Learning Semantic Similarity in a Continuous Space:

Semantic Similarity Learning Using Deep Generative Model

He Ying

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CONTENT

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- VAE-Siamese Framework
  - VAE: inferring and learning intents (sentence presentations)
  - Variational Siamese Network: learning semantic similarity in a latent continuous space
- Results Analysis & Conclusion
- Brief Introduction to Seq2Seq Attention Mechanism

1. Introduction to Semantic Similarity Learning

- Semantics: used for understanding human expressions.
- Application of semantic similarity measurement between pairs of sentences:
  - Conversation systems (chatbots, FAQ)
  - Knowledge deduplication
  - Image captioning

1. Introduction to Semantic Similarity Learning

- Semantic representations of words:
  - One-hot Vector (Too sparse, lack of capability to relate to similarity in space)
  - Word2Vec (CBOW, Skip-gram)
  - GloVe
  - ELMo
  - BERT

1. Introduction to Semantic Similarity Learning

- Measuring Semantic Similarity:

  - WMD (Word Mover's Distance)

  (Measuring the dissimilarity between two bag-of-vectors (embedded words) with an optimal transport distance metric, Wasserstein 1)

  (Eg. "*why do cats like mice ?*" and "*why do mice like cats ?*" ==> Label Y: duplicate)

  - TF-IDF, Okapi BW-25, SIF etc.

  (Simple approaches to obtain a sentence representation from words' embeddings is to compute the barycenter of embedded words.)

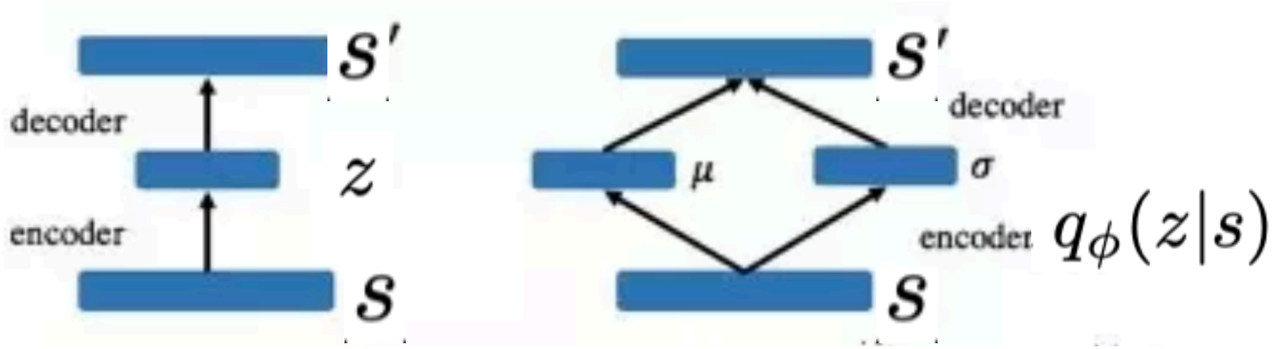
  (Still fail to capture semantics because of the bag-of-word assumption.)

2. VAE-Siamese Framework

2.1. VAE (Variational Auto-encoder)

Generative Models

- VAE in NLP
- GAN in CV

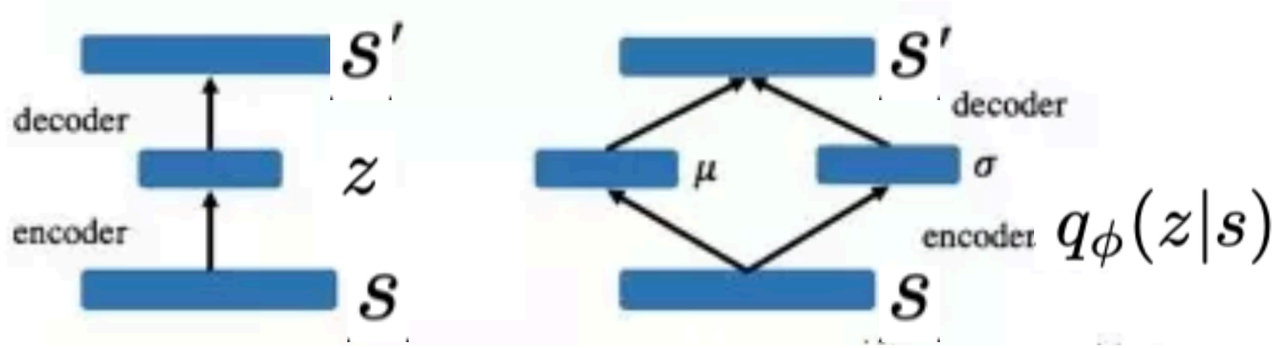


Standard Auto-encoder **Variational Auto-encoder**

VAE can be regarded as a regularized version of SAE by introducing a random latent variable.

2. VAE-Siamese Framework

2.1. VAE (Variational Auto-encoder)



Standard Auto-encoder **Variational Auto-encoder**

- The VAE learns, for any input s , a posterior distribution $q_\phi(z|s)$ over latent code z , where $z \sim N(\mu(s), \sigma(s))$, $z \in R^h$.

- The VAE's decoder parameterizes another distribution $p_\theta(s|z)$.

$$L_{\theta;\phi}(s) = E_{q_\phi(z|s)}[\log p_\theta(s|z)] - KL(q_\phi(z|s)||p(z))$$

2. VAE-Siamese Framework

2.1. VAE (Variational Auto-encoder)

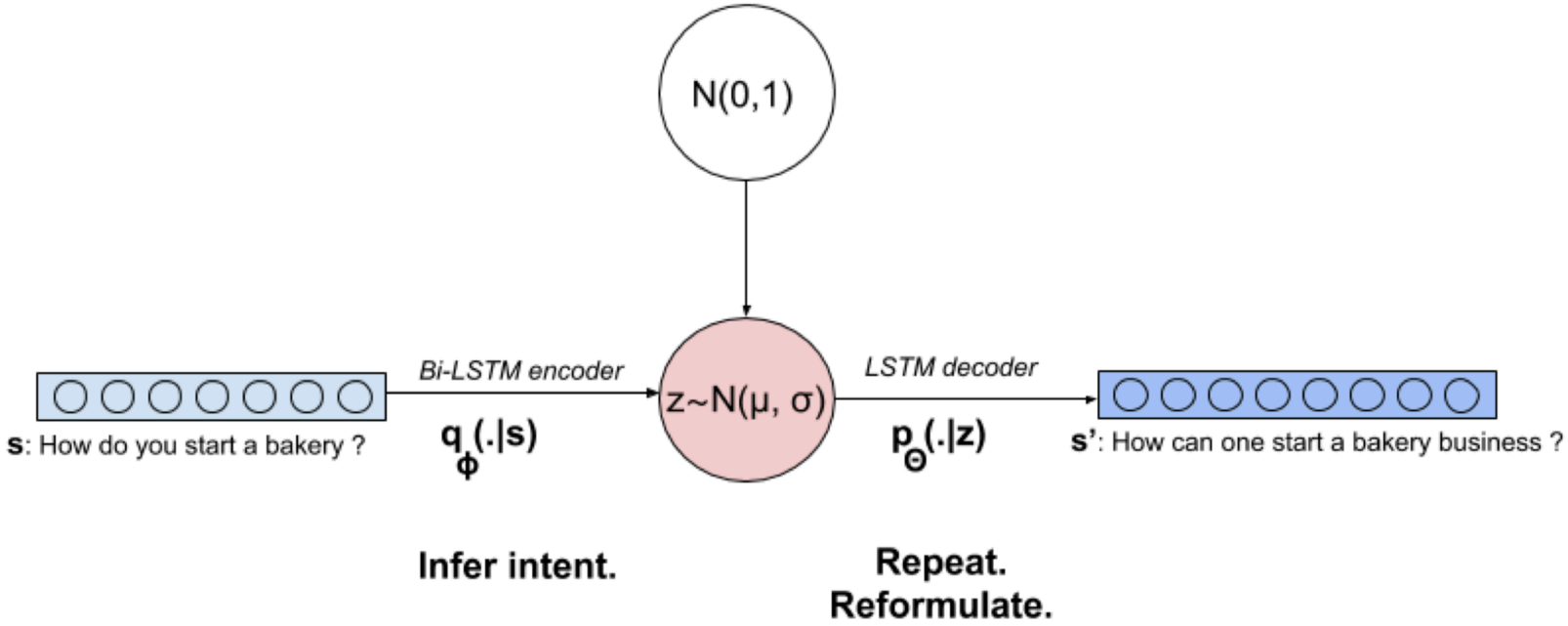


Figure 2. Bayesian framework and neural architecture to learn semantic representation of sentences.

$$-L_{\theta;\phi}(s,s') = -E_{q_\phi(z|s)}[\log p_\theta(s'|z)] + \kappa KL(q_\phi(z|s)||N(0,I))$$

$$\kappa = sigmoid(0.002(step - 2500))$$

2. VAE-Siamese Framework

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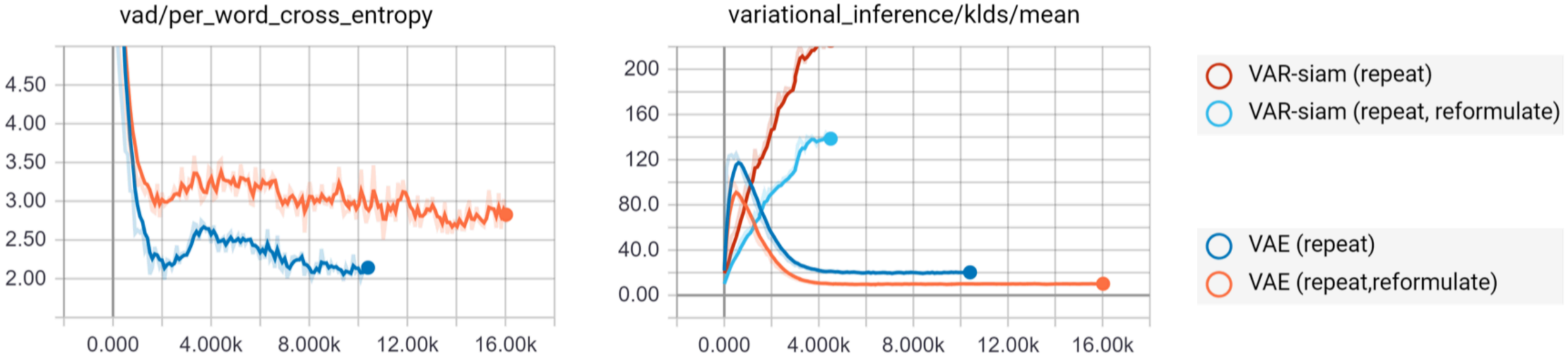


Figure 3: Results from our generative pretraining: $repeat$ (dark blue), $repeat, reformulate$ (orange). Left: Per word cross entropy. Right: KL divergence $KL(q_\phi(z|s)||N(0, I))$.

2. VAE-Siamese Framework

2.2. Variational Siamese Network

– We train our model successively on two tasks (generative and discriminative) and use the first step as a smooth initialization ($N(0, I)$ prior and semi-supervised setting) for the second one, learning similarity.

– Metrics of Similarity: Wasserstein 2 (W_2^2) , Hadamard product $\mu_1 \mu_2 \in \mathbb{R}^h$.

$$W_2^2(p_1, p_2) = \sum_{i=1}^{h} (\mu_1^i - \mu_2^i)^2 + (\sigma_1^i - \sigma_2^i)^2$$

where, $p_1 = N(\mu_1, \sigma_1) \in \mathbb{R}^h$, $p_2 = N(\mu_2, \sigma_2) \in \mathbb{R}^h$.

2. VAE-Siamese Framework

2.2. Variational Siamese Network

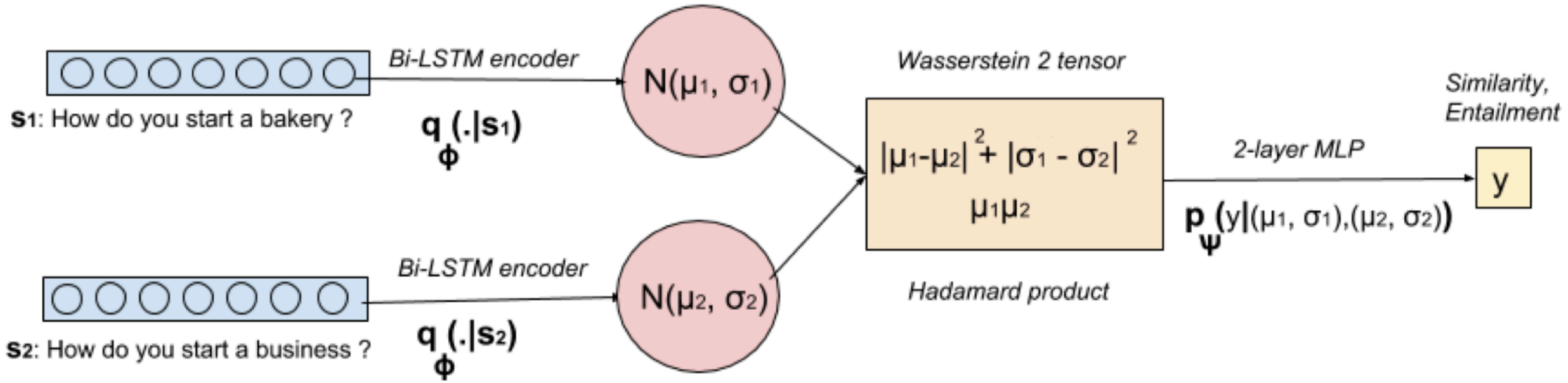


Figure 4: Our *variational siamese* network to measure and learn semantic similarity.

$$L_{\psi;\phi}(s_1, s_2) = -y \log p_\psi(y|q_\phi(.|s_1), q_\phi(.|s_2)) + \lambda||\psi||_1$$

$$\lambda = 0.00001$$

3. Results Analysis

3.1. Experimental details

- Embedding words in a 300 dimensional space using Glove vectors pre-trained on Wikipedia 2014 and Gigaword 5 as initialization.
- Variational space (μ, σ) is of dimension $h = 1000$.
- Our bi-LSTM encoder network consists of a single layer of 2h neurons and our LSTM and the LSTM decoder has a single layer with 1000 neurons.
- The MLP's inner layer has 1000 neurons.
- SGD with ADAM optimizer (learning rate = 0.001) and batches of size 256 and 128.

3. Results Analysis

3.2. Results

Table 1: Quora question pairs dataset result. The split considered is that of BiMPM [47]. Models are sorted by decreasing test accuracy. Results with † are reported in [22] and ‡ in [25]. SWEM [49] stands for Simple Word Embedding based Models.

Model	Read pairs separately	Accuracy Dev	Accuracy Test	Generative (pre)training
DIIN [22] †	False	89.44	89.06	False
VAR-Siamese (with repeat/reformulate)	**True**	**89.05**	**88.86**	**True**
pt-DECATTchar [48] †	False	88.89	88.40	False
VAR-Siamese (with repeat)	**True**	**88.18**	**88.24**	**True**
BiMPM [47] †	False	88.69	88.17	False
pt-DECATTword [48] †	False	88.44	87.54	False
L.D.C †	False	-	85.55	False
Siamese-GRU Augmented [25] ‡	True	-	85.24	False
Multi-Perspective-LSTM †	False	-	83.21	False
SWEM-concat [49]	True	-	83.03	False
SWEM-aver [49]	True	-	82.68	False
Siamese-LSTM †	True	-	82.58	False
SWEM-max [49]	True	-	82.20	False
Multi-Perspective CNN †	False	-	81.38	False
DeConv-LVM [37]	True	-	80.40	True
Siamese-CNN †	True	-	79.60	False
VAR-Siamese (w/o pretraining)	**True**	**62.16**	**62.48**	**False**
Bias in dataset (baseline)	-	62.16	62.48	-

3. Results Analysis

3.2. Results

Table 2: Question retrieval (best match, confidence) with our proposed model on Quora question pairs dataset (537 088 unique questions). All queries were retrieved in less than a second on two Tesla K80 GPU.

Query	Retrieved question 1/537088	MLP's output, Confidence
Hi! If I run the speed of the light, what would the world look like?	What would happen if I travel with a speed of light?	99.68%
How do you do a good gazpacho?	How can I make good gazpacho ?	99.52%
What can I do to save our planet?	How can I save the planet?	95.91%
What is the difference between a cat?	What is the benefit of a cat?	90.99%
Can we trust data?	Can I trust google drive with personal data?	57.13%

3. Results Analysis

3.2. Results

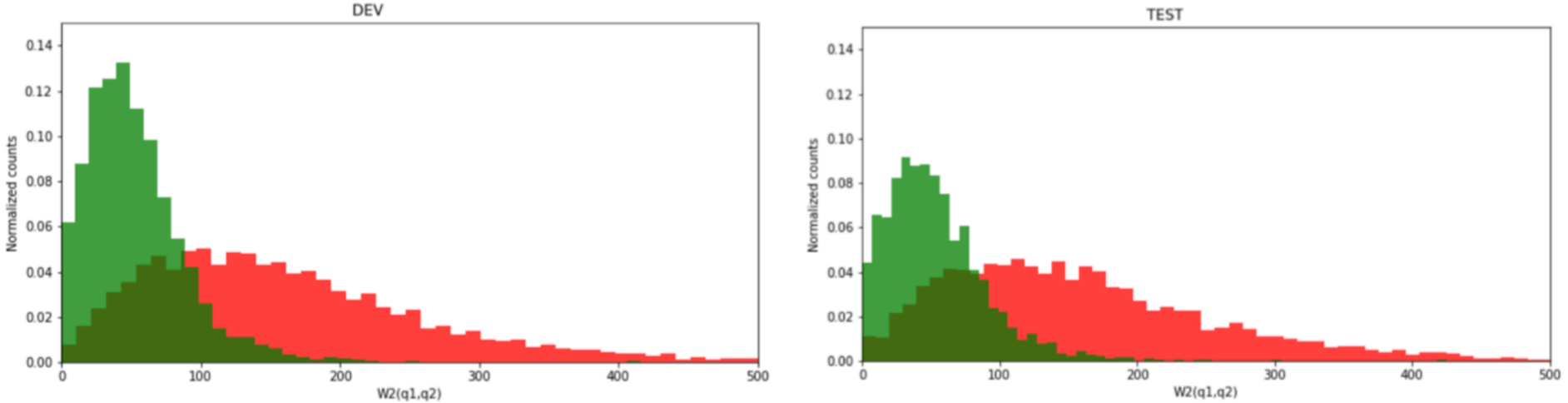


Figure 5: Empirical distribution of Wasserstein 2 distance between pairs of intents for duplicate (green) and not duplicate (red) pairs, after variational siamese training (with repeat, reformulate pretraining). Left: Quora Dev set. Right: Quora Test set.

3. Results Analysis

3.2. Results

Table 3: Discriminative power of Wasserstein 1 and 2 on Quora dataset.

Encoding	Wasserstein	Area under ROC curve		Training
		Dev set	Test set	labels
VAR-siamese (with repeat)	W2	87.11	86.74	Positive
VAR-siamese (with repeat/reformulate)	W2	86.88	86.27	& Negative
VAE (repeat/reformulate)	W2	77.70	77.44	Positive
Word Mover's Distance [1] (bag-of-word)	W1	73.47	73.10	None
VAE (repeat)	W2	70.67	69.91	None

4. Conclusion

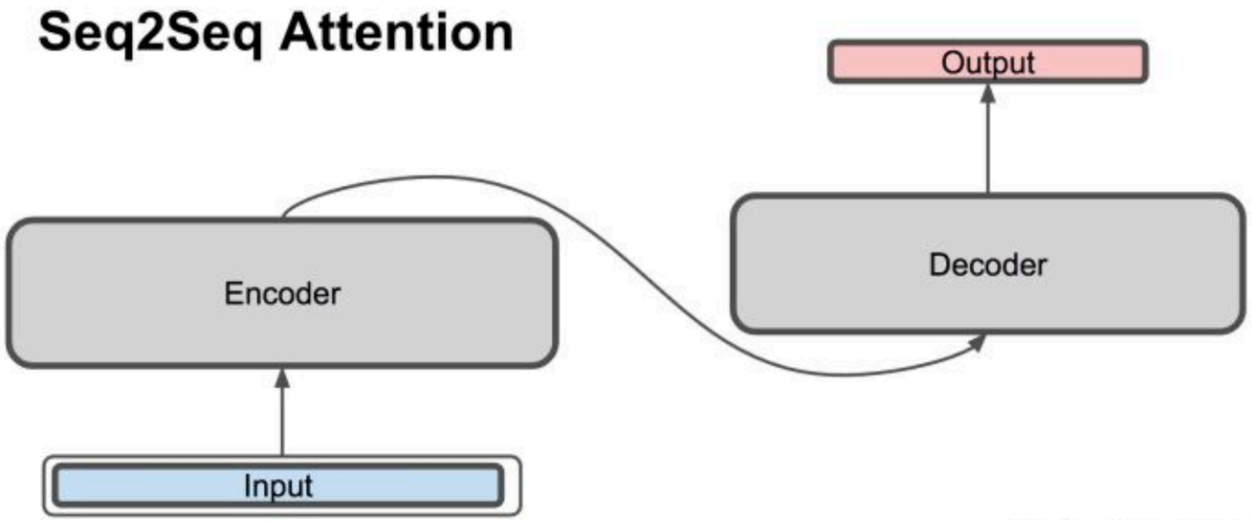
- Decompose the representation of a sentence in a mean vector and a diagonal covariance matrix to account for uncertainty and ambiguity in language.

- Encoding semantic information in an explicit sentence representation by learning to repeat, reformulate with the generative framework.

- The variational siamese network extends Word Mover's Distance to continuous representation of sentences in measuring semantic similarity.

- Our approach performs strongly on Quora question pairs dataset and experiments show its effectiveness for question retrieval in knowledge databases with a million entries.

5. Seq2Seq Attention Mechanism



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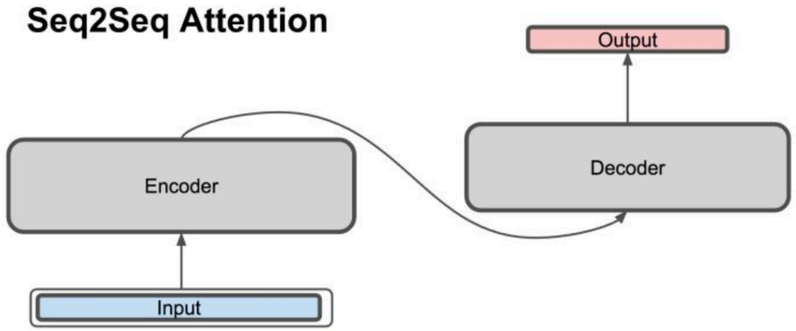

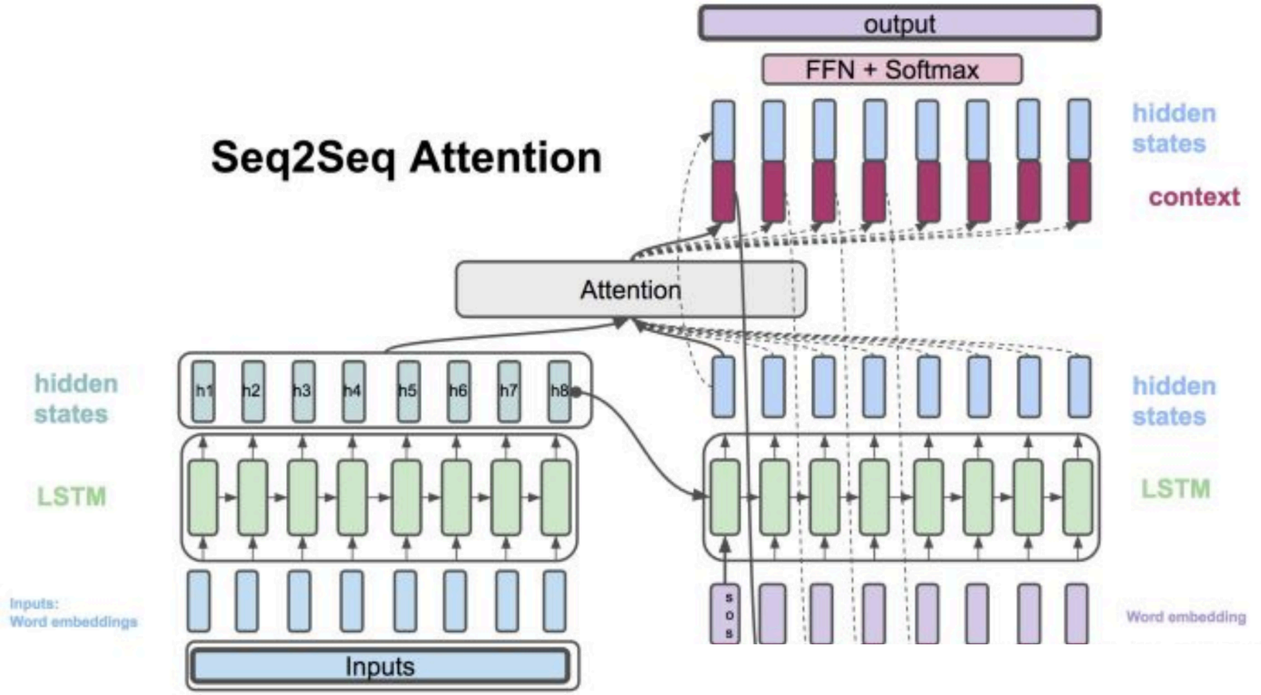

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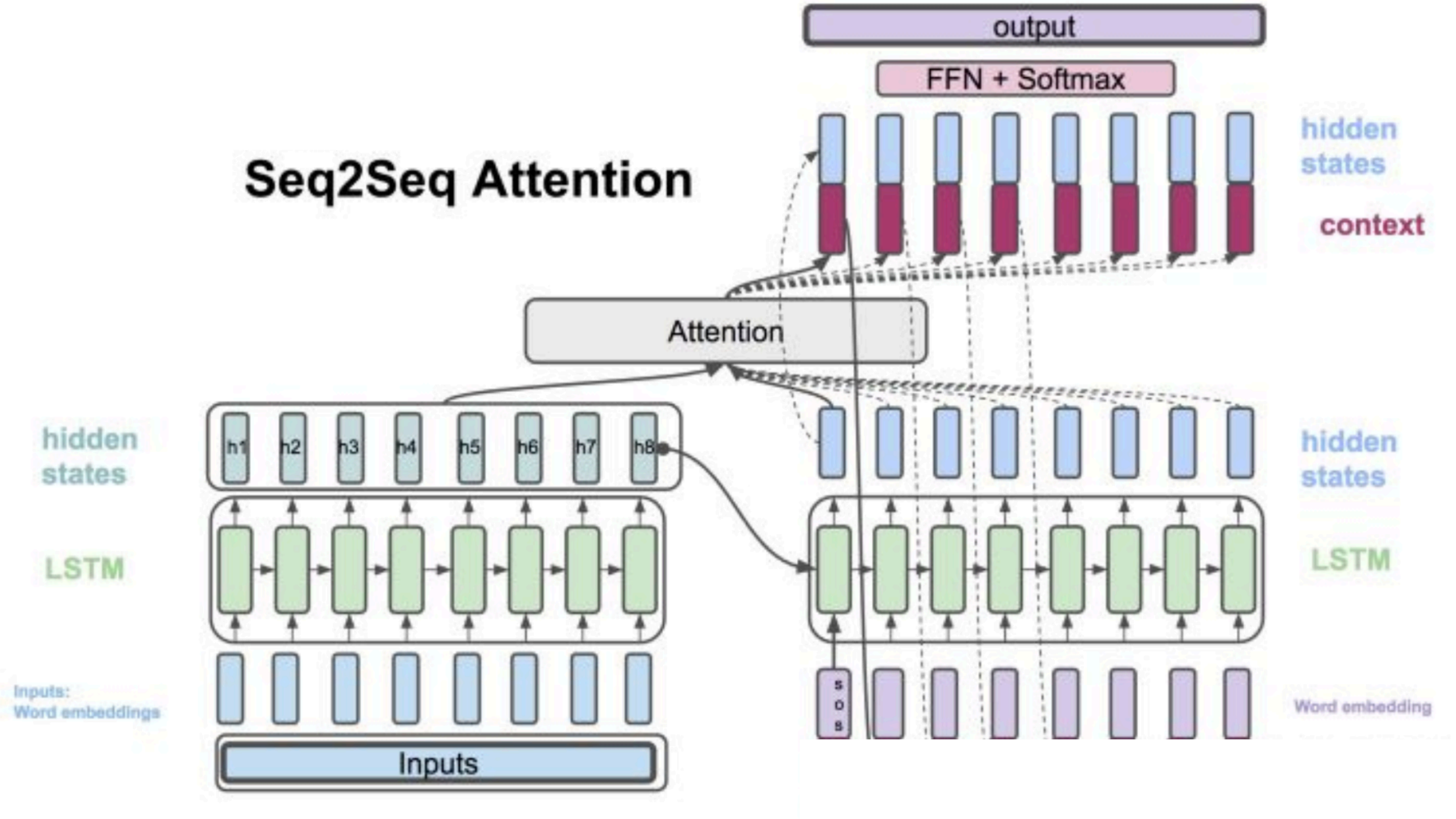

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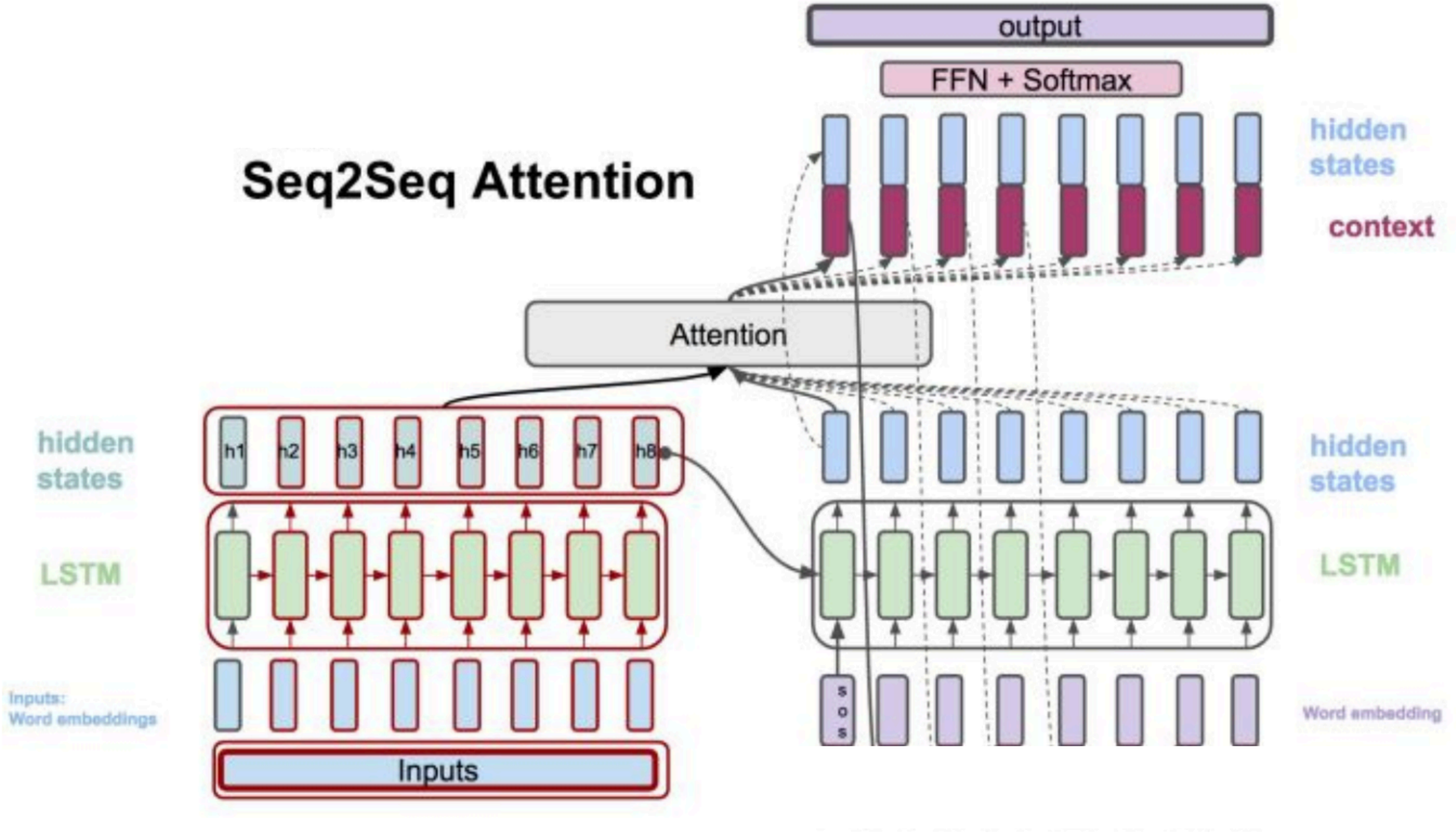

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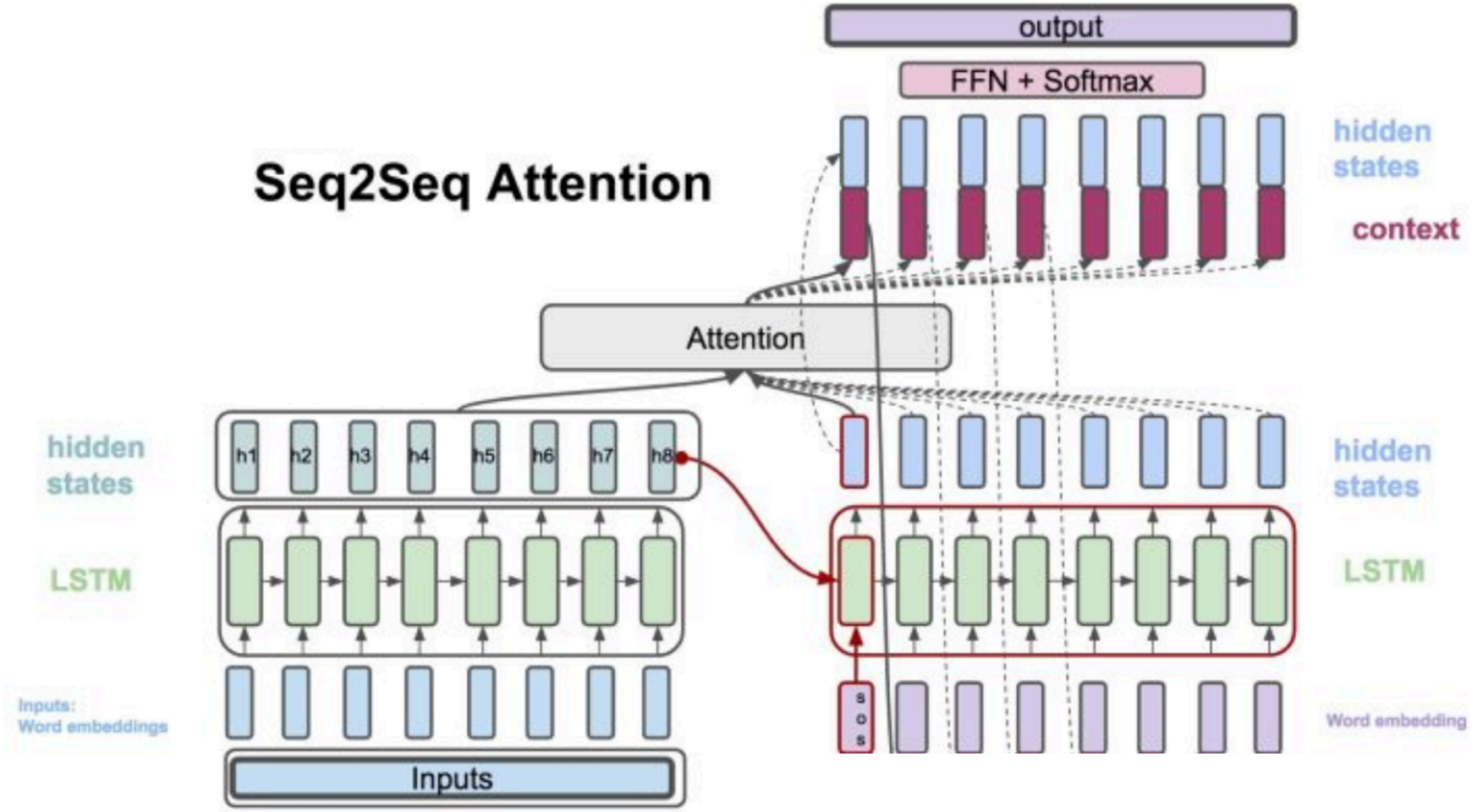

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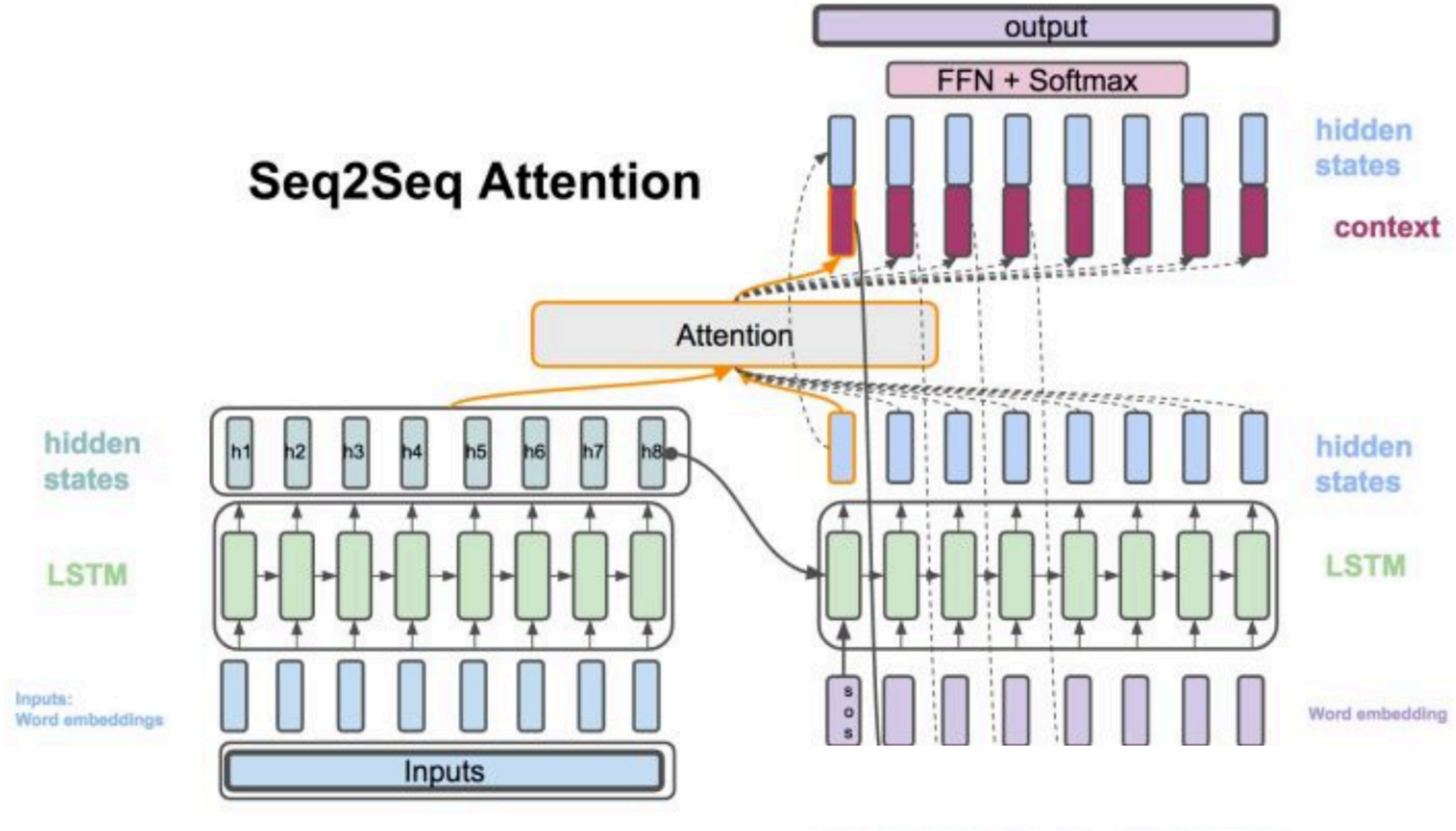

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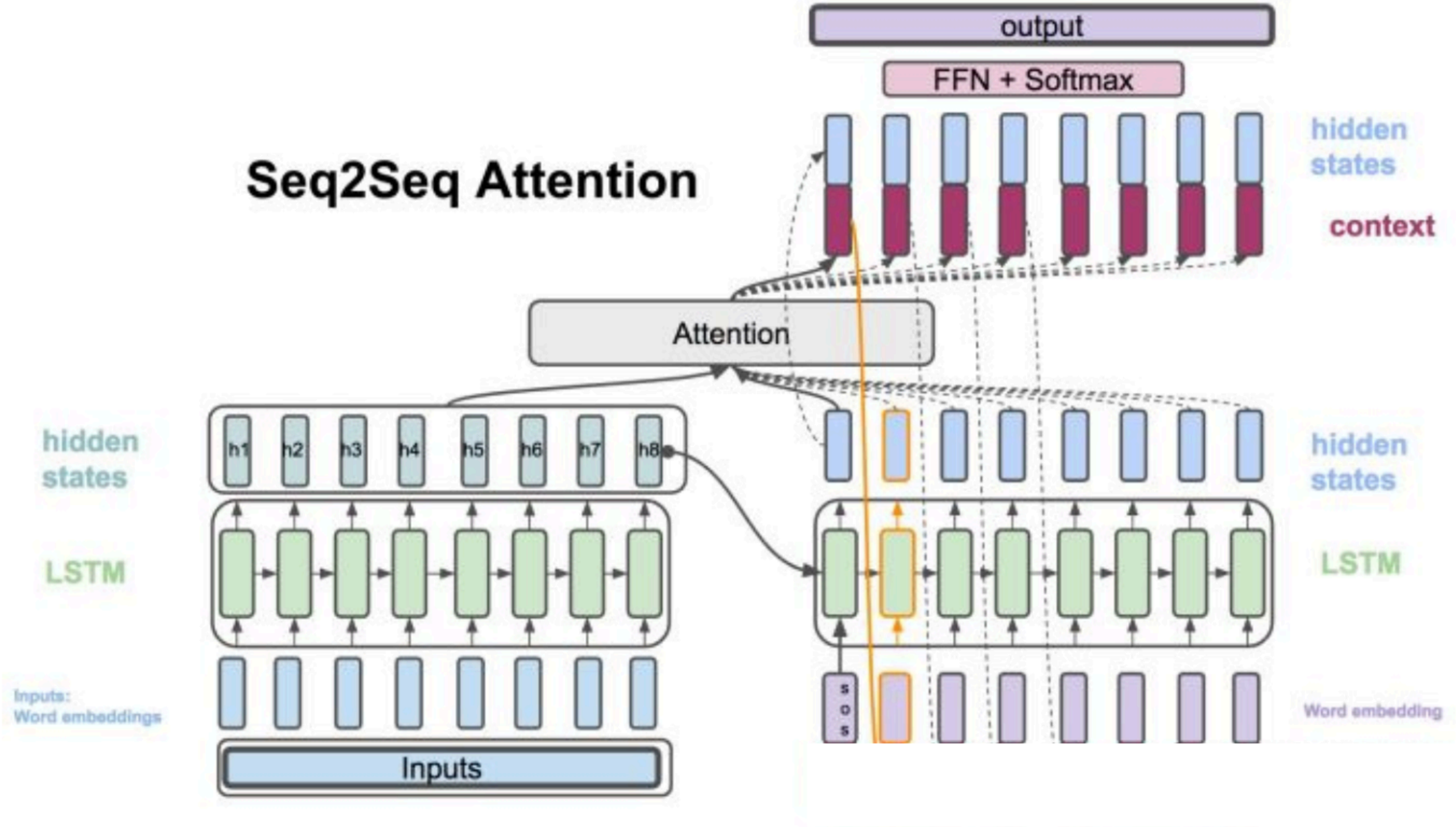

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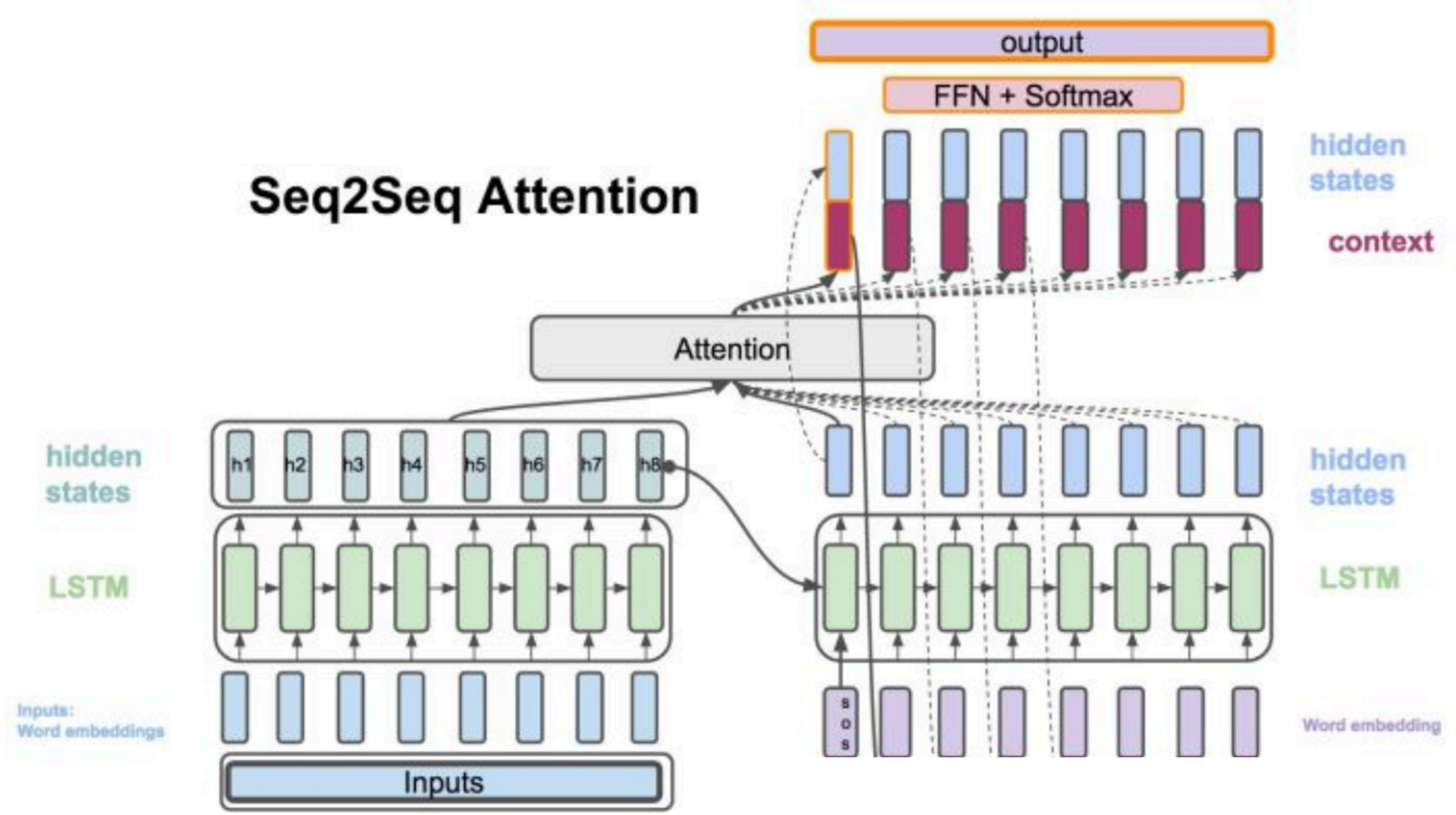

Thank You !