Lyrics feature sets 000000

Experiments

Conclusions and future work 00

# Combination of Audio & Lyrics Features for Genre Classication in Digital Audio Collections

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ACM Multimedia 2008

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#### Motivation

- Music Information Retrieval (MIR)
  - Search & find music, organise music collections
- Music is inherently multi-modal
  - Music: audio, symbolic, scores, ...







- Text: Song lyrics, artist biographies, websites, ...
- Community data: playlists, ...
- Video, image: album covers, music videos





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#### Motivation

- Musical genre classification: automatically assign genre labels to new music, usually based on
  - Digital signal processing (zero crossings, MFCCs, Rhythm Patterns)
  - Cultural data (artist biographies, album reviews)
  - Social network info (playlists of users, e.g. last.fm)
- Our contribution: extend scope to lyrics
  - New feature sets based on song lyrics
  - Motivation:

complementary characteristics - improved results





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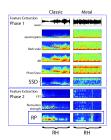
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#### Contributions

- Develop new feature sets based on song lyrics
  - Rhymes, part-of-speech, text genre descriptions
- Compare to 'traditional' bag-of-words
- Compare to audio features
  - Rhythm Patterns (RP)
  - Rhythm Histograms (RH)
  - Statistical Spectrum Descriptors (SSD)
- Build various combinations of feature sets
- Evaluate genre classification performance







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- 1. Introduction Motivation
- 2. Lyrics feature sets

Feature representations for song lyrics

3. Experiments

Test collections in Music IR and experimental setting

4. Conclusions and future work Things to do and see





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#### 'Bag-of-words' features

- Different genres different topics
- Covered by 'bag-of-words' approach
  - Index every word as feature, count frequencies
  - Optional: remove stop words (manual list, frequency thresholding)
  - Optional: apply stemming
- Apply  $tf \times idf$  weighting to vector values





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### Text genre features: statistics (1/2)

- Assumption that some genres use 'simpler' or just fewer unique words than others
- Some genres might use more explicit language different punctuations, usage of numbers, etc.
- $\bullet \ \rightarrow$  Measures for text genre descriptions





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#### Text genre features: statistics (2/2)

Feature name	Description
ExclamationMark, colon, single-	simple counts
Quote, comma, questionMark, dot,	
hyphen, semicolon	
d0 - d9	Counts of digits
WordsPerLine	Words / #of lines
UniqueWordsPerLine	Unique words / #of lines
UniqueWordsRatio	Unique words / words
CharsPerWord	# of chars / # of words
WordsPerMinute	# of words / length





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### Text genre features: part-of-speech

- Assumption that categories of words used will differ across genres
- 'lexical categorisation' or 'grammatical tagging'
  - nouns, verbs, pronouns, prepositions, adverbs, articles, modals, and adjectives
- We use simple counts, normalised by song length





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## Rhyme features (1/2)

- Assumption that different genres use different rhyme styles (and that they can be detected from lyrics text)
  - e.g. Hip-Hop: sound with a dominant bass, lyrics make heavy use of rhymes
- Rhymes
  - 'Linguistic style, based on consonance of similar sound of two or more syllables or whole words'
  - We consider only rhymes at ends of lines
  - We perform a phoneme transcription (rather than using lexical word endings)





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#### Rhyme features used (2/2)

Feature name	Description
AA	Sequence of rhyming lines ('Couplet')
AABB	Two blocks of rhyming lines ('Cleri-
	hew)
ABAB	Alternating rhymes
ABBA	Nested rhyme sequence ('Enclosing
	rhyme')
RhymePercent	Percentage of blocks that rhyme
UniqueRhymeWords	Fraction of unique terms used to build
	rhymes





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#### Test collections in MIR

- Legal situation
  - Music is a big business...
  - Copyright restrictions apply
  - Rather delicate to publish test corpora officially
- Well-known collections not suitable:
  - No lyrics available/retrievable
    - ISMIR/MIREX 'Genre' and 'Rhythm' collections
  - No meta-data available to automatically fetch lyrics
    - Collection used with MARSYAS





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#### Compiling test collections

- Western popular music 10 genres
  - Country, Folk, Grunge, Hip-Hop, Metal, Pop, Punk Rock, R&B, Reggae, Slow Rock
- 'Small' Collection: 600 songs
  - 159 artists
  - Classes of equal size
  - Lyrics manually cleansed!
- 'Large' Collection: 3010 songs
  - 188 artists
  - 180-380 songs per class
  - Lyrics automatically fetched, no manual cleansing

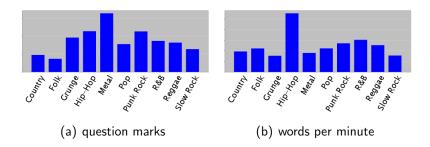


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#### Text genre statistic feature analysis





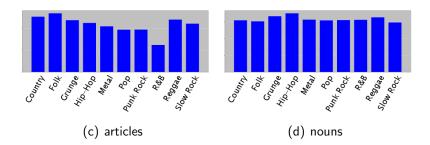


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#### Part-of-speech feature analysis





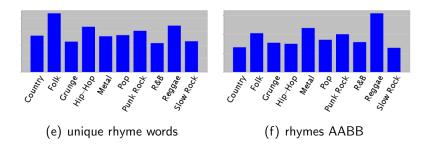


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#### Rhyme feature analysis







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#### Experimental setup

- 25 combinations of all feature sets (RP, RH, SSD, BOW, Rhyme, Part-of-Speech, Text genre statistic)
- Different classifiers: k-NN, Naïve Bayes, Decision Trees, Support Vector Machines
  - Similar trends with all classifiers
- Assuming SSD as best audio-only classifier to be baseline
- Statistical significance tests against that baseline
- 10-fold cross-validation





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### Classification results (600 songs)

Feature combination	Dim	SVM
ssd (base classifier)	168	59.17
rh	60	35.37
rp	1440	48.37
textstatistic	23	29.83
pos	9	19.21
rhyme	6	14.46
textstatistic/pos	32	31.29
BOW/ssd	9434	53.46
BOW/ssd/textstatistic/pos/rhyme	9472	54.21
ssd/textstatistic	191	64.33
ssd/textstatistic/pos	200	64.50
ssd/textstatistic/rhyme	197	63.71



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### Classification results (3010 songs)

Feature combination	Dim	SVM
ssd (base classifier)	168	66.32
rh	60	35.01
rp	1440	55.37
textstatistic	23	28.72
pos	9	12.66
rhyme	6	15.83
textstatistic/pos	32	28.72
BOW/ssd	2140	66.44
BOW/ssd/textstatistic/pos/rhyme	2178	67.06
ssd/textstatistic	191	68.72
ssd/textstatistic/pos	200	68.72
ssd/textstatistic/rhyme	197	68.16



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#### Experiment variations

- Analyse effect of stemming
  - Stemming lead to slightly better results
- Analyse effect of manual cleansing of lyrics
  - Cleansed lyrics yielded slightly better results





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- Music is inherently multi-modal
- New feature sets for lyrics genre categorisation
- Classification results on combinations
- Clearly outperforms bag-of-words only approach
- Improves classification of audio-only features
- Automatically fetched lyrics still are significantly better
- New features strong where audio already strong...





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#### Future work

- More sophisticated text and rhyme features for lyrics
- Ensemble learning
  - Maybe one classifier per feature set?
- Integrate automated lyrics alignment / preprocessing
- Extend multi-modal classification to other modalities
  - Album covers
  - Music videos





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Experiments

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Evaluation of feature extractors and psycho-acoustic transformations for music genre classification.

In Proceedings of the 6th International Conference on Music Information Retrieval (ISMIR'05), pages 34–41, London, UK, September 11-15 2005.

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