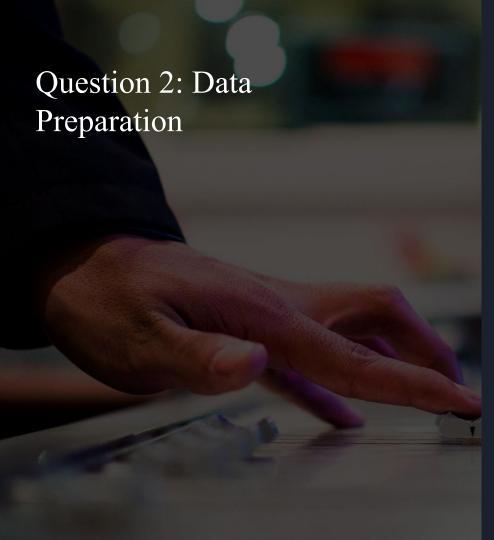
DS Practicum 3: Diabetes



Given a database consisting of profiles from patients from the CDC's research, we are to figure out patterns as to what engenders higher rates of diabetes based on correlation from attributes and fields taken from the data, such as financial status, education, general health as reported by the patient both physical and mental, with more to come. In order to do so, we must appropriately organize and sort the data, before doing exploratory analysis of its properties, visualizing the results to sift for patterns and trends, and present and defend any conclusions which may come of it.



Field Alterations

Checking for Abnormal Values

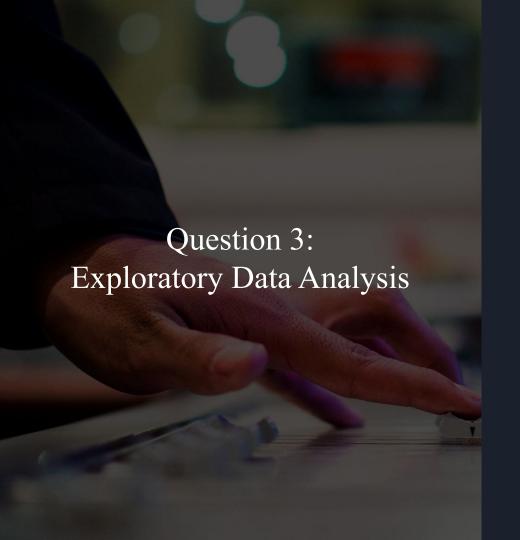
Field Alterations

```
Data columns (total 22 columns):
     Column
                          Non-Null Count
                                           Dtype
                          253680 non-null float64
    Diabetes 012
    HighBP
                          253680 non-null float64
    HighChol
                          253680 non-null float64
    CholCheck
                          253680 non-null float64
     BMI
                          253680 non-null float64
     Smoker
                          253680 non-null float64
    Stroke
                          253680 non-null float64
    HeartDiseaseorAttack 253680 non-null float64
    PhysActivity
                          253680 non-null float64
     Fruits
                          253680 non-null float64
     Veggies
                          253680 non-null float64
    HvyAlcoholConsump
                          253680 non-null float64
     AnyHealthcare
                          253680 non-null float64
    NoDocbcCost
                          253680 non-null float64
    GenHlth
                          253680 non-null float64
    MentHlth
                          253680 non-null float64
     PhysHlth
                          253680 non-null float64
    DiffWalk
                          253680 non-null float64
    Sex
                          253680 non-null float64
    Age
                          253680 non-null float64
 19
    Education
                          253680 non-null float64
    Income
                          253680 non-null float64
dtypes: float64(22)
```

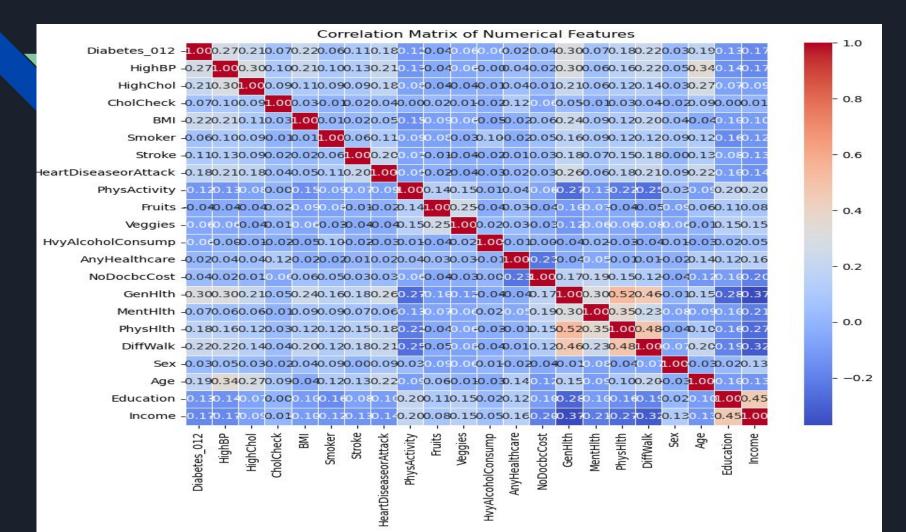
Data	columns (total 22 colu	umns):	
#	Column	Non-Null Count	Dtype
0	Diabetes_012	253680 non-null	int32
1	HighBP	253680 non-null	bool
2	HighChol	253680 non-null	bool
3	CholCheck	253680 non-null	bool
4	BMI	253680 non-null	int32
5	Smoker	253680 non-null	bool
6	Stroke	253680 non-null	bool
7	HeartDiseaseorAttack	253680 non-null	bool
8	PhysActivity	253680 non-null	bool
9	Fruits	253680 non-null	bool
10	Veggies	253680 non-null	bool
11	HvyAlcoholConsump	253680 non-null	bool
12	AnyHealthcare	253680 non-null	bool
13	NoDocbcCost	253680 non-null	bool
14	GenHlth	253680 non-null	int32
15	MentHlth	253680 non-null	int32
16	PhysHlth	253680 non-null	int32
17	DiffWalk	253680 non-null	bool
18	Sex	253680 non-null	bool
19	Age	253680 non-null	int32
20	Education	253680 non-null	int32
21	Income	253680 non-null	int32
	es: bool(14), int32(8) ry usage: 11.1 MB		

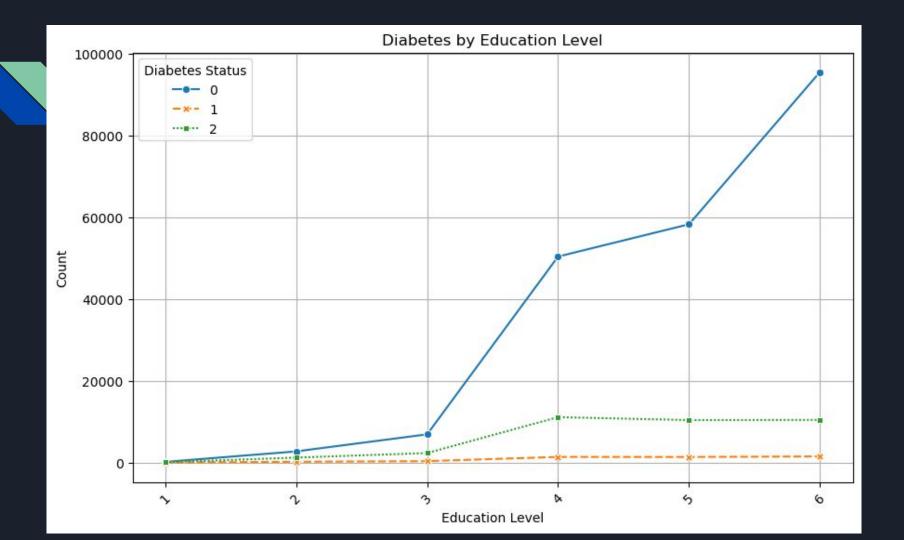
Checking for Abnormal Values

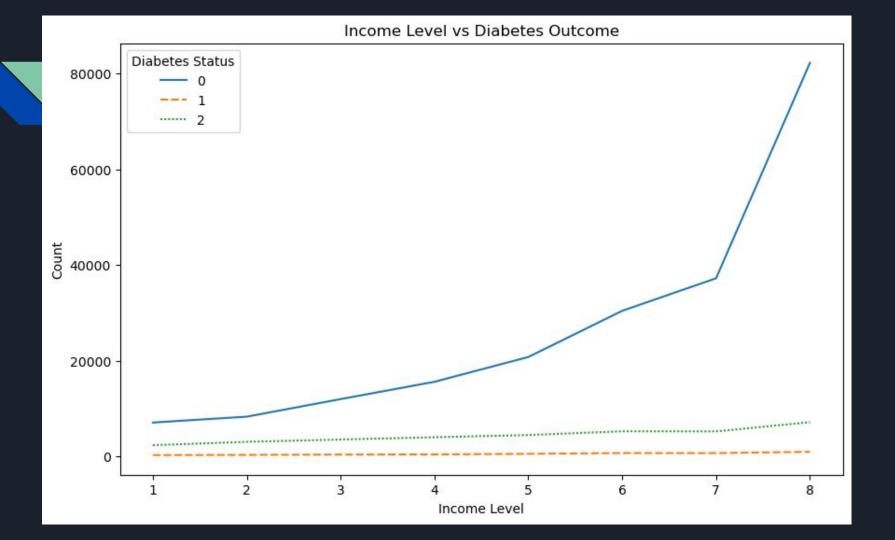
```
Max and Min of BMI:
Max: 98
Min: 12
Max and Min of MentHlth:
Max: 30
Min: 0
Max and Min of PhysHlth:
Max: 30
Min: 0
Max and Min of Age:
Max: 13
Min: 1
Max and Min of Income:
Max: 8
Min: 1
```

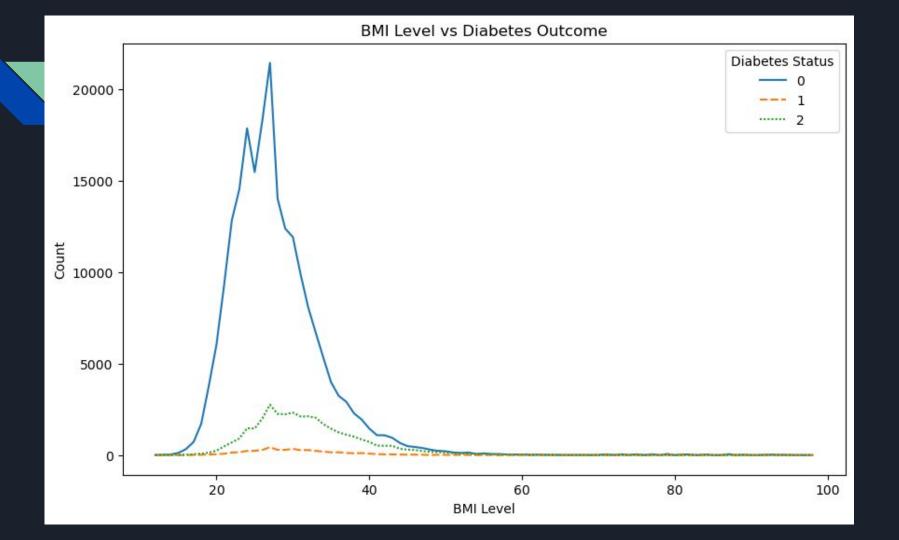


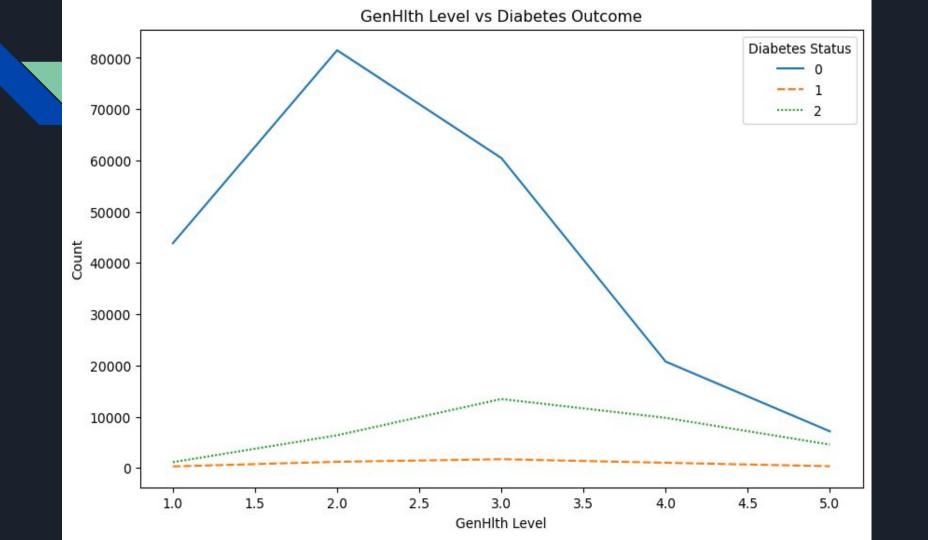
- . Correlation Matrix
- 2. Diabetes by Income
- 3. Diabetes by Education
- 4. Diabetes by BMI
- 5. Diabetes by GenHlth





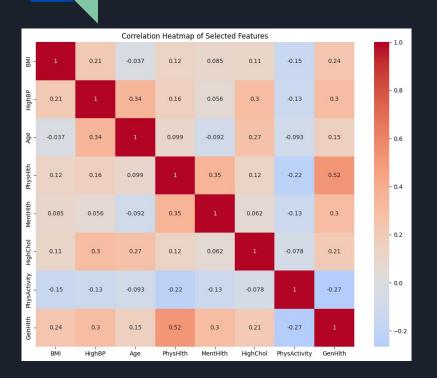








Perform significance tests to determine if the patterns that are detected above are statistically significant.



Three Significant Features Selected:

BMI and Diabetes

High Blood Pressure and Diabetes

Physical and Mental Health Correlation

Question 4 Bonus

Machine learning models can benefit greatly from feature engineering. Create a new feature that can be included in the model and perform significance testing to determine if it's statistically significant. Explain the results and justify if the feature will be included in the ML model. If you decide that you will not include the new feature in the ML model, explain the reasons.

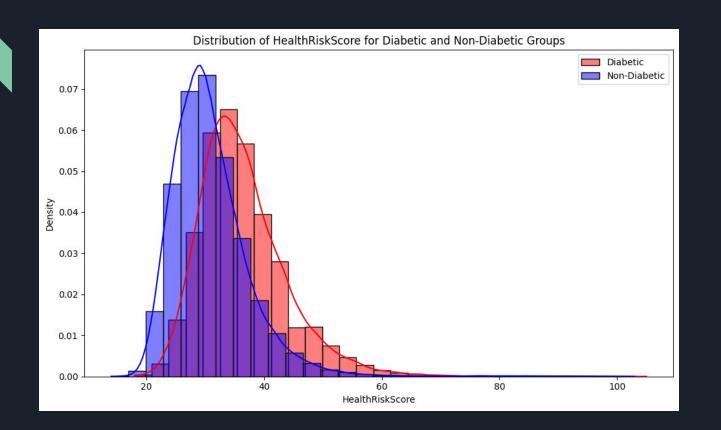
Question 6

Building the Models

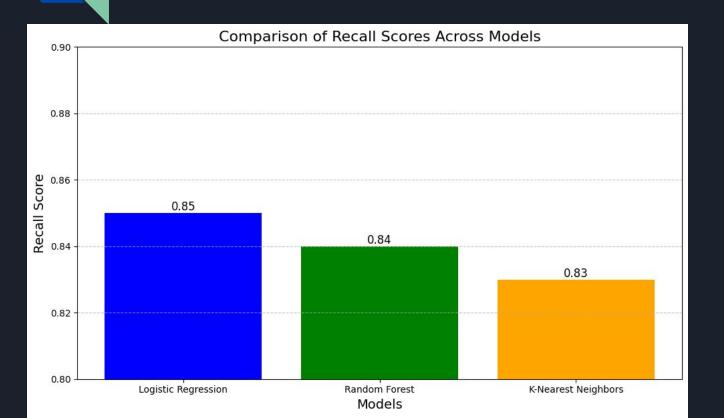
- Logistic Regression Model
- K-Nearest Neighbors (KNN)
- Random Forest Classifier

Model Results

- Even with the optimal parameters (n_neighbors=3, weights='distance'), the KNN Classifier struggled to balance precision and recall, as evidenced by its recall (39.54%) and F1-score (40.22%), despite its 81.22% accuracy.
- Despite having a similar recall (38.64%) and F1-score (39.65%), the Logistic Regression scored somewhat better in accuracy (84.75%), indicating that it might not adequately capture the underlying relationships between attributes and the multiclass target.
- The Random Forest Classifier was also a balanced model, with the best accuracy (85.26%) and demonstrating enhanced recall (42.15%) and F1-score (43.78%) with optimal settings (max_depth=20, n_estimators=50).

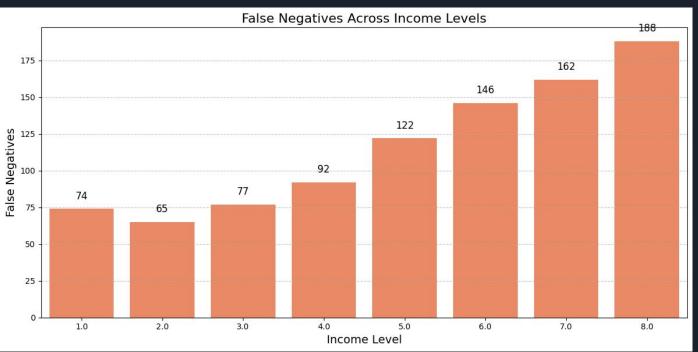


Question 7



- Random Forest Classifier -0.84
- K- Nearest
 Neighbors
 Classifier 0.83
- <u>Logistic</u> <u>Regression</u> -0.85

Question 8



- Income levels with fewer samples may have lower recall due to imbalanced representation.
- False negatives disproportionately affect lower-income groups, highlighting inequity in model predictions.