Object Tracking in videos (cours 2)
Rob 313

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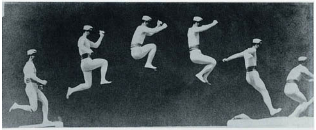
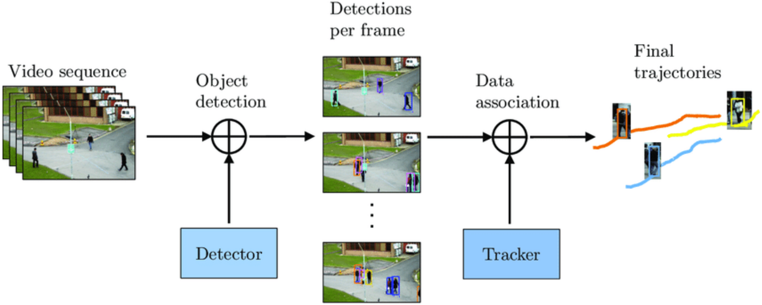


Fundamental Components of Tracking by detection

An object tracking algorithm is made of two fundamental elements:

- **Association**: associate the objects on two different frames
- **Detection**: localize the objects.

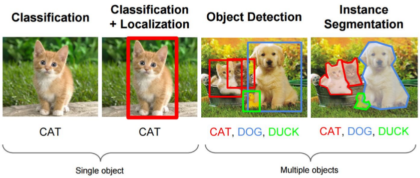


Fundamental Components of Tracking by detection

Some of the most important challenges of Tracking by detection include:

- **Missed detections:** long-term occlusions are usually present in semi-crowded scenarios. In this case, it is very hard for the tracker to re-identify the pedestrian.
- **False alarms:** the detector can be triggered by regions in the image that actually do not contain any pedestrian, creating false positive.
- **Similar appearance:** one source of information commonly used for pedestrian iden-tification is appearance. However, in some videos similar clothing can lead to virtually identical appearance models for two different pedestrians.
- **Groups and other special behaviors:** when dealing with semi-crowded scenarios, it is very common to observe social behaviors like grouping.

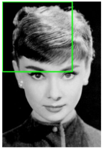
What is object detection?



Before Deep Learning

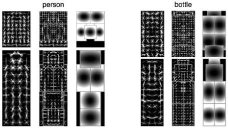
Sliding windows.

- Score every subwindow.



Deformable part models (DPM)

- Uses HOG features
- Very fast



Before Deep Learning

Different type of Object detection

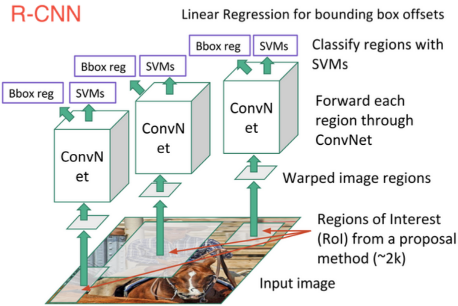
Two stage strategy:

- RCNN
- Fast RCNN
- Faster RCNN

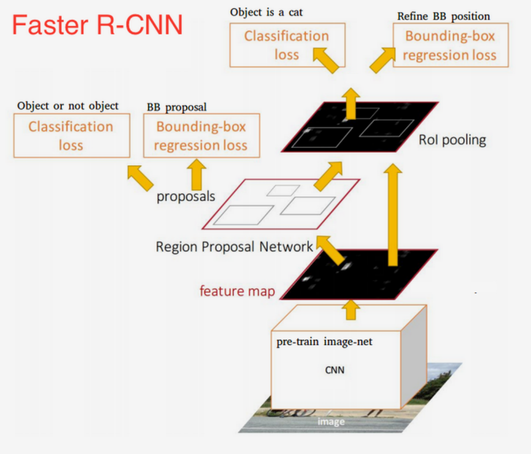
One stage strategy:

- Yolo
- SSD
- RetinaNet

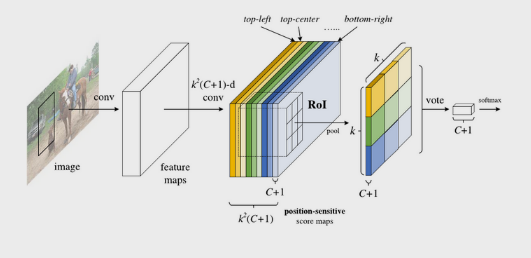
RCNN


R-CNN
Linear Regression for bounding box offsets
Bbox reg
SVMs
Bbox reg
SVMs
Bbox reg
SVMs
Classify regions with SVMs
ConvNet
ConvNet
ConvNet
Forward each region through ConvNet
Warped image regions
Regions of Interest (RoI) from a proposal method (~2k)
Input image

Faster RCNN


Faster R-CNN
Object is a cat
Classification loss
Refine BB position
Bounding-box regression loss
Object or not object
Classification loss
BB proposal
Bounding-box regression loss
RoI pooling
proposals
Region Proposal Network
feature map
pre-train image-net
CNN
image

R-FCNN

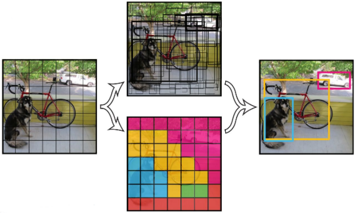

top-left
top-center
bottom-right
image
conv
feature maps
$k^2(C+1)$-d conv
RoI
pool
k
k
$C+1$
$C+1$
$k^2(C+1)$
position-sensitive score maps
vote
softmax
$C+1$

Yolo: You Only Look Once

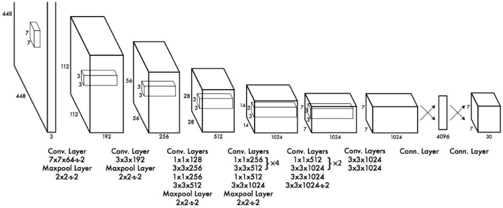
The following predictions are made for each cell in an $S \times S$ grid.
output of YOLO:

- C conditional class probabilities $P(\text{Classi}|\text{Obj})$
- B bounding boxes (4 parameters each)
- B confidence scores $P(\text{Obj})$
- Output is $SxSx(5B + C)$ tensor

conditional class probabilities $P(\text{Classi}|\text{Obj})$



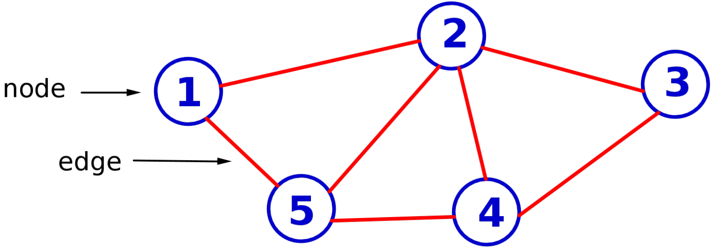
Yolo: You Only Look Once



Graph Theory Basics (Remember)

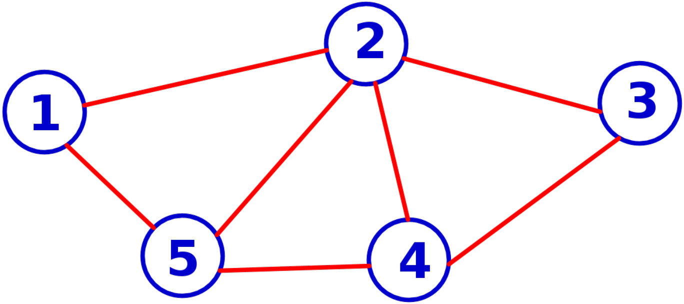
A graph is a data structure that is defined by two components :

- edges
- nodes (vertices)



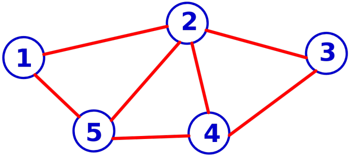
Graph Theory Basics

We write a graph $G = (V, E)$ where V is the set of nodes E is the set of edges. $E \subseteq \{(x, y) | (x, y) \in V^2\}$
On the following case $V = \{1, 2, 3, 4, 5\}$ and
$E = \{(1, 2), (1, 5), (2, 5), (2, 4), (2, 3)\}$

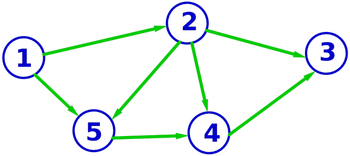


Directed/Undirected graphs (Remember)

First, let us make a distinction between a directed graph and an undirected graph. A directed graph or digraph is a graph in which edges have orientations, while it doesn't for an undirected graph.



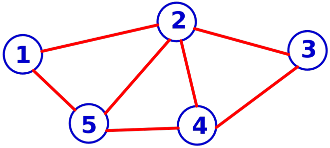
Undirected



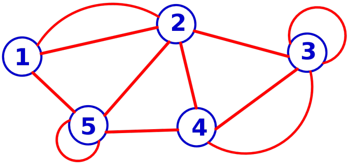
Directed

Simple graphs / Multigraphs (Remember)

A simple graph is a graph without any loop in which two nodes are connected by at most one edge.
A multigraph is a graph that can have multiple edges that have the same nodes. Thus two nodes may be connected by more than one edge. One node can also have a self-loop.



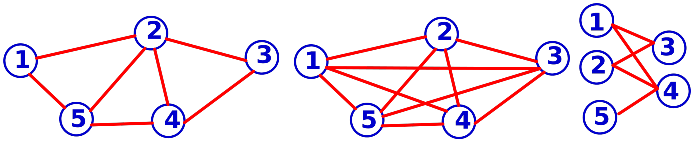
Simple graph



Multigraph

Connected, Complete, Bipartite graphs (Remember)

A connected graph is a graph composed of at least one vertex and there is a path (=finite or infinite sequence of edges which joins two nodes) between every pair of nodes.
A complete graph is a graph whose each nodes are connected to all other nodes .
A bipartite graph is a graph whose vertices can be divided into two disjoint and independent sets U and V such that all edges connect a node in U to one in V .



Connected graph Complete graph Bipartite graph

Connected, Complete, Bipartite graphs (Remember)

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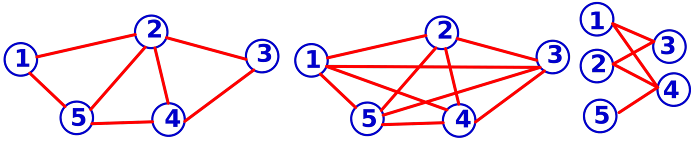
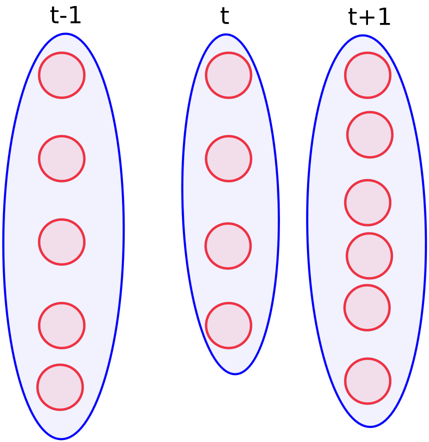


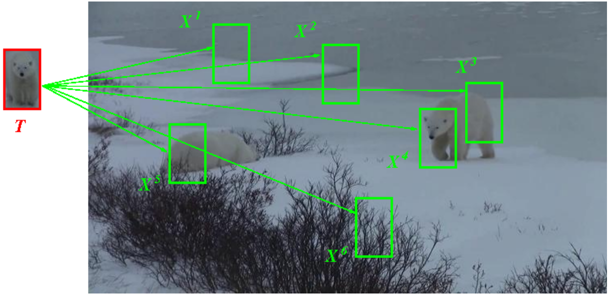
Connected graph
Complete graph
Bipartite graph

Matching problem



Local Matching

Global (di)similarity measures are applied between two vectors T and X of the same dimension n, one of which being the model (template) of the object, (usually) represented by a rectangular patch, and the other a patch extracted from the current image, that corresponds to a location hypothesis.

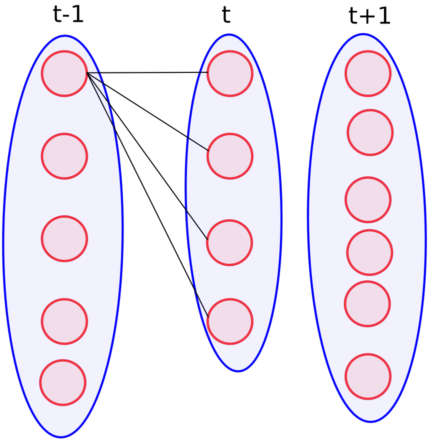


Local Matching

Principle

- At each frame we build all the possible associations between the set of active tracks and the current set of detections.
- We select first the association with the smallest distance and the corresponding track and detection $\mathcal{D}_k(X_{t-1,i}, X_{t,i})$.
- we discard this object from the association problem.
- we repeat the previous step up to when there is not object at time $t-1$
- Remaining detections are used to create new tracks, while non associated tracks are ended.

Local Matching



Global Matching

Principle

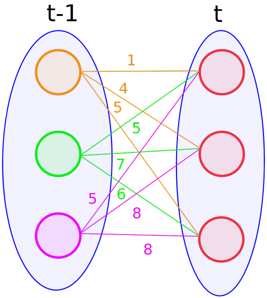
We look for the set of associations between tracks at time $t-1$ and N detections at time t with the smallest sum of distances : $\sum_{i=1}^{n_{t-1}} \sum_{j=1}^{n_t} \|X_{t-1,i} - X_{t,j}\|^2$. In practice, it is necessary to enumerate all the possible combinations of associations, which may turn out to be time consuming. On efficient algorithm to perfom this task is the hungarian algorithm.

Hungarian Algorithm

Converting this problem to a formal mathematical definition we can form the following equations:

- let us define a cost matrix $C \in M_n(\mathbb{R})$, where C_{ij} is the matching cost of object i at time $t-1$ to object j at time t.
- let us define a result binary matrix $R \in M_n(\mathbb{R})$, where $R_{ij} = 1$ if and only if object i at time $t-1$ is assigned to object j at time t.
- One object i at time $t-1$ has just one object j at time t assign $\sum_{j=1}^{n} R_{ij} = 1$
- one object j at time t is assign to just one object i at time $t-1$ assign $\sum_{i=1}^{n} R_{ij} = 1$
- the total cost function is :$\sum_{i=1}^{n} \sum_{j=1}^{n} R_{ij} C_{ij}$

Hungarian Algorithm



$$\begin{pmatrix} 1 & 4 & 5 \\ 5 & 7 & 6 \\ 5 & 8 & 8 \end{pmatrix} \tag{1}$$

Hungarian Algorithm

- This problem is known as the assignment problem.
- It is a special case of the transportation problem, which in turn is a special case of the min-cost flow problem
- It could also be optimized thanks to linear programming problem

Hungarian Algorithm

- For each row of the matrix, find the smallest element and subtract it from every element in its row.
- Do the same (as first step) for all columns.
- Cover all zeros in the matrix using minimum number of horizontal and vertical lines.
- Test for Optimality: If the minimum number of covering lines is n, an optimal assignment is possible and we are finished. Else if lines are lesser than n, we haven't found the optimal assignment, and must proceed to the next step
- Determine the smallest entry not covered by any line. Subtract this entry from each uncovered row, and then add it to each covered column. Return to step

Hungarian Algorithm: example

$$\begin{pmatrix} 1 & 4 & 5 \\ 5 & 7 & 6 \\ 5 & 8 & 8 \end{pmatrix}$$

$$\begin{pmatrix} 0 & 3 & 4 \\ 0 & 2 & 1 \\ 0 & 3 & 3 \end{pmatrix}$$

Hungarian Algorithm: example

$$\begin{pmatrix} 0 & 3 & 4 \\ 0 & 2 & 1 \\ 0 & 3 & 3 \end{pmatrix}$$

$$\begin{pmatrix} 0 & 1 & 3 \\ 0 & 0 & 0 \\ 0 & 1 & 2 \end{pmatrix}$$

Hungarian Algorithm: example

$$\begin{pmatrix} 0 & 1 & 3 \\ 0 & 0 & 0 \\ 0 & 1 & 2 \end{pmatrix}$$

$$\begin{pmatrix} \color{red}{0} & 1 & 3 \\ \color{red}{0} & \color{red}{0} & \color{red}{0} \\ \color{red}{0} & 1 & 2 \end{pmatrix}$$

just 2 lines, so we need to do one more step.

Hungarian Algorithm: example

$$\begin{pmatrix} \color{red}{0} & 1 & 3 \\ \color{red}{0} & \color{red}{0} & \color{red}{0} \\ \color{red}{0} & 1 & 2 \end{pmatrix}$$

$$\begin{pmatrix} -1 & 0 & 2 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{pmatrix}$$

$$\begin{pmatrix} \color{blue}{0} & 0 & 2 \\ 1 & 0 & \color{blue}{0} \\ 0 & \color{blue}{0} & 1 \end{pmatrix}$$

the cost is 15.

Multiple object tracking as Maximum likelihood as a global objective function

Principle

- We propose here to consider the tracking task as the construction of the set of the most probable trajectories given the observed data.
- Let $\theta_i = \{o_i^{t_{\text{init}}}, \dots, o_i^{t_{\text{end}}}\}$ denote a track: a sequence of an arbitrary number of states at discrete time .
- Let $\Theta = \cup_{i=1}^{N} \theta_i$ denotes the set of trajectories composed of N tracks
- Let $Z^I = \{o_i^{t_k}\}_{i,k}$ is the observed data over the time sequence.

For tracking purposes we want to find the tracks Θ that maximize the likelihood of the tracks:

$$\mathcal{L}(\Theta) = P(\Theta / Z^I) \tag{2}$$

Multiple object tracking as Maximum likelihood as a global objective function

The likelihood of the tracks is

$$\mathcal{L}(\Theta) = P(\Theta/Z^l) \tag{3}$$

By applying the Bayes rule, we can rewrite it:

$$\mathcal{L}(\Theta) = \frac{P(\Theta, Z^l)}{P(Z^l)} \tag{4}$$

We can just maximize the numerator then we have
$P(\Theta, Z^l) = P(Z^l/\Theta)P(\Theta)$.
We also make the usual assumption that objects are detected and move independently, that the tracks are independent.

$$P(\Theta, Z^l) = \prod_{i,k} P(o_i^{t_k}/\Theta) \prod_i P(\theta_i) \tag{5}$$

Multiple object tracking as Maximum likelihood as a global objective function

$P(o_i^{t_k}/\Theta)$ is the probability that $o_i^{t_k}$ is a good detection that belongs to the tracks.

$$P(o_i^{t_k}/\Theta) = \begin{cases} 1-\beta_{i,k} & \text{if } \exists \theta_j \text{ such that } o_i^{t_k} \in \theta_j \\ \beta_{i,k} & \text{otherwise.} \end{cases} \tag{6}$$

The likelihood function $P(o_i^{t_k}/\Theta)$ can model that the observations that are associated are true detections, and those that are not associated are false alarms

Multiple object tracking as Maximum likelihood as a global objective function

$$P(\theta_i) = P(\{o_i^{t_{\text{init}}}, \dots, o_i^{t_{\text{end}}}\} \quad (7)$$

By assuming the track follow te Markov assumption :

$$P(\theta_i) = P_{in}(o_i^{t_{\text{init}}}) P_{in}(o_i^{t_{\text{init}}+1} / o_i^{t_{\text{init}}}) \dots P_{out}(o_i^{t_{\text{end}}}) \quad (8)$$

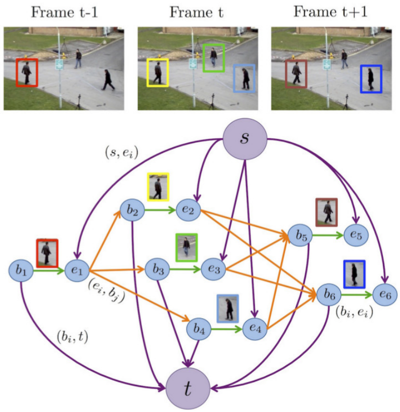
where $P_{in}(o_i^{t_{\text{init}}})$ is the probability that a trajectory i is initiated with detection $o_i^{t_{\text{init}}}$, $P_{out}(o_i^{t_{\text{end}}})$ is the probability the probability that the trajectory is terminated at $o_i^{t_{\text{end}}}$ and $P_{in}(o_i^{t_{\text{init}}+1} / o_i^{t_{\text{init}}})$ that $o_i^{t_{\text{init}}}$ is followed by $o_i^{t_{\text{init}}+1}$ in the trajector

Multiple object tracking as Maximum likelihood as a global objective function

How to solve this global objective function?

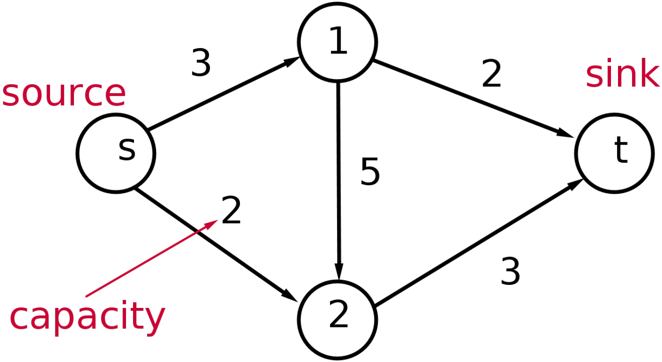
- Linear Programming
- Multiple hypotesis testing
- Max flow **[Zhang2008]**

Multiple object tracking as Max flow problem [Laura14]



Maximum flow:Introduction

The objective of the algorithm is to calculate the maximum amount of flow passing from the source to the sink.



Maximum flow: Problem Definition

- Each edge is labeled with a capacity, that represents the maximum amount of stuff that it can carry.
- The goal is to figure out how much stuff can be pushed from the source to the sink while respecting all edges' capacitie

Maximum flow: Problem Definition

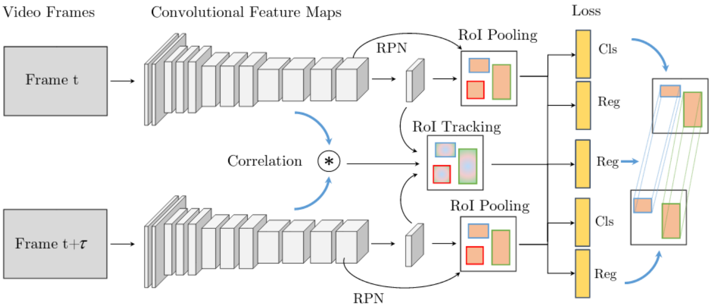
Formally:

- Let us consider a directed graph $G = (V, E)$,
- One special node is the souce $s \in V$,
- each edge $e \in E$ has a non nonnegative and integer capacity u_e,
- we want to find for each edge $e \in E$ has a non nonnegative and integer flow f_e,

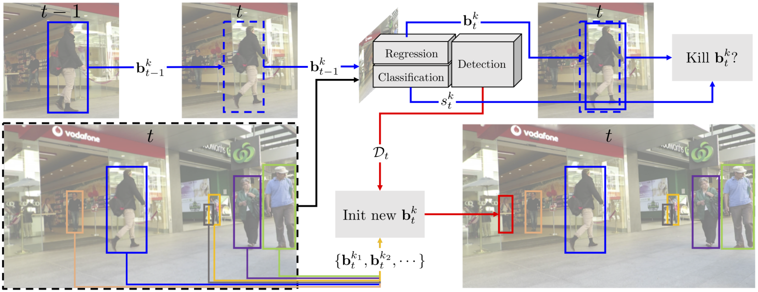
The goal is to find the flow f_e

- **Capacity constraints:** $f_e \leq ue \ \forall e \in E$
- **Conservation constraints:** for every node v expect s and k amount of flow entering v = amount of flow exiting v.

Detect to track and track to detect [Feichtenhofer2017]

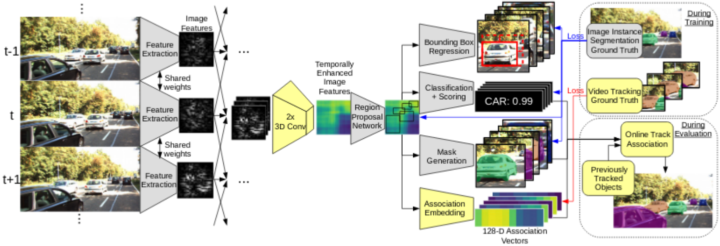


Tracking with just an object detection algorithm [Bergmann2019]

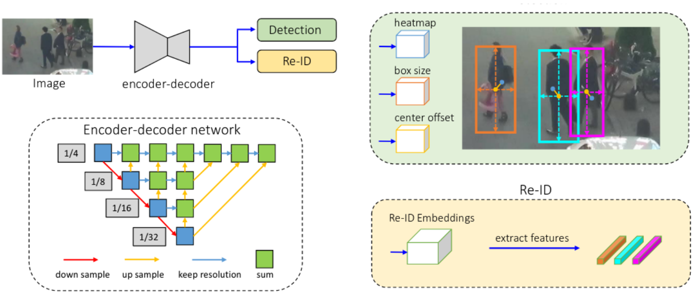


The presented Tracktor accomplishes multi-object tracking only with an object detector and consists of two primary processing steps, indicated in blue and red, for a given frame t. First, the regression of the object detector aligns already existing track bounding boxes $\mathbf{b}_{t-1}^k$ of frame $t-1$ to the object's new position at frame t. The corresponding object classification scores s_t^k of the new bounding box positions are then used to kill potentially occluded tracks. Second, the object detector (or a given set of public detections) provides a set of detections $\mathcal{D}_t$ of frame t. Finally, a new track is initialized if a detection has no substantial Intersection over Union with any bounding box of the set of active tracks $B_t = \{\mathbf{b}_t^{k1}, \mathbf{b}_t^{k2}, \cdots\}$.

Tracking with just an object detection and REID[Voigtlaender2019]



Winner of MOT challenge 2020 [Wang2020]



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