Dissertation_code_Adhiraj

September 11, 2024

[ ]:
```
dbutils.library.restartPython()
```

1 Transformer model training

[ ]:
```
import numpy as np
import pandas as pd
import yfinance as yf
import tensorflow as tf
from tensorflow.keras.layers import LayerNormalization, Dropout, Dense,␣
↪MultiHeadAttention, Input, GlobalAveragePooling1D, Reshape
from tensorflow.keras.models import Model
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
from sklearn.preprocessing import MinMaxScaler,StandardScaler
from scipy.optimize import minimize
import matplotlib.pyplot as plt
import random
import datetime

# Get the current date
current_date = datetime.datetime.now().date()

# Convert the date to a string
date_string = current_date.strftime('%Y-%m-%d')  # Formats the date as␣
↪"Year-Month-Day"


# Full list of symbols in Russell 2000 - placeholder for actual list
all_symbols = ['SMCI', 'MSTR', 'CVNA', 'DOC', 'PR', 'PSN', 'INSM', 'FIX',␣
↪'FTAI', 'COKE',
               'APG', 'ELF', 'AMKR', 'APPF', 'ONTO', 'PCVX', 'LNW', 'WFRD',␣
↪'ITCI', 'SFM',
               'FLR', 'CERE', 'AIT', 'ATI', 'ENSG', 'FN', 'LNTH', 'ANF',␣
↪'UFPI', 'MTDR',
               'SSD', 'MLI', 'HLNE', 'SPSC', 'VKTX', 'RVMD', 'DRS', 'SSB',␣
↪'DUOL',
```

```
              'ALTR', 'BPMC', 'CHRD', 'SMMT', 'HALO', 'NSIT', 'MTSI', 'IBP',␣
↪'TMHC', 'AAON', 'CRS',
              'EVLO','PRST', 'VAXX', 'TWOU', 'LPTV', 'AKTS', 'MAXN',
               'DZSI', 'CMAX', 'CARA', 'XAIR', 'VLD', 'WKHS', 'CUTR', 'BIG',
               'BTAI', 'FTCI', 'CUE', 'GORV', 'IMRX', 'EVA', 'BGFV', 'SPWR',
               'RBOT', 'ATRA', 'CARM', 'DFLI', 'BHIL', 'RENT', 'KZR', 'FGEN',
               'VATE', 'BGXX', 'VTNR', 'RPHM', 'PRTS', 'EYEN', 'XGN', 'AVTE',
               'RLYB', 'CMBM', 'VOXX', 'DNMR', 'EGRX', 'TSBX', 'MURA', 'OM',
               'GRTS', 'VOR','BRBS','FOSL'
]

start_date = '2021-07-01'
end_date = '2024-07-01'
# Download data
try:
    data = yf.download(all_symbols, start=start_date, end=end_date)['Adj␣
↪Close'].dropna(axis=1, how='all')
except Exception as e:
    print(f"Failed to download data: {e}")
    raise SystemExit("Exiting due to data download error.")

weekly_data = data.resample('W').last()
weekly_returns = weekly_data.pct_change().dropna()

scaler = StandardScaler()
mean_returns = np.mean(np.array(weekly_returns), axis=0)
mean_returns = scaler.fit_transform(mean_returns.reshape(-1,1))
scores = mean_returns / scaler.fit_transform(np.std(np.array(weekly_returns),␣
↪axis=0).reshape(-1,1))
top_indices = np.argsort(scores.flatten())[-len(all_symbols):] # Select top␣
↪stocks
top_stocks = [all_symbols[i] for i in top_indices]

# Filter data to include only top stocks
data = data[top_stocks]
#weekly_data = data.resample('W').last()
#weekly_returns = weekly_data.pct_change().dropna()
weekly_data = data.resample('W').last()
weekly_returns = weekly_data.pct_change().dropna()

# Scale features
scaler = MinMaxScaler()
scaled_features = scaler.fit_transform(weekly_returns)
forecast_horizon = 8

# Prepare sequences for training
def create_sequences(data, seq_length=10, forecast_horizon=4):
```

```
    X, Y = [], []
    for i in range(len(data) - seq_length - forecast_horizon + 1):
        X.append(data[i:i + seq_length])
        Y.append(data[i + seq_length:i + seq_length + forecast_horizon])
    return np.array(X), np.array(Y)

X, Y = create_sequences(scaled_features, 12, forecast_horizon =
 ↪forecast_horizon)

# Define the Transformer model
class TransformerBlock(tf.keras.layers.Layer):
    def __init__(self, embed_dim, num_heads, ff_dim, rate=0.1):
        super().__init__()
        self.att = MultiHeadAttention(num_heads=num_heads, key_dim=embed_dim)
        self.ffn = tf.keras.Sequential([Dense(ff_dim, activation="relu"),
 ↪Dense(embed_dim)])
        self.layernorm1 = LayerNormalization(epsilon=1e-6)
        self.layernorm2 = LayerNormalization(epsilon=1e-6)
        self.dropout1 = Dropout(rate)
        self.dropout2 = Dropout(rate)

    def call(self, inputs, training=False):
        attn_output = self.att(inputs, inputs)
        attn_output = self.dropout1(attn_output, training=training)
        out1 = self.layernorm1(inputs + attn_output)
        ffn_output = self.ffn(out1)
        ffn_output = self.dropout2(ffn_output, training=training)
        return self.layernorm2(out1 + ffn_output)

def build_transformer_model(input_shape, num_features):
    inputs = Input(shape=input_shape)
    x = inputs
    for _ in range(4):  # Number of Transformer blocks
        x = TransformerBlock(embed_dim=input_shape[-1], num_heads=4,
 ↪ff_dim=256, rate=0.5)(x)
    x = GlobalAveragePooling1D()(x)
    x = Dense(128, activation='relu')(x)
    x = Dropout(0.5)(x)
    outputs = Dense(forecast_horizon * num_features, activation='linear')(x)
    outputs = Reshape((forecast_horizon, num_features))(outputs)  # Ensure
 ↪output is reshaped to [forecast_horizon, num_features]
    model = Model(inputs=inputs, outputs=outputs)
    model.compile(optimizer=tf.keras.optimizers.SGD(learning_rate=3e-5),
 ↪loss="mse")
    return model
```

```python
num_features = data.shape[1]  # Adjust this if your data preprocessing changes␣
↪the number of features
model = build_transformer_model((X.shape[1], X.shape[2]), num_features)
model.summary()  # Always good to check the model structure

model.fit(X, Y, epochs=200, batch_size=10, verbose=1, validation_split=0.2,
          callbacks=[ModelCheckpoint("best_model.keras", save_best_only=True),
                     EarlyStopping(patience=5,␣
↪restore_best_weights=True,min_delta=1e-4,monitor='val_loss')])

# Forecast future weekly returns
forecasted_returns = model.predict(X[-1].reshape(1, *X[-1].shape)).reshape(-1,␣
↪len(data.columns))
forecasted_returns = scaler.inverse_transform(forecasted_returns)
```

```
[*********************100%***********************]  101 of 101 completed
```

Model: "functional_124"

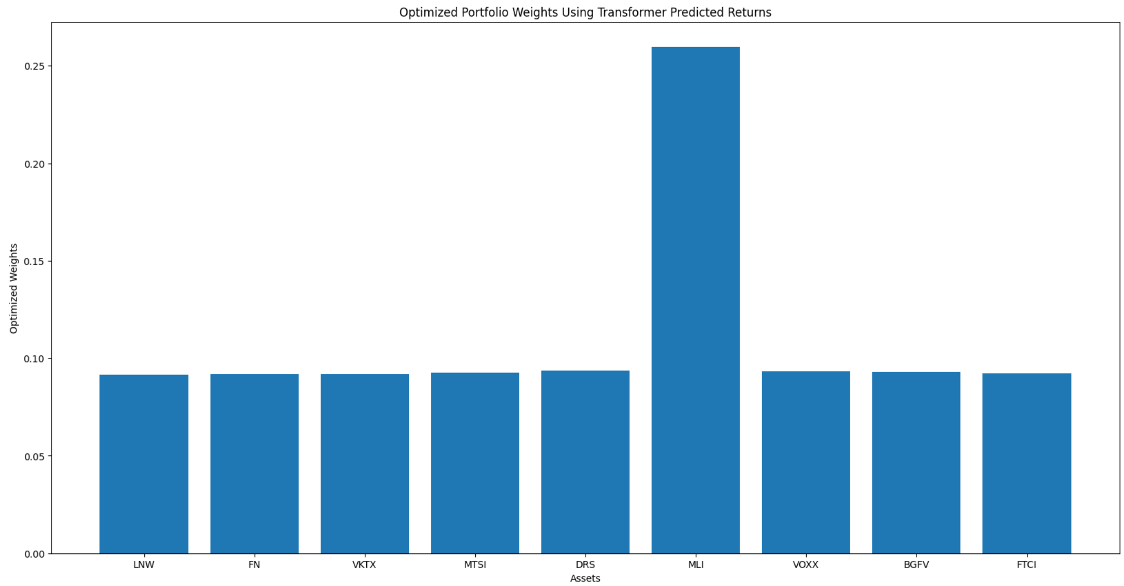
Layer (type)	Output Shape	Param #
input_layer_120 (InputLayer)	(None, 12, 101)	0
transformer_block_96 (TransformerBlock)	(None, 12, 101)	217,002
transformer_block_97 (TransformerBlock)	(None, 12, 101)	217,002
transformer_block_98 (TransformerBlock)	(None, 12, 101)	217,002
transformer_block_99 (TransformerBlock)	(None, 12, 101)	217,002
global_average_pooling1d_24 (GlobalAveragePooling1D)	(None, 101)	0
dense_248 (Dense)	(None, 128)	13,056
dropout_324 (Dropout)	(None, 128)	0
dense_249 (Dense)	(None, 808)	104,232
reshape_24 (Reshape)	(None, 8, 101)	0

```
 Total params: 985,296 (3.76 MB)

 Trainable params: 985,296 (3.76 MB)

 Non-trainable params: 0 (0.00 B)

Epoch 1/200
1/1              7s 7s/step - loss:
0.2963 - val_loss: 0.3003
Epoch 2/200
1/1              1s 789ms/step - loss:
0.3008 - val_loss: 0.3003
Epoch 3/200
1/1              1s 989ms/step - loss:
0.2960 - val_loss: 0.3003
Epoch 4/200
1/1              1s 750ms/step - loss:
0.2961 - val_loss: 0.3002
Epoch 5/200
1/1              1s 860ms/step - loss:
0.3038 - val_loss: 0.3002
Epoch 6/200
1/1              1s 761ms/step - loss:
0.3058 - val_loss: 0.3002
1/1              1s 660ms/step
```

2 Portfolio Optimisation

[ ]:
```
def markowitz_optimization(returns, cov_matrix, risk_aversion=4):
    n_assets = returns.shape[0]
    def objective(weights):
        return -(np.dot(weights, returns) - risk_aversion * np.dot(weights.T,
 ↪np.dot(cov_matrix, weights)))
    constraints = [{'type': 'eq', 'fun': lambda weights: np.sum(weights) - 1}]
    bounds = [(0, 1) for _ in range(n_assets)]
    result = minimize(objective, np.full(n_assets, 1/n_assets), method='SLSQP',
 ↪bounds=bounds, constraints=constraints)
    if not result.success:
        print("Optimization failed: ", result.message)
        return None
    return result.x

risk_av = 3
```

```python
# Combine historic and forecasted returns
all_returns = np.concatenate((weekly_returns.values, forecasted_returns), axis=0)
scaler = StandardScaler()
mean_returns = np.mean(all_returns, axis=0)
mean_returns = scaler.fit_transform(mean_returns.reshape(-1,1))
volatility = scaler.fit_transform(np.std(all_returns, axis=0).reshape(-1,1))
factor = 0.2

def allocate_portfolio(risk_aversion, high_cap_weight_base, low_cap_weight_base):
    high_cap_weight = high_cap_weight_base + factor * (risk_aversion - 1.5) * (1 - high_cap_weight_base)
    low_cap_weight = low_cap_weight_base - factor * (risk_aversion - 1.5) * low_cap_weight_base
    return high_cap_weight, low_cap_weight

# Base weights assuming a balanced risk aversion (lambda = 1)
high_cap_weight_base = 0.55  # 55% to high cap at neutral risk aversion
low_cap_weight_base = 0.45  # 45% to low cap at neutral risk aversion

high_cap_weight, low_cap_weight = allocate_portfolio(risk_av, high_cap_weight_base, low_cap_weight_base)


top_indices_high = np.argsort(mean_returns[:50].flatten())[-int(high_cap_weight*10):] # Select top stocks
top_indices_low = np.argsort(-mean_returns[50:].flatten())[:int(low_cap_weight*10)] + 50
top_indices = []
top_indices.extend(top_indices_high)
top_indices.extend(top_indices_low)
top_stocks = [all_symbols[i] for i in top_indices]
top_mean_returns = mean_returns[top_indices]
cov_matrix = np.cov(top_mean_returns, rowvar=False)

optimized_weights = markowitz_optimization(top_mean_returns, cov_matrix,risk_av)

# Visualize the optimized portfolio weights
plt.figure(figsize=(20, 10))
plt.bar(top_stocks, optimized_weights)
plt.xlabel('Assets')
plt.ylabel('Optimized Weights')
plt.title('Optimized Portfolio Weights Using Transformer Predicted Returns')
plt.show()
```



[ ]:
```
df = pd.DataFrame({
    'Stock': top_stocks,
    'Optimized Weight': optimized_weights
})
df.columns = ['Stock', 'Optimized_Weight']

# Convert the DataFrame to a Spark DataFrame
spark_df = spark.createDataFrame(df)

# Create the database if it doesn't exist
spark.sql("CREATE DATABASE IF NOT EXISTS adhi_db")

# Write the DataFrame to the Spark SQL table, trying to overwrite the existing␣
↪data
if isinstance(risk_av, float):
    formatted_risk_av = str(risk_av).replace('.', '_')
else:
    formatted_risk_av = str(risk_av)

spark_df.write.option("overwriteSchema", "true").mode("overwrite").
↪saveAsTable(f"adhi_db.trans_weights_{formatted_risk_av}")
```

[ ]:
```
# Symbols for your stocks and weights from Markowitz Optimization
weights = optimized_weights

# Fetch historical data
data = yf.download(top_stocks, start=start_date, end=end_date)['Adj Close']
```

```
# Function to calculate returns for holding periods
def calculate_returns_for_periods(data, periods):
    if isinstance(data, pd.Series):
        # Handle Series input for single stock/index data
        returns = pd.DataFrame(index=data.index)
        for period in periods:
            returns[f'{period} day return'] = (data.pct_change(periods=period)*␣
 ↪weights).sum(axis=1)
    elif isinstance(data, pd.DataFrame):
        # Handle DataFrame input for multiple stocks
        returns = pd.DataFrame(index=data.index)
        for period in periods:
            returns[f'{period} day return'] = (data.pct_change(periods=period)*␣
 ↪weights).sum(axis=1)
    return returns

# Calculate returns for various holding periods
holding_periods = list(range(5,405,5))  # Example holding periods
portfolio_returns = calculate_returns_for_periods(data, holding_periods)
risks = portfolio_returns.std()
```

```
[*********************100%***********************]  9 of 9 completed
```

[ ]:
```
# Fetch market index data
market_data = yf.download('^GSPC', start=start_date, end=end_date)['Adj Close']␣
 ↪ # Russell 2000 as the market index

def calculate_returns_for_periods_market(data, periods):
    if isinstance(data, pd.Series):
        # Handle Series input for single stock/index data
        returns = pd.DataFrame(index=data.index)
        for period in periods:
            returns[f'{period} day return'] = data.pct_change(periods=period)
    elif isinstance(data, pd.DataFrame):
        # Handle DataFrame input for multiple stocks
        returns = pd.DataFrame(index=data.index)
        for period in periods:
            returns[f'{period} day return'] = data.pct_change(periods=period)
    return returns

# Calculate market returns for the same holding periods
market_returns = calculate_returns_for_periods_market(market_data,␣
 ↪holding_periods)
market_risks = market_returns.std()
```

```
[*********************100%***********************]  1 of 1 completed
```

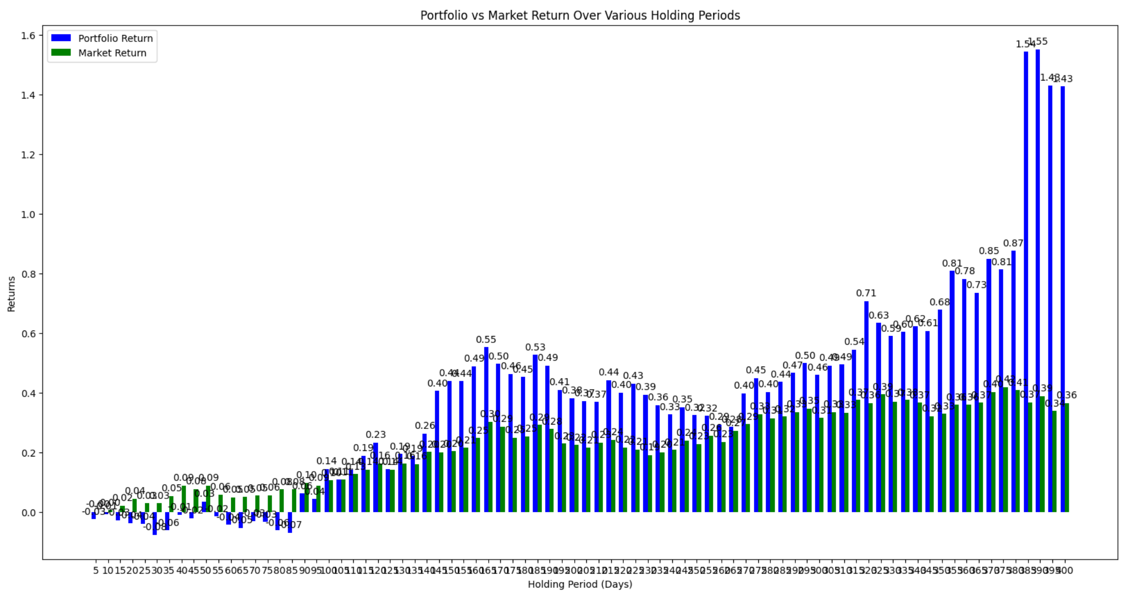
```
[ ]: # Extract the last value for each period to represent the period return
final_portfolio_returns = {period: portfolio_returns[f'{period} day return'].
 ↪iloc[-1] for period in holding_periods}
final_market_returns = {period: market_returns[f'{period} day return'].iloc[-1]␣
 ↪for period in holding_periods}
```

```
[ ]: comparison_df = pd.DataFrame({
    'Holding Period': holding_periods,
    'Portfolio Return': list(final_portfolio_returns.values()),
    'Market Return': list(final_market_returns.values()),
    'Portfolio Risk' : risks,
    'Market Risk' :  market_risks
})
```

3 Returns for transformer-based optimised portfolio

```
[ ]: # Set the width for each bar
bar_width = 0.35

# Set positions for the groups of bars
index = np.arange(len(comparison_df['Holding Period']))

plt.figure(figsize=(20,10))

# Create a bar plot for the portfolio returns
portfolio_bars = plt.bar(index - bar_width/2, comparison_df['Portfolio␣
 ↪Return'], bar_width, label='Portfolio Return', color='blue')

# Create a bar plot for the market returns, positioned next to the first
market_bars = plt.bar(index + bar_width/2, comparison_df['Market Return'],␣
 ↪bar_width, label='Market Return', color='green')

# Annotate each bar with its respective data value
for bar in portfolio_bars:
    yval = bar.get_height()
    plt.annotate(f'{yval:.2f}',
                 (bar.get_x() + bar.get_width() / 2, yval),
                 ha='center', va='bottom', textcoords="offset points",␣
 ↪xytext=(0,3))

for bar in market_bars:
    yval = bar.get_height()
    plt.annotate(f'{yval:.2f}',
                 (bar.get_x() + bar.get_width() / 2, yval),
                 ha='center', va='bottom', textcoords="offset points",␣
 ↪xytext=(0,3))
```

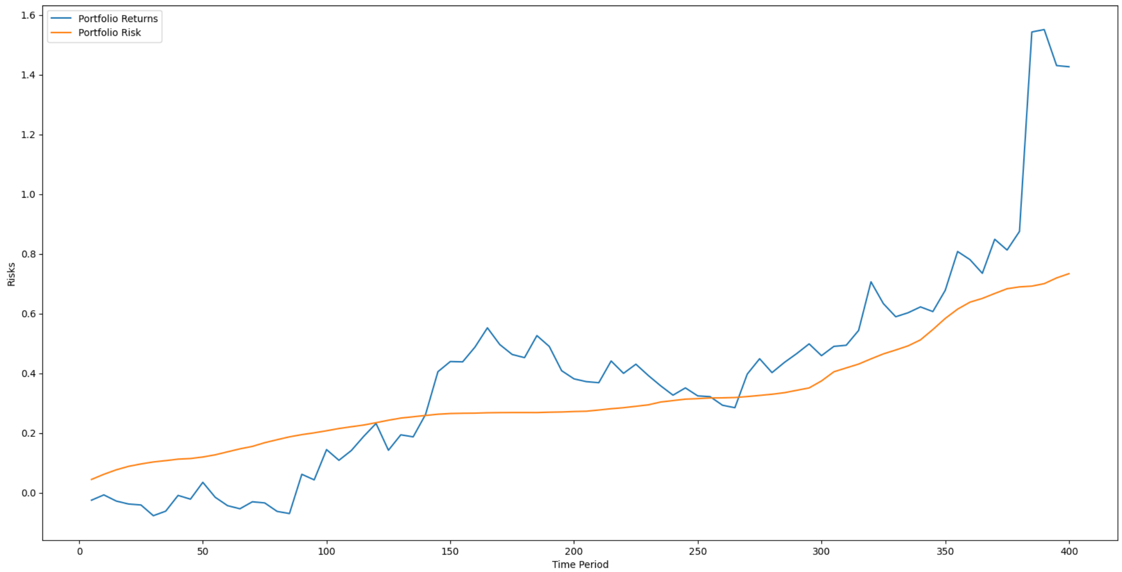
```
# Add labels, title, and legend
plt.xlabel('Holding Period (Days)')
plt.ylabel('Returns')
plt.title('Portfolio vs Market Return Over Various Holding Periods')
plt.xticks(index, comparison_df['Holding Period'])  # Set x-ticks to match the␣
↪holding periods
plt.legend()

# Show the plot
plt.show()
```



4 Risk-returns tradeoff

[ ]:
```
plt.figure(figsize=(20,10))

plt.plot(comparison_df['Holding Period'],comparison_df['Portfolio␣
↪Return'],linewidth = 1.5)
plt.plot(comparison_df['Holding Period'],comparison_df['Portfolio␣
↪Risk'],linewidth = 1.5)

legend = ['Portfolio Returns', 'Portfolio Risk']

plt.xlabel('Time Period')
plt.ylabel('Risks')
plt.legend(legend)
```

[ ]: <matplotlib.legend.Legend at 0x7f71e8e54b20>

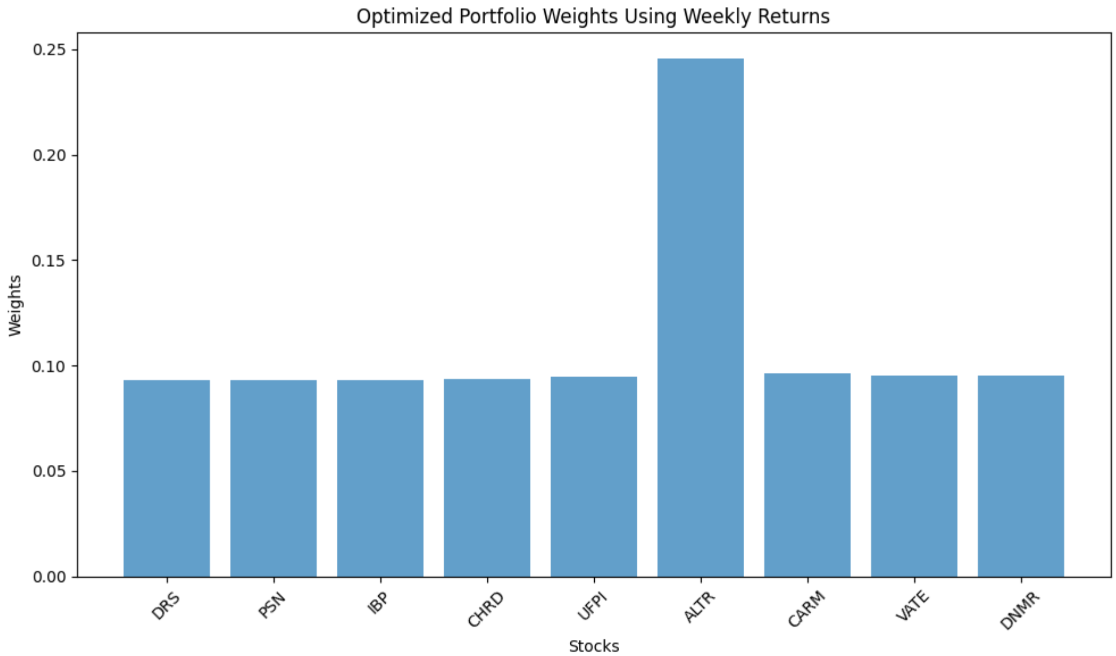


5 Markowitz w/o transformer

[ ]:
```
import numpy as np
import pandas as pd
import yfinance as yf
from sklearn.preprocessing import StandardScaler
from scipy.optimize import minimize
import matplotlib.pyplot as plt

# Fetch historical stock data
try:
    data = yf.download(all_symbols, start=start_date, end=end_date)['Adj␣
 ↪Close'].dropna(axis=1, how='all')
except Exception as e:
    print(f"Failed to download data: {e}")
    raise SystemExit("Exiting due to data download error.")


# Calculate weekly returns
weekly_data = data.resample('W').last()
weekly_returns = weekly_data.pct_change().dropna()

mean_daily_returns = weekly_returns.mean()
```

```
# Scale the returns
scaler = StandardScaler()
scaled_daily_returns = scaler.fit_transform(np.array(mean_daily_returns).
↪reshape(-1,1))

top_indices_high = np.argsort(scaled_daily_returns[:50].
↪flatten())[-int(high_cap_weight*10):] # Select top stocks
top_indices_low = np.argsort(-scaled_daily_returns[50:].flatten())[:
↪int(low_cap_weight*10)] + 50
top_indices = []
top_indices.extend(top_indices_high)
top_indices.extend(top_indices_low)
top_stocks1 = [all_symbols[i] for i in top_indices]
top_mean_returns = scaled_daily_returns[top_indices]
cov_matrix = np.cov(top_mean_returns, rowvar=False)


#cov_matrix = np.cov(scaled_daily_returns, rowvar=False)

# Function for the Markowitz optimization
def markowitz_optimization(returns, cov_matrix, risk_aversion=4):
    n_assets = returns.shape[0]
    def objective(weights):
        return -(np.dot(weights, returns) - risk_aversion * np.dot(weights.T,␣
↪np.dot(cov_matrix, weights)))
    constraints = [{'type': 'eq', 'fun': lambda weights: np.sum(weights) - 1}]
    bounds = [(0, 1) for _ in range(n_assets)]
    result = minimize(objective, np.full(n_assets, 1/n_assets), method='SLSQP',␣
↪bounds=bounds, constraints=constraints)
    if not result.success:
        print("Optimization failed: ", result.message)
        return None
    return result.x

# Run Markowitz optimization
optimized_result = markowitz_optimization(top_mean_returns, cov_matrix,risk_av)

# Visualize the optimized portfolio weights
plt.figure(figsize=(10, 6))
plt.bar(top_stocks1, optimized_result, alpha=0.7)
plt.title('Optimized Portfolio Weights Using Weekly Returns')
plt.xlabel('Stocks')
plt.ylabel('Weights')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
[*********************100%***********************]  101 of 101 completed
```




```
[ ]: df = pd.DataFrame({
         'Stock': top_stocks1,
         'Optimized Weight': optimized_result
     })
     spark_df = spark.createDataFrame(df)
     spark.sql("CREATE DATABASE IF NOT EXISTS adhi_db")
     if isinstance(risk_av, float):
         formatted_risk_av = str(risk_av).replace('.', '_')
     else:
         formatted_risk_av = str(risk_av)

     spark_df.write.format("parquet").mode("overwrite").saveAsTable(f"adhi_db.
      ↪wotrans_weights_{formatted_risk_av}")
```

```
[ ]: # Symbols for your stocks and weights from Markowitz Optimization
     weights = optimized_result

     # Fetch historical data
     data = yf.download(top_stocks1, start=start_date, end=end_date)['Adj Close']

     # Function to calculate returns for holding periods
     def calculate_returns_for_periods(data, periods):
         if isinstance(data, pd.Series):
```

```
        # Handle Series input for single stock/index data
        returns = pd.DataFrame(index=data.index)
        for period in periods:
            returns[f'{period} day return'] = (data.pct_change(periods=period)*␣
 ↪weights).sum(axis=1)
    elif isinstance(data, pd.DataFrame):
        # Handle DataFrame input for multiple stocks
        returns = pd.DataFrame(index=data.index)
        for period in periods:
            returns[f'{period} day return'] = (data.pct_change(periods=period)*␣
 ↪weights).sum(axis=1)
    return returns

# Calculate returns for various holding periods
#holding_periods = list(range(5,205,5))  # Example holding periods
portfolio_returns1 = calculate_returns_for_periods(data, holding_periods)
```

```
[*********************100%***********************]  9 of 9 completed
```

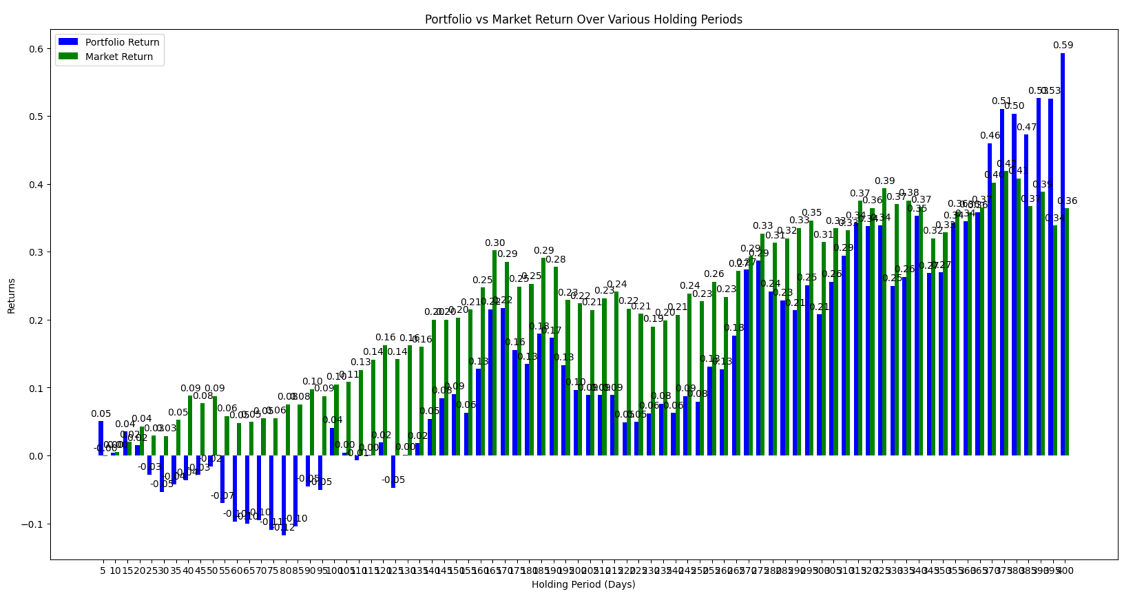
[ ]:
```
# Extract the last value for each period to represent the period return
final_portfolio_returns1 = {period: portfolio_returns1[f'{period} day return'].
 ↪iloc[-1] for period in holding_periods}
final_market_returns1 = {period: market_returns[f'{period} day return'].
 ↪iloc[-1] for period in holding_periods}
```

[ ]:
```
comparison_df1 = pd.DataFrame({
    'Holding Period': holding_periods,
    'Portfolio Return': list(final_portfolio_returns1.values()),
    'Market Return': list(final_market_returns1.values())
})
```

6 Returns for traditional optimised portfolio

[ ]:
```
# Set the width for each bar
bar_width = 0.35

plt.figure(figsize=(20,10))

# Set positions for the groups of bars
index = np.arange(len(comparison_df1['Holding Period']))

# Create a bar plot for the portfolio returns
portfolio_bars = plt.bar(index - bar_width/2, comparison_df1['Portfolio␣
 ↪Return'], bar_width, label='Portfolio Return', color='blue')

# Create a bar plot for the market returns, positioned next to the first
```

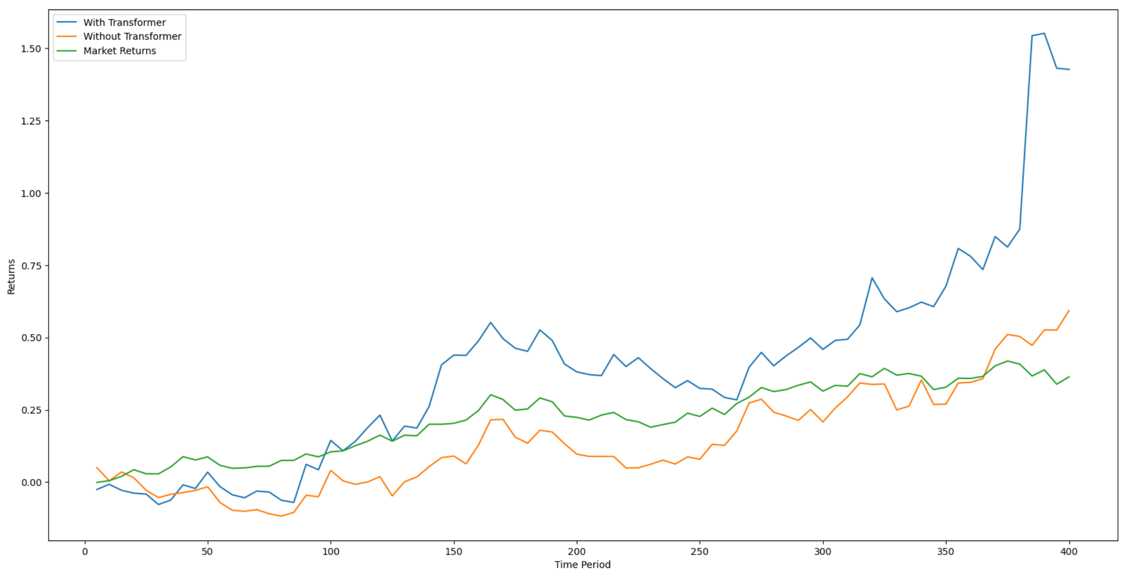
```python
market_bars = plt.bar(index + bar_width/2, comparison_df1['Market Return'], bar_width, label='Market Return', color='green')

# Annotate each bar with its respective data value
for bar in portfolio_bars:
    yval = bar.get_height()
    plt.annotate(f'{yval:.2f}',
                 (bar.get_x() + bar.get_width() / 2, yval),
                 ha='center', va='bottom', textcoords="offset points", xytext=(0,3))

for bar in market_bars:
    yval = bar.get_height()
    plt.annotate(f'{yval:.2f}',
                 (bar.get_x() + bar.get_width() / 2, yval),
                 ha='center', va='bottom', textcoords="offset points", xytext=(0,3))

# Add labels, title, and legend
plt.xlabel('Holding Period (Days)')
plt.ylabel('Returns')
plt.title('Portfolio vs Market Return Over Various Holding Periods')
plt.xticks(index, comparison_df1['Holding Period'])  # Set x-ticks to match the holding periods
plt.legend()

# Show the plot
plt.show()
```



7 Returns curves

[ ]:
```
plt.figure(figsize=(20,10))

plt.plot(comparison_df['Holding Period'],comparison_df['Portfolio␣
  ↪Return'],linewidth = 1.5)
plt.plot(comparison_df['Holding Period'],comparison_df1['Portfolio␣
  ↪Return'],linewidth = 1.5)
plt.plot(comparison_df['Holding Period'],comparison_df['Market␣
  ↪Return'],linewidth = 1.5)

legend = ['With Transformer','Without Transformer', 'Market Returns']

plt.xlabel('Time Period')
plt.ylabel('Returns')
plt.legend(legend)
```

[ ]:
```
<matplotlib.legend.Legend at 0x7f71e832bdc0>
```



[ ]:
```
df = pd.DataFrame({
    'With Transformer': comparison_df['Portfolio Return'],
    'Without Transformer': list(final_portfolio_returns1.values()),
    'Market Returns' : comparison_df['Market Return'],
    'Holding Periods' : comparison_df['Holding Period'],
    'Portfolio Risk' : comparison_df['Portfolio Risk'],
```

```
    'Market Risk' : comparison_df['Market Risk']
})

spark_df = spark.createDataFrame(df)
spark.sql("CREATE DATABASE IF NOT EXISTS adhi_db")
if isinstance(risk_av, float):
    formatted_risk_av = str(risk_av).replace('.', '_')
else:
    formatted_risk_av = str(risk_av)
spark_df.write.format("parquet").mode("overwrite").saveAsTable(f"adhi_db.
 ↪stock_returns_{formatted_risk_av}")
```

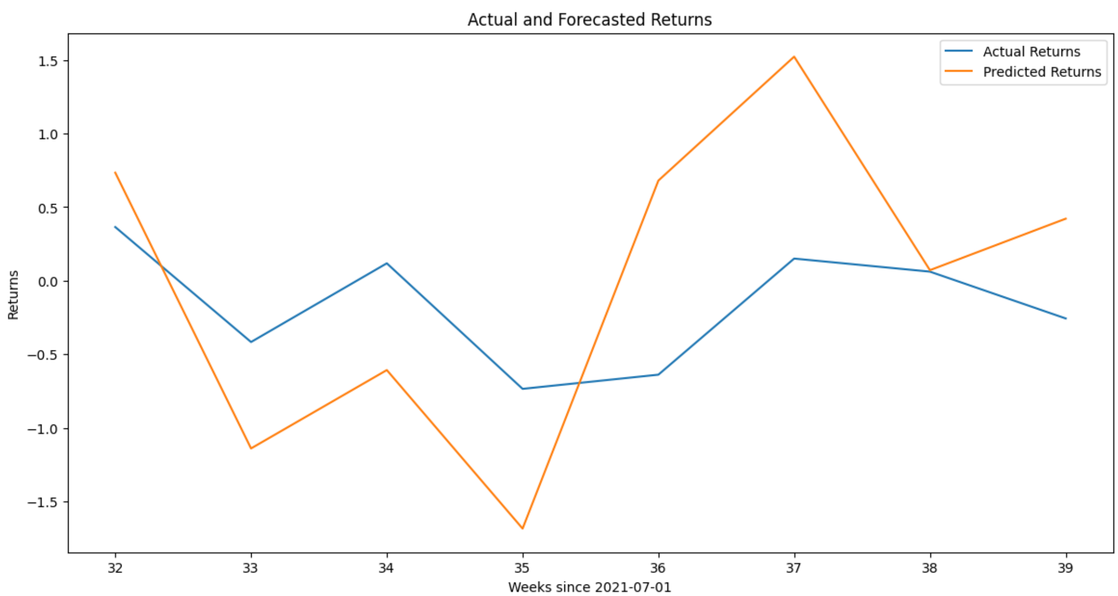
8 Model Performance

```
[ ]: from datetime import datetime, timedelta

forecasted_returns1 = np.mean(forecasted_returns,axis = 1)

date = datetime.strptime(end_date, '%Y-%m-%d')

# Calculate the date 8 weeks before
end_date1 = date + timedelta(weeks=forecast_horizon)

# Download and process data
try:
    data1 = yf.download(all_symbols, start=start_date, end=end_date1)['Adj␣
 ↪Close'].dropna(axis=1, how='all')
except Exception as e:
    print(f"Failed to download data: {e}")
    raise SystemExit("Exiting due to data download error.")
weekly_data1 = data1.resample('W').last()
weekly_returns1 = weekly_data1.pct_change().dropna()

# Combine actual and predicted for plot
all_actual_returns = np.mean(weekly_returns1,axis=1)
scaler = StandardScaler()
predicted_returns = scaler.fit_transform(forecasted_returns1.reshape(-1,1))
all_actual_returns = scaler.fit_transform(np.array(all_actual_returns).
 ↪reshape(-1,1))
predicted_index = range(len(all_actual_returns) - forecast_horizon,␣
 ↪len(all_actual_returns))

# Plotting
plt.figure(figsize=(14, 7))
plt.plot(predicted_index,all_actual_returns[predicted_index], label='Actual␣
 ↪Returns')
```

```
plt.plot(predicted_index, predicted_returns, label='Predicted Returns')
#plt.plot(predicted_index, forecasted_returns, label='Predicted Returns')
plt.title('Actual and Forecasted Returns')
plt.xlabel('Weeks since ' + start_date)
plt.ylabel('Returns')
plt.legend()
plt.show()
```

```
[*********************100%***********************]  101 of 101 completed
```

```
1/1              1s 551ms/step
```



8.1 RMSE

[ ]:
```
np.mean((all_actual_returns[predicted_index] - predicted_returns)**2)**0.5
```

[ ]:
```
0.8777246402749992
```