



## Purpose & motivation

To make a predictive model of whether or not someone makes over 50k

- Market segmentation
- Characteristics of the two groups



## Data collection.

- Source of dataset: the US Census
- Data contains 32561 observations
- Includes one target variable and 14 explanatory variables

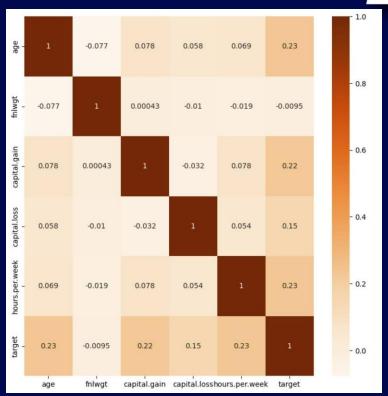


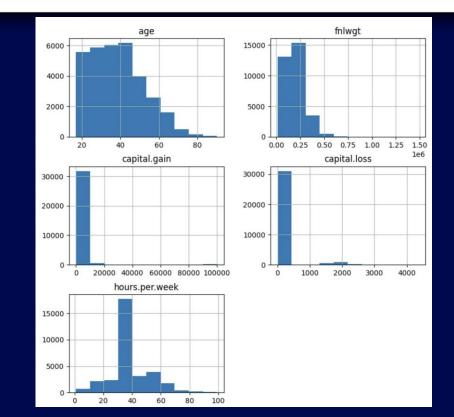
## Dataset and null data

#	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



## Dataset...







# Data Split

80% 20%

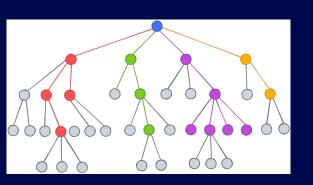
we splitted our data into 20% training and 80% test set with random state = 200 because our data set is large.



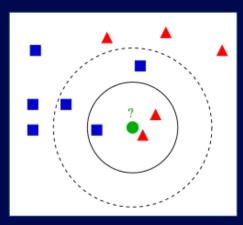
## **Previous Models**

\*\*As we are going to predict a class variable we chose these models\*\*

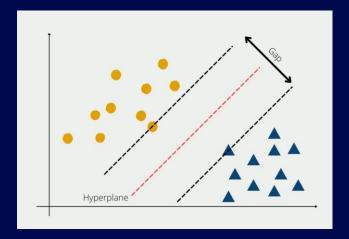
#### **Decision Tree**



#### KNN

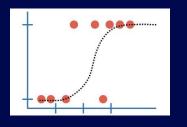


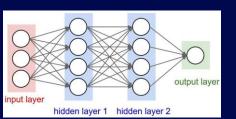
#### **SVM**

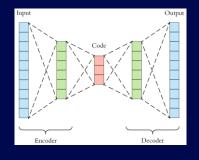


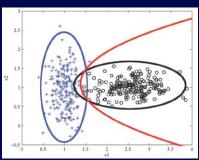


## **New Models**

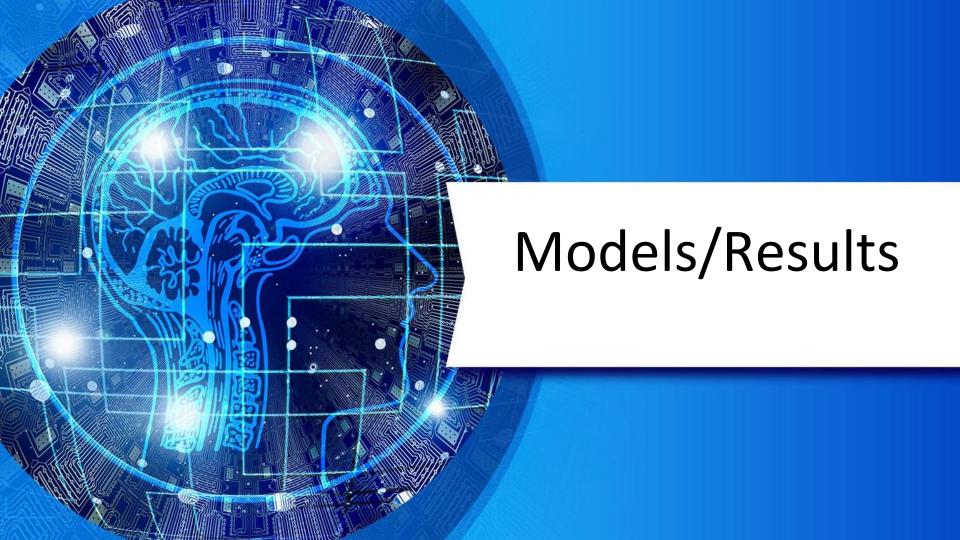








- Logistic Regression
- **DNN**
- Autoencoder
- **❖** GNB





#### **Parameters**

```
from sklearn.neighbors import KNeighborsClassifier
model_KNN = KNeighborsClassifier()
parameters_KNN = {'n_neighbors' : range(1,20)}
```

#### Results

Fitting 5 folds for each of 19 candidates, totalling 95 fits KNeighborsClassifier {'n\_neighbors': 19} 0.7999845166843597 0.7941040994933211 0.7452889439434973



#### **Parameters**

```
from sklearn.naive_bayes import GaussianNB
model_GNB = GaussianNB()
parameters_GNB = {'var_smoothing': np.logspace(0,-9, num=100)}
```

#### Results

Fitting 5 folds for each of 100 candidates, totalling 500 fits GaussianNB {'var\_smoothing': 1.2328467394420658e-05} 0.805129038070459 0.7976354982343006 0.7598007329112451



## **Logistic Regression**

#### **Parameters**

```
from sklearn.linear_model import LogisticRegression
model_LR = LogisticRegression()
parameters_LR = {'C' : np.logspace(-2, 2, 10)}
```

#### Results

LogisticRegression {'C': 0.0774263682681127} 0.7987945343379923 0.7913403961308153 0.7507386774102396



#### **Decision Tree**

#### **Parameters**

#### Results

Fitting 5 folds for each of 252 candidates, totalling 1260 fits

DecisionTreeClassifier {'criterion': 'gini', 'max\_depth': 9, 'max\_leaf\_nodes': 100, 'min\_samples\_leaf': 1, 'min\_samples\_split': 2} 0.8596824262156633 0.8550591125441425 0.8477944986756594



#### **Parameters**

```
## DNN model
DNN_model = Sequential()
DNN_model.add(Dense(units = 16, input_dim = X_train.shape[1], activation='relu'))
DNN_model.add(Dense(units = 8, activation='relu'))
DNN_model.add(Dense(units = 8, activation='relu'))
DNN_model.add(Dense(1, activation='sigmoid'))
print(DNN_model.summary())
```

Model: "sequential\_7"

Layer (type)	Output	Shape	Param #
dense (Dense)	(None,	16)	1600
dense_1 (Dense)	(None,	8)	136
dense_2 (Dense)	(None,	8)	72
dense_3 (Dense)	(None,	1)	9

Total params: 1,817 Trainable params: 1,817 Non-trainable params: 0

epochs = 10, batch\_size = 32, verbose=1,

#### Results

```
loss: 0.5625 - accuracy: 0.7620 - f1_score: 0.0348
```

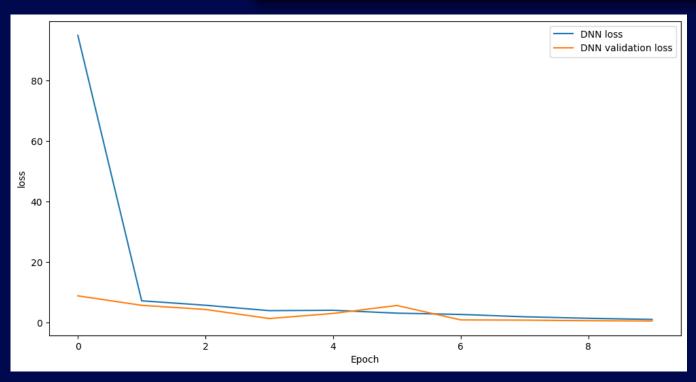
#### Train

```
val_loss: 0.5547 - val_accuracy: 0.7634 - val_f1_score: 0.0280
```

Test



# DNN

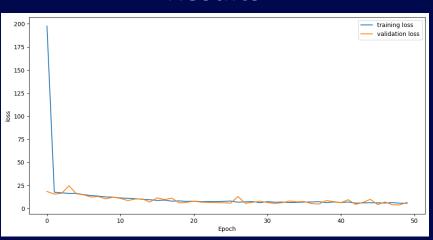




#### Autoencoder

#### **Parameters**

#### Results



Classifier Test Loss: 6.6469 Classifier Test Accuracy: 0.3204



## Feature Selection (Variance)

```
Variance values:
                                   1.860614e+02
 age
fnlwgt
                                  1.114080e+10
capital.gain
                                  5.454254e+07
capital.loss
                                  1.623769e+05
hours.per.week
                                  1.524590e+02
native.country_Thailand
                                  5.525199e-04
native.country_Trinadad&Tobago
                                  5.831976e-04
native.country_United-States
                                  9.330010e-02
native.country_Vietnam
                                  2.053505e-03
native.country_Yugoslavia
                                  4.911590e-04
Length: 99, dtype: float64
```



## Feature Selection Logistic Regression

#### **Parameters**

# Apply variance threshold feature selection
selector = VarianceThreshold(threshold=0.1)

clf = LogisticRegression(random\_state = 0)

,,	precision	recall	f1-score	support
False	0.81	0.94	0.87	4945
True	0.62	0.29	0.39	1568
accuracy			0.79	6513
macro avg	0.71	0.62	0.63	6513
weighted avg	0.76	0.79	0.76	6513



#### **Feature Selection KNN**

#### **Parameters**

# Apply variance threshold feature selection selector = VarianceThreshold(threshold=0.1)

clf = KNeighborsClassifier(n\_neighbors = 19)

	precision	recall	f1-score	support	
5-1	0.00	0.00	0.00	40.45	
False	0.80	0.98	0.88	4945	
True	0.77	0.21	0.33	1568	
accuracy			0.79	6513	
macro avg	0.78	0.59	0.60	6513	
_					
weighted avg	0.79	0.79	0.75	6513	
1					



#### **Feature Selection GNB**

#### **Parameters**

# Apply variance threshold feature selection
selector = VarianceThreshold(threshold=0.1)

clf = GaussianNB(var\_smoothing = 1.2328467394420658e-05)

	precision	recall	f1-score	support
False True	0.81 0.72	0.97 0.26	0.88 0.38	4945 1568
accuracy macro avg weighted avg	0.76 0.78	0.61 0.80	0.80 0.63 0.76	6513 6513 6513



#### Feature Selection Decision Tree

#### **Parameters**

# Apply variance threshold feature selection
selector = VarianceThreshold(threshold=0.1)

clf = DecisionTreeClassifier(max\_depth = 9, max\_leaf\_nodes = 100, min\_samples\_leaf = 1, min\_samples\_split = 2)

	precision	recall	f1-score	support	
False	0.88	0.94	0.91	4945	
True	0.76	0.58	0.66	1568	
accuracy			0.85	6513	
macro avg weighted avg	0.82 0.85	0.76 0.85	0.78 0.85	6513 6513	
weighted avg	0.85	0.85	0.85	6513	



# Feature Selection Vs. Usual (KNN- DT- GNB- LR)

Model	Accuracy	F1-Score
DT	0.859	0.847
GNB	0.80	0.76
KNN	0.794	0.745
LogisticRegression	0.798	0.75

Model	Accuracy	F1-Score
DT	0.85	0.85
GNB	0.80	0.76
KNN	0.79	0.75
LogisticRegression	0.79	0.76

Usual Feature Selection



# **Final Comparison**

#### **Performance Measures**

Model	Accuracy	F1-Score	Best Model
DT	0.859	0.847	*
DNN	0.763	0.028	
Autoencoder	0.32		
GNB	0.797	0.759	
KNN	0.794	0.745	
SVM	0.79	0.88	
LogisticRegression	0.798	0.75	



## Conclusion

- Based on both graph and statistical comparison, Decision tree model is still more fitted model Vs all the other models.
   PS: however, it may be better to choose the DT with feature selection
  - PS: however, it may be better to choose the DT with feature selection as it uses less feature hence less resources.
- As shown in the comparison, An autoencoder model was the lowest performer. Autoencoder model is a neural network model that can be used to learn a compressed representation of raw data and input values, however our data set is large and have lots of details so maybe if we reduce the number of input values, we can make the model less likely be confused by tiny (and irrelevant) details.



## Recommendation

- Usually we use neural networks when we do forecasting and time series applications, sentiment analysis and other text applications. It is not recommend for studies like this one where we have a binary output because:
  - Hard to interpret most of the times
  - They require too much data
  - They take time to be developed
  - They take a lot of time in the training phase

