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# Multiple object tracking using Mixture Density Networks for trajectory estimation

## Motivation

Exploit trajectory information for MOT

We built TrajE, a lightweight trajectory estimator that uses mixture density networks and beam search to forecast trajectories. We also use these trajectories to reconstruct tracks during an occlusion. We incorporate TrajE into two MOT trackers, boosting their performance.

**Conclusion:** exploiting trajectory forecasting is a natural way to improve tracking.

## Results

Qualitative results



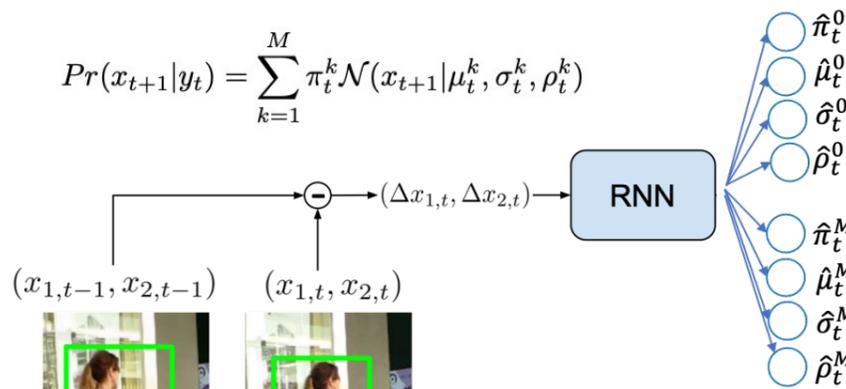
MOT17

Method	MOTA ↑	IDF1 ↑	MT % ↑	ML % ↓	FP ↓	FN ↓
CenterTrack	61.5	59.6	26.4	31.9	14076	200672
+TrajE	67.4(+5.9)	61.2(+1.6)	34.8	24.9	18652	161347
+TrajE+occ	67.8(+6.3)	61.4(+1.8)	36.0	24.5	20982	157468
Tracktor	56.3	55.1	21.1	35.3	8866	235449
+TrajE	56.3(+0.0)	57.8(+2.7)	21.4	35.8	10068	233885
+TrajE+occ	56.6(+0.3)	58.2(+3.1)	21.9	35.7	10119	231091

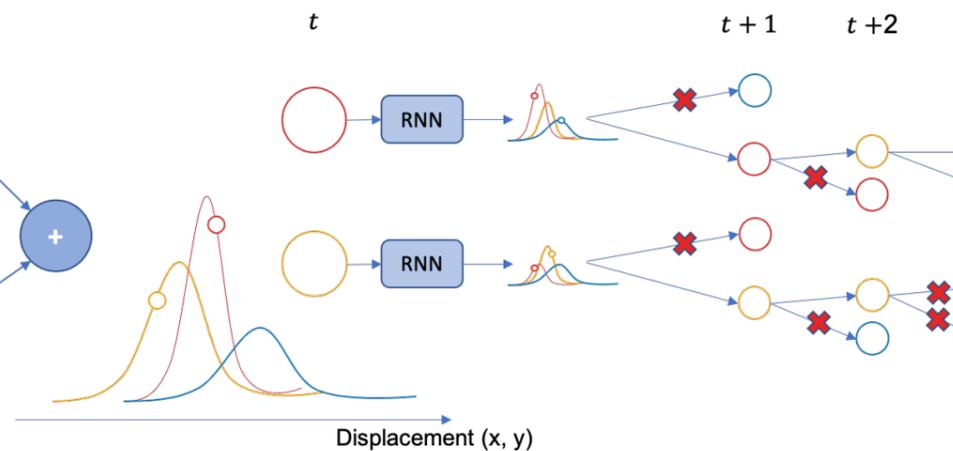
## Mixture Density Networks

Projections of the object in the next time step

$$Pr(x_{t+1}|y_t) = \sum_{k=1}^M \pi_t^k \mathcal{N}(x_{t+1}|\mu_t^k, \sigma_t^k, \rho_t^k)$$

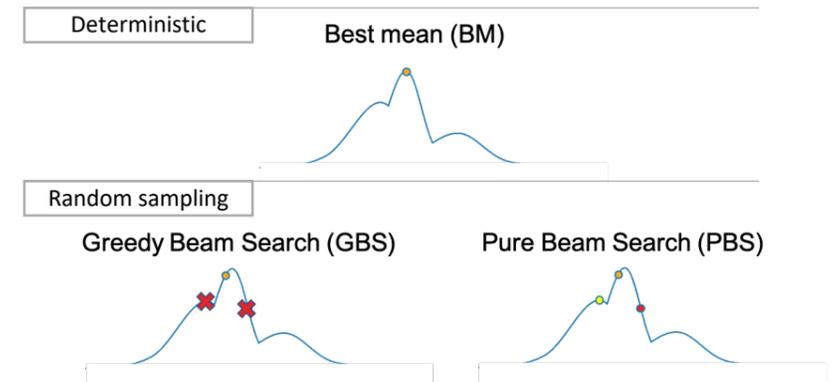


## Generate trajectory hypotheses



## Beam search

Trajectory exploration strategies



## Occlusion reconstruction

Use forecasted trajectory to reconstruct tracks



Loss function

$$\mathcal{L}(\mathbf{x}) = \sum_{t=1}^T -\log \left( \sum_k \pi_t^k \mathcal{N}(x_{t+1}|\mu_t^k, \sigma_t^k, \rho_t^k) \right)$$

Bias the GMM

$$\pi_t^k = \frac{\exp(\hat{\pi}_t^k(1+b))}{\sum_{k'=1}^M \exp(\hat{\pi}_t^{k'}(1+b))}$$

$$\sigma_t^k = \exp(\hat{\sigma}_t^k - b)$$