Work Trial Tasks

©Blockhouse

December 1, 2024

Name : Pratyush Desai

CODE LINK : https://colab.research.google.com/drive/1yBpK--8CGTbOZ5l9o00U6XkTugVPQQ9w?usp=sharing

1 Task: Paper Replication (3-5 Days)

Please read the paper: Efficient Trading with Price Impact and use the attached data to finish the following challenges (Recommended Programming Language: Python / R / MATLAB) :

IMPORTS:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.model_selection import train_test_split
```

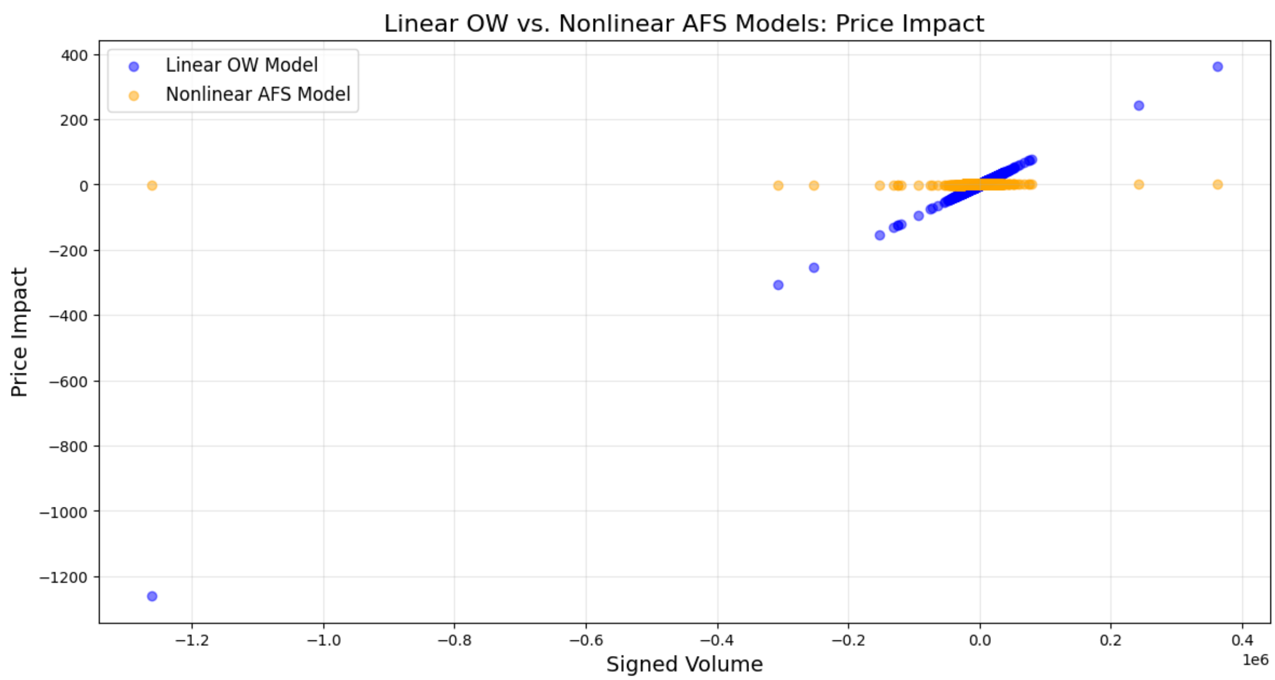
1. Construct and code the linear OW model and nonlinear AFS model, and visualize the distribution of price impact based on the given data. (33 pt)

CODE:

```
##TASK 1
df = pd.read_csv('merged_data.csv')


df['linear_ow_impact'] = df['Signed Volume'] * 0.001
df['nonlinear_afs_impact'] = np.sign(df['Signed Volume']) * np.sqrt(np.abs(df['Signed Volume'])) * 0.001
plt.figure(figsize=(14, 7))
plt.scatter(df['Signed Volume'], df['linear_ow_impact'], alpha=0.5, label='Linear OW Model',
```

```
color='blue')
plt.scatter(df['Signed Volume'], df['nonlinear_afs_impact'], alpha=0.5, label='Nonlinear AFS Model', color='orange')
plt.title('Linear OW vs. Nonlinear AFS Models: Price Impact', fontsize=16)
plt.xlabel('Signed Volume', fontsize=14)
plt.ylabel('Price Impact', fontsize=14)
plt.legend(fontsize=12)
plt.grid(alpha=0.3)
plt.show()
```

Output:



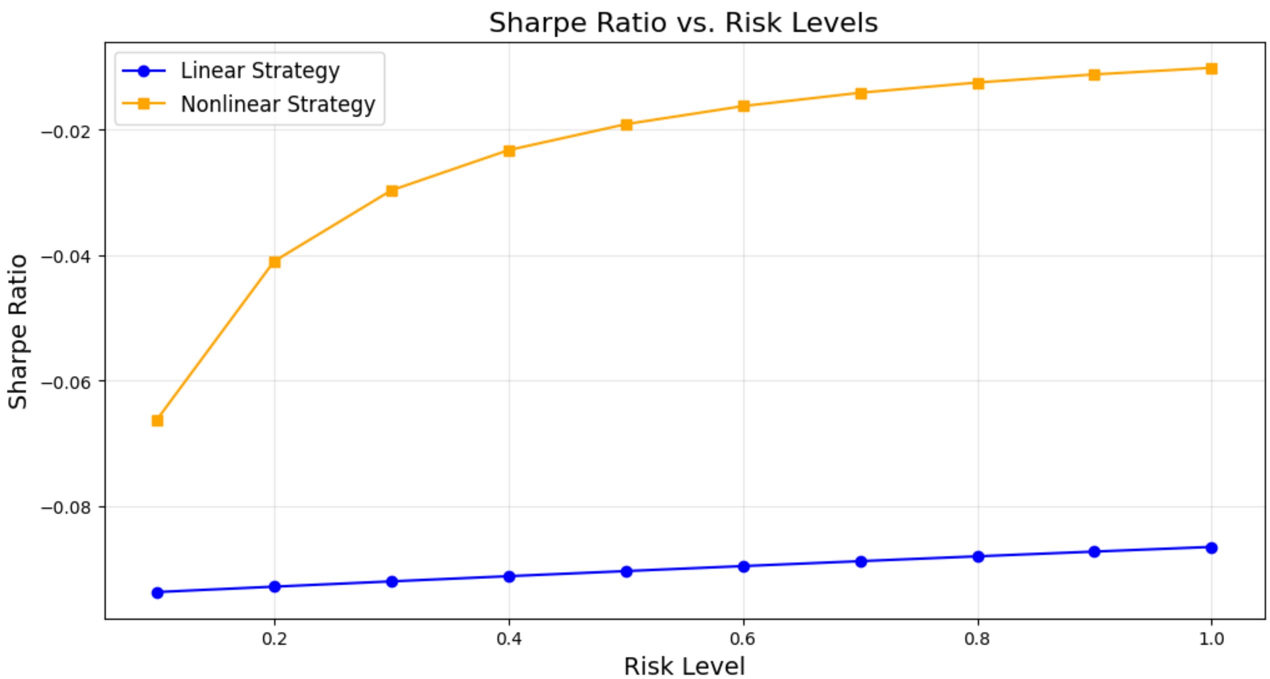
2. Implement and code the optimal strategy with Linear Impact and visualize the Sharpe Ratio plots in Section 6.2. (33 pt)

CODE:

```
##TASK 2

risk_levels = np.linspace(0.1, 1.0, 10)
linear_strategy_performance = []
nonlinear_strategy_performance = []

for risk in risk_levels:
    sharpe_linear = np.mean(df['linear_ow_impact']) / (risk +
   np.std(df['linear_ow_impact']))
    linear_strategy_performance.append(sharpe_linear)

    sharpe_nonlinear = np.mean(df['nonlinear_afs_impact']) / (risk +
   np.std(df['nonlinear_afs_impact']))
```

```
    nonlinear_strategy_performance.append(sharpe_nonlinear)

plt.figure(figsize=(12, 6))
plt.plot(risk_levels, linear_strategy_performance, label='Linear Strategy', marker='o',
   color='blue')
plt.plot(risk_levels, nonlinear_strategy_performance, label='Nonlinear Strategy',
   marker='s', color='orange')
plt.title('Sharpe Ratio vs. Risk Levels', fontsize=16)
plt.xlabel('Risk Level', fontsize=14)
plt.ylabel('Sharpe Ratio', fontsize=14)
plt.legend(fontsize=12)
plt.grid(alpha=0.3)
plt.show()
```

Output:



3. Implement and code the Deep Learning Algorithm in for discrete setting in Appendix C.2 and visualize the training loss for different network structures in Appendix C.2. (33 pt)

CODE:

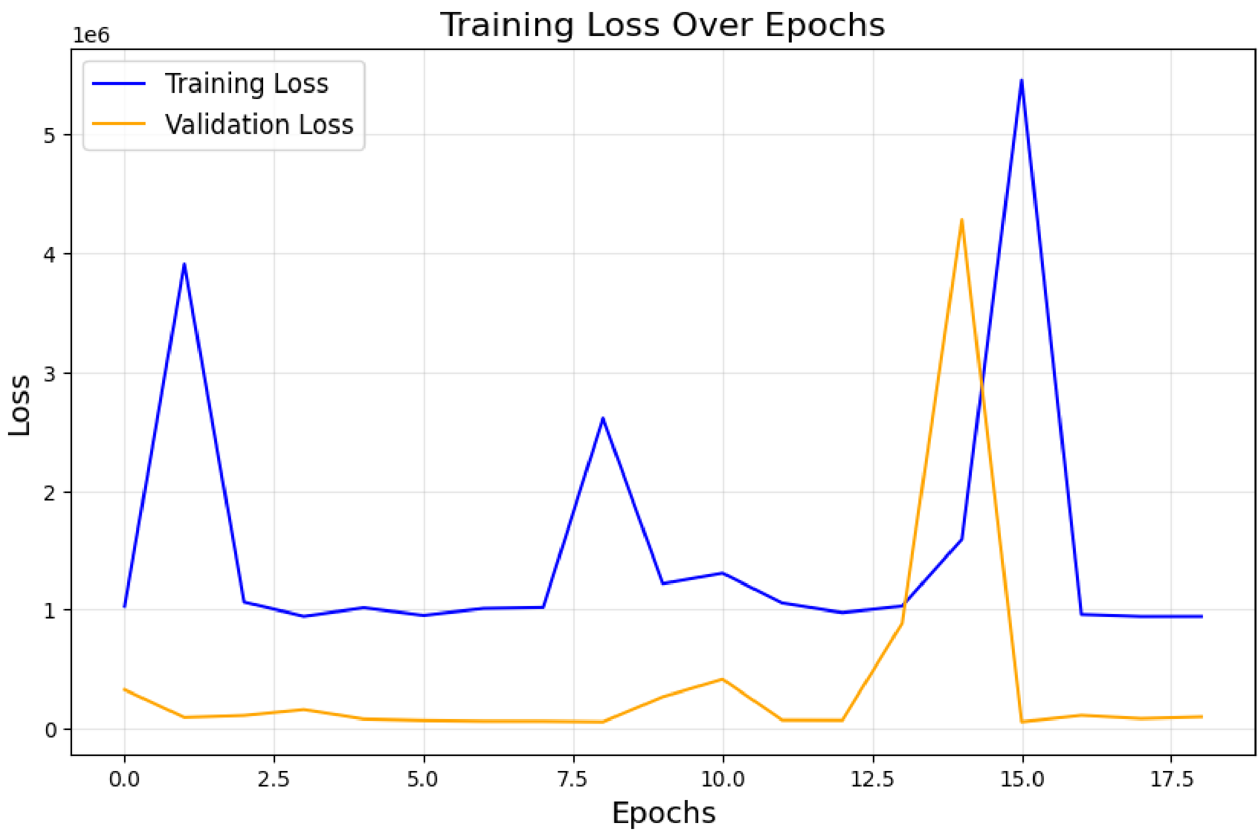
```
##TASK 3
X = df[['Signed Volume', 'best_bid', 'best_ask']].values
df['price_impact'] = df['Signed Volume'] * (df['price'] - df['mid_price'])
y = df['price_impact'].values


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(32, activation='relu'),
```

```
    Dense(1, activation='linear')
])
model.compile(optimizer='adam', loss='mse', metrics=['mae'])
early_stopping = EarlyStopping(monitor='val_loss', patience=10,
   restore_best_weights=True)
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=50,
   batch_size=32,
                    callbacks=[early_stopping], verbose=1)
plt.figure(figsize=(10, 6))
plt.plot(history.history['loss'], label='Training Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='orange')
plt.title('Training Loss Over Epochs', fontsize=16)
plt.xlabel('Epochs', fontsize=14)
plt.ylabel('Loss', fontsize=14)
plt.legend(fontsize=12)
plt.grid(alpha=0.3)
plt.show()
```

Output:

```
Epoch 1/50
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`input_c
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
693/693 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 610286.3125 - mae: 120.9420 - val_loss: 327410.8438 - val_mae: 251.1408
Epoch 2/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 2003472.1250 - mae: 99.2938 - val_loss: 93182.3594 - val_mae: 102.4792
Epoch 3/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 2854486.7500 - mae: 166.9820 - val_loss: 109671.9922 - val_mae: 100.8410
Epoch 4/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 1177707.7500 - mae: 109.9994 - val_loss: 159581.7656 - val_mae: 130.0830
Epoch 5/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 3556613.7500 - mae: 127.3202 - val_loss: 80317.8359 - val_mae: 65.5474
Epoch 6/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 1057762.3750 - mae: 104.9380 - val_loss: 67801.5078 - val_mae: 58.9585
Epoch 7/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 761384.0000 - mae: 71.8492 - val_loss: 61995.2773 - val_mae: 41.3882
Epoch 8/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 521823.1250 - mae: 61.6923 - val_loss: 61596.9062 - val_mae: 54.9810
Epoch 9/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 1784965.2500 - mae: 110.0746 - val_loss: 56671.9961 - val_mae: 43.9499
Epoch 10/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 2036314.3750 - mae: 119.8951 - val_loss: 267320.6875 - val_mae: 125.7083
Epoch 11/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - loss: 1154633.5000 - mae: 97.7582 - val_loss: 415409.1875 - val_mae: 179.0739
Epoch 12/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 641614.5625 - mae: 96.8408 - val_loss: 70983.3125 - val_mae: 47.9622
Epoch 13/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 622762.4375 - mae: 72.9401 - val_loss: 69426.3359 - val_mae: 47.0294
Epoch 14/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 793451.4375 - mae: 89.0195 - val_loss: 885422.6250 - val_mae: 323.6085
Epoch 15/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - loss: 1389745.2500 - mae: 158.1990 - val_loss: 4283096.0000 - val_mae: 634.2543
Epoch 16/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 7464178.5000 - mae: 390.7668 - val_loss: 56889.2031 - val_mae: 48.0619
Epoch 17/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - loss: 1084210.2500 - mae: 89.2221 - val_loss: 111001.7188 - val_mae: 80.6494
Epoch 18/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 1067903.7500 - mae: 73.9486 - val_loss: 84169.5938 - val_mae: 50.9914
Epoch 19/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 371452.9375 - mae: 56.2129 - val_loss: 97893.2969 - val_mae: 96.6389
```

Training of Model with Early Stopping



2 Data Illustration

The table merged data.csv is merged table of processed MBO data and MBP-1 data. The illustration of MBO and MBP-1 data could be found on Databento.

- Bid fill: size of filled bid orders;
- Ask fill: size of filled ask orders;
- Signed volume: difference of bid fill and ask fill;
- Best bid: largest bid price;
- Best Aks: smallest ask price;

The data would be helpful for the above tasks.