

FILLING IN THE GAPS: EFFICIENT EVENT COREFERENCE RESOLUTION USING GRAPH AUTOENCODER NETWORKS

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INTRODUCTION: CD EVENT COREFERENCE RESOLUTION

- Link textual events (either real or fictional) if they refer to the same conceptual event (same time, same place, same participants)
- Events can be either noun phrases (NPs) or verb phrases (VPs)







SCALING CROSS-DOCUMENT COREFERENCE

- Most present-day coreference models rely on pairwise computation between anaphora and lacksquarecandidate antecedents
- In cross-document settings this means that the number of needed computations grows • exponentially
- Some mitigation strategies in place, but these often rely on document-level clustering Within- \bullet document models' output







A GRAPH-BASED COMPLETION MODEL

- Graph Auto-encoders
 - Introduced by Kipf and Welling (2016)
 - Reconstructs incomplete graph data based on a set of given edges
 - Mostly used in citation network prediction or molecule completion, not many applications in NLP
 - Probabilistic (VGAE) and non-probabilistic (GAE) settings \bullet





EXPERIMENTAL SETUP WITH GVAE

- Training Setup
 - Assume that coreference chains can be modelled as undirected, unweighed graphs, where each node represents an event and each edge represents a coreferential relation between two events
 - Mask 15% of edges, 5% to be used as validation data and 10% as test data
 - Experiments using both the Probabilistic (VGAE) and non-probabilistic (GAE) setting

- Input Features
 - Average-pooled BERT embeddings of the tokens in the mention span based on final (768-dim) or 4 final (3072-dim) layer(s)



EXPERIMENTAL SETUP





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DATA AND BASELINE MODELS

• Dutch ENCORE corpus

- 1015 documents, 12875 annotated events
- Cross-document coreference annotations between the events \bullet

- Baseline model
 - Encoder-based mention-pair model which creates pairwise representations and scores them through a \bullet coreference scoring layer
 - No SpanBERT encoder available for Dutch, use of standard BERT-based encoders instead (BERTje, RobBERT, RobBERTje)



RESULTS AND ABLATION STUDY





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<u>RESULTS</u>

Model	CONLL F1	Training Runtime (s)	Inference Runtime (s)	Trainable Parameters	Disk Space (MB)
MP RobBERTje	0.767	7962	16.31	74M	297
MP BERTje _{ADPT}	0.780	12 206	20.61	0.9M	3.5
MP BERTje	0.799	9737	21.78	110M	426
GAE BERTje768	0.835 ± 0.010	975	0.263	51200	0.204
GAE BERTje ₃₀₇₂	0.852 ± 0.006	1055	0.294	198656	0.780
GAE RobBERT ₇₆₈	0.838 ± 0.004	1006	0.273	51200	0.204
GAE RobBERT ₃₀₇₂	0.841 ± 0.007	1204	0.292	198656	0.780
VGAE BERTje768	0.822 ± 0.011	1233	0.282	53248	0.212
VGAE BERTje ₃₀₇₂	0.842 ± 0.009	1146	0.324	200704	0.788
VGAE RobBERT ₇₆₈	0.828 ± 0.0021	1141	0.288	53248	0.212
VGAE RobBERT ₃₀₇₂	0.831 ± 0.004	1209	0.301	200704	0.788



ABLATION STUDY: DATA AVAILABILITY

- Reduce the amount of available training data by increments of 5%
- Interestingly, the drop in performance for the traditional MP model is larger than for the graph-based models





nts of 5% MP model is larger than for

FURTHER THOUGHTS AND CONCLUSION





CONCLUSION

- Graph Auto-encoders can be a fast and efficient alternative to traditional mention- \bullet pair coreference setups (when some links are known!)
- (V)GAE models do not need a lot of data to provide a satisfactory reconstruction \bullet
- The setting in which edge data is given is still guite artificial \rightarrow In the future, evaluate graph-based models for graphs were no edges are given Integrate VGAE-based method in end-to-end settings

