Using Mise-en-Scène Visual Features based on MPEG-7 and Deep Learning for Movie Recommendation

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ABSTRACT

Item features play an important role in movie recommender systems, where recommendations can be generated by using explicit or implicit preferences of users on traditional features (attributes) such as tag, genre, and cast. Typically, movie features are human-generated, either editorially (e.g., genre and cast) or by leveraging the wisdom of the crowd (e.g., tag), and as such, they are prone to noise and are expensive to collect. Moreover, these features are often rare or absent for new items, making it difficult or even impossible to provide good quality recommendations.

In this paper, we show that user’s preferences on movies can be better described in terms of the Mise-en-Scène features, i.e., the visual aspects of a movie that characterize design, aesthetics and style (e.g., colors, textures). We use both MPEG-7 visual descriptors and Deep Learning hidden layers as example of mise-en-scène features that can visually describe movies. Interestingly, mise-en-scène features can be computed automatically from video files or even from trailers, offering more flexibility in handling new items, avoiding the need for costly and error-prone human-based tagging, and providing good scalability.

We have conducted a set of experiments on a large catalogue of 4K movies. Results show that recommendations based on mise-en-scène features consistently provide the best performance with respect to richer sets of more traditional features, such as genre and tag.

Keywords

mpeg-7 features, movie recommendation, visual, deep learning

1. INTRODUCTION

Multimedia recommender systems base their recommendations on human-generated content features which are either crowd-sourced (e.g., tag) or editorial-generated (e.g., genre, director, cast). The typical approach is to recommend items sharing features with the other items the user liked in the past.

In the movie domain, information about movies (e.g., tag, genre, cast) can be exploited to either use Content-Based Filtering (CBF) or to boost Collaborative Filtering (CF) with rich side information [30]. A necessary prerequisite for both CBF and CF with side information is the availability of a rich set of descriptive features about movies.

An open problem with multimedia recommender systems is how to enable or improve recommendations when user ratings and “traditional” human-generated features are nonexistent or incomplete. This is called the new item problem [16, 29] and it happens frequently in video-on-demand scenarios, when new multimedia content is added to the catalog of available items (as an example, 500 hours of movie are uploaded to YouTube every minute[1]).

Movie content features can be classified into three hierarchical levels [35].

- At the highest level, we have semantic features that deal with the conceptual model of a movie. An example of semantic feature is the plot of the movie The Good, the Bad and the Ugly, which revolves around three gunslingers competing to find a buried cache of gold during the American Civil War;

- At the intermediate level, we have syntactic features that deal with objects in a movie and their interactions. As an example, in the same noted movie, there are Clint Eastwood, Lee Van Cleef, Eli Wallach, plus several horses and guns;

- At the lowest level, we have stylistic features, related to the Mise-en-Scène of the movie, i.e., the design aspects that characterize aesthetic and style of a movie (e.g., colors or textures); As an example, in the same movie predominant colors are yellow and brown, and camera shots use extreme close-up on actors’ eyes.

The same plot (semantic level) can be acted by different actors (syntactic level) and directed in different ways (stylistic level). In general, there is no direct link between the high-level concepts and the low-level features. Each combination of features convey different communication effects and stimulate different feelings in the viewers.

[1]http://www.reelseo.com/hours-minute-uploaded-youtube/
Recommender systems in the movie domain mainly focus on high-level or intermediate-level features – usually provided by a group of domain experts or by a large community of users – such as movie genres (semantic features, high level), actors (syntactic features, intermediate level) or tags (semantic and syntactic features, high and intermediate levels) [32, 17, 21]. Movie genres and actors are normally assigned by movie experts and tags by communities of users [33]. Human-generated features present a number of disadvantages:

1. features are prone to user biases and errors, therefore not fully reflecting the characteristics of a movie;
2. new items might lack features as well as ratings;
3. unstructured features such as tags require complex Natural Language Processing (NLP) in order to account for stemming, stop words removal, synonyms detection and other semantic analysis tasks;
4. not all features of an item have the same importance related to the task at hand; for instance, a background actor does not have the same importance as a guest star in defining the characteristics of a movie.

In contrast to human-generated features, the content of movie streams is itself a rich source of information about low-level stylistic features that can be used to provide movie recommendations. Low-level visual features have been shown to be very representative of the users feelings, according to the theory of Applied Media Aesthetics [37]. By analyzing a movie stream content and extracting a set of low-level features, a recommender system can make personalized recommendations, tailored to a user’s taste. This is particularly beneficial in the new item scenario, i.e., when movies without ratings and without user-generated tags are added to the catalogue.

Moreover, while low-level visual features can be extracted from full-length movies, they can also be extracted from shorter version of the movies (i.e., trailers) in order to have a scalable recommender system. In previous works, we have shown that mise-en-scène visual features extracted from trailers can be used to accurately predict genre of movies [12, 13].

In this paper, we show how to use low-level visual features extracted automatically from movie files as input to a hybrid CF+CBF algorithm. We have extracted the low-level visual features by using two different approaches:

- MPEG-7 visual descriptors [22]
- Pre-trained deep-learning neural networks (DNN) [31]

Based on the discussion above, we articulate the following research hypothesis: “a recommender system using low-level visual features (mise-en-scène) provides better accuracy compared to the same recommender system using traditional content features (genre and tag)”.

We articulate the research hypothesis along the following research questions:

**RQ1:** do visual low-level features extracted from any of MPEG-7 descriptors or pre-trained deep-learning networks provide better top-N recommendations than genre and tag features?

**RQ2:** do visual low-level features extracted from MPEG-7 descriptor in conjunction with pre-trained deep-learning networks provide better top-N recommendations than genre and tag features?

We have performed an exhaustive evaluation by comparing low-level visual features with respect to more traditional features (i.e., genre and tag). For each set of features, we have used a hybrid CBF+CF algorithm that includes item features as side information, where item similarity is learned with a Sparse Linear Method (SLIM) [25].

We have used visual and content features either individually or in combination, in order to obtain a clear picture of the real ability of visual features in learning the preferences of users and effectively generating relevant recommendations.

We have computed different relevance metrics (precision, recall, and mean average precision) over a dataset of more than 8M ratings provided by 242K users to 4K movies. In our experiments, recommendations based on mise-en-scène visual features consistently provide the best performance.

Overall, this work provides a number of contributions to the RSs field in the movie domain:

- we propose a novel RS that automatically analyzes the content of the movies and extracts visual features in order to generate personalize recommendations for users;
- we evaluate recommendations by using a dataset of 4K movies and compare the results with a state-of-the-art hybrid CF+CBF algorithm;
- we have extracted mise-en-scène visual features adopting two different approaches (i.e., MPEG-7 and DNN) and fed them to the recommendation algorithm, either individually or in combination, in order to better study the power of these types of features;
- the dataset, together with the user ratings and the visual features extracted from the videos (both MPEG-7 and deep-networks features), is available for download.

The rest of the paper is organized as follows. Section 2 reviews the relevant state of the art, related to content-based recommender systems and video recommender systems. This section also introduces some theoretical background on Media Aesthetics that helps us to motivate our approach and interpret the results of our study. It describes the possible relation between the visual features adopted in our work and the aesthetic variables that are well known for artists in the domain of movie making. In Section 3 we describe our method for extracting and representing mise-en-scène visual features of the movies and provide the details of our recommendation algorithms. Section 4 introduces the evaluation method and presents the results of the study and Section 5 discusses them. Section 6 draws the conclusions and identifies open issues and directions for future work.

## 2. RELATED WORK

[2 recsys.deib.polimi.it]
2.1 Multimedia Recommender Systems

Multimedia recommender systems typically exploit high-level or intermediate-level features in order to generate movie recommendations [8, 24]. This type of features express semantic and syntactic properties of media content that are obtained from structured sources of meta-information such as databases, lexicons and ontologies, or from less structured data such as reviews, news articles, item descriptions and social tags.

In contrast, in this paper, we propose exploiting low-level features to provide recommendations. Such features express stylistic properties of the media content and are extracted directly from the multimedia content files [22].

While this approach has already been investigated in the music recommendation domain [23], it has received marginal attention for movie recommendations. The very few approaches only consider low-level features to improve the quality of recommendations based on other type of features. The work in [30] proposes a video recommender system, called VideoReach, which incorporates a combination of high-level and low-level video features (such as textual, visual and aural) in order to improve the click-through-rate metric. The work in [39] proposes a multi-task learning algorithm to integrate multiple ranking lists, generated by using different sources of data, including visual content.

While low-level features have been marginally explored in the community of recommender systems, they have been studied in other fields such as computer vision and content-based video retrieval. The works in [20, 1] discuss a large body of low-level features (visual, auditory or textual) that can be considered for video content analysis. The work in [27] proposes a practical movie genre classification scheme based on computable visual cues. [26] discusses a similar approach by considering also the audio features. Finally, the work in [10] proposes a framework for automatic classification of videos using visual features, based on the intermediate level of scene representation.

We note that, while the scenario of using the low-level features, as an additional side information, to hybridize the existing recommender systems is interesting, however, this paper addresses a different scenario, i.e., when the only available information is the low-level visual features and the recommender system has to use it effectively for recommendation generation. Indeed, this is an extreme case of new item problem [23], where traditional recommender systems fail in properly doing their job. It is worthwhile to note that while the present work has a focus on exploiting computer vision techniques on item description of products (i.e. the item-centric aspect), computer vision techniques are also exploited in studying users’ interaction behavior for example through studying their eye, gaze and head movement while navigating with a recommender system (i.e. the user-centric aspect) [1, 7, 10].

2.2 Aesthetic View

The relation of mise-en-scène elements with the reactions they are able to evoke in viewers, is one of the main concerns of Applied Media Aesthetic [37]. Examples of mise-en-scène elements that are usually addressed in the literature on movie design are Lighting and Color [15].

Lighting is the deliberate manipulation of light for a certain communication purpose and it is used to create viewers’ perception of the environment, and establish an aesthetic context for their experiences. The two main lighting alternatives are usually addressed to as chiascuro and flat lighting [38]. Figure 1a and Figure 1b exemplifies these two alternatives.

Colors can strongly affect our perceptions and emotions in unsuspected ways. For instance, red light gives the feeling of warmth, but also the feeling that time moves slowly, while blue light gives the feeling of cold, but also that time moves faster. The expressive quality of colors strongly depends on the lighting, since colors are a property of light [38]. Figure 2a and Figure 2b present two examples of using colors in movies to evoke certain emotions.

Interestingly, most mise-en-scène elements can be computed from the video data stream as statistical values [27, 5]. We call these computable aspects as visual low level features [11].

3. METHODOLOGY

The methodology adopted to provide recommendations based on visual features comprises five steps:

1. Video Segmentation: the goal is to segment each video into shots and to select a representative key-frame from each shot;
2. Feature Extraction: the goal is to extract visual feature vectors from each key-frame. We have considered two different types of visual features for this purpose: (i) vectors extracted from MPEG-7 visual descriptors, and (ii) vectors extracted from pre-trained deep-learning networks;
3. Feature Aggregation: feature vectors extracted from the key-frame of a video are aggregated to obtain a feature vector descriptive of the whole video.
4. Feature Fusion: in this step, features extracted from the same video but with different methods (e.g., MPEG-7 descriptors and deep-learning networks) are combined into a fixed-length descriptor;
5. Recommendation: the (eventually aggregated) vectors describing low-level visual features of videos are used to feed a recommender algorithm. For this purpose, we have considered the method Collective SLIM as a feature-enhanced collaborative filtering (CF).

The flowchart of the methodology is shown in Figure 3 and the steps are elaborated in more details in the following subsections.

3.1 Video segmentation

Shots are sequences of consecutive frames captured without interruption by a single camera. The transition between two successive shots of the video can be abrupt, where one frame belongs to a shot and the following frame belongs to the next shot, or gradual, where, two shots are combined using chromatic, spatial or spatial-chromatic video production effects (e.g., fade in/out, dissolve, wipe), which gradually replace one shot by another.

The color histogram distance is one of the most standard descriptors used as a measure of (dis)similarity between consecutive video frames in applications including: content-based video retrieval, object recognition, and others. A histogram is computed for each frame in the video and the histogram intersection is used as the means of comparing the local activity according to Equation 1.
Figure 1: a. *Out of the past* (1947) an example of highly contrasted lighting. b. *The wizard of OZ* (1939) flat lighting example.

Figure 2: a. An image from *Django Unchained* (2012). The red hue is used to increase the scene sense of violence. b. An image from *Lincoln* (2012). Blue tone is used to produce the sense of coldness and fatigue experienced by the characters.

\[ s(h_t, h_{t+1}) = \sum_b \min(h_t(b), h_{t+1}(b)) \]  

where \( h_t \) and \( h_{t+1} \) are histograms of successive frames and \( b \) is the index of the histogram bin. By comparing \( s \) with a predefined threshold, we segment the videos in our dataset into shots. We set the histogram similarity threshold to 0.75.

### 3.2 Feature extraction

For each key frame, visual features are extracted by using either MPEG-7 descriptors or pre-trained deep-learning networks.

#### 3.2.1 MPEG-7 features

The MPEG-7 standard specifies descriptors that allow users to measure visual features of images. More specifically, MPEG-7 specifies 17 descriptors divided into four categories: color, texture, shape, and motion [22]. In our work we have focused our attention on the following five color and texture descriptors, as previous experiments have proven the expressiveness of color and texture for similarity-based visual retrieval applications [22, 34]:

- **Color Descriptors.**
  - *Scalable Color Descriptor (SCD)* is the color histogram of an image in the HSV color space. In our implementation we have used SCD with 256 coefficients (histogram bins).
  - *Color Structure Descriptor (CSD)* creates a modified version of the SCD histogram to take into account the physical position of each color inside the images, and thus it can capture both color content and information about the structure of this content. In our implementation, CSD is described by a feature vector of length 256.
  - *Color Layout Descriptor (CLD)* is a very compact and resolution-invariant representation of color obtained by applying the DCT transformation on a 2-D array of representative colors in the YUV color space. CLD is described by a feature vector of length 120 in our implementation.
- **Texture Descriptors.**
  - *Edge Histogram Descriptor (EHD)* describes local edge distribution in the frame. The image is divided into 16 non-overlapping blocks (subimages). Edges within each block are classified into one of five edge categories: vertical, horizontal, left diagonal, right diagonal and non-directional edges. The final local edge descriptor is composed of a histogram with 5 x 16 = 80 histogram bins.
  - *Homogeneous Texture Descriptor (HTD)* describes homogeneous texture regions within a frame, by using a vector of 62 energy values.

#### 3.2.2 Deep-Learning features

An alternative way to extract visual features from an im-
age is to use the inner layers of pre-trained deep-learning networks [19]. We have used the 1024 inner neurons of GoogLeNet, a 22 layers deep network trained to classify over 1.2 million images classified into 1000 categories [31]. Each key frame is provided as input to the network and the activation values of inner neurons are used as visual features for the frame.

### 3.3 Feature aggregation

The previous step extracts a vector of features from each key-frame of a video. We need to define a function to aggregate all these vectors into a single feature vector descriptive of the whole video. The MPEG-7 standard defines an extension of the descriptors to a collection of pictures known as group of pictures descriptors [23, 2]. The main aggregation functions are *intersection histogram*, *average* and *median*. Inspired by this, our proposed aggregation functions consist of the following:

- **intersection histogram**: each element of the aggregated feature vector is the minimum of the corresponding elements of the feature vectors from each key-frame;
- **average**: each element of the aggregated feature vector is the average of the corresponding elements of the feature vectors from key-frame;
- **median**: each element of the aggregated feature vector is the median of the corresponding elements of the feature vectors from key-frame.

- **union histogram**: each element of the aggregated feature vector is the maximum of the corresponding elements of the feature vectors from key-frame.

In our experiments we have applied each aggregation function to both MPEG-7 and deep-learning features.

### 3.4 Feature Fusion

Motivated by the approach proposed in [14], we employed the fusion method based on Canonical Correlation Analysis (CCA) which exploits the low-level correlation between two set of visual features and learns a linear transformation that maximizes the pairwise correlation between two set of MPEG-7 and deep-learning networks visual features.

### 3.5 Recommendations

In order to test the effectiveness of low-level visual features in video recommendations, we have experimented with a widely adopted hybrid collaborative-filtering algorithm enriched with side information.

We use Collective SLIM (Sparse Linear Method), a widely adopted sparse CF method that includes item features as side information to improve quality of recommendations [25]. The item similarity matrix $S$ is learned by minimizing the following optimization problem

$$
\underset{S}{\text{argmin}} \alpha \| R - RS \| + (1 - \alpha) \| F - FS \| + \gamma \| S \|
$$

where $R$ is the user-rating matrix, $F$ is the feature-item matrix, and parameters $\alpha$ and $\gamma$ are tuned with cross validation. The algorithm is trained using Bayesian Pairwise Ranking [28].

### 4. Evaluation and Results

We have used the latest version of the 20M Movielens dataset [18]. For each movie in the Movielens dataset, the title has been automatically queried in YouTube to search for the trailer.

The final dataset contains 8'931'665 ratings and 586'994 tags provided by 242'209 users to 3'964 movies (sparsity 99.06%) classified along 19 genres: action, adventure,
animation, children’s, comedy, crime, documentary, drama, fantasy, film-noir, horror, musical, mystery, romance, sci-fi, thriller, war, western, and unknown.

For each movie, the corresponding video trailer is available. Low-level features have been automatically extracted from the trailers according to the methodology described in the previous section. The dataset, together with trailers and low-level features, is available for download [1].

In order to evaluate the effectiveness of low-level visual features, we have used two baseline set of features: genre and tag. We have used Latent Semantic Analysis (LSA) to pre-process the tag-item matrix in order to better exploit the implicit structure in the association between tags and items. The technique includes decomposing the tag-item matrix into a set of orthogonal factors whose linear combination approximates the original matrix [2].

We evaluate the Top-N recommendation quality by adopting a procedure similar to the one described in [3].

- We randomly placed 80% of the ratings in the training set, 10% in the validation set, and 10% in the test set. Additionally, we performed a 5-fold cross validation test to compute confidence intervals.
- For each relevant item \( i \) rated by user \( u \) in the test set, we form a list containing the item \( i \) and all the items not rated by the user \( u \), which we assume to be irrelevant to her. Then, we form a recommendation list by picking the top-\( N \) ranked items. Being \( r \) the rank of \( i \), we have a hit if \( r < N \), otherwise we have a miss.
- We measure the quality of the recommendations in terms of recall, precision and mean average precision (MAP) for different cutoff values \( N = 1, 10, 20 \).

We feed the recommendation algorithm with MPEG-7 features, deep-learning networks features, genres and tags (tags are preprocessed with LSA). We also feed the algorithm with a combinations of MPEG-7 and deep-learning networks features.

Tables [1] present the results of the experiments in terms of precision, recall, and MAP, for different cutoff values, i.e., 1, 10, and 20. First of all, we note that our initial analysis have shown that the best recommendation results are obtained by the intersection aggregation function for MPEG-7 and average for deep-learning networks features. Hence, we report the results for these two aggregation functions.

As it can be seen, in terms of almost all the considered metrics, and all the cutoff values, MPEG-7 + DNN has shown the best results, and MPEG-7 alone has shown the second best results. The only exceptions are Precision at 10 and MAP at 10. In the former case, MPEG-7 is the best and Genre is the second. In the latter case, MPEG-7 is the best and MPEG-7 + DNN is the second. Unexpectedly, the recommendation based on tag is always the worst method.

These results are very promising and overall present the power of recommendation based on MPEG-7 features, used individually or in combination with DNN features. Indeed, the results show that recommendation based on MPEG-7 features always outperform genre and tag based recommendations, and the combination of MPEG-7 features with deep-learning networks significantly improves the quality of the hybrid CF+CBF algorithm and provides the best recommendation results overall.

5. DISCUSSION

Our results provide empirical evidence that visual low-level features extracted from MPEG-7 descriptors provide better top-N recommendations than genres and tags while the same does not apply to visual low-level features extracted from pre-trained deep-learning networks.

Overall, our experiments prove the effectiveness of movie recommendations based on visual features automatically extracted from trailers of movies. Recommendations based on deep-learning networks visual features can provide good quality recommendations, in line with recommendations based on human-generated attributes such as genres and tags while visual features extracted from MPEG-7 descriptors consistently provide better recommendations. Moreover, fusion of the deep-learning networks and MPEG-7 visual features performs the best recommendation results. These results suggest an interesting consideration: users’ opinions on movies are influenced more by style than content.

Given the small number of mise-en-scène features (e.g., the combined MPEG-7 feature vector contains 774 elements only, compared with half a million tags) and the fact that we extracted them from movie trailers, we did not expect this result. In fact, we would view it as a good news for practitioners of movie recommender systems, as low-level features combine multiple advantages. First, mise-en-scène features have the convenience of being computed automatically from video files, offering designers more flexibility in handling new items, without the need to wait for costly editorial or crowd-based tagging. Moreover, it is also possible to extract low level features from movie trailers, without the need to work on full-length videos [12]. This guarantees good scalability. Finally, viewers are less consciously aware of movie styles and we expect that recommendations based on low level features could to be more attractive in terms of diversity, novelty and serendipity.

We would like to offer an explanation as to why mise-en-scène low-level features consistently deliver better top-N recommendations than a much large number of high-level attributes. This may have to do with a limitation of high-level features, which are binary in nature: movies either have or not have a specific attribute. On the contrary low-level features are continuous in their values and they are present in all movies, but with different weights.

A potential difficulty in exploiting mise-en-scène low-level visual features is the computational load required for the extraction of features from full-length movies. However, we have observed that low-level visual features extracted from the movie trailers are highly correlated with the corresponding features extracted from full-length movies [12]. Accordingly, the observed strong correlation indicates that the movie trailers are indeed perfect representatives of the corresponding full-length movies. Hence, instead of analyzing the lengthy full movies the trailers can be properly analyzed which can result in significant reduction in the computational load of using mise-en-scène low-level visual features.

6. CONCLUSION AND FUTURE WORK

This work presents a novel approach in the domain of movie recommendations. The technique is based on the analysis of movie content and extraction of stylistic low-level features that are used to generate personalized recom-
Table 1: Recommendation based on MPEG-7 and DNN features in comparison with the traditional genre and tag features

| Features     | Recall 1 | Recall 10 | Recall 20 | Precision 1 | Precision 10 | Precision 20 | MAP 1 | MAP 10 | MAP 20 |
|--------------|----------|-----------|-----------|-------------|--------------|--------------|-------|--------|--------|
| MPEG-7       | 0.0337   | 0.1172    | 0.1751    | 0.1785      | 0.1354       | 0.1060       | 0.1785| 0.1114 | 0.1001 |
| DNN          | 0.0238   | 0.0872    | 0.1381    | 0.1346      | 0.1021       | 0.0831       | 0.1346| 0.0785 | 0.0714 |
| MPEG-7 + DNN | 0.0385   | 0.1773    | 0.2466    | 0.2005      | 0.1063       | 0.0771       | 0.2005| 0.1051 | 0.1040 |
| Genre        | 0.0294   | 0.0904    | 0.1381    | 0.1596      | 0.1108       | 0.0892       | 0.1596| 0.0892 | 0.0792 |
| Tag-LSA      | 0.0127   | 0.0476    | 0.0684    | 0.1001      | 0.0686       | 0.0523       | 0.1001| 0.0493 | 0.0389 |

recommendations for users. This approach makes it possible to recommend items to users without relying on any high-level semantic features (such as, genre, or tag) that are expensive to obtain, as they require expert level knowledge, and shall be missing (e.g., in new item scenario).

While the results of this study would not underestimate the importance of high-level semantic features, however, they provide a strong argument for exploring the potential of low-level visual features that are automatically extracted from movie content.

For future work, we consider the design and development of an online web application in order to conduct online studies with real user. The goal is to evaluate the effectiveness of recommendations based on low-level visual features not only in terms of relevance, but also in terms of novelty and diversity. Moreover, we will extend the range of low-level features extracted, and also, include audio features. We will also extend the evaluation to user-generated videos (e.g., YouTube). Finally, we would feed the MPEG-7 features as input to the initial layer of deep-networks and build the model accordingly. We are indeed, interested to investigate the possible improvement of recommendation based on the features provided by the deep-networks trained in this way.

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