Model_v3

July 15, 2025

1 Model V3

[24]:
```
best_config = {'lstm_bidirectional': False,
               'batch_size': 32,
               'lstm_hidden': 32,
               'lstm_layers': 2,
               'lstm_dropout': 0.0,
               'gat_hidden': 80,
               'gat_dropout': 0.30000000000000004,
               'gat_alpha': 0.25,
               'final_dropout': 0.25,
               'learning_rate': 0.0012666916605679301,
               'lstm_weight_decay': 1.0769334723318358e-06,
               'gat_weight_decay': 0.002783257131313509,
               'final_weight_decay': 0.0020135817014909426}
```

[25]:
```
import os
import torch
import torch.nn as nn
import torch.nn.functional as F
import pandas as pd
import numpy as np
import random
from sklearn.preprocessing import StandardScaler
from tqdm import tqdm

def set_seed(seed=42):
    torch.manual_seed(seed)
    np.random.seed(seed)
    random.seed(seed)
    if torch.cuda.is_available():
        torch.cuda.manual_seed(seed)
        torch.cuda.manual_seed_all(seed)
        torch.backends.cudnn.deterministic = True
        torch.backends.cudnn.benchmark = False
    os.environ['PYTHONHASHSEED'] = str(seed)
set_seed(42)
```

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Using device:", device)
```

```
Using device: cpu
```

[26]:
```
import os
import pandas as pd
import numpy as np

tickers = ['AAPL', 'AMZN', 'BA', 'COST', 'JNJ', 'NVDA', 'TMO', 'TSLA', 'VLO']
data_dir = "Data"
features = [ 'close', 'volume', 'log_return',
            'ann_return_1w', 'ann_return_2w', 'ann_return_1m',
            'rolling_vol_7d',  'macd_1w_1m',
             'sentiment_variance', 'product']

all_data = {}
min_length = float('inf')

for stock in tickers:
    df = pd.read_csv(os.path.join(data_dir,␣
 ↪f"{stock}_with_sentiment_features_with_product.csv"))

    # If log_return is not already present, add it
    if 'log_return' not in df.columns:
        df['log_return'] = np.log(df['close'] / df['close'].shift(1))

    # Fill missing price features using forward fill (safer for price data)
    price_feats = ['close', 'volume',
                   'ann_return_1w', 'ann_return_2w', 'ann_return_1m',
                   'rolling_vol_7d', 'macd_1w_1m', 'log_return',
                    'sentiment_variance',  'news_count','product']
    for feat in price_feats:
        if feat in df.columns:
            df[feat] = df[feat].ffill()

    # Fill missing sentiment/news features with 0 (standard for no news days)
    for feat in ['news_count', 'sentiment_variance','product' ]:
        if feat in df.columns:
            df[feat] = df[feat].fillna(0)

    # Drop rows where the main features are still missing (e.g., very early␣
 ↪rows)
    df = df.dropna(subset=features).reset_index(drop=True)
    all_data[stock] = df
    min_length = min(min_length, len(df))
```

```
# Align all stocks to same length from the end (for parallel modeling)
for stock in tickers:
    all_data[stock] = all_data[stock].tail(min_length).reset_index(drop=True)

# Unified date array
dates = all_data[tickers[0]]['date'].values
total_len = len(dates)

# Train/test split
test_size = 0.3
split_idx = int(total_len * (1 - test_size))
train_dates = dates[:split_idx]
test_dates = dates[split_idx:]

print(f"Train: {train_dates[0]}~{train_dates[-1]}")
print(f"Test: {test_dates[0]}~{test_dates[-1]}")
```

```
Train: 2021-02-03~2024-02-09
Test: 2024-02-12~2025-05-30
```

[27]:

```
scalers = {}
for stock in tickers:
    train_df = all_data[stock][all_data[stock]['date'].isin(train_dates)]
    scaler = StandardScaler()
    scaler.fit(train_df[features])
    scalers[stock] = scaler
print("Scaler finished.")
```

```
Scaler finished.
```

[28]:

```
train_price_data = pd.DataFrame({'date': train_dates})
for stock in tickers:
    train_price_data[stock] = all_data[stock][all_data[stock]['date'].
 ↪isin(train_dates)]['close'].values
train_corr_matrix = train_price_data.drop(columns='date').corr()

edge_index, edge_attr = [], []
for i in range(len(tickers)):
    for j in range(len(tickers)):
        if i != j:
            edge_index.append([i, j])
            edge_attr.append(train_corr_matrix.iloc[i, j])

edge_index = torch.tensor(edge_index, dtype=torch.long).t().contiguous()
edge_attr = torch.tensor(edge_attr, dtype=torch.float32)
print("Edges weighted prepared.")
```

```
Edges weighted prepared.
```

2 Define LSTM and GAT

[29]:
```
class StockLSTMEncoder(nn.Module):
    def __init__(self, input_dim, hidden_dim, num_layers=1, dropout=0.0,
 ↪bidirectional=False):
        super().__init__()
        self.lstm = nn.LSTM(input_dim, hidden_dim, batch_first=True,
 ↪num_layers=num_layers, dropout=dropout if num_layers > 1 else 0,
 ↪bidirectional=bidirectional)
    def forward(self, x):
        output, (h_n, _) = self.lstm(x)
        return output[:, -1, :]

# WeightedGATConv
class WeightedGATConv(nn.Module):
    def __init__(self, in_channels, out_channels, dropout=0.0, alpha=0.2):
        super().__init__()
        self.lin = nn.Linear(in_channels, out_channels)
        self.dropout = nn.Dropout(dropout)
        self.leaky_relu = nn.LeakyReLU(alpha)
    def forward(self, x, edge_index, edge_weight):
        x = self.lin(x)
        x = self.dropout(x)
        num_nodes = x.size(0)
        agg = torch.zeros_like(x)
        for idx in range(edge_index.size(1)):
            src = edge_index[0, idx]
            tgt = edge_index[1, idx]
            agg[tgt] += edge_weight[idx] * x[src]
        return self.leaky_relu(agg + x)

class GATEncoder(nn.Module):
    def __init__(self, in_dim, hidden_dim, out_dim, dropout=0.0, alpha=0.2):
        super().__init__()
        self.gat1 = WeightedGATConv(in_dim, hidden_dim, dropout, alpha)
        self.gat2 = WeightedGATConv(hidden_dim, out_dim, dropout, alpha)
    def forward(self, x, edge_index, edge_weight):
        x = self.gat1(x, edge_index, edge_weight)
        x = self.gat2(x, edge_index, edge_weight)
        return x

#      final_dropout
class PortfolioNet(nn.Module):
    def __init__(self, config, input_dim, tickers):
        super().__init__()
        self.lstm_encoder = StockLSTMEncoder(
            input_dim=input_dim,
```

```
            hidden_dim=config['lstm_hidden'],
            num_layers=config['lstm_layers'],
            dropout=config['lstm_dropout'],
            bidirectional=config['lstm_bidirectional']
        )
        gat_input_dim = config['lstm_hidden'] * (2 if␣
 ↪config['lstm_bidirectional'] else 1)
        self.gat_encoder = GATEncoder(
            in_dim=gat_input_dim,
            hidden_dim=config['gat_hidden'],
            out_dim=config['gat_hidden'],
            dropout=config['gat_dropout'],
            alpha=config['gat_alpha']
        )
        self.final_dropout = nn.Dropout(config.get('final_dropout', 0.2))
        self.final_layer = nn.Linear(config['gat_hidden'], 1)
        self.tickers = tickers

    def forward(self, seq_features, edge_index, edge_attr):
        # seq_features: [N_stocks, seq_len, feature_dim]
        x = self.lstm_encoder(seq_features)
        x = self.gat_encoder(x, edge_index, edge_attr)
        x = self.final_dropout(x)
        raw_scores = self.final_layer(x).squeeze(-1)
        weights = torch.tanh(raw_scores)
        norm_weights = weights / (weights.sum() + 1e-8)
        return norm_weights
```

[30]:
```
def sharpe_ratio_loss(weights, returns, cov_matrix):
    expected_return = torch.dot(weights, returns)
    portfolio_var = weights.unsqueeze(0) @ cov_matrix @ weights.unsqueeze(1)
    portfolio_std = torch.sqrt(portfolio_var + 1e-8).squeeze()
    sharpe = expected_return / (portfolio_std + 1e-8)
    return -sharpe
```

3 Training Loop

[31]:
```
epochs = 40
batch_size = best_config['batch_size']
seq_len = 30

model = PortfolioNet(best_config, input_dim=len(features), tickers=tickers).
 ↪to(device)
optimizer = torch.optim.Adam(
    [
```

```
        {'params': model.lstm_encoder.parameters(), 'weight_decay': best_config['lstm_weight_decay']},
        {'params': model.gat_encoder.parameters(), 'weight_decay': best_config['gat_weight_decay']},
        {'params': model.final_layer.parameters(), 'weight_decay': best_config.get('final_weight_decay', 0.0)}
    ],
    lr=best_config['learning_rate']
)

date2idx = {d: i for i, d in enumerate(dates)}
train_indices = [date2idx[d] for d in train_dates]

for epoch in range(epochs):
    total_loss = 0.0
    train_points = train_indices[seq_len:-1]
    random.shuffle(train_points)
    num_batches = len(train_points) // batch_size
    if len(train_points) % batch_size != 0:
        num_batches += 1

    progress_bar = tqdm(range(num_batches), desc=f"Epoch {epoch+1}/{epochs}")
    for batch_idx in progress_bar:
        start_idx = batch_idx * batch_size
        end_idx = min(start_idx + batch_size, len(train_points))
        batch_indices = train_points[start_idx:end_idx]
        stock_embeddings_batch = []
        future_returns_batch = []
        past_returns_batch = []

        for t in batch_indices:
            seq_batch = []
            future_returns = []
            skip_flag = False
            for stock in tickers:
                df = all_data[stock]
                if t - seq_len < 0 or t + 1 >= len(df):
                    skip_flag = True
                    break
                seq = df[features].iloc[t-seq_len:t]
                seq = scalers[stock].transform(seq)
                seq_batch.append(seq)
                future_returns.append(df['log_return'].iloc[t+1])
            if skip_flag: continue

            stock_embeddings_batch.append(torch.tensor(seq_batch, dtype=torch.float32, device=device)) # shape: [N_stocks, seq_len, feature_dim]
```

```
            future_returns_batch.append(torch.tensor(future_returns,␣
↪dtype=torch.float32, device=device))
            window = min(20, t)
            past_returns = np.array([
                all_data[stock]['log_return'].iloc[t-window:t].values
                for stock in tickers
            ])
            past_returns_batch.append(torch.tensor(np.cov(past_returns) +␣
↪1e-6*np.eye(len(tickers)), dtype=torch.float32, device=device))

        if len(stock_embeddings_batch) == 0: continue

        x_t_batch = torch.stack(stock_embeddings_batch).to(device)
        future_returns_tensor = torch.stack(future_returns_batch).to(device)
        cov_matrices_tensor = torch.stack(past_returns_batch).to(device)

        batch_loss = 0.0
        for i in range(x_t_batch.shape[0]):
            norm_weights = model(
                x_t_batch[i],
                edge_index.to(device),
                edge_attr.to(device)
            )

            loss = sharpe_ratio_loss(norm_weights, future_returns_tensor[i],␣
↪cov_matrices_tensor[i])
            batch_loss += loss

        avg_batch_loss = batch_loss / x_t_batch.shape[0]
        optimizer.zero_grad()
        avg_batch_loss.backward()
        optimizer.step()
        total_loss += avg_batch_loss.item()
        progress_bar.set_postfix(loss=avg_batch_loss.item())

    avg_epoch_loss = total_loss / num_batches
    print(f"Epoch {epoch+1} | Avg Loss: {avg_epoch_loss:.6f}")

print("Training Finished.")
```

```
Epoch 1/40: 100%|      | 23/23 [00:13<00:00,  1.66it/s, loss=-0.0493]

Epoch 1 | Avg Loss: -0.075298

Epoch 2/40: 100%|      | 23/23 [00:13<00:00,  1.75it/s, loss=0.0307]

Epoch 2 | Avg Loss: -0.083032

Epoch 3/40: 100%|      | 23/23 [00:13<00:00,  1.74it/s, loss=-0.00845]
```

```
Epoch 3 | Avg Loss: -0.087446
Epoch 4/40: 100%|     | 23/23 [00:14<00:00,  1.62it/s, loss=0.0854]
Epoch 4 | Avg Loss: -0.089805
Epoch 5/40: 100%|     | 23/23 [00:12<00:00,  1.83it/s, loss=0.0176]
Epoch 5 | Avg Loss: -0.081379
Epoch 6/40: 100%|     | 23/23 [00:12<00:00,  1.83it/s, loss=-0.0494]
Epoch 6 | Avg Loss: -0.093752
Epoch 7/40: 100%|     | 23/23 [00:13<00:00,  1.76it/s, loss=-0.0218]
Epoch 7 | Avg Loss: -0.098699
Epoch 8/40: 100%|     | 23/23 [00:12<00:00,  1.88it/s, loss=0.0124]
Epoch 8 | Avg Loss: -0.101888
Epoch 9/40: 100%|     | 23/23 [00:12<00:00,  1.83it/s, loss=-0.0393]
Epoch 9 | Avg Loss: -0.106376
Epoch 10/40: 100%|     | 23/23 [00:12<00:00,  1.82it/s, loss=-0.0935]
Epoch 10 | Avg Loss: -0.105222
Epoch 11/40: 100%|     | 23/23 [00:12<00:00,  1.83it/s, loss=-0.146]
Epoch 11 | Avg Loss: -0.085354
Epoch 12/40: 100%|     | 23/23 [00:12<00:00,  1.83it/s, loss=-0.198]
Epoch 12 | Avg Loss: -0.086997
Epoch 13/40: 100%|     | 23/23 [00:12<00:00,  1.82it/s, loss=-0.0247]
Epoch 13 | Avg Loss: -0.083436
Epoch 14/40: 100%|     | 23/23 [00:12<00:00,  1.81it/s, loss=-0.0377]
Epoch 14 | Avg Loss: -0.087027
Epoch 15/40: 100%|     | 23/23 [00:12<00:00,  1.83it/s, loss=-0.000716]
Epoch 15 | Avg Loss: -0.107512
Epoch 16/40: 100%|     | 23/23 [00:12<00:00,  1.84it/s, loss=0.0509]
Epoch 16 | Avg Loss: -0.096568
Epoch 17/40: 100%|     | 23/23 [00:12<00:00,  1.85it/s, loss=-0.167]
Epoch 17 | Avg Loss: -0.086324
Epoch 18/40: 100%|     | 23/23 [00:12<00:00,  1.80it/s, loss=-0.419]
Epoch 18 | Avg Loss: -0.071686
Epoch 19/40: 100%|     | 23/23 [00:12<00:00,  1.85it/s, loss=-0.194]
```

```
Epoch 19 | Avg Loss: -0.080709
Epoch 20/40: 100%|     | 23/23 [00:12<00:00,  1.87it/s, loss=-0.112]
Epoch 20 | Avg Loss: -0.074076
Epoch 21/40: 100%|     | 23/23 [00:11<00:00,  1.94it/s, loss=-0.296]
Epoch 21 | Avg Loss: -0.097865
Epoch 22/40: 100%|     | 23/23 [00:11<00:00,  1.93it/s, loss=0.0388]
Epoch 22 | Avg Loss: -0.067713
Epoch 23/40: 100%|     | 23/23 [00:11<00:00,  1.93it/s, loss=0.0993]
Epoch 23 | Avg Loss: -0.111311
Epoch 24/40: 100%|     | 23/23 [00:11<00:00,  1.95it/s, loss=-0.238]
Epoch 24 | Avg Loss: -0.096847
Epoch 25/40: 100%|     | 23/23 [00:11<00:00,  1.96it/s, loss=-0.482]
Epoch 25 | Avg Loss: -0.088260
Epoch 26/40: 100%|     | 23/23 [00:11<00:00,  1.93it/s, loss=0.0222]
Epoch 26 | Avg Loss: -0.074545
Epoch 27/40: 100%|     | 23/23 [00:11<00:00,  1.95it/s, loss=0.168]
Epoch 27 | Avg Loss: -0.020951
Epoch 28/40: 100%|     | 23/23 [00:11<00:00,  1.94it/s, loss=0.181]
Epoch 28 | Avg Loss: -0.043791
Epoch 29/40: 100%|     | 23/23 [00:11<00:00,  1.96it/s, loss=-0.0559]
Epoch 29 | Avg Loss: -0.050319
Epoch 30/40: 100%|     | 23/23 [00:11<00:00,  1.94it/s, loss=-0.0792]
Epoch 30 | Avg Loss: -0.060616
Epoch 31/40: 100%|     | 23/23 [00:11<00:00,  1.95it/s, loss=0.184]
Epoch 31 | Avg Loss: -0.042398
Epoch 32/40: 100%|     | 23/23 [00:11<00:00,  1.95it/s, loss=-0.202]
Epoch 32 | Avg Loss: -0.074784
Epoch 33/40: 100%|     | 23/23 [00:11<00:00,  1.94it/s, loss=-0.36]
Epoch 33 | Avg Loss: -0.046440
Epoch 34/40: 100%|     | 23/23 [00:11<00:00,  1.95it/s, loss=-0.0185]
Epoch 34 | Avg Loss: -0.051148
Epoch 35/40: 100%|     | 23/23 [00:13<00:00,  1.76it/s, loss=-0.138]
```

```
Epoch 35 | Avg Loss: -0.058341

Epoch 36/40: 100%|      | 23/23 [00:12<00:00,  1.77it/s, loss=-0.364]

Epoch 36 | Avg Loss: -0.088314

Epoch 37/40: 100%|      | 23/23 [00:12<00:00,  1.78it/s, loss=-0.263]

Epoch 37 | Avg Loss: -0.069740

Epoch 38/40: 100%|      | 23/23 [00:12<00:00,  1.80it/s, loss=-0.0178]

Epoch 38 | Avg Loss: -0.085739

Epoch 39/40: 100%|      | 23/23 [00:12<00:00,  1.87it/s, loss=-0.0115]

Epoch 39 | Avg Loss: -0.095133

Epoch 40/40: 100%|      | 23/23 [00:11<00:00,  1.95it/s, loss=0.202]

Epoch 40 | Avg Loss: -0.098147
Training Finished.
```

[32]:

```
# Save
torch.save(model.state_dict(), "best_portfolio_model_v3.pth")

# Load
model.load_state_dict(torch.load("best_portfolio_model_v3.pth"))
model.eval()
print("Model is saved and reload.")
```

```
Model is saved and reload.
```

4 Start Testing

[33]:

```
test_indices = [date2idx[d] for d in test_dates]
test_points = test_indices[seq_len:-1]

weights_all_days = []
test_dates_list = []

num_batches = len(test_points) // batch_size
if len(test_points) % batch_size != 0:
    num_batches += 1

for batch_idx in tqdm(range(num_batches), desc="Predicting (test set)"):
    start_idx = batch_idx * batch_size
    end_idx = min(start_idx + batch_size, len(test_points))
    batch_indices = test_points[start_idx:end_idx]

    stock_embeddings_batch = []
```

```
    for t in batch_indices:
        seq_batch = []
        skip_flag = False
        for stock in tickers:
            df = all_data[stock]
            if t - seq_len < 0 or t + 1 >= len(df):
                skip_flag = True
                break
            seq = df[features].iloc[t-seq_len:t]
            seq = scalers[stock].transform(seq)
            seq_batch.append(seq)
        if skip_flag: continue
        stock_embeddings_batch.append(torch.tensor(seq_batch, dtype=torch.
↪float32, device=device))
        test_dates_list.append(dates[t])


    if len(stock_embeddings_batch) == 0: continue
    x_t_batch = torch.stack(stock_embeddings_batch).to(device)
    for i in range(x_t_batch.shape[0]):
        x_t = x_t_batch[i]
        with torch.no_grad():
            norm_weights = model(
                x_t,
                edge_index.to(device),
                edge_attr.to(device)
            )
        weights_all_days.append(norm_weights.cpu().numpy())

weights_df = pd.DataFrame(weights_all_days, columns=tickers)
weights_df['date'] = test_dates_list
weights_df.to_csv("Result/predicted_weights_v3.csv", index=False)
print("File path: Result/predicted_weights_v3.csv")
```

```
Predicting (test set): 100%|      | 10/10 [00:02<00:00,  4.83it/s]

File path: Result/predicted_weights_v3.csv
```

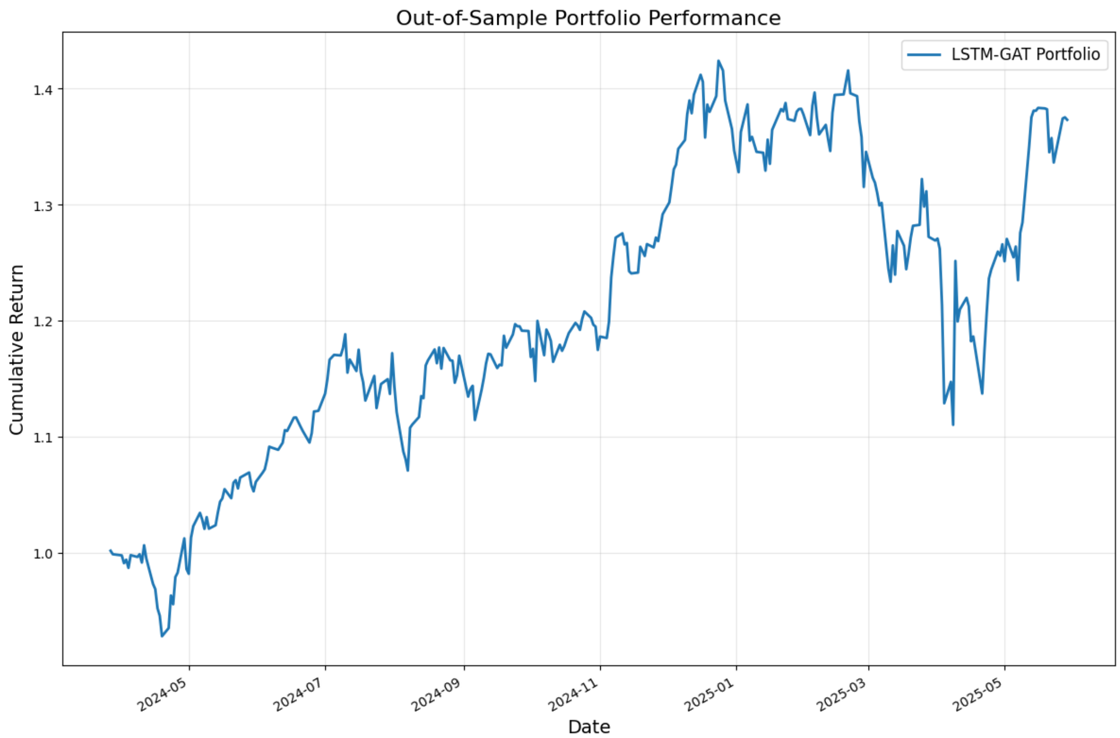
[34]:

```
# Build DataFrame
test_price_data = pd.DataFrame({'date': test_dates_list})
for stock in tickers:
    prices = []
    for d in test_dates_list:
        idx = date2idx[d]
        prices.append(all_data[stock].iloc[idx]['close'])
```

```python
    test_price_data[stock] = prices

# Calculate Daily Return
returns = test_price_data[tickers].pct_change().dropna().reset_index(drop=True)
weights = weights_df[tickers].iloc[:-1].reset_index(drop=True)

# Portfolio returns and equal-weight return
portfolio_returns = (returns.values * weights.values).sum(axis=1)
equal_weights = np.ones(len(tickers)) / len(tickers)
equal_returns = (returns.values * equal_weights).sum(axis=1)

# Cumulative return
cumulative_portfolio = (1 + portfolio_returns).cumprod()
cumulative_equal = (1 + equal_returns).cumprod()

import numpy as np
cumulative_return = cumulative_portfolio[-1] - 1
mean_ret = np.mean(portfolio_returns)
std_ret  = np.std(portfolio_returns, ddof=1)
sharpe_ratio = mean_ret / std_ret * np.sqrt(252)
```

[35]:

```python
# Visualize
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

plot_dates = pd.to_datetime(test_price_data['date'].iloc[1:])

plt.figure(figsize=(12, 8))
plt.plot(plot_dates, cumulative_portfolio, label='LSTM-GAT Portfolio',␣
 ↪linewidth=2)
plt.title('Out-of-Sample Portfolio Performance', fontsize=16)
plt.xlabel('Date', fontsize=14)
plt.ylabel('Cumulative Return', fontsize=14)
plt.legend(fontsize=12)
plt.grid(True, alpha=0.3)
plt.gca().xaxis.set_major_locator(mdates.AutoDateLocator())
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m'))
plt.gcf().autofmt_xdate()
plt.tight_layout()
plt.savefig('out_of_sample_performance.png', dpi=300)
plt.show()
```

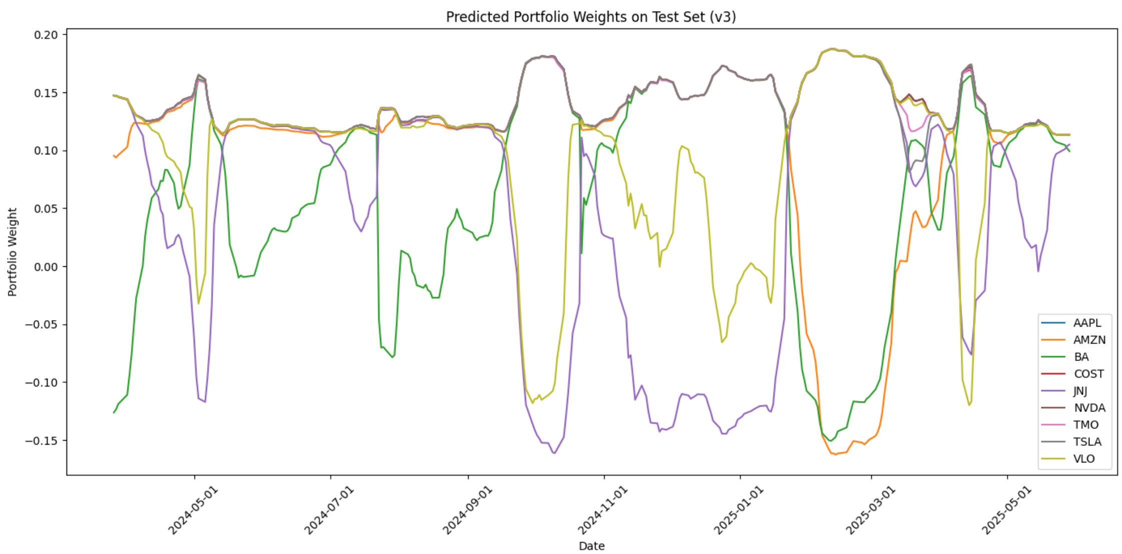


[36]:
```
# Load DataFrame
result_df = pd.DataFrame({
    'date': plot_dates,
    'lstm_gat_return': portfolio_returns,
    'lstm_gat_cum_return': cumulative_portfolio,
    'equal_weight_return': equal_returns,
    'equal_weight_cum_return': cumulative_equal
})

result_df.to_csv('Result/portfolio_returns_v3.csv', index=False)
print("File path: Result/portfolio_returns_v3.csv")
```

```
File path: Result/portfolio_returns_v3.csv
```

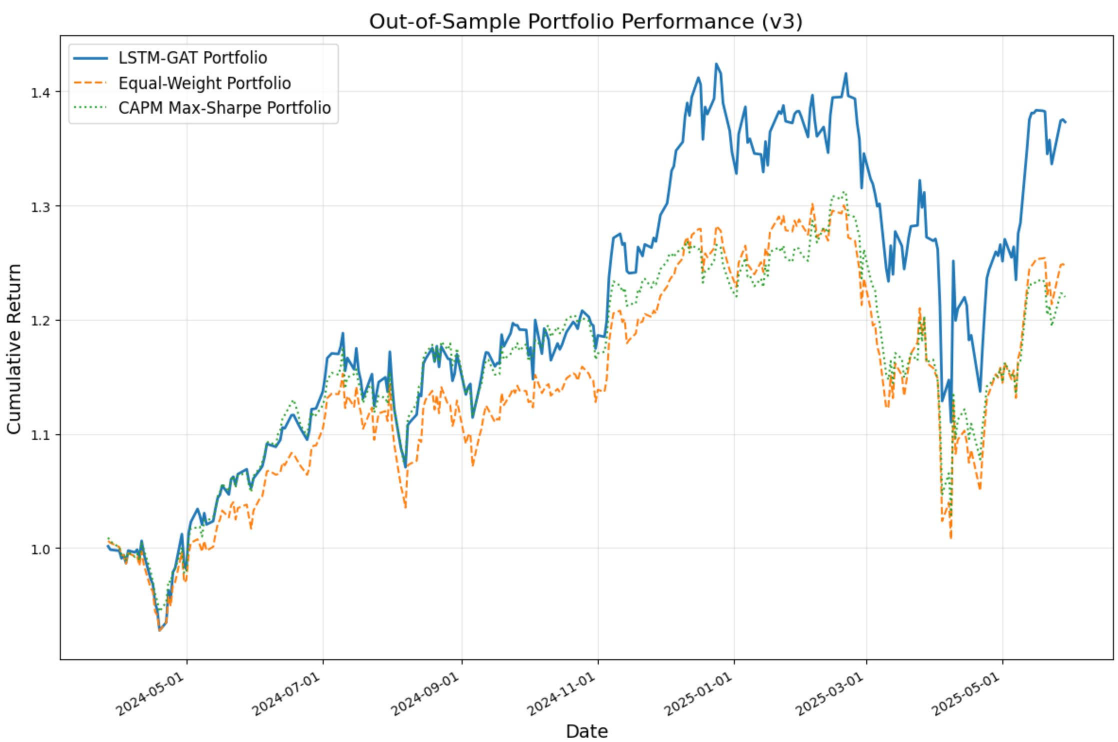
[37]:
```
capm_df = (
    pd.read_csv("Result/capm_cumulative_returns.csv",
                parse_dates=["date"])
      .rename(columns={"cumulative_return": "capm_cumulative"})
)

capm_df = capm_df[capm_df["date"].between(
    test_price_data['date'].iloc[1],
    test_price_data['date'].iloc[-1])]
```

[38]:
```
import matplotlib.pyplot as plt
import matplotlib.dates as mdates  # For formatting date ticks

plt.figure(figsize=(14, 7))
weights_df['date'] = pd.to_datetime(weights_df['date'])

# Plot portfolio weights
for stock in tickers:
    plt.plot(weights_df['date'], weights_df[stock], label=stock)


plt.gca().xaxis.set_major_locator(mdates.AutoDateLocator())
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
plt.xticks(rotation=45)  # Rotate labels for readability

plt.xlabel('Date')
plt.ylabel('Portfolio Weight')
plt.title('Predicted Portfolio Weights on Test Set (v3)')
plt.legend()

plt.tight_layout()
plt.show()
```



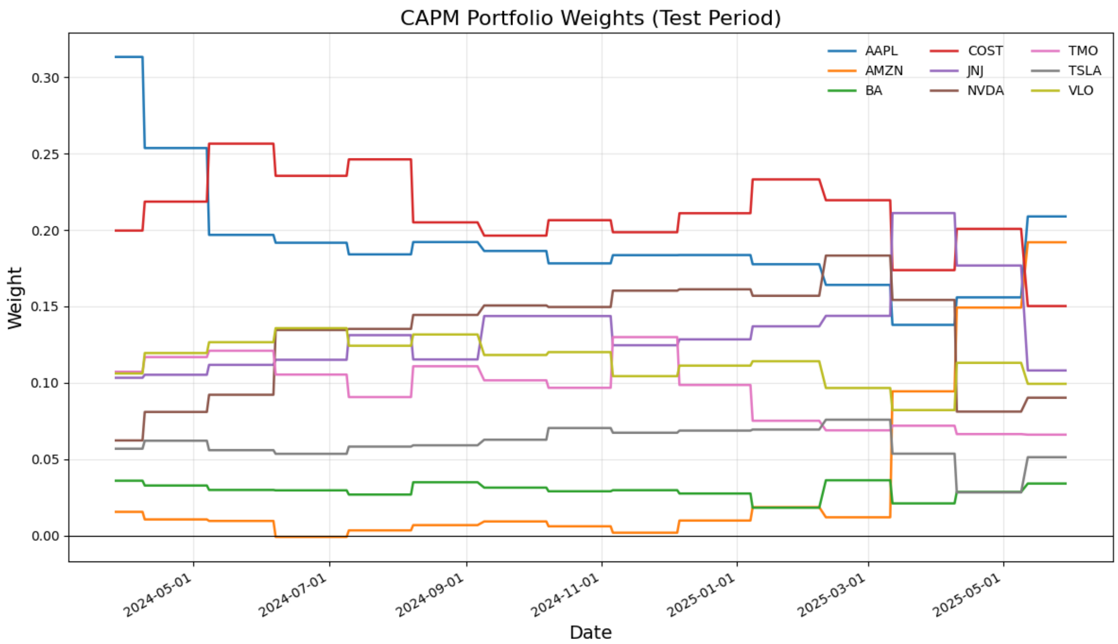
[39]:
```
plt.figure(figsize=(12, 8))

plt.plot(plot_dates, cumulative_portfolio,
         label='LSTM-GAT Portfolio', linewidth=2)
plt.plot(plot_dates, cumulative_equal,
```

```
        label='Equal-Weight Portfolio', linestyle='--')


plt.plot(capm_df['date'], capm_df['capm_cumulative'],
         label='CAPM Max-Sharpe Portfolio', linestyle=':')

plt.title('Out-of-Sample Portfolio Performance (v3)', fontsize=16)
plt.xlabel('Date', fontsize=14)
plt.ylabel('Cumulative Return', fontsize=14)
plt.legend(fontsize=12)
plt.grid(True, alpha=0.3)
plt.gca().xaxis.set_major_locator(mdates.AutoDateLocator())
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
plt.gcf().autofmt_xdate()
plt.tight_layout()

plt.savefig('Result/V3_out_of_sample_performance_with_capm.png', dpi=300)
plt.show()
```



5 CAPM-MVO Result

[40]:
```python
capm_weights_df = (
    pd.read_csv("Result/capm_daily_weights.csv", parse_dates=["date"])
      .sort_values("date")
)



TICKERS = ["AAPL", "AMZN", "BA", "COST", "JNJ", "NVDA", "TMO", "TSLA", "VLO"]

import matplotlib.pyplot as plt
import matplotlib.dates as mdates

plt.figure(figsize=(12, 7))

for stk in TICKERS:
    plt.plot(capm_weights_df["date"],
             capm_weights_df[stk],
             label=stk, linewidth=1.8)

plt.title("CAPM Portfolio Weights (Test Period)", fontsize=16)
plt.xlabel("Date",  fontsize=14)
plt.ylabel("Weight", fontsize=14)
plt.axhline(0, color="black", linewidth=0.8)
plt.gca().xaxis.set_major_locator(mdates.AutoDateLocator())
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
plt.gcf().autofmt_xdate()

plt.grid(alpha=0.3)
plt.legend(ncol=3, fontsize=10, frameon=False)
plt.tight_layout()
plt.savefig("Result/capm_weight_paths.png", dpi=300)
plt.show()
```



6 Evaluation

[41]:
```
import numpy as np
import pandas as pd

def calculate_metrics(returns, var_conf_level=0.95):
    returns = pd.Series(returns)
    cumulative = (1 + returns).cumprod()
    total_return = cumulative.iloc[-1] - 1
    annualized_return = (1 + total_return) ** (252 / len(returns)) - 1
    volatility = returns.std() * np.sqrt(252)
    sharpe_ratio = annualized_return / volatility if volatility > 0 else 0
    max_drawdown = (cumulative / cumulative.cummax() - 1).min()

    # Historical Value at Risk (e.g., 5% worst return)
    var_percentile = 100 * (1 - var_conf_level)
    value_at_risk = -np.percentile(returns, var_percentile)

    return total_return, annualized_return, volatility, sharpe_ratio,␣
 ↪max_drawdown, value_at_risk

port_metrics = calculate_metrics(portfolio_returns)
equal_metrics = calculate_metrics(equal_returns)
capm_df = pd.read_csv('Result/capm_daily_returns.csv')
capm_returns = capm_df['daily_return'].values[1:]
```

```python
capm_metrics = calculate_metrics(np.exp(capm_returns) - 1)
```

[42]:

```python
print("\n" + "="*80)
print("Out-of-Sample Performance Comparison (Test Period)")
print("="*80)
print(f"{'Metric':<20}{'LSTM-GAT (v3)':>20}{'Equal-Weight':>20}{'CAPM':>20}")
print(f"{'Total Return':<20}{port_metrics[0]:>20.6%}{equal_metrics[0]:>20.
↪6%}{capm_metrics[0]:>20.6%}")
print(f"{'Annualized Return':<20}{port_metrics[1]:>20.6%}{equal_metrics[1]:>20.
↪6%}{capm_metrics[1]:>20.6%}")
print(f"{'Volatility':<20}{port_metrics[2]:>20.6%}{equal_metrics[2]:>20.
↪6%}{capm_metrics[2]:>20.6%}")
print(f"{'Sharpe Ratio':<20}{port_metrics[3]:>20.6f}{equal_metrics[3]:>20.
↪6f}{capm_metrics[3]:>20.6f}")
print(f"{'VaR (95%)':<20}{port_metrics[5]:>20.6%}{equal_metrics[5]:>20.
↪6%}{capm_metrics[5]:>20.6%}")
print(f"{'Max Drawdown':<20}{port_metrics[4]:>20.6%}{equal_metrics[4]:>20.
↪6%}{capm_metrics[4]:>20.6%}")
print("="*80)
```

```
================================================================================
Out-of-Sample Performance Comparison (Test Period)
================================================================================
Metric                     LSTM-GAT (v3)        Equal-Weight                CAPM
Total Return                  37.315090%          24.731242%          24.340720%
Annualized Return             31.233354%          20.854965%          20.607402%
Volatility                    27.189590%          24.890545%          22.234806%
Sharpe Ratio                    1.148725            0.837867            0.926808
VaR (95%)                      2.526716%           2.526864%           2.022031%
Max Drawdown                 -22.051718%         -22.604449%         -21.032717%
================================================================================
```