

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 occurred 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

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

Data preprocessing

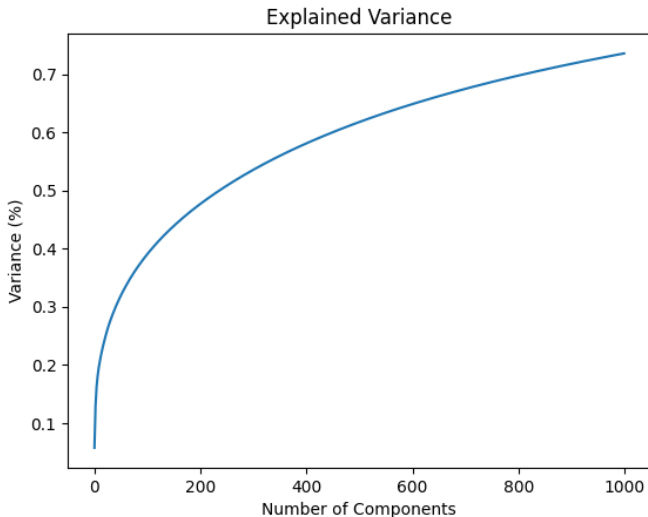
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For input preprocessing we tried:

- Bag of Words
- TF-IDF
- Hashing vectorizer

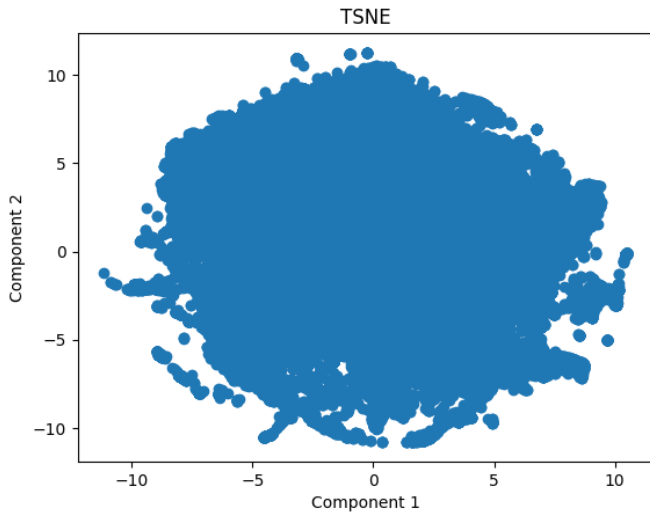
We decided to check if there are some patterns in the data that we can use to improve our model.

Figure: PCA analysis on Bag of Words



Data preprocessing

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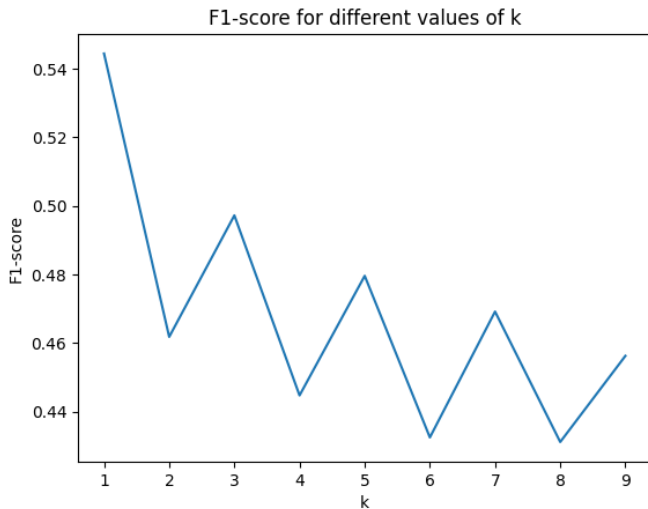
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- Intersection over union score
this evaluation does not treat each label separately, but check ratio of intersection and union

Results - KNN

Figure: KNN comparison with different number of neighbors



Results - Decision Tree

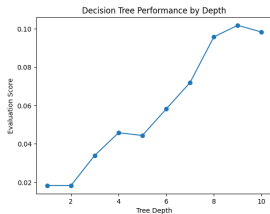


Figure: Exact match

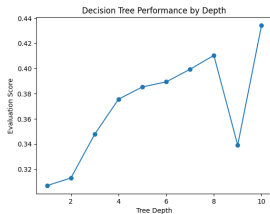


Figure: F1-score



Figure: Hamming loss

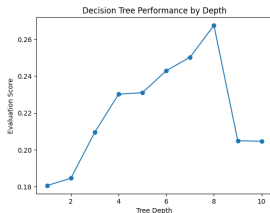


Figure: Intersection

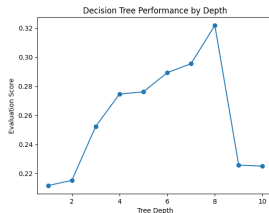
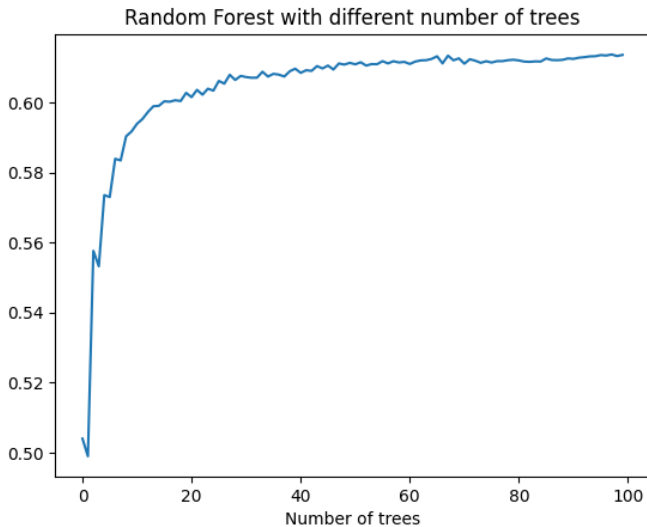


Figure: Recall

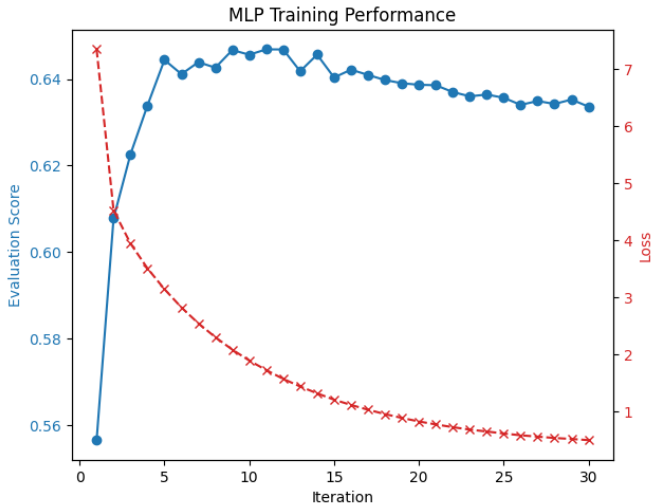
Results - Random Forest

Figure: Comparison with different number of trees



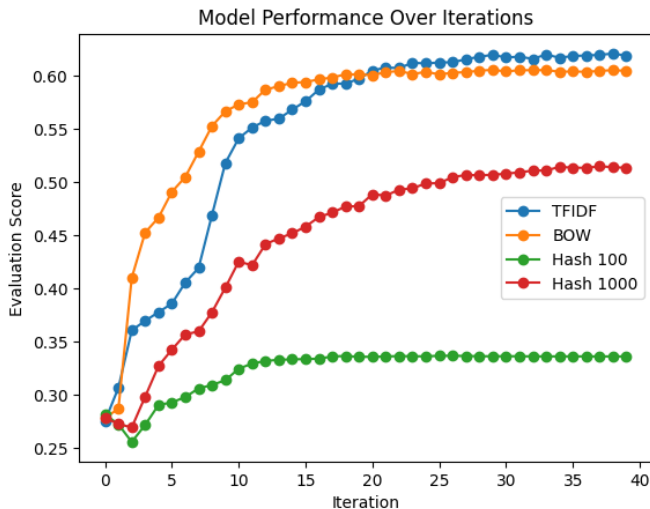
Results - Neural Network

Figure: Multilayer Perceptron



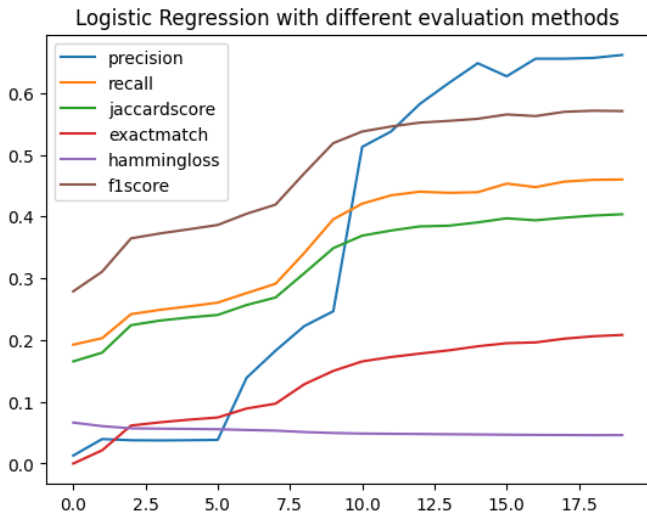
Logistic Regression

Figure: Different input preprocessing methods



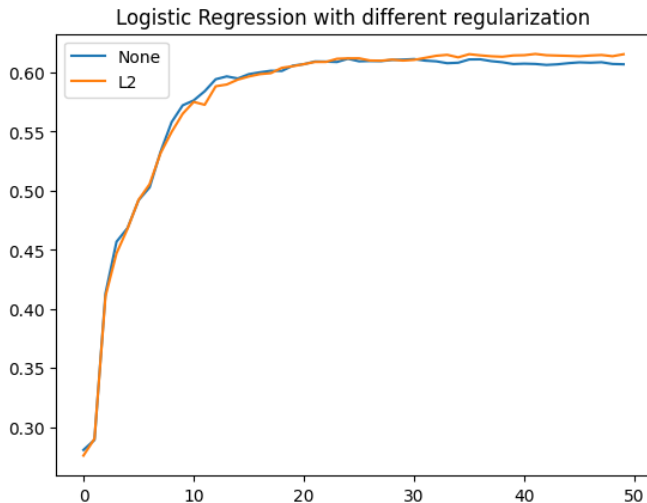
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Figure: Different evaluation metrics



Logistic Regression

Figure: Different regularization methods



Conclusions

- yes

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- no