STOCK MARKET FORECASTING: APPLE’S CLOSING PRICE

By: Math & Physics Fun with Gus

INITIAL DATA ANALYSIS OF TOP TECH IN S&P500

- Similar dips and spikes patterns in plot
- Seems to be a correlation between technology stock prices
- Theory: Maybe one can model stocks using other stocks
- Question: Is there a linear relationship between stock price trends?

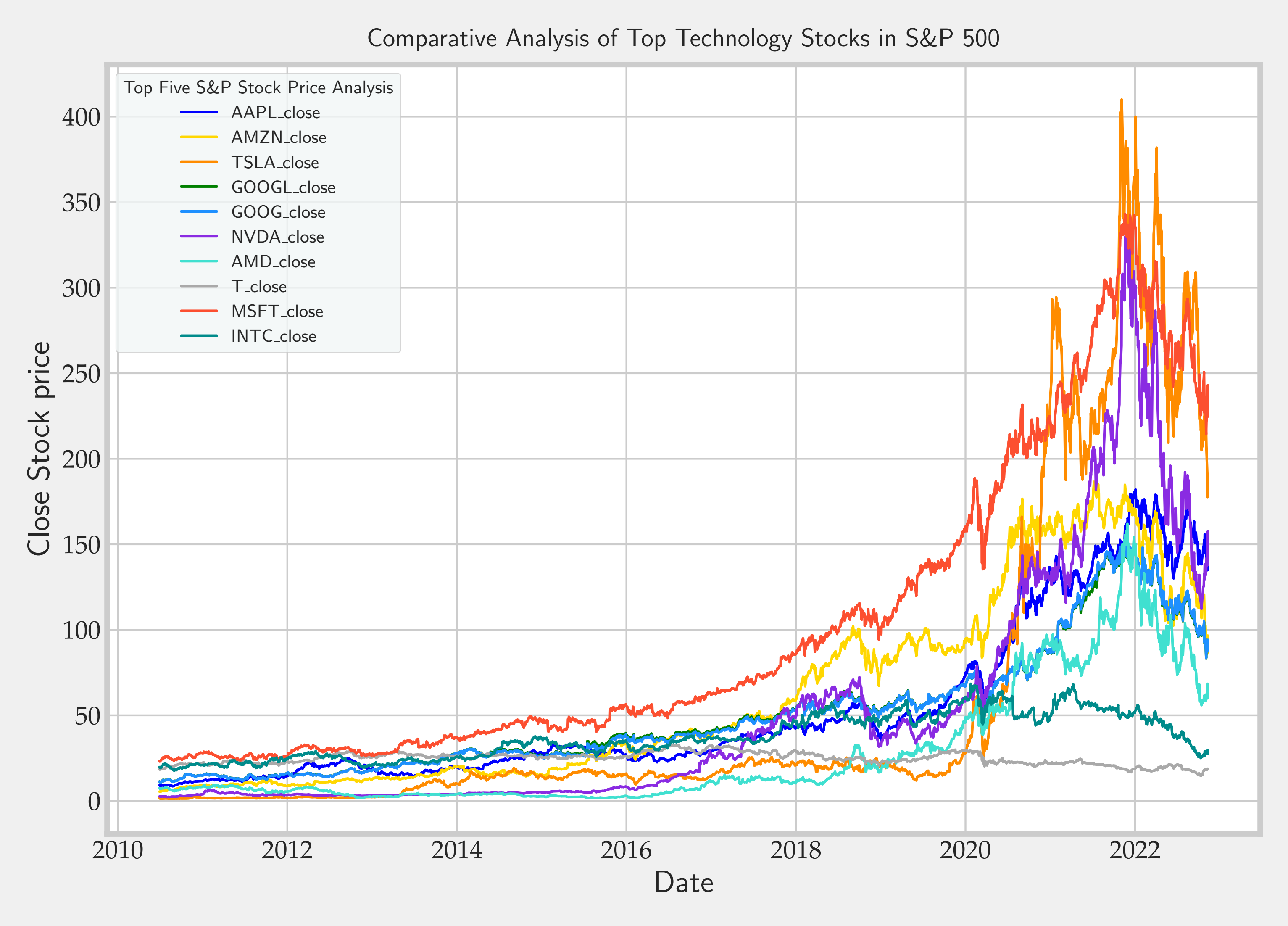

Figure 1: Top Technology Stokes in S&P500

APPLE & MICROSOFT PERCENT CHANGE

- Percent change is important for stock growth
- Plot of percent change of four months prior to test data
- Here we see a very similar trend for two top tech stocks

$$\texttt{Percent Change} = 100\left(\frac{\texttt{Close Price} - \texttt{Open Price}}{\texttt{Open Price}}\right)$$

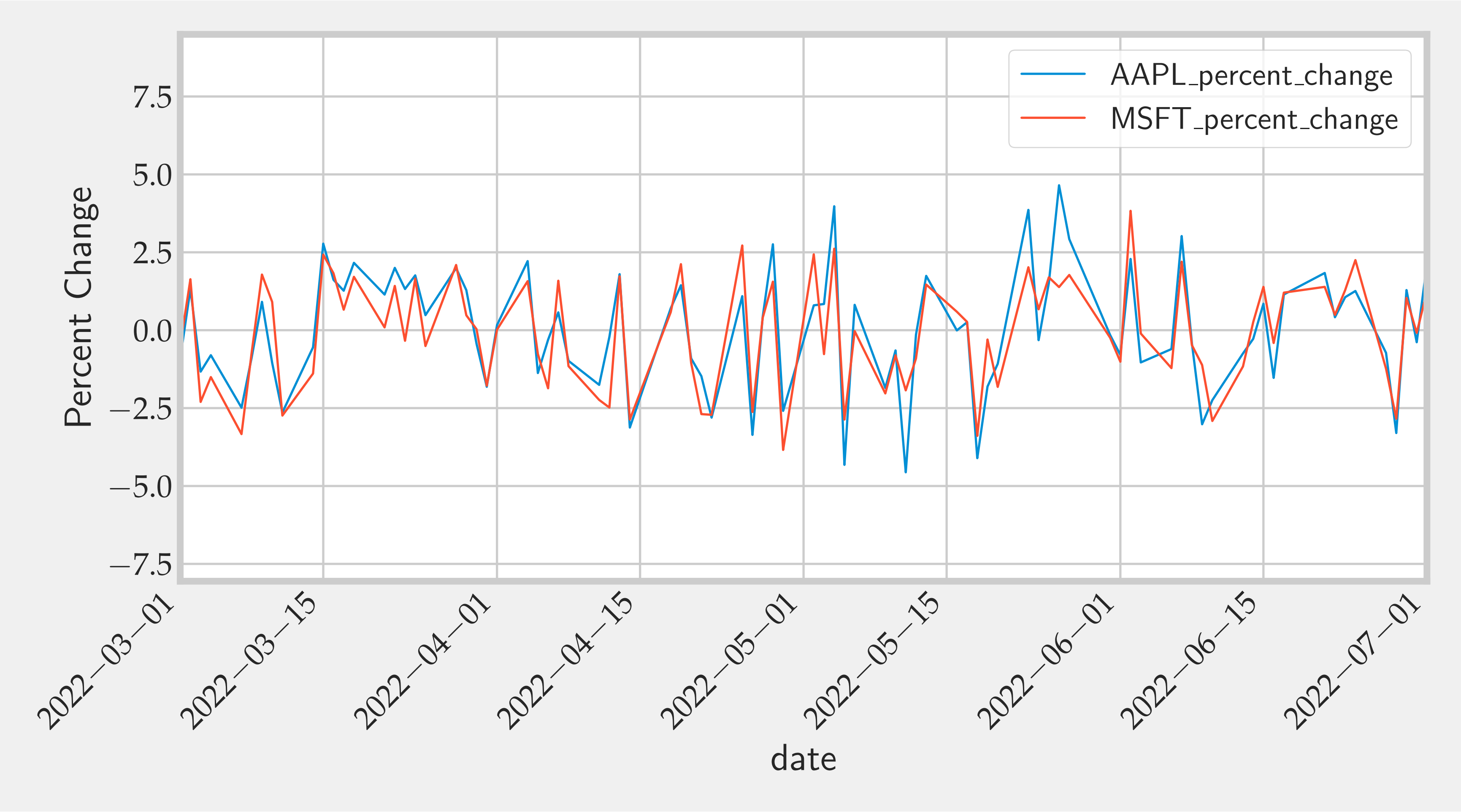

Figure 2: Apple and Microsoft's Percent Change Plot

LINEAR MODELS: APPLE'S CLOSING STOCK PRICE - PART 1

	coef	std err	t	P>|t|
Intercept	-3.1953	1.022	-3.128	0.002
AMZN_close	0.0807	0.009	9.069	0.000
TSLA_close	0.1753	0.005	38.768	0.000
NVDA_close	0.0410	0.009	4.441	0.000
GOOGL_close	-0.2286	0.024	-9.577	0.000
T_close	0.4901	0.043	11.405	0.000
AMD_close	-0.1168	0.023	-5.038	0.000
MSFT_close	0.4128	0.014	29.075	0.000
INTC_close	-0.0456	0.023	-1.975	0.048

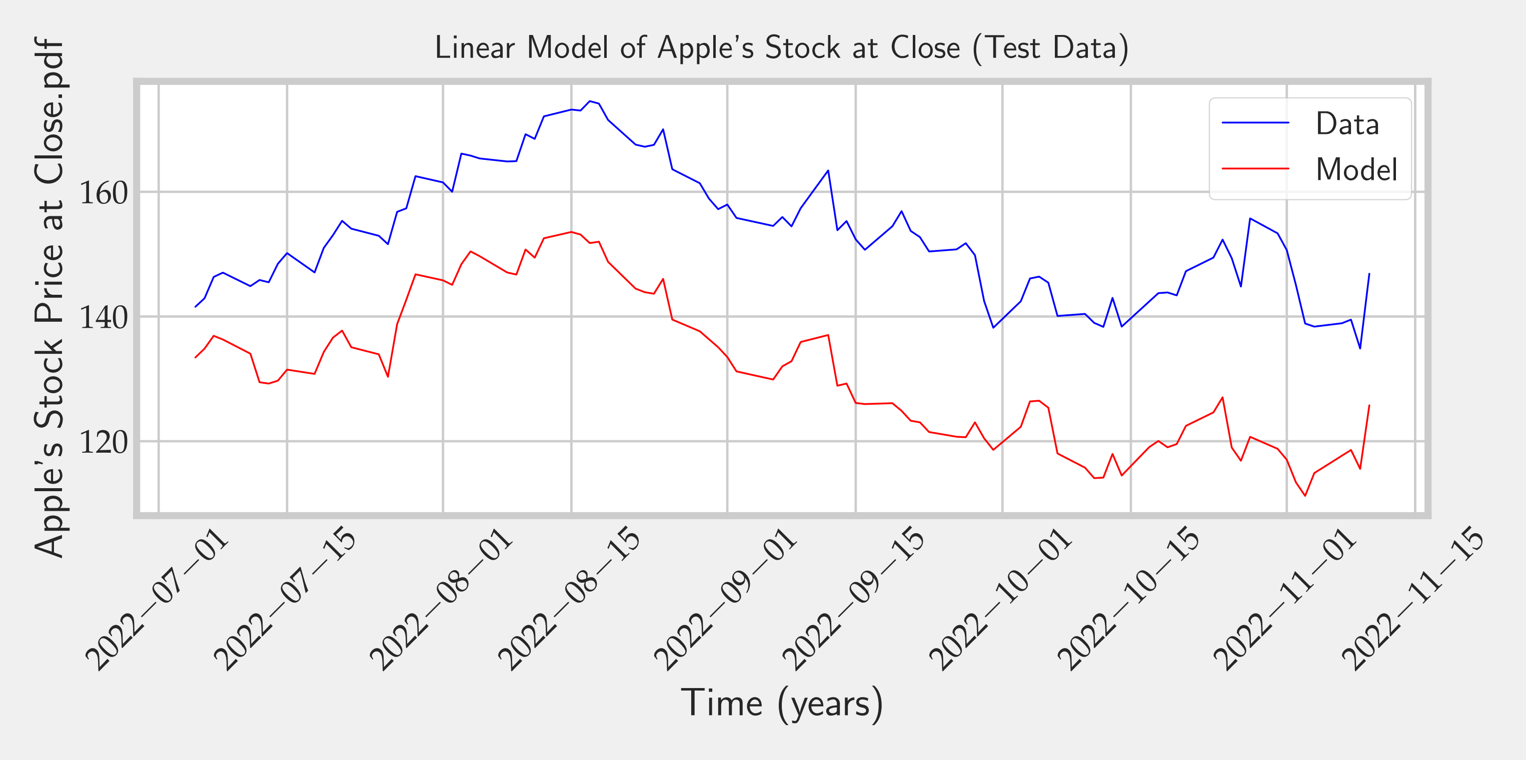

Figure 3: Apple's closing price as a function of other tech stock's closing price. Trend lines follow the test data well up to some constant. We see a strong slope with Microsoft and AT&T.

LINEAR MODEL: PERCENT CHANGE MODEL – PART 2

- Model of percent change (%Δ) as a function of other tech percent changes
- Strongest slope with MSFT
- Trend lines are followed very well
- Implications: Predicting stock outcomes per-day are related to tech stocks in field

	coef	std err	t	$P(>\|t\|)$
Intercept	0.0116	0.019	0.619	0.536
AMZN %Δ	0.1133	0.016	7.005	0.000
TSLA %Δ	0.0308	0.007	4.223	0.000
NVDA %Δ	0.0735	0.011	6.481	0.000
AMD %Δ	0.0279	0.008	3.575	0.000
GOOGL %Δ	0.2526	0.022	11.376	0.000
MSFT %Δ	0.2683	0.021	12.633	0.000

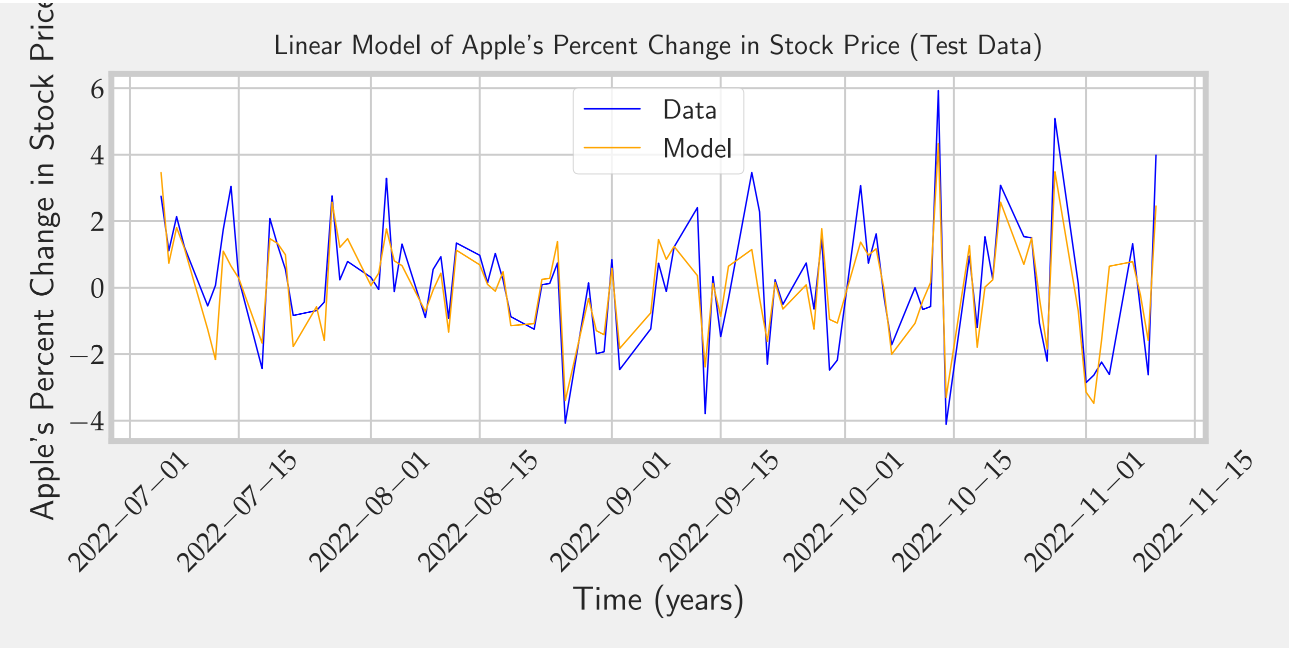

Figure 4: Linear Model of Apple's percent change

LINEAR MODEL: LAG TERMS – PART 3

- Follows trend well but of by shift factor
- Of all linear models smallest error measurements
  - MSE =2.58
  - RMSE=1.61,
  - SEE = 1112.45
- MSFT lag slightly increased model's accuracy
- CON: Not good for long term forecasting
- Conclusion: VAR model should be good: It combines lag and relationships

	coef	std err	t	P(> |t|)
Intercept	0.0370	0.035	1.047	0.295
AAPL_close_LAG	1.0001	0.001	1861.525	0.000
MSFT_close_LAG	0.0075	0.002	4.629	0.000

$$\mathtt{Apple}(\mathtt{AAPL}_{t-1},\ \mathtt{MSFT}_{t-1}) = \alpha + \beta_0 \mathtt{AAPL}_{t-1} + \beta_1 \mathtt{MSFT}_{t-1}$$

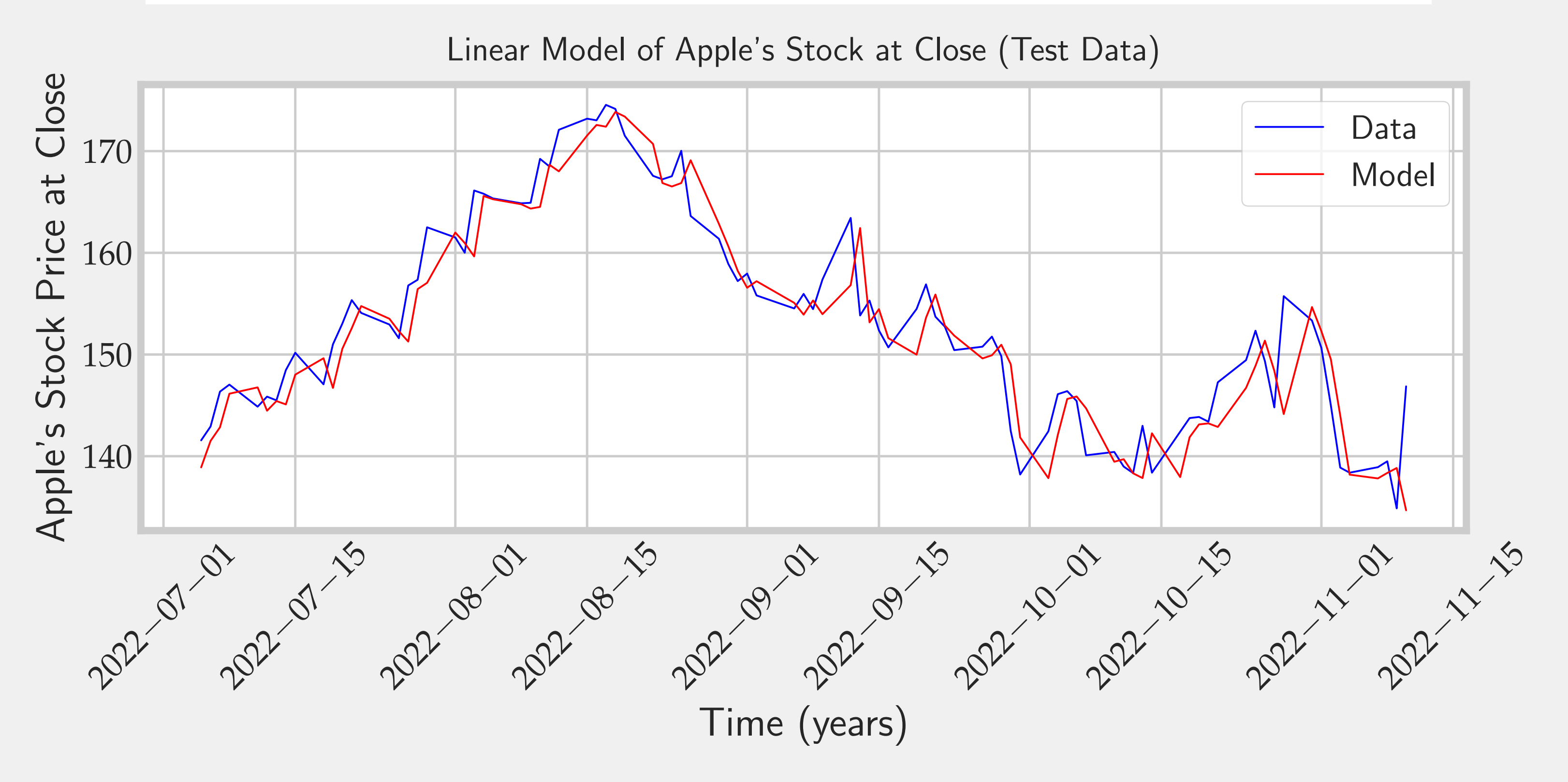

Figure 5: Apple's closing price model as a function of lag terms

VAR MODEL TECH STOCKS

- VAR stands for Vector Autoregression

- VAR model:
  - Top tech stocks in S&P500: n=10,
  - Number of lag terms: N=100
  - Error terms: ε_t

- Returned smaller errors over forecasting quarter:
  - MAE = 8.82
  - RMSE = 7.32
  - SEE = 7177.46

- AIC dropped with more lag terms added but more N slows algorithm

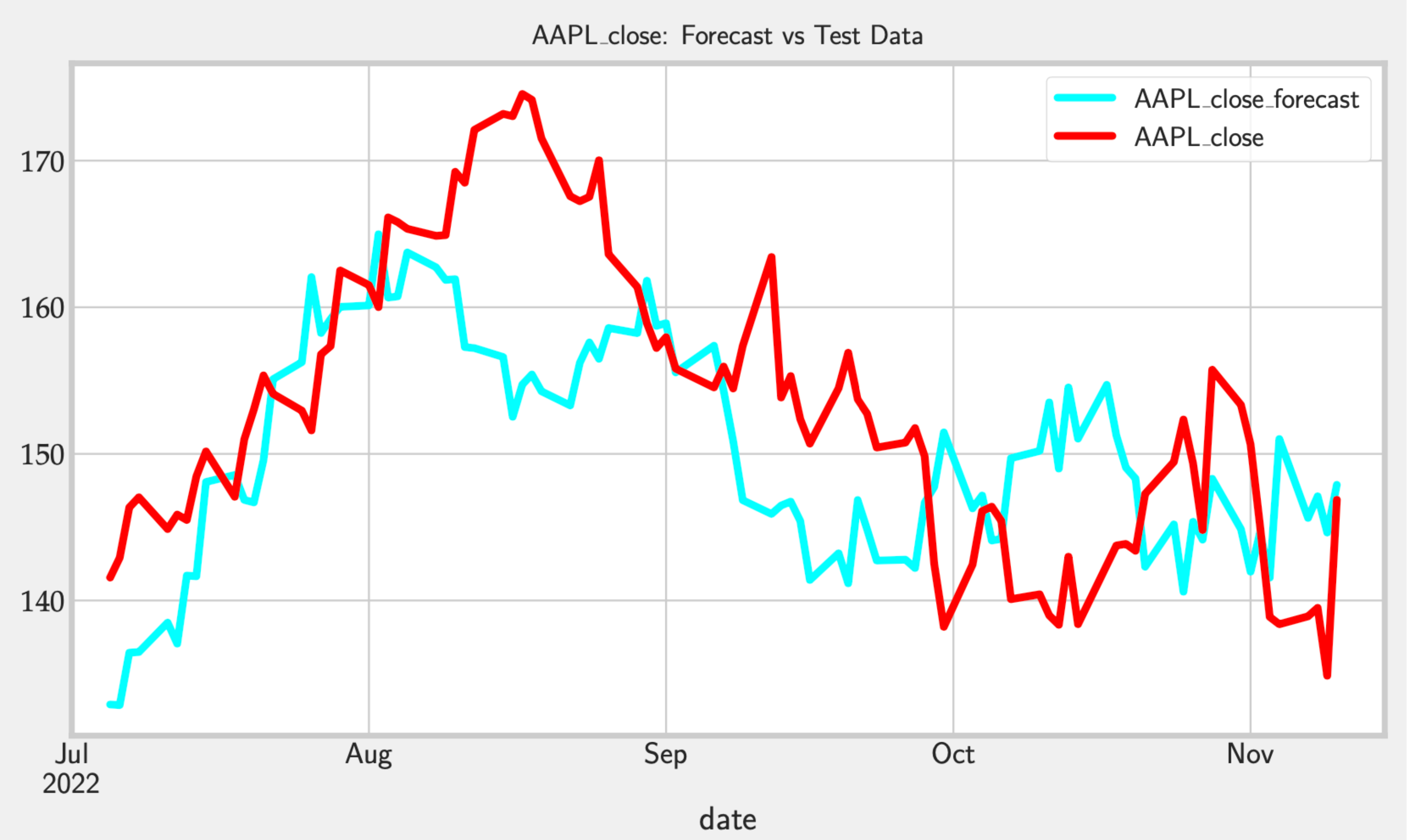

Figure 6: VAR model forecasting compared to test sample

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \\ \vdots \\ Y_{n,t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{pmatrix} + \begin{pmatrix} \beta_{11,1} & \dots & \beta_{1n,1} \\ \beta_{21,1} & \dots & \beta_{1n,1} \\ \vdots & \ddots & \vdots \\ \beta_{n1,1} & \dots & \beta_{nn,1} \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ \vdots \\ Y_{n,t-1} \end{pmatrix} + \dots + \begin{pmatrix} \beta_{11,N} & \dots & \beta_{1n,N} \\ \beta_{21,N} & \dots & \beta_{1n,N} \\ \vdots & \ddots & \vdots \\ \beta_{n1,N} & \dots & \beta_{nn,N} \end{pmatrix} \begin{pmatrix} Y_{1,t-N} \\ Y_{2,t-N} \\ \vdots \\ Y_{n,t-N} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{n,t} \end{pmatrix}$$

Equation of Vector Autoregression equation

ARIMA MODEL: FORMING MODEL – PART 1

- What Arima means:
  - AR - auto-regression: equation based on previous data
  - I - differencing: based on “trends” in data
  - MA - moving average: equation based on noise from past data
- Arima Model denoted as ARIMA(p,d,q)(P,D,Q)$_m$:
  - p is related to the PACF critical points
  - d is the differencing needed to remove non-stationarity
  - q is related to the ACF critical points.
  - (P,D,Q)$_m$ are seasonality terms which were not considered

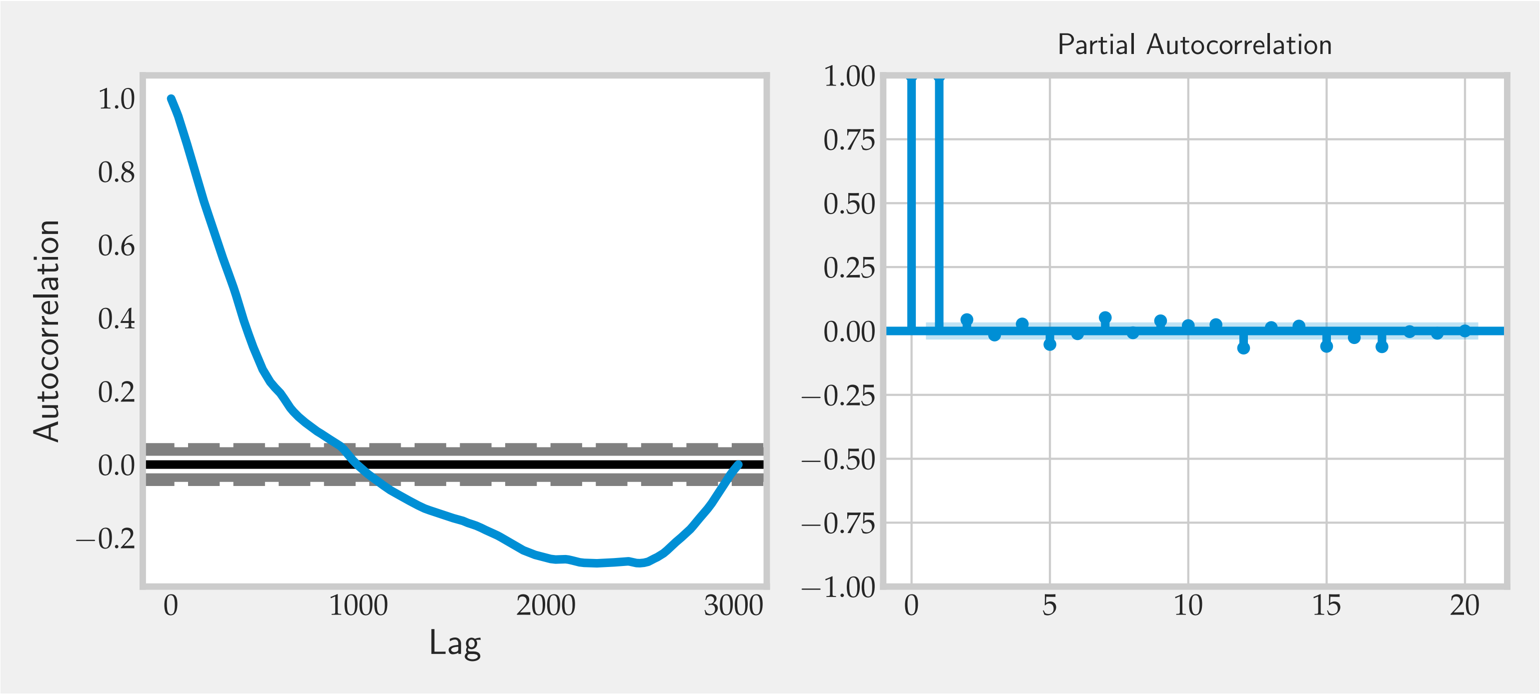

Figure 7: ACF gives large q ~ 900, and small p = 2
d was found using differencing and Dickey-Fuller Test, this gave d = 1

ARIMA MODEL: PLOT AND ERRORS – PART 2

- Arima models:
  - Auto Arima: ARIMA(6,1,4) for p,q extremes of 15
  - Ideal Manual Model: ARIMA(2,1,900).
  - Due to run time I used Manual: ARIMA(2,1,90) decent results.
- Auto Arima gave
  - MSE = 13.17
  - RMSE = 16.27
  - SSE = 24358.63
- Manual Model gave
  - MSE = 10.53
  - RMSE = 13.38
  - SEE = 16464.26
- Manual Model performed better

Figure 8: Plot of manual model ARIMA(2,1,90): Where the x-axis indicates the data points since 06/29/2010, and the y-axis is Apple's closing price.

MODEL GROUPS

- Two model groups for stock forecasting:
  - Short term: Lag terms and current stock market price models
  - Long term: VAR and Arima Models
- Short term prediction model (day-to-day):
  - Linear Regression model gave small errors
  - CON: Takes prior day value thus can't long term forecasting
- Long term predictions, solution, VAR and ARIMA
- Due to tech stock relationships, I postulated that the VAR would perform better than ARIMA
- Using test data, I found this to be true!

MODEL CONCLUSION FOR FORECASTING

- VAR model is better for forecasting
- Linear model is better for short term trading
- Method for PROFIT using linear lag model:
  - Buy when model crosses stock from above
  - Sell when model passes stock from under
  - Net profit of around
    - ~ $33 per stock pre-rescission
    - ~ $4 per stock during recession
    - ~ $37 per stock during quarter
- VAR model forecasted the rescission well
  - Use it with the linear model to better predict when to invest larger sums
- Conclusion: Stocks are hard to predict but using various models together can help aid in profits