blsc_architecture_call

March 20, 2025

[30]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from scipy.stats import norm
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from keras.models import Sequential
from keras.layers import Dense, LeakyReLU
from keras.optimizers import Adam
```

[31]:
```
def blsc(S, K, T, r, sigma, call=True):
    """
    Black-Scholes option pricing model.
    S: Current stock price
    K: Option strike price
    T: Time to expiration (in years)
    r: Risk-free interest rate
    sigma: Volatility of the underlying asset
    call: True for call option, False for put option
    """
    d1 = (np.log(S / K) + ((r + (0.5 * (sigma ** 2))) * T)) / (sigma * np.
 ↪sqrt(T))
    d2 = d1 - (sigma * np.sqrt(T))

    if call:
        return ((S * norm.cdf(d1)) - (K * np.exp(-r * T) * norm.cdf(d2)))
    else:
        return ((K * np.exp(-r * T) * norm.cdf(-d2)) - (S * norm.cdf(-d1)))
```

[32]:
```
def error(x,y):
        error = np.sum(np.abs(np.array(x) - np.array(y)))*100/np.sum(np.
 ↪array(y))
        return error
```

[33]:
```
def aggregate(data, size=1):
    return np.array([np.mean(data[i:i + size]) for i in range(0, len(data),␣
 ↪size)])
```

[34]:

```
df = pd.read_csv('nvda_options_data.csv')
df = df.dropna()
```

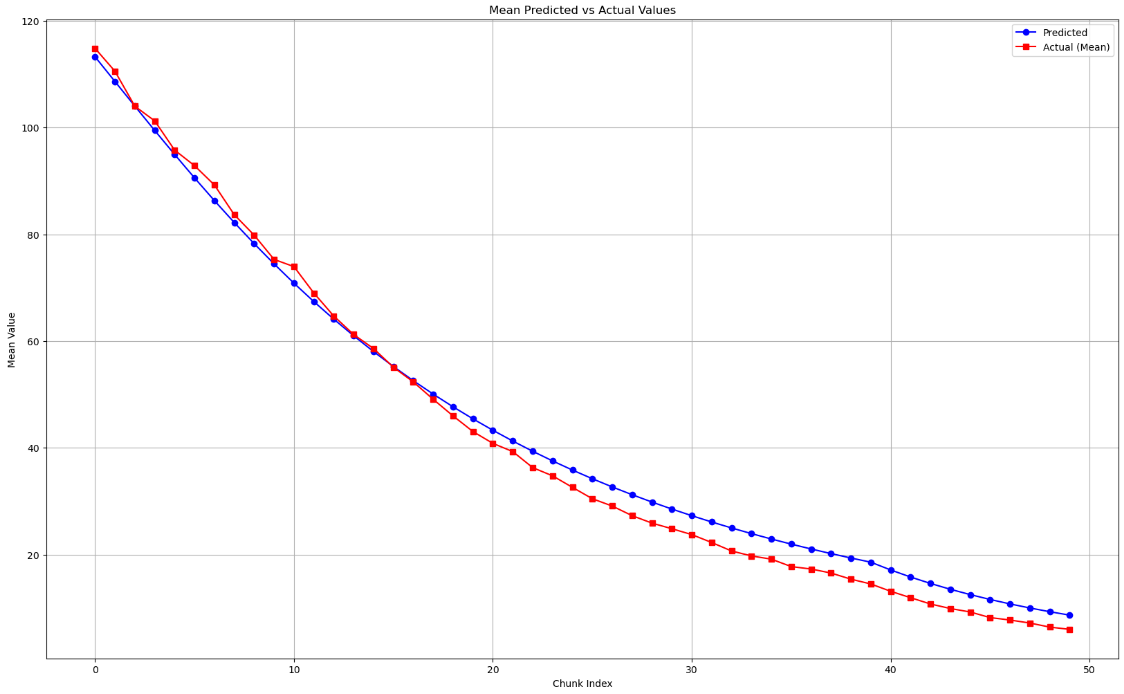
[35]:

```
def algo():
    y_blsc = blsc(df['Stock_Price'], df['strike'], df['Time_to_Expire'],␣
 ↪df['Risk_Free_Rate'], df['IV'], call=True)
    loss = error(y_blsc,df['CallPrice'])
    print('Loss:',loss)

     # Plot the average results
    plt.figure(figsize=(20, 12))
    plt.plot(aggregate(pd.DataFrame(y_blsc)), label='Predicted', marker='o',␣
 ↪linestyle='-', color='blue')
    plt.plot(aggregate(df['CallPrice']), label='Actual (Mean)', marker='s',␣
 ↪linestyle='-', color='red')
    plt.title('Mean Predicted vs Actual Values')
    plt.xlabel('Chunk Index')
    plt.ylabel('Mean Value')
    plt.grid()
    plt.legend()
    plt.show()
    return y_blsc
```

[36]:

```
blsc_price = algo()
```

```
Loss: 6.2211221613320475
```



[37]:

```
df['blsc_price'] = blsc_price
```

[38]:

```
X = df[['strike', 'IV','Stock_Price',␣
 ↪'Time_to_Expire','Risk_Free_Rate','blsc_price']]
y = df[['CallPrice']]
X.head()
```

[38]:

```
   strike        IV  Stock_Price  Time_to_Expire  Risk_Free_Rate  blsc_price
0     5.0  0.566315   117.889999        1.820671          0.0422  113.259815
1    10.0  0.566315   117.889999        1.820671          0.0422  108.632243
2    15.0  0.566315   117.889999        1.820671          0.0422  104.021540
3    20.0  0.566315   117.889999        1.820671          0.0422   99.454637
4    25.0  0.566315   117.889999        1.820671          0.0422   94.962941
```

[39]:

```
X.head()
```

[39]:

```
   strike        IV  Stock_Price  Time_to_Expire  Risk_Free_Rate  blsc_price
0     5.0  0.566315   117.889999        1.820671          0.0422  113.259815
1    10.0  0.566315   117.889999        1.820671          0.0422  108.632243
2    15.0  0.566315   117.889999        1.820671          0.0422  104.021540
3    20.0  0.566315   117.889999        1.820671          0.0422   99.454637
4    25.0  0.566315   117.889999        1.820671          0.0422   94.962941
```

[40]:

```
print(f"X shape: {X.shape}, Y shape: {y.shape}")
```

```
X shape: (50, 6), Y shape: (50, 1)
```

[41]:

```
X = StandardScaler().fit_transform(X)
```

[42]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=500)
```

[43]:

```
X_train, y_train = tf.convert_to_tensor(X_train, dtype=tf.float32), tf.
 ↪convert_to_tensor(y_train, dtype=tf.float32)
X_test, y_test = tf.convert_to_tensor(X_test, dtype=tf.float32), tf.
 ↪convert_to_tensor(y_test, dtype=tf.float32)
```

[44]:

```
# Hyperparams
n_units = X_train.shape[1]
n1_units = 400
layers = 4
```

[45]:

```
model = Sequential()
model.add(Dense(n_units, input_dim=X_train.shape[1]))
model.add(LeakyReLU())
for _ in range(layers - 1):
    model.add(Dense(n1_units))
    model.add(LeakyReLU())

model.add(Dense(1, activation='relu'))
```

```
/Users/aadityatrivedee/tf_lib/env/lib/python3.10/site-
packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

[46]:
```
model.summary()
```

```
Model: "sequential_1"


 Layer (type)                      Output Shape                  Param #

 dense_5 (Dense)                   (None, 6)                          42

 leaky_re_lu_4 (LeakyReLU)         (None, 6)                           0

 dense_6 (Dense)                   (None, 400)                     2,800

 leaky_re_lu_5 (LeakyReLU)         (None, 400)                         0

 dense_7 (Dense)                   (None, 400)                   160,400

 leaky_re_lu_6 (LeakyReLU)         (None, 400)                         0

 dense_8 (Dense)                   (None, 400)                   160,400

 leaky_re_lu_7 (LeakyReLU)         (None, 400)                         0

 dense_9 (Dense)                   (None, 1)                         401


 Total params: 324,043 (1.24 MB)

 Trainable params: 324,043 (1.24 MB)

 Non-trainable params: 0 (0.00 B)
```

[47]:
```
model.compile(loss='mae', optimizer=Adam(learning_rate=0.001))
```

[48]:

```
batch_size = 32
losses = model.fit(X_train, y_train, validation_data=(X_test,␣
 ↪y_test),batch_size=batch_size, epochs=30, verbose=1)
```

```
Epoch 1/30
2/2               1s 231ms/step - loss:
43.5256 - val_loss: 39.6543
Epoch 2/30
2/2               0s 34ms/step - loss:
43.2403 - val_loss: 38.9783
Epoch 3/30
2/2               0s 32ms/step - loss:
42.8744 - val_loss: 37.9395
Epoch 4/30
2/2               0s 32ms/step - loss:
40.9056 - val_loss: 36.3397
Epoch 5/30
2/2               0s 32ms/step - loss:
38.4437 - val_loss: 33.9855
Epoch 6/30
2/2               0s 32ms/step - loss:
37.0492 - val_loss: 30.8307
Epoch 7/30
2/2               0s 32ms/step - loss:
34.9449 - val_loss: 27.7252
Epoch 8/30
2/2               0s 32ms/step - loss:
33.2288 - val_loss: 24.0686
Epoch 9/30
2/2               0s 32ms/step - loss:
27.1228 - val_loss: 19.3980
Epoch 10/30
2/2               0s 32ms/step - loss:
21.6728 - val_loss: 13.2119
Epoch 11/30
2/2               0s 32ms/step - loss:
14.0384 - val_loss: 8.9930
Epoch 12/30
2/2               0s 33ms/step - loss:
7.3270 - val_loss: 14.1342
Epoch 13/30
2/2               0s 32ms/step - loss:
10.1690 - val_loss: 14.1775
Epoch 14/30
2/2               0s 32ms/step - loss:
10.3434 - val_loss: 10.1471
Epoch 15/30
2/2               0s 32ms/step - loss:
```

```
8.1471 - val_loss: 5.4890
Epoch 16/30
2/2           0s 32ms/step - loss:
5.2695 - val_loss: 3.2875
Epoch 17/30
2/2           0s 32ms/step - loss:
5.4066 - val_loss: 3.9589
Epoch 18/30
2/2           0s 31ms/step - loss:
5.4125 - val_loss: 2.0966
Epoch 19/30
2/2           0s 32ms/step - loss:
2.6881 - val_loss: 4.0663
Epoch 20/30
2/2           0s 32ms/step - loss:
3.2455 - val_loss: 5.2862
Epoch 21/30
2/2           0s 32ms/step - loss:
4.5081 - val_loss: 1.9360
Epoch 22/30
2/2           0s 32ms/step - loss:
1.5940 - val_loss: 1.5758
Epoch 23/30
2/2           0s 31ms/step - loss:
1.6502 - val_loss: 1.0476
Epoch 24/30
2/2           0s 32ms/step - loss:
0.9818 - val_loss: 1.2850
Epoch 25/30
2/2           0s 32ms/step - loss:
1.3668 - val_loss: 1.1116
Epoch 26/30
2/2           0s 32ms/step - loss:
1.1414 - val_loss: 1.1607
Epoch 27/30
2/2           0s 32ms/step - loss:
1.0302 - val_loss: 1.3102
Epoch 28/30
2/2           0s 32ms/step - loss:
1.3164 - val_loss: 1.1206
Epoch 29/30
2/2           0s 32ms/step - loss:
0.9189 - val_loss: 1.1506
Epoch 30/30
2/2           0s 32ms/step - loss:
1.0611 - val_loss: 0.7011
```

```
[49]: model.evaluate(X_test[:3], y_test[:3],batch_size=batch_size)
```

```
1/1              0s 31ms/step - loss:
0.5523
```

```
[49]: 0.5523300170898438
```

```
[50]: model.predict(pd.DataFrame(X_test).iloc[0:10])
```

```
1/1              0s 43ms/step
```

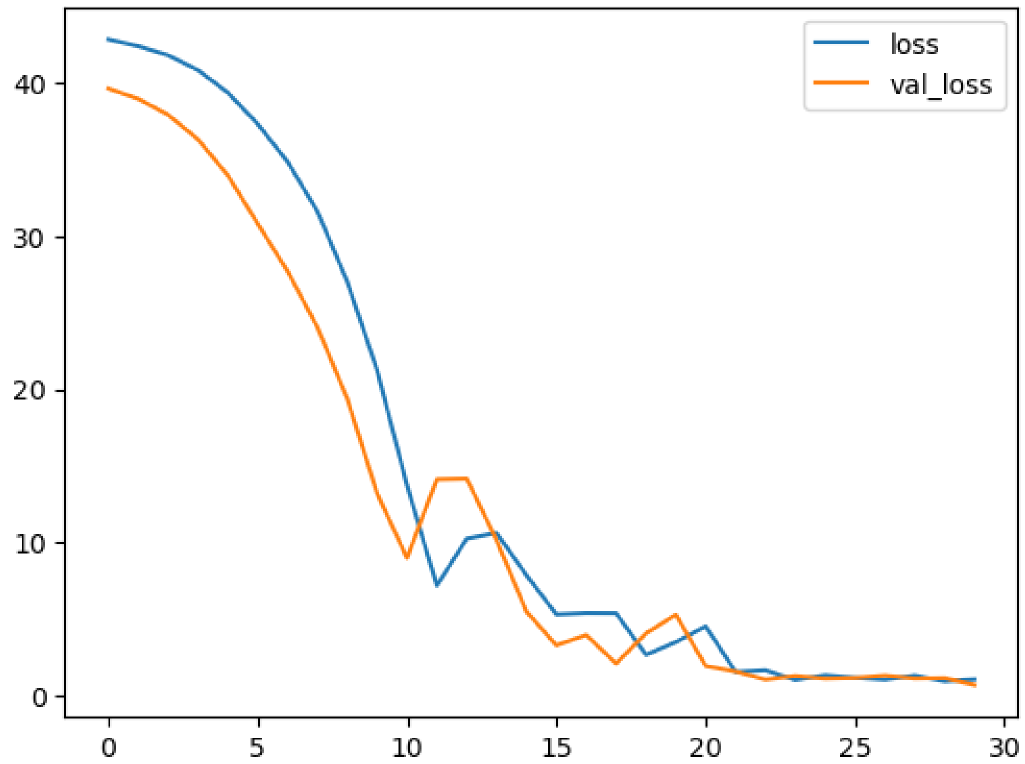
```
[50]: array([[ 17.95041 ],
              [ 33.037785],
              [ 10.468796],
              [ 36.12249 ],
              [  8.433231],
              [  9.392245],
              [ 14.417397],
              [ 66.097595],
              [ 96.46638 ],
              [113.41064 ]], dtype=float32)
```

```
[51]: pd.DataFrame(y_test).iloc[0:10]
```

```
[51]:             0
      0   17.299999
      1   32.599998
      2    9.900000
      3   36.299999
      4    8.200000
      5    9.250000
      6   13.130000
      7   64.699997
      8   95.779999
      9  114.839996
```

```
[52]: loss_df = pd.DataFrame(losses.history)
      loss_df.loc[:,['loss','val_loss']].plot()
```

```
[52]: <Axes: >
```



[53]:

```
def model_error(x,y):
    error = np.sum(np.abs(model.predict(pd.DataFrame(x)) - pd.
 ↪DataFrame(y)))*100/(np.sum(np.array(y)))
    return error
print('Mean Square Percentage Error in train:', model_error(X_train, y_train))
print('Mean Square Percentage Error in test:', model_error(X_test, y_test))
```

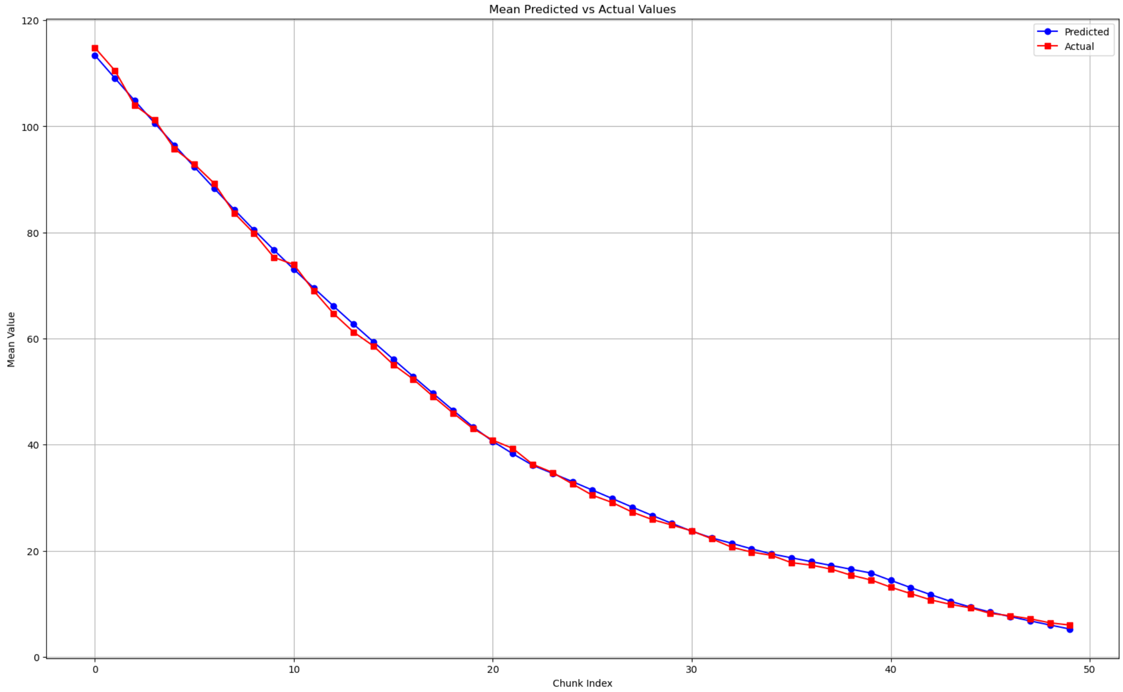
```
2/2               0s 20ms/step
Mean Square Percentage Error in train: 0    1.654118
dtype: float32
1/1               0s 14ms/step
Mean Square Percentage Error in test: 0    1.743959
dtype: float32

/Users/aadityatrivedee/tf_lib/env/lib/python3.10/site-
packages/numpy/core/fromnumeric.py:86: FutureWarning: The behavior of
DataFrame.sum with axis=None is deprecated, in a future version this will reduce
over both axes and return a scalar. To retain the old behavior, pass axis=0 (or
do not pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
/Users/aadityatrivedee/tf_lib/env/lib/python3.10/site-
packages/numpy/core/fromnumeric.py:86: FutureWarning: The behavior of
DataFrame.sum with axis=None is deprecated, in a future version this will reduce
```

```
over both axes and return a scalar. To retain the old behavior, pass axis=0 (or
do not pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

[54]:

```
plt.figure(figsize=(20, 12))
X_plt=model.predict(pd.DataFrame(X))
plt.plot(aggregate(X_plt), label='Predicted', marker='o', linestyle='-',␣
  ↪color='blue')
plt.plot(aggregate(pd.DataFrame(y)), label='Actual', marker='s', linestyle='-',␣
  ↪color='red')
plt.title('Mean Predicted vs Actual Values')
plt.xlabel('Chunk Index')
plt.ylabel('Mean Value')
plt.grid()
plt.legend()
plt.show()
```

```
2/2              0s 20ms/step
```



[55]:

```
model.save('hybrid_call.h5')
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.
```