

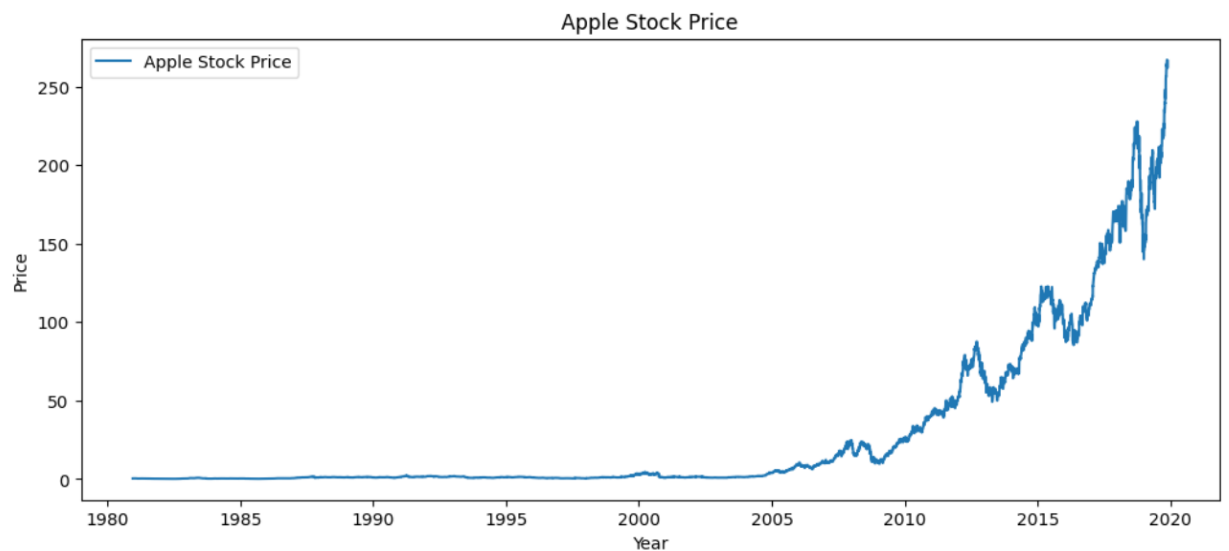
Apple Stock Predictions Using SimpleRNN - Documentation

- Importing necessary libraries: pandas, NumPy, Matplotlib, Scikit-learn and Tensorflow)

Approach-1:

Data-Preprocessing:

- Loading the dataset into the dataframe.
- Dataset Shape: (9823, 7) --- 9823 rows and 7 columns.
- Getting basic info of the dataset.
- The 'Date' column is of object data type, so it is converted into datetime format using pandas.
- For time-series predictions, the 'Date' column is set as **index**.
- Checking Null values (1 Null Values).
- Used **forward fill** to handle missing values, since stock prices are sequential and cannot be dropped arbitrarily.
- Plotted the 'Adj Close' (**Target variable**) column to analyse the trends and patterns.



- I. The stock price remains flat from 1980 till 2005.
- II. After 2005 a sharp upward trend growth happens with several peaks and drops.

Scaling the data:

- Using Min-Max scaler, as neural networks works best for scaled values.
- Setting feature range between **0** to **1**. And selected the target variable as 'Adj Close'

Adj Close	
Date	
1980-12-12	0.000943
1980-12-15	0.000863
1980-12-16	0.000757
1980-12-17	0.000790
1980-12-18	0.000830

Creating Time-sequences:

- Defined a function to create sequences.
- Applied that function into the dataset where we selected the **target variable ('Adj Close')**.
- Used **60 time steps**, where the model learns from the past 60 days to predict the next day's price.
- After applying the shape of X,y variables are,
X.shape = (9763, 60, 1)
 - I. 9763 → Number of samples (data points available after sequence creation)
 - II. 60 → Each sample contains 60 past days (time steps) as input
 - III. 1 → Only one feature (Adj Close price)**y.shape = (9763,)**
 - I. 9763 → The number of target values (corresponding next-day prices)

Train Test Split:

- The training and testing data were split with an 80-20 ratio:
Train Shape: (7810, 60, 1), Test Shape: (1953, 60, 1)
 - I. Total samples before splitting = 9763.
 - II. Training set (80%) → 7810 sequences
 - III. Testing set (20%) → 1953 sequences
 - IV. Each sample contains → 60 past days as input (time_steps = 60)
 - V. Features per timestep → 1 (only Adj Close price).

Defining the RNN:

- Since predicting the Apple Stock Prices is Time Series, we are using Sequential with SimpleRNN.
 - I. **20 hidden units** are used in the SimpleRNN layer.
 - II. **ReLU** activation is used to introduce non-linearity and improve training stability.
 - III. **return_sequences=False**, meaning the layer returns only the final output of the sequence.
 - IV. **input_shape** defines the number of time steps and features per step.
 - I. **Dropout=0.4**, where randomly it turns off 40% of neurons during training which helps to prevent overfitting
 - II. **Dense=1**, where it is the output layer which predicts stock price.

Compiling the Model:

- Used the Adam optimizer with a learning rate of $1e-4$.
- Loss is Mean Squared Error.

Model Summary:

Model: "sequential_3"

Layer (type)	Output Shape	Param #
simple_rnn_3 (SimpleRNN)	(None, 20)	440
dropout_3 (Dropout)	(None, 20)	0
dense_3 (Dense)	(None, 1)	21

Total params: 461 (1.80 KB)

Trainable params: 461 (1.80 KB)

Non-trainable params: 0 (0.00 B)

Training the Model:

- Initially early stopping and model checkpoints are used, where early stopping prevents unnecessary learning if there is no improvement in val loss.
- Model Checkpoint is used to save the best model.
- Although the model was set to train for 50 epochs, it stopped at 27 due to early stopping.

Training Loss vs Validation Loss:



- Validation loss starts around **0.4** and drops down in first few epochs.
- At Epoch 4 the validation loss reaches near zero, indicates the model is fit and learning very well.
- Training and validation loss are closely aligned.

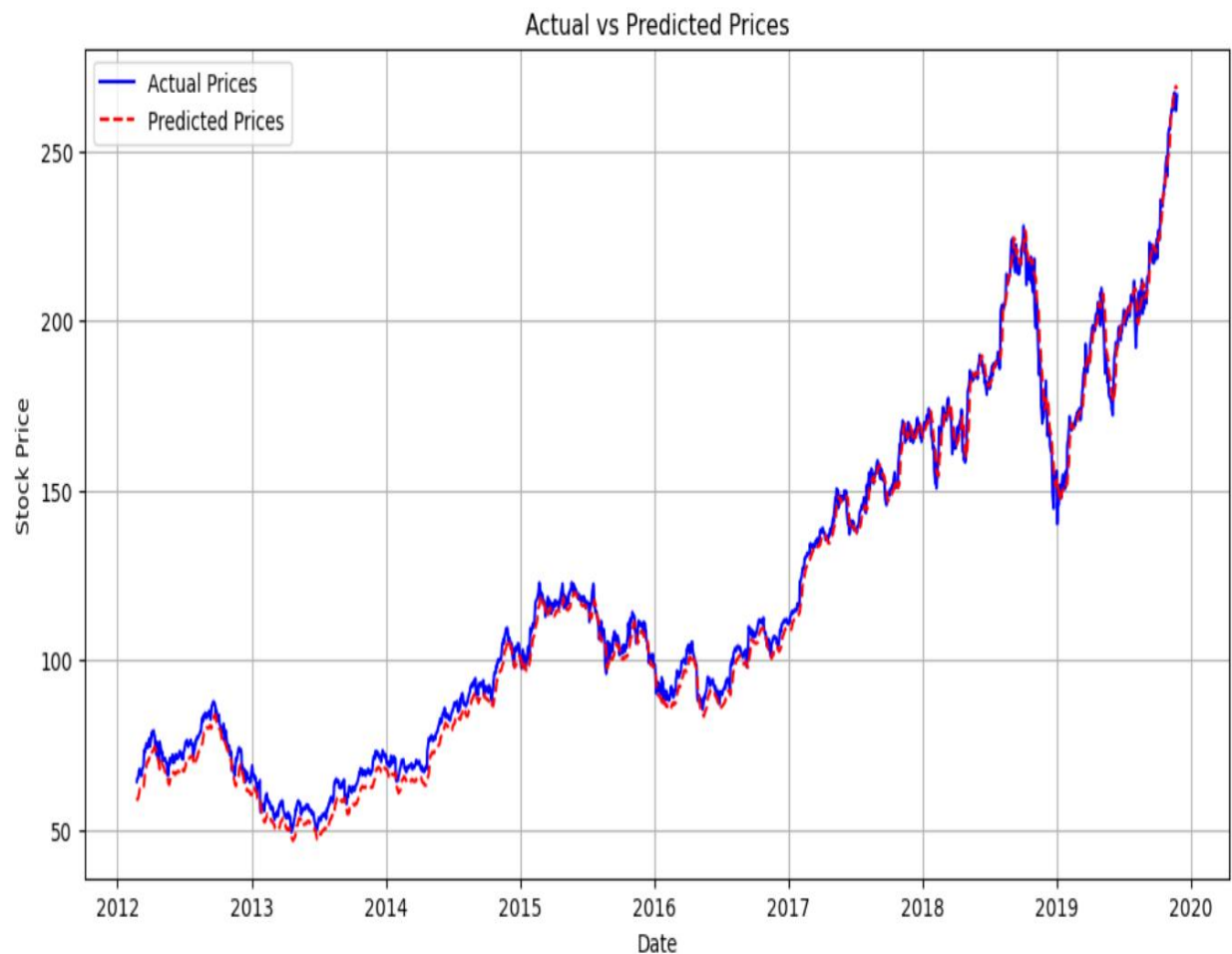
Predictions:

- Predictions are made on test data.
- Applied inverse transformation using MinMaxScaler to convert predictions back to original scale.
- Calculated the Mean Squared Error.

Mean Squared Error (MSE): 18.370028660377844

- Lower Mean Squared Error indicates lower error, which means the predicted stock prices are closer to the actual stock prices.

Actual vs Predicted Prices Visualization:



- Predicted stock prices closely follow the actual prices.
- This suggests that SimpleRNN model has learned the trends well.

Predictions of 1,5 and 10 days behavior:

1. Next Day stock price prediction:

1/1 ————— 0s 35ms/step

Predicted stock price for the next day: \$268.23807

2. Next 5 days stock price prediction:

1/1 ————— 0s 50ms/step
1/1 ————— 0s 29ms/step
1/1 ————— 0s 34ms/step
1/1 ————— 0s 36ms/step
1/1 ————— 0s 42ms/step

Predicted stock prices for the next 5 days: \$[268.23807, 268.00827, 267.84427, 268.79752, 270.62558]

3. Next 10 days stock price predictions:

1/1 ————— 0s 33ms/step
1/1 ————— 0s 48ms/step
1/1 ————— 0s 40ms/step
1/1 ————— 0s 26ms/step
1/1 ————— 0s 33ms/step
1/1 ————— 0s 36ms/step
1/1 ————— 0s 34ms/step
1/1 ————— 0s 32ms/step
1/1 ————— 0s 38ms/step
1/1 ————— 0s 38ms/step

Predicted Stock prices for the next 10 days: [268.23807, 268.00827, 267.84427, 268.79752, 270.62558, 272.1009, 273.0738, 274.06784, 275.29303, 276.6051]

Difficulties Faced:

- Initially only executed with 7 Epochs, then increased the dropout as 0.4, learning rate = 0.0005 and early stopping patience to 7 then executed/learned until 17 Epochs.
- Re-executed the training after a few days; this time, the model trained up to 22 epochs. The loss curves and MSE changed significantly (**MSE = 769.4176**).
- The best-performing model was previously saved as Final_AAPL_SimpleRNN.h5. So opened a new jupyter notebook and done data pre-processing, scaling and create_sequences function and loaded the above mentioned model and predicted the MSE which now we achieved same as previous: **18.37002**.