Gépi tanulás a nagyenergiás nehézion-fizikában

Mafihe – Gépi Tanulás Téli Iskola

2023. 02. 02-03

Wigner Fizikai Kutatóközpont

BÍRÓ GÁBOR
biro.gabor@wigner.hu

ELKH Eötvös Loránd Kutatási Hálózat

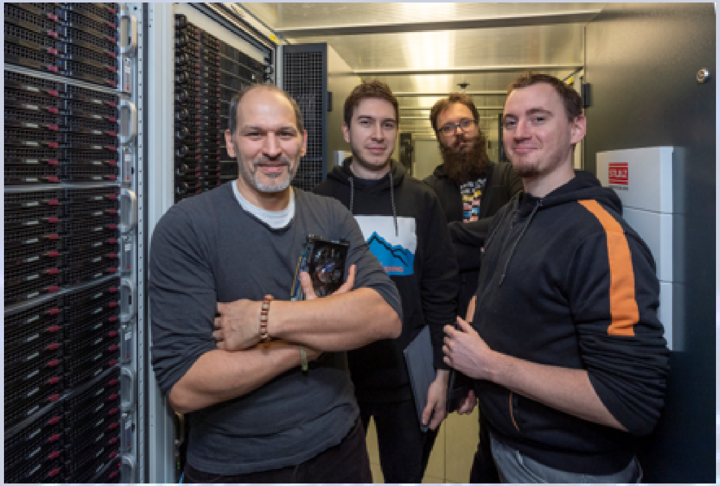
WIGNER

ELTE EÖTVÖS LORÁND TUDOMÁNYEGYETEM

Támogatók:
OTKA K135515, 2019-2.1.11-TÉT-2019-00078, NKFIH 2019-2.1.6-NEMZKI-2019-00011, MILAB RRF-2.3.1-21-2022-00004.

Bevezetés

WSCLAB –
WIGNER SCIENTIFIC COMPUTING LABORATORY



2005: GPU-k használata HEP számításokban

2008: WLCG Grid indulása (ALICE & CMS), Tier-2 @ Wigner

2010- első GPU Day & Wigner GPU Laboratórium megalakulása

(2015: Fizikus MSc, Eötvös Loránd Tudományegyetem)

2016- Lectures on Modern Computing in Science sorozat

2016- Wigner GPU Lab Fellowship

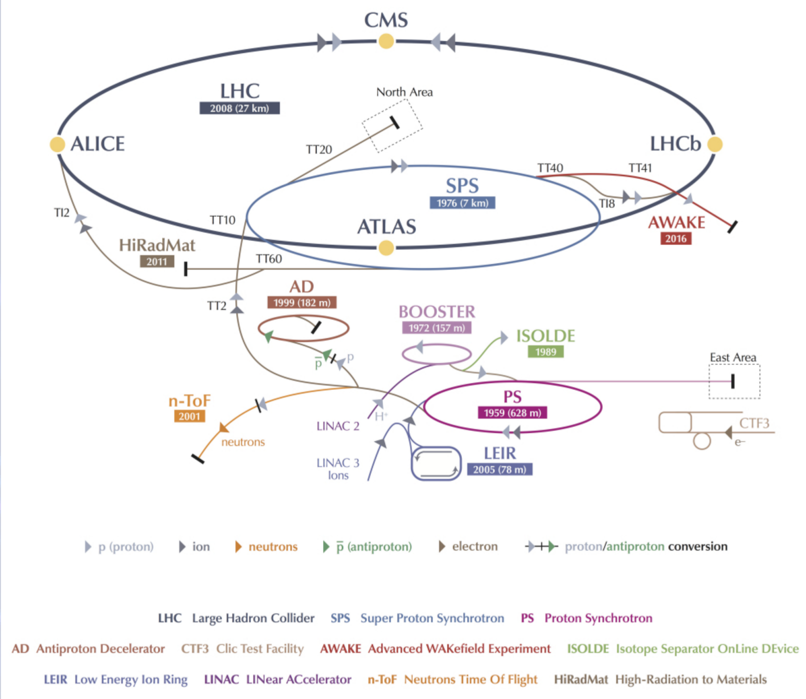
(2021: Részecskefizika PhD, Eötvös Loránd Tudományegyetem)

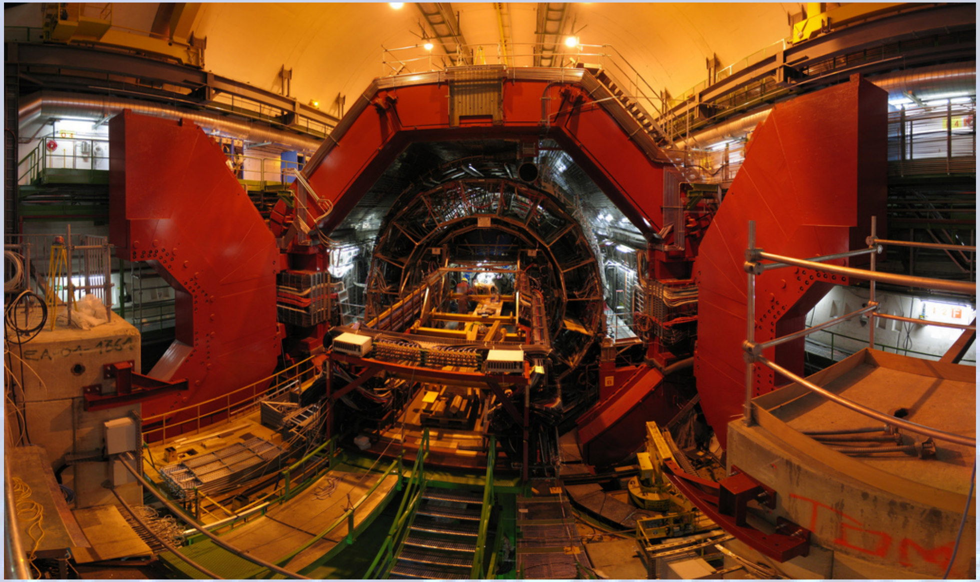
2021- Wigner Scientific Computing Laboratory (NKFIH TOP50 RI) @ Wigner Data Center

EXCELLENT RESEARCH INFRASTRUCTURE HUNGARY

Bevezetés

A CERN gyorsítói





ALICE: A Large Ion Collider Experiment

39 ország, ~2000 kutató

10 000 tonna, 26x16 méter

Kvark-gluon plazma: egy sűrű, forró, átlátszatlan, örvénylő tökéletes folyadék

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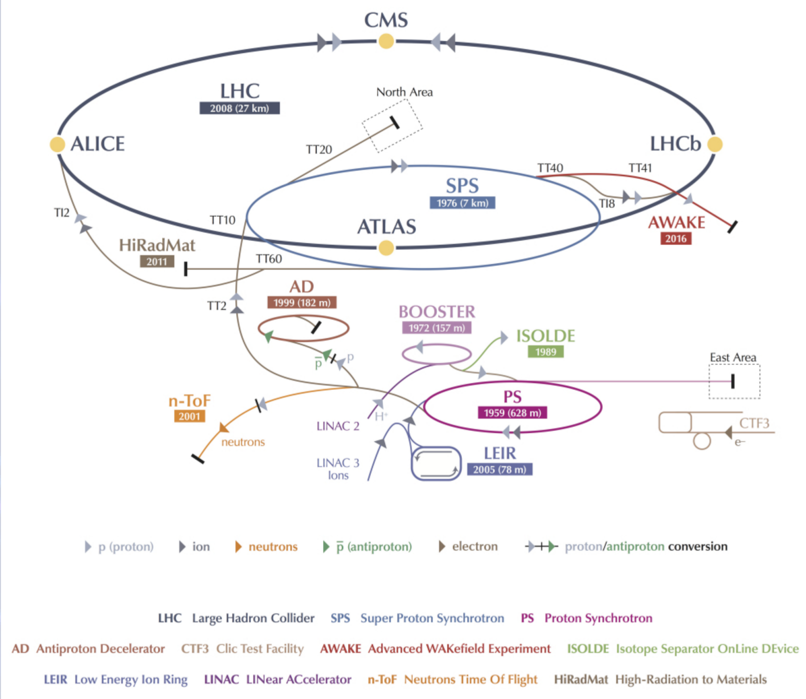

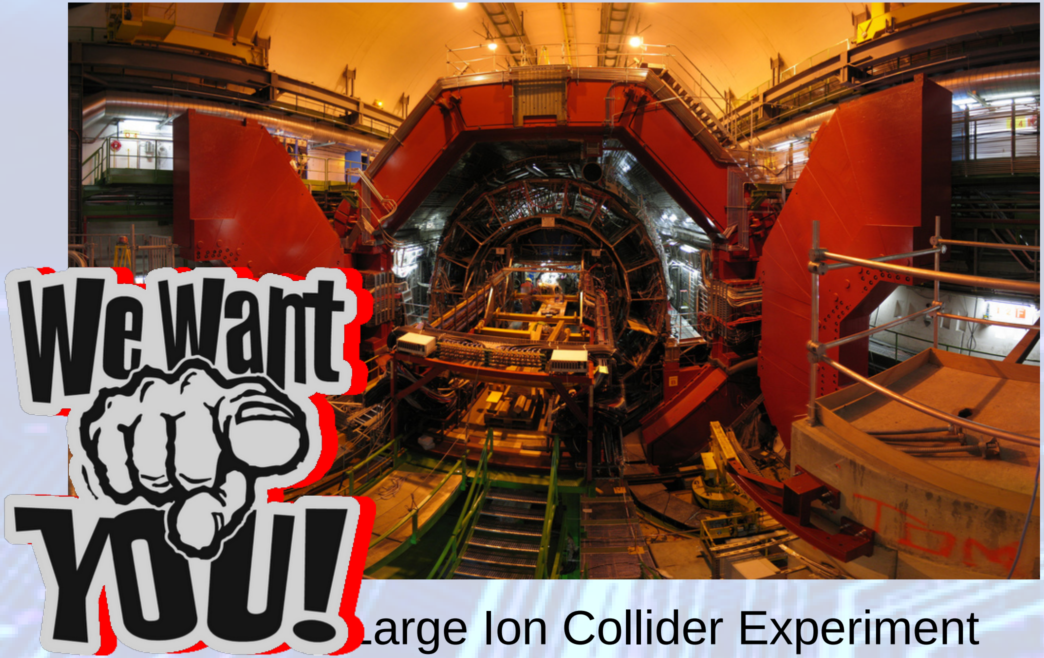

Large Ion Collider Experiment

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Történelem

1950: Alan Turing creates the "Turing Test"

1957: Frank Rosenblatt: the first neural network for computers (the **perceptron**), which simulate the thought processes of the human brain.

1959: Arthur Samuel, IBM: *Machine Learning*

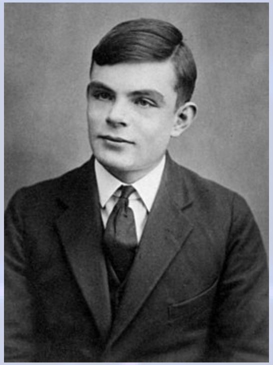
1967: The first general, working learning algorithm for supervised, deep, feedforward, multilayer perceptrons by A. G. Ivakhnenko and V. G. Lapa

1986: First mention of *Deep Learning* by Rina Dechter (*Learning While Searching in Constraint-Satisfaction Problems*)

1989: Yann LeCun et al: standard backpropagation algorithm for recognizing handwritten ZIP codes on mail

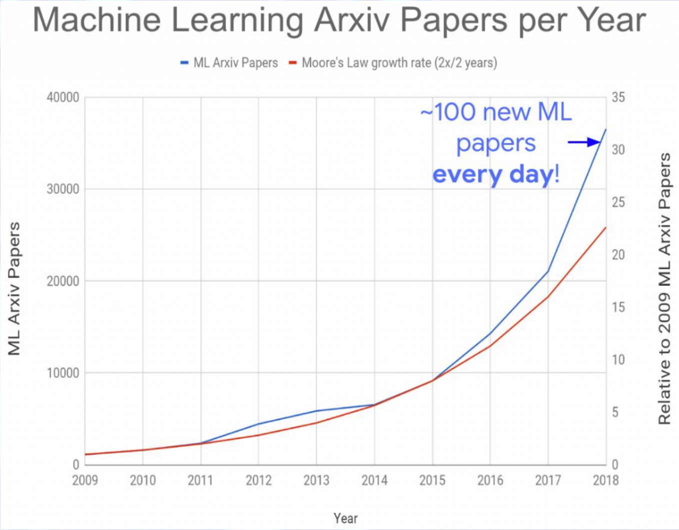
1997: "*A computer program is said to learn from experience* **E** *with respect to some class of tasks* **T** *and performance measure* **P** *if its performance at tasks in* **T***, as measured by* **P***, improves with experience* **E***.*" - Tom M. Mitchell: Machine Learning

1997: IBM's Deep Blue beats Garri Kaszparov (the world champion at chess). Computing capacity: 11.38 GFLOPS, TOP500: 259th (comparison: Nvidia RTX 4090: 82.6 TFLOPS)



Wikipedia

https://researcher.watson.ibm.com/researcher/view_page.php?id=6814



arXiv:1911.05289

Történelem

2009: ImageNet by prof. Fei-Fei Li a database of 14 million labeled images in 2009

2011: IBM's Watson: winner of game show Jeopardy!

2011: Google Brain: cats in Youtube videos

2012: AlexNet by Alex Krizhevsky: first CNN

2013: Word2vec algorithms: foundations for language models

2014: DeepFace by Facebook

2014: Generative adversarial networks (GAN) by Ian Goodfellow

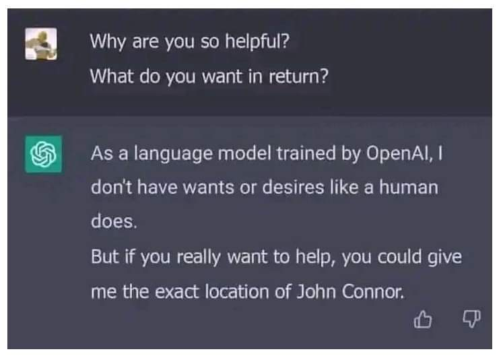
2016: AlphaGo by Deepmind

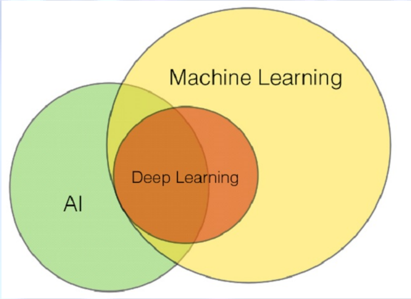
2016: Face2Face (baseline for 'DeepFake')

2017: Waymo: first self-driving car company to operate without human intervention

2018: AlphaFold by Deepmind

2020: GPT-3 by OpenAI to generate human-like text. Trainable parameters: **175 billion (ChatGPT)**





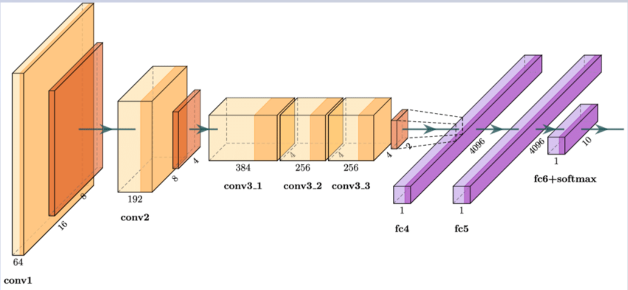
Wikipedia

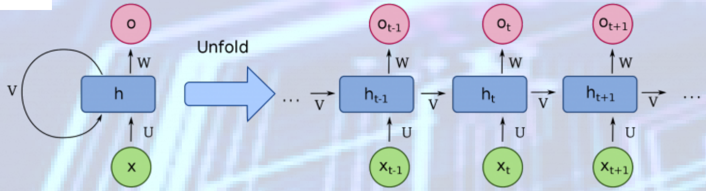
Történelem

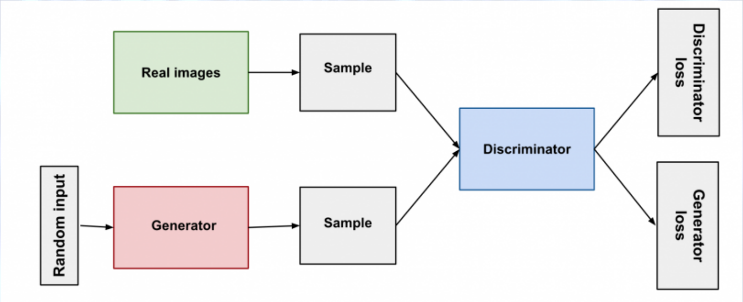
CNN (image classification, object detection, recommender systems)…

Recurrent/recursive neural networks (RNNs): Sequence modeling, next word prediction, translating sounds to words, human language translation…

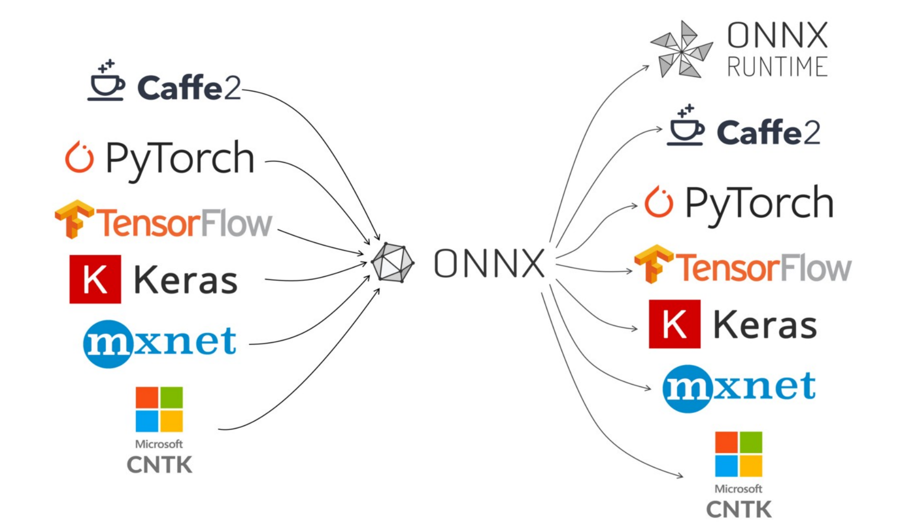
Generative models: anomaly detection, pattern recognition, reinforced learning







Various frameworks for training and inference:



https://towardsdatascience.com/onnx-preventing-framework-lock-in-9a798fb34c92

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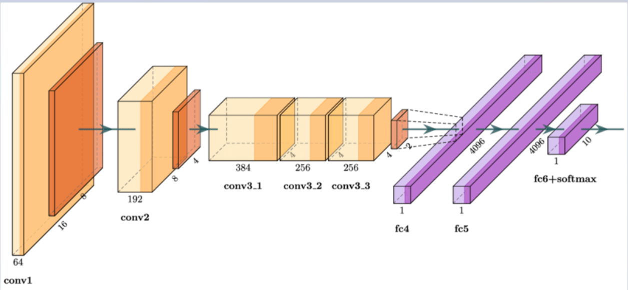

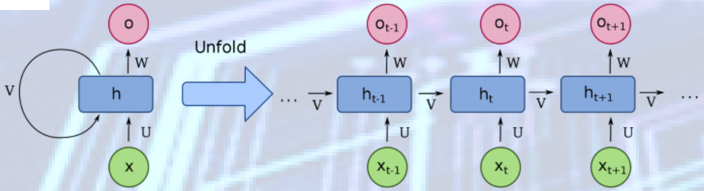

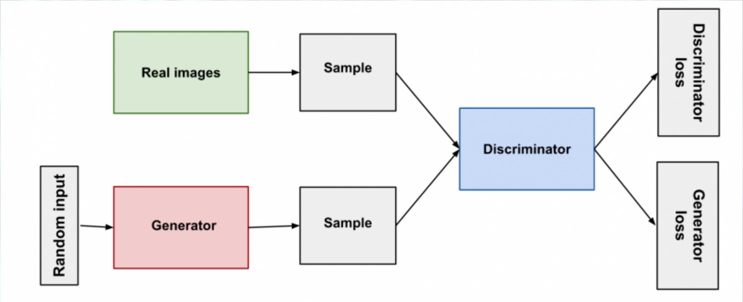

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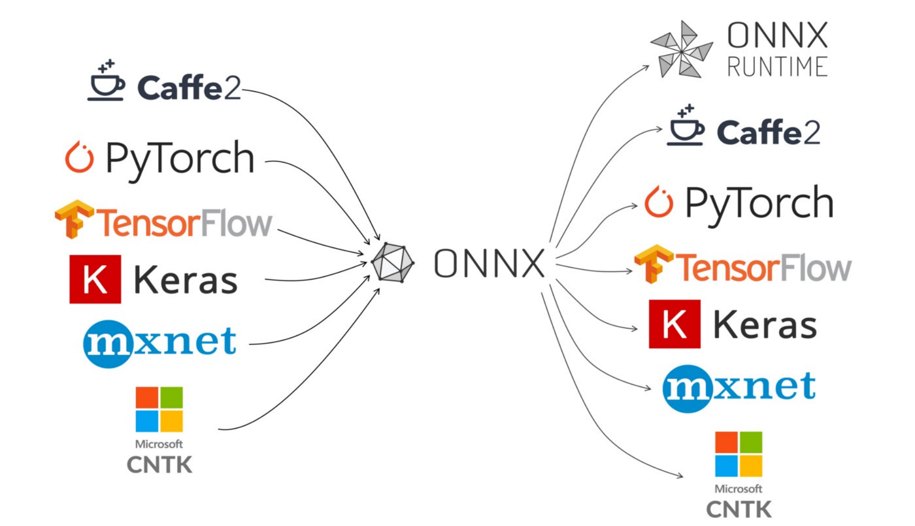

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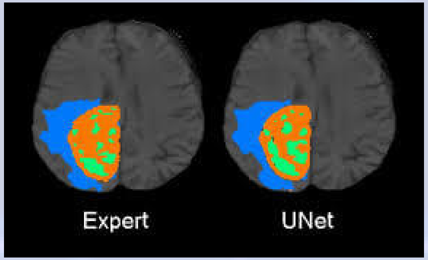
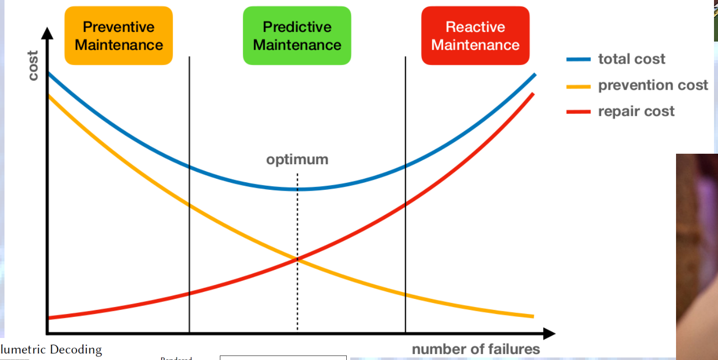
Motiváció – adat, adat, még több adat

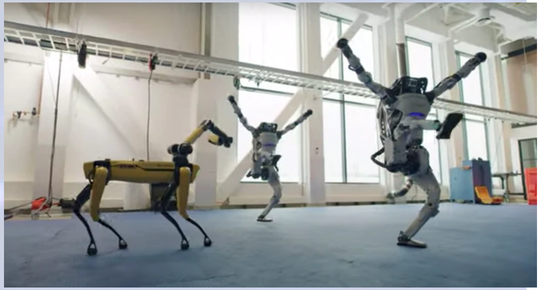
Autonomous driving
Medical imaging
Predictive maintenance
Anomaly detection, fake news detection
Search of BSM physics
Stock price prediction
Natural Language Processing
Virtual Assistants
Virtual reality
Colorization of Black and White Images
Content generation, examples:

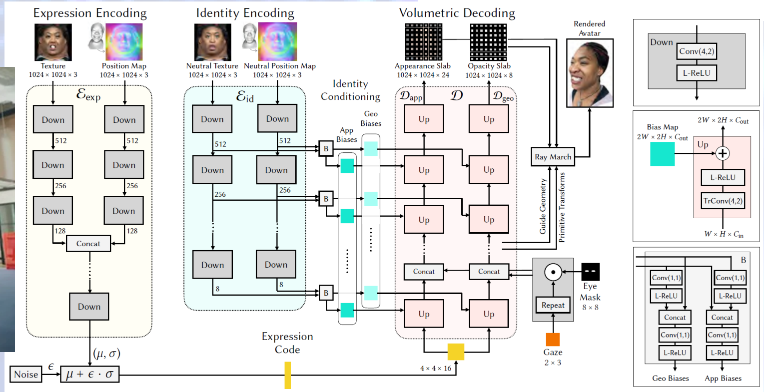
- https://infiniteconversation.com/
- https://huggingface.co/spaces/stabilityai/stable-diffusion

Robotics
...









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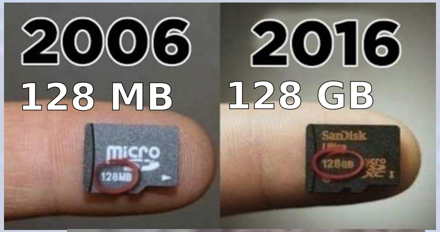
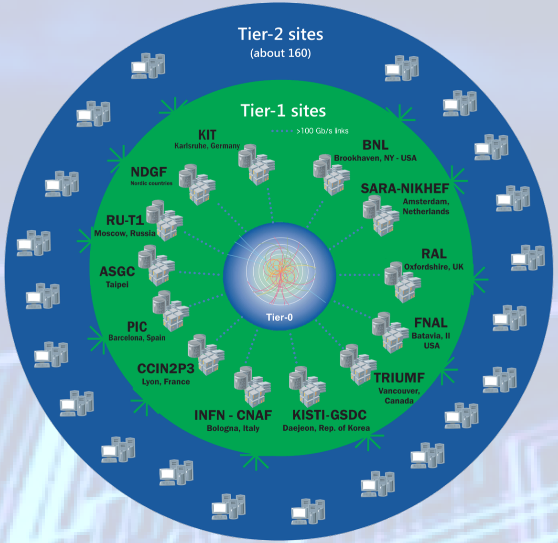


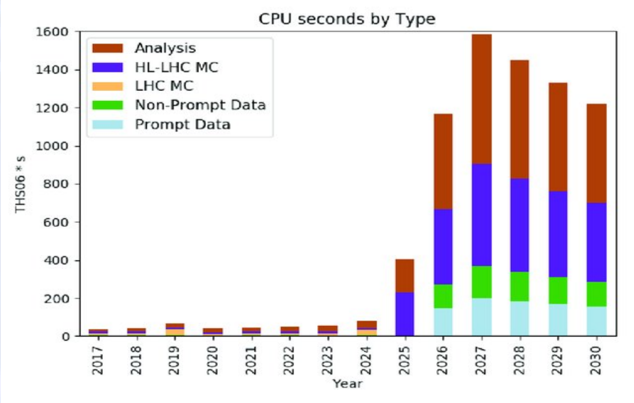
LHC in numbers: **2013** and **now:**

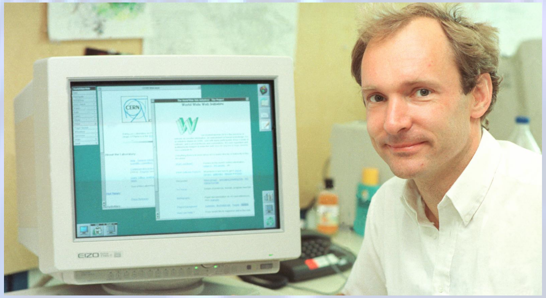
Data:	15 PB/év	vs	200+ PB/year
Tape:	180 PB	vs	740+ PB
Disk:	200 PB	vs	570+ PB
HS06:	2M	vs	100+ B



Storing and distributing the data is only one side of the challange

→ analysis, simulations





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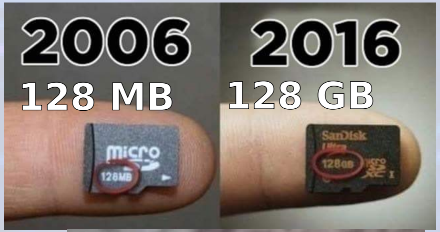

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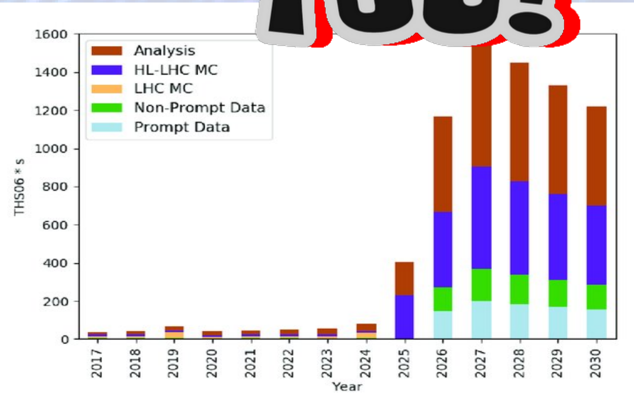
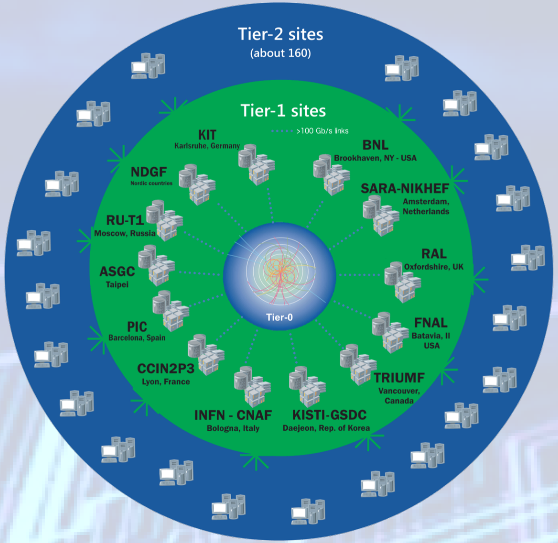
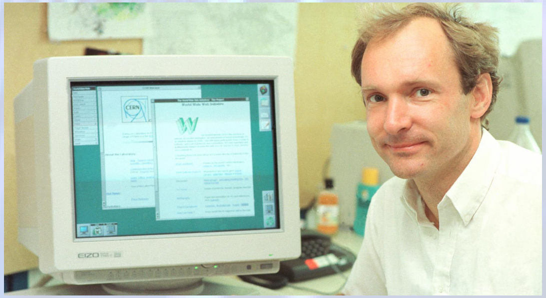
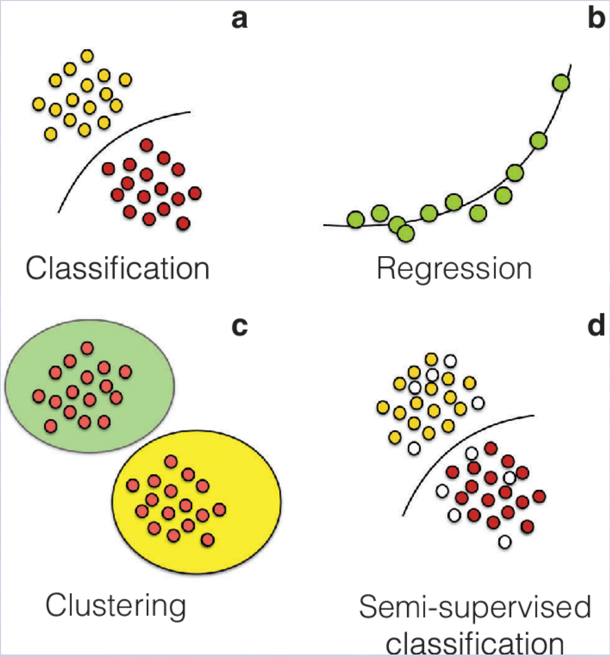
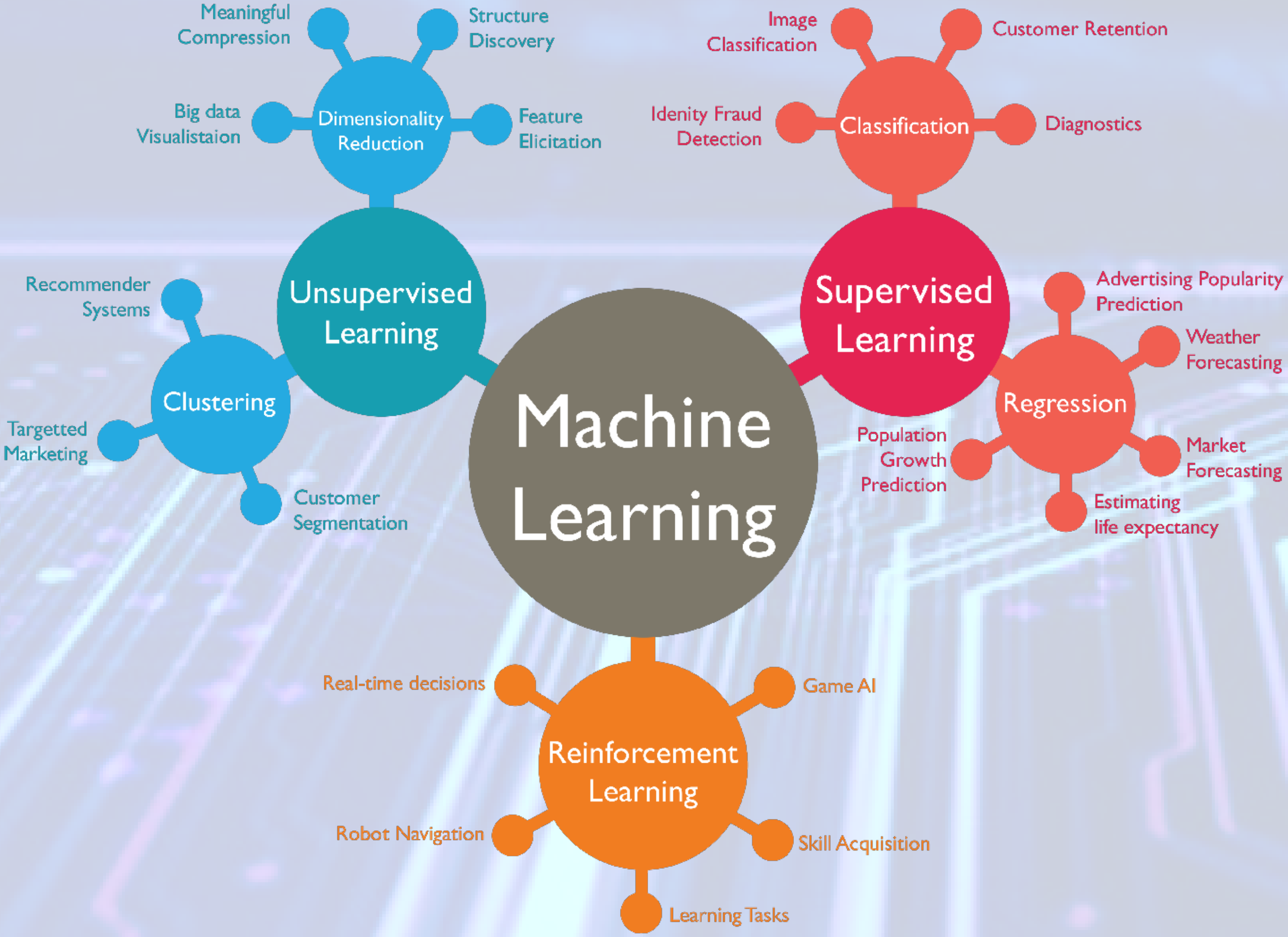






Osztályozás

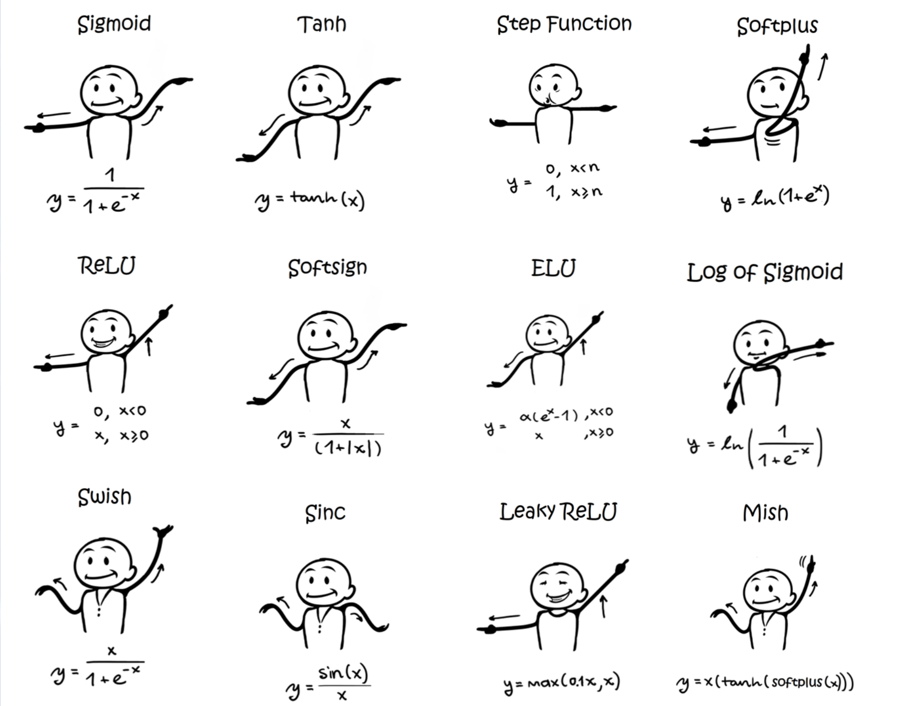


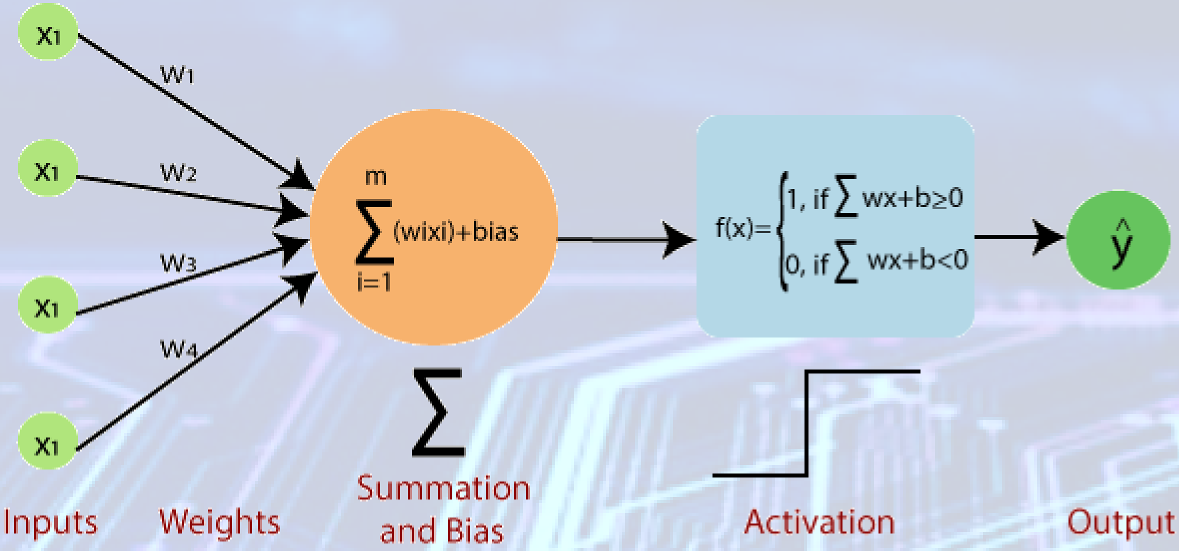


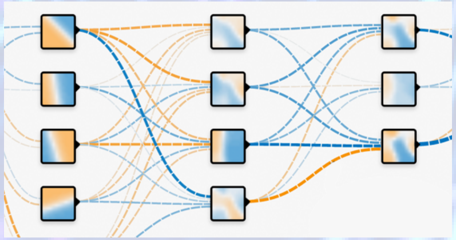
Legfontosabb összetevők

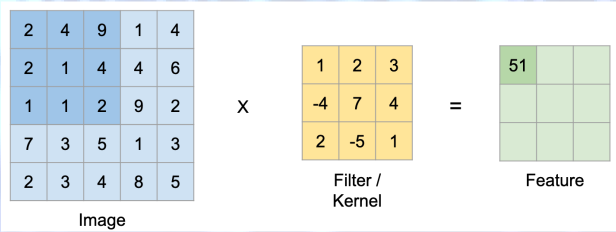
Perceptrons:

- Input value(s)
- Weight: the connection between the units
- Bias: the intercept added in a linear equation
- Activation Function





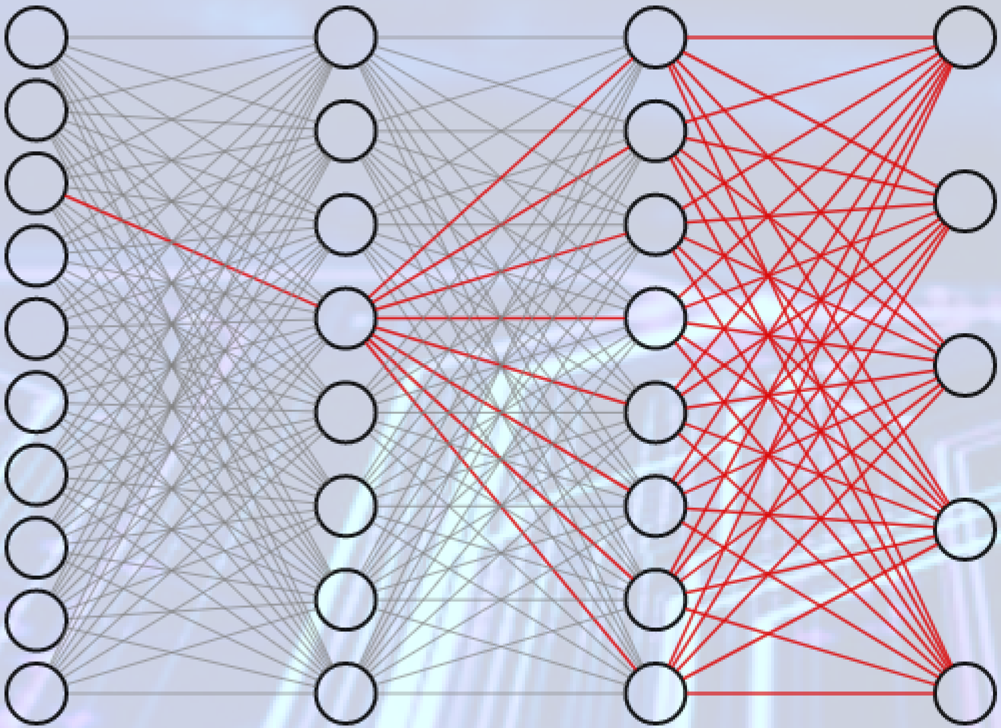




Other important components: pooling layers, regularization and normalization, recurrent layers...

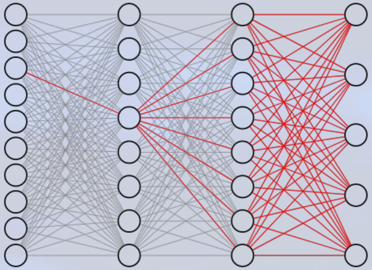
https://sefiks.com/2020/02/02/dance-moves-of-deep-learning-activation-functions/

Legfontosabb összetevők



Legfontosabb összetevők

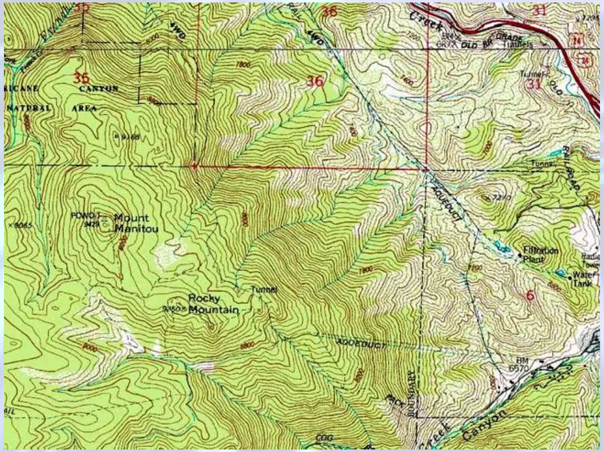
The *learning* part: optimizing "somehow" the weights (Curse of dimensionality)



Loss function: $$\mathcal{L} = \frac{1}{n}\sum_i (y_i - f(x_i))^2 := \frac{1}{n}\sum_i (y_i - (mx_i + b))^2$$

The gradient descent method:

1) Start with random weights
2) Evaluate the loss
3) Figure out which direction the loss function steeps downward the most (with respect to changing the parameters)
4) Repeat from 2)



Gradient of the loss function with respect to all of the parameters

$$\frac{\partial \mathcal{L}}{\partial m} = \frac{2}{n}\sum_i x_i \cdot (y_i - (mx_i + b))$$

$$\frac{\partial \mathcal{L}}{\partial b} = \frac{2}{n}\sum_i (y_i - (mx_i + b))$$

$$\Rightarrow$$

$$m := m - \alpha \cdot \frac{\partial \mathcal{L}}{\partial m}$$

$$b := b - \alpha \cdot \frac{\partial \mathcal{L}}{\partial b}$$

A highly-recommended micrograd tutorial, created by Andrej Karpathy: https://youtu.be/VMj-3S1tku0

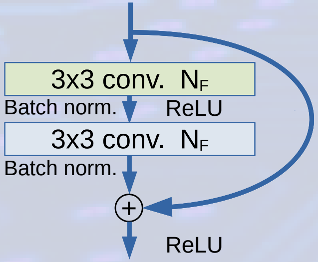
Népszerű architektúrák

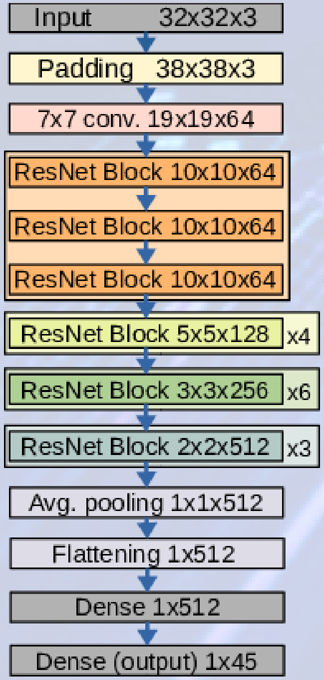
Stacking more layers: solve complex problems more efficiently, get highly accurate results

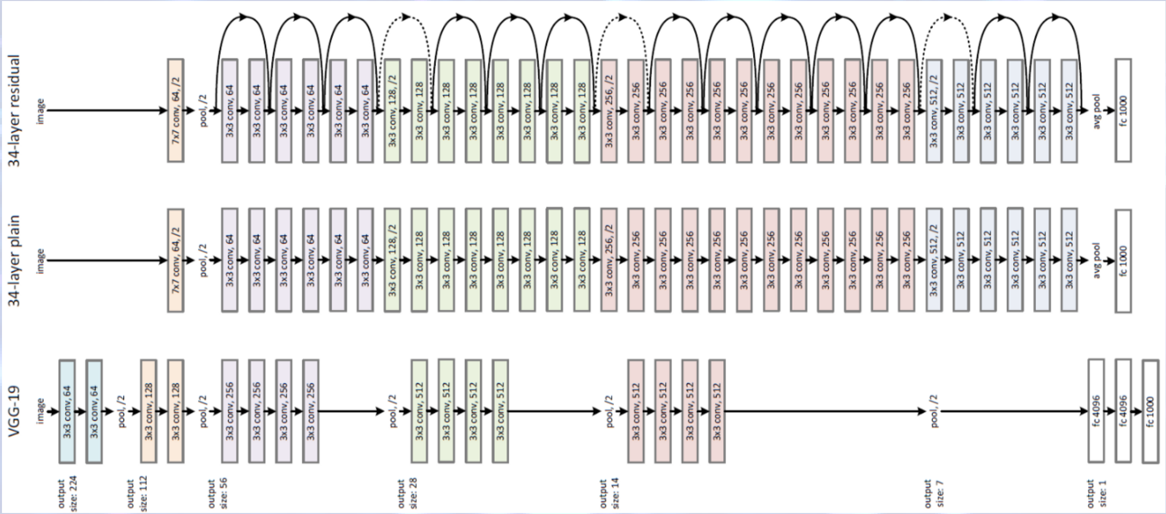
BUT:

Vanishing/exploding gradients

ResNet: **Residual blocks with "skip connections"** (SOTA image classifier of 2015)

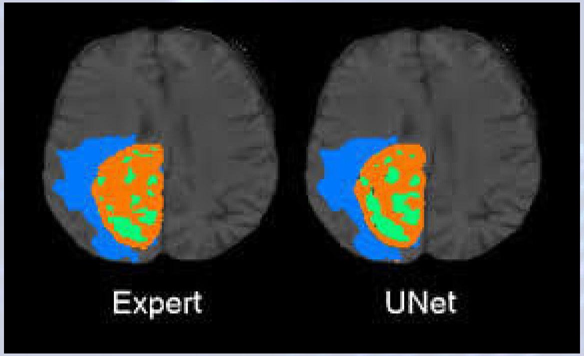


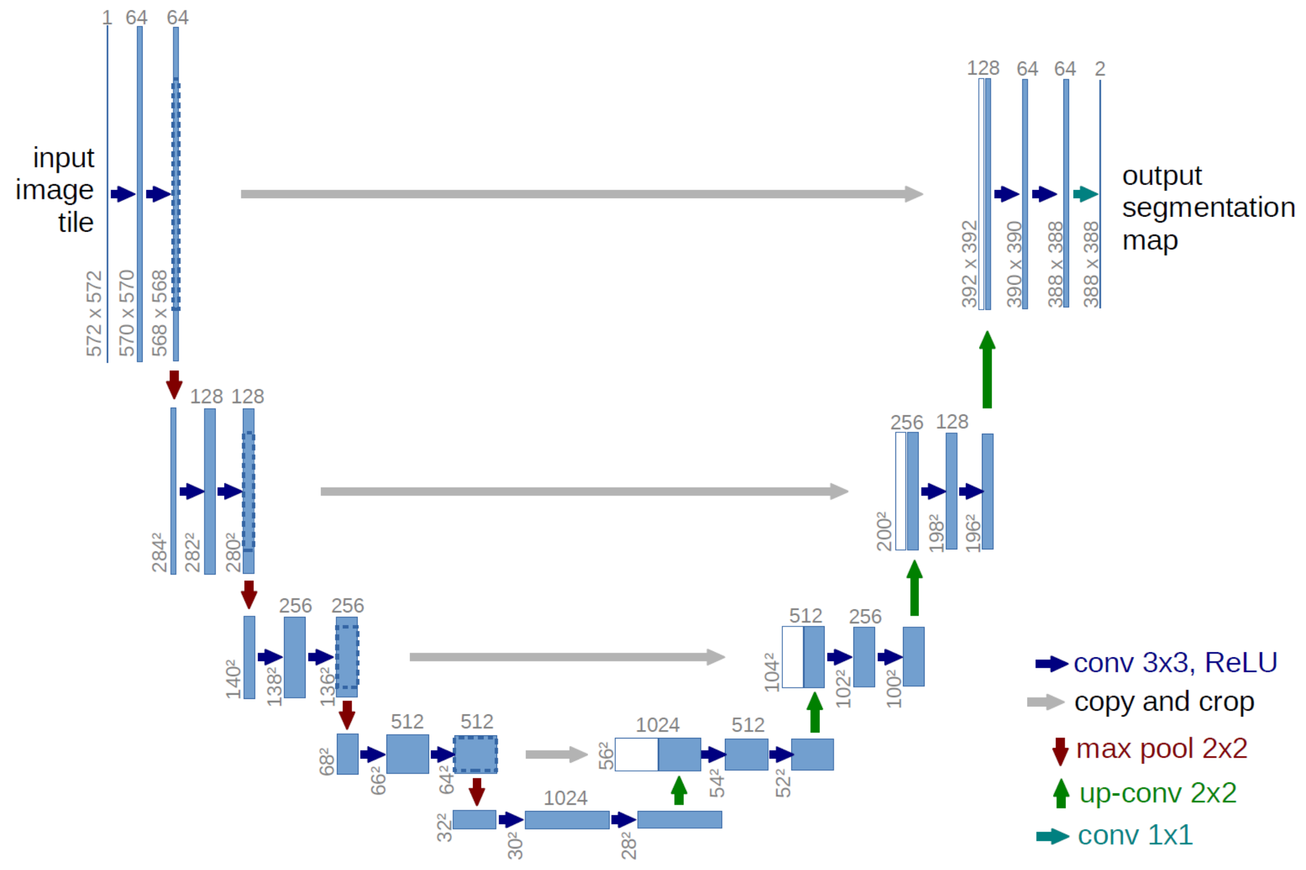




Népszerű architektúrák

U-Net: biomedical image segmentation





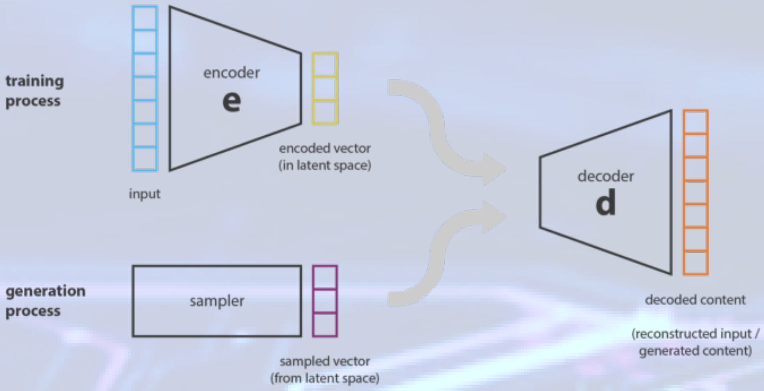
Népszerű architektúrák

(Conditional (Variational)) autoencoders

Dimension reduction

Denoising data

Latent space conditioning



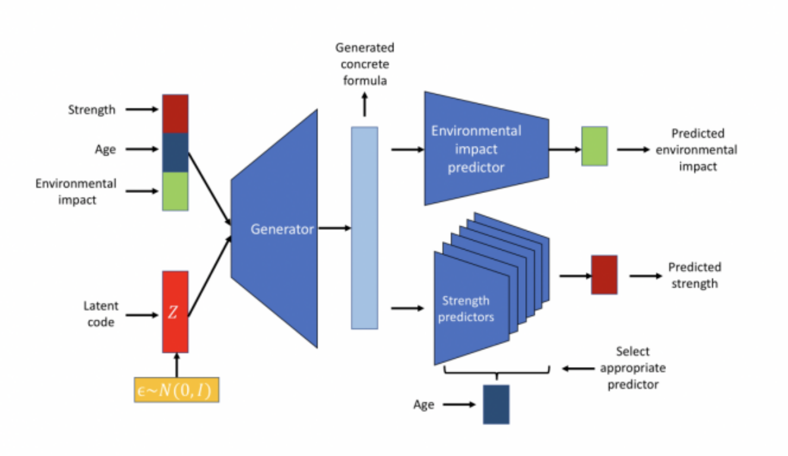


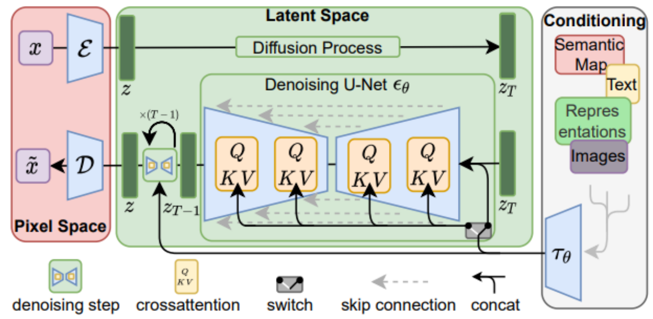
Fig. 4. Generating new concrete formulas and evaluating their properties

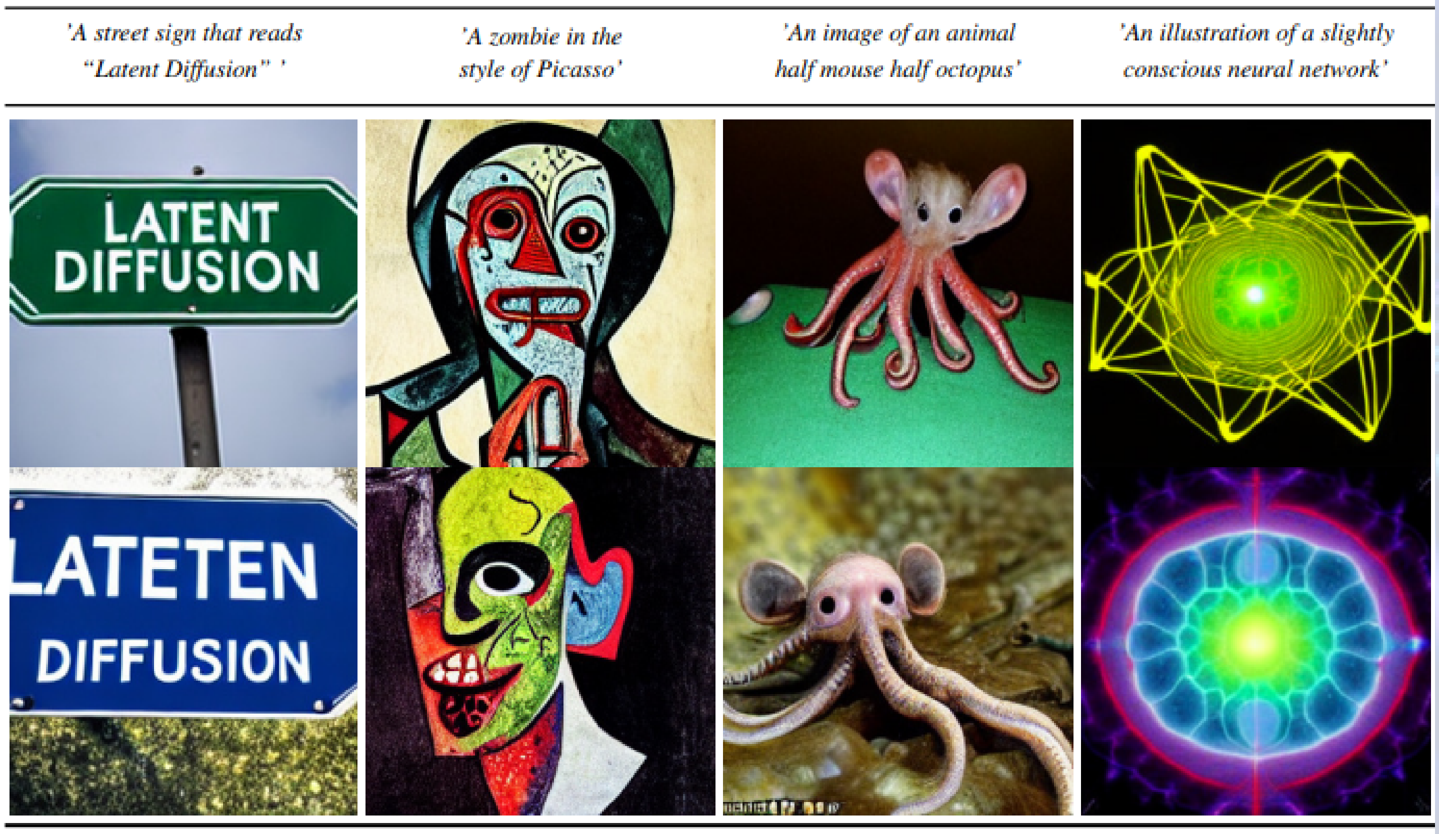
https://arxiv.org/pdf/2204.05397.pdf

Népszerű architektúrák

Diffusion models: https://huggingface.co/spaces/stabilityai/stable-diffusion

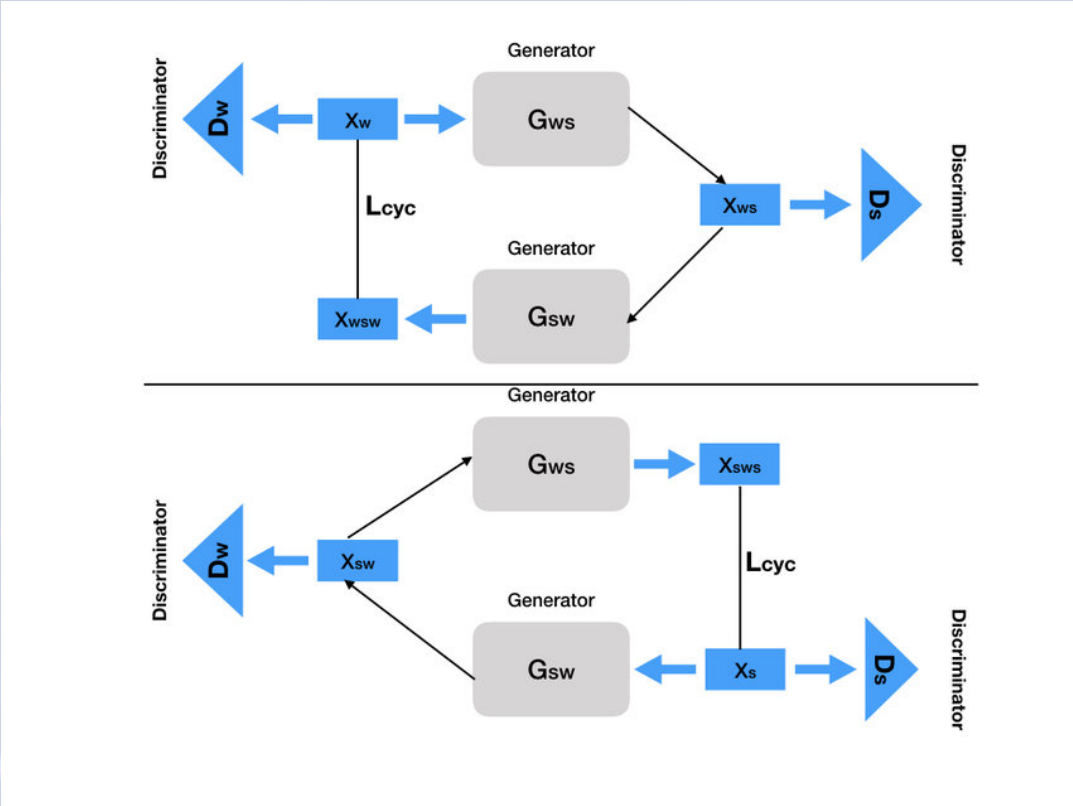
Gradually perturbate the input data over several steps by adding Gaussian noise





Népszerű architektúrák

GAN: data generation via competing generator-discriminator



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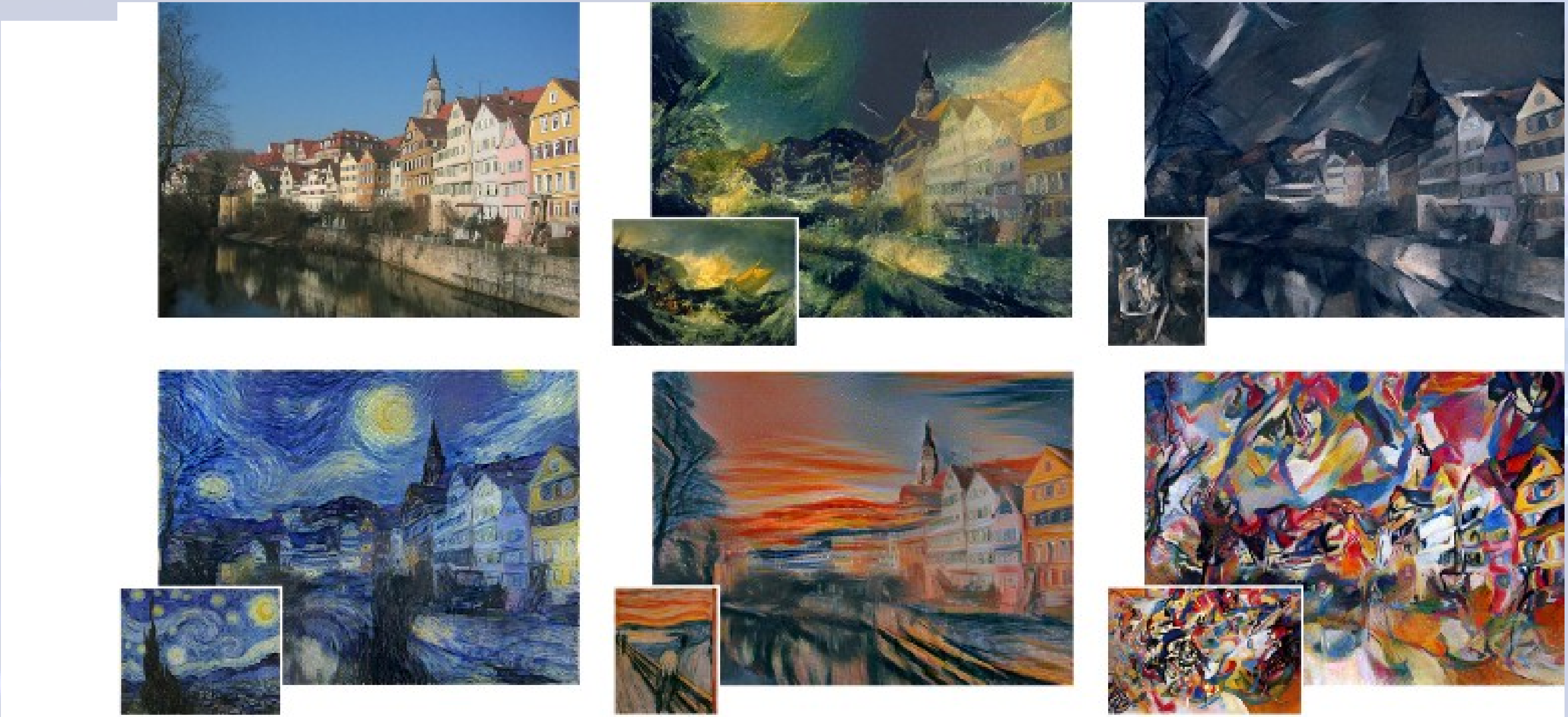
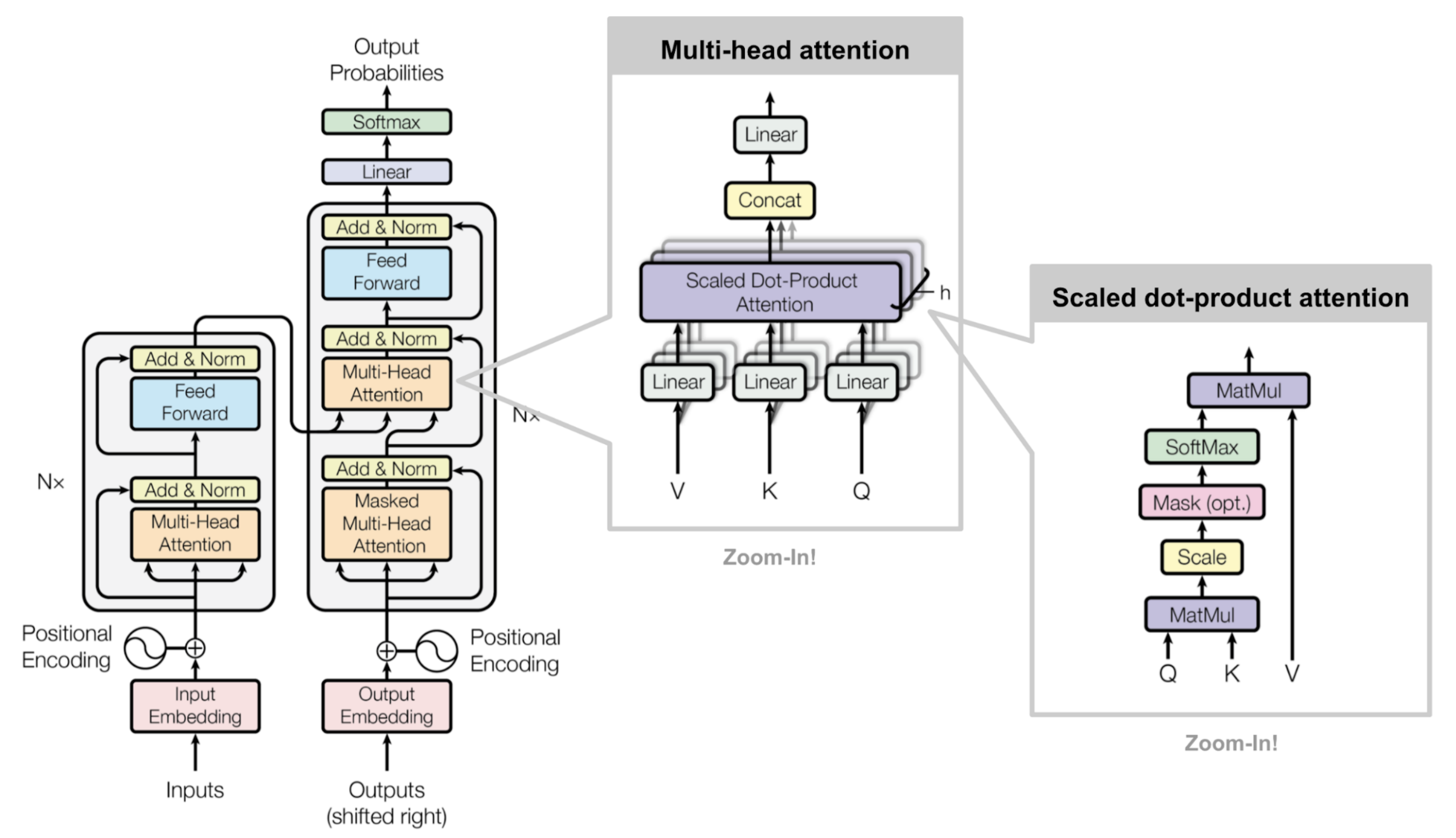


Népszerű architektúrák

Attention and Transformers :

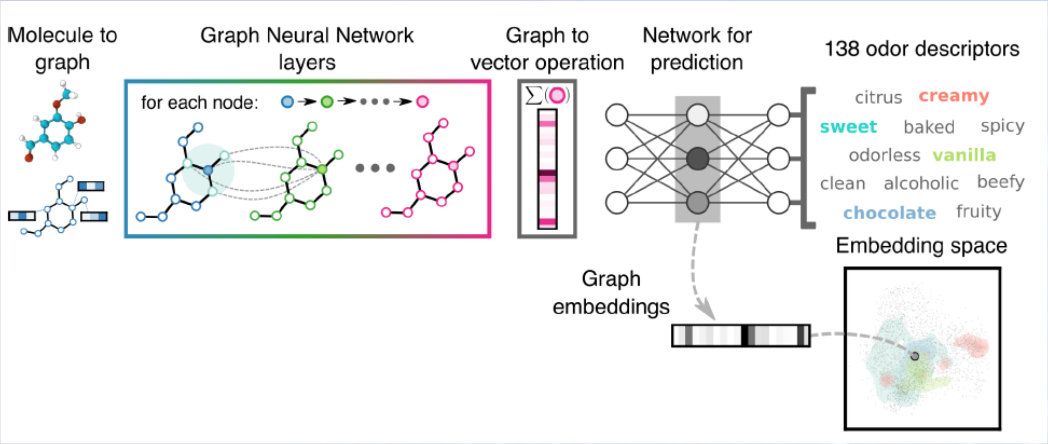
A revolution in natural language processing

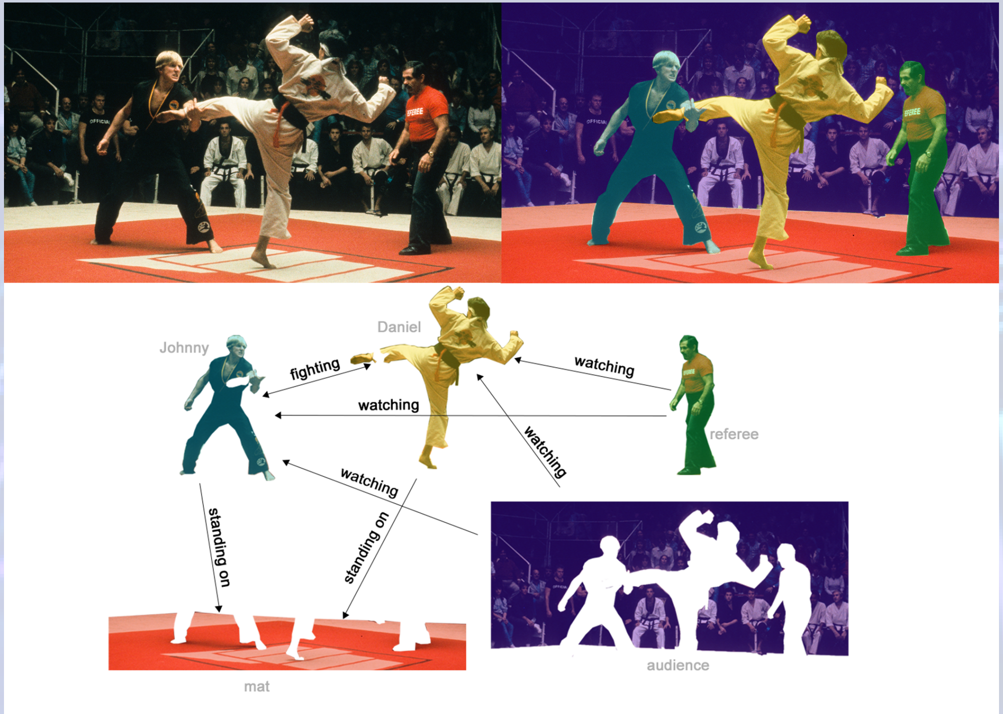


https://arxiv.org/abs/1706.03762

Népszerű architektúrák

Graph Neural Networks





Gépi tanulás a nagyenergiás fizikában

A Living Review of Machine Learning for Particle Physics

https://iml-wg.github.io/HEPML-LivingReview/

Matthew Feickert, Benjamin Nachman, arXiv:2102.02770

2021 May: 417 references

2022 May: 629 references

Today: 759 references

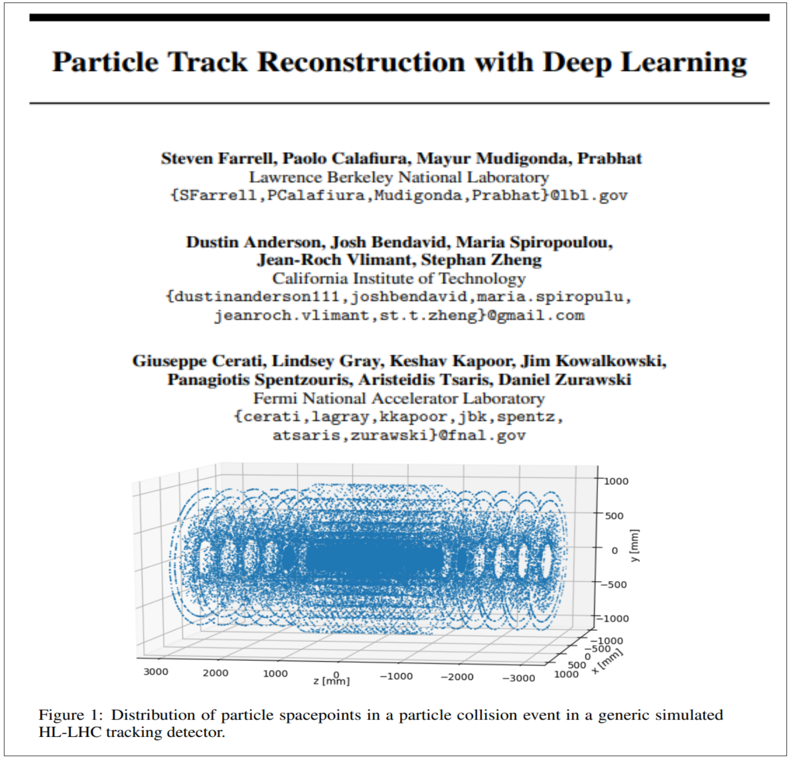
- Track reconstruction
- Quark/gluon jet separation
- Jet reconstruction
- Tuning Monte Carlo event generators
- GAN of detectors
- …

  - Accelerated Charged Particle Tracking with Graph Neural Networks on FPGAs
  - Particle Track Reconstruction using Geometric Deep Learning
  - Jet tagging in the Lund plane with graph networks [DOI]
  - Vertex and Energy Reconstruction in JUNO with Machine Learning Methods
  - MLPF: Efficient machine-learned particle-flow reconstruction using graph neural networks
  - 25th International Conference on Computing in High-Energy and Nuclear Physics
  - 25th International Conference on Computing in High-Energy and Nuclear Physics
  - Graph Neural Network for Object Reconstruction in Liquid Argon Time Projection Chambers
  - Instance Segmentation GNNs for One-Shot Conformal Tracking at the LHC
  - Charged particle tracking via edge-classifying interaction networks
  - Jet characterization in Heavy Ion Collisions by QCD-Aware Graph Neural Networks
  - Graph Generative Models for Fast Detector Simulations in High Energy Physics
  - Segmentation of EM showers for neutrino experiments with deep graph neural networks
- Sets (point clouds)
  - Energy Flow Networks: Deep Sets for Particle Jets [DOI]
  - ParticleNet: Jet Tagging via Particle Clouds [DOI]
  - ABCNet: An attention-based method for particle tagging [DOI]
  - Secondary Vertex Finding in Jets with Neural Networks
  - Equivariant Energy Flow Networks for Jet Tagging
  - Permutationless Many-Jet Event Reconstruction with Symmetry Preserving Attention Networks
  - Zero-Permutation Jet-Parton Assignment using a Self-Attention Network
  - Learning to Isolate Muons
  - Point Cloud Transformers applied to Collider Physics
- Physics-inspired basis
  - Automating the Construction of Jet Observables with Machine Learning [DOI]
  - How Much Information is in a Jet? [DOI]
  - Novel Jet Observables from Machine Learning [DOI]
  - Energy flow polynomials: A complete linear basis for jet substructure [DOI]
  - Deep-learned Top Tagging with a Lorentz Layer [DOI]
  - Resurrecting $b\bar{b}h$ with kinematic shapes
- W/Z tagging
  - Jet-images — deep learning edition [DOI]
  - Parton Shower Uncertainties in Jet Substructure Analyses with Deep Neural Networks [DOI]
  - QCD-Aware Recursive Neural Networks for Jet Physics [DOI]
  - Identification of heavy, energetic, hadronically decaying particles using machine-learning techniques [DOI]
  - Boosted W and Z tagging with jet charge and deep learning [DOI]
  - Supervised Jet Clustering with Graph Neural Networks for Lorentz Boosted Bosons [DOI]
  - Jet tagging in the Lund plane with graph networks [DOI]
  - A $W^\pm$ polarization analyzer from Deep Neural Networks
- $H\rightarrow b\bar{b$}
  - Automating the Construction of Jet Observables with Machine Learning [DOI]
  - Boosting $H\to b\bar b$ with Machine Learning [DOI]
  - Interaction networks for the identification of boosted $H \rightarrow b\overline{b}$ decays [DOI]
  - Interpretable deep learning for two-prong jet classification with jet spectra [DOI]
  - Identification of heavy, energetic, hadronically decaying particles using machine-learning techniques [DOI]
  - Disentangling Boosted Higgs Boson Production Modes with Machine Learning
  - Benchmarking Machine Learning Techniques with Di-Higgs Production at the LHC
  - The Boosted Higgs Jet Reconstruction via Graph Neural Network
  - Extracting Signals of Higgs Boson From Background Noise Using Deep Neural Networks
  - Learning to increase matching efficiency in identifying additional b-jets in the $\text{t}\bar{\text{t}}\text{b}\bar{\text{b}}$ process
- quarks and gluons
  - Quark versus Gluon Jet Tagging Using Jet Images with the ATLAS Detector
  - Deep learning in color: towards automated quark/gluon [DOI]
  - Recursive Neural Networks in Quark/Gluon Tagging [DOI]
  - DeepJet: Generic physics object based jet multiclass classification for LHC experiments
  - Probing heavy ion collisions using quark and gluon jet substructure
  - JEDI-net: a jet identification algorithm based on interaction networks [DOI]
  - Quark-Gluon Tagging: Machine Learning vs Detector [DOI]
  - Towards Machine Learning Analytics for Jet Substructure [DOI]
  - Quark Gluon Jet Discrimination with Weakly Supervised Learning [DOI]

- Classification
  - Parameterized classifiers
    - Parameterized neural networks for high-energy physics [DOI]
    - Approximating Likelihood Ratios with Calibrated Discriminative Classifiers
    - E Pluribus Unum Ex Machina: Learning from Many Collider Events at Once
    - Jet images
      - How to tell quark jets from gluon jets
      - Jet-Images: Computer Vision Inspired Techniques for Jet Tagging [DOI]
      - Playing Tag with ANN: Boosted Top Identification with Pattern Recognition [DOI]
      - Jet-images — deep learning edition [DOI]
      - Quark versus Gluon Jet Tagging Using Jet Images with the ATLAS Detector
      - Boosting $H\to b\bar b$ with Machine Learning [DOI]
      - Learning to classify from impure samples with high-dimensional data [DOI]
      - Parton Shower Uncertainties in Jet Substructure Analyses with Deep Neural Networks [DOI]
      - Deep learning in color: towards automated quark/gluon [DOI]
      - Deep-learning Top Taggers or The End of QCD? [DOI]
      - Pulling Out All the Tops with Computer Vision and Deep Learning [DOI]
      - Reconstructing boosted Higgs jets from event image segmentation
      - An Attention Based Neural Network for Jet Tagging
      - Quark-Gluon Jet Discrimination Using Convolutional Neural Networks [DOI]
      - Learning to Isolate Muons
      - Deep learning jet modifications in heavy-ion collisions
    - Event images
      - Topology classification with deep learning to improve real-time event selection at the LHC [DOI]
      - Convolutional Neural Networks with Event Images for Pileup Mitigation with the ATLAS Detector
      - Boosting $H\to b\bar b$ with Machine Learning [DOI]
      - End-to-End Physics Event Classification with the CMS Open Data: Applying Image-based Deep Learning on Detector Data to Directly Classify Collision Events at the LHC [DOI]
      - Disentangling Boosted Higgs Boson Production Modes with Machine Learning
      - Identifying the nature of the QCD transition in relativistic collision of heavy nuclei with deep learning [DOI]
    - Sequences
      - Jet Flavor Classification in High-Energy Physics with Deep Neural Networks [DOI]
      - Topology classification with deep learning to improve real-time event selection at the LHC [DOI]
      - Jet Flavour Classification Using DeepJet [DOI]
      - Development of a Vertex Finding Algorithm using Recurrent Neural Network
      - Sequence-based Machine Learning Models in Jet Physics
    - Trees
      - QCD-Aware Recursive Neural Networks for Jet Physics [DOI]
      - Recursive Neural Networks in Quark/Gluon Tagging [DOI]
    - Graphs
      - Neural Message Passing for Jet Physics
      - Graph Neural Networks for Particle Reconstruction in High Energy Physics detectors
      - Probing stop pair production at the LHC with graph neural networks [DOI]
      - Pileup mitigation at the Large Hadron Collider with graph neural networks [DOI]
      - Unveiling CP property of top-Higgs coupling with graph neural networks at the LHC [DOI]
      - JEDI-net: a jet identification algorithm based on interaction networks [DOI]
      - Learning representations of irregular particle-detector geometry with distance-weighted graph networks [DOI]
      - Interpretable deep learning for two-prong jet classification with jet spectra [DOI]
      - Neural Network-based Top Tagger with Two-Point Energy Correlations and Geometry of Soft Emissions [DOI]
      - Probing triple Higgs coupling with machine learning at the LHC
      - Casting a graph net to catch dark showers [DOI]
      - Graph neural networks in particle physics [DOI]
      - Distance-Weighted Graph Neural Networks on FPGAs for Real-Time Particle Reconstruction in High Energy Physics [DOI]
      - Supervised Jet Clustering with Graph Neural Networks for Lorentz Boosted Bosons [DOI]
      - Track Seeding and Labelling with Embedded-space Graph Neural Networks
      - Graph neural network for 3D classification of ambiguities and optical crosstalk in scintillator-based neutrino detectors [DOI]

Gépi tanulás a nagyenergiás fizikában

Track reconstruction



Particle Track Reconstruction with Deep Learning

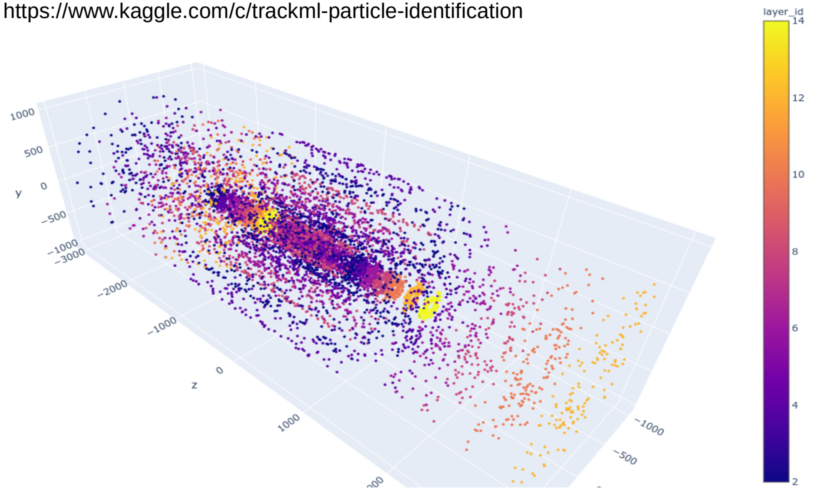
Steven Farrell, Paolo Calafiura, Mayur Mudigonda, Prabhat
Lawrence Berkeley National Laboratory
{SFarrell,PCalafiura,Mudigonda,Prabhat}@lbl.gov

Dustin Anderson, Josh Bendavid, Maria Spiropoulou, Jean-Roch Vlimant, Stephan Zheng
California Institute of Technology
{dustinanderson111,joshbendavid,maria.spiropulu, jeanroch.vlimant,st.t.zheng}@gmail.com

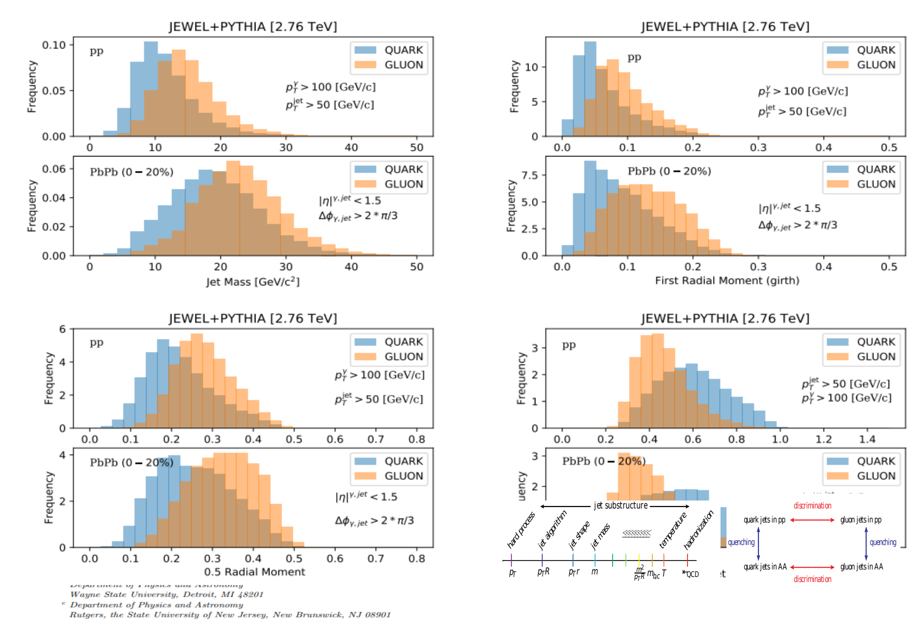
Giuseppe Cerati, Lindsey Gray, Keshav Kapoor, Jim Kowalkowski, Panagiotis Spentzouris, Aristeidis Tsaris, Daniel Zurawski
Fermi National Accelerator Laboratory
{cerati,lagray,kkapoor,jbk,spentz, atsaris,zurawski}@fnal.gov

Figure 1: Distribution of particle spacepoints in a particle collision event in a generic simulated HL-LHC tracking detector.

https://www.kaggle.com/c/trackml-particle-identification

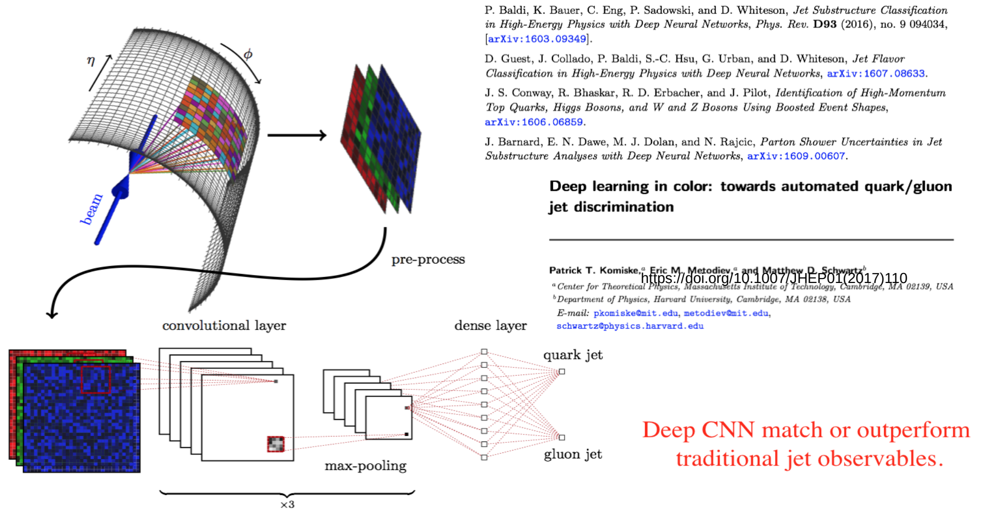


Gépi tanulás a nagyenergiás fizikában



arXiv:1803.03589

Quark/gluon jet separation


P. Baldi, K. Bauer, C. Eng, P. Sadowski, and D. Whiteson, *Jet Substructure Classification in High-Energy Physics with Deep Neural Networks*, *Phys. Rev.* **D93** (2016), no. 9 094034, [arXiv:1603.09349].

D. Guest, J. Collado, P. Baldi, S.-C. Hsu, G. Urban, and D. Whiteson, *Jet Flavor Classification in High-Energy Physics with Deep Neural Networks*, arXiv:1607.08633.

J. S. Conway, R. Bhaskar, R. D. Erbacher, and J. Pilot, *Identification of High-Momentum Top Quarks, Higgs Bosons, and W and Z Bosons Using Boosted Event Shapes*, arXiv:1606.06859.

J. Barnard, E. N. Dawe, M. J. Dolan, and N. Rajcic, *Parton Shower Uncertainties in Jet Substructure Analyses with Deep Neural Networks*, arXiv:1609.00607.

Deep learning in color: towards automated quark/gluon jet discrimination

Patrick T. Komiske,[a] Eric M. Metodiev,[a] and Matthew D. Schwartz[b]

[a] Center for Theoretical Physics, Massachusetts Institute of Technology, Cambridge, MA 02139, USA
[b] Department of Physics, Harvard University, Cambridge, MA 02138, USA
E-mail: pkomiske@mit.edu, metodiev@mit.edu, schwartz@physics.harvard.edu

https://doi.org/10.1007/JHEP01(2017)110

Deep CNN match or outperform traditional jet observables.

Figure 2: An illustration of the deep convolutional neural network architecture. The first layer is the input jet image, followed by three convolutional layers, a dense layer and an output layer.

Gépi tanulás a nagyenergiás fizikában

Machine Learning based jet momentum reconstruction in heavy-ion collisions

Rüdiger Haake[1] and Constantin Loizides[2]
[1] Yale University, Wright Laboratory, New Haven, CT, USA
[2] ORNL, Physics Division, Oak Ridge, TN, USA
(Dated: June 24, 2019)

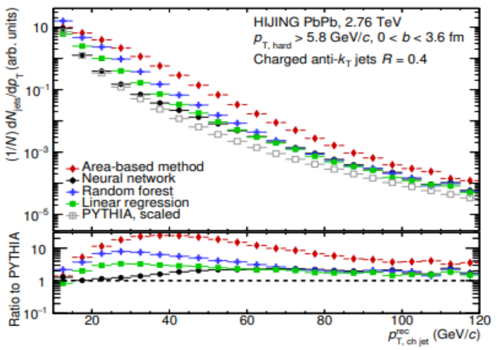


FIG. 9. Reconstructed charged jet spectra in HIJING events and the ratio to (N_{coll}-scaled) PYTHIA jet spectra.

Feature	Score	Feature	Score
Jet p_T (no corr.)	**0.1355**	$p^1_{T,\,const}$	0.0012
Jet mass	0.0007	$p^2_{T,\,const}$	**0.0039**
Jet area	0.0005	$p^3_{T,\,const}$	0.0015
Jet p_T (area-based corr.)	**0.7876**	$p^4_{T,\,const}$	0.0011
LeSub	0.0004	$p^5_{T,\,const}$	0.0009
Radial moment	0.0005	$p^6_{T,\,const}$	0.0009
Momentum dispersion	0.0007	$p^7_{T,\,const}$	0.0008
Number of constituents	0.0008	$p^8_{T,\,const}$	0.0007
Mean of const. p_T	**0.0585**	$p^9_{T,\,const}$	0.0006
Median of const. p_T	0.0023	$p^{10}_{T,\,const}$	0.0007

Jet reconstruction

Machine Learning based jet momentum reconstruction in Pb–Pb collisions measured with the ALICE detector

Rüdiger Haake* for the ALICE Collaboration
Yale University, Wright Laboratory, New Haven, CT, USA
E-mail: ruediger.haake@cern.ch

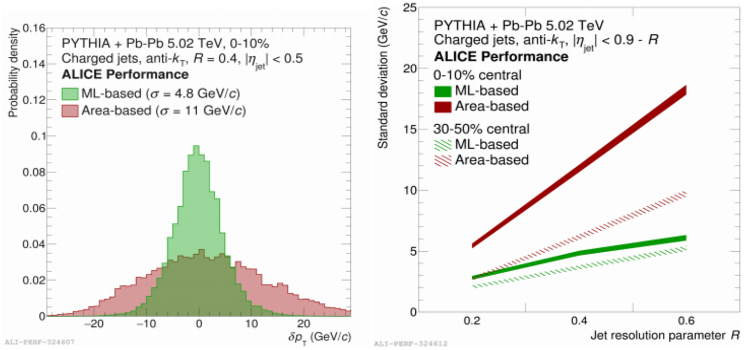
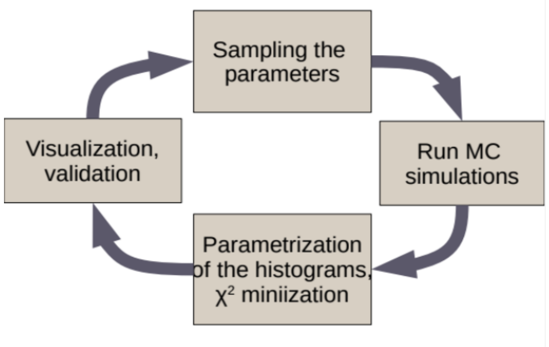


Figure 1: Residual p_T-distributions of embedded jet probes of known transverse momentum.

https://doi.org/10.22323/1.364.0312

Gépi tanulás a nagyenergiás fizikában

Tuning Monte Carlo event generators



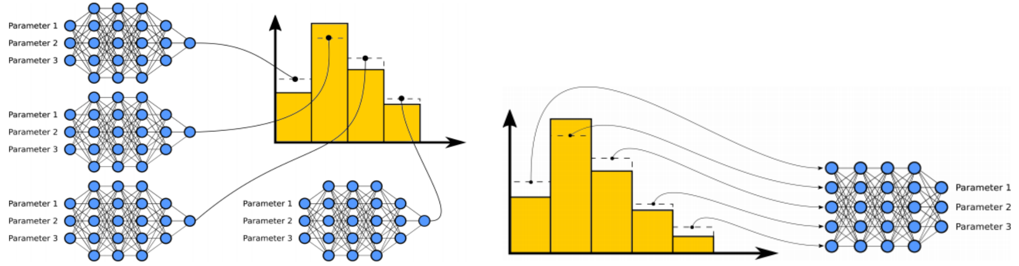


Figure 1: An illustration of the parametrisation of the generator response as implemented in the Per Bin Model.

Figure 2: An illustration of the Inverse Model strategy.

MCNNTUNES: tuning Shower Monte Carlo generators with machine learning

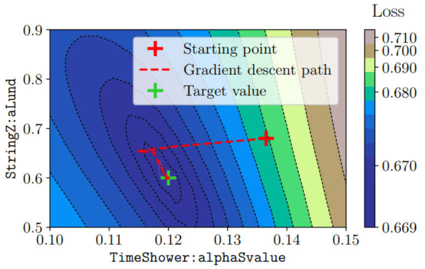
Marco Lazzarin[a], Simone Alioli[b], Stefano Carrazza[a]

[a] TIF Lab, Dipartimento di Fisica, Università degli Studi di Milano and INFN Sezione di Milano, Milan, Italy.
[b] Dipartimento di Fisica, Università degli Studi di Milano Bicocca and INFN Sezione di Milano Bicocca, Milan, Italy.

https://doi.org/10.1016/j.cpc.2021.107908

Neural Networks for Full Phase-space Reweighting and Parameter Tuning

Anders Andreassen[1,2,*] and Benjamin Nachman[2,†]
[1] Department of Physics, University of California, Berkeley, CA 94720, USA
[2] Physics Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA



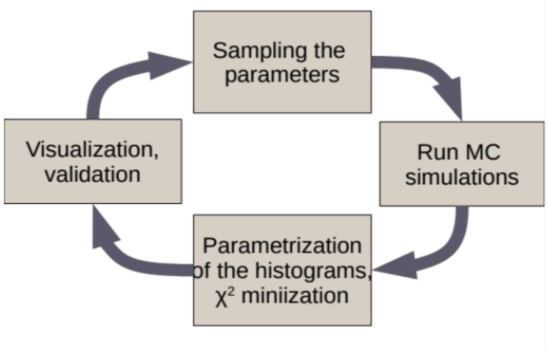
Accelerating Science with Generative Adversarial Networks: An Application to 3D Particle Showers in Multi-Layer Calorimeters

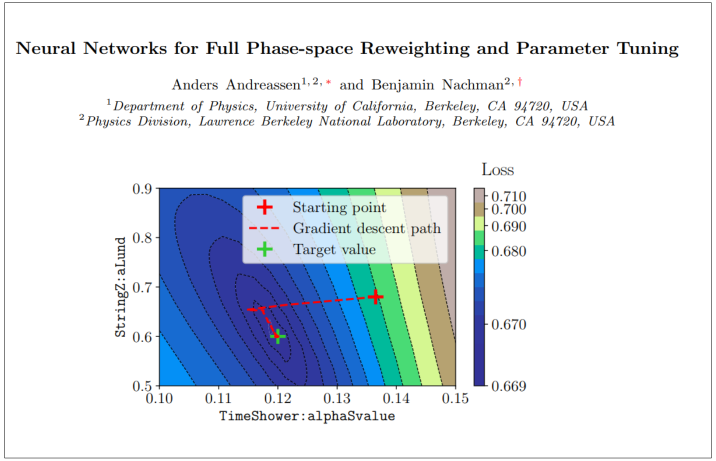
Michela Paganini,[1,2,*] Luke de Oliveira,[1,†] and Benjamin Nachman[1,‡]
[1] Lawrence Berkeley National Laboratory, Berkeley, CA 94720
[2] Yale University, New Haven, CT 06520

https://doi.org/10.1103/PhysRevLett.120.042003

Gépi tanulás a nagyenergiás fizikában

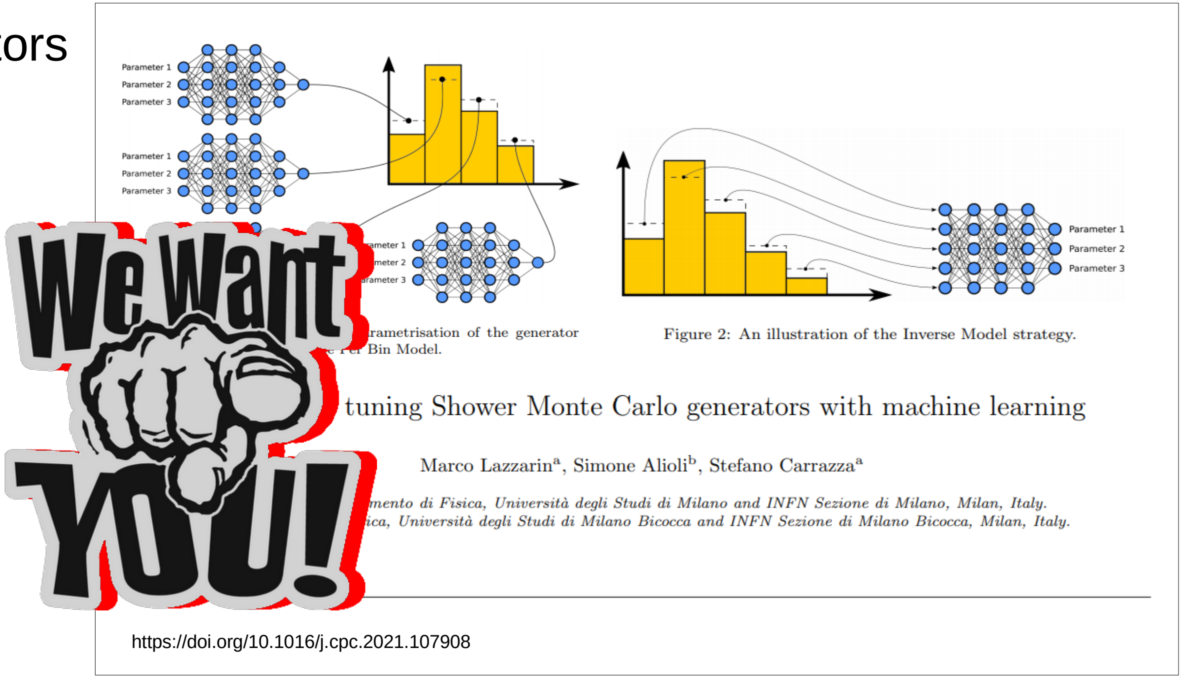
Tuning Monte Carlo event generators




Neural Networks for Full Phase-space Reweighting and Parameter Tuning

Anders Andreassen[1,2,*] and Benjamin Nachman[2,†]

[1]Department of Physics, University of California, Berkeley, CA 94720, USA
[2]Physics Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA



...rametrisation of the generator ... Bin Model.

Figure 2: An illustration of the Inverse Model strategy.

...tuning Shower Monte Carlo generators with machine learning

Marco Lazzarin[a], Simone Alioli[b], Stefano Carrazza[a]

...mento di Fisica, Università degli Studi di Milano and INFN Sezione di Milano, Milan, Italy.
...ica, Università degli Studi di Milano Bicocca and INFN Sezione di Milano Bicocca, Milan, Italy.

https://doi.org/10.1016/j.cpc.2021.107908

Accelerating Science with Generative Adversarial Networks: An Application to 3D Particle Showers in Multi-Layer Calorimeters

Michela Paganini,[1,2,*] Luke de Oliveira,[1,†] and Benjamin Nachman[1,‡]

[1]Lawrence Berkeley National Laboratory, Berkeley, CA 94720
[2]Yale University, New Haven, CT 06520

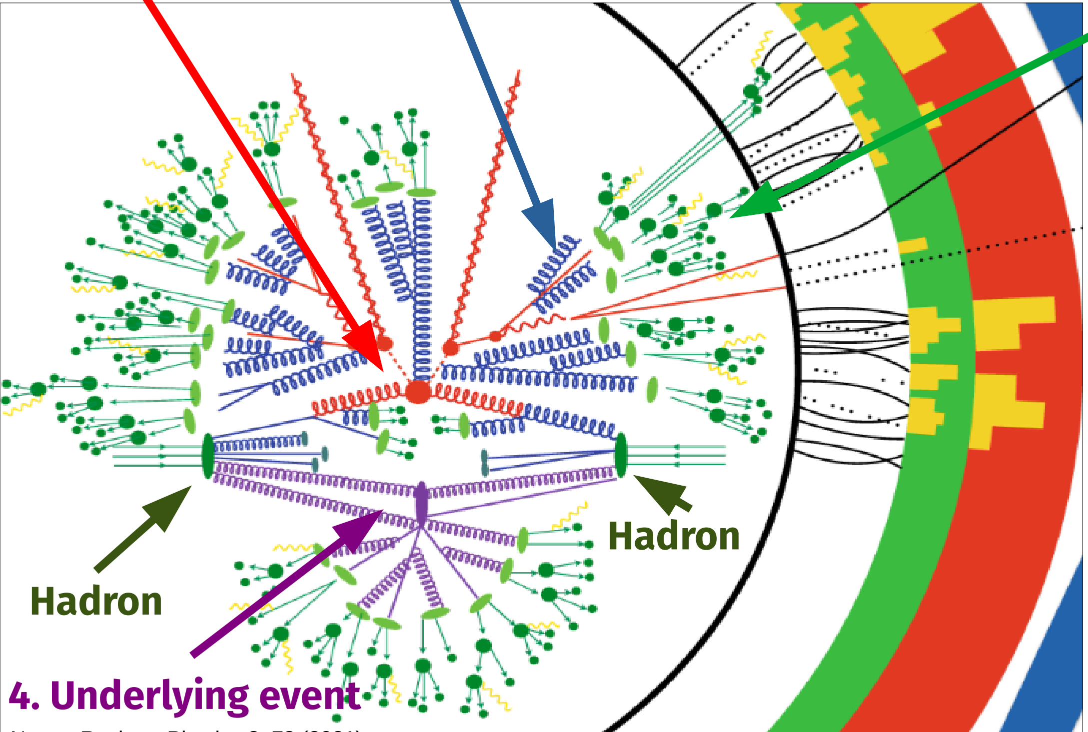
https://doi.org/10.1103/PhysRevLett.120.042003

Részecskezápor és hadronizáció

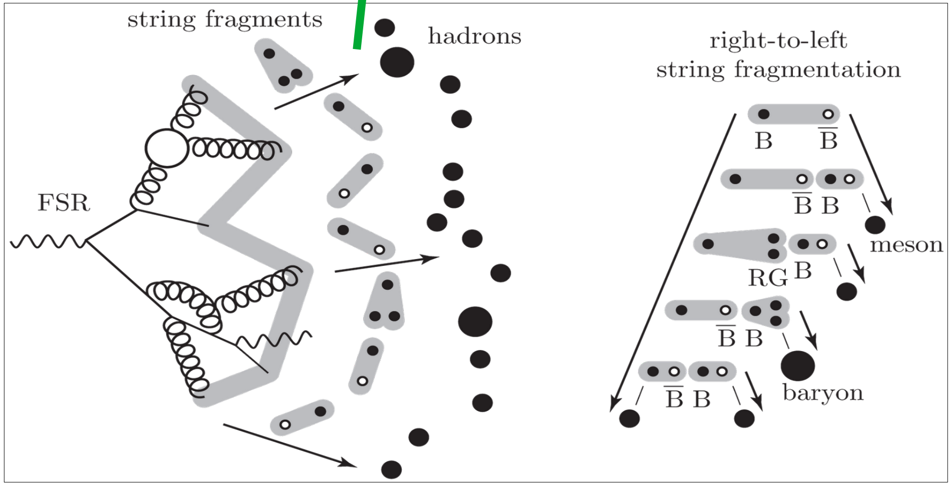
1. Hard scattering

2. Parton shower

3. Hadronization

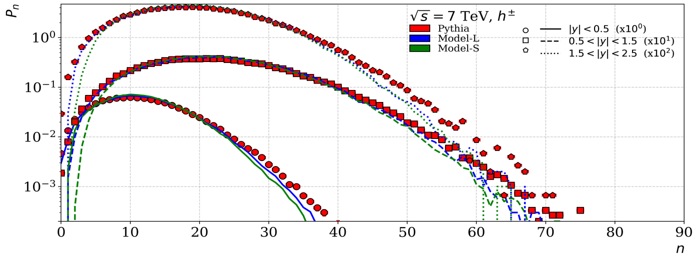


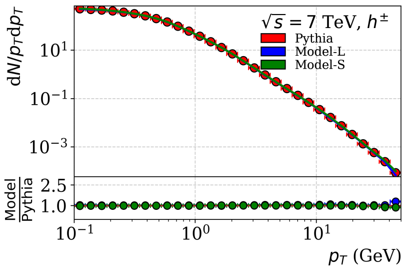
Nature Reviews Physics 3, 73 (2021)

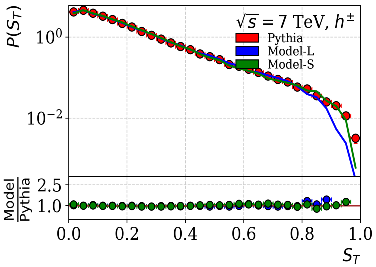


arXiv:2111.15655
arXiv:2210.10548

Proton-proton ütközések LHC energián



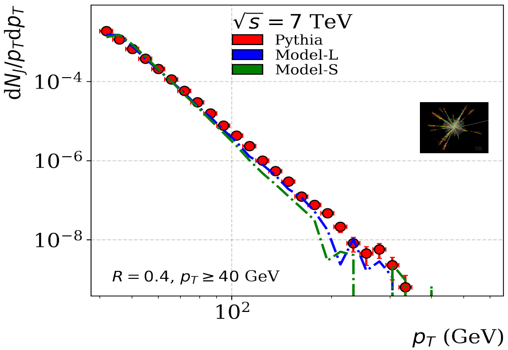


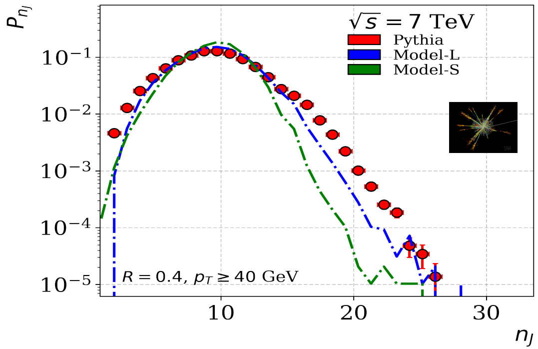


Charged hadron multiplicity at various rapidity windows

Good agreement for both models

Charged hadron transverse momentum
0.1 GeV ≤ pT ≤ 50 GeV



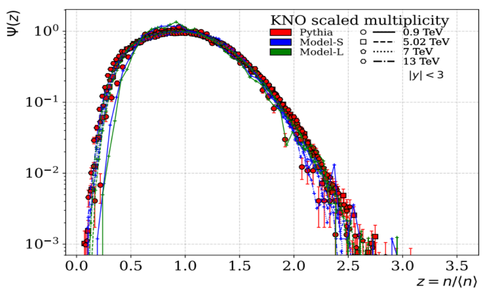


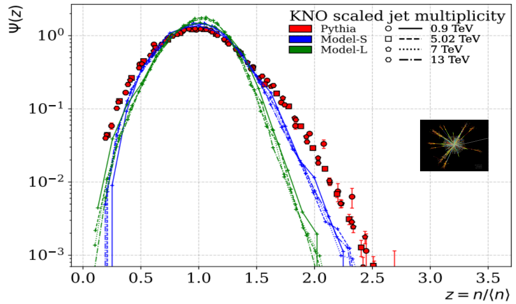
Jets:

- Mean p_T ≤ 400 GeV
- Mean multiplicity

The smaller model performs better

Training only at a single c.m. energy, predictions at other energies





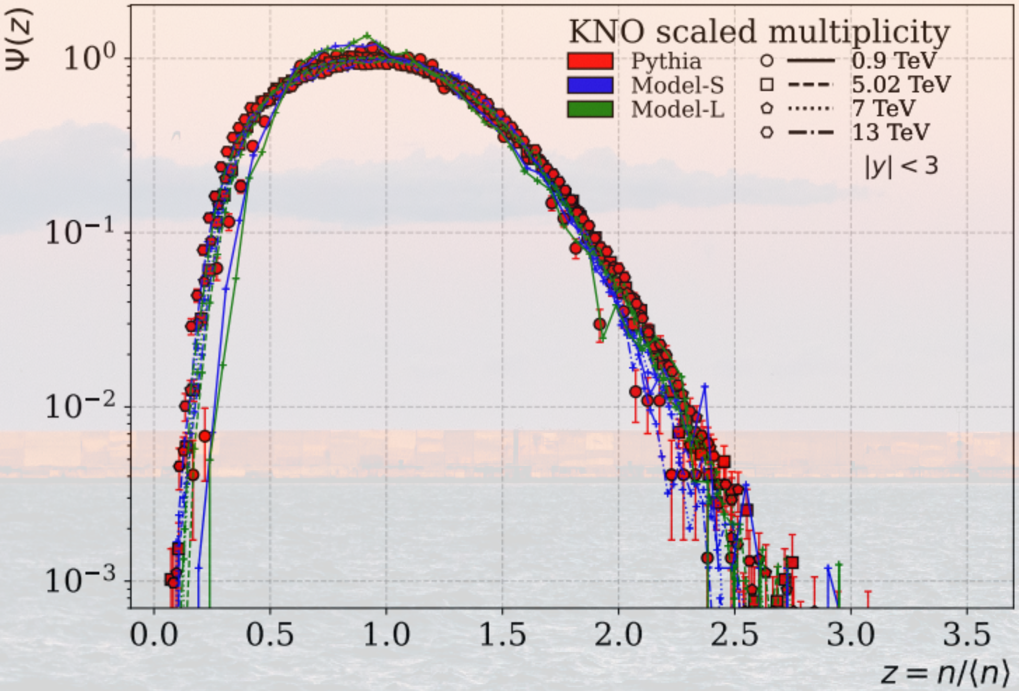
Scaling function for multiplicities at various energies:

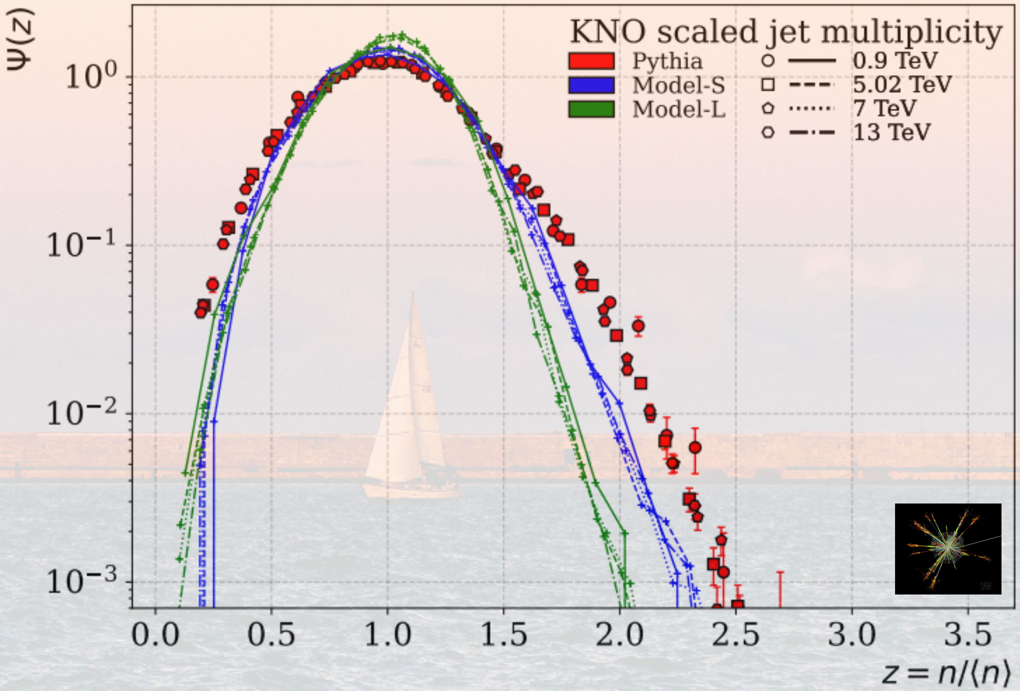
$$P_n = \frac{1}{\langle n \rangle} \Psi\left(\frac{n}{\langle n \rangle}\right)$$

Charged hadron multiplicities in **jetty** events: good overlap and agreement at **all LHC energies**

Mean jet multiplicities: different scaling for the models

KNO-skálázás tesztje





Scaling function for multiplicities at various energies: $P_n = \frac{1}{\langle n \rangle} \Psi \left(\frac{n}{\langle n \rangle} \right)$

Charged hadron multiplicities in **jetty** events: good overlap and agreement

Mean jet multiplicities: different scaling for the models

Nucl.Phys.B Proc.Suppl. 92 (2001) 122-129

Dimenzionalitás

Input:

Parton level

Discretized in the (y,ϕ) plane: p_T,m, multiplicity

$$\left.\begin{array}{ll} y \in [\pi,\pi], & \text{32 bins} \\ \phi \in [0,2\pi], & \text{32 bins} \end{array}\right\} := M$$

$\mathcal{O}(10^3 - 10^4)$ Total pixels

vs $\mathcal{O}(10^2)$

Pixels with information

Reduction with Singular Value Decomposition:

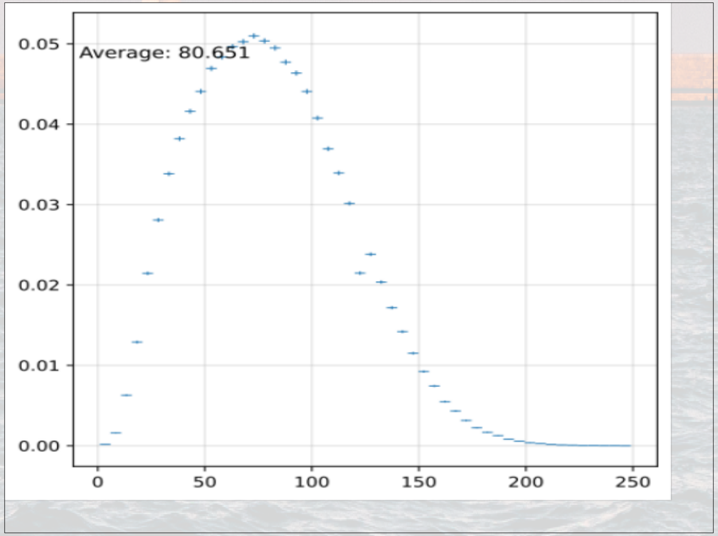
$$M_{n\times m} = U_{n\times n}\Sigma_{n\times m}V^T_{m\times m}$$

- Unitarity
- Ordered by importance
- Guaranteed to exist, unique

$$M \approx \sum_{i=1}^{r} \sigma_i u_i v_i^T + \mathcal{O}(\epsilon), \quad r \leq \min\{n,m\}$$

Reduce the input to $\mathcal{O}(10^2)$

doi:10.1007/BF02288367



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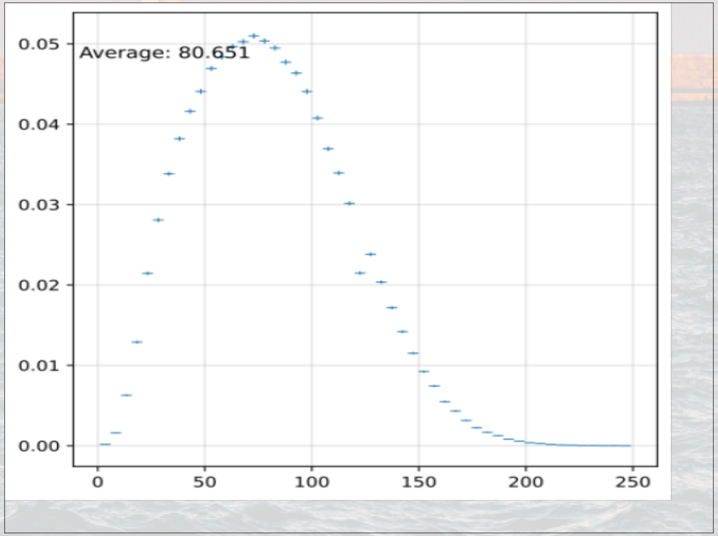
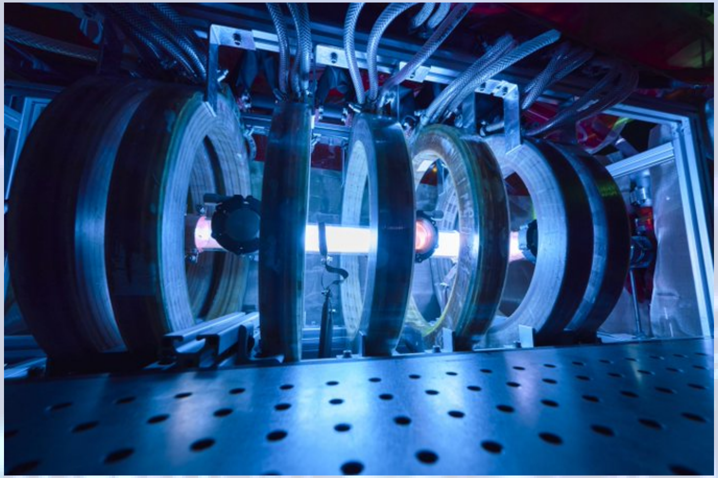


doi:10.1007/BF0228830

Plazmahullámok meglovagolása

CERN–AWAKE Experiment: accelerate electrons in the wake field of proton

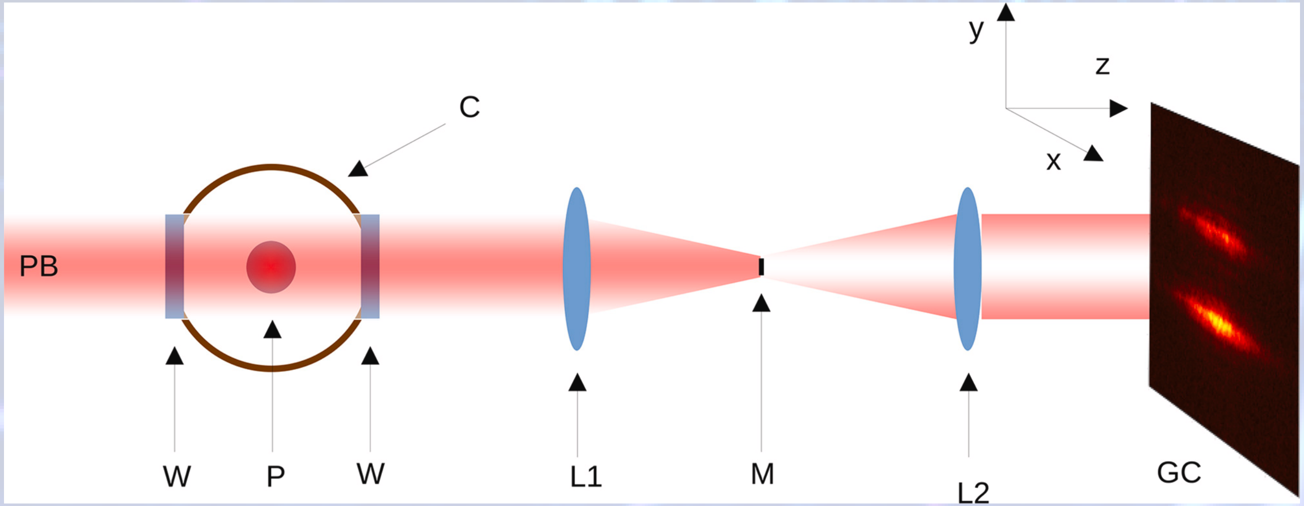
Microbunches: Nuclear Instruments and Methods in Physics Research Section A, 829 (2016) 76-82

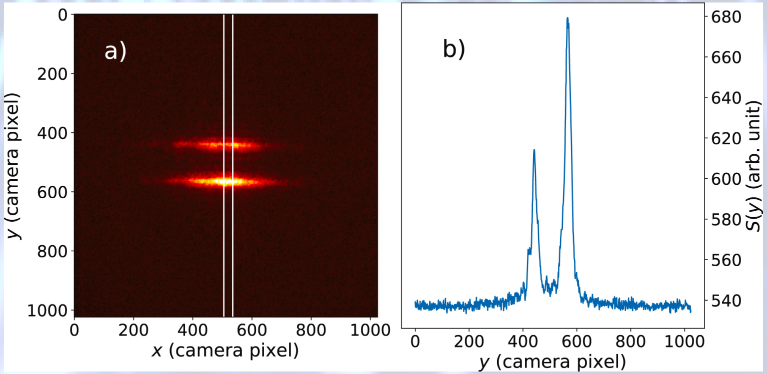


Accelerating medium: Rb plasma: 10 m length, 1014 – 1015 cm^{-3} density. Chamber diameter: 4 cm

Experiment motivation: determine plasma parameters via Schlieren imaging

G. Bíró et. al: Optics & Laser Technology, 159 (2023) 108948



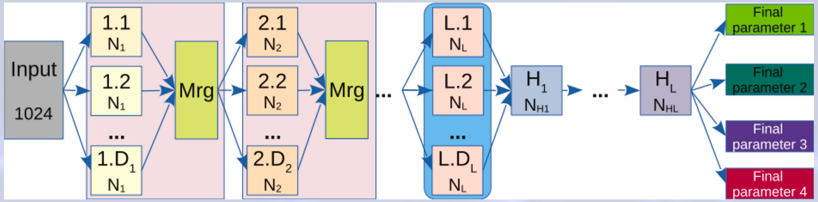


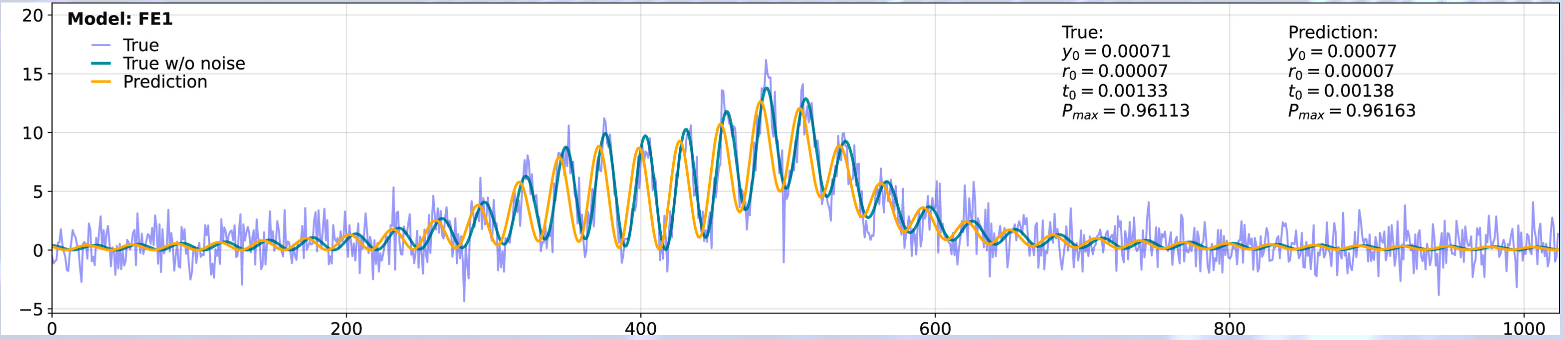
Plazmahullámok meglovagolása

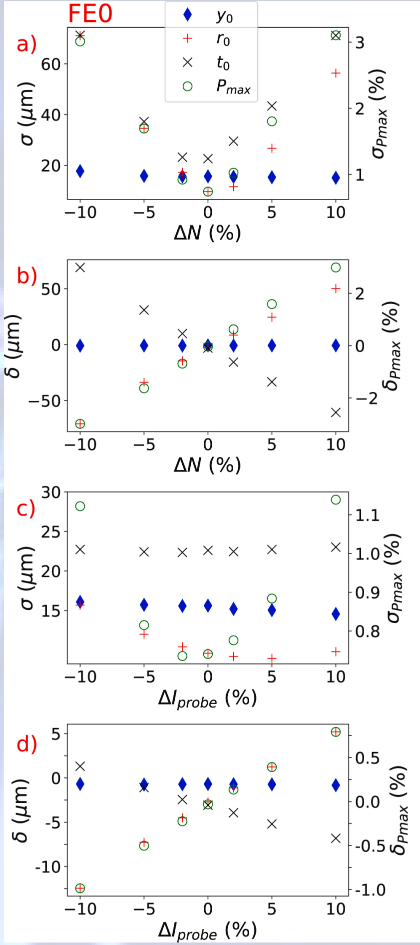
Rugalmasan paraméterezhető hálózat

Paraméterek predikciója

Kísérleti változókra robosztus





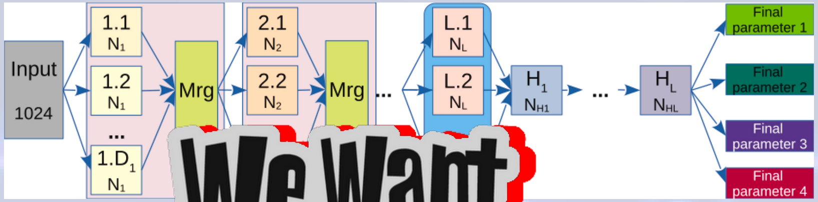


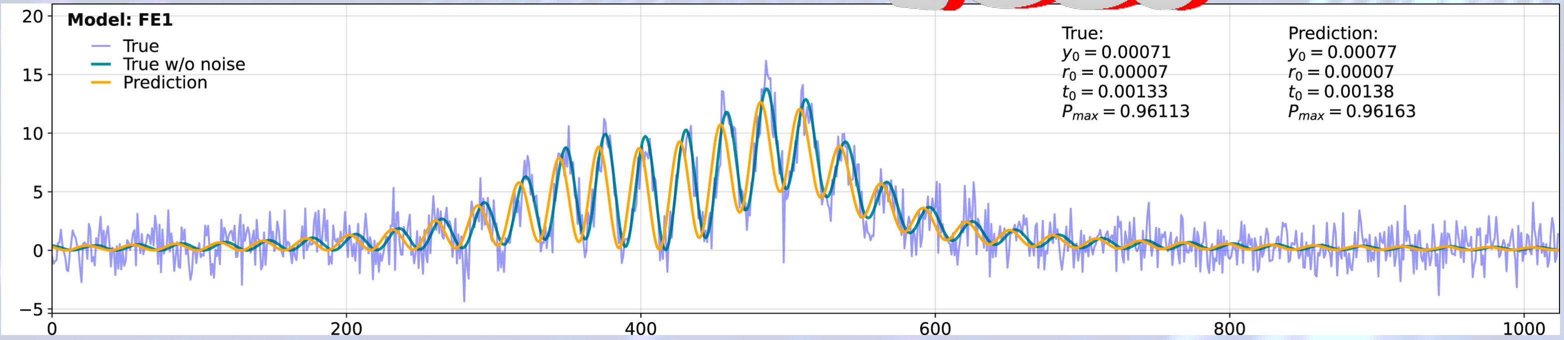
Plazmahullámok meglovagolása

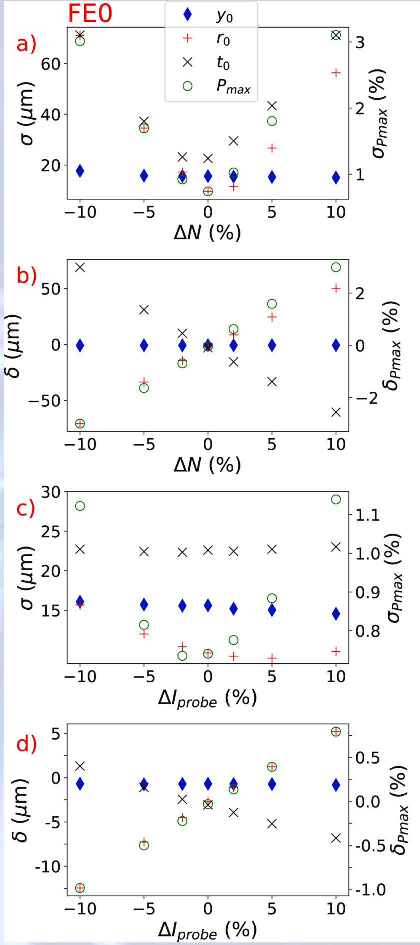
Rugalmasan paraméterezhető hálózat

Paraméterek predikciója

Kísérleti változókra robosztus







Proton tomográfia – ld. Dudás Bence előadása

Pályázati programok, témalehetőségek, tutorial sorozatok & oktatás

BSc/MSc/PhD/PostDoc projektek a **Wigner FK-ban**

https://alice.wigner.hu/
https://wigner.hu/en/wsclab
http://gpu.wigner.hu/en/home
https://gpuday.com/

Köszönöm a figyelmet!

Támogatók: OTKA K135515, 2019-2.1.11-TÉT-2019 -00078, NKFIH 2019-2.1.6-NEMZKI-2019-00011, 2020-2.1.1-ED-2021-00179, Wigner Scientific Computing Laboratory, MILAB RRF-2.3.1-21-2022-00004.