

# Tracking Estimation and Beginner Data Association

Diane Theriault; '00 (BA), '15 (PhD)  
March 25, 2021

# Who am I



University Student Link

Academics Money Matters Personal Work Food & Shelter Basics Index

## RSITY CLASS SCHEDULE - REPORT

Spring 2014 Search by: Class Number

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

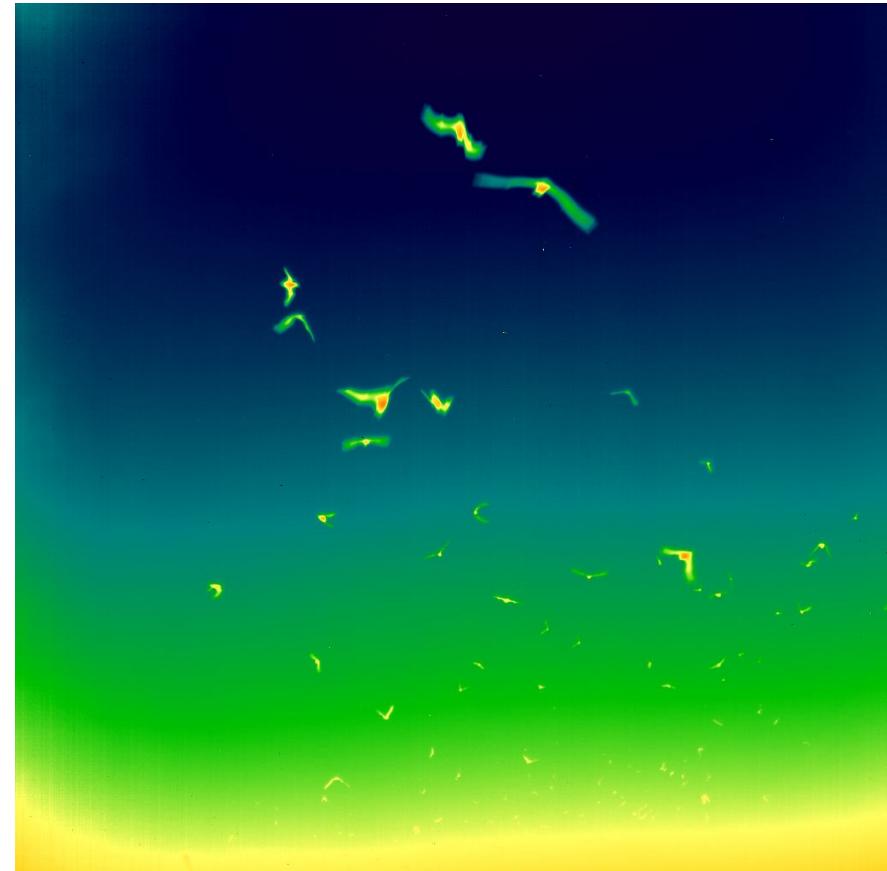
“How many are there?”



Nathan Fuller  
Boston University

# Bats

Infrared thermal video is cool



# Bats

“How many  
are there?”

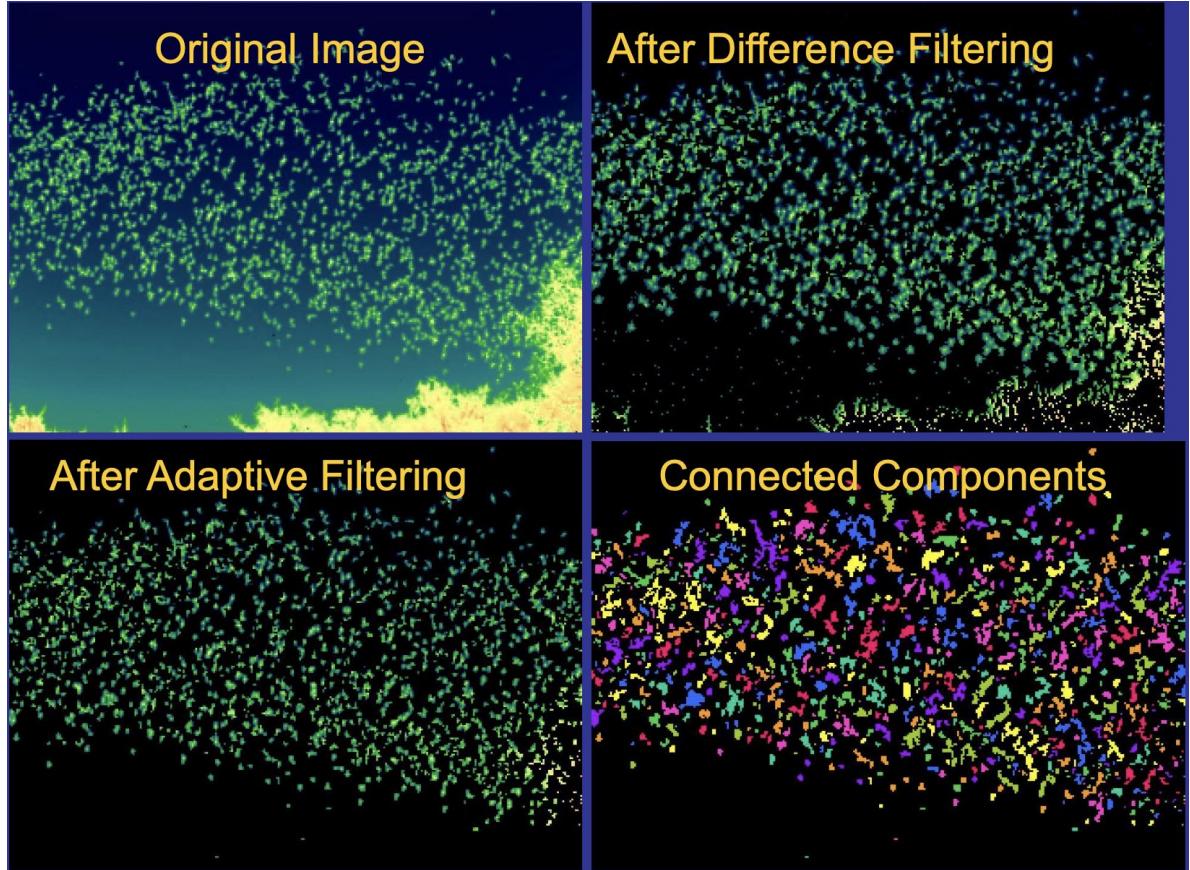
“How do they  
do that?”



[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

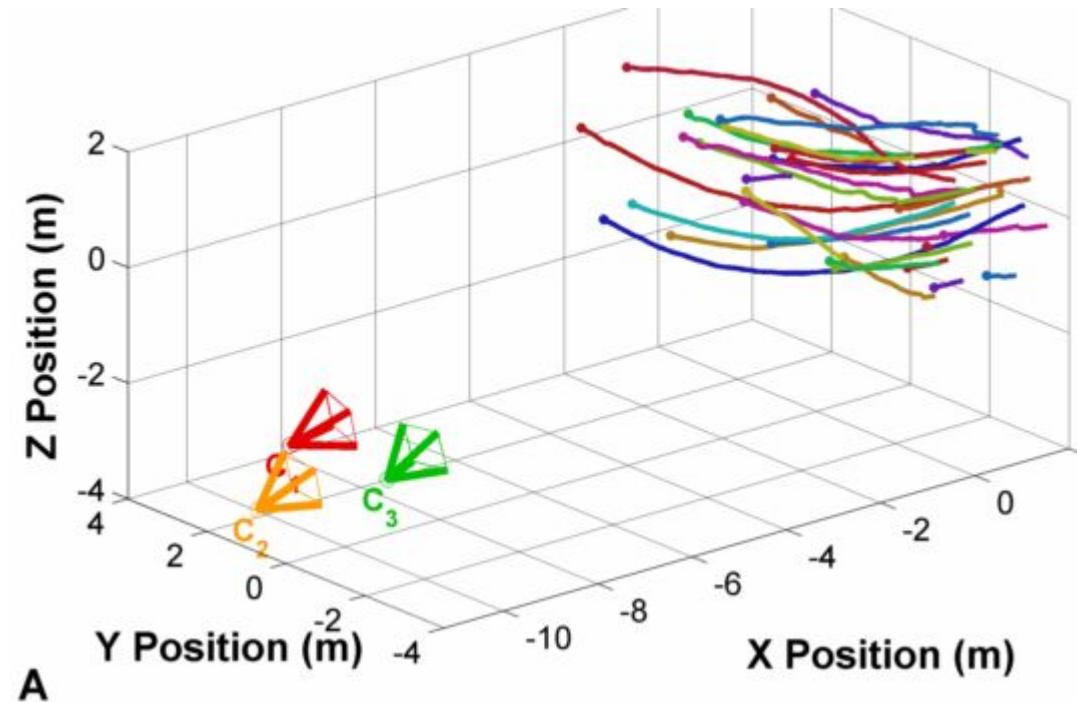
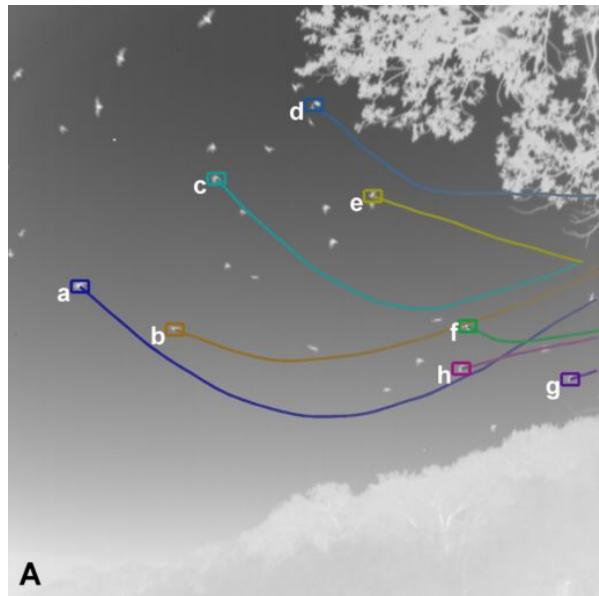
State: what you think is true

Example: Estimated Position

Example Derived Velocity (finite differences)

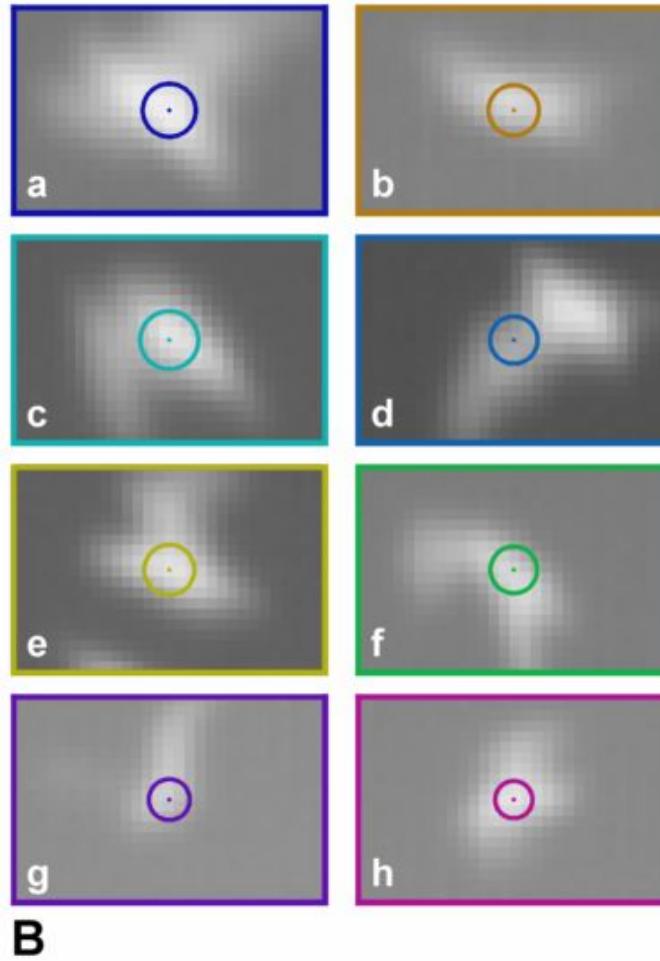
# Measurements vs State

Measurement: Projected image position; State: 3D position



# Why Estimation

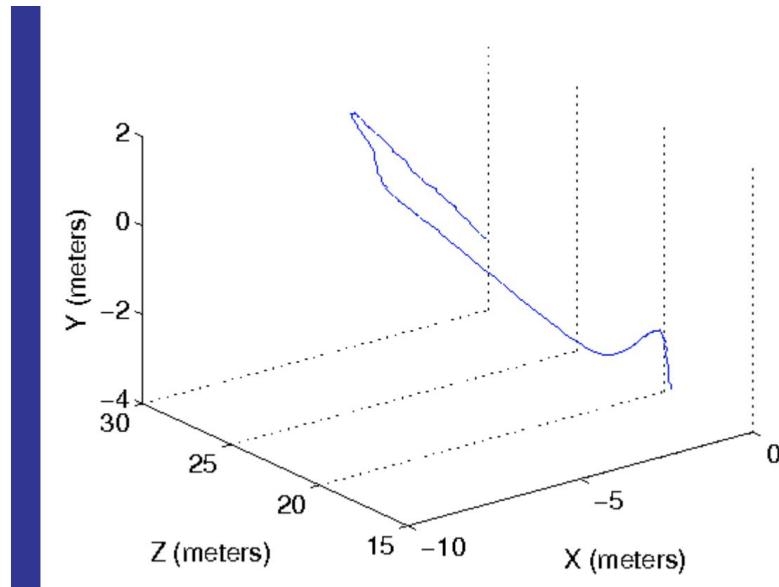
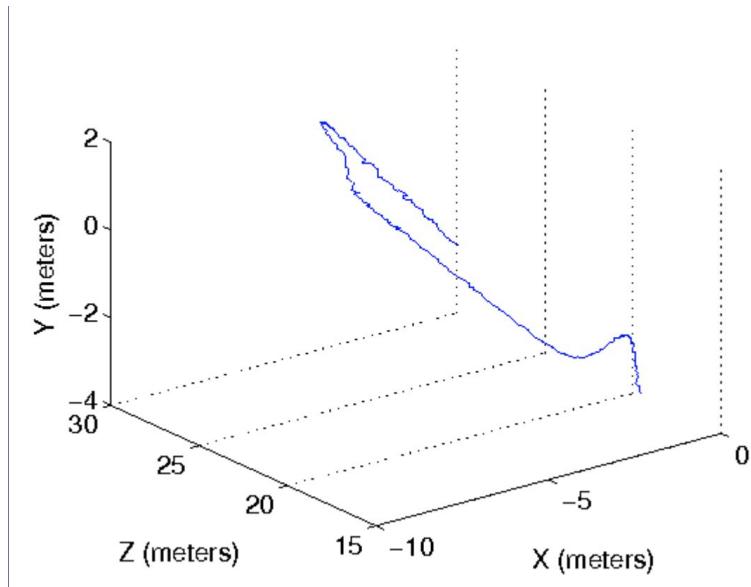
Measurements are noisy



# Why Estimation

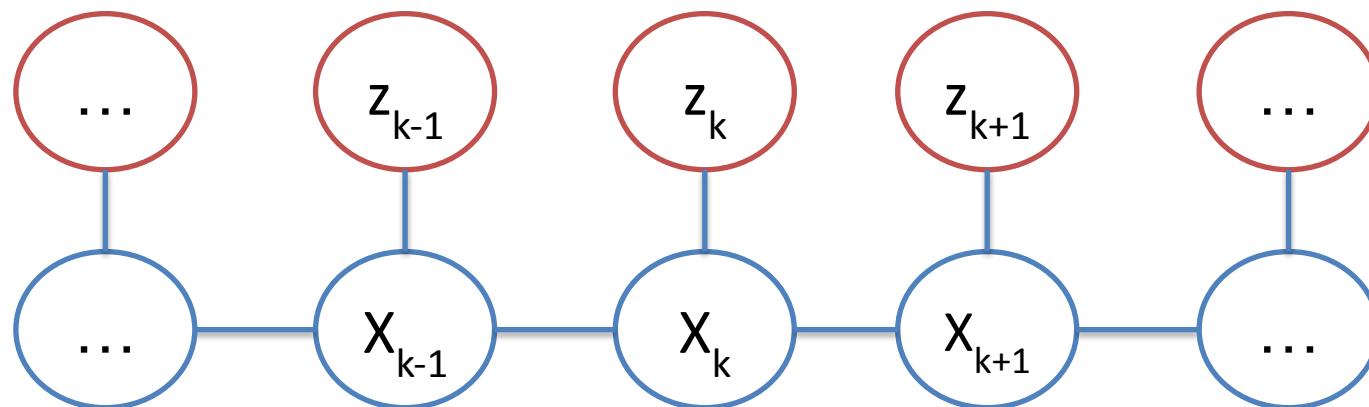
Measurements are noisy

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

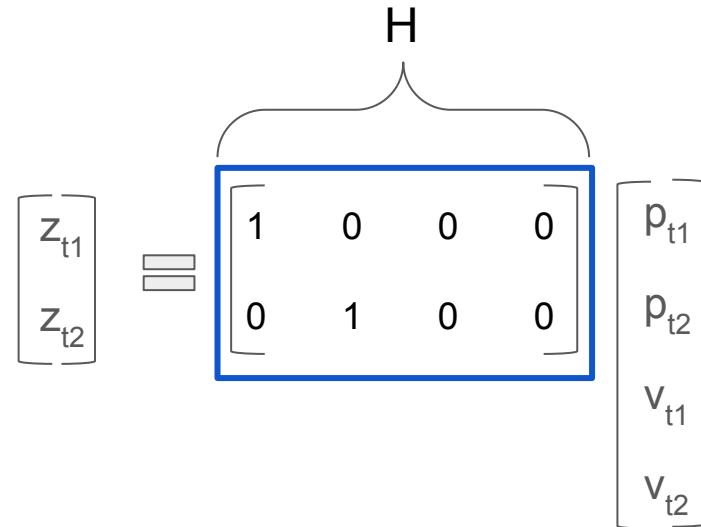
In: estimated state  $x_t$

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

Example:

Position ( $p$ ) + velocity ( $v$ )  $\rightarrow$  collapse to position

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



# Kinematic Model (State Evolution Model)

In: previous state  $x_t$

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

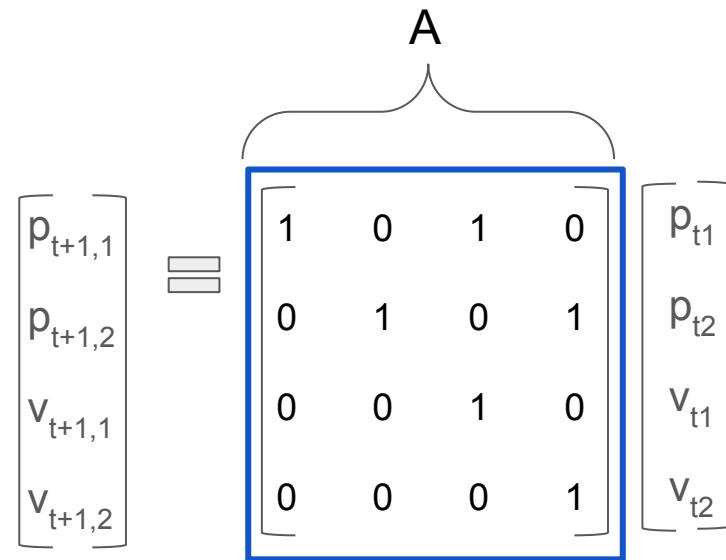
“Prediction” or “evolution”

Example:

Constant velocity

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

Other options: Constant position, acceleration



# “Residual” or “Innovation”

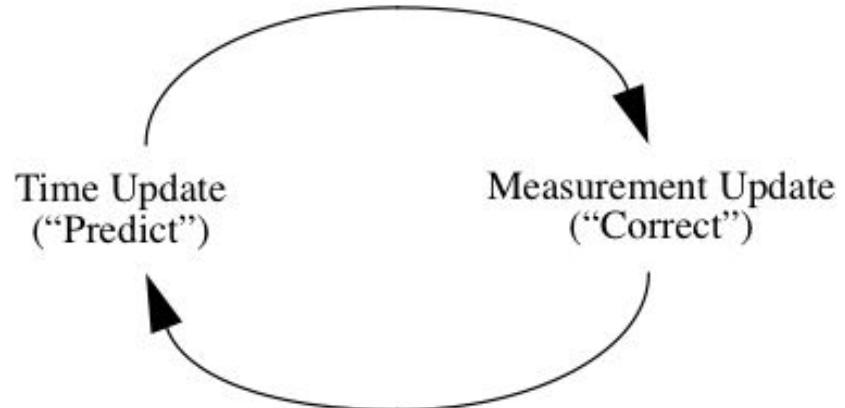
Diff b/t actual measurement and prediction

$$r_{k+1} = z_{k+1} - H(x_{t+1})$$

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

# 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](https://en.wikipedia.org/wiki/Alpha_beta_filter)

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

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

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

# 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

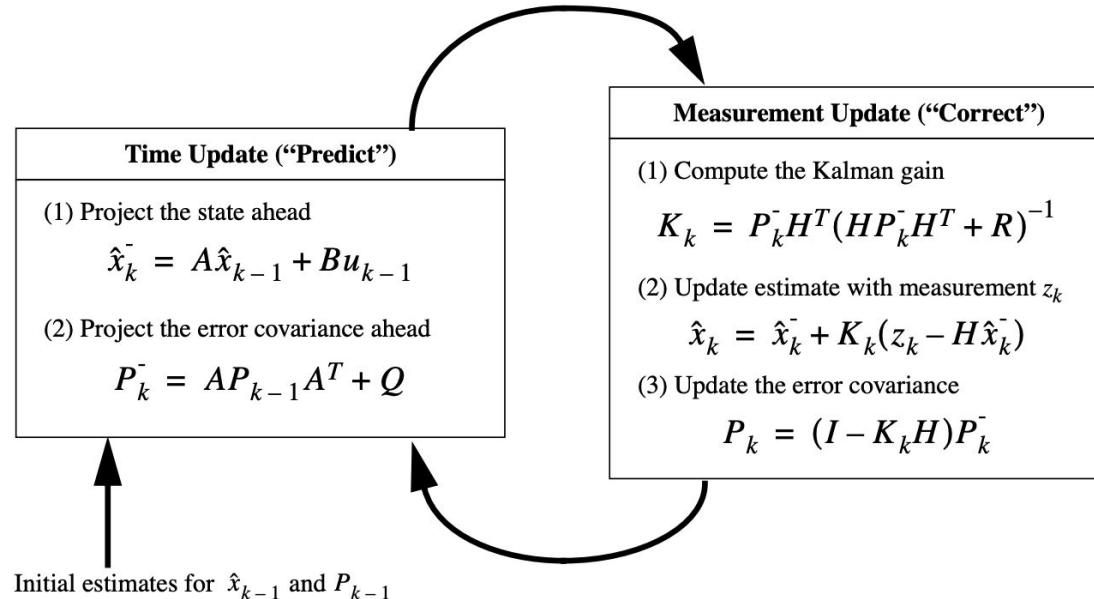
- $z_t = H(x_t) + v_t$  (v is noise term. ex: Gaussian with covariance R  $\neq Q$ )
- $x_{t+1} = A(x_t) + B_t u_t + w_t$  (w is noise term. ex: Gaussian with covariance Q)
- $P_t$  Covariance matrix representing uncertainty

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](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

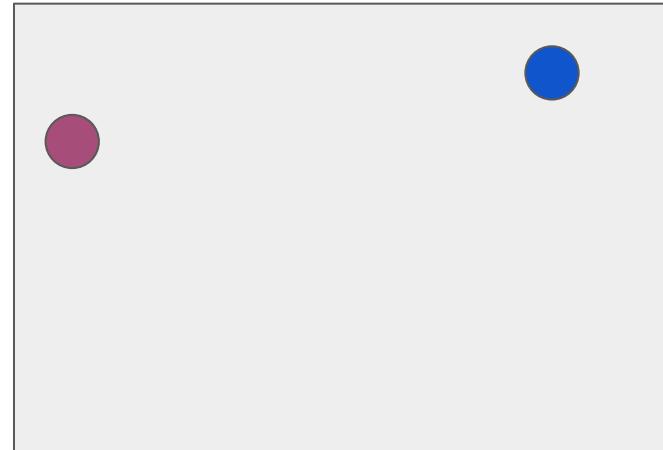
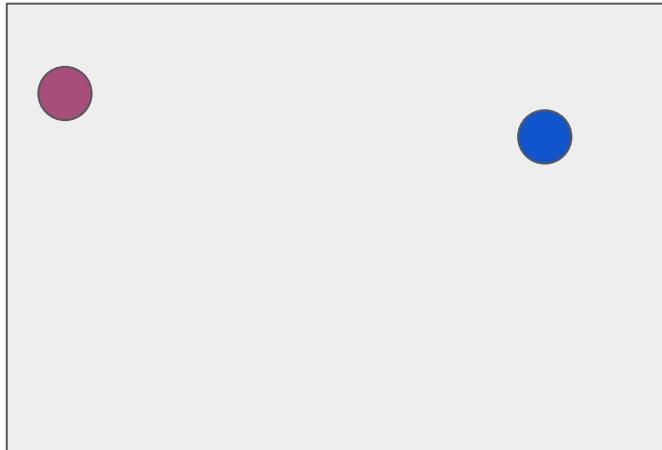
We are about to shift to a new topic

# 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

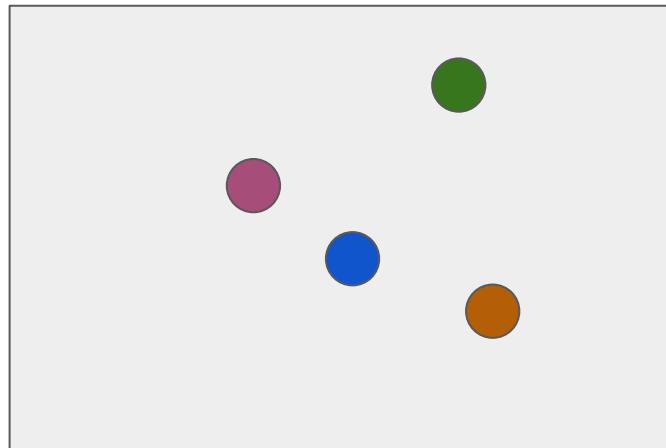
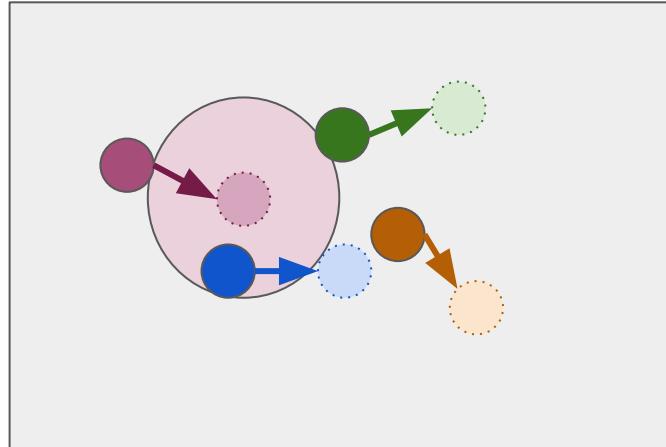
Decide which dots go together

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**

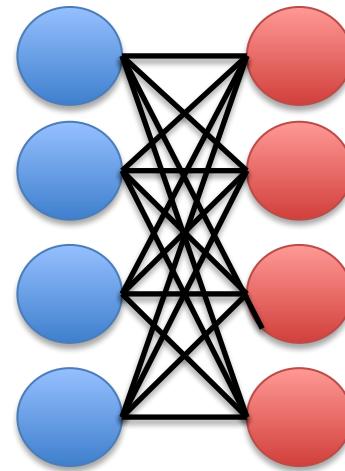


# Beginner Data Association

“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](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!)

| measurements    |                 |
|-----------------|-----------------|
| tracks          | 0.8 0.3 0.9 0.7 |
| 0.2 0.9 0.8 0.7 |                 |
| 0.9 0.3 0.8 0.2 |                 |
| 0.8 0.9 0.4 0.9 |                 |

Cost matrix ( $c$ )

| measurements |         |
|--------------|---------|
| tracks       | 0 1 0 0 |
| 1 0 0 0      |         |
| 0 0 0 1      |         |
| 0 0 1 0      |         |

Assignment matrix ( $x$ )

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

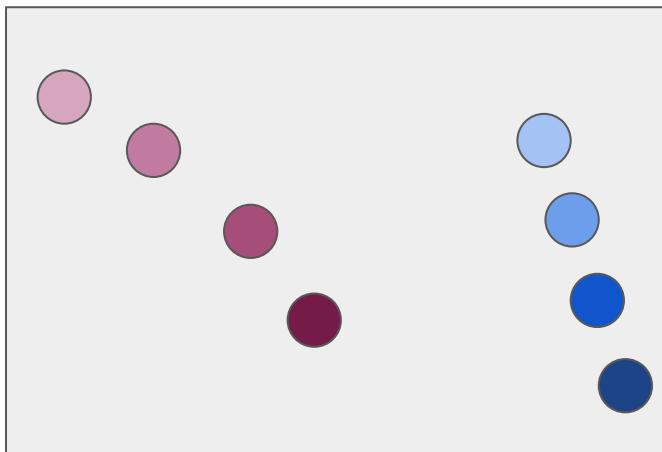
# Multi-target Tracking - Put it all together

You need to do this in your assignment

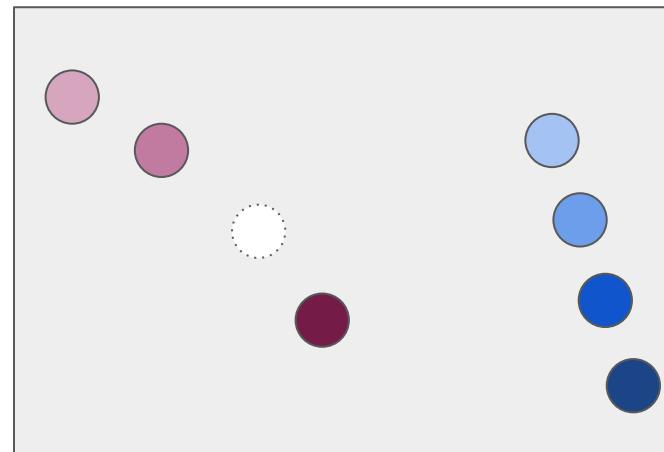
- Run detection / localization to find things in your first image
- for v in video frames:
  - Predict state of known objects
  - Run detection / localization to get measurements from your image
  - Do data association to decide which measurements should go with which state
  - Update state of known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

# Data association fails - Missing data

Answer: Coasting / dummy variables



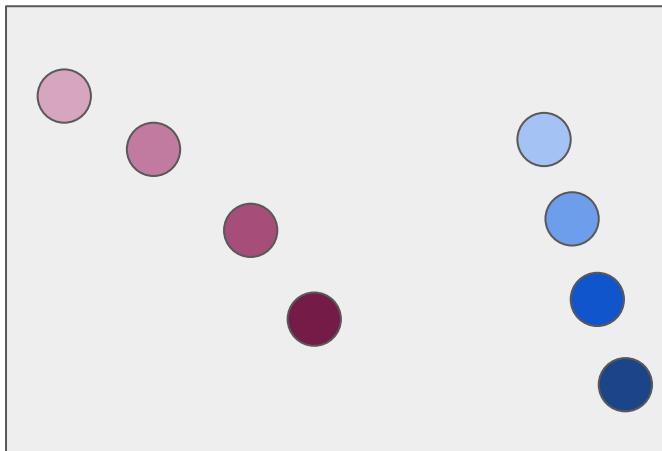
Aspirational



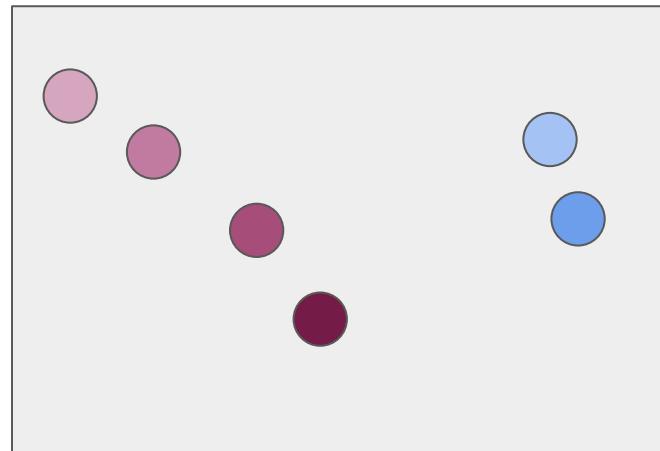
Actual

# Data association fails - Lost tracks

Answer: “dummy” nodes, cost for lost track



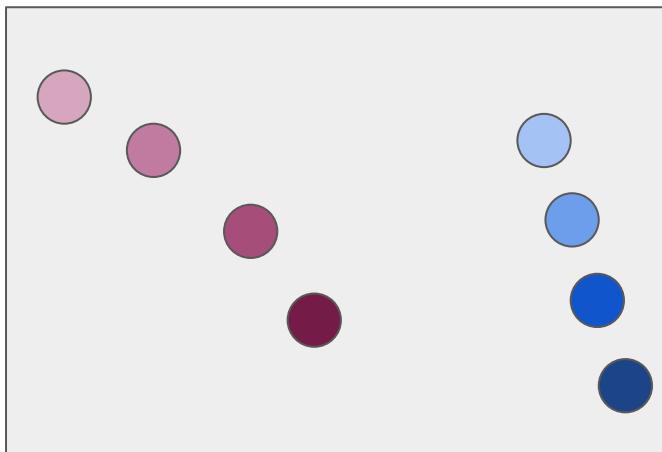
Aspirational



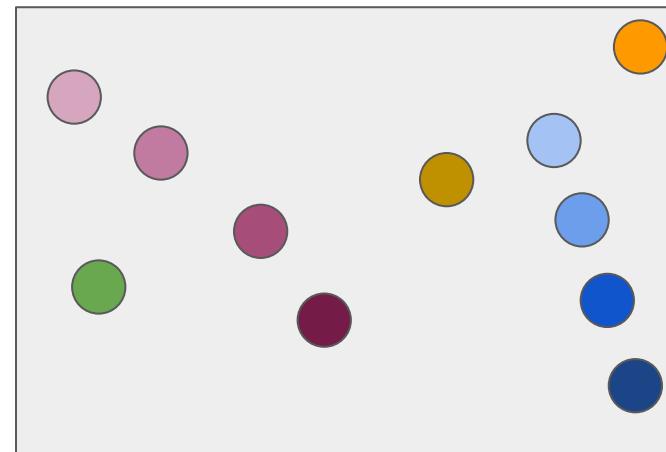
Actual

# Data association fails - Spurious measurements

Answer: “dummy” nodes, gating



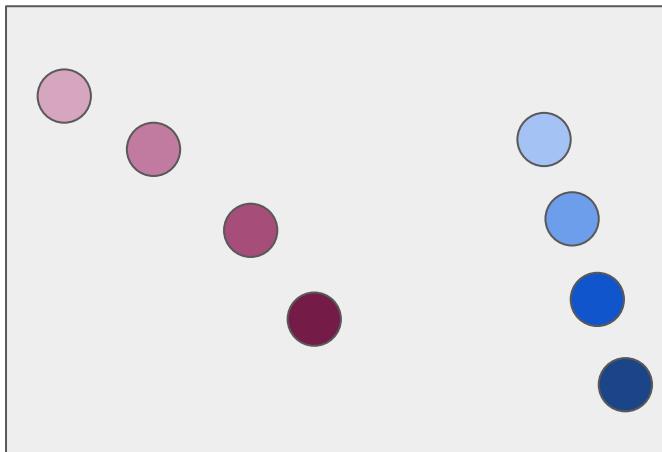
Aspirational



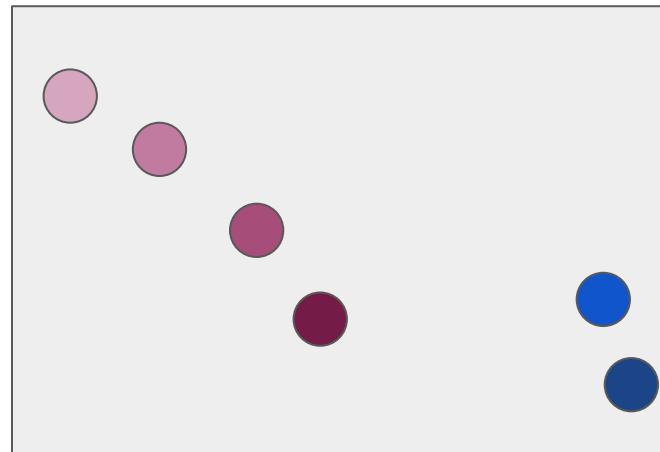
Aspirational

# Data association fails - New tracks

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



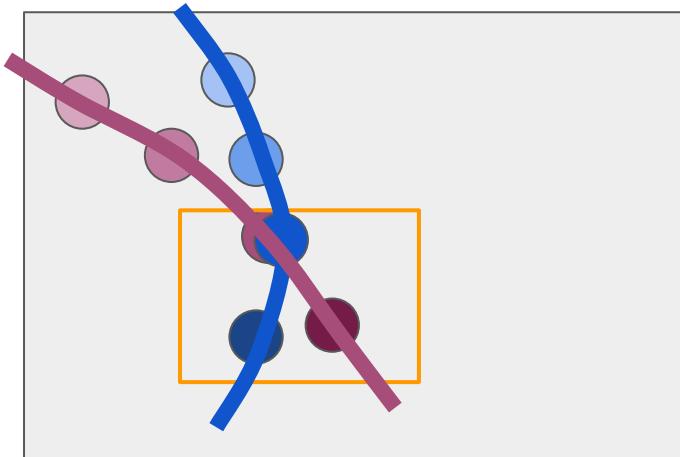
Aspirational



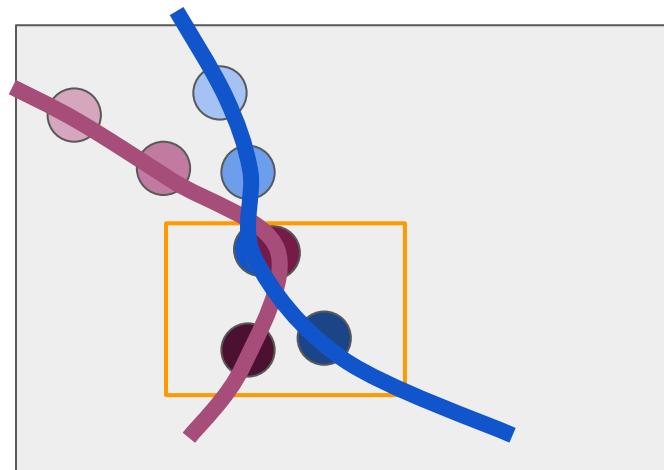
Actual

# Data association fails - ambiguous motion / track switching

Answer: MHT



Aspirational



Janky Track Switch

# Questions

</>

# Tracking Estimation and Beginner Data Association

Diane Theriault; '00 (BA), '15 (PhD)  
March 25, 2021

# Tracking Advanced Data Association and The Importance of Data Collection

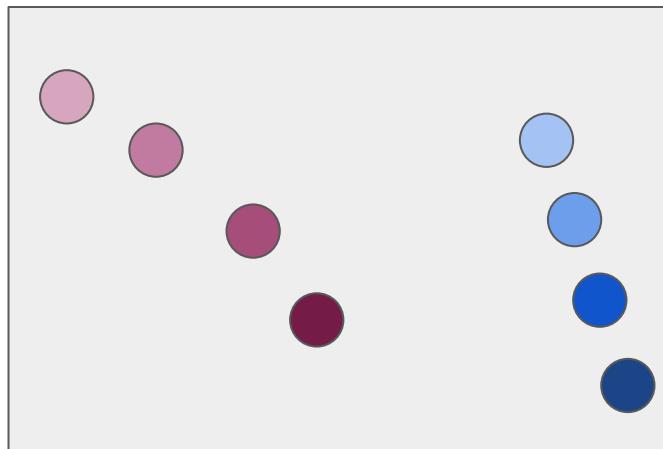
Diane Theriault; '00 (BA), '15 (PhD)  
March 30, 2021

# Last time

- State  $\neq$  Measurements
- Estimation means “how to use measurements to infer state”
  - Kinematic model uses current state to **predict** future state
  - Measurement model uses state to predict measurement
  - The “innovation” or “residual” is the  
**difference between the prediction and measurement**
- Kalman filter is a popular tool for doing estimation
  - Key feature: uncertainty estimate along with state estimate

# Last time

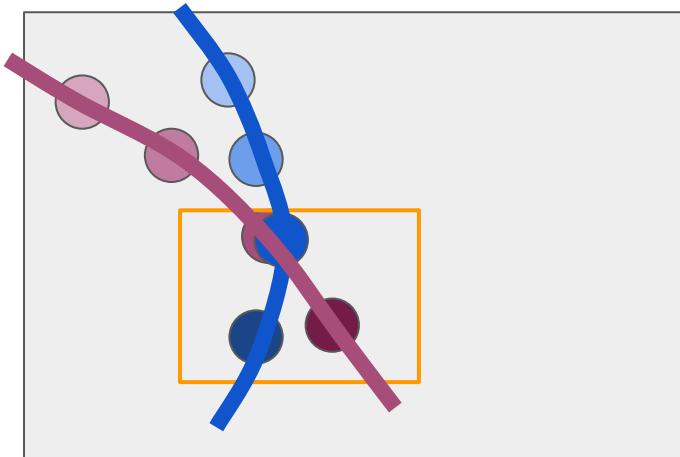
- Data Association = “put the dots together”
- Data Association  $\neq$  Estimation
- **The harder your problem is, the more important it is to be able to formulate it in math to use general solvers**



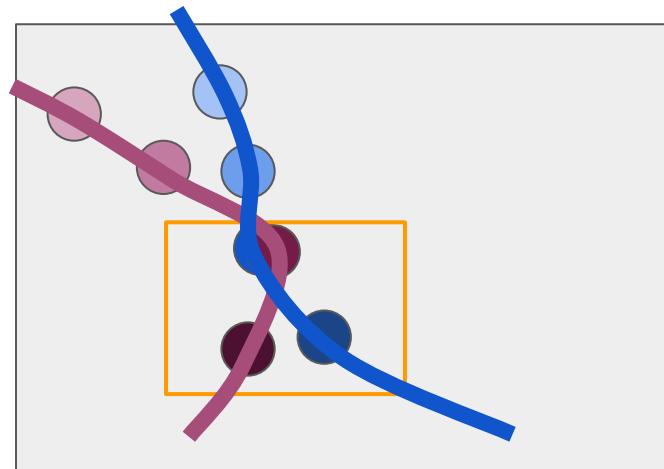
- Bi-partite matching is polynomial
- Cost Matrix is real-valued
- Constraint Matrix is integer (boolean) valued

# Data association fails - ambiguous motion / track switching

Answer: MHT (Multiple Hypothesis Tracking)



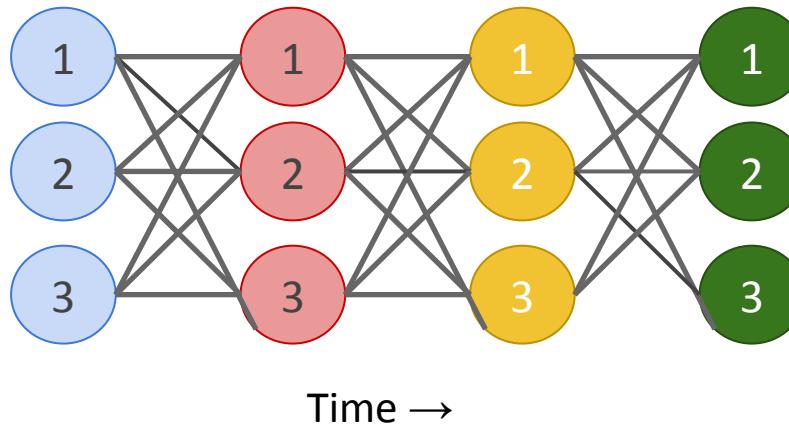
Aspirational



Janky Track Switch

# Advanced Data Association: Multidimensional Assignment

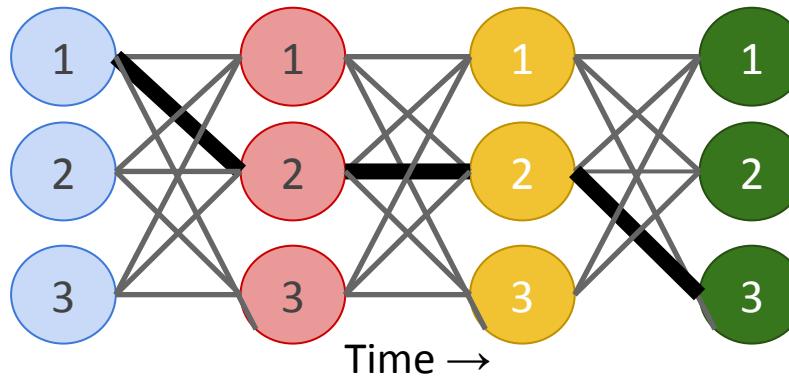
- Tri-partite (or higher) matching
- Ex: measurements from 3 or more frames of video.



- This actually is NP Complete (but we won't let that stop us)
- <https://www.optimization101.org/> Chapters 12 and 13

# Advanced Data Association: Multidimensional Assignment

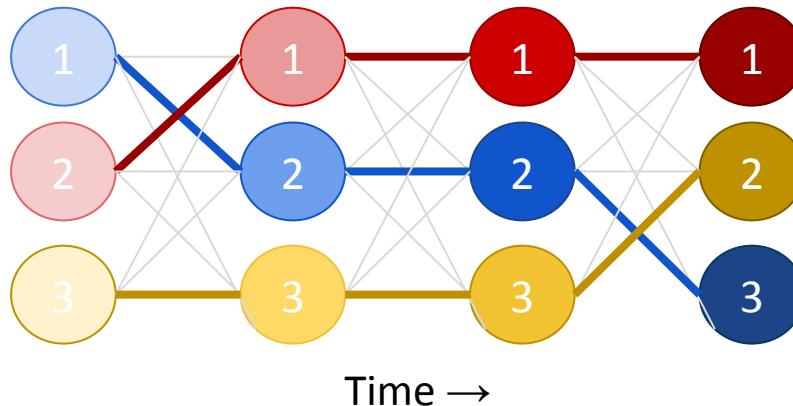
- Nodes are measurements
- Links are (potential) associations



- Path through the graph from left to right is a track

# Tracking as Multi-dimensional Assignment

- Restate Multi-target tracking as multi-dimensional assignment:
- “Choose the best possible set of tracks so that each measurement is used only once”

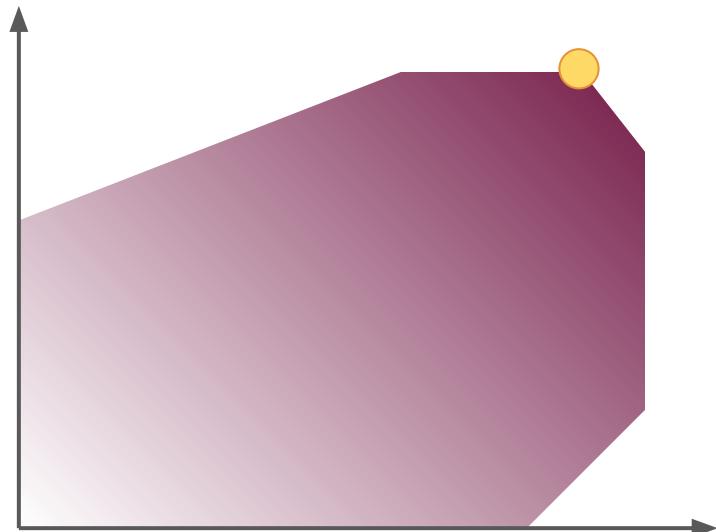


- How to formulate data association task mathematically?

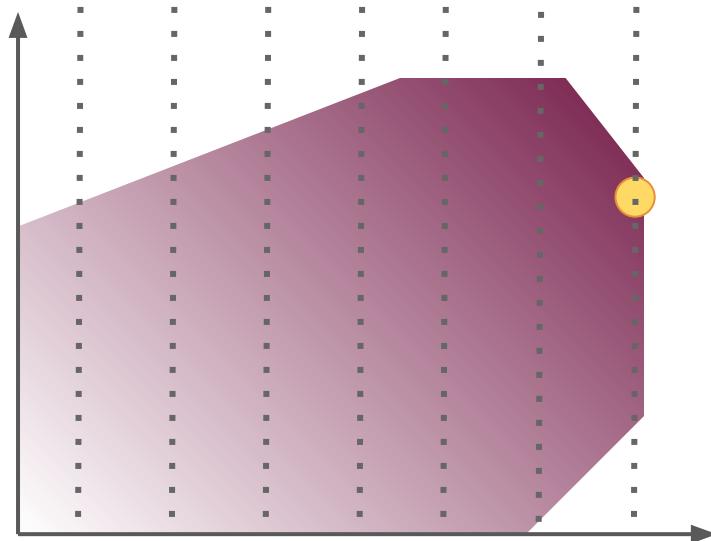
# Questions

# Linear and integer programming

[https://en.wikipedia.org/wiki/Linear\\_programming](https://en.wikipedia.org/wiki/Linear_programming)

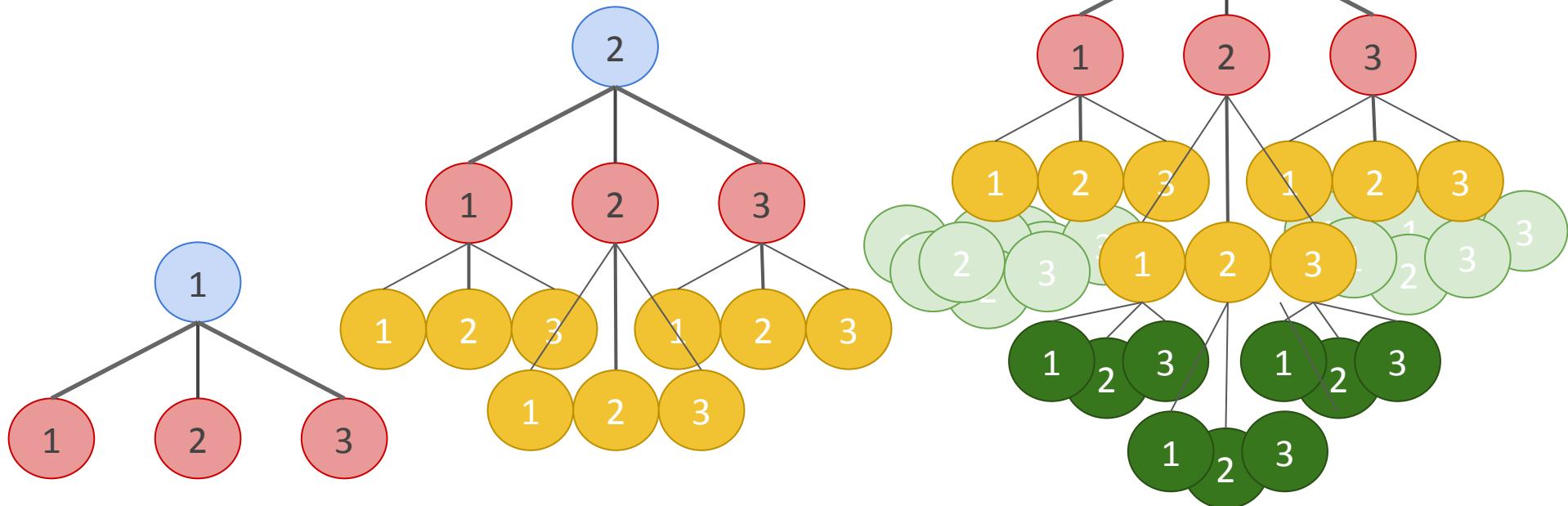


[https://en.wikipedia.org/wiki/Integer\\_programming](https://en.wikipedia.org/wiki/Integer_programming)



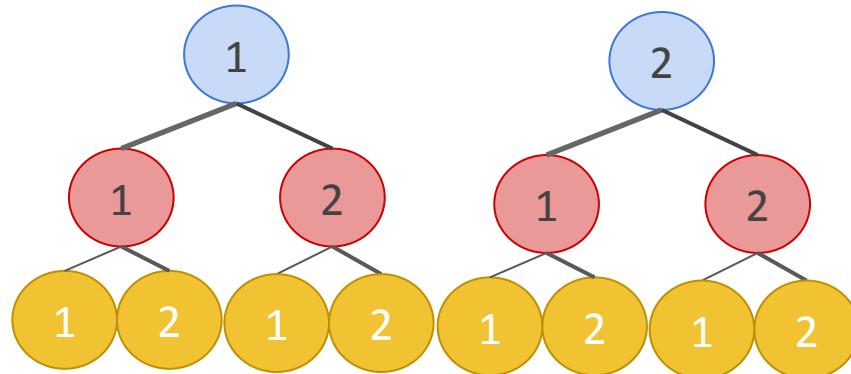
# Solving Multi-dimensional Assignment with Integer programming

Flatten the graph to a tree, maintained in software



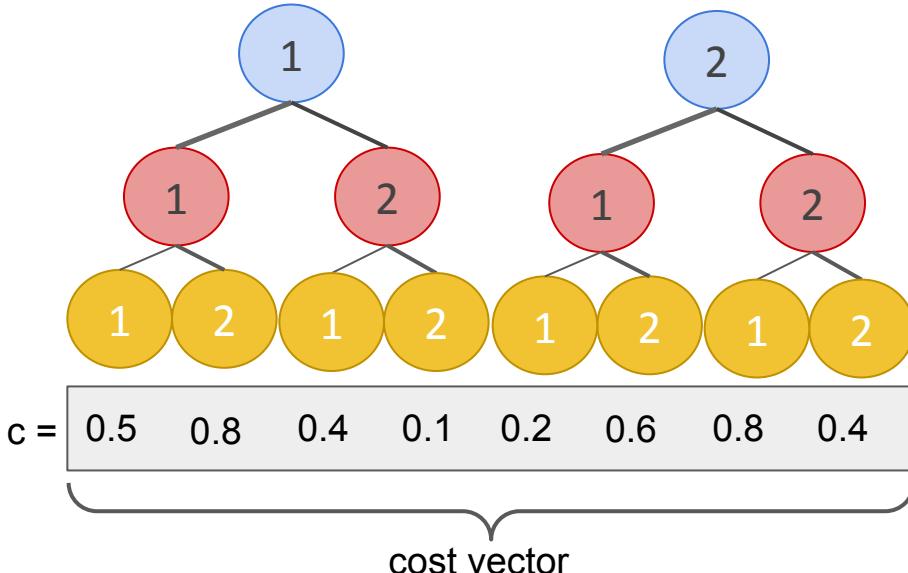
# Solving Multi-dimensional Assignment with Integer programming

(Visualization pruned)



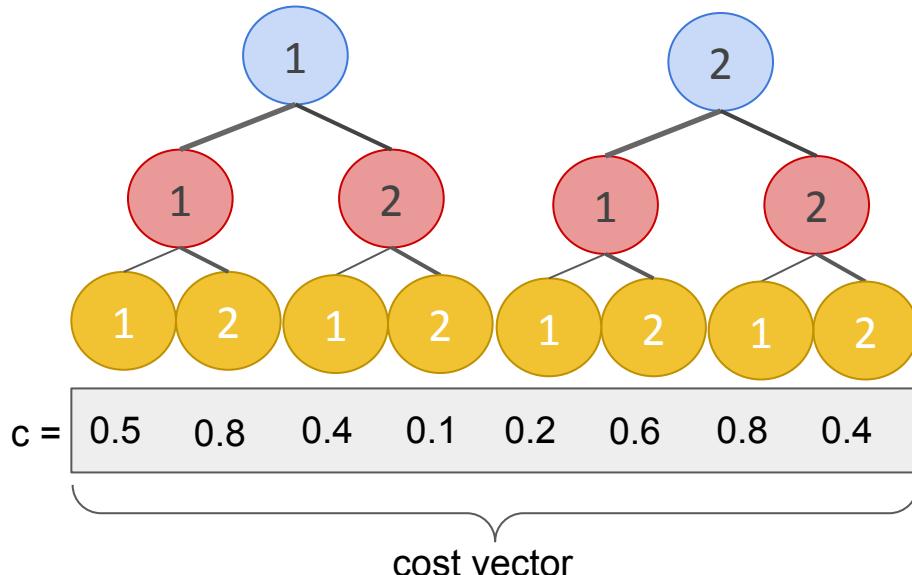
# Solving Multi-dimensional Assignment with Integer programming

Score the leaves; e.g. average magnitude of residuals, or probabilistic formulation from Kalman uncertainties



# Solving Multi-dimensional Assignment with Integer programming

Construct constraint matrix. Columns are tracks, Rows are measurements



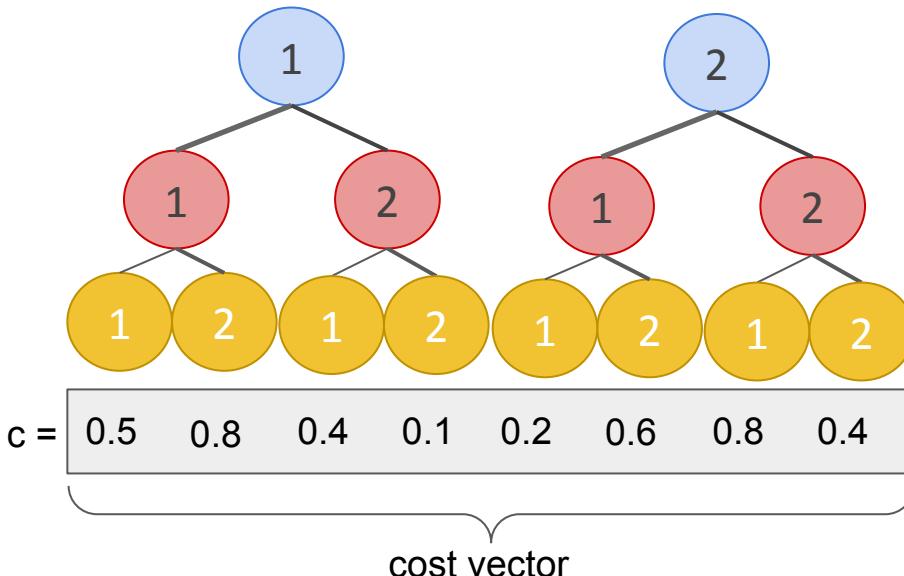
| measurements | tracks / leaves |   |   |   |   |   |   |   |   |
|--------------|-----------------|---|---|---|---|---|---|---|---|
|              | 1               | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| 1            | 0               | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| 0            | 1               | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| 1            | 0               | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 |
| 0            | 1               | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 |
| 1            | 0               | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 |
| 0            | 1               | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 |

Constraint matrix (Z)

# Solving Multi-dimensional Assignment with Integer programming

$$\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x} \text{ s.t. } \mathbf{Zx} = [1]$$

(column vector)



Assignment / selection vector ( $\mathbf{x}$ )

$\mathbf{x} = [0 \ 0 \ 0 \ 1 \ 1 \ 0 \ 0 \ 0]$

tracks / leaves

measurements

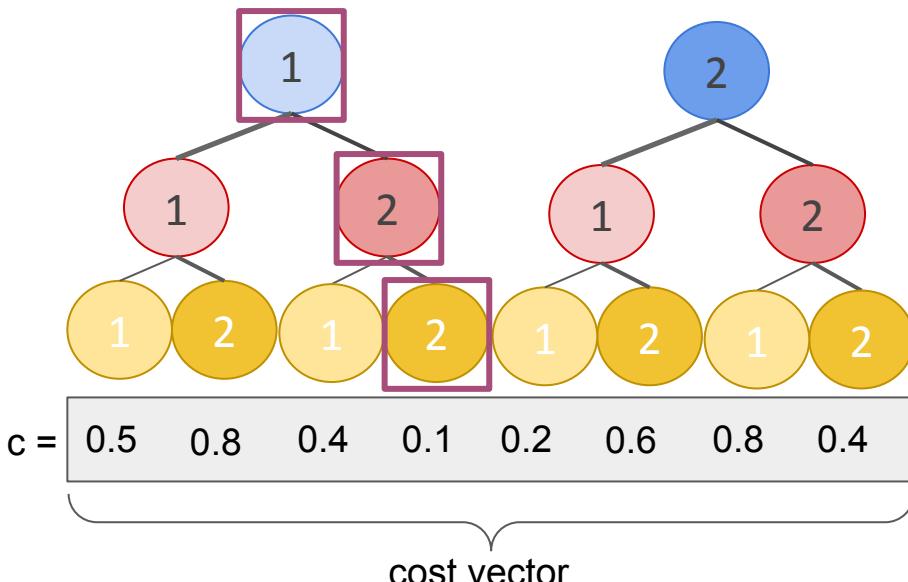
Constraint matrix ( $\mathbf{Z}$ )

|   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 |
| 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |

# Solving Multi-dimensional Assignment with Integer programming

$$\min c^T x \text{ s.t. } Zx = [1]$$

$x$



Assignment / selection vector ( $x$ )

$x = [0 \ 0 \ 0 \ 1 \ 1 \ 0 \ 0 \ 0]$

tracks / leaves

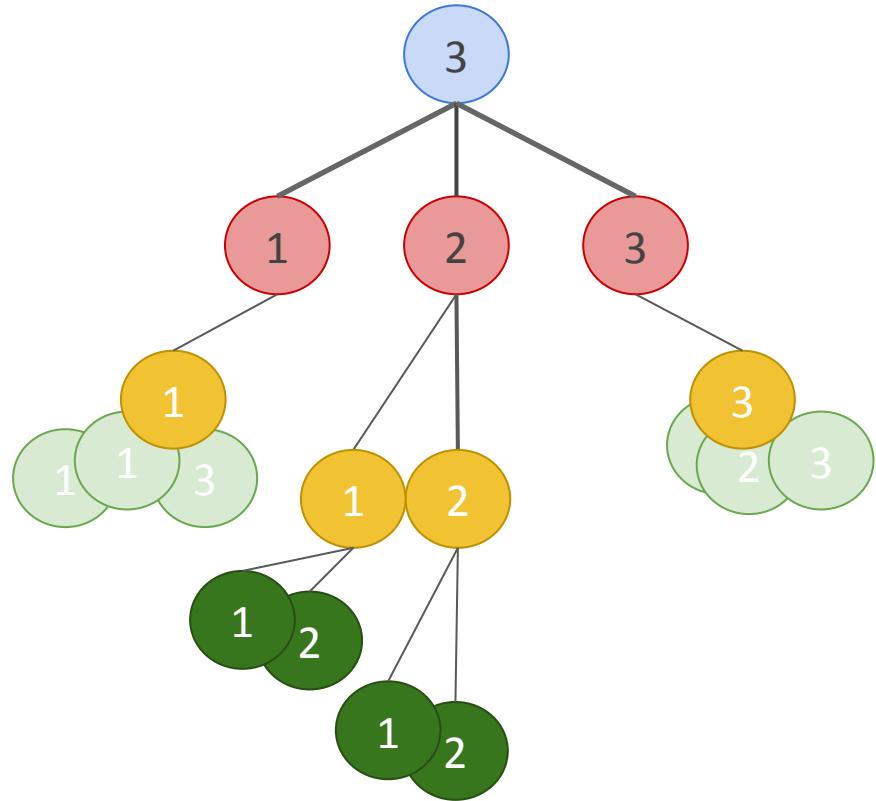
measurements

Constraint matrix ( $Z$ )

|   | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 |
| 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 1 |

# Solving Multi-dimensional Assignment with Integer programming

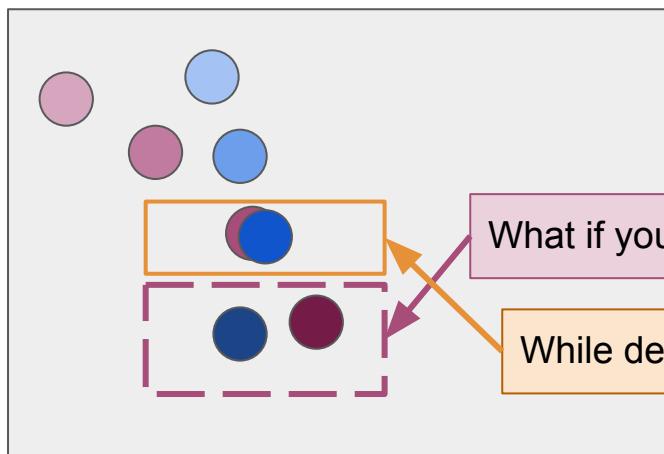
No need to maintain obviously bad associations in software



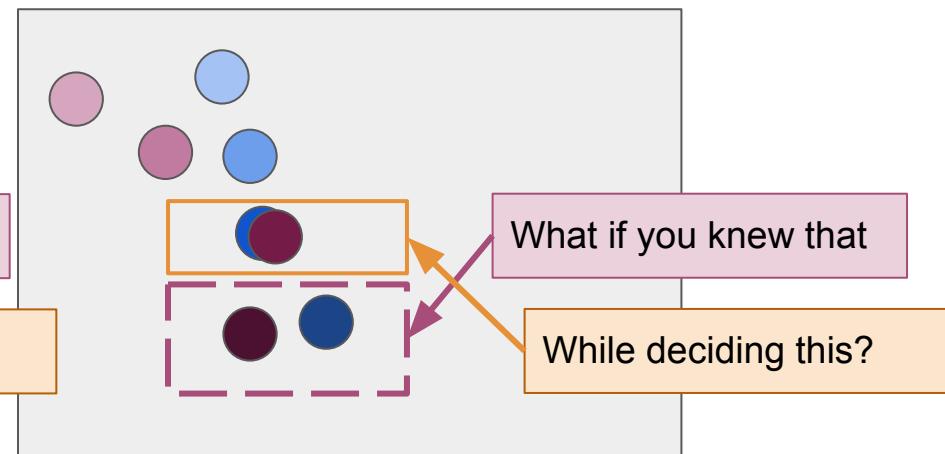
# Questions

# Multiple Hypothesis Tracking

Look ahead tracking



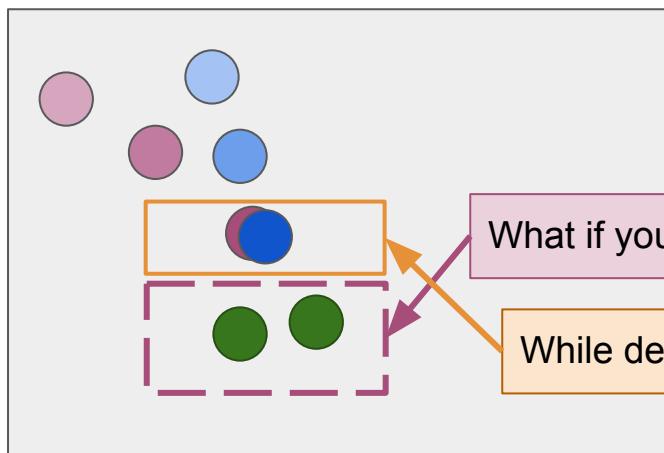
Aspirational



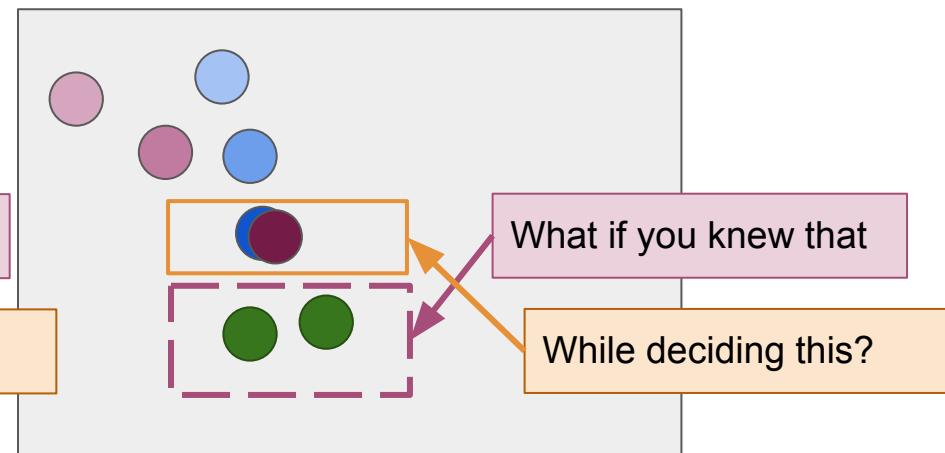
Janky Track Switch

# Multiple Hypothesis Tracking

Answer: MHT (Multiple Hypothesis Tracking)



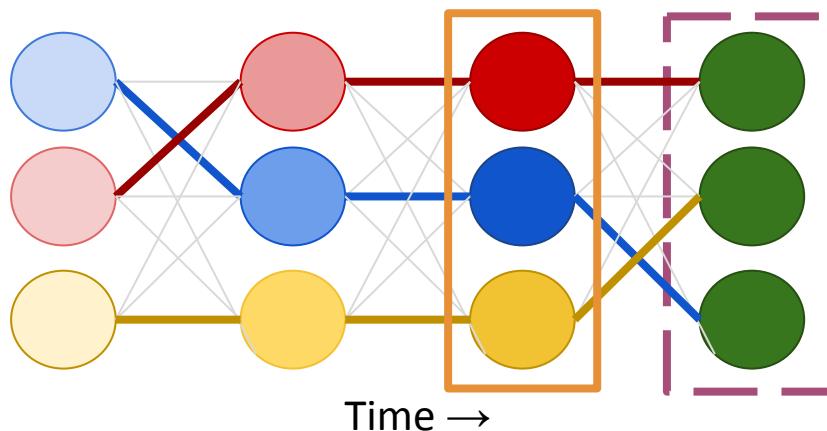
Aspirational



Janky Track Switch

# Multiple Hypothesis Tracking

- In software, don't construct full trees. Treat early nodes as fixed, designate a resolution layer of fixed depth



# Questions

We are about to move to a new topic

# The importance of data collection

The one thing I use every day during my day job

# Story Time

The one thing I use every day during my day job

Trigger Warning: personal loss

Spoiler:

Two problems that appear superficially similar may actually be very different

You must design your data collection to match your problem



# Group Behavior with Multi-view Stereo Multi-target Tracking



# 2010: Where should we put the cameras?

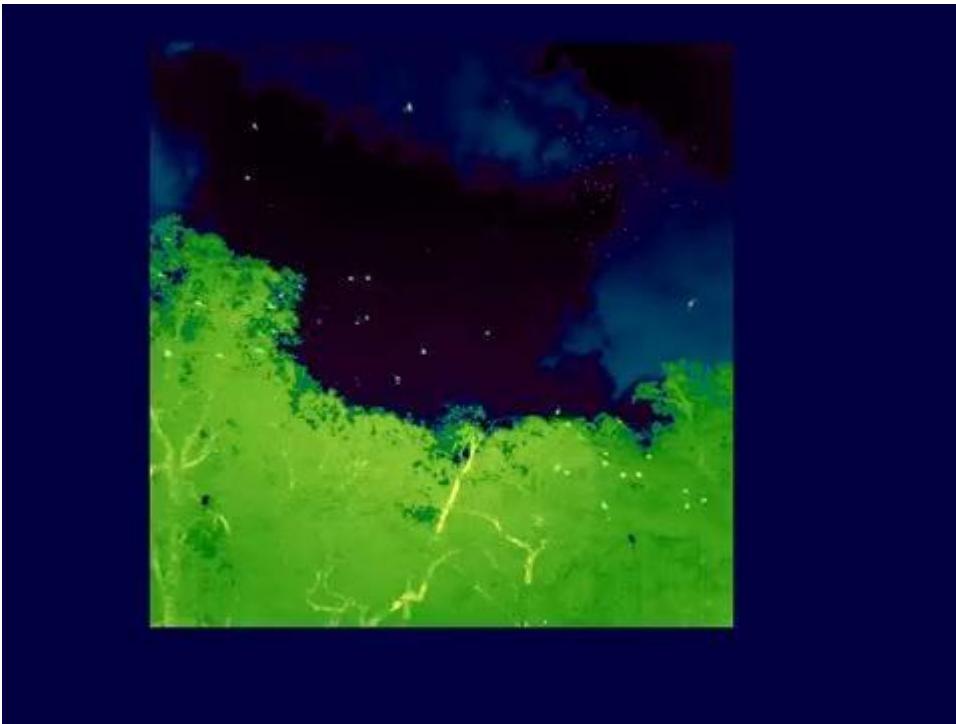


Unprepared, I needed to come up with something fast.

To do depth maps on robots,  
image planes parallel;  
cameras in a line

Horizontal search for corresponding points is efficient

# What could possibly go wrong?



- 3D Multi-target tracking:  
TWO data association problems
- 1.) 3D matching and reconstruction  
(epipolar geometry)
  - 2.) Multi-target tracking

# What could possibly go wrong?

Reprojected 3D points nowhere near bats in the image

3D points behind the camera

Tracking switching and chaos with more than 50 bats

>> Epipolar constraints not enough to disambiguate image detections

# Epipolar Geometry in 30 seconds

Spatial relationship between two cameras constrains the relationship between image locations corresponding to the same object

View from Mike's Camera



“Epipole”: image of other camera



Image Point

View from Diane's Camera



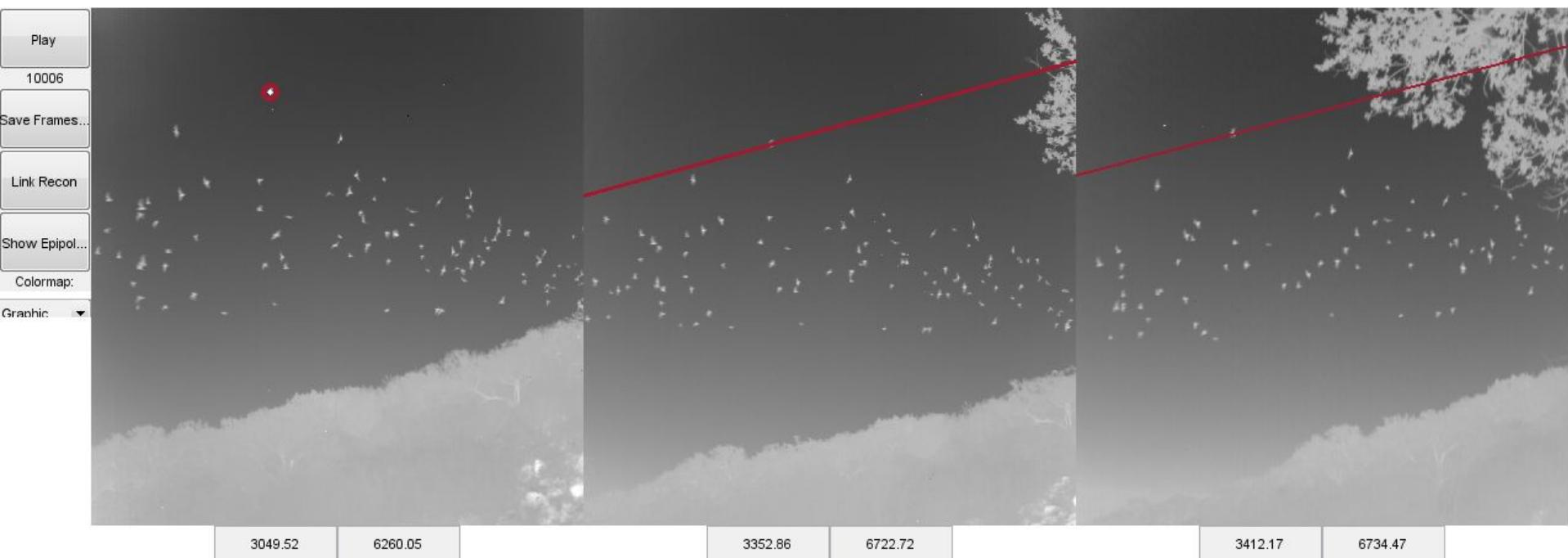
All epipolar lines intersect at the epipole

Corresponding Image Point

“Epipolar line”: image of ray from camera center through 3D scene point



# Epipolar line constraints, applied to bats



# 2011: Try again!

Tried stacking cameras vertically

Tried aiming at the sky

Tried all kinds of things

Garbage.

# 2011 - 2012: And then the stakes went up



## CAS Professor Seriously Injured by Car

"Bat Man" Thomas Kunz in ICU

November 7, 2011



By Art Jahnke

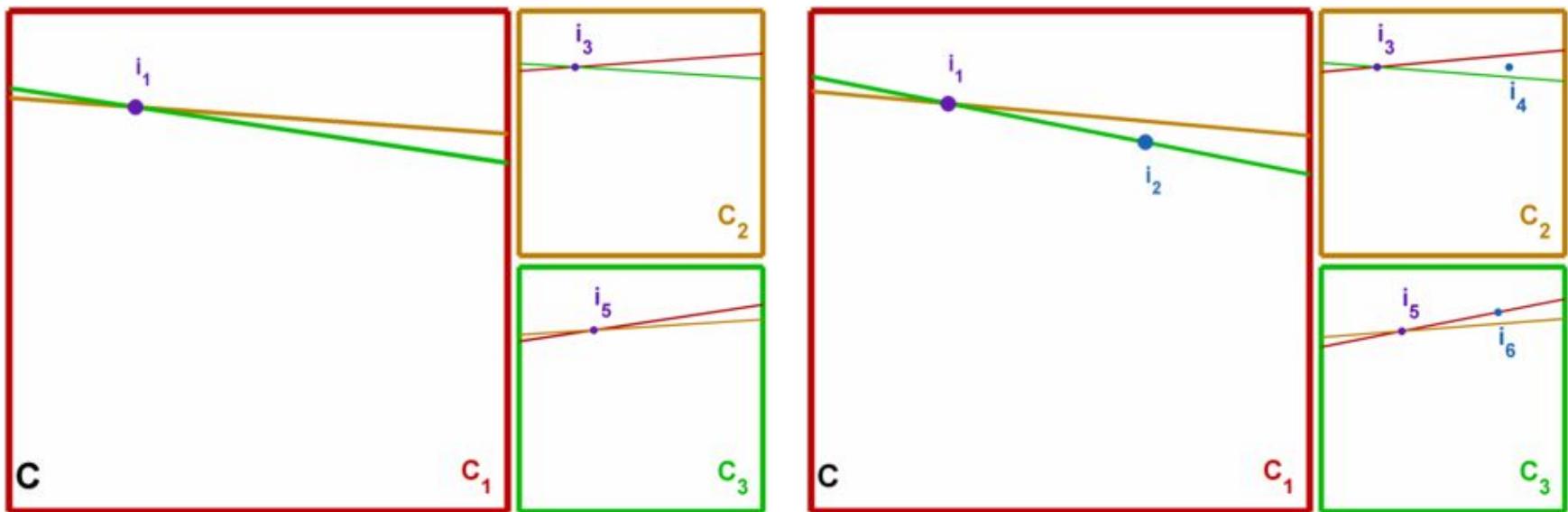


2013: “We need to go back to Texas one more time.”

“I’ll go. But you need to prove to me  
that we are going to nail it this time.  
This is our last shot.”



# Why are there zeros in the denominator?

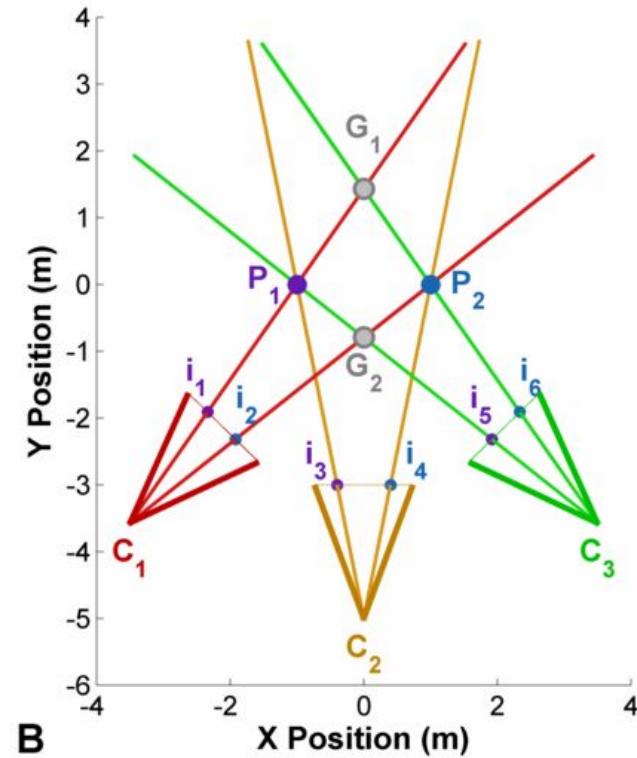


**Parallel epipolar lines were wrong.**

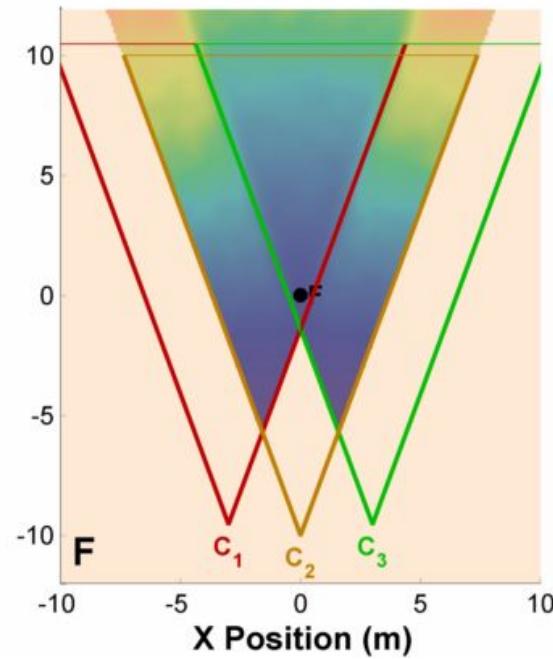
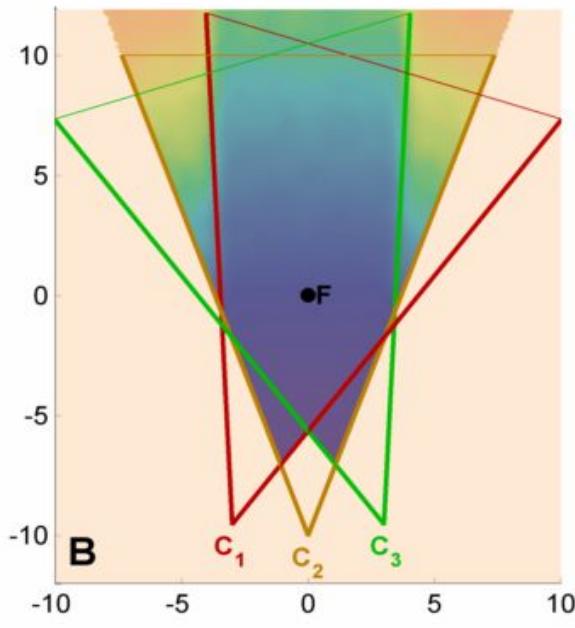
Data association of image dots != Depth Map

# Correct camera placement was easy to implement

We lost valuable time because we guessed instead of planned.



# Parallel image planes were even worse than we thought



And that is how I  
spent 3 years  
wondering which  
way was up and if  
time moved  
forwards.

50 bats → 200 bats  
with **no algorithm  
changes**.



[Alternate Link](#)

# Moral of the Story

**Two problems that appear superficially similar may actually be very different**  
No fancy algorithm would save us from data that broke our objective function.

**You must design your data collection to match your problem**  
Or you will burn precious time, unless you get very lucky

# How do I use this every day?

In the real world, you don't operate on nice, clean academic data sets.

Data collection, logging, sanitization IS the work.

Data-driven business decisions require good data.

Good data starts with good planning.

Good planning requires detailed understanding of the problem you are trying to solve.

# How do I use this every day?

Understand the product goals you are trying to serve

Identify the tactical decisions that you need to make.

How you will know that you made the right decisions?

What information will you need in order to change your decisions?

What data collection do you need so that you can calculate the metrics you need to make decisions? Don't forget to cover your denominators.

**Design your data collection to serve your problem.**

Don't guess and hope for the best. It rarely works out.

# Questions

</>

# Tracking Advanced Data Association and The Importance of Data Collection

Diane Theriault; '00 (BA), '15 (PhD)  
March 30, 2021