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Mining the drivers of job satisfaction using algorithmic variable importance measures (*)

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1. Introduction

The identification of the most important predictors of the analyzed target variable strongly affects the accuracy of its interpretation and prediction, and many methods have been proposed in the literature aiming at variable selection. Sometimes they are based on simple descriptive features of data (for example the ratio of between to within group sums of squares), but more frequently variable selection arises as a sort of sub-product of some prediction tool (for example, when regression is used, the variable importance can be roughly measured with the absolute *t*-ratio of the estimated parameter for that variable or alternatively step-wise procedures can be used). To assess the importance of each predictor, we propose the use of two *algorithmic models* (Breiman, 2001b) to construct two specific measures: *Predictive Importance* and *Constructive Importance*. We apply this procedure using *classification and regression trees* (CART, Breiman *et al.*, 1984) to investigate the effects of specific job satisfaction facets on overall job satisfaction, using a sample of workers of public and private nonprofit organizations in the Italian social service sector.

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2. Algorithmic variable importance measures

Recent research is focusing on model-free prediction techniques and variable selection schemes. Structured approaches in this context are the recently introduced learning ensembles, algorithmic models where each ensemble member is given by a different function of the input variables derived from the training data, and predictions are obtained by somehow averaging the predictions of all the members (Breiman, 1996). Popular examples in this class are Random Forests (RF - Breiman, 2001a) and the Gradient Boosting Machine (GBM - Friedman, 2001) with TreeBoost (TB) as its particular case. The basic feature of RF and TB is to use CART as base learner. Specifically, RF is an ensemble of trees grown injecting a randomization, while TB sequentially fits a tree to current pseudo-residuals, computed according to some predetermined loss function. These schemes allow the construction of some interesting model-free variable importance measures (Sandri and Zuccolotto, 2006). We propose to use two variable importance measures, computed respectively with RF and TreeBoost:

- M_1: new RF predictions are obtained with data where all the values of h-th variable X_h are randomly permuted. The importance of X_h is given by the increase in the prediction error due to its randomization (Breiman, 2001a).
- M_2: at each tree of the TreeBoost the improvements (in terms of the used measure of homogeneity) due to variable h over the set of the nonterminal nodes are summed up and the importance of variable X_h is computed averaging the results over all the trees of the ensemble (Friedman, 2001).

The distinct way the two measures are obtained reflects two different approaches to variable importance evaluation, the former focused on the impact of the variable in the model performance, the latter based on the role it plays on the CART mechanism. M_1 and M_2 can be accordingly called respectively *Predictive Importance* and *Constructive Importance*.

3. Overall and facet job satisfaction

Job satisfaction (JS; Spector, 1996) is generally viewed as the degree to which workers like their job, and its importance in economics has been clearly recognized a long time ago because high levels of JS have been related to extra work effort and performance (Freeman, 1977; Bertrand and Mullainathan, 2001; Fisher, 2003; Schleicher *et al.*, 2004). The two major methods for measuring JS consist in the use of a single global measure (*overall JS*) and of dimensional measures (*facet JS*), usually constructed using a multi-item questionnaire asking to the worker an evaluation of the satisfaction with his/her job (Cranny *et al.*, 1992; Highhouse and Becker, 1993). Overall JS is concerned with the broader domain of an employee's satisfaction with his/her job, whereas facet JS focus on narrow areas of job tasks (satisfaction with pay, career progress, co-workers, etc.). Therefore, another single measure of JS can be obtained summing up all the responses of facet JS, but it's argued that a single-item global measure is more appropriate for measuring JS because it is a more comprehensive evaluation and has fewer methodological concerns than a multi-item measure roughly summing up the facets (Ironson *et al.*, 1989; Wanous *et al.*, 1997). On the other side, each facet is intended to be a specific and different JS measure from the others, and facet JS scales are intended to cover separately each of the principal areas within the generals JS domain. Sometimes both approaches can be used to get a complete picture of JS, but some studies point out that overall JS can be not equivalent to facet JS (the two measures can have low correlation), because the former is referred to an absolute (not relative) frame of reference (Smith *et al*., 1969) and can include the worker's considerations about aspects typically not measured by the items of the facet JS (like for example off the job experiences; Scarpello and Campbell, 1983). However, the literature suggests that the worker's overall JS depends on the facet JS: from this point of view, we consider every item of facet JS as a *driver* of the overall JS. To study the importance of the single drivers of the facet JS on the overall JS, some researchers have used items of facet JS as predictor variables for the single item of overall JS in many linear and non-linear statistical models (Aldag and Brief, 1978; Ferratt, 1981; Allen *et al*., 2004). As a possible alternative, the two above mentioned algorithmic measures can be employed.

4. Case study

For our application we used the data of the FIVOL-FEO 1998 survey (Borzaga and Musella, 2003), involving a sample of workers of about 200 organizations providers of social services and operating in 15 Italian provinces. A specific questionnaire was addressed to each worker, asking for personal and professional information, work-related attitudes, job satisfaction. We focused our attention on the analysis of 1.516 paid workers' JS, described in the questionnaire by 14 items[1] where respondents indicated, on a scale ranging from 1 to 7, the level of satisfaction with respect to each aspect, with higher scores reflecting more satisfaction. An interesting unusual exploit of variable importance measures can be made applying them to a model where the overall JS (OVERALL) is modelled as a function of the 13 remaining facet JS items[2]. For the modern theory of labour economics, employees in nonprofit firms are believed to be intrinsically motivated and there is a strong notion they derive some other kind of utility from work (e.g. by the relations with co-workers and clients) than just the extrinsically-monetary reward for their effort (Frey, 1997; Benz, 2005).

4.1 Analysis of the association

Before assessing the importance of each predictor with algorithmic models, we have to preliminarily verify the existence and direction of the statistical association between it and the outcome. As in our analysis predictors are ordinal variables and the objective is a dichotomous one, for this simple bivariate analysis we used indices based on the odds ratio (Agresti, 1990).

[1] Satisfaction about: the overall work (OVERALL); Formative and professional growth (GROWTH), Decisional and operative independence (INDEP), Variety and creativity of work (VARIETY), Relationships with superiors (SUPERIORS), Relationships with colleagues (COLLEAGUES), Benefit of work for the clients (CLIENTS), Recognition by the others (RECOG), WAGE, Working hours (HOURS), Career promotions achieved (CARPROM), Career prospects (CARPROSP), Stability of job (STABILITY), Physical environment of work (PHYSICAL).

[2] A dichotomous response variable is used (level 1 to 4: *not satisfied* – approximately 25% workers; level 5 to 7: *satisfied* – approximately 75% workers). We made this choice because (1) the two extreme categories of the answer were "*completely unsatisfied*" - "*completely satisfied*" and (2) the frequencies of the first three categories were low.

In particular, let the variables X and Y have respectively k ordered $(1;2;\ldots;k)$ and two $(a;b)$ categories, then the following *trend ratios* can be computed:

$$r_j(Y \mid X) = (n_{a1} \cdot n_{bj})/(n_{aj} \cdot n_{b1}) \qquad j = 2, 3, \ldots, k$$

with n_{ij} the frequency $(i; j)$ of the 2×2 table for the categories $(1; j)$ of X and $(a\,; b)$ of Y. If the ratio $r_j(Y \mid X)$ is strictly greater than unity and increases with $j \rightarrow k$ we can say that there is a positive and strong association between X and Y.

Following our algorithmic approach, we verified the stability of these associations: Figure 1 represents, for each driver of facet JS, the three *bootstrap quartiles* (10.000 replications) of its trend ratios with the overall JS. As expected, $r_j(Y \mid X) > 1$ and has increasing values for $j \rightarrow k$, pointing out the positive association of each driver of facet JS with the overall JS. Moreover, this preliminary analysis highlights that stronger association is present with intrinsic-relational items as GROWTH, INDIP and RECOG; at the same time, the last two categories of these drivers are characterized by higher instability.

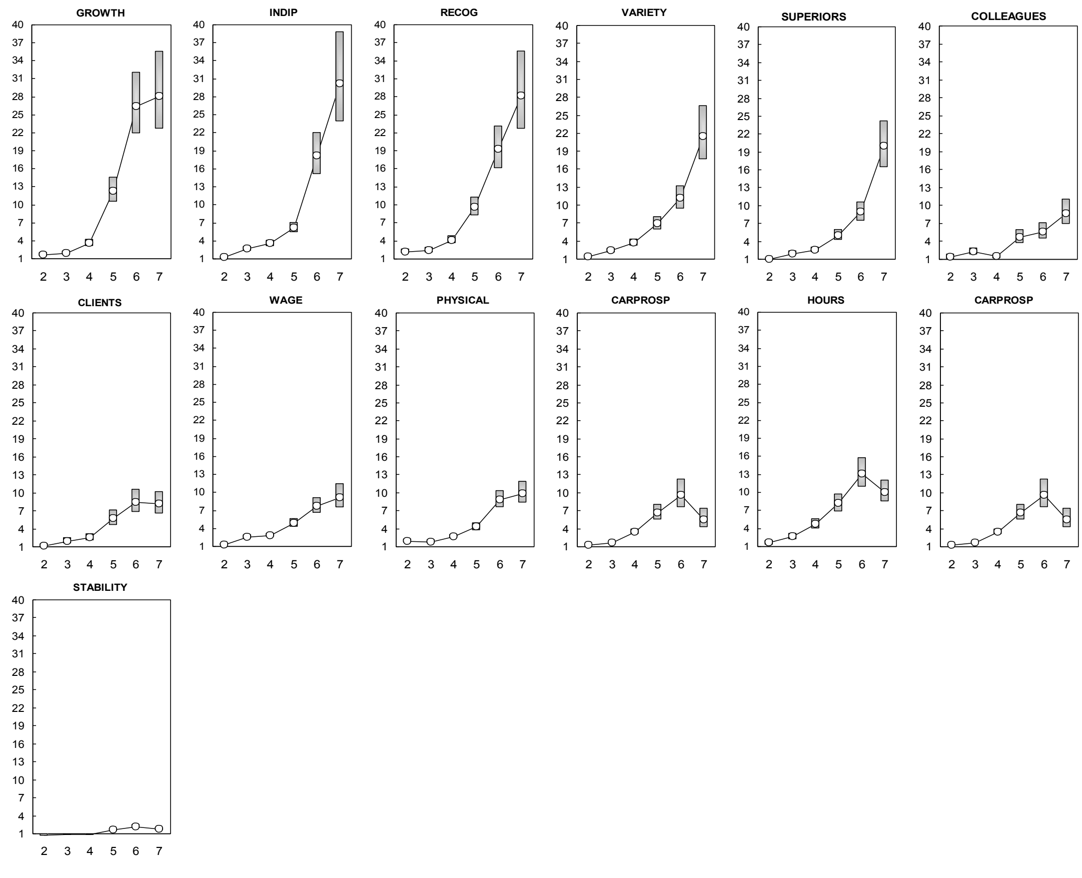

Fig. 1 – Trend ratios between drivers and overall JS (10.000 bootstrap replications)

4.2 Analysis of the importance

From the original sample three datasets was extracted, corresponding to workers employed in Religious Nonprofit Organizations (RNP, 193 workers), in Lay Nonprofit Organizations (LNP, 863 workers), in Public Bodies (PB, 460 workers), so as to inspect the eventual difference among drivers of JS in distinct types of Organization. RF and TB were fitted to each sub-subsample and the two variable importance measures M_1 and M_2 were accordingly computed. The six models exhibit good performances, with out-of-bag misclassification error rates (Breiman, 1996) lower than 20%, meaning that in this study overall JS depends on the facet JS and every item of facet JS can be considered as a *driver* of the overall JS, whose importance can be evaluated by mean of the above described measures. The items have been divided in two groups: extrinsic-remunerative and intrinsic-relational, respectively represented in white and grey in the figures. In Figure 2 and 3 the rankings induced by respectively M_1 and M_2 are displayed.

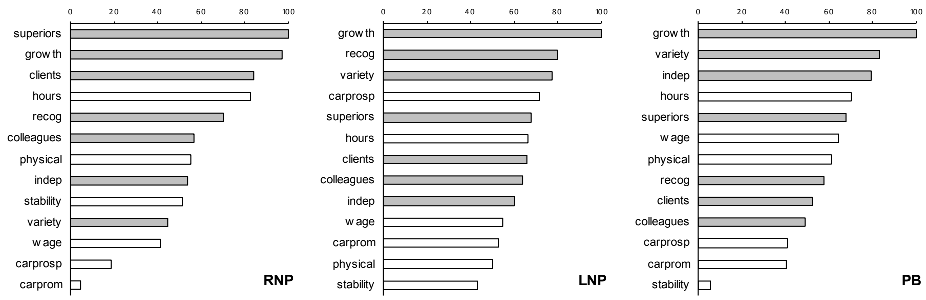

Fig. 2 – Random Forests variable importance measure M_1 (*Predictive Importance*)

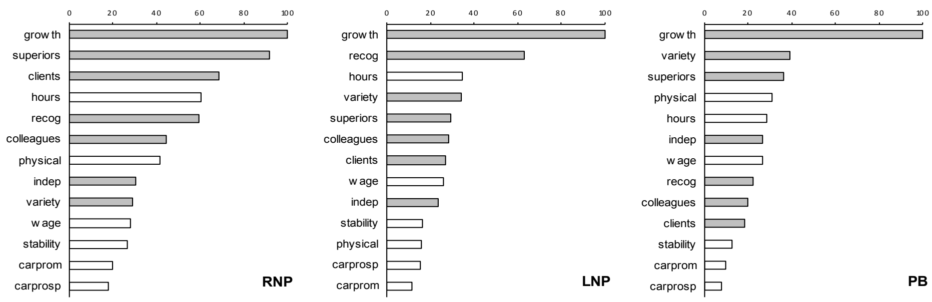

Fig. 3 – TreeBoost variable importance measure M_2 (*Constructive Importance*)

Figure 4 displays a scatterplot of the two importance measures. The most important (unimportant) drivers of job satisfaction can be recognized by finding out the variables exhibiting an effective agreement of the two measures. The results with M_1 and M_2 confirm what suggested by economic literature about the state of mind of workers employed in non-profit and public organizations: in the former case the awareness of the benefit for clients and of the relations with other employees tends to produce more overall satisfaction than the monetary aspects of job, in the latter the predominance is reversed.

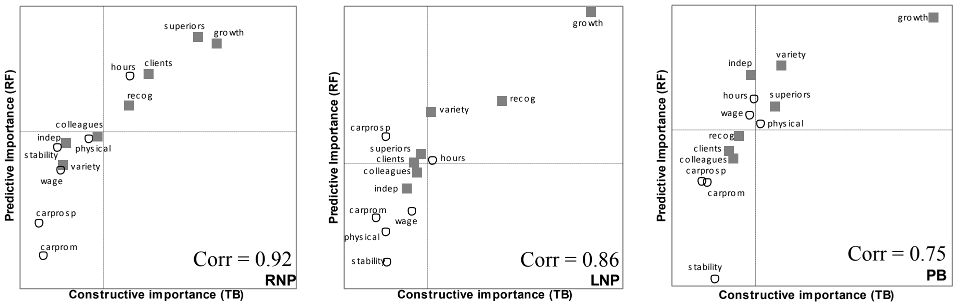

Fig. 4 – Constructive vs. Predictive Importance

5. Concluding remarks

In this paper we propose to assess the importance of a predictor using *Predictive Importance* and *Constructive Importance* measures obtained by algorithmic models. We attain interesting results using these two measures as a means to assess the drivers of the job satisfaction for a sample of workers of the Italian social service sector. Our data analysis confirms the recent economic theory: for the overall job satisfaction, intrinsic-relational facets are relatively more important than extrinsic-remunerative facets, especially for the workers of nonprofit organizations.

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