Song Lyrics Genre Classification

Project Group 18

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Overview

Introduction: Importance of Song Classification

Context

- **Growth**: Exponential increase in song availability on the web.
- **Popularity**: Rise of music streaming platforms.

Significance

- **User Impact**: Essential for enhancing user experience through effective music categorization and recommendation.
- **Engagement**: Classification influences user satisfaction and platform engagement.

The Problem of Genre Classification

Problem

- Songs often *don't fit* into a **single** genre
- **Manual** classification is impractical and subjective

Need

- **Automation**: Necessity for automated music classification in vast and expanding music collections.

Lyrics-Based Approach and Study Objective

Traditionally Approach

Genre classification has relied on various features extracted from music audio signals such as

- melody
- harmony
- rhythm
- timbre

Lyrics-Based Approach

- Song lyrics provide thematic and stylistic information
- Analyzing lyrics with advanced NLP techniques

Study Objective

- Explore genre classification based on lyrics
- Utilize pre-trained language models

Prior Work

Neural Methods

- Costa et al. [1]: Compared CNNs and SVMs using spectrograms.
- Jeong and Lee [2]: Used temporal features in audio with a deep neural network.
- Bahuleyan [3]: Success of combining convolutional and hand-crafted features in ensembles.

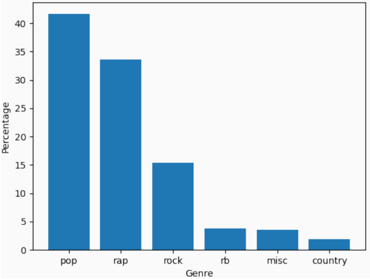
Lyrics-Based Classification

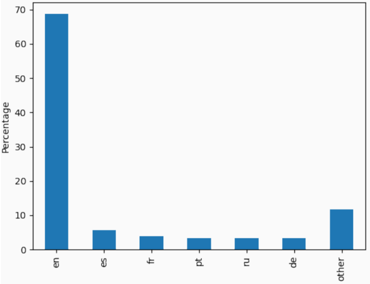
- Mayer et al. [4]: Evaluated models on textual features from song lyrics.
- Lima et al. [5]: Proposed BILSTM for Brazilian song lyrics.
- Tsaptsinos [6]: Used hierarchical attention networks.
- Boonyanit et al. [7]: Developed GloVe embeddings for LSTM models, achieving an accuracy of 68%

Pre-Trained Language Models

- Akalp et al. [8]: Investigated BERT and DistilBERT for genre classification.

Dataset





- Genius Song Lyrics Dataset from Kaggle
- Contains song lyrics up to 2022
- Information includes:
  - title
  - artist
  - year
  - genre
  - views
  - etc...

Data Preprocessing

Steps

1. **Remove Incomplete Entries:** Eliminated entries with 'None' values.
2. **Exclude Non-Musical Pieces:** Removed `misc` tagged entries.
3. **English Texts Only:** Focused on English lyrics.
4. **Retain Popular Tracks:** Kept tracks with over 1,000 views for reliability.
5. **Balance by Tag Attribute:** Subsampled to balance tags and avoid genre overrepresentation.
6. **Remove Metadata:** Content removed in square brackets.

Result

A tag-balanced dataset of 70,178 entries.

Models Overview

We focus on the **performance** of Baseline models, RNNs, and pre-trained language models under **partial** and **complete** fine-tuning, comparing F1 score, precision, and recall

Baseline Models

Feedforward neural networks with tokenization and FastText embeddings

Recurrent Neural Models

RNNs with GloVe embeddings

Pre-trained Models

DistilRoBERTa, DistilGPT2

Baseline Model

Model

Feedforward Neural Network

Model Architecture

- **Hidden Layer:** Single layer with 300 units.
- **Batch Normalization:** Utilizes ReLU activation function.

Preprocessing Steps

1. **Tokenization:** Using NLTK word tokenizer.
2. **Non-Alphabetic Tokens Removal:** Eliminates tokens without alphabetic characters.
3. **Punctuation Removal:** Removes all punctuation.
4. **Stopwords Removal:** Excludes common stopwords.
5. **Conversion to Lowercase:** Converts all text to lowercase.
6. **Embedding Calculation:** Computes 300-dimensional FastText embeddings.
7. **Vector Averaging:** Takes the mean of these embedding vectors.

Pre-trained Models

Recurrent Neural Models

- **Approach**:
  - Uses Recurrent Neural Networks to scan lyrics.
  - Last token's context used as song embedding for linear classifier.
- **Embedding**: 300-dimensional token embeddings with GloVe.
- **Recurrent Layers**: Based on GRU units.
- **Context Length**: Limited to 150 tokens due to parallelization issues.

Pretrained Language Models

DistilRoBERTa:

- *Discriminative* model with 82.8M parameters.
- Pretrained with bidirectional context.

DistilGPT2:

- *Generative* model with 88.2M parameters.
- Causally pretrained model.

Experiments

We began training and evaluating the model to maximize accuracy on new data sets.

Training Process

- **Epochs**: Up to 1000, with early stopping based on validation loss.
- **Optimization**: Cross entropy loss and Adam optimizer.
- **Dataset Split**: 60% training, 20% validation, 20% testing.

Model Selection

- **Validation**: Use of hold-out validation set for selection.
- **Criteria**: Best model based on macro F1 score.
- **Retraining**: Final retraining on combined training and validation set.

Additional Details

RNN and Pretrained Models

- Use Optuna for hyperparameter search.
- 3 epochs for both initial and final retraining phases.

Summary of Model Performances

Model	**Fine-Tuning**	**Macro-Averaged F1 Score**	**Best Genres**
Baseline Model	None	0.55	Country, Rap
RNN	None	0.55	-
DistilGPT2	Partial	0.19	-
DistilGPT2	Full	0.66	-
DistilRoBERTa	Partial	0.59	Rap
DistilRoBERTa	Full	0.66	Rap, Country

Error Analysis

Observations

- **Misclassifications**: Frequent errors between similar genres, such as pop and rock.
- **Recognition Issues**: The least well-recognized genre is always pop, highlighting its mixed nature.

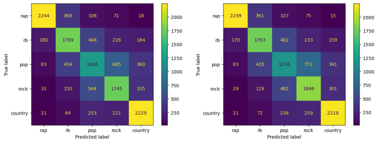


Figure: Left: DistilGPT2 (full), Right: DistilRoBERTa (full)

Insights

- **Confusion Matrices**: Evidence from confusion matrices.
- **Cause**: Blending of stylistic elements in lyrics confuses models.

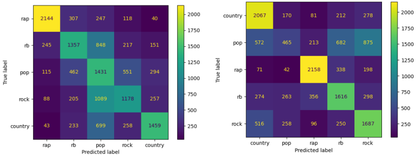


Figure: Left: Baseline model, Right: RNN model

Conclusions

Our Conclusions

- Pre-trained models show good performance in genre classification
- Full fine-tuning significantly improves results
- Achieved notable average F1 score of 0.66 in complete fine-tuning scenarios.

Future Research Directions

1. **Integrate Audio Features**: Enhance genre classification using melody and rhythm.
2. **Model Comparison**: Evaluate trade-offs by comparing distilled models with larger versions.
3. **Enhance Optimization**: Implement advanced regularization and data augmentation.

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