Commercial Video Evaluation via Low Level Feature Selection

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Abstract. To discover the influence from the commercial videos’ low-level features to the popularity of the videos, the feature selection method should be used to get the video features influenced the videos’ evaluation mostly after analyzing the source data and the audiences’ evaluations of the videos. After extracting the low-level features of the his paper improved the Correlation-Based Feature Selection (CFS) which is widely used and proposed an algorithm named CFS-Spearmen which combined the Spearmen correlation coefficient and the classical CFS to select features. The SVM was used to test the method in this paper. Finally, the proposed method was employed in commercial videos’ feature selection and the most influential feature set was chosen.

1. Introduction

As a major kind of commercial multimedia, commercial videos’ popularity is concerned by related companies and producers. There are many factors influenced the audiences’ evaluation to the commercial videos, such as the actor/actress, director, story and so on. But it is too subjective if these factors are employed to evaluate the videos. It is because that these factors are not quantitative in the evaluation procedure. So, the importance of design a model to analysis the videos and calculate the evaluation of them should be realized by the researchers[1]. The article [2] proposed the objective video quality evaluation method based on motion and disparity information. The article [3] proposed a video quality evaluation method based on Quaternion Singular Value Decomposition. But only a few video features were used in [2] and [3]. The video features should include many features such as color features, motion features and shot features which might influence the audiences’ evaluation to the videos. So, all the features should be analyzed and selected to obtain the most influential feature set to commercial the videos. However, the relationships between video features and their popularity and there is no accurate model yet. Then, for all the features extracted, we can select the most influential feature set through the feature selection methods according the commercial videos’ evaluation data. Of cause, the feature dimension reduction methods could also be used here.

Different feature set might be selected by different feature selection or dimension reduction methods. The feature dimension reduction algorithms, such as PCA[4,5], FDA[6], KPCA[7,8], would reduce the high dimension features to lower dimension features by . While, feature selection algorithms would select the optimized feature set from all the original features. Compared with the dimension reduction algorithms, the feature selection might maintain the physical meanings of the original features and this is more convenient for data analysis[9].
The main idea of feature selection is selecting a few valuable features and removing the useless ones from all the features extracted. The methods, such as Relief\[10\], mRMR\[11\] and CFS\[13,14\] are widely used now. Only the correlation between feature and class was concerned in Relief algorithm but not the correlation between features. So, the selected feature set was not the optimized\[10\]. For mRMR algorithm, both the correlation between features and feature-class were concerned to get the best feature set\[11\]. For the classifier, all the contribution of the features selected by mRMR were same, and the feature set was selected from the original features. The main idea of CFS was selecting the feature set with lower correlation between features and higher correlation between feature and class. After this procedure, the redundant features and the features which were not related with the class would be removed. The Pearson linear correlation coefficient was used in [15] and [16] by Huanjing Wang and Qingning Sun to calculate the correlation between features and feature-class. But only linear correlation coefficient could be measured in Pearson formula. For continuous data, discretization methods or kernel density estimation methods should be employed to solve the problem. This procedure would generate probability estimation error.

So, the effectiveness of the correlation calculation is the key of successful CFS method. Currently, some correlation calculation methods were concerned by researchers and in these methods, which is better should be determined by experiment results. Except Pearson Coefficient, some other correlation calculation methods are used. Spearman Rank Correlation Coefficient was used in the article of Marie Therese Puth\[17\] to describe the correlation of two vectors. The experiment result showed that the Spearman Rank Correlation Coefficient is better than Pearson Coefficient. In the research of Xiaoyuan Xu\[18\], the Spearman Rank Correlation Coefficient was employed to describe the correlation between features of wind speed. In the article of Jing Feng\[19\], a non parametric method based on Spearman Rank Correlation Coefficient was proposed to measure the principle of storage degradation failure.

Spearman Rank Correlation Coefficient was not widely used in feature selection yet. In this paper, a CFS-Spearman algorithm is presented an used to process the four data set, including ‘Cancer’, ‘Glass’, ‘Bank’ and ‘Credit’, in the UCI Machine Learning Data Base. The experiment results are compared with CFS and mRMR. The LibSVM classifier is utilitzed to test the effectiveness of CFS-Spearman. Then, the method in this paper is used to select the low=level features of the commercial videos to predict the popularity of them.

2. Video low level feature extraction

2.1 Color features
Color is an important feature of vision. The color features are combined with 10 ones including means and variances of Brightness, Contrast, Saturation, Colorfulness and Simplicity. Brightness is calculated by average the brightness of every pixels in every frame in HSV space. It is similar as Saturation calculation procedure. The Contrast could be expressed by the following formula.

$$\text{cont} = \text{var}((\max(r,b,g) + \min(r,b,g))/2)$$

in which, r, g and b represent red, green and blue value of a pixel. Var is the variance calculation function.

Colorfulness is a parameter reflecting the combination of image’s color. It is defined as

$$Cf = A + 0.3B$$

In which,

$$A = \sqrt{\text{var}(r-g) + \text{var}((r+g)/2 - b)}$$

$$B = \sqrt{[\text{Mean}(r-g)]^{2} + [\text{Mean}((r+g)/2 - b)]^{2}}$$

Mean is the function to get the average the input value.

To attract the audiences’ attention in the progress of movie making, the director and the cameraman always make the scenes simpler than the objects. The Simplicity is used to measure this character in some article. It is defined in [23] and the final Simplicity is the mean value of every frame.
2.2 Motion features
Motion features reflect the changing rate of the scene or objects in the videos. It could be regarded as the camera moving speed while shooting. In this article, the motion features are calculated as following. Firstly, every frame is separated into $16 \times 16$ blocks. The pixel barycenter of every block is get, and then, the frame $n$ and the frame $n+1$ are compared to obtain the changing rate of the corresponding blocks of the two neighbor frames. The motion feature mean is the mean value of pixel barycenter coordinate changing and the motion feature variance is the variance of it.

2.3 Shot features
Shot features are also important for video evaluation. To get every shot in a video, the key frames, which are located at the edge of the shots, of the video should be selected firstly. We compare the color histogram of every two neighbor frames to calculate the similarity of them. After key frame selection, the four features, “Shot length mean”, “Shot number”, “Shot length variance” and “Video length”, are calculated.

Then, the 16 features including, “Brightness mean”, “Contrast mean”, “Saturation mean”, “Colorfulness mean”, “Simplicity mean”, “Brightness variance”, “Contrast variance”, “Saturation variance”, “Colorfulness variance”, “Simplicity variance”, “Motion mean”, “Motion variance”, “Trailer length”, “Shot number”, “Shot length mean” and “Shot length variance”, are get as shown in Figure 1.

3. Feature selection
When the features are extracted, the relationship between features and video evaluation is still not so clear. It is because that some features influence video viewers’ evaluation but others do not. We should select these features influence the video evaluation mostly. Some feature selection methods might be introduced here.

3.1 mRMR
mRMR is a typical feature dimension reduction method which use mutual information to measure the correlation between two features and feature-class. The formulas are listed below.

$$\max D(S,c), D = \frac{1}{|S|} \sum_{i \in S} I(x_i;c)$$

(5)
\[
\min R(S), R = \frac{1}{|S|} \sum_{x_i, x_j \in S} I(x_i, x_j)
\]

in which, \( S \) is the feature set, \(|S|\) is the feature number, \( c \) is the class index, \( I(x_i, c) \) is the mutual information between the \( i^{th} \) feature and class \( c \), and \( I(x_i, x_j) \) is the mutual information between the \( i^{th} \) feature and class the \( j^{th} \) feature.

The mutual information between \( x \) and \( y \) here is defined as

\[
I(x, y) = \int \int p(x, y) \log \frac{p(x, y)}{p(x)p(y)} \, dx \, dy
\]

Then, we get the criterion of feature selection as following.

\[
\text{Max}(D - R)
\]

3.2 CFS

CFS is a simple feature selection method. It calculate the correlation value between every two features and feature-class to select the features related to classes most closely. As shown in (9) and (10), this method try to maximize the \( M_s \).

\[
M_s = \frac{k^2 r_f}{(k + k(k - 1)r_f)}
\]

\[
r_{xy} = \frac{\sum_{i=1}^{N} x_i y_i - \frac{\sum_{i=1}^{N} x_i \sum_{i=1}^{N} y_i}{N}}{\sqrt{\frac{\sum_{i=1}^{N} x_i^2 - \left(\frac{\sum_{i=1}^{N} x_i}{N}\right)^2}{N} \cdot \frac{\sum_{i=1}^{N} y_i^2 - \left(\frac{\sum_{i=1}^{N} y_i}{N}\right)^2}{N}}}
\]

In the formulas above, \( M_s \) is a measure of feature set \( S \) with \( k \) features. \( r_{xy} \) is the average correlation calculation method of \( x \) and \( y \) which are all features or feature and class. \( N \) is the number of samples. According to formula (10), in the feature set \( S \), the value of \( M_s \) will be bigger when the average correlation between features is minor and the average correlation between features and class is bigger. Then, the feature set is a optimized one. This algorithm is called Pearson correlation coefficient.

3.3 Spearman rank correlation coefficient

Pearson correlation coefficient was employed in traditional CFS. But there are some other correlation calculation methods could be used. Spearman's rank correlation coefficient is one of them. It could be defined as following.

\[
r_{xy} = \frac{\sum_{i=1}^{N} [R_i - \bar{R}][S_i - \bar{S}]}{\sqrt{\sum_{i=1}^{N} (R_i - \bar{R})^2} \sqrt{\sum_{i=1}^{N} (S_i - \bar{S})^2}}
\]

In the formula above, we first define random variable \( X \) and \( Y \) with \( N \) samples expressed by \((x_i, y_i)\). Then, let \( R_i \) and \( S_i \) be the ranks of \( x_i \) and \( y_i \) in the corresponding sample. \( \bar{R} \) and \( \bar{S} \) are the average ranks of the sample. The Spearman rank correlation coefficient described the monotonic dependence of variable \( X \) and \( Y \). The monotonic direction could be recognized by the sign of \( r_{xy} \). When \( Y \) creases with \( X \) creasing, the sign of \( r_{xy} \) is positive, and it is negative conversely. \( Y \) will not change with \( X \) while the sign of \( r_{xy} \) is 0.
The linear correlation coefficient is a widely used correlation measurement and it is easy to be calculated. When the random variables are elliptical distribution, the linear correlation coefficient could express the correlation between the variables. But the short points of it is, it is non-existent when the variables’ first and second order moments could not be get, it’s value should change when the variables distribution function changed, and after nonlinear strictly increasing, the linear relationships between variables would change[18]. It is most important that the relationship could not be expressed accurately while the variables does not distributed as elliptical distribution.

The Spearman correlation coefficient is a non-parametric statistic method. Let the rank correlation coefficient of the two variables $X$ and $Y$ is $r_{X,Y}$.

$$r(X,Y) = \rho(F_X(X), F_Y(Y))$$

In which, $F_X(x)$ and $F_Y(y)$ are the cumulative probability of $X$ and $Y$ respectively.

The two random variables’ rank correlation coefficient is the linear correlation coefficient of the cumulative probability distribution function expressed as $F_X(x) = P(X \leq x)$. If the inverse function of it exist, the variable $F_X(x)$ distributed as uniform distribution in [0,1] because of the following formula.

$$P(F_X(x) \leq r) = P(X \leq F_X^{-1}(r)) = F_X(F_X^{-1}(r)) = r \quad r \in [0,1]$$

So, the rank correlation coefficient is just an expression of relationship after transformation from the original variables to the variables in uniform distribution. Compared with linear correlation coefficient, the rank correlation coefficient’s advantages are: 1) always exist; 2) does not changing with edge distribution; 3) does not changing after strict non-linear transform. So, it is chosen in this paper to measure the relationships between feature and feature or feature and class.

4. Videos evaluation

In this paper, the CFS-Spearman feature selection method was used in video low-level feature selecting for videos’ popularity prediction. The low-level feature included 16 features as expressed in the second part of this paper. There 300 videos, which were downloaded from “Youtube”, used in experiments. The 16 features were extracted for each video and the numbers of them were showed in Tab. 1.

To evaluate the popularity of them, the audiences’ “Like/Dislike” votes number were employed to calculate the popularity degree.

As shown in

| Tab. 1 Extracted video features and classes |
|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Class |
| Mean of motion | Variance of motion | Mean of brightness | Mean of contrast | Mean of saturation | Mean of colorfulness | Mean of simplicity | Variance of brightness | Good(1) Bad(0) |
| 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |

$$\text{Score} = \frac{\text{LN}}{\text{LN} + \text{DN}} \times 5$$

in which, $\text{LN}$ is the vote number of “like”, $\text{DN}$ is the vote number of “dislike” for a video. We set 4.7 as the threshold of classification for “good” videos and “bad” videos. It means, if the score of a video is higher than or equal to 4.7, it is a good video. Otherwise, it’s regarded as bad one. All the extracted features were listed in Tab. 7. We used the three methods to select the features in Tab.7, and the selecting results were shown in Tab.8. If the selected features were employed to classify the videos in to two classes, good and bad, the correct classification rates were listed in Tab.2.
The results showed that, most correct classification rates of CFS-Spearman method were higher than that of the other two ones. And when the feature number is 3, the correct classification rates is the highest one which is 78%. And in this case, the features “Mean of contrast”, “Variance of Simplicity” and “Variance of shot length” were selected as the most influential features. So, they could be used as the feature set to predict the popularity of commercial videos.

The correct classification rates curves were drawn in Figure.2

![Figure 2. Correct classification rate using video features by different methods](image)

than that of the other two ones. And when the feature number is 3, the correct classification rates is the highest one which is 78%. And in this case, the features “Mean of contrast”, “Variance of Simplicity” and “Variance of shot length” were selected as the most influential features. So, they could be used as the feature set to predict the popularity of commercial videos.

The correct classification rates curves were drawn in Figure.2

5. Conclusion
This paper researched the low-level feature selection methods in commercial videos’ popularity prediction. To select the more influential features in the feature set, the paper proposed a CFS-based

| Feature number | Feature set | CFS-Spearman (%) | CFS (%) | mRMR (%) |
|----------------|-------------|------------------|---------|----------|
| k=1            | 14          | 56.6667          | 56.6667 | 70.6667  |
| k=2            | 4,14        | 69.3333          | 59.3333 | 63.3333  |
| k=3            | 4,12,14     | 78               | 56.6667 | 63.3333  |
| k=4            | 4,7,12,14   | 75.3333          | 68.6667 | 73.3333  |
| k=5            | 2,5,7       | 77.3333          | 69.3333 | 74.6667  |
| k=6            | 2,5,7,14    | 76               | 75.3333 | 74.6667  |
| k=7            | 1,5,7,14    | 76               | 74.6667 | 76       |
| k=8            | 1,5,7-8,14  | 74.6667          | 74.6667 | 76       |
| k=9            | 1,8,14      | 74.6667          | 74.6667 | 76       |
| k=10           | 1,8,13-14   | 74.6667          | 74.6667 | 76       |
| k=11           | 1,8,13-15   | 74.6667          | 74.6667 | 76       |
| k=12           | 1,8,12-15   | 74.6667          | 74.6667 | 76       |
| k=13           | 1,8,12-16   | 76               | 74.6667 | 76       |
| k=14           | 1,8,10-14,16| 72               | 76      | 74       |
| k=15           | 1,8,10-16   | 75.3333          | 75.3333 | 76       |
method in which, the Spearman correlation coefficient was employed to take place of original Pearson correlation coefficient. Then, to select the influential low-level features for commercial videos, 300 videos were downloaded from Youtube. For all the videos, 16 features were extracted. And the videos were separated into two classes, “good” and “bad” according to their scores which were calculated through the “like/dislike” number voted by audiences. When the feature number is 3 by CFS-spearman, the correct classification rates is the highest one which is 78%. The features “Mean of contrast”, “Variance of Simplicity” and “Variance of shot length” were selected as the most influential ones.

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