Assignment 1

October 6, 2022

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10/06/22

1 Walmart Data

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
from sklearn.impute import KNNImputer
from sklearn.preprocessing import MinMaxScaler
```

[2]:
```
walmart = pd.read_csv("WalmartSalesData.csv")
```

[3]:
```
walmart.head(6)
```

[3]:

	Store	Date	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3	MarkDown4	MarkDown5	CPI	Unemployment	IsHoliday
0	1	2010-02-05	42.31	2.572	NaN	NaN	NaN	NaN	NaN	211.096358	8.106	False
1	1	2010-02-12	38.51	2.548	NaN	NaN	NaN	NaN	NaN	211.242170	8.106	True
2	1	2010-02-19	39.93	2.514	NaN	NaN	NaN	NaN	NaN	211.289143	8.106	False
3	1	2010-02-26	46.63	2.561	NaN	NaN	NaN	NaN	NaN	211.319643	8.106	False
4	1	2010-03-05	46.50	2.625	NaN	NaN	NaN	NaN	NaN	211.350143	8.106	False
5	1	2010-03-12	57.79	2.667	NaN	NaN	NaN	NaN	NaN	211.380643	8.106	False

[4]:
```
walmart.tail(6)
```

[4]:

	Store	Date	Temperature	Fuel_Price	MarkDown1	MarkDown2
8184	45	2013-06-21	70.13	3.626	4989.34	385.31
8185	45	2013-06-28	76.05	3.639	4842.29	975.03

```
8186     45  2013-07-05        77.50       3.614    9090.48    2268.58
8187     45  2013-07-12        79.37       3.614    3789.94    1827.31
8188     45  2013-07-19        82.84       3.737    2961.49    1047.07
8189     45  2013-07-26        76.06       3.804     212.02     851.73

      MarkDown3  MarkDown4  MarkDown5  CPI  Unemployment  IsHoliday
8184     178.56    2463.42    3117.94  NaN           NaN      False
8185       3.00    2449.97    3169.69  NaN           NaN      False
8186     582.74    5797.47    1514.93  NaN           NaN      False
8187      85.72     744.84    2150.36  NaN           NaN      False
8188     204.19     363.00    1059.46  NaN           NaN      False
8189       2.06      10.88    1864.57  NaN           NaN      False
```

[5]:
```
walmart.shape
```

[5]:
```
(8190, 12)
```

[6]:
```
walmart.isnull().any(axis=1).sum()
```

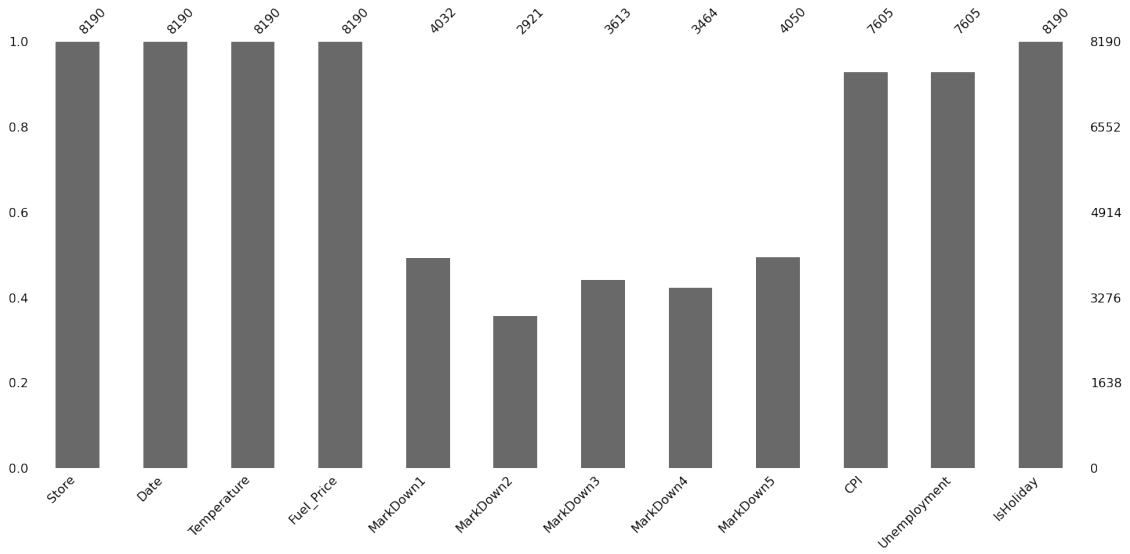
[6]:
```
6121
```

[7]:
```
walmart.isnull().sum()
```

[7]:
```
Store              0
Date               0
Temperature        0
Fuel_Price         0
MarkDown1       4158
MarkDown2       5269
MarkDown3       4577
MarkDown4       4726
MarkDown5       4140
CPI              585
Unemployment     585
IsHoliday          0
dtype: int64
```

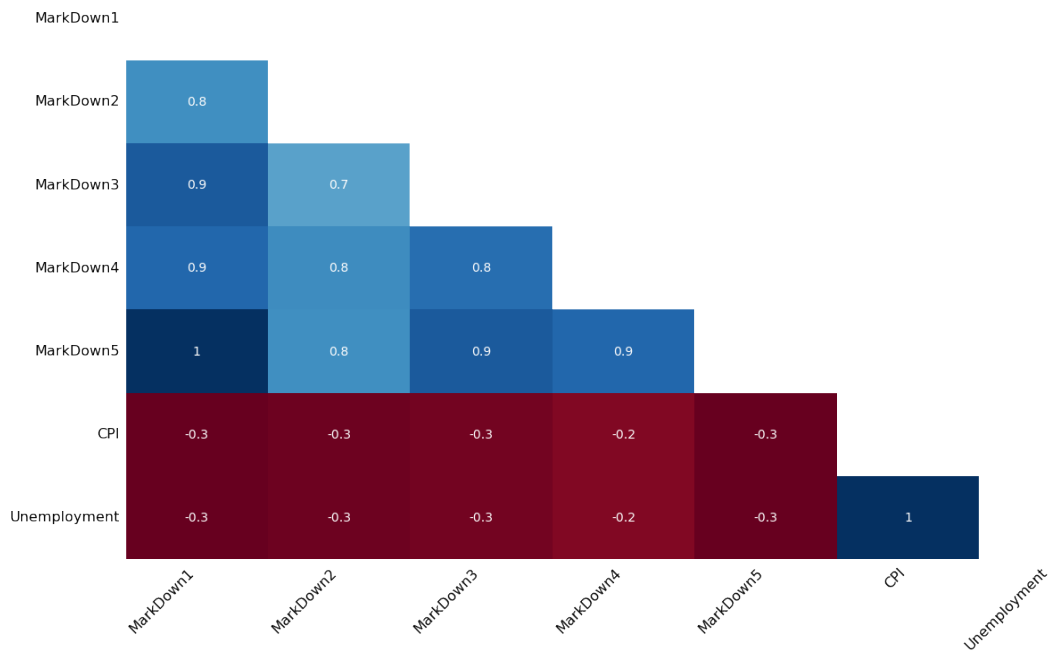
[8]:
```
msno.bar(walmart)
```

[8]:
```
<AxesSubplot:>
```



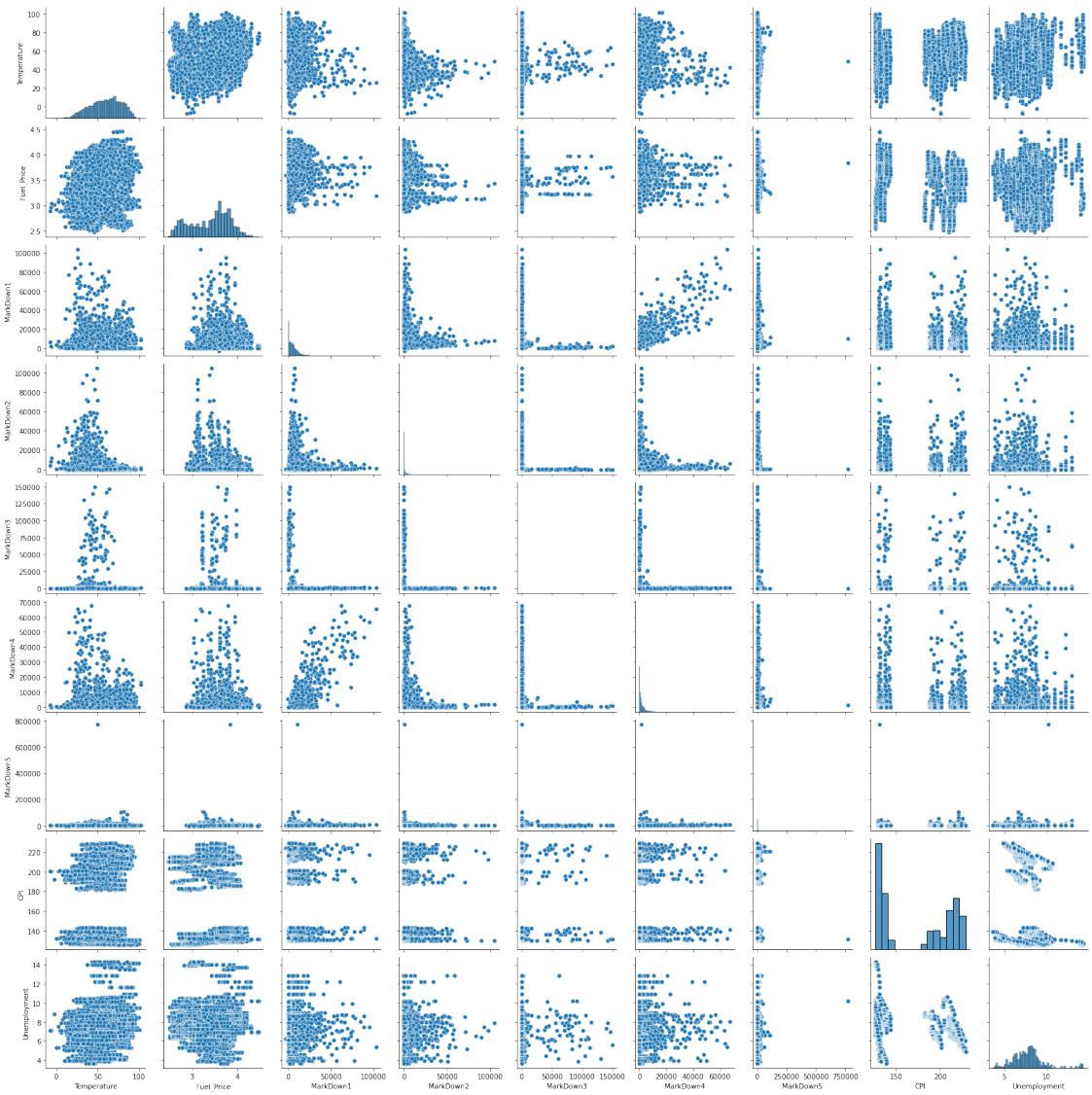
[9]:
```
msno.heatmap(walmart)
```

[9]: <AxesSubplot:>



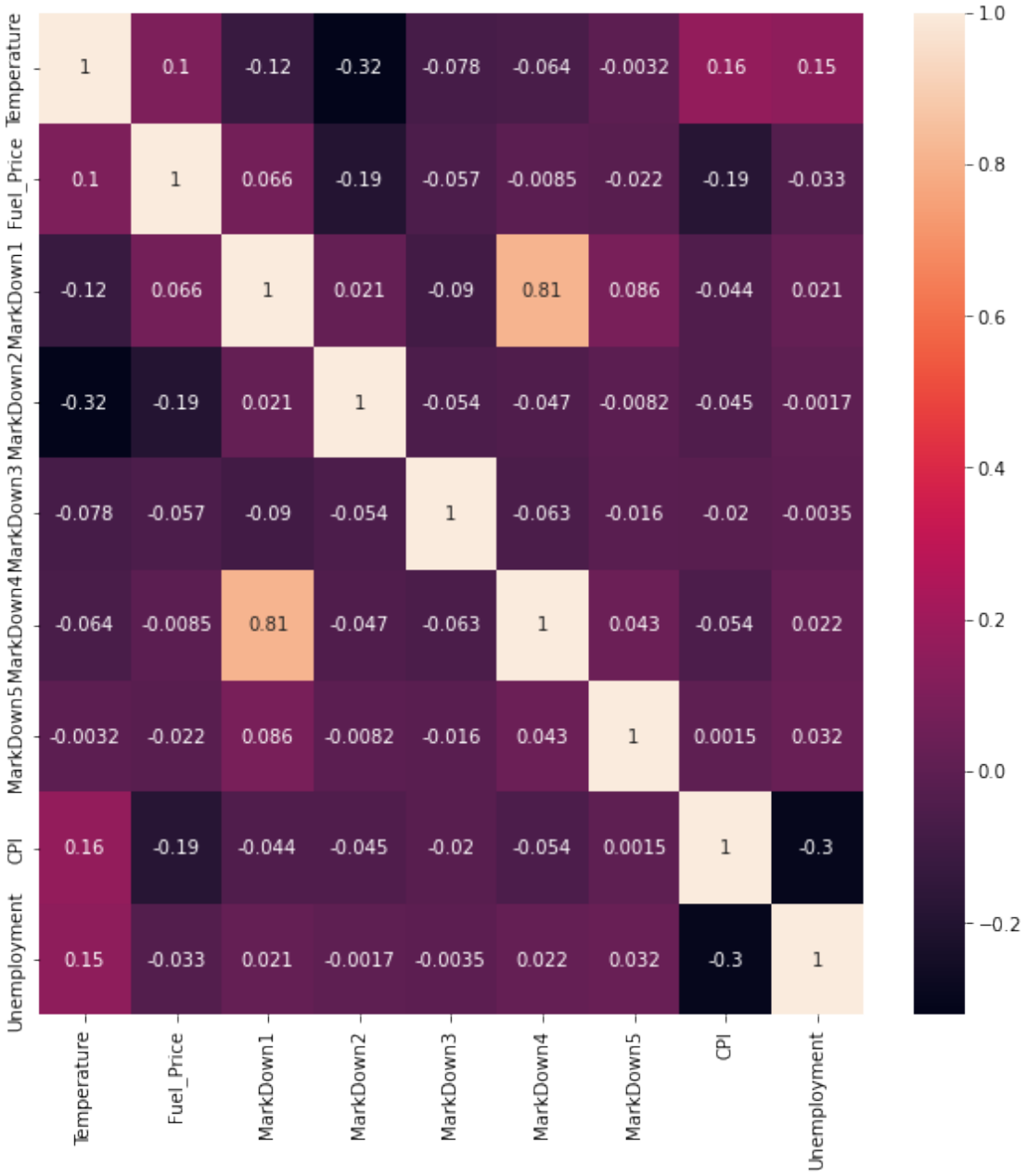
[10]:
```
sns.pairplot(walmart.iloc[:, 1:11])
```

[10]: <seaborn.axisgrid.PairGrid at 0x23f12fba850>



[11]:
```
plt.figure(figsize = (10,10))
sns.heatmap(walmart.iloc[:, 1:11].corr(),annot = True)
```

[11]: <AxesSubplot:>



[12]:
```
walmart_knn = walmart.
 ↪filter(['Store','Temperature','Fuel_Price','MarkDown1","MarkDown2","MarkDown3","MarkDown4",
 ↪axis=1).copy()


scaler = MinMaxScaler(feature_range=(0, 1))
walmart_knn = pd.DataFrame(scaler.fit_transform(walmart_knn), columns =␣
 ↪walmart_knn.columns)
```

```
# Define KNN imputer and fill missing values
knn_imputer = KNNImputer(n_neighbors=5, weights='uniform',␣
 ↪metric='nan_euclidean')
walmart_knn_imputed = pd.DataFrame(scaler.inverse_transform(knn_imputer.
 ↪fit_transform(walmart_knn)), columns=walmart_knn.columns)
walmart_knn_imputed["Date"] = walmart["Date"]
```

[13]:
```
walmart_knn_imputed
```

[13]:

	Store	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3	\
0	1.0	42.31	2.572	5487.830	36.532	789.202	
1	1.0	38.51	2.548	8277.274	49308.442	203.818	
2	1.0	39.93	2.514	5239.752	86.308	532.316	
3	1.0	46.63	2.561	4195.576	41.932	797.390	
4	1.0	46.50	2.625	4195.576	41.932	797.390	
…	…	…	…	…	…	…	
8185	45.0	76.05	3.639	4842.290	975.030	3.000	
8186	45.0	77.50	3.614	9090.480	2268.580	582.740	
8187	45.0	79.37	3.614	3789.940	1827.310	85.720	
8188	45.0	82.84	3.737	2961.490	1047.070	204.190	
8189	45.0	76.06	3.804	212.020	851.730	2.060	

	MarkDown4	MarkDown5	CPI	Unemployment	IsHoliday	Date
0	1999.654	10602.652	211.096358	8.1060	0.0	2010-02-05
1	554.166	2645.896	211.242170	8.1060	1.0	2010-02-12
2	2408.448	6755.190	211.289143	8.1060	0.0	2010-02-19
3	1212.702	9625.110	211.319643	8.1060	0.0	2010-02-26
4	1212.702	9625.110	211.350143	8.1060	0.0	2010-03-05
…	…	…	…	…	…	
8185	2449.970	3169.690	153.941456	7.3862	0.0	2013-06-28
8186	5797.470	1514.930	129.224090	6.5600	0.0	2013-07-05
8187	744.840	2150.360	142.555580	6.2930	0.0	2013-07-12
8188	363.000	1059.460	179.302707	8.4154	0.0	2013-07-19
8189	10.880	1864.570	187.197010	8.6160	0.0	2013-07-26

[8190 rows x 12 columns]

[14]:
```
walmart_knn_imputed.isnull().sum()
```

[14]:
```
Store           0
Temperature     0
Fuel_Price      0
MarkDown1       0
MarkDown2       0
MarkDown3       0
MarkDown4       0
```

```
MarkDown5       0
CPI             0
Unemployment    0
IsHoliday       0
Date            0
dtype: int64
```

2 Credit Card Data

[15]:
```
from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFECV
```

[16]:
```
card = pd.read_csv("CreditCardData.csv", index_col = "ID")
```

[17]:
```
card.isnull().sum()
```

[17]:
```
Gender             0
Own_car            0
Own_property       0
Work_phone         0
Phone              0
Email              0
Unemployed         0
Num_children       0
Num_family         0
Account_length     0
Total_income       0
Age                0
Years_employed     0
Income_type        0
Education_type     0
Family_status      0
Housing_type       0
Occupation_type    0
Target             0
dtype: int64
```

[18]:
```
card.head()
```

[18]:

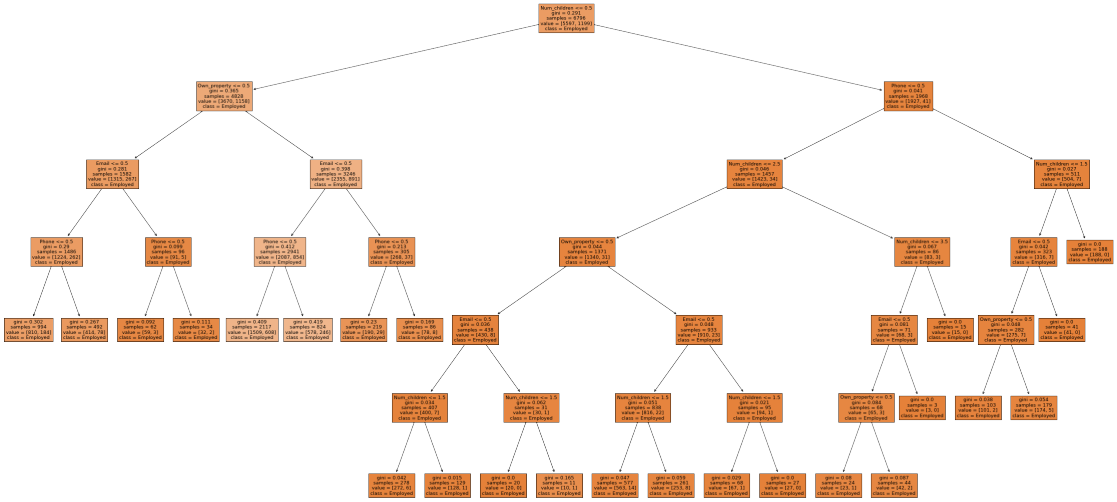
ID	Gender	Own_car	Own_property	Work_phone	Phone	Email	Unemployed	\
5008804	1	1	1	1	0	0	0	
5008806	1	1	1	0	0	0	0	

```
5008808       0        0             1           0      1      1           0
5008812       0        0             1           0      0      0           1
5008815       1        1             1           1      1      1           0

         Num_children  Num_family  Account_length  Total_income        Age  \
ID
5008804             0           2              15      427500.0  32.868574
5008806             0           2              29      112500.0  58.793815
5008808             0           1               4      270000.0  52.321403
5008812             0           1              20      283500.0  61.504343
5008815             0           2               5      270000.0  46.193967

         Years_employed           Income_type                 Education_type  \
ID
5008804      12.435574               Working               Higher education
5008806       3.104787               Working  Secondary / secondary special
5008808       8.353354  Commercial associate  Secondary / secondary special
5008812       0.000000             Pensioner               Higher education
5008815       2.105450               Working               Higher education

               Family_status       Housing_type Occupation_type  Target
ID
5008804        Civil marriage   Rented apartment           Other       1
5008806               Married  House / apartment  Security staff       0
5008808  Single / not married  House / apartment     Sales staff       0
5008812             Separated  House / apartment           Other       0
5008815               Married  House / apartment     Accountants       0
```

[19]:
```
card_train, card_test = train_test_split(card, test_size=0.3, random_state=101)
```

[20]:
```
X_1 = card_train[["Own_property","Phone","Email","Num_children"]]
y_1 = card_train["Unemployed"]
clf = tree.DecisionTreeClassifier()
clf = clf.fit(X_1, y_1)
```

[21]:
```
plt.figure(figsize = (40,20))
fn=X_1.columns
cn = ["Employed", "Unemployed"]
tree.plot_tree(clf, feature_names = fn,
               class_names=cn,
               filled = True);
```

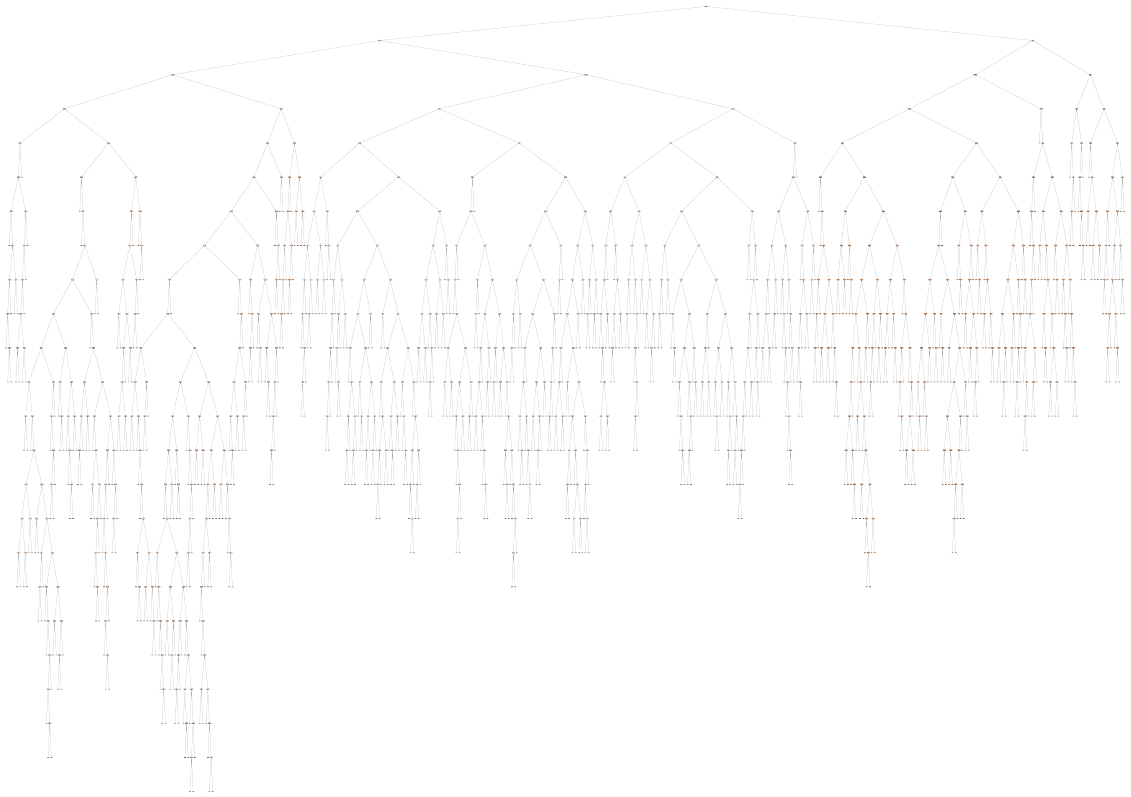


[22]:
```
test_1 = card_test[["Own_property","Phone","Email","Num_children"]]
truth_1 = card_test["Unemployed"]
pred_1 = clf.predict(test_1)
accuracy_score(truth_1, pred_1)
```

[22]: 0.8293855132166151

[23]:
```
X_2 = card_train[["Total_income","Num_children","Unemployed","Own_property"]]
y_2 = card_train["Age"]
reg = tree.DecisionTreeRegressor()
reg = reg.fit(X_2, y_2)
```

[24]:
```
plt.figure(figsize = (100,75))
fn=X_2.columns

tree.plot_tree(reg, feature_names = fn,
               filled = True);
```



[25]:
```
test_2 = card_train[["Total_income","Num_children","Unemployed","Own_property"]]
truth_2 = card_train["Age"]
pred_2 = reg.predict(test_2)
mean_squared_error(truth_1, pred_1, squared = False)
```

[25]: 0.4130550650741192

[26]:
```
X_train = card_train.iloc[:,:13]
y_train = card_train.iloc[:,18:]
X_test = card_test.iloc[:,:13]
y_test = card_test.iloc[:,18:]
```

[27]:
```
clf = tree.DecisionTreeClassifier()
clf = clf.fit(X_train, y_train)
```

[28]:
```
y_pred = clf.predict(X_test)
accuracy_score(y_test, y_pred)
```

[28]: 0.7693099897013388

[29]:
```
selector = RFECV(tree.DecisionTreeClassifier(), step=1,␣
↪min_features_to_select=4, cv=5)
selector = selector.fit(X_train, y_train)
```

[30]:
```
selector.ranking_
```

[30]:
```
array([ 3,  4,  8,  7,  6,  9, 10,  5,  2,  1,  1,  1,  1])
```

[31]:
```
y_pred = selector.predict(X_test)
accuracy_score(y_test, y_pred)
```

[31]:
```
0.7641606591143152
```

[32]:
```
selector = RFECV(tree.DecisionTreeClassifier(), step=1,␣
↪min_features_to_select=3, cv=5)
selector = selector.fit(X_train, y_train)
```

[33]:
```
selector.ranking_
```

[33]:
```
array([2, 1, 4, 3, 1, 5, 6, 1, 1, 1, 1, 1, 1])
```

[34]:
```
y_pred = selector.predict(X_test)
accuracy_score(y_test, y_pred)
```

[34]:
```
0.7693099897013388
```

[35]:
```
selector = RFECV(tree.DecisionTreeClassifier(), step=1,␣
↪min_features_to_select=2, cv=5)
selector = selector.fit(X_train, y_train)
```

[36]:
```
selector.ranking_
```

[36]:
```
array([ 7,  5, 11, 10,  6,  9, 12,  8,  4,  2,  3,  1,  1])
```

[37]:
```
y_pred = selector.predict(X_test)
accuracy_score(y_test, y_pred)
```

[37]:
```
0.7789220734637831
```

[38]:
```
selector = RFECV(tree.DecisionTreeClassifier(), step=1,␣
↪min_features_to_select=1, cv=5)
selector = selector.fit(X_train, y_train)
```

[39]:
```
selector.ranking_
```

[39]:
```
array([ 8,  7, 11, 10,  6, 12, 13,  9,  5,  3,  4,  1,  2])
```

[40]:
```
y_pred = selector.predict(X_test)
accuracy_score(y_test, y_pred)
```

[40]:
```
0.7964297974596636
```

Account Length, Total Income, Age, and Years Employed had the highest feature importance with regards to predicting the risk of a client. Decsion Tree with highest importance on age leads to highest validation accuracy.

NOTE TO GRADER: I have no idea how to interpret **"Using the accuracy on the test dataset which 4 independent variables (features) do you choose reporting the accuracy for the alternatives list at least 3)?"** I am assuming recursive feature selection is being asked for, but if that is not the case, please comment on webcourses to clarify its meaning. If this is not what the professor asked for, I would like to know so I can recode this small section. Thanks!

[41]:
```
reg = LinearRegression()
X_train = card_train[["Account_length","Age"]]
y_train = card_train["Total_income"]
X_test = card_test[["Account_length","Age"]]
y_test = card_test["Total_income"]
reg.fit(X_train, y_train)
```

[41]:
```
LinearRegression()
```

[42]:
```
X_train.iloc[:,0:].min()
```

[42]:
```
Account_length     0.000000
Age               21.095573
dtype: float64
```

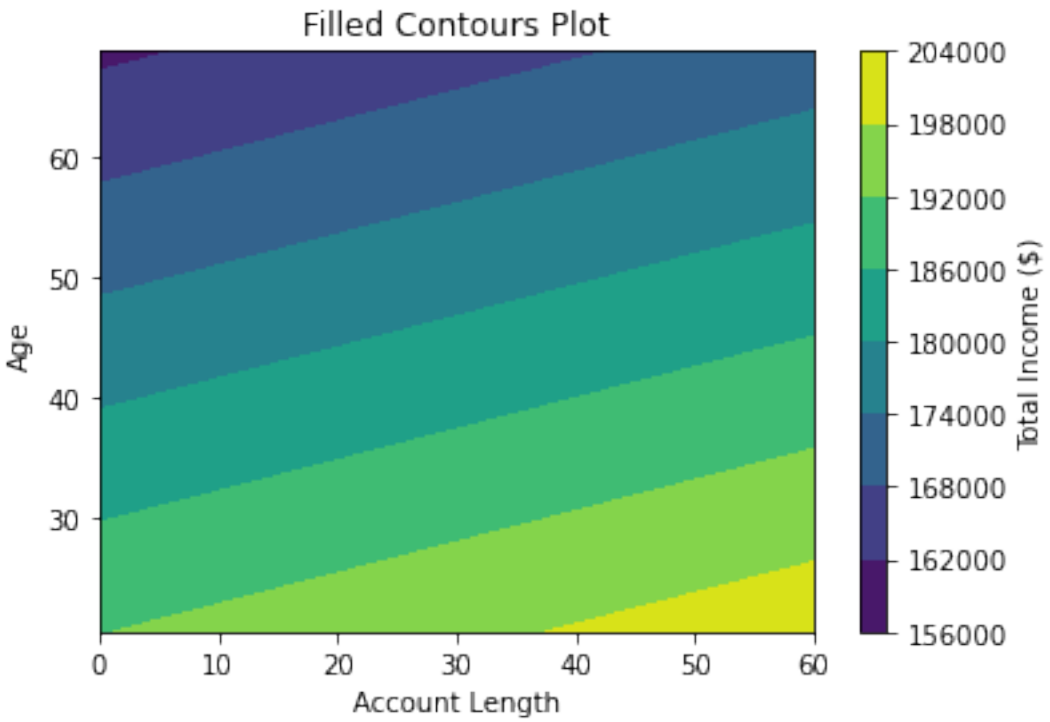
[43]:
```
feature_x = np.linspace(X_test.iloc[:, 0].min(),X_test.iloc[:, 0].max(),100)
feature_y = np.linspace(X_test.iloc[:, 1].min(),X_test.iloc[:, 1].max(),100)
```

[44]:
```
dim1, dim2 = np.meshgrid(feature_x, feature_y)
```

[45]:
```
mesh_df = np.array([X_test.mean(axis=0) for i in range(dim1.size)])
mesh_df[:,0] = dim1.ravel()
mesh_df[:,1] = dim2.ravel()
```

[46]:
```
Z = reg.predict(mesh_df).reshape(dim1.shape)
```

[47]:
```
fig, ax = plt.subplots()

cp = ax.contourf(dim1, dim2, Z)
ax.set_title('Filled Contours Plot')
ax.set_xlabel('Account Length')
ax.set_ylabel('Age')
fig.colorbar(cp).set_label('Total Income ($)')
plt.show()
```


Filled Contours Plot
Age
60
50
40
30
0
10
20
30
40
50
60
Account Length
204000
198000
192000
186000
180000
174000
168000
162000
156000
Total Income ($)