Tracking objects in videos

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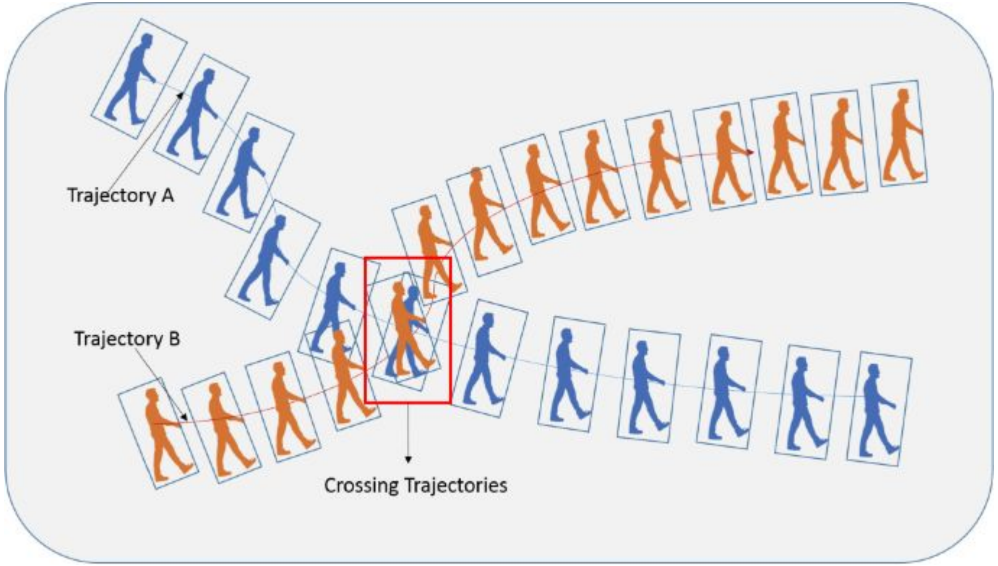
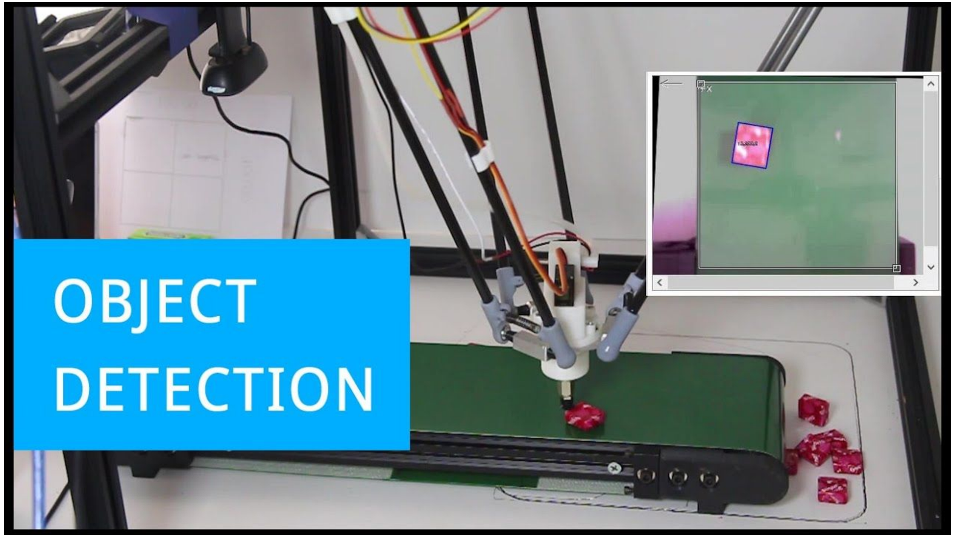


Limitations of detection algorithms

- Surveillance
  - Anomaly Detection

Limitations of detection algorithms

- Simple Robotic Picking
  - Pose estimation
  - Stable setup



Limitations of detection algorithms

- Temperature checking
  - Face Detection
  - Thermal camera

Limitations of detection algorithms

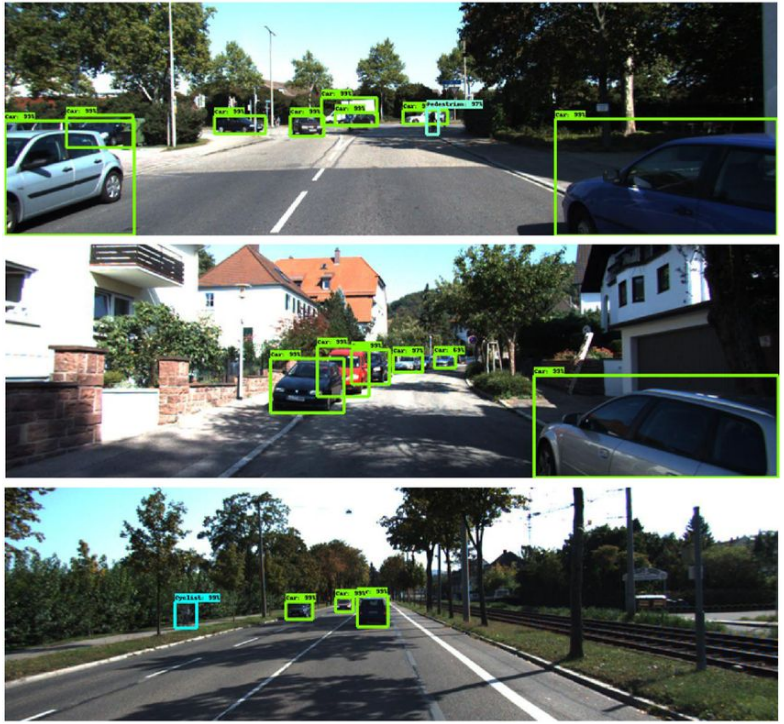
- Crowd-surveillance
  - Detection
  - Tracking
    - Counting

Limitations of detection algorithms

- Sports tracking
    - Detection
    - Tracking
    - 3D triangulation

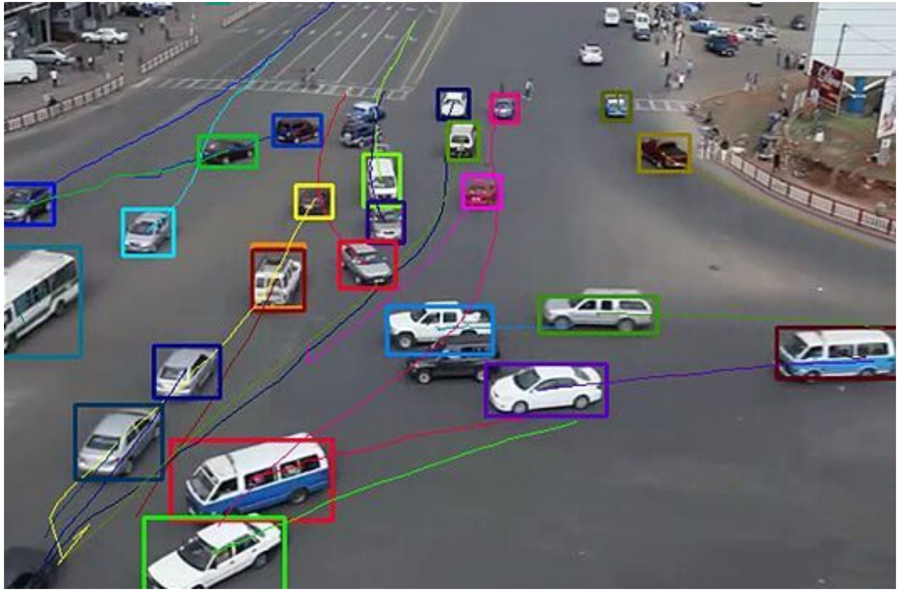
Limitations of detection algorithms

- Self-Driving
  - Detection
  - Tracking
    - Trajectory prediction
  - 3D pose estimation



Tracking Task

- Perform object detection and identification of targets
- Requires pose and visual matching of multiple objects
    - Multi Object Tracking (MOT)



Tracking Task

- Very simple task

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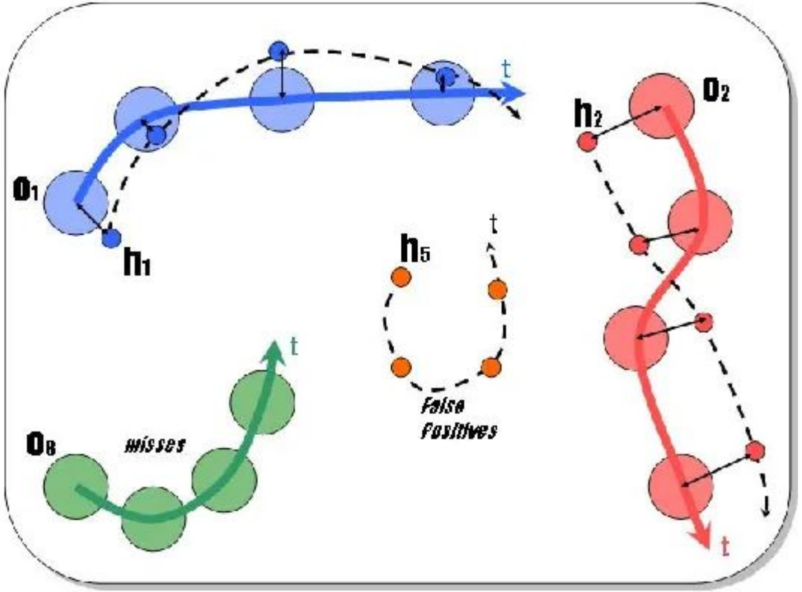
    - Objects don't change their appearance instantaneously
    - The position of objects changes slowly and predictable

Tracking Task

- Very simple task
  - Objects don't change their appearance instantaneously
  - The position of objects changes slowly and predictable
- In practice is hard to automate
  - several types of error can occur

Tracking metrics

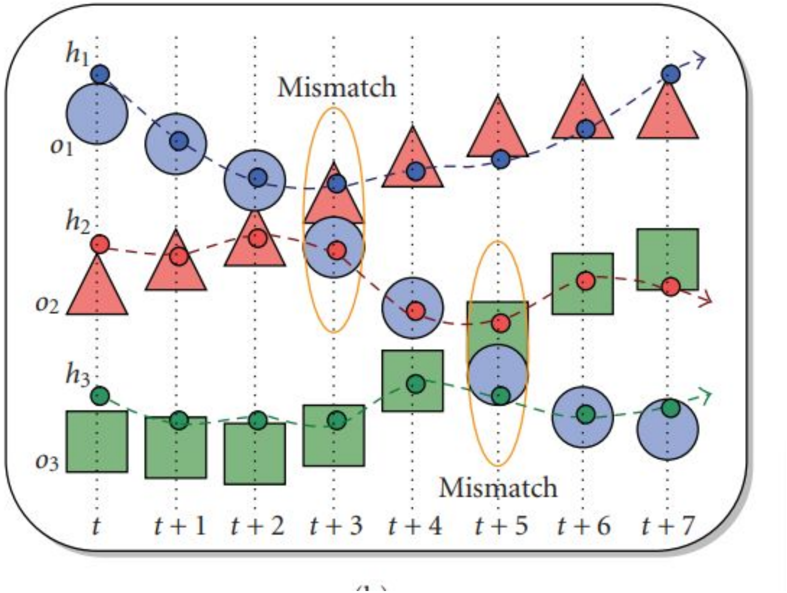
- Positional Metrics
    - Distance L2



Evaluating Multiple Object Tracking Performance: The CLEAR MOT Metrics. 2007

Tracking metrics

- Positional Metrics
  - Distance L2
- Identity Metrics
  - True Positives TP



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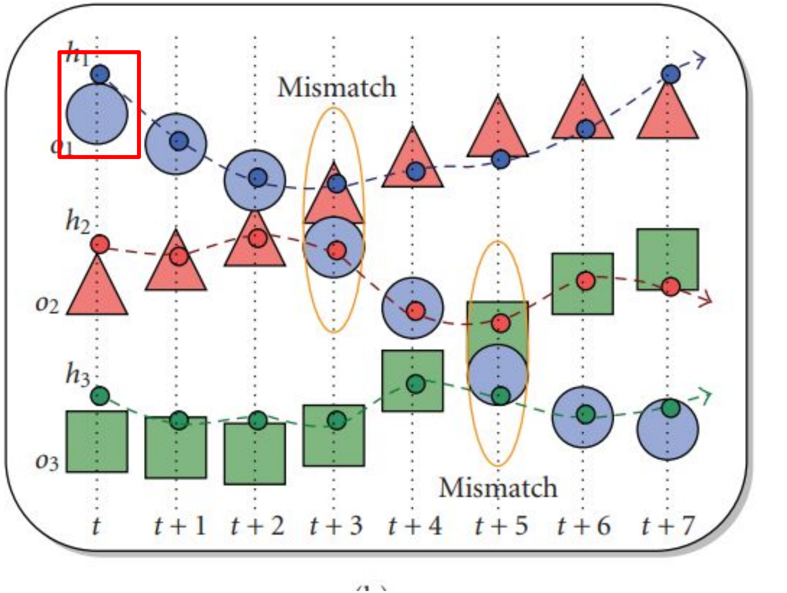

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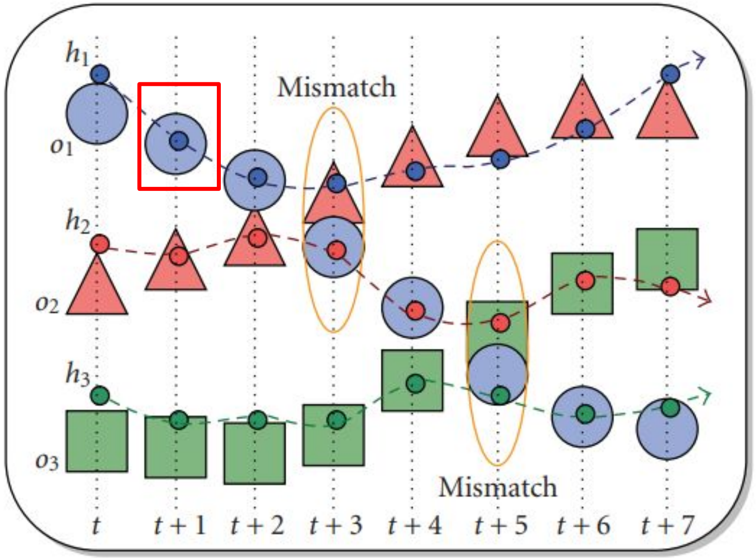

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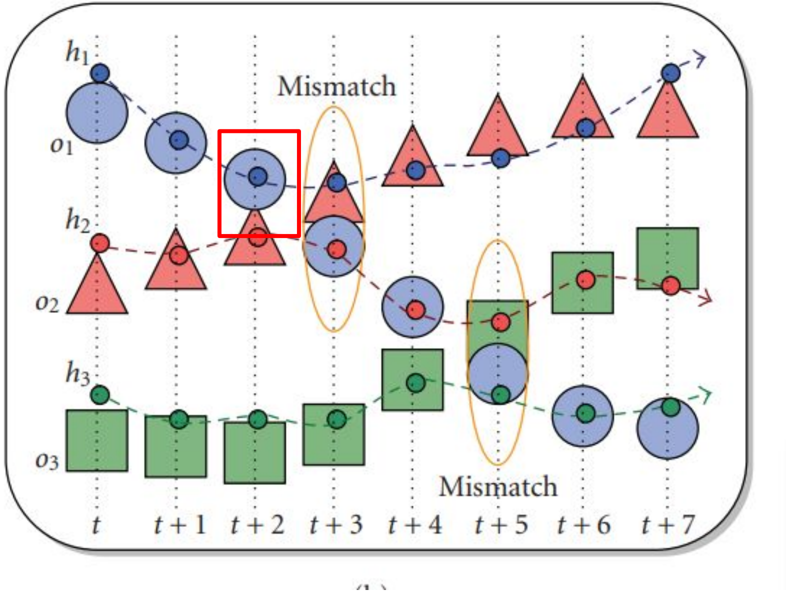
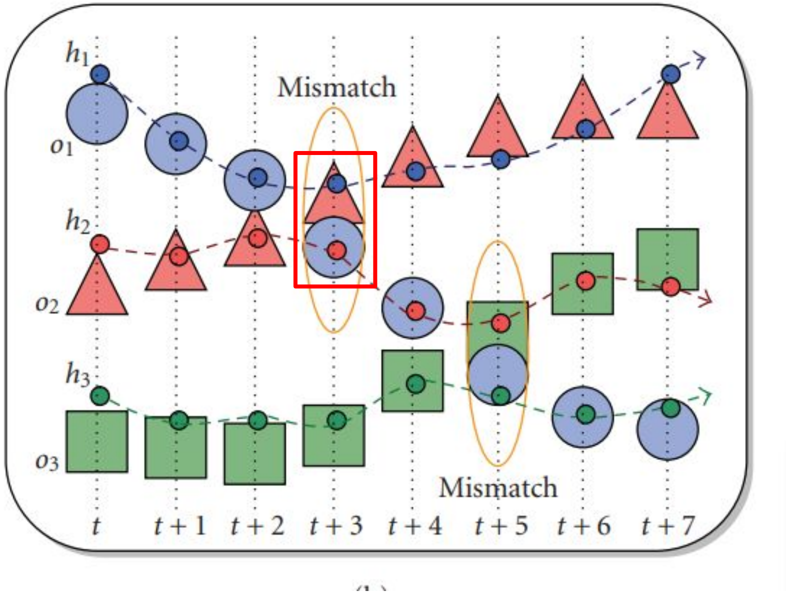


Evaluating Multiple Object Tracking Performance: The CLEAR MOT Metrics. 2007

Tracking metrics

- Positional Metrics
  - IoU
  - Distance L2
  - Multi object tracking precision (MOTP)
- Identity Metrics
  - True Positives TP
  - Mismatched



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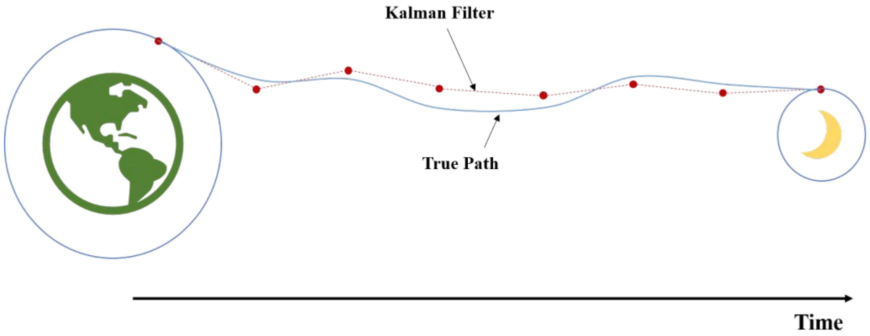
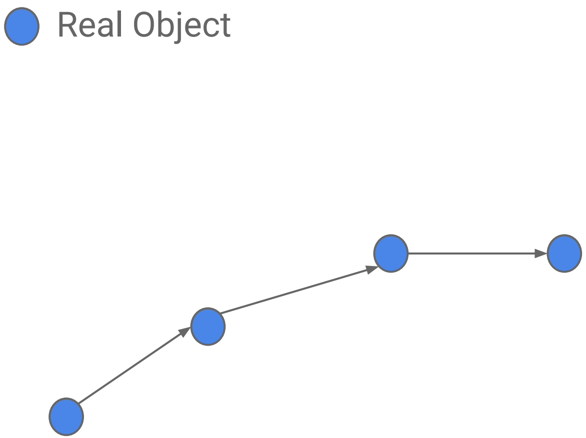
Kalman Tracking



- Kalman Filtering
    - Control algorithm to estimate position of an object
    - One their first uses was the development of a guiding mechanism for the apollo mission.
    - Estimate the position and overall direction of an object using sparse observations.

Kalman Tracking



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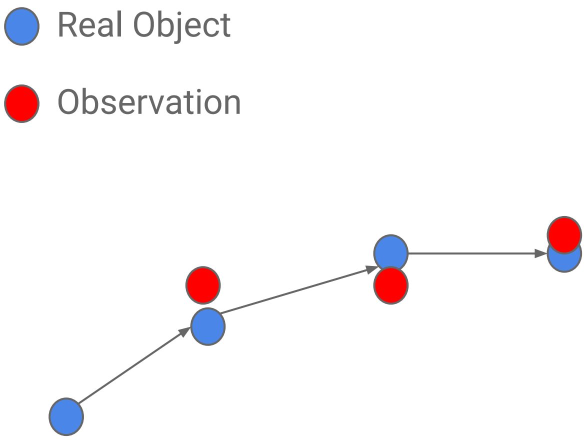

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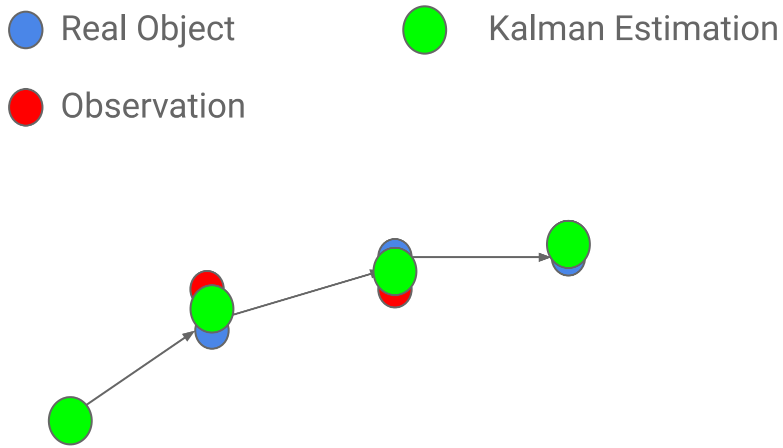

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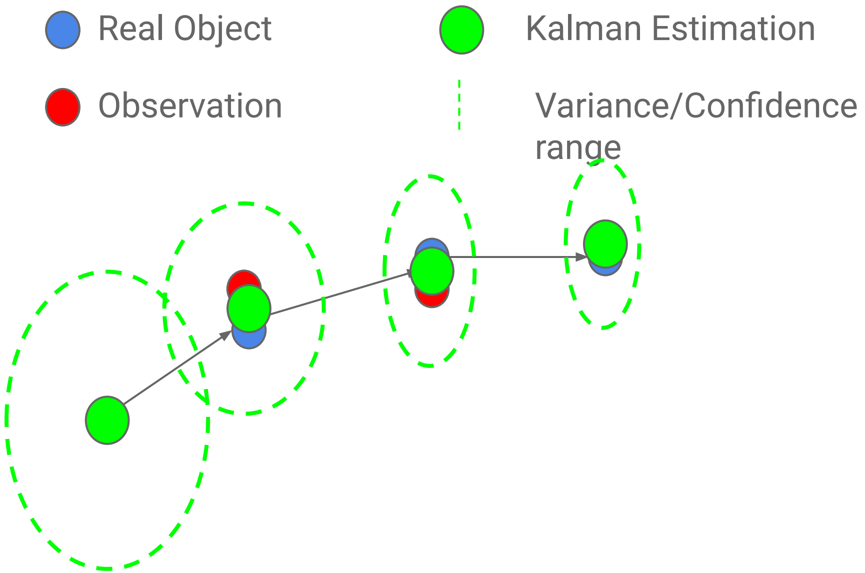

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    - We model the uncertainty of the measurements and the model with a range of confidence/variance.

Kalman Tracking

1. $\hat{X}_{k|k-1} = A\hat{X}_{k-1|k-1} + Bu_k$
2. $P_{k|k-1} = AP_{k-1|k-1}A^T + Q$
3. $J_k = P_{k|k-1}C^T \left(CP_{k|k-1}C^T + R\right)^{-1}$
4. $\hat{X}_{k|k} = \hat{X}_{k|k-1} + J_k \left(Y_k - C\hat{X}_{k|k-1}\right)$
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Kalman Tracking

Previous position in k-1

1. $\hat{X}_{k|k-1} = A\boxed{\hat{X}_{k-1|k-1}} + Bu_k$
2. $P_{k|k-1} = AP_{k-1|k-1}A^T + Q$
3. $J_k = P_{k|k-1}C^T \left(CP_{k|k-1}C^T + R\right)^{-1}$
4. $\hat{X}_{k|k} = \hat{X}_{k|k-1} + J_k\left(Y_k - C\hat{X}_{k|k-1}\right)$
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Kalman Tracking

Dynamic of the system

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Kalman Tracking

Prior/ expected next step

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Prior variance/uncertainty (NxN)

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Kalman Tracking

Observation

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Kalman Tracking

Error between expected position / prior and the Observation

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Kalman Tracking

Posterior/predicted position

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Posterior variance

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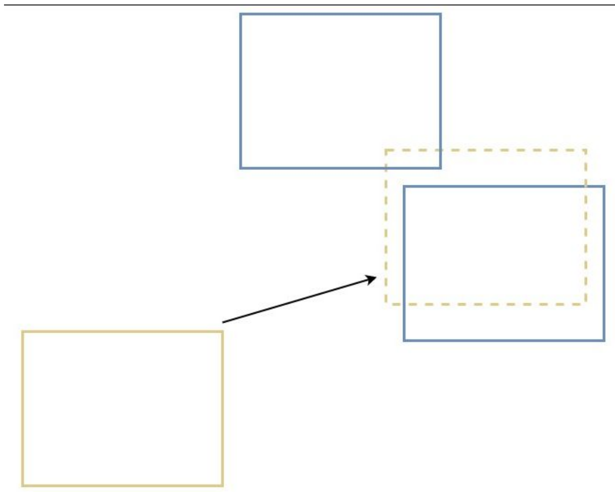
Detection + Kalman Filtering



- What are poses in video tracking?
  - Detections and speeds
    x1,y1,x2,y2,x’1,y’1,x’2,y’2
- What is our input
  - Detections

Previous location
Prior Prediction
Detection

Detection + Kalman Filtering

- What are poses in video tracking?
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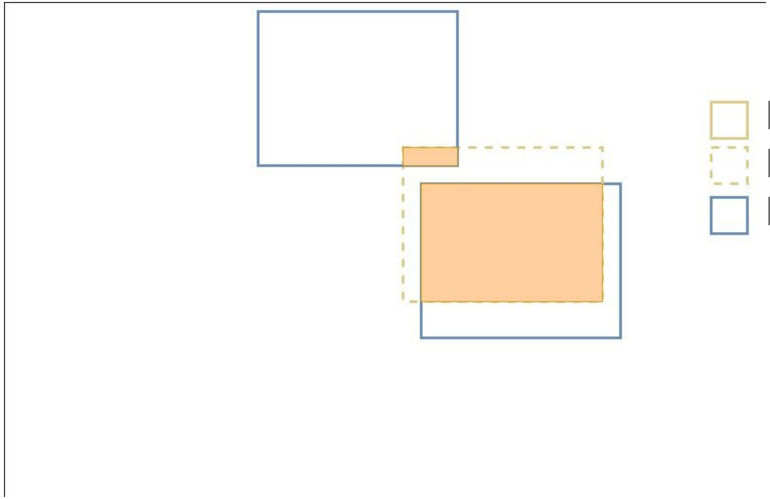

- Match track with detection
  - Larger IoU

Detection + Kalman Filtering

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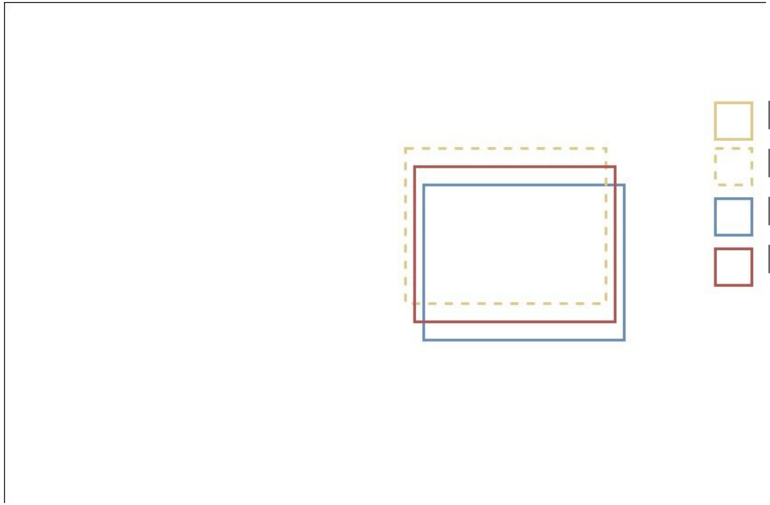
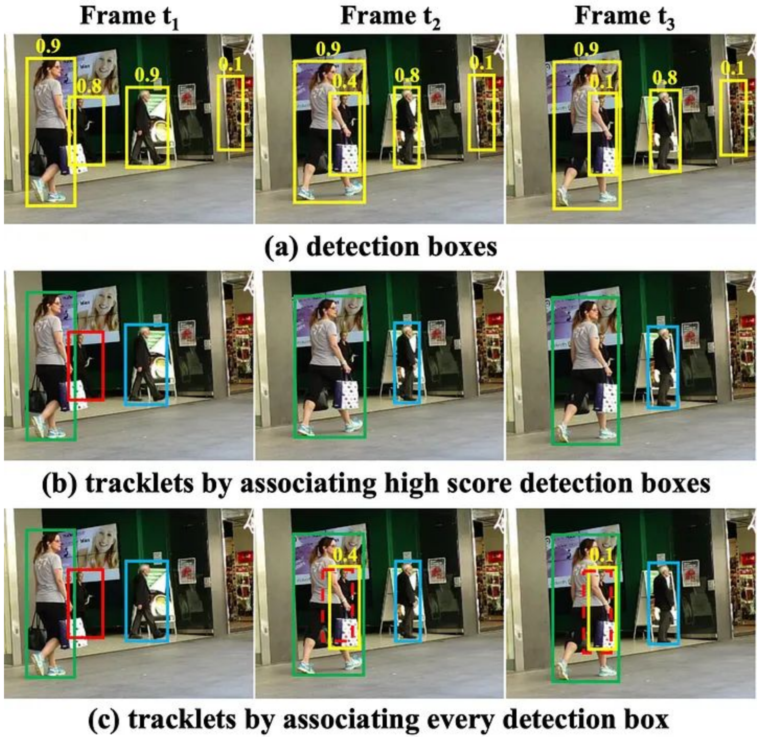


- Match track with detection
  - Larger IoU
- Final Prediction

ByteTrack

- ByteTrack = Kalman++
    - Overlapping object often lead to low confidences detections (if any)



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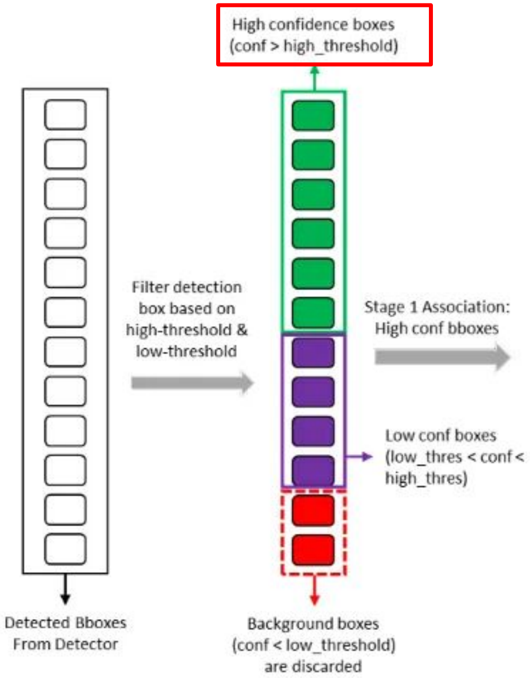
  - This leads to a two tier detection hierarchy
    - High confidence
    - Low confidence



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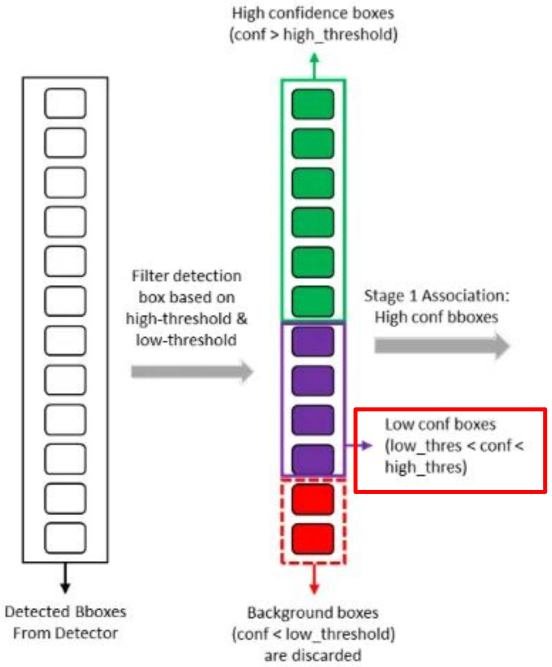

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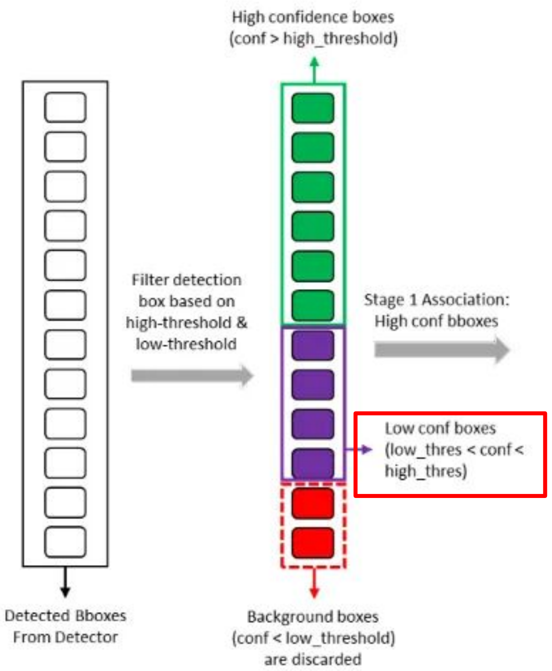

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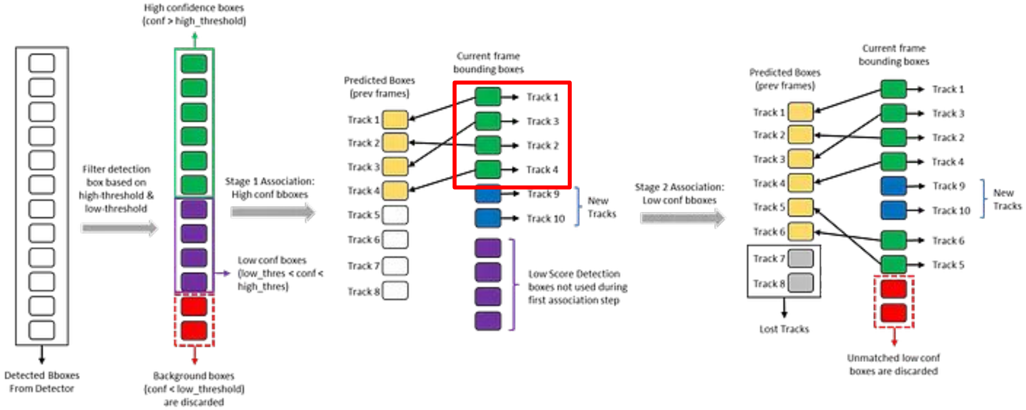
      - Matching detections are assigned to existing objects
    - Low confidence



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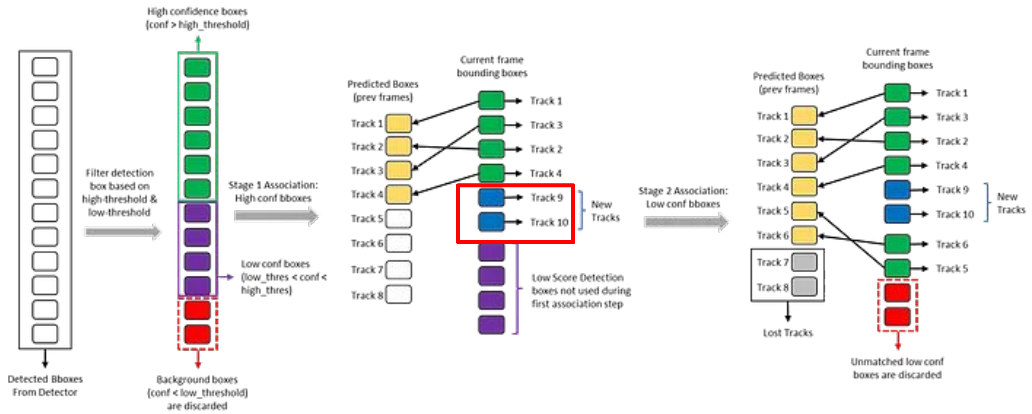

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            - Matching detections are assigned to existing objects
            - Unmatched detections are considered new objects
        - Low confidence
            - Matched detections are matched