Model Training and Evaluating it

Wednesday 10th December, 2025

Description: This notebook creates various models and evaulates them as needed.

```
#Setting everything up
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import sys

from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
from statsmodels.tsa.arima.model import ARIMA
import tensorflow as tf
from tensorflow.keras import layers, models

sys.path.append(os.path.abspath(os.path.join('..')))
from scripts.data_process import make_supervised_frame, time_series_split
from scripts.data_modeling import compute_regression_metrics, directional_accuracy, make_lst

np.random.seed(42)
tf.random.set_seed(42)
plt.rcParams["figure.figsize"] = (10, 5)
plt.rcParams["axes.grid"] = True
```

```
2025 -12 -10 01:00:04.138126: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:31] Could not
2025 -12 -10 01:00:04.138576: I tensorflow/core/util/port.cc:153] oneDNN custom operations a
2025 -12 -10 01:00:04.199951: I tensorflow/core/platform/cpu_feature_guard.cc:210] This Tens
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other operations, reb

2025 -12 -10 01:00:06.801074: I tensorflow/core/util/port.cc:153] oneDNN custom operations a
2025 -12 -10 01:00:06.802886: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:31] Could not
```

```
#Loading data
df = pd.read_csv("../data/sp500.csv", index_col = "Date", parse_dates = True)

df_sup = make_supervised_frame(df, target_col="LogReturn", horizon=1, lags=3)

df_sup.head()
```

	Close	High	Low	Open	Volume	MA10	MA50	EMA10	EMA50	Return	LogReturn	Volatility20	Momentum10	MACD	MACD_signal	y	LogReturn_lag1	LogReturn_lag2	LogReturn_lag3
Date																			
1990-03-13	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1990-03-14	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1990-03-15	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1990-03-16	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1990-03-19	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

```
df_train, df_val, df_test = time_series_split(df_sup, train_frac=0.6, val_frac=0.2)

feature_cols = [c for c in df_sup.columns if c !=["y"]]

X_train, y_train = df_train[feature_cols], df_train["y"]
X_val, y_val = df_val[feature_cols], df_val["y"]
X_test, y_test = df_test[feature_cols], df_test["y"]

print("Train size:", len(X_train))
print("Val size:", len(X_val))
print("Test size:", len(X_test))
```

```
Train size: 5401
Val size: 1800
Test size: 1801
```

```
#baseline
y_test_naive = df_test["LogReturn_lag1"]
```

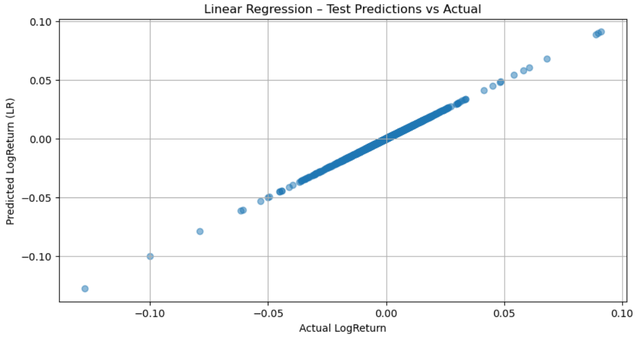
```
baseline_metrics = compute_regression_metrics(y_test, y_test_naive)
baseline_dir_acc = directional_accuracy(y_test, y_test_naive)

print("Naive baseline metrics:", baseline_metrics)
print("Naive baseline directional accuracy:", baseline_dir_acc)
```

```
Naive baseline metrics: {'RMSE': np.float64(0.016940516181126818), 'MAE': 0.0116095086299034
Naive baseline directional accuracy: 0.5091615769017213
```

```
# Linear Regression
linreg = LinearRegression()
linreg.fit(X_train, y_train)

y_val_lr = linreg.predict(X_val)
y_test_lr = linreg.predict(X_test)

lr_val_metrics = compute_regression_metrics(y_val, y_val_lr)
lr_test_metrics = compute_regression_metrics(y_test, y_test_lr)
lr_dir_acc = directional_accuracy(y_test, y_test_lr)

print("Linear Regression - Validation Metrics:", lr_val_metrics)
print("Linear Regression - Test Metrics:", lr_test_metrics)
print(f"Linear Regression - Directional Accuracy: {lr_dir_acc:.2%}")
```

```
Linear Regression - Validation Metrics: {'RMSE': np.float64(7.178125137080271e -08), 'MAE':
Linear Regression - Test Metrics: {'RMSE': np.float64(1.9145641052797167e -07), 'MAE': 1.41
Linear Regression - Directional Accuracy: 100.00%
```

```
plt.scatter(y_test, y_test_lr, alpha=0.5)
plt.xlabel("Actual LogReturn")
plt.ylabel("Predicted LogReturn (LR)")
plt.title("Linear Regression - Test Predictions vs Actual")
plt.savefig("../images/LR.png")
plt.show()
```



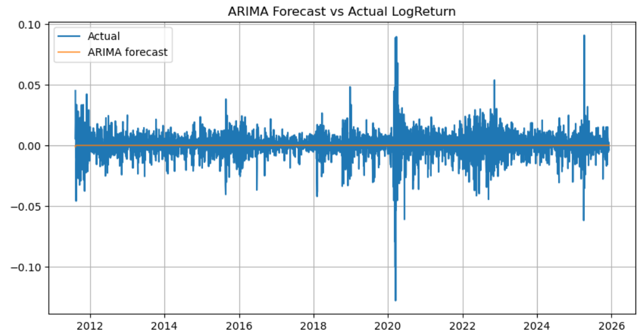
```
rf = RandomForestRegressor(n_estimators=200, max_depth=None, random_state=42)
rf.fit(X_train, y_train)

y_val_rf = rf.predict(X_val)
y_test_rf = rf.predict(X_test)

rf_val_metrics = compute_regression_metrics(y_val, y_val_rf)
rf_test_metrics = compute_regression_metrics(y_test, y_test_rf)
rf_dir_acc = directional_accuracy(y_test, y_test_rf)

print("Random Forest - validation metrics:", rf_val_metrics)
print("Random Forest - test metrics:", rf_test_metrics)
print("Random Forest - test directional accuracy:", rf_dir_acc)
```

```
Random Forest - validation metrics: {'RMSE': np.float64(3.989333611068483e -05), 'MAE': 8.73
Random Forest - test metrics: {'RMSE': np.float64(0.0011719469383807014), 'MAE': 8.215782319
Random Forest - test directional accuracy: 0.9994447529150472
```

```
# 10. ARIMA baseline (simplified, univariate)


# We'll model LogReturn as a univariate series
logret_series = df["LogReturn"].dropna()

# Align with df_sup range (so we're forecasting over the same overall period)
logret_aligned = logret_series.loc[df_sup.index]

train_end_idx = df_train.index[ -1]
val_end_idx = df_val.index[ -1]

logret_train = logret_aligned.loc[:train_end_idx]
logret_val = logret_aligned.loc[train_end_idx:val_end_idx]
logret_test = logret_aligned.loc[val_end_idx:]

# Fit a simple ARIMA(1,0,1) on the training portion
arima_model = ARIMA(logret_train, order=(1, 0, 1))
arima_result = arima_model.fit()

# Forecast over validation + test window
n_forecast = len(logret_val) + len(logret_test)
arima_forecast = arima_result.forecast(steps=n_forecast)

# Take the last n_forecast actual values to compare against
logret_val_test = logret_aligned.iloc[ -n_forecast:]

# - - - Clean and align for metrics (avoid NaNs) - - -
```

```
# Put both into arrays
y_true = logret_val_test.to_numpy()
y_pred = np.asarray(arima_forecast)

# In case lengths differ for any reason, clip to the shorter one
min_len = min(len(y_true), len(y_pred))
y_true = y_true[:min_len]
y_pred = y_pred[:min_len]

# Drop any NaNs that might still be present
mask = (~np.isnan(y_true)) & (~np.isnan(y_pred))
y_true_clean = y_true[mask]
y_pred_clean = y_pred[mask]

# Compute metrics
arima_metrics = compute_regression_metrics(y_true_clean, y_pred_clean)
arima_dir_acc = directional_accuracy(y_true_clean, y_pred_clean)

print("ARIMA metrics (val+test window):", arima_metrics)
print("ARIMA directional accuracy:", arima_dir_acc)

# Plot actual vs forecast on the same time index
plot_index = logret_val_test.index[:len(y_true_clean)]
plt.plot(plot_index, y_true_clean, label="Actual")
plt.plot(plot_index, y_pred_clean, label="ARIMA forecast", alpha=0.7)
plt.legend()
plt.title("ARIMA Forecast vs Actual LogReturn")
plt.savefig("../images/ARIMA.png")
plt.show()
```

```
/home/jovyan/.local/share/envs/final -group13/lib/python3.10/site -packages/statsmodels/tsa/
  self._init_dates(dates, freq)
/home/jovyan/.local/share/envs/final -group13/lib/python3.10/site -packages/statsmodels/tsa/
  self._init_dates(dates, freq)
/home/jovyan/.local/share/envs/final -group13/lib/python3.10/site -packages/statsmodels/tsa/
  self._init_dates(dates, freq)

/home/jovyan/.local/share/envs/final -group13/lib/python3.10/site -packages/statsmodels/tsa/
  return get_prediction_index(
/home/jovyan/.local/share/envs/final -group13/lib/python3.10/site -packages/statsmodels/tsa/
  return get_prediction_index(

ARIMA metrics (val+test window): {'RMSE': np.float64(0.010885095016858535), 'MAE': 0.007145
ARIMA directional accuracy: 0.5456563974465723
```




```
#LTSM Data Prep
tf.random.set_seed(42)
scaler = StandardScaler()
X_train_sc = scaler.fit_transform(X_train)
X_val_sc = scaler.transform(X_val)
X_test_sc = scaler.transform(X_test)

SEQ_LEN = 30
X_train_lstm, y_train_lstm = make_lstm_sequences(X_train_sc, y_train.values, SEQ_LEN)
X_val_lstm, y_val_lstm = make_lstm_sequences(X_val_sc, y_val.values, SEQ_LEN)
X_test_lstm, y_test_lstm = make_lstm_sequences(X_test_sc, y_test.values, SEQ_LEN)

#LTSM Build
model = models.Sequential([
    layers.Input(shape=(X_train_lstm.shape[1], X_train_lstm.shape[2])),
    layers.LSTM(32, return_sequences=False),
    layers.Dropout(0.2),
    layers.Dense(16, activation='relu'),
    layers.Dense(1)
])

model.compile(optimizer='adam', loss='mse')

history = model.fit(
    X_train_lstm, y_train_lstm,
    validation_data=(X_val_lstm, y_val_lstm),
    epochs=15,
    batch_size=32,
    verbose=1
)

plt.figure()
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('LSTM Training Loss')
```

```
plt.legend()
plt.savefig("../images/lstm_training_curve.png")
plt.show()
```

```
Epoch 1/15

2025 -12 -10 01:00:27.758075: E external/local_xla/xla/stream_executor/cuda/cuda_platform.cc

1/168            4:18 2s/step - loss: 0.0659


  6/168            1s 10ms/step - loss: 0.0519


 12/168            1s 10ms/step - loss: 0.0434


 18/168            1s 10ms/step - loss: 0.0383


 24/168            1s 9ms/step - loss: 0.0349


 30/168            1s 9ms/step - loss: 0.0322


 36/168            1s 9ms/step - loss: 0.0301


 42/168            1s 9ms/step - loss: 0.0284


 48/168            1s 9ms/step - loss: 0.0269


 54/168            1s 9ms/step - loss: 0.0257


 60/168            0s 9ms/step - loss: 0.0246


 66/168            0s 9ms/step - loss: 0.0236


 72/168            0s 9ms/step - loss: 0.0227


 78/168            0s 9ms/step - loss: 0.0219
```

```
 84/168            0s 9ms/step - loss: 0.0212

 90/168            0s 9ms/step - loss: 0.0205

 96/168            0s 9ms/step - loss: 0.0199

102/168            0s 9ms/step - loss: 0.0193

108/168            0s 9ms/step - loss: 0.0188

114/168            0s 9ms/step - loss: 0.0183

120/168            0s 9ms/step - loss: 0.0179

126/168            0s 9ms/step - loss: 0.0174

132/168            0s 9ms/step - loss: 0.0170

138/168            0s 9ms/step - loss: 0.0166

144/168            0s 9ms/step - loss: 0.0163

150/168            0s 9ms/step - loss: 0.0159

157/168            0s 9ms/step - loss: 0.0156

163/168            0s 9ms/step - loss: 0.0153

168/168            4s 12ms/step - loss: 0.0071 - val_loss: 2.7630e -04
Epoch 2/15
1/168            4s 28ms/step - loss: 0.0015
```

```
  7/168            1s 9ms/step - loss: 0.0020

 13/168            1s 9ms/step - loss: 0.0020

 19/168            1s 9ms/step - loss: 0.0020

 25/168            1s 9ms/step - loss: 0.0019

 31/168            1s 9ms/step - loss: 0.0019

 37/168            1s 9ms/step - loss: 0.0018

 43/168            1s 9ms/step - loss: 0.0018

 49/168            1s 9ms/step - loss: 0.0018

 55/168            1s 9ms/step - loss: 0.0018

 61/168            0s 9ms/step - loss: 0.0018

 67/168            0s 9ms/step - loss: 0.0017

 73/168            0s 9ms/step - loss: 0.0017

 79/168            0s 9ms/step - loss: 0.0017

 85/168            0s 9ms/step - loss: 0.0017

 91/168            0s 9ms/step - loss: 0.0017

 97/168            0s 9ms/step - loss: 0.0017

103/168            0s 9ms/step - loss: 0.0016
```

```
109/168              0s 9ms/step - loss: 0.0016

115/168              0s 9ms/step - loss: 0.0016

121/168              0s 9ms/step - loss: 0.0016

127/168              0s 9ms/step - loss: 0.0016

133/168              0s 9ms/step - loss: 0.0016

139/168              0s 9ms/step - loss: 0.0016

145/168              0s 9ms/step - loss: 0.0015

151/168              0s 9ms/step - loss: 0.0015

157/168              0s 9ms/step - loss: 0.0015

163/168              0s 9ms/step - loss: 0.0015

168/168              2s 10ms/step - loss: 0.0011 - val_loss: 1.3414e -04
Epoch 3/15
1/168              5s 30ms/step - loss: 6.7609e -04

  7/168              1s 9ms/step - loss: 7.5495e -04

 13/168              1s 9ms/step - loss: 7.2350e -04

 19/168              1s 9ms/step - loss: 6.9969e -04

 25/168              1s 9ms/step - loss: 6.9050e -04
```

```
 31/168             1s 9ms/step - loss: 6.8531e -04

 37/168             1s 9ms/step - loss: 6.8148e -04

 43/168             1s 9ms/step - loss: 6.7856e -04

 49/168             1s 9ms/step - loss: 6.7763e -04

 55/168             1s 9ms/step - loss: 6.7576e -04

 61/168             0s 9ms/step - loss: 6.7458e -04

 67/168             0s 9ms/step - loss: 6.7229e -04

 73/168             0s 9ms/step - loss: 6.7041e -04

 79/168             0s 9ms/step - loss: 6.6839e -04

 85/168             0s 9ms/step - loss: 6.6559e -04

 91/168             0s 9ms/step - loss: 6.6239e -04

 97/168             0s 9ms/step - loss: 6.5863e -04

103/168             0s 9ms/step - loss: 6.5498e -04

109/168             0s 9ms/step - loss: 6.5124e -04

115/168             0s 9ms/step - loss: 6.4737e -04

121/168             0s 9ms/step - loss: 6.4362e -04

127/168             0s 9ms/step - loss: 6.3986e -04
```

```
133/168             0s 9ms/step - loss: 6.3634e -04

139/168             0s 9ms/step - loss: 6.3279e -04

145/168             0s 9ms/step - loss: 6.2934e -04

151/168             0s 9ms/step - loss: 6.2599e -04

157/168             0s 9ms/step - loss: 6.2266e -04

163/168             0s 9ms/step - loss: 6.1934e -04

168/168             2s 10ms/step - loss: 5.2956e -04 - val_loss: 8.0141e -05
Epoch 4/15
1/168             5s 32ms/step - loss: 4.4027e -04

  7/168             1s 9ms/step - loss: 4.1018e -04

 13/168             1s 9ms/step - loss: 3.9620e -04

 19/168             1s 9ms/step - loss: 3.9031e -04

 25/168             1s 9ms/step - loss: 3.9210e -04

 31/168             1s 9ms/step - loss: 3.9565e -04

 37/168             1s 9ms/step - loss: 3.9872e -04

 43/168             1s 9ms/step - loss: 4.0290e -04

 49/168             1s 9ms/step - loss: 4.0694e -04
```

```
 55/168            1s 9ms/step - loss: 4.1017e -04

 61/168            0s 9ms/step - loss: 4.1593e -04

 67/168            0s 9ms/step - loss: 4.1909e -04

 73/168            0s 9ms/step - loss: 4.2113e -04

 79/168            0s 9ms/step - loss: 4.2290e -04

 85/168            0s 9ms/step - loss: 4.2409e -04

 91/168            0s 9ms/step - loss: 4.2467e -04

 97/168            0s 9ms/step - loss: 4.2449e -04

103/168            0s 9ms/step - loss: 4.2414e -04

109/168            0s 9ms/step - loss: 4.2380e -04

115/168            0s 9ms/step - loss: 4.2334e -04

121/168            0s 9ms/step - loss: 4.2278e -04

127/168            0s 9ms/step - loss: 4.2203e -04

133/168            0s 9ms/step - loss: 4.2110e -04

139/168            0s 9ms/step - loss: 4.2002e -04

145/168            0s 9ms/step - loss: 4.1889e -04

151/168            0s 9ms/step - loss: 4.1767e -04
```

```
157/168             0s 9ms/step - loss: 4.1646e -04

163/168             0s 9ms/step - loss: 4.1521e -04

168/168             2s 11ms/step - loss: 3.7602e -04 - val_loss: 6.9167e -05
Epoch 5/15
1/168             5s 30ms/step - loss: 4.9068e -04

  7/168             1s 9ms/step - loss: 3.1018e -04

 13/168             1s 9ms/step - loss: 2.9280e -04

 19/168             1s 9ms/step - loss: 2.9199e -04

 25/168             1s 9ms/step - loss: 2.8865e -04

 31/168             1s 9ms/step - loss: 2.8467e -04

 37/168             1s 9ms/step - loss: 2.8300e -04

 43/168             1s 9ms/step - loss: 2.8519e -04

 49/168             1s 9ms/step - loss: 2.8850e -04

 55/168             1s 9ms/step - loss: 2.9163e -04

 61/168             0s 9ms/step - loss: 2.9433e -04

 67/168             0s 9ms/step - loss: 2.9620e -04

 73/168             0s 9ms/step - loss: 2.9711e -04
```

```
 79/168          0s 9ms/step - loss: 2.9758e -04

 85/168          0s 9ms/step - loss: 2.9776e -04

 91/168          0s 9ms/step - loss: 2.9754e -04

 97/168          0s 9ms/step - loss: 2.9693e -04

103/168          0s 9ms/step - loss: 2.9628e -04

109/168          0s 9ms/step - loss: 2.9567e -04

115/168          0s 9ms/step - loss: 2.9505e -04

121/168          0s 9ms/step - loss: 2.9451e -04

127/168          0s 9ms/step - loss: 2.9395e -04

133/168          0s 9ms/step - loss: 2.9327e -04

139/168          0s 9ms/step - loss: 2.9265e -04

144/168          0s 9ms/step - loss: 2.9217e -04

150/168          0s 9ms/step - loss: 2.9152e -04

156/168          0s 9ms/step - loss: 2.9088e -04

162/168          0s 9ms/step - loss: 2.9026e -04

168/168          0s 9ms/step - loss: 2.8965e -04

168/168          2s 10ms/step - loss: 2.7244e -04 - val_loss: 6.8015e -05
```

```
Epoch 6/15
1/168           5s 30ms/step - loss: 2.5459e -04
  7/168           1s 9ms/step - loss: 2.3608e -04
 13/168           1s 9ms/step - loss: 2.2994e -04
 19/168           1s 9ms/step - loss: 2.3191e -04
 25/168           1s 9ms/step - loss: 2.3113e -04
 31/168           1s 9ms/step - loss: 2.2987e -04
 37/168           1s 9ms/step - loss: 2.2966e -04
 43/168           1s 9ms/step - loss: 2.2930e -04
 49/168           1s 9ms/step - loss: 2.2900e -04
 55/168           1s 9ms/step - loss: 2.2934e -04
 61/168           0s 9ms/step - loss: 2.2971e -04
 67/168           0s 9ms/step - loss: 2.2983e -04
 73/168           0s 9ms/step - loss: 2.2962e -04
 79/168           0s 9ms/step - loss: 2.2940e -04
 85/168           0s 9ms/step - loss: 2.2920e -04
 91/168           0s 9ms/step - loss: 2.2880e -04
```

```
 97/168            0s 9ms/step - loss: 2.2824e -04

103/168            0s 9ms/step - loss: 2.2771e -04

109/168            0s 9ms/step - loss: 2.2734e -04

115/168            0s 9ms/step - loss: 2.2711e -04

121/168            0s 9ms/step - loss: 2.2699e -04

127/168            0s 9ms/step - loss: 2.2677e -04

133/168            0s 9ms/step - loss: 2.2652e -04

139/168            0s 9ms/step - loss: 2.2623e -04

145/168            0s 9ms/step - loss: 2.2600e -04

151/168            0s 9ms/step - loss: 2.2578e -04

157/168            0s 9ms/step - loss: 2.2555e -04

163/168            0s 9ms/step - loss: 2.2537e -04

168/168            2s 10ms/step - loss: 2.2120e -04 - val_loss: 7.0077e -05
Epoch 7/15
1/168            5s 33ms/step - loss: 2.9188e -04

  6/168            1s 10ms/step - loss: 2.3806e -04

 12/168            1s 9ms/step - loss: 2.3674e -04
```

```
18/168               1s 9ms/step - loss: 2.3599e -04

24/168               1s 9ms/step - loss: 2.3220e -04

30/168               1s 9ms/step - loss: 2.2813e -04

36/168               1s 9ms/step - loss: 2.2600e -04

42/168               1s 9ms/step - loss: 2.2464e -04

48/168               1s 9ms/step - loss: 2.2352e -04

54/168               1s 9ms/step - loss: 2.2263e -04

60/168               0s 9ms/step - loss: 2.2212e -04

66/168               0s 9ms/step - loss: 2.2106e -04

72/168               0s 9ms/step - loss: 2.1992e -04

78/168               0s 9ms/step - loss: 2.1896e -04

84/168               0s 9ms/step - loss: 2.1803e -04

90/168               0s 9ms/step - loss: 2.1706e -04

96/168               0s 9ms/step - loss: 2.1600e -04

102/168              0s 9ms/step - loss: 2.1516e -04

108/168              0s 9ms/step - loss: 2.1454e -04

114/168              0s 9ms/step - loss: 2.1403e -04
```

```
120/168            0s 9ms/step - loss: 2.1367e -04

126/168            0s 9ms/step - loss: 2.1335e -04

132/168            0s 9ms/step - loss: 2.1301e -04

137/168            0s 9ms/step - loss: 2.1270e -04

143/168            0s 9ms/step - loss: 2.1238e -04

149/168            0s 9ms/step - loss: 2.1204e -04

155/168            0s 9ms/step - loss: 2.1168e -04

161/168            0s 9ms/step - loss: 2.1134e -04

167/168            0s 9ms/step - loss: 2.1101e -04

168/168            2s 11ms/step - loss: 2.0142e -04 - val_loss: 7.3925e -05
Epoch 8/15
1/168            5s 30ms/step - loss: 2.5238e -04

  7/168            1s 10ms/step - loss: 1.8993e -04

 13/168            1s 9ms/step - loss: 1.8659e -04

 19/168            1s 9ms/step - loss: 1.8877e -04

 25/168            1s 9ms/step - loss: 1.8877e -04

 31/168            1s 9ms/step - loss: 1.8923e -04
```

```
 37/168            1s 9ms/step - loss: 1.9008e -04

 43/168            1s 9ms/step - loss: 1.9012e -04

 49/168            1s 9ms/step - loss: 1.9001e -04

 55/168            1s 9ms/step - loss: 1.9023e -04

 61/168            0s 9ms/step - loss: 1.9125e -04

 67/168            0s 9ms/step - loss: 1.9170e -04

 73/168            0s 9ms/step - loss: 1.9170e -04

 79/168            0s 9ms/step - loss: 1.9157e -04

 85/168            0s 9ms/step - loss: 1.9143e -04

 91/168            0s 9ms/step - loss: 1.9112e -04

 97/168            0s 9ms/step - loss: 1.9069e -04

103/168            0s 9ms/step - loss: 1.9035e -04

109/168            0s 9ms/step - loss: 1.9016e -04

115/168            0s 9ms/step - loss: 1.9009e -04

121/168            0s 9ms/step - loss: 1.9014e -04

127/168            0s 9ms/step - loss: 1.9018e -04

133/168            0s 9ms/step - loss: 1.9023e -04
```

```
139/168            0s 9ms/step - loss: 1.9022e -04

145/168            0s 9ms/step - loss: 1.9021e -04

151/168            0s 9ms/step - loss: 1.9020e -04

157/168            0s 9ms/step - loss: 1.9019e -04

163/168            0s 9ms/step - loss: 1.9015e -04

168/168            2s 10ms/step - loss: 1.8843e -04 - val_loss: 7.0693e -05
Epoch 9/15
1/168            5s 30ms/step - loss: 3.2748e -04

  7/168            1s 9ms/step - loss: 2.2604e -04

 13/168            1s 9ms/step - loss: 2.0402e -04

 19/168            1s 9ms/step - loss: 1.9686e -04

 25/168            1s 9ms/step - loss: 1.9264e -04

 31/168            1s 9ms/step - loss: 1.8949e -04

 37/168            1s 9ms/step - loss: 1.8783e -04

 43/168            1s 9ms/step - loss: 1.8631e -04

 49/168            1s 9ms/step - loss: 1.8562e -04

 55/168            1s 9ms/step - loss: 1.8567e -04
```

```
 61/168              0s 9ms/step - loss: 1.8569e -04

 67/168              0s 9ms/step - loss: 1.8510e -04

 73/168              0s 9ms/step - loss: 1.8433e -04

 78/168              0s 9ms/step - loss: 1.8369e -04

 84/168              0s 9ms/step - loss: 1.8290e -04

 90/168              0s 9ms/step - loss: 1.8207e -04

 96/168              0s 9ms/step - loss: 1.8128e -04

102/168              0s 9ms/step - loss: 1.8059e -04

108/168              0s 9ms/step - loss: 1.8011e -04

114/168              0s 9ms/step - loss: 1.7975e -04

120/168              0s 9ms/step - loss: 1.7961e -04

126/168              0s 9ms/step - loss: 1.7949e -04

132/168              0s 9ms/step - loss: 1.7934e -04

138/168              0s 9ms/step - loss: 1.7917e -04

144/168              0s 9ms/step - loss: 1.7904e -04

150/168              0s 9ms/step - loss: 1.7888e -04

156/168              0s 9ms/step - loss: 1.7870e -04
```

```
162/168            0s 9ms/step - loss: 1.7857e -04

168/168            0s 9ms/step - loss: 1.7850e -04

168/168            2s 11ms/step - loss: 1.7658e -04 - val_loss: 6.9025e -05
Epoch 10/15
1/168            5s 31ms/step - loss: 2.5594e -04

  7/168            1s 9ms/step - loss: 1.8167e -04

 13/168            1s 9ms/step - loss: 1.7392e -04

 19/168            1s 9ms/step - loss: 1.7335e -04

 25/168            1s 9ms/step - loss: 1.7149e -04

 31/168            1s 9ms/step - loss: 1.7062e -04

 37/168            1s 9ms/step - loss: 1.7073e -04

 43/168            1s 9ms/step - loss: 1.7076e -04

 49/168            1s 9ms/step - loss: 1.7074e -04

 55/168            1s 9ms/step - loss: 1.7107e -04

 61/168            0s 9ms/step - loss: 1.7178e -04

 67/168            0s 9ms/step - loss: 1.7201e -04

 73/168            0s 9ms/step - loss: 1.7191e -04
```

```
 79/168          0s 9ms/step - loss: 1.7172e -04

 85/168          0s 9ms/step - loss: 1.7146e -04

 91/168          0s 9ms/step - loss: 1.7104e -04

 97/168          0s 9ms/step - loss: 1.7057e -04

103/168          0s 9ms/step - loss: 1.7022e -04

109/168          0s 9ms/step - loss: 1.7007e -04

115/168          0s 9ms/step - loss: 1.7015e -04

121/168          0s 9ms/step - loss: 1.7036e -04

127/168          0s 9ms/step - loss: 1.7056e -04

134/168          0s 9ms/step - loss: 1.7067e -04

141/168          0s 9ms/step - loss: 1.7073e -04

147/168          0s 9ms/step - loss: 1.7082e -04

153/168          0s 9ms/step - loss: 1.7087e -04

159/168          0s 9ms/step - loss: 1.7094e -04

165/168          0s 9ms/step - loss: 1.7098e -04

168/168          2s 10ms/step - loss: 1.7079e -04 - val_loss: 6.7987e -05
Epoch 11/15
```

```
  1/168          5s 30ms/step - loss: 3.4878e -04

  7/168          1s 9ms/step - loss: 2.1028e -04

 13/168          1s 9ms/step - loss: 1.8907e -04

 19/168          1s 9ms/step - loss: 1.8030e -04

 25/168          1s 9ms/step - loss: 1.7460e -04

 31/168          1s 9ms/step - loss: 1.7076e -04

 37/168          1s 9ms/step - loss: 1.6925e -04

 43/168          1s 9ms/step - loss: 1.6776e -04

 49/168          1s 9ms/step - loss: 1.6662e -04

 55/168          1s 9ms/step - loss: 1.6605e -04

 61/168          0s 9ms/step - loss: 1.6613e -04

 67/168          0s 9ms/step - loss: 1.6595e -04

 73/168          0s 9ms/step - loss: 1.6565e -04

 79/168          0s 9ms/step - loss: 1.6531e -04

 85/168          0s 9ms/step - loss: 1.6494e -04

 91/168          0s 9ms/step - loss: 1.6446e -04

 97/168          0s 9ms/step - loss: 1.6397e -04
```

```
103/168             0s 9ms/step - loss: 1.6365e -04

109/168             0s 9ms/step - loss: 1.6353e -04

115/168             0s 9ms/step - loss: 1.6359e -04

121/168             0s 9ms/step - loss: 1.6382e -04

127/168             0s 9ms/step - loss: 1.6396e -04

133/168             0s 9ms/step - loss: 1.6404e -04

139/168             0s 9ms/step - loss: 1.6407e -04

145/168             0s 9ms/step - loss: 1.6411e -04

151/168             0s 9ms/step - loss: 1.6411e -04

157/168             0s 9ms/step - loss: 1.6410e -04

163/168             0s 9ms/step - loss: 1.6407e -04

168/168             2s 10ms/step - loss: 1.6282e -04 - val_loss: 6.9519e -05
Epoch 12/15
1/168             5s 33ms/step - loss: 1.8450e -04

  7/168             1s 9ms/step - loss: 1.4972e -04

 13/168             1s 9ms/step - loss: 1.4701e -04

 19/168             1s 9ms/step - loss: 1.4861e -04
```

```
 25/168          1s 9ms/step - loss: 1.4878e -04
 31/168          1s 9ms/step - loss: 1.4870e -04
 37/168          1s 9ms/step - loss: 1.4944e -04
 43/168          1s 9ms/step - loss: 1.4994e -04
 49/168          1s 9ms/step - loss: 1.5040e -04
 55/168          0s 9ms/step - loss: 1.5123e -04
 61/168          0s 9ms/step - loss: 1.5264e -04
 67/168          0s 9ms/step - loss: 1.5336e -04
 73/168          0s 9ms/step - loss: 1.5372e -04
 79/168          0s 9ms/step - loss: 1.5392e -04
 85/168          0s 9ms/step - loss: 1.5398e -04
 91/168          0s 9ms/step - loss: 1.5390e -04
 97/168          0s 9ms/step - loss: 1.5377e -04
103/168          0s 9ms/step - loss: 1.5375e -04
109/168          0s 9ms/step - loss: 1.5391e -04
115/168          0s 9ms/step - loss: 1.5422e -04
121/168          0s 9ms/step - loss: 1.5464e -04
```

```
127/168            0s 9ms/step - loss: 1.5502e -04

132/168            0s 9ms/step - loss: 1.5525e -04

138/168            0s 9ms/step - loss: 1.5549e -04

144/168            0s 9ms/step - loss: 1.5575e -04

150/168            0s 9ms/step - loss: 1.5599e -04

156/168            0s 9ms/step - loss: 1.5621e -04

162/168            0s 9ms/step - loss: 1.5642e -04

168/168            0s 9ms/step - loss: 1.5660e -04

168/168            2s 10ms/step - loss: 1.6101e -04 - val_loss: 6.8521e -05
Epoch 13/15
1/168            4s 28ms/step - loss: 2.2210e -04

  7/168            1s 9ms/step - loss: 1.6654e -04

 13/168            1s 9ms/step - loss: 1.6005e -04

 19/168            1s 9ms/step - loss: 1.5796e -04

 25/168            1s 9ms/step - loss: 1.5574e -04

 31/168            1s 9ms/step - loss: 1.5437e -04

 37/168            1s 9ms/step - loss: 1.5426e -04
```

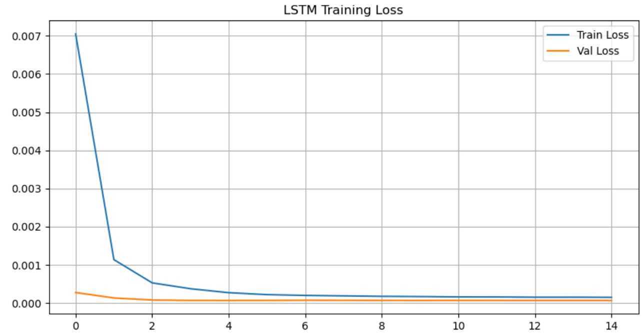
```
 43/168          1s 9ms/step - loss: 1.5402e -04

 49/168          1s 9ms/step - loss: 1.5375e -04

 55/168          0s 9ms/step - loss: 1.5396e -04

 62/168          0s 9ms/step - loss: 1.5450e -04

 68/168          0s 9ms/step - loss: 1.5447e -04

 74/168          0s 9ms/step - loss: 1.5432e -04

 80/168          0s 9ms/step - loss: 1.5421e -04

 86/168          0s 9ms/step - loss: 1.5397e -04

 92/168          0s 9ms/step - loss: 1.5371e -04

 98/168          0s 9ms/step - loss: 1.5345e -04

104/168          0s 9ms/step - loss: 1.5328e -04

110/168          0s 9ms/step - loss: 1.5325e -04

116/168          0s 9ms/step - loss: 1.5343e -04

122/168          0s 9ms/step - loss: 1.5369e -04

128/168          0s 9ms/step - loss: 1.5386e -04

134/168          0s 9ms/step - loss: 1.5394e -04

140/168          0s 9ms/step - loss: 1.5398e -04
```

```
146/168            0s 9ms/step - loss: 1.5403e -04

152/168            0s 9ms/step - loss: 1.5405e -04

158/168            0s 9ms/step - loss: 1.5408e -04

164/168            0s 9ms/step - loss: 1.5410e -04

168/168            2s 10ms/step - loss: 1.5406e -04 - val_loss: 6.7993e -05
Epoch 14/15
1/168            5s 30ms/step - loss: 2.2555e -04

  7/168            1s 9ms/step - loss: 1.6614e -04

 13/168            1s 9ms/step - loss: 1.5605e -04

 19/168            1s 9ms/step - loss: 1.5096e -04

 25/168            1s 9ms/step - loss: 1.4884e -04

 31/168            1s 9ms/step - loss: 1.4801e -04

 37/168            1s 9ms/step - loss: 1.4815e -04

 43/168            1s 9ms/step - loss: 1.4804e -04

 49/168            1s 9ms/step - loss: 1.4807e -04

 55/168            0s 9ms/step - loss: 1.4855e -04

 61/168            0s 9ms/step - loss: 1.4924e -04
```

```
 67/168          0s 9ms/step - loss: 1.4950e -04

 73/168          0s 9ms/step - loss: 1.4962e -04

 79/168          0s 9ms/step - loss: 1.4968e -04

 85/168          0s 9ms/step - loss: 1.4964e -04

 91/168          0s 9ms/step - loss: 1.4945e -04

 97/168          0s 9ms/step - loss: 1.4928e -04

103/168          0s 9ms/step - loss: 1.4920e -04

109/168          0s 9ms/step - loss: 1.4931e -04

115/168          0s 9ms/step - loss: 1.4955e -04

121/168          0s 9ms/step - loss: 1.4992e -04

127/168          0s 9ms/step - loss: 1.5022e -04

133/168          0s 9ms/step - loss: 1.5047e -04

139/168          0s 9ms/step - loss: 1.5068e -04

145/168          0s 9ms/step - loss: 1.5090e -04

151/168          0s 9ms/step - loss: 1.5107e -04

157/168          0s 9ms/step - loss: 1.5121e -04

163/168          0s 9ms/step - loss: 1.5136e -04
```

```
168/168          2s 10ms/step - loss: 1.5460e -04 - val_loss: 6.8454e -05
Epoch 15/15
1/168          5s 31ms/step - loss: 1.8362e -04

  7/168          1s 9ms/step - loss: 1.4532e -04

 13/168          1s 9ms/step - loss: 1.4250e -04

 19/168          1s 9ms/step - loss: 1.4203e -04

 25/168          1s 9ms/step - loss: 1.4099e -04

 31/168          1s 9ms/step - loss: 1.4012e -04

 37/168          1s 9ms/step - loss: 1.4049e -04

 43/168          1s 9ms/step - loss: 1.4056e -04

 49/168          1s 9ms/step - loss: 1.4080e -04

 55/168          1s 9ms/step - loss: 1.4157e -04

 61/168          0s 9ms/step - loss: 1.4254e -04

 67/168          0s 9ms/step - loss: 1.4300e -04

 73/168          0s 9ms/step - loss: 1.4334e -04

 79/168          0s 9ms/step - loss: 1.4361e -04

 85/168          0s 9ms/step - loss: 1.4373e -04
```

```
 91/168            0s 9ms/step - loss: 1.4374e -04

 97/168            0s 9ms/step - loss: 1.4372e -04

103/168            0s 9ms/step - loss: 1.4377e -04

109/168            0s 9ms/step - loss: 1.4400e -04

115/168            0s 9ms/step - loss: 1.4436e -04

121/168            0s 9ms/step - loss: 1.4486e -04

128/168            0s 9ms/step - loss: 1.4530e -04

134/168            0s 9ms/step - loss: 1.4556e -04

141/168            0s 9ms/step - loss: 1.4581e -04

148/168            0s 9ms/step - loss: 1.4604e -04

154/168            0s 9ms/step - loss: 1.4619e -04

160/168            0s 9ms/step - loss: 1.4638e -04

166/168            0s 9ms/step - loss: 1.4654e -04

168/168            2s 10ms/step - loss: 1.5080e -04 - val_loss: 6.8355e -05
```



```
#LSTM evaluations
y_pred_lstm = model.predict(X_test_lstm).flatten()

lstm_metrics = compute_regression_metrics(y_test_lstm, y_pred_lstm)
lstm_dir_acc = directional_accuracy(y_test_lstm, y_pred_lstm)

print("LSTM Metrics:", lstm_metrics)
print(f"Directional Accuracy: {lstm_dir_acc:.2%}")
```

```
1/56            7s 138ms/step


18/56            0s 3ms/step


36/56            0s 3ms/step


53/56            0s 3ms/step


56/56            0s 5ms/step


56/56            0s 6ms/step
```

```
LSTM Metrics: {'RMSE': np.float64(0.021962368050795756), 'MAE': 0.010625985694445502, 'MAPE'
Directional Accuracy: 46.98%
```

```
summary_rows = []

summary_rows.append(
    {"Model": "Naive",
     **baseline_metrics,
     "DirAcc": baseline_dir_acc}
)

summary_rows.append(
    {"Model": "LinearRegression",
     **lr_test_metrics,
     "DirAcc": lr_dir_acc}
)

summary_rows.append(
    {"Model": "RandomForest",
     **rf_test_metrics,
     "DirAcc": rf_dir_acc}
```

```
)

summary_rows.append(
    {"Model": "ARIMA(1,0,1)",
     **arima_metrics,
     "DirAcc": arima_dir_acc}
)

summary_rows.append(
    {"Model": "LSTM",
     **lstm_metrics,
     "DirAcc": lstm_dir_acc}
)

summary_df = pd.DataFrame(summary_rows)
summary_df.to_csv("../data/final_metrics.csv")
summary_df.head()
```

	Model	RMSE	MAE	MAPE	R2	DirAcc
0	Naive	1.694052e-02	1.160951e-02	5.502865e+07	-0.766366	0.509162
1	LinearRegression	1.914564e-07	1.411566e-07	6.262626e+02	1.000000	1.000000
2	RandomForest	1.171947e-03	8.215782e-05	4.043183e+05	0.991546	0.999445
3	ARIMA(1,0,1)	1.088510e-02	7.145005e-03	3.433071e+07	-0.000894	0.545656
4	LSTM	2.196237e-02	1.062599e-02	4.704331e+07	-1.986357	0.469791

```
fig, axes = plt.subplots(1, 2, figsize=(12, 4))

axes[0].bar(summary_df["Model"], summary_df["R2"])
axes[0].set_title("R2 by Model")
axes[0].set_xticklabels(summary_df["Model"], rotation=45, ha="right")

axes[1].bar(summary_df["Model"], summary_df["DirAcc"])
axes[1].set_title("Directional Accuracy by Model")
axes[1].set_xticklabels(summary_df["Model"], rotation=45, ha="right")

plt.tight_layout()
plt.savefig("../images/R2_Accuracy.png")
plt.show()
```

```
/tmp/ipykernel_4825/602907317.py:5: UserWarning: set_ticklabels() should only be used with a
  axes[0].set_xticklabels(summary_df["Model"], rotation=45, ha="right")
/tmp/ipykernel_4825/602907317.py:9: UserWarning: set_ticklabels() should only be used with a
  axes[1].set_xticklabels(summary_df["Model"], rotation=45, ha="right")
```