

Artist Classification with Web-based Data

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Outline

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Aims

- Classification of artists into genres
- Using text features from the web
- Explore
 - number of examples necessary to define genres
 - application as similarity measure
 - validity of descriptors over time

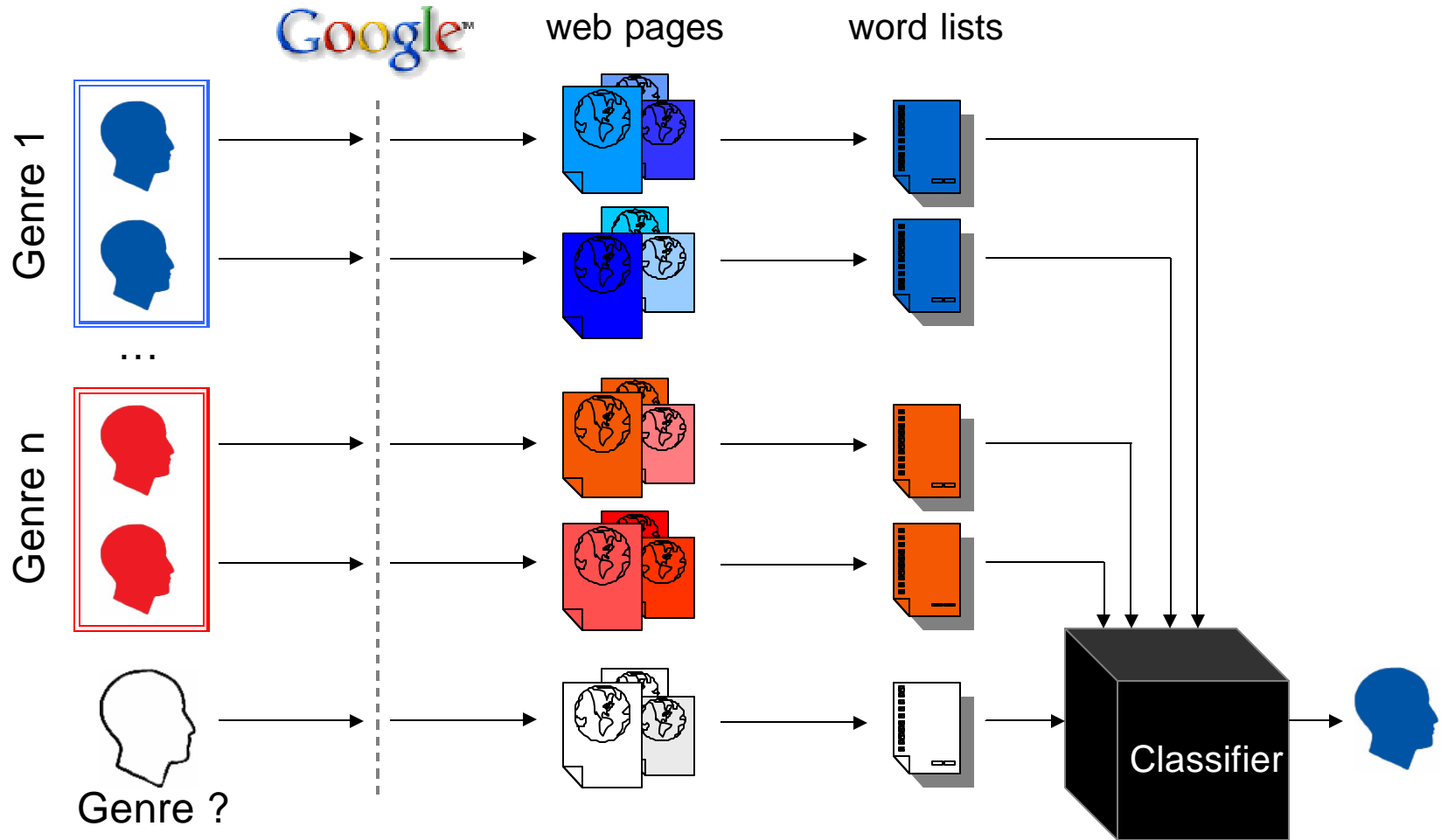


Related Work

- Artist Similarity using Metadata
 - Whitman & Lawrence (2002)
 - Baumann & Hummel (2003)
 - Cano, Koppenberger & Celma (2004)
- “Style” Classification (Audio and Metadata combined)
 - Whitman & Smaragdis (2002)
- General
 - Pachet & Cazaly (2000)
 - Pachet, Westermann & Laigre (2001)
 - Ellis, Whitman, Berenzweig & Lawrence (2002)



System Overview



Data Source

- Retrieval of web pages containing the artist's name
- Top 50 sites from Yahoo! or Google (in avg. 40 available)
- Query string:
 - “*artist name*” +music +genre +style
 - “*artist name*” +music +review(cf. Whitman & Lawrence, 2002)



Method (1)

- Remove all HTML tags
- Ignore stop words
- Count term (*tf*) and document frequency (*df*)
- Calculate *tf x idf*
$$tfidf_{ta} = tf_{ta} \log_2 \frac{N}{df_t}$$
 - Rewards frequent terms (high *tf*)
 - Penalizes terms that occur in many documents (high *df* — low inverse *df*)



Method (2)

- Term Selection
 - For each genre find most discriminative terms
 - Use χ^2 test for ranking
 - Best results with top 100 terms per genre
- Cosine normalization
- Classification with Support Vector Machines



Example of τ^2 ranked Term List

Top 40 for Heavy Metal

defined through Black Sabbath, Pantera, Metallica, Def Leppard

100	sabbath	40	dimebag	28	hammett	24	halford
97	pantera	40	anselmo	27	bloody	24	dio
89	metallica	40	pyromania	27	thrash	23	reinventing
72	leppard	40	paranoid	27	phil	23	lange
58	metal	39	osbourne	26	lep	23	newsted
56	hetfield	37	def	26	heavy	21	leppards
55	hysteria	34	euphoria	26	ulrich	21	adrenalize
53	ozzy	32	geezer	26	vulgar	21	mutt
52	iommi	29	vinnie	25	megadeth	20	kirk
42	puppets	28	collen	25	pigs	20	riffs

(normalized: max. = 100)

Experiments

- Using 14 genres:
Country, Folk, Jazz, Blues, R&B/Soul, Heavy Metal, Alternative/Indie, Punk, Rap/HipHop, Electronic, Reggae, Classical, Rock'n'Roll, Pop
- Manually gather 16 representatives per genre
- 50 hold out experiments
 - 2, 4, and 8 artists to learn a genre (rest as test set)
 - For two search engines and both query strings



Results (1)

query string	<i>+music +genre +style</i>			<i>+music +review</i>		
	2	4	8	2	4	8
# artists for training						
Google	70%	80%	86%	71%	81%	87%
Yahoo!	61%	72%	79%	65%	78%	87%

Mean accuracy from 50 hold out experiments
(using 100 top ranked terms per genre)



Results (2)

Real Class	Country	Folk	Jazz	Blues	R&B/Soul	Heavy Metal	Alt/Indie	Punk	Rap/HipHop	Electro	Reggae	Classical	R&R	Pop
Country	91 ±7	2 ±6				2 ±4			1 ±3				2 ±4	
Folk	11 ±8	55 ±22		1 ±3	5 ±8	2 ±5	9 ±7	1 ±3	1 ±3				15 ±16	1 ±3
Jazz		1 ±2	93 ±4		4 ±4								1 ±2	1 ±3
Blues				88 ±14	4 ±6								8 ±14	
R&B/Soul				1 ±3	75 ±12				4 ±7				14 ±9	6 ±8
Heavy Metal		2 ±4			1 ±2	75 ±16	9 ±11	6 ±11					2 ±4	6 ±8
Alt/Indie		1 ±3			1 ±3	7 ±10	57 ±23	13 ±14		12 ±9			1 ±4	8 ±10
Punk		1 ±2			1 ±2	8 ±11	11 ±12	69 ±14						10 ±7
Rap/HipHop					1 ±3				91 ±9	4 ±4				3 ±6
Electro								5 ±7	1 ±2					
Reggae					3 ±6		1 ±4		4 ±5	2 ±4	86 ±9		1 ±2	2 ±4
Classical												100 ±0		
Rock n' Roll	4 ±4	3 ±6		2 ±5	2 ±6	5 ±4	8 ±10	2 ±5		1 ±3			74 ±15	1 ±3
Pop		1 ±2			2 ±5	1 ±2	5 ±6	1 ±3	1 ±3	2 ±4			1 ±3	87 ±8

Confusion Matrix from 50 hold out experiments

upper value: mean
lower value: std

Google, +music +review, top 100 terms per genre, used 4 artists each to learn a genre



Classification Results

Knees, Pampalk, Widmer - Artist Classification with Web-based Data

Results (3)

Similarity (SOM-Visualization with 224 artists)

REGGAE (14)	country (1) rnbsoul (1)	COUNTRY (1) folk (2) rocknroll (1)	ROCKNROLL (8) folk (2) blues (1) rnbsoul (1)	BLUES (14) folk (1) rnbsoul (1) rocknroll (1)	CLASSIC (16)
altindie (3) rocknroll (3) folk (2) punk (2) electro (2) pop (1)	FOLK (5)	rnbsoul (4) folk (4)	rnbsoul (3) jazz (1) pop (1)	blues (1)	rocknroll (1)
altindie (5) punk (4) rocknroll (2)	altindie (1) electro (1) pop (1)	POP (5)	RNBSOUL (5) pop (2)		JAZZ (15)
HEAVY (15) PUNK (9) ALTINDIE (6)	electro (2) altindie (1) punk (1)	ELECTRO (10) pop (1)	RAPHIPHOP (13) pop (1)	raphiphop (2) reggae (1) pop (1)	pop (3) folk (2) rnbsoul (1) heavy (1) raphiphop (1) electro (1) reggae (1)



Results (3)

Similarity (SOM-Visualization with 224 artists)

REGGAE (14)	country (1) rnbsoul (1)	COUNTRY (1) folk (2) rocknroll (1)	ROCKNROLL (8) folk (2) blues (1) rnbsoul (1)	BLUES (14) folk (1) rnbsoul (1) rocknroll (1)	CLASSIC (16)
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altindie (5) punk (4) rocknroll (2)	altindie (1) electro (1) pop (1)	POP (5)	<div style="border: 1px solid black; background-color: yellow; padding: 10px; text-align: center;"> <p>k-NN ... 77%</p> <p>k=7, 8 artists defining each genre, Google, +review, no ?² cut-off</p> </div>		
HEAVY (15) PUNK (9) ALTINDIE (6)	electro (2) altindie (1) punk (1)	ELECTRO (10) pop (1)			



Results (4)

- Stability of descriptors over time
 - Repeatedly sent queries for 12 artists
 - For a period of 4 months (56 times)
- SOM-Visualization:

AK ... Alicia Keys SO ... Stacie Orrico
 DP ... Daft Punk Stro ... The Strokes
 MJ ... M. Jackson Sub ... Sublime
 Moz ... Mozart YND ... Youssour N'Dour
 RW ... Robbie Williams

Marshall Mathers = Eminem!

Sub 56			RW 56		SO 54		YND 56
					SO 2		
Moz 56							AK 21
			MJ 56				AK 35
MM 56	Em 24	Em 32		DP 56		Pulp 56	Stro 56



Conclusions

- 87% accuracy for 14 genres
(using only web-based data)
- Features can be used for similarity
- Seems robust to fluctuations over time

But ...

- “popularity” of artist (number of webpages)
- uniqueness of artist name



Future Work

- Hierarchical genre taxonomies
- Improve filtering techniques
- Extend to song/album level
- Larger evaluation sets / longer time periods
- Combine with audio signal based approaches
- Combine with the Islands of Music approach to explore different views of music collections

