

Explainable AI to Gain Insight into Big Five Personality Predictions from Financial Transaction Records

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INTRODUCTION

- Psychological profiling from digital footprints data
- Models built from sparse, high-dimensional data with many relevant features are “black box”
- Explainable AI is important to understand, validate and improve models for psychological profiling

METHODS: CASE STUDY

- **Data:**
N=6,408 users of mobile app
Big Five personality survey data
578 pre-processed spending features
- **Predictability of Personality:**
Decent accuracies to predict Big Five personality (*min*=53.4%, *max*=61.8%) (Suppl. Material 1)
- **Explainable AI Techniques:**
Global: rule-extraction & feature importance ranking
Local: counterfactual explanation rules

“Local explanations reveal granular insights into why classifications are made. Our experiments show that individuals are classified as exhibiting a personality trait for reasons that reflect their unique financial spending behavior.”

Example 1 of local explanation:

IF Person A spent less frequently in {Computer & Electronics}, {Insurance} and {Shops}, and more frequently in {Clothing} and {Restaurants} → THEN not predicted “High Neurotic”

Example 2 of local explanation:

IF Person B spent less frequently in {Tobacco} and {Shops}, and spent less money on {Subscription} and {Tobacco} → THEN not predicted “High Neurotic”

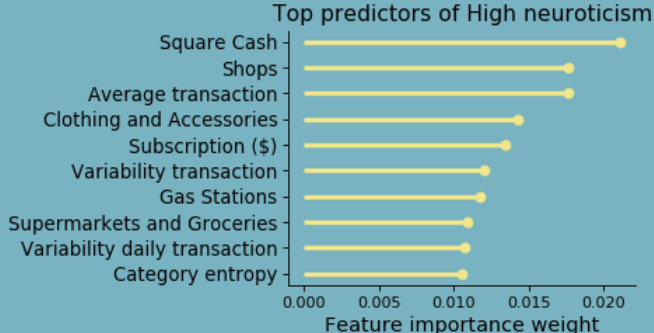


Fig.1: Global feature importance for “Neuroticism” model.

Local explanations differ from global explanations (see Fig. 1). For example, ‘Tobacco’ is ranked 73rd out 578 features (not shown in Fig. 1), but it is an important feature in example explanation 2.

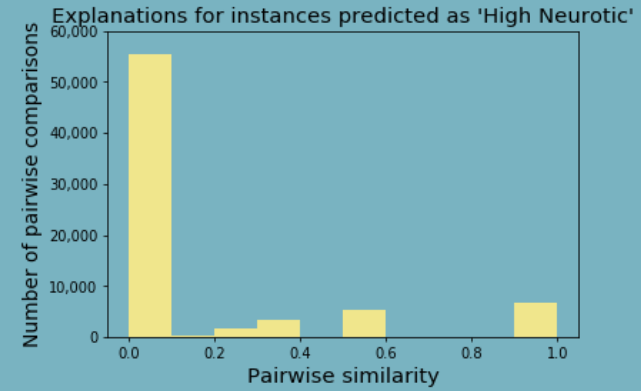


Fig.2: Similarity of local explanations for “Neurotic” predictions. A similarity of 1 indicates that two explanations are the same.

Fig.2 shows that people receive different explanations for predictions made about them. In the “Neuroticism” model, 91.1% of the explanations are unique.



RESULTS

- Local explanations for predictions are unique & concise (Suppl. Material 2A)
- Global explanation rules for predictions reflect overall classification behavior (Suppl. Material 2B)

DISCUSSION

- **Local Explanations Useful When Modeling Digital Footprints Data:**
Insights into how data is used
Validation of individual predictions
- **Implications of Explainable AI:**
For Academia:
Validation and improved insights
Robustness and replicability
For Industry:
Improved human-machine interaction
Transparency to data subjects (e.g., “Why am I seeing this ad?”)

FUNDING & CREDITS

Funding by Research Foundation Flanders. Thanks to SaverLife for providing us with the data.

