PAPER PRESENTATION LUDOVICA SCHAERF DH-500

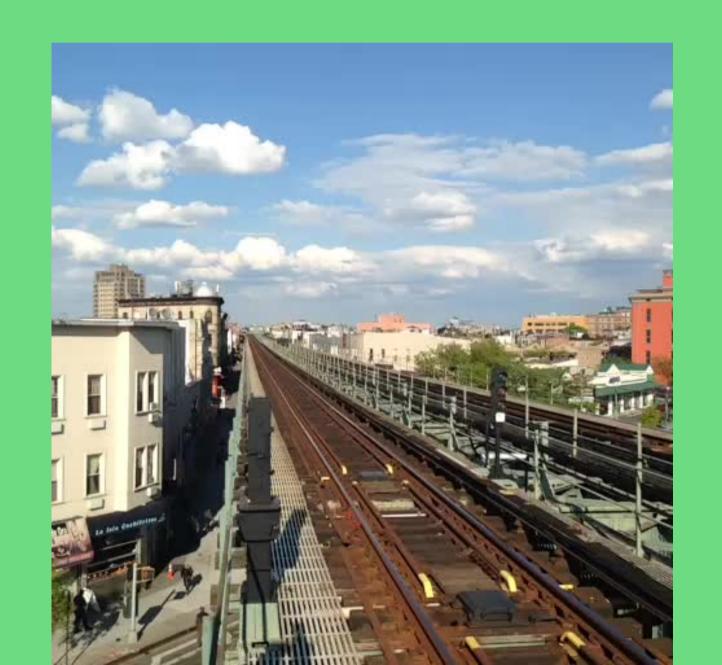
6 Seconds of Sound and Vision: Creativity in Micro-Videos

Miriam Redi, Neil O'Hare, Rossano Schifanella, Michele Trevisiol, Alejandro Jaimes

Published in CVPR in 2014

What are microvideos?

Vine (2013–2017) 6 seconds of creativity





unique in a significant way

What is creativity?

Weisberg: "for something to be creative, it is not enough for it to be novel: it must have value, or be appropriate to the cognitive demands of the situation

specifically aesthetic values

 Kant: judgements of aesthetic value involve sensory, emotional and intellectual components.

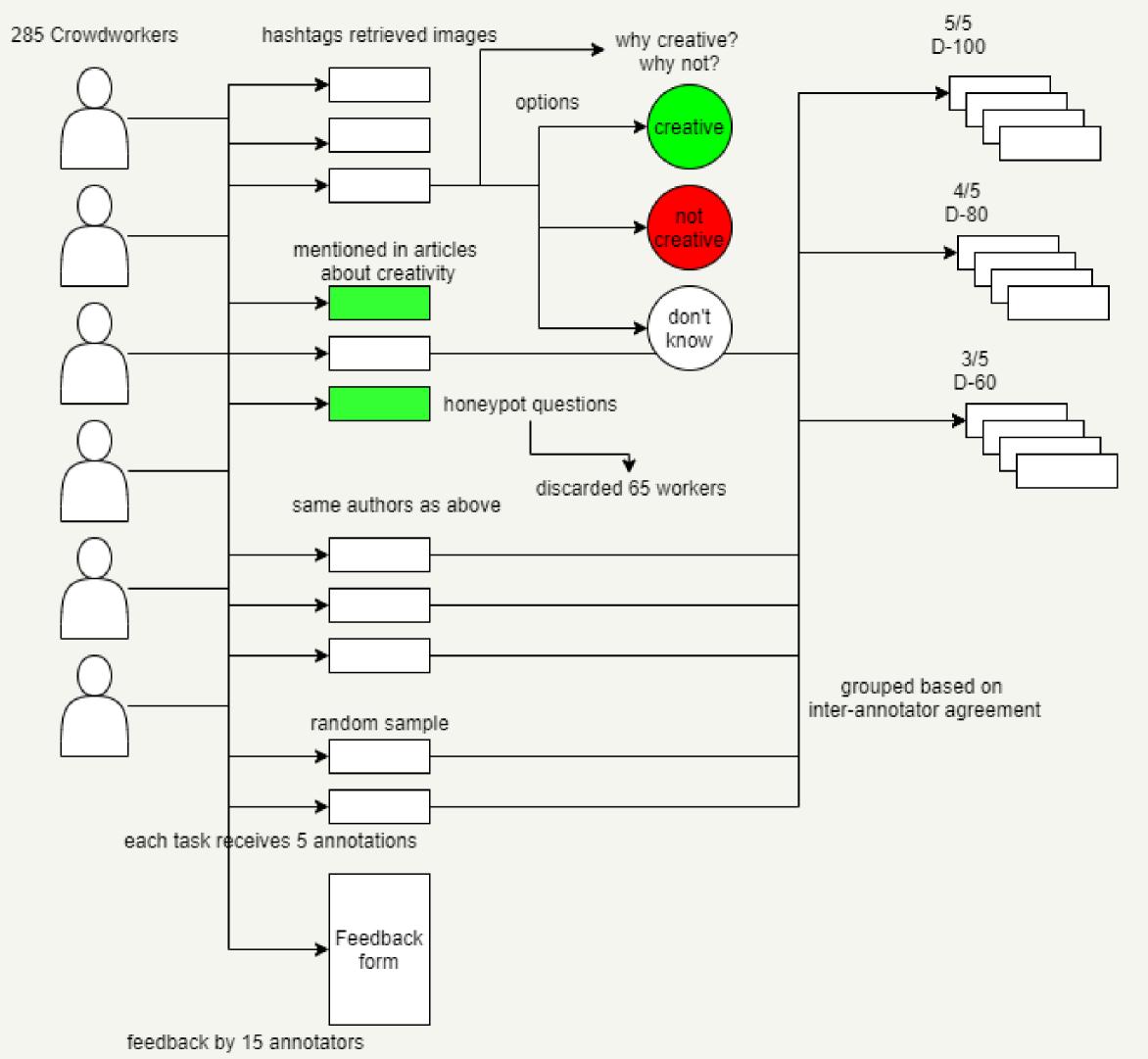
Research Question

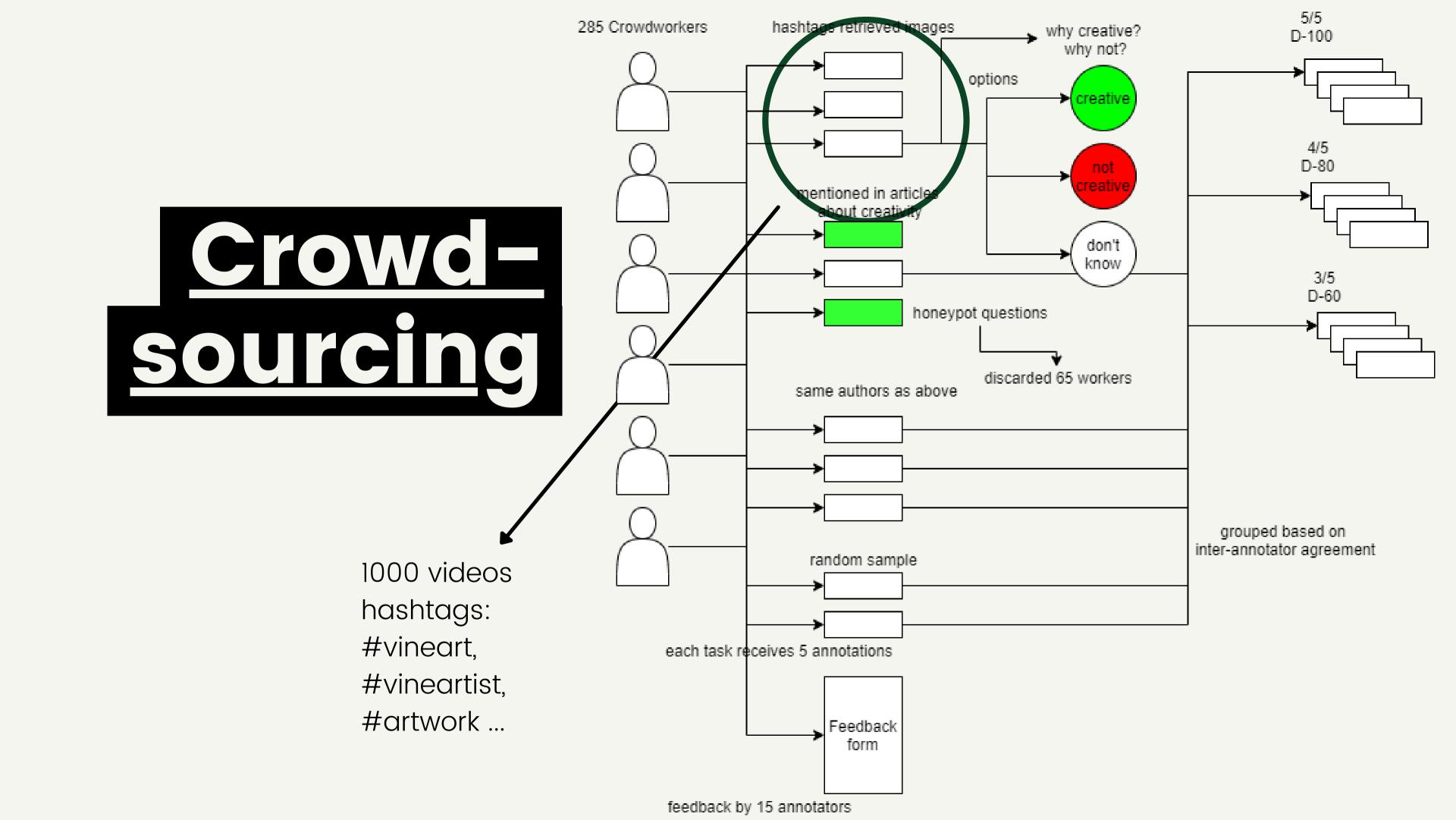
"We study the audio-visual features of creative vs non-creative videos and present a computational framework to automatically classify these categories. In particular, we conduct a crowdsourcing experiment to annotate over 3,800 Vine videos, [...]. We go on to use this dataset to study creative micro-videos and to evaluate approaches to automatic detection of creative micro-videos."

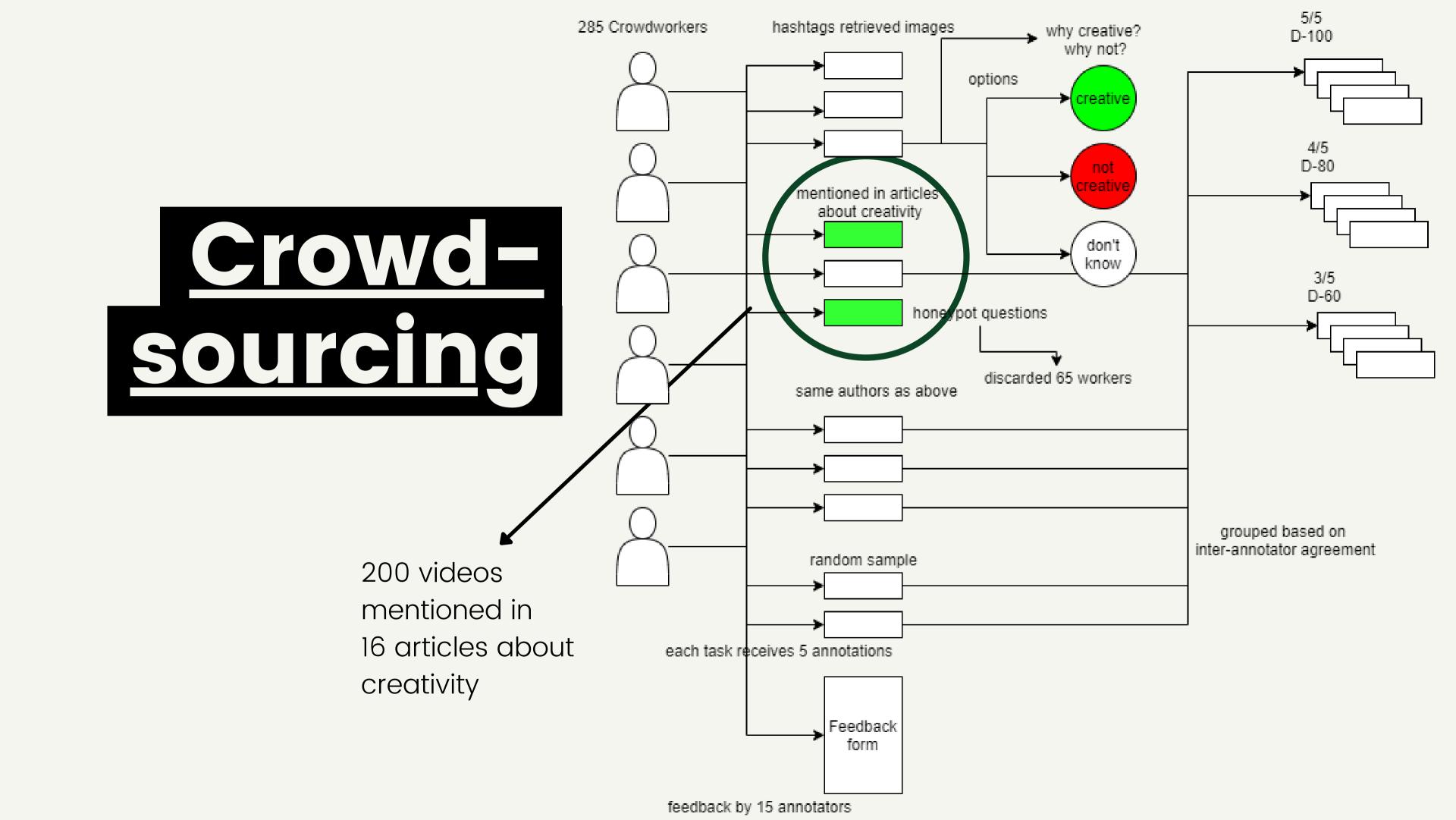
Research Question

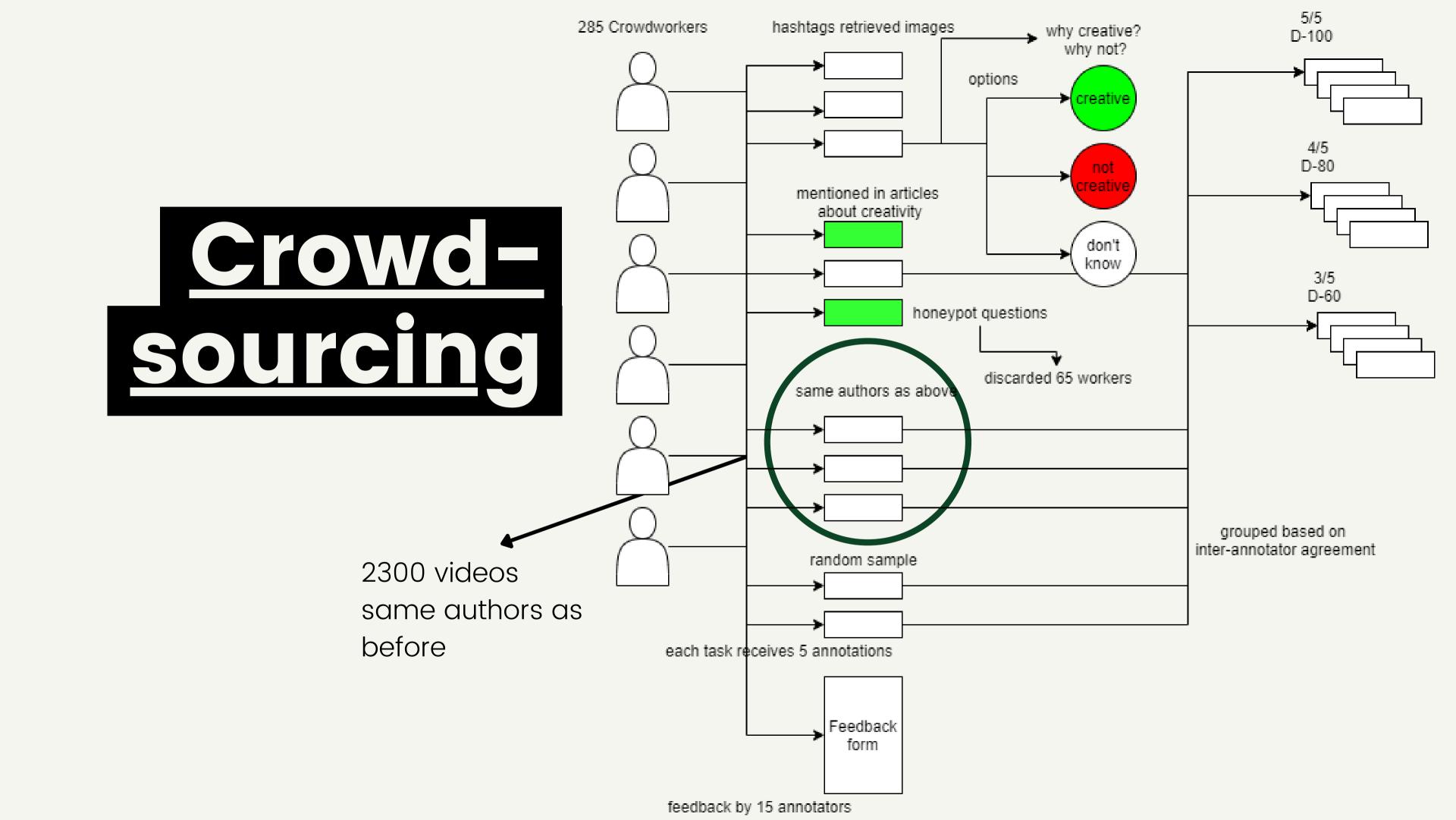
Can we create a reliable crowdsourced dataset?
Can we extract features that identify creativity in micro-videos?
Can these be used to automatically classify a micro-video into creative and non-creative?

Crowdsourcing



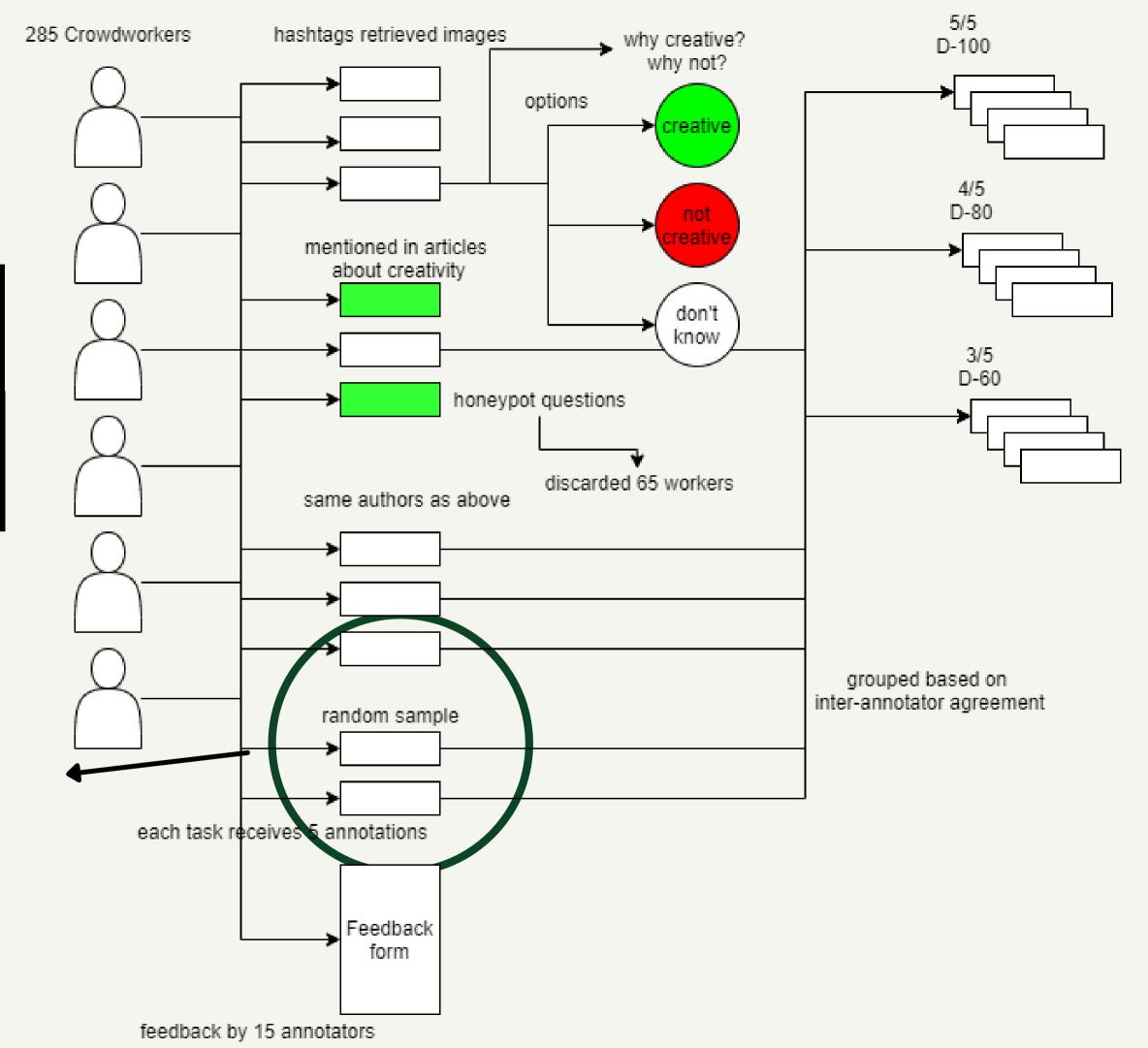




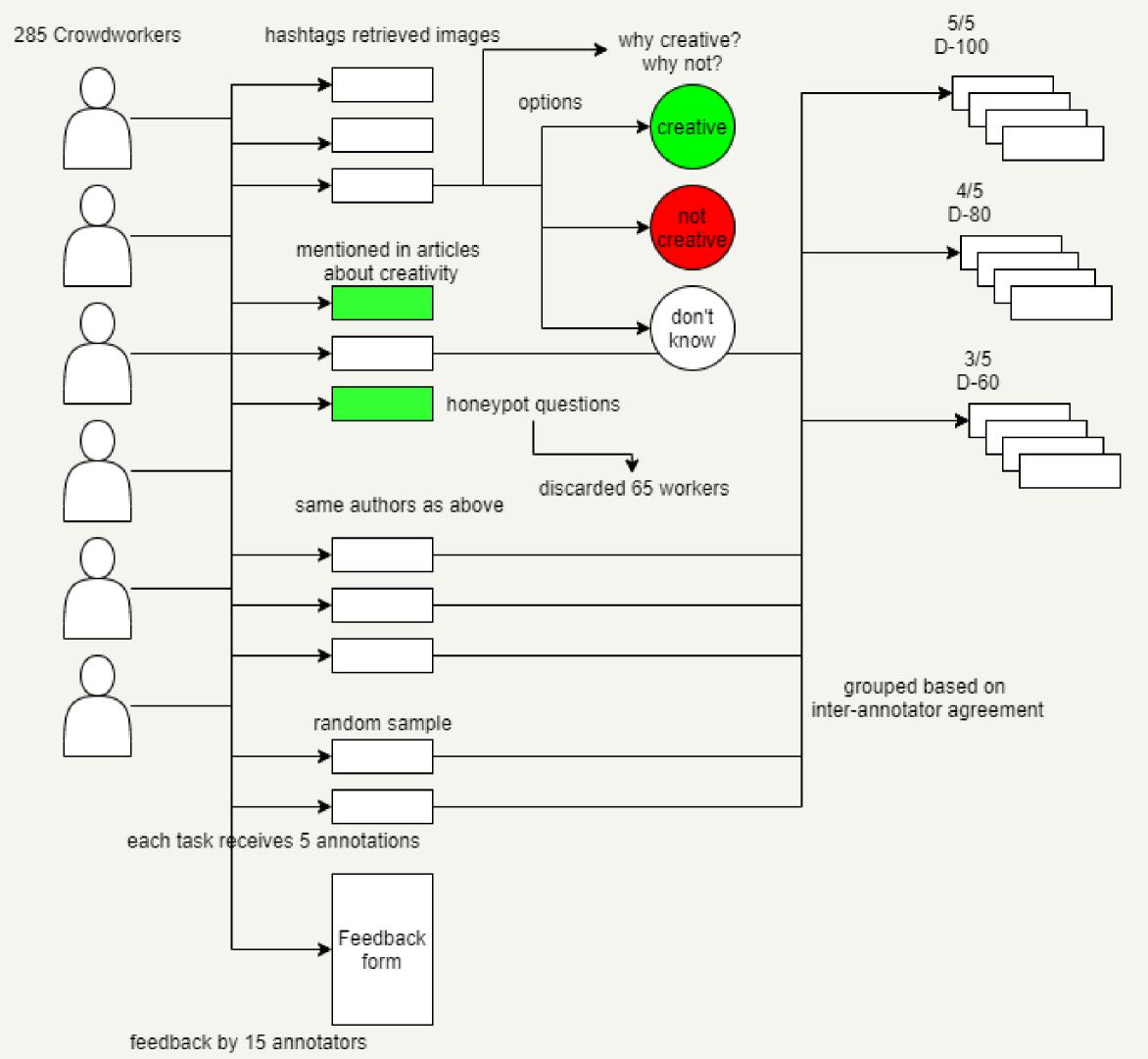


Crowdsourcing

500 videos from video streamline



Crowdsourcing





Dataset	% Videos	# Creative (%)	# Non-creative (%)
D-60	100%	1141 (30%)	2708 (70%)
D-80	77%	789 (27%)	2196 (73%)
D-100	48%	471 (25%)	1382 (75%)

Table 2. Summary of the results of the labeling experiment. D-60: videos with at least 60% agreement between annotators. D-80: at least 80% agreement. D-100: 100% agreement.

	(a) Hashtags	(b) Blogs	(c) Creators	(d) Random
Creative	34.05%	79.57%	27.41%	1.88%
Non-Creative	65.95%	20.43%	72.59%	98.12%

Table 3. Creative vs non-creative videos per sampling strategy, for the D-100 dataset (100% agreement).



Dataset	% Videos	# Creative (%)	# Non-creative (%)
D-60	100%	1141 (30%)	2708 (70%)
D-80	77%	789 (27%)	2196 (73%)
D-100	48%	471 (25%)	1382 (75%)

Table 2. Summary of the results of the labeling experiment. D-60: videos with at least 60% agreement between annotators. D-80: at least 80% agreement. D-100: 100% agreement.

	(a) Hashtags	(b) Blogs	(c) Creators	(d) Random
Creative	34.05%	79.57%	27.41%	1.88%
Non-Creative	65.95%	20.43%	72.59%	98.12%

Table 3. Creative vs non-creative videos per sampling strategy, for the D-100 dataset (100% agreement).

less than 2% of the videos on Vine are creative

Research Question

Can we create a reliable crowdsourced dataset?
Can we extract features that identify creativity in micro-videos?
Can these be used to automatically classify a micro-video into creative and non-creative?

Features

Group

Feature

	Group	Teuture		Description	
			AEST	THETIC VALUE	
			Ser	isory Features	
	Scene Content	Saliency Moments [26]	462	Frame content is represented by summarizing the shape of the salient region	
		General Video Properties	2	Number of Shots, Number of Frames	
	Filmmaking	Stop Motion	1	Number of non-equal adjacent frames	
	Technique	Loop	1	Distance between last and first frame	
		Movement	1	Avg. distance between spectral residual [9] saliency maps of adjacent frames	
		Camera Shake	1	Avg. amount of camera shake [1] per frame	
		Rule of Thirds [5]	3	HSV average value of the inner quadrant of the frame $(H(RoT), S(RoT), V(RoT))$	
	Composition	Low Depth of Field [5]	9	LDOF indicators computed using wavelet coefficients	
	and Photographic	Contrast [6]	1	Ratio between the sum of max and min luminance values and their difference	
new features	Technique	Symmetry [27]	1	Difference between edge histograms of left and right halves of the image	
riow roataros		Uniqueness [27]	1	Distance between the frame spectrum and the average image spectrum	
		Image Order [28]	2	Order values obtained through Kologomorov Complexity and Shannon's Entropy	
R	Emotional Affect Features				
	Visual Affect	Color Names [17]	9	Amount of color clusters such as red, blue, green,	
		Graylevel Contrast Matrix Properties [17]	10	Entropy, Dissimilarity, Energy, Homogeneity and Contrast of the GLCM matrix	
	Visual Affect	HSV statistics [17]	3	Average Hue, Saturation and Brightness in the frame	
		Pleasure, Arousal, Dominance [30]	3	Affective dimensions computed by mapping HSV values	
		Loudness [15]	2	Overall <i>Energy</i> of signal and avg <i>Short-Time Energy</i> in a 2-seconds window	
	Audio Affect	Mode [15]	1	Sums of key strength differences between major keys and their relative minor keys	
	Addio Affect	Roughness [15]	1	Avg of the dissonance values between all pairs of peak in the sound track spectrum	
		Rythmical Features [15]	2	Onset Rate and Zero-Crossing Rate	
•			I	NOVELTY	
	Novelty	Audio Novelty	10	Distance between the audio features and the audio space	
	Hoverty	Visual Novelty	40	Distance between the visual features and each visual feature space	
	Table 4. Audiovisual features for creativity modeling				

Description

Features

Group

Feature

sensory features

emotion

features

AESTHETIC VALUE Sensory Features Frame content is represented by summarizing the shape of the salient region **Scene Content** Saliency Moments [26] 462 General Video Properties Number of Shots, Number of Frames Filmmaking Stop Motion Number of non-equal adjacent frames Technique Distance between last and first frame Loop Avg. distance between spectral residual [9] saliency maps of adjacent frames Movement Camera Shake Avg. amount of camera shake [1] per frame HSV average value of the inner quadrant of the frame (H(RoT), S(RoT), V(RoT))Rule of Thirds [5] Composition LDOF indicators computed using wavelet coefficients Low Depth of Field [5] and Photographic Ratio between the sum of max and min luminance values and their difference Contrast [6] Technique Difference between edge histograms of left and right halves of the image Symmetry [27] Distance between the frame spectrum and the average image spectrum Uniqueness [27] Order values obtained through Kologomorov *Complexity* and Shannon's Entropy Image Order [28] **Emotional Affect Features** Amount of color clusters such as red, blue, green, ... Color Names [17] Graylevel Contrast Matrix Properties [17] Entropy, Dissimilarity, Energy, Homogeneity and Contrast of the GLCM matrix 10 Visual Affect HSV statistics [17] Average Hue, Saturation and Brightness in the frame Pleasure, Arousal, Dominance [30] Affective dimensions computed by mapping HSV values Overall Energy of signal and avg Short-Time Energy in a 2-seconds window Loudness [15] Sums of key strength differences between major keys and their relative minor keys *Mode* [15] **Audio Affect** Avg of the dissonance values between all pairs of peak in the sound track spectrum Roughness [15] Onset Rate and Zero-Crossing Rate Rythmical Features [15] **NOVELTY** Distance between the audio features and the audio space Audio Novelty Novelty Distance between the visual features and each visual feature space Visual Novelty

Description

Dim

Table 4. Audiovisual features for creativity modeling

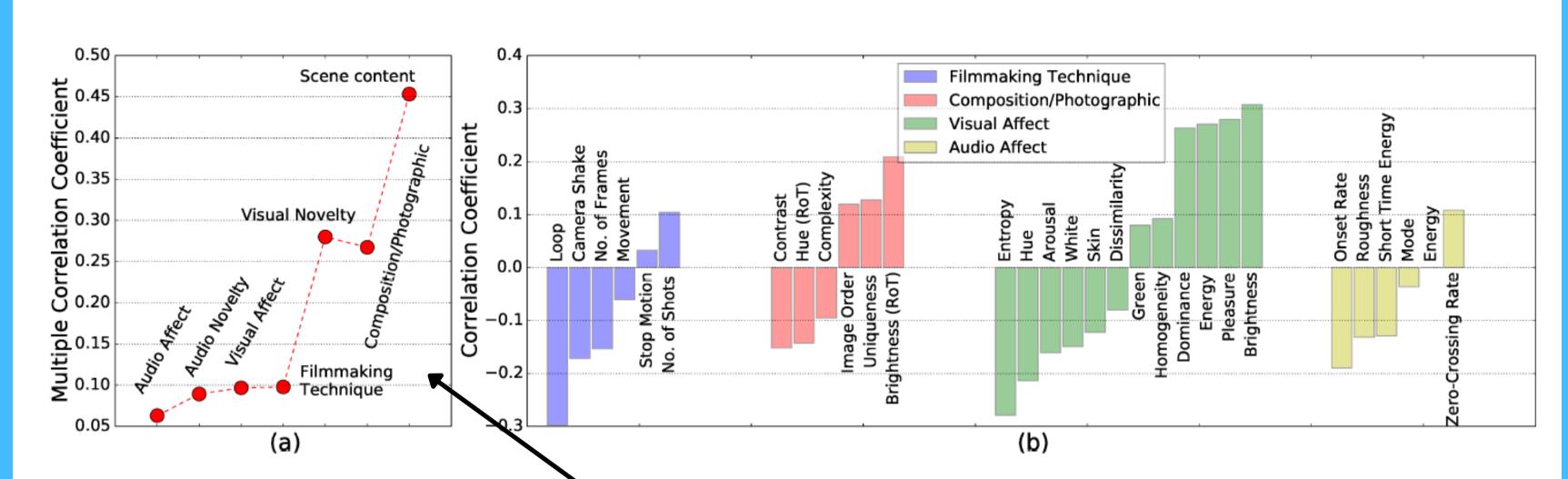


Figure 1. Analysis of the most relevant features and components for video creativity prediction

Correlation

Data: D100

Features: 7 groups of features on the left

Method: Multiple Correlation Coefficient (MCC)

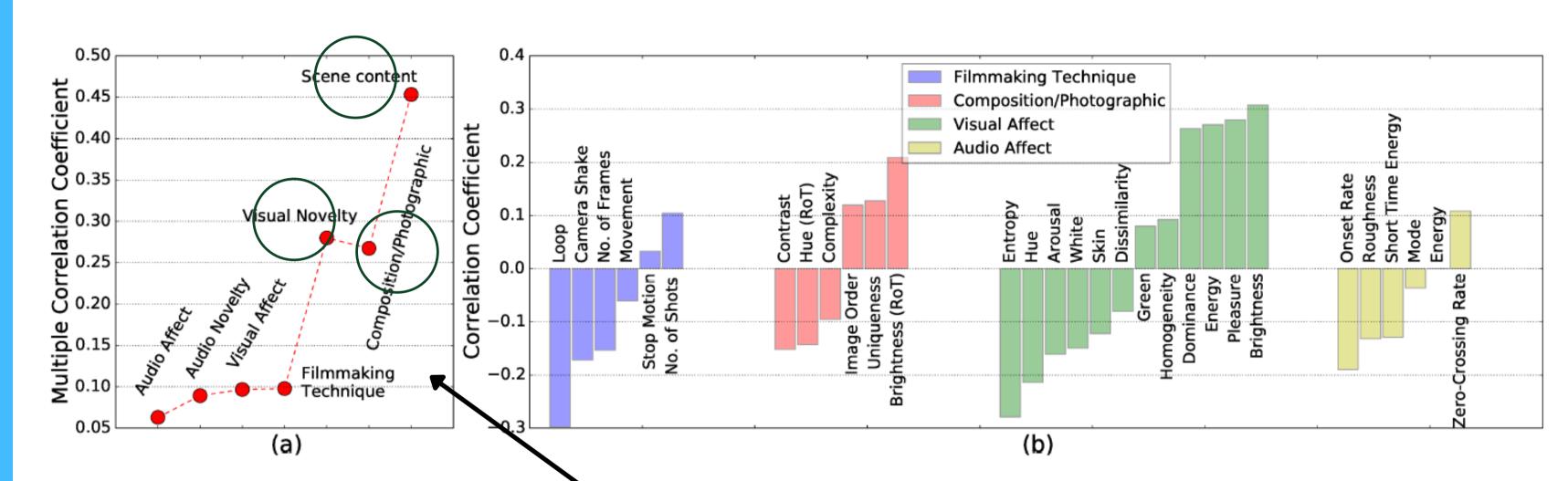
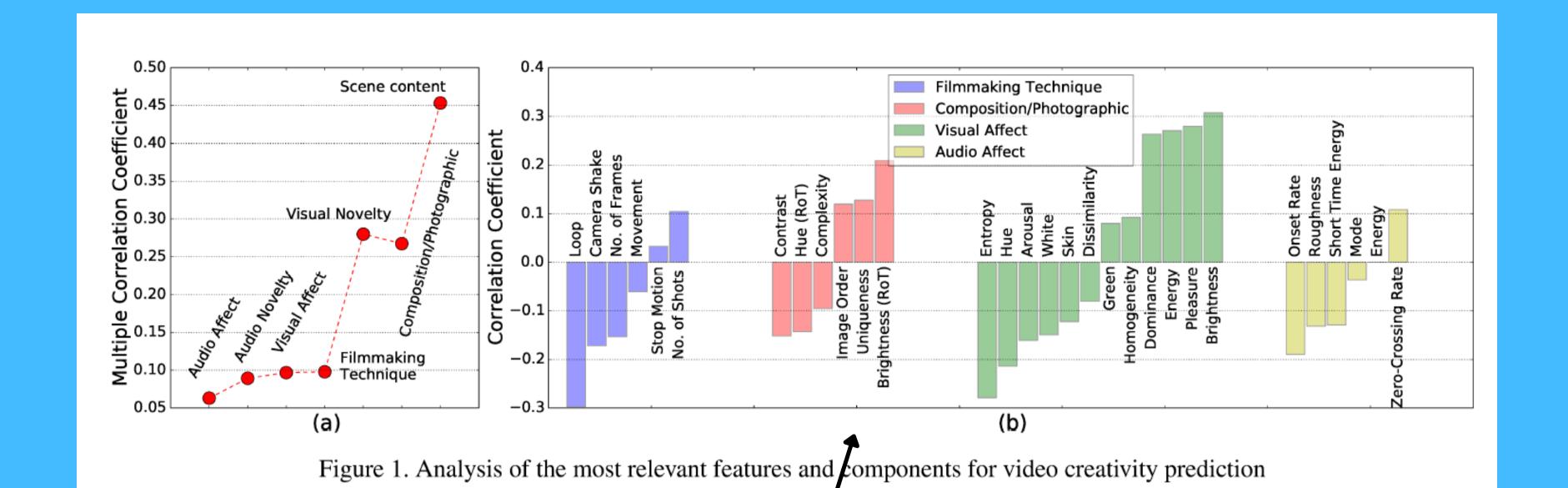


Figure 1. Analysis of the most relevant features and components for video creativity prediction



Both Novelty and Aesthetic features are important



Correlation

Data: **D100**

Features: All individual features but Scene Content and Novelty

Method: Pearson Correlation Coefficient (PCC)

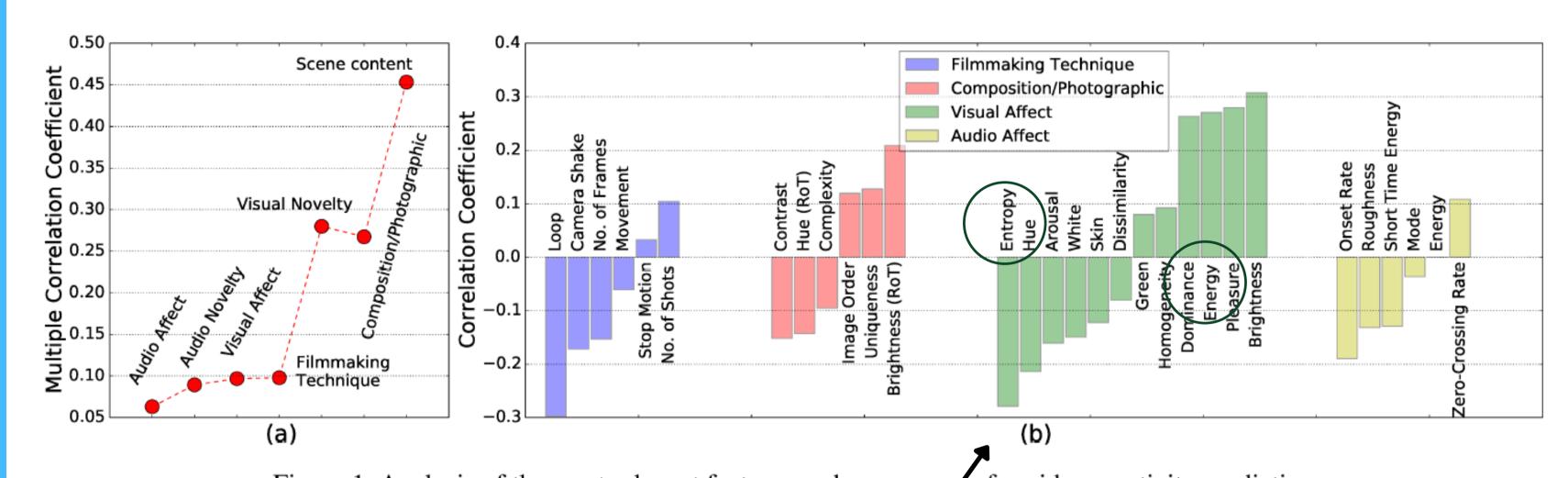


Figure 1. Analysis of the most relevant features and components for video creativity prediction



Favour visual uniformity

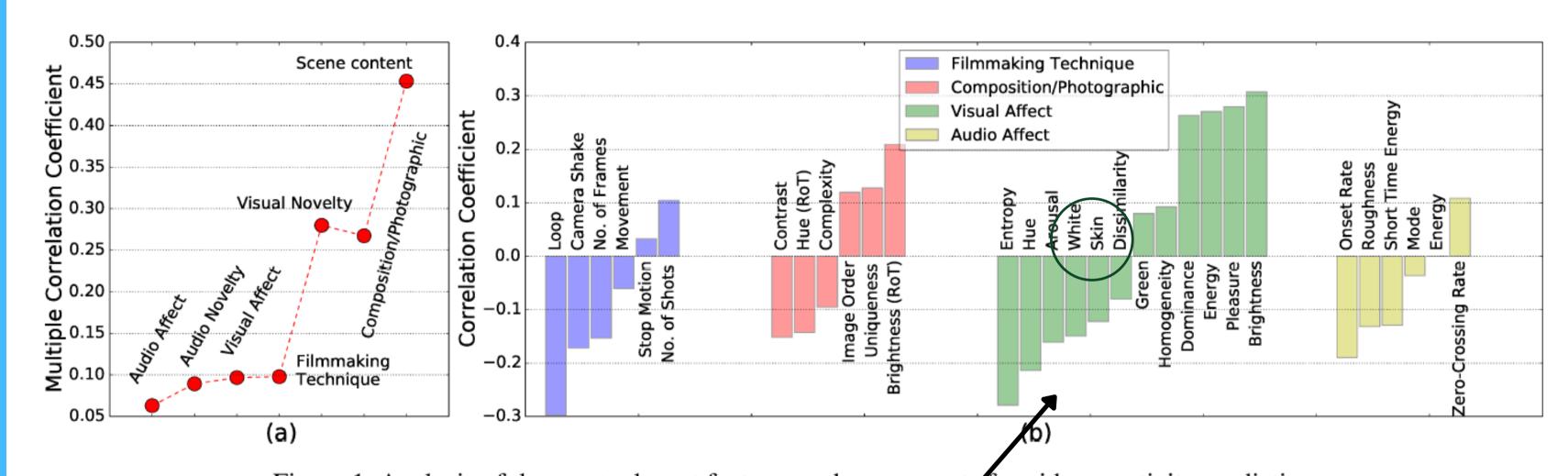


Figure 1. Analysis of the most relevant features and components for video creativity prediction



favour scenes without people

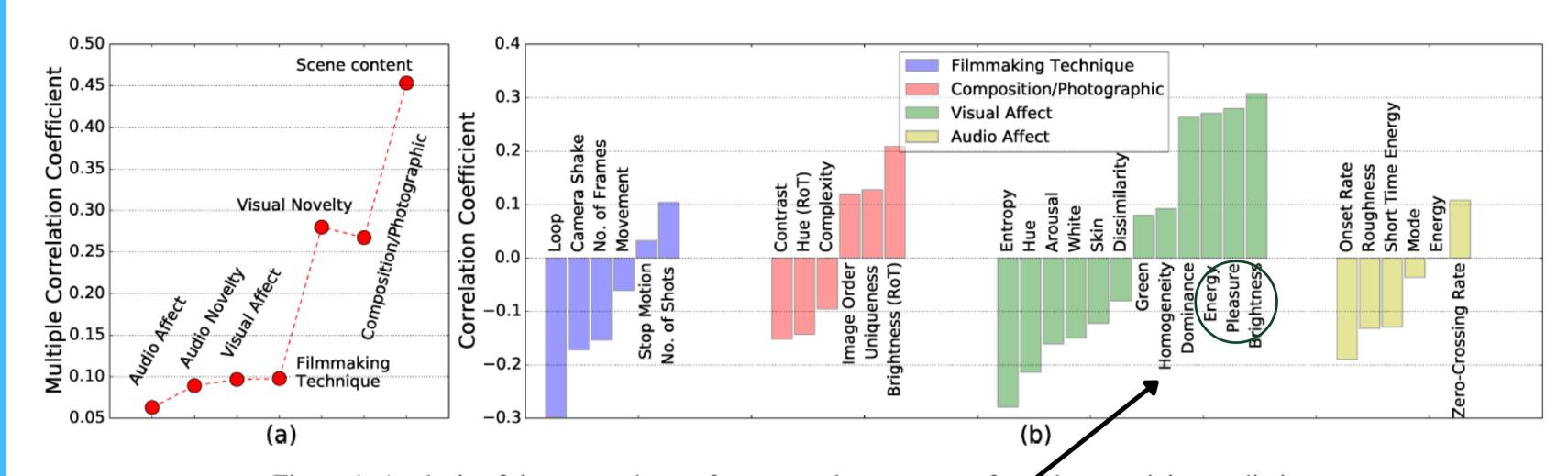


Figure 1. Analysis of the most relevant features and components for video creativity prediction



dominant non-overwhelming emotions

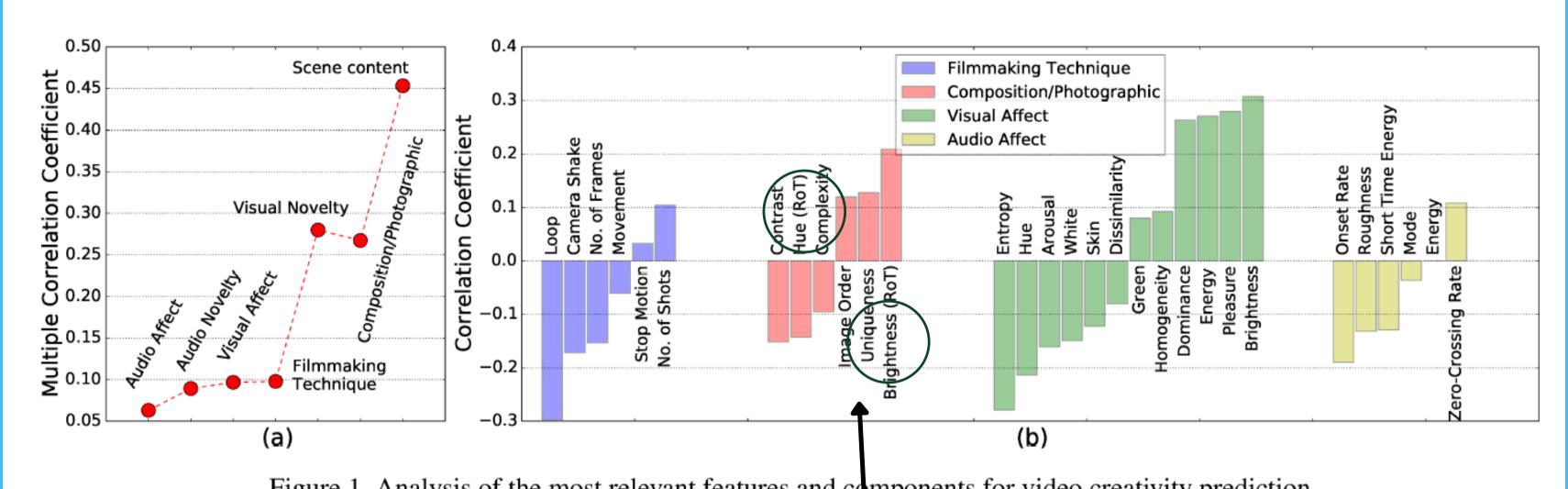


Figure 1. Analysis of the most relevant features and components for video creativity prediction



Warm bright colors

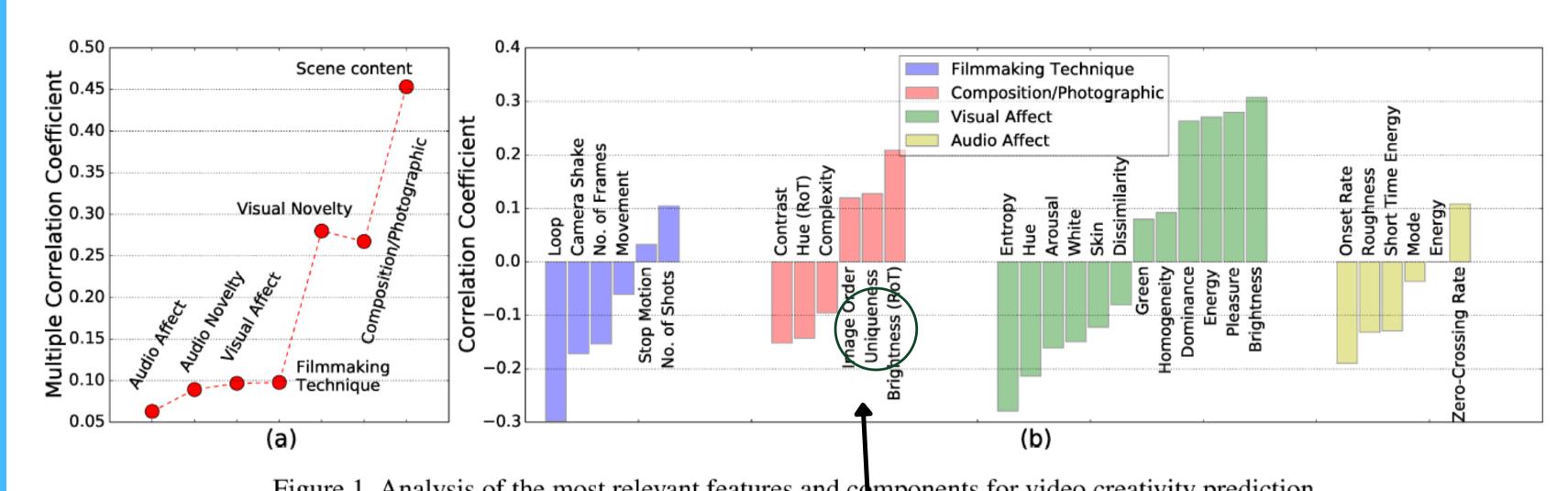


Figure 1. Analysis of the most relevant features and components for video creativity prediction



favour less familiar layout

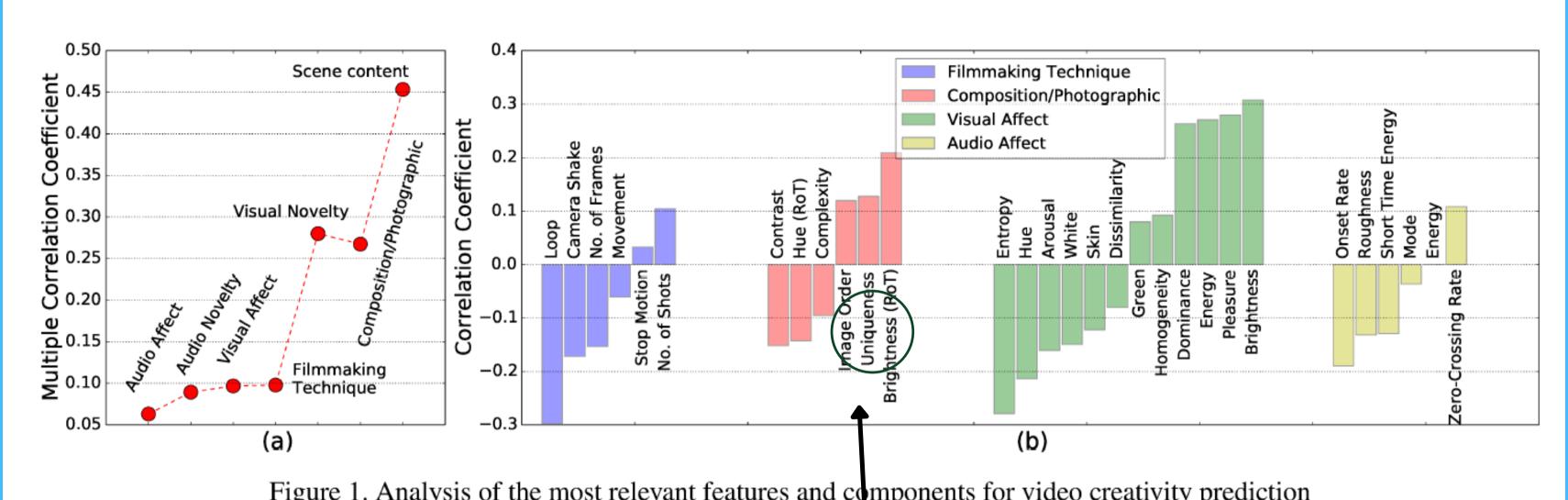


Figure 1. Analysis of the most relevant features and components for video creativity prediction

Correlation

favour less familiar layout

but no symmetry or depth of field

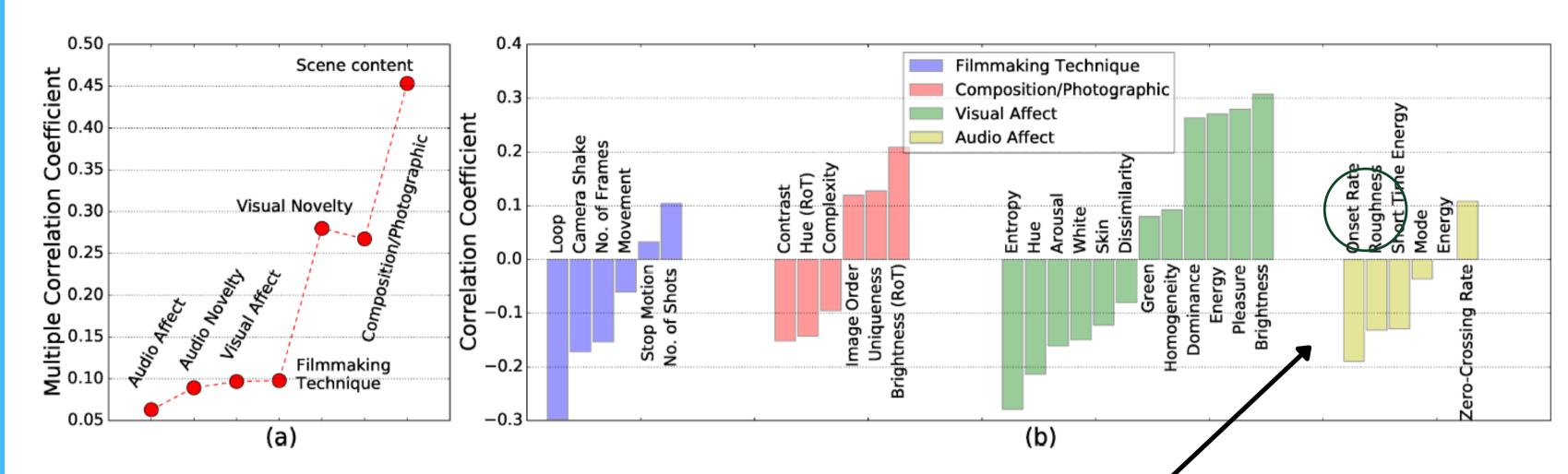


Figure 1. Analysis of the most relevant features and components for video creativity prediction



less-frenetic, low volume

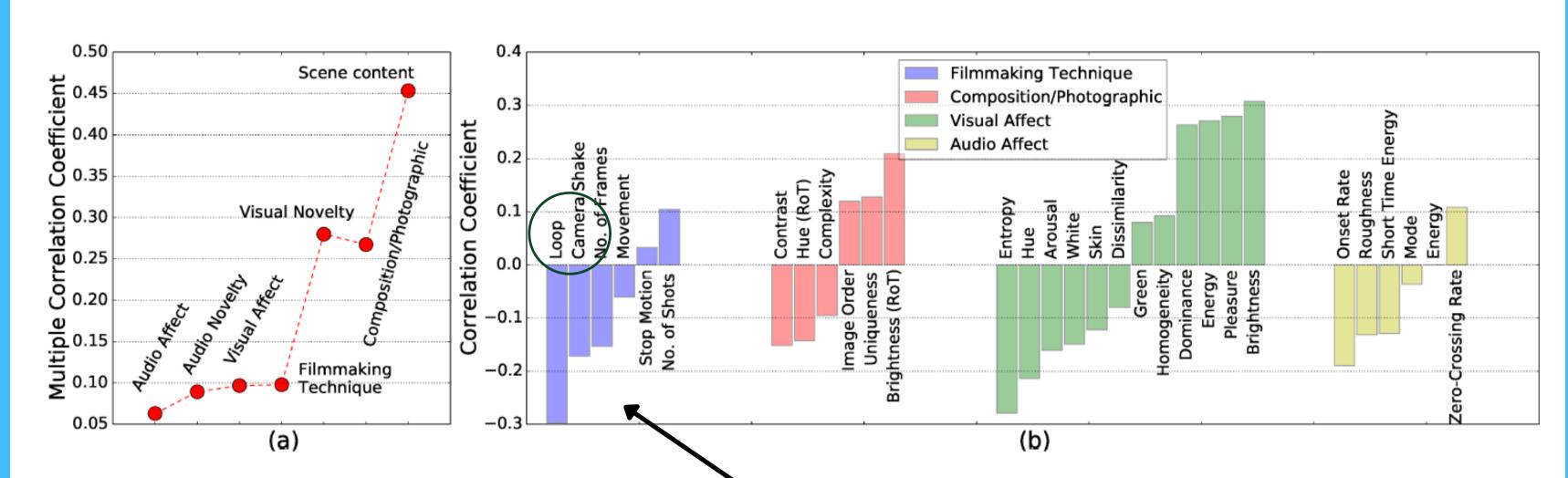


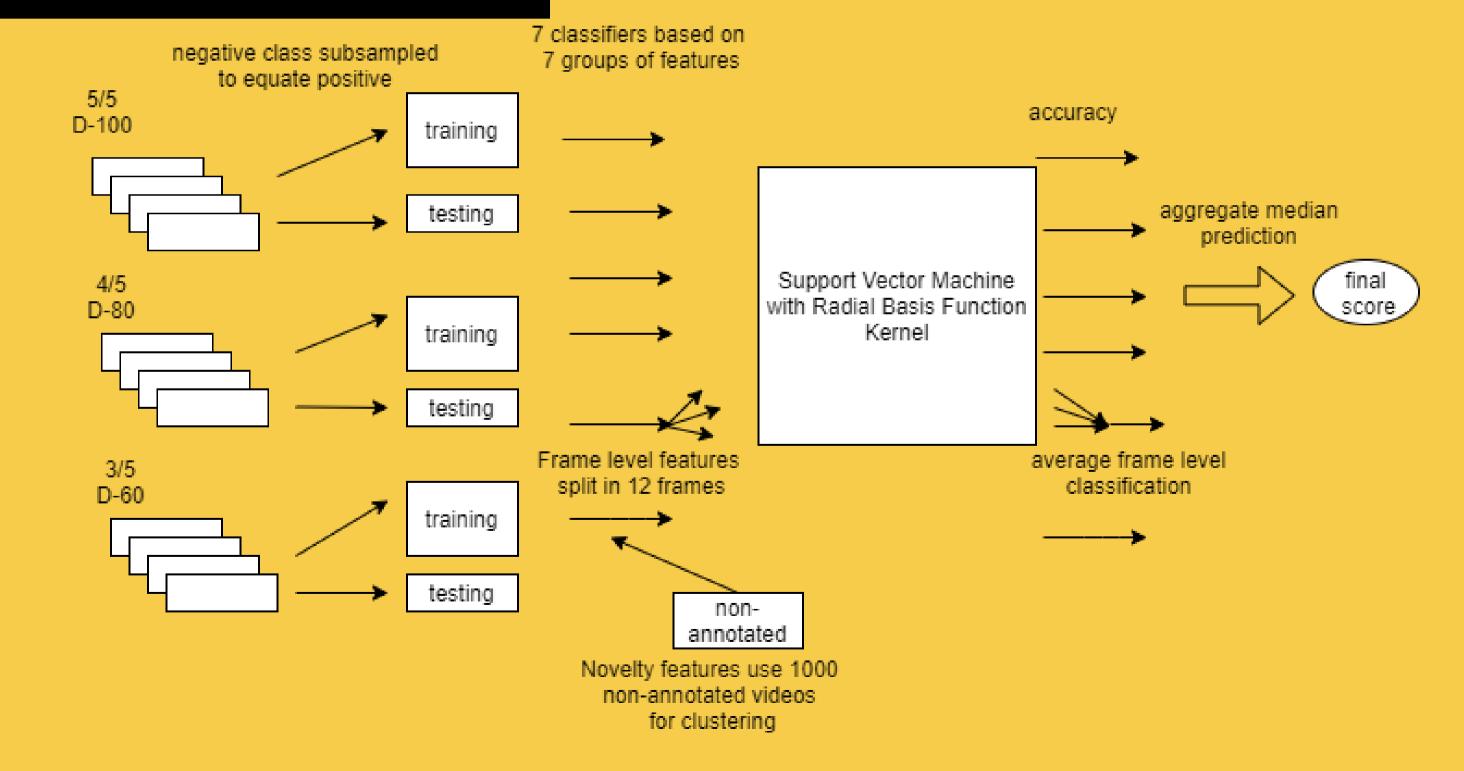
Figure 1. Analysis of the most relevant features and components for video creativity prediction

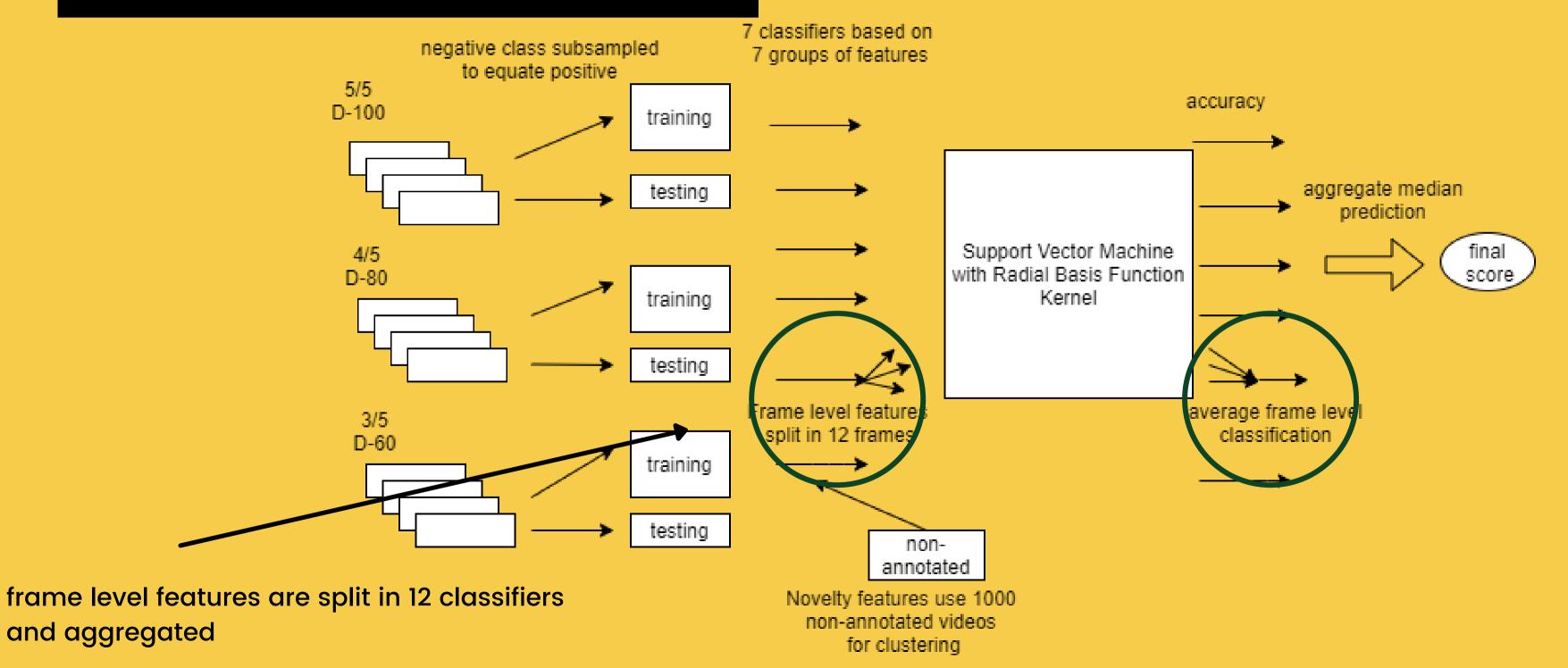


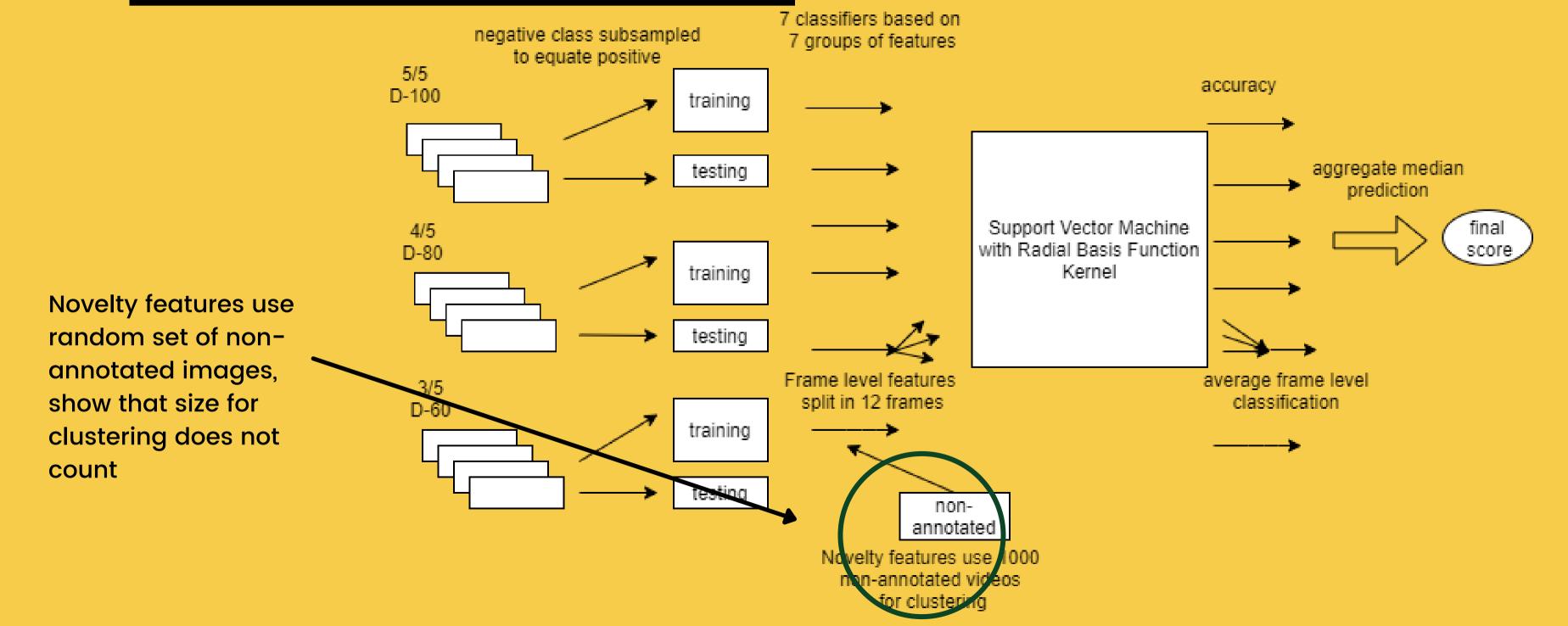
loops are characteristic, polished videos

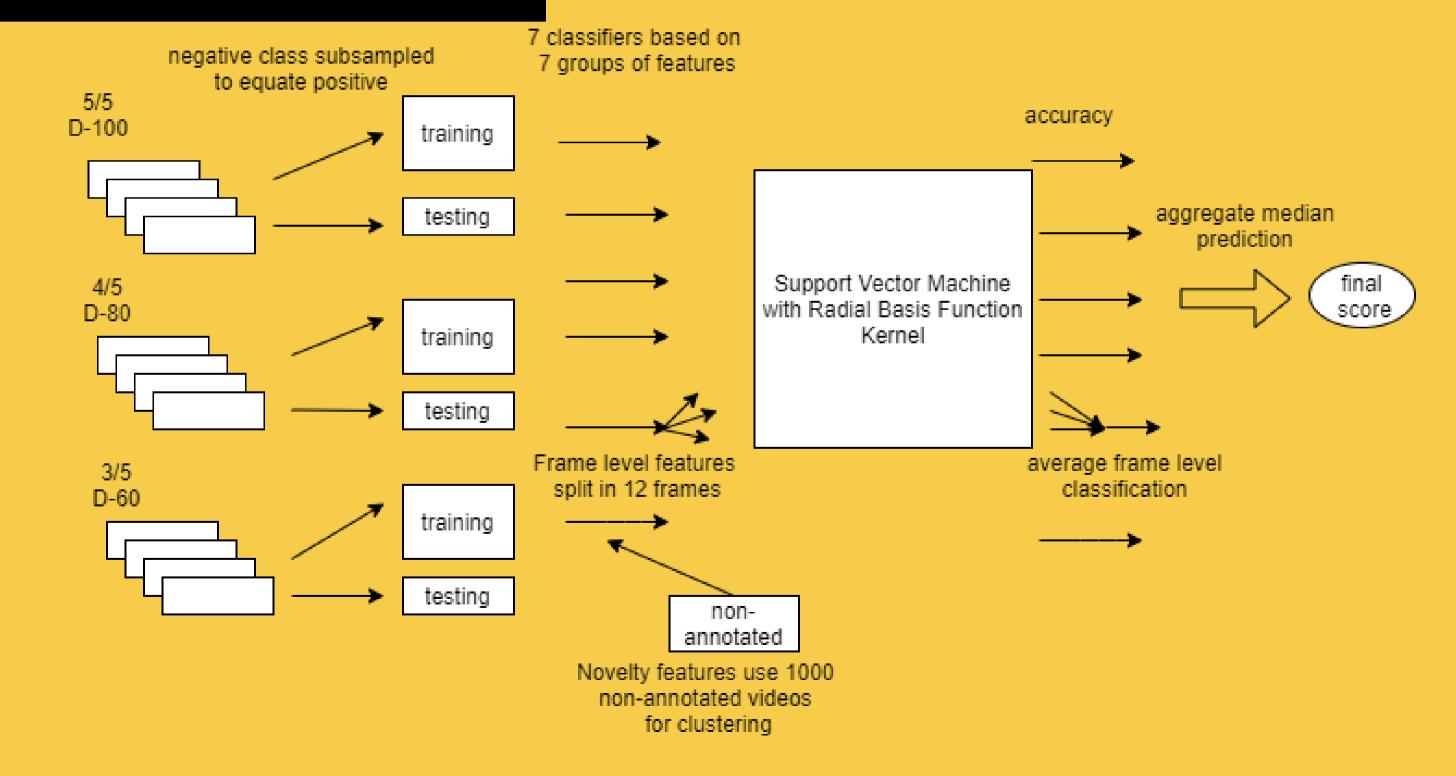
Research Question

Can we create a reliable crowdsourced dataset?
Can we extract features that identify creativity in micro-videos?
Can these be used to automatically classify a micro-video into creative and non-creative?









Feature	Accuracy			
reature	D-60	D-80	D-100	
Aesthetic Value				
Sensory Features				
Scene Content	0.67	0.69	0.74	
Filmmaking Techniques	0.65	0.69	0.73	
Composition & Photographic Technique	0.67	0.74	0.77	
All Sensory Features	0.69	0.75	0.77	
Emotional Affect Features				
Audio Affect	0.59	0.53	0.67	
Visual Affect	0.65	0.66	0.66	
All Emotional Affect Features	0.62	0.56	0.71	
All Aesthetic Value Features	0.68	0.72	0.79	
Novelty				
Audio	0.58	0.58	0.63	
Visual	0.63	0.67	0.74	
Audio + Visual Novelty	0.59	0.63	0.69	
Novelty + Aesthetic Value	0.69	0.73	0.80	

Table 5. Prediction results for value and novelty features

Results

Feature	Accuracy		
reature	D-60	D-80	D-100
Aesthetic Value			
Sensory Features			
Scene Content	0.67	0.69	0.74
Filmmaking Techniques	0.65	0.69	0.73
Composition & Photographic Technique	0.67	0.74	0.77
All Sensory Features	0.69	0.75	0.77
Emotional Affect Features			
Audio Affect	0.59	0.53	0.67
Visual Affect	0.65	0.66	0.66
All Emotional Affect Features	0.62	0.56	0.71
All Aesthetic Value Features	0.68	0.72	0.79
Novelty			
Audio	0.58	0.58	0.63
Visual	0.63	0.67	0.74
Audio + Visual Novelty	0.59	0.63	0.69
Novelty + Aesthetic Value	0.69	0.73	0.80

Table 5. Prediction results for value and novelty features

Results

Best individual features correspond to PCC results

Feature	Accuracy			
reature	D-60	D-80	D-100	
Aesthetic Value				
Sensory Features				
Scene Content	0.67	0.69	0.74	
Filmmaking Techniques	0.65	0.69	0.73	
Composition & Photographic Technique	0.67	0.74	0.77	
All Sensory Features	0.69	0.75	0.77	
Emotional Affect Features				
Audio Affect	0.59	0.53	0.67	
Visual Affect	0.65	0.66	0.66	
All Emotional Affect Features	0.62	0.56	0.71	
All Aesthetic Value Features	0.68	0.72	0.79	
Novelty				
Audio	0.58	0.58	0.63	
Visual	0.63	0.67	0.74	
Audio + Visual Novelty	0.59	0.63	0.69	
Novelty + Aesthetic Value	0.69	0.73	0.80	

Table 5. Prediction results for value and novelty features

Results

Combination of emotion and sensory features shows great improvement, complementarity

Feature	Accuracy			
reature	D-60	D-80	D-100	
Aesthetic Value				
Sensory Features				
Scene Content	0.67	0.69	0.74	
Filmmaking Techniques	0.65	0.69	0.73	
Composition & Photographic Technique	0.67	0.74	0.77	
All Sensory Features	0.69	0.75	0.77	
Emotional Affect Features				
Audio Affect	0.59	0.53	0.67	
Visual Affect	0.65	0.66	0.66	
All Emotional Affect Features	0.62	0.56	0.71	
All Aesthetic Value Features	0.68	0.72	0.79	
Novelty				
Audio	0.58	0.58	0.63	
Visual	0.63	0.67	0.74	
Audic + Visual Novelty	0.59	0.63	0.69	
Novelly + Aesthetic Value	0.69	0.73	0.80	

Table 5. Prediction results for value and novelty features

Results

Mild improvement adding also novelty

Conclusion

Crowdsourcing

Good interannotator agreement

Three datasets.

Features

New features encoding:

- aesthetic values
- novelty

Model

Promising results,

80% accuracy

Future Work

- intellectual features
- metadata
- application toother micro-videoplatforms