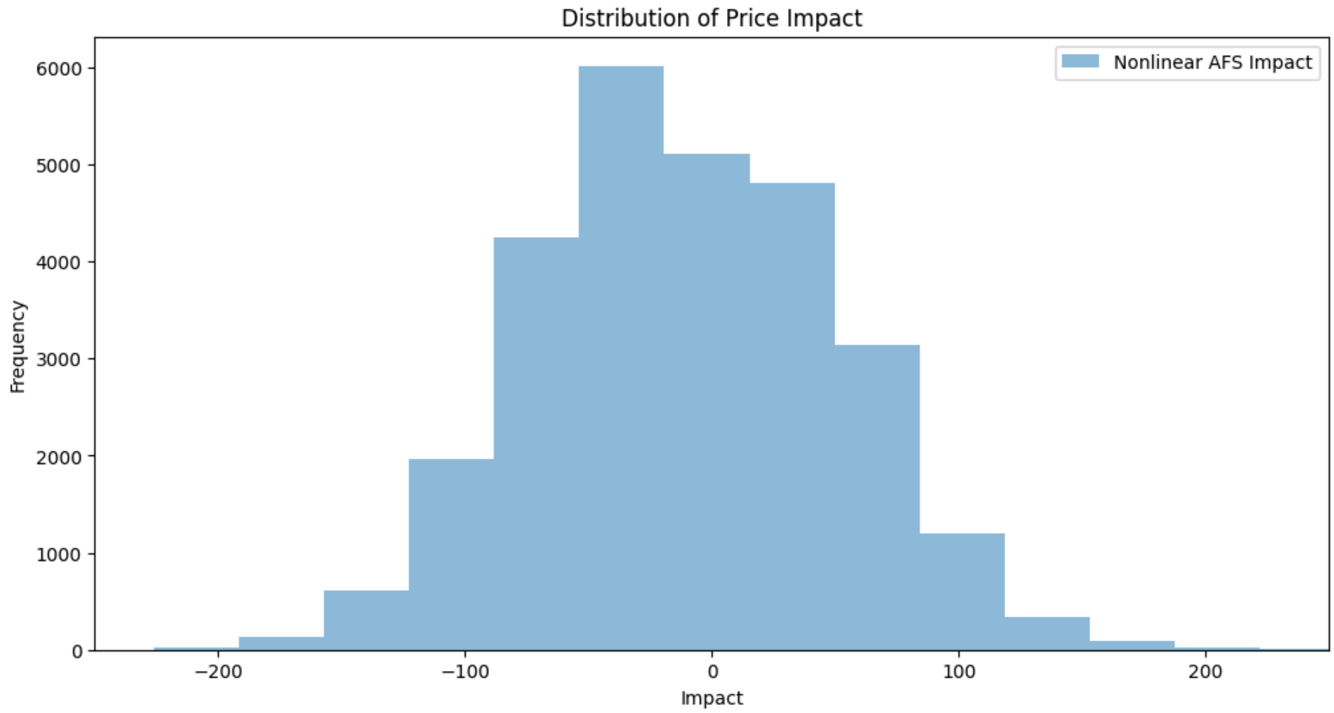
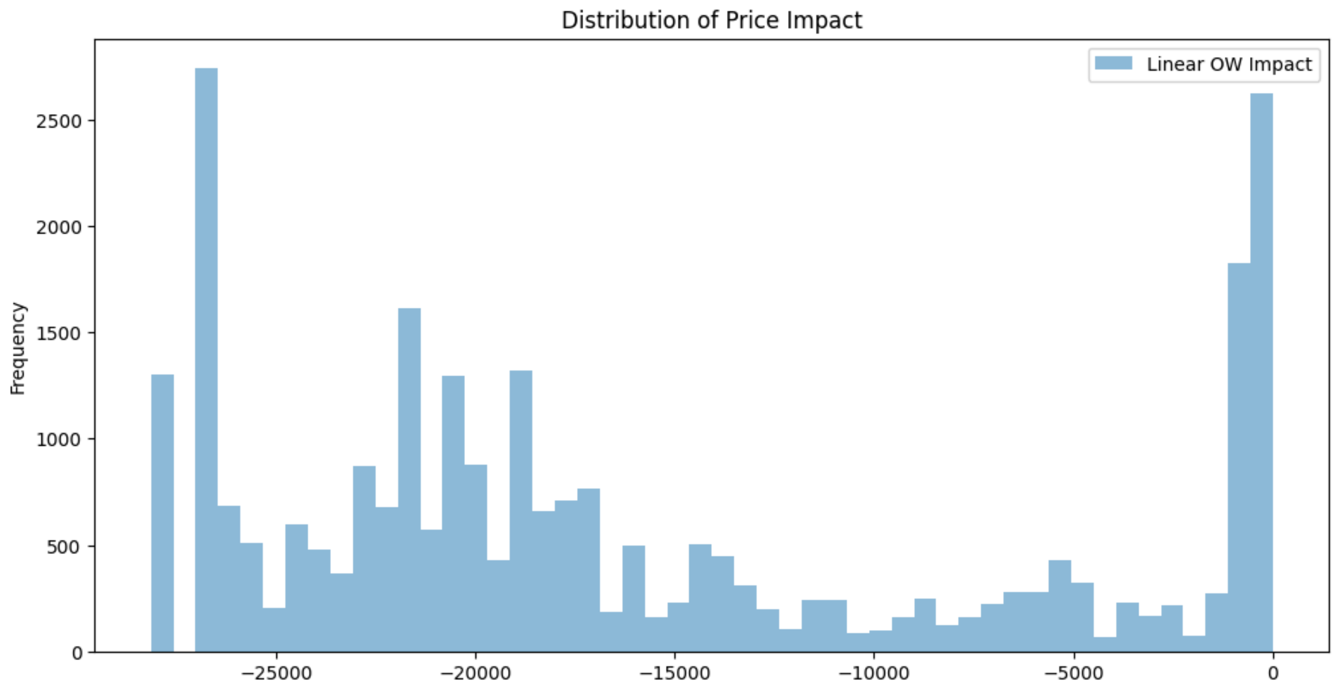
Blockhouse Work Trial Task - Melissa Oliver

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)

```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

#dataset
data = pd.read_csv('merged_data.csv')

#data for signed volume
data['Signed Volume'] = data['bid_fill'] - data['ask_fill']

#linear OW model
data['OW_impact'] = data['Signed Volume'].cumsum() * 0.001

#nonlinear AFS model
data['AFS_impact'] = np.sign(data['Signed Volume']) * np.sqrt(np.abs(data['Signed V

#plot nonlinear AFS model
plt.figure(figsize = (12, 6))
plt.hist(data['AFS_impact'], bins = 50, alpha = 0.5, label = 'Nonlinear AFS Impact'
plt.title('Distribution of Price Impact')
plt.xlim(-250, 250)
plt.xlabel('Impact')
plt.ylabel('Frequency')
plt.legend()
plt.show()

#plot linear OW model
plt.figure(figsize = (12, 6))
plt.hist(data['OW_impact'], bins = 50, alpha = 0.5, label = 'Linear OW Impact')
plt.title('Distribution of Price Impact')
plt.xlabel('Impact')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```

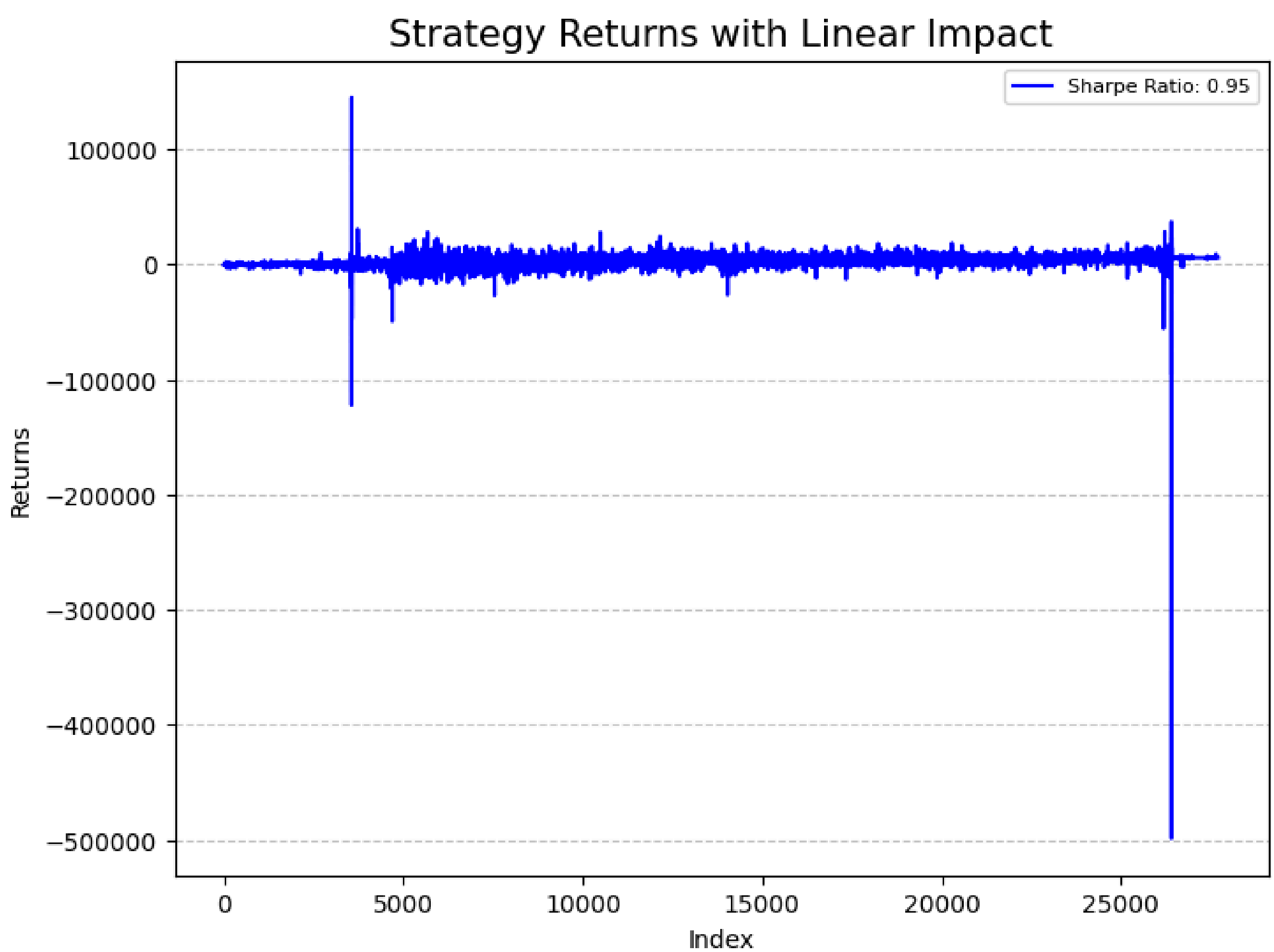




2. Implement and code the optimal strategy with Linear Impact and visualize the Sharpe Ratio plots in Section 6.2. (33 pt)

```
#linear strategy
def linear_strategy(signal, imapct, alpha, beta):
  return alpha * signal - beta * impact

signal = data['Signed Volume']
data['price_impact'] = data['Signed Volume'].cumsum() * 0.001
impact = data['price_impact']
alpha = 0.4
```

```
beta = 0.2

#strategy returns
strategy_returns = linear_strategy(signal, impact, alpha, beta)
clipped_returns = np.clip(strategy_returns, -1000, 1000)

sharpe_ratio = clipped_returns.mean() / clipped_returns.std()

#plot of strategy returns
plt.figure(figsize = (8, 6))
plt.plot(strategy_returns, label = f'Sharpe Ratio: {sharpe_ratio:.2f}', color = 'blue')
plt.title('Strategy Returns with Linear Impact', fontsize = 15)
plt.xlabel('Index', fontsize = 10)
plt.ylabel('Returns', fontsize = 10)
plt.legend(fontsize = 8)
plt.grid(axis = 'y', linestyle = '--', alpha = 0.7)
plt.show()
```



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)

```
from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout
```

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split

if 'holdings' not in data.columns:
  data['holdings'] = alpha * data['Signed Volume'] - beta * data['price_impact']

scaler = MinMaxScaler()
features = scaler.fit_transform(data[['Signed Volume', 'OW_impact', 'AFS_impact']])
labels = scaler.fit_transform(data[['holdings']])

Xtrain, Xtest, ytrain, ytest = train_test_split(features, labels, test_size = 0.2,

Xtrain = np.reshape(Xtrain, (Xtrain.shape[0], Xtrain.shape[1], 1))
Xtest = np.reshape(Xtest, (Xtest.shape[0], Xtest.shape[1], 1))

model = Sequential()
model.add(LSTM(50, return_sequences = True, input_shape = (Xtrain.shape[1], 1)))
model.add(Dropout(0.2))
model.add(LSTM(50, return_sequences = False))
model.add(Dense(1))
model.compile(optimizer = 'adam', loss = 'mse')

history = model.fit(Xtrain, ytrain, epochs = 50, batch_size = 32, validation_data =

plt.plot(history.history['loss'], label = 'Training Loss')
plt.plot(history.history['val_loss'], label = 'Validation Loss')
plt.title('Training Loss Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
Epoch 1/50
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning:
  super().__init__(**kwargs)
693/693 ━━━━━━━━━━━━━━━━━━━━ 7s 6ms/step - loss: 0.0584 - val_loss: 1.0548e-04
Epoch 2/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 1.4302e-04 - val_loss: 2.8634e-05
Epoch 3/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - loss: 7.7563e-05 - val_loss: 2.8863e-05
Epoch 4/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - loss: 8.4683e-05 - val_loss: 3.0947e-05
Epoch 5/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 6s 5ms/step - loss: 6.6344e-05 - val_loss: 3.7806e-05
Epoch 6/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 4.1763e-05 - val_loss: 3.0954e-05
Epoch 7/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 4.1340e-05 - val_loss: 4.8465e-05
Epoch 8/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 2.8627e-05 - val_loss: 9.7892e-05
Epoch 9/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 4.7135e-05 - val_loss: 3.7485e-05
Epoch 10/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 4s 6ms/step - loss: 4.9925e-05 - val_loss: 2.6038e-05
Epoch 11/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 2.9258e-05 - val_loss: 2.6449e-05
Epoch 12/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - loss: 2.6165e-05 - val_loss: 4.4105e-05
Epoch 13/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - loss: 3.2518e-05 - val_loss: 1.8909e-05
Epoch 14/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 6s 6ms/step - loss: 2.2771e-05 - val_loss: 1.3307e-05
Epoch 15/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - loss: 2.5012e-05 - val_loss: 1.1846e-05
Epoch 16/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 1.0925e-05 - val_loss: 1.1283e-04
Epoch 17/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 7s 7ms/step - loss: 4.7210e-05 - val_loss: 2.0675e-05
Epoch 18/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - loss: 2.2241e-05 - val_loss: 9.1780e-06
Epoch 19/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 1.2342e-05 - val_loss: 2.0728e-05
Epoch 20/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 1.4637e-05 - val_loss: 1.4301e-05
Epoch 21/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - loss: 1.1466e-05 - val_loss: 1.0573e-05
Epoch 22/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 6s 6ms/step - loss: 2.2836e-05 - val_loss: 1.5456e-05
Epoch 23/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 4.7918e-05 - val_loss: 1.2531e-05
Epoch 24/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 2.9413e-05 - val_loss: 8.7147e-06
Epoch 25/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 6s 6ms/step - loss: 9.0177e-06 - val_loss: 1.4723e-05
Epoch 26/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 1.5483e-05 - val_loss: 9.3956e-06
Epoch 27/50
693/693 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - loss: 2.5067e-05 - val_loss: 9.6431e-06
```