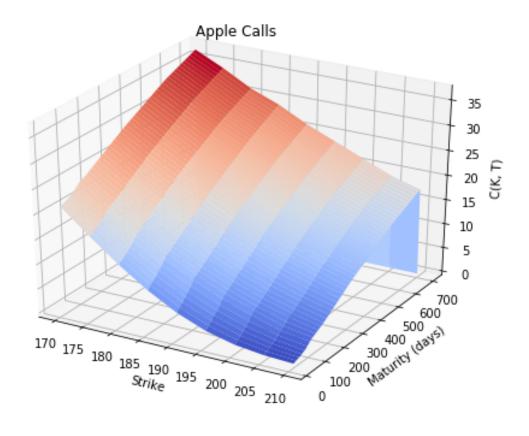
## Apple\_Heston\_Calls

### January 7, 2019

```
In [1]: import warnings
        warnings.filterwarnings("ignore")
        import modulesForCalibration as mfc
        import matplotlib.pyplot as plt
        \#import\ readPlotOptionSurface\_granular\_k2\_5\ as\ marketSurface
        import readPlotOptionSurfaceedited as marketSurface
        import numpy as np
        import pandas as pd
        from mpl_toolkits.mplot3d import Axes3D
        import matplotlib.pyplot as plt
        from matplotlib import cm
        import cmath
        import math
        from scipy.optimize import fmin
        import plotly.plotly as py
        import plotly.graph_objs as go
<Figure size 800x600 with 1 Axes>
```

- 1 This report reflects the work of Lisa He, Alban Zapke, and Naijia Yao, for the project of volatility surface in Computational Methods in Finance with Prof. Hirsa.
- 1.1 APPL
- 1.1.1 We set up Grid for Model Prices as provided in readPlotOptionSurface.py provided by Prof. Hirsa
- 1.1.2 deltaK = 5 & deltaTau = 1/52
  In [2]: maturities, strikes, marketPrices = marketSurface.readNPlot()



In [3]: maturities\_years = maturities/365

### 2 I. Model Prices

### 2.0.1 Global Parameters

```
# step-size in log strike space --> FFT constraint
#lda = (2*np.pi/N)/eta

# Choice of beta
#beta = np.log(S0)-N*lda/2
# beta = np.log(K)
```

• Grid for Model Prices was set up in readPlotOptionSurface

# 2.1 1. Finding a starting point; code provided as in exampleCalibration\_FindingStartingPoint.py by Prof. Hirsa

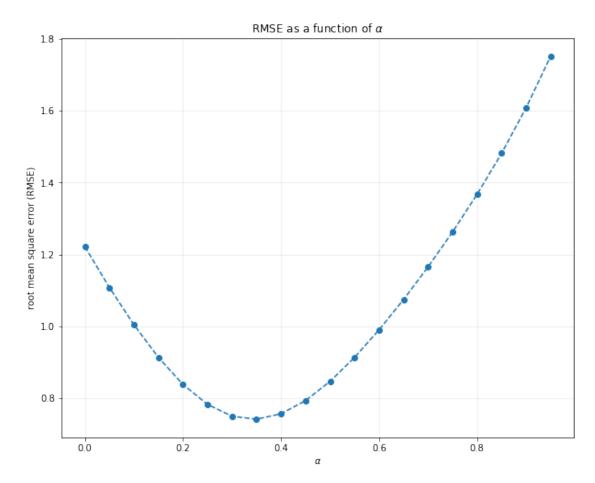
```
In [5]: iArray = []  # The alphas (0,1) which are plotted agains RMSE
    rmseArray = []
    rmseMin = 1e10  # Random; in order to have an error to start wit
```

### 2.1.1 Model specific parameters:

#### Heston

```
In [6]: model = 'Heston'
        #set 1: promising starting point
        params1 = (1.0, 0.02, 0.05, -0.4, 0.08)
        params2 = (3.0, 0.06, 0.10, -0.6, 0.04)
In [7]: lenT = len(maturities_years)
        lenK = len(strikes)
        modelPrices = np.zeros((lenT, lenK))
In [8]: modelPrices.shape == marketPrices.shape
Out[8]: True
In [9]: marketPrices.shape
Out[9]: (98, 9)
In [10]: iArray = []
         rmseArray=[]
         for i in mfc.myRange(0.0, 1.0, 0.05):
             params = i*np.array(params1) + (1.0-i)*np.array(params2)
             iArray.append(i)
             rmse = mfc.eValue(params, marketPrices, maturities_years, strikes, r, q, S0, alpha,
             rmseArray.append(rmse)
             if (rmse < rmseMin):</pre>
                 rmseMin = rmse
                 optimParams = params
```

```
In [27]: len(rmseArray) == len(iArray)
         print(len(rmseArray))
         print(len(iArray))
         #print(rmseArray)
         #print(iArray)
20
20
In [28]: fig = plt.figure(figsize=(10,8))
        plt.plot(iArray, rmseArray, 'o--')
         plt.grid(alpha=0.25)
         plt.xlabel('$\\alpha$')
         plt.ylabel('root mean square error (RMSE)')
         plt.title('RMSE as a function of $\\alpha$')
         plt.savefig('startingPoint4.png')
         plt.show()
         print(rmseMin)
         print(optimParams)
```



```
0.7410834358357488
[ 2.3
        0.046 0.0825 -0.53 0.054 ]
In [29]: # Starting point Parameters
       kappa = 2.3
        theta = 0.046
       sig = 0.0825
       rho = -0.53
        v0 = 0.054
2.2 2. Optimization of Parameter Set
- Objective Function -
In [30]: def objFunc(v, x0, x1, x2):
           # Paraboloid centered on (x, y), with scale factors (10, 20) and minimum 30
           return 10.0*(v[0]-x0)**2 + 20.0*(v[1]-x1)**2 + 30.0*(v[2]-x2)**2 + 40.0
In [31]: lenT = len(maturities)
        lenK = len(strikes)
A) Brute Force Algorithm
In [33]: # maturities, strikes, marketPrices = marketSurface.readNPlot()
        # Grid Search around the starting point
        #-----
        ind_iter = 1
        rmseMin = 1.0e6
        for kappa in mfc.myRange(1.8, 2.8, 0.5):
           for theta in mfc.myRange(0.036,0.056,0.01):
               for sig in mfc.myRange(0.0725,0.0925,0.01):
                   for rho in mfc.myRange(-0.63,-0.43,0.1):
                      for v0 in mfc.myRange(0.044,0.064,0.01):
                          params = []
                          params.append(kappa)
                          params.append(theta)
                          params.append(sig)
                          params.append(rho)
                          params.append(v0)
                          print('i = ' + str(ind_iter))
```

```
ind_iter += 1
                              print(params)
                              rmse = mfc.eValue(params, marketPrices, maturities_years, strikes,
                              if (rmse < rmseMin):</pre>
                                  rmseMin = rmse
                                  params2 = params
                                  print('\nnew min found')
                                  print(rmseMin)
                                  print(params2)
                                  print('')
         print('\nSolution of grid search:')
         print(params2)
         print('Optimal rmse = ' + str(rmseMin))
i = 1
[1.7, 0.034, 0.07, -0.62, 0.046]
new min found
0.9061558281366756
[1.7, 0.034, 0.07, -0.62, 0.046]
i = 2
[1.7, 0.034, 0.07, -0.62, 0.056]
new min found
0.7495517706837034
[1.7, 0.034, 0.07, -0.62, 0.056]
i = 3
[1.7, 0.034, 0.07, -0.62, 0.066]
i = 4
[1.7, 0.034, 0.07, -0.52, 0.046]
[1.7, 0.034, 0.07, -0.52, 0.056]
i = 6
[1.7, 0.034, 0.07, -0.52, 0.066]
i = 7
[1.7, 0.034, 0.07, -0.4200000000000004, 0.046]
i = 8
[1.7, 0.034, 0.07, -0.4200000000000004, 0.056]
[1.7, 0.034, 0.07, -0.4200000000000004, 0.066]
i = 10
[1.7, 0.034, 0.08, -0.62, 0.046]
i = 11
[1.7, 0.034, 0.08, -0.62, 0.056]
```

```
new min found
0.7480136822229901
[1.7, 0.034, 0.08, -0.62, 0.056]
i = 12
[1.7, 0.034, 0.08, -0.62, 0.066]
i = 13
[1.7, 0.034, 0.08, -0.52, 0.046]
i = 14
[1.7, 0.034, 0.08, -0.52, 0.056]
i = 15
[1.7, 0.034, 0.08, -0.52, 0.066]
i = 16
[1.7, 0.034, 0.08, -0.4200000000000004, 0.046]
i = 17
[1.7, 0.034, 0.08, -0.4200000000000004, 0.056]
i = 18
[1.7, 0.034, 0.08, -0.4200000000000004, 0.066]
i = 19
[1.7, 0.034, 0.09, -0.62, 0.046]
i = 20
[1.7, 0.034, 0.09, -0.62, 0.056]
new min found
0.7471040695013035
[1.7, 0.034, 0.09, -0.62, 0.056]
i = 21
[1.7, 0.034, 0.09, -0.62, 0.066]
i = 22
[1.7, 0.034, 0.09, -0.52, 0.046]
i = 23
[1.7, 0.034, 0.09, -0.52, 0.056]
i = 24
[1.7, 0.034, 0.09, -0.52, 0.066]
i = 25
[1.7, 0.034, 0.09, -0.4200000000000004, 0.046]
i = 26
[1.7, 0.034, 0.09, -0.4200000000000004, 0.056]
i = 27
[1.7, 0.034, 0.09, -0.4200000000000004, 0.066]
i = 28
[1.7, 0.04400000000000004, 0.07, -0.62, 0.046]
new min found
0.3925847869697346
[1.7, 0.04400000000000004, 0.07, -0.62, 0.046]
```

```
i = 29
[1.7, 0.04400000000000004, 0.07, -0.62, 0.056]
i = 30
[1.7, 0.04400000000000004, 0.07, -0.62, 0.066]
i = 31
[1.7, 0.04400000000000004, 0.07, -0.52, 0.046]
i = 32
[1.7, 0.04400000000000004, 0.07, -0.52, 0.056]
[1.7, 0.04400000000000004, 0.07, -0.52, 0.066]
i = 34
[1.7, 0.04400000000000004, 0.07, -0.4200000000000004, 0.046]
i = 35
[1.7, 0.04400000000000004, 0.07, -0.4200000000000004, 0.056]
i = 36
[1.7, 0.0440000000000004, 0.07, -0.4200000000000004, 0.066]
i = 37
[1.7, 0.04400000000000004, 0.08, -0.62, 0.046]
new min found
0.387074050793953
[1.7, 0.04400000000000004, 0.08, -0.62, 0.046]
i = 38
[1.7, 0.04400000000000004, 0.08, -0.62, 0.056]
i = 39
[1.7, 0.04400000000000004, 0.08, -0.62, 0.066]
i = 40
[1.7, 0.04400000000000004, 0.08, -0.52, 0.046]
i = 41
[1.7, 0.04400000000000004, 0.08, -0.52, 0.056]
i = 42
[1.7, 0.04400000000000004, 0.08, -0.52, 0.066]
i = 43
[1.7, 0.04400000000000004, 0.08, -0.4200000000000004, 0.046]
i = 44
[1.7, 0.04400000000000004, 0.08, -0.4200000000000004, 0.056]
i = 45
[1.7, 0.04400000000000004, 0.08, -0.4200000000000004, 0.066]
i = 46
[1.7, 0.04400000000000004, 0.09, -0.62, 0.046]
new min found
0.3822081498347296
[1.7, 0.04400000000000004, 0.09, -0.62, 0.046]
```

i = 47

```
[1.7, 0.04400000000000004, 0.09, -0.62, 0.056]
i = 48
[1.7, 0.04400000000000004, 0.09, -0.62, 0.066]
i = 49
[1.7, 0.04400000000000004, 0.09, -0.52, 0.046]
i = 50
[1.7, 0.04400000000000004, 0.09, -0.52, 0.056]
i = 51
[1.7, 0.04400000000000004, 0.09, -0.52, 0.066]
i = 52
[1.7, 0.04400000000000004, 0.09, -0.4200000000000004, 0.046]
i = 53
[1.7, 0.04400000000000004, 0.09, -0.4200000000000004, 0.056]
i = 54
[1.7, 0.04400000000000004, 0.09, -0.4200000000000004, 0.066]
i = 55
[1.7, 0.054000000000000006, 0.07, -0.62, 0.046]
i = 56
[1.7, 0.054000000000000006, 0.07, -0.62, 0.056]
i = 57
[1.7, 0.054000000000000006, 0.07, -0.62, 0.066]
i = 58
[1.7, 0.054000000000000006, 0.07, -0.52, 0.046]
i = 59
[1.7, 0.054000000000000006, 0.07, -0.52, 0.056]
i = 60
[1.7, 0.05400000000000006, 0.07, -0.52, 0.066]
i = 61
[1.7, 0.054000000000000006, 0.07, -0.4200000000000004, 0.046]
i = 62
[1.7, 0.054000000000000000, 0.07, -0.4200000000000000, 0.056]
i = 63
[1.7, 0.05400000000000000, 0.07, -0.420000000000000, 0.066]
i = 64
[1.7, 0.054000000000000006, 0.08, -0.62, 0.046]
i = 65
[1.7, 0.054000000000000006, 0.08, -0.62, 0.056]
i = 66
[1.7, 0.054000000000000006, 0.08, -0.62, 0.066]
i = 67
[1.7, 0.05400000000000006, 0.08, -0.52, 0.046]
i = 68
[1.7, 0.05400000000000006, 0.08, -0.52, 0.056]
i = 69
[1.7, 0.05400000000000006, 0.08, -0.52, 0.066]
i = 70
[1.7, 0.05400000000000000, 0.08, -0.420000000000000, 0.046]
i = 71
```

```
[1.7, 0.05400000000000000, 0.08, -0.420000000000000, 0.056]
i = 72
[1.7, 0.05400000000000000, 0.08, -0.4200000000000004, 0.066]
i = 73
[1.7, 0.054000000000000006, 0.09, -0.62, 0.046]
i = 74
[1.7, 0.054000000000000006, 0.09, -0.62, 0.056]
i = 75
[1.7, 0.054000000000000006, 0.09, -0.62, 0.066]
i = 76
[1.7, 0.05400000000000006, 0.09, -0.52, 0.046]
i = 77
[1.7, 0.05400000000000006, 0.09, -0.52, 0.056]
i = 78
[1.7, 0.05400000000000006, 0.09, -0.52, 0.066]
i = 79
[1.7, 0.05400000000000000, 0.09, -0.4200000000000004, 0.046]
i = 80
[1.7, 0.05400000000000000, 0.09, -0.4200000000000000, 0.056]
i = 81
[1.7, 0.054000000000000006, 0.09, -0.42000000000000004, 0.066]
i = 82
[2.2, 0.034, 0.07, -0.62, 0.046]
i = 83
[2.2, 0.034, 0.07, -0.62, 0.056]
i = 84
[2.2, 0.034, 0.07, -0.62, 0.066]
i = 85
[2.2, 0.034, 0.07, -0.52, 0.046]
i = 86
[2.2, 0.034, 0.07, -0.52, 0.056]
i = 87
[2.2, 0.034, 0.07, -0.52, 0.066]
i = 88
[2.2, 0.034, 0.07, -0.4200000000000004, 0.046]
i = 89
[2.2, 0.034, 0.07, -0.4200000000000004, 0.056]
[2.2, 0.034, 0.07, -0.4200000000000004, 0.066]
i = 91
[2.2, 0.034, 0.08, -0.62, 0.046]
i = 92
[2.2, 0.034, 0.08, -0.62, 0.056]
i = 93
[2.2, 0.034, 0.08, -0.62, 0.066]
i = 94
[2.2, 0.034, 0.08, -0.52, 0.046]
i = 95
```

```
[2.2, 0.034, 0.08, -0.52, 0.056]
i = 96
[2.2, 0.034, 0.08, -0.52, 0.066]
i = 97
[2.2, 0.034, 0.08, -0.4200000000000004, 0.046]
i = 98
[2.2, 0.034, 0.08, -0.4200000000000004, 0.056]
i = 99
[2.2, 0.034, 0.08, -0.4200000000000004, 0.066]
i = 100
[2.2, 0.034, 0.09, -0.62, 0.046]
i = 101
[2.2, 0.034, 0.09, -0.62, 0.056]
i = 102
[2.2, 0.034, 0.09, -0.62, 0.066]
i = 103
[2.2, 0.034, 0.09, -0.52, 0.046]
i = 104
[2.2, 0.034, 0.09, -0.52, 0.056]
i = 105
[2.2, 0.034, 0.09, -0.52, 0.066]
i = 106
[2.2, 0.034, 0.09, -0.4200000000000004, 0.046]
i = 107
[2.2, 0.034, 0.09, -0.4200000000000004, 0.056]
i = 108
[2.2, 0.034, 0.09, -0.4200000000000004, 0.066]
i = 109
[2.2, 0.04400000000000004, 0.07, -0.62, 0.046]
i = 110
[2.2, 0.04400000000000004, 0.07, -0.62, 0.056]
i = 111
[2.2, 0.04400000000000004, 0.07, -0.62, 0.066]
i = 112
[2.2, 0.04400000000000004, 0.07, -0.52, 0.046]
i = 113
[2.2, 0.04400000000000004, 0.07, -0.52, 0.056]
[2.2, 0.04400000000000004, 0.07, -0.52, 0.066]
i = 115
[2.2, 0.0440000000000004, 0.07, -0.4200000000000004, 0.046]
i = 116
[2.2, 0.0440000000000004, 0.07, -0.4200000000000004, 0.056]
i = 117
[2.2, 0.0440000000000004, 0.07, -0.4200000000000004, 0.066]
i = 118
[2.2, 0.04400000000000004, 0.08, -0.62, 0.046]
i = 119
```

```
[2.2, 0.04400000000000004, 0.08, -0.62, 0.056]
i = 120
[2.2, 0.04400000000000004, 0.08, -0.62, 0.066]
i = 121
[2.2, 0.04400000000000004, 0.08, -0.52, 0.046]
i = 122
[2.2, 0.04400000000000004, 0.08, -0.52, 0.056]
i = 123
[2.2, 0.04400000000000004, 0.08, -0.52, 0.066]
i = 124
[2.2, 0.0440000000000004, 0.08, -0.4200000000000004, 0.046]
i = 125
[2.2, 0.0440000000000004, 0.08, -0.4200000000000004, 0.056]
i = 126
[2.2, 0.04400000000000004, 0.08, -0.4200000000000004, 0.066]
i = 127
[2.2, 0.04400000000000004, 0.09, -0.62, 0.046]
i = 128
[2.2, 0.04400000000000004, 0.09, -0.62, 0.056]
i = 129
[2.2, 0.04400000000000004, 0.09, -0.62, 0.066]
i = 130
[2.2, 0.04400000000000004, 0.09, -0.52, 0.046]
i = 131
[2.2, 0.04400000000000004, 0.09, -0.52, 0.056]
i = 132
[2.2, 0.04400000000000004, 0.09, -0.52, 0.066]
i = 133
[2.2, 0.04400000000000004, 0.09, -0.4200000000000004, 0.046]
i = 134
[2.2, 0.04400000000000004, 0.09, -0.4200000000000004, 0.056]
i = 135
[2.2, 0.04400000000000004, 0.09, -0.4200000000000004, 0.066]
i = 136
[2.2, 0.054000000000000006, 0.07, -0.62, 0.046]
i = 137
[2.2, 0.054000000000000006, 0.07, -0.62, 0.056]
i = 138
[2.2, 0.05400000000000006, 0.07, -0.62, 0.066]
i = 139
[2.2, 0.05400000000000006, 0.07, -0.52, 0.046]
i = 140
[2.2, 0.05400000000000006, 0.07, -0.52, 0.056]
i = 141
[2.2, 0.05400000000000006, 0.07, -0.52, 0.066]
i = 142
[2.2, 0.05400000000000000, 0.07, -0.4200000000000000, 0.046]
i = 143
```

```
[2.2, 0.05400000000000006, 0.07, -0.4200000000000004, 0.056]
i = 144
[2.2, 0.05400000000000006, 0.07, -0.4200000000000004, 0.066]
i = 145
[2.2, 0.05400000000000006, 0.08, -0.62, 0.046]
i = 146
[2.2, 0.054000000000000006, 0.08, -0.62, 0.056]
i = 147
[2.2, 0.05400000000000006, 0.08, -0.62, 0.066]
i = 148
[2.2, 0.05400000000000006, 0.08, -0.52, 0.046]
i = 149
[2.2, 0.05400000000000006, 0.08, -0.52, 0.056]
i = 150
[2.2, 0.05400000000000006, 0.08, -0.52, 0.066]
i = 151
[2.2, 0.05400000000000006, 0.08, -0.4200000000000004, 0.046]
i = 152
[2.2, 0.05400000000000000, 0.08, -0.4200000000000004, 0.056]
i = 153
[2.2, 0.054000000000000006, 0.08, -0.42000000000000004, 0.066]
i = 154
[2.2, 0.054000000000000006, 0.09, -0.62, 0.046]
i = 155
[2.2, 0.054000000000000006, 0.09, -0.62, 0.056]
i = 156
[2.2, 0.05400000000000006, 0.09, -0.62, 0.066]
i = 157
[2.2, 0.054000000000000006, 0.09, -0.52, 0.046]
i = 158
[2.2, 0.05400000000000006, 0.09, -0.52, 0.056]
i = 159
[2.2, 0.054000000000000006, 0.09, -0.52, 0.066]
i = 160
[2.2, 0.05400000000000000, 0.09, -0.4200000000000000, 0.046]
i = 161
[2.2, 0.054000000000000006, 0.09, -0.42000000000000004, 0.056]
[2.2, 0.05400000000000000, 0.09, -0.4200000000000000, 0.066]
i = 163
[2.7, 0.034, 0.07, -0.62, 0.046]
i = 164
[2.7, 0.034, 0.07, -0.62, 0.056]
i = 165
[2.7, 0.034, 0.07, -0.62, 0.066]
i = 166
[2.7, 0.034, 0.07, -0.52, 0.046]
i = 167
```

```
[2.7, 0.034, 0.07, -0.52, 0.056]
i = 168
[2.7, 0.034, 0.07, -0.52, 0.066]
i = 169
[2.7, 0.034, 0.07, -0.4200000000000004, 0.046]
i = 170
[2.7, 0.034, 0.07, -0.4200000000000004, 0.056]
i = 171
[2.7, 0.034, 0.07, -0.4200000000000004, 0.066]
i = 172
[2.7, 0.034, 0.08, -0.62, 0.046]
i = 173
[2.7, 0.034, 0.08, -0.62, 0.056]
i = 174
[2.7, 0.034, 0.08, -0.62, 0.066]
i = 175
[2.7, 0.034, 0.08, -0.52, 0.046]
i = 176
[2.7, 0.034, 0.08, -0.52, 0.056]
i = 177
[2.7, 0.034, 0.08, -0.52, 0.066]
i = 178
[2.7, 0.034, 0.08, -0.4200000000000004, 0.046]
i = 179
[2.7, 0.034, 0.08, -0.4200000000000004, 0.056]
i = 180
[2.7, 0.034, 0.08, -0.4200000000000004, 0.066]
i = 181
[2.7, 0.034, 0.09, -0.62, 0.046]
i = 182
[2.7, 0.034, 0.09, -0.62, 0.056]
i = 183
[2.7, 0.034, 0.09, -0.62, 0.066]
i = 184
[2.7, 0.034, 0.09, -0.52, 0.046]
i = 185
[2.7, 0.034, 0.09, -0.52, 0.056]
i = 186
[2.7, 0.034, 0.09, -0.52, 0.066]
i = 187
[2.7, 0.034, 0.09, -0.4200000000000004, 0.046]
i = 188
[2.7, 0.034, 0.09, -0.4200000000000004, 0.056]
i = 189
[2.7, 0.034, 0.09, -0.4200000000000004, 0.066]
i = 190
[2.7, 0.04400000000000004, 0.07, -0.62, 0.046]
i = 191
```

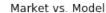
```
[2.7, 0.04400000000000004, 0.07, -0.62, 0.056]
i = 192
[2.7, 0.04400000000000004, 0.07, -0.62, 0.066]
i = 193
[2.7, 0.04400000000000004, 0.07, -0.52, 0.046]
i = 194
[2.7, 0.04400000000000004, 0.07, -0.52, 0.056]
i = 195
[2.7, 0.04400000000000004, 0.07, -0.52, 0.066]
i = 196
[2.7, 0.0440000000000004, 0.07, -0.4200000000000004, 0.046]
i = 197
[2.7, 0.0440000000000004, 0.07, -0.4200000000000004, 0.056]
i = 198
[2.7, 0.0440000000000004, 0.07, -0.4200000000000004, 0.066]
i = 199
[2.7, 0.04400000000000004, 0.08, -0.62, 0.046]
i = 200
[2.7, 0.04400000000000004, 0.08, -0.62, 0.056]
i = 201
[2.7, 0.04400000000000004, 0.08, -0.62, 0.066]
i = 202
[2.7, 0.04400000000000004, 0.08, -0.52, 0.046]
i = 203
[2.7, 0.04400000000000004, 0.08, -0.52, 0.056]
i = 204
[2.7, 0.04400000000000004, 0.08, -0.52, 0.066]
i = 205
[2.7, 0.04400000000000004, 0.08, -0.4200000000000004, 0.046]
i = 206
[2.7, 0.0440000000000004, 0.08, -0.4200000000000004, 0.056]
i = 207
[2.7, 0.04400000000000004, 0.08, -0.4200000000000004, 0.066]
i = 208
[2.7, 0.04400000000000004, 0.09, -0.62, 0.046]
i = 209
[2.7, 0.04400000000000004, 0.09, -0.62, 0.056]
i = 210
[2.7, 0.04400000000000004, 0.09, -0.62, 0.066]
i = 211
[2.7, 0.04400000000000004, 0.09, -0.52, 0.046]
i = 212
[2.7, 0.04400000000000004, 0.09, -0.52, 0.056]
i = 213
[2.7, 0.04400000000000004, 0.09, -0.52, 0.066]
i = 214
[2.7, 0.04400000000000004, 0.09, -0.4200000000000004, 0.046]
i = 215
```

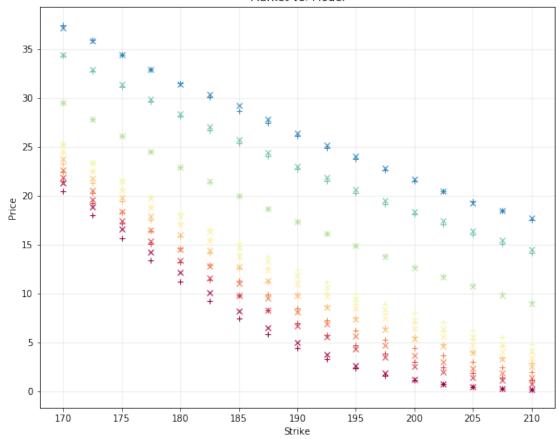
```
[2.7, 0.04400000000000004, 0.09, -0.4200000000000004, 0.056]
i = 216
[2.7, 0.0440000000000004, 0.09, -0.4200000000000004, 0.066]
i = 217
[2.7, 0.054000000000000006, 0.07, -0.62, 0.046]
i = 218
[2.7, 0.054000000000000006, 0.07, -0.62, 0.056]
i = 219
[2.7, 0.05400000000000006, 0.07, -0.62, 0.066]
i = 220
[2.7, 0.05400000000000006, 0.07, -0.52, 0.046]
i = 221
[2.7, 0.05400000000000006, 0.07, -0.52, 0.056]
i = 222
[2.7, 0.05400000000000006, 0.07, -0.52, 0.066]
i = 223
[2.7, 0.05400000000000006, 0.07, -0.4200000000000004, 0.046]
i = 224
[2.7, 0.05400000000000000, 0.07, -0.4200000000000004, 0.056]
i = 225
[2.7, 0.05400000000000000, 0.07, -0.4200000000000000, 0.066]
i = 226
[2.7, 0.054000000000000006, 0.08, -0.62, 0.046]
i = 227
[2.7, 0.054000000000000006, 0.08, -0.62, 0.056]
i = 228
[2.7, 0.05400000000000006, 0.08, -0.62, 0.066]
i = 229
[2.7, 0.054000000000000006, 0.08, -0.52, 0.046]
i = 230
[2.7, 0.05400000000000006, 0.08, -0.52, 0.056]
i = 231
[2.7, 0.054000000000000006, 0.08, -0.52, 0.066]
i = 232
[2.7, 0.054000000000000006, 0.08, -0.42000000000000004, 0.046]
i = 233
[2.7, 0.054000000000000006, 0.08, -0.42000000000000004, 0.056]
i = 234
[2.7, 0.05400000000000000, 0.08, -0.4200000000000004, 0.066]
i = 235
[2.7, 0.05400000000000006, 0.09, -0.62, 0.046]
i = 236
[2.7, 0.05400000000000006, 0.09, -0.62, 0.056]
i = 237
[2.7, 0.05400000000000006, 0.09, -0.62, 0.066]
i = 238
[2.7, 0.05400000000000006, 0.09, -0.52, 0.046]
i = 239
```

```
[2.7, 0.05400000000000006, 0.09, -0.52, 0.056]
i = 240
[2.7, 0.05400000000000006, 0.09, -0.52, 0.066]
i = 241
[2.7, 0.05400000000000000, 0.09, -0.4200000000000000, 0.046]
i = 242
[2.7, 0.05400000000000000, 0.09, -0.4200000000000000, 0.056]
i = 243
[2.7, 0.05400000000000000, 0.09, -0.4200000000000000, 0.066]
Solution of grid search:
[1.7, 0.04400000000000004, 0.09, -0.62, 0.046]
Optimal rmse = 0.3822081498347296
In []: # Solution of grid search:
        # [1.7, 0.04400000000000004, 0.09, -0.62, 0.046]
        # Optimal rmse = 0.3822081498347296
- Market vs. Model Surface -
In [34]: params2
Out[34]: [1.7, 0.04400000000000004, 0.09, -0.62, 0.046]
In [35]: lenT = len(maturities)
         lenK = len(strikes)
         modelPrices = np.zeros((lenT, lenK))
         for i in range(lenT):
             for j in range(lenK):
                 T = maturities_years[i]
                 K = strikes[j]
                 [km, cT_km] = mfc.genericFFT(params2, S0, K, r, q, T, alpha, eta, n, model)
                 modelPrices[i,j] = cT_km[0]
In [36]: modelPrices.shape == marketPrices.shape
Out [36]: True
In [37]: # plot
         fig = plt.figure(figsize=(10,8))
         labels = []
         colormap = cm.Spectral
         plt.gca().set_color_cycle([colormap(i) for i in np.linspace(0, 0.9, len(maturities))])
         for i in range(len(maturities)):
             plt.plot(strikes, marketPrices[i,:], 'x')
             labels.append('T = ' + str(maturities[i]))
```

```
for i in range(len(maturities)):
    plt.plot(strikes, modelPrices[i,:], '+')
    labels.append('T = ' + str(maturities[i]))

#plt.legend(labels, loc='upper right', ncol=2)
plt.grid(alpha=0.25)
plt.xlabel('Strike')
plt.ylabel('Price')
plt.title('Market vs. Model')
plt.savefig('MarketvsModel_GridSearch.png')
plt.show()
```





### B) Nelder Mead Algorithm (Gradient-free) from example Calibration\_Nelder Mead.py

```
params = [2.3, 0.046, 0.0825, -0.53, 0.054]
          def callbackF(xi):
             global num_iter
              global arg
              print('i = ' + str(num_iter))
              print('x_i = ' + str(xi))
              print('f_i = ' + str(mfc.eValue(xi, *arg)))
             num_iter += 1
          arg = (marketPrices, maturities_years, strikes, r, q, SO, alpha, eta, n, model)
         num_iter = 1
          #xopt, fopt, iters, funcalls, warnflag, allvecs = fmin(
          t = fmin(
                 mfc.eValue,
                  params,
                  args=arg,
                  xtol=1e-4,
                  ftol=1e-4,
                 maxiter=200,
                 maxfun=400,
                  callback=callbackF,
                  disp=True,
                 retall=False,
                  full_output=True)
         print('optimal params = ')
         print(t[0])
         print('f = ' + str(t[1]))
i = 1
x_i = [2.266]
                          0.0824 -0.5356
                0.0396
                                           0.05768]
f_i = 0.5999402451624422
i = 2
x_i = [2.3056]
                           0.08384 -0.54496
                                               0.0514087
                  0.04136
f_i = 0.42666037838617843
i = 3
x_i = [2.3056]
                            0.08384 -0.54496
                                                0.051408]
                  0.04136
f_i = 0.42666037838617843
i = 4
x_i = [2.3056]
                 0.04136
                            0.08384 -0.54496
                                                0.051408]
f_i = 0.42666037838617843
i = 5
x_i = [2.3056]
                  0.04136
                           0.08384 -0.54496
                                                0.051408]
f_i = 0.42666037838617843
i = 6
x_i = [2.3056]
                 0.04136
                           0.08384 -0.54496
                                                0.051408]
```

```
f_i = 0.42666037838617843
i = 7
x_i = [2.49878886 \ 0.04269028 \ 0.08596905 \ -0.54232522 \ 0.04635825]
f_i = 0.3534186703723513
i = 8
x_i = [2.49878886 \ 0.04269028 \ 0.08596905 \ -0.54232522 \ 0.04635825]
f_i = 0.3534186703723513
i = 9
x_i = [2.49878886 \ 0.04269028 \ 0.08596905 \ -0.54232522 \ 0.04635825]
f i = 0.3534186703723513
i = 10
x_i = [2.49878886 \ 0.04269028 \ 0.08596905 \ -0.54232522 \ 0.04635825]
f_i = 0.3534186703723513
i = 11
x_i = [2.49878886 \ 0.04269028 \ 0.08596905 \ -0.54232522 \ 0.04635825]
f_i = 0.3534186703723513
i = 12
x_i = [2.44169614 \quad 0.04398799 \quad 0.08715379 \quad -0.55740401 \quad 0.04247574]
f_i = 0.33298501802396074
i = 13
x_i = [2.42325954 \ 0.04692504 \ 0.08731114 \ -0.53580678 \ 0.04048194]
f_i = 0.23513172993769496
x_i = [2.42325954 \quad 0.04692504 \quad 0.08731114 \quad -0.53580678 \quad 0.04048194]
f i = 0.23513172993769496
i = 15
x_i = [2.42325954 \ 0.04692504 \ 0.08731114 \ -0.53580678 \ 0.04048194]
f_i = 0.23513172993769496
x_i = [2.42325954 \ 0.04692504 \ 0.08731114 \ -0.53580678 \ 0.04048194]
f_i = 0.23513172993769496
i = 17
x_i = [2.42325954 \quad 0.04692504 \quad 0.08731114 \quad -0.53580678 \quad 0.04048194]
f_i = 0.23513172993769496
i = 18
x_i = [2.42325954 \ 0.04692504 \ 0.08731114 \ -0.53580678 \ 0.04048194]
f_i = 0.23513172993769496
x_i = [2.42325954 \quad 0.04692504 \quad 0.08731114 \quad -0.53580678 \quad 0.04048194]
f_i = 0.23513172993769496
i = 20
x_i = [2.42325954 \ 0.04692504 \ 0.08731114 \ -0.53580678 \ 0.04048194]
f_i = 0.23513172993769496
i = 21
x_i = [2.42325954 \quad 0.04692504 \quad 0.08731114 \quad -0.53580678 \quad 0.04048194]
f_i = 0.23513172993769496
i = 22
x_i = [2.42325954 \quad 0.04692504 \quad 0.08731114 \quad -0.53580678 \quad 0.04048194]
```

```
f_i = 0.23513172993769496
i = 23
x_i = [2.42325954 \ 0.04692504 \ 0.08731114 \ -0.53580678 \ 0.04048194]
f_i = 0.23513172993769496
i = 24
x_i = [2.42325954 \ 0.04692504 \ 0.08731114 \ -0.53580678 \ 0.04048194]
f_i = 0.23513172993769496
i = 25
x_i = [2.42325954 \ 0.04692504 \ 0.08731114 \ -0.53580678 \ 0.04048194]
f i = 0.23513172993769496
i = 26
x_i = [2.46419308 \quad 0.04703995 \quad 0.08916744 \quad -0.54093642 \quad 0.03954043]
f_i = 0.23495361056125946
i = 27
x_i = [2.46419308 \quad 0.04703995 \quad 0.08916744 \quad -0.54093642 \quad 0.03954043]
f_i = 0.23495361056125946
i = 28
x_i = \begin{bmatrix} 2.44407125 & 0.04746913 & 0.08894755 & -0.54238945 & 0.03926347 \end{bmatrix}
f_i = 0.2334855910436223
i = 29
x_i = [2.44407125 \ 0.04746913 \ 0.08894755 \ -0.54238945 \ 0.03926347]
f_i = 0.2334855910436223
x_i = [2.44407125 \quad 0.04746913 \quad 0.08894755 \quad -0.54238945 \quad 0.03926347]
f i = 0.2334855910436223
i = 31
x_i = [2.44407125 \quad 0.04746913 \quad 0.08894755 \quad -0.54238945 \quad 0.03926347]
f_i = 0.2334855910436223
x_i = [2.45888952 \ 0.04754798 \ 0.09050239 \ -0.54436559 \ 0.03897749]
f_i = 0.23331041745177195
i = 33
x_i = [2.45888952 \quad 0.04754798 \quad 0.09050239 \quad -0.54436559 \quad 0.03897749]
f_i = 0.23331041745177195
i = 34
x_i = [2.4338437 \quad 0.04718557 \quad 0.08906251 \quad -0.54097841 \quad 0.04001404]
f_i = 0.23303728327928516
i = 35
x_i = [2.4338437 \quad 0.04718557 \quad 0.08906251 \quad -0.54097841 \quad 0.04001404]
f_i = 0.23303728327928516
i = 36
x_i = [2.471399 \quad 0.04758943 \quad 0.09078664 \quad -0.5535581 \quad 0.03911045]
f_i = 0.2322910629820369
i = 37
x_i = [2.46976699 \ 0.04710791 \ 0.09156002 \ -0.5480975 \ 0.03974459]
f_i = 0.23141349148948395
i = 38
x_i = [2.46976699 \ 0.04710791 \ 0.09156002 \ -0.5480975 \ 0.03974459]
```

```
f_i = 0.23141349148948395
i = 39
x_i = [2.46976699 \ 0.04710791 \ 0.09156002 \ -0.5480975 \ 0.03974459]
f_i = 0.23141349148948395
i = 40
x_i = [2.46349108 \quad 0.04720803 \quad 0.09133552 \quad -0.55427754 \quad 0.04007794]
f_i = 0.23128352877397965
i = 41
x_i = [2.53367192 \ 0.04777634 \ 0.09599563 \ -0.57398734 \ 0.0385934]
f_i = 0.2300813828859211
i = 42
x_i = [2.49592508 \ 0.04708077 \ 0.09567277 \ -0.5610855 \ 0.04009036]
f_i = 0.2280967783363342
i = 43
x_i = [2.49592508 \ 0.04708077 \ 0.09567277 \ -0.5610855 \ 0.04009036]
f_i = 0.2280967783363342
i = 44
x_i = [2.55636063 \ 0.04682898 \ 0.09867294 \ -0.5783442 \ 0.04025472]
f_i = 0.22620387456850474
i = 45
x_i = [2.58925274 \ 0.04739773 \ 0.10266448 \ -0.60155193 \ 0.03974208]
f_i = 0.22347969311384042
x_i = [2.67726156 \quad 0.04731132 \quad 0.10991087 \quad -0.6175565 \quad 0.03887386]
f i = 0.22005882084564993
x_i = [2.67726156 \ 0.04731132 \ 0.10991087 \ -0.6175565 \ 0.03887386]
f_i = 0.22005882084564993
x_i = [2.75017756 \ 0.04682787 \ 0.11766632 \ -0.64786441 \ 0.04049507]
f_i = 0.21437450622562637
x_i = [2.90793717 \ 0.04677154 \ 0.12877825 \ -0.70152804 \ 0.03996189]
f_i = 0.20924858754412817
i = 50
x_i = [2.99801201 \quad 0.04724067 \quad 0.14084111 \quad -0.74092096 \quad 0.03945747]
f_i = 0.2062199430236543
i = 51
x_i = [2.99801201 \ 0.04724067 \ 0.14084111 \ -0.74092096 \ 0.03945747]
f_i = 0.2062199430236543
i = 52
x_i = [2.99801201 \ 0.04724067 \ 0.14084111 \ -0.74092096 \ 0.03945747]
f_i = 0.2062199430236543
i = 53
x_i = [2.99801201 \ 0.04724067 \ 0.14084111 \ -0.74092096 \ 0.03945747]
f_i = 0.2062199430236543
i = 54
x_i = [2.99801201 \ 0.04724067 \ 0.14084111 \ -0.74092096 \ 0.03945747]
```

```
f_i = 0.2062199430236543
i = 55
x_i = [2.99801201 \ 0.04724067 \ 0.14084111 \ -0.74092096 \ 0.03945747]
f_i = 0.2062199430236543
i = 56
x_i = [2.99801201 \quad 0.04724067 \quad 0.14084111 \quad -0.74092096 \quad 0.03945747]
f_i = 0.2062199430236543
i = 57
x_i = [3.07844395 \quad 0.04700464 \quad 0.14570419 \quad -0.75947765 \quad 0.03944928]
f_i = 0.20611712621077014
i = 58
x_i = [3.11078825 \ 0.04698636 \ 0.14881083 \ -0.77662041 \ 0.03987304]
f_i = 0.20580841413396422
i = 59
x_i = [3.11078825 \ 0.04698636 \ 0.14881083 \ -0.77662041 \ 0.03987304]
f_i = 0.20580841413396422
i = 60
x_i = [3.11078825 \ 0.04698636 \ 0.14881083 \ -0.77662041 \ 0.03987304]
f_i = 0.20580841413396422
i = 61
x_i = [3.02952496 \quad 0.04697977 \quad 0.14141585 \quad -0.74629067 \quad 0.03969883]
f_i = 0.2057839906463977
x_i = [3.02952496 \quad 0.04697977 \quad 0.14141585 \quad -0.74629067 \quad 0.03969883]
f i = 0.2057839906463977
i = 63
x_i = [3.03942212 \ 0.04712709 \ 0.14351705 \ -0.75258016 \ 0.0395411]
f_i = 0.20569217128348014
x_i = [3.03942212 \ 0.04712709 \ 0.14351705 \ -0.75258016 \ 0.0395411]
f_i = 0.20569217128348014
i = 65
x_i = [3.04824114 \quad 0.04694959 \quad 0.14402064 \quad -0.75590816 \quad 0.03995908]
f_i = 0.20565162344905752
i = 66
x_i = [3.06494591 \ 0.04703355 \ 0.14538897 \ -0.76286 \ 0.03980384]
f_i = 0.20562436599538997
x_i = [3.08194991 \ 0.04699576 \ 0.14654873 \ -0.76667313 \ 0.03981498]
f_i = 0.20561692398466672
i = 68
x_i = [3.08194991 \ 0.04699576 \ 0.14654873 \ -0.76667313 \ 0.03981498]
f_i = 0.20561692398466672
i = 69
x_i = [3.04503042 \ 0.04699813 \ 0.14321891 \ -0.75309011 \ 0.03973858]
f_i = 0.205607302334112
i = 70
```

 $x_i = [3.05053983 \ 0.0470589 \ 0.14423969 \ -0.75628585 \ 0.03967946]$ 

```
f_i = 0.2055854674098366
i = 71
x_i = [3.05053983 \ 0.0470589 \ 0.14423969 \ -0.75628585 \ 0.03967946]
f_i = 0.2055854674098366
i = 72
x_i = [3.06394254 \quad 0.04702411 \quad 0.14520855 \quad -0.76139219 \quad 0.03976881]
f_i = 0.20558077441140762
i = 73
x_i = [3.06394254 \ 0.04702411 \ 0.14520855 \ -0.76139219 \ 0.03976881]
f i = 0.20558077441140762
i = 74
x_i = [3.06944046 \ 0.04701759 \ 0.14551612 \ -0.76246892 \ 0.03976185]
f_i = 0.20557736410766028
i = 75
x_i = [3.06944046 \ 0.04701759 \ 0.14551612 \ -0.76246892 \ 0.03976185]
f_i = 0.20557736410766028
i = 76
x_i = [3.05359746 \ 0.04701855 \ 0.14410517 \ -0.75664868 \ 0.03972742]
f_i = 0.20557215865223796
i = 77
x_i = [3.05359746 \ 0.04701855 \ 0.14410517 \ -0.75664868 \ 0.03972742]
f_i = 0.20557215865223796
i = 78
x_i = [3.05359746 \ 0.04701855 \ 0.14410517 \ -0.75664868 \ 0.03972742]
f i = 0.20557215865223796
i = 79
x_i = [3.05765215 \ 0.04702068 \ 0.14425245 \ -0.75776744 \ 0.03973954]
f_i = 0.2055644665110863
i = 80
x_i = [3.05765215 \ 0.04702068 \ 0.14425245 \ -0.75776744 \ 0.03973954]
f_i = 0.2055644665110863
i = 81
x_i = [3.05765215 \ 0.04702068 \ 0.14425245 \ -0.75776744 \ 0.03973954]
f_i = 0.2055644665110863
i = 82
x_i = [3.05765215 \ 0.04702068 \ 0.14425245 \ -0.75776744 \ 0.03973954]
f_i = 0.2055644665110863
i = 83
x_i = [3.05765215 \ 0.04702068 \ 0.14425245 \ -0.75776744 \ 0.03973954]
f_i = 0.2055644665110863
i = 84
x_i = [3.05765215 \ 0.04702068 \ 0.14425245 \ -0.75776744 \ 0.03973954]
f_i = 0.2055644665110863
i = 85
x_i = [3.05765215 \ 0.04702068 \ 0.14425245 \ -0.75776744 \ 0.03973954]
f_i = 0.2055644665110863
i = 86
```

 $x_i = [3.05765215 \ 0.04702068 \ 0.14425245 \ -0.75776744 \ 0.03973954]$ 

```
f_i = 0.2055644665110863
i = 87
x_i = [3.05765215 \quad 0.04702068 \quad 0.14425245 \quad -0.75776744 \quad 0.03973954]
f_i = 0.2055644665110863
i = 88
x_i = [3.05765215 \ 0.04702068 \ 0.14425245 \ -0.75776744 \ 0.03973954]
f_i = 0.2055644665110863
i = 89
x_i = [3.05765215 \ 0.04702068 \ 0.14425245 \ -0.75776744 \ 0.03973954]
f_i = 0.2055644665110863
i = 90
x_i = [3.05765215 \ 0.04702068 \ 0.14425245 \ -0.75776744 \ 0.03973954]
f_i = 0.2055644665110863
i = 91
x_i = [3.06799906 \ 0.04701001 \ 0.14475348 \ -0.76101962 \ 0.03976142]
f_i = 0.2055605910861548
i = 92
x_i = [3.06799906 \ 0.04701001 \ 0.14475348 \ -0.76101962 \ 0.03976142]
f_i = 0.2055605910861548
i = 93
x_i = [3.06799906 \ 0.04701001 \ 0.14475348 \ -0.76101962 \ 0.03976142]
f_i = 0.2055605910861548
x_i = [3.06799906 \ 0.04701001 \ 0.14475348 \ -0.76101962 \ 0.03976142]
f_i = 0.2055605910861548
i = 95
x_i = [3.0654622 \quad 0.04701048 \quad 0.14422387 \quad -0.75921912 \quad 0.03974836]
f_i = 0.20555518923365526
i = 96
x_i = \begin{bmatrix} 3.07661197 & 0.0470128 & 0.14478376 & -0.76276344 & 0.03973727 \end{bmatrix}
f_i = 0.20555177636427058
i = 97
x_i = [3.07661197 \ 0.0470128 \ 0.14478376 \ -0.76276344 \ 0.03973727]
f_i = 0.20555177636427058
i = 98
x_i = [3.07661197 \ 0.0470128 \ 0.14478376 \ -0.76276344 \ 0.03973727]
f_i = 0.20555177636427058
i = 99
x_i = [3.07661197 \ 0.0470128 \ 0.14478376 \ -0.76276344 \ 0.03973727]
f_i = 0.20555177636427058
i = 100
x_i = [3.08742797 \ 0.04699453 \ 0.14451399 \ -0.76398809 \ 0.03974151]
f_i = 0.2055342943403706
i = 101
x_i = [3.08742797 \ 0.04699453 \ 0.14451399 \ -0.76398809 \ 0.03974151]
f_i = 0.2055342943403706
i = 102
x_i = [3.08742797 \quad 0.04699453 \quad 0.14451399 \quad -0.76398809 \quad 0.03974151]
```

```
f_i = 0.2055342943403706
i = 103
x_i = [3.08742797 \quad 0.04699453 \quad 0.14451399 \quad -0.76398809 \quad 0.03974151]
f_i = 0.2055342943403706
i = 104
x_i = [3.11201839 \ 0.04699966 \ 0.14525198 \ -0.7705261 \ 0.03971244]
f_i = 0.20552973199545577
i = 105
x_i = [3.12749392 \ 0.0469586 \ 0.1450021 \ -0.77280958 \ 0.03974454]
f_i = 0.20551026804146919
i = 106
x_i = [3.12749392 \ 0.0469586 \ 0.1450021 \ -0.77280958 \ 0.03974454]
f_i = 0.20551026804146919
i = 107
x_i = [3.14307272 \ 0.04695976 \ 0.14522142 \ -0.77638145 \ 0.03975298]
f_i = 0.20550263757717865
i = 108
x_i = [3.16752297 \quad 0.04695916 \quad 0.14516866 \quad -0.7803125 \quad 0.03967948]
f_i = 0.20547135416522996
i = 109
x_i = [3.16752297 \ 0.04695916 \ 0.14516866 \ -0.7803125 \ 0.03967948]
f_i = 0.20547135416522996
i = 110
x_i = [3.20991087 \ 0.04688664 \ 0.14465561 \ -0.78734952 \ 0.03973077]
f i = 0.20544203569898412
i = 111
x_i = [3.20991087 \ 0.04688664 \ 0.14465561 \ -0.78734952 \ 0.03973077]
f_i = 0.20544203569898412
x_i = [3.29546808 \ 0.04687738 \ 0.14582341 \ -0.80597051 \ 0.03966586]
f_i = 0.2054142564795019
i = 113
x_i = [3.35574771 \ 0.04682562 \ 0.14574598 \ -0.8165802 \ 0.0395967]
f_i = 0.20539766196492626
i = 114
x_i = [3.3972258 \quad 0.04677179 \quad 0.14534905 \quad -0.82295233 \quad 0.03963962]
f_i = 0.20537872409414049
i = 115
x_i = [3.3972258 \quad 0.04677179 \quad 0.14534905 \quad -0.82295233 \quad 0.03963962]
f_i = 0.20537872409414049
i = 116
x_i = [3.4522621 \quad 0.04674059 \quad 0.14510963 \quad -0.83293753 \quad 0.03959121]
f_i = 0.20536725513309545
i = 117
x_i = [3.4522621 \quad 0.04674059 \quad 0.14510963 \quad -0.83293753 \quad 0.03959121]
f_i = 0.20536725513309545
i = 118
x_i = [3.36516991 \quad 0.04683781 \quad 0.14542267 \quad -0.81722308 \quad 0.03956532]
```

```
f_i = 0.20535420249192016
i = 119
x_i = [3.36516991 \quad 0.04683781 \quad 0.14542267 \quad -0.81722308 \quad 0.03956532]
f_i = 0.20535420249192016
i = 120
x_i = [3.51200588 \ 0.0467045 \ 0.14505441 \ -0.84345762 \ 0.03961179]
f_i = 0.20532781451293086
i = 121
x_i = [3.51200588 \ 0.0467045 \ 0.14505441 \ -0.84345762 \ 0.03961179]
f_i = 0.20532781451293086
i = 122
x_i = [3.42981745 \quad 0.04681001 \quad 0.14483497 \quad -0.82828809 \quad 0.03953995]
f_i = 0.20529224475037422
i = 123
x_i = [3.56689879 \ 0.04667954 \ 0.14367543 \ -0.85000773 \ 0.03950407]
f_i = 0.20528541836421607
i = 124
x_i = [3.44088958 \quad 0.04679574 \quad 0.14433549 \quad -0.82833564 \quad 0.03955055]
f_i = 0.20526398452316652
i = 125
x_i = [3.55826963 \ 0.04668169 \ 0.14358758 \ -0.84849511 \ 0.03957052]
f_i = 0.20525226617579528
i = 126
x_i = [3.64416537 \quad 0.04665962 \quad 0.14396981 \quad -0.86522728 \quad 0.0394775]
f i = 0.20523357257216507
i = 127
x_i = [3.54401044 \ 0.04674615 \ 0.1431069 \ -0.84468391 \ 0.03944524]
f_i = 0.2052090042895352
x_i = [3.54401044 \ 0.04674615 \ 0.1431069 \ -0.84468391 \ 0.03944524]
f_i = 0.2052090042895352
i = 129
x_i = [3.57678565 \ 0.04671978 \ 0.14337853 \ -0.85125376 \ 0.03950514]
f_i = 0.20520198126241795
i = 130
x_i = [3.57678565 \ 0.04671978 \ 0.14337853 \ -0.85125376 \ 0.03950514]
f_i = 0.20520198126241795
i = 131
x_i = [3.57678565 \ 0.04671978 \ 0.14337853 \ -0.85125376 \ 0.03950514]
f_i = 0.20520198126241795
i = 132
x_i = [3.60379984 \ 0.04672948 \ 0.14337089 \ -0.85602063 \ 0.03940654]
f_i = 0.20519351195967195
i = 133
x_i = [3.60379984 \ 0.04672948 \ 0.14337089 \ -0.85602063 \ 0.03940654]
f_i = 0.20519351195967195
i = 134
x_i = [3.6186887 \quad 0.04671477 \quad 0.14244879 \quad -0.8565904 \quad 0.0394049]
```

```
f_i = 0.20518632434010048
i = 135
x_i = [3.6186887 \quad 0.04671477 \quad 0.14244879 \quad -0.8565904 \quad 0.0394049]
f_i = 0.20518632434010048
i = 136
x_i = [3.6186887 \quad 0.04671477 \quad 0.14244879 \quad -0.8565904 \quad 0.0394049]
f_i = 0.20518632434010048
i = 137
x_i = [3.76051159 \ 0.04663786 \ 0.14325221 \ -0.88448468 \ 0.03940466]
f i = 0.20517195847900568
i = 138
x_i = [3.76051159 \ 0.04663786 \ 0.14325221 \ -0.88448468 \ 0.03940466]
f_i = 0.20517195847900568
i = 139
x_i = [3.76051159 \ 0.04663786 \ 0.14325221 \ -0.88448468 \ 0.03940466]
f_i = 0.20517195847900568
i = 140
x_i = [3.7457418 \quad 0.04663922 \quad 0.14290222 \quad -0.88078964 \quad 0.03937301]
f_i = 0.20517134484132976
i = 141
x_i = [3.79667339 \ 0.04661039 \ 0.14250723 \ -0.88941256 \ 0.03936481]
f_i = 0.205169026703801
i = 142
x_i = [3.79667339 \ 0.04661039 \ 0.14250723 \ -0.88941256 \ 0.03936481]
f i = 0.205169026703801
i = 143
x_i = [3.82192684 \ 0.04662083 \ 0.1424049 \ -0.89349698 \ 0.03931203]
f_i = 0.20516221110910463
x_i = [3.82192684 \ 0.04662083 \ 0.1424049 \ -0.89349698 \ 0.03931203]
f_i = 0.20516221110910463
i = 145
x_i = [3.82192684 \quad 0.04662083 \quad 0.1424049 \quad -0.89349698 \quad 0.03931203]
f_i = 0.20516221110910463
i = 146
x_i = [3.82192684 \ 0.04662083 \ 0.1424049 \ -0.89349698 \ 0.03931203]
f_i = 0.20516221110910463
i = 147
x_i = [3.82192684 \ 0.04662083 \ 0.1424049 \ -0.89349698 \ 0.03931203]
f_i = 0.20516221110910463
i = 148
x_i = [3.82192684 \ 0.04662083 \ 0.1424049 \ -0.89349698 \ 0.03931203]
f_i = 0.20516221110910463
i = 149
x_i = [3.82192684 \quad 0.04662083 \quad 0.1424049 \quad -0.89349698 \quad 0.03931203]
f_i = 0.20516221110910463
i = 150
```

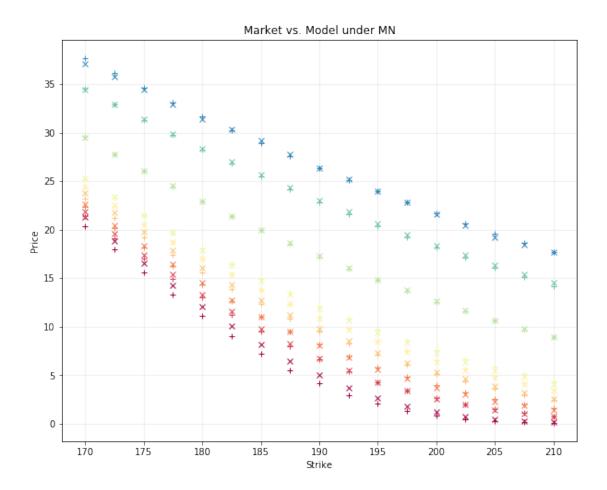
 $x_i = [3.82192684 \quad 0.04662083 \quad 0.1424049 \quad -0.89349698 \quad 0.03931203]$ 

```
f_i = 0.20516221110910463
i = 151
x_i = [3.82192684 \quad 0.04662083 \quad 0.1424049 \quad -0.89349698 \quad 0.03931203]
f_i = 0.20516221110910463
i = 152
x_i = [3.82192684 \ 0.04662083 \ 0.1424049 \ -0.89349698 \ 0.03931203]
f_i = 0.20516221110910463
i = 153
x_i = [3.82192684 \ 0.04662083 \ 0.1424049 \ -0.89349698 \ 0.03931203]
f_i = 0.20516221110910463
i = 154
x_i = [3.82192684 \quad 0.04662083 \quad 0.1424049 \quad -0.89349698 \quad 0.03931203]
f_i = 0.20516221110910463
i = 155
x_i = [3.82192684 \ 0.04662083 \ 0.1424049 \ -0.89349698 \ 0.03931203]
f_i = 0.20516221110910463
i = 156
x_i = [3.82192684 \quad 0.04662083 \quad 0.1424049 \quad -0.89349698 \quad 0.03931203]
f_i = 0.20516221110910463
i = 157
x_i = [3.82192684 \ 0.04662083 \ 0.1424049 \ -0.89349698 \ 0.03931203]
f_i = 0.20516221110910463
i = 158
x_i = [3.80737104 \ 0.04662733 \ 0.14250091 \ -0.89119261 \ 0.03933151]
f_i = 0.2051621858643872
i = 159
x_i = [3.80737104 \ 0.04662733 \ 0.14250091 \ -0.89119261 \ 0.03933151]
f_i = 0.2051621858643872
i = 160
x_i = [3.81561488 \ 0.04662026 \ 0.14246581 \ -0.89263123 \ 0.03933588]
f_i = 0.20516206326376413
i = 161
x_i = [3.82370747 \ 0.04661984 \ 0.14247685 \ -0.89408041 \ 0.03932488]
f_i = 0.2051620438566246
i = 162
x_i = [3.79864941 \ 0.04663028 \ 0.14258011 \ -0.88967592 \ 0.03933943]
f_i = 0.20516204286511666
i = 163
x_i = [3.79864941 \ 0.04663028 \ 0.14258011 \ -0.88967592 \ 0.03933943]
f_i = 0.20516204286511666
i = 164
x_i = [3.81796742 \ 0.04662234 \ 0.14244282 \ -0.89290288 \ 0.0393205]
f_i = 0.205161934377883
i = 165
x_i = [3.83363975 \quad 0.04661389 \quad 0.14240554 \quad -0.8955673 \quad 0.03931729]
f_i = 0.20516174332579296
i = 166
x_i = [3.83363975 \ 0.04661389 \ 0.14240554 \ -0.8955673 \ 0.03931729]
```

```
f_i = 0.20516174332579296
i = 167
x_i = [3.81982929 \quad 0.04662396 \quad 0.14255262 \quad -0.89326105 \quad 0.03931471]
f_i = 0.20516160224353272
i = 168
x_i = [3.80878062 \ 0.0466248 \ 0.14254295 \ -0.89127419 \ 0.0393287]
f_i = 0.20516147634167492
i = 169
x_i = [3.80878062 \ 0.0466248 \ 0.14254295 \ -0.89127419 \ 0.0393287]
f_i = 0.20516147634167492
i = 170
x_i = [3.80878062 \ 0.0466248 \ 0.14254295 \ -0.89127419 \ 0.0393287]
f_i = 0.20516147634167492
i = 171
x_i = [3.80878062 \ 0.0466248 \ 0.14254295 \ -0.89127419 \ 0.0393287]
f_i = 0.20516147634167492
i = 172
x_i = [3.81252988 \ 0.04662304 \ 0.14266439 \ -0.89204075 \ 0.03933429]
f_i = 0.20516105062573195
i = 173
x_i = [3.81252988 \ 0.04662304 \ 0.14266439 \ -0.89204075 \ 0.03933429]
f_i = 0.20516105062573195
i = 174
x_i = [3.81252988 \ 0.04662304 \ 0.14266439 \ -0.89204075 \ 0.03933429]
f i = 0.20516105062573195
i = 175
x_i = [3.81378985 \quad 0.04662675 \quad 0.14274924 \quad -0.89205814 \quad 0.03931481]
f_i = 0.20516082433349742
i = 176
x_i = [3.81378985 \quad 0.04662675 \quad 0.14274924 \quad -0.89205814 \quad 0.03931481]
f_i = 0.20516082433349742
i = 177
x_i = [3.8217028 \quad 0.04662007 \quad 0.14280091 \quad -0.89361345 \quad 0.03932402]
f_i = 0.20516066914854622
i = 178
x_i = [3.8217028 \quad 0.04662007 \quad 0.14280091 \quad -0.89361345 \quad 0.03932402]
f_i = 0.20516066914854622
i = 179
x_i = [3.82027433 \ 0.04662059 \ 0.14290361 \ -0.89308302 \ 0.0393256]
f_i = 0.20515963716490657
i = 180
x_i = [3.82027433 \quad 0.04662059 \quad 0.14290361 \quad -0.89308302 \quad 0.0393256]
f_i = 0.20515963716490657
i = 181
x_i = [3.82027433 \ 0.04662059 \ 0.14290361 \ -0.89308302 \ 0.0393256]
f i = 0.20515963716490657
i = 182
x_i = [3.82027433 \quad 0.04662059 \quad 0.14290361 \quad -0.89308302 \quad 0.0393256]
```

```
f_i = 0.20515963716490657
i = 183
x_i = [3.82027433 \quad 0.04662059 \quad 0.14290361 \quad -0.89308302 \quad 0.0393256]
f_i = 0.20515963716490657
i = 184
x_i = [3.82027433 \ 0.04662059 \ 0.14290361 \ -0.89308302 \ 0.0393256]
f_i = 0.20515963716490657
i = 185
x_i = [3.84386961 \ 0.04661213 \ 0.1430048 \ -0.8968736 \ 0.03930303]
f_i = 0.205159499306971
i = 186
                     0.04661259 0.14312423 -0.89723276 0.03931445]
x_i = [3.8448443]
f_i = 0.205159207585719
i = 187
x_i = [3.8448443 \quad 0.04661259 \quad 0.14312423 \quad -0.89723276 \quad 0.03931445]
f_i = 0.205159207585719
i = 188
x_i = [3.85253844 \ 0.0466042 \ 0.14291273 \ -0.8984554 \ 0.03931795]
f_i = 0.20515905398701123
i = 189
x_i = [3.81803333 \ 0.04662593 \ 0.14338234 \ -0.8922191 \ 0.03932578]
f_i = 0.20515847505315768
i = 190
x_i = [3.81803333 \ 0.04662593 \ 0.14338234 \ -0.8922191 \ 0.03932578]
f i = 0.20515847505315768
i = 191
x_i = [3.81803333 \ 0.04662593 \ 0.14338234 \ -0.8922191 \ 0.03932578]
f_i = 0.20515847505315768
x_i = [3.85238791 \ 0.04661123 \ 0.14328722 \ -0.89814229 \ 0.03931229]
f_i = 0.20515811792567681
i = 193
x_i = [3.83974316 \ 0.04661179 \ 0.14351064 \ -0.89550329 \ 0.03933317]
f_i = 0.20515685928014438
i = 194
x_i = [3.83974316 \ 0.04661179 \ 0.14351064 \ -0.89550329 \ 0.03933317]
f_i = 0.20515685928014438
i = 195
x_i = [3.83974316 \ 0.04661179 \ 0.14351064 \ -0.89550329 \ 0.03933317]
f_i = 0.20515685928014438
i = 196
x_i = [3.8051818 \quad 0.04663538 \quad 0.14364609 \quad -0.88916331 \quad 0.03933284]
f_i = 0.20515655774883437
i = 197
x_i = [3.87299009 \ 0.04660308 \ 0.14369465 \ -0.90039543 \ 0.03930726]
f_i = 0.20515491820753376
i = 198
x_i = [3.87299009 \ 0.04660308 \ 0.14369465 \ -0.90039543 \ 0.03930726]
```

```
f_i = 0.20515491820753376
i = 199
x_i = [3.82879801 \ 0.04661798 \ 0.14376313 \ -0.89199663 \ 0.03933305]
f_i = 0.20515098097908327
Warning: Maximum number of iterations has been exceeded.
optimal params =
[ 3.82879801  0.04661798  0.14376313  -0.89199663  0.03933305]
f = 0.20515098097908327
In [ ]: # AT 199 ITERATIONS IT BLEW UP - MAX # OF ITERATIONS
       #f = 0.20515098097908327
- Market vs. Model Surface -
In [38]: params_NM = [ 3.82879801, 0.04661798, 0.14376313, -0.89199663, 0.03933305]
        lenT = len(maturities)
        lenK = len(strikes)
        modelPrices_MN = np.zeros((lenT, lenK))
        for i in range(lenT):
            for j in range(lenK):
                T = maturities_years[i]
                K = strikes[j]
                [km, cT_km] = mfc.genericFFT(params_NM, SO, K, r, q, T, alpha, eta, n, model)
                modelPrices_MN[i,j] = cT_km[0]
In [39]: # plot
        fig = plt.figure(figsize=(10,8))
        labels = []
        colormap = cm.Spectral
        plt.gca().set_color_cycle([colormap(i) for i in np.linspace(0, 0.9, len(maturities))])
        for i in range(len(maturities)):
            plt.plot(strikes, marketPrices[i,:], 'x')
            labels.append('T = ' + str(maturities[i]))
        for i in range(len(maturities)):
            plt.plot(strikes, modelPrices_MN[i,:], '+')
            labels.append('T = ' + str(maturities[i]))
        #plt.legend(labels, loc='upper right', ncol=2)
        plt.grid(alpha=0.25)
        plt.xlabel('Strike')
        plt.ylabel('Price')
        plt.title('Market vs. Model under MN')
        #plt.savefig('MarketvsModel_NelderMead.png')
        plt.show()
```



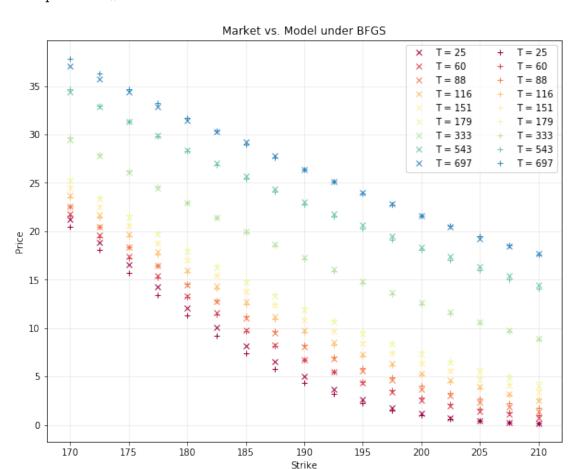
### C) BFGS Algorithm (Gradient-based) from exampleCalibration\_BFGS.py

```
print(' ')
             print('i = ' + str(num_iter))
             print('x_i = ' + str(xi))
             print('f_i = ' + str(mfc.eValue(xi, *arg)))
             num_iter += 1
         arg = (marketPrices, maturities_years, strikes, r, q, SO, alpha, eta, n, model)
         num_iter = 1
         [xopt, fopt, gopt, Bopt, func_calls, grad_calls, warnflg] = fmin_bfgs(
                 mfc.eValue,
                 params,
                 args=arg,
                 fprime=None,
                 callback=callbackF,
                 maxiter=20,
                 full_output=True,
                 retall=False)
         print('optimal params = ')
         print(xopt)
         print('f = ' + str(fopt))
i = 1
x_i = [2.30000933 \ 0.03976261 \ 0.08258009 \ -0.53000747 \ 0.04813749]
f_i = 0.5369125315296658
i = 2
x_i = [2.30001144 \ 0.04317609 \ 0.08272487 \ -0.53002916 \ 0.04179787]
f_i = 0.46072398862013314
i = 3
x_i = [2.33026752 \ 0.04588309 \ 0.21801585 \ -0.55012924 \ 0.04134229]
f_i = 0.3662316103511714
i = 4
x_i = [2.37026569 \ 0.04765539 \ 0.1975895 \ -0.54910741 \ 0.04115752]
f_i = 0.3211739202480106
i = 5
x_i = [2.37348347 \ 0.04704073 \ 0.22614396 \ -0.57784545 \ 0.04361032]
f_i = 0.31514088046246974
i = 6
x_i = [2.38705214 \quad 0.04739526 \quad 0.22906021 \quad -0.57220899 \quad 0.04277752]
f_i = 0.313251725805429
```

```
i = 7
x_i = [2.43903372 \quad 0.04746071 \quad 0.2448277 \quad -0.5199881 \quad 0.04265592]
f_i = 0.31240909739188943
i = 8
x_i = [2.54290583 \quad 0.04763839 \quad 0.28286388 \quad -0.431771 \quad 0.04267665]
f_i = 0.3112141393930959
i = 9
x_i = [2.65751598 \quad 0.04785946 \quad 0.32979541 \quad -0.36291643 \quad 0.04289731]
f_i = 0.30979083155613935
i = 10
x_i = [2.75773659 \ 0.04807037 \ 0.37338272 \ -0.33428837 \ 0.04324972]
f_i = 0.307244154183504
i = 11
x_i = [2.91561544 \ 0.04840977 \ 0.44088241 \ -0.31654452 \ 0.04388996]
f_i = 0.3030361174051982
i = 12
x_i = [3.0896001 \quad 0.04875473 \quad 0.51167015 \quad -0.27548456 \quad 0.04447014]
f i = 0.3005202365445257
i = 13
x_i = [3.20937499 \quad 0.04895842 \quad 0.55967972 \quad -0.26367453 \quad 0.04494586]
f_i = 0.29862290220158677
i = 14
x_i = [3.27200366 \ 0.04905342 \ 0.58370243 \ -0.25888835 \ 0.0451924]
f_i = 0.2977594248539742
i = 15
x_i = [3.31728461 \ 0.04911341 \ 0.60042281 \ -0.25555136 \ 0.04536675]
f_i = 0.29721582022037235
i = 16
x_i = [3.32571199 \ 0.04902366 \ 0.59653591 \ -0.2789372 \ 0.04551571]
f_i = 0.296995197222578
i = 17
x_i = [3.35738369 \ 0.04900884 \ 0.60202594 \ -0.2745725 \ 0.04560096]
f_i = 0.29661607994768713
i = 18
x_i = [3.39639817 \ 0.04885382 \ 0.60225583 \ -0.26671659 \ 0.04564811]
f_i = 0.29623979850099913
```

```
i = 19
x_i = [3.48513134 \quad 0.04867759 \quad 0.60355456 \quad -0.26671592 \quad 0.04567234]
f_i = 0.29554387639279156
i = 20
x_i = [3.63793835 \ 0.04837702 \ 0.60186371 \ -0.2696817 \ 0.04564052]
f_i = 0.29430818842741424
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.294308
         Iterations: 20
         Function evaluations: 287
         Gradient evaluations: 41
optimal params =
[ 3.63793835  0.04837702  0.60186371  -0.2696817  0.04564052]
f = 0.29430818842741424
In [ ]: #optimal params =
        #[ 3.63793835  0.04837702  0.60186371  -0.2696817  0.04564052]
        #f = 0.29430818842741424
In [46]:
         params_BFGS = xopt
         lenT = len(maturities)
         lenK = len(strikes)
         modelPrices_BFGS = np.zeros((lenT, lenK))
         for i in range(lenT):
             for j in range(lenK):
                 T = maturities_years[i]
                 K = strikes[j]
                 [km, cT_km] = mfc.genericFFT(params_BFGS, SO, K, r, q, T, alpha, eta, n, model)
                 modelPrices_BFGS[i,j] = cT_km[0]
In [47]: # plot
         fig = plt.figure(figsize=(10,8))
         labels = []
         colormap = cm.Spectral
         plt.gca().set_color_cycle([colormap(i) for i in np.linspace(0, 0.9, len(maturities))])
         for i in range(len(maturities)):
             plt.plot(strikes, marketPrices[i,:], 'x')
             labels.append('T = ' + str(maturities[i]))
         for i in range(len(maturities)):
             plt.plot(strikes, modelPrices_BFGS[i,:], '+')
             labels.append('T = ' + str(maturities[i]))
         plt.legend(labels, loc='upper right', ncol=2)
         plt.grid(alpha=0.25)
```

```
plt.xlabel('Strike')
plt.ylabel('Price')
plt.title('Market vs. Model under BFGS')
#plt.savefig('MarketvsModel_BFGS.png')
plt.show()
```



## 2.2.1 Evaluate which Optimization yields best results: Loss Function

```
print('')
            print(i)
            print(params)
            iArray.append(i)
            rmse = mfc.eValue(params, marketPrices, maturities_years, strikes, r, q, S0, alpha,
            rmseArray.append(rmse)
            if (rmse < rmseMin):</pre>
                rmseMin = rmse
                optimParams = params
        print(rmseMin)
        print(optimParams)
-0.5
-0.45
[ 4.78675711  0.04779607  0.16795654 -1.01439511  0.03633292]
-0.4
[ 4.68031721  0.04766517  0.16526838 -1.00079528  0.03666627]
-0.35000000000000003
[ 4.57387731  0.04753427  0.16258023  -0.98719545  0.03699962]
-0.30000000000000004
[ 4.46743741  0.04740337  0.15989207 -0.97359562  0.03733297]
-0.25000000000000006
[ 4.36099751  0.04727248  0.15720391  -0.95999579  0.03766631]
-0.20000000000000007
[ 4.25455761  0.04714158  0.15451576  -0.94639596  0.03799966]
-0.150000000000000008
[ 4.14811771  0.04701068  0.1518276  -0.93279612  0.03833301]
-0.10000000000000007
[ 4.04167781  0.04687978  0.14913944  -0.91919629  0.03866635]
-0.05000000000000007
[ 3.93523791  0.04674888  0.14645129  -0.90559646  0.0389997 ]
-6.938893903907228e-17
[ 3.82879801  0.04661798  0.14376313  -0.89199663  0.03933305]
```

```
0.04999999999999
[ 3.72235811  0.04648708  0.14107497 -0.8783968  0.0396664 ]
0.099999999999999
\begin{bmatrix} 3.61591821 & 0.04635618 & 0.13838682 & -0.86479697 & 0.03999975 \end{bmatrix}
0.1499999999999999
[ 3.50947831  0.04622528  0.13569866  -0.85119714  0.04033309]
0.199999999999999
[ 3.40303841  0.04609438  0.1330105  -0.8375973  0.04066644]
0.249999999999999
[ 3.29659851  0.04596348  0.13032235  -0.82399747  0.04099979]
0.299999999999999
[ 3.19015861  0.04583259  0.12763419 -0.81039764  0.04133314]
0.349999999999999
[3.08371871 0.04570169 0.12494603 -0.79679781 0.04166648]
0.39999999999999
[ 2.97727881  0.04557079  0.12225788  -0.78319798  0.04199983]
0.449999999999999
[ 2.87083891  0.04543989  0.11956972  -0.76959815  0.04233318]
0.499999999999999
[ 2.76439901  0.04530899  0.11688156  -0.75599832  0.04266652]
0.549999999999999
[ 2.6579591   0.04517809   0.11419341   -0.74239848   0.04299987]
0.6
[ 2.5515192  0.04504719  0.11150525  -0.72879865  0.04333322]
0.65
0.7000000000000001
[ 2.3386394
             0.04478539 0.10612894 -0.70159899 0.04399992]
0.7500000000000001
[ 2.2321995
                         0.10344078 -0.68799916 0.04433326]
             0.0446545
0.8000000000000000
```

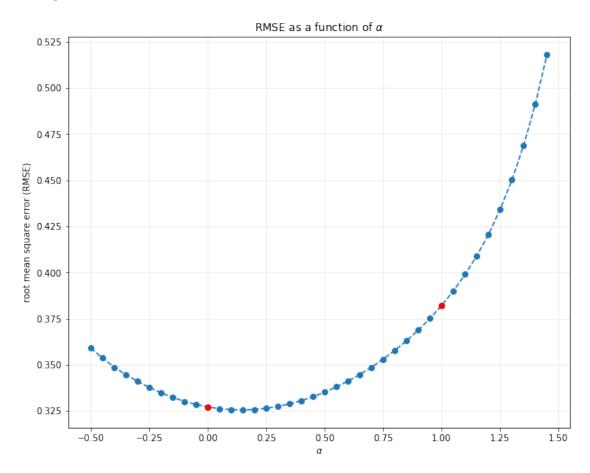
[ 2.1257596

0.0445236

0.10075263 -0.67439933 0.04466661]

```
0.85000000000000002
[ 2.0193197
        0.0443927 0.09806447 -0.66079949 0.04499996]
0.9000000000000002
        0.9500000000000003
[ 1.8064399
        0.0441309 0.09268816 -0.63359983 0.04566665]
1.00000000000000000
[ 1.7
     0.044 0.09 -0.62 0.046]
1.0500000000000003
1.1000000000000000
1.1500000000000004
1.2000000000000004
[ 1.2742404
       0.0434764 0.07924737 -0.56560067 0.047333391
1.25000000000000004
1.3000000000000005
1.3500000000000005
[ \ 0.9549207 \quad 0.04308371 \quad 0.0711829 \quad -0.52480118 \quad 0.04833343]
1.4000000000000006
1.450000000000000
0.32557393153218905
[ 3.50947831  0.04622528  0.13569866  -0.85119714  0.04033309]
In [ ]: #optimal results are:
    #0.32557393153218905
    #NM is better
In [51]: fig = plt.figure(figsize=(10,8))
     plt.plot(iArray, rmseArray, 'o--')
```

```
plt.plot(iArray[10], rmseArray[10], 'ro')
plt.plot(iArray[30], rmseArray[30], 'ro')
plt.grid(alpha=0.25)
plt.xlabel('$\\alpha$')
plt.ylabel('root mean square error (RMSE)')
plt.title('RMSE as a function of $\\alpha$')
#plt.savefig('NelderMeadvsBruteForce.png')
plt.show()
```



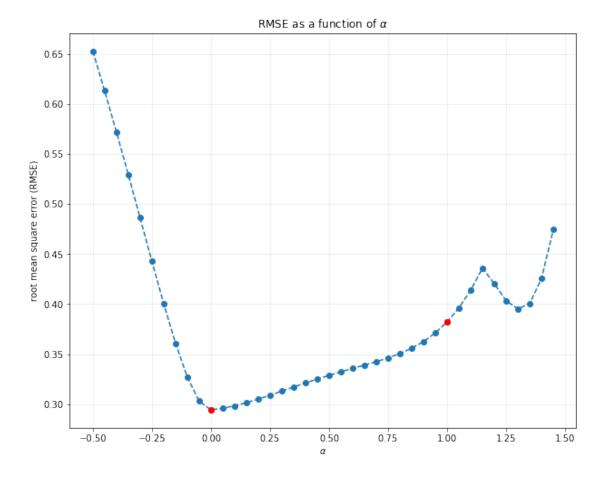
## Concludes that NM Parameters yield better result

```
params = i*np.array(params_BF) + (1.0-i)*np.array(params_BFGS)
            print('')
            print(i)
            print(params)
            iArray.append(i)
            rmse = mfc.eValue(params, marketPrices, maturities_years, strikes, r, q, S0, alpha,
            rmseArray.append(rmse)
            if (rmse < rmseMin):</pre>
                rmseMin = rmse
                optimParams = params
        print(rmseMin)
        print(optimParams)
-0.5
[ 4.60690753  0.05056553  0.85779557 -0.09452255  0.04546078]
-0.45
[ 4.51001061  0.05034668  0.83220238  -0.11203846  0.04547875]
-0.4
[ 4.41311369  0.05012783  0.80660919  -0.12955438  0.04549673]
-0.35000000000000003
[ 4.31621677  0.04990898  0.78101601  -0.1470703
                                                 0.0455147 ]
-0.30000000000000004
[ 4.21931986  0.04969013  0.75542282  -0.16458621  0.04553268]
-0.250000000000000006
[ 4.12242294  0.04947127  0.72982964 -0.18210213  0.04555065]
-0.20000000000000007
[ 4.02552602  0.04925242  0.70423645  -0.19961804  0.04556862]
-0.15000000000000008
[ 3.9286291
             -0.10000000000000007
[ 3.83173219  0.04881472  0.65305008  -0.23464987  0.04560457]
-0.05000000000000007
[ 3.73483527  0.04859587  0.6274569  -0.25216579  0.04562255]
-6.938893903907228e-17
[ 3.63793835  0.04837702  0.60186371  -0.2696817
                                                 0.04564052]
```

- 0.049999999999999 0.099999999999999 0.1499999999999999 0.199999999999999 0.249999999999999 0.299999999999993
- [ 3.54104143 0.04815817 0.57627052 -0.28719762 0.04565849]
- [ 3.44414452 0.04793932 0.55067734 -0.30471353 0.04567647]
- [ 3.25035068 0.04750162 0.49949097 -0.33974536 0.04571242]
- [ 3.15345376 0.04728277 0.47389778 -0.35726127 0.04573039]
- [ 3.05655685 0.04706391 0.4483046 -0.37477719 0.04574836]
- 0.349999999999999
- [ 2.95965993 0.04684506 0.42271141 -0.39229311 0.04576634]
- 0.399999999999999
- [ 2.86276301 0.04662621 0.39711823 -0.40980902 0.04578431]
- 0.449999999999999
- [ 2.76586609 0.04640736 0.37152504 -0.42732493 0.04580229]
- 0.499999999999999
- [ 2.66896918 0.04618851 0.34593186 -0.44484085 0.04582026]
- 0.549999999999999
- [ 2.57207226 0.04596966 0.32033867 -0.46235677 0.04583823]
- 0.6
- [ 2.47517534 0.04575081 0.29474548 -0.47987268 0.04585621]
- 0.65
- [ 2.37827842 0.04553196 0.2691523 -0.4973886 0.04587418]
- 0.7000000000000001
- 0.7500000000000001
- [ 2.18448459 0.04509425 0.21796593 -0.53242043 0.04591013]
- 0.8000000000000002
- [ 2.08758767 0.0448754 0.19237274 -0.54993634 0.0459281 ]

```
0.85000000000000002
[ 1.99069075  0.04465655  0.16677956  -0.56745226  0.04594608]
0.9000000000000000
[ 1.89379383  0.0444377  0.14118637 -0.58496817  0.04596405]
0.9500000000000003
[ 1.79689692  0.04421885  0.11559319  -0.60248409  0.04598203]
1.00000000000000000
[ 1.7  0.044  0.09  -0.62  0.046]
1.0500000000000003
1.1000000000000003
[ 1.50620616  0.0435623  0.03881363  -0.65503183  0.04603595]
1.15000000000000004
[ 1.40930925  0.04334345  0.01322044  -0.67254775  0.04605392]
1.2000000000000004
[ 1.31241233  0.0431246  -0.01237274  -0.69006366  0.0460719 ]
1.2500000000000004
[ 1.21551541  0.04290575  -0.03796593  -0.70757958  0.04608987]
1.300000000000005
[ 1.11861849  0.04268689  -0.06355911  -0.72509549  0.04610784]
1.3500000000000005
[ 1.02172158  0.04246804  -0.0891523  -0.74261141  0.04612582]
1.4000000000000006
[0.92482466 \quad 0.04224919 \quad -0.11474548 \quad -0.76012732 \quad 0.04614379]
1.4500000000000006
[ 0.82792774  0.04203034 -0.14033867 -0.77764324  0.04616177]
0.29430818581882634
[ 3.63793835  0.04837702  0.60186371  -0.2696817  0.04564052]
In [ ]: #optimal results are
       #0.29430818581882634
        #[ 3.63793835  0.04837702  0.60186371  -0.2696817  0.04564052]
In [54]: fig = plt.figure(figsize=(10,8))
        plt.plot(iArray, rmseArray, 'o--')
```

```
plt.plot(iArray[10], rmseArray[10], 'ro')
plt.plot(iArray[30], rmseArray[30], 'ro')
plt.grid(alpha=0.25)
plt.xlabel('$\\alpha$')
plt.ylabel('root mean square error (RMSE)')
plt.title('RMSE as a function of $\\alpha$')
#plt.savefig('NelderMeadvsBruteForce.png')
plt.show()
```

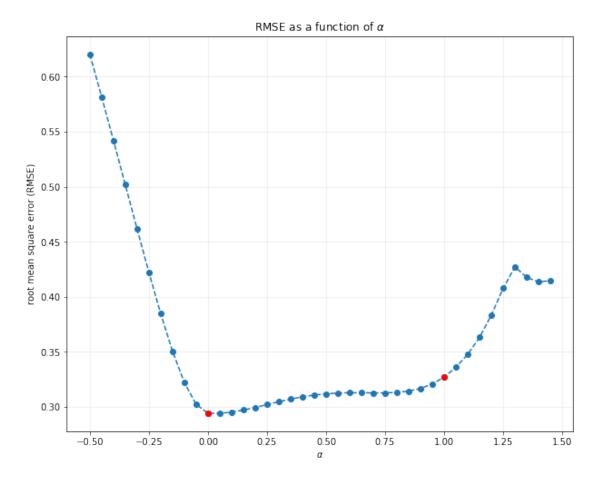


```
for i in mfc.myRange(-0.5, 1.5, 0.05):
             params = i*np.array(params_NM) + (1.0-i)*np.array(params_BFGS)
             print('')
             print(i)
             print(params)
             iArray.append(i)
             rmse = mfc.eValue(params, marketPrices, maturities_years, strikes, r, q, S0, alpha,
             rmseArray.append(rmse)
             if (rmse < rmseMin):</pre>
                 rmseMin = rmse
                 optimParams = params
         print(rmseMin)
         print(optimParams)
-0.5
[3.54250852 0.04925654 0.830914 0.04147576 0.04879425]
-0.45
[3.5520515 0.04916859 0.80800897 0.01036002 0.04847888]
-0.4
[ 3.56159449  0.04908064  0.78510394  -0.02075573  0.04816351]
-0.35000000000000003
[ 3.57113747  0.04899268  0.76219891 -0.05187147  0.04784813]
-0.30000000000000004
[ 3.58068045  0.04890473  0.73929388  -0.08298722  0.04753276]
-0.25000000000000006
[ 3.59022344  0.04881678  0.71638886  -0.11410297  0.04721739]
-0.20000000000000007
[ 3.59976642  0.04872883  0.69348383  -0.14521871  0.04690201]
-0.150000000000000008
[ 3.6093094
              0.04864088    0.6705788    -0.17633446    0.04658664]
-0.10000000000000007
[ 3.61885238  0.04855292  0.64767377 -0.20745021  0.04627127]
-0.05000000000000007
[ 3.62839537  0.04846497  0.62476874  -0.23856595  0.04595589]
```

-6.938893903907228e-17 [ 3.63793835  0.04837702	0.60186371 -0.2696817	0.04564052]
0.04999999999999999999 [ 3.64748133	0.57895868 -0.30079745	0.04532515]
0.0999999999999999999 [ 3.65702432	0.55605365 -0.33191319	0.04500977]
0.14999999999999999999999999999999999999	0.53314862 -0.36302894	0.0446944 ]
0.1999999999999996 [ 3.67611028	0.51024359 -0.39414469	0.04437903]
0.2499999999999999 [ 3.68565327	0.48733857 -0.42526043	0.04406365]
0.2999999999999993 [ 3.69519625	0.46443354 -0.45637618	0.04374828]
0.3499999999999999 [ 3.70473923	0.44152851 -0.48749193	0.04343291]
0.3999999999999999 [ 3.71428221	0.41862348 -0.51860767	0.04311753]
0.4499999999999999 [ 3.7238252	0.39571845 -0.54972342	0.04280216]
0.499999999999999 [ 3.73336818	0.37281342 -0.58083916	0.04248678]
0.5499999999999999 [ 3.74291116	0.34990839 -0.61195491	0.04217141]
0.6 [ 3.75245415	0.32700336 -0.64307066	0.04185604]
0.65 [ 3.76199713	0.30409833 -0.6741864	0.04154066]
0.7000000000000001 [ 3.77154011	0.2811933 -0.70530215	0.04122529]
0.7500000000000001 [ 3.7810831	0.25828827 -0.7364179	0.04090992]

```
0.80000000000000002
[\ 3.79062608 \ \ 0.04696979 \ \ 0.23538325 \ \ -0.76753364 \ \ 0.04059454]
0.8500000000000002
[ 3.80016906  0.04688184  0.21247822  -0.79864939  0.04027917]
0.9000000000000000
[ 3.80971204  0.04679388  0.18957319  -0.82976514  0.0399638 ]
0.9500000000000003
[ 3.81925503  0.04670593  0.16666816  -0.86088088  0.03964842]
1.0000000000000000
[ 3.82879801  0.04661798  0.14376313  -0.89199663  0.03933305]
1.0500000000000000
[ 3.83834099  0.04653003  0.1208581  -0.92311238  0.03901768]
1.1000000000000003
[ 3.84788398  0.04644208  0.09795307  -0.95422812  0.0387023 ]
1.1500000000000004
[ 3.85742696  0.04635412  0.07504804  -0.98534387  0.03838693]
1.20000000000000004
[ 3.86696994  0.04626617  0.05214301 -1.01645962  0.03807156]
1.2500000000000004
[ 3.87651293  0.04617822  0.02923798  -1.04757536  0.03775618]
1.3000000000000005
[ 3.88605591  0.04609027  0.00633296  -1.07869111  0.03744081]
1.3500000000000005
[ 3.89559889  0.04600232 -0.01657207 -1.10980686  0.03712544]
1.4000000000000006
[ 3.90514187  0.04591436  -0.0394771  -1.1409226  0.03681006]
1.45000000000000006
[ 3.91468486  0.04582641 -0.06238213 -1.17203835  0.03649469]
0.29424796472109044
[ 3.64748133  0.04828907  0.57895868 -0.30079745  0.04532515]
In [ ]: #Optimal results are:
        #0.29424796472109044
```

#[ 3.64748133 0.04828907 0.57895868 -0.30079745 0.04532515]



In [ ]: #BFGS is the best

### 2.3 3. Plot Model Price Surface

```
width=800,
             height=700,
             autosize=False,
             title='Calibrated Call Premium Surface Heston',
             scene=dict(
                 xaxis=dict(
                     gridcolor='rgb(255, 255, 255)',
                     zerolinecolor='rgb(255, 255, 255)',
                     showbackground=True,
                     backgroundcolor='rgb(230, 230,230)'
                 ),
                 yaxis=dict(
                     gridcolor='rgb(255, 255, 255)',
                     zerolinecolor='rgb(255, 255, 255)',
                     showbackground=True,
                     backgroundcolor='rgb(230, 230,230)'
                 ),
                 zaxis=dict(
                     gridcolor='rgb(255, 255, 255)',
                     zerolinecolor='rgb(255, 255, 255)',
                     showbackground=True,
                     backgroundcolor='rgb(230, 230,230)'
                 ),
                 aspectratio = dict(x=1, y=1, z=0.7),
                 aspectmode = 'manual'
         )
         fig = dict(data=data, layout=layout)
In [65]: py.iplot(fig, filename='Calibrated-Call-Premium-Surface-Heston')
Aw, snap! We didn't get a username with your request.
Don't have an account? https://plot.ly/api_signup
Questions? accounts@plot.ly
        PlotlyError
                                                  Traceback (most recent call last)
        <ipython-input-65-7d4ed6937f16> in <module>()
    ----> 1 py.iplot(fig, filename='Calibrated-Call-Premium-Surface-Heston')
```

```
~/anaconda3/lib/python3.6/site-packages/plotly/plotly/plotly.py in iplot(figure_or_data,
                embed_options['height'] = str(embed_options['height']) + 'px'
    168
    169
--> 170
            return tools.embed(url, **embed_options)
    171
    172
    ~/anaconda3/lib/python3.6/site-packages/plotly/tools.py in embed(file_owner_or_url, file
    399
                else:
    400
                    url = file_owner_or_url
--> 401
                return PlotlyDisplay(url, width, height)
    402
            else:
                if (get_config_defaults()['plotly_domain']
    403
    ~/anaconda3/lib/python3.6/site-packages/plotly/tools.py in __init__(self, url, width, he
                def __init__(self, url, width, height):
   1479
   1480
                    self.resource = url
                    self.embed_code = get_embed(url, width=width, height=height)
-> 1481
                    super(PlotlyDisplay, self).__init__(data=self.embed_code)
   1482
   1483
    ~/anaconda3/lib/python3.6/site-packages/plotly/tools.py in get_embed(file_owner_or_url,
    304
    305
                        "\nRun help on this function for more information."
                        "".format(url, plotly_rest_url))
--> 306
                urlsplit = six.moves.urllib.parse.urlparse(url)
    307
    308
                file_owner = urlsplit.path.split('/')[1].split('~')[1]
```

PlotlyError: Because you didn't supply a 'file\_id' in the call, we're assuming you're tr Run help on this function for more information.

# 3 II. Local Volatility Surface

\*\* Explicitly compute local volatility for each point in our grid \*\*

### 3.1 1. Calculate Finite differences

```
modelPrices = np.zeros((lenT, lenK))
        for i in range(lenT):
            for j in range(lenK):
                T = maturities_years[i]
                K = strikes[j]
                [km, cT_km] = mfc.genericFFT(params_BFGS, SO, K, r, q, T, alpha, eta, n, model)
                modelPrices[i,j] = cT_km[0]
In [16]: modelPrices.shape
Out[16]: (98, 9)
In [17]: # v_{-}j, k Option prices for all points on the grid
        modelPrices_df = pd.DataFrame(modelPrices, columns = strikes)
        modelPrices_df.head()
Out[17]:
               170.0
                          175.0
                                    180.0
                                              185.0
                                                        190.0
                                                                 195.0
                                                                           200.0 \
        0 20.440630 15.703254 11.277736 7.401358 4.333137
                                                              2.223275 0.997278
        1 20.647614 16.010738 11.708753 7.940705 4.911118 2.739629 1.379419
        2 20.873399 16.324738 12.121172 8.433477 5.430860 3.213591 1.751035
        3 21.109894 16.638245 12.515266 8.890375 5.908046 3.654954 2.110730
        4 21.351979 16.947915 12.892556 9.318729 6.352544 4.070433 2.458881
              205.0
                        210.0
        0 0.396668 0.143132
        1 0.634839 0.271969
        2 0.888469
                    0.426244
        3 1.149274 0.597788
        4 1.412864 0.781102
dC/dT for every point on the grid
In [18]: dcdT = (modelPrices_df.diff()/deltaT).shift(-1)
        dcdT.head()
Out[18]:
               170.0
                          175.0
                                    180.0
                                               185.0
                                                          190.0
                                                                    195.0 \
        0 10.763172 15.989144 22.412853
                                           28.046028 30.055008 26.850400
        1 11.740827 16.328011 21.445817
                                           25.624179 27.026631 24.646026
        2 12.297724 16.302395 20.492861
                                           23.758661 24.813646 22.950895
        3 12.588442 16.102817
                                19.619106
                                           22.274414 23.113899 21.604901
        4 12.712139 15.823386 18.836836
                                           21.063130 21.760838 20.508010
               200.0
                          205.0
                                   210.0
        0 19.871359 12.384895 6.699522
        1 19.324051 13.188751 8.022271
        2 18.704099 13.561850 8.920292
        3 18.103895 13.706706 9.532348
        4 17.551166 13.727735 9.953967
```

```
Out[19]: 15.989168000000028
dC/dK for every point on the grid
In [20]: dcdK = (modelPrices_df.diff(axis=1, periods = 2)/(2*deltaK)).shift(-1,axis=1)
         dcdK.head()
            170.0
Out [20]:
                      175.0
                                180.0
                                           185.0
                                                     190.0
                                                               195.0
                                                                         200.0 \
              NaN -0.916289 -0.830190 -0.694460 -0.517808 -0.333586 -0.182661
              NaN -0.893886 -0.807003 -0.679763 -0.520108 -0.353170 -0.210479
              NaN -0.875223 -0.789126 -0.669031 -0.521989 -0.367983 -0.232512
         2
         3
              NaN -0.859463 -0.774787 -0.660722 -0.523542 -0.379732 -0.250568
              NaN -0.845942 -0.762919 -0.654001 -0.524830 -0.389366 -0.265757
               205.0 210.0
         0 -0.085415
                        NaN
         1 -0.110745
                        NaN
         2 -0.132479
                        NaN
         3 -0.151294
                        NaN
         4 -0.167778
                        NaN
In [22]: (11.277736 - 20.440630)/(2*deltaK)
Out[22]: -0.916289399999998
In [23]: # For vol surface calculation
         dcdK_v = dcdK
         for i in modelPrices_df.columns:
             dcdK_v[i] = i * dcdK[i]*(r-q)
In [24]: dcdK_v.head()
Out [24]:
                                                                         200.0 \
            170.0
                      175.0
                                180.0
                                           185.0
                                                     190.0
                                                               195.0
         0
              NaN -3.126837 -2.913965 -2.505264 -1.918480 -1.268460 -0.712377
              NaN -3.050386 -2.832581 -2.452247 -1.926999 -1.342928 -0.820868
         1
              NaN -2.986697 -2.769832 -2.413530 -1.933968 -1.399253 -0.906798
         3
              NaN -2.932917 -2.719503 -2.383554 -1.939723 -1.443930 -0.977215
              NaN -2.886778 -2.677844 -2.359309 -1.944494 -1.480565 -1.036452
               205.0 210.0
         0 -0.341445
                        NaN
         1 -0.442703
                        NaN
         2 -0.529586
                        NaN
         3 -0.604799
                        NaN
         4 -0.670692
                        NaN
In [25]: (r-q)*175*(-0.916289)
Out[25]: -3.1268362125
```

In [19]: (16.010738 - 15.703254)/ deltaT

#### d2C/dK2 for every point on the grid

```
In [26]: # For d2C/dK2: - 2*v_j,k
        modelPrices_df_neg2 = modelPrices_df*(-2)
In [27]: modelPrices_df_neg2.head()
Out[27]:
                170.0
                           175.0
                                      180.0
                                                 185.0
                                                            190.0
                                                                      195.0
                                                                                200.0 \
        0 \ -40.881260 \ -31.406508 \ -22.555472 \ -14.802716 \ -8.666273 \ -4.446550 \ -1.994555
         1 -41.295228 -32.021475 -23.417505 -15.881410 -9.822235 -5.479257 -2.758838
         2 -41.746798 -32.649475 -24.242344 -16.866955 -10.861721 -6.427181 -3.502071
         3 -42.219787 -33.276491 -25.030531 -17.780750 -11.816092 -7.309908 -4.221459
         4 -42.703958 -33.895830 -25.785112 -18.637458 -12.705088 -8.140866 -4.917763
               205.0
                         210.0
         0 -0.793336 -0.286264
         1 -1.269678 -0.543938
        2 -1.776938 -0.852487
        3 -2.298547 -1.195575
        4 -2.825728 -1.562204
In [28]: d2cdK2 = pd.DataFrame()
         for i in range(len(modelPrices_df.columns)):
                 d2cdK2[modelPrices_df.columns[i]] = (modelPrices_df[modelPrices_df.columns[i-1]
             except:
                 d2cdK2[modelPrices_df.columns[i]] = np.repeat(np.nan, len(modelPrices_df))
In [29]: modelPrices_df.shape == modelPrices_df_neg2.shape == d2cdK2.shape
Out [29]: True
In [30]: d2cdK2[modelPrices_df.columns[0]] = np.repeat(np.nan, len(modelPrices_df))
        d2cdK2.head()
Out[30]:
            170.0
                      175.0
                                180.0
                                          185.0
                                                    190.0
                                                              195.0
                                                                        200.0 \
         0
              NaN 0.012474 0.021966 0.032326 0.038334 0.035355 0.025016
             NaN 0.013396 0.021357 0.029538 0.034324 0.032451 0.024625
             NaN 0.013804 0.020635 0.027403 0.031414 0.030189 0.024000
         3
             NaN 0.013947 0.019924 0.025702 0.029169 0.028355 0.023311
              NaN 0.013948 0.019261 0.024306 0.027363 0.026822 0.022621
              205.0 210.0
         0 0.013883
                       NaN
         1 0.015268
                       NaN
         2 0.016014
                       NaN
        3 0.016399
                     NaN
         4 0.016570
                      NaN
In [349]: (15.627181 - 2* 17.977095 + 20.385484)/(deltaK**2)
```

```
Out [349]: 0.00935600000000079
In [31]: # For vol surface calculation
        d2cdK2_v = d2cdK2
        for i in modelPrices_df.columns:
            d2cdK2_v[i] = i**2 * d2cdK2[i] * 1/2
In [32]: d2cdK2_v.head()
Out [32]:
           170.0
                       175.0
                                   180.0
                                              185.0
                                                          190.0
                                                                      195.0 \
        0
             {\tt NaN}
                  191.012999 355.842620 553.183163 691.935619 672.179047
        1
             NaN
                  205.120967
                              345.991343 505.476229
                                                     619.546941 616.977958
        2
             {\tt NaN}
                  211.371079 334.284423 468.935647 567.020655 573.960416
        3
             NaN
                  213.559529
                              322.761671 439.833656 526.509011 539.093772
             NaN
                  213.582058 312.032542 415.931126 493.901238 509.960650
                            205.0 210.0
                200.0
          500.310079
                       291.715554
                                     NaN
          492.503585 320.827411
                                     NaN
        2 479.990887 336.486917
                                     NaN
        3 466.214671 344.579821
                                     NaN
        4 452.427236 348.181557
                                    NaN
In [366]: 0.009356*172.5**2*0.5
Out [366]: 139.1997375
In [33]: dcdT.shape == modelPrices_df.shape == dcdK_v.shape == d2cdK2_v.shape
Out[33]: True
3.2 2. Calculate Local Volatility Surface
In [34]: # Vol Surface
        vol_surface = ((dcdT + dcdK_v + q*modelPrices_df)/d2cdK2_v)**0.5
In [36]: vol_surface
Out [36]:
            170.0
                      175.0
                                180.0
                                          185.0
                                                   190.0
                                                             195.0
                                                                       200.0 \
        0
              NaN 0.260285 0.234424 0.215029 0.201730 0.195128 0.195715
        1
              NaN 0.255188 0.232306 0.214290 0.201377
                                                          0.194401 0.193865
        2
              NaN 0.251760 0.230649 0.213561 0.200994 0.193848 0.192605
        3
              NaN 0.249115 0.229245 0.212896 0.200680 0.193473 0.191724
        4
              NaN 0.246914 0.228019 0.212322 0.200465 0.193265 0.191127
        5
              NaN 0.245008 0.226942 0.211848 0.200357 0.193206 0.190756
        6
              NaN 0.243322 0.225995 0.211472 0.200347 0.193273 0.190567
        7
              NaN 0.241815 0.225169 0.211190 0.200424 0.193445 0.190530
        8
              NaN 0.240463 0.224452 0.210993 0.200577
                                                          0.193705 0.190616
        9
              NaN 0.239247 0.223836
                                      0.210872 0.200794 0.194034 0.190802
```

```
10
                      0.223310
                                 0.210817
                                            0.201062
                                                       0.194420
      NaN
           0.238155
                                                                 0.191071
11
      NaN
           0.237175
                      0.222866
                                 0.210820
                                            0.201374
                                                       0.194851
                                                                  0.191406
12
           0.236295
                      0.222495
                                 0.210872
                                            0.201719
                                                       0.195316
      NaN
                                                                  0.191793
                      0.222189
                                 0.210966
                                            0.202092
13
      NaN
           0.235508
                                                       0.195807
                                                                  0.192223
14
      NaN
           0.234804
                      0.221941
                                 0.211096
                                            0.202486
                                                       0.196317
                                                                  0.192686
                      0.221745
                                 0.211255
                                            0.202896
15
      NaN
           0.234176
                                                       0.196841
                                                                  0.193174
16
      NaN
           0.233616
                      0.221593
                                 0.211439
                                            0.203317
                                                       0.197374
                                                                  0.193681
17
      NaN
           0.233118
                      0.221481
                                 0.211644
                                            0.203746
                                                       0.197913
                                                                 0.194201
                      0.221403
                                 0.211866
18
      NaN
           0.232676
                                            0.204180
                                                       0.198453
                                                                  0.194731
                                                                  0.195266
19
      NaN
           0.232284
                      0.221356
                                 0.212102
                                            0.204617
                                                       0.198992
20
           0.231937
                      0.221336
                                 0.212348
                                            0.205054
                                                       0.199529
      NaN
                                                                  0.195804
                                 0.212603
                                                       0.200062
21
      NaN
           0.231630
                      0.221338
                                            0.205490
                                                                  0.196343
22
           0.231361
                      0.221361
                                 0.212865
                                            0.205924
                                                       0.200590
      NaN
                                                                  0.196880
23
      NaN
           0.231124
                      0.221402
                                 0.213131
                                            0.206353
                                                       0.201110
                                                                  0.197413
24
      NaN
           0.230917
                      0.221457
                                 0.213401
                                            0.206779
                                                       0.201623
                                                                  0.197942
25
           0.230736
                      0.221527
                                 0.213673
                                            0.207199
                                                       0.202129
      NaN
                                                                  0.198465
26
      NaN
           0.230580
                      0.221607
                                 0.213946
                                            0.207613
                                                       0.202625
                                                                  0.198981
27
           0.230446
                      0.221697
                                 0.214220
                                            0.208021
                                                       0.203113
      NaN
                                                                  0.199490
28
           0.230331
                      0.221796
                                 0.214493
                                            0.208423
                                                       0.203591
      NaN
                                                                  0.199991
29
           0.230234
                      0.221903
                                 0.214765
                                            0.208817
                                                       0.204061
                                                                  0.200484
      NaN
. .
      . . .
                 . . .
68
           0.231510
                      0.227018
                                 0.223045
                                            0.219547
                                                       0.216487
                                                                  0.213834
      \mathtt{NaN}
69
      NaN
           0.231583
                      0.227136
                                 0.223203
                                            0.219736
                                                       0.216701
                                                                  0.214065
70
                      0.227254
                                 0.223358
                                            0.219923
      NaN
           0.231656
                                                       0.216912
                                                                 0.214293
71
           0.231729
                      0.227372
                                 0.223512
                                            0.220107
                                                       0.217119
      \mathtt{NaN}
                                                                  0.214518
72
           0.231803
                      0.227488
                                 0.223664
                                            0.220288
                                                       0.217323
                                                                  0.214739
      NaN
73
                      0.227603
                                 0.223815
                                            0.220467
                                                       0.217525
           0.231877
                                                                  0.214956
      NaN
74
      NaN
           0.231951
                      0.227717
                                 0.223963
                                            0.220644
                                                       0.217723
                                                                  0.215171
75
                                 0.224110
                                                       0.217919
      NaN
           0.232025
                      0.227831
                                            0.220818
                                                                  0.215382
76
      NaN
           0.232100
                      0.227944
                                 0.224255
                                            0.220989
                                                       0.218111
                                                                  0.215590
77
           0.232174
                      0.228056
                                 0.224398
                                            0.221159
                                                       0.218301
      NaN
                                                                  0.215795
78
           0.232249
                      0.228167
                                 0.224540
                                            0.221326
                                                       0.218488
                                                                  0.215997
      NaN
79
      NaN
           0.232324
                      0.228277
                                 0.224681
                                            0.221491
                                                       0.218673
                                                                  0.216197
           0.232399
                      0.228387
                                 0.224819
                                            0.221654
                                                       0.218855
80
      NaN
                                                                  0.216393
81
           0.232474
                      0.228495
                                 0.224957
                                            0.221815
                                                       0.219035
                                                                  0.216587
      NaN
82
      NaN
           0.232549
                      0.228603
                                 0.225093
                                            0.221974
                                                       0.219212
                                                                  0.216778
83
      NaN
           0.232624
                      0.228710
                                 0.225227
                                            0.222131
                                                       0.219387
                                                                  0.216967
84
      NaN
           0.232699
                      0.228817
                                 0.225360
                                            0.222286
                                                       0.219560
                                                                 0.217153
85
      NaN
           0.232774
                      0.228923
                                 0.225492
                                            0.222439
                                                       0.219731
                                                                  0.217337
86
      NaN
           0.232849
                      0.229028
                                 0.225622
                                            0.222591
                                                       0.219899
                                                                  0.217518
87
           0.232925
                      0.229132
                                 0.225751
                                            0.222741
                                                       0.220066
      NaN
                                                                  0.217698
                      0.229236
88
      NaN
           0.233000
                                 0.225879
                                            0.222889
                                                       0.220230
                                                                  0.217874
89
           0.233075
                      0.229339
                                 0.226006
                                            0.223035
                                                       0.220392
      NaN
                                                                  0.218049
90
      NaN
           0.233150
                      0.229441
                                 0.226131
                                            0.223180
                                                       0.220553
                                                                  0.218222
91
      NaN
           0.233225
                      0.229543
                                 0.226256
                                            0.223323
                                                       0.220711
                                                                  0.218392
92
      NaN
           0.233300
                      0.229644
                                 0.226379
                                            0.223465
                                                       0.220868
                                                                  0.218560
93
           0.233375
                      0.229744
                                 0.226501
                                            0.223605
                                                       0.221023
                                                                  0.218727
      {\tt NaN}
94
           0.233450
                      0.229844
                                 0.226622
                                            0.223744
                                                       0.221176
      NaN
                                                                  0.218891
```

```
95
      NaN 0.233525 0.229943 0.226742 0.223881 0.221328 0.219054
96
          0.233600
                      0.230042
                                0.226861
                                           0.224017
                                                      0.221478 0.219215
      NaN
97
      NaN
                 NaN
                           {\tt NaN}
                                      NaN
                                                 {\tt NaN}
                                                           {\tt NaN}
                                                                      NaN
       205.0 210.0
    0.203204
                 NaN
0
1
    0.199345
                 NaN
2
    0.196834
                 NaN
3
    0.195037
                 NaN
    0.193703
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4
5
    0.192708
                 {\tt NaN}
6
    0.191978
                 NaN
7
    0.191465
                 NaN
8
    0.191130
                 NaN
    0.190944
9
                 NaN
10 0.190883
                 NaN
11 0.190925
                 {\tt NaN}
12 0.191054
                 NaN
13 0.191255
                 NaN
14 0.191516
                 NaN
15 0.191825
                 NaN
16 0.192174
                 NaN
17 0.192555
                 NaN
18 0.192962
                 {\tt NaN}
19 0.193390
                 NaN
20 0.193833
                 {\tt NaN}
21 0.194288
                 NaN
22 0.194752
                 NaN
23 0.195221
                 NaN
24 0.195694
                 NaN
25 0.196169
                 NaN
26 0.196644
                 NaN
27 0.197117
                 NaN
28 0.197587
                 NaN
29 0.198054
                 NaN
. .
         . . .
                 . . .
68 0.211561
                 NaN
69 0.211803
                 NaN
70 0.212042
                 NaN
71 0.212277
                 NaN
72 0.212508
                 {\tt NaN}
73 0.212736
                 NaN
74 0.212961
                 NaN
75 0.213182
                 NaN
76 0.213400
                 NaN
77 0.213615
                 NaN
78 0.213827
                 NaN
79 0.214037
                 NaN
```

```
80 0.214243
                         NaN
         81 0.214446
                         NaN
         82 0.214647
                         NaN
         83 0.214845
                         NaN
         84 0.215040
                         NaN
         85 0.215233
                         NaN
         86 0.215424
                         NaN
         87 0.215612
                         NaN
         88 0.215798
                         NaN
         89 0.215981
                         NaN
         90 0.216162
                         NaN
         91 0.216341
                         NaN
         92 0.216518
                         NaN
         93 0.216693
                         NaN
         94 0.216865
                         NaN
         95 0.217036
                         NaN
         96 0.217205
                         NaN
         97
                  {\tt NaN}
                         NaN
         [98 rows x 9 columns]
In [101]: vol_surface_new = vol_surface[[175.0, 180.0,185.0,190.0,195.0,200.0,205.0]]
          \#pd.DataFrame.to\_csv(vol\_surface)
In [102]: vol_surface_new = vol_surface_new.loc[np.arange(0,97)]
In [107]: vol_surface_new.to_csv('heston_call.csv')
In [111]: import plotly
          plotly.tools.set_credentials_file(username='lisayhe', api_key='FioDIUbTjZMAu76NCdei')
In [115]: data = [
              go.Surface(
                  z=vol_surface_new.as_matrix()
              )
          layout = go.Layout(
              title='Apple Heston Call Vol Surface',
              autosize=True,
          fig = go.Figure(data=data, layout=layout)
          py.iplot(fig, filename='elevations-3d-surface', auto_open=True)
High five! You successfully sent some data to your account on plotly. View your plot in your bro
```

Out[115]: <plotly.tools.PlotlyDisplay object>