Census Analysis

A Tech Talent South Production

Powered by Conor and Owen

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1. Overview

What? Who? Why?

Hello!

We are Conor and Owen!

Aspiring Data Scientists hoping to bring some unique insights using historical Census Data

Objective

- Provide high-level analysis of the Census data set
- Predict if an individual's income is more or less than $50k/year

Data Overview

- Extracted from 1994 census bureau database
- 15 original data columns such as age, education, marital.status etc.
    - Transformed based on preliminary analysis (see Data Cleaning and Data Engineering slides)

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education.num   32561 non-null  int64 
 5   marital.status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital.gain    32561 non-null  int64 
 11  capital.loss    32561 non-null  int64 
 12  hours.per.week  32561 non-null  int64 
 13  native.country  32561 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	capital.loss	hours.per.week	native.country	income
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-family	White	Female	0	4356	40	United-States	<=50K
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Female	0	4356	18	United-States	<=50K
2	66	?	186061	Some-college	10	Widowed	?	Unmarried	Black	Female	0	4356	40	United-States	<=50K
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	White	Female	0	3900	40	United-States	<=50K
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-child	White	Female	0	3900	40	United-States	<=50K

2. Preliminary Analysis

Data Cleaning and Visualization

Data Cleaning

- "?" in 'workclass', 'occupation', and 'native.country' columns
  - Change to null values, then fill them with the mode (most commonly appearing value) for that column

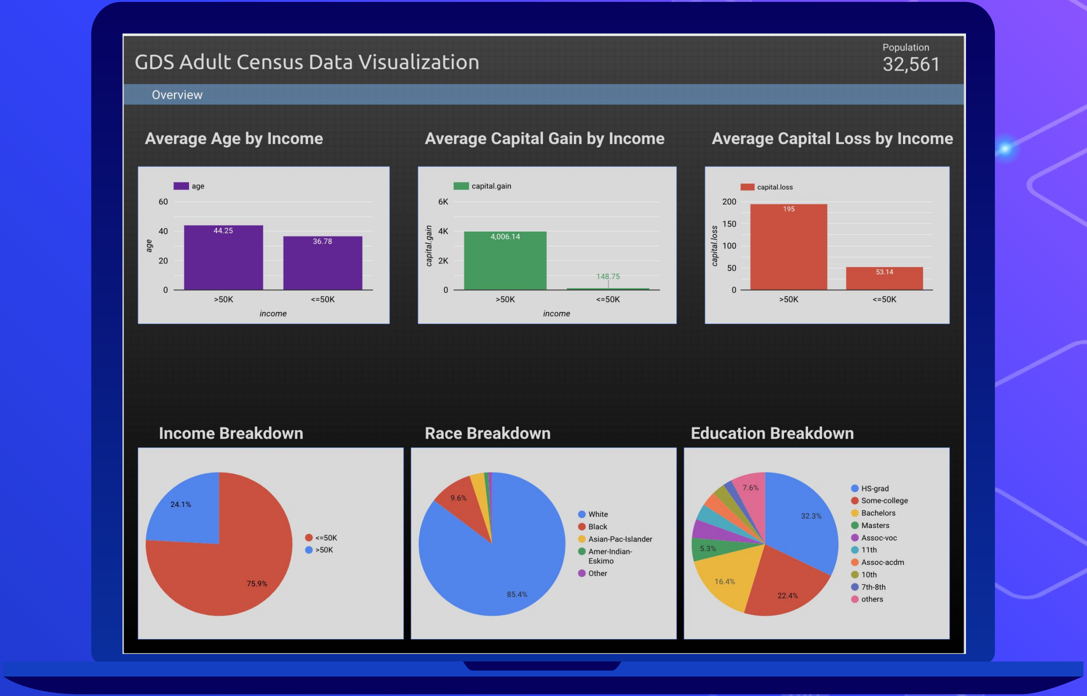
```
data[data == '?'] = np.nan
for column in ['workclass','occupation','native.country']:
    data[column].fillna(data[column].mode()[0], inplace=True)
```

- Income is a categorical variable
  - '<=50K' or '>50K'
- As the target variable, it needs to be numerical

```
#Replace the categorical variables with numerical variables
data['income'] = data['income'].replace({'<=50K':0, '>50K' :1})
```

Data Visualization

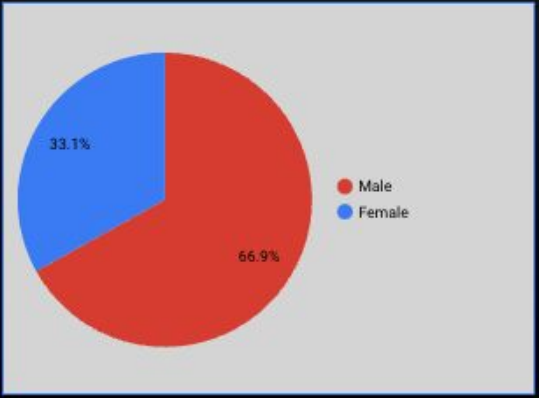
GDS Overview



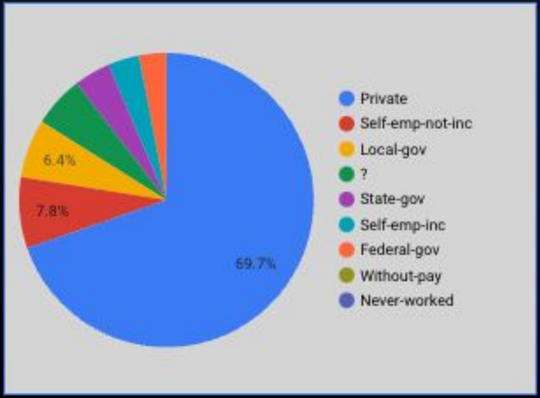
https://datastudio.google.com/reporting/3a9c195c-3a28-4a99-bda7-6acbfa4a068f

GDS Zoom In: Demographics

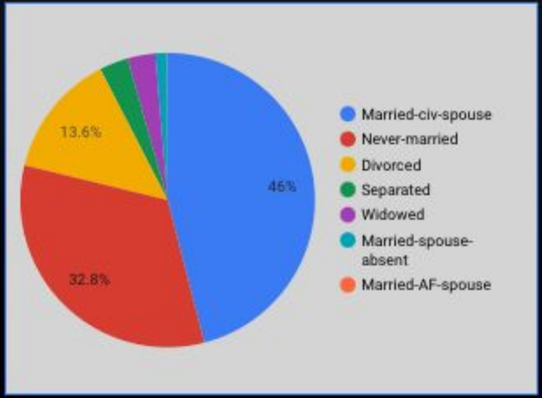
Sex Breakdown



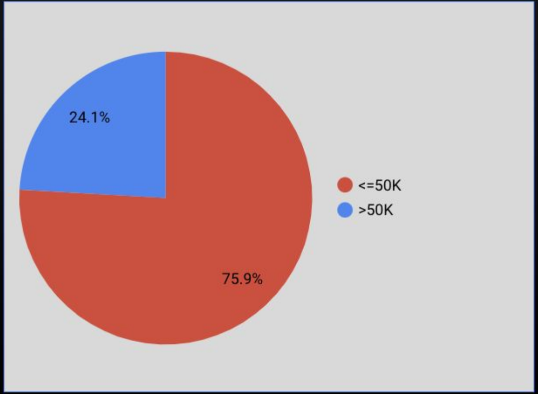
Employment Breakdown



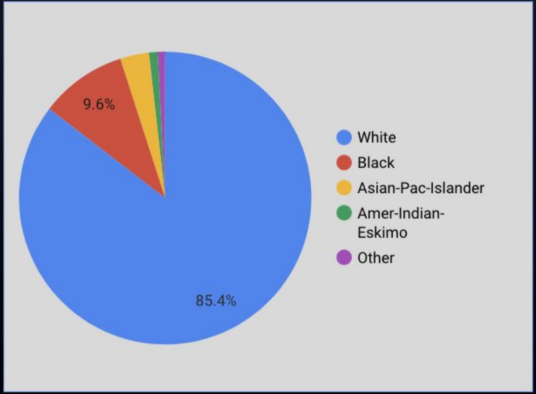
Marital Status



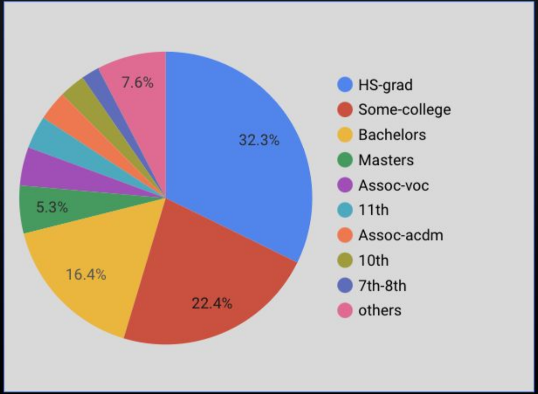
Income Breakdown



Race Breakdown

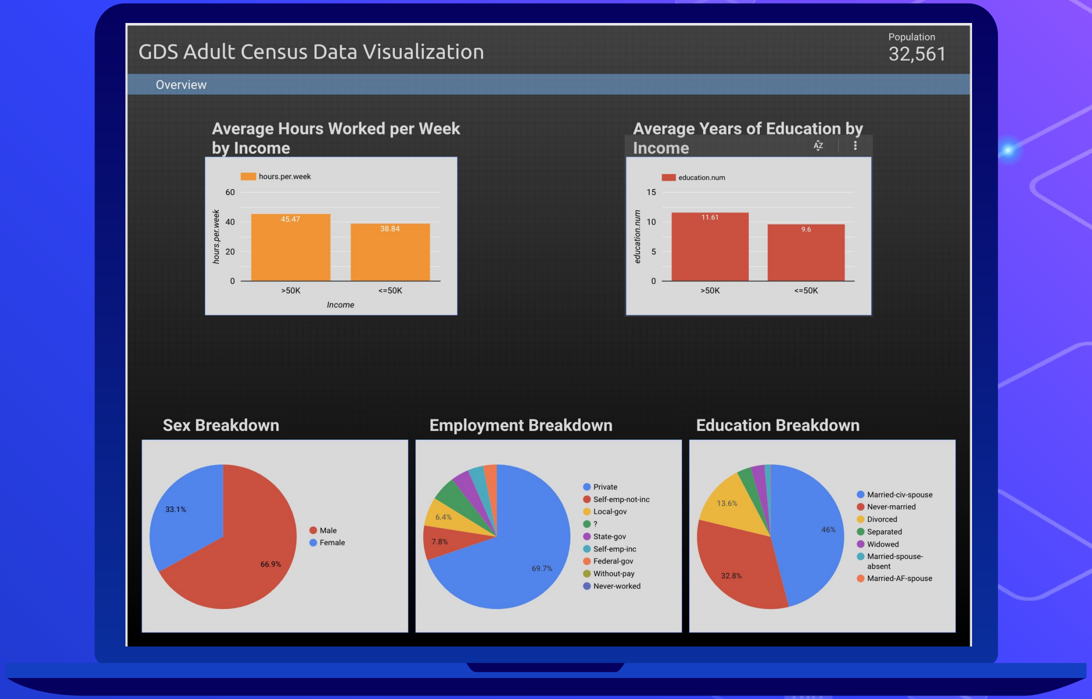


Education Breakdown



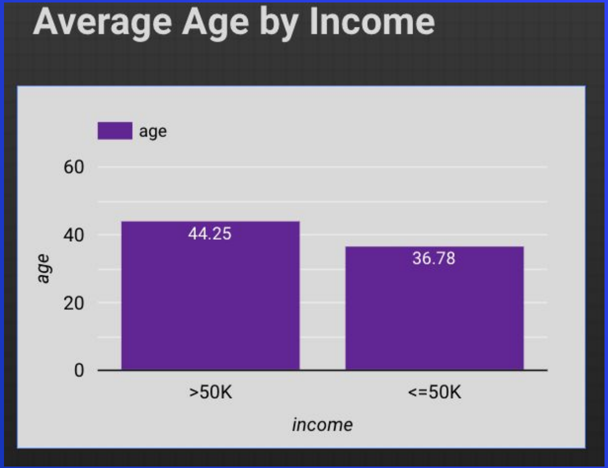
Data Visualization

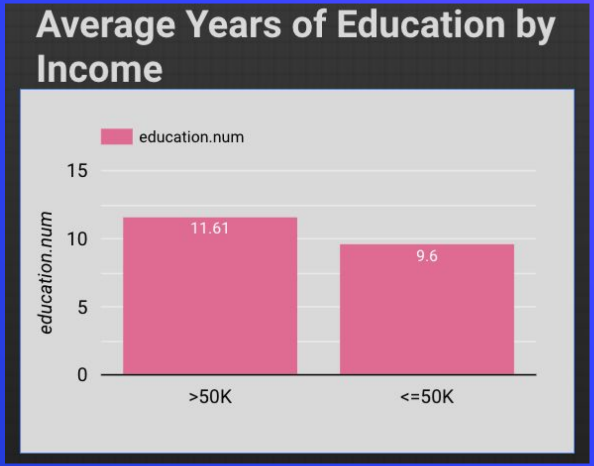
GDS
Overview 2

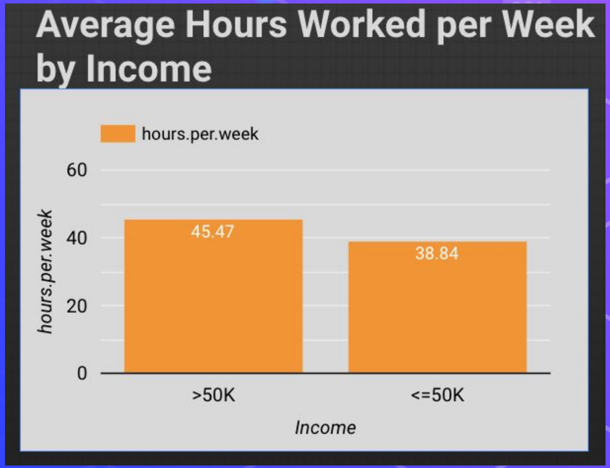


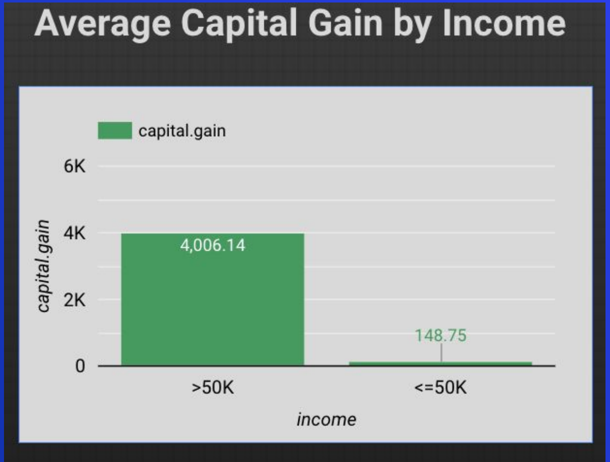
https://datastudio.google.com/reporting/3a9c195c-3a28-4a99-bda7-6acbfa4a068f

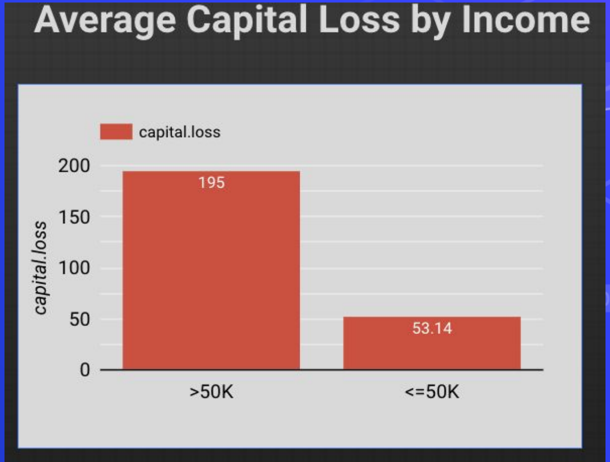
GDS Zoom In: Income







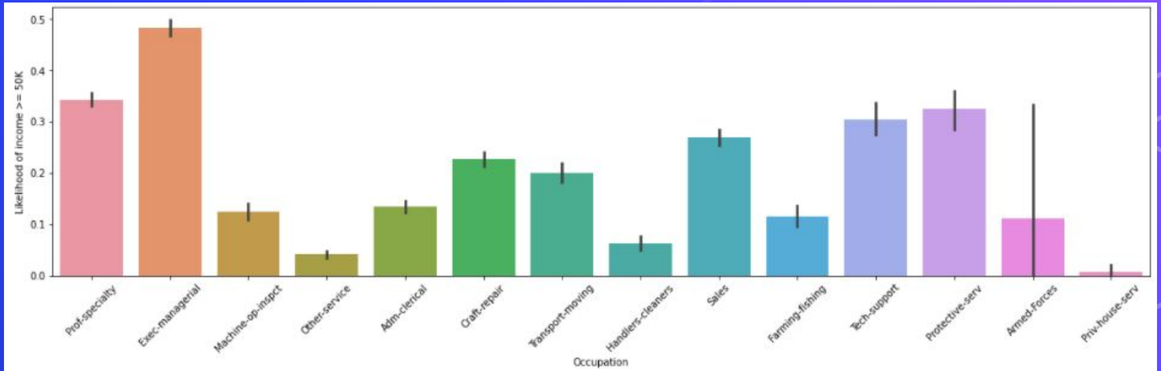


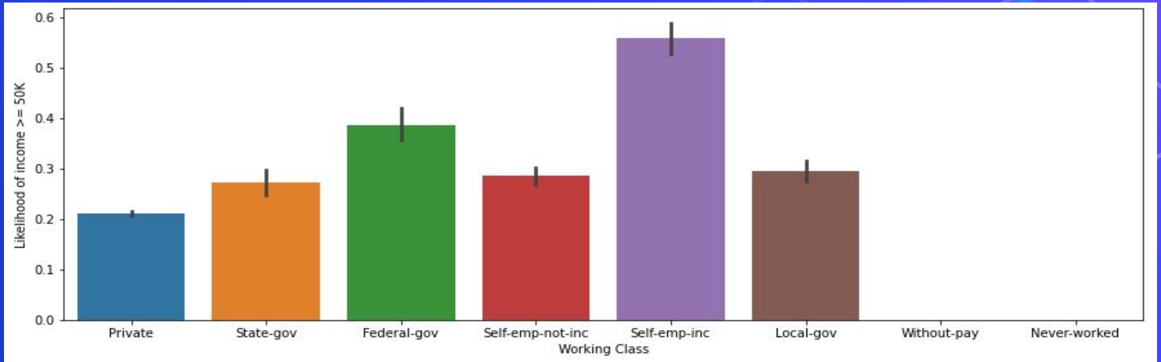


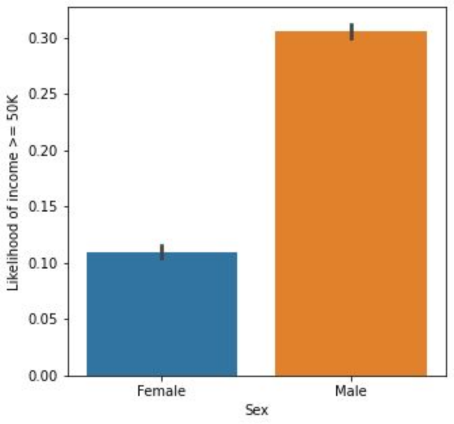
Visuals - Categorical part 1

- Occupation vs Workclass

- Sex

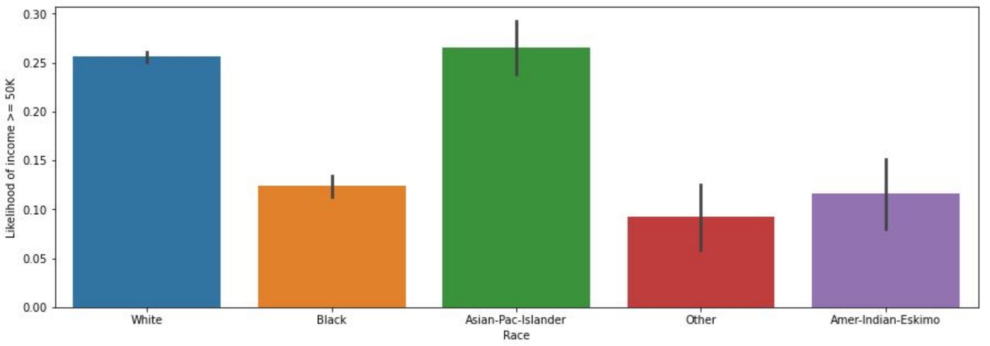




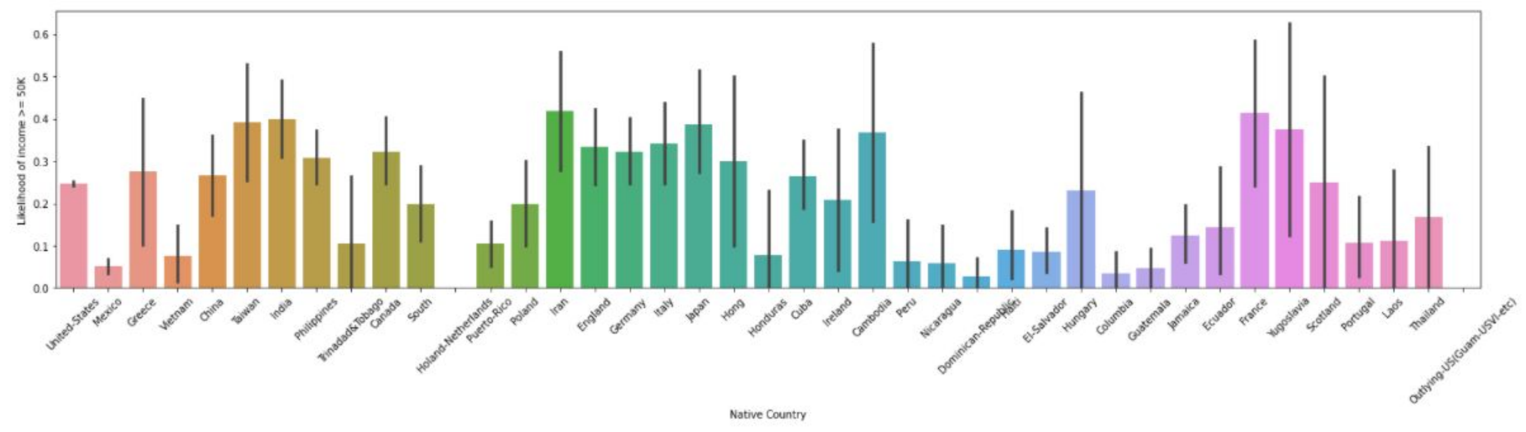


Visuals - Categorical part 2

- Race

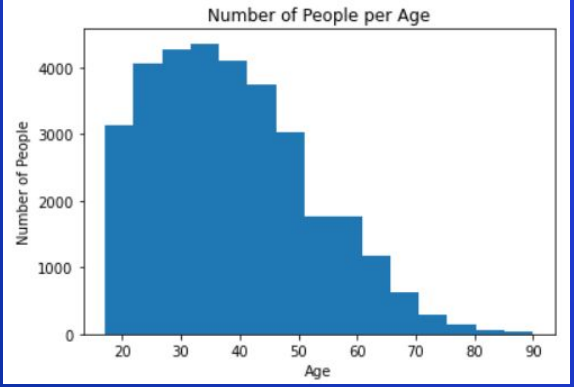


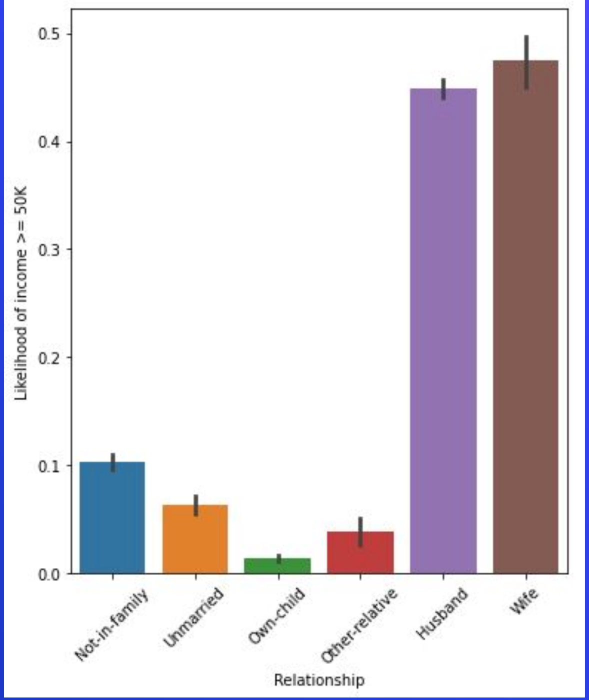
- Native Country

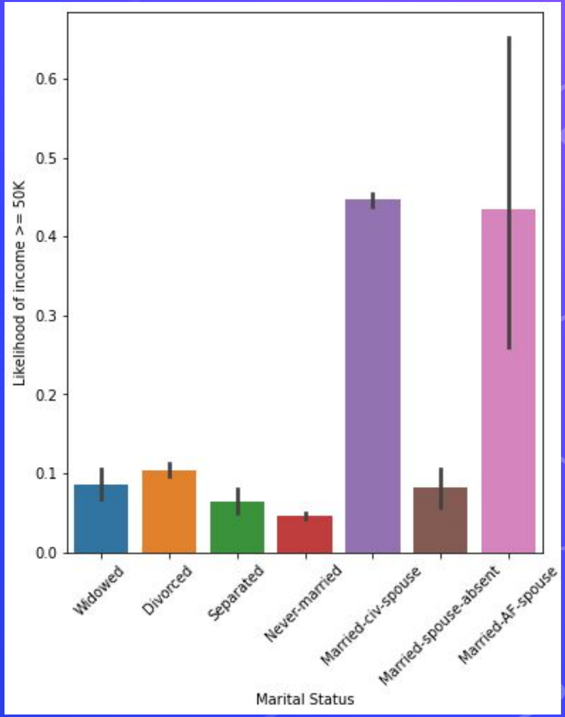


Visuals - Categorical part 2

- Relationship vs Marital Status

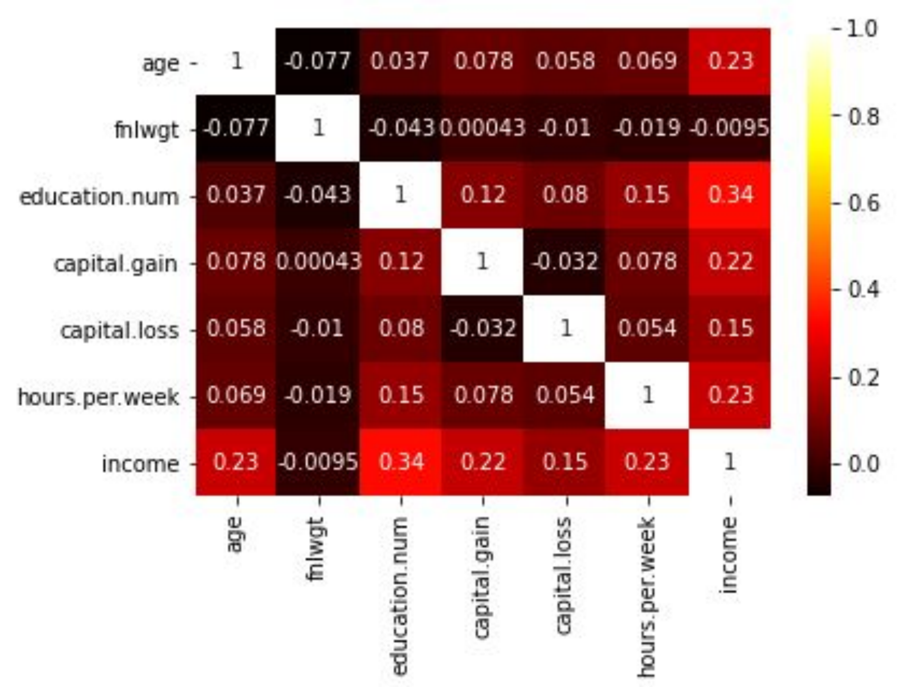






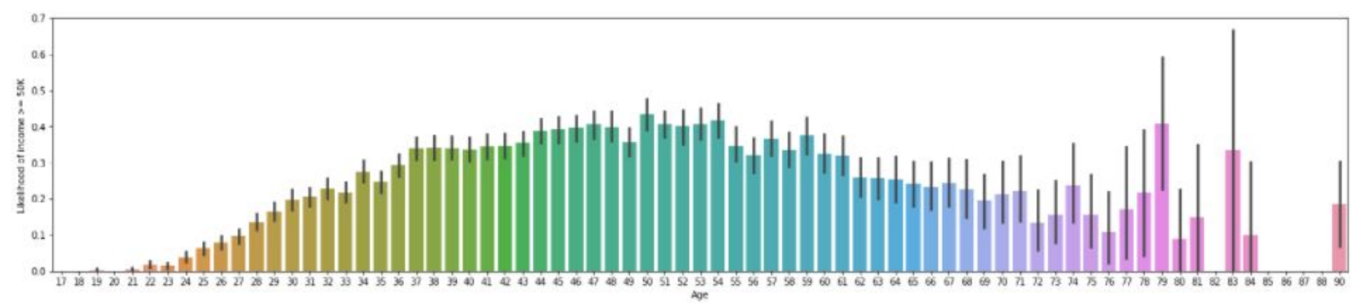
Visuals - Numerical part 1

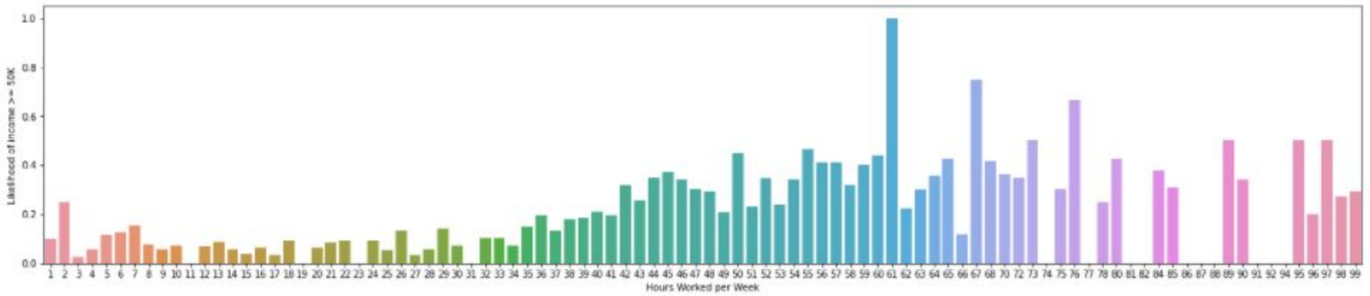
- Education.num strong correlation (.34) with income
- Age, Capital.gain and Hours/week all decent indicators

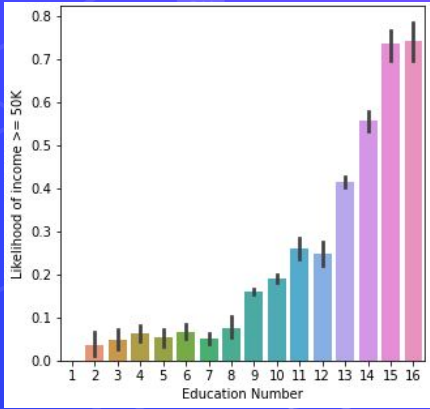


Visuals - Numerical part 2

- Age, Hours/Week, Education Number







3.
Data Engineering

Data Engineering

- Group ‘relationship’, ‘race’, ‘sex’, and ‘occupation’ by observed changes (from visualizations) and assign binary groups (0 or 1) to them
- Drop ‘native.country’, ‘workclass’, ‘marital.status’, ‘education’
  - Redundant and uninformative columns

```
#Use .replace to set 0s and 1s
data['relationship'] = data['relationship'].replace(['Husband','Wife'], 1)\
                                           .replace(['Not-in-family','Unmarried','Own-child','Other-relative'], 0)
data['race'] = data['race'].replace(['White','Asian-Pac-Islander'], 1)\
                           .replace(['Black','Other','Amer-Indian-Eskimo'], 0)
data['sex'] = data['sex'].replace('Male', 1)\
                         .replace('Female', 0)
data['occupation'] = data['occupation'].replace(['Exec-managerial', 'Prof-specialty','Adm-clerical', 'Sales',\
                                                 'Tech-support'], 1)\
                                       .replace(['Machine-op-inspct', 'Other-service', 'Craft-repair', 'Transport-moving',\
                                                 'Handlers-cleaners', 'Farming-fishing', 'Protective-serv', 'Armed-Forces',\
                                                 'Priv-house-serv'], 0)
data.drop(labels = ['native.country','workclass','marital.status','education'], axis = 1, inplace = True)
```

4.

ML Modeling

Data Cleaning and Visualization

“ All models are wrong, but some are useful.

- George E. P. Box

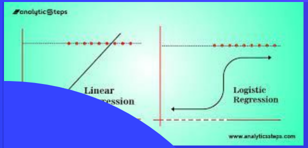
Model Choices

NAIVE BAYES

- Requires predictors be independent
- Works well with binary classification data and many data points
- Fast to employ

$$P(A|B) = \frac{P(A,B)}{P(B)}$$

N



L

LOGISTIC REGRESSION

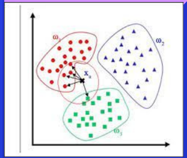
- The dependent variable is binary, multinomial, or ordinal (most often binary)
- No multicollinearity in the model (independence tenet)

- Can handle both numerical and categorical data.
- High Variance in the data can create totally unique "trees" (results)

DECISION TREE

D

K



- Used for both classification and regression problems
- Groups by "neighbors"

K-NEAREST NEIGHBOR

Applying Models

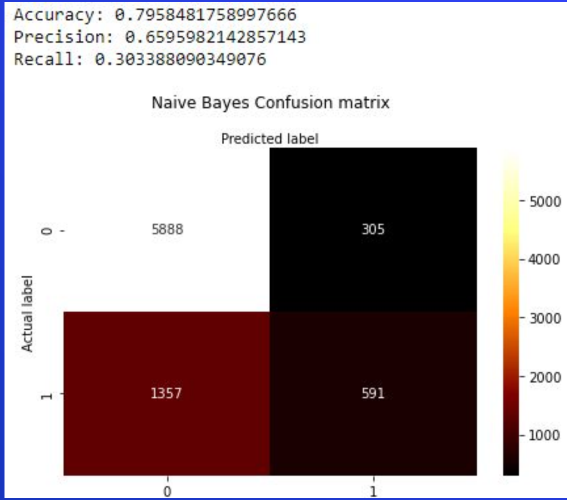
- Using Naive Bayes, Logistic Regression, K-Nearest Neighbors and Decision Trees
- Test_size set to 25%
- Seed set to 0

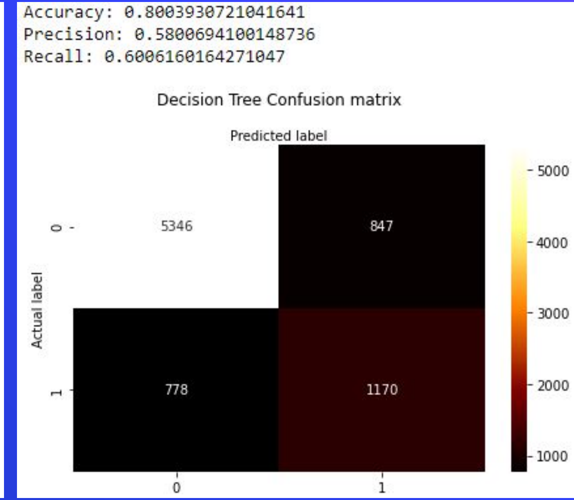
```
#Set features
X = data[['occupation', 'relationship', 'race', 'sex', 'age', 'fnlwgt', 'capital.gain', 'capital.loss', 'hours.per.week']]
#Set target Variable
y = data['income']

#Set test/train split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_state=0)

#select the model
nb = GaussianNB()
#fit the model
nb.fit(X_train,y_train)
#predict based on the model
y_pred=nb.predict(X_test)
```

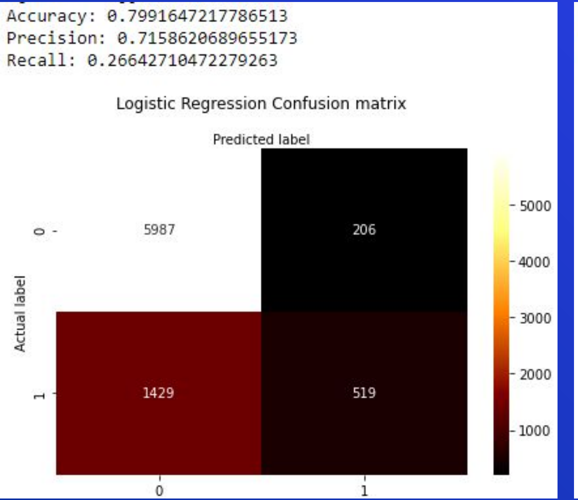
How to measure a model

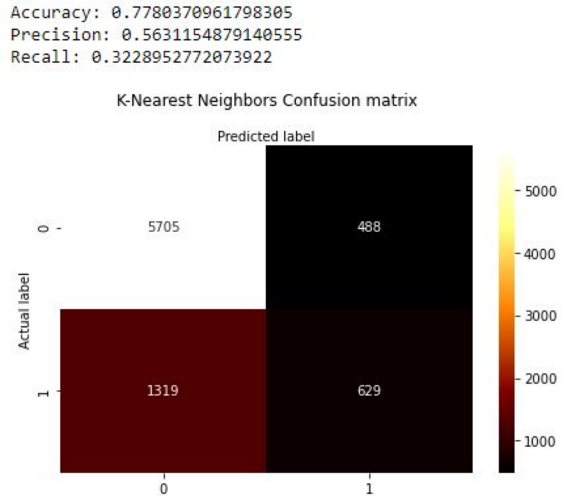
- TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative
- **Accuracy**
  - (TP + TN) / (TP + TN + FP + FN)
  - Compares accurate predictions vs total # of predictions
  - Describes overall accuracy of the model
  - Sample = Entire dataset
- **Precision**
  - (TP) / (TP + FP)
  - Compares accurate positive predictions vs all positive predictions
  - Describes a model's accuracy when only considering positive predictions made
  - Sample = All positives predicted
- **Recall**
  - (TP) / (TP + FN)
  - Compares accurate positive predictions vs the true total of positive values
  - Describes model's accuracy to predict positives in relation to the entire dataset
  - Sample = All positives in the dataset

5. Results









Comparing Models

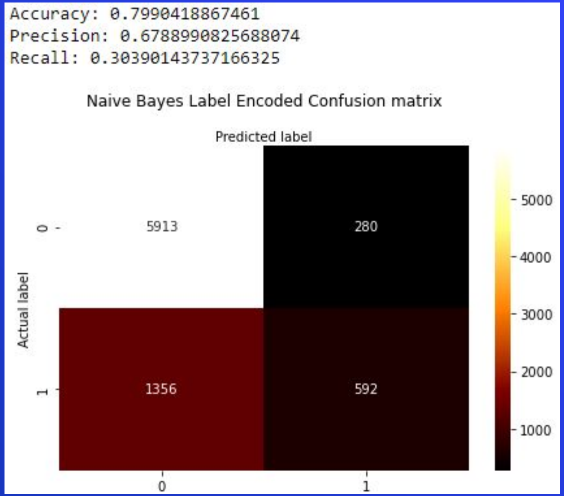
- Using our handmade, binary numeric variables

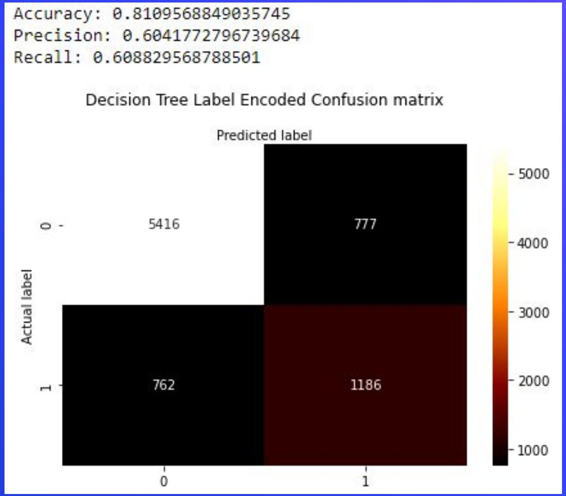
Model	Accuracy	Precision	Recall
Naive Bayes	79.58%	65.95%	30.33%
Decision Tree	**80.03%**	58.00%	**60.06%**
Logistic Regression	79.91%	**71.58%**	26.64%
KNN	77.80%	56.31%	32.28%

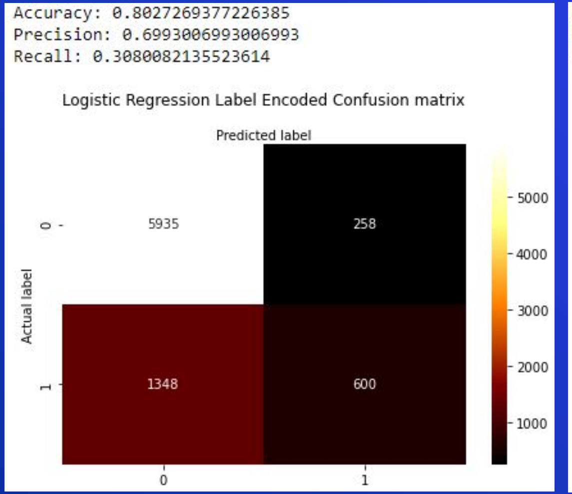
Applying sklearn preprocessing

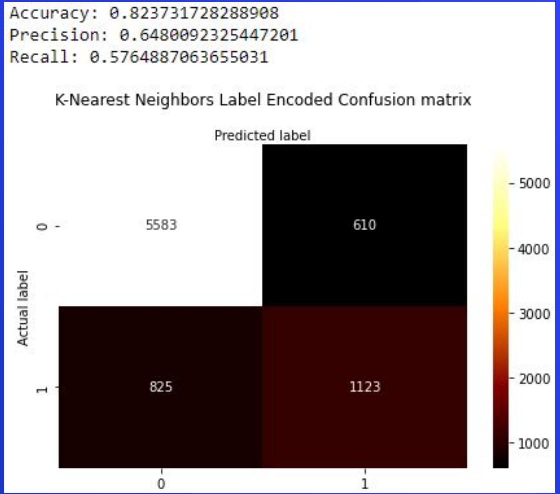
- Easy way of turning categorical data into numerical, and standardizing it.

```
#create a list of our categorical columns for our for loop to iterate over
cats = ['workclass','education','marital.status','occupation','relationship','race','sex','native.country']
#set our sklearn LabelEncoder to a varialbe
label_encoder = LabelEncoder()
#For each column from our list, fit the LabelEncoder and then transform the column as such
for column in cats:
    label_encoder.fit(data2[column])
    data2[column] = label_encoder.transform(data2[column])
#set our sklearn StandardScaler to a variable (this is like standardizing with z-scores, applied to all our columns)
scaler = StandardScaler()
#set our train/test split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, random_state = 0)
#apply the scaler to the columns in test and train
x_train = pd.DataFrame(scaler.fit_transform(x_train), columns = x.columns)
x_test = pd.DataFrame(scaler.transform(x_test), columns = x.columns)
```









Label Encoding

- Using sklearn’s LabelEncoder and StandardScaler functions for categorical variable transformation.
- Applying the same models to this new dataset

Model	Accuracy	Precision	Recall
Naive Bayes	79.90% ↑	67.88% ↑	30.39% ↑
Decision Tree	81.09% ↑↑	60.41% ↑	**60.88%** ↑
Logistic Regression	80.27% ↑	**69.93%** ↓	30.80% ↑
KNN	**82.37%** ↑↑↑	64.80% ↑↑↑	57.64% ↑↑↑

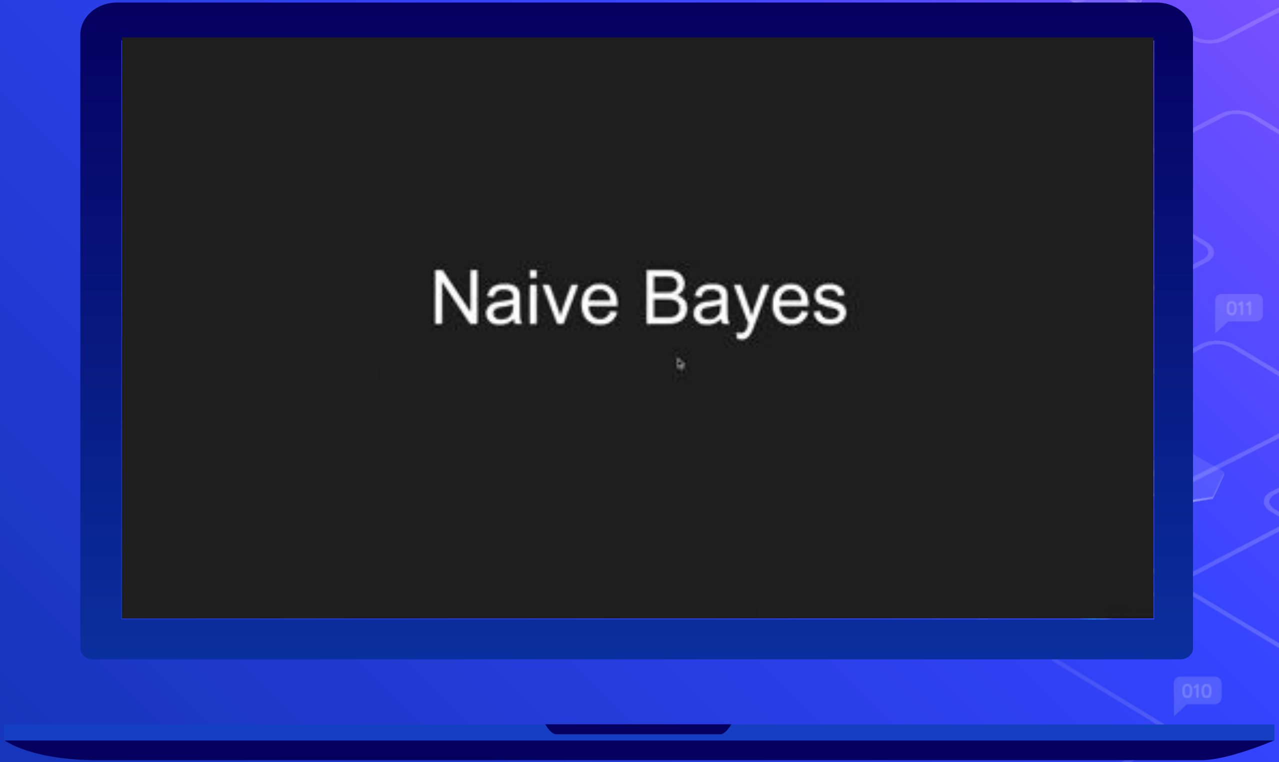
No single statistic tells the whole story.

Changing the Seed

- Seed originally set to 0
  - Iterating through seeds 0-9 for each model

```
#Set test/train split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_state=0)
```

Naive Bayes



https://media.giphy.com/media/EmF3ZMJ078JlZxfQq6/giphy.gif

Logistic Regression

https://media.giphy.com/media/bzl4qktSFgdJ8WMzRs/giphy.gif

Decision Tree

https://media.giphy.com/media/ZVpzkB8yWMxjm33SOn/giphy.gif

K-Nearest Neighbors

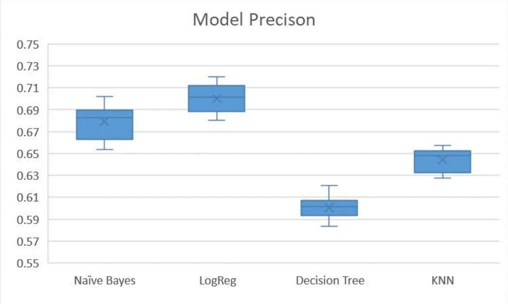
https://media.giphy.com/media/v2qOZXMdNxsB3SWqps/giphy.gif

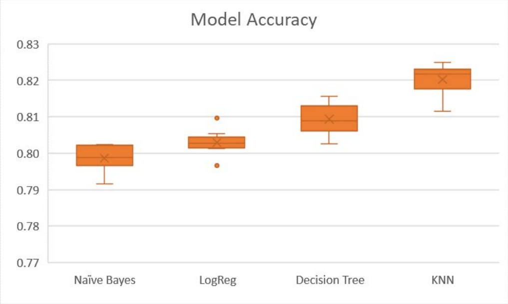
Results

- Most Accurate - KNN
- Most Precise - Logistic Regression
- Highest Recall - Decision Tree

Summary

- Since there is neither a high cost associated with False Negatives nor False Positives, the best model to use to predict an individual’s Income using the 1994 Census data is KNN.
- We are able to predict with over **80%** accuracy whether or not someone will make **greater than or less than $50k**
- Capital Gain, Age, and Hours Worked per Week were the **strongest predictors of Income**. All were **positively** correlated with **>$50k Income** (i.e. as capital.gain/age/hours.worked increased so did likelihood of earning greater than $50k





Appendix

Credits

Special thanks to all the people who made and released these awesome resources for free:

- Presentation template by SlidesCarnival designed by Jimena Catalina https://www.slidescarnival.com/aliena-free-presentation-template/4597#preview
- Photographs by Unsplash
- This data was extracted from the 1994 Census bureau database by Ronny Kohavi and Barry Becker (Data Mining and Visualization, Silicon Graphics
- Ron Kohavi, "Scaling Up the Accuracy of Naive-Bayes Classifiers: a Decision-Tree Hybrid", Proceedings of the Second International Conference on Knowledge Discovery and Data Mining, 1996. (PDF)
- Kaggle inspiration: https://www.kaggle.com/uciml/adult-census-income
- George Box image: https://en.wikipedia.org/wiki/File:GeorgeEPBox_(cropped).jpg

SlidesCarnival icons are editable shapes.

This means that you can:

- Resize them without losing quality.
- Change fill color and opacity.
- Change line color, width and style.

Isn’t that nice? :)

Examples:

Find more icons at
slidescarnival.com/extra-free-resources-icons-and-maps

Thank you!

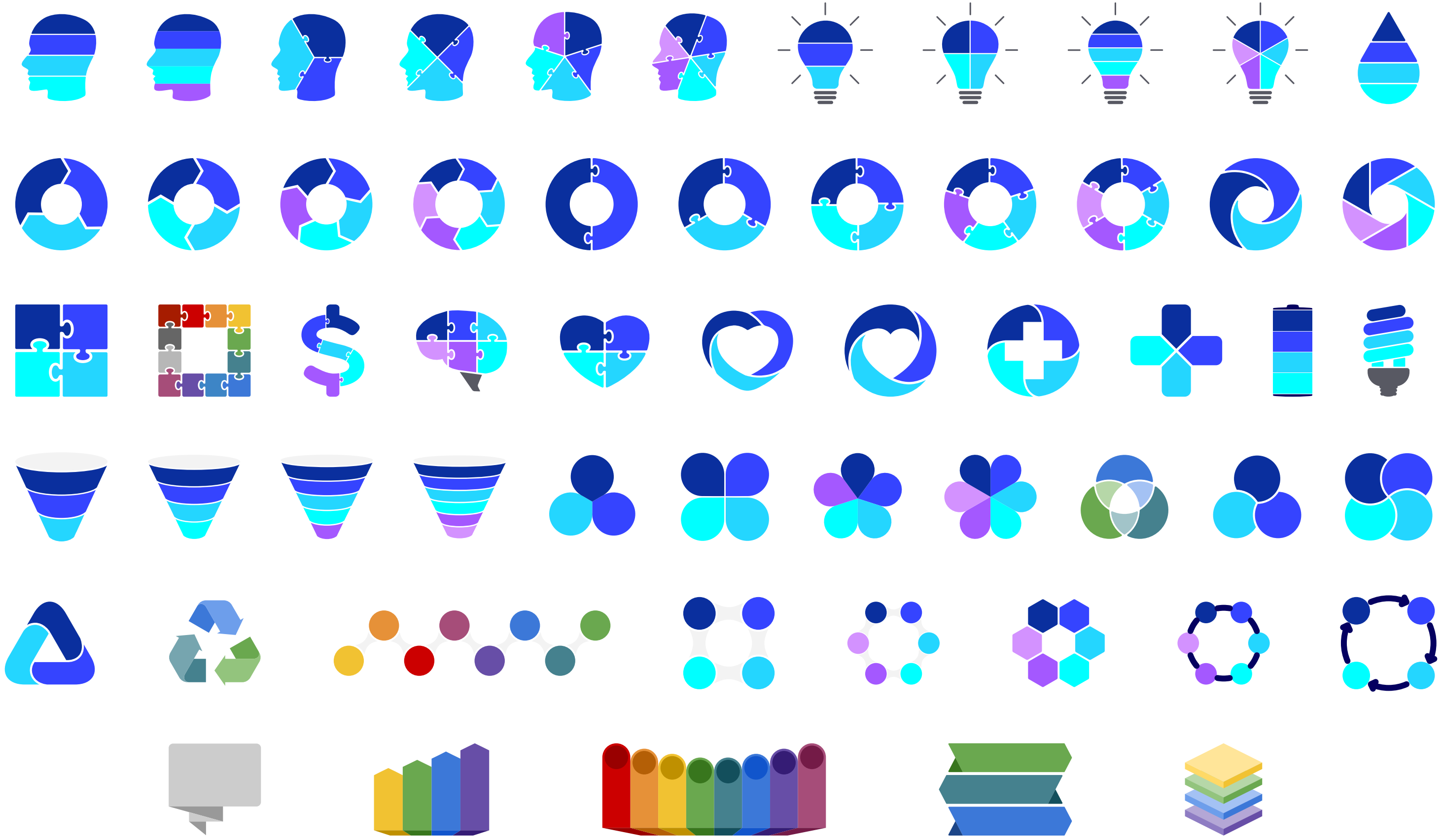
Any questions?

You can find us at:

owinters58@gmail.com

conoranderson2@gmail.com

Diagrams and infographics



You can also use any emoji as an icon!
And of course it resizes without losing quality.

How? Follow Google instructions
https://twitter.com/googledocs/status/730087240156643328

✋👆👉👍👤👦👧👨👩👪💃🏃
💑🖤😂😉😋😒😭👶😸🐟🍒🍔💣
📌📖🔨🎃🎈🎨🏈🏰🌏🔌🔑 and many more...