

Application of Multi-Layer Perceptron Classification Model to Predict the Professional Direction of Sports Undergraduates Through Personality Traits

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Abstract

Background & Aims: Personality traits play a stable and intrinsic role in the process of sport undergraduates coping with the multiple stresses of classroom academic performance and maintaining extracurricular sport. The purpose of this study is to determine the correlation of multilayer perceptron (MLP) models in predicting gender status and major choice among sport undergraduates.

Method: Personality surveys based on the classic Eysenck questionnaire was carried out and MLPs feedforward neural networks with back propagation algorithm were processed by SPSS and cross-validated among the 332 undergraduates. Descriptive analyses and T tests were used to analyze the personality traits of the overall participating subjects. MLP models the original scores of items in the Eysenck Personality Scale were set as covariates, and "gender" and "major" was set to be the predicted output, respectively. Choose the best predictive models from all models.

Results: The personality characteristics of subjects were more extroverted ($t = 20.838, p = 0.000$) and more neurotic ($t = 4.892, p = 0.000$) and unlikely to be psychotic ($t = -0.321, p = 0.749$). The test outcomes are credible suggested by the Lie score ($t = -17.679, p = 0.000$). The top four items that play an important role in predicting the gender are: N67, N28, E22, E1. The most important items of the E and N dimension scales in the "professional" prediction model are in turn: E85, E1 & N66, N28.

Conclusions: The type of the personality model is ENqI, meaning extroverted, neurotic, unlikely psychotic and trusted in the personality characteristics. The application of MLP prediction models is to help undergraduates in choosing their major more easily.

Keywords: Multilayer Perceptron (MLP); Artificial Neural Networks (ANN); Extraversion; Neuroticism

Introduction

Personality traits can provide important insights into the biological basis of individual differences [1]. However, reading data of personality across occupation relies on subjective standards and a limited set of behaviors, which can lead to inconsistent results [2]. For example, predicting the controllability of athletic performance behavior of college athlete is one of the issues. Multiple personality studies on neurobiology have shown that the neurological mechanisms of neuroticism, extroversion, and psychosis are universal psychological and behavioral characteristics and are common among individuals from different cultural or environmental backgrounds [3, 4]. Psychotic-like experiences involve knowledge of clinical, biological behavior and environmental risks, as well as protective factors related to the development of psychiatry [5, 6].

Individuals personality has been studied abundantly in the field of

psychology, mostly in the field of Extraversion and Neuroticism [7-10]. Extraversion-introversion is a major personality trait which is believed to have a biological basis, which impact on outcomes including mental health and adjustment in educational and occupational settings [11]. Extraversion encompasses a number of specific characteristics such as sociability, assertiveness, high activity level, positive emotions, and impulsivity. And a number of different mechanisms have been proposed to underlie the trait [12]. It is associated with cortical arousal and the dopaminergic system. A wide range of human behaviors, from academic achievement and occupational performance to antisocial behaviors and risk taking are linked with Extraversion [13]. Neuroticism is a unique dimensional measure of personality thought to capture emotional stability and a temperamental sensitivity to negative stimuli [14]. Neuroticism predicts a wide range of negative outcomes, including psychopathology. Most psychological disorders are associated with

elevated scores on this dimension, and evidences have shown that this trait significant predict marital and job dissatisfaction, and subjective health complaints [15]. Psychoticism is a third major dimension of personality suggested by Eysenck. This dimension included traits such as aggressiveness, manipulation, tough-mindedness, risk taking, irresponsibility, and impulsivity versus their opposites. High levels of Psychoticism were not only associated with criminal behavior, but also with various mental illnesses (including manic-depressiveness and schizophrenia) and even with creativity. Biologically, Psychoticism link with high levels of testosterone and low levels of monoamine oxidase (MAO), which influences the levels of neurotransmitters [16. Psychoticism-Impulse Control, Extraversion-Introversion, and Neuroticism-Emotional Stability is the three-factor structure of the PEN model across scale versions [17].

Personality traits have such strong genetic foundation and highly stable over time. It's believed to be true that it can predict important societal outcomes. We use Artificial neural network (ANN), useful prediction tool in the field of artificial intelligence, to predict an undergraduate's gender and his/her major. Multilayer perceptron (MLP) is a kind of deep-learning method of convolutional neural network use minimal preprocessing to a powerful tool to make accurate predictions from complex data [18-20]. Build accurate predictive models through personality aspects with MLP among sport undergraduates is a developing practical strategy on courses setting in education.

Methods

Data Collection

In order to compare with the norm data of other occupations, we conducted the classic Eysenck personality test among the sport undergraduates. The questionnaire survey was conducted for undergraduates in their sophomore year, and the total survey time was 3 years. Participants agree to the informed consent before filling out the questionnaires.

The survey uses the Chinese version of the Eysenck Personality Questionnaire (EPQ). This is a self-rating scale with 85 questions. According to Eysenck's trait theory, EPQ covers four dimensions, including 21 items from EPQ-E (Extraversion-introversion) subscales, 24 items from EPQ-N (Neuroticism-stability) subscales, 20 items from EPQ-P (Psychoticism) scales and 20 items from the EPQ-L (lie) subscales. Participants click in the boxes of "yes" or "no" answers according to their own situation, and the experimenters will score according to the scoring criteria.

The experimental process is monitored and all questionnaires entries were unified explained by the experimenter. Participants take their choices after they saw and understood the questionnaire items. They scored themselves after completing the Questionnaires and learned the calculation rules. All items use a dichotomous response format. For positive scoring items (0 = "No", 1 = "Yes"), for negative scoring items, that is, questions with a (-) sign, (0 = "Yes", 1 = "No").

All initial scores are converted into standard scores according to the statistics table by the experimenter. Participants in experiments of this survey are undergraduates at their sophomore years. Each time the questionnaires were gathered on the spot. The personality questionnaire test is approved by the university ethics committee.

Data Processing

Original points of each subscale score were calculated. Then standard score can be checked in the standard table. The research and analysis of the test results are mainly based on the standard score. The standard score conversion method of the EPQ is converted as follows:

$$T = 50 + 10(X - M) / SD$$

In the formula, represents a rough questionnaire score of a certain subject, and , represent the mean and standard deviation of the sample of this population, respectively. represents standard score. The scoring rules for each entry are as follows.

$$N_E = E1 + E5 + E9 + E13 + E16 + E22 + E26(-) + E29 + E32 + E35 + E37(-) + E40 + E43 + E46 + E49 + E53 + E56 + E61 + E72 + E76 + E85$$

$$N_N = N3 + N6 + N11 + N14 + N18 + N20 + N24 + N28 + N30 + N34 + N36 + N42 + N47 + N51 + N54 + N59 + N63 + N66 + N67 + N74 + N78 + N82 + N84$$

$$N_P = P2(-) + P8(-) + P10(-) + P17(-) + P19 + P23 + P27 + P33(-) + P38 + P41 + P44 + P50(-) + P57 + P58 + P62(-) + P65 + P69 + P73 + P77 + P80(-)$$

$$N_L = L4(-) + L7(-) + L12 + L15(-) + L21(-) + L25(-) + L31 + L39(-) + L45(-) + L48 + L52(-) + L55(-) + L60(-) + L64(-) + L68 + L71 + L75(-) + L79 + L81 + L83(-)$$

Data for processing as descriptive analysis, T test, single factor analysis were performed by IBM SPSS22.0.

The Multilayer Perceptron (MLP) procedure produces a predictive model for one or more dependent (target) variables based on the values of the predictor variables. MLP using the backpropagation(BP) algorithm to classify data. The forward phase where the activations are propagated from the input to the output layer, and the backward phase where the error between the observed actual and the requested nominal value in the output layer is propagated backwards in order to modify the weights and bias values are in the BP algorithm. A differentiable activation function is required in BP algorithm. One or more hidden layers of sigmoid neurons followed by an output layer of linear neurons in the feed-forward networks. This structure allows the network to learn nonlinear and linear relationships between input and output vectors. The training data set is used to calculate the error gradients and to update the weights; and the validation data set allows selecting the optimum number of iterations to avoid overlearning. As the number of iterations increases, the training error drops, whereas the validation data set error begins to drop, then reaches a minimum and finally increases. Continuing the learning process after the validation error arrives at a minimum lead to overlearning. Once the learning process is finished, another data set (test set) is used to validate and confirm the prediction accuracy. Properly trained BP networks will give reasonable answers when presented with new inputs [21].

SPSS easily classify data by using MLP. Choose "gender" or "university major" as the dependent variable, which is the predicted target variable. Take each item score (0 or 1) of a single dimension as covariates. Specify 7, 3, and 0 as training, and the relative numbers of test and retained samples correspond to 70%, 30%, and 0%, respectively. The procedure can select the "best" architecture automatically. Batch training is preferred because it directly minimizes the total error. Use the conjugate gradient method for batch training types. Check all the box in Network Structure, which is

"Description", "Diagram", "Synaptic weight". Also check any boxes you can possibly check in Network Performance (including " Model summary", " Classification results", "ROC curve", "Cumulative gains chart", "Lift chart", "Predicted by observed chart". Then tick the options of "Case processing summary" and "Independent variable importance analysis".

Results

General data

332 valid response participants took part in this survey. 283 male and 49 female students had completed these personality questionnaires. Subjects' major in different expertise: 33.43% of total are majoring in SCUBA, 51.20% are in Physical Education and 15.35% in Sport Science (Tab.1 & Fig.1).

Table 1: Table demonstrate the frequency and percentages in gender & major of valid subjects

		Fre- quency	Percent- age	Effec- tive percent- age	Cumu- lative percent- age
Gender	Male	283	85.2	85.2	85.2
	Female	49	14.8	14.8	100
	Total	332	100	100	
Major	SCUBA	111	33.4	33.4	100
	Physical Educa- tion	170	51.2	51.2	66.6
	Sport Science	51	15.4	15.4	15.4
	Total	332	100	100	

Figure 1: Pie charts of valid subjects

- Descriptive data of gender;
- Descriptive data of major

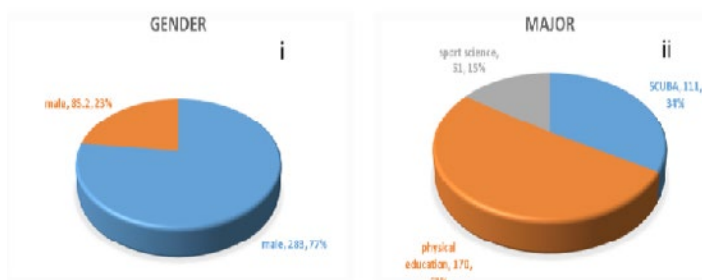


Fig. 1 Pie charts of valid subjects
i) Descriptive data of gender: ii) Descriptive data of major

Preliminary Statistics of Personality Scale

After obtaining the preliminary scores of each dimension of the subjects, we convert their initial scores into standard scores according to the following the formulas above.

The gender-based norms data(M+/-SD)of EPQ personality trait in our country for reference listed as follows:

$$M_{E-male} \pm SD_{E-male} = 9.93 \pm 4.39 \quad M_{N-male} \pm SD_{N-male} = 10.06 \pm 4.62$$

$$M_{P-male} \pm SD_{P-male} = 6.06 \pm 3.22 \quad M_{L-male} \pm SD_{L-male} = 13.30 \pm 5.77$$

$$M_{E-female} \pm SD_{E-female} = 9.03 \pm 4.12 \quad M_{N-female} \pm SD_{N-female} = 10.95 \pm 4.66$$

$$M_{P-female} \pm SD_{P-female} = 5.34 \pm 2.95 \quad M_{L-female} \pm SD_{L-female} = 11.99 \pm 3.50$$

Sport undergraduates extraversion personality trait score (58.00 ± 7.59) was significantly higher than that of normal people ($t = 20.80, p = 0.00$). Their neuroticism (52.88 ± 10.33) was also higher than that of normal people ($t = 5.07, p = 0.00$). The difference between the scores of psychoticism dimension of the sample group and the norm is not significant ($t = -0.17, p = 0.865$). The score of the lie scale (43.66 ± 6.56) being far lower than the standard value ($t = -17.62, p = 0.00$) indicates that the scale results are credible.

Among the sample students of similar age, female sport students (44.92 ± 10.70 vs. 43.44 ± 5.53) score higher than the opposite gender in Lie dimension ($F = 53.87, P = 0.00$).

Figure 2: Box plot demonstrate standard scores:

- Male subjects score in E, N, P, L;
- Female subjects score in E, N, P, L

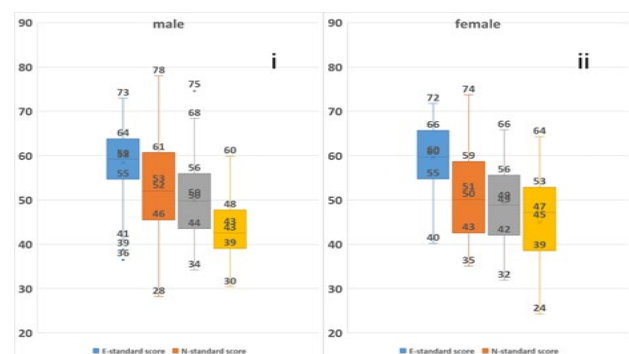
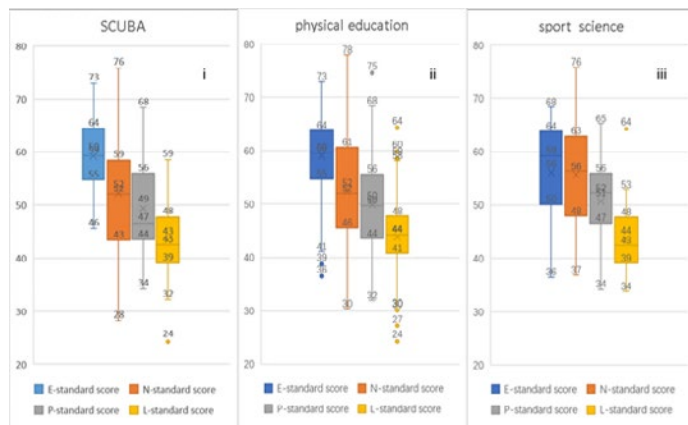


Table 2: Table demonstrate the description data in of original score of different major

Major		X_E	X_N	X_P	X_L
SCUBA	M	59.25	52.29	49.50	43.36
	n	111	111	111	111
	SD	7.178	10.599	7.830	6.037
Physical education	M	59.04	52.41	49.96	43.85
	n	170	170	170	170
	SD	7.452	10.134	7.974	7.061
Sport science	M	56.12	55.71	50.76	43.67
	n	51	51	51	51
	SD	8.484	10.138	6.930	5.959

The one-way ANOVA analysis of variance showed that the dimension of the Extraversion standard scores of different majors was significantly different ($F = 3.462, p = 0.033$), while the other three dimensions were not significantly different ($p > 0.05$).

Figure 3: Box plot demonstrate standard scores:
i) Score of subjects from SCUBA in E, N, P, L;
ii) Score of subjects from physical education in E, N, P, L;
iii) score of subjects from sport science in E, N, P, L



The Neuro Network Model Prediction Models

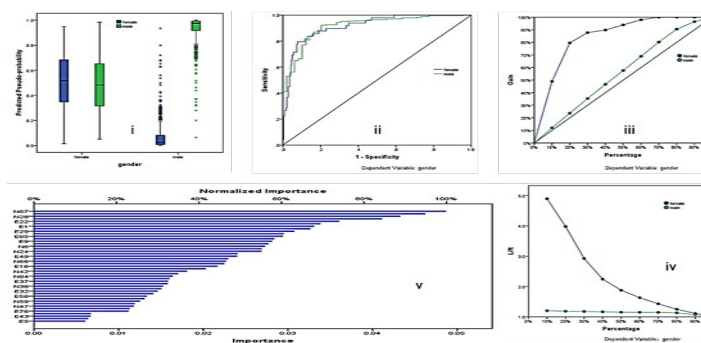
Since the characteristics of Psychoticism dimension are not well significant and the Lie dimension score only used as a reference scale for measuring reliability, ultimately we chose the original scores of the Extraversion and Neuroticism dimension scores to be the covariates for the prediction models.

Gender Prediction Models

In this model the sample is set to 72.3% in the training set and 27.7% in the testing set. 45 items from E, N dimension of EPQ excluded the bias unit are selected to be as the input variables. "Gender" is set to be the Dependent Variable as well as the predictive outcome. Number of units in hidden layer is 1. Activation Function of the hidden layer(s) is the hyperbolic tangent and the activation function of the output layer is SoftMax. Percent incorrect prediction of training samples is 8.8%, and 13.0% in testing samples. Correspondingly, the overall percent correct of the training samples is 91.3%, while 87.0% in the testing samples. As regarding the ROC curve, the areas of gender "male" and "female" in the area model below the curve are both 0.916, indicating that the model has good predictive ability. Answers to items of N67(Do you often feel lonely?), N28(Do you consider yourself "oversensitive"?), E22(If conditions permit, do you like to go out (travel) often?), E1(Do you have a wide range of hobbies?) Play very strong predictive roles to de gender prediction model.

Figure 4: Gender prediction model by Multilayer Perceptron

- Graph of predicted pseudo-probability;
- ROC curve;
- Gain graph;
- Lift graph;
- Graph of Independent Variables Importance



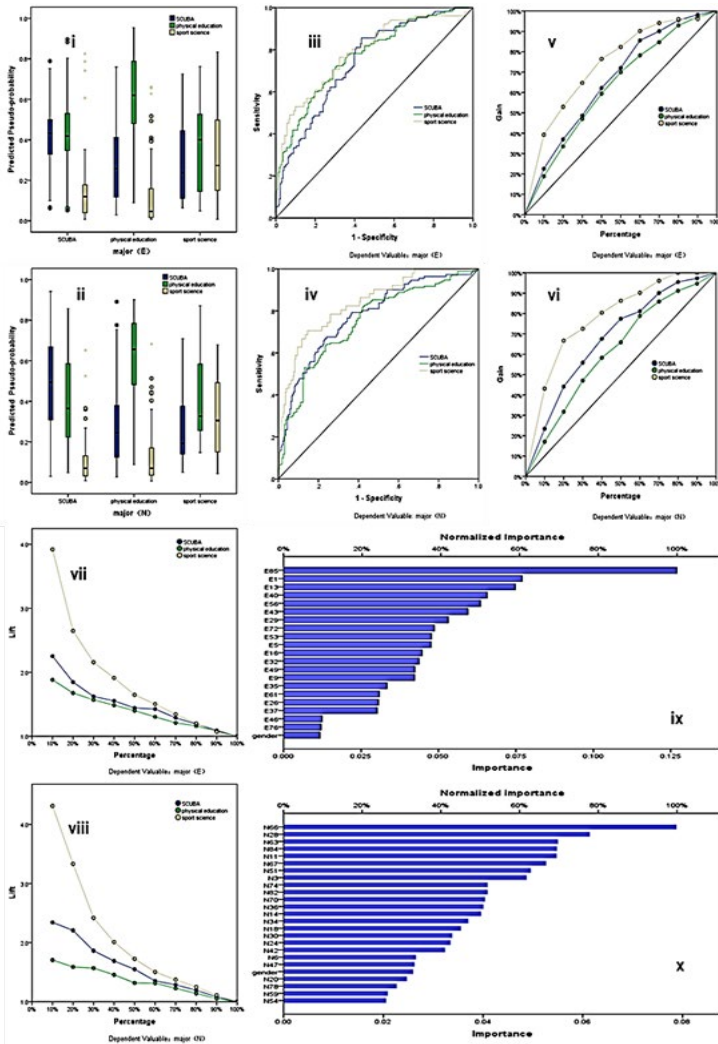
Major Prediction Models

21 items from E dimension and 24 from N dimension are separately input as the input layer units to construct the prediction models for major. Because not all dimension score could perfectly predict the major.

In the model base on E dimension items, the sample is set to 72.3% in the training set and 27.7% in the testing set. 21 items from E dimension of EPQ excluded the bias unit are selected to be the input variables with 2 units in "Gender" factor (1=male, 2=female). "Major" is set to be the Dependent Variable as well as the predictive outcome. Number of units in hidden layer is 1. Activation Function of the hidden layer(s) is the hyperbolic tangent and the activation function of the output layer is SoftMax. Percent incorrect prediction of training samples is 37.9%, and 35.9% in the testing samples. Correspondingly, the overall percent correct of the training samples is 62.1%, and 64.1% in the testing samples. Areas of major "SCUBA", "physical education" and "sport science" below the curve are 0.745, 0.769 and 0.787 as regarding the ROC curve, indicating that the model has good predictive ability. In this model, the most important variable contribute to the prediction is item E85. And the second important item is E1 (Fig. 5: i,iii,v,vii,ix).

In the model base on N dimension items, the sample is set to 68.7% in the training set and 31.3% in the testing set. 24 items from N dimension of EPQ excluded the bias unit are selected to be the input variables with 2 units in "Gender" factor. Percent incorrect prediction of training samples is 33.3%, and 38.5% in the testing samples. Correspondingly, the overall percent correct of the training samples is 66.7%, while 61.5% in the testing samples. Good predictive ability in the areas of major "SCUBA", "physical education" and "sport science" below the curve are 0.777, 0.749 and 0.839 regarding the ROC curve. In the model of Major prediction, E85(Are you a social person?), E1(Do you have a wide range of hobbies?), N66(Are you easily nervous?), N28(Do you consider yourself "oversensitive"?) are the four most important predictive variables. Those students who chose "yes" option to the content of the item E85(Are you a social person?) can predict their choice and persistency in university major most. And "yes" to the item E1(Do you have a wide range of hobbies?) also very crucial to the major chosen. Item N66(Are you easily nervous?) and N28(Do you consider yourself "oversensitive"?) ranked the first and the second place among all the chosen N dimension item variables (Figure 5: ii, iv, vi, vii, x).

Figure 5: Major prediction model by Multilayer Perceptron
 i ~ ii) Graphs of major predicted pseudo-probability by E, N items;
 iii ~ iv) ROC curves of E, N items for predicting Major;
 v ~vi) Gain graphs for major prediction via E, N items;
 vii ~ viii) Lift graphs for major prediction via E, N items;
 ix ~ x) Graphs of Independent Variables Importance for major prediction via E, N items



Discussions

Personality Characteristics of Sport Undergraduates

Personality characteristics of sport undergraduates are extroverted and neurotic. The observational results of the physical education college students' personality in the extrovert-introvert and the neuroticism-stability dimension meet the social expectations and curriculum requirements. Behavior genetic evidence and psychophysiological studies showing that extraversion correlates with various indices of brain functioning. Individual differences of extraversion in sensitivity to reward, supported by dopaminergic brain pathways [11]. Clear differences exhibit between extroverts and introverts in their occupation choices that influence major choosing. Studies of vocational interests show that extroverts have stronger social and enterprising preferences. Extroversion also relates to superior

performance during training, perhaps because extroverts handle novelty better than do introverts [22]. Extroversion was found to have a high genetic correlation with attention deficit hyperactivity disorder. Neuroticism associated cognitive bias, poor coping, and autonomic nervous system(ANS) inflexibility [23]. Elevated neuroticism has been linked to a wide array of clinical syndromes associated with psychological disorders. Some investigation finds out high level of neuroticism benefit from speed-accuracy in a cricket-based decision-making [24]. The fact implies us that genetic factors also affected out personality that shaping our behavior outcomes [25].

Personality traits predict the participation in sports. There are differences in the courses setting of different majors. SCUBA undergraduates will get a lot of non-traditional outdoor swimming and diving training. Undergraduates majoring in physical education will receive a lot of traditional physical training, including team sports and individual physical training. Undergraduates in sports sciences receive mounts of classroom theoretical academic, and not much physical training.

Outdoor swimming and diving activities in environments with extreme psychophysiological requirements determine the incremental effectiveness of personality. Personality traits have an increasing effectiveness in predicting the diver's performance relative to general mental ability, and underwater adaptability. personality traits as predictors of effective response to the changing environment of diving, and can also improve understanding of the behavioral impact and psychophysiological complications of diving, as well as psychological provide guidance on intervention and risk prevention [26]. Divers' character traits from the perspective of behavior results analysis of the relationship between personality variables and diving performance may provide tangible benefits in enhancing safety and improving underwater performance [27]. The adapting to environmental stressors is complex and requires processing physiologically and psychologically to overcome extreme environmental barriers, thus implement effective and efficient work. It was wildly recognized that anxiety could directly lead to panic behavior. And stable personality characteristics help acclimatization to change in an extreme environment. Extraverted personality is more attracted by the high risk of sports.

In traditional exercises of team sport and individual training, differences between personality characteristics just according to the categories of competition and their relationship with the perception of performance because with less challenges from coping with extreme environments and adapting to environmental changes.

The Extraversion personality traits of sports science undergraduates who mainly receive academic education with little physical training are not that distinct. Academic behavior and personality interact with each other mutually. More time for academic curriculum arrangement reduces the disturbance of social interaction, which is suitable for the development of students with introvert personality.

MLP model prediction for Gender and Major

The widely used multilayer perceptron (MLP) network in many fields is one of the most popular Deep learning (DL) architectures, which is a powerful tool that can make accurate predictions based on complex data [19]. An MLP consists of an input layer that simply receives the external inputs, and of a set of neural units organized

into $L \geq 1$ hidden layers and one output layer, which constitute one of the most popular classes of neural networks for classification and regression [28].

By knowing the personality variables, we can predict Gender and help major choice which is essential for cultivate sport undergraduates according to their nature personality aspects and help forming their future careers. Neural network models with high accuracy for predicting gave us a new insight to explore their potential. Artificial neural network (ANN) is a flexible nonlinear mathematical system for modeling complex functions. Applies to independent predictors (inputs) and dependent predictors (outputs) that have relationships, even if the relationship is compound, multidimensional, and nonlinear. The artificial neural network obtains the known data, that is, the previously solved example, recognizes the complex patterns between the input and output, and then applies this knowledge to the unknown data. Learned the hidden relationship between input and output, and then ANN can predict the output based on the given input of the new data. Neural networks have contributed to the explosive growth of data science and artificial intelligence.

Predicting gender through personality traits helps to identify the gender social identity of sports undergraduates. Gender is but one aspect or dimension of identity that could be actively and purposefully altered [29]. Gender triggers differences in exercise performance among sports undergraduates both physically and psychologically, because gender identity norms are responsible for gender differences in psychological attributes. Some have argued that a higher degree of risk aversion is viewed as the norm for females while part of the male identity is to be risk-takers. Expectations could be part of the socially constructed gender norms, rather than a reflection on innate differences; behaving according to these expectations may reflect a willingness to conform with what is expected from one's social category. Our original collected data show us that the gender predicted by personality traits meet the most of the expectations of social identity. The classification accuracy is high up to 85.0%.

Prediction model establish for major help freshmen choose considering their own condition. Sport activities relate to psychosocial outcomes even though sports development models support the hypothesis that the psychosocial experiences of young athletes vary due to seemingly small changes in the design of their sports activities [30]. personality issues are among the psychological factors in athletes affect their psychological response to injury and illness [31]. High levels of extraversion are related to the amount of activities. Most of sport undergraduates will choose their preference course based on their personality besides their quality of performance and sport participation. Personality is related to long-term athletic success and moderate exercises help shaping healthier personality.

For application in the major prediction in case. A social person and have a wide range of hobbies appear to not the best for major in sport science. easily nervous and consider themselves "oversensitive" probably is the sign for confirm unstable personality. In contrast, those individuals who are outspoken, competitive, driven, and even aggressive, will prefer to SCUBA or physical education.

Perspectives

The prediction model can be used to help sport students to make choice in major. This prediction models are multilayer perceptron

models (MLPs) of the neural network models in the IBM SPSS 22.0. They help to simplify the complexity of the major selection process. The prediction effects are good, with high classification accuracy. However, over-fitting is a problem in our predictions because of the lack of a large sample size. Our study provides preliminary results for the prediction of gender and major. More subjects are needed for further research. some limitations of our studies are noted. firstly, the specific indicators of academic and sports performance should be tracked but only the Eysenck Personality Scale data were used due to limitation of research. Secondly the measurement scales are subjective. It would be more convinced if more objective indicators were introduced into the prediction models.

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References

1. Oren Forkosh, Stoyo Karamihalev, Simone Roeh, Uri Alon, Sergey Anpilov, et al. (2019) Identity domains capture individual differences from across the behavioral repertoire. *Nature neuroscience* 22: 2023-2028.
2. Martin Gerlach, Beatrice Farb, William Revelle, Luis A Nunes Amaral (2018) A robust data-driven approach identifies four personality types across four large data sets. *Nature human behaviour* 2: 735-742.
3. Kumari V, Ffytche DH, Williams SCR, Jeffrey A Gray (2004) Personality Predicts Brain Responses to Cognitive Demands. *Journal of Neuroscience* 24: 10636-10641.
4. Nathan A Gillespie, Gu Zhu, David M Evans, Sarah E Medland, Margie J Wright, et al. (2008) A genome-wide scan for Eysenckian personality dimensions in adolescent twin sibships: psychoticism, extraversion, neuroticism, and lie. *Journal of personality* 76: 1415-1446.
5. Monica E Calkins, Tyler M Moore, Theodore D Satterthwaite, Daniel H Wolf, Bruce I Turetsky, et al. (2017) Persistence of psychosis spectrum symptoms in the Philadelphia Neurodevelopmental Cohort: a prospective two-year follow-up. *World psychiatry: official journal of the World Psychiatric Association (WPA)* 16: 62-76.
6. Ilanit Hasson-Ohayon, Anne Neeltje Scholte-Stalenhoeft, Frederike Schirmbeck, Lieuwe de Haan, Wiepke Cahn, et al. (2018) Insight, personality, and symptoms among individuals with psychosis: Cross-sectional and longitudinal relationships. *Schizophrenia research* S0920-9964: 30296-6.
7. Mark S Allen, Emma E Walter (2018) Linking big five personality traits to sexuality and sexual health: A meta-analytic review. *Psychological bulletin* 144: 1081-1110.
8. Daniel N Klein, Roman Kotov, Sara J Bufferd (2011) Personality and depression: explanatory models and review of the evidence. *Annual review of clinical psychology* 7: 269-295.
9. Charles S Carver, Jennifer Connor-Smith (2010) Personality and coping. *Annual review of psychology* 61: 679-704.
10. Trull TJ, Durrett CA (2005) Categorical and dimensional models of personality disorder. *Annual review of clinical psychology* 1: 355-380.
11. Matthews G (2019) Extraversion-Introversion[M]. Reference Module in Neuroscience and Biobehavioral Psychology,

- Elsevier.
12. Lucas RE, Diener E (2001) Extraversion[M]. International Encyclopedia of the Social & Behavioral Sciences, Smelser NJ, Baltes PB, Oxford: Pergamon 2001: 5202-5205.
 13. Saklofske DH, Eysenck HJ, Eysenck SB G (2012) Extraversion–Introversion[M]. Encyclopedia of Human Behavior (Second Edition), Ramachandran V S, San Diego: Academic Press 2012: 150-159.
 14. Nash MW (2007) Neuroticism, Genetic Mapping of[M]. Encyclopedia of Stress (Second Edition), Fink G, New York: Academic Press 2007: 910-913.
 15. Watson D (2001) Neuroticism[M]. International Encyclopedia of the Social & Behavioral Sciences, Smelser N J, Baltes P B, Oxford: Pergamon 2001: 10609-10612.
 16. Ashton MC (2013) Chapter 5 - Biological Bases of Personality[M]. Individual Differences and Personality (Second Edition), Ashton M C, San Diego: Academic Press 2013: 101-121.
 17. Ruch W, Heintz S, Gander F, Jennifer Hofmann, Tracey Platt, et al. (2020) The long and winding road: A comprehensive analysis of 50 years of Eysenck instruments for the assessment of personality[J]. Personality and Individual Differences 2020: 110070.
 18. Durstewitz D, Koppe G, Meyer-Lindenberg A (2019) Deep neural networks in psychiatry[J]. Molecular psychiatry 24: 1583-1598.
 19. Perez-Enciso M, Zingaretti LM (2019) A Guide for Using Deep Learning for Complex Trait Genomic Prediction[J]. Genes (Basel) 10: 553.
 20. Sandra Vieira, Walter H L Pinaya, Andrea Mechelli (2017) Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications. Neuroscience and biobehavioral reviews 74: 58-75.
 21. Puig-Arnavat M, Bruno JC (2015) Chapter 5 - Artificial Neural Networks for Thermochemical Conversion of Biomass[M]. Recent Advances in Thermo-Chemical Conversion of Biomass, Pandey A, Bhaskar T, Stöcker M, et al, Boston: Elsevier 2015: 133-156.
 22. Matthews G (2004) Extroversion–Introversion[M]. Encyclopedia of Applied Psychology, Spielberger C D, New York: Elsevier 2004: 869-873.
 23. Ormel J, Bastiaansen A, Riese H, Elisabeth H Bos, Michelle Servaas, et al. (2013) The biological and psychological basis of neuroticism: Current status and future directions. Neuroscience & Biobehavioral Reviews 37: 59-72.
 24. Bell J J, Mawn L, Poynor R (2013) Haste makes waste, but not for all: The speed-accuracy trade-off does not apply to neurotics[J]. Psychology of Sport and Exercise 14: 860-864.
 25. Diab SY, Isosävi S, Qouta SR, Kuittinen S, Punamäki RL (2018) The protective role of maternal post-traumatic growth and cognitive trauma processing in Palestinian mothers and infants: a longitudinal study. Lancet (London, England) 2018: S39.
 26. Colodro J, Garcés-De-Los-Fayos EJ, López-García JJ, Lucía Colodro-Conde (2015) Incremental Validity of Personality Measures in Predicting Underwater Performance and Adaptation[J]. The Spanish journal of psychology 18: E15.
 27. Charles H Van Wijk (2017) Personality and behavioral outcomes in diving: current status and recommendations for future research[J]. Diving and hyperbaric medicine 47: 248-252.
 28. Luigi Grippo, Andrea Manno, Marco Sciandrone (2016) Decomposition Techniques for Multilayer Perceptron Training. IEEE transactions on neural networks and learning systems 27: 2146-2159.
 29. Evans W (2011) 1 - Mapping virtual worlds[M]. Information Dynamics in Virtual Worlds, Evans W, Chandos Publishing 2011: 3-21.
 30. M Blair Evans, Veronica Allan, Karl Erickson, Luc J Martin, Ross Budziszewski, et al. (2017) Are all sport activities equal? A systematic review of how youth psychosocial experiences vary across differing sport activities. British journal of sports medicine 51: 169-176.
 31. Cindy J Chang, Margot Putukian, Giselle Aerni, Alex B Diamond, Eugene S Hong, et al. (2020) Mental health issues and psychological factors in athletes: detection, management, effect on performance and prevention: American Medical Society for Sports Medicine Position Statement-Executive Summary. British journal of sports medicine 54: 216-220.

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