# Make Me Happy: A Multivariate Analysis of Predicting Happiness Rates Among U.S. Adults

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## 1 Introduction

As society grows ever-more depressed[2] and the state of American citizens' growing physical unhealthiness becomes more and more concerning[3], it's important that the relationship between physical health and mental health becomes more defined. Or, rather, it's important that a linkage (if it exists) between happiness and other aspects of one's life is proposed, scrutinized, and understood. Using the recent 2022 release of the GSS, the largest reliable database dealing with health and happiness polling, this project aims to train and test an Artificial Neural Network (ANN) capable of accurately predicting one of three happiness levels: "very happy", "pretty happy", or "not too happy"[4]. Further, to determine if our neural network is predicting via an excess of variables, Spectral Clustering will be used to determine the existence of any hidden clusters of data, all in an effort to answer the question: is there statistical evidence that one could predict - and manipulate - their own happiness levels?

## 2 Literature Review

Happiness psychology is a relatively under researched field, due to the sheer complexity of the question "why am I (un)happy?"[5] However, there is a general consensus among most psychologists that, as a baseline, happiness is heavily influenced by both the character of a person and the contexts in which they live[6]. Specifically, there are certain personality traits that are generally associated with a happier standard of living. These include extraversion, optimism, trust, agreeableness, a desire to control, hardiness, high self-esteem, hopefulness, gratitude, love, and curiosity. It's worth noting that increased levels of neuroticism have a strong negative correlation with happiness. However, the GSS does not have anything that measures neuroticism beyond measuring depression levels; the latter is reused later as a direct foil to happiness levels.

Further, there are other contextual factors that are associated with a positive increase in happiness. These include a person's level of education, their wealth, how religious they are, their subjective health, their friendships, marital status, how many children they have, their metaphysical drive (né life purpose), and the amount of leisure experienced. There is a distinct difference between subjective health and objective health that should be heeded. Objective health - things like actually being sick, illness diagnoses, and the amount one visits the doctor - have a net zero effect on happiness levels[6]. Subjective health - things like thinking you're sick and feeling as though something is wrong without any specific prognosis - have a net positive correlation with happiness. Meaning, the less ill one believes they are, the happier they will report being. All together, both the contextual and characteristic traits that influence happiness are relatively logical: of course people who are optimistic and feel physically well will be more inclined to consider themselves "happy".

These aren't the only factors that influence happiness, however. There is a clear relationship between happiness and age[7][8]. Specifically, happiness is seen to increase up until the mid-60's, wherein general downward trend is seen among persons older than 65[8]. There is also a linkage between race and happiness: people of color (and particularly Black Men) are more inclined to report being unhappy at all periods of their life, regardless of temperament of circumstance[9]. All together, this backdrop illuminates a decently-clear picture of what the variables of interest will be when attempting to predict happiness levels.

## 3 The Data

The GSS - or General Social Survey - is an open-source data project gathered from NORC at the University of Chicago. Polling roughly 4,000 Americans[4] every other year, the GSS collects information on the demographic, behaviors, and attitudes of their polling population, along with a suite of special interest questions, including those related to psychological well-being. The latter group includes the most crucial question to this analysis: "Taken all together, how would you say things are these days–would you say that you are very happy, pretty happy, or not too happy?"

Most of the questions in the GSS take a similar format to the above, asking respondents to provide an answer given a group of possible choices. This leads to most of the questions in the GSS being categorical data, something that became a crucial challenge to tackle when forming the models used in this analysis. In 2022, the GSS was both offered in-person and virtually; the first year to do so. To minimize any assumptions that would be required when merging the answers of both virtual and in-person respondents, only the latter was used in this analysis. This negated 38% of the data.

The 2022 GSS comprises 1156 individual questions; there is no single respondent who answered all of these. Additionally, many questions were only posed to certain respondents depending on how they responded prior, as well as a suite of questions that were asked towards the interviewer themselves. These limitations effectively reduce the total number of questions to roughly 600 and the total

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number of respondents whose information we can use to sub-2,500 people. This, however, is not much of a concern.

It would be both computationally expensive and time consuming to find the relationship between all 600 questions and the happiness rating of a participant. Instead, we can selectively pick only the questions that relate to the qualities that prior research has deemed related to the happiness level of a person. For ease, let us group together those qualities into 8 different categories: Character, Wealth, *Religion, Health, Friendship, Life, Leisure,* and *Education.* The distribution of questions to category will be as follows:

- *Character*: How satisfied are you with your life?; Can most people be trusted?; Is it more important for a child to learn how to obey, be popular, work hard, or think for themselves?; How often do you feel sad/depressed?
- *Wealth*: Rate your total family income; Rate your total personal income; How satisfied are you with your financial situation?; The value of respondents inflation-adjusted personal income from 1976-2006.
- *Religion*: What is your religious preference? How often do you attend religious services? Rate how strongly affiliated you are with your religion; How often do you pray? How strongly do you believe in God?
- *Health*: Would you say your health is good, excellent, or poor?; Do you have a long-standing illness, chronic condition, or disability?; How often have you had difficulty with work or household activities due to health problems?; How often do you visit the doctor?
- *Friendship*: How often do you attend social gatherings with relatives?; How often do you attend social gatherings with neighbors?; How often do you attend social gatherings with friends?; How often do you attend social gatherings in bars?
- *Life*: What is your age?; What is your race (White/Black/Other)?; What is your marital status? How many children do you have? Do you believe in life after death?
- *Leisure*: In the past 12 months, how often have you seen live music?; How often have you gone to a museum?; How often have you gone to the movies?; How often have you created your own art?; How often have you read a work of literature?; How often have you toured an online museum?; How often have you watched a livestream of a performance?; How often have you watched a recorded performance (non-live filmed performance)?; How often have you gone to a live streamed book reading?; How often have you watched a recorded book reading? How often have you taken online art classes? How often have you listened to an art-based podcast?
- *Education*: How many years of education have you completed?

All together these variables seek to capture both the characteristics and contextual traits of respondents that could influence their overall happiness. Most questions follow a similar format where respondents were presented with 1-4 answer choices, where 1 corresponds to the "best" answer and 4 the "worst". As an example, "Would you say your health is good, excellent, or poor?" presents answer choices as: "1. Excellent; 2. Good; 3. Poor" and logs into the GSS the index of the choice chosen; if I considered my own health "good", my response in the GSS would be recorded as a "2". The most notable exceptions to this format are the answers to "Rate your total family income" and "Rate your total personal income", where each is scored on a scale of 1 to 26. Because the respondent's age was a quantitative variable and age's effect on happiness is only significant for persons of 65, answers were processed into a zero-one binary where 0 corresponds with the respondent being under 65; 1 with the respondent being over 65. See Appendix A for the GSS variables corresponding to each question posed above.

For every question, each respondent was given a choice whether or not they would like to answer that question. To process these missing values, per each category, respondents who failed to answer any of the questions within were left unrecorded for the sake of the analysis. All categories inherently include the respondents' answer to the "How happy are you?" question that is central to the analysis. Table 1 shows a full-processed example subset of the data extracted directly from the GSS. The STATA files for the GSS were used in construction.

Table 1. Example GSS data

| Happy | Age | Race | Marital | Childs | Income | Life Satisfaction |
|---|---|---|---|---|---|---|
| 3 | 0 | 1 | 3 | 1 | 22 | 2 |
| 3 | 1 | 1 | 3 | 11 | 18 | 2 |
| 2 | 1 | 1 | 5 | 2 | 15 | 2 |
| 2 | 1 | 1 | 5 | 0 | 19 | 1 |
| 2 | 1 | 3 | 5 | 0 | 17 | 2 |

## 4 Models and Methodology

Ultimately, our goals are twofold: develop an ANN capable of predicting the happiness level of any given person (assuming a particular suite of variables are used as inputs), verifying the accuracy of these ANN derivations through Spectral cluster, and to draw overarching sociological conclusions about the relationships between the various qualities presented in the GSS and their relationship with happiness. Although it's non-traditional to use Spectral Clustering as a verification tool, due to the relationship we are trying to model, it's actually quite effective.

Recall our central question of "How happy are you?" There are three possible answers: "very happy", "pretty happy" and "not too happy"[4]. Logically, if we were to use any kind of clustering algorithm, the optimal number of clusters should be at least 3; one for each possible answer to that central question. Of course there can be more than three clusters depending on the underlying relationships that exist between variables. That situation would not signify any potential issues with the model beyond any overfitting that would arise from using too many predictor variables. What would identify an issue, however, is if the optimal number of clusters is less than 3.

This would imply that, within the structure of the data, there are only two distinct groups. Somehow, one of the three possible happiness levels is being wrongly grouped in with others. Therefore, the results of our Spectral Clustering identify not an issue with the ANN, but with the data itself. Or, rather, an issue with the particular subset of the data that's being fed into the ANN. We will use both

Silhouette Scores and the Calinski-Harabasz Index to identify the optimal number of clusters and ultimately what the underlying groupings of the data can confer on our analysis of each model.

To adapt an ANN such that it is capable of predicting, a few requirements are necessary. To continue with the theme of working in threes, every variation of the ANN used in our analysis will contain three layers, where the first two of which make use of the Rectified Linear Unit (ReLU) activation function. Consider how happiness is both an objective and subjective metric that can be influenced by millions of things and nothing at all[6]. In other words: a model detailing happiness needs sparsity to avoid overfitting, something provided by the ReLu function[10].

The third and final layer (the "output" layer) makes use of a SoftMax activation function, due to that predicting intention the model carries[11]. The SoftMax function nets out probability distributions once all layers have been exhausted, which can then be converted back into the categories depicted by the central question ("Very happy", "Pretty happy", "Not so happy"). This allows the direct and accurate comparison of predicted values with the test set comprising 30% of the available data.

The loss function is a trickier decision. The GSS is composed of almost entirely categorical data (see The Data); ergo we need a loss function for the model capable of interfacing successfully with the SoftMax function and account for the non-qualitative data. Traditionally, because we are using a SoftMax activation function in the output layer, we should make use of a Cross-Entropy Loss function[11]. However, due to the uniqueness of the data, we can remold that loss function to be a Categorical Cross-Entropy Loss function that penalizes the prediction made by the SoftMax output layer based on the distance a prediction is from the actual data[12]. This allows us to account for both over and underestimates of the categorical data.

In order for the categorical data to properly process through the ANN such that both the SoftMax output layer and Categorical Cross-Entropy loss function are working as intended, we will need to one-hot encode all the input features. What this does is split a categorical feature into multiple binary classifications. For example, assume the first 5 respondents answered the "How happy are you?" question such that it resulted in the following vector:

$$\begin{bmatrix} 1 \\ 3 \\ 2 \\ 1 \\ 2 \end{bmatrix}$$

One-hot encoding would split those five responses across three columns, resulting in the following matrix:

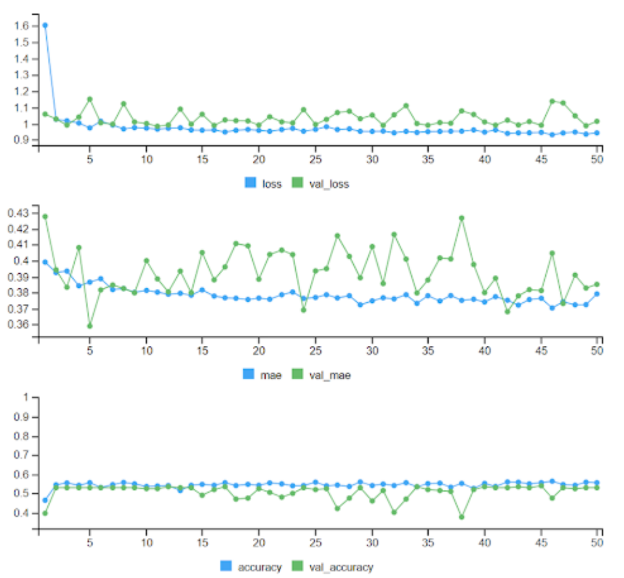
$$\left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \right\}$$

Each vector in the matrix is a binary representation of the answers provided previously: respondents 1 and 4 answered with a "1"; respondents 3 and 5 answered with a "2"; respondent 2 answered with a "3". This allows us to properly calculate and penalize the probability distributions, resulting in a prediction.

Because we are tackling a total of 40 different input variables, there exist over one trillion possible combinations; testing them all to determine the best selection of variables for our ANN is a massive undertaking and far outside the scope of computational feasibility. Generally, because our variable of interest is the answers to "How happy are you?", every ANN model will receive this data as the training/testing output vector. We will begin by taking each of the defined categories (see The Data) individually, running them through the ANN to determine which overarching category is the most accurate. From there, individual pruning and trial-error testing is necessary to find the most optimal combination.

## 5 Results

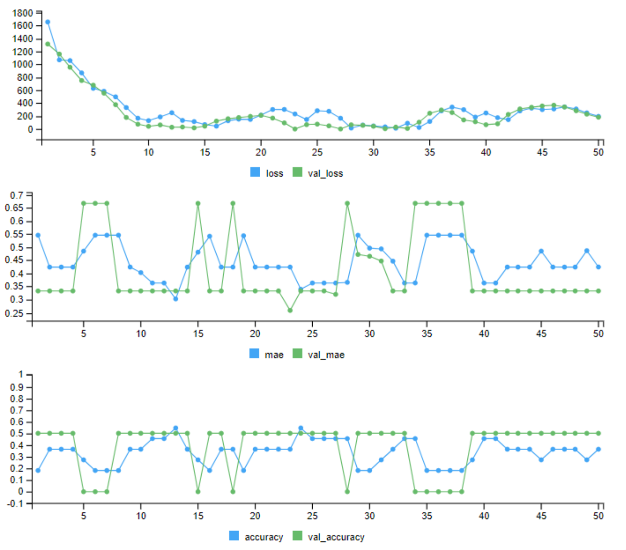
Beginning with the categories, we see that, in isolation, the most optimal groups of more than one variable were Life and Character with respective accuracies of 0.554275 and 0.5421687. When we cluster the data, we see that the Character group presents us with an optimal number of clusters at 6, and the Life group with an optimal number of clusters at 10. Both of these are a relatively high number of clusters associated with low Silhouette Scores and low CH indices (see Appendix B and Appendix C), implying unmeaningful clusters. Considering we assumed that there would be somewhat of a meaningful structure, this presents us with considerable encouragement to keep tweaking the model inputs. Figure 2 shows the ANN results from the Life grouping.



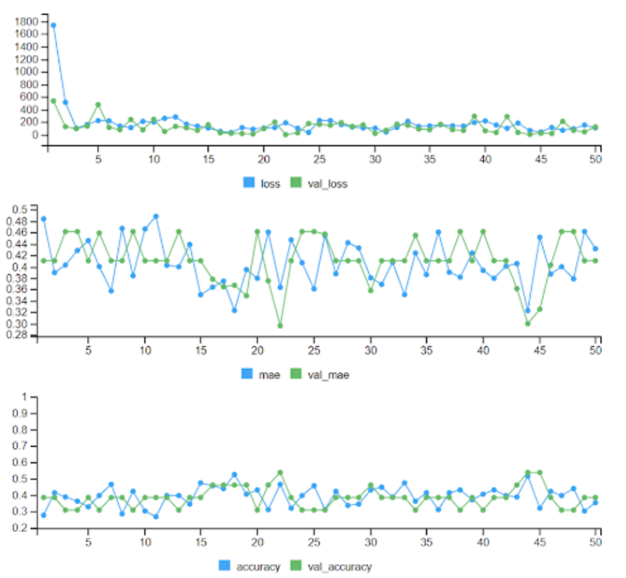

From these results, we know that subsequent analyses require a mixing of groups. The full order of groupings was *Life, Education, Character, Friendship, Health, Leisure, Religion,* and *Wealth*; to determine the best initial starting combination, we "power match" the models. This means we combine the data of Life and Education and run the model, then Education and Character, so on and so forth.

In addition, the number of epochs, the percentage split of variables, and the size of each layer in the ANN is adjusted as necessary to reduce the overall loss of each model's results.

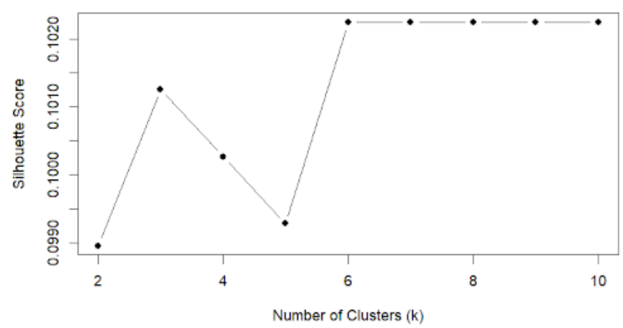
The most effective models from power matching were Education and Character, along with Health and Leisure. This gives credence to future models incorporating some elements of the respondents character, along with their education, overall health, and if they take time to themselves. Curiously, when we combine all models into a massive input set, adjusting ANN hyperparameters as needed, we get the highly inaccurate model shown below in Figure 3, with an accuracy score of 0.1666667.




The accuracy immediately improves once the Leisure data grouping is completely filtered out, as seen in Figure 4.



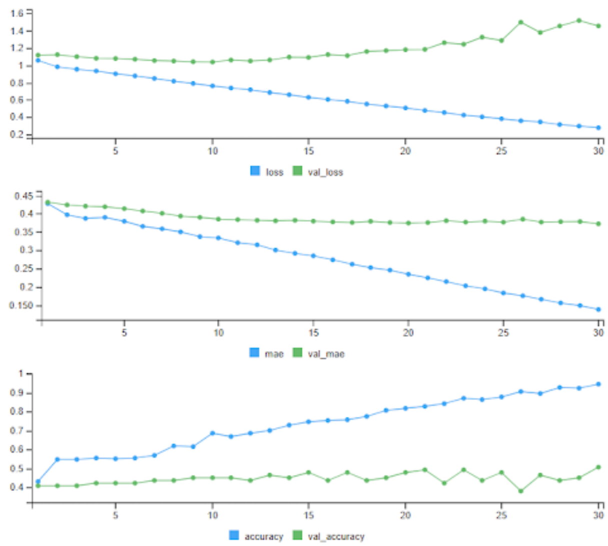

In actuality, the above model is the most accurate with an accuracy of 0.5892857. This strongly implies a varying combination of variables from these groups (all groups excluding *Leisure*). After performing selection, the most accurate model is one that makes use of the following respondent information: their race, if they're married, their life satisfaction, their personal (subjective) view of their health, their religion, and their education level. The model has an accuracy of 0.505848 which, although not stellar, is made all the more impactful by the results from Spectral Clustering. Shown in Figure 5, the Silhouette Scores show peaks at both a total of 3 and 6 clusters; however, the CH index is maximized at 3 clusters with a value of 6.9503. This implies that the optimal number of underlying groupings is 3, which is in-line with our prior assumption about the separation of the data. These input variables must be in the optimal model by proxy.

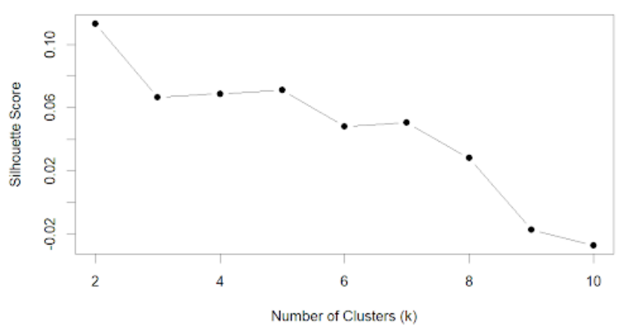



This model will operate as a baseline as we feed in different combinations of the variables found in the *Character* grouping, the *Religion* grouping, the *Health* grouping, and the *Wealth* grouping. The variables in the Friendship grouping are excluded due to a lack of sizable respondent pool as, when coupled with the variables already in our model, we net less than 50 columns in our input matrix.

Through this, the "best" model is one that incorporates the race of the respondent, their marital status, their life satisfaction rate, how devout they are, how often they pray, if they believe there's a god, their subject health, and their education. It's interesting to note that, when attempting to reintroduce any of the wealth variables into our baseline model, we actually reduced the overall accuracy. With this "best" model, we reintroduced the age of the respondents, how many children they have, and if they believe there's a life after death as all of those variables have shown some positive correlation with overall happiness in prior studies [6], testing various different combinations of those three additional features.

This produced one final model that contained all of the above, as well as the age of the respondent. This model had an ANN accuracy of 0.5899404 with an optimal number of two underlying clusters (with a CH value of 3.232282) determined via Spectral Clustering. Figures 6 and 7 show the respective ANN results and Silhouette score plot. Additional analyses were performed investigating the individual relationship each variable had with answers to the "How happy are you?" question.




## 6 Takeaways and Conclusions

The above analysis - and our overall model - actually poses some really interesting findings in relation to the overarching question "is there statistical evidence supporting a method of maximizing happiness?" In short: it's complicated.

All the models have roughly plateaued between 40-50% accuracy. Although this may seem poor, it's worth remembering that we are predicting a variable that has three possible outcomes. Therefore, random choice would dictate an accuracy of 33%, much lower than what we see. That's not to say the ANN's are supremely accurate - they're just not inaccurate. The final model (see Figure 6) with the highest accuracy score of roughly 60% is thereby doubly as effective than random guess. In a way, this implies that happiness, generally speaking, is a quality that can be predicted; if the converse were true, we would expect to see accuracy numbers much closer to that 33%.

In reference to that final model, consider now the difference between the ANN and the results of the Spectral Clustering. Recall that we expected there to be at least three underlying clusters in the data. However, in the most accurate model, we only have an optimal number of two clusters. This dissonance implies the scope in which this model is capable of estimating someone's happiness.

If the model is developing only two clusters, that must mean at least one of the varying levels of happiness is getting consistently misclassified and grouped together with another. From the actual results of the final model (see Appendix D), level 2 was the most consistently misclassified value - the model was able to accurately classify who was "Very happy" and "Not so happy", but not those in the middle. This demonstrates that the ANN can identify the binary of happy/unhappy, but not those who are simply "OK"; roughly 31% of the population falls into that middle ground[13]. Overall, this means that the ANN model we developed can only predict in very broad strokes: either you're likely to be happy, or you're likely to not.

There are a few other developments we can scry from these results. Recall that, when we incorporated wealth metrics into the data, the models did not improve in any clear way. Actually, the models decreased in accuracy, one of the few times this occurred. This provides some supporting evidence to the adage "money can't buy you happiness" - quite literally, an increase in wealth, when considering other factors, actually has a negative impact on overall happiness.

But can you "game" your life in order to become happier? Could one reasonably make certain changes that, in some way, lead to an improvement in overall happiness? The evidence in favor of this is relatively inconclusive. Firstly, the ANN does not present us with a hierarchy of effect: only what variables are relevant to predicting any level of happiness. To the contrary, however, there is a clear focus on religious belief and engagement in the final model. It is reasonable to assume that if one intended to become "happier", it would be worthwhile to grow invested in a religious group or similar body that assuages the mind of post-death existential concerns.

There is much more to be done with this course study. There were plenty of issues related to the GSS that impeded the accuracy of this paper, as well as an insurmountable volume of potential models that would require time and dedication to individually investigate. However, there are important takeaways from the analysis completed here. This paper serves as a proof-of-concept of a seemingly undeveloped application of Neural Networks - emotion science - that could possibly revolutionize the way we approach the treatment and understanding of cognitive disorders.

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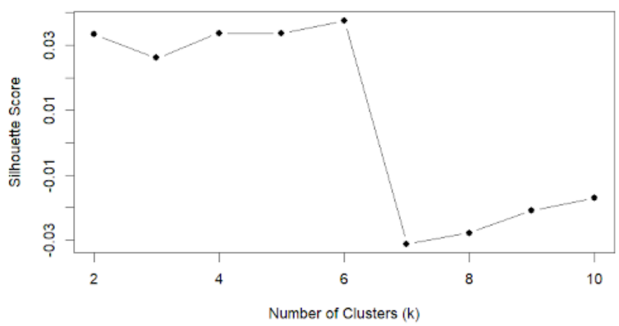
## A GSS Variable Names and Associated Definitions

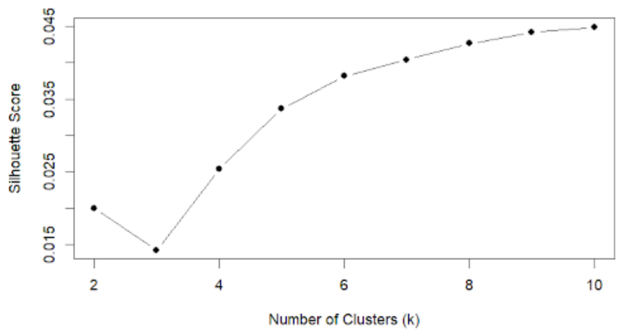
How happy are you? - happy
How satisfied are you with your life? - life
Can most people be trusted? - trust
Is it more important for a child to learn how to obey, be popular, work hard, or think for themselves? - obey, workhard
How often do you feel sad/depressed? - feeldown
Rate your total family income - income16
Rate your total personal income - rincom16
How satisfied are you with your financial situation? - satfin
The value of respondents inflation-adjusted personal income from 1976-2006 - conrinc
What is your religious preference? - relig
How often do you attend religious services? - attend
Rate how strongly affiliated you are with your religion - reliten
How often do you pray? - pray
How strongly do you believe in God? - god
Would you say your health is good, excellent, or poor? - health
Do you have a long-standing illness, chronic condition, or disability? - disblty
How often have you had difficulty with work or household activities due to health problems? - hlthprb
How often do you visit the doctor? - docvst
How often do you attend social gatherings with relatives? - socrel
How often do you attend social gatherings with neighbors? - socommun
How often do you attend social gatherings with friends? - socfrend
How often do you attend social gatherings in bars? - socbar
What is your age? - age
What is your race (White/Black/Other)? - race
What is your marital status? - marital
How many children do you have? - childs
Do you believe in life after death? - postlife
In the past 12 months, how often have you seen live music? - yrlvmus
How often have you gone to a museum? - yrartxbt
How often have you gone to the movies? - yrmovie
How often have you created your own art? - yrcreat
How often have you read a work of literature? - yrrdg
How often have you toured an online museum? - yrtour
How often have you watched a livestream of a performance? - yrstmus
How often have you watched a recorded performance (non-live filmed performance)? - yrarmus
How often have you gone to a live streamed book reading? - yrstpo
How often have you watched a recorded book reading? - yrarpo
How often have you taken online art classes? - yrclass
How often have you listened to an art-based podcast? - yrpod
How many years of education have you completed? - educ

## B Character Grouping Spectral Clustering Metrics

Silhouette Scores: 0.00000000, 0.03323110, 0.02598472, 0.03367810, 0.03367810, 0.03752781, -0.03120049, -0.02781219, -0.02079865, -0.01699785

CH Index: 0.000000, 2.565804, 1.278220, 1.726945, 1.290447, 1.296718, 2.015559, 1.590918, 1.287961, 1.273529




## C Life Grouping Spectral Clustering Metrics

Silhouette Scores: 0.000000000, -0.002884092, -0.007741451, 0.013145512, 0.036355135, 0.038606202, 0.047619592, 0.039356759, 0.049123264, 0.049875255

CH Index: 0.00000, 50.91713, 39.05643, 31.03285, 29.95309, 25.91292, 21.57905, 19.67607, 16.36878, 14.90971

## D Raw Results from the Final Model ANN

```
$Actual
  [1] 2 2 2 1 3 3 2 3 1 1 1 2 1 3 3 2 3 2 3 1 3 3 1 2 2 2 2 2 2 2 3 1 2 1 2 2 2 2 1 1 2 2 1 2 2 2 2 3 3 3 3 2 3 2
 [55] 3 3 3 2 3 3 1 3 3 2 3 2 2 1 2 2 2 3 1 2 1 1 2 2 3 1 1 1 2 2 3 2 2 2 3 2 3 3 2 2 1 2 2 1 2 2 3 1 3 3 3 2 2 3
[109] 2 2 3 2 2 2 1 1 2 1 3 3 2 2 1 2 2 2 2 2 3 3 2 1 2 2 1 1 3 2 3 2 3 2 2 2 2 1 2 3 2 3 1

$Predicted
  [1] 3 2 2 2 3 2 2 3 2 2 2 3 3 1 3 2 3 1 2 2 2 3 2 2 3 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 1 1 3 2 2 2 2 3 3 2 3 2
 [55] 2 3 2 2 2 3 1 2 2 2 2 2 2 1 3 3 2 3 2 2 1 1 2 3 2 2 1 2 2 3 3 2 3 1 2 2 2 2 2 2 1 2 2 1 2 3 3 3 3 2 2 3 3 2
[109] 1 2 3 2 3 2 1 3 2 1 1 2 2 2 3 2 2 1 2 2 2 3 1 2 2 2 2 2 3 2 3 2 2 2 2 3 2 2 3 2 2 2 1

$Accurate
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 [28] "Y" "Y" "Y" "N" "Y" "Y" "N" "Y" "N" "Y" "Y" "N" "N" "Y" "Y" "Y" "N" "N" "Y" "Y" "N" "N" "Y" "Y" "Y" "Y" "Y"
 [55] "N" "Y" "N" "Y" "N" "Y" "Y" "N" "N" "Y" "N" "Y" "Y" "Y" "N" "N" "Y" "Y" "N" "Y" "Y" "Y" "Y" "N" "N" "N" "Y"
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[109] "N" "Y" "Y" "Y" "N" "Y" "Y" "N" "Y" "Y" "N" "N" "Y" "Y" "N" "Y" "Y" "N" "Y" "Y" "N" "Y" "N" "N" "Y" "Y" "N"
[136] "N" "Y" "Y" "Y" "Y" "N" "Y" "Y" "N" "Y" "N" "N" "N" "Y" "N" "Y"
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