

## **Music Video Information Retrieval**

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## **MVIR Objectives**

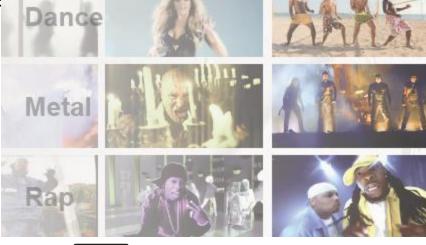
- Multimodal Approach to MIR Problems
  - Classification / Tagging
  - Mood estimation
  - Music Similarity Retrieval



- visual layer of music videos conta related information
- Research Aims
  - Can this information be used?
    - Improve MIR solutions
    - Use images as queries









## **Music Video Dataset**

MV	D-VIS			MVD-MM		
Genre	Videos	Artists	Genre		Videos	Artists
Bollywood	100	32	80s		100	72
Country	100	70	Dubstep		100	78
Dance	100	84	Folk		100	66
Latin	100	72	Hard Rock		100	69
Metal	100	76	Indie		100	64
Opera	100	NA	Pop Rock		100	65
Rap	100	81	Reggaeton		100	69
Reggae	100	75	RnB		100	67
MV	es					
			Christmas		56	42
MVD-VIS + MVD-MM	1600	1040	K-Pop		50	39
16 Genres			Broken Hear	·t	56	48
			Protest Song	50	42	
		MVD-	Artists			
Artist Name	Videos	Artist Name	Videos	Artist Name	Vid	leos
Aerosmith	23	Jennifer Lopez	23	Nickelback		18
Avril Lavigne	20	Justin Timberla	ake 12	P!nk		23
Beyonce	26	Katy Perry	12	Rihanna		25
Bon Jovi	27	Madonna	30	Shakira		24
Britney Spears	25	Maroon 5	14 Taylor Swift			20
Christina Aguilera	15	Matchbox Twer	nty 13	Train		11
Foo Fighters	23	Nelly Furtado	16			
		MVD-C	omplete			
MVD-VIS + MVD-MM -		2212				





# **Audio Classification Baseline Results**

#### **MVD-Results**

	(a) Content Based Audio Features											
a1	Chroma	48	36.34	28.09	23.03	25.26	20.11	19.41	19.64	14.68	12.08	
a2	MFCC	52	62.28	48.58	46.95	42.14	29.16	34.17	37.02	26.60	27.11	
a3	SSD	168	85.78	73.18	58.81	68.74	50.28	48.41	65.11	44.64	38.92	
a4	RP	1440	(87.26)	69.81	64.04	60.35	42.38	41.63	63.19	43.06	41.39	
a5	TRH	420	71.04	55.83	53.86	49.50	38.28	39.66	46.61	33.02	35.70	
a6	TSSD	1176	(86.81)	72.58	62.61	69.97	53.33	<b>53.65</b>	66.19	47.40	44.22	
a7	a4+a6	2616	93.08	79.47	71.88	74.44	54.00	51.03	74.64	53.06	48.54	
a8	a4+a3+a5	2028	92.19	75.93	67.45	71.00	50.26	44.85	72.73	49.88	43.65	
a9	a4+a3	1608	92.55	77.74	67.36	71.64	52.44	44.40	74.38	51.60	43.52	
a10	a4+a5+a6	3036	93.79	80.85	71.46	74.76	55.00	52.20	75.91	54.16	48.32	

#### **Baseline**

### **Comparison with MIR Datasets**

ISMIR Genre Dataset									
Classifiers	chro spfe timb mfcc rp rh trh ssd tssd EN0 EN3 EN4 EN5 TEN								
SVM Poly	50.3 54.9 67.7 62.1 75.1 64.0 66.5 78.8 80.9 67.0 67.2 78.5 80.4 <b>81.1</b>								
Latin Music Database									
SVM Poly	39.4 38.2 68.6 60.4 86.3 59.9 62.8 86.2 87.3 70.5 69.6 82.9 87.1 <b>89.0</b>								
GTZAN									
SVM Poly	41.1 43.1 75.2 67.8 64.9 45.5 38.9 73.2 66.2 56.4 53.6 63.9 65.2 <b>66.9</b>								
ISMIR Rhythm									
SVM Poly	38.1 41.4 60.7 54.5 88.0 82.6 73.7 58.6 56.0 55.1 51.7 62.7 63.7 <b>67.3</b>								



### **Artist Identification**

**Detect Faces in Video Frames Summarize Face Predictions Build Face Recognizer** Artist 1 LBP Face Recognizer gregation Train Audio Classifier Artist 1 Artist 2 Artist 3 Machine Artist 4 **Extract Features from Audio** Combining Audio and Video Preparing the Ensemble **VIDEO ENSEMBLE** 





## **Artist Identification**

#### **MVD-Artists Results**

Ense	Ensemble		dio	Vio	deo	
Prec.	Recall	Prec.	Recall	Prec.	Recall	Artist
0.36	0.57	0.33	0.52	0.14	0.33	Aerosmith
0.64	0.45	0.50	0.45	0.62	0.25	Avril Lavigne
0.55	0.32	0.33	0.26	0.28	0.42	Beyonce
0.24	0.27	0.28	0.36	0.20	0.04	Bon Jovi
0.34	0.42	0.32	0.33	0.16	0.17	Britney Spears
0.33	0.50	0.48	0.71	0.18	0.43	Christina Aguilera
0.62	0.53	0.41	0.47	0.00	0.00	Foo Fighters
0.27	0.19	0.22	0.24	0.33	0.14	Jennifer Lopez
0.30	0.24	0.27	0.28	0.50	0.12	Madonna
0.35	0.70	0.20	0.10	0.12	0.80	Maroon 5
0.58	0.44	0.55	0.38	1.00	0.18	Nickelback
0.75	0.14	0.29	0.19	0.40	0.10	Rihanna
0.28	0.65	0.44	0.40	0.25	0.21	Shakira
1.00	0.16	0.60	0.32	0.50	0.06	Taylor Swift
0.47	0.38	0.37	0.36	0.34	0.21	avg



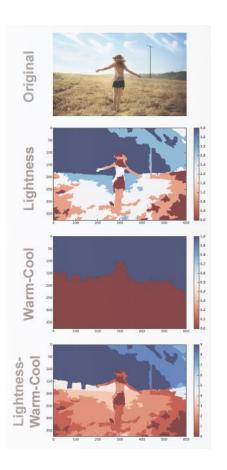
## Low-Level image processing features

- 7 feature sets
- 360 descriptors
- Colorfulness
- Itten Contrasts
- Lightness Fluctuation Patterns
- Etc.

#### **Color Names**



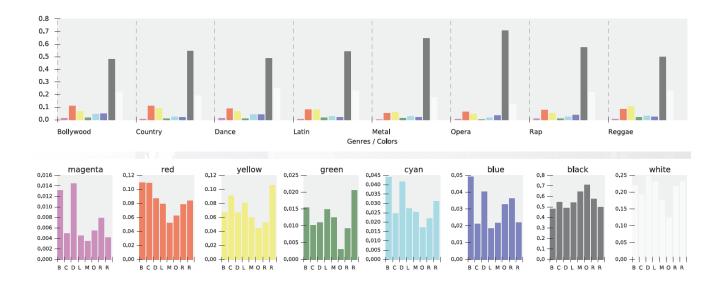
#### **Affective Contrasts**





### **Low-Level features Results**

	(b) Low-level Color and Affect related Image Features											
$v_{co}1$	LFP	60	33.21	23.59	25.45	20.38	16.74	16.46	16.93	11.71	13.36	
$v_{co}2$	CF	7	34.89	25.49	31.50	21.84	17.06	20.41	18.53	11.92	16.49	
$v_{co}3$	IC	28	36.80	27.55	27.51	24.83	19.43	19.68	21.44	13.54	12.66	
$v_{co}4$	GEV	21	39.45	<b>29.84</b>	34.15	20.81	17.04	18.51	20.27	14.47	17.89	
$v_{co}5$	GCS	42	40.55	29.76	33.91	24.08	17.29	18.15	23.72	15.40	17.34	
$v_{co}6$	WAF	126	41.01	26.43	29.86	26.01	19.08	21.38	22.86	13.90	16.60	
$v_{co}7$	CN	56	43.68	29.04	32.23	26.74	19.13	18.77	23.48	14.76	15.99	
$v_{co}8$	Combi	360	50.13	34.04	39.38	31.69	21.16	23.38	32.22	17.89	21.16	





## **High-Level Visual Concepts**

- Convolutional Neural Networks
- Applied Model
  - 1000 concepts of the Large Scale ImageNet classification campaing
  - Wide range of different semantic concepts

Synset	t Example Images		rnset Example Images 5		Example Images
Micro- phone		Brassiere		Abaya	
Stage	CIP AN	Cowboy		Capuchin	
Spotlight		Wig		Hoopskirt	



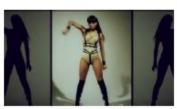
### Top concepts of music video frames examples



stage	0.3162
electric guitar	0.1169
bassoon	0.0649
accordion	0.0611
drumstick	0.0386
microphone	0.0313
marimba	0.0276



mosquito net	0.0932			
wardrobe	0.0857			
brassiere	0.0815			
shower curtain	0.0471			
candle	0.0400			
plastic bag	0.0204			
hoopskirt	0.0187			



maillot	0.2745		
bolo tie	0.0732		
Windsor tie	0.0550		
letter opener	0.0486		
brassiere	0.0390		
bikini	0.0384		
bassoon	0.0364		



lumbermill	0.1925		
tow truck	0.1215		
harvester	0.1152		
thresher	0.0513		
jeep	0.0484		
half track	0.0473		
pickup truck	0.0460		



wig	0.4399
neck brace	0.0577
chimpanzee	0.0418
hair spray	0.0375
orangutan	0.0366
cloak	0.0267
Windsor tie	0.0236

### **Classification results (visual concepts only)**

	(c) High-level Visual Concepts											
$v_{in}1$	MEAN	1000	66.86	42.09	53.69	51.26	31.23	37.05	46.87	23.90	33.07	
$v_{in}2$	STD	1000	69.78	46.76	50.08	51.95	29.99	32.88	48.29	26.83	29.63	
$v_{in}3$	MAX	1000	73.15	44.26	46.41	54.60	33.05	31.94	50.07	26.93	27.49	
$v_{in}4$	$v_{in}3+v_{in}2$	2000	73.61	46.53	51.21	55.04	31.48	34.00	51.30	27.03	31.04	
$v_{in}5$	$v_{in}$ 3+ $v_{in}$ 1	2000	<b>(74.36)</b>	47.70	53.65	55.99	33.70	<b>37.83</b>	(51.58)	28.88	33.83	



## **Multimodal Improvements?**

- Improvements
  - MVD-VIS => 2.94%
  - MVD-MM => 6.84%
  - MVD-MIX => 10.82%
- Largest Improvement: TSSD (MVD-MIX) => 16.43%

(a) Content Based Audio Features  a6 TSSD 1176 86.81 72.58 62.61 69.97 53.33 <b>53.65</b> 66.19 47.40 44.22 a10 a4+a5+a6 3036 <b>93.79 80.85</b> 71.46 <b>74.76 55.00</b> 52.20 <b>75.91 54.16</b> 48.32											
a6	TSSD	1176	86.81	72.58	62.61	69.97	53.33	53.65	66.19	47.40	44.22
a10	a4+a5+a6	3036	93.79	80.85	71.46	74.76	55.00	52.20	75.91	54.16	48.32

	(e) Audio-Visual Combinations										
av1	$a10+v_{in}5$	5036	96.73	81.13	65.00	81.60	<b>55.73</b>	49.31	86.73	59.01	47.48
av2	$a9+v_{in}5$	3608	95.63	77.05	64.16	77.83	49.54	46.58	79.44	51.31	43.71
av3	$a9+v_{pl}5$	2118	94.50	79.95	68.08	72.96	53.29	45.99	77.40	53.73	45.51
av4	$av2+v_{pl}5$	4118	95.76	75.76	61.00	77.55	50.31	44.59	80.16	52.43	41.79
av4	$a6+v_{in}5$	3176	94.65	68.61	63.64	78.49	53.01	50.41	82.62	48.94	48.53
av5	$a4+v_{in}5$	3440	91.24	68.80	63.40	71.95	43.78	44.86	74.14	45.53	42.69
av6	$a3+v_{in}5$	2168	89.85	62.11	57.89	70.13	43.16	42.93	70.30	37.98	38.88

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## **Music Tagging / MVD-Themes Classification**

#### Non-Audible Themes

- Cross-genre problem
- Aligned to MusiClef music tagging task

#### Improvements

- Christmas => 45.5%
- K-Pop => 14.1%
- Protest Song => 22.6%
- Broken Heart => No improvement

#### Video features outperform audio-content descriptors

	Audio-Only			Visual-Only				Audio-Visual				
Theme	VIS	MM	MIX	TH	VIS	MM	MIX	$\mathbf{TH}$	VIS	MM	MIX	TH
Christmas	67.6	36.7	29.5	52.9	4.7	65.5	64.0	88.9	87.5	70.8	75.0	90.4
K-Pop	86.0	65.4	68.6	86.0	88.4	81.6	80.4	91.7	95.5	88.2	82.7	90.0
Protest Song	50.0	21.7	(7.7)	47.5	23.7	33.3	16.7	75.5	44.4	57.1	30.3	77.5
Broken Heart	75.0	28.6	28.6	54.9	51.2	21.9	16.7	70.2	61.0	31.9	25.5	68.6



# **Salient Visual Concepts**

Country	Dance	Metal	Opera	Reggae
cowboy hat	1. brassiere	1. spotlight	theater curtain	1. seashore coast
5. drumstick	3. maillet	2. electric-guitar	3. hoopskirt	2. academic gown
8. restaurant	4. lipstick	4. drumstick	5. stage	3. capuchin
9. tobacco shop	9 seashore coast	6. matchstick	11. flute	<ol><li>black stork</li></ol>
10. pickup truck	10. bikini	7. drum	19. harmonica	7. sunglasses
11. acoustic guitar	15. sarong	8. barn spider	21. marimba	8. orangutan
13 violin fiddle	16. perfume	10. radiator	25. oboe	9. titi monkey
16. jeep landrover	17. trunks	12. chain	26. french horn	10. lakeshore
18. tractor trailer	18. ice lolly	14. grand piano	27. panpipe	11. cliff drop
19. tow truck	19. pole	23. spider web	30. grand piano	17. elephant
21. minibus	20. bubble	24. nail	31. cello	23. steel drum
23. electric guitar	30 miniskirt	28. br <del>assier</del> e	48. pipe organ	24. macaw
33. thresher	42. feather boa	37 loudspeaker	55. harp	25. coonhound

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## **Summary**

- Visual Layer of Music Video contains music relevant information
- Can be harnessed using visual concept detection
- Significantly improves performance of multi-modal approaches
- Outperforms audio-only approaches in audio-tagging tasks

**Thank You!**