

# Multi-level Context Response Matching in Retrieval-Based Dialog Systems

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## 1. Task Description

We participated in the *sentence selection* task of the 7<sup>th</sup> edition of DSTC challenges. This task addresses the following points.

- The currently built systems are evaluated on **non realistic** scenarios.
- The number of candidate responses is **small**.
- Possibility of having **more than one** correct response.
- Sometimes **none** of the candidate responses is correct.

## 2. Subtasks

Our participation concerns the following three subtasks of sentence selection out of five.

- Subtask 1: One correct response among 100 candidate responses.
- Subtask 3: Between one and five correct responses (paraphrases) are correct among 100.
- Subtask 4: The 100 candidate responses may not include the correct response.

## 3. Datasets & Metrics

- Ubuntu Dialogue Corpus: Ubuntu related chat.
- Advising Corpus: Teacher-student conversations.
- We used the Recall@k, MRR and MAP evaluation metrics.

## 4. Approach

- Encode the context and the response with a **shared** LSTM and compute their cross product: **sequence-level similarity**.
- In parallel, compute a dot product between the embedding matrices and encode it with another LSTM: **word-level similarity**.
- Concatenate both vectors and transform them into a probability using a FFNN: **response ranking score**.

## 5. Multi-Level Retrieval-Based Dialog System

- Our system is inspired by the dual encoder [1] and the Sequential Matching Network (SMN) [2].

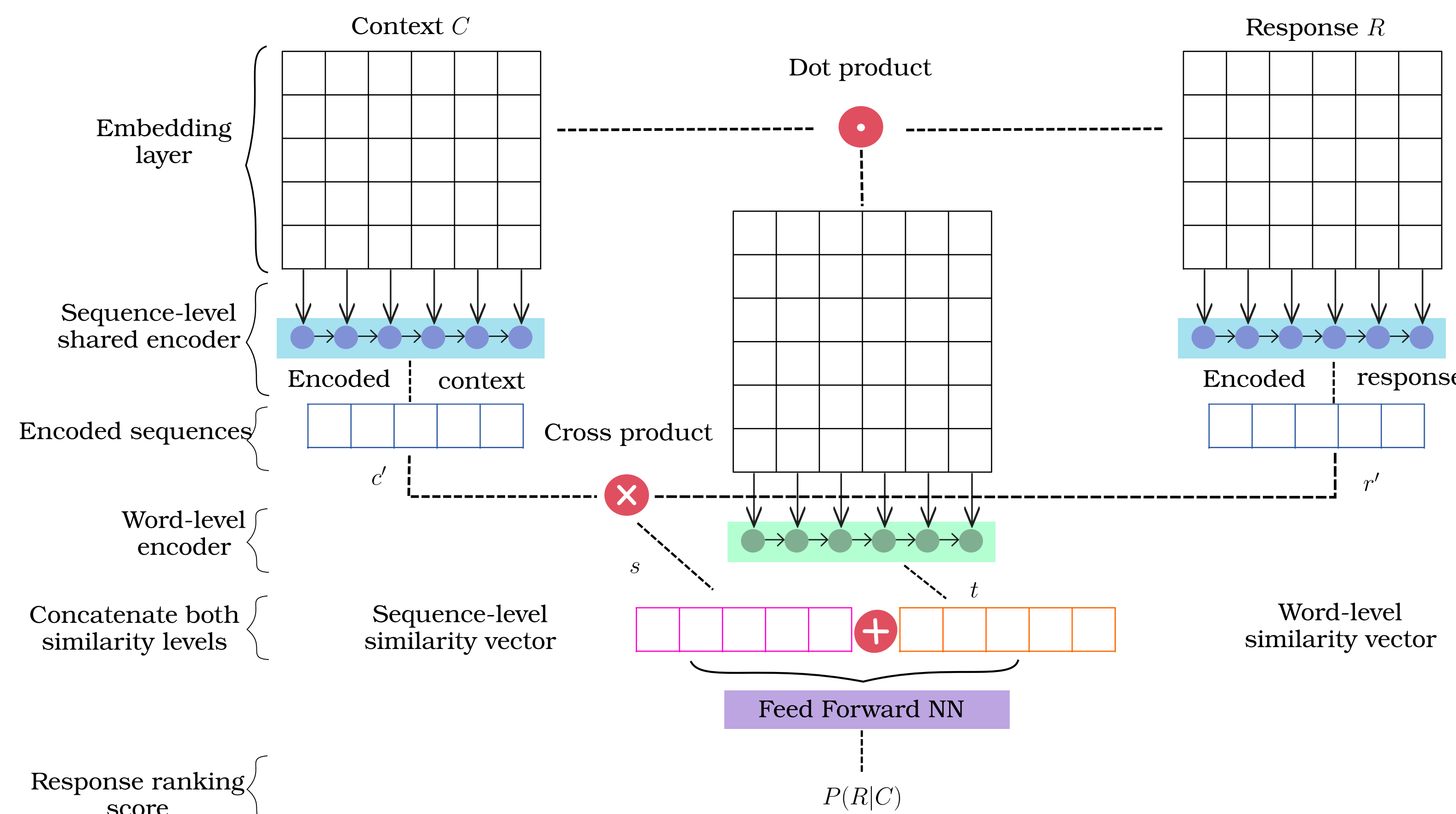


Figure 1: Architecture of our multi-level context response matching dialog system.

## 6. Experiments

System	Subtask	Measure	Ubuntu Dialogue Corpus	Advising Corpus case 1	Advising Corpus case 2
Baseline	Subtask 1	R@1	0.083	0.008	0.008
		R@10	0.359	0.102	0.094
		R@50	0.794	0.542	0.498
		MRR	0.175	0.053	0.048
Our system	Subtask 1	R@1	<b>0.446</b>	<b>0.114</b>	<b>0.1</b>
		R@10	<b>0.732</b>	<b>0.398</b>	<b>0.42</b>
		R@50	<b>0.937</b>	<b>0.782</b>	<b>0.802</b>
		MRR	<b>0.551</b>	<b>0.205</b>	<b>0.200</b>
	Subtask 3	R@1	-	<b>0.212</b>	<b>0.176</b>
		R@10	-	<b>0.586</b>	<b>0.57</b>
		R@50	-	<b>0.906</b>	<b>0.926</b>
		MRR	-	<b>0.338</b>	<b>0.297</b>
	Subtask 4	MAP	-	<b>0.37</b>	<b>0.343</b>
		R@1	<b>0.388</b>	<b>0.088</b>	<b>0.066</b>
		R@10	<b>0.592</b>	<b>0.31</b>	<b>0.316</b>
		R@50	<b>0.751</b>	<b>0.618</b>	<b>0.686</b>
	MRR	<b>0.462</b>	<b>0.163</b>	<b>0.15</b>	

Table 1: Experimental results on test sets of Subtasks 1, 3 and 4.

## 7. Discussion

- Our system outperforms the baseline system on both datasets and on all metrics.
- Retrieving **paraphrases** was easier compared to retrieving only one response.
- Only 20% of training samples are cases where no correct response is available.

	Train	Dev	Test	
			Case 1	Case 2
Ubuntu	20%	20%	20.20%	-
Advising	20.05%	18.80%	23.40%	18.40%

Table 2: Percentage of cases where no correct response is available (Subtask 4).

## 8. System Ablation

- Both** similarity levels are important.
- With only sequence-level similarity, our system outperforms the baseline.

		Ubuntu		Advising	
		R@1	R@10	R@1	R@10
Baseline	R@1	0.083	0.062	0.008	0.008
	R@10	0.359	0.296	0.102	0.094
	R@50	0.800	0.728	0.542	0.498
	MRR	-	-	0.053	0.048
Only seq sim	R@1	0.290	0.080	<b>0.114</b>	<b>0.1</b>
	R@10	0.575	0.364	<b>0.398</b>	<b>0.42</b>
	R@50	0.910	0.800	<b>0.782</b>	<b>0.802</b>
	MRR	0.389	0.176	<b>0.205</b>	<b>0.200</b>
Word + seq sim	R@1	<b>0.399</b>	<b>0.116</b>	<b>0.212</b>	<b>0.176</b>
	R@10	<b>0.693</b>	<b>0.444</b>	<b>0.586</b>	<b>0.57</b>
	R@50	<b>0.944</b>	<b>0.848</b>	<b>0.906</b>	<b>0.926</b>
	MRR	<b>0.501</b>	<b>0.219</b>	<b>0.338</b>	<b>0.297</b>

Table 3: Ablation results on valid of Subtask 1.

## 9. System Extension

Subtask 4 requires the model to recognize cases where no candidate response is correct.

- We added the following classifier on top of our system.
- The candidate scores are fed into a SVM classifier.
- It predicts the presence of a correct response.

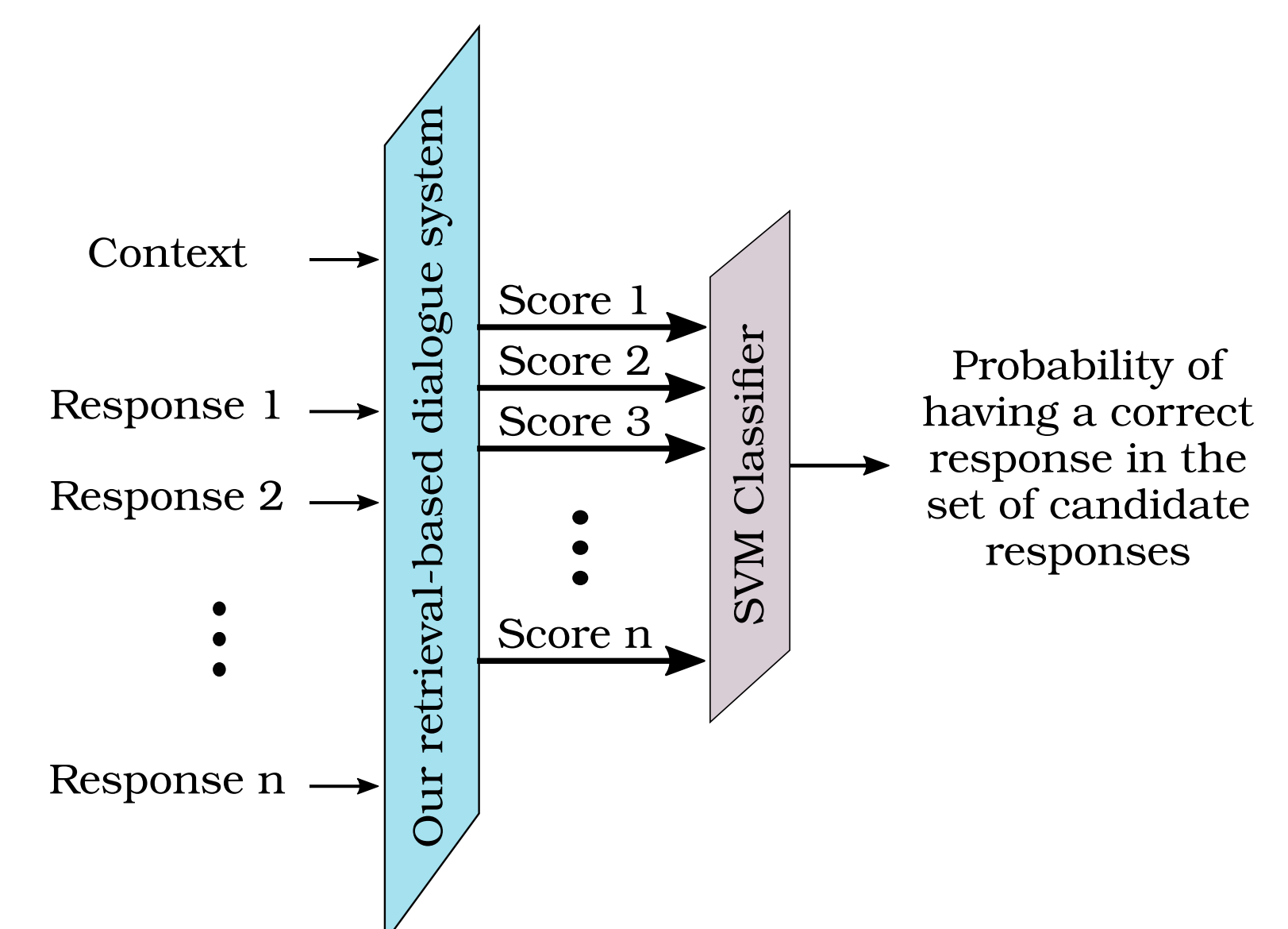


Figure 2: Extension of our proposed system for subtask 4.

## 10. Conclusion

- We proposed an end-to-end retrieval-based dialog system that matches the context with the correct response on **two levels**.
- Performance improvement compared to the baseline system.
- One simple system for the three subtasks.

## 11. References

- Ryan L., Nissan P., Iulian S., and Joelle P. The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. In *SIGDIAL 2015*.
- Yu W., Wei W., Chen X., Ming Z., and Zhoujun L. Sequential matching network: A new architecture for multi-turn response selection in retrieval-based chatbots. In *ACL 2017*.

## Contact Information

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## Code and data

Available at [https://github.com/basma-b/multi\\_level\\_chatbot](https://github.com/basma-b/multi_level_chatbot)