An Empirical Investigation of Implementing Pattern Recognition Applications in Executive Career Success

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Abstract

As for information technology advancement plays significant role into many other fields of sciences, the demand for sufficient software increases. In previous work we outlined the usage of pattern recognition applications in one of the branch of psychology known as Physiognomy. Using face recognition applications we distinguished different types of persons and tried to demonstrate importance of personal types. In this present work there is discussion on pattern recognition algorithms as a tool of object detection. If in previous paper there was highlighted the possible reasons of students' low GPA rate at University, here in this article we try to apparent why successful people are successful. Face characteristic traits and image processing techniques together can propose better future for human life.

Keywords: Pattern Recognition, Physiognomy, Face Coding Algorithms, Physiognomic typologies, Educational Systems

Introduction

Career success is much more than just finding a job and not being fired. True career success combines skill, motivation, determination, and personality to create a livelihood that is fulfilling as well as financially rewarding. Each of these things can be weighted differently by people, but they are all in there somewhere if you have a truly successful career.

If you take on a career that does not suit your personality type and provide some sense of personal fulfillment, you will constantly struggle to stay motivated and enthusiastic about your job. If you take on a career that fits to your personality type, you will have far fewer troubles staying motivated, fulfilling your responsibilities and feeling satisfied with your job. Even during difficult times and the inevitable challenges of life, if your career fits well with your personality you will do well. Psychologists talk about the period of life estimation, when people start to evaluate their life primarily based on the career successfulness after age forty. When result is negative self-appraisal is low and then depression starts (Spremulli, 2006).

Our career impacts our personal life. This is evident from the following: we tend to define who we are by what we do. We will say, I am a nurse, a teacher, a secretary and immediately everyone knows where we fit into the community. For this reason our choice of work says something about us. It gives some indication about our abilities, background and the things which are important to us. These are the ways in which society judges us. How society criticizes us has a direct effect on how we view ourselves and therefore on our personal life.

Sometimes we choose particular job because it seemed the right one, prestigious and well paid. If, however, we are not suited to that type of work and it makes us miserable it is safer to give it up and try something less sought after but which suits our abilities. These decisions affect our peace of mind, welfare and sense of right. (Redfern, 2010)

Similarly, the role of choosing right profession at universities was demonstrated in previous paper, where low Grade Point Average (GPA) was supposed as a consequence of mismatching between personal type and selected careers.

The paper is structured as follows: Section II outlines the personal characteristics towards the successful career and its literature roots. Section III describes the future extraction using pattern recognition techniques; as for last section evaluation of research results on successful people is completed.

Review of Literature

Efforts to help people identify appropriate careers can be traced to the fifteenth century, and by the nineteenth century at least sixty five books had been published on the topic. (Zytowski, 1972). The first vocational guidance program emerged in San Francisco in 1888 – in Cogswell High School – and subsequently

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in high school in Detroit in 1897 (Brewer, 1942). However, the roots of career development theory did not merge until Frank Parsons (Jones, 1994) advanced the three-step "formula": a) Gathering information about yourself; b) Gathering information on the many dimensions of various career options; c) Putting the pieces together to reach a good decision. Parsons's schema for successfully choosing a career cannot be called a theory in the strict sense, but it was the first conceptual framework for career decision making and became the first guide for career analysts.

In the wise choice of vocation there are three broad factors: 1) a clear understanding of yourself, your attitudes, abilities, interests, ambitions, resources, limitations, and knowledge of their causes; 2) a knowledge of the requirements, conditions of success, advantages and disadvantages, compensation, opportunities, and prospects in different lines of work; 3) true reasoning on the relations of these two groups of facts.

Parsons (Jones, 1994) believed that if people actively engage in choosing their vocations rather than allow chance to operate in the hunt for a job, they are more satisfied with their careers, employers, costs decrease and employees' efficiency increases.

Career development theories are explanations of how people develop certain traits, personalities, and self-percepts and how these developments influence decision making. (Brown, 2002)

Career success can be defined as the real or perceived achievements individuals have accumulated as a result of their work experiences. (Judge D. M., 1995). Most research has divided career success into extrinsic and intrinsic components. Extrinsic success is relatively objective and observable and typically consists of highly tangible outcomes such as pay and ascendancy (Jaskolka, 1985). Conversely, intrinsic success is defined as individuals' subjective appraisal of their success and is most commonly expressed in terms of job, career, or life satisfaction (Gattiker, 1988) (Judge D. M., 1995).

A number of investigations confirm the idea that extrinsic and intrinsic career success can be assessed as relatively independent outcomes, as they are only moderately correlated (Judge T. A., 1994).

Intrinsic career success is measured in several distinct ways. The most common marker for intrinsic career success is a subjective rating of one's satisfaction with one's career.

Starting from the premise that personality can be related to numerous work-relevant outcomes; it is worth considering how personality traits might have an effect on careers. To this end, that Figure 1 represents the most important and empirically supported linkages between personality and career-relevant outcomes personality leads individuals to possess certain jobs both through the process of attraction to the jobs of interest as well as by leading organizations to select certain individuals.

Personality also influences individual performance on the job in a way that will lead to higher compensation, new job responsibilities, and promotions into higher organizational ranks. Finally, personality influences the ways in which individuals engage in social interactions at work.

Data Visualization: Sammon Mapping

Data visualization is itself a large field and covering it in a single paper is not possible. Nevertheless, some issues concerned with high-dimensional and non-vectorial data are relevant for pattern recognition and are discussed here. Graphically representing one or

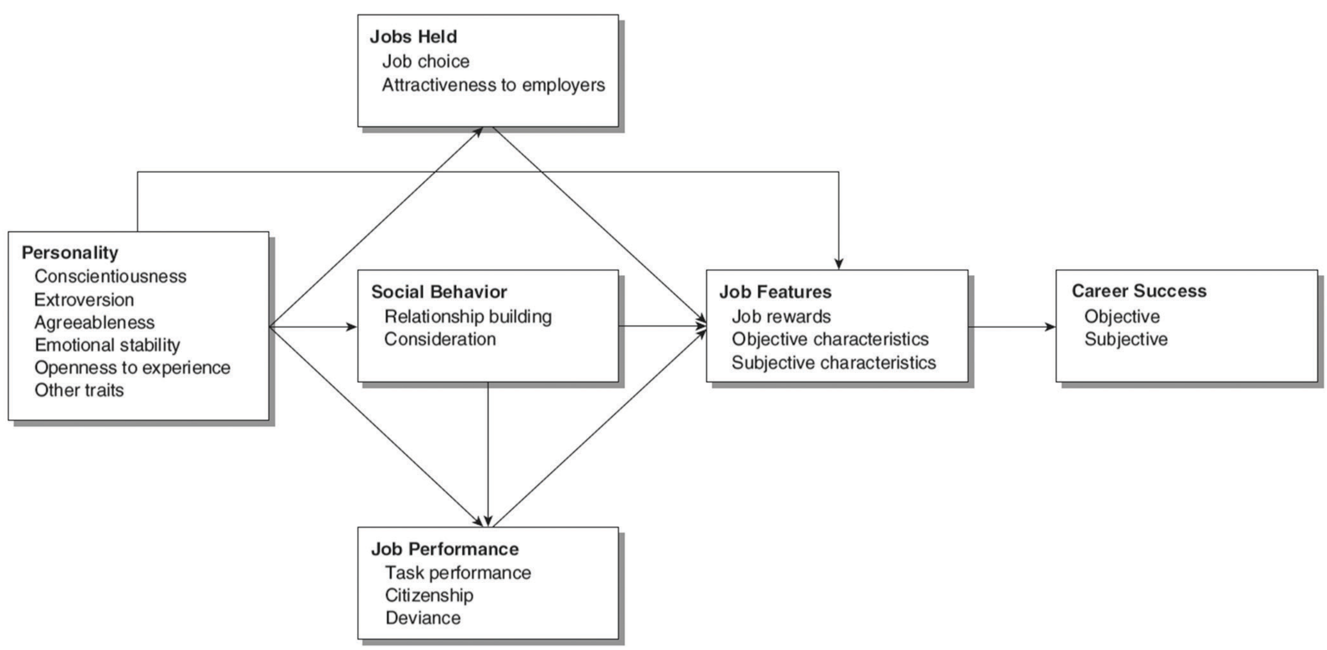

Figure1
Conceptual Model of Personality and Career Success

two-dimensional vectors in a Cartesian coordinate system is the most straightforward possibility, easily done with a pencil and paper. With modern computers and graphics software, three-dimensional data can also be successfully visualized. From four dimensions on and for data other than vectors, more sophisticated techniques have to be used. If the data come from a metric space, the following idea can be pursued: Each datum is to be projected onto a lower-dimensional space (typically two-dimensional) in such way that the distances between the projections are as close as possible to the distances between the original points. If the input space metric correctly reflects the data structure, the structure remains preserved in the mapping. As a consequence, one can easily visually inspect the mapped vectors and infer properties of the original data: similarities, clusters etc.

Sammon's non-linear mapping (Sammon, 1969) is the earliest implementation of this idea and a number of improvements have been proposed, like distance mapping (Duin, 1999) or curvilinear component analysis (J.A. Lee, A robust nonlinear projection, 2000) among others. However, the original Sammon's method still prevails in practice, and scientists can rely on a number of software implementations, many of them freely available (T. Kohonen, 1996), (Murtagh, 1992), (Ripley, 2001). The mapping has become an established tool in data analysis, with applications from document retrieval, as reported in the Sammon's original paper, to logo-therapy (A. Hatzis, 1996) and molecular biology (Agrafiotis, 1997) to name just few.

To reach an approximate solution, Sammon proposed minimizing the following criterion (**Figure 2**).

Only by taking into account both axes simultaneously, the optimal step size can be computed.

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Finally, in the fourth case, the parabola is convex, but with the angular point below zero. Here, no obvious favorite exists and it is a matter of design which of the above three adaptation steps is chosen. Newton's rule is the most conservative, leading to smaller steps and consequently to slower convergence but also less oscillations, whereas jumping directly into the parabola's angular point is the most radical choice with opposite consequences.

Overview of Clustering

The general assumption behind clustering is that the data form more or less identifiable groups (clusters), such that a certain degree of commonness is higher inside the groups than between them. Distance-based methods assume that the commonness is somehow reflected in the distance between data – the lower the distance, the higher the commonness. The primary task of clustering is to identify the data forming clusters, e.g. by enumerating them and listing all data belonging to the same cluster. Often, additional information is provided, for example: where are the clusters centers, what are their boundaries, which shapes do the clusters have, and so on.

The insight obtained by clustering can already be helpful by itself, but it can also support further processing steps. For example, a comprehensive summary about data, their distribution and shape can reveal relevant features and give clues about meaningful parameter settings for classification or about the applicability of different classification algorithms.

Many of the popular clustering algorithms consid-

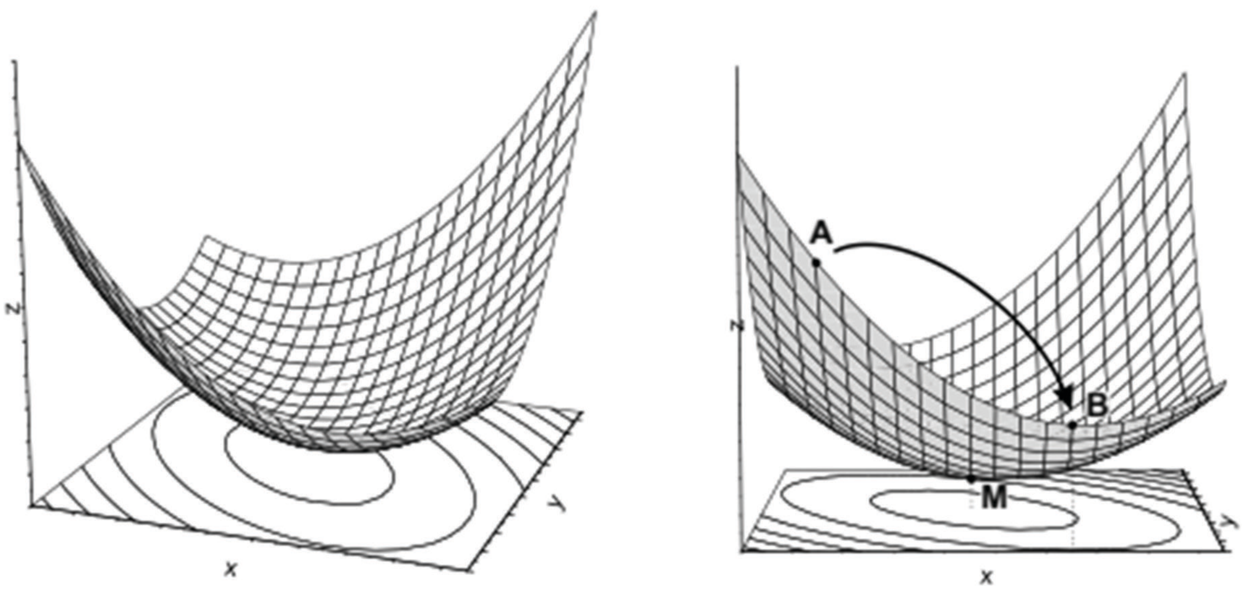

Figure2

Finding the minimum of an elliptical paraboloid. Left: a percpective view of the paraboloid. Right: a view from the xz-plane. Starting from point A, the optimal adaptation of the x-coordinate alone leads to point B, which is the angular point of the parabola in the plane passing through A and being parallel to xz-plane. However, in search for the paraboloid minimum M, this approach overshoots it. The same holds for y-axis.

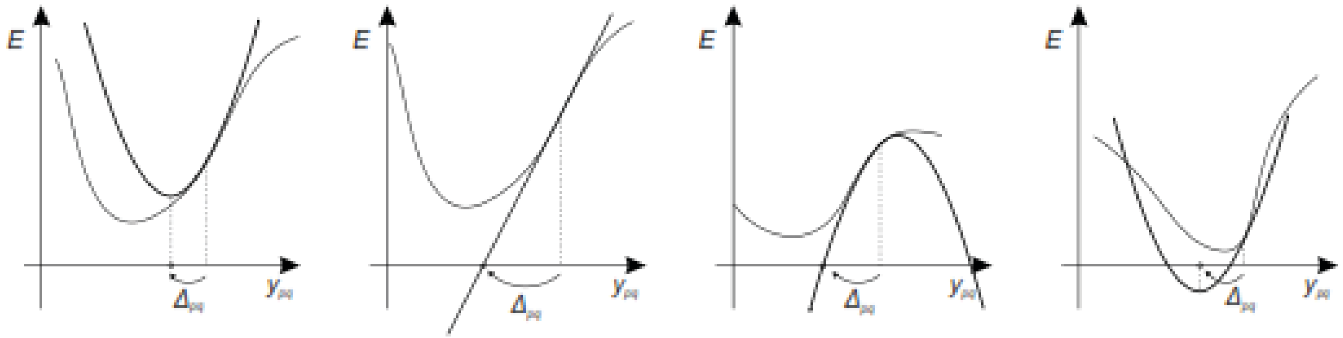

Figure3
Four cases of error function shape and its quadratic approximation. From left to-right: (1) error function is locally convex and the angular point of the approximation is above zero; (2) current minimum estimate is in the inflexion point and the parabola degenerates to a line; (3) concave error function; (4) convex error function and the angular point of the parabola is below zero.

er clusters to be equal, in the sense that they compete each other. In other words, the data structure is considered flat. Other categories are hierarchical algorithms: they assume data to form nested clusters, so each cluster can contain subclusters, each of them can contain further subclusters and so on. For certain applications, hierarchical clustering is a very natural representation and conceptually easy to understand. For example, relationships between species in biology are most naturally explained in terms of hierarchical families, subfamilies etc. Also, pattern recognition algorithms can be divided into three clusters: clustering, classification and function approximation algorithms; clustering consists of flat and hierarchical algorithms and so on. However, computational complexity of hierarchical algorithms is usually much higher than for the flat ones.

An important and still largely unsolved question concerns the number of clusters to derive. Some algorithms, most prominently K-means, return a user-specified number of clusters, regardless of their validity. It is then the user's responsibility to specify a meaningful number. Another possibility is to rely on a criterion function. For example, one can take the criterion function of the form:

$$J_e = \frac{1}{N}\sum_{k=1}^{K}\sum_{x\in C_k} d\left(x,\mu_k\right)^2, \tag{1}$$

where C1, C2 ,…….. Ck are the disjoint sets of points x, each represented by μ_k. The criterion J_e can be minimized by choosing optimal K and μ_k's. The purpose is to minimize the quadratic deviation of the data from the cluster centers. Clearly, the minimum is reached when each datum is the center of its own cluster, since the distance would always be zero. A reasonable number of clusters can be found iteratively. The above criterion function falls monotonically with the increasing number of clusters, but beyond a certain value - the natural number of clusters – it falls only insignificantly. Such a function assumes spherical clusters and prefers clusters of similar sizes to diverse-sized clusters. Also, the choice of distance measure influences the outcome.

Other criterion functions can be defined, each having its own advantages and disadvantages. The main problem, however, is the computational complexity: the problem of finding the optimal partition is NP-hard (Johnson, 1979). There are an exponential number of possible partitions and an exact algorithm would have to check a large part, if not all of them in order to find the solution. Therefore, a number of heuristics have been proposed, aimed at achieving an acceptable computation time. The basic idea is to start with a reasonable guess for the number of clusters and their positions and to iteratively improve the values. Like all iterative approaches, this one is prone to local minimums.

Methodology

The methodology is relied on the sample data taken from the population of successful people. Based on the Physiognomy theories for sixteen types of humans there exist different activities. We took a group of successful people in variety of fields. By employing special physiognomy detector system (known as "Digital Physiognomy"), we were able to measure suitability of suggested and real professions. The program takes a picture and through the special factor, indicates personal type and suggests right professions. Besides, we gathered information on person's real and all suitable activities throughout the sixteen types of persons. Thus, the experiment was divided into two parts, firstly we compared suggested and real professions (primarily, based on the software derived information) and secondly, we determined how properly these people have chosen their professions according to their personal type in wide range of proposed fields.
See Table 1.

For the outcomes we used an input in digital form, namely 0 and 1 and correspondingly we were able to define proportion of each consequence to total in percentages. The special factor weight which was assigned to the system, we considered as the weights of probability, which means that high factor indicates

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Table 1. *Overview of Real and Possible Career Paths on the Example of Famous People*

Name Surname	Personal Type	Real Profession	Software Suggestion (confidence level of 65.64)	Possible Career Paths for Each Personal Type
Abbie Hoffman	ENFP	Politicien and social activist	Journalist	Consultant, Psychologist, Entrepreneur, Actor, Teacher, Counselor, Politician/Diplomat, Writer /Journalist, Television Reporter, Computer Programmer/Systems Analyst , Scientist , Engineer, Artist.
Abu Musab Al-Zarqawi	ENTJ	Militant	Fieldmarshal	Corporate Executive Officer; Organization Builder, Entrepreneur, Computer consultant, Lawyer, Judge, Business Administrators and Managers, University Professors and Administrators.
Adigail Johnson	ENTP	Businesswoman	Inventor	Lawyers, Psychologists, Entrepreneurs, Photographers, Consultants, Engineers, Scientists, Actors, Sales Representatives, Marketing Personnel, Computer Programmer or Systems Analyst.
Adolf Merckle	ESFP	Businessman, stock trader	Entertainer	Artists, Performers and Actors, Sales Representatives, Counselors / Social Work, Child Care, Fashion Designers, Interior Decorators, Consultants.
Arnold Schwarzenegger	ESTJ	Former Governor of California	Administrator	Military leaders, Business Administrators and Managers, Police / Detective work, Judges, Financial Officers, Teachers, Sales Representatives.
Michael Cherney	ESTP	Entrepreneur	Promoter	Sales Representatives, Marketing Personnel, Police / Detective Work, Paramedic / Emergency Medical, Technician, PC Technicians or Network Administrators, Computer Technical Support, Entrepreneurs.
Alfred Nobel	INTP	Chemist, engineer, innovator, and armaments manufacturer	Architect	Scientists, Chemistry, Photographers, Strategic Planners, Mathematicians, University, Professors, Computer Programmers or Systems Analysts, Technical Writers, Engineers, Lawyers / Attorneys, Judges.
Abraham Lincoln	ISFJ	President of the United States	Conservator	Interior Decorators, Designers, Administrators and Managers, Administrative Assistants, Social Work / Counselors, Office, Managers, Shopkeepers, Bookkeepers, Home Economics.

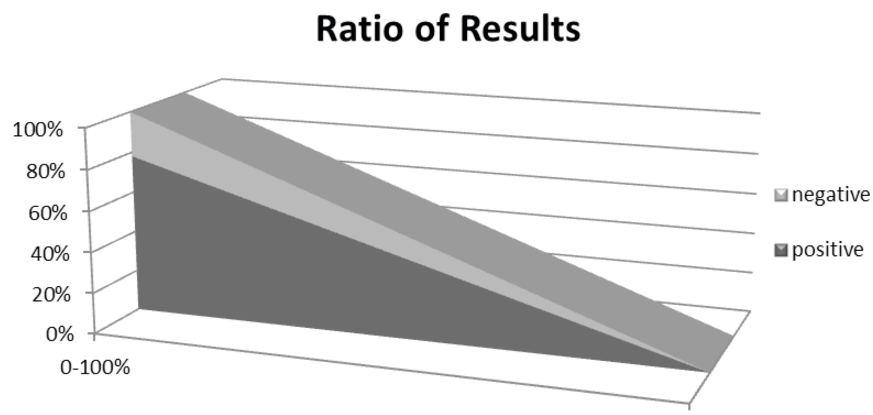

Image 4
Research analysis: coincidence of personal type and career.

the matching of type and professions to each sample data.

We used general formulas of standard deviation and mean (average), those are very important tools in statistic and mathematics and they are calculated according the following way:

1. Sample mean

$$\overline{x} = \sum x / n \tag{2}$$

2. Sample variance

$$s^2 = \sum \left(x - \overline{x}\right)^2 / \left(n - 1\right) \tag{3}$$

As for Standard deviation it is determined as a square root of variance.

Conclusion

The presented investigation gave promising results as it showed 78% of positive outcome in matching of real profession and personal type (see Figure 4). As for the relationship among real and software proposed professions did not coincide to each other with high levels of accuracy which can be explained as the cause of limited varieties of suitable professions into the program. Moreover, in order to declare if personal type and real profession are suitable we required to check all possible recommended professions for each personal type.

In overall the paper demonstrates a brief review of special techniques in pattern recognition in order to provide better future for human life. We defined the role of personality in prosperous career and attempted to strengthen the hypothesis via the investigation on studying successful people's personality and career choice. Further research on enlarged number of samples can better approximate our result by employing the weight factor and standard deviation.

The research showed that most successful people in the world have selected suitable professions to their personality and hence this fact can be considered as one of the key of success which provides the answer of remarkable question: why successful people are successful.

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