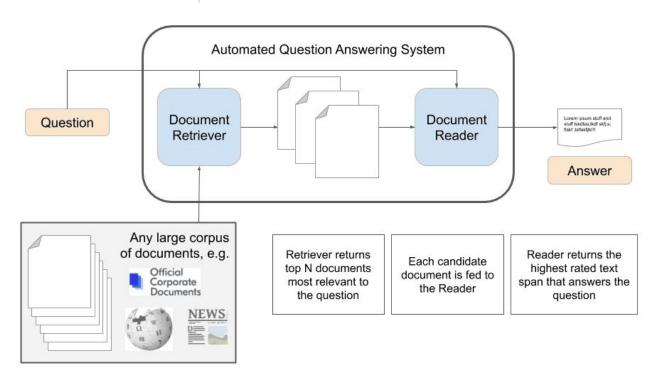
Evaluation of Semantic Answer Similarity Metrics

Overview



- Question Answering (QA)
- Semantic Answer Similarity (SAS)
- SAS model metrics
- Similarity score distributions
- Does it matter how deep the model is?
- Where do the models get confused?
- Contributions and future work

QA Pipeline



What is Semantic Answer Similarity (SAS)?

Question: How many plant species are esti-

mated to be in the Amazon region?

Context: The region is home to about 2.5 million insect species, tens of thousands of plants, and some 2,000 birds and mammals. To date,

at least 40,000 plant species [...]

Ground-Truth Answer: "40,000"

Predicted Answer: "tens of thousands"

Exact Match: 0.00

F1-Score: 0.00

Top-1-Accuracy: 0.00

SAS: 0.55

Human Judgment: 0.50

Question: Who killed Natalie and Ann in

Sharp Objects?

Ground-truth answer: Amma

Predicted Answer: Luke

EM: 0.00 **F**₁: 0.00

Top-1-Accuracy: 0.00

SAS: 0.0096

Human Judgment: 0

 f_{BERT} : 0.226 f'_{BERT} : 0.145

Bi-Encoder: 0.208

 f_{BERT} : 0.00

Bi-Encoder (new model): -0.034

Candi Emb.

CANDIDATE AGGREGATOR

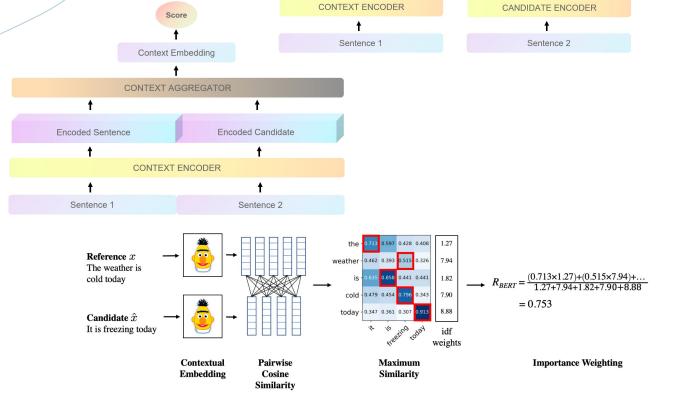
Encoded Candidate



Bi-Encoder

Cross-encoder

BERTScore



Context Emb.

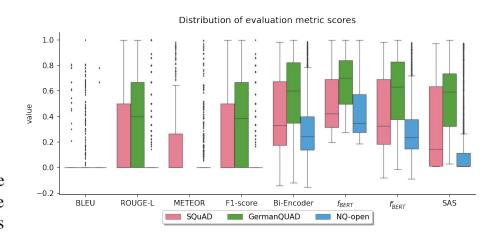
CONTEXT AGGREGATOR

Encoded Context

Distribution of scores

	SQuAD	GermanQuAD	NQ-open
Label 0	56.7	27.3	71.7
Label 1	30.7	51.5	16.6
Label 2	12.7	21.1	11.7
$\mathbf{F_1} = 0$	565	124	3030
$\mathbf{F_1} eq 0$	374	299	529
Size	939	423	3559
Avg answer size	23	68	13

Table 1: Statistics on the subsets of datasets used in the analyses. The average answer size column refers to the average of both the first and second answers as well as ground-truth answer and predicted answer (NQ-open only). $F_1 = 0$ indicates no string similarity, $F_1 \neq 0$ indicates some string similarity. Label distribution is given in percentages.



Metric Comparison

	SQuad					NQ-open						
		$F_1 = 0$	H	$F_1 \neq 0$		$F_1 = 0$			$F_1 \neq 0$			
Metrics	\overline{r}	ρ	au	\overline{r}	ρ	au	\overline{r}	ρ	au	\overline{r}	ρ	au
BLEU	0.000	0.000	0.000	0.182	0.168	0.159	0.000	0.000	0.000	0.052	0.054	0.051
ROUGE-L	0.100	0.043	0.041	0.556	0.537	0.455	0.220	0.163	0.159	0.450	0.458	0.377
METEOR	0.398	0.207	0.200	0.450	0.464	0.378	0.233	0.152	0.148	0.188	0.179	0.139
F1-score	0.000	0.000	0.000	0.594	0.579	0.497	0.000	0.000	0.000	0.394	0.407	0.337
Bi-Encoder	0.487	0.372	0.303	0.684	0.684	0.566	0.294	0.212	0.170	0.454	0.446	0.351
f_{BERT}	0.249	0.132	0.108	0.612	0.601	0.492	0.156	0.169	0.135	0.165	0.142	0.112
f_{BERT}^{\prime}	0.516	0.391	0.318	0.698	0.688	0.571	0.319	0.225	0.181	0.452	0.449	0.354
SAS	0.561	0.359	0.291	0.743	0.735	0.613	0.422	0.196	0.158	0.662	0.647	0.512
New Bi-Encoder	0.501	0.391	0.318	0.694	0.690	0.572	0.338	0.252	0.203	0.501	0.501	0.392
$ ilde{f}_{BERT}$	0.519	0.399	0.324	0.707	0.698	0.581	0.351	0.257	0.208	0.498	0.507	0.398

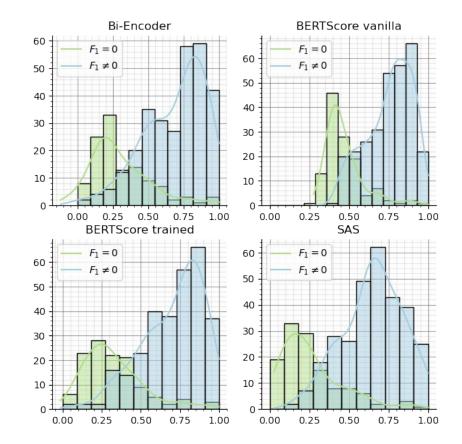
Table 4: Pearson, Spearman's, and Kendall's rank correlations of annotator labels and automated metrics on subsets of SQuAD and NQ-open. f_{BERT} is BERTScore vanilla and f'_{BERT} is BERTScore trained, and \tilde{f}_{BERT} is the new BERTScore trained on names.

GermanQuAD

	GermanQuAD						
	$F_1 = 0$			$F_1 \neq 0$			
Metrics	r	ρ	au	r	ho	au	
BLEU	0.000	0.000	0.000	0.153	0.095	0.089	
ROUGE-L	0.172	0.106	0.100	0.579	0.554	0.460	
F_1 -score	0.000	0.000	0.000	0.560	0.534	0.443	
Bi-Encoder	0.392	0.337	0.273	0.596	0.595	0.491	
f_{BERT}	0.149	0.008	0.006	0.599	0.554	0.457	
f_{BERT}^{\prime}	0.410	0.349	0.284	0.606	0.592	0.489	
SAS	0.488	0.432	0.349	0.713	0.690	0.574	

Table 3: Pearson, Spearman's, and Kendall's rank correlations of annotator labels and automated metrics on subsets of GermanQuAD. f_{BERT} is BERTScore vanilla and f'_{BERT} is BERTScore trained.

Distribution of metric scores for GermanQuAD ($F_1 = 0$ vs. $F_1 \neq 0$)



Embedding Layer Extraction

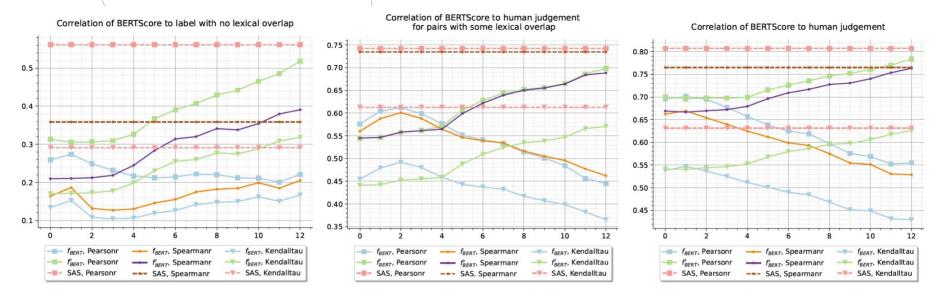


Figure 4: Pearson, Spearman's, and Kendall's rank correlations for different embedding extractions for when there is no lexical overlap ($F_1 = 0$), when there is some overlap ($F_1 \neq 0$) and aggregated for the SQuAD subset. f_{BERT} is BERTScore vanilla and f'_{BERT} is BERTScore trained.

Model Errors

- Names
 - Geographical names
 - Co-references
 - Aliases
- Translation
- Numeric types
 - Numbers & Dates
- Synonyms
- Scientific terminology

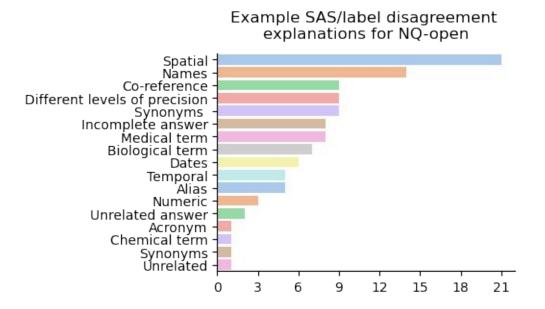
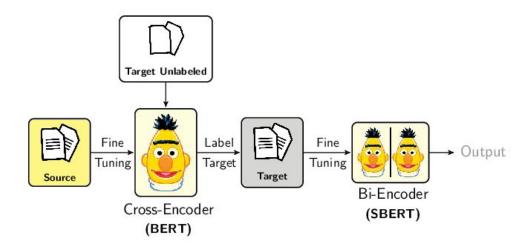


Figure 5: Subset of NQ-open test set, where SAS score < 0.01 and human label is 2, manually annotated for explanation of discrepancies. Original questions and Google search has been used to assess the correctness of the gold labels.

Contributions

- Improved (by finding and correcting for errors) a paper to be published on EMNLP 2021 (workshop paper)
- A new names dataset
- Relabelled NQ-open dataset
- An improved single configuration of BERTScore model



Future work

- Annotate prediction and ground-truth pairs (instead of two ground-truth answers)
- Improve the performance on non-common names in English contexts and spatial names
- Use BERTScore as a training objective to generate soft predictions, allowing the network to remain differentiable end-to-end

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