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SOME DECISION MAKING PARAMETERS AND THEIR INFLUENCE ON QUALITY OF DECISIONS

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In real time, given the same set of inputs, people take different decisions based on their understanding of the domain, the problem and their previous experiences. Decision making depends on many factors. A combination of these factors leads to good decisions, bad ones or unpredictable ones. An Intelligent decision making machine has to be aware of the major factors in human decision making and their expected consequences. This paper focuses on these factors, assigning categorical values to the possible outputs, creating a prediction model given some of the possible permutations of feature values, and the expected results. The results are found to be encouraging.
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1. Introduction

Given some more information about the same problem and its other facets, the same person takes a different decision; a consequence illustrating the dynamic physical symbol system. This paper analyzes the major features of the decision making and looks at a model for prediction of the quality of decision making. Decisions are evaluated based on outcomes [2]. If the outcome is as expected or better than expected, then the decision causing this outcome is a good decision. Similarly, if the outcome of a decision results in loss or failure, then, the corresponding decision is bad. Similarly, in high risk situations, the outcome can go both ways – such a decision is said to be unpredictable. These, then, are the three outputs to our prediction model – Good, Bad and Unpredictable decisions.

Some people leave decisions to chance and fate. Decisions that 'turn out' good because of Luck are not in the purview of this work. Similarly, this work assumes an ideal case where all other factors, such as economic and other resources, are favorable. The parameters used in this work are those suggested by a wide variety of papers on decision making. Using these parameters, a feature set is constructed with nine standard features discussed popularly as the criteria for decision making, with three of these traits picked from personal traits. We convert our decision making problem to that of classification with three outputs – good, bad and unpredictable. The aim of this work is to use these pointers to make intelligent machines good decision makers. The parameters considered for decision making are described in the next section.

2. Important factors in Decision Making

Popular literature on Decision making [1] speaks about seven factors that affect decision making in real life. These factors range from the presence or absence of a rule book [12], to the prejudices and attitude of the decision maker. Each of them is examined from a machine learning standpoint [18] in sections 2.1 through 2.9.

2.1. Programmed versus Non-Programmed Decisions

A decision can be based on the question – "Was the decision based on a set of previously laid down set of rules?" In such a case, the rules are coded into a system like ELIZA, and it leads to a complete tree for all possible scenarios. In this case, the decision is said to be 'programmed' and there are no surprises in the decision made [13]. In Non-Programmed cases, which is often the first time a problem scenario is witnessed[3], it is the prerogative of the decision maker alone and, if the decision leads to 'success', then, it becomes a programmed decision the second time around. This parameter, in concurrence with others, determines a good or bad decision.

2.2. Information Inputs

For a proper decision to be made, it is very important that all the inputs are available [1]. In the presence of these inputs, both programmed and non-programmed decision making is easier. In the absence of some inputs, i.e., if the data made available is fuzzy, then decision making becomes all the more difficult. Sometimes, the missing data is very important - that is when decisions can go bad. Again, this parameter is not stand alone - it gets affected by the values of the other parameters such as programmed decisions, IQ of the decision maker, etc.

2.2.1. Decision making under Uncertainty

Where the decision is non-programmed and/or the inputs are fuzzy, the decision maker is said to be taking decisions under uncertainty [5]. In situations where the inputs are fuzzy, two methods are usually used - the availability heuristic and the representativeness heuristic. In availability heuristic, decisions are based on past experiences of similar situations heard of (and not necessarily - experienced) [4]. If no such situation comes to mind, one probably takes a risk. In representativeness heuristic, decisions are based on a visualization of a prototype of a similar situation with our image (how we see ourselves) in it.

2.3. Prejudice

Many of us have fixed notions about non-essential and non-scientific features. Some of us are inclined towards a certain race, color of skin, gender, religion, caste etc. These prejudices overwhelm or override the decision making process such that we are only interested in the furtherance of our prejudice and nothing else [6]. Prejudice single-handedly overrides all other parameters in decision making such that even in the best scenarios with programmed decisions and complete inputs, the decision taken is bad [16]. It takes the values Yes and No.

2.4. Cognitive Constraints

Many of us are unable to comprehend the inputs given to us in real-time due to many factors [8]. It could be temporary. For example, while taking audio inputs, a momentary interruption or lack of concentration can cause partial loss in comprehending inputs. Also, where the decision maker has hearing or visual impairment and the inputs are not carefully given; there is a possibility of bad decisions. A lack of proper processing skills may also lead to bad decisions.

2.5. Personal Habits

Decision makers can be rigid, which means they may stick to their decisions even if decisions are not optimal [17]. They are the rigid decision makers. On the other hand, the decision maker may be flexible, and adapt to changing environments. Their decisions are considered good.

2.6. Attitudes about Risk and Uncertainty - IQ of Decision Maker

A decision maker with a good IQ is able to comprehend and analysis various inputs, rules and risks, with or without a programmed environment and can reach a better decision than one with a poor IQ. In a programmed decision making environment, average IQ holders can also make good decisions. A decision maker with low IQ may make a bad decision even in the best of circumstances.

2.7. Attitudes about Risk and Uncertainty - Expectation of Decision Maker

If the expectations of a decision maker are too high, then, he/she will take unnecessary risks [9]. This may then lead to bad decisions. When expectations are low, no risk is taken and that may also lead to bad decision making. Where expectations are Nil, which is rarely the case, the best decisions are made.

2.8. Attitudes about Risk and Uncertainty - Time Constraints

Most of the decisions made in corporate sector have a real-time constraint. Therefore, there is a limit on how much one can analyze before taking a decision. Time constraints also mean that some important parameters are ignored since their data is not made available within the time limit imposed on the decision maker [14]. Where there is no pressure of time limit, good decisions are made.

2.9. Social and Cultural Influences

Many people are bound by social and cultural influences [15]. For example, even in today's context many businessmen do not transact on Tuesdays. Many people do not make payments on Fridays. So, if there is a decision to be made that require transactions on one of these days, it would lead to a bad decision of not transacting, though there is no valid logical reason for this.

When the decision is programmed and all Inputs are known, we call it Decision making under certainty. A Single-feature model is one where we are focused on primary purpose and not on the secondary ones. On the other hand, Additive feature model is one where, you pick up a set of features instead of one and compare them for various similar products. Elimination of aspects model - Amos Tversky [6] that evaluates options one characteristic at a time, dropping the ones that do not satisfy a particular characteristic and so on until only one option is left.

The methodology for creation of feature sets, data sets and developing a prediction model for decision making is explained in the next sections.

3. Creation of Feature Set

From the exhaustive set of parameters used for decision making, pick the nine primary ones – the ones that are described in section 2. Therefore, the various parameters are Programmed versus NonProgrammed Decisions, information Inputs, Decision making under Uncertainty, Prejudice, Cognitive Constraints, Personal Habits, Attitudes about risk and uncertainty (IQ of Decision maker, Expectation of Decision maker, Time Constraints) and, Social and Cultural Influences. The possible values taken by these features are given in Table 1.

For each of these parameters, determine if there is a dependency of outcome of one on the others from a study of existing literature. For example, consider the parameter – "Programmed vs Non-Programmed decisions". It takes two values – Programmed decision and Non-Programmed decision. If the decision is programmed, then Inputs are expected to be complete. If inputs are incomplete, "programmed decision" will fail. Similarly, if the decision maker is prejudiced, then, no other decision feature can override the decision process and therefore, the consequence would be a bad decision. A similar case happens with social and cultural influences.

Table 1. The various primary decision making factors and possible values Decision Making ParameterPossible Values

Decision Making Parameter	Possible Values		
Programmed versus Non-programmed Decisions.	Programmed,	Non-programmed	
Information Inputs	Complete,	Fuzzy	
Prejudice	Yes,	No	
Cognitive Constraints	Yes,	No	
Personal Habits	Flexible,	Rigid	
Attitudes About Risk and Uncertainty - IQ of Decision Maker	High,	Average,	Low
Attitudes About Risk and Uncertainty - Expectation of Decision Maker	High,	Low	
Attitudes About Risk and Uncertainty - Time Constraints	Yes,	No	
Social and Cultural Influences	Yes,	No	
Decision Label	Good,	Bad,	Unpredictable

A person with no prejudice will still not be able to make a good decision, given these influences, even if there is no official law preventing good decision making. For a person who is risk averse, there is every possibility of making a bad decision. Also, if there is a Cognitive constraint, then, the decision could be bad though it is programmed.

4. Data Set

For developing the prediction model, a minimal set of categorical inputs are determined for each feature in the decision feature set using the literature on decision making. A data set is created with some permutation of these values. Labels are assigned as outcomes/decision labels for each of these permutations, based on outcomes observed in literature, some of which are illustrated in the previous section. This data is presented as rows on an excel worksheet and is saved as a comma separated vector (a .csv) file. The various feature sets under consideration are (I) Programmed versus Non-Programmed Decisions, (II) Information Inputs, (III) Prejudice, (IV) Cognitive Constraints, (V) Attitudes about risk and Uncertainty, (VI) IQ of Decision Maker, (VII) Expectation of Decision Maker, (VIII) Time Constraints, and, (IX) Social and Cultural Influences. Sample data is presented in Table 2 below.

Table 2. Sample Data Set for 5 permutations of some Decision Making Features. The

last column shows Decision Quality as Label

I	II	III	IV	V	VI	VII	VIII	IX	Decision Label
P	C	No	No	Q	High	L	No	A	Good
P	F	No	No	Q	High	L	No	A	Good
P	C	Yes	No	Q	High	H	No	A	Bad
P	C	No	No	Q	High	H	No	O	Bad
P	F	No	No	Q	High	H	No	O	Bad
P	C	No	Yes	Q	High	H	No	A	Good
N	C	No	No	Q	High	L	No	A	Good
N	F	No	No	Q	Low	L	No	A	Bad
N	F	No	No	Q	High	H	N	A	Good
N	F	No	Yes	Q	High	H	N	A	Bad
P	C	No	Yes	Q	Low	L	N	A	Bad

P – Programmed, N – Non-programmed, C-complete, F- fuzzy, Q – Positive, L- low, A-Acceptable, O – Objectionable, H-High

5. Prediction Model

The problem of predicting the decision outcome of a permutation of factor feature sets is viewed as a classification problem. The input parameters are saved as a comma separated vector file that is input to Weka 3.8.6 explorer [7]. Three classification algorithms are applied to compare the results of the various classifiers – Naïve Bayes, Decision Tree (J48), Decision Forest and Multi-layer Perceptron [10], with 10-fold cross validation. A comparison of performances of these methods is presented in Table 4.

Table 3. Sample test cases and their results in Regression Analysis

Input parameters									Output
I	II	III	IV	V	VI	VII	VIII	IX	G/B/U
1	0	0	0	0	0	0	0	0	4
0	1	0	1	0	1	0	1	0	5
0	0	0	0	0	0	0	0	0	6

Multiple Linear Regression analysis is performed using the numerical data set [11]. The significance level α is at .05, effect type is ‘f’, effect size is 0.39 and the precision - number of digits considered after decimal point, is 4.

5.1. Regression Analysis

The derived equation of regression with nine predictors is: $y=5.5198 + 0.0462\cdot x1 - 0.1326\cdot x2 - 0.4801\cdot x3 - 0.3454\cdot x4 - 0.46\cdot x5 - 0.1741\cdot x6 + 0.2308\cdot x7 - 0.0453\cdot x8 - 0.5785\cdot x9$

A comparison of statistics for the nine predictors x1 through x9 is presented in Table 5.

Table 5. Predictor statistics of Estimate, Standard Error, t-statistic and p-value

Predictor	Estimate	Standard Error	t-statistic	p-value
Constant	5.5198	0.3664	15.0628	0
x1 (factor I)	0.0462	0.2407	0.1918	0.8492
x2 (factor II)	-0.1326	0.2364	-0.561	0.579
x3 (factor III)	-0.4801	0.301	-1.5948	0.1212
x4 (factor IV)	-0.3454	0.2374	-1.4548	0.1561
x5 (factor V)	-0.46	0.2552	-1.8024	0.0815
x6 (factor VI)	-0.1741	0.1484	-1.1726	0.2502
x7 (factor VII)	0.2308	0.1639	1.4083	0.1693
x8 (factor VIII)	-0.0453	0.3237	-0.1398	0.8897
x9 (factor IX)	-0.5785	0.2928	-1.9759	0.0574

The statistics for r2 is 0.4373, adjusted is 0.2685, residual standard error is found to be 0.7166 on 30 degrees of freedom. The overall f-statistic and p-values are favorably at 2.5902 on 9 and 30 degrees of freedom and 0.0243 respectively.

The regression model, when applied to 15 test cases, yields a precision of 0.8667, which is much higher than the average precision (0.796) of the other prediction models.

6. Results

The comparison of results of classification on Weka for Naïve Bayes classifier, Bayes Net, Multi-layer Perceptron and Naïve Bayes classifier are presented in Table 4.

Table 4. Comparison of Decision Quality for Naïve Bayes Classifier (I), Bayes Net (II), Multi-layer Perceptron (III) and Decision Tree (IV) for the Decision classes Good, Bad and Unpredictable. Weighted averages are also presented.

Classifier	TP Rate	FP Rate	Precision	Recall	F-Measure	Class
I	0.667	0.258	0.429	0.667	0.522	Good
II	1.000	0.129	0.692	1.000	0.818	
III	1.000	0.129	0.692	1.000	0.818	
IV	0.222	0.258	0.200	0.222	0.211	
I	0.583	0.375	0.700	0.583	0.636	Bad
II	0.750	0.125	0.900	0.750	0.818	
III	0.750	0.125	0.900	0.750	0.818	
IV	0.583	0.688	0.560	0.583	0.571	
I	0.286	0.121	0.333	0.286	0.308	Unpredictable
II	0.571	0.091	0.571	0.571	0.571	
III	0.571	0.091	0.571	0.571	0.571	
IV	0.143	0.121	0.200	0.143	0.167	
I	0.550	0.304	0.575	0.550	0.553	Weighted Avg.
II	0.775	0.120	0.796	0.775	0.775	
III	0.775	0.120	0.796	0.775	0.775	
IV	0.425	0.492	0.416	0.425	0.419	

The results show best precision values for Multi-layer Perceptron for all three class labels, closely followed by Bayes' Net.

7. Conclusions

This paper is a small step towards building intelligent decision making machines by teaching them the basics of human decision making. It explores the factors affecting human decision making and their combined effect on the quality of decision making by modeling decision quality as a classification problem. A Regression model is also developed for the same. On comparison, regression model is found to predict more precisely than Multi-layer Perceptron, Decision Trees, Bayes Net and Naïve Bayes methods.

8. Future Work

The prediction statistics presented in this work can be further improved upon by adding some more data to the data set. The work can be furthered by addition of secondary features to the feature set. The feature inputs may be refined using scaled input instead of categorical or boolean input. Factors of decision making in highly dynamic environments can be analyzed.

References

1. Turpin, Marita & Marais, Mario. Decision-making: Theory and practice, ORiON, (2004), doi: 20. 10.5784/20-2-12.
2. Hsieh, CJ., Fifić, M. & Yang, CT. A new measure of group decision-making efficiency. Cogn. Research, 2020, Vol. 5, 45, https://doi.org/10.1186/s41235-020-00244-3.
3. Tve Tversky, A, Elimination by aspects: A theory of choice in Psychological Review, 1972, Vol. 79(4), pp. 281–299, https://doi.org/10.1037/h0032955.
4. Taghavifard, Mohammad Taghi & Khalili-Damghani, Kaveh & Tavakkoli-Moghaddam, Reza, Decision Making Under Uncertain and Risky Situations, 2009.
5. Tversky, Amos, Kahneman, Daniel. Availability: A heuristic for judging frequency and probability, Cognitive Psychology, 1973. Vol.5 (2), pp 207–232. doi:10.1016/0010-0285(73)90033-9. ISSN 0010-0285.
6. Kahneman, Daniel, Paul Slovic, and Amos Tversky. Judgment Under Uncertainty: Heuristics and Biases, Cambridge: Cambridge University Press, 1982.
7. Eibe Frank, Mark A. Hall, and Ian H. Witten. The WEKA Workbench. Online Appendix for - Data Mining: Practical Machine Learning Tools and Techniques, Morgan Kaufmann, Fourth Edition, 2016.
8. Lebiere C and Anderson JR. Cognitive constraints on decision making under uncertainty, Front. Psychology, 2011, Vol.(2)305, doi: 10.3389/fpsyg.2011.00305.
9. Ari, Riabacke. Managerial Decision Making Under Risk and Uncertainty, IAENG International Journal of Computer Science, 2006, pp.32.
10. kdnuggets.com [Internet], How to Create a Simple Neural Network in Python; c2018 [cited 2018 Oct]. Available from: https://www.kdnuggets.com/2018/10/simple-neural-network-python.html.
11. stats.blue [Internet], Multiple Linear Regression Calculator; c2019 [cited 2019], Available from: https://stats.blue/Stats_Suite/multiple_linear_regression_calculator.html.
12. Peter F. Drucker, The Effective Decision. Harvard Business Review, 1967, Jan.

13. Ward Edwards, The theory of decision making, Psychological Bulletin, 1954, Vol. 51(4), pp.380-417.
14. Brian Christian, Tom Griffiths, Algorithms to Live By: The Computer Science of Human Decisions, 2017.
15. openstax.org [Internet], Barriers to Effective Decision making, c2022, [cited April 2022], Available from: https://openstax.org/books/principles-management/pages/2-4-barriers-to-effective-decision-making.
16. Bias Doesn't Pay, SA Mind, 2009, Vol. 20(1): pp. 9. doi:10.1038/scientificamericanmind0209-9b.
17. Erjavec, Jure; Zaheer Khan, Nadia; and Trkman, Peter, The impact of personality traits and domain knowledge on decision making – a behavioral experiment. Research-in-Progress Papers, 2016, pp. 38, doi: http://aisel.aisnet.org/ecis2016_rip/38.
18. Phillips-Wren, Gloria & Ichalkaranje, Nikhil & Jain, Lakhmi. Intelligent Decision Making: An AI-Based Approach, 2008, doi: 10.1007/978-3-540-76829-6.
19. Liu XL, Willis K, Fulbrook P, Wu CJ, Shi Y, Johnson M. Factors influencing self-management priority setting and decision-making among Chinese patients with acute coronary syndrome and type 2 diabetes mellitus. Eur J Cardiovasc Nurs, 2019, Vol. 18(8), pp.700-710. doi: 10.1177/1474515119863178.