Deep Tracking : Seeing Beyond Seeing Using Recurrent Neural Networks

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Outline

The Bayes Model

Graphical Model

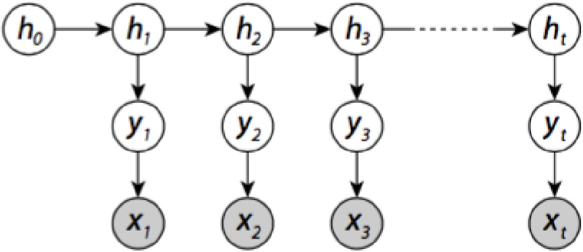

Figure 2: The assumed graphical model of the generative process. World dynamics are modelled by the hidden Markov process h_t with appearance y_t which is partially observed by sensor measurements x_t.

The Bayes Model

Joint Probability

$$P(y_{1:N}, x_{1:N}, h_{1:N}) = \prod_{t=1}^{N} P(x_t|y_t)P(y_t|h_t)P(h_t|h_{t-1}) \tag{1}$$

- $P(h_t|h_{t-1})$: the hidden state transition probability capturing the dynamics of the world;
- $P(y_t|h_t)$: modelling the instantaneous unoccluded sensor space;
- $P(x_t|y_t)$: describes the actual sensing process.

The Bayes Model

Bayes:

- notation : $Bel(h_t) = P(h_t | x_{1:t})$: denotes the corrected belief after the latest measurement has become available, Bel^- : belief prediction one time step into the future.

$$Bel^-(h_t) = \int_{h_{t-1}} P(h_t | h_{t-1}) Bel(h_{t-1}) \tag{2}$$

$$Bel(h_t) \propto \int_{y_t} P(x_t | y_t) P(y_t | h_t) Bel^-(h_t) \tag{3}$$

$$P(y_t | x_{1:t}) = \int_{h_t} P(y_t | h_t) Bel(h_t) \tag{4}$$

Filtering Using a Recurrent Neural Network

Set Belif : $\mathcal{B}_t$

$$\mathcal{B}_t = F(\mathcal{B}_{t-1}, x_t) \tag{5}$$

then :

$$P(y_t|x_{1:t}) = P(y_t|\mathcal{B}^t) \tag{6}$$

Moreover

Proving empty observations of the form $x_{(t+1):(t+n)} = \varnothing$, can alse use $\mathcal{B}_t$ to predict $P(y_{t+n}|x_{1:t})$.

Supervised mode

Loss

$$\mathcal{L} = -\sum_{t=1}^{N} \log P(y_t | x_{1:t}) \tag{7}$$

- Input : $x_{1:T}$ and $y_{1:T}$ are both known.
- Output : the parameters.
- Use BPTT

Unsupervised mode(difficult)

Aim

Learning $F(\mathcal{B}_t, x_t)$ and $P(y_t|\mathcal{B}_t)$ only using $x_{1:t}$