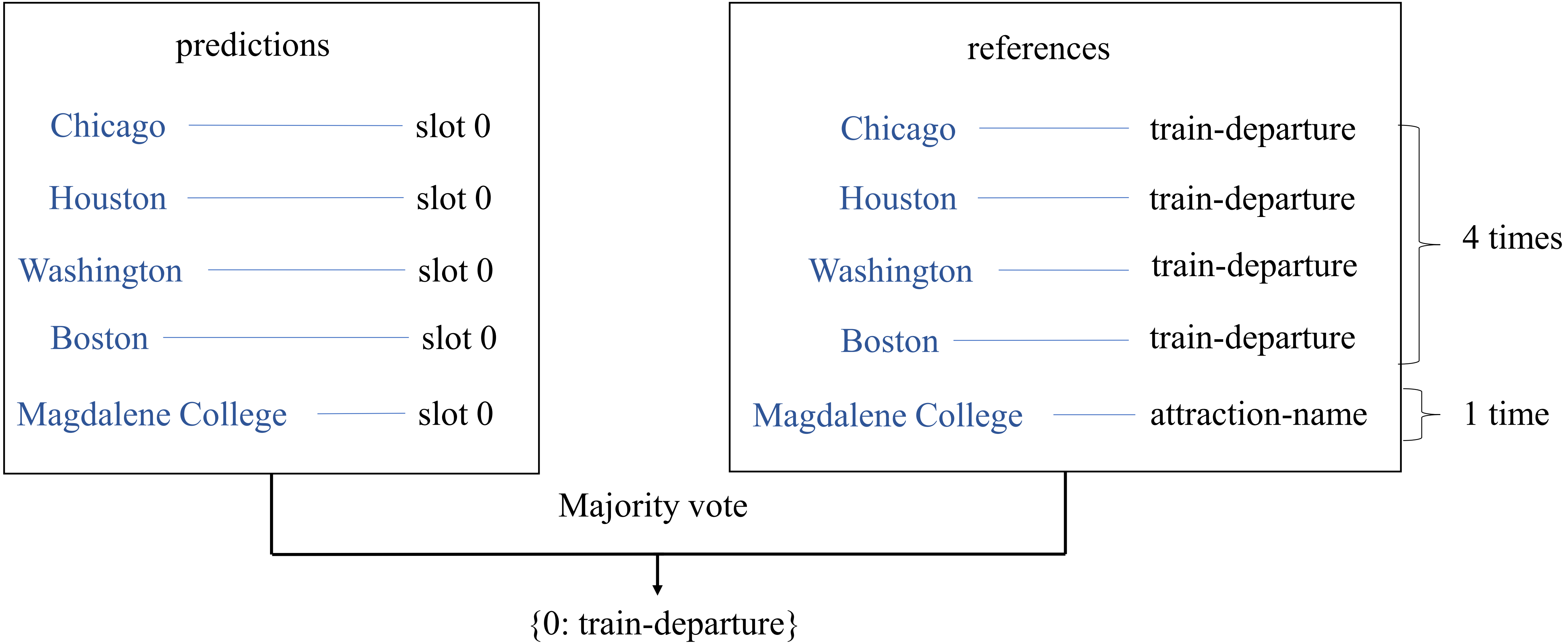


DSI-base inference



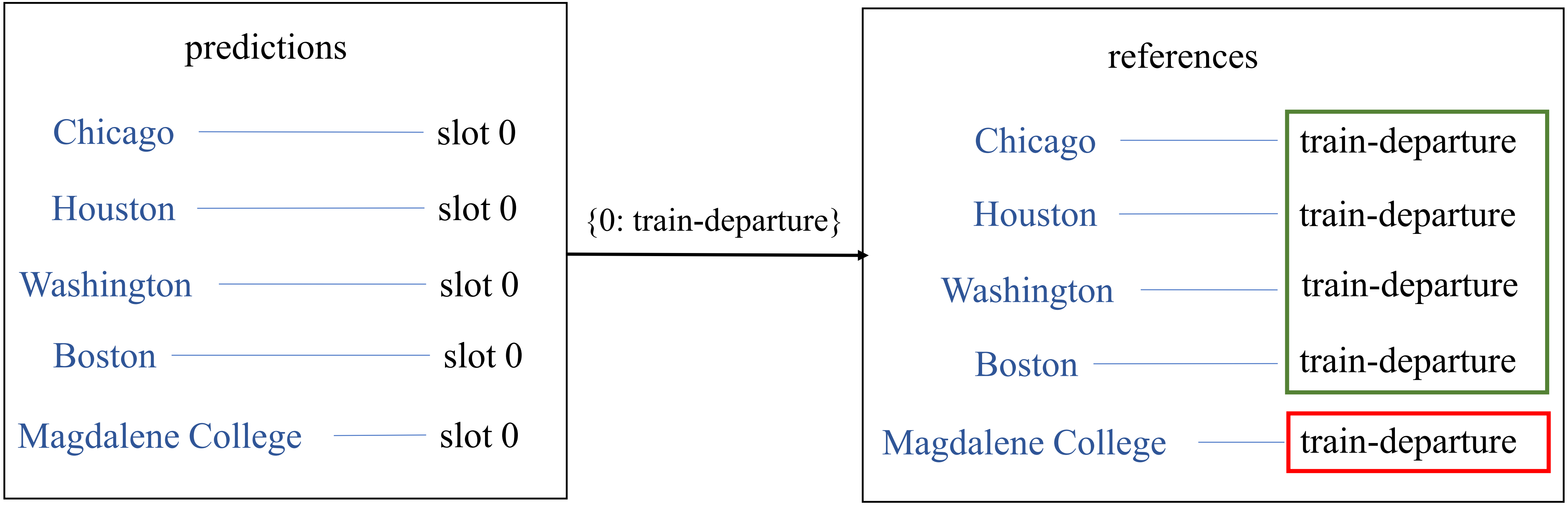
Post-processing: slot mapping

Mapping from slot indexes to labels?

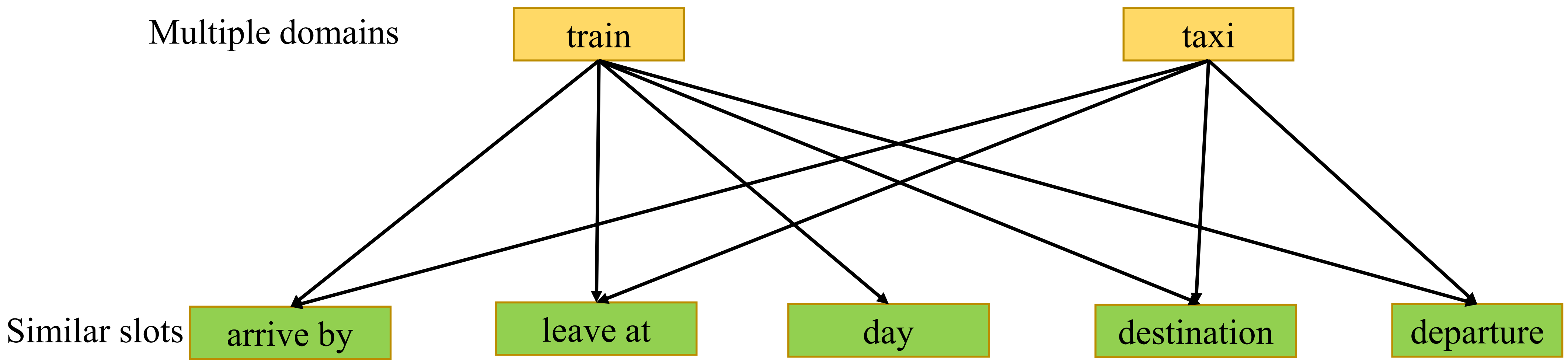


Post-processing: slot mapping

Mapping from slot indexes to labels?



What is the problem with *DSI-base*?



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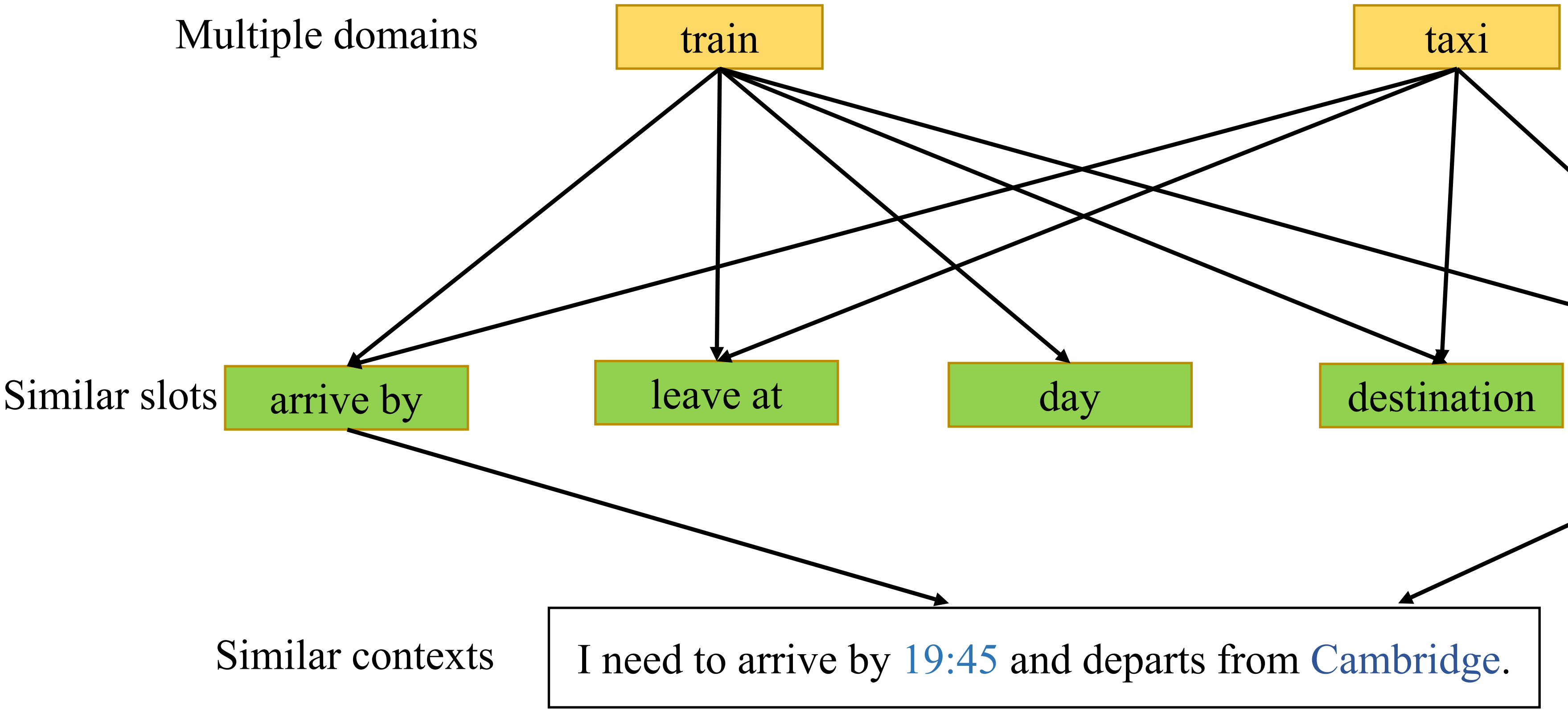
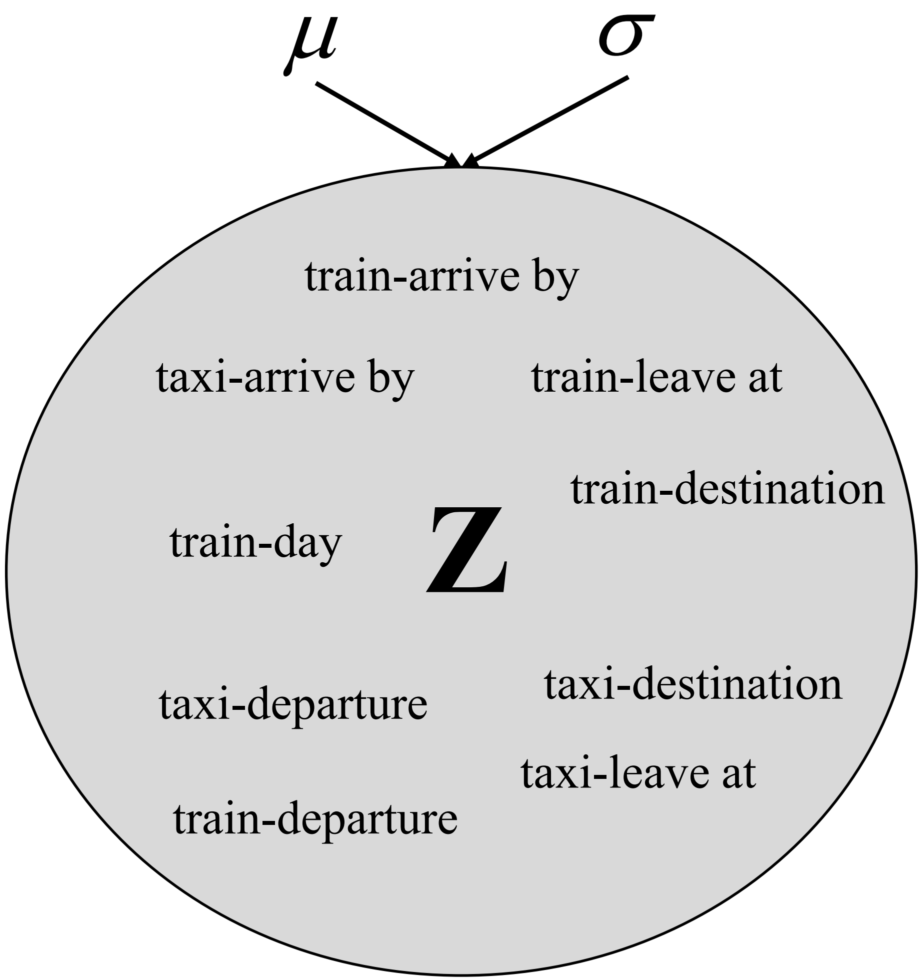


How does *DSI-GM* work?

A single Gaussian prior



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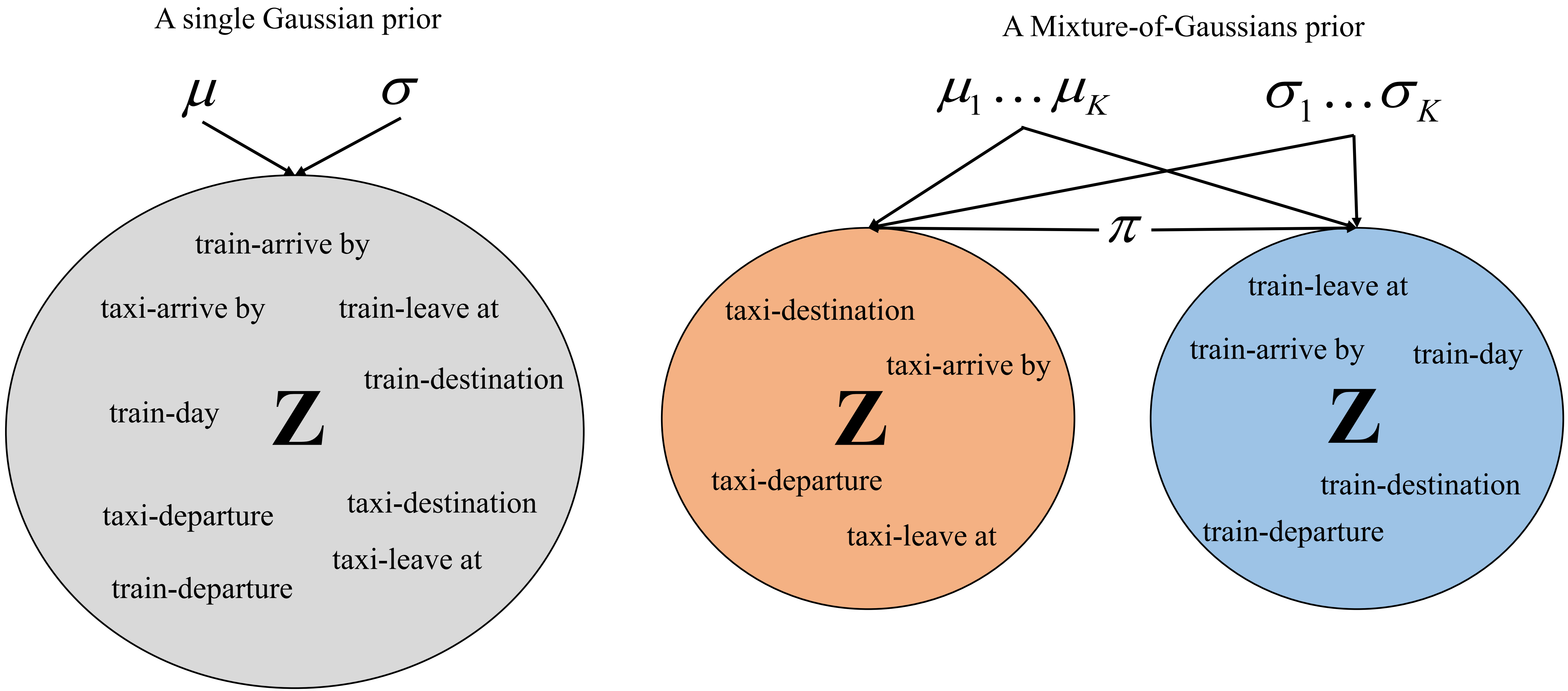

How does *DSI-GM* work?

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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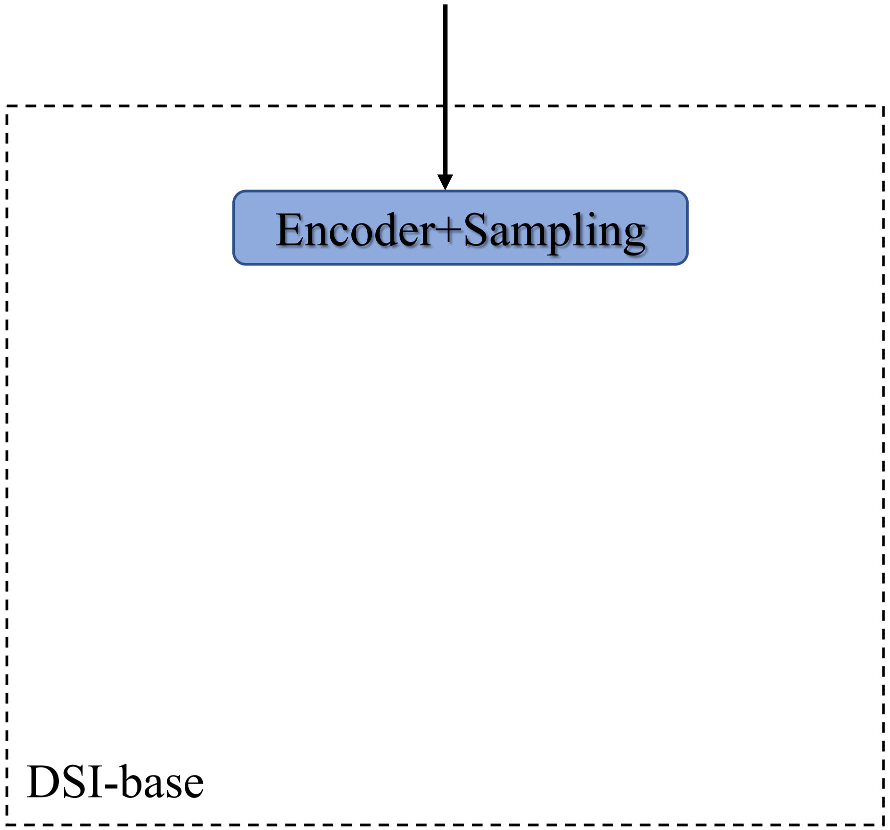

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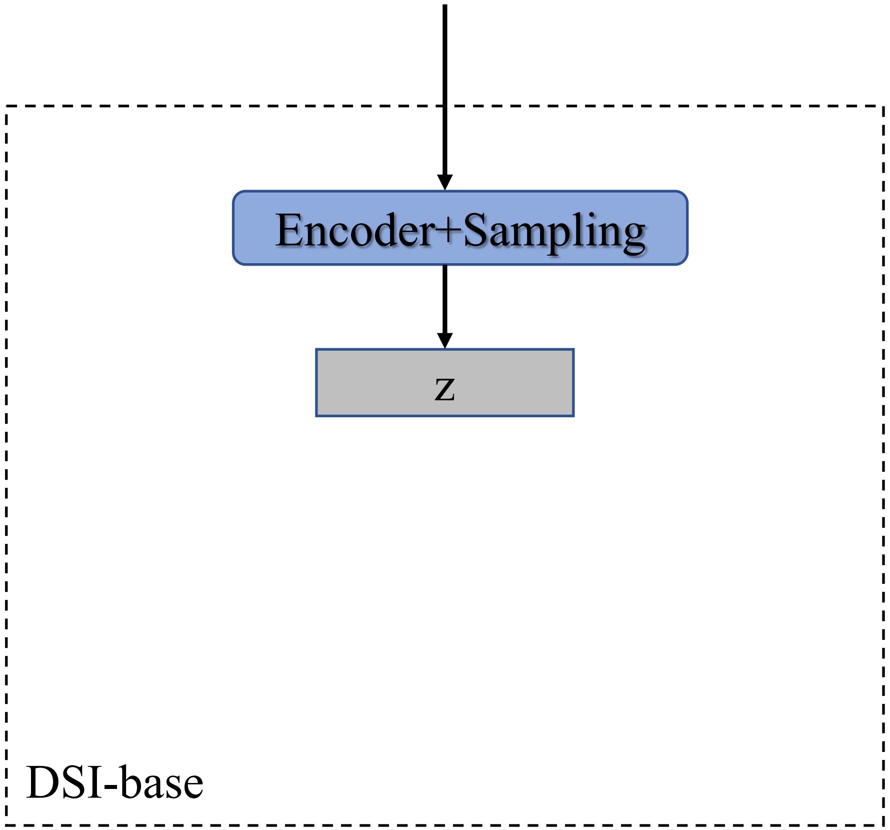

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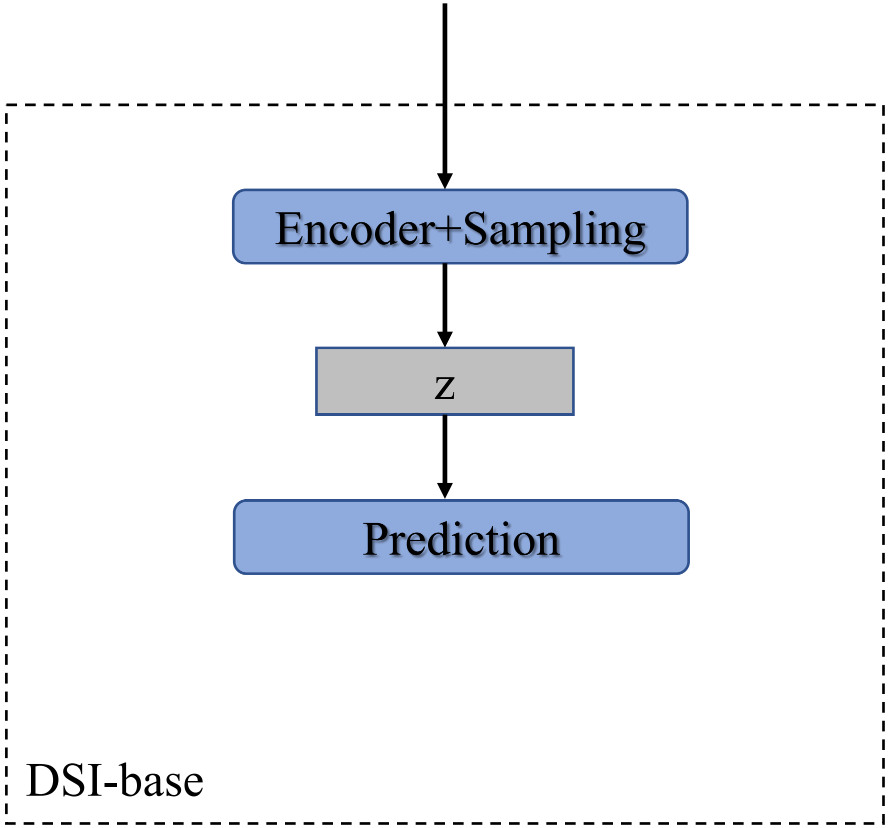

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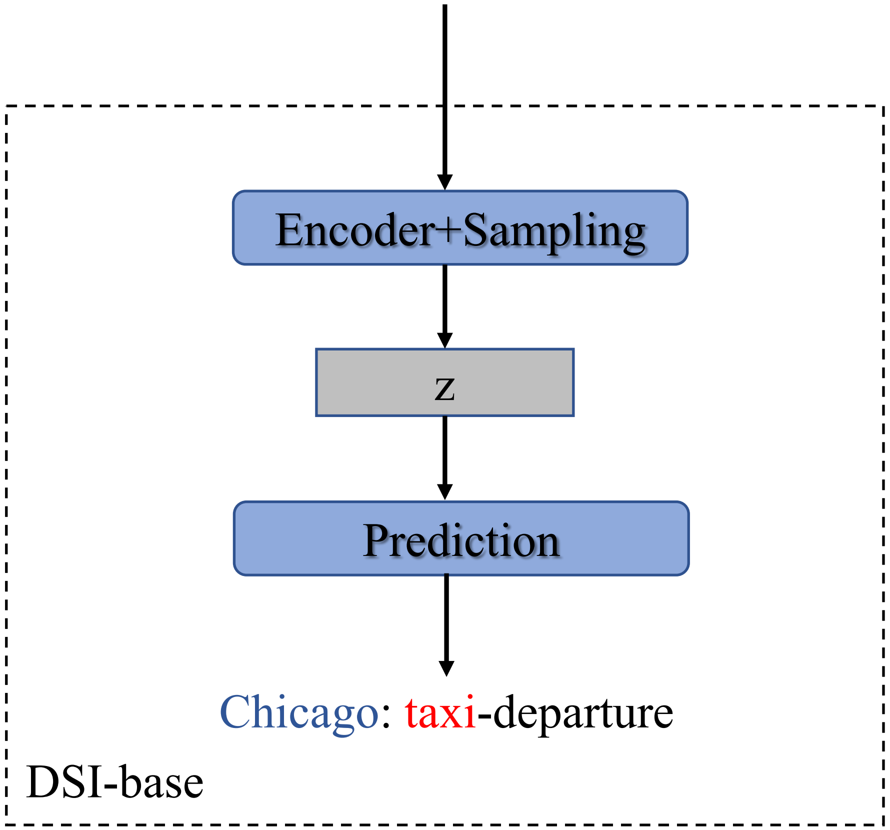

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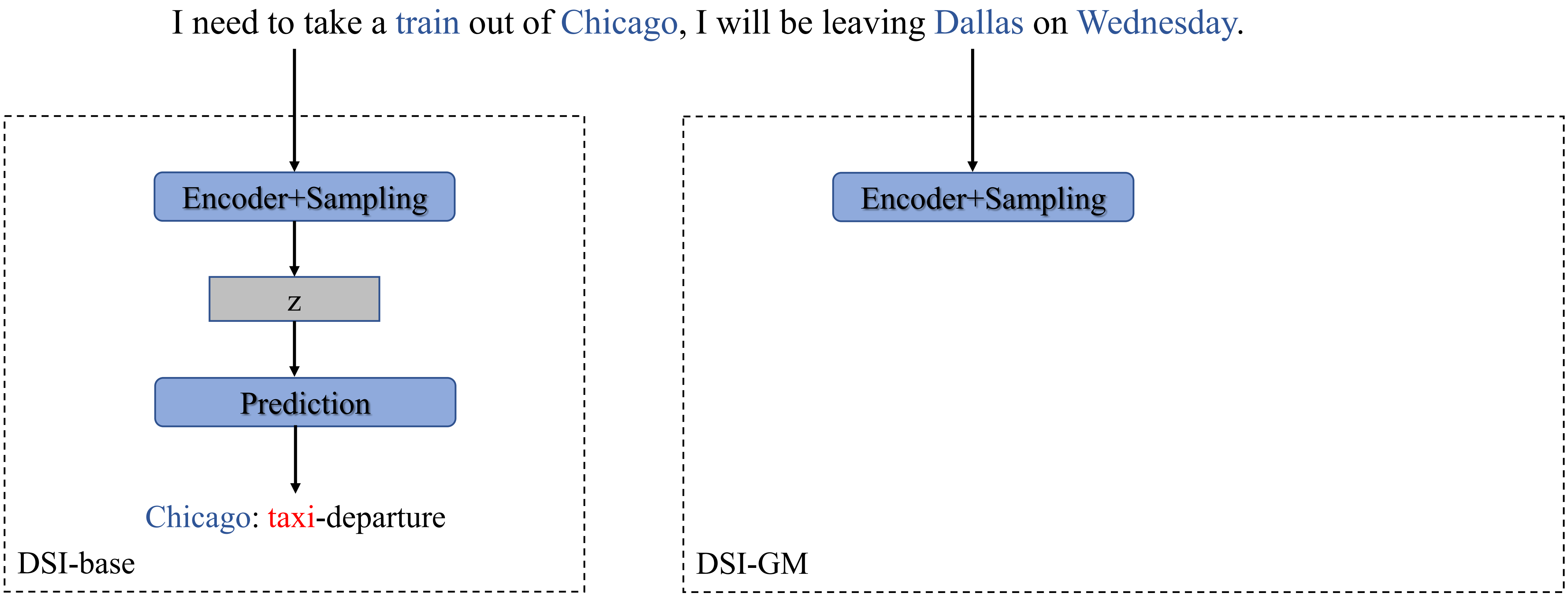
How does *DSI-GM* work?



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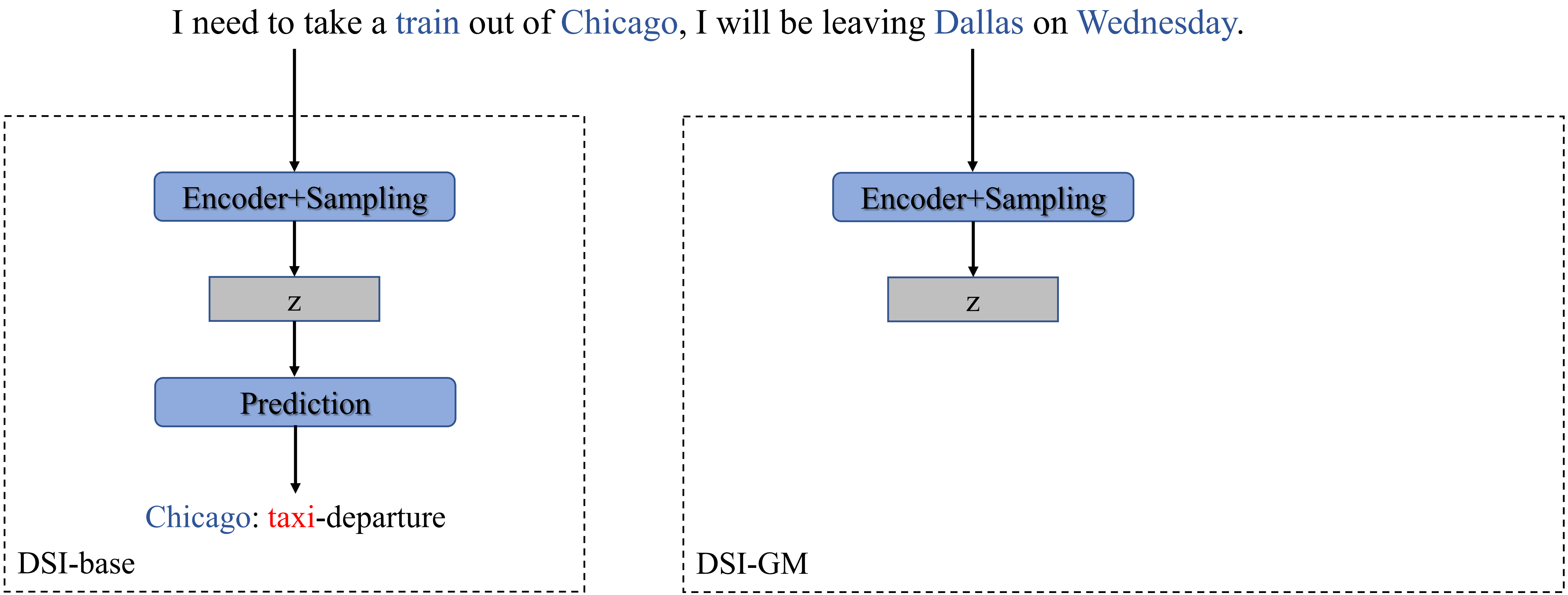
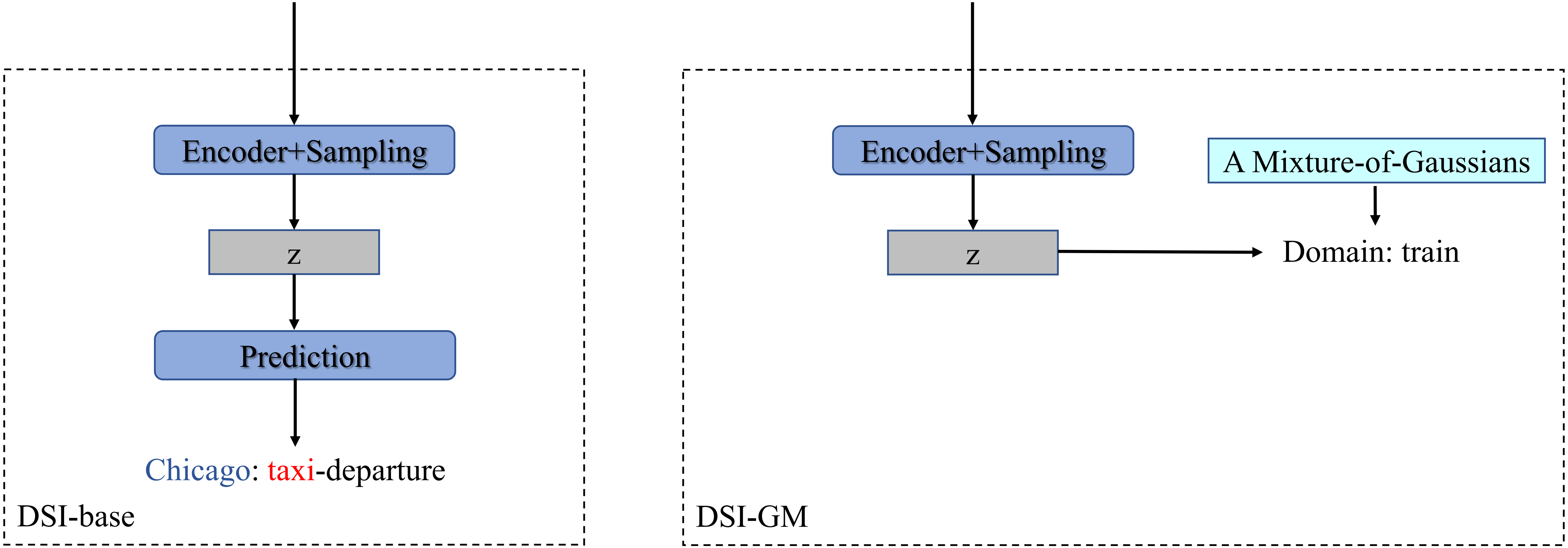
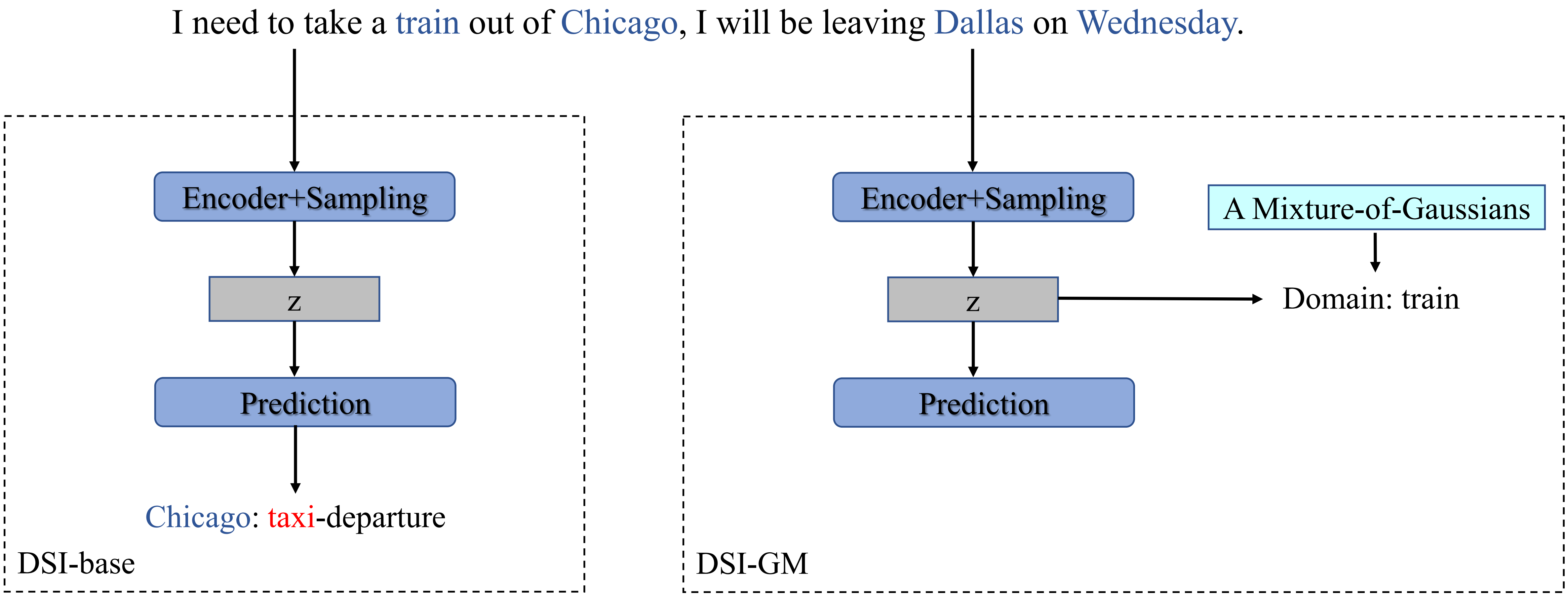


How does *DSI-GM* work?

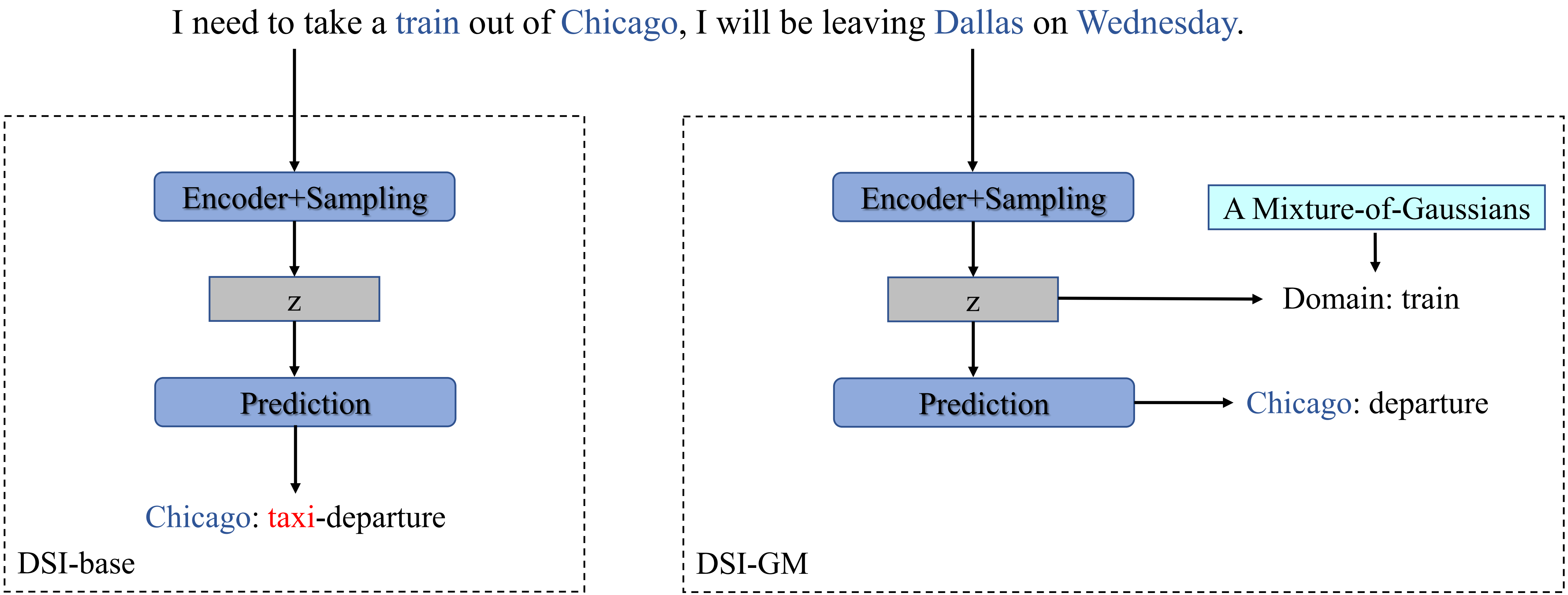
I need to take a train out of Chicago, I will be leaving Dallas on Wednesday.



How does *DSI-GM* work?



How does *DSI-GM* work?



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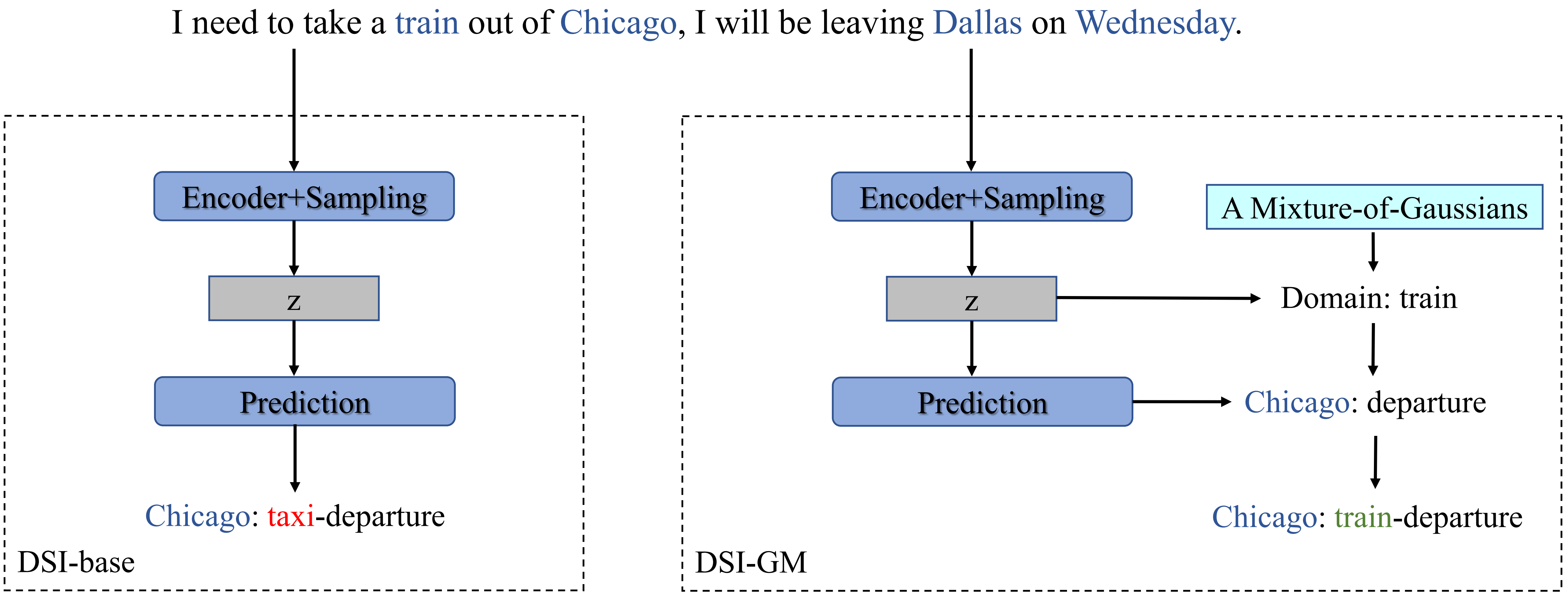

CHAPTER 3

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							
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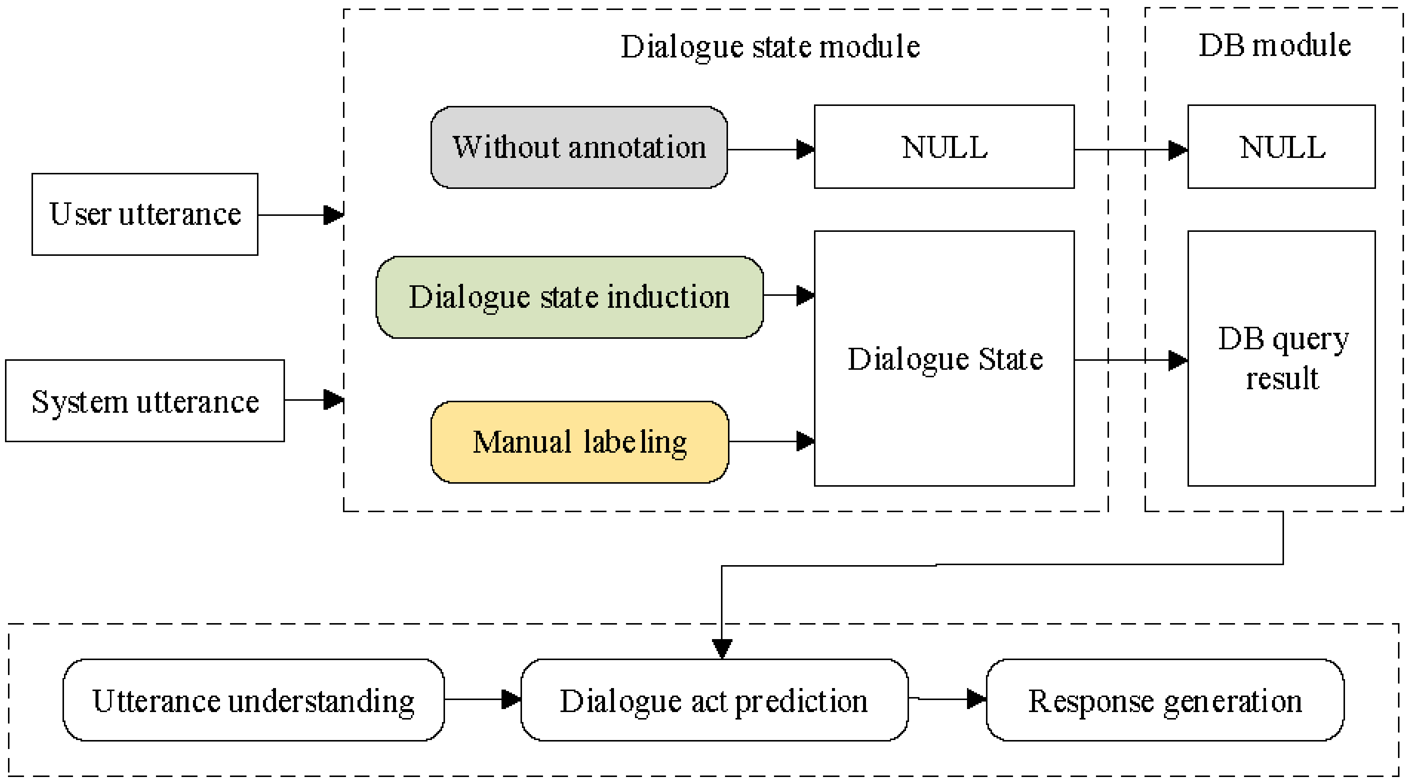
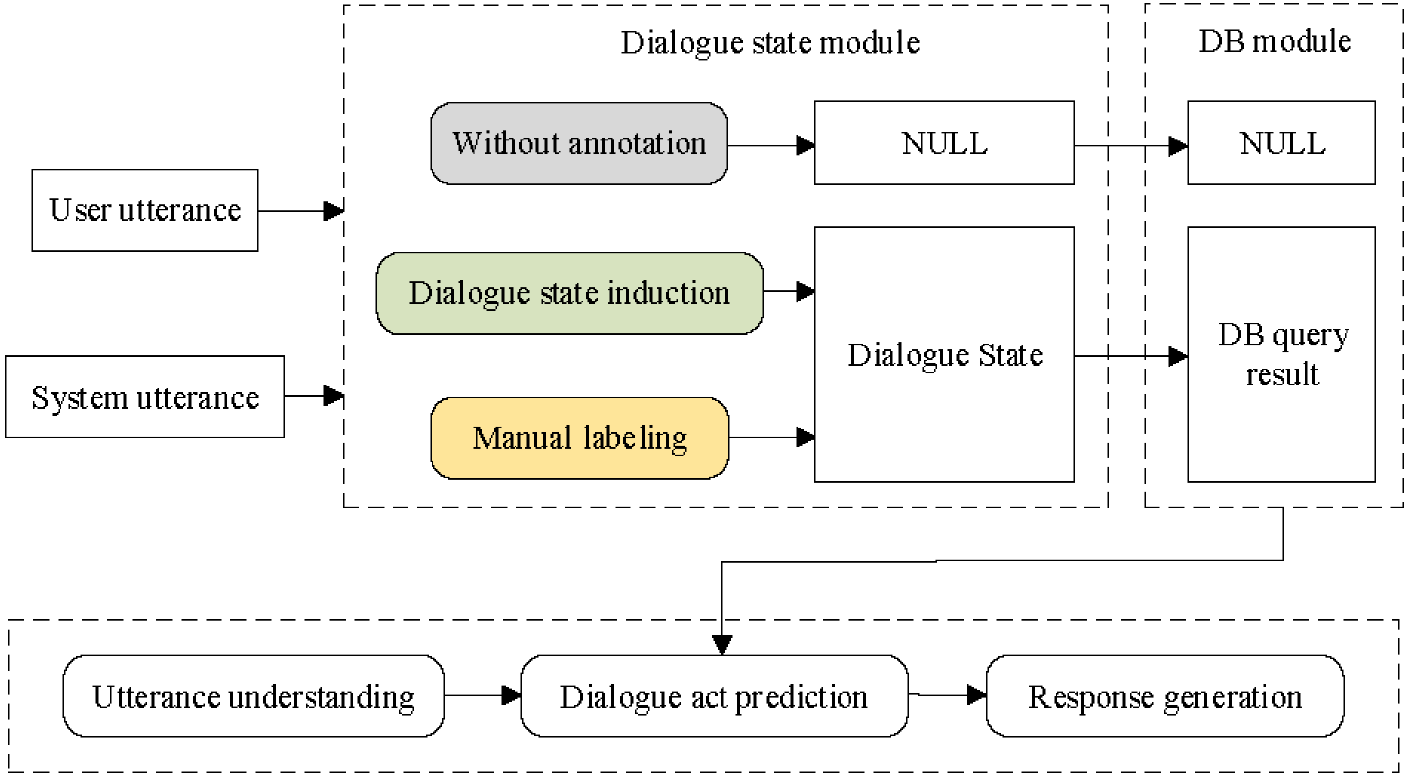
DSI-Based Response Generation

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.

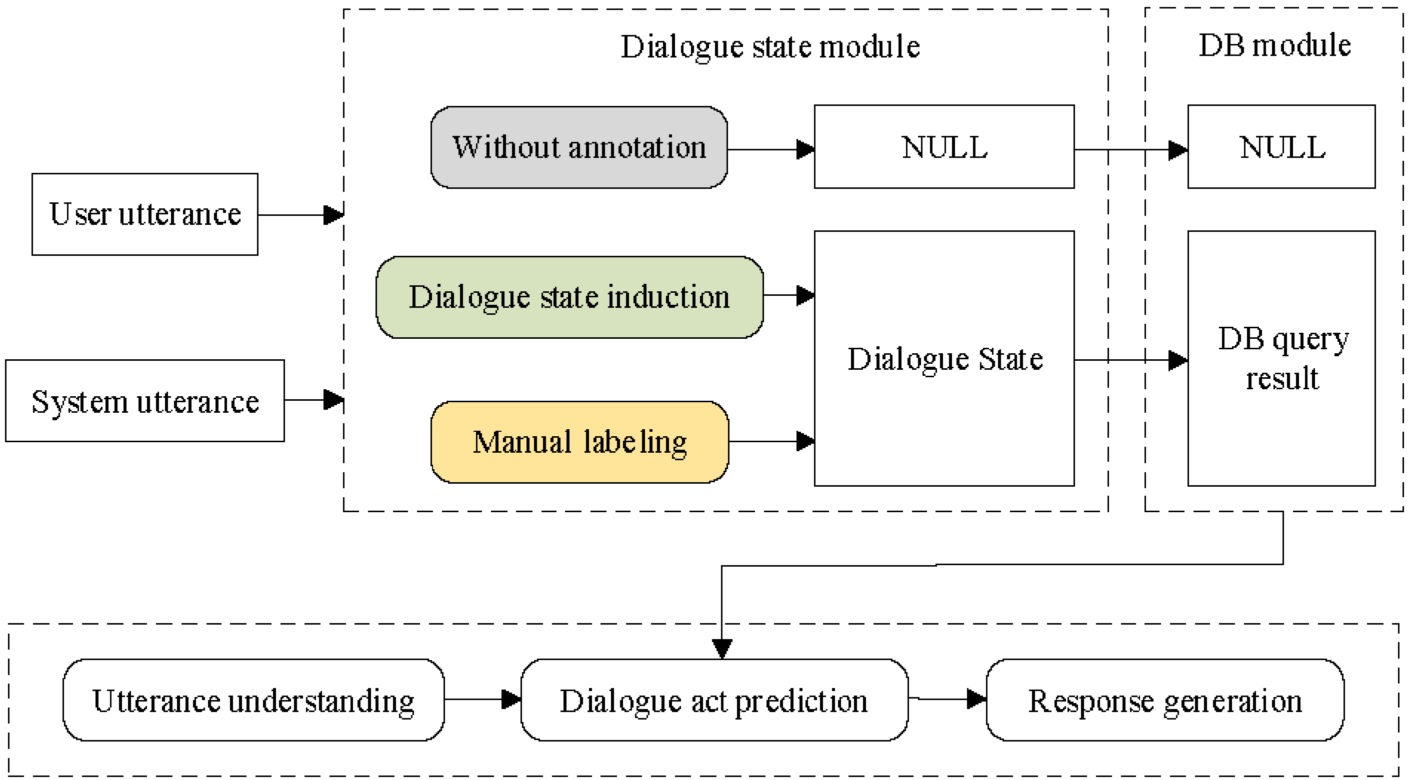
DSI-Based Response Generation



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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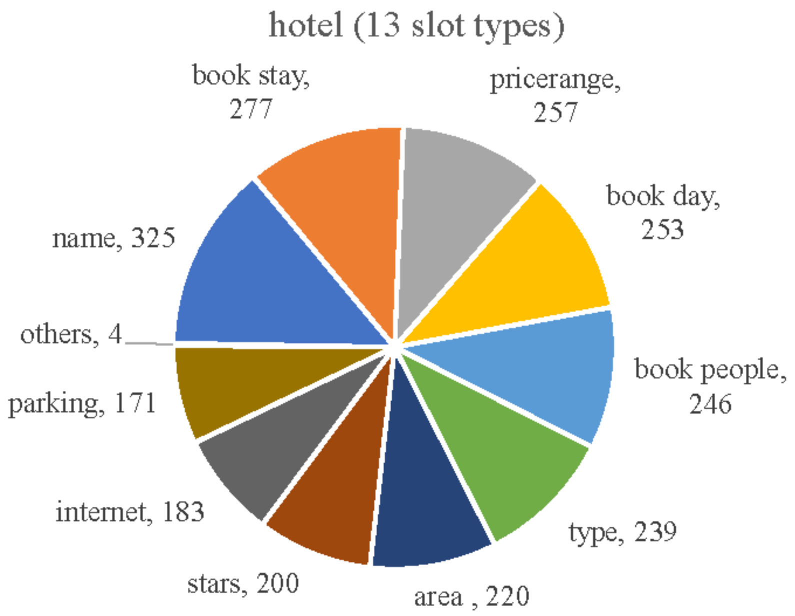
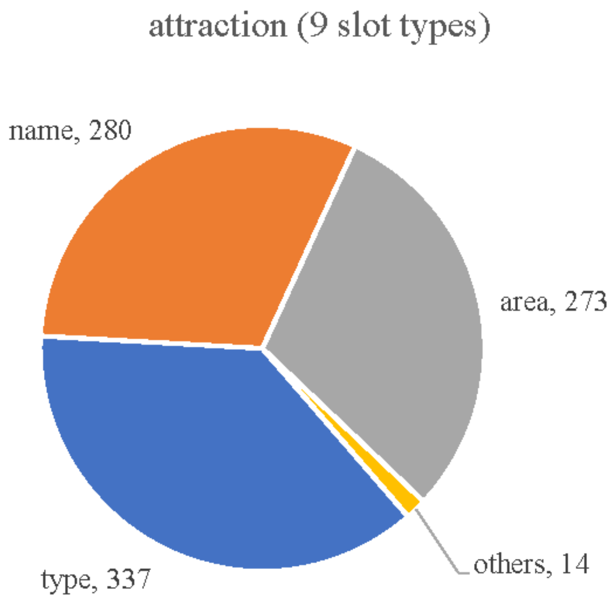
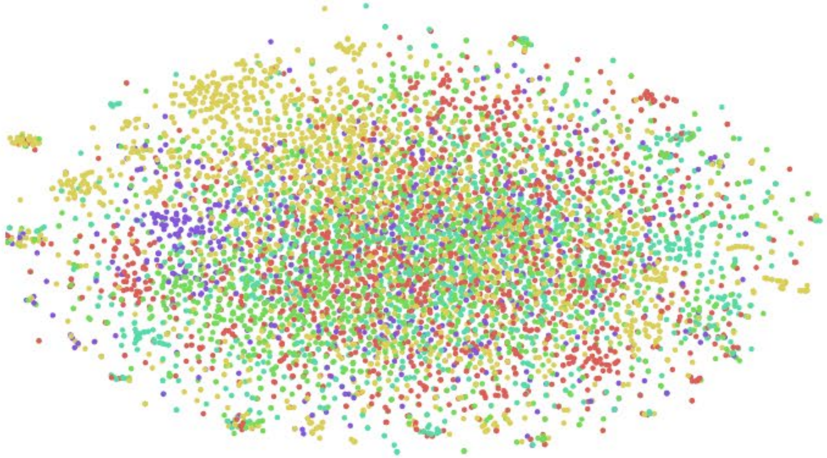
Analysis

	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

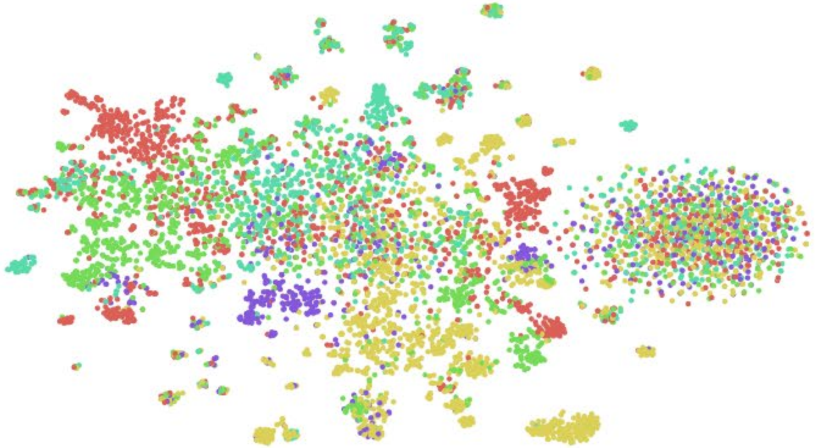
Table 4: Turn goal accuracy per domain.







(a) *DSI-base*



(b) *DSI-GM*

Domain level comparison of the latent representation z.

CHAPTER 4

Conclusion

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Conclusion

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

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

paper

GitHub