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Incremental criterion prediction of personality facets over factors: Obtaining unbiased estimates and confidence intervals

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ABSTRACT

Many researchers have argued that higher order models of personality such as the Five Factor Model are insufficient, and that facet-level analysis is required to better understand criteria such as well-being, job performance, and personality disorders. However, common methods in the extant literature used to estimate the incremental prediction of facets over factors have several shortcomings. This paper delineates these shortcomings by evaluating alternative methods using statistical theory, simulation, and an empirical example. We recommend using differences between Olkin–Pratt adjusted *r*-squared for factor versus facet regression models to estimate the incremental prediction of facets and present a method for obtaining confidence intervals for such estimates using double adjusted-*r*-squared bootstrapping. We also provide an *R* package that implements the proposed methods.

1. Introduction

Personality trait researchers have long been interested in how many personality traits are required to adequately capture individual differences. Hierarchical models of personality traits provide multiple levels of description, typified by the Five Factor Model in which the global factors of extraversion, neuroticism, conscientiousness, agreeableness and openness each consist of six facets representing a more detailed level of personality. Despite the popularity of the Big Five, there has been substantial debate about the relative merits of factor and facet assessments of personality (Ashton, 1998; Ashton, Jackson, Paunonen, Helmes, & Rothstein, 1995; Ashton, Paunonen, & Lee, 2014; Christiansen & Robie, 2011; O'Neill, Paunonen, Christiansen, & Tett, 2013; Paunonen, 1998; Paunonen & Ashton, 2001; Paunonen, Haddock, Forsterling, & Keinonen, 2003; Paunonen, Rothstein, & Jackson, 1999; Salgado, Moscoso, & Berges, 2013). Additionally, comparing the predictive value of a model with 30 facet predictors to one with only five factor predictors has presented a challenge for researchers concerned with issues of over fitting. Personality researchers seeking to predict outcomes such as well-being (Siegler & Brummett, 2000), job performance (Ashton, 1998; Christiansen & Robie, 2011; Ones & Viswesvaran, 1996; Salgado et al., 2013; Tett, Steele, & Beauregard, 2003), and personality disorders (Bagby, Costa, Widiger, Ryder, & Marshall, 2005; Dyce & O'Connor, 1998) have then had to decide whether to include facets or only the Big Five factors as predictors.

Typically, incremental prediction of facets over factors has been estimated by subtracting the variance explained in a criterion by factors from that explained by facets. However, researchers have used many different estimators of variance explained, including unadjusted *r*-squared, adjusted *r*-squared, and cross-validated *r*-squared, combined with different regression procedures including direct entry (Mershon & Gorsuch, 1988) and stepwise regression (Baudin, Aluja, Rolland, & Blanch, 2011; Dyce & O'Connor, 1998; Ekehammar & Akrami, 2007; Quevedo & Abella, 2011; Schimmack, Oishi, Furr, & Funder, 2004); some studies have simply reported zero-order correlations (e.g., Rothmann & Coetzer, 2002; Siegler & Brummett, 2000). Thus, a principled selection of estimators is lacking (e.g., see critical review by O'Connor and Paunonen, 2007). Furthermore, the use of small sample sizes (e.g., Ashton et al., 1995; Mershon & Gorsuch, 1988; Schimmack et al., 2004) and incomplete facet–factor comparisons, based on the selection of subsets of either facets or factors (e.g., Ashton et al., 1995; Bagby et al., 2005; Dudley, Orvis, Lebiecki, & Cortina, 2006; Fruyt, Clercq, Wiele, & Heeringen, 2006; Hastings & O'Neill, 2009; Paunonen & Ashton, 2001; Salgado et al., 2013; Stephan, 2009), has limited the available empirical evidence regarding the overall incremental value of facets over factors. Also, existing research has not explicitly specified a population parameter of interest.

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Furthermore, as will be shown many existing methods that have been used for estimating incremental prediction result in biased estimates. The lack of reporting of confidence intervals further compounds these issues. Further clarity is needed about these foundational issues in order to more clearly quantify the gains that can be achieved by the inclusion of facets in predictive models. Thus, existing approaches are insufficient for researchers seeking to make conclusions about the relative utility of facet- versus factor-level analysis in personality research.

The purpose of the current paper is (1) to identify the population parameter of interest for research on incremental prediction of facets over factors; (2) to compare methods for obtaining an estimate of this population parameter to demonstrate relative bias across methods through a series of simulations, and (3) to provide a method for reporting confidence intervals around this estimate. We also critically review the broader set of approaches that have been used to compare factor versus facet prediction of criterion variables. Based on our comparison of methods, we recommend the use of the Olkin–Pratt adjusted *r*-squared as an estimator, and the reporting of double-adjusted *r*-squared bootstrap (DAB) confidence intervals. We also review and make recommendations regarding methods for identifying which particular facets are of greatest incremental benefit. Finally, we present an *R* package that implements all the proposed methods.

2. Identifying the parameter of interest for incremental prediction research

The present paper focuses on the scenario where factors and facets come from a hierarchical measure, such as the 30 facets and five factors from the NEO-Personality Inventory (Costa & McCrae, 1995). Notably however, the method presented in this paper could readily be extended to scenarios where factors and facets are not derived from a hierarchical measure, such as when additional facet predictors are included. We also note that various other questions can meaningfully be asked, such as how predictive validity of specific facets compares with specific factors, and whether equivalent numbers of facet predictors explain more variance than equivalent numbers of factors. However, the focus of this paper is to evaluate the relative predictive utility of a full set of facets versus factors in relation to the Five Factor Model, an issue that is important for personality research given the popularity of factor-level measures (Judge, Klinger, Simon, & Yang, 2008).

We contend that researchers interested in incremental prediction of facets over factors should focus on the change in population variance explained from a regression with facets versus a regression with factors as predictors. We can denote this difference as $\Delta\rho^2$ (i.e., delta-rho-squared), where $\Delta\rho^2 = \rho^2_{(\text{facets})} - \rho^2_{(\text{factors})}$, and where $\rho^2_{(\text{facets})}$ and $\rho^2_{(\text{factors})}$ correspond to population variance explained for models with facets and factors as predictors respectively. Note that factors are not included as predictors in the facet regression equation when factors are a weighted composite of facets as per hierarchical measures of personality such as the NEO-PI. We also note as advocated by Ozer (1985) that multiple rho (i.e., $\Delta|\rho| = \left|\rho_{(\text{facets})}\right| - \left|\rho_{(\text{factors})}\right|$) provides a legitimate alternative metric.

As a minor point, we advocate the use of ρ^2 and $\Delta\rho^2$ implied by random-score rather than fixed-score regression models sometimes referred to as random-*x* and fixed-*x* assumptions (for further discussion, see Fox, 2002; Yin & Fan, 2001). In a fixed-score regression, it is assumed that the values of predictors are fixed across studies. In a random-score regression it is assumed that the predictors are to be sampled from an underlying population. Given that the aim is to draw inferences about the full population of personality data, the random-score regression model is more appropriate.

It is also important to note that ρ^2, which is the variance explained in the population using the population regression equation, differs from ρ^2_c (i.e., cross-validated rho-square) which is the variance explained by the regression equation obtained in the sample when applied to the population (Yin & Fan, 2001). Specifically, ρ^2 is relevant to understanding true theoretical relationships, whereas ρ^2_c is relevant where the aim is to apply a sample estimated regression equation to a practical prediction context.

We note that when facets come from a hierarchical measure where factors are defined as a weighted composite of facets, a regression with facets will always explain as much variance as or more variance than factors ($\Delta\rho^2 \geqslant 0$). Thus, for a given criterion, once a regression approach is adopted, the question is not *whether* facets explain more variance than factors but rather *how much more* variance they explain. So, an important substantive question for personality researchers is whether the amount of incremental prediction for a given criterion justifies the increased complexity associated with the increased number of predictors.

3. Selecting an estimator of incremental variance explained

3.1. Description of estimators

We now review the different methods that have been used to estimate the incremental population variance explained by a regression with factors as predictors versus one with facets as predictors, denoted $\Delta\rho^2$. In general, estimates of $\Delta\rho^2$ are obtained by first obtaining estimates of ρ^2 for facets and for factors, and then subtracting one from the other: $\Delta\hat{\rho}^2 = \hat{\rho}^2_{\text{facets}} - \hat{\rho}^2_{\text{factors}}$, i.e., where the hats indicate estimates of corresponding population parameters. Three major classes of estimators of ρ^2 are (a) unadjusted *r*-squared (i.e., R^2), (b) adjusted *r*-squared (i.e., R^2_{adj}, and (c) cross-validated *r*-squared (i.e., R^2_c). Typically, but not always, use of adjusted *r*-squared has been combined with direct entry of all factors or all facets as predictors, and unadjusted *r*-squared has been used with stepwise entry of factors or facets, whereas cross-validated *r*-squared has rarely been used in the facet–factor comparison literature.

Unadjusted *r*-squared is the variance explained in the sample data by the sample estimated regression equation. Cross-validated *r*-squared represents a broad class of techniques that attempt to estimate ρ^2_c, i.e., the population prediction using the sample regression equation. Adjusted *r*-squared shrinks unadjusted *r*-squared. The shrinkage is greater when sample sizes are smaller and the number of predictors is greater. Adjusted *r*-squared is designed to provide an unbiased estimate of ρ^2. There are several adjusted *r*-squared formulas (for a review see Raju, Bilgic, Edwards, & Fleer, 1997). The Ezekiel and Fox (1959) formula is commonly used in statistical packages, where

$$R^2_{\text{adj}(E)} = 1 - (1 - R^2)\frac{n-1}{n-p-1} \tag{1}$$

and where n is the sample size and p is the number of predictors. Adjusted *r*-squared formulas differ based on whether they are designed to estimate fixed-*x* ρ^2 or random-*x* ρ^2. In particular, the standard Ezekiel formula shown above is an estimator of fixed-*x* ρ^2 whereas the Olkin and Pratt (1958) R^2_{adj} formula and several other approximations are designed to estimate random-*x*. Specifically, the Olkin–Pratt formula is

$$R^2_{\text{adj}(OP)} = 1 - (1 - R^2)\frac{n-3}{n-p-1}F\left[1, 1; \frac{n-p+1}{2}; (1 - R^2)\right] \tag{2}$$

where F is the hypergeometric function. As discussed earlier, given that personality research samples the predictor values from a population, researchers should be making the random-*x* assumption.