Storylines

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1 Introduction

Our goal is to improve the coherency of generative story models by modeling storylines. As an alternative to black-box models with little explicit structure, prior work has noted that including structure in the generative model improves coherence in the generations [1, 3].

However, prior investigations into narrative structure used hand-crafted representations, such as entity coreference or keywords. We hope to alleviate the need for hand-crafted structure via structured generative models.

2 Storyline Induction

As an initial step, we turn to sequence alignment algorithms to induce storylines. If a parameterized distance measure (with associated representations) is correlated with human judgements for stories, then it may be possible to engineer an unsupervised objective that allows training of the parameterized distance to further improve performance. We may then use the resulting representations to induce interpretable storylines through a discretization procedure. This approach to analysis allows us to initially avoid expensive likelihood-based methods that reconstruct full stories.

(What if there's too much information in SBERT? What information is relevant to a storyline? What is a storyline? Current approach: random search to identify whether certain methods produce storylines)

3 Pairwise Alignment with SBERT and DTW

We first investigate whether we can recover structure that resembles a storyline using pretrained models. In particular, we use SBERT [2] to map sentences $\mathbf{x}_i \in \mathcal{X}^*$ to vector representations $\mathbf{y}_i \in \mathbb{R}^n$. As each story consists of several sentences, we obtain a sequence of representations corresponding to each sentence in a given story $\mathbf{Y} = \langle \mathbf{y}_0, \ldots, \mathbf{y}_T \rangle$. We then compute an alignment between the sentences of two stories using DTW.

We evaluate the efficacy of SBERT and DTW without fine-tuning by determining whether $DTW(Y_i, Y_j)$ correlates with an intuitive distance of stories. For a given story we obtain the top K closest stories under DTW and compare the ranking with human annotation.

We additionally evaluate the alignments (TBD)

Analysis forthcoming.

4 Multisequence Alignment

Although we found that the pairwise comparison using DTW correlated with intuitive distance, we aim to further extract robust storylines that are common to multiple stories. To accomplish this, we turn to multisequence alignment (MSA) which considers multiple stories and produces a global alignment across multiple stories.

We use the multisequence generalization of DTW [4]. We perform an evaluation of this measure: For a given collection of stories, we compare the K-subset with the lowest mDTW verus a human-annotated subset. We obtain a collection of stories by obtaining the $M > K$ closest stories to a given story, as measured by DTW.

Analysis forthcoming.

5 A Generative Model

We wish to improve the accuracy of DTW and mDTW without human annotation. We optimize a nonparametric time-series modeling objective that extends builds on pairwise DTW:

$$\log p(Y_i) = \log \sum_j p(Y_i, Y_j)$$

Details TBD, but will use DTW distance to approximate integral. If preliminary evaluation in Sections 3 and 4 are positive, then there is hope that the approximation grids do not have to be extremely large or updated as training progresses.

We also experiment with the multi-sequence extension.

References

[1] Angela Fan, Mike Lewis, and Yann N. Dauphin. Strategies for structuring story generation. *CoRR*, abs/1902.01109, 2019. URL `http://arxiv.org/abs/1902.01109`.

[2] Nils Reimers and Iryna Gurevych. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3982–3992, Hong Kong, China, November 2019. Association for Computational Linguistics. doi: 10.18653/v1/D19-1410. URL `https://www.aclweb.org/anthology/D19-1410`.

[3] Lili Yao, Nanyun Peng, Ralph M. Weischedel, Kevin Knight, Dongyan Zhao, and Rui Yan. Plan-and-write: Towards better automatic storytelling. *CoRR*, abs/1811.05701, 2018. URL `http://arxiv.org/abs/1811.05701`.

[4] F. Zhou and F. De la Torre. Generalized canonical time warping. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 38(2):279–294, 2016.