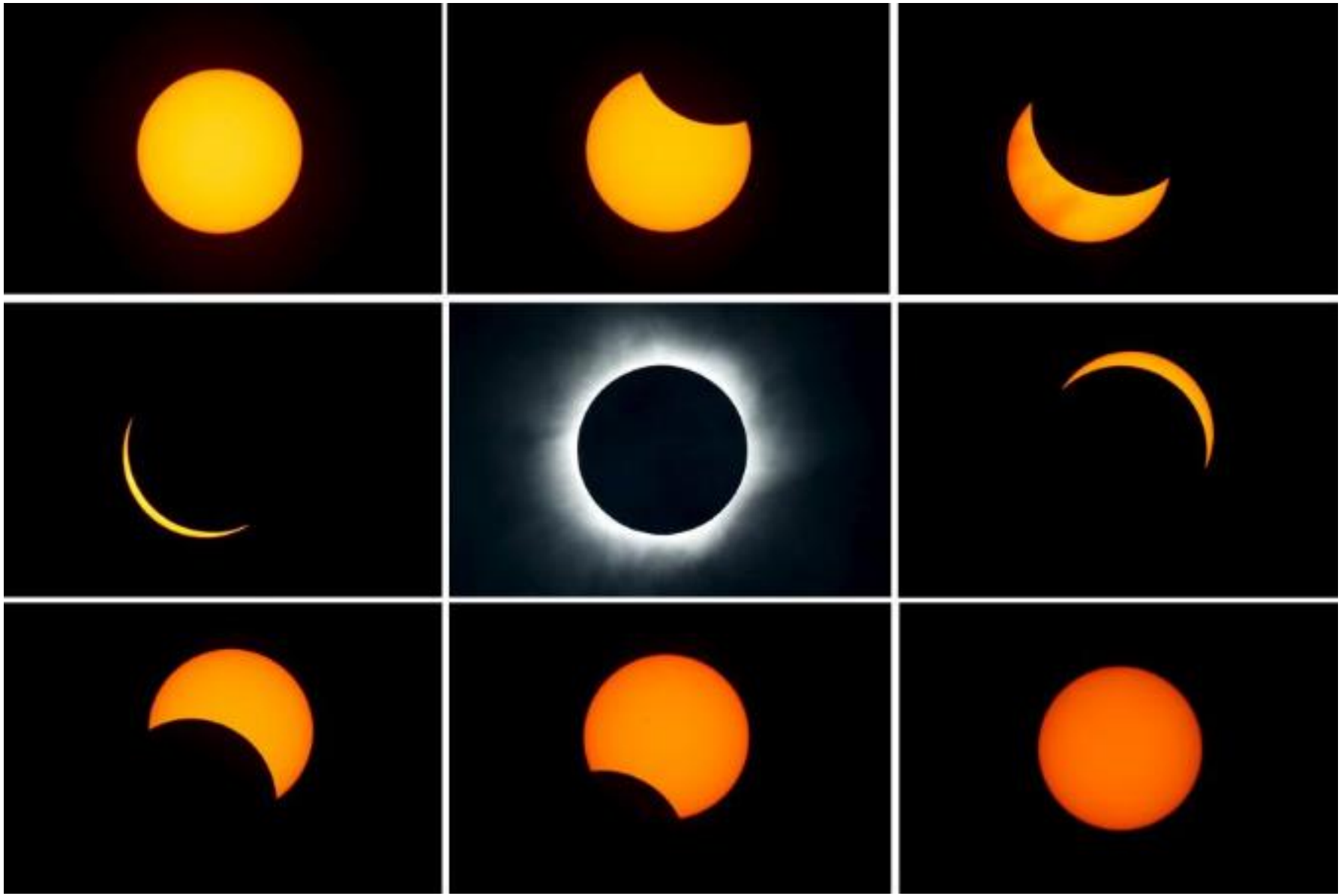
ACAT2017
onference Summary

Pushpa Bhat
Fermilab

August 21-25, 2017
University of Washington, Seattle, USA

The Great American Eclipse!



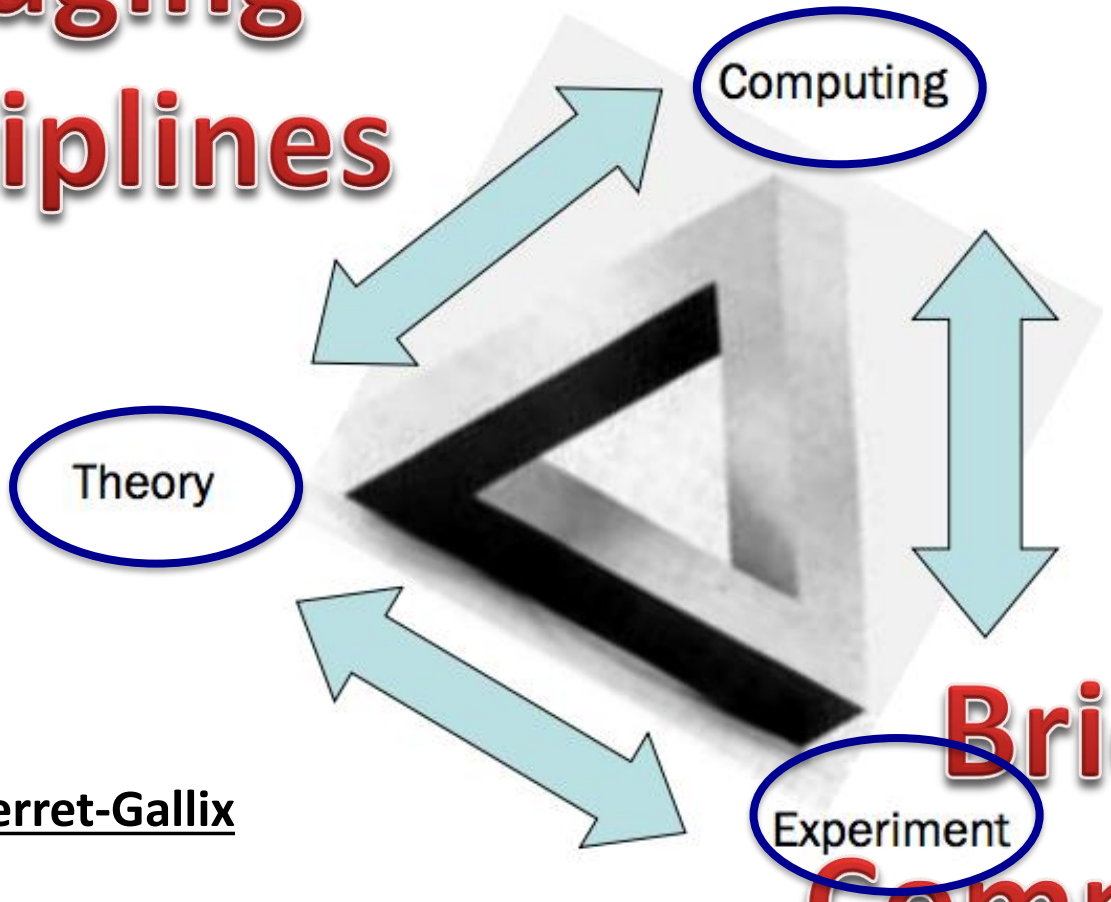
ACAT Workshop Series

- Track 1: Computing Technology for Physics Research
  - Languages, Software Quality, IDE, User interfaces
  - Distributed and Parallel Computing
  - Architecture
  - Visualization
  - Networking
  - Online Computing
- Track 2: Data Analysis – Algorithms and Tools
  - Machine Learning
  - Advanced Data Analysis environments
  - Simulation, Reconstruction and Visualization Techniques
  - Advanced Computing
- Track 3: Computations in theoretical physics – Techniques and Methods
  - Automatic Systems
  - Higher Orders
  - Computer Algebra Techniques and Applications
  - Computational Physics, Theoretical and Simulation Aspects

ACAT Workshop Series

Raison d'être

Bridging Disciplines



Bridging Communities

Denis Perret-Gallix

ACAT History

The Aztec Feather Shield

- Started in 1990 as AIHENP workshop

  Artificial Intelligence in

  High Energy and Nuclear Physics
- 1990 Lyon, France, March 19-24
- 1992 La Londe Les Maures, France, Jan. 13-18
- 1995 Pisa, Italy, April 3-8
- 1996 Lausanne, Sep. 2-6
- 1999 Heraklion, Crete, April 12-16

Some Early Pioneers of AIHENP

- Denis Perret-Gallix
- Rene Brun
- Bruce Denby (NN)
- Slava Ilyin
- Fred James
- Andrei Kataev
- Christian Kiesling (NN)

Close to the time of transition in 2000

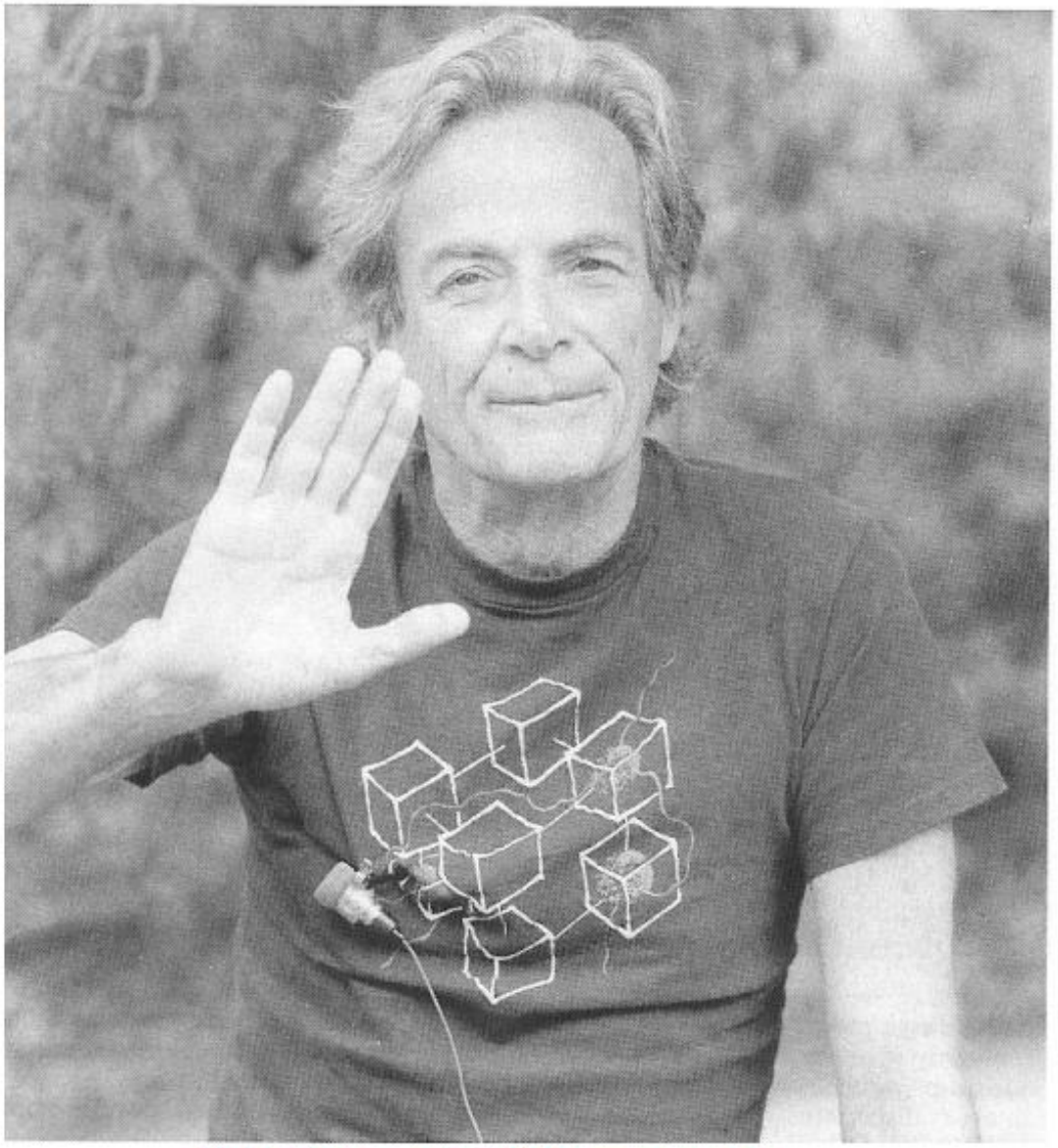
- Leif Lonnblad (NN)
- Carsten Petersen (NN)
- Jos Vermaseren
- Monique Werlen

AIHENP becomes ACAT

Richard Feynman at the Thinking Machines, Inc. (1983) The schematic representation of the Connection Machine that Feynman helped design, inspired the ACAT 2000 logo.

Feynman worked out in some detail the program for computing Hopfield's neural network on the Connection Machine

Feynman also worked on cellular automata-based programs on the connection machine



Richard Feynman

AIHENP → ACAT

VII International Workshop on Advanced Computing and Analysis Techniques in Physics Research

ACAT 2000
(Formerly AIHENP)

October 16-20, 2000

Fermi National Accelerator Laboratory

Artificial Intelligence, Innovative Software Algorithms and Tools, Symbolic Problem solving and Large Scale Computing
in High Energy Physics, Astrophysics, Accelerator Physics and Nuclear Physics

http://conferences.fnal.gov/acat2000/
Checkout videos of plenary talks

ACAT2000 Heavy-Weights

- Bjarne Stroustrup (C++)
  - Initiation of HEP/Fermilab representation on International C++ Standards Committee
- Ian Foster (Grid)
  - Impetus for Grid Partnerships
- Stephen Wolfram
- John Moody (ML)
- Alex Szalay
- Robert Ryne
  - Large scale simulations collaborations
- Rene Brun
  - Launches the effort for TMVA in ROOT

ACAT since 2000

- 2000 Fermilab, USA (Oct. 16 - 20)
- 2002 Moscow, Russia (June 24 – 28)
- 2003 KEK, Japan (Dec. 1 – 5)
- 2005 DESY, Germany (May 22 – 27)
- 2007 NIKEHF, The Netherlands (April 23 -27)
- 2008 Erice, Sicily (Nov. 3 -7)
- 2010 Jaipur, India (Feb. 22 -27)
- 2011 Uxbridge, UK (Sep. 5 – 9)
- 2013 IHEP, Beijing, China (May 16 -21)
- 2014 Prague, Czech Republic (Sep. 1 – 5)
- 2016 Valparaiso, Chile (Jan 18 – 22, 2016)

ACAT Highlights

Computational theory 1990

World Wide Web 1992

Multi-Loops 1993

Neural Nets, ROOT 1995

Parallel, distributed Computing 1996

Large scale simulation 2000

Quantum computing 2007

Many cores 2009

Cloud computing 2011

Earth and astro sciences 2013

Bridging Disciplines 2014

2016

AI Reloaded!

2017

18th edition of AIHENP-ACAT Series

ACAT 2017

- ~200 participants
- 24 Plenary talks
- 4 round table discussions
- 86 parallel session talks
- 69 posters

Highlights
of
ACAT 2017

Some Impressions

Track 1: Computing Technology for Physics Research

- Heterogeneous Architectures
  - Use of GPUs in CMS High level Trigger
  - Use of GPUs in NA62
  - Promising applications of FPGAs in lattice QCD computing
  - Software development should adapt to exploit
- Data Preservation Projects
  - INFN CNAF
  - Tevatron, LHC
- Online systems and Triggers
- Containers rising in importance
  - for software deployment
  - portability and scalability on super computers
- Tools for software builds
- Machine learning tools for fast simulations
- Fast calorimeter Simulation in ATLAS
- HEP visualization challenges in Reconstruction at the LHC/HL-LHC

Track 3:
Computations in Theoretical Physics

- New Developments in methods for symbolic calculations, loop integrals
- Loopedia: a new database for loop integrals
- Higher order radiative corrections
- Developments and optimizations of generators
- Go-HEP: A new language for concurrent programming
- Round table on Analytical vs Numerical methods for NNLO+ Computations for the LHC
- ML in theoretical physics: PDFs to MC tools
- Possible ML to accelerate Lattice QCD calculations

AI Reloaded!

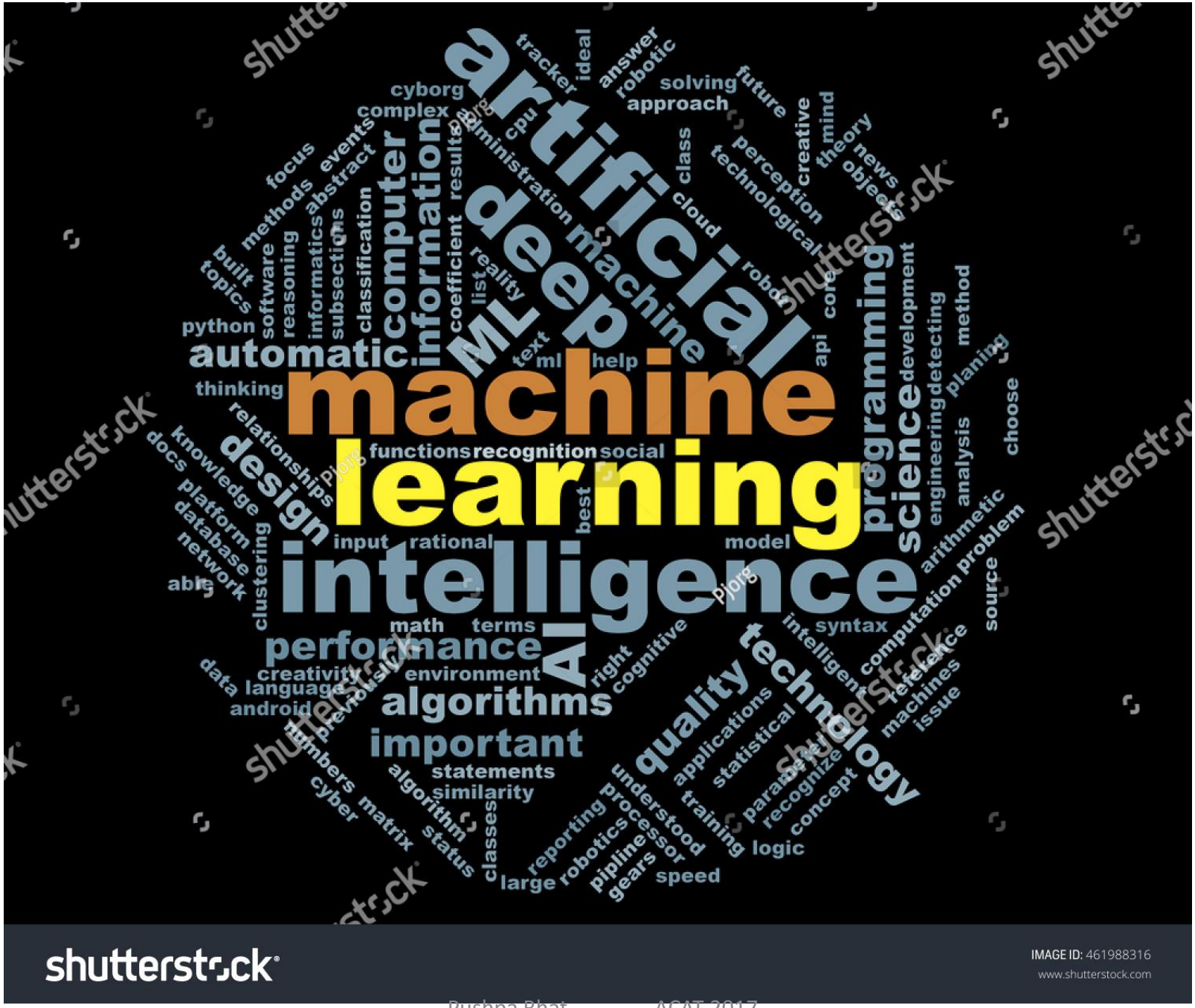
2017

18th edition of AIHENP-ACAT Series

Track-2

Data Analysis: Algorithms and Tools

- ML Algorithms
  - NN, BDT, Many flavors of DNN
- Applications
  - Triggers, tracking, Objects, ID, Signal/background simulations, Physics
  - Every aspects of data reconstruction
  - End-to-end event reconstruction
- Examples
  - NN and BDTs in triggers in Belle II, LHC
  - Pile-up mitigation at LHC
  - Event reconstruction in neutrino experiments
  - DNN for online, office tracking
  - ML in theoretical physics: pdf to MC tools in lattice QCD
  - Contributions even on Expert systems, cellular automata


artificial
machine
learning
intelligence
deep
ML
AI
automatic
computer
information
programming
science
design
performance
algorithms
important
quality
technology
machine
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Machine Learning (1)

- Paradigm for automated learning from data, using computer algorithms
- Requiring little *a priori* information about the function to be learned
- A method that can approximate a continuous non-linear function to arbitrary accuracy is called a universal approximator

Machine Learning (2)

- Over the past ~three decades, Multivariate analysis (MVA) methods have gained gradual acceptance in HEP.
  - They are now "state of the art"
- Some of the most important physics results in HEP, in the past two decades, have come from the use MVA methods.
- In 1990's, I'd have on my title slide

  "We are riding the wave of the future"
- That future is here, and MVA/ML methods are only going to grow in importance!

Machine Learning (3)

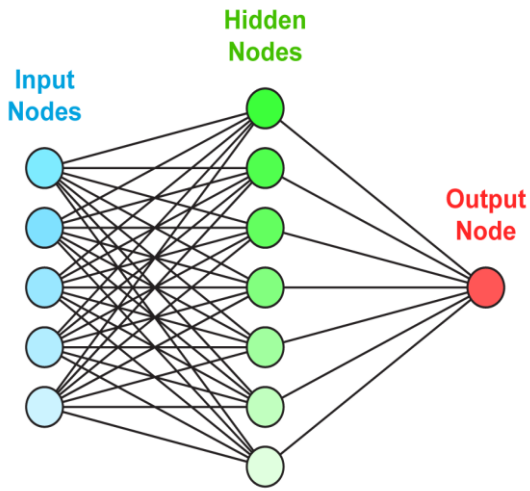
- Multivariate Analysis Methods (MVA)
  - 1990: Proponents and practitioners driven outside the mainstream
  - 1990-2000: Struggle for Acceptance by the HEP community
    - JetNet, MLPFIT,...
    - Applications at LEP, Tevatron, etc.
  - 2000: MVA/ML Getting more Accepted
  - 2010: MVA/ML becoming ubiquitous
  - 2017: Machine Learning on Steroids !? ☺

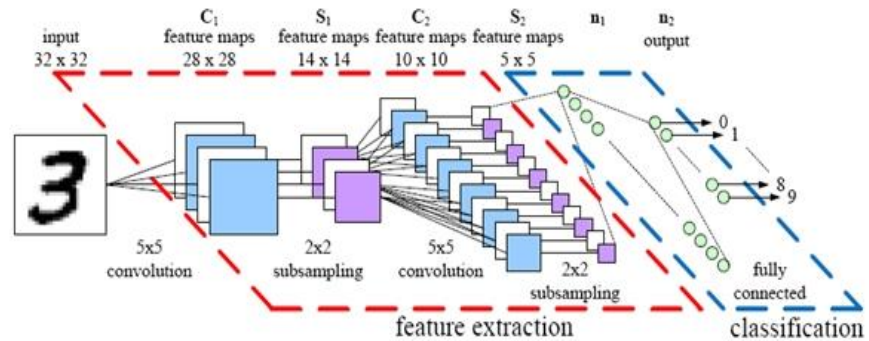
The Buzz about Deep Learning

- Multi-scale Feature Learning with multiple hidden layers
  - Each high-level layer learns increasingly higher-level features in the data
  - Pre-train initial hidden layers with unsupervised learning
- Use raw data inputs instead of derived "intelligent" variables (or use both)
  - Pre-processing or feature extraction in the DNN
- Final learning better than shallow networks, particularly when inputs are unprocessed raw variables!
- **However, need**
  - **a lot of processing power (implement in GPUs)**
  - **A lot of training data**
    - We have lots of data, lots of MC (but never enough), can also generate "limitless" data by small perturbations of generated data

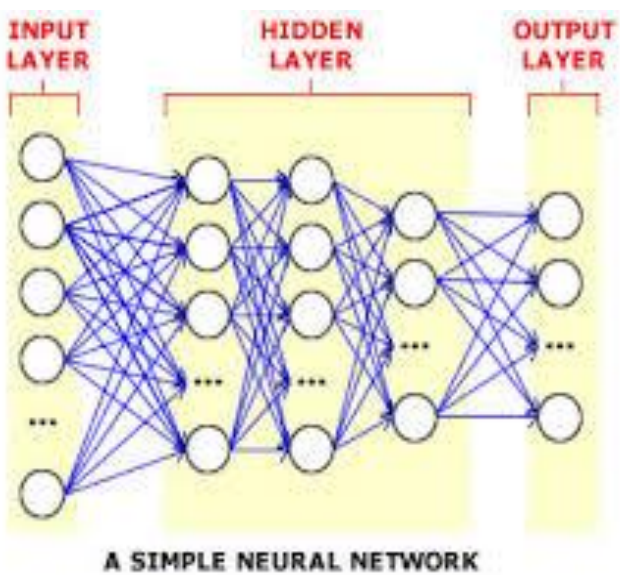
Deep Learning

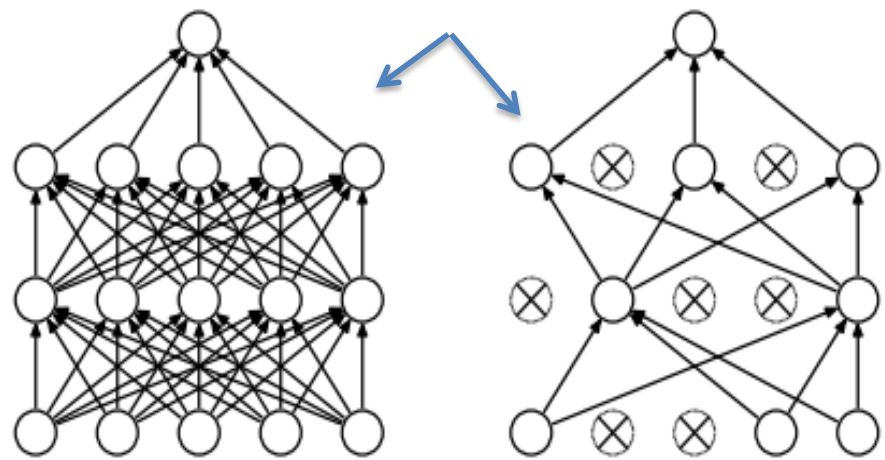
Single hidden layer NN





"Dropout" algorithm
to avoid overfitting (pruning)





(a) Standard Neural Net (b) After applying dropout.

Multiple hidden layer NN

Deep Learning and all that Jazz

Many flavors of DNN

- Deep FF FC neural networks
- Convolutional
- Recurrent
- Adversarial

Many Applications:

- Object ID
- Signal/background discrimination
- Regression
- Fast simulation
- End-to-end reconstruction

The resources required may not justify use in every case

THE CYBERSCIENTIST

Artificial intelligence isn't just a tool. In some labs, it conceives and carries out experiments—and then interprets the results

AI IN ACTION

AI's early proving ground: the hunt for new particles

Particle physicists began fiddling with artificial intelligence (AI) in the late 1980s, just as the term "neural network" captured the public's imagination. Their field lends itself to AI and machine-learning algorithms because nearly every experiment centers on finding subtle spatial patterns in the countless, similar readouts of complex particle detectors—just the sort of thing at which AI excels. "It took us several years to convince people that this is not just some magic, hocus-pocus, black box stuff," says Boaz Klima, of Fermi National Accelerator Laboratory (Fermilab) in Batavia, Illinois, one of the first physicists to embrace the techniques. Now, AI techniques number among physicists' standard tools.

Particle physicists strive to understand the inner workings of the universe by smashing subatomic particles together with enormous energies to blast out exotic new bits of matter. In 2012, for example, teams working with the world's largest proton collider, the Large Hadron Collider (LHC) in Switzerland, discovered the long-predicted Higgs boson, the fleeting particle that is the linchpin to physicists' explanation of how all other fundamental particles get their mass.

Such exotic particles don't come with labels, however. At the LHC, a Higgs boson emerges from roughly one out of every 1 billion proton collisions, and within a billionth of a picosecond it decays into other particles, such as a pair of photons or a quartet of particles called muons. To "reconstruct" the Higgs, physicists must spot all those more-common particles and see whether they fit together in a way that's consistent with them coming from the same parent—a job made far harder by the hordes of extraneous particles in a typical collision.

Algorithms such as neural networks excel in sifting signal from background, says Pushpalatha Bhat, a physicist at Fermilab. In a particle detector—usually a huge barrel-shaped assemblage of various sensors—a photon typically creates a spray of particles or "shower" in a subsystem called an electromagnetic calorimeter. So do electrons and particles called hadrons, but their showers differ subtly from those of photons. Machine-learning algorithms can tell the difference by sniffing out correlations among the multiple variables that describe the showers. Such algorithms can also, for example, help distinguish the pairs of photons that originate from a Higgs decay from random pairs. "This is the proverbial needle-in-the-haystack problem," Bhat says. "That's why it's so important to extract the most information we can from the data."

Neural networks search for fingerprints of new particles in the debris of collisions at the LHC.

Machine learning hasn't taken over the field. Physicists still rely mainly on their understanding of the underlying physics to figure out how to search data for signs of new particles and phenomena. But AI is likely to become more important, says Paolo Calafiura, a computer scientist at Lawrence Berkeley National Laboratory in Berkeley, California. In 2024, researchers plan to upgrade the LHC to increase its collision rate by a factor of 10. At that point, Calafiura says, machine learning will be vital for keeping up with the torrent of data. —Adrian Cho

Prospects are great!
Stakes are high!

- Until the Standard Model was incomplete, discoveries were (sort of) guaranteed.
- Now there are no more such guarantees!
- The stakes are very high as we try to discover new fundamental and profound principles of nature and, therefore, the bar for discoveries ought to be very high!
- ML community has a serious responsibility!

Some Impressions

- Amazing, diverse array of topics/applications
- Excellent presentations and posters
- 13 collaborations represented
- Great to see many new faces, and especially lots of passionate, talented young people!
- ACAT 2017 provided a very friendly atmosphere for a productive meeting, lots of food, and food for thought, and inspiration for action!

Possible Special Tracks/Topics for Future ACATs

- Accelerator Physics
  - Simulations
  - ML in accelerator controls
- Astrophysics
  - Already many ML applications
- Statistics
- Other Disciplines

Future Prospects

Lots of challenges

And

Exciting prospects for Awesome Discoveries

Develop the tools & skills to unravel the mysteries of the universe!

Big Thanks to

- Scientific Program Committee
  - Federico Carminati (Chair)

  and Track Coordinators (+ IAC)

- Track Coordinators

Track 1	Niko Neufeld (Chair), Graeme Stewart, Mira Girone, Shih-Chieh Hsu
Track 2	Sergei Gleyzer (Chair), Gregory Golovanov, Andy Haas, Toby Burnett
Track 3	Ayres Freitas, Stephen Jones, Fukuko Yuasa

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Huge Thanks to

- Local Organizers
  - Gordon Watts (Chair)
  - Shih-Chieh Hsu (Co-chair)

  and team

for a great, fantastic conference!

- All speakers and Participants