

Economics 144

Economic Forecasting

Lecture 16

State Space Models

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State Space Models (SSM)

(e.g., Kalman Filter)

- **Q:** Why would you use Filtering techniques instead of e.g., ARIMA?
- **A:** Smoothing techniques (such as filtering and spectral analysis) are often used to *filter* out random noise.
- All previous time-series techniques discussed, relied **consisted of regressions of present on past observations → Time Domain** in time domain data can be too noisy
- Now we consider regressions of the present on periodic sines and cosines → Frequency Domain

Abandon time domain and move to frequency domain
- clean up data and looking for signals.

State Space Models (e.g., Kalman Filter)

- Main goals of filtering methods:
 - Identify the dominant frequencies in a series.
 - Find an explanation of the system from which the measurements were derived. This ‘explanation’ usually consists of only a few oscillations, therefore, its simpler and more physically meaningful.

Example: Deterministic Signal

$$x_1 = \overset{A}{2} \cos(2\pi t \overset{f}{6/100}) + \overset{A}{3} \sin(2\pi t 6/100)$$

$$x_2 = 4 \cos(2\pi t 10/100) + 5 \sin(2\pi t 10/100)$$

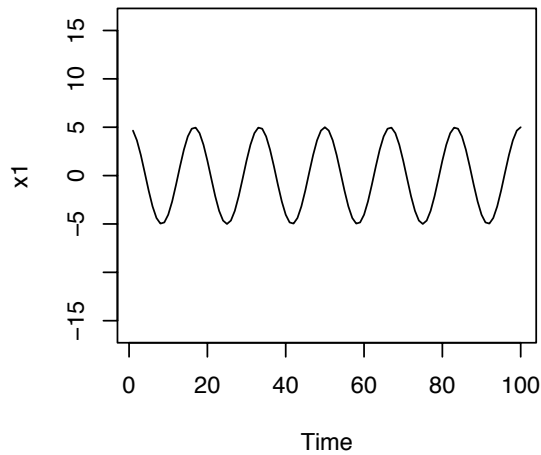
$$+ x_3 = 6 \cos(2\pi t 40/100) + 7 \sin(2\pi t 40/100)$$

$$x = x_1 + x_2 + x_3$$

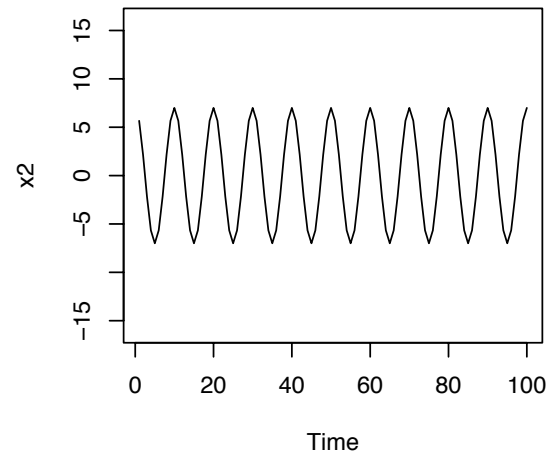
- **Summary:** x is constructed from 3 signals with respective (f, A^2) given by $(0.06, 13)$, $(0.10, 41)$, and $(0.4, 85)$

Example: Deterministic Signal

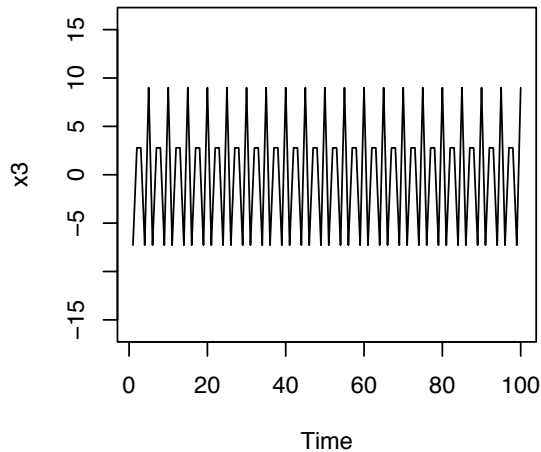
$$f=0.06, A^2 = 13$$



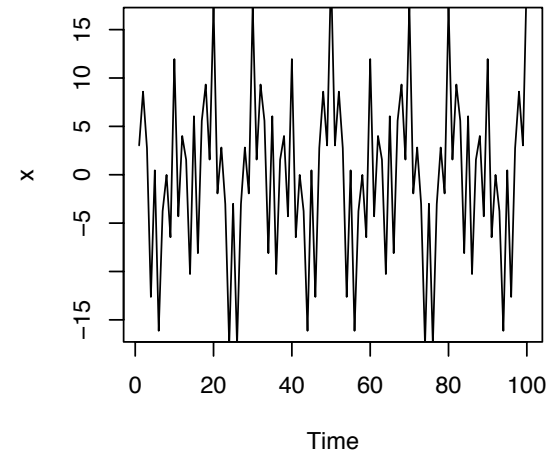
$$f=0.10, A^2 = 41$$



$$f=0.40, A^2 = 85$$



Sum



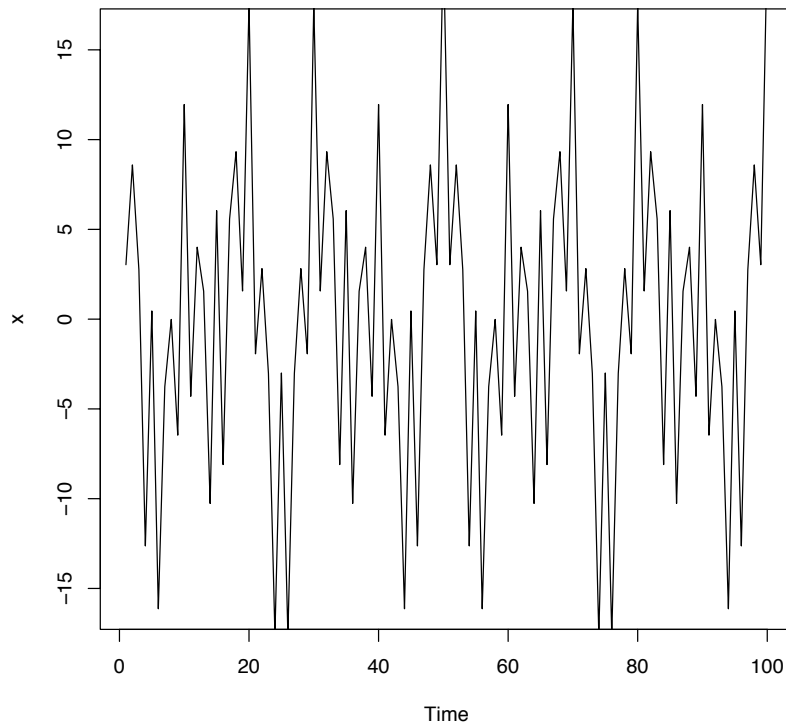
Quite noisy

reverse-engineer
the components

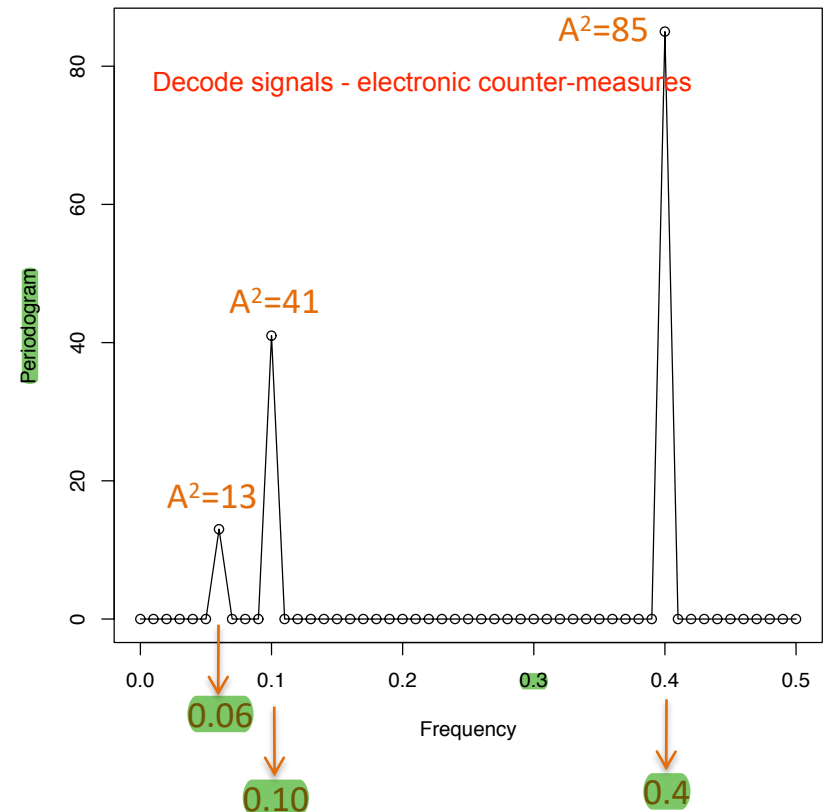
Example: Deterministic Signal

Q: If we only observe the final signal, can we infer its main 'components'?

Yes! We look at the **periodogram's** (FFT) frequencies and amplitudes.

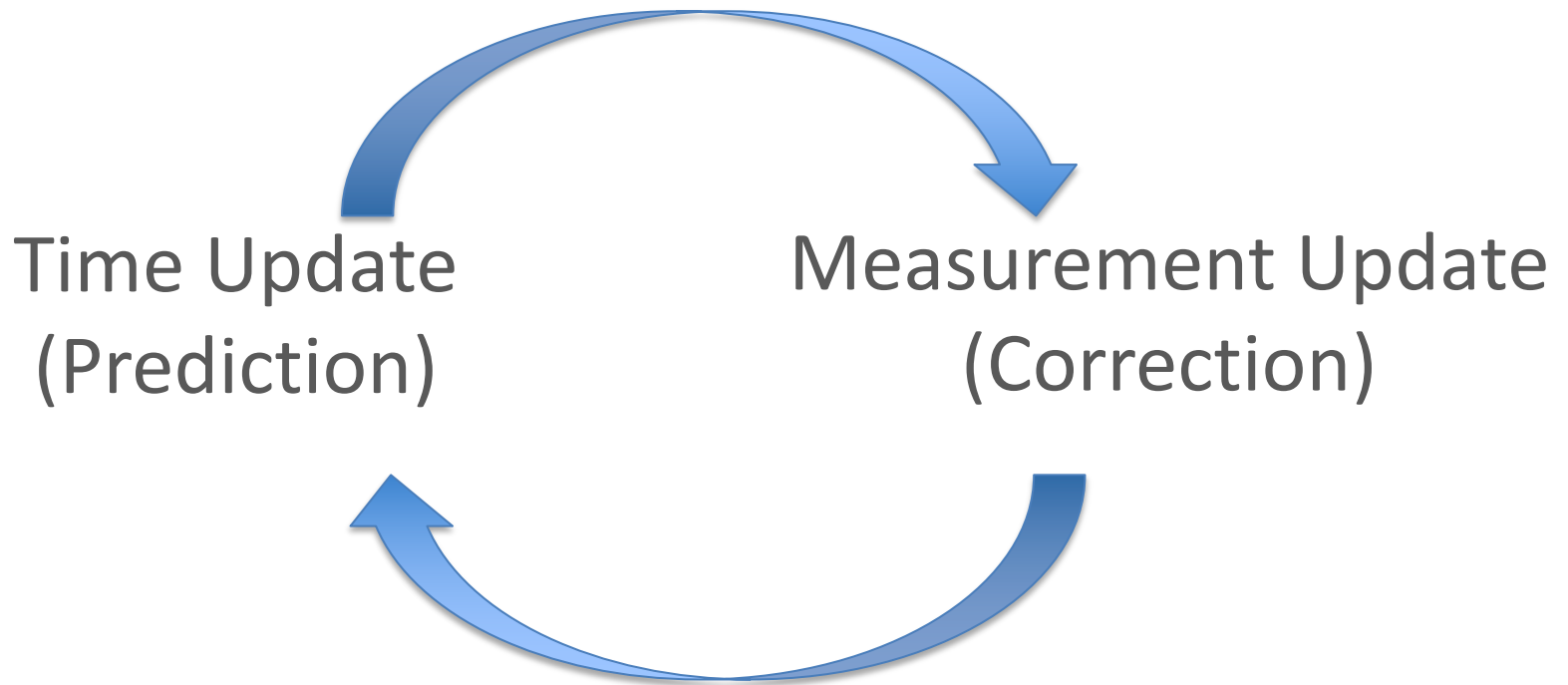


added components



matches the three series that made up the signal

Example: Kalman Filter



The time update projects the current state estimate ahead in time.
The measurement update adjusts the projected estimate by an actual measurement at that time.

Example: Kalman Filter

action based on all the information coming in - at the heart - take a ton of other diffusion and fuse it

- The KF 'data fusion algorithm' consists of updating the means and (co)variances of process modeled.

Control Input Matrix

non-constant acceleration Effect of acceleration → position and velocity

$$\vec{x}_t = \underbrace{\mathbf{F}_t}_{\text{Transition Matrix}} \underbrace{\vec{x}_{t-1}}_{\text{State vector (position, velocity,...)}} + \underbrace{\mathbf{B}_t \vec{u}_t}_{\text{Control Input Matrix}} + \underbrace{\vec{e}_t}_{\text{comprised of kinematic variables}}$$

Transition Matrix

Position at t-1 → position at t

Velocity at t-1 → velocity at t

same equation as $V = V_0 + at$

can also have acceleration

$$\vec{z}_t = \underbrace{\mathbf{H}_t}_{\text{Transformation Matrix}} \underbrace{\vec{x}_t}_{\text{state vector}} + \underbrace{\vec{v}_t}_{\text{Vector of measurements}}$$

Transformation Matrix

Maps the state vector parameters

into the measurement domain

explained by decomposition

Example: Kalman Filter

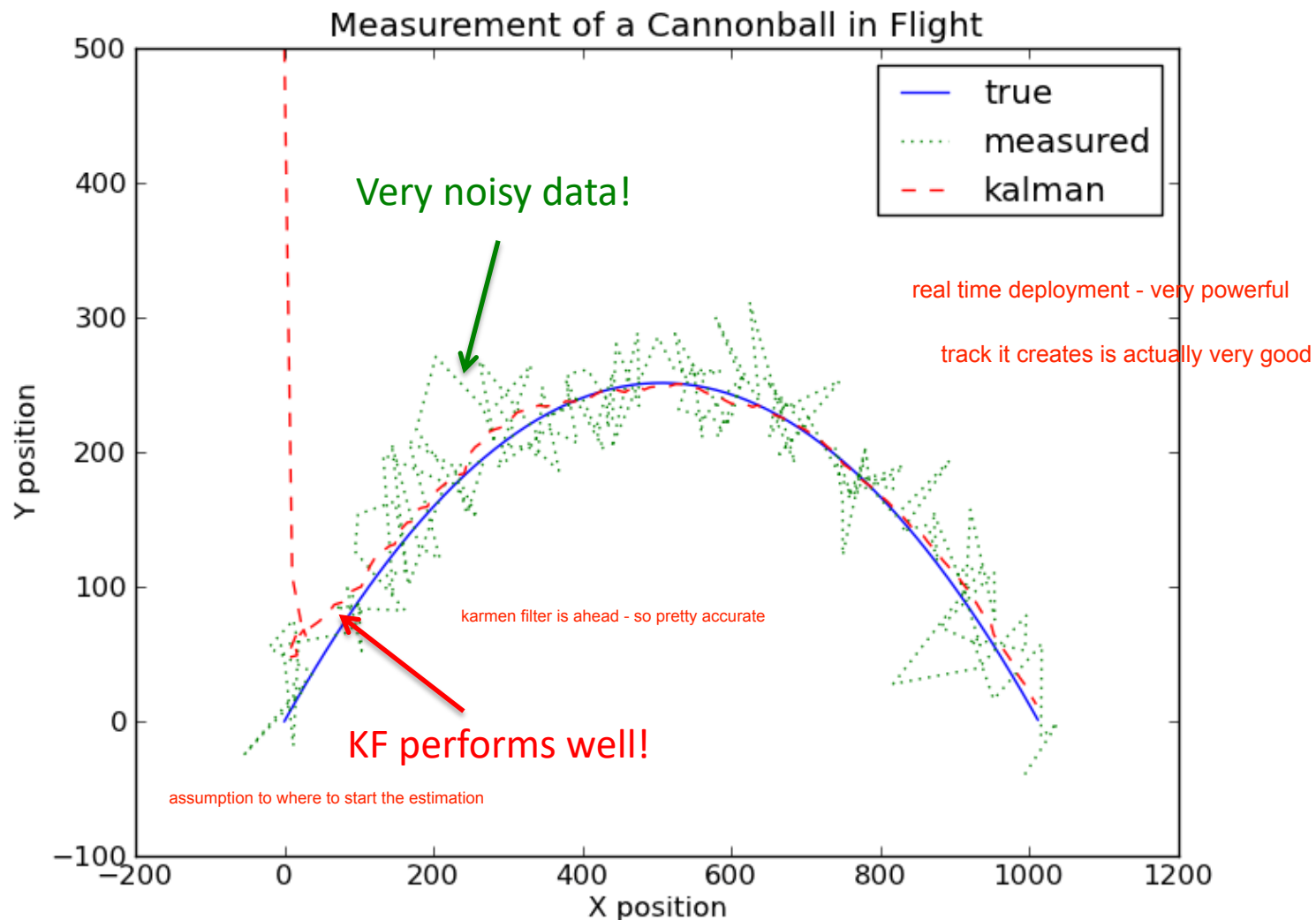
$$\underbrace{x_t}_{\text{position}} = x_{t-1} + \underbrace{\dot{x}}_{\text{velocity}} \Delta t + \underbrace{\frac{1}{2} \left(\frac{f_t}{m} \right) (\Delta t)^2}_{\text{acceleration}}$$

$$\underbrace{\dot{x}_t}_{\text{velocity}} = \dot{x}_{t-1} + \left(\frac{f_t}{m} \right) \Delta t$$

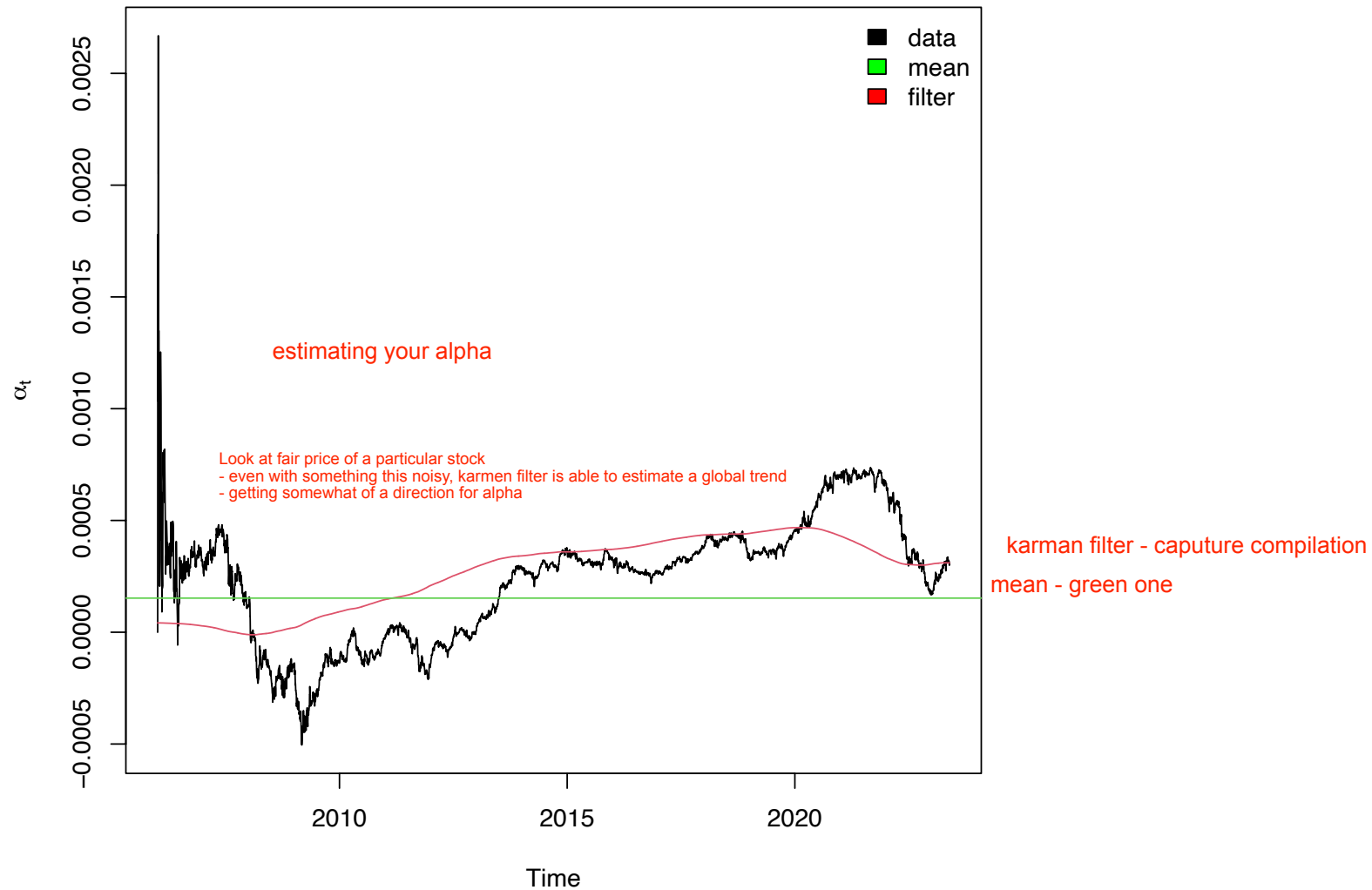
Kinematic Equations of Motion

$$\underbrace{\begin{bmatrix} x_t \\ \dot{x}_t \end{bmatrix}}_{\mathbf{x}_t} = \underbrace{\begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}}_{\mathbf{F}_t} \underbrace{\begin{bmatrix} x_{t-1} \\ \dot{x}_{t-1} \end{bmatrix}}_{\mathbf{x}_{t-1}} + \underbrace{\begin{bmatrix} \frac{1}{2} (\Delta t)^2 \\ \Delta t \end{bmatrix}}_{\mathbf{B}_t} \underbrace{\left(\frac{f_t}{m} \right)}_{\mathbf{u}_{t-1}}$$

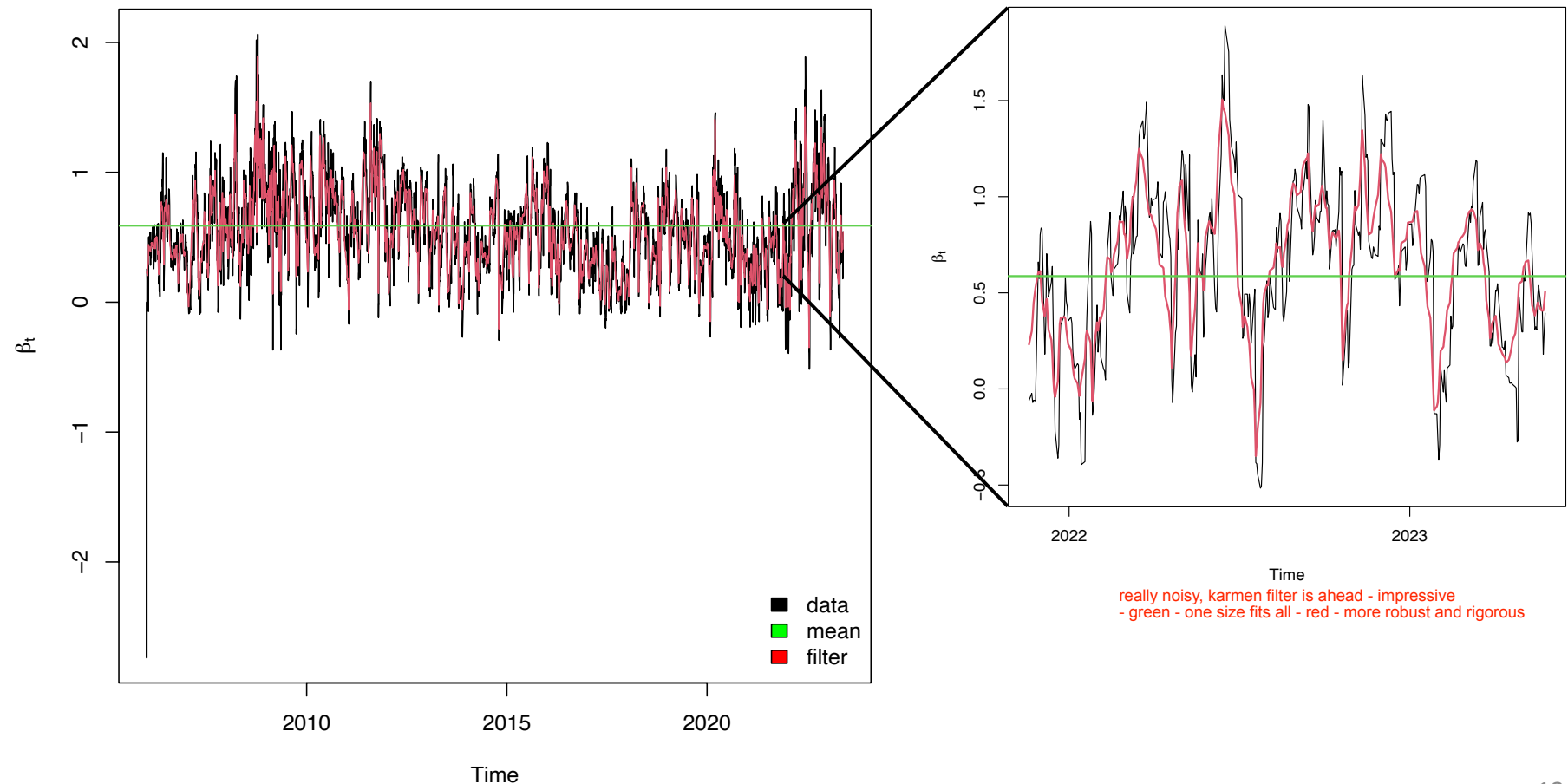
Example: Kalman Filter



Application: CAPM (alpha estimate)

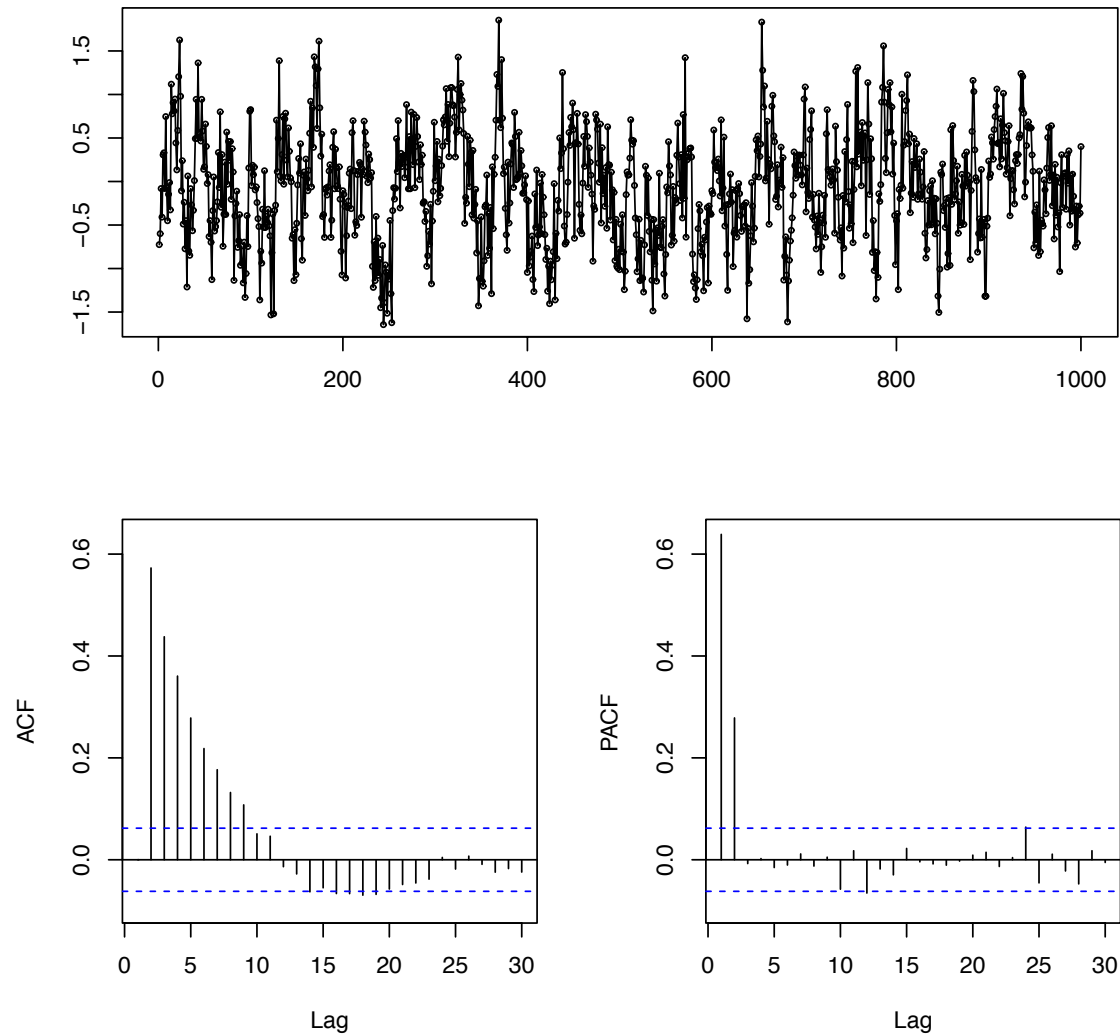


Application: CAPM (beta estimate)

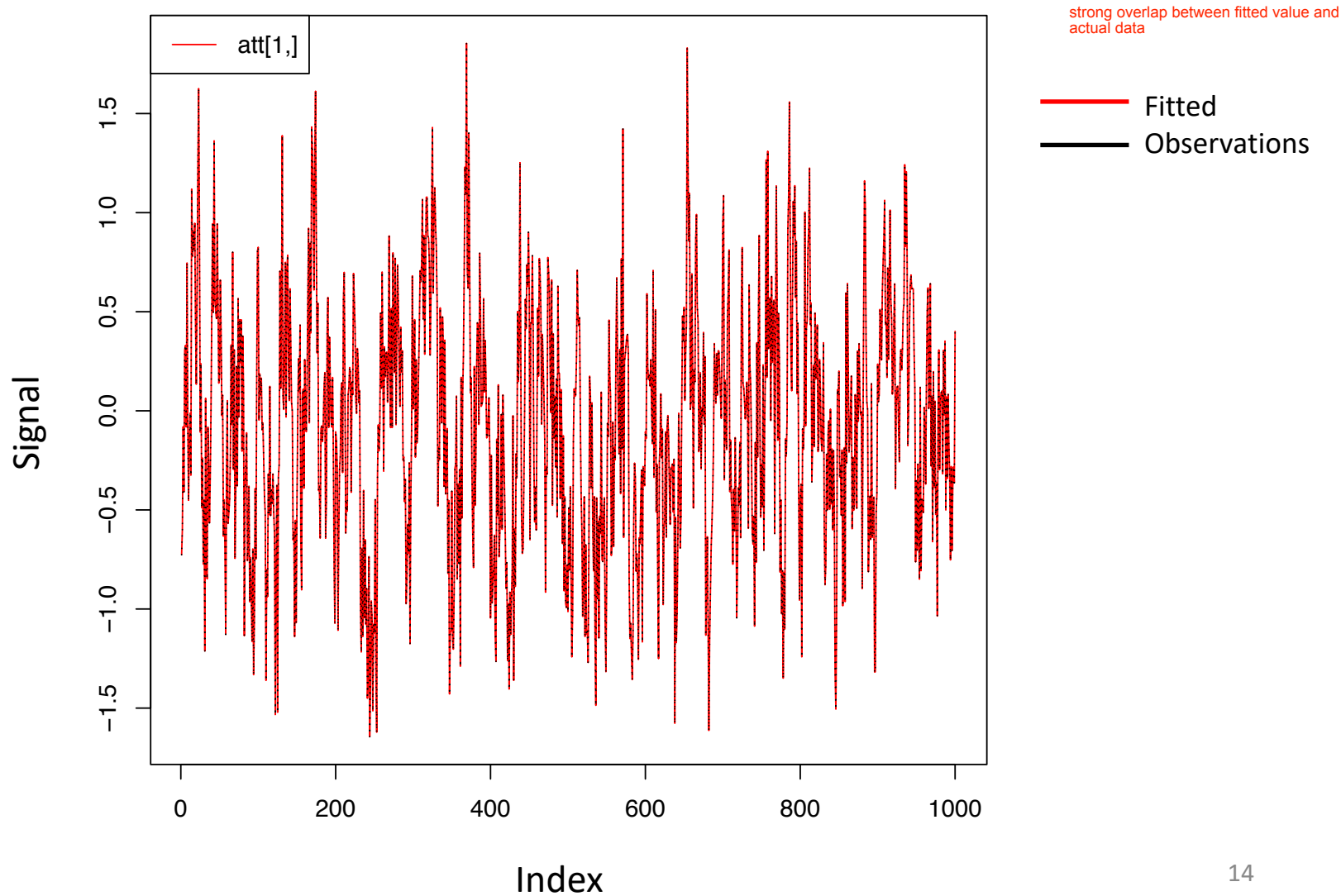


Filters vs. ARIMA

Simulated ARMA(2,1)



Filters vs. ARIMA



Results from the Kalman Filter

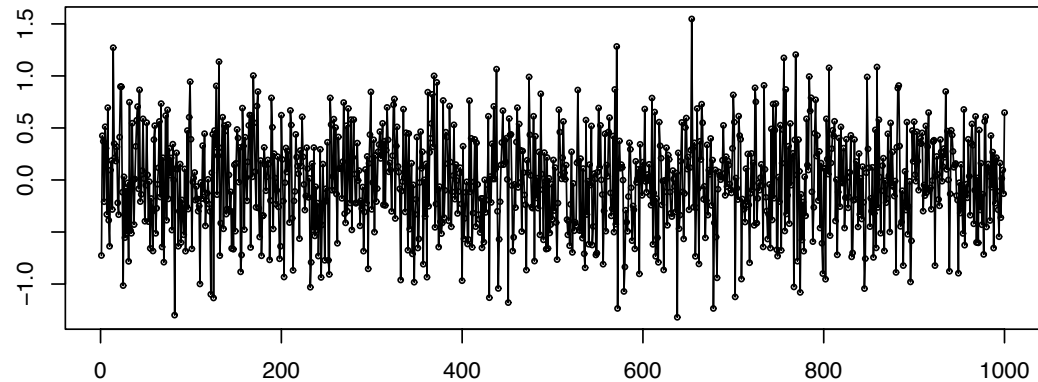
Test sample, look at overall fit, use RMSE(accuracy).

White noise statistical test suggest the autocorrelation functions are consistent white noise at 1%.

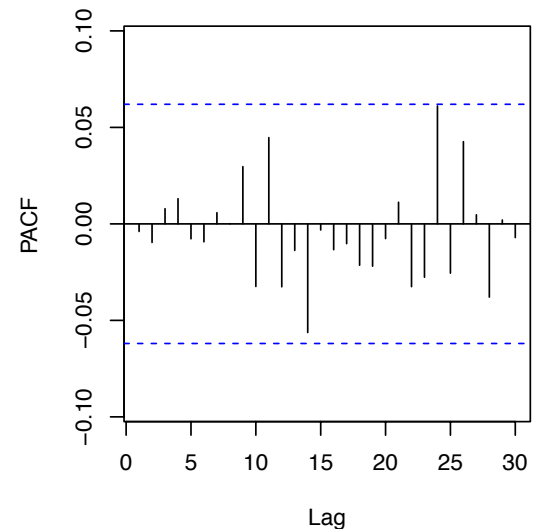
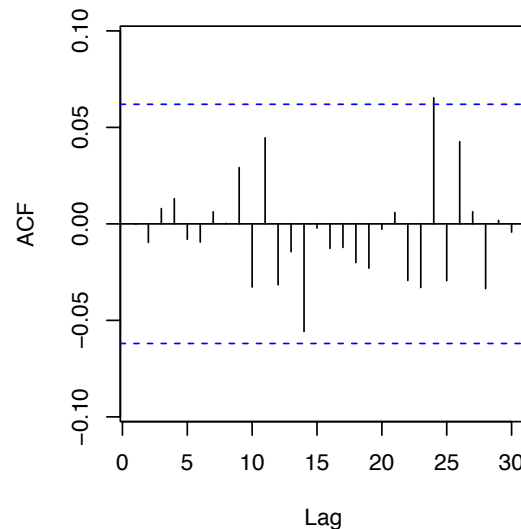


Our model seems to have captured all the dynamics.

Kalman-Filter Residuals



Check residuals - these spikes are within the window - done a pretty good job of wiping out the dynamics
- done a good job in estimating the models.



Results from ARMA

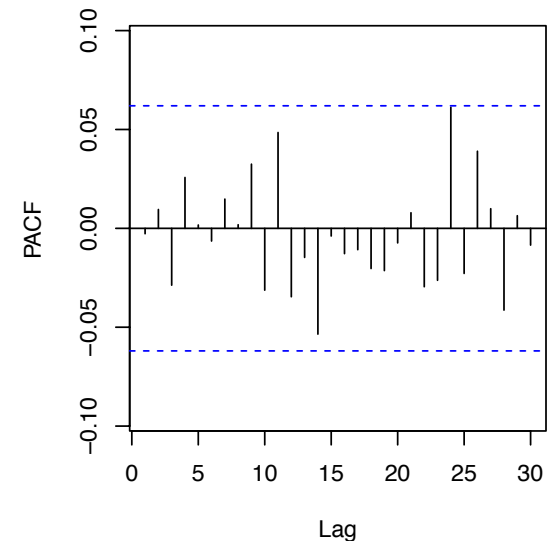
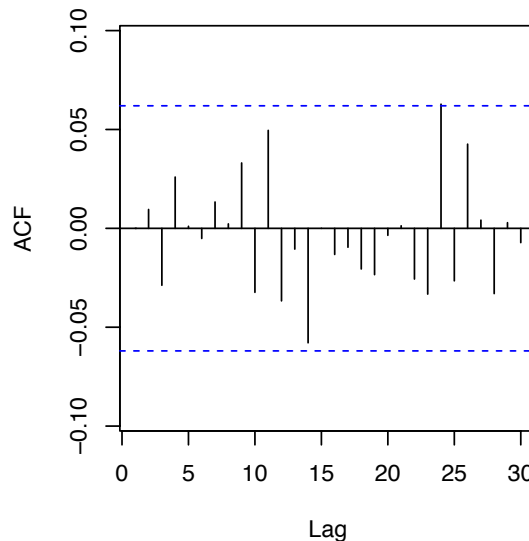
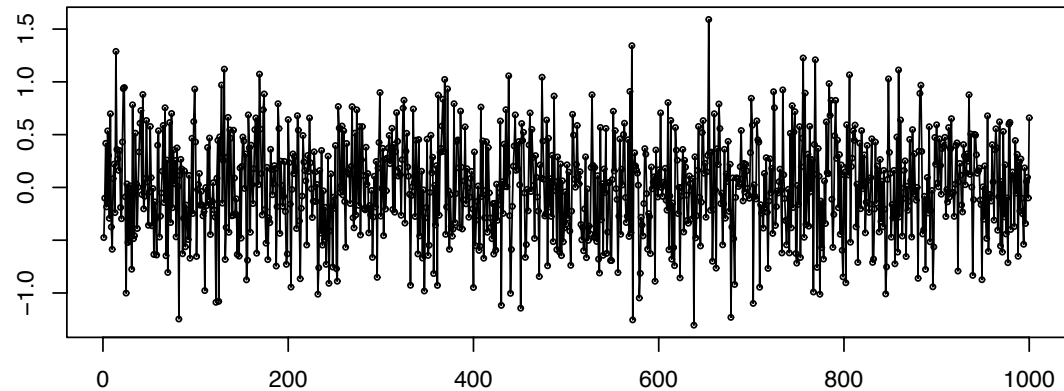
ARMA results are almost identical to the KF results.

White noise statistical test suggest the autocorrelation functions are consistent white noise at 1%.



Our model seems to have captured all the dynamics.

ARMA(2,1) Residuals



State Space Models

vs. ARIMA, VAR, and others

Some Advantages of SSM over ARIMA, VAR, ...

- Any ARIMA model can be represented in a state-space form, but only simple state-space models can be represented exactly in ARIMA form.
- SSM easily handles structural breaks, shifts, and time-varying parameters of some static model.
- SSM handles missing (and/or irregular) data better than e.g., ARIMA, VAR, ...
- SSM allows for changes on-a-fly parameters of the state-space model itself.
- SSM models allows use of data from different sources simultaneously in the same model to estimate one underlying quantity.