Data Mining: Fundamentals

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Group 12

Bruno Barbieri, Noemi Dalmasso, Gaia Federica Francesca Ferrara

The aim of this report is to display an analysis carried out on the IMDb dataset; the analysis has been conducted making use of data mining methodologies. After the data understanding and preparation phase, clustering, classification, regression and pattern mining techniques have been applied.

Contents

1. Data Understanding and Preparation

The dataset *train.csv* contains 16431 titles of different forms of visual entertainment that have been rated on IMDb, an online database of information related to films, television series etc. Each record is described by 23 attributes, both numerical and non-numerical.

1.1 Discrete Attributes

Table 1.1 shows the discrete attributes of the dataset, their types and a brief description of each attribute.

Attribute	**Type**	**Description**
`originalTitle`	Categorical	Title in its original language
`rating`	Ordinal	IMDB title rating class The range is from `(0,1]` to `(9,10]`
`worstRating`	Ordinal	Worst title rating
`bestRating`	Ordinal	Best title rating
`titleType`	Categorical	The format of the title
`canHaveEpisodes`	Binary	Whether or not the title can have episodes `True`: can have episodes; `False`: cannot have episodes
`isRatable`	Binary	Whether or not the title can be rated by users `True`: it can be rated; `False`: cannot be rated
`isAdult`	Binary	Whether or not the title is for adults `0`: non-adult title; `1`: adult title
`countryOfOrigin`	List	The country(ies) where the title was produced
`genres`	List	The genre(s) associated with the title (3 at most)

Table 1.1: Description of discrete attributes

1.1.1 Merging and Removal of Discrete Attributes

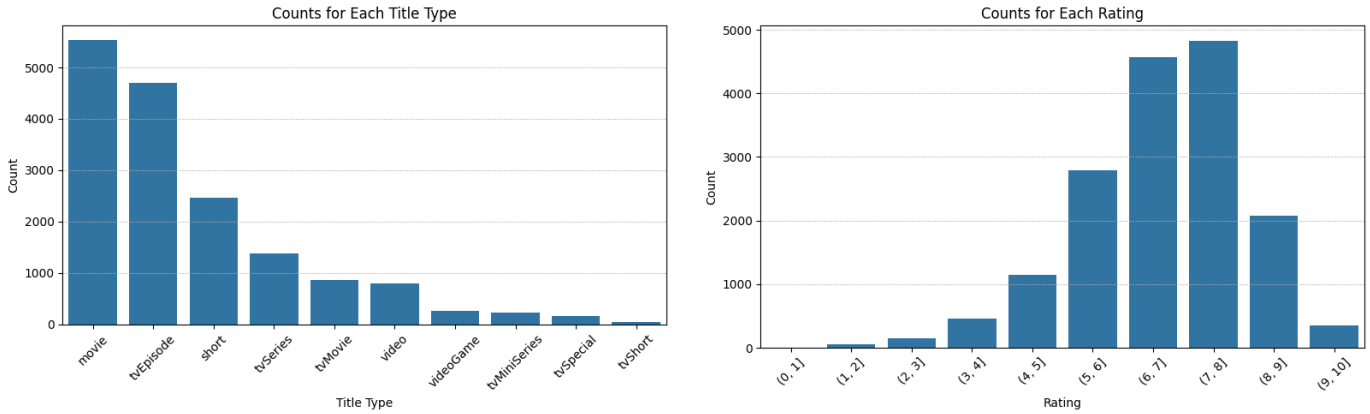
The following discrete attributes were removed from the dataset:

- `originalTitle` was removed because it is not relevant for the analysis;
- the `isRatable` variable was removed because all the titles in the dataset are ratable;
- `worstRating` and `bestRating` attributes were removed because they assume the same values for all records (1 and 10 respectively).

Additionally, the `isAdult` attribute is highly correlated with the presence or absence of *Adult* in `genre` (16 records differ in the train set, 1 in the test set), so the two were merged with a logical OR operation.

1.1.2 Discrete Attributes Analysis

This paragraph provides an overview of the discrete attributes in the dataset, focusing on their distributions and statistics. The following figures 1.1a and 1.1b show bar plots of `titleType` and `rating` attributes, respectively.



(a) Distribution of `titleType`

(b) Distribution of `rating`

Figure 1.1: Distribution of the `titleType` and `rating` attributes

From figure 1.1a it is observed that the classes of the titleType attribute are unbalanced, with *movie* being the most frequent class (5535 records). It was observed that the class *tvShort* is the least frequent in the dataset, with only 40 records (around 0.24% of the dataset). Because of this, these rows were discarded from the dataset, as they were considered irrelevant for the analysis. The decision was not repeated for *tvSpecial* and *tvMiniSeries*, as they cover slightly more than 1% of the dataset each (166, 1.01% and 224, 1.36%, respectively).

As shown in figure 1.1b, the `rating` attribute roughly follows a normal distribution, with a slightly asymmetric peak: a significant number of titles falls within the (6,7] and (7, 8] ranges (4565 and 4822 titles, respectively) while only a total amount of 67 titles falls within (0,1] and (1,2].

1.1.3 Encoding and Transformation of Categorical Attributes

The attribute `rating` was transformed by taking the upper bound of each rating interval's string representation. This approach was chosen because the minimum rating is 1, meaning the lowest interval corresponds only to ratings of 1. For consistency, the same transformation was applied to all other intervals.

Multi-label one-hot encoding was applied to the `genres` column. Each unique genre was represented as a binary feature, allowing records that belong to multiple genres simultaneously to maintain this information; this generated 28 new features. Depending on the task, some were often discarded to avoid overfitting or to reduce the number of features. This will be discussed in the corresponding sections. Rows with no genres were assigned a vector of all zeros, indicating the absence of any genres.

The attribute `countryOfOrigin` was represented by grouping the countries by continent. The following variables

have been created:

- `countryOfOrigin_AF` (Africa);
- `countryOfOrigin_AS` (Asia);
- `countryOfOrigin_EU` (Europe);
- `countryOfOrigin_NA` (North America);
- `countryOfOrigin_SA` (South America);
- `countryOfOrigin_OC` (Oceania);
- `countryOfOrigin_UNK` (Unknown country);
- `countryOfOrigin_freq_enc` (frequency encoding of the original list).

For each record, the first six features provide the number of countries for each continent.
The `countryOfOrigin_UNK` variable counts the number of countries that are not recognized as belonging to a continent for that record.
Additionally, `countryOfOrigin_freq_enc` provides the frequency encoding of the original list of countries as a whole, showing how frequently a specific combination of countries appears across the entire dataset. These transformations allow to keep a most of the original information, while limiting the number of new features.

1.2 Continuous Attributes

Table 1.2 shows the continuous attributes of the dataset, their type and a brief description.

Attribute	**Type**	**Description**
`runtimeMinutes`	Integer	Runtime of the title expressed in minutes
`startYear`	Integer	Release/start year of a title
`endYear`	Integer	TV Series end year
`awardWins`	Float	Number of awards the title won
`numVotes`	Integer	Number of votes the title has received
`totalImages`	Integer	Number of Images on the IMDb title page
`totalVideos`	Integer	Number of Videos on the IMDb title page
`totalCredits`	Integer	Number of Credits for the title
`criticReviewsTotal`	Integer	Total Number of Critic Reviews
`awardNominationsExcludeWins`	Integer	Number of award nominations excluding wins
`numRegions`	Integer	The regions number for this version of the title
`userReviewsTotal`	Integer	Number of User Reviews
`ratingCount`	Integer	The total number of user ratings for the title

Table 1.2: Description of continuous attributes

1.2.1 Removal and Merging of Continuous Attributes

The plot in figure 1.2 is a Pearson's correlation matrix that takes into account the continuous attributes of the dataset.

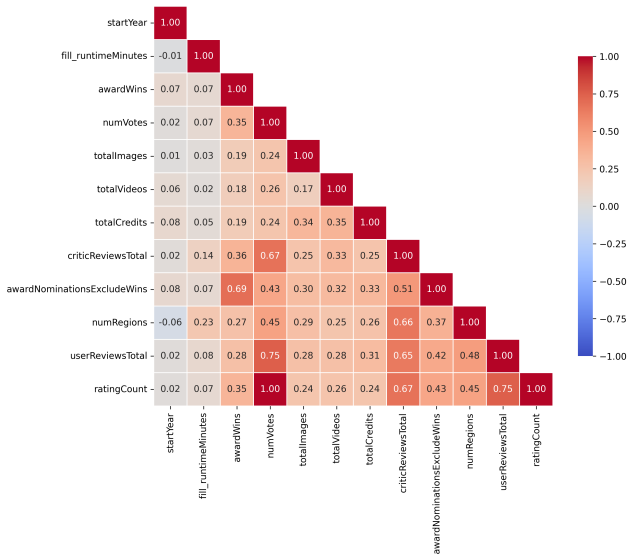
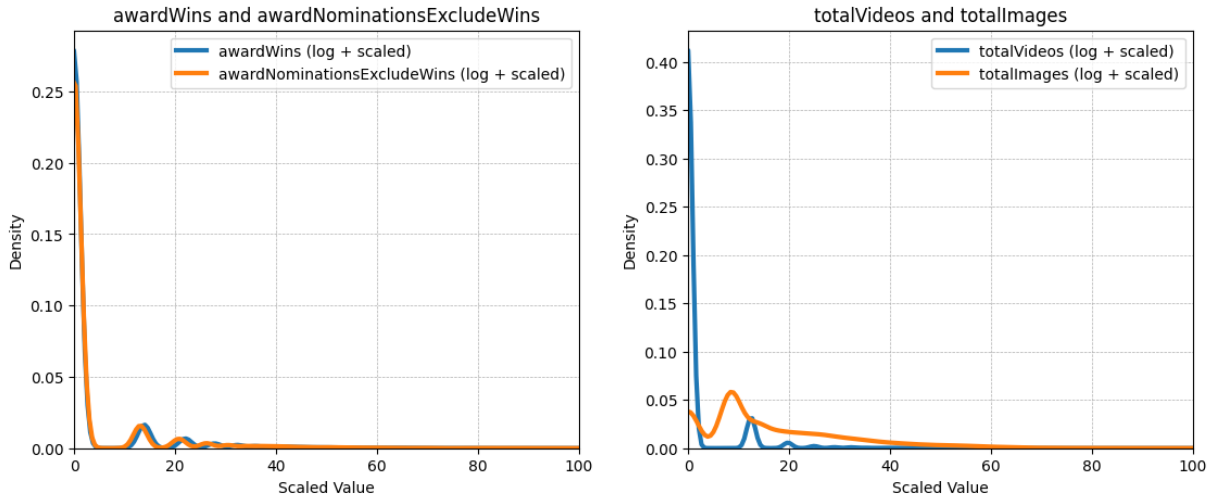


Figure 1.2: Correlation matrix

The correlation matrix shows that `ratingCount` and `numVotes` are perfectly correlated; for their redundancy, `ratingCount` was discarded.

The attributes `awardNominationsExcludeWins` and `awardWins` were combined into a single feature, i.e. `totalNominations`, due to their strong semantic similarity and high correlation (0.69). The new feature represents the sum of the two original attributes. This transformation also helps mitigate the impact of their heavy right skew (shown in figure 1.3a), resulting in a more meaningful and interpretable feature.

Similarly, the `totalVideos` and `totalImages` attributes were combined into a single feature, i.e. `totalMedia`, representing the total number of media items associated with a title. Although the original attributes are not highly correlated, both exhibit skewed distributions (as in figure 1.3b), `totalVideos` in particular. Due to this, and to their similar semantic meaning, they were merged to form a more consolidated and interpretable feature.



(a) Kernel Density Estimation of `awardWins` and `awardNominationsExcludeWins`

(b) Kernel Density Estimation of `totalVideos` and `totalImages`

Figure 1.3: Distribution of the attributes that form the `totalNominations` and `totalMedia` features

Although `criticReviewsTotal` and `userReviewsTotal` also have a relatively high correlation (0.65), as well as a right-skewed distribution, it was decided that the two attributes should be kept separate because of their relevance in meaning. It is also worth noting that the two have high correlations with `numVotes` (0.67 and 0.75 respectively), but they were all kept because of the difference between votes and reviews.

1.3 Data Quality

Next, a proper evaluation of the observed data was conducted in preparation for the analysis. Once having checked that there are no duplicates and no incomplete rows in the dataset, attention was given at identifying missing values and outliers.

1.3.1 Syntactic Inconsistencies

Even though `awardWins` was the only feature having missing values marked with `NaN`, it has been noticed that there were missing values also in other columns - `endYear`, `runtimeMinutes` and `genres` - marked with the string "\N" instead. To avoid this inconsistency those values have been replaced with `NaN`.

1.3.2 Missing Values

The missing values in the above-mentioned attributes were handled as follows:

- `endYear`: it is the feature with the highest number of `NaN` values (15617; about 95%). Although the feature is only relevant for *TVSeries* and *TVMiniSeries* titles, it still had approximately 50% missing values within those categories, limiting its usefulness even in the appropriate context. For this reason, the feature was discarded.

- `runtimeMinutes`: this attribute has 4,852 missing values (29.5%). Two imputation strategies were employed, both based on random sampling within the interquartile range. One strategy used the `titleType` feature to define the range, while the other imputed values independently of any other features. The choice of which of the two strategies to use depends on the specific task, and will be specified in the corresponding sections.

- `awardWins`: this feature has 2618 `NaN` values (about 16%). Since the mode associated with this variable is 0, it has been decided to substitute the missing values with 0.

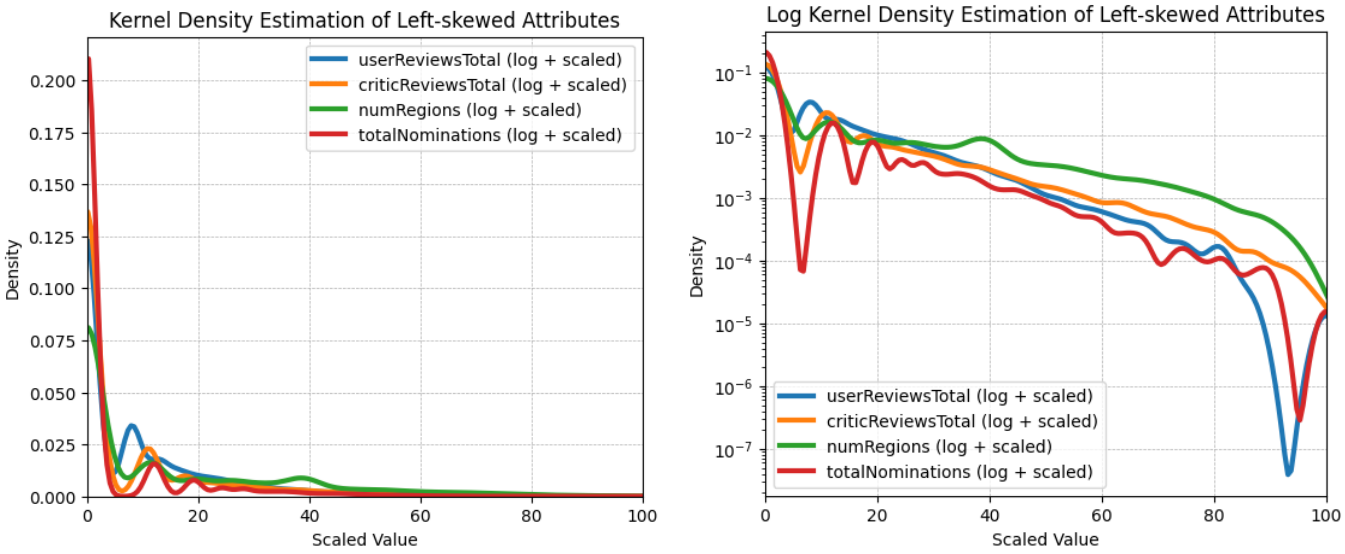
- `genres`: it has 382 missing values (2.3%). Having dealt this variable with a multi-label one-hot encoding process (as has been described in the *Encoding and Transformation of categorical attributes* section), a vector of all zeros is assigned to record with missing genres values.

1.3.3 Semantic Inconsistencies, Feature Transformations and Outlier detection

While analyzing the dataset, it was observed that the *Videogame* type of the `titleType` attribute (259 records - around 1.58% of the dataset) was not consistent with the other values of the same feature, being *Videogame* a fundamentally different titleType. Other then this semantic inconsistency, these rows generated problems for some of the other attributes, such as `runtimeMinutes`, resulting in most values being missing and difficult to

impute. Because of this, the samples were removed from the dataset.

Some features showed a heavy right-skewed distribution, with typical traits of Power-Law Distributions. Their Kernel Density Estimations are shown in figure 1.4.



(a) KDE of right-skewed attributes

(b) KDE of right-skewed attributes with log density

Figure 1.4: Kernel Density Estimation of the left-skewed attributes

The decay of these features is exponential in linear space (1.4a), while in logarithmic space there is a decline that can be approximated to a linear trend (1.4b). For this reason, a log-transformation was applied to these attributes to reduce the skewness and make them more suitable for analysis. Because of right-skewness (without a power-law distribution), other attributes were also log-transformed:

- `numVotes`;
- `totalCredits`;
- `totalMedia`.

Regarding outliers, the feature that was found to be more problematic was `runtimeMinutes`. Figure 1.5 reports an analysis of the feature through the IQR method, on each titleType separately. The boxplot shows that there are samples that have been misreported, with runtimes of over 1000 minutes for *tvSeries*. This might be because of an inconsistency with the understanding of the meaning of the attribute, and it might be possible that in those cases, the value refers to the total runtime of the series, rather than the runtime of a single episode.

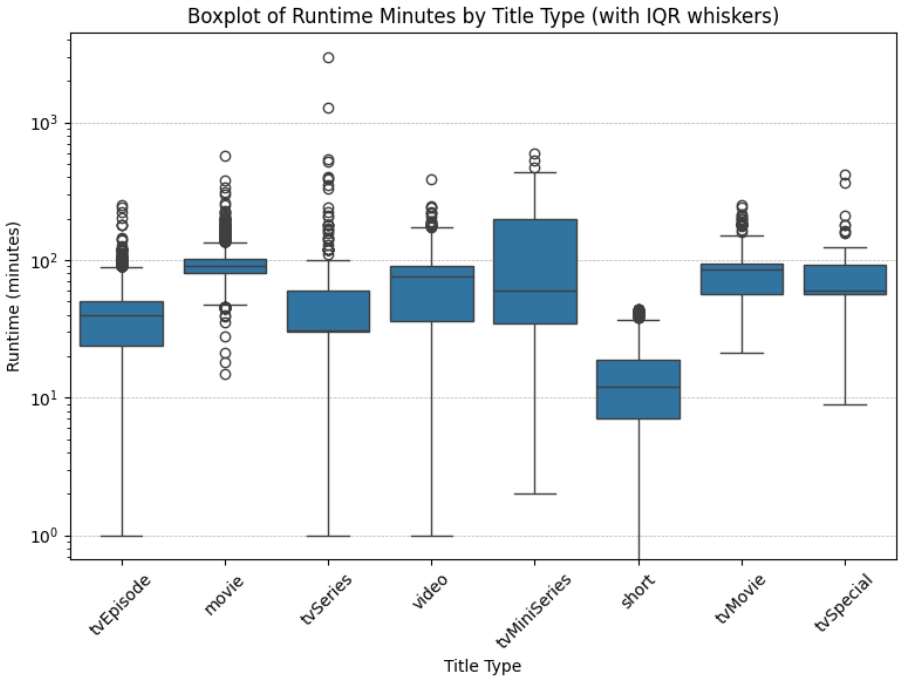


Figure 1.5: Boxplot of the `runtimeMinutes` attribute for each titleType

Another interesting observation regards the presence of a record with a runtime of 0 minutes for the *short* type; although it was not considered an outlier, the record was removed from the dataset because it was regarded as a mistake.

In this phase, outliers were not removed from the dataset, as it was decided to proceed on a case-by-case basis, depending on the task to be performed.

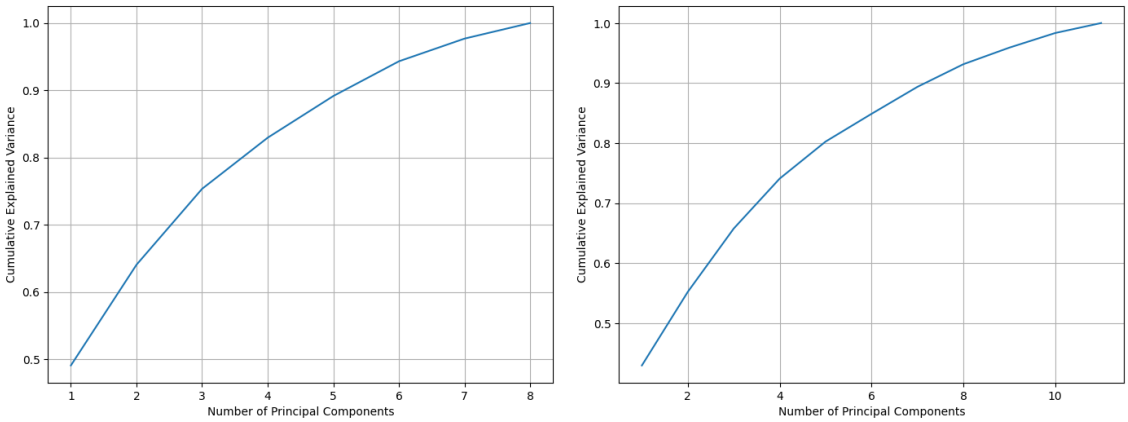
2. Clustering

This chapter of the report aims at illustrating the clustering analysis performed on the dataset at hand. The employed clustering techniques are K-means (Centroid-based), DBSCAN (density-based) and hierarchical clustering.

The analysis conducted using these methods focused only exclusively on the dataset's numerical attributes, which were appropriately log-transformed (as mentioned in the *Variable Transformation* section) and normalized using `MinMaxScaler`. For the K-means algorithm, `totalNominations` and `totalMedia` were excluded due to their high proportion of zero values, which negatively affected cluster formation.

In addition, an attempt was made to incorporate categorical variables to the analysis with the K-means algorithm by converting them into binary attributes and constructing a mixed-distances matrix. Distances were then calculated using the Euclidean distance for numerical (log-tranformed and scaled) features and the Jaccard similarity for binary ones. However, this approach was computationally expensive and did not lead to any improvement in the results.

RIVEDERE PARTE PCA Principal Component Analysis (PCA) was applied to the preprocessed data just for clusters visualization purposes. Analysis of the numerical attributes reveals that 4 principal components are optimal when excluding variables with many zero values, while 5 components are needed when including all variables. These numbers of components capture the maximum meaningful variance, as shown by the point in the plots where where the line starts to flatten, indicating that adding more components doesn't increase explained variance significantly. The plots in figure 2.1 show the differences between these two approaches. **IN REALTA' NON SI VEDE TROPPO LA DIFFERENZA, QUINDI MAGARI NON FARE PCA MA SOLO VISUALIZZAZIONE CON ISTOGRAMMI??? oppure semplicemente tenere solo uno dei due plot?**



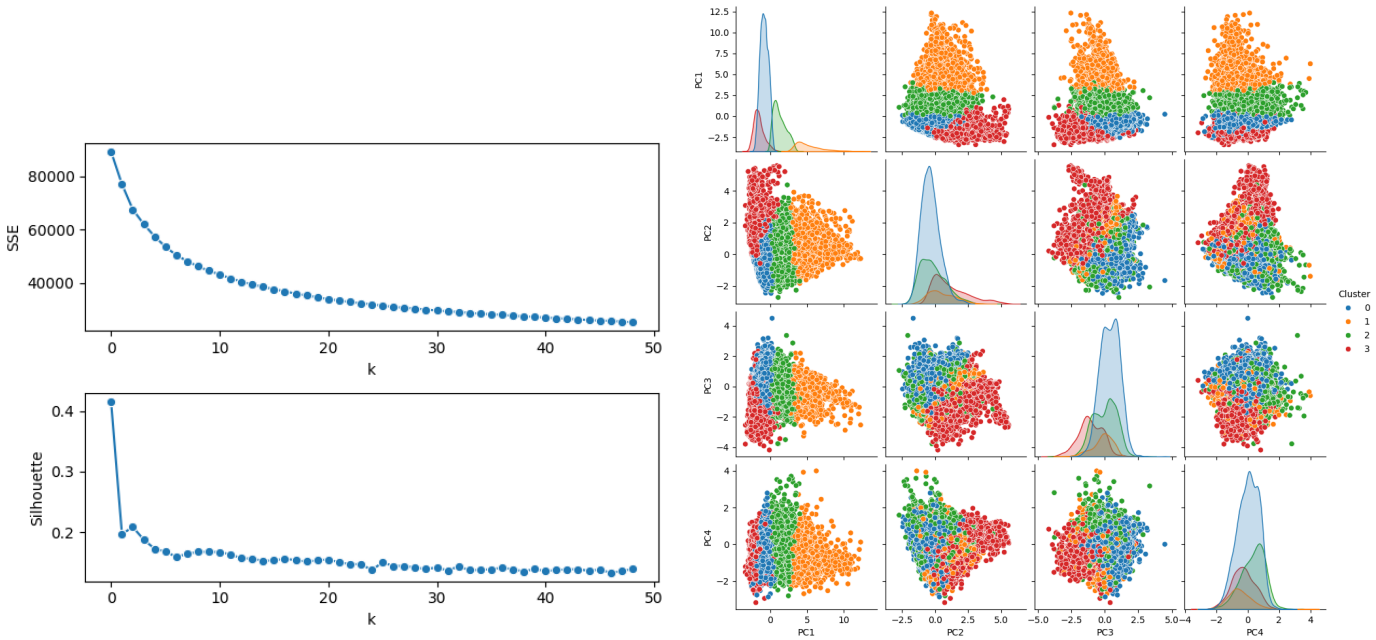
(a) PCA excluding variables

(b) PCA with all variables

Figure 2.1: Principal Component Analysis

2.1 K-means

To identify the optimal number of clusters, both the SSE and Silhouette scores were computed. The goal was to find a configuration that minimizes the SSE while maintaining a robust Silhouette score and a proper k. The plots in figure 2.2a demonstrate that k = ??? provides the optimal balance between these metrics. Choosing k = ??? returns a SSE score of ??? and Silhouette score of ???. **VALORI TROPPO ALTI, VEDERE SE CAMBIANO CAMBIANDO SCALING E/O TOGLIENDO OUTLIER**
The cluster results are presented in figure 2.2b.



(a) SSE and Silhouette scores

(b) K-means Visualization

Figure 2.2: K-means clustering analysis

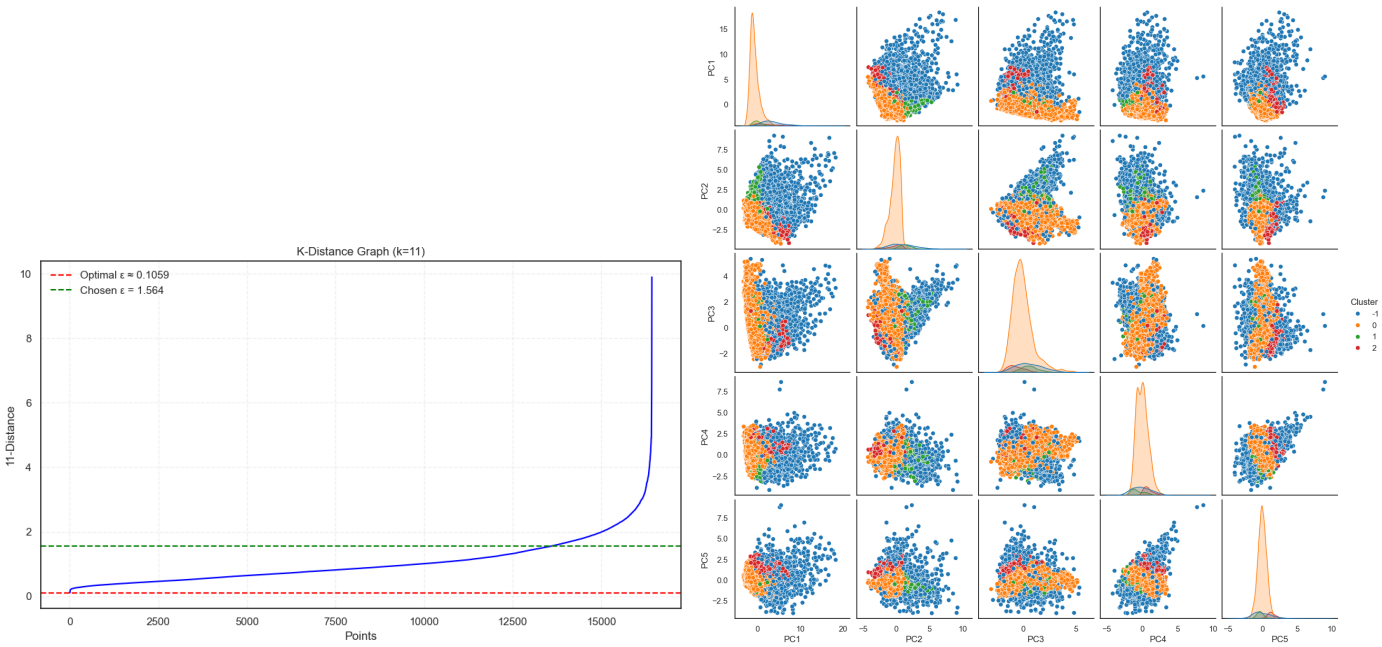
The distribution of data points across the four clusters is as follows (shown in percentage of data points per cluster):

2.2 DBSCAN

To determine the optimal DBSCAN parameters, the k^{th} *nearest neighbors* method was used: this allows to identify *eps* (the maximum distance between two points for them to be considered neighbors) given the value of *Minpts* (minimum number of points in a neighborhood for a point to be considered a core point). Initially, *Minpts* was set to 22, following the rule of setting it above twice the number of dimensions. However, due to the dataset's unbalanced nature and the sparsity of high-dimensional data, reducing *Minpts* to 11 allowed the formation of smaller clusters while preventing the risk of detecting only one dominant cluster and classifying many minority groups as noise instead of distinct clusters. To determine *eps*, the k^{th} nearest neighbors plot with k = 11 was analyzed (figure 2.3a). While the "knee" point suggested an eps of around 0.1, this value would have resulted in excessive noise and a single dominant cluster. To address this, eps was set to 1.564, allowing for meaningful connectivity while preserving the detection of smaller clusters without merging them

into a single entity. The algorithm identified 4 groups in the dataset, including one representing noise (1,753 points). The largest cluster contains 13,198 points, while the smaller clusters consist of 733 and 747 points, respectively.The results are shown in figure 2.3b

To conclude, by adjusting *eps* and *Minpts* appropriately, the clustering results achieved a Silhouette score of 0.139 **(SIL CONTANDO OUTLIERS)**, indicating little improved cluster separation and reduced noise, which is considered good enough for an unbalanced, high-dimensional dataset.



(a) k^{th} nearest neighbors

(b) DBSCAN Visualization

Figure 2.3: DBSCAN clustering analysis

2.3 Hierarchical clustering

2.4 General considerations

3. Classification

Classification was performed on the available training set using three different algorithms: K-NN (*K-Nearest Neighbours*), Naïve Bayes and Decision Trees. For K-NN **and Naïve Bayes**, a portion of the training set (referred to as the validation set) was used to select the best hyperparameters **each** model. The features used in K-NN and Naïve Bayes were normalized, as these models are sensitive to unscaled values. In particular, a log-transformation and **SCRIVERE SE StandardScaler O MINMAX** were applied to data. After training, the models were evaluated on the test set using standard performance metrics. The target variables chosen for this task are 2: `titleType`, and `has_LowEngagement`. These will be discussed in more detail in the corresponding sections below.

3.1 Binary classification

The binary target variable used in this task, `has_LowEngagement`, was specifically defined for this purpose. It identifies records where the `numVotes` attribute is less than 100.

K-NN

Naïve Bayes

Decision Trees

Table 3.1: Classification report for binary classification (`has_LowEngagement`)

Class	Precision	Recall	F1-score	Support
Low engagement	0.86	0.91	0.88	3686
High engagement	0.78	0.66	0.72	1698
Macro avg	0.82	0.79	0.80	5384
Weighted avg	0.83	0.83	0.83	5384
Accuracy			0.83	5384

3.2 Multiclass classification

Among the multiclass features of the training set, `titleType` was chosen as the target variable for this task due to its relevance in the dataset.
An important aspect to highlight is the usage of `fill_runtimeMinutes_notitleType` as one of the variables to train the models. This feature was created to impute the missing values of the original `runtimeMinutes` variable, but without using the median value according to the titleType. Instead, the missing values were

imputed using the help of two variables: `canHaveEpisodes` and `is_Short` (as one of the resulting variables of the multi-label one-hot encoding process of the `genres` attribute). In particular, **SCRIVERE COME E' STATA IMPUTATA NO_TT - con canhaveepisodes e is_short preso dai generi**. This approach prevents a significant error, as it would be methodologically incorrect to use `titleType`-based imputation for an attribute when `titleType` itself is the target variable to predict.

K-NN

Naïve Bayes

Decision Trees

Table 3.2: Classification report for multiclass classification (`titleType`)

Class	Precision	Recall	F1-score	Support
movie	0.85	0.88	0.87	1877
short	0.92	0.94	0.93	766
tvEpisode	0.89	0.92	0.90	1599
tvMiniSeries	0.51	0.35	0.41	81
tvMovie	0.36	0.29	0.32	299
tvSeries	0.89	0.94	0.91	447
tvShort	0.00	0.00	0.00	16
tvSpecial	0.32	0.12	0.18	49
video	0.55	0.46	0.50	250
Macro avg	0.59	0.54	0.56	5384
Weighted avg	0.82	0.84	0.83	5384
Accuracy			0.84	5384

3.3 General considerations

4. Regression

4.1 General considerations

5. Pattern Mining

The pattern mining technique chosen for this task was Apriori. To perform this task, continuous attributes were discretized according to their distributions. The objective of this process was creating bins that were both meaningful and balanced in terms of number of attributes for each bin. Among all the available attributes, the ones chosen for the pattern mining task are the following (with their corresponding binning): **AGGIUSTARE QUANDO VERRANNO GESTITI OUTLIER e quando avremo var definitive - cambiare nome var runtimebruno**

- `runTimeMinutes_Bruno`: VeryLowRT (0-25), LowRT (26-60), MediumRT (61-120), HighRT (121-180), VeryHighRT (181-3000)
- `numVotes`: VeryLowV (5-15), LowV (16-50), MediumV (51-150), HighV (151-997), VeryHighV (1001-966565)
- `rating`: VeryLowR (1-3), LowR (4-6), MediumR (7), HighR (8), VeryHighR (9-10)
- `userReviewsTotal`: NoUR (0), FewUR (1-2), ManyUR (4-13), VeryManyUR (31-149)
- `countryOfOrigin_EU, _NA, _OC, _AS, _AF, _SA`: not_from_[continent name], is_from_[continent name]

In addition, `titleType` was **come l'abbiamo gestita per PM? non c'è one hot encoding quindi l'abbiamo usata così com'è**. The data on which this task was performed was not normalized.

5.1 Extraction of frequent patterns

5.2 Extraction of rules

5.3 Exploiting rules for target prediction