

KALMAN FILTERS

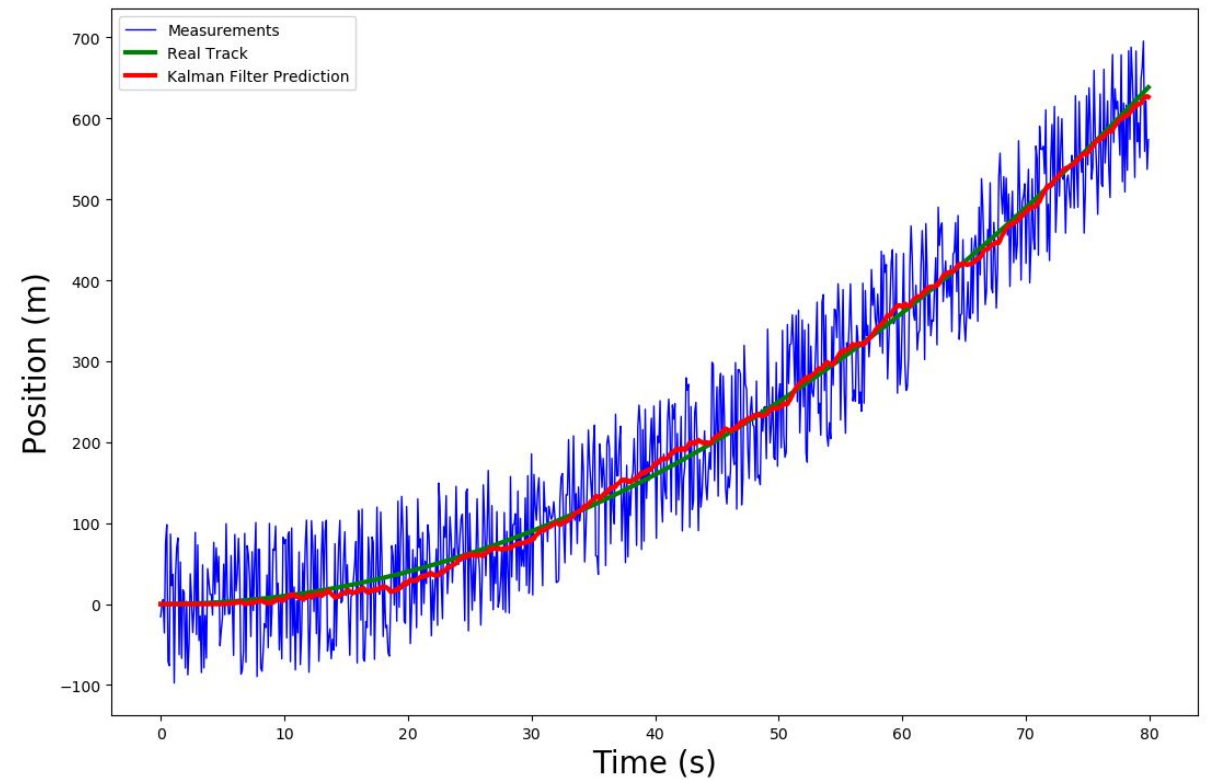
WHY?

PREDICTION:

- TEMPERATURE
- ECONOMICS
- **OBJECT TRACKING**



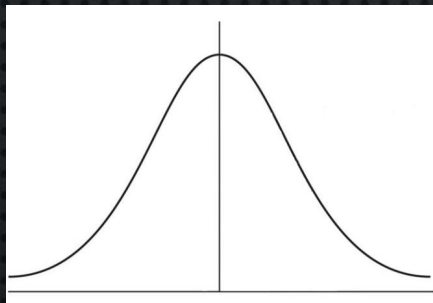
Example of Kalman filter for tracking a moving object in 1-D



WHAT DO THEY DO?

PROBLEM:

- Given a system with sensors
- The system is linear
- The sensors have Gaussian Noise

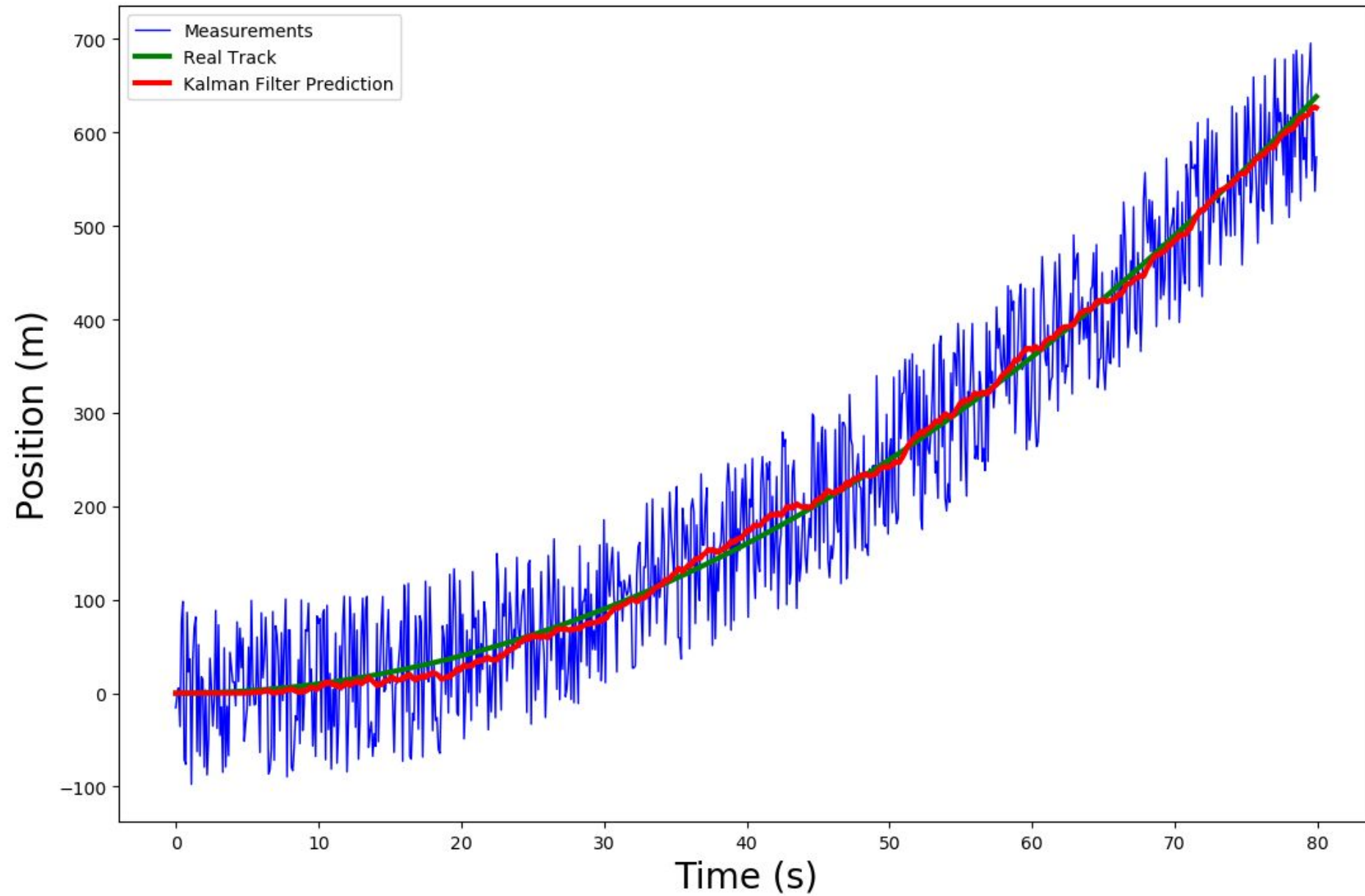


KF SOLUTION:

- Uses previous state of system
 - only needs last state (none before)
- Uses current measurement from sensors
- Combines 2 sources into one output
- This output attempts to eliminate noise from sensors to predict the true state of the system

GOAL: Predict next state of a system

Example of Kalman filter for tracking a moving object in 1-D



WHAT DO THEY DO? PART 2

Can be split up into 2 parts:

- Requires 8 parameters:

- 1.) F – state transition matrix
- 2.) B – control input matrix
- 3.) Q – covariance matrix of process noise
- 4.) u – control input vector (closely tied with x)
- 5.) x_0 – initial state of system
- 6.) H – measurement matrix
- 7.) R – covariance matrix of measurement noise
- 8.) z_1, \dots, z_k – measurements from sensor



1. Process Model

2. Measurement Model

SETTING UP BOTH MODELS

Parameters:

- 1.) F – state transition matrix
- 2.) B – control input matrix
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Process Model

$$x_{k+1} = Fx_k + Bu_k + w_k$$

- w_k is associated with Q
- It is the process noise vector
- $w_k \sim N(0, Q)$

Measurement Model

$$z_{k+1} = Hx_k + v_k$$

- v_k is associated with R
- It is the measurement noise vector
- $v_k \sim N(0, R)$

QUICK NOTES BEFORE IMPLEMENTATION

Parameters:

- 1.) F – state transition matrix
- 2.) B – control input matrix
- 3.) Q – covariance matrix of process noise
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- 8.) z_1, \dots, z_k – measurements from sensor

- Q and R are the noises
 - They are not known and must be tuned
- The covariances of variables are often 0 in object tracking
 - Spatial dimensions are independent

THE ALGORITHM

STAGE 1 (Prediction):

- Predicted State Estimate (\tilde{x}_k)

$$\tilde{x}_k = Fx_{k-1}^+ + Bu_{k-1}$$

- Predicted Error Covariance (P_k^-)

$$P_k^- = FP_{k-1}^+ F^T + Q$$

STAGE 2 (Update):

- Measurement Residual (\tilde{y}_k)

$$\tilde{y}_k = z_k - H\tilde{x}_k$$

- Kalman Gain (K_k)

$$K_k = P_k^- H^T (R + HP_k^- H^T)^{-1}$$

- Updated State Estimate (x_k^+)

$$x_k^+ = \tilde{x}_k + K_k \tilde{y}_k$$

- Updated Error Covariance (P_k^+)

$$P_k^+ = (I - K_k H) P_k^-$$

Parameters:

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1D EXAMPLE

GOAL: Predict next x position

State Vector: $\bar{x}_k = \begin{bmatrix} x_k \\ v_k \end{bmatrix} \longrightarrow \begin{matrix} x_{k+1} = x_k + v_k \Delta t + \frac{1}{2} a \Delta t^2 \\ v_{k+1} = v_k + a \Delta t \end{matrix} \longrightarrow \bar{x}_{k+1} = \underbrace{\begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}}_F \bar{x}_k + \underbrace{\begin{bmatrix} \frac{1}{2} \Delta t^2 \\ \Delta t \end{bmatrix}}_B * a$

Measurement Vector: $\bar{z}_k = \begin{bmatrix} z_k \end{bmatrix} \longrightarrow \bar{z}_{k+1} = H \bar{x}_k \longrightarrow \bar{z}_{k+1} = \underbrace{\begin{bmatrix} 1 & 0 \end{bmatrix}}_H \bar{x}_k$

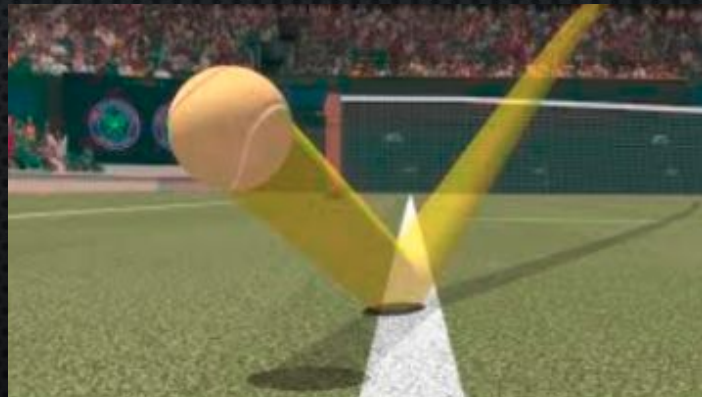
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SUMMARY OF K.F. AND ITS CONS

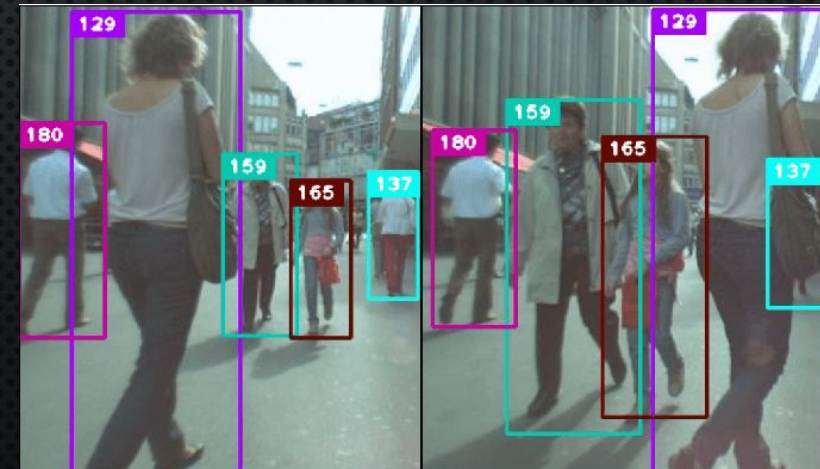
- Uses last state and measurements
- Uses Q and R as the error which are tunable parameters
 - $w_k \sim N(0, Q)$
 - $v_k \sim N(0, R)$
- Only works if the equation is linear
- Only works if Q and R are Gaussian

* Real-world is non-linear
(i.e. angles of measurements)



Why wouldn't Q and R be Gaussian?

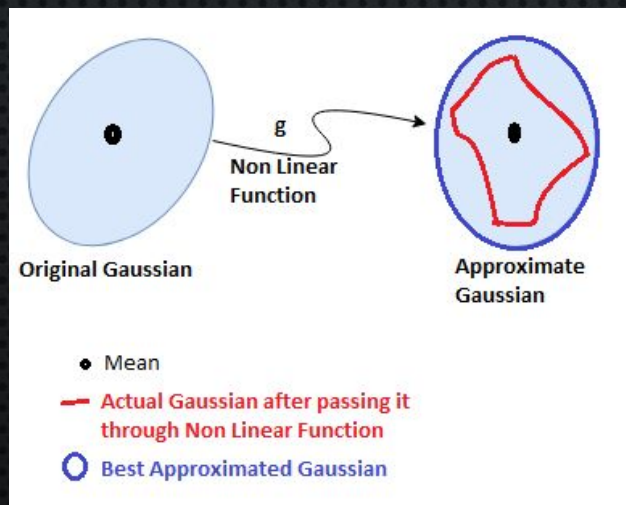
- Obstruction and misdetection of object
- Example:
 - Computer vision detects part of the background as additional part of the object



BEYOND K.F. LIMITATIONS

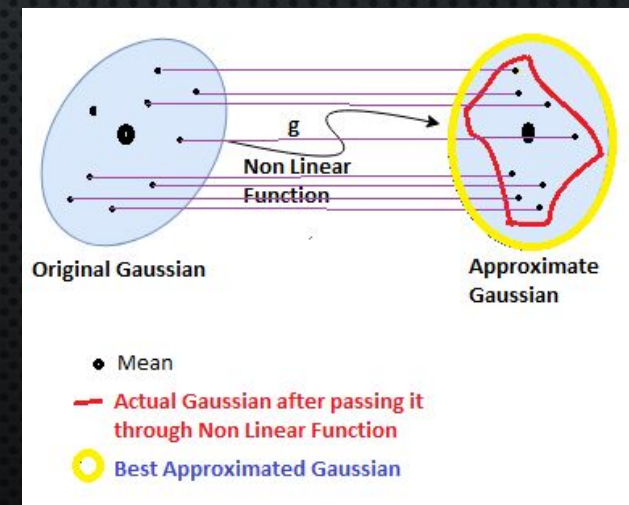
Extended Kalman Filter

- Deals with non-linear problems
- Linearizes the problem
- Does this by approximating around the mean
- Able to use same equations as in Kalman Filter after linearized



Unscented Kalman Filter

- Deals with non-linear problems
- Also linearizes the problem
- Approximates around sigma points
 - One of these points is the mean
 - Each point has an associated weight
- More computationally expensive





"That's all, Folks!"