Predicting whether a customer would be signing a loan or not

```
from google.colab import files
uploaded = files.upload()
```

Importing modules

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Reading the dataset

```
import io
dataset = pd.read_csv("/content/Project-9.csv")
dataset
```

₽		entry_id	age	pay_schedule	home_owner	income	months_employed	years_employed	current_address_year	personal
	0	7629673	40	bi-weekly	1	3135	0	3	3	
	1	3560428	61	weekly	0	3180	0	6	3	
	2	6934997	23	weekly	0	1540	6	0	0	
	3	5682812	40	bi-weekly	0	5230	0	6	1	
	4	5335819	33	semi-monthly	0	3590	0	5	2	
	17903	9949728	31	monthly	0	3245	0	5	3	
	17904	9442442	46	bi-weekly	0	6525	0	2	1	
	17905	9857590	46	weekly	0	2685	0	5	1	
	17906	8708471	42	bi-weekly	0	2515	0	3	5	
	17907	1498559	29	weekly	1	2665	0	4	10	
	17908 rc	ws × 21 colu	ımns							

17908 rows × 21 columns

dataset.info()

```
<<class 'pandas.core.frame.DataFrame'>
     RangeIndex: 17908 entries, 0 to 17907
     Data columns (total 21 columns):
                         Non-Null Count Dtype
      # Column
     # Column Non-Null Count Dtype

0 entry_id 17908 non-null int64

1 age 17908 non-null int64

2 pay_schedule 17908 non-null object

3 home_owner 17908 non-null int64

4 income 17908 non-null int64

5 months_employed 17908 non-null int64

6 years_employed 17908 non-null int64
     --- -----
      7
           current_address_year 17908 non-null int64
                                       17908 non-null int64
           personal_account_m
                                       17908 non-null int64
           personal_account_y
      10 has_debt
                                       17908 non-null int64
      11 amount_requested
                                       17908 non-null int64
                             17908 non-null float64
17908 non-null float64
17908 non-null float64
      12 risk_score
      13 risk_score_2
      14 risk_score_3
      15 risk_score_4
      16 risk_score_5
                                       17908 non-null float64
                                       17908 non-null float64
      17 ext_quality_score
      18 ext_quality_score_2
                                       17908 non-null float64
      19 inquiries_last_month 17908 non-null int64
                                       17908 non-null int64
      20 e_signed
     dtypes: float64(6), int64(14), object(1)
```

dataset.shape

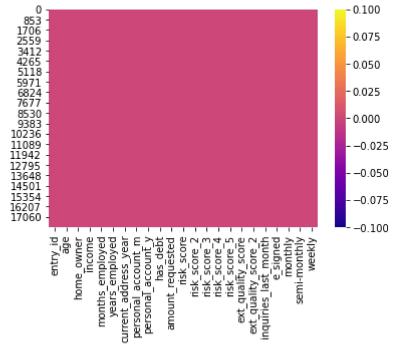
[→ (17908, 21)

Ensuring there's no missing data

memory usage: 2.9+ MB

sns.heatmap(dataset.isnull(), cmap='plasma')

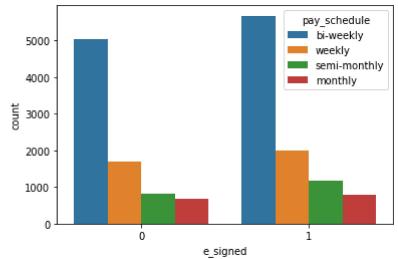
<matplotlib.axes._subplots.AxesSubplot at 0x7fec9bd031d0>



Data visualization

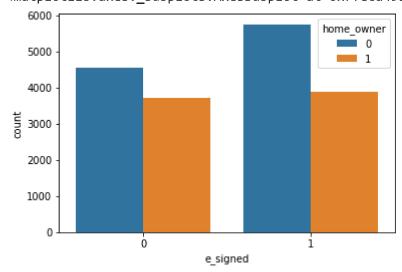
sns.countplot(x='e_signed', hue='pay_schedule', data= dataset)

<matplotlib.axes._subplots.AxesSubplot at 0x7feca1598358>



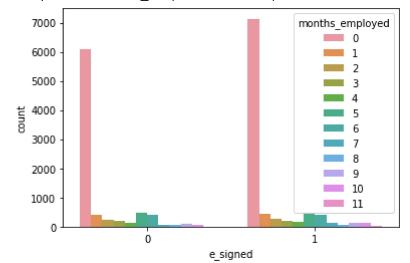
sns.countplot(x='e_signed', hue='home_owner', data= dataset)

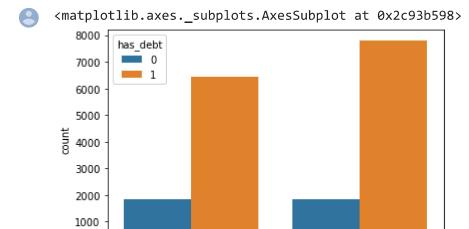
cmatplotlib.axes._subplots.AxesSubplot at 0x7feca4916668>



sns.countplot(x='e_signed', hue='months_employed', data= dataset)

<matplotlib.axes._subplots.AxesSubplot at 0x7feca44aab38>





Encoding categorical data

0

pay = pd.get_dummies(dataset['pay_schedule'], drop_first = True)
pay

e_signed

₽		monthly	semi-monthly	weekly
	0	0	0	0
	1	0	0	1
	2	0	0	1
	3	0	0	0
	4	0	1	0
	17903	1	0	0
	17904	0	0	0
	17905	0	0	1
	17906	0	0	0
	17907	0	0	1

17908 rows × 3 columns

dataset = pd.concat([dataset,pay], axis=1)
dataset.drop(['pay_schedule'], axis =1 ,inplace = True)
dataset

>		entry_id	age	home_owner	income	months_employed	years_employed	current_address_year	personal_account_m pe	
	0	7629673	40	1	3135	0	3	3	6	
	1	3560428	61	0	3180	0	6	3	2	
	2	6934997	23	0	1540	6	0	0	7	
	3	5682812	40	0	5230	0	6	1	2	
	4	5335819	33	0	3590	0	5	2	2	
,	17903	9949728	31	0	3245	0	5	3	2	
,	17904	9442442	46	0	6525	0	2	1	3	
,	17905	9857590	46	0	2685	0	5	1	1	
,	17906	8708471	42	0	2515	0	3	5	6	
	17907	1498559	29	1	2665	0	4	10	4	

17908 rows × 23 columns

Extracting features and labels

```
x = dataset.drop('e_signed', axis= 1)
x
```

 \Box

	entry_id	age	home_owner	income	months_employed	years_employed	current_address_year	personal_account_m ρε
0	7629673	40	1	3135	0	3	3	6
1	3560428	61	0	3180	0	6	3	2
2	6934997	23	0	1540	6	0	0	7
3	5682812	40	0	5230	0	6	1	2
4	5335819	33	0	3590	0	5	2	2
17903	9949728	31	0	3245	0	5	3	2
17904	9442442	46	0	6525	0	2	1	3
17905	9857590	46	0	2685	0	5	1	1
17906	8708471	42	0	2515	0	3	5	6
17907	1498559	29	1	2665	0	4	10	4
dataset['e_signed']						

```
y = dataset['e_signed']
y
```

Splitting the dataset into Training set and Test set

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 1/3, random_state = 7)
```

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr.fit(x_train, y_train)
y_pred = lr.predict(x_test)
```

```
y_pred
```

```
\rightarrow array([0, 1, 1, ..., 1, 1, 1])
```

```
from sklearn.metrics import accuracy_score
acc_score = accuracy_score(y_test, y_pred)
print(acc_score)
```

Г⇒ 0.5785594639865996

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier(criterion = 'entropy', random_state = 7)
dtc.fit(x_train, y_train)
```

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                            max_depth=None, max_features=None, max_leaf_nodes=None,
                            min immunity dacrasca-0 0 min immunity colit-Nona
y_pred = dtc.predict(x_test)
y_pred
    array([0, 1, 1, ..., 1, 0, 0], dtype=int64)
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
acc_score = accuracy_score(y_test, y_pred)
print(acc_score)
 [] [1172 1554]
      [ 962 2282]]
                                recall f1-score
                   precision
                                                   support
                0
                        0.55
                                  0.43
                                            0.48
                                                      2726
                        0.59
                                  0.70
                                            0.64
                                                      3244
                                                      5970
                                            0.58
         accuracy
                        0.57
                                  0.57
                                                      5970
        macro avg
                                            0.56
                        0.57
                                  0.58
                                            0.57
                                                      5970
     weighted avg
```

Naive Bayes

0.5785594639865996

```
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit(x_train, y_train)
y_pred = nb.predict(x_test)
```

y_pred

```
\rightarrow array([0, 1, 1, ..., 1, 1, 1])
```

```
from sklearn import metrics
print("Accuracy: ", metrics.accuracy_score(y_test, y_pred))
```

Accuracy: 0.5753768844221105

Random Forest

```
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators = 30, random_state = 7)
classifier.fit(x_train, y_train)
y_pred = classifier.predict(x_test)

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
[[1598 1128]
 [1134 2110]]
                            recall f1-score
              precision
                                               support
           0
                    0.58
                              0.59
                                        0.59
                                                  2726
           1
                    0.65
                              0.65
                                        0.65
                                                  3244
                                        0.62
                                                  5970
    accuracy
                                                  5970
   macro avg
                    0.62
                              0.62
                                        0.62
weighted avg
                    0.62
                              0.62
                                        0.62
                                                  5970
```

0.6211055276381909