End-To-End Imitation Learning of Lane Following Policies Using Sum-Product Networks

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Sum-product networks

Sum-product networks (SPNs) are deep tractable density estimators with a neural network-like structure subject to only sums and products as activation functions.

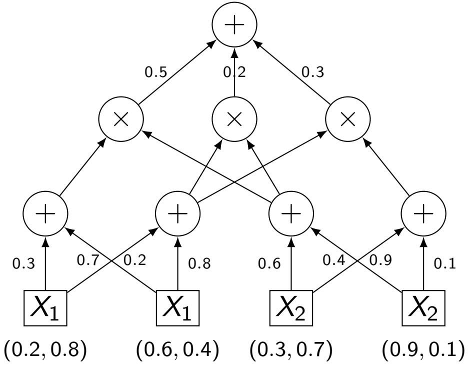
Definition 1 (Sum-product network).

A sum-product network (SPN) is a DAG where each node n is either:

1. A tractable univariate probability distribution;
2. A product of SPNs: $v_n = \prod_{j \in \mathrm{Ch}(n)} v_j$; or
3. A weighted sum of SPNs: $v_n = \sum_{j \in \mathrm{Ch}(n)} w_{n,j} v_j$.

Where v_n is the value of node n, $\mathrm{Ch}(n)$ its set of children and $w_{n,j}$ the weight of edge $n \to j$.

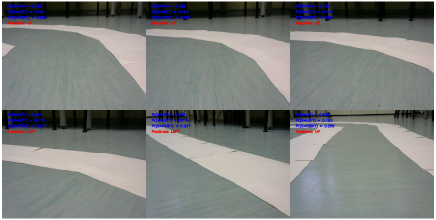
Example



Where each leaves are binomial distributions over each RV X_i.

The task

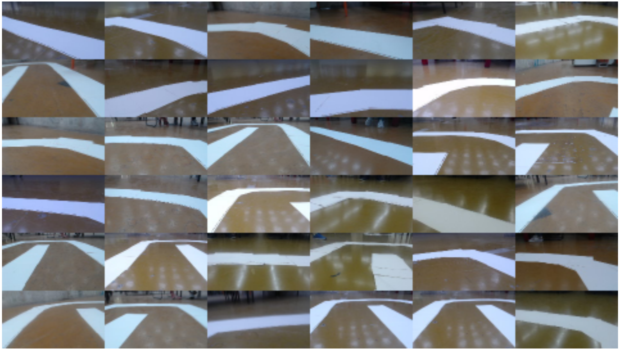
Given a track, bot must autonomously complete the whole course without going off road by making use of a single frontal camera.



Inspired by Moraes and Salvatore 2018, which was itself inspired by Bojarski et al. 2016.

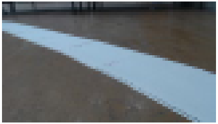
Dataset

Dataset used: Moraes and Salvatore 2018

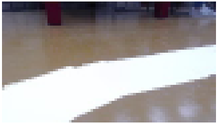


Lane tracking dataset with 80×45 RGB images. Each labeled with either UP, LEFT or RIGHT.

Self-driving as image classification


LEFT


UP


RIGHT

Training track in Moraes and Salvatore 2018.

Berry

Raspberry Pi 3 Model B — Berry

CPU: Quad Core 1.2GHz Broadcom BCM2837 64bit ARMv7

Memory: 1GB RAM

Storage: 16GB SSD

Brick

Lego Mindstorms NXT v2 — Brick

CPU: Atmel AT91SAM7S256 48MHz 32bit ARMv4

Memory: 64KB RAM

Storage: 256KB Flash

Robot

Message passing through USB cable.

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 with k-means and G-test
- DV: Clustering on Variables

Three weight setups:

- g: Generative gradient descent
- d: Discriminative gradient descent
- 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

B: binarization, Q_n: n-bit quantization, E: histogram equalization.

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

B: binarization, Q_n: n-bit quantization, E: histogram equalization.

Chosen models

Model 1: Q_4, **GD+d**

Accuracy: 78.2%
Desktop time: 170ms
Berry time: 700ms

Model 2: Q_6, **GD+d**

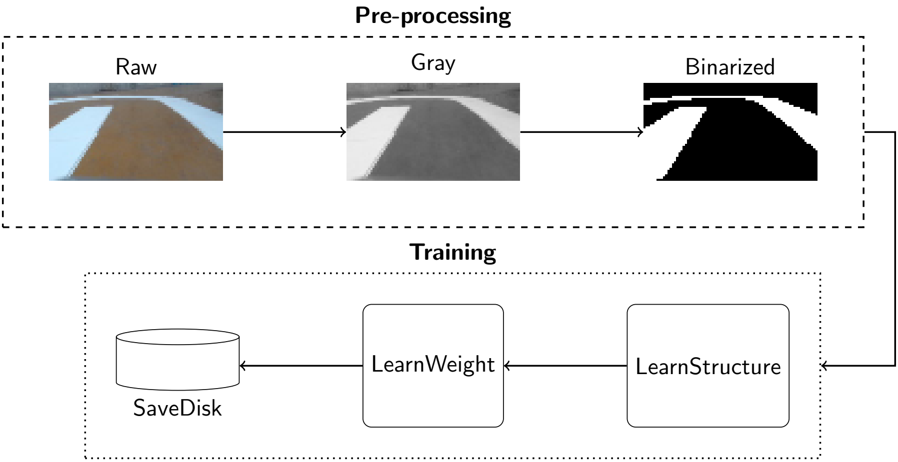
Accuracy: 74.4%
Desktop time: 50ms
Berry time: 150ms

Model 3: $\emptyset$, **GD+d**

Accuracy: 62.4%
Desktop time: $<$ 10ms
Berry time: 75ms

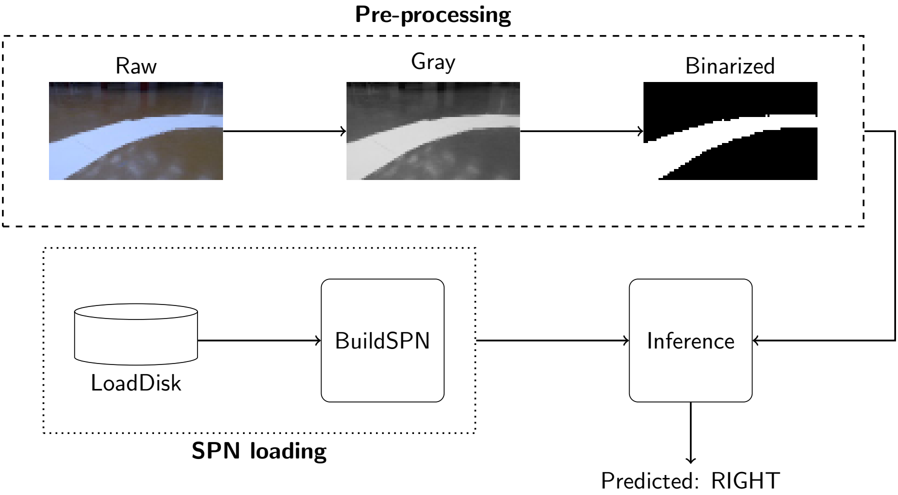
Training

Training was done on an Intel i7-4500U CPU 1.80 Hz.



Saved SPN was then passed to the Raspberry.

Prediction


Pre-processing
Raw
Gray
Binarized
LoadDisk
BuildSPN
SPN loading
Inference
Predicted: RIGHT

Comparison to neural networks

Comparison to Moraes and Salvatore 2018:

Model	**Accuracy (%)**	**Speed (seconds)**
DFN	81.3	$\approx$1.35
CNN	80.6	$\approx$1.35
Q_4, GD-SPN+d	78.2	$\approx$0.70
Q_6, GD-SPN+d	74.4	$\approx$0.15
GD-SPN+d	62.4	$\approx$0.07

Neural networks were slightly more accurate, but real-time prediction with them is unfeasible.

Our implementation did not make use of the GPU, which could increase speed dramatically.

"Real world" scenario

Mobile Robot Self-Driving Through Image Classification Using Discriminative Learning of Sum-Product Networks — YouTube (`https://youtu.be/vhpWQDX2cQU`)

Implementation

Inference and learning: GoSPN
(`https://github.com/RenatoGeh/gospn`)

Mobile robot implementation: GoDrive
(`https://github.com/RenatoGeh/godrive`)

Thank you.

Questions?

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