



New Generation Robots

Beyond Moore's Law and Rebooting Computing with Probabilistic Machines

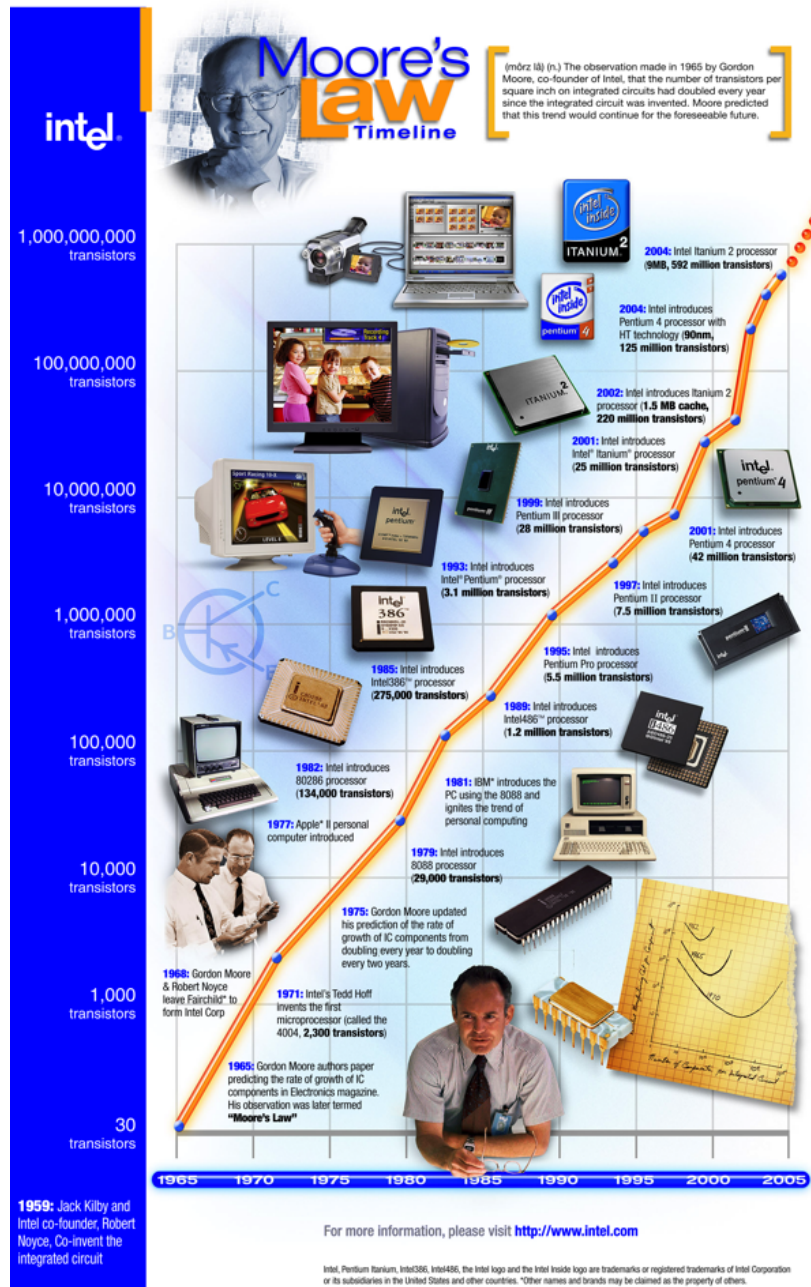


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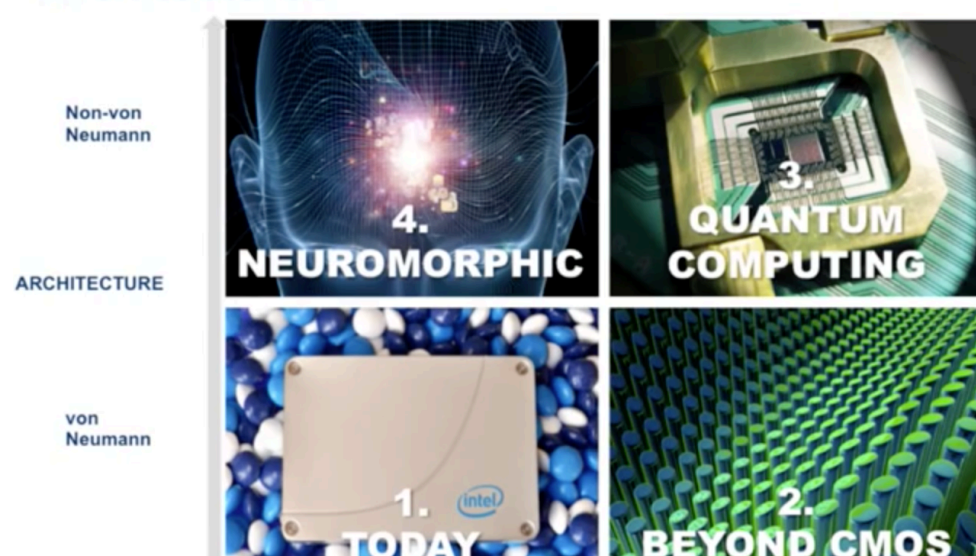


Moore's Law

- number of transistors doubles every two years
- Fantastic exponential growth
- Enabled the boom in digital electronics and computing
- The dark side:
 - Power wall
 - Costs
 - Hardware limits
- *Its slowing down !*
- *Any good news?*

Beyond Moore...

- A lot of different ideas thought up over the years have been put on a shelf because we could always rely on getting smaller and faster transistors.
- Now it's time to go back through the library of things that we've thought of.
 - Computing models and architectures
 - Materials
 - Etc
- *What about robots?*



Robots?

Institute of Systems and Robotics University of Coimbra

- *The Institute Systems and Robotics, has activities in the areas of:*
 - *robotics vision,*
 - *autonomous systems,*
 - *multi-sensor fusion and integration,*
 - *tele-operation,*
 - *sensor development,*
 - *soft-control and motors and drives.*



Robots?

ARTIFICIAL PERCEPTION TEAM

FOR INTELLIGENT SYSTEMS AND ROBOTICS

Multisensory
Perception

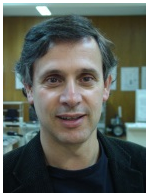
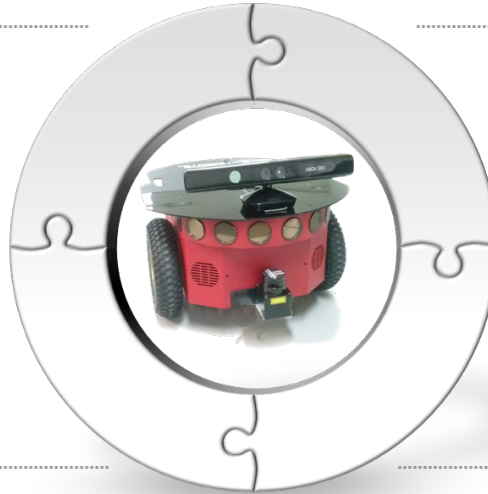
Cooperative
Behaviour

Fundamentals

Applications

Computation and
Models

Human-Machine
Interaction



Jorge Miranda Dias (jorge@isr.uc.pt), Dr. Habil., Ph.D.
Local PI.

Computer Vision; Multi-Sensor Fusion; Bayesian Perception; Autonomous Robotic Systems.



Jorge Lobo (jlobo@isr.uc.pt), Ph.D.
Senior researcher (PI deputy).

Visuoinertial Sensor Fusion; Bayesian Perception; Reconfigurable Hardware; Autonomous Robotic Systems.



João Filipe Ferreira (jfilipe@isr.uc.pt), Ph.D.
Senior researcher.

Bioinspired Perception; Human-Robot Interaction; Probabilistic Modelling; Autonomous Systems.

Robots?

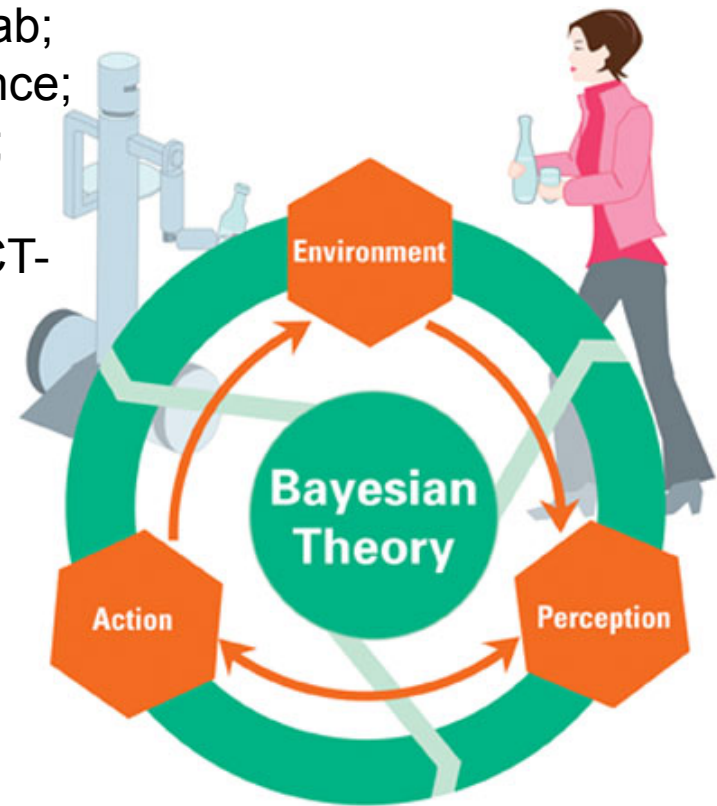
BACS - Bayesian Approach to Cognitive Systems

- **BACS - EU FP6-IST-027140**

- Coordenator: Roland Siegwart, ETH Zurich.
- Partners: ETH Zurich Autonomous Systems Lab; INRIA, e-Motion; CNRS-LPPA-Collège de France; CNRS-LSCP-Institut des Sciences Cognitives; CNRS-Grenoble; MPS, Inst. for Biological Cybernetics; HUG, Neurology Department; FCT-UC, DEEC; BlueBotics; Probayes SAS; EDF, R&D; Aeroscout; EPFL.
- <http://www.bacs.ethz.ch/>
- Jan. 2006 - Feb. 2010



BAYESIAN APPROACH TO COGNITIVE SYSTEMS

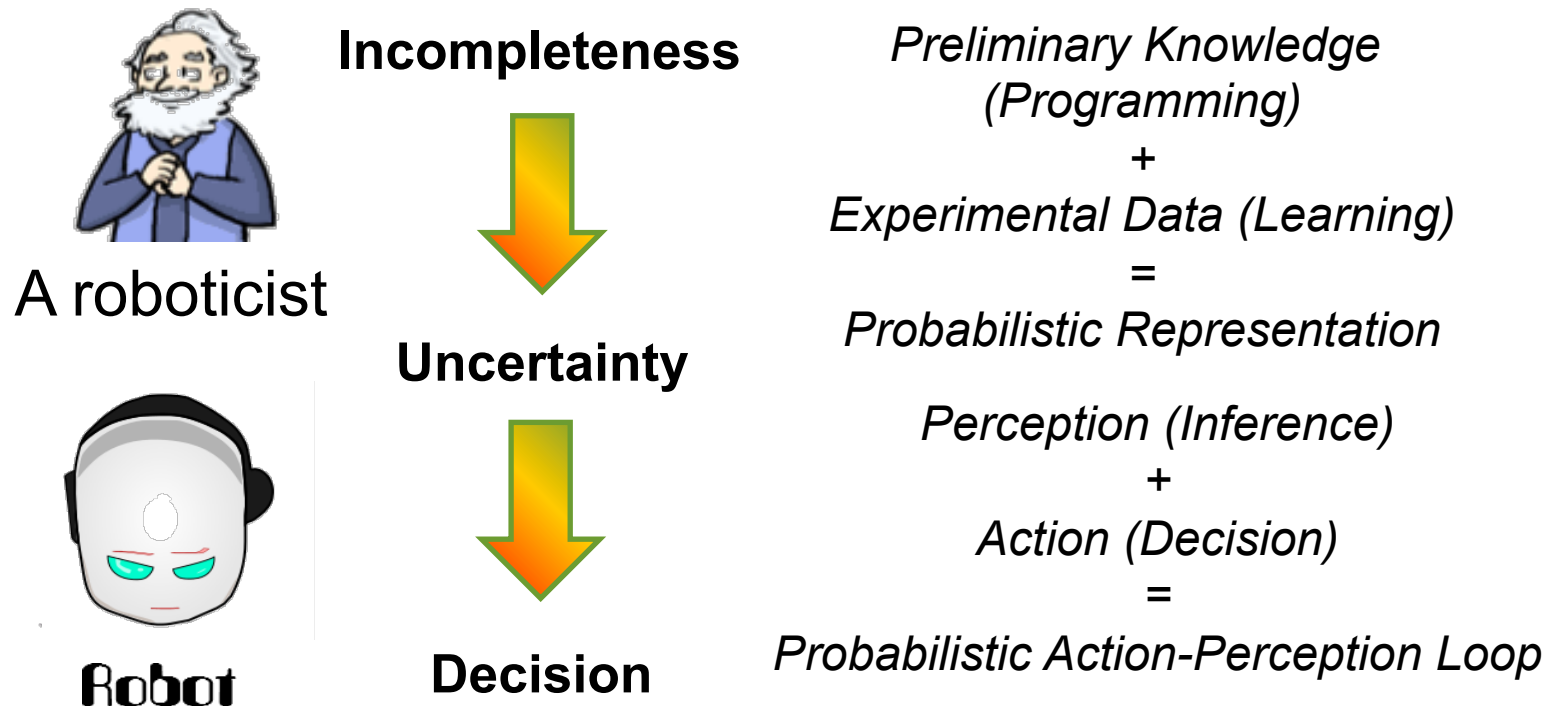


Robots?



- Bayesian modeling:

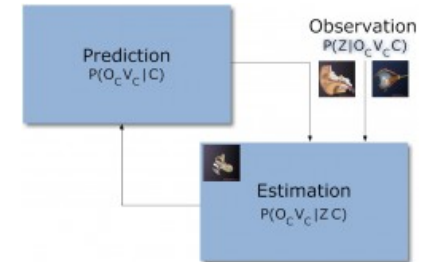
helping robot to deal with uncertainty and incompleteness



Robots?

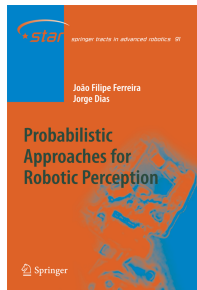
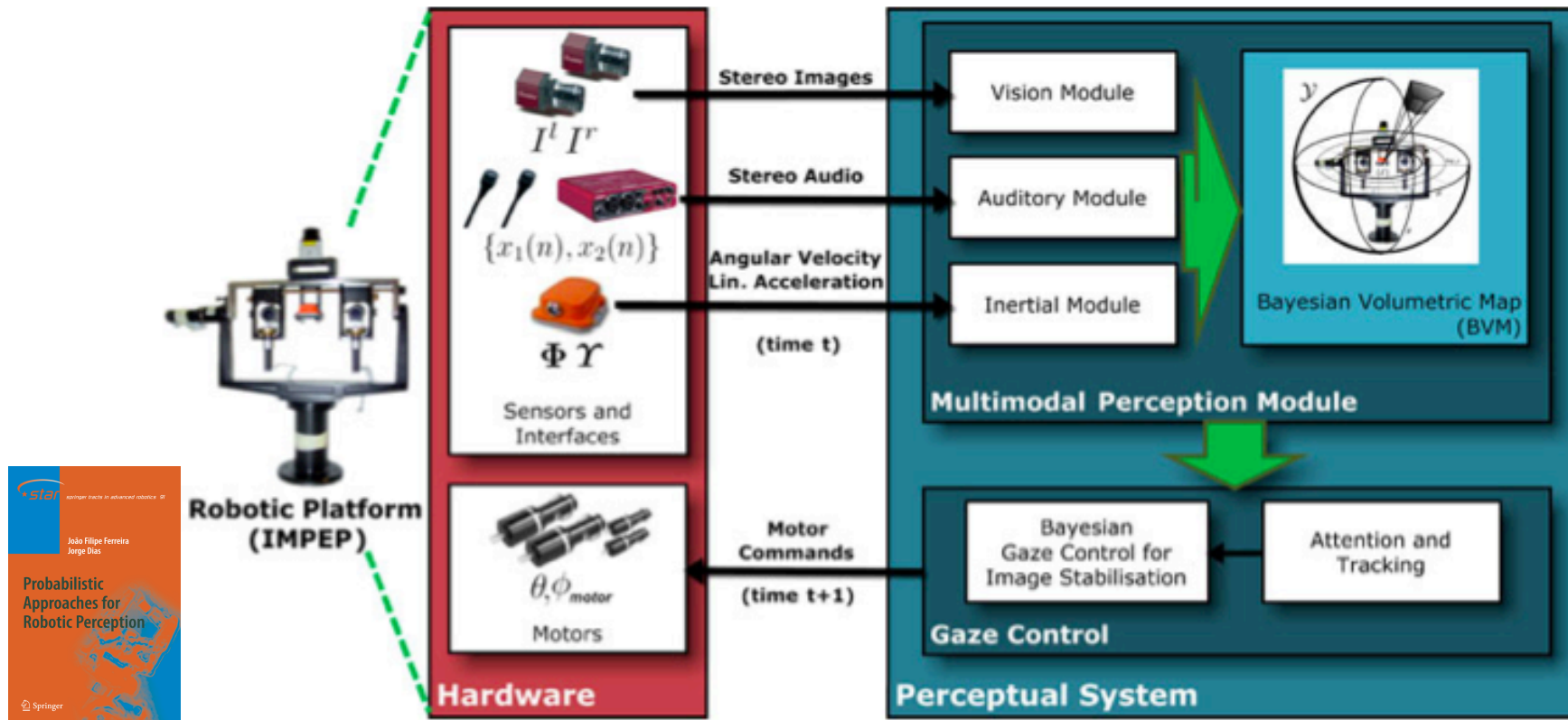
From Bioinspired to Biomimetic The Bayesian Approach

BACS



Robots?

AP4ISR Bayesian Know-How

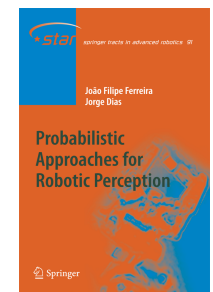
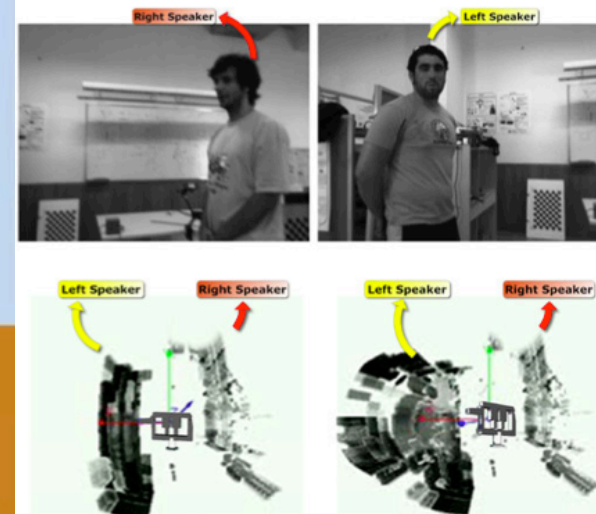
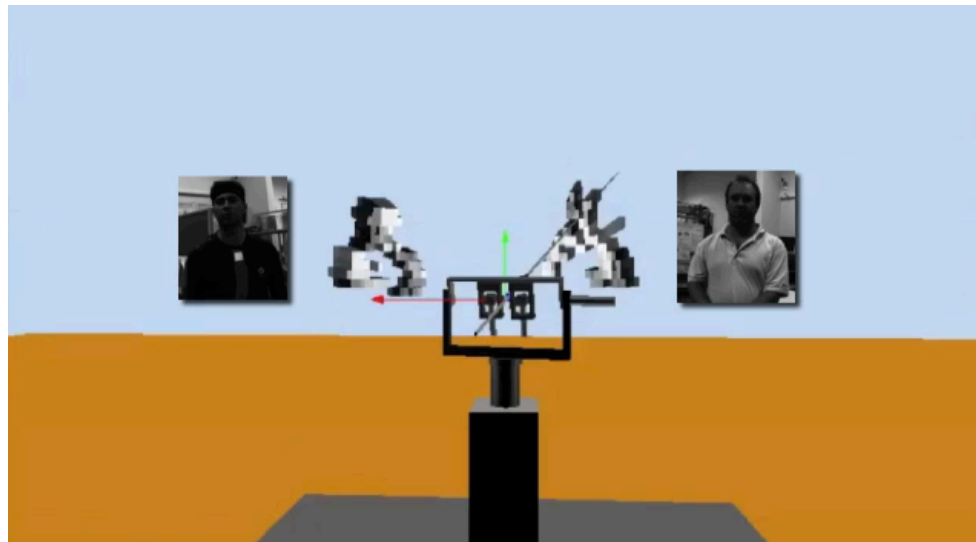
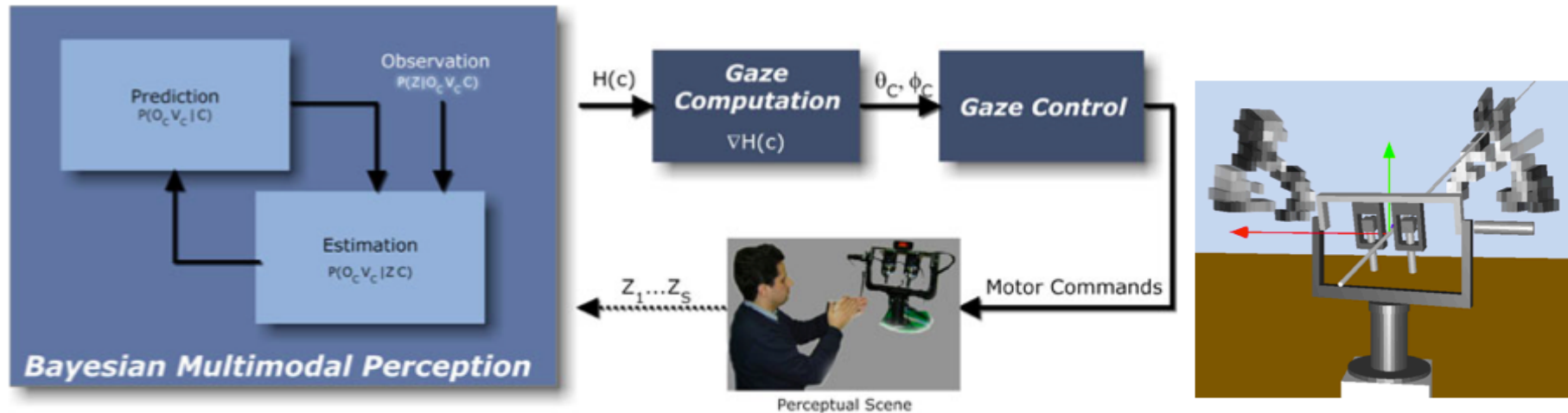


Bayesian real-time perception algorithms on GPU
Real-time implementation of Bayesian models for multimodal perception using CUDA

João Filipe Ferreira, Jorge Lobo and Jorge Dias

Robots?

AP4ISR Bayesian Know-How



Robots need computation power...

- Need to perceive the environment, infer, decide and act efficiently enough to survive
- To deal with uncertainty in the data and incompleteness of the models, computations are done with probability distributions, overloading current architectures



- Look at nature and biology
- Revisit correctness contract between hardware and software



IROS UCBI and IJAR special issue

IEEE/RSJ International Conference on
Intelligent Robots and Systems

iROS
Hamburg 2015

IROS 2015 workshop on
Unconventional computing for
Bayesian inference



Main Menu

- ▢ Welcome
- ▢ Abstract
- ▢ Organisers
- ▢ List of speakers
- ▢ Schedule
- ▢ Submissions
- ▢ Important dates

Workshop on Unconventional computing for Bayesian inference

:: Followup and News

November 2015: the call for contributions for the **International Journal of Approximate Reasoning (IJAR) special issue on Unconventional computing for Bayesian inference** is now open, accepting submissions until May 1, 2016. [UCBI special issue of IJAR](#).

October 2015:

The workshop was a success, we had a packed room and nice interchange of ideas throughout the day.



BAMBI

Bottom-up Approaches to Machines dedicated to Bayesian Inference

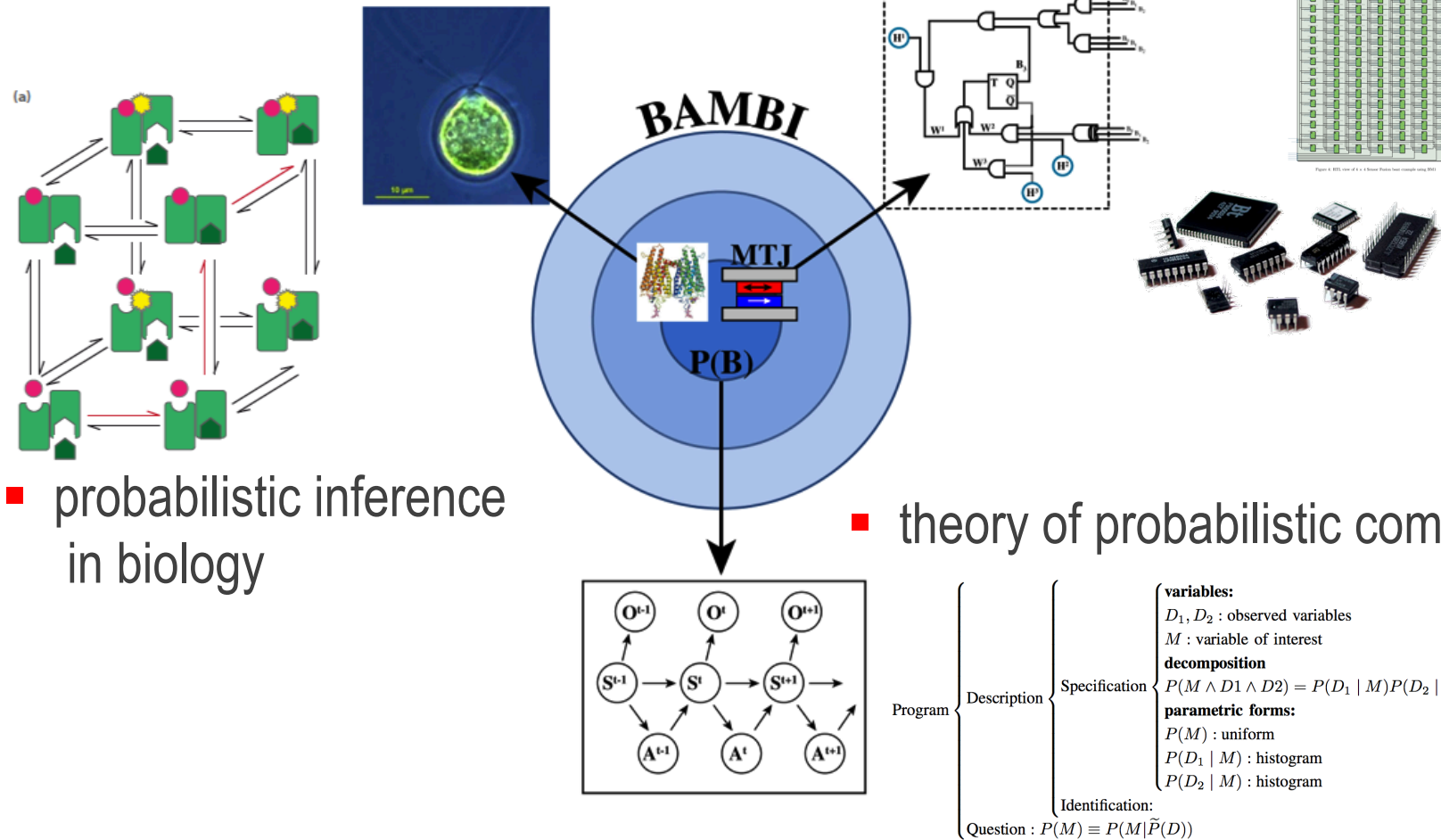
- We propose a theory and a hardware implementation of probabilistic computation inspired by biochemical cell signaling.
- Following a global vision of a future probabilistic computer we will advance toward this long term goal following three axes: **algebra, biology, and hardware.**
- EU collaborative FET Project,
www.bambi-fet.eu
FP7-ICT-2013-C, project number 618024



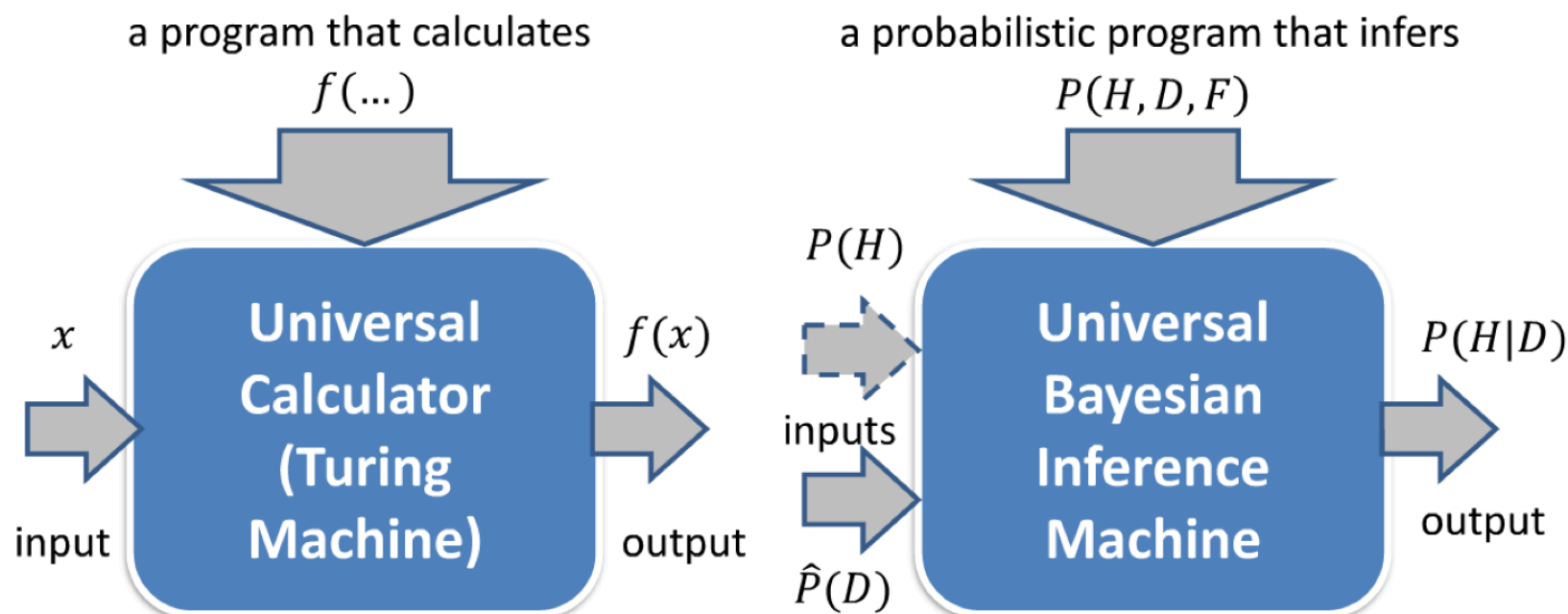
BAMBI project



■ hardware implementation

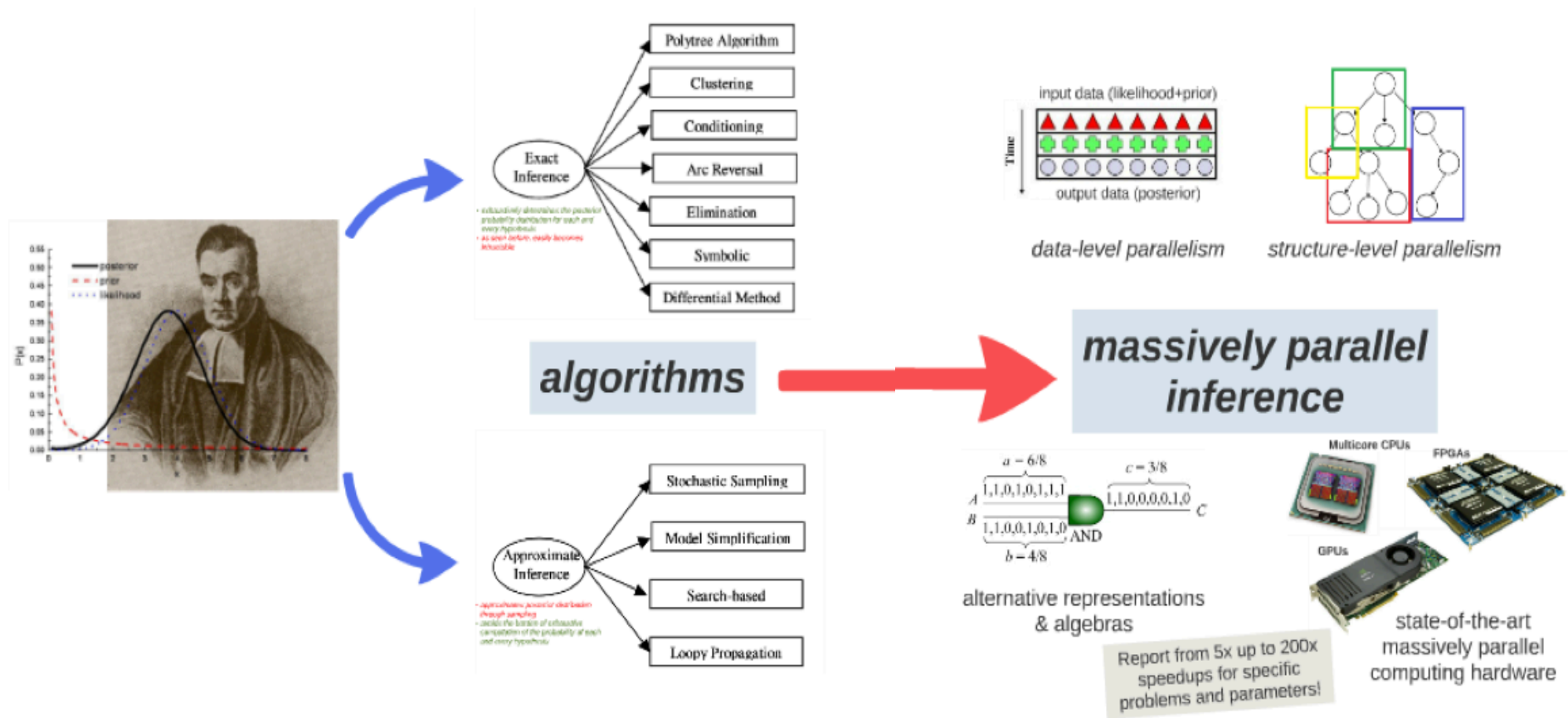


where to now?



Beyond von Neumann architectures, towards a "Bayesian computer"?

Implementing Bayesian Computing



- Algorithms >> Modelling Languages >> hardware

ISR-UC in BAMBI



Reconfigurable logic will play a key role within the project on the **emulation hardware implementation** and also on testing on hardware the **computational architecture** to be developed, namely in the composition of **basic building blocks for probabilistic computation**.



variables:
 i : indexes a cell on the BVM;
 A_C : identifier of the antecedents of cell i (stored as with C);
 $Z_S \in \{\text{"No Detection"}\} \cup \mathbb{R}$: independent measurements taken by S sensors;
 o_C^{-1} : binary values describing the occupancy of cell C ,
 t : instant and preceding instants, respectively;
 v_C : velocity of cell C ,
 v_C is divided into $N + 1$ possible cases $\in V_C = \{v_0, \dots, v_N\}$.

Equation:

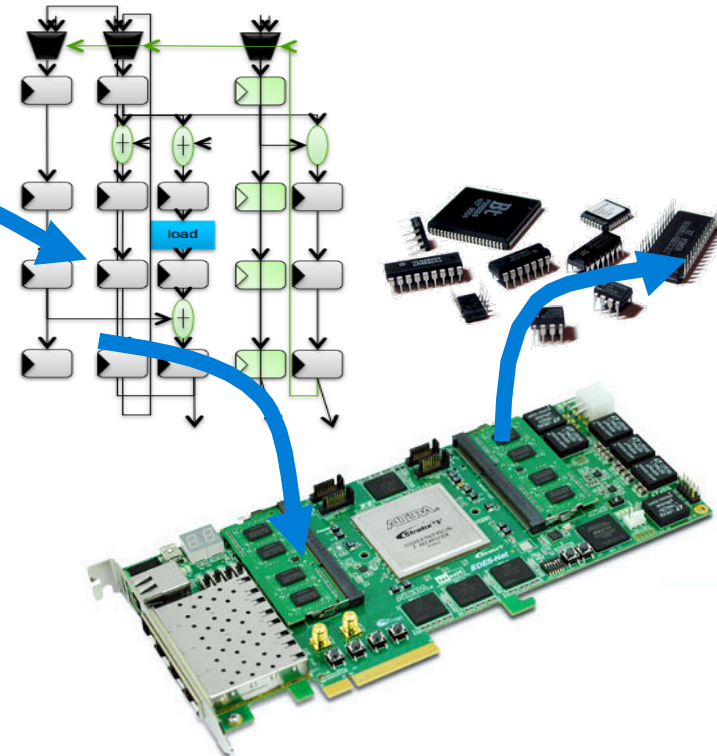
$$P(O_C A_C O_C^{-1} V_C Z_1 \dots Z_S) =$$

$$P(A_C) P(V_C | A_C) P(C | V_C A_C) P(O_C^{-1} | A_C) P(O_C | O_C^{-1}) \prod_{i=1}^S P(Z_i | V_C O_C C)$$

Parametric forms:
 $P(A_C)$: uniform;
 $P(V_C | A_C)$: histogram;
 $P(C | V_C A_C)$: Dirac, 1 iff $c_{10g_b} \rho = a_{10g_b} \rho + v_{10g_b} \rho \delta t$, $c_\theta = a_\theta + v_\theta \delta t$ and $c_\phi = a_\phi + v_\phi \delta t$
 (constant velocity assumption);
 $P(O_C^{-1} | A_C)$: probability of preceding state of occupancy given set of antecedents;
 $P(O_C | O_C^{-1})$: defined through transition matrix $T = \begin{bmatrix} 1-\epsilon & \epsilon \\ \epsilon & 1-\epsilon \end{bmatrix}$,
 where ϵ represents the probability of non-constant velocity;
 $P(Z_i | V_C O_C C)$: direct measurement model for each sensor i , given by respective sub-BP.

Identification:
 None.

Questions:
 $P(O_C V_C | z_1 \dots z_S c) \rightarrow \begin{cases} P(O_C | z_1 \dots z_S c) \\ P(V_C | z_1 \dots z_S c) \end{cases}$



Revisiting Stochastic Computing

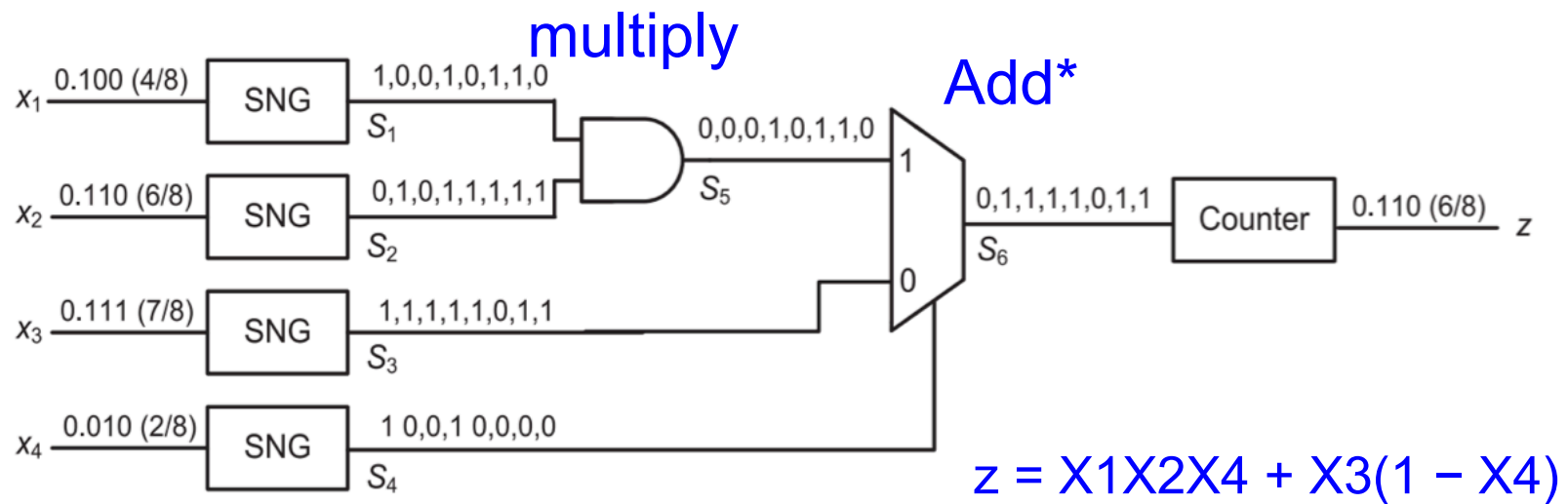
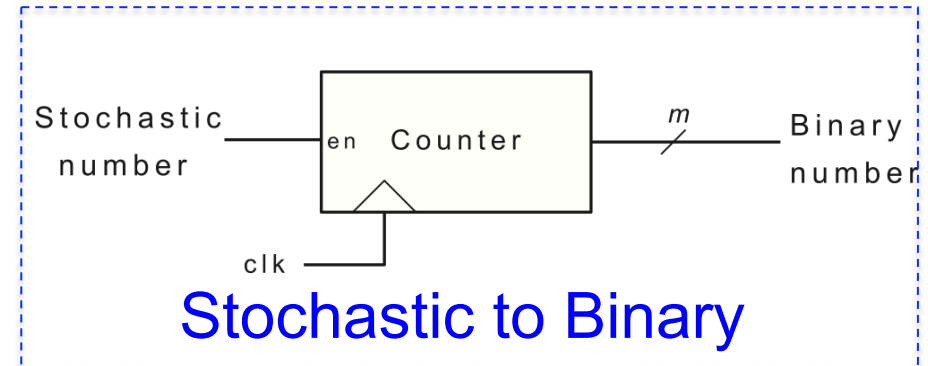
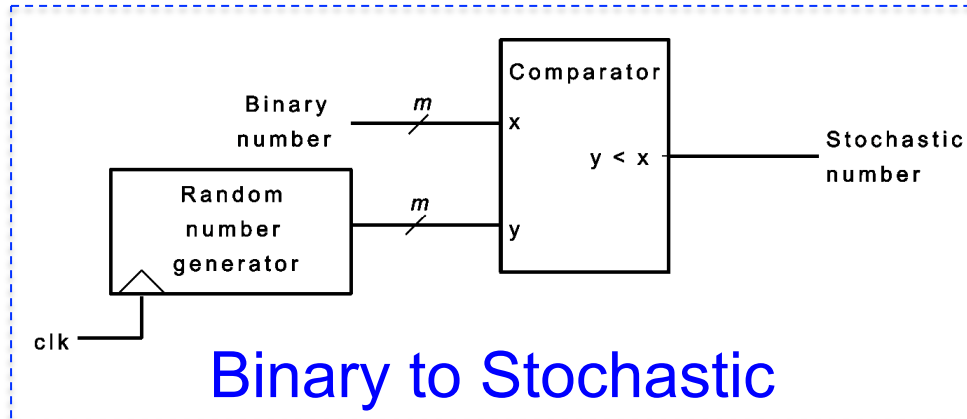


- Stochastic computing was developed to perform precise computations with unreliable hardware
- We want to do approximate computations with little hardware:

Revisiting stochastic computing methods for parallel probabilistic computations with limited resources

- main limitations:
 - linear increase in precision requires exponential increase in bit-stream,
 - sensitivity to temporal correlations
 - limited dynamic range of the representation.

Revisiting Stochastic Computing



Specifying a Bayesian Machine: BM1

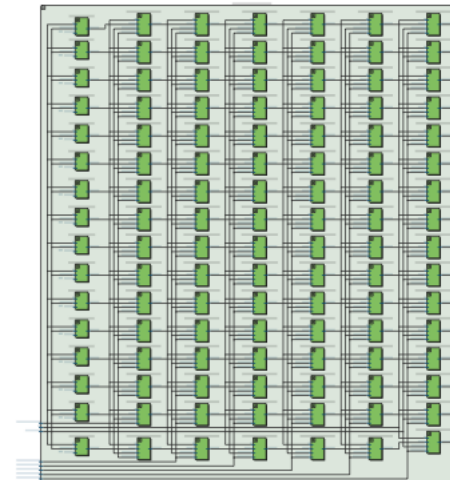
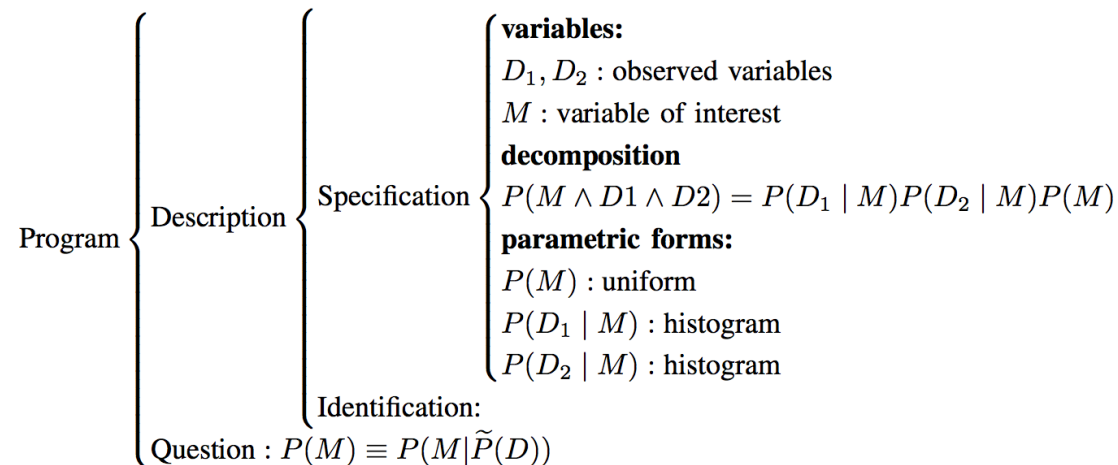
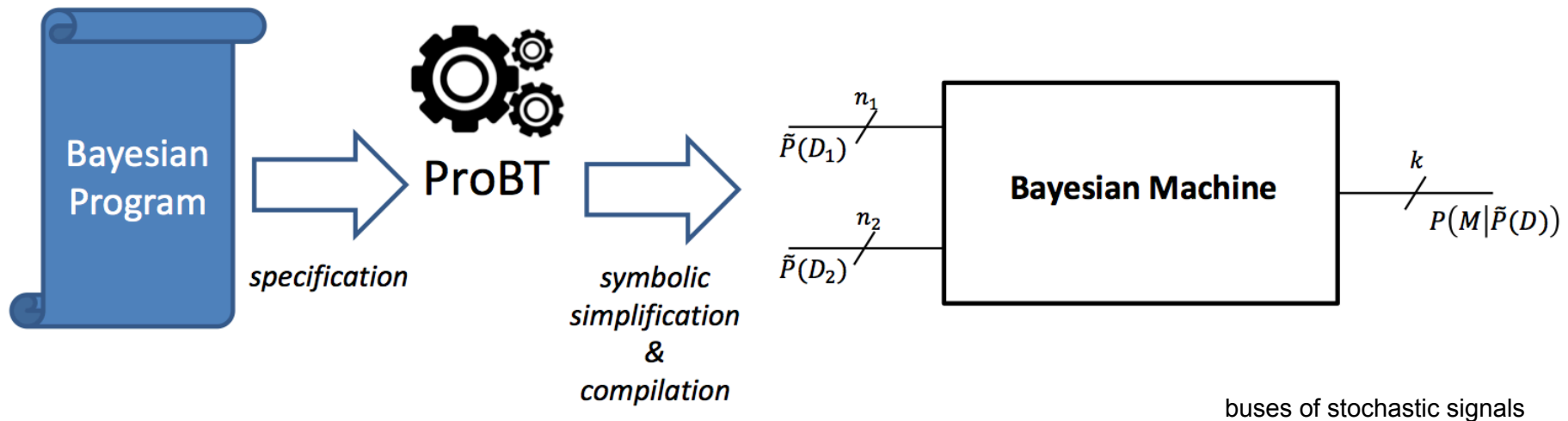


Figure 4: RTL view of 4 x 4 Sensor Fusion board example using BM1



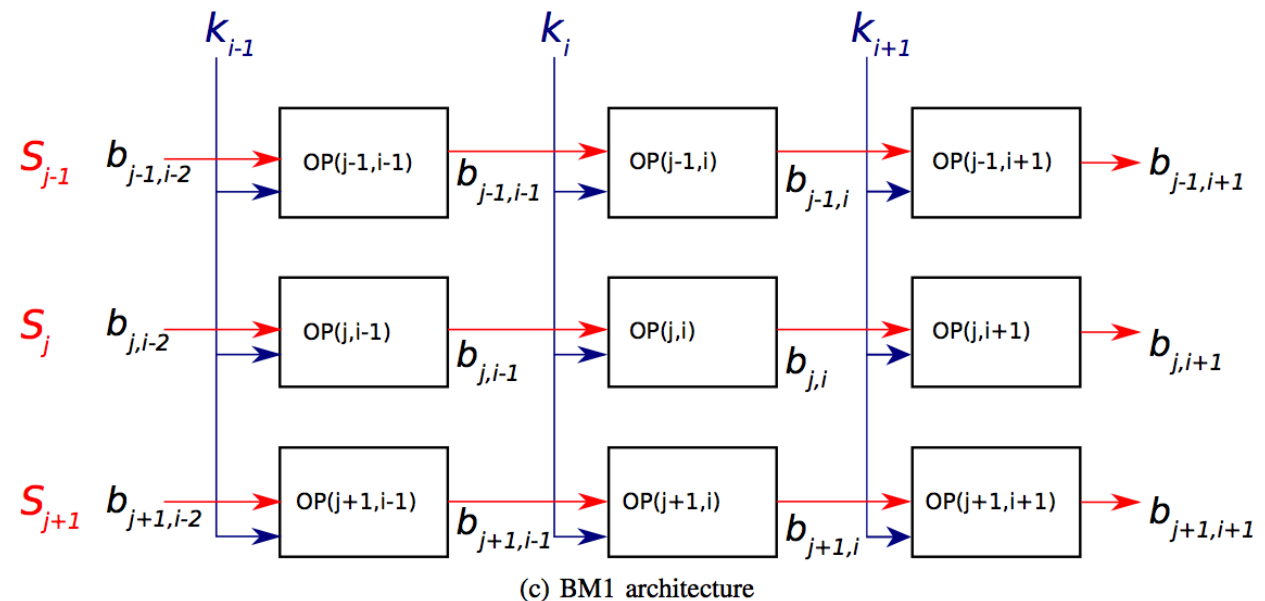
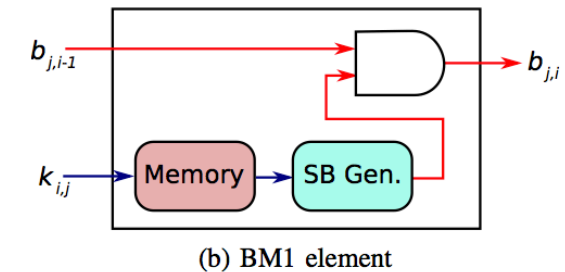
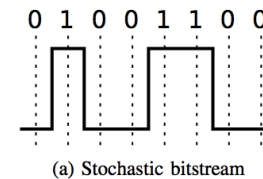
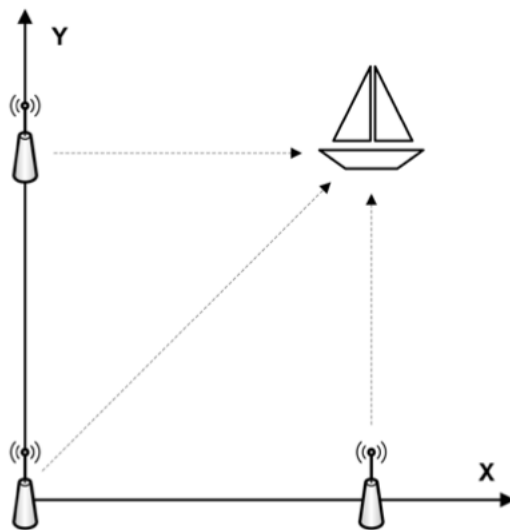
BM1: Bayesian Sensor Fusion with Fast and Low Power Stochastic Circuits



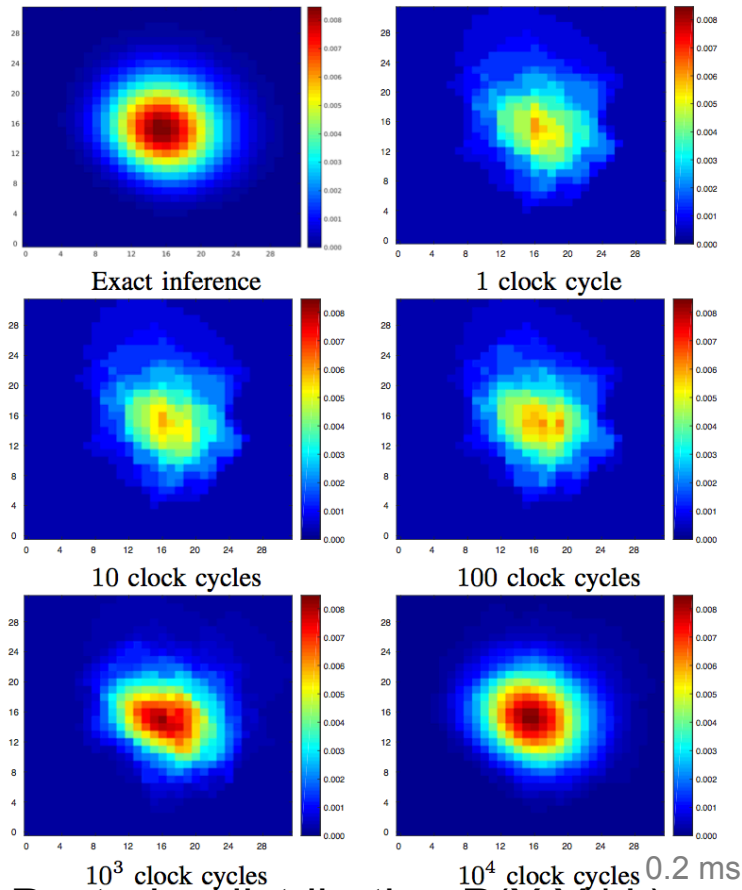
- Exact inference with approximate computations

$$P([S = s_j] | k_1, \dots, k_n) = \frac{1}{Z} P([S = s_j]) \prod_{i=1}^N P(k_i | [S = s_j])$$

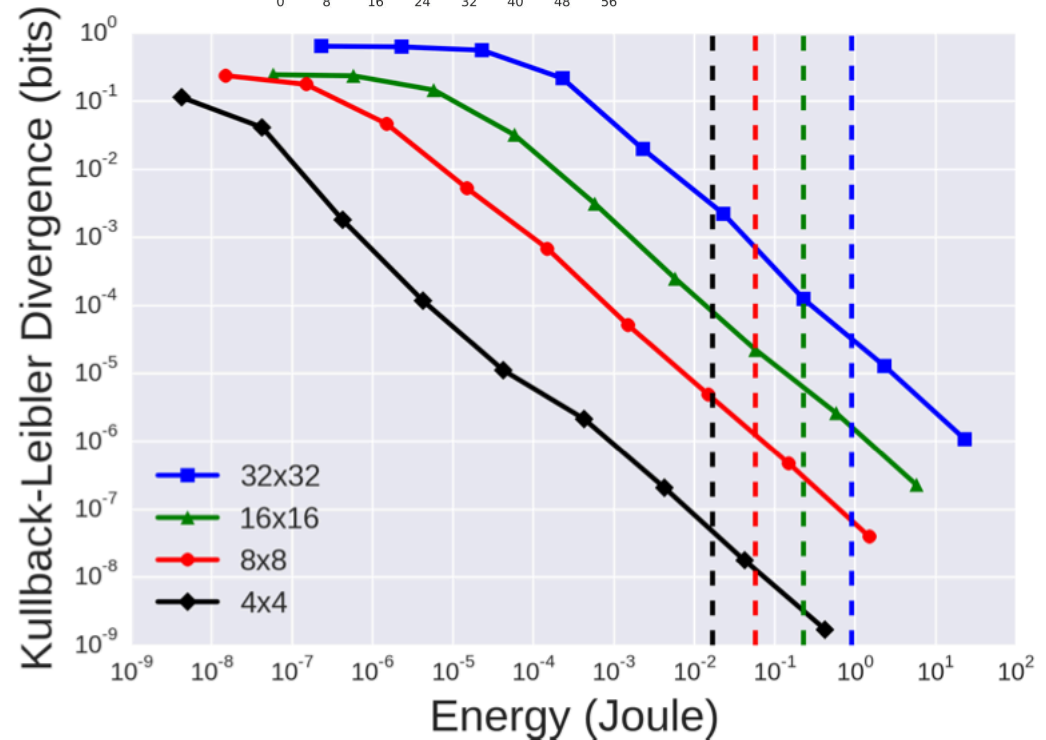
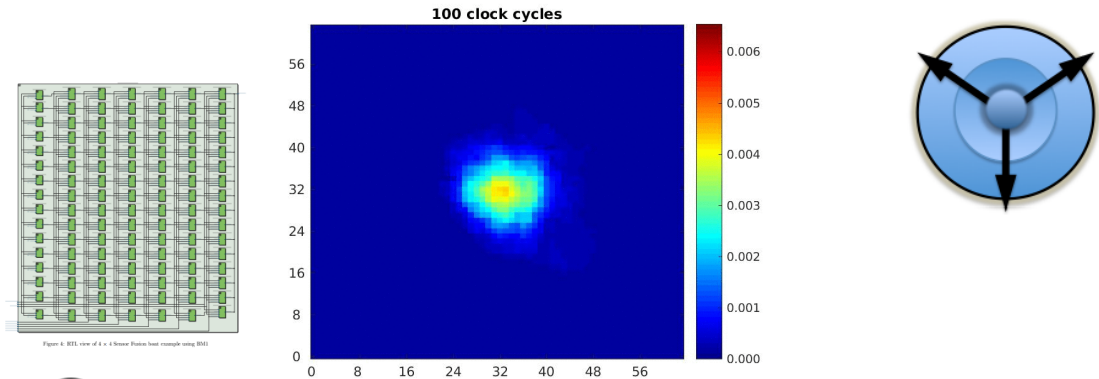
Infer boat coordinates of the boat on grid given distance and bearing sensor readings to three landmarks.



BM1: Bayesian Sensor Fusion



Posterior distribution $P(X, Y | k)$
with bitstream lengths of 1, 10,
100, 1000, 10000.

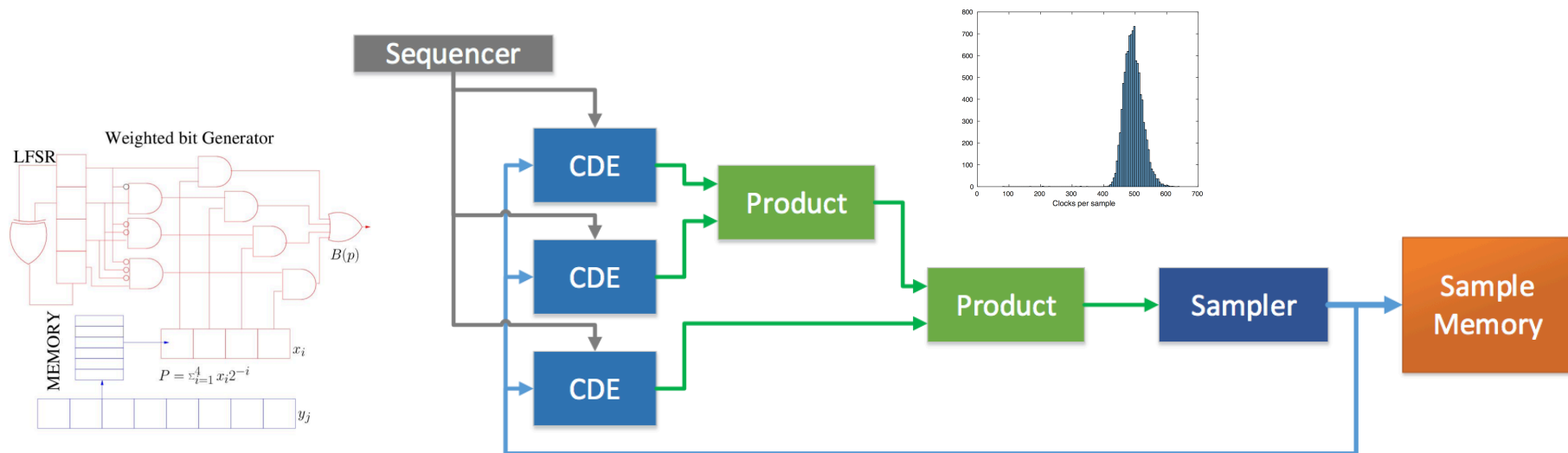


KL divergence for increasing energy use
Vertical lines indicate typical laptop performance

BM2 Approximate Inference



- Gibbs sampling: Computations are performed using stochastic elements and a Gibbs sampler to compute approximate Bayesian inference



- Gibbs sampling approach adapted to operate at the bit level
- Stochastic signals are sampled

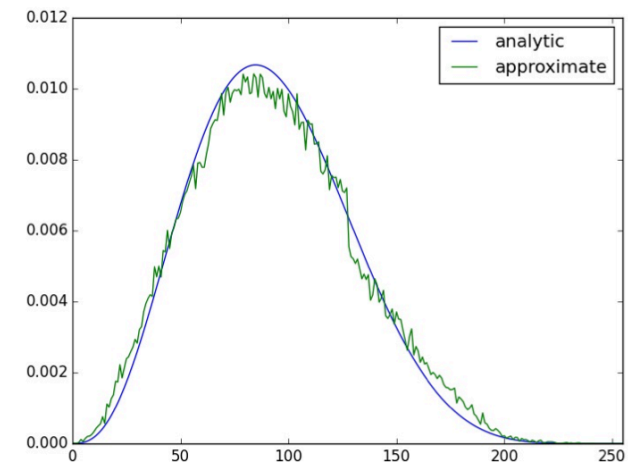
An intractable problem

- To BM2 on intractable inference problems
- inference problem with circular dependences between its variables (as happens in some image processing applications)
- chose the parametric forms so that we could compute an analytic solution to be used as reference.

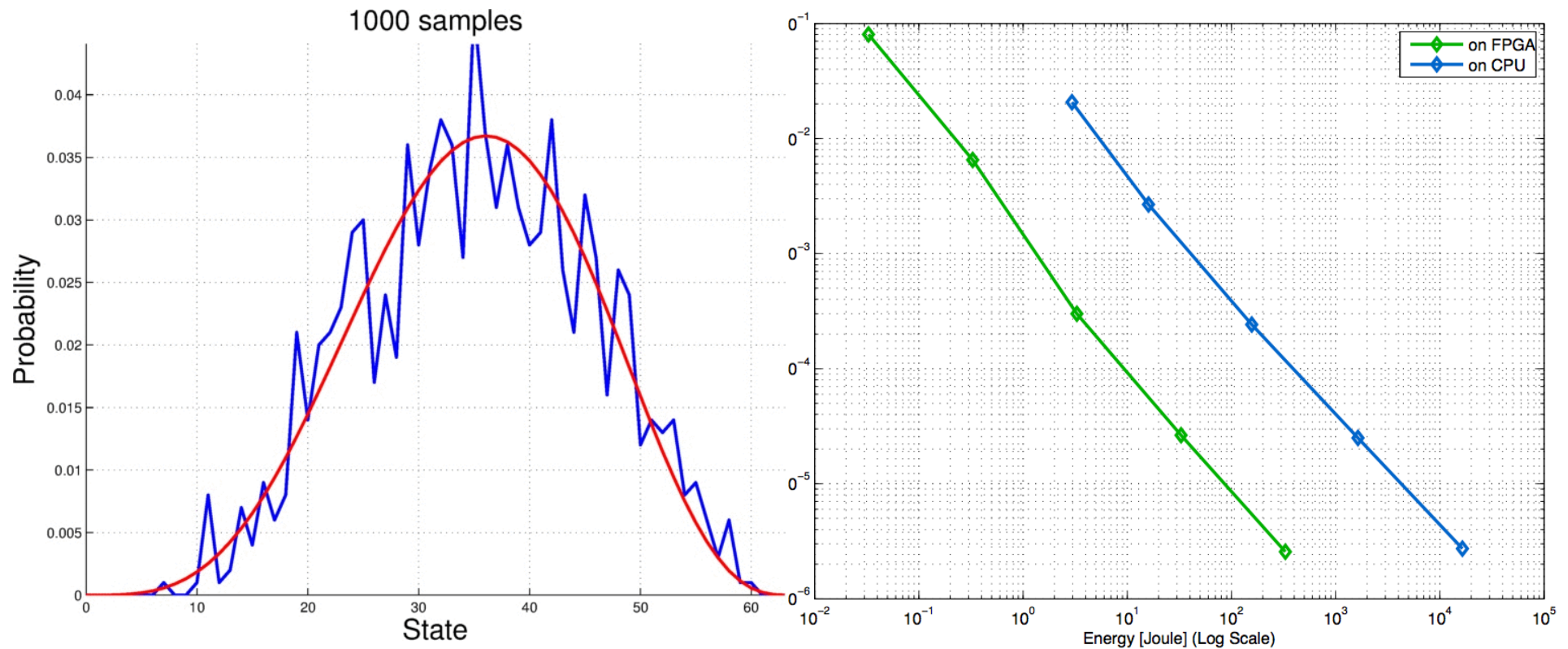
$$P(V_1, \dots, V_n, B_1, \dots, B_n) = \left(\prod_{i=1}^n P(V_i) \right) \prod_{i=1}^n P(B_i | V_i V_{1+i\%n})$$

$$P(V_i = k | b_1 = 1, \dots, b_n = 1) \approx 2^{-m} \text{Beta}((k + 0.5)2^{-m}, \alpha, \beta)$$

- 5-bit variables
- 20 searched variables (outputs)
- 64 possible states for each searched variable
- Exact inference requires 2^{100} operations



BM2 solves Intractable Problem

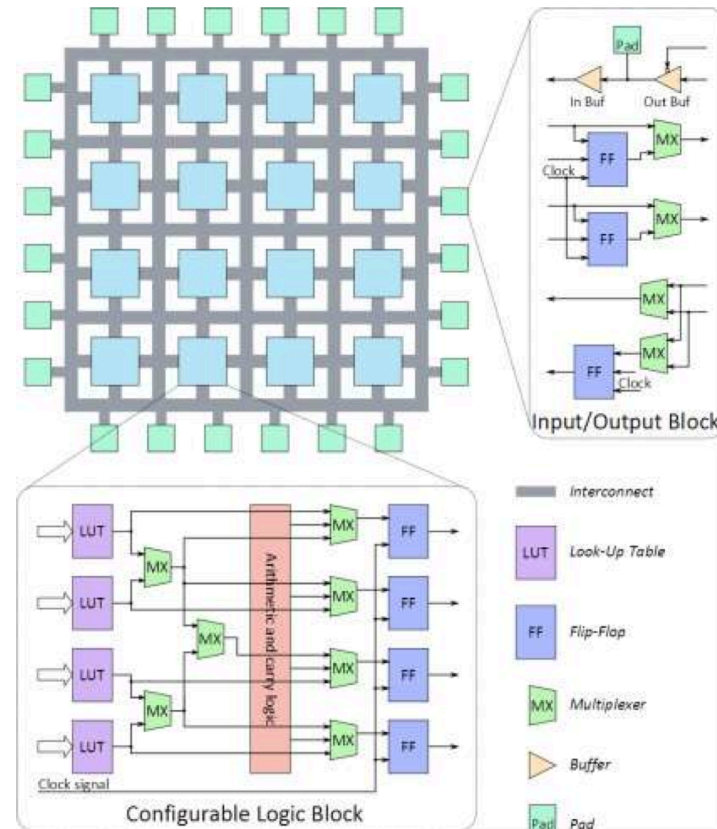
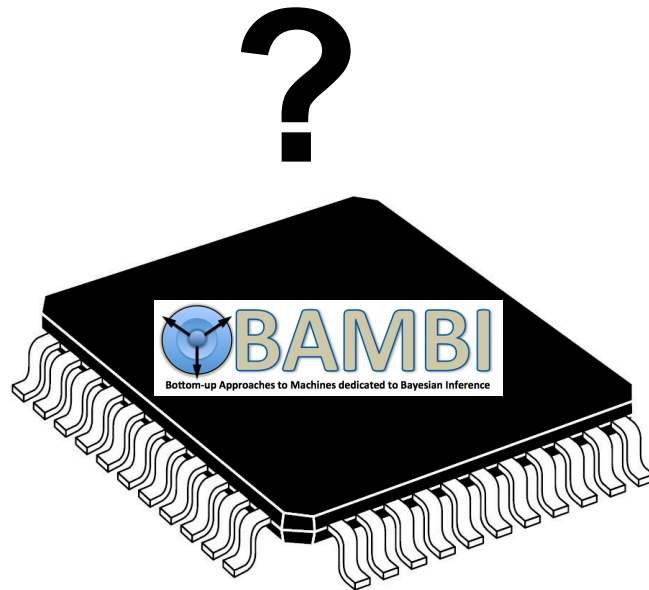


- Example of one pdf output and average KL Divergence of the 5-bit intractable problem as a function of energy consumption

Future perspectives



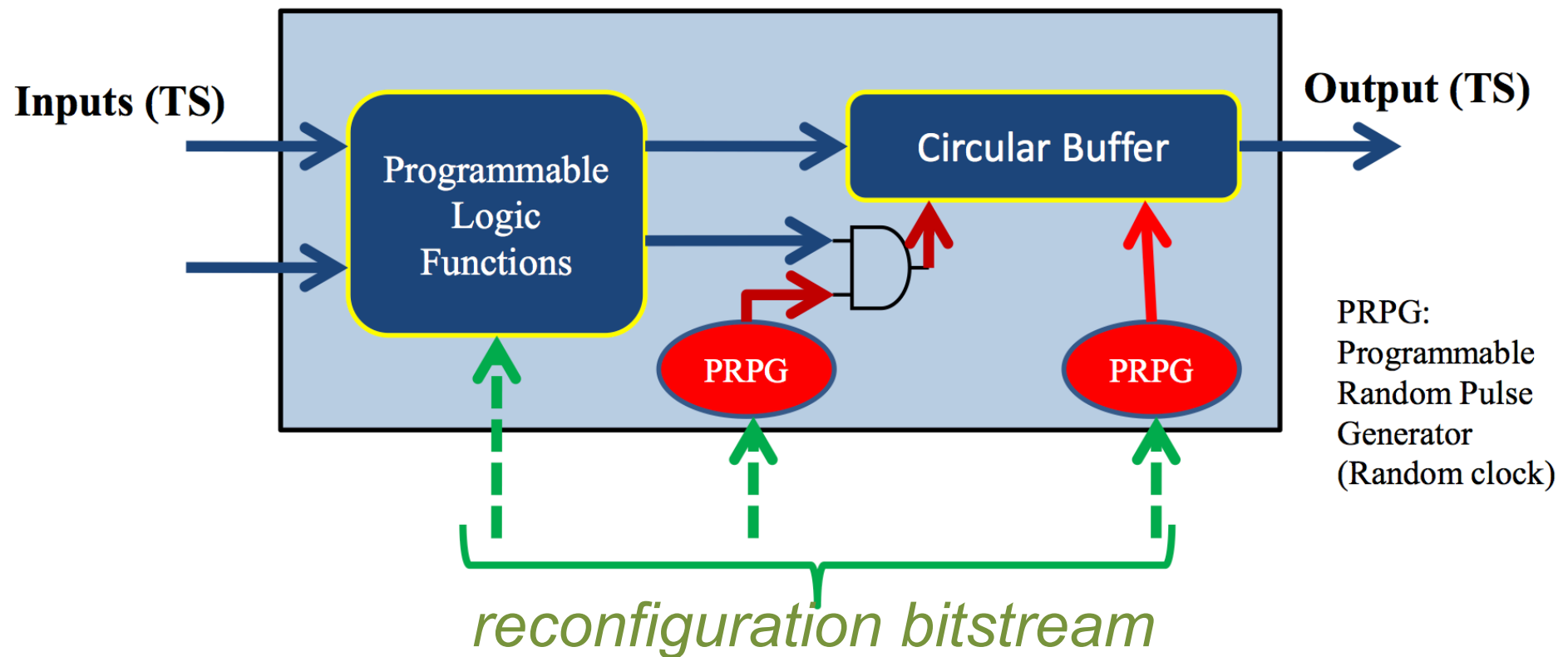
- Possible CLB (configurable logic blocks) of future FPGA?



Future perspectives



- Possible CLB (configurable logic blocks) of future FPGA



Probabilistic Machines for an Uncertain (Robotic) World...

- Moore's Law allowed us to have increasingly smart robots
- Going beyond Moore's law: novel approaches needed to support sustainable computing
- Look at nature and biology
- Revisit correctness contract between hardware and software
- Bayesian probabilistic machines
 - Using stochastic bit streams massively parallel circuits can compute inferences efficiently



- *Efficient robots dwelling in uncertainty **but dealing with it!** 😊*



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