How Smart Does Your Profile Image Look?
Estimating Intelligence from Social Network Profile Images

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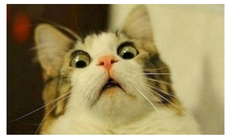
1. Introduction



Can a user's intelligence be inferred from profile images?

Motivation

To help Web users to better manage self-representation

Why Profile images ?

- Important avenue to share self-representation
- Have a big effect on how friends and strangers judge us
- Normally are public by default

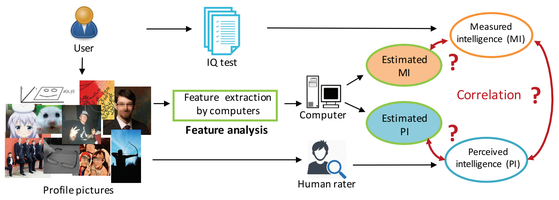
Why Intelligence ?

- Related to important life outcomes, e.g., income, relationships
- First impressions of intelligence can have significant consequences in social scenarios, e.g., employment
- High intelligence is a trait that people want to project to others by self-representation

Research questions

- Q1: Can humans make intelligence judgments for others from profile images ?
- Q2: Can computers make such judgments?
- Q3: What visual elements an intelligent person will use?
- Q4: What visual elements make a person perceived to be intelligent?

2. Method



Measured intelligence (MI)

- A user's intelligence score measured by an IQ test

Perceived intelligence (PI)

- A user's intelligence score rated by human observers' perceptions based on the self-representation of users

2.1 Data collection

myPersonality database (mypersonality.org)

- 1,122 users took an IQ test and provided FB profile images
  - 51% men, age mean±std=25.9±9.2, range:14~69
  - MI score mean±std=112.4±14.5, range: 64.9~138.6
- 739 human raters rated the 1,122 images
  - 49% men, age mean±std=24.2±6.2, range:15~72
  - Each rater was randomly shown 50 or 100 images
  - Each image was finally rated by at least 24 raters
  - PI score of each image (user): **median value of rated scores**
- Profile images
  - Normally of size 200×200 pixels
  - 16% non-person images (e.g., cartoons, drawings, animals, signs, etc.)
  - 60% with only one person
  - 21% with two or three persons
  - 3% group images (more than four persons)

2.2 Feature extraction

	Category	Name	Len.	Description
Low-level	Colour	HSV statistics	5	Circular variance of H channel, average of S, average of V (use of light), standard deviation of S, standard deviation of V
		Emotion-based	3	*Valence*, *Arousal* and *Dominance* in V and S channels
		Colourfulness	1	Colour diversity
		Colour name	11	The percentage of black, blue, brown, grey, green, orange, pink, purple, red, white and yellow pixels
		Dark channel	1	The minimum filter output on RGB channel (reflects image clarity, saturation and hue)
		Colour sensitivity	1	The peak of a weighted colour histogram representing the sensitivity with respect to human eye
	Composition	Edge pixels	1	The percentage of edge pixels to present the structure of an image
		Regions	2	Number of regions, average size of regions
		Symmetry	2	Horizontal symmetry and vertical symmetry
	Texture	Entropy	1	Gray distribution entropy
		Sharpness	4	The average, variance, minimal and maximal value of sharpness
		Wavelet	12	Wavelet textures (spatial smoothness/graininess) in 3 levels in each HSV channel, sum of wavelet textures in each HSC channel
		Tamura	3	Coarseness, contrast and directionality of texture
		GLCM	12	Contrast, correlation, energy, homogeneousness for each HSV channel
		GIST	24	Low dimensional representation of a scene, extracting from a whole image
	Local	Colour histogram	512	Histogram of colour from local blocks
		LBP	944	Local Binary Pattern ($LBP^{u2}_{8,2}$) from local blocks
		GIST	512	GIST features extracted from local blocks
		SIFT	2048	Dense SIFT features from local blocks
High-level	Body & face	Body	2	The presence of body* and the proportion of the main body
		Skin	1	The percentage of skin pixels
		Face	4	The number of faces*, the proportion of main face, the horizontal and vertical locations of main face
		Glasses	2	The presence of normal glasses* or sunglasses*
		Pose	3	The pitch angle, roll angle and yaw angle of head

∗ with manual check to make sure the automatic detection results are correct

2.3 Feature selection

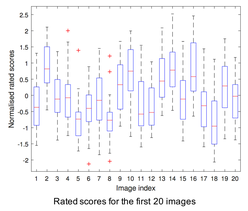
- Dimension reduction: PCA
- Filter based feature selection: univariate statistical test on features and target variable (MI or PI) in training set and select features according to p-value

2.4 Intelligence estimation

- Using SVR for regression: input: visual features, output: MI or PI scores
- Leave-one-out cross-validation

3. Results

Q1: Can humans make intelligence judgments for others from profile images ?



Rated scores for the first 20 images

- Inter-rater reliability: **0.86**
  (0.4-0.59: fair; 0.6-0.74: good; 0.75-1: excellent)
- Raters' PI scores are relatively consistent within images but there are differences between images

- Most raters agree with one another in their perception of each image's intelligence

Is there any difference when human raters make intelligence judgment for male users and female users?

Spearman correlation between PI and MI

	Male users	Female users	Together
Male raters	0.23	0.21	0.24
Female raters	0.23	0.18	0.22
Together	0.25	0.20	0.24

All correlations are significant at p <0.001 level

- PI are significantly correlated with MI for both male and female users
- Correlation for female users are lower than that for male users in all rater groups

Q2: Can computers make such judgments?

	Spearman ρ	RMSE	NRMSE
MI			
Human (PI vs. MI)	0.24^{***}	–	–
Computer (estimated MI vs. MI)	0.27^{***}	14.50	0.20
Random	$< 0^{*}$	15.13	0.21
Mean	–	14.49	0.20
PI			
Computer (estimated PI vs. PI)	0.36^{***}	0.54	0.15
Random	$< 0^{**}$	0.58	0.17
Mean	–	0.56	0.16

$***: p < 0.001, **: p < 0.01, *: p < 0.05$

- Intelligence estimation from images is a difficult task even for humans, but it is possible to use algorithms to estimate it beyond a random guess

Contact

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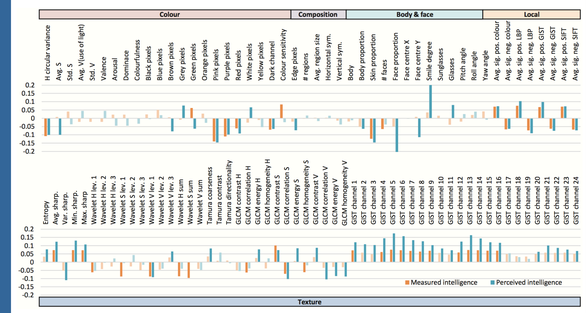
Q3: What visual elements an intelligent person will use?
Q4: What visual elements make a person perceived to be intelligent?



Correlations between image features and MI (orange bars) or PI (blue bars). Darker bars indicate correlations which are statistically significant ($p < 0.05$)

- High MI & high PI

Do not like to use the colour pink, purple or red, and images are usually less diversified in colour, more clear in texture, and contain less skin area

- High MI

Like to use the colour green, and have fewer faces, but this does not affect how others judge them

- Inaccurate stereotypes-correlated with PI but not MI:

More grey and white, but less brown and green, with higher chromatic purity, smiling and wearing glasses, and faces at a proper distance from the camera, **make people look intelligent no matter how smart they really are**

Possible applications

Automatic profile picture rating system