

# Tracking Kaggle Challenge

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for the Tracking Kaggle Group  
Slides by Paolo Calafiura

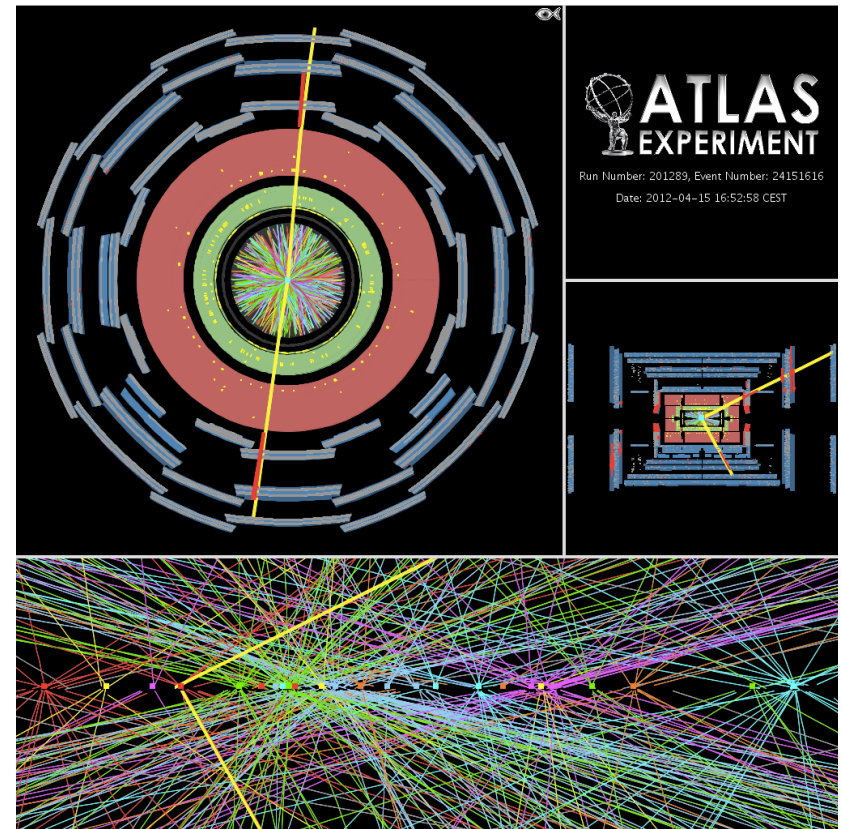
# Tracking in Run 4

~60M track/s (20x Run 2)

- x2-5 CPU shortage  
offline (another one...)

If we can't write ~40GB/s  
RDOs we'll need to gain (a  
lot) more than that **online**.

- Surely we can parallelize  
our way out of trouble?



# Why is Parallel Tracking so hard?

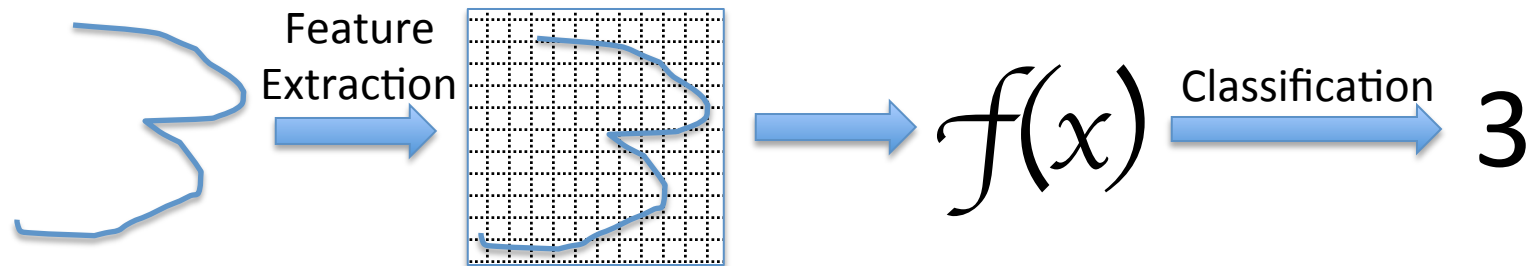
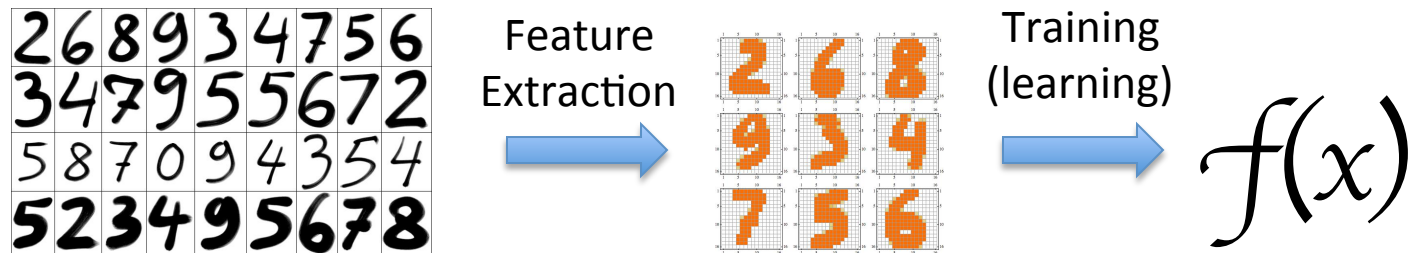
Algorithms: Iterative (propagation, fitting), irregular (combinatorial searches with lots of branch points)

Data: sparse (hits), non-local (B-field integration)

*Can Machine Learning (ML) provide a solution that uses regular, simple algorithms, and is naturally data parallel?*

# Machine Learning

Data-driven adaptive modeling of a system

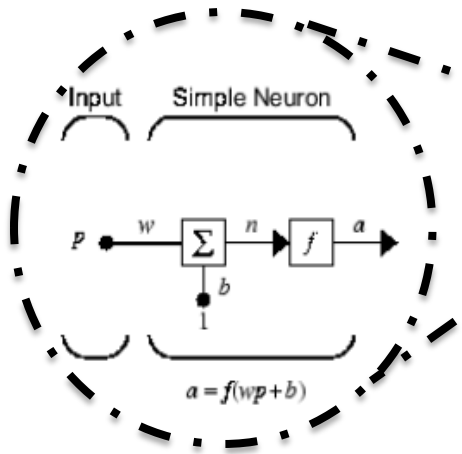


# Why Now?

Current hardware (HPC, GPUs) make possible to train very complex NNs with millions of inputs and thousands of outputs.

Exploiting GPUs, FPGAs, upcoming Neuromorphic hardware pushes us towards **Computing with many simple elements**

# Computing with simple elements



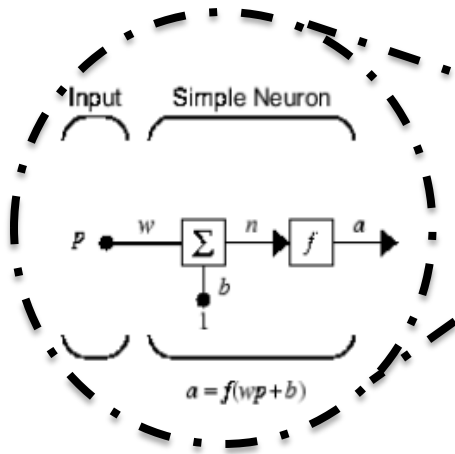
'neuron'

Simple computing elements...

by themselves, limited functional repertoire.

(Kristofer Bouchard, LBNL)

# Feed-forward NN: Classification

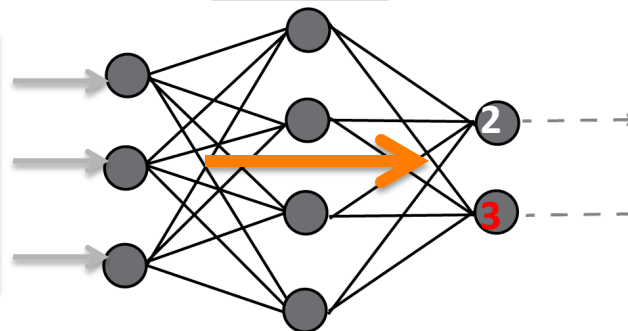
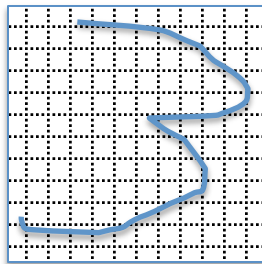


'neuron'

Simple computing elements...

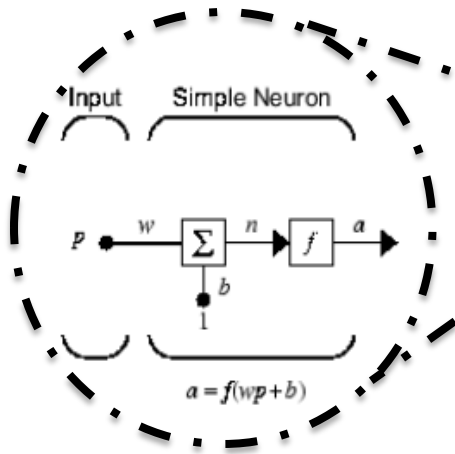
as a network, learn to perform diverse functions

Flow of information



Classification

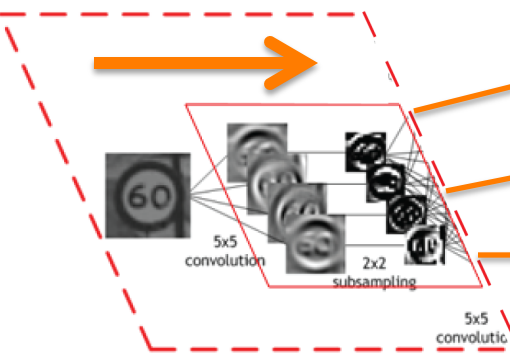
# Convolutional NN: Feature Extraction



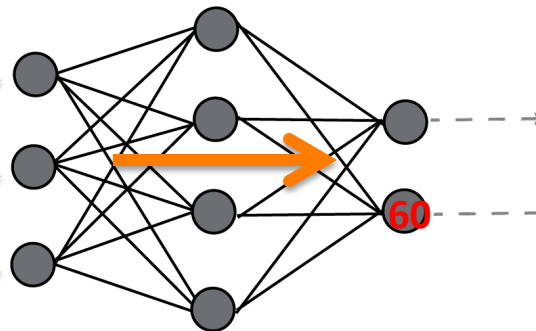
'neuron'

Simple computing elements...

as a network, learn to perform diverse functions



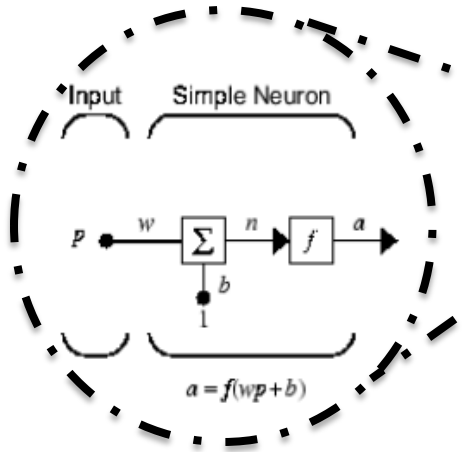
Feature Extraction



Classification



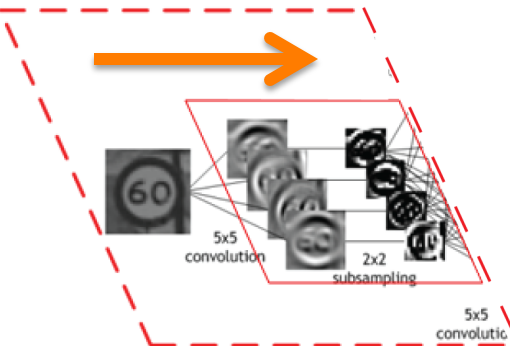
# Recurrent NN: Time-varying Functions



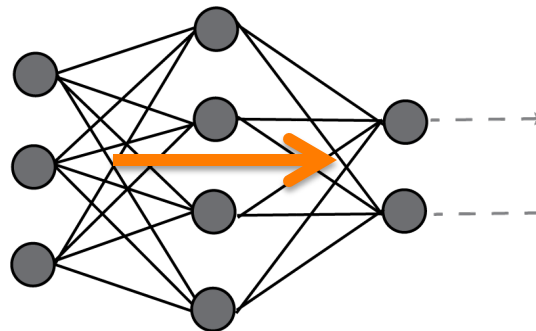
'neuron'

Simple computing elements...

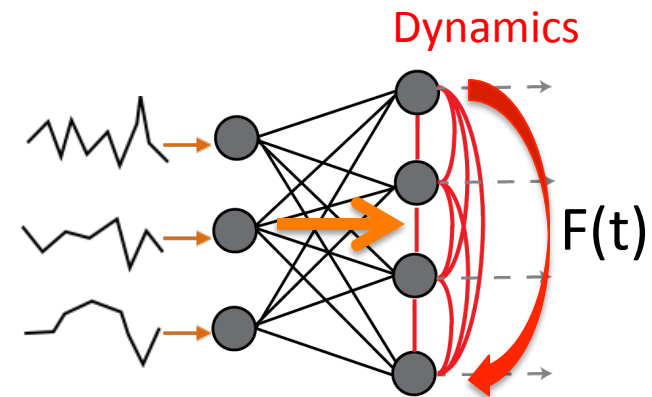
as a network, learn to perform diverse functions



Feature Extraction



Classification



Time-varying Functions

# Higgs ML Challenge

Huge success

ML already in use for Higgs analysis

Still a big effort to setup (~2 years)

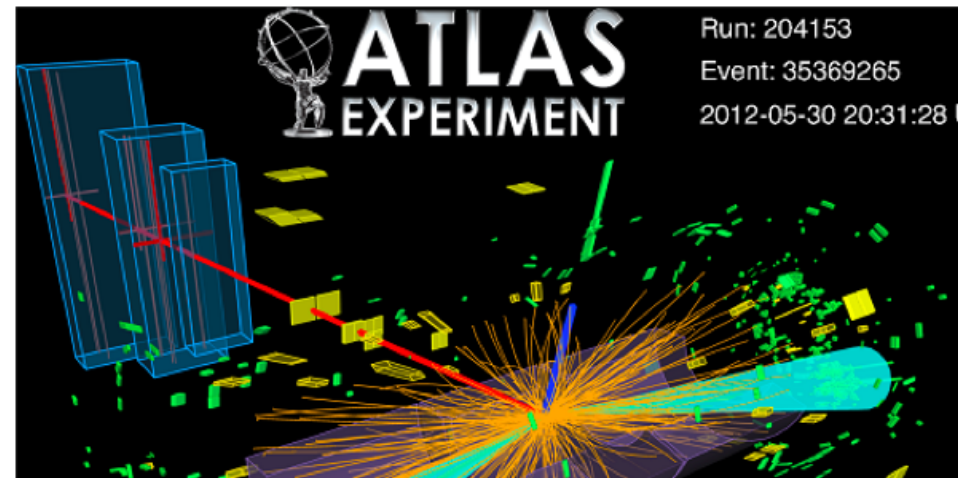
Completed • \$13,000 • 1,785 teams

## Higgs Boson Machine Learning Challenge

Mon 12 May 2014 – Mon 15 Sep 2014 (9 months ago)

[Competition Details](#) » [Get the Data](#) » [Make a submission](#)

Use the ATLAS experiment to identify the Higgs boson



# Connecting The Dots 2015

**A Workshop on Pattern Recognition in  
Sparsely Sampled Data**

The Berkeley Experimental Particle Physics  
Center Workshop Series



Connecting The Dots 2015  
LBNL, Feb. 9-11, 2015

David R, Markus E, and PC volunteered to  
organize a Tracking Challenge

# Tracking Kaggle Challenge

- One question (follow-up questions possible)
- One evaluation metric (training function)
- Two data samples: Training (labelled), Test
- One “starting kit” (reference solution)

# Our Question

## Immediate Goal:

Build a fast, **scalable**, pattern recognition engine

## Real Goal:

Learn if-how-where to apply ML to reconstruction

## Question:

Given a list of space-points, identify those belonging together (to a track).

May add fitting at a later time

# Evaluation Metric

- Non-trivial, still under discussion
  - Positive weight for each hit correctly assigned to track
  - Negative weight for fake hits
- Issues
  - Balance efficiency, fake rate, and complexity
  - Need to fold into metric instructions needed to run.

# Data Sample

json format, may move to HDF5 ( on afs ~calaf/public/kaggle)

```
{  
  "Identifier" : 147838943612633088,  
  "GlobalX" : 33.180407,  
  "GlobalY" : -3.219767,  
  "GlobalZ" : -112.9625,  
  "WidthPhiR" : 0.05,  
  "WidthZ" : 0.5,  
  "energyLoss" : -28,  
  "splitProbability1" : 0,  
  "splitProbability2" : 0,  
  "Deposits" : [  
    {  
      "Charge" : 13051.327148,  
      "TruthEventIndex" : 0,  
      "Barcode" : 200001  
    }  
  ]  
},
```

- Per-job, geometry info in separate file

- Not there for noise hits.
- Training file only

Currently Run 2 Pixel with single mu events. Will try tau soon.  
Next we will use ITK (Run 4) configuration. Later will add pileup.  
No idea how many events will be needed, expect  $O(10^9)$  tracks.

# Starting Kit

Provide reference solution to kaggle competitors

- Typically a simple ML solution
- Could provide simplified HEP Tracking, issue is how to package to run standalone.

David Clark (UCB) started working on single track classifier using [Caffe](#).

- Outputs probability N hits belong to track
- Trained using chisquare(hit, propagated GenParticle)

See <https://github.com/davidclark1/TrackNet>



# Tracking Kaggle Group

- [tracking-kaggle@googlegroups.com](mailto:tracking-kaggle@googlegroups.com)  
(open, currently 20 members)
- Members from
  - ATLAS, CMS, LHCb (since last week)
  - ML experts from HiggsML
  - Tracking experts from Connecting The Dots
- Meets every other Mon at 17:10 CET on vidyo
- Time-frame next CTD workshop (Feb 16?)
  - Settle on question, data samples, starting kit strategy by Sep 15

# Final Thoughts

- In 2025 ML will be more mainstream than C++
  - Ideally suited for highly parallel architectures with simple computing nodes (GPUs, FPGAs, ...)
  - Likely **part of** any Run 4 tracking solution
- ML is not a trivial subject, will take years to build HEP expertise.
- The Kaggle Tracking Challenge is a great opportunity to enter this brave new world.

# Thanks

- Paolo Calafiura and Collaborators
- Kristofer Bouchard
- Maurice Garcia-Sciveres
- Beate Heinemann
- Peter Nugent
- Peter Sadowski
- ...

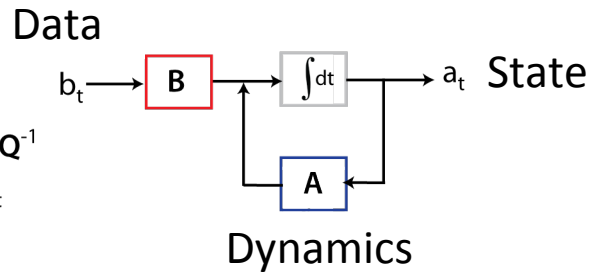
# Backup

# Kalman Filters and Recurrent NNs

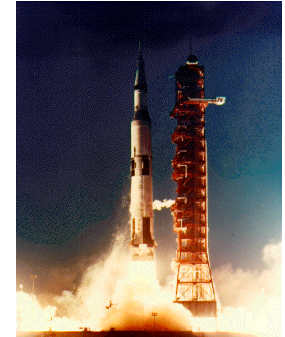
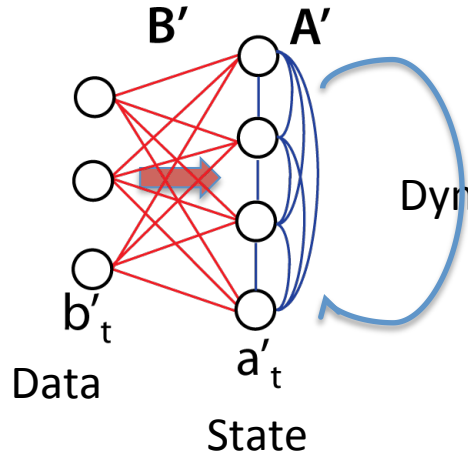
Classic Data Assimilation algorithm (1960, NASA)  
Iteratively **track** evolution of a **dynamic** system

**Kalman Filter**

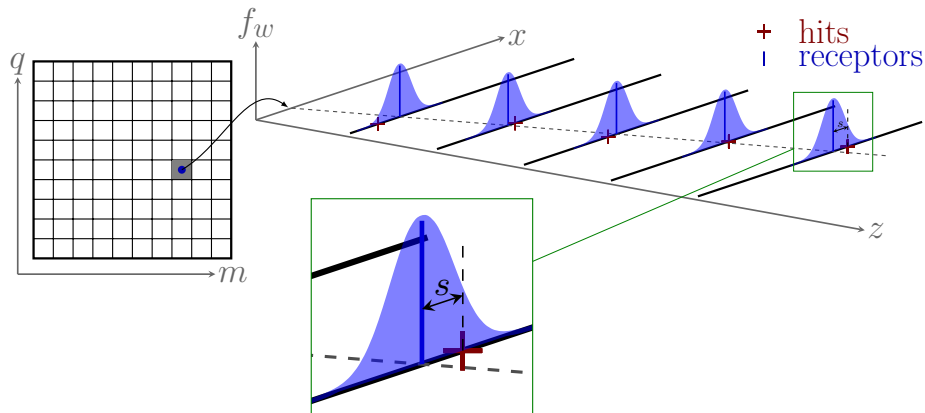
- (1)  $a_t = Aa_{t-1} + N(0, W)$
- (2)  $b_t = Ba_t + N(0, Q)$
- (3)  $K = (I - WBQ^{-1}C)^{-1}WBQ^{-1}$
- (4)  $\hat{a}_t = (I - KB)A\hat{a}_{t-1} + Kb_t$



**Recurrent Neural Network**

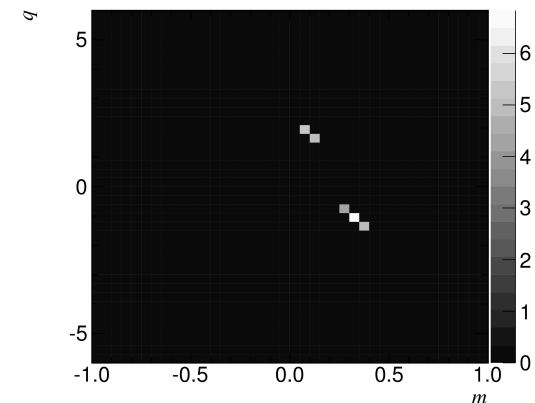
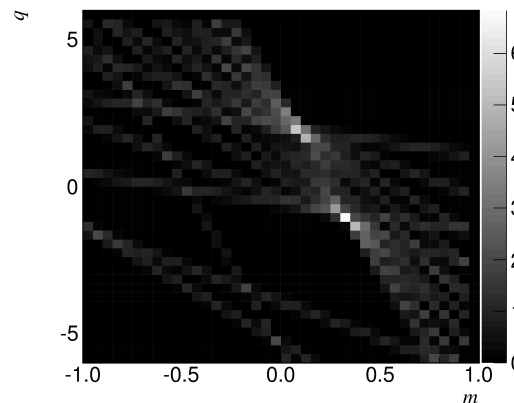


# LHCb Trigger Retina Processor



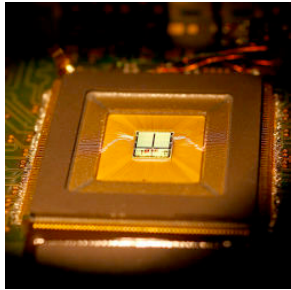
Transform to track parameter space  
22K bins, one “receptor” per bin

FPGA implementation  
1 $\mu$ s tracking  
Offline-quality performance  
Certainly good enough for seeding



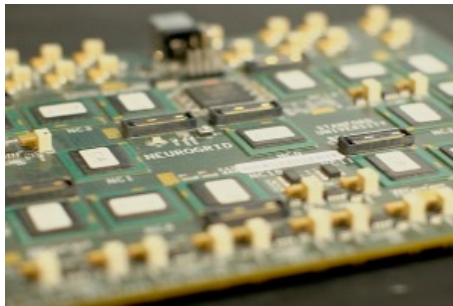
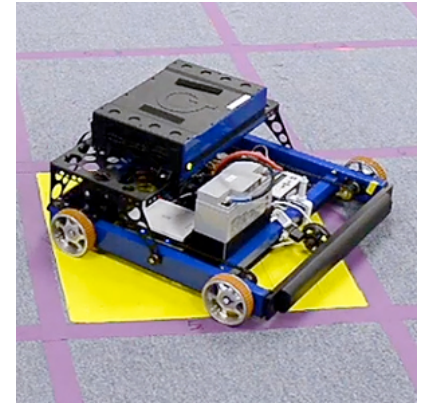
(Simone Stracka, Pisa)

# Neuromorphic Computing

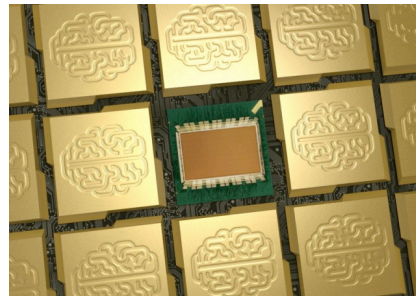


“Spikey” from Electronic Visions group in Heidelberg

Qualcomm’s NPU’s for robots.

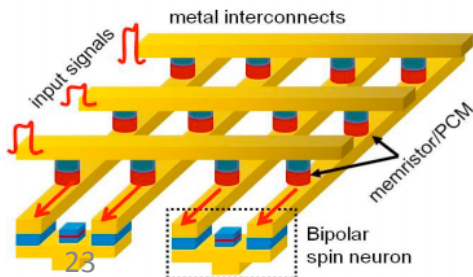
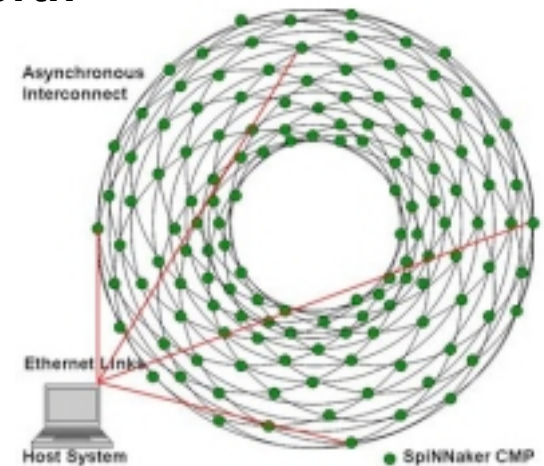


Stanford’s Neurogrid



IBM’s TrueNorth

SpiNNaker’s 1B neuron machine

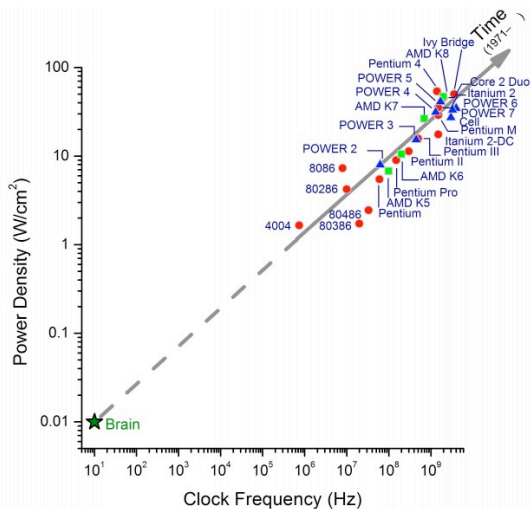


Intel’s concept design...

(Peter Nugent, LBNL) at IASCBs Week



# IBM TrueNorth



- 1 million programmable neurons
- 256 million synapses
- 4096 neurosynaptic cores
- **Uses 70mW per chip**
- 5.4 billion transistors
- Spiking rate >1000Hz

A single chip can process color video in real-time while consuming 176,000 times less energy than a current Intel chip performing the exact same analysis. Note the Intel chip can *not* do this analysis in real-time and is in fact 300 times slower!



Merolla+ Science (2014)