Games classifier

Team name

Members: Julia Cygan, Borys Adamiak, Patryk Flama
Supervisor: Marek Adamczyk

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

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.

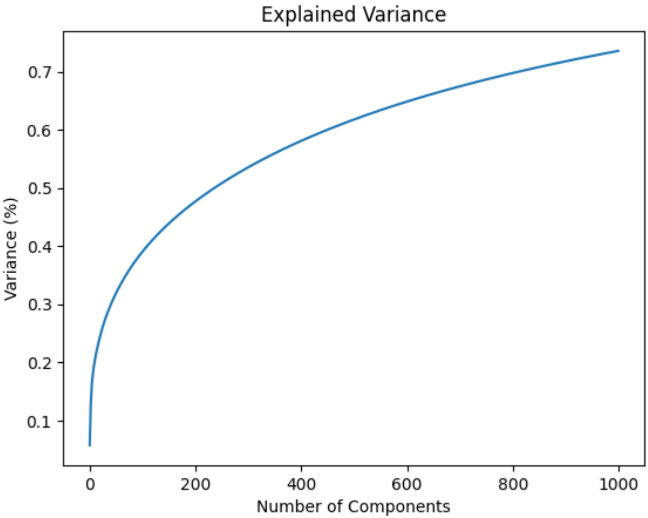
For input preprocessing we tried:

- 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.

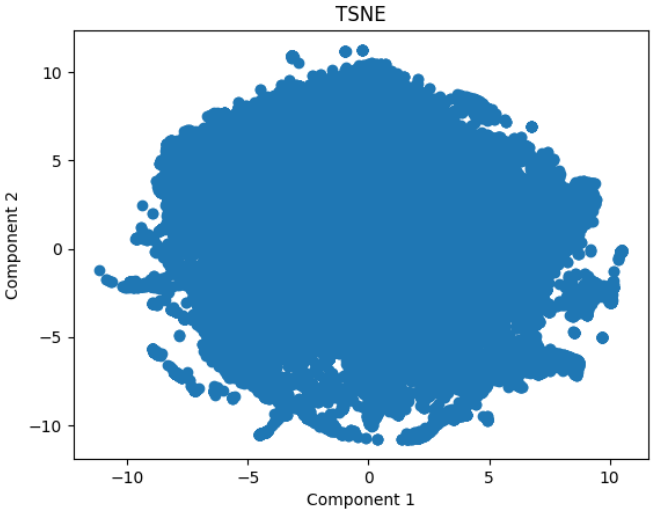
Data preprocessing

Figure: PCA analysis on Bag of Words



Data preprocessing

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



Models

- KNN
  Seemed to be a good baseline for our project, since its so simple

Models

- KNN
  Seemed to be a good baseline for our project, since its so simple
- Naive Bayes
  Also quite simple in practice, but a bit more interesting in the context of text classification

Models

- KNN
  Seemed to be a good baseline for our project, since its so simple
- Naive Bayes
  Also quite simple in practice, but a bit more interesting in the context of text classification
- Logistic Regression
  Classical approach

Models

- KNN
  Seemed to be a good baseline for our project, since its so simple
- Naive Bayes
  Also quite simple in practice, but a bit more interesting in the context of text classification
- Logistic Regression
  Classical approach
- Decision Trees
  Do not have the best reputation, so we wanted to check how they perform

Models

- KNN
  Seemed to be a good baseline for our project, since its so simple
- Naive Bayes
  Also quite simple in practice, but a bit more interesting in the context of text classification
- Logistic Regression
  Classical approach
- Decision Trees
  Do not have the best reputation, so we wanted to check how they perform
- Random Forest
  Natural extension of Decision Trees

Models

- KNN
  Seemed to be a good baseline for our project, since its so simple
- Naive Bayes
  Also quite simple in practice, but a bit more interesting in the context of text classification
- Logistic Regression
  Classical approach
- Decision Trees
  Do not have the best reputation, so we wanted to check how they perform
- Random Forest
  Natural extension of Decision Trees
- Simple perceptron-based neural network
  It is a neural network, thus we could not skip it

Models

- KNN
  Seemed to be a good baseline for our project, since its so simple
- Naive Bayes
  Also quite simple in practice, but a bit more interesting in the context of text classification
- Logistic Regression
  Classical approach
- Decision Trees
  Do not have the best reputation, so we wanted to check how they perform
- Random Forest
  Natural extension of Decision Trees
- Simple perceptron-based neural network
  It is a neural network, thus we could not skip it
- Support Vector Machine
  Interesting concept

Evaluation

Since choosing proper evaluation function is a major part of our project (because we have specific multi-label classification) we decided to use following metrics:

Evaluation

Since choosing proper evaluation function is a major part of our project (because we have specific multi-label classification) we decided to use following metrics:

- Exact match
  typical approach for one label - the prediction must be exact

Evaluation

Since choosing proper evaluation function is a major part of our project (because we have specific multi-label classification) we decided to use following metrics:

- Exact match
  typical approach for one label - the prediction must be exact
- Precision *TP/(TP+FP)*
  we focus on minimizing FP

Evaluation

Since choosing proper evaluation function is a major part of our project (because we have specific multi-label classification) we decided to use following metrics:

- Exact match
  typical approach for one label - the prediction must be exact
- Precision *TP/(TP+FP)*
  we focus on minimizing FP
- Recall *TP/(TP+FN)*
  we focus on minimizing FN

Evaluation

Since choosing proper evaluation function is a major part of our project (because we have specific multi-label classification) we decided to use following metrics:

- Exact match
  typical approach for one label - the prediction must be exact
- Precision *TP/(TP+FP)*
  we focus on minimizing FP
- Recall *TP/(TP+FN)*
  we focus on minimizing FN
- F1-score *(2 * precision * recall) / (precision + recall)*
  combines precision and recall

Evaluation

Since choosing proper evaluation function is a major part of our project (because we have specific multi-label classification) we decided to use following metrics:

- Exact match
  typical approach for one label - the prediction must be exact
- Precision *TP/(TP+FP)*
  we focus on minimizing FP
- Recall *TP/(TP+FN)*
  we focus on minimizing FN
- F1-score *(2 * precision * recall) / (precision + recall)*
  combines precision and recall
- Hammming loss
  it is a loss function, which calculates fraction of wrong labels

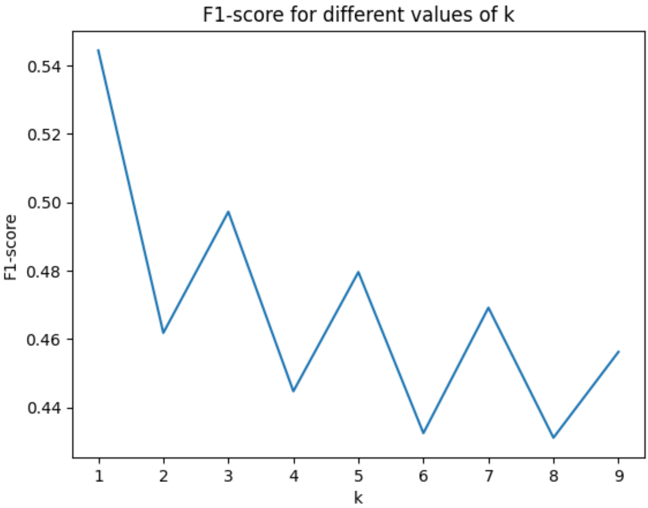
Evaluation

Since choosing proper evaluation function is a major part of our project (because we have specific multi-label classification) we decided to use following metrics:

- Exact match
  typical approach for one label - the prediction must be exact
- Precision *TP/(TP+FP)*
  we focus on minimizing FP
- Recall *TP/(TP+FN)*
  we focus on minimizing FN
- F1-score *(2 * precision * recall) / (precision + recall)*
  combines precision and recall
- Hammming loss
  it is a loss function, which calculates fraction of wrong labels
- 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

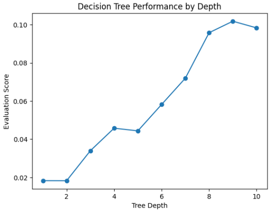


Figure: Exact match

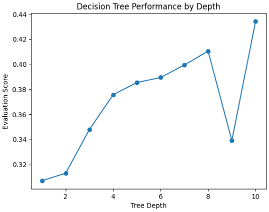


Figure: F1-score

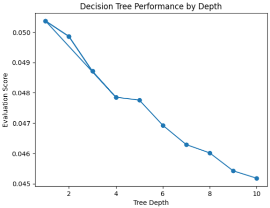


Figure: Hamming loss

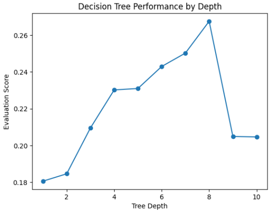


Figure: Intersection

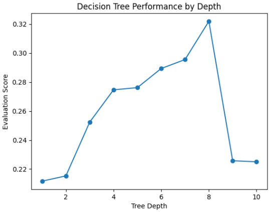


Figure: Recall