

# CS201: Computer Vision

## Tracking: Kalman Filter and Multi-Target Tracking

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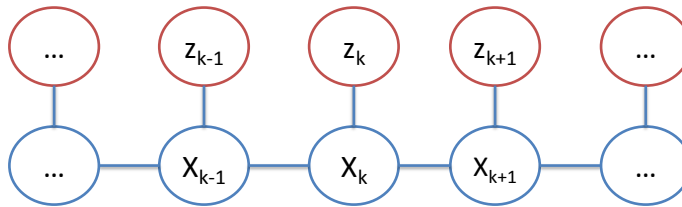
Slides Courtesy of  
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### Question of the Day:

- How can we use measurements to estimate state?
- Kalman Filter:  
[http://www.cs.unc.edu/~welch/media/pdf/kalman\\_intro.pdf](http://www.cs.unc.edu/~welch/media/pdf/kalman_intro.pdf)

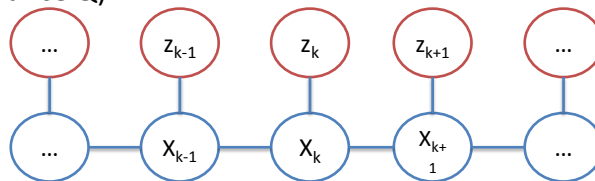
## State vs Measurements

- Graphical model
- Goal: Estimate state by using measurements



## State Changes Over Time

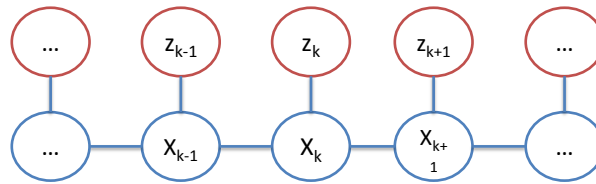
- Markov assumption: next state depends only on immediately preceding state
- State evolution function:  $A: x_{t+1} = A(x_t)$
- Corrupted by noise (to absorb what you can't model)  
 $x_{t+1} = A(x_t) + w_t$  ( $w$  is noise term. ex: Gaussian with covariance  $Q$ )



- Example: state = [pos vel].  $A$  = constant velocity

## Measuring State

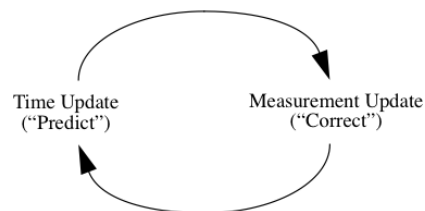
- Measurement Model:  $H$
- Measurements:  $z_t = H(x_t)$
- Corrupted by noise  $z_t = H(x_t) + v_t$   
( $v$  is noise term. ex: Gaussian with covariance  $R \neq Q$ )



- Ex: state is [pos vel]. Measurement is just pos

## Kalman Filter Concept

- Predict / Correct
- Each state estimate has associated uncertainty ( $P_k$ )
- Recursive: each estimate uses previous estimate (not just data)



## Kalman Filter Prediction

- Given:
  - Previous state estimate ( $\hat{x}_{k-1}$ )  $\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1}$
  - Previous uncertainty ( $P_{k-1}$ )  $P_k^- = AP_{k-1}A^T + Q$
  - Linear State evolution fn as matrix A
  - Process noise (Q)
- Output:
  - Prediction (guess/estimate) of state at next time ( $\hat{x}_k^-$ )
  - Certainty of that estimate ( $P_k^-$ )
  - (Predicted measurement:  $H \hat{x}_k^-$ )

## Kalman Filter Update

- Given:
  - Current state prediction ( $\hat{x}_k^-$ ) and uncertainty ( $P_k^-$ )
  - Measurement prediction ( $H \hat{x}_k^-$ )
  - Actual measurement ( $z_k$ )
  - Measurement noise (R)  $\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-)$
- Output:
  - Updated state estimate  $\hat{x}_k$   $K_k = P_k^- H^T (H P_k^- H^T + R)^{-1}$
  - Updated uncertainty  $P_k$   $P_k = (I - K_k H) P_k^-$

# Kalman Filter Update

- Notes:

- “Innovation” ( $z_k - H \hat{x}_k^-$ ) – the difference between the measurement prediction and observation
- State update is basically a weighted average with a special weight  $K$ , the “Kalman Gain”

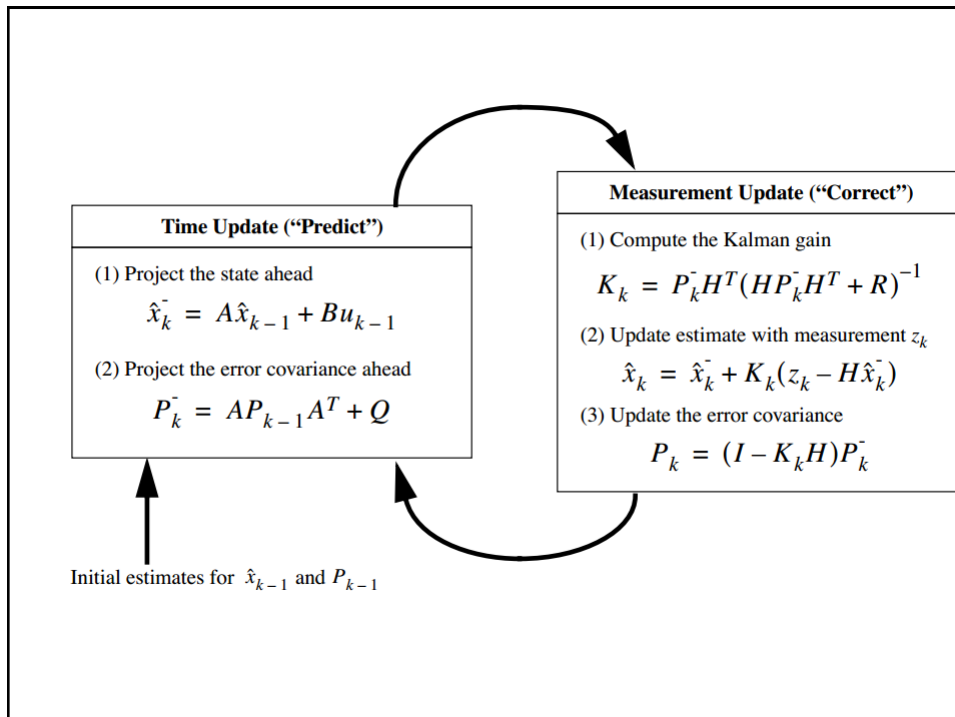
$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-)$$

$$P_k^- = AP_{k-1}A^T + Q$$

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

- Kalman gain both:

- Transforms from the measurement space to state space
- Balances the process noise and measurement noise



## Noise Terms

- Process Noise (Q): how much uncertainty do you expect in your state evolution?
  - Ex: bats fly 10m/s. frame rate 131.5 fps :  
7 cm per frame.
- Measurement Noise: how much uncertainty do you have in your measurements?
  - Ex: with three cameras, we can use camera geometry to estimate our expected uncertainty

## Kalman Filter for Smoothing

- That's easy: For every time step, use the state estimate instead of the state backed out from the measurement

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-)$$

## Kalman Filter for Scoring

- After prediction: you have a probability distribution: mean and covariance of a Gaussian centered on predicted future measurement

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1}$$

$$P_k^- = AP_{k-1}A^T + Q$$

$$H\hat{x}_k^-$$

$$(HP_k^-H^T + R)$$

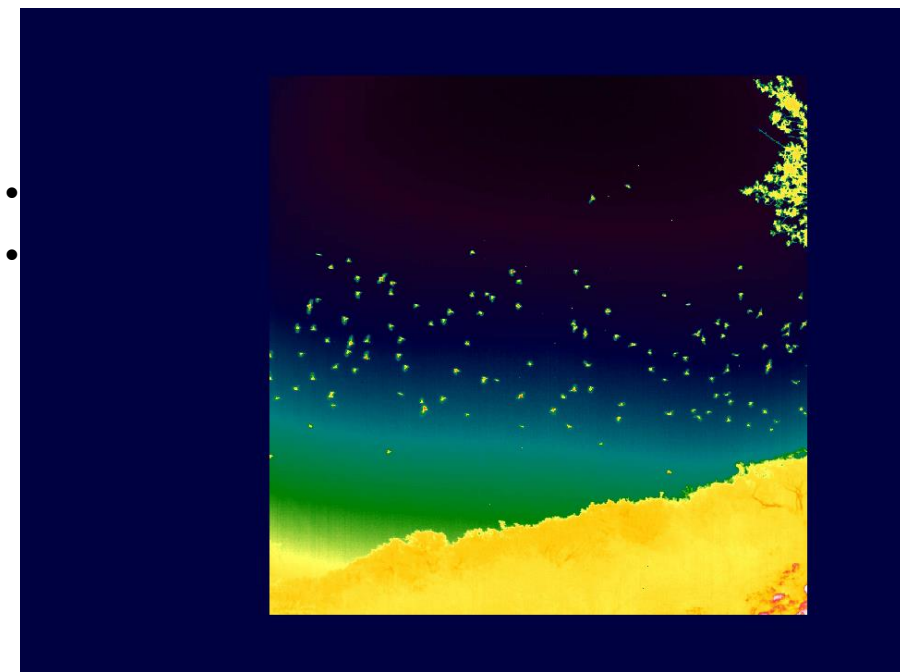
- Plug in the observed measurement to get probability
- Take product (sum logs) over all measurements

## Discussion Questions:

- What does the Kalman filter give you?
- What do you need to know to use the Kalman filter?

## Question of the Day (2):

- How can we simultaneously track many objects?



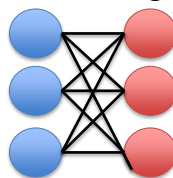


## Multi-target tracking

- Many detections in each frame
- Need to put them together somehow
- Two problems:
  - State estimation (e.g. Kalman Filter)
  - **Data Association**
  - Data Association  $\neq$  Kalman Filter

## Assignment Problem

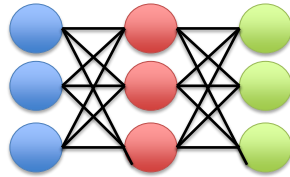
- Ex: Match workers and jobs
- Ex: Measurements from two consecutive frames
- Bipartite graph. Weights on each edge  
Find lowest cost / best matching



- Hungarian / Kuhn-Munkres assignment algorithm
- POLYNOMIAL (don't let anyone tell you otherwise)
- [http://en.wikipedia.org/wiki/Hungarian\\_algorithm](http://en.wikipedia.org/wiki/Hungarian_algorithm)

## Multi-dimensional Assignment

- Tri-partite (or higher) matching
- Ex: measurements from 3 or more frames of video.



- This is NP Complete (but we won't let that stop us)  
<http://www.sce.carleton.ca/faculty/chinneck/po/Chapter12.pdf>  
<http://www.sce.carleton.ca/faculty/chinneck/po/Chapter13.pdf>

## Multiple Hypothesis Tracking

- “Choose the best possible set of tracks so that each measurement is used only once”
- How to formulate data association task mathematically?
- Kalman filter gives us state estimation, but we have to put the measurements together in the right order

## Multiple Hypothesis Tracking

- Build out the MHT trees
- Set up corresponding matrices
- Score each leaf (using a Kalman filter)
- Formulate Integer Programming problem.

## Practical Strategies

- Windowing
- Gating

## Practical Considerations

- Missing measurements and new tracks  
(dummy measurements)
- Coasting