S3O1

November 1, 2020

```
import pandas as pd
[4]: df_vols = pd.read_csv('EURUSD_volsurface.csv')
[5]: df_vols.head() #shape of df_vols = (24,6)
[5]:
       TENOR
                     25D Call EUR
                                    25D Put EUR
                                                 10D Call EUR
                                                               10D Put EUR
                MTA
                             9.054
     0
          1D
             8.717
                                          8.651
                                                         9.457
                                                                      8.742
          1W 6.922
                             7.321
                                          6.814
                                                         7.820
                                                                      6.905
     1
     2
          2W 8.477
                             8.889
                                          8.406
                                                         9.415
                                                                      8.570
     3
          3W 8.090
                             8.485
                                          8.050
                                                         9.004
                                                                      8.221
     4
          1M 7.855
                             8.258
                                          7.808
                                                                      7.984
                                                         8.771
[6]: df_vols.tail()
[6]:
        TENOR
                      25D Call EUR
                                     25D Put EUR
                                                  10D Call EUR
                 MTA
                                                                10D Put EUR
     19
          10Y
              8.415
                              8.785
                                           8.765
                                                          9.610
                                                                        9.640
     20
               8.417
                              8.815
                                           8.717
                                                          9.662
                                                                        9.579
          15Y
     21
          20Y
               8.419
                              8.845
                                           8.692
                                                          9.705
                                                                       9.528
     22
          25Y
               8.422
                              8.871
                                           8.671
                                                          9.743
                                                                        9.485
     23
          30Y 8.425
                              8.896
                                           8.653
                                                          9.777
                                                                        9.446
    0.1
         Q(1) part(b)
[7]: def countDaysFromTenor(arr_of_tenors):
         1 = len(arr_of_tenors)
         day_arr = np.array([None]*1)
         key = {'D':1,'W':7,'M':30,'Y':365}
         for i in range(1):
             tenor = str(arr_of_tenors[i])
             day = float(tenor[:-1])*key[tenor[-1]]
             day_arr[i]=day
         day_arr = day_arr.astype(np.float)
```

Tests of countDaysFromTenor

return day_arr

[3]: import numpy as np

```
[8]: countDaysFromTenor(['1W','2W','4M','2Y'])
```

[8]: array([7., 14., 120., 730.])

0.2 Q1 part(c)

```
[9]: import scipy.stats as stats
def strikeFromDelta(delta,S,sigma,T,cp):
    d1 = (1/cp)*stats.norm.ppf(delta/cp,0,1)
    K = S/np.exp(sigma*np.sqrt(T)*d1-sigma*sigma*T/2)
    return K
```

0.3 Q1part(d)

```
[10]: T_vec = countDaysFromTenor(df_vols['TENOR'].values)/365
S_vec = np.array([1.166]*len(df_vols))
keys = {'25D Call EUR':[0.25,1],'25D Put EUR':[-0.25,-1],'10D Call EUR':[0.

$\int_1,1],'10D Put EUR':[-0.1,-1]}
K_array = np.concatenate((S_vec[:,np.newaxis],np.zeros((len(df_vols),4))),axis=1)
for i in range(4):
    sigma_vec = (df_vols.iloc[:,i+2].values)/100
    column = df_vols
    (delta,cp) = keys[(df_vols.columns)[i+2]]
    delta_vec = np.array([delta]*len(df_vols))
    cp_vec = np.array([cp]*len(df_vols))
    K_vec = strikeFromDelta(delta_vec,S_vec,sigma_vec,T_vec,cp_vec)
    K_array[:,i+1]=K_vec
    df_K =pd.DataFrame(np.concatenate((T_vec[:,np.newaxis],K_array),axis=1),columns_u

$\int = (['Maturity in year']+list((df_vols.columns)[1:])))
```

[11]: df_K

```
[11]:
          Maturity in year
                               ATM
                                    25D Call EUR
                                                  25D Put EUR
                                                               10D Call EUR \
                  0.002740 1.166
      0
                                        1.169746
                                                     1.162456
                                                                    1.173435
      1
                  0.019178 1.166
                                        1.174061
                                                     1.158654
                                                                    1.182365
      2
                  0.038356
                            1.166
                                        1.179951
                                                     1.153281
                                                                    1.194084
      3
                  0.057534 1.166
                                        1.182361
                                                     1.151127
                                                                    1.199003
      4
                  0.082192 1.166
                                        1.185101
                                                     1.148815
                                                                    1.204568
                                                                    1.218848
      5
                  0.164384 1.166
                                        1.191751
                                                     1.143245
      6
                  0.246575 1.166
                                        1.196371
                                                     1.139608
                                                                    1.229511
      7
                  0.328767 1.166
                                        1.201051
                                                     1.135892
                                                                    1.240136
      8
                  0.410959 1.166
                                        1.205339
                                                     1.132592
                                                                    1.250638
      9
                  0.493151 1.166
                                        1.209361
                                                     1.129596
                                                                    1.260181
                                        1.220441
      10
                  0.739726 1.166
                                                     1.121678
                                                                    1.286857
      11
                  1.000000 1.166
                                        1.230546
                                                     1.114915
                                                                    1.312329
      12
                  1.479452 1.166
                                        1.247330
                                                     1.102800
                                                                    1.347483
```

```
13
            2.000000
                      1.166
                                   1.262956
                                                 1.092456
                                                                1.383084
14
                       1.166
            3.000000
                                   1.292360
                                                 1.074778
                                                                1.446023
15
            4.000000
                       1.166
                                   1.319927
                                                 1.060160
                                                                1.505461
                       1.166
16
            5.000000
                                   1.344602
                                                 1.047894
                                                                1.558731
17
            6.000000
                       1.166
                                   1.368244
                                                 1.037527
                                                                1.604181
18
            7.00000
                       1.166
                                   1.390842
                                                 1.028559
                                                                1.647907
19
           10.000000
                       1.166
                                   1.461619
                                                 1.005054
                                                                1.802568
20
                       1.166
           15.000000
                                   1.556019
                                                0.983002
                                                                2.020129
21
           20.000000
                       1.166
                                   1.646439
                                                 0.967484
                                                                2.234430
22
           25.000000
                       1.166
                                   1.735191
                                                 0.956128
                                                                2.451119
           30.000000
23
                       1.166
                                                 0.947641
                                                                2.673117
                                   1.823824
```

10D Put EUR 0 1.159195 1 1.151851 2 1.141348 3 1.137124 4 1.132590 5 1.121067 6 1.113280 7 1.105190 8 1.097635 9 1.090806 10 1.073071 11 1.057469 12 1.032085 13 1.009525 14 0.972440 15 0.941747 16 0.915598 17 0.895037 18 0.877204 19 0.826439 20 0.776429 21 0.739550 22 0.710533 23 0.686858

0.4 Q1part(e)

```
[12]: S=1.166
m_array = K_array/S
df_m =pd.DataFrame(np.concatenate((T_vec[:,np.newaxis],m_array),axis=1),columns
→= df_K.columns)
```

```
[13]: df_m
```

[13]:	Maturity in year	ATM	25D Call EUR	25D Put EUR	10D Call EUR	\
0	0.002740	1.0	1.003213	0.996961	1.006376	
1	0.019178	1.0	1.006913	0.993700	1.014035	
2	0.038356	1.0	1.011965	0.989091	1.024086	
3	0.057534	1.0	1.014032	0.987245	1.028304	
4	0.082192	1.0	1.016381	0.985262	1.033077	
5	0.164384	1.0	1.022085	0.980485	1.045324	
6	0.246575	1.0	1.026048	0.977365	1.054469	
7	0.328767	1.0	1.030061	0.974178	1.063582	
8	0.410959	1.0	1.033739	0.971348	1.072589	
9	0.493151	1.0	1.037188	0.968778	1.080772	
10	0.739726	1.0	1.046690	0.961988	1.103651	
11	1.000000	1.0	1.055357	0.956188	1.125496	
12	1.479452	1.0	1.069751	0.945798	1.155645	
13	2.000000	1.0	1.083153	0.936926	1.186178	
14	3.000000	1.0	1.108371	0.921765	1.240157	
15	4.000000	1.0	1.132013	0.909228	1.291133	
16	5.000000	1.0	1.153175	0.898708	1.336819	
17	6.000000	1.0	1.173451	0.889818	1.375798	
18	7.000000	1.0	1.192832	0.882126	1.413299	
19	10.000000	1.0	1.253532	0.861967	1.545941	
20	15.000000	1.0	1.334493	0.843055	1.732529	
21	20.000000	1.0	1.412040	0.829746	1.916321	
22	25.000000	1.0	1.488157	0.820007	2.102160	
23	30.000000	1.0	1.564171	0.812728	2.292553	
	10D Put EUR					
0	0.994163					
1	0.987865					
2	0.978858					
3	0.975235					
4	0.971347					
5	0.961464					
6	0.954786					
7	0.947847					
8	0.941368					
9	0.935511					
10	0.920301					
11	0.906920					
12	0.885150					
13	0.865802					
14	0.833996					
15	0.807673					
1.6	0.705047					

0.785247

0.767613

0.752319

0.708782

16

17

18

19

```
20 0.665891
21 0.634262
22 0.609376
23 0.589072
```

0.5 Q1 part(f)

```
[14]: from math import * def g(x,y,h1=0.05,h2=0.05): return np.exp(-x*x/(2*h1))*np.exp(-y*y/(2*h2))/(2*pi)
```

```
[15]: def volEstimate(m_i_array, T_i_vec, v_arr,g,m,T):
           N = len(m_i_array)*(m_i_array.shape)[1]
           m_mat = np.matmul(m.reshape(len(m),1),np.ones((1,N))) #m_mat.shape = m_size *_{\sqcup}
       \hookrightarrow N
           T_{mat} = np.matmul(T.reshape(len(m),1),np.ones((1,N))) \#T_{mat.shape} = m_size *_{\sqcup}
       \rightarrow N (len(T)=len(m))
          m_i_mat = np.matmul(np.ones((len(m),1)),m_i_array.reshape((1,N))) #m_i_array.
       \rightarrowshape = m_size * N
           v_array = np.matmul(np.ones((len(m),1)),v_arr.reshape((1,N))) #m_i_array.
       \rightarrowshape = m_size * N
           T_i_array = np.matmul(T_i_vec.reshape(len(T_i_vec),1), np.ones((1,(m_i_array.
       →shape)[1])))
           T_i_array = T_i_array.reshape((1,N))
           T_i_array = np.matmul(np.ones((len(m),1)),T_i_array.reshape((1,N)))
           g_mat = g(m_mat-m_i_mat,T_mat-T_i_array)
           sum_g = np.sum(g_mat, axis = 1)
           sum_v_g = np.sum(v_array*g_mat,axis=1)
           vol_estimator = sum_v_g/sum_g
           return vol_estimator
```

```
[16]: m_min = np.min(m_array)
m_max = np.max(m_array)
t_min = np.min(T_vec)
t_max = np.max(T_vec)
v_mat = (df_vols.values[:,1:]).astype(np.float)
mx = np.linspace(m_min,m_max,10)
ty = np.linspace(t_min,t_max,10)
v_estimator = volEstimate(m_array,T_vec,v_mat,g,mx,ty)
```

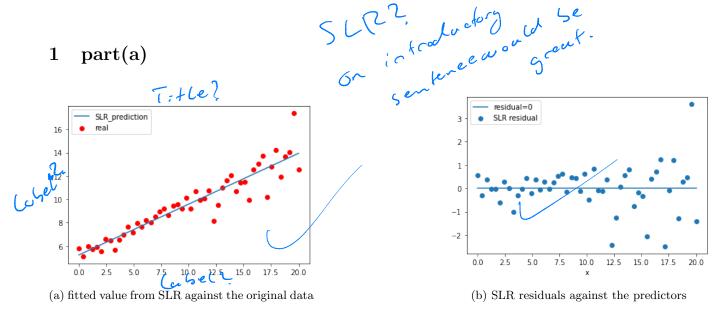


Figure 1: plots of fitted value and residuals from SLR

From figure 1 (b), we can observe that residuals deviate from the zero line more when x is larger than (approx.) 11, indicating that the standard deviations of residuals are not consistent all the time.

2 part(b)

We choose our weights in WLR to be the inverse of df_WLS['weights']².

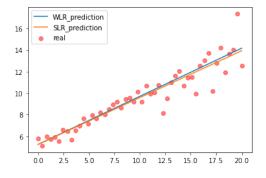


Figure 2: fitted values from SLR and WLR against the original data

	const-coeff	const-std err	x1-coeff	x1-std err			
WLR	5.2469	0.143/	0.4466	0.018			
SLR	5.2426	0.271	0.4349	0.023			

Table 1: estimated coefficients from WLS and from QLS and their respective deviations

We can observe that the standard error gets smaller after introducing the weights, indicating better model.

3 part(c)

Suggested by the df-WLS['weights'] columns, the standard deviation of residuals changes after the 30th data point, so we calculate the standard deviations of residual[:30] and residual[30:] respectively, and our 95% confidence prediction interval = fitted values \pm 1.96 \times standard deviation of residual (different std values depending on whether the data point is in the first 30 or not).

From figure 3, we observe that except two points (one is around x = 3.5, the other is around x = 19), all points lie inside the predicted interval.

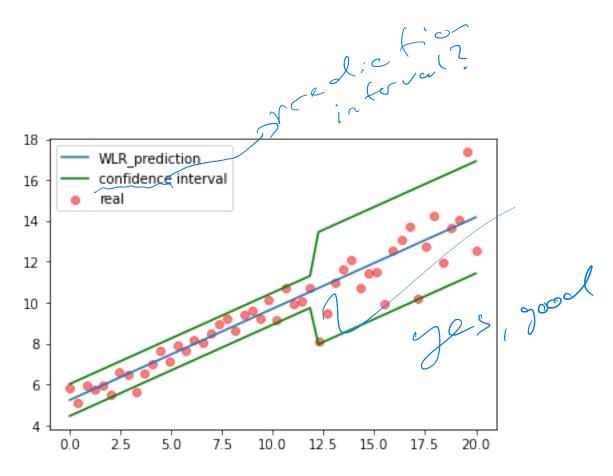


Figure 3: Plots of predicted interval, fitted values and original data