Tracking Estimation and Beginner Data Association

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March 25, 2021

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RSITY CLASS SCHEDULE - REPORT

Spring 2014 **Search by:** Class Number

s	Title /Instructor	Cr Hrs	Type	Open Seats	Bld	Room	Day	Start	Stop	Notes
Stdents registering for CAS CS585 must register for two sections: a Lec section, and a Lab section.										
CAS CS585 A1	Imagevideo COM Theriault	4.0	Lecture	40			Tue,Thu	12:30pm	2:00pm	
CAS CS585 A2	Imagevideo COM Theriault	0.0	Lab	20			Fri	9:00am	10:00am	
CAS CS585 A3	Imagevideo COM Theriault	0.0	Lab	20			Fri	11:00am	12:00pm	

https://www.linkedin.com/in/dhtheriault

Bats

Bats are super cute

Bats eat bugs (moths, not really mosquitos)

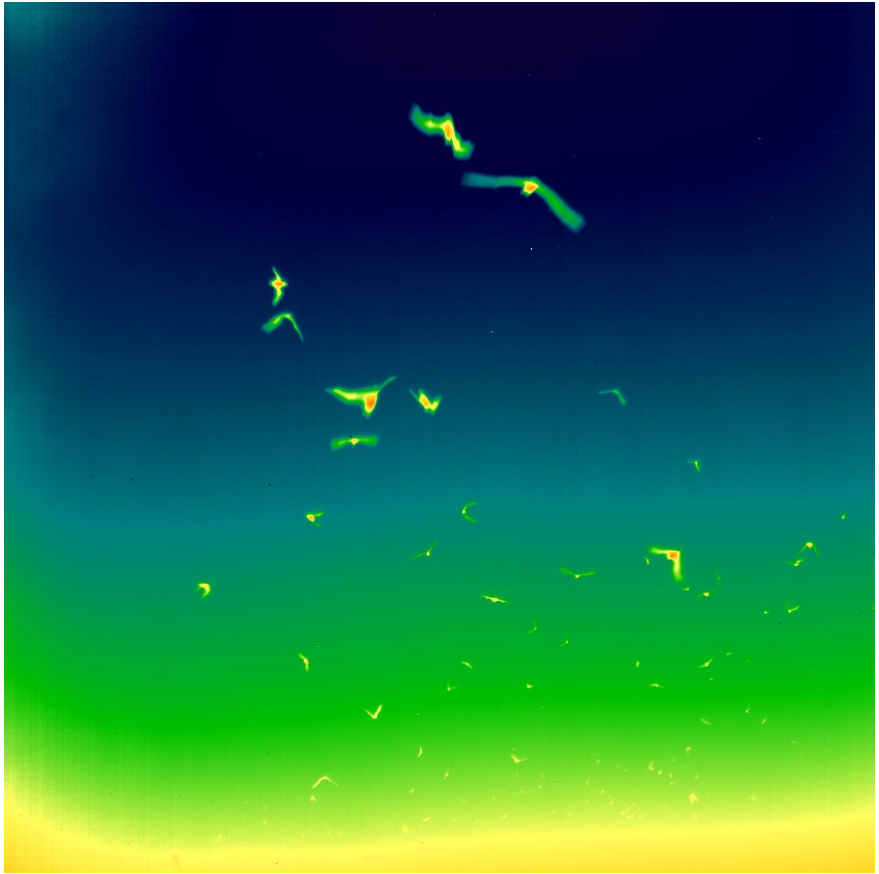
Bats

Bat colonies in TX
are very big

“How many are there?”

Bats

Infrared thermal video is cool



Bats

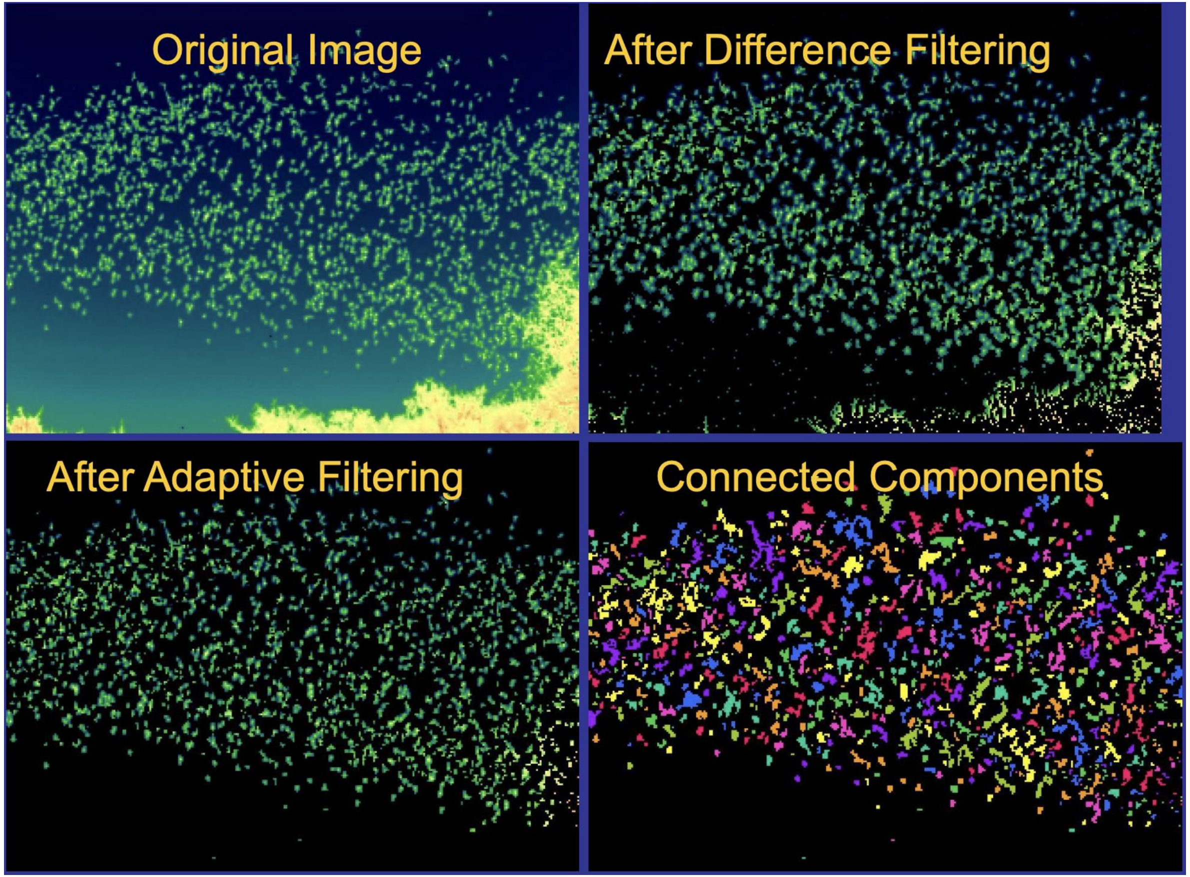
“How many are there?”

“How do they do that?”

[Alternate Link]

Assume: Detection

Given an image, find the regions that are interesting



Assume: Localization

Repeatably identify location of objects

Measurements vs State

Measurement: what you are able to observe

Example: Image position

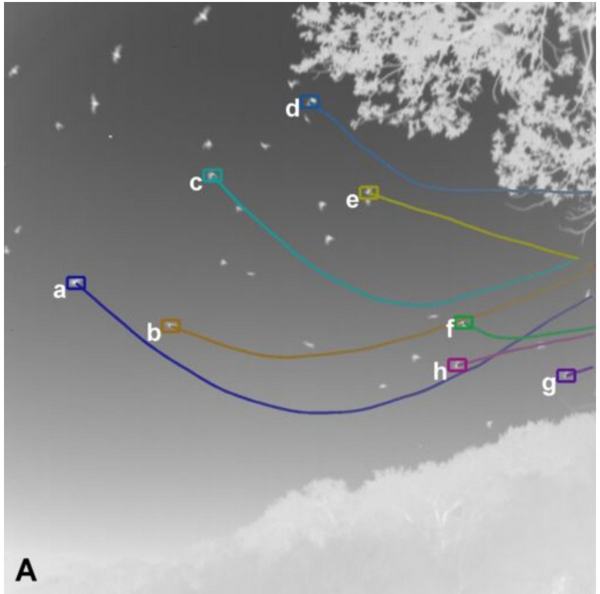
State: what you think is true

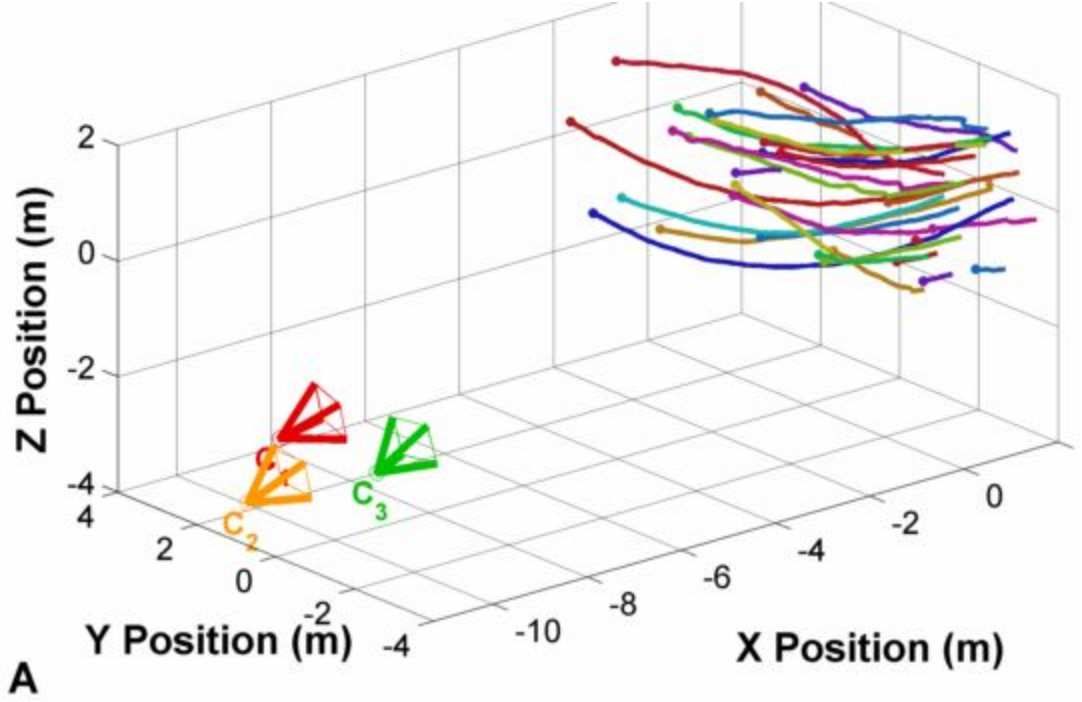
Example: Estimated Position

Example Derived Velocity (finite differences)

Measurements vs State

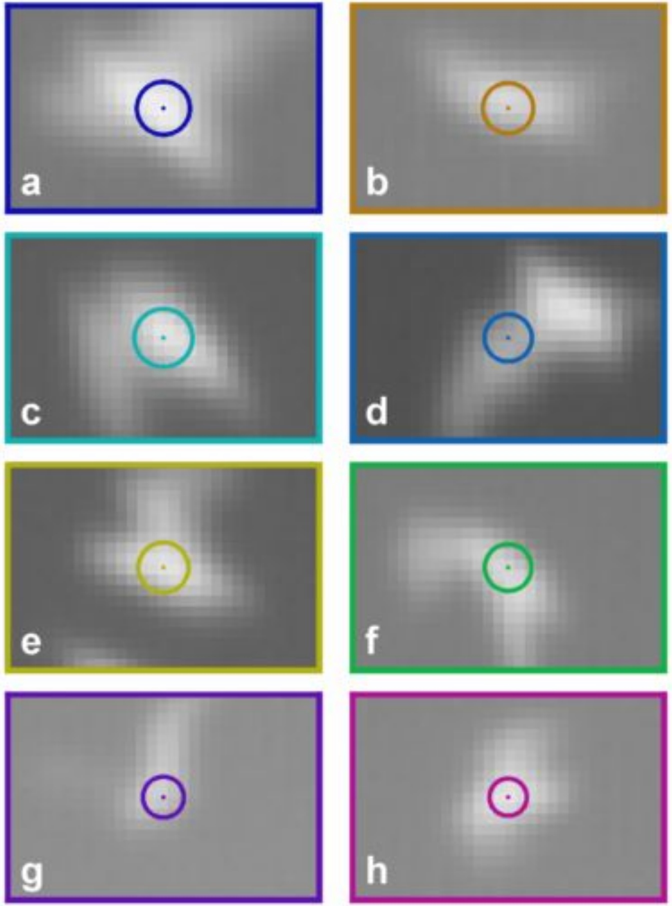
Measurement: Projected image position; State: 3D position





Why Estimation

Measurements are noisy



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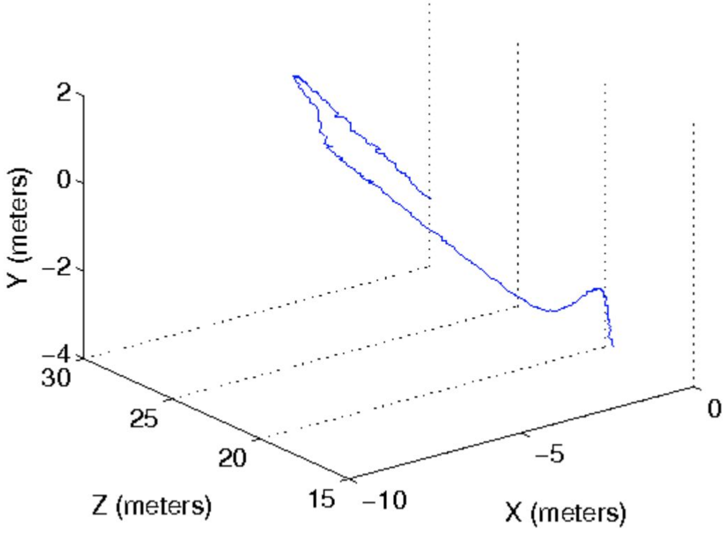
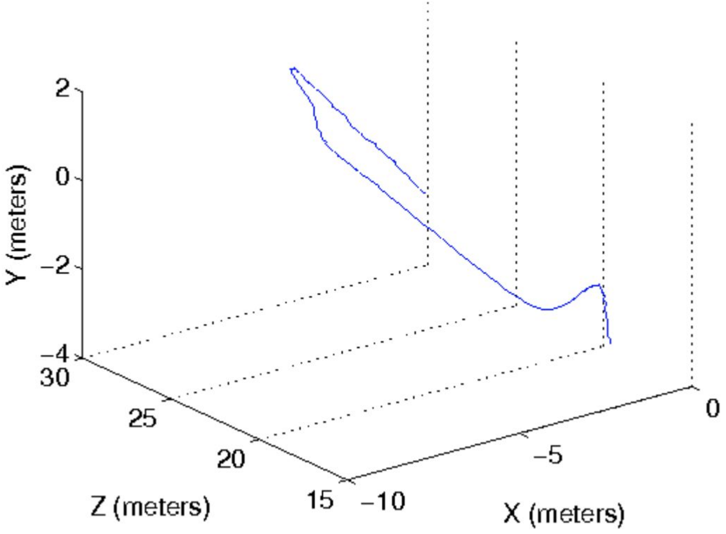
Why Estimation

Measurements are noisy

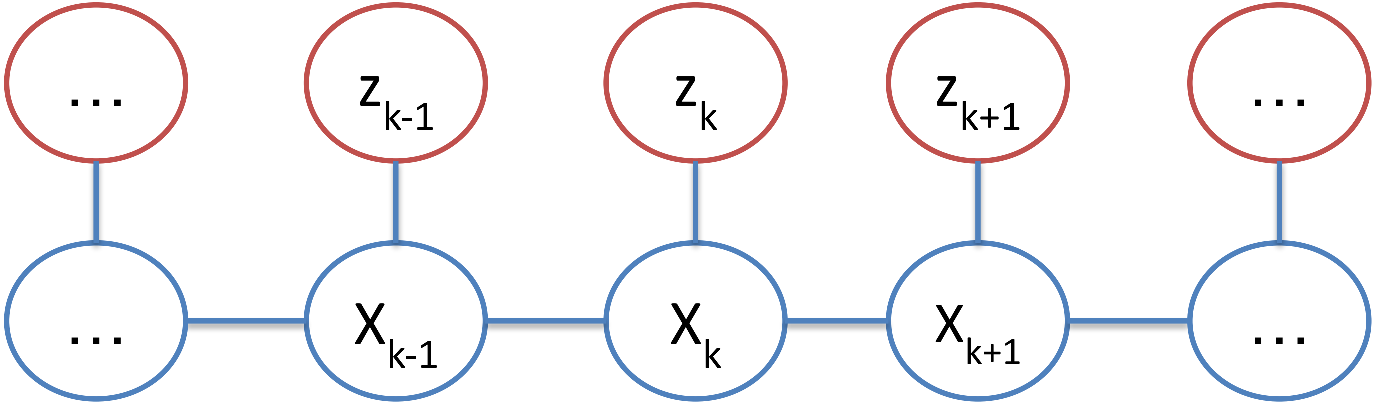
Measurements may contain high frequency info that’s not interesting





What estimation

Goal: Infer state from measurements. State cannot be directly observed.



Components of Estimation

Measurement Model

Kinematic / State evolution Model

Math representation

Beliefs about the system, formatted for your math

Measurement Model

In: estimated state x_t

Out: estimated measurement $z_t = H(x_t)$

Example:

Position (p) + velocity (v) → collapse to position

$[p_{t1}\ p_{t2}\ v_{t1}\ v_{t2}] \rightarrow [z_{t1}\ z_{t2}]$

$$\begin{bmatrix} z_{t1} \\ z_{t2} \end{bmatrix} = \overbrace{\boxed{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}}}^{H} \begin{bmatrix} p_{t1} \\ p_{t2} \\ v_{t1} \\ v_{t2} \end{bmatrix}$$

Kinematic Model (State Evolution Model)

In: previous state x_t

Out: estimated next state $x^-_{t+1} = A(x_t)$

"Prediction" or "evolution"

Example:

Constant velocity

$[p_{t+1,1}, p_{t+1,2}, v_{t+1,1}, v_{t+1,2}] = [p_{t1}+v_{t1}, p_{t2}+v_{t2}, v_{t1}, v_{t2}]$

$$\begin{bmatrix} p_{t+1,1} \\ p_{t+1,2} \\ v_{t+1,1} \\ v_{t+1,2} \end{bmatrix} = \overbrace{\boxed{\begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}}^{H} \begin{bmatrix} p_{t1} \\ p_{t2} \\ v_{t1} \\ v_{t2} \end{bmatrix}$$

Other options: Constant position, acceleration

“Residual” or “Innovation”

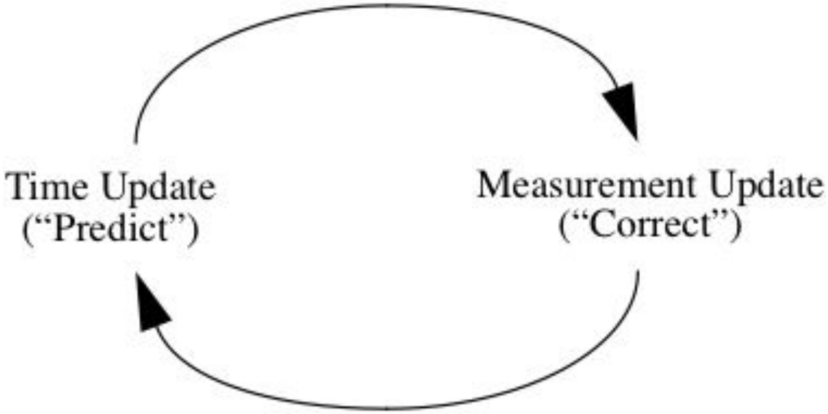
Diff b/t actual measurement and prediction

$r_{k+1} = z_{k+1} - H(x^{-}_{t+1})$

$r_{k+1} = z_{k+1} - H(A(x_t))$

Update

Blend measurements and predictions



Tracking by detection: New state is the measurement

Recursive estimators: each estimate uses previous state as input

- Blend with hand-picked constants (alpha / beta filter)
- Blend with super fancy constants (Kalman filter)

How estimation: Alpha / Beta filter

Hand-picked constants

https://en.wikipedia.org/wiki/Alpha_beta_filter

State = [position (p), velocity (v)]

$p_{t+1} = p_t + \underline{\alpha}\, r_{t+1}$

$v_{t+1} = v_t + \square\, / \,[\Delta T]\, r_{t+1}$

How estimation: Kalman Filter

Main extra piece: Uncertainty estimates for both state evolution and measurement

Other extra piece: Knowledge about how state *should* change (e.g. robot steering)

$B_t u_t$ are the control model and control vector

- $z_t = H(x_t) + v_t$ (v is noise term. ex: Gaussian with covariance R != Q)

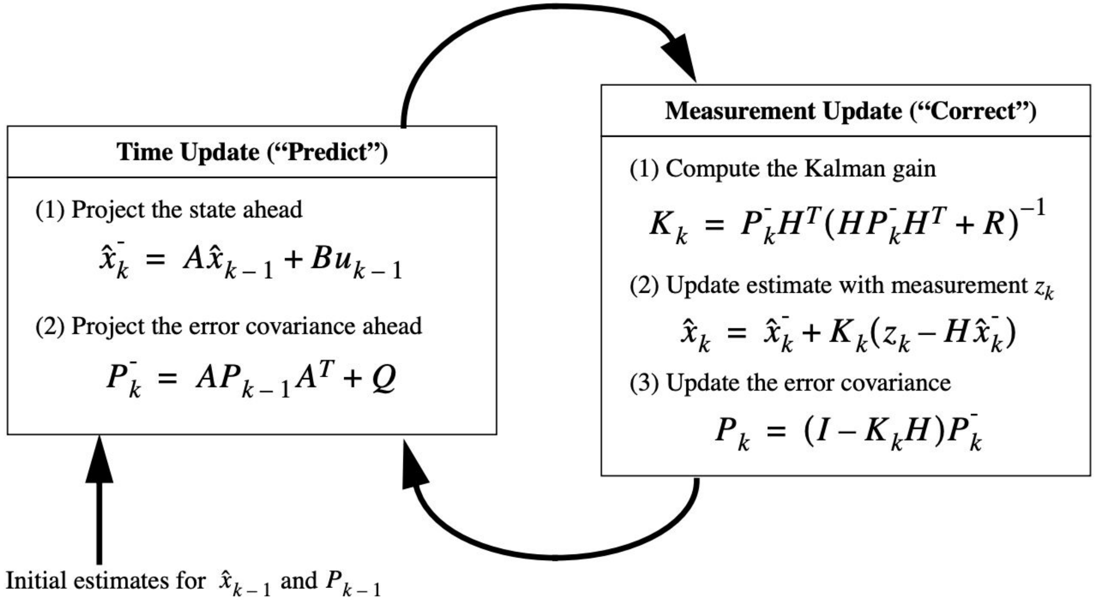
- $x_{t+1} = A(x_t) + B_t u_t + w_t$ (w is noise term. ex: Gaussian with covariance Q)
- P_t Covariance matrix representing uncertainty

Update x_t and P_t by choosing weights based on uncertainty estimates

How estimation: Kalman Filter

Super fancy derivation formulated as **minimization of residuals**, but the result of the derivation is that you **can compute in terms of noise only**

http://www.cs.unc.edu/~welch/media/pdf/kalman_intro.pdf



How estimation: Kalman Filter

Accurate uncertainty covariances are actually really important

If your process noise is too large, your tracks won't follow maneuverable objects well
If your process noise is too small, your tracks will be very wobbly

- 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 (R): how much uncertainty do you have in your measurements?
  - Ex: with three cameras, we can use camera geometry to estimate our expected uncertainty

How estimation: Kalman Filter

How to produce a smoothed / filtered track:

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

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

Questions about estimation

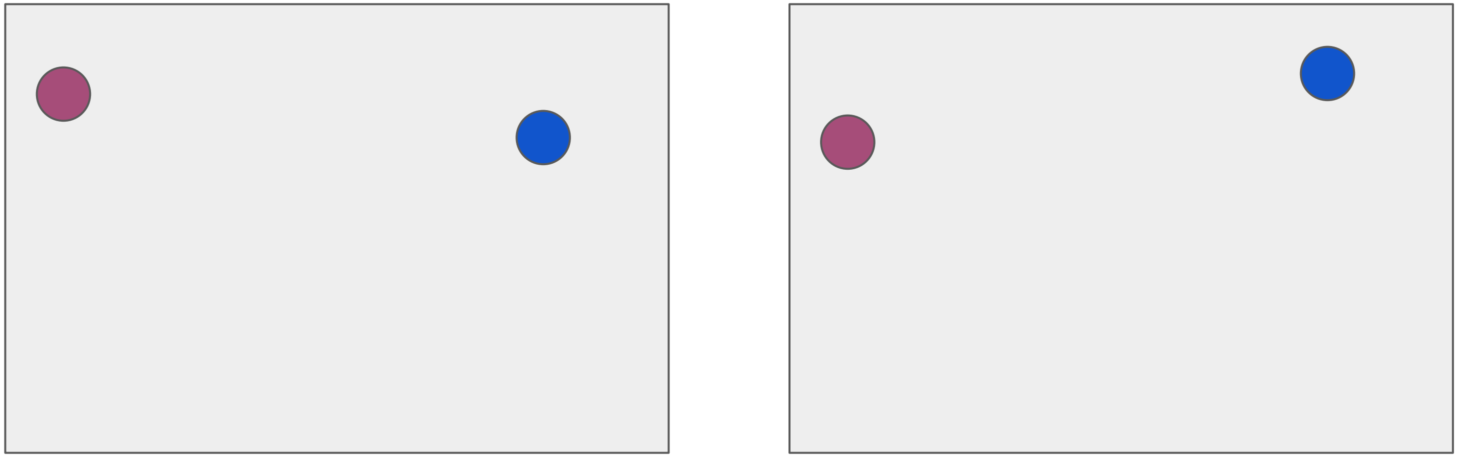
We are about to shift to a new topic

Beginner Data Association

Track two objects far apart

Decide which dots go together

Track by detection if velocities are small



Beginner Data Association

Track many objects

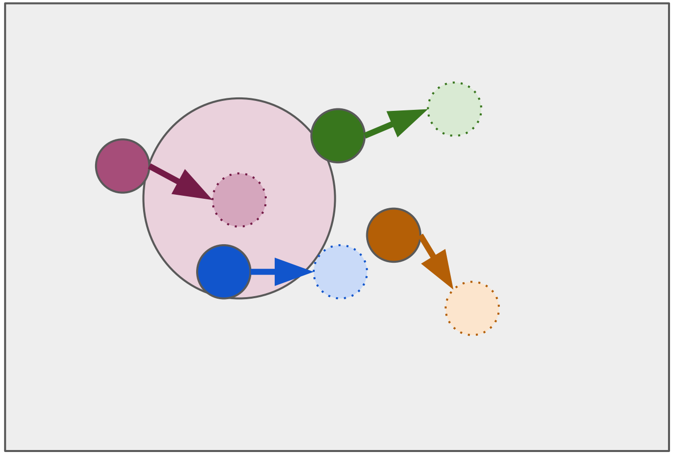
Decide which dots go together

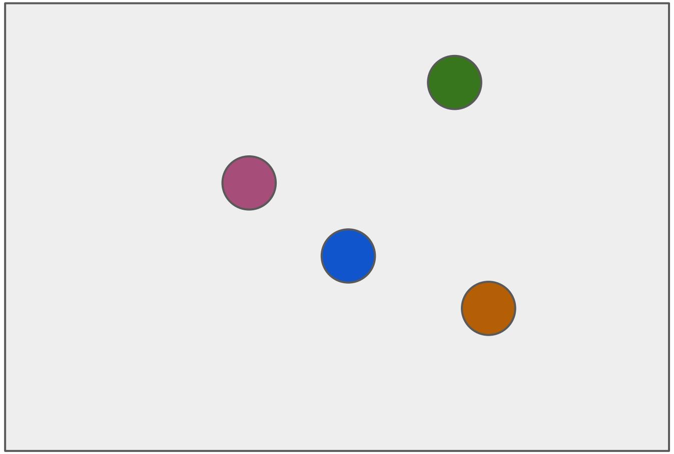
Using predictions

Gates

Lots of potential algorithms / data structures

The harder your problem is, the more important it is to be able to formulate it in math to use general solvers



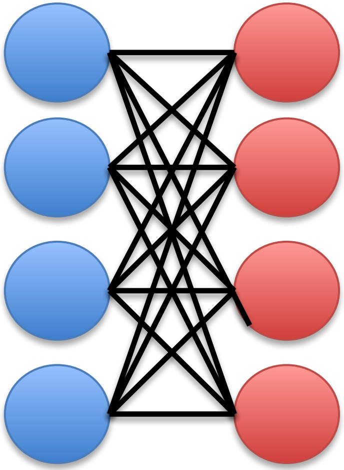


Beginner Data Association

"Global Nearest Neighbor Standard Filter" (GNNSF)

Bipartite matching

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



Beginner Data Association

"Global Nearest Neighbor Standard Filter" (GNNSF)

Matrix formulation (check rows and columns with your library docs!)

$$\begin{array}{cc} & \text{measurements} \\ \text{tracks} & \underbrace{\begin{bmatrix} 0.2 & 0.7 & 0.1 & 0.3 \\ 0.8 & 0.1 & 0.2 & 0.3 \\ 0.1 & 0.7 & 0.2 & 0.8 \\ 0.2 & 0.1 & 0.6 & 0.1 \end{bmatrix}}_{\text{Cost matrix (c)}} \end{array} \qquad \begin{array}{cc} & \text{measurements} \\ \text{tracks} & \underbrace{\begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}}_{\text{Assignment matrix (x)}} \end{array}$$

$$\begin{aligned} \min_{x_{i,j}} \sum c_{i,j} x_{i,j} \\ s.t. \sum_{i:i>0} x_{i,j} = 1 \\ \sum_{j:j>0} x_{i,j} = 1 \\ x_{i,j} \in \{0,1\} \end{aligned}$$

Multi-target Tracking - Put it all together

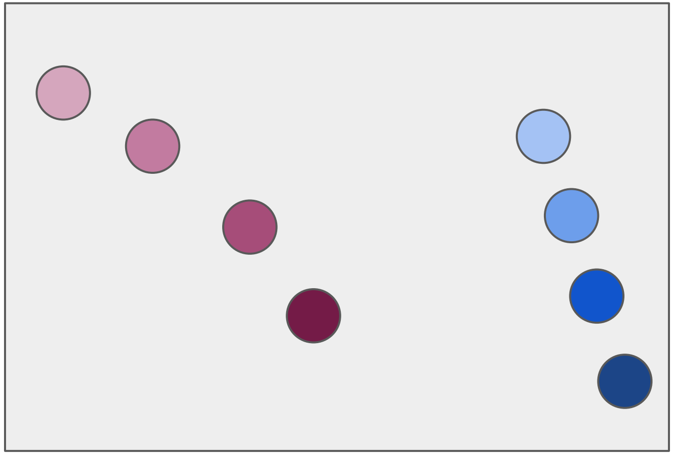
You need to do this in your assignment

- Run detection / localization to find things in your first image

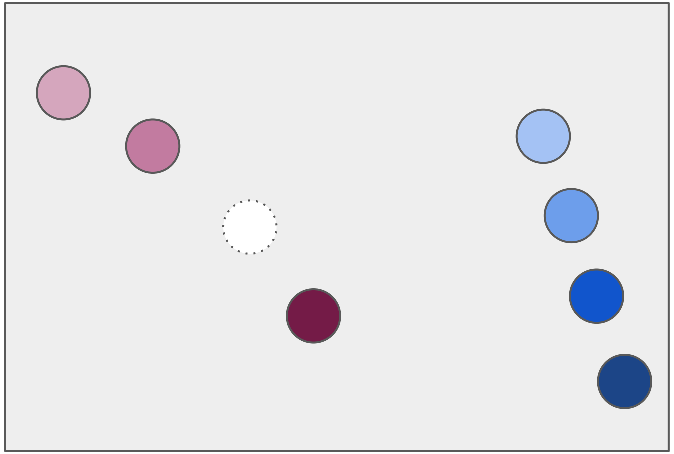
- for v in video frames:
    - Predict state of known objects
    - Run detection / localization to get measurements from your image
    - Do data association to decide which measurements should go with which state
    - Update state of known objects

Data association fails - Missing data

Answer: Coasting / dummy variables



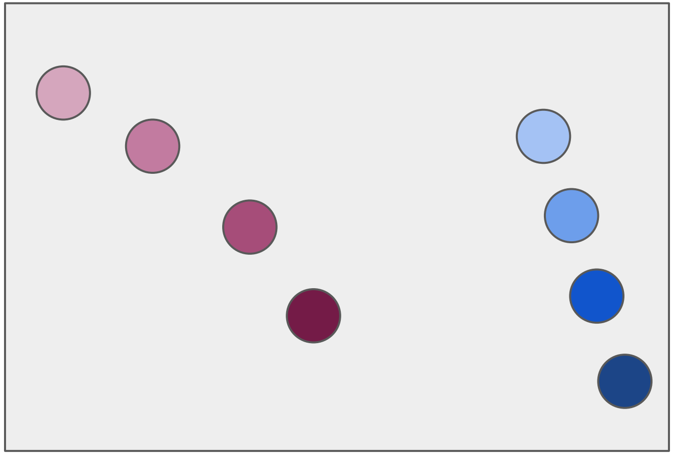
Aspirational



Actual

Data association fails - Lost tracks

Answer: “dummy” nodes, cost for lost track



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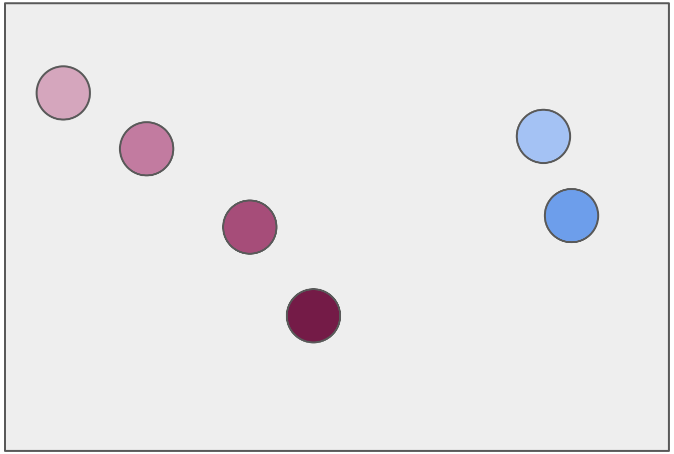
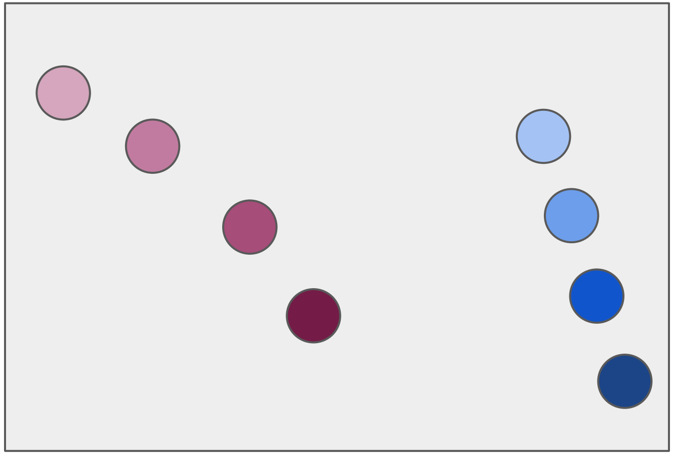


Actual

Data association fails - Spurious measurements

Answer: “dummy” nodes, gating



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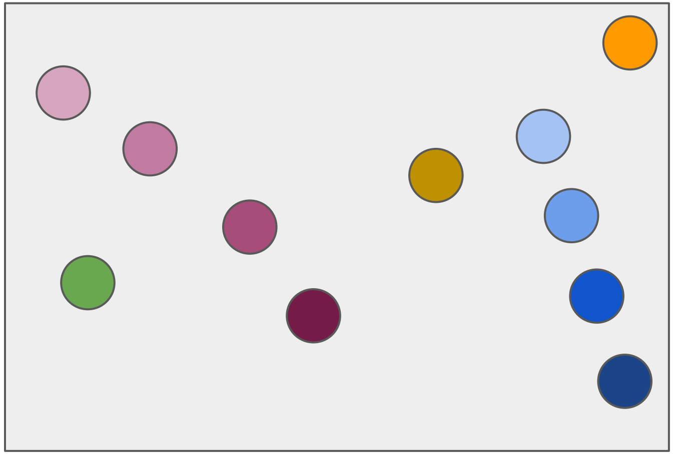
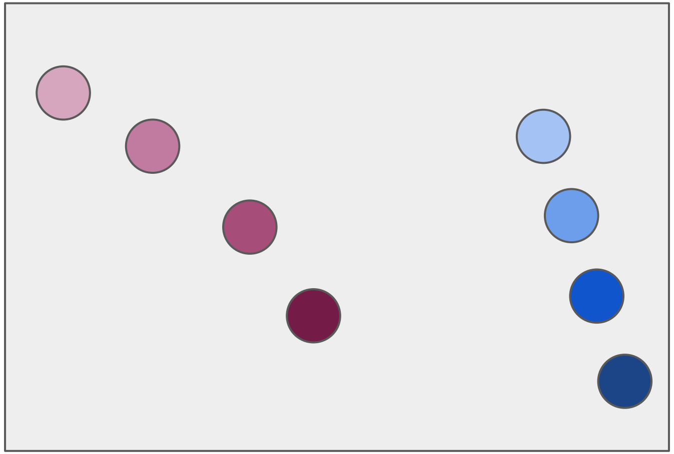


Aspirational

Data association fails - New tracks

Answer: “dummy” nodes, cost for new tracks (how do you know it’s not spurious?)



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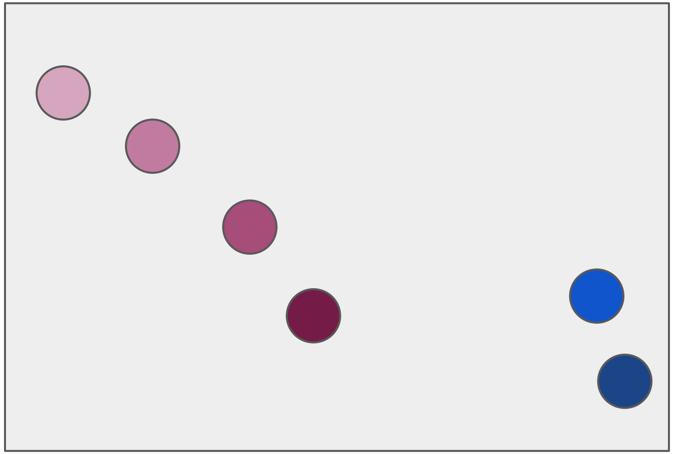
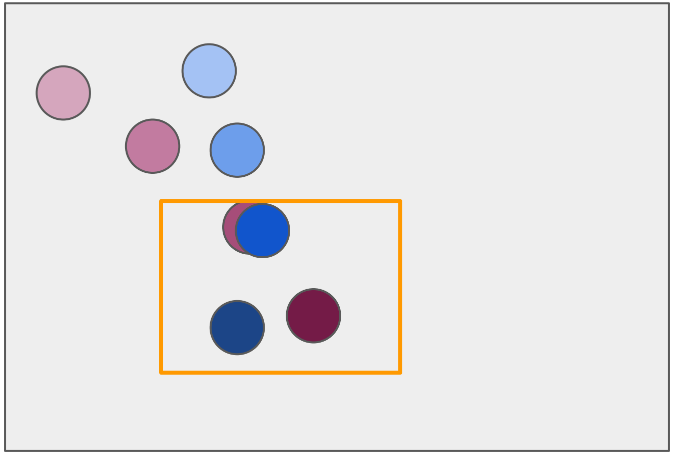


Actual

Data association fails - ambiguous motion / track switching

Answer: MHT



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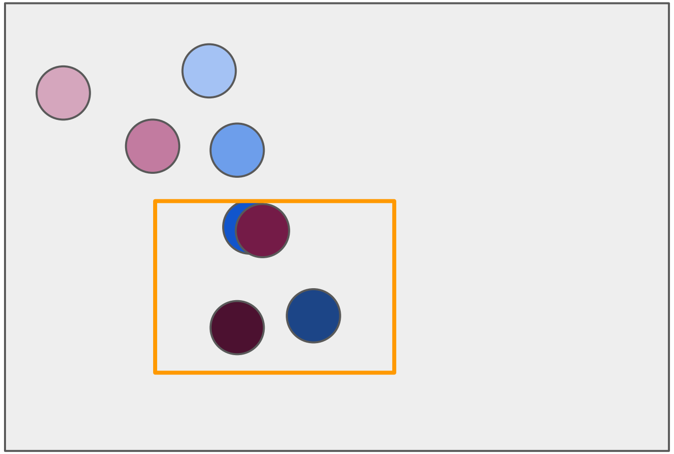

Aspirational

Questions

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