## Credit Card

### June 10, 2020

```
[1]: import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import StandardScaler
    from sklearn.linear_model import LogisticRegression
    from sklearn.metrics import classification_report
    from sklearn.metrics import confusion_matrix
    from sklearn.metrics import accuracy_score
    from sklearn.tree import DecisionTreeClassifier
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.ensemble import BaggingClassifier
    from sklearn import svm
    from sklearn.neighbors import KNeighborsClassifier
[2]: credit = pd.read_csv('Credit_Card.csv')
[3]: credit.head()
[3]:
       clientid
                                     loan
                                             LTI
                   income
                             age
                                                  default10yr
              1 66155.93 59.02 8106.53 0.123
                                                            0
              2 34415.15 48.12
                                  6564.75 0.191
                                                            0
    1
              3 57317.17 63.11 8020.95
                                           0.140
                                                            0
    3
                                                            0
              4 42709.53 45.75 6103.64 0.143
              5 66952.69 18.58 8770.10 0.131
                                                            1
[4]: credit.shape
[4]: (2000, 6)
[5]: credit.info()
   <class 'pandas.core.frame.DataFrame'>
   RangeIndex: 2000 entries, 0 to 1999
   Data columns (total 6 columns):
                  2000 non-null int64
   clientid
   income
                  2000 non-null float64
                  2000 non-null float64
   age
   loan
                 2000 non-null float64
```

LTI 2000 non-null float64 default10yr 2000 non-null int64

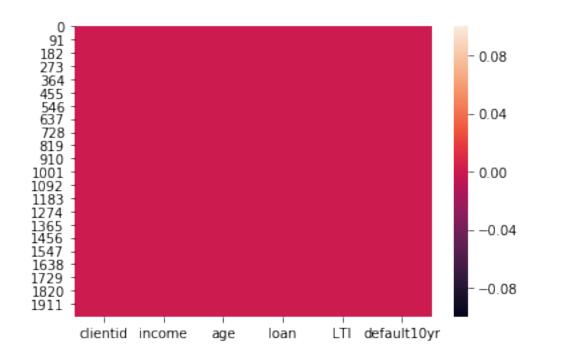
dtypes: float64(4), int64(2)

memory usage: 93.8 KB

# [6]: credit.isnull().sum()

[6]: clientid 0 income 0 age 0 loan 0 LTI 0 default10yr 0 dtype: int64

### [7]: sns.heatmap(credit.isnull());



### [8]: credit.default10yr.value\_counts()

[8]: 0 1717 1 283

Name: default10yr, dtype: int64

### [9]: credit.head()

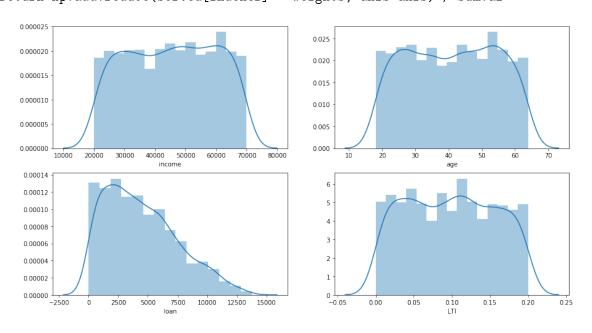
[9]: clientid income loan LTI default10yr age 66155.93 59.02 8106.53 0.123 0 0 2 34415.15 48.12 0.191 0 6564.75

```
2
               3 57317.17 63.11
                                   8020.95
                                            0.140
                                                              0
     3
               4 42709.53 45.75
                                                              0
                                   6103.64
                                            0.143
                  66952.69 18.58
                                   8770.10 0.131
                                                              1
[10]: credit = credit.drop('clientid', axis=1)
[11]: credit.head()
[11]:
          income
                            loan
                                    LTI
                                         default10yr
                    age
                 59.02 8106.53
        66155.93
                                  0.123
     1 34415.15
                  48.12
                        6564.75 0.191
                                                   0
     2 57317.17
                  63.11 8020.95 0.140
                                                   0
                                                   0
     3 42709.53
                  45.75
                         6103.64 0.143
       66952.69
                 18.58 8770.10 0.131
                                                   1
[12]: plt.figure(figsize=(15,8))
     plt.subplot(2,2,1)
     sns.distplot(credit.income, bins=15);
     plt.subplot(2,2,2)
     sns.distplot(credit.age, bins=15);
     plt.subplot(2,2,3)
     sns.distplot(credit.loan, bins=15);
     plt.subplot(2,2,4)
     sns.distplot(credit.LTI, bins=15);
```

/home/nbuser/anaconda3\_501/lib/python3.6/site-

packages/scipy/stats/stats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a different result.

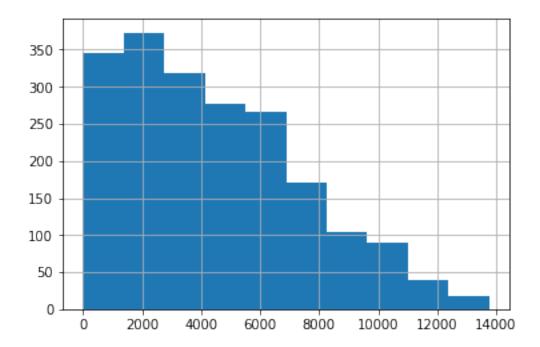
return np.add.reduce(sorted[indexer] \* weights, axis=axis) / sumval



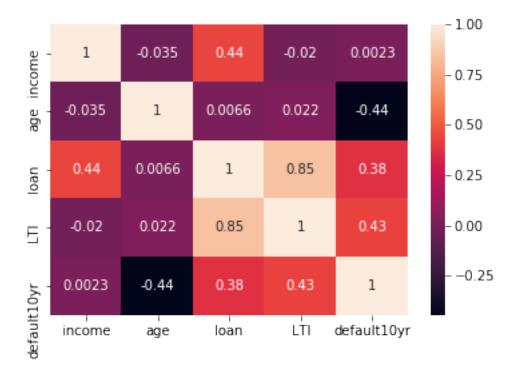
## [13]: credit.describe()

[13]:		income	age	loan	LTI	default10yr
	count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
	mean	45331.599930	40.927245	4444.369635	0.098392	0.141500
	std	14326.327142	13.262516	3045.409995	0.057619	0.348624
	min	20014.490000	18.060000	1.380000	0.000000	0.000000
	25%	32796.457500	29.060000	1939.705000	0.048000	0.00000
	50%	45789.120000	41.380000	3974.720000	0.099500	0.000000
	75%	57791.285000	52.600000	6432.407500	0.148000	0.000000
	max	69995.690000	63.970000	13766.050000	0.200000	1.000000

## [14]: credit.loan.hist();



[15]: sns.heatmap(credit.corr(),annot=True);



```
[16]: credit.head()
[16]:
          income
                    age
                            loan
                                    LTI
                                          default10yr
        66155.93
                  59.02 8106.53
                                  0.123
                                                    0
                                                    0
     1 34415.15
                  48.12
                         6564.75
                                  0.191
     2 57317.17
                  63.11
                         8020.95
                                  0.140
                                                    0
     3 42709.53
                  45.75
                         6103.64 0.143
                                                    0
     4 66952.69
                  18.58 8770.10
                                  0.131
                                                    1
[17]: | y = credit['default10yr']
     X = credit.drop(['default10yr'], axis=1)
[18]: X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,__
      →random state=100)
[19]: sc = StandardScaler()
     X_train = sc.fit_transform(X_train)
     X_test = sc.transform(X_test)
```

### 0.1 Logistic Model

```
[20]: model_logistic = LogisticRegression()
[21]: model_logistic.fit(X_train,y_train)
```

/home/nbuser/anaconda3\_501/lib/python3.6/site-packages/sklearn/linear\_model/logistic.py:433: FutureWarning: Default solver

will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning. FutureWarning)

```
[22]: y_pred_logistic = model_logistic.predict(X_test)
```

[23]: print(confusion\_matrix(y\_pred\_logistic, y\_test))

[[320 9] [11 60]]

[24]: classification\_report(y\_pred\_logistic, y\_test)

[24]: ' precision recall f1-score support\n\n 0 0.97 0.97 0.97 329\n 1 0.85 0.86 0.87  $71\n\n$ 0.95 0.95 0.95 400\n micro avg macro avg 0.92 0.91 0.91 400\nweighted avg 0.95 0.95 0.95 400\n'

...... £4 ......

[25]: print(classification\_report(y\_pred\_logistic, y\_test))

		precision	recall	Il-score	support
	0	0.97	0.97	0.97	329
	1	0.87	0.85	0.86	71
micro	avg	0.95	0.95	0.95	400
macro	avg	0.92	0.91	0.91	400
weighted	avg	0.95	0.95	0.95	400

```
[26]: accuracy_score(y_pred_logistic, y_test)
```

[26]: 0.95

Accuracy of Logistic Model is 95.0 %

#### 0.1.1 Accuracy of Logistic Model is 95.0%

#### 0.2 Decision Tree Model

```
[28]: model_decision = DecisionTreeClassifier()
[29]: model_decision.fit(X_train,y_train)
[29]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                 max_features=None, max_leaf_nodes=None,
                 min_impurity_decrease=0.0, min_impurity_split=None,
                 min_samples_leaf=1, min_samples_split=2,
                 min_weight_fraction_leaf=0.0, presort=False, random_state=None,
                 splitter='best')
[30]: y_pred_decision = model_decision.predict(X_test)
[31]: print(classification_report(y_pred_decision, y_test))
                                recall f1-score
                   precision
                                                    support
                0
                        1.00
                                  0.99
                                             1.00
                                                         333
                1
                        0.97
                                   1.00
                                             0.99
                                                          67
                                                         400
       micro avg
                        0.99
                                  0.99
                                             0.99
       macro avg
                        0.99
                                   1.00
                                             0.99
                                                         400
    weighted avg
                        1.00
                                   0.99
                                             1.00
                                                         400
[32]: confusion_matrix(y_pred_decision, y_test)
[32]: array([[331,
                    2],
            [ 0,
                   67]])
[33]: accuracy_score(y_pred_decision, y_test)
[33]: 0.995
[34]: print("Accuracy of Decision Tree Model is", (accuracy_score(y_pred_decision, ___
      \rightarrowy_test)*100),"%")
    Accuracy of Decision Tree Model is 99.5 %
    0.2.1 Accuracy of Decision Tree Model is 99.5%
         Bagging Ensemble Model (To reduce Variance or Noise or Complexity)
```

```
[35]: model_bagging = BaggingClassifier()
[36]: model_bagging.fit(X_train, y_train)
```

[36]: BaggingClassifier(base\_estimator=None, bootstrap=True, bootstrap\_features=False, max\_features=1.0, max\_samples=1.0,

```
n_estimators=10, n_jobs=None, oob_score=False, random_state=None,
verbose=0, warm_start=False)
```

```
[37]: y_pred_bagging = model_bagging.predict(X_test)
```

[38]: print(classification\_report(y\_pred\_bagging, y\_test))

		precision	recall	f1-score	support
	0	1.00	0.99	1.00	333
	1	0.97	1.00	0.99	67
micro	avg	0.99	0.99	0.99	400
macro	avg	0.99	1.00	0.99	400
weighted	avg	1.00	0.99	1.00	400

```
[39]: print(confusion_matrix(y_pred_bagging, y_test))
```

[[331 2] [ 0 67]]

```
[40]: accuracy_score(y_pred_bagging, y_test)
```

[40]: 0.995

```
[41]: print("Accuracy of Bagging Ensemble Model is",(accuracy_score(y_pred_bagging, ⊔ →y_test)*100),"%")
```

Accuracy of Bagging Ensemble Model is 99.5 %

### 0.3.1 Accuracy of Bagging Ensemble Model is 99.50%

#### 0.4 Random Forest Model

```
[42]: model_random = RandomForestClassifier(n_estimators=100)
```

[43]: model\_random.fit(X\_train, y\_train)

```
[44]: y_pred_random = model_random.predict(X_test)
```

[45]: print(classification\_report(y\_pred\_random, y\_test))

```
recall f1-score
               precision
                                                  support
           0
                    1.00
                               0.99
                                          1.00
                                                      333
            1
                    0.97
                               1.00
                                          0.99
                                                       67
                    0.99
                               0.99
                                          0.99
                                                      400
   micro avg
   macro avg
                    0.99
                               1.00
                                          0.99
                                                      400
weighted avg
                    1.00
                               0.99
                                          1.00
                                                      400
```

[46]: print(confusion\_matrix(y\_pred\_random, y\_test))

[[331 2] [ 0 67]]

[47]: accuracy\_score(y\_pred\_random, y\_test)

[47]: 0.995

[48]: print("Accuracy of Random Forest Model is", (accuracy\_score(y\_pred\_random, ⊔ →y\_test)\*100),"%")

Accuracy of Random Forest Model is 99.5 %

### 0.4.1 Accuracy of Random Forest Model is 99.5 %

### 0.5 Support Vector Machine Model

- [49]: model\_svm = svm.SVC()
- [50]: model\_svm.fit(X\_train,y\_train)
- [51]: y\_pred\_svm = model\_svm.predict(X\_test)
- [52]: print(classification\_report(y\_pred\_svm, y\_test))

support	f1-score	recall	precision		
331 69	0.99	0.99 0.94	0.99	0	
400	0.98	0.98	0.98	avo	micro
400	0.96	0.96	0.96	_	macro
400	0.98	0.98	0.98	avg	weighted

```
[53]: print(confusion_matrix(y_pred_svm, y_test))
    [[327]
            41
     [ 4 65]]
[54]: accuracy_score(y_pred_svm, y_test)
[54]: 0.98
[55]: print("Accuracy of Supprt vector Machine Model is", (accuracy_score(y_pred_svm,_
      →y_test)*100),"%")
    Accuracy of Supprt vector Machine Model is 98.0 %
    0.5.1 Accuracy of Supprt vector Machine Model is 98.0 %
    0.6 XG Boosting Ensemble Model
[56]: | !pip install xgboost
    Requirement already satisfied: xgboost in
    /home/nbuser/anaconda3_501/lib/python3.6/site-packages (1.1.1)
    Requirement already satisfied: numpy in /home/nbuser/anaconda3_501/lib/python3.6
    /site-packages (from xgboost) (1.16.2)
    Requirement already satisfied: scipy in /home/nbuser/anaconda3_501/lib/python3.6
    /site-packages (from xgboost) (1.1.0)
    WARNING: You are using pip version 19.3.1; however, version 20.1.1 is
    available.
    You should consider upgrading via the 'pip install --upgrade pip' command.
[57]: pip install --upgrade pip
    The following command must be run outside of the IPython shell:
        $ pip install --upgrade pip
    The Python package manager (pip) can only be used from outside of IPython.
    Please reissue the 'pip' command in a separate terminal or command prompt.
    See the Python documentation for more information on how to install packages:
        https://docs.python.org/3/installing/
[58]: import xgboost as xgb
     from xgboost import XGBClassifier
[59]: model_xgb = XGBClassifier()
```

```
[60]: model_xgb.fit(X_train, y_train)
[60]: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
            colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
            importance_type='gain', interaction_constraints='',
            learning_rate=0.300000012, max_delta_step=0, max_depth=6,
            min_child_weight=1, missing=nan, monotone_constraints='()',
            n_estimators=100, n_jobs=0, num_parallel_tree=1,
            objective='binary:logistic', random_state=0, reg_alpha=0,
            reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
            validate_parameters=1, verbosity=None)
[61]: y_pred_xgb = model_xgb.predict(X_test)
[62]: print(classification_report(y_pred_xgb, y_test))
                  precision
                                recall f1-score
                                                    support
               0
                        1.00
                                  0.99
                                            1.00
                                                        333
                                  1.00
                1
                        0.97
                                            0.99
                                                         67
                                  0.99
                                            0.99
                                                        400
                        0.99
       micro avg
                        0.99
                                  1.00
                                            0.99
                                                        400
       macro avg
                                            1.00
    weighted avg
                        1.00
                                  0.99
                                                        400
[63]: print(confusion_matrix(y_pred_xgb, y_test))
    [[331
            2]
     [ 0 67]]
[64]: accuracy_score(y_pred_xgb, y_test)
[64]: 0.995
[65]: print("Accuracy of XG Boost Model is", (accuracy_score(y_pred_xgb,_
      →y_test)*100),"%")
    Accuracy of XG Boost Model is 99.5 %
    0.6.1 Accuracy of XG Boost Model is 99.5 %
    0.7 K Nearest Neighbors Model
[66]: model_knn = KNeighborsClassifier(n_neighbors = 20, p=2, metric='euclidean')
[67]: import math
     math.sqrt(len(y_test))
[67]: 20.0
```

```
[68]: model_knn.fit(X_train, y_train)
[68]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='euclidean',
                metric_params=None, n_jobs=None, n_neighbors=20, p=2,
                weights='uniform')
[69]: y_pred_knn = model_knn.predict(X_test)
[70]: print(classification_report(y_pred_knn, y_test))
                   precision
                                recall f1-score
                                                    support
               0
                        1.00
                                  0.98
                                             0.99
                                                        338
                1
                        0.88
                                  0.98
                                             0.93
                                                         62
```

```
[71]: print(confusion_matrix(y_pred_knn, y_test))
```

```
[[330 8]
[ 1 61]]
```

- [72]: accuracy\_score(y\_pred\_knn, y\_test)
- [72]: 0.9775
- [73]: print("Accuracy of K Nearest Neighbors Model is", (accuracy\_score(y\_pred\_knn, \_ →y\_test)\*100),"%")

Accuracy of K Nearest Neighbors Model is 97.75 %

#### 0.7.1 Accuracy of K Nearest Neighbors Model is 97.75 %

```
Accuracy of Logistic Model is 95.0 %
Accuracy of Decision Tree Model is 99.5 %
Accuracy of Bagging Ensemble Model is 99.5 %
Accuracy of Random Forest Model is 99.5 %
Accuracy of Supprt vector Machine Model is 98.0 %
Accuracy of XG Boost Model is 99.5 %
Accuracy of K Nearest Neighbors Model is 97.75 %
```

- 0.7.2 Accuracy of Logistic Model is 95.0 %
- 0.7.3 Accuracy of K Nearest Neighbors Model is 97.75 %
- 0.7.4 Accuracy of Supprt vector Machine Model is 98.0 %
- 0.7.5 Accuracy of Decision Tree Model is 99.5 %
- 0.7.6 Accuracy of Bagging Ensemble Model is 99.5 %
- 0.7.7 Accuracy of XG Boost Model is 99.5 %
- 0.8 Accuracy of Random Forest Model is 99.75 %. So we will prefer this as Best Model with High Accuracy.