

Emotion detection in song lyrics

Simone Quadrelli (938667)





Introduction



Introduction

O1 Detect emotions and their intensity from song lyrics

O2 Study the correlation between genre and sentiment

O3 Compute personalized playlists

Objectives



Objectives

- OT Detect emotions and their intensity in song lyrics exploiting predictors trained with labelled tweets
- O2 Analyze the correlation between genre and sentiment
- Compute personalized playlists given genre and sentiment

Datasets



Dataset: tweets

O Tweet annotated dataset

O2 Emotions: anger, joy, fear, sadness

O3 Intensity \in [0,1]

Dataset: Song lyrics

Ol Song lyrics

02 Title

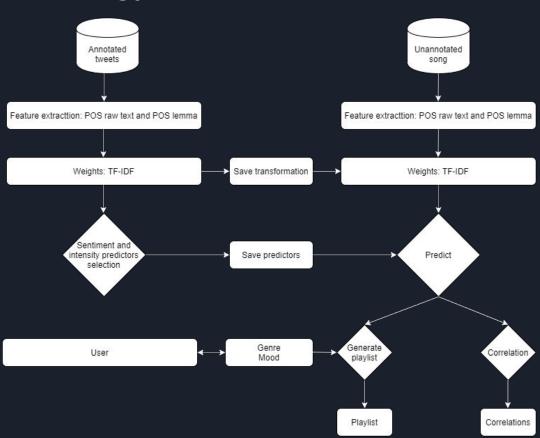
O3 Genre

04 Artist

Methodology



Methodology



Preprocessing and feature extraction

Ol Punctuation removal

O2 Stop words removal

03 Lemmatization

O4 Part of speech (POS) selection of adjectives and nouns for raw text and lemmatized text

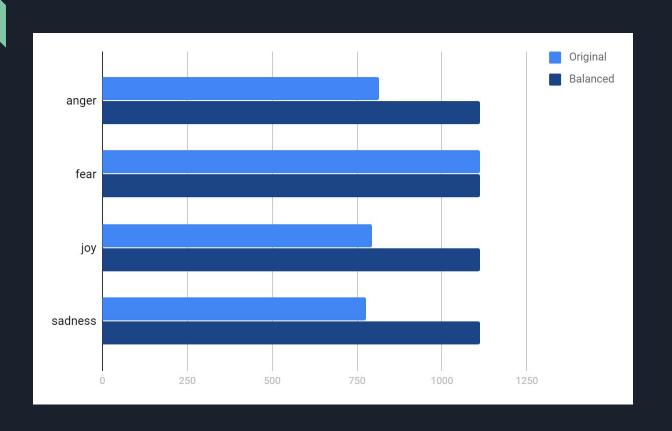
Independence

Spearman's correlation test between intensity and emotions

	sentiment	intensity
sentiment	1.000000	-0.012154
intensity	-0.012154	1.000000

Since sentiment and intensity are uncorrelated it is possible to train two independent predictors

Unbalancedness



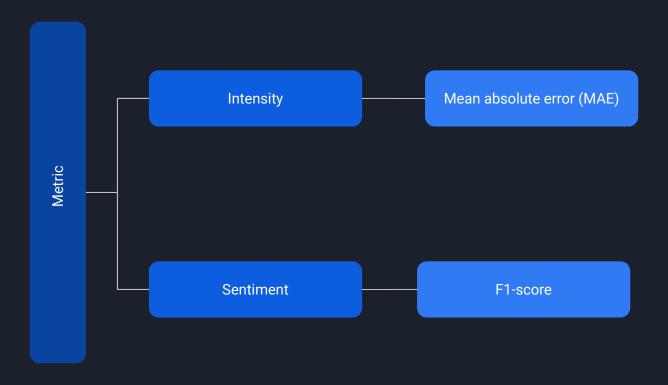
Weighting

OT Term frequency - inverse document frequency (tf-idf)

Assign high weight to very rares word in the corpus which are repeated in a document

O3 Assign low weight to very common words

Metrics



Predictors: sentiment and intensity

O1 K-nearest neighbours

02 Random forests

O3 Support vector machines

Predictors: sentiment

Predictor	Features	F1-score
KNN	POS lemma	0.66
KNN	POS raw	0.61
RF	POS lemma	0.70
RF	POS raw	0.70
SVM	POS lemma	0.87
SVM	POS raw	0.89

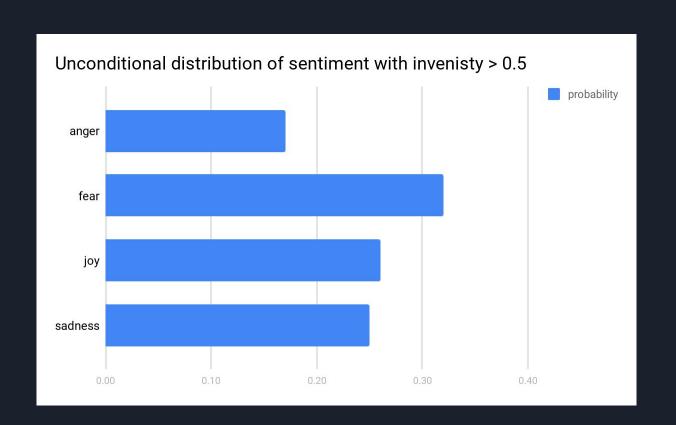
Save the best classifier

Predictors: intensity

Predictor	Features	MAE
KNN	POS lemma	0.14
KNN	POS raw	0.14
RF	POS lemma	0.15
RF	POS raw	0.15
SVM	POS lemma	0.11
SVM	POS raw	0.11

Save the best predictor

Predictions



χ-square test

Test for independence of genre and sentiment

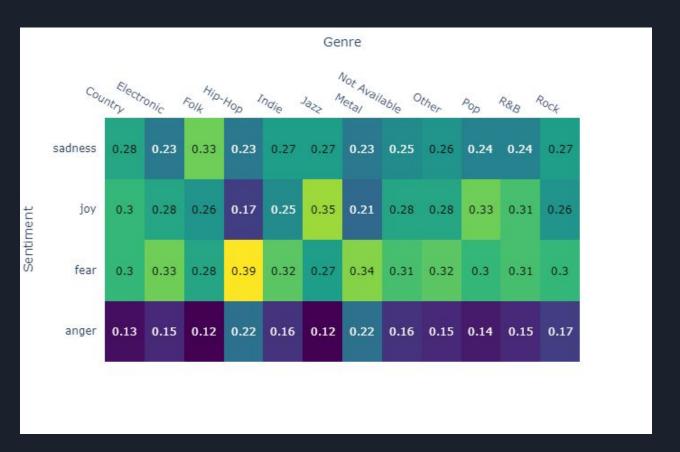
```
Power_divergenceResult(statistic=59236142.0970242, pvalue=0.0)
Power_divergenceResult(statistic=11203428.310288608, pvalue=0.0)
Power_divergenceResult(statistic=869650.506747599, pvalue=0.0)
Power_divergenceResult(statistic=221392022.56083325, pvalue=0.0)
Power_divergenceResult(statistic=2198070.1291956482, pvalue=0.0)
Power_divergenceResult(statistic=12938333.560142726, pvalue=0.0)
Power_divergenceResult(statistic=159398734.2544964, pvalue=0.0)
Power_divergenceResult(statistic=84988573.01230262, pvalue=0.0)
Power_divergenceResult(statistic=4968962.380629653, pvalue=0.0)
Power_divergenceResult(statistic=310096282.6461709, pvalue=0.0)
Power_divergenceResult(statistic=2732474.551130772, pvalue=0.0)
Power_divergenceResult(statistic=2563877910.467037, pvalue=0.0)
```

Genre and sentiments are correlated

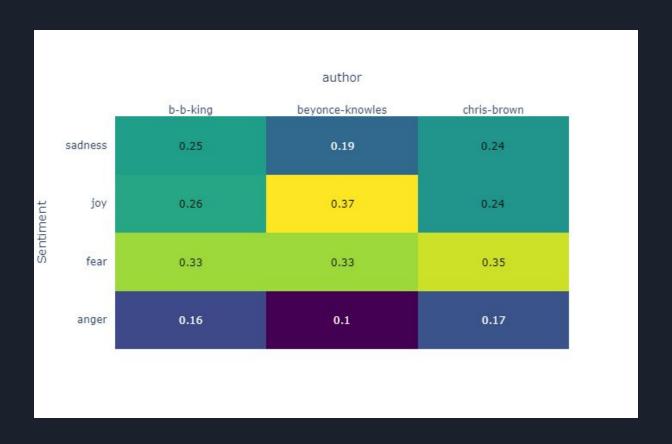
Results



Genre and sentiment relationships



Author and sentiment relationships



Playlist computation

Enter a gerne: Jazz
Enter a mood: joy
september song
body and soul
i am loved
body soul
sunny
i didn t know about you
it s a whistling kinda morning
what game shall we play today

Enter a gerne: Metal
Enter a mood: fear
nervous heart
unleashed upon mankind
from beyond the grave
seeds of mans destruction
intro unleashed upon mankind
stigmata
spellbound by the devil

Conclusions



Conclusions

Ol Genre and sentiments are correlated

O2 Authors may have a sentiment distribution very far from that of their genre

O3 Song provided by the playlist seem pertinent

Issues

The high frequence of fear may depend on the bias of the umbalancedness of the original twitts dataset

O2 Melody may convey sentiment

Future work

O7 Compare the results with a dataset of annotated songs

O2 Use melody to construct a predictor

Thanks for your attention

