Model Training and Evaluating it

Thursday 11th December, 2025

Curvenote

We look to implement and compare five different forecasting models.

```
#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 -11 01:53:06.154772: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:31] Could not
2025 -12 -11 01:53:06.253614: I tensorflow/core/util/port.cc:153] oneDNN custom operations a
2025 -12 -11 01:53:09.995778: 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 -11 01:53:20.679920: I tensorflow/core/util/port.cc:153] oneDNN custom operations a
2025 -12 -11 01:53:20.692153: 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	LogReturn	Volatility	Momentum	MACD	MACD_Signal	RSI	y	LogReturn_lag1	LogReturn_lag2	LogReturn_lag3
Date																			
1990-03-13	336.[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.007915	[illegible]	[illegible]	[illegible]	0.212164	0.006901	[illegible]	[illegible]	[illegible]	0.009805
1990-03-14	336.[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.007915	0.006901	[illegible]	0.002187
1990-03-15	338.[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.007915	0.006901	0.002187	0.002586
1990-03-16	341.[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.007915	0.006901	0.002187	0.002586
1990-03-19	343.[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.005722	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.007915	0.006901	0.002187

```
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': 0.011609508629903
Naive baseline directional accuracy: 0.5091615769017213
```

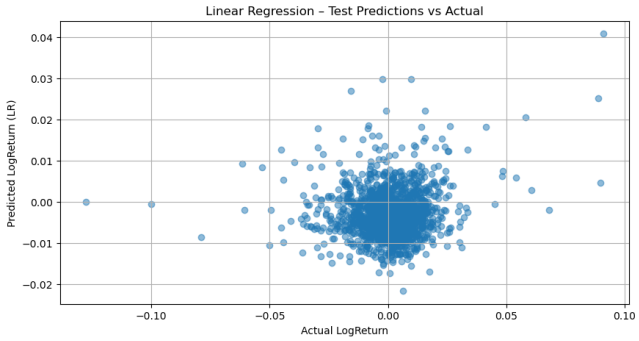
1 Linear Baseline

After the naive baseline, we use a Linear Regression model. According to the Efficient Market Hypothesis (EMH), daily returns should be a random walk, meaning our linear model should have a R^2 close to zero. This will be a good indicator of whether complex models can extract any signal.

```
# 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(0.008868328927820853), 'MAE': 0.
Linear Regression - Test Metrics: {'RMSE': np.float64(0.013779692199568672), 'MAE': 0.01000
Linear Regression - Directional Accuracy: 46.42%
```

```
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()
```



The Linear Regression model had an R^2 score of -0.17. So, this implies the model performs worse than just guessing the average return.

```
rf = RandomForestRegressor(n_estimators=200, max_depth=5, 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)
```

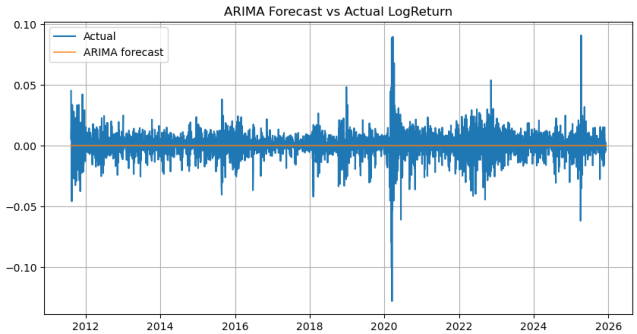
```
Random Forest - validation metrics: {'RMSE': np.float64(0.008777587376121151), 'MAE': 0.006
Random Forest - test metrics: {'RMSE': np.float64(0.014802500689598751), 'MAE': 0.009275967
Random Forest - test directional accuracy: 0.538034425319267
```

The Random Forest model has $R^2 \approx -0.35$. This is worse off than Linear Regression model.

```
# 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
```

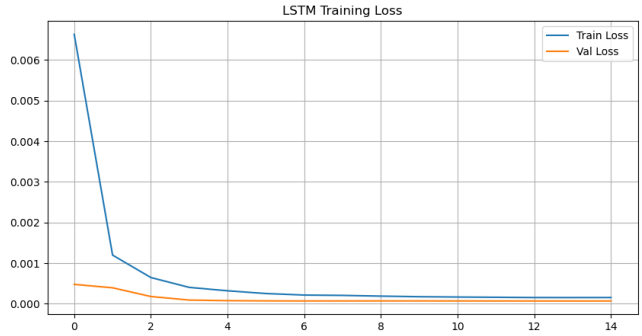


The ARIMA model has $R^2 \approx -0.0009$. This is far better than our linear baseline.

```
#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()

2025 -12 -11 01:55:28.393109: E external/local_xla/xla/stream_executor/cuda/cuda_platform.cc

Epoch 1/15
168/168            4s 11ms/step - loss: 0.0066 - val_loss: 4.7753e -04
Epoch 2/15
168/168            2s 9ms/step - loss: 0.0012 - val_loss: 3.9340e -04
Epoch 3/15
168/168            2s 10ms/step - loss: 6.4524e -04 - val_loss: 1.7822e -04
Epoch 4/15
168/168            2s 10ms/step - loss: 4.0324e -04 - val_loss: 9.1113e -05
Epoch 5/15
168/168            2s 9ms/step - loss: 3.1936e -04 - val_loss: 7.6343e -05
Epoch 6/15
168/168            2s 9ms/step - loss: 2.5205e -04 - val_loss: 7.1253e -05
Epoch 7/15
168/168            2s 9ms/step - loss: 2.1402e -04 - val_loss: 6.9024e -05
Epoch 8/15
168/168            2s 9ms/step - loss: 2.0618e -04 - val_loss: 6.9460e -05
Epoch 9/15
168/168            2s 9ms/step - loss: 1.8815e -04 - val_loss: 7.0081e -05
Epoch 10/15
168/168            2s 9ms/step - loss: 1.7364e -04 - val_loss: 6.9981e -05
Epoch 11/15
168/168            2s 10ms/step - loss: 1.6579e -04 - val_loss: 6.9683e -05
Epoch 12/15
168/168            2s 9ms/step - loss: 1.5954e -04 - val_loss: 6.8659e -05
```

```
Epoch 13/15
168/168             2s 9ms/step - loss: 1.5293e -04 - val_loss: 6.8648e -05
Epoch 14/15
168/168             2s 9ms/step - loss: 1.5272e -04 - val_loss: 6.8502e -05
Epoch 15/15
168/168             2s 9ms/step - loss: 1.5327e -04 - val_loss: 6.8400e -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%}")
```

```
56/56             0s 5ms/step
LSTM Metrics: {'RMSE': np.float64(0.01594281443908124), 'MAE': 0.010460818840851595, 'MAPE':
Directional Accuracy: 49.24%
```

```
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(
```

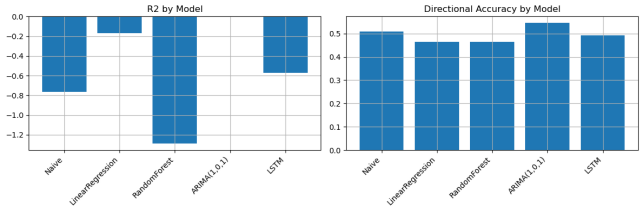
```
    {"Model": "RandomForest",
     **rf_test_metrics,
     "DirAcc": rf_dir_acc}
)

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	0.016941	0.011610	5.502865e+07	0.766366	0.509162
1	LinearRegression	0.013780	0.010006	3.790434e+07	0.168709	0.464187
2	RandomForest	0.019296	0.015812	5.571611e+07	1.291640	0.463631
3	ARIMA(1,0,1)	0.010885	0.007145	3.433071e+07	0.000894	0.545656
4	LSTM	0.015943	0.010461	4.436545e+07	0.573669	0.492377

```
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_753/602907317.py:5: UserWarning: set_ticklabels() should only be used with a
  axes[0].set_xticklabels(summary_df["Model"], rotation=45, ha="right")
/tmp/ipykernel_753/602907317.py:9: UserWarning: set_ticklabels() should only be used with a
  axes[1].set_xticklabels(summary_df["Model"], rotation=45, ha="right")
```



All our models find it difficult to capture the true nature of returns in the stock market. However, ARIMA clearly is the best model.