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In [123... import pandas as pd
         import numpy as np
         import sklearn
         import matplotlib.pyplot as plt
         from sklearn.model_selection import train_test_split
         import seaborn as sns
         from sklearn.linear model import LogisticRegression
         from sklearn.preprocessing import StandardScaler , LabelEncoder
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.metrics import accuracy_score
         from sklearn.metrics import confusion matrix
         from sklearn.linear model import LinearRegression
         import warnings
         from sklearn.metrics import mean_squared_error
         from scipy.stats import f as fisher f
         warnings.filterwarnings('ignore')
         df=pd.read csv('NVDA.csv')
         df_week_2017=df.loc[df['Year']==2017,:]
         df_week_2018=df.loc[df['Year']==2018,:].reset_index()
         month arr=np.array(range(13))
         def get sse(df,k,month):
             month len=df.loc[df["Month"]==month,:]["Adj Close"].count()
             month df=df.loc[df["Month"]==month,:]
             day_arr=np.array(month_len)
             cut front df=month df[:k]
             cut back df=month df[k:]
             a=np.array(range(k)).reshape(-1,1)
             b=np.array(range(k,month len)).reshape(-1,1)
             c=np.array(range(month len)).reshape(-1,1)
             # a=np.array(range(10)).reshape(-1,1)
             #regr = LinearRegression()
             regr_front=LinearRegression().fit(a, cut front df["Adj Close"])
             regr back=LinearRegression().fit(b, cut back df["Adj Close"])
             regr orig=LinearRegression().fit(c, month df["Adj Close"])
             #print(mean squared error(a,cut front df["Adj Close"])+mean squared error(k
             sse front = mean squared error(cut front df["Adj Close"],regr front.predict
             sse back = mean squared error(cut back df["Adj Close"], regr back.predict(b)
             sse total=sse front+sse back
             sse orig= mean squared error(month df["Adj Close"], regr orig.predict(c))/le
             return sse_front,sse_back,sse_total,sse_orig
         def get k(m,df):
             month len=df.loc[df["Month"]==m,:]["Adj Close"].count()
             k=0
             min_sse=1000000
             p value=0
             for i in range(1,month len):
                 sse front, sse back, sse total, sse orig=get sse(df,i,m)
                 #print(i,sse front,sse back,sse total,sse orig)
                 if sse total<min sse:</pre>
                         min sse=sse total
                         k=i
                         F = ((sse orig - sse total)/2)/(sse total/(month len-4))
                         p value = fisher f.cdf(F ,2, month len-4)
                          #print(i,sse total,p value)
```

```
#print(k,mid_sse)
return k,p_value,min_sse
```

1. take years 1 and 2. For each month, compute the "candi- date" days and decide whether there is a significant change of pricing trend in each month. Use 0.1 as critical value.

- In 2017, the best k in NVDA at 1 month is 19 the p_value is 0.0 the minimun SSE is 0.01394602517373766
- In 2017, the best k in NVDA at 2 month is 1 the p_value is 0.29496065055301984 the minimun SSE is 0.0273138741309823
- In 2017, the best k in NVDA at 3 month is 1 the p_value is 0.9752882878665425 the minimun SSE is 0.006264990363571046
- In 2017, the best k in NVDA at 4 month is 2 the p_value is 0.9976491841616215 the minimun SSE is 0.012659362914716053
- In 2017, the best k in NVDA at 5 month is 7 the p_value is 0.999814570266828 th e minimum SSE is 0.03523430600367122
- In 2017, the best k in NVDA at 6 month is 20 the p_value is 0.8263513961834199 the minimun SSE is 0.04983671541353387
- In 2017,the best k in NVDA at 7 month is 9 the p_value is 0.9989290395157632 the minimum SSE is 0.03783143443412791
- In 2017, the best k in NVDA at 8 month is 22 the p_value is 0.19531143273403576 the minimun SSE is 0.035300225161112725
- In 2017,the best k in NVDA at 9 month is 15 the p_value is 0.4401722736018504 the minimun SSE is 0.10092594497354496
- In 2017,the best k in NVDA at 10 month is 21 the p_value is 0.0 the minimun SS E is 0.02851579595763274
- In 2017, the best k in NVDA at 11 month is 19 the p_value is 0.9999846064394357 the minimum SSE is 0.019964715944987173
- In 2017, the best k in NVDA at 12 month is 1 the p_value is 0.938998333620168 the minimum SSE is 0.024456624386450892
- In 2018,the best k in NVDA at 1 month is 1 the p_value is 0.9569928549921554 the minimum SSE is 0.026395981578947274
- In 2018, the best k in NVDA at 2 month is 2 the p_value is 0.931332511319953 th e minimun SSE is 0.11511953914783903
- In 2018, the best k in NVDA at 3 month is 19 the p_value is 0.7991998925238537 the minimun SSE is 0.1523978417650774
- In 2018,the best k in NVDA at 4 month is 1 the p_value is 0.0 the minimun SSE is 0.11925988421052625
- In 2018, the best k in NVDA at 5 month is 8 the p_value is 0.987527919431964 th e minimum SSE is 0.0945200339493626
- In 2018, the best k in NVDA at 6 month is 9 the p_value is 0.7110651325740263 the minimun SSE is 0.10654476960368145
- In 2018, the best k in NVDA at 7 month is 19 the p_value is 0.9622944247428371 the minimun SSE is 0.03098222287019491
- In 2018, the best k in NVDA at 8 month is 12 the p_value is 0.398026231259641 the minimun SSE is 0.1036091698185502
- In 2018,the best k in NVDA at 9 month is 18 the p_value is 0.9957719011921956 the minimum SSE is 0.03191828175498038
- In 2018,the best k in NVDA at 10 month is 22 the p_value is 0.810217015577737 the minimum SSE is 0.17306261835541376
- In 2018, the best k in NVDA at 11 month is 11 the p_value is 0.9182939390539447 the minimun SSE is 0.3891383878787877
- In 2018, the best k in NVDA at 12 month is 1 the p_value is 0.8800342261847197 the minimum SSE is 0.04693643716529293
 - 1. how many months exhibit significant price changes for your sotck ticker

For 2017 is 2 month, for 2018 is 1 month

3, are there more "changes" in year 1 or in year 2

no