Project Presentation - Kalman Filtering for Stocks Price Prediction and Control

Jean-Luc DeRieux

ECE 5606 – 04/23/2025

Presentation Outline

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  - Process Noise
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- Conclusion

Paper Selection

VIRGINIA TECH

Journal of Computer Science

Original Research Paper

Kalman Filtering for Stocks Price Prediction and Control

[1]Jimbo Henri Claver, [2]Mbiazi Dave and [2]Shu Felix Che

[1]*Department of Applied Mathematics and Computing, American International University, Kuwait*
[2]*Department of Mathematics and Computer Science, University of Bamenda, Bamenda, Cameroon*

Article history
Received: 24-10-2022
Revised: 16-12-2022
Accepted: 07-01-2023

Corresponding Author:
Jimbo Henri Claver
Department of Applied Mathematics and Computing, American International University, Kuwait
Email: jimbo.maths@gmail.com

Abstract: Stocks price analysis has been a critical area of research as the stock market is a very fluctuating market. Stocks price is affected by demand and supply dynamics making it difficult to forecast the price of a stock at a particular instant. The entire idea of predicting stocks price is to gain significant profits but predicting how the stock market will perform is a difficult task to carry out. In an attempt to do this, we construct a dynamical system for the stock's price and simulate it using the Kalman filter. The dynamic tracking features of the filter here enable us to track the price of the Boeing stock. The stock price variation appears to be a maneuvering system from which we derive the state space model. Further, the robustness of the model is investigated by examining observability and controllability in the state space and proving that the system can be stabilized through state feedback. Finally, the forecasting result of 252 stock closing prices from January 01, 2021, to January 01, 2022, is provided by Kalman predictor and Python simulation. The evaluation of the prediction is done using absolute and relative error which gives relatively small values and thus makes the filter accurate for prediction.

Keywords: Stocks Price, Maneuvering System, State Space Model, Controllability, Observability, Stability, Kalman Filter, Predictor, Python Simulation, Absolute and Relative Error

Introduction

A number of papers on the use of the Kalman filter have been published in recent years contributing many variations and solutions to specific problems especially related to robotic systems. This filter has many applications for example in the military, biomedical and automotive industry. Therefore, it is not limited only to the field of engineering but also works in computational finance (Urrea and Agramonte, 2021).

Recently, financial time series has become an important topic in quantitative finance. Accurate analysis and forecasting of a range of financial changes can provide operators and investors with reliable management and decision-making (Sezer *et al*., 2020). It consists of a collection of values known as a time series. Research and analysis of these categories will help investors make appropriate investment decisions and a suitable method should be found to predict and control the stock price. Filtering is an iterative process that helps infer a model's parameter when the latter relies upon a large quantity of observable and un-observable data (Javaheri *et al*., 2003). The problem of estimating these unobserved latent variables from observed market data often arises in mathematical finance (Date and Ponomareva, 2011). In the year 1960, American researcher Rudolf Kalman and Ruslan Bucy introduced the concept of state variables and state space of dynamical systems Meinhold and Singpurwalla (1983). At that time they proposed the state space method and developed the concept of the Kalman filter, and for decades its generalizations have been a key tool in econometrics and engineering for estimating unobserved variables from observed variables and now their use has become commonplace in finance. The Kalman filter is an estimator of the conditional moments of a Gaussian linear system and an optimal recursive algorithm that has real-time implementation in a computer (Kleeman, 1996). It is also used in the calibration of time series model predictor variables and data smoothing applications. It is suitable for dealing with multivariable systems time-varying systems and non-stationary stochastic processes. Antoulas (2013). The stock market fluctuates greatly and changes with time and the Kalman filter has good real-time dynamic tracking characteristics. The stock price

Highlights:

- Published in the Journal of Computer Science.
- The authors derive a dynamic system to use for a Kalman Filter.
- The authors emphasis Kalman Filter for stock prediction, but they never plot predictions. They only use filtering.

Reference:

J. H. Claver, D. Mbiazi and F. C. Shu, “Kalman Filtering for Stocks Price Prediction and Control,” Journal of Computer Science, vol. 19, no. 6, pp. 739–748, 2023, doi: 10.3844/jcssp.2023.739.748.

Overview of the paper: Maneuvering system

x_{t+1} : Predicted stock price at time $t+1$
$\dot{x}_{t+1}$: Predicted price change (i.e. first difference) at time $t+1$
x_t : Price at time t
$\dot{x}_t$: Price change (first difference) at time t
$\ddot{x}_t$: "Acceleration" (second difference) at time t
Δt : Sampling interval (i.e. the time-step)

η_t : Measurement noise on the observed price
Y_t : The observed (noisy) stock closing price at time t.

$x_{t+1|t}$: One-step-ahead a priori estimate of the stock price
$\dot{x}_{t+1|t}$: One-step-ahead a priori estimate of the price change

A : state-transition (or system) matrix:
B : input (or control) matrix
C : observation (or output) matrix:

Maneuvering System

$$x_{t+1} = x_t + \dot{x}_t \Delta t + \frac{1}{2}\ddot{x}_t(\Delta t)^2$$
$$\dot{x}_{t+1} = \dot{x}_t + \ddot{x}_t \Delta t$$
$$Y_t = C_1 x_{t+1|t} + C_2 \dot{x}_{t+1|t} + \eta_t$$

Vector Form

$$X_t = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_t \\ \dot{x}_t \end{bmatrix} + \begin{bmatrix} \frac{1}{2}(\Delta t)^2 \\ \Delta t \end{bmatrix} \ddot{x}_t$$
$$Y_t = \begin{bmatrix} C_1 & C_2 \end{bmatrix} \begin{pmatrix} x_{t+1|t} \\ \dot{x}_{t+1|t} \end{pmatrix} + \eta_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{pmatrix} x_{t+1|t} \\ \dot{x}_{t+1|t} \end{pmatrix} + \eta_t$$

System Matrices

$$A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, \qquad B = \begin{bmatrix} \frac{1}{2}(\Delta t)^2 \\ \Delta t \end{bmatrix}, \qquad C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

Overview of the paper: Process Noise

Q : Process Noise Covariance
R : Measurement Noise Variance
σ_x : Position-noise standard deviation
$\sigma_{\dot{x}}$: Velocity-noise standard deviation
$\sigma_{\ddot{x}}$: Acceleration-noise standard deviation
Δt : Sampling interval (i.e. the time-step)

ε_t : Process Noise (model noise)
η_t : Measurement Noise

$$\varepsilon_t \sim \mathcal{N}(0, Q), \qquad \eta_t \sim \mathcal{N}(0, R)$$

$$\sigma_{\dot{x}} = \sigma_{\ddot{x}} \Delta t, \qquad \sigma_x = \sigma_{\ddot{x}} \frac{\Delta t^2}{2}$$

$$\Delta t = 1, \qquad \sigma_x = \frac{1}{2}, \qquad \sigma_{\dot{x}} = 1, \qquad \sigma_{\ddot{x}} = 1$$

$$Q = \begin{pmatrix} \sigma_{\ddot{x}}^2 & \sigma_x \sigma_{\dot{x}} \\ \sigma_{\dot{x}} \sigma_x & \sigma_{\ddot{x}}^2 \end{pmatrix} = \sigma_{\ddot{x}}^2 \begin{pmatrix} \frac{\Delta t^4}{4} & \frac{\Delta t^3}{2} \\ \frac{\Delta t^3}{2} & \Delta t^2 \end{pmatrix} = \begin{pmatrix} \frac{1}{4} & \frac{1}{2} \\ \frac{1}{2} & 1 \end{pmatrix}$$

They set the measurement-noise standard deviation σ_y to 1 (a common normalizing assumption)

$$R = \sigma_y^2 = 1$$

Overview of the paper: Kalman Filter

(1) Time-update (Predicted Price)

$$\hat{x}_{t+1|t} = A\hat{x}_t$$

(2) Time-update (Covariance prediction)

$$P_{t+1|t} = AP_tA^T + Q$$

(3) Innovation covariance

$$S_{t+1} = CP_{t+1|t}C^T + R$$

(4) Kalman Gain

$$K_{t+1} = P_{t+1|t}C^T S_{t+1}^{-1}$$

(5) Measurement-update (Filtered Price)

$$\hat{x}_{t+1|t+1} = \hat{x}_{t+1|t} + K_{t+1}\left(y_{t+1} - C\hat{x}_{t+1|t}\right)$$

(6) Measurement-update (Covariance correction)

$$P_{t+t|t+1} = (I - K_{t+1}C)P_{t+1|t}$$

Initial State and Covariance

$$\hat{x}_o = \begin{bmatrix} 210.71 \\ 0.74 \end{bmatrix}, \qquad \mathrm{P_o} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

System Matrices ($\boldsymbol{\Delta t = 1}$)

$$A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, \qquad B = \begin{bmatrix} 1/2 \\ 1 \end{bmatrix}, \qquad C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

Noise Covariance

$$Q = \begin{pmatrix} 1/4 & 1/2 \\ 1/2 & 1 \end{pmatrix}, \qquad R = 1$$

Iterate $\mathbf{1} \rightarrow \mathbf{6}$ over all n daily closing prices .

Demo: Code

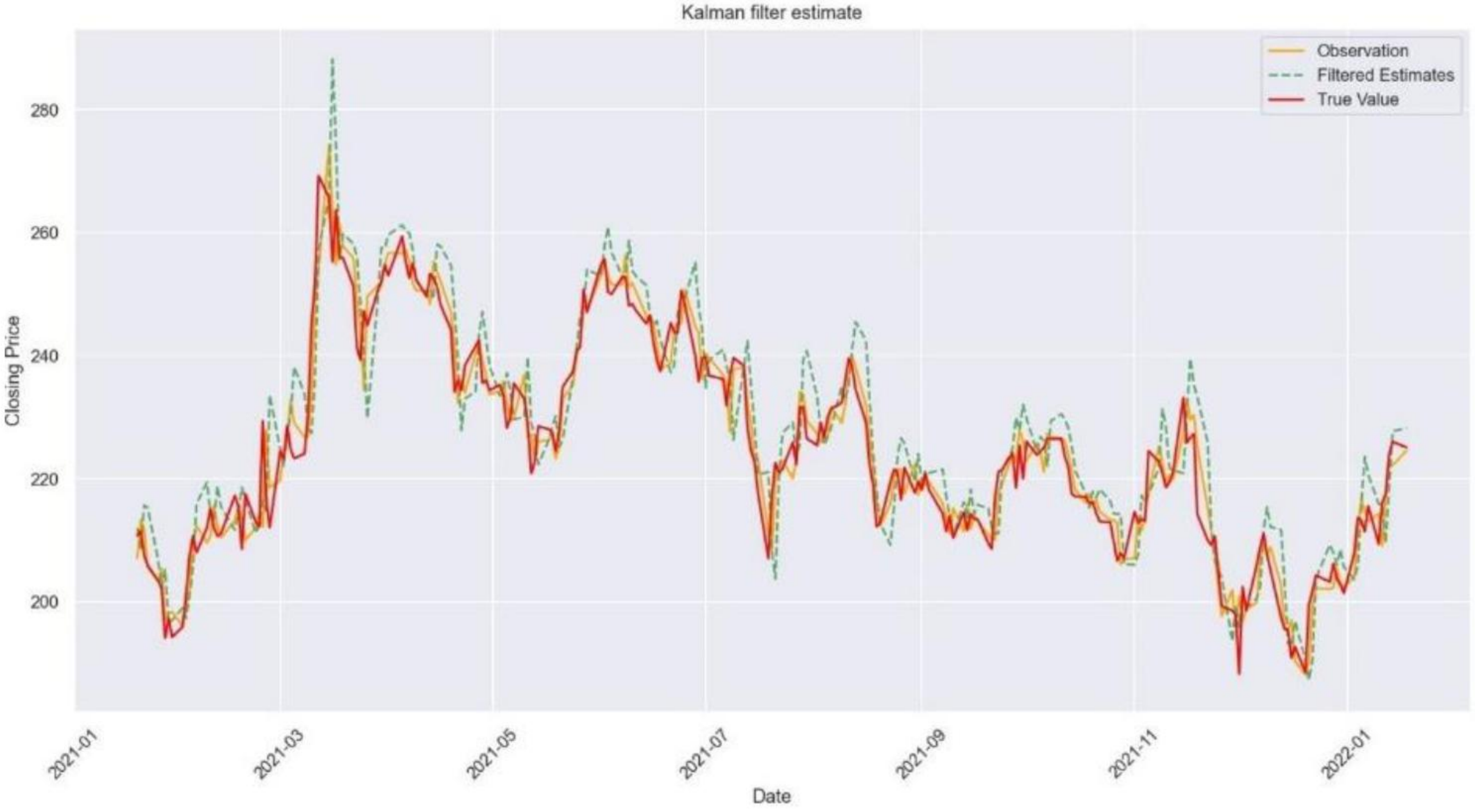
```python
43  # 3) Kalman components
44  dt = 1.0
45  A  = np.array([[1, dt],[0, 1]])
46  C  = np.array([[1, 0]])
47  Q  = np.array([[dt**4/4, dt**3/2],
48                 [dt**3/2,    dt**2]])
49  R  = 1.0
50
51  # 4) Initialize state
52  start_price = df_after.loc[0, 'Close']
53  x = np.array([start_price, 0.0])
54  P = np.diag([start_price, 1.0])
```

Note: After filter stage stops the next stage is just calculating line 61 for prediction
current_price = prev_price + (last est. velocity)

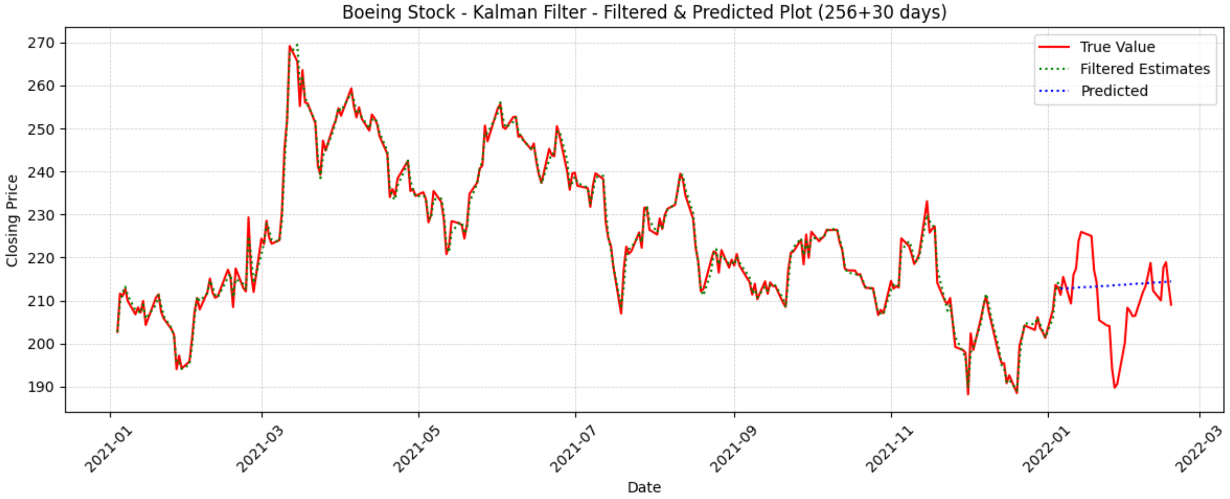
Its just showing you the probable trend unless you include real observed values to correct prediction

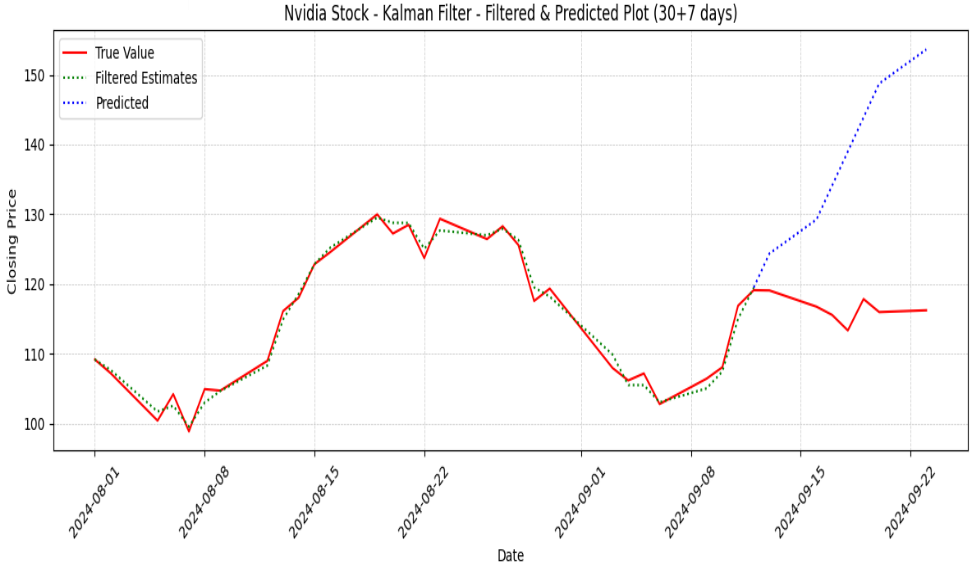
```python
56  # 5) Kalman-filter and prediction
57  filt_vals = []
58  pred_vals = []
59  for i in range(n_filter + predict_days):
60      # Predict step (always)
61      x = A @ x
62      P = A @ P @ A.T + Q
63
64      if i < n_filter:
65          # Update step (only for real observations)
66          actual = y_actual[i]
67          y_pred = (C @ x)[0]
68          S = (C @ P @ C.T)[0,0] + R
69          K = P @ C.T / S
70          x = x + (K.flatten() * (actual - y_pred))
71          P = (np.eye(2) - K @ C) @ P
72          filt_vals.append(x[0])
73      else:
74          # Prediction step (no update)
75          pred_vals.append((C @ x)[0])
```

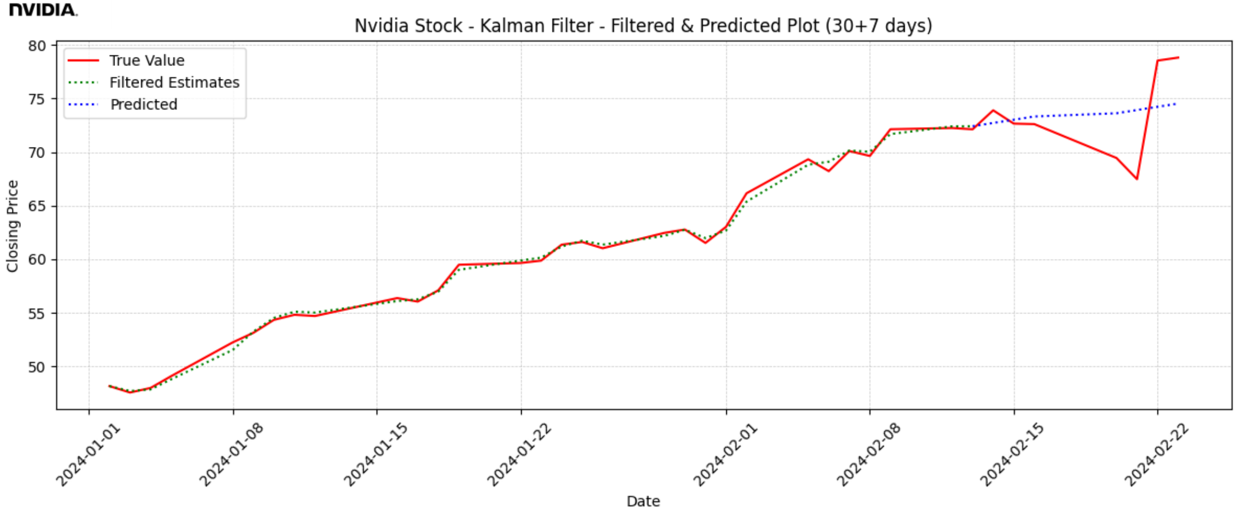
Demo: Paper Results



Demo: Personal Demo







https://github.com/Jean-LucDeRieux/kalman-filter-stock-predictor

Conclusion

Final Comments:

- Filtering vs. Forcasting: Paper does a good job describing filtering noisy price data but doesn’t forecast future prices
- Richer Measurements: Ideally you would want another measurement to aid in stock prediction. This could be trading volume, news sentiments, economic data etc.
- State-Space Expressiveness: Constant velocity state-space model is too simple to capture real world stock uncertainty. Adding an acceleration state would aid in a bull/bear dynamics that are common with stock prices. (they only taken in price and velocity for x_o)

Journal of Computer Science

Original Research Paper

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Science Publications

Thank you!

Feel free to check out my code

https://github.com/Jean-LucDeRieux/kalman-filter-stock-predictor