Yandex

Deep Learning for Image Processing in Astrophysical Experiments

Maxim Borisyak, Andrey Ustyuzhanin, Mikhail Usvyatsov et al.

National Research University Higher School of Economics; Yandex School of Data Analysis

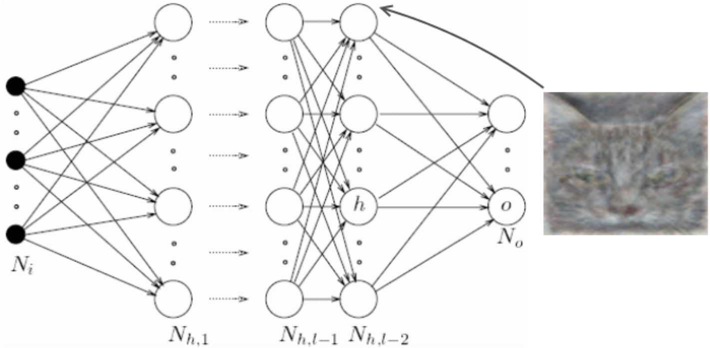
Content

- Deep Learning overview;
- CRAYFIS experiment:
  - track detection;
  - learning readout approximation.

Deep Learning

Deep Learning

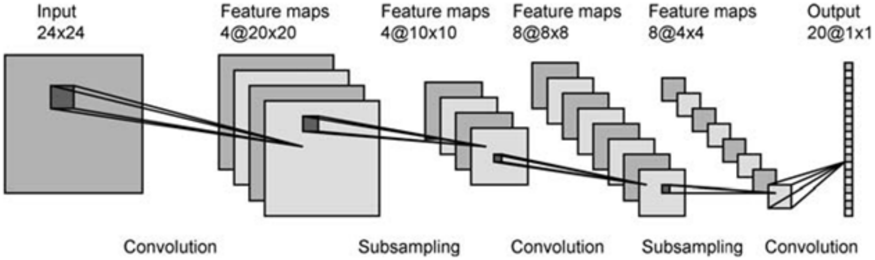
Deep Learning almost always refers to Deep Artificial Neural Networks.



Credits to DeepLearning.net

Convolutional Neural Networks

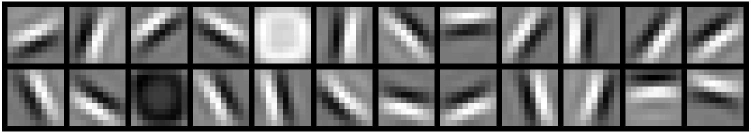
Convolutional Neural Networks is a generic model for Image Processing.



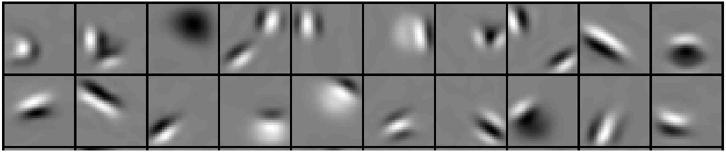
Why deep?

> Each successive layer extracts more abstract representation of data.

Layer 1:



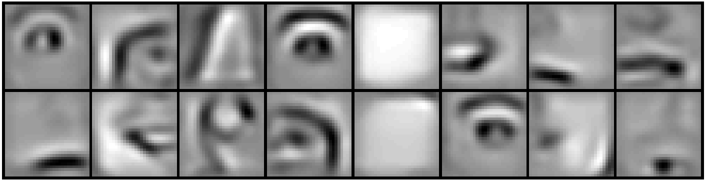
Layer 2:



Visualization of filters (faces). Figures from [Lee et al., 2009].

Why deep?

Layer 3:

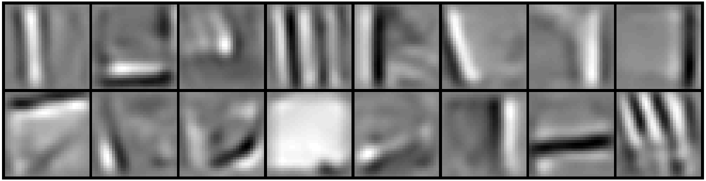


Layer 4:

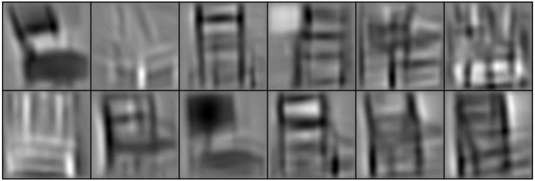
Visualization of filters (faces). Figures from [Lee et al., 2009].

Why deep?

Layer 3:

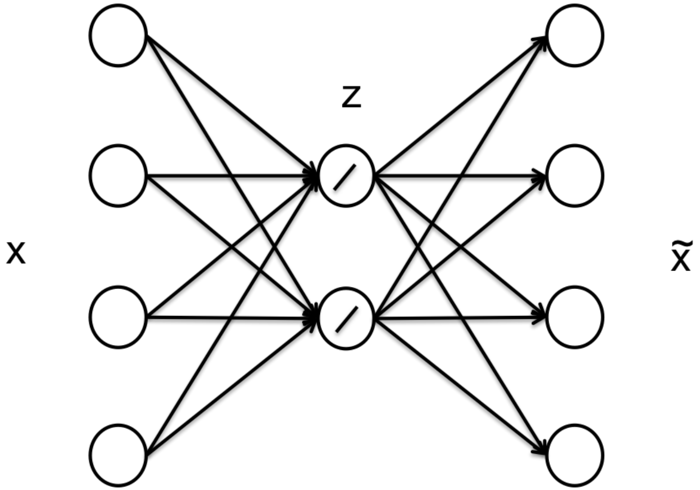


Layer 4:



Visualization of filters (chairs). Figures from [Lee et al., 2009].

Autoencoders (PCA)



Credits to Quoc V. Le.

Convolutional AutoEncoder

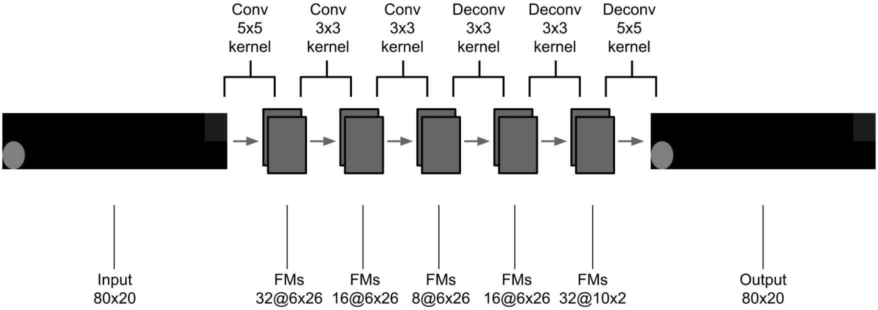
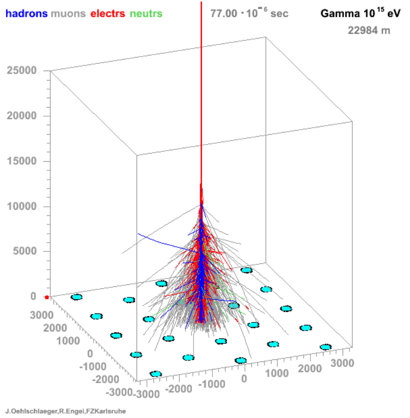


Figure from [Masci et al., 2011].

CRAYFIS experiment

CRAYFIS experiment

Cosmic RAYs Found In Smartphones experiment proposes usage of private phones for observing Ultra-High Energy Cosmic Rays.



Air Shower image by J. Oehlschläger and R. Engel, Institut für Kernphysik, Forschungszentrum Karlsruhe.

CRAYFIS
cosmic rays found in smartphones

SCHOOL OF DATA ANALYSIS

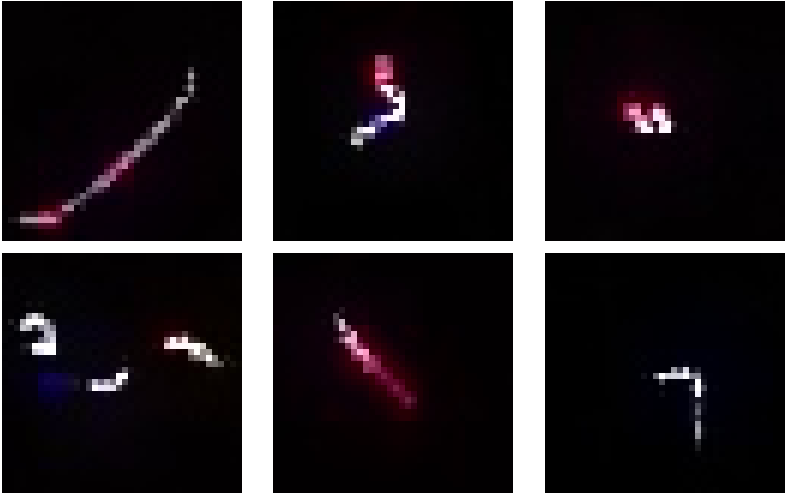
UCI

UCDAVIS

NYU

An event example

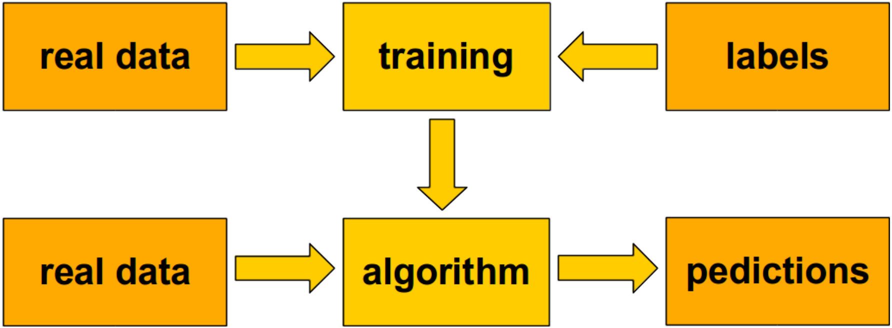
Examples



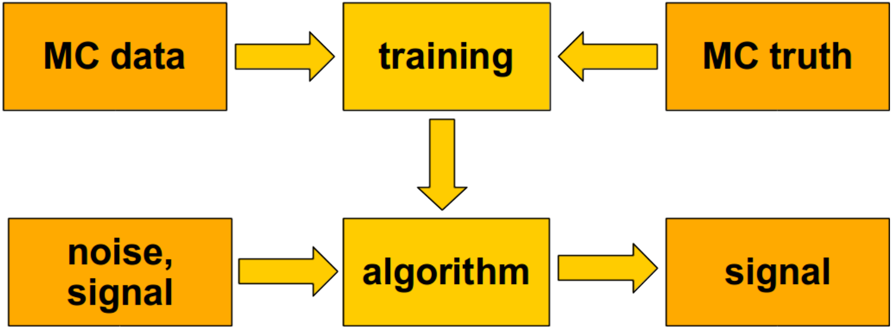
Images above have size 40×40 pixels.

Data Science In CRAYFIS

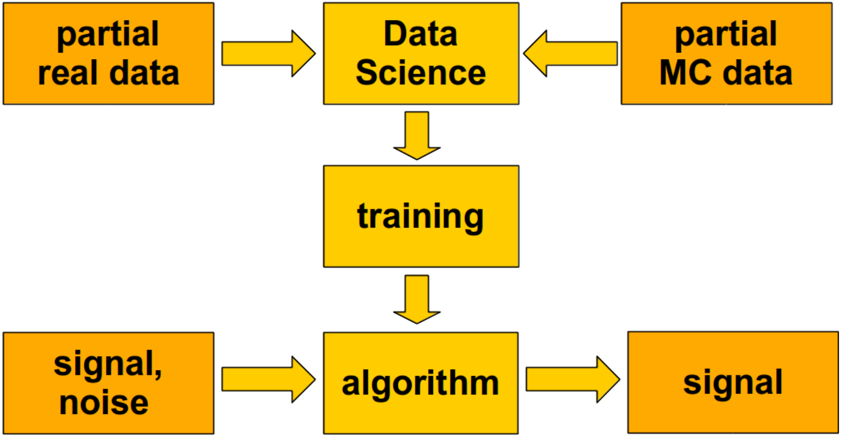
Usual Data Science workflow



HEP Data Science workflow



CRAYFIS workflow



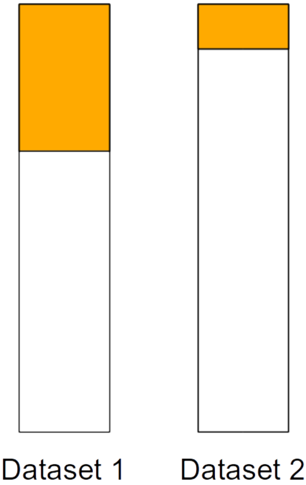
CRAYFIS experiment

Track detection

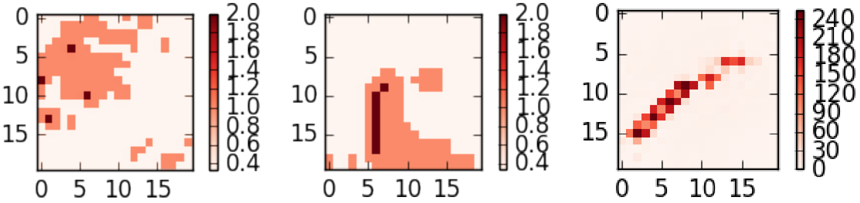
Data

Specially for this trick, two sets of images, D_1 and D_2 were collected:

- the same phone
- under the same conditions
- was exposed to 2 radioactive sources:
  - Cobalt 60;
  - Radium 226.



Labeling problem



noise ? a track

Track detection

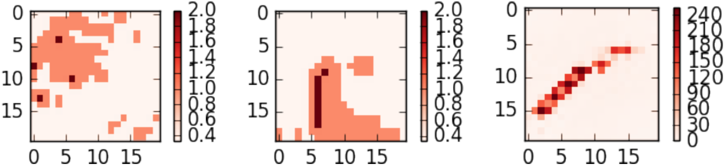
Assumptions:

$$\begin{aligned}
P(\text{noise} \mid X, D_1) &\approxeq P(\text{noise} \mid X, D_2); \\
P(\text{track} \mid X, D_1) &\approxeq P(\text{track} \mid X, D_2); \\
P(\text{track} \mid D_1) &\gg P(\text{track} \mid D_2); \\
P(\text{track} \mid X) = 1 &\quad \text{or} \quad P(\text{track} \mid X) = 0
\end{aligned}$$

> A classifier that recovers
>
> $$f(X) \approx P(D_1 \mid X)$$
>
> can be turned into
>
> $$g(X) \approx P(\text{track} \mid X)$$

Relation $P(A) \approxeq P(B)$ means that our classifier (model) can not distinguish A from B.

Labeling problem solved



f(x)	0.5	0.5	0.83
label	noise	noise	a particle

Reverse engineering of readout

Smartphones simulation

> Monte-Carlo simulation of smartphone's camera is complicated.

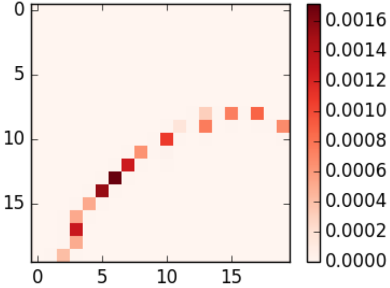
Problems:

- exact structure of camera is usually unknown;
- variety of different models;
- the readout process is complex.

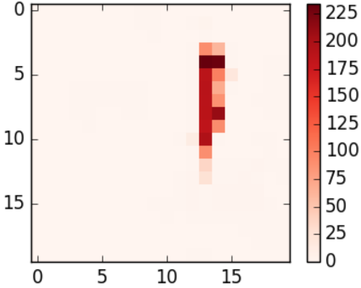
...nevertheless ...

> Simulation of particle interaction with grid of CMOS cells is feasible.

Real data and simulation comparison



simulation



real data

Smartphones simulation

$$\left[\begin{array}{c}\text{CMOS-particle}\\ \text{interaction}\end{array}\right] + \left[\ \text{readout}\ \right] = \left[\begin{array}{c}\text{real}\\ \text{data}\end{array}\right]$$

$$\left[\begin{array}{c}\text{simulation of}\\ \text{CMOS-particle}\\ \text{interation}\end{array}\right]$$

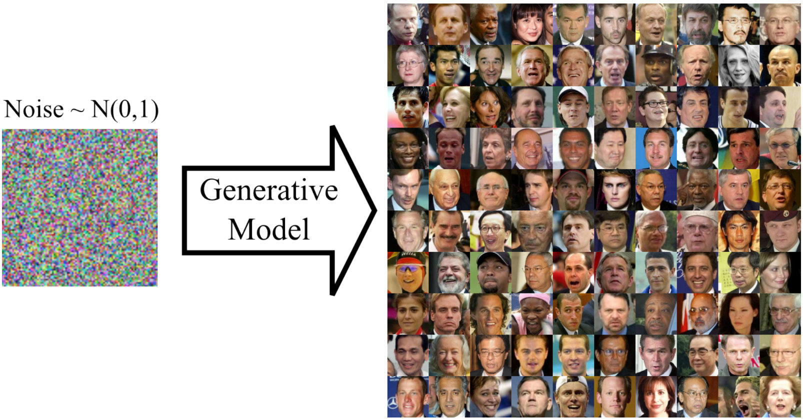
Smartphones simulation

$$\begin{bmatrix} \text{CMOS-particle} \\ \text{interaction} \end{bmatrix} + \quad \begin{bmatrix} \text{readout} \end{bmatrix} = \quad \begin{bmatrix} \text{real} \\ \text{data} \end{bmatrix}$$

$$\begin{bmatrix} \text{simulation of} \\ \text{CMOS-particle} \\ \text{interation} \end{bmatrix} + \quad \begin{bmatrix} \text{approx.} \\ \text{readout} \end{bmatrix} = \quad \begin{bmatrix} \text{realistic} \\ \text{data} \end{bmatrix}$$

Generative Adversarial Networks

GAN is a generative model, capable of generating realistic images from e.g. Gaussian noise.



Borisyak et al.

Generative Adversarial Networks

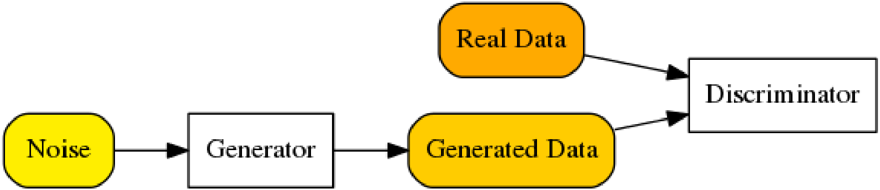
GAN is a game between two networks.

- generator:

$$\mathcal{L}(X_{real}, X_{gen}) \to \max$$

- discriminator:

$$\mathcal{L}(X_{real}, X_{gen}) \to \min$$



Transformation Adversarial Networks

- generator:

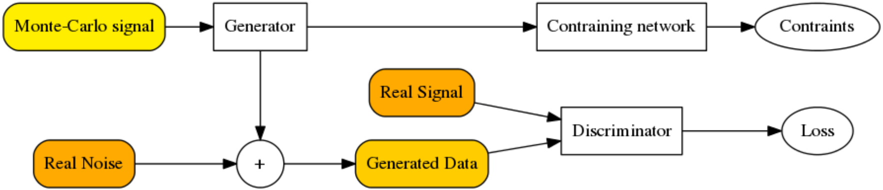
$$\mathcal{L}(X_{\text{real}}, X_{\text{gen}}) \to \text{max}$$

- discriminator:

$$\mathcal{L}(X_{\text{real}}, X_{\text{gen}}) \to \text{min}$$

- constraints:

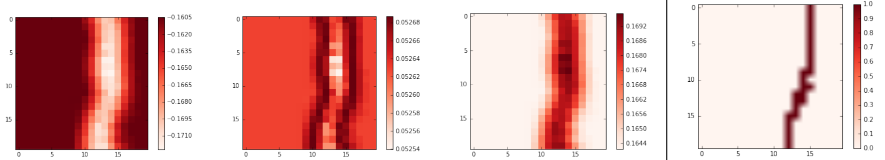
$$\mathcal{L}_0(\dots) \to \text{min}$$



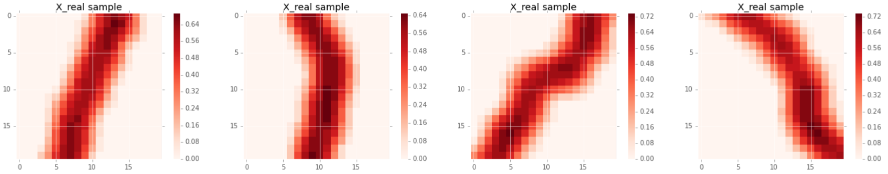
Borisyak et al.

Training process

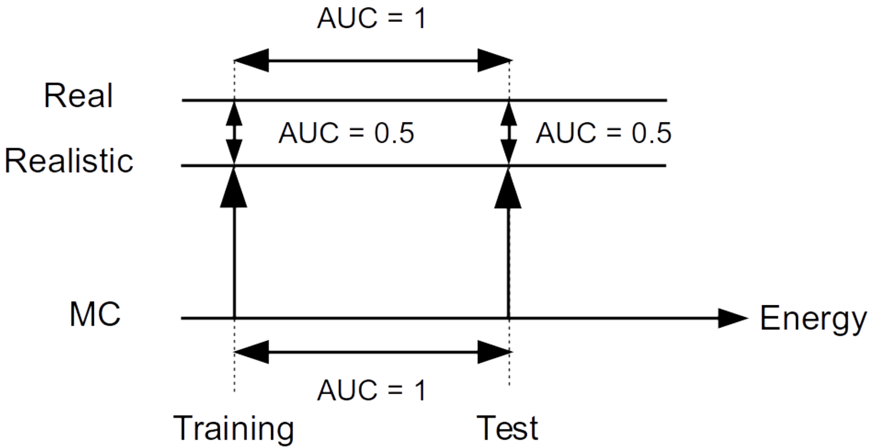
epoch 1 | epoch 2 | epoch 3 | original



Samples of real tracks.



Model testing



Summary

Summary

Deep Learning:

- high abstractions;
- Convolutional Neural Networks and AutoEncoders;

CRAYFIS experiment:

- search for Ultra-High Energy Cosmic Rays;
- global distributed observatory based on smartphones.

Deep Learning in CRAYFIS:

- Data Science plays key role in natural sciences;
- Deep Learning is extremely powerful tool.

Examples:

- track detection;
- readout simulation.

Contacts

CRAYFIS experiment

crayfis.io

Maxim Borisyak

mborisyak@hse.ru

References I

Barth-Maron, G.
Learning deep state representations with convolutional autoencoders.

Lee, H., Grosse, R., Ranganath, R., and Ng, A. Y. (2009).
Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations.
In Proceedings of the 26th annual international conference on machine learning, pages 609--616. ACM.

Masci, J., Meier, U., Cireşan, D., and Schmidhuber, J. (2011).
Stacked convolutional auto-encoders for hierarchical feature extraction.
In International Conference on Artificial Neural Networks, pages 52--59. Springer.

Whiteson, D., Mulhearn, M., Shimmin, C., Cranmer, K., Brodie, K., and Burns, D. (2016).
Searching for ultra-high energy cosmic rays with smartphones.
Astroparticle Physics, 79:1--9.