

Do Response Selection Models Really Know What's Next? Utterance Manipulation Strategies for Multi-turn Response Selection

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Motivation

- Domain adaptation based on an additional training on a target corpus is extremely time-consuming and computationally costly.
- Formulating response selection as a dialog-response binary classification task is insufficient to represent intra- and interutterance interactions as the dialog context is formed by concatenating all utterances.
- The models tend to select the optimal response depending on how

Contribution

- We show that existing response selection models are more likely to predict a semantically relevant response with its dialog rather than the next utterance (Adversarial Experiment).
- We propose highly effective self-supervised learning methods, **utterance manipulation strategies (UMS)**, which aid the model towards maintaining dialog coherence.
- We obtain state-of-the-art performance on multiple public

Proposed Method



Utterance Insertion

- Find where the selected utterance should be inserted.
- [INS] tokens are positioned before each utterance and after the last utterance.
- u_t is the target utterance and $[INS]_t$ is the target insertion token.

 $\mathbf{X}_{\text{INS}} = [[\text{CLS}] [\text{INS}]_1 u_1 [\text{INS}]_2 u_2 \dots u_{t-1} \\ [\text{INS}]_t u_{t+1} \dots u_k [\text{INS}]_k [\text{SEP}] u_t [\text{SEP}]]$

Utterance Deletion

- Find an unrelated utterance to the dialog.
- The unrelated utterance is sampled from the random dialog.
- [DEL] tokens are positioned before each utterance.
- u^{rand} is the utterance from the random dialog and $[DEL]_t$ is the target deletion token.

$$\mathbf{X}_{\text{DEL}} = \left[[\text{CLS}] \left[\text{DEL} \right]_1 u_1 \left[\text{DEL} \right]_2 u_2 \dots \left[\text{DEL} \right]_t \\ u^{rand} \left[\text{DEL} \right]_{t+1} u_t \dots \left[\text{DEL} \right]_{k+1} u_k \left[\text{SEP} \right] \right]$$

Multi-task Learning

- The output representations of special are used to classify whether each toke is in a correct position to be inserted, deleted, and searched.
- Target tokens for each task ([INS]_t, [DEL]_t, and [SRCH]_t) are labeled as 1, otherwise 0.
- Binary cross-entropy loss for all auxiliary tasks to optimize the model.

 $p(y_{\text{TASK}} = 1 | \mathbf{X}_{\text{TASK}}) = \sigma(\mathbf{w}^{\top} \mathbf{x}_{\text{TASK}} + b)$

Utterance Search

- Find the previous utterance of the last utterance from the jumbled utterances.
- Shuffle utterances except for the last utterance.
- [SRCH] tokens are positioned before each utterance.
- $u'_t(u_{k-1})$ is the previous utterance of the last utterance u_k and $[SRCH]_t$ is the target search token.

 $\mathbf{X}_{\mathsf{SRCH}} = \left[[\mathsf{CLS}] \, [\mathsf{SRCH}]_1 \, u_1' [\mathsf{SRCH}]_2 \, u_2' \dots \\ [\mathsf{SRCH}]_t \, u_t' \dots u_{k-1}' [\mathsf{SEP}] \, u_k \, [\mathsf{SEP}] \right]$

Results and Discussion

Quantitative Results

Models	Ubuntu			Douban					E-commerce			
	$R_{10}@1$	$R_{10}@2$	$R_{10}@5$	MAP	MRR	P@1	$R_{10}@1$	$R_{10}@2$	$R_{10}@5$	$R_{10}@1$	$R_{10}@2$	$R_{10}@5$
BERT (ours)	0.820	0.906	0.978	0.597	0.634	0.448	0.279	0.489	0.823	0.641	0.824	0.973
ELECTRA	0.826	0.908	0.978	0.602	0.642	0.465	0.287	0.483	0.839	0.609	0.804	0.965
UMS _{BERT}	0.843	0.920	0.982	0.597	0.639	0.466	0.285	0.471	0.829	0.674	<u>0.861</u>	0.980
UMS _{ELECTRA}	<u>0.854</u>	<u>0.929</u>	<u>0.984</u>	0.608	<u>0.650</u>	<u>0.472</u>	<u>0.291</u>	0.488	<u>0.845</u>	0.648	0.831	0.974
BERT+	0.862	0.935	0.987	0.609	0.645	0.463	0.290	0.505	0.838	0.725	0.890	0.984
ELECTRA+	0.861	0.932	0.985	0.612	0.655	0.480	0.301	0.499	0.836	0.673	0.835	0.974
UMS _{BERT+}	0.875 [†]	0.942 [†]	0.988 [†]	0.625	0.664	0.499	0.318	0.482	0.858	0.762	0.905	0.986
UMS _{ELECTRA+}	0.875	0.941	0.988	0.623	0.663	0.492	0.307	0.501	0.851	0.707	0.853	0.974

Visualization



Adversarial Experiment

Approach	Model	Orig	inal	Adversarial		
	110001	$R_{10}@1$	MRR	$R_{10}@1$	MRR	
	BERT	0.820	0.887	0.199	0.561	
	BERT+	0.862	0.915	0.203	0.573	
Baselines	ELECTRA	0.826	0.890	0.304	0.614	
	ELECTRA+	0.861	0.914	0.329	0.636	
	Avg	0.842	0.902	0.259	0.596	
	BERT	0.843	0.902	0.310	0.622	
	BERT+	0.875	0.923	0.363	0.656	
UMS	ELECTRA	0.854	0.910	0.397	0.668	
	ELECTRA+	0.875	0.922	0.437	0.692	
	Avg	0.862	0.914	0.377	0.660	

Ablation Study

	Auxiliary Tasks	$R_{10}@1$	$R_{10}@2$	$R_{10}@5$	MRR
1	None	0.826	0.908	0.978	0.890
2	INS	0.836	0.917	0.980	0.897
3	DEL	0.848	0.924	0.983	0.905
4	SRCH	0.834	0.915	0.981	0.896
5	INS + DEL	0.853	0.927	0.984	0.909
6	INS + SRCH	0.841	0.920	0.982	0.901
7	DEL + SRCH	0.852	0.927	0.983	0.908
8	INS + DEL + SRCH	0.854	0.929	0.984	0.910