Ideal Atlas Professional Profile

Optimizing Career Choice and Development via User-Defined Parameters

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Contents

1 Introduction

Another way of thinking about optimal career choice and development is to start not with the individual's current capacities, but rather their desired outcome. That is, instead of matching users to their most compatible occupations, and then optimizing parameters such as wage, level of education, and so on, we could invert the process by asking users what they'd like their career to look like in the future.

Both procedures are completely valid and serve different purposes. There is a lot of value in estimating optimal career choice and development using either method. However, the user-defined "ideal career" could work best for younger people, who don't yet have as many competencies. It is also an interesting approach psychologically speaking, as it makes people think about what they really want and become more aware of their own career preferences, which helps guide them in the appropriate direction. For one thing is to be compatible with an occupation, and another is to actually want to work at those jobs.

2 Rewriting the Career Choice Problem

2.1 Consumer Economics

We could think of user-defined career optimization as a typical economic maximization problem, like so:

$$\max_{\mathbf{a}}[u(\psi(\mathbf{a}), g(\mathbf{a}, \nu), \phi)], \text{ s.t.}$$
$$\sum_{i=1}^{m} p_i a_i \geq \overline{w},$$
$$\sum_{i=1}^{m} \lambda_i a_i \geq \overline{\Lambda},$$
$$\sum_{i=1}^{m} t_i a_i \leq \overline{\eta},$$
$$\sum_{i=1}^{m} k_i a_i \geq \overline{k},$$
$$\sum_{i=1}^{m} K_i a_i \geq \overline{K},$$
$$\sum_{i=1}^{m} c_i a_i \leq \overline{c},$$

where $\nu_i,\ \phi,\ p_i,\ \lambda_i,\ t_i,\ k_i,\ K_i,\ c_i \geq 0;\ \overline{w},\ \overline{\eta} \geq 0;$ and $a_i,\ \overline{\Lambda},\ \overline{k},\ \overline{K},\ \overline{c} \in [0, 100]$. The functions and parameters above are summarized as follows:

Table 1: Career Optimization Parameters

Symbol	Name	Description
$\mathbf{a}$	Professional profile	$\mathbf{a} = (a_1, ..., a_m)$ is a vector of m professional attributes, which characterize an individual.
$u(.)$	Utility function	Measures the user's satisfaction with their career as defined by $\mathbf{a}$.
ψ	Factor scores vector	Factor score estimates based on a professional profile $\mathbf{a}$ and a vector $\mathbf{\Psi} = (\Psi_1, ..., \Psi_F)$ of F factors.

Symbol	Name	Description
$g(.)$	Aggregate AI impact coefficient	Measures a professional profile's total exposure to AI-driven automation as a percentage.
ν_i	Marginal AI impact coefficient	Measures the level of exposure to AI-driven automation per each additional point in an attribute.
ϕ	Fear	Measures the user-defined fear of exposure to AI-driven automation.
p_i	Marginal cost of human capital	Market prices of each additional point in an attribute, estimated via NNLS regression.
$\overline{w}$	Minimum acceptable wage	User-defined minimum level of compensation, in USD.
λ_i	Marginal employability of human capital	Employability increase per each additional point in an attribute, estimated via BVLS regression.
$\overline{\Lambda}$	Minimum acceptable employability level	User-defined minimum level of employability, on a 0 to 100 scale.
t_i	Marginal time investment on human capital	Time investment to gain each additional point in an attribute, estimated via NNLS regression.
$\overline{\eta}$	Maximum acceptable time investment	User-defined tolerance for total time investment or estimated time of arrival (ETA), in years.
k_i	Marginal human capital micro-flexibility	Cross-attribute carryover of each additional point in an attribute, estimated via a system of BVLS regressions.
$\overline{k}$	Minimum acceptable human capital micro-flexibility level	User-defined aggregate cross-attribute carryover requirements, on a 0 to 100 scale.
K_i	Marginal human capital macro-flexibility	Cross-occupation carryover of each additional point in an attribute, estimated with the $K_i(.)$ formula outlined in a previous note.
$\overline{K}$	Minimum acceptable human capital macro-flexibility level	User-defined aggregate cross-occupation carryover requirements.
c_i	Marginal competitiveness of human capital	Competitiveness increment per each additional point in an attribute, estimated via NNLS or BVLS regression.
$\overline{c}$	Maximum acceptable level of competition	User-defined tolerance for competition for job posts, on a 0 to 100 scale (with a bounded model), or using an unbouded ratio scale (number of applicants per job post).

Though it can appear complicated, the intuition behind this formulation is simple: an individual maximizes their career satisfaction $u(.)$ by rationally selecting an "ideal" professional profile $\mathbf{a}$, which best approximates their inclinations, such that the resulting attributes' factor scores come as close as possible to their $u(\psi_1(\mathbf{a})), ..., u(\psi_F(\mathbf{a}))$ factor preferences, while still minimizing exposure to AI-driven automation (proportional to their ϕ fear of AI), and also satisfying their own constraints with regards to compensation ($\overline{w}$), employability ($\overline{\Lambda}$), maximum years of education ($\overline{\eta}$), macro ($\overline{K}$) and micro ($\overline{k}$) human capital flexibility, and competitiveness for job posts ($\overline{c}$).

The solution of this maximization problem is derived by applying the generalized Lagrange multiplier. This can be done numerically without much difficulty.

However, we could also think of a different maximization problem, where the described metrics are incorporated into the individual's utility function, with optional constraints:

$$\max_{\mathbf{a}}[u(\psi(\mathbf{a}), g(\mathbf{a}, \nu), \phi, \mathbf{pa}, \lambda\mathbf{a}, \mathbf{ta}, \mathbf{ka}, \mathbf{Ka}, \mathbf{ca})], \text{ s.t. } a_i \in [0, 100]$$

2.2 Regression Method

Yet another approach to user-defined optimization of career choice and development would be to employ a simple BVLS regression:

$$\text{arg min}_{\mathbf{a}} ||\mathbf{B_c a} - \pi||_2^2, \text{ s.t. } a_i \in [0, 100],$$

where $\pi = (\pi_1, ..., \pi_n)$ is the user-defined vector of preferences for each of n criteria, and $\mathbf{B_c}$ the matrix of β_i^c criteria associated with each metric:

$$\mathbf{B_c} = \begin{bmatrix} \beta_1^{c_1} & \dots & \beta_m^{c_1} \\ \vdots & \ddots & \vdots \\ \beta_1^{c_n} & \dots & \beta_m^{c_n} \end{bmatrix},$$

which in this case is

$$\mathbf{B_c} = \begin{bmatrix} \nu_1 & \dots & \nu_m \\ p_1 & \dots & p_m \\ \lambda_1 & \dots & \lambda_m \\ t_1 & \dots & t_m \\ k_1 & \dots & k_m \\ K_1 & \dots & K_m \\ c_1 & \dots & c_m \\ \psi_{1,1} & \dots & \psi_{1,m} \\ \vdots & \ddots & \vdots \\ \psi_{F,1} & \dots & \psi_{F,m} \end{bmatrix},$$

where $\psi_{f,i}$ is the factor loading of attribute i to the f-th factor.

Finally, the BVLS regression problem becomes:

$$\text{arg min}_{\mathbf{a}} \left\| \begin{bmatrix} \nu_1 & \dots & \nu_m \\ p_1 & \dots & p_m \\ \lambda_1 & \dots & \lambda_m \\ \vdots & \ddots & \vdots \\ \psi_{1,1} & \dots & \psi_{1,m} \\ \vdots & \ddots & \vdots \\ \psi_{F,1} & \dots & \psi_{F,m} \end{bmatrix} \begin{bmatrix} a_1 \\ \vdots \\ a_m \end{bmatrix} - \begin{bmatrix} \overline{\phi} \\ \overline{w} \\ \overline{\Lambda} \\ \vdots \\ \overline{\psi_1} \\ \vdots \\ \overline{\psi_F} \end{bmatrix} \right\|_2^2, \text{ s.t. } a_i \in [0, 100]$$

Thus, the BVLS regression will estimate bounded parameters $\mathbf{a} = (a_1, ..., a_m)$ that minimize the distance between the user's "ideal" professional profile and their own predetermined preferences $\pi = (\overline{\phi}, \overline{w}, \overline{\Lambda}, ..., \overline{\psi_1}..., \overline{\psi_F})$. The problem does not have any constraints other than $a_i \in [0, 100]$, and so the resulting vector of attributes is understood here as the best linear approximation of the user's "ideal" professional profile.