Games classifier

Team name

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Use case example:
Imagine that you run a online game store where users can add their games to your library. Instead of manually checking if user tagged correctly the game, you can use our model to do that job for you.

Goal:
We want to be able to automatically assign tags (or genres) to games, based on their (text) description.

Additionally, in aspect of ML project, we want to make a small comparison of different models and methods for solving such multilabel classification problem.

Info about the dataset

Steam has its own official API, from which we downloaded games, their descriptions, tags and genres. That resulted in a bit over *200'000* games.

To clean the data we:

- Converted descriptions to alphanumeric lowercase
- Removed html tags
- Removed empty descriptions or tags
- (optional) Removed tags/genres that occured at most n times

After that we ended up with a dataset of size around *50'000* games and *400* unique tags or *100* unique genres.

To represent the output we decided to use multi label binary vector.
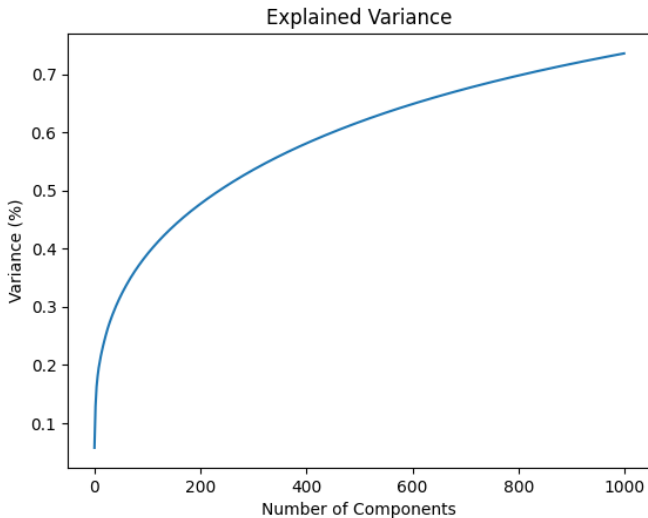
Data preprocessing

To represent the output we decided to use multi label binary vector.

For input preprocessing we tried:
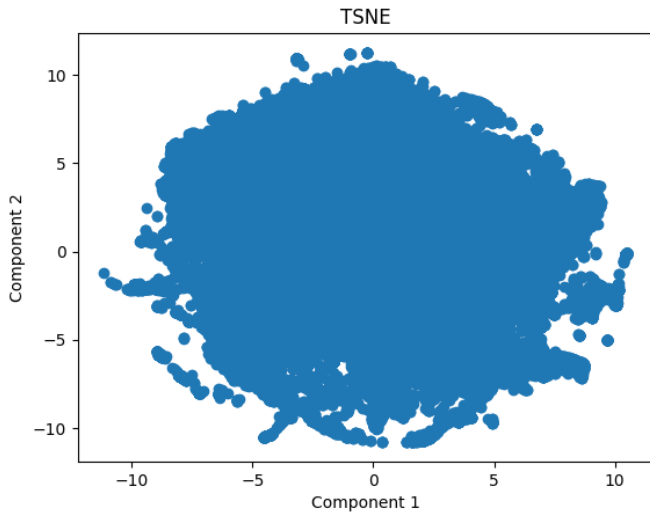- Bag of Words
- TF-IDF
- Hashing vectorizer

We decided to check if there are some patterns in the data that we can use to improve our model.

Figure: PCA analysis on Bag of Words

Figure: t-SNE 300 iterations + PCA to 50 on Bag of Words

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- Support Vector Machine
  Interesting concept

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- Intersection over union score
  this evaluation does not treat each label separately, but check ratio of intersection and union

Results - KNN

Figure: Different number of neighbors

F1-score for different values of k
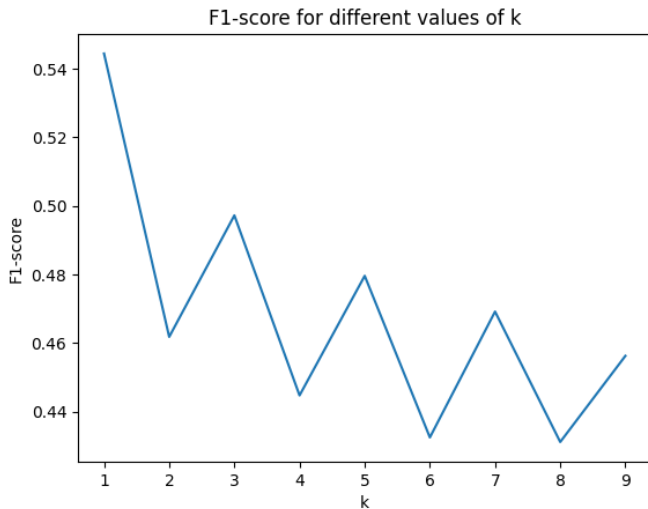
Figure: Comparison of evaluations

Scores over different evaluation methods
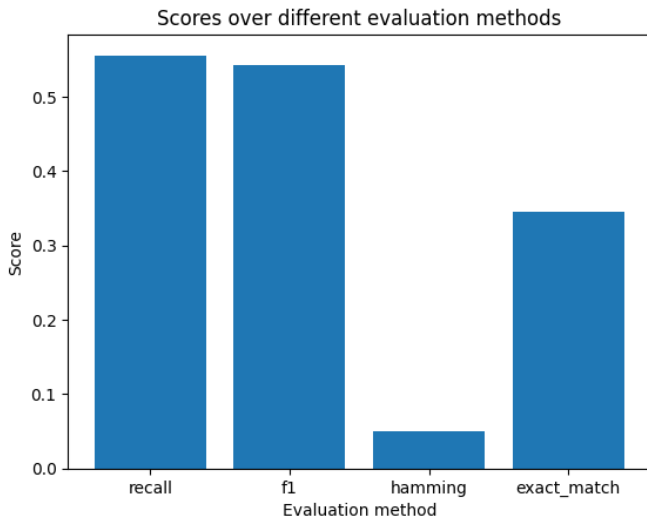
Results - Logistic Regression

Logistic Regression with different regularization
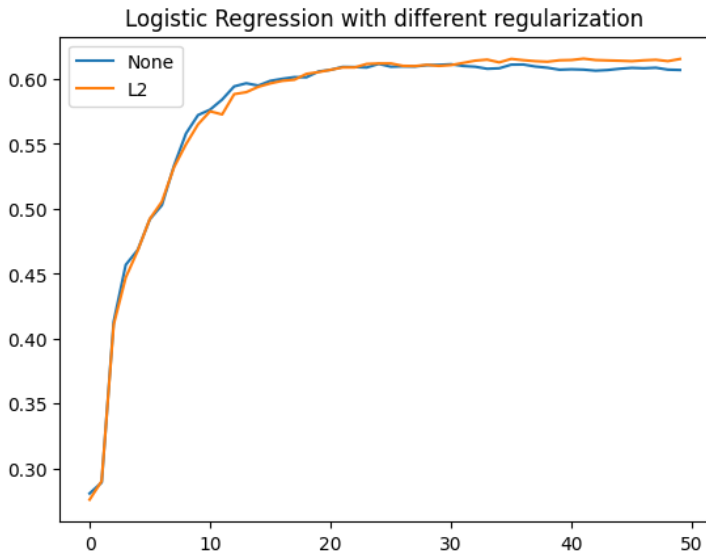
Results - Decision Tree
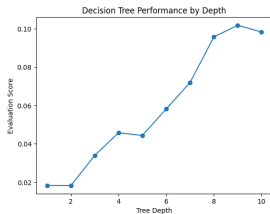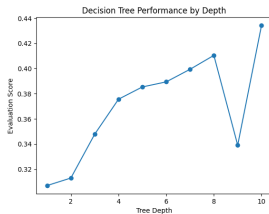

Figure: Exact match

Figure: F1-score

Figure: Hamming loss
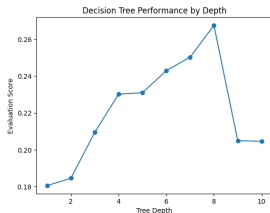
Figure: Intersection
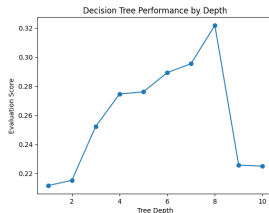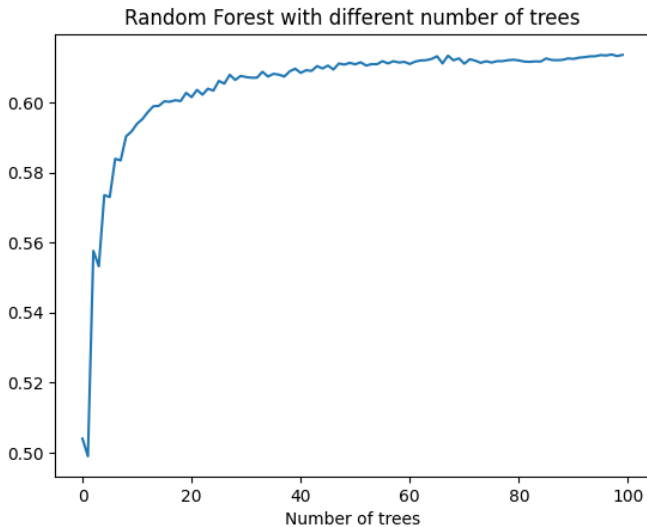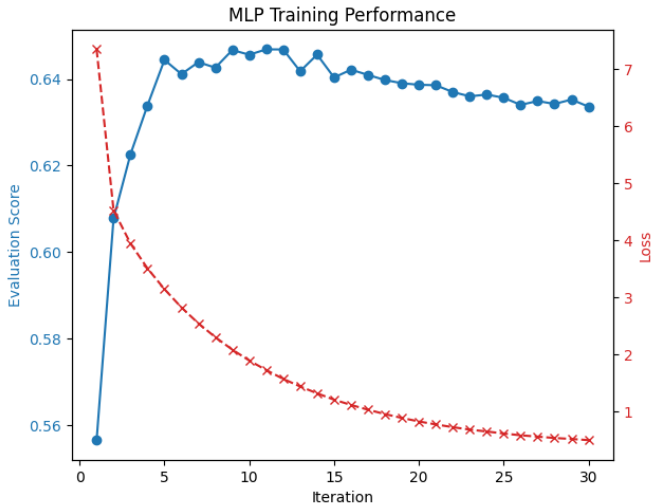

Figure: Recall

Comparison with different number of trees

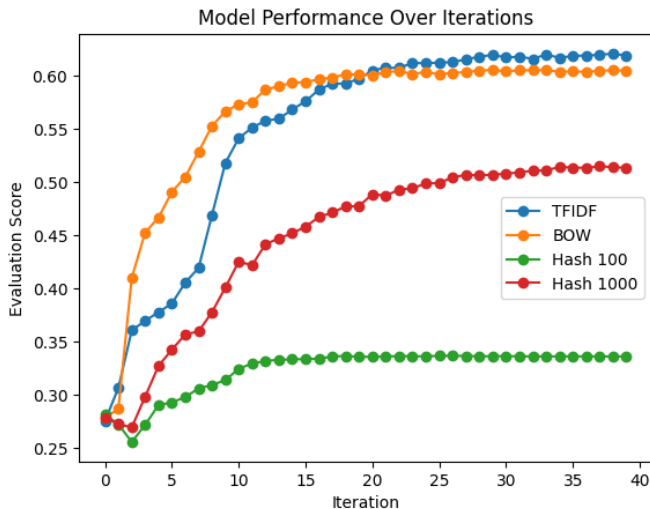Random Forest with different number of trees

Results - Neural Network

Figure: Multilayer Perceptron

MLP Training Performance

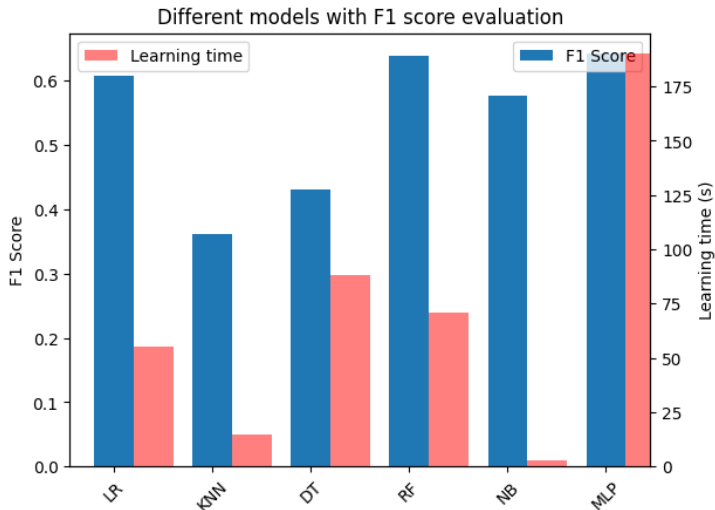Figure: Logistic Regression, F1-score

Evaluation metrics

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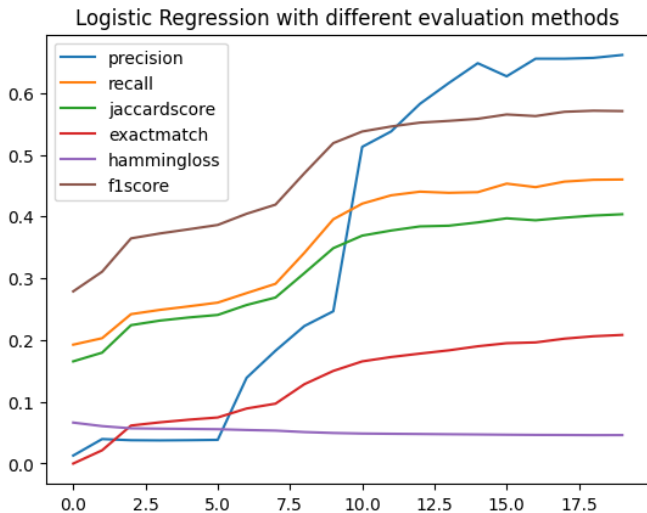
Logistic Regression with different evaluation methods

Models Comparison

Different models with F1 score evaluation

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- The best model was neural network, with random forest and logistic regression not far behind
(additionally neural network was the most time consuming to train)
- KNN indeed was far from the best model
but naive bayes, which was the fastest, was quite good
- Decision trees were empirically proven (again) that they are not the best choice