Games classifier

Team name

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UWr

January 28, 2025

Goal and motivation

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.

Data preprocessing

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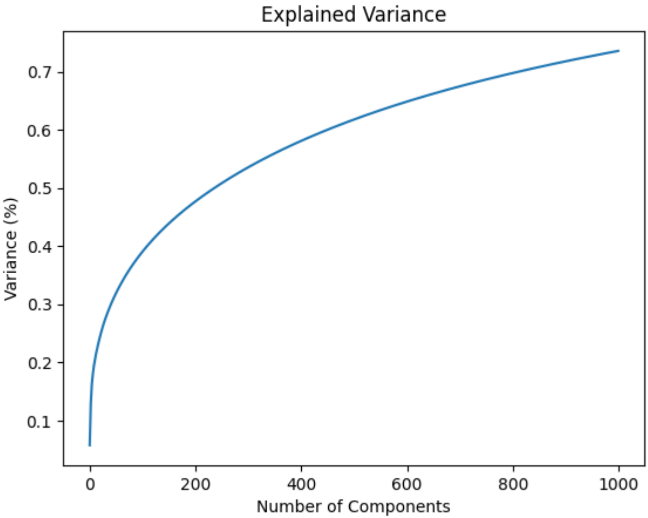
For input preprocessing we tried:

- 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.

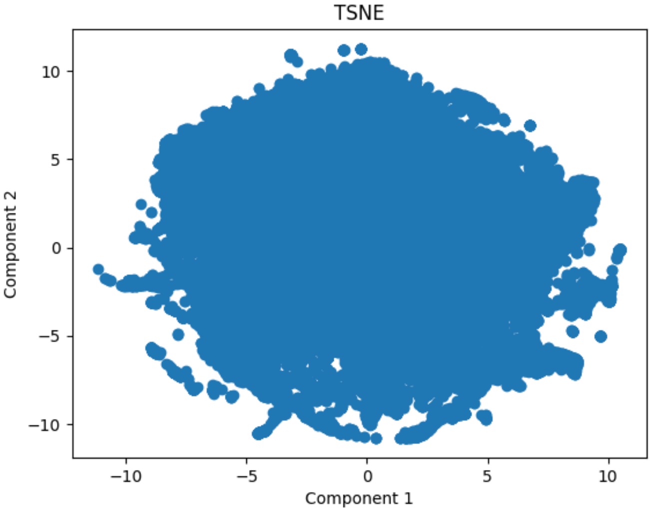
Data preprocessing

Figure: PCA analysis on Bag of Words



Data preprocessing

Figure: t-SNE 300 iterations + PCA to 500 on Bag of Words



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- Support Vector Machine
  Interesting concept

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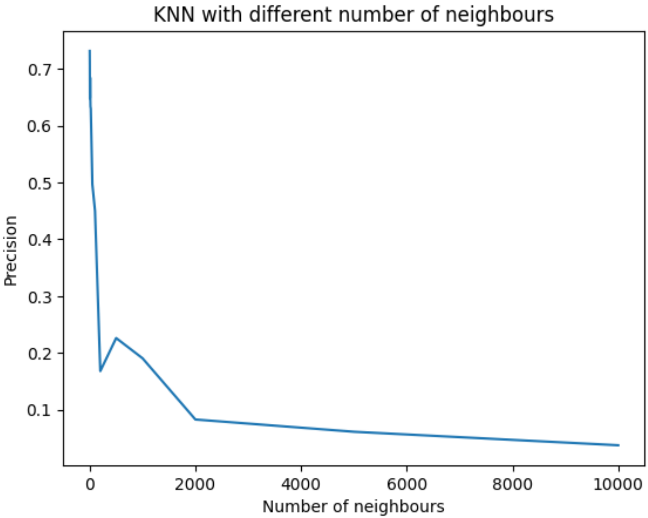
- Hamming loss
  How would a loss function compare to score functions

Figure: Different number of neighbors



Results - KNN

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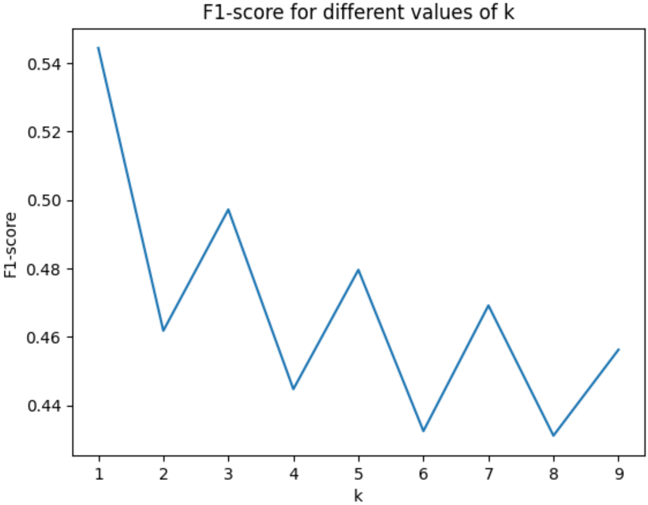
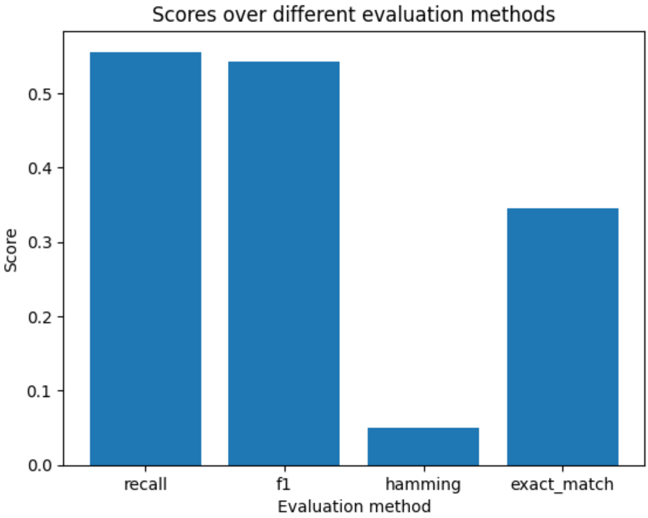
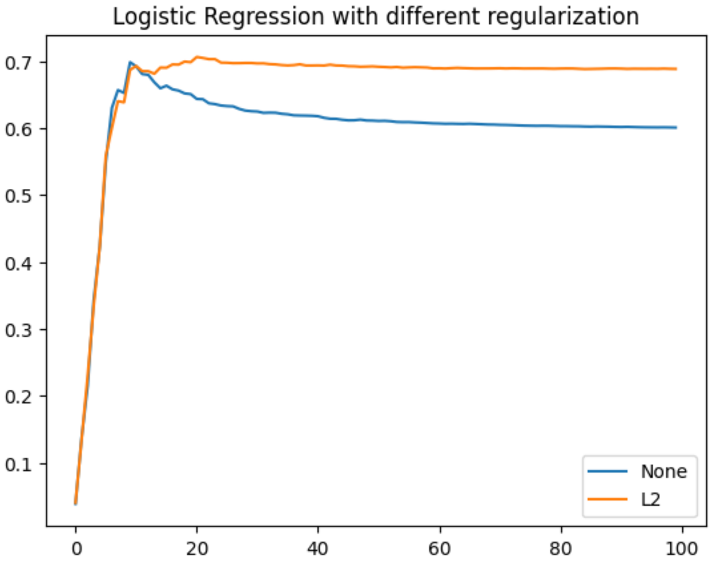


Results - KNN

Figure: Comparison of evaluations



Results - Logistic Regression



Results - Decision Tree

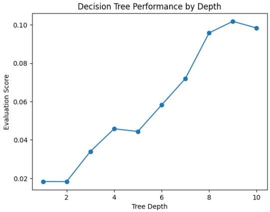


Figure: Exact match

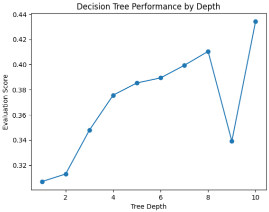


Figure: F1-score

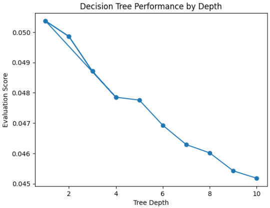


Figure: Hamming loss

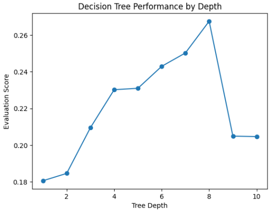


Figure: Intersection

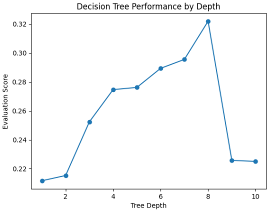


Figure: Recall

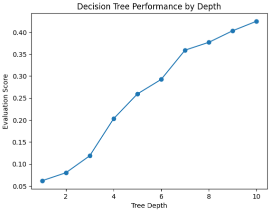
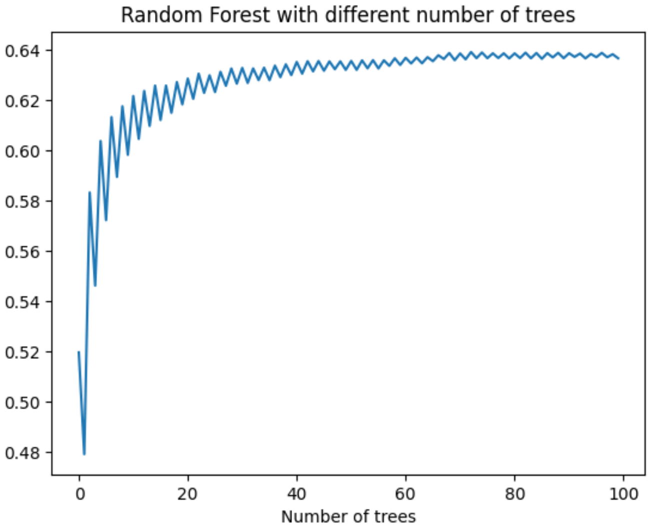


Figure: Precision

Results - Random Forest

Figure: Different number of trees, no depth limit



Results - Random Forest

Figure: Different number of trees, depth limited to 100

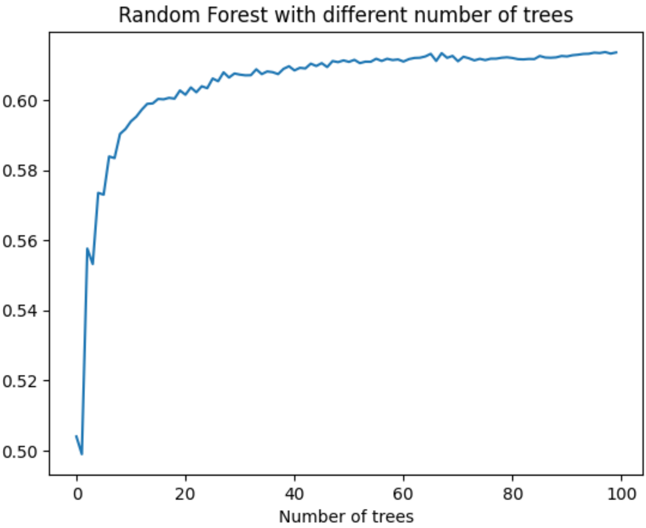
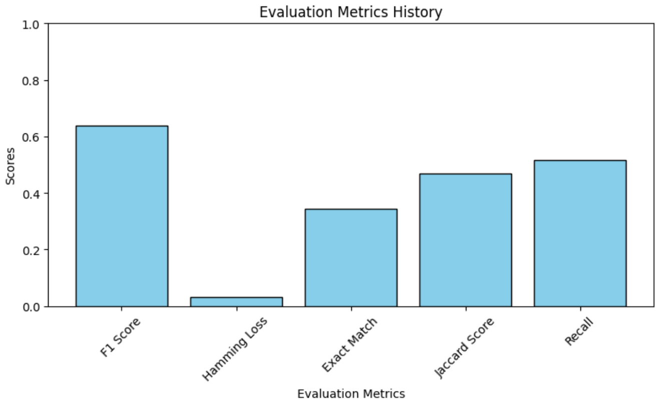
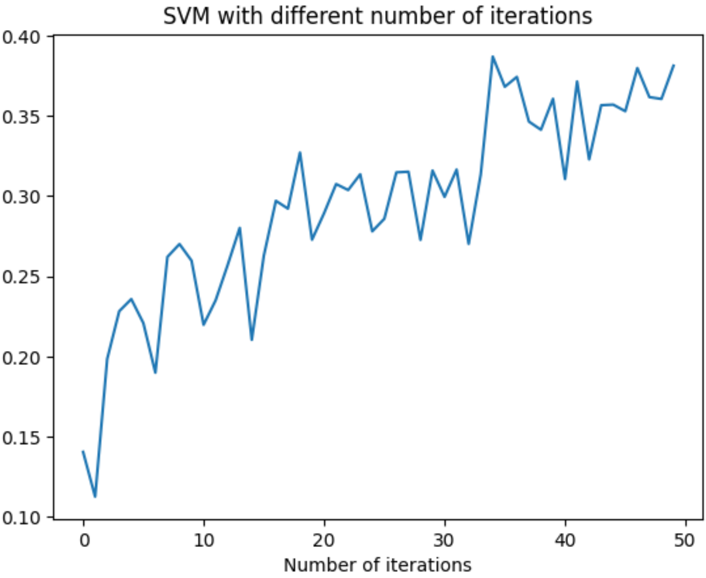


Figure: Evaluation comparison

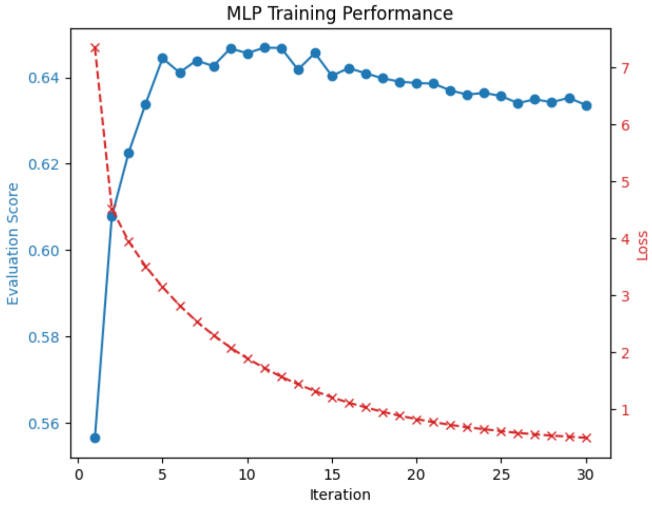


Results - Support Vector Machine



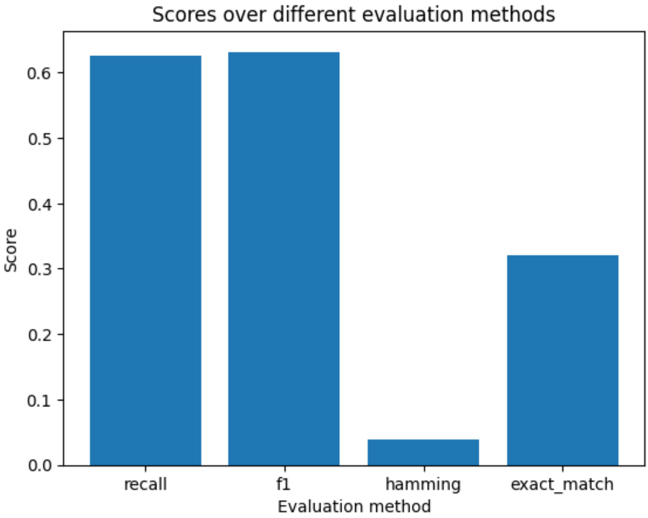
Results - Neural Network

Figure: Multilayer Perceptron



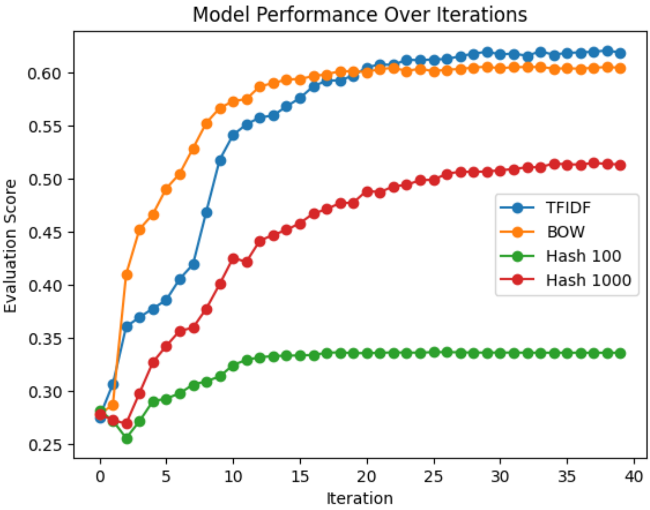
Results - Neural Network

Figure: Different evaluation methods



Input preprocessing

Figure: Logistic Regression, F1-score



Evaluation metrics

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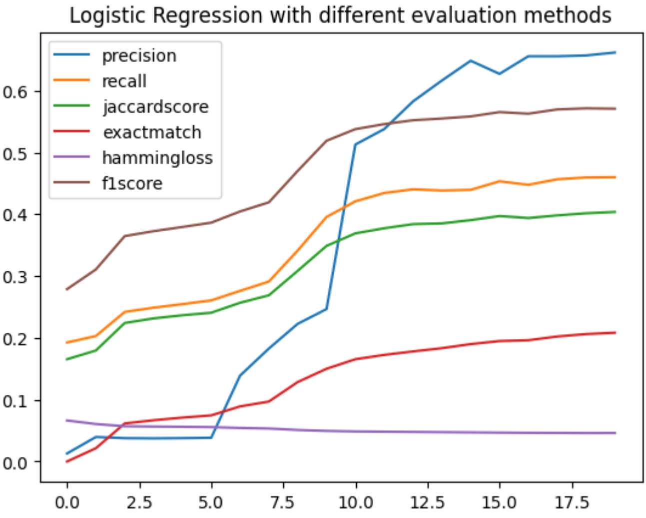
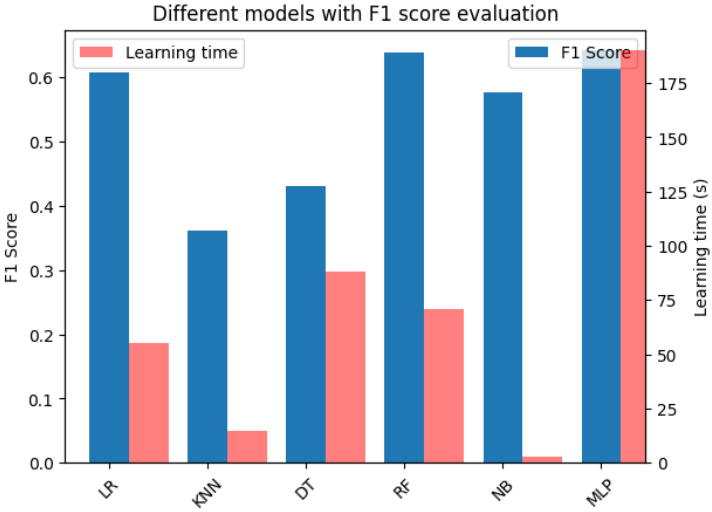


Models Comparison



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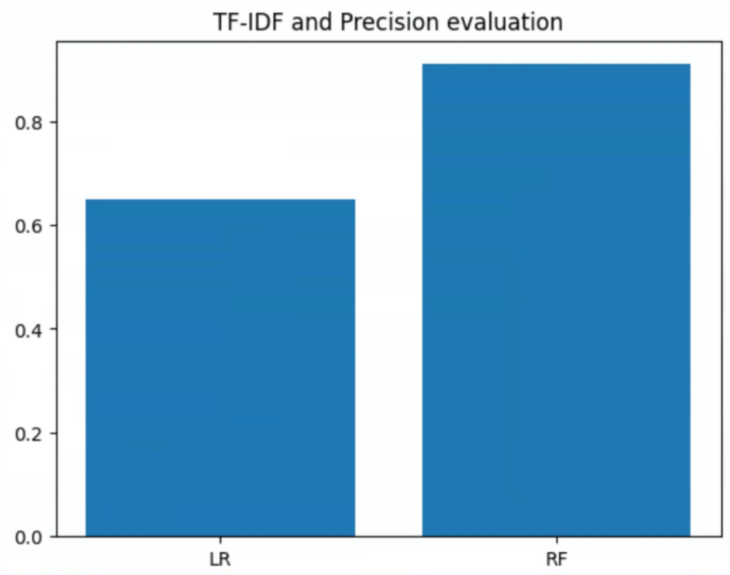

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- **Decision trees** were empirically proven (again) that they are not the best choice
- **SVM** did not perform too bad, nor too good we suspect that, based on how it works, it could **eventually** perform way better (but that would require a lot of time)