In [2]:
```
# Project 2: Credit Clustering
# Manuel Duran
# DSC 680
```

In [3]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import plotly as py
import os
import plotly.io as pio
pio.renderers.default='notebook'
```

In [4]:
```
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler
from sklearn.cluster import KMeans
```

In [5]:
```
import category_encoders as ce
plt.style.use('seaborn-colorblind')
%matplotlib inline
```

EDA

In [62]:
```
df = pd.read_csv('german_credit_data.csv', index_col = 'Unnamed: 0')
```

In [65]:
```
dfeda = pd.read_csv("german_credit_data.csv")
```

In [66]:
```
dfeda.drop("Unnamed: 0", inplace=True, axis=1)
dfeda.head()
```

Out[66]:

	Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount	Duration	Purpose
0	67	male	2	own	NaN	little	1169	6	radio/TV
1	22	female	2	own	little	moderate	5951	48	radio/TV
2	49	male	1	own	little	NaN	2096	12	education
3	45	male	2	free	little	little	7882	42	furniture/equipment
4	53	male	2	free	little	little	4870	24	car

In [67]:
```
job_dictionary = {0:"unskilled and non-resident", 1:"unskilled and resident", 2:"skille
```

```
dfeda = dfeda.replace({"Job":job_dictionary})
dfeda.head()
```

Out[67]:

	Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount	Duration	Purpose
0	67	male	skilled	own	NaN	little	1169	6	radio/TV
1	22	female	skilled	own	little	moderate	5951	48	radio/TV
2	49	male	unskilled and resident	own	little	NaN	2096	12	education
3	45	male	skilled	free	little	little	7882	42	furniture/equipment
4	53	male	skilled	free	little	little	4870	24	car

In [7]:

```
# Review the dataset variables
df.head()
```

Out[7]:

	Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount	Duration	Purpose
0	67	male	2	own	NaN	little	1169	6	radio/TV
1	22	female	2	own	little	moderate	5951	48	radio/TV
2	49	male	1	own	little	NaN	2096	12	education
3	45	male	2	free	little	little	7882	42	furniture/equipment
4	53	male	2	free	little	little	4870	24	car

In [8]:

```
df.describe()
```

Out[8]:

	Age	Job	Credit amount	Duration
count	1000.000000	1000.000000	1000.000000	1000.000000
mean	35.546000	1.904000	3271.258000	20.903000
std	11.375469	0.653614	2822.736876	12.058814
min	19.000000	0.000000	250.000000	4.000000
25%	27.000000	2.000000	1365.500000	12.000000
50%	33.000000	2.000000	2319.500000	18.000000
75%	42.000000	2.000000	3972.250000	24.000000
max	75.000000	3.000000	18424.000000	72.000000

In [9]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000 entries, 0 to 999
```

```
Data columns (total 9 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   Age               1000 non-null   int64 
 1   Sex               1000 non-null   object
 2   Job               1000 non-null   int64 
 3   Housing           1000 non-null   object
 4   Saving accounts   817 non-null    object
 5   Checking account  606 non-null    object
 6   Credit amount     1000 non-null   int64 
 7   Duration          1000 non-null   int64 
 8   Purpose           1000 non-null   object
dtypes: int64(4), object(5)
memory usage: 78.1+ KB
```

In [10]:

```
df.describe(include=['object'])
```

Out[10]:

	Sex	Housing	Saving accounts	Checking account	Purpose
count	1000	1000	817	606	1000
unique	2	3	4	3	8
top	male	own	little	little	car
freq	690	713	603	274	337

In [11]:

```
numeric = ['Age', 'Job', 'Credit amount', 'Duration']
categorical = ['Sex', 'Housing', 'Saving accounts', 'Checking account', 'Purpose']
```

In [12]:

```
def check_missing(data, output_path=None):

    result = pd.concat([data.isnull().sum(), data.isnull().mean()], axis=1)
    result = result.rename(index=str, columns={0: 'total missing', 1: 'proportion'})
    if output_path:
        result.to_csv(f'{output_path}missing.csv')
        print(output_path, 'missing.csv')
    return result
```

In [13]:

```
check_missing(data=df)
```

Out[13]:

	total missing	proportion
Age	0	0.000
Sex	0	0.000
Job	0	0.000
Housing	0	0.000
Saving accounts	183	0.183
Checking account	394	0.394
Credit amount	0	0.000

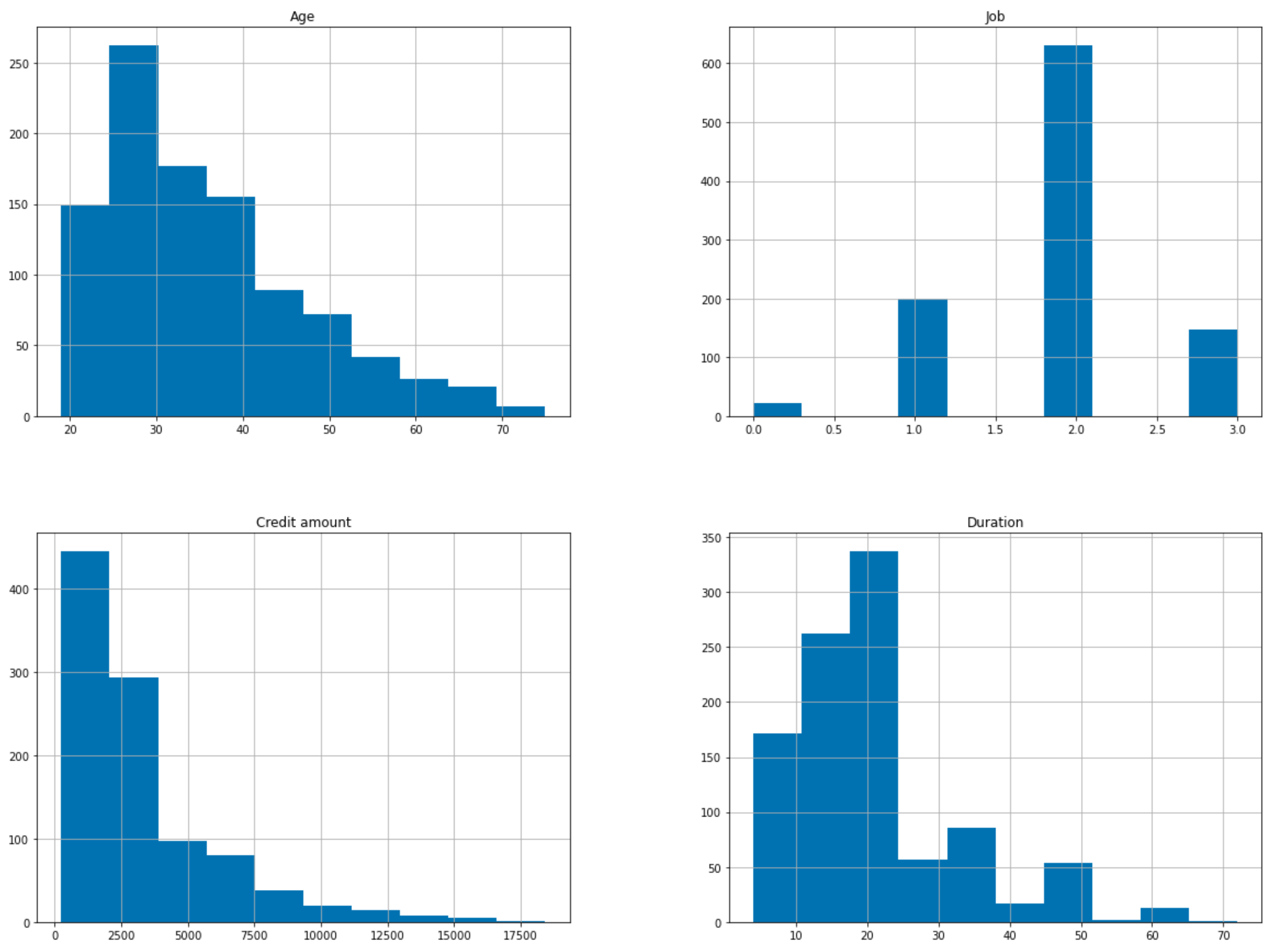
	total missing	proportion
Duration	0	0.000
Purpose	0	0.000

In [14]:

```
df= df.fillna('unknown')
```

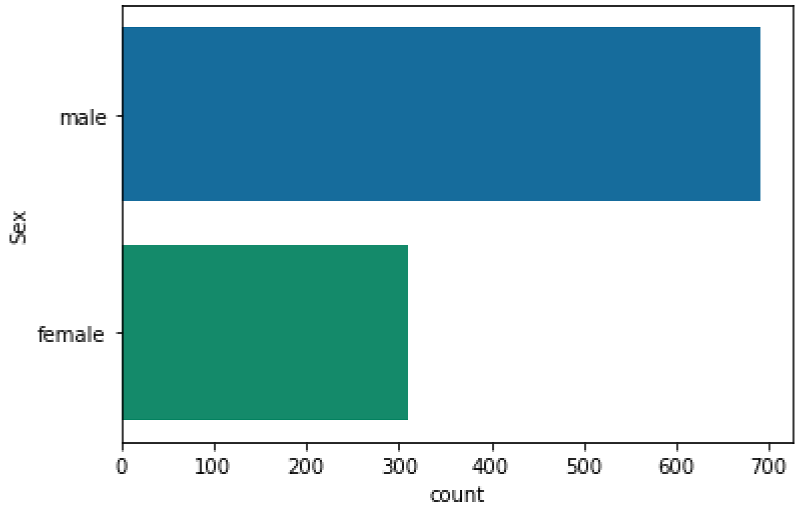
In [15]:

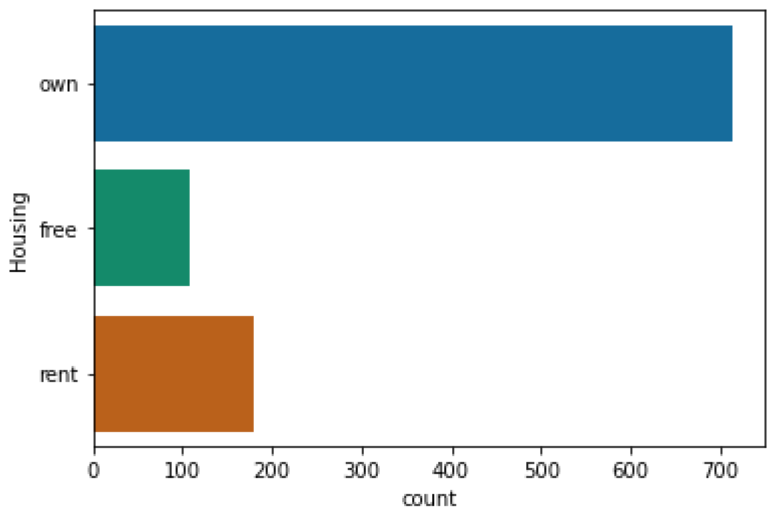
```
df.hist(figsize = (20,15));
```

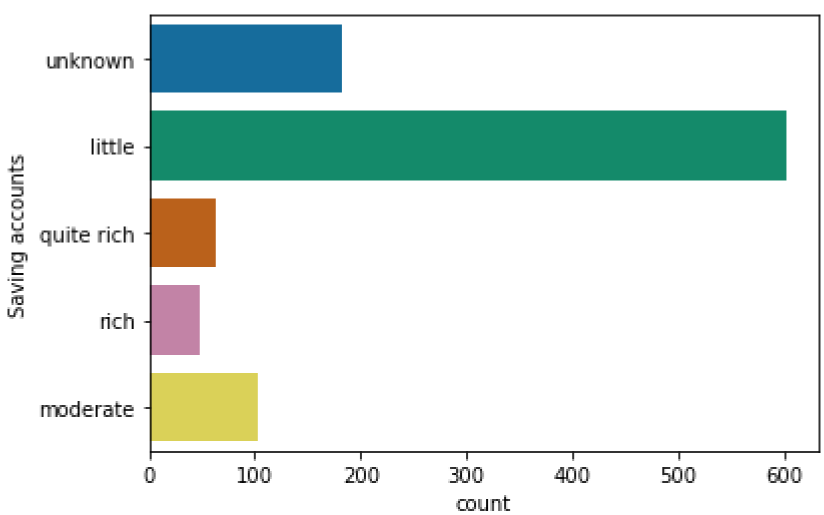


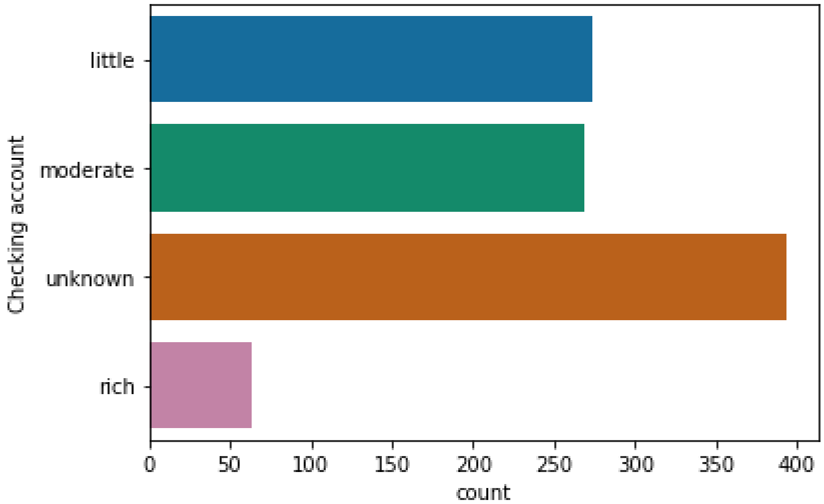
In [16]:

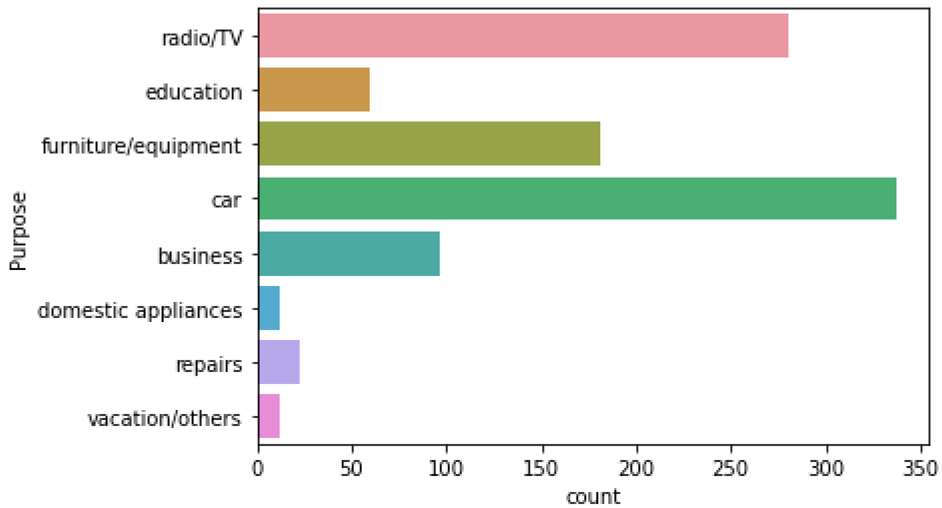
```
for col in df[categorical].columns:
    sns.countplot(y =col, data = df)
    plt.show()
```


male
female
Sex
0
100
200
300
400
500
600
700
count

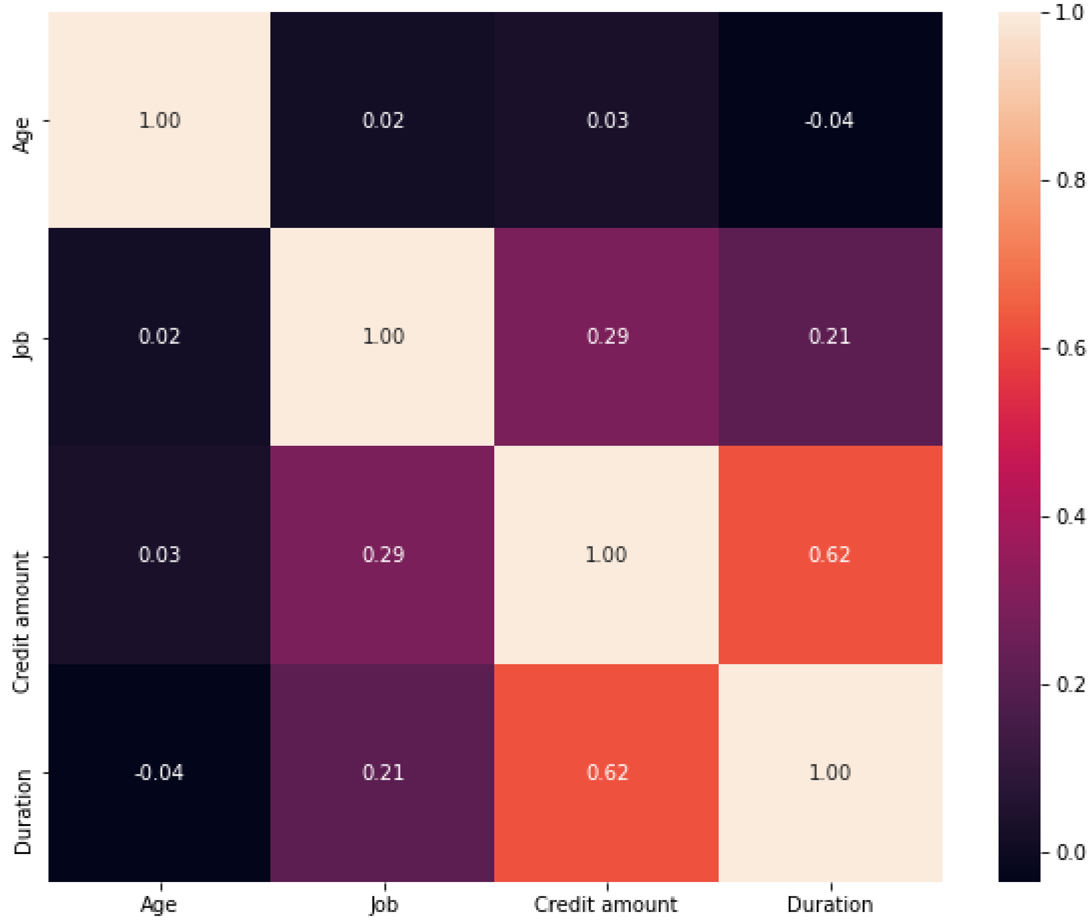

own
free
rent
Housing
0
100
200
300
400
500
600
700
count


unknown
little
quite rich
rich
moderate
Saving accounts
0
100
200
300
400
500
600
count





In [17]:
```
corr = df.corr()
plt.figure(figsize=(10,8));
sns.heatmap(corr, annot=True, fmt='.2f');
```



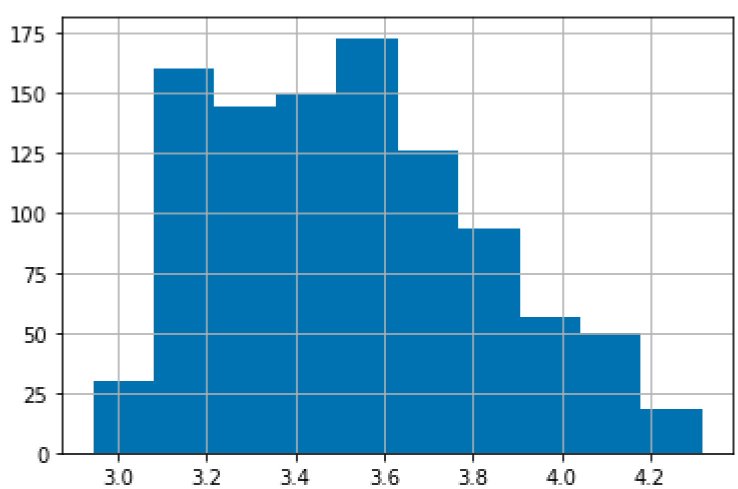
In [18]:

```
data = df.copy()
```

In [19]:

```
np.log(data['Age']).hist()
```

Out[19]: <AxesSubplot:>



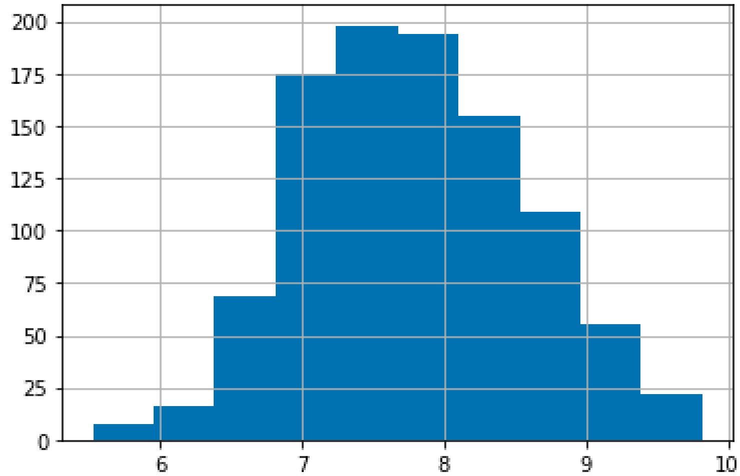
In [20]:

```
data['Age'] = np.log(data['Age'])
```

In [21]:

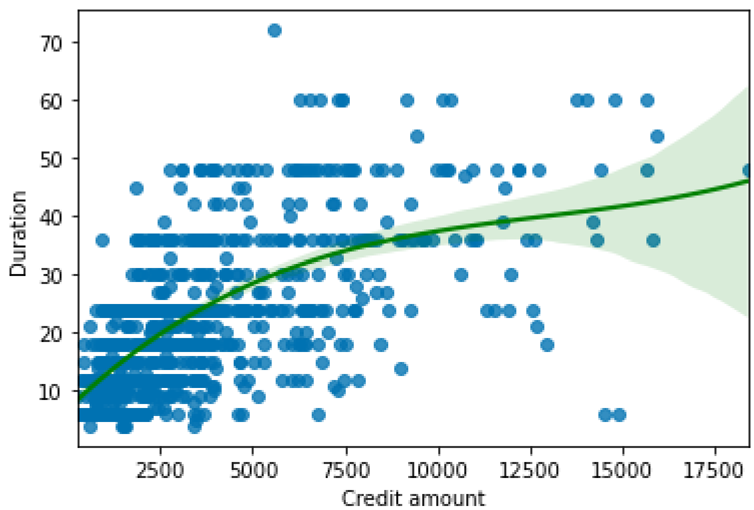
```
np.log(data['Credit amount']).hist()
```

Out[21]: <AxesSubplot:>



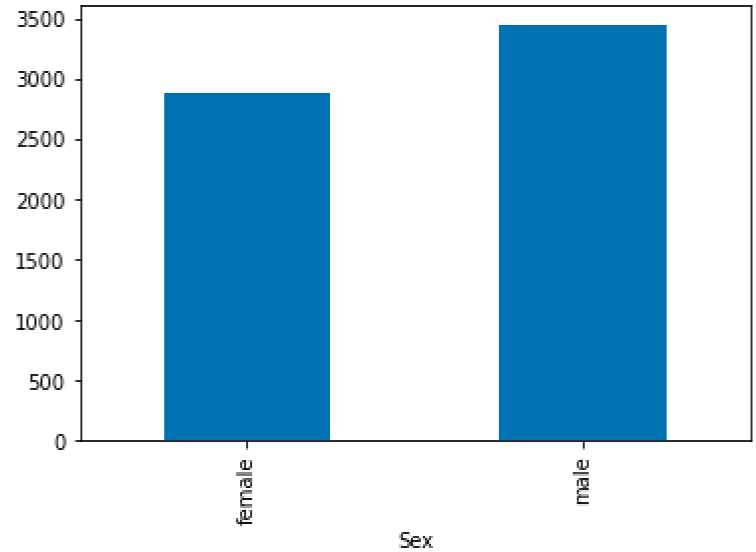
In [69]:
```
sns.regplot(x=dfeda["Credit amount"], y=dfeda["Duration"],order=3, line_kws={"color":"g
```

Out[69]: <AxesSubplot:xlabel='Credit amount', ylabel='Duration'>



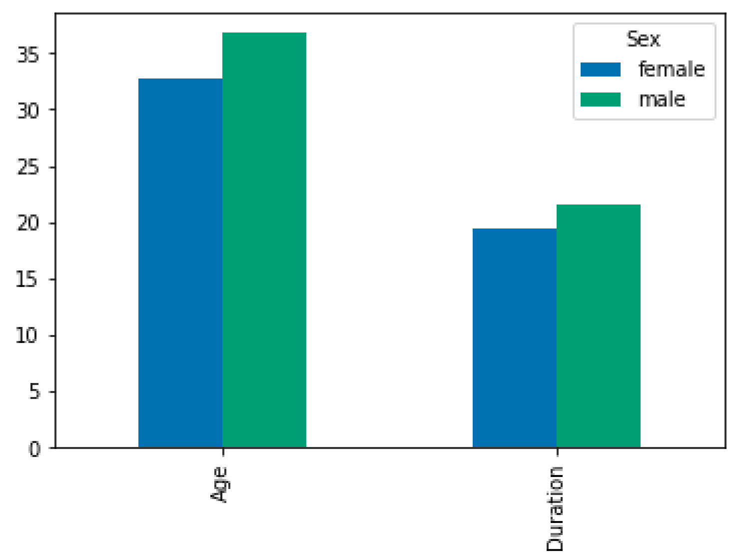
In [70]:
```
dfeda.groupby("Sex").mean()["Credit amount"].T.plot(kind="bar")
```

Out[70]: <AxesSubplot:xlabel='Sex'>



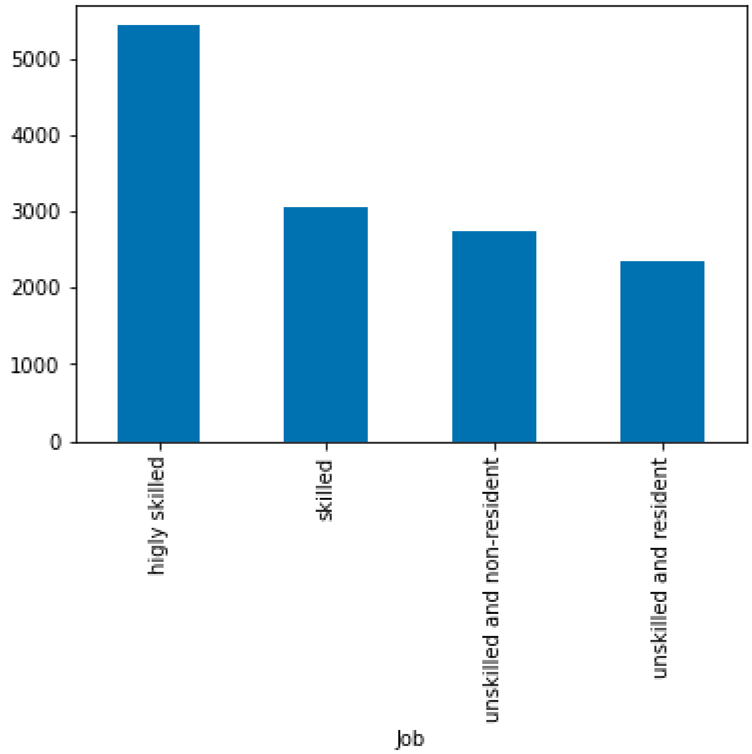
In [71]:
```
dfeda.groupby("Sex").mean()[["Age", "Duration"]].T.plot(kind="bar")
```

Out[71]: <AxesSubplot:>



In [72]:
```
dfeda.groupby("Job").mean()["Credit amount"].T.plot(kind="bar")
```

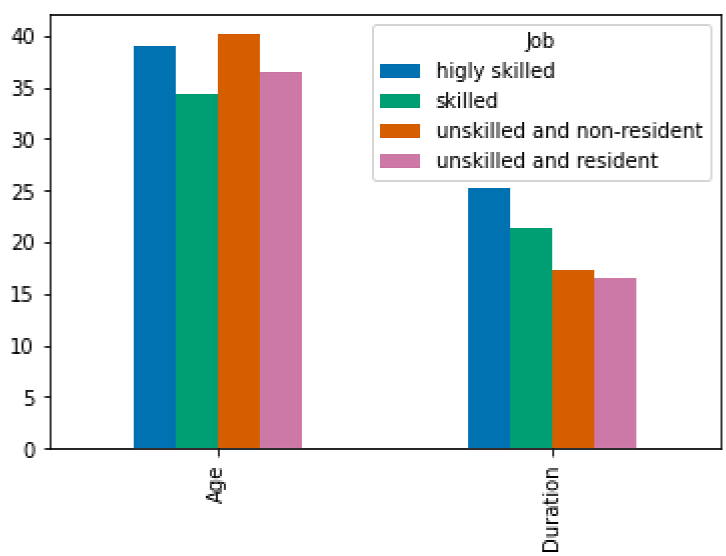
Out[72]: <AxesSubplot:xlabel='Job'>



In [73]:

```
dfeda.groupby("Job").mean()[["Age", "Duration"]].T.plot(kind="bar")
```

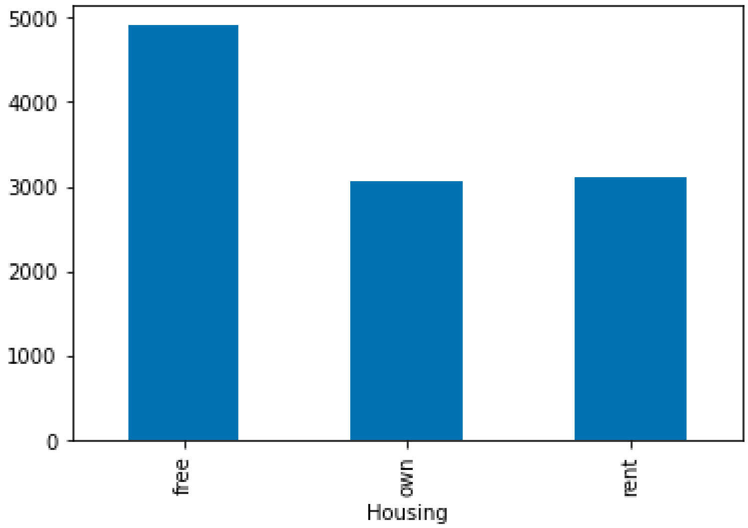
Out[73]: <AxesSubplot:>



In [74]:

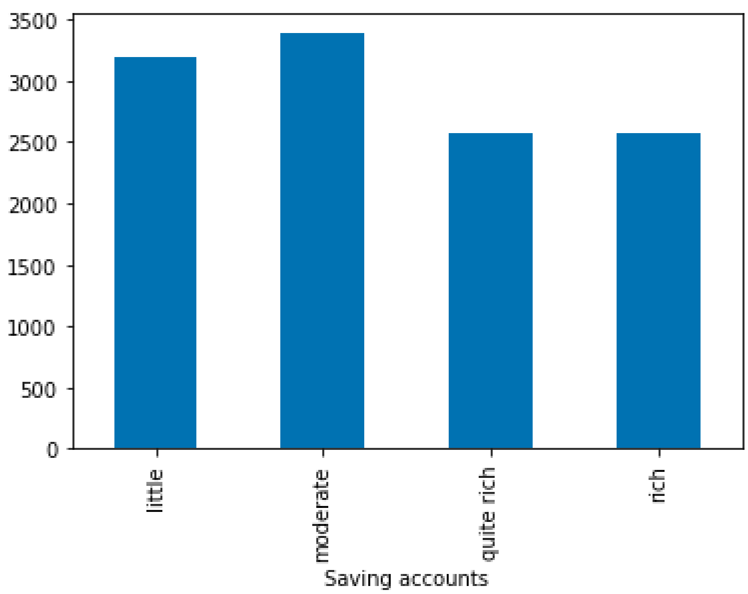
```
dfeda.groupby("Housing").mean()["Credit amount"].T.plot(kind="bar")
```

Out[74]: <AxesSubplot:xlabel='Housing'>



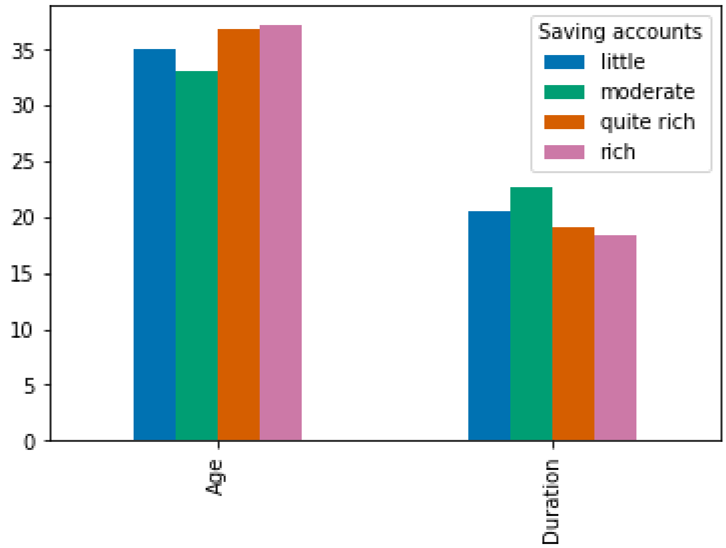
In [75]:
```
dfeda.groupby("Saving accounts").mean()["Credit amount"].T.plot(kind="bar")
```

Out[75]: <AxesSubplot:xlabel='Saving accounts'>



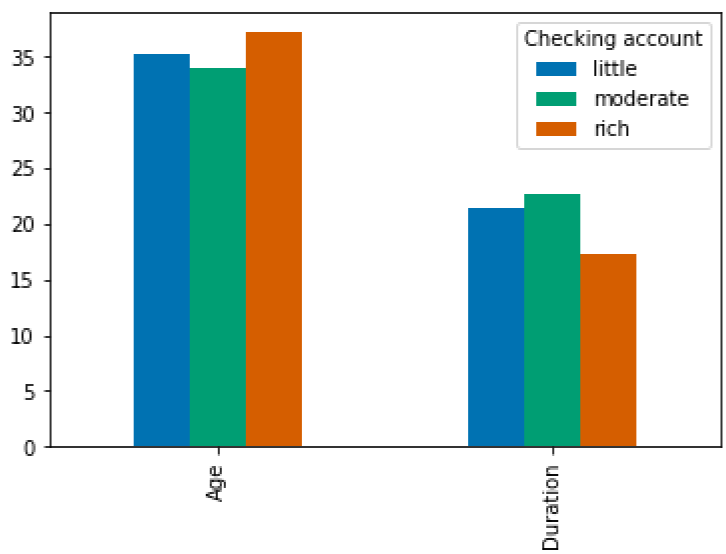
In [76]:
```
dfeda.groupby("Saving accounts").mean()[["Age", "Duration"]].T.plot(kind="bar")
```

Out[76]: <AxesSubplot:>



In [77]:
```
dfeda.groupby("Checking account").mean()[["Age", "Duration"]].T.plot(kind="bar")
```

Out[77]: <AxesSubplot:>



In [22]:
```
data['Credit amount'] = np.log(data['Credit amount'])
```

In [23]:
```
from sklearn.preprocessing import LabelEncoder
```

In [24]:
```
encoder = LabelEncoder()
from sklearn.preprocessing import LabelEncoder
for label in categorical:
    data[label] = encoder.fit_transform(data[label])
```

In [25]:
```
data[categorical]
```

Out[25]:

	Sex	Housing	Saving accounts	Checking account	Purpose

	Sex	Housing	Saving accounts	Checking account	Purpose
0	1	1	4	0	5
1	0	1	0	1	5
2	1	1	0	3	3
3	1	0	0	0	4
4	1	0	0	0	1
...	...	...	...	...	...
995	0	1	0	3	4
996	1	1	0	0	1
997	1	1	0	3	5
998	1	0	0	0	5
999	1	1	1	1	1

1000 rows × 5 columns

In [26]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(data)
data_scaled = pd.DataFrame(X_scaled, columns=data.columns)
data_scaled.head()
```

Out[26]:

	Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount	Duration	Purpose
0	2.271006	0.670280	0.146949	-0.133710	1.833169	-1.254566	-0.933901	-1.236478	1.073263
1	-1.446152	-1.491914	0.146949	-0.133710	-0.699707	-0.459026	1.163046	2.248194	1.073263
2	1.226696	0.670280	-1.383771	-0.133710	-0.699707	1.132053	-0.181559	-0.738668	0.061705
3	0.942455	0.670280	0.146949	-2.016956	-0.699707	-1.254566	1.525148	1.750384	0.567484
4	1.488620	0.670280	0.146949	-2.016956	-0.699707	-1.254566	0.904743	0.256953	-0.949853

In [27]:

```
from sklearn.decomposition import PCA
```

In [28]:

```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
```

In [29]:

```
X_pca.shape
```

Out[29]: (1000, 2)

In [30]:

```
import umap.umap_ as umap
```

In [31]:
```
reducer = umap.UMAP(random_state=42)
X_umap = reducer.fit_transform(X_scaled)
```

In [32]:
```
X_umap.shape
```

Out[32]: (1000, 2)

In [33]:
```
from sklearn.manifold import TSNE
```

In [34]:
```
tsne = TSNE(n_components=2, random_state=10)
X_tsne = tsne.fit_transform(X_scaled)
```

In [35]:
```
X_tsne.shape
```

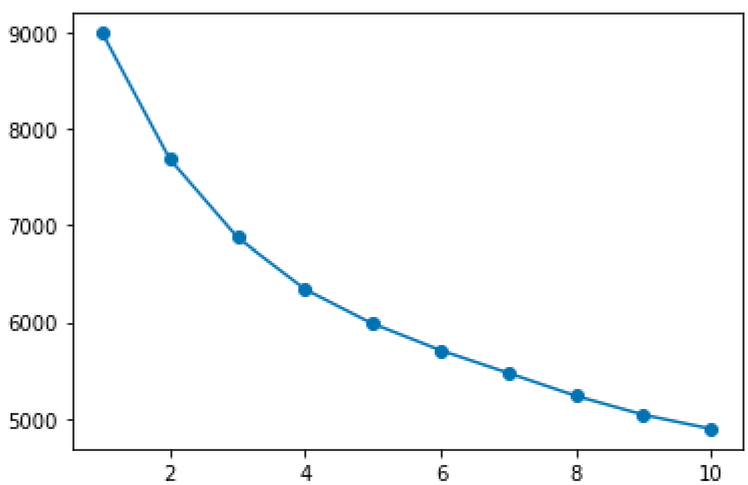
Out[35]: (1000, 2)

In [36]:
```
# K-Means
inertia = []
for i in range(1,11):
    kmeans = KMeans(n_clusters=i, random_state=10).fit(data_scaled)
    labels = kmeans.labels_
    inertia_i = kmeans.inertia_
    inertia.append(inertia_i)
```

```
C:\Users\manny\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:881: UserWarning:

KMeans is known to have a memory leak on Windows with MKL, when there are less chunks th
an available threads. You can avoid it by setting the environment variable OMP_NUM_THREA
DS=4.
```

In [37]:
```
plt.plot(range(1,11), inertia, marker='o');
```

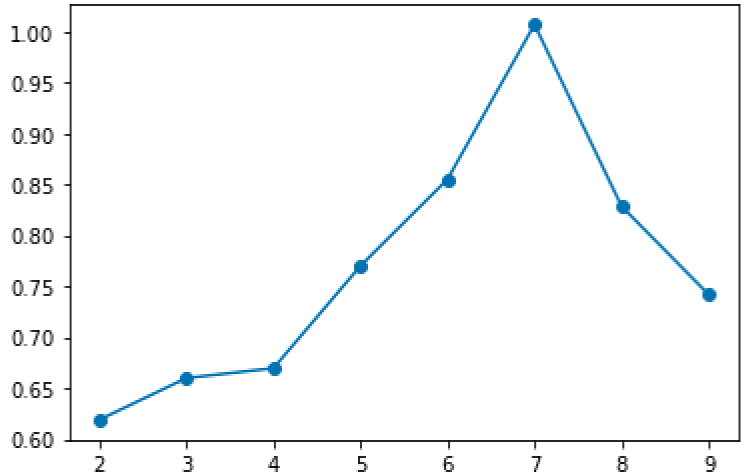


In [38]:

```
D = []
for i in range(1,9):
    Di = (inertia[i] - inertia[i+1])/(inertia[i-1] - inertia[i])
    D.append(Di)
```

In [39]:

```
plt.plot(range(2,10), D, marker='o');
```

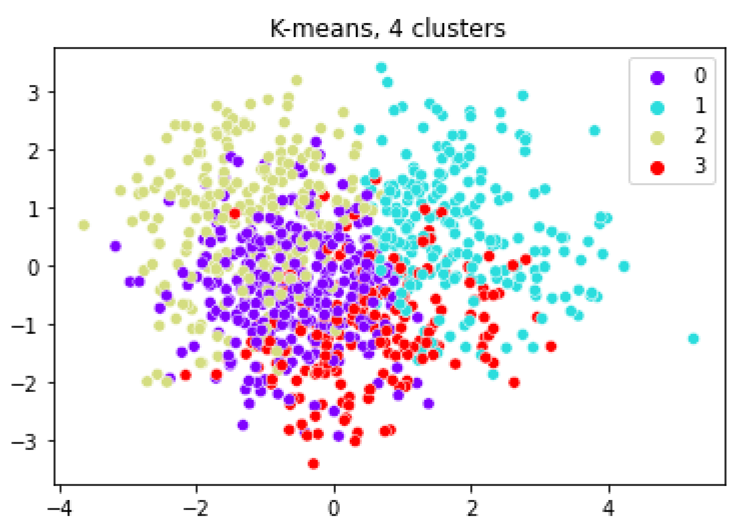


In [40]:

```
kmeans = KMeans(n_clusters=4, random_state=10).fit(X_scaled)
labels_kmeans = kmeans.labels_
```

In [41]:

```
plt.title('K-means, 4 clusters')
sns.scatterplot(x = X_pca[:,0], y = X_pca[:,1], hue=labels_kmeans, palette='rainbow');
```



In [42]:

```
data_clustered = df.copy()
data_clustered['cluster_kmeans'] = labels_kmeans
```

In [43]:

```
data_clustered.groupby('cluster_kmeans').mean()[['Age', 'Job', 'Credit amount', 'Durati
```

Out[43]:

	Age	Job	Credit amount	Duration

cluster_kmeans	Age	Job	Credit amount	Duration
cluster_kmeans				
0	35.611765	1.747059	2022.617647	15.138235
1	36.449541	2.293578	6669.500000	36.087156
2	31.458498	1.739130	2073.667984	16.371542
3	39.857143	1.957672	3200.947090	19.825397

In [44]:

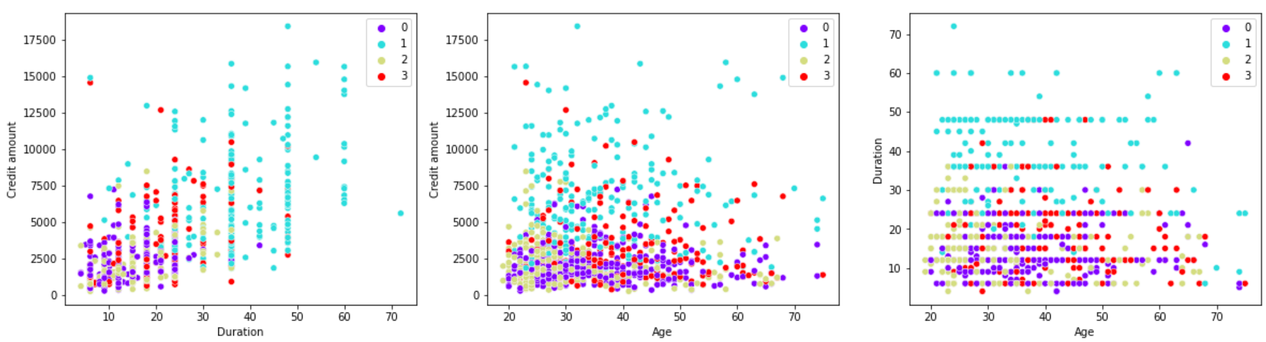
```
data_clustered['cluster_kmeans'].value_counts()
```

Out[44]:

```
0    340
2    253
1    218
3    189
Name: cluster_kmeans, dtype: int64
```

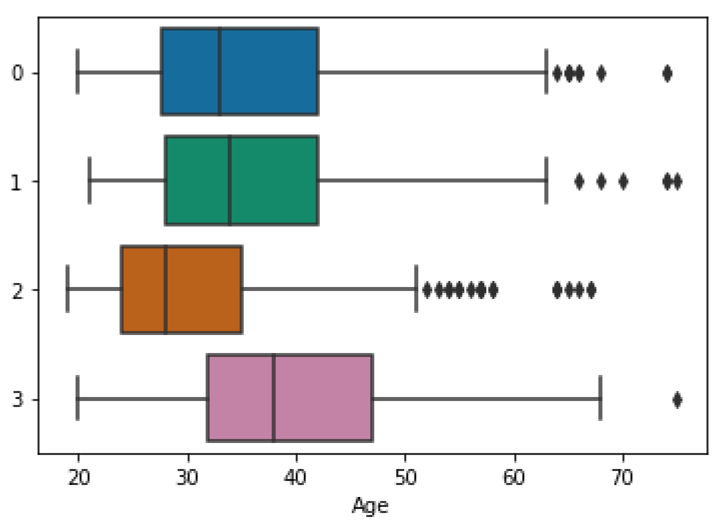
In [45]:

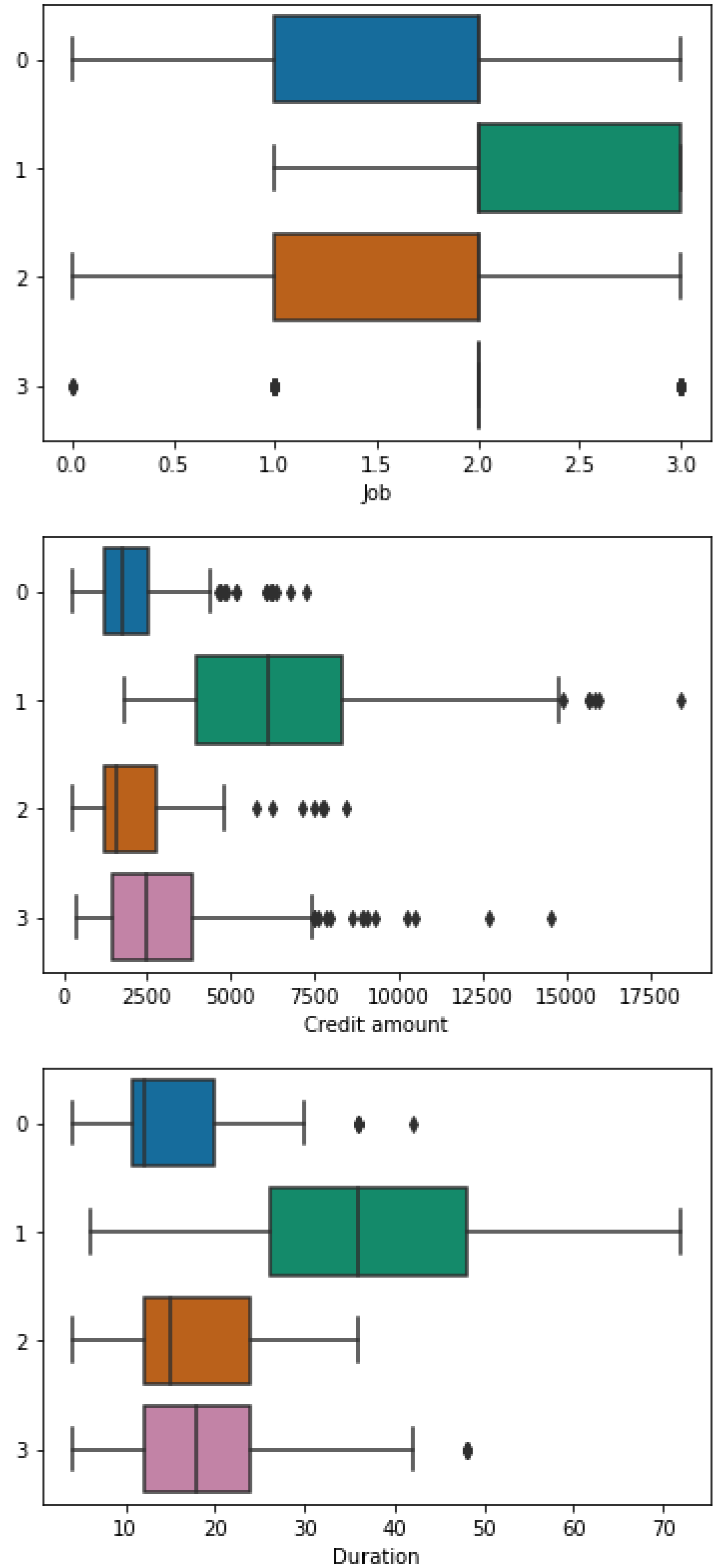
```
fig, ax  = plt.subplots(1,3,figsize=(20,5))
sns.scatterplot(x = data_clustered['Duration'], y = data_clustered['Credit amount'], hu
sns.scatterplot(x = data_clustered['Age'], y = data_clustered['Credit amount'], hue=lab
sns.scatterplot(x = data_clustered['Age'], y = data_clustered['Duration'], hue=labels_k
```



In [46]:

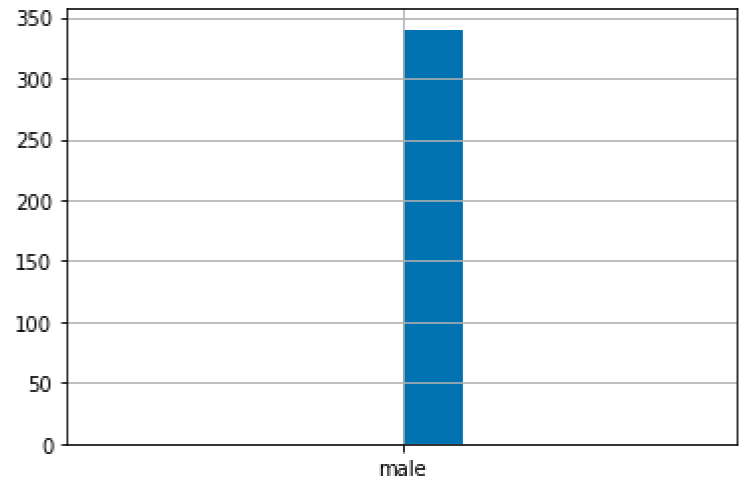
```
for col in data_clustered[numeric].columns:
    sns.boxplot(data=data_clustered, x=col, y=labels_kmeans, orient='h')
    plt.show();
```





In [47]:
```
data_clustered[data_clustered['cluster_kmeans']==0]['Sex'].hist()
```

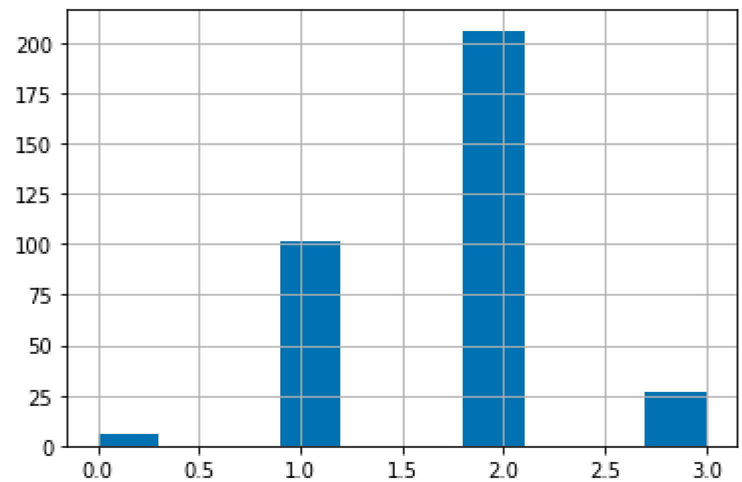
Out[47]: <AxesSubplot:>



In [48]:

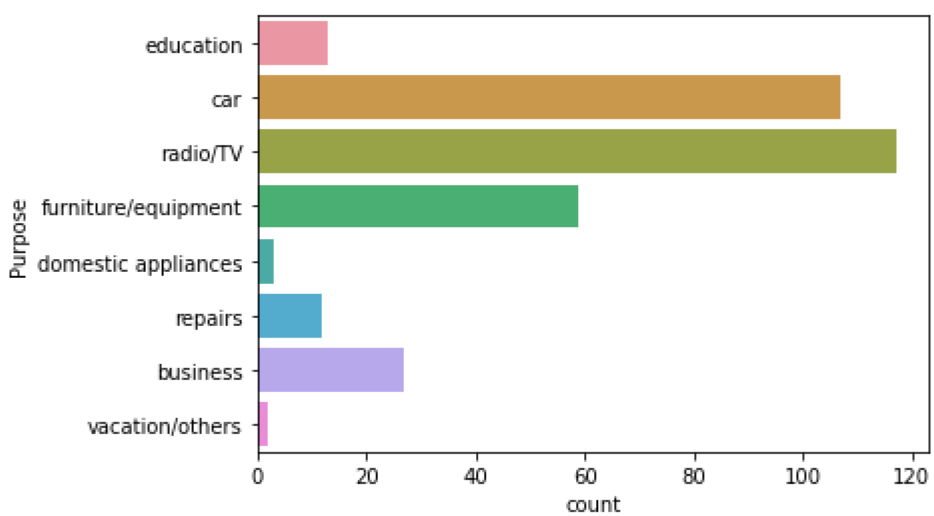
```
data_clustered[data_clustered['cluster_kmeans']==0]['Job'].hist()
```

Out[48]: <AxesSubplot:>



In [49]:

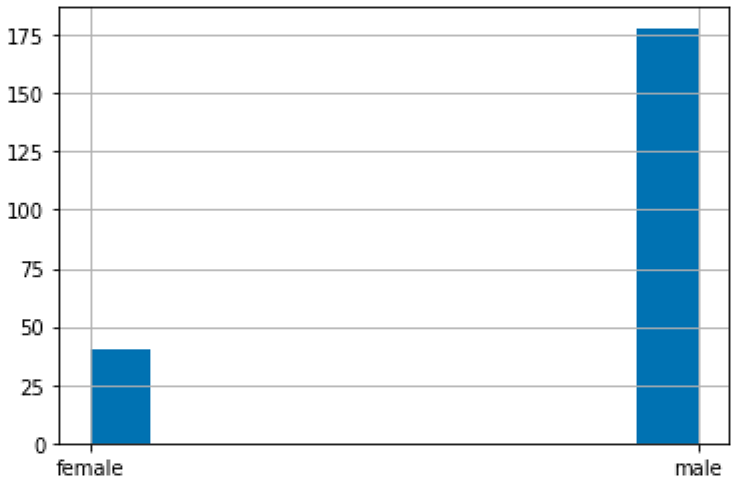
```
sns.countplot(y ='Purpose', data = data_clustered[data_clustered['cluster_kmeans']==0])
plt.show()
```



In [50]:

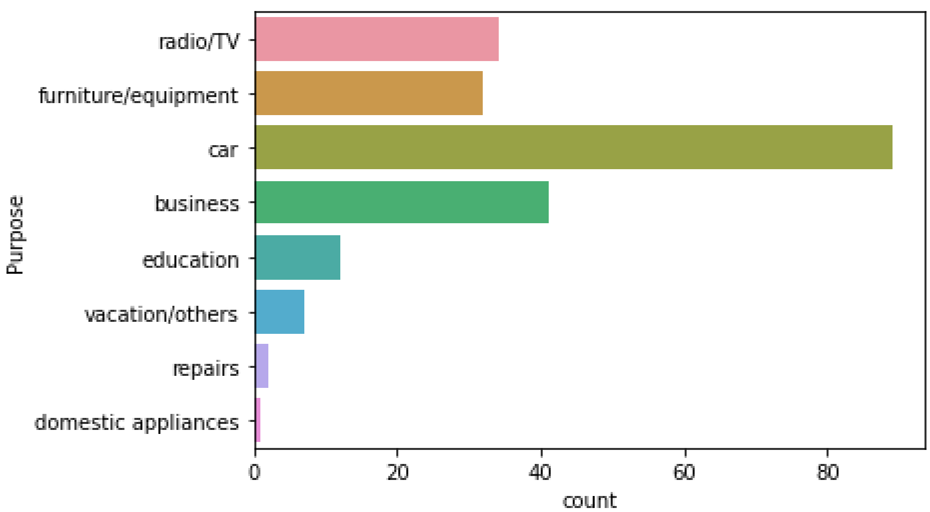
```
data_clustered[data_clustered['cluster_kmeans']==1]['Sex'].hist()
```

Out[50]: <AxesSubplot:>



In [51]:

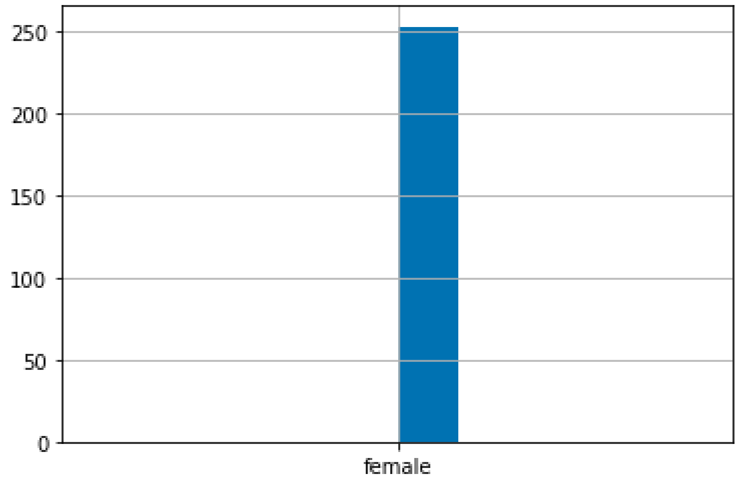
```
sns.countplot(y ='Purpose', data = data_clustered[data_clustered['cluster_kmeans']==1])
plt.show()
```



In [52]:

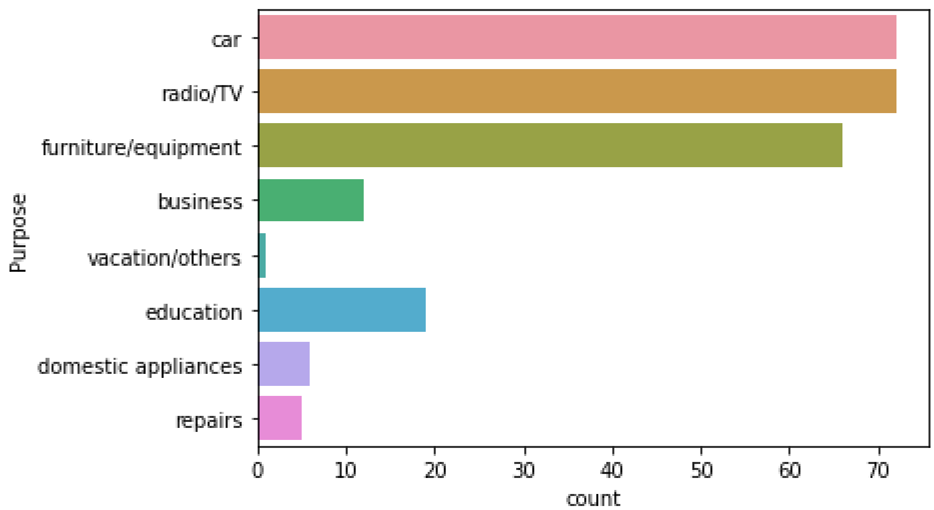
```
data_clustered[data_clustered['cluster_kmeans']==2]['Sex'].hist()
```

Out[52]: <AxesSubplot:>



In [53]:

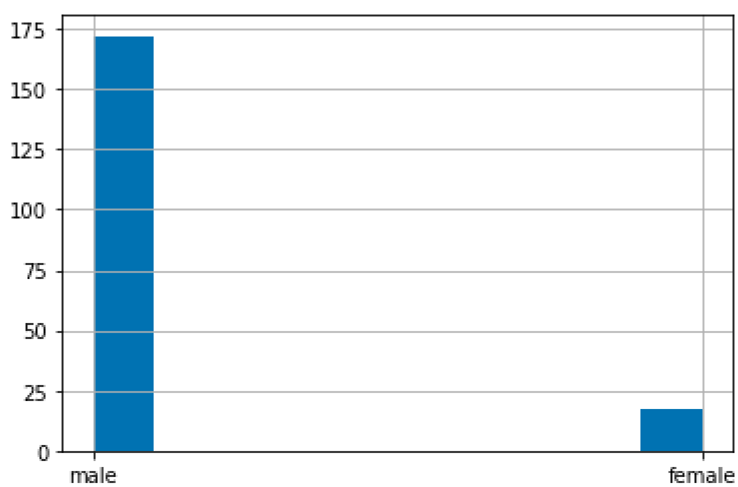
```
sns.countplot(y ='Purpose', data = data_clustered[data_clustered['cluster_kmeans']==2])
plt.show()
```



In [54]:

```
data_clustered[data_clustered['cluster_kmeans']==3]['Sex'].hist()
```

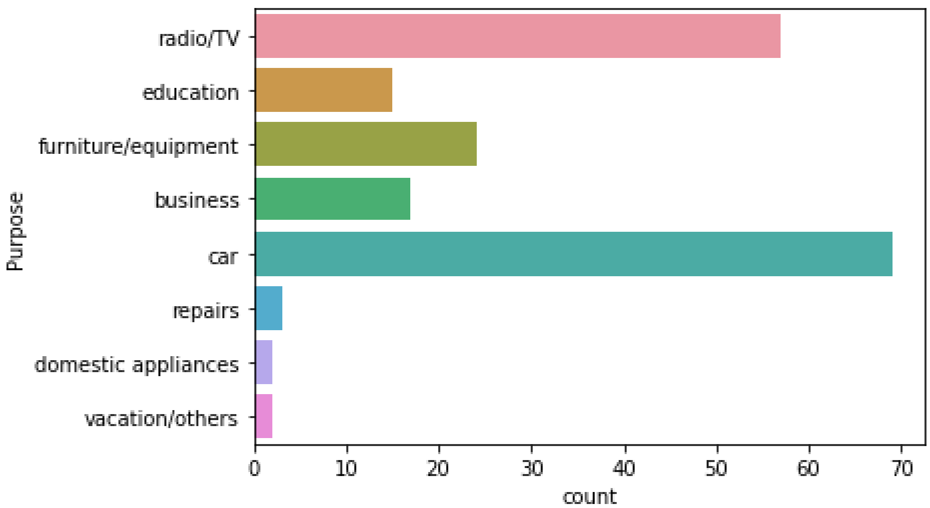
Out[54]: <AxesSubplot:>



In [55]:

```
sns.countplot(y ='Purpose', data = data_clustered[data_clustered['cluster_kmeans']==3])
```

```
plt.show()
```


radio/TV
education
furniture/equipment
business
car
repairs
domestic appliances
vacation/others
Purpose
0
10
20
30
40
50
60
70
count