Hierarchical Encoders for Modeling and Interpreting Screenplays

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Abstract

While natural language understanding of long-form documents is still an open challenge, such documents often contain structural information that can inform the design of models for encoding them. Movie scripts are an example of such richly structured text. Scripts are segmented into scenes, which are further decomposed into dialogue and descriptive components. In this work, we propose a neural architecture for encoding this structure, which performs robustly on a pair of multi-label tag classification datasets, without the need for handcrafted features. We add a layer of insight by augmenting an unsupervised interpretability module to the encoder, allowing for the extraction and visualization of narrative trajectories. Though this work specifically tackles screenplays, we discuss how the underlying approach can be generalized to a range of structured documents.

1 Introduction

As natural language understanding of sentences and short documents continues to improve, there has been growing interest in tackling longer-form documents such as academic papers (Ren et al., 2014; Bhagavatula et al., 2018), novels (Iyyer et al., 2016) and screenplays (Gorinski and Lapata, 2018). Analyses of such documents can take place at multiple levels, e.g. identifying both document-level labels (such as genre), as well as narrative trajectories (how do levels of humor and romance vary over the course of a romantic comedy?). However, one of the key challenges for these tasks is that the signal-to-noise ratio over lengthy texts is generally low (as indicated by the performance of such models on curated datasets like NarrativeQA (Kočiský et al., 2018)), making it difficult to apply end-to-end neural network solutions that have recently achieved state-of-the-art on other tasks (Barrault et al., 2019; Williams et al., 2018; Wang et al., 2019).

Instead, models either rely on a) a pipeline that provides a battery of syntactic and semantic information from which to craft features (e.g., the BookNLP pipeline (Bamman et al., 2014) for literary text, graph-based features (Gorinski and Lapata, 2015) for movie scripts, or outputs from a discourse parser (Ji and Smith, 2017) for text categorization) and/or b) the linguistic intuitions of the model designer to select features relevant to the task at hand (e.g., rather than ingesting the entire text, Bhagavatula et al. (2018) only consider certain subsections like the title and abstract of an academic publication). While there is much to recommend these approaches, end-to-end neural modeling offers several key advantages: in particular, it obviates the need for auxiliary feature-generating models, minimizes the risk of error propagation, and offers improved generalization across large-scale corpora. This work explores how models can leverage the inherent structure of a document class to facilitate an end-to-end approach. Here, we focus on screenplays, investigating whether we can effectively extract key information by first segmenting them into scenes, and then further exploiting the structural regularities within each scene.

With an average of >20k tokens per script in our evaluation corpus, extracting salient aspects is far from trivial. Through a series of carefully controlled experiments, we show that a structure-aware approach significantly improves document classification by effectively collating sparsely distributed information. Further, this method produces both document- and scene-level embeddings, which can be used downstream to visualize narrative trajectories of interest (e.g., the prominence of various themes across the script). The overarching strategy of this work is to incorporate structural priors as biases into the architecture of the

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neural network model itself (e.g., Socher et al. (2013), Strubell et al. (2018), inter alia). The methods we propose can readily generalize to any long-form text with an exploitable internal structure, including novels (chapters), theatrical plays (scenes), chat logs (turn-taking), online games (levels/rounds/gameplay events), and academic texts (sections and subsections).

The paper is organized as follows: In §2, we detail how a script can be formally decomposed into scenes, and each scene can be further decomposed into granular elements with distinct discourse functions. §3 elaborates on how this structure can be effectively leveraged with a proposed encoder based on hierarchical attention (Yang et al., 2016). In §5.3, the predictive performance of the hierarchical encoder is validated on two multi-label tag prediction tasks, one of which rigorously establishes the utility of modeling structure at multiple granularities (i.e., at the level of line, scene, and script). Notably, while the resulting scene-encoded representation is useful for prediction tasks, it is not amenable to easy interpretation or examination. To shed further light on encoded document representation, in §4, we propose an unsupervised interpretability module that can be attached to an encoder of any complexity. §5.5 outlines our application of this module to the scene encoder, and the resulting visualizations of the screenplay, which neatly illustrate how plot elements vary over the course of the narrative arc. §6 draws connections to related work, before concluding.

2 Script Structure

Movie and television scripts, also known as screenplays, are traditionally segmented into scenes, with a rough rule of thumb that each scene lasts about a minute on-screen. A scene is not necessarily a distinct narrative unit (which are most often sequences of several consecutive scenes), but is constituted by

| Title      | Line | Scene | Type   | Character | Text                          |
|------------|------|-------|--------|-----------|-------------------------------|
| Pulp Fiction | 204  | 4     | Scene  | Ext. Apart. | Vincent and Jules. |
| Pulp Fiction | 205  | 4     | Action | Vincent    | What's her name?             |
| Pulp Fiction | 206  | 4     | Action | Jules      | Mia                           |
| Pulp Fiction | 207  | 4     | Dial.  | Vincent    | How did we get here?          |

Fig. 1 contains a segment of a scene from the screenplay for the movie Pulp Fiction, a 1994 American film. These segments tend to follow a standard format. Each scene starts with a scene heading or “slug line” that briefly describes the scene setting, followed by a sequence of statements. Screenwriters typically use formatting to distinguish between dialogue and action statements (Argentini, 1998). The first kind contains lines of a dialogue and identifies the character who utters it either on- or off-screen (the latter is often indicated with ‘(V.O.)’ for voice-over). Occasionally, parentheticals are used to include special instructions for how an utterance should be delivered by the character. Action statements, on the other hand, are all non-dialogue constituents of the screenplay “often used by the screenwriter to describe character actions, camera movement, appearance, and other details” (Pavel et al., 2015). In this work, we consider action and dialogue statements, as well as character identities for each dialogue segment, and ignore slug lines and parentheticals.

3 Hierarchical Scene Encoders

Given the size of a movie script, it is computationally infeasible to treat these screenplays as single blocks of text to be ingested by a recurrent encoder. Instead, we propose a hierarchical encoder that mirrors the standard structure of a screenplay (§2) – a sequence of scenes, each of which is in turn an interwoven sequence of action and dialogue statements. The encoder is three-tiered, as illustrated in Fig. 2 and processes the text of a script as follows.

3.1 Model Architecture

First, an action-statement encoder transforms the sequence of words in an action statement (represented by their pretrained word embeddings) into an action statement embedding. Next, an action-scene encoder transforms the chronological sequence of action statement embeddings within a scene into an action scene embedding. Analogously, a dialogue-statement encoder and
a **dialogue-scene encoder** are used to obtain dialogue statement embeddings and aggregate them into dialogue scene embeddings. To evaluate the effect of character information, characters with at least one dialogue statement in a given scene are represented by an individual character embedding (these are randomly initialized and estimated during model training), and a scene-level character embedding is constructed by averaging the embeddings of all the characters in the scene\(^1\). Finally, the action, dialogue and scene-level character embeddings for each scene are concatenated into a single scene embedding.

![Figure 2: The architecture of our script encoder, largely following the structure in Fig. 1.](image)

Scene-level predictions or analyses can then be obtained by feeding the scene embeddings into a subsequent module of the neural architecture, e.g. a feedforward layer can be used for supervised tagging tasks. Alternatively, if a single representation of the entire screenplay is required, a final **script encoder** is used to transform the sequence of scene embeddings for a script into a single script embedding. A key assumption underlying the model is that action and dialogue statements — as instances of written narrative and spoken language respectively — are distinct categories of text and must therefore be processed separately. We evaluate this assumption in the tag classification experiments (§5.3).

### 3.2 Encoders

The proposed model incorporates strong inductive biases regarding the overall structure of input documents. In addition, each of the aforementioned encoders in §3.1 can be specified in multiple ways, and we evaluate three different instantiations of the encoder components:

1. **Sequential (GRU):** A bidirectional GRU (Bahdanau et al., 2015) is used to encode the temporal sequence of inputs (of words, statements or scenes). Given a sequence of input embeddings \(e_1, \ldots, e_T\) for a sequence of length \(T\), we obtain GRU outputs \(c_1, \ldots, c_T\), and use \(c_T\) as the recurrent encoder’s final output. Other sequential encoders could also be used as alternatives.

2. **Sequential with Attention (GRU + Attn):** Attention (Bahdanau et al., 2015) can be used to combine sequential outputs \(c_1, \ldots, c_T\), providing a mechanism for more or less informative inputs to be filtered accordingly. We calculate attention weights using a parametrized vector \(p\) of the same dimensionality as the GRU outputs (Sukhbaatar et al., 2015; Yang et al., 2016):

\[
\alpha_i = \frac{p^T c_i}{\sum_{j=1}^T p^T c_j}
\]

These weights are used to compute the final output of the encoder as:

\[
c = \sum_{j=1}^T \alpha_i c_i
\]

Other encoders with attention could be used as alternatives to this formulation.

3. **Bag-of-Embeddings with Attention (BoE + Attn):** Another option is to disregard the sequential encoding and simply compute an attention-weighted average of the inputs to the encoder as follows:

\[
\alpha_i = \frac{p^T e_i}{\sum_{j=1}^T p^T e_j}
\]

\[
c = \sum_{j=1}^T \alpha_i e_i
\]

This encoder stands in contrast to a bag-of-embeddings (BoE) encoder which computes a simple average of its inputs. While defining a far more constrained function space than recurrent encoders, BoE and BoE + Attn representations have the advantage of being interpretable (in the sense that the encoder’s output is in the same space as the input word embeddings). We leverage this property in §4 where we develop an interpretability layer on top of the encoder outputs.

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\(^1\)We only take into account characters at the *scene* level i.e., we do not associate characters with each dialogue statement, leaving this addition to future work.
3.3 Loss for Tag Classification

The final script embedding being passed into a feedforward classifier (FFNN). As both supervised learning tasks in our evaluation are multi-label classification problems, we use a variant of a simple multi-label one-versus-rest loss, where correlations among tags are ignored. The tag sets have high cardinalities and the fractions of positive samples are inconsistent across tags (Table 7 in A.1); this motivates us to train the model with a reweighted loss function:

\[
L(y, z) = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{L} y_{ij} \log \sigma(z_{ij}) + \lambda_j (1 - y_{ij})(1 - \log \sigma(z_{ij})) \tag{1}
\]

where \( N \) is the number of samples, \( L \) is the number of tag labels, \( y \in \{0, 1\} \) is the tag label, \( z \) is the output of the FFNN, \( \sigma \) is the sigmoid function, and \( \lambda_j \) is the ratio of positive to negative samples (precomputed over the entire training set, since the development set is too small to tune this parameter) for the tag label indexed by \( j \). With this loss function, we account for label imbalance without using separate thresholds for each tag tuned on the validation set.

4 Interpreting Scene Embeddings

As the complexity of learning methods used to encode sentences and documents has increased, so has the need to understand the properties of the encoded representations. Probing-based methods (Linzen et al., 2016; Conneau et al., 2018) are used to gauge the information captured in an embedding by evaluating its performance on downstream classification tasks, either with manually collected annotations (Shi et al., 2016) or carefully selected self-supervised proxies (Adi et al., 2016). In our case, it is laborious and costly to collect such annotations at the scene level (requiring domain experts), and the proxy evaluation tasks proposed in the literature do not probe the narrative properties we wish to surface.

Instead, we take inspiration from Iyyer et al. (2016) and learn a scene descriptor model that can be trained without relying on any such annotations. Using a dictionary learning perspective (Olshausen and Field, 1997), the model learns to represent each scene embedding as a weighted mixture of various topics estimated over the entire corpus. It thus acts as an “interpretability layer” that can be applied over the scene encoder. This model class is similar in spirit to dynamic topic models (Blei and Lafferty, 2006), with the added advantage of producing topics that are both more coherent and more interpretable than those generated by LDA (He et al., 2017; Mitcheltree et al., 2018).

4.1 Scene Descriptor Model

The model has three main components: a scene encoder, a set of topics or descriptors that form the “basis elements” used to describe an interpretable scene, and a predictor that predicts weights over descriptors for a given scene embedding. The scene encoder uses the text of a given scene \( s_t \) to produce a corresponding scene embedding \( \mathbf{v}_t \). This encoder can take any form—from an extractor that derives a hand-crafted feature set from the scene text, as in Gorinski and Lapata (2018), to an instantiation of the scene encoder in §3.

Figure 3: A pictorial representation of the scene descriptor model.

To probe the contents of scene embedding \( \mathbf{v}_t \), we compute the descriptor-based representation \( \mathbf{w}_t \in \mathbb{R}^d \) in terms of a descriptor matrix \( \mathbf{R}^{k \times d} \), where \( k \) is the number of topics or descriptors:

\[
\mathbf{w}_t = \text{softmax}(f(\mathbf{v}_t)) \tag{2}
\]

\[
\mathbf{o}_t = \mathbf{R}^T \mathbf{w}_t
\]

where \( \mathbf{o}_t \in \mathbb{R}^k \) is the weight (probability) vector over \( k \) descriptors and \( f(\mathbf{v}_t) \) is a predictor (illustrated by the leftmost pipeline in Fig. 3) which converts \( \mathbf{v}_t \) into \( \mathbf{o}_t \). Two variants are \( f = \text{FFNN}(\mathbf{v}_t) \) and \( f = \text{FFNN}(\mathbf{v}_t; \mathbf{o}_{t-1}) \) (concatenation); we use the former in §5.5. Furthermore, we can incorporate additional recurrence into the model by modifying Eq. 2 to add the previous state:

\[
\mathbf{o}_t = (1 - \alpha) \cdot \text{FFNN}(\mathbf{v}_t; \mathbf{o}_{t-1}) + \alpha \cdot \mathbf{o}_{t-1} \tag{3}
\]

4.2 Reconstruction Task

We wish to minimize the reconstruction error between two scene representations: (1) the descriptor-based embedding \( \mathbf{w}_t \) which depends on the scene
We evaluate the proposed script encoder architecture on an AWS p2.8xlarge machine. We use the 100-dimensional GloVe embeddings (Pennington et al., 2014). Our sequential models are biGRUs with a single 50-dimensional hidden layer in each direction, resulting in 100-dimensional outputs. The attention model is parametrized by a 100-dimensional vector \( p \); BoE models naturally output 100-dimensional representations, and character embeddings are 10-dimensional. The output of the script encoder is passed through a linear layer with a sigmoid activation function and binarized by thresholding at 0.5.

One simplification in our experiments is to utilize the same encoder type for all encoders described in §3.1. However, it is conceivable that different encoder types might perform better at different tiers of the architecture: e.g. scene aggregation can be done in a permutation-invariant manner, since narratives are interwoven and scenes may not be truly sequential.

We implement the script encoder on top of AllenNLP (Gardner et al., 2017) and PyTorch (Paszke et al., 2019), and all experiments were conducted on an AWS p2.8xlarge machine. We use the

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**Script Preprocessing**

As in Pavel et al. (2015), we leveraged the standard screenplay format (Argentini, 1998) to extract a structured representation of the scripts (relevant formatting cues included capitalization and tab-spacing; see Fig. 1 and Table 1 for an example). Filtering erroneously processed scripts removed 6% of the corpus, resulting in 857 scripts total. We set aside 20% (172 scripts) for heldout evaluation; the remainder was used for training. The average number of tokens per script is around 23k; additional statistics are shown in Table 5.

Next, we split extremely long scenes into smaller ones, capping the maximum number of lines in a scene (across both action and dialogue) to 60 (keeping within GPU memory limits). For the vocabulary, a word count of 5 across the script corpus was set as the minimum threshold. The number of samples (scripts) per tag value ranges from high (e.g., for some genre tags) to low (for most plot and mood tags) in both datasets (§A.1), and coupled with high tag cardinality for each attribute, motivates the need for the reweighted loss in Eq. 1.

**5.2 Experimental Setup**

All inputs to the hierarchical scene encoder are 100-dimensional GloVe embeddings (Pennington et al., 2014). Our sequential models are biGRUs with a single 50-dimensional hidden layer in each direction, resulting in 100-dimensional outputs. The attention model is parametrized by a 100-dimensional vector \( p \); BoE models naturally output 100-dimensional representations, and character embeddings are 10-dimensional. The output of the script encoder is passed through a linear layer with a sigmoid activation function and binarized by thresholding at 0.5.

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2https://github.com/EdinburghNLP/scriptbase
Adam optimizer with an initial learning rate of $5e^{-3}$, clip gradients at a maximum norm of 5, and do not use dropout. The model is trained for a maximum of 20 epochs to maximize average precision score, and with early stopping in place if the validation metric does not improve for 5 epochs.

### 5.3 Tag Prediction Experiments

ScriptBase-J also comes with “loglines”, or short, 1-2 sentence human-crafted summaries of the movie’s plot and mood (see Table 6). A model trained on these summaries can be expected to provide a reasonable baseline for tag prediction, since human summarization is likely to pick out relevant parts of the text for this task. The loglines model is a bidirectional GRU with inputs of size 100 (GloVe embeddings) and hidden units of size 50 in each direction, whose output feeds into a linear classifier.

| Model   | Genre | Plot | Mood   |
|---------|-------|------|--------|
| Loglines | 49.9  | 12.7 | 17.5   |
| BoE     | 49.0  | 8.3  | 12.9   |
| BoE + Attn | 51.9 | 11.3 | 16.3   |
| GRU     | 57.9  | 13.0 | 19.1   |
| GRU + Attn | 60.5 | 15.2 | 22.9   |

*Comparing encoder variations:*

| Variant          | Genre | Plot | Mood   |
|------------------|-------|------|--------|
| + Chars          | 62.5  | 11.7 | 18.2   |
| - Action         | 60.5  | 13.5 | 20.0   |
| - Dialogue       | 60.5  | 13.4 | 19.1   |
| 2-tier           | 61.3  | 13.7 | 20.6   |
| HAN              | 61.5  | 14.2 | 20.7   |

Table 2: Investigation of the effects of different architectural (BoE +/- Attn, GRU +/- Attn) and structural choices on a tag prediction task, using an internally tagged dataset: F-1 scores with sample standard deviation in parentheses. Across the 3 tag attributes we find that modeling sentential and scene-level structure helps, and attention helps extract representations more salient to the task at hand.

Table 2 contains results for the tag prediction task on our internally-tagged dataset. First, a set of models trained using action and dialogue inputs are used to evaluate the architectural choices in §3.1. We find that modeling recurrence at the sentential and scene levels, and using attention to select relevant words or scenes, help considerably and are necessary for robust improvement over the loglines’ baseline (see the first five rows in Table 2).

Next, we assess the effect that various structural elements of a screenplay have on classification performance. Notably, the difficulty of the prediction task is directly related to the set size of the tag attribute: higher-cardinality tag attributes with correlated tag values (like plot and mood) are significantly more difficult to predict than lower-cardinality tags with more discriminable values (like genre). We find that adding character information to the best-performing GRU + Atttn model (+Char) improves prediction of genre, while using both dialogue and action statements improves performance on plot and mood, compared to using only one or the other. We also evaluate (1) a 2-tier variant of the GRU+Atttn model without action/diologue-statement encoders (i.e., all action statements are concatenated into a single sequence of words and passed into the action-scene encoder, and similarly with dialogue) and (2) a variant similar to Yang et al. (2016) (HAN) that does not distinguish between action and dialogue (i.e., all statements in the text of a scene are encoded using a statement encoder and statement embeddings are passed to a single scene encoder, the output of which is passed into the script encoder). Both models perform slightly better than GRU+Atttn on genre, but worse on plot and mood, showing that for more difficult prediction tasks, it helps to incorporate hierarchy and to distinguish action and dialogue statements.

For the results in Table 3, we compared the GRU+Atttn configuration in Table 2 (HSE) with an implementation of Gorinski and Lapata (2018) (G&L) that was run on the previous train-test split. G&L contains a number of handcrafted lexical, graph-based, and interactive features that were designed for optimal performance for screenplay analysis. In contrast, HSE directly encodes standard screenplay structure into a neural network architecture, and is an alternative, arguably more lightweight way of building a domain-specific textual representation. Our results are comparable, with the exception of “place”, which can often be identified deterministically from scene headings.

| Tag   | G&L | HSE |
|-------|-----|-----|
| Attitude | 72.6 | 70.1 |
| Flag   | 52.5 | 52.6 |
| Genre  | 55.1 | 42.5 |
| Mood   | 45.5 | 51.2 |
| Place  | 57.7 | 29.1 |
| Plot   | 34.6 | 34.5 |

Table 3: F-1 scores on ScriptBase-J provided tag set, comparing Gorinski and Lapata (2018)’s approach to ours.

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4We tried both with and without attention and found the variant without attention to give slightly better results.
5.4 Similarity-based F-1

Results in Tables 2 and 3 are stated using standard multi-label F-1 score (one-vs-rest classification evaluation, micro-averaged over each tag attribute), which requires an exact match between predicted and actual tag value to be deemed correct. However, the characteristics of our tag taxonomies suggest that this measure may not be ideal. In particular, our human-crafted tag sets have tag attributes with dozens of highly correlated, overlapping values, as well as missing tags not assigned by the annotator. A standard scoring procedure may underestimate model performance when, e.g., a prediction of “Crime” for a target label of “Heist”, is counted as equivalently wrong to “Romance” (Table 9 in A.1).

One way to deal with tag sets is to leverage a similarity-based scoring procedure (see Maynard et al. (2006) for related approaches). Such a measure takes into account the latent relationships among tags via similarity thresholding, wherein a prediction is counted as correct if it is within a certain distance of the target. In particular, we treat a prediction as correct based the percentile of its similarity to the actual label. The percentile cutoff can be varied to illustrate how estimated model performance varies as a function of the degree of “enforced” similarity between target and prediction.

In Fig. 4 we examine how our results might vary if we adopted a similarity-based scoring procedure, by re-evaluating the GRU + Attn model outputs (row 5 in Table 2) with this evaluation metric. When the similarity percentile cutoff equals 100, the result is identical to the standard F-1 score. Even decreasing the cutoff to the 90th percentile shows striking improvements for high-cardinality attributes (180% for mood and 250% for plot). Leveraging a similarity-based scoring procedure for complex tag taxonomies may yield results that more accurately reflect human perception of the model’s performance (Maynard et al., 2006).

5.5 Qualitative Scene-level Analysis

To extract narrative trajectories with the scene descriptor model, we compared the three model variants in §3.1 for the choice of scene encoder and found that while attention aids the creation of interpretable descriptors (in-line with previous work), sequential and non-sequential models produce similarly interpretable clusters – thus, we use the BoE+Attn model. Similar to Iyyer et al. (2016), we limit the input vocabulary for both BoW + Attn encoders to words occurring in at least 50 movies (7.3% of the training set), outside the 500 most frequent words.

The number of descriptors $k$ is set to 25 to allow for a wide range of topics while keeping manual examination feasible. Descriptors are initialized either randomly (Glorot and Bengio, 2010) or with the centroids of a $k$-means clustering of the input word embeddings. For the predictor, $f$ is a two-layer FFNN with ReLU activations and a softmax final layer that transforms $v_t$ (from the scene encoder) into a 100-dimensional intermediate state and then into $o_t$. Further modeling choices are evaluated using the semantic coherence metric (Mimno et al., 2011), which assesses the quality of word clusters induced by topic modeling algorithms. These choices include: the presence of recurrence in the predictor (i.e., toggling between Eqns. 2 and 3, with $\alpha = 0.5$) and the value of hyperparameter $\lambda$. While the $k$-means initialized descriptors score slightly higher on semantic coherence, they are qualitatively quite similar to the initial centroids and do not reflect the corpus as well as the randomly initialized version. We also find that incorporating recurrence and $\lambda = 10$ (tuned using simple grid search) result in the highest coherence.

The outputs of the scene descriptor model are shown in Table 4 and Figure 5. Table 4 presents five example descriptors, each identified by representative words closest to them in the word embedding space, with their topic names manually
Figure 5: Descriptor Trajectories for *Pearl Harbor*, *Pretty Woman*, and *Pulp Fiction*. The y-axis is a smoothed and rescaled descriptor weight, i.e. $o_t$ in Eq.2. Events: (A) Attack on Pearl Harbor begins (B) Rising tension at the equestrian club and (C) Confrontation at the pawn shop. Word clusters corresponding to each descriptor are in Table 4.

announced. Figure 5 presents the corresponding narrative trajectories of a subset of these descriptors over the course of three sample screenplays: Pretty Woman, Pulp Fiction, and Pearl Harbor, using a streamgraph (Byron and Wattenberg, 2008). The descriptor weight $o_t$ (Eq.2) as a function of scene order is rescaled and smoothed, with the width of a region at a given scene indicating the weight value. A critical event for each screenplay is indicated by a letter on each trajectory. A qualitative analysis of such events indicates general alignment between scripts and their topic trajectories, and the potential applicability of this method to identifying significant moments in long-form documents.

| Topic   | Words                                      |
|---------|--------------------------------------------|
| Violence| fires, blazes, explosions, grenade, blasts |
| Residential| loft, terrace, courtyard, foyer, apartments |
| Military | leadership, army, victorious, commanding, elected |
| Vehicles | suv, automobile, wagon, sedan, cars |
| Geography | sand, slope, winds, sloping, cliffs |

Table 4: Examples of retrieved descriptors. Trajectories for “Violence”, “Military”, and “Residential” are shown in Fig. 5.

6 Related Work

Computational narrative analysis of large texts has been explored in a number of contexts (Mani, 2012) and for a number of years (Lehnert, 1981). More recent work has analyzed narrative from a plot (Chambers and Jurafsky, 2008; Goyal et al., 2010) and character (Elsner, 2012; Bamman et al., 2014) perspective. While movie narratives have received attention (Bamman et al., 2013; Chaturvedi et al., 2018; Kar et al., 2018), the computational analysis of entire screenplays has not been as common.

Notably, Gorinski and Lapata (2015) introduced a summarization method that takes into account an entire script at a time, extracting graph-based features that summarize the key scene sequences. Gorinski and Lapata (2018) then build on top of this work, crafting additional features for use in a specially-designed multi-label encoder. Our work suggests an orthogonal approach – our automatically learned scene representations offer an alternative to their feature-engineered inputs.

Gorinski and Lapata (2018) emphasize the difficulty of their tag prediction task, which we find in our tasks as well. One possibility we consider is that at least some of this difficulty owes not to the length or richness of the text per se, but rather to the complexity of the tag taxonomy. The pattern of results we obtain from a similarity-based scoring measure offers a significantly brighter picture of model performance, and suggests more broadly that the standard multilabel F1 measure may not be appropriate for complex, human-crafted tag sets (Maynard et al., 2006).

Nevertheless, dealing with long-form text remains a significant challenge. One possible solution is to infer richer representations of latent structure by using a structured attention mechanism (Liu and Lapata, 2018), which might highlight key dependencies between scenes in a script. Another method could be to define auxiliary tasks as in Jiang and Bansal (2018) to encourage better selection and memorization. Lastly, sparse versions of the softmax function (Martins and Astudillo, 2016) can be used to enforce the notion that salient information for downstream tasks is sparsely distributed across the screenplay.

7 Conclusion

In this work, we propose and evaluate various neural network architectures for learning fixed-dimensional representations of full-length film
scripts. We hypothesize that designing the network to mimic the documents’ internal structure will boost performance. Experiments conducted on two tag prediction tasks provide evidence in favour of this hypothesis, confirming the benefits of (1) using hierarchical attention-based models and (2) incorporating distinctions between different kinds of scene components directly into the model. Additionally, as a means of exploring the information contained within scene-level embeddings, we presented an unsupervised technique for bootstrapping “scene descriptors” and visualizing their trajectories through the screenplay.

For future work, we plan to investigate richer ways of incorporating character identities into the model. For example, character embeddings could be used to analyze character archetypes across different movies. A persona-based characterization of the screenplay would provide a complementary view to the plot-based analysis elucidated here.

Finally, as noted at the outset, our structure-aware methods are fundamentally generalizable, and can be adapted to natural language understanding across virtually any domain in which structure can be extracted, including books, technical reports, and online chat logs, among others.

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A Appendix

A.1 Additional Dataset Statistics

In this section, we present additional statistics on the evaluation sets used in this work.

| Min | 10th % | 90th % | Max |
|-----|--------|--------|-----|
| 4025 | 16,240 | 29,376 | 52,059 |

Table 5: Statistics on the number of tokens per script in the Scriptbase-J corpus. We use the same script corpus with two different tag sets – the Jinni tags provided with ScriptBase and a tag set designed by internal annotators.

| Tag   | Value                                      |
|-------|--------------------------------------------|
| Genre | Crime, Independent                         |
| Mood  | Clever, Witty, Stylized                   |
| Attitude | Semi Serious, Realistic                 |
| Plot  | Tough Heroes, Violence Spree, On the Run |
| Place | California, Los Angeles, Urban            |
| Flag  | Drugs/Alcohol, Profanity, Violent Content |

Logline: “The lives of two mob hit men, a boxer, a gangster’s wife, and a pair of diner bandits intertwine in four tales of violence and redemption.”

Table 6: Examples of Scriptbase-J tag attributes, tag values, and a logline, for the film “Pulp Fiction”.

| Tag          | Internal Scriptbase-J |
|--------------|-----------------------|
| Genre        | 9                     |
| Mood         | 65                    |
| Attitude     | -                     |
| Plot         | 82                    |
| Place        | -                     |
| Flag         | -                     |

Table 7: The number of distinct tag values for each tag attribute across the two datasets. Cardinalities for Scriptbase-J tag attributes are identical to Gorinski and Lapata (2018) except for the removal of one mood tag value when filtering for erroneously preprocessed scripts.

| Tag | Avg. #tags/script | Min #scripts/tag | Max #scripts/tag |
|-----|-------------------|------------------|-----------------|
| Genre | 1.74              | 17               | 347             |
| Mood  | 3.29              | 15               | 200             |
| Plot  | 2.50              | 15               | 73              |

Table 8: Statistics for the three tag attributes applied in our internally-tagged dataset: average number of tags per script, and the minimum/maximum number of movies associated with any single value.

A.2 Tag Similarity Scoring

To estimate tag-tag similarity percentiles, we calculate the distance between tag embeddings learned via an auxiliary model trained on a related supervised learning task. In our case, the related task is to predict the audience segment of a movie, given a tag set. The general approach is easily replicable via any model that projects tags into a well-defined similarity space (e.g., knowledge-graph embeddings (Nguyen, 2017) or tag-based autoencoders).

Given a tag embedding space, the similarity percentile of a pair of tag values is estimated as follows. For a given tag attribute, the pairwise cosine distance between tag embeddings is computed for all tag-tag value pairs. For a given pair, its similarity percentile is then calculated with reference to the overall distribution for that attribute.

Similarity thresholding simplifies the tag prediction task by significantly reducing the perplexity of the tag set, while only marginally reducing its cardinality. Cardinality can be estimated via permutations. If \( n \) is the cardinality of the tag set, the number of permutations \( p \) of different tag pairs \( (k = 2) \) is:

\[
p(n, k) = \frac{n!}{(n - k)!}
\]

which simplifies to \( n^2 - n - p = 0 \).

Likewise, the entropy of a list of \( n \) distinct tag values of varying probabilities is given by:

\[
H(X) = H(\text{tag}_1, \ldots, \text{tag}_n) = -\sum_{i=1}^{n} \text{tag}_i \log_2 \text{tag}_i
\]

The perplexity over tags is then simply \( 2^{H(X)} \).

| Tag     | Perplexity | Cardinality |
|---------|------------|-------------|
| Genre   | 42%        | 16%         |
| Mood    | 77%        | 16%         |
| Plot    | 79%        | 16%         |

Table 9: Examples of closely related and unrelated tag values in the Scriptbase-J tag set.

Table 10: The percent decrease in perplexity and cardinality, respectively, as the similarity threshold decreases from 100th percentile similarity (baseline) to 70th percentile.

As the similarity threshold decreases, the number of tags treated as equivalent correspondingly increases. Mapping these “equivalents” to a shared
label in our list of tag values allows us to calculate updated values for tag (1) perplexity and (2) cardinality. As illustrated by Table 10, rather than leading to large reductions in the overall cardinality of the tag set, similarity thresholding mainly serves to decrease perplexity by eliminating redundant/highly similar alternatives. Thus, thresholding at once significantly decreases the complexity of the prediction task, while yielding a potentially more representative picture of model performance.