The background of the slide is a dark, grayscale photograph of the New York Stock Exchange building. The image shows the classical architecture with large columns and the words "NEW YORK STOCK EXCHANGE" inscribed on the pediment. The text is overlaid in white, and there are white L-shaped corner brackets in the top right and bottom left corners.

# Constructing Volatility Smile and Heston Model Calibration with Quantlib

Financial Algorithm - Midterm Project

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## CODE 說明

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```
In [3]: day_count = ql.Actual365Fixed()
calendar = ql.Taiwan() #using Taiwan Calender

calculation_date = ql.Date(21, 11, 2018) #from 2018/11/21 to 2020/11/18

spot = df.loc['2018-11-21']['Close']
ql.Settings.instance().evaluationDate = calculation_date

dividend_yield = ql.QuoteHandle(ql.SimpleQuote(0.0))
risk_free_rate = 0.01
dividend_rate = 0.0
flat_ts = ql.YieldTermStructureHandle(
    ql.FlatForward(calculation_date, risk_free_rate, day_count)) #construct risk-free rate termstructure
dividend_ts = ql.YieldTermStructureHandle(
    ql.FlatForward(calculation_date, dividend_rate, day_count)) #construct dividend rate termstructure
```

## CODE 說明

---

### Implied Volatility Surface

```
In [5]: implied_vols = ql.Matrix(len(strikes), len(expiration_dates))
        for i in range(implied_vols.rows()):
            for j in range(implied_vols.columns()):
                implied_vols[i][j] = data[j][i]
```

```
In [6]: black_var_surface = ql.BlackVarianceSurface(
        calculation_date, calendar,
        expiration_dates, strikes,
        implied_vols, day_count)
```

```
In [7]: strike = 9100.0
        expiry = 1.0 #years
        black_var_surface.blackVol(expiry, strike)
```

```
Out[7]: 0.34330230156325797
```

將所有data導入Quantlib Matrix

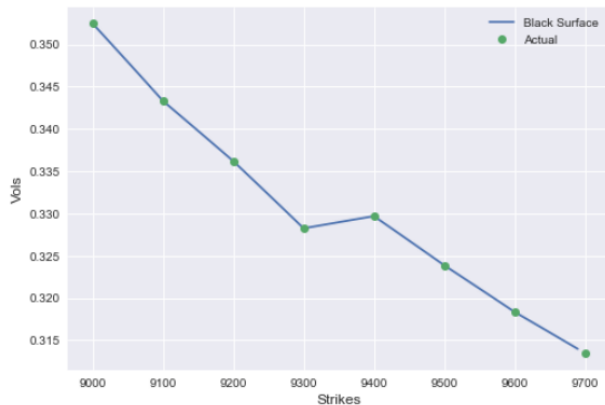
每個row代表不同的到期時間，每個column代表不同的strike price

最後只要輸入strike price與到期時間就可以得知implied volatility

# CODE 說明

```
In [8]: strikes_grid = np.arange(strikes[0], strikes[-1],10)
expiry = 1.0 #years
implied_vols = [black_var_surface.blackVol(expiry, s)
                for s in strikes_grid]
actual_data = data[11]

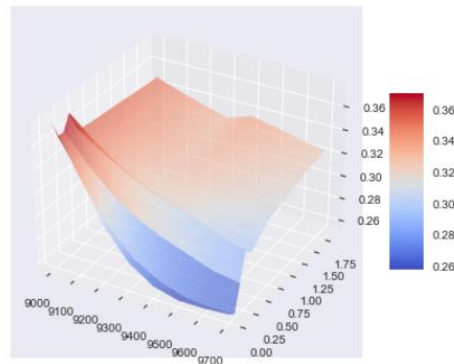
fig, ax = plt.subplots()
ax.plot(strikes_grid, implied_vols, label="Black Surface")
ax.plot(strikes, actual_data, "o", label="Actual")
ax.set_xlabel("Strikes", size=12)
ax.set_ylabel("Vols", size=12)
legend = ax.legend(loc="upper right")
```



```
In [9]: plot_years = np.arange(0, 2, 0.1)
plot_strikes = np.arange(9001, 9700, 1)
fig = plt.figure()
ax = fig.gca(projection='3d')
X, Y = np.meshgrid(plot_strikes, plot_years)
Z = np.array([black_var_surface.blackVol(float(y), float(x))
              for xr, yr in zip(X, Y)
              for x, y in zip(xr, yr) ])
              ).reshape(len(X), len(X[0]))

surf = ax.plot_surface(X,Y,Z, rstride=1, cstride=1, cmap=cm.coolwarm,
                      linewidth=0.1)
fig.colorbar(surf, shrink=0.5, aspect=5)
```

Out[9]: <matplotlib.colorbar.Colorbar at 0x18670d9c6d0>



透過 Quantlib 可以畫出 2D/3D volatility smile

## CODE 說明

```
In [11]: v0 = 0.01; kappa = 0.2; theta = 0.02; rho = -0.75; sigma = 0.5;

process = ql.HestonProcess(flat_ts, dividend_ts,
                           ql.QuoteHandle(ql.SimpleQuote(spot)),
                           v0, kappa, theta, sigma, rho)
model = ql.HestonModel(process)
engine = ql.AnalyticHestonEngine(model)

In [12]: heston_helpers = []
black_var_surface.setInterpolation("bicubic")
one_year_idx = 11
date = expiration_dates[one_year_idx]
for j, s in enumerate(strikes):
    t = (date - calculation_date)
    p = ql.Period(t, ql.Days)
    sigma = data[one_year_idx][j]

    helper = ql.HestonModelHelper(p, calendar, spot, s,
                                   ql.QuoteHandle(ql.SimpleQuote(sigma)),
                                   flat_ts,
                                   dividend_ts)
    helper.setPricingEngine(engine)
    heston_helpers.append(helper)
```

透過 Heston Model 校準市場報價，假設我們想知道一年期的 option，我們需要 calibrate the Heston Model，在此之前我們還需要建構 Pricing engine

## CODE 說明

---

```
In [13]: lm = ql.LevenbergMarquardt(1e-8, 1e-8, 1e-8)
model.calibrate(heston_helpers, lm,
               ql.EndCriteria(500, 50, 1.0e-8, 1.0e-8, 1.0e-8))
theta, kappa, sigma, rho, v0 = model.params()
```

```
In [14]: print("theta = {}, kappa = {}, sigma = {}, rho = {}, v0 = {}".format(theta, kappa, sigma, rho, v0))

theta = 0.1435086943220949, kappa = 2.149809280806962, sigma = 0.10000619553604377, rho = -0.9999995896777616, v0 = 0.030767452
780416215
```

已經有建構完 Heston Model & pricing engine 後，選擇所有 strike price 和 1 年 maturity，即可算出所需參數

# CODE 說明

```
avg = 0.0

print ("%15s %15s %15s %20s" % (
    "Strikes", "Market Value",
    "Model Value", "Relative Error (%)"))
print("="*70)
for i, opt in enumerate(heston_helpers):
    err = (opt.modelValue()/opt.marketValue() - 1.0)
    print("%15.2f %14.5f %15.5f %20.7f " % (
        strikes[i], opt.marketValue(),
        opt.modelValue(),
        100.0*(opt.modelValue()/opt.marketValue() - 1.0)))
    avg += abs(err)
avg = avg*100.0/len(heston_helpers)
print("-" * 70)
print ("Average Abs Error (%) : %5.3f" % (avg))
```

Strikes	Market Value	Model Value	Relative Error (%)
9000.00	1175.74319	1082.47993	-7.9322816
9100.00	1185.55000	1129.51708	-4.7263224
9200.00	1204.43866	1177.61387	-2.2271617
9300.00	1220.10195	1226.76171	0.5458363
9400.00	1278.08406	1276.95148	-0.0886156
9500.00	1304.53643	1328.17351	1.8119144
9600.00	1332.96946	1380.41761	3.5595825
9700.00	1365.05515	1433.67313	5.0267558

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Average Abs Error (%) : 3.240

使用模型得到calibration後的option price 還有市場價值的誤差