Movies2Scenes: Learning Scene Representations Using Movie Similarities

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Figure 1: Approach Overview – Our approach employs readily accessible sources of movie-information (e.g., genre, synopsis, more-like-this information) to define a measure of movie-similarity which is then used to guide the process of learning a general-purpose scene-representation. The illustration shown in this figure presents two similar movies with the same genre along with four non-similar movies with different genres. We automatically select thematically similar scenes from similar movies, and use them in a contrastive-learning setting along with randomly selected scenes from non-similar movies. This allows us to learn a general-purpose scene-representation that achieves state-of-the-art results for a wide variety of downstream tasks related to understanding movie scenes.

Abstract
Automatic understanding of movie-scenes is an important problem with multiple downstream applications including video-moderation, search and recommendation. The long-form nature of movies makes labeling of movie scenes a laborious task, which makes applying end-to-end supervised approaches for understanding movie-scenes a challenging problem. Directly applying state-of-the-art visual representations learned from large-scale image datasets for movie-scene understanding does not prove to be effective given the large gap between the two domains. To address these challenges, we propose a novel contrastive learning approach that uses commonly available sources of movie-information (e.g., genre, synopsis, more-like-this information) to learn a general-purpose scene-representation. Using a new dataset (MovieCL30K) with 30,340 movies, we demonstrate that our learned scene-representation surpasses existing state-of-the-art results on eleven downstream tasks from multiple datasets [50][25][39]. To further show the effectiveness of our scene-representation, we introduce another new dataset (MCD) focused on large-scale video-moderation with 44,581 clips containing sex, violence, and drug-use activities covering 18,330 movies and TV episodes, and show strong gains over existing state-of-the-art approaches.

1. Introduction
Automatic understanding of movie-scenes is a challenging problem [50] [25] that offers a variety of applications including video-moderation, search and recommendation. The long-form nature of movies makes labeling of their scenes a laborious and expensive process. This dearth of scene-level labels makes it challenging to apply end-to-end supervised approaches for movie-scene understanding.

The general problem of learning in limited-label settings has been looked at from a variety of alternative perspectives [48], among which contrastive learning [27] has emerged as a particularly promising direction. Specifically, methods that use natural language supervision to guide contrastive learning [38] have shown impressive results specially for zero-shot image-classification tasks. However, these methods rely on the availability of image-text pairs which are particularly hard to collect for long-form videos. Another important set of methods within the space of contrastive learning focuses on using a pre-text task to contrast similar data-points with randomly selected ones [22][9]. However, most of the relatively simple data-augmentation schemes [22] used to define the pre-text tasks for these approaches have been shown to be not as effective for tasks
related to scene understanding [8]. To address these challenges, we propose a novel contrastive learning algorithm to find a general purpose scene-representation that works well for a diverse set of scene-understanding tasks.

Our key intuition is that commonly available sources of movie-information (e.g., genre, synopsis, more-like-this information) can be used to effectively guide the process of learning a generalizable scene-representation. Specifically, we use such movie-level information to define a measure of movie-similarity, and use it during contrastive learning to limit our search for positive scene-pairs to only the movies that are considered similar to each other. This allows us to find positive scene-pairs that are not only visually similar but are also semantically relevant, and can therefore provide us with a much richer set of semantic and thematic data-augmentations compared to previously employed augmentation schemes [22][8] (see Figure 1 for illustration). Furthermore, unlike previous contrastive learning approaches that mostly focus on images [22][9][13] or shots [8], our approach builds on the recent developments in vision transformers [12] to allow using variable-length multi-shot inputs. This enables our method to seamlessly incorporate the interplay among multiple shots resulting in a more effective and general-purpose scene-representation.

Using a new dataset (MovieCL30K) with 30, 340 movies, we demonstrate the flexibility of our model to handle scenes, shots and multi-shot clips as inputs to surpass existing state-of-the-art results on eleven downstream tasks on multiple benchmarks [50][25][39]. Furthermore, as an important practical application of long-form video understanding, we introduce another new dataset (MCD) focused on the problem of large-scale video-moderation with 44,581 video clips from 18,330 movies and TV episodes containing sex, violence, and drug-use activities. We show that learning our general-purpose scene-representation is crucial to recognize such age-appropriate video-content where existing representations learned for short-form action recognition or image classification are not as effective.

2. Related Work

a. Long-Form Video Understanding: Recent work on semantic understanding of long-form movies and TV episodes have used multi-shot scenes as their processing unit. For example in MovieNet [25], manually annotated multi-shot scenes were used to train various recently proposed models [7][16] to evaluate their performance on multiple tasks related to scene-tagging e.g., recognizing places or actions in those scenes. In [35], multi-shot clips of movies and TV episodes were categorized into 25 event-classes for their temporal localization. The results in [35] show that state-of-the-art event localization models [32][33] do not perform as well on long-form movie and TV episodes compared to their performance on short-form video datasets like THUMOS14 [28]. A long-form video understanding (LVU) dataset was recently proposed in [50] with nine different tasks related to semantic understanding of video-clips that were cut-out from full-length movies. This work also proposed an object-centric transformer-based video recognition architecture that outperformed SlowFast [16] and VideoBert [43] models on their LVU [50] dataset. To compliment existing datasets focusing on regular everyday activity-categories, we propose a new dataset focusing on video-moderation of sensitive activities including sex, violence, and drug-use, and show how our proposed scene-representation can be applied to recognize these activities.

b. Contrastive Learning: As an important subset of self-supervised learning [29], contrastive learning [32] attempts to learn data representations by contrasting similar data against dissimilar data while using a contrastive loss. Recent approaches for contrastive learning [22][9] have successfully been extended for a variety of applications in image classification [44][24][19] as well as video understanding [21][8][55]. More recently, various visio-linguistic models [38] have adopted natural language supervision during contrastive learning to learn correspondences between image and text pairs, which has achieved impressive results especially for zero-shot image classification tasks. Most of these approaches however focus on images or short-videos, and our experiments show that they do not perform as well on tasks related to long-form video-understanding.

c. Vision Transformer: Derived from the work on self-attention [46], transformers have been extensively studied in natural language processing [49][11]. Building on this line of work, recently proposed vision transformer (ViT) [12] has successfully exceeded state-of-the-art results when pre-trained on large-scale datasets. The data-efficiency of ViT was recently improved by [45] by using token-based distillation for model training. More recently, ViT-based architectures were adopted to video recognition, with models including TimeSformer [3], ViViT [2], and MViT [14]. These models take images or short-form videos as inputs, and therefore cannot be directly applied to longer videos without additional tuning.

3. Method

For consistency, let us define a shot as a series of frames captured from the same camera over a consecutive period of time [42]. We define a scene as a series of consecutive shots without requiring manually annotated scene-boundaries. Note that our definition of scenes is less constrained than what has previously been used [25][39][8], and enables our approach to work seamlessly with settings that do [25] or do not have [50] scene boundaries available.

Our approach consists of three key steps. First, we use commonly available movie information (e.g., genre, syn-
Figure 2: **Movie Similarity Learning** – Shots of a movie-pair \( m_1 \) and \( m_2 \) are provided to an encoder with fixed parameters (\( E_{\text{fixed}} \)) followed by an encoder with learnable parameters (\( E_{\text{learnable}} \)). We take the inner-product of shot-feature matrices followed by successive pooling and flattening operations to get an output vector \( V \) which is regressed against movie-level similarity \( S \) between \( m_1 \) and \( m_2 \).

![Diagram of Movie Similarity Learning](image)

Figure 3: **Contrastive Scene Representation Learning** – Given a pair of similar movies \( m_1 \) and \( m_2 \) as determined by \( S \), we use a set of pre-processing operations (as identified in Figure 2) to select a set of similar scene-pairs. This process is applied to all pairs of similar movies to get a collection of paired scenes that is used for scene-level contrastive learning.

As illustrated in Figure 2, we divide a given movie-pair \( m_1 \) and \( m_2 \) into their constituent shots \[41\] \( x_1 \) and \( x_2 \) respectively. We extract features of these shots using a fixed pre-trained encoder \( E_{\text{fixed}} \), so that \( x_1 \) and \( x_2 \) are represented by two feature matrices \( E_{\text{fixed}}(x_1) \) and \( E_{\text{fixed}}(x_2) \) respectively. These feature matrices are passed through an encoder with learnable parameters \( E_{\text{learnable}} \), followed by their inner-product to create a shot-adjacency matrix \( A_{x_1,x_2} \), i.e.:

\[
A_{x_1,x_2} = E_{\text{learnable}}(E_{\text{fixed}}(x_1)) \cdot E_{\text{learnable}}(E_{\text{fixed}}(x_2))
\]

Note that entries in \( A_{x_1,x_2} \) represent pair-wise similarities between shots in movies \( m_1 \) and \( m_2 \).

Using \( k_s \) contiguous shots as scenes, we convert the shot-adjacency matrix \( A_{x_1,x_2} \) into a scene-adjacency matrix \( B_{x_1,x_2} \) by applying average-pooling with kernel size \( k_s \) and stride \( s_a \) on \( A_{x_1,x_2} \) to calculate the average values in each \( k_s \times k_s \) window in \( A_{x_1,x_2} \). Furthermore, we apply max-pooling with kernel size \( k_m \) and stride \( s_m \) on \( B_{x_1,x_2} \) followed by flattening the output to get vector \( V_{x_1,x_2} \). Intuitively, this step finds the most similar scene-pairs between \( x_1 \) and \( x_2 \), where each value in \( V_{x_1,x_2} \) represents the highest similarity of scene-pair in a neighborhood of \( k_m \times k_m \) scenes in \( B_{x_1,x_2} \). Finally, we learn the projection between \( V_{x_1,x_2} \) and the output using layer \( L_{\text{output}} \), where our goal is to predict if \( x_1 \) and \( x_2 \) are similar at movie-level. That is, if \( x_1 \) and \( x_2 \) are shots from similar movies as defined by \( S \), our target label is 1, and 0 otherwise. During training, we use cross-entropy loss to update \( E_{\text{learnable}} \) and \( L_{\text{output}} \) while \( E_{\text{fixed}} \) remains unchanged.

A useful way to interpret our movie similarity learning step is to view it from a multiple instance learning (MIL) perspective [5], where the shot-adjacency matrix \( A_{x_1,x_2} \) can be considered as a bag, while similar scene-pairs can be thought of as positive instances. Unlike some of the recent MIL-based approaches [1] [17] [34], we simplify our learning process by adopting standard network operations and loss function instead of specially designed ones, which allows us to use existing well-engineered implementations to get better efficiency and scalability in practice.

3.1. Movie-Level Similarity Learning

As illustrated in Figure 2, we divide a given movie-pair \( m_1 \) and \( m_2 \) into their constituent shots \[41\] \( x_1 \) and \( x_2 \) respectively. We extract features of these shots using a fixed pre-trained encoder \( E_{\text{fixed}} \), so that \( x_1 \) and \( x_2 \) are represented by two feature matrices \( E_{\text{fixed}}(x_1) \) and \( E_{\text{fixed}}(x_2) \) respectively. These feature matrices are passed through an encoder with learnable parameters \( E_{\text{learnable}} \), followed by their inner-product to create a shot-adjacency matrix \( A_{x_1,x_2} \), i.e.:

\[
A_{x_1,x_2} = E_{\text{learnable}}(E_{\text{fixed}}(x_1)) \cdot E_{\text{learnable}}(E_{\text{fixed}}(x_2))
\]

Note that entries in \( A_{x_1,x_2} \) represent pair-wise similarities between shots in movies \( m_1 \) and \( m_2 \).

Using \( k_s \) contiguous shots as scenes, we convert the shot-adjacency matrix \( A_{x_1,x_2} \) into a scene-adjacency matrix \( B_{x_1,x_2} \) by applying average-pooling with kernel size \( k_s \) and stride \( s_a \) on \( A_{x_1,x_2} \) to calculate the average values in each \( k_s \times k_s \) window in \( A_{x_1,x_2} \). Furthermore, we apply max-pooling with kernel size \( k_m \) and stride \( s_m \) on \( B_{x_1,x_2} \) followed by flattening the output to get vector \( V_{x_1,x_2} \). Intuitively, this step finds the most similar scene-pairs between \( x_1 \) and \( x_2 \), where each value in \( V_{x_1,x_2} \) represents the highest similarity of scene-pair in a neighborhood of \( k_m \times k_m \) scenes in \( B_{x_1,x_2} \). Finally, we learn the projection between \( V_{x_1,x_2} \) and the output using layer \( L_{\text{output}} \), where our goal is to predict if \( x_1 \) and \( x_2 \) are similar at movie-level. That is, if \( x_1 \) and \( x_2 \) are shots from similar movies as defined by \( S \), our target label is 1, and 0 otherwise. During training, we use cross-entropy loss to update \( E_{\text{learnable}} \) and \( L_{\text{output}} \) while \( E_{\text{fixed}} \) remains unchanged.

3.2. Scene Contrastive Learning

Given a similar movie-pair as defined by \( S \), we apply \( E_{\text{learnable}} \) to their constituent shots, followed by successive pooling operations to find the scene adjacency matrix \( B \), which is used to select the top 50% similar scene-pairs. We apply this selection process to all pairs of similar movies to get a collection of paired scenes \( P_{\text{scene}} \) that is used for scene-level contrastive learning. Our contrastive learning approach is shown in Figure 3, and explained below.

3.2.1 Scene Encoder

As the inputs to our encoder \( E_{\text{scene}} \) for scene-contrastive learning are multi-shot sequences, it is important to design \( E_{\text{scene}} \) so that it can effectively model the various relationships among input shots. To this end, we build on recent work of ViT [12], and propose a transformer based \( E_{\text{scene}} \) that treats patches in input shots as tokens.
Specifically, following [12] [38], for a \(k\)-frame shot of dimension \((k, w, h, c)\), we first divide it into a sequence of \((k, \frac{w}{p}, \frac{h}{p}, c)\) patches, where \((p, p)\) is the size of each patch. To input the shot to a transformer with latent vector size of \(D\) dimensions, we apply \(D \times c\) convolutional kernels with kernel size \((p, p)\) and stride \((p, p)\) to the \((k, \frac{w}{p}, \frac{h}{p}, c)\) patches. This converts the shot into patch-embeddings with dimension \((k, D, \frac{w}{p}, \frac{h}{p}, c)\), which is further flattened to a \((k, D, N)\) dimensional tensor where \(N = (w \cdot h)/p^2\). Furthermore, we prepend a learnable embedding to the patch embeddings similar to the class token used in [11]. After permutation, the result is \((N + 1, D)\) dimensional patch-embeddings for each of the \(k\) frames. We add \((N + 1, D)\) dimensional positional embeddings to patch-embeddings to retain positional information, and pass them to successive multi-headed self-attention (MSA) layers as done in [12].

Similarly, for the input of a scene with \(n\) shots, we first divide it into a sequence of \((n \cdot k, \frac{w}{p}, \frac{h}{p}, c)\) patches. After convolution and flattening, we get \((D, N \cdot n \cdot k)\) dimensional patch embeddings. Notice that this is different from the dimension of a frame, and does not match with the dimension of position embeddings. Inspired by [12] where they mentioned that pre-trained position embeddings can be interpolated to fine-tune input of higher resolutions, we propose to generalize this property from frame to shot and scene. That is, we interpolate the \(N\)-dimensional position embeddings to \(N \cdot n \cdot k\), excluding the 1-dimensional corresponding to class token, and add the interpolated position embeddings to patch embeddings before providing them to MSA layers.

This operation offers two key advantages:

a. Use of Pre-trained Models: Note that ViT [12] offers impressive performance when trained on large-scale datasets (14M-300M images). Available datasets for long-form video understanding are of significantly smaller scale compared to large-scale image datasets. Our proposed way to apply 2-D interpolation to position embeddings allows us to scale them from single frame to shots and scenes, and enables us to readily adopt powerful models [38] pre-trained on large image datasets for long-form video understanding without explicit temporal modeling as required in [3] [2].

b. Flexibility for Downstream Tasks: Using 2-D interpolation to the position embeddings of our encoder allows it to take variable-length shot-sequences as inputs. This enables our approach to be applicable to the common setting where the lengths of multi-shot sequences in contrastive learning are different from those available in downstream tasks.

### 3.2.2 Contrastive Learning

Our scene-contrastive learning step follows some of the recent works [22] [8] with two key differences: (a) unlike the image or shot-augmentation focused pre-text tasks previously used, we define scene-level pretext task that uses commonly available movie-level information making it more effective for long-form video understanding, and (b) our use of ViT-based [12] scene-encoder allows variable-length inputs and the possibility to adopt large-scale pre-trained models, which is not something that previously used ResNet-based encoders [8] could offer.

Specifically, we define our pretext task as a dictionary look-up for the scenes selected at the end of our movie similarity learning step. That is, given a query scene \(q\), its positive key scene \(k_0\) is determined in \(P_{\text{scene}}\), and the objective is to find \(k_0\) among a set of random scenes \(\{k_1, k_2, \ldots, k_K\}\).

The problem is converted to a \(K + 1\)-way classification task by calculating similarity with dot product, and we use InfoNCE as the contrastive loss function [37]:

\[
\mathcal{L}_q = -\log \frac{\exp(f(q|\theta_q) \cdot g(k_0|\theta_k)/\tau)}{\sum_{i=0}^{K} \exp(f(q|\theta_q) \cdot g(k_i|\theta_k)/\tau)}
\]

where \(f(\cdot|\theta_q)\) is the query encoder with parameters \(\theta_q\) updated during back-propagation, \(g(\cdot|\theta_k)\) is the key encoder with parameters \(\theta_k\) learned by momentum update as done in [22], and \(\tau\) is the temperature as illustrated in [51].

During contrastive learning, the scene encoder \(E_{\text{scene}}\) is the query encoder \(q\) without the last fully-connected layer, and is updated based on the selected similar scenes \(P_{\text{scene}}\). After training converges, \(E_{\text{scene}}\) is the outcome from this stage, which can then be used for downstream tasks.

### 3.3 Application to Downstream Tasks

We train encoder \(E_{\text{scene}}\) as detailed above and apply it to downstream tasks as a general-purpose scene-level encoder. Specifically, depending on the downstream task, we first process the video-data to a sequence of shots or frames. Then, we extract features for each sample by \(E_{\text{scene}}\), which then can be used as input for downstream classifiers.

### 4. Experiments

We start by presenting one of our newly collected movie data (MovieCL30K) that we used to learn our scene representation followed by describing the implementational details of our algorithm. We then present comparative results on multiple benchmark datasets [50] [25] [39] demonstrating significant gains of our approach over existing state-of-the-art models for eleven downstream tasks. To further demonstrate the generalizability of our scene-representation, we introduce another new dataset (MCD) focused on the problem of large-scale moderation of age-sensitive activities including sex, violence, and drug-use and show substantial gains over existing state-of-the-art models.

#### 4.1. MovieCL30K Dataset

For unsupervised learning of our scene-representation, we compiled a new dataset called MovieCL30K with 30,340
movies from 11 genres (see Figure 4 for genre-distribution).

To compute movie-similarity in this data, we used readily accessible movie information available on IMDb including: (i) more-like-this, (ii) synopsis, and (iii) genre.

More-like-this is a pre-computed comprehensive similarity measure between movies on IMDb which takes into account multiple factors including genres, country-of-origin and actors [26]. For each input movie, we select its most similar movies based on their more-like-this ranking. Similarly, to use synopsis for movie-level similarity, we first extract textual-embeddings of movie-synopsis using a pre-trained NLP model [36], and then compute pairwise movie-similarities as the inner-product of their textual-embeddings, followed by selecting the closest movies. Lastly, to use genre to find movies similar to an input movie, we randomly select movies with the same genre as the input movie. When using any of the aforementioned movie-similarity measures, we select three most similar movies on average for each movie in MovieCL30K.

4.2. Implementation Details

We divide movies in MovieCL30K into their constituent ~33 million shots, and only keep one frame per shot for efficiency. Representations of all shots are first extracted using the visual encoder of pre-trained CLIP model [38] denoted as $E_{\text{fixed}}$ in Figure 2. The encoder $E_{\text{learnable}}$ comprises of two fully-connected layers each with 512 dimensions, and a dropout layer with 0.5 probability between them. The fact that each movie in MovieCL30K consists more than 1,000 shots on average leads us to keep our $E_{\text{fixed}}$ Constant and to only update parameters of $E_{\text{learnable}}$ during training to help us achieve high efficiency. We keep length of each movie to be 1,024 shots, and zero-padded the movies that are shorter than that. Kernel size for both max and average pooling are set to $16 \times 16$, with a stride of 8.

After the completion of movie-level similarity learning (Figure 2), we select the top 50% of most-similar scene-pairs from each movie-pair, and use a scene-length of 9 shots for contrastive learning (Figure 3). We follow the implementation in [22] for momentum contrastive learning and use the ViT [12] from pre-trained CLIP [38] as our scene encoder instead of the ResNet [23]-based encoder used in [22]. Moreover, we optimize with Adam [31] instead of SGD [18]. Unlike movie-level learning where we directly use ViT [12] as a shot-encoder, for scene-representation learning we interpolate the pre-trained position embeddings of ViT[12] (see § 3.2.1) so that the encoder can take variable-length multi-shot sequences as input.

For supervised learning on downstream tasks, unless otherwise specified, we use a simple MLP with two hidden layers, where the output layer is modified based on each of the various classification or regression tasks.

4.3. Comparisons on Benchmark Datasets

4.3.1 LVU Benchmark

We first compare our model with the state-of-the-art approaches using the benchmark LVU dataset [50] which contains nine diverse tasks including: place (scene), director, relationship, way-of-speaking, writer, year, genre, view-count, and like-ratio. The total number of labeled videos in LVU dataset [50] is 11K with the splits of training, validation and testing sets to be 70%, 15% and 15%, respectively.

a. Effectiveness of Learned Representation: To demonstrate the effectiveness of our learned scene-representation, we use the place-labeled scenes from LVU data [50] in a retrieval-setting. Specifically, using query scenes each with a particular place-label from the validation-set, we retrieve 1, 5 and 10 nearest neighbors from the training-set using their $L_2$ distances. Precision results for various settings are given in Table 1 where our encoder is compared with the pre-trained visual encoder of CLIP [38] and the SlowFast model [16] pre-trained on Kinetics [6] and AVA [33].

Furthermore, to provide qualitative insights into the effectiveness of our learned scene-representation, Figure 5 shows the retrieval results using an example query for 4 of the 6 categories based on ours as well as CLIP [38] visual representation. It can be seen that although CLIP [38] visual representation can capture local appearance-based patterns effectively, it is not able to capture the longer-duration semantic aspects of scenes. In contrast, our representation is able to capture the appearance as well as semantic aspects of scenes effectively, and is therefore able to avoid the types of confusions that confound the CLIP [38] representation.

b. Comparative Empirical Analysis: We further compare our approach with state-of-the-art results on LVU [50] test set quantitatively. Following [50], view-count and like-ratio are evaluated by mean-squared-error in regression (lower is better), while other seven tasks are evaluated using top-1 accuracy in classification (higher is better). Table 2 shows our results compared with SlowFast [16], Video Bert [43], Ob-ject Transformer [50] and CLIP visual encoder [38], where our approach comfortably outperforms on all 9 tasks.

Table 2 also shows comparison of our approach with different types of movie-level similarities. As shown, while
Figure 5: Qualitative results of place retrieval using LVU data [50] are shown. For each query scene in validation-set, two similar scenes from training-set are retrieved based on ours and CLIP visual representation [38]. Example results show that our feature can capture both scene-appearance as well as their broader thematic signature, while CLIP [38] can only capture scene-appearance effectively.

| Models          | CLIP [38] | SlowFast [16] | Ours   |
|-----------------|-----------|---------------|--------|
| Architecture    | ViT-B/16  [12] | ResNet-101 [23] | ViT-B/16 [12] |
| Pre-training data | 400M image-text pairs | Kinetics [6]+AVA [33] | MovieCL30K |
| Pre-training task | image-text similarity | action recognition | scene contrast |

| Place       | Precision (%)       |
|-------------|---------------------|
|             | top-1  | top-5  | top-10 | top-1  | top-5  | top-10 | top-1  | top-5  | top-10 |
| office      | 30     | 20     | 19     | 0      | 16     | 17     | 40     | 28     | 30     |
| airport     | 0      | 15     | 10     | 0      | 0      | 10     | 0      | 20     | 22.5   |
| school      | 28.57  | 26.66  | 25     | 0      | 16     | 17     | 69.04  | 53.33  | 48.80  |
| hotel       | 35.71  | 28.57  | 29.28  | 0      | 16     | 17     | 76.19  | 20.47  | 32.14  |
| prison      | 52.94  | 42.94  | 42.94  | 35.29  | 40     | 20.29  | 44.11  | 36.47  | 37.05  |
| restaurant  | 20     | 13.99  | 13.99  | 0      | 20     | 10     | 14.28  | 27.14  | 30     |
| all queries | 35.08  | 29.64  | 28.85  | 38.59  | 22.63  | 21.84  | 47.36  | 38.59  | 38.24  |

Table 1: The place-labeled scenes in LVU data [50] are formulated to a retrieval setting, where the goal is to retrieve similar scenes from training-set given query scenes from validation-set. Representations pre-trained on different configurations as specified in the table are compared. The precision results for different place categories are reported with the size of retrieved set to be 1, 5 and 10.

4.3.2 MovieNet Benchmark

MovieNet is a large-scale movie understanding dataset with 1,100 movies covering a variety of tasks [25]. However, unlike LVU [50] where videos are publicly available, the movies in MovieNet are not publicly released yet due to copyright issues. Only keyframes from each shot are provided, which makes tasks that demand high frame-rate (e.g., action recognition) infeasible. We therefore focus our comparison to two scene understanding related tasks in MovieNet that do not demand particularly high frame-rate, i.e.: (i) place-tagging, and (ii) scene-boundary-detection. The key difference between these two tasks is that place-tagging focuses more on the holistic understanding of the scene, while scene-boundary-detection requires the understanding of the relationships among multiple-shots. Our results demonstrate that our scene-representation can work well under both these settings and surpasses their existing state-of-the-art approaches.

a. Place Tagging: The MovieNet [25] dataset contains 90 categories of places with 19.6K place tags. The place-tagging problem is formulated as a multi-label classification task where each manually-labeled scene can have multiple place-tags. The results are evaluated by mean average precision (mAP) on the test-set as shown in Table 3. We compare our approach with two sets of models: (i) fine-tuning models, and (ii) feature-based approaches. The results on fine-tuning are reported by [25] where they mentioned that standard action recognition models were adopted. For feature-based approaches, we compare our encoder with CLIP vi-
Table 2: Quantitative comparisons on test-set of benchmark LVU dataset [50]. Our approach is evaluated on nine diverse tasks and compared against multiple state-of-the-art models. Comparisons of our approach using different movie-level similarities are also provided.

| Models | Classification & Regression | Mean Avg. Precision |
|--------|-----------------------------|---------------------|

| Fine-tuning | Models | Pre-training setting | Avg. Precision |
|-------------|--------|----------------------|---------------|
| ImageNet [10] | SimCLR [9] | same-domain | 41.65 |
| Place [54] | MoCo [22] | same-domain | 42.51 |
| CLIP [38] | ShotCoL [8] | same-domain | 53.37 |
| Ours (genre) | LGSS [39] | cross-domain | 47.1 |
| Ours (synopsis) | CLIP [38] | cross-domain | 47.4 |
| Ours (more-like-this) | ShotCoL [8] | cross-domain | 48.4 |
| Ours | Ours | cross-domain | 54.11 |

Table 3: Comparisons with state-of-the-art results on MovieNet place scene tagging using methods based on: (a) action recognition models fine-tuned for this task, and (b) commonly used pre-trained representations for generic downstream tasks.

Table 4: Comparisons with state-of-the-art results on scene boundary detection, showing that our approach outperforms state-of-the-art even when pre-trained in cross-domain setting.

4.4. Video Moderation

To further demonstrate the generalizability of our scene-representation, we focus on video-moderation particularly to detect sex, violence, and drug-use activities in movies and TV shows. Video-moderation is one of the most pressing challenges faced by all video-streaming services. However, most of the existing activity datasets (e.g., Kinetics [30, 6], Thumos14 [28]) do not focus on movies and TV series. Also, existing movie datasets (AVA [20], MovieNet [25]) do not focus on detecting age-appropriate activities. In
Figure 6: Examples of 3 types of age-appropriate activities in our data. Sensitive parts of images have been intentionally redacted here.

| Models            | Pre-training data | sex  | violence | drug-use | average |
|-------------------|-------------------|------|----------|----------|---------|
| SlowFast R50 [16] | K400 [30]         | 63.9 | 46.5     | 49.4     | 53.3    |
| SlowFast R101 [16]| K600 [6]+AVA2.2 [33]| 61.0 | 57.3     | 54.0     | 57.4    |
| X3D-L [15]        | K400 [30]         | 69.2 | 49.4     | 56.4     | 58.4    |
| CLIP [38]         | 400M image-text pairs      | 78.5 | 62.1     | 55.1     | 65.2    |
| Ours              | MovieCL30K        | 79.4 | 72.4     | 62.8     | 71.5    |

Table 5: Comparison of our approach with state-of-the-art pre-trained action recognition models and CLIP visual encoder [38] on MCD.

the following, we first go over a newly collected data for large-scale video-moderation in studio-produced content, followed by presenting comparative results using this data.

**a. Mature Content Dataset (MCD):** Our dataset focuses on three age-appropriate activities, i.e., (a) sex, (b) violence, and (c) drug-use (see Figure 6 for examples). To have consistent and reliable annotations among data-annotators, we provided annotation guidelines to them consisting of 17 instructions for sex, 34 for violence and 14 for drug-use. Examples of these instructions include: “intentional murder and/or suicide that involves bloody injury” for violence, and “strip-tease or erotic dancing with full nudity” for sex. All annotators were fluent English speakers and went through multiple training sessions to prepare for their assignment. Moreover, each annotator was asked to label sample-videos and received feedback on their labeling quality before they could start to label the data independently. Our data contains 44,581 clips from 18,330 movies and TV episodes with 4,580, 8,248, 8,271, and 23,482 clips containing sex, violence, drug-use, and none-of-the-above activities respectively. These clips have a mean duration of 5 seconds, and were divided into training, validation, and testing sets with 70%, 10%, and 20% ratio respectively.

**b. Results:** We extract embeddings of our mature-content dataset using our pre-trained scene encoder and use them as input to train a 4-class MLP model for predicting age-appropriate activities. We compare our representation with the representations learned using state-of-the-art models on existing action recognition as well as image classification datasets. To this end, we apply action recognition models [16] [14] [15] trained on Kinetics [30, 6] and AVA [20] as well as CLIP visual encoder [38] on clips in our dataset, extract the embeddings from these models, and provide them as inputs to the aforementioned MLP model for training. Table 5 presents the AP results on our test data, and shows that our scene representation outperforms the alternatives by a large margin. Notice that CLIP visual feature performed close to our representation on the task of sex but not other tasks. This might indicate that in the pre-training data of CLIP, there might be a considerable amount of image-text pairs related to sex concepts. Similar observations [4] have been made on other large scale datasets [40].

5. Conclusions

We presented a novel contrastive learning approach that uses movie-level similarity to learn a general-purpose scene-level representation. Our approach adopts recent developments in vision transformer, where by incorporating the interpolation of pre-trained position-embedding, we were able to train a scene-encoder that can take variable-length multi-shot inputs. We empirically validated that our approach works effectively with different types of movie-level similarities including genre, synopsis and more-like-this information. Qualitative and quantitative results on diverse tasks from multiple benchmark datasets highlight the strengths of our approach. We also presented a new application of our scene-representation for video moderation focused on three age-appropriate activities, where our approach outperformed state-of-the-art action recognition features. Going forward, we plan to further improve the computational efficiency of our approach to help it scale even more. We will also explore other types of commonly available movie-level information to find a representation that is effective on additional tasks including action recognition and image classification.
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Supplementary Material:
Movies2Scenes: Learning Scene Representations Using Movie Similarities

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In this supplementary material, we provide two sections to better support the arguments and results in the main paper: (a) more details of the specific settings in our experiments for better reproducibility, and (b) more extensive qualitative results to better demonstrate the interpretability of our learned representations. The sections will be presented with information corresponding to different datasets used in the main paper including: Movie Contrastive Learning 30K (MovieCL30K) dataset, Long-Form Video Understanding (LVU) dataset [11], MovieNet dataset [6] [10] and Mature Content Dataset (MCD).

1. Experiment Details

We use PyTorch [8] as our deep learning library and Tesla V100 GPUs for computation. During contrastive learning, we use 8 GPUs with distributed data parallelism. For supervised learning of MLP on downstream tasks, only 1 GPU is needed.

1.1. MovieCL30K

This section corresponds to §4.2 in the main paper.

a. Movie-Level Similarity Learning: When using movie-level information to train the learnable parameters (Figure 2 in the main paper) on MovieCL30K, we used SGD to optimize with learning rate of 0.1, batch size of 256 and epoch number of 20. The same set of hyper-parameters was applied to all three types of movie-level information (more-like-this, genre and synopsis). Recall that within each batch, there are 256 pairs of movies represented by feature matrices extracted from fixed pre-trained visual encoder in CLIP [9], and the dimension of each feature matrix is 1024×512. These pairs are passed through E\textsubscript{learnable} to predict whether two movies are similar based on movie-level information.

b. Scene Contrastive Learning: After movie-level similarity learning, we select the set of similar scene-pairs based on the learned space in E\textsubscript{learnable}. Specifically, after extracting the CLIP visual feature [9] of all shots in each input movie, the movie is represented as a matrix of $M \times 512$, where $M$ is the number of shots in the movie. Notice that the length of the movie is no longer restricted to 1024, so that all shots can be considered during similar scene selection. The feature matrix is then passed to E\textsubscript{learnable} before the last fully-connected layer, and becomes a new feature matrix. Similar process is done on another movie considered similar to the input movie with $N$ shots, and the shot adjacency matrix $A$ of these two movies takes the size of $M \times N$. We then go through all $9 \times 9$ windows in $A$ with stride 1, and calculate the average value in each window to represent the scene-level similarity of the two movies. Finally, we pop the scene-pairs with top 50% highest scene-level similarity scores while keeping the selected scenes to be non-overlapping in each movie. This generates a set of scene-pairs for each type of movie-level information.

With the generated set of scene pairs, we use them for scene contrastive learning following the MoCo framework, while substituting encoder to be ViT [1] in pre-trained CLIP [9] and optimization to be Adam [7] instead of SGD [4]. Specifically, following [5], we use feature dimension of 128, queue size of 65, 536, MoCo momentum of 0.999 and softmax temperature of 0.07 during momentum contrastive learning. Following [1][9], we use learning rate of $5e^{-6}$, weight decay of $1e^{-8}$, number of warm-up epochs of 5, batch size of 128 and number of epoch of 20.

We present the top-1 and top-5 accuracy during pre-training on different movie-level information (more-like-this, genre and synopsis) in Figure 1. We can see that more-like-this information gets the highest top-1 and top-5 accuracy during pre-training, while synopsis gets the lowest ones, which indicates that more discriminating features have been learned from more-like-this information leading to give better performance on downstream tasks validated in Table 2 in the main paper. Also notice that the accuracy at the beginning of each epoch is less stable therefore producing the peaks in Figure 1.

1.2. LVU

This section corresponds to §4.3.1 in the main paper.

a. Effectiveness of Learned Representation: We pre-
### Models

| Models  | place | director | relationship | speaking | writer | year | genre | view | like |
|---------|-------|----------|--------------|----------|--------|------|-------|------|------|
| learning rate | 0.1   | 0.1      | 0.5          | 0.01     | 0.1    | 0.1  | 0.01  | 0.01 | 0.1  |
| batch size | 64    | 16       | 16           | 32       | 16     | 64   | 128   | 16   | 16   |
| epoch    | 400   | 400      | 400          | 400      | 400    | 400  | 400   | 500  | 500  |
| drop out | 0.25  | 0.875    | 0.25         | 0.75     | 0.75   | 0.75 | 0.25  | 0.75 | 0.5  |

Table 1: Hyper-parameters used in the MLPs for LVU tasks.

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**1.3. MovieNet**

This section corresponds to §4.3.2 in the main paper.

**a. Place Tagging:** For the results of Ours in Table 3 in the main paper, we used MLP with two 512-dimensional hidden layers optimized by SGD with learning rate of 5.0, drop out of 0.25, epoch number of 200 and batch size of 512. The problem was formulated as a multi-label classification task and optimized by BCEWithLogitsLoss [8].

**b. Scene Boundary Detection:** For the results of Ours in Table 4 in the main paper, we used MLP with two 512-dimensional hidden layers optimized by SGD with learning rate of 0.03, drop out of 0.8, epoch number of 800 and batch size of 4096.

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**1.4. MCD**

We used SlowFast 8x8 R50 and SlowFast 8x8 R101 for the SlowFast models [3] used in Table 5 in the main paper. Both models take 64 frames from each video clips. When extracting representation from the SlowFast models, we used the average pooling layers before the final classification layer, and the representation has 2304 dimensions concatenated from the slow and fast pathways. Similarly for the X3D-L model [2], we used the fully connected layer before the final classification layer, which has 2048 dimensions, and the X3D-L model takes 16 frames from each video clips. For the CLIP model[9], we used ViT-B/16 based visual encoder, and it takes the same 9 frames as the input to our model from each video clip. We first extracted the embeddings with 512 dimensions from each frame and then do an average pooling across all 9 frames, which is used as the representation for the CLIP model. For training the model to classify the age-appropriate activities, we used a 3-layer MLP model with 512 nodes in the intermediate layers.

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**2. Qualitative Results**

**2.1. MovieCL30K**

We present the similar scene pairs selected by our scene representation learned on more-like-this in Figure 2. We also present the similar scene-pairs found by pre-trained CLIP visual features [9] in Figure3. We can clearly see that scene-pairs found by our approach are much more thematically meaningful, while the ones found by CLIP focus more on appearance-based similarity and are mostly related to human faces, which are not sufficiently semantically mean-
Figure 2: Similar scene-pairs found by our representation - Given a similar movie-pair Need For Speed and The Fast & Furious: Tokyo Drift, we present representative examples from the set of similar scene-pairs (connected by orange arrow) found by our representation (sorted by similarity). Comparing with the ones found by CLIP visual feature [9] in Figure 3, these scene-pairs are more thematically meaningful, which contributes to the effectiveness of our representation on downstream tasks related to semantic scene understanding.
Figure 3: Similar scene-pairs found by CLIP - Given a similar movie-pair *Need For Speed* and *The Fast & Furious: Tokyo Drift*, we present representative examples from the set of similar scene-pairs (connected by orange arrow) found by CLIP visual feature [9] (sorted by similarity). Comparing with the ones found by our representation in Figure 2, these scene-pairs focus more on appearance-based similarity and are mostly related to human faces, which are not sufficiently semantically meaningful for semantic scene understanding.
Figure 4: Additional qualitative results on LVU datasets [11]. Five example scenes with their ground truth genre labels as well as our predictions are shown. For example 5, our prediction is different from the label even though looking only at the visual content of this particular scene it makes sense to infer it as a romantic scene. Our hypothesis is that as the genre label of the LVU dataset was acquired from movie-level meta data, sometimes it is not directly applicable to the genre of all of the constituent scenes of a movie. This underscores the effectiveness of our approach on downstream tasks related to semantic scene understanding.

2.2. LVU

We present some additional qualitative results on LVU dataset [11]. Specifically, in Figure 4, we show five example scenes with their ground truth genre in LVU as well as our prediction. We can see that our model was able to capture the feature that is useful for correct genre prediction in most cases. For cases like example 5 on the last row, we assume it is because it is sometimes difficult to identify genre from just one scene in the movie, and since the meta information like genre in LVU was retrieved from IMDB entries [11], they cannot always reflect the genre of a specific scene.

Figure 5: Six examples from the way-of-speaking prediction task in LVU [11]. Results show that when visual information is sufficient to predict way-of-speaking, our method can perform well, and for cases like example 6, it might be beneficial to add audio modality to further improve the accuracy.

In Figure 5, we show six examples from the way-of-speaking prediction task in LVU. We can see that when the visual information is sufficient to make predictions, our model can perform well, but for cases like example 6 on the last row, it can be insufficient to predict just based on visual cues, and this might indicate that for tasks like way-of-speaking prediction, it may be beneficial to include audio modality for better accuracy. This also corresponds to the results in Table 2 of the main paper, where the accuracy of way-of-speaking is apparently lower than other tasks.
Sometimes the relationship can be ambiguous when there are more than two leading characters in the scene. This may indicate that when analyzing relationship in scenes, it might be helpful to focus more on leading characters in that scene for better results.

### 2.3. MovieNet

We present qualitative results on MovieNet [6] [10] dataset in Figure 7. This corresponds to Table 3 and Table 4 in the main paper and includes examples on place tagging as well as scene boundary detection (SBD) tasks. We show three examples from test set of MovieNet, and in each example, there are two scenes divided by the green dotted line. For each scene, the task is to predict what are the multi-label place tags of the scene, and for the two scenes together, the goal is to predict whether the shot boundaries between each pair of shots are also scene boundaries.

We can see that for SBD, our model can perform well to clearly identify the scene boundaries. For place tagging, it is a much more difficult task involving holistic understanding of the scenes, and although our model outperformed existing state-of-the-art models by a large margin in Table 3 in the main paper, multi-labeled place tagging is still a really challenging and unsolved problem. Some tags may not be apparent and the intra-category variance is large in this task.

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2.4. MCD

We present representative examples for each of the 4 classes of our MCD dataset in Figure 8 along with the corresponding detection results (i.e., the class with maximum probability) from both our model and CLIP model. For sex examples, we can see that our model has higher confidence scores compared to CLIP model especially when the images have dark illumination. For violence, the CLIP model sometimes mistakes scenes with two closed persons as sex as shown in the first example. Similarly for drug-use examples, our model classifies them more confidently, and CLIP model misses the small cigarette in the third example and classifies it as none. The none examples show that the CLIP model often mistakes them with other classes, such as violence and drug-use, while our model is able to classify them correctly. This indicates our scene representation performs better than CLIP on age-appropriate activities, demonstrating the effectiveness of our representation in video moderation.

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