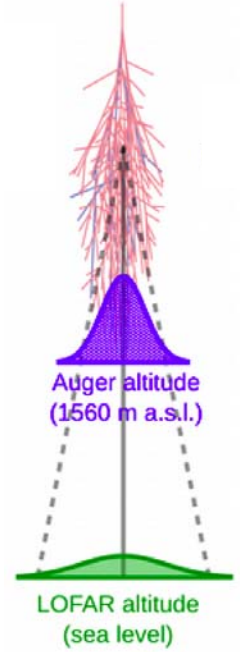
Advances in Detection Techniques

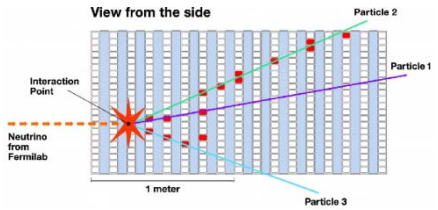
Instrumentation - Calibration - Monitoring

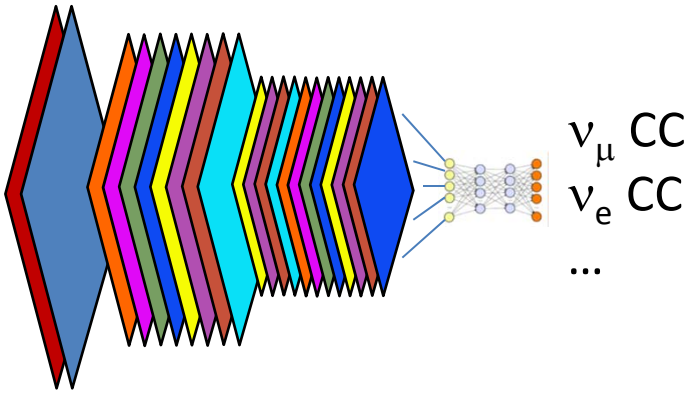


Cosmic ray 1 EeV

MHz: 15.8 MeV

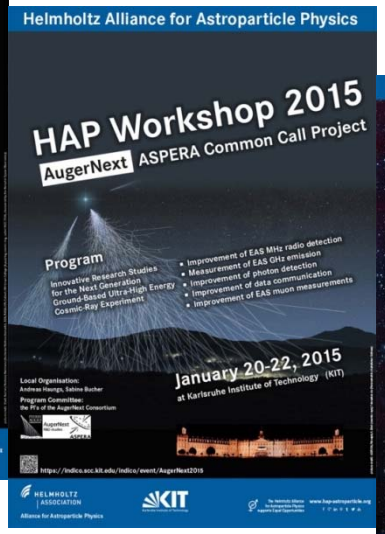
Deep Learning

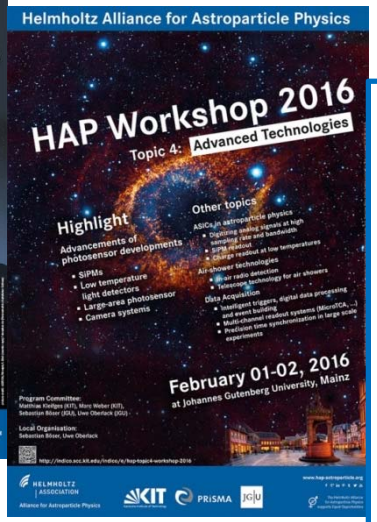




Martin Erdmann, RWTH Aachen University, 21-Sep-2016

HAP Technology Workshops!





2013 2014 2015 2016 2017

This Workshop

Robert LAHMANN 17:00 - 17:15	**Acoustics**
Thomas BRETZ 17:15 - 17:30	**SiPMs in Astroparticle Physics**
Christine PETERS 17:30 - 17:45	**SiPM FAMOUS & AMD**
Martin TLUCZYKONT 17:45 - 18:00	**HiScore**
Peter PEIFFER 18:00 - 18:20	**New Optical Sensors for IceCube-Gen2**
Tim HUEGE 12:00 - 12:15	**AERA**
Frank SCHRÖDER 12:15 - 12:30	**Radio detection of air showers with Tunka-Rex**
Radomir SMIDA 14:00 - 14:15	**Microwave signal of air showers measured with the CROME experiment**
Samridha KUNWAR 14:15 - 14:30	**Status and recent developments with TAXI**
Max RENSCHLER 14:30 - 14:45	**SiPM for Space Application**
Daniela DORNER 14:45 - 15:05	**FACT & M@TE - Monitoring at TeV Energies**
Andreas HAUNGS 11:10 - 11:35	**Technological Challenges next 5 years....**

Acoustics (kHz)

(Silicon-) Photomultipliers

Air Cherenkov (non-)imaging

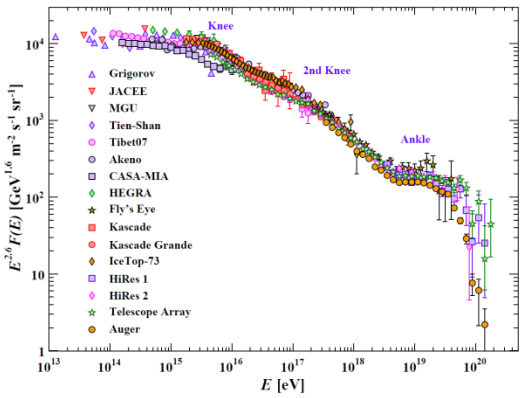
Radio (MHz, GHz)

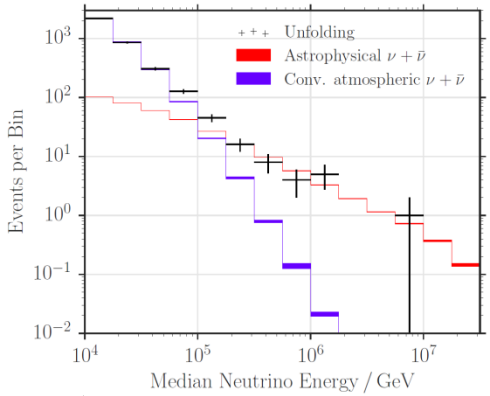
R&D System (TAXI)

INSTRUMENTATION
CALIBRATION
MONITORING

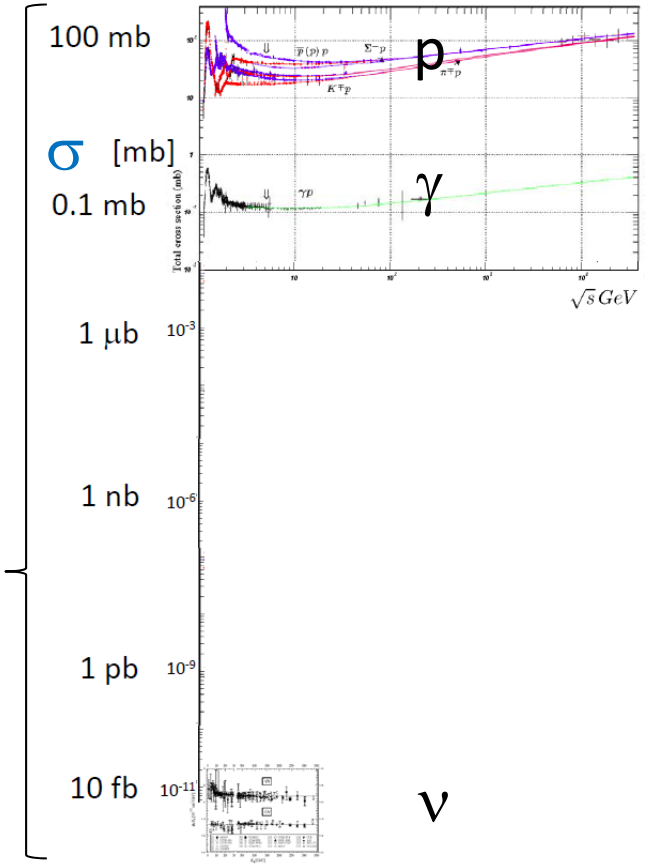
Cosmic messenger detection challenge

flux of cosmic messengers



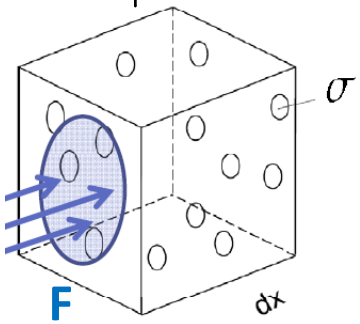


cross section



measured event rate

$$\dot{N} = \frac{\dot{N}_{cosmic}}{F} \cdot n_{target\ density} \cdot (F\,dx)_{target} \cdot \sigma$$

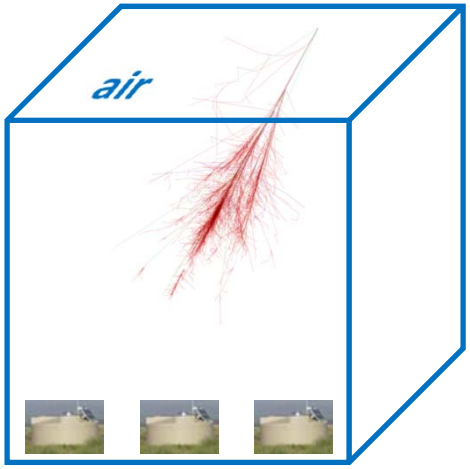


Natural giant target volumes

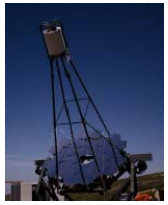
Natural giant target instrumentation

nuclei, photons

Cherenkov
Fluorescence
Radio

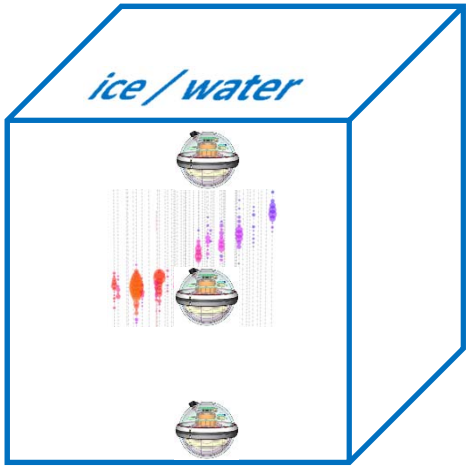


Particle




neutrinos

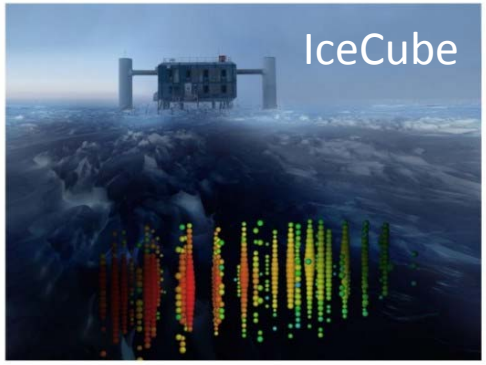
Cherenkov
Acoustics
Radio

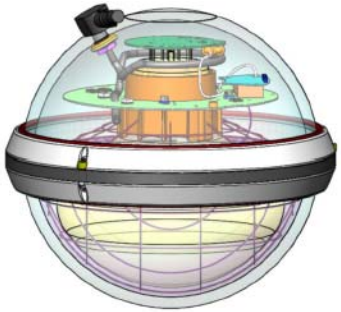


Instrumentation ! Monitoring ! Calibration !

Instrumentation

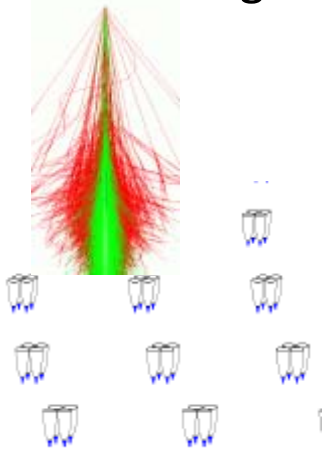
Cherenkov light in ice





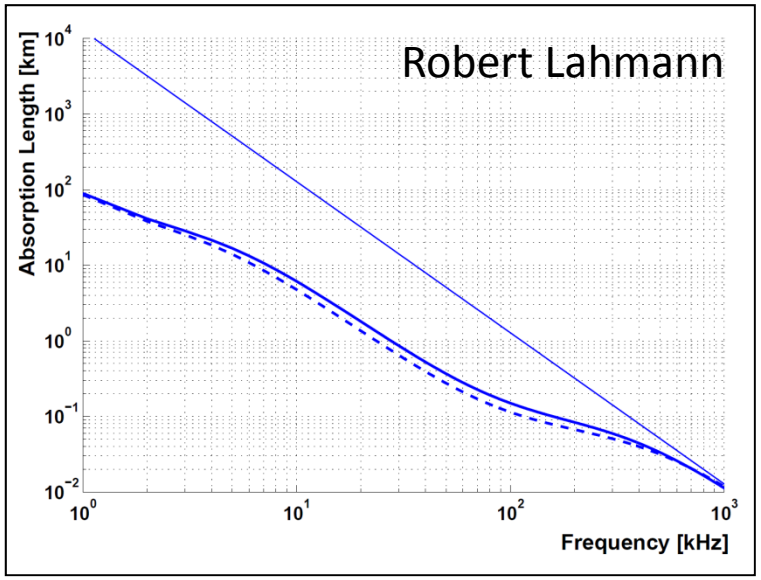
Peter Peiffer

Cherenkov light in air



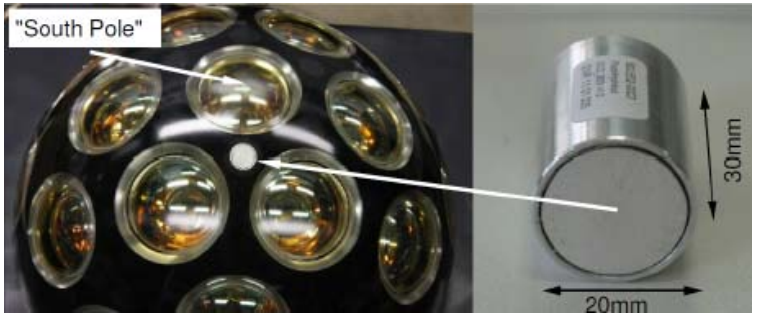
Martin Tluczykont
HiScore

Thermo-acoustic effect

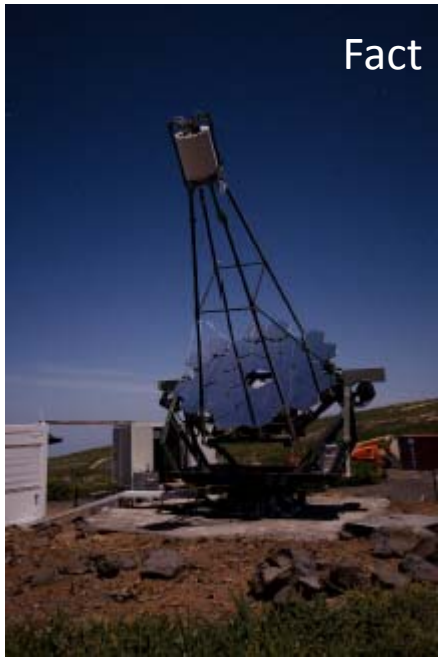


KM3NeT

piezo sensor

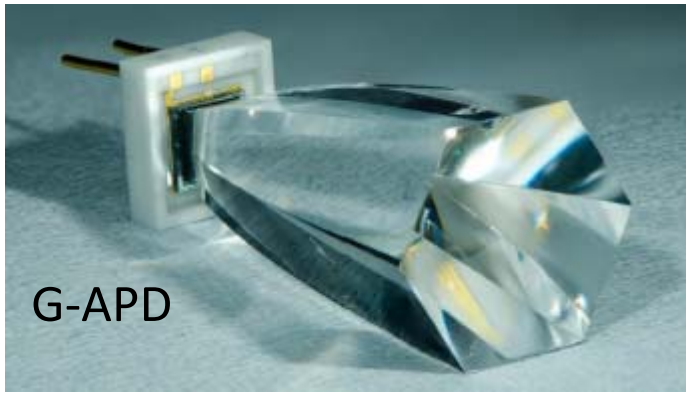


Instrumentation & Monitoring



TAXI

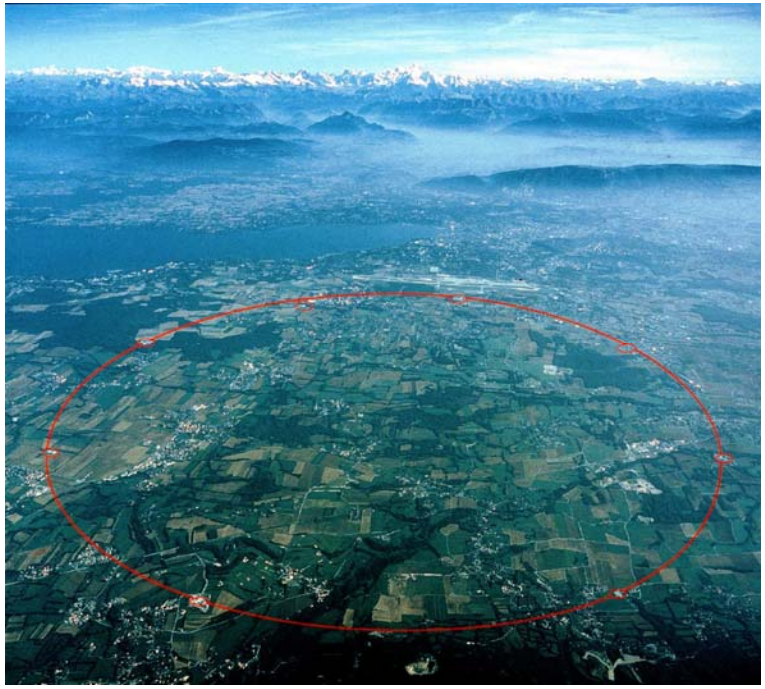
Samridha Kunwar

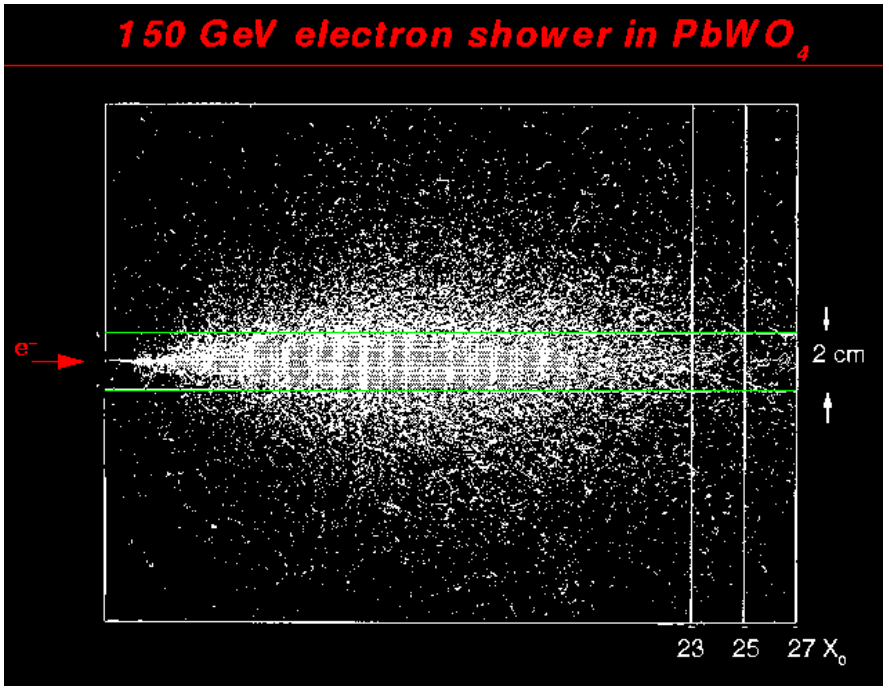


Photomultipliers and Silicon Photomultipliers: a race for most efficient photon detection

Thomas Bretz, Daniela Dorner, Christine Peters, Max Renschler

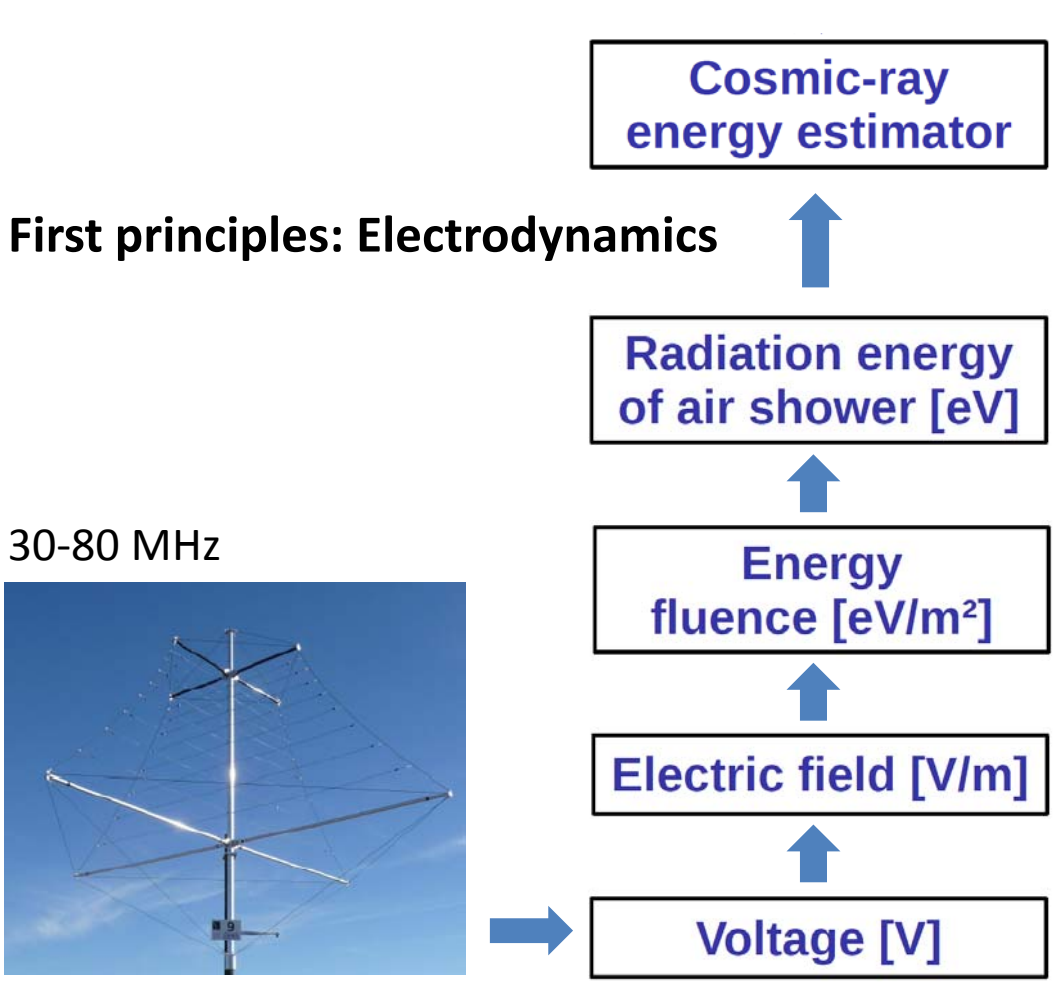
Calibration: usually by test beam

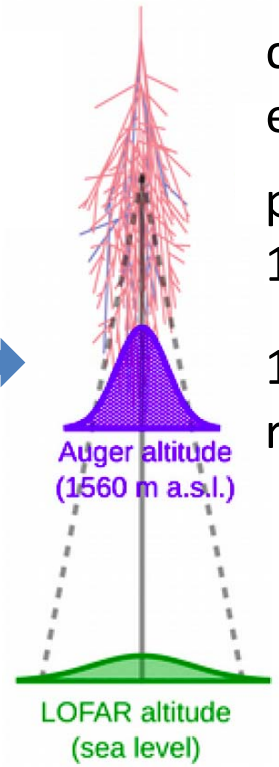




…but for EeV energies?

Energy Calibration: by radiation energy





cosmic ray energy 1 EeV

perspective 10-15% error

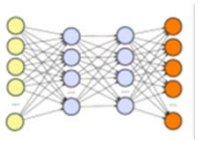
15.8 MeV radiation energy

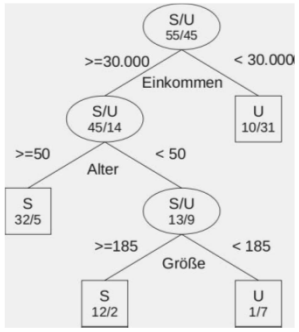
Radio: Tim Huege, Radomir Smida, Frank Schröder

DEEP LEARNING

Deep Learning

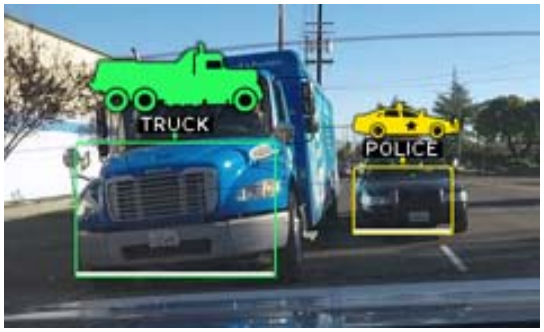
Since 1990s: Neural Networks, Boosted Decision Tree, etc.





- Signal / Noise
- Particle identification

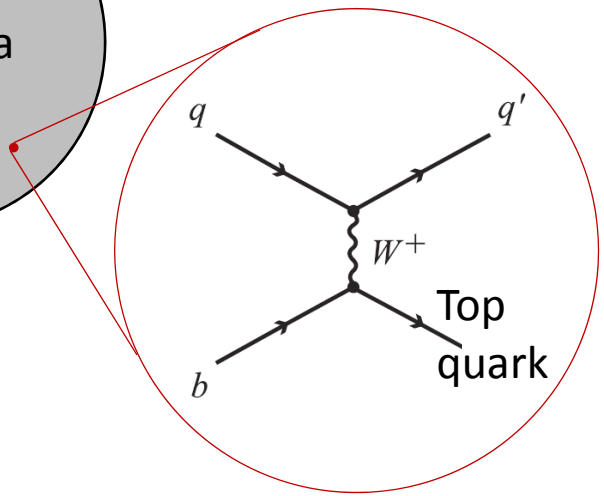
Since 2006: Deep Learning



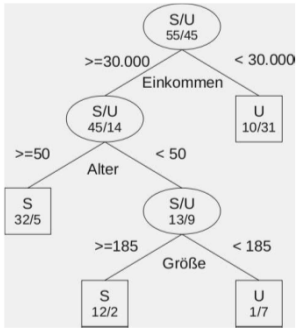
- Speech recognition
- Image recognition
- Pattern recognition
- Anomaly detection
- Ambiguity solving
- Multi-Classification
- Autoclassification (unsupervised learning)
- …

Multivariate Analysis Methods (MVA)

2010
CMS Data
36 pb^{-1}

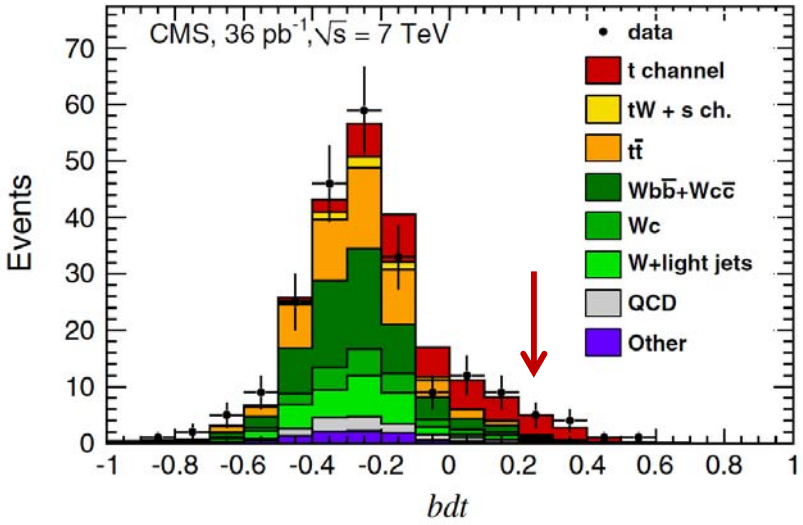


Boosted
Decision
Trees



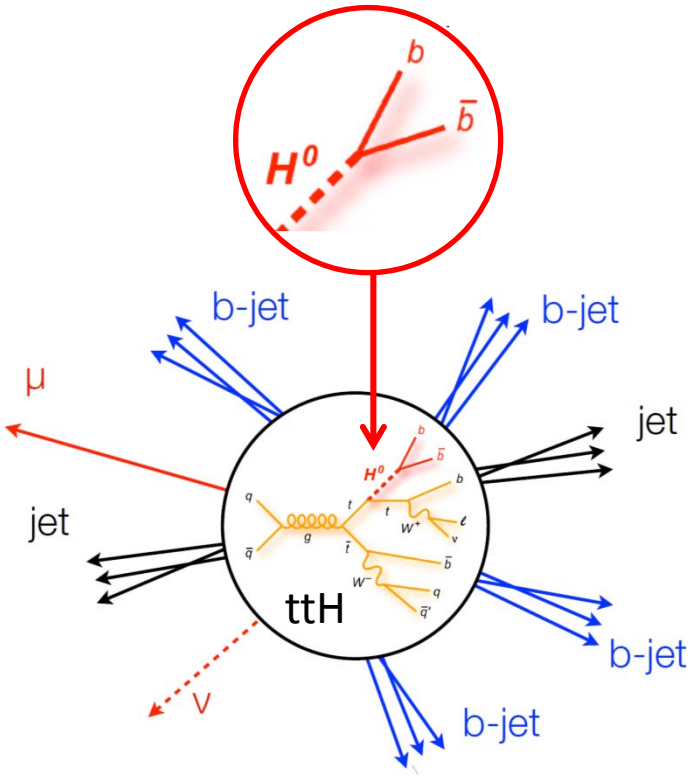
Dennis Klingebiel Aachen PhD student

PRL **107,** 091802 (2011)



First measurement at LHC !
with only 1/30 of the luminosity
compared to initial estimates

Ambiguity solving: Higgs→bb



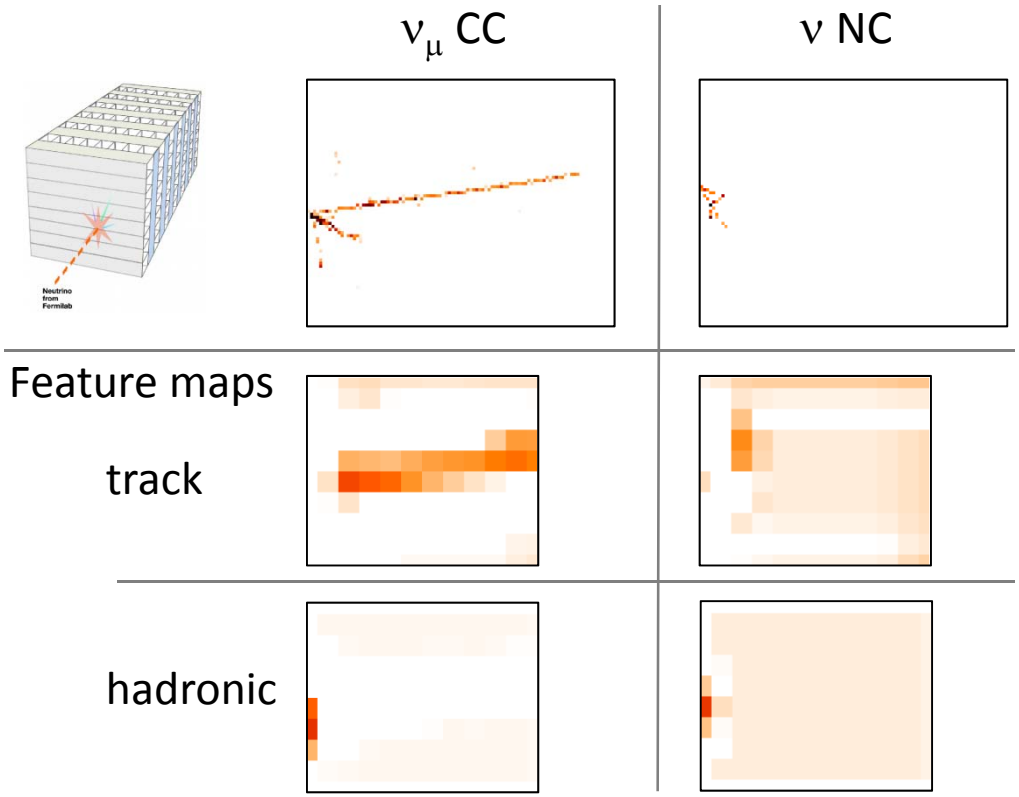
Benjamin Fischer Aachen Bachelor student, 2015

Method	Higgs finding efficiency
Boosted decision tree	35%
Deep learning neural network	52%

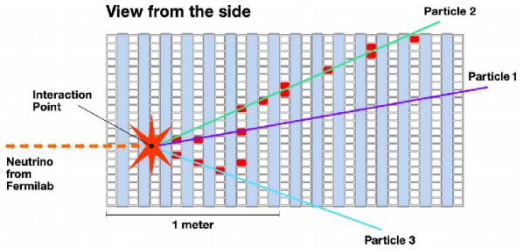
Deep learning solved ambiguities better by 50% !
exploiting „high level“ observables (physicists ideas)
plus „low level“ observables (e.g. particle px, py, pz)

A. Aurisano et al, publ. 1-Sep-16: 2016 JINST 11 P09001

A convolutional neural network neutrino event classifier



NOvA neutrino oscillations

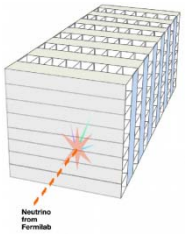


Method	ν_e **efficiency** (same purity)
Physicists algorithm	**35%**
Deep learning neural network	**49%**

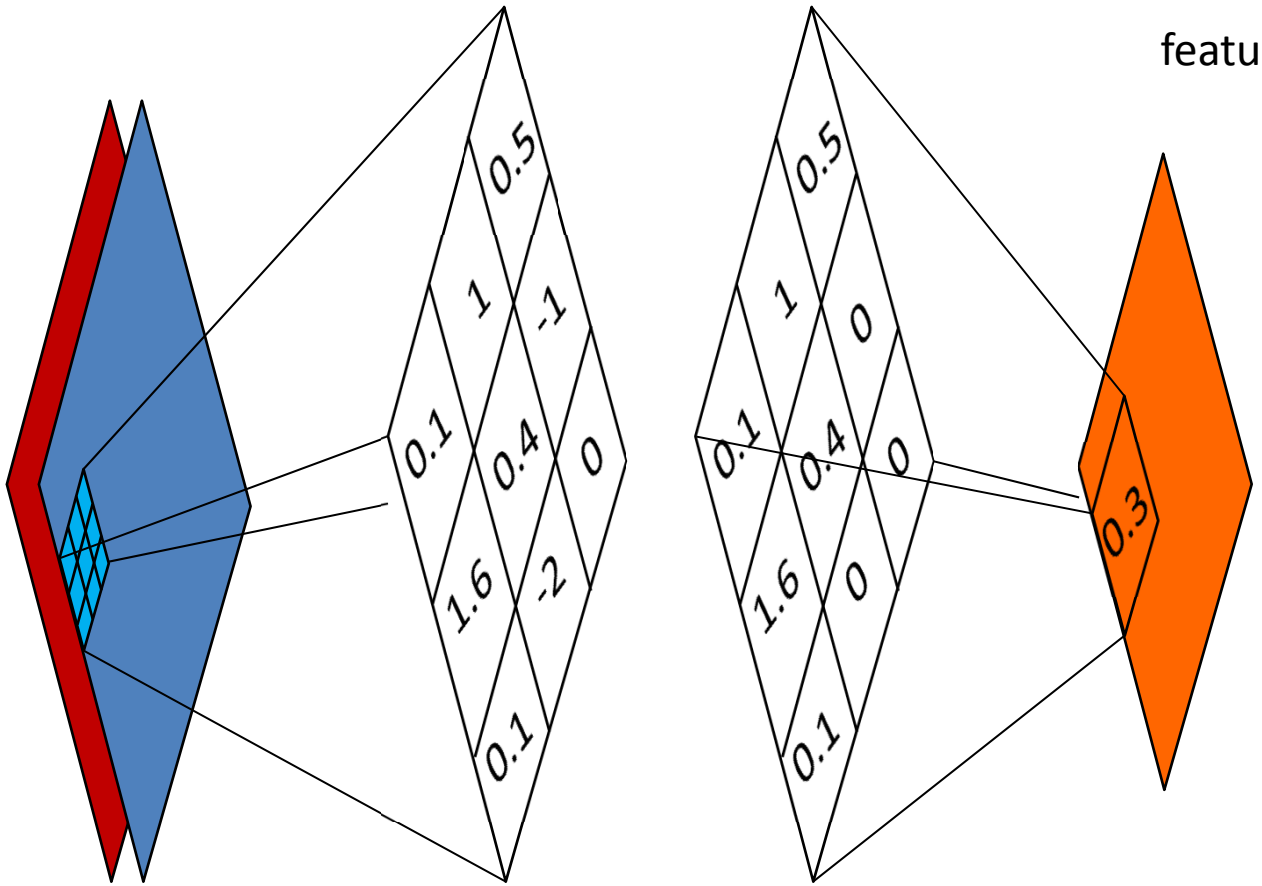
Convolutional Neural Networks

y=ax+b ➡ z=max(0,y) ➡ < z >

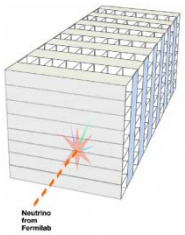
input image
(2 projections)



feature map



Convolutional Neural Networks



input image

feature maps

classification

$\max(p_i)$

$\Sigma p_i = 1$

ν_μ CC

ν_e CC

…

ν NC

Deep Learning in Astroparticle Physics

Physicist supported by deep learning techniques
to maximally exploit experimental data

Common instruments & knowledge

- Projects benefiting from deep learning
- Data assessment for deep learning
- Deep Learning network design
- Performance & diagnostic tools
- Optimization strategies

Data characteristics

Astroparticle physics

„Standard“

Data & Goals

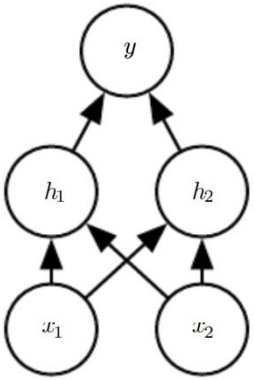
Dimension	Single channel	Multi-channel
1 D	Audio waveform	Skeleton animation data
2 D	Audio data (Fourier transformed)	Color image data
3 D	Volumetric data (e.g. medical imaging)	Color video data

„Deep Learning“ I. Goodfellow, Y. Bengio, A. Courville, MIT Press in press
http://www.deeplearningbook.org/

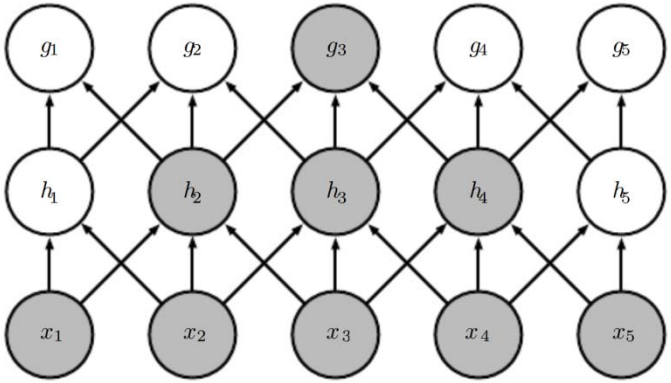
New data classifications ?

Neural Network Architectures

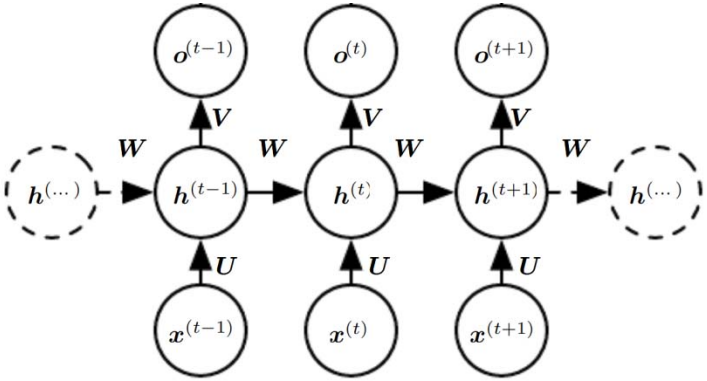
Feed forward



Convolutional

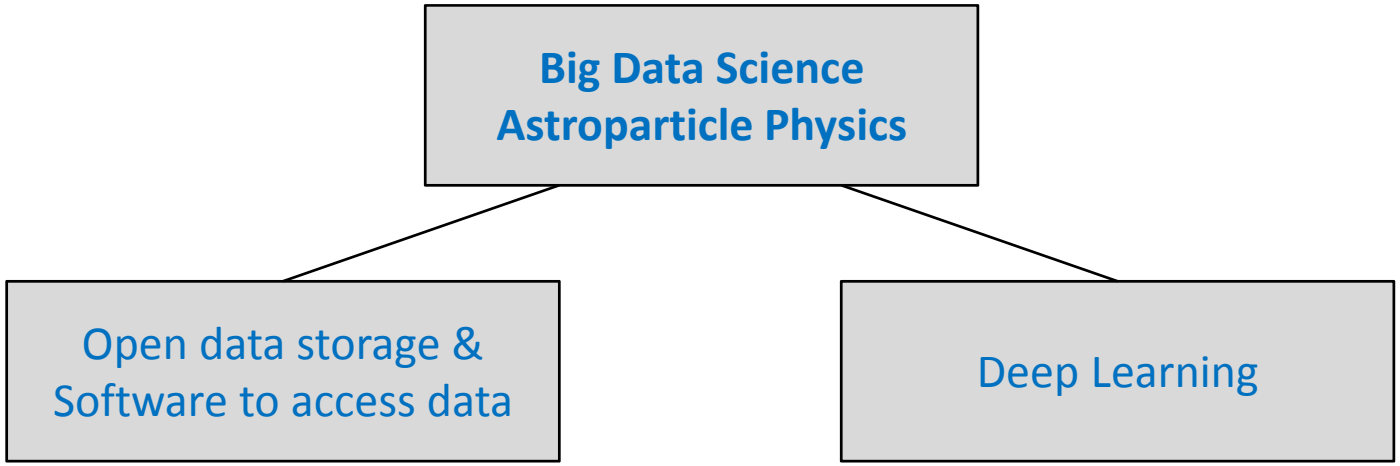


Recurrent



many variants & combinations can be inherited from deep learning research

HAP Workshop 2/2017



HAP workshop on
Big Data Science in Astroparticle Physics
Feb 2017

@ RWTH AACHEN UNIVERSITY

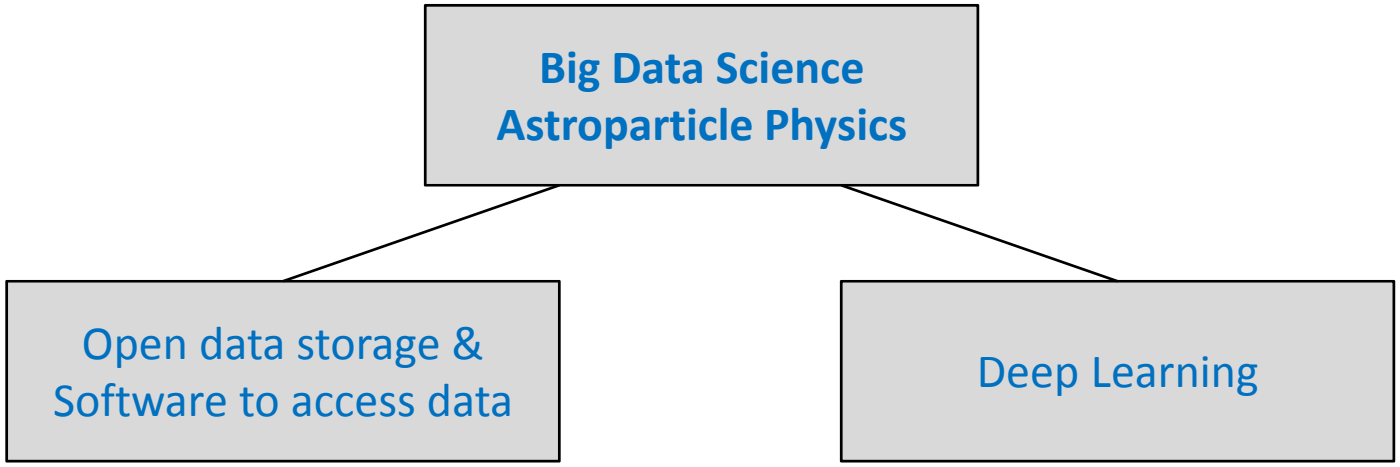
Martin Erdmann, Andreas Haungs

Big Data Science: Astroparticle Physics

Digitale Agenda

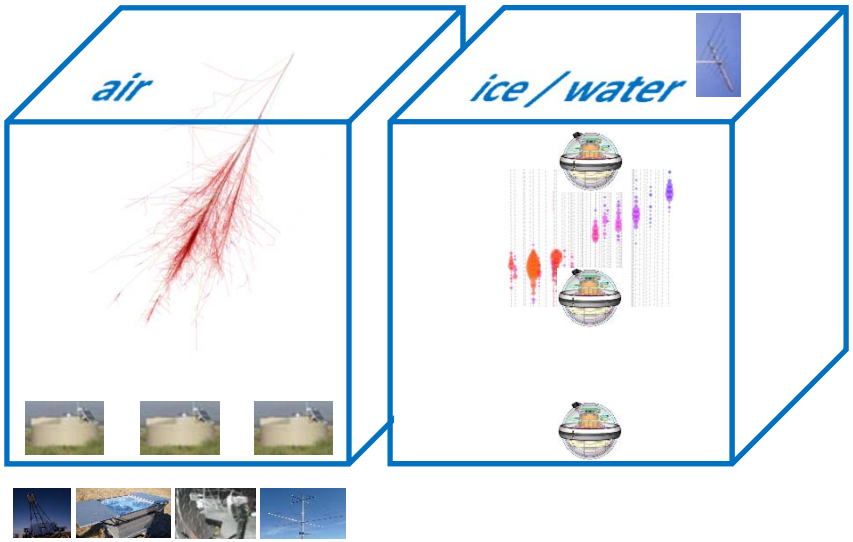
Bundesministerium für Bildung und Forschung

1. Digitalen Wandel in der Wissenschaft forcieren
2. Zugang zu Wissen als Grundlage für Innovation sichern
3. Bildungsoffensive für die digitale Wissensgesellschaft
4. Innovationspotenziale der Digitalisierung nutzen
5. Durch Forschung den digitalen Wandel verstehen
6. Kultur und Medien



Summary

Exciting progress:
instrumentation + calibration + monitoring of natural giant target volumes



Action item:
deep learning becoming central to exploiting astroparticle measurements