Deep Learning in High Energy Physics

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SLAC

Machine Learning in High Energy Physics
Summer School at Oxford
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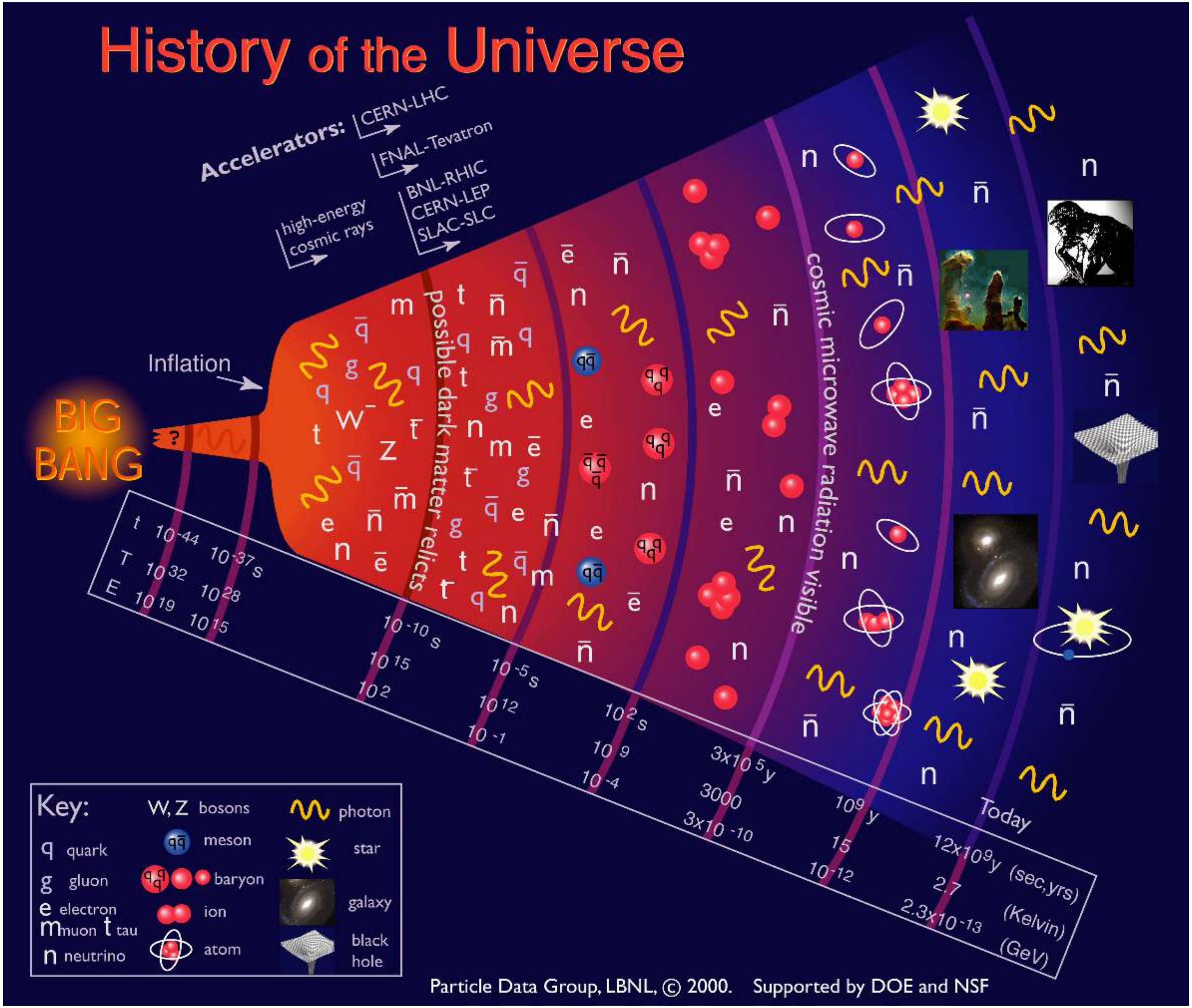
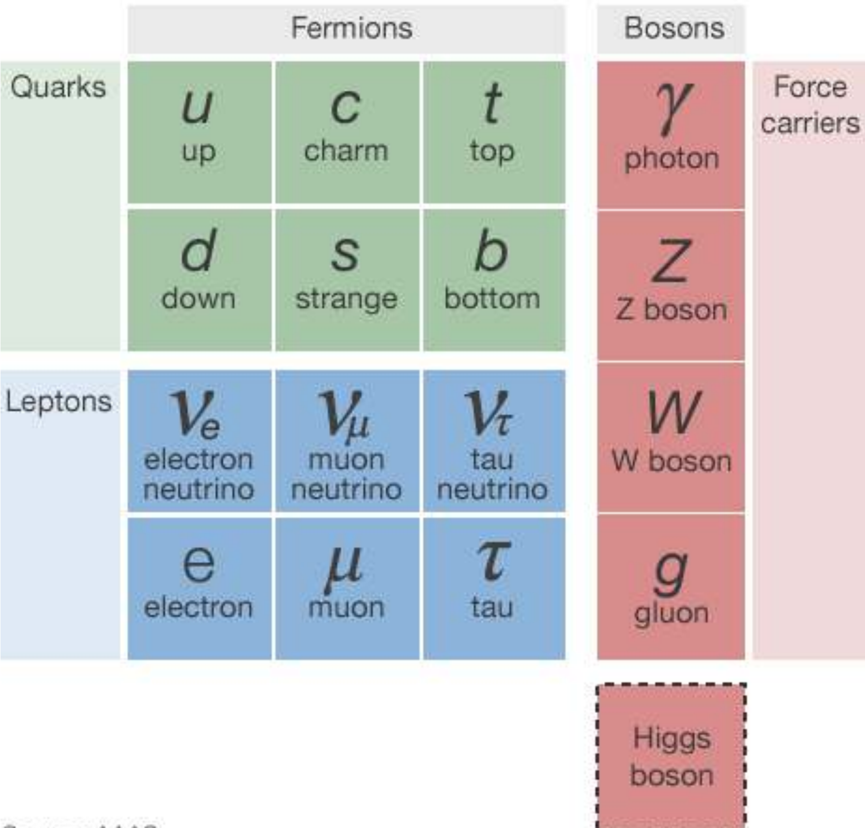
Particle Physics



What We Know: The Standard Model



Source: AAAS

$$
\begin{gathered}
-\tfrac{1}{2}\partial_\nu g^a_\mu \partial_\nu g^a_\mu - g_s f^{abc}\partial_\mu g^a_\nu g^b_\mu g^c_\nu - \tfrac{1}{4}g^2_s f^{abc} f^{ade} g^b_\mu g^c_\nu g^d_\mu g^e_\nu + \\
\tfrac{1}{2} i g^2_s (\bar{q}^\sigma_i \gamma^\mu q^\sigma_j) g^a_\mu + \bar{G}^a \partial^2 G^a + g_s f^{abc} \partial_\mu \bar{G}^a G^b g^c_\mu - \partial_\nu W^+_\mu \partial_\nu W^-_\mu - \\
M^2 W^+_\mu W^-_\mu - \tfrac{1}{2}\partial_\nu Z^0_\mu \partial_\nu Z^0_\mu - \tfrac{1}{2c^2_w} M^2 Z^0_\mu Z^0_\mu - \tfrac{1}{2}\partial_\mu A_\nu \partial_\mu A_\nu - \tfrac{1}{2}\partial_\mu H \partial_\mu H - \\
\tfrac{1}{2} m^2_h H^2 - \partial_\mu \phi^+ \partial_\mu \phi^- - M^2 \phi^+ \phi^- - \tfrac{1}{2}\partial_\mu \phi^0 \partial_\mu \phi^0 - \tfrac{1}{2c^2_w} M \phi^0 \phi^0 - \beta_h [\tfrac{2M^2}{g^2} + \\
\tfrac{2M}{g} H + \tfrac{1}{2}(H^2 + \phi^0 \phi^0 + 2\phi^+ \phi^-)] + \tfrac{2M^4}{g^2}\alpha_h - i g c_w [\partial_\nu Z^0_\mu (W^+_\mu W^-_\nu - \\
W^+_\nu W^-_\mu) - Z^0_\nu (W^+_\mu \partial_\nu W^-_\mu - W^-_\mu \partial_\nu W^+_\mu) + Z^0_\mu (W^+_\nu \partial_\nu W^-_\mu - \\
W^-_\nu \partial_\nu W^+_\mu)] - i g s_w [\partial_\nu A_\mu (W^+_\mu W^-_\nu - W^+_\nu W^-_\mu) - A_\nu (W^+_\mu \partial_\nu W^-_\mu - \\
W^-_\mu \partial_\nu W^+_\mu) + A_\mu (W^+_\nu \partial_\nu W^-_\mu - W^-_\nu \partial_\nu W^+_\mu)] - \tfrac{1}{2} g^2 W^+_\mu W^-_\mu W^+_\nu W^-_\nu + \\
\tfrac{1}{2} g^2 W^+_\mu W^-_\nu W^+_\mu W^-_\nu + g^2 c^2_w (Z^0_\mu W^+_\mu Z^0_\nu W^-_\nu - Z^0_\mu Z^0_\mu W^+_\nu W^-_\nu) + \\
g^2 s^2_w (A_\mu W^+_\mu A_\nu W^-_\nu - A_\mu A_\mu W^+_\nu W^-_\nu) + g^2 s_w c_w [A_\mu Z^0_\nu (W^+_\mu W^-_\nu - \\
W^+_\nu W^-_\mu) - 2 A_\mu Z^0_\mu W^+_\nu W^-_\nu] - g \alpha [H^3 + H \phi^0 \phi^0 + 2 H \phi^+ \phi^-] - \\
\tfrac{1}{8} g^2 \alpha_h [H^4 + (\phi^0)^4 + 4(\phi^+ \phi^-)^2 + 4(\phi^0)^2 \phi^+ \phi^- + 4 H^2 \phi^+ \phi^- + 2(\phi^0)^2 H^2] - \\
g M W^+_\mu W^-_\mu H - \tfrac{1}{2} g \tfrac{M}{c^2_w} Z^0_\mu Z^0_\mu H - \tfrac{1}{2} i g [W^+_\mu (\phi^0 \partial_\mu \phi^- - \phi^- \partial_\mu \phi^0) - \\
W^-_\mu (\phi^0 \partial_\mu \phi^+ - \phi^+ \partial_\mu \phi^0)] + \tfrac{1}{2} g [W^+_\mu (H \partial_\mu \phi^- - \phi^- \partial_\mu H) - W^-_\mu (H \partial_\mu \phi^+ - \\
\phi^+ \partial_\mu H)] + \tfrac{1}{2} g \tfrac{1}{c_w} (Z^0_\mu (H \partial_\mu \phi^0 - \phi^0 \partial_\mu H) - i g \tfrac{s^2_w}{c_w} M Z^0_\mu (W^+_\mu \phi^- - W^-_\mu \phi^+) + \\
i g s_w M A_\mu (W^+_\mu \phi^- - W^-_\mu \phi^+) - i g \tfrac{1-2c^2_w}{2c_w} Z^0_\mu (\phi^+ \partial_\mu \phi^- - \phi^- \partial_\mu \phi^+) + \\
i g s_w A_\mu (\phi^+ \partial_\mu \phi^- - \phi^- \partial_\mu \phi^+) - \tfrac{1}{4} g^2 W^+_\mu W^-_\mu [H^2 + (\phi^0)^2 + 2\phi^+ \phi^-] - \\
\tfrac{1}{4} g^2 \tfrac{1}{c^2_w} Z^0_\mu Z^0_\mu [H^2 + (\phi^0)^2 + 2(2s^2_w - 1)^2 \phi^+ \phi^-] - \tfrac{1}{2} g^2 \tfrac{s^2_w}{c_w} Z^0_\mu \phi^0 (W^+_\mu \phi^- + \\
W^-_\mu \phi^+) - \tfrac{1}{2} i g^2 \tfrac{s^2_w}{c_w} Z^0_\mu H (W^+_\mu \phi^- - W^-_\mu \phi^+) + \tfrac{1}{2} g^2 s_w A_\mu \phi^0 (W^+_\mu \phi^- + \\
W^-_\mu \phi^+) + \tfrac{1}{2} i g^2 s_w A_\mu H (W^+_\mu \phi^- - W^-_\mu \phi^+) - g^2 \tfrac{s_w}{c_w} (2c^2_w - 1) Z^0_\mu A_\mu \phi^+ \phi^- - \\
g^1 s^2_w A_\mu A_\mu \phi^+ \phi^- - \bar{e}^\lambda (\gamma\partial + m^\lambda_e) e^\lambda - \bar{\nu}^\lambda \gamma\partial \nu^\lambda - \bar{u}^\lambda_j (\gamma\partial + m^\lambda_u) u^\lambda_j - \\
\bar{d}^\lambda_j (\gamma\partial + m^\lambda_d) d^\lambda_j + i g s_w A_\mu [-(\bar{e}^\lambda \gamma^\mu e^\lambda) + \tfrac{2}{3}(\bar{u}^\lambda_j \gamma^\mu u^\lambda_j) - \tfrac{1}{3}(\bar{d}^\lambda_j \gamma^\mu d^\lambda_j)] + \\
\tfrac{ig}{4c_w} Z^0_\mu [(\bar{\nu}^\lambda \gamma^\mu (1+\gamma^5) \nu^\lambda) + (\bar{e}^\lambda \gamma^\mu (4s^2_w - 1 - \gamma^5) e^\lambda) + (\bar{u}^\lambda_j \gamma^\mu (\tfrac{4}{3}s^2_w - \\
1 - \gamma^5) u^\lambda_j) + (\bar{d}^\lambda_j \gamma^\mu (1 - \tfrac{8}{3}s^2_w - \gamma^5) d^\lambda_j)] + \tfrac{ig}{2\sqrt{2}} W^+_\mu [(\bar{\nu}^\lambda \gamma^\mu (1+\gamma^5) e^\lambda) + \\
(\bar{u}^\lambda_j \gamma^\mu (1+\gamma^5) C_{\lambda\kappa} d^\kappa_j)] + \tfrac{ig}{2\sqrt{2}} W^-_\mu [(\bar{e}^\lambda \gamma^\mu (1+\gamma^5) \nu^\lambda) + (\bar{d}^\kappa_j C^\dagger_{\lambda\kappa} \gamma^\mu (1 + \\
\gamma^5) u^\lambda_j)] + \tfrac{ig}{2\sqrt{2}} \tfrac{m^\lambda_e}{M} [-\phi^+ (\bar{\nu}^\lambda (1-\gamma^5) e^\lambda) + \phi^- (\bar{e}^\lambda (1+\gamma^5) \nu^\lambda)] - \\
\tfrac{g}{2} \tfrac{m^\lambda_e}{M} [H (\bar{e}^\lambda e^\lambda) + i \phi^0 (\bar{e}^\lambda \gamma^5 e^\lambda)] + \tfrac{ig}{2M\sqrt{2}} \phi^+ [-m^\kappa_d (\bar{u}^\lambda_j C_{\lambda\kappa} (1-\gamma^5) d^\kappa_j) + \\
m^\lambda_u (\bar{u}^\lambda_j C_{\lambda\kappa} (1+\gamma^5) d^\kappa_j] + \tfrac{ig}{2M\sqrt{2}} \phi^- [m^\lambda_d (\bar{d}^\lambda_j C^\dagger_{\lambda\kappa} (1+\gamma^5) u^\kappa_j) - m^\kappa_u (\bar{d}^\lambda_j C^\dagger_{\lambda\kappa} (1 - \\
\gamma^5) u^\kappa_j] - \tfrac{g}{2} \tfrac{m^\lambda_u}{M} H (\bar{u}^\lambda_j u^\lambda_j) - \tfrac{g}{2} \tfrac{m^\lambda_d}{M} H (\bar{d}^\lambda_j d^\lambda_j) + \tfrac{ig}{2} \tfrac{m^\lambda_u}{M} \phi^0 (\bar{u}^\lambda_j \gamma^5 u^\lambda_j) - \\
\tfrac{ig}{2} \tfrac{m^\lambda_d}{M} \phi^0 (\bar{d}^\lambda_j \gamma^5 d^\lambda_j) + \bar{X}^+ (\partial^2 - M^2) X^+ + \bar{X}^- (\partial^2 - M^2) X^- + \bar{X}^0 (\partial^2 - \\
\tfrac{M^2}{c^2_w}) X^0 + \bar{Y} \partial^2 Y + i g c_w W^+_\mu (\partial_\mu \bar{X}^0 X^- - \partial_\mu \bar{X}^+ X^0) + i g s_w W^+_\mu (\partial_\mu \bar{Y} X^- - \\
\partial_\mu \bar{X}^+ Y) + i g c_w W^-_\mu (\partial_\mu \bar{X}^- X^0 - \partial_\mu \bar{X}^0 X^+) + i g s_w W^-_\mu (\partial_\mu \bar{X}^- Y - \\
\partial_\mu \bar{Y} X^+) + i g c_w Z^0_\mu (\partial_\mu \bar{X}^+ X^+ - \partial_\mu \bar{X}^- X^-) + i g s_w A_\mu (\partial_\mu \bar{X}^+ X^+ - \\
\partial_\mu \bar{X}^- X^-) - \tfrac{1}{2} g M [\bar{X}^+ X^+ H + \bar{X}^- X^- H + \tfrac{1}{c^2_w} \bar{X}^0 X^0 H] + \\
\tfrac{1-2c^2_w}{2c_w} i g M [\bar{X}^+ X^0 \phi^+ - \bar{X}^- X^0 \phi^-] + \tfrac{1}{2c_w} i g M [\bar{X}^0 X^- \phi^+ - \bar{X}^0 X^+ \phi^-] + \\
i g M s_w [\bar{X}^0 X^- \phi^+ - \bar{X}^0 X^+ \phi^-] + \tfrac{1}{2} i g M [\bar{X}^+ X^+ \phi^0 - \bar{X}^- X^- \phi^0]
\end{gathered}
$$

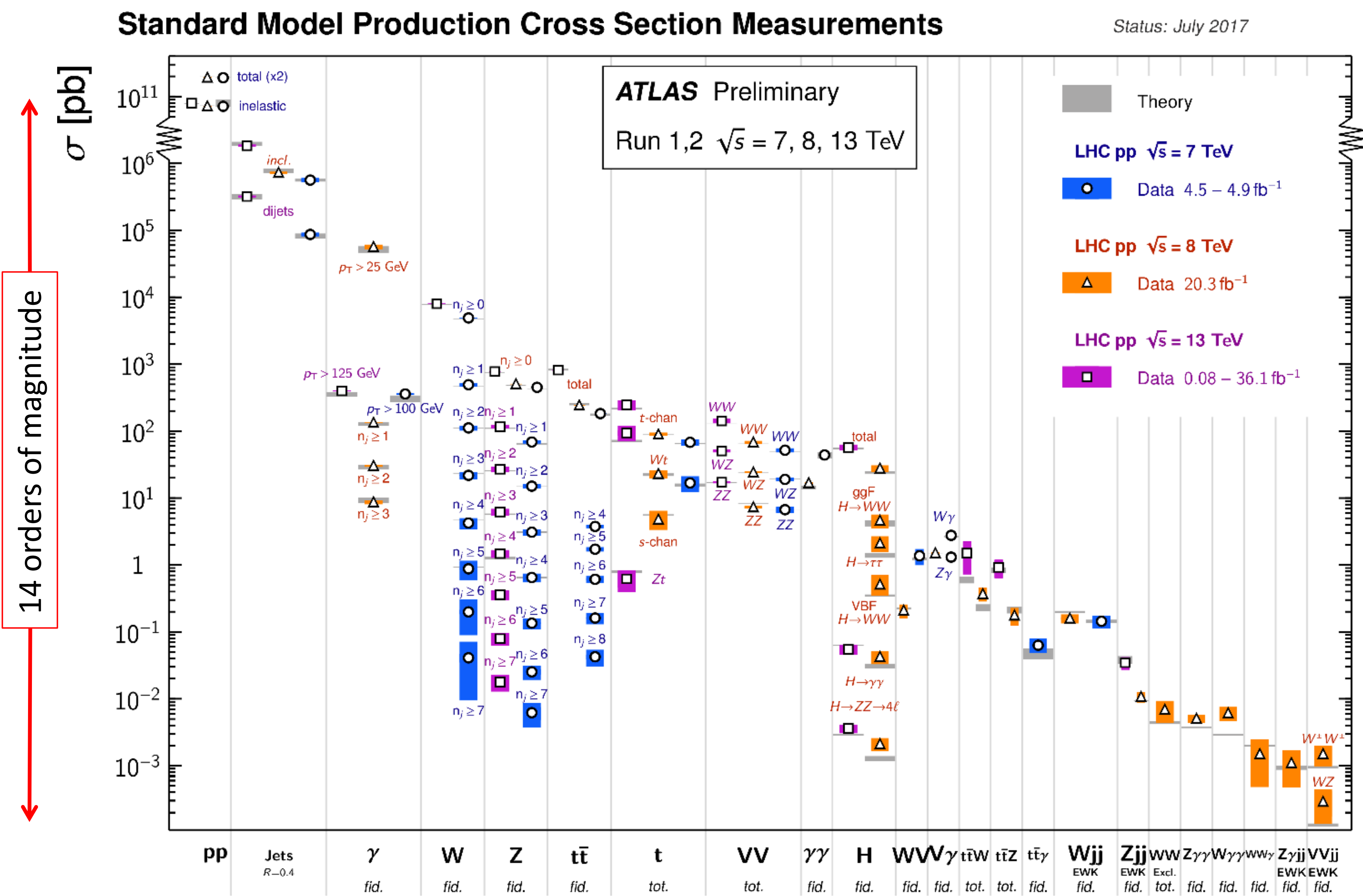
What We Know: The Standard Model

19 parameters

Symbol	Description	Value
m_e	Electron mass	511 keV
m_μ	Muon mass	105.7 MeV
m_τ	Tau mass	1.78 GeV
m_u	Up quark mass	1.9 MeV
m_d	Down quark mass	4.4 MeV
m_s	Strange quark mass	87 MeV
m_c	Charm quark mass	1.32 GeV
m_b	Bottom quark mass	4.24 GeV
m_t	Top quark mass	172.7 GeV
θ_{12}	CKM 12-mixing angle	13.1°
θ_{23}	CKM 23-mixing angle	2.4°
θ_{13}	CKM 13-mixing angle	0.2°
δ	CKM CP-violating Phase	0.995
g_1	U(1) gauge coupling	0.357
g_2	SU(2) gauge coupling	0.652
g_3	SU(3) gauge coupling	1.221
θ_{QCD}	QCD vacuum angle	~0
v	Higgs vacuum expectation value	246 GeV
m_H	Higgs mass	125 GeV

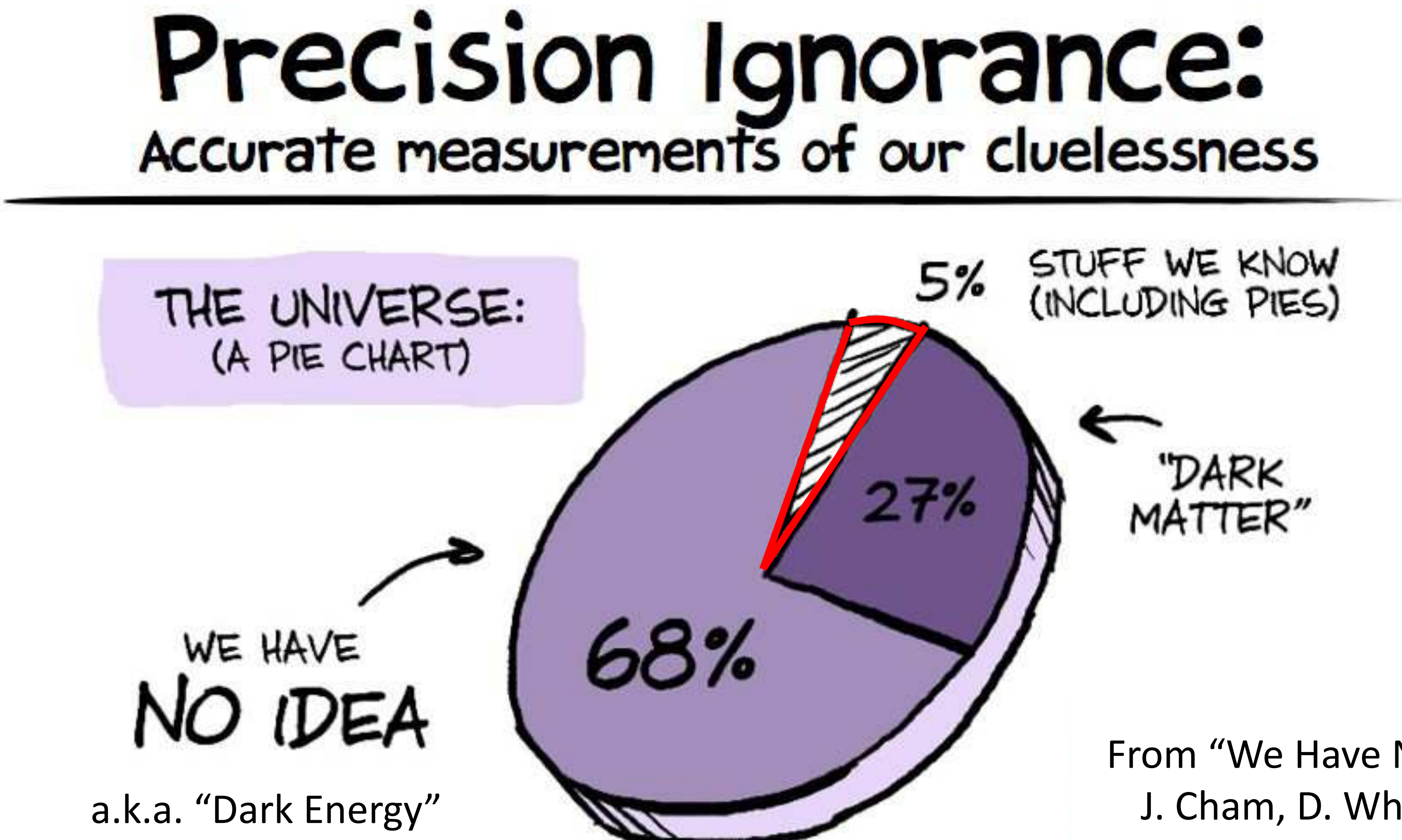
$$
\begin{gathered}
-\tfrac{1}{2}\partial_\nu g^a_\mu \partial_\nu g^a_\mu - g_s f^{abc}\partial_\mu g^a_\nu g^b_\mu g^c_\nu - \tfrac{1}{4}g_s^2 f^{abc}f^{ade}g^b_\mu g^c_\nu g^d_\mu g^e_\nu + \\
\tfrac{1}{2}ig_s^2(\bar{q}^\sigma_i\gamma^\mu q^\sigma_j)g^a_\mu + \bar{G}^a\partial^2 G^a + g_s f^{abc}\partial_\mu\bar{G}^a G^b g^c_\mu - \partial_\nu W^+_\mu\partial_\nu W^-_\mu - \\
M^2 W^+_\mu W^-_\mu - \tfrac{1}{2}\partial_\nu Z^0_\mu\partial_\nu Z^0_\mu - \tfrac{1}{2c_w^2}M^2 Z^0_\mu Z^0_\mu - \tfrac{1}{2}\partial_\mu A_\nu\partial_\mu A_\nu - \tfrac{1}{2}\partial_\mu H\partial_\mu H - \\
\tfrac{1}{2}m_h^2 H^2 - \partial_\mu\phi^+\partial_\mu\phi^- - M^2\phi^+\phi^- - \tfrac{1}{2}\partial_\mu\phi^0\partial_\mu\phi^0 - \tfrac{1}{2c_w^2}M\phi^0\phi^0 - \beta_h[\tfrac{2M^2}{g^2} + \\
\tfrac{2M}{g}H + \tfrac{1}{2}(H^2 + \phi^0\phi^0 + 2\phi^+\phi^-)] + \tfrac{2M^4}{g^2}\alpha_h - igc_w[\partial_\nu Z^0_\mu(W^+_\mu W^-_\nu - \\
W^+_\nu W^-_\mu) - Z^0_\nu(W^+_\mu\partial_\nu W^-_\mu - W^-_\mu\partial_\nu W^+_\mu) + Z^0_\mu(W^+_\nu\partial_\nu W^-_\mu - \\
W^-_\nu\partial_\nu W^+_\mu)] - igs_w[\partial_\nu A_\mu(W^+_\mu W^-_\nu - W^+_\nu W^-_\mu) - A_\nu(W^+_\mu\partial_\nu W^-_\mu - \\
W^-_\mu\partial_\nu W^+_\mu) + A_\mu(W^+_\nu\partial_\nu W^-_\mu - W^-_\nu\partial_\nu W^+_\mu)] - \tfrac{1}{2}g^2 W^+_\mu W^-_\mu W^+_\nu W^-_\nu + \\
\tfrac{1}{2}g^2 W^+_\mu W^-_\nu W^+_\mu W^-_\nu + g^2 c_w^2(Z^0_\mu W^+_\mu Z^0_\nu W^-_\nu - Z^0_\mu Z^0_\mu W^+_\nu W^-_\nu) + \\
g^2 s_w^2(A_\mu W^+_\mu A_\nu W^-_\nu - A_\mu A_\mu W^+_\nu W^-_\nu) + g^2 s_w c_w[A_\mu Z^0_\nu(W^+_\mu W^-_\nu - \\
W^+_\nu W^-_\mu) - 2A_\mu Z^0_\mu W^+_\nu W^-_\nu] - g\alpha[H^3 + H\phi^0\phi^0 + 2H\phi^+\phi^-] - \\
\tfrac{1}{8}g^2\alpha_h[H^4 + (\phi^0)^4 + 4(\phi^+\phi^-)^2 + 4(\phi^0)^2\phi^+\phi^- + 4H^2\phi^+\phi^- + 2(\phi^0)^2H^2] - \\
gMW^+_\mu W^-_\mu H - \tfrac{1}{2}g\tfrac{M}{c_w^2}Z^0_\mu Z^0_\mu H - \tfrac{1}{2}ig[W^+_\mu(\phi^0\partial_\mu\phi^- - \phi^-\partial_\mu\phi^0) - \\
W^-_\mu(\phi^0\partial_\mu\phi^+ - \phi^+\partial_\mu\phi^0)] + \tfrac{1}{2}g[W^+_\mu(H\partial_\mu\phi^- - \phi^-\partial_\mu H) - W^-_\mu(H\partial_\mu\phi^+ - \\
\phi^+\partial_\mu H)] + \tfrac{1}{2}g\tfrac{1}{c_w}(Z^0_\mu(H\partial_\mu\phi^0 - \phi^0\partial_\mu H) - ig\tfrac{s_w^2}{c_w}MZ^0_\mu(W^+_\mu\phi^- - W^-_\mu\phi^+) + \\
igs_w MA_\mu(W^+_\mu\phi^- - W^-_\mu\phi^+) - ig\tfrac{1-2c_w^2}{2c_w}Z^0_\mu(\phi^+\partial_\mu\phi^- - \phi^-\partial_\mu\phi^+) + \\
igs_w A_\mu(\phi^+\partial_\mu\phi^- - \phi^-\partial_\mu\phi^+) - \tfrac{1}{4}g^2 W^+_\mu W^-_\mu[H^2 + (\phi^0)^2 + 2\phi^+\phi^-] - \\
\tfrac{1}{4}g^2\tfrac{1}{c_w^2}Z^0_\mu Z^0_\mu[H^2 + (\phi^0)^2 + 2(2s_w^2 - 1)^2\phi^+\phi^-] - \tfrac{1}{2}g^2\tfrac{s_w^2}{c_w}Z^0_\mu\phi^0(W^+_\mu\phi^- + \\
W^-_\mu\phi^+) - \tfrac{1}{2}ig^2\tfrac{s_w^2}{c_w}Z^0_\mu H(W^+_\mu\phi^- - W^-_\mu\phi^+) + \tfrac{1}{2}g^2 s_w A_\mu\phi^0(W^+_\mu\phi^- + \\
W^-_\mu\phi^+) + \tfrac{1}{2}ig^2 s_w A_\mu H(W^+_\mu\phi^- - W^-_\mu\phi^+) - g^2\tfrac{s_w}{c_w}(2c_w^2 - 1)Z^0_\mu A_\mu\phi^+\phi^- - \\
g^1 s_w^2 A_\mu A_\mu\phi^+\phi^- - \bar{e}^\lambda(\gamma\partial + m_e^\lambda)e^\lambda - \bar{\nu}^\lambda\gamma\partial\nu^\lambda - \bar{u}^\lambda_j(\gamma\partial + m_u^\lambda)u^\lambda_j - \\
\bar{d}^\lambda_j(\gamma\partial + m_d^\lambda)d^\lambda_j + igs_w A_\mu[-(\bar{e}^\lambda\gamma^\mu e^\lambda) + \tfrac{2}{3}(\bar{u}^\lambda_j\gamma^\mu u^\lambda_j) - \tfrac{1}{3}(\bar{d}^\lambda_j\gamma^\mu d^\lambda_j)] + \\
\tfrac{ig}{4c_w}Z^0_\mu[(\bar{\nu}^\lambda\gamma^\mu(1+\gamma^5)\nu^\lambda) + (\bar{e}^\lambda\gamma^\mu(4s_w^2 - 1 - \gamma^5)e^\lambda) + (\bar{u}^\lambda_j\gamma^\mu(\tfrac{4}{3}s_w^2 - \\
1 - \gamma^5)u^\lambda_j) + (\bar{d}^\lambda_j\gamma^\mu(1 - \tfrac{8}{3}s_w^2 - \gamma^5)d^\lambda_j)] + \tfrac{ig}{2\sqrt{2}}W^+_\mu[(\bar{\nu}^\lambda\gamma^\mu(1+\gamma^5)e^\lambda) + \\
(\bar{u}^\lambda_j\gamma^\mu(1+\gamma^5)C_{\lambda\kappa}d^\kappa_j)] + \tfrac{ig}{2\sqrt{2}}W^-_\mu[(\bar{e}^\lambda\gamma^\mu(1+\gamma^5)\nu^\lambda) + (\bar{d}^\kappa_j C^\dagger_{\lambda\kappa}\gamma^\mu(1 + \\
\gamma^5)u^\lambda_j)] + \tfrac{ig}{2\sqrt{2}}\tfrac{m_e^\lambda}{M}[-\phi^+(\bar{\nu}^\lambda(1-\gamma^5)e^\lambda) + \phi^-(\bar{e}^\lambda(1+\gamma^5)\nu^\lambda)] - \\
\tfrac{g}{2}\tfrac{m_e^\lambda}{M}[H(\bar{e}^\lambda e^\lambda) + i\phi^0(\bar{e}^\lambda\gamma^5 e^\lambda)] + \tfrac{ig}{2M\sqrt{2}}\phi^+[-m_d^\kappa(\bar{u}^\lambda_j C_{\lambda\kappa}(1-\gamma^5)d^\kappa_j) + \\
m_u^\lambda(\bar{u}^\lambda_j C_{\lambda\kappa}(1+\gamma^5)d^\kappa_j] + \tfrac{ig}{2M\sqrt{2}}\phi^-[m_d^\lambda(\bar{d}^\lambda_j C^\dagger_{\lambda\kappa}(1+\gamma^5)u^\kappa_j) - m_u^\kappa(\bar{d}^\lambda_j C^\dagger_{\lambda\kappa}(1 - \\
\gamma^5)u^\kappa_j] - \tfrac{g}{2}\tfrac{m_u^\lambda}{M}H(\bar{u}^\lambda_j u^\lambda_j) - \tfrac{g}{2}\tfrac{m_d^\lambda}{M}H(\bar{d}^\lambda_j d^\lambda_j) + \tfrac{ig}{2}\tfrac{m_u^\lambda}{M}\phi^0(\bar{u}^\lambda_j\gamma^5 u^\lambda_j) - \\
\tfrac{ig}{2}\tfrac{m_d^\lambda}{M}\phi^0(\bar{d}^\lambda_j\gamma^5 d^\lambda_j) + \bar{X}^+(\partial^2 - M^2)X^+ + \bar{X}^-(\partial^2 - M^2)X^- + \bar{X}^0(\partial^2 - \\
\tfrac{M^2}{c_w^2})X^0 + \bar{Y}\partial^2 Y + igc_w W^+_\mu(\partial_\mu\bar{X}^0 X^- - \partial_\mu\bar{X}^+ X^0) + igs_w W^+_\mu(\partial_\mu\bar{Y}X^- - \\
\partial_\mu\bar{X}^+ Y) + igc_w W^-_\mu(\partial_\mu\bar{X}^- X^0 - \partial_\mu\bar{X}^0 X^+) + igs_w W^-_\mu(\partial_\mu\bar{X}^- Y - \\
\partial_\mu\bar{Y}X^+) + igc_w Z^0_\mu(\partial_\mu\bar{X}^+ X^+ - \partial_\mu\bar{X}^- X^-) + igs_w A_\mu(\partial_\mu\bar{X}^+ X^+ - \\
\partial_\mu\bar{X}^- X^-) - \tfrac{1}{2}gM[\bar{X}^+ X^+ H + \bar{X}^- X^- H + \tfrac{1}{c_w^2}\bar{X}^0 X^0 H] + \\
\tfrac{1-2c_w^2}{2c_w}igM[\bar{X}^+ X^0\phi^+ - \bar{X}^- X^0\phi^-] + \tfrac{1}{2c_w}igM[\bar{X}^0 X^-\phi^+ - \bar{X}^0 X^+\phi^-] + \\
igMs_w[\bar{X}^0 X^-\phi^+ - \bar{X}^0 X^+\phi^-] + \tfrac{1}{2}igM[\bar{X}^+ X^+\phi^0 - \bar{X}^- X^-\phi^0]
\end{gathered}
$$

The Standard Model in Action



What Are We Missing? … A Lot

- “We are in an era of precision ignorance”
  - Daniel Whiteson



a.k.a. “Dark Energy”

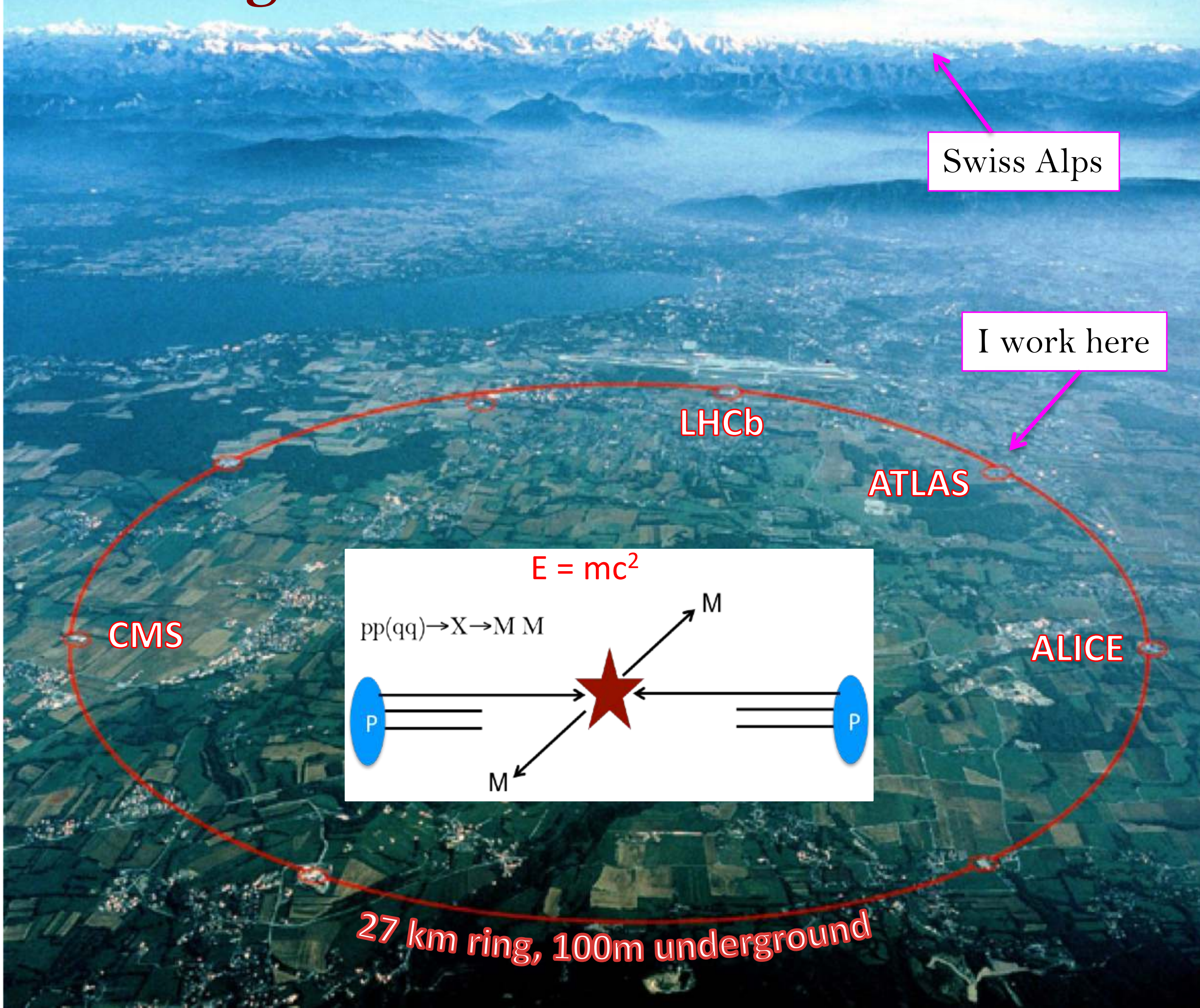
From “We Have No Idea”
J. Cham, D. Whiteson

What are we missing?

- Why Gravity so much weaker then the other forces?
- What are Dark Matter and Dark Energy?
- What gives neutrinos their mass?
- Why is there anything at all?
  - Matter and anti-matter should have annihilated in the early universe
- …

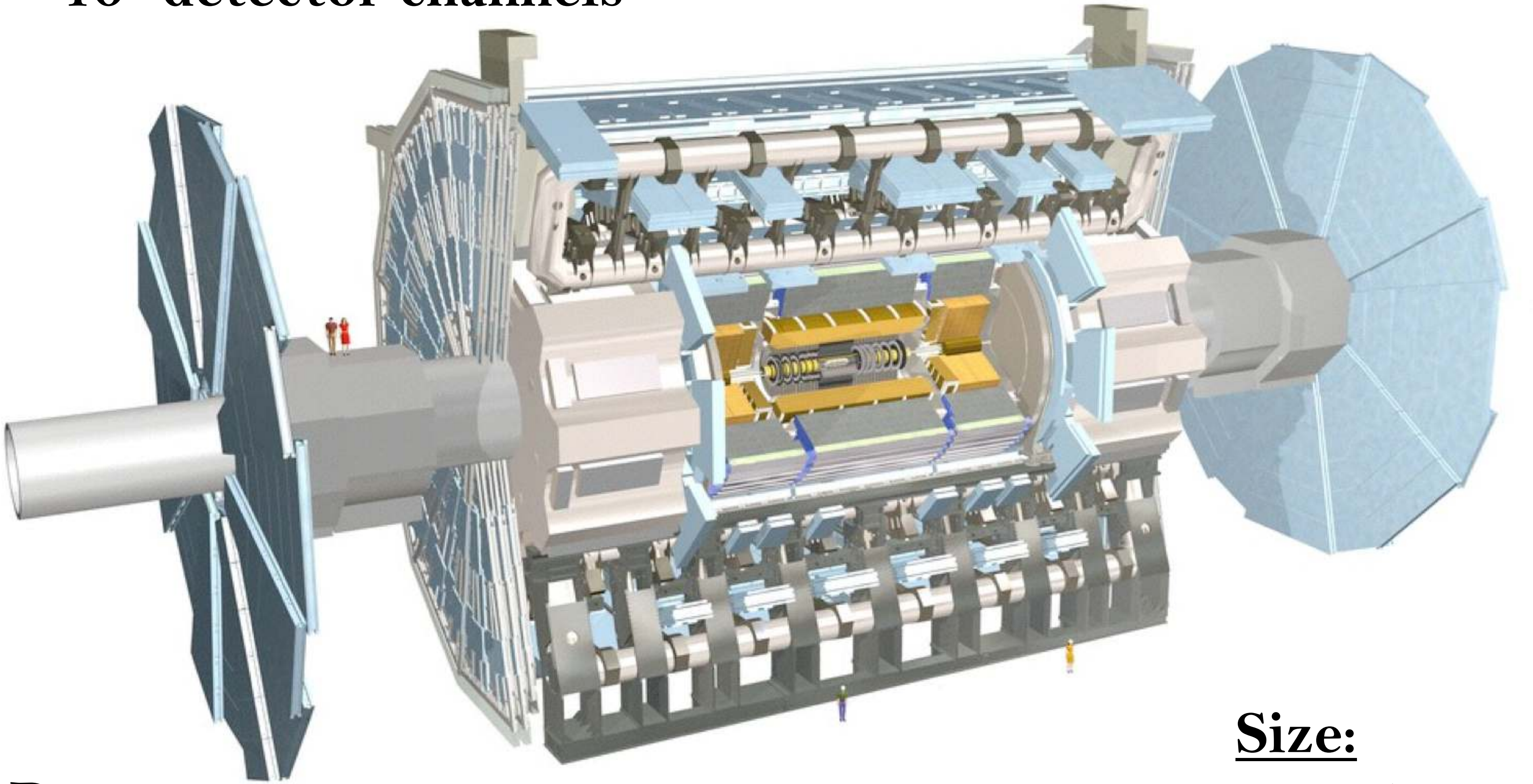
- New forces and heavy particles may have been active during the early universe that explain these phenomena
- We can look for them in high energy physics experiments!
- How can machine learning help?

The Large Hadron Collider at CERN



The ATLAS Experiment

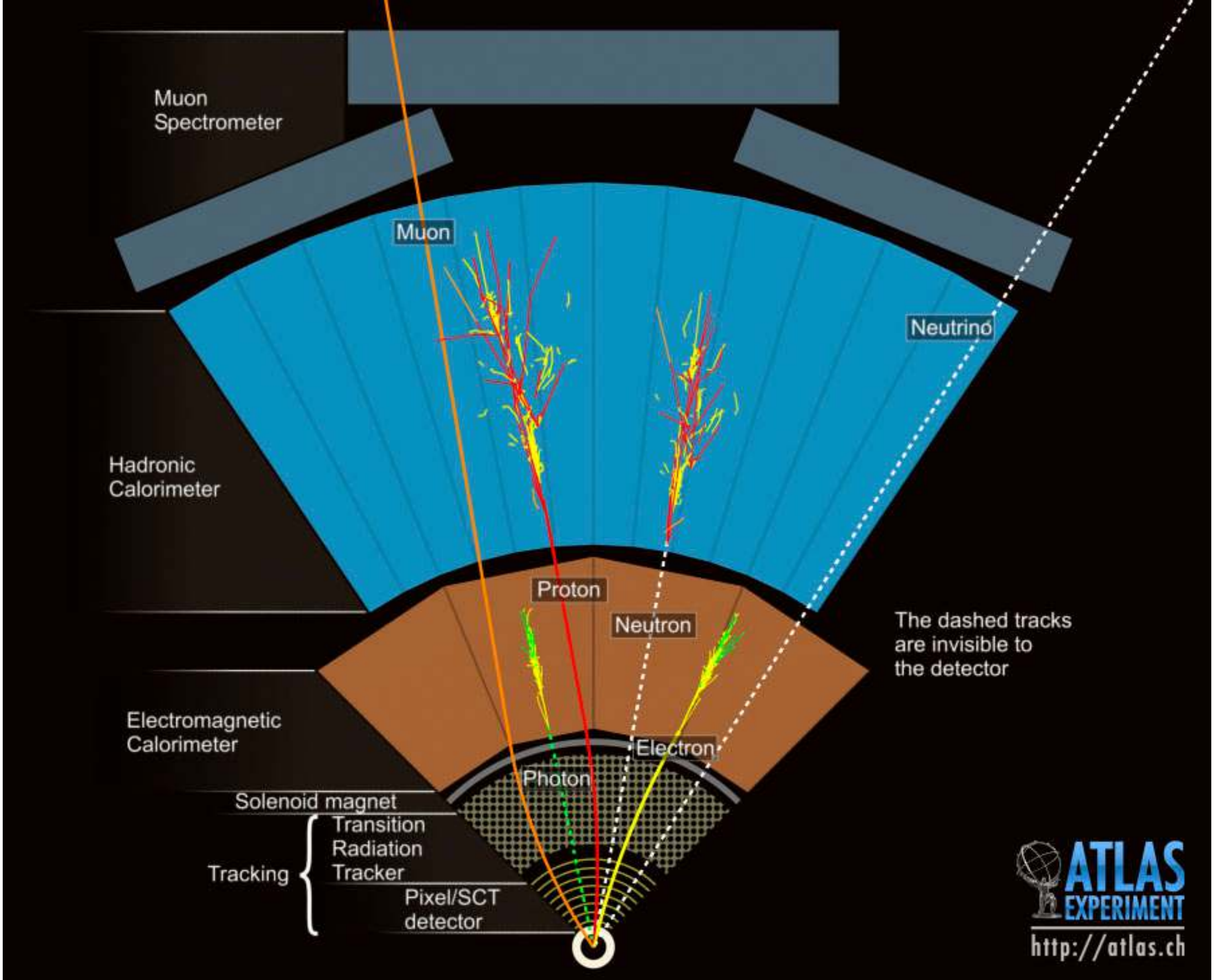
~10^8 detector channels



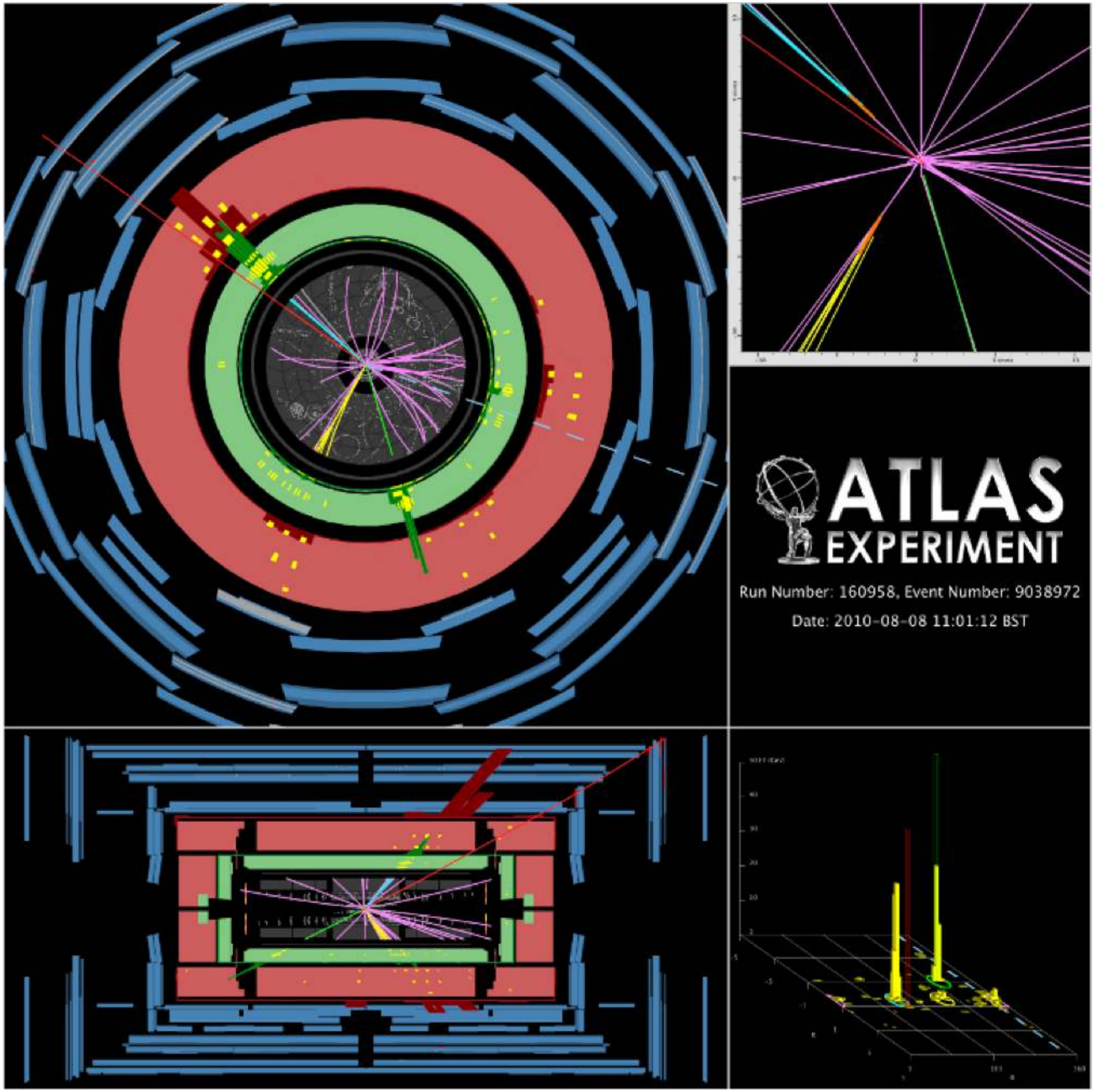
Data:
~300 MB / sec
~3000 TB / year

Weight:
7000 tons

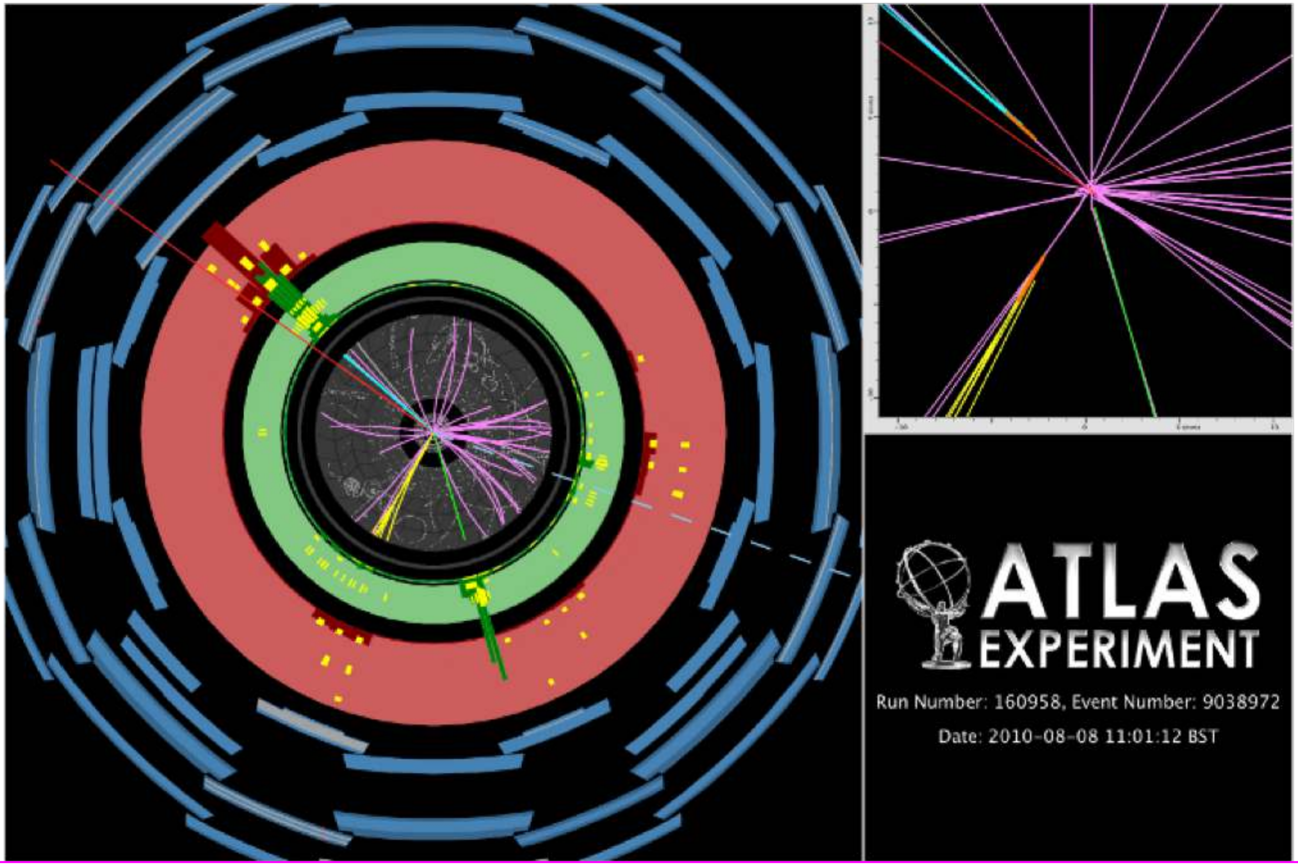
Size:
46 m long,
25 m high,
25 m wide


Muon Spectrometer
Hadronic Calorimeter
Electromagnetic Calorimeter
Solenoid magnet
Tracking
Transition Radiation Tracker
Pixel/SCT detector
Muon
Neutrino
Proton
Neutron
Electron
Photon
The dashed tracks are invisible to the detector
ATLAS EXPERIMENT
http://atlas.ch

Studying Collisions



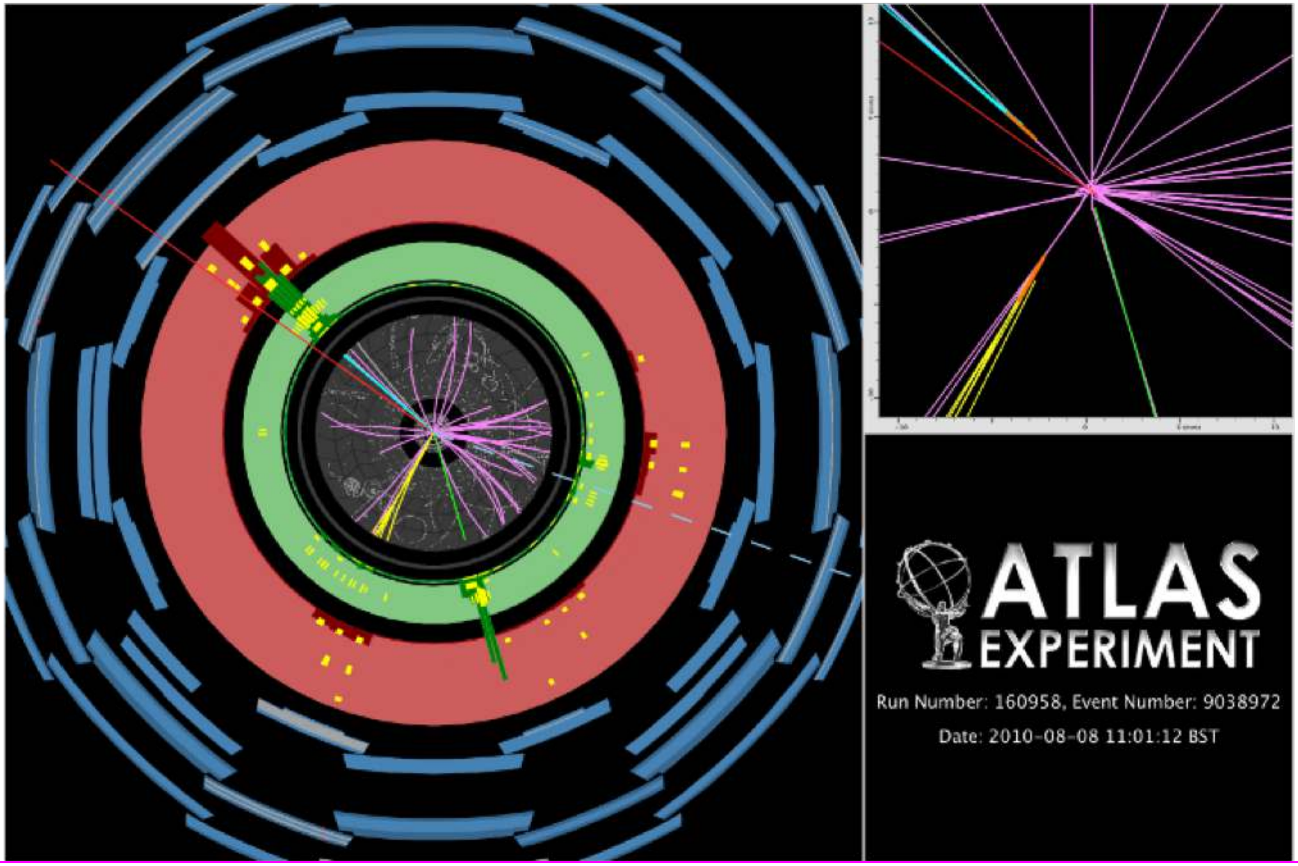
Studying Collisions



- Causal and Compositional Structure

Collision → particle X → "final state" particles → detector data

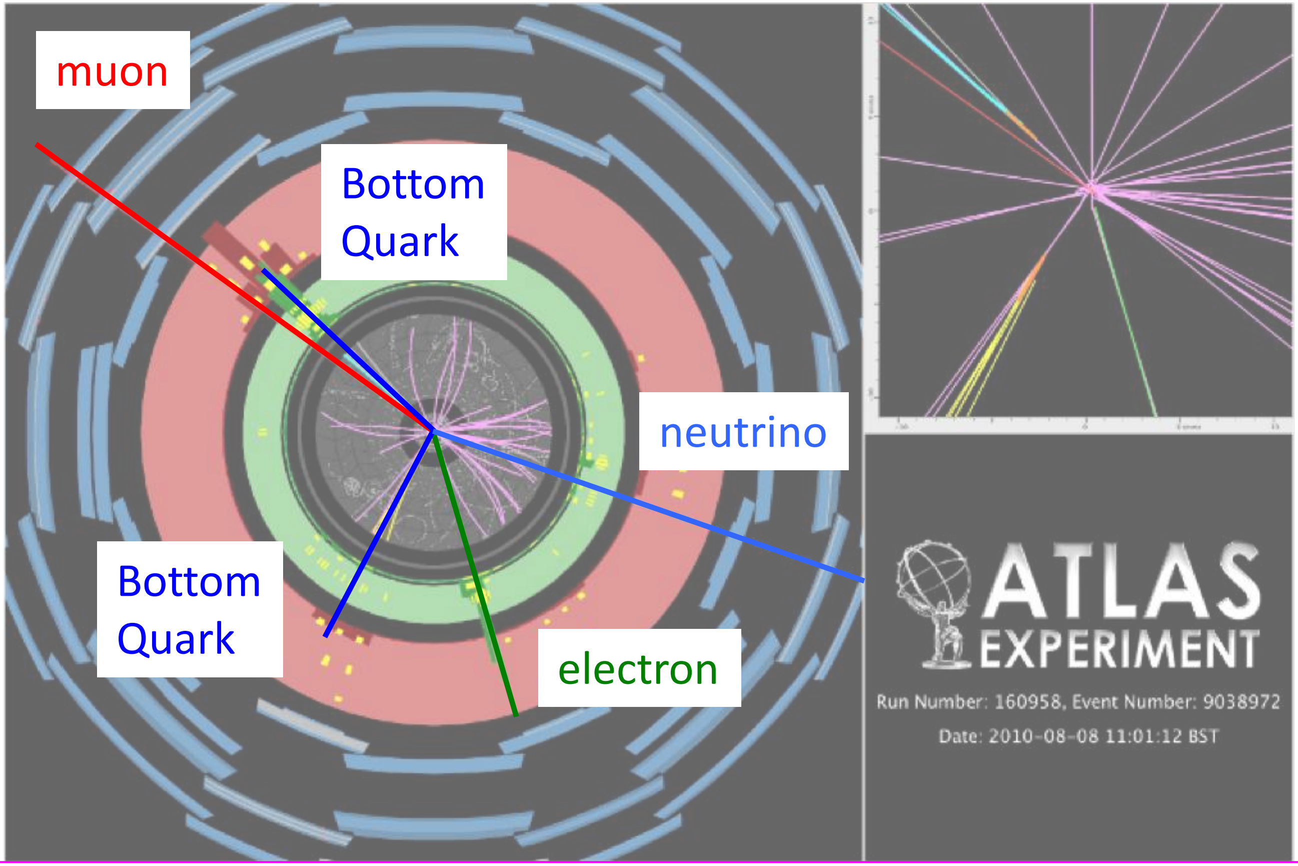
Studying Collisions



- Causal and Compositional Structure

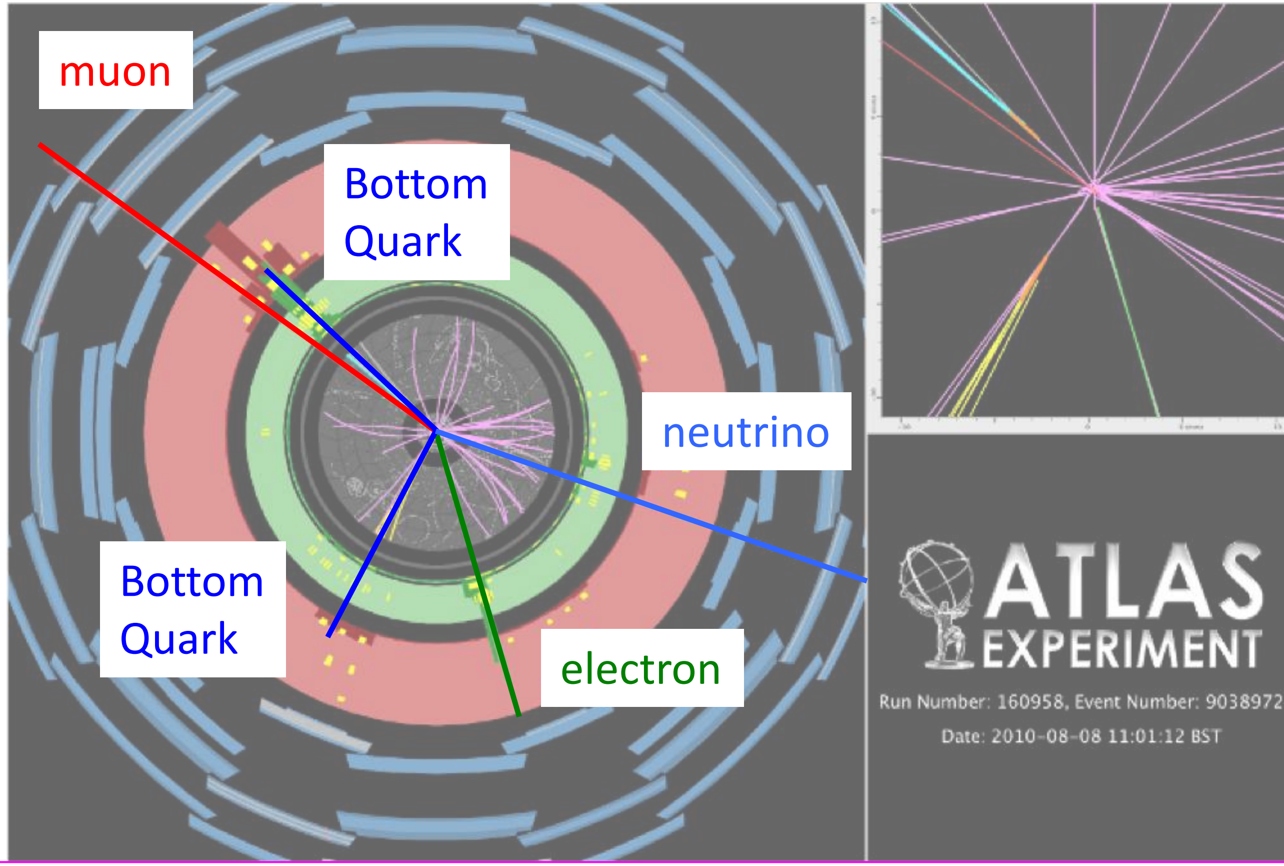
particle X ← "final state" particles ← detector data

Studying Collisions

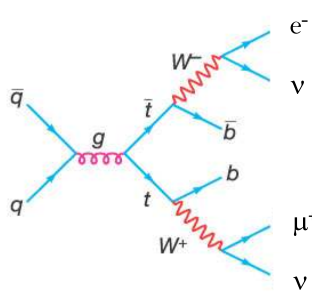


- Reconstruction: Find the “final state” particles in the detector

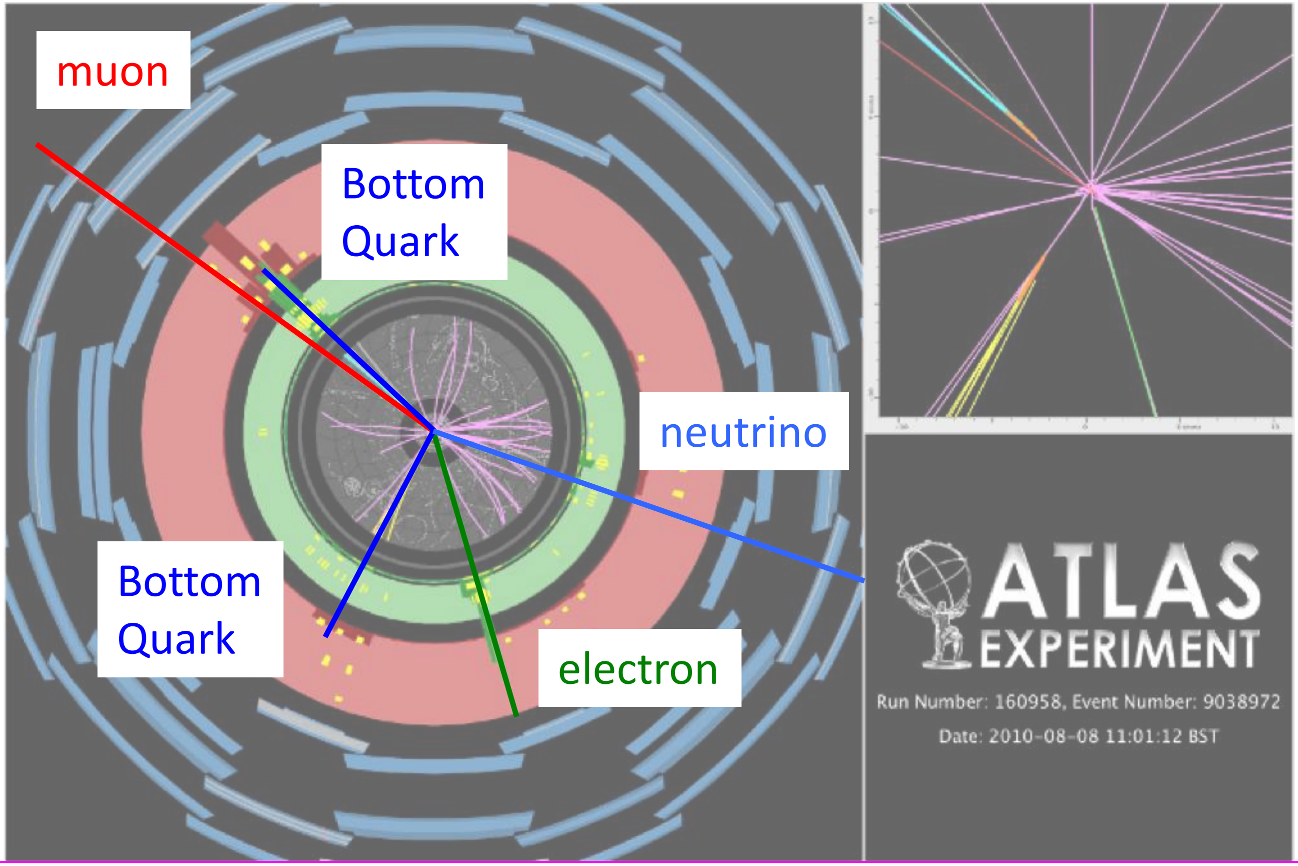
Studying Collisions



- Add them together to study underlying collision



Studying Collisions

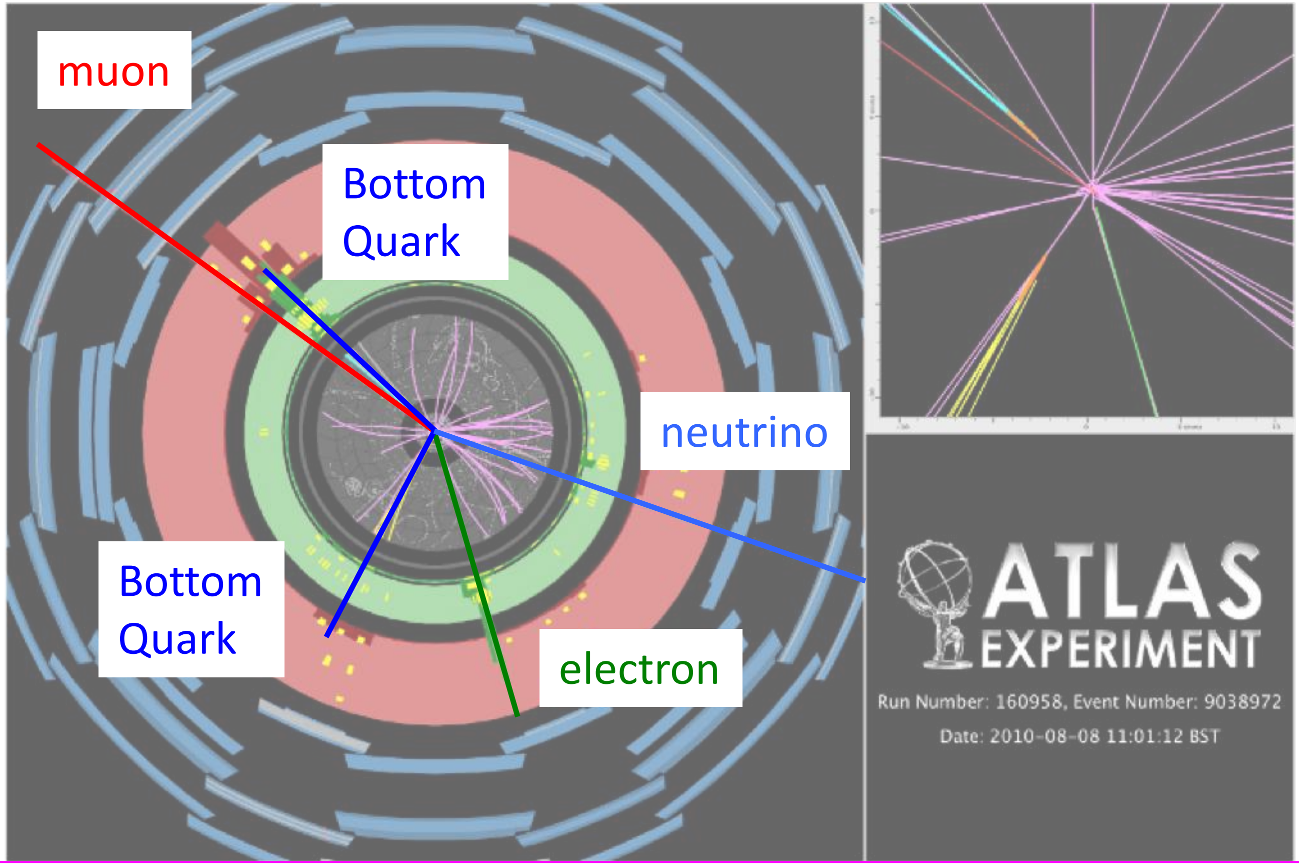


- Works because of energy and momentum conservation:

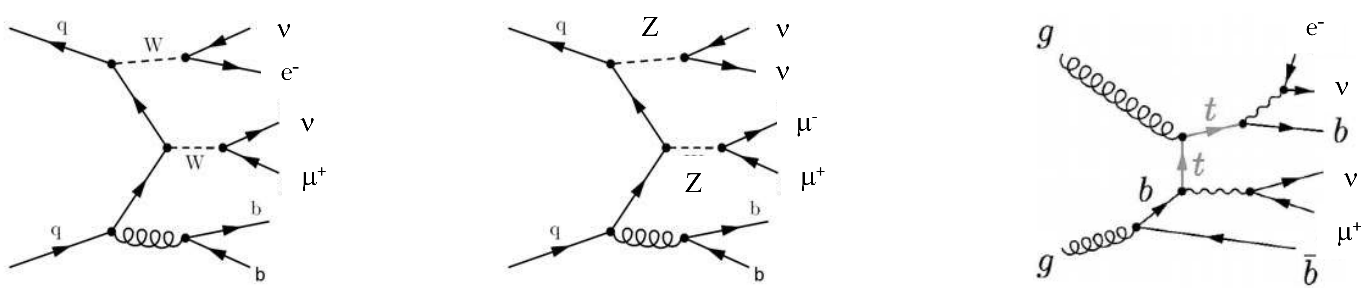
$$(E_{\mathrm{X}}, \vec{p}_{\mathrm{X}}) = \sum_{i \in \text{decay products}} (E_i, \vec{p}_i)$$

$$M_{\mathrm{X}} c^2 = \sqrt{E_{\mathrm{X}}^2 - \vec{p}_{\mathrm{X}}^{\,2}\, c^2}$$

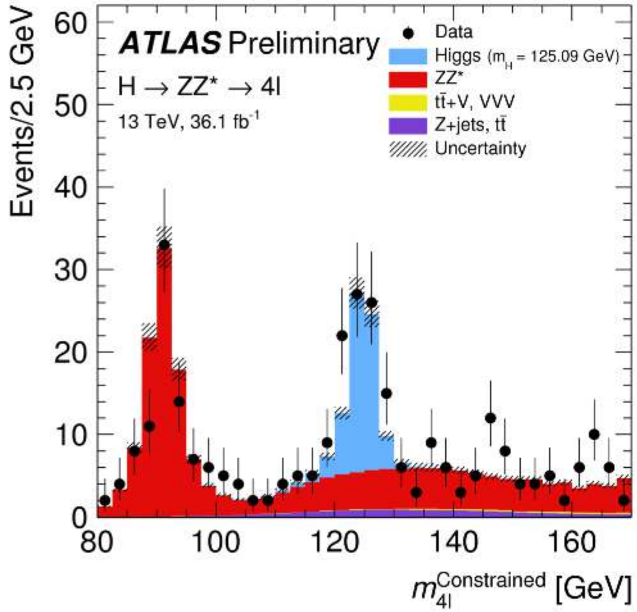
Studying Collisions



- Multiple processes contribute to same signature

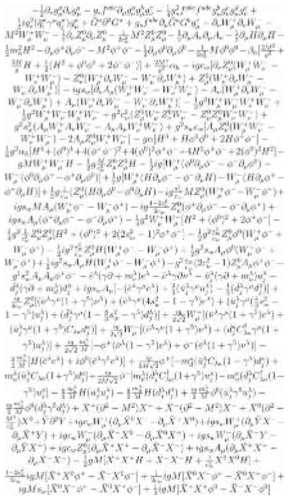


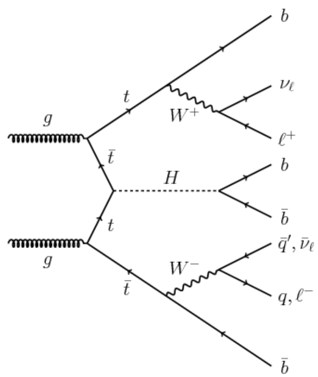
Studying Collisions



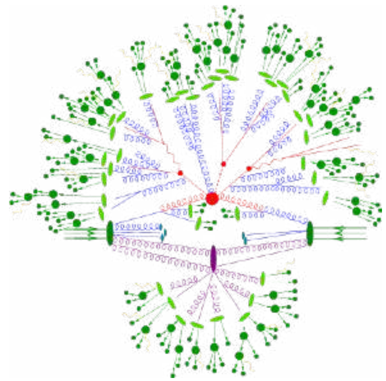
- With a collection of collisions we can perform:
  - Hypothesis testing: new particle present?
  - Measurement: Inference of latent parameters, e.g. Higgs mass
- Extremely accurate simulations + knowledge of the data generating process (i.e. physics) to analyze our data!

From Theory to Experiment

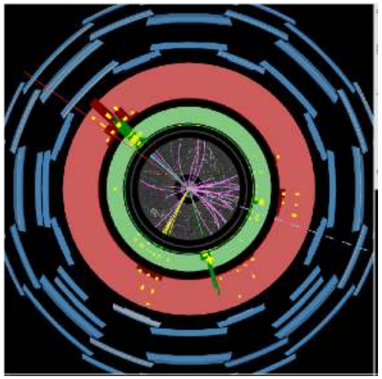




O(10) particles

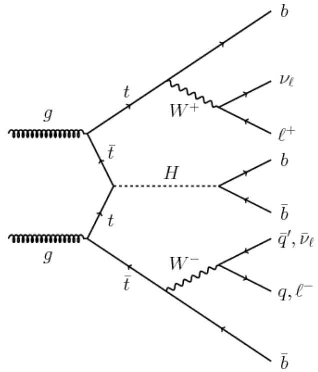


O(100) particles

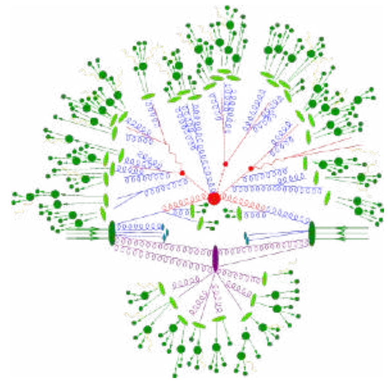


O(10^8) detector elements

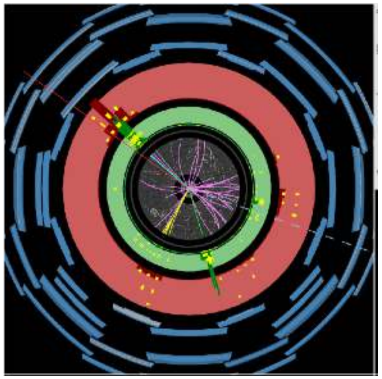
From Theory to Experiment



O(10) particles



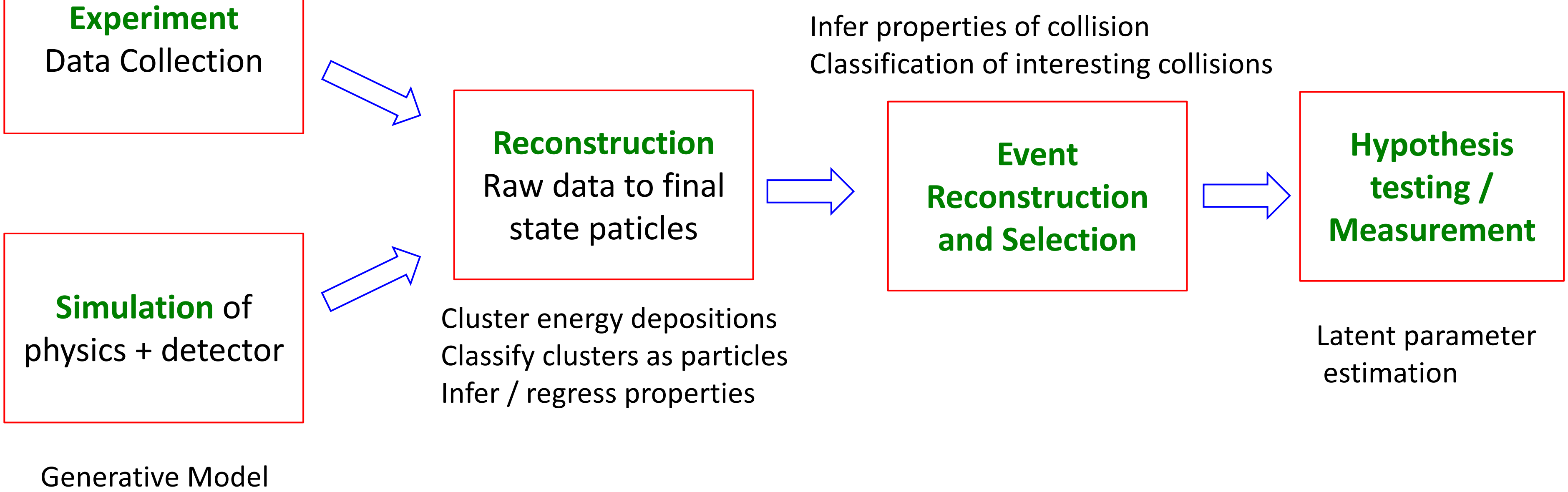
O(100) particles



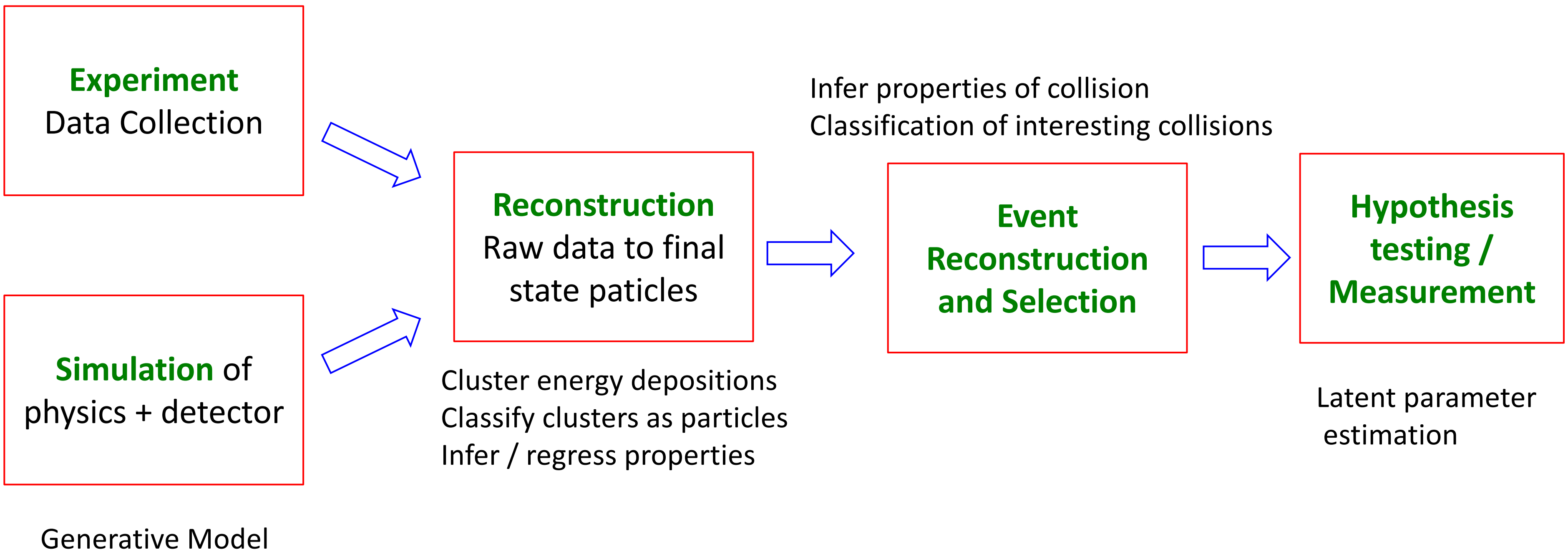
O(10^8) detector elements

Hypothesis testing / Measurement ← **Event Reconstruction and Selection** ← **Reconstruction of particles** ← **Detector data**

Pipeline


Experiment
Data Collection
Simulation of
physics + detector
Generative Model
Reconstruction
Raw data to final
state paticles
Cluster energy depositions
Classify clusters as particles
Infer / regress properties
Infer properties of collision
Classification of interesting collisions
Event
Reconstruction
and Selection
Hypothesis
testing /
Measurement
Latent parameter
estimation

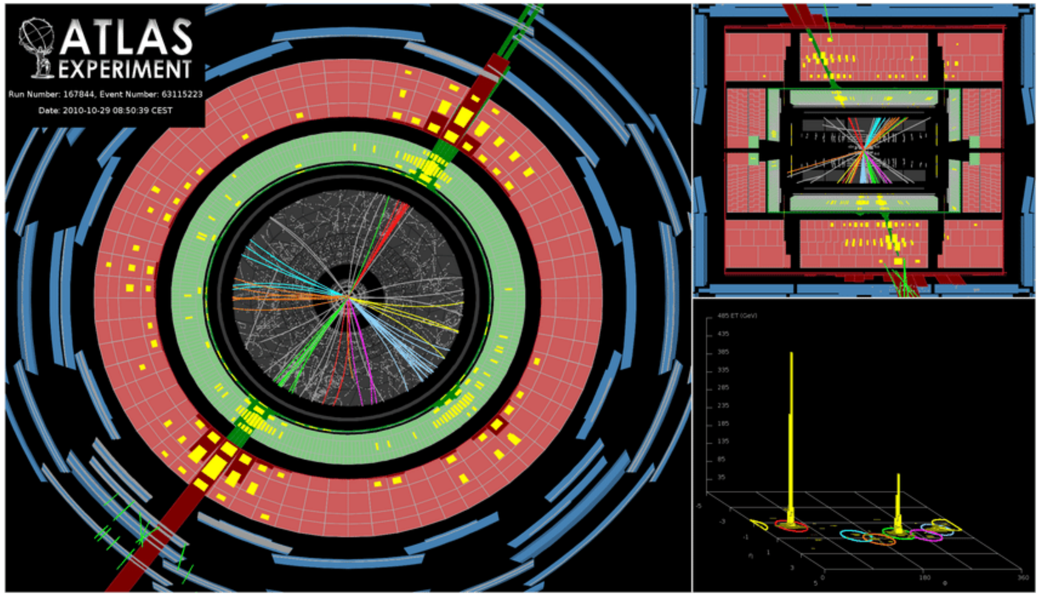
Pipeline



- Build on our knowledge of how the data is created
  - Use our simulation to design and study reconstruction algorithms, and to compare predictions with our experimental data

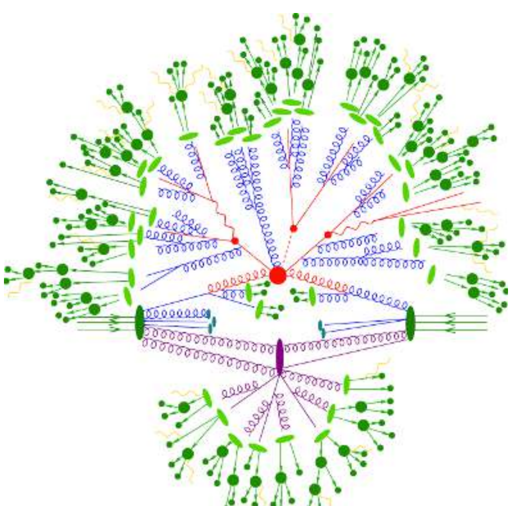
- Use Machine learning to improve (or rethink) the steps of this process?

Simulation

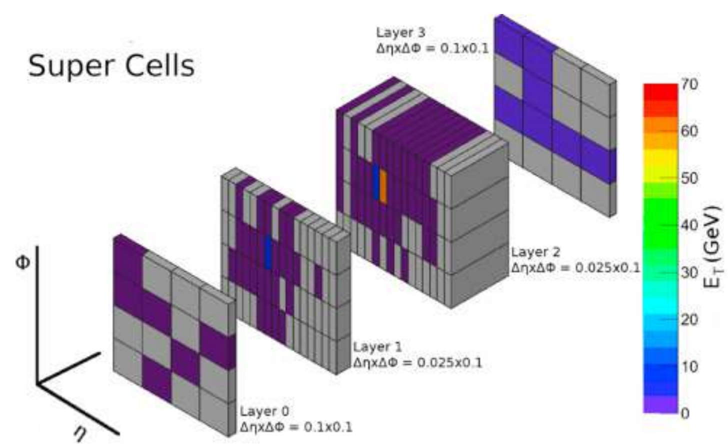


$p(particles \mid interation\ type)$

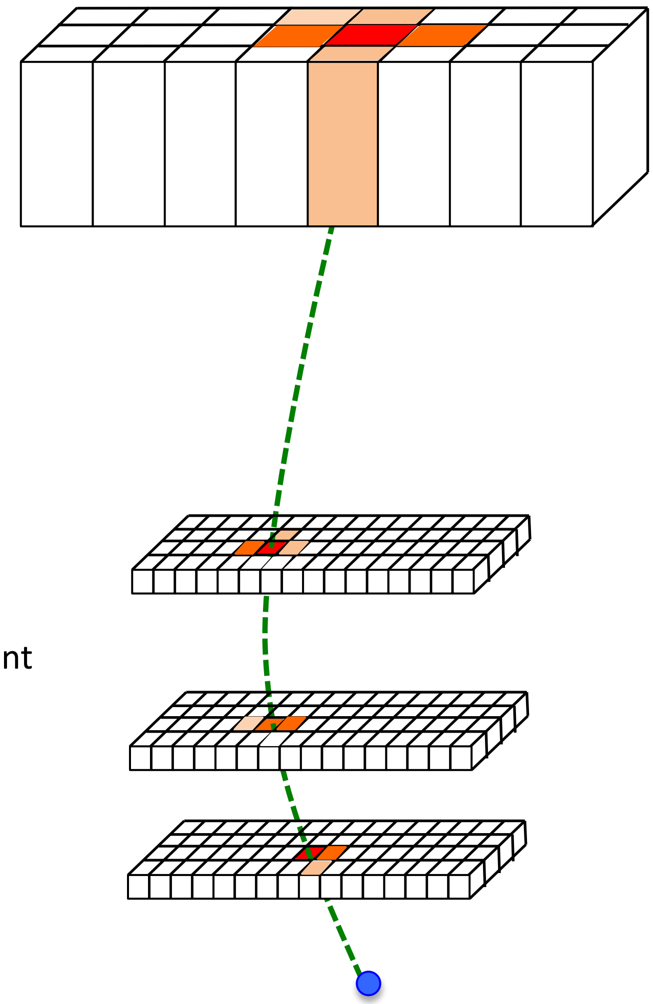
$p(detector\ signature \mid particle)$



[Sherpa]



Reconstructing Particles



Calorimeter:
Stops particle and destructively measure energy / direction

Tracking detector:
Typically Si-pixel detector
Non-destructive space-point measurement

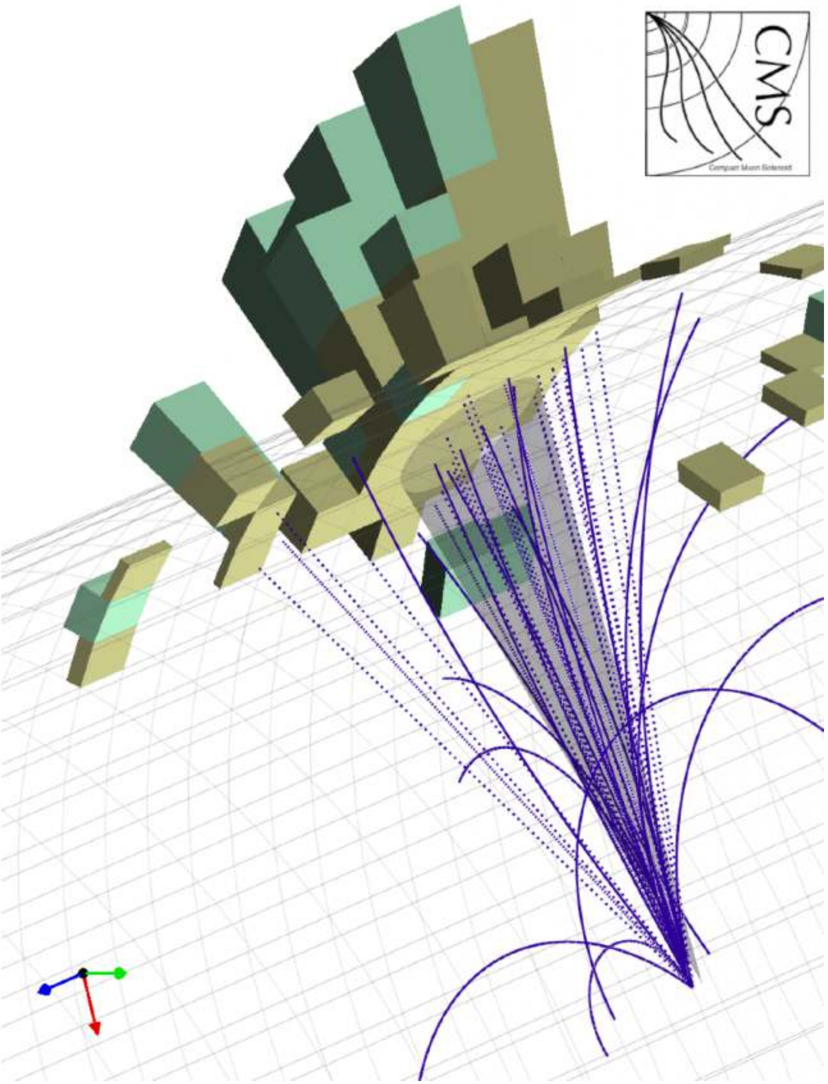
- Particle identification = Classification

$$p(\text{electron} \mid \text{data})$$

- Energy estimation = Inference, regression

$$p(E_{\text{true}}^{\text{electron}} \mid \text{electron data})$$

Understanding Clusters of Particles: Jets



- **Jet**: stream of particles produced by high energy quarks and gluons
  - Clustering algorithms used to find them

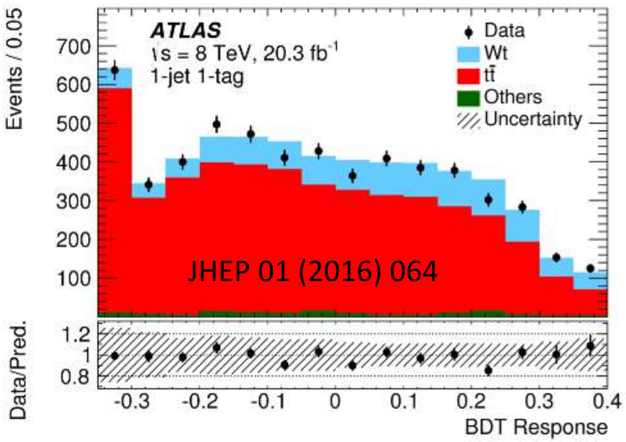
- Jet identification = Classification

$$p(parent\ particle \mid jet\ cluster)$$

- Energy estimation = Inference, regression

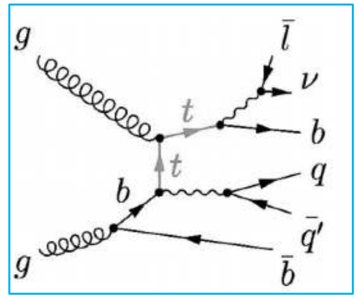
$$p(E_{true}^{jet} \mid jet\ cluster)$$

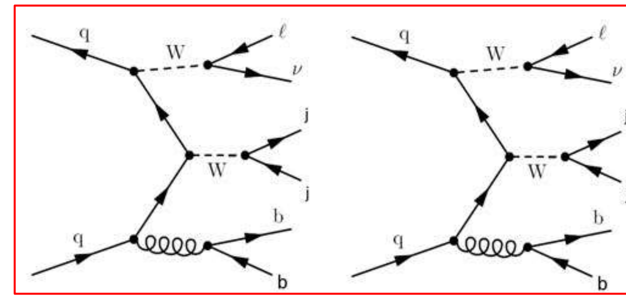
Analyzing Events and Hypothesis Testing

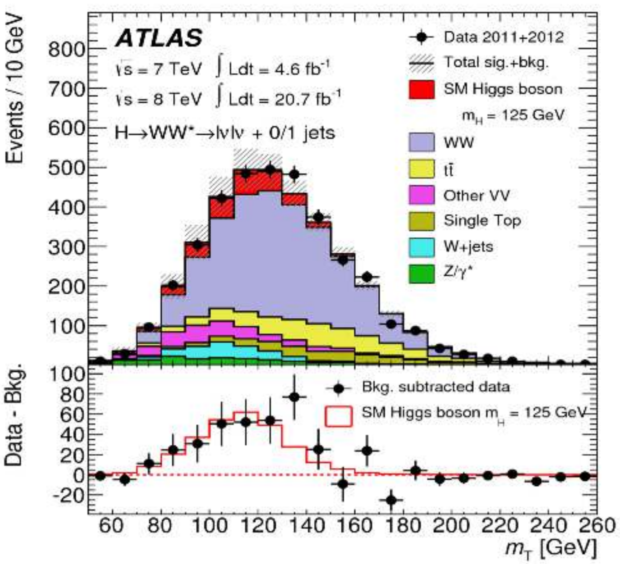


Analyzing Events

Signal vs background



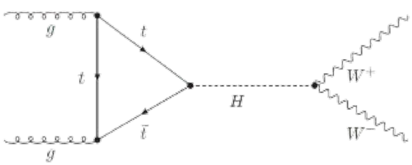




Phys. Lett. B 726 (2013)

Hypothesis Testing and Parameter Estimation

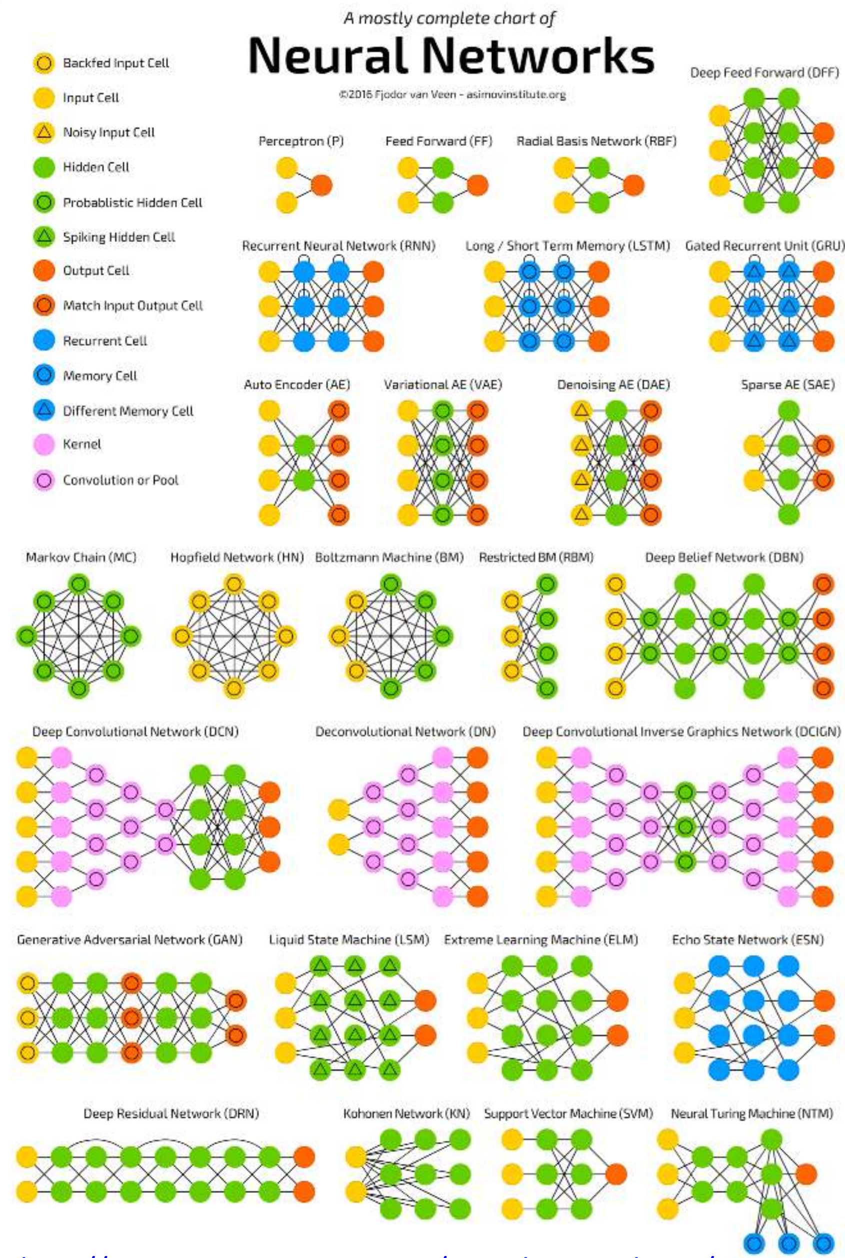
Is there a Higgs?
What is the Higgs mass?



$$\lambda = \prod_{\mathbf{x}\in\mathcal{D}} \frac{p(\mathbf{x}|\text{background})}{p(\mathbf{x}|\text{signal+background})}$$

Deep Learning for HEP

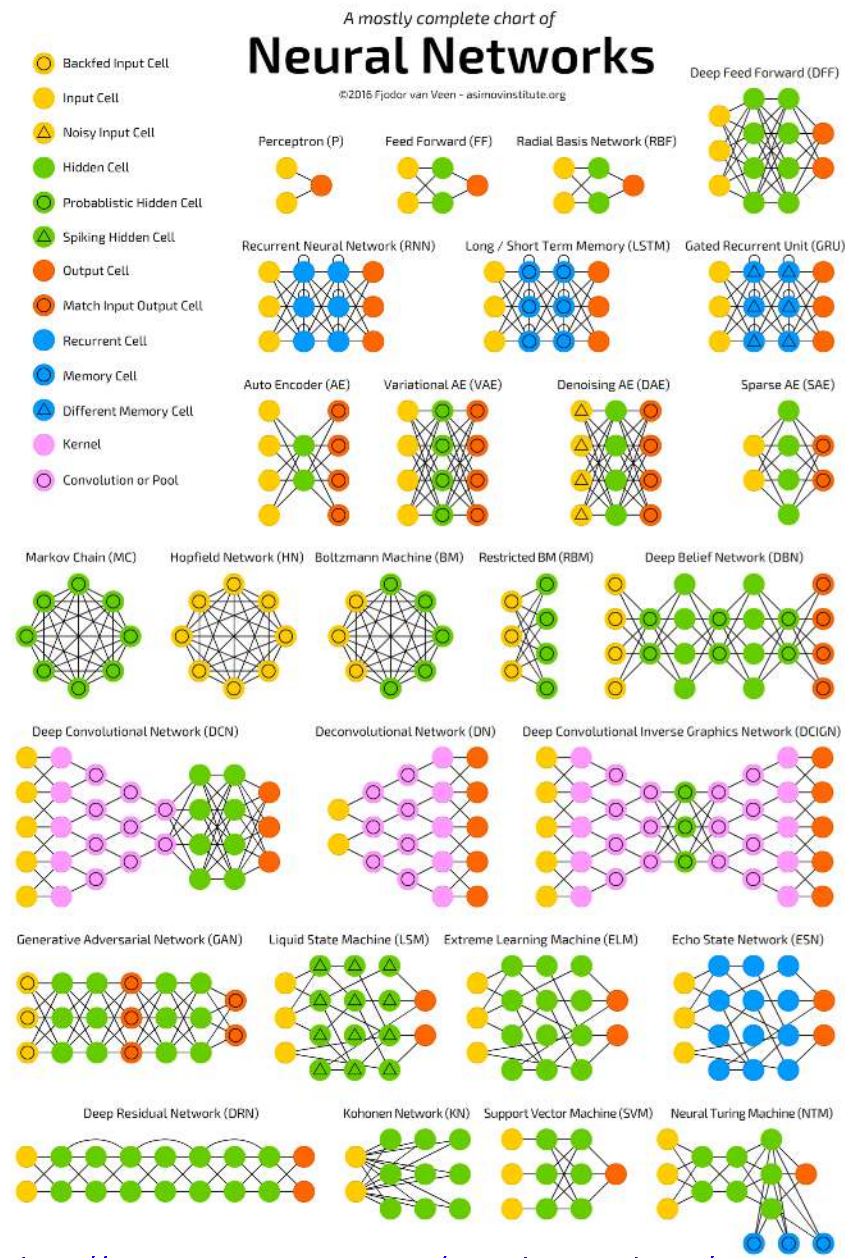
- Moving **inductive bias** from feature engineering to machine learning (neural network) model design
  - Inductive bias ~ knowledge about the problem
  - Feature engineering ~ hand crafted variables
  - Model design ~ the data representation and the structure of the machine learning model / network



http://www.asimovinstitute.org/neural-network-zoo/

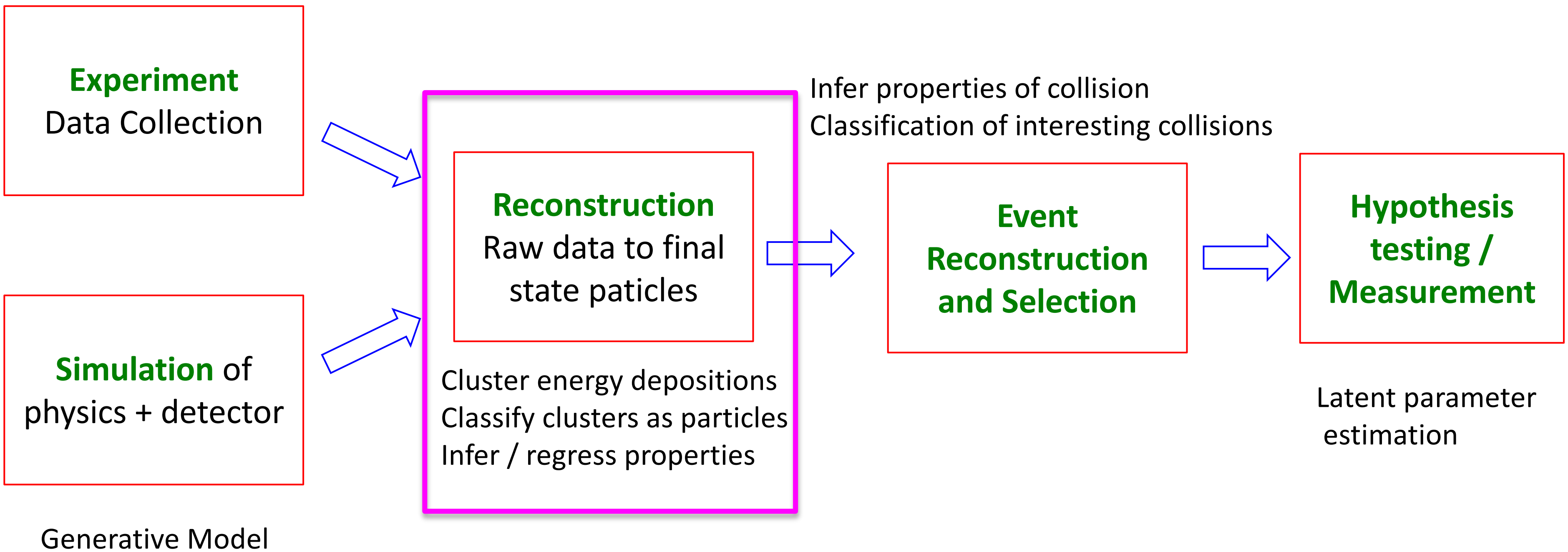
Deep Learning for HEP

- How do we move deep learning advancements into HEP?
  - Translate problems in HEP into problems in ML domain
  - Incorporate HEP domain knowledge: physical motivation for designing data representation, architectures, or new methods if needed
  - How do we extract what is learned?

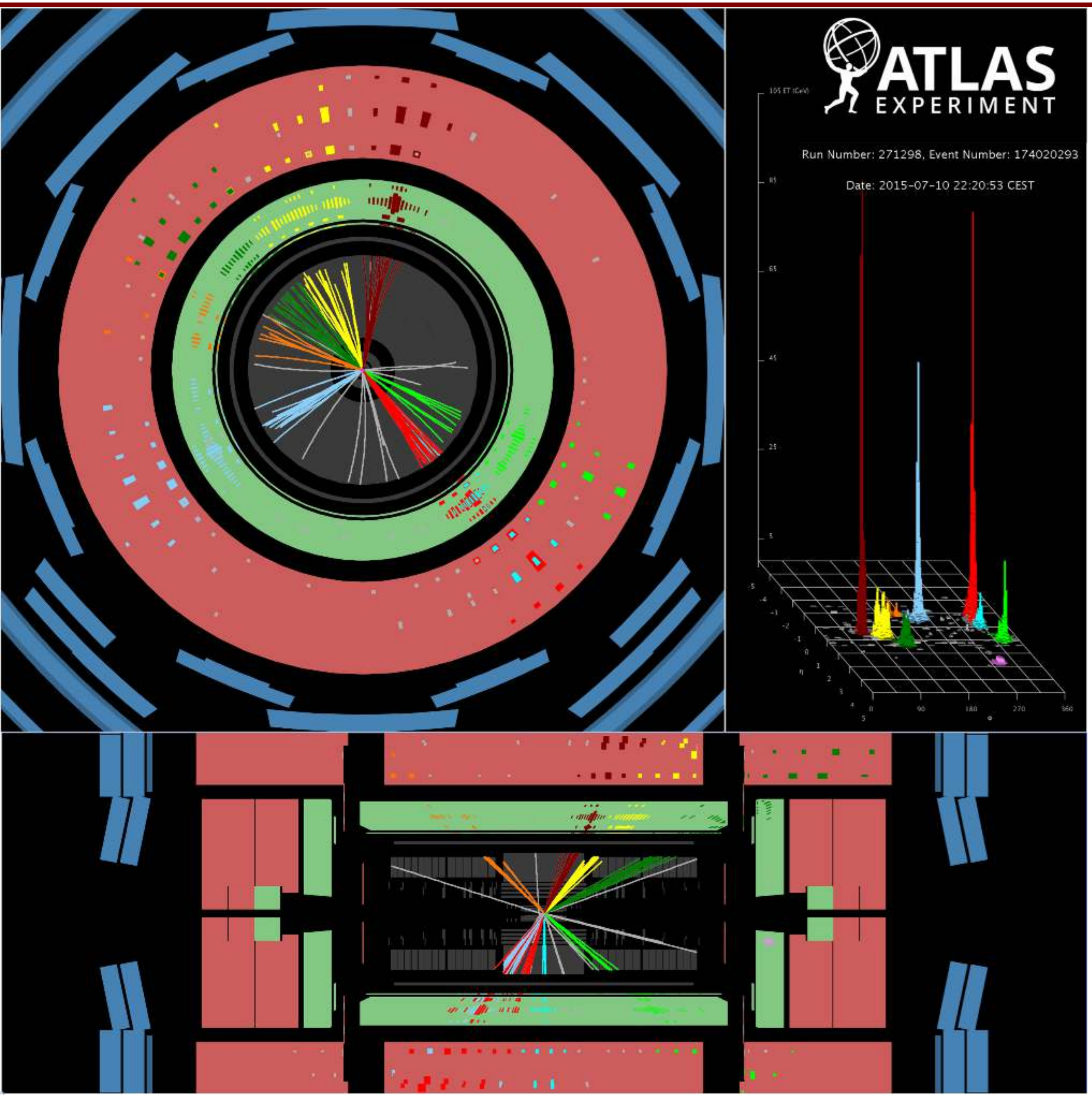


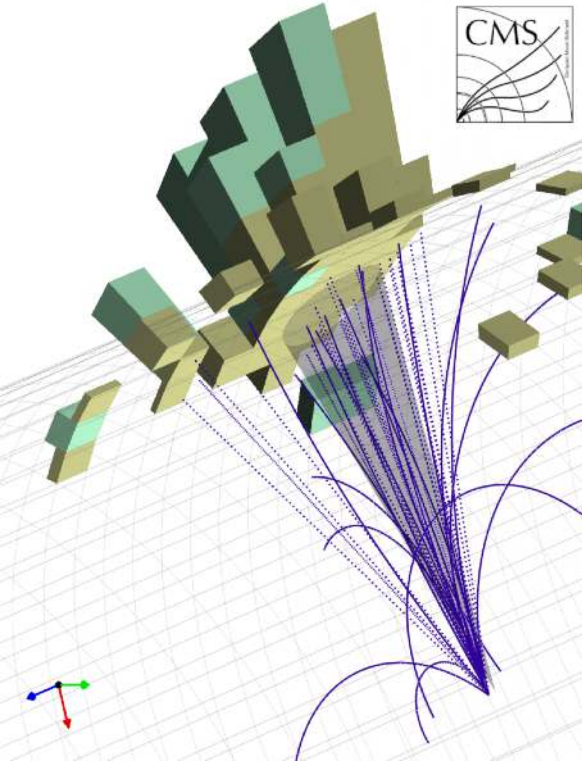
http://www.asimovinstitute.org/neural-network-zoo/

Deep Learning in the Pipeline



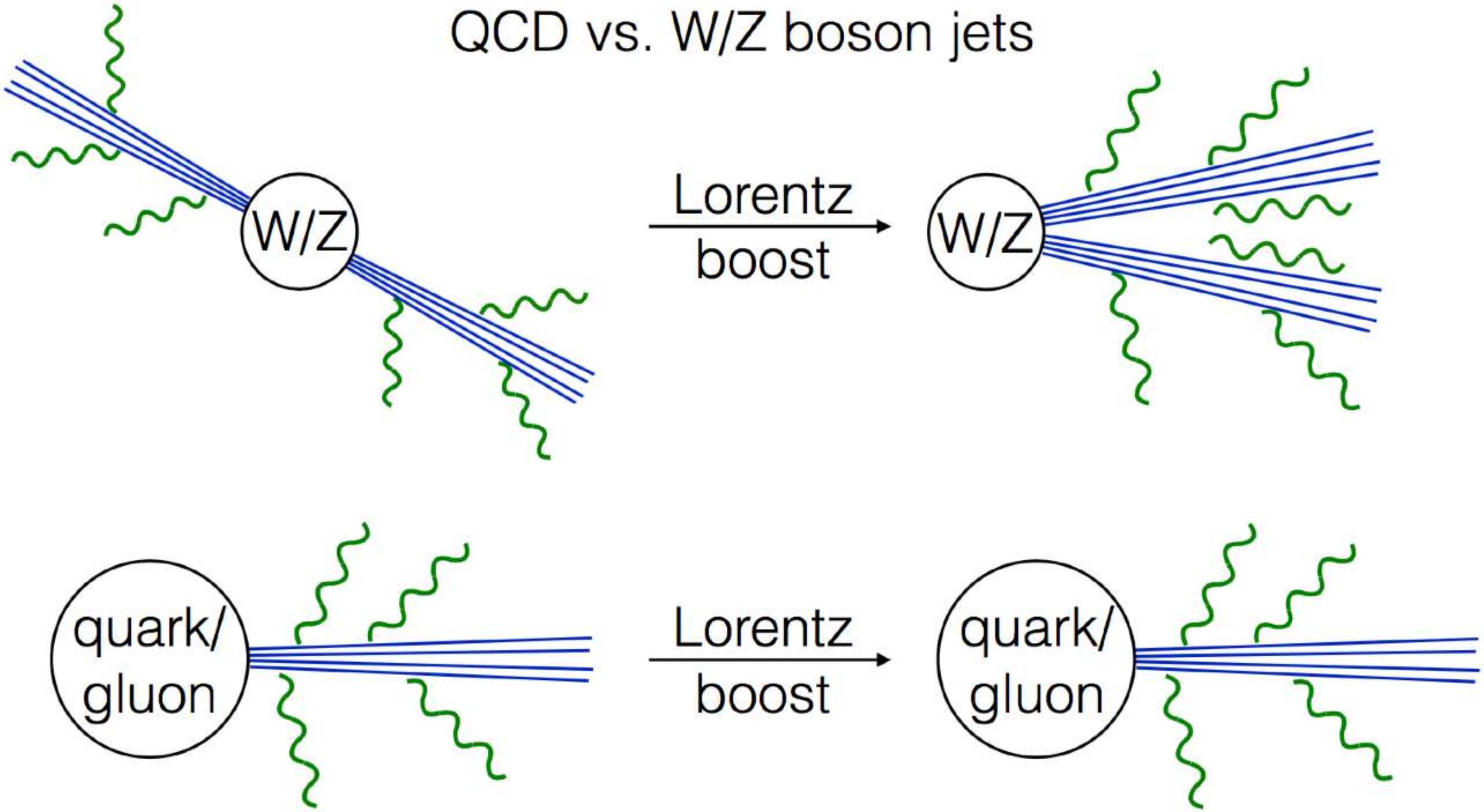
Jets at the LHC





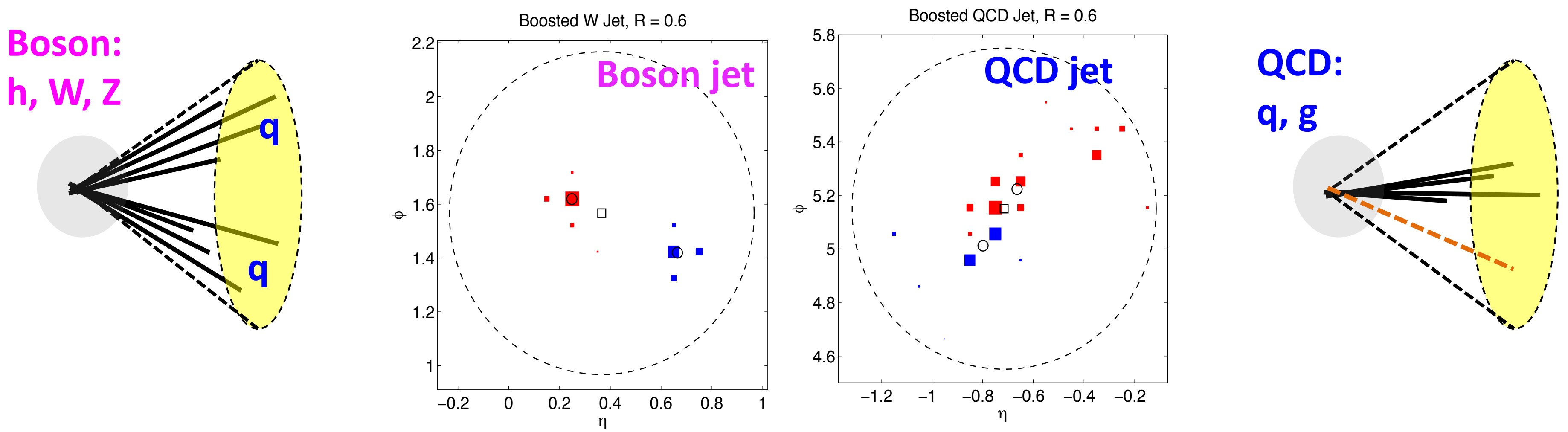
Jet Identification

Canonical Discrimination Problem:
QCD vs. W/Z boson jets



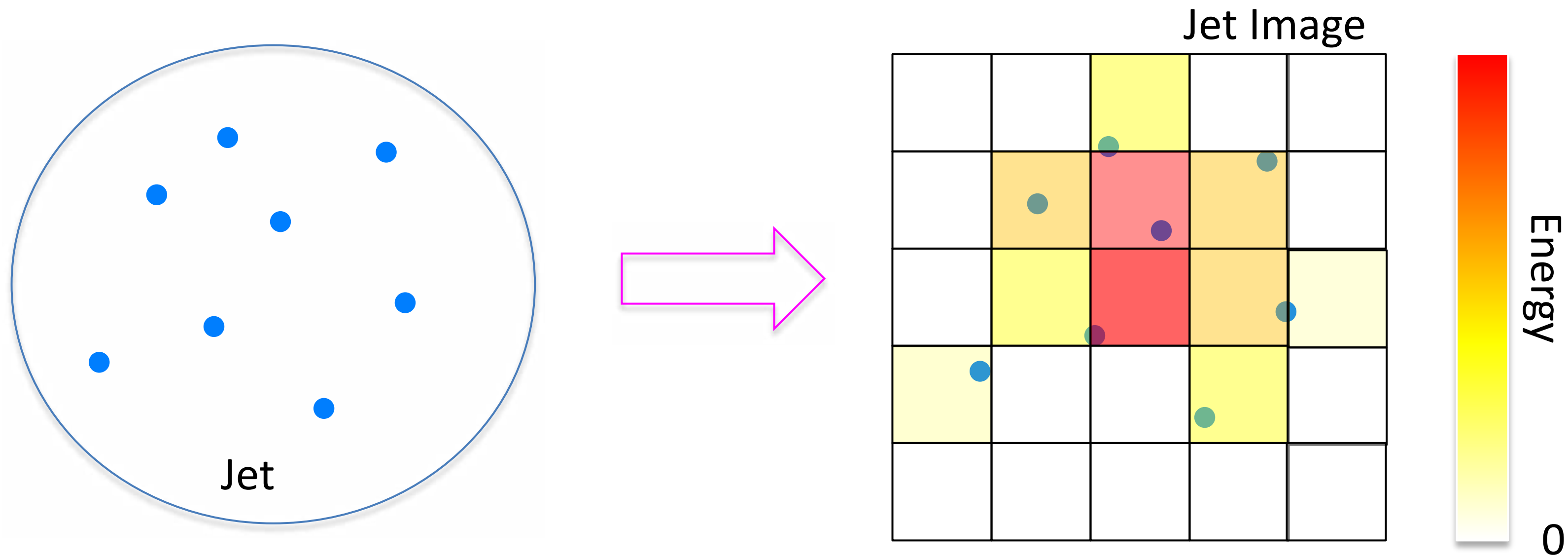
Slide from A. Larkoski

Machine Learning and Jet Physics



- Can use internal structure of a jet for classification
  - Also known as Jet Substructure
- A wealth of domain expertise has gone in feature engineering
- Can deep learning perform this classification?

Jets as Images

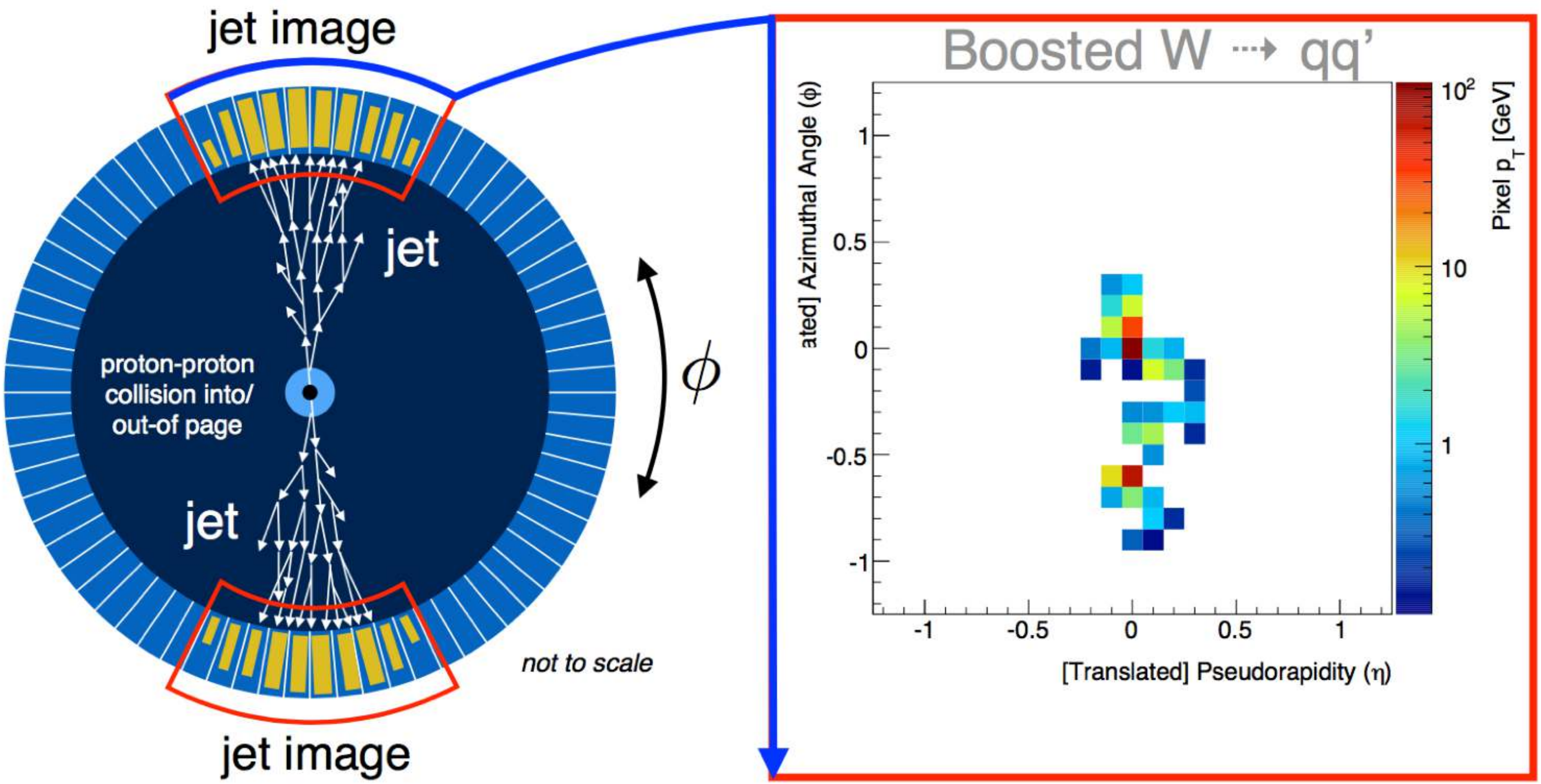


- A jet induces a distribution of energy over $\eta - \phi$
  - Essentially how energy from a jet is seen by calorimeters

- **Jet-image** – fixed size 2D representation of the jet as a distribution of energy
  - Can make use of the full power of Computer Vision!

Jet Images

Unrolled slice of detector



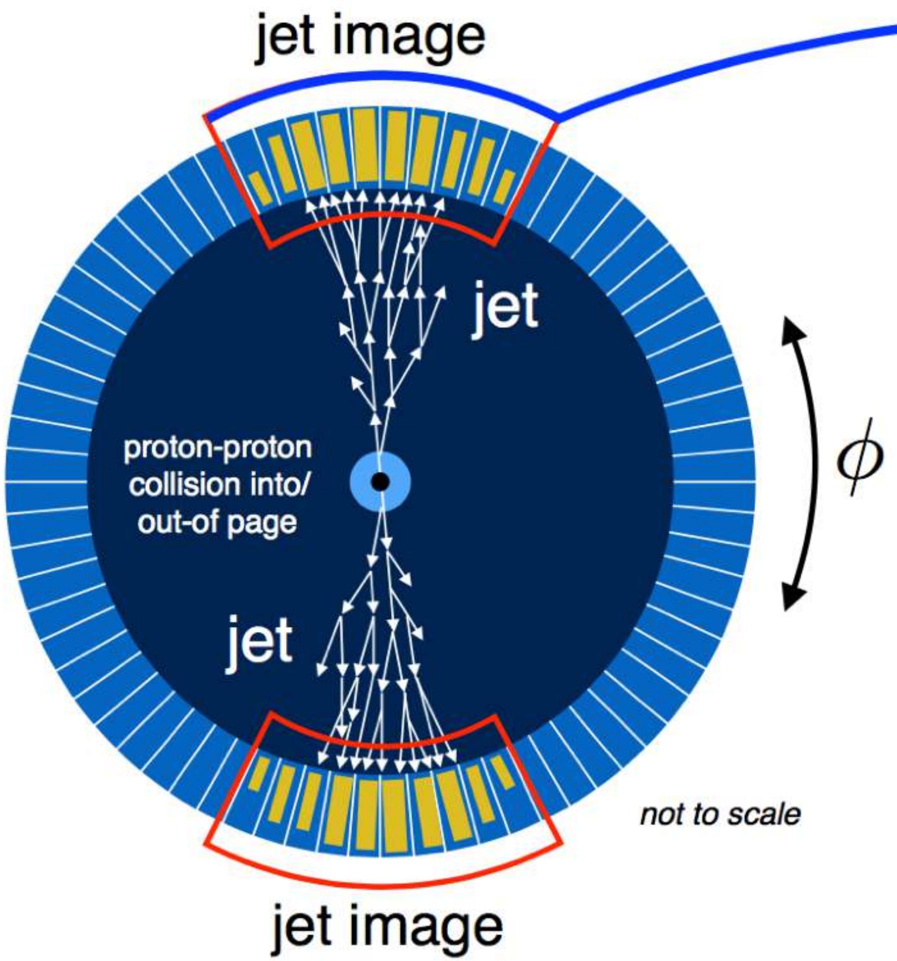
Calorimeter towers as pixels

Energy depositions as intensity

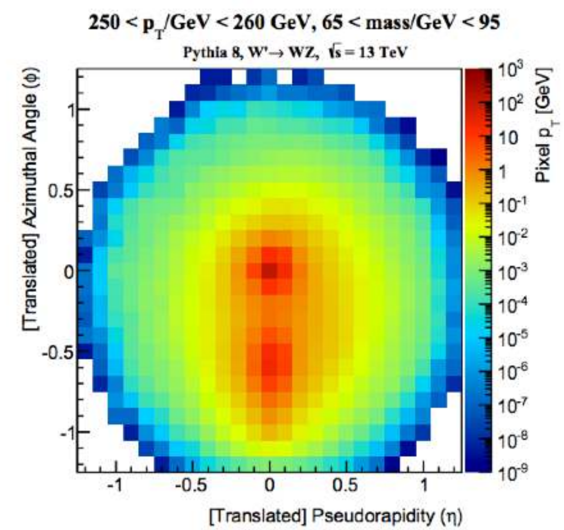
B. Nachman: https://indico.cern.ch/event/567550/contributions/2656471/

Jet Images

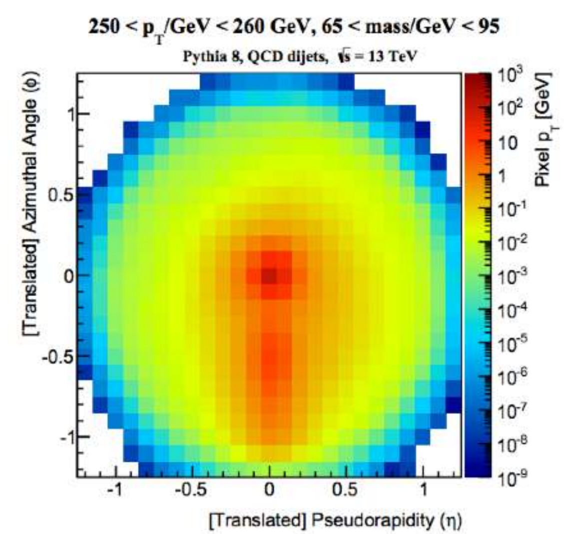
Average of large number of Jet Images



W-jets

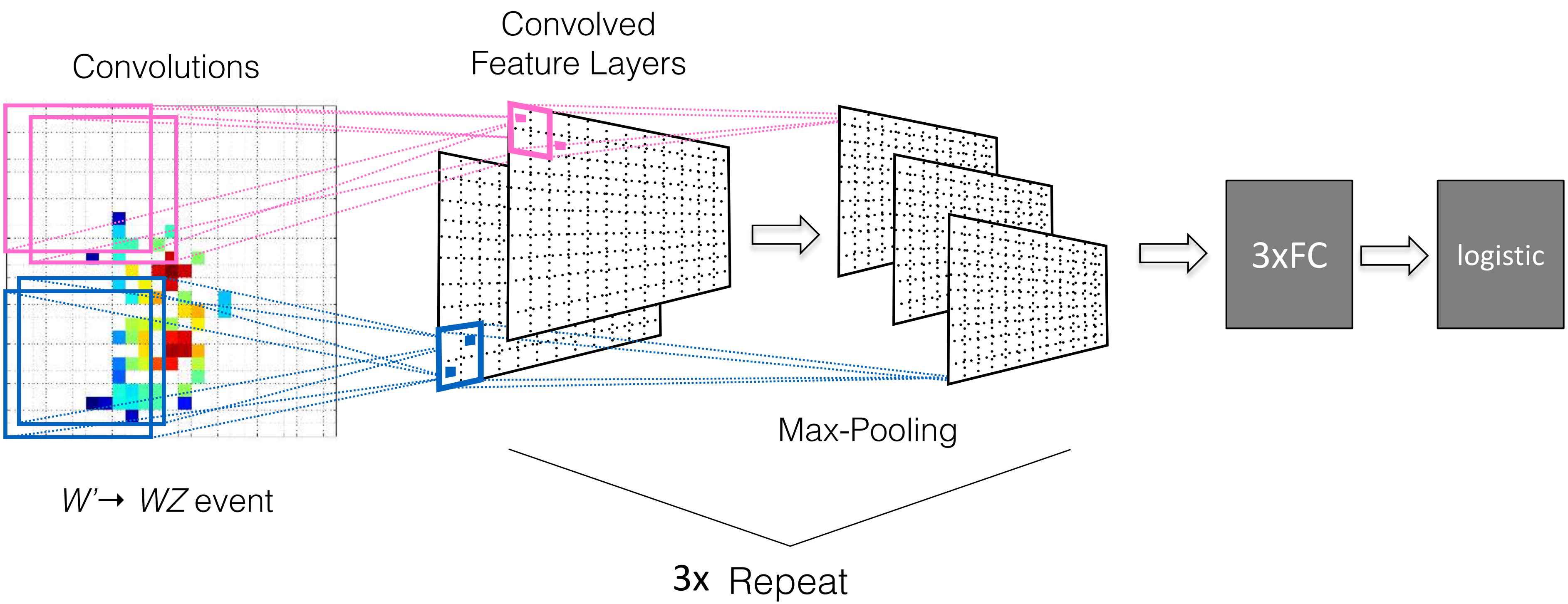


QCD-jets



B. Nachman:
https://indico.cern.ch/event/567550/contributions/2656471/

Deep Jets – Convolutional Neural Networks

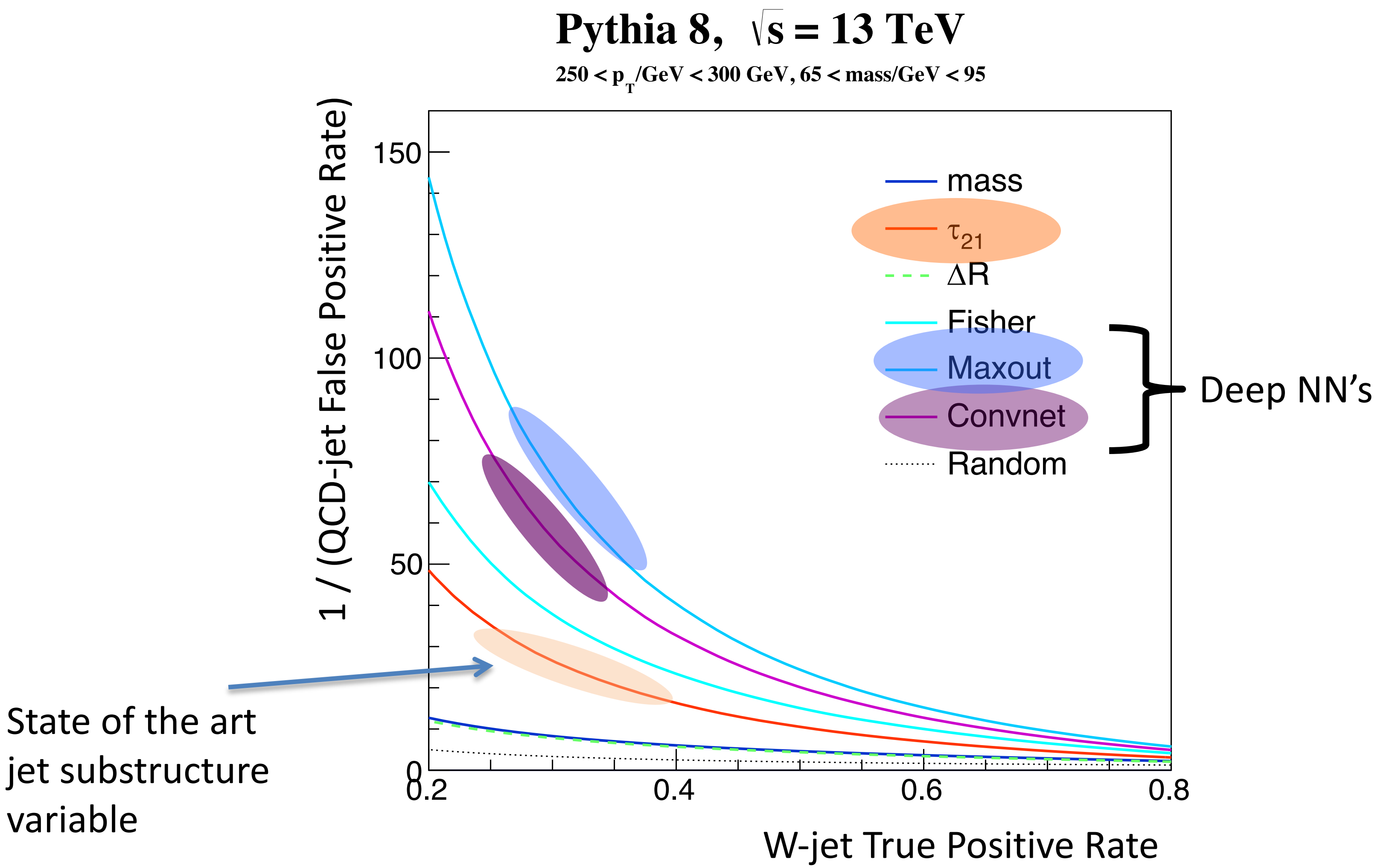


<u>Jet-image based developments</u>

P. Baldi et al. 1603.09349 (W-tagging)
J. Barnard et al. 1609.00607 (W-tagging)
P. Komiske et al. 1612.01551 (q/g-tagging)
L. de Oliveira et. al. 1701.05927 (jet-image GAN)
G. Kasieczka et al. 1701.08784 (top-tagging)

arXiv:1511.05190

Performance with Deep Neural Networks

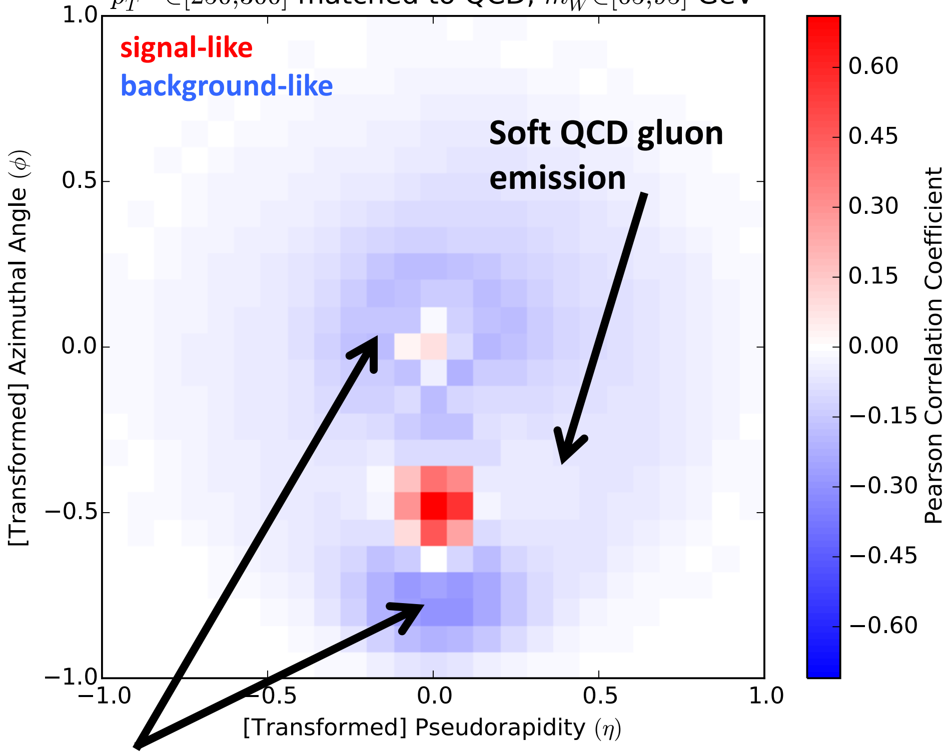


Learning from the Machines

arXiv:1511:05190

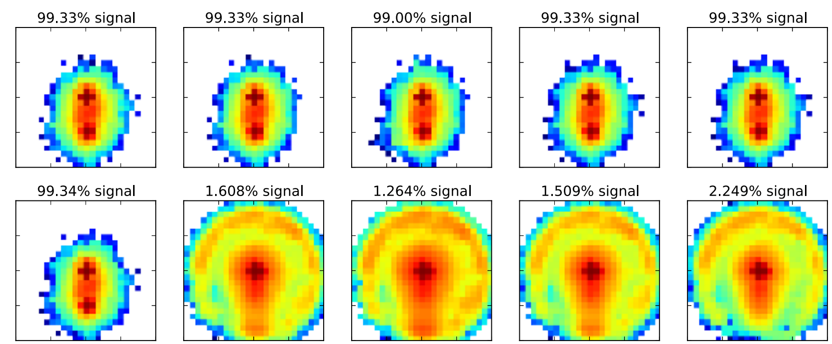
Correlation of Deep Network output with pixel activations.

$p_T^W \in [250,300]$ matched to QCD, $m_W \in [65,95]$ GeV

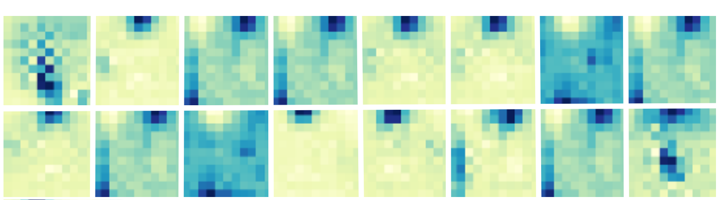


Additional radiation in QCD jets

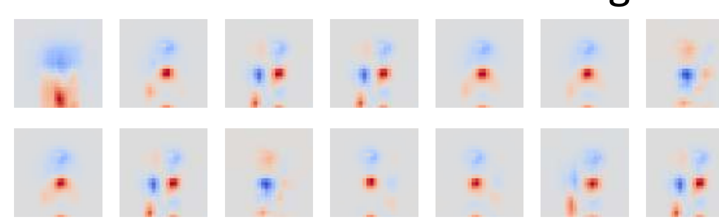
Average of most activating jets for a given neural



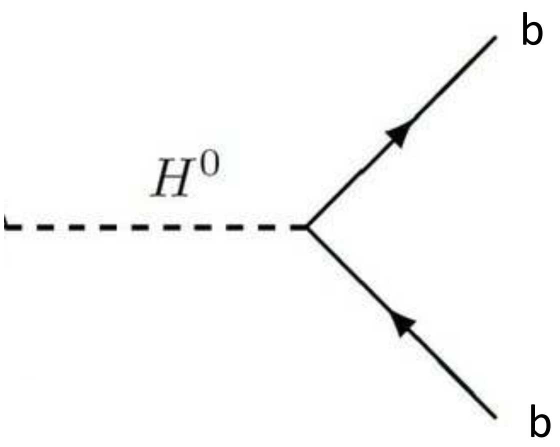
Filters

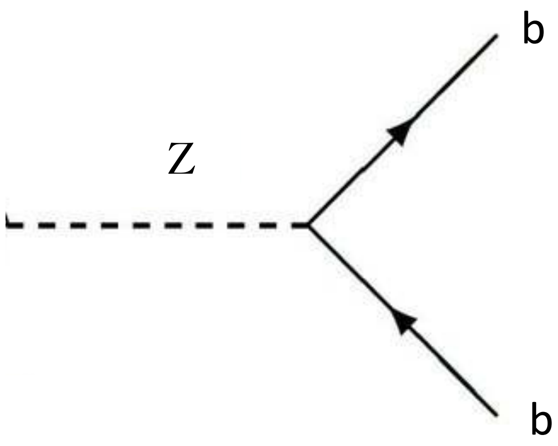


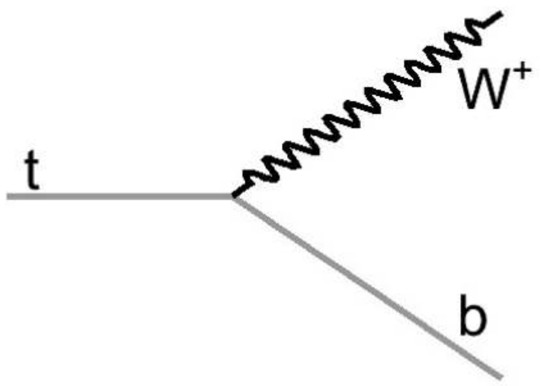
Filters convolved with images



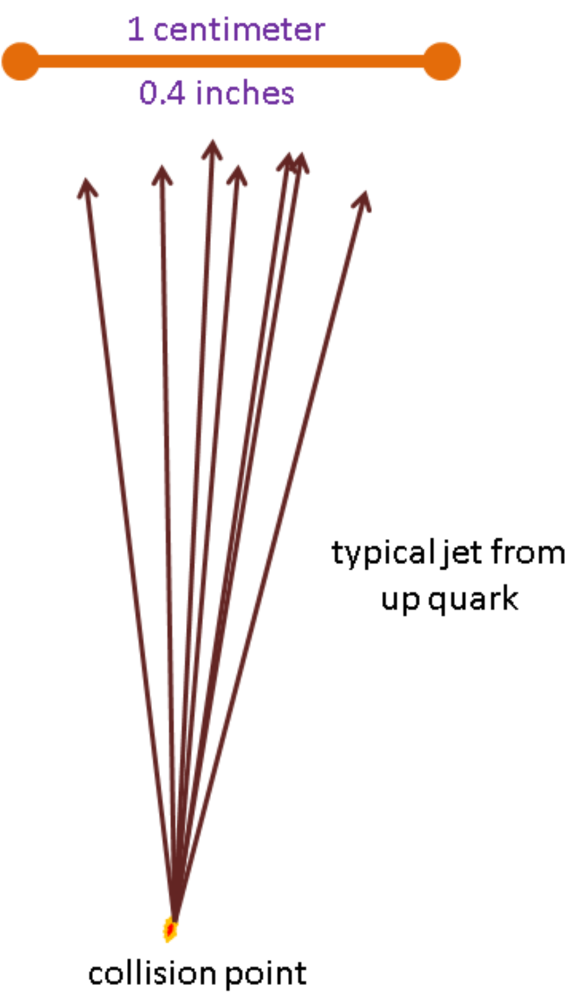
Reconstructing Bottom Quark Jets

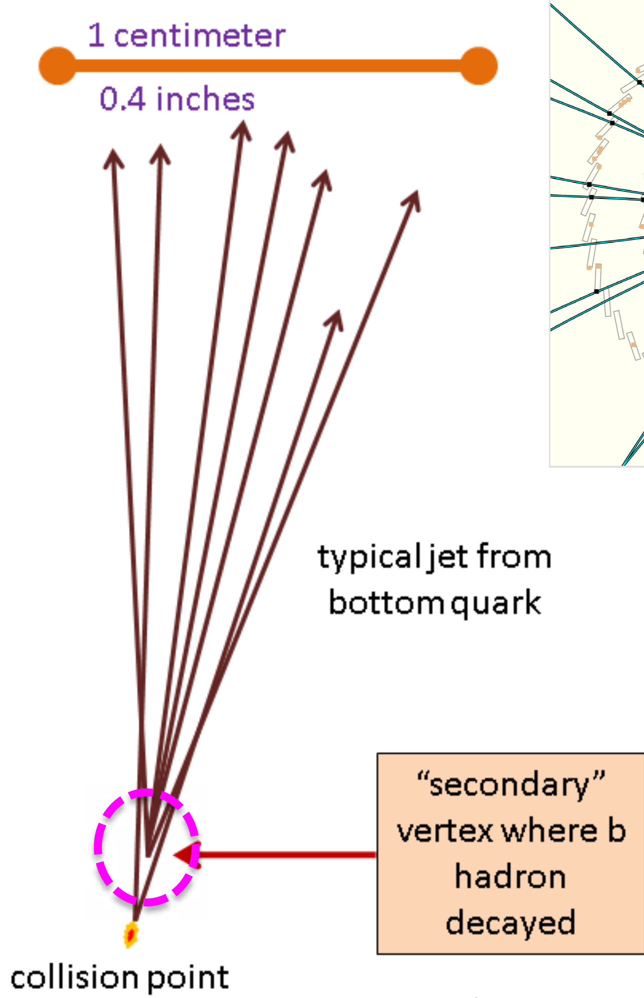




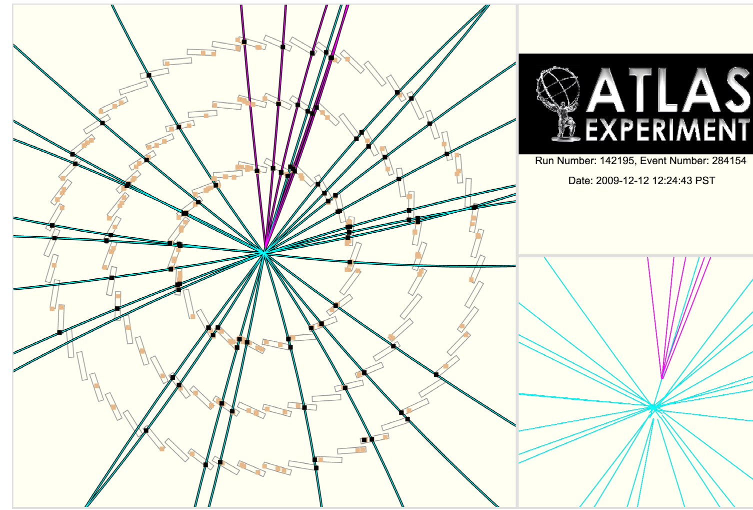


Bottom Quark Decays

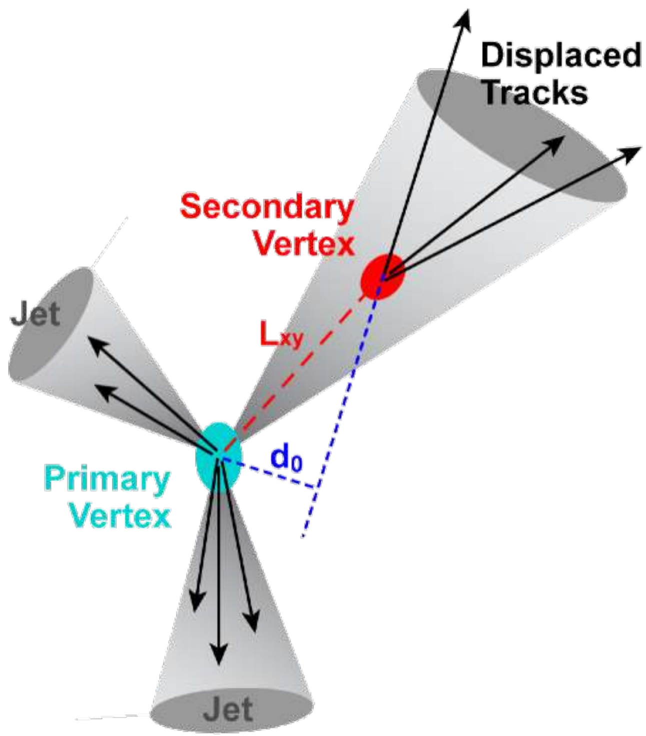




M. Strassler 2012



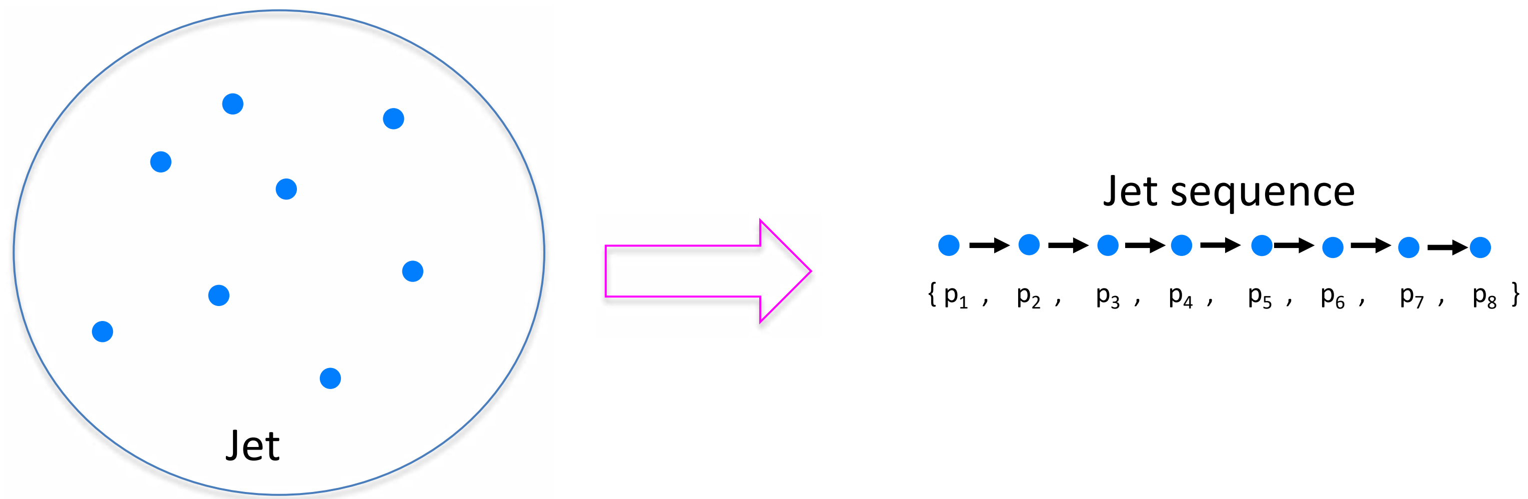
Bottom Quark Jet Identification



- Goal: Discriminate b-jets from non-b-jets

- **Track based** taggers: $p(jet\ flavor \mid tracks\ in\ jet)$
  - Dimensionality too high for easy density estimation
  - Often make naïve Bayes assumption that tracks independent!

Jets as Sequences



- Jets are a grouping of a variable number of particles

- With physically motivated ordering: **jet as a sequence**
  - Can make use of the power of Natural Language Processing

Sequence based developments in HEP (not complete)

ATLAS, ATL-PHYS-PUB-2017-003, (b-tagging)

CMS, DP-2017-013 (b-tagging)

D. Guest et. al.. 1607.08633 (b-tagging)

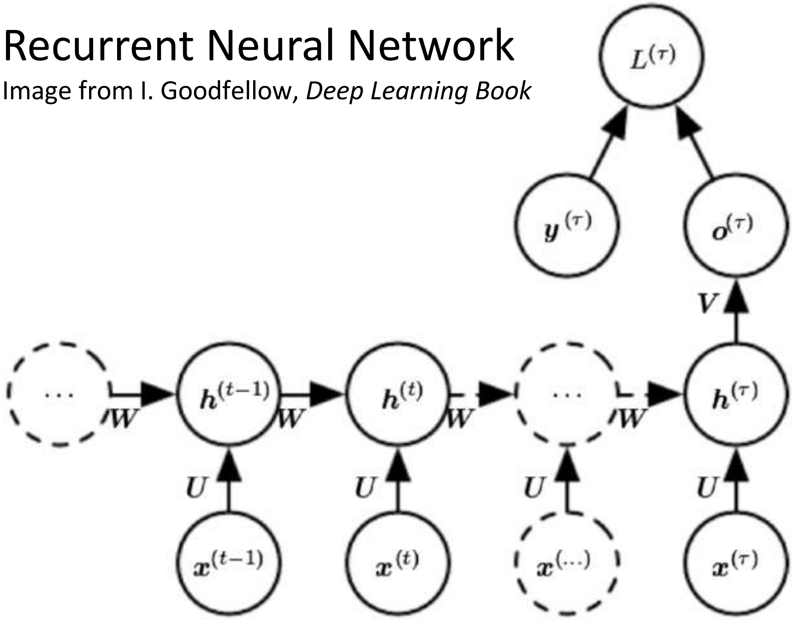
S. Egan et al. 1711:09059 (top-tagging)

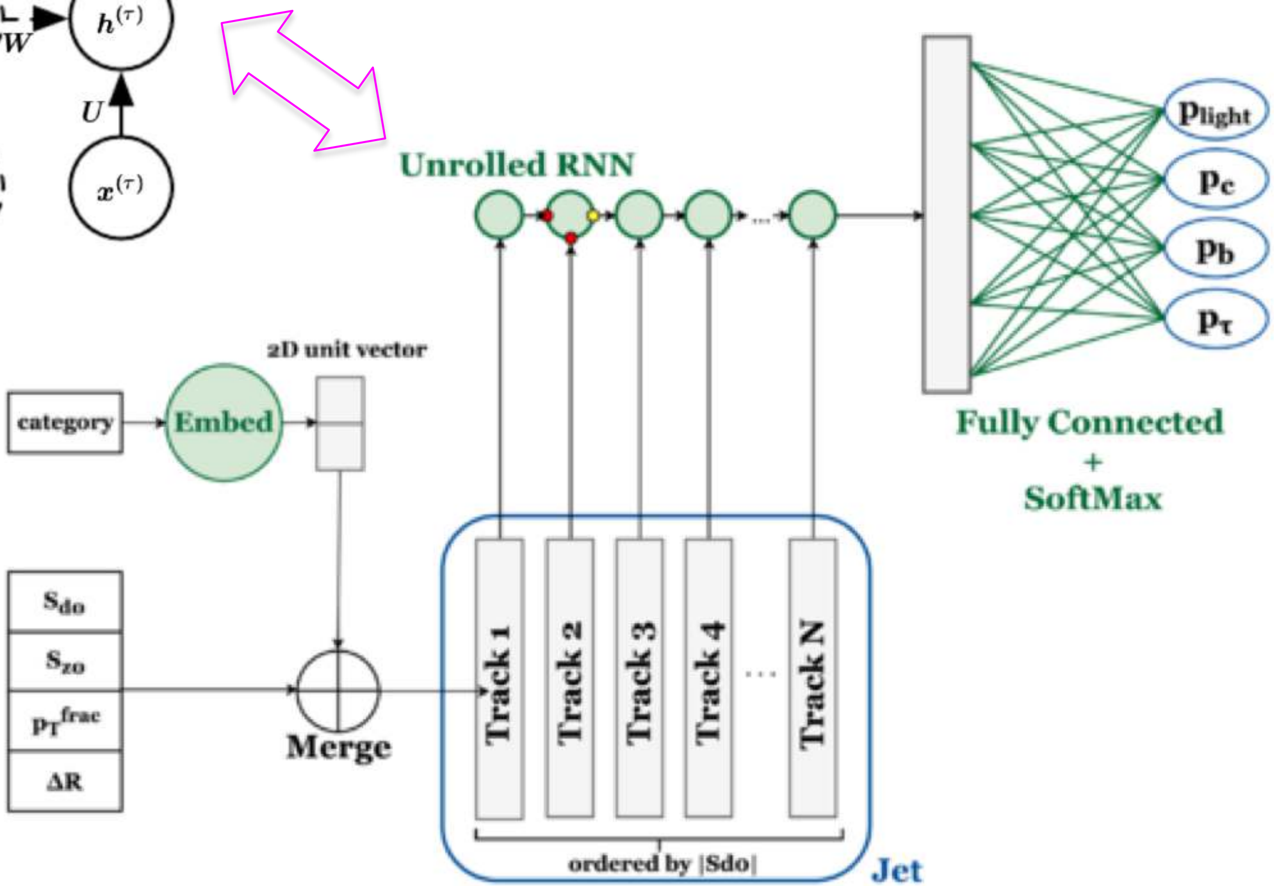
K. Fraser et al. 1803:08066 (jet charge, q/g-tagging)

Jets and Sequence Processing

Recurrent Neural Network

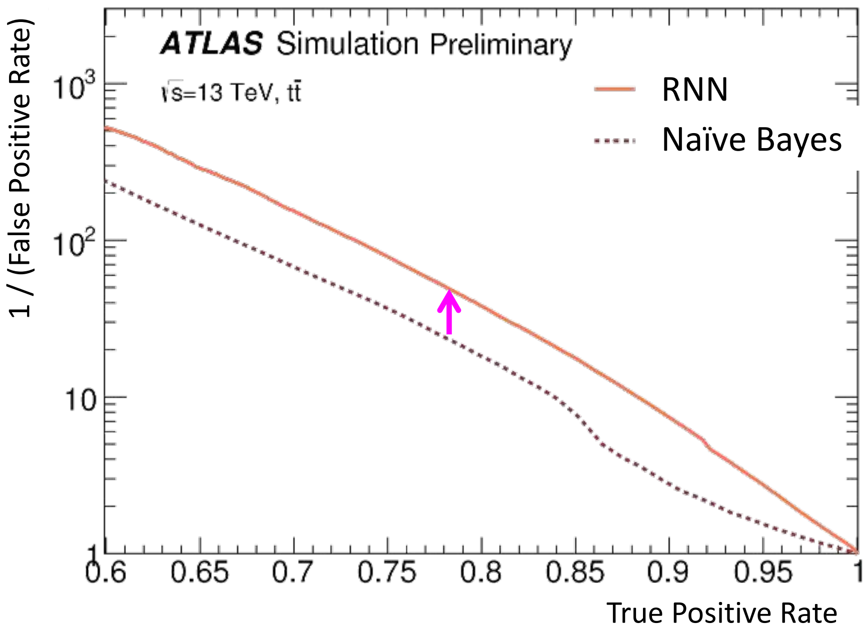
Image from I. Goodfellow, *Deep Learning Book*

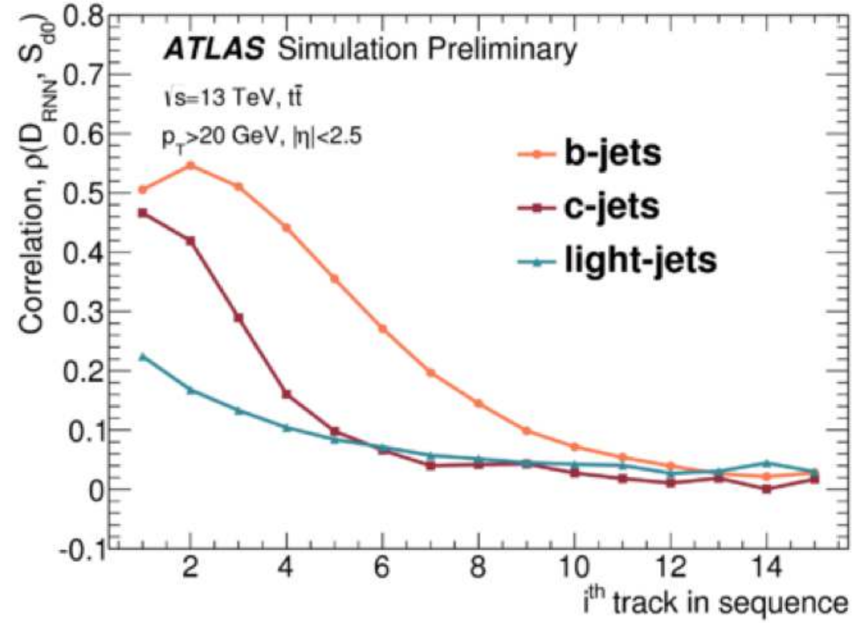




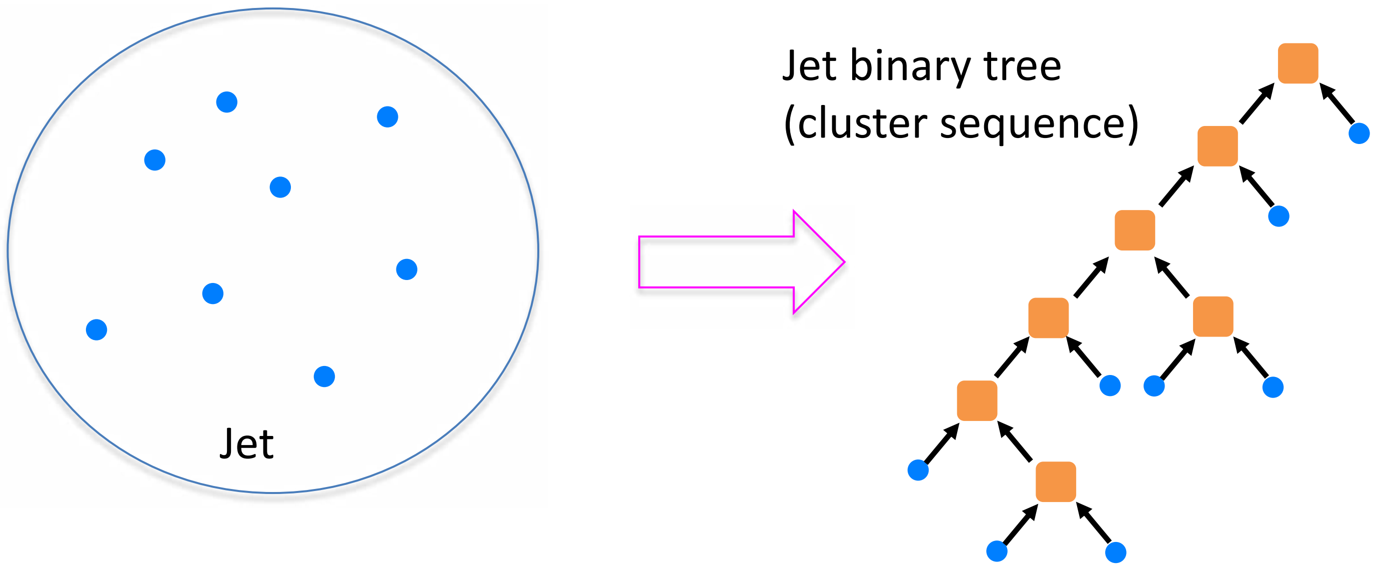
RNN b-tagging

- Order tracks by impact parameter
- RNN can learn inter-track dependencies

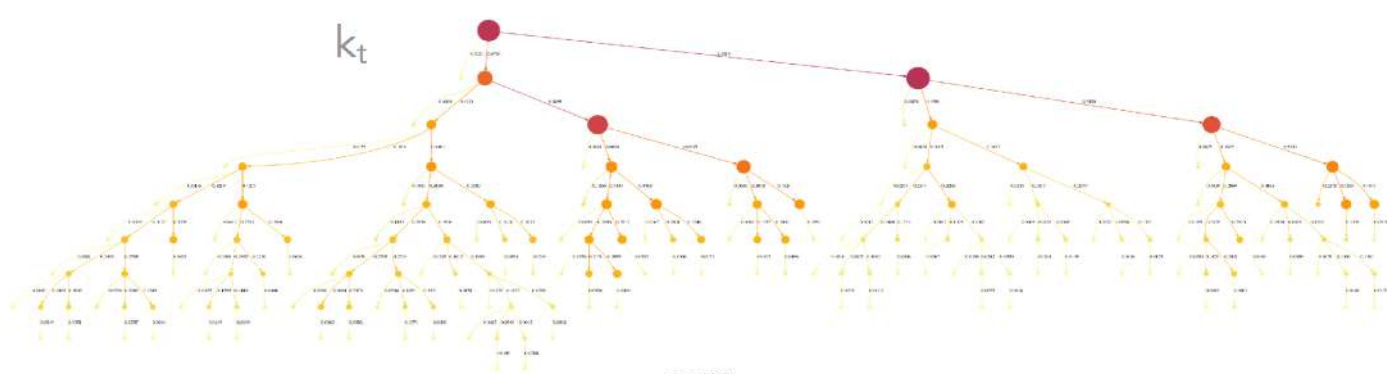




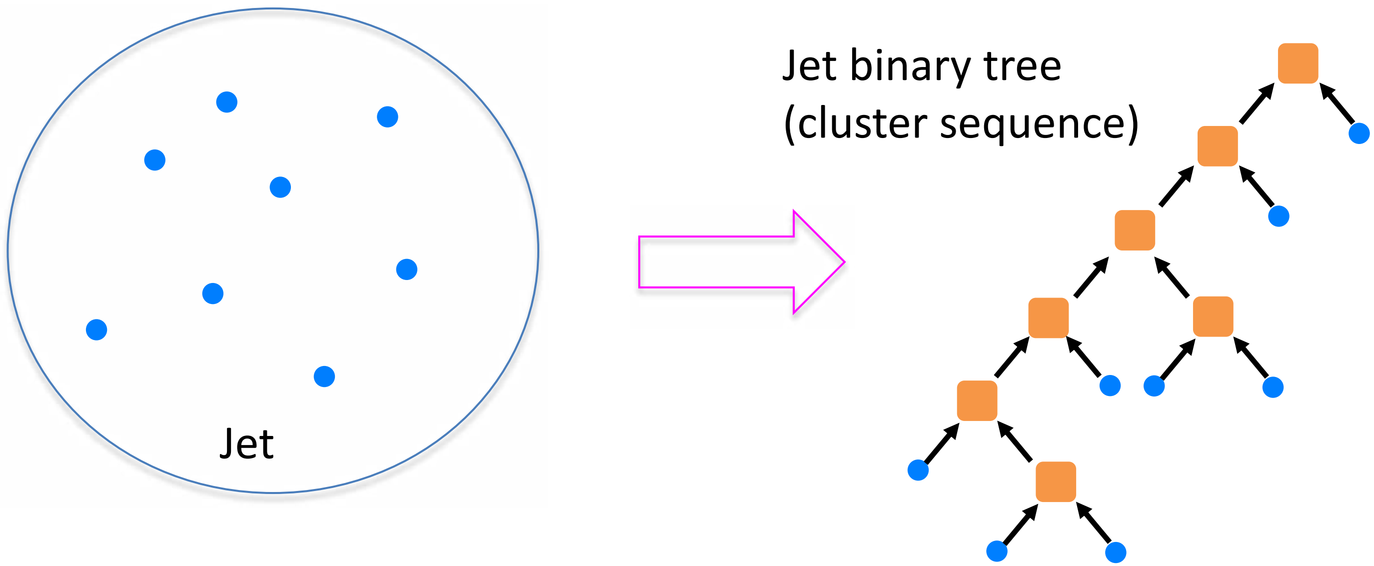
Jets as Hierarchical Clusters



- Jets are reconstructed with hierarchical agglomerative clustering algorithms (pairs wise combinations)
  - Inputs: particles, calorimeter energy clusters, …



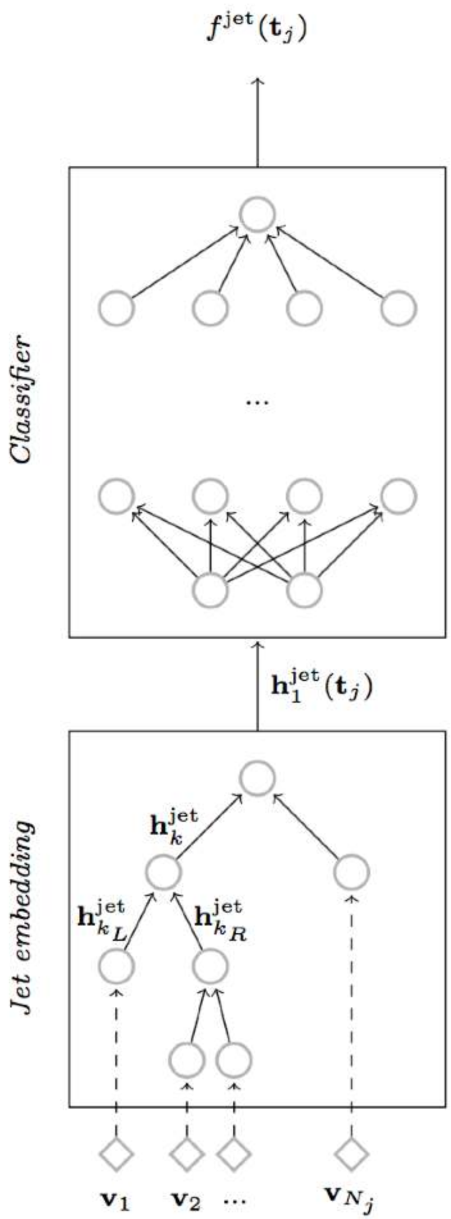
Jets as Hierarchical Clusters

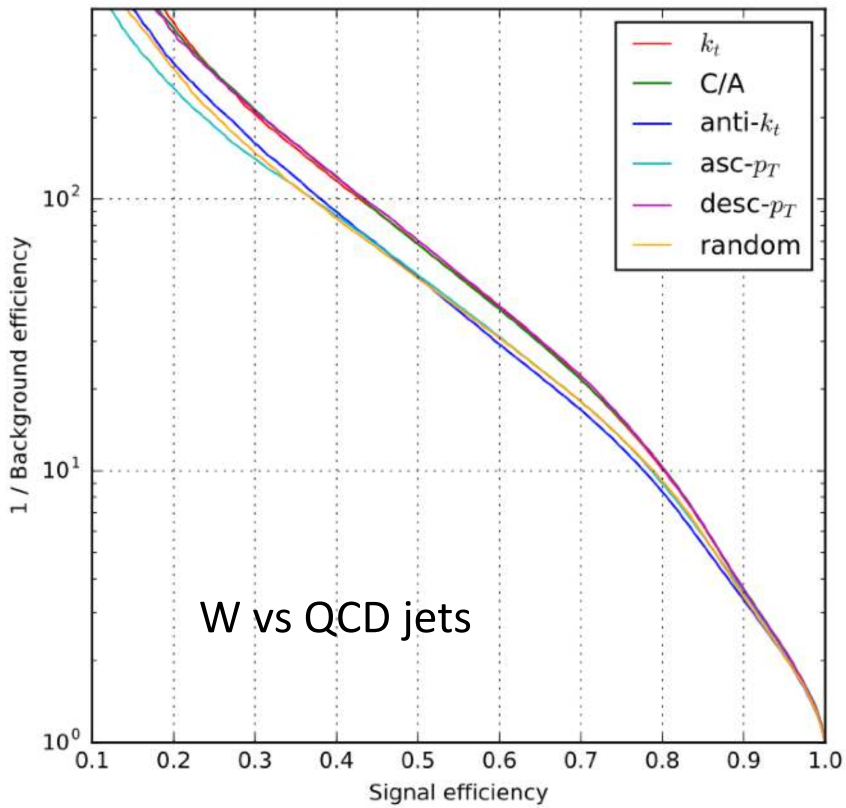


- Jets are reconstructed with hierarchical agglomerative clustering algorithms (pairs wise combinations)
  - Inputs: particles, calorimeter energy clusters, …
- Clustering sequence defines how the particles form a jet
- Can we make use of the cluster sequence itself?

Recurrent NN based developments (not complete)
G. Louppe, et. al. , 1702.00748 (W-tagging)
T. Cheng, 1711.02633 (quark/gluon tagging)
K. Fraser et al. 1803:08066 (jet charge, q/g-tagging)

Recursive Neural Networks for Jet Tagging





arXiv:1702.00748

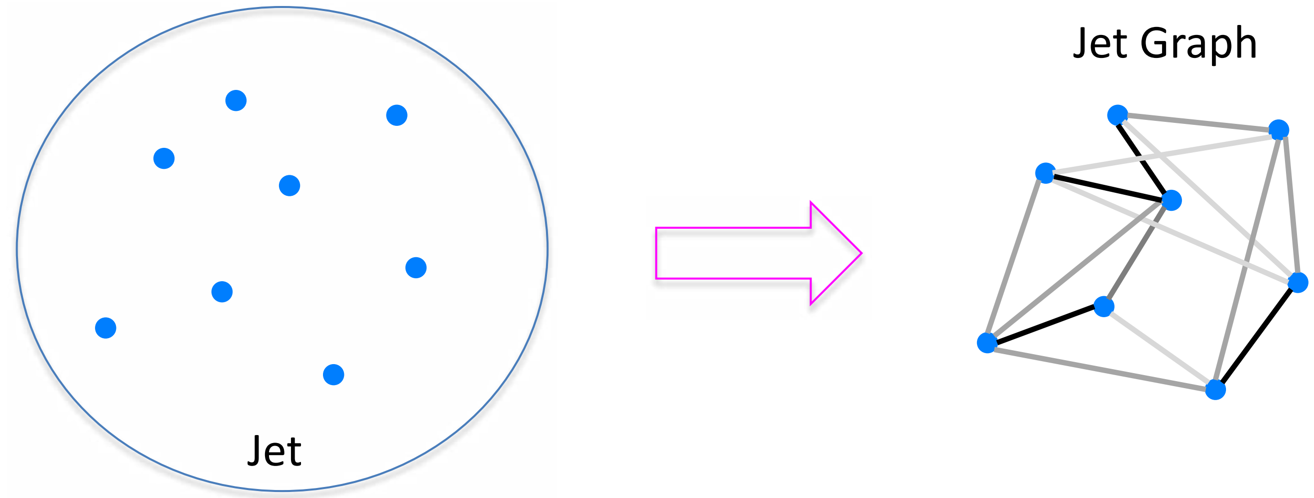
Visualizing Discrimination

Observations:
In the gradient plots, the largest gradients reside in different part of the tree structure

gluon jet from q/g discrimination

gluon jet from W/QCD discrimination

Jets as Graphs



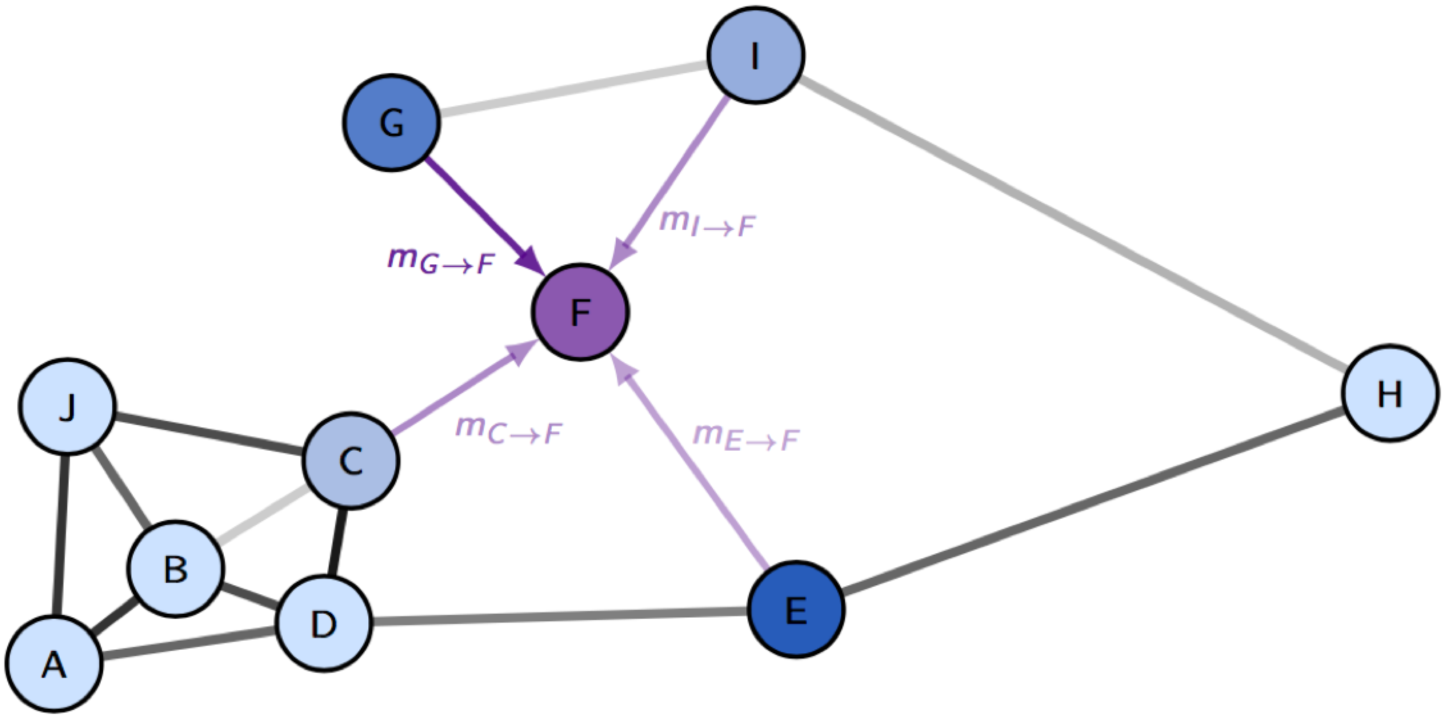
- What if the cluster sequence is not the best structure for all tasks?

- Impose less constraints on jets: **Jets as graphs**

- Can we learn a graph structure and compute over the graph to best perform a discrimination task?

I. Henrion et. al. , presented at NIPS workshop on deep learning for physics sciences

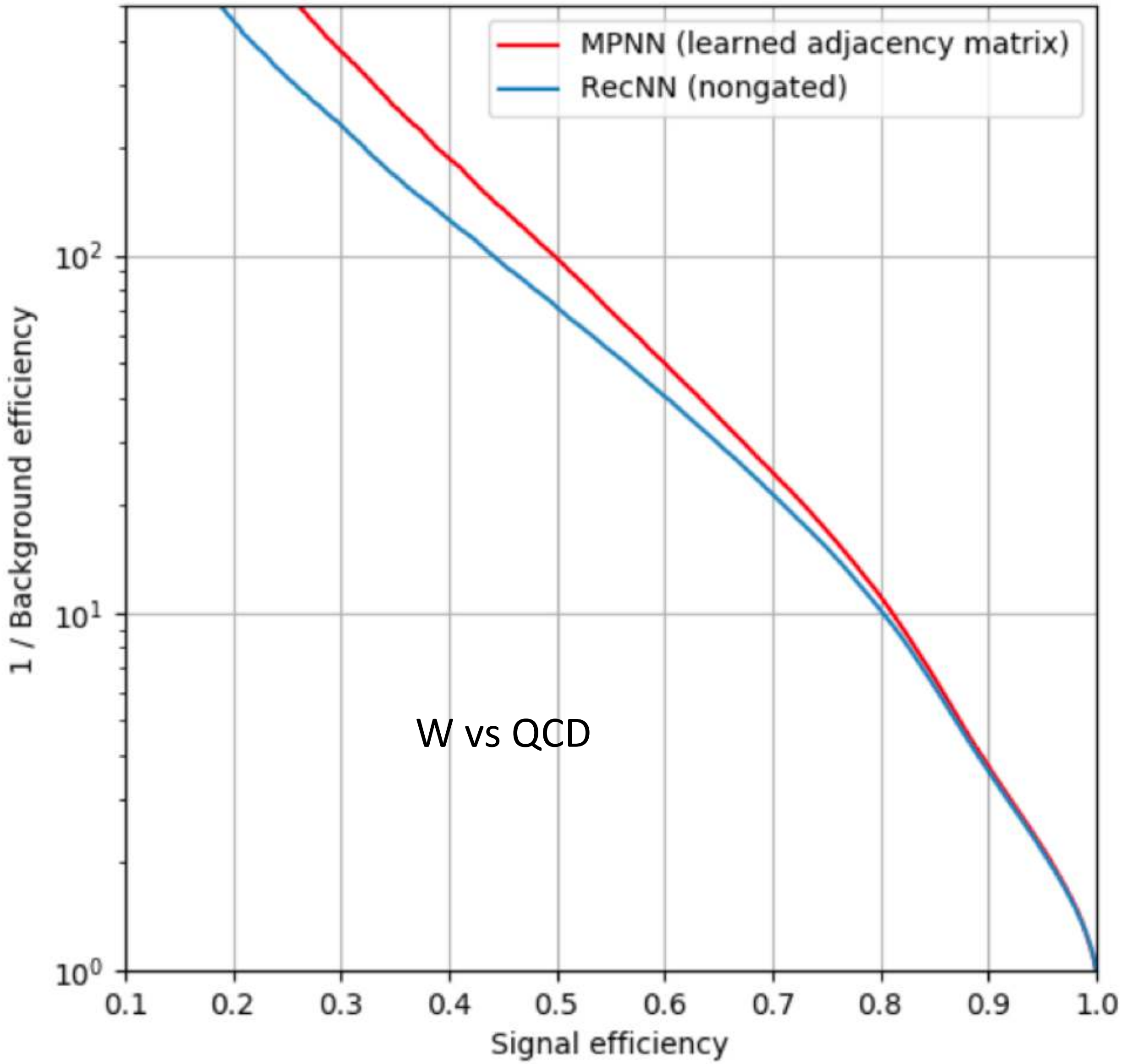
Graph Neural Networks and Neural Message Passing



$$\tilde{m}_j^t = f(h_j^{t-1})$$
$$m_{j\to i}^t = \sigma(A_{ij}\tilde{m}_j^t)$$
$$h_i^t = \mathrm{GRU}(h_i^{t-1}, \Sigma_j m_{j\to i}^t)$$

Slide from I. Henrion

Jet Discrimination with NMP



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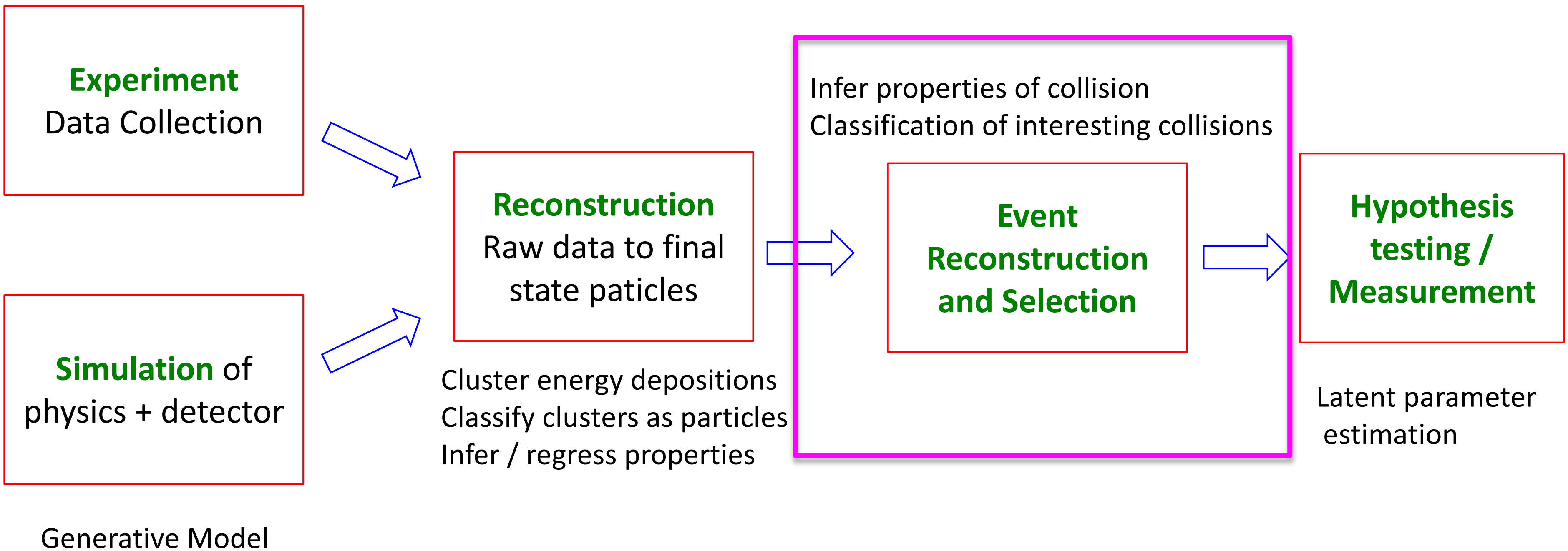
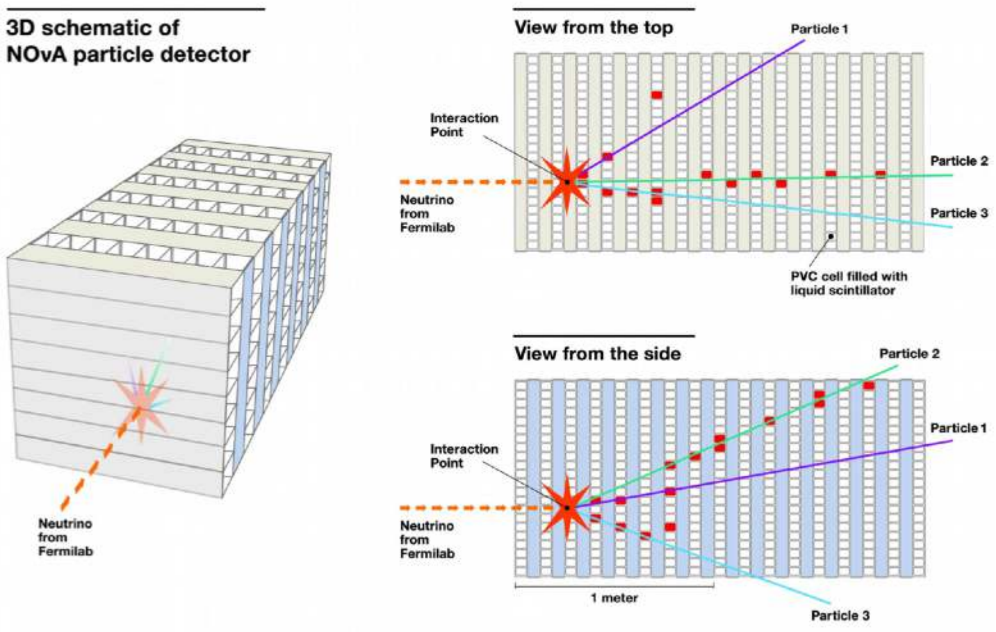
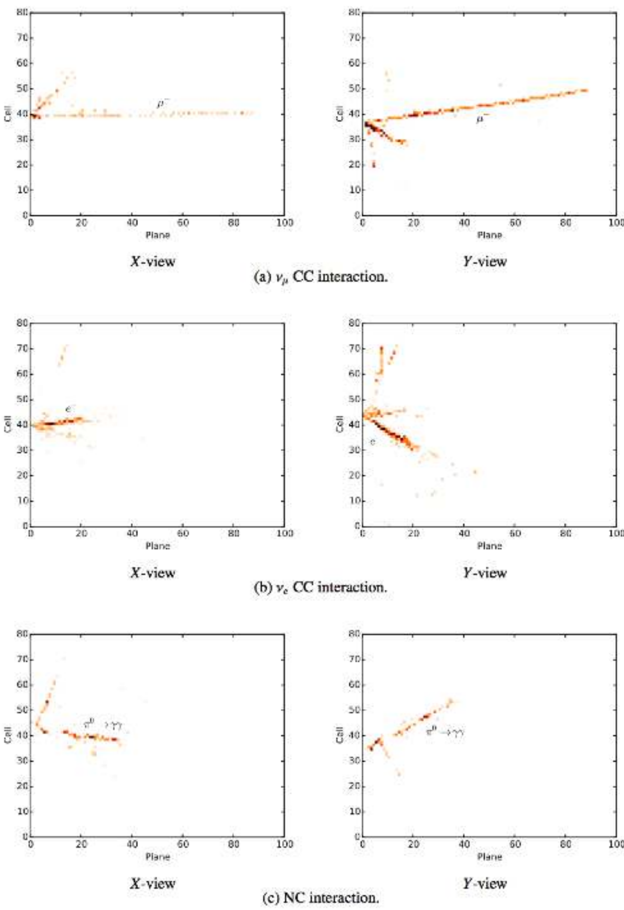
Deep Learning in the Pipeline



Neutrino Identification at NOvA

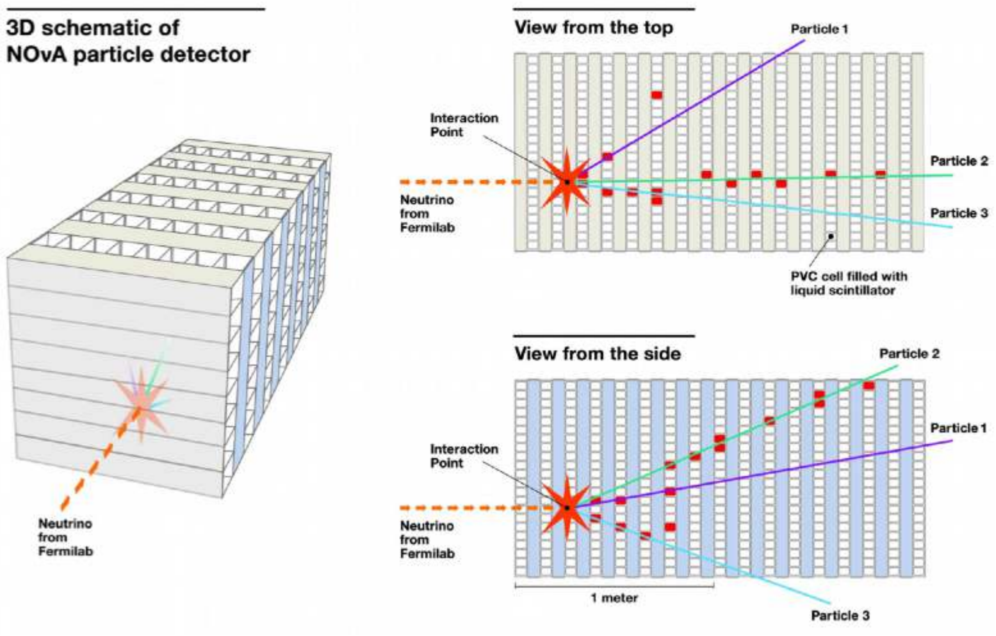


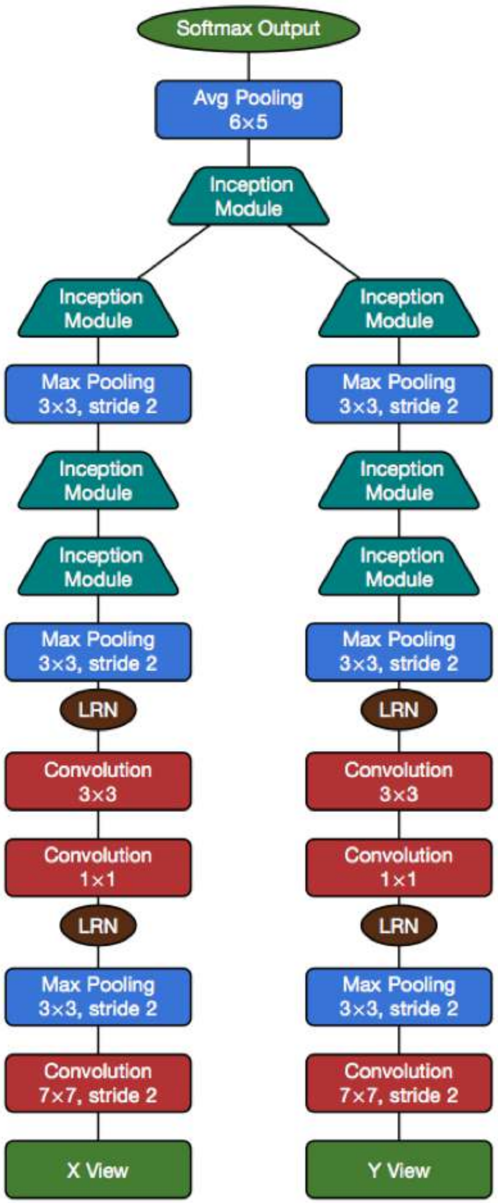


- Two 2D projections of the interactions
- Goal: discriminate between different neutrino interactions / backgrounds

Neutrino Identification at NOvA

arXiv:1604.01444





- Two 2D projections of the interactions
- Goal: discriminate between different neutrino interactions / backgrounds
- Make use of powerful computer vision architectures, here GoogLeNet, and adapt to our challenges

Neutrino Identification at NOvA

arXiv:1604.01444

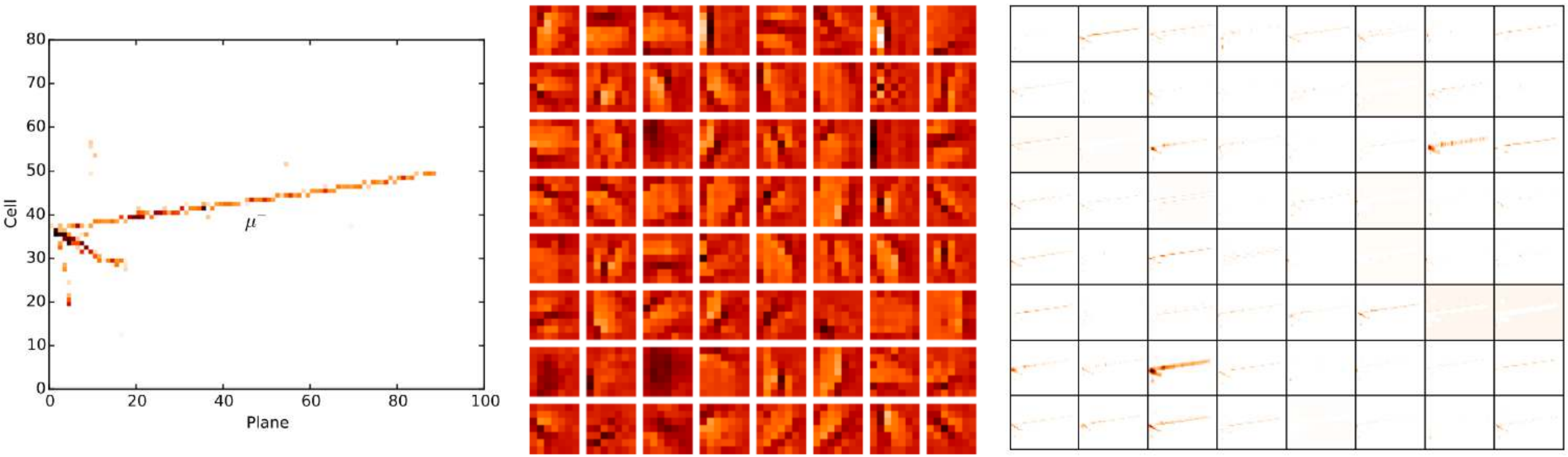
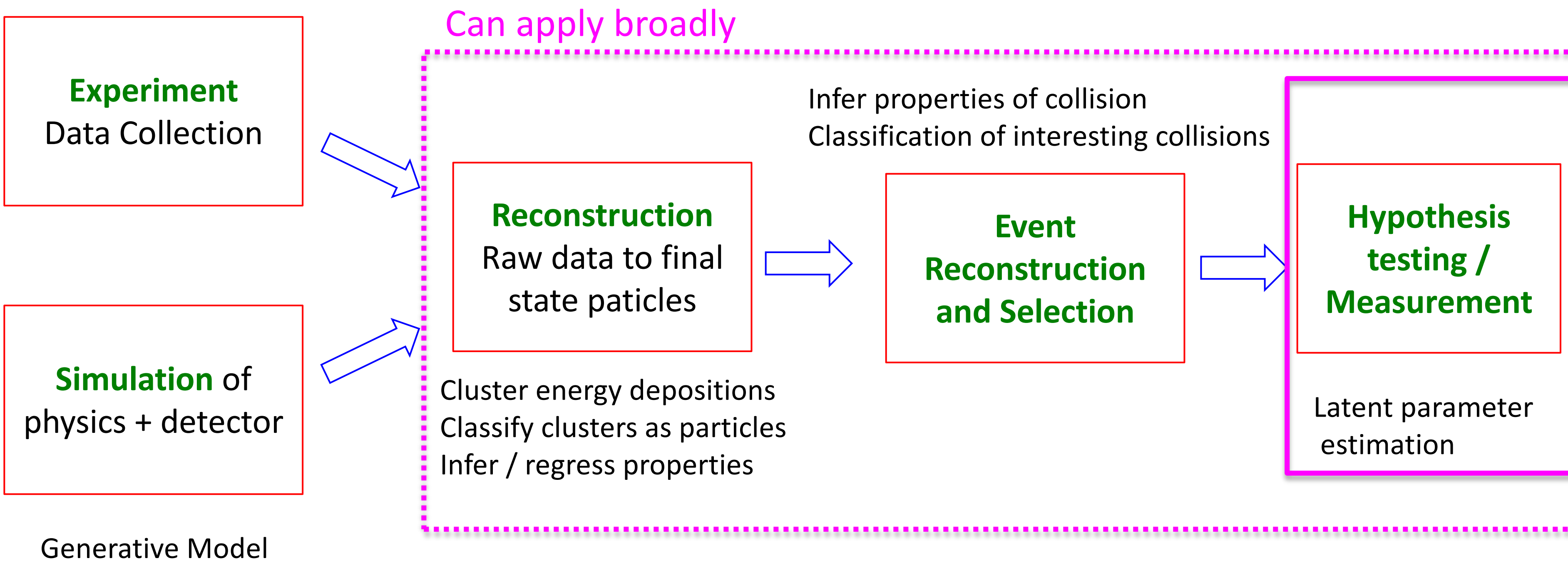


Image Y-view → First CONV layer filters → Output of convolution

- Convolution filters and outputs show interesting features about how the NN is providing discrimination

- Major gains over current algorithms in ν_e-CC discrimination:
  35% → 49% signal efficiency for the same background rejection

Deep Learning in the Pipeline

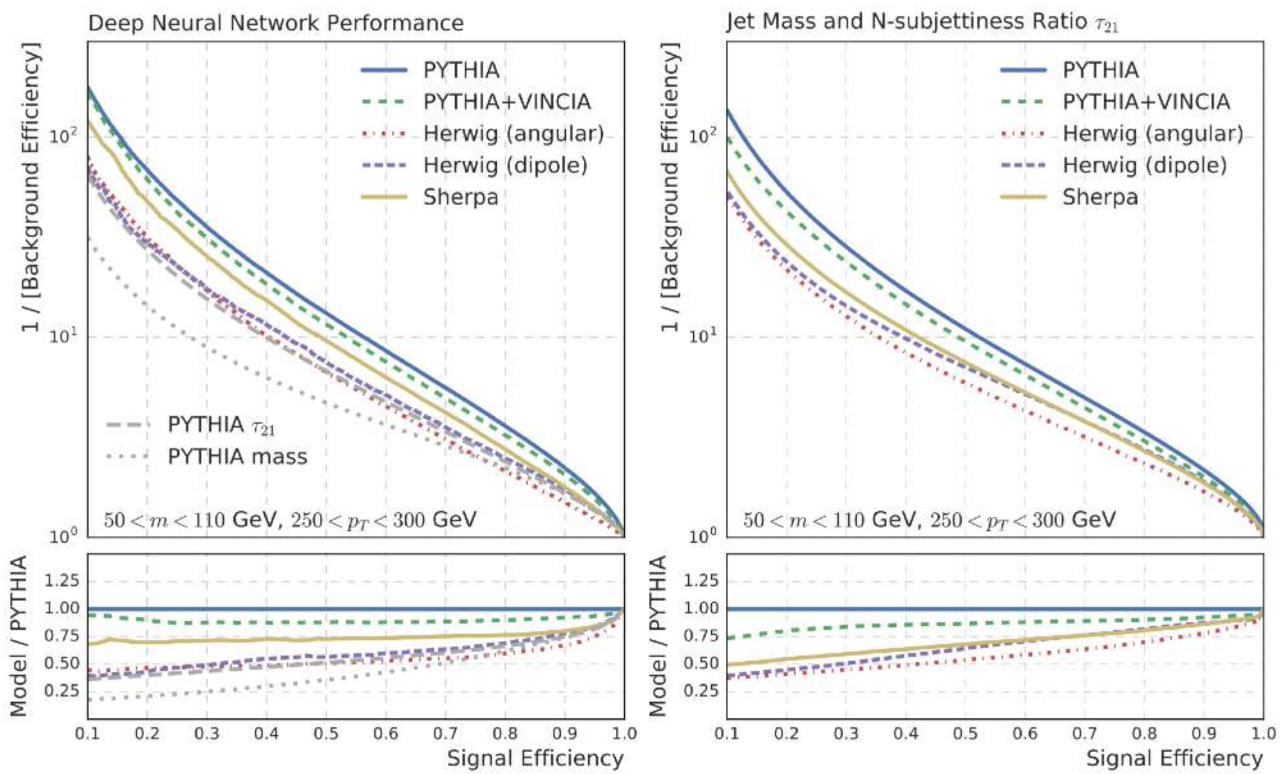


- Developing new ways to train our algorithms. Examples:
  - Parametrized learning [EPJ C76 (2016) no.5, 235]
  - **Adversarial learning to pivot** [NIPS 2017, 1611.01046]
  - Learning from label proportions [1702.00414]

Dealing with Systematic Uncertainties

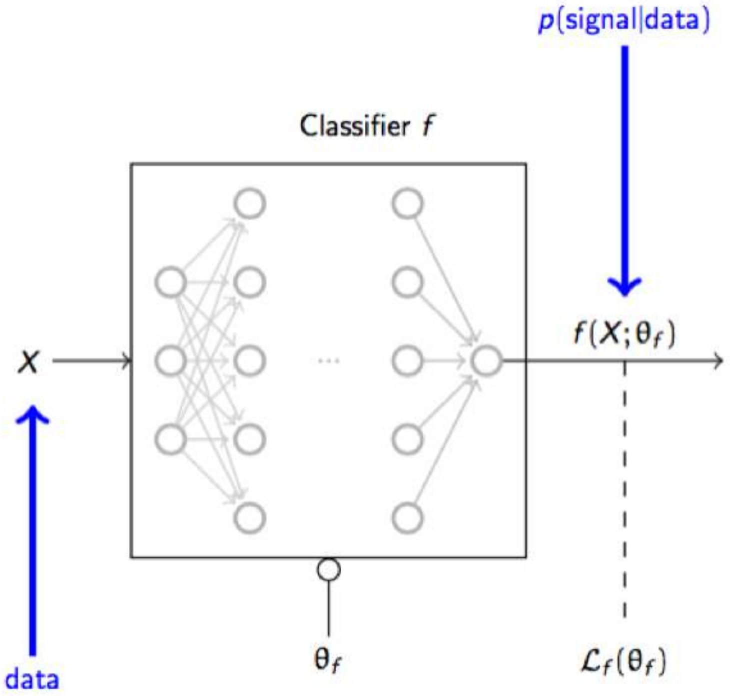
- Systematic uncertainties encapsulate our incomplete knowledge of physical processes and detectors

- Can we teach a classifier to be robust to these kinds of uncertainties?



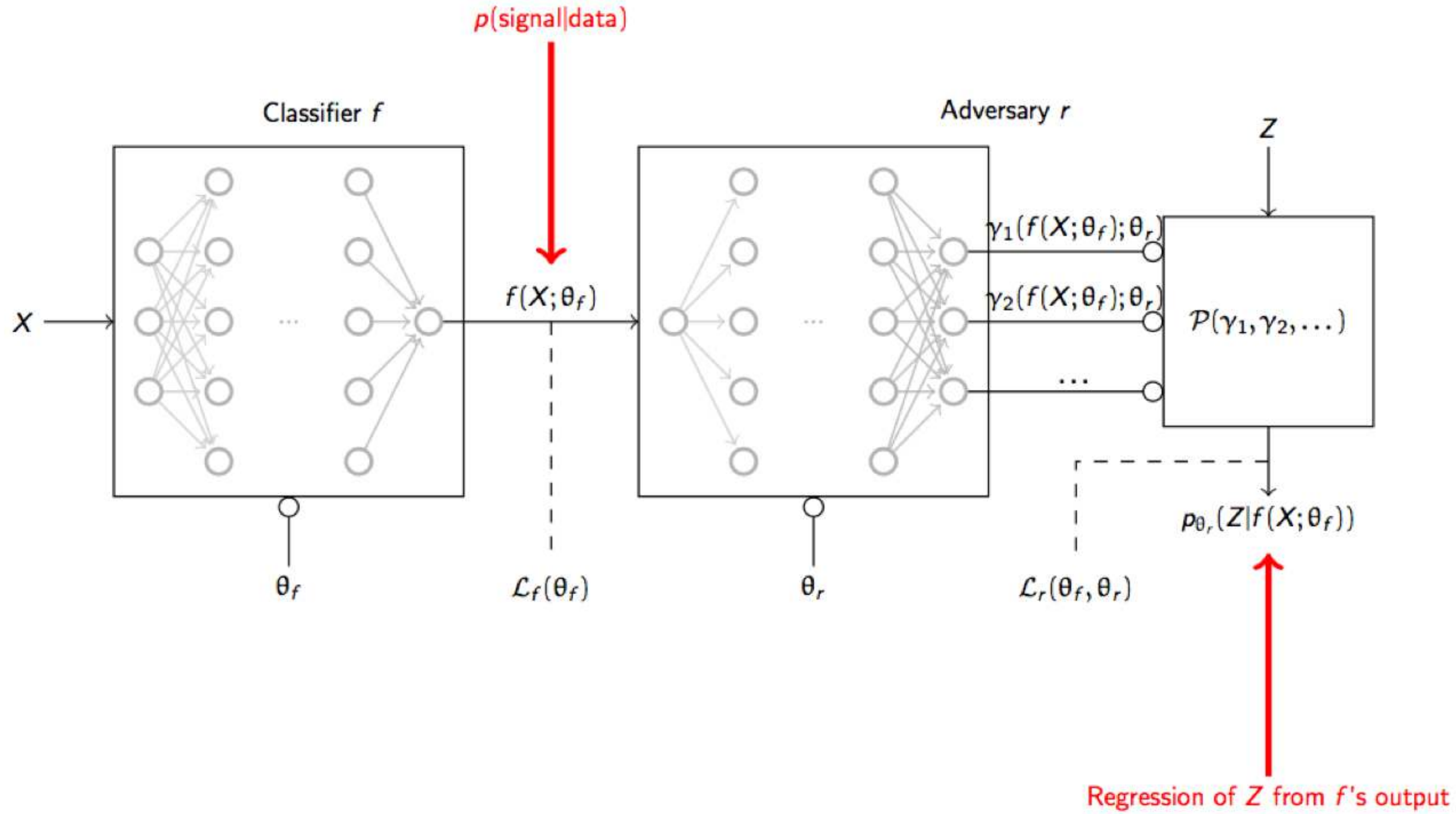
arXiv:1609.00607

Adversarial Networks



- Classifier built to solve problem at hand

Adversarial Networks



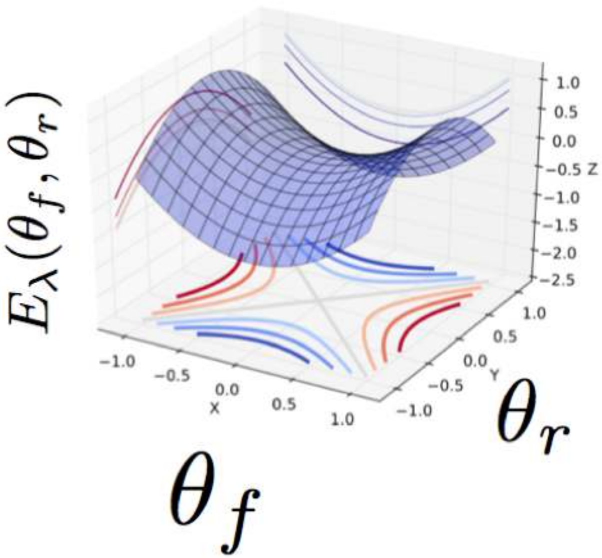
- Systematic uncertainty encoded as nuisance parameters, Z
- Adversary to predict the value of Z given classifier output

Adversarial Networks

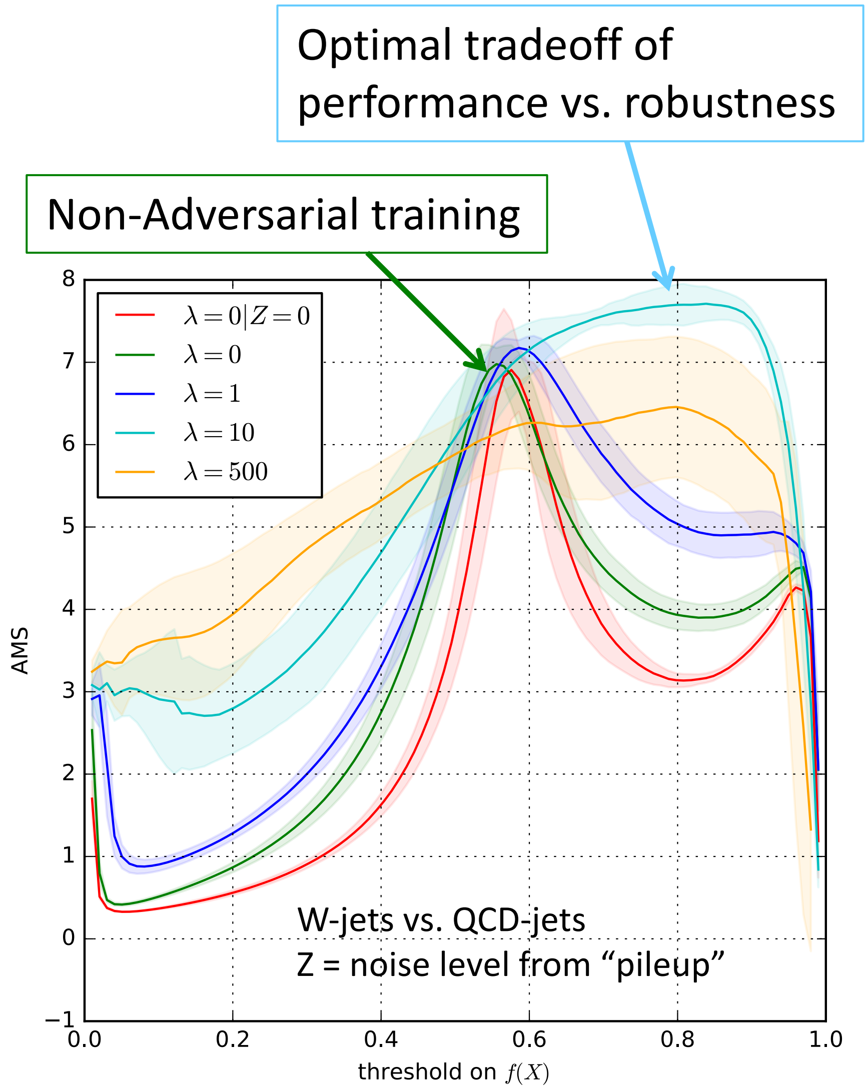
G. Louppe, M. K., K. Cranmer, arXiv:1611.01046

$$\hat{\theta}_f, \hat{\theta}_r = \arg \min_{\theta_f} \max_{\theta_r} E(\theta_f, \theta_r).$$

$$E_\lambda(\theta_f, \theta_r) = \mathcal{L}_f(\theta_f) - \lambda \mathcal{L}_r(\theta_f, \theta_r),$$



- Loss encodes performance of classifier and adversary
  - Classifier penalized when adversary does well at predicting Z
- Hyper-parameter λ controls trade-off
  - Large λ enforces f(…) to be pivotal, e.g. robust to nuisance
  - Small λ allows f(…) to be more optimal



[AMS = Estimate of statistical significance including systematic uncertainty]

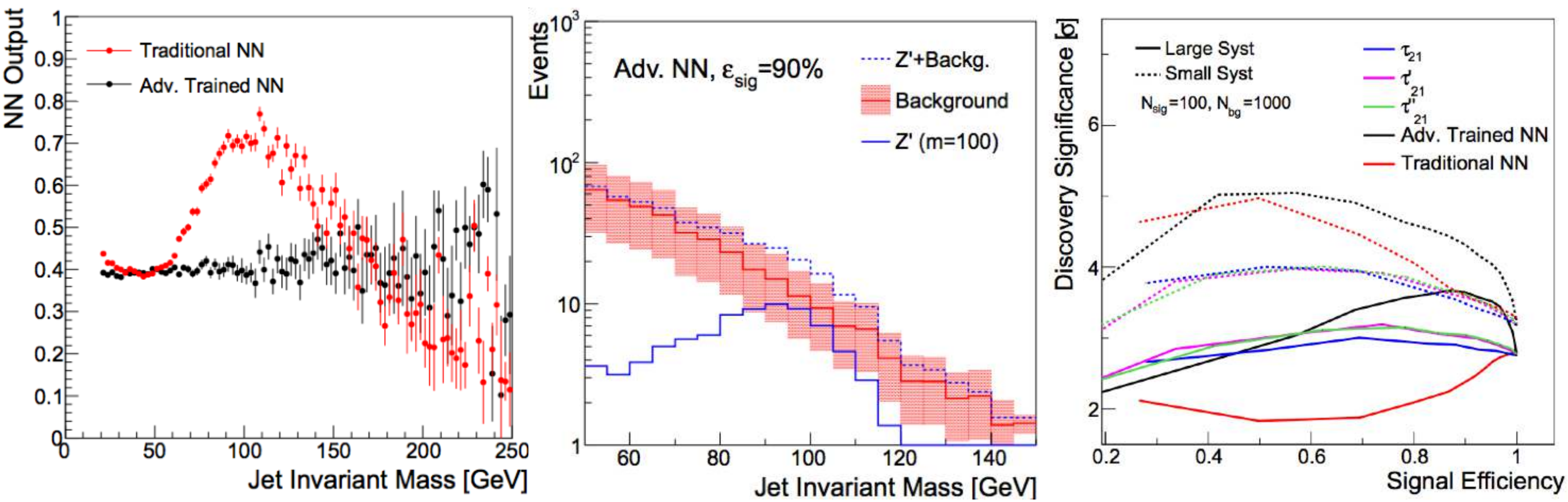
- λ=0, Z=0
  - Standard training with no systematics during training, evaluate systematics after training
- λ=0
  - Training samples include events with systematic variations, but no adversary used
- λ=10
  - Trading accuracy for robustness results in net gain in terms of statistical significance

Decorrelating Variables

arXiv:1703.03507

- Same adversarial setup can decorrelate a classifier from a chosen variable (rather than nuisance parameter)

- In this example, decorrelate classifier from jet mass, so as not to sculpt jet mass distribution with classifier cut



Deep Learning in the Pipeline

Experiment
Data Collection

Simulation of
physics + detector

Generative Model

Reconstruction
Raw data to final
state paticles

Cluster energy depositions
Classify clusters as particles
Infer / regress properties

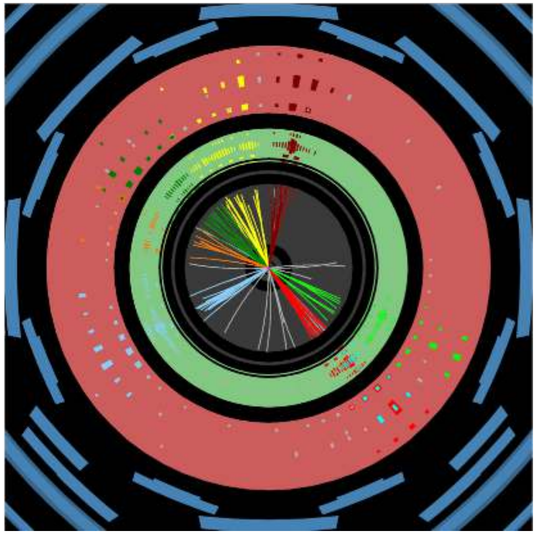
Event Reconstruction and Selection

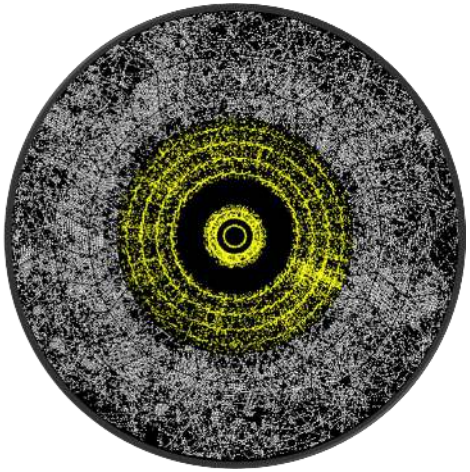
Infer properties of collision
Classification of interesting collisions

Hypothesis testing / Measurement

Latent parameter
estimation

Generative Adversarial Networks (GAN)



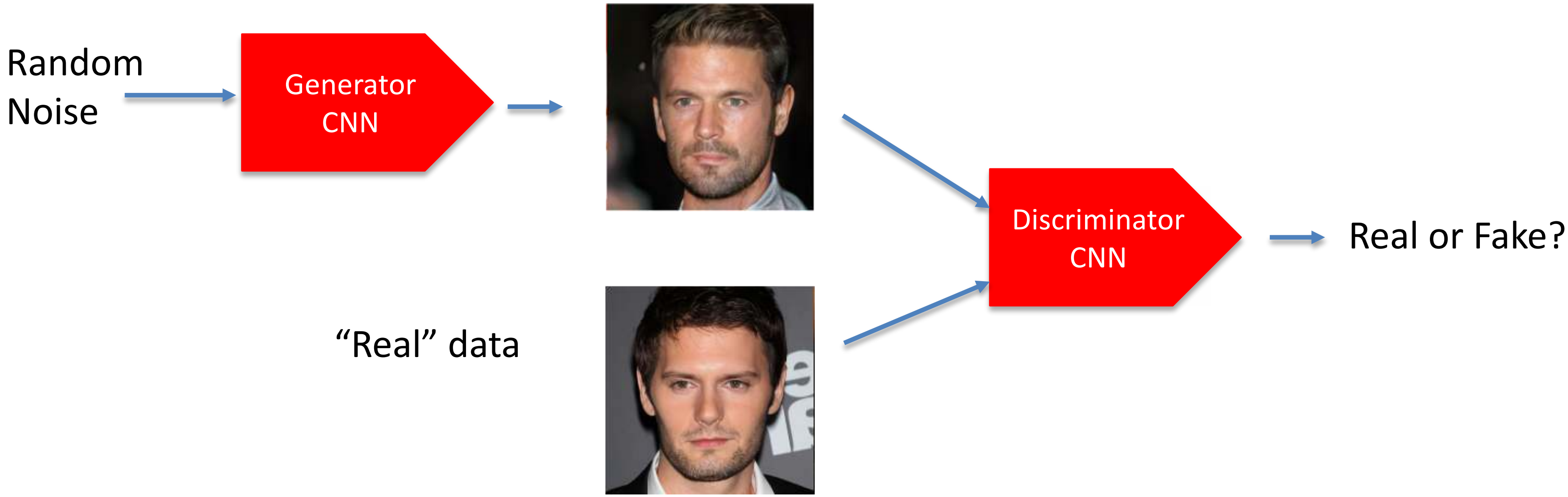


- Full Simulation: accurate simulation of particle interactions with material
  - Computationally very costly
  - Only produce sample, can't compute analytically P(energy deposits | particle)

- Fast Simulation: simplified parametric model of energy deposits

- Generative models to learn data distribution, p(x), and produce samples?
  - Generative Adversarial Networks (GAN)
  - Variational Auto-Encoders (VAE)

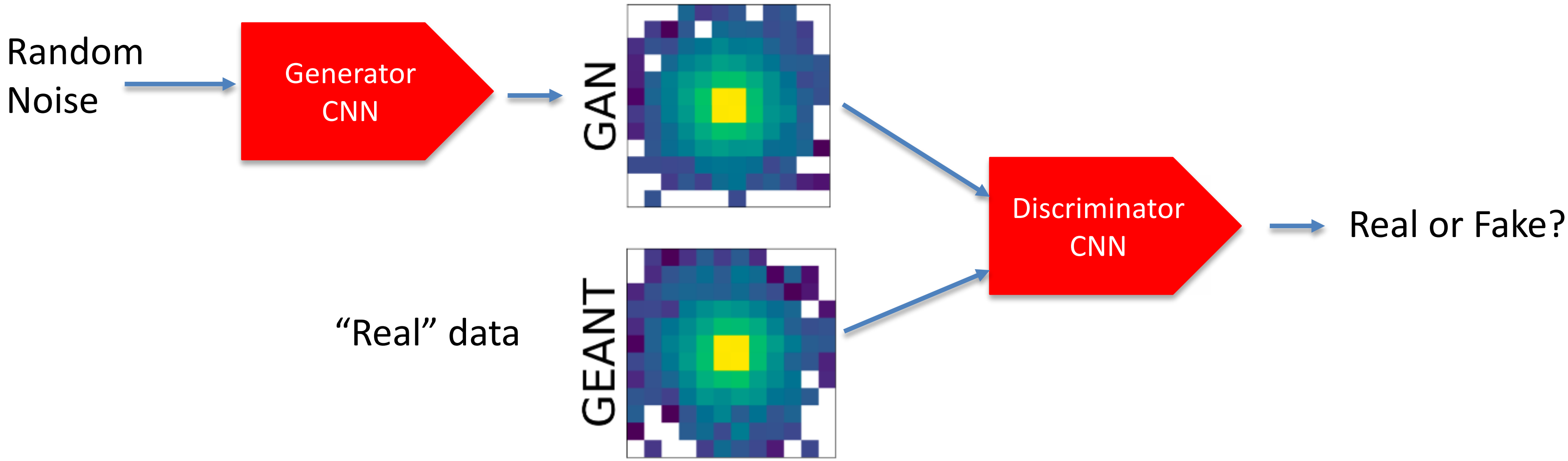
GANs



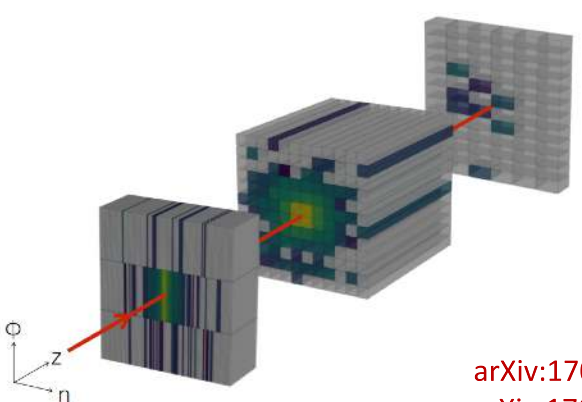
- Generator produces images from random noise and tries to trick discriminator into thinking they are real
- Classifier tries to tell the difference between real and fake images

Images: arXiv:1710.10196

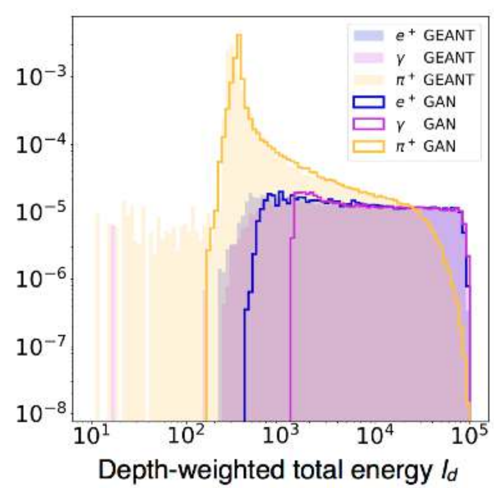
GANs for HEP

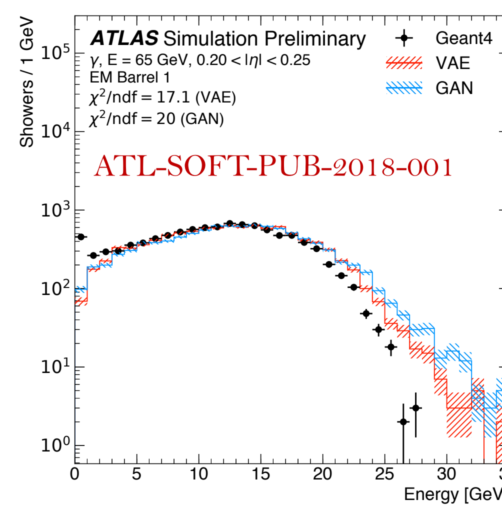


- GANs and VAEs being studied for generating Jet-images, and 3D calorimeter energy depositions in toy simulation and at the LHC experiments!



arXiv:1705.02355
arXiv:1701.05927





Directions in DL in HEP

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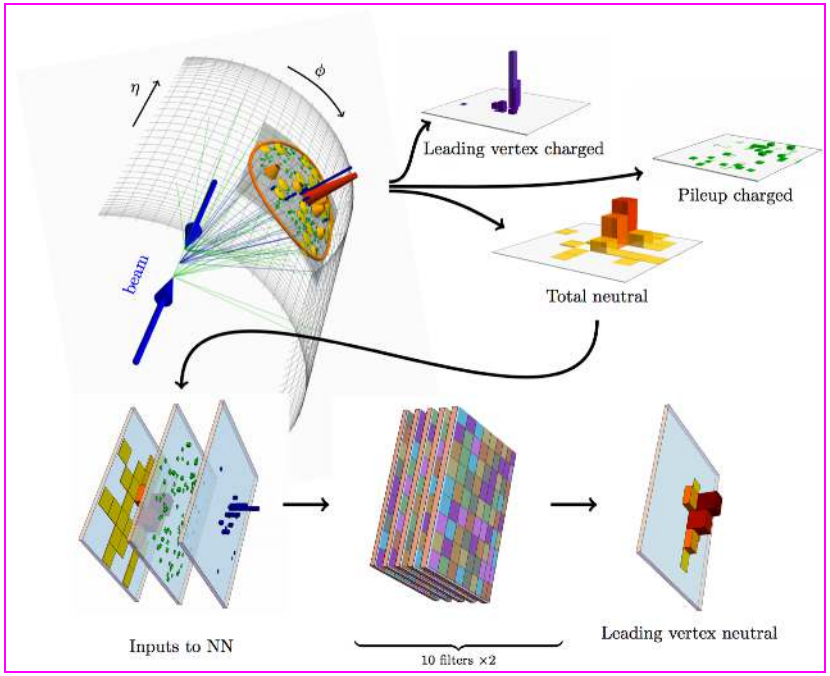
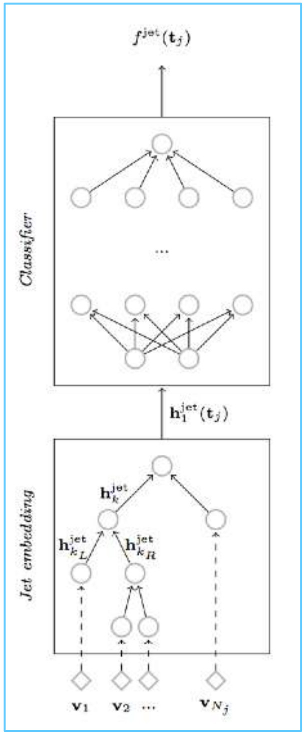
- Better understanding how to use computer vision and natural language processing techniques

- Thinking about new data structures, like trees and graphs, that can be analyzed with Deep Learning



arXiv:1707.08600



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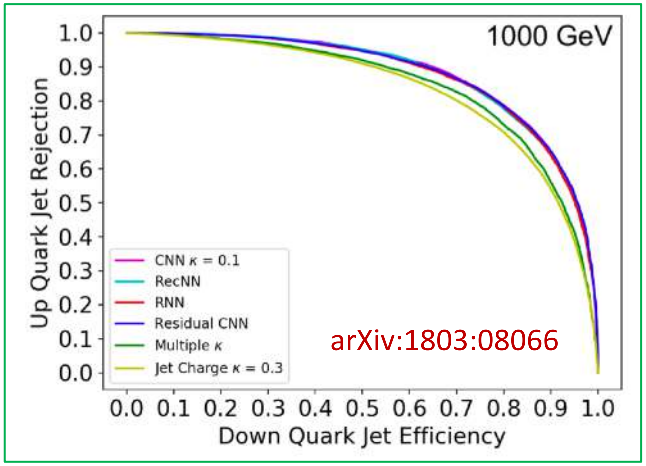

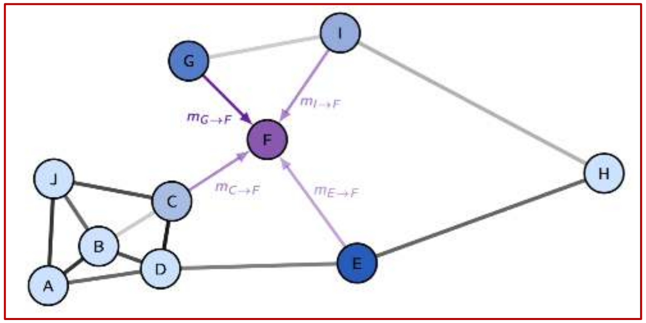

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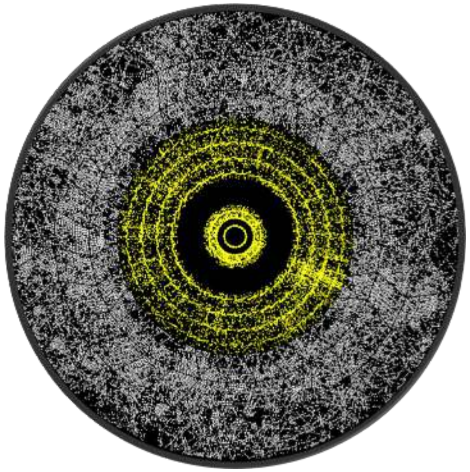
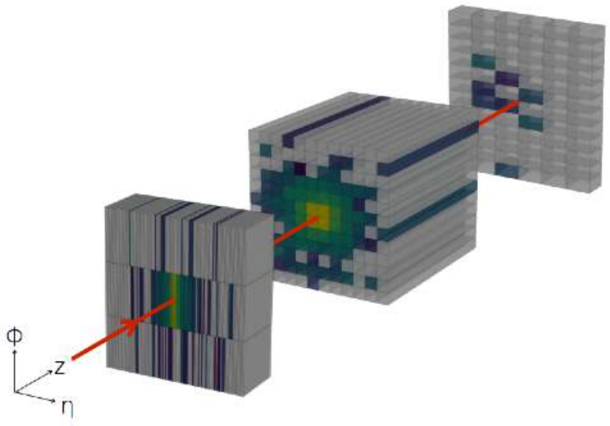
Directions in DL in HEP

- Better understanding how to use computer vision and natural language processing techniques
- Thinking about new data structures, like trees and graphs, that can be analyzed with Deep Learning
- Can ML help with our most computationally costly problems, like simulation or the combinatorial challenge of tracking?





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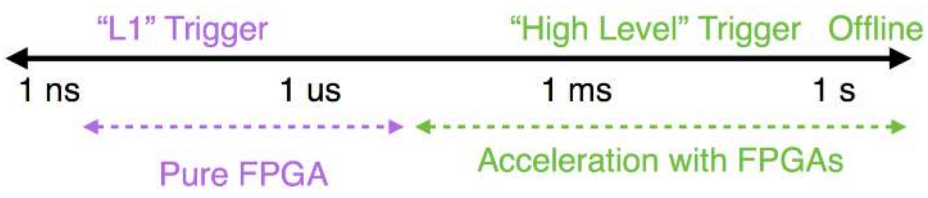

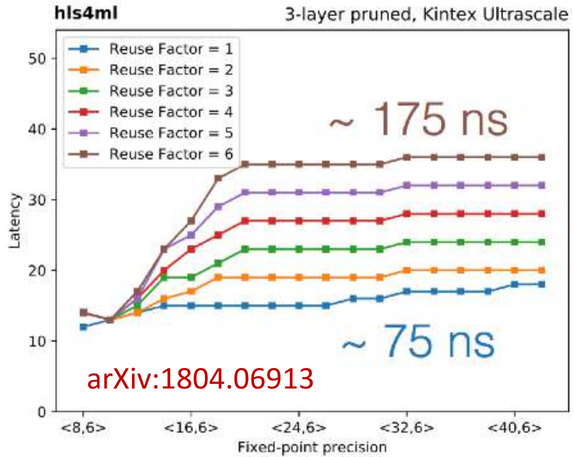

Image from:
https://indico.cern.ch/event/714134/contributions/2960185/attachments/1640629/2620365/20180426_hls4ml_kreis.pdf

Directions in DL in HEP

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- Thinking about new data structures, like trees and graphs, that can be analyzed with Deep Learning
- Can ML help with our most computationally costly problems, like simulation or the combinatorial challenge of tracking?
- Can fast O(ns-μs) NN inference be done with FPGAs to put ML early in the trigger / data acquisition process?
- Can we design better architectures and training algorithms to tackle our HEP challenges?
- How can we make best use of our simulation for inference without the PDF, i.e. Likelihood Free Inference?

Conclusion

- Just touched the surface of the rapid progress in Machine Learning in HEP

- Deep learning application developing quickly in High Energy Physics, across the whole data acquisition, simulations, and analysis pipeline

- Many new developments and performance improvements driven by thinking about HEP challenges in completely new ways

Collaborators

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