“Theoretical” Introduction

David Shih
NHETC, Rutgers University

BOOST 2019

July 22, 2019

My first BOOST conference

Why am I giving this talk?

My first BOOST conference

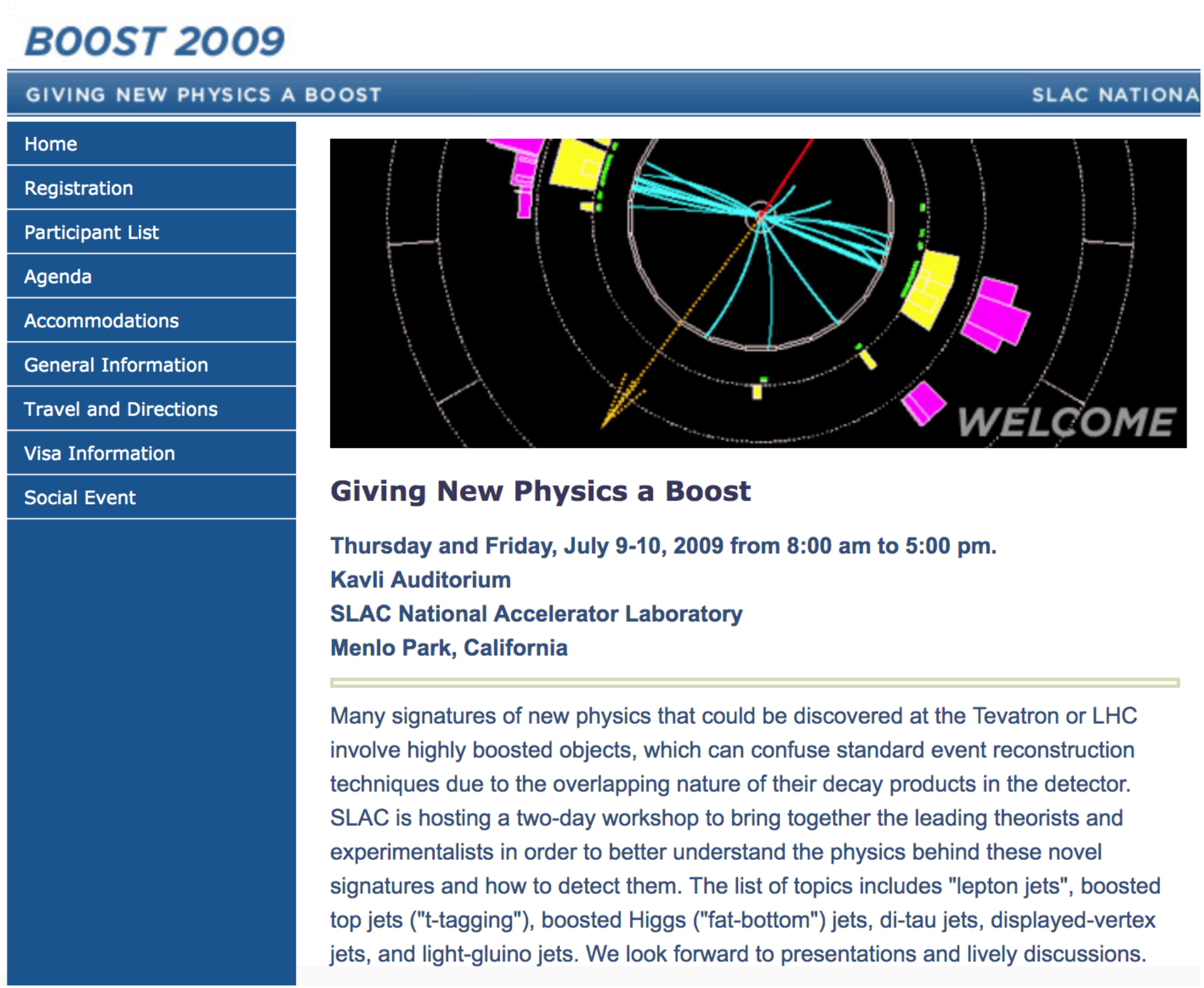
Why am I giving this talk?

Give 'em enough rope…

My first BOOST conference

“We want an outsider’s perspective…” — P. Harris

The first BOOST conference: 2009



Giving New Physics a Boost

Thursday and Friday, July 9-10, 2009 from 8:00 am to 5:00 pm.
Kavli Auditorium
SLAC National Accelerator Laboratory
Menlo Park, California

Many signatures of new physics that could be discovered at the Tevatron or LHC involve highly boosted objects, which can confuse standard event reconstruction techniques due to the overlapping nature of their decay products in the detector. SLAC is hosting a two-day workshop to bring together the leading theorists and experimentalists in order to better understand the physics behind these novel signatures and how to detect them. The list of topics includes "lepton jets", boosted top jets ("t-tagging"), boosted Higgs ("fat-bottom") jets, di-tau jets, displayed-vertex jets, and light-gluino jets. We look forward to presentations and lively discussions.

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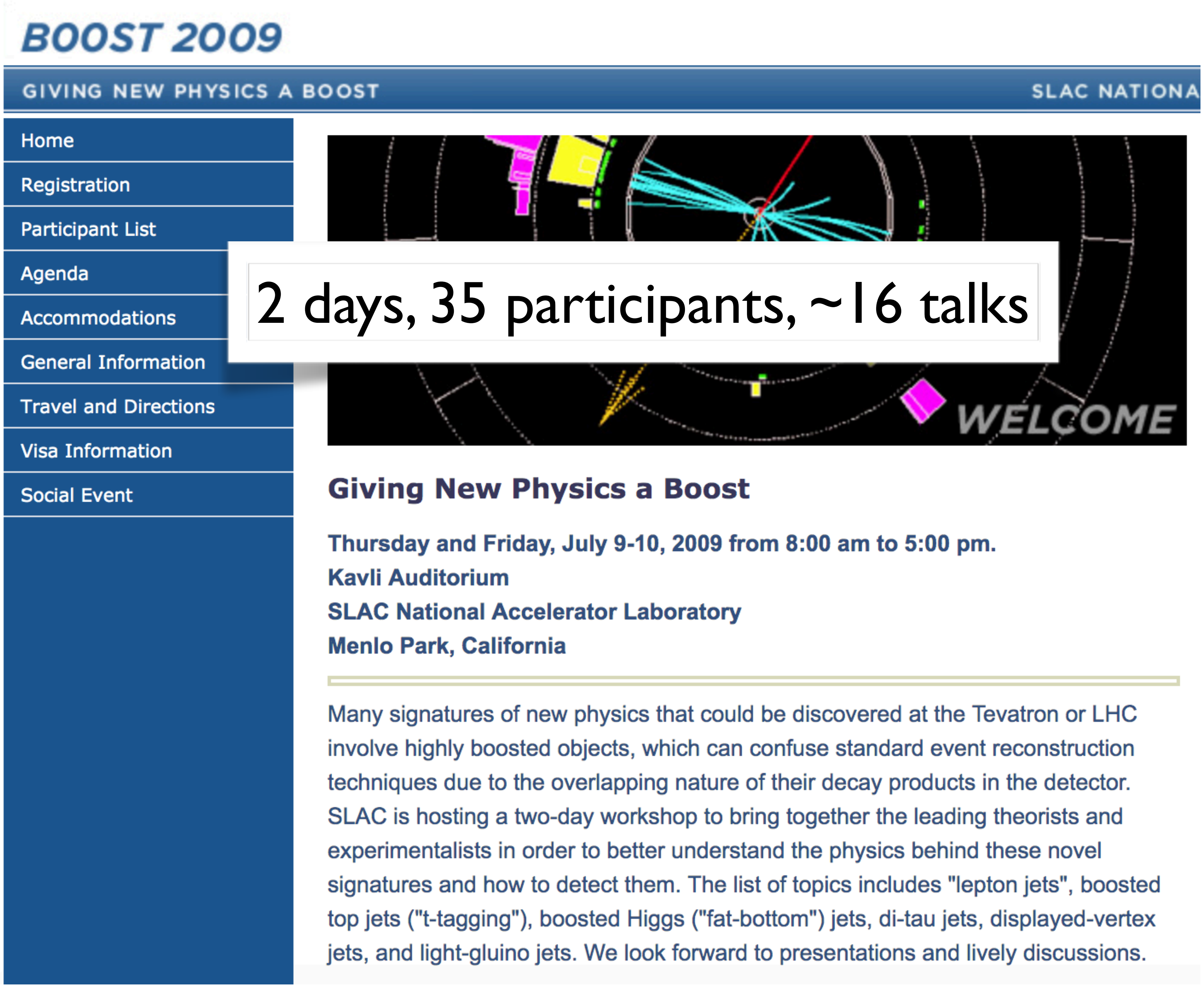

2 days, 35 participants, ~16 talks

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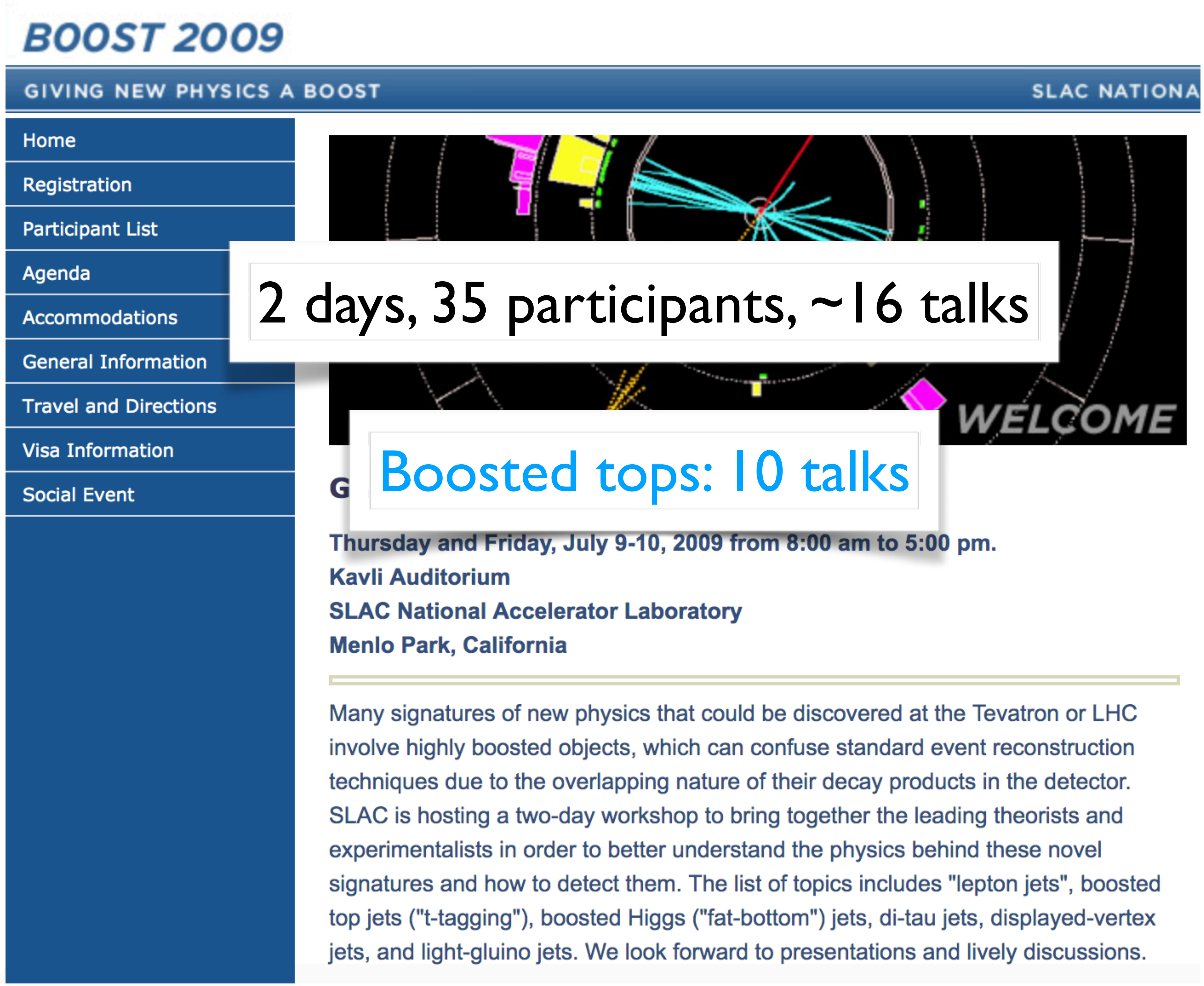

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Boosted tops: 10 talks

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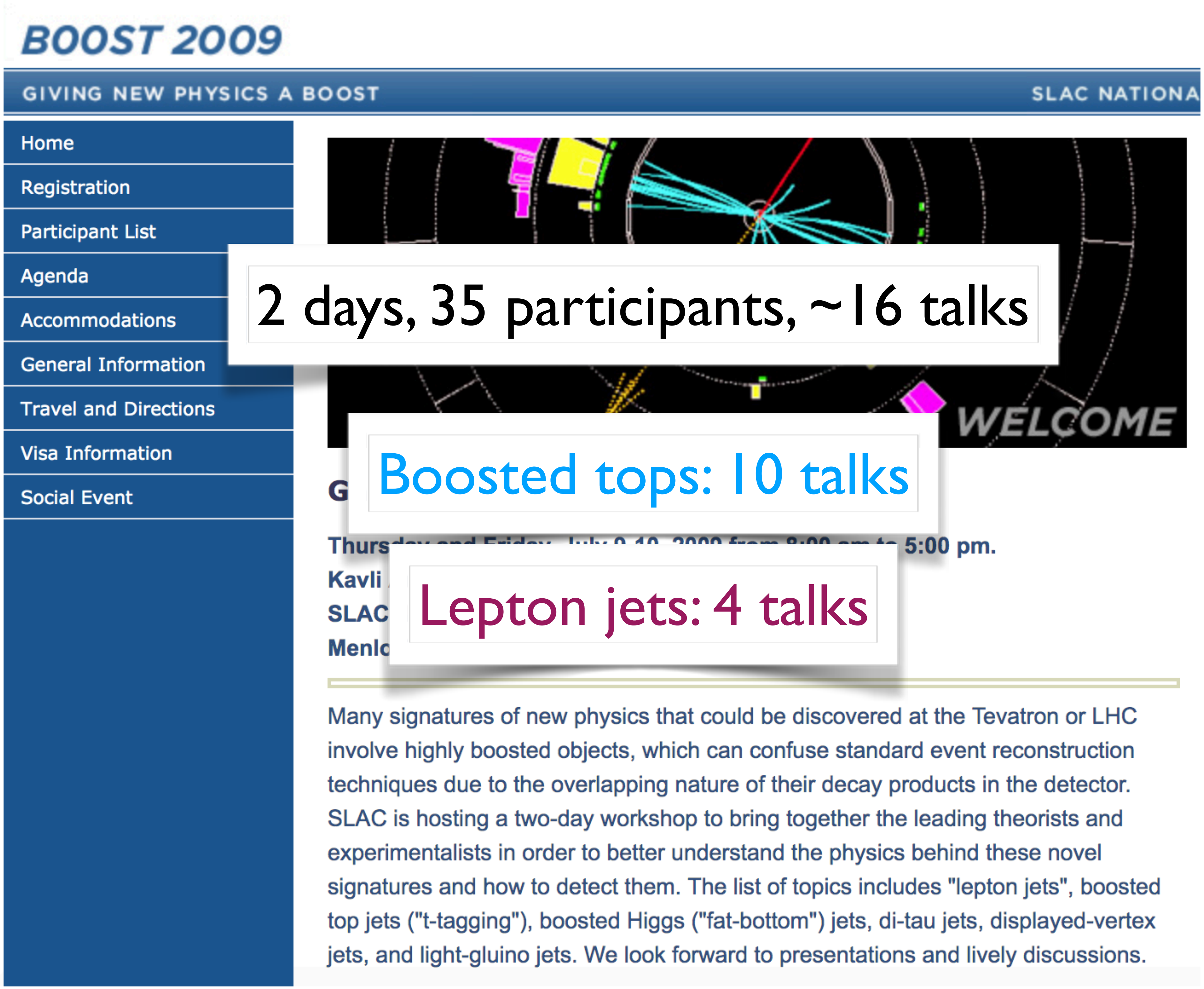

BOOST 2009

GIVING NEW PHYSICS A BOOST

SLAC NATIONA

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- Visa Information
- Social Event

2 days, 35 participants, ~16 talks

G

Boosted tops: 10 talks

Thurs

5:00 pm.

Kavli

SLAC

Menlo

Lepton jets: 4 talks

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WELCOME

G

Thurs 5:00 pm.

Kavli

SLAC

Menlo

Many signatures of new physics that could be discovered at the Tevatron or LHC

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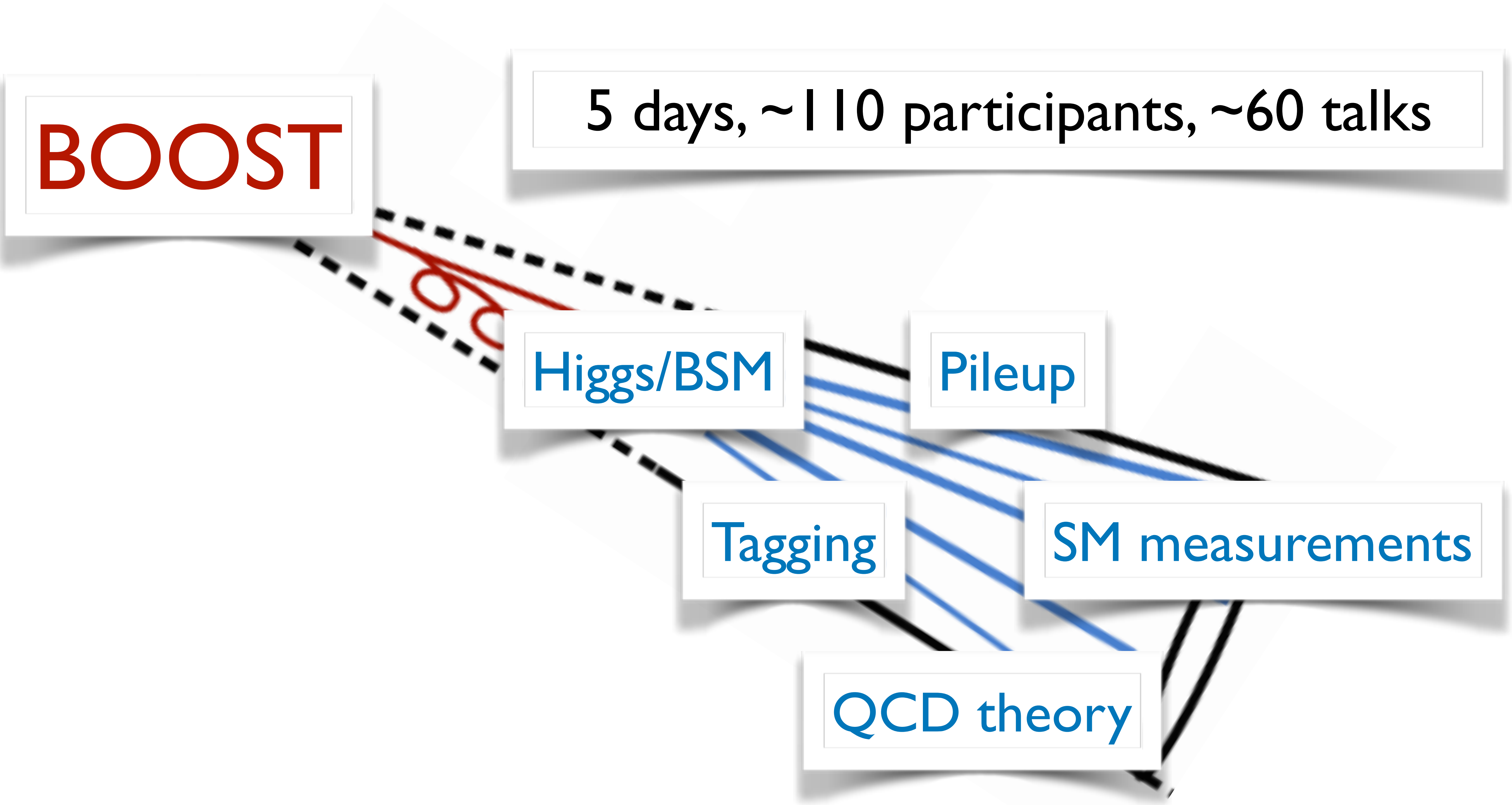
2 days, 35 participants, ~16 talks

Boosted tops: 10 talks

Lepton jets: 4 talks

BOOST = boosted tops and lepton jets !!??

This BOOST conference: 2019



BOOST

5 days, ~110 participants, ~60 talks

Higgs/BSM

Pileup

Tagging

SM measurements

QCD theory

A rich and vibrant field at the interface of theory and experiment

Purpose of this talk

Motivation

Overview / Setting the Stage

Inspiration

Purpose of this talk

Motivation

Overview / Setting the Stage

Inspiration

Disclaimer: a highly personal take, focused primarily on *BSM* and *deep learning.*

Apologies in advance that I don't cover every topic.
Stay tuned for many interesting talks at this conference!

Purpose of this talk

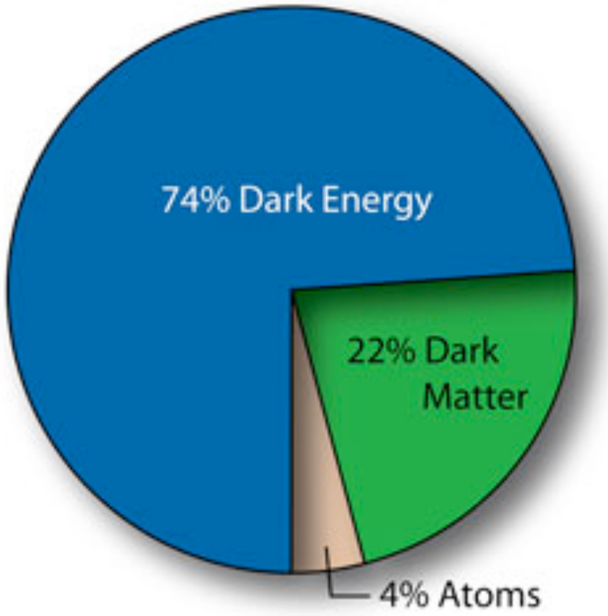
Motivation

Overview / Setting the Stage

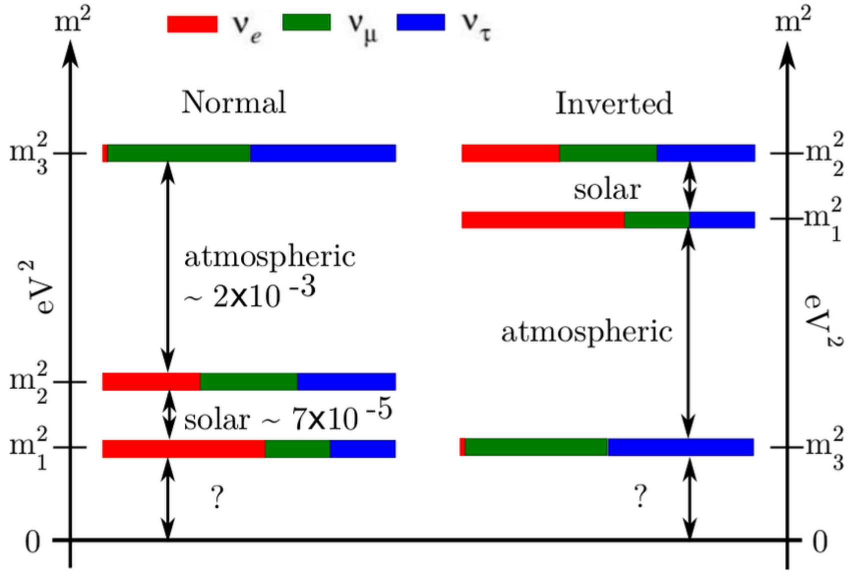
Inspiration

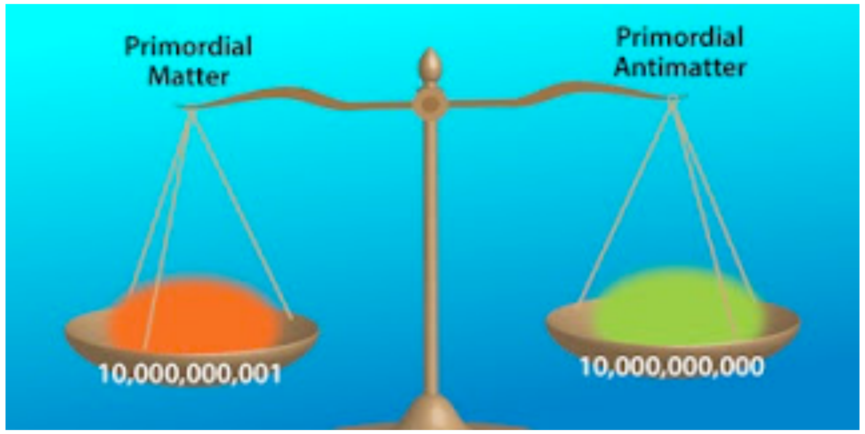
Where is the new physics????

dark matter



neutrino masses

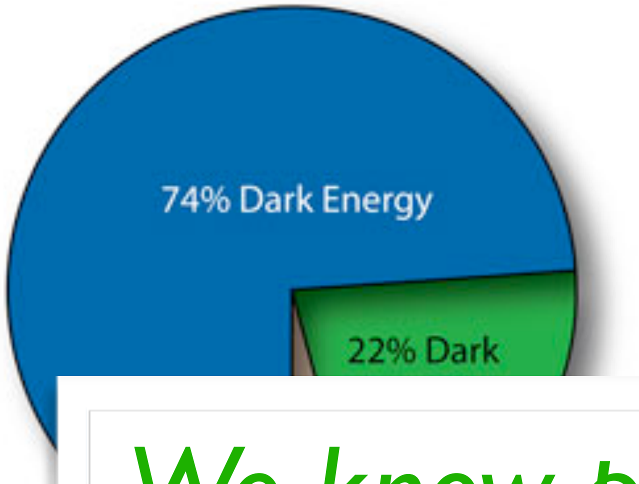




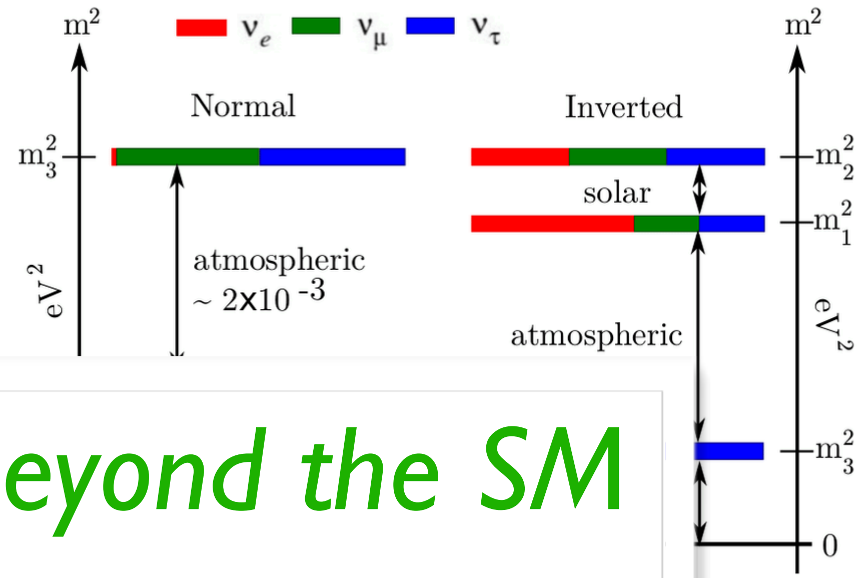
matter/anti-matter asymmetry

Where is the new physics????

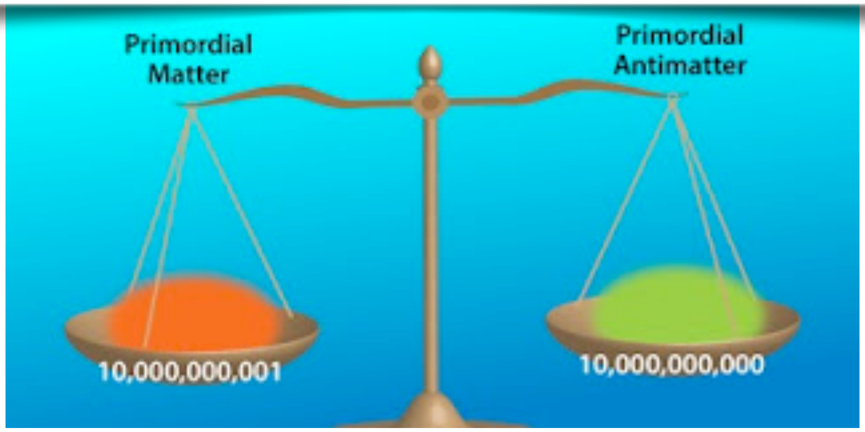
dark matter



neutrino masses



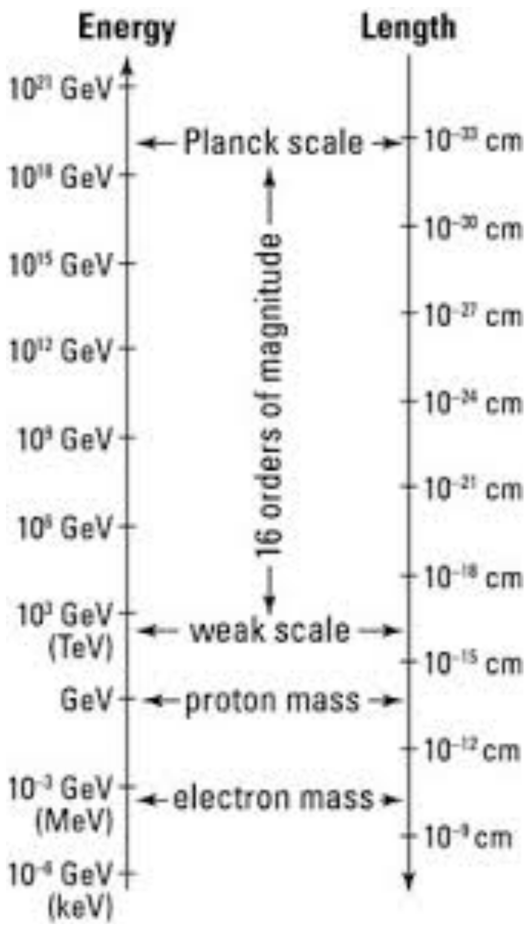
We know physics beyond the SM must exist…



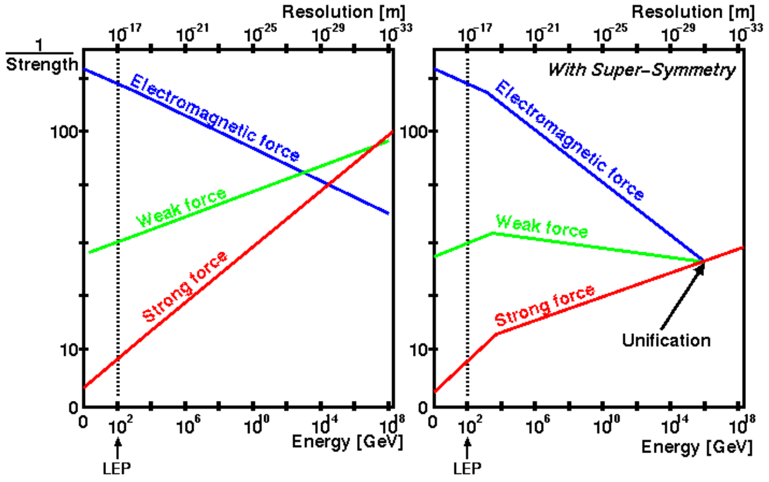
matter/anti-matter asymmetry

Where is the new physics????

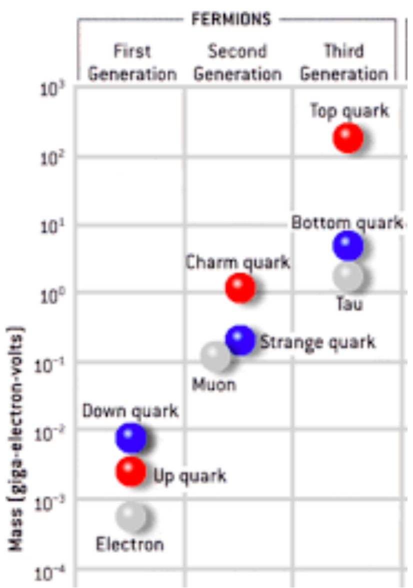
hierarchy problem



grand unification



flavor puzzle



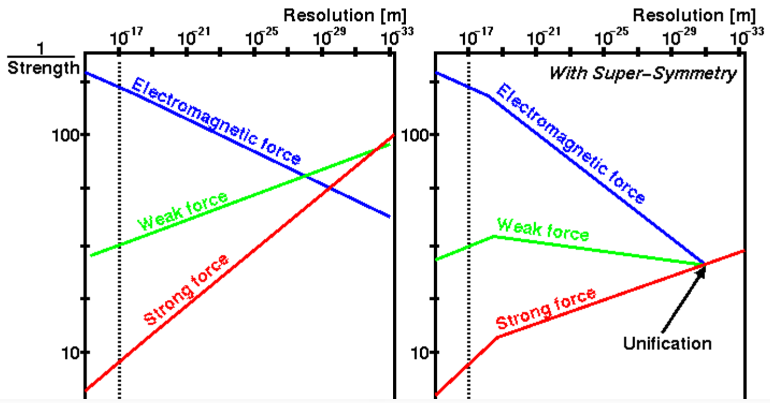
$$\mathcal{L} \supset \theta \, \frac{\alpha_s}{8\pi} G_{\mu\nu}\tilde{G}^{\mu\nu}$$

$$\theta \lesssim 10^{-10}$$

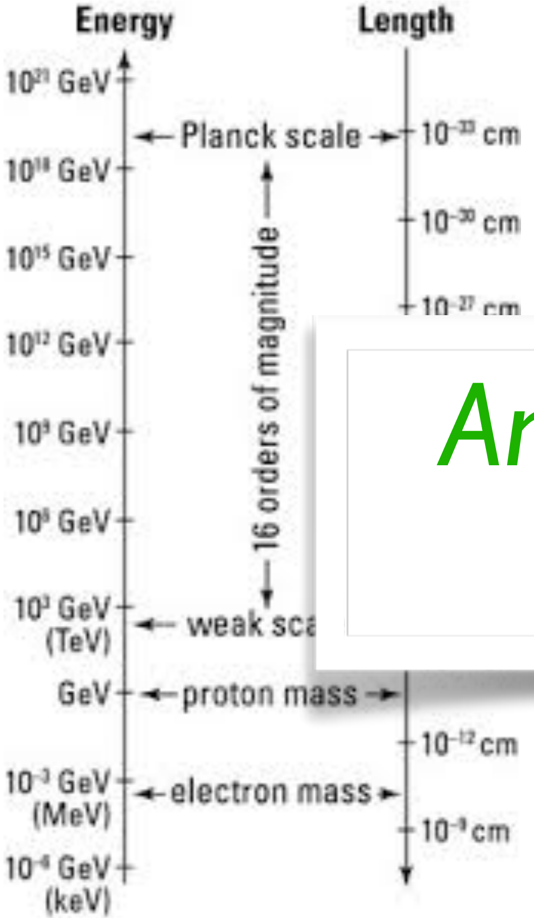
strong CP problem

Where is the new physics????

grand unification



hierarchy problem



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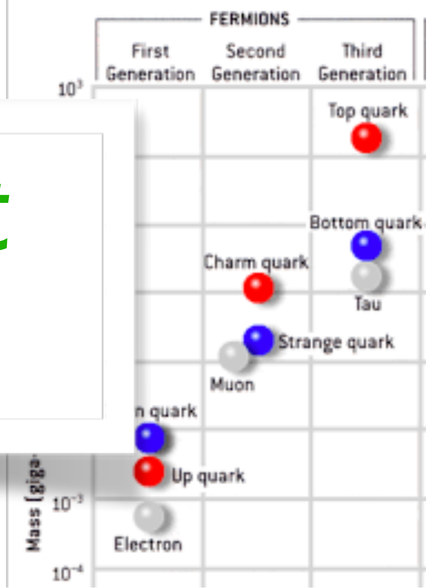


And many other puzzles hint at new physics…

$$\mathcal{L} \supset \theta \, \frac{\alpha_s}{8\pi} G_{\mu\nu}\tilde{G}^{\mu\nu}$$

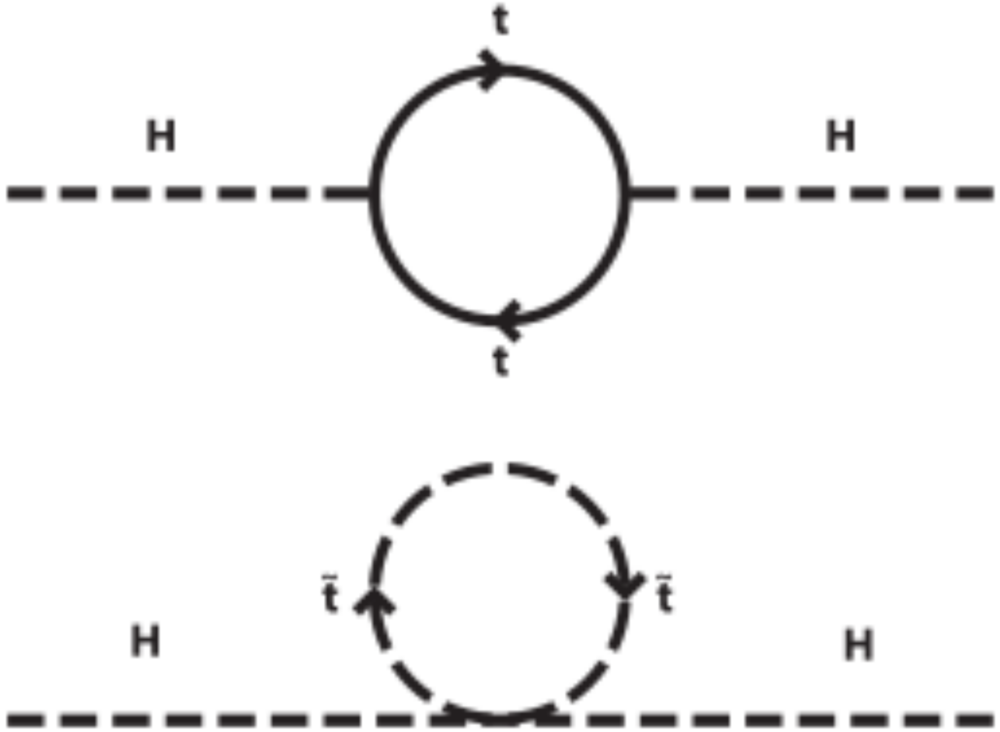
$$\theta \lesssim 10^{-10}$$

strong CP problem

Hierarchy problem

In particular, naturalness strongly motivates "top partners" at the TeV-scale.

Example: SUSY
scalar top partners (stops)



$$\delta m_h^2 \sim \frac{y_t^2}{16\pi^2}\Lambda^2 - \frac{\lambda_{\tilde{t}}}{16\pi^2}\Lambda^2$$

Hierarchy problem

In particular, naturalness strongly motivates “top partners” at the TeV-scale.

Example: composite Higgs
fermonic top parters

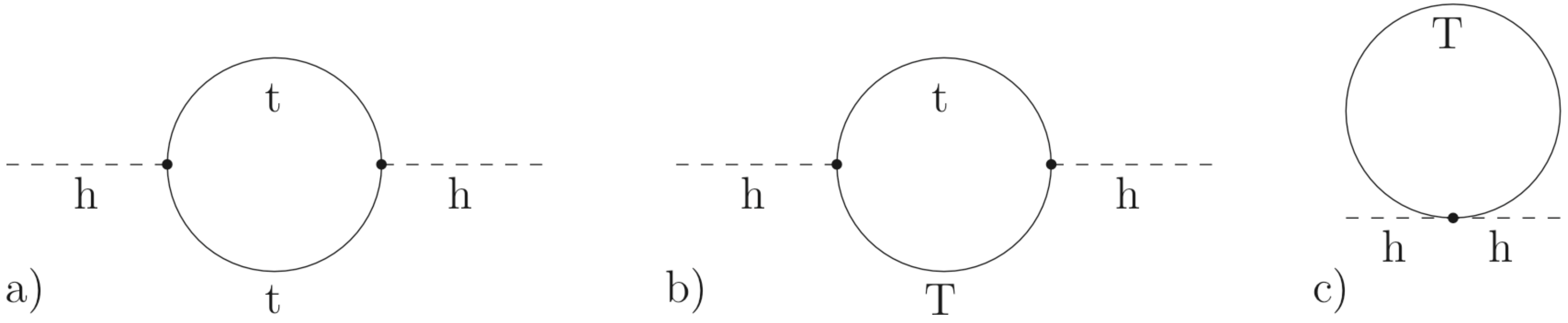
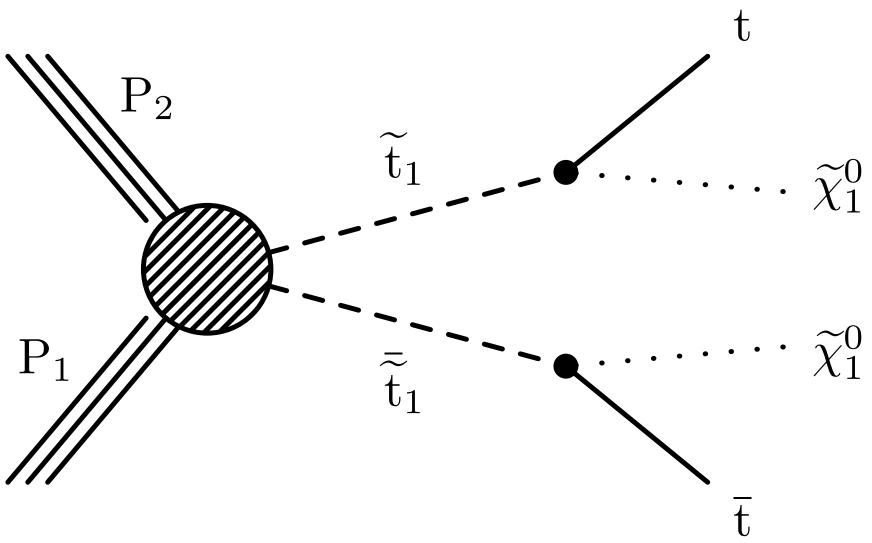


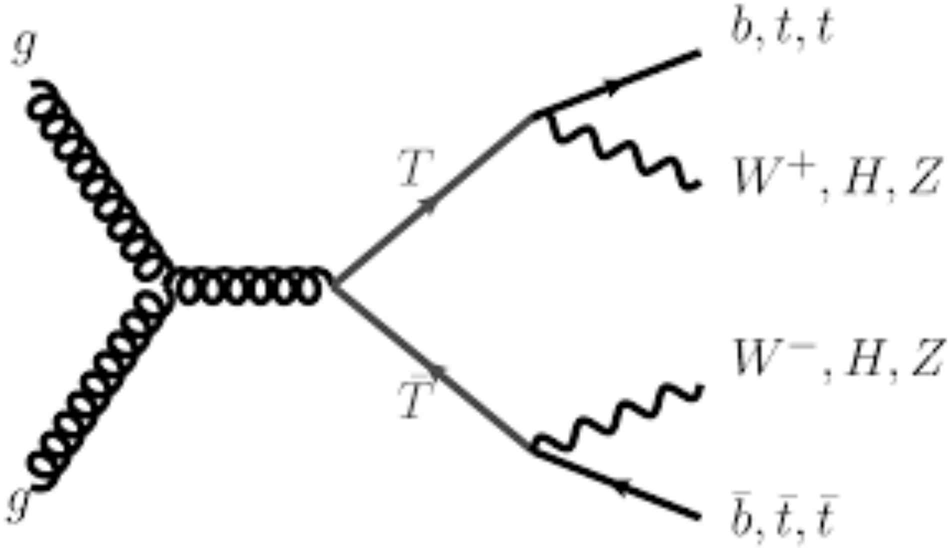
fig. from 1205.0013

Boosted jets from top partners

Decays of heavy top partners

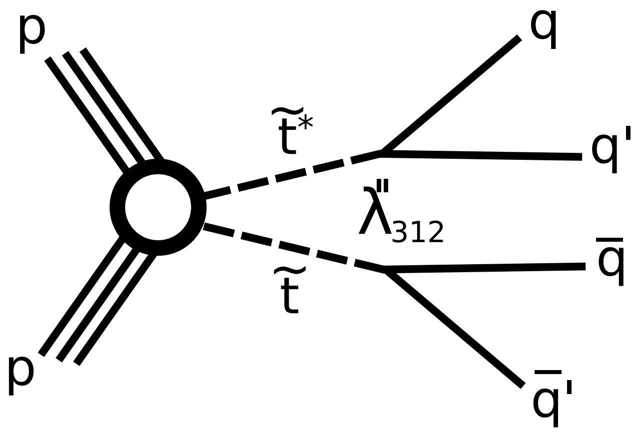
⇒ highly boosted tops, W/Z's and Higgs

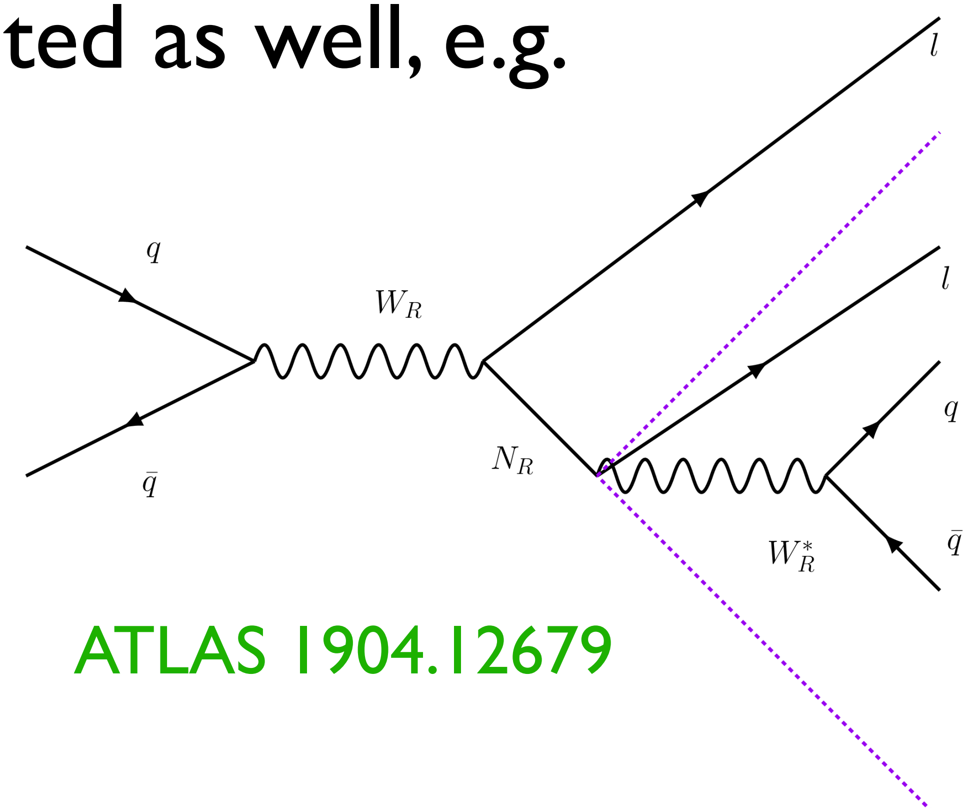




Boosted new physics

NP itself could be highly boosted as well, e.g.





ATLAS 1904.12679

+ countless other scenarios…

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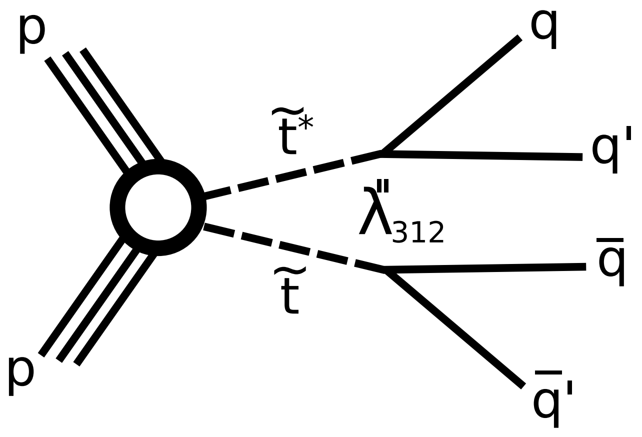

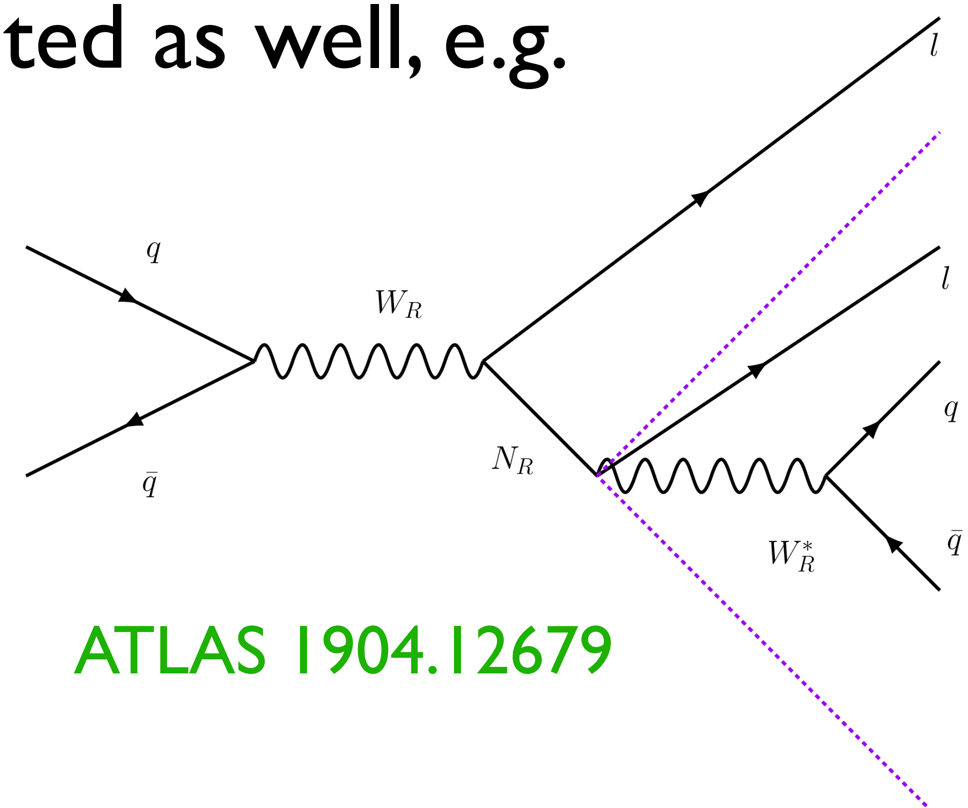

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+ countless other scenarios…

(Can we find it if we don’t know what we’re looking for??)

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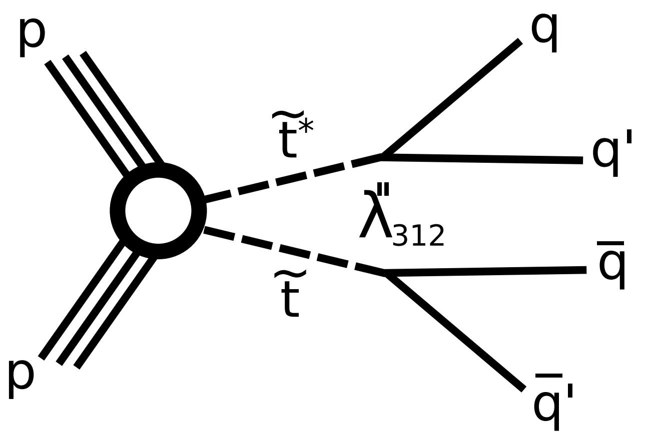

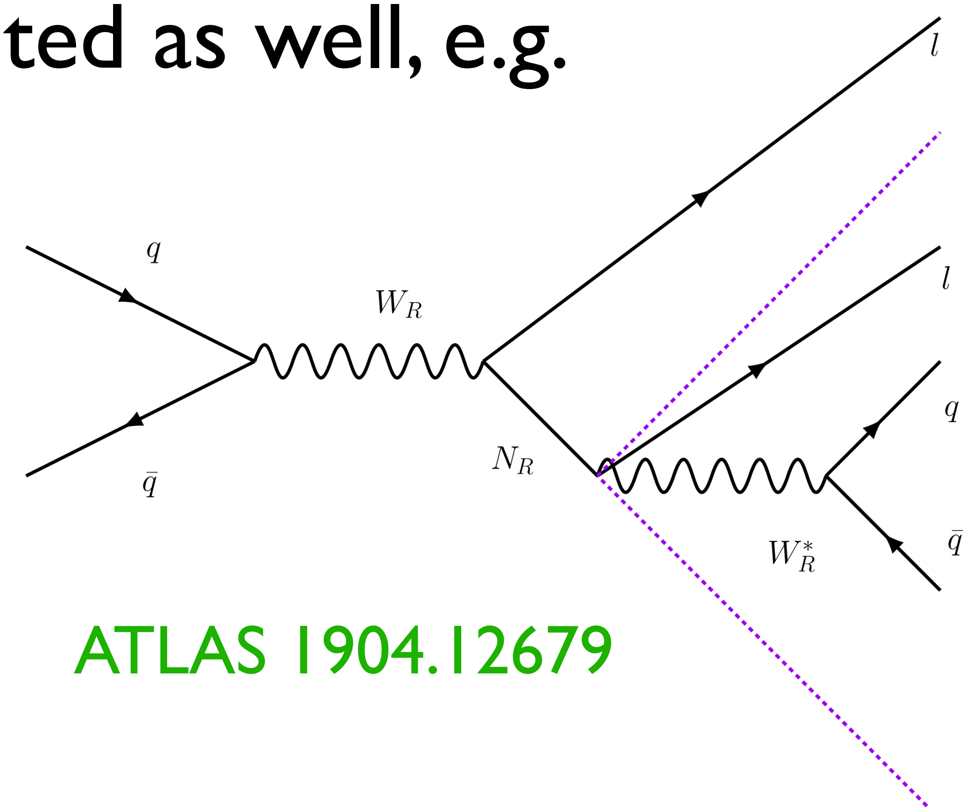

ATLAS 1904.12679

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Many opportunities for boosted jet substructure at the LHC!

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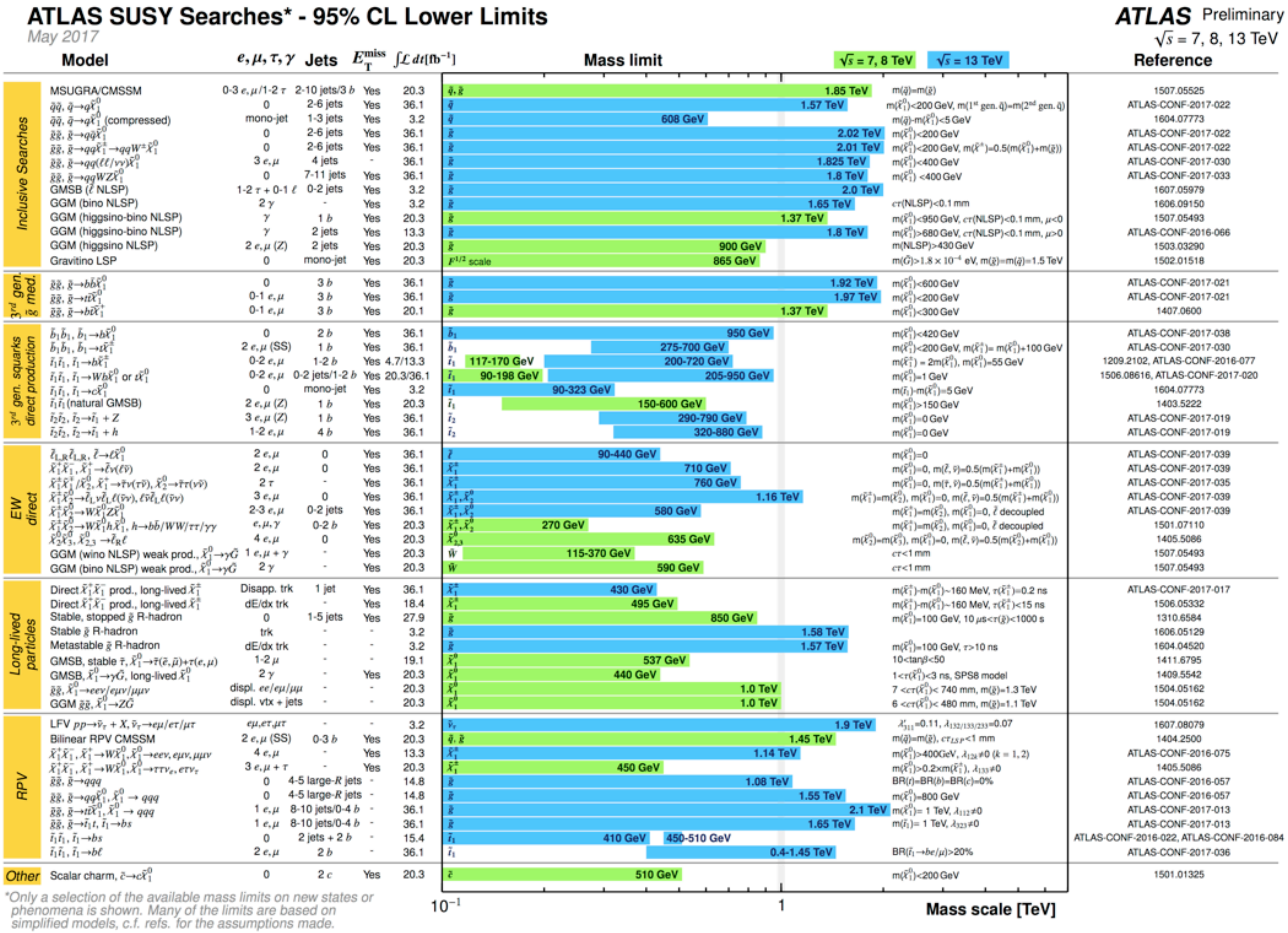


ATLAS SUSY Searches* - 95% CL Lower Limits

May 2017

ATLAS Preliminary

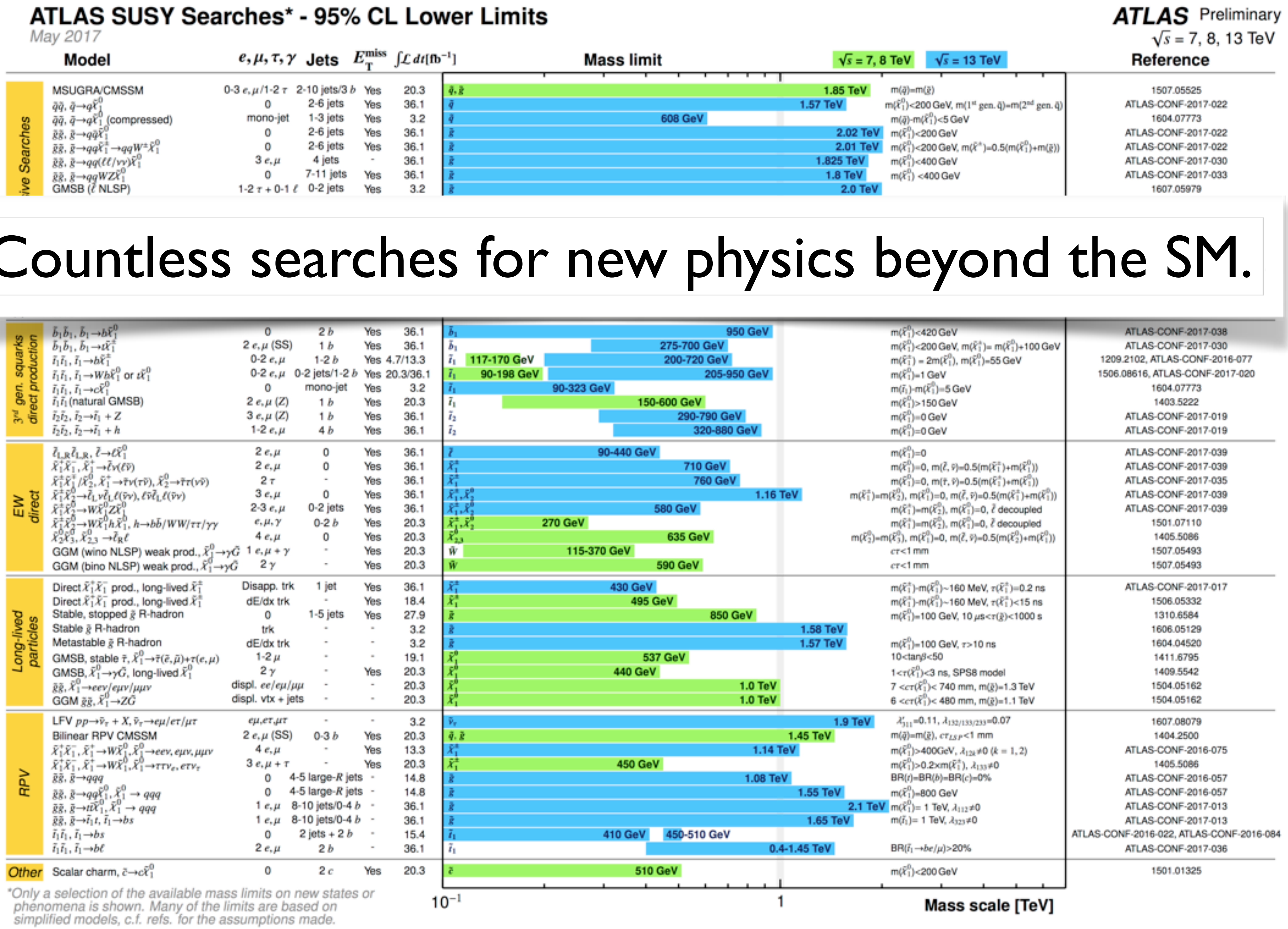
$\sqrt{s}$ = 7, 8, 13 TeV

🟩 $\sqrt{s}$ = 7, 8 TeV 🟦 $\sqrt{s}$ = 13 TeV

	Model	e, μ, τ, γ	Jets	E_T^{miss}	$\int \mathcal{L}\, dt[\text{fb}^{-1}]$	Mass limit		Reference
Inclusive Searches	MSUGRA/CMSSM	0-3 e,μ/1-2 τ	2-10 jets/3 b	Yes	20.3	$\tilde q, \tilde g$ 🟩 1.85 TeV	m($\tilde q$)=m($\tilde g$)	1507.05525
	$\tilde q\tilde q$, $\tilde q \to q\tilde\chi_1^0$	0	2-6 jets	Yes	36.1	$\tilde q$ 🟦 1.57 TeV	m($\tilde\chi_1^0$)<200 GeV, m(1st gen. $\tilde q$)=m(2nd gen. $\tilde q$)	ATLAS-CONF-2017-022
	$\tilde q\tilde q$, $\tilde q \to q\tilde\chi_1^0$ (compressed)	mono-jet	1-3 jets	Yes	3.2	$\tilde q$ 🟦 608 GeV	m($\tilde q$)-m($\tilde\chi_1^0$)<5 GeV	1604.07773
	$\tilde g\tilde g$, $\tilde g \to q\bar q\tilde\chi_1^0$	0	2-6 jets	Yes	36.1	$\tilde g$ 🟦 2.02 TeV	m($\tilde\chi_1^0$)<200 GeV	ATLAS-CONF-2017-022
	$\tilde g\tilde g$, $\tilde g \to q\bar q\tilde\chi_1^\pm \to qqW^\pm\tilde\chi_1^0$	0	2-6 jets	Yes	36.1	$\tilde g$ 🟦 2.01 TeV	m($\tilde\chi_1^0$)<200 GeV, m($\tilde\chi^\pm$)=0.5(m($\tilde\chi_1^0$)+m($\tilde g$))	ATLAS-CONF-2017-022
	$\tilde g\tilde g$, $\tilde g \to qq(\ell\ell/\nu\nu)\tilde\chi_1^0$	3 e,μ	4 jets	-	36.1	$\tilde g$ 🟦 1.825 TeV	m($\tilde\chi_1^0$)<400 GeV	ATLAS-CONF-2017-030
	$\tilde g\tilde g$, $\tilde g \to qqWZ\tilde\chi_1^0$	0	7-11 jets	Yes	36.1	$\tilde g$ 🟦 1.8 TeV	m($\tilde\chi_1^0$) <400 GeV	ATLAS-CONF-2017-033
	GMSB ($\tilde\ell$ NLSP)	1-2 τ + 0-1 ℓ	0-2 jets	Yes	3.2	$\tilde g$ 🟦 2.0 TeV		1607.05979
	GGM (bino NLSP)	2 γ	-	Yes	3.2	$\tilde g$ 🟦 1.65 TeV	$c\tau$(NLSP)<0.1 mm	1606.09150
	GGM (higgsino-bino NLSP)	γ	1 b	Yes	20.3	$\tilde g$ 🟩 1.37 TeV	m($\tilde\chi_1^0$)<950 GeV, $c\tau$(NLSP)<0.1 mm, μ<0	1507.05493
	GGM (higgsino-bino NLSP)	γ	2 jets	Yes	13.3	$\tilde g$ 🟦 1.8 TeV	m($\tilde\chi_1^0$)>680 GeV, $c\tau$(NLSP)<0.1 mm, μ>0	ATLAS-CONF-2016-066
	GGM (higgsino NLSP)	2 e,μ (Z)	2 jets	Yes	20.3	$\tilde g$ 🟩 900 GeV	m(NLSP)>430 GeV	1503.03290
	Gravitino LSP	0	mono-jet	Yes	20.3	$F^{1/2}$ scale 🟩 865 GeV	m($\tilde G$)>1.8×10^{-4} eV, m($\tilde g$)=m($\tilde q$)=1.5 TeV	1502.01518
3rd gen. $\tilde g$ med.	$\tilde g\tilde g$, $\tilde g \to b\bar b\tilde\chi_1^0$	0	3 b	Yes	36.1	$\tilde g$ 🟦 1.92 TeV	m($\tilde\chi_1^0$)<600 GeV	ATLAS-CONF-2017-021
	$\tilde g\tilde g$, $\tilde g \to t\bar t\tilde\chi_1^0$	0-1 e,μ	3 b	Yes	36.1	$\tilde g$ 🟦 1.97 TeV	m($\tilde\chi_1^0$)<200 GeV	ATLAS-CONF-2017-021
	$\tilde g\tilde g$, $\tilde g \to b\bar t\tilde\chi_1^+$	0-1 e,μ	3 b	Yes	20.1	$\tilde g$ 🟩 1.37 TeV	m($\tilde\chi_1^0$)<300 GeV	1407.0600
3rd gen. squarks direct production	$\tilde b_1\tilde b_1$, $\tilde b_1 \to b\tilde\chi_1^0$	0	2 b	Yes	36.1	$\tilde b_1$ 🟦 950 GeV	m($\tilde\chi_1^0$)<420 GeV	ATLAS-CONF-2017-038
	$\tilde b_1\tilde b_1$, $\tilde b_1 \to t\tilde\chi_1^\pm$	2 e,μ (SS)	1 b	Yes	36.1	$\tilde b_1$ 🟦 275-700 GeV	m($\tilde\chi_1^0$)<200 GeV, m($\tilde\chi_1^\pm$)= m($\tilde\chi_1^0$)+100 GeV	ATLAS-CONF-2017-030
	$\tilde t_1\tilde t_1$, $\tilde t_1 \to b\tilde\chi_1^\pm$	0-2 e,μ	1-2 b	Yes	4.7/13.3	$\tilde t_1$ 🟩 117-170 GeV 🟦 200-720 GeV	m($\tilde\chi_1^\pm$) = 2m($\tilde\chi_1^0$), m($\tilde\chi_1^0$)=55 GeV	1209.2102, ATLAS-CONF-2016-077
	$\tilde t_1\tilde t_1$, $\tilde t_1 \to Wb\tilde\chi_1^0$ or $t\tilde\chi_1^0$	0-2 e,μ	0-2 jets/1-2 b	Yes	20.3/36.1	$\tilde t_1$ 🟩 90-198 GeV 🟦 205-950 GeV	m($\tilde\chi_1^0$)=1 GeV	1506.08616, ATLAS-CONF-2017-020
	$\tilde t_1\tilde t_1$, $\tilde t_1 \to c\tilde\chi_1^0$	0	mono-jet	Yes	3.2	$\tilde t_1$ 🟦 90-323 GeV	m($\tilde t_1$)-m($\tilde\chi_1^0$)=5 GeV	1604.07773
	$\tilde t_1\tilde t_1$ (natural GMSB)	2 e,μ (Z)	1 b	Yes	20.3	$\tilde t_1$ 🟩 150-600 GeV	m($\tilde\chi_1^0$)>150 GeV	1403.5222
	$\tilde t_2\tilde t_2$, $\tilde t_2 \to \tilde t_1 + Z$	3 e,μ (Z)	1 b	Yes	36.1	$\tilde t_2$ 🟦 290-790 GeV	m($\tilde\chi_1^0$)=0 GeV	ATLAS-CONF-2017-019
	$\tilde t_2\tilde t_2$, $\tilde t_2 \to \tilde t_1 + h$	1-2 e,μ	4 b	Yes	36.1	$\tilde t_2$ 🟦 320-880 GeV	m($\tilde\chi_1^0$)=0 GeV	ATLAS-CONF-2017-019
EW direct	$\tilde\ell_{L,R}\tilde\ell_{L,R}$, $\tilde\ell \to \ell\tilde\chi_1^0$	2 e,μ	0	Yes	36.1	$\tilde\ell$ 🟦 90-440 GeV	m($\tilde\chi_1^0$)=0	ATLAS-CONF-2017-039
	$\tilde\chi_1^+\tilde\chi_1^-$, $\tilde\chi_1^+ \to \tilde\ell\nu(\ell\tilde\nu)$	2 e,μ	0	Yes	36.1	$\tilde\chi_1^\pm$ 🟦 710 GeV	m($\tilde\chi_1^0$)=0, m($\tilde\ell$, $\tilde\nu$)=0.5(m($\tilde\chi_1^\pm$)+m($\tilde\chi_1^0$))	ATLAS-CONF-2017-039
	$\tilde\chi_1^\pm\tilde\chi_1^\mp/\tilde\chi_2^0$, $\tilde\chi_1^+ \to \tilde\tau\nu(\tau\tilde\nu)$, $\tilde\chi_2^0 \to \tilde\tau\tau(\nu\tilde\nu)$	2 τ	-	Yes	36.1	$\tilde\chi_1^\pm$ 🟦 760 GeV	m($\tilde\chi_1^0$)=0, m($\tilde\tau$, $\tilde\nu$)=0.5(m($\tilde\chi_1^\pm$)+m($\tilde\chi_1^0$))	ATLAS-CONF-2017-035
	$\tilde\chi_1^\pm\tilde\chi_2^0 \to \tilde\ell_L\nu\tilde\ell_L\ell(\tilde\nu\nu)$, $\ell\tilde\nu\tilde\ell_L\ell(\tilde\nu\nu)$	3 e,μ	0	Yes	36.1	$\tilde\chi_1^\pm, \tilde\chi_2^0$ 🟦 1.16 TeV	m($\tilde\chi_1^\pm$)=m($\tilde\chi_2^0$), m($\tilde\chi_1^0$)=0, m($\tilde\ell$, $\tilde\nu$)=0.5(m($\tilde\chi_1^\pm$)+m($\tilde\chi_1^0$))	ATLAS-CONF-2017-039
	$\tilde\chi_1^\pm\tilde\chi_2^0 \to W\tilde\chi_1^0 Z\tilde\chi_1^0$	2-3 e,μ	0-2 jets	Yes	36.1	$\tilde\chi_1^\pm, \tilde\chi_2^0$ 🟦 580 GeV	m($\tilde\chi_1^\pm$)=m($\tilde\chi_2^0$), m($\tilde\chi_1^0$)=0, $\tilde\ell$ decoupled	ATLAS-CONF-2017-039
	$\tilde\chi_1^\pm\tilde\chi_2^0 \to W\tilde\chi_1^0 h\tilde\chi_1^0$, $h \to b\bar b/WW/\tau\tau/\gamma\gamma$	e,μ,γ	0-2 b	Yes	20.3	$\tilde\chi_1^\pm, \tilde\chi_2^0$ 🟩 270 GeV	m($\tilde\chi_1^\pm$)=m($\tilde\chi_2^0$), m($\tilde\chi_1^0$)=0, $\tilde\ell$ decoupled	1501.07110
	$\tilde\chi_2^0\tilde\chi_3^0$, $\tilde\chi_{2,3}^0 \to \tilde\ell_R\ell$	4 e,μ	0	Yes	20.3	$\tilde\chi_{2,3}^0$ 🟩 635 GeV	m($\tilde\chi_2^0$)=m($\tilde\chi_3^0$), m($\tilde\chi_1^0$)=0, m($\tilde\ell$, $\tilde\nu$)=0.5(m($\tilde\chi_2^0$)+m($\tilde\chi_1^0$))	1405.5086
	GGM (wino NLSP) weak prod., $\tilde\chi_1^0 \to \gamma\tilde G$	1 e,μ + γ	-	Yes	20.3	$\tilde W$ 🟩 115-370 GeV	$c\tau$<1 mm	1507.05493
	GGM (bino NLSP) weak prod., $\tilde\chi_1^0 \to \gamma\tilde G$	2 γ	-	Yes	20.3	$\tilde W$ 🟩 590 GeV	$c\tau$<1 mm	1507.05493
Long-lived particles	Direct $\tilde\chi_1^+\tilde\chi_1^-$ prod., long-lived $\tilde\chi_1^\pm$	Disapp. trk	1 jet	Yes	36.1	$\tilde\chi_1^\pm$ 🟦 430 GeV	m($\tilde\chi_1^\pm$)-m($\tilde\chi_1^0$)~160 MeV, τ($\tilde\chi_1^\pm$)=0.2 ns	ATLAS-CONF-2017-017
	Direct $\tilde\chi_1^+\tilde\chi_1^-$ prod., long-lived $\tilde\chi_1^\pm$	dE/dx trk	-	Yes	18.4	$\tilde\chi_1^\pm$ 🟩 495 GeV	m($\tilde\chi_1^\pm$)-m($\tilde\chi_1^0$)~160 MeV, τ($\tilde\chi_1^\pm$)<15 ns	1506.05332
	Stable, stopped $\tilde g$ R-hadron	0	1-5 jets	Yes	27.9	$\tilde g$ 🟩 850 GeV	m($\tilde\chi_1^0$)=100 GeV, 10 μs<τ($\tilde g$)<1000 s	1310.6584
	Stable $\tilde g$ R-hadron	trk	-	-	3.2	$\tilde g$ 🟦 1.58 TeV		1606.05129
	Metastable $\tilde g$ R-hadron	dE/dx trk	-	-	3.2	$\tilde g$ 🟦 1.57 TeV	m($\tilde\chi_1^0$)=100 GeV, τ>10 ns	1604.04520
	GMSB, stable $\tilde\tau$, $\tilde\chi_1^0 \to \tilde\tau(\tilde e, \tilde\mu)+\tau(e,\mu)$	1-2 μ	-	-	19.1	$\tilde\chi_1^0$ 🟩 537 GeV	10<tanβ<50	1411.6795
	GMSB, $\tilde\chi_1^0 \to \gamma\tilde G$, long-lived $\tilde\chi_1^0$	2 γ	-	Yes	20.3	$\tilde\chi_1^0$ 🟩 440 GeV	1<τ($\tilde\chi_1^0$)<3 ns, SPS8 model	1409.5542
	$\tilde g\tilde g$, $\tilde\chi_1^0 \to ee\nu/e\mu\nu/\mu\mu\nu$	displ. $ee/e\mu/\mu\mu$	-	-	20.3	$\tilde\chi_1^0$ 🟩 1.0 TeV	7 <$c\tau$($\tilde\chi_1^0$)< 740 mm, m($\tilde g$)=1.3 TeV	1504.05162
	GGM $\tilde g\tilde g$, $\tilde\chi_1^0 \to Z\tilde G$	displ. vtx + jets	-	-	20.3	$\tilde\chi_1^0$ 🟩 1.0 TeV	6 <$c\tau$($\tilde\chi_1^0$)< 480 mm, m($\tilde g$)=1.1 TeV	1504.05162
RPV	LFV $pp \to \tilde\nu_\tau + X, \tilde\nu_\tau \to e\mu/e\tau/\mu\tau$	$e\mu, e\tau, \mu\tau$	-	-	3.2	$\tilde\nu_\tau$ 🟦 1.9 TeV	λ'_{311}=0.11, $\lambda_{132/133/233}$=0.07	1607.08079
	Bilinear RPV CMSSM	2 e,μ (SS)	0-3 b	Yes	20.3	$\tilde q, \tilde g$ 🟩 1.45 TeV	m($\tilde q$)=m($\tilde g$), $c\tau_{LSP}$<1 mm	1404.2500
	$\tilde\chi_1^+\tilde\chi_1^-$, $\tilde\chi_1^+ \to W\tilde\chi_1^0$, $\tilde\chi_1^0 \to ee\nu, e\mu\nu, \mu\mu\nu$	4 e,μ	-	Yes	13.3	$\tilde\chi_1^\pm$ 🟦 1.14 TeV	m($\tilde\chi_1^0$)>400GeV, $\lambda_{12k}\neq0$ (k = 1, 2)	ATLAS-CONF-2016-075
	$\tilde\chi_1^+\tilde\chi_1^-$, $\tilde\chi_1^+ \to W\tilde\chi_1^0$, $\tilde\chi_1^0 \to \tau\tau\nu_e, e\tau\nu_\tau$	3 e,μ + τ	-	Yes	20.3	$\tilde\chi_1^\pm$ 🟩 450 GeV	m($\tilde\chi_1^0$)>0.2×m($\tilde\chi_1^\pm$), $\lambda_{133}\neq0$	1405.5086
	$\tilde g\tilde g$, $\tilde g \to qqq$	0	4-5 large-R jets	-	14.8	$\tilde g$ 🟦 1.08 TeV	BR(t)=BR(b)=BR(c)=0%	ATLAS-CONF-2016-057
	$\tilde g\tilde g$, $\tilde g \to qq\tilde\chi_1^0$, $\tilde\chi_1^0 \to qqq$	0	4-5 large-R jets	-	14.8	$\tilde g$ 🟦 1.55 TeV	m($\tilde\chi_1^0$)=800 GeV	ATLAS-CONF-2016-057
	$\tilde g\tilde g$, $\tilde g \to t\bar t\tilde\chi_1^0$, $\tilde\chi_1^0 \to qqq$	1 e,μ	8-10 jets/0-4 b	-	36.1	$\tilde g$ 🟦 2.1 TeV	m($\tilde\chi_1^0$)= 1 TeV, $\lambda_{112}\neq0$	ATLAS-CONF-2017-013
	$\tilde g\tilde g$, $\tilde g \to \tilde t_1 t$, $\tilde t_1 \to bs$	1 e,μ	8-10 jets/0-4 b	-	36.1	$\tilde g$ 🟦 1.65 TeV	m($\tilde t_1$)= 1 TeV, $\lambda_{323}\neq0$	ATLAS-CONF-2017-013
	$\tilde t_1\tilde t_1$, $\tilde t_1 \to bs$	0	2 jets + 2 b	-	15.4	$\tilde t_1$ 🟦 410 GeV 🟦 450-510 GeV		ATLAS-CONF-2016-022, ATLAS-CONF-2016-084
	$\tilde t_1\tilde t_1$, $\tilde t_1 \to b\ell$	2 e,μ	2 b	-	36.1	$\tilde t_1$ 🟦 0.4-1.45 TeV	BR($\tilde t_1 \to be/\mu$)>20%	ATLAS-CONF-2017-036
Other	Scalar charm, $\tilde c \to c\tilde\chi_1^0$	0	2 c	Yes	20.3	$\tilde c$ 🟩 510 GeV	m($\tilde\chi_1^0$)<200 GeV	1501.01325

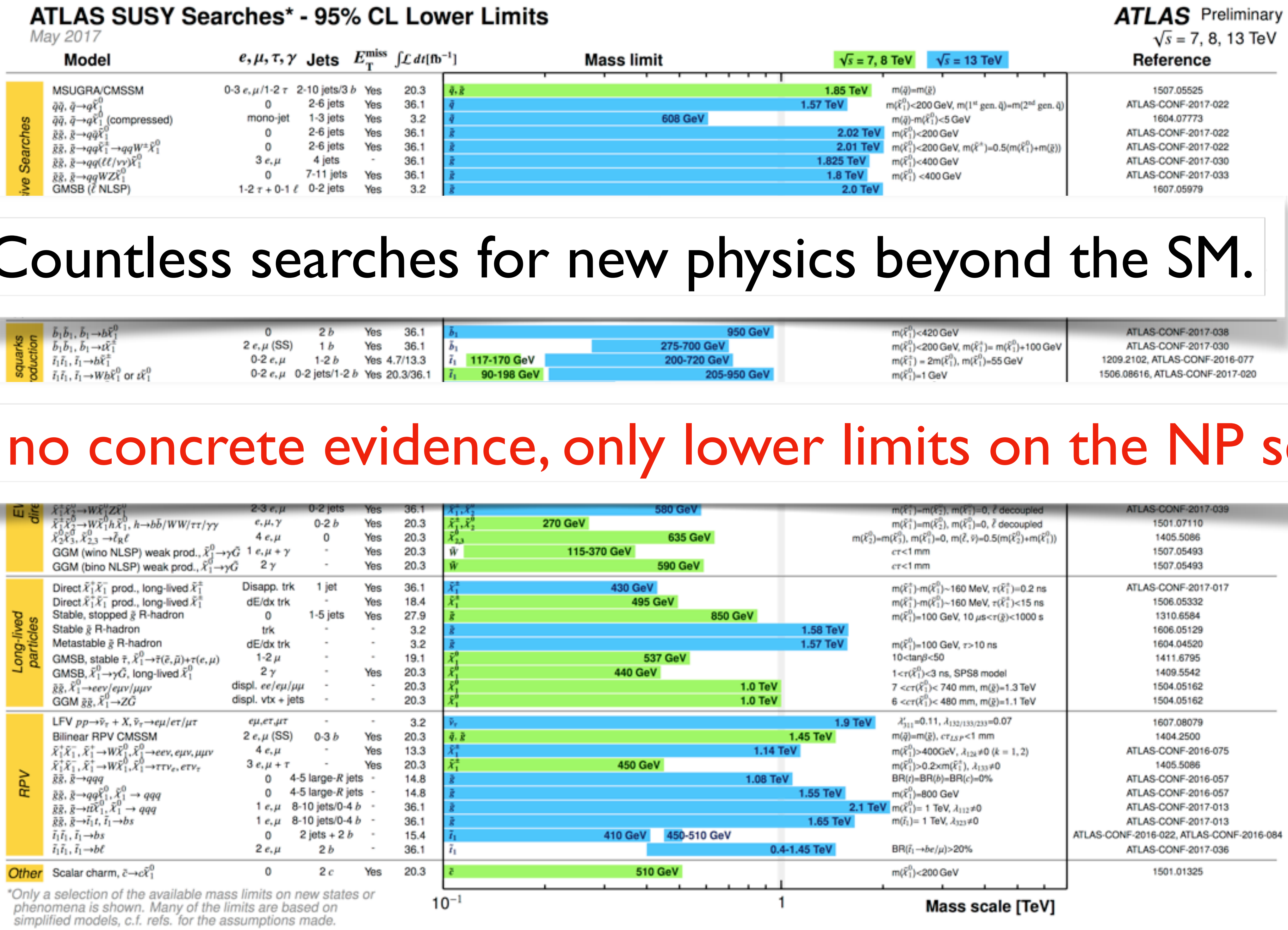
*Only a selection of the available mass limits on new states or phenomena is shown. Many of the limits are based on simplified models, c.f. refs. for the assumptions made.

Where is the new physics????



Countless searches for new physics beyond the SM.

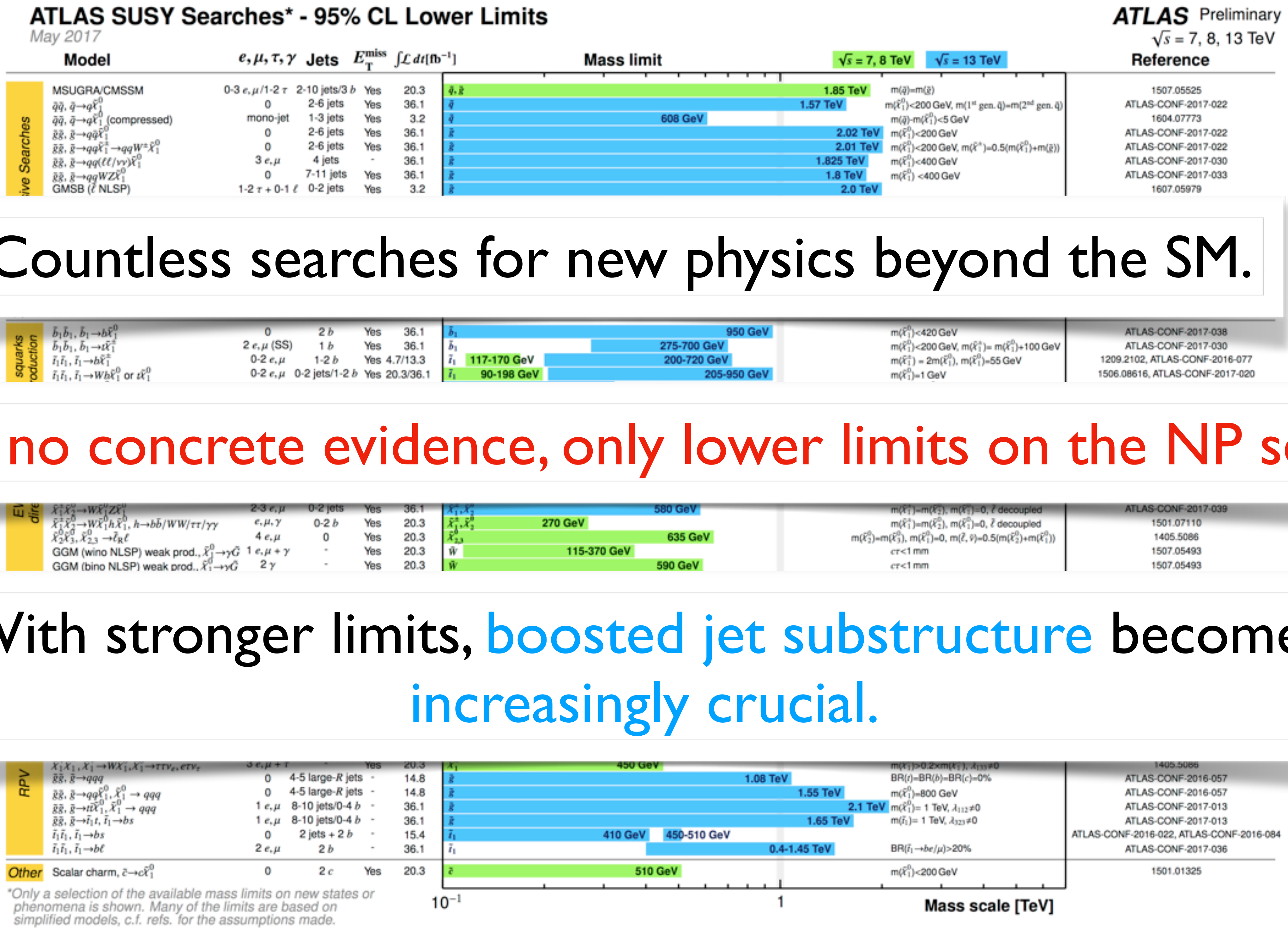
Where is the new physics????



Countless searches for new physics beyond the SM.

So far no concrete evidence, only lower limits on the NP scale.

Where is the new physics????

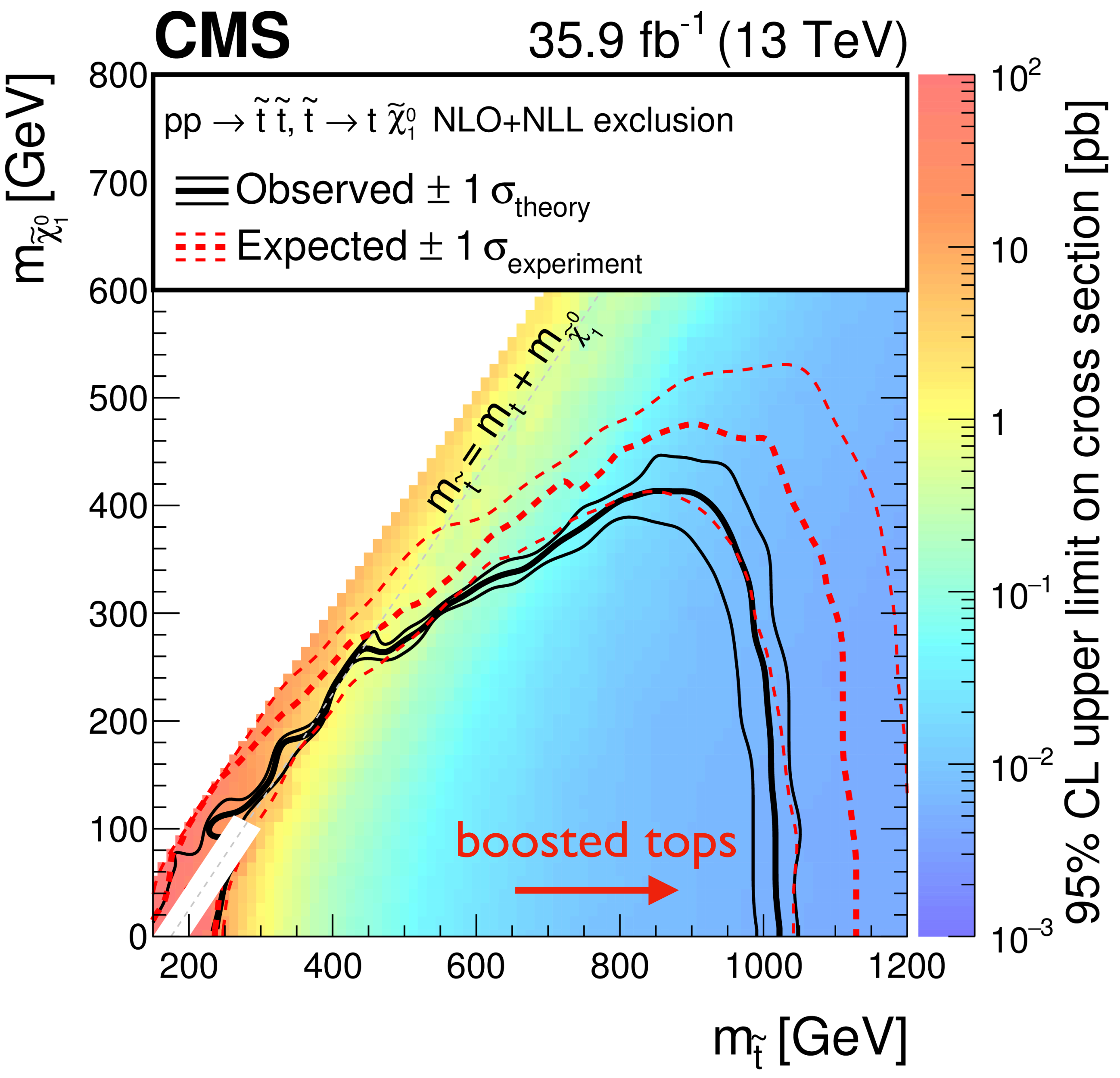


Countless searches for new physics beyond the SM.

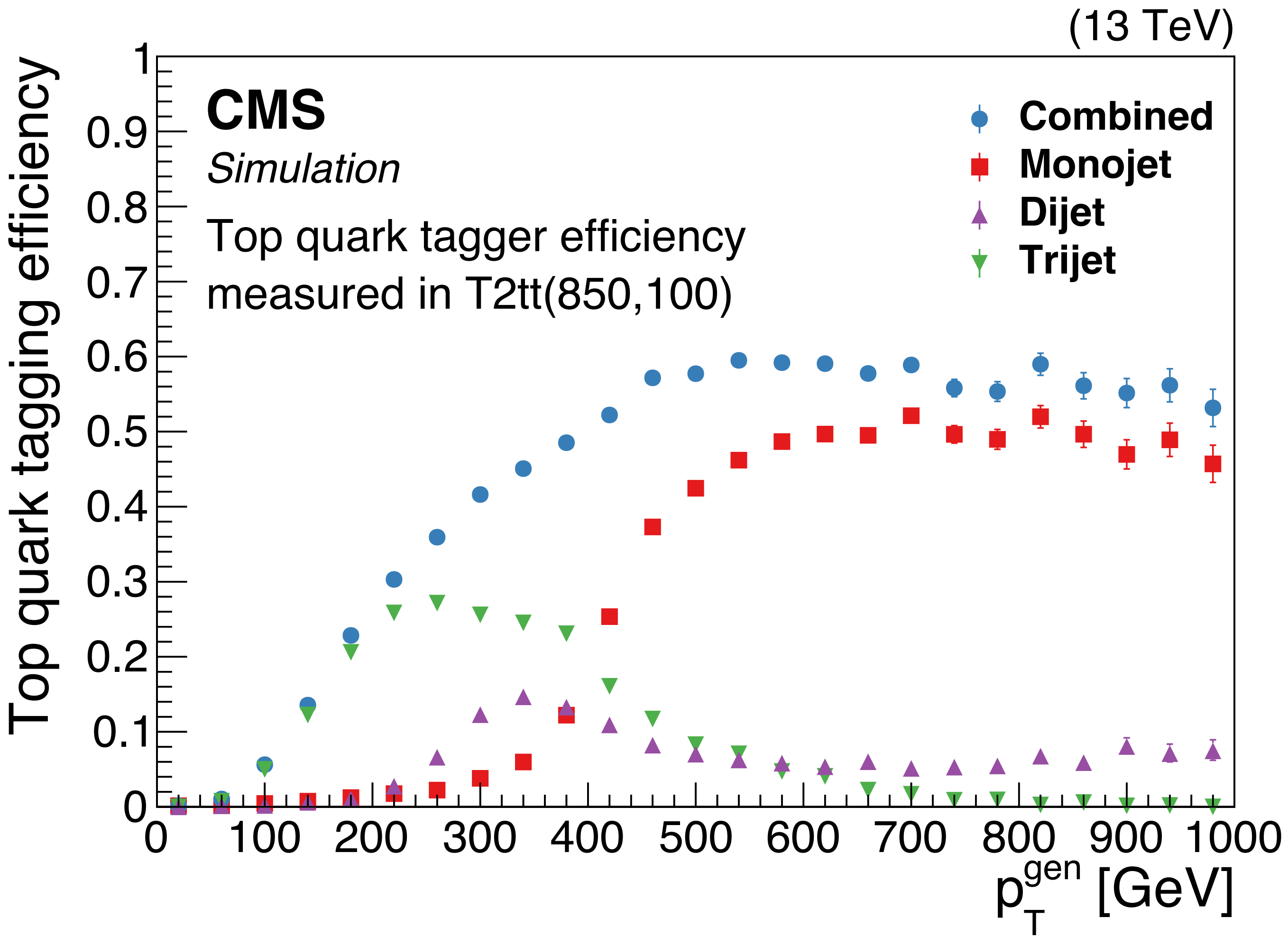
So far no concrete evidence, only lower limits on the NP scale.

With stronger limits, boosted jet substructure becomes increasingly crucial.

Example: stop searches



(CMS 1710.11188)

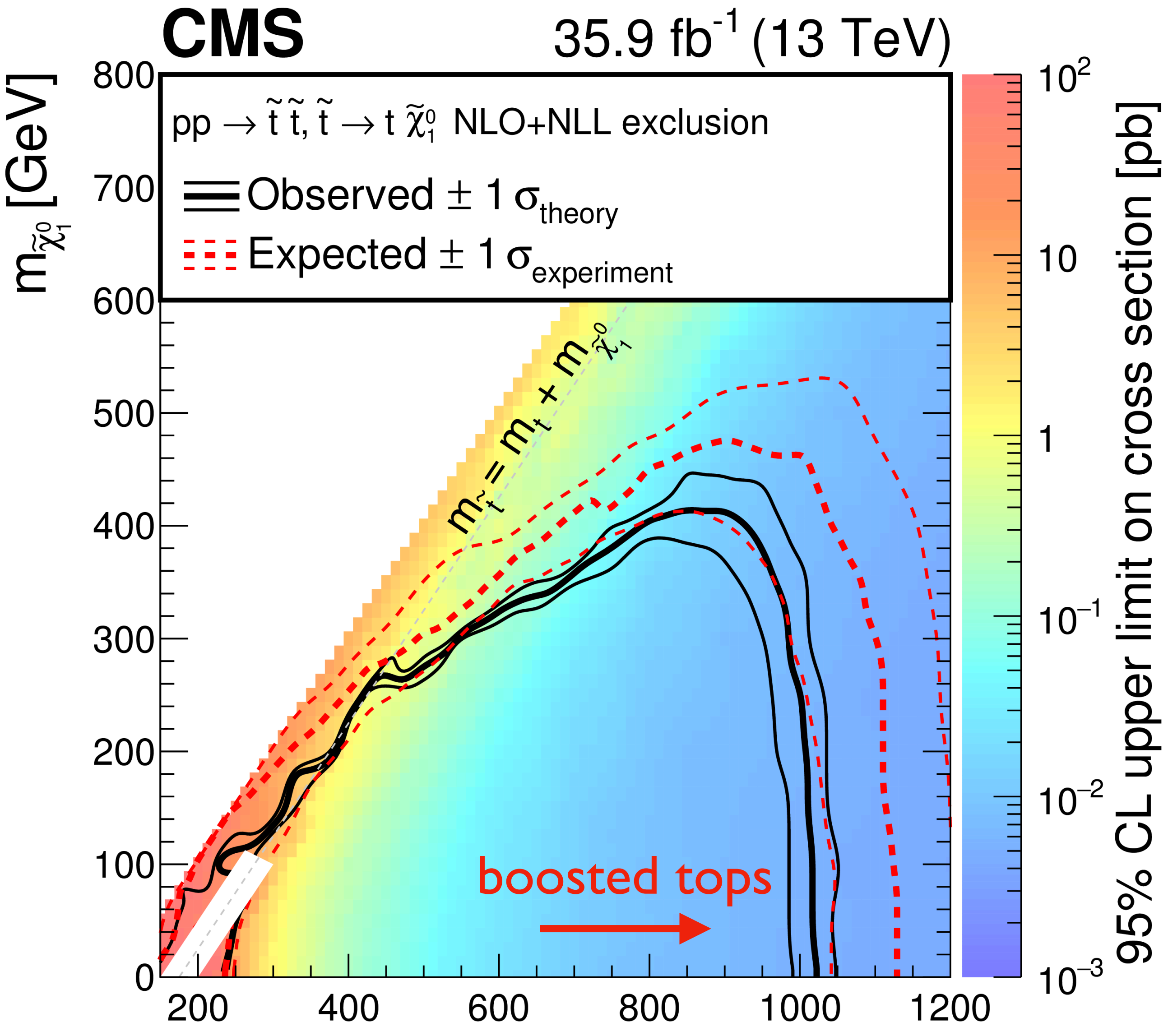


Example: stop searches

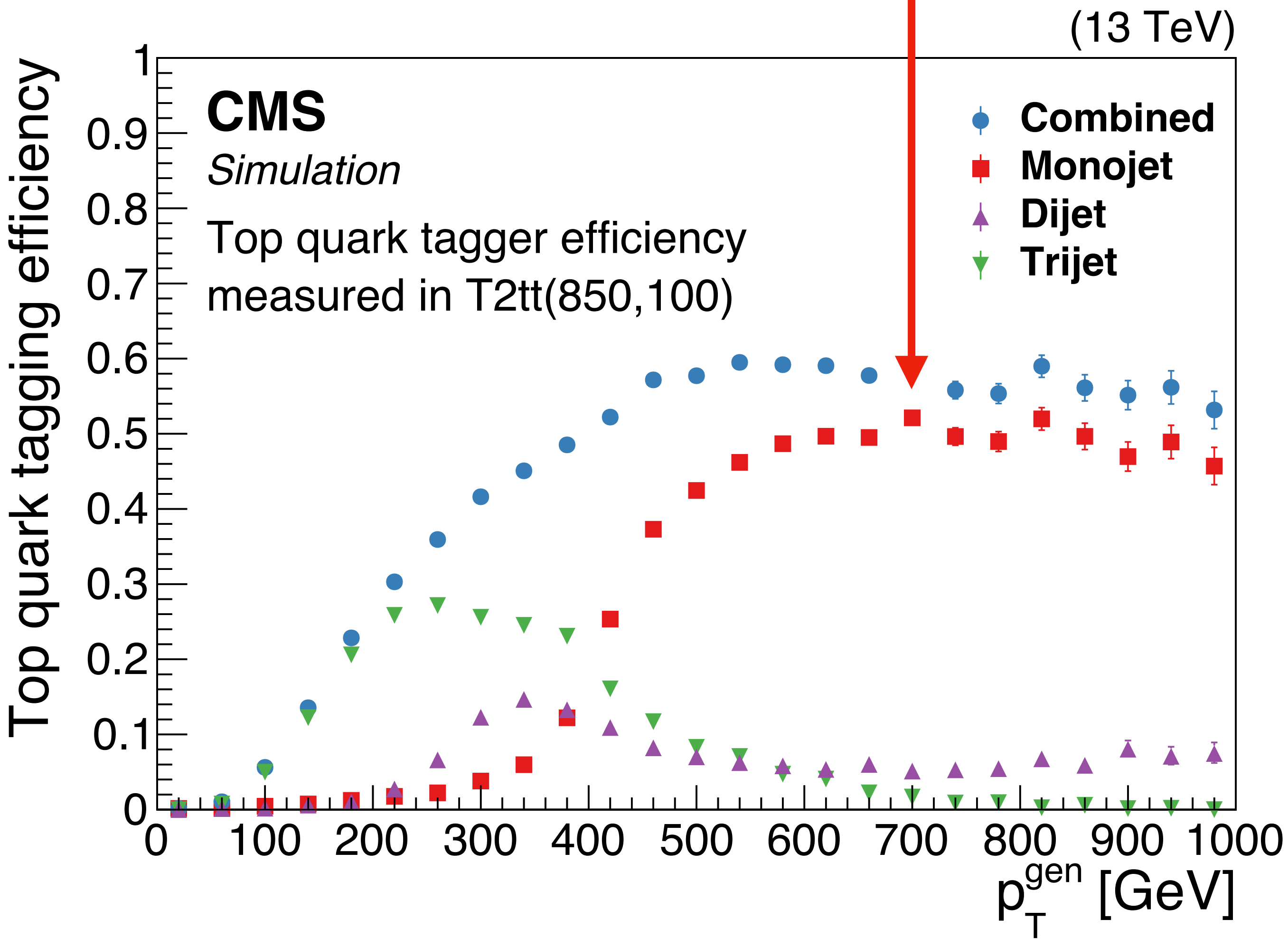
AK8 jets

$m_{SD} \in (105,210)$, $\tau_{32} < 0.65$

(CMS 1710.11188)

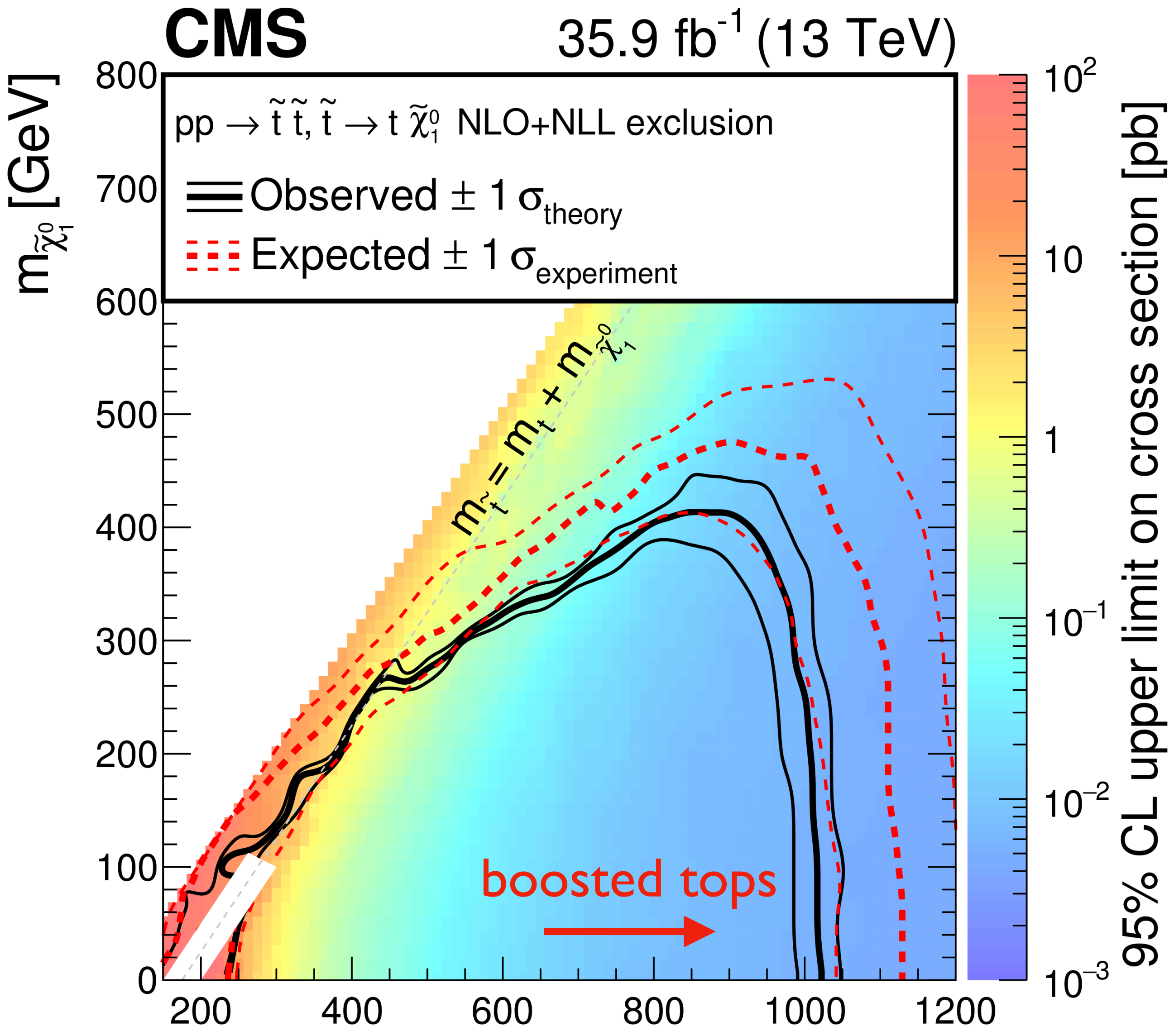


boosted tops



Search relies heavily on a (not very sophisticated) boosted top tagger.

Example: stop searches



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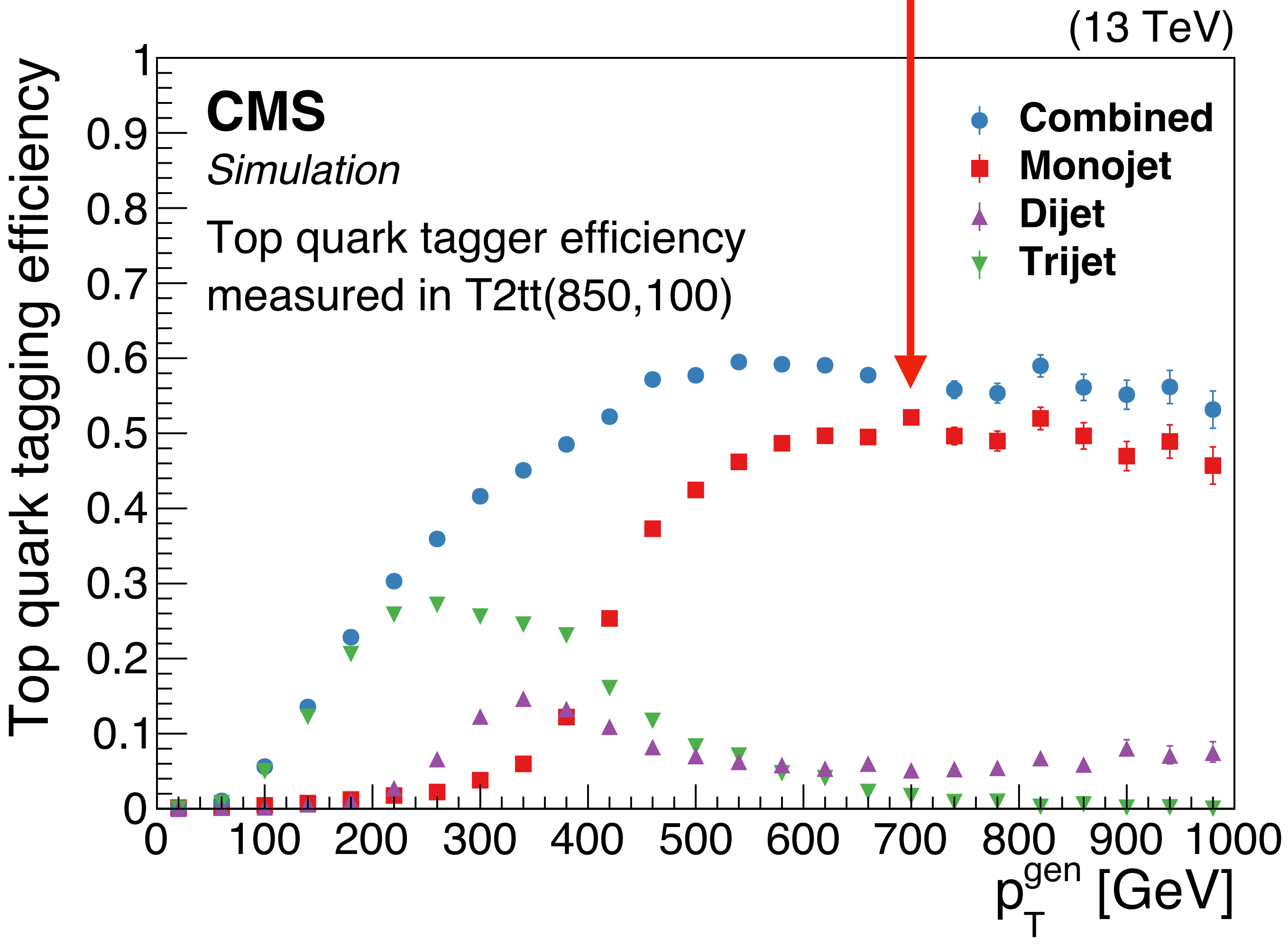
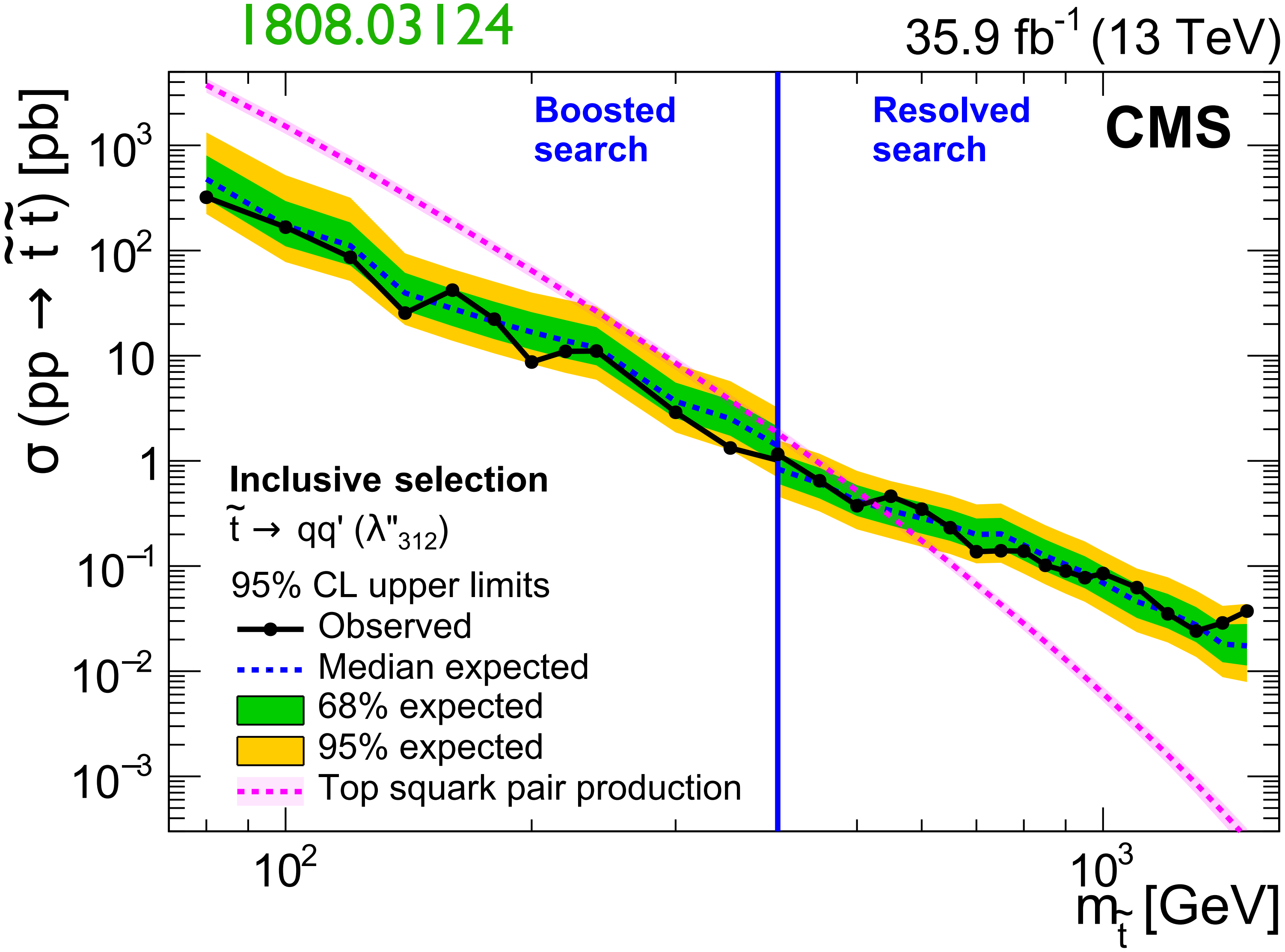


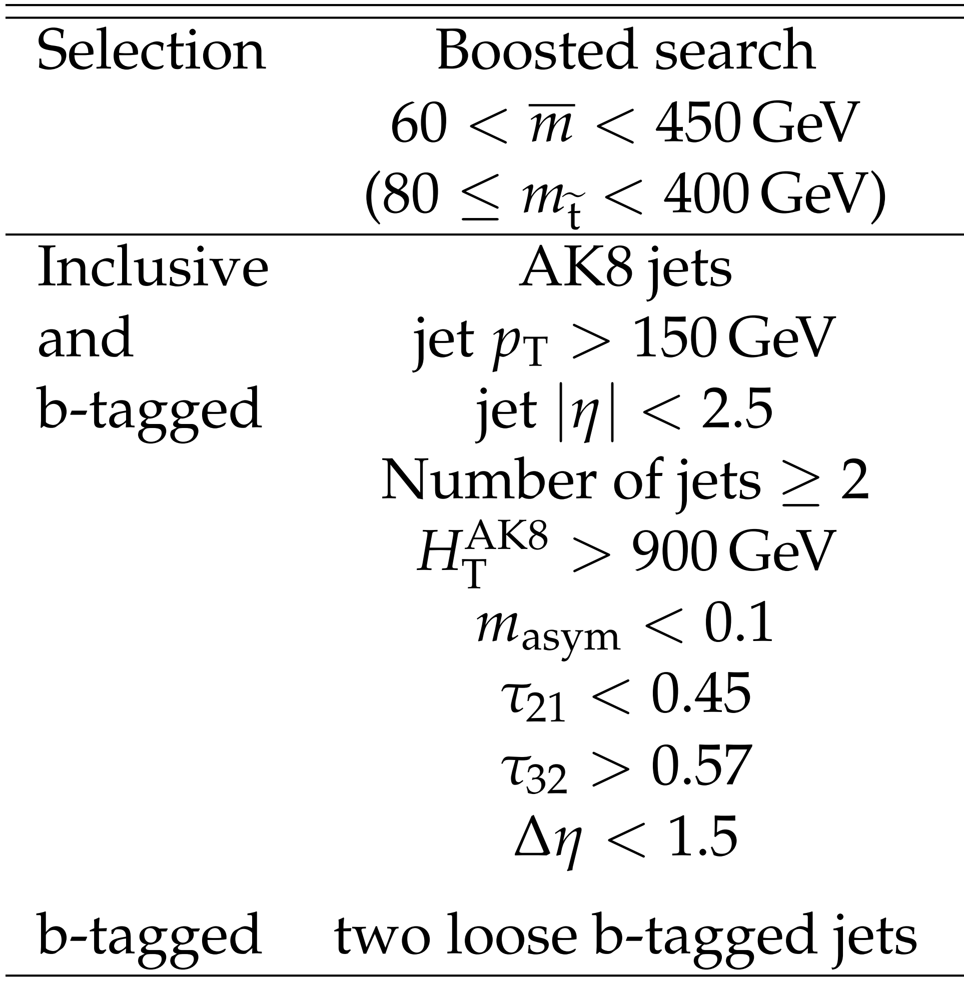
Search relies heavily on a (not very sophisticated) boosted top tagger.

How would reach improve with state-of-the-art tagger?

Example: squark RPV

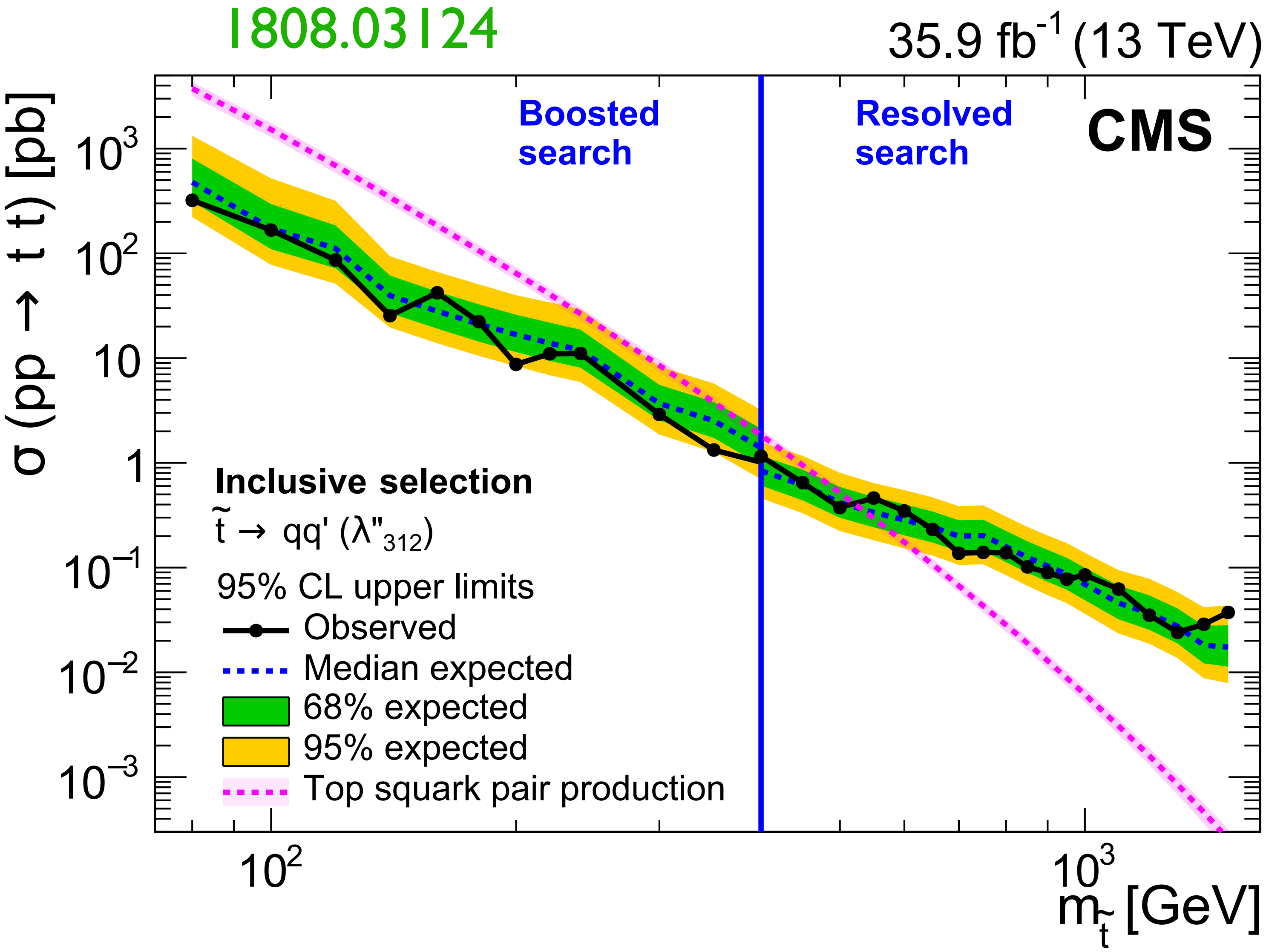
1808.03124

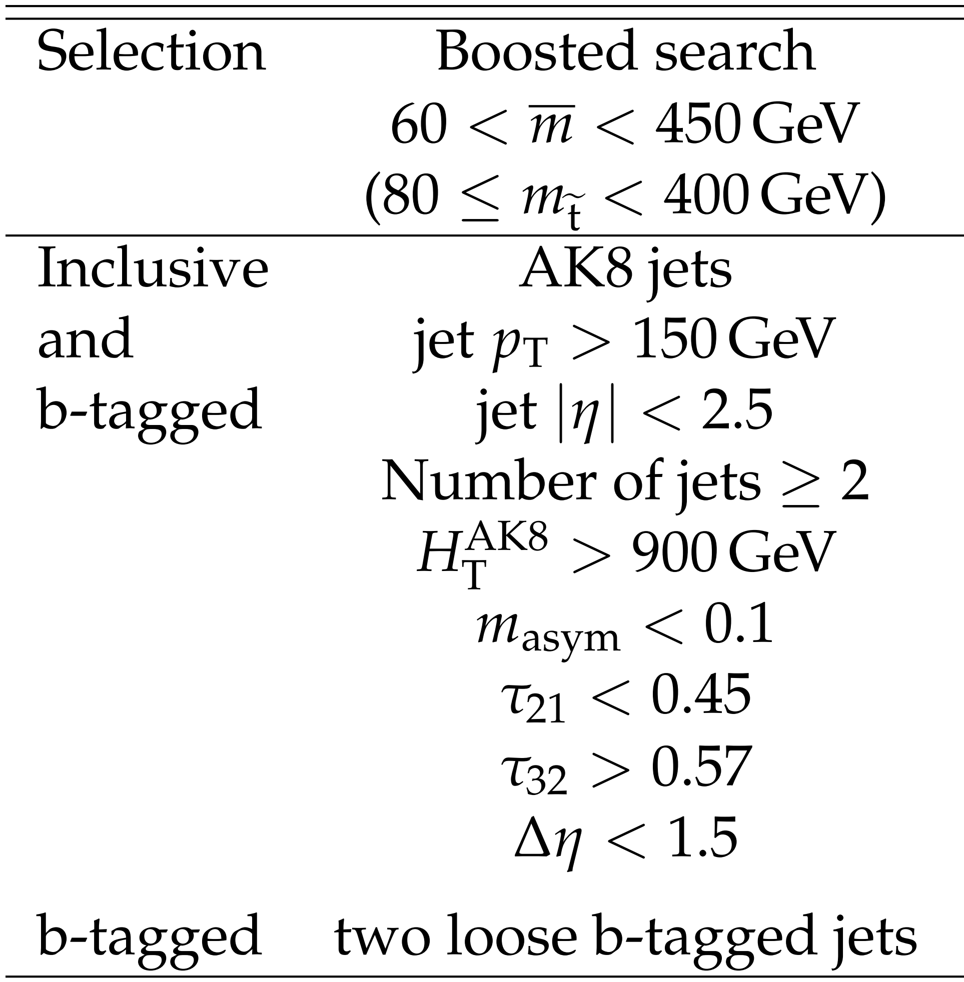




Selection	Boosted search
	$60 < \overline{m} < 450\,\mathrm{GeV}$
	$(80 \leq m_{\tilde{t}} < 400\,\mathrm{GeV})$
Inclusive and b-tagged	AK8 jets
	jet $p_{\mathrm{T}} > 150\,\mathrm{GeV}$
	jet $\lvert\eta\rvert < 2.5$
	Number of jets ≥ 2
	$H_{\mathrm{T}}^{\mathrm{AK8}} > 900\,\mathrm{GeV}$
	$m_{\mathrm{asym}} < 0.1$
	$\tau_{21} < 0.45$
	$\tau_{32} > 0.57$
	$\Delta\eta < 1.5$
b-tagged	two loose b-tagged jets

Example: squark RPV


1808.03124

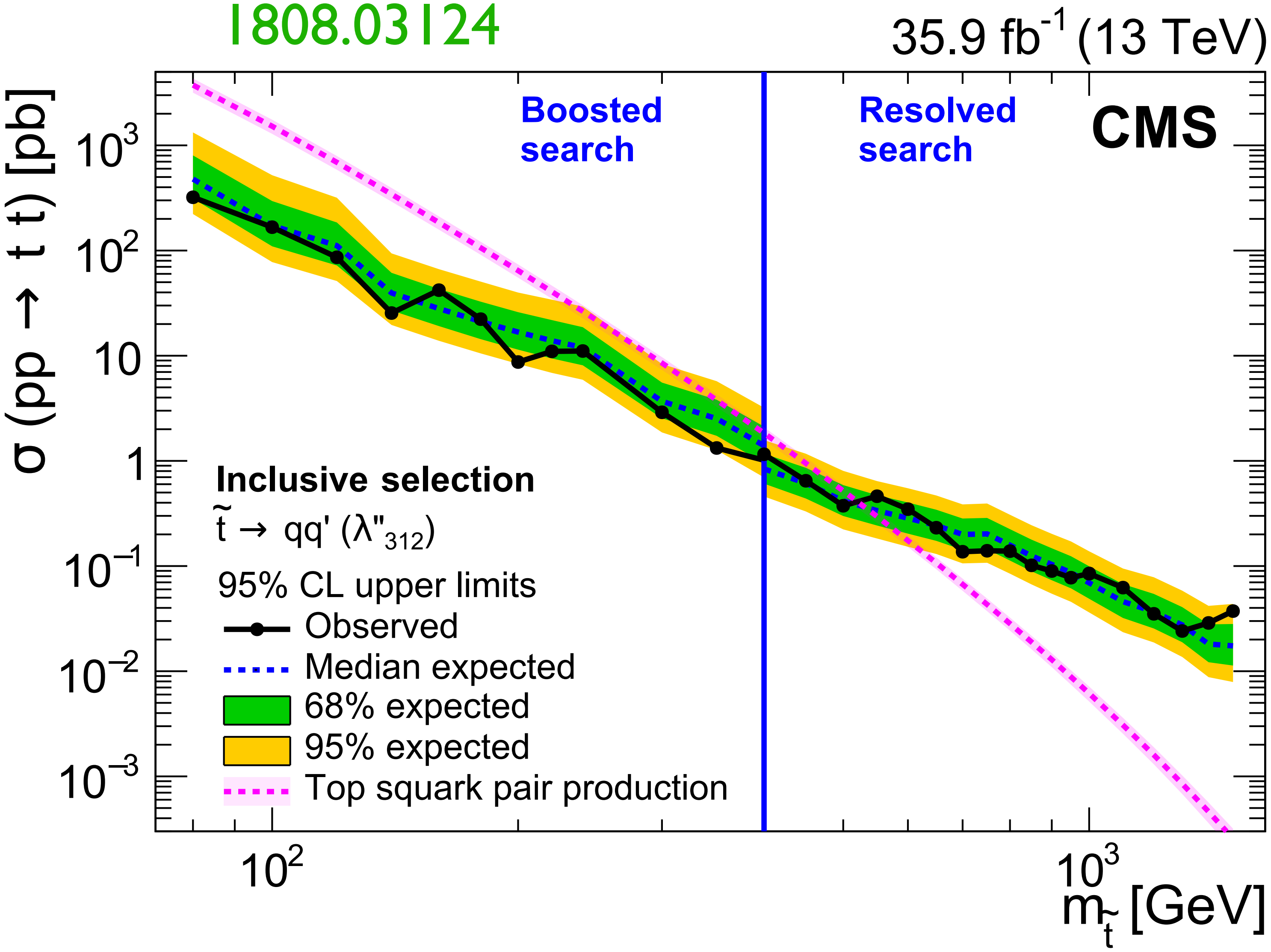


Selection	Boosted search $60 < \overline{m} < 450\,\mathrm{GeV}$ $(80 \leq m_{\tilde{t}} < 400\,\mathrm{GeV})$
Inclusive and b-tagged	AK8 jets jet $p_{\mathrm{T}} > 150\,\mathrm{GeV}$ jet $\lvert\eta\rvert < 2.5$ Number of jets ≥ 2 $H_{\mathrm{T}}^{\mathrm{AK8}} > 900\,\mathrm{GeV}$ $m_{\mathrm{asym}} < 0.1$ $\tau_{21} < 0.45$ $\tau_{32} > 0.57$ $\Delta\eta < 1.5$
b-tagged	two loose b-tagged jets

Relatively simple 2-prong substructure tagger…

Example: squark RPV

1808.03124



Selection	Boosted search
	$60 < \overline{m} < 450\,\text{GeV}$ $(80 \leq m_{\tilde{t}} < 400\,\text{GeV})$
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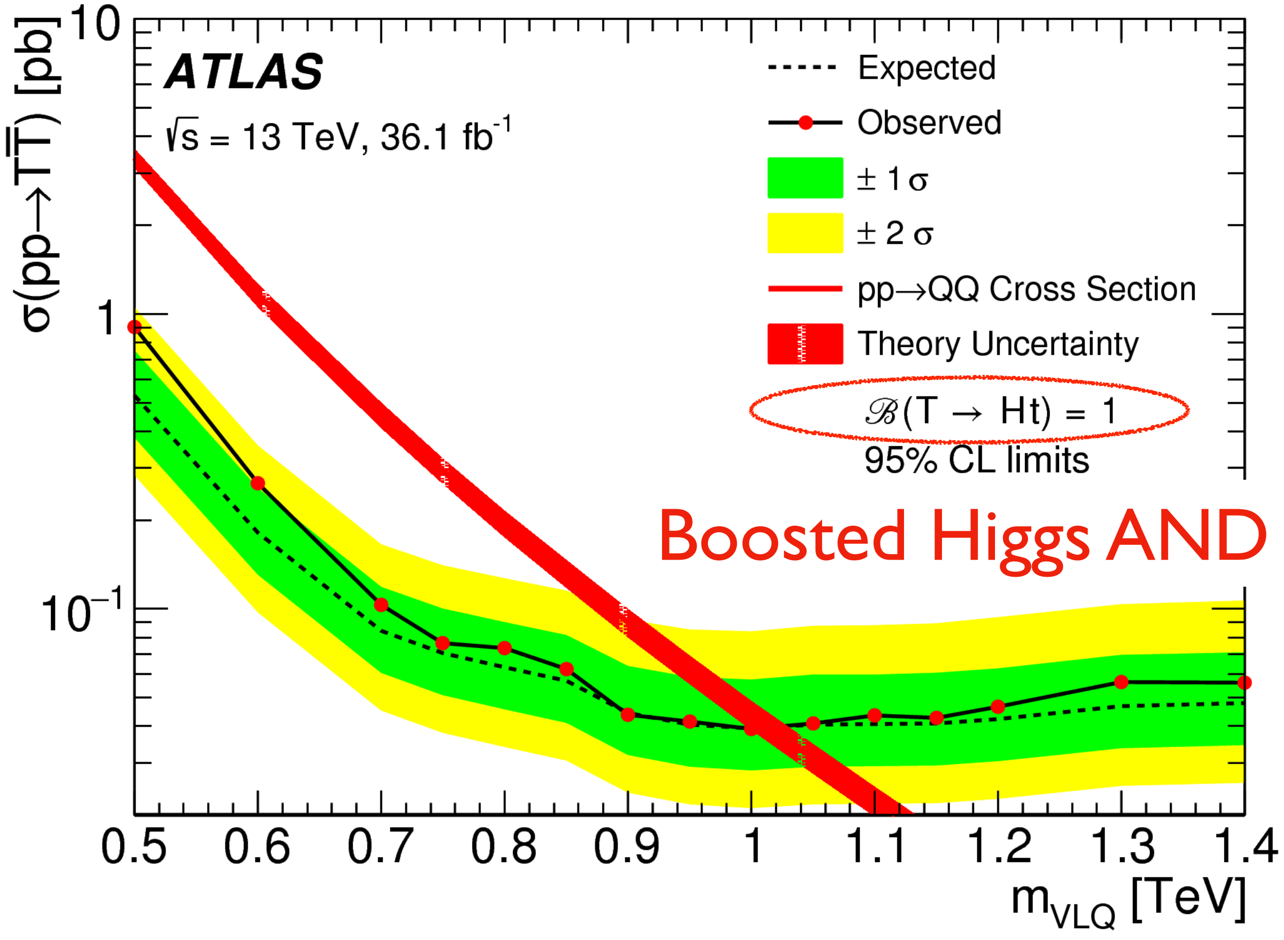
b-tagged	two loose b-tagged jets

Relatively simple 2-prong substructure tagger…

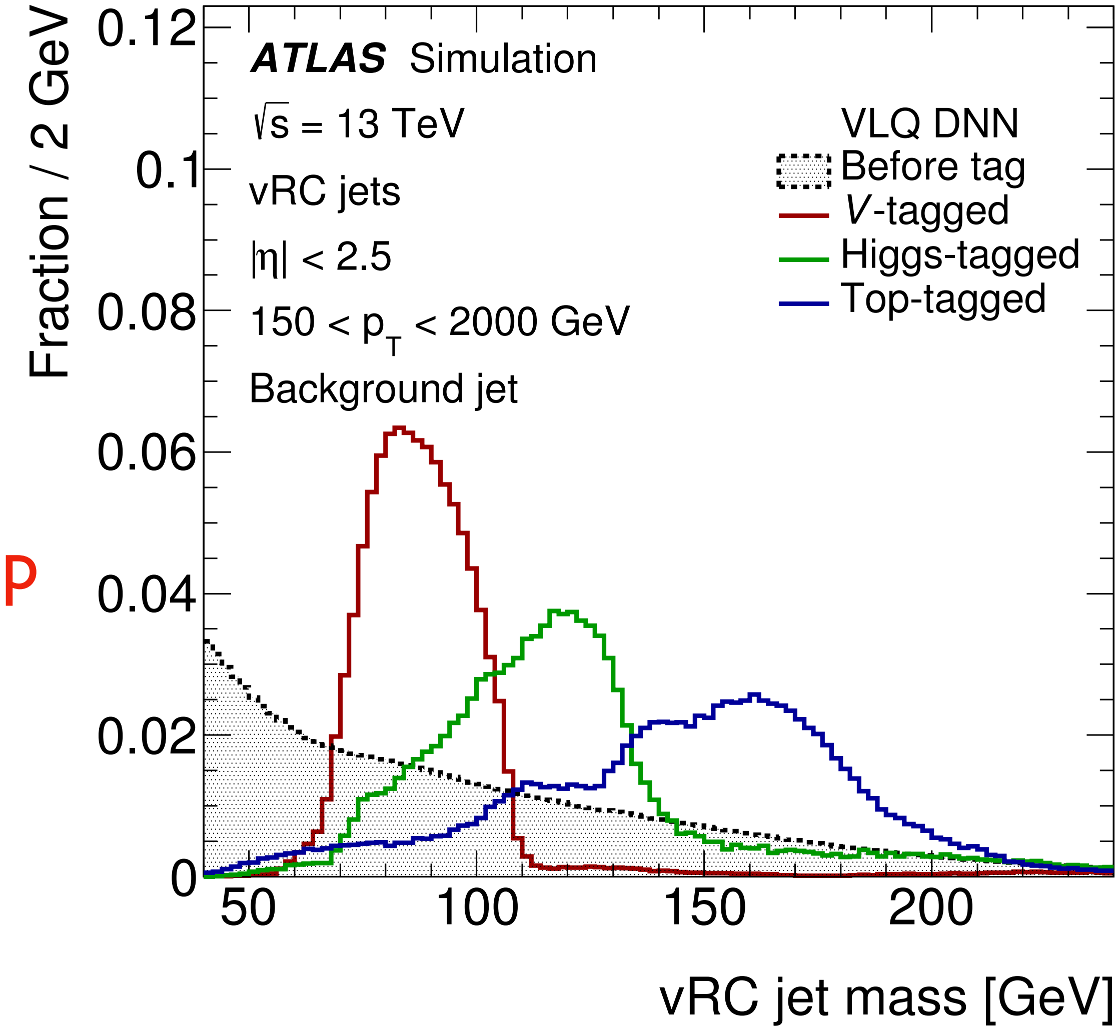
How would reach improve with state-of-the-art tagger?

Example: vectorlike quark searches

1808.01771

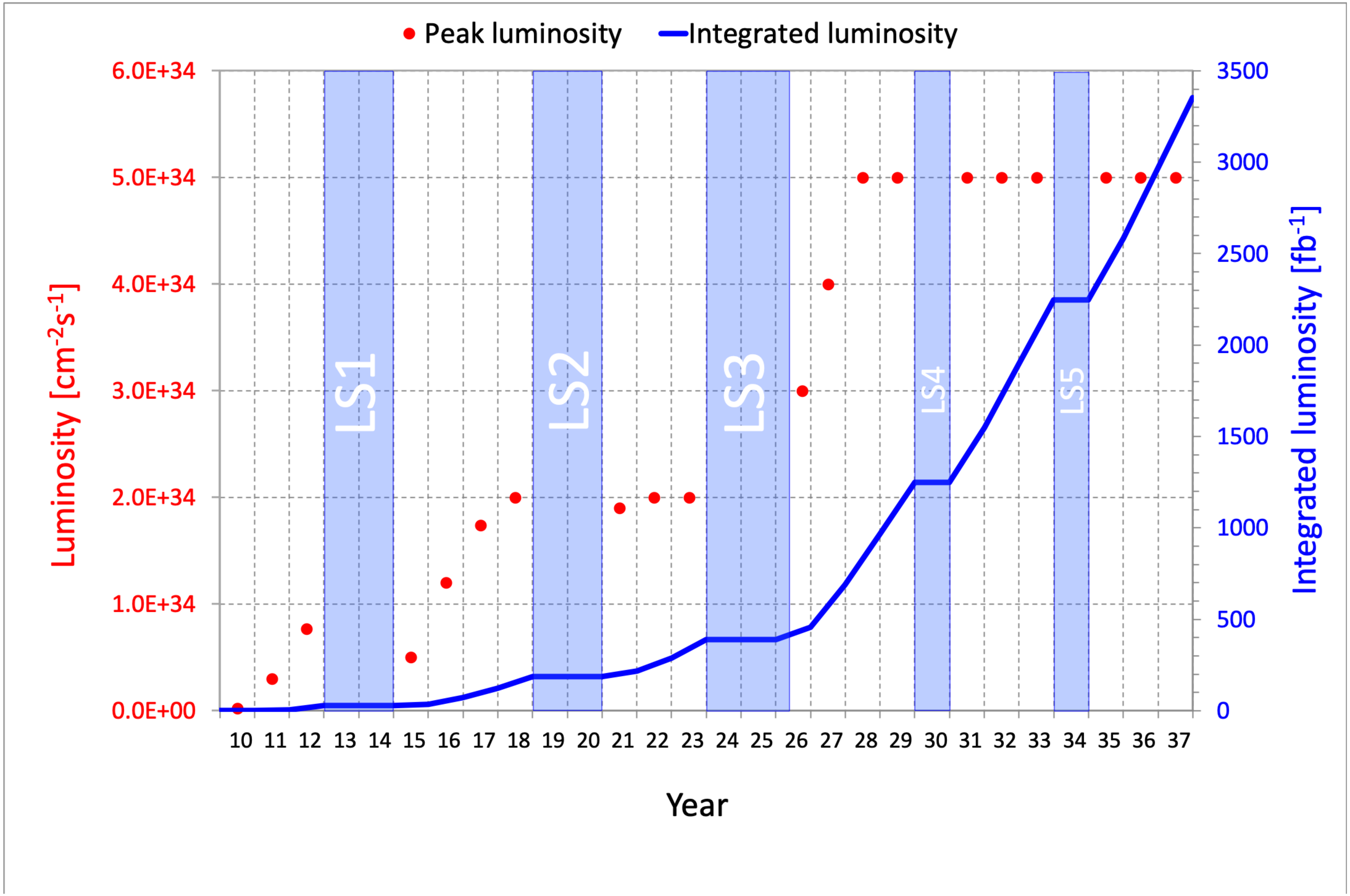


Boosted Higgs AND top

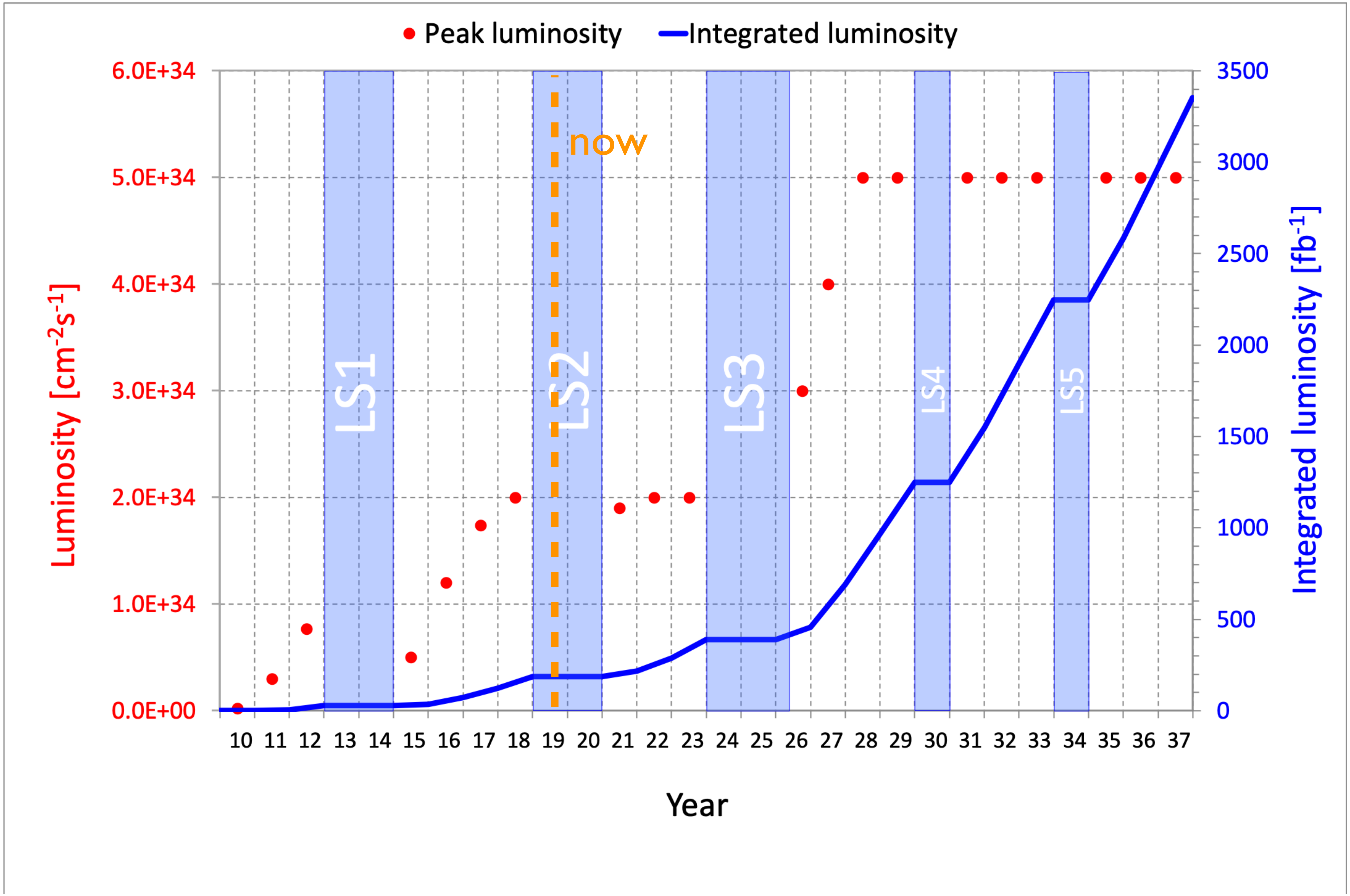


Uses variable-cone jets and DNN to identify boosted W/Z, Higgs and tops!

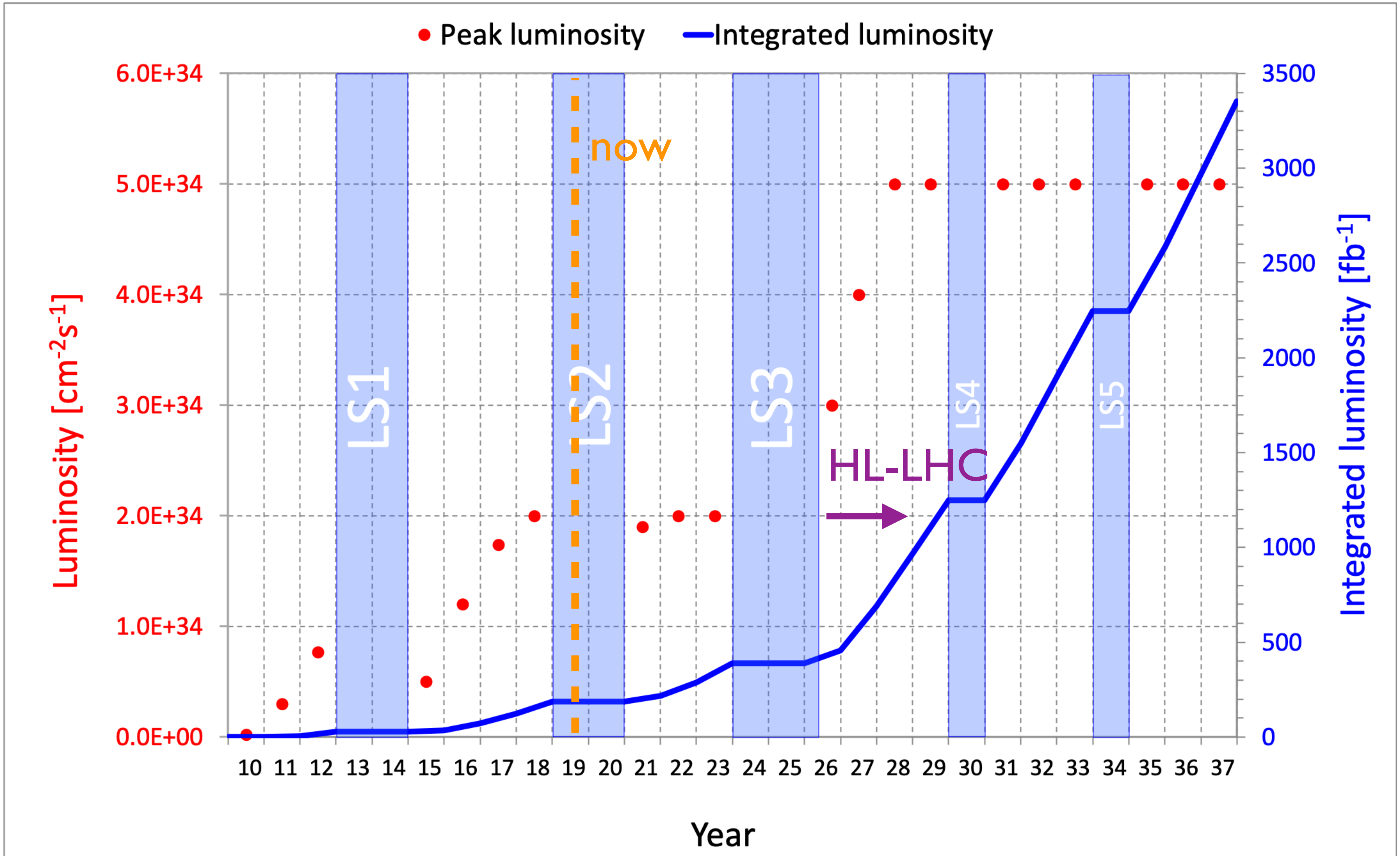
Future of the LHC



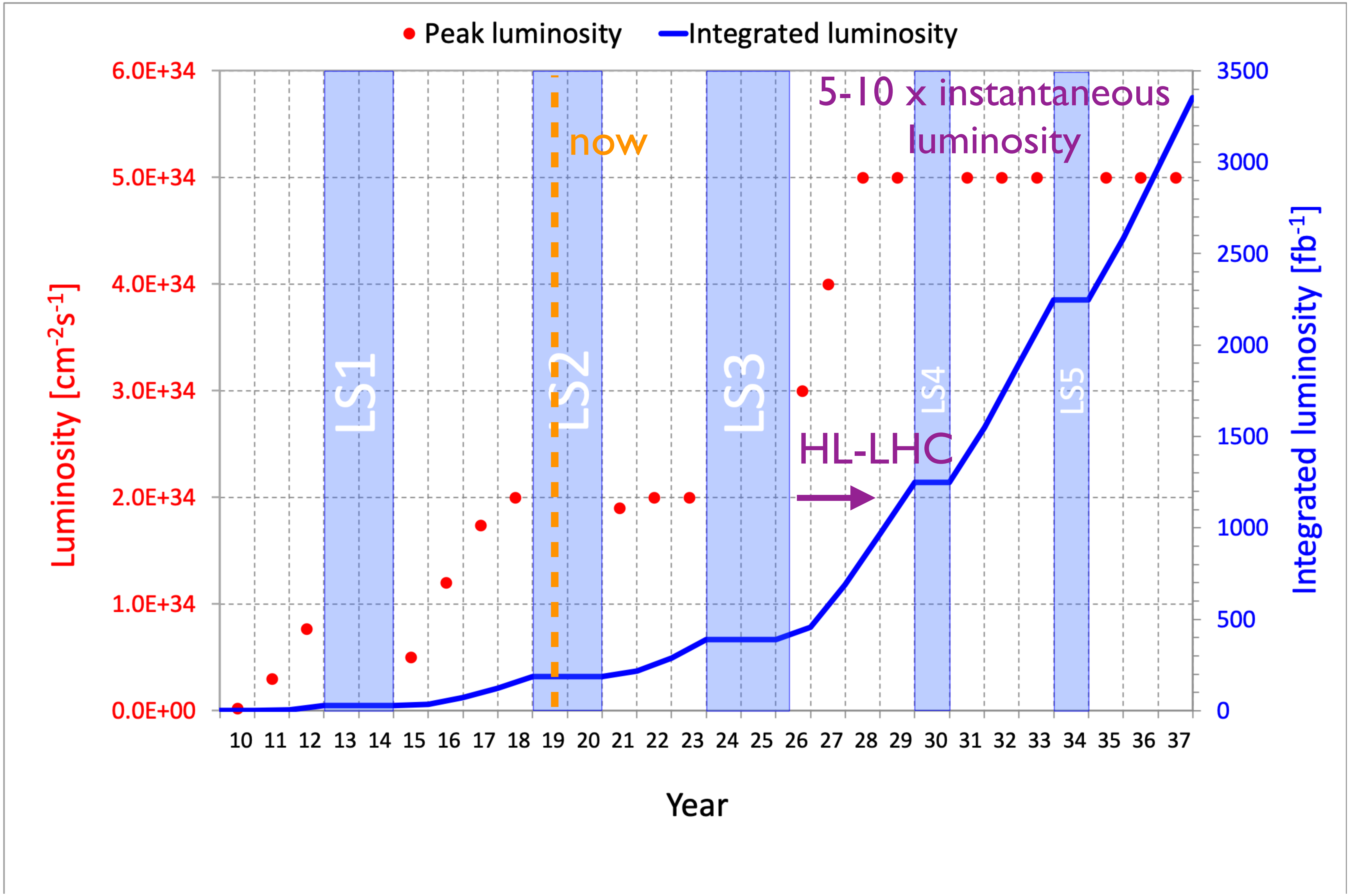
Future of the LHC



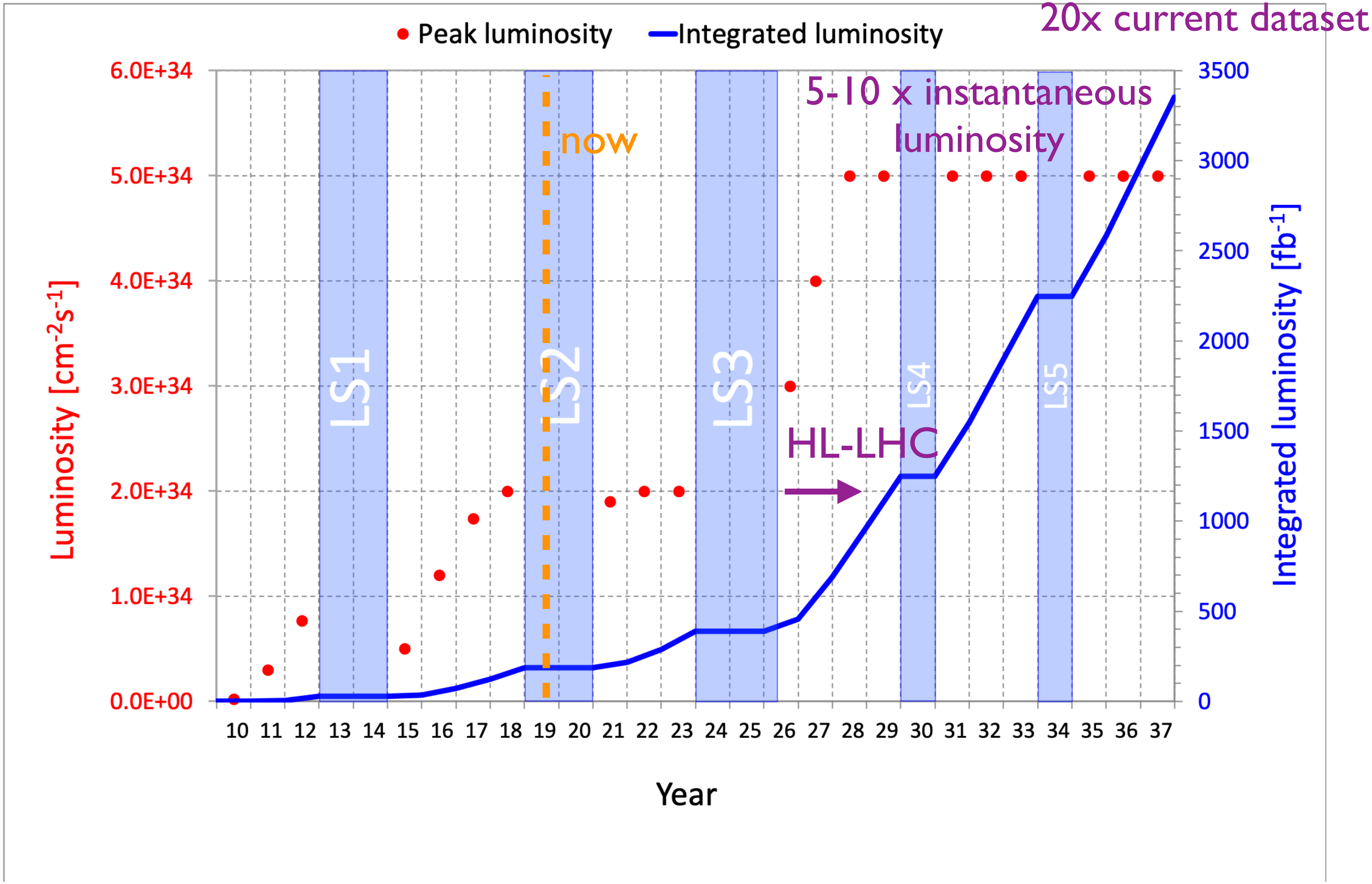
Future of the LHC



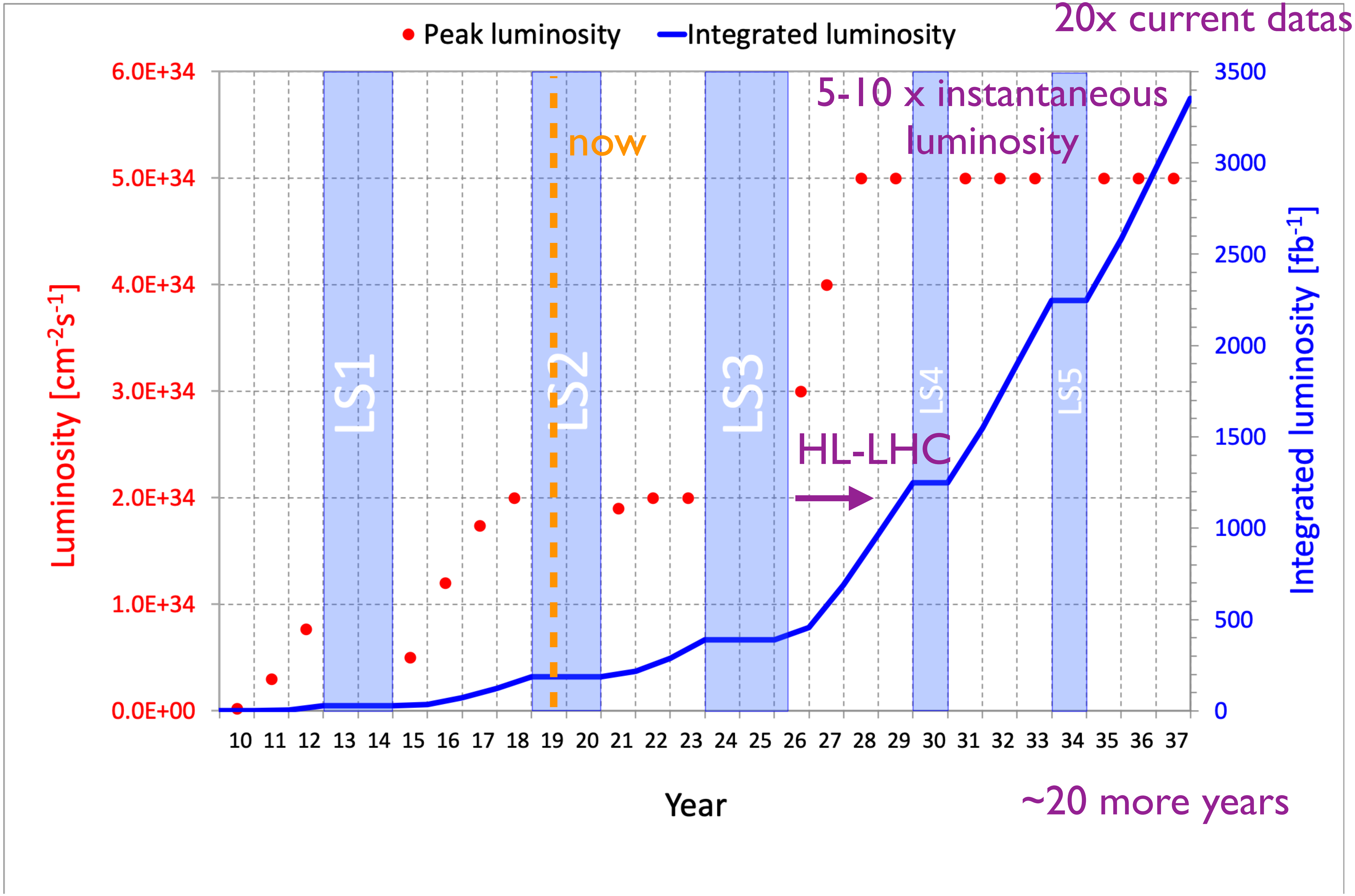
Future of the LHC



Future of the LHC



Future of the LHC



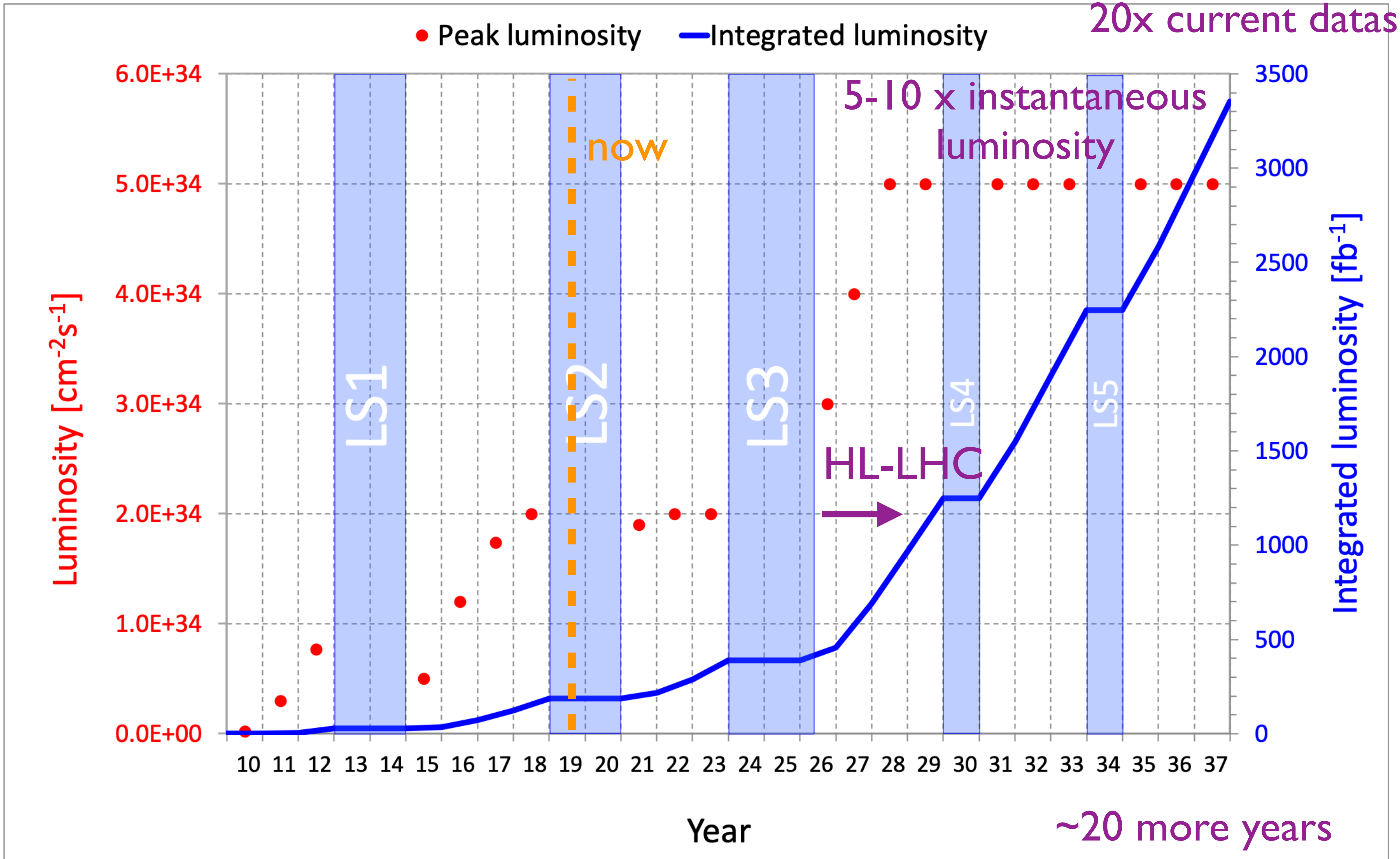
20x current dataset

5-10 x instantaneous luminosity

HL-LHC

~20 more years

Future of the LHC



20x current dataset

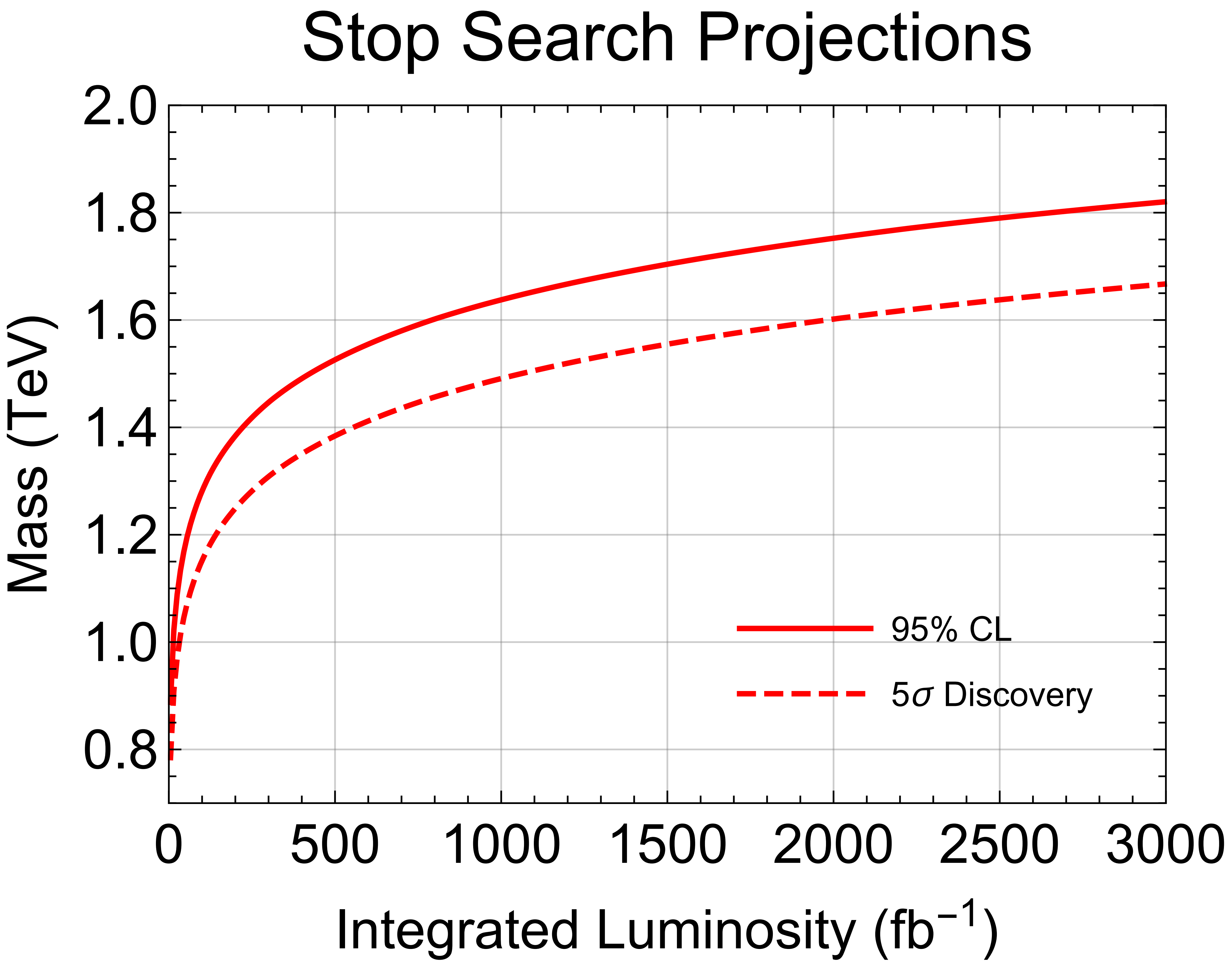
5-10 x instantaneous luminosity

now

HL-LHC

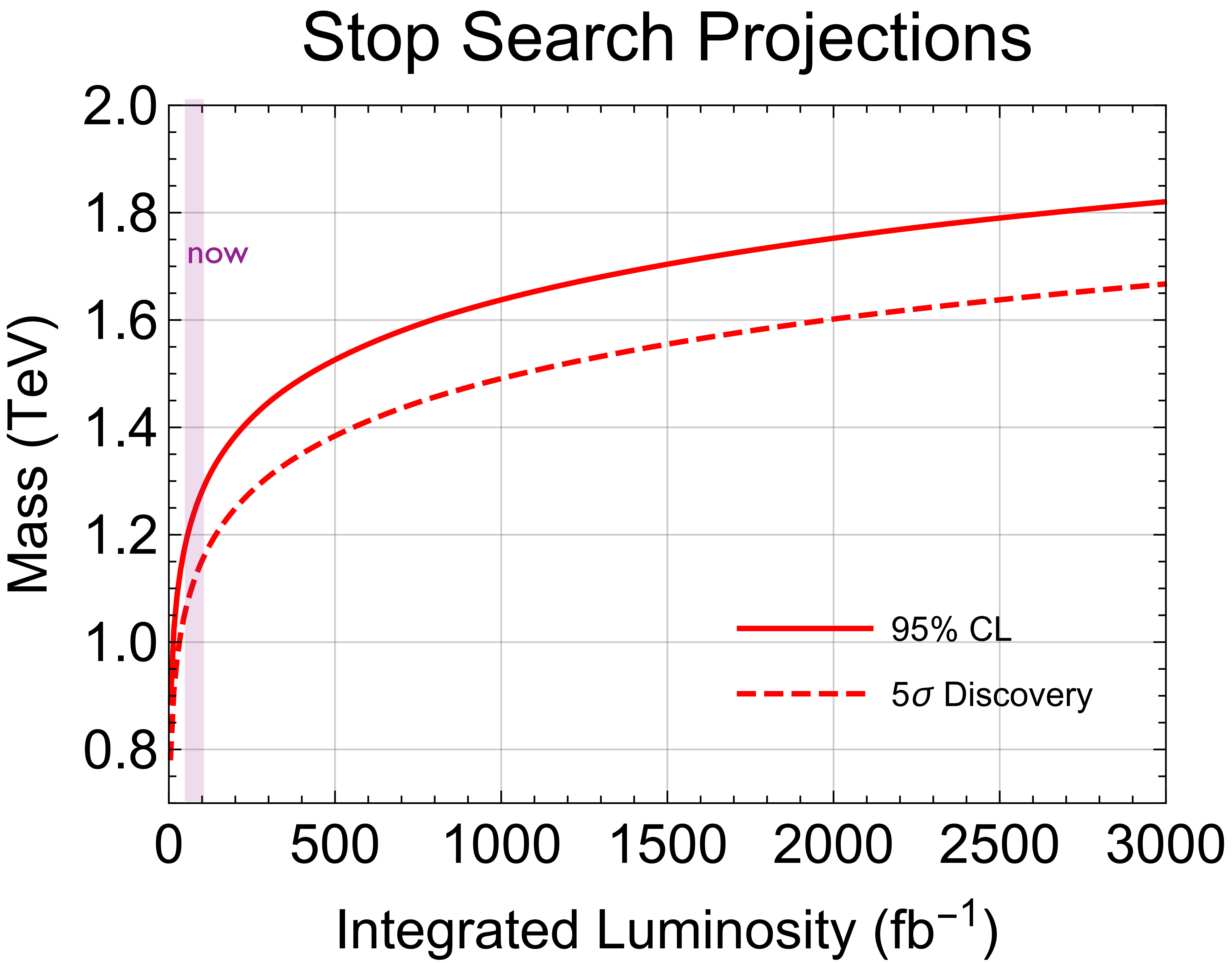
~20 more years

How do we maximize the discovery potential of this enormous dataset??



Naive projections of future search sensitivity, assuming analyses maintain the status quo

Salam & Weiler http://collider-reach.web.cern.ch/collider-reach/



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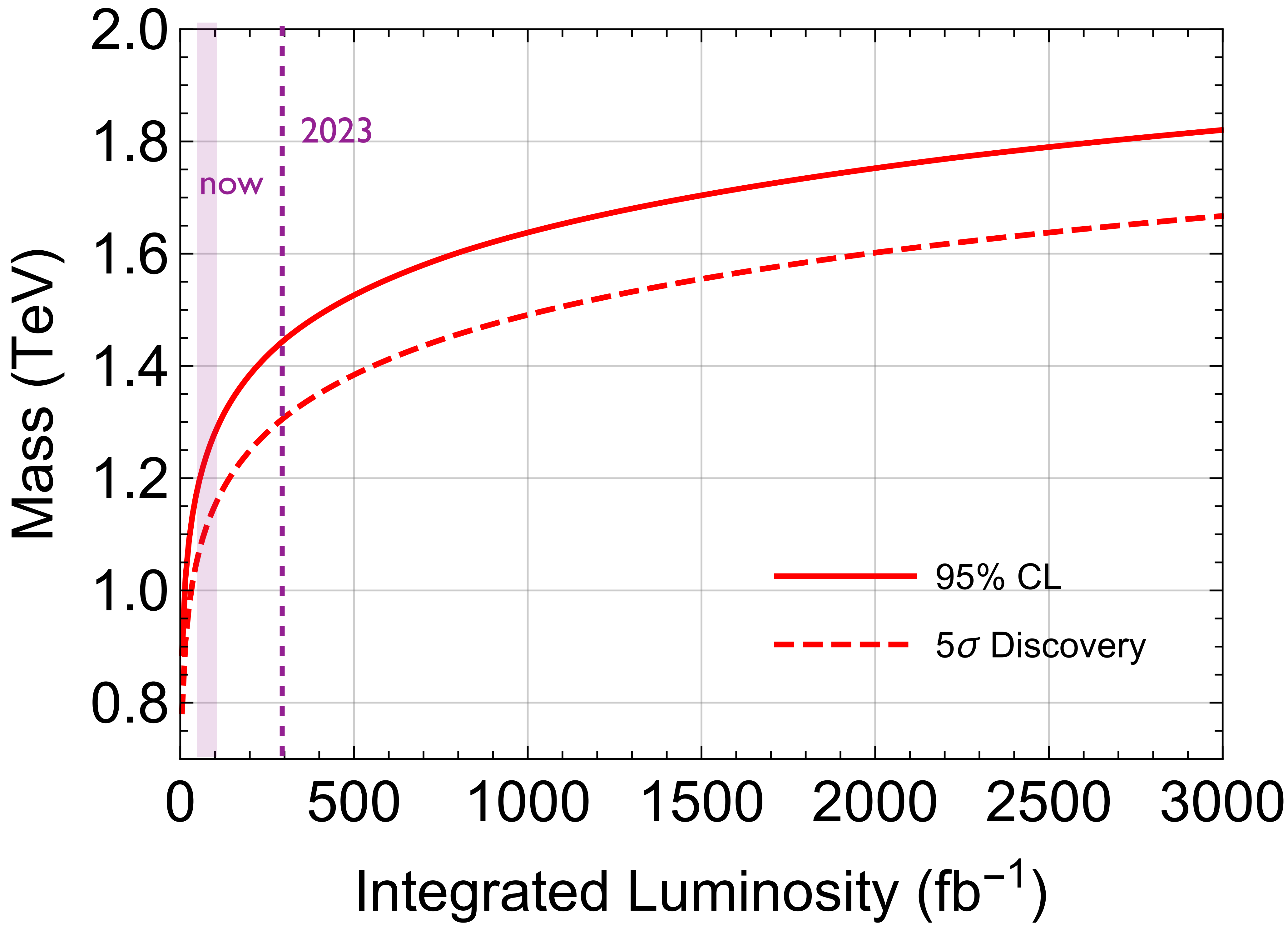
Stop Search Projections



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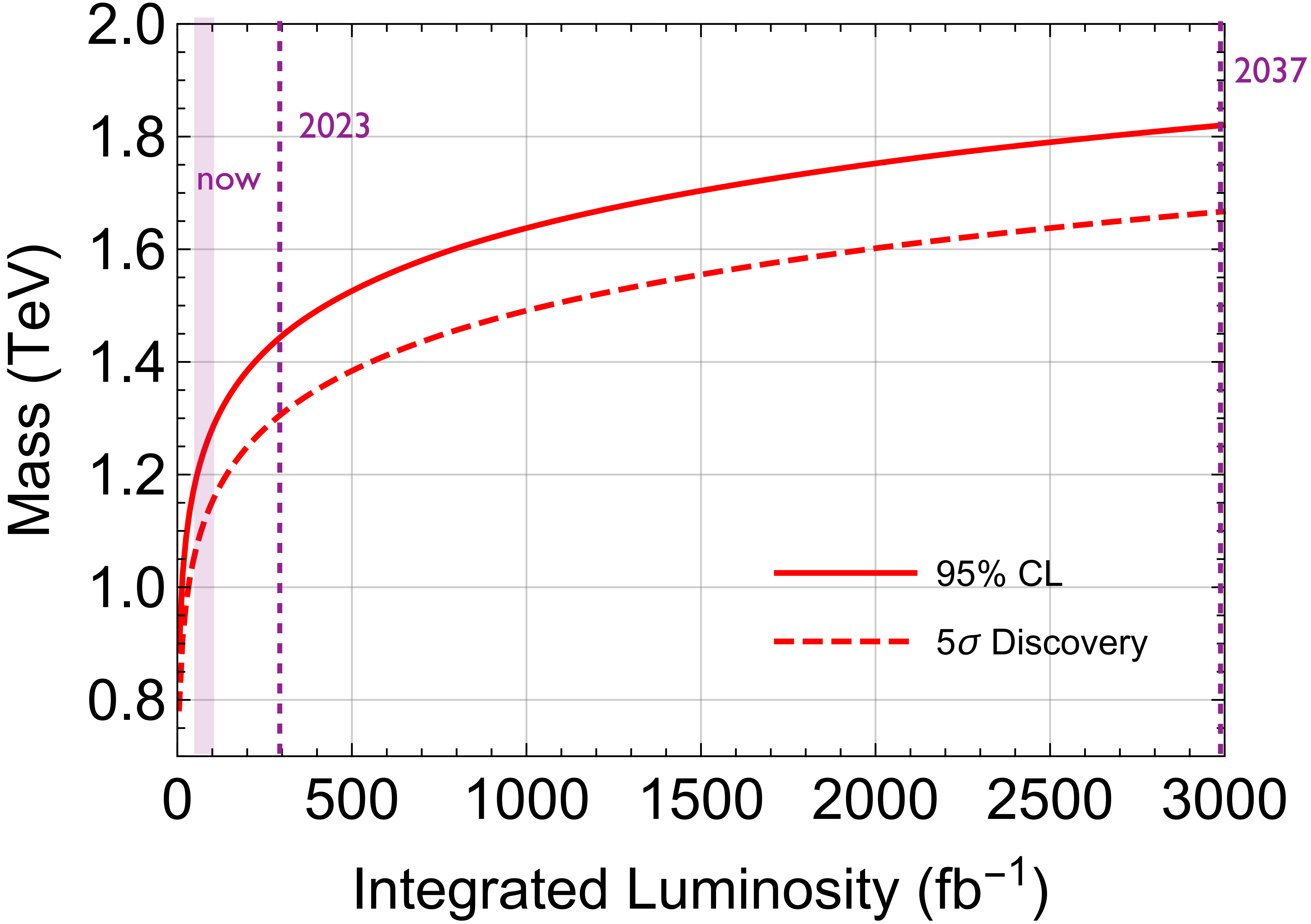

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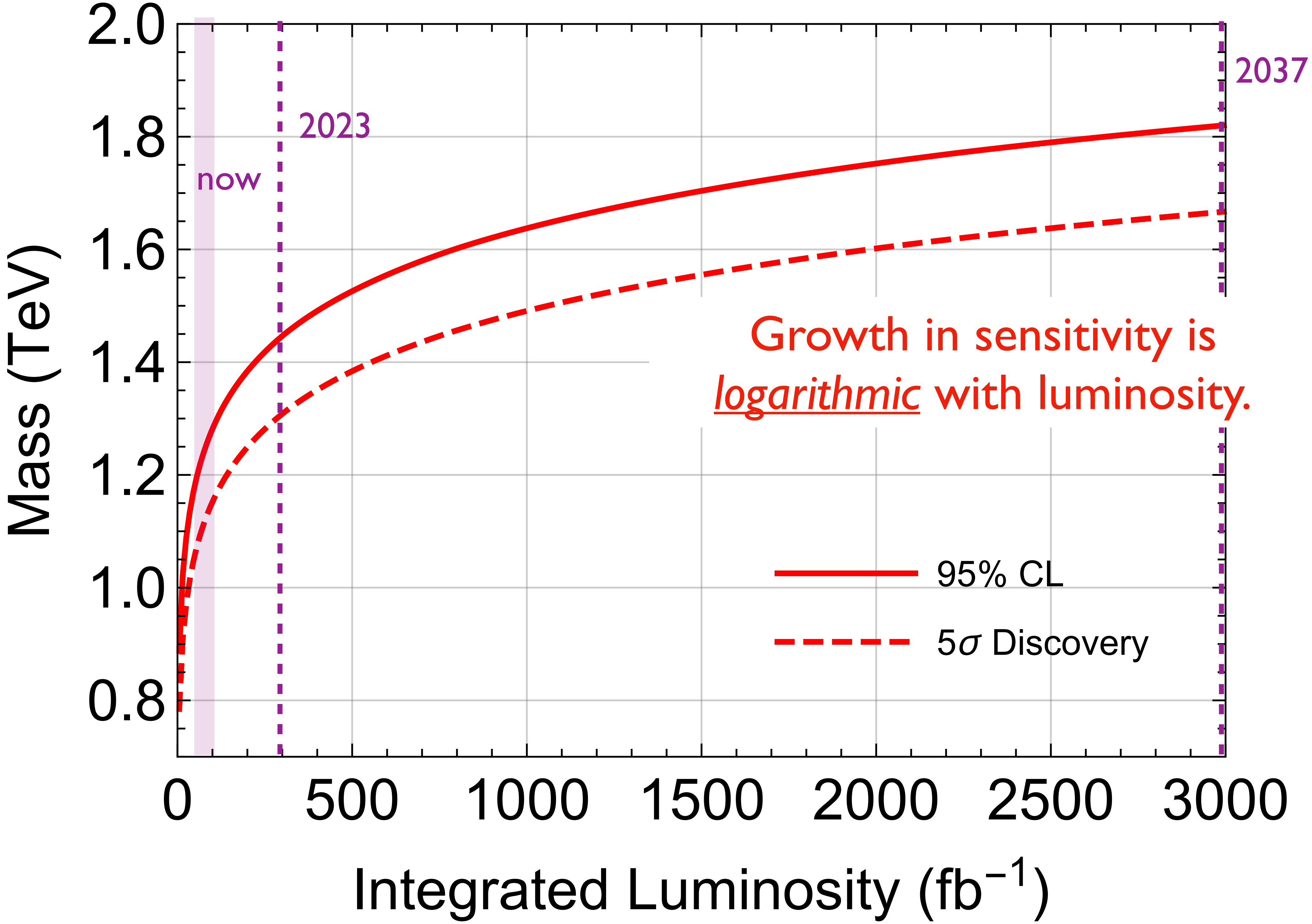
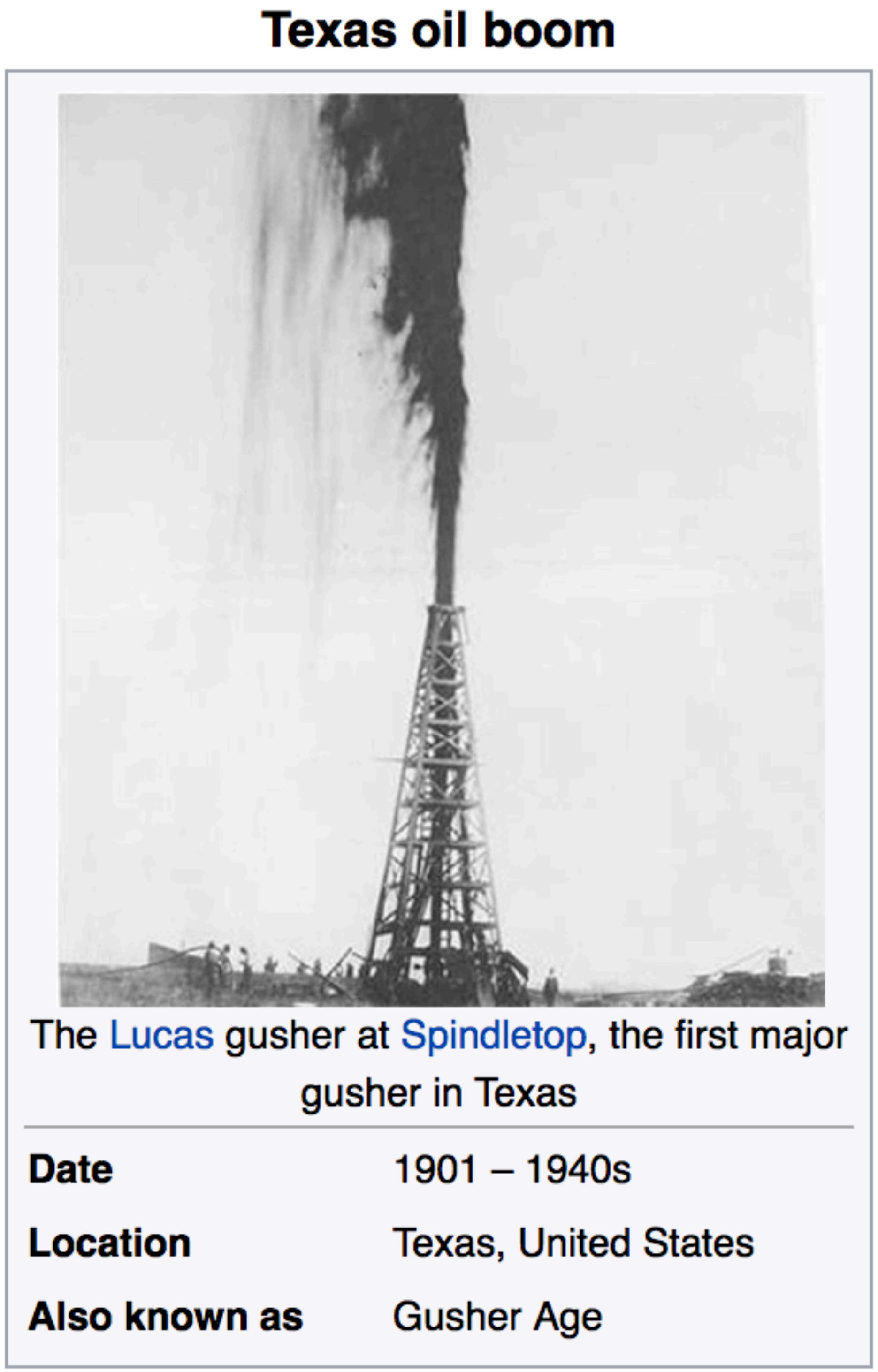


Growth in sensitivity is *logarithmic* with luminosity.

Naive projections of future search sensitivity, assuming analyses maintain the status quo

Salam & Weiler http://collider-reach.web.cern.ch/collider-reach/



Texas oil boom

The Lucas gusher at Spindletop, the first major gusher in Texas

Date	1901 – 1940s
Location	Texas, United States
Also known as	Gusher Age

In the early days of LHC, progress was relatively easy.

Energy increase (8 TeV → 13 TeV) and rapid luminosity gains led to huge gains in sensitivity.

Analyses did not need to be very sophisticated.

Could go after many low-hanging fruits.

In the future, the status quo will mean much slower progress. The data-taking rate will plateau, and no increases in energy are foreseen.

To maintain the rapid growth in sensitivity, we need new, more sophisticated analysis techniques.

Also, with this enormous dataset, we need to make sure we haven't overlooked any subtle and unexpected signals of new physics.

We need new ideas for how to look for new physics in the data!

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To maint … re
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Also, wit … haven’t
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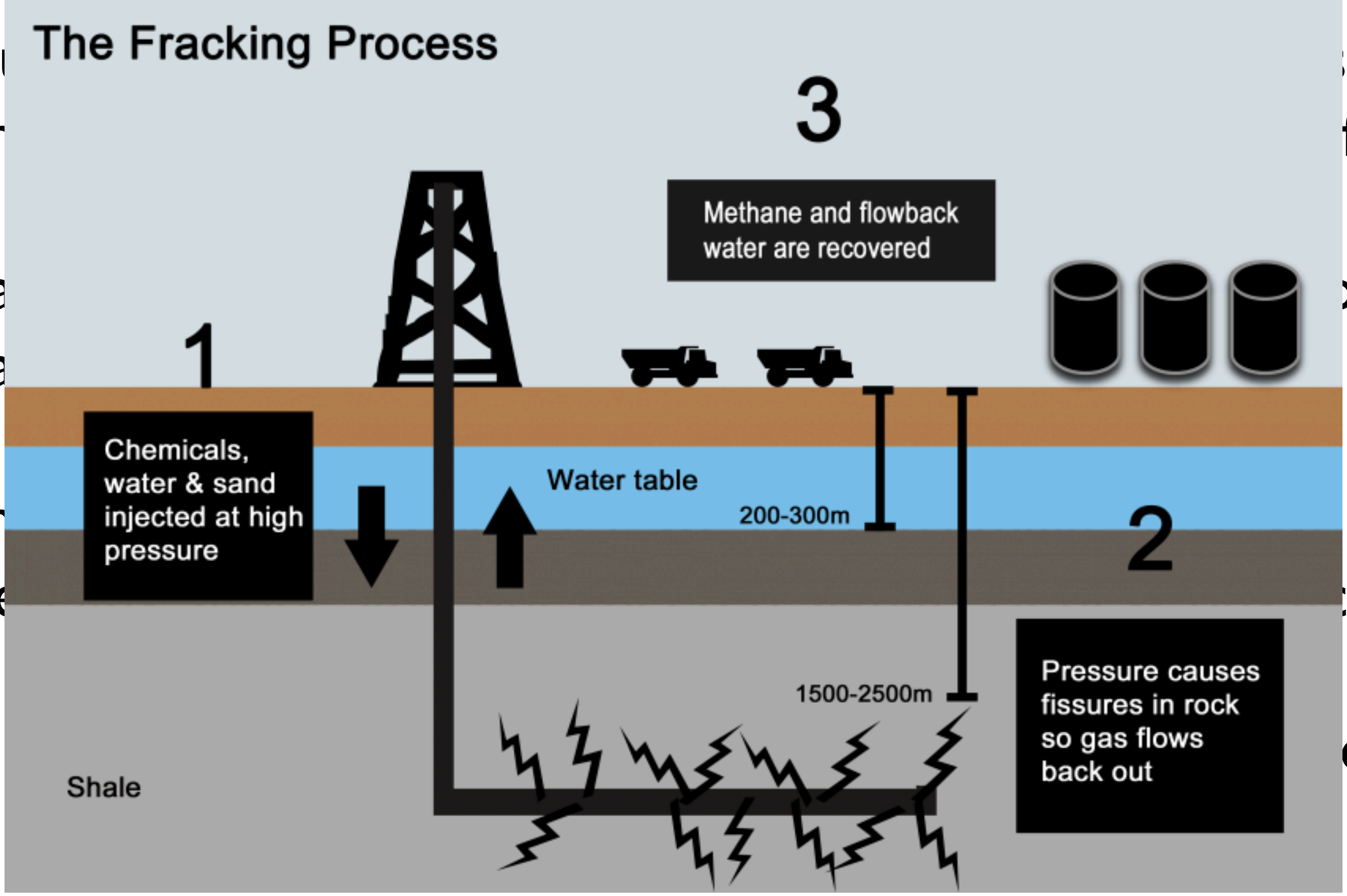
We need … data!



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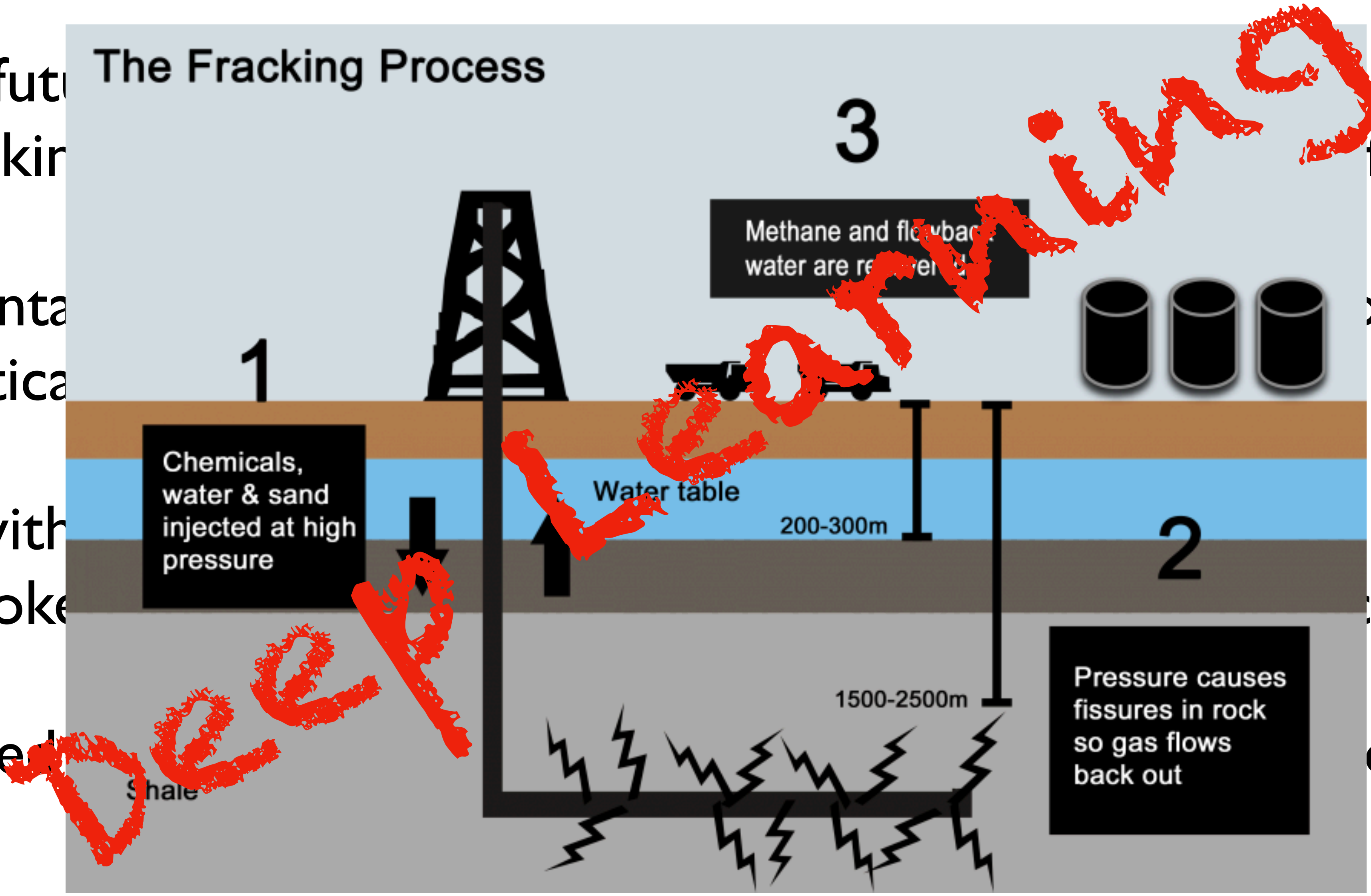


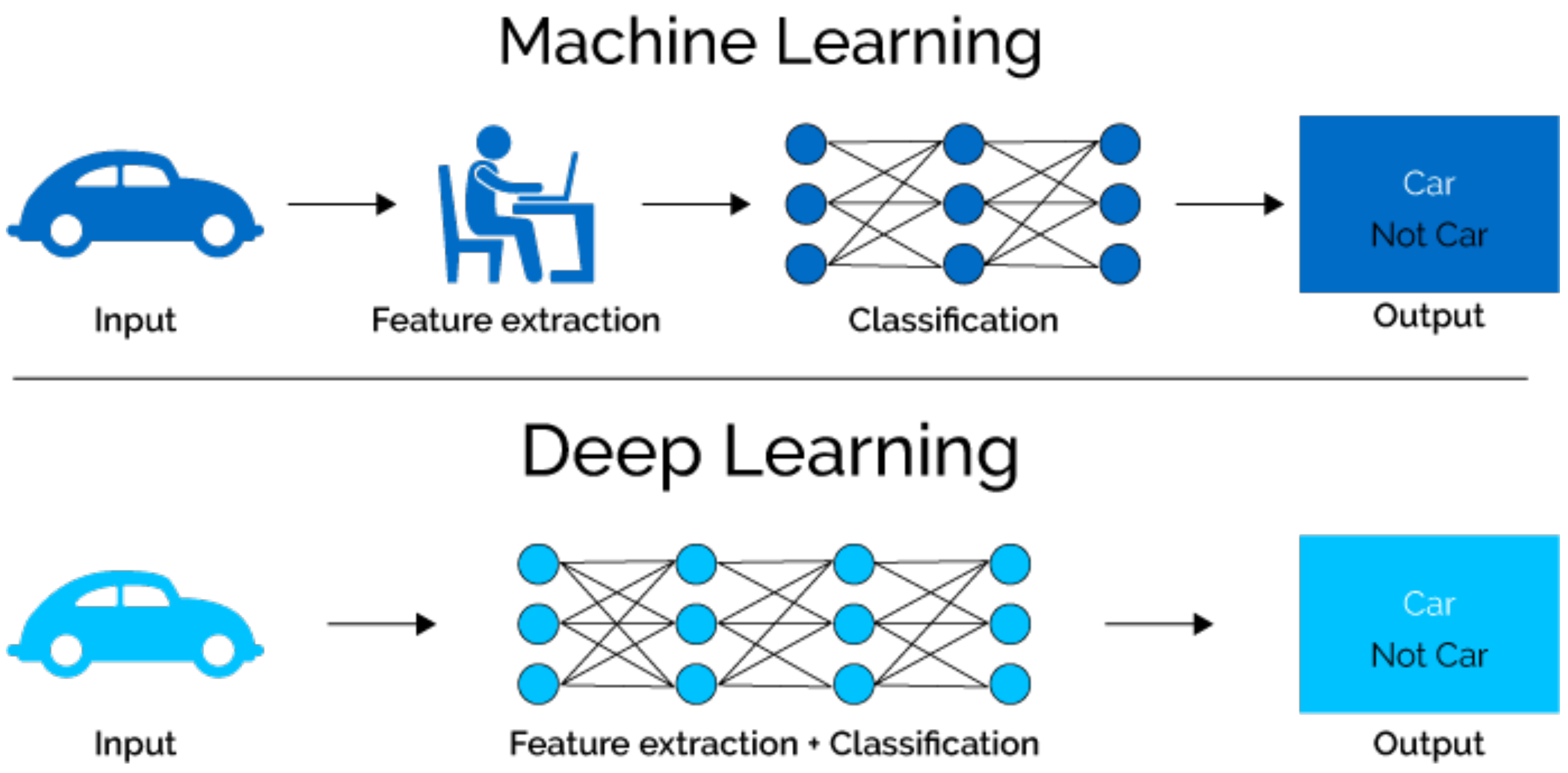
Purpose of this talk

Motivation

Overview / Setting the Stage

Inspiration

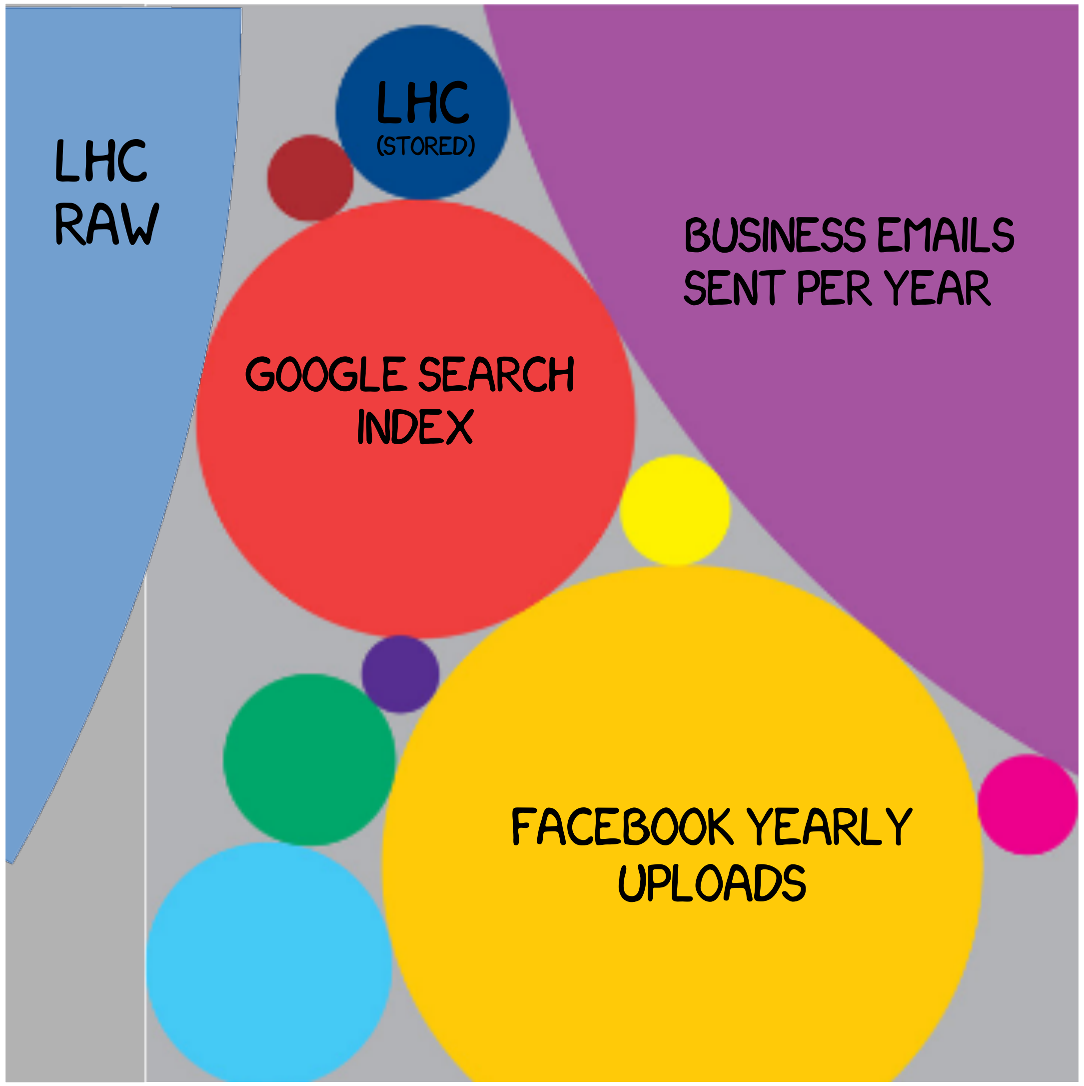
Potential of Deep Learning



From towardsdatascience.com

- High-level concepts from low-level inputs
- Automated feature engineering
- Robust against overfitting

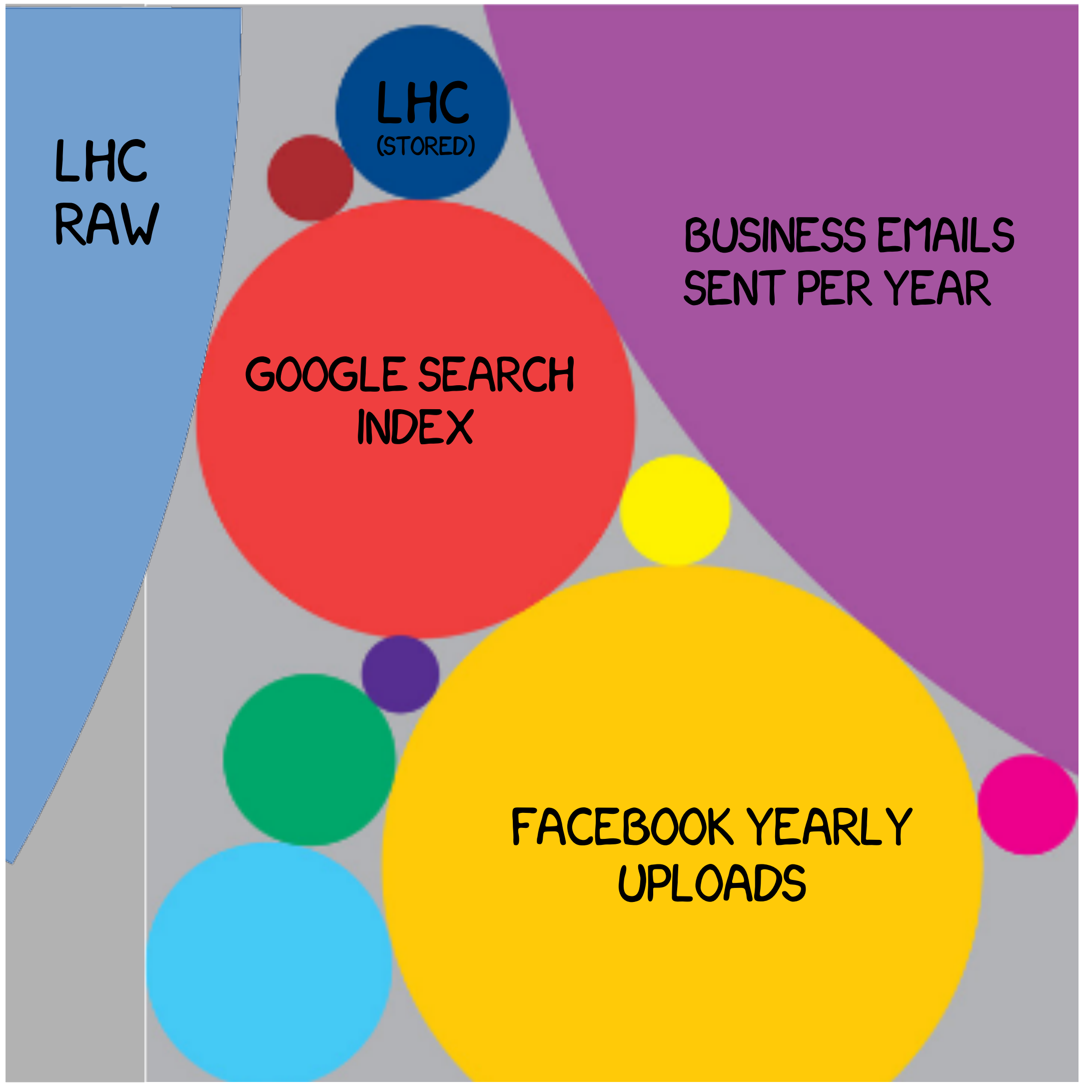
Big Data and Deep Learning



https://www.wired.com/2013/04/bigdata/

Pasquale Musella, ETH-Zurich seminar

Big Data and Deep Learning



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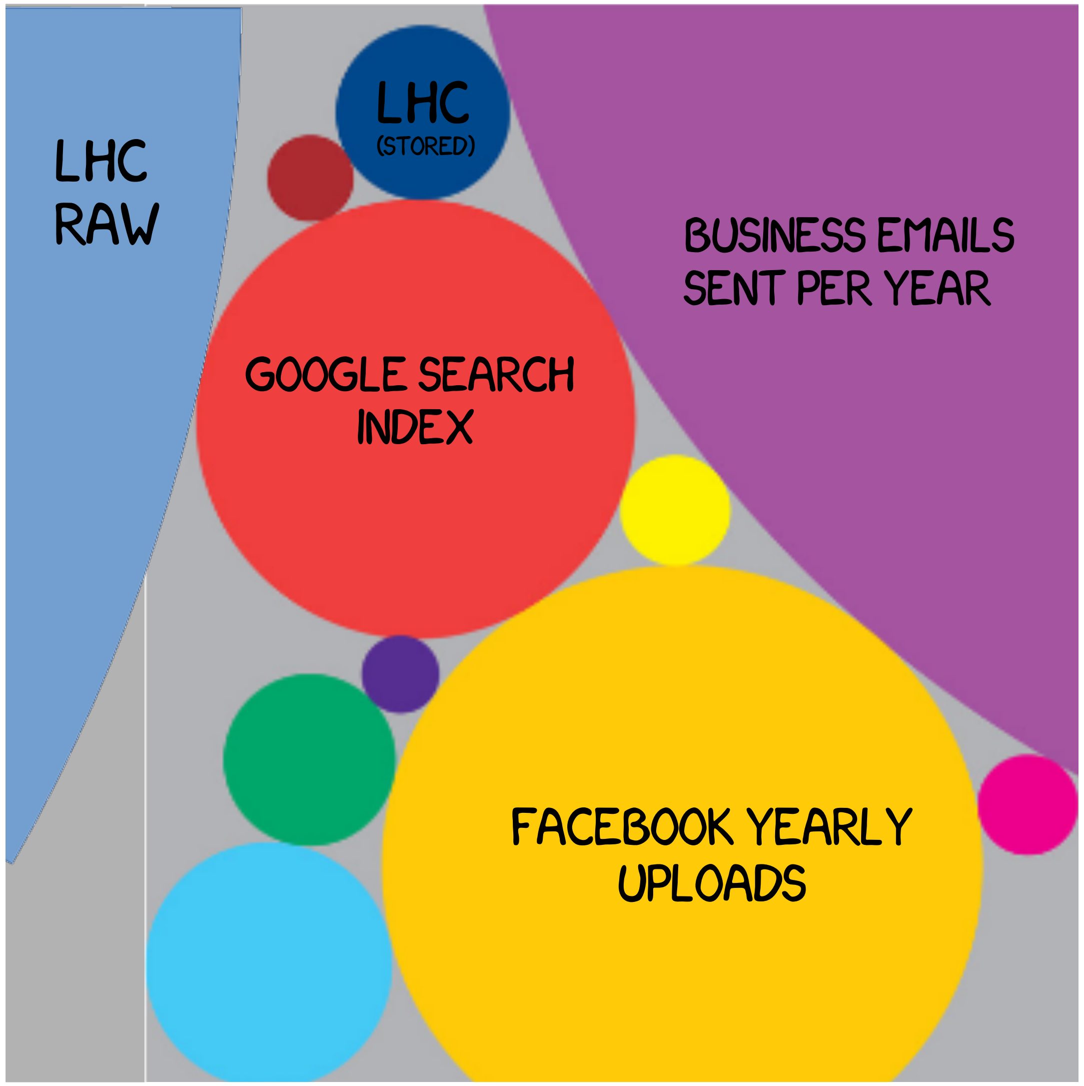
Pasquale Musella, ETH-Zurich seminar

Key prerequisite to successful deep learning: large, complex, well-understood dataset.

Big Data and Deep Learning



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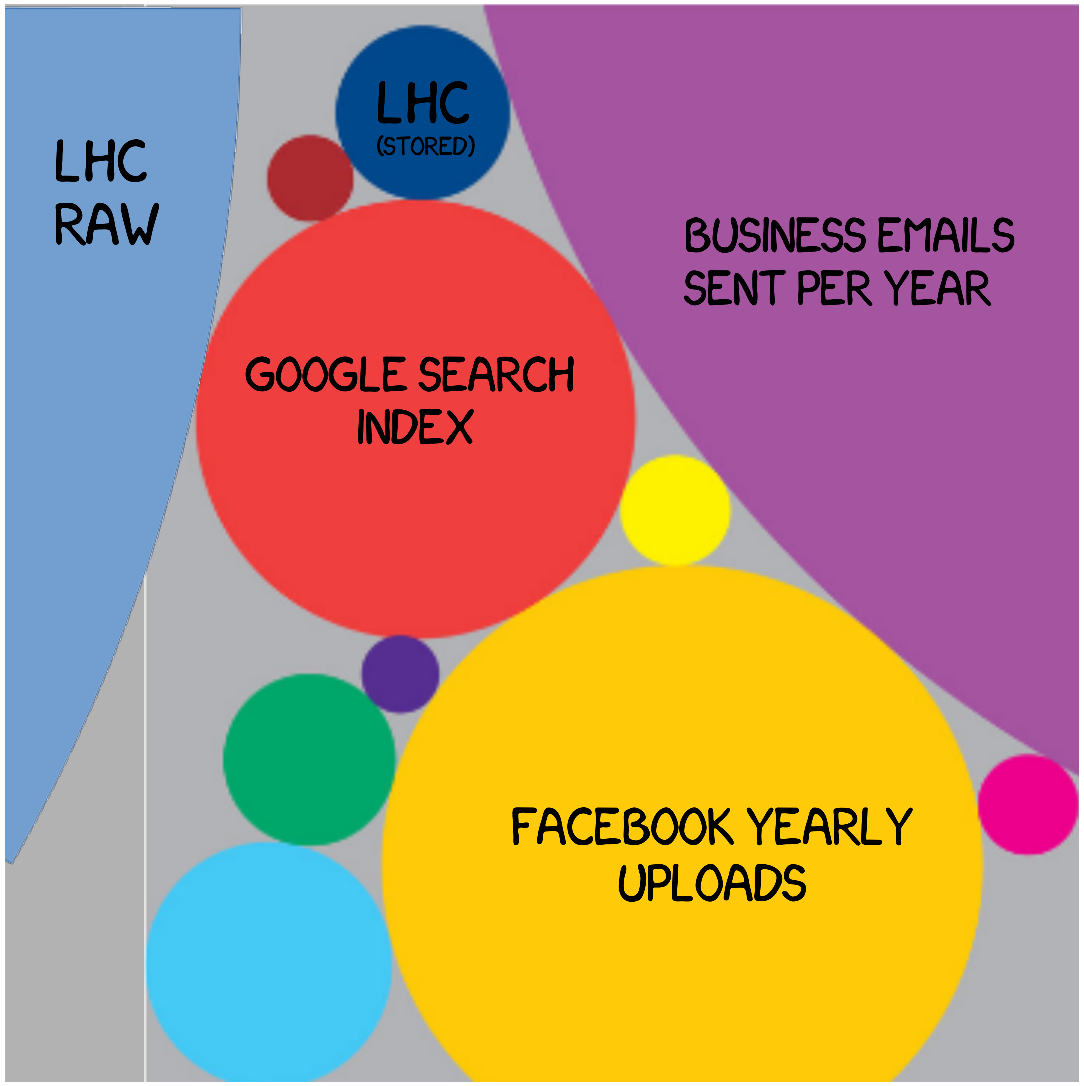
Key prerequisite to successful deep learning: large, complex, well-understood dataset.

Ability to cheaply generate realistic simulations also very beneficial for supervised ML.

Big Data and Deep Learning



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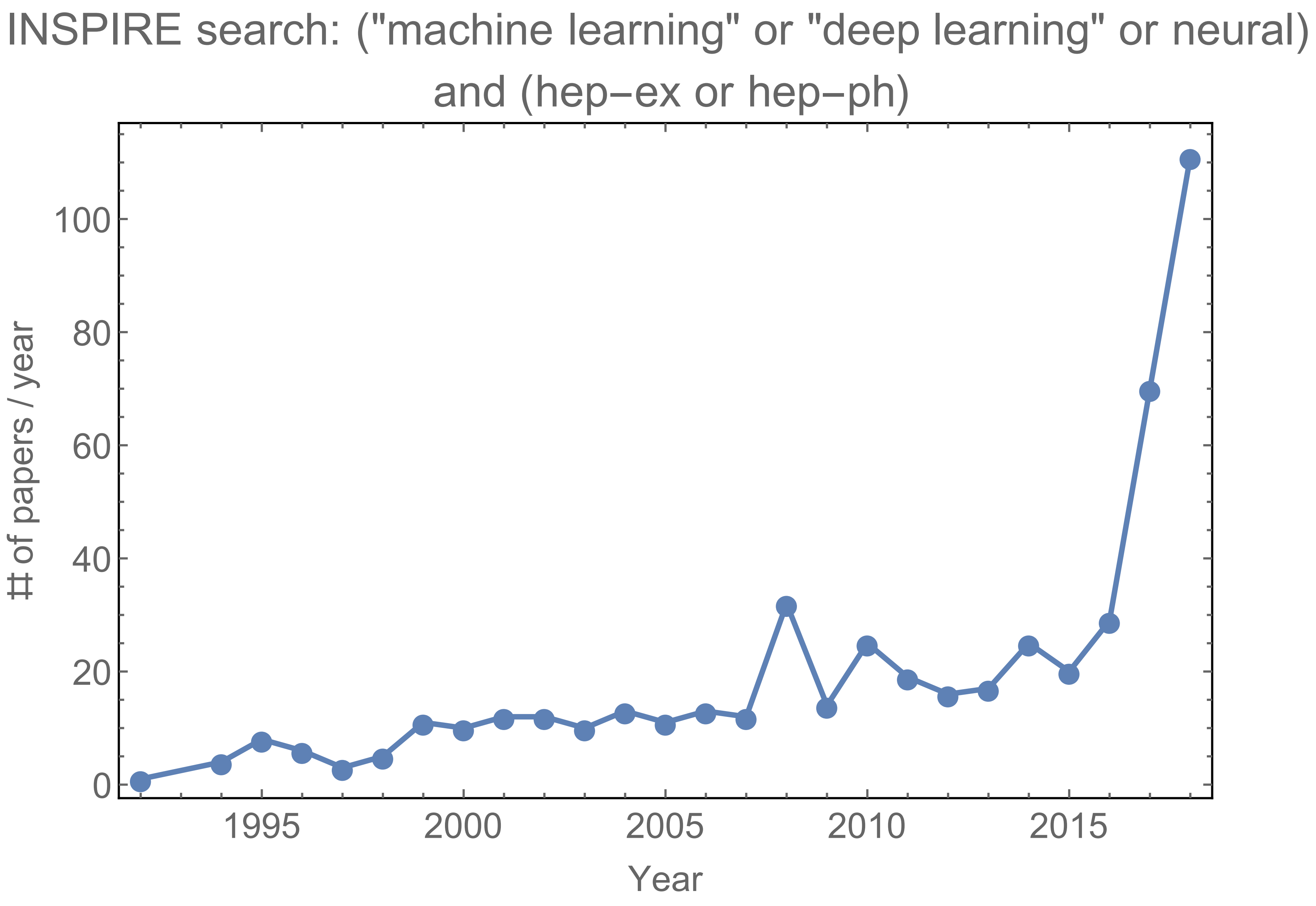
Pasquale Musella, ETH-Zurich seminar

Key prerequisite to successful deep learning: large, complex, well-understood dataset.

Ability to cheaply generate realistic simulations also very beneficial for supervised ML.

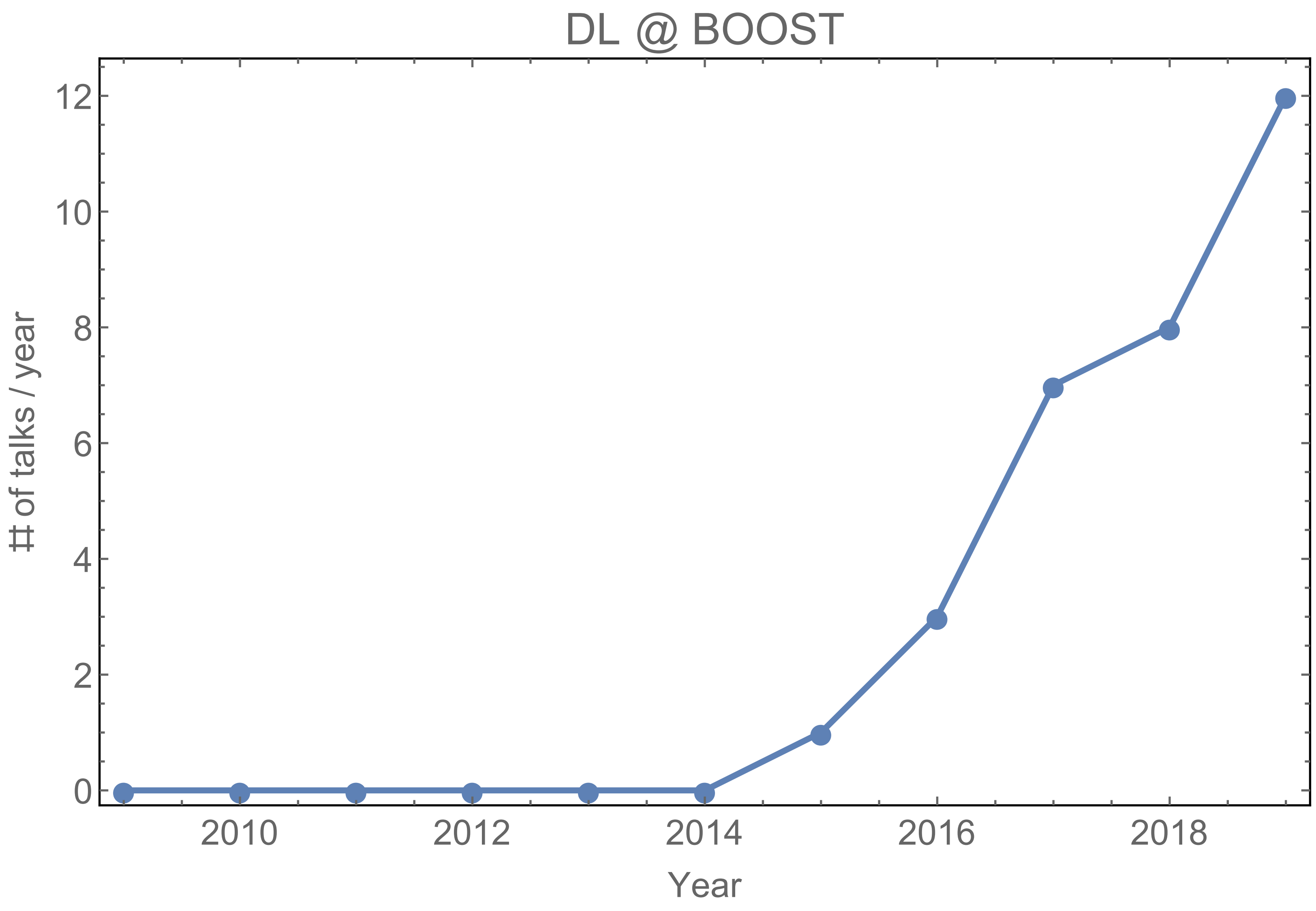
The LHC is the perfect setting for deep learning!

Deep Learning Papers



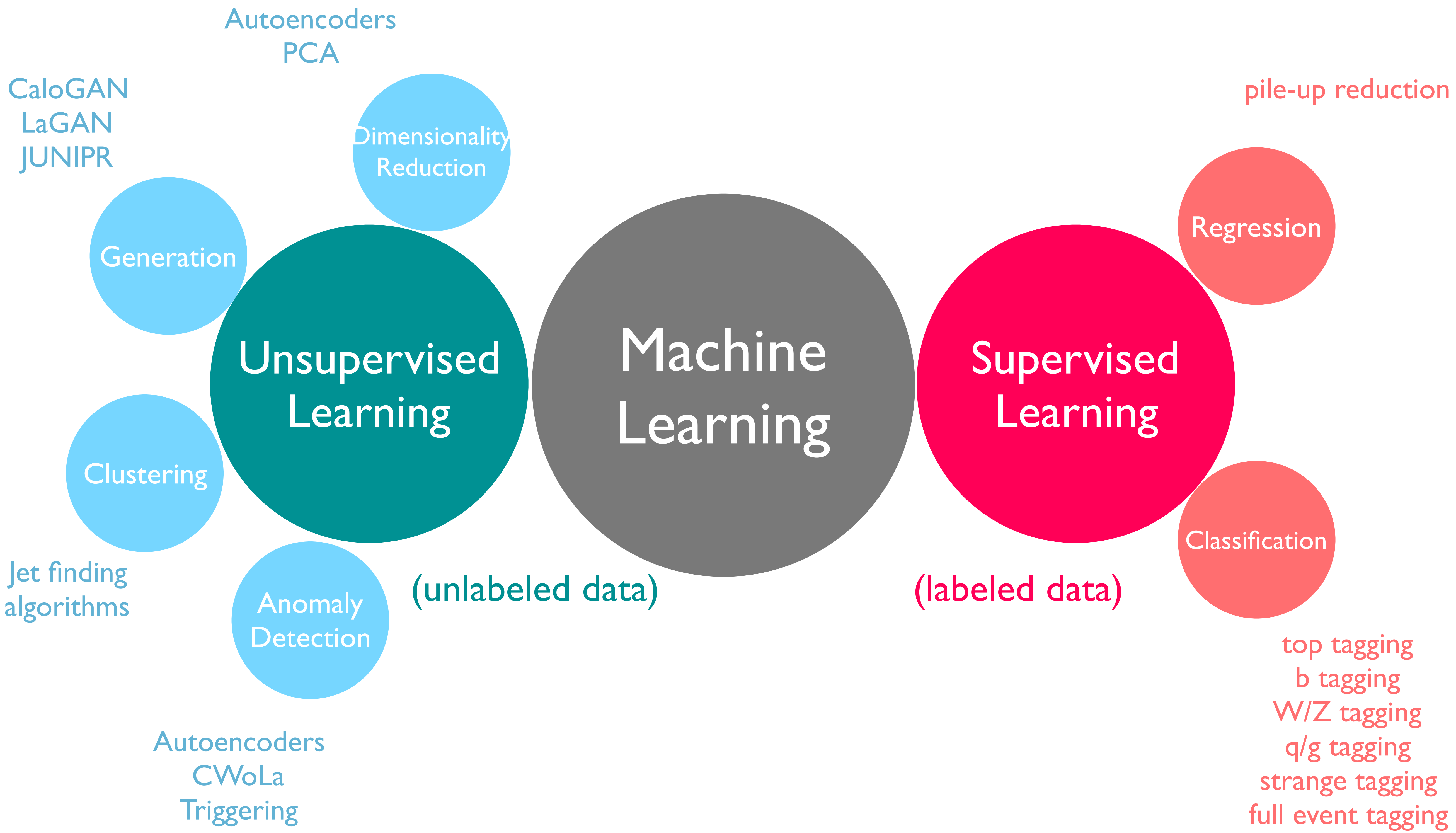
An explosion of interest in machine learning!

Deep Learning at BOOST



Jet substructure is a natural arena for deep learning!

The Landscape of DL @ LHC



Machine Learning

Unsupervised Learning

(unlabeled data)

Generation

CaloGAN
LaGAN
JUNIPR

Dimensionality Reduction

Autoencoders
PCA

Clustering

Jet finding algorithms

Anomaly Detection

Autoencoders
CWoLa
Triggering

Supervised Learning

(labeled data)

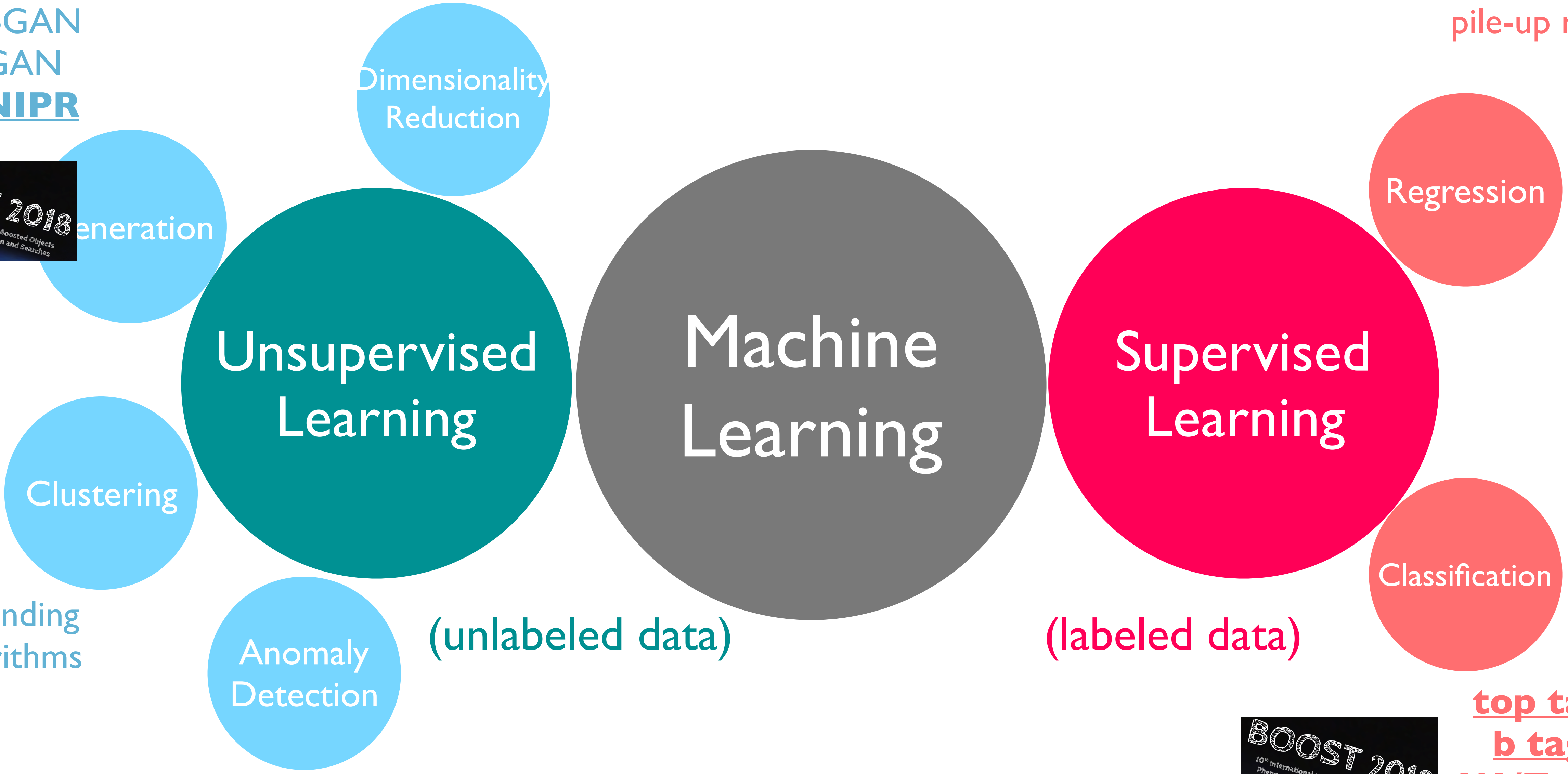
Regression

pile-up reduction

Classification

top tagging
b tagging
W/Z tagging
q/g tagging
strange tagging
full event tagging

The Landscape of DL @ LHC



Autoencoders
PCA

CaloGAN
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JUNIPR

Dimensionality
Reduction

pile-up reduction

eneration

Regression

Unsupervised
Learning

Machine
Learning

Supervised
Learning

Clustering

Classification

Jet finding
algorithms

Anomaly
Detection

(unlabeled data)

(labeled data)

top tagging
b tagging
W/Z tagging
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full event tagging

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Deep Learning @ BOOST '18

- Deep Learning for Jet Tagging at CMS and ATLAS
- Recursive NNs for Jet Tagging

New ideas for
jet tagging

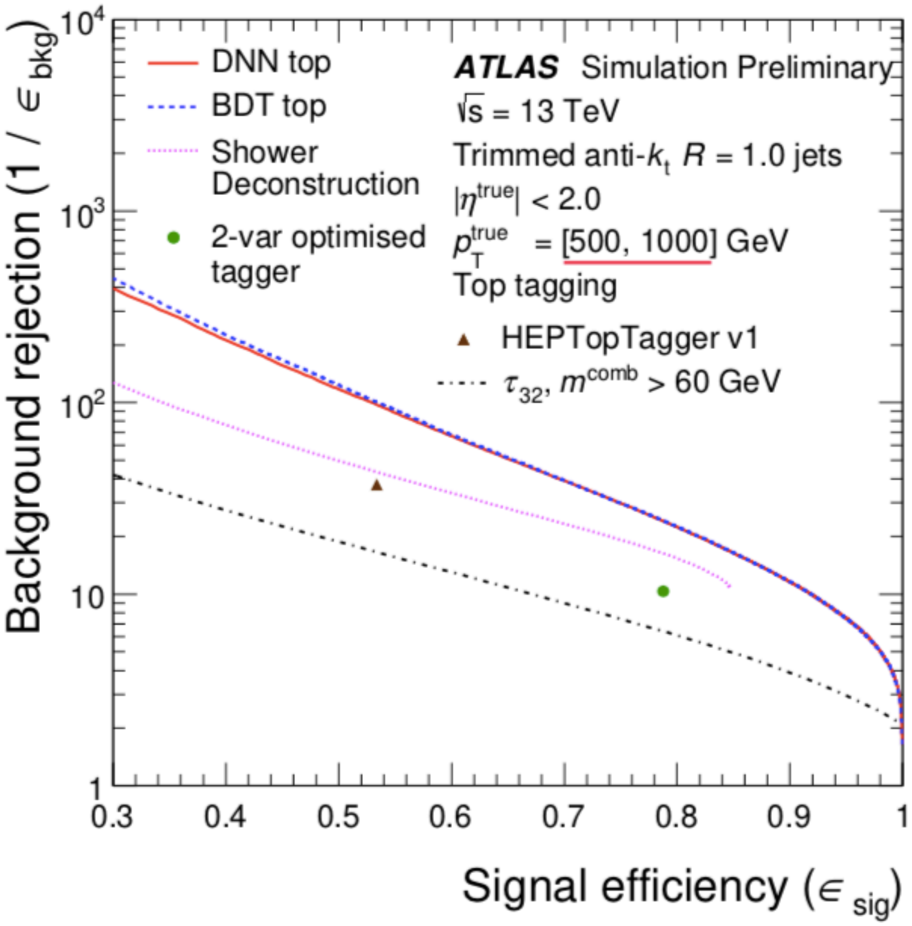
- Autoencoders
- Classification Without Labels
- Jet Topics
- JUNIPR

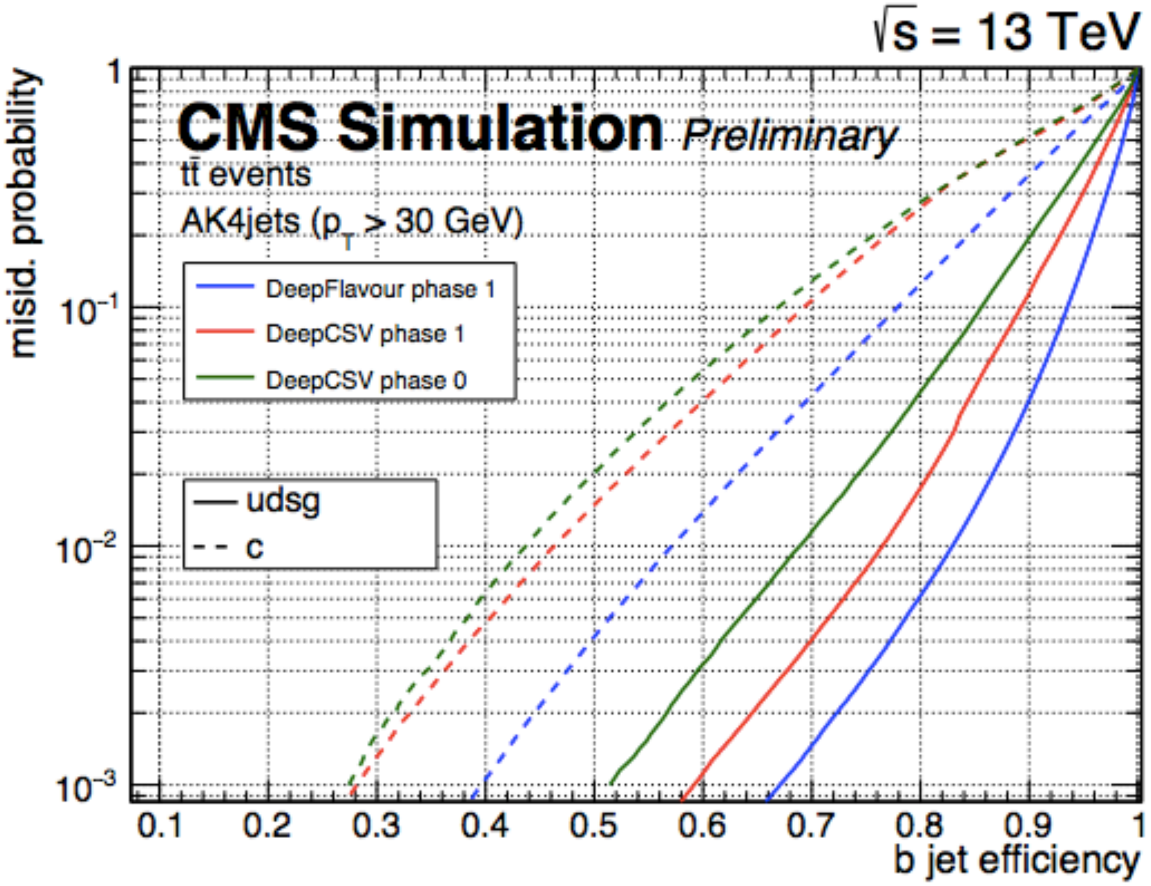
Unsupervised
deep learning

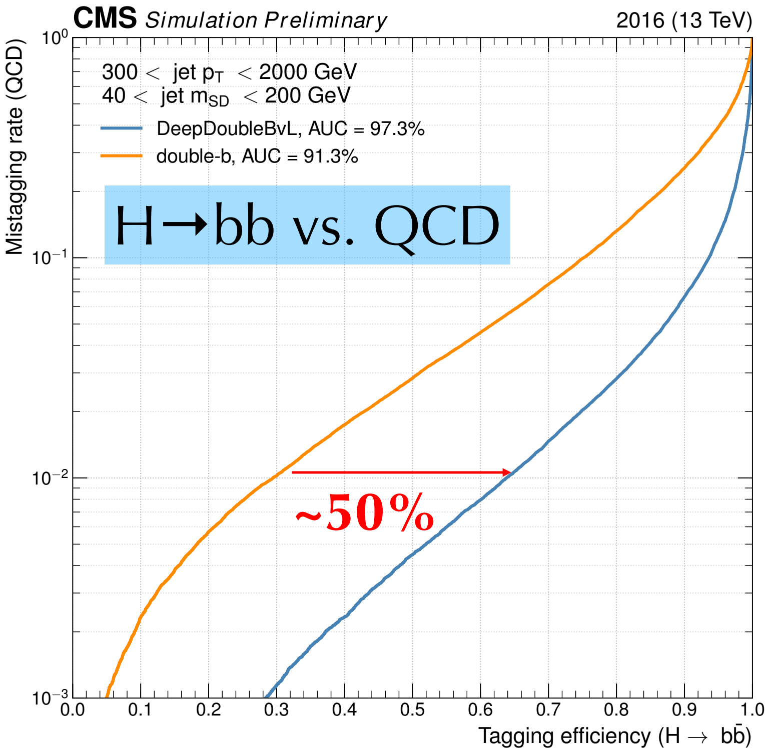
- Energy Flow Networks
- New observables from DL

Learning from
deep learning

)

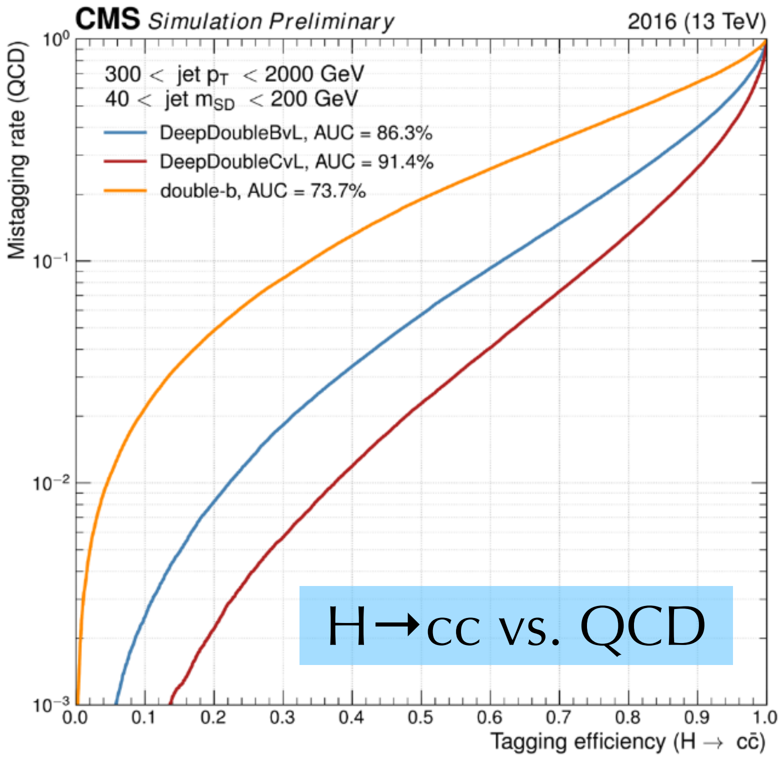






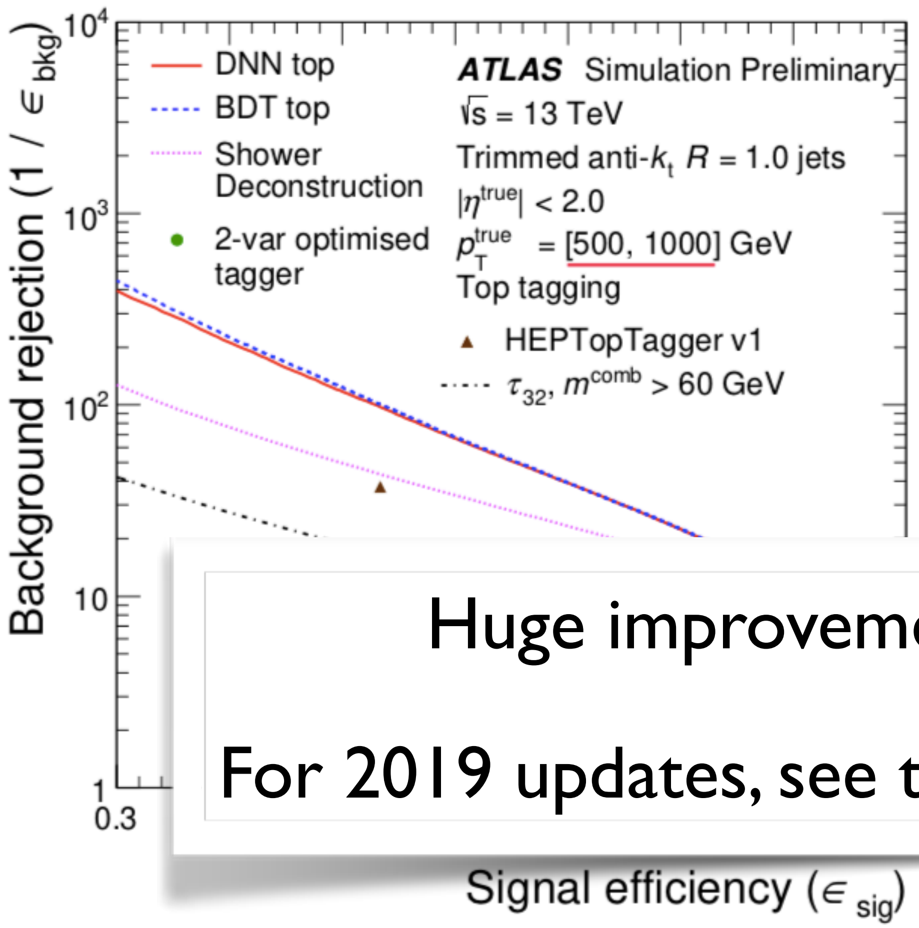
H→bb vs. QCD

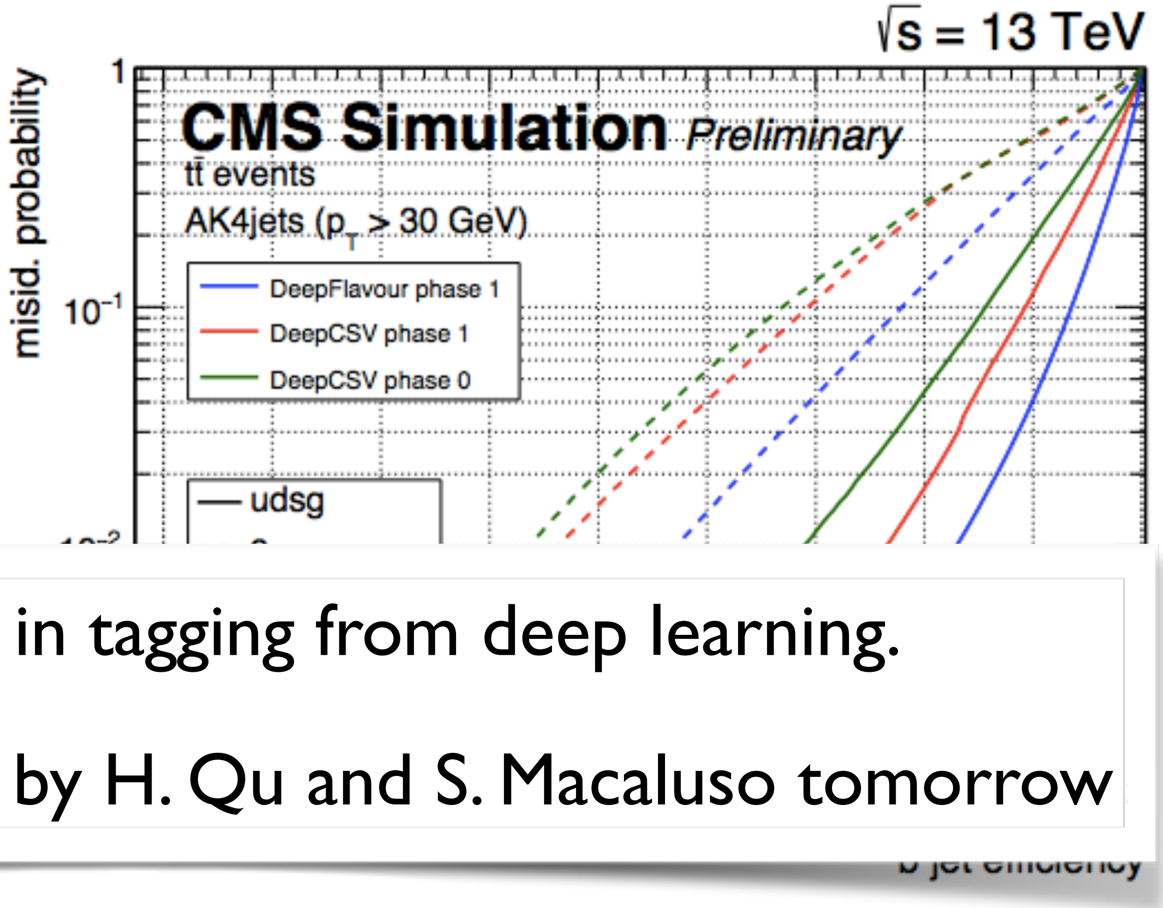
~50%



H→cc vs. QCD

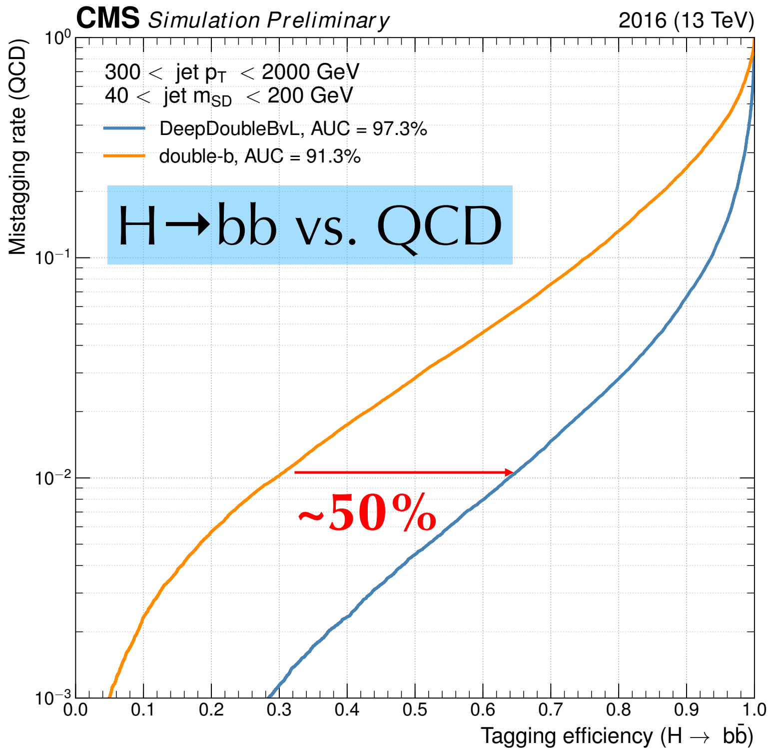
)





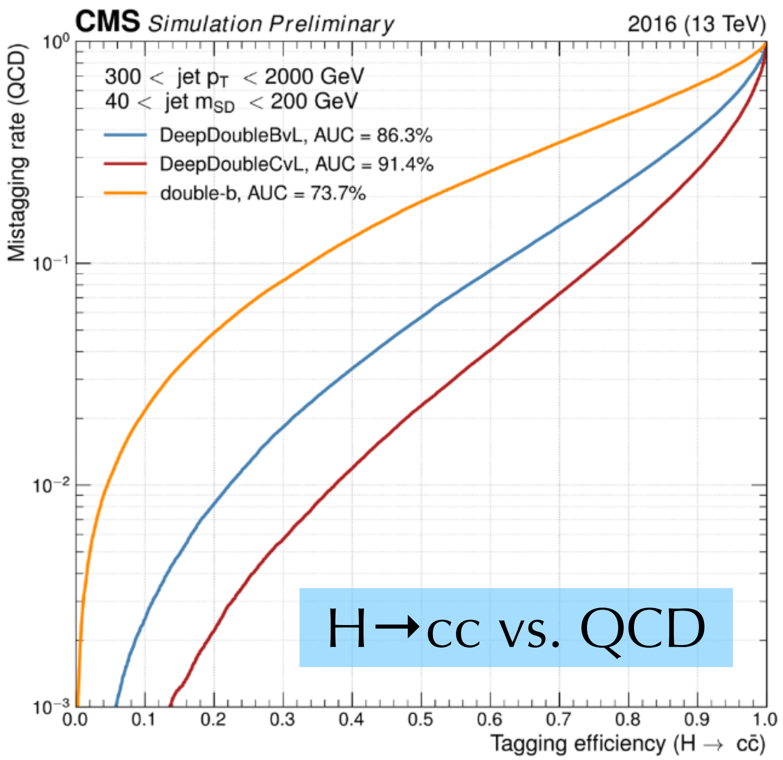
Huge improvements in tagging from deep learning.

For 2019 updates, see talks by H. Qu and S. Macaluso tomorrow

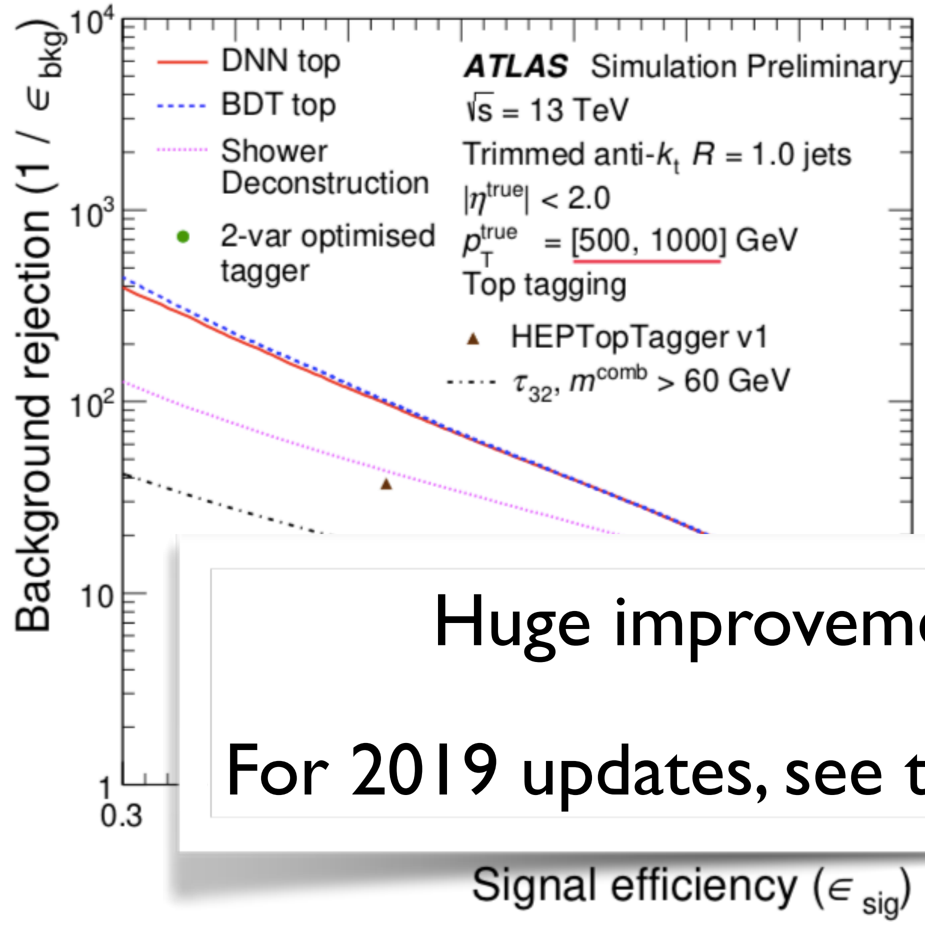


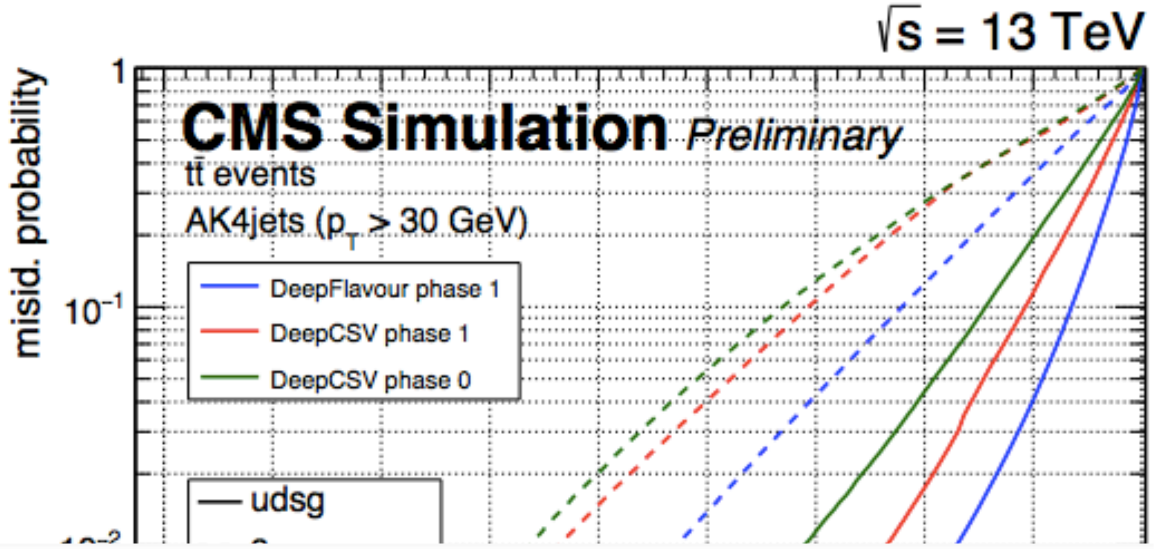
H→bb vs. QCD

~50%



H→cc vs. QCD



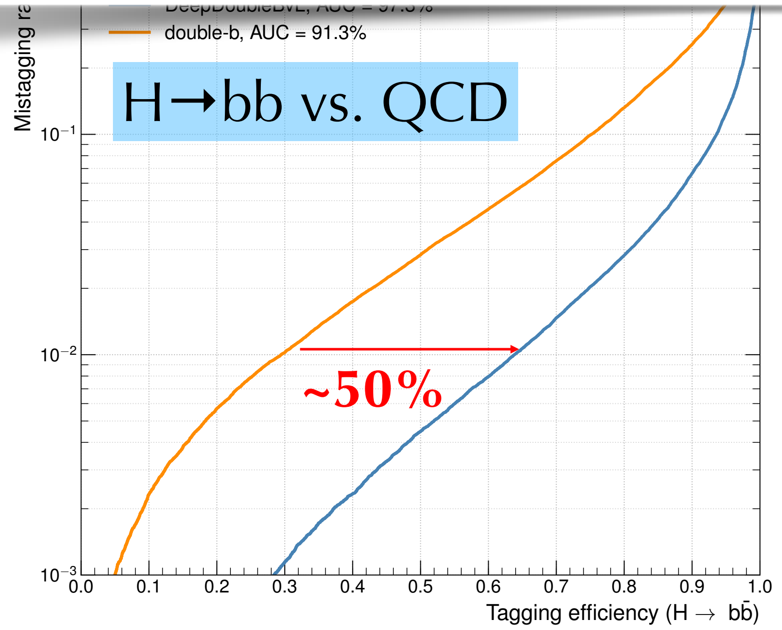


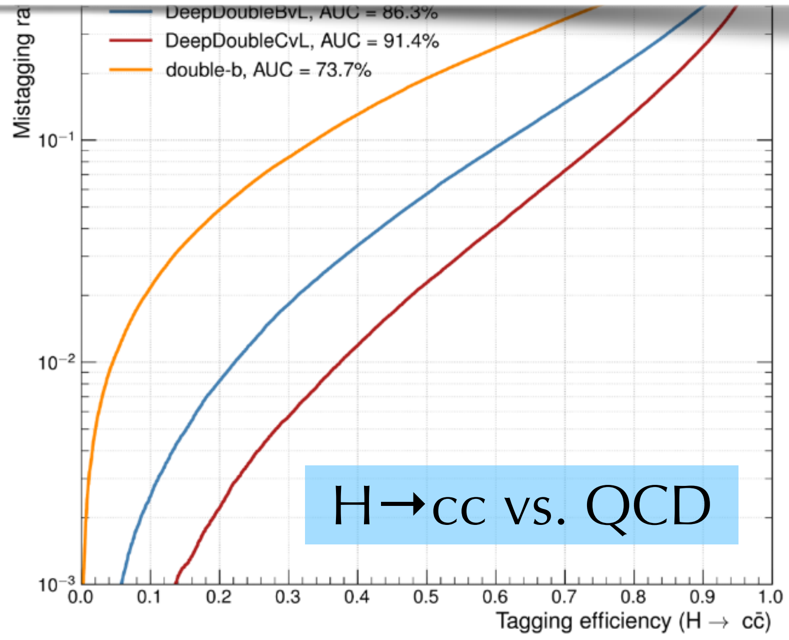
Huge improvements in tagging from deep learning.

For 2019 updates, see talks by H. Qu and S. Macaluso tomorrow

Realized in data???

See ATLAS and CMS talks by Schramm and Narain later today





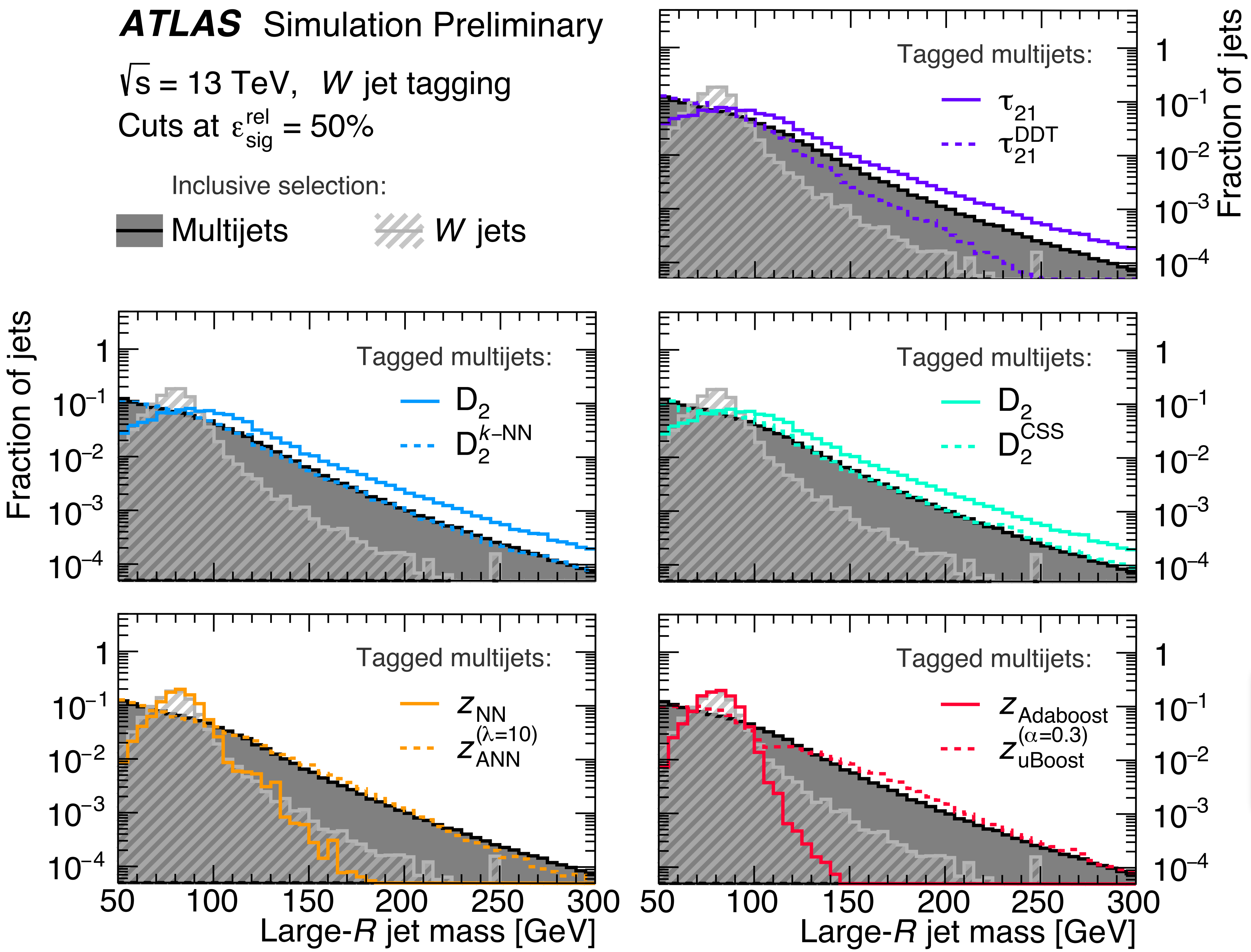
Beyond tagging: mass decorrelation

Raw tagger performance not the only consideration.

For robust background estimation, often need to ensure tagger does not bias the background mass distribution.

State of the art in mass decorrelation methods was presented by ATLAS for W-tagging at BOOST ’18 (ATL-PHYS-PUB-2018-014)

ATL-PHYS-PUB-2018-014



Analytical / single-variable

Multivariate (MVA)

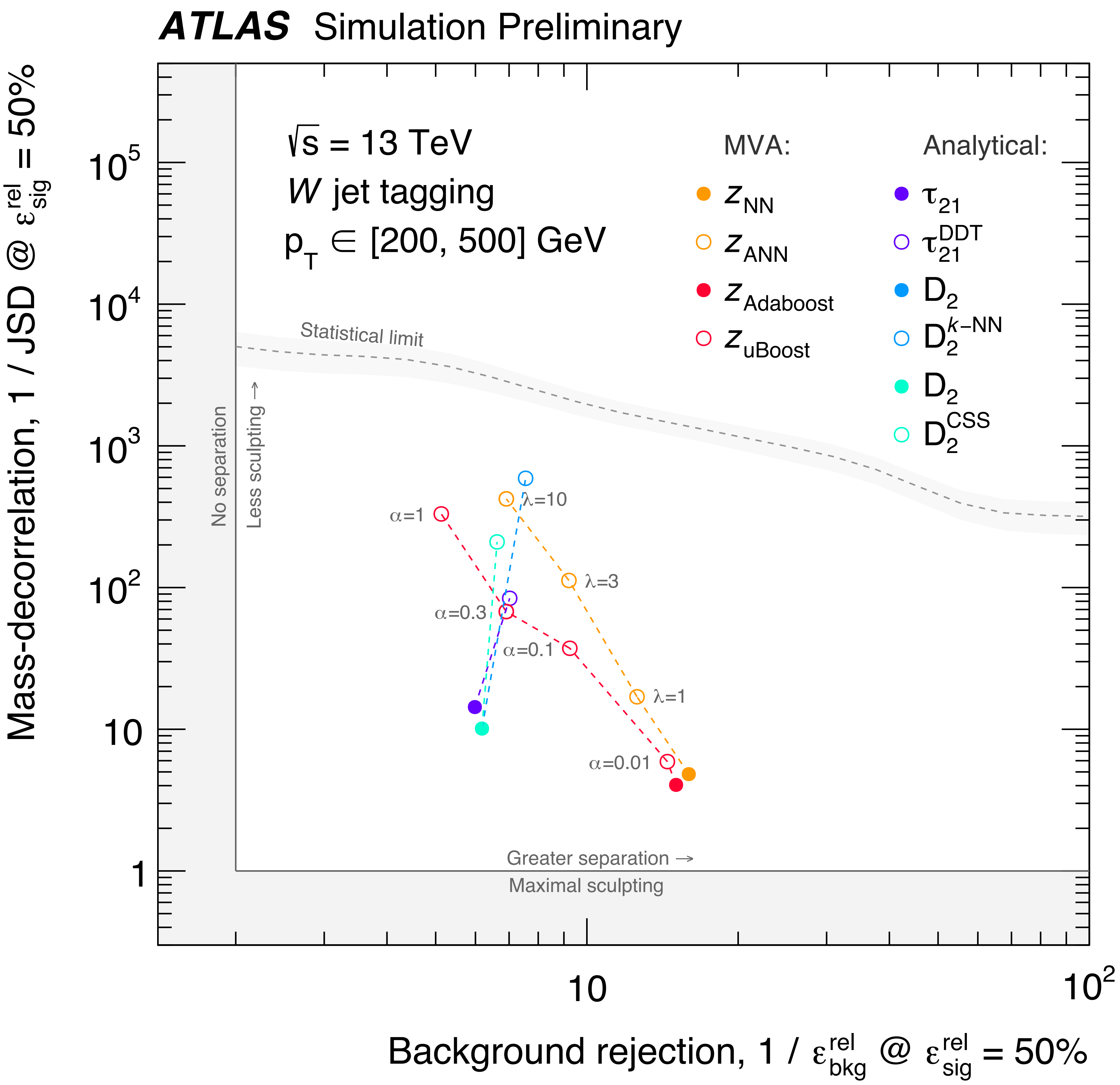
DDT

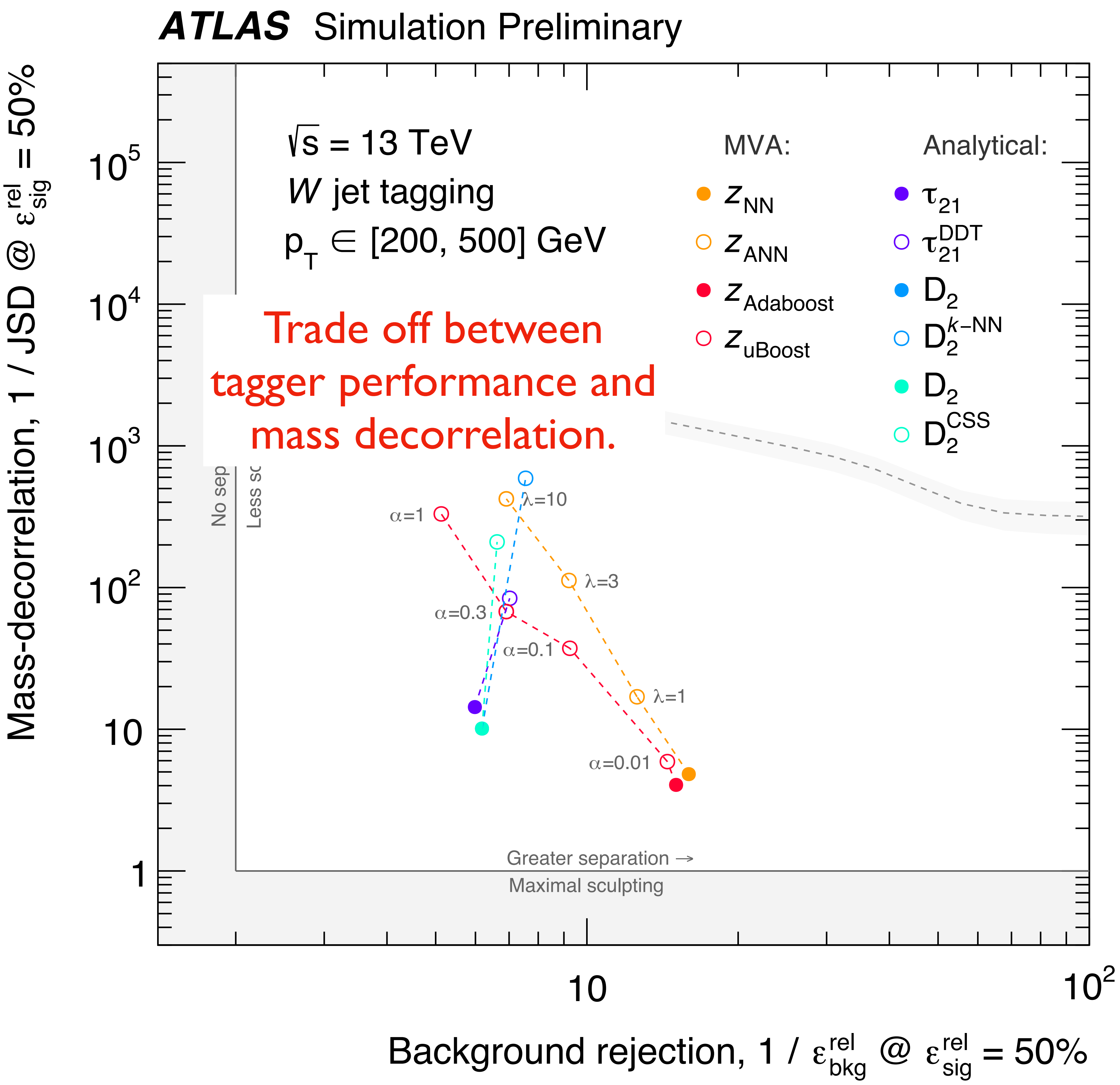
***k*-NN**

CSS

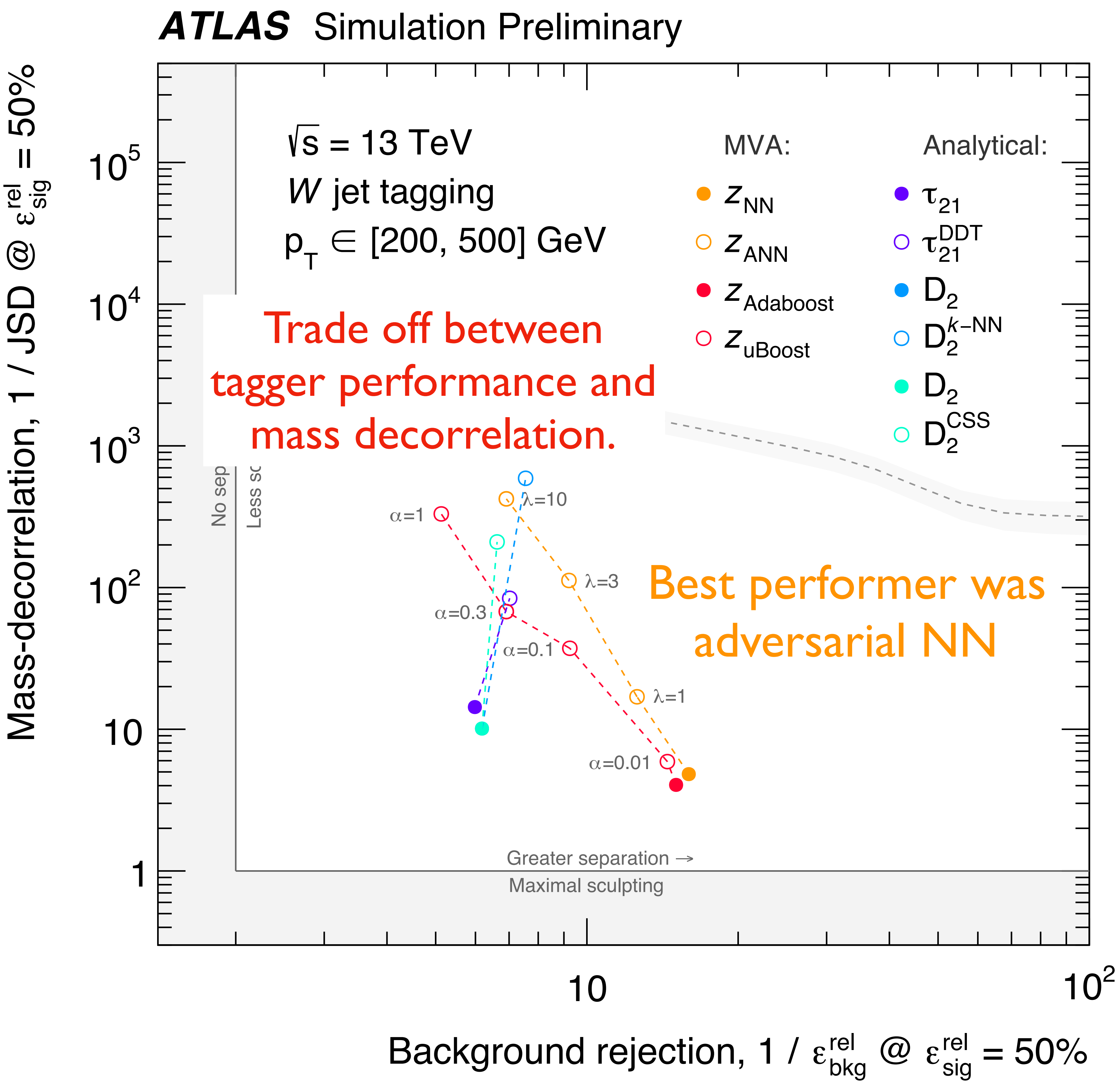
ANN

uBoost

ATLAS Simulation Preliminary
√s = 13 TeV
W jet tagging
p_T ∈ [200, 500] GeV
MVA:
z_NN
z_ANN
z_Adaboost
z_uBoost
Analytical:
τ_21
τ_21^DDT
D_2
D_2^k−NN
D_2
D_2^CSS
Statistical limit
No separation
Less sculpting →
Greater separation →
Maximal sculpting
λ=10
λ=3
λ=1
α=1
α=0.3
α=0.1
α=0.01
10^5
10^4
10^3
10^2
10
1
10
10^2
Mass-decorrelation, 1 / JSD @ ε_sig^rel = 50%
Background rejection, 1 / ε_bkg^rel @ ε_sig^rel = 50%



Trade off between tagger performance and mass decorrelation.



Trade off between tagger performance and mass decorrelation.

Best performer was adversarial NN

Alternatives to adversaries

Work in progress with Gregor Kasieczka

Adversaries are notoriously **tricky to train** — saddle point optimization

$$\min_{\theta_{\rm clf}} \max_{\theta_{\rm adv}} L_{\rm clf}(y(\theta_{\rm clf})) - \lambda L_{\rm adv}(y(\theta_{\rm clf}), m; \theta_{\rm adv})$$

y: NN prediction
m: mass

Would be great if we could achieve the same performance but with a convex regularizer term

$$\min_{\theta_{\rm clf}} L_{\rm clf}(y(\theta_{\rm clf})) + \lambda C_{\rm reg}(y(\theta_{\rm clf}), m)$$

First idea: can we just use Pearson correlation coefficient?

$$C_{\rm reg} = R(y,m) \propto \sum_i y_i m_i$$

Problem: this only measures linear correlations

Distance (de)correlation

Work in progress with Gregor Kasieczka

Promising idea: "distance correlation" (Szekely, Rizzo, Bakirov 2007; Szekely & Rizzo 2009)

$$X_{ij} = |X_i - X_j|, \qquad Y_{ij} = |Y_i - Y_j|$$

Matrix of distances

$$\hat{X} = CXC, \qquad \hat{Y} = CYC$$

Double-centering

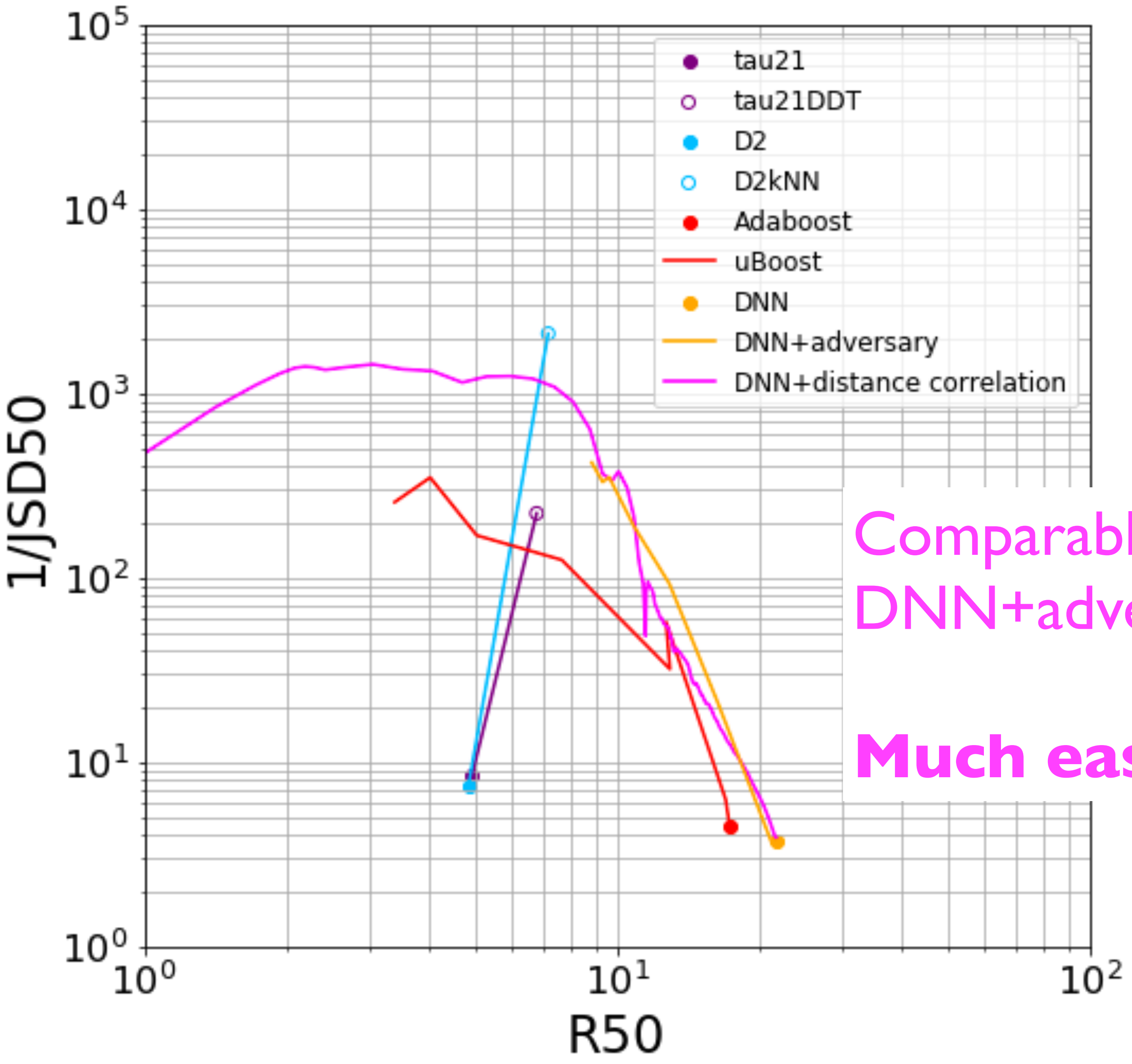
$$\boxed{\mathrm{dCov}^2(X,Y) \equiv \mathrm{tr}\, \hat{X}\hat{Y}}$$

Distance covariance

- Zero iff X, Y are independent; positive otherwise!
- Computationally tractable!
- Doesn't require binning!

Distance (de)correlation

Work in progress with Gregor Kasieczka



Comparable performance to DNN+adversary.

Much easier to train.

Beyond tagging: unsupervised ML

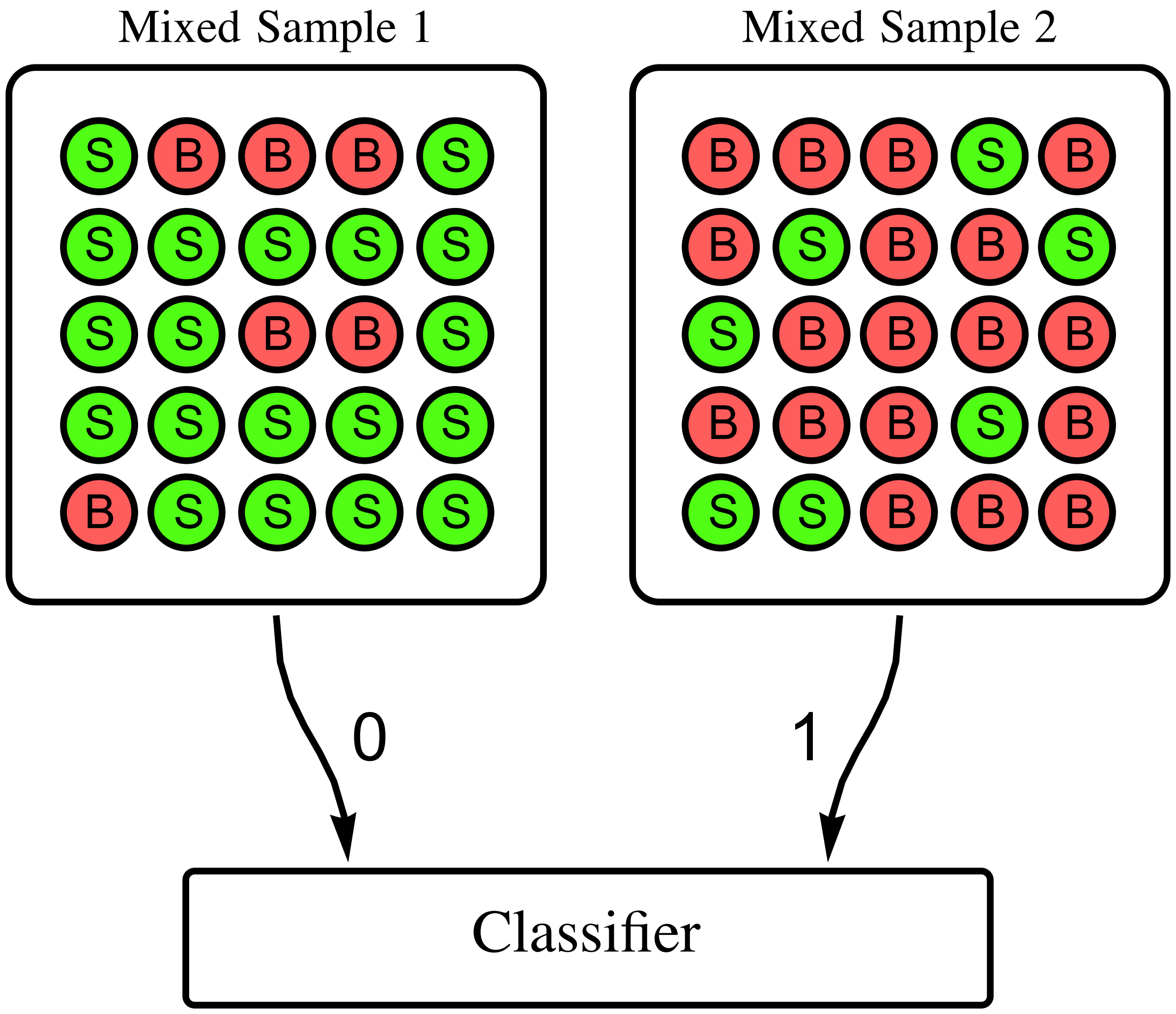
Jet tagging is a prime example of supervised machine learning.
Perfect when you know what you're looking for.

Increasing interest in applications of unsupervised ML to LHC.

- Learning without labels
- Learning directly from the data
- Anomaly detection
- Triggering

Classification WithOut Labels (CWoLa)

Dery et al 1702.00414, Cohen, Freytsis & Ostdiek 1706.09451, Metodiev, Nachman & Thaler 1708.02949, Komiske et al 1801.10158, Collins, Howe & Nachman 1805.02664, 1902.02634



from 1708.02949

$$P_1^{signal} = P_2^{signal}$$

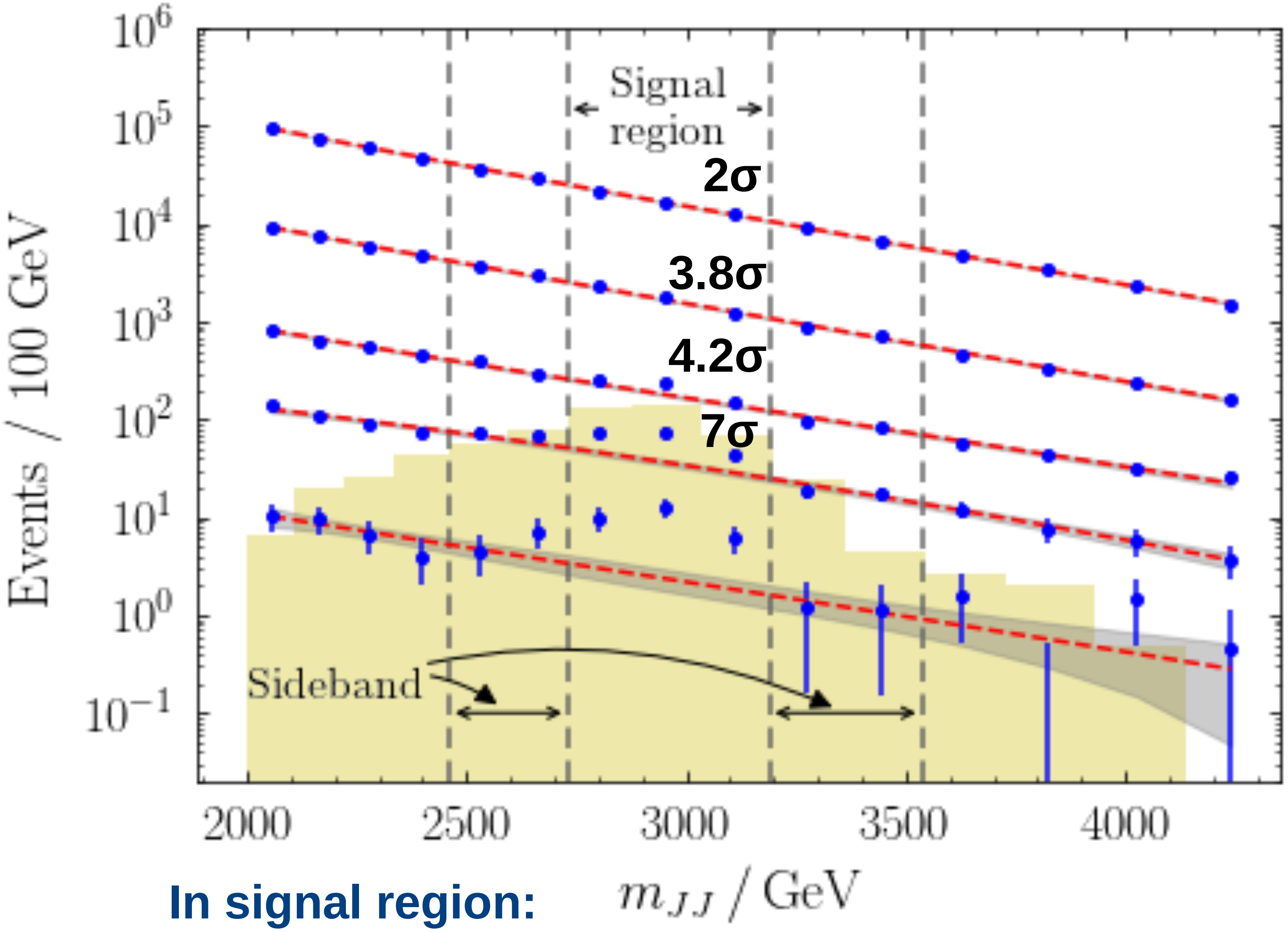
$$P_1^{background} = P_2^{background}$$

Suppose we are given two mixtures of signal and background.

If signal and background are drawn from the same distributions in each sample, then under certain mild assumptions, one can train a classifier to distinguish signal from background directly from the data.

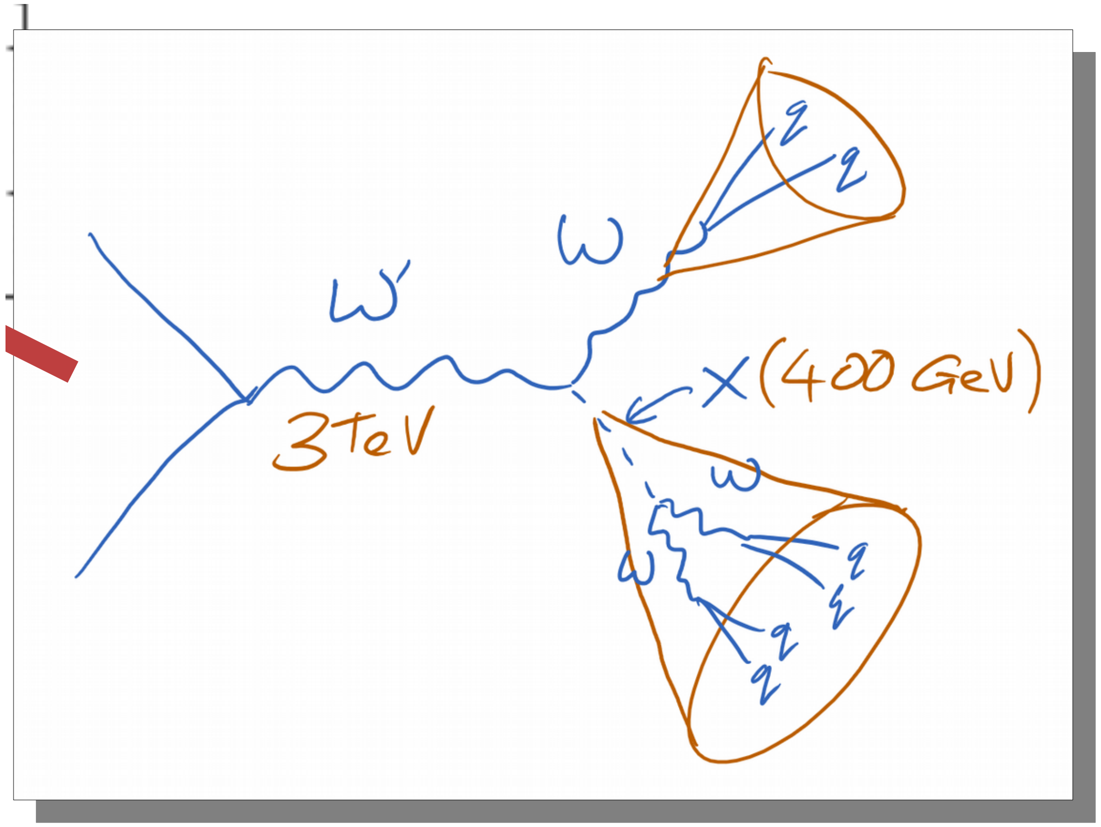
CWoLa Hunting

Collins, Howe & Nachman 1805.02664, 1902.02634



In signal region:
S = 522,
S/B = 0.64%

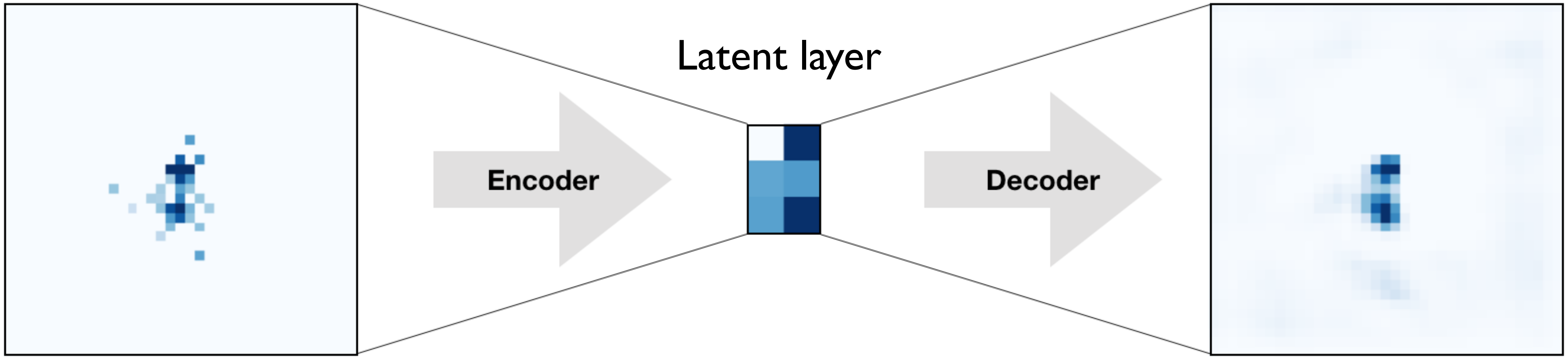
J. Collins, BOOST ‘18



Can look for anomalies in the data without a detailed signal hypothesis in mind

Unsupervised anomaly detection with deep autoencoders

Heimel et al 1808.08979;   Farina, Nakai & DS 1808.08992

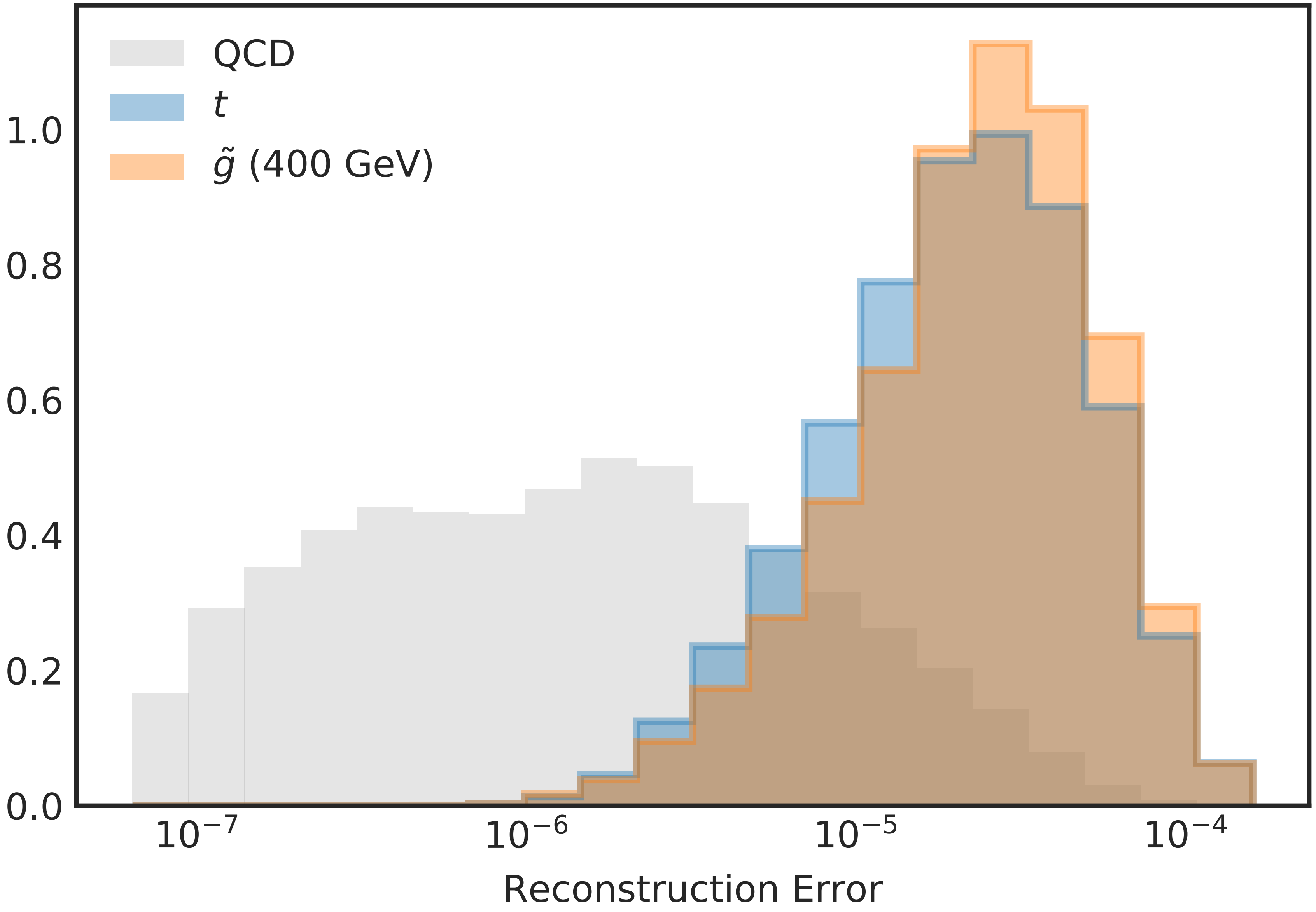


An autoencoder maps an input into a "latent representation" and then attempts to reconstruct the original input from it.

The encoding is lossy, so the decoding cannot be perfect.

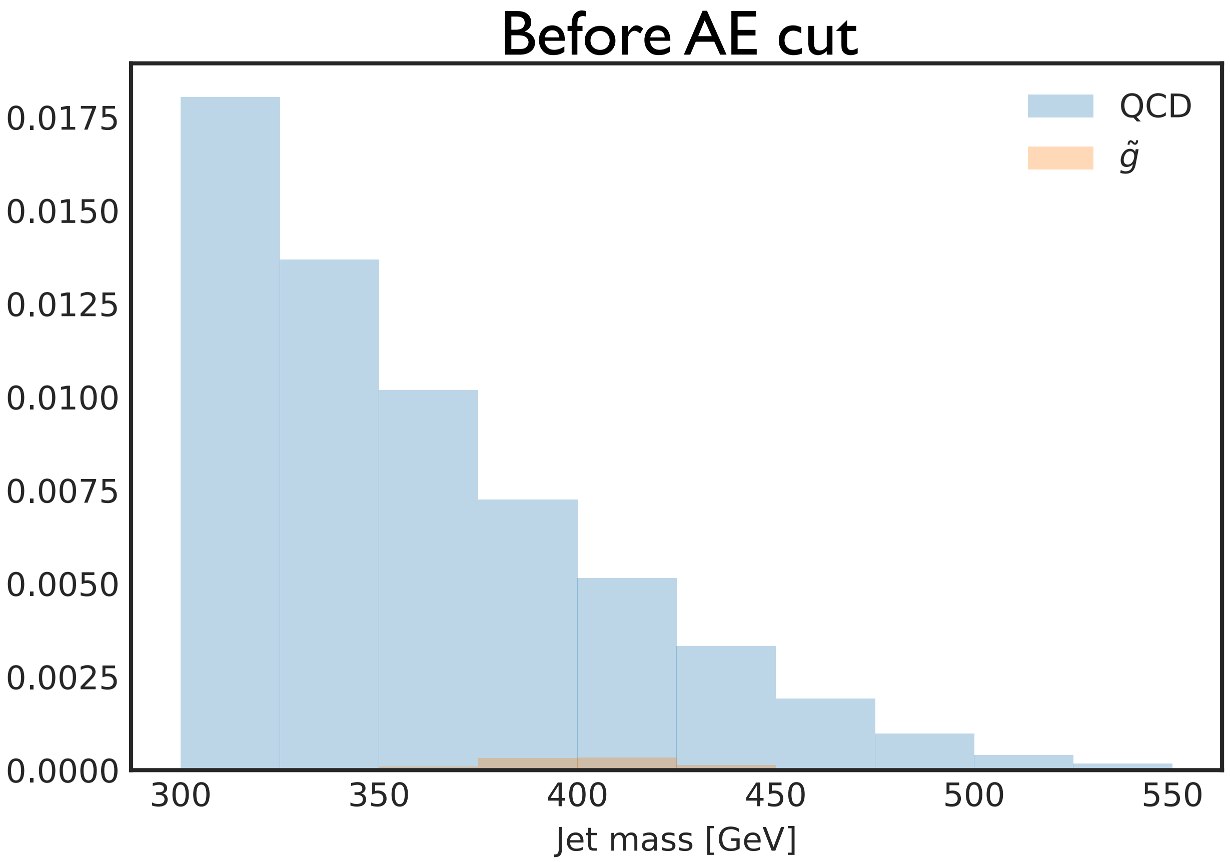
See also:
Hajer et al "Novelty Detection Meets Collider Physics" 1807.10261
Cerri et al "Variational Autoencoders for New Physics Mining at the Large Hadron Collider" 1811.10276

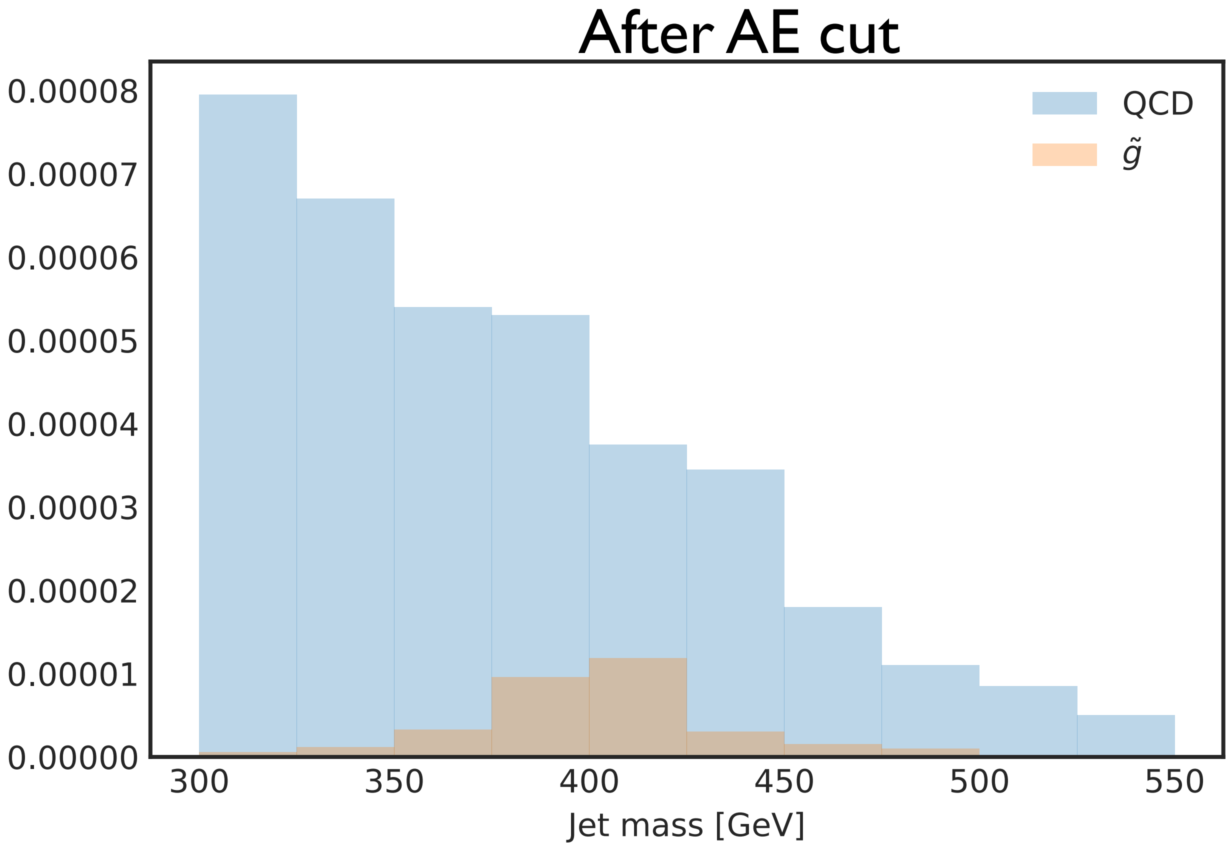
Can use reconstruction error as an anomaly threshold.



The algorithm works when trained on “real data”!
(QCD + a small fraction of signal)

Bump hunt with deep autoencoder


Before AE cut


After AE cut

Can train directly on data that contains 400 GeV gluinos,
use the AE to clean away “boring” SM events,
and improve S/N by a lot.

Could potentially discover new physics this way!

ML4Jets2020

15-17 January 2020
Europe/Zurich timezone

- Overview
- Timetable
- Participant List
- LHCOlympics2020
- Slack channel

LHCOlympics2020

Come join us for the LHC Olympics 2020!

Despite an impressive and extensive effort by the LHC collaborations, there is currently no convincing evidence for new particles produced in high-energy collisions. At the same time, there has been a growing interest in machine learning techniques to enhance potential signals using all of the available information.

In the spirit of the first LHC Olympics (circa 2005-2006) [1st, 2nd, 3rd, 4th], we are organizing the 2020 LHC Olympics. Our goal is to ensure that the LHC search program is sufficiently well-rounded to capture "all" rare and complex signals. The final state for this olympics will be focused (generic dijet events) but the observable phase space and potential BSM parameter space(s) are large: all hadrons in the event can be used for learning (be it "cuts", supervised machine learning, or unsupervised machine learning).

For setting up, developing, and validating your methods, we provide background events and a benchmark signal model. You can download these from this page. To help get you started, we have also prepared simple python scripts to read in the data and do some basic processing.

The final test will happen 2 weeks before the ML4Jets2020 workshop. We will release a new dataset where the "background" will be similar to but not identical to the one in the development set (as is true in real data!). The goal of the challenge is to see who can "best" identify BSM (yes/no, what mass, what cross-section) in the dataset. There are many ways to quantify "best" and we will use all of the submissions to explore the pros/cons of the various approaches.

Conclusions/Outlook

Boosted jet substructure is a crucial ingredient in the search for NP.

Deep learning is an exciting new tool with enormous potential to enhance the sensitivity to jet substructure and NP in the HL-LHC era.

Boosted heavy resonance tagging is being greatly accelerated by deep learning, along with many other tasks. Important higher-order questions such as mass decorrelation are now being actively investigated.

Besides boosted tops, W/Z's and Higgses, new physics itself could be highly boosted. Could NP be hiding in jet substructure? Can we find it if we don't know what we're looking for?

Thanks for your attention!

HL-LHC projections

Can make simple yet accurate projections for growth of sensitivity with luminosity. Salam & Weiler http://collider-reach.web.cern.ch/collider-reach/

Assume future sensitivity set by

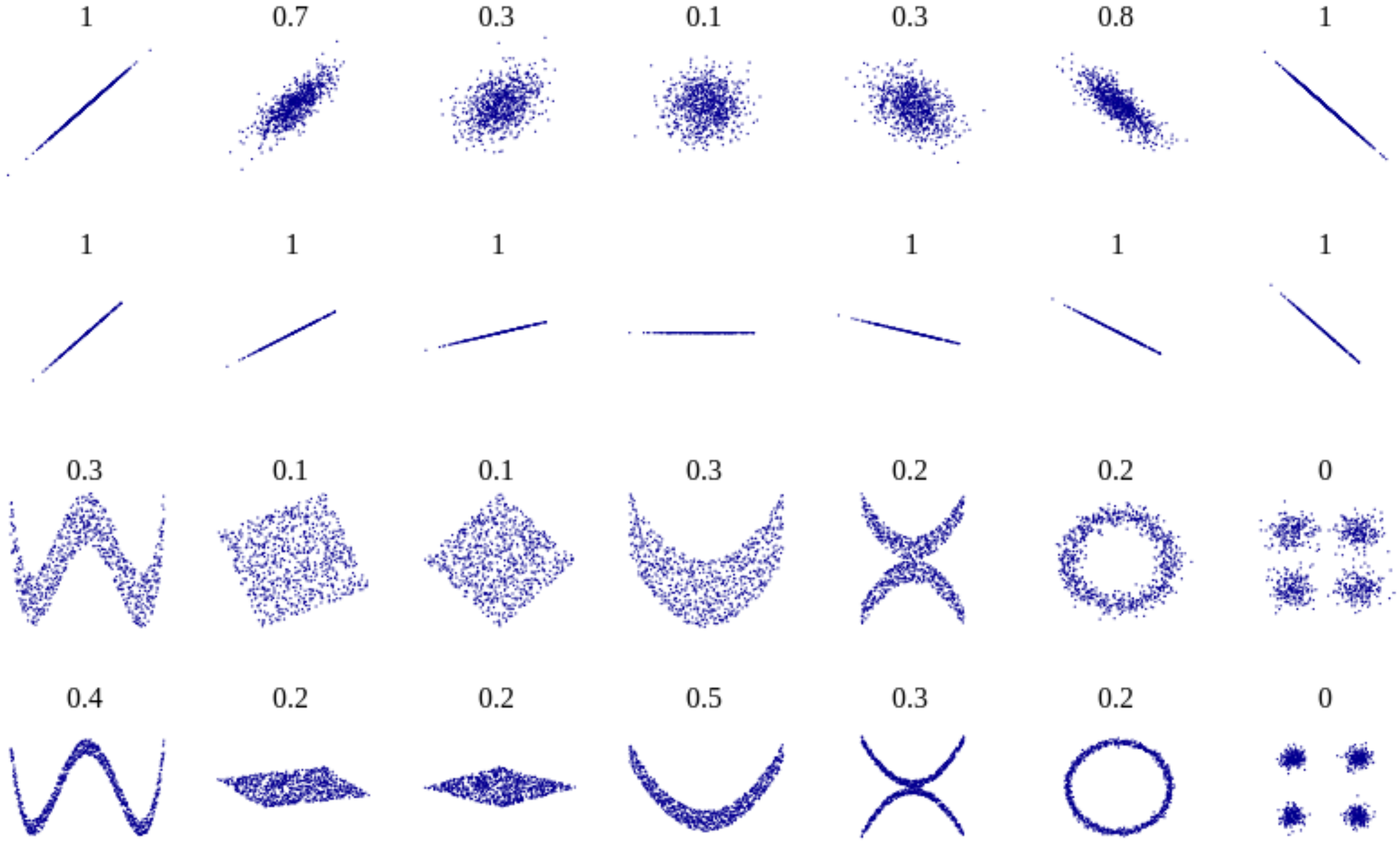
$$N_{sig}(M_{future}, L_{future}) = N_{sig}(M_{now}, L_{now})$$

$$N_{sig}(M, L) \sim \sigma(M) \times L$$

$$\sigma(M) \sim \frac{1}{M^2} f_{parton}(x = 2M/E_{CM})$$

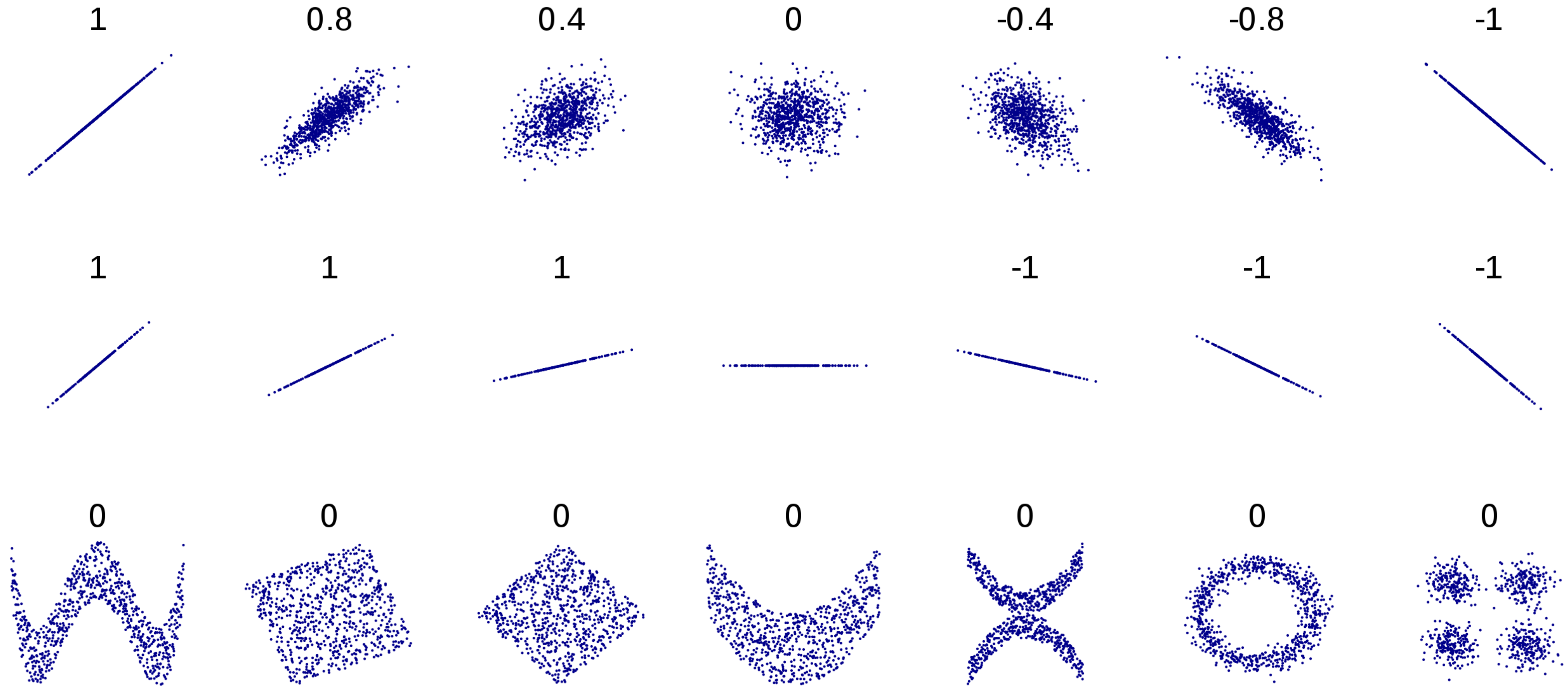
Assume future background negligible with comparable signal efficiency.

Distance correlation vs Pearson correlation



Distance correlation

Distance correlation vs Pearson correlation



Pearson correlation