```
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
```

```
In [382... df=pd.read_csv('NVDA.csv')
    df_week=df.groupby(["Year","Week_Number"]).nth(-1)
    df_week=df_week.reset_index()
    df_week_2017=df_week.loc[df_week['Year']==2017,:]
    df_week_2018=df_week.loc[df_week['Year']==2018,:].reset_index()
    #print(df_week_2018)
    df_week_2017["ture_label"]=df_week_2017['Return'].apply(lambda x:'green' if x>0
    # plt.plot(df_week_2017["Close"])
    # plt.show()
    df_week_2018["ture_label"]=df_week_2018['Return'].apply(lambda x:'green' if x>0
    print(df_week_2018)
```

		inea_model								
	index	Year	Week_Nu	mber	Date	Month	_		Year_Week	\
0	52	2018		0	2018-01-05	1	5	Friday	2018-00	
1	53	2018		1	2018-01-12	1	12	Friday	2018-01	
2	54	2018		2	2018-01-19	1		Friday		
3	55	2018		3	2018-01-26	1		Friday		
4	56	2018		4	2018-02-02	2	2	Friday	2018-04	
5	57	2018		5	2018-02-09	2	9	Friday	2018-05	
6	58	2018		6	2018-02-16	2	16	Friday	2018-06	
7	59	2018		7	2018-02-23	2	23	Friday	2018-07	
8	60	2018		8	2018-03-02	3	2	Friday	2018-08	
9	61	2018		9	2018-03-09	3	9	Friday		
10	62	2018		10	2018-03-16	3		Friday	2018-10	
11	63	2018		11	2018-03-23	3		Friday	2018-11	
12	64	2018		12	2018-03-29	3	29	Thursday	2018-12	
13	65	2018		13	2018-04-06	4	6	Friday	2018-13	
14	66	2018		14	2018-04-13	4	13	Friday	2018-14	
15	67	2018		15	2018-04-20	4	20	Friday	2018-15	
16	68	2018		16	2018-04-27	4	27	Friday	2018-16	
17	69	2018		17	2018-05-04	5	4	Friday		
18	70	2018		18	2018-05-11	5	11	Friday	2018-18	
19	71	2018		19	2018-05-18	5	18	Friday	2018-19	
20	72	2018		20	2018-05-25	5	25	Friday	2018-20	
21	73	2018		21	2018-06-01	6	1	Friday	2018-21	
22	74	2018		22	2018-06-08	6	8	Friday	2018-22	
23	75	2018		23	2018-06-15	6	15	Friday	2018-23	
24	76	2018		24	2018-06-22	6	22	Friday	2018-24	
25	77	2018		25	2018-06-29	6	29	Friday	2018-25	
26	78	2018		26	2018-07-06	7	6	Friday	2018-26	
27	79	2018		27	2018-07-13	7	13	Friday	2018-27	
28	80	2018		28	2018-07-20	7	20	Friday	2018-28	
29	81	2018		29	2018-07-27	7	27	Friday	2018-29	
30	82	2018		30	2018-08-03	8	3	Friday	2018-30	
31	83	2018		31	2018-08-10	8	10	Friday	2018-31	
32	84	2018		32	2018-08-17	8	17	Friday	2018-32	
33	85	2018		33	2018-08-24	8	24	Friday	2018-33	
34	86	2018		34	2018-08-31	8	31	Friday	2018-34	
35	87	2018		35	2018-09-07	9	7	Friday	2018-35	
36	88	2018		36	2018-09-14	9	14	Friday	2018-36	
37	89	2018		37	2018-09-21	9	21	Friday	2018-37	
38	90	2018		38	2018-09-28	9	28	Friday	2018-38	
39	91	2018		39	2018-10-05	10	5	Friday	2018-39	
40	92	2018		40	2018-10-12	10	12	Friday	2018-40	
41	93	2018		41	2018-10-19	10	19	Friday	2018-41	
42	94	2018		42	2018-10-26	10	26	Friday	2018-42	
43	95	2018		43	2018-11-02	11	2	Friday	2018-43	
44	96	2018		44	2018-11-09	11	9	Friday	2018-44	
45	97	2018		45	2018-11-16	11	16	Friday	2018-45	
46	98	2018		46	2018-11-23	11	23	Friday	2018-46	
47	99	2018		47	2018-11-30	11	30	Friday	2018-47	
48	100	2018		48	2018-12-07	12	7	Friday	2018-48	
49	101	2018		49	2018-12-14	12	14	Friday	2018-49	
50	102	2018		50	2018-12-21	12	21	Friday	2018-50	
51	103	2018		51	2018-12-28	12	28	Friday	2018-51	
52	104	2018		52	2018-12-31	12	31	Monday	2018-52	
	Open	High	Low	Close	e Volume	Δd÷	Close	Return	Short MA	\
0	53.55	54.23	52.77	53.85		_	53.32	0.008474	49.506429	
1	55.90	56.25	55.33	55.74				-0.004909	51.917857	
2	57.02	57.77	56.75	57.53			56.96	0.025263	53.900714	
3	59.53	60.83	59.40	60.83			60.23	0.029532	56.619286	
5	57.55	55.05	57.40	00.00	. 31033000		55.25	0.027552	50.017200	

					linear_i	model		
4	59.25	59.49	57.79	58.38	71846400	57.81	-0.029023	58.294286
5	59.56	59.72	54.38	58.02	167460400	57.45	0.066936	58.022143
6	61.35	62.50	60.87	60.96	63765600	60.36	-0.010791	57.866429
7	61.14	61.48	60.63	61.48	41530000	60.92	0.015610	58.157143
8	56.97	59.20	55.46	59.13	91342800	58.59	0.018647	59.685714
9	60.78	61.46	60.61	61.33	50552400	60.77	0.017207	59.941429
10	62.50	62.81	62.12	62.62	39945600	62.04	0.004572	60.313571
11	60.60	60.62	58.13	58.24	73562000	57.71	-0.036717	60.693571
12	56.03	58.88	55.17	57.90	91662800	57.36	0.046261	59.852143
13	54.31	55.40	53.27	53.56	66298800	53.07	-0.032207	57.415000
14	59.29	59.38	57.39	57.88	50303600	57.34	-0.013214	56.030000
15	57.17	58.03	56.86	57.18	38620000	56.65	-0.001441	56.369286
16	57.38	57.58	56.15	56.58	40084800	56.06	0.004928	56.557857
17	57.96	59.80	57.78	59.76	40066000	59.21	0.026052	56.534286
18	63.19	64.95	62.63	63.63	121445600	63.05	-0.021528	58.551429
19	62.45	63.09	61.44	61.49	48371600	60.92	-0.007146	60.785000
20	62.05	62.49	61.69	62.32	29211200	61.78	0.006419	61.806429
21	63.50	64.47	63.41	64.40	42196800	63.85	0.021531	61.649286
22	64.99	66.00	64.80	65.57	36045600	65.01	-0.002358	63.073571
23	66.15	66.87	65.84	66.32	43226000		-0.006182	64.606429
24	64.49	64.62	62.58	62.74	43416000	62.20	-0.023958	64.950000
25	60.87	61.00	59.21	59.22	39230000	58.72	-0.016441	62.800714
26	60.44	61.92	60.22	61.83	29635200	61.30	0.018951	61.242857
27	62.99	62.99	61.90	62.33	24698800		-0.007603	60.446429
28	62.98	63.38	62.61	62.72	22235200	62.18	-0.004523	61.542143
29	64.08	64.15	62.46	63.01	29542000	62.46	-0.011066	62.222857
30	62.90	63.26	62.73	63.03	21428800	62.48	0.005905	62.022143
31	63.29	64.03	63.17	63.70	25639600		-0.006512	62.427143
32	63.24	63.24	60.93	61.21	114318800		-0.049021	62.910714
33	66.79	68.20	66.75	68.06	53151200	67.47	0.020162	63.883571
34	69.25	70.30	69.15	70.17	30659200	69.60	0.010331	65.741429
35	67.25	69.23	66.80	67.96	29542000		-0.003153	67.237857
36	68.75	69.78	68.38	69.11	38693600	68.55	0.018759	68.321429
37	66.69	67.15	65.53	65.86	43512800	65.33	-0.010627	67.608571
38	68.18	70.48	67.90	70.25	70939600	69.69	0.050935	67.042143
39	69.57	70.20	66.89	67.46	42663600		-0.033764	67.910000
40	61.38	62.38	59.91	61.63	60823600	61.14	0.048526	66.497857
41	60.44	60.64	56.92	57.29	61360800	56.83	-0.043251	63.306429
42	49.58	51.21	48.28	49.57	66478400		-0.045949	57.455714
43	54.43	55.50	52.55	53.73	45296000		-0.014626	53.987143
44	50.60	52.33	50.26	51.42	41324000	51.00	-0.001553	51.498571
45	40.83	42.67	40.40	41.11	196352000		-0.187559	50.447857
46	35.83	37.40	35.70	36.25	41196800	35.96	0.002004	45.782857
47	39.44	40.97	38.93	40.86	72956400	40.57		41.170714
48	39.62	39.72	36.40	36.90	68167600		-0.067471	38.429286
49	36.80	37.65	36.38	36.61	47182000		-0.016388	38.377857
50	34.04	34.38	32.12	32.39	86374000		-0.040933	36.721429
51	33.00	34.35	32.58	33.41	62872800	33.18		34.806429
52	33.85	34.18	33.06	33.38	46514000		-0.001122	34.480714

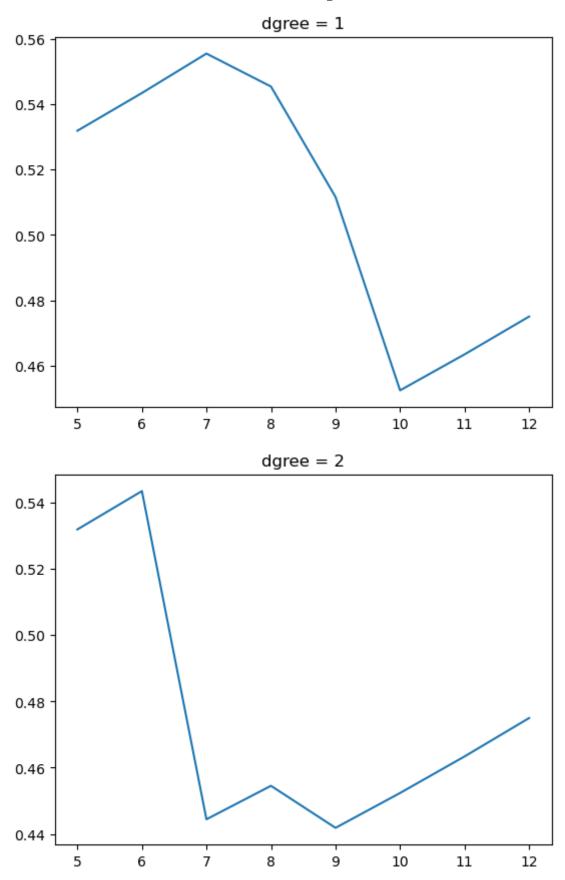
Long\_MA ture\_label 50.1008 green 0 1 50.6628 red 2 51.0022 green 3 51.6632 green 4 52.4006 red 5 52.6238 green 53.7292 6 red 7 54.7766 green 8 56.0202 green

```
9
    57.1360
                 green
10 58.3582
                 green
11
    58.9430
                   red
12
   59.0994
                 green
    58.8320
13
                   red
14
    58.4424
                   red
15
    58.5502
                   red
16
    58.3634
                 green
17
    58.0064
                 green
18
    58.2874
                   red
19
    58.5016
                   red
20
    58.4572
                 green
21
    58.5680
                 green
22
   59.3354
                   red
23
    60.2914
                   red
24
    61.1730
                   red
25
   61.3188
                   red
26 61.7116
                 green
27
    62.3132
                   red
28 62.4638
                   red
29
    62.4442
                   red
30
    62.4970
                 green
31
    62.6454
                   red
32
   62.4634
                   red
   62.4052
33
                 green
34
    62.7908
                 green
35
    63.4822
                   red
36
    64.2984
                 green
37
    64.7880
                   red
38
    65.2600
                 green
39
    66.0370
                   red
40
    66.1424
                 green
41
    65.7244
42 64.5820
                   red
43
    63.3794
                   red
44
   61.7426
                   red
45
   59.5878
                   red
46
   57.0902
                 green
47
   54.2546
                 green
48
   52.1180
                   red
    48.8152
49
                   red
50
   45.6818
                   red
51
   43.5128
                 green
52
   42.9702
                   red
/var/folders/by/3jf2bh0x2ks63rycd0ctbzsh0000gn/T/ipykernel 6093/1886444954.py:
7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row indexer,col indexer] = value instead
```

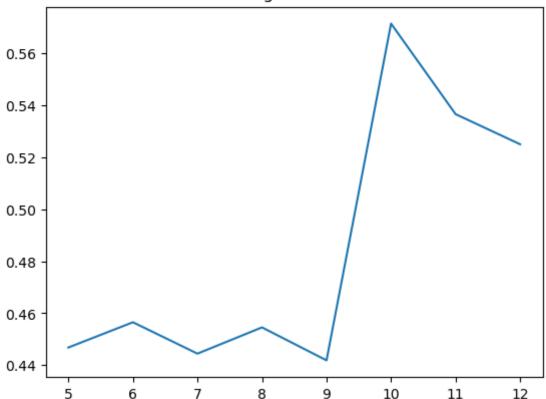
```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user guide/indexing.html#returning-a-view-versus-a-copy
 df_week_2017["ture_label"]=df_week_2017['Return'].apply(lambda x:'green' if
x>0 else 'red')
```

1. take weekly data for year 1. For each W = 5,6,...,12 and for each d = 1, 2, 3 construct the corresponding polynomials Use these polynomials to predict weekly labels. Plot the accuracy - on x axis you have W and you plot three curves for accuracy (separate curve for each d)

```
In [383... def q1 predect(w,d,df week):
              X train = list(range(0, w))
             X_test = list(range(w,len(df_week)))
              y_train = df_week['Close'][:w]
              y_test = df_week['Close'][w:]
             weights= np.polyfit(X_train,y_train, d)
              #print(weights)
             model = np.poly1d(weights)
              predict=model(X_test)
             pred_arr=[]
              for i in range(len(predict)):
                  if predict[i]>y_train[w-1]:
                      pred_arr.append('green')
                  elif predict[i]<y_train[w-1]:</pre>
                      pred arr.append('red')
                  else:
                       pred_arr.append(X_train[w-1])
              res=accuracy_score(df_week[w:]['ture_label'],pred_arr)
              return(res)
         degree 1=[]
         degree 2=[]
         degree_3=[]
         week_list=list(range(5,13))
         for i in week list:
              degree_1.append(q1_predect(i,1,df_week_2017))
              degree_2.append(q1_predect(i,2,df_week_2017))
              degree_3.append(q1_predect(i,3,df_week_2017))
         plt.plot(week list,degree 1)
         plt.title('dgree = 1')
         plt.show()
         plt.plot(week list,degree 2)
         plt.title('dgree = 2')
         plt.show()
         plt.plot(week list,degree 3)
         plt.title('dgree = 3')
         plt.show()
```



## dgree = 3



1. for each d take the best W that gives you the highest accu- racy. Use this W to predict labels for year 2. What is your accuracy?

```
In [384... print('for year 2, the degree = 1, the best w in year 1 is 7, and the accurcy is
         print('for year 2,the degree = 2,the best w is year 1 is 6, and the accurcy is
         print('for year 2, the degree = 3, the best w is year 1 is 10, and the accurcy is
         for year 2, the degree = 1, the best w in year 1 is 7, and the accurcy is
         04347826086957
         for year 2, the degree = 2, the best w is year 1 is 6, and the accurcy is
         7446808510638
         for year 2, the degree = 3, the best w is year 1 is 10, and the accurcy is 0.37
         209302325581395
In [385...
         def q3 predect(w,d,df week):
              X train = list(range(0, w))
              X test = list(range(w,len(df week)))
              y train = df week['Close'][:w]
              y_test = df_week['Close'][w:]
              weights= np.polyfit(X train,y train, d)
              #print(weights)
              model = np.poly1d(weights)
              predict=model(X test)
              pred_arr=[]
              for i in range(len(predict)):
                  if predict[i]>y train[w-1]:
                      pred_arr.append('green')
                  elif predict[i]<y train[w-1]:</pre>
                      pred arr.append('red')
                  else:
                       pred arr.append(X train[w-1])
```

```
temp=np.array(df week[w:]['ture label'])
    TN, FP, FN, TP=confusion matrix(temp, np.array(pred arr)).ravel()
    return(TN, FP, FN, TP)
for i in week list:
    for j in [1,2,3]:
        print('degree:',j,"week",i,"TN, FP, FN, TP:",q3 predect(i,j,df week 201
degree: 1 week 5 TN, FP, FN, TP: (20, 0, 28, 0)
degree: 2 week 5 TN, FP, FN, TP: (0, 20, 0, 28)
degree: 3 week 5 TN, FP, FN, TP: (0, 20, 0, 28)
degree: 1 week 6 TN, FP, FN, TP: (19, 0, 28, 0)
degree: 2 week 6 TN, FP, FN, TP: (0, 19, 0, 28)
degree: 3 week 6 TN, FP, FN, TP: (0, 19, 0, 28)
degree: 1 week 7 TN, FP, FN, TP: (19, 0, 27, 0)
degree: 2 week 7 TN, FP, FN, TP: (0, 19, 0, 27)
degree: 3 week 7 TN, FP, FN, TP: (19, 0, 27, 0)
degree: 1 week 8 TN, FP, FN, TP: (18, 0, 27, 0)
degree: 2 week 8 TN, FP, FN, TP: (0, 18, 0, 27)
degree: 3 week 8 TN, FP, FN, TP: (18, 0, 27, 0)
degree: 1 week 9 TN, FP, FN, TP: (17, 0, 27, 0)
degree: 2 week 9 TN, FP, FN, TP: (0, 17, 0, 27)
degree: 3 week 9 TN, FP, FN, TP: (17, 0, 27, 0)
degree: 1 week 10 TN, FP, FN, TP: (16, 0, 27, 0)
degree: 2 week 10 TN, FP, FN, TP: (0, 16, 0, 27)
degree: 3 week 10 TN, FP, FN, TP: (16, 0, 27, 0)
degree: 1 week 11 TN, FP, FN, TP: (15, 0, 27, 0)
degree: 2 week 11 TN, FP, FN, TP: (0, 15, 0, 27)
degree: 3 week 11 TN, FP, FN, TP: (15, 0, 27, 0)
degree: 1 week 12 TN, FP, FN, TP: (15, 0, 26, 0)
degree: 2 week 12 TN, FP, FN, TP: (1, 14, 0, 26)
degree: 3 week 12 TN, FP, FN, TP: (1, 14, 0, 26)
```

1. implement three trading strategies for year 2 (for each d using the "best" values for W from year 1 that you have computed)

```
In [386...
         def q4 predect(w,d,df week):
             X train = list(range(0,w))
             X test = list(range(w,len(df week)))
             y train = df week['Close'][:w]
             y test = df week['Close'][w:]
             weights= np.polyfit(X_train,y_train, d)
             #print(weights)
             return(weights)
         print(q4 predect(7,1,df week 2018))
         print(q4 predect(6,2,df week 2018))
         print(q4_predect(10,3,df_week_2018))
         [ 0.955
                      55.036428571
         [-0.50375]
                       3.43503571 53.42178571]
         [ 2.50077700e-02 -4.48059441e-01 2.81864608e+00 5.37467133e+01]
```