DSC530_Final_Litschewski

July 28, 2020

1 DSC 530 : Final Project

Bellevue University Litschewski, Matthew July 2020 RE: Using Exploratory Data Analysis to evaluate a data set.

[109]:
```
import numpy as np
import pandas as pd
import scipy as stats
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import seaborn as sns
import thinkstats2
import thinkplot
import statsmodels.api as sm
import statsmodels.formula.api as smf
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
```

[43]:
```
# Import data set and convert it a data frame to run EDA
df = pd.read_csv('Bank1.csv')

df = df.dropna()
df.head()
```

[43]:

	age	education	balance	housing	duration	campaign	y
0	58	tertiary	2143	yes	261	1	no
1	44	secondary	29	yes	151	1	no
2	33	secondary	2	yes	76	1	no
3	47	unknown	1506	yes	92	1	no
4	33	unknown	1	no	198	1	no

Variables that will be looked at will be "age", "balance", Campaign, Contact time, and how they and if they effect Desired out come. Which is the memeber made a deposit transaction. Age, balance, campign and contact time are numerical data desired out come is a binary catogorical (Yes/No). Historgrams of the variables will be plotted first. Age is the age of the customer, education is the highest reported education obrained by the customer, balance is the balaance in their account at time of data collection, housing is if they have a loan, duration is how long they were engaged for a particular campaign and 'y' is if the campaign was successful.

[79]:
```
#df['education']= df['education'].map({'unknown':1, 'primary': 2, 'secondary':
↪3, 'tertiary':4})
#df['housing'] = df['housing'].map({'yes': 1, 'no':0})
df['y']= df['y'].map({'yes': 1, 'no':0})
# clean data so that all variables are float/int64
```

[80]:
```
df.describe()
```

[80]:

	age	balance	duration	campaign	y
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.936210	1362.272058	258.163080	2.763841	0.116985
std	10.618762	3044.765829	257.527812	3.098021	0.321406
min	18.000000	-8019.000000	0.000000	1.000000	0.000000
25%	33.000000	72.000000	103.000000	1.000000	0.000000
50%	39.000000	448.000000	180.000000	2.000000	0.000000
75%	48.000000	1428.000000	319.000000	3.000000	0.000000
max	95.000000	102127.000000	4918.000000	63.000000	1.000000

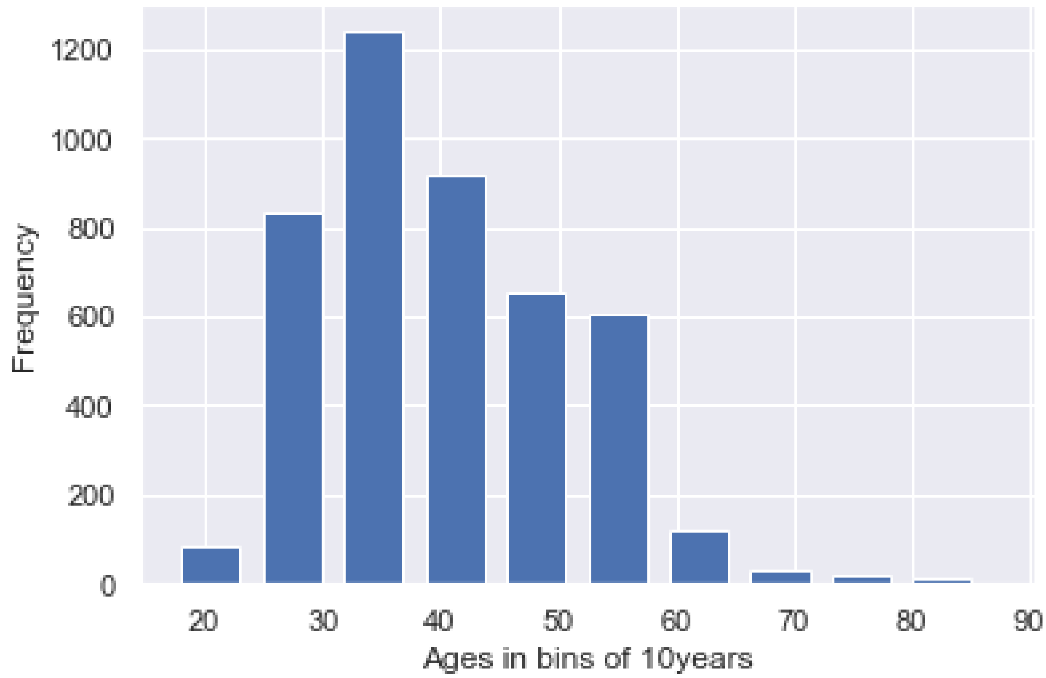
Given that there is 45,000 entries in this dataset and new random dataset will be created containing only 10,000 entries for ease of computing.

[81]:
```
df_train , df_test = train_test_split(df, test_size=0.9)
df_train.describe()
```

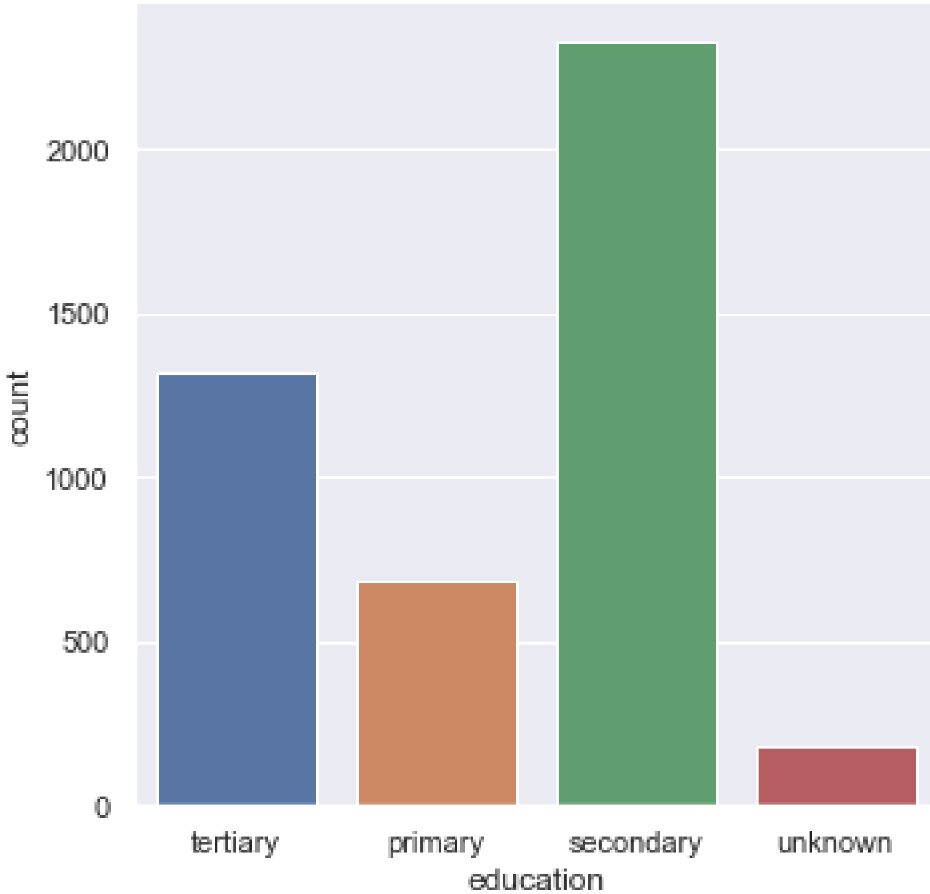
[81]:

	age	balance	duration	campaign	y
count	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000
mean	41.047335	1396.496572	254.721079	2.763548	0.107277
std	10.717551	3044.831247	255.932452	3.122861	0.309500
min	18.000000	-2282.000000	5.000000	1.000000	0.000000
25%	33.000000	73.000000	102.000000	1.000000	0.000000
50%	39.000000	455.000000	176.000000	2.000000	0.000000
75%	49.000000	1483.000000	316.000000	3.000000	0.000000
max	87.000000	66721.000000	3366.000000	46.000000	1.000000

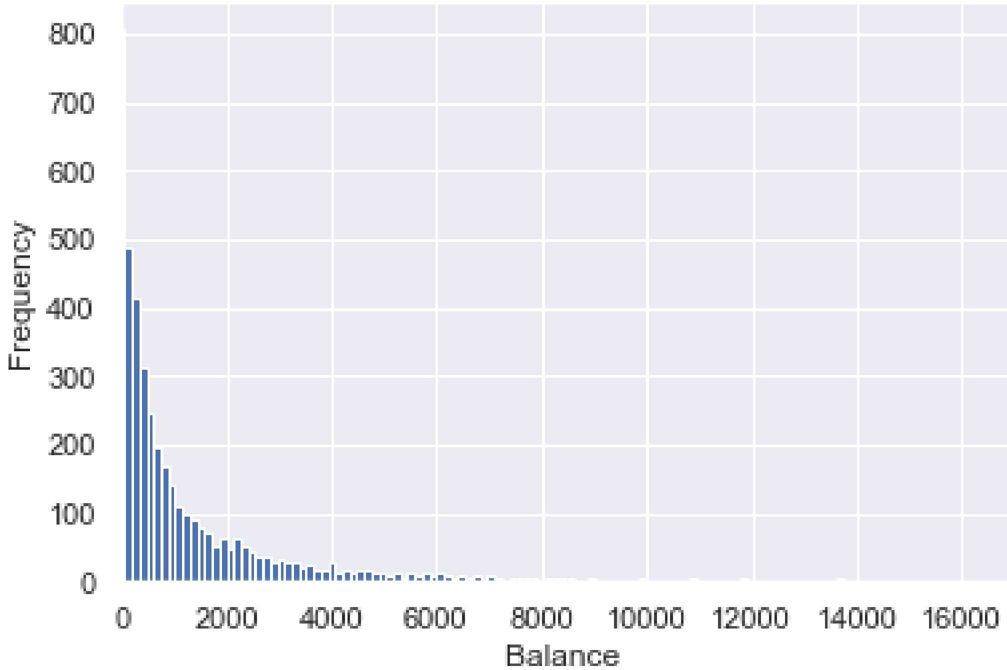
[82]:
```
age = df_train['age']
_= plt.hist(age, bins = 10, width = 5)
_=plt.xlabel('Ages in bins of 10years')
_= plt.ylabel( 'Frequency')
plt.show()
```



[83]:
```
ed = df_train['education']
_= sns.catplot(x='education', kind='count', data = df_train)
```

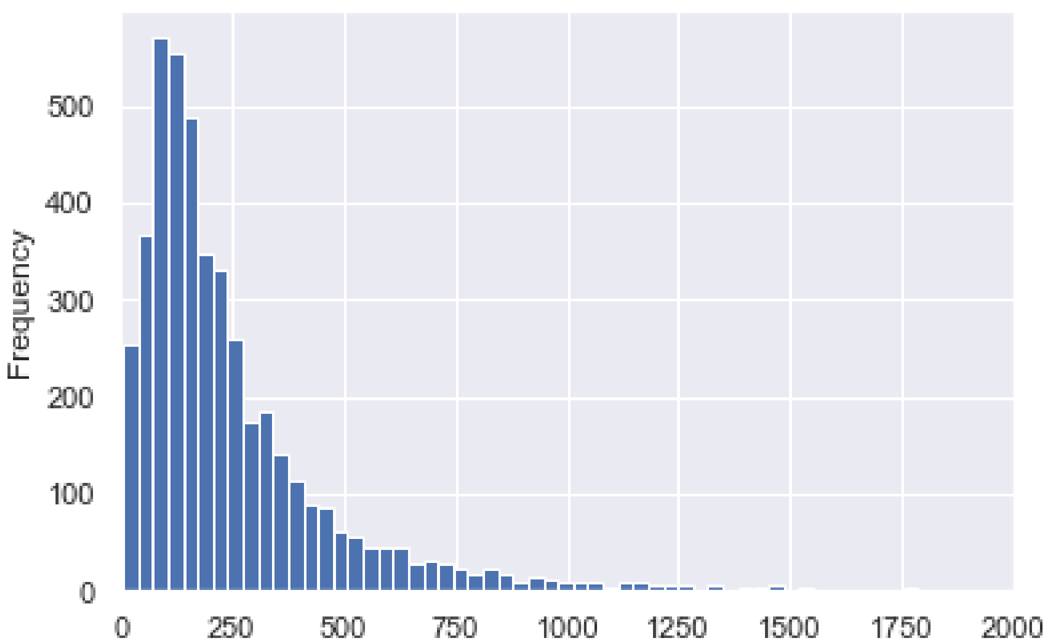


[84]:
```
bal = df_train['balance']
bal.plot.hist(bins = 500)
plt.xlim(xmin = 0, xmax = 17000)
_=plt.xlabel('Balance ')
_= plt.ylabel( 'Frequency')
plt.show()
```



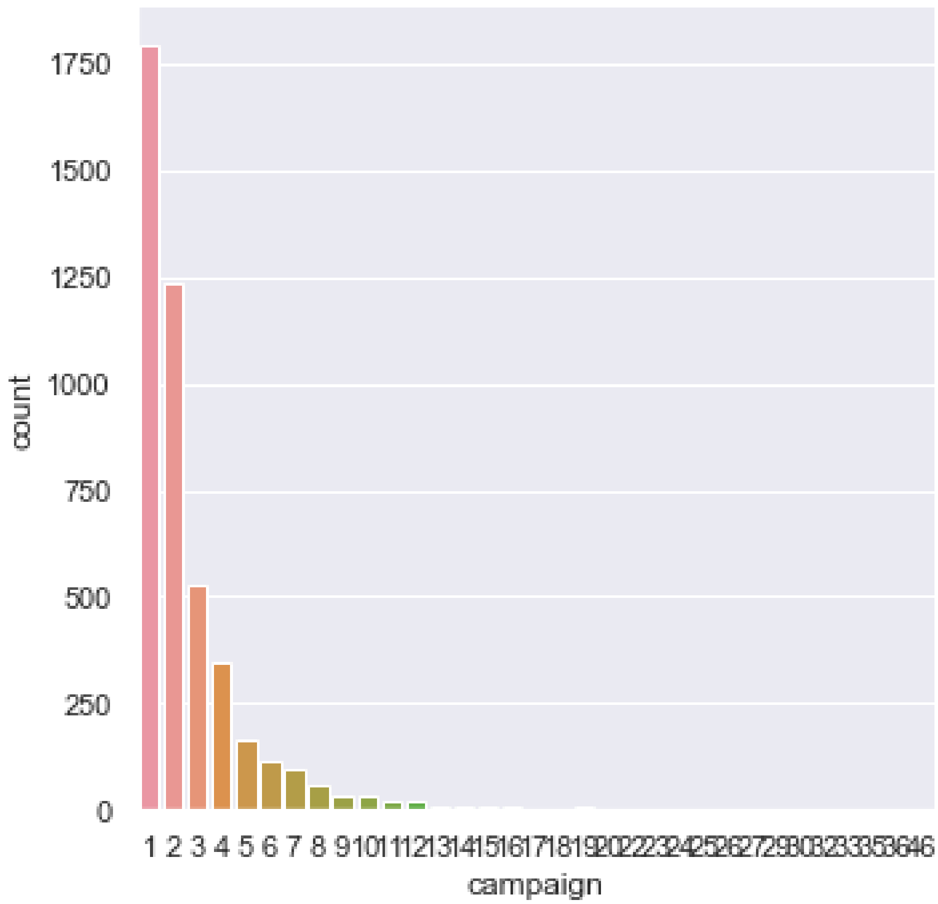
[85]:
```
time = df_train['duration']
time.plot.hist(bins = 100)
plt.xlim(xmin = 0, xmax = 2000)
```

[85]: (0, 2000)



There are two things to really look at which campaigns were the most successful at a positive outcomt and how much time engaging in the client was needed in those particular campaigns to achieve a postive outcome. Once the most effective outcomes are identified those will be seperated out and used in sepreate predictions.

[86]:
```python
_= sns.catplot(x= 'campaign', kind= 'count', data = df_train )
```



[87]:
```python
def ecdf(data):
    """Compute ECDF for a one-dimensional array of measurements."""
    # Number of data points: n
    n = len(data)

    # x-data for the ECDF: x
    x = np.sort(data)

    # y-data for the ECDF: y
```

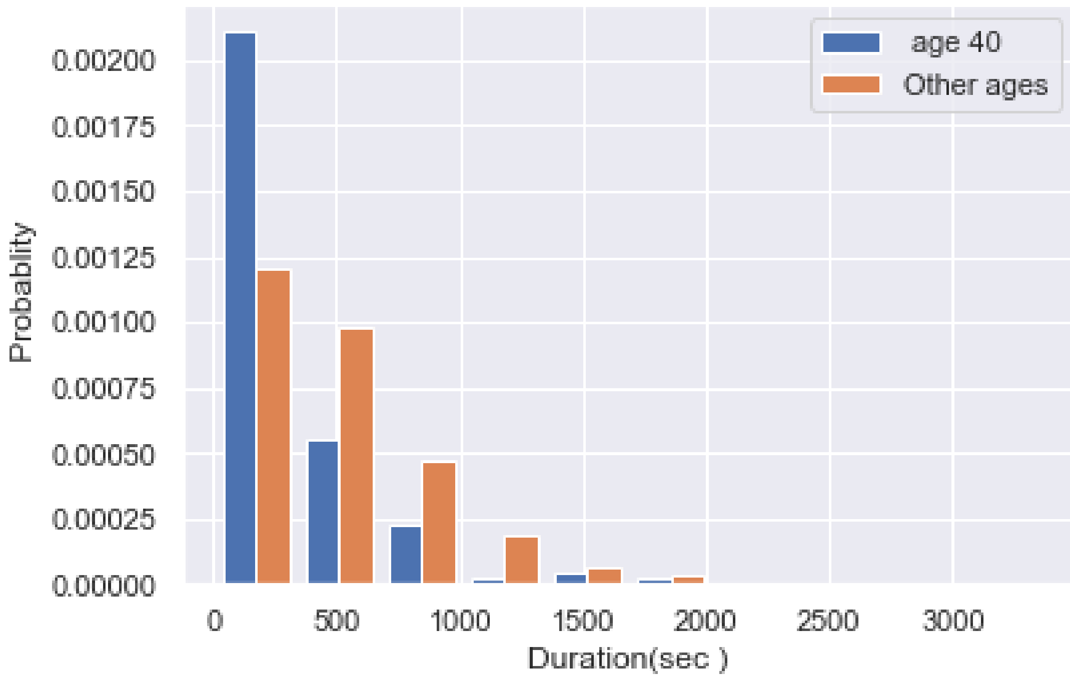
```
    y = np.arange(1,len(x)+1) / n

    return x, y
```

[88]:
```
def PMF(df):
    l= len(df)
    hist = {}
    for x in df:
        hist[x]=hist.get(x,0)+1
    data = pd.DataFrame.from_dict(hist, orient="index")
    data.columns = ['counts']
    data['PMF']= data['counts']/l
    return data
```

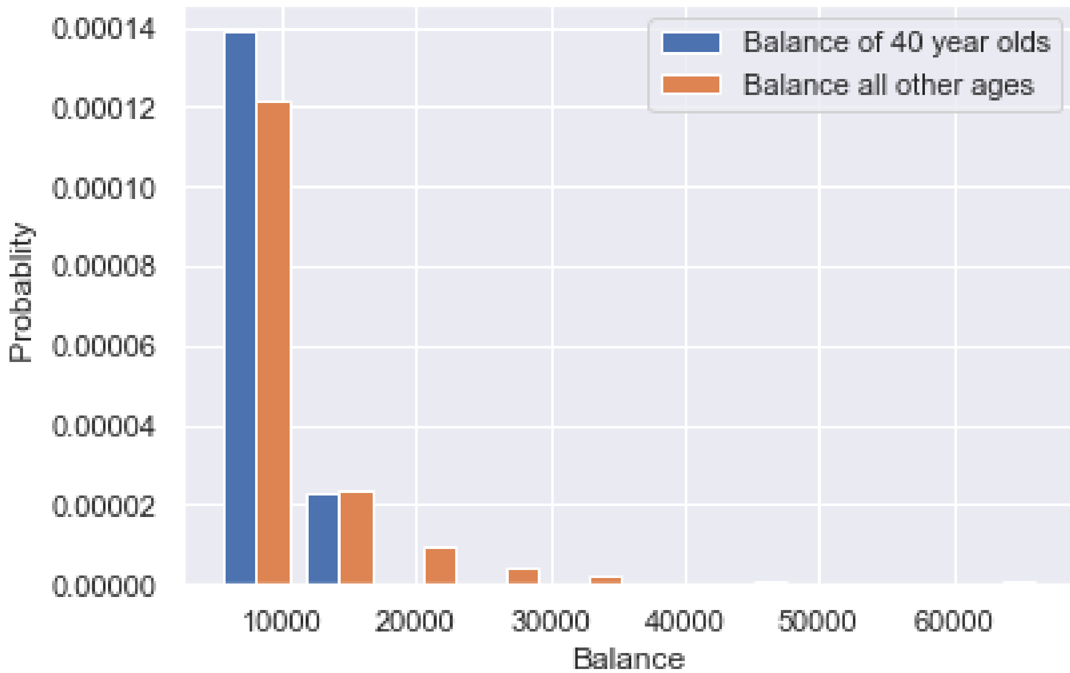
[89]:
```
age_df = df_train[df_train.age ==40]
age2_df = df_train[df_train.age!=40]
bal40_df = age_df[age_df.balance> 5000]
bal_df = age2_df[age2_df.balance>5000]
```

[90]:
```
age40_pmf = thinkstats2.Pmf(age_df.duration)
age_pmf = thinkstats2.Pmf(age2_df.duration)
bal40_pmf = thinkstats2.Pmf(bal40_df.balance)
bal_pmf = thinkstats2.Pmf(bal_df.balance)
```

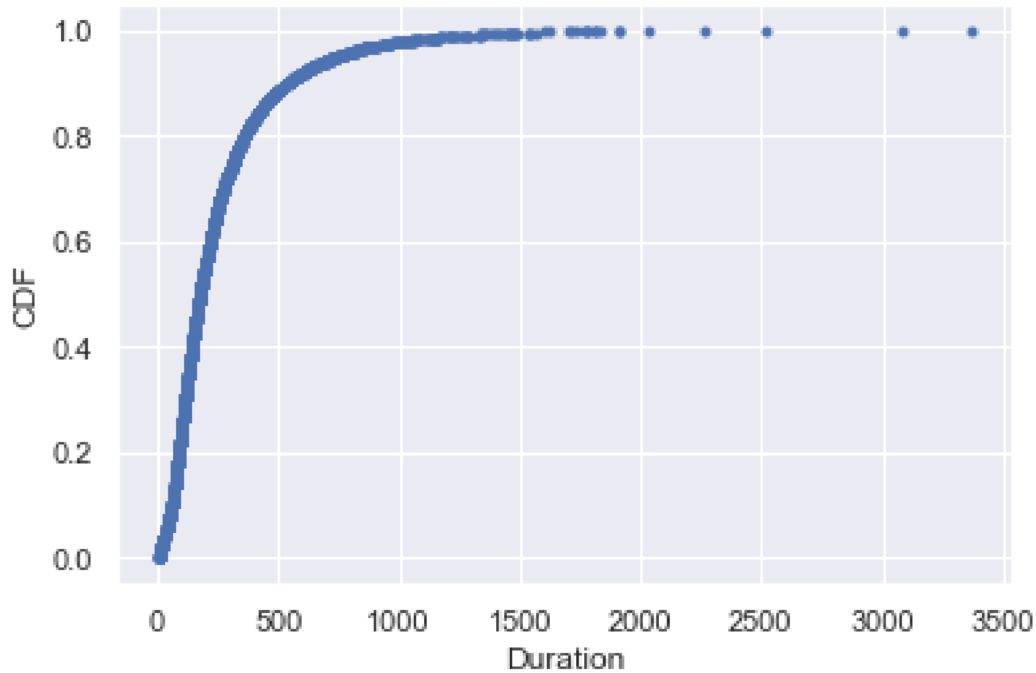
[91]:
```
# Histogram of age40 Durations vs all other ages:
plt.hist([age40_pmf, age_pmf], density = "True",label=[' age 40', 'Other ages'])
plt.legend(loc='upper right')
plt.xlabel('Duration(sec )')
plt.ylabel(' Probablity')
plt.show()
```



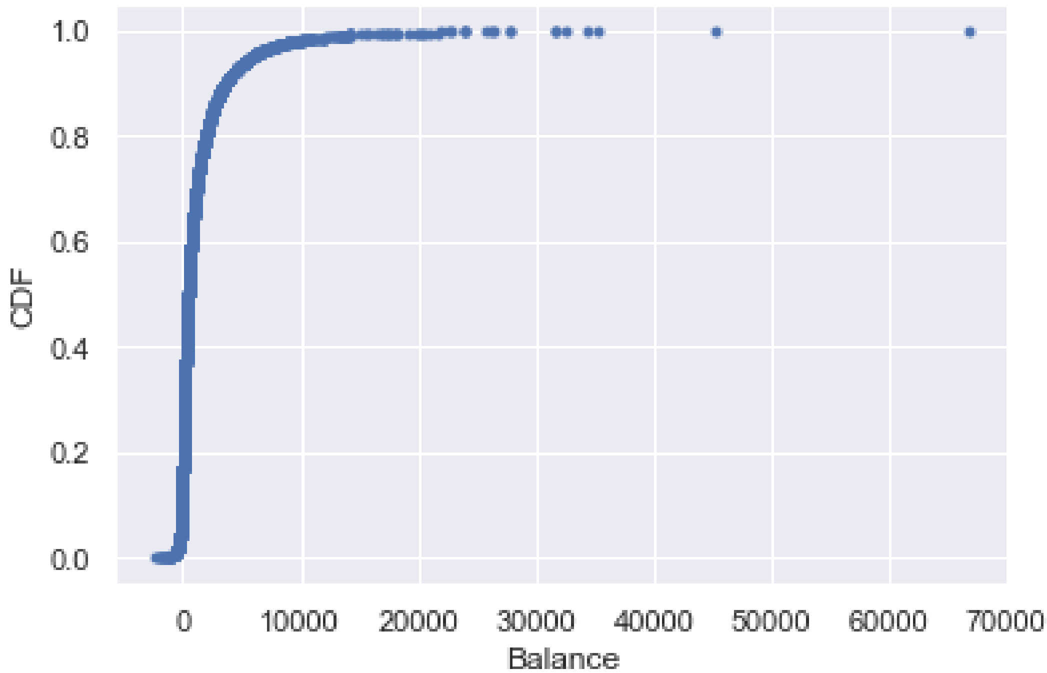
[92]:
```
# Histogram of age40 balances vs all other ages:
plt.hist([bal40_pmf, bal_pmf], density = "True",label=['Balance of 40 year␣
→olds', 'Balance all other ages'])
plt.legend(loc='upper right')
plt.xlabel('Balance')
plt.ylabel(' Probablity')
plt.show()
```



[93]:
```
x,y = ecdf(time)
_=plt.plot(x,y, marker = '.', linestyle = 'none')
_=plt.xlabel('Duration')
_=plt.ylabel('CDF')
plt.show()
```



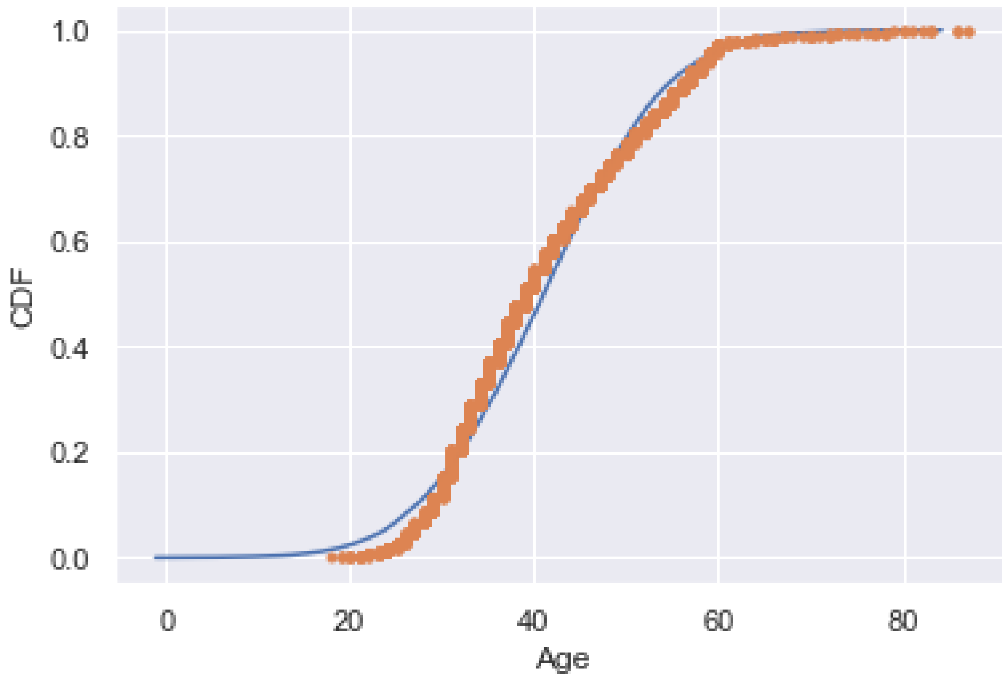
[94]:
```
x,y = ecdf(bal)
_=plt.plot(x,y, marker = '.', linestyle = 'none')
_=plt.xlabel('Balance')
_=plt.ylabel('CDF')
plt.show()
```



1.1 Running an analytic plot of age against normal distribution

[95]:
```
mean = np.mean(age)
std = np.std(age)
samples = np.random.normal(mean, std, size = 20000)
x_thry, y_thry = ecdf(samples)
x,y = ecdf(age)
```

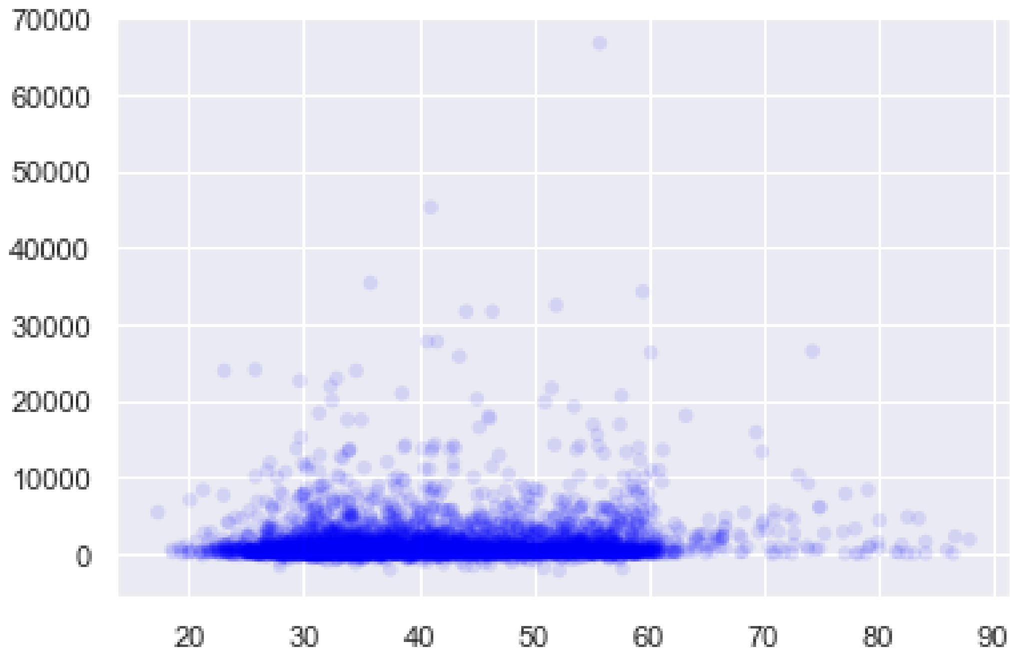
[96]:
```
sns.set()
_= plt.plot(x_thry, y_thry)
_= plt.plot(x,y, marker= '.', linestyle = 'none')
_= plt.xlabel("Age")
_= plt.ylabel('CDF')
plt.show()
```



It would appear from this graph that the age of people in the data set fit the expected normal distribution of ages from a random sampling. There is only a slight deviation around ages 20-25 and 35-40 showing that the banks patrens are slightly higher in these age groups then in others.

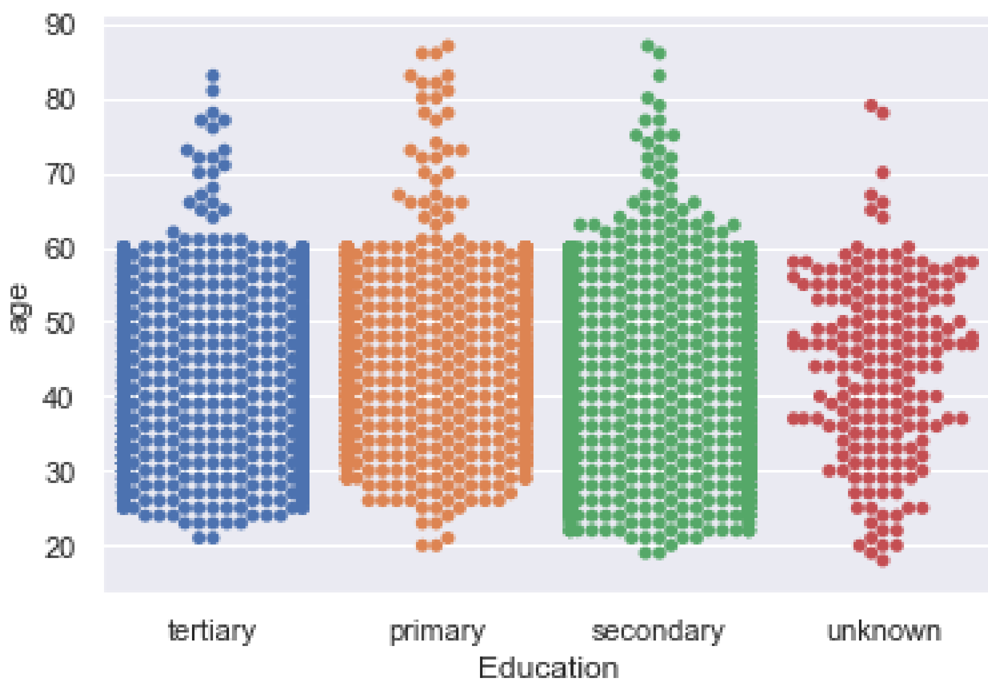
1.2 Scatter plots (2) comparing two variables

[97]:
```
age_j = thinkstats2.Jitter(age,1)
bal_j = thinkstats2.Jitter(bal, 1)
thinkplot.Scatter(age_j, bal_j, alpha = 0.1)
```



[98]:

```
#swarm plot of education and balance
_ = sns.swarmplot(x='education', y='age', data=df_train)
_ = plt.xlabel('Education')
_ = plt.ylabel('age')
plt.show()
```



2 Hypthesis Test

[99]:
```
edUNK = df_train[df_train.education == "unknown"]
edAll = df_train[df_train.education != "unknown"]
ED_bal = edAll['age']
edUNK_bal =edUNK['age']
# Null that the age of those with unknown education is the same as with␣
↪education.
```

[100]:
```
sm.stats.ztest(ED_bal, edUNK_bal, alternative = "two-sided")
```

[100]:
```
(-3.969433340184176, 7.204375745108388e-05)
```

After computing some test statistics the p-value was 1.6e-7 much less than 0.05 meaning the null hypothesis can be rejected.

3 Logistic Regression Analysis

```
The goal is to see if that will certain variables it is possible to predict a positive outcome
```

[101]:
```
df_train['y'].value_counts()
```

[101]:
```
0    4036
1     485
Name: y, dtype: int64
```

[102]:
```
count_no_sub = len(df_train[df_train['y']==0])
count_sub = len(df_train[df_train['y']==1])
pct_of_no_sub = count_no_sub/(count_no_sub+count_sub)
print("percentage of no subscription is", pct_of_no_sub*100)
pct_of_sub = count_sub/(count_no_sub+count_sub)
print("percentage of subscription", pct_of_sub*100)
```

```
percentage of no subscription is 89.27228489272285
percentage of subscription 10.72771510727715
```

[124]:
```
model = smf.logit('y ~ age + duration + balance', data = df_train)
results = model.fit()
print(results.params)
```

```
Optimization terminated successfully.
         Current function value: 0.284321
         Iterations 7
Intercept   -3.726694
```

```
age          0.008577
duration     0.003512
balance      0.000053
dtype: float64
```

```
[ ]:
```