

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

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ENIAC 2019

The task

Given a track, bot must autonomously complete the whole course without going off road. The only available input is a single frontal camera.



Decision making must be done in real-time under a resource constrained, low-budget robot environment.

Robot

Raspberry Pi 3 Model B

CPU: Quad Core 1.2GHz
Broadcom BCM2837 64bit
ARMv7

Memory: 1GB RAM

Storage: 16GB SSD

Lego Mindstorms NXT

CPU: Atmel AT91SAM7S256
48MHz 32bit ARMv4

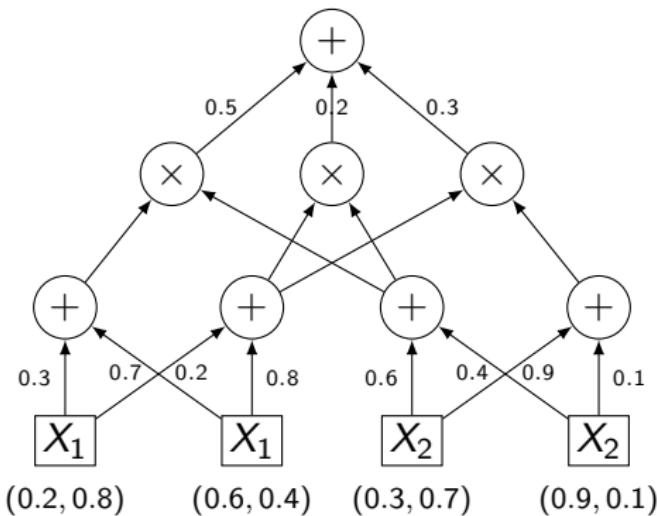
Memory: 64KB RAM

Storage: 256KB Flash



Sum-product networks

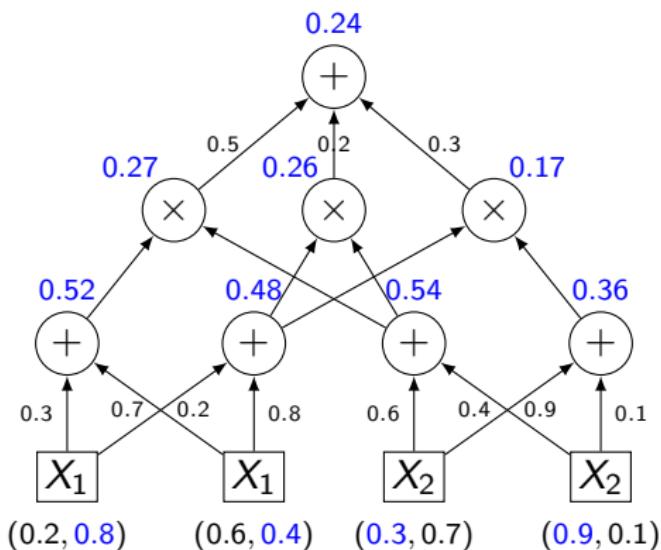
Sum-product networks (SPNs) are deep tractable density estimators with a neural network-like structure subject to only sums and products as activation functions.



In the above example, leaves are binomial distributions over each RV X_i .

Computing probability of evidence

For some evidence $\mathbf{e} = \{X_1 = 1, X_2 = 0\}$, $P(\mathbf{e})$ is the value of the SPN at its root.



$$P(\mathbf{e} = \{X_1 = 1, X_2 = 0\}) = 0.24$$

Why SPNs?

- Probabilistic semantics (efficiently compute probability of input and detect outliers);
- Easy to build and debug (efficient algorithms for learning structure from data; probabilistic semantics);
- No need for heavy packages (e.g. Tensorflow);
- Good performance with much smaller models;
- Not been tried “in the wild” yet.

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

Experiments

Training

- Trained models with samples from a single simple track;
- 500 training samples (corresponding to 0.9% of the dataset);
- Training took from 30 mins to 9 hours (time dependent on parameters, pre-processing and learning algorithms) on an Intel i7-4500U 1.8GHz CPU.

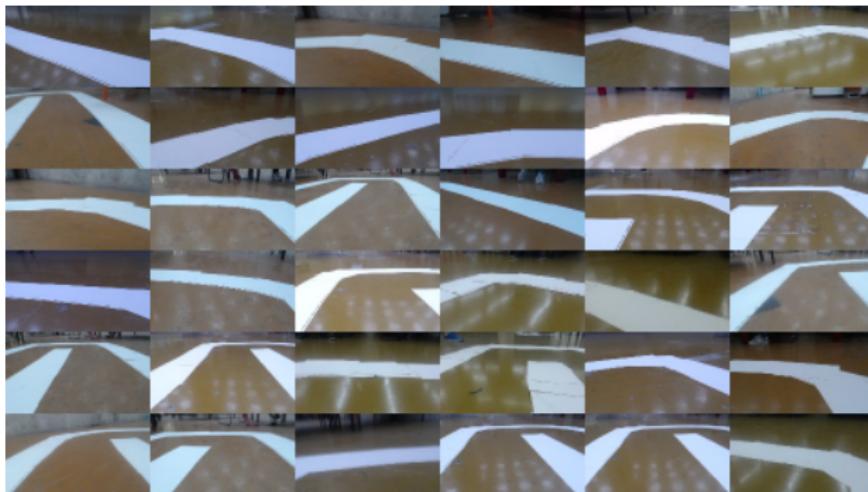
Evaluation

- Tests run on three different tracks;
- Different floor and lighting conditions from training dataset.



Dataset

Dataset used: Moraes and Salvatore 2018



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

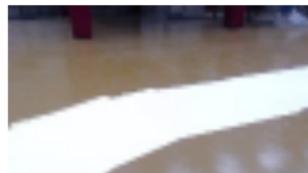
Self-driving as image classification



LEFT



UP



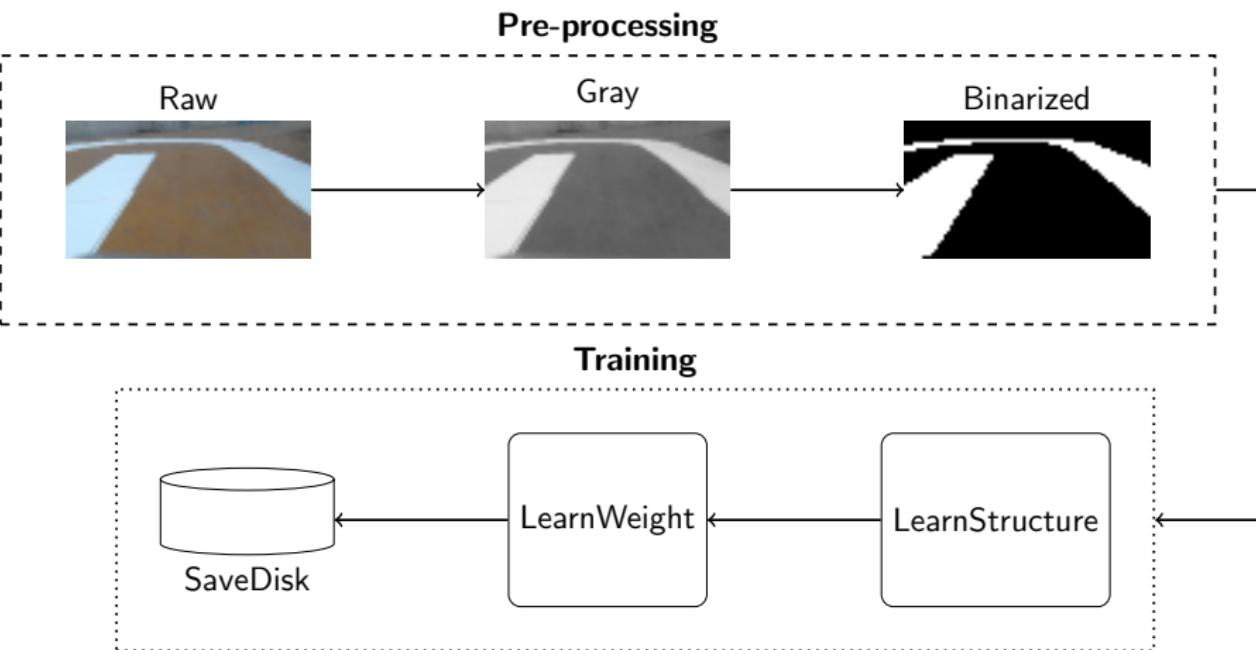
RIGHT



Training track in Moraes and Salvatore 2018.

Training

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



Saved SPN was then passed to the Raspberry.

Prediction

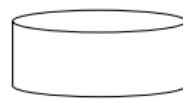
Pre-processing



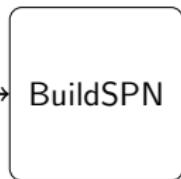
Gray



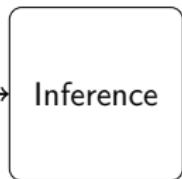
Binarized



LoadDisk



BuildSPN



Inference

Predicted: RIGHT

SPN loading

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

Comparison to neural networks

Comparison to Moraes and Salvatore 2018:

Model	Accuracy (%)	Speed (seconds)
DFN	81.3	≈ 1.35
CNN	80.6	≈ 1.35
Q_4 , GD-SPN+d	78.2	≈ 0.70
Q_6 , GD-SPN+d	74.4	≈ 0.15
GD-SPN+d	62.4	≈ 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-time decision making poses new challenges: timely decisions are often more important than accurate decisions.

“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?

Sum-product networks

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: $v_n = \prod_{j \in \text{Ch}(n)} v_j$; or
- ③ A weighted sum of SPNs: $v_n = \sum_{j \in \text{Ch}(n)} w_{n,j} v_j$.

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

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.

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