MicroBayes

https://persyval-lab.org/en/sites/content/microbayes

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Agenda

• Context
• Project Description
• First results
• Future work
Motivation

• Need for low power computing
• The actual technology reaches some limits
• Need to better understand computation
Energy consumption

~ 200 kW
~ 3.9 m³

1 Stereo Camera
+
2 lidars

~ 20 W
~ 1.3 L

~ 1 kW
~ 0.5 m³
Moore's Law limits
The rebooting computing endeavour

- Quantum computing
- Neuromorphic computing
  - IBM True North
  - HBP SpiNNaker
  - Machine dedicated to Deep Neural Nets, Conv Nets
    - Google Convnet
    - Facebook Big Basin
    - CEA-leti N2 D2
    - Nvidia....
  - Reservoir computing
Specialized hardware for Bayesian inference

- Vigoda (MIT) -> Lyrics – analog device
  - Analog computing
- Jonas – Masingka (MIT)
  - Probabilistic programming
  - Sampling machines with fixed point arithmetic's
- Blanche (University of Arizona)
  - Bayesian inference with optical hardware
- Takhir (Sydney University), Friedman (IEF)
  - Magnetic Tunnel Junction
• Design of a first generation of stochastic machines dedicated to Bayesian Inference
MicroBayes

• Goal: Design and implementation of stochastic Machines for Low-level Sensor Interpretation with Bayesian inference.

• Started in November 2016
• 1 Phd: Raphael Frisch (Persyval)
• 1 Post-doc for 6 months (Bambi)
• 1 Post-doc for 2 years (Persyval)
Scientific Days, June 13th & 14th, 2017

Project team

- Laurent Girin
- Didier Piau
- Laurent Fesquet
- Emmanuel Mazer
- Raphael Frisch

- Mathematical Proofs
- Applications
- Programming
- Architecture Hardware
PhD thesis

• Use of dedicated machines for Bayesian inference

• Explore new approaches of sampling strategies

• Applications
  – Sound source localization
  – Sound source separation

• Started 11/2016
• Currently writing a paper for ICRC 2017
• Summer 2017: attending a summer school on Probabilistic Programming in Washington DC
Bayesian machines

- **BM1: Parallel sampling**
  - Very fast machine
  - Search space < $2^{12}$

- **BM2: Sequential sampling**
  - Untractable problems > $2^{100}$
Sampling Machines

- Representing probability distributions
  - With parameters: \( \text{Normal}(\mu, \sigma) \)
  - With \( N \) samples
    \[
P(x_i, y_i) \approx \frac{\sum_{k=1}^{N} \delta(x_k, y_k = x_i, y_j)}{N}
    \]
  - Stochastic bus: Parallel sampling
  - With constraints
    - Maximum entropy distribution:
Sound source localization

- Use of parallel sampling
  - Bayesian Machine with FPU preprocessing
Principle with source localization

6.4m

Communauté
UNIVERSITÉ Grenoble Alpes
Sound source localization: evidences

- **Sensors**: pair of microphones
- **Assuming the free field model**
- **Evidence**: InterChannel Phase Difference (ICPD)

\[
R(k) = \frac{Y_2(k, l)}{Y_1(k, l)} \sim \frac{A_2(k) \cdot S(k, l)}{A_1(k) \cdot S(k, l)} = \frac{A_2(k)}{A_1(k)}
\]

\[
ICPD(k) = \arg(R(k))
= \arg(A_2(k)) - \arg(A_2(k))
= \Delta \Phi(k)
= \Phi_2(k) - \Phi_1(k)
\]
Stochastic bit streams

- **Probability encoding**
  
  Bit stream: 1010011001110100

  Probability: 0.5

- **Probability multiplication**

  
  \[ p_1 \cdot p_2 = 0.5 \cdot 0.25 = 0.125 \]
Principle of a parallel sampling machine

Priors on $x_i, y_j$

Posterior

$P(x_i, y_i) \propto \prod_l P(k_l | x_i, y_j)$

$b_{i,i-1}$

$b_{i,j}$

$P(k | x_i, y_j)$
Sound source localization (3)

• Workflow

  Simulation of sound waves → Feature extraction → Calculation of probability distributions → Simulation of BM1

• BM1 – Sliced with fast simulator

• Tackling the temporal dilution
  – Re-sampling of the probability distribution after a small subset of sensors
Sound source localization (4) (simulation)

- Results after run(100000)
Future work – Source localization

• Move to FPGA
• Remove the time-frequency domain analysis
  – Use of the Fourier transform
  – Currently done on a normal CPU
• Compression of probability distributions
• Localize a moving source using a filter
Sound source separation

- Use of sequential sampling
- Design of new algorithms for stochastic inference based on generating sets
- Planned during the second year

Problem: Recover all \(a_{ji}(t), s_j(t)\) given only the \(x_i(t)\)
Future work – Source separation

• Explore new ways of sampling
  – MCMC
  – Generating sets
Industrial perspective

- Discussion with ProbaYes to launch an ambitious R&D program on stochastic Machines (3 Years -> 6M€)
Conclusion

• MicroBayes on track

The future Bayesian valley