Machine Learning, the Proton Structure, and Higgs Physics at the LHC

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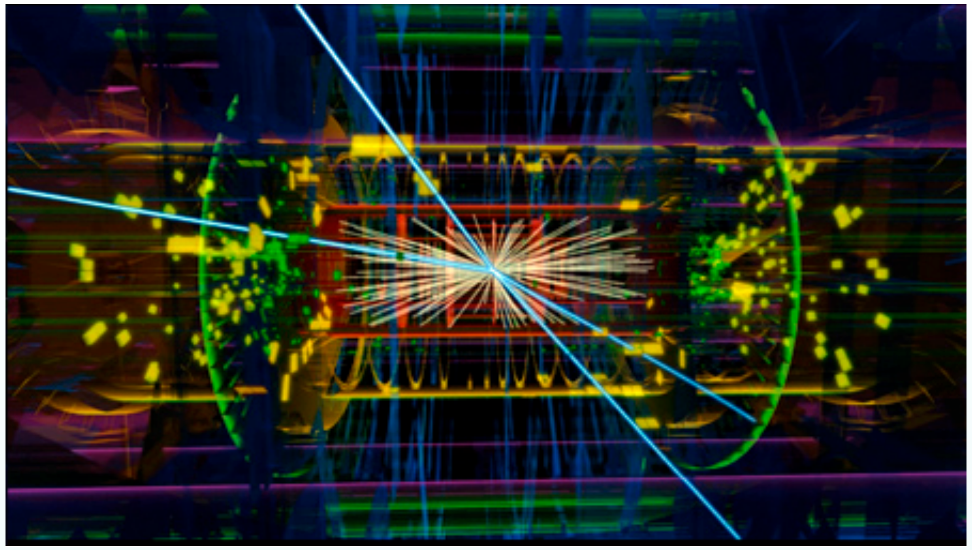
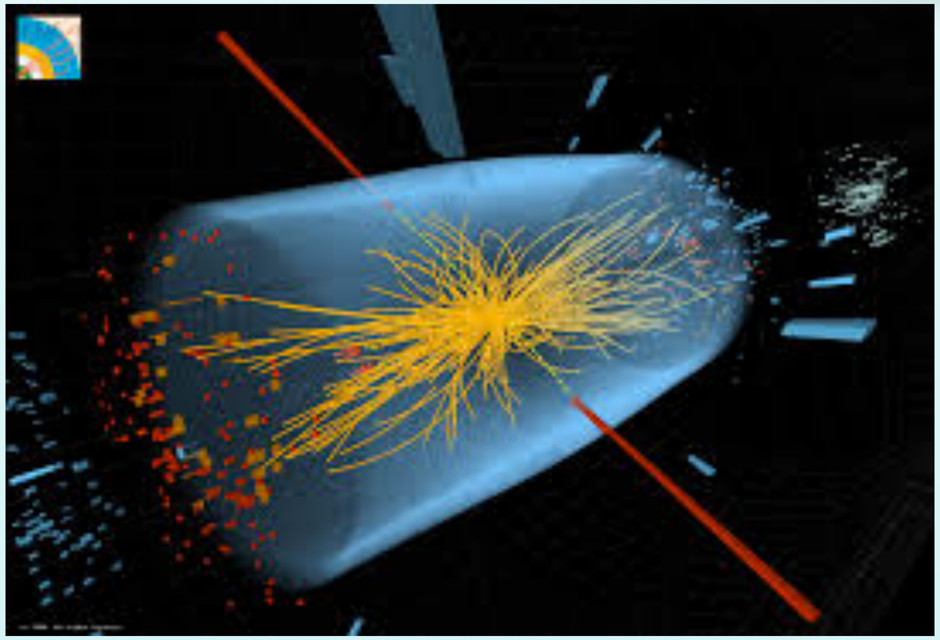


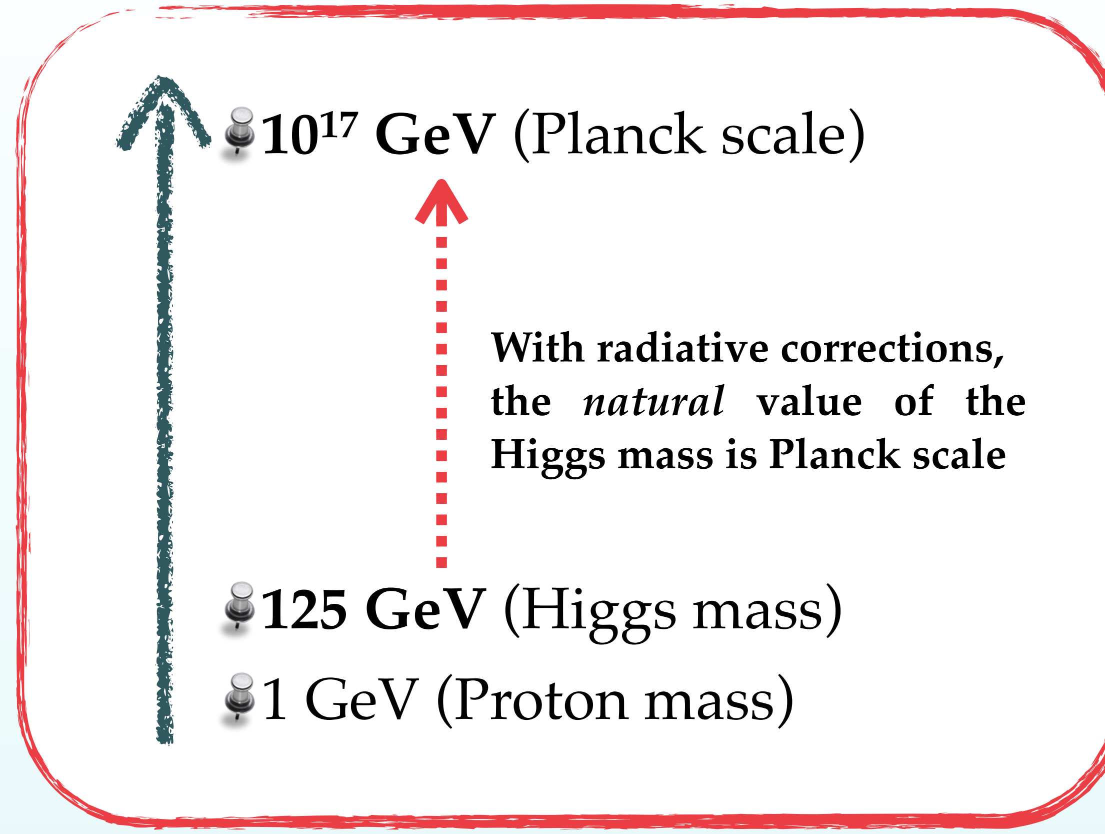
Exploring the high-energy frontier at the Large Hadron Collider

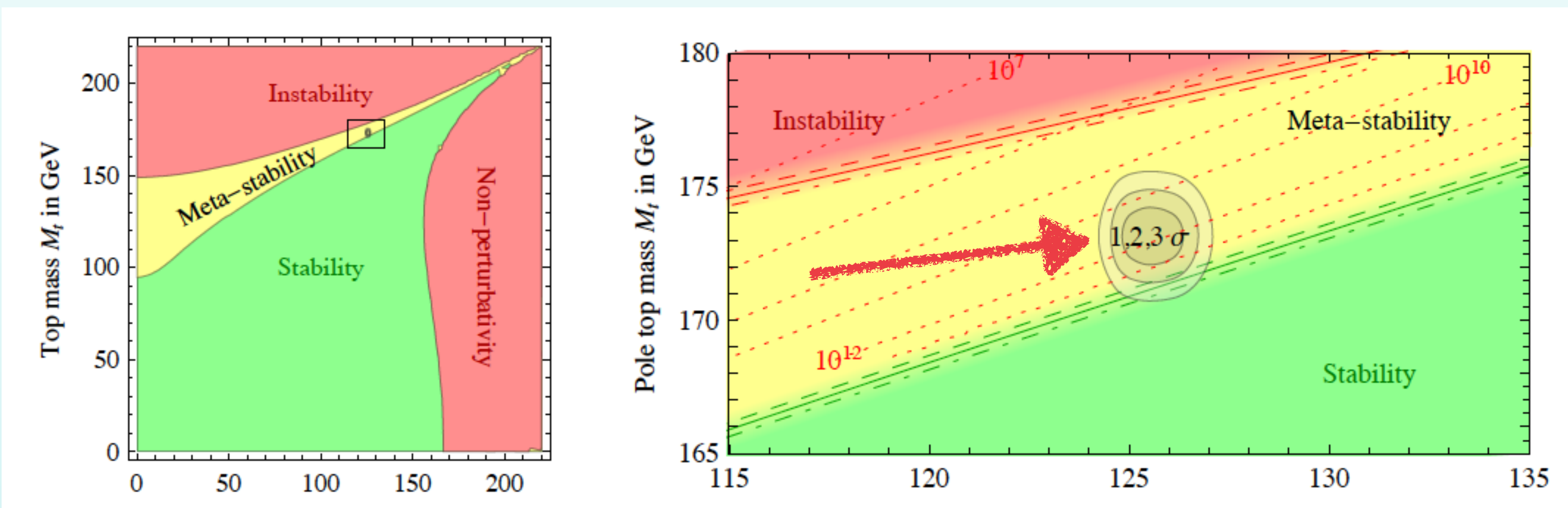


Outstanding questions in Particle Physics

The Higgs boson

- ☑ Huge gap, 10^{17}, between **Higgs and Plank scales**
- ☑ **Elementary or composite**? Additional Higgs bosons?
- ☑ Coupling to **Dark Matter**? Role in cosmological phase transitions?
- ☑ Is the **vacuum state of the Universe** stable?





Degrassi et al 12

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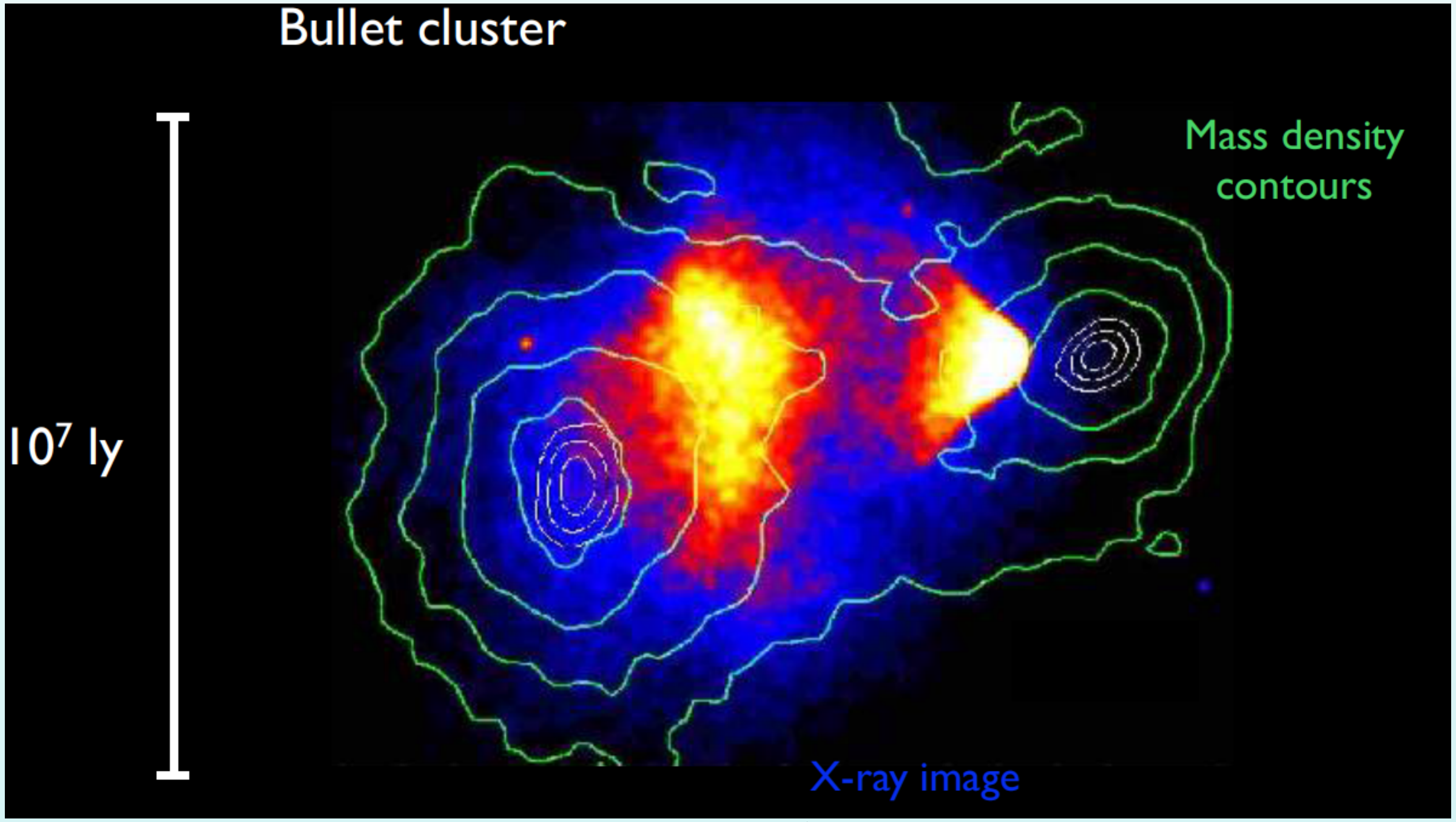
Dark Matter

- **Weakly interacting massive particles**? Sterile neutrinos? **Extremely light particles** (axions)?
- **Interactions** with Standard Model particles?
- What is the **structure of the Dark Sector**? Is Dark Matter self-interacting?



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Quarks and leptons

- **Why three families? Can we explain masses and mixings**?
- Origin of **Matter-Antimatter asymmetry** in the Universe?
- Are **neutrinos Majorana or Dirac**? CP violation in the lepton sector?

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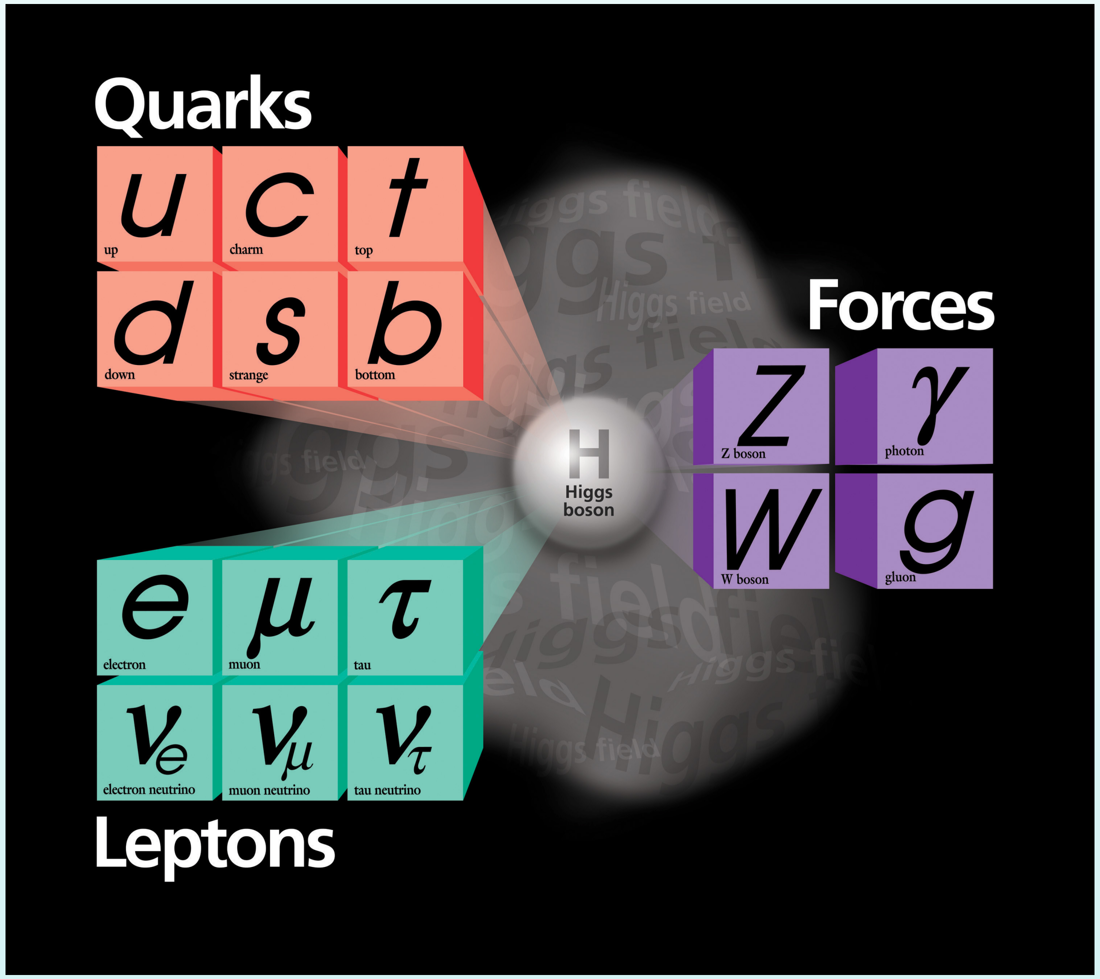

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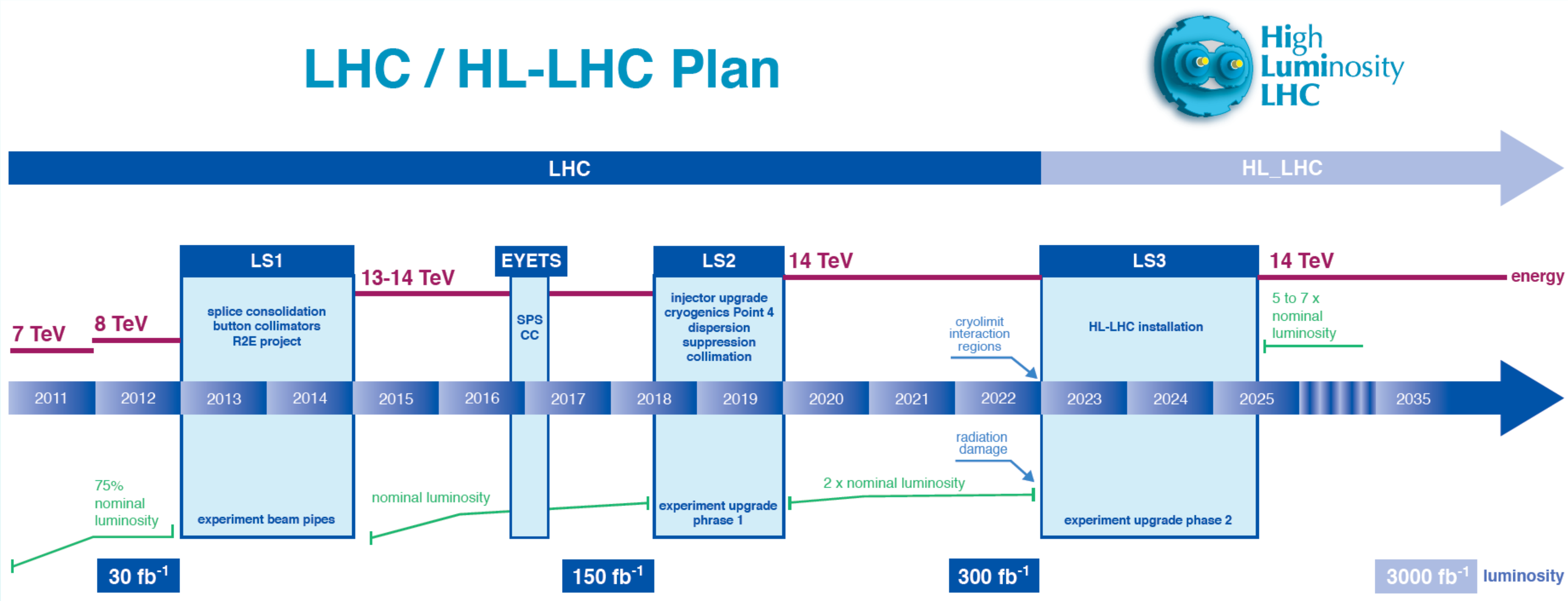
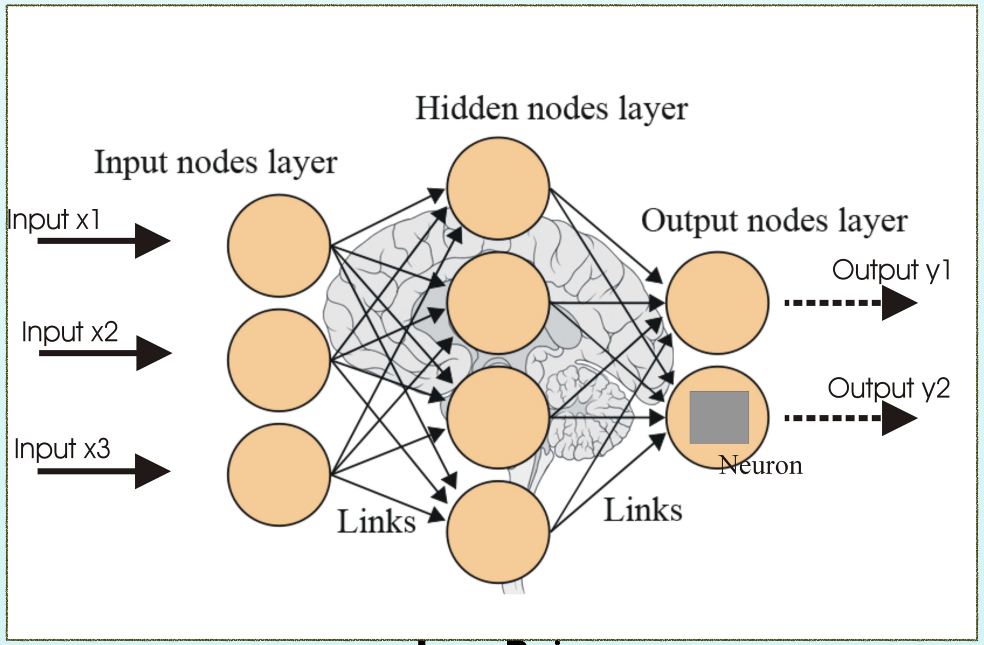


Many of these crucial questions can be addressed at the Large Hadron Collider

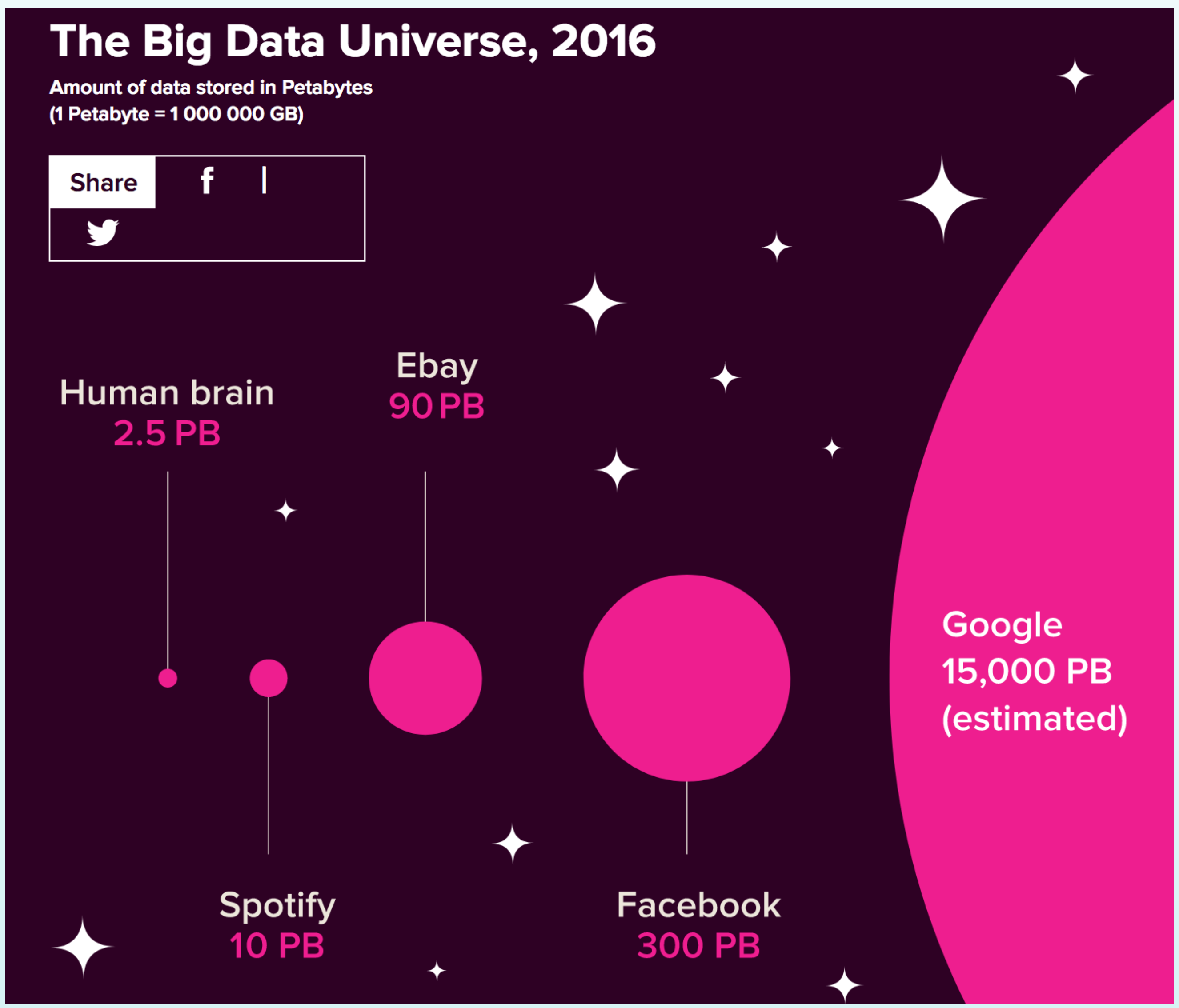
For the next 20 years, LHC will be the forefront of the exploration of the high-energy frontier

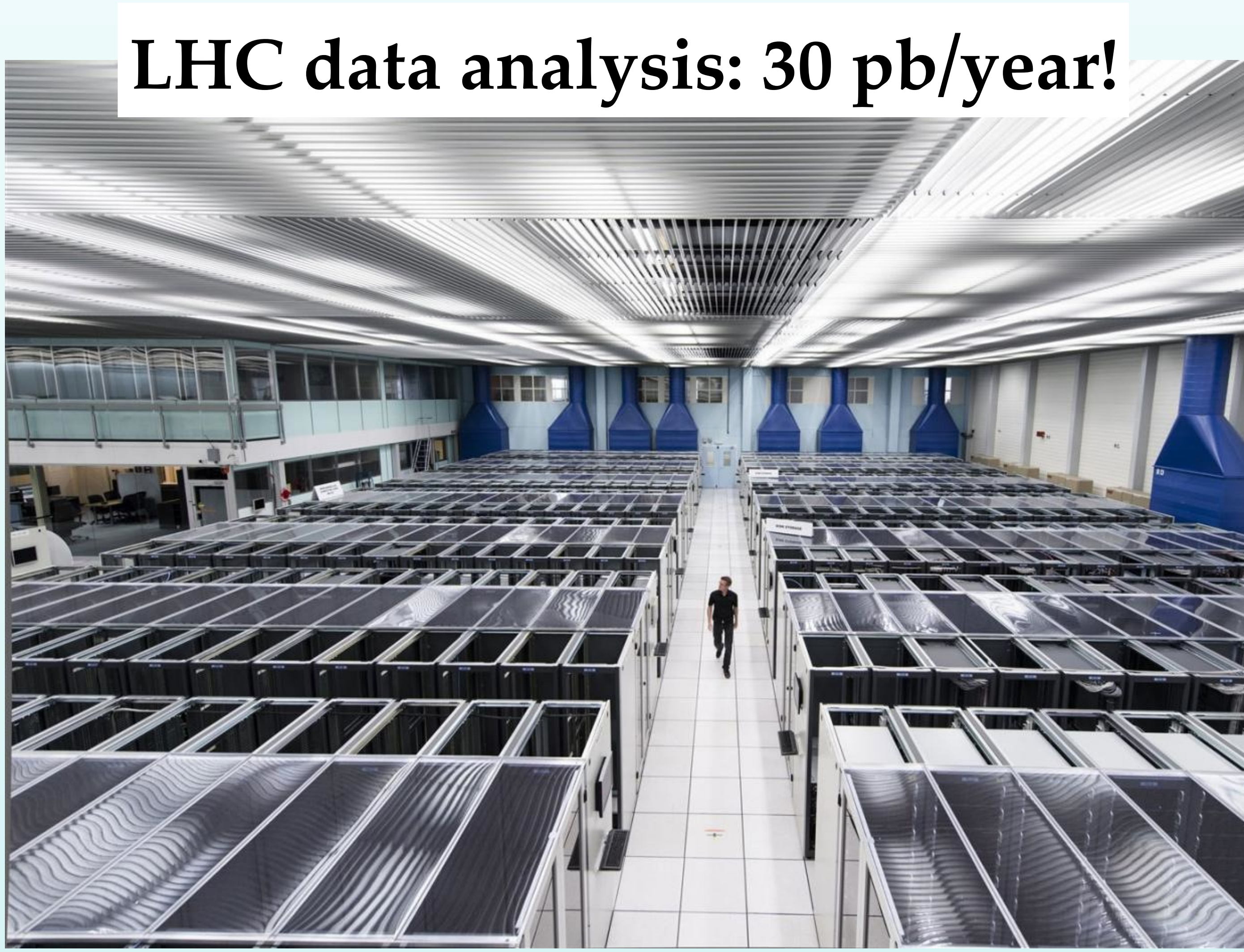
Machine Learning and Artificial Neural Networks



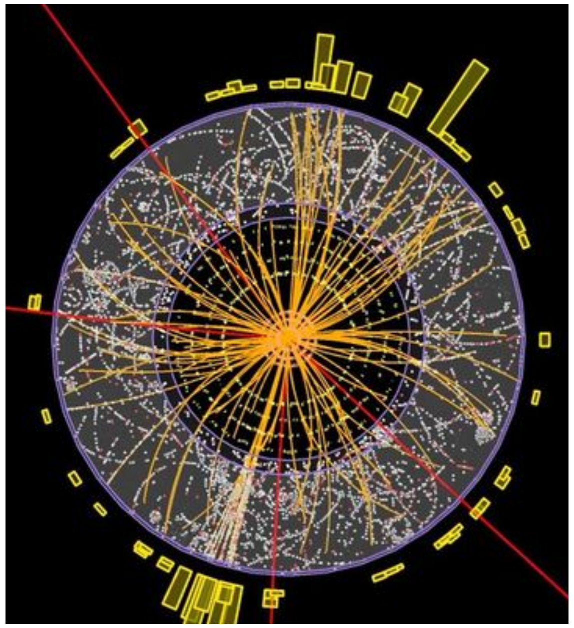
Machine Learning at the LHC

- By **Machine Learning** we usually denote those families of computer algorithms that **learn how to excel on a task** based on a **large sample of examples**, rather than on some a priori fixed rules
- ML algorithms are nowadays ubiquitous, from **driverless cars** to **Amazon's purchase suggestions**, to **automated medical imaging recognition** to beating the words best players at Go and chess
- ML tools rely on the **efficient exploitation of immense datasets**. And the **LHC** has a lot of data!

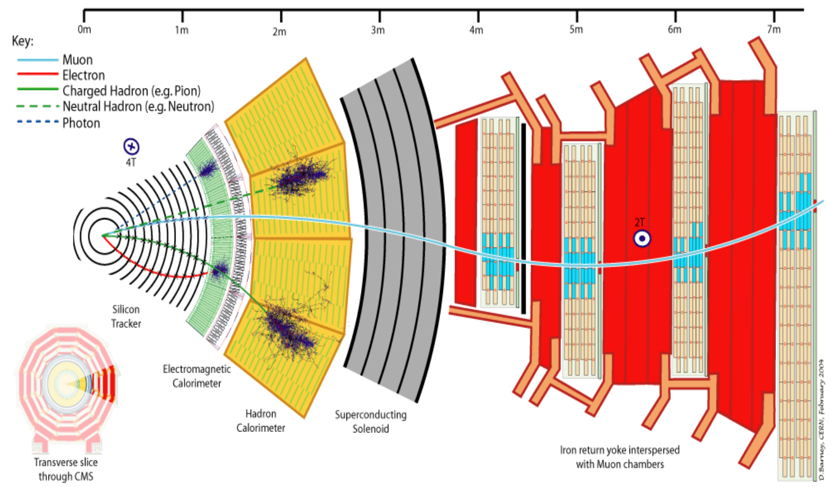




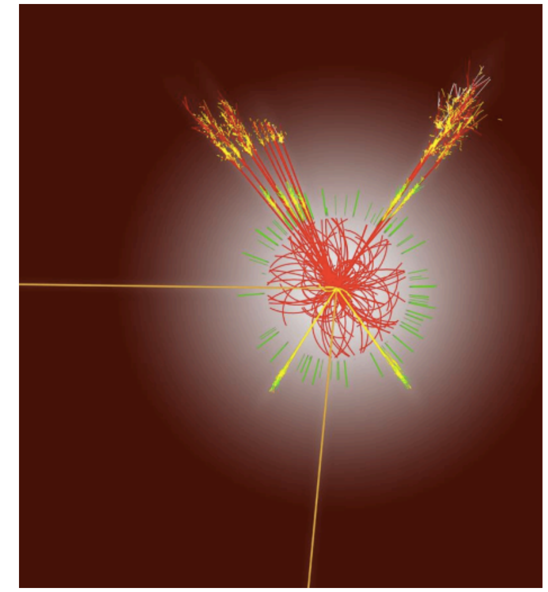
Machine Learning tools are everywhere!



Deep Kalman RNNs

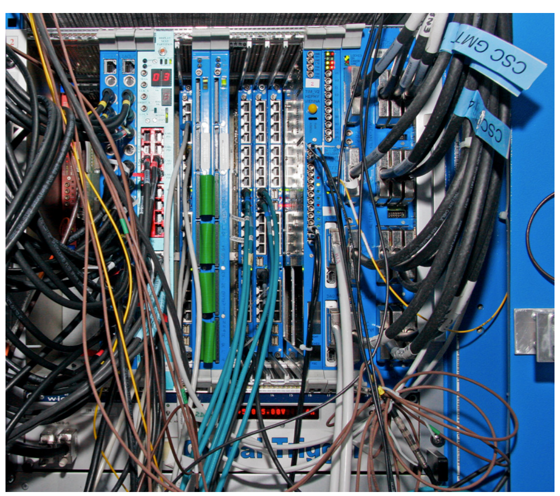


Generative Models, Adversarial Networks

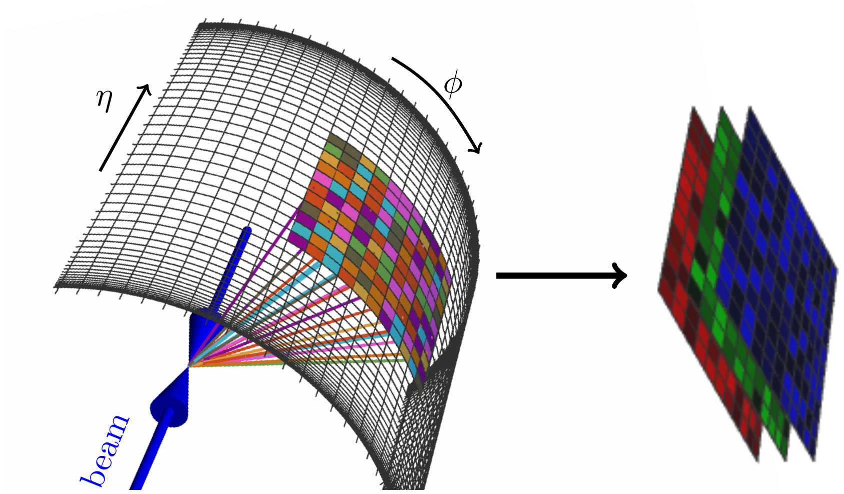


FCN, Recurrent, LSTM NN

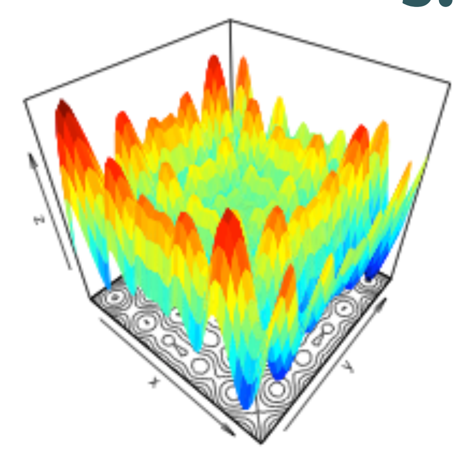
S. Glayzer



Deep ML +FPGA



Convolutional DNN

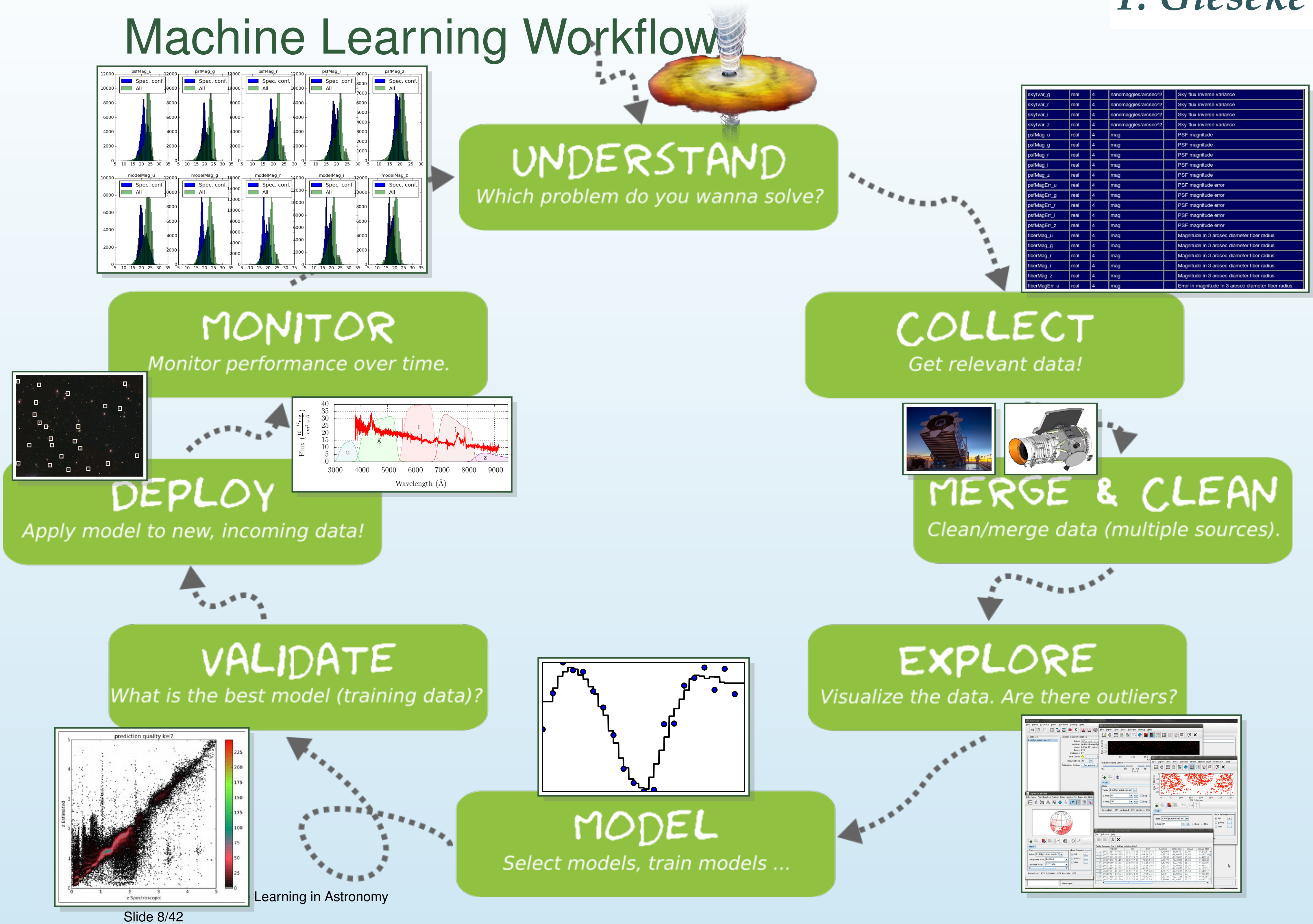


Multiobjective Regression

For many crucial applications, ML tools not just one option, but **the only option**

ML cheat sheet

F. Gieseke



Endless possibilities - but also many non-trivial hurdles to overcome

Machine Learning at the LHC

- Several summary talks would be needed to cover the fascinating topic of **ML at LHC**!
- Here focus on a specific type of ML algorithms: **Artificial Neural Networks**

For the ML / Big data aficionados, please check the ``**Data Science at LHC**" workshops

https://indico.fnal.gov/conferenceDisplay.py?confId=13497

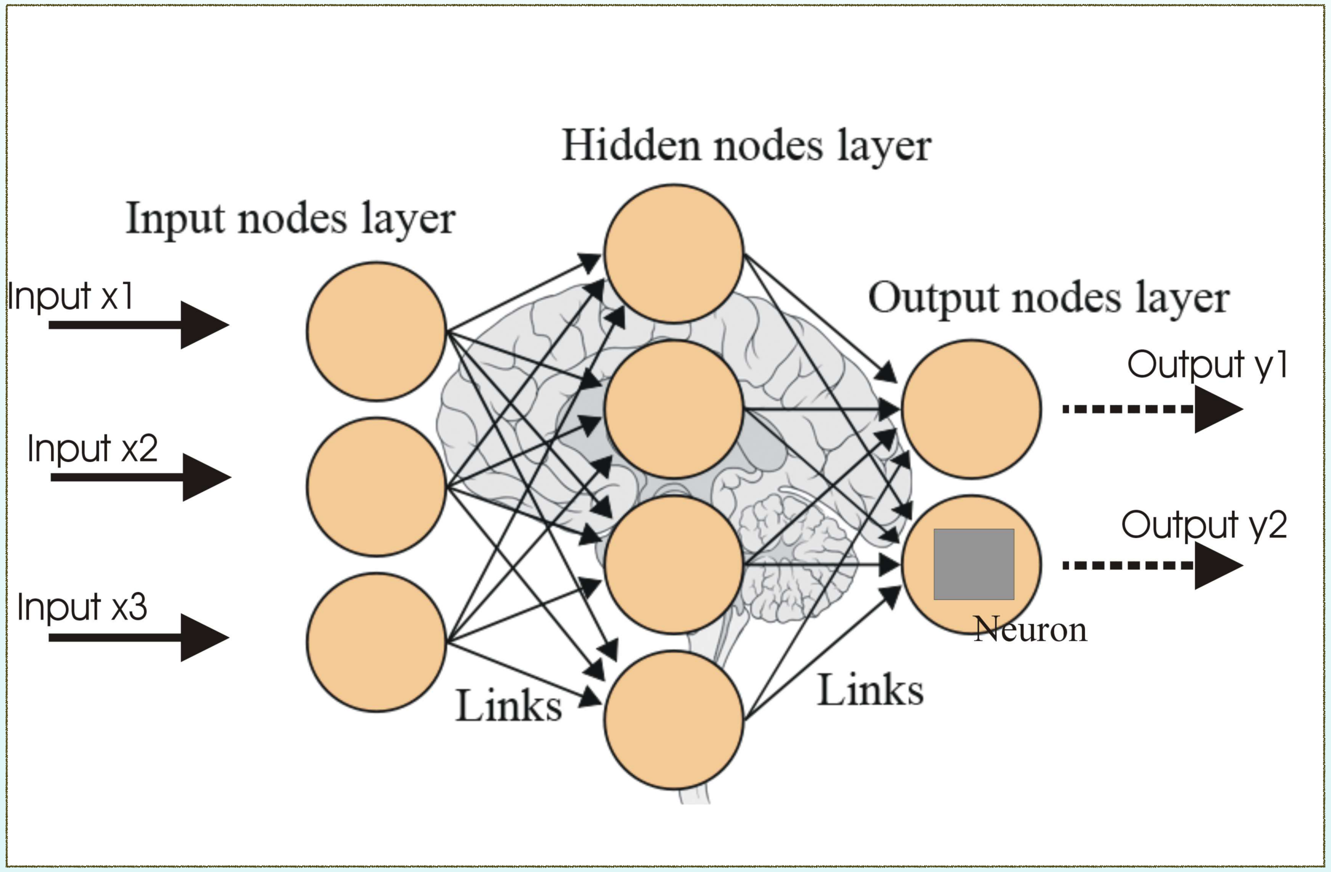
and the recent ``Big Data Tools for Physics and Astronomy" workshop in Amsterdam

https://indico.cern.ch/event/622093/

Artificial Neural Networks

Inspired by **biological brain models**, **Artificial Neural Networks** are **mathematical algorithms** widely used in a wide range of applications, from **HEP** to **targeted marketing** and **finance forecasting**

From Biological to Artificial Neural Networks



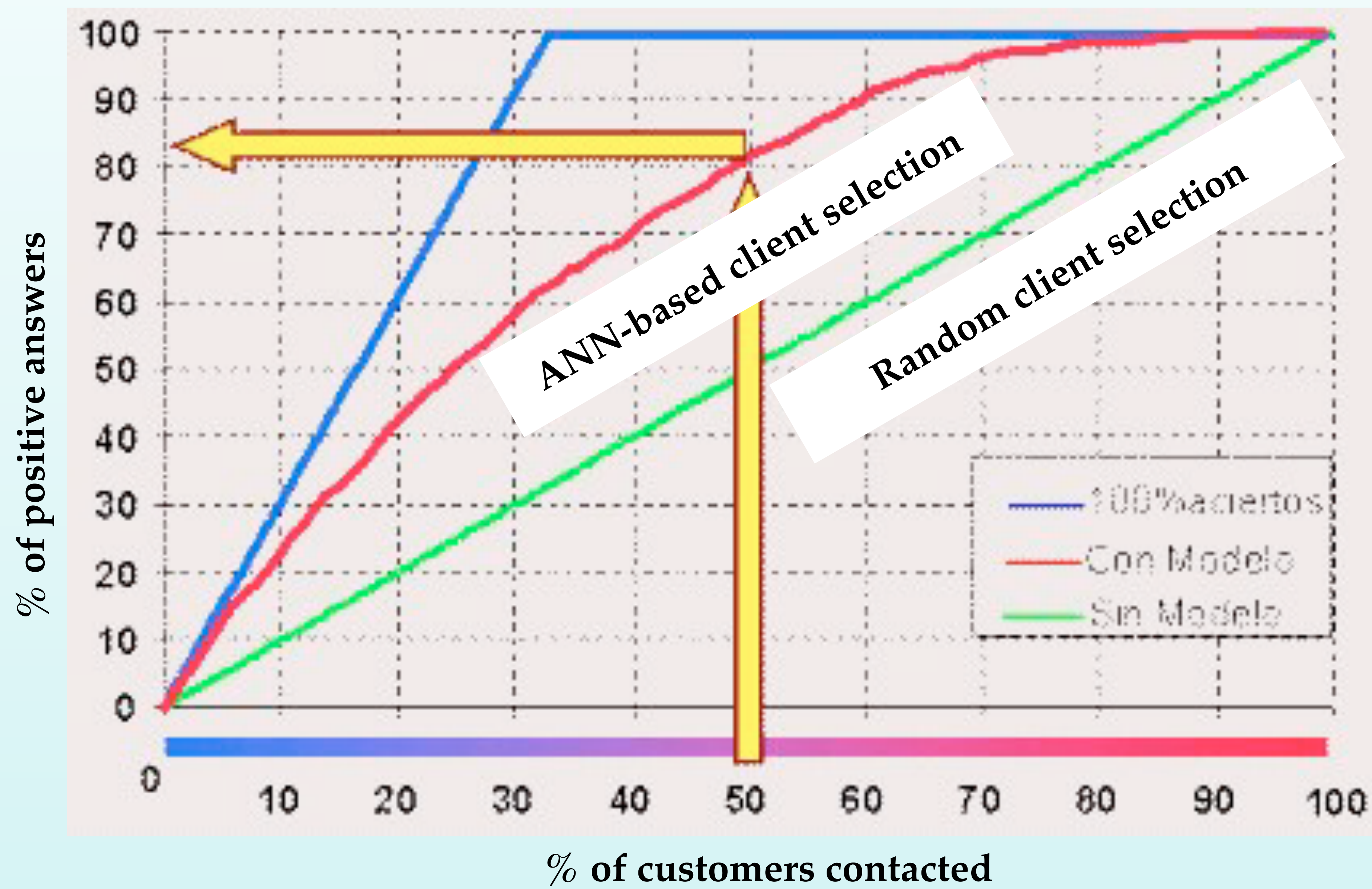
Artificial neural networks aim to excel where domains as their **evolution-driven counterparts outperforms traditional algorithms in tasks such as pattern recognition, forecasting, classification**, …

ANNs - a marketing example

A bank wants to offer a new credit card to their clients. Two possible strategies:

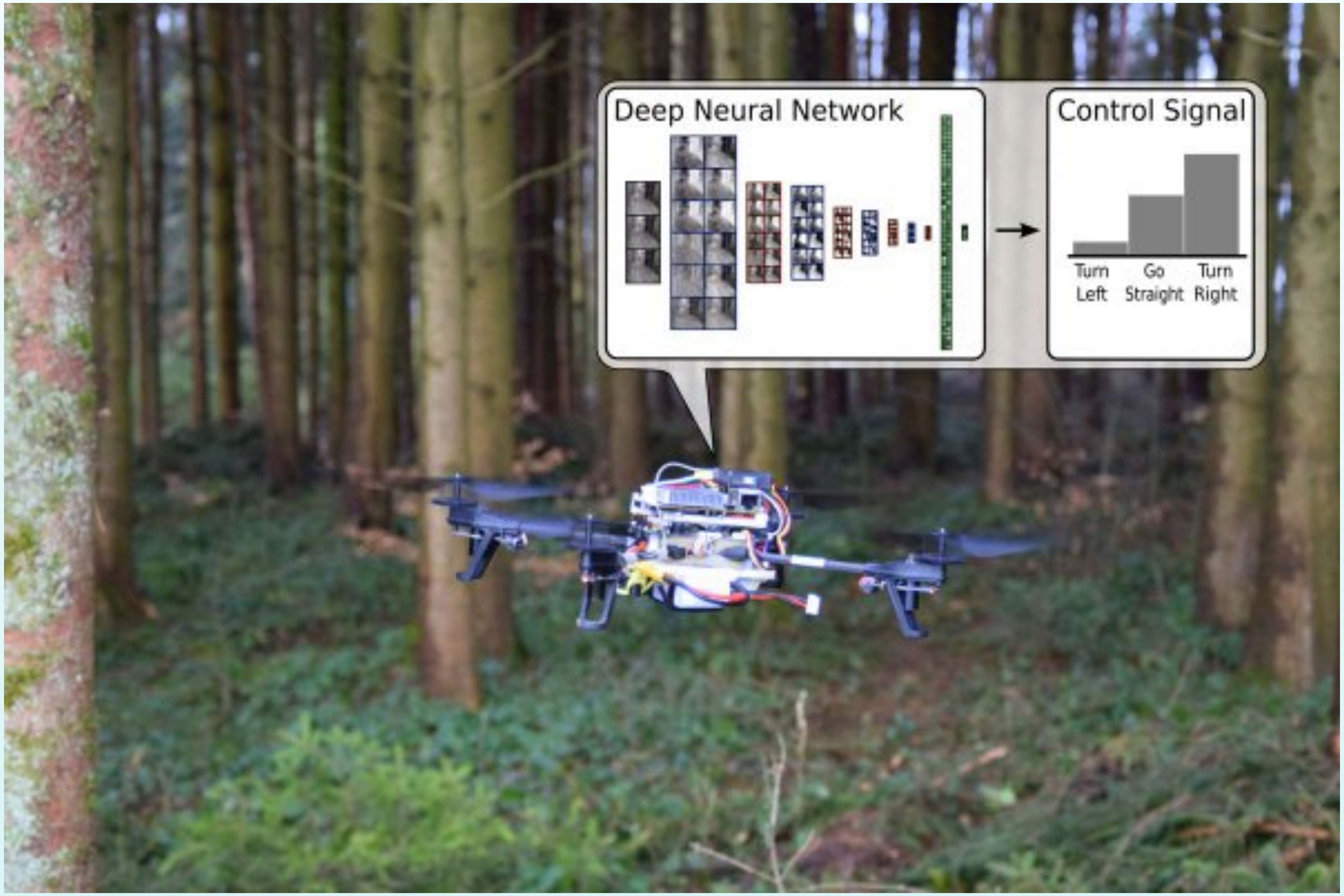
- **Contact all customers**: slow and costly
- Contact **5%** of the customers, **train a ANN with their input** (gender, income, loans) and **their output** (yes/no) and use the information to c**ontact only clients likely to accept the product**

Cost-effective method to improve marketing performance!



ANNs and pattern recognition

- ANNs can enable an **autonomous vision-control drone** to recognize and follow forest trails
- Image classifier operates directly on **pixel-level image intensities**
- If a trail is visible, the **software steers the drone** in the corresponding direction

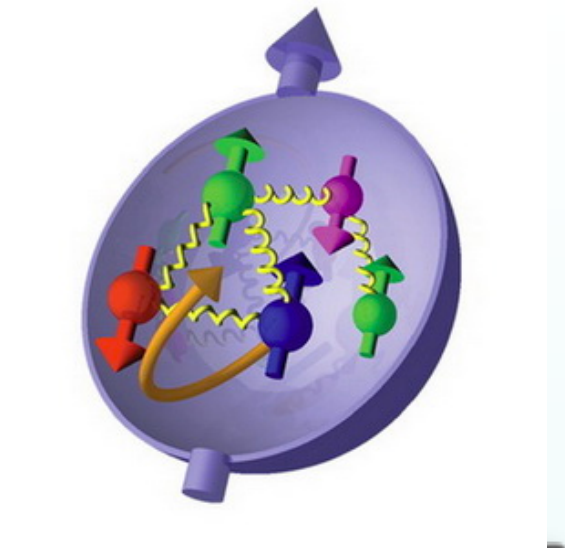


Giusti et al, IEEE Robotics and Automation Letters, 2016

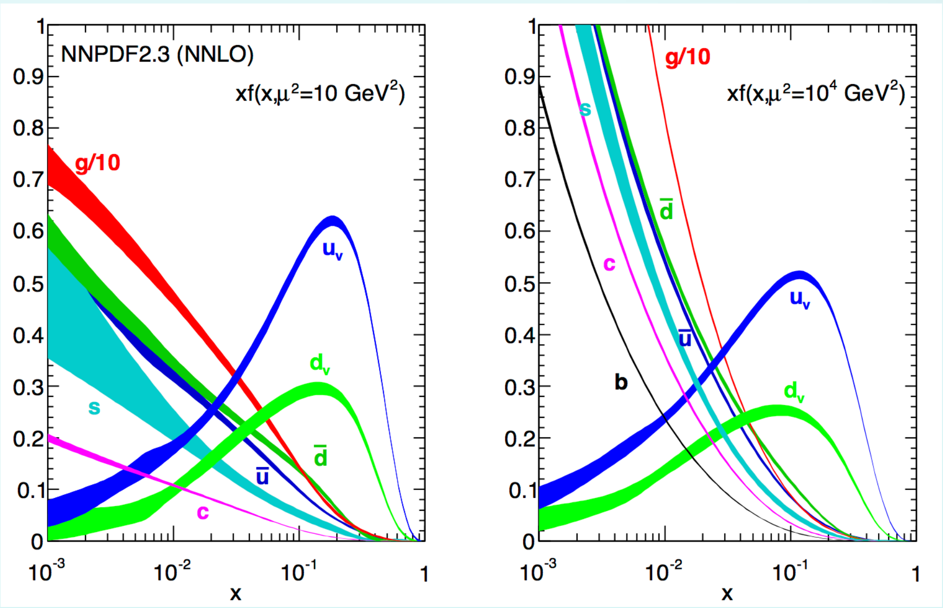
Similar algorithms at work in self-driving cars!

ANNs and pattern recognition

And of course ML tools can be used just for fun!

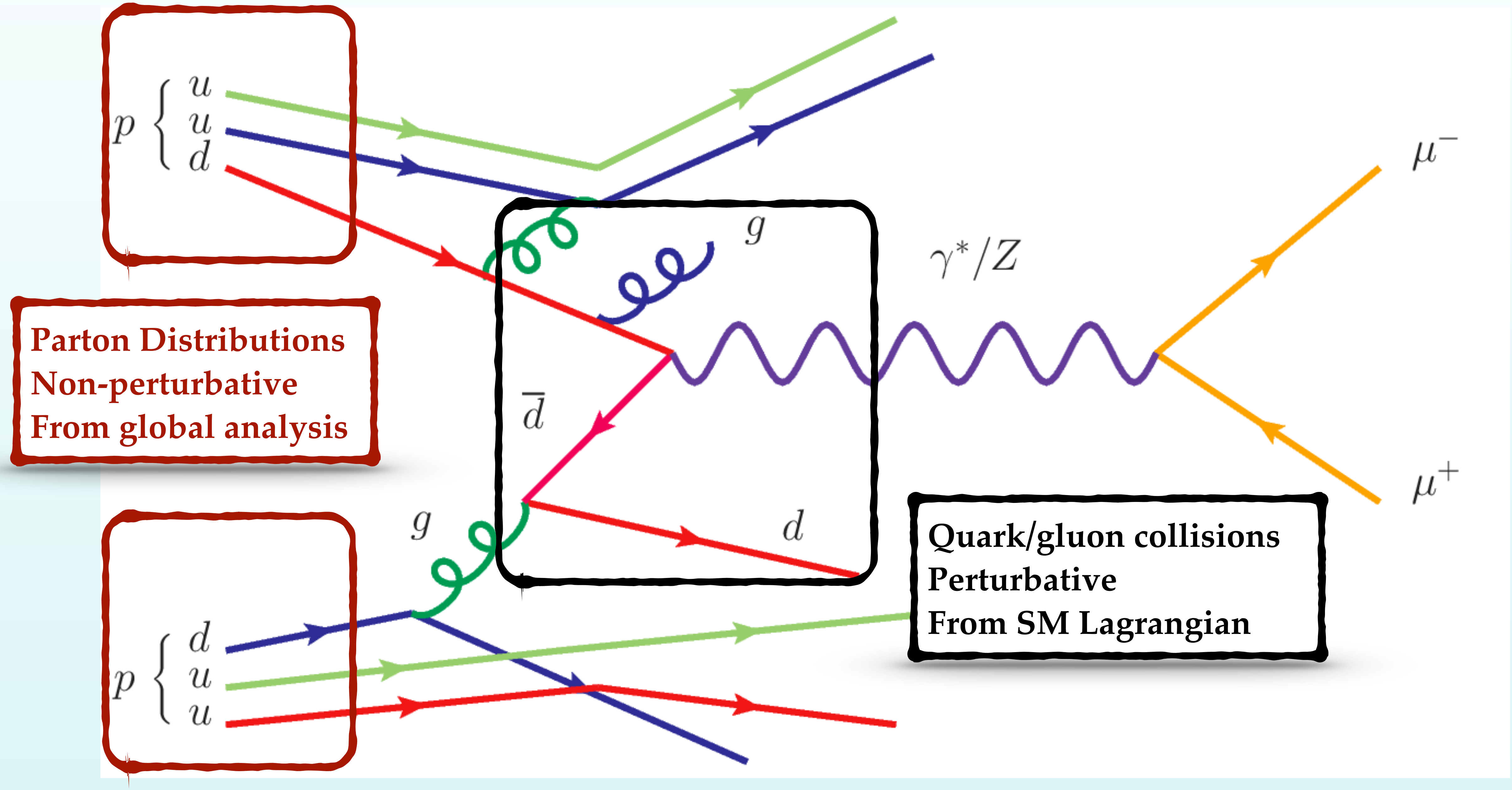


The inner life of protons : Parton Distribution Functions



Anatomy of a proton-proton collision

In high-energy **hadron colliders**, such as the LHC, the collisions involve **composite particles** (protons) with internal structure (quarks and gluons)



Calculations of **cross-sections** in hadron collisions require the combination of **perturbative, quark/gluon-initiated processes**, and **non-perturbative, parton distributions**, information

Parton Distributions

The distribution of energy that **quarks and gluons carry inside the proton** is quantified by the **Parton Distribution Functions (PDFs)**

$$g(x, Q)$$

Q: **Energy of the quark/gluon collision**
Inverse of the resolution length

$g(x,Q)$: **Probability** of **finding a gluon inside a proton**, carrying a fraction x of the proton momentum, when probed with energy Q

x: **Fraction of the proton's momentum**

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- **Energy conservation**

$$\int_0^1 dx\, \mathbf{x} \left(g(x,Q) + \sum_q q(x,Q) \right) = 1$$

- **Dependence with quark/gluon collision energy Q** determined in perturbation theory

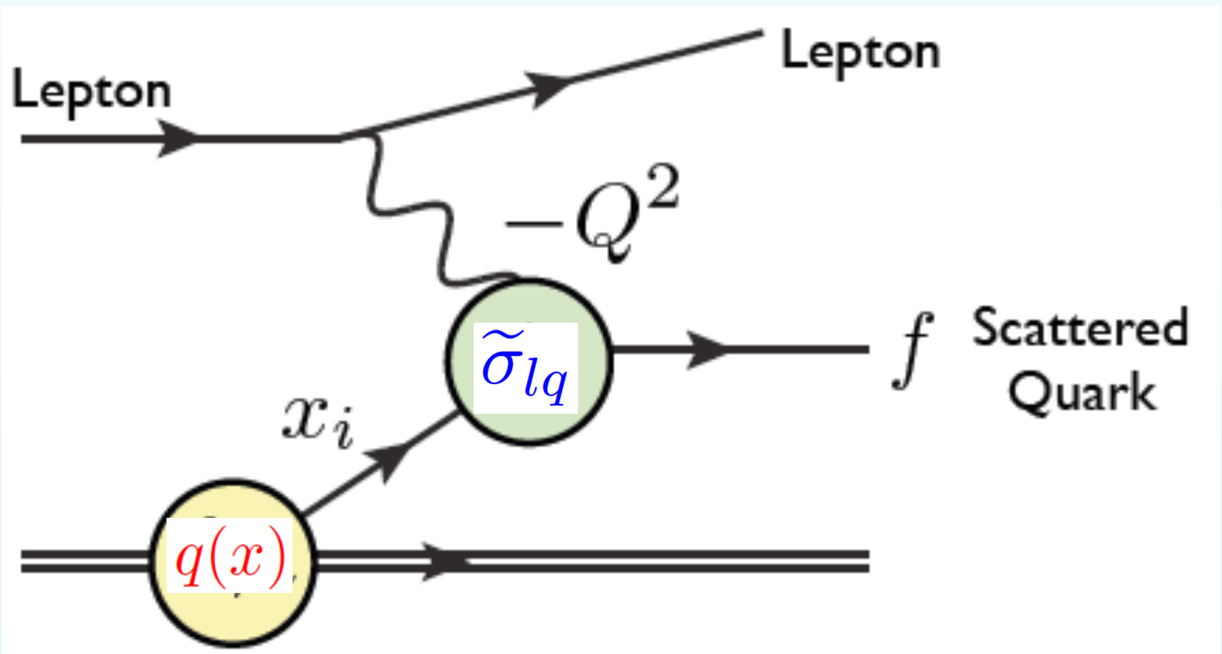
$$\frac{\partial g(x,Q)}{\partial \ln Q} = P_g\left(\alpha_s\right) \otimes g(x,Q) + P_q\left(\alpha_s\right) \otimes q(x,Q)$$

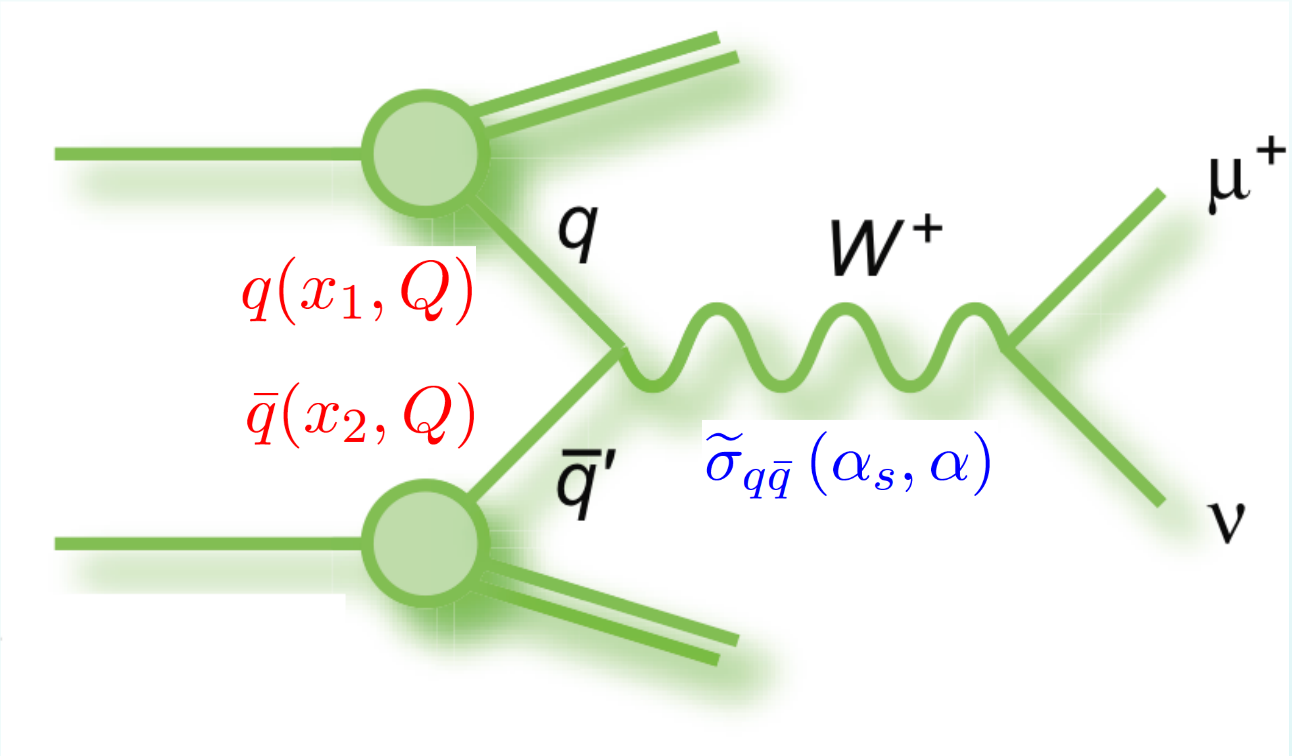
The Factorization Theorem

The **QCD Factorization Theorem** guarantees **PDF universality: extract them from a subset of** process and use them to provide pure predictions for new processes

$$\sigma_{lp} \simeq \widetilde{\sigma}_{lq}\left(\alpha_s, \alpha\right) \otimes q(x, Q)$$

$$\sigma_{pp} \simeq \widetilde{\sigma}_{q\bar{q}}\left(\alpha_s, \alpha\right) \otimes q(x_1, Q) \otimes \bar{q}(x_2, Q)$$





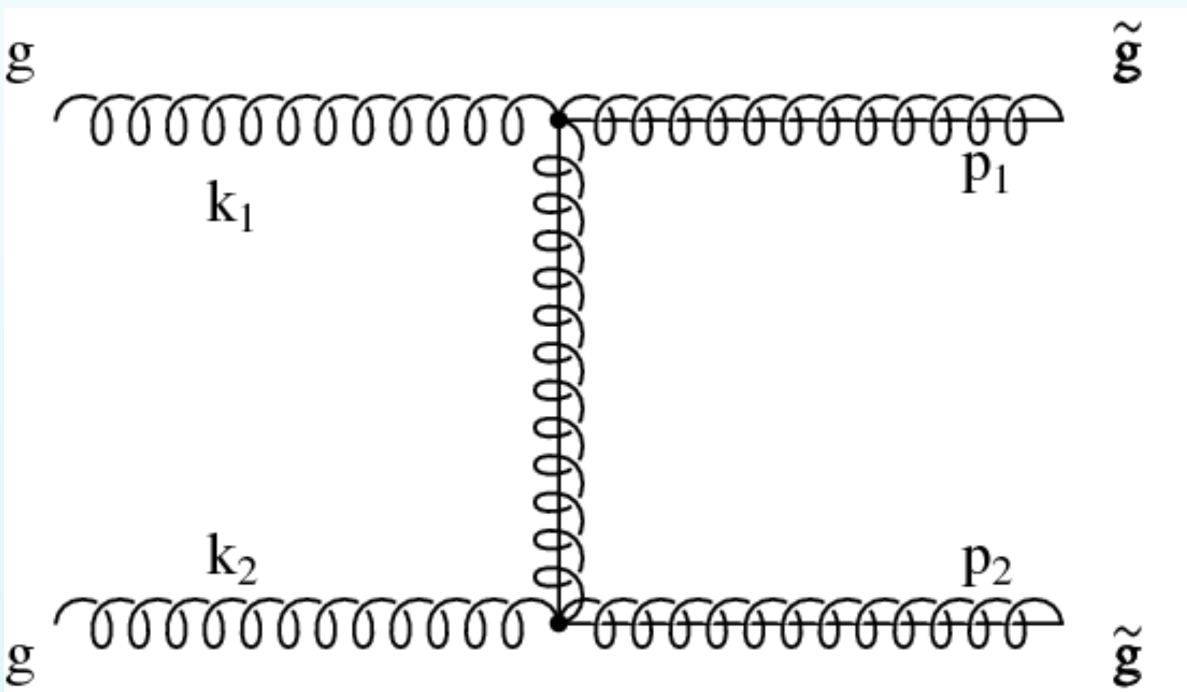
Determine PDFs in lepton-proton collisions ….

And use them to compute cross-sections in proton-proton collisions at the LHC

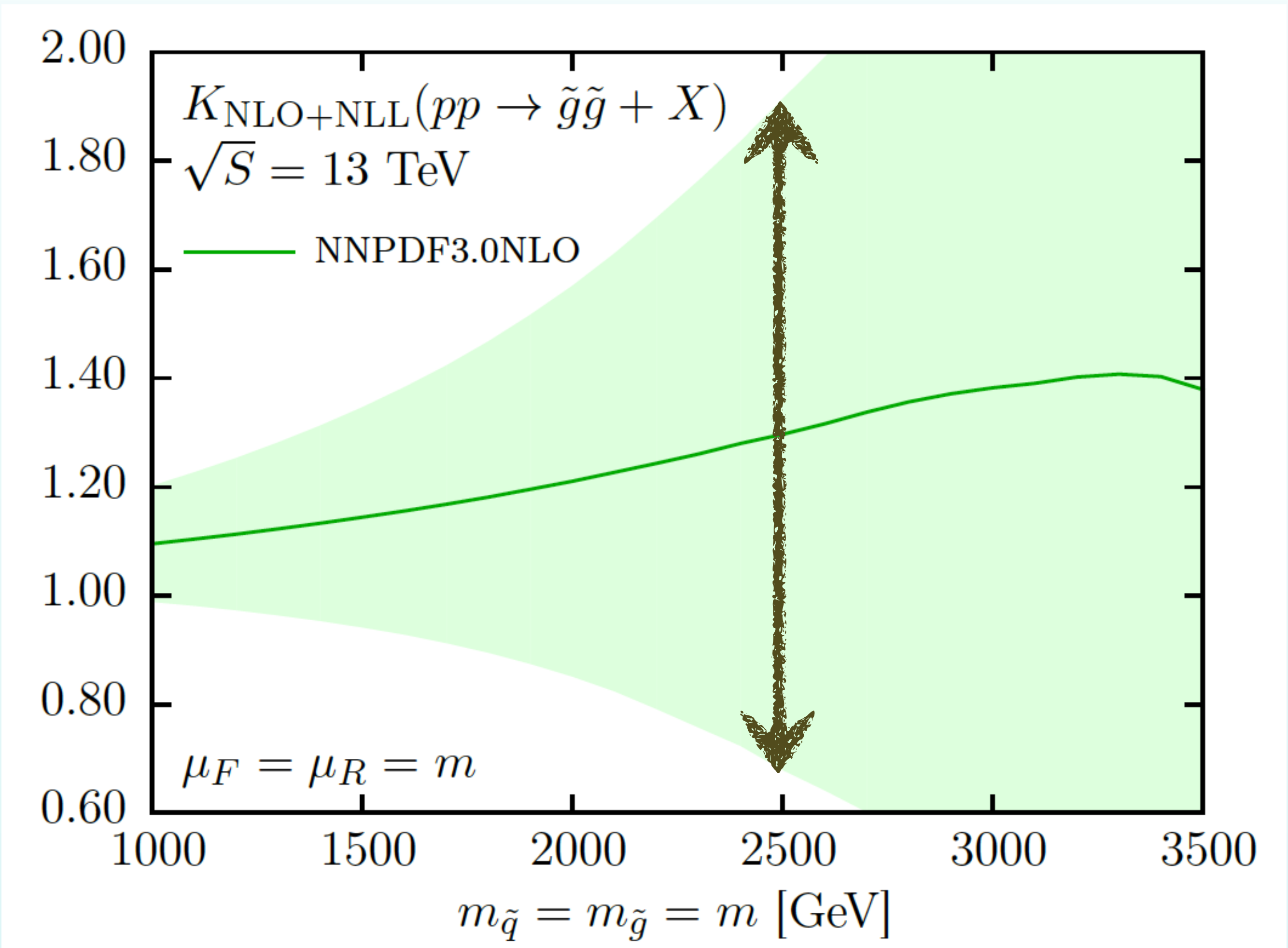
Beyond BSM discovery

PDF uncertainties in the production of **New Physics heavy resonances** can be al large as **100%!**

Crucial *i.e.* in searches for ***supersymmetry*** and any BSM scenario that predicts new heavy particles within the reach of the LHC



Gluino pair production at the LHC



Beenakker, Borchensky, Kramer, Kulesza, Laenen, Marzani, Rojo 13

*Unless we **improve PDF uncertainties**, even if we discover New Physics, it will be extremely **difficult to characterise the underlying BSM scenario***

ANNs as universal unbiased interpolants

ANNs provide **universal unbiased interpolants** to parametrize the non-perturbative dynamics that determines the **size and shape of the PDFs** from experimental data

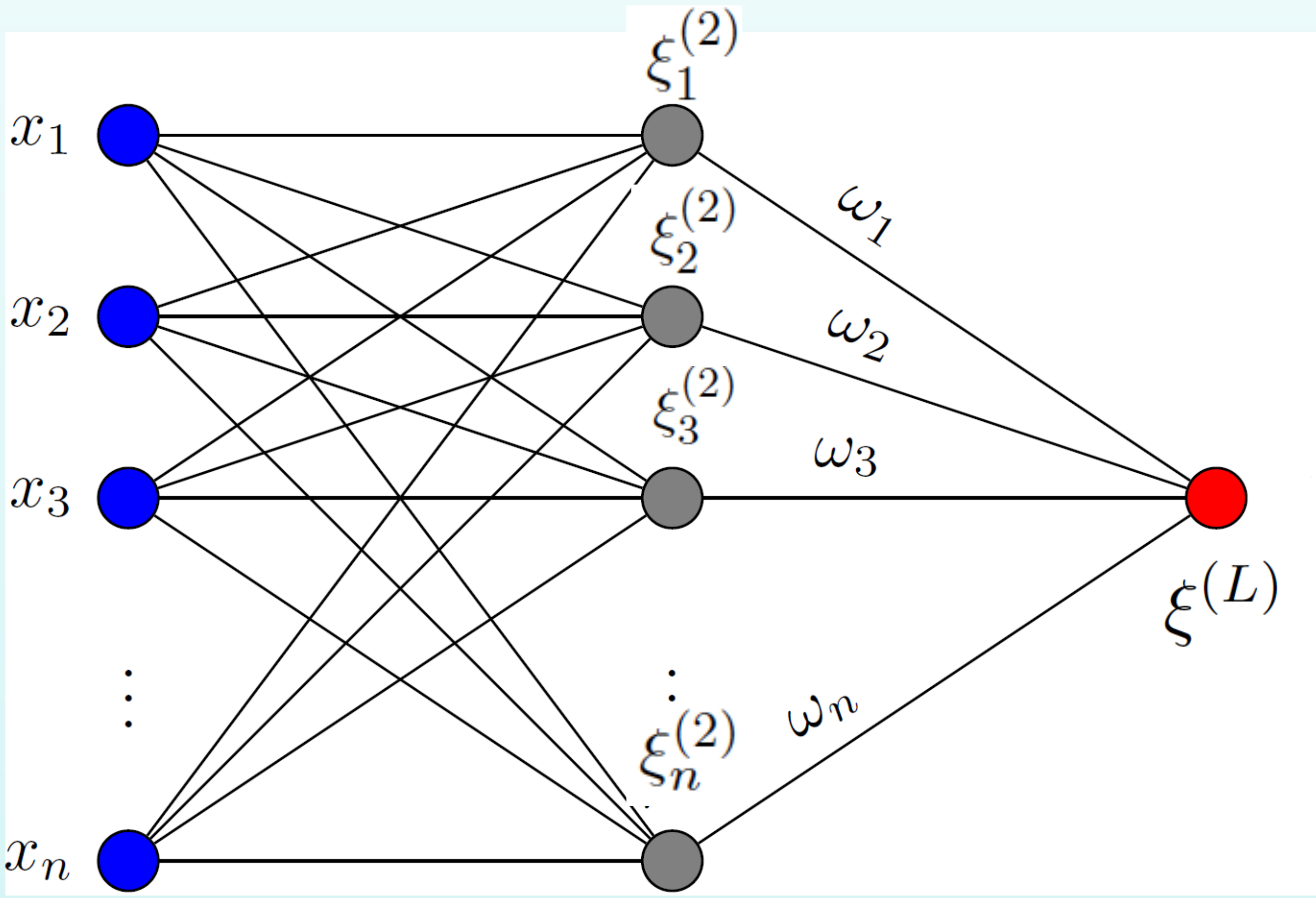
not from QCD!

Traditional approach

$$g(x,Q_0) = A_g(1-x)^{a_g}x^{-b_g}\left(1+c_g\sqrt{s}+d_g x+\ldots\right)$$

NNPDF approach

$$g(x,Q_0) = A_g \mathrm{ANN}_g(x)$$



$$\mathrm{ANN}_g(x) = \xi^{(L)} = \mathcal{F}\left[\xi^{(1)},\{\omega_{ij}^{(l)}\},\{\theta_i^{(l)}\}\right]$$

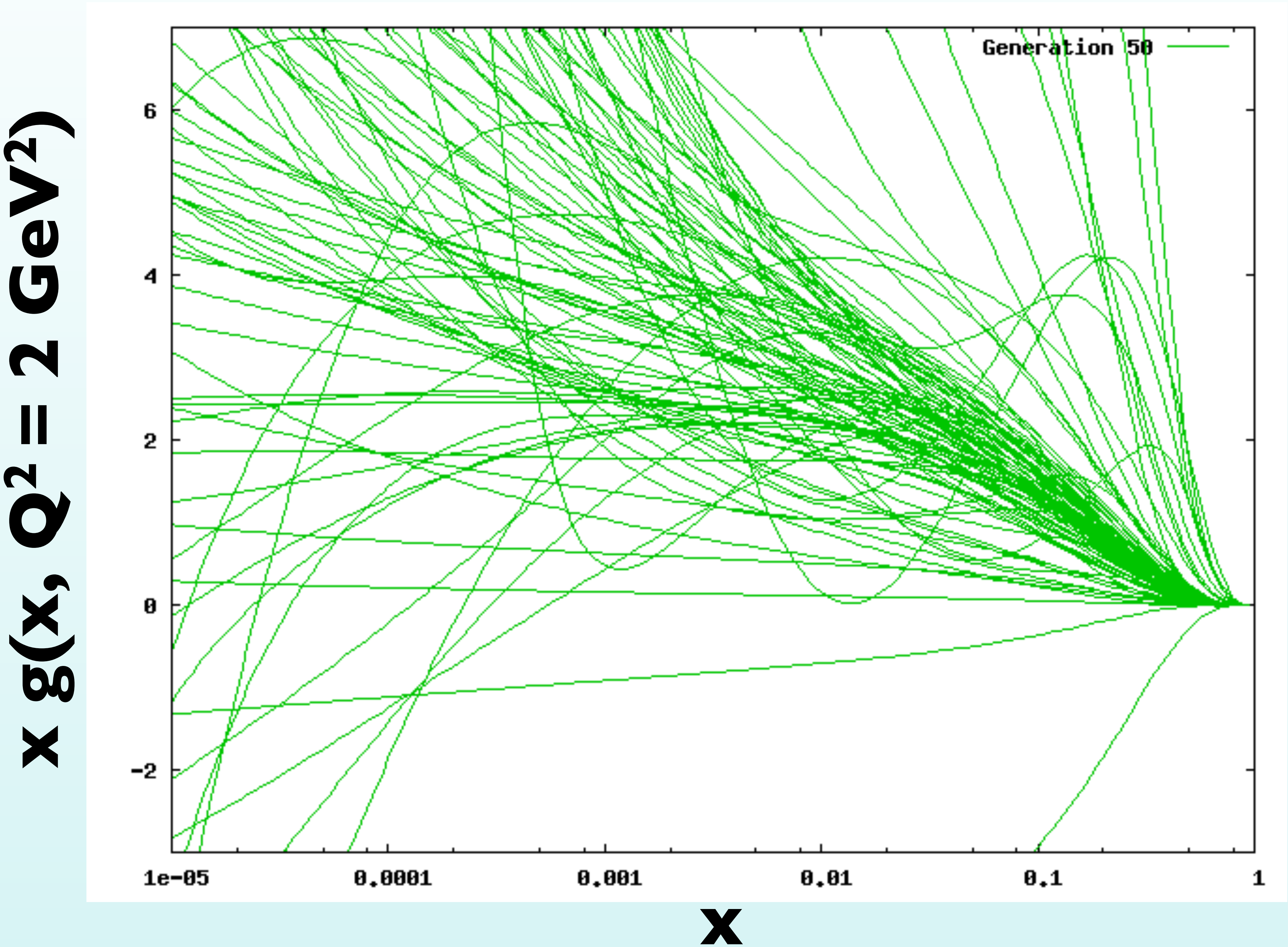
$$\xi_i^{(l)} = g\left(\sum_{j=1}^{n_{l-1}}\omega_{ij}^{(l-1)}\xi_j^{(l-1)}-\theta_i^{(l)}\right)$$

- ANNs eliminate **theory bias** introduced in PDF fits from choice of *ad-hoc* functional forms
- NNPDF fits used **O(400) free parameters**, to be compared with O(10-20) in traditional PDFs. Results stable if **O(4000) parameters used!**

PDF Replica Neural Network Learning

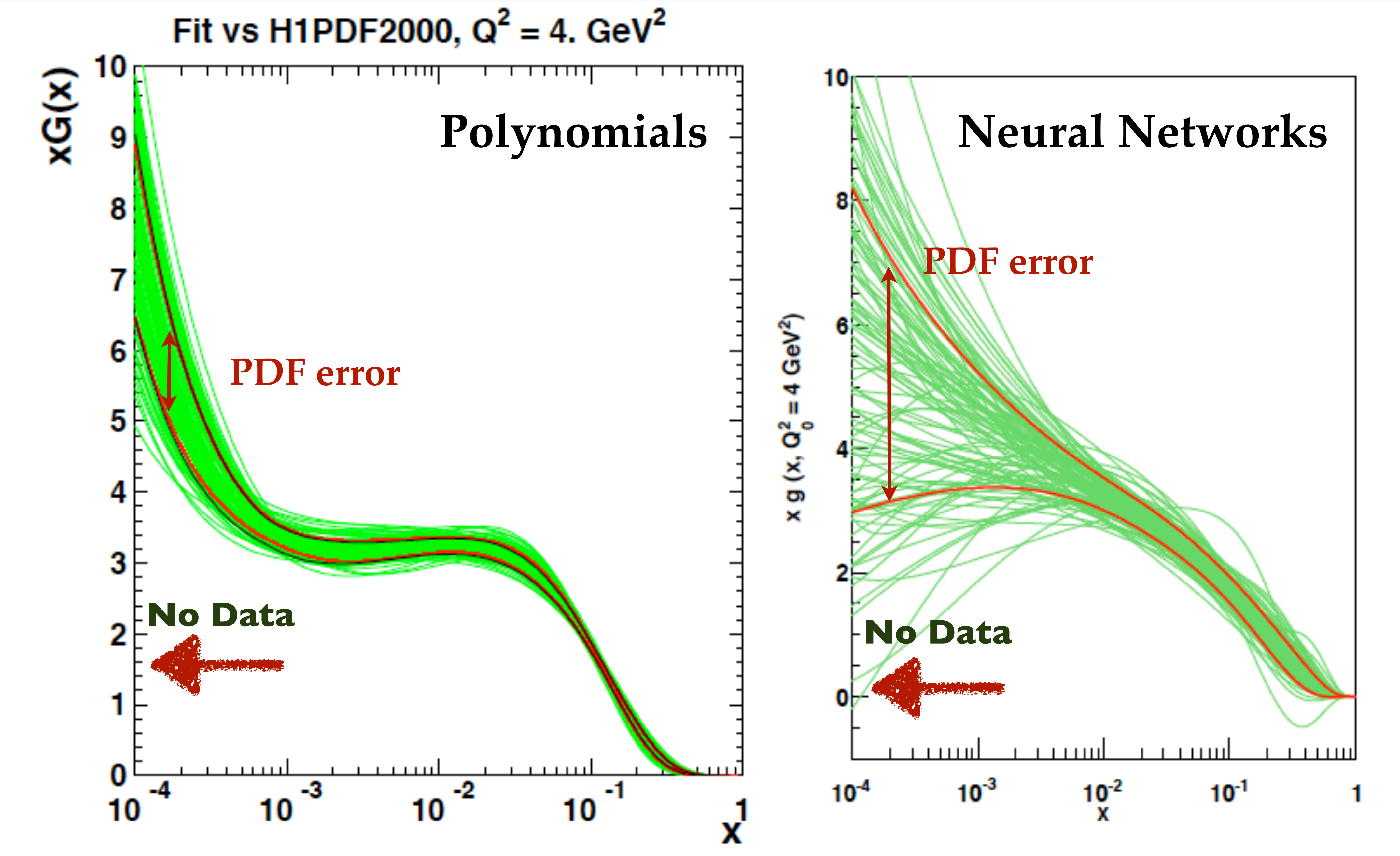
The minimisation of the **data vs theory χ^2** is performed using **Genetic Algorithms**

Each **green curve** corresponds to a **gluon PDF Monte Carlo** replica

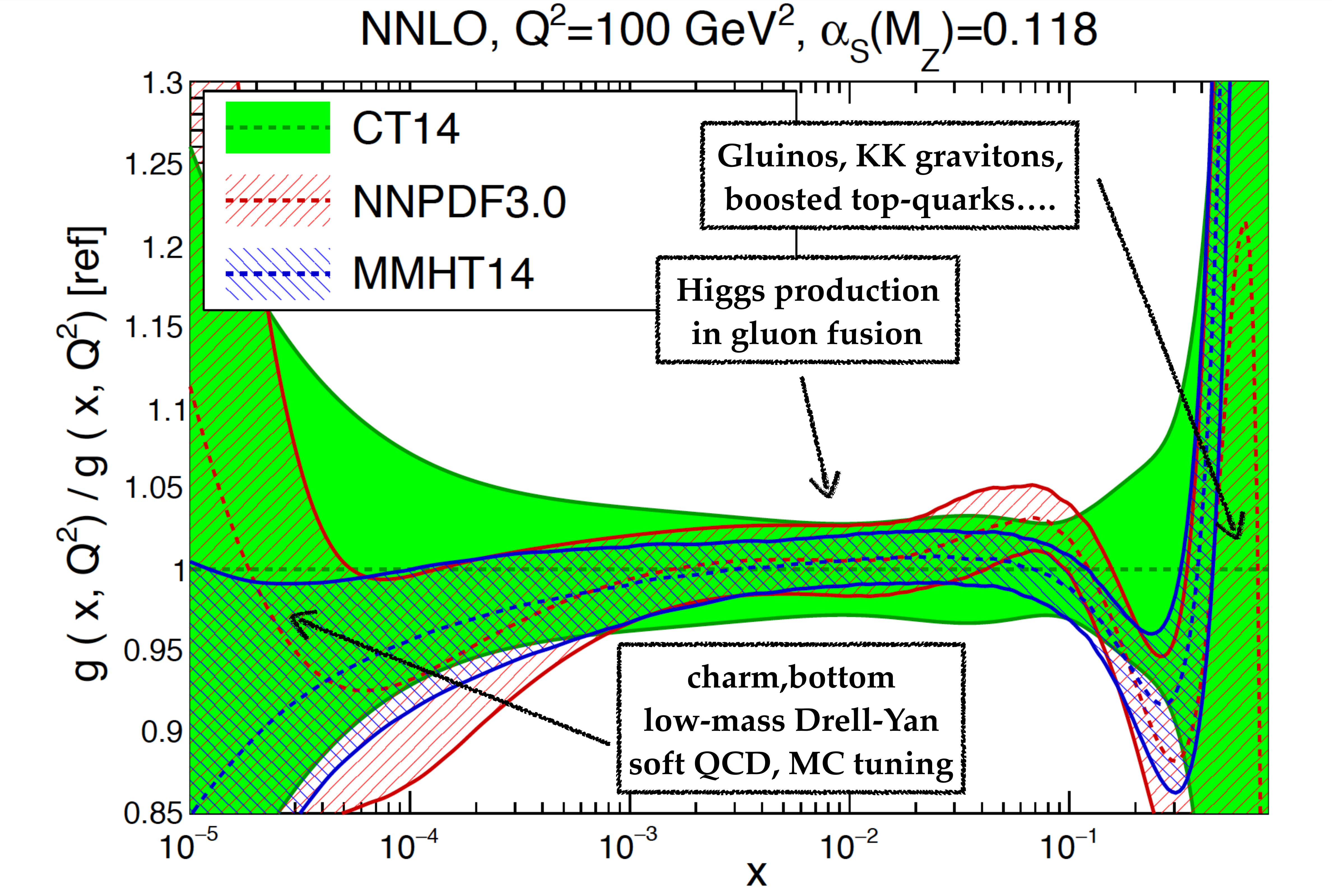


Artificial Neural Networks vs Polynomials

- Compare a **benchmark PDF analysis** where **the same dataset** is fitted with **Artificial Neural Networks** and with **standard polynomials,** other settings identical)
- **ANNs** avoid biasing the PDFs, **faithful extrapolation at small-x** (very few data, thus error blow up)

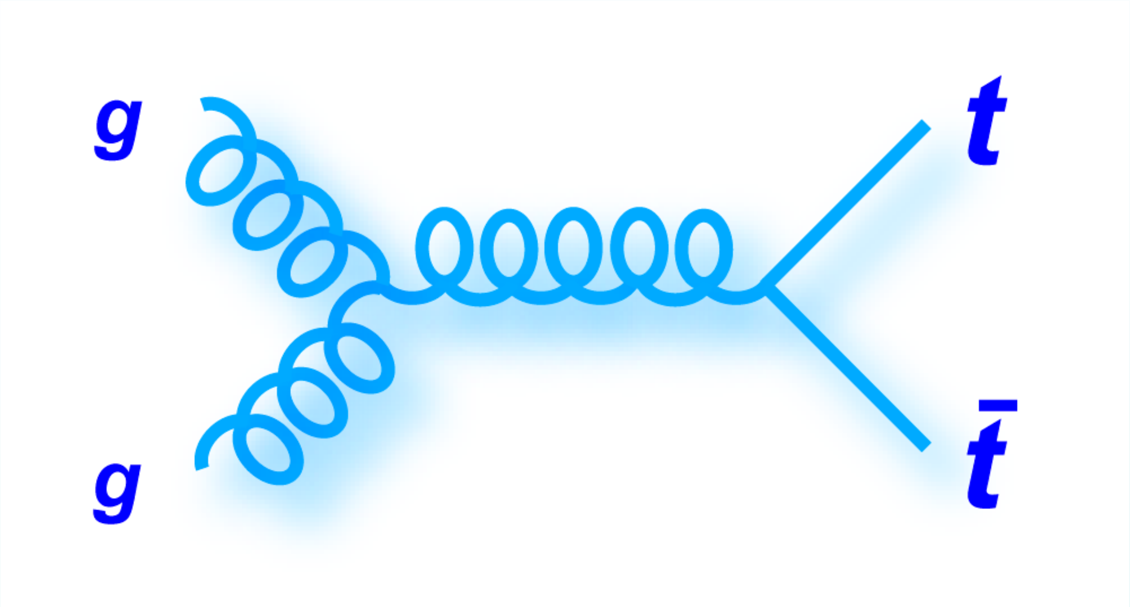


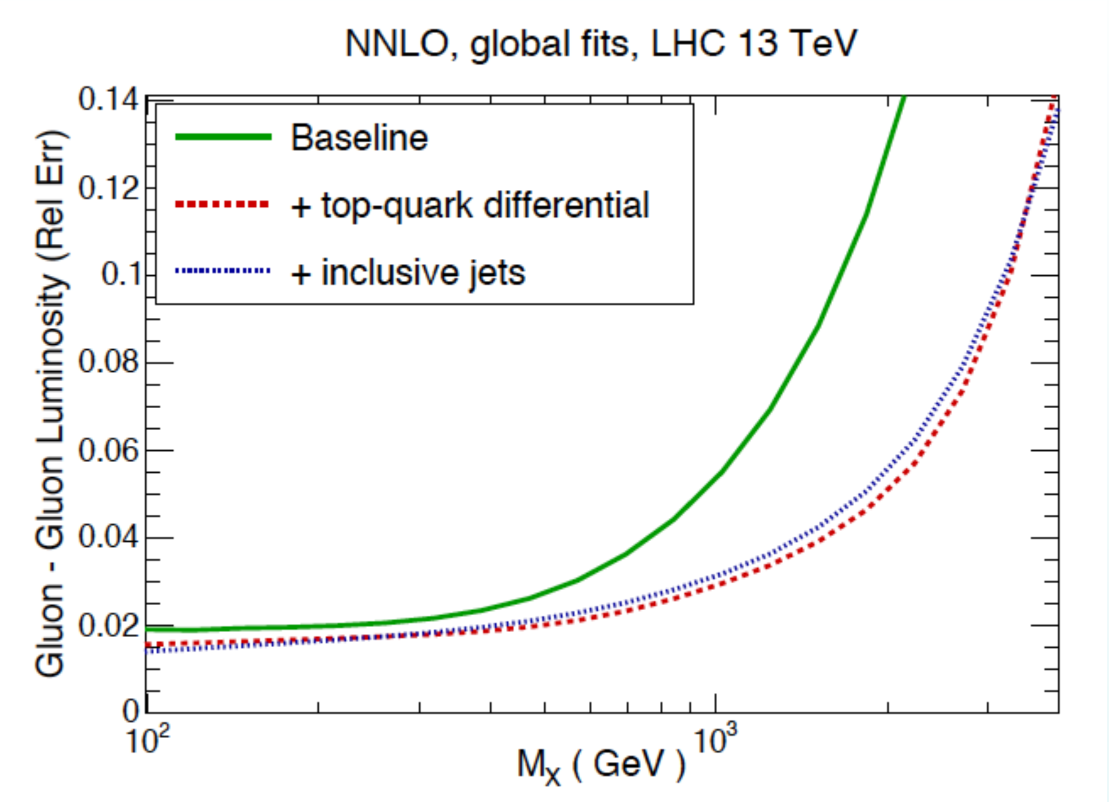
One glue to bind them all



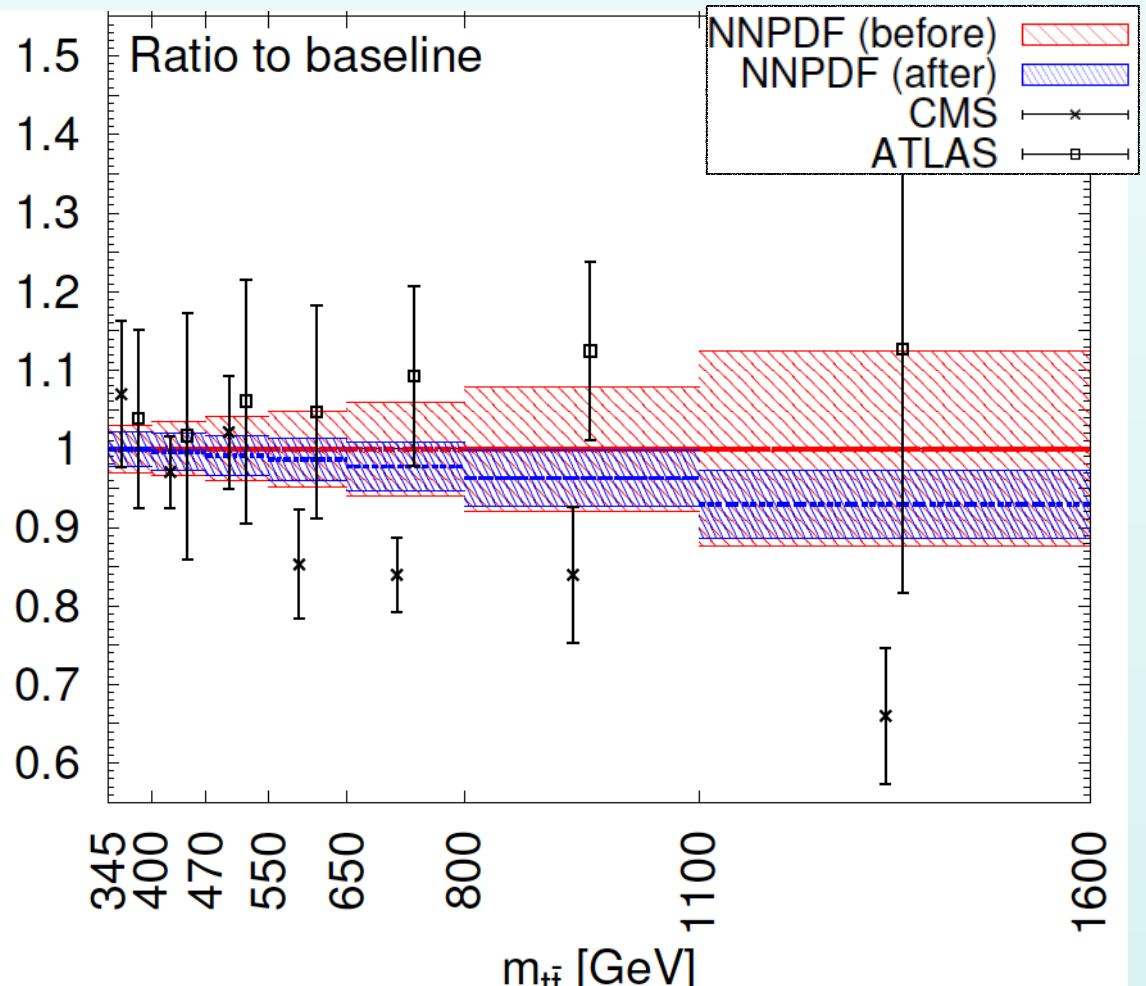
At the LHC, precise knowledge of the gluon is required **from small-x to large-x**

The large-x gluon from differential top quarks





- Top-quark pair production driven by **gluon-gluon lumi**
- **NNLO calculations for stable top quarks** available *Czakon, Mitov et al 2015-2017*
- **Data from ATLAS and CMS at 8 TeV** available with breakdown of systematic uncertainties
- Included **differential top data into NNPDF3.0**: constraints on the **large-*x* gluon** comparable to those of inclusive jet production *Czakon et al 2017*
- Improved theory uncertainties in **regions crucial for BSM searches**, *i.e.*, $\mathbf{m_{tt} > 1}$ **TeV** (while fitting only $\mathbf{y_t}$ and $\mathbf{y_{tt}}$)



The medium-x gluon from NNLO Z p_T

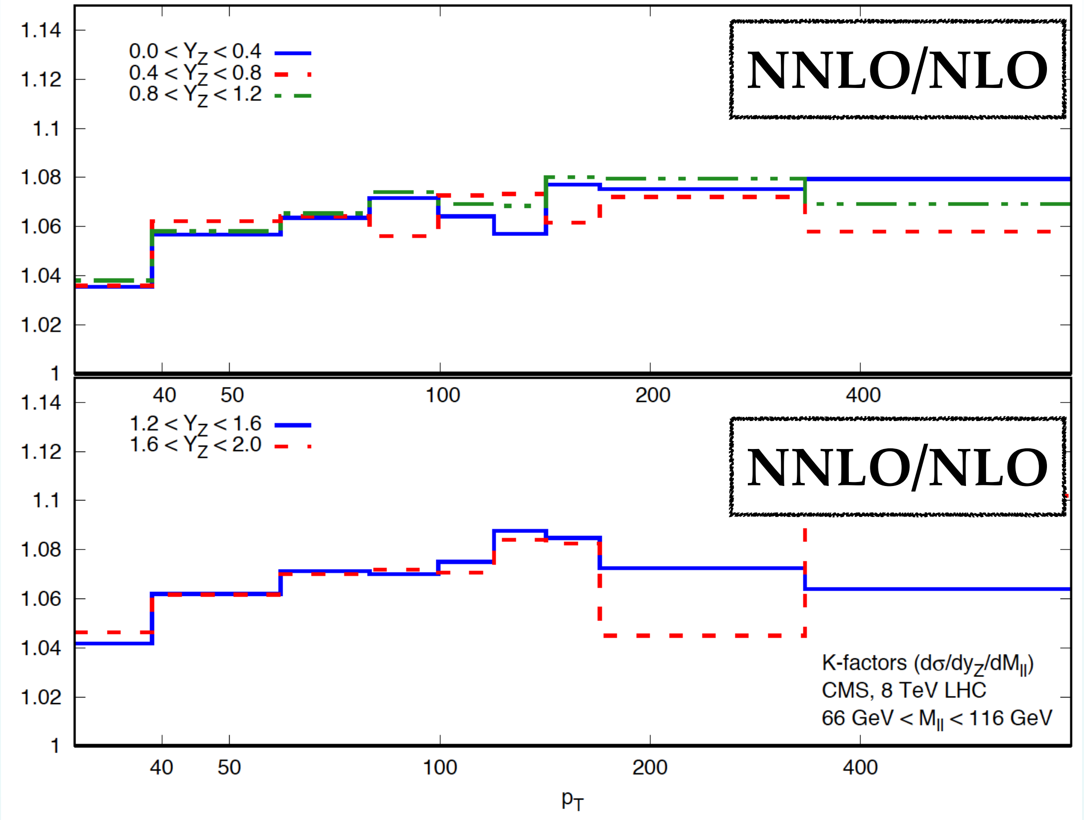
- Dominated by **quark-gluon scattering**, thus sensitive to the gluon PDF at intermediate values of *x*

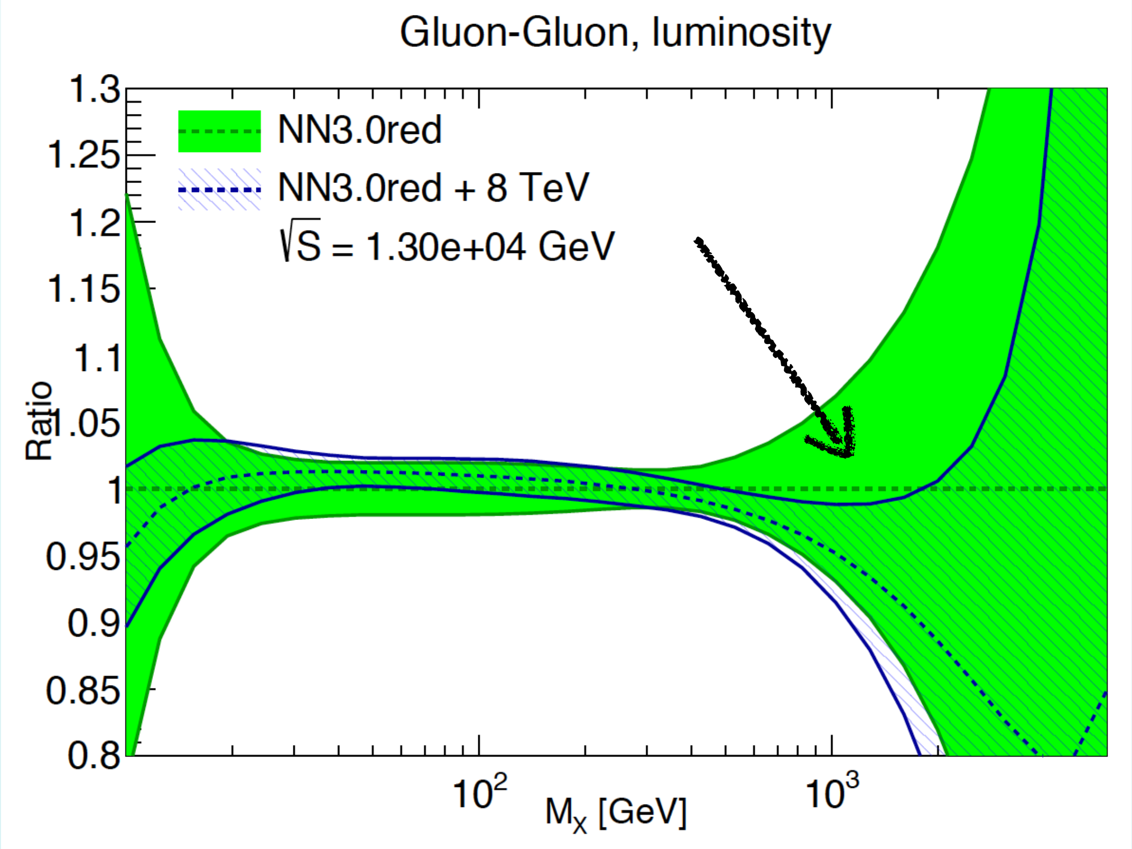
  Malik and Watt 2013, Boughezal et al 2017

- **NNLO corrections to the Z p_T** also available: **up to 10% effects** for a measurement that has **sub-percent exp errors**

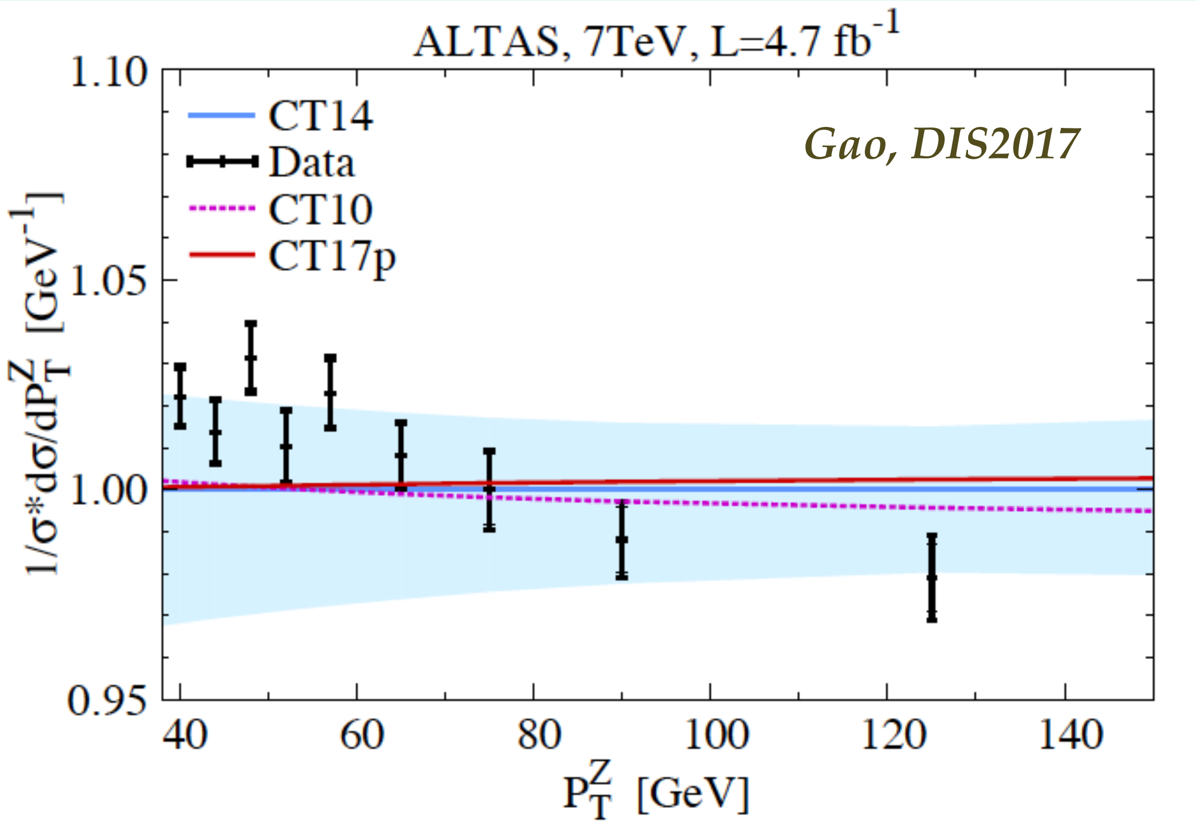
  Boughezal et al 2015-2017, Gerhmann et al 2015-2017

- **Complementary information on the gluon** as compared to inclusive jets and differential top pair production





Boughezal et al 2017



The small-x gluon from forward charm production

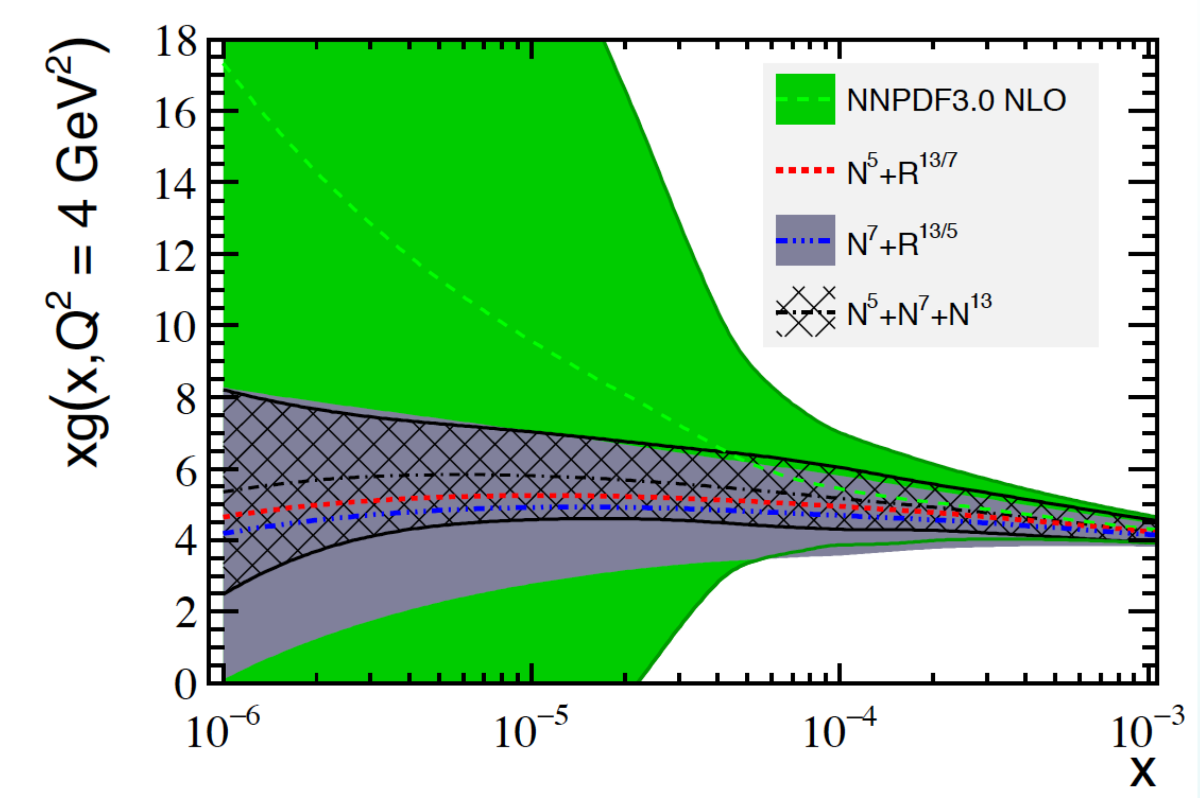
- **D and B meson production from LHCb** allow accessing the **gluon down to x≃10^{-6}**, well below the HERA coverage

PROSA 2015, Gauld et al 2015

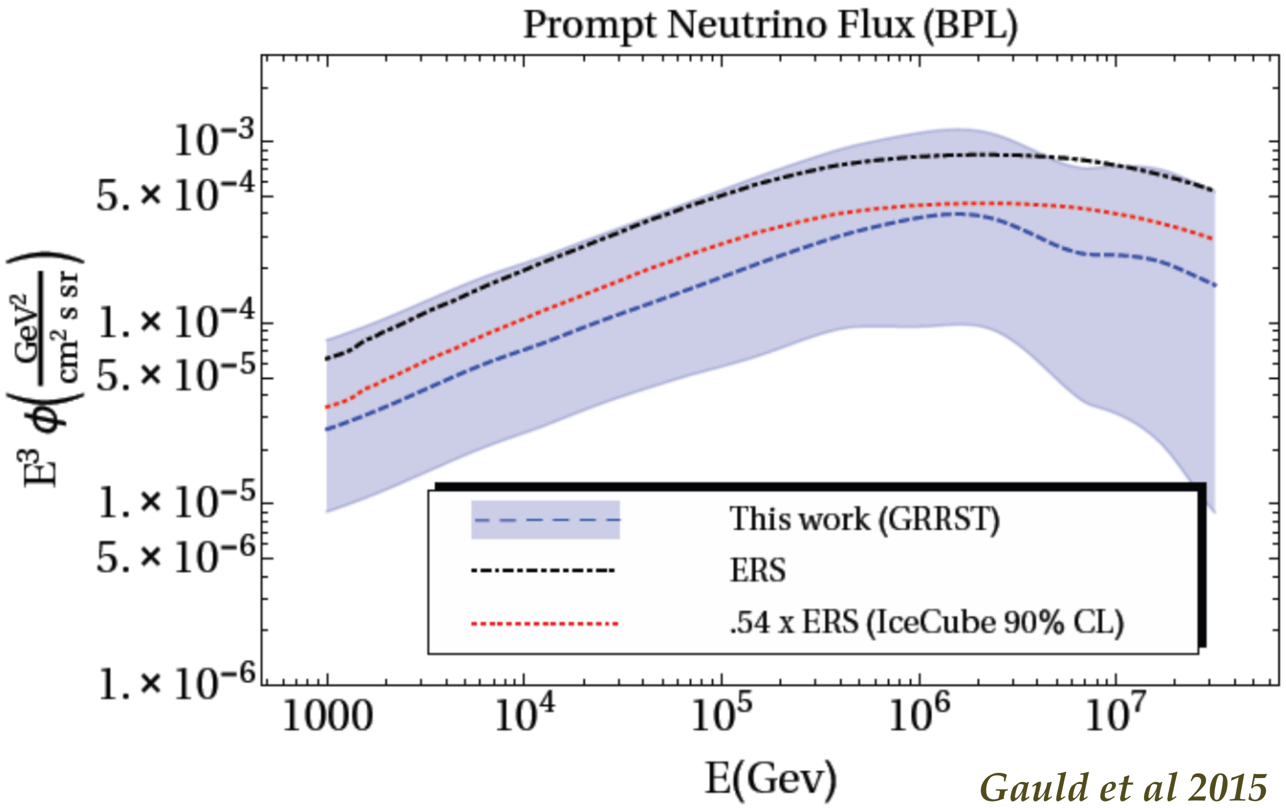
- Gluon PDF errors **reduced by up to a factor 10!**

- Allows robust estimate for the ***prompt* neutrino flux**, the main background for astrophysical neutrinos at IceCube

- Precision calculation of the **UHE neutrino-nucleus cross-section**, with few-percent TH errors up to $E_\nu=10^{12}$ GeV

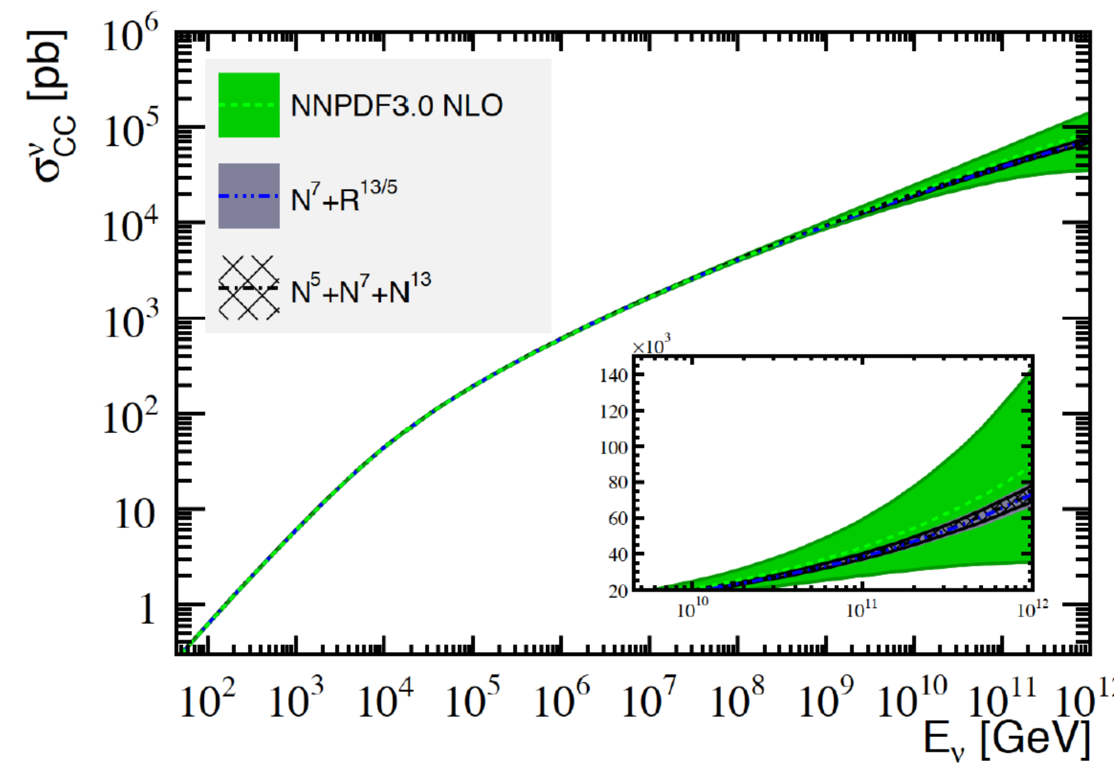


Prompt neutrino flux at IceCube

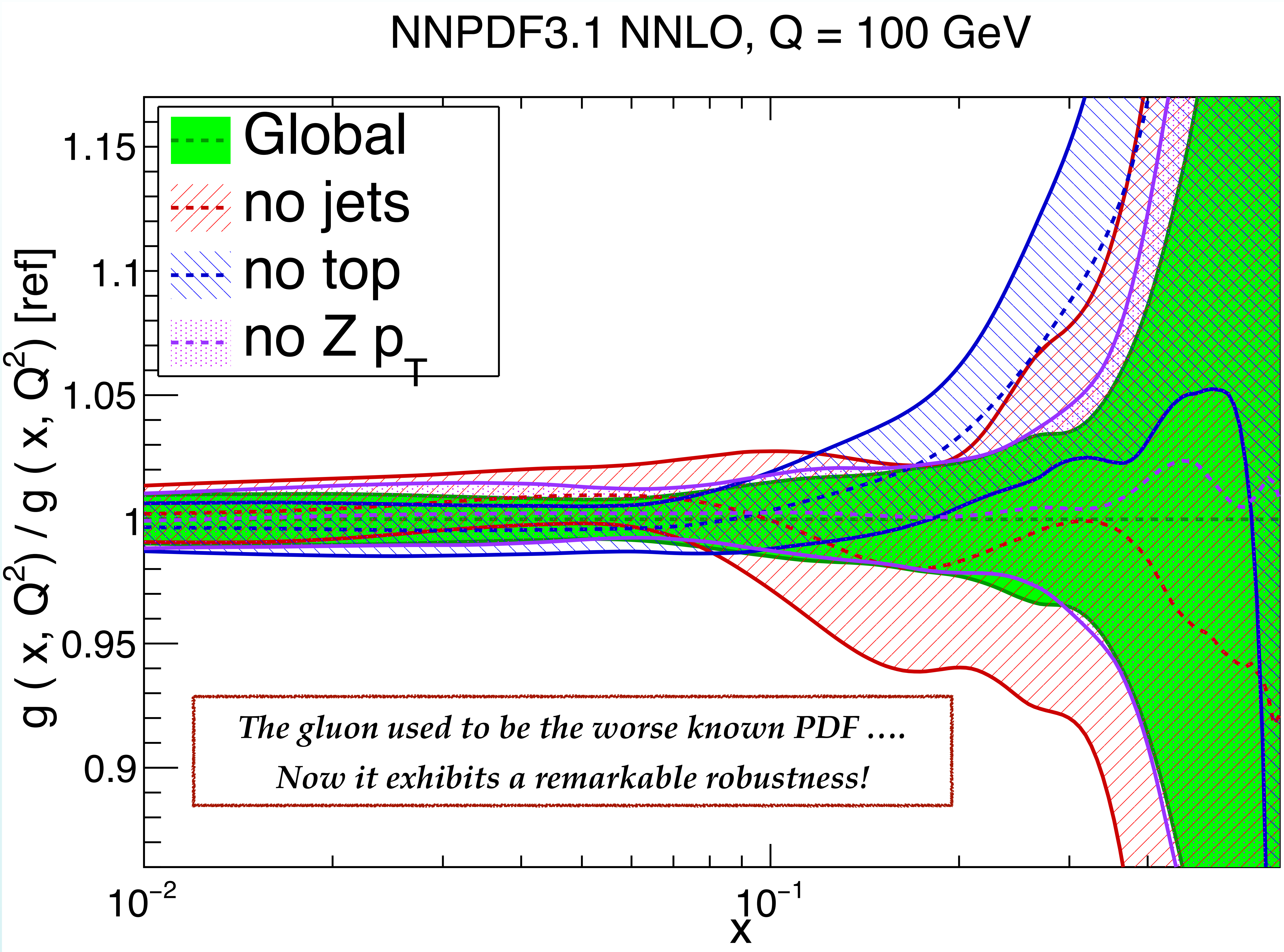


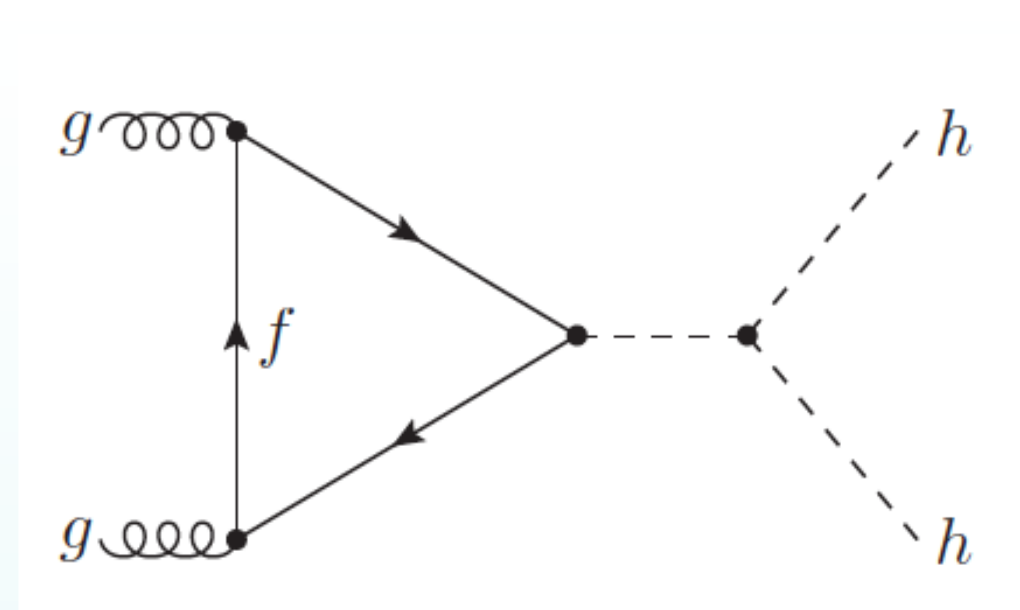
Gauld et al 2015

UHE neutrino-nucleus xsecs

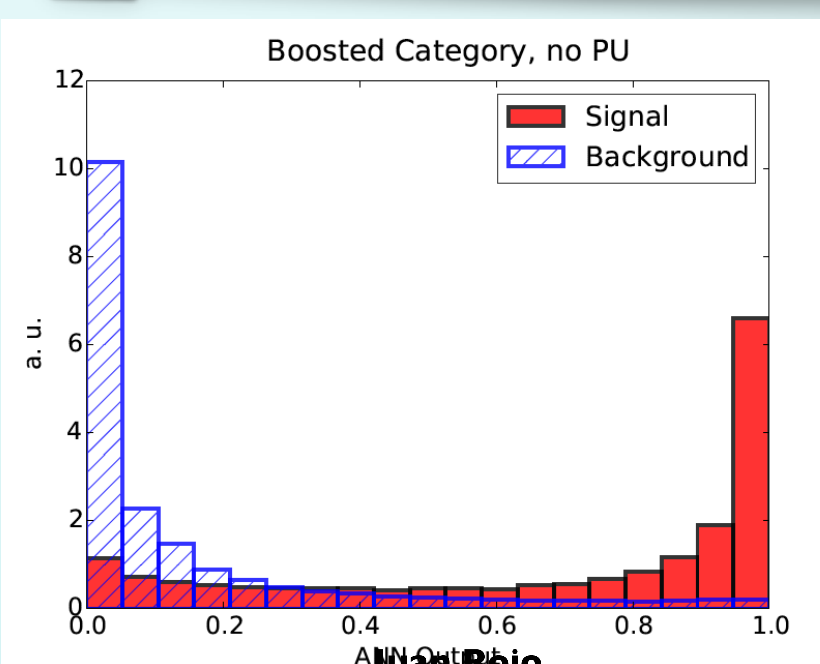


One (upgraded) glue to bind them all



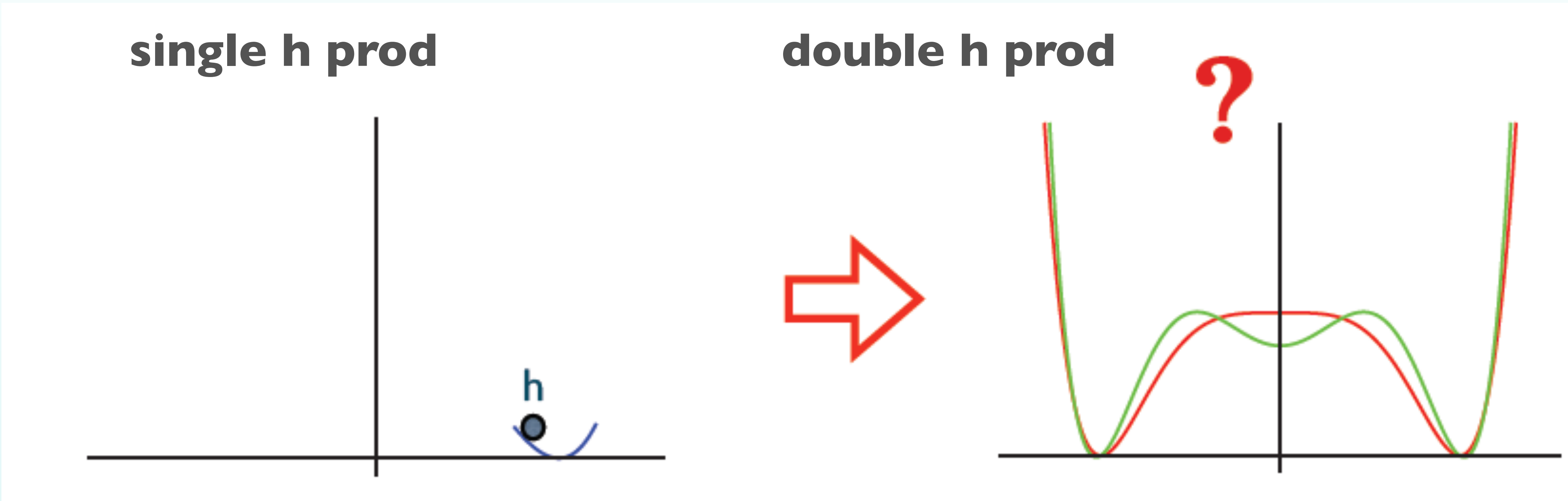


Does the God Particle talk to Itself? Unravelling the Higgs Self-Coupling



Probing Electroweak Symmetry breaking

- **Current measurements** (couplings in single Higgs production) probe **Higgs potential close to minimum**
- Double Higgs production essential to **reconstruct the full Higgs potential** and clarify EWSB mechanism
- Higgs SM potential is *ad-hoc*: not fixed by the SM symmetries, **many other EWSB mechanisms conceivable**



Higgs mechanism

$$V(h) = m_h^2 h^\dagger h + \frac{1}{2}\lambda(h^\dagger h)^2$$

Coleman-Weinberg mechanism

$$V(h) \to \frac{1}{2}\lambda(h^\dagger h)^2 \log\left[\frac{(h^\dagger h)}{m^2}\right]$$

Each possibility associated to **completely different EWSB mechanism**, with crucial implications for the **hierarchy problem**, the structure of quantum field theory, and **New Physics at the EW scale**

Arkani-Hamed, Han, Mangano, Wang, arxiv:1511.06495

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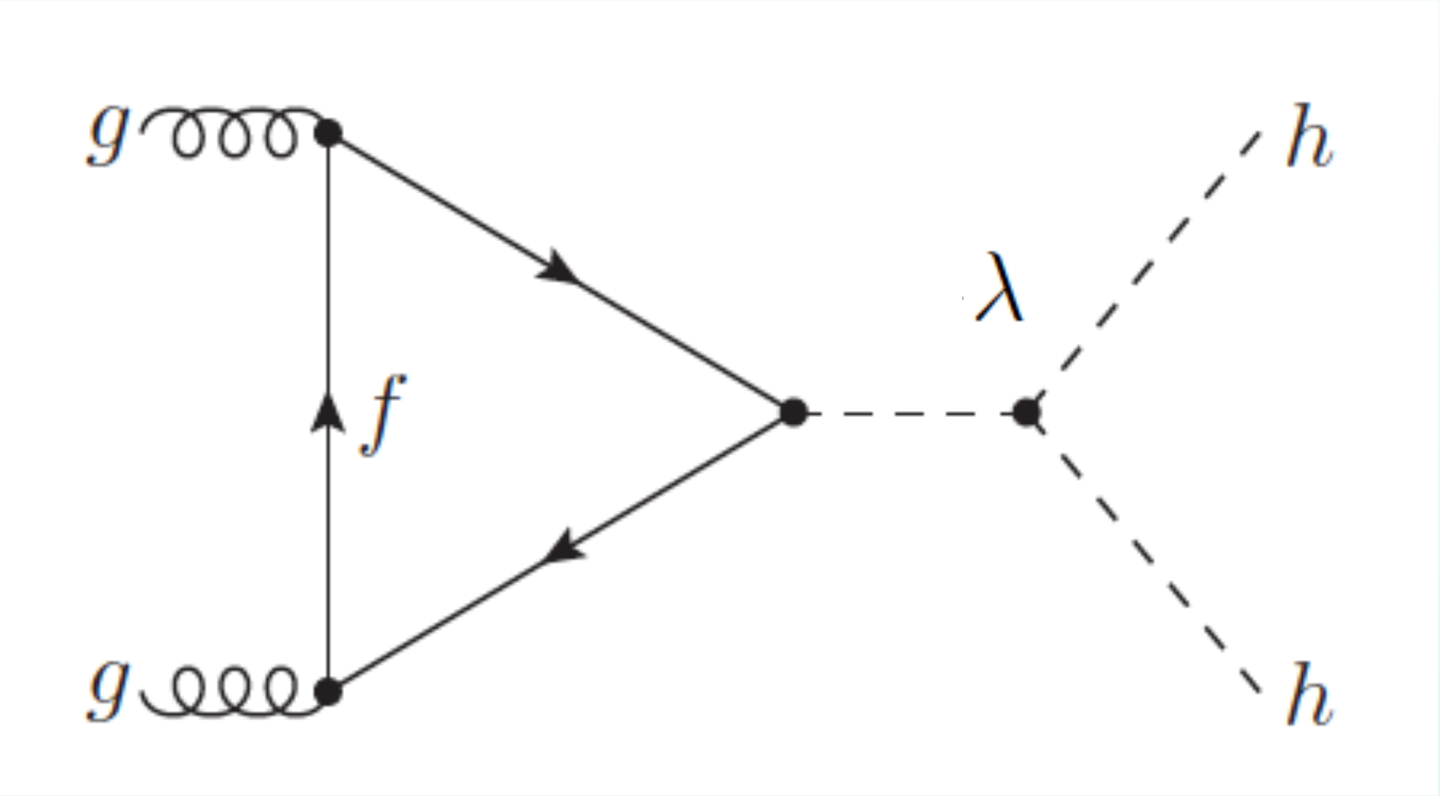


Higgs mechanism

$$V(h) = m_h^2 h^\dagger h + \frac{1}{2}\lambda(h^\dagger h)^2$$

Coleman-Weinberg mechanism

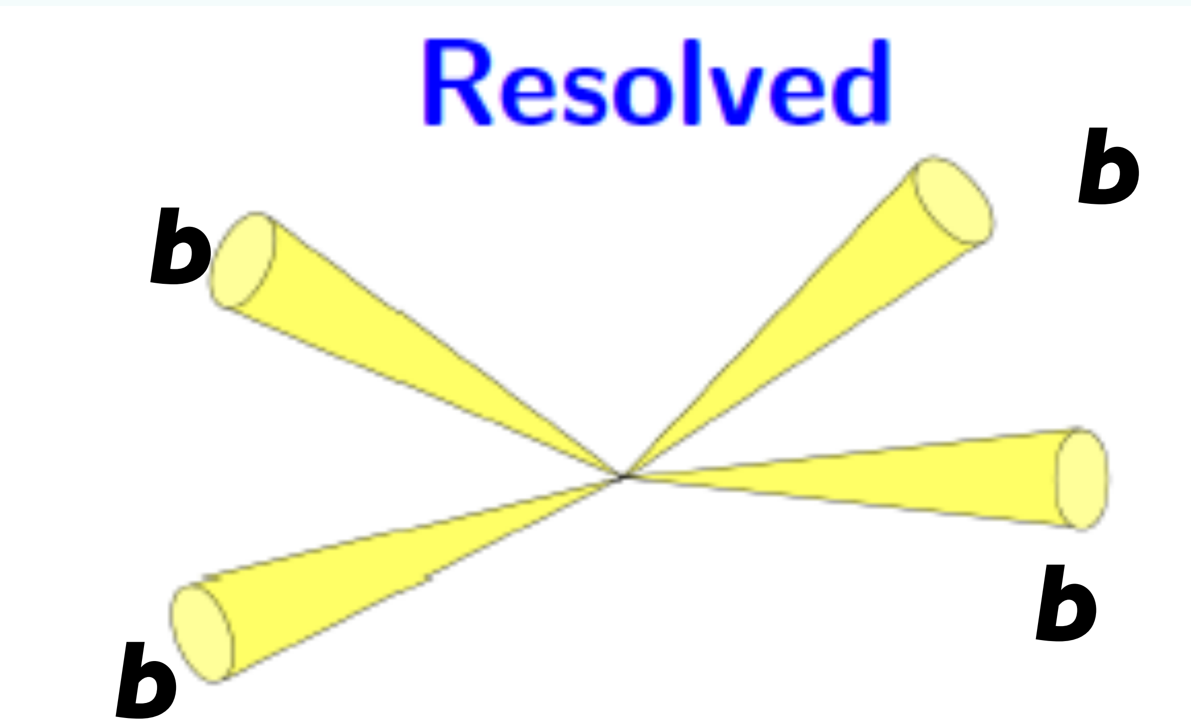
$$V(h) \to \frac{1}{2}\lambda(h^\dagger h)^2 \log\left[\frac{(h^\dagger h)}{m^2}\right]$$

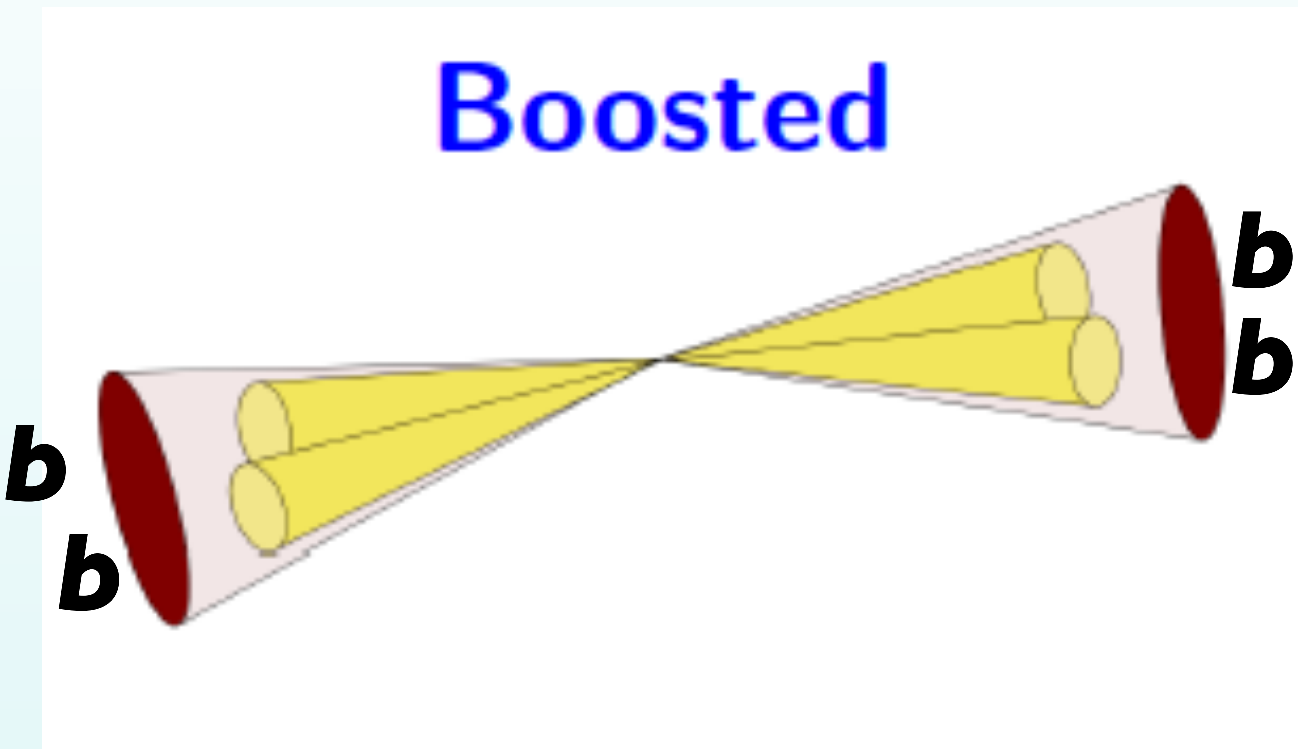
Each possibility associated to **completely different EWSB mechanism**, with crucial implications for the **hierarchy problem**, the structure of quantum field theory, and **New Physics at the EW scale**

Arkani-Hamed, Han, Mangano, Wang, arxiv:1511.06495

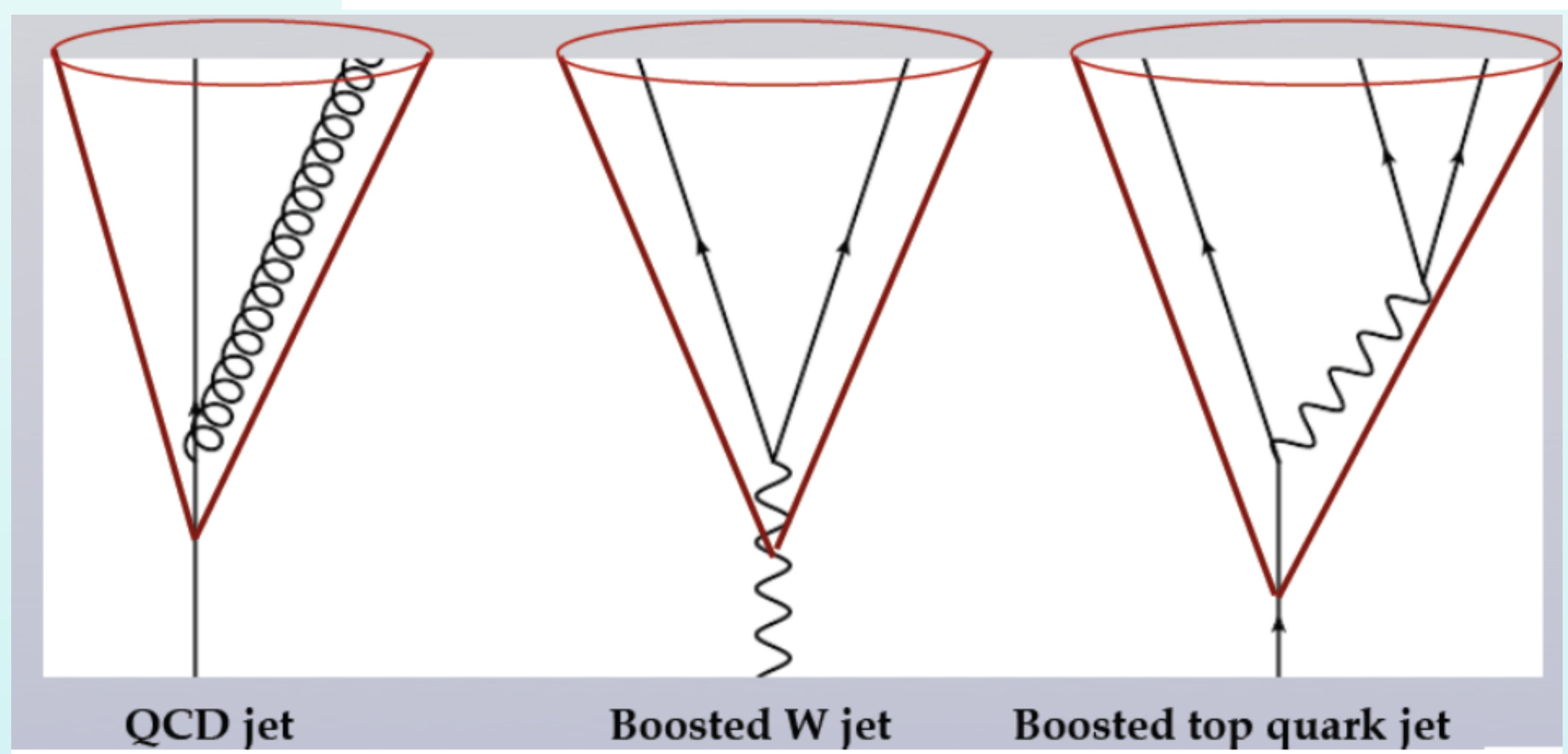
hh->bbbb: selection strategy

- Exploit **4b final state**: highest signal yields, but **overwhelming QCD background** (by orders of magnitude!)
- Carefully chosen selection strategies ensure that **all relevant event topologies can be reconstructed**

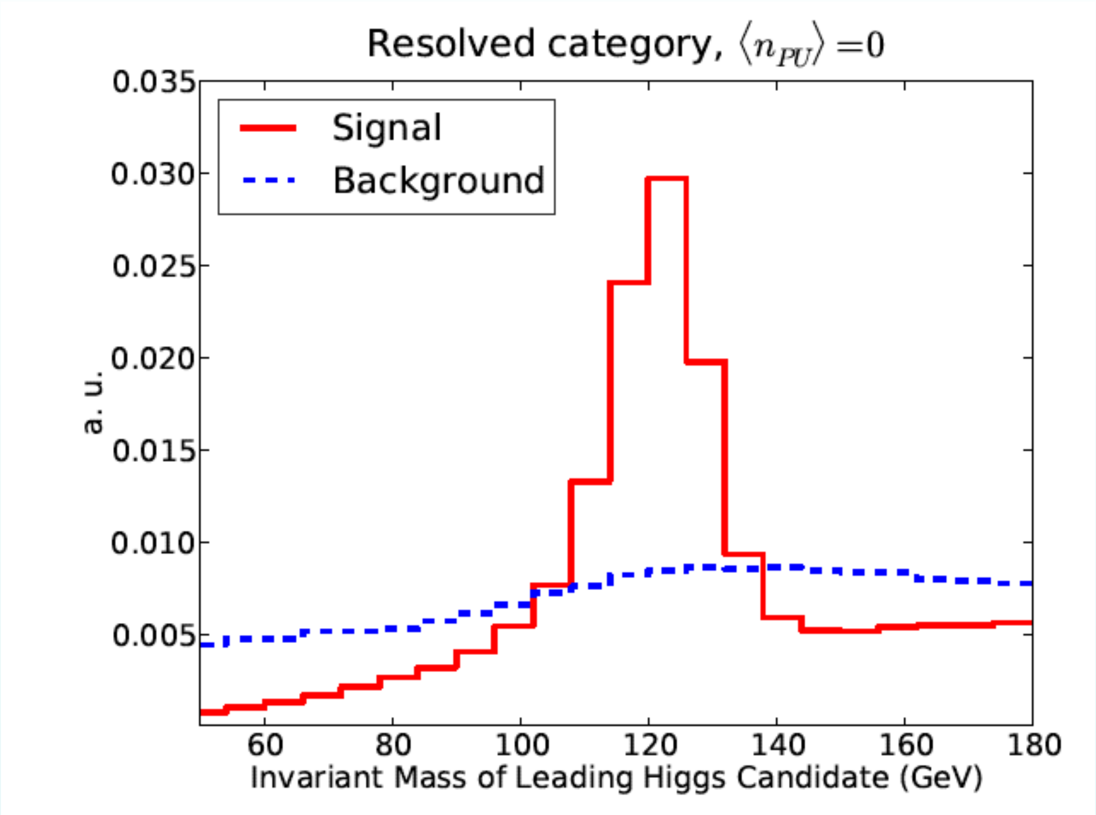


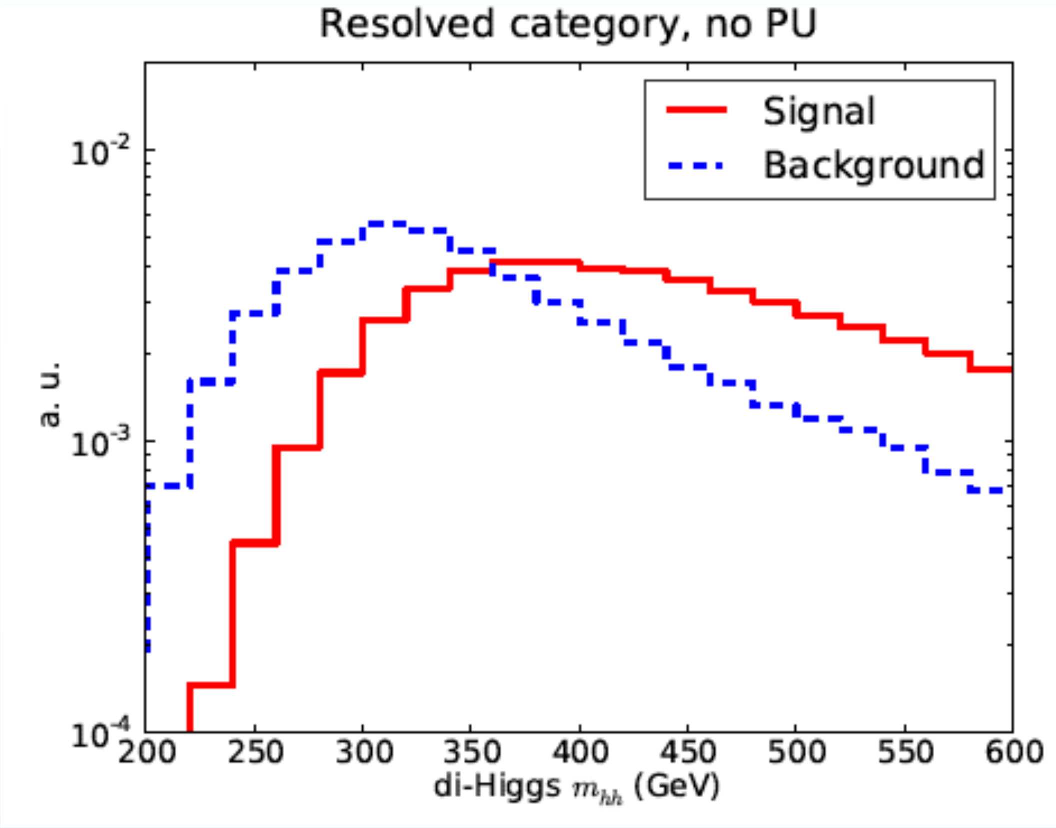


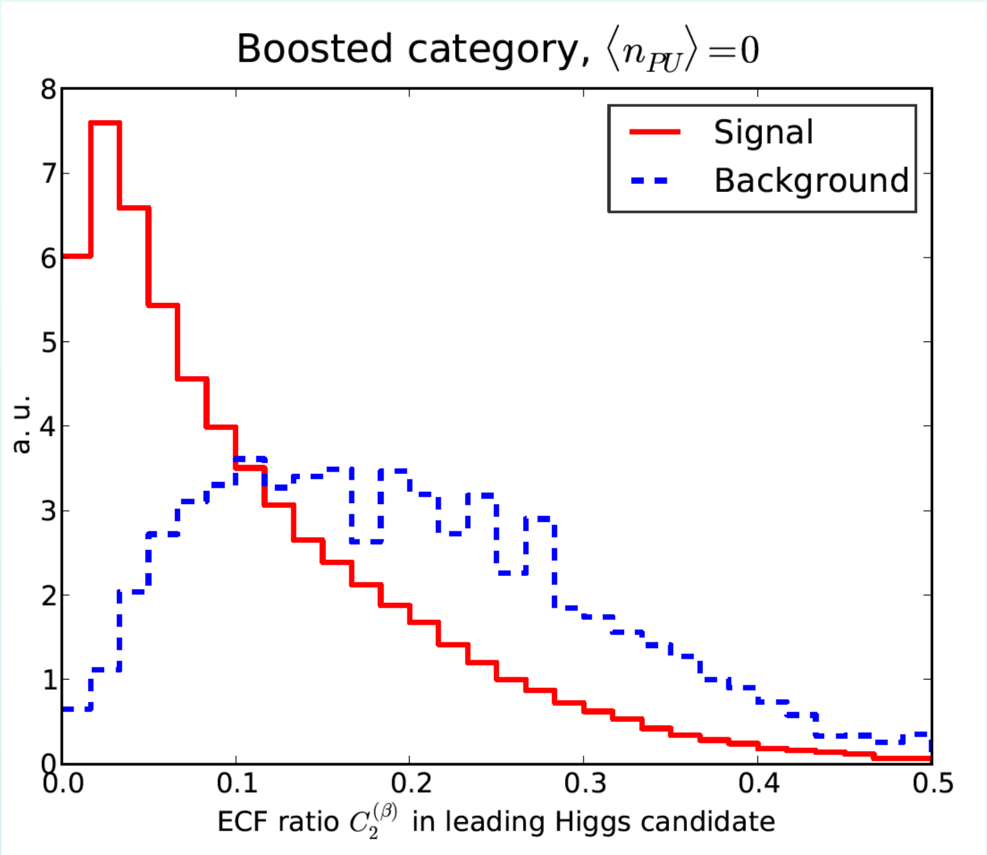
Recent progress in **jet substructure** techniques important to reduced QCD background in the **boosted regime**

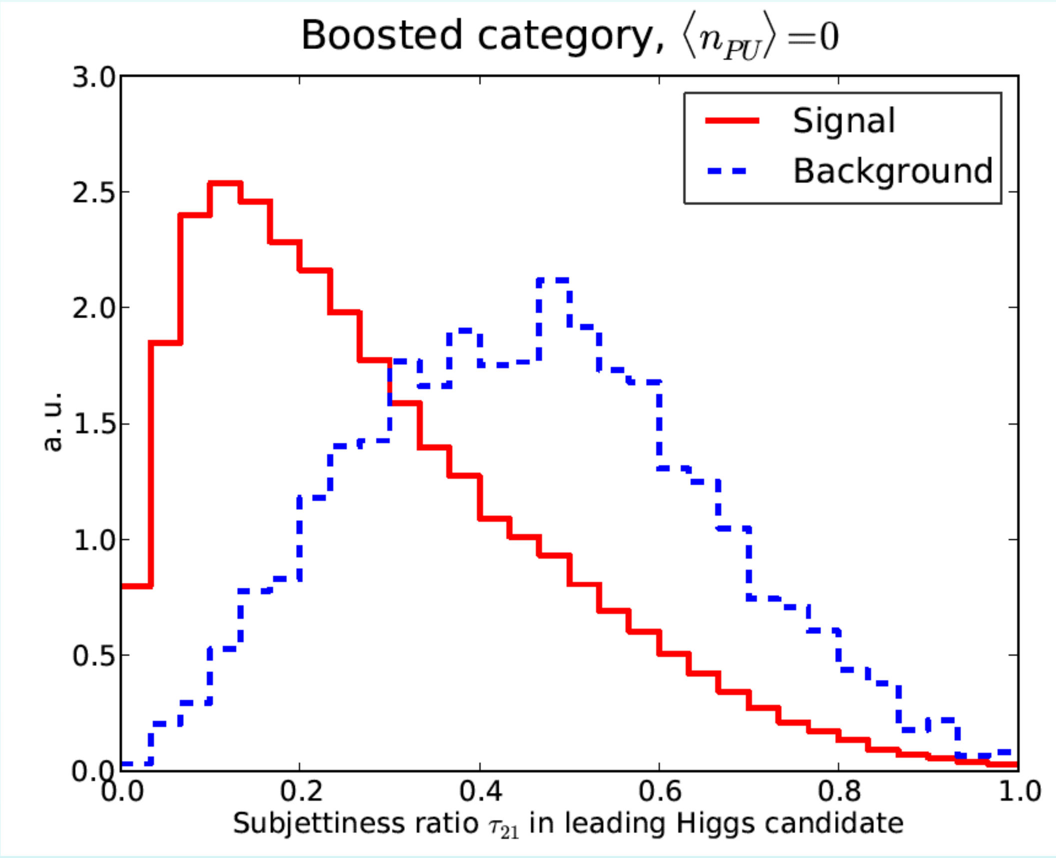


di-Higgs kinematic distributions









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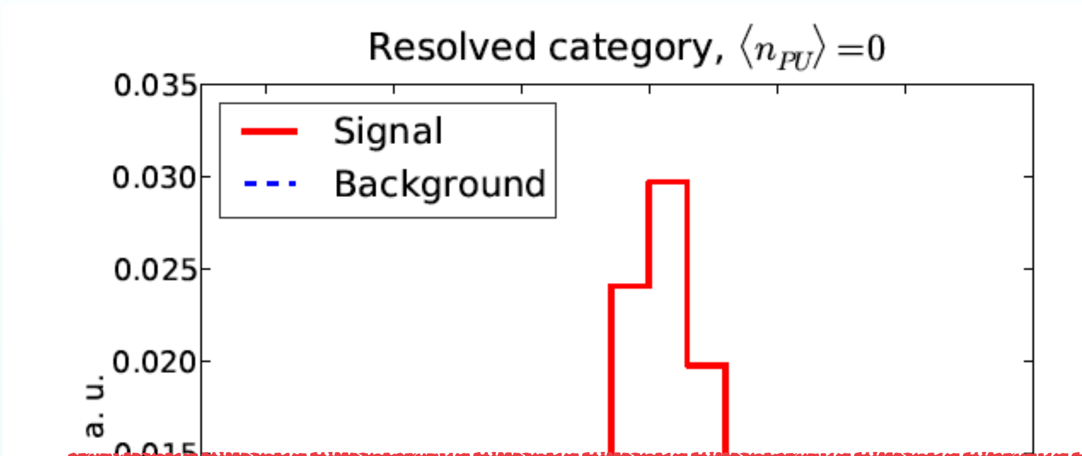
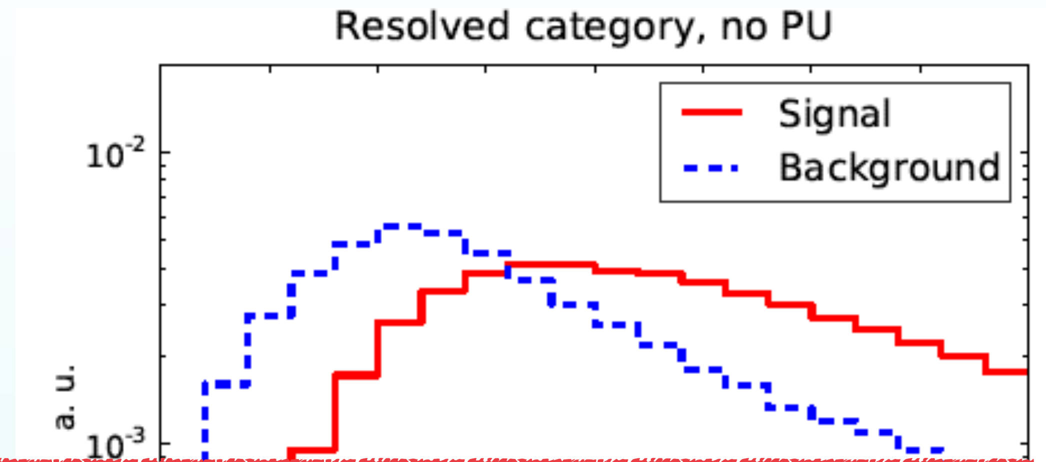
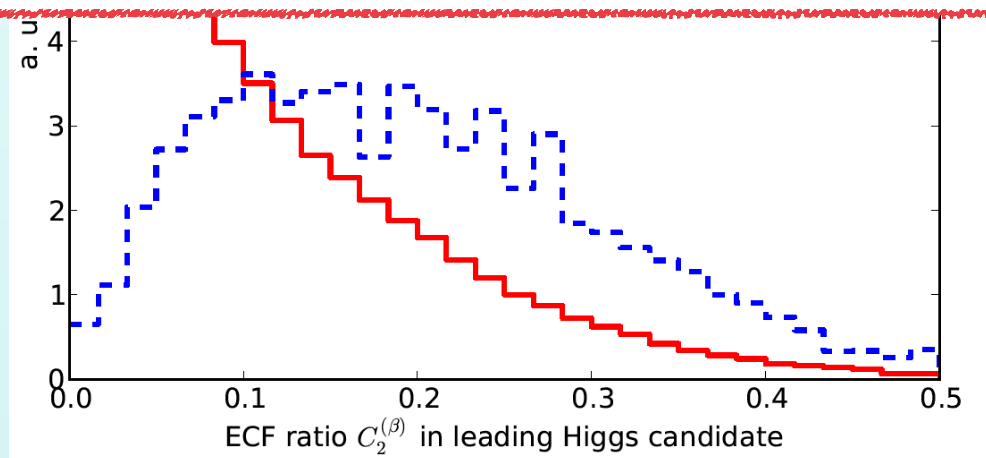


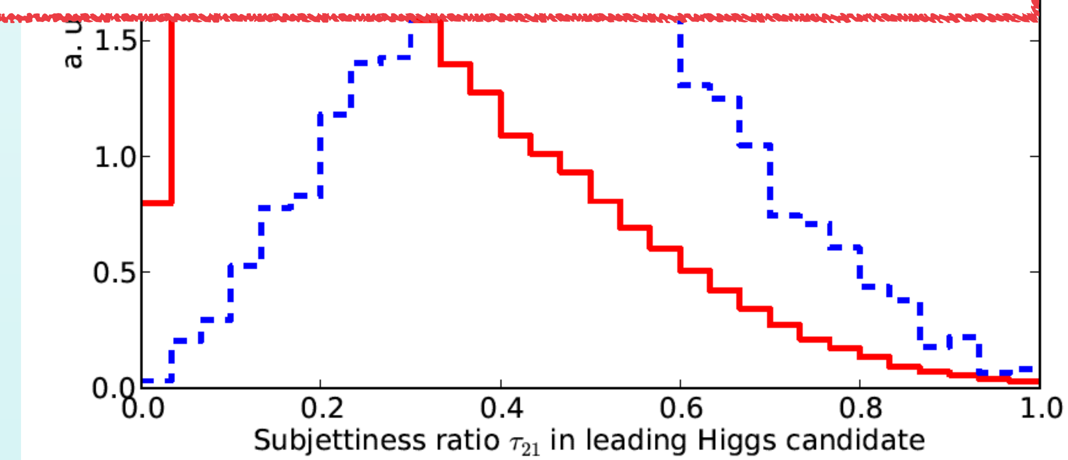


Many kinematic variables can be used to **disentangle signal and background**

How do we select which ones to use? And the optical cuts? And the cross-correlations among variables?

We don't need to! Use **ML methods to identify automatically** the combination of kinematical variables with the highest discrimination power!





Multivariate techniques

Input

Higgs pT

Higgs m

di-Higgs m

ECF

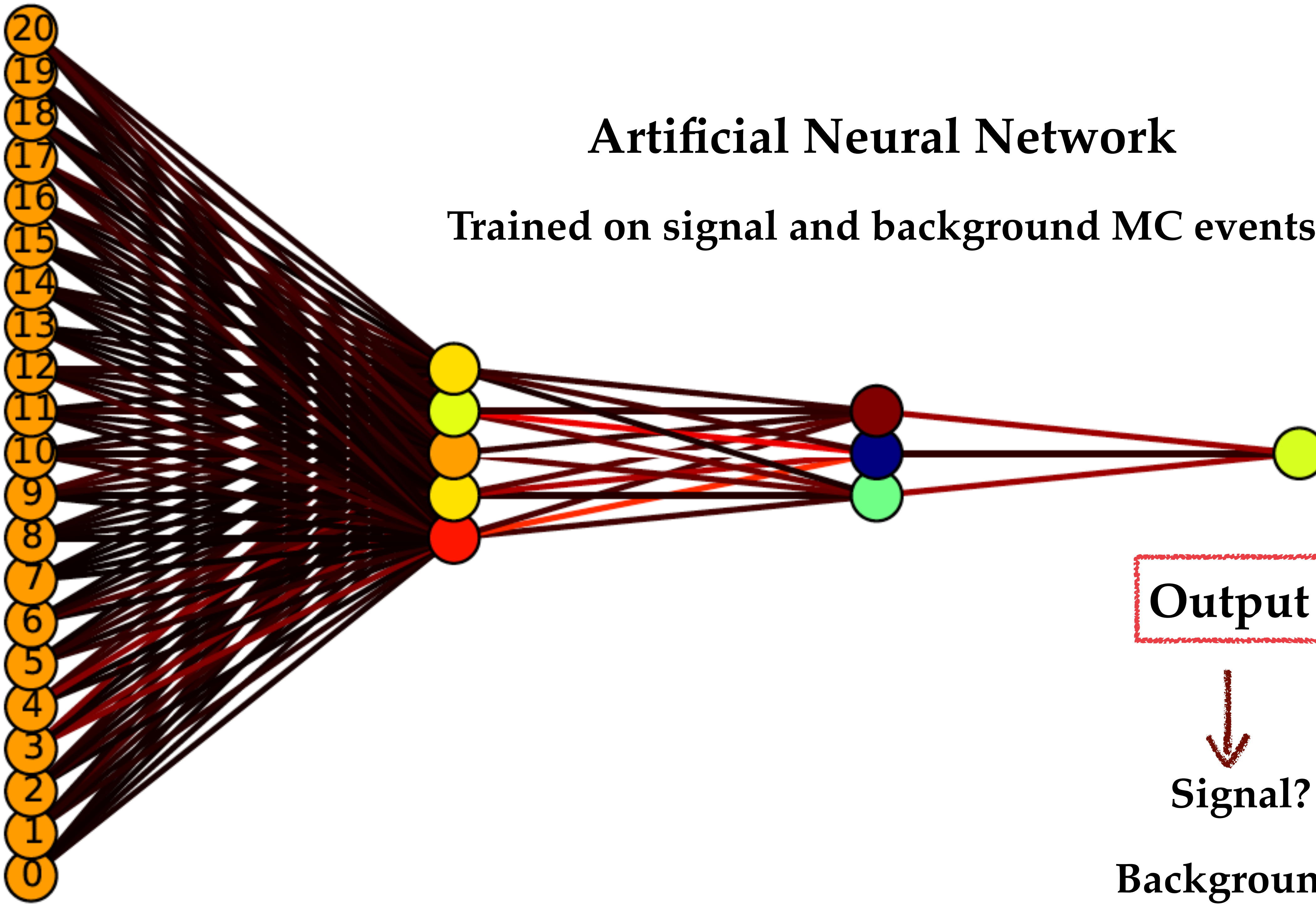
τ_{12}

Subjet pT

…..

Artificial Neural Network

Trained on signal and background MC events



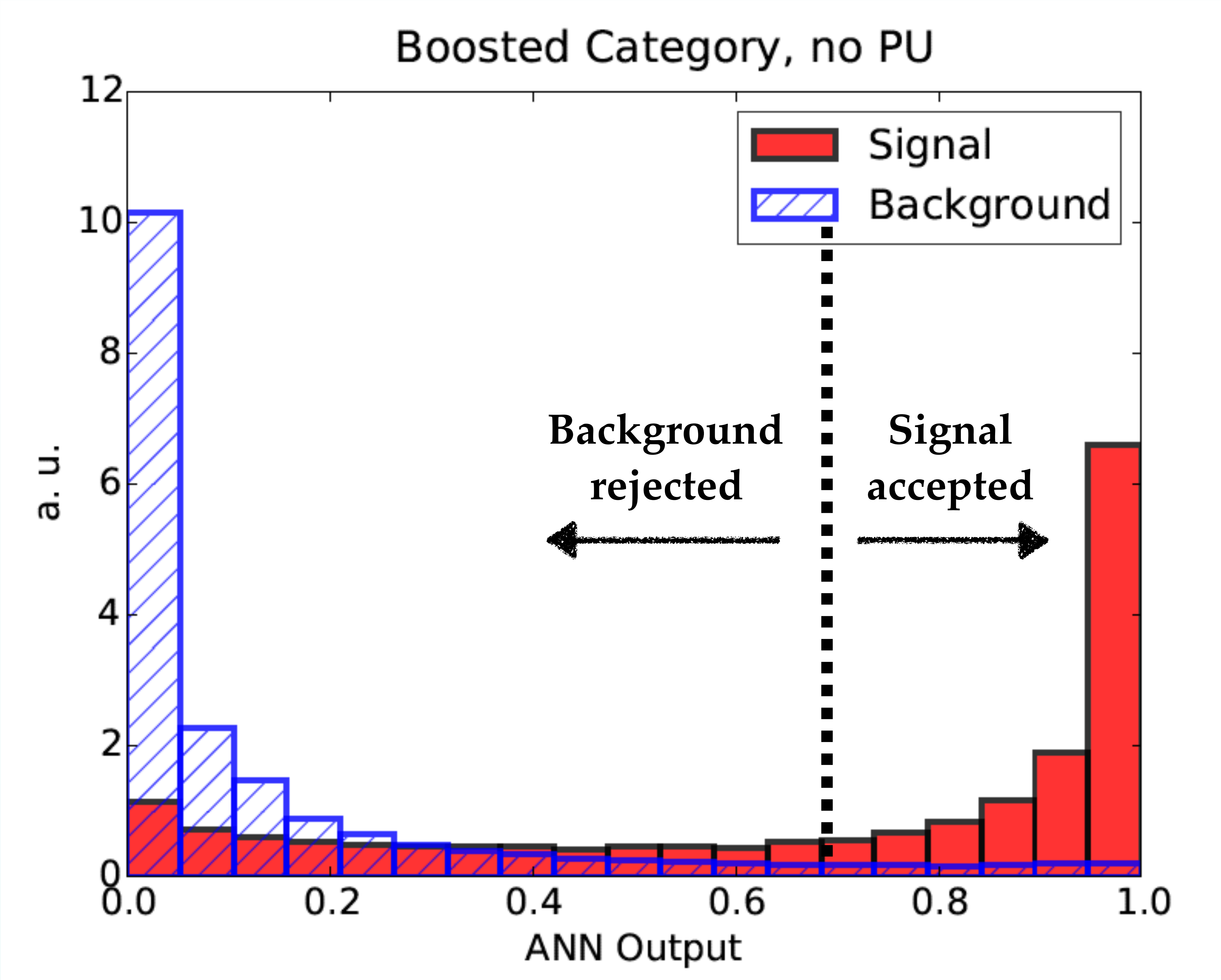
Output

Signal?

Background?

Multivariate techniques

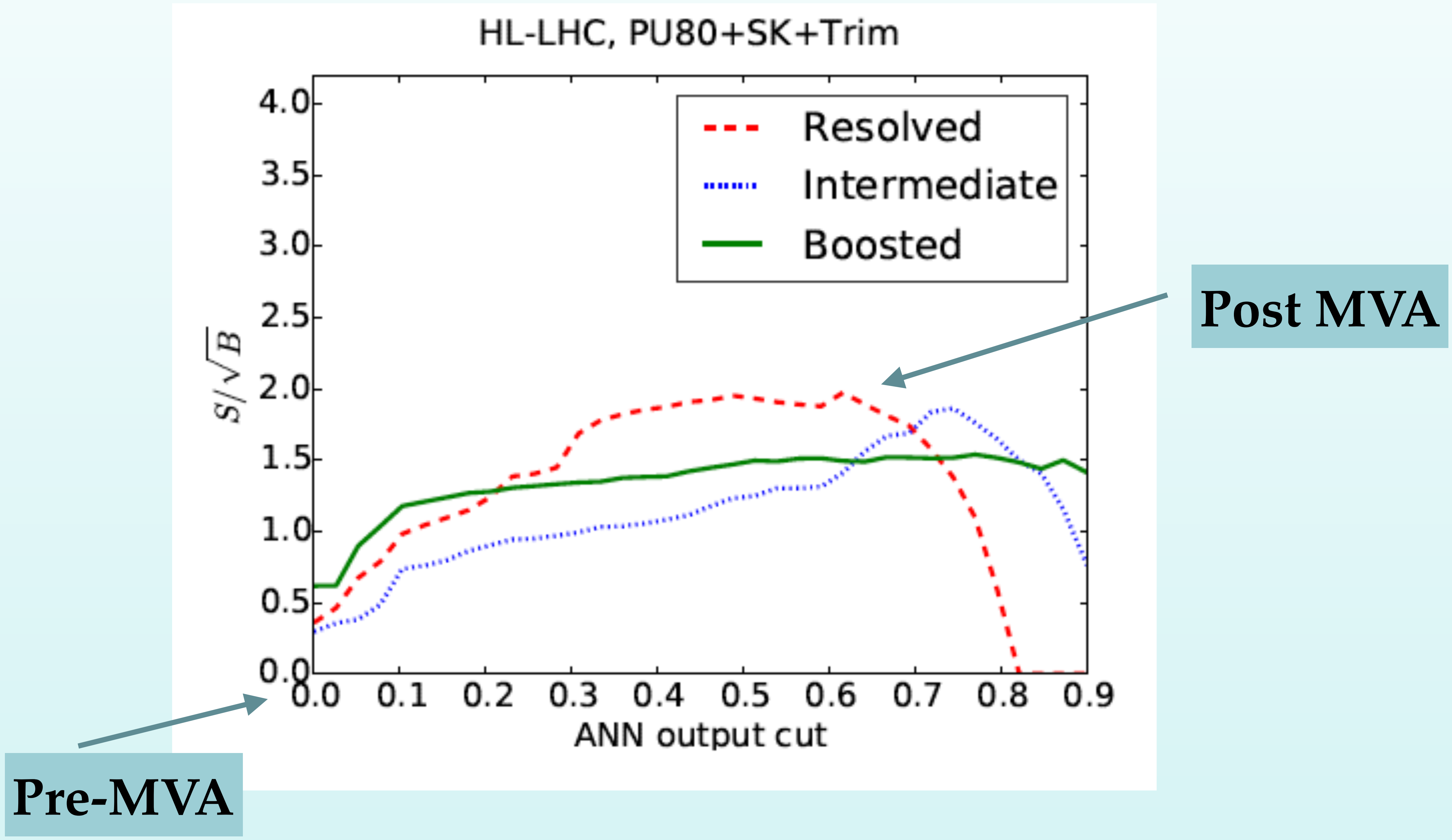
Combining information from all kinematic variables in MVA: **excellent signal/background discrimination**



Discovering Higgs self-interactions

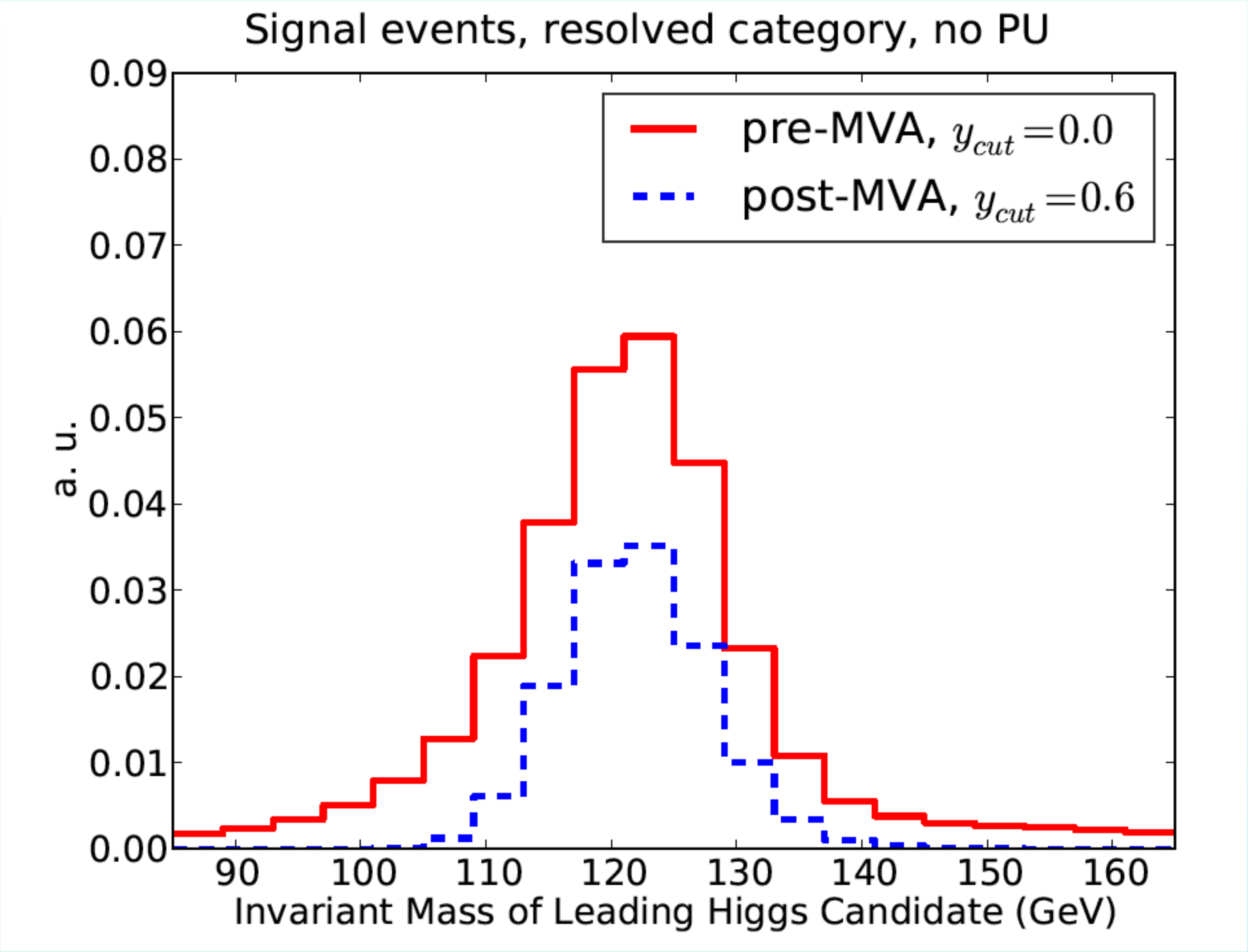
ML techniques allow to **substantially improve the signal significance** for this process **observe Higgs pair production in the 4b final state** at the HL-LHC. Observation (maybe discovery) within reach!

$$\left(\frac{S}{\sqrt{B_{4b}}}\right)_{\rm tot} \simeq 4.7\ (1.5)\,, \quad \mathcal{L} = 3000\ (300)\ {\rm fb}^{-1}$$



Opening the Black Box

- ANNs are sometimes criticised by being **black boxes**, with little understanding of what happens inside them
- But ANNs are simply a **set of combined kinematical cuts**, nothing mysterious in them!
- Kin distributions **after and before the ANN cut** allow determining the **effective kinematic cuts** being optimised by the MVA, which would allow a cut-based analysis



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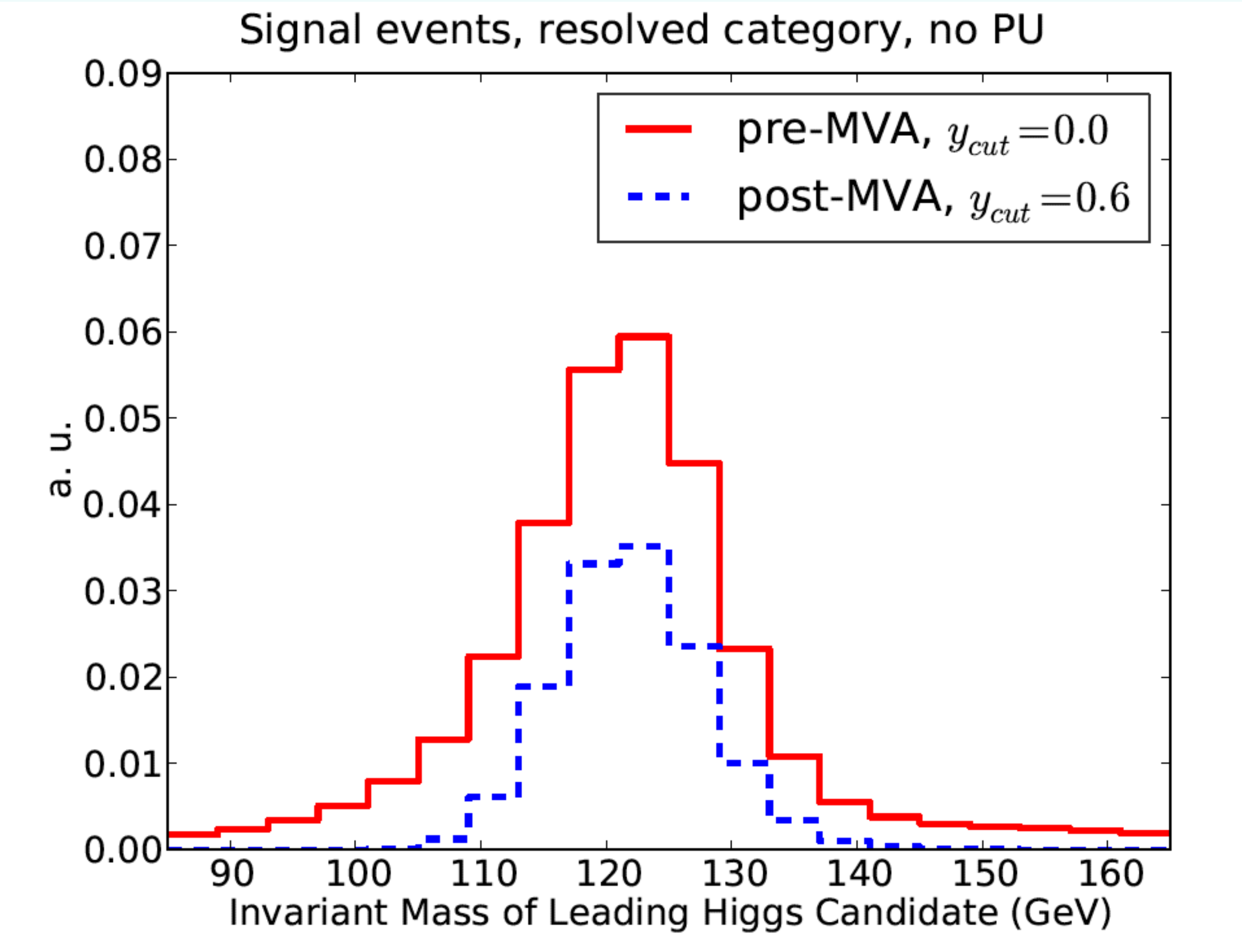
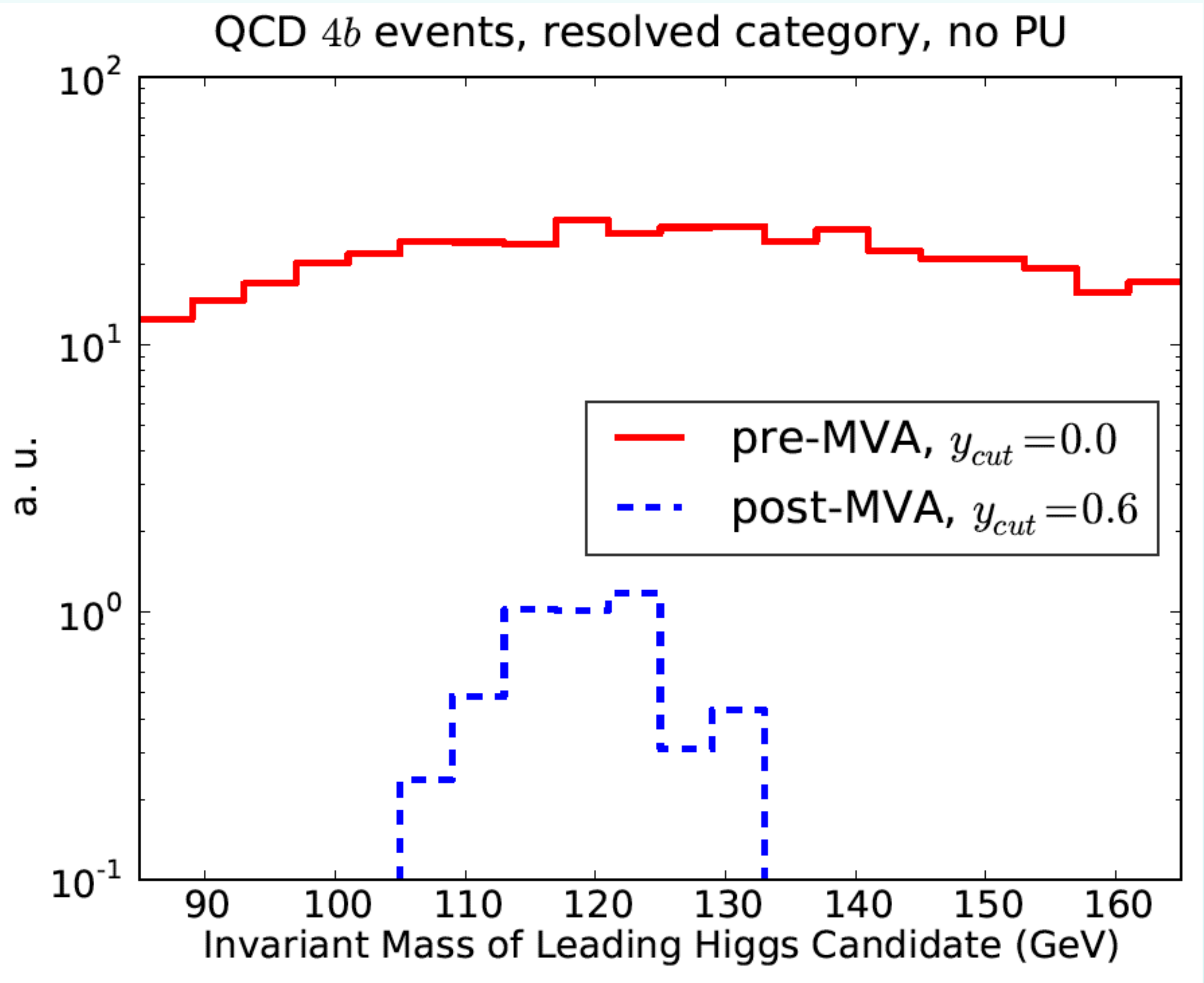




The MVA sculpts a Higgs peak in the QCD background!

ANNs and LHC phenomenology

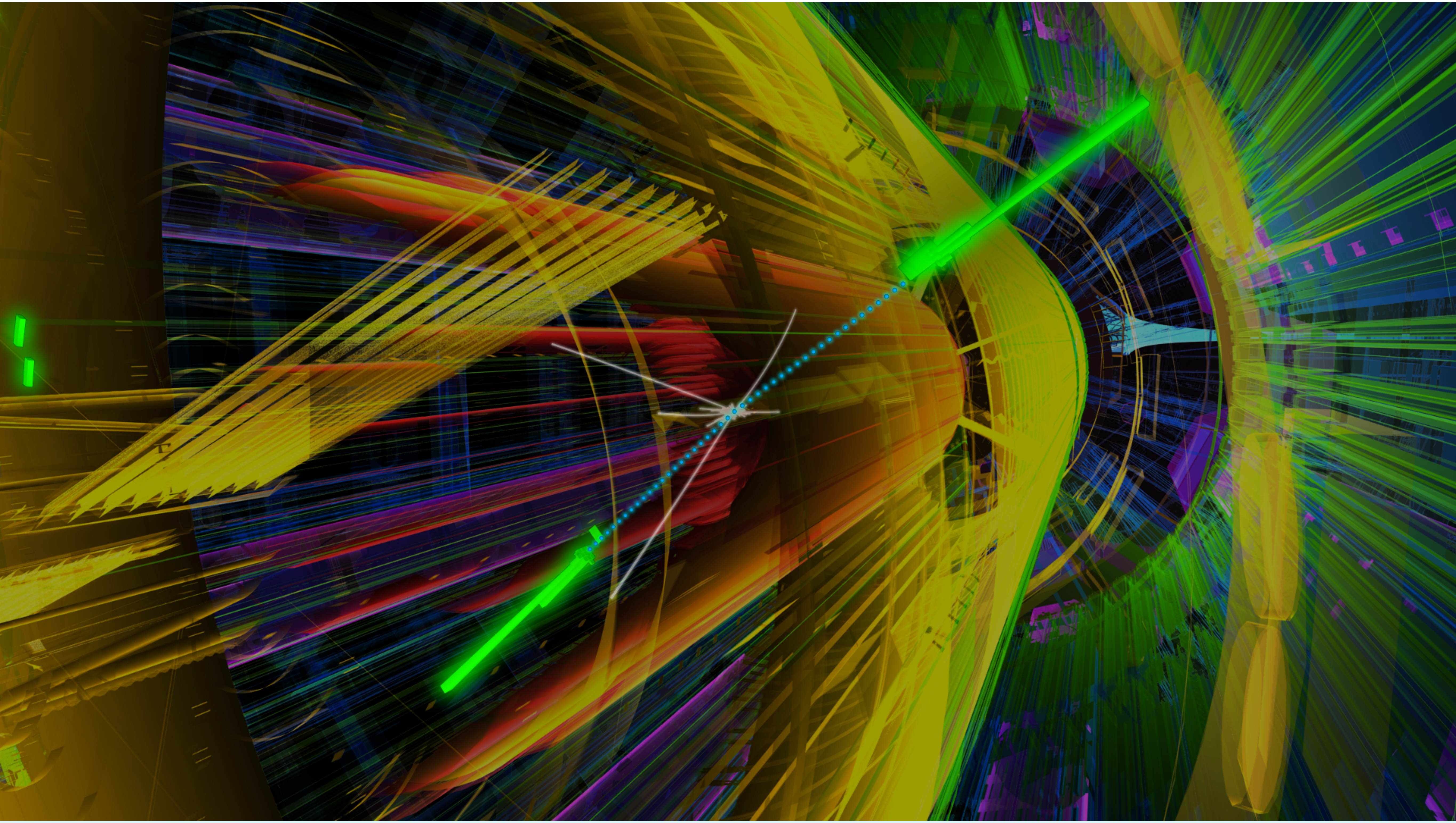
- **Machine Learning algorithms** are already **transforming our world**, from the way we move, shop and heal ourselves, to our understanding of what makes us unique as humans

- In the context of **LHC data analysis and interpretation, ML tools are ubiquitous**, from event selection deep in the detector chain (triggering) to bottom-quark tagging and automated BSM models classification (and exclusion)

- Artificial Neural Networks can be used as **universal unbiased interpolators in global analysis of the proton structure**, with implications from BSM heavy particle production to ultra-high energy neutrino astrophysics

- ANNs can also be used as **classifiers (discriminators) between signal and background** in very busy collision environments, improving LHC physics prospects *i.e.* for **Higgs pair production**

Fascinating times ahead at the high-energy frontier!



And stay tuned for news from the LHC!

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