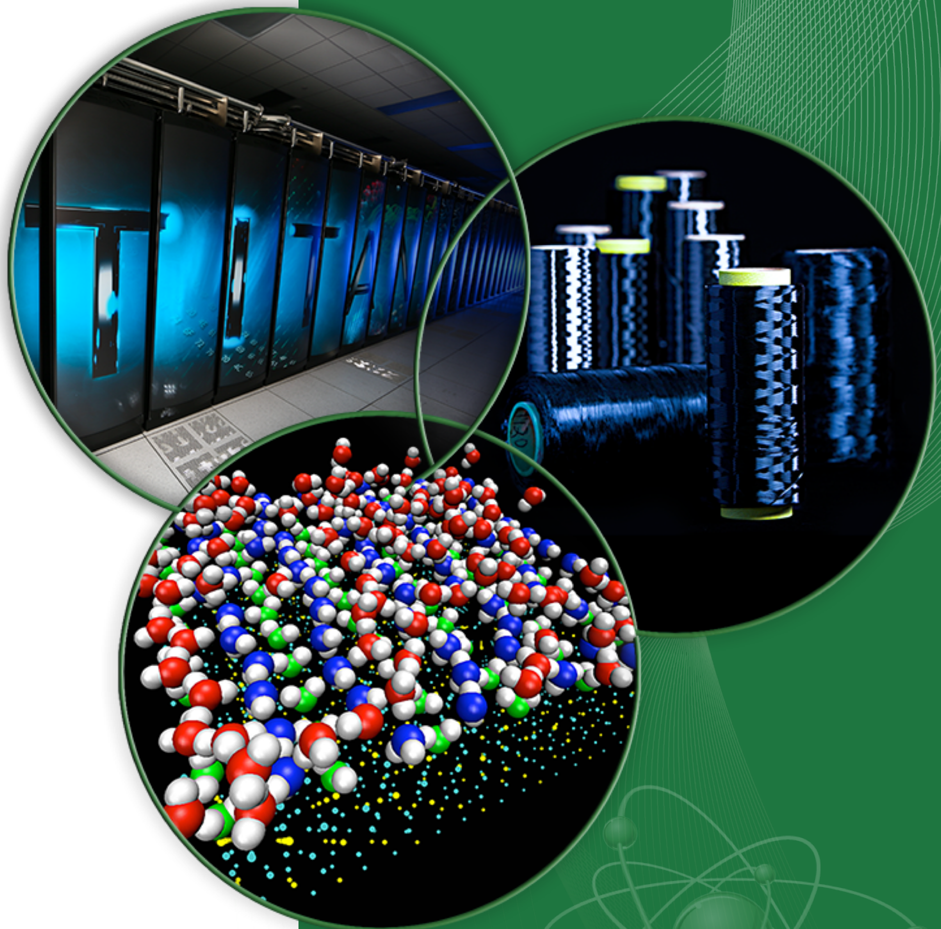
Neuromorphic Program



Thomas E. Potok, PhD
Computational Data Analytics Group
Oak Ridge National Laboratory

ICONS
International Conference on Neuromorphic Computing Systems

ORNL is managed by UT-Battelle
for the US Department of Energy

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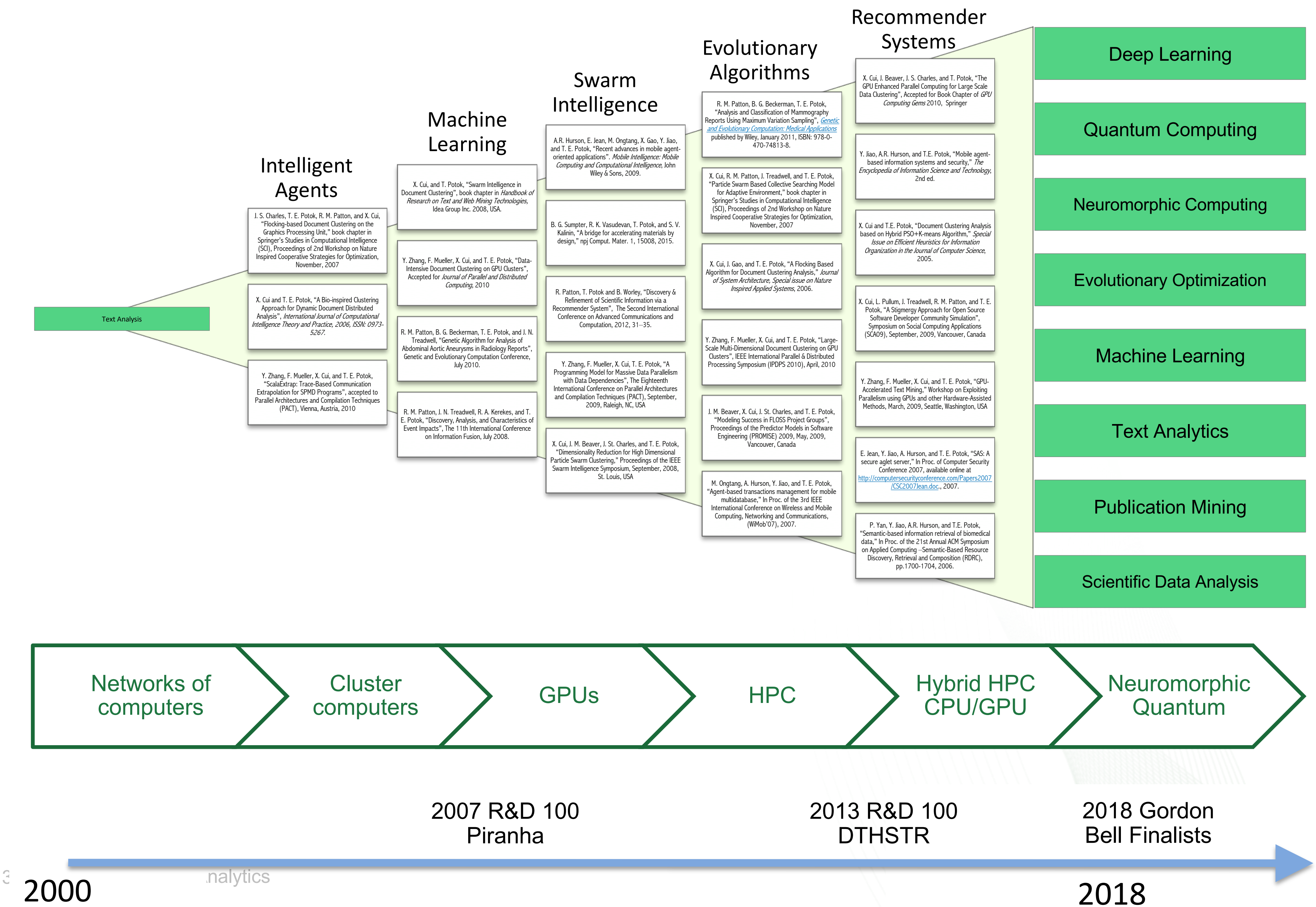
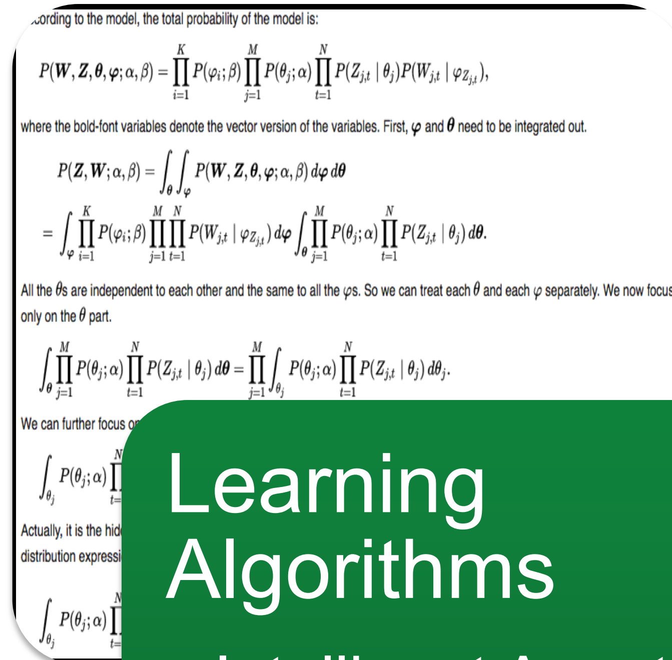
Message

- We all believe in the potential of a computer patterned after the brain
- We also know that this is REALLY hard to do
- Time is right
  - Moore's Law
  - AI resurgence
  - Worldwide investment in neuromorphic computing
- Neuromorphic computing needs a paradigm shift
  - Native learning
  - Native data
  - Broader program

Computational Data Analytics



Why ORNL is important?


...cording to the model, the total probability of the model is:

$$P(\boldsymbol{W},\boldsymbol{Z},\boldsymbol{\theta},\boldsymbol{\varphi};\alpha,\beta)=\prod_{i=1}^{K}P(\varphi_i;\beta)\prod_{j=1}^{M}P(\theta_j;\alpha)\prod_{t=1}^{N}P(Z_{j,t}\mid\theta_j)P(W_{j,t}\mid\varphi_{Z_{j,t}}),$$

where the bold-font variables denote the vector version of the variables. First, $\boldsymbol{\varphi}$ and $\boldsymbol{\theta}$ need to be integrated out.

$$P(\boldsymbol{Z},\boldsymbol{W};\alpha,\beta)=\int_{\boldsymbol{\theta}}\int_{\boldsymbol{\varphi}}P(\boldsymbol{W},\boldsymbol{Z},\boldsymbol{\theta},\boldsymbol{\varphi};\alpha,\beta)\,d\boldsymbol{\varphi}\,d\boldsymbol{\theta}$$

$$=\int_{\boldsymbol{\varphi}}\prod_{i=1}^{K}P(\varphi_i;\beta)\prod_{j=1}^{M}\prod_{t=1}^{N}P(W_{j,t}\mid\varphi_{Z_{j,t}})\,d\boldsymbol{\varphi}\int_{\boldsymbol{\theta}}\prod_{j=1}^{M}P(\theta_j;\alpha)\prod_{t=1}^{N}P(Z_{j,t}\mid\theta_j)\,d\boldsymbol{\theta}.$$

All the θs are independent to each other and the same to all the φs. So we can treat each θ and each φ separately. We now focus only on the θ part.

$$\int_{\boldsymbol{\theta}}\prod_{j=1}^{M}P(\theta_j;\alpha)\prod_{t=1}^{N}P(Z_{j,t}\mid\theta_j)\,d\boldsymbol{\theta}=\prod_{j=1}^{M}\int_{\theta_j}P(\theta_j;\alpha)\prod_{t=1}^{N}P(Z_{j,t}\mid\theta_j)\,d\theta_j.$$

We can further focus o...

Actually, it is the hid...

distribution expressi...

Powerful Computers

- Titan
- Summit
- Exascale

Learning Algorithms

- Intelligent Agents
- Machine Learning
- Evolutionary Optimization
- Deep Learning

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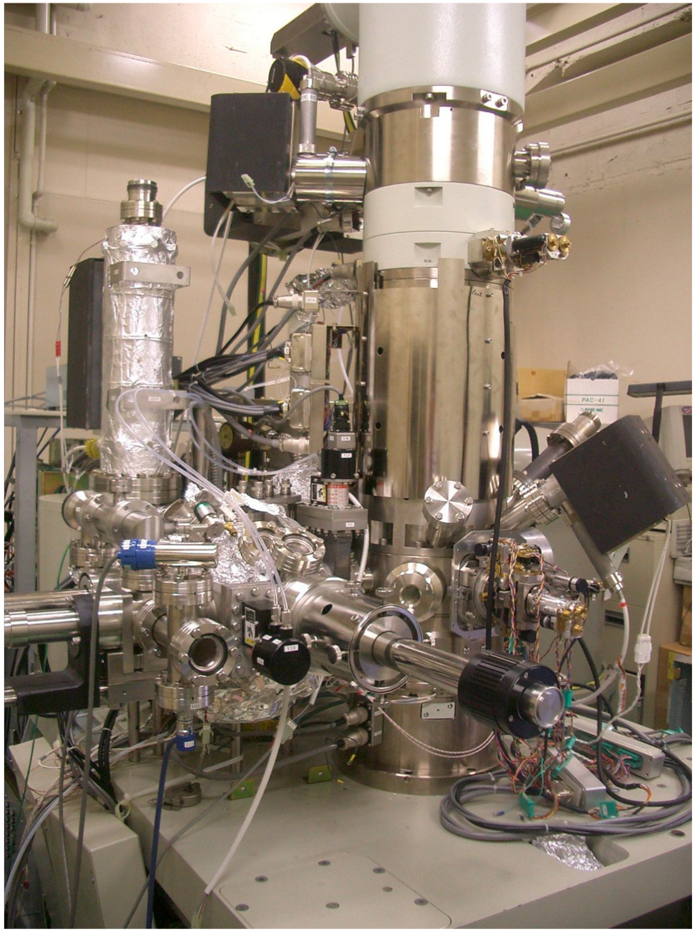
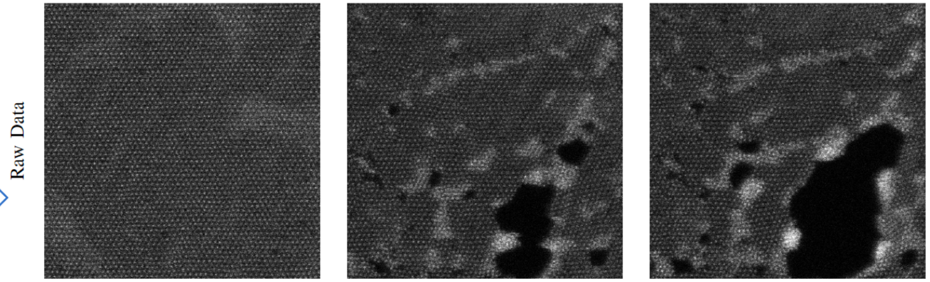
Expert driven

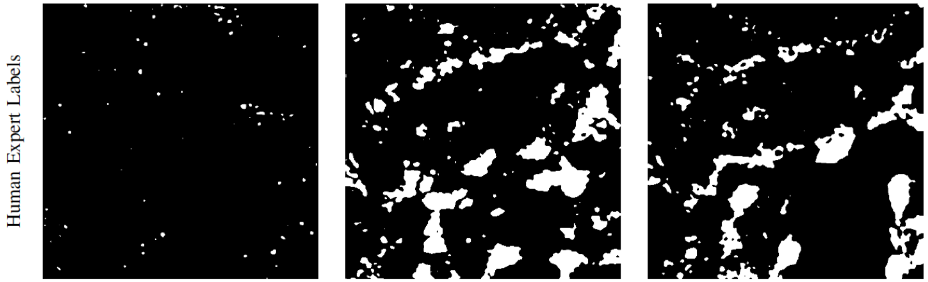


Electron Microscope



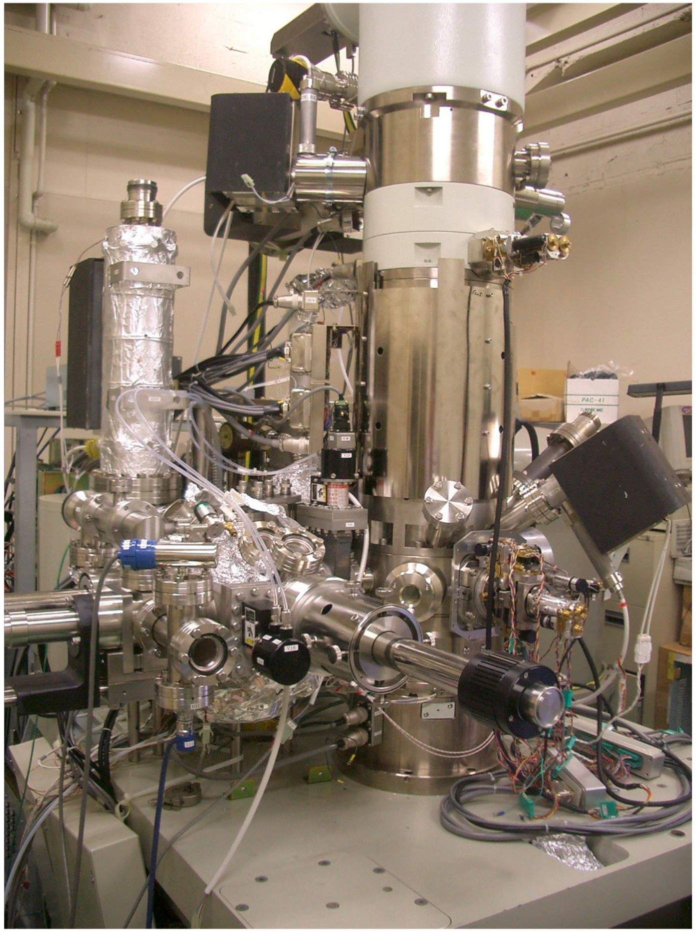
Atomic Structure

Expert Analysis

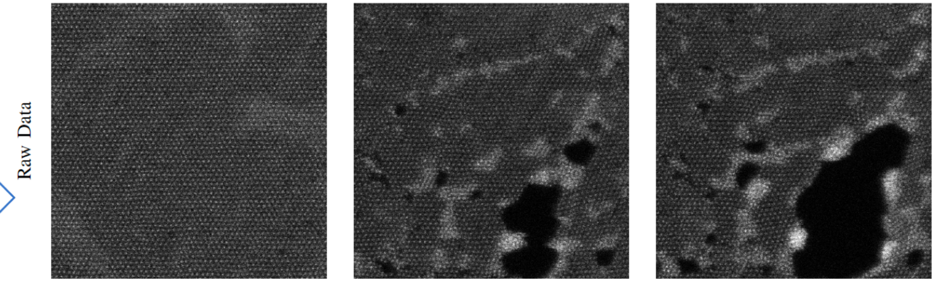


Output

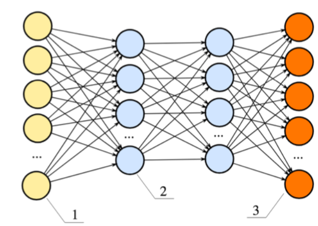
Automated Analysis



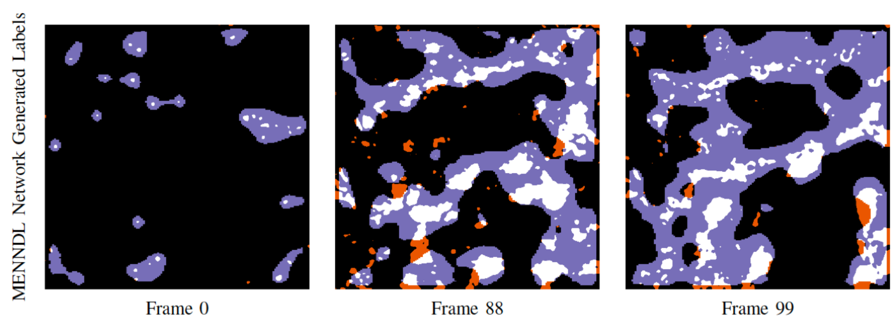
Electron Microscope



Atomic Structure



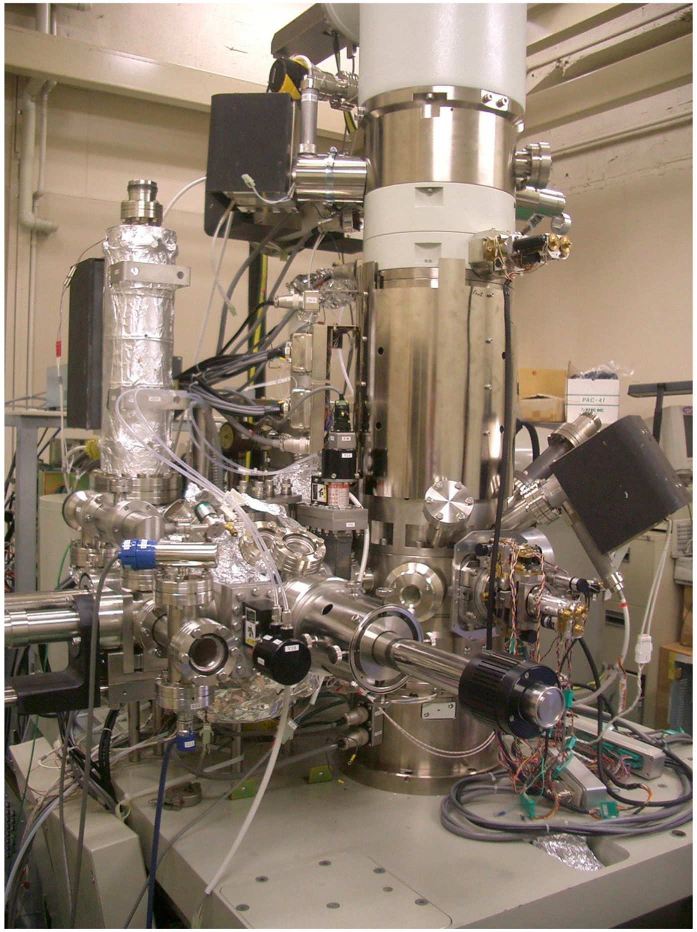
Deep Learning



Output

“Self Driving” Nanofabrication

Material Characteristics



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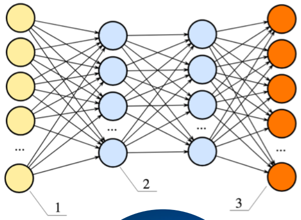
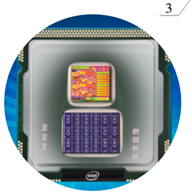




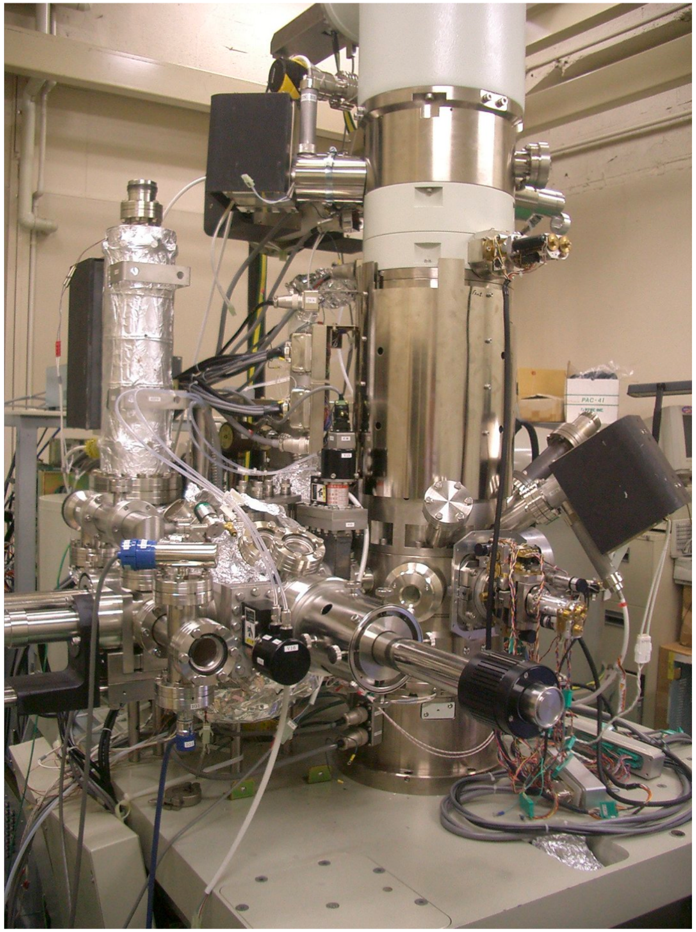
Neuromorphic

Data Driven Material Fabrication

T. E. Potok, C. D. Schuman, S. R. Young, R. M. Patton, F. Spedalieri, J. Liu, K. Yao, G. Rose, and G. Chakma. 2016. A study of complex deep learning networks on high performance, neuromorphic, and quantum computers. In *Proceedings of the Workshop on Machine Learning in High Performance Computing Environments* (MLHPC '16).

T. E. Potok, C. D. Schuman, S. R. Young, R. M. Patton, F. Spedalieri, J. Liu, K. Yao, G. Rose, and G. Chakma. A study of complex deep learning networks on high performance, neuromorphic, and quantum computers, *ACM Journal of Emerging Technologies in Computing Systems*

Learning and data Shift



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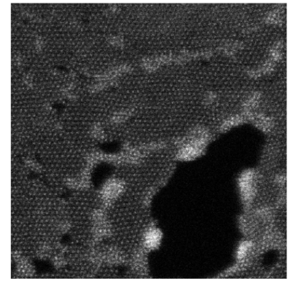
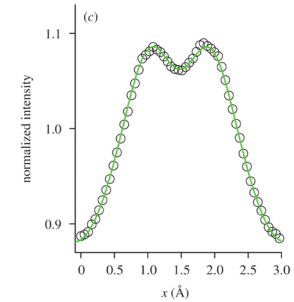
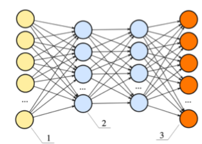


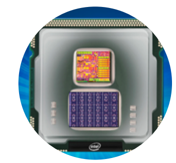


Atomic Structure and Paths

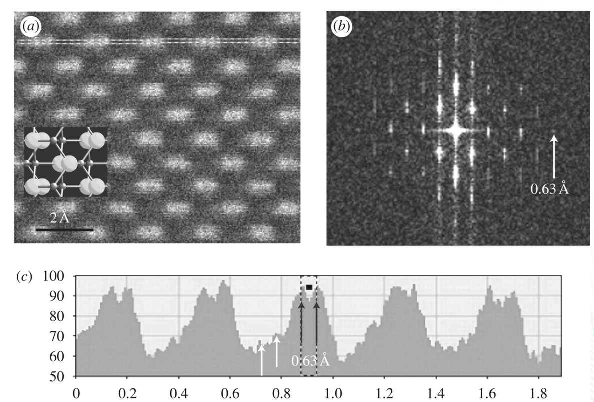


Deep Learning

HPC

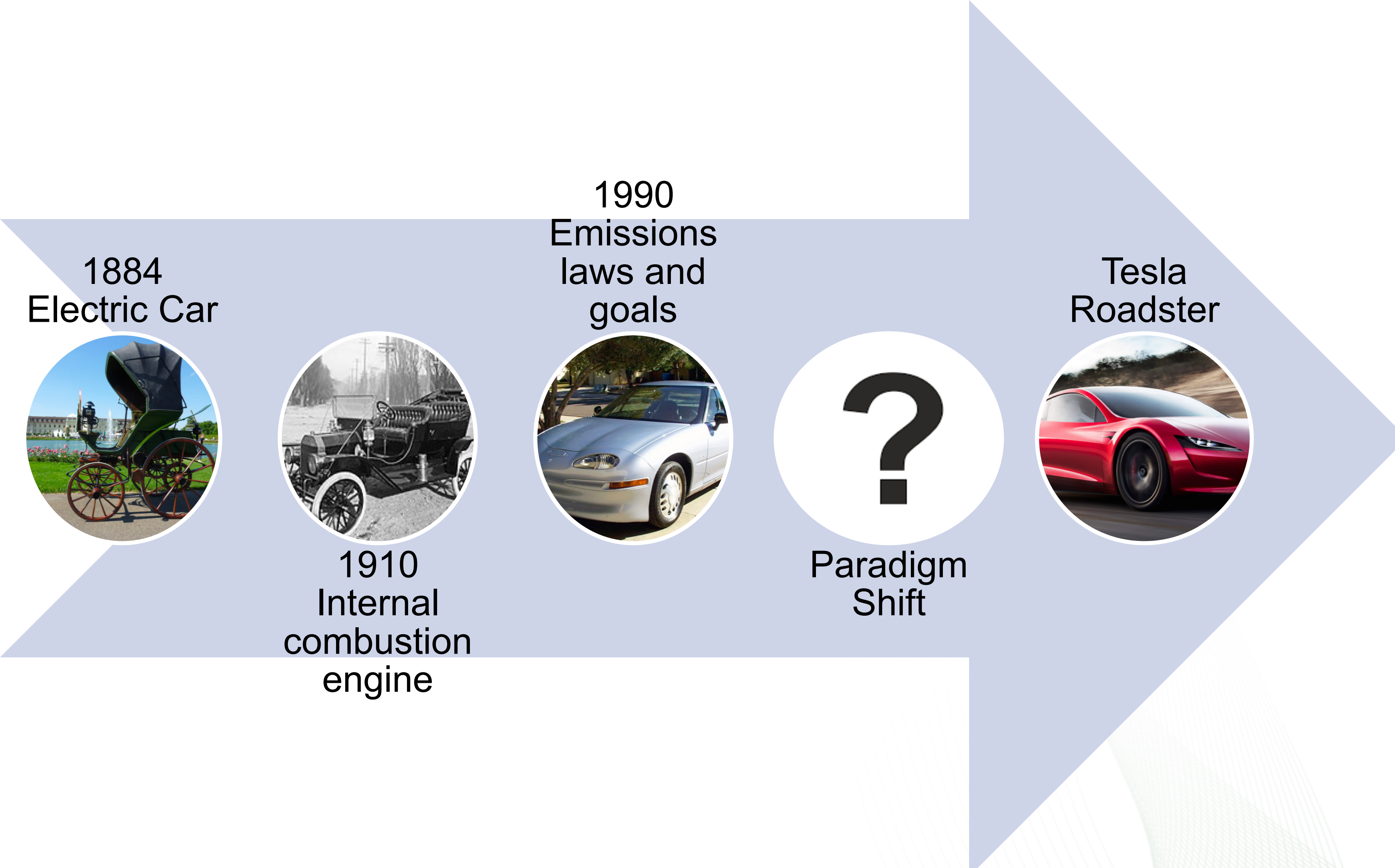


Neuromorphic Learning



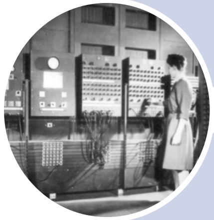
Aberration-corrected scanning transmission electron microscopy: from atomic imaging and analysis to solving energy problems, S. J. Pennycook et al. Trans. R. Soc. A 2009 367 3709 3733; DOI: 10.1098/rsta.2009.0112. Published 17 August 2009

Technology Drivers

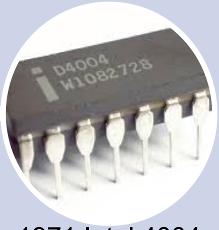


Neuromorphic Drivers

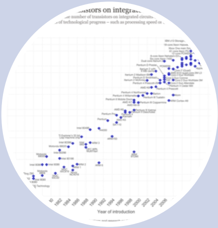
1948 ENIAC



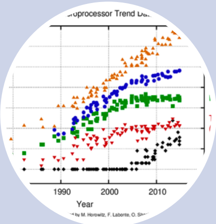
1971 Intel 4004
Microprocessor



1975 Moore's
law



2015 End of
Moore's law
soon...



2018 Rise of
neuromorphic

?

Paradigm
Shift

We need a
neuromorphic
Tesla

Challenges

- Machine learning is driven by current computer architectures
  – Not natively suited for neuromorphic computing
- Datasets are driven by deep learning models
  – Not natively suited for neuromorphic computing
- Need neuromorphic learning with neuromorphic datasets

Challenges

- Using deep learning algorithms on neuromorphic devices trained on deep learning benchmarks
- Is like bringing a motorcycle to a NASCAR race

Challenges

- Machine learning is driven by current computer architectures
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Machine learning Methods

Statistics

Design experiment, generate data, test hypothesis

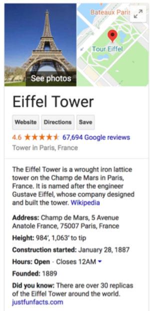
Unsupervised learning

Classify/group data based on features to gain insights

Supervised learning

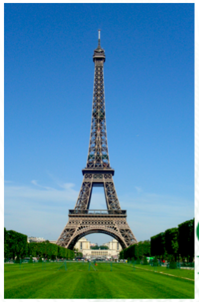
Learn model from labelled data for prediction

"Eiffel Tower"



Deep learning

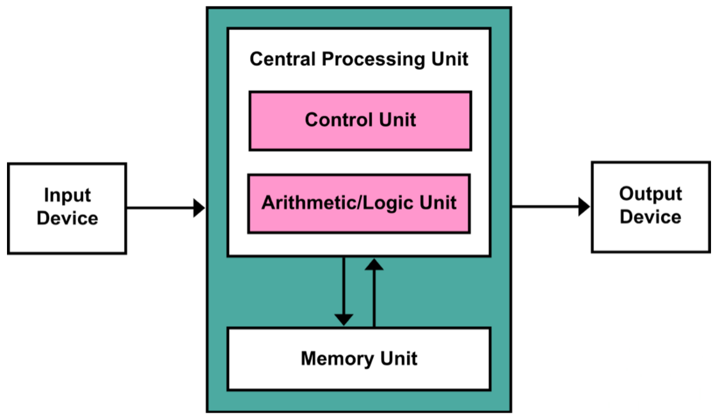
Learn features and model from labeled data for automated classification



ML Algorithm Requirements

Parallel CPUs/GPUs

High number of numeric comparisons

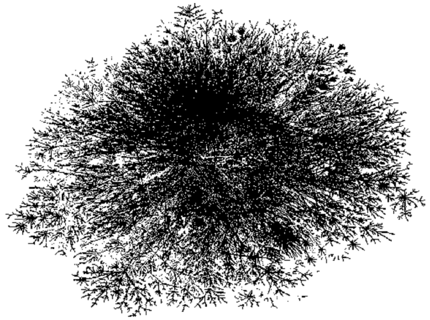


Von Neumann Architecture

Efficient data representation

Fast I/O large, fast memory, fast disks

Machine learning drivers



- Data must be sparse, weakly connected
  - Easy to parallelize on multiple cores/CPUs
- Graphs need to be flatten to tables
  - Locality of reference, fast retrieval from disk
- Heuristics/tricks to avoid NP algorithm complexity
  - Transformation
  - Feature reduction
- Adapt to the available architectures and hardware
  - Cluster computers
  - Multicore CPUs
  - GPU accelerators

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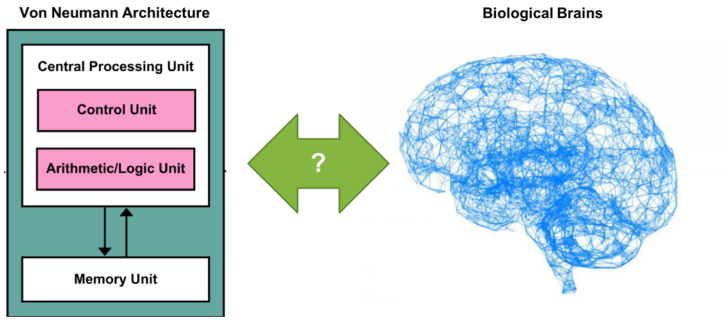
Learning

Learning by a machine

- Is driven by the available hardware
- Filtered by the characteristics of the data
- We need a paradigm shift in how we look at learning



Human Learning

- Sensory
- Pleasure/pain
- Repetition
- Language
- Passion

Neuromorphic Learning ideas

- Natural graph representation
- Generalized (innate) structures for learning
- Temporal based learning
- Need new ideas

Challenges

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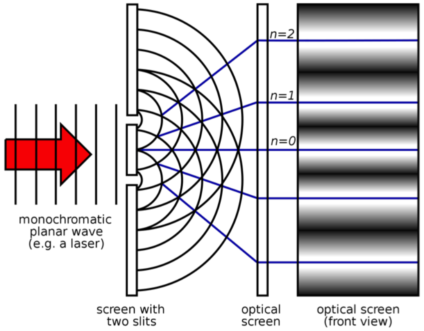
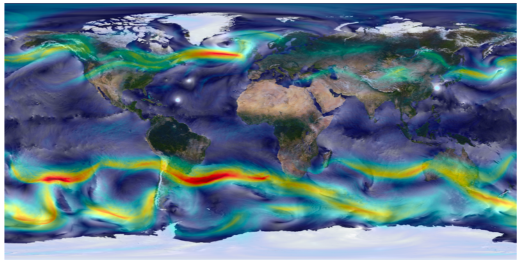
Data Evolution

- Experimentally driven
  - Well designed, hypothesis driven, suited for statistical analysis
  - CERN, Public opinion survey
- Simulation driven
  - Well designed, very large outputs, generate data that cannot be easily observed
  - Astrophysics and Climate models
- Observation driven
  - No design, available, what does it mean? Can it be used to predict?
  - Facebook and Google





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Observed Data Characteristics

- Large, high dimensional, non-numeric
  - Search results
  - Product purchases
  - Social media connections
- Curated hand labelled datasets to evaluate algorithms
  - MNIST
  - ImageNet
  - Wikipedia database

- Research challenge to find the best algorithms

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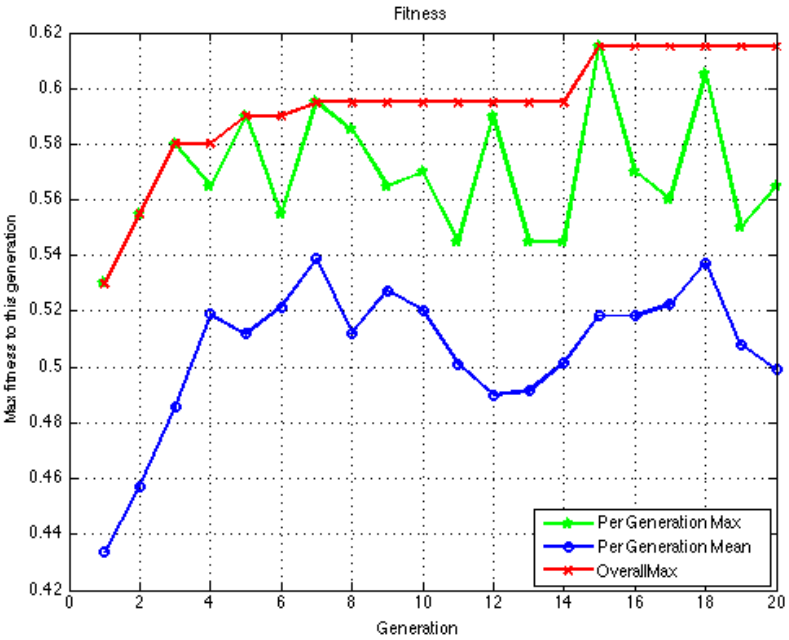
Neuromorphic Datasets Characteristics

- Highly connected data
- Time series
- Multi-modal
- Need new ideas?

Next steps

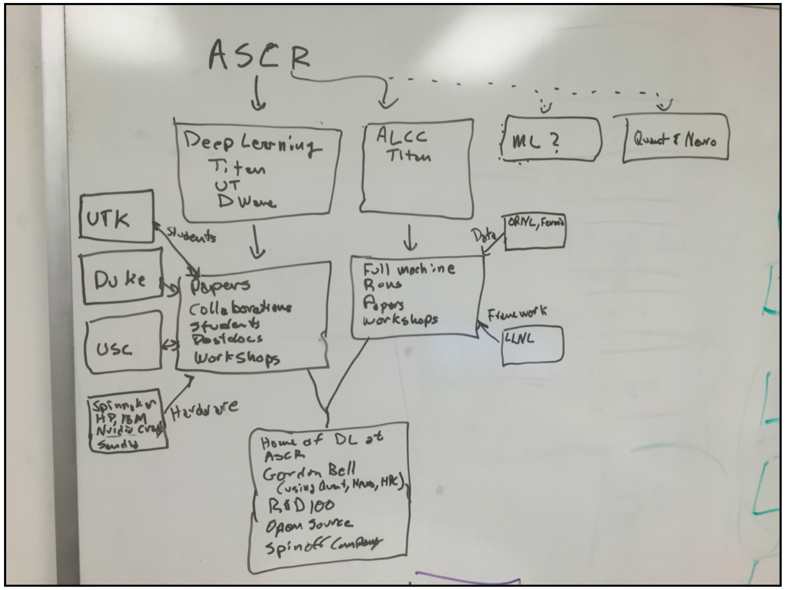
- Develop benchmark dataset for neuromorphic computing
  – Hard problems for traditional computing
- Metrics
- Create data challenges and prizes
- Publish results against datasets

Neuromorphic Program MENNDL 10/2014



Passion: Scaling to Titan

2 years ago



Today

- ASCEND project awarded
- MENNDL running on all of Titan AND Summit
- Strong collaborations
- ACM JETC, Entropy article
- Gordon Bell Finalists
- Neuromorphic and Deep Learning ensemble

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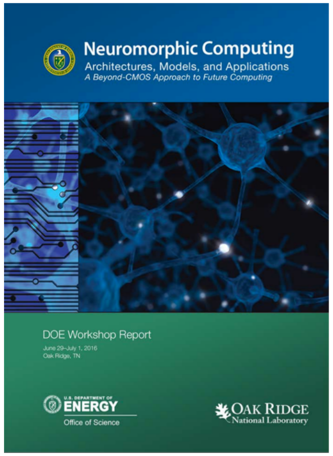
Neuromorphic Program

- National and market need
  - Neuromorphic Computing 2016 Report
- Research paradigm shift
  - Need broad collaboration
  - New learning algorithms
  - Standard datasets
- Funding
  - DOE, DOD, Industry
- Need a Tesla
  - Targeting problems not solved with traditional computers



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The future is bright

- We need your help to create big, novel, creative, clever ideas
- Creating broad and open collaboration
- Developing native learning algorithms
- Building neuromorphic datasets and challenges

Contact Information:

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