PERSONALITY ASSESSMENT

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MACHINE LEARNING

Personality assessment

BETWEEN PAST, NOW,FUTURE

Abstract

The increasing availability of high-dimensional, fine-grained data about human behavior, gathered from mobile sensing studies and in the form of digital footprints, is poised to drastically alter the way personality psychologists perform research and undertake personality assessment. These new kinds and quantities of data raise important questions about how to analyze the data and interpret the results appropriately. Machine learning models are well-suited to these kinds of data, allowing researchers to model highly complex relationships and to evaluate the generalizability and robustness of their results using resampling methods. The correct usage of machine learning models requires specialized methodological training that considers issues specific to this type of modeling

I. Introduction and Background

People generate data whenever they go online, use their smartphones, or communicate
through social media. The exponential explosion in the amount of data people are generating
online offers researchers unprecedented opportunities for tracking, analyzing, and predicting
human behavior. Recent advances in computer technology allow researchers to
unobtrusively gather and automatically analyze large amounts of data from users of digital
devices and services. Most often, these massive amounts of data are not collected with a
specific research question in mind, but rather because it is affordable and because these data
may be useful to answer future questions (Markowetz, Błaszkiewicz, Montag, Switala, &
Schlaepfer, 2014). bipolar scales,
namely:

1) Extraversion (x) (sociable vs shy)
2) Neuroticism (n) (neurotic vs calm)
3) Agreeableness (a) (friendly vs uncooperative)
4) Conscientiousness (c) (organized vs careless)
5) Openness (o) (insightful vs unimaginative).

II. Why, how research in this field change the future of coming work force

These days, many companies use assessments such as personality tests as part of the hiring process or in career development programs. As dr Fred Oswald . PhD, (is a professor of industrial/organizational psychology and director of the Organization and Workforce Laboratory at Rice University in Houston, Texas.) , He studies the factors that contribute to workplace success , per saying as the DR said , have you applied for a job recently and found a resume and cover letter weren't enough to get you the job , many companies now also use some form of pre-employment testing, including personality assessments, to help determine whether a candidate will be a good fit for the job. In fact, one 2018 survey of human resources professionals found that 79% of them use testing when making external hiring decisions, and 72% use testing for internal hires. So even if you've been in your job for a while, you may find yourself taking an assessment at work. The same survey found that 79% of respondents used assessments in their companies' career development programs.

A useful framework to go off of is think of a three-legged stool of reliability, validity and fairness. Reliability deals with whether what you're measuring is stable over time. In the case of job applicants, in other words, you don't want an applicant to be taking a test that is essentially a roll of the dice or is measuring something like mood that fluctuates. Instead, what you want are characteristics that are likely to appear on the job upon the point of hire, and that's where the employee and the organization starts out with the employee to move them forward through training and development and, as you mentioned, leadership and career progression as well.

And so, reliability is as a cornerstone of measurement, to make sure that a test that claims to measure personality, for instance, actually is doing so. We could put labels on any test and make the claim that it's measuring what we say. But how do we know? And we need data to inform that. And so, there are data based approaches to ensure that scores are measuring what they shed personality, job knowledge, motivation, etc.

If we need to talk about the importance of personality assessment here an article explaining the importance of doing so

6 reasons why personality assignments is so important in the workforce :

1. Personality as a predictor of future job success
2. A data-driven recruitment leads to better hiring decisions
3. Using personality assessment improves candidate screening at the top of the funnel
4. It's possible to assess if a candidate has the ideal personality regarding a wide range of job categories
5. Finding the most suitable candidates increases employee quality and retention
6. Driving an evidence-based recruitment process increases legal defensibility

II. Future Directions for machine learning Personality Research

1. Collaborating with multidisciplinary colleagues who can inform personality research, who have expertise and experience in selecting and justifying the analytical approach chosen to analyze data, for example, deciding between different prediction models, training and tuning those models, and accurately interpreting their results.
2. Emphasizing analytic procedures that avoid overfitting models to personality data (e.g., *k*–fold cross–validation and bootstrapping), which is an emphasis in machine learning, but can be applied equally usefully in traditional modelling.
3. Investigating predictive patterns involving personality measures: statically, in terms of convergent, discriminant, and criterion–related validity; and dynamically, where mediational and multilevel (cross–level) relationships can be tested with longitudinal ml models.
4. Evaluating the nature of data collected over time—as well as results from the clustering and prediction algorithms applied dynamically to those data over time—such that inferences about both populations and personality can be drawn from big data, and the scope of the generalizability and malleability of personality can be further broadened, understood, and advanced.

➢ Impact: Fairness and ethics

1. Striving to ensure that personality measurement is fair across demographic subgroups (e.g. race/ethnicity, gender, and culture), while realizing that fairness is a concept that encompasses broad issues such as cultural sensitivity, conflicting definitions such as equity versus merit, and equal opportunities to provide data.
2. Detecting and reducing personality–related biases and other irrelevancies detected by algorithms. Bias is a statistical concept, referring to empirically reliable subgroup differences in personality that are due to construct irrelevancies in the data, the models, or their combination.
3. Ensuring that personality data collection (e.g. data privacy, anonymity, and security) and data use (e.g. analysis and interpretation) are sensitive to and consistent with updated professional, legal, and ethical standards (e.g. AERA, APA, NCME, 2014; Equal Employment Opportunity Commission, 1978).
4. Transparently reporting the process of personality data collection and analysis, disclosing, and

reflecting on any key limitations alongside any key benefits. Open science practices can critically assist in improving transparency (e.g. preregistration, sharing relevant measures and protocols, and sharing the variable codebook and code for analyses, if not the data set itself).

Implementation

The model I used went through different stages starting from finding the right dataset to cleaning to preprocessing to modeling to finally going through evaluation

Stages :

- Loading the dataset
- Understanding the data set
- Participants nationality distribution
- Swapping the abbreviation of the columns to more understandable format
- Defining a function to visualize the questions and answers
- Visualization for every attribute
- Clusters I defined
- Visualizing the elbow
- Clustering participants into 5 clusters
- Analyzing the model and prediction

Previous Work

In recent years there have been many different attempts to automatically classify personality traits from text or from other cues, like social network usage. Oberlander & Nowson 2006 (Ob06) classified extraversion, stability, agreeableness, and conscientiousness of blog authors using n-grams as features and Naïve Bayes (NB) as learning algorithm. They experimented with different percentiles (using only the authors with the highest and lowest scores, in table 1 we report the results of 50% splitting) and reported that binary classes and automatic feature selection yield the best improvement over the baseline. Mairesse et al. 2007 (Ma07) ran personality recognition in both conversation (using observer judjements) and text (using self assessments via Big5). They exploited two lexical resources as features, LIWC (Pennebaker et al. 2001) and MRC (Coltheart 1981), and predicted both personality scores and classes (we report results over classes in table 1) using Support Vector Machines (SVMs) and M5 trees respectively. They also reported a long list of correlations between Big5 personality traits and two lexical resources they used. Iacobelli et Al. 2011 (Ia11) used as features word n-grams extracted from a large corpus of blogs, testing different extraction settings, such as the presence/absence of stop words or inverse document frequency. They found that bigrams, treated as boolean features and keeping stop words, yield very good results using SVMs as learning algorithm, although the features extracted are few in a very large corpus.

As for the extraction of personality recognition from social network sites, Golbeck et al. 2011a (G11f) predicted personality scores of 279 Facebook users, exploiting both linguistic features (from LIWC) and social features (i.e. friend count, relationship status). Golbeck et al. 2011b (G11t) also predicted the personality of 279 Twitter users, exploiting LIWC, structural features (i.e. hastags, links) and sentiment features, and using a Gaussian Process (GP) as learning algorithm. Quercia et Al. 2011 (Qu11) used network features (followers, following, klout[1] score) to predict the personality scores of 335 Twitter users. They used M5 rules as learning algorithm. Bai et Al. 2012 (Bi12) predicted personality classes of 335 users of RenRen, a popular Chinese social network. They exploited network features such as friend count, self comments and recent statuses counts and experimented either with a median split and 3 percentile grips. They obtained good results using decision trees (C4.5), the best performance was achieved using a median split (results reported in table 1). Bachrach et al. 2012 (Bc12) made an extensive analysis of the network traits (i.e. such as size of friendship network, uploaded photos, events attended, times user has been tagged in photos) that correlate with personality of 180000 Facebook users. They predicted personality scores using multivariate linear regression (mLR), and reported good results on extraversion.

A comparison of the results described here is reported in table 1. Basically there are two different approaches to personality recognition: bottom-up and top-down. The Bottomup approach (Oberlander & Nowson 2006, iacobelli et al. 2011, Bachrach et al. 2012) starts from the data and seeks for linguistic cues associated to personality traits, while the topdown approach (Argamon et al. 2005, Mairesse et Al. 2007, Golbeck et al. 2011a) makes heavy use of external resources, such as LIWC and MRC, and tests the correlations between those resources and personality traits. The former approach seems to achieve the best improvement from the baselines,

Author	Alg.	Eval.	Traits	Users	Result	B.line
Ob06	NB	acc	xnac	71	.866	.549
Ma07	SVM	acc	xnaco	2.4m	.57	.5
Ia11	SVM	acc	xnaco	3m	.767	.5
G11f	M5	mae	xnaco	279	.115*	.118*
G11t	GP	mae	xnaco	279	.146*	.147*
Qu11	M5	rmse	xnaco	335	.794*	-

[1] http://klout.com/kscore

Bi12	C4.5	f	xnaco	335	.783	-
Bc12	mLR	rmse	xnaco	180m	.282*	-
Ce13	-	f	xnaco	2.4m	.686	.6

Table 1: Overview of Personality Recognition from Text and Personality Recognition for Social Networks. *=lower scores are best. Results are averaged over the five traits.

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