Data Mining: Fundamentals

A.Y. 2024/2025

Group 12

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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, either discrete or continuous.

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, 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 the title can have episodes: `True`/`False`
`isRatable`	Binary	Whether the title can be rated: `True`/`False`
`isAdult`	Binary	Whether the title is adult content: `0` (non-adult), `1` (adult)
`countryOfOrigin`	List	Countries where the title was produced
`genres`	List	Genre(s) associated with the title (up to 3)

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:

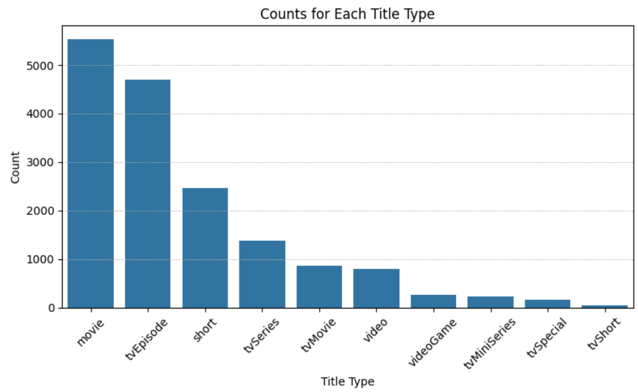
- `originalTitle` was removed because it is not relevant for the analysis;
- the `isRatable` variable was removed because all the titles in the dataset are ratable;
- `worstRating` and `bestRating` attributes were removed because they assume the same values for all records (1 and 10 respectively).

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. This is not true for the *short* type in `titleType`, with 491 records having different values from the obtained feature. For this reason, the two were kept separate.

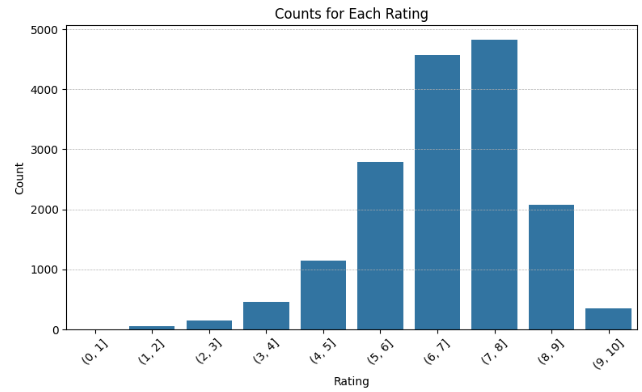
1.1.2 Discrete Attributes Analysis

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.
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).



(a) Distribution of `titleType`



(b) Distribution of `rating`

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

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 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`	Integer	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	Number of regions for this version of the title
`userReviewsTotal`	Integer	Number of user reviews
`ratingCount`	Integer	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. The matrix shows that `ratingCount` and `numVotes` are perfectly correlated; for their redundancy, `ratingCount` was discarded.

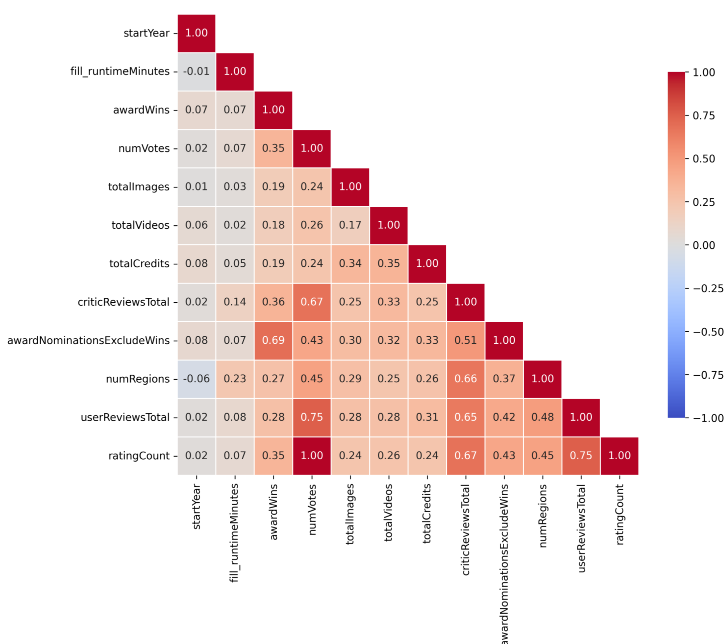
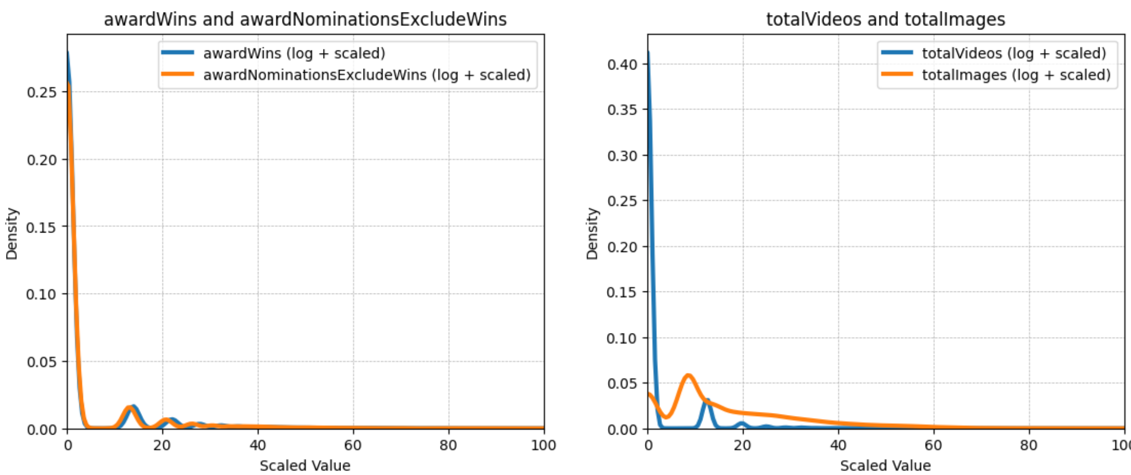


Figure 1.2: Correlation matrix

The attributes `awardNominationsExcludeWins` and `awardWins` were combined into `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 Missing Values

The following attributes were found to have missing values[1]:

- `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.

[1] `awardWins` was the only feature with missing values marked as `NaN`, while the other listed columns had missing values marked as `"\N"`, hence they were replaced with `NaN`.

- `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 based off of the attribute's distribution alone. The choice of which of the two strategies to use depends on the specific task, and will be specified in the corresponding sections.

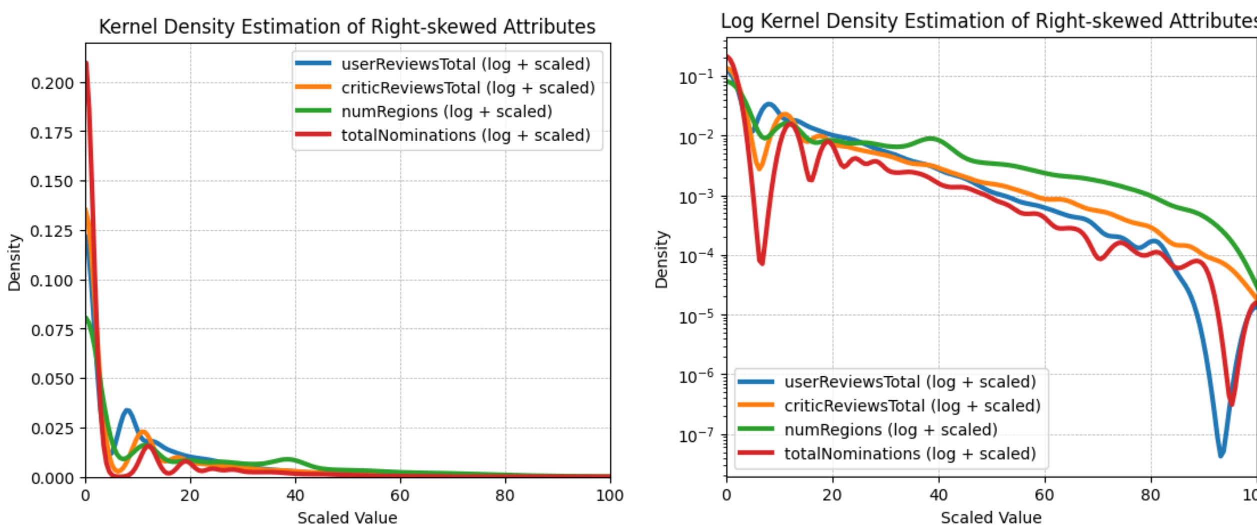
- `awardWins`: this feature has 2618 `NaN` values (about 16%). Since the mode associated with this variable is 0, it has been decided to substitute the missing values with 0.

- `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.

1.3.2 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, when needed, a log-transformation was applied to these attributes to reduce the skewness and make them more suitable for some specific 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`. Similarly to missing values imputation (1.3.1), outlier detection was performed using two different strategies: the first approach computes outliers on each `titleType` separately, while the second is based on the distribution of the `runtimeMinutes` attribute alone. Figure 1.5 reports an analysis of the feature through the IQR method separately on each type.

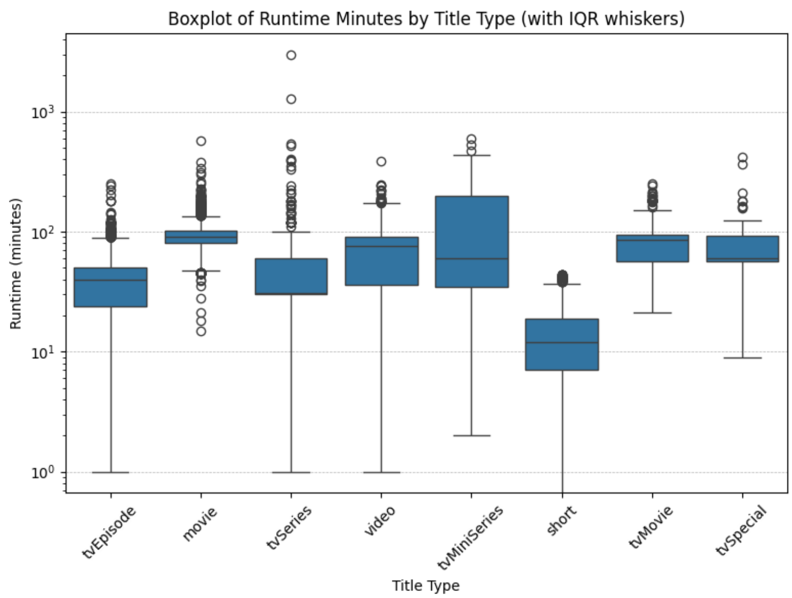


Figure 1.5: Boxplot of the `runtimeMinutes` attribute for each `titleType`

The boxplots show 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 in those cases it might be possible that the value refers to the total runtime of the series, rather than the runtime of a single episode.

Another interesting observation regards the presence of a record with a runtime of 0 minutes for the *short* type; the record was removed from the dataset because it was regarded as an erroneous sample.

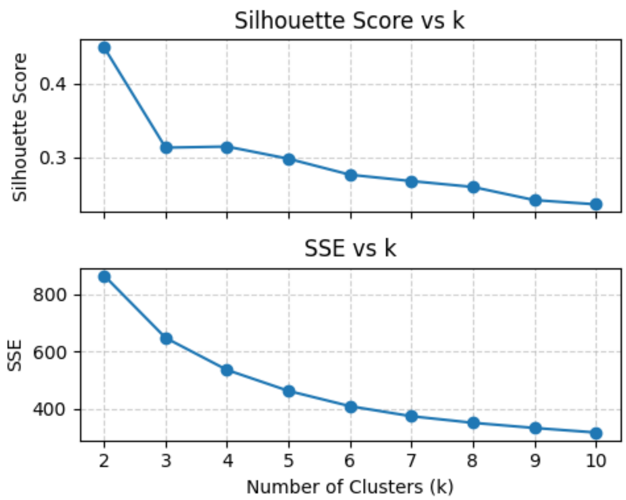
In this phase, outliers were not removed from the dataset by default. Instead, a case-by-case approach was adopted, testing each task and analysis both with and without the outliers. Notably, in every case, better results were obtained when outliers were excluded.

2 Clustering

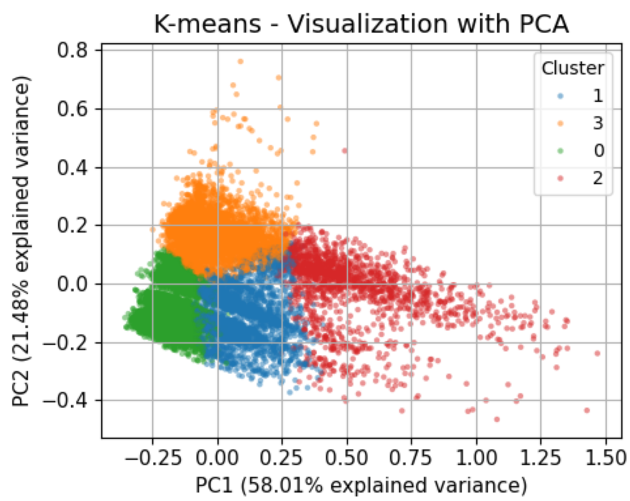
This chapter of the report aims at illustrating the clustering analysis performed on the dataset at hand. The employed clustering techniques are K-means (Centroid-based), DBSCAN (density-based) and hierarchical clustering. The analysis conducted using these methods focused on a selection of the continuous attributes of the dataset, which were appropriately log-transformed (when needed - as mentioned in subsection 1.3.2), and normalized using `MinMaxScaler`.

2.1 K-means

Clustering analysis with K-means was performed using a carefully selected subset of features. This step was motivated by the algorithm's sensitivity to the curse of dimensionality, as including too many variables can negatively affect SSE and Silhouette scores. For this reason, although only `numVotes`, `totalCredits`, `userReviewsTotal`, `runtimeMinutes`, and `criticReviewsTotal`, were chosen for this task, they proved to be a solid choice due to their ability to represent meaningful aspects of the data. To identify the proper number of clusters, both SSE and Silhouette scores were evaluated. The objective was to find a configuration that reduces the SSE while maintaining a robust Silhouette score and a proper k. The plots in Figure X show that $k = 4$ provides a balance between the two values (obtaining SSE equal to 535.51 and 0.315 for the Silhouette score). Only for visualization purposes, Principal Component Analysis (PCA) was employed. The first two components account for 58.01% and 21.48% of the total variance, indicating that this projection provides a fairly informative view of the clustering structure. The cluster results are presented in figure 2.2b. The 4 distinct clusters appear well-separated, suggesting that K-means managed to capture meaningful groupings in the data.



(a) SSE and Silhouette scores

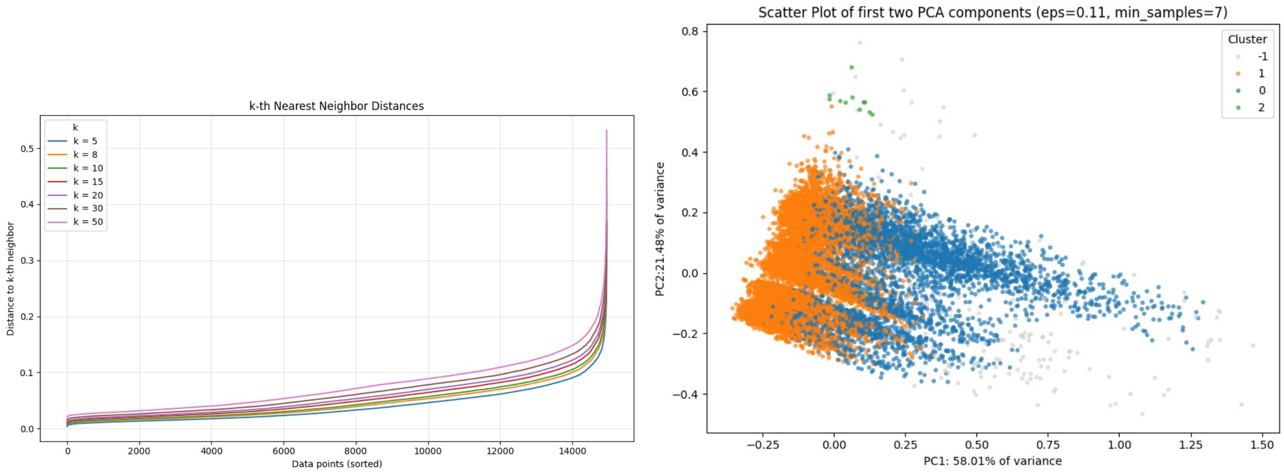


(b) Clustering Visualization with PCA

Figure 2.1: K-means - Cluster analysis

2.2 DBSCAN

To determine suitable DBSCAN parameters, the k-th distance plot was used as starting point (Figure 2.2a). By varying k (*MinPts*) and observing the corresponding distance curves, the range between 0.8 and 0.2 was identified for a possible *Eps* value. **mettere curve k edue linee per racchiuderla**



(a) K-th distance plot

(b) Visualization with PCA

Figure 2.2: K-means - Cluster analysis

From initial attempts DBSCAN's sensibility towards high-sparsed and imbalanced dataset emerged clearly, **often resulting in the formation of a single cluster in correspondence of the dominant dense region, while sparser regions remained largely unstructured**. To try to overcome this and achieve a meaningful clustering structure, different parameters were tested, using different combination of `min_eps` and `min_points` in the following ranges:

- `eps_list` = [0.8, 0.9, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.3, 0.4, 1.0];
- `min_points_list` = [4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 20].

Each parameter combination was evaluated based on the number of clusters (with a minimum threshold of 2), size of the clusters, noise points, and silhouette score (filtered for values ¿ 0.1), excluding the cases where only one cluster was created, or where the silhouette value was really low However, even the best configurations did not yield fully satisfactory results. First of all it is interesting to report that setting *Eps* value ¿ 0.16 never led to the formation of more than one cluster. Similarly, eps value between 0.13 and 0.16 consistently led to the collapse of most points into a single large cluster, with, occasionally, one/two minor residual clusters.

Note that, in this context, the high Silhouette score is misleading, as it tends to favor cohesion of the main cluster, at the expense of structural granularity. On the other side the combination of lower epsilon values (as 0.10) and few `min_pts` (4-5) often resulted in over-fragmentation, producing several clusters of very few elements (5/6), typically corresponding to isolated outliers or noise points rather than meaningful groups. In general with *Eps* values (between 0.09-0.12) the algorithm was able to differentiate between regions of varying density, as *Eps* = 0.13 was identified as the threshold below which DBSCAN starts splitting the big cluster in two different ones. **- EVENT METTI GRAFICO- as Shown in Figure X**

One of the most interesting compromise (though still suboptimal in absolute terms, with max Silhouette score = 0.2699) was found with *Eps* = 0.11, `min_samples` = 7:

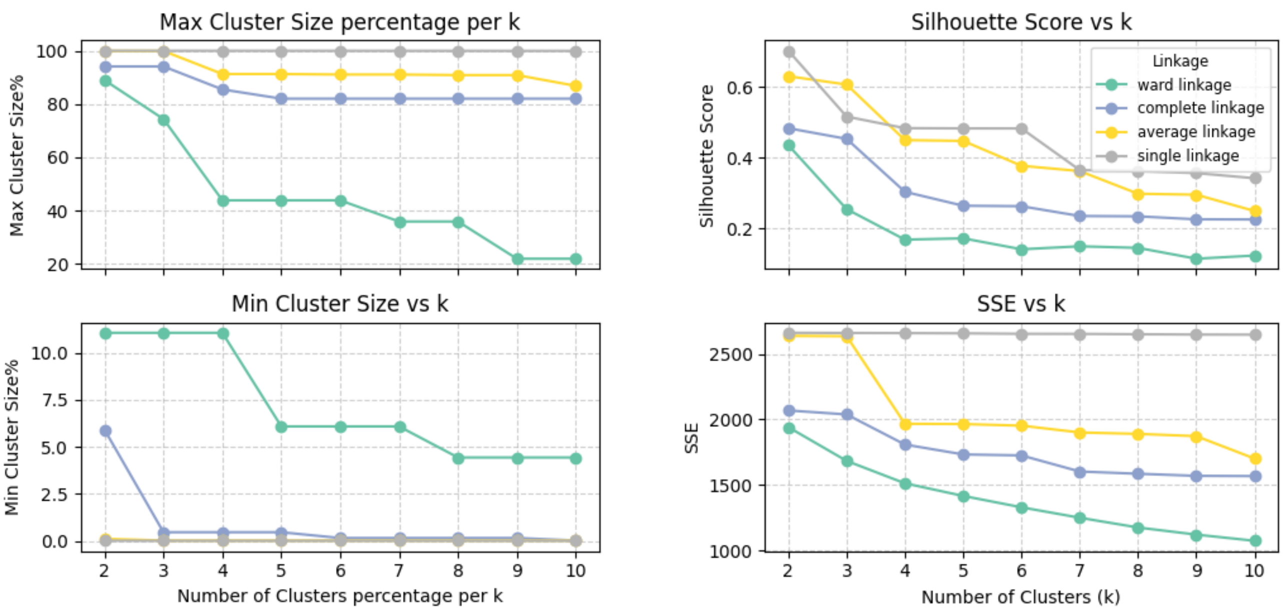
- eps=0.11, min_samples=7 → Clusters: 3, Noise: 219, Composition: [219,4347, 10378,11], Silhouette Score: 0.2699, **eventualmente mettere composition nel grafico**

As shown in Figure X, this setting resulted in a 3 cluster structure, with a compact cluster extracted from the densest region (1), a broader one capturing intermediate-density areas or mild outliers (0), and one very small but well-separated cluster (2) that may represent meaningful local patterns.

To conclude, these observations highlight DBSCAN's limitations when applied to datasets with skewed feature distributions and unbalanced local densities. Nonetheless, the exploration helped isolate parameter ranges where meaningful subclusters begin to emerge,beyond the dominant density mass.

2.3 Hierarchical clustering

Hierarchical clustering was performed using all linkages (Ward, Average, Complete, Single), with the Euclidean distance metric. Figure 2.3 shows the results of the analysis, which includes the Silhouette and SSE scores, as well as the maximum and minimum percentage of points per cluster.



(a) Max/Min percentage of points per cluster

(b) Silhouette and SSE scores

Figure 2.3: Hierarchical clustering metrics for different numbers of clusters

From figure 2.3a, it can be observed that Single linkage produces a single cluster which contains basically all data points. This makes it unsuitable for this use case. Average and Complete linkages produce a cluster with a high maximum cluster size (above 90% of the dataset for all the number of clusters tested for Average, and 80% for Complete). These results are likely due to two main causes:

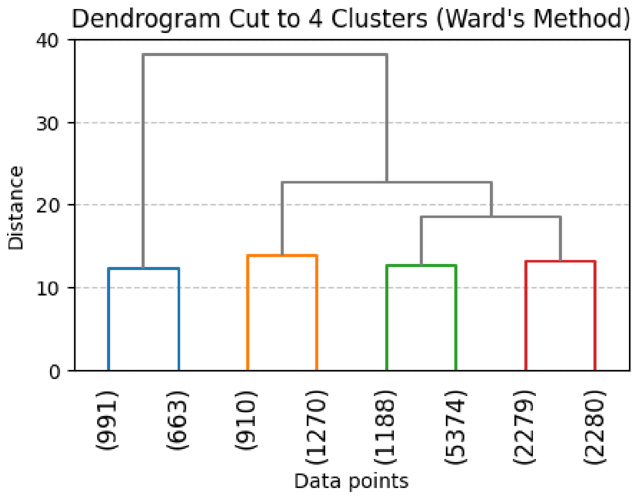
- Usage of skewed features, which lead to areas with a very high density of points;
- High dimensionality of the dataset, which makes it more difficult to separate clusters effectively.

These issues are mitigated by Ward's method, which doesn't show a dominant biggest cluster, for all numbers of clusters tested. The minimum cluster size is also consistently more balanced across different numbers of clusters.

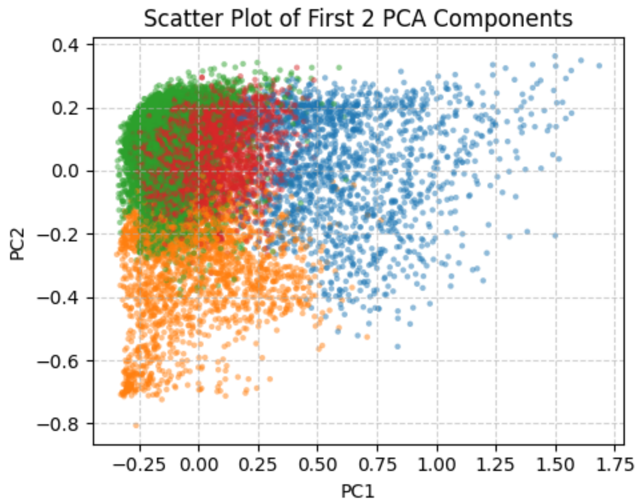
Since Ward's method is based on Squared Error, it's not surprising how its SSE is consistently lower than other linkages, as shown in the second graph of figure 2.3b. What's more interesting is that Ward's method has the lowest Silhouette scores for all numbers of clusters tested, which indicates that the clusters are not well separated. This is due to the fact that Ward's method groups the data which resides in the high-density area mentioned above into smaller clusters, leading to less well-defined boundaries between them.

2.3.1 Ward's method

Figure 2.4 a dendrogram and a scatter plot for a clustering obtained through Ward's Method. Because of the parameters observed in the previous section, cleaner dendrograms, as well as consistency with other clustering methods, the hierarchical clustering is cut at 4 clusters.



(a) Ward's Method Dendrogram



(b) Ward's Method Scatter plot

Figure 2.4: Ward's method clustering

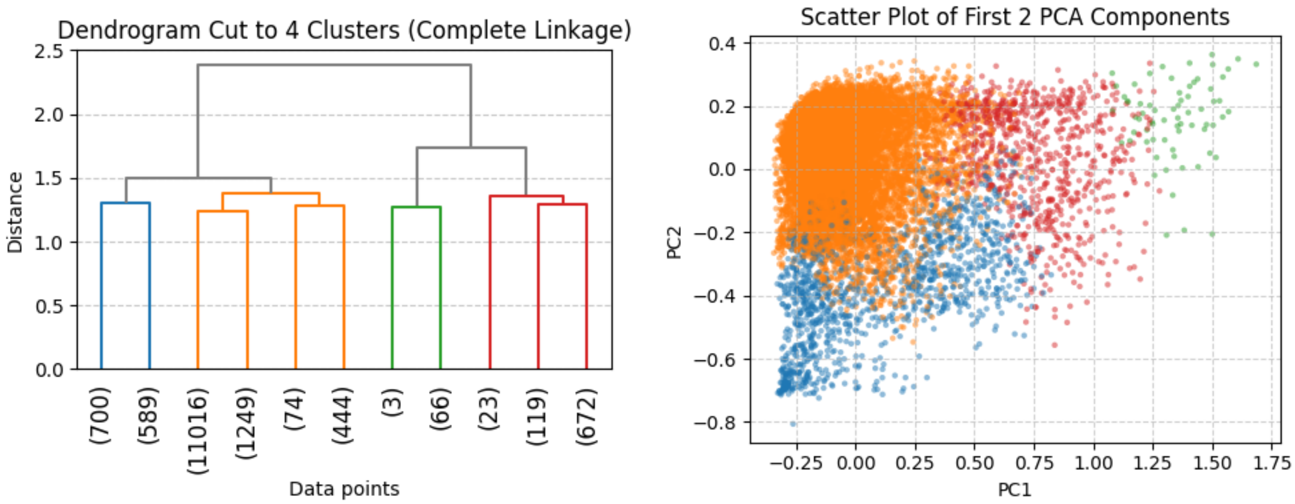
The dendrogram in Figure 2.4a reveals well-separated clusters, all of which merge at a similar linkage distance (approximately 12). This indicates that the increase in within-cluster sum of squares (SSE) is relatively consistent across all cluster merges, as expected from Ward's method. Notably, the smallest cluster is the last to be merged, which suggests it is more distinct from the others. As shown in Figure 2.4b, this cluster lies in a sparser region of the dataset. In contrast, the remaining three clusters originate from the denser region and are therefore spatially closer to one another. Compared to K-Means, the clusters identified by Ward's method appear less clearly separated in the PCA projection, resulting in some overlap between adjacent groups.

2.3.2 Complete Linkage

Figure 2.5 shows the dendrogram and scatter plot for a clustering obtained through Complete Linkage. Since the tendency of this linkage is to merge into a single cluster, the clustering is cut at 4 clusters, which helps mitigating the issue. While selecting five clusters would have introduced an additional split within the largest cluster with similar SSE and Silhouette scores, the resulting group was found to be poorly separated and lacked meaningful distinction. As such, it was not considered a valuable contribution to the overall clustering structure.

As shown in the dendrogram in Figure 2.5a, the clusters merge at similar linkage distances (approximately between 1.2 and 1.4), indicating that the maximum within-cluster distances are comparable across clusters. With respect to the clustering obtained through Ward's method, the clusters have clearer boundaries along the PCA axes, as the denser area of the dataset is not split into multiple clusters.

It is also interesting to observe how the dendrogram structure differs from that of Ward's method. In the previous case, the smallest cluster was the last to be merged, reflecting its distinctiveness in terms of within-cluster variance. In contrast, the Complete Linkage dendrogram shows the two smaller clusters being merged before the root.



(a) Complete Linkage Dendrogram

(b) Complete Linkage Scatter plot

Figure 2.5: Dendrograms for hierarchical clustering with Complete Linkage

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.

An analysis of semantically related features was run, in order to decide whether to discard any other feature. `userReviewsTotal` showed a 75% correlation with `numVotes`, while `criticReviewsTotal` has 67% correlation. Despite the similarity in correlation values, `userReviewsTotal` was deemed too semantically similar to `numVotes`, whereas `criticReviewsTotal` was considered to provide distinct and complementary information. The correlation value of the second considered not sufficiently high to make the problem trivial.

An important aspect of the chosen binary classification task is the class imbalance, with 10287 records classified as *Low Engagement* and 4668 as *High Engagement* in the training set. This imbalance was taken into account during model training and evaluation, with a focus on macro-averaged F1-score to mitigate its impact on the results.

3.1.1 K-NN

3.1.2 Naïve Bayes

3.1.3 Decision Trees

For explainability purposes, features were not normalized nor transformed for the Decision Tree model, as it does not require such preprocessing because it's not based on distance measures, but rather on decision thresholds.

To identify the optimal hyperparameters, a Randomized Search was performed using Repeated Stratified 5-Fold Cross-Validation with 10 repeats on the training set, optimized for the macro-averaged F1-score. The best configuration found used Gini index as the splitting criterion, a maximum tree depth of 26, and a minimum of 3 samples per leaf. The obtained decision tree is shown in figure 3.1.

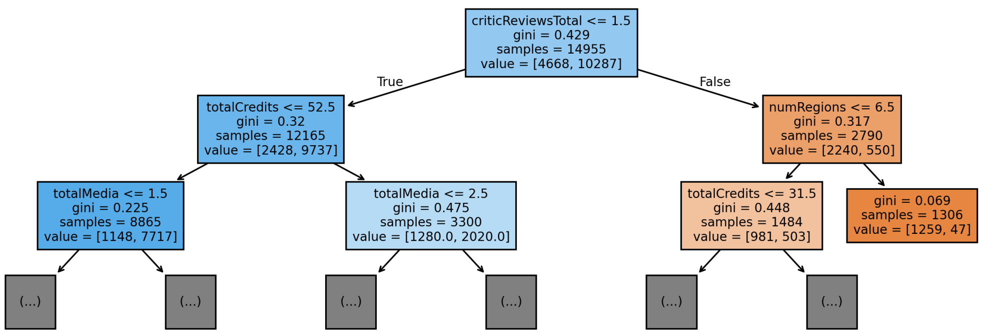


Figure 3.1: Decision Tree for binary classification

Unsurprisingly, the most important feature for the model was `criticReviewsTotal`, which amounted to 0.6 in the feature importance ranking. The following other 3 more important features were `totalCredits` (0.15), `totalMedia` (0.10) and `numRegions` (0.09). These four features take up around 93% of the total feature importance, and are all present in the first two splits shown in the Decision Tree.

Train performance was overall similar to the test performance; in particular, the respective accuracies were of 0.83 and 0.84, and macro-F1 scores were 0.82 and 0.80. In any case, post-pruning was tested, but did not yield any performance improvement, and was therefore not applied. The *High Engagement* class showed low Recall values (0.71 on train set, 0.68 on test set). This might be a consequence of class imbalance, as well as poor separability of the two classes. This assumption is further supported by the Precision scores of the class (0.78 on train, 0.75 on test).

3.1.4 Model Comparison

3.2 Multiclass classification

Among the multiclass features in the training set, `titleType` was selected as the target variable for this task, due to its relevance within the dataset. Because of their strong correlation with `titleType`, the feature `canHaveEpisodes` and the genre *Short* were excluded from the feature set. Furthermore, since the primary imputation method for missing values in `runtimeMinutes` relied on information from the target variable, these values were re-imputed to avoid data leakage. Specifically, missing entries were filled by sampling from the overall distribution of `runtimeMinutes`, without referencing `titleType`.

One final point to note is the imbalance in the target feature (previously shown in figure 1.1a), which was explicitly taken into account during the design of the models. As for the binary classification task, macro-averaged F1-score was a key metric for model evaluation, as it provides a balance between each class's precision and recall.

3.2.1 K-NN

3.2.2 Naïve Bayes

3.2.3 Decision Trees

Like for the binary classification task, the Decision Tree model was trained without normalizing or transforming the features, making the model more interpretable. To identify the optimal hyperparameters, a Randomized Search was performed using Repeated Stratified 5-Fold Cross-Validation with 5 repeats on the training set, optimized for the macro-averaged F1-score. The best configuration found used Entropy as splitting criterion, had a max depth of 14, a minimum of 5 samples per leaf, and a minimum of 8 samples in order to split an internal node. Regarding overfitting, many configurations were tested.

The models, applied to the task, showed a general tendency towards overfitting, observed with all configurations. Although the accuracy doesn't show a significant drop (from 0.86 on the train set, to 0.75 on the test set), the macro-averaged F1-score dropped from 0.65 to 0.52. This was given from the *tvMiniSeries* and *tvSpecial* classes: these had f1-scores of 0.35, 0.22 respectively on the train set, and both had 0.10 on the test set. Since they were by far the least represented classes, they required a trade-off between low-represented classes classification and generalization. In order to mitigate this, post-pruning was tested, but did not give particular benefits. Higher values for the parameter α had minor positive effects on the generalization capabilities of the models, but drastically hindered the performances on the less represented classes.

3.2.4 Model Comparison

Because of class imbalance, for evaluation purposes, macro-averaged F1-score was heavily considered.

4 Regression

4.1 Univariate Regression

4.2 Multiple Regression

4.3 Multivariate Regression

5 Pattern Mining

To perform this task, continuous attributes were discretized based on their distributions, aiming for bins that were both semantically meaningful and reasonably balanced in size. The selected numerical attributes (not normalized) for the pattern mining task, along with their binning, are:
Regarding discrete attributes, `titleType` was considered for this task, kept in its original form. On the other hand, the values of each of the 7 attributes `countryOfOrigin_[continent code]`[1] were binarized into:

[1]see subsection 1.1.3 for the list of the features

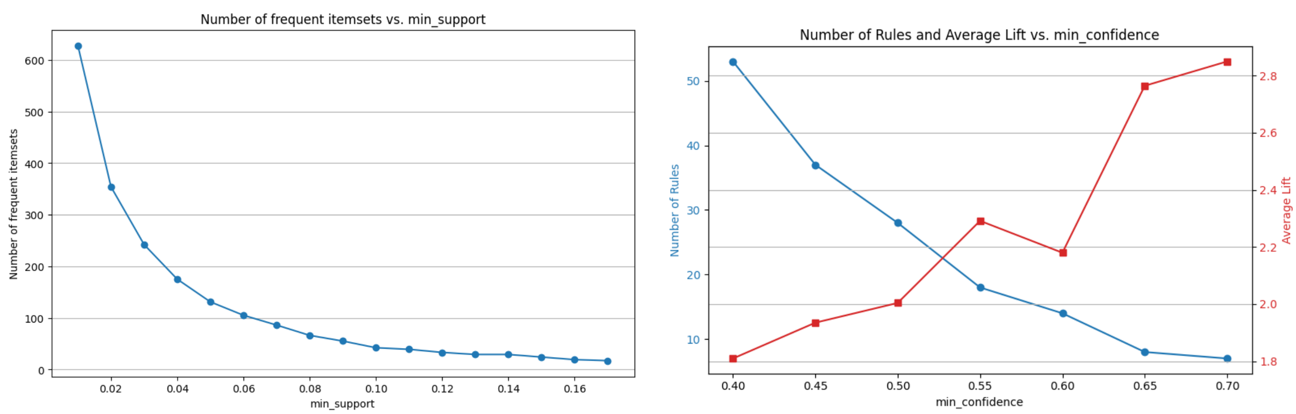
Attribute	Binning
`runtimeMinutes`	VeryLowRTM (1-30), LowRTM (31-60), MediumRTM (61-90), HighRTM (91-220)
`rating`	VeryLowR (1-3), LowR (4-6), MediumR (7), HighR (8), VeryHighR (9-10)
`totalCredits`	VeryLowC (0-15), LowC (16-35), MediumC (36-65), HighC (66-15742)

Table 5.1: Binning of the continuous attributes

- `not_from_[continent code]`: when the value of the attribute is 0
- `is_from_[continent code]`: when the value of the attribute is ≥ 1

Binarization was preferred over creation of multiple bins, as it allows for a more linear interpretation of the results. An attempt was performed to include genres; however, this did not lead to more interesting results.

5.1 Extraction and discussion of frequent patterns



(a) Plot of frequent itemsets with varying *support*

(b) Plot of lift and number of rules with varying *confidence*

Figure 5.1: Plots of minimum support and confidence - *Apriori* algorithm

Apriori was the algorithm chosen to extract frequent patterns. Figure 5.1a shows how the number of frequent itemsets changes with support values ranging from 0.01 to 0.18. The curve of the plot begins to flatten between 0.08 and 0.1, so a support value of 0.08 was selected, resulting in 66 frequent patterns.

It is interesting to observe the top frequent itemsets of size 1, 2, and 3, as shown in Table 5.2. From the itemset of size 1 it was noticed that approximately 48.5% of the objects in the dataset are from North America, highlighting the prevalence of this region.

The size-2 itemset reveals that 1/4 of the objects is both from North America and has a very low runtime. This pattern becomes more specific in the top size-3 itemset, where almost 10% of the data corresponds to TV episodes with both characteristics.

Size	Support	Itemsets
1	0.485	(is_from_NA)
2	0.204	(VeryLowRTM, is_from_NA)
3	0.094	(tvEpisode, VeryLowRTM, is_from_NA)

Table 5.2: Top itemsets of sizes 1, 2, and 3

5.2 Extraction of rules

After extracting the frequent patterns, association rules were generated. To find a value of *confidence* that balances the number of rules and their strength (measured with *lift*), the plot in Figure5.1b was analysed. A `min_confidence` of 0.55 was selected, guaranteeing an average *lift* of 2.3 and a significant number of rules, i.e. 18. The top 10 rules extracted (ranked by lift) are:

Rule	Antecedents	Consequents	Ant. Sup.	Cons. Sup.	Sup.	Conf.	Lift
0	(short)	(VeryLowC, VeryLowRTM)	0.160	0.128	0.093	0.583	4.568
1	(VeryLowC, VeryLowRTM)	(short)	0.128	0.160	0.093	0.731	4.568
2	(HighRTM)	(movie)	0.177	0.319	0.154	0.866	2.719
3	(is_from_NA, short)	(VeryLowRTM)	0.082	0.375	0.082	0.995	2.654
4	(VeryLowC, short)	(VeryLowRTM)	0.094	0.375	0.093	0.994	2.650
5	(short)	(VeryLowRTM)	0.160	0.375	0.159	0.993	2.648
6	(VeryLowRTM, short)	(VeryLowC)	0.159	0.234	0.093	0.588	2.513
7	(short)	(VeryLowC)	0.160	0.234	0.094	0.587	2.511
8	(is_from_NA, LowRTM)	(tvEpisode)	0.121	0.303	0.090	0.742	2.447
9	(MediumRTM)	(movie)	0.229	0.319	0.165	0.720	2.260

Table 5.3: Top 10 rules extracted with *Apriori* (ranked by lift)

5.3 Exploiting rules for target prediction

One way to exploit the previously extracted rules is for target prediction. Firstly, rules with `VeryLowC` as target (rows 6 and 7 in the Table 5.3), show that short contents with very low runtime are highly likely to be associated with very low credits, probably reflecting the involvement of a limited production or cast. Both rules show a strong association, with a *lift* greater than 2.5, with the more specific one (VeryLowRTM and short) offering a better potential for targeted prediction.

The target `is_from_NA` was then analysed to find the antecedents (as shown in Table 5.4), that increase the likelihood of an object of being from North America. Even though the *lift* value of those rules is below average, these rules were still considered, due to their meaningful interpretability. The analysis suggests that North American origin is associated with TV episodes, shorter durations, and high ratings or numerous production credits.

Rule	Antecedents	Consequents	Ant. Sup.	Cons. Sup.	Sup.	Conf.	Lift
12	(HighR, tvEpisode)	(is_from_NA)	0.144	0.485	0.092	0.639	1.317
13	(HighC)	(is_from_NA)	0.152	0.485	0.156	0.627	1.292
14	(tvEpisode, LowRTM)	(is_from_NA)	0.144	0.485	0.090	0.624	1.285
15	(tvEpisode)	(is_from_NA)	0.303	0.485	0.186	0.612	1.261
16	(tvEpisode, VeryLowRTM)	(is_from_NA)	0.153	0.485	0.093	0.611	1.259
17	(LowRTM)	(is_from_NA)	0.219	0.485	0.121	0.553	1.139

Table 5.4: `is_from_NA` as target