Understanding the tracker parameters

3 key tracker parameters: **max age, min hints and iou threshold**.

- **Max age** is the max number of frames to keep alive a track without associated detections. It ensures the case of occlusion. If a track is lost then we don't keep it aside, instead we try to track that object until max age.
  L249: *if(trk.time_since_update* $>$ *self.max_age)*
  L250: self.trackers.pop(i)
- **Min hits** is the minimum number of associated detections before track is initialised.
  L245: *if (trk.time_since_update* $<$ *1) and (trk.hit_streak* $\geq$ *self.min_hits or self.frame_count* $\leq$ *self.min_hits):*
- **IoU threshold** is the minimum intersection-over-union (IOU) for match. Pair with IoU $<$ threshold is set up as unmatched.
  L186: for m in matched_indices:
  L187: if(iou_matrix[m[0], m[1]]<iou_threshold):
  L188: unmatched_detections.append(m[0])
  L189: unmatched_trackers.append(m[1])

Sort class. Update function.

The **update function** in the Sort class is **the key part of the tracker**. The logic of the implementation is as this

1. Predict the object state vector using the Kalman filter
   L224-229
2. Find the matches between the object's prediction and detection state vectors using the Hungarian algorithm.
   L232
3. Update matched trackers with assigned detections.
   L235-236
4. Create and initialise new trackers for unmatched detections.
   L239-241
5. Max age and min hits creteria to remove/keep some tracked objects.
   L243-250

Kalman filter: problem statement.

We try to **estimate the state** $x \in \Re^n$ of a discrete-time process

$$\boxed{x_k = Ax_{k-1} + Bu_k + \xi_{k-1}} \tag{1}$$

with a measurement $z \in \Re^m$ that is

$$\boxed{z_k = Hx_k + \nu_k} \tag{2}$$

where ξ_k and ν_k represent the **process and measurement white noise** with normal probability distributions $p(\xi) \sim N(0, Q)$ and $p(\nu) \sim N(0, R)$ respectively.

- A $(n \times n)$ is the state transition matrix
- B $(n \times l)$ is the control input to state matrix (optional)
- $u \in \Re^l$ is the control input vector
- H $(m \times n)$ is the state to measurement matrix

We assume A, B, H, Q and R to be time-independent.

Kalman filter: problem formalization

- $\hat{x}_k^-$ *a priori* state estimate at step k given knowledge of the process prior to step k.
- $\hat{x}_k$ *a posteriori* state estimate at step k given measurement z_k.

Main objective: minimize the a posteriori error covariance

$$\boxed{P_k = E[e_k e_k^T] = E[(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T]} \tag{3}$$

Use the following **ansatz**:

$$\boxed{\hat{x}_k = \hat{x}_k^- + K(z_k - H\hat{x}_k^-)} \tag{4}$$

where K $(n \times m)$ matrix is **the Kalman gain** or blening factor to be found from minimization.