



# **ISMIR 2022**

# Verse Versus Chorus: Structure-aware Feature Extraction for Lyrics-based Genre Recognition

Maximilian Mayerl, Stefan Brandl, Günther Specht, Markus Schedl, Eva Zangerle



## Core Idea and Findings

We investigate what impact lyrics structure has on the predictive power of genre recognition models. To that end, we train models on features extracted only from the verses and choruses of songs, and compare how those models perform overall, as well as for different music genres.

We found that, for rap and pop, verse features perform better, while for rock, chorus features do.



#### Data

We combine data from the LFM-2b dataset with lyrics and genre data from genius.com, leveraging crowd-sourced annotations provided by genius.com to segment song lyrics into structural parts. This gives us a dataset containing 295,416 songs with English lyrics, covering five musical genres (pop, rock, country, rap, and r&b).

Property	Value
Number of Songs	295,416
Number of Artists	39,357
Number of Tokens in Choruses	193,696,032
Number of Tokens in Verses	195,567,571
Average Number of Choruses per Song	3.46
Average Number of Verses per Song	2.37



#### Features and Models

We extract lyrics features separately for verses and choruses, covering a variety of features sets used in lyrics-based genre recognition:

- Bag-of-words features (separately for unigrams, bigrams, trigrams and (1,3)-grams)
- Rhyme features
- Readability features
- Lexical features
- Lexical diversity features
- Part-of-speech features
- Morphological features

Further, we used three different machine learning models, also chosen because of their common use in lyrics-based genre recognition:

- Random Forest
- Support Vector Machine
- Feed-forward Neural Network



## Experiment Design

For our experiments, we separately trained and evaluated models for each combination of (1) model type, (2) feature set, and (3) song part (verse or chorus). This gives us a total of 60 concrete models that we trained and evaluated.

We then investigated the differences between models trained on verses against models trained on choruses. Furthermore, we computed those same performance differences for individual genres. For all our experiments, we performed significance tests to make sure the differences we observed were statistically significant.

To evaluate the performance of the models, we used to macroaveraged F1 score, since our dataset is imbalanced in the distribution of songs over genres.



#### Main Results

	Random Forest			Support Vector Machine			Neural Network			
	Chorus	Verse	Diff.	Chorus	Verse	Diff.	Chorus	Verse	Diff.	
Feature Set										
$\mathbf{F}_1$ macro										
unigrams	.377 (±.002)	$.428 \ (\pm .002)$	$.0506^{\dagger}$	.414 (±.002)	.502 (±.002)	$.0880^{\dagger}$	.419 (±.003)	.505 (±.003)	.0858 <sup>†</sup>	
bigrams	$.364 (\pm .000)$	$.416 (\pm .003)$	$.0522^{\dagger}$	$.396 (\pm .002)$	$.485 (\pm .001)$	$.0888^{\dagger}$	$.396 (\pm .003)$	$.479 (\pm .005)$	$.0824^{\dagger}$	
trigrams	$.328 (\pm .002)$	$.385 (\pm .001)$	$.0562^{\dagger}$	.333 (±.002)	$.422 (\pm .001)$	$.0894^{\dagger}$	$.342 (\pm .003)$	$.419 (\pm .003)$	$.0772^{\dagger}$	
(1,3)-grams	$.379 (\pm .002)$	$.430 (\pm .002)$	$.0502^{\dagger}$	.432 (±.002)	$.511 (\pm .002)$	$.0792^{\dagger}$	.424 (±.002)	$.508 (\pm .003)$	$.0846^{\dagger}$	
rhyme	$.254 (\pm .002)$	$.318 (\pm .002)$	$.0638^{\dagger}$	.200 (±.001)	$.280 (\pm .001)$	$.0796^{\dagger}$	$.230 (\pm .004)$	$.307 (\pm .009)$	$.0776^{\dagger}$	
readability	.263 (±.001)	$.371 (\pm .002)$	$.1078^{\dagger}$	.224 (±.001)	$.355 (\pm .001)$	$.1308^{\dagger}$	$.264 (\pm .006)$	$.360 (\pm .002)$	$.0964^{\dagger}$	
lexical	$.359 (\pm .002)$	$.400 (\pm .002)$	<u>.0412</u> †	.291 (±.002)	$.363 (\pm .001)$	$.0720^{\dagger}$	$.360 (\pm .004)$	$.403 (\pm .001)$	<u>.0430</u> †	
lexical diversity	$.253 (\pm .002)$	$.351 (\pm .001)$	$.0980^{\dagger}$	$.195 (\pm .000)$	$.319 (\pm .000)$	$.1242^{\dagger}$	$.245 (\pm .002)$	$.333 (\pm .001)$	$.0878^{\dagger}$	
part-of-speech	$.223 (\pm .001)$	$.297 (\pm .001)$	$.0738^{\dagger}$	$.180 (\pm .000)$	$.187 (\pm .001)$	$.0068^{\dagger}$	$.207 (\pm .005)$	$.289 (\pm .002)$	$.0816^{\dagger}$	
morphological	$.201 (\pm .002)$	$.315 (\pm .001)$	$.1146^{\dagger}$	$.164 (\pm .002)$	$.169 (\pm .000)$	$.0056^{\dagger}$	$.181 (\pm .003)$	$.291 (\pm .005)$	$.1100^{\dagger}$	

The overall results show that there is a clear difference in performance between models trained on verses or choruses, respectively. In general, models trained and evaluated on features extracted from verses perform better than their chorus counterparts. In every case, this difference is statistically significant (shown by the † symbol behind the numbers).

	r	eadability		lexical			
Genre	RF	SVM	NN	RF	SVM	NN	
country	0.0054	0.0000	0.0011	$-0.0448^{\dagger}$	0.0001	-0.0076	
pop	0.0298†	$0.0367^{\dagger}$	$0.0360^{\dagger}$	$0.0110^{\dagger}$	$0.0271^{\dagger}$	0.0193	
r&b	0.0048	0.0000	-0.0021†	$0.0271^{\dagger}$	$-0.0113^{\dagger}$	-0.0583†	
rap	0.4995†	$0.6587^{\dagger}$	0.4878†	$0.3009^{\dagger}$	$0.3820^{\dagger}$	$0.2950^{\dagger}$	
rock	-0.0001	-0.0402 <sup>†</sup>	-0.0412†	$-0.0154^{\dagger}$	-0.0383 <sup>†</sup>	-0.0383	

For investigating the per-genre differences, we looked at the feature sets for which we observed the biggest (readability) and smallest (lexical) overall differences. This table shows the performance difference between verse and chorus in terms of F1 score.

We observe that rap and pop songs show a consistently better performance for verse models. The opposite is true for rock songs, were models trained and evaluated on choruses consistently performed better.