Predicting Personality through Multimodal Signals

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- 2 First Impressions
- 3 Approaches



Computer understanding of human behaviour:

- Enhancing human-computer interaction, e.g. conversations.
- Augmenting interactions between humans, e.g. sales.

Exploring the ability of deep learning approaches to predict the personality traits of people based on data provided by them.

- Text
- Audio
- Images

Big five model (OCEAN):

- Openness
- Conscientiousness
- Extraversion
- Agreeableness
- Neuroticism

Creativity and imagination versus being predictable and straight forward.



Correlation with used words (Yarkoni 2010):

- Positive: culture, films and poetry
- Negative: anniversary, diaper and hubby

ChaLearn LAP 2016: First Round Challenge on First Impressions - Dataset and Results, Victor et al.

A measure of self-discipline and dedication, a sign of long term success.



Correlation with used words (Yarkoni 2010):

- Positive: achieved, discipline and persistence
- Negative: boring, drunk and deny

ChaLearn LAP 2016: First Round Challenge on First Impressions - Dataset and Results, Victor et al.

Willingness to share emotions with others and enjoying their company.



Correlation with used words (Yarkoni 2010):

- Positive: bar, concert and friends
- Negative: books, computer and winter

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Understanding or helpful versus selfish and cautious with other people.



Correlation with used words (Yarkoni 2010):

- Positive: gifts, together and joy
- Negative: a**hole, harm and violence

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Emotional stability versus vulnerability to displeasing emotions.



Correlation with used words (Yarkoni 2010):

- Positive: poem, mountain and sunset
- Negative: awful, ashamed and stress

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Predicting personality traits from short videos.

- 15 sec video clips
- Collected from Youtube vloggers
- 10,000 clips (total of 41 hours)
- Regression labels in [0, 1]



http://chalearnlap.cvc.uab.es/dataset/20/description/

| Team | AVG | E | A | С | Ν | 0 |
|---------|------|------|------|------|------|------|
| NJU | 91.3 | 91.3 | 91.3 | 91.7 | 91.0 | 91.2 |
| evolgen | 91.2 | 91.5 | 91.2 | 91.2 | 91.0 | 91.2 |
| DCC | 91.1 | 91.1 | 91.0 | 91.4 | 90.9 | 91.1 |

Figure: Percentages of mean absolute accuracy by top-3 competitors

$$MAA = 1 - MAE = 1 - \frac{1}{n} \sum_{r=1}^{n} |Y_{pred} - Y_{true}|$$











Figure: Character-based model for text modality



Figure: End-to-End audio model for audio modality



Figure: DAN+ model for video modality

Deep Bimodal Regression of Apparent Personality Traits from Short Video Sequences, Wei et al.

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Figure: DAN+V model for video modality

Fusion techniques:



Figure: Early fusion



Figure: Late fusion (ensemble)



- 2 First Impressions
- 3 Approaches



| Model | AVG | E | A | С | Ν | 0 |
|-----------------|------|------|------|------|------|------|
| Baseline | 88.4 | 88.1 | 89.9 | 87.4 | 87.9 | 88.5 |
| Video | 91.5 | 91.7 | 91.3 | 92.2 | 91.1 | 91.5 |
| DAN+ (NJU) | 91.1 | - | _ | _ | — | — |
| ResNet (NJU) | 91.0 | - | _ | _ | _ | — |
| Audio | 89.7 | 89.6 | 90.3 | 89.0 | 89.8 | 90.1 |
| EtE. (NJU) | 89.5 | - | _ | _ | — | — |
| Lin. Reg. (NJU) | 89.0 | _ | — | _ | _ | — |
| Text | 88.8 | 88.3 | 89.9 | 88.4 | 88.6 | 88.8 |

Table: Percentages of models' accuracies that use one modality

| Model | AVG | E | А | C | N | 0 |
|--------------------------|------|------|------|------|------|------|
| Baseline | 88.4 | 88.1 | 89.9 | 87.4 | 87.9 | 88.5 |
| Audio, Text, Video(E.F.) | 91.3 | 91.4 | 91.1 | 91.9 | 91.0 | 91.1 |
| NJU follow-up | 92.1 | - | _ | _ | | _ |
| Audio, Video(E.F.) | 91.5 | 91.5 | 91.3 | 91.9 | 91.3 | 91.3 |
| Audio, Video(L.F.) | 91.4 | 91.4 | 91.3 | 91.5 | 91.1 | 91.5 |
| ULN | 91.3 | 91.3 | 91.3 | 91.7 | 91.0 | 91.2 |
| evolgen | 91.2 | 91.5 | 91.2 | 91.2 | 91.0 | 91.2 |
| Video, Text(E.F.) | 91.2 | 91.2 | 90.8 | 91.8 | 90.9 | 91.2 |
| Audio, Text(E.F.) | 89.8 | 89.6 | 90.3 | 89.2 | 89.8 | 90.0 |

Table: Percentages of models' accuracies that use multiple modalities



Figure: Agreeableness data distribution

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Receiver Operating Characteristic curve

Area Under ROC Curve (AUC).

- Classification metric
- Plots TPR against FPR
- Distinguishing between positive and negative examples



Figure: ROC curve example

| Model | AVG | E | А | С | Ν | 0 |
|----------|------|------|------|------|------|------|
| Baseline | 51.0 | 49.9 | 51.3 | 51.6 | 50.1 | 51.9 |
| Video | 82.7 | 84.2 | 76.5 | 88.0 | 82.5 | 82.4 |
| Audio | 74.2 | 74.9 | 71.3 | 72.5 | 76.4 | 75.9 |
| Text | 65.3 | 63.0 | 65.3 | 67.5 | 66.9 | 64.0 |

Table: AUC percentages of models that use one modality

| Model | AVG | E | A | С | Ν | 0 |
|--------------------------|------|------|------|------|------|------|
| Baseline | 51.0 | 49.9 | 51.3 | 51.6 | 50.1 | 51.9 |
| Video, Audio, Text(L.F.) | 83.5 | 84.2 | 79.0 | 87.1 | 84.1 | 83.4 |
| Video, Audio(L.F.) | 84.1 | 84.8 | 79.1 | 88.0 | 84.5 | 83.9 |
| Video, Audio(E.F.) | 83.2 | 84.1 | 77.9 | 87.4 | 83.9 | 82.5 |
| NJU | 82.3 | 83.9 | 76.3 | 87.0 | 82.0 | 82.2 |
| evolgen | 82.1 | 83.8 | 77.7 | 84.9 | 82.6 | 81.4 |
| Video, Text(L.F.) | 83.2 | 84.4 | 78.0 | 87.7 | 83.4 | 82.7 |
| Audio, Text(L.F.) | 74.0 | 74.2 | 71.3 | 73.5 | 76.0 | 75.2 |

Table: AUC percentages of models that use multiple modalities

| Model | AUC | MAA |
|--------------------------|------|------|
| Baseline | 51.0 | 88.4 |
| Video | 82.7 | 91.5 |
| Video, Audio, Text(E.F.) | 81.7 | 91.3 |
| Video, Audio, Text(L.F.) | 83.5 | 90.8 |
| Video, Audio(E.F.) | 83.2 | 91.5 |
| Video, Audio(L.F.) | 84.1 | 91.4 |
| Video, Text(E.F.) | 81.5 | 91.2 |
| Video, Text(L.F.) | 83.2 | 90.9 |
| Audio, Text(E.F.) | 74.1 | 89.8 |
| Audio, Text(L.F.) | 74.0 | 89.6 |

Table: A comparison between AUC and MAA performances

- Automatic personality prediction from different data types
- Best MAA performance for single modality models
- Best AUC performance
- Comparing different fusion techniques for the same models

Demo

Questions?

Backup slides: AUC validation



Figure: Validation AUC performance through training time

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Backup slides: MAA train



Figure: Train MAA performance through training time

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Backup slides: MAA validation



Figure: Validation MAA performance through training time

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Backup slides: Heat maps



Figure: Saliency heat maps of a ResNet that predict OCEAN

Prediction of Personality First Impressions With Deep Bimodal LSTM. Yang et al.

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Backup slides: Heat maps



Figure: Saliency heat maps of different CNNs that predict OCEAN

Deep Bimodal Regression of Apparent Personality Traits from Short Video Sequences. Wei et al. 2017

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Backup slides: Personality questionnaire

| I see myself as someone who | Disagree strongly | Disagree a little | Neither agree nor disagree | Agree a little | Agree strongly |
|---------------------------------|-------------------|----------------------|-------------------------------|-------------------|-------------------|
| is reserved | (1) | (2) | (3) | (4) | (5) |
| is generally trusting | (1) | (2) | (3) | (4) | (5) |
| tends to be lazy | (1) | (2) | (3) | (4) | (5) |
| is relaxed, handles stress well | (1) | (2) | (3) | (4) | (5) |
| has few artistic interests | (1) | (2) | (3) | (4) | (5) |
| is outgoing, sociable | (1) | (2) | (3) | (4) | (5) |
| tends to find fault with others | (1) | (2) | (3) | (4) | (5) |
| does a thorough job | (1) | (2) | (3) | (4) | (5) |
| gets nervous easily | (1) | (2) | (3) | (4) | (5) |
| has an active imagination | (1) | (2) | (3) | (4) | (5) |

Instruction: How well do the following statements describe your personality?

Figure: BFI-10

Measuring personality in one minute or less. Rammstedt et al.(2007)

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Backup slides: Image model



Figure: Conv-3d model

Backup slides: Text model



Figure: Word based model

Investigating Audio, Video, and Text Fusion Methods for End-to-End Automatic Personality Prediction. Kampman et al.

Visual demo of AUC: http://www.navan.name/roc/

$$TPR = \frac{TP}{TP + FN}$$
$$FPR = \frac{FP}{FP + TN}$$



Figure: Openness data distribution of First Impressions dataset

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Figure: Conscientiousness data distribution of First Impressions dataset



Figure: Extraversion data distribution of First Impressions dataset

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Figure: Neuroticism data distribution of First Impressions dataset

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First Impressions labels:

- Collected by Amazon Mechanical Turk (AMT)
- Uses pairwise comparisons
- The labels are output of a Bradley Terry Luce (BTL) model
- Fits a maximum likelihood
- Sigmoid output layer

Backup slides: Pairwise comparisons



Please assign the following attributes to one of the videos:

| Friendly (vs. reserved) | Left | Don't know | Right |
|---------------------------------|------|------------|-------|
| Authentic (vs. self-interested) | Left | Don't know | Right |
| Organized (vs. sloppy) | Left | Don't know | Right |
| Comfortable (vs. uneasy) | Left | Don't know | Right |
| Imaginative (vs. practical) | Left | Don't know | Right |

Who would you rather invite for a job interview?

| Left | Don't k | Right | |
|------|---------|-------|--|
| | Submit | Skip | |

Figure: Data labeling

ChaLearn LAP 2016: First Round Challenge on First Impressions - Dataset and Results, Victor et al.

PAN dataset:

- Text dataset from twitter.
- A tweet is maximum 140 characters.
- The dataset has more than 28,000 tweet.



Figure: Openness data distribution of the PAN dataset

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Figure: Conscientiousness data distribution of the PAN dataset

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Figure: Extraversion data distribution of the PAN dataset

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Figure: Agreeableness data distribution of the PAN dataset

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Predicting personality

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Figure: Neuroticism data distribution of the PAN dataset

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