

Understanding the Effect of Certain Socioeconomic Factors on Mental Health Outcomes

Medha Pappula, Kade Yen

ML1 - Q1 Project

Thomas Jefferson High School for Science and Technology

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Part 1 - Statement / Project Goal

Mental health has emerged as a significant global concern in recent years, encompassing various challenges individuals face. The impact of socioeconomic factors on mental well-being has garnered considerable attention, revealing a complex relationship between the two. Individuals with lower socioeconomic status (SES) tend to experience higher rates of mental disorders, encounter barriers in accessing mental health services, and often suffer from increased psychological distress. Conversely, individuals with higher SES generally exhibit lower rates of mental disorders, possess better access to resources and support, and enjoy stronger social networks. Understanding the influence of socioeconomic factors on mental health outcomes is crucial for developing targeted interventions and policies. This overview aims to provide a foundation for further exploration of the connection between mental health and socioeconomic factors, emphasizing the need to comprehend and address these factors to improve mental health outcomes globally.

This leads to our research question: *What specific socioeconomic factors among adults in the United States have a profound impact on mental health severity?*

To answer this question, we will look at the 2023 National Health Interview Survey provided by the CDC. This is a dataset consisting of a broad range of health topics collected through personal household interviews. Specifically, to ensure low variability in results, we will look at adult interviews.

We specifically chose to look at *severity* as opposed to *presence* since it's more important to assess the level of an individual has been affected by mental health as opposed to the presence of it. This can help ensure medical professionals are utilizing their resources to help those who are the most vulnerable.

Part 2 - Description of Dataset

This dataset has 29522 rows of information for 647 attributes. Each row represents an adult interview conducted and their responses to certain questions.

Link to dataset: <https://www.cdc.gov/nchs/nhis/2023nhis.htm>

Below is an explanation of each attribute:

Attribute Description.pdf -

<https://drive.google.com/open?id=14JO5mxtoPb2VAMDX68zPNtwcqRXZsrwt>

For this study, we are classifying the attributes listed as “brief mental health assessment” which includes the PHQ41_A, PHQ42_A, PHQ44_A, and PHQ44_A attributes. These attributes ask questions related to certain behaviors such as loss of interest and anxiety within the past 2 weeks. It also asks for different medical conditions that an individual may have had in the past to try to correlate that with their mental health.

Classifying for this attribute will be useful because we can directly see the impact of specific socioeconomic factors on the mental health of the individual and use this information to create conclusions on infrastructure/public policy plans to alleviate mental health crises. For

example, if the level of education affects mental health outcomes, then we can suggest more plans to keep people in education for longer. When it comes to different health conditions, if a certain cancer or illness leads to a higher correlation of mental health problems, then we would know the relative target area to help stop and find solutions to mitigate this issue and lower overall mental health problems.

Part 3 - Pre-Processing

Removing Attributes with >70% Missing Values

Utilizing the Weka software all attributes with missing percentages greater than 70% were subsequently removed. This is done for a variety of reasons:

1. **Lack of Information:** If 70% of the data is missing, the attribute provides little value or information to the class variable.
2. **Difficulty in imputation:** Attempting to fill in so much missing data would introduce noise or biases rather than useful insight, leading to poor model performance
3. **The Curse of Dimensionality:** Keeping too many incomplete features increases the complexity of the model without any large improvement. Removing these features simplifies the model
4. **Avoiding overfitting:** Filling in a lot of the missing values could result in the model overfitting to the data, where the model learns the values from the filled in values rather than the actual values.

This resulted in the removal of 311 attributes, leaving values with more data useful for predicting the class. While this seems like a lot, we still have 336 attributes to preprocess.

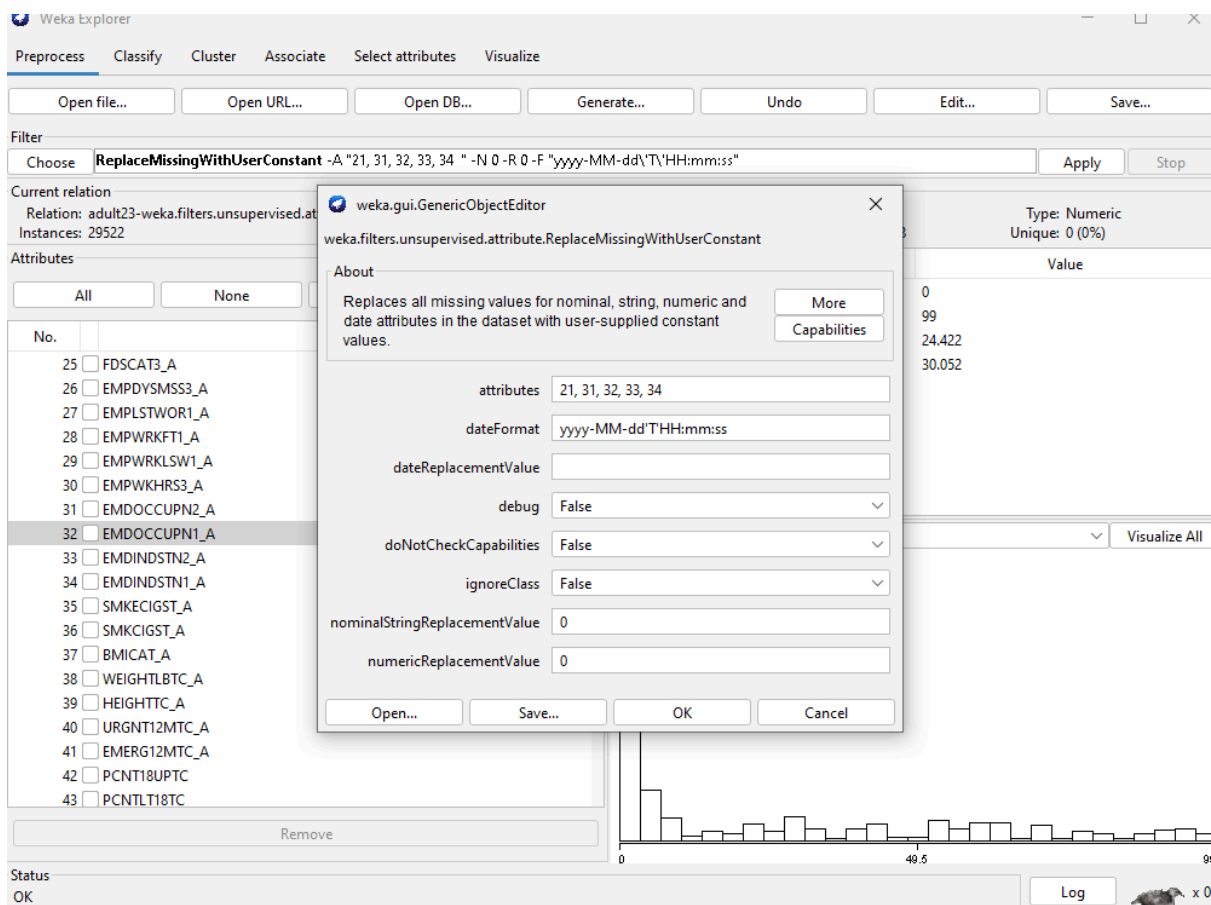
Filling In Default Values

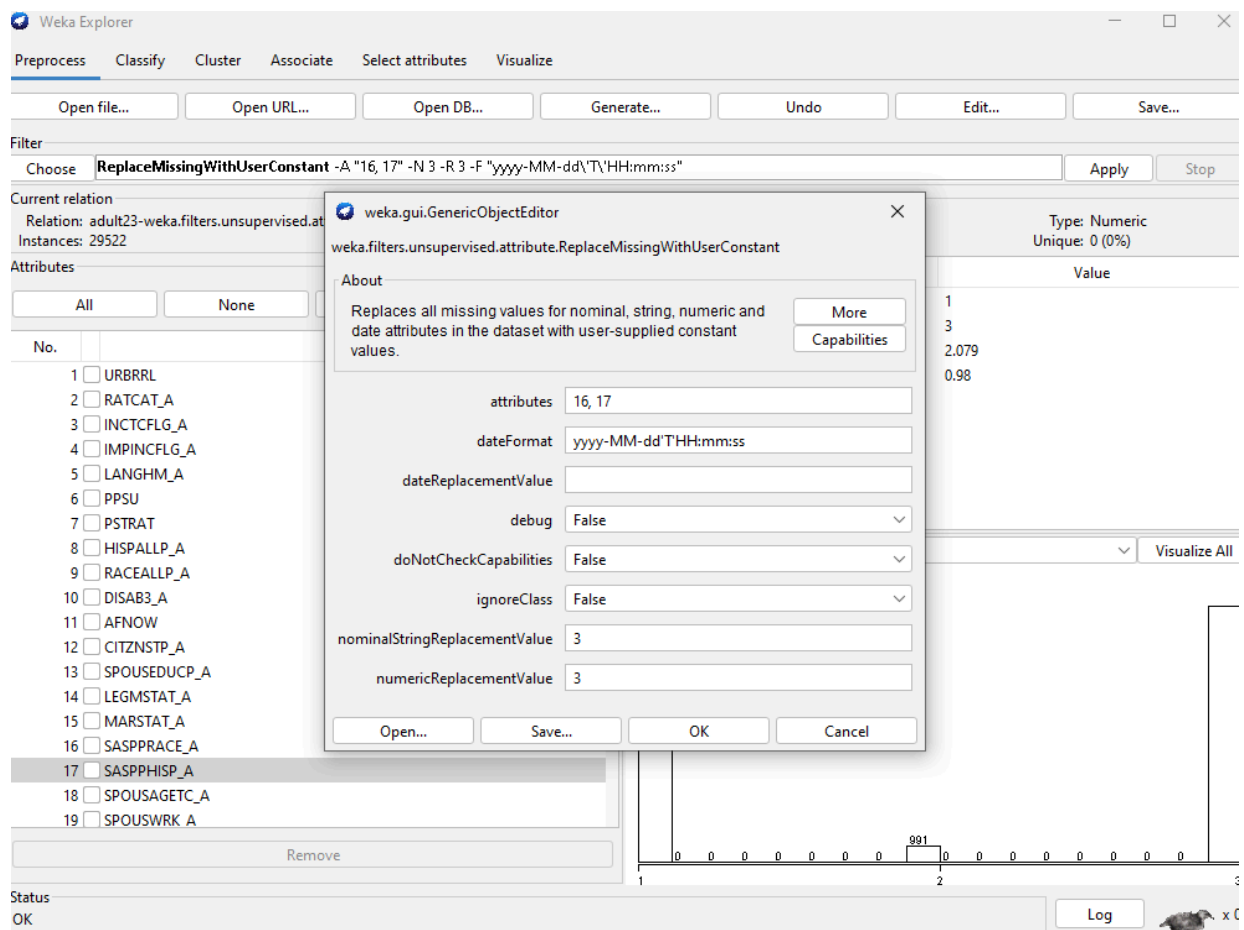
All attributes with missing values have a default value meaning “Don’t Know” according to the codebook. To fill in these values, each attribute with a missing value was compared against the codebook to find this default value, the following attributes have the given default value, which was replaced to remove all missing values from the dataset.

Specified Attributes Index	Default Value
21, 31, 32, 33, 34	0
16, 17	3
47	6
46	7
48, 60	8
5, 11, 19, 20, 27, 28, 87, 89, 90, 91, 92, 93, 96, 98, 99, 100, 101, 102, 104, 109, 110, 116, 117, 122, 125, 127, 136, 142, 143, 144, 145, 146, 147, 148,	9

149, 150, 168, 169, 170, 179, 181, 182, 183, 185, 188, 193, 194, 195, 199, 200, 201, 202, 203, 204, 205, 206, 207, 208, 209, 210, 211, 212, 213, 214, 218, 219, 220, 222, 223, 224, 225, 231, 233, 238, 242, 243, 244, 245, 246, 247, 248, 249, 250, 251, 252, 253, 254, 255, 256, 257, 258, 259, 282, 283, 284, 291, 292, 293, 310, 314, 315, 320, 321, 323, 324, 325	
13, 18, 30, 50, 62, 103, 186, 187, 191	99
27	999
190	9999
51	99999

These values were filled in using Weka's *ReplaceMissingWithUserConstant* feature. After completion, there were no more missing values within the dataset.





Engineering Class Attribute

To create the class variable, we combined the following 4 variables about questions used in a mental health assessment. These attributes are similar to each other such as feeling down and having little interest in things for the past 2 weeks.

MHA: Brief mental health assessment

Variable #	Question #	Variable Name	Source Variables	Description	Type	Location	Length
1	MHA.0020.00.4	PHQ41_A		How often little interest in things, past 2 weeks	Num	518	1
2	MHA.0030.00.4	PHQ42_A		How often feeling down, past 2 weeks	Num	519	1
3	Recode	PHQ2SCREEN_A	PHQ41_A; PHQ42_A	PHQ-2 screener result	Num	520	1
4	MHA.0040.00.4	PHQ43_A		How often felt nervous/anxious/on edge, past 2 weeks	Num	521	1
5	MHA.0050.00.4	PHQ44_A		How often can't stop/control worrying, past 2 weeks	Num	522	1
6	Recode	GAD2SCREEN_A	PHQ43_A; PHQ44_A	GAD-2 screener result	Num	523	1

The codes for these 4 attributes breakdown as so:

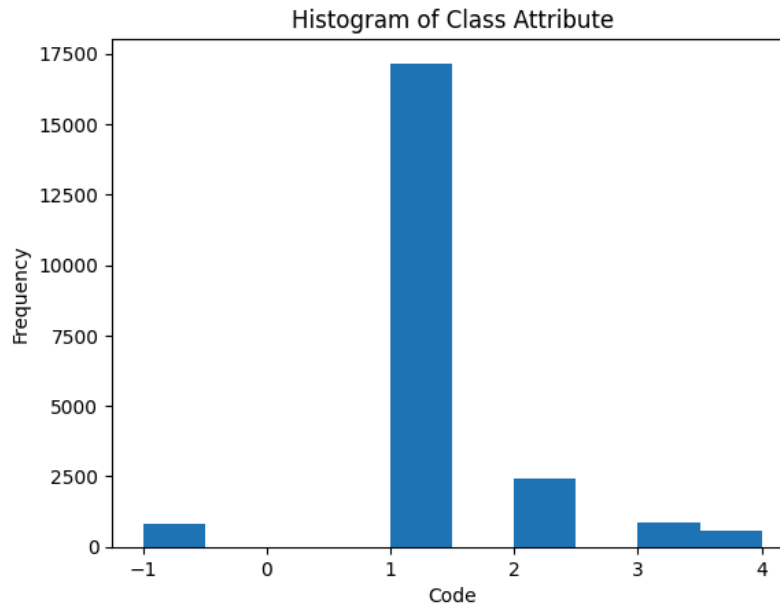
Code	Description
1	Not at all
2	Several days
3	More than half the days
4	Nearly every day
7	Refused
8	Not Ascertained
9	Don't Know

There are multiple approaches we could have taken to combine these 4 attributes. All 4 attributes have 0 missing values, so there is no risk of bias. The values placed in the engineered attribute will be as follows: (1) Average then round values between 2-4 to get the average number of days where the individual faced a mental health issue, (2) 1 if all values are coded as 1 and, -1 if all values are between values 7-9.

This is a complex expression, so we opted to utilize Python via Google Colaboratory to alter the data frame. We utilized Pandas to manipulate the data frame.

```
def engineer_attribute(row):  
    """  
    Engineers a new attribute based on PHQ41_A, PHQ42_A, PHQ43_A, PHQ44_A.  
    row: A pandas Series representing a row in the DataFrame.  
    Returns: The engineered attribute value.  
    """  
  
    phq_values = [row['PHQ41_A'], row['PHQ42_A'], row['PHQ43_A'], row['PHQ44_A']]  
    if all(1 <= val <= 1 and not np.isnan(val) for val in phq_values):  
        return 1  
    elif all(7 <= val <= 9 and not np.isnan(val) for val in phq_values):  
        return -1  
    else:  
        average = np.nanmean(phq_values)  
        if 2 <= average <= 4:  
            return round(average)  
        else:  
            return np.nan # Or another default value if needed  
  
# Apply the function to create a new column  
df['engineered_attribute'] = df.apply(engineer_attribute, axis=1)  
  
# Print the DataFrame with the new column  
print(df[['PHQ41_A', 'PHQ42_A', 'PHQ43_A', 'PHQ44_A', 'engineered_attribute']])
```

This results in this new distribution of the dataset.



Training/Validation/Test Dataset

For the next steps of figuring out which features are important and which to choose to build the model, the data is split into a training, testing, and validation dataset. We did this using Python sklearn's `train_test_split` function.

```
from sklearn.model_selection import train_test_split

# Split the data into training and a temporary set (test + validate)
train_df, temp_df = train_test_split(df, test_size=0.3, random_state=42)

# Split the temporary set into test and validate sets
test_df, validate_df = train_test_split(temp_df, test_size=0.5, random_state=42)

# Now you have three DataFrames: train_df, test_df, and validate_df
print(f"Train size: {len(train_df)}")
print(f"Test size: {len(test_df)}")
print(f"Validate size: {len(validate_df)}")
```

Now that these three have been created, the study can continue.

Part 4 - Attribute Selection Algorithms and Model Classifiers Used

Now that the data has been preprocessed, the most important features can be extracted to build the final algorithm. Below we tested a multitude of algorithms.

CfsSubsetEval with BestFirst

The evaluator selects feature subsets based on their predictive ability and redundancy. The key idea is to find features that have high correlation with the class (predictive power) and have low correlation with each other (redundancy).

This method works on the assumption that a good subset of features contains features highly correlated with the target class but uncorrelated with each other. This is calculated by getting the ‘merit’ of each subset.

$$r_{zc} = \frac{k\overline{r_{zi}}}{\sqrt{k + k(k-1)\overline{r_{ii}}}}$$

Where r_{zc} is the merit of subset C

k = number of features in the subset

$\overline{r_{zi}}$ is the average correlation between the class and selected features

$\overline{r_{ii}}$ is the average correlation among the selected features

Best first is a search strategy used to explore the space of possible feature subsets. It’s essentially a greedy hill-climbing algorithm that can backtrack if necessary. The algorithm searches for the best subset by evaluating neighboring subsets (adding removing one feature at a time) and selects the best one based on the CfsSubsetEval merit score. There are three steps:

1. Forward Selection: Empty set of features and add features incrementally
2. Backward Elimination: Start with all features and remove one by one
3. Bidirectional Search: Combine both forward and backward elimination

Correlation (Non-Weka Attribute Selection)

This process was done in Google Colaboratory by first calculating the Spearman rank correlation index of each attribute in relation to the class “engineered attribute”. Then by taking the absolute value of the correlation coefficients, we render a list of which attributes are most correlated with the class variable. From this list we take the top 10, around a threshold of 0.6 on both the positive and negative end.

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)}$$

```
# Calculate Spearman rank correlations
correlations = df.corr(method='spearman')['engineered_attribute'].drop('engineered_attribute')
```

```
# Take the absolute value of the correlations
absolute_correlations = correlations.abs()

# Get the top 10 most correlated attributes
top_10_correlations = absolute_correlations.nlargest(10)

print(top_10_correlations)
```

CorrelationAttributeEval with Ranker

CorrelationAttributeEval evaluates attributes based on their correlation with the class label (for classification tasks). It measures the relationship between each feature and target class. This evaluation is done independently for each attribute, meaning that it calculates the correlation of one attribute at a time with the class. In our case, it uses the Pearson correlation.

$$r = \frac{\sum (x - m_x)(y - m_y)}{\sqrt{\sum (x - m_x)^2 \sum (y - m_y)^2}}$$

The ranker search method ranks attributes based on their individual merit (correlation scores). They are sorted in descending order of their evaluation score, meaning the most predictive attribute appears at the top of the list. Ranker can also be set to eliminate attributes under a certain threshold, ensuring the resulting attributes are actually useful for prediction.

GainRatioAttributeEval with Ranker

We used Weka for this approach. It utilized the following formulas to calculate the GainRatio for a particular attribute

$$\begin{aligned} \text{GainRatio}(A) &= \text{Gain}(A) / \text{SplitInfo}_A(D) \\ \text{SplitInfo}_A(D) &= - \sum_{j=1}^v \frac{|D_j|}{|D|} \times \log_2 \left(\frac{|D_j|}{|D|} \right) \\ \text{Gain}(A) &= \text{Info}(D) - \text{Info}_A(D) \end{aligned}$$

Where the expected information (or entropy) needed to classify a value in D is

$$\text{Info}(D) = - \sum_{i=1}^m p_i \log_2(p_i)$$

where p_i is the probability that a value D is part of class C, m here represents the number of classes.

$Info_A$ uses attribute A to split D into v partitions before using that information to put D in a class:

$$Info_A(D) = \sum_{j=1}^v \frac{|D_j|}{|D|} \times Info(D_j)$$

v here is the number of unique values in attribute 5.

SymmetricUncertAttributeEval with Ranker

SymmetricUncertAttributeEval is an attribute evaluator based on the concept of Symmetrical Uncertainty (SU), which is derived from information gain (IG). This works in combination with a search method like Ranker. Entropy is a measure of the uncertainty or randomness in data. Information gain measures the reduction in entropy when an attribute X is shown. Symmetrical uncertainty is a normalized form of information gain, designed to remove biases towards attributes with many values. Ranker uses these normalized merit scores to rank the top N attributes, which can be selected using a threshold.

Part 5 - Selection Algorithm Results

CfsSubsetEval with BestFirst

Search Method:

Best first.

Start set: no attributes

Search direction: forward

Stale search after 5 node expansions

Total number of subsets evaluated: 5616

Merit of best subset found: 0.723

Attribute Subset Evaluator (supervised, Class (numeric): 321 engineered_attribute):

CFS Subset Evaluator

Including locally predictive attributes

Selected attributes: 10,63,107,134,140,150,154,159,160,189

DISAB3_A
MLTFAMFLG_A
EVRMARRIED_A
SMKNOW_A
PAITOOOTH3M_A
VIGIL4_A
DISCRIM5_A
MHTHND_A
MHTHDLY_A
HYSTEV2_A

Correlation (Non-Weka Attribute Selection)

0.634879	121	HRTESTLAST_A
0.610201	26	EMPDYSMSS3_A
0.596229	1	URBRRL
0.593039	70	REGION
0.592348	7	PSTRAT
0.590748	224	LONGCOVD1_A
0.587731	150	VIGIL4_A
0.58613	134	SMKNOW_A
0.582264	71	INTV_QRT
0.579129	151	VIGIL3_A

CorrelationAttributeEval with Ranker

All values with correlation above 0.3 (positive) and greater than -0.4 (negative) are included, as those are highly correlated. These are the attributes that are best for predicting for the class.

Search Method:

Attribute ranking.

Attribute Evaluator (supervised, Class (numeric): 321 engineered_attribute):

Correlation Ranking Filter

Ranked attributes:

0.633966	261	SOCSCCLPAR_A
0.633344	266	COGMEMDFF_A
0.568578	311	LSATIS4_A
0.538037	312	PHSTAT_A
0.511334	262	SOCERRNDS_A
... [omitted for length]		
-0.703882	154	DISCRIM5_A
-0.724287	150	VIGIL4_A
-0.745768	160	MHTHDLY_A
-0.747032	159	MHTHND_A

GainRatioAttributeEval with Ranker

Search Method:

Attribute ranking.

Attribute Evaluator (supervised, Class (nominal): 321 engineered_attribute):

Gain Ratio feature evaluator

Ranked attributes:

0.697292 159 MHTHND_A
 0.6864 160 MHTHDLY_A
 0.632153 261 SOCSCLPAR_A
 0.510287 136 TBIHLSBMC_A
 0.506297 318 WTFA_A
 0.505223 137 TBILCDCMG_A
 0.50145 161 HOMEHC12M_A
 0.593591 203 RXDG12M_A
 0.590783 214 MEDNG12M_A
 0.589613 215 MEDDL12M_A
 [... omitted for length]

Selected attributes: 159,160,261,136,318,137,161,203,214,215

SymmetricUncertAttributeEval with Ranker

Search Method:

Attribute ranking.

Attribute Evaluator (supervised, Class (nominal): 321 engineered_attribute):
 Symmetrical Uncertainty Ranking Filter

Ranked attributes:

0.564391 322 FAM_A
 0.192102 318 WTFA_A
 0.19129 159 MHTHND_A
 0.088267 160 MHTHDLY_A
 0.083587 261 SOCSCLPAR_A
 0.078292 150 VIGIL4_A
 0.09597 311 LSATIS4_A
 0.0568936 156 DISCRIM3_A
 0.064919 266 COGMEMDFF_A
 0.063711 154 DISCRIM5_A
 0.061754 153 VIGIL1_A
 [... omitted for length]

Selected attributes: 318,159,160,261,150,311,156,266,154,153,158

This leaves the following selected attributes for each attribute selection algorithm, these will from this point in the report be referred to as:

cfsEVAL - 10,63,107,134,140,150,154,159,160,189

reliefEVAL - 121, 26, 1, 70, 7, 224, 150, 134, 71, 151

corrEVAL - 261, 266, 311, 312, 262, 154, 150, 160, 159

gainEVAL - 159, 160, 261, 136, 318, 137, 161, 203, 214, 215

symmEVAL - 318, 159, 160, 261, 150, 311, 156, 266, 154, 153, 158

Part 6 - Model Selection

We chose the following 4 models to test the selected attributes:

Decision Table

Decision tables are concise visual representations of which actions to perform based on a given dataset. The structure of a decision table is a condition that is the inputs or features of the model. Each row responds to a combination of feature values, an action/decision that outputs the result of applying the model to the conditions which is the class model, and rules which are the specific values/conditions in which the decision is made which becomes a rule. A decision table is considered balanced if it includes every possible combination of the input variables. This model is good for interpretation and creates rules that might be valuable for analysis, however, it is not suitable for continuous variables and may be impractical for complex models.

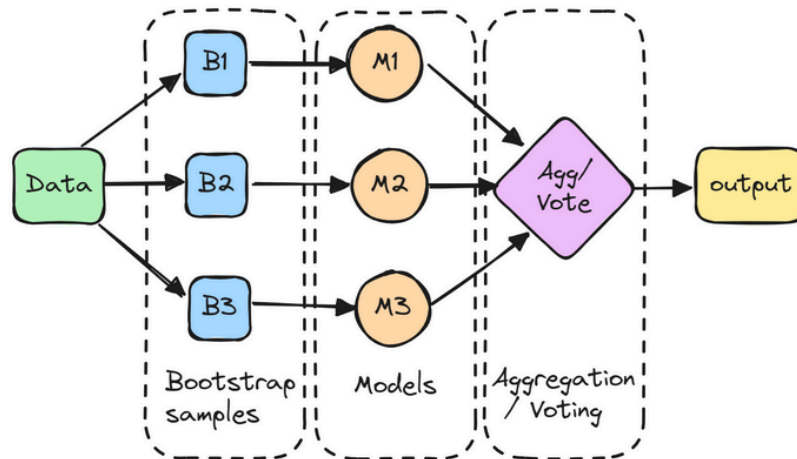
Age Group	Income Level	Purchase (Yes/No)
Young	Low	No
Young	High	Yes
Middle-aged	Low	Yes
Middle-aged	High	Yes
Senior	Low	No
Senior	High	No

J48

This classifier is a subset of existing decision tree algorithms. It is an open-source Java implementation of the C4.5 decision tree algorithm. It is similar to decision tables however it uses a recursive process to build the tree. It also uses information gain to measure how much a feature reduces the uncertainty for the class label. Due to its recursive nature, J48 is great for larger datasets as well as handling both categorical and continuous variables. However, it is prone to overfitting and bias towards certain features due to the use of gain ratios.

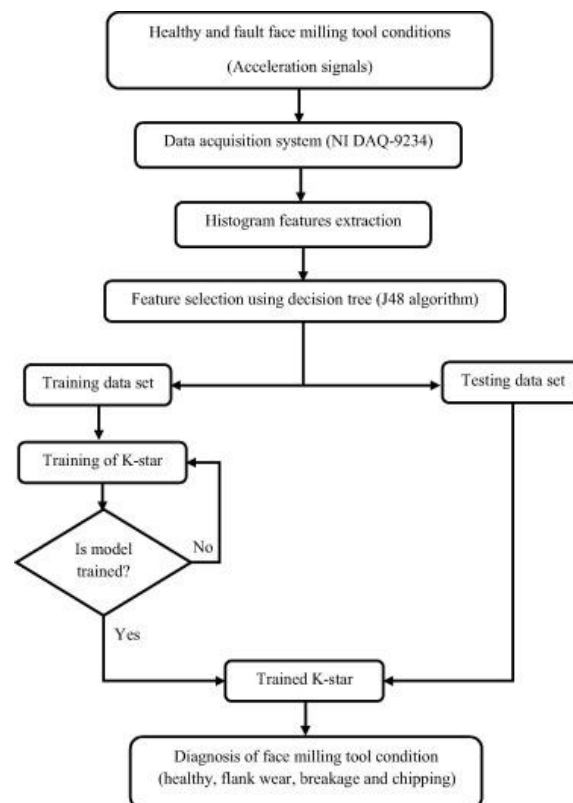
Bagging

Bagging involves training multiple models independently on different subsets of the data. First, the data will be randomly sampled an n amount of times with replacement. Then the model will train it on each of the data samples which would then create predictions. The models' predictions will be combined through simple averaging to make an overall prediction. Bagging can reduce variance and improve stability because it trains on multiple different models with different subsets of data. However, this leads to an increased computation because requires training of multiple models as well as not being useful for low variance models.



KStar

KStar is an instance-based classification model where it stores all the training data and makes predictions only when a new instance is classified. It makes decisions based on distances between new instances and the stored training data. Instances that are closer to the new instance have more influence and more weight on the final prediction. K star is good for complex distributions of data as well as categorical and continuous data. However, it is complex and may be slow for large datasets as well as being memory intensive because it saves all the training instances.



Part 7 - Results

Decision Table on cfsEVAL

=== Summary ===

Correctly Classified Instances	18343	88.7636 %
Incorrectly Classified Instances	2322	11.2364 %
Kappa statistic	0.8051	
Mean absolute error	0.074	
Root mean squared error	0.1876	
Relative absolute error	32.3704 %	
Root relative squared error	55.5117 %	
Total Number of Instances	20665	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.875	0.039	0.900	0.875	0.887	0.843	0.958	0.904	-1
	0.919	0.093	0.932	0.919	0.926	0.824	0.963	0.970	1
	0.856	0.034	0.694	0.856	0.766	0.748	0.960	0.747	2
	0.635	0.007	0.717	0.635	0.674	0.666	0.963	0.638	3
	0.639	0.007	0.645	0.639	0.642	0.635	0.962	0.631	4
Weighted Avg.	0.888	0.069	0.891	0.888	0.889	0.815	0.961	0.917	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
5199	459	182	52	47	a = -1
453	11046	415	51	53	b = 1
66	114	1458	38	27	c = 2
24	153	25	380	16	d = 3
37	79	22	9	260	e = 4

J48 on cfsEVAL

=== Summary ===

Correctly Classified Instances	18381	88.9475 %
Incorrectly Classified Instances	2284	11.0525 %
Kappa statistic	0.8059	
Mean absolute error	0.0686	
Root mean squared error	0.1879	
Relative absolute error	30.0186 %	
Root relative squared error	55.5871 %	
Total Number of Instances	20665	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.877	0.041	0.895	0.877	0.886	0.841	0.946	0.865	-1
	0.932	0.109	0.922	0.932	0.927	0.824	0.950	0.955	1
	0.776	0.023	0.754	0.776	0.765	0.743	0.943	0.743	2
	0.664	0.009	0.694	0.664	0.679	0.669	0.945	0.630	3
	0.636	0.006	0.673	0.636	0.654	0.648	0.917	0.533	4
Weighted Avg.	0.889	0.077	0.889	0.889	0.889	0.814	0.948	0.894	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
5208	471	148	59	53	a = -1
475	11195	244	65	39	b = 1
72	250	1322	39	20	c = 2
24	139	24	397	14	d = 3
38	82	16	12	259	e = 4

Bagging on cfsEVAL

=== Summary ===

Correctly Classified Instances	6228	88.6422 %
Incorrectly Classified Instances	798	11.3578 %
Kappa statistic	0.8027	
Mean absolute error	0.0694	
Root mean squared error	0.1877	
Relative absolute error	30.3482 %	
Root relative squared error	55.4338 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.882	0.046	0.886	0.882	0.884	0.837	0.957	0.903	-1
	0.921	0.097	0.929	0.921	0.925	0.822	0.962	0.974	1
	0.812	0.026	0.736	0.812	0.772	0.752	0.956	0.759	2
	0.675	0.010	0.662	0.675	0.668	0.659	0.944	0.667	3
	0.594	0.006	0.676	0.594	0.632	0.626	0.953	0.656	4
Weighted Avg.	0.886	0.072	0.887	0.886	0.887	0.812	0.959	0.920	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1787	142	54	24	20	a = -1
179	3749	99	30	14	b = 1
25	64	465	12	7	c = 2
14	41	7	135	3	d = 3
12	41	7	3	92	e = 4

KStar on cfsEVAL

=== Summary ===

Correctly Classified Instances	6044	86.0233 %
Incorrectly Classified Instances	982	13.9767 %
Kappa statistic	0.7409	
Mean absolute error	0.1013	
Root mean squared error	0.2096	
Relative absolute error	44.2851 %	
Root relative squared error	61.8989 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.858	0.044	0.889	0.858	0.873	0.823	0.961	0.907	-1
	0.956	0.224	0.854	0.956	0.902	0.756	0.965	0.977	1
	0.503	0.011	0.809	0.503	0.620	0.614	0.960	0.736	2
	0.370	0.003	0.763	0.370	0.498	0.523	0.966	0.597	3
	0.335	0.001	0.839	0.335	0.479	0.525	0.956	0.600	4
Weighted Avg.	0.860	0.144	0.858	0.860	0.850	0.752	0.963	0.918	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1740	251	27	6	3	a = -1
149	3890	26	5	1	b = 1
31	244	288	6	4	c = 2
18	101	5	74	2	d = 3
20	67	10	6	52	e = 4

Decision Table on reliefEVAL

=== Summary ===

Correctly Classified Instances	6186	88.0444 %
Incorrectly Classified Instances	840	11.9556 %
Kappa statistic	0.7935	
Mean absolute error	0.0757	
Root mean squared error	0.1913	
Relative absolute error	33.1173 %	
Root relative squared error	56.5101 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.881	0.049	0.879	0.881	0.880	0.831	0.958	0.894	-1
	0.910	0.093	0.931	0.910	0.921	0.814	0.958	0.966	1
	0.864	0.033	0.698	0.864	0.772	0.755	0.959	0.739	2
	0.570	0.008	0.671	0.570	0.616	0.608	0.964	0.601	3
	0.555	0.007	0.632	0.555	0.591	0.584	0.968	0.521	4
Weighted Avg.	0.880	0.071	0.883	0.880	0.881	0.803	0.958	0.906	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1785	139	60	20	23	a = -1
183	3706	142	24	16	b = 1
27	33	495	9	9	c = 2
20	57	7	114	2	d = 3
15	46	5	3	86	e = 4

J48 on reliefEVAL

=== Summary ===

Correctly Classified Instances	6184	88.0159 %
Incorrectly Classified Instances	842	11.9841 %
Kappa statistic	0.7932	
Mean absolute error	0.0757	
Root mean squared error	0.1939	
Relative absolute error	33.0887 %	
Root relative squared error	57.2844 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.875	0.045	0.887	0.875	0.881	0.833	0.950	0.867	-1
	0.911	0.094	0.930	0.911	0.921	0.814	0.946	0.950	1
	0.866	0.034	0.694	0.866	0.770	0.753	0.943	0.640	2
	0.570	0.008	0.671	0.570	0.616	0.608	0.941	0.598	3
	0.587	0.009	0.595	0.587	0.591	0.582	0.952	0.516	4
Weighted Avg.	0.880	0.071	0.884	0.880	0.881	0.804	0.947	0.881	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1773	139	65	20	30	a = -1
175	3710	142	24	20	b = 1
25	33	496	9	10	c = 2
19	58	7	114	2	d = 3
8	48	5	3	91	e = 4

Bagging on reliefEVAL

=== Summary ===

Correctly Classified Instances	6058	86.2226 %
Incorrectly Classified Instances	968	13.7774 %
Kappa statistic	0.7613	
Mean absolute error	0.0782	
Root mean squared error	0.204	
Relative absolute error	34.2046 %	
Root relative squared error	60.2582 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.872	0.053	0.871	0.872	0.871	0.819	0.945	0.871	-1
	0.901	0.115	0.915	0.901	0.908	0.783	0.942	0.954	1
	0.815	0.033	0.687	0.815	0.745	0.724	0.916	0.656	2
	0.550	0.011	0.591	0.550	0.570	0.558	0.937	0.520	3
	0.303	0.011	0.385	0.303	0.339	0.329	0.924	0.347	4
Weighted Avg.	0.862	0.085	0.863	0.862	0.862	0.772	0.940	0.880	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1768	139	63	26	31	a = -1
192	3666	136	40	37	b = 1
30	61	467	8	7	c = 2
22	62	6	110	0	d = 3
19	79	8	2	47	e = 4

KStar on reliefEVAL

=== Summary ===

Correctly Classified Instances	5316	75.6618 %
Incorrectly Classified Instances	1710	24.3382 %
Kappa statistic	0.5398	
Mean absolute error	0.1212	
Root mean squared error	0.2675	
Relative absolute error	52.979 %	
Root relative squared error	79.0162 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.675	0.089	0.755	0.675	0.713	0.607	0.886	0.767	-1
	0.915	0.350	0.783	0.915	0.844	0.597	0.892	0.904	1
	0.316	0.021	0.569	0.316	0.406	0.388	0.856	0.418	2
	0.140	0.008	0.337	0.140	0.198	0.203	0.832	0.206	3
	0.077	0.006	0.231	0.077	0.116	0.123	0.802	0.151	4
Weighted Avg.	0.757	0.230	0.733	0.757	0.736	0.561	0.884	0.789	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1369	570	47	25	16	a = -1
257	3726	62	13	13	b = 1
95	275	181	14	8	c = 2
49	109	11	28	3	d = 3
43	80	17	3	12	e = 4

Decision Table on corrEVAL

=== Summary ===

Correctly Classified Instances	6029	85.8098 %
Incorrectly Classified Instances	997	14.1902 %
Kappa statistic	0.7693	
Mean absolute error	0.1029	
Root mean squared error	0.2275	
Relative absolute error	39.8257 %	
Root relative squared error	63.1198 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.906	0.056	0.860	0.906	0.882	0.837	0.924	0.811	-1
	0.973	0.172	0.854	0.973	0.910	0.812	0.901	0.847	1
	0.694	0.012	0.866	0.694	0.770	0.753	0.843	0.646	2
	0.441	0.004	0.870	0.441	0.585	0.605	0.705	0.429	3
	0.331	0.002	0.897	0.331	0.483	0.530	0.669	0.353	4
Weighted Avg.	0.858	0.104	0.860	0.858	0.844	0.784	0.876	0.763	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1743	151	19	7	4	a = -1
65	3477	19	7	4	b = 1
65	142	496	7	5	c = 2
58	142	18	174	3	d = 3
96	159	21	5	139	e = 4

J48 on corrEVAL

=== Summary ===

Correctly Classified Instances	6029	85.8098 %
Incorrectly Classified Instances	997	14.1902 %
Kappa statistic	0.7693	
Mean absolute error	0.1025	
Root mean squared error	0.2275	
Relative absolute error	39.6781 %	
Root relative squared error	63.1127 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.906	0.056	0.860	0.906	0.882	0.837	0.924	0.810	-1
	0.973	0.172	0.854	0.973	0.910	0.812	0.901	0.846	1
	0.694	0.012	0.866	0.694	0.770	0.753	0.843	0.646	2
	0.441	0.004	0.870	0.441	0.585	0.605	0.705	0.429	3
	0.331	0.002	0.897	0.331	0.483	0.530	0.669	0.353	4
Weighted Avg.	0.858	0.104	0.860	0.858	0.844	0.784	0.876	0.763	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1743	151	19	7	4	a = -1
65	3477	19	7	4	b = 1
65	142	496	7	5	c = 2
58	142	18	174	3	d = 3
96	159	21	5	139	e = 4

Bagging on corrEVAL

=== Summary ===

Correctly Classified Instances	6029	85.8098 %
Incorrectly Classified Instances	997	14.1902 %
Kappa statistic	0.7693	
Mean absolute error	0.1025	
Root mean squared error	0.2286	
Relative absolute error	39.6624 %	
Root relative squared error	63.4071 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.906	0.056	0.860	0.906	0.882	0.837	0.925	0.813	-1
	0.973	0.172	0.854	0.973	0.910	0.812	0.902	0.849	1
	0.692	0.012	0.867	0.692	0.770	0.753	0.838	0.650	2
	0.441	0.004	0.870	0.441	0.585	0.605	0.721	0.463	3
	0.333	0.003	0.892	0.333	0.485	0.531	0.665	0.387	4
Weighted Avg.	0.858	0.104	0.860	0.858	0.844	0.784	0.877	0.770	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1743	151	19	7	4	a = -1
65	3477	19	7	4	b = 1
65	142	495	7	6	c = 2
58	142	18	174	3	d = 3
96	159	20	5	140	e = 4

KStar on corrEVAL

=== Summary ===

Correctly Classified Instances	5783	82.3086 %
Incorrectly Classified Instances	1243	17.6914 %
Kappa statistic	0.7058	
Mean absolute error	0.1419	
Root mean squared error	0.2546	
Relative absolute error	54.9056 %	
Root relative squared error	70.6392 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.903	0.062	0.846	0.903	0.874	0.825	0.921	0.809	-1
	0.974	0.234	0.811	0.974	0.885	0.758	0.902	0.855	1
	0.533	0.013	0.819	0.533	0.646	0.632	0.844	0.636	2
	0.266	0.003	0.861	0.266	0.406	0.464	0.722	0.410	3
	0.195	0.003	0.820	0.195	0.315	0.385	0.651	0.312	4
Weighted Avg.	0.823	0.138	0.825	0.823	0.797	0.725	0.876	0.762	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1737	162	17	6	2	a = -1
68	3478	17	7	2	b = 1
71	257	381	2	4	c = 2
66	196	18	105	10	d = 3
111	193	32	2	82	e = 4

Decision Table on gainEVAL

=== Summary ===

Correctly Classified Instances	6232	88.6991 %
Incorrectly Classified Instances	794	11.3009 %
Kappa statistic	0.8028	
Mean absolute error	0.0745	
Root mean squared error	0.1887	
Relative absolute error	32.5629 %	
Root relative squared error	55.7469 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.871	0.036	0.907	0.871	0.889	0.845	0.957	0.885	-1
	0.923	0.114	0.918	0.923	0.921	0.811	0.959	0.962	1
	0.866	0.033	0.697	0.866	0.772	0.755	0.961	0.732	2
	0.555	0.004	0.799	0.555	0.655	0.658	0.969	0.628	3
	0.645	0.005	0.758	0.645	0.697	0.693	0.960	0.640	4
Weighted Avg.	0.887	0.079	0.890	0.887	0.887	0.809	0.959	0.904	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1766	179	62	8	12	a = -1
152	3759	142	10	8	b = 1
19	40	496	8	10	c = 2
7	73	7	111	2	d = 3
4	44	5	2	100	e = 4

J48 on gainEVAL

=== Summary ===

Correctly Classified Instances	6029	85.8098 %
Incorrectly Classified Instances	997	14.1902 %
Kappa statistic	0.7693	
Mean absolute error	0.1025	
Root mean squared error	0.2275	
Relative absolute error	39.6781 %	
Root relative squared error	63.1127 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.906	0.056	0.860	0.906	0.882	0.837	0.924	0.810	-1
	0.973	0.172	0.854	0.973	0.910	0.812	0.901	0.846	1
	0.694	0.012	0.866	0.694	0.770	0.753	0.843	0.646	2
	0.441	0.004	0.870	0.441	0.585	0.605	0.705	0.429	3
	0.331	0.002	0.897	0.331	0.483	0.530	0.669	0.353	4
Weighted Avg.	0.858	0.104	0.860	0.858	0.844	0.784	0.876	0.763	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1743	151	19	7	4	a = -1
65	3477	19	7	4	b = 1
65	142	496	7	5	c = 2
58	142	18	174	3	d = 3
96	159	21	5	139	e = 4

Bagging on gainEVAL**=== Summary ===**

Correctly Classified Instances	6029	85.8098 %
Incorrectly Classified Instances	997	14.1902 %
Kappa statistic	0.7693	
Mean absolute error	0.1025	
Root mean squared error	0.2286	
Relative absolute error	39.6624 %	
Root relative squared error	63.4071 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.906	0.056	0.860	0.906	0.882	0.837	0.925	0.813	-1
	0.973	0.172	0.854	0.973	0.910	0.812	0.902	0.849	1
	0.692	0.012	0.867	0.692	0.770	0.753	0.838	0.650	2
	0.441	0.004	0.870	0.441	0.585	0.605	0.721	0.463	3
	0.333	0.003	0.892	0.333	0.485	0.531	0.665	0.387	4
Weighted Avg.	0.858	0.104	0.860	0.858	0.844	0.784	0.877	0.770	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1743	151	19	7	4	a = -1
65	3477	19	7	4	b = 1
65	142	495	7	6	c = 2
58	142	18	174	3	d = 3
96	159	20	5	140	e = 4

KStar on gainEVAL**=== Summary ===**

Correctly Classified Instances	5999	85.3829 %
Incorrectly Classified Instances	1027	14.6171 %
Kappa statistic	0.7241	
Mean absolute error	0.1051	
Root mean squared error	0.2099	
Relative absolute error	45.9521 %	
Root relative squared error	62.0032 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.873	0.038	0.902	0.873	0.887	0.843	0.959	0.899	-1
	0.959	0.264	0.833	0.959	0.892	0.727	0.959	0.962	1
	0.405	0.005	0.885	0.405	0.556	0.578	0.959	0.752	2
	0.275	0.002	0.809	0.275	0.410	0.464	0.968	0.569	3
	0.252	0.002	0.765	0.252	0.379	0.432	0.954	0.595	4
Weighted Avg.	0.854	0.164	0.855	0.854	0.838	0.735	0.959	0.908	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1770	239	10	3	5	a = -1
153	3903	12	2	1	b = 1
20	313	232	4	4	c = 2
8	133	2	55	2	d = 3
11	95	6	4	39	e = 4

Decision Table on symmEVAL

=== Summary ===

Correctly Classified Instances	6248	88.9268 %
Incorrectly Classified Instances	778	11.0732 %
Kappa statistic	0.806	
Mean absolute error	0.0759	
Root mean squared error	0.1883	
Relative absolute error	33.1669 %	
Root relative squared error	55.6112 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.875	0.045	0.888	0.875	0.881	0.834	0.960	0.905	-1
	0.932	0.107	0.923	0.932	0.928	0.827	0.964	0.972	1
	0.806	0.022	0.765	0.806	0.785	0.766	0.965	0.782	2
	0.620	0.008	0.705	0.620	0.660	0.652	0.966	0.634	3
	0.606	0.007	0.676	0.606	0.639	0.633	0.970	0.615	4
Weighted Avg.	0.889	0.077	0.889	0.889	0.889	0.815	0.963	0.920	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1773	163	49	20	22	a = -1
167	3795	83	16	10	b = 1
25	63	462	13	10	c = 2
20	46	7	124	3	d = 3
11	44	3	3	94	e = 4

J48 on symmEVAL

=== Summary ===

Correctly Classified Instances	6286	89.4677 %
Incorrectly Classified Instances	740	10.5323 %
Kappa statistic	0.817	
Mean absolute error	0.0677	
Root mean squared error	0.1853	
Relative absolute error	29.6203 %	
Root relative squared error	54.7355 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.874	0.039	0.900	0.874	0.887	0.842	0.951	0.874	-1
	0.931	0.092	0.933	0.931	0.932	0.839	0.952	0.956	1
	0.815	0.024	0.750	0.815	0.781	0.761	0.948	0.722	2
	0.725	0.009	0.704	0.725	0.714	0.706	0.943	0.670	3
	0.723	0.008	0.675	0.723	0.698	0.691	0.934	0.662	4
Weighted Avg.	0.895	0.067	0.896	0.895	0.895	0.826	0.951	0.899	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1772	152	54	23	26	a = -1
160	3790	86	23	12	b = 1
19	61	467	13	13	c = 2
9	35	8	145	3	d = 3
9	24	8	2	112	e = 4

Bagging on symmEVAL

=== Summary ===

Correctly Classified Instances	6058	86.2226 %
Incorrectly Classified Instances	968	13.7774 %
Kappa statistic	0.7613	
Mean absolute error	0.0782	
Root mean squared error	0.204	
Relative absolute error	34.2046 %	
Root relative squared error	60.2582 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.872	0.053	0.871	0.872	0.871	0.819	0.945	0.871	-1
	0.901	0.115	0.915	0.901	0.908	0.783	0.942	0.954	1
	0.815	0.033	0.687	0.815	0.745	0.724	0.916	0.656	2
	0.550	0.011	0.591	0.550	0.570	0.558	0.937	0.520	3
	0.303	0.011	0.385	0.303	0.339	0.329	0.924	0.347	4
Weighted Avg.	0.862	0.085	0.863	0.862	0.862	0.772	0.940	0.880	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1768	139	63	26	31	a = -1
192	3666	136	40	37	b = 1
30	61	467	8	7	c = 2
22	62	6	110	0	d = 3
19	79	8	2	47	e = 4

KStar on symmEVAL

=== Summary ===

Correctly Classified Instances	6004	85.454 %
Incorrectly Classified Instances	1022	14.546 %
Kappa statistic	0.7291	
Mean absolute error	0.0974	
Root mean squared error	0.2087	
Relative absolute error	42.599 %	
Root relative squared error	61.6362 %	
Total Number of Instances	7026	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.811	0.044	0.882	0.811	0.845	0.787	0.962	0.914	-1
	0.965	0.238	0.848	0.965	0.903	0.757	0.970	0.979	1
	0.510	0.010	0.825	0.510	0.630	0.626	0.963	0.745	2
	0.395	0.004	0.767	0.395	0.521	0.542	0.966	0.606	3
	0.394	0.002	0.803	0.394	0.528	0.556	0.963	0.598	4
Weighted Avg.	0.855	0.151	0.853	0.855	0.845	0.745	0.967	0.922	

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1644	348	26	6	3	a = -1
122	3928	18	1	2	b = 1
47	220	292	9	5	c = 2
28	81	7	79	5	d = 3
22	53	11	8	61	e = 4

Part 8 - Analysis

Summary of all the accuracies

	Model Type				
Attribute Group	Decision Table	J48	Bagging	KStar	Averages
cfsEVAL	88.7636	88.9475	88.6422	86.0233	88.09415
reliefEVAL	88.0444	88.0159	86.2226	75.6618	84.486175
corrEVAL	85.8098	86.4098	85.8098	82.3086	85.0845
gainEVAL	88.6991	85.8098	85.8098	85.3829	86.4254
symmEVAL	88.9268	89.4677	86.2226	85.454	87.517775
Averages	88.04874	87.73014	86.5414	82.96612	

This suggests that the Decision Table model is best for this classification task. Additionally, the cfsEVAL attribute group was the best performing subgroup of attributes, suggesting that it captured the output group well. However, the difference between the Decision Table and J48 models' as well as cfsEVAL and symmEVAL groups' averages is minimal, so there needs to be a deeper look into other metrics. One such metric we can look at is the available error scores (mean absolute error, root mean squared error, relative absolute error, and root relative squared error).

Across these scores, **J48 with SymmetricUncertAttributeEval** had the lowest error outputs. This gives confidence that in future datasets, this model will be able to run with similar precision, recall, and accuracy as demonstrated in this test. In other words, the likelihood of false classifications will be small.

The main goal of this study was to identify which socioeconomic factors play a large role in determining the severity of one's mental health status. One way to look at this is by iterating through the branches of the J48 tree generated, however that only considers the values in this specific model. To get a more thorough understanding of selected attributes, we can look at the attribute groups:

cfsEVAL	reliefEVAL	corrEVAL	gainEVAL	symmEVAL
DISAB3_A	HRTESTLAST_A	SOCSCLPAR_A	MHTHND_A	FAM_A
MLTFAMFLG_A	EMPDYSMSS3_A	COGMEMDFF_A	MHTHDLY_A	WTFA_A
EVRMARRIED_A	URBRRL	LSATIS4_A	SOCSCLPAR_A	MHTHND_A
SMKNOW_A	REGION	PHSTAT_A	TBIHLSBMC_A	MHTHDLY_A

PAITOOOTH3M_A	PSTRAT	SOCERRNDS_A	WTFA_A	SOCSCLPAR_A
VIGIL4_A	LONGCOVD1_A	DISCRIM5_A	TBILCDCMG_A	VIGIL4_A
DISCRIM5_A	VIGIL4_A	VIGIL4_A	HOMEHC12M_A	LSATIS4_A
MHTHND_A	SMKNOW_A	MHTHDLY_A	RXDG12M_A	DISCRIM3_A
MHTHDLY_A	INTV_QRT	MHTHND_A	MEDNG12M_A	COGMEMDFF_A
HYSTEV	VIGIL3_A		MEDDL12M_A	DISCRIM5_A
				VIGIL1_A

There are some overlaps within each group, such as MHTHND_A and MHTHDLY_A. To get a better understanding, each attribute is defined below.

Attribute	Description
DISAB3_A	The Washington Group Short Set Composite Disability Indicator
MLTFAMFLG_A	Indicator for multifamily households
EVRMARRIED_A	Sample adult has ever been married
SMKNOW_A	Now smoke cigarettes
PAITOOOTH3M_A	Toothache or jaw pain
VIGIL4_A	Avoid certain situations and places
DISCRIM5_A	You are threatened or harassed
MHTHND_A	Needed counseling, therapy but did not get it due to cost, past 12 months
MHTHDLY_A	Delayed counseling, therapy due to cost, past 12 months
HRTESTLAST_A	A How long since hearing test
EMPDYSMSS3_A	Days missed work, past 12 months (top-coded)
URBRRL	2013 NCHS Urban-Rural Classification Scheme for Counties
LONGCOVD1_A	Had COVID-19 symptoms for 3 or more months
SMKNOW_A	Now smoke cigarettes
VIGIL3_A	Watch what you say and how you say it

SOCSCLPAR_A	Language socially
COGMEMDFF_A	Difficulty remembering/concentrating
PHSTAT_A	General health status
SOCERRNDS_A	Difficulty doing errands alone
TBIHLSBMC_A	Headache, sensitivities, balance problems or mood change, past 12 months
WTFA_A	Weight - Final Annual
TBILCDCMG_A	A Lost consciousness, dazed or confused, or had gap in memory, past 12 months
HOMEHC12M_A	Received care at home, past 12 months
RXDG12M_A	Needed prescription medication but did not get it due to cost, past 12 months
MEDNG12M_A	Needed medical care but did not get it due to cost, past 12 months
MEDDL12M_A	Delayed medical care due to cost, past 12 months
VIGIL1_A	Prepare for possible insults before leaving home
FAM_A	Number of Emergency Contacts

In general, it can be seen that these attributes fall in 1 of 4 main categories:

→ General Health:

- ◆ Have been smoking in past
- ◆ Annual Weight
- ◆ Disabled

→ Personality Specifics:

- ◆ Prepares for insults when leaving home
- ◆ Difficulty doing errands alone

→ Delay of Medical attention due to cost

- ◆ Needed therapy, but couldn't get it due to cost
- ◆ Delayed medical care due to cost

→ Family Structure

- ◆ Married to someone else
- ◆ Received care at home
- ◆ Lives in a multifamily household

◆ Lives in urban/suburban/rural area

There are additionally some other attributes that don't fall in this category, such as having COVID-19 for three or more months and days missed at work for the past 12 months. This data is pulled from the 2023 survey, a time where the effects of COVID-19 still played some role. This could have created a potential bias towards these values being significant since they were of relevance at the time. A future study utilizing data from a more recent study would be better able to tell if the impact of the COVID-19 pandemic still plays a role in the severity of Mental Health. Both of these attributes are NOT present in the SymmetricUncertAttributeEval attribute group, meaning that the final model selected doesn't include these attributes. This independence means that it can be more generalizable to years without inherent COVID-19 impact, however external testing is needed to validate that claim.

In general, these attributes suggest that health, financial status, family support, and internal thoughts contribute to the severity of mental health. Three of these can be assessed in a non-psychological setting. For example, when a new patient is admitted, a hospital can check what outside family support the individual has, their general health, and how long they waited to come. Using these, hospitals can make recommendations as to sending an individual for a psych eval, ensuring more individuals receive the care they need. Even as mental health becomes a more widely accepted topic, there are many taboos associated with it and this information can help ensure that those who are most vulnerable have no barriers to support.

Part 9 - Conclusions/Steps for Reproduction

As stated above, the J48 model with Symmetric Uncertainty Attribute Evaluation Selection had the best results of the 20 runs for this project. We were successfully able to train and test a predictive classification model that predicted the severity of mental health onset for adult individuals and feel confident about our results. However, there is some potential bias due to the data coming from NIH's 2023 study, future projects should look into gathering more recent data to properly assess the potential impact of COVID-19 on severity. Future studies could also initially group attributes into subgroups based on relatedness, combining similar attributes to create a stronger model.

Steps to Reproduce Our Model: J48 model with Symmetric Uncertainty Attribute Evaluation Selection:

All csv files can be found in the project folder under "train/test/val files"

OPTIONAL:

1. Open Weka and load the adult23_train+test.csv in the zip file.
2. Under the Preprocess tab, click Filter → Choose → Filters → Unsupervised → Attribute
3. then select Numeric to Nominal
4. Click on the white space and ensure that all attributes are selected. Hit Apply.
5. Go to the "Select Attributes" tab and choose the correct class "engineered_attribute"
6. Select SymmetricUncertAttributeEval (Symmetric Uncertainty Attribute Evaluation)

- Selection) as the Attribute Evaluator, and Ranker as the Search Method
7. Hit Start and wait for the program to finish
 8. Take note of top 11 features; keep the index values for these features
 9. Go back to the Preprocess tab and click Filter → Choose → Filters → Unsupervised → Remove
 10. Click on the white space and paste in the selected attribute indexes, add in 321 as this is the class attribute
 11. Set invertSelection to be True
 12. Save and Click Apply
 13. Click on the Classify tab and click “Percentage Split” under Test Options, write 70%
 14. Select the J48 model under trees
 15. Click start and wait for it to complete

The final model can be found here:

<https://drive.google.com/file/d/10dGNMBCDxjRuOy1RWt79ywOtHUK64zLH/view?usp=sharing>

Part 10 - Teamwork Makes the Dreamwork

Medha:

- Finding Data
- Project Statement
- Initial Attribute visualization and understanding
- Engineered class variable in Python
- Running the 20 Models on Attribute Selection Groups
- Information on how Attribute Selection methods worked

Kade:

- Removed Unnecessary Attributes (involved going through 600+ attributes 3 times)
- Filling in Missing values from each attribute
- Generating Attribute Selection Groups
- Information on how Models worked
- Citing sources, proofreading paper

Part 11 - Sources and Citations

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