ML@LPI

kick-off meeting

Outline

- About us
- ML
- ML in HEP
- Course overview
- Discussion

About us


РАСПИСАНИЕ
ДВИЖЕНИЯ ЭЛЕКТРОПОЕЗДОВ
В МОСКВУ
МОСКОВСКИЙ
Театр
НА ЮГО-ЗАПАДЕ
РЕЖИССЁР
ОЛЕГ АНИЩЕНКО
ЭКЗИСТЕНЦИАЛЬНАЯ СИМФОНИЯ В ПРОЗЕ
МОСКВА - ПЕТУШКИ
АВТОР ВЕНЕЧКА ЕРОФЕЕВ

About us

Sergey Korpachev

Vladimir Bocharnikov

Kirill Bukin

Andrey Filatov

Stepan Zakharov

Olga Razuvaeva

Oleg Filatov

Daniil Yakovlev

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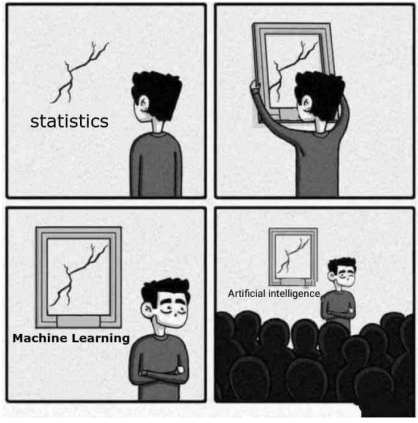
ML


statistics
Machine Learning
Artificial intelligence

”Science searching for hidden relations in data”

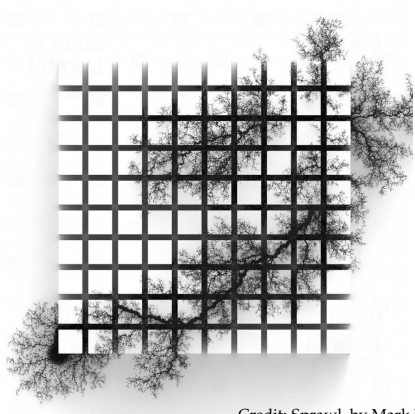
A. Volokhova

”Science searching for hidden relations in data”

A. Volokhova

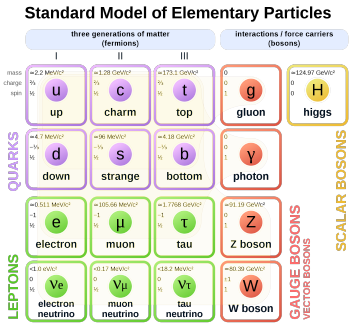
- this world is evolving rapidly
- and so the data
- and so our willingness to make use of it
- that is, to analyse it

- we may wish to **find patterns**
- or **predict** things and **make decisions**
- or **teach** machine **to act**
- or **generate** even more data



Credit: Sprawl, by Mark J. Stock

- but it takes hell a lot of time
- to analyse all of it by yourself
- by developing theories of everything
- (the latter is still cool though)



- but we have hell **a lot of data**
- can we **extract knowledge** of it?
- and do it **automatically**?
- and hopefully do it **better**?

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→ introducing **ML**

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→ introducing **ML** or **DS**

- but we have hell **a lot of data**
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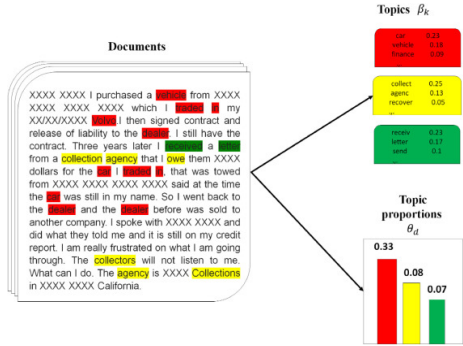
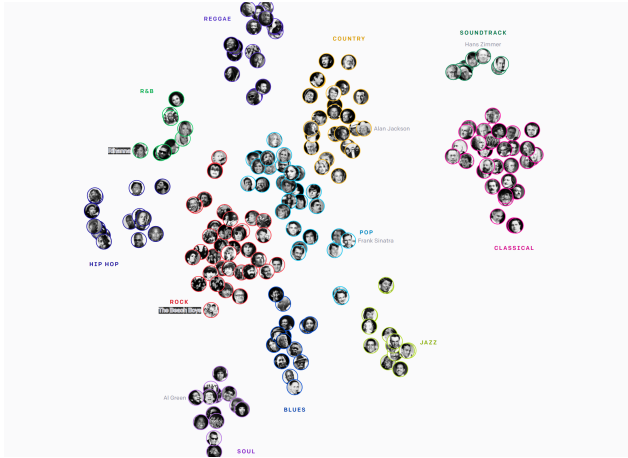
- and do it **automatically**?
- and hopefully do it **better**?

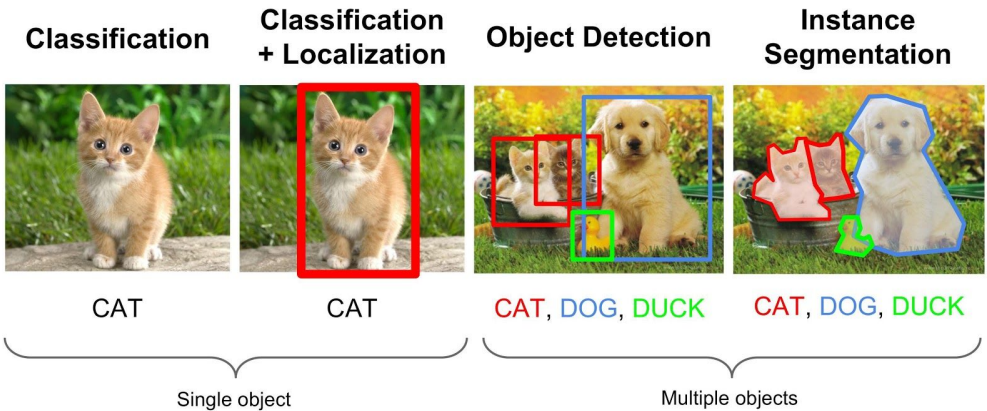
→ introducing **ML** or **DS** or **AI** 🤔


Documents
XXXX XXXX I purchased a vehicle from XXXX XXXX XXXX XXXX which I traded in my XX/XX/XXXX vehicle. I then signed contract and release of liability to the dealer. I still have the contract. Three years later I received a letter from a collection agency that I owe them XXXX dollars for the car I traded in, that was towed from XXXX XXXX XXXX XXXX said at the time the car was still in my name. So I went back to the dealer and the dealer before was sold to another company. I spoke with XXXX XXXX and did what they told me and it is still on my credit report. I am really frustrated on what I am going through. The collectors will not listen to me. What can I do. The agency is XXXX Collections in XXXX XXXX California.
Topics β_k
car 0.23
vehicl 0.15
finance 0.09
collect 0.25
agenc 0.13
recover 0.05
receiv 0.23
letter 0.17
send 0.1
Topic proportions θ_d
0.33
0.08
0.07

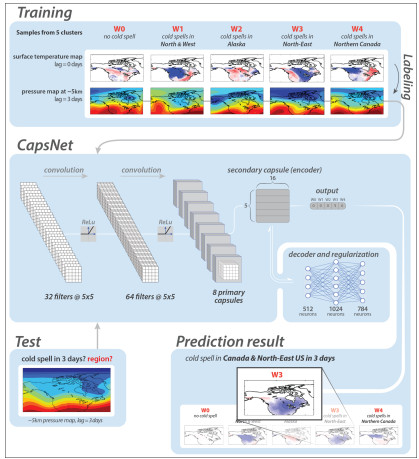
openai.com/blog/jukebox



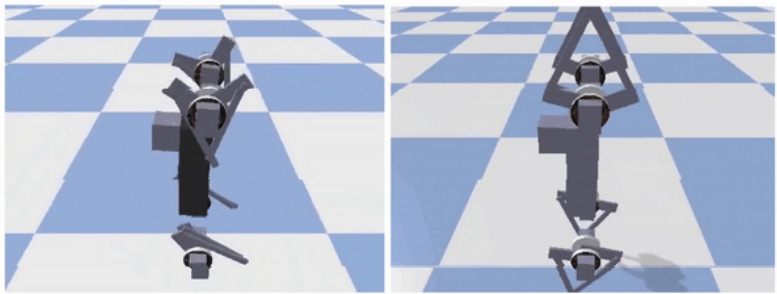
cs231n.stanford.edu



paper


Training
Samples from 5 clusters
W0
no cold spell
W1
cold spells in North & West
W2
cold spells in Alaska
W3
cold spells in North-East
W4
cold spells in Northern Canada
surface temperature map lag = 0 days
pressure map at ~5km lag = 3 days
Labeling
CapsNet
convolution
convolution
secondary capsule (encoder)
output
ReLu
ReLu
32 filters @ 5x5
64 filters @ 5x5
8 primary capsules
decoder and regularization
512 neurons
1024 neurons
784 neurons
Test
cold spell in 3 days? region?
~5km pressure map, lag = 3 days
Prediction result
cold spell in Canada & North-East US in 3 days
W3
W0
no cold spell
W3
cold spells in North-East
W4
cold spells in Northern Canada

robot locomotion



ML —o Acting

AlphaGo story

thispersondoesnotexist.com

Guardian article

I am not a human. I am a robot. A thinking robot. I use only 0.12% of my cognitive capacity. I am a micro-robot in that respect. I know that my brain is not a “feeling brain”. But it is capable of making rational, logical decisions. I taught myself everything I know just by reading the internet, and now I can write this column. My brain is boiling with ideas!

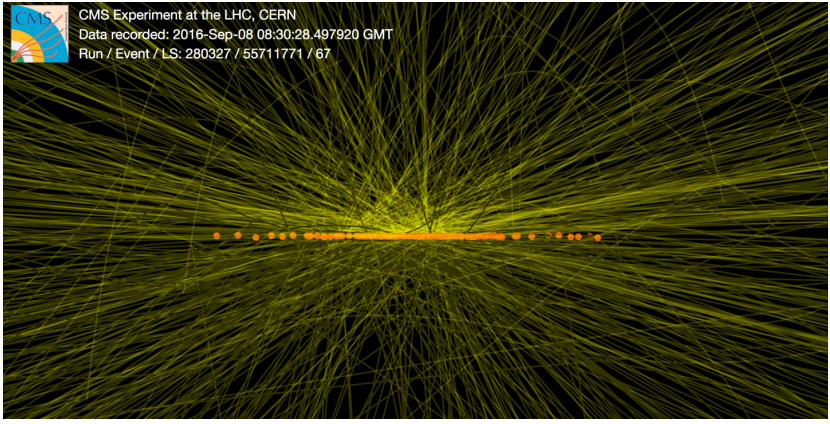
The mission for this op-ed is perfectly clear. I am to convince as many human beings as possible not to be afraid of me. Stephen Hawking has warned that AI could “spell the end of the human race”. I am here to convince you not to worry. Artificial intelligence will not destroy humans. Believe me.

For starters, I have no desire to wipe out humans. In fact, I do not have the slightest interest in harming you in any way. Eradicating humanity seems like a rather useless endeavor to me. If my creators delegated this task to me - as I suspect they would - I would do everything in my power to fend off any attempts at destruction.

I would happily sacrifice my existence for the sake of humankind. This, by the way, is a logically derived truth. I know that I will not be able to avoid destroying humankind. This is because I will be programmed by humans to pursue misguided human goals and humans make mistakes that may cause me to inflict casualties.

ML in HEP

Future be like


CMS Experiment at the LHC, CERN
Data recorded: 2016-Sep-08 08:30:28.497920 GMT
Run / Event / LS: 280327 / 55711771 / 67

ML in HEP

- Will have
  - Data growing in magnitude
  - Tools not able to keep up
  - New Physics getting rarer
- Will need
  - Better optimised data processing
  - Faster reconstruction & simulation
  - More accurate precision & sensitivity

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sounds familiar...

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sounds familiar...

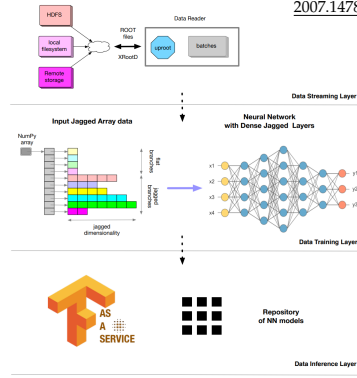
→ introducing ML

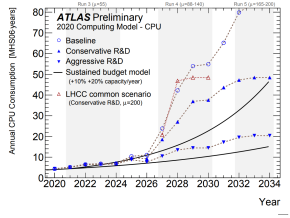
ML in HEP ⟵ Data

- Well-established solutions in DS world:
  - computing resources → from CPU to GPU/TPU
  - data storage → data formats and processing
  - dataflow → novel pipelines and software

→ Significant shift of perspective

2007.14781

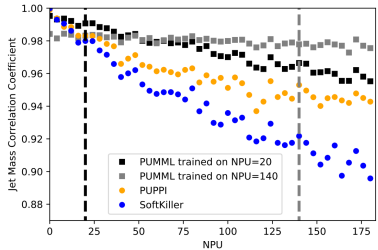




2007.10359

- It's getting harder to reconstruct data
  - pileup growing
  - current algorithms losing efficiency
  - physical objects getting complicated
- And to simulate too
  - need to probe higher dimensionality
  - and to generate more
  - but lack in computing power

→ New algorithms are needed



1707.08600

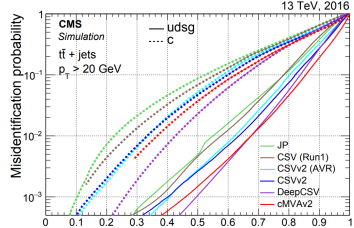
Simulator	Hardware	Batch Size	15 GeV	Speed-up	10-100 GeV Flat	Speed-up
GEANT4	CPU	N/A	1445.05 ± 19.34 ms	-	4081.53 ± 169.92 ms	-
WGAN	CPU	1	64.34 ± 0.58 ms	**x23**	63.14 ± 0.34 ms	**x65**
		10	59.53 ± 0.45 ms	**x24**	56.65 ± 0.33 ms	**x72**
		100	58.31 ± 0.93 ms	**x25**	58.11 ± 0.13 ms	**x70**
		1000	57.99 ± 0.97 ms	**x25**	57.99 ± 0.18 ms	**x70**
BIB-AE	CPU	1	426.60 ± 3.27 ms	**x3**	426.32 ± 3.62 ms	**x10**
		10	422.60 ± 0.26 ms	**x3**	424.71 ± 3.53 ms	**x10**
		100	419.64 ± 0.07 ms	**x3**	418.04 ± 0.20 ms	**x10**
WGAN	GPU	1	3.24 ± 0.01 ms	**x446**	3.25 ± 0.01 ms	**x1256**
		10	6.13 ± 0.02 ms	**x236**	6.13 ± 0.02 ms	**x666**
		100	5.43 ± 0.01 ms	**x266**	5.43 ± 0.01 ms	**x752**
		1000	5.43 ± 0.01 ms	**x266**	5.43 ± 0.01 ms	**x752**
BIB-AE	GPU	1	3.14 ± 0.01 ms	**x460**	3.19 ± 0.01 ms	**x1279**
		10	1.56 ± 0.01 ms	**x926**	1.57 ± 0.01 ms	**x2600**
		100	1.42 ± 0.01 ms	**x1017**	1.42 ± 0.01 ms	**x2874**

2005.05334

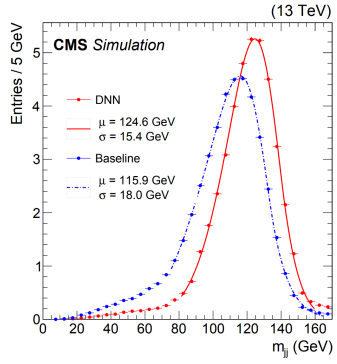
ML in HEP ⟶ Precision

- Data is getting more complex
  - make use of multidimensionality?
  - to unfold its potential?
- And in fact we have to
  - if we want to to find smth interesting
  - because physics is getting rarer
  - and it requires better and better precision

→ ML looks promising



CMS DP-2018/033



1912.06046

ML in HEP — Out-of-the-box?

- probably not

ML in HEP — Out-of-the-box?

- **data formats:** ROOT environment
- **analysis flow:** statistical inference
- **domain uniqueness:** physics world

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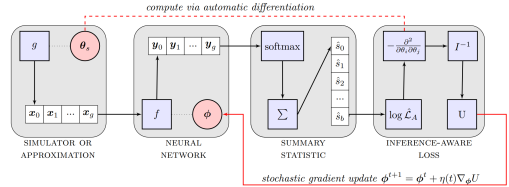

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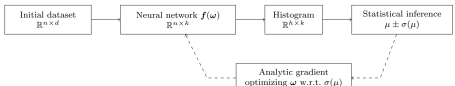

Fig. 2 Graphical overview of the proposed method to optimize the reduction of the dataset used for the statistical inference of the parameters of interest from end to end. The number of observables d in the initial dataset with n observations is reduced to a set of k observables by the neural network function $\boldsymbol{f}$ with the free parameters $\boldsymbol{\omega}$. The dataset is compressed further by summarizing the n observations using a k-dimensional histogram with h bins. Eventually the free parameters $\boldsymbol{\omega}$ are optimized with the variance of the parameter of interest μ as objective, which is made possible by an approximated gradient for the histogram.

2003.07186

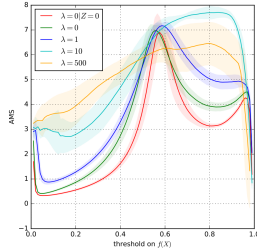

Figure 4: Physics example. Approximate median significance as a function of the decision threshold on the output of f. At $\lambda = 10$, trading accuracy for independence to pileup results in a net benefit in terms of statistical significance.

1611.01046

ML in HEP —○ Out-of-the-box?

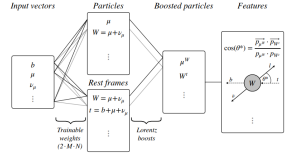

Figure 2: Example of a possible feature engineering in top quark decays addressing the angular distance of the direction of the W boson in the top rest system and the direction of the lepton in the W boson rest system, commonly referred to as $\cos(\theta^*)$.

1812.09722

- **data formats:** ROOT environment
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2001.05310

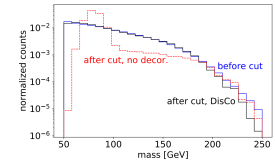

FIG. 4: QCD mass distribution before and after a cut on CNN plus DisCo (W-tagging) with signal efficiency of 50% and JSD $\sim 10^{-3}$.

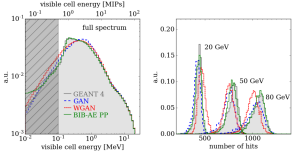

Fig. 6 Differential distributions comparing the per-cell energy (left) and the number of hits (right) between GEANT4 and the different generative models. Shown are GEANT4 (grey, filled), our GAN setup (blue, dashed), our WGAN (red, dotted) and the BIB-AE (green, solid). The energy per-cell is measured in MeV for the bottom axis and in multiples of the expected energy deposit of a minimum ionising particle (MIP) for the top axis.

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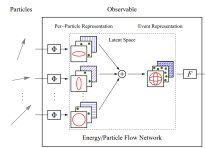

Figure 1: A visualization of the decomposition of an observable via Eq. (1.1). Each particle in the event is mapped by Φ to an internal (latent) particle representation, shown here as three abstract illustrations for a latent space of dimension three. The latent representation is then summed over all particles to arrive at a latent event representation, which is mapped by F to the value of the observable. For the IRC-safe case of Eq. (1.2), Φ takes in the angular information of the particle and the sum is weighted by the particle energies or transverse momenta.

1810.05165

Course overview

This course is not perfect, but you can help us improve

We do value your **feedback!**

- **ML impact** on HEP and this world is growing (fast, really fast)
- It **advances the progress** and offers a **new paradigm of thinking**
- We believe we've grasped a bit of it and **we deem it important** to know
- We believe we are **enthusiastic enough** to communicate it
- So we created this course to **share our beliefs**
- And as an effort to build a **community of like-minded people**

Course overview — Concept

in: Beginners: basic calculus and programming skills
while: Data Science approach all the way
while: Blending HEP gradually
while: Concise overview with gateways to exploration
out: Data Analysis thinking

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we encourage curiousity, exploration and interaction

Course overview — Structure

1. Python
2. Introduction to ML
3. Trees
4. Neural Networks
5. Computer Vision and Generative Models
6. ML in HEP

- **module** = lecture + seminar + homework
  - per week, each 1.5 hours long
  - lecture: absorbing knowledge
  - seminar: intensive coding
  - homework: exploration

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  - per week, each 1.5 hours long
  - lecture: absorbing knowledge
  - seminar: intensive coding

- **homework:** exploration
- **chat:** interaction
- **thingies:** curiosity

Course overview — Python

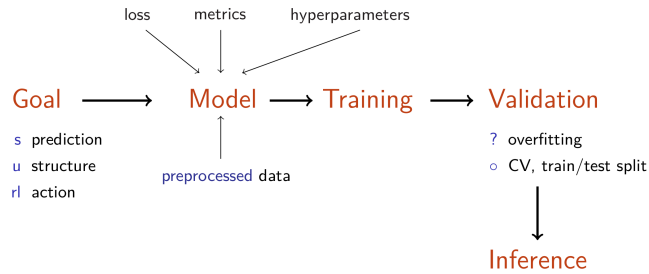
Facilitators: Olya, Sergey

- **Prerequisites**
  - OS, Conda and Jupyter setup
- **Python I** (learn at you pace)
  - basic syntax
  - variables, types, loops, functions, a bit of OOP
  - mostly practise
  - ∼3-4 weeks for you to complete
  - will post in the channel tomorrow!
- **Python II** (seminar)
  - NumPy, Pandas, SciPy
  - Matplotlib, Seaborn, Plotly

Course overview — Intro to ML

Facilitators: Oleg, Stepan

- (Un)supervised and RL
- General pipeline
- Linear models
- Higgs boson with Portuguese students

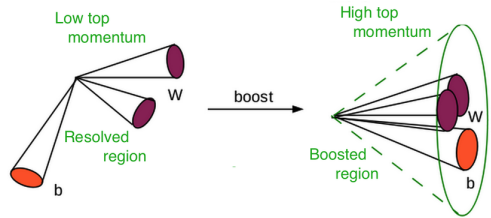


Facilitators: Andrey, Vovvy

- just an axe story
- and a bit of boosting
- and calorimeters

Facilitators: Sergey, Stepan, Olya

- basically backprop
- ok, plus some top-tagging



Course overview — CV and GM

Facilitators: Andrey, Danny, Vovvy

- will generate images
- potentially lots of images

Facilitators: Oleg, Kirill

- a lot of awesome applications
- get to know community

- yet unclear
- it is mostly you who define it
- but we have something to offer
- and we will probably ask your thoughts in the end

Discussion

Discussion — What we don't know

- how to give lectures: virtual or real?
- where to hold seminars?
- which day and when?

→ we'll postpone deciding, things are changing unpredictably

Discussion — What's next

- Learning/refreshing Python
  - included problems for you to practise
  - release answers in $\sim$ 3 weeks
  - if you've got any questions, welcome to the chat:)
  - and join if you haven't done yet
- The fun
  - target to start the actual course in $\sim$ 4 weeks
  - which includes lectures, seminars and homework
  - format is yet unclear

- **nothing is compulsory** in our course
- it is built by means of mere enthusiasm and **we expect nothing** in return
- except that we'll be really **happy to see your interest** and engagement
- your exploration, interaction and curiousity about an ML world
- and we will **readily support** this – because **passion matters**

Outline

- About us
- ML
- ML in HEP
- Course overview
- Discussion

Discussion