

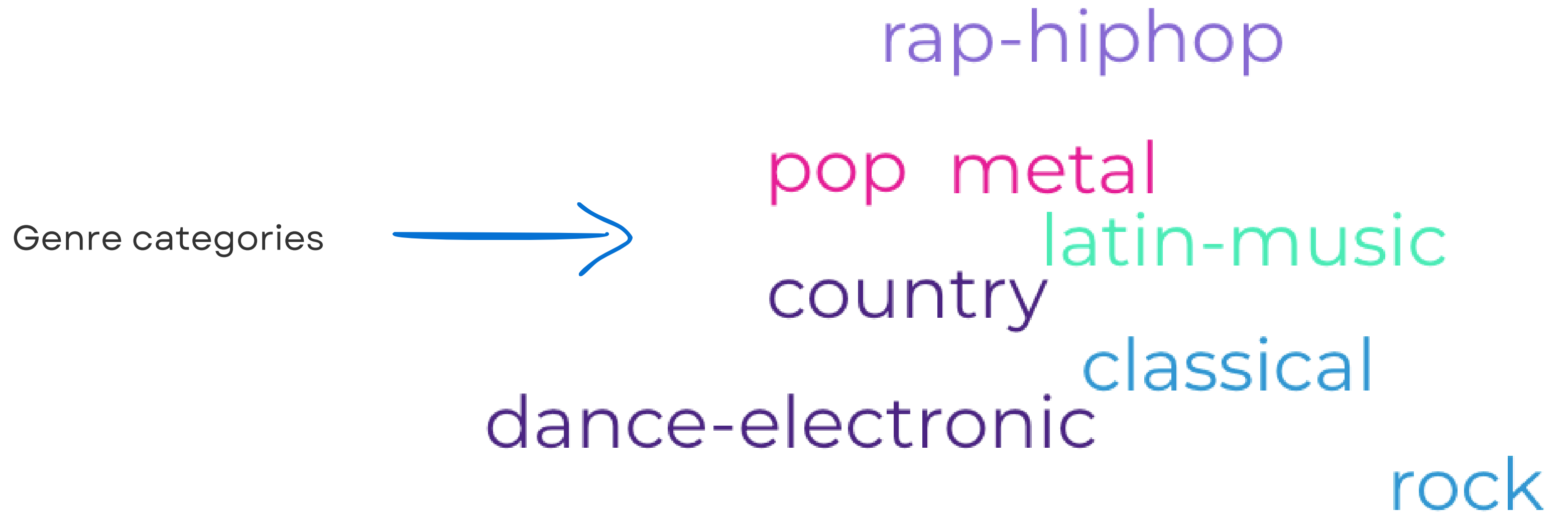
Analyzing Customer Reviews for Music Genre Classification

Customer Reviews, Sentiment, and Semantic Analysis for Music Genre Classification

Enrico Gioia

Objective

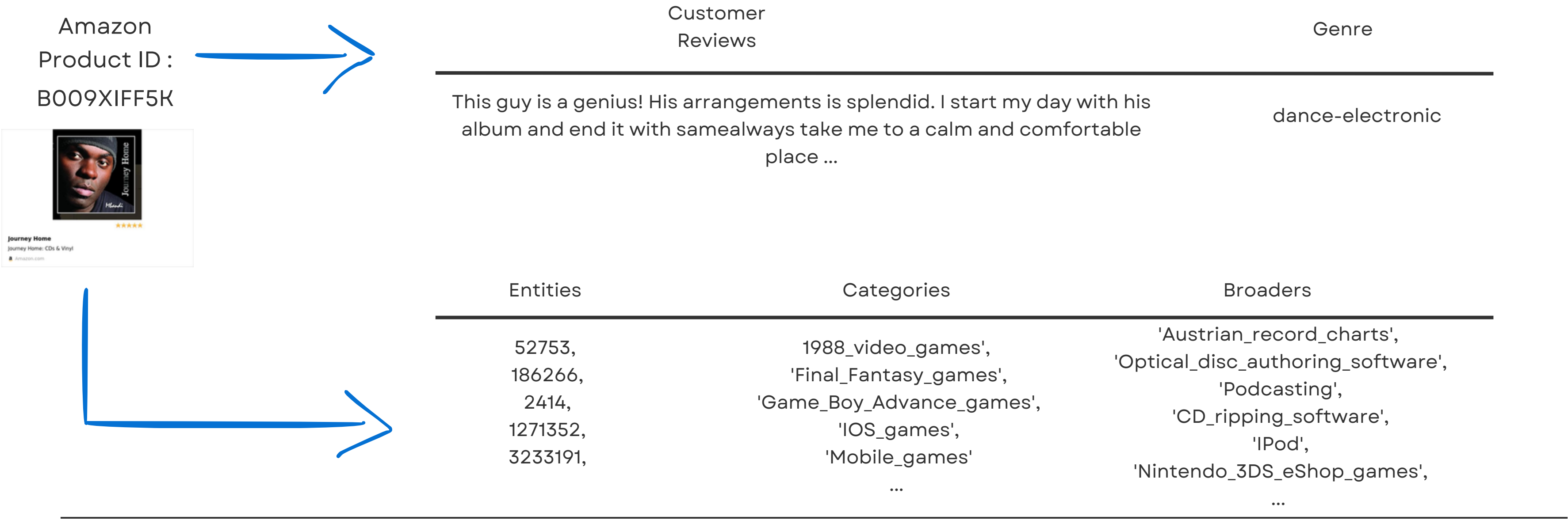
This project aims to classify music album reviews into one of eight genres using a combination of Bag-of-Words (BoW), sentiment features, and semantic features



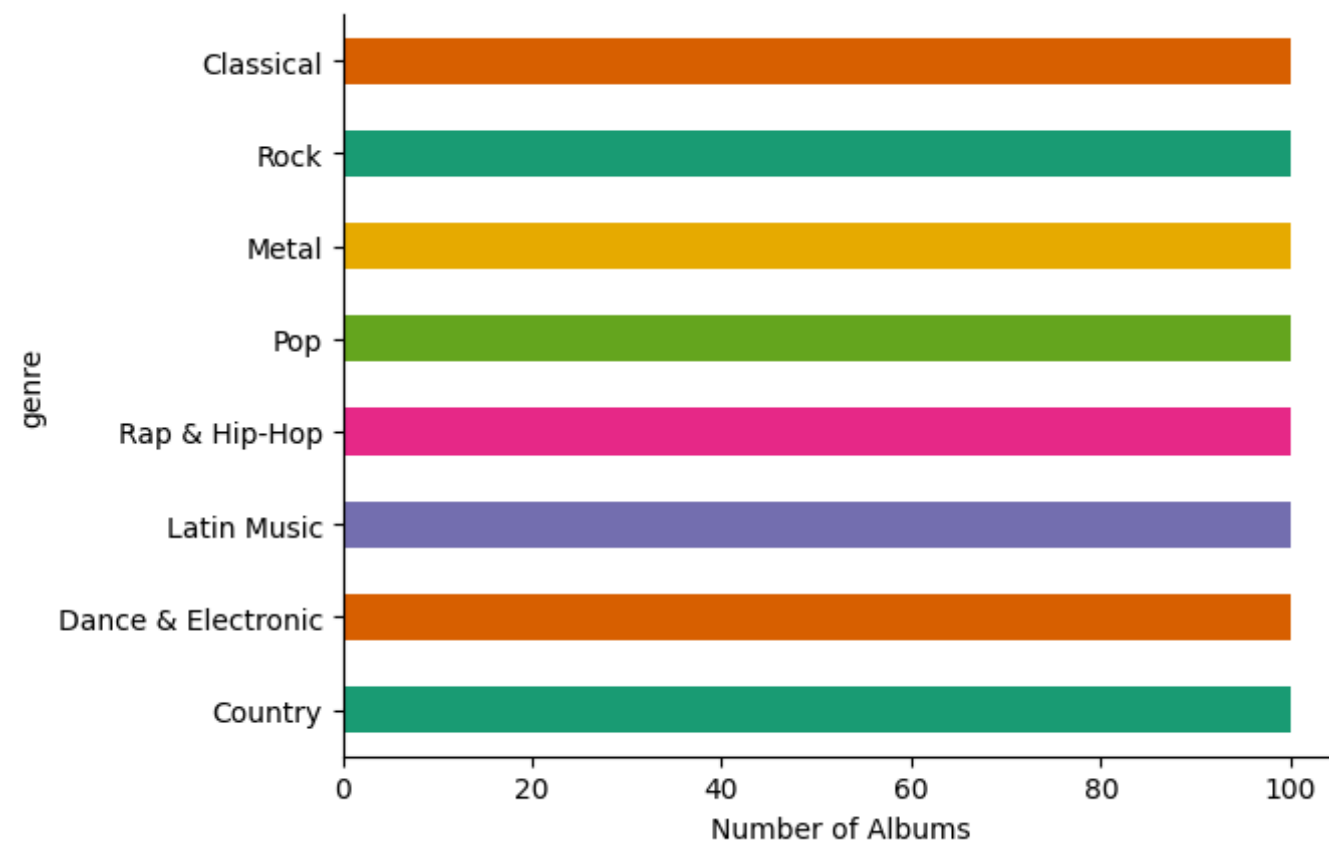
Datasets Overview

Two datasets are used

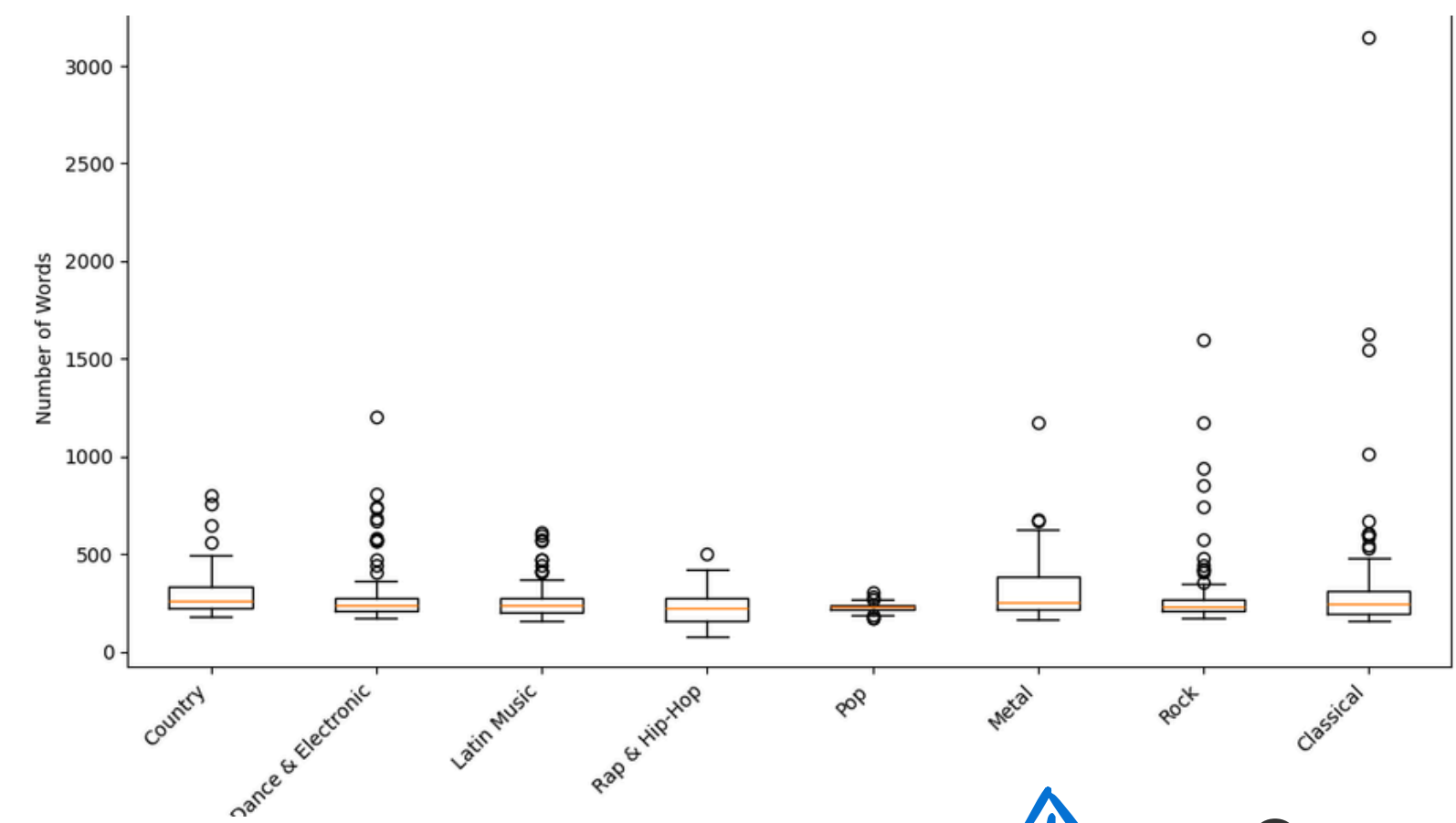
- Album Reviews : textual reviews of music albums, each associated with a specific genre
- Album Semantics : semantic features associated to the music albums



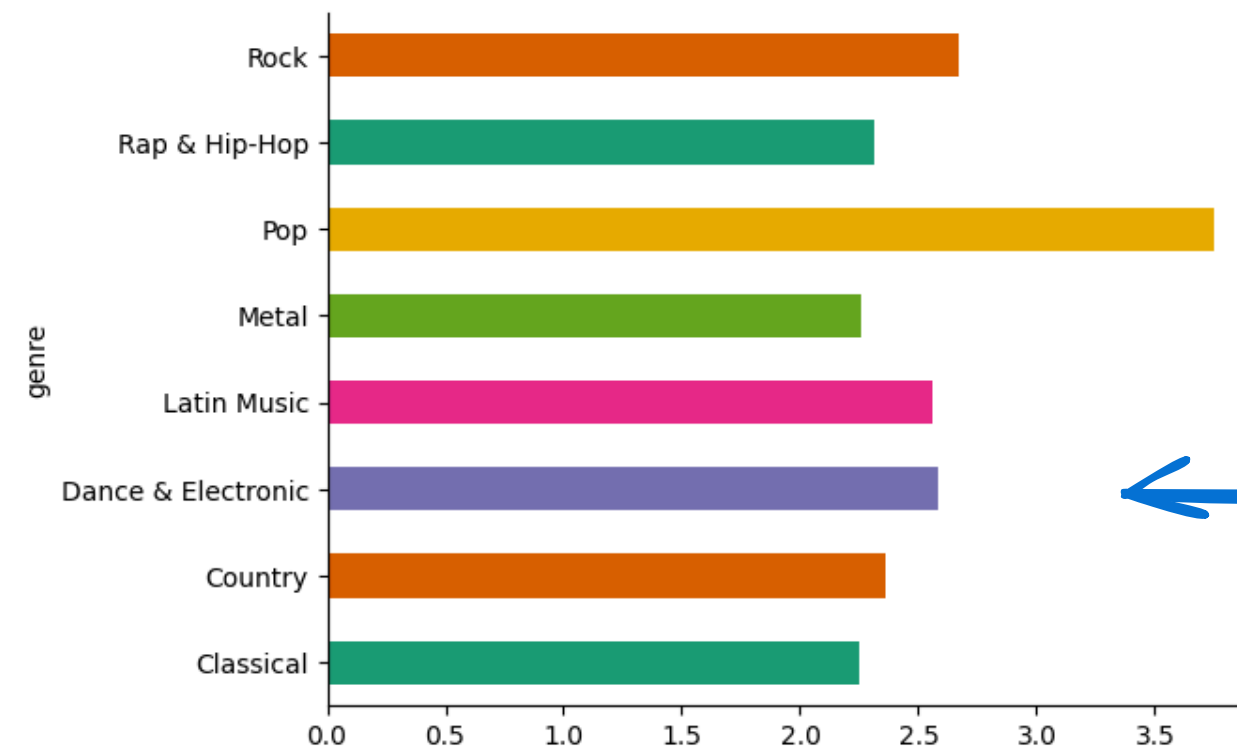
Datasets Overview : Album Reviews



The Album Reviews dataset contains 100 albums per genre class



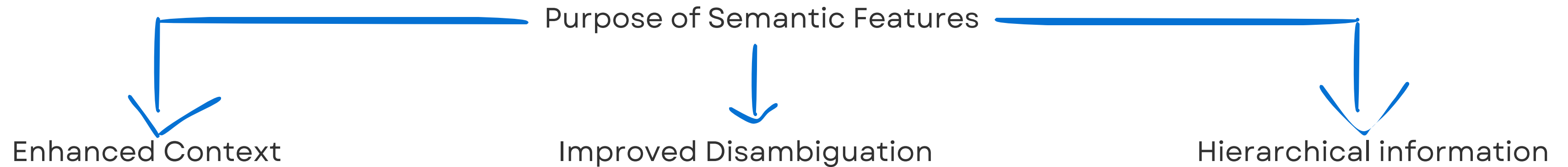
On average reviews have between 200 and 500 words



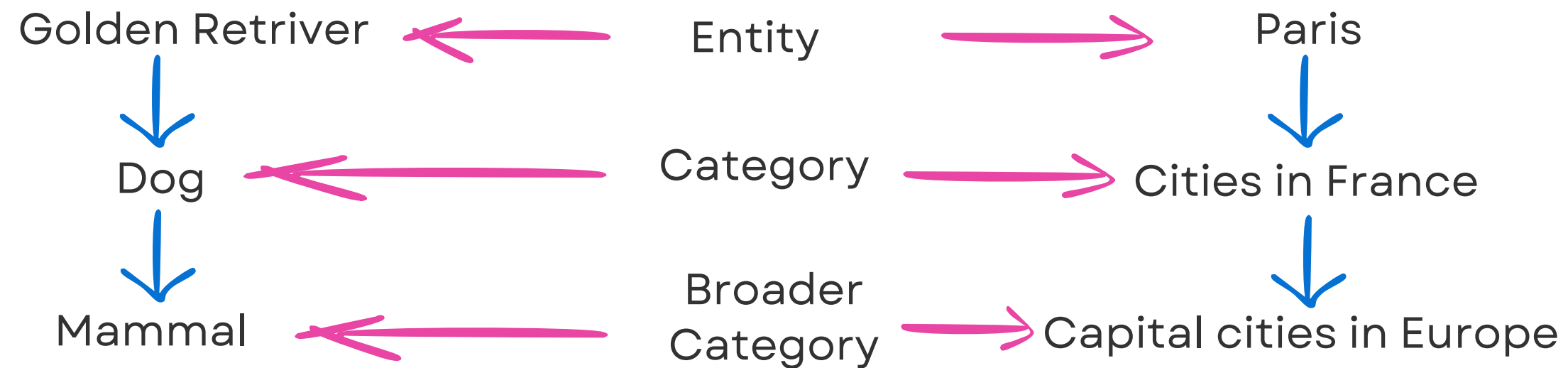
On average there are more than 2 reviews per genre

Datasets Overview : Album Semantics

Semantic Features are attributes providing additional context to music albums, aiding in improved disambiguation

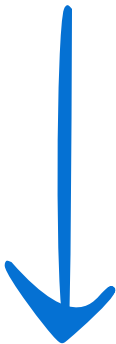


Example of semantic features



Datasets Overview : Album Semantics

In the specific case of the Album Semantics Dataset



Amazon
Product ID :
B009XIFF5K

Entities

52753,
186266,
2414,
1271352,
3233191,



Wikipedia
pages ID

Categories

1988_video_games',
'Final_Fantasy_games',
'Game_Boy_Advance_games',
'IOS_games',
'Mobile_games'

...



Wikipedia
categories

Broaders

'Austrian_record_charts',
'Optical_disc_authoring_software',
'Podcasting',
'CD_ripping_software',
'iPod',
'Nintendo_3DS_eShop_games',

...



Wikipedia
broader
categories

Methodology

The classification is evaluated using different combinations of feature sets :

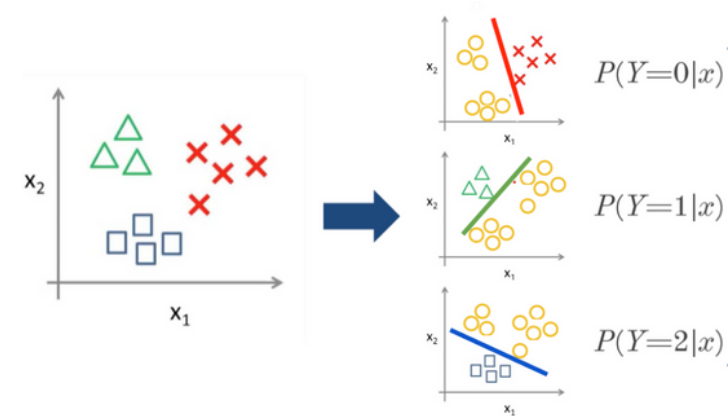
Bag-of-Word(BoW), sentiment, and semantic

Bag-of-Word (BoW)	BoW + Semantics	BoW + Sentiments	BoW + Semantic + Sentiments
Genre Classification based on standard vectorization of review texts	Genre Classification based on standard vectorization of review texts enriched with semantic features	Genre Classification based on standard vectorization of review texts enriched with sentimental analysis scores of review texts	Genre Classification based on standard vectorization of review texts enriched with semantic features and sentimental analysis scores of review texts

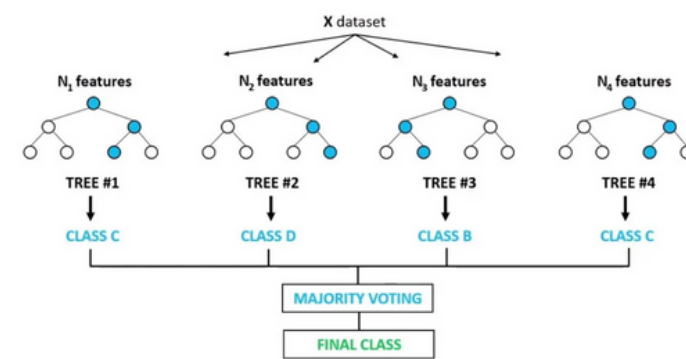
Classification Models

The following models were trained and evaluated using different combinations of feature sets

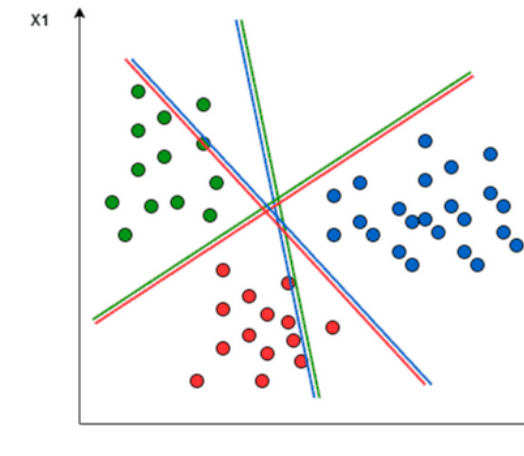
Logistic
Regression



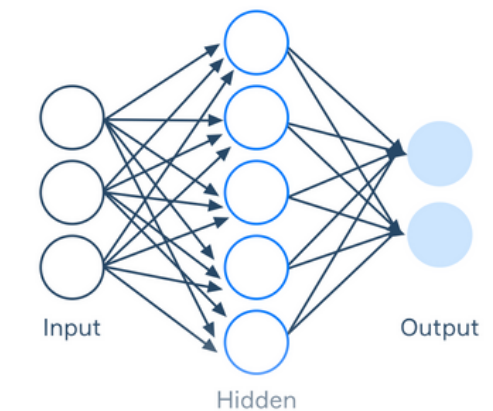
Random
Forest



Linear SVM

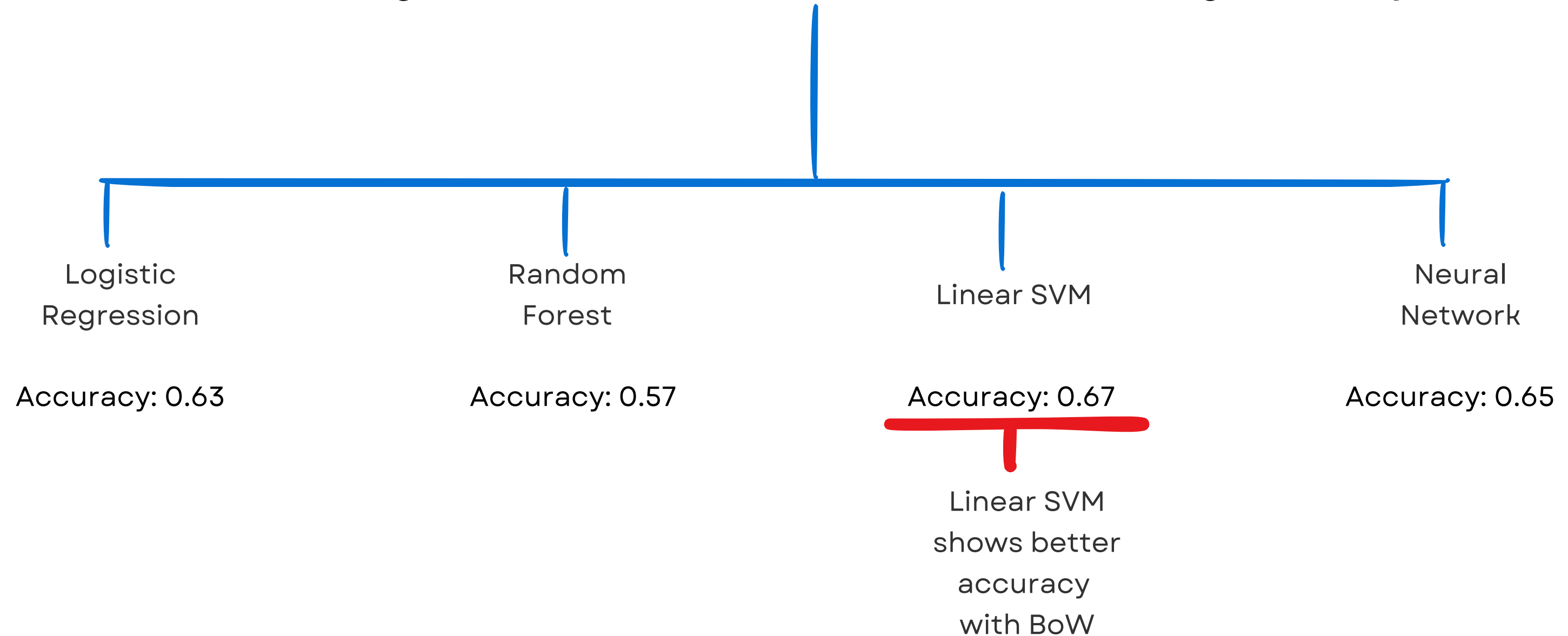


Neural
Network



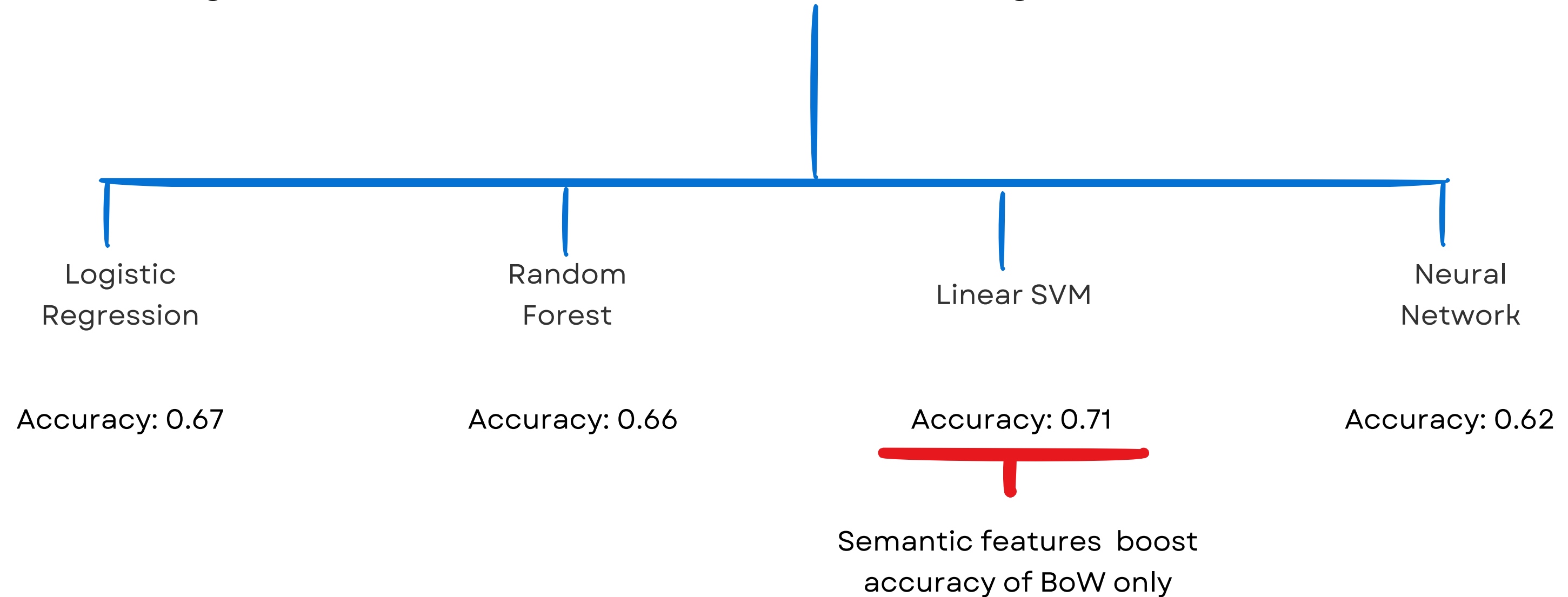
Experiment: BoW

The following models were trained and evaluated using BoW only



Experiment: BoW + Semantics

The following models were trained and evaluated using BoW and Semantics features



Sentiment Features

Two approaches were used to extract sentiment features:

```
graph LR; A[Two approaches were used to extract sentiment features:] --- B[NRCLex: Extracted emotional scores (anger, joy, sadness, etc.) from the BoW]; A --- C[Custom Features: Designed metrics like eStrength, eRatio, and posToAllRatio to evaluate sentiment intensity, the ratio of emotional words to total words, and the positivity balance]; C --> D[Advantages];
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NRCLex: Extracted emotional scores (anger, joy, sadness, etc.) from the BoW

Extracted anger, joy, sadness, and other emotional scores using NRCLex from reviews

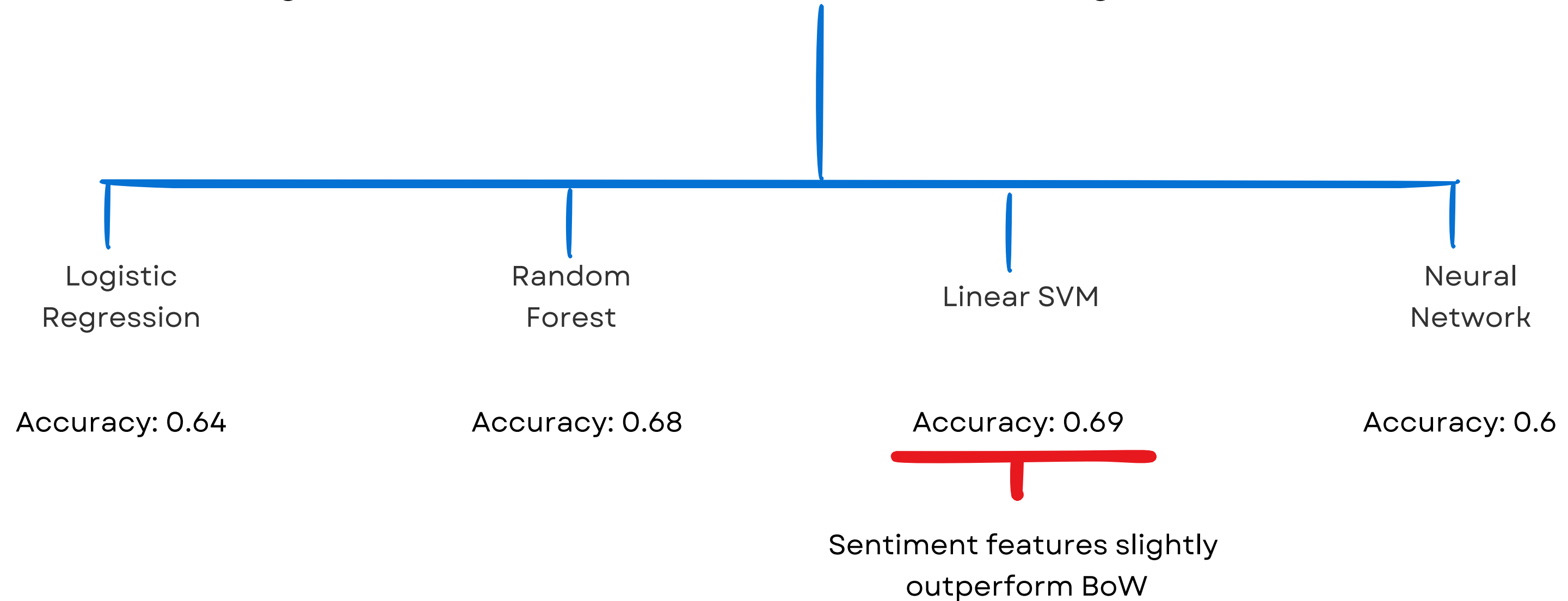
Custom Features: Designed metrics like eStrength, eRatio, and posToAllRatio to evaluate sentiment intensity, the ratio of emotional words to total words, and the positivity balance

Advantages

- Produces domain-specific and interpretable features
- Reduces dimensionality compared to NRCLex
- Introduces new metrics that are more discriminative than raw emotion counts

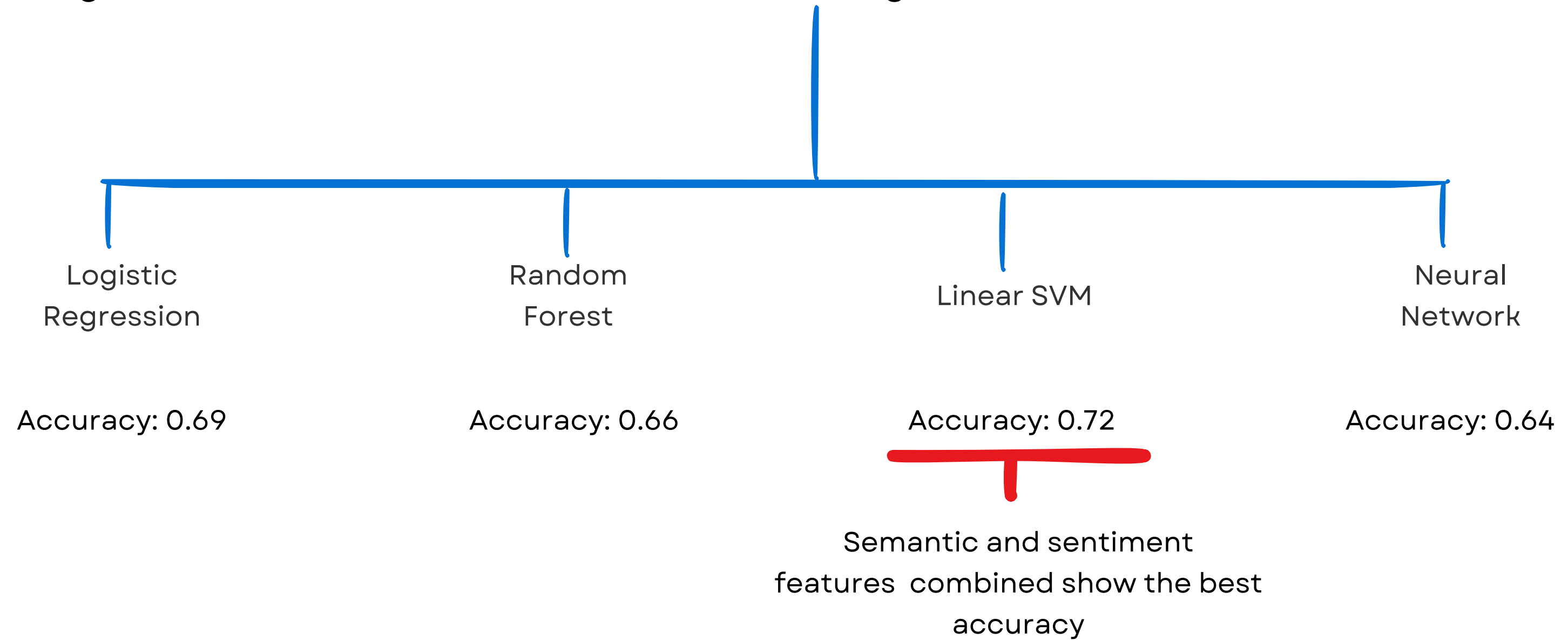
Experiment: BoW + Sentiments

The following models were trained and evaluated using BoW and Sentiments



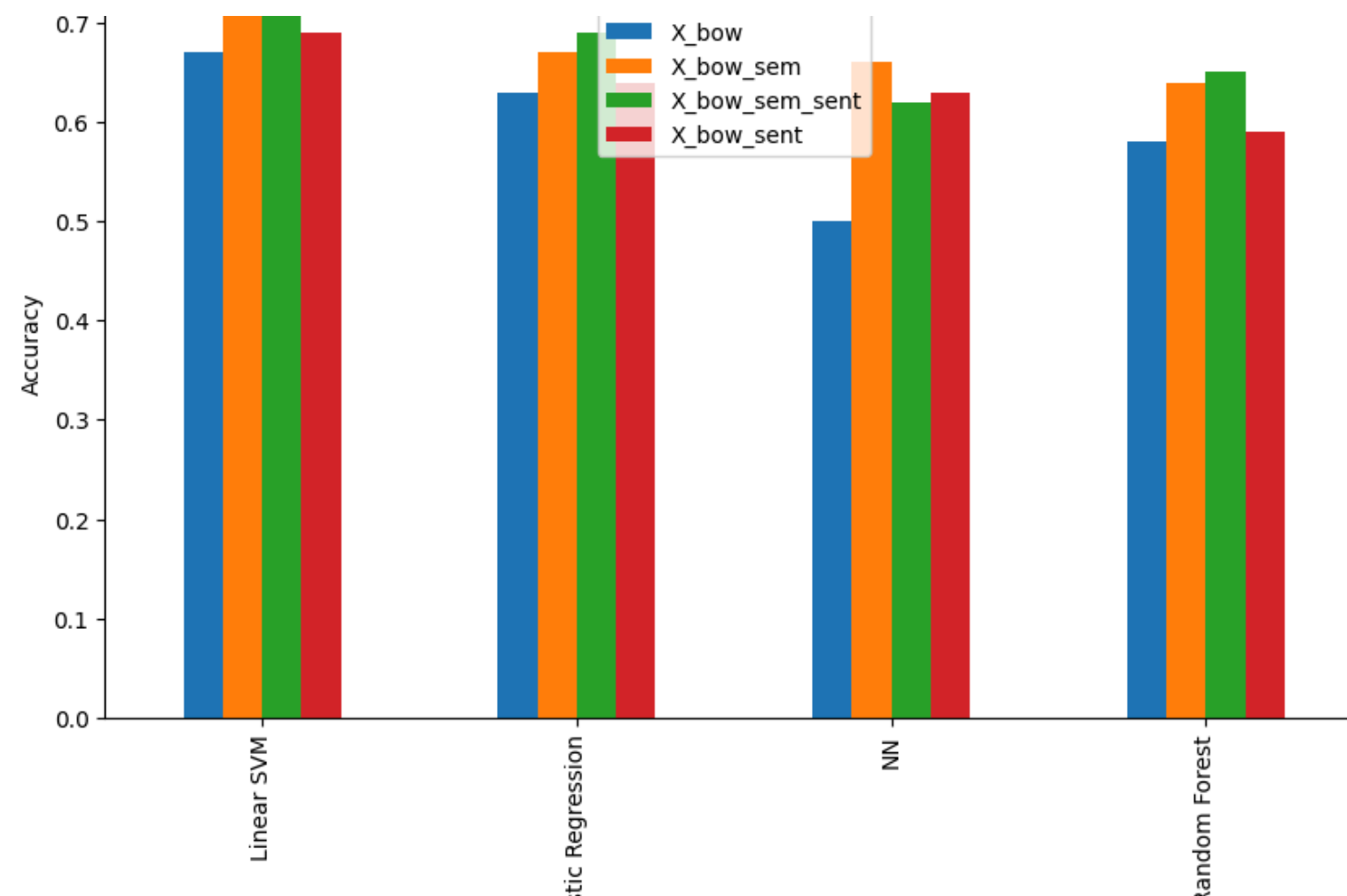
Experiment: BoW + Sem + Sent

The following models were trained and evaluated using BoW, Semantics and Sentiments features



Results Visualization

	X_bow	X_bow_sem	X_bow_sem_sent	X_bow_sent
Linear SVM	0.67	0.71	0.72	0.69
Logistic Regression	0.63	0.67	0.69	0.64
NN	0.50	0.66	0.62	0.63
Random Forest	0.58	0.64	0.65	0.59



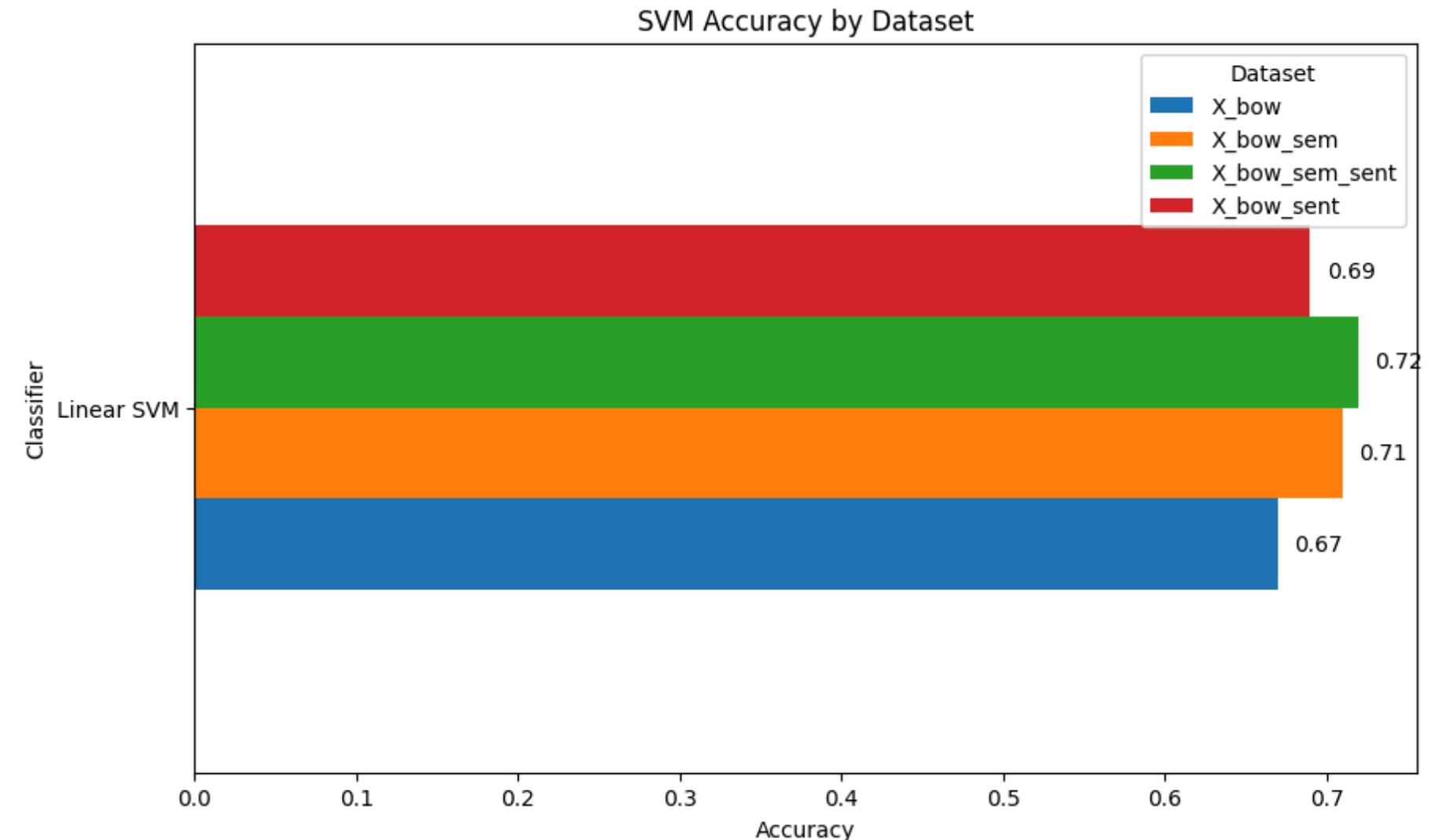
- The Bag-of-Words (BoW) approach yielded a moderate performance, with the Linear SVM model achieving the highest accuracy of 67%. This validates BoW as a reliable baseline for text classification tasks
- Incorporating semantic features into BoW improved classification accuracy across most models. The Linear SVM again performed best, with an accuracy increase from 67% to 71%
- Adding sentiment features provided a slight performance boost compared to BoW alone
- Combining all feature sets yielded the best performance. The Linear SVM achieved the highest accuracy of 72%, illustrating the synergy between semantic and sentiment features when integrated with BoW

Conclusions

This study demonstrates that enriching traditional text classification techniques with semantic and sentiment analysis enhances the predictive accuracy of music genre classification.

Semantic features improve the contextual understanding of text, while sentiment analysis captures emotional tones relevant to genre characteristics.

The results emphasize the importance of a multi-faceted approach in text-based classification tasks.



Conclusions and Future Work

This study demonstrates that enriching traditional text classification techniques with semantic and sentiment analysis enhances the predictive accuracy of music genre classification

Semantic features improve the contextual understanding of text, while sentiment analysis captures emotional tones relevant to genre characteristics

The results emphasize the importance of a multi-faceted approach in text-based classification tasks

Future Work

Advanced Feature Engineering: Exploring deep learning-based embeddings like BERT or GPT to capture deeper semantic and syntactic relationships

Cross-Domain Applications: Applying the methodology to other domains, such as movie or book reviews, to validate its adaptability and scalability

Thanks!