Mobile Robot Self-Driving Through Image Classification Using Discriminative Learning of Sum-Product Networks

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In an Ideal world...

$$\overbrace{\overbrace{\overbrace{\textbf{Mobile Robot}}^{1}\ \overbrace{\textbf{Self-Driving}}^{2}}^{3}\ \textbf{Through}\ \overbrace{\textbf{Image Classification}}^{4}}^{5}$$

$$\textbf{Using}\ \underbrace{\underbrace{\textbf{Discriminative Learning}}_{6}\ \textbf{of}\ \underbrace{\textbf{Sum-Product Networks}}_{7}}_{8}$$

...but life is short

$$\underbracket{\begin{gathered}\overbrace{\textbf{Mobile Robot Self-Driving Through Image Classification}}^{\text{Section 2}}\\ \textbf{Using Discriminative Learning of }\underbrace{\textbf{Sum-Product Networks}}_{\text{Section 1}}\end{gathered}}_{\text{Section 3: (1+2)}}$$

Sum-Product Networks

Definition

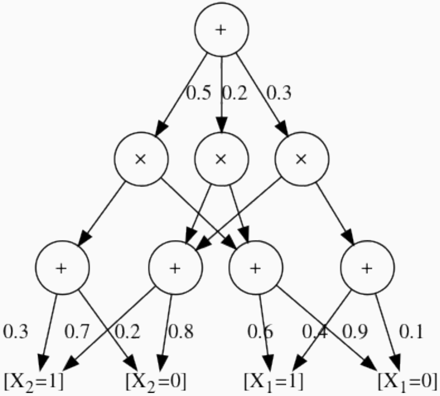
Definition 1 (Gens and Domingos 2013).

A sum-product network (SPN) is a DAG where each node can be defined recursively as follows.

1. A tractable univariate probability distribution is an SPN.
2. A product of SPNs with disjoint scopes is an SPN.
3. A weighted sum of SPNs with the same scope is an SPN, provided all weights are positive.
4. Nothing else is an SPN.

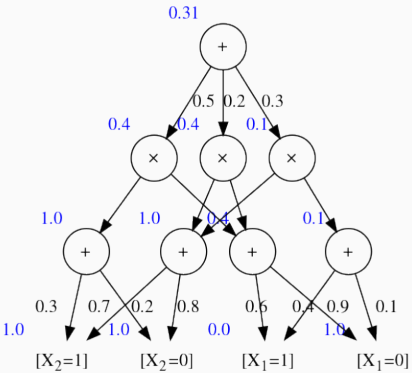
Sum-product network

The value $S(X)$ of an SPN is equal to $\phi(X)$, an unnormalized probability function, if it obeys certain properties. If all weights sum to one, $S(X) = P_\phi(X)$ (Poon and Domingos 2011).



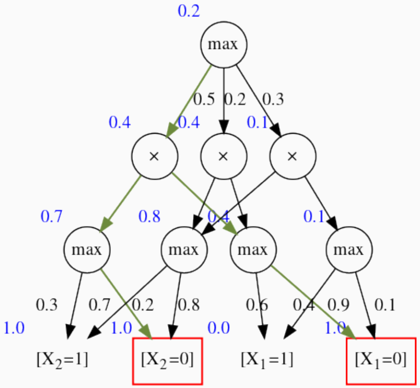
Probability of evidence

Single forward pass computes $S(X = \{X_1 = 0\}) = 0.31$. Linear on the number of edges



Maximum a posteriori probability

Replace sums with max nodes. Forward pass followed by backward pass computes most probable explanation, i.e. find $\arg\max_{x \in X} P(X, E)$.



Learning

Structure

- PD-Dense architecture (Poon and Domingos 2011)
- **Clustering on Variables** (Dennis and Ventura 2012)
- **Gens-Domingos LearnSPN** (Gens and Domingos 2013)
- Using deep learning techniques (Peharz et al. 2018)
- many others...

Weights

- **Generative and discriminative gradient descent**
- Generative Expectation-Maximization
- Extended Baum-Welch (Rashwan, Poupart, and Zhitang 2018)
- many others...

Self-Driving

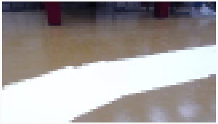
Self-driving as image classification

Let $X = \{X_0, X_1, \dots, X_{n-1}\}$ be an **image**. Every $X_i = x_i$ refers to the i-th pixel with a grayscale intensity of x_i.

Let $Y = \{\text{UP}, \text{LEFT}, \text{RIGHT}\}$ be the **classification variable**.

LEFT

UP



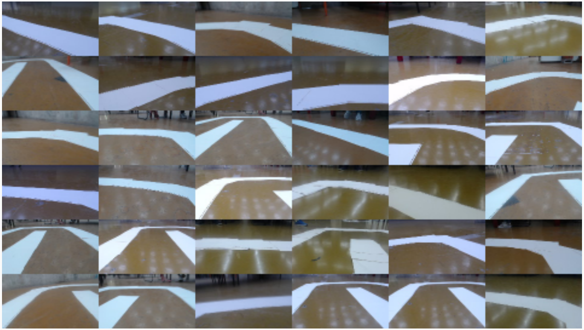
RIGHT

The entire scope of variables is $X \cup Y$.

Objective: $\arg\max_{y \in Y} P(Y = y | X)$

Dataset

Dataset used: Moraes and Salvatore 2018



Lane tracking dataset with 80×45 RGB images. Each labeled with either UP, LEFT or RIGHT.

Pre-processing

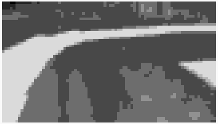
Pipeline:

original RGB image $\rightarrow$ grayscale $\rightarrow$ some T transformation.

Three transformations tested:

1. Otsu binarization (Otsu 1979)
2. Quantization (resolution downscaling)
3. Histogram equalization

1



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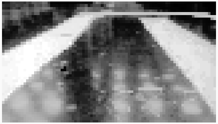

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Raspberry Pi 3 Model B — Berry

CPU: Quad Core 1.2GHz Broadcom BCM2837 64bit ARMv7

Memory: 1GB RAM

Storage: 16GB SSD

Lego Mindstorms NXT v2 — Brick

CPU: Atmel AT91SAM7S256 48MHz 32bit ARMv4

Memory: 64KB RAM

Storage: 256KB Flash

Robot

Berry handles inference, passing predicted label to **Brick**.

Brick handles motors according to label received from **Berry**.

Message passing through USB cable.

Driving with SPNs

Modelling

Every pixel X_i is a variable in the distribution represented by the SPN, i.e. no additional feature extraction, end-to-end.

Two architectures:

GD: LearnSPN (Gens and Domingos 2013)

DV: Clustering on Variables (Dennis and Ventura 2012)

Three weight setups:

g: Generative gradient descent (Poon and Domingos 2011)

d: Discriminative gradient descent (Gens and Domingos 2012)

s: Proportional weights for GD, random weights for DV

Accuracy

Accuracy (%)	DV+g	DV+d	DV+s	GD+g	GD+d	GD+s
B	78.8	78.8	78.8	82.8	83.8	85.0
Q_2	78.6	78.0	78.0	78.6	80.4	79.4
$Q_2 + E$	76.6	76.6	76.8	79.6	82.8	81.8
Q_3	77.4	77.4	77.4	77.6	80.2	79.8
$Q_3 + E$	70.4	76.6	76.6	79.2	81.2	77.4
Q_4	78.2	78.4	78.2	76.0	78.2	76.4
$Q_4 + E$	76.6	76.6	76.8	76.0	74.6	80.6
Q_5	77.8	78.4	78.4	77.6	74.0	73.8
$Q_5 + E$	76.6	76.6	76.6	72.0	72.8	72.0
Q_6	77.4	78.4	78.4	75.2	74.4	72.0
$Q_6 + E$	76.0	76.4	76.4	73.0	75.0	73.6
Q_7	78.2	78.4	78.4	62.8	72.2	71.4
$Q_7 + E$	76.2	76.4	76.4	70.6	71.4	71.6
$\emptyset$	78.0	78.4	78.4	62.4	62.4	62.4
E	76.4	76.4	76.4	60.4	60.0	61.2

Inference time

Inference (secs)	DV+g	DV+d	DV+s	GD+g	GD+d	GD+s
B	0.23	0.25	0.25	0.38	0.37	0.31
Q_2	0.22	0.24	0.23	0.28	0.34	0.16
$Q_2 + E$	0.22	0.23	0.23	0.38	0.30	0.27
Q_3	0.22	0.23	0.22	0.22	0.32	0.17
$Q_3 + E$	0.22	0.23	0.22	0.34	0.32	0.31
Q_4	0.22	0.22	0.23	0.16	0.17	0.13
$Q_4 + E$	0.23	0.27	0.29	0.13	0.14	0.13
Q_5	0.22	0.26	0.28	0.07	0.05	0.02
$Q_5 + E$	0.22	0.29	0.25	0.05	0.05	0.02
Q_6	0.23	0.24	0.23	0.04	0.05	0.01
$Q_6 + E$	0.22	0.24	0.28	0.03	0.04	0.02
Q_7	0.23	0.23	0.26	0.03	0.01	0.01
$Q_7 + E$	0.22	0.26	0.24	0.01	0.01	0.01
$\emptyset$	0.22	0.26	0.23	0.02	0.01	0.01
E	0.23	0.23	0.22	0.01	0.01	0.02

“Real world” scenario

Mobile Robot Self-Driving Through Image Classification Using Discriminative Learning of Sum-Product Networks — YouTube

Thank you.

Questions?

References i

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