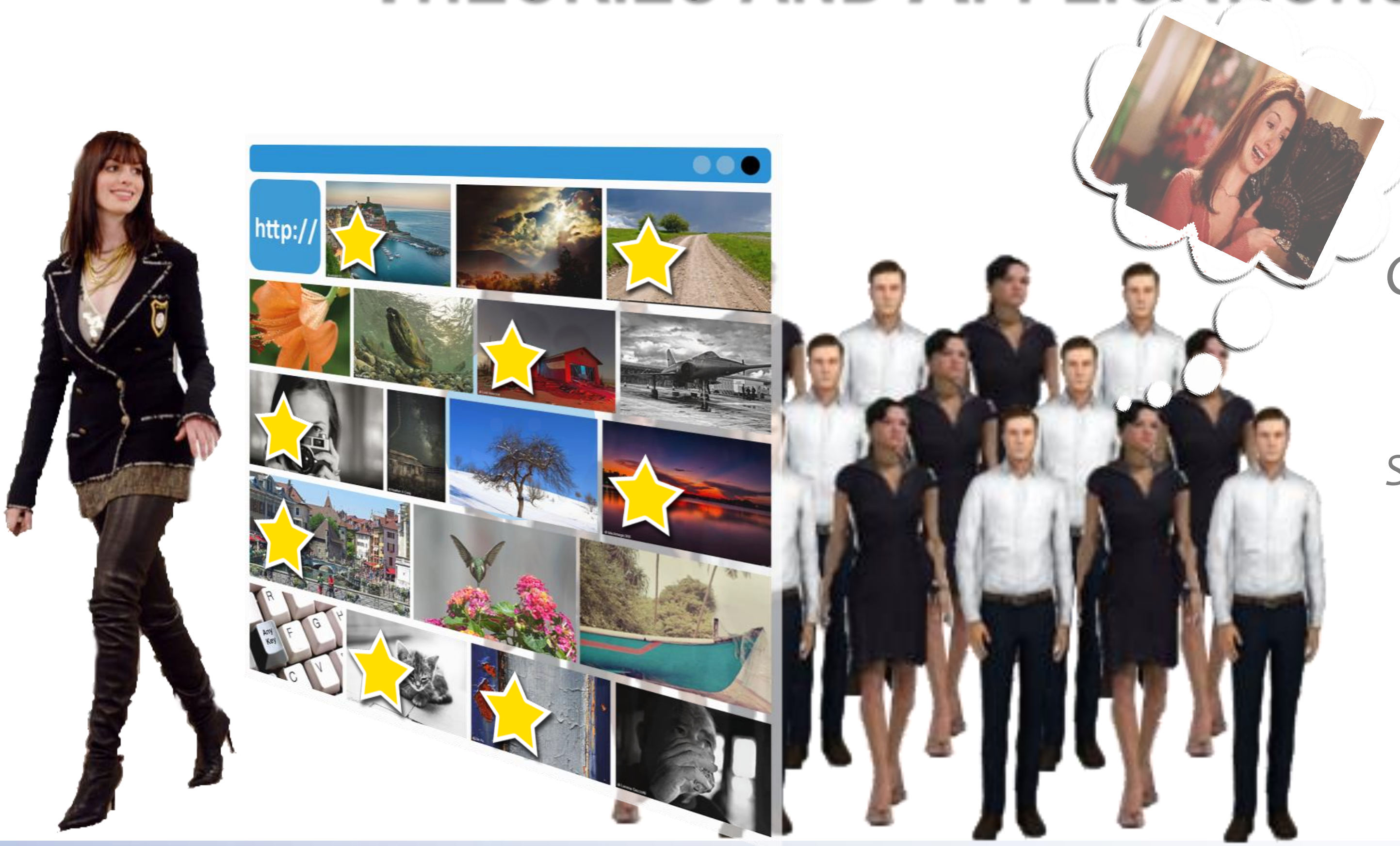
A Social Signal Processing Perspective on Computational Aesthetics: Theories and Applications



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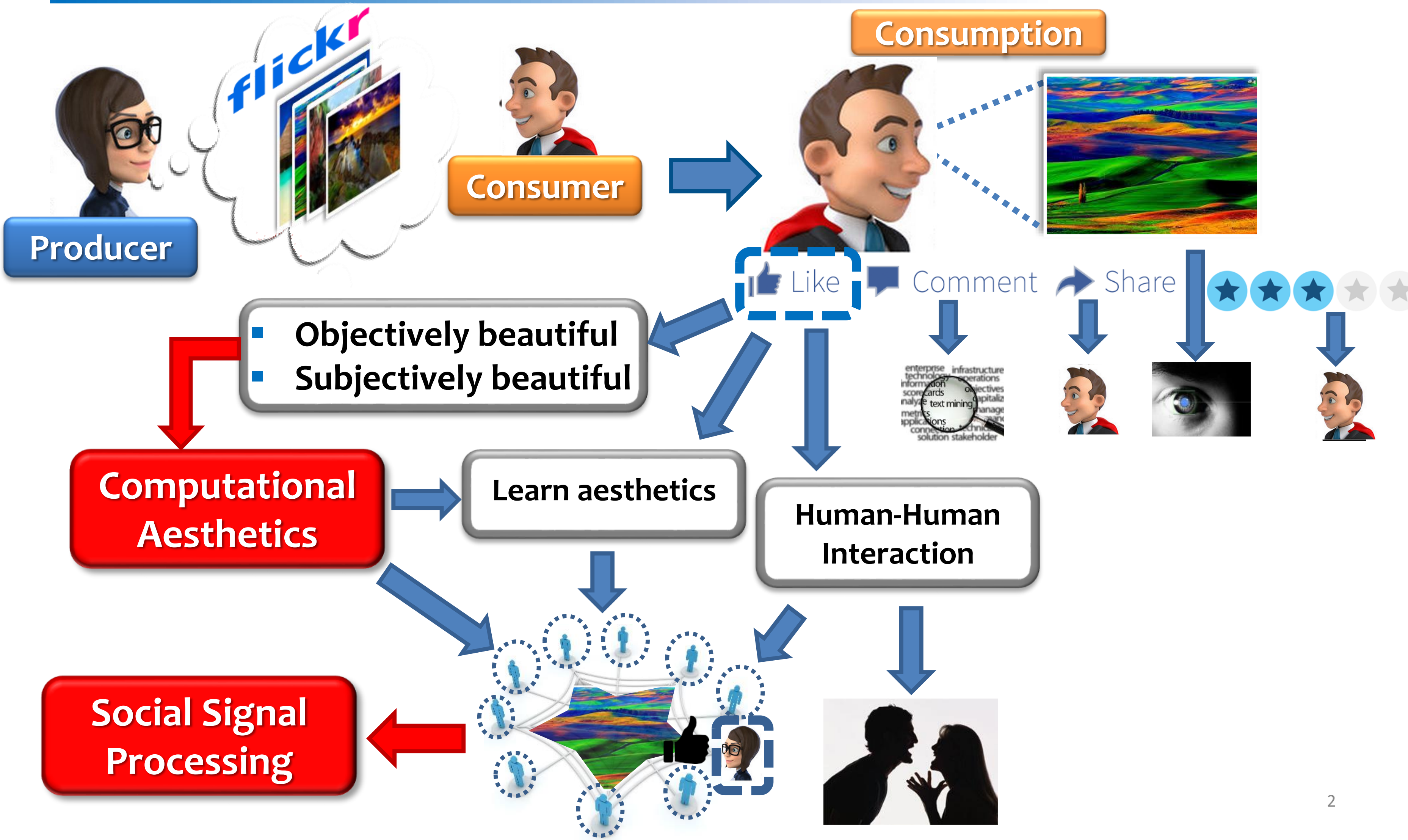
Overview



flickr
Producer
Consumer
Consumption
Like
Comment
Share
Objectively beautiful
Subjectively beautiful
Computational Aesthetics
Learn aesthetics
Human-Human Interaction
Social Signal Processing

Goals and Contributions

- **Goals**:
  1. Enrich the computational aesthetics field, by **accounting for the personal sphere**
  2. Consider an aesthetical preference as a **social signal**, that can be captured and interpret by **others**

- **Contributions**:

  Personal Aesthetics:
  - A new soft biometric trait
  - A new social signal for Personality Computing
    - Collection of a personality-augmented image dataset of aesthetical preferences: **PsychoFlickr**

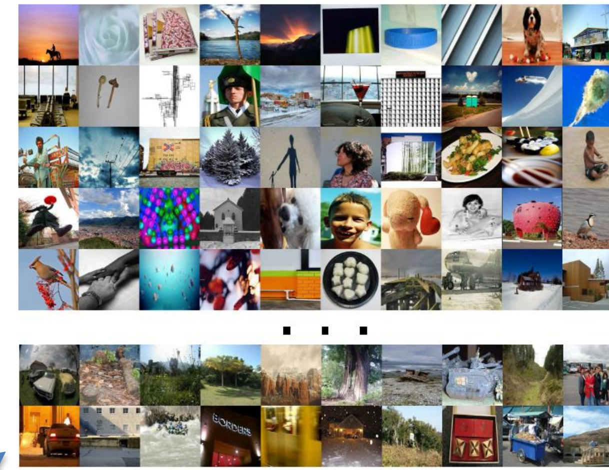
Outline

- **Part I:**
  - Personal Aesthetics for Soft Biometrics
    - Computational Aesthetics (features)
    - A new soft biometric trait
      - Lasso Regression approach
      - Multiresolution Regression approach
- **Part II:**
  - Personal Aesthetics for Personality Computing
    - Social Signal Processing
    - A new social signal for Personality Computing
      - Multiple Instance Regression approach
      - Convolutional Neural Network
- Conclusions and Future Works

Computational Aesthetics

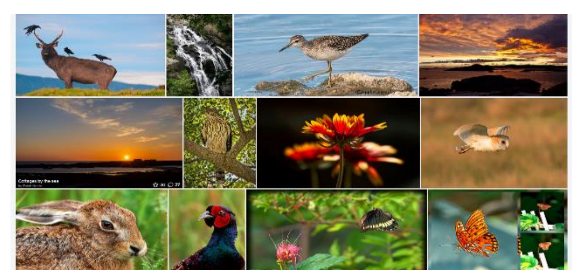
Definition

Computational Aesthetics: aims at developing «*computational methods that can make applicable aesthetic decisions in a similar fashion as humans can*»



- Aesthetics: study of beauty and taste [Honeig '05]
- Computational Aesthetics focuses mostly on capturing and modeling a **general and shared** sense of beauty… [Adams '03]

- … automatically select high aesthetic quality images from large image collections [Dhar et al. '11]
- … but the beauty is in the eye of the beholder! [Beiderman & Vessel '03]



→ ***personal aesthetics!***

State of the art

- **Aesthetics - Psychology**
  - ✓ Applied mainly to paintings [Rawlings '98]
  - ✓ It studies how individual preferences can be modeled, depending on the subject at hand [Furham '01]
  - ✓ Guidelines of appreciation

- **Computational Aesthetics - Computer Vision**
  - ✓ Applied to digital images
  - ✓ It aims at finding a general sense of beauty
  - ✓ Many applications: prediction of aesthetic score, recommender systems, features engineering
  - ✓ It studies features which capture perceptual and content based features [Biederman '06, Furham '01, Girshick '10]
  - ✓ Recently, it exploit the wisdom of crowds for learning common preferences (Flickr, etc) [Bacukhage'13, Dhar '11, Murray '12]

Computational Aesthetics Features:

Low level representation

Category	Name	L	Short Description
Color	Use of light	1	Average pixel intensity of V channel
	HSV statistics	3	Mean of S channel and standard deviation of S, V channels
	Emotion-based	3	Amount of *Pleasure*, *Arousal*, *Dominance*
	Circular Variance	1	*Circular variance* of the H channel in the IHLS color space
	Colorfulness	1	Colorfulness measure based on Earth Mover's Distance (EMD)
	Color Name	11	Amount of *Black*, *Blue*, *Brown*, *Green*, *Gray*, *Orange*, *Pink*, *Purple*, *Red*, *White*, *Yellow*
Composition	Edges	1	Total number of edge points, extracted with Canny
	Level of detail	1	Number of regions (after mean shift segmentation)
	Regions	1	Average *size* of the regions (after mean shift segmentation)
	Low depth of field (DOF)	3	Amount of focus sharpness in the inner part of the image w.r.t. the overall focus
	Rule of thirds	2	Mean of S,V channels in the inner rectangle of the image
	Image parameters	1	Size of the image
Texture	Entropy	1	Image entropy
	Wavelet textures	12	Level of spatial graininess measured with a three-level (L1,L2,L3) Daubechies wavelet transform on the HSV channels
	Tamura	3	Amount of *Coarseness*, *Contrast*, *Directionality*
	GLCM-features	12	Amount of *Contrast*, *Correlation*, *Energy*, *Homogeneity* for each HSV channel
Content	Objects	28	Objects detectors : in particular, here are the objects for which detectors are available: *people*, *plane*, *bike*, *bird*, *boat*, *bottle*, *bus*, *car*, *cat*, *dog*, *table*, *horse*, *motorbike*, *chair*. In all the cases we kept the number of instances and their average bounding box *size*
	Faces	2	Number and *size* of faces after Viola-Jones face detection algorithm

Personal Aesthetics for Soft Biometrics

Soft Biometrics

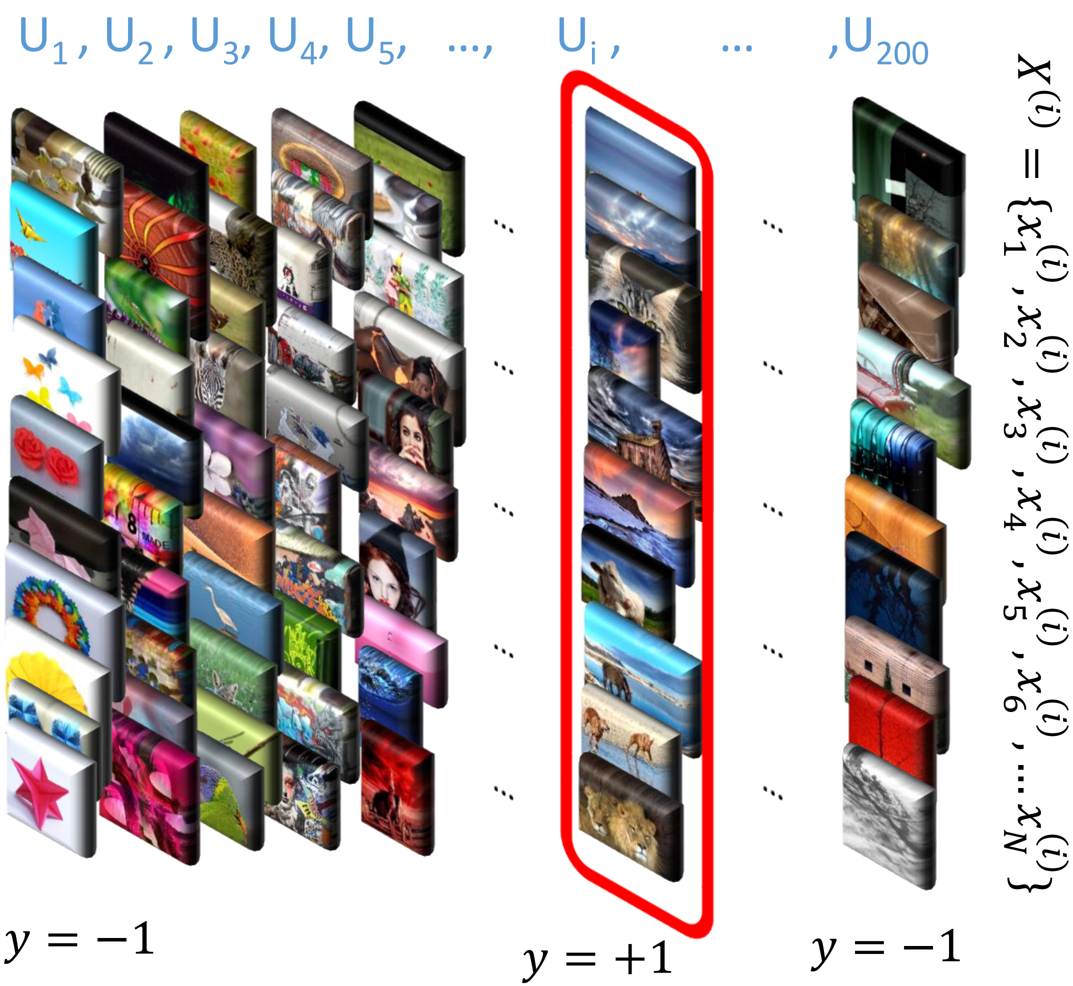
Soft Biometrics: physical, behavioral or HCI human characteristics, classifiable in pre-defined human compliant categories, for establishing the identity of an individual.

Traits which accept this definition include, but are not limited to:

- *Physical*: skin color, eye color, hair color, presence of beard, presence of moustache, height, weight.
- *Behavioral*: gait, postures, gestures.
- *Adhered human characteristics*: clothes color, tattoos, accessories.
- HCI-based: use of Internet applications, chatting, browsing histories, mouse dynamics ⟹ *personal aesthetics* new

A New Soft Biometric Trait based on Personal Aesthetics

MIR approach

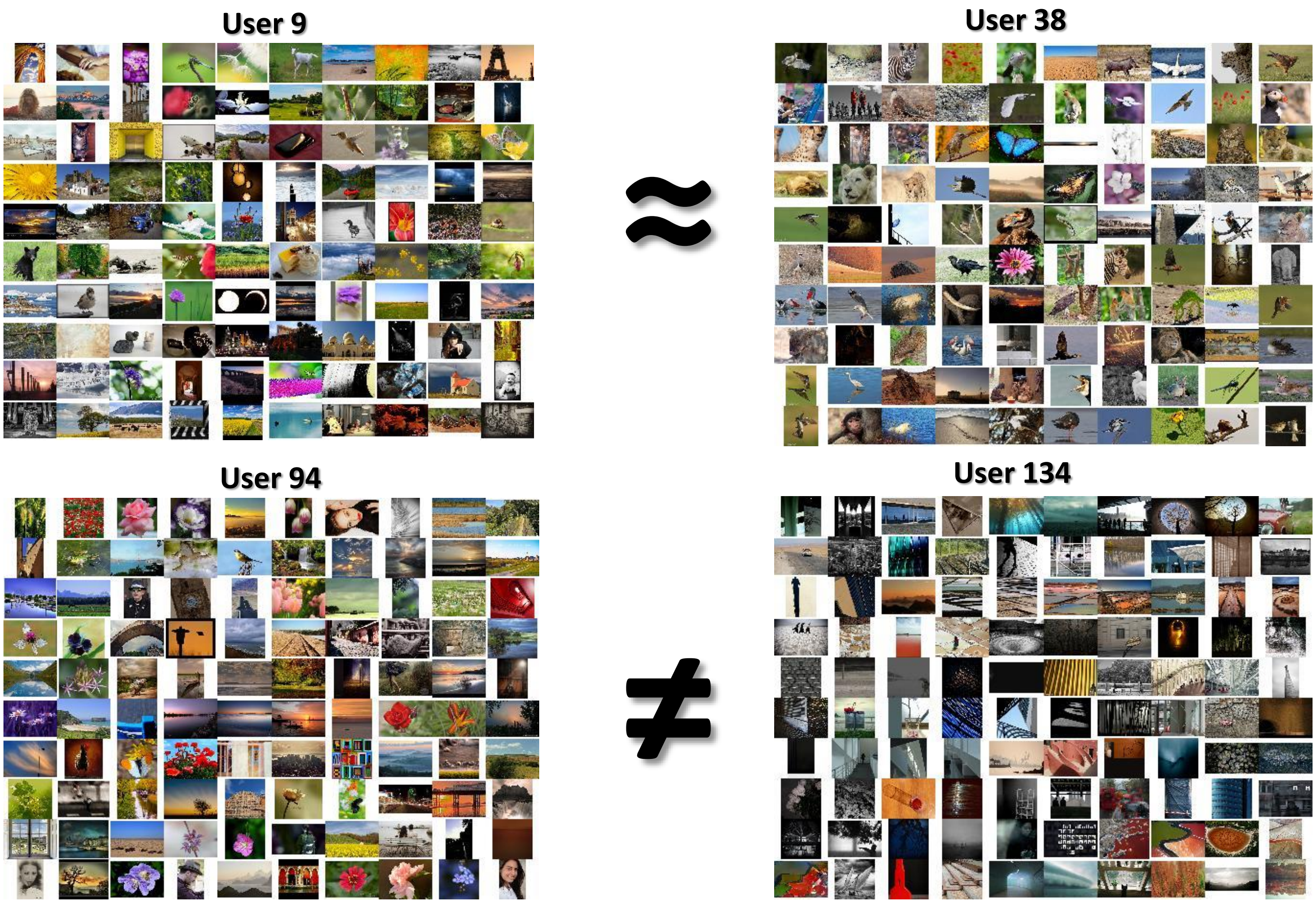


- Goal: discriminate a single user from all the other ones
- Personal aesthetics is exploited into a biometric recognition/authentication system:
  - ✓ **Enrollment stage**: the "preference model" of a user is learned from a set of *preferred images*
  - ✓ **Verification/recognition phase**, the user model is tested with an unseen set of favorites preferred by a probe subject.

[P. Lovato M. Bicego C. Segalin A. Perina N. Sebe M. Cristani. Faved! biometrics: tell me which image you like and Ill tell you who you are. IEEE Transactions on Information Forensics and Security 2014.]

A New Soft Biometric Trait based on Personal Aesthetics

MIR approach – Examples of users' preferred pictures



A New Soft Biometric Trait based on Personal Aesthetics

MIR approach - Enrollment

Learning of the loading is performed by LASSO regression as a binary problem on all the training set

the feature vector

$$\mathbf{y}_n = \mathbf{w}^{(u)\mathrm{T}} \mathbf{x}_n$$

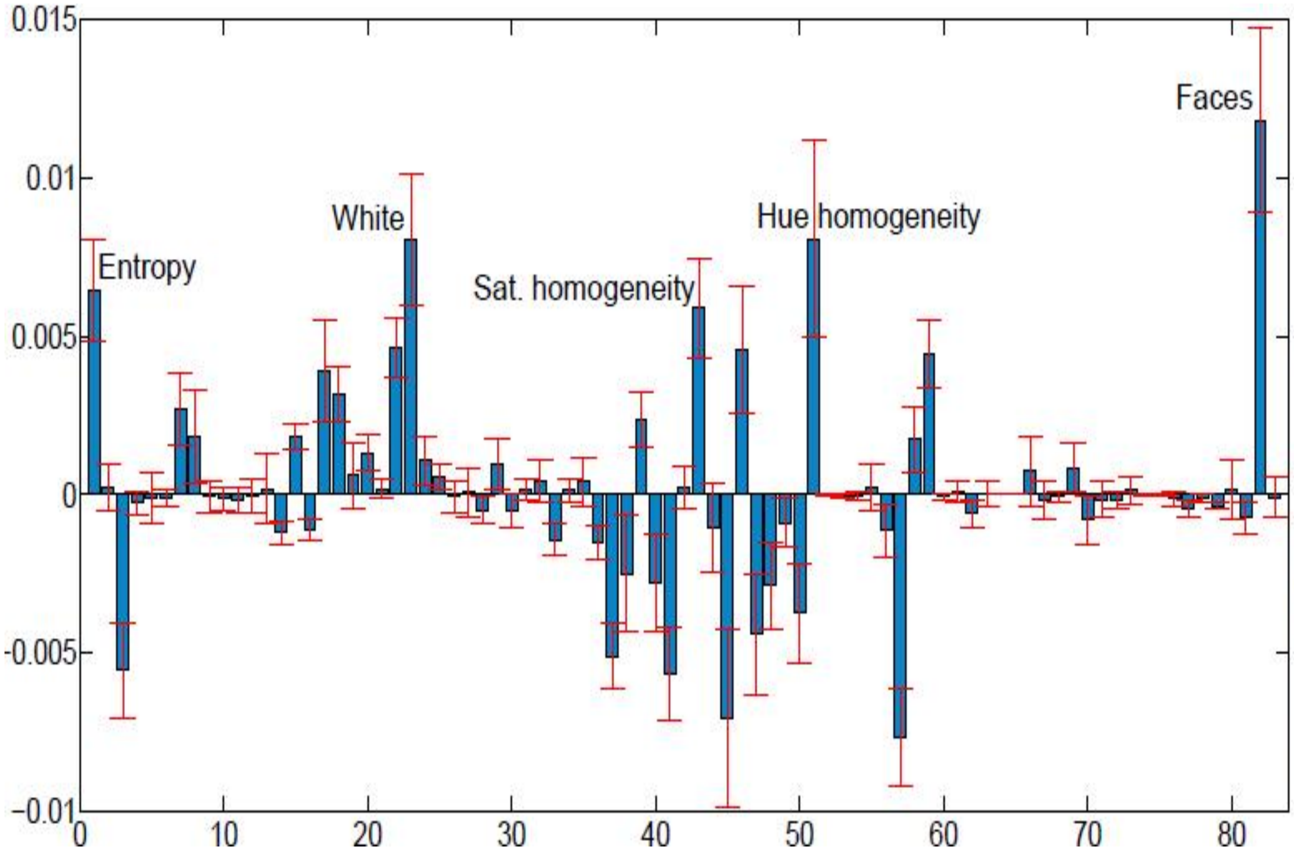
the coefficients vector

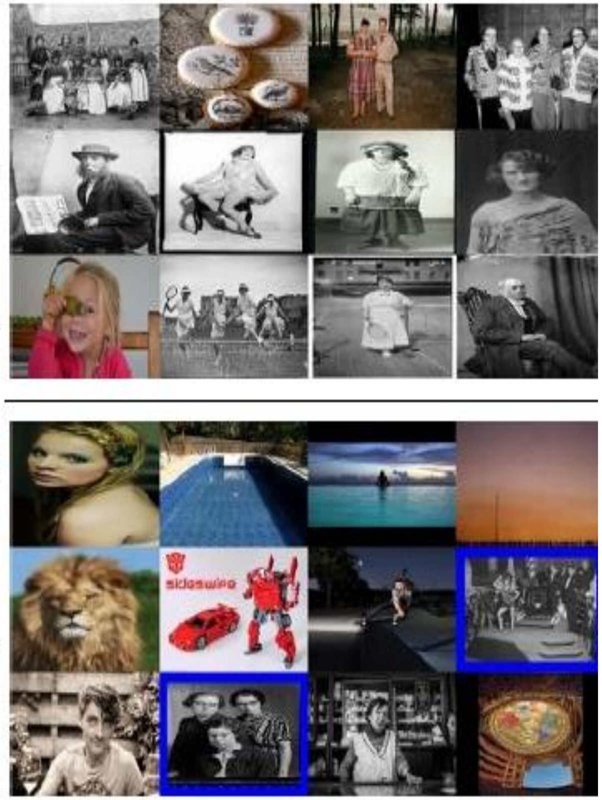
where $E\left(\mathbf{w}^{(u)}\right) = \sum_{n=1}^{N_{TR}} \left(\mathbf{y}_n - \mathbf{w}^{(u)} \mathbf{x}_n\right)^2$

subject to the sparsity constraint $\sum_{d=1}^{D} \left| w_d \right| \le t$

A New Soft Biometric Trait based on Personal Aesthetics

MIR approach - Result of enrollment





A New Soft Biometric Trait based on Personal Aesthetics

MIR approach - Matching score

- Given an image n of the unknown subject v, the goal is to evaluate how probably it is preferred by a subject u (to check if u and v do match!)

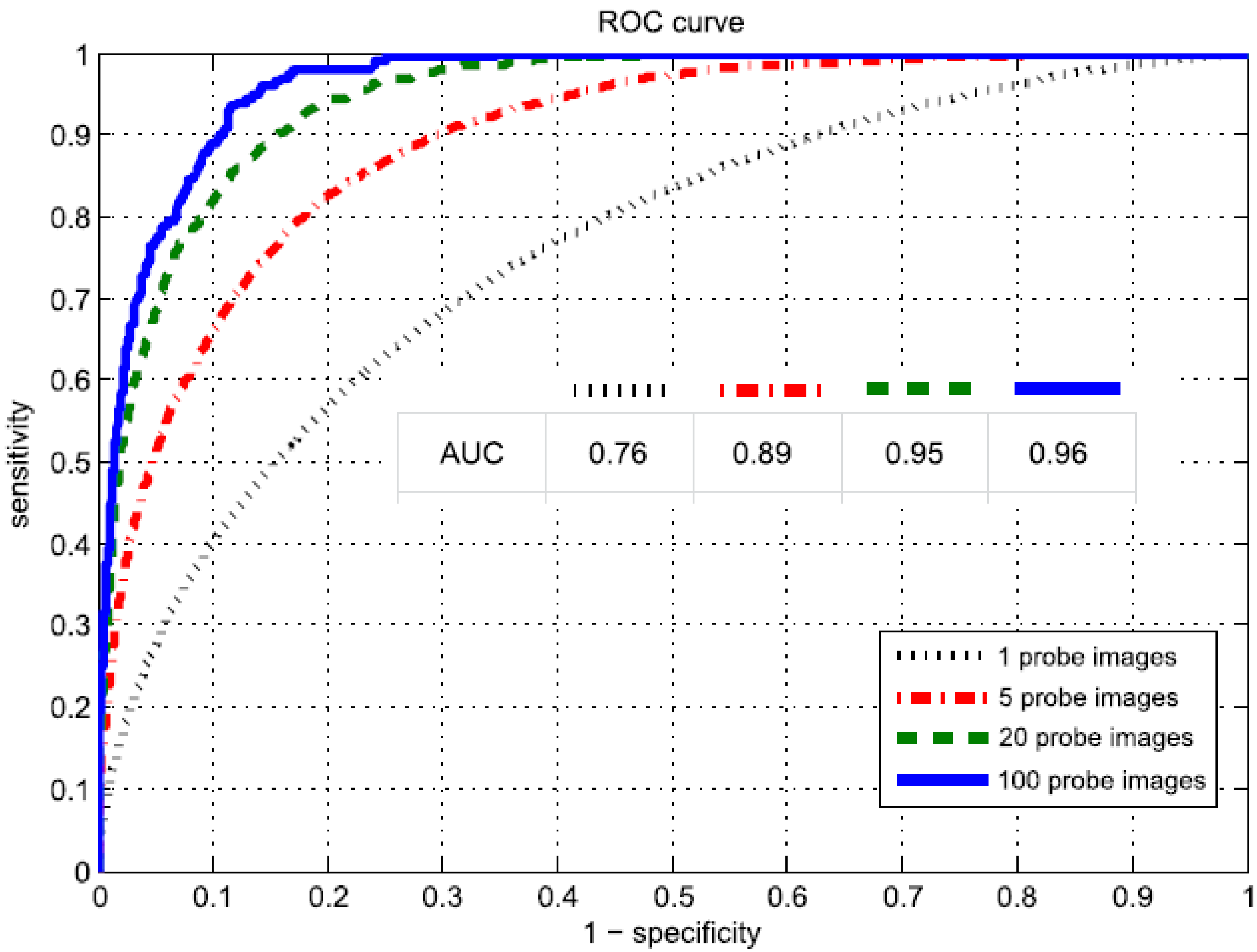
- Intuitively, the expressivity of a single image is limited, so multiple test images (N_{TE}) belonging to the same subject are taken into account, and the final matching score is

$$\beta_n^{(u,v)} = \mathbf{w}^{(u)\mathrm{T}} \mathbf{x}_n^{(v)}$$

$$\beta^{(u,v)} = \frac{1}{N_{TE}} \sum_{n=1}^{N_{TE}} \beta_n^{(u,v)}$$

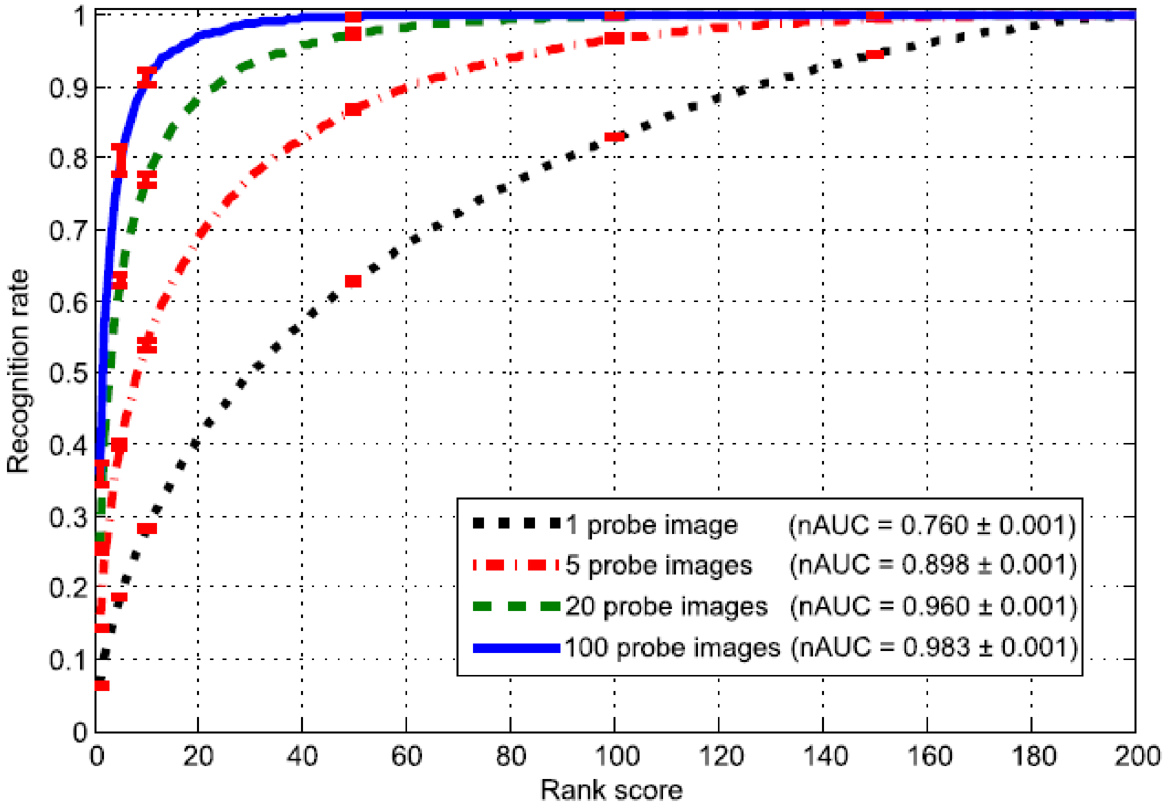
A New Soft Biometric Trait based on Personal Aesthetics

MIR approach - Results of Authentication (Verification)



A New Soft Biometric Trait based on Personal Aesthetics

MIR approach - Results of Recognition (Identification)

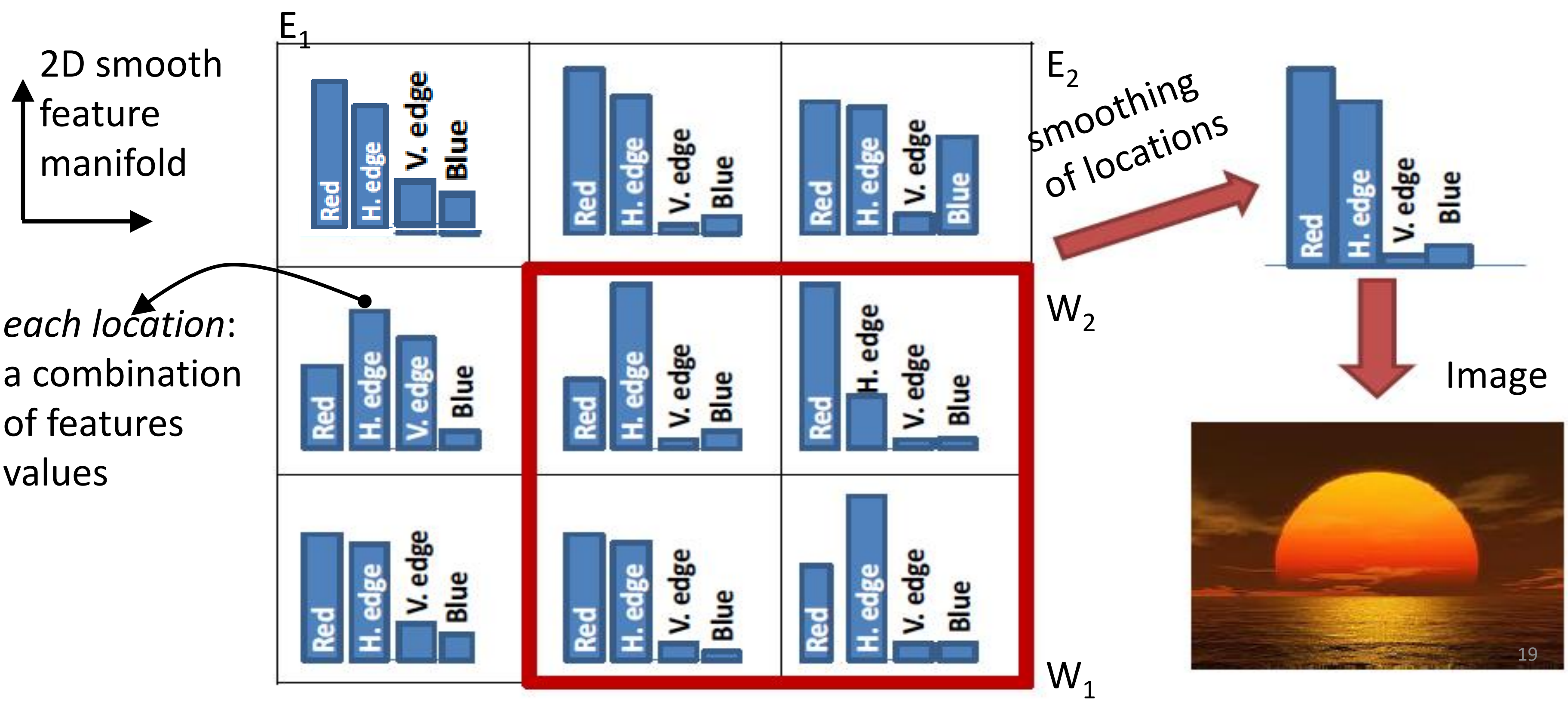


Protocol	**rank 1**	**rank 5**	**rank 20**	**rank 100**
1 probe image	0.063	0.188	0.408	0.829
5 probe images	0.143	0.399	0.688	0.966
20 probe images	0.254	0.629	0.883	0.998
100 probe images	0.359	0.796	0.970	0.999

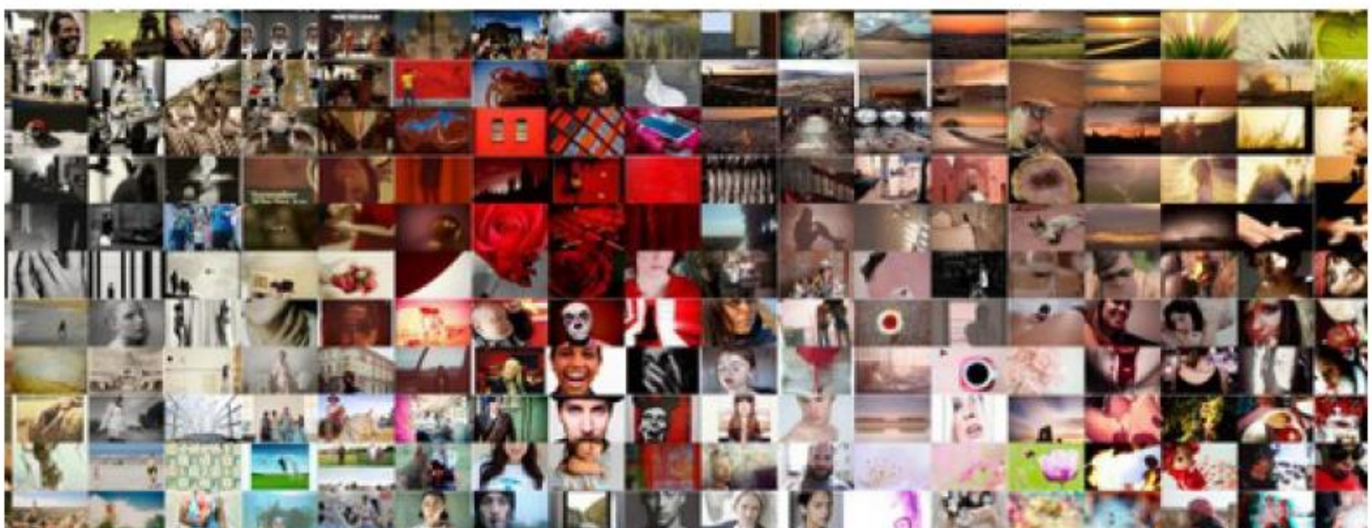
Mapping Image Preferences on a Counting Grid

Organizing and making sense of Bag of Words

- Generative model for feature extraction and information visualization [Perina & Jojic CVPR 2011, under patenting]
- An image is modeled as an *histogram of features*




Textured images, people inside
Landscapes, no people inside
Yellow scenes, some faces
Red, mono-chromatic
People in the foreground, light background
Faces in the foreground, light background



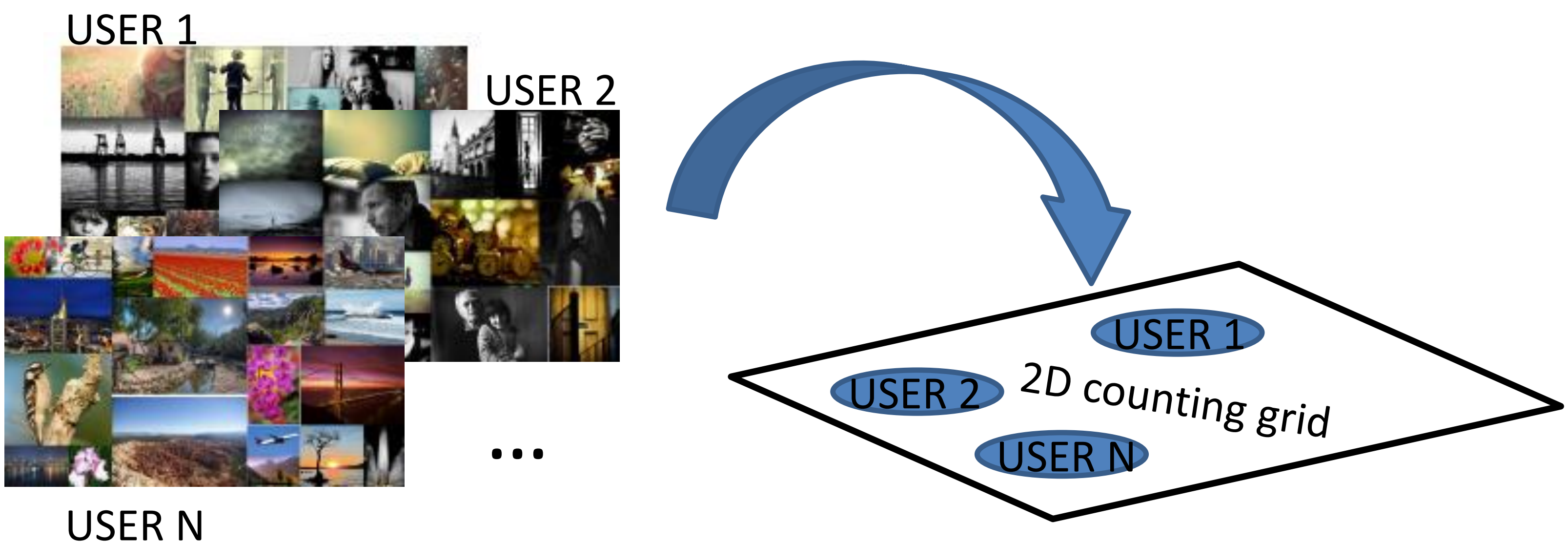
Mapping Image Preferences on a Counting Grid

Embedding map of user aesthetic preferences

- Inferences have been used to extract where the images of a user are, creating *user maps*

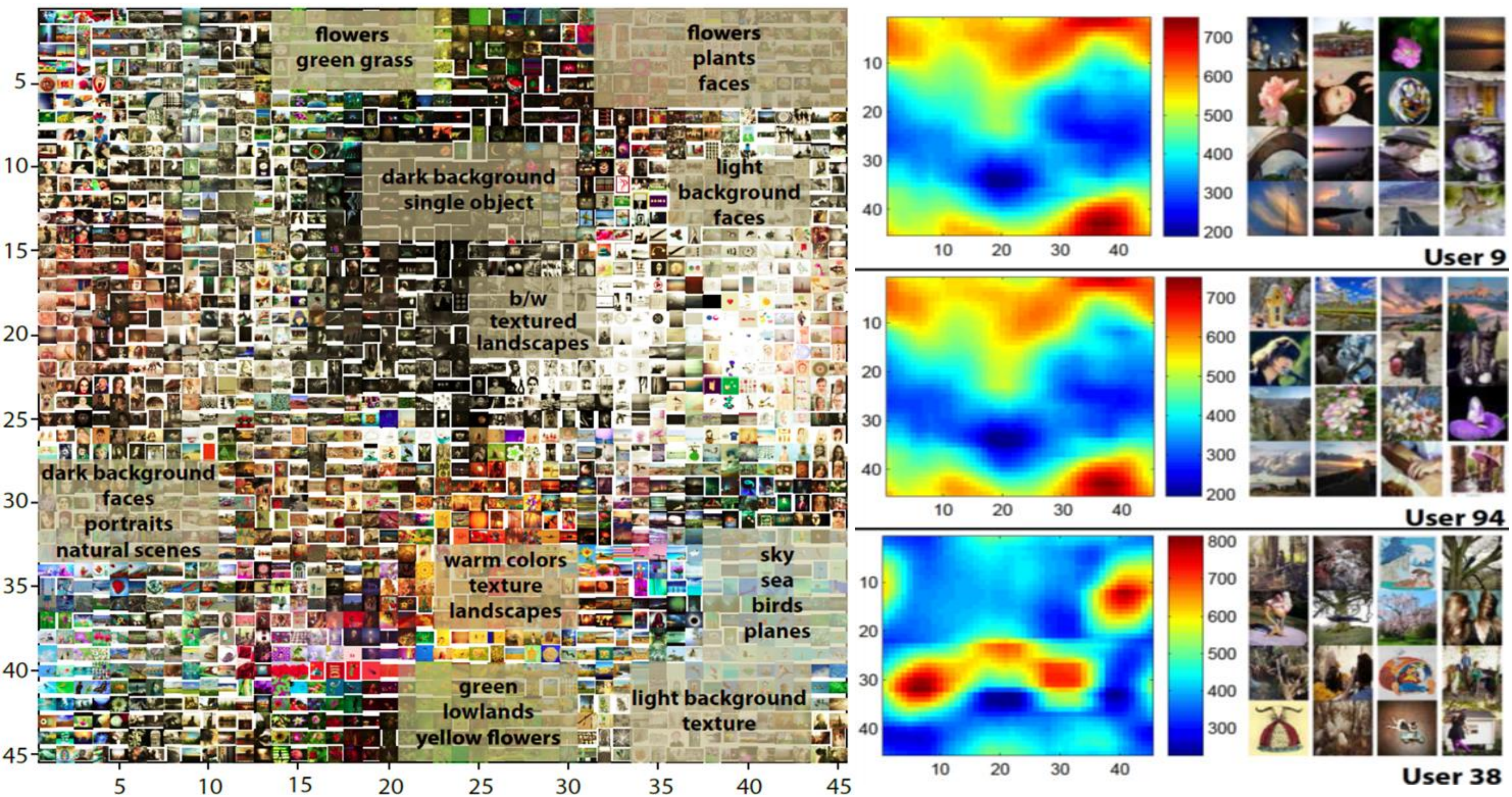
$$\gamma(\mathbf{i}) = \frac{\sum_t \sum_{\mathbf{k}|\mathbf{i}\in W_{\mathbf{k}}} q_{\mathbf{k}^t} \cdot y^t}{\sum_t \sum_{\mathbf{k}|\mathbf{i}\in W_{\mathbf{k}}} q_{\mathbf{k}^t}}$$

- People's preferences are clusters in the grid!



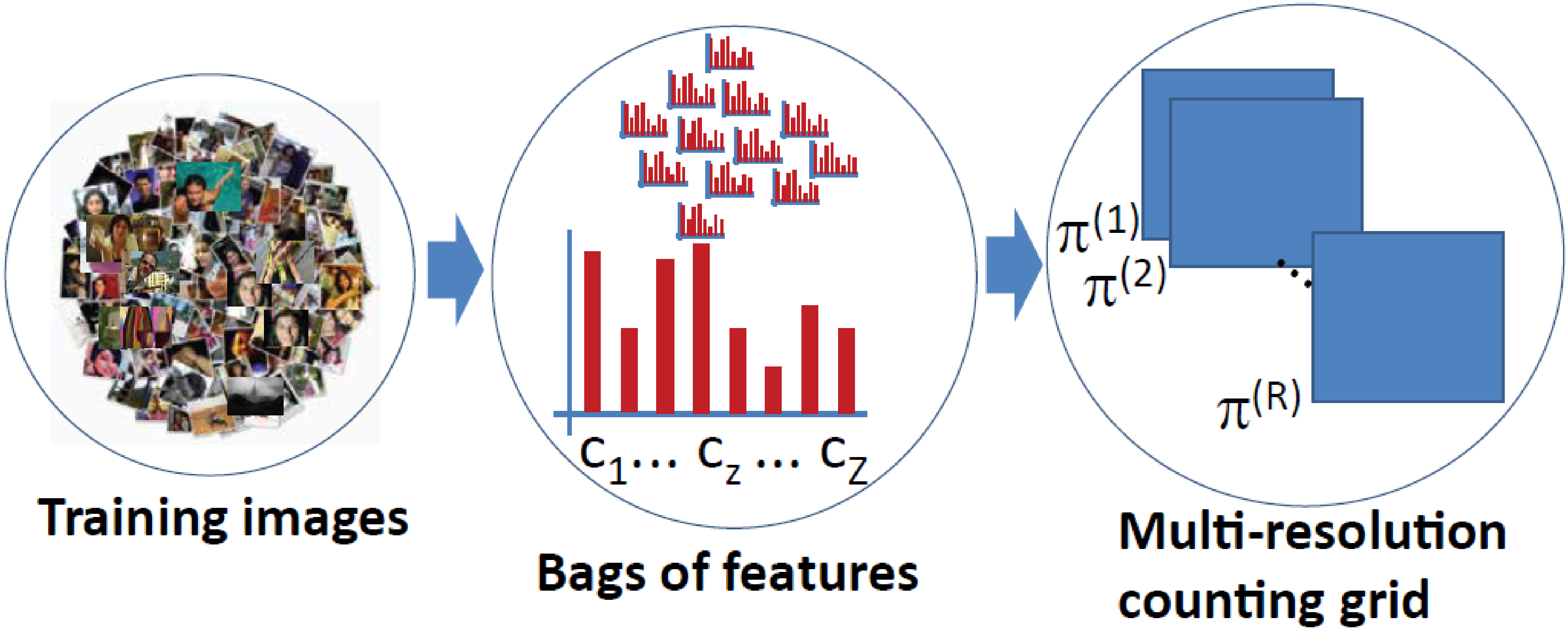
Mapping Image Preferences on a Counting Grid

Embedding map of user aesthetic preferences



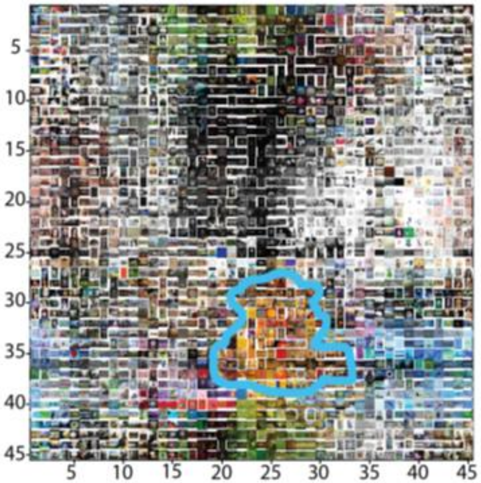
Statistical Generative Multiresolution Approach

MRCG approach - Initialization step

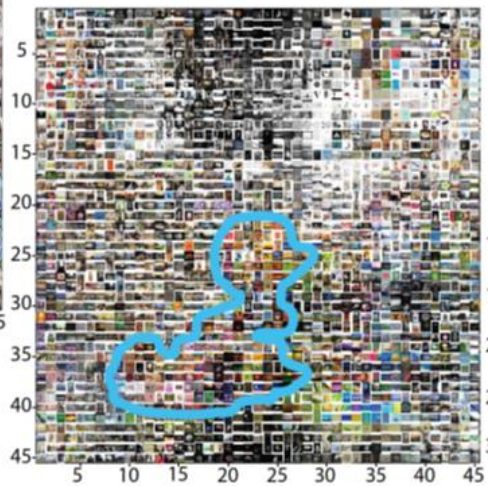


Statistical Generative Multiresolution Approach

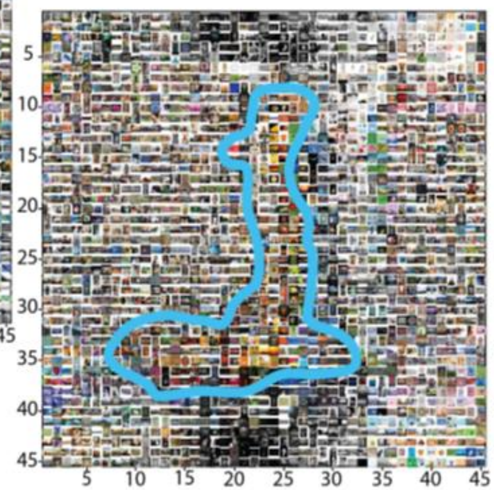
MRCG approach – Visualization of mutliresolution CGs



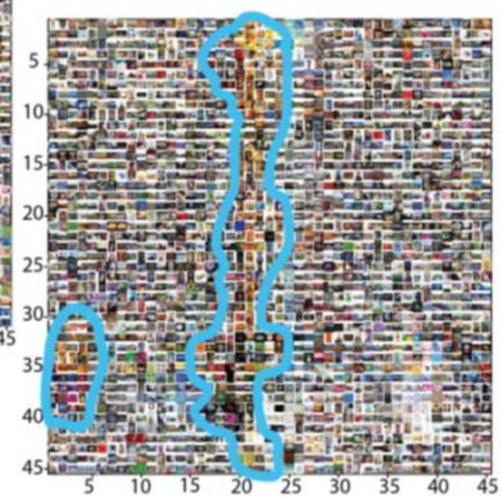
res 35 (S = 10)



res 25 (S = 20)



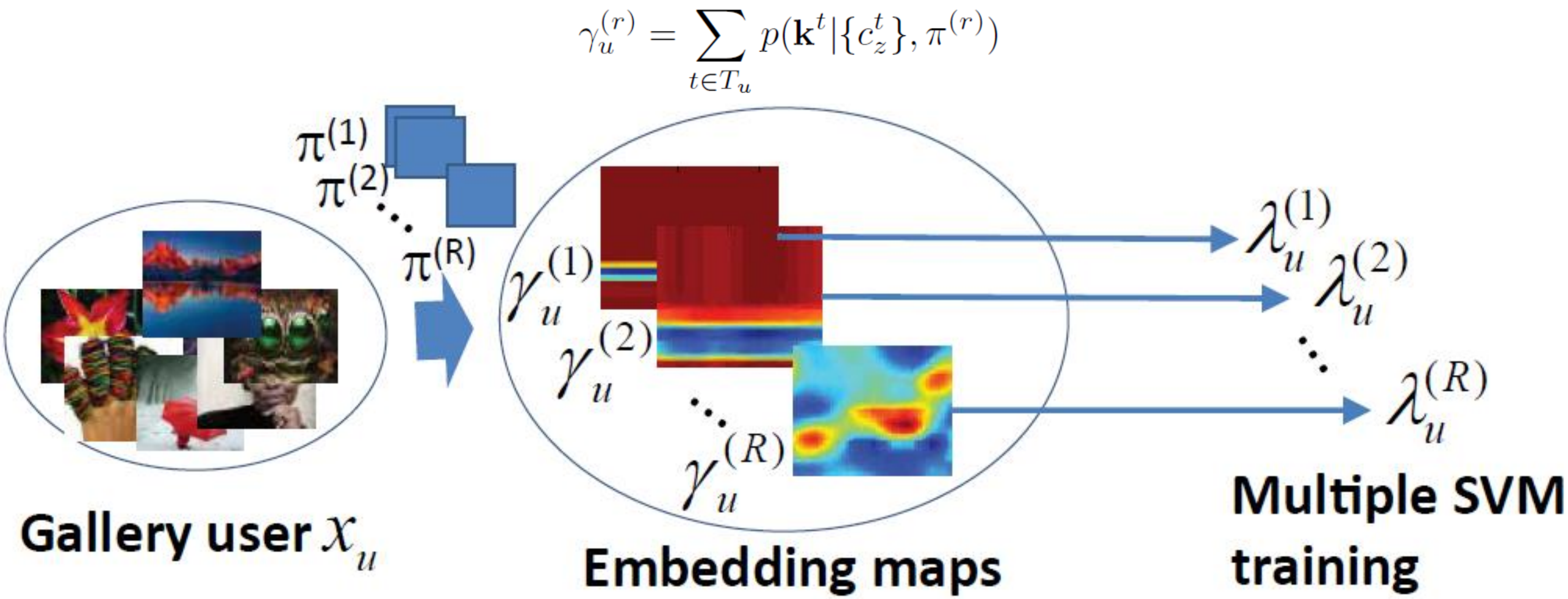
res 15 (S = 30)



res 5 (S = 40)

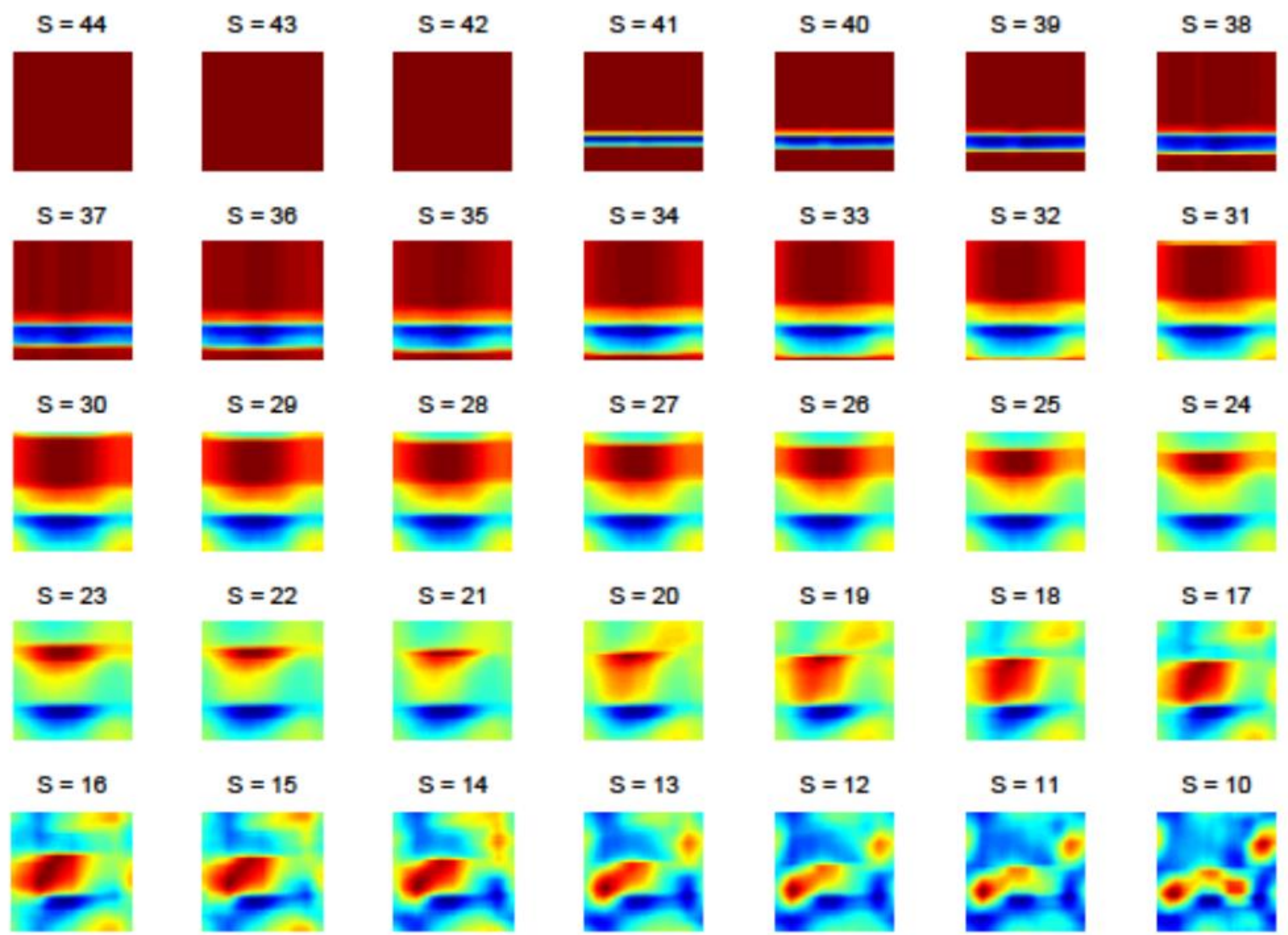
Statistical Generative Multiresolution Approach

MRCG approach - Enrollment



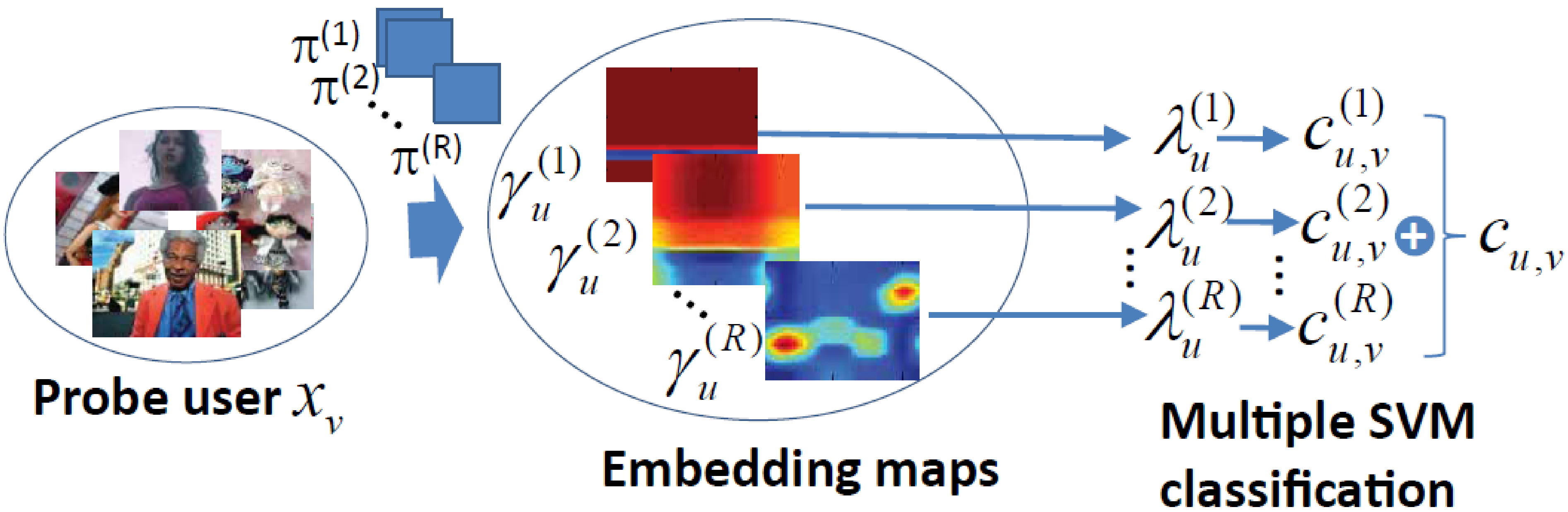
Statistical Generative Multiresolution Approach

MRCG approach - Visualization of embedding maps



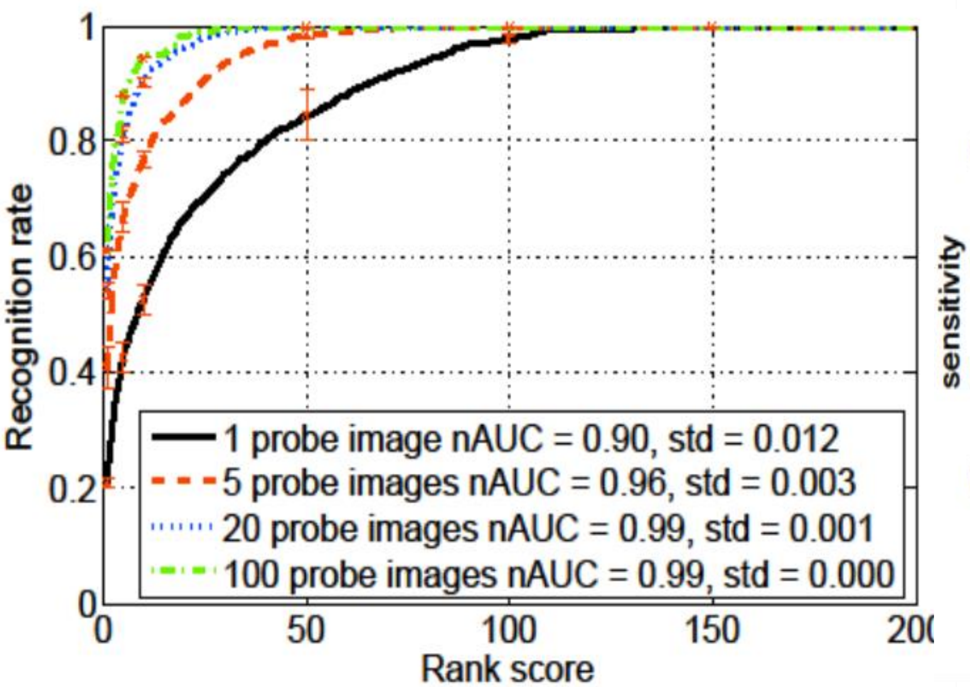
Statistical Generative Multiresolution Approach

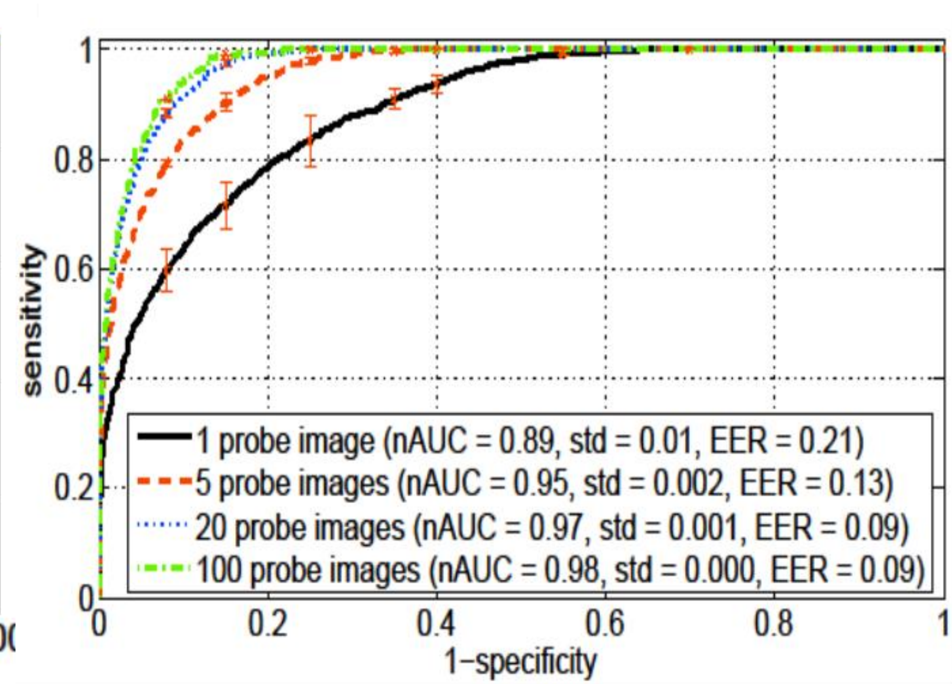
MRCG approach - Identification/Verification



Statistical Generative Multiresolution Approach

MRCG approach – Identification/Verification results

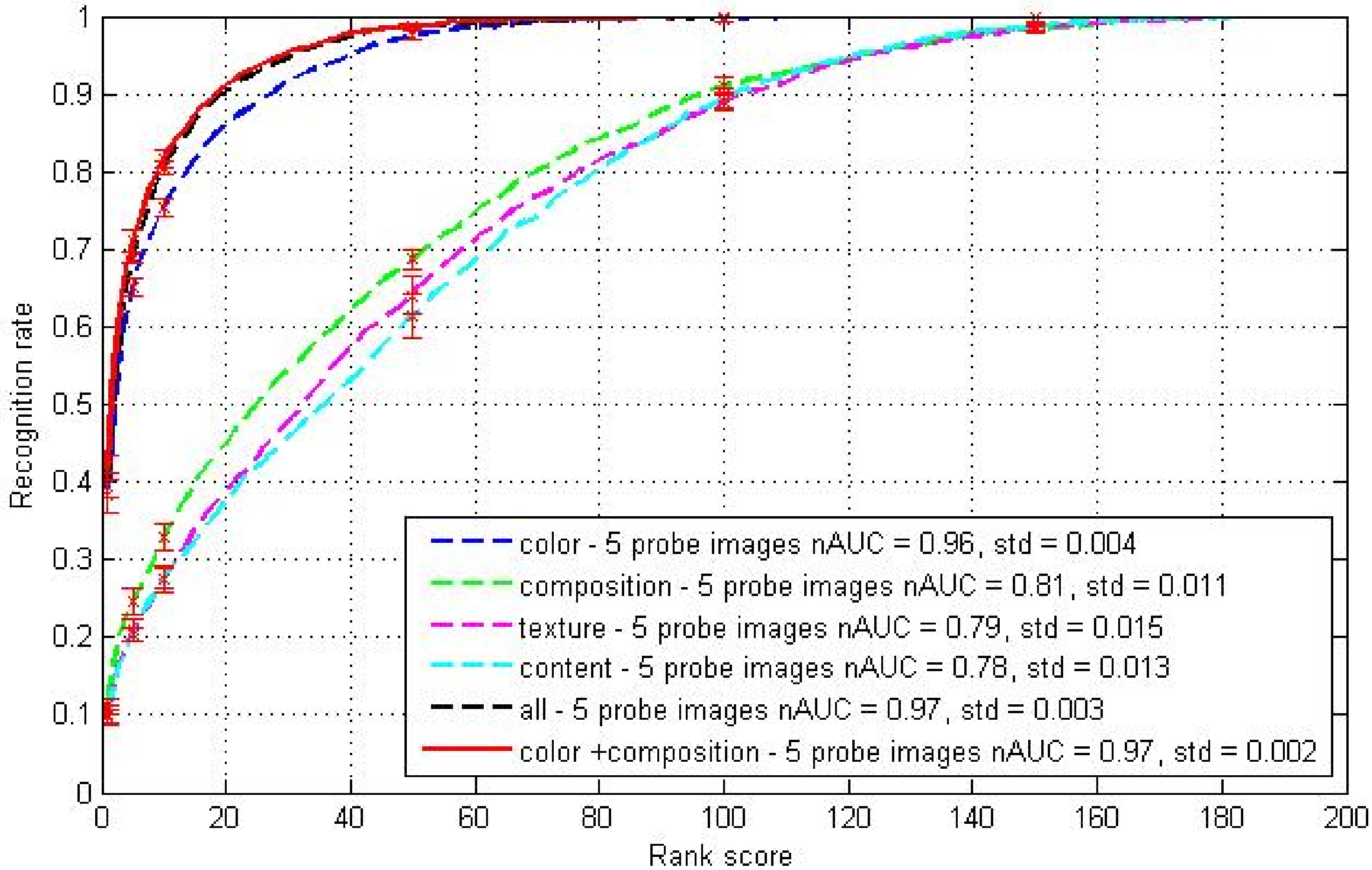




[C.Segalin, A.Perina, M.Cristani, Personal Aesthetics for Soft Biometrics: A generative Multi-resolution Approach, ICMI 2014]

Statistical Generative Multiresolution Approach

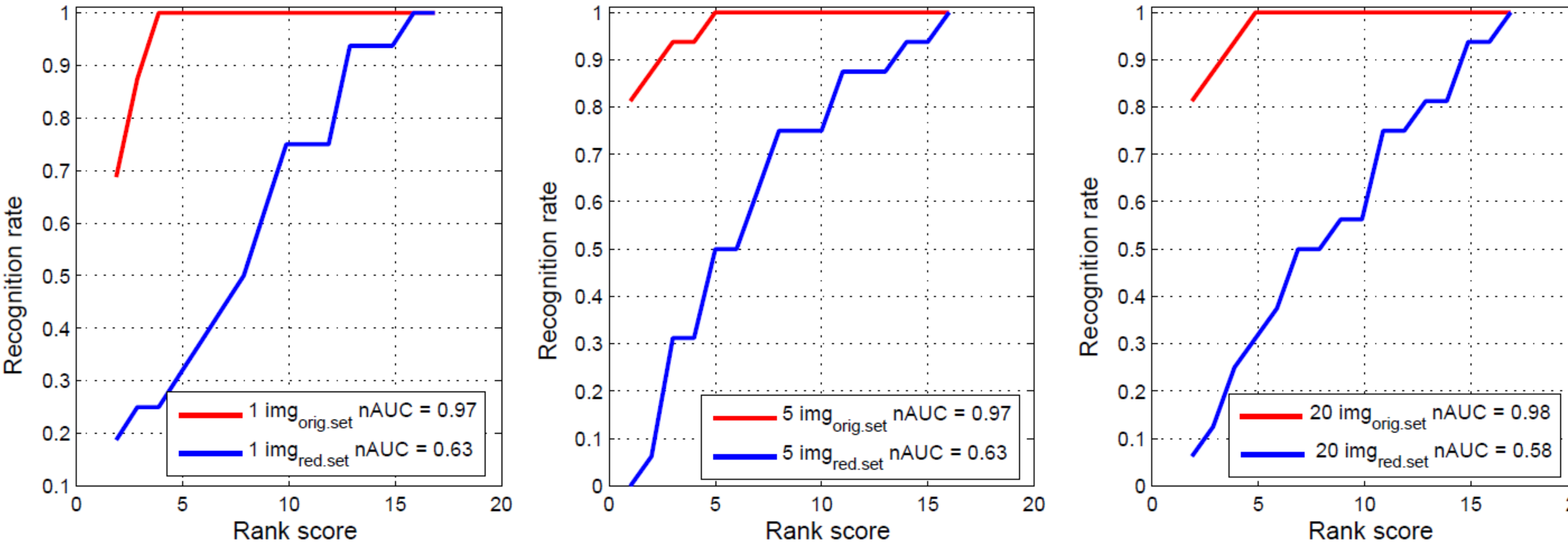
MRCG approach - Feature Analysis



[C.Segalin, A.Perina, M.Cristani, Personal Aesthetics for Soft Biometrics: A generative Multi-resolution Approach, ICMI 2014]

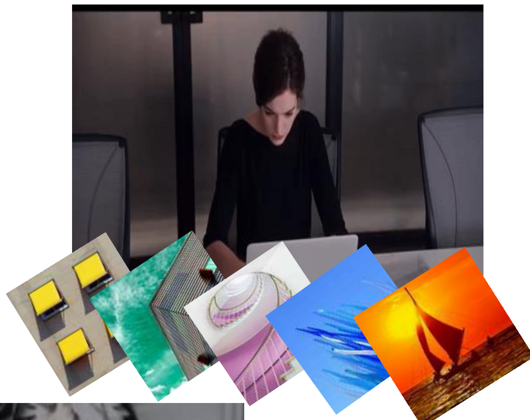
Statistical Generative Multiresolution Approach

MRCG approach - Limitations



- Robustness of features → **Feature Learning**
- Missed disliked asethetics → **Future work**
- Lack of distinctiveness
- Variability of aesthetics
- Number of images

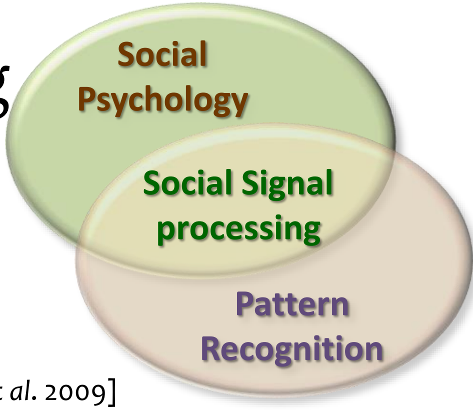
Personality Computing



Computing Personality from Aesthetic Preferences

Statement: Social Signal Processing

Motivation and definition



Social Signal Processing: aims at understanding «*social signals*» i.e.,

- ✓implicit, unconscious cues that communicate something, outside the verbal content
- ✓that depend on implicit cognitive processes [Vinciarelli *et al.* 2009]

Social cues	Example social behaviours							Tech.		
	Emotion	Personality	Status	Dominance	Persuasion	Regulation	Rapport	Speech analysis	Computer vision	Biometry
Physical appearance										
Height			√	√					√	√
Attractiveness		√	√	√	√		√		√	√
Body shape		√		√					√	√
Gesture and posture										
Hand gestures	√	√			√	√	√		√	√
Posture	√	√	√	√	√	√	√		√	√
Walking		√	√	√					√	√
Face and eyes behaviour										
Facial expressions	√	√	√	√	√	√	√		√	√
Gaze behaviour	√	√	√	√	√	√	√		√	
Focus of attention	√	√	√	√	√	√	√		√	
Vocal behaviour										
Prosody	√	√		√	√		√	√		
Turn taking	√	√	√	√		√	√	√		
Vocal outbursts	√	√		√	√	√	√	√		
Silence	√		√				√	√		
Space and environment										
Distance	√	√	√		√		√		√	
Seating arrangement				√	√		√		√	

[Social Signal Processing Survey of an Emerging Domain. Vinciarelli, Pantic, Bourlard, JIVC]

The Big Five

- Extraversion: Active, Assertive, Energetic, Outgoing
- Agreeableness: Appreciative, Forgiving, Generous, Kind, Sympathetic, Trusting
- Conscientiousness: Efficient, Organized, Reliable, Responsible, Thorough
- Neuroticism: Anxious, Self-pitying, Tense, Touchy, Unstable, Worrying
- Openness: Artistic, Curious, Imaginative, Insightful

[Saucier, Goldberg, "The Language of Personality: Lexical Perspectives on the Five-Factor Model", in "The Five-Factor Model of Personality", Wiggins (ed.), 21-50, 1996]

State of the art

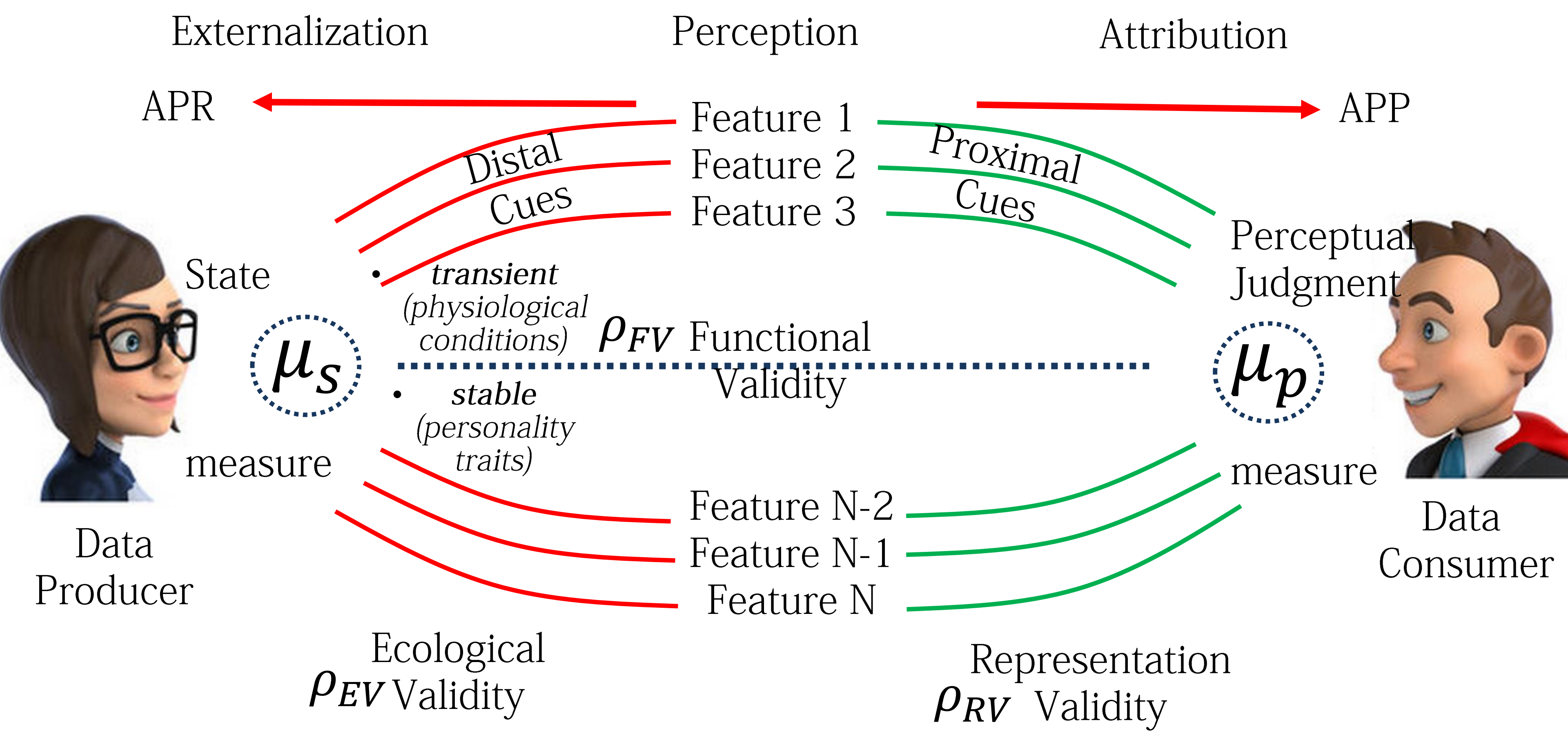
- **Implicit cognitive processes:**
  - ✓ Study the perception of profile pictures on social media [Fitzgerald '09]
  - ✓ Perception of profile from all elements that can appear in a online profile [Gosling '08]
  - ✓ Prediction of favorite images [Lovato '12]
  - ✓ Emotions through the characteristics of paintings [Sebe '08]

- **Main result:**
  - ✓ Confirm the action of the implicit cognitive processes when using multimedia data
  - ✓ Identification of correlations between aesthetic preferences and personality

State of the art

- **Aesthetics – Psychology**
  - ✓ Big Five personality traits are taken as individual characterization [Rammstedt '07]
  - ✓ High Openness correlates to liking pictures with few elements [Rawling '98]
  - ✓ High Openness correlates to liking pictures with ``complex'' and ``meaningful'' polygons [Rawling '98]
  - ✓ Extrovert people prefer humanized landscape [Abello '86]

The Brunswick Lens Model



Personality from aesthetic preferences

MIR approach – Dataset Collection

- 300 Flickr professional users (the *data producer*)
- For each user:
  - ✓ Take 200 random *faved* images, from which we extract
    - 15 computational aesthetic features [Datta '06, Machajdick'10]
    - 14 objects, scenes [Felzenszwalb et al. '10,Oliva et al. '01]
  - ✓ Let him fill a personality questionary (the Big Five Inventory 10)
    - It gives **5 scores** (-4…4) for the personality traits of *Openness, Consciousness, Extraversion, Agreableness, Neuroticism*

→ the State

[C.Segalin, M.Cristani, A.Perina, A.Vinciarelli, A Multiple Instance Regression Approach for Mapping Aesthetic Preferences into Personality Traits, IEEE on Affective Computing, 2014]

Personality from aesthetic preferences

MIR approach– Dataset collection

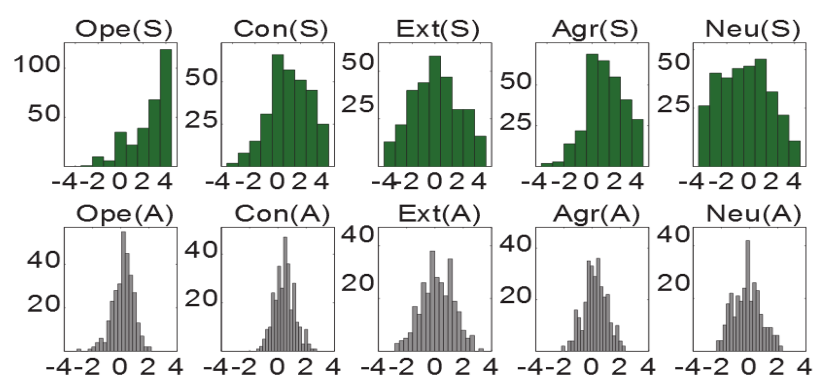
- 12 assessors (the *data consumer*)
- For each assessor:
  - ✓ Check the 200 favorites of each user
  - ✓ For each user, fill the BFI questionnaire, *inferring how the user could be!*
  - ✓ We check homogeneity in the scores and the average of the test was computed.

→ Perceived State

Personality from aesthetic preferences

MIR approach - Goals

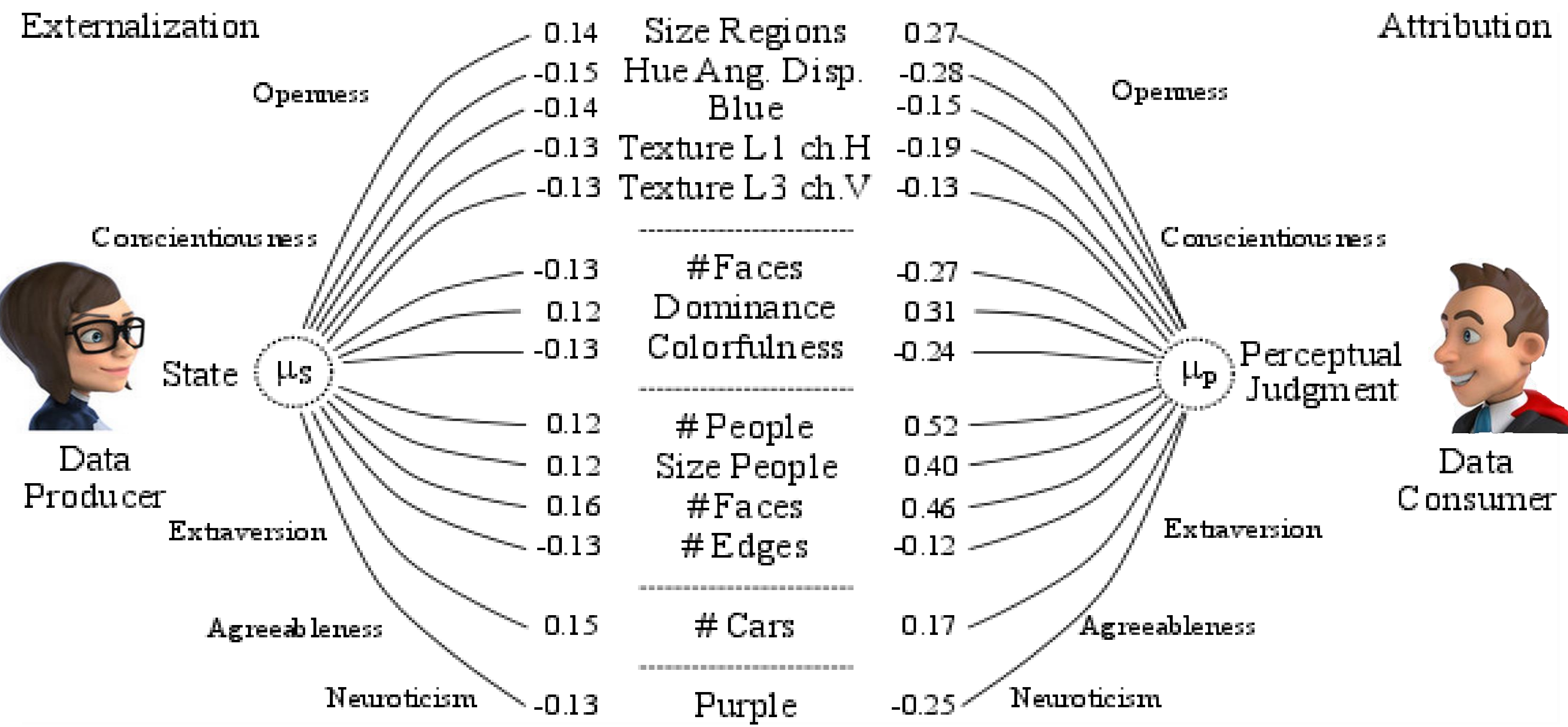
- At this point we want to:
    1. Measure *correlations* state/perc. state, *state/feats*, *perc. state/feats*
    2. Given the faved pictures of a user
        - infer the *state*
        - infer the *perceived state*



Personality from aesthetic preferences

MIR approach - Statistically significant correlations

Corr. *state*/*perceived state* ≤ 0.26



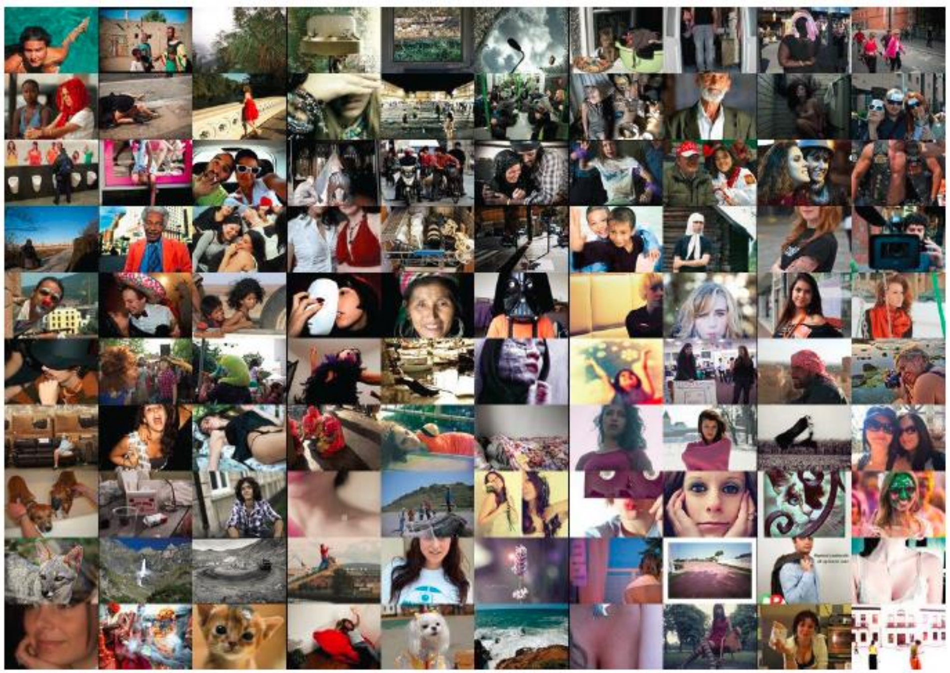
state/feats *perceived state/feats*

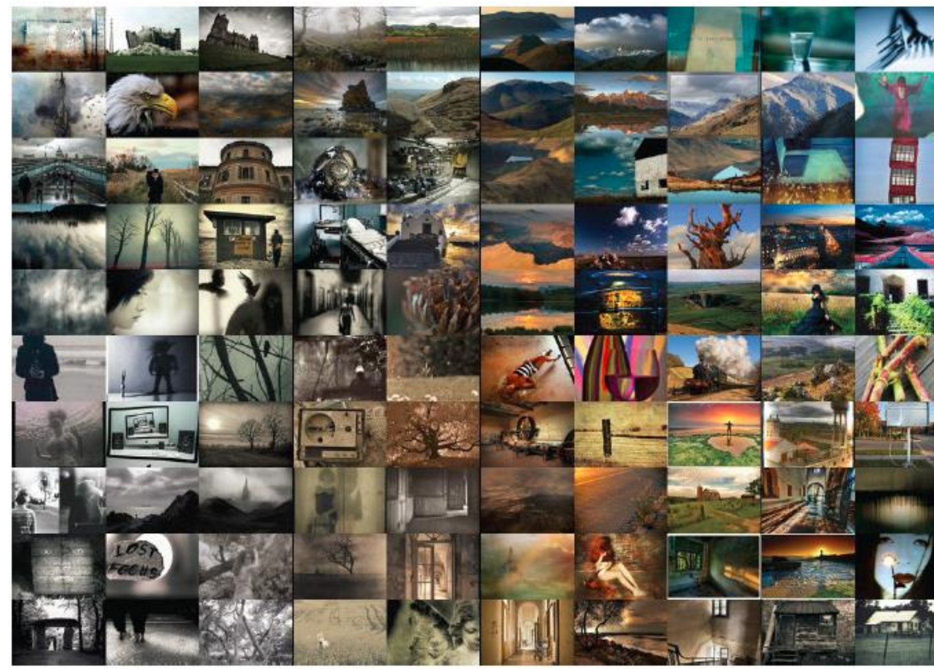
Personality from aesthetic preferences

MIR approach– Visualization of correlations

Extraversion

0.12	#People	0.52
0.12	Size People	0.40
0.16	# Faces	0.46





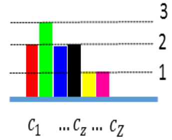
(perceived) High

(perceived) Low

Personality from aesthetic preferences

MIR approach – Regression approach

Discretization



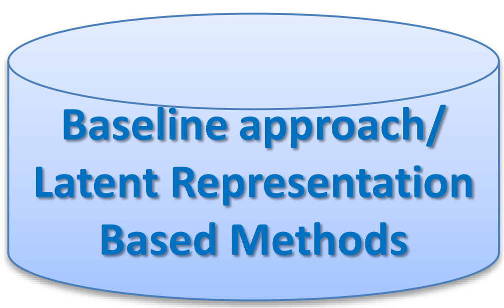
C_z^t Histogram view of the Counts matrix

	1	1	2	2	3	3	-4	-4
gray **'	0	0	0,9	0	0	0	0	0
gray ***'	0,1	0,1	0,1	0	0,1	0,1	0,1	0,1
gray ****'	0,8	0,8	0	0,1	0,8	0,8	0,8	0,8
'pink **'	0,1	0,1	0	0,8	0,1	0,1	0,1	0,1
'pink ***'	0	0	0	0,1	0	0	0	0
'pink ****'	0	0	0	0	0	0	0	0
'purple **'	0	0	0	0	0,04	0	0	0
'purple ***'	0	0	0	0	0	0,1	0	0
'purple ****'	0,1	0	0	0	0,1	0,8	0,1	0

t, u, z

$y_p^u = y_p^{v(t)}$ B^u

t_i^u



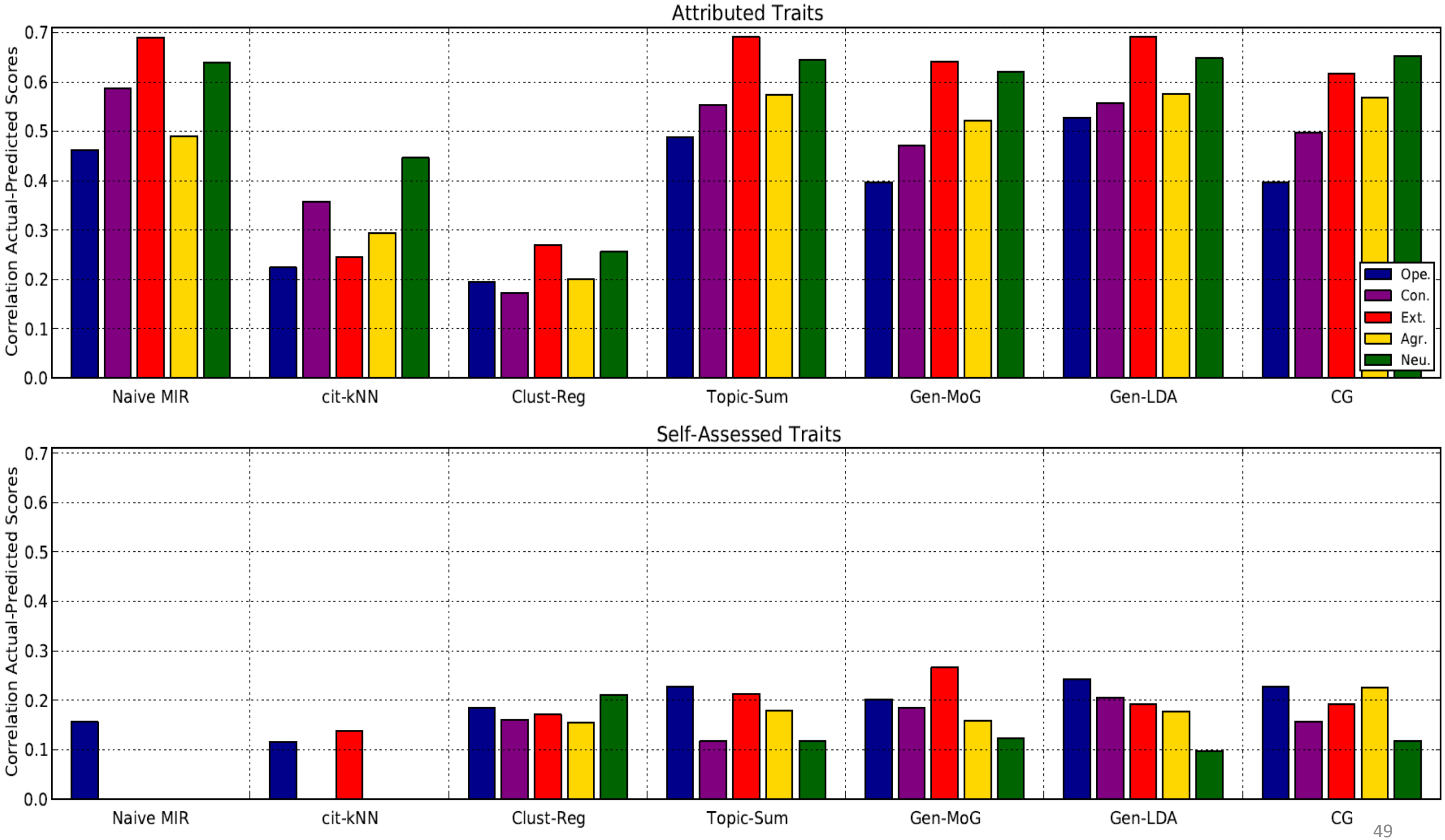
$$E(\beta) = \sum_{u=1}^{U} (y_p^u - \beta^T \cdot X^u)^2$$

$$y_p^{test(i)} = \beta^T \cdot c_z^{test(i)} \quad \widehat{y_u} = \overline{y_p^{test}}$$

- It is an interesting problem:
  - ✓ We have multiple images connected with only a user
  - ✓ Not all of them are equally important
  - ✓ Seems suitable the Multiple Instance Learning paradigm
  - ✓ So far, simple regression on a low dimensional image representation has been performed [Babenko '08]

Personality from aesthetic preferences

MIR approach - Prediction results

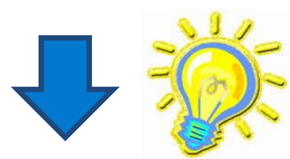


Discussion

Approach Weaknesses and Breakthrough with CNN

Hand-crafted features:

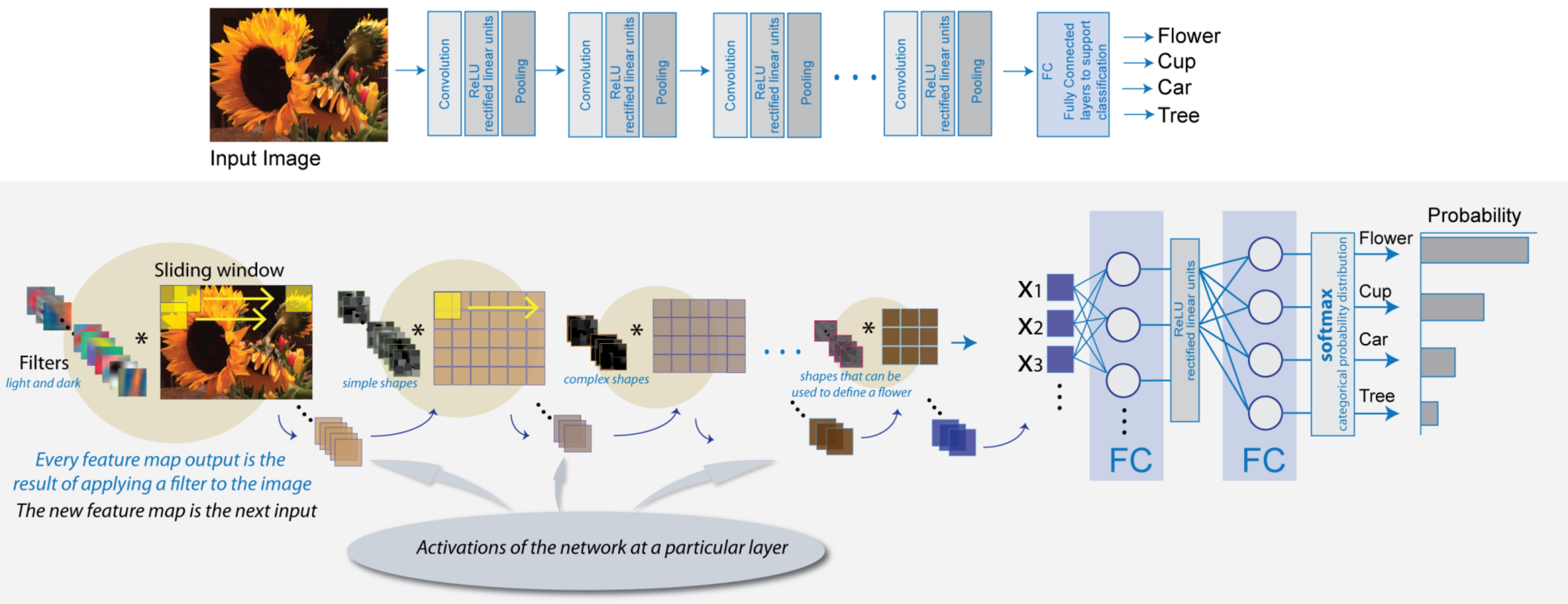
- Computational Aesthetics hand-crafted features focus on designing features explaining how a particular image has been captured, discarding the content of the images
- Standard object recognition and feature extraction techniques might not be sufficient to capture significant dependences between pictures and personality traits
- Non linear relation between image features - user likes
- Time consuming
- No disentangle of all explanatory factors of data



Deep/ Feature Learning:

- Automatic discovery of new high level representation
- Non-linear transformation of data
- Disantangle factors of observed data in multilple level of abstractions
- Distributed representation

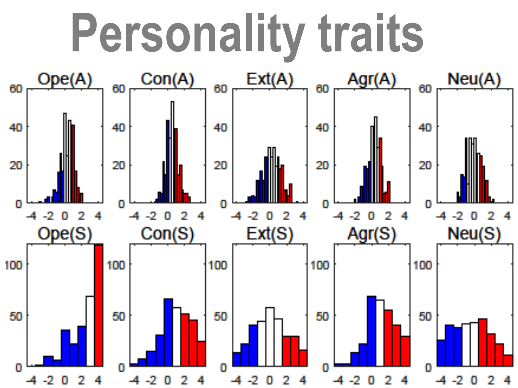
Feature Learning via Convolutional Neural Networks

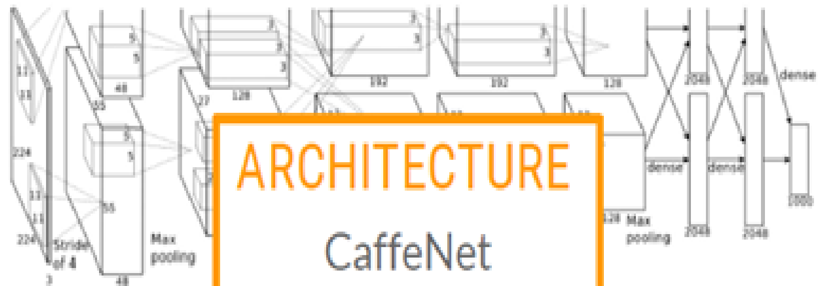


[A. Krizhevsky et al , Imagenet classification with deep convolutional neural networks, in: Advances in neural information processing systems]
[Y. Jia et al., Caffe: Convolutional architecture for fast feature embedding.]

Social Profiling through Image Understanding:

CNN approach





ARCHITECTURE

CaffeNet

Fine-tuning ➡ DATASET [PsychoFlickr]

✚

IMAGENET

Pre-training ➡ DATASET [Deng'09]

Model

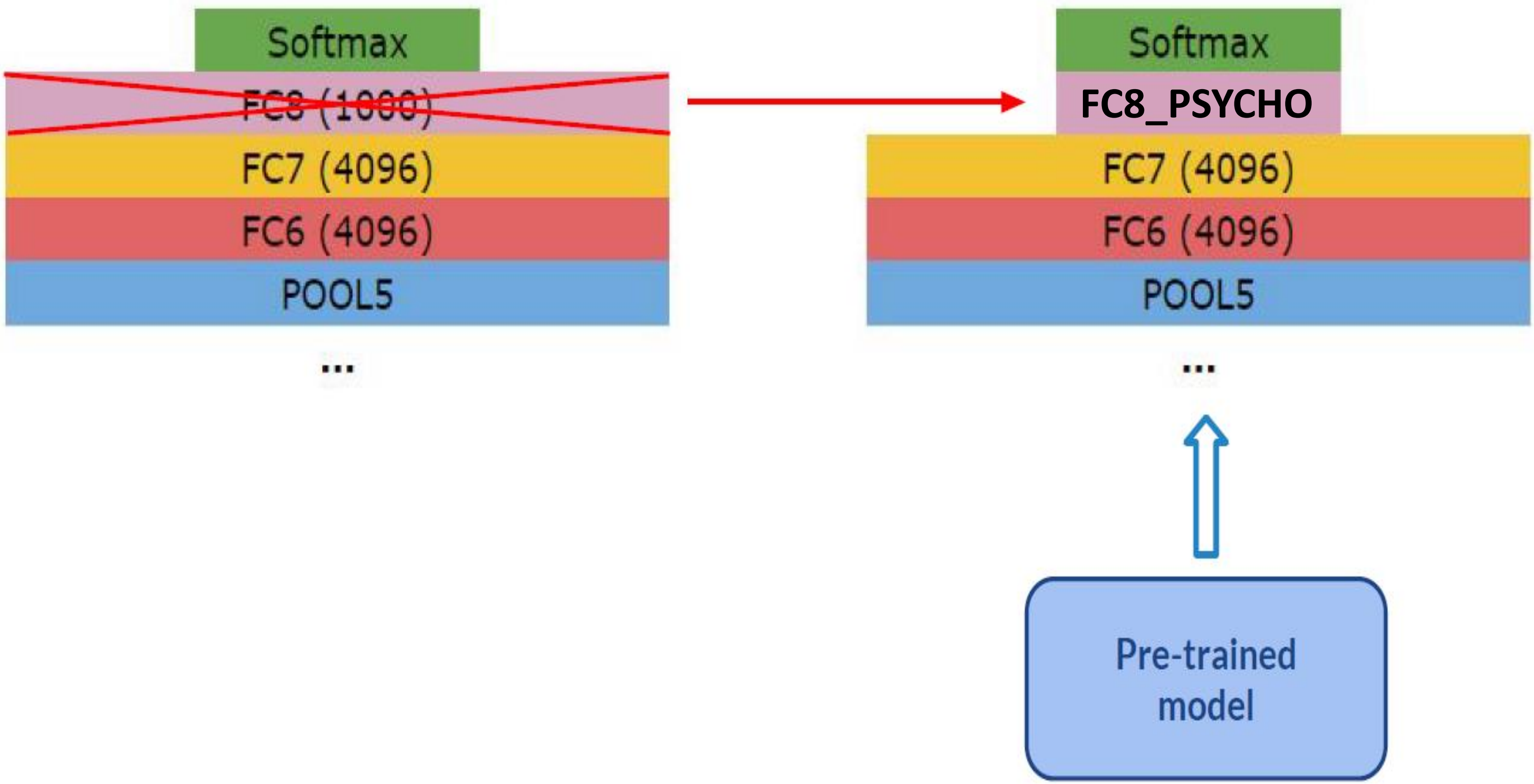
Caffe

SOFTWARE

[Jia'14]

Social Profiling through Image Understanding:

CNN approach – fine-tuning process



Social Profiling through Image Understanding:

CNN approach - Classification results

	SELF		ATTRIBUTED	
	TRAIN	TEST	TRAIN	TEST
O	0.57	0.53	0.73	0.61
C	0.59	0.54	0.81	0.66
E	0.60	0.54	0.76	0.64
A	0.57	0.54	0.76	0.64
N	0.55	0.52	0.81	0.68

Accuracy on training and testing set

	SELF		ATTRIBUTED	
	IEEEAC	our	IEEEAC	our
O	0.49	0.53	0.59	0.62
C	0.50	0.54	0.51	0.66
E	0.52	0.54	0.64	0.65
A	0.47	0.54	0.56	0.64
N	0.51	0.53	0.75	0.69

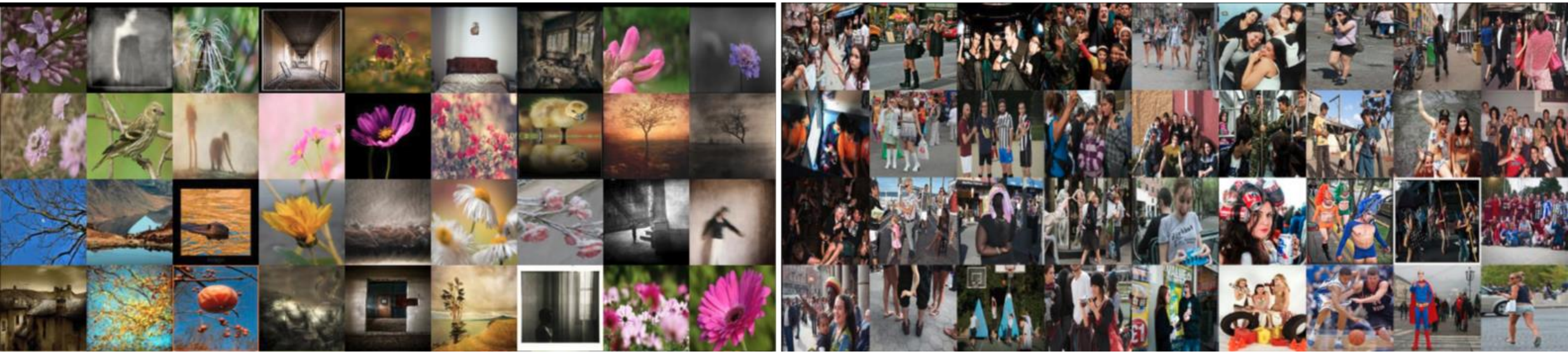
Comparison with previous approach

[M. Cristani et al., Unveiling the multimedia unconscious: implicit cognitive processes and multimedia content analysis, in: Proceedings of the ACM international conference on Multimedia, ACM, 2013, pp.]

Social Profiling through Image Understanding:

CNN approach - Learned Attributes

Extraversion



(perceived) Low

(perceived) High

Social Profiling through Image Understanding:

CNN approach - Learned Attributes

Neuroticism

(perceived) Low

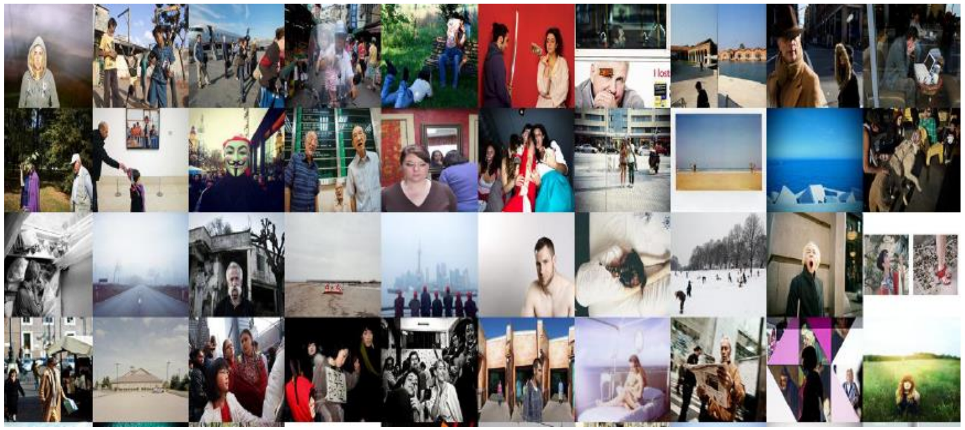
Agreeableness

(perceived) High

Social Profiling through Image Understanding:

CNN approach - Learned Attributes

Conscientiousness



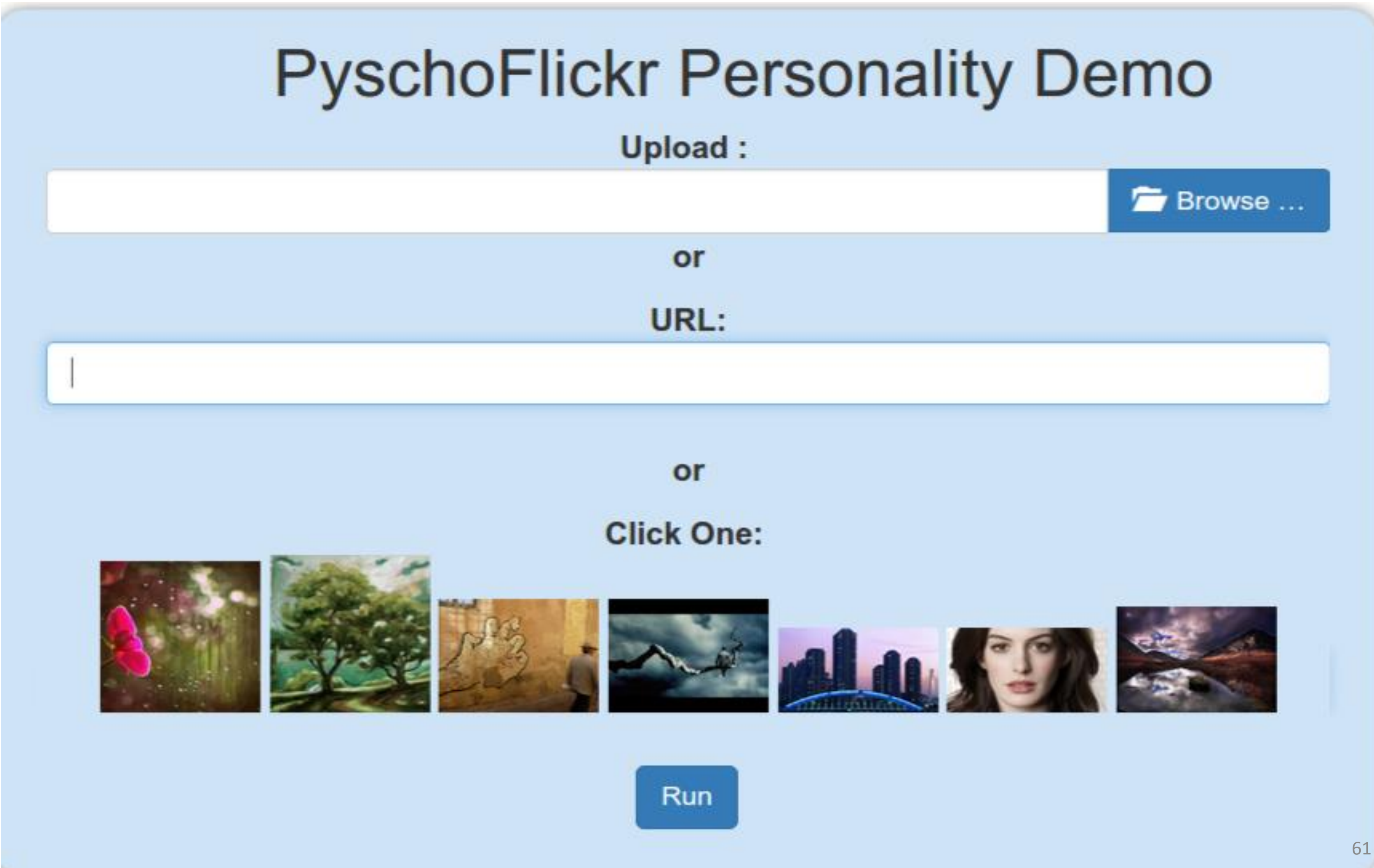
(perceived) Low

Openness

(perceived) High

Social Profiling through Image Understanding:

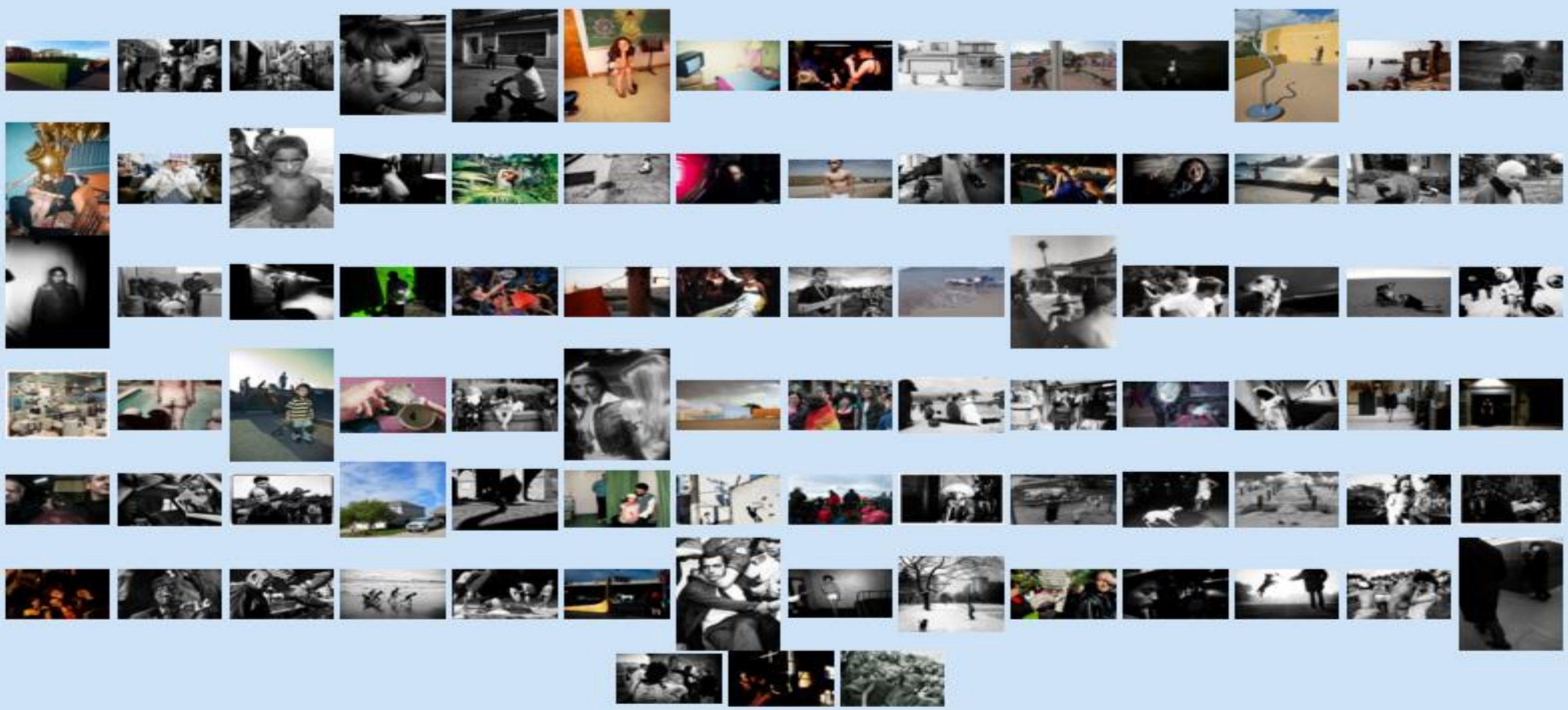
Demo: http://psychoflickr.di.univr.it:8000/demo/



Social Profiling through Image Understanding:

Demo: http://psychoflickr.di.univr.it:8000/demo/

VIPS PyschoFlickr Personality Demo



Predictions:

Openness	Low
Coscientiousness	Low
Extrovertion	High
Agreableness	Low
Neuroticism	High

Conclusions

1. **Key Idea**: Multimedia content as social signal
   - ✓ Multimedia role has changed with Social Networks and Big Data
   - ✓ Images associated to people are spread through social platforms
   - ✓ Image not just as a message, a social signal: personal aesthetics preferences, that reveal something about its author
   - ✓ Implicit cognitive processes of image appreciation are unique and personal and can capture/produce this social signal to understand the state of a person

2. **Soft biometric trait**
   - ✓ We considered images tagged as favorites by a person
   - ✓ Proposed Computational Aesthetic features capturing the aesthetic of images
   - ✓ Built Hybrid model personal aesthetic preferences for Re-identification

3. **Personality Computing**
   - ✓ PyshcoFlickr dataset
   - ✓ Multiple Instance Regression and Deep Learning approaches to map aesthetic preferences into personality traits, to model producer and consumer state
   - ✓ Demo application

Future Perspective

1. **Social network:** Infer demographic information from aesthetics preferences
2. **Marketing:** evaluation of impact of set of images for hypothetical customers
3. **Viral Marketing:** implicit cognitive processes might contribute to explain and enhance virality
4. **Big Data:** making sense of large amount of data
5. **Virtual agents:** improve machines that exhibit human-like features and behavior like robots, animated characters, embodied conversation agents
6. **Neuroscience/Phototherapy:** understand the role/ activation of neurons when appreciating images
7. **Online Games:** Customization using user preferences and profile

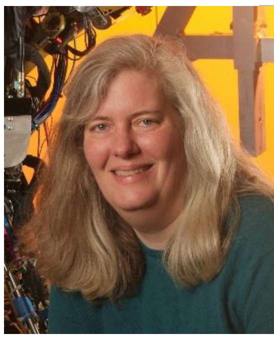
PhD Publications

- **Journal**
  - ✓ **C.Segalin**, D.S.Cheng*, Social Profiling through Image Understanding: Personality Inference using Convolutional Neural Networks*, (submitted CVIU)
  - ✓ **C.Segalin**, M. Cristani, A.Perina, A. Vinciarelli, *The Pictures we Like are our Image: Continuous Mapping of Favorite Pictures into Self-Assessed and Attributed Personality Traits*, IEEE on Affective Computing, 2016
  - ✓ P. Lovato, M. Bicego, **C. Segalin**, A. Perina, N. Sebe, M. Cristani. *"Faved!" biometrics: tell me which image you like and I'll tell you who you are*. IEEE Transactions on Information Forensics and Security 2014.

- **Conference**
  - ✓ **C.Segalin**, F.Celli, B.Lepri, M.Kosinski, M.Cristani, L.Polonio*, What your Facebook Profile Picture Reveals about your Personality: A Feature-based Approach, IEEE Multimedia (submitted ICMI)*
  - ✓ **C. Segalin**, A. Vinciarelli, M. Cristani and M. Musolesi. *Visual Contagion: Understanding the Influence of Textual, Visual and Social Cues on Information Propagation in Twitter*. (Submitted CIKM)
  - ✓ **C.Segalin**, A.Perina, M.Cristani, *Biometrics on Visual preferences: A «Pump and Distill» Regression Approach*, ICIP 2014
  - ✓ **C.Segalin**, A.Perina, M.Cristani, *Personal Aesthetics for Soft Biometrics: A generative Multi-resolution Approach*, ICMI 2014
  - ✓ **C.Segalin**, A.Perina, M.Cristani, *Recognizing People by Their Personal Aesthetics: a Statistical Multi-level Approach*, ACCV 2014
  - ✓ **C. Segalin**, A. Pesarin, A. Vinciarelli, M. Tait and M. Cristani. *The expressivity of turn-taking: Understanding children pragmatics by hybrid classifiers*. WIAMIS 2013
  - ✓ M. Cristani, A. Vinciarelli, **C. Segalin**, A. Perina. *Unveiling the multimedia unconscious: implicit cognitive processes and multimedia content analysis*, ACM MM Brave New Idea 2013
  - ✓ P. Lovato, A. Perina, D.S. Cheng, **C. Segalin**, N. Sebe, M. Cristani, *We like it! mapping image preferences on the counting grid*, ICIP 2013
  - ✓ G. Roffo, **C. Segalin**, A. Vinciarelli, V. Murino and M. Cristani*. Reading between the turns: Statistical modeling for identity recognition and verification in chats*. AVSS 2013
  - ✓ G. Roffo, M. Cristani, F. Pollick, **C. Segalin** and V. Murino. *Statistical Analysis of Visual Attentional Patterns for Video Surveillance*. CIARP. 2013

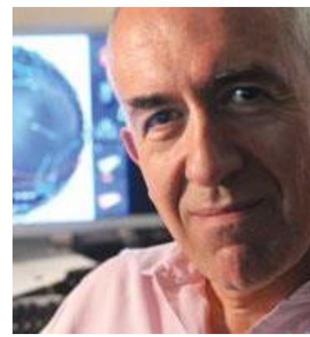
What's next?

February-April 2016
Internship

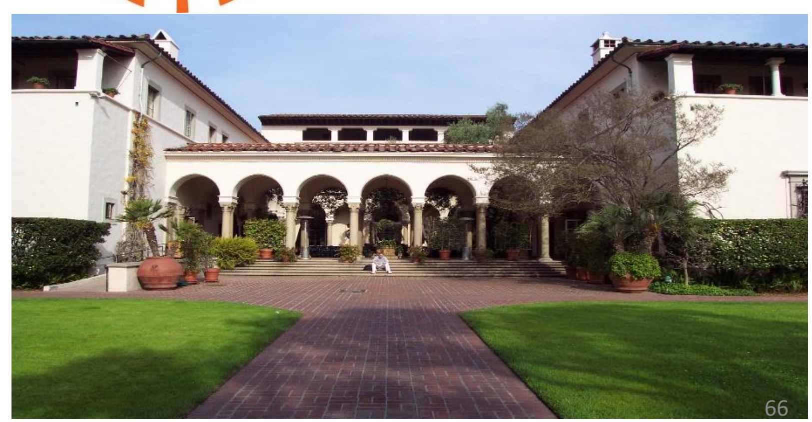
 

Disney
Research, Pittsburgh

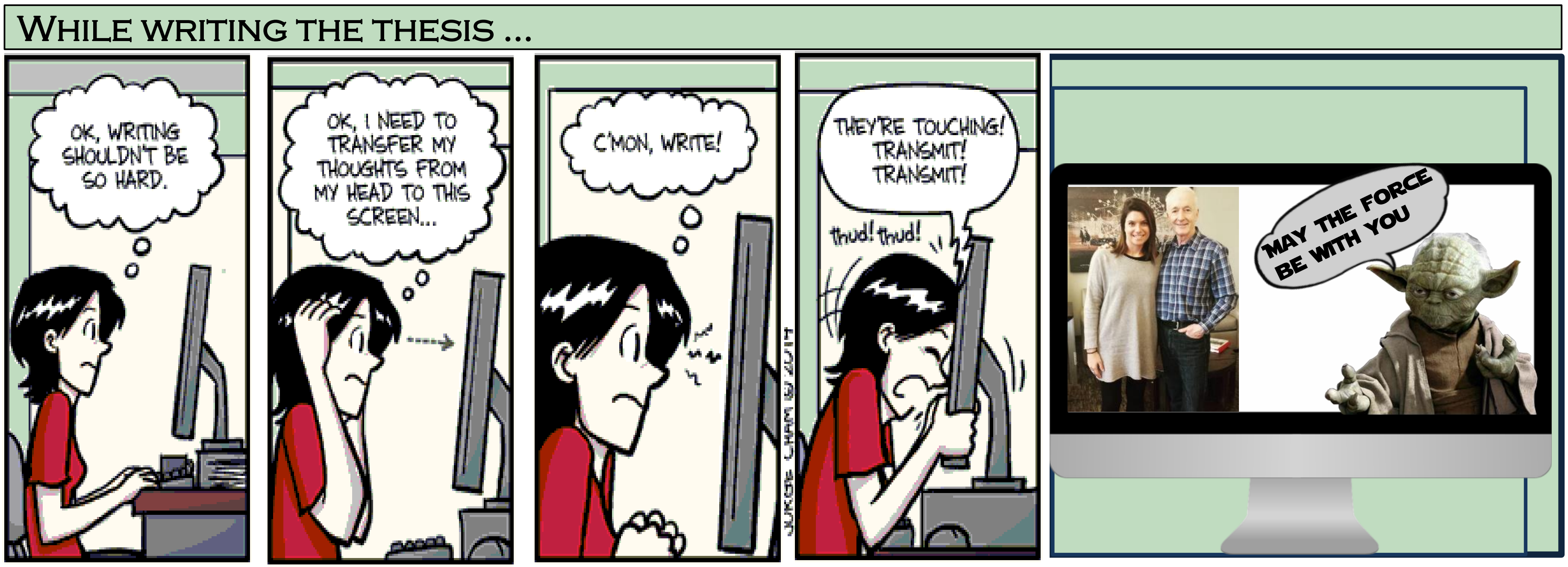
August 2016-2017
Postdoc

Caltech



Thanks to all the VIPS people and …



… to you for your attention !!