

TWO FOR THE PRICE OF ONE

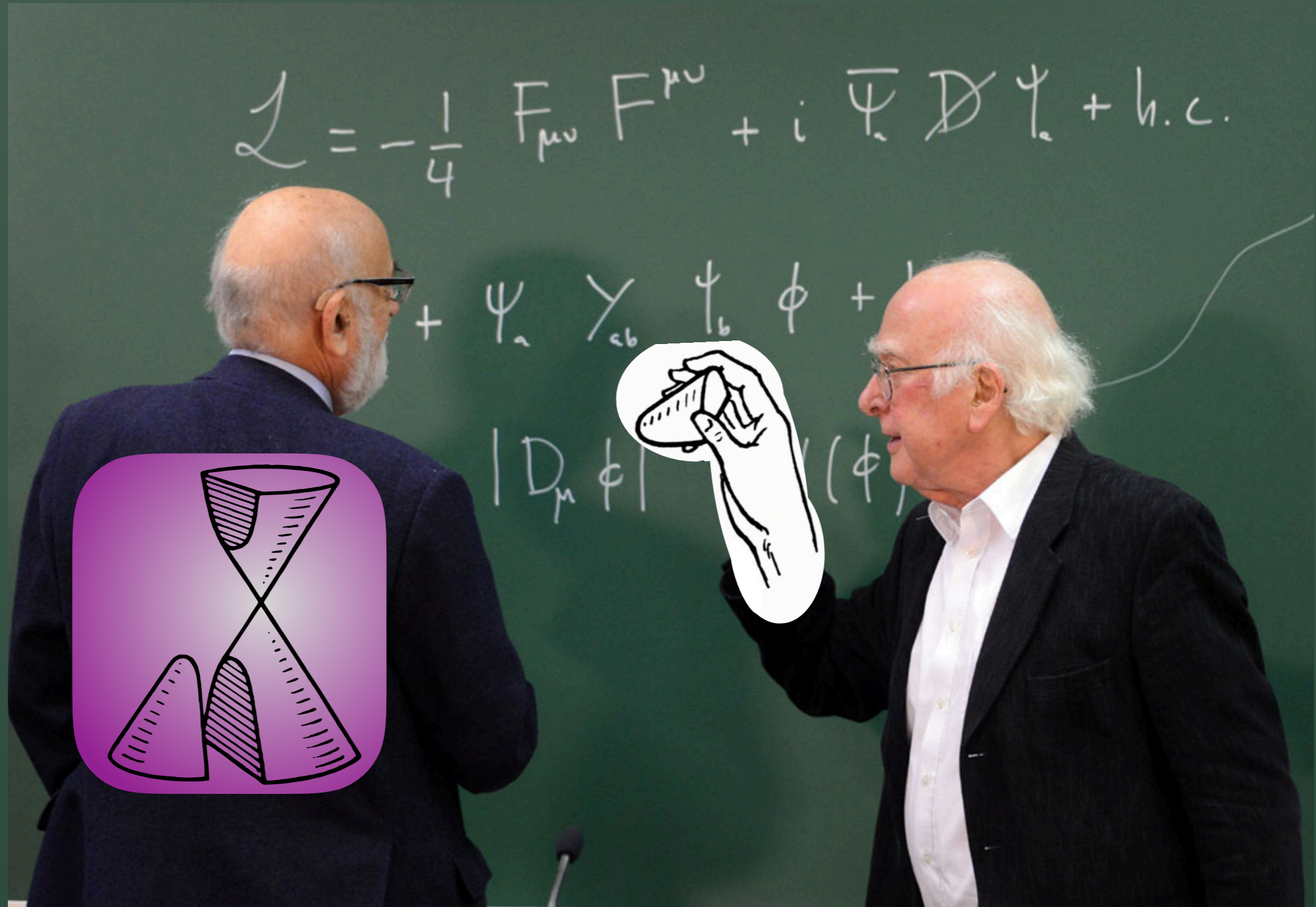
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UC Davis Joint Theory Seminar
April 16, 2018

THE HYPERBOLIC HIGGS



with Nathaniel Craig, Gian Giudice, and Matthew McCullough
arXiv:1803.03647

WHERE'S THE NEW PHYSICS?!?

ATLAS SUSY Searches* - 95% CL Lower Limits

December 2017

ATLAS Preliminary

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

Model	e, μ, τ, γ	Jets	E_T^{miss}	$\int \mathcal{L} dt [fb^{-1}]$	Mass limit	$\sqrt{s} = 7, 8$ TeV	$\sqrt{s} = 13$ TeV	Reference	
Inclusive Searches	$\tilde{q}\tilde{q}, \tilde{q} \rightarrow q\tilde{\chi}_1^0$	0	2-6 jets	Yes	36.1	\tilde{q}	1.57 TeV	$m(\tilde{\chi}_1^0) < 200$ GeV, $m(1^{st} \text{ gen. } \tilde{q}) = m(2^{nd} \text{ gen. } \tilde{q})$	1712.02332
	$\tilde{q}\tilde{q}, \tilde{q} \rightarrow q\tilde{\chi}_1^0$ (compressed)	mono-jet	1-3 jets	Yes	36.1	\tilde{q}	710 GeV	$m(\tilde{q}) - m(\tilde{\chi}_1^0) < 5$ GeV	1711.03301
	$\tilde{g}\tilde{g}, \tilde{g} \rightarrow q\tilde{q}\tilde{\chi}_1^0$	0	2-6 jets	Yes	36.1	\tilde{g}	2.02 TeV	$m(\tilde{\chi}_1^0) < 200$ GeV	1712.02332
	$\tilde{g}\tilde{g}, \tilde{g} \rightarrow q\tilde{q}\tilde{\chi}_1^0 \rightarrow qqW^\pm\tilde{\chi}_1^0$	0	2-6 jets	Yes	36.1	\tilde{g}	2.01 TeV	$m(\tilde{\chi}_1^0) < 200$ GeV, $m(\tilde{\chi}^\pm) = 0.5(m(\tilde{\chi}_1^0) + m(\tilde{g}))$	1712.02332
	$\tilde{g}\tilde{g}, \tilde{g} \rightarrow q\tilde{q}(\ell\ell)\tilde{\chi}_1^0$	$ee, \mu\mu$	2 jets	Yes	14.7	\tilde{g}	1.7 TeV	$m(\tilde{\chi}_1^0) < 300$ GeV,	1611.05791
	$\tilde{g}\tilde{g}, \tilde{g} \rightarrow qq(\ell\ell/\nu\nu)\tilde{\chi}_1^0$	$3e, \mu$	4 jets	-	36.1	\tilde{g}	1.87 TeV	$m(\tilde{\chi}_1^0) = 0$ GeV	1706.03731
	$\tilde{g}\tilde{g}, \tilde{g} \rightarrow qqWZ\tilde{\chi}_1^0$	0	7-11 jets	Yes	36.1	\tilde{g}	1.8 TeV	$m(\tilde{\chi}_1^0) < 400$ GeV	1708.02794
	GMSB ($\tilde{\ell}$ NLSP)	$1-2\tau + 0-1\ell$	0-2 jets	Yes	3.2	\tilde{g}	2.0 TeV	$cr(NLSP) < 0.1$ mm	1607.05979
	GGM (bino NLSP)	2γ	-	Yes	36.1	\tilde{g}	2.15 TeV	$cr(NLSP) < 0.1$ mm, $\mu > 0$	ATLAS-CONF-2017-080
	GGM (higgsino-bino NLSP)	γ	2 jets	Yes	36.1	\tilde{g}	2.05 TeV	$m(\tilde{\chi}_1^0) = 1700$ GeV, $cr(NLSP) < 0.1$ mm, $\mu > 0$	ATLAS-CONF-2017-080
Gravitino LSP	0	mono-jet	Yes	20.3	\tilde{g}	$R^{1/2}$ scale	865 GeV	$m(\tilde{G}) > 1.8 \times 10^{-4}$ eV, $m(\tilde{g}) = m(\tilde{q}) = 1.5$ TeV	1502.01518
3^{rd} gen. \tilde{g} med.	$\tilde{g}\tilde{g}, \tilde{g} \rightarrow b\tilde{b}\tilde{\chi}_1^0$	0	3 b	Yes	36.1	\tilde{g}	1.92 TeV	$m(\tilde{\chi}_1^0) < 600$ GeV	1711.01901
	$\tilde{g}\tilde{g}, \tilde{g} \rightarrow t\tilde{t}\tilde{\chi}_1^0$	$0-1e, \mu$	3 b	Yes	36.1	\tilde{g}	1.97 TeV	$m(\tilde{\chi}_1^0) < 200$ GeV	1711.01901
3^{rd} gen. squarks direct production	$\tilde{b}_1\tilde{b}_1, \tilde{b}_1 \rightarrow b\tilde{\chi}_1^0$	0	2 b	Yes	36.1	\tilde{b}_1	950 GeV	$m(\tilde{\chi}_1^0) < 420$ GeV	1708.09266
	$\tilde{b}_1\tilde{b}_1, \tilde{b}_1 \rightarrow t\tilde{\chi}_1^0$	$2e, \mu$ (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	1706.03731
	$\tilde{t}_1\tilde{t}_1, \tilde{t}_1 \rightarrow b\tilde{\chi}_1^0$	$0-2e, \mu$	1-2 b	Yes	4.7/13.3	\tilde{t}_1	117-170 GeV	$m(\tilde{\chi}_1^\pm) = 2m(\tilde{\chi}_1^0), m(\tilde{\chi}_1^0) = 55$ GeV	1209.2102, ATLAS-CONF-2016-077
	$\tilde{t}_1\tilde{t}_1, \tilde{t}_1 \rightarrow Wb\tilde{\chi}_1^0$ or $t\tilde{\chi}_1^0$	$0-2e, \mu$	0-2 jets/1-2 b	Yes	20.3/36.1	\tilde{t}_1	90-198 GeV	$m(\tilde{\chi}_1^0) = 1$ GeV	1506.08616, 1709.04183, 1711.11520
	$\tilde{t}_1\tilde{t}_1, \tilde{t}_1 \rightarrow c\tilde{\chi}_1^0$	0	mono-jet	Yes	36.1	\tilde{t}_1	90-430 GeV	$m(\tilde{t}_1) - m(\tilde{\chi}_1^0) = 5$ GeV	1711.03301
	$\tilde{t}_1\tilde{t}_1$ (natural GMSB)	$2e, \mu$ (Z)	1 b	Yes	20.3	\tilde{t}_1	150-600 GeV	$m(\tilde{\chi}_1^0) > 150$ GeV	1403.5222
	$\tilde{t}_2\tilde{t}_2, \tilde{t}_2 \rightarrow \tilde{t}_1 + Z$	$3e, \mu$ (Z)	1 b	Yes	36.1	\tilde{t}_2	290-790 GeV	$m(\tilde{\chi}_1^0) = 0$ GeV	1706.03986
	$\tilde{t}_2\tilde{t}_2, \tilde{t}_2 \rightarrow \tilde{t}_1 + h$	$1-2e, \mu$	4 b	Yes	36.1	\tilde{t}_2	320-880 GeV	$m(\tilde{\chi}_1^0) = 0$ GeV	1706.03986
EW direct	$\tilde{\ell}_{L,R}\tilde{\ell}_{L,R}, \tilde{\ell} \rightarrow \ell\tilde{\chi}_1^0$	$2e, \mu$	0	Yes	36.1	$\tilde{\ell}$	90-500 GeV	$m(\tilde{\chi}_1^0) = 0$	ATLAS-CONF-2017-039
	$\tilde{\chi}_1^+\tilde{\chi}_1^-, \tilde{\chi}_1^+ \rightarrow \tilde{\ell}\nu(\tilde{\ell}\bar{\nu})$	$2e, \mu$	0	Yes	36.1	$\tilde{\chi}_1^\pm$	750 GeV	$m(\tilde{\chi}_1^0) = 0, m(\tilde{\ell}, \nu) = 0.5(m(\tilde{\chi}_1^\pm) + m(\tilde{\chi}_1^0))$	ATLAS-CONF-2017-039
	$\tilde{\chi}_1^+\tilde{\chi}_1^-, \tilde{\chi}_1^+ \rightarrow \tilde{\tau}\nu(\tilde{\tau}\bar{\nu}), \tilde{\chi}_2^0 \rightarrow \tilde{\tau}\tau(\tilde{\nu}\bar{\nu})$	2τ	0	Yes	36.1	$\tilde{\chi}_1^\pm$	760 GeV	$m(\tilde{\chi}_1^0) = 0, m(\tilde{\tau}, \nu) = 0.5(m(\tilde{\chi}_1^\pm) + m(\tilde{\chi}_1^0))$	1708.07875
	$\tilde{\chi}_1^+\tilde{\chi}_2^0 \rightarrow \tilde{\ell}_L\nu\tilde{\ell}_L\ell(\tilde{\nu}\bar{\nu}), \tilde{\ell}\nu\tilde{\ell}_L\ell(\tilde{\nu}\bar{\nu})$	$3e, \mu$	0	Yes	36.1	$\tilde{\chi}_1^\pm, \tilde{\chi}_2^0$	1.13 TeV	$m(\tilde{\chi}_1^\pm) = m(\tilde{\chi}_2^0), m(\tilde{\chi}_1^0) = 0, m(\tilde{\ell}, \nu) = 0.5(m(\tilde{\chi}_1^\pm) + m(\tilde{\chi}_1^0))$	ATLAS-CONF-2017-039
	$\tilde{\chi}_1^+\tilde{\chi}_2^0 \rightarrow W\tilde{\chi}_1^0 Z\tilde{\chi}_1^0$	$2-3e, \mu$	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
	$\tilde{\chi}_1^+\tilde{\chi}_2^0 \rightarrow W\tilde{\chi}_1^0 h\tilde{\chi}_1^0, h \rightarrow b\tilde{b}/WW/\tau\tau/\gamma\gamma$	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
	$\tilde{\chi}_2^0\tilde{\chi}_3^0, \tilde{\chi}_2^0 \rightarrow \tilde{\ell}_R\tilde{\ell}$	$4e, \mu$	0	Yes	20.3	$\tilde{\chi}_{2,3}^0$	635 GeV	$m(\tilde{\chi}_2^0) = m(\tilde{\chi}_3^0), m(\tilde{\chi}_1^0) = 0, m(\tilde{\ell}, \nu) = 0.5(m(\tilde{\chi}_2^0) + m(\tilde{\chi}_1^0))$	1405.5086
	GGM (wino NLSP) weak prod., $\tilde{\chi}_1^0 \rightarrow \gamma\tilde{G}$	$1e, \mu + \gamma$	-	Yes	20.3	\tilde{W}	115-370 GeV	$cr < 1$ mm	1507.05493
	GGM (bino NLSP) weak prod., $\tilde{\chi}_1^0 \rightarrow \gamma\tilde{G}$	2γ	-	Yes	36.1	\tilde{W}	1.06 TeV	$cr < 1$ mm	ATLAS-CONF-2017-080
	Long-lived particles	Direct $\tilde{\chi}_1^+\tilde{\chi}_1^-$ prod., long-lived $\tilde{\chi}_1^\pm$	Disapp. trk	1 jet	Yes	36.1	$\tilde{\chi}_1^\pm$	460 GeV	$m(\tilde{\chi}_1^\pm) - m(\tilde{\chi}_1^0) \sim 160$ MeV, $\tau(\tilde{\chi}_1^\pm) = 0.2$ ns
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	$m(\tilde{\chi}_1^\pm) - m(\tilde{\chi}_1^0) \sim 160$ MeV, $\tau(\tilde{\chi}_1^\pm) < 15$ 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, $10 \mu s < \tau(\tilde{g}) < 1000$ 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, $\tau > 10$ ns	1604.04520
Metastable \tilde{g} R-hadron, $\tilde{g} \rightarrow q\tilde{q}\tilde{\chi}_1^0$		displ. vtx	-	Yes	32.8	\tilde{g}	2.37 TeV	$\tau(\tilde{g}) = 0.17$ ns, $m(\tilde{\chi}_1^0) = 100$ GeV	1710.04901
GMSB, stable $\tilde{\tau}, \tilde{\chi}_1^0 \rightarrow \tilde{\tau}(\tilde{e}, \tilde{\mu}) + \tau(e, \mu)$		$1-2\mu$	-	-	19.1	$\tilde{\chi}_1^0$	537 GeV	$10 < \tan\beta < 50$	1411.6795
GMSB, $\tilde{\chi}_1^0 \rightarrow \gamma\tilde{G}$, long-lived $\tilde{\chi}_1^0$		2γ	-	Yes	20.3	$\tilde{\chi}_1^0$	440 GeV	$1 < \tau(\tilde{\chi}_1^0) < 3$ ns, SPS8 model	1409.5542
$\tilde{g}\tilde{g}, \tilde{\chi}_1^0 \rightarrow e\tilde{\nu}/e\mu/\mu\mu\nu$		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
RPV		LFV $pp \rightarrow \tilde{\nu}_\tau + X, \tilde{\nu}_\tau \rightarrow e\mu/\tau\mu$	$e\mu, e\tau, \mu\tau$	-	-	3.2	$\tilde{\nu}_\tau$	1.9 TeV	$\lambda_{311} = 0.11, \lambda_{132/133/233} = 0.07$
	Bilinear RPV CMSSM	$2e, \mu$ (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
	$\tilde{\chi}_1^+\tilde{\chi}_1^-, \tilde{\chi}_1^+ \rightarrow W\tilde{\chi}_1^0, \tilde{\chi}_1^0 \rightarrow e\tilde{\nu}, e\mu\nu, \mu\mu\nu$	$4e, \mu$	-	Yes	13.3	$\tilde{\chi}_1^\pm$	1.14 TeV	$m(\tilde{\chi}_1^0) > 400$ GeV, $\lambda_{12k} \neq 0$ ($k = 1, 2$)	ATLAS-CONF-2016-075
	$\tilde{\chi}_1^+\tilde{\chi}_1^-, \tilde{\chi}_1^+ \rightarrow W\tilde{\chi}_1^0, \tilde{\chi}_1^0 \rightarrow \tau\nu_e, e\tau\nu_\tau$	$3e, \mu + \tau$	-	Yes	20.3	$\tilde{\chi}_1^\pm$	450 GeV	$m(\tilde{\chi}_1^0) > 0.2 \times m(\tilde{\chi}_1^\pm), \lambda_{133} \neq 0$	1405.5086
	$\tilde{g}\tilde{g}, \tilde{g} \rightarrow q\tilde{q}\tilde{\chi}_1^0, \tilde{\chi}_1^0 \rightarrow qq\tilde{q}$	0	4-5 large-R jets	-	36.1	\tilde{g}	1.875 TeV	$m(\tilde{\chi}_1^0) = 1075$ GeV	SUSY-2016-22
	$\tilde{g}\tilde{g}, \tilde{g} \rightarrow t\tilde{t}\tilde{\chi}_1^0, \tilde{\chi}_1^0 \rightarrow qq\tilde{g}$	$1e, \mu$	8-10 jets/0-4 b	-	36.1	\tilde{g}	2.1 TeV	$m(\tilde{\chi}_1^0) = 1$ TeV, $\lambda_{112} \neq 0$	1704.08493
	$\tilde{g}\tilde{g}, \tilde{g} \rightarrow \tilde{t}_1 t, \tilde{t}_1 \rightarrow bs$	$1e, \mu$	8-10 jets/0-4 b	-	36.1	\tilde{g}	1.65 TeV	$m(\tilde{t}_1) = 1$ TeV, $\lambda_{323} \neq 0$	1704.08493
	$\tilde{t}_1\tilde{t}_1, \tilde{t}_1 \rightarrow bs$	0	2 jets + 2 b	-	36.7	\tilde{t}_1	100-470 GeV	$m(\tilde{t}_1) = 1$ TeV, $\lambda_{323} \neq 0$	1710.07171
$\tilde{t}_1\tilde{t}_1, \tilde{t}_1 \rightarrow b\tilde{\ell}$	$2e, \mu$	2 b	-	36.1	\tilde{t}_1	0.4-1.45 TeV	$BR(\tilde{t}_1 \rightarrow b\tilde{\mu}) > 20\%$	1710.05544	
Other	Scalar charm, $\tilde{c} \rightarrow c\tilde{\chi}_1^0$	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.

10^{-1}

1

Mass scale [TeV]

GUIDANCE FROM NATURALNESS

DO THIS
NOT THAT



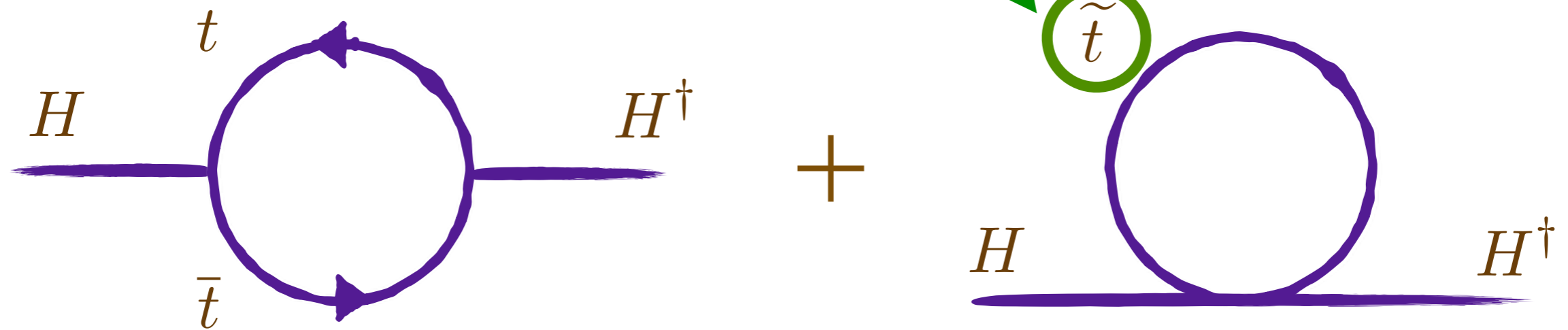
GUIDANCE FROM NATURALNESS

This talk



NORMAL NATURALNESS

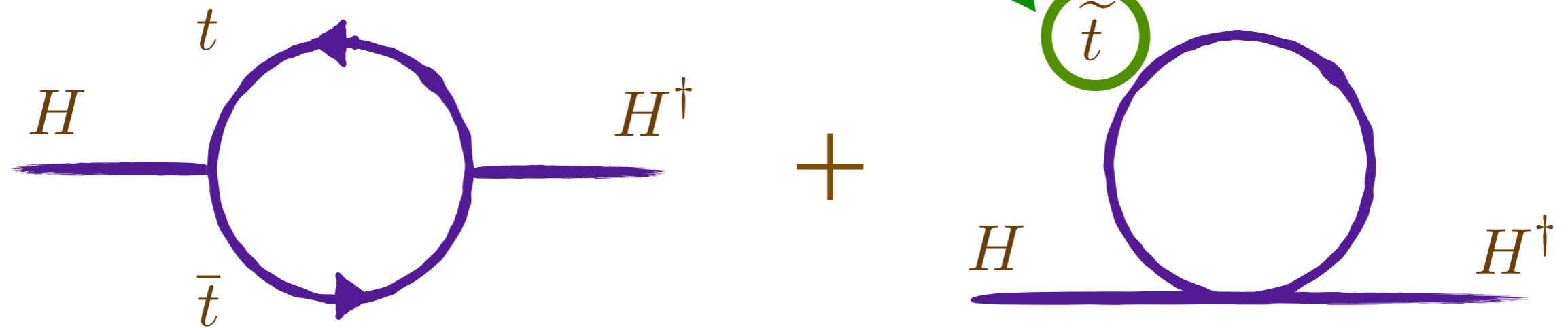
Same charge as the top



= UV insensitive

~~NORMAL~~ NATURALNESS NEUTRAL

No Standard Model charges



= UV insensitive (at one-loop)

STATE OF THE ART

		<i>scalar</i>	<i>fermion</i>
<i>strong direct production</i> {	<i>QCD</i>	SUSY	Composite Higgs/ RS
<i>DY direct production</i> {	<i>EW</i>	folded SUSY	Quirky Little Higgs
<i>Higgs portal direct production</i> {	<i>singlet</i>	?	Twin Higgs

Mirror Glueballs

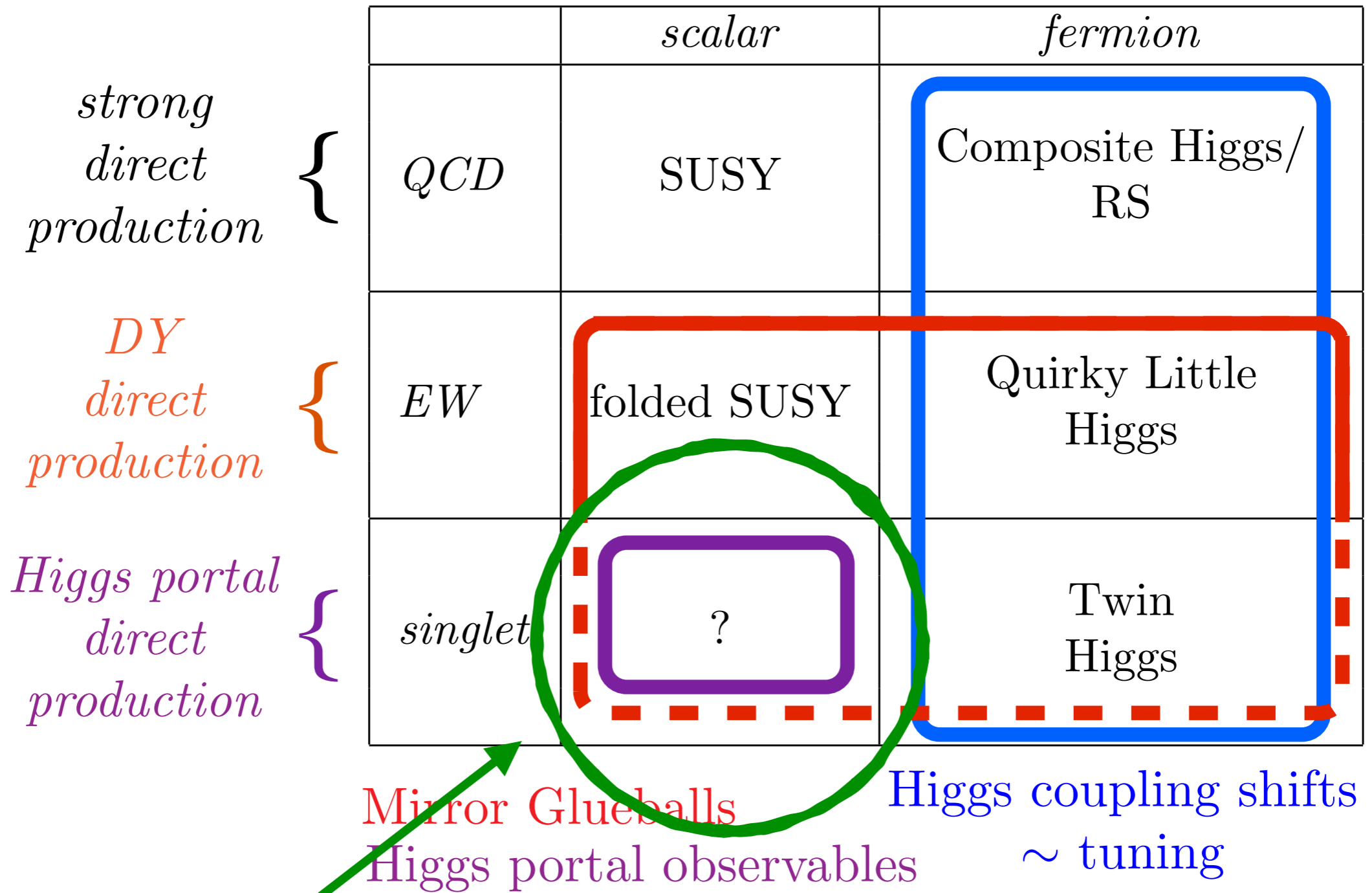
Higgs portal observables

Higgs coupling shifts

~ tuning

Curtin and Varhaaren [arXiv:1506.06141]

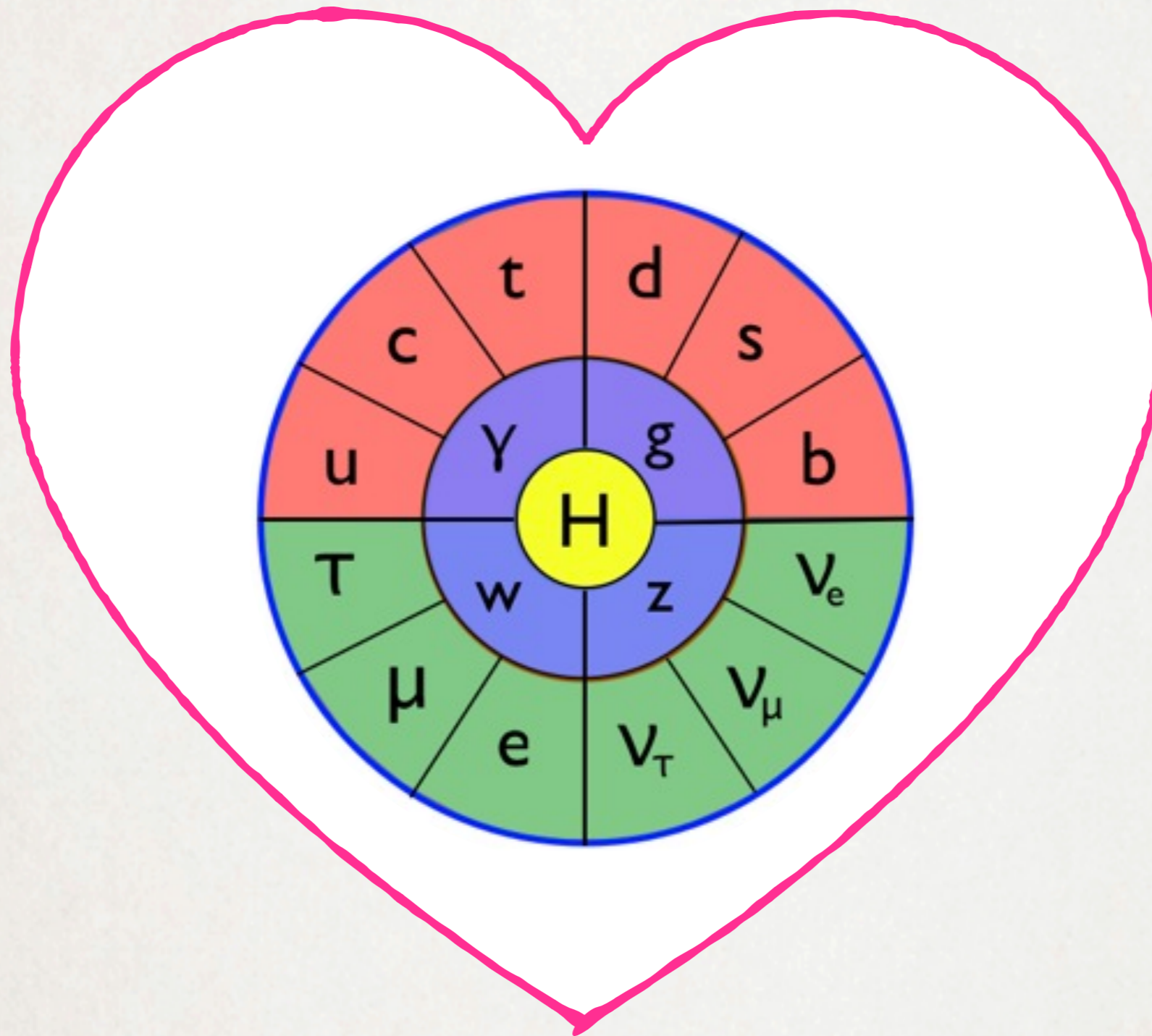
STATE OF THE ART



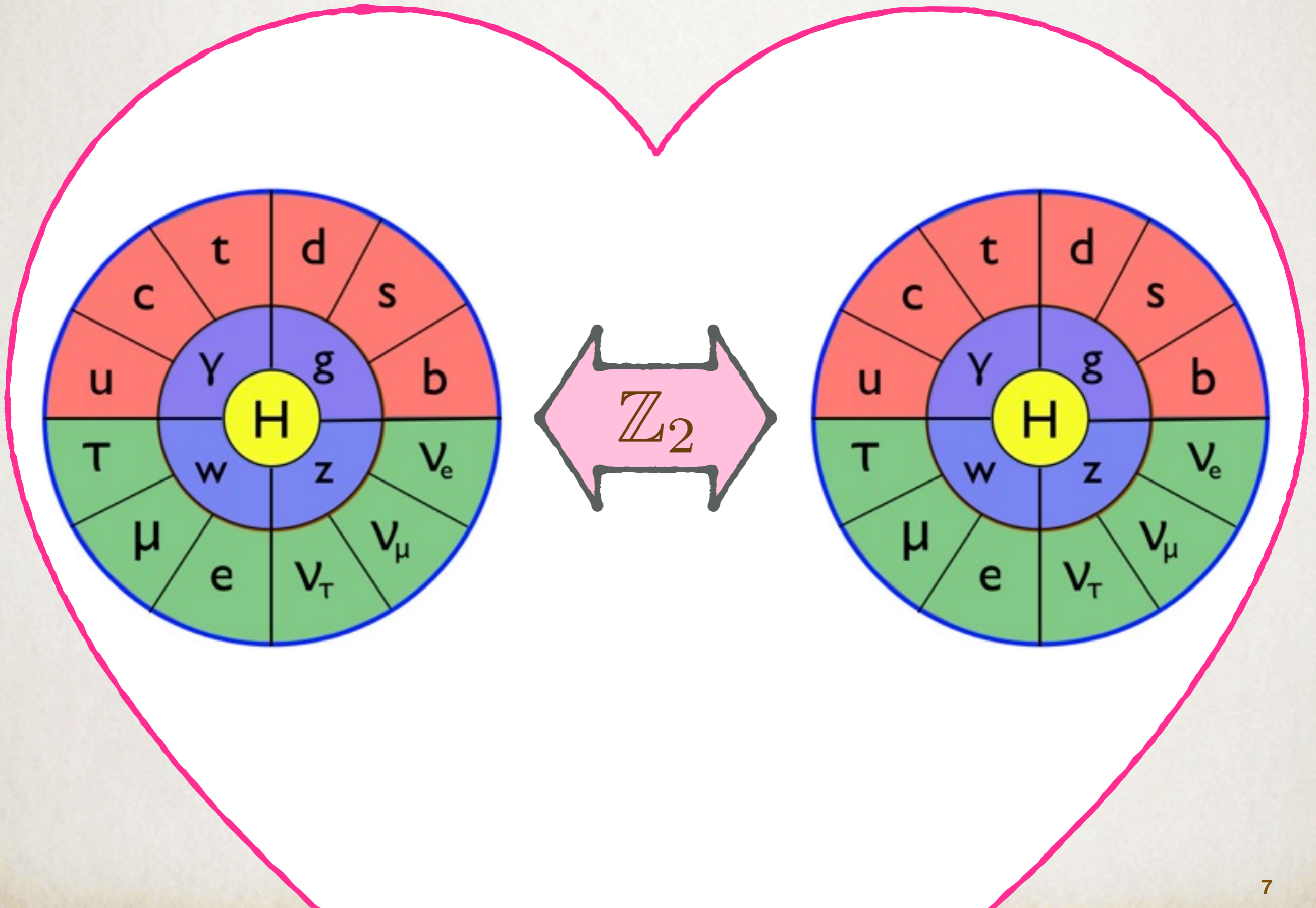
Curtin and Varhaaren [arXiv:1506.06141]

This talk!!

DOUBLE DOWN!



DOUBLE DOWN!



TWIN HIGGS

Accidental $SU(4)$

$$V = \lambda (|H|^2 + |H_T|^2 - f^2)^2$$

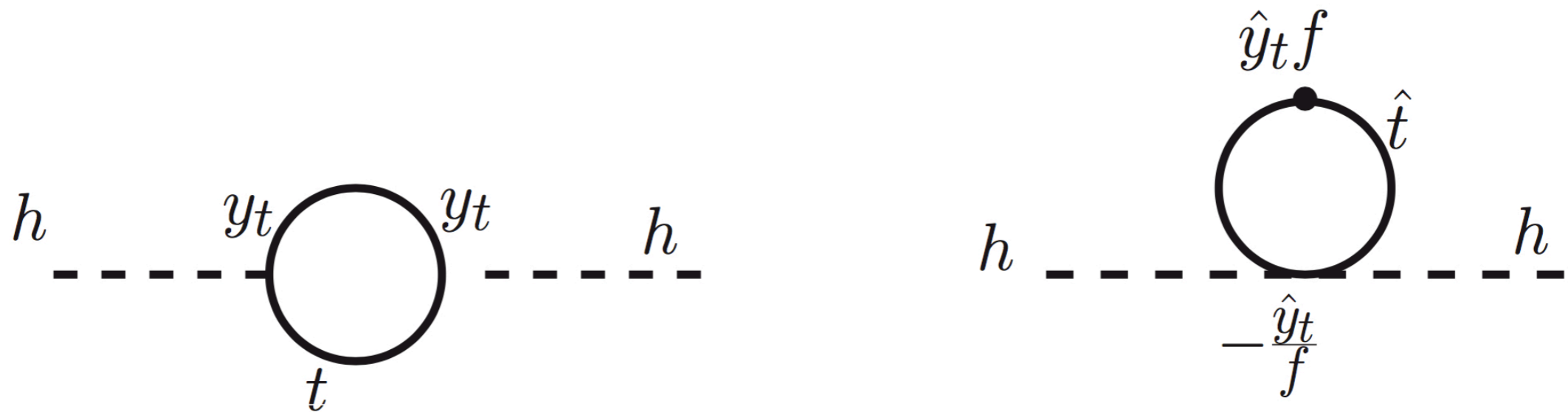
$$f^2 = v^2 + v_T^2$$

$$SU(4) \rightarrow SU(3)$$

7 Goldstones: 6 eaten \longrightarrow 1 light scalar

Chacko, Goh, Harnik [arXiv:hep-ph/0506256],
see also Craig, Katz, Strassler, Sundrum [arXiv:1501.05310]

TWIN QUADRATIC CORRECTIONS



$$\delta m_h^2 \simeq \frac{3 \Lambda^2}{4 \pi} (y_t^2 - \hat{y}_t^2)$$

THE HYPERBOLIC HIGGS

Accidental $U(2, 2)$

$$V = \lambda \left(|H_{\mathcal{H}}|^2 - |H|^2 - f^2 \right)^2$$

$$|H_{\mathcal{H}}|^2 - |H|^2 = \frac{m^2}{\lambda}$$

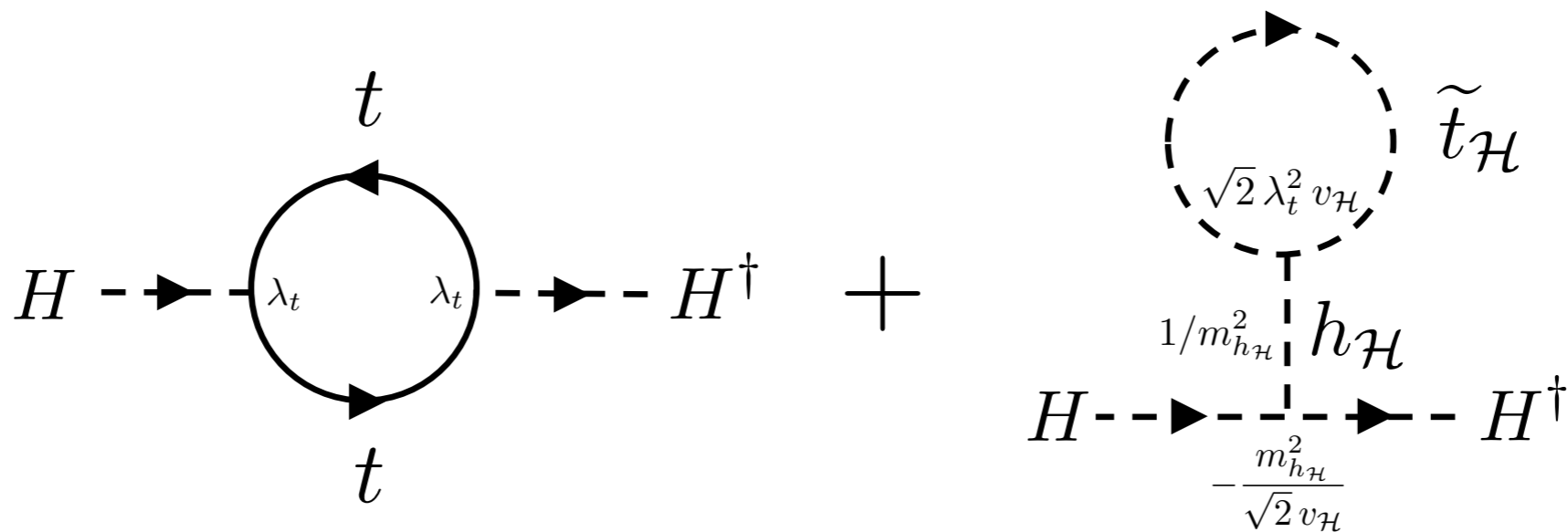
Flat-direction

QUADRATIC CORRECTIONS

$$\mathcal{L} = (\lambda_t H \psi_Q \psi_{U^c} + \text{h.c.}) + \lambda_t^2 \left(|H_{\mathcal{H}} \cdot \tilde{Q}_{\mathcal{H}}|^2 + |H_{\mathcal{H}}|^2 |\tilde{U}_{\mathcal{H}}^c|^2 \right)$$



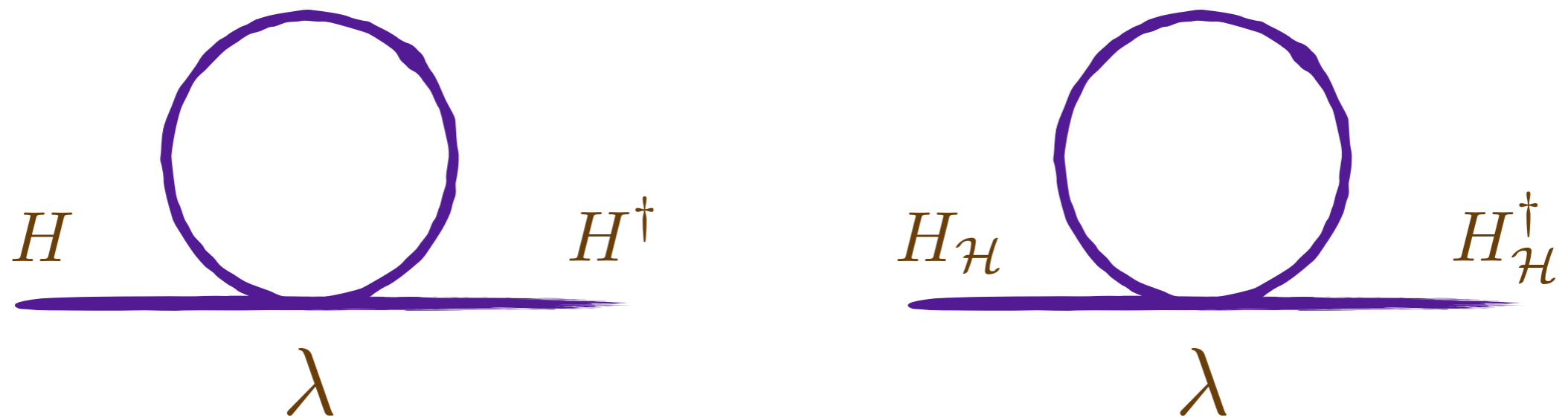
$$\mathcal{L} = (\lambda_t H \psi_Q \psi_{U^c} + \text{h.c.}) + \lambda_t^2 |H|^2 \left(|\tilde{Q}_{\mathcal{H}}|^2 + |\tilde{U}_{\mathcal{H}}^c|^2 \right)$$



$$\delta V \propto \lambda_t^2 \Lambda^2 \left(|H_{\mathcal{H}}|^2 - |H|^2 \right)$$

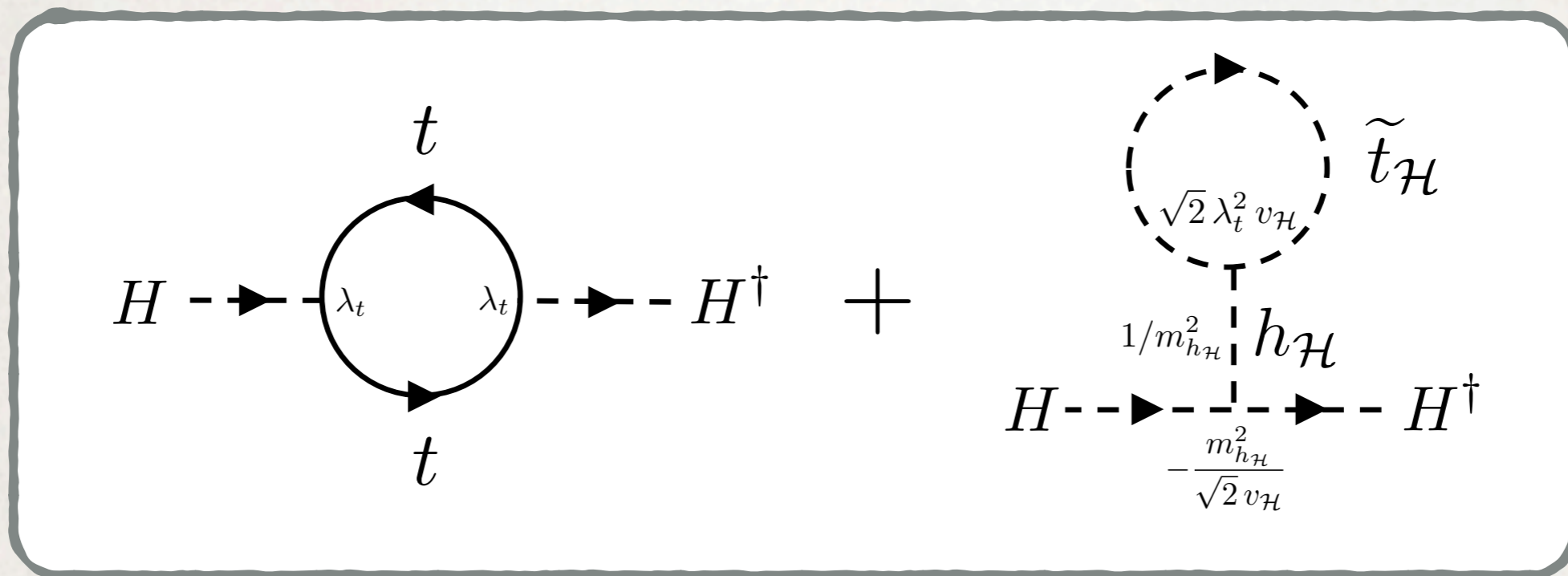
IR ISSUES - I

$$V_{\mathcal{H}} = m^2 \left(|H|^2 - |H_{\mathcal{H}}|^2 \right) + \frac{\lambda}{2} \left(|H|^2 - |H_{\mathcal{H}}|^2 \right)^2$$



$$\delta V \propto \lambda \Lambda^2 \left(|H|^2 + |H_{\mathcal{H}}|^2 \right)$$

IR ISSUES - II



$$\text{Want } \delta V \propto \lambda_t^2 \Lambda^2 (|H|^2 - |H_{\mathcal{H}}|^2)$$

$$\text{Get } \delta V \propto \lambda_t^2 \Lambda^2 (|H_{\mathcal{H}}|^2 - |H|^2)$$

PHENOMENOLOGY

Higgs portal

Top partner vevs

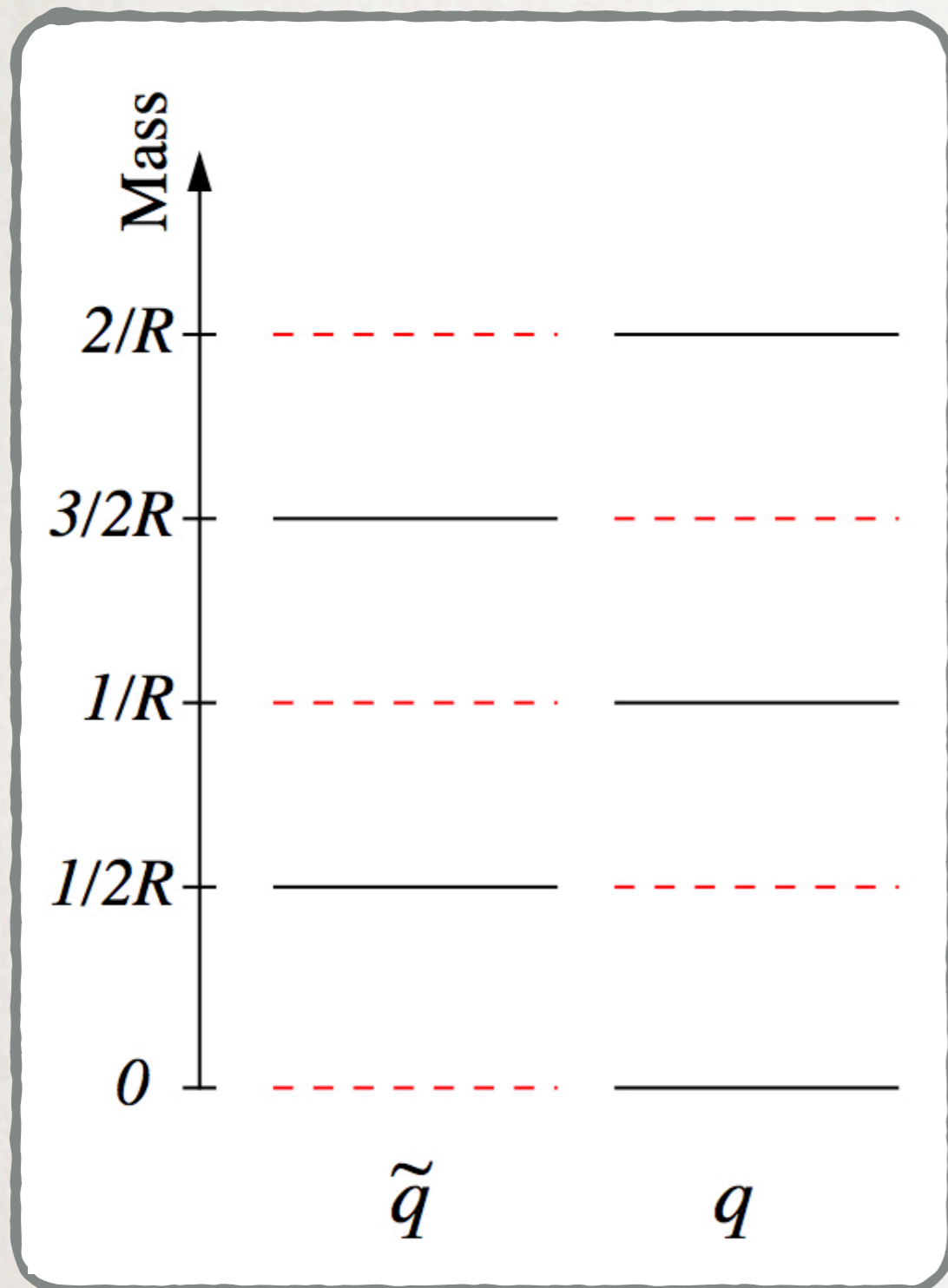
Higgs-top partner mixing

Eaten top partners

Modified dark shower phenomenology

UV COMPLETION

ASIDE: FOLDED SUSY



Uncolored stops

5D SUSY

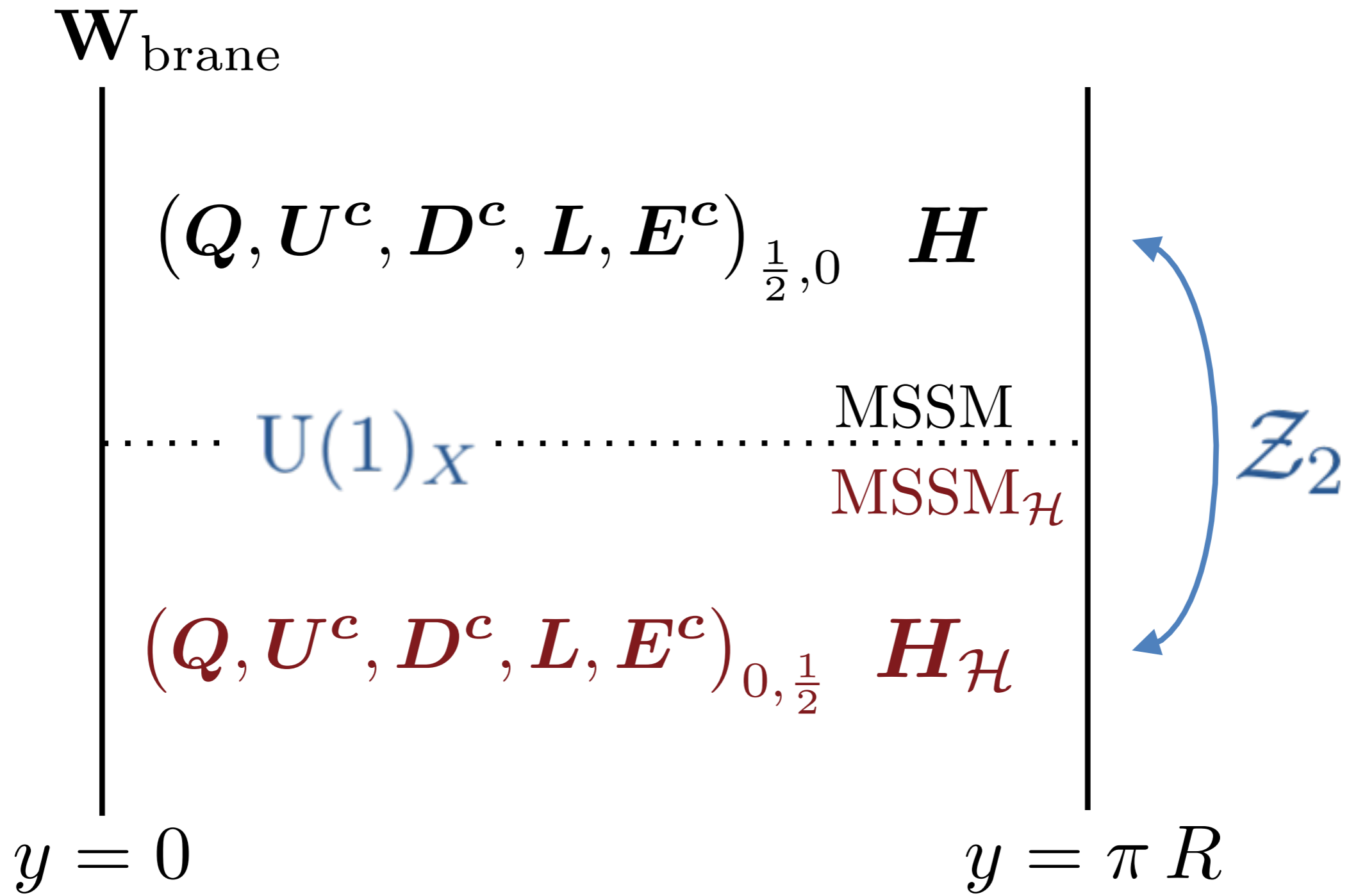
Double the MSSM

Boundary conditions
lift colored stops

Electroweak charged

[Burdman, Chacko, Goh, Harnik \[arXiv:hep-ph/0609152\]](#)

A MODEL



TOP YUKAWA LOOPS

$$V_{\text{CW}}(H) = \frac{1}{2} \sum_n \int \frac{d^4 p}{(2\pi)^4} \left[\log \frac{p^2 + (n + \omega_B^+)^2 / R^2}{p^2 + (n + \omega_F^+)^2 / R^2} + \log \frac{p^2 + (n + \omega_B^-)^2 / R^2}{p^2 + (n + \omega_F^-)^2 / R^2} \right]$$

$$\omega_{B,F}^\pm = q_{B,F} \pm R m_t(H) \quad \text{Boundary conditions}$$

$$V_{\text{CW}}(H) = -\frac{3 N_c}{32 \pi^6 R^4} \left[\text{Cl}_5(2\pi\omega_B^+) + \text{Cl}_5(2\pi\omega_B^-) - \text{Cl}_5(2\pi\omega_F^+) - \text{Cl}_5(2\pi\omega_F^-) \right]$$

$$\text{Cl}_n(x) = \begin{cases} \frac{i}{2} \left(\text{Li}_n(e^{-ix}) - \text{Li}_n(e^{ix}) \right) & n \text{ even;} \\ \frac{1}{2} \left(\text{Li}_n(e^{-ix}) + \text{Li}_n(e^{ix}) \right) & n \text{ odd.} \end{cases}$$

$$V_{\text{CW}} = -\frac{21 \zeta(3) \lambda_t^2}{32 \pi^2 (\pi R)^2} \left\{ N_c \left(|H|^2 - |H_{\mathcal{H}}|^2 \right) - |\tilde{Q}_{\mathcal{H}}|^2 - 2 |\tilde{U}_{\mathcal{H}}^c|^2 \right\}$$

$U(1)_X$

$$V_{U(1)_X} = \frac{g_X^2}{2} \xi \left(|H_{\mathcal{H}}|^2 - |H|^2 - f_X^2 \right)^2$$

Hyperbolic quartic!

$$\xi = \left(1 - \frac{M_X^2}{M_S^2} \right)$$

Non-decoupling D -term



$$\Delta\rho = \frac{4 g_X^2 M_W^2}{g^2 M_X^2} \longrightarrow \frac{M_X}{g_X} > 8.6 \text{ TeV}$$

TENSION

$$V_{\text{U}(2,2)} = (\tilde{m}^2 + \tilde{m}_X^2) \left(|H|^2 + |H_{\mathcal{H}}|^2 \right) + \frac{g_Z^2}{2} \left(|H|^4 + |H_{\mathcal{H}}|^4 \right)$$

$$\tilde{m}_X^2 = -\frac{g_X^2 M_X^2}{16 \pi^2} \log \left(\frac{(1 - \xi)^3}{(1 - \xi/2)^4} \right)$$



$$|\tilde{m}_X^2| \gtrsim \left(\frac{g_X}{0.8} \right)^4 \log \left(\frac{(1 - \xi)^3}{(1 - \xi/2)^4} \right) (440 \text{ GeV})^2$$

MINIMIZE

Conditions for vevs

$$\tilde{m}^2 + \tilde{m}_X^2 \simeq v_{\mathcal{H}}^2 \left(\frac{N_c \lambda_t^4}{48 \pi^2} [11 + 21 \zeta(3) - 6 \log(\lambda_t v_{\mathcal{H}} \pi R)] - \frac{1}{4} \frac{M_Z^2}{v^2} \right)$$

$$f_X^2 \simeq v_{\mathcal{H}}^2 - v^2 + \frac{1}{4 g_X^2 \xi} \left(\frac{21 N_c \zeta(3) \lambda_t^2}{8 \pi^4 R^2} + v_{\mathcal{H}}^2 \frac{M_Z^2}{v^2} \right)$$

Physical Higgs mass

$$m_h^2 \simeq \left(2 M_Z^2 + \frac{N_c \lambda_t^4}{2 \pi^2} v^2 \log \frac{v_{\mathcal{H}}}{v} \right) \frac{v_{\mathcal{H}}^2}{v_{\mathcal{H}}^2 + v^2}$$

t - $\tilde{t}_{\mathcal{H}}$ loop

Mixing

Factor of 2 bigger than MSSM

SCALES

Cutoff Λ --- $\frac{1}{2R}$

Hyperbolic $m_{h_{\mathcal{H}}}$ --- $\sqrt{2\xi} g_X v_{\mathcal{H}}$

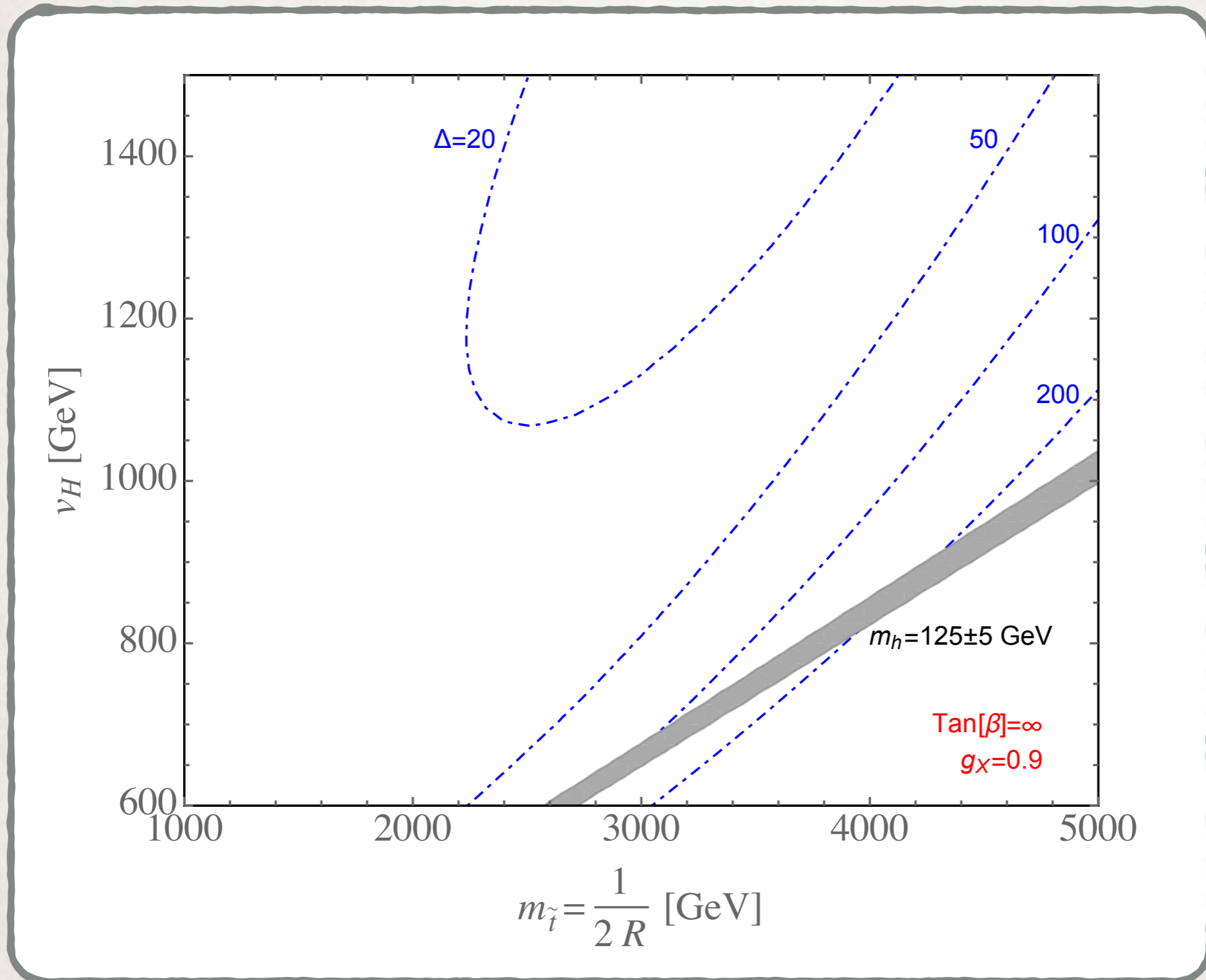
Weak m_h --- $\sqrt{2M_Z^2 + \frac{N_c \lambda_t^4}{2\pi^2} v^2 \log \frac{v_{\mathcal{H}}}{v}}$




FINE TUNING

PLEASE BE PATIENT

PARAMETER SPACE



OUTLOOK

	<i>scalar</i>	<i>fermion</i>
<i>QCD</i>	SUSY	Composite Higgs/ RS
<i>EW</i>	folded SUSY	Quirky Little Higgs
<i>singlet</i>		Twin Higgs

**The
Hyperbolic
Higgs**

Accidental $U(2, 2)$ global symmetry

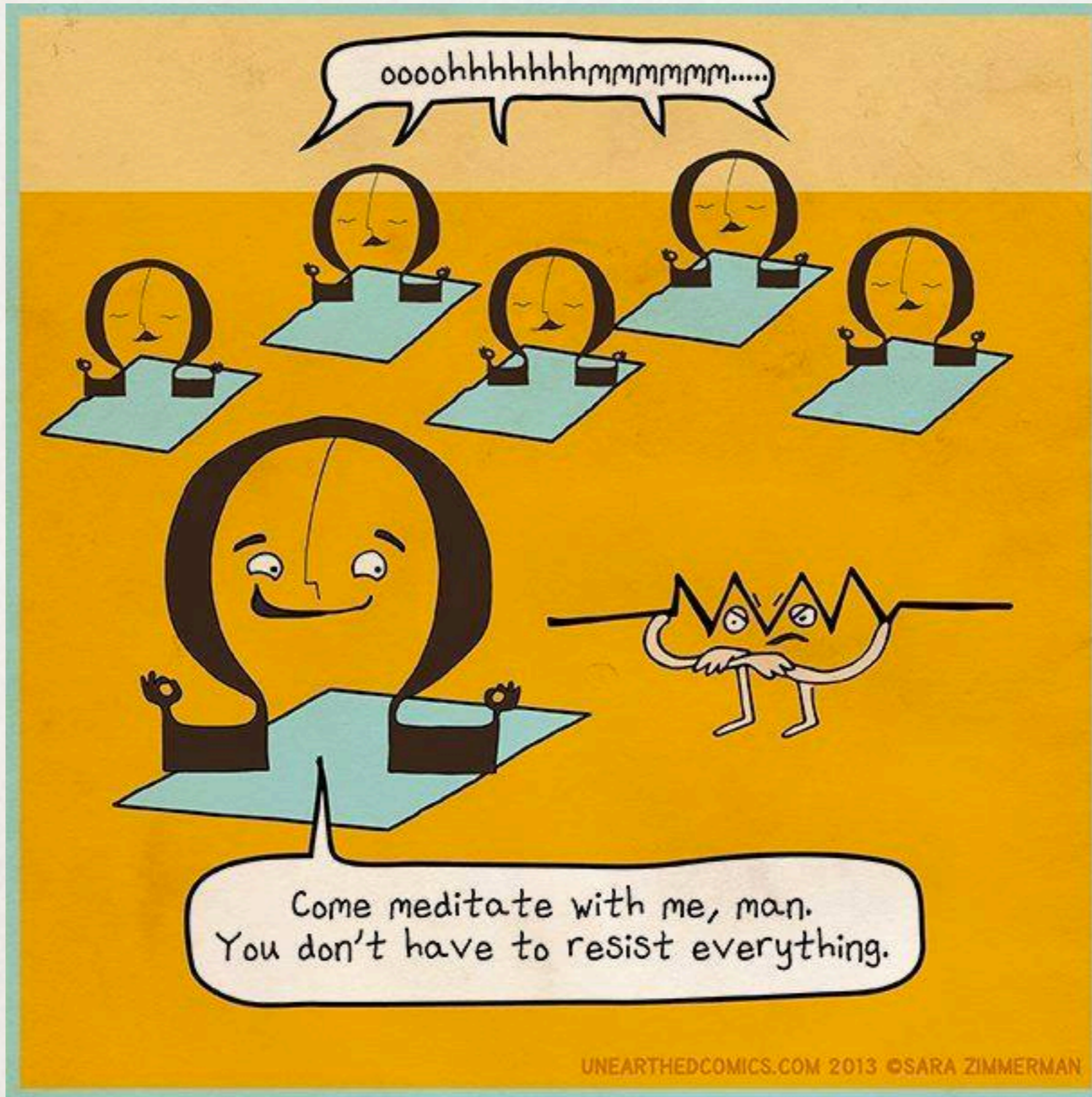
SM neutral scalar top partners

5D SUSY UV completion

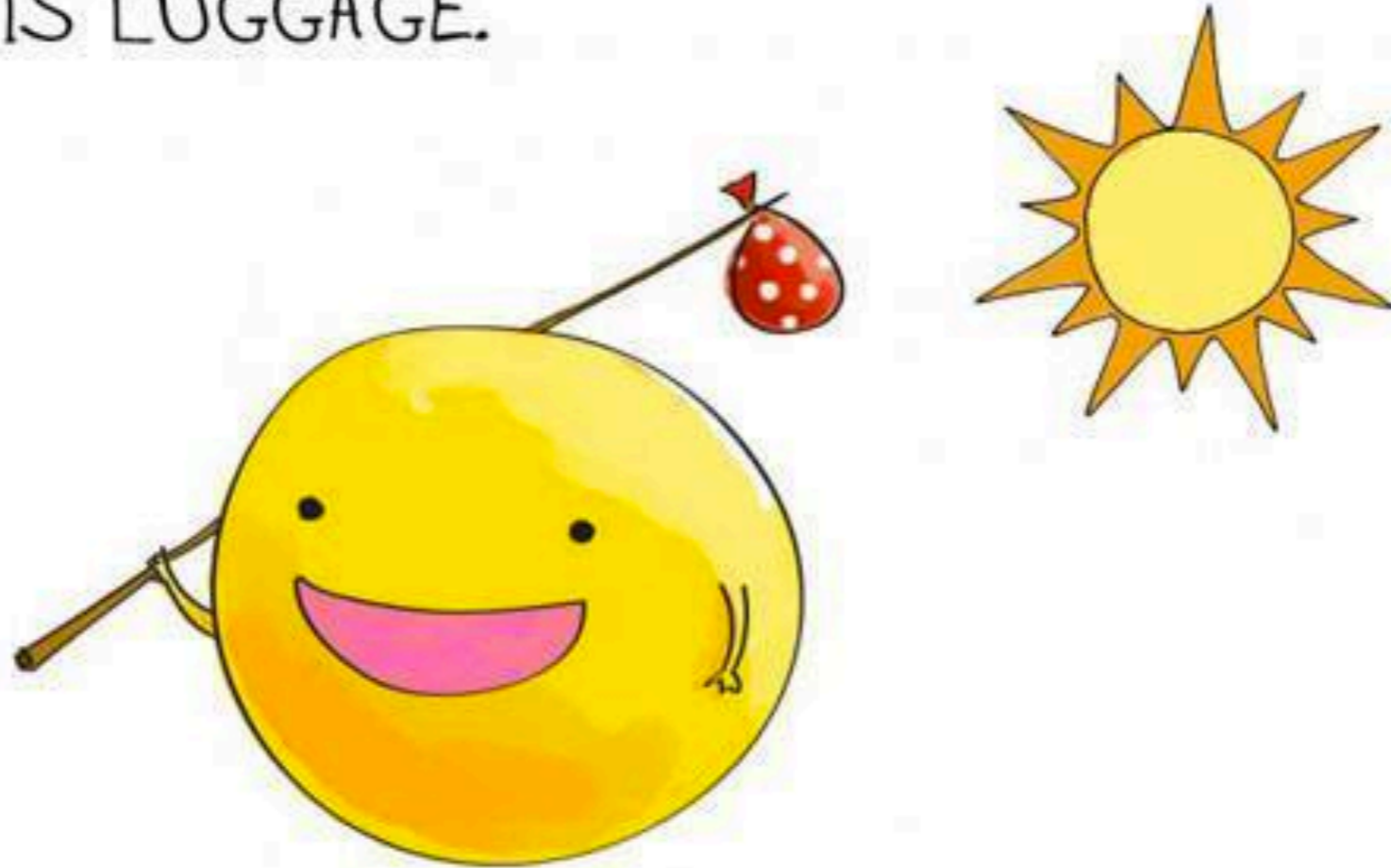
Top partner vevs!

**And now
for something
completely different...**





A PHOTON CHECKS INTO A HOTEL AND
IS ASKED IF HE NEEDS ANY HELP WITH
HIS LUGGAGE.



"NO, I'M TRAVELLING LIGHT."

WHAT IS THE MACHINE LEARNING?



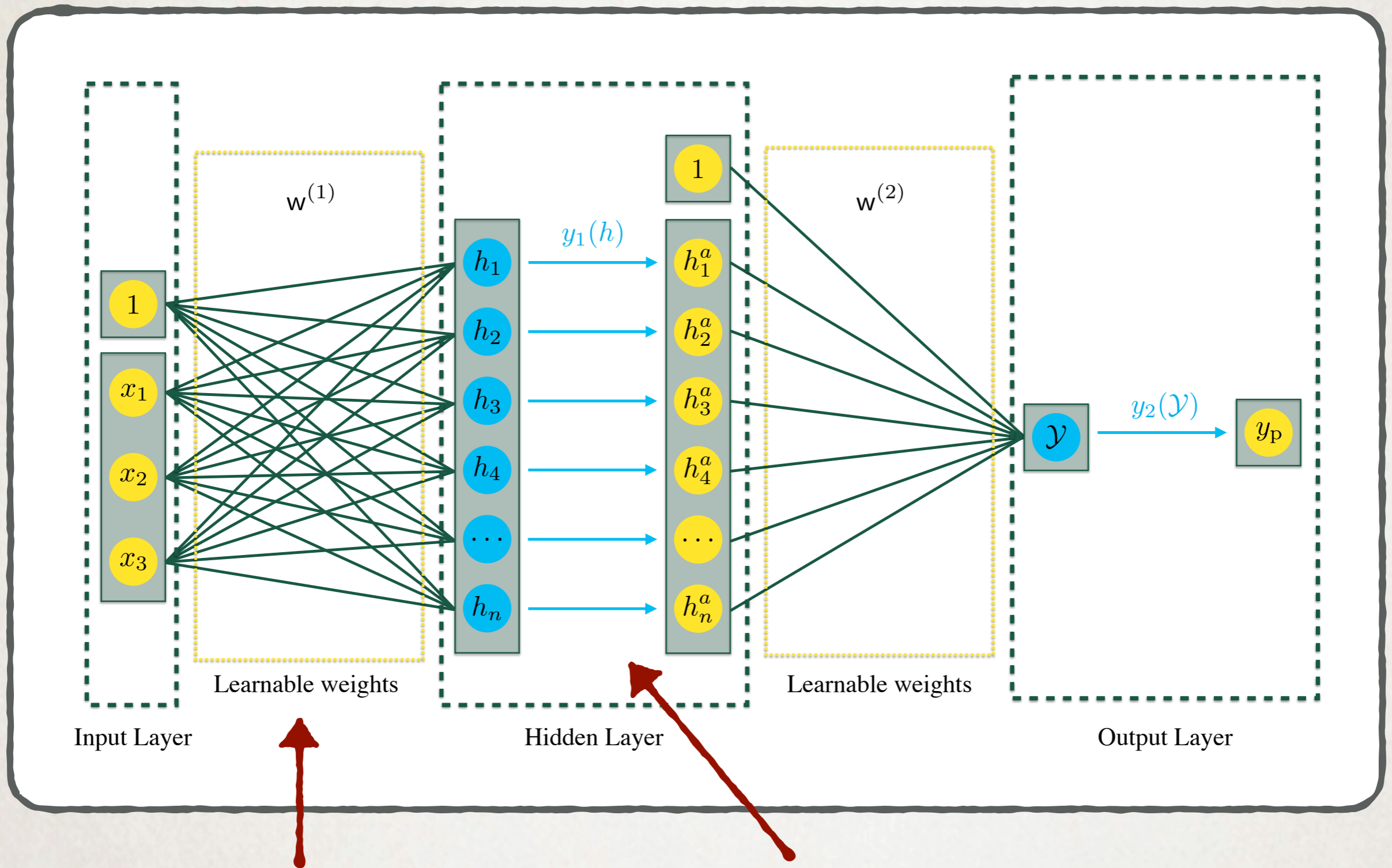
with Spencer Chang and Bryan Ostdiek

arXiv:1709.10106

RISE OF THE MACHINES

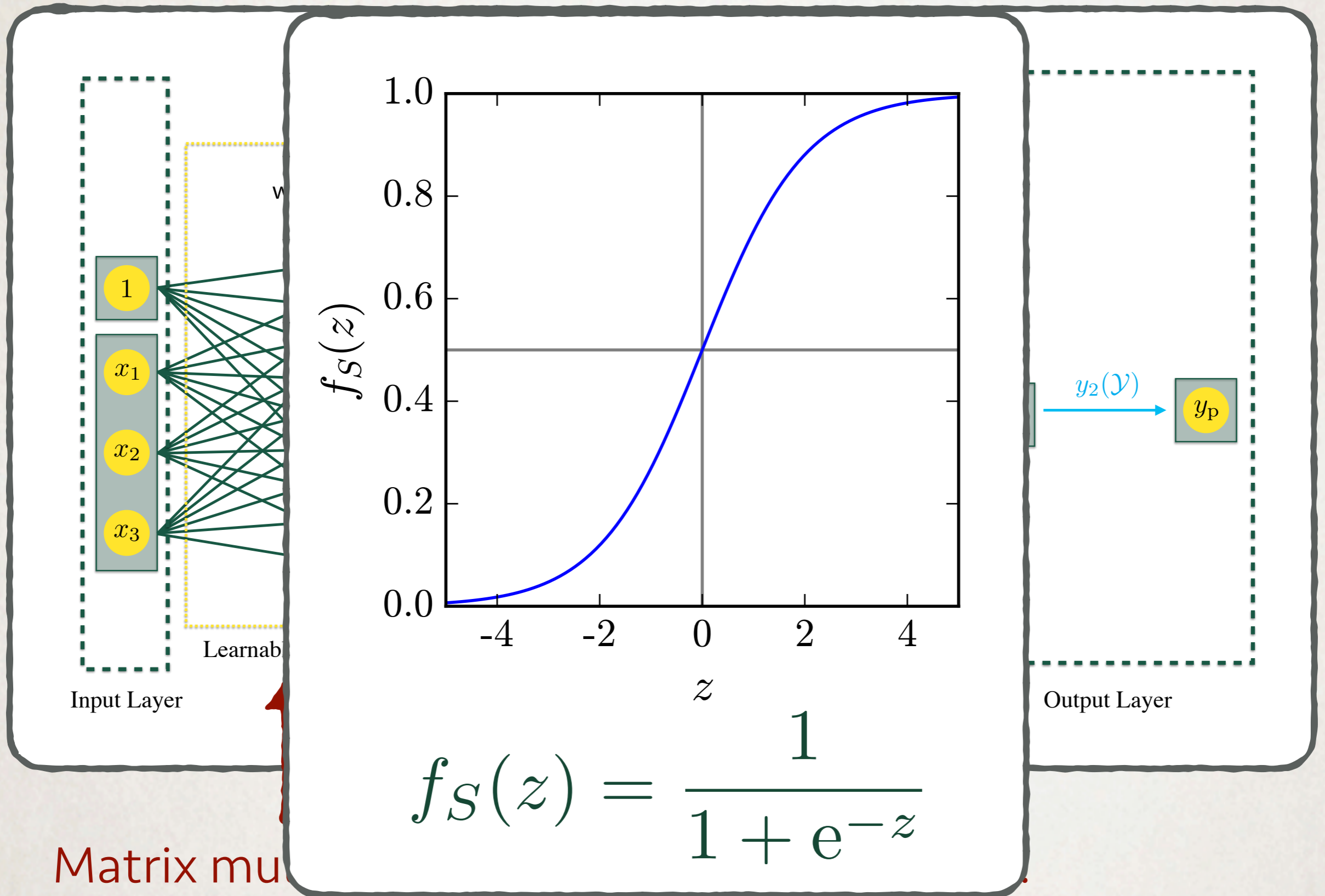


(DEEP) NEURAL NETWORKS



Matrix multiplication. Activation function.

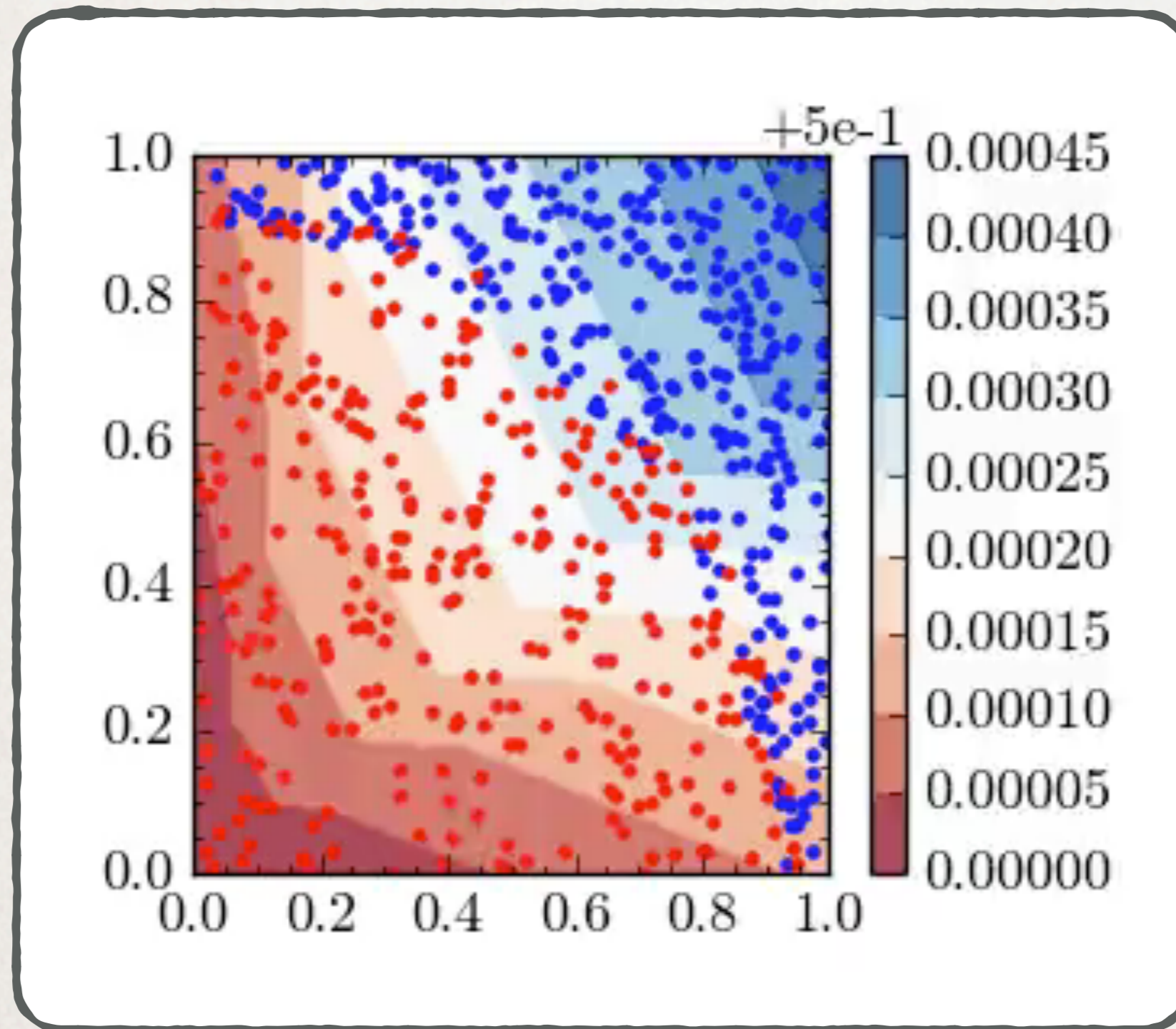
(DEEP) NEURAL NETWORKS



Matrix mu

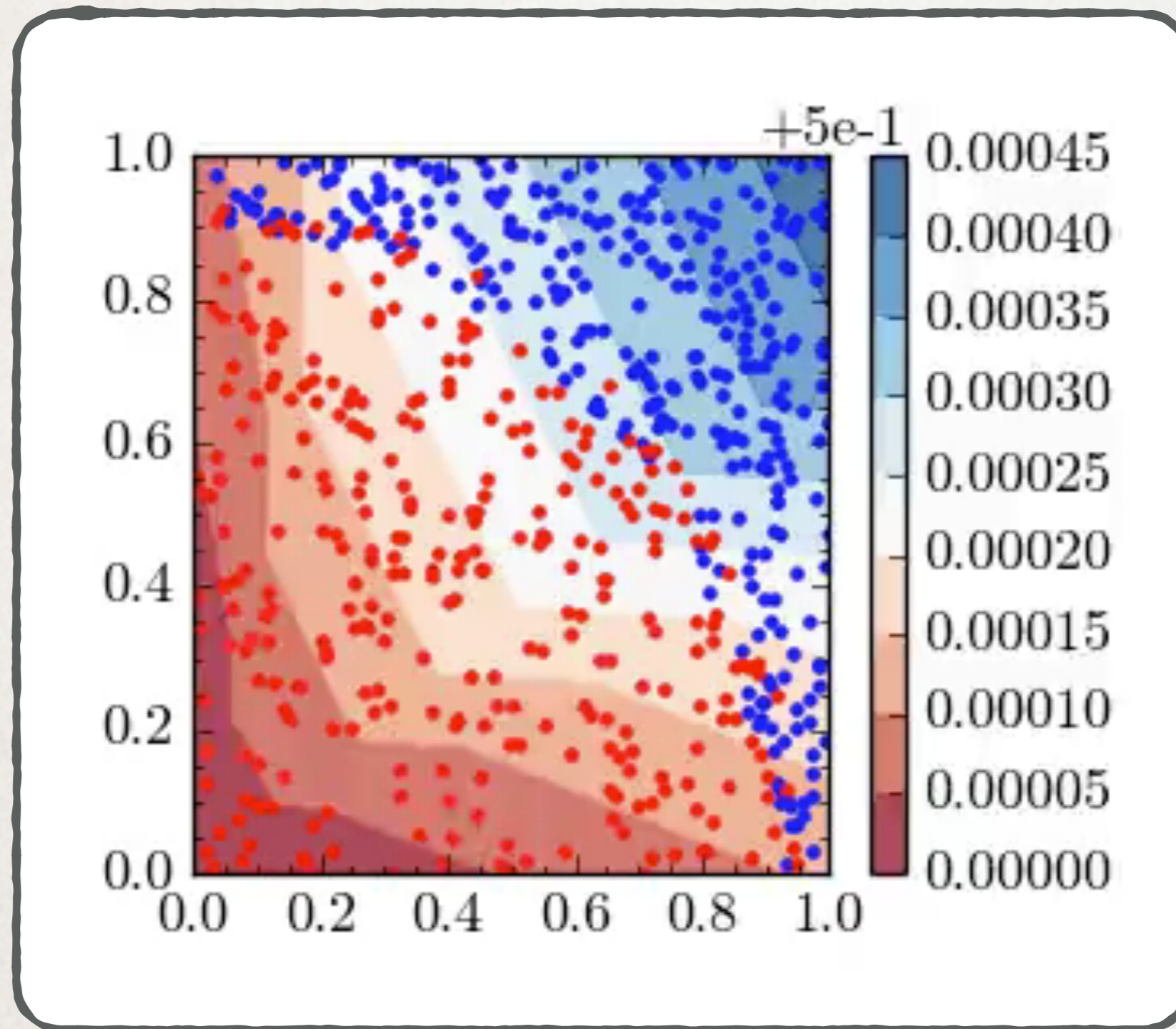
TRAINING

Loss function: minimize comparison between network output and input labels



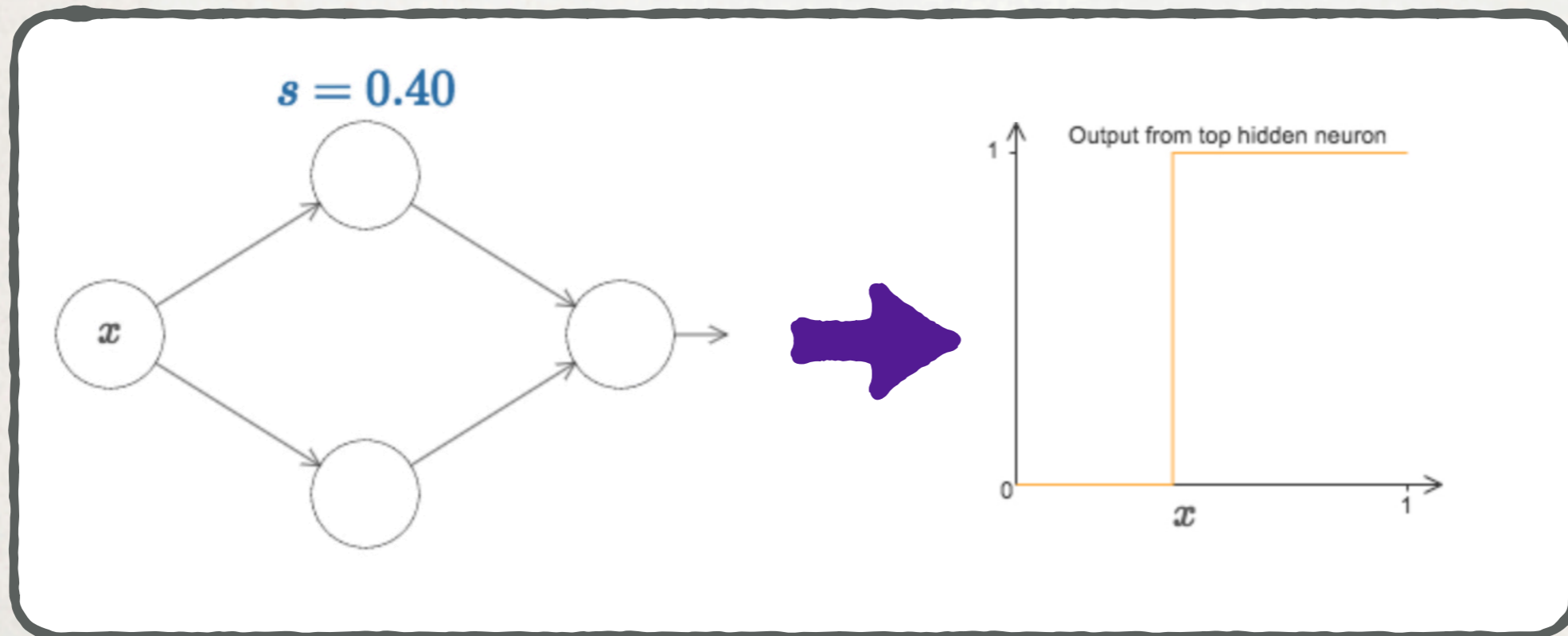
TRAINING

Loss function: minimize comparison between network output and input labels



UNIVERSAL APPROXIMATORS

Michael Nielsen [<http://neuralnetworksanddeeplearning.com/>]



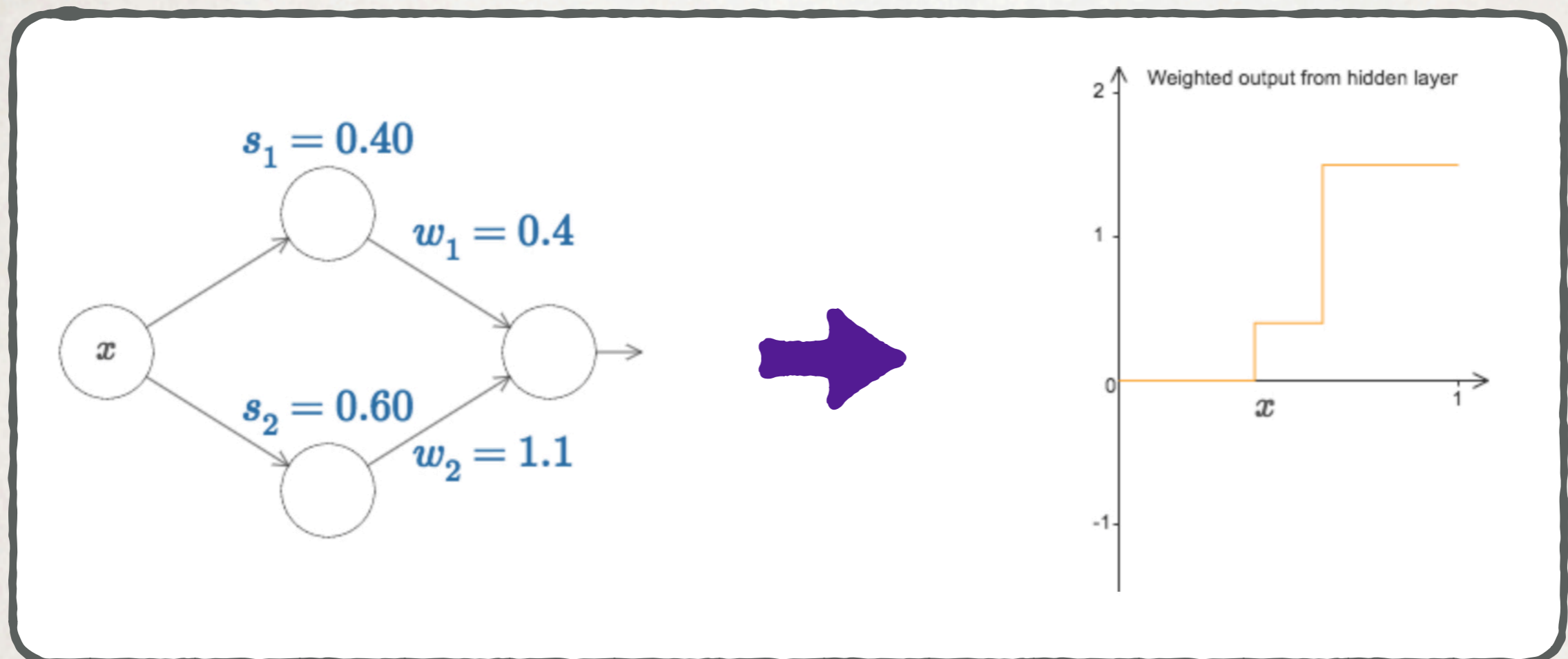
Early important papers:

George Cybenko, Approximation by superpositions of a sigmoidal function [1989];

Kurt Hornik, Maxwell Stinchcombe, and Halbert White, Multilayer Feedforward Networks are Universal Approximators [1989].

UNIVERSAL APPROXIMATORS

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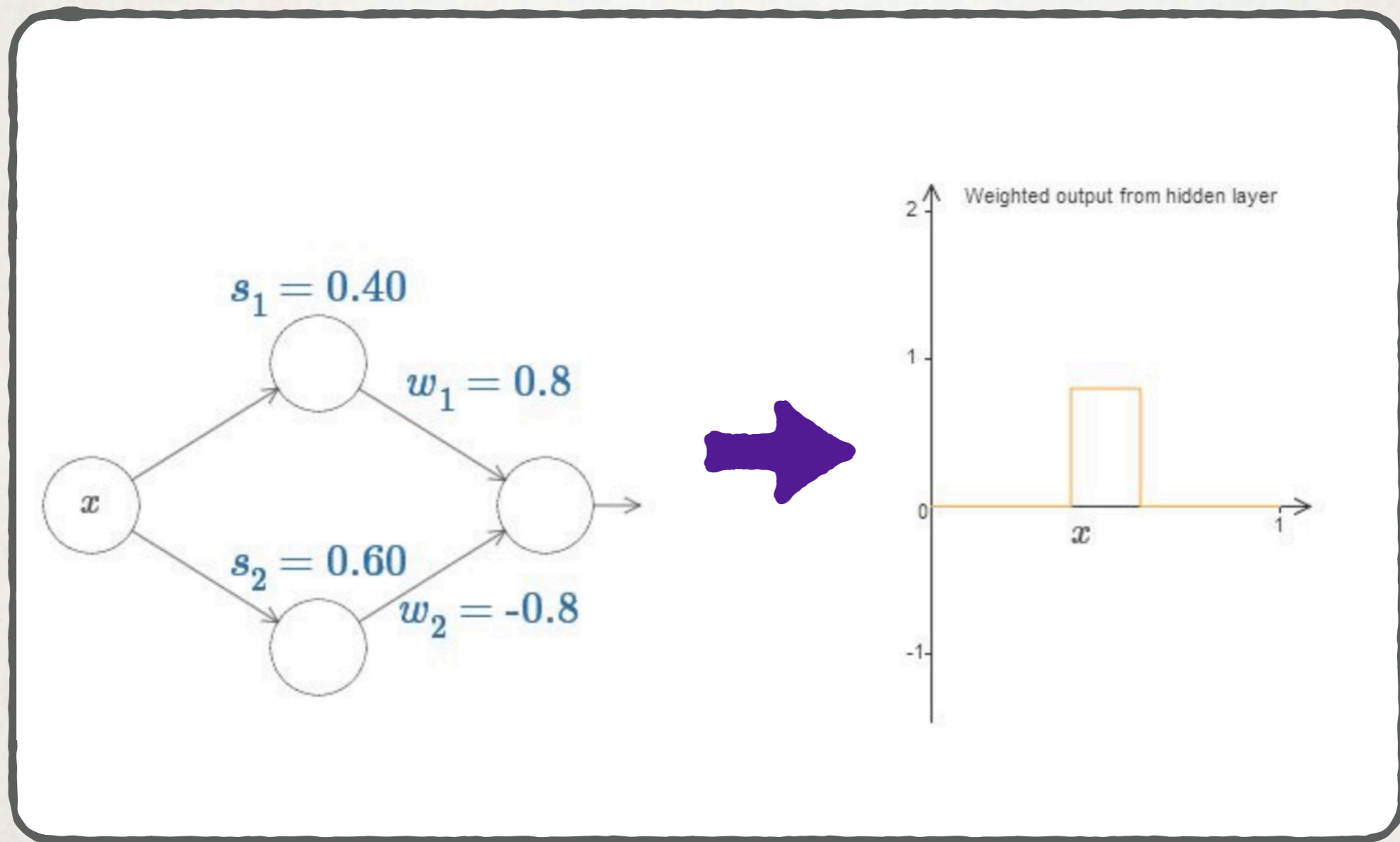
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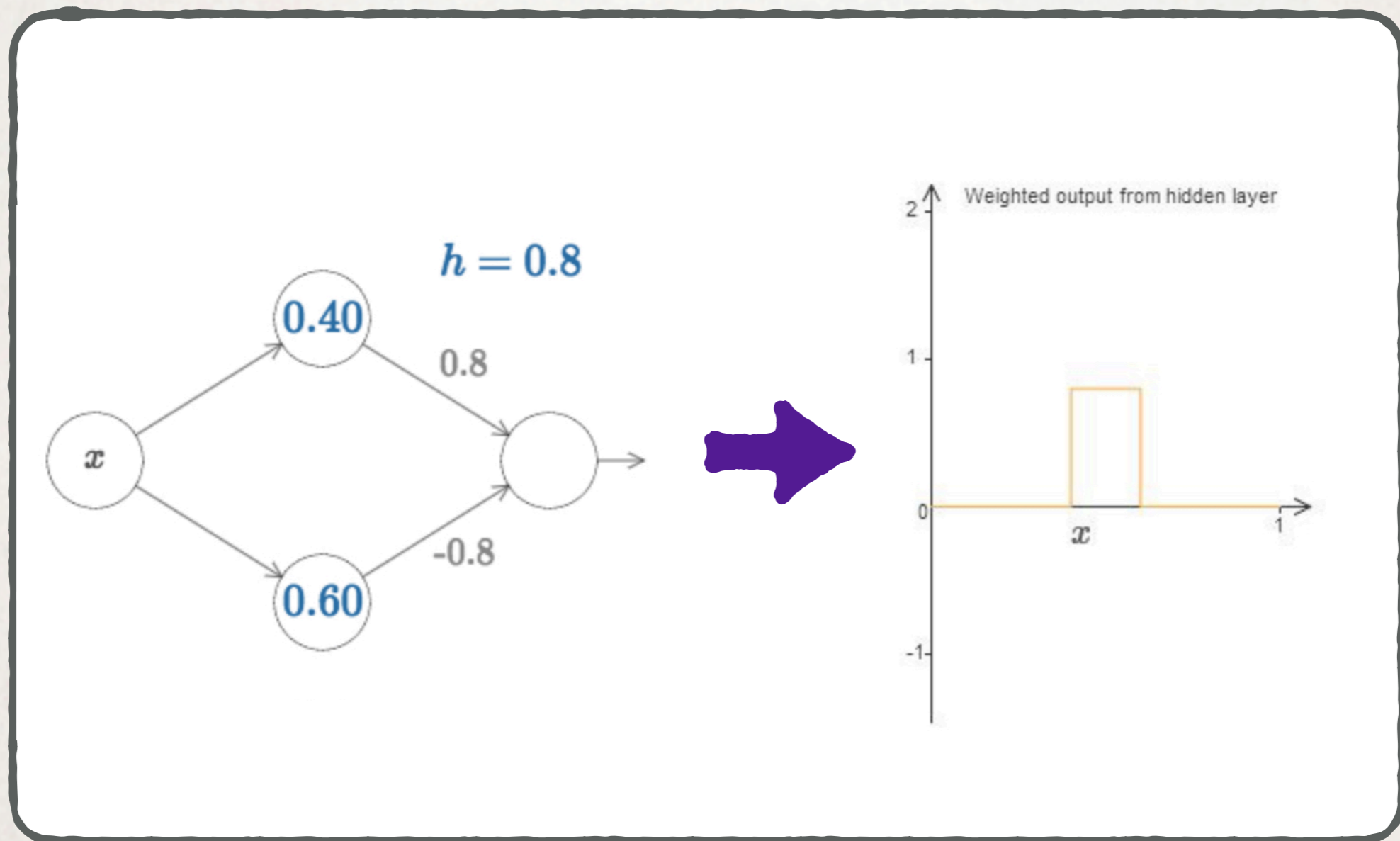
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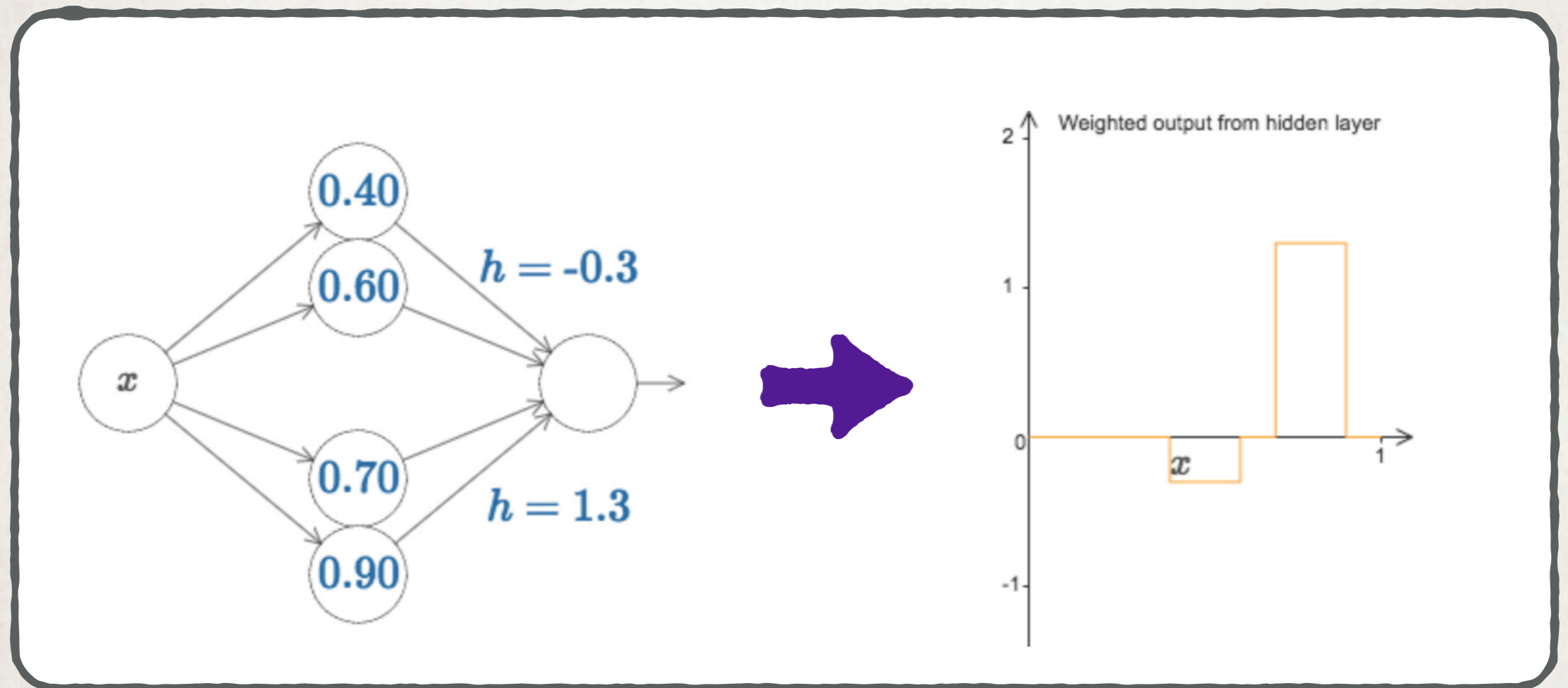
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UNIVERSAL APPROXIMATORS

Michael Nielsen [<http://neuralnetworksanddeeplearning.com/>]



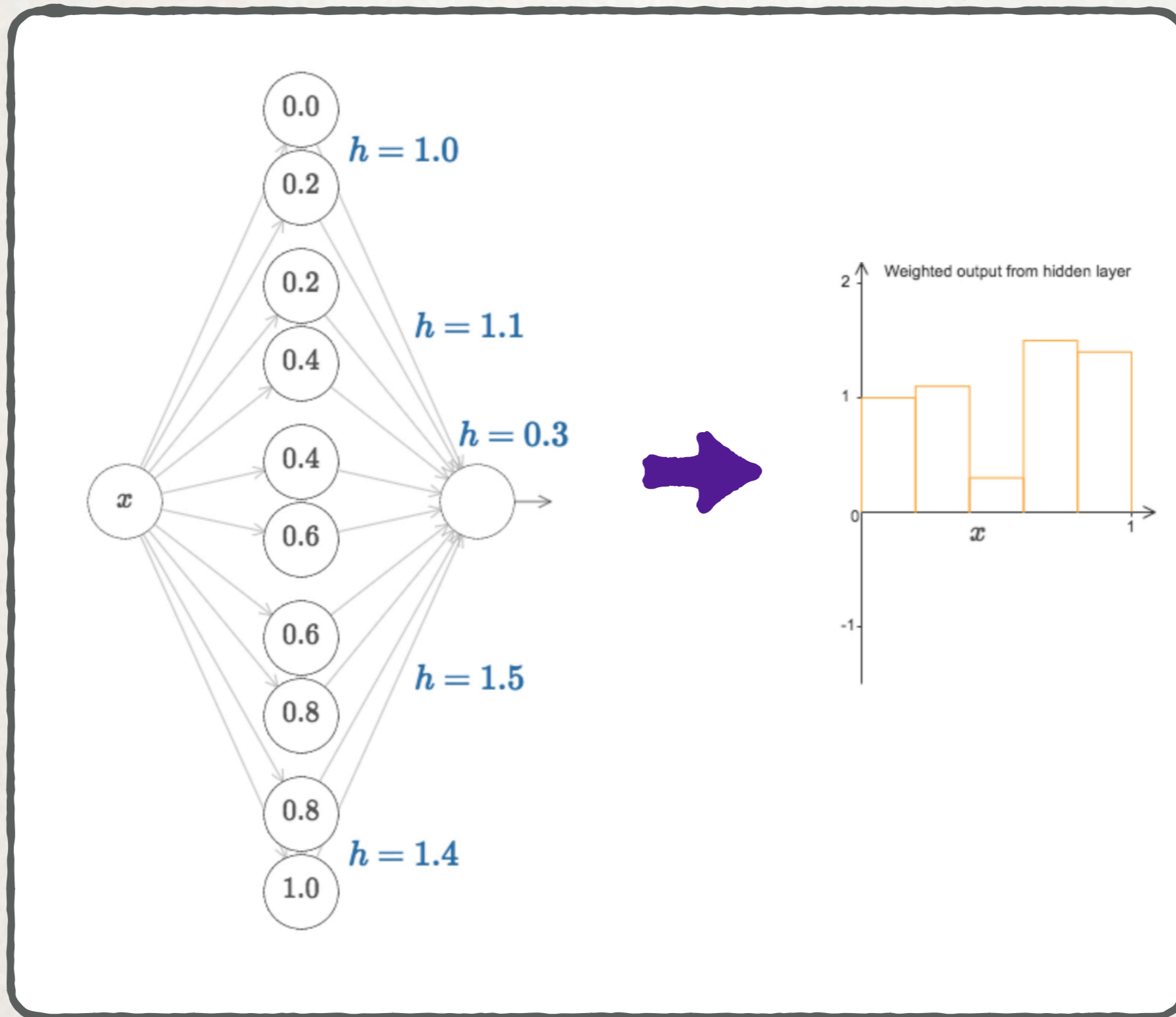
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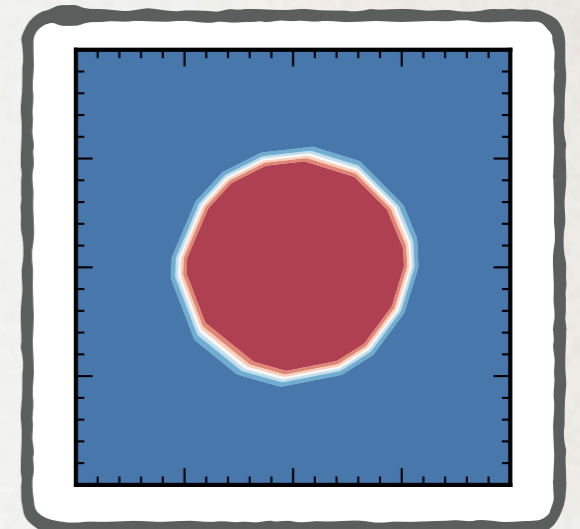
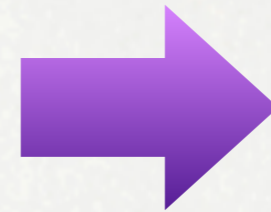
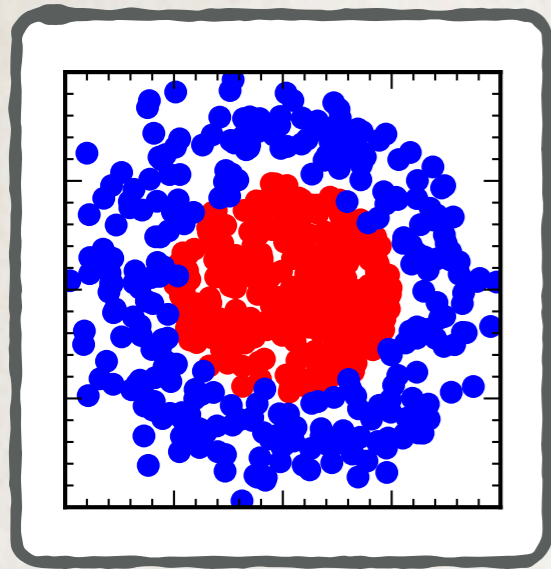
Kurt Hornik, Maxwell Stinchcobe, and Halbert White, Multilayer Feedforward Networks are Universal Approximators [1989].

UNIVERSAL APPROXIMATORS

Michael Nielsen [<http://neuralnetworksanddeeplearning.com/>]



PREMISE



Machine learning algorithm
finds all available features
for discriminating signal
from background.

GOING DEEPER

Shallow networks require exponential nodes to model functions to arbitrary accuracy.



Deep networks converge faster
(at the expense of transparency).

GOING DEEPER

Shallow networks require exponential nodes to model functions to arbitrary accuracy.



Practically:

Small single layer networks are linear discriminators;
Deep networks are sensitive to non-linearities.



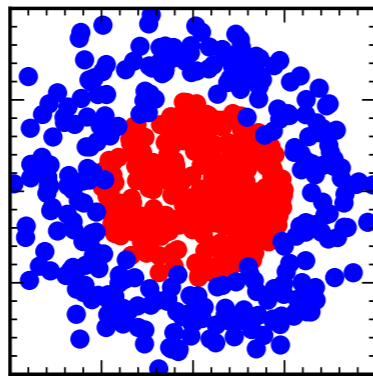
Deep networks converge faster
(at the expense of transparency).

WHAT IS THE MACHINE LEARNING?

Spencer Chang, TC, Bryan Ostdiek [[arXiv:1709.10106](https://arxiv.org/abs/1709.10106)]

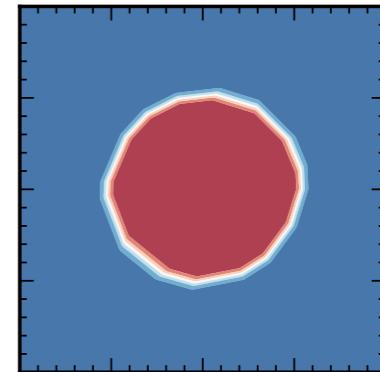
FRAMING THE QUESTION

Given
input
data



;

An ideal
classifier
will yield



Did the machine learn that the boundary is a circle?

Does it know that " $x^2 + y^2 = r^2$ " ?

A SIMPLE PROPOSAL

See also de Oliveria, Kagan, Nachman, Schwartzman [arXiv:1511.05190]

Machine relies on presence of relations between variables that distinguish signal from background.

Human wants to infer what drives classification.

Proposal: DATA PLANING

- (a) Train machine on low level data
- (b) Compute low level AUC
- (c) Choose a variable: compute (planing) weights
- (d) Train machine on weighed (planed) data
- (e) Compute planed AUC
- (f) Compare: looking for significant performance drop



(AUC = area under ROC curve; sub with favorite performance metric.)

PLANING VS SATURATION

Used in Baldi, Sadowski, Whiteson [arXiv:1402.4735 and 1410.3469]; Baldi, Bauer, Eng, Sadowski, Whiteson [arXiv:1603.09349]; Guest, Collado, Baldi, Hsu, Urban, Whiteson [arXiv:1607.08633]; Datta, Larkoski [arXiv:1704.08249]; Aguilar-Saavedra, Collins, Mishra [arXiv:1709.01087]

“Saturation”: another way to ask
What is the Machine Learning?

- (a) Train network on low level data
- (b) Compute low level AUC
- (c) Choose a high level variable
- (d) Train new machine using low + high level variables
- (e) Compute low/high hybrid AUC
- (f) No performance change implies network has saturated

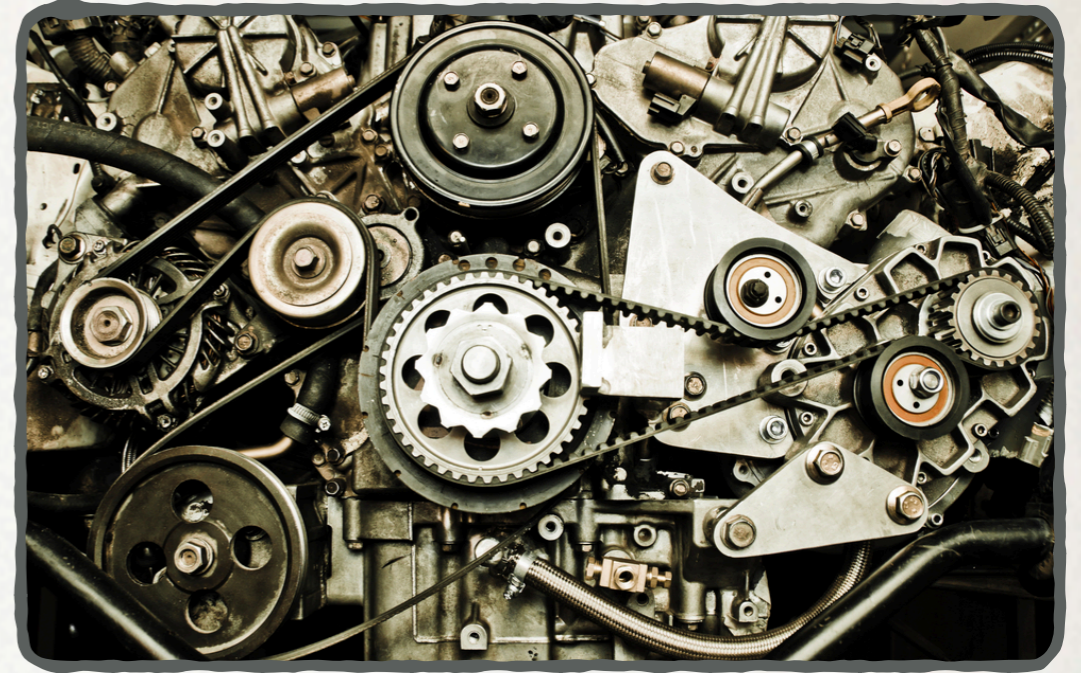


Saturation: expect minimal changes in performance.

Planing: large qualitative changes.

Measure how much power variables are providing.

TECHNICAL ASIDE



All machines are neural networks.

Linear network = 0 hidden layers.

Deep network = 3 hidden layers.

Hidden layer has 50 nodes.

Sigmoid activation on final node, otherwise ReLu activation

Test set = 10% of events, 4.5% for validation.

Error bars from 10 networks with random initial conditions.

Implemented by Keras package with TensorFlow backend.

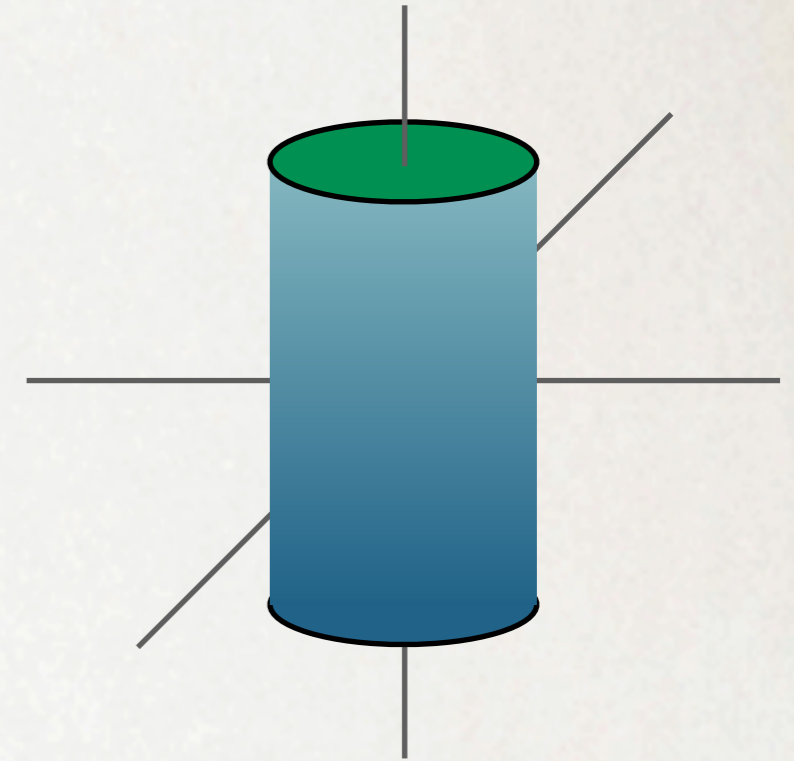
Metrics computed on test set using scikit-learn.

DATA PLANING: TOY MODEL

Signal

$$f(\vec{x}) = \left[\Theta(r_0 - r) + C_r \right] \cdot \left[z \cdot B_z + C_z \right]$$

constants



Background is uniform.

RESULTS

(x, y, z)	r	PLANED	LINEAR AUC	DEEP AUC
✓	✗	✗	0.61275(01)	0.81243(45)
✓	✓	✗	0.79672(01)	0.81388(23)
✓	✗	r	0.61030(01)	0.61026(02)
✓	✗	(r, z)	0.5081(16)	0.49998(03)



Check saturation.



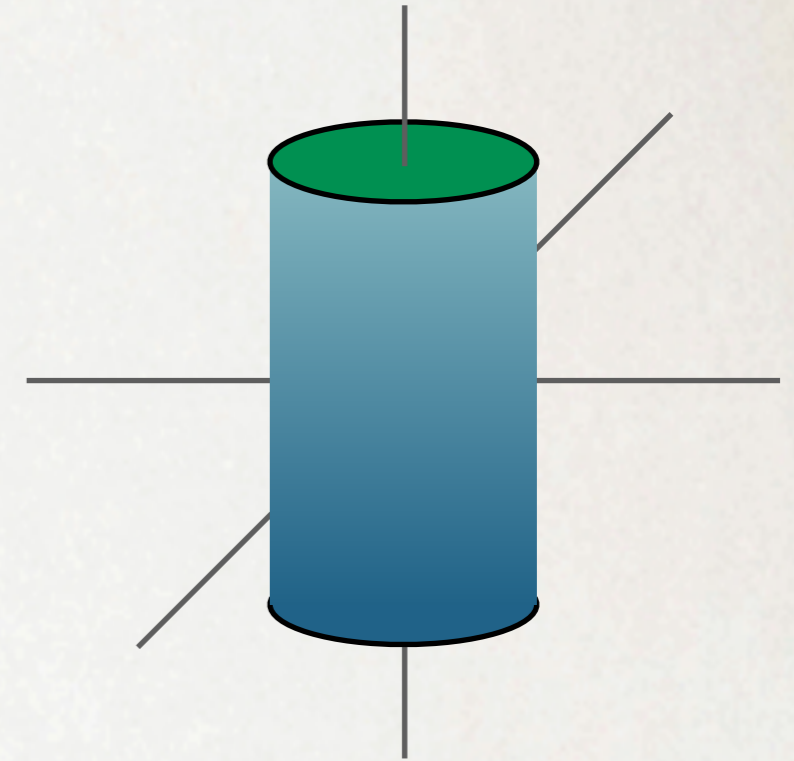
No remaining ability to discriminate.

DATA PLANING: TOY MODEL

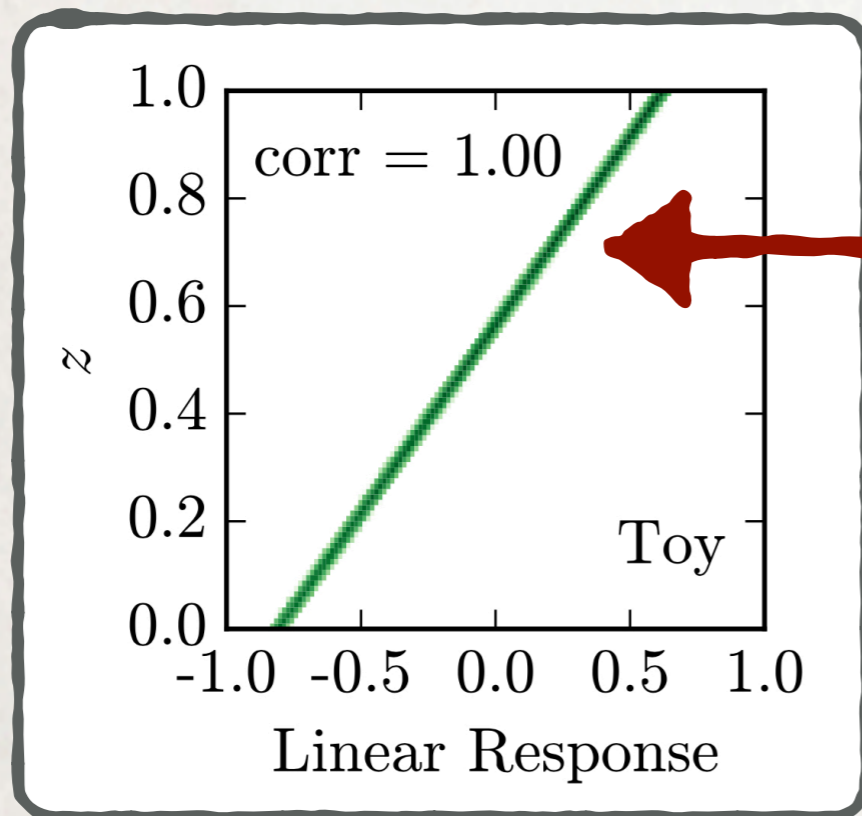
Signal

$$f(\vec{x}) = \left[\Theta(r_0 - r) + C_r \right] \cdot \left[z \cdot B_z + C_z \right]$$

constants



Background is uniform.

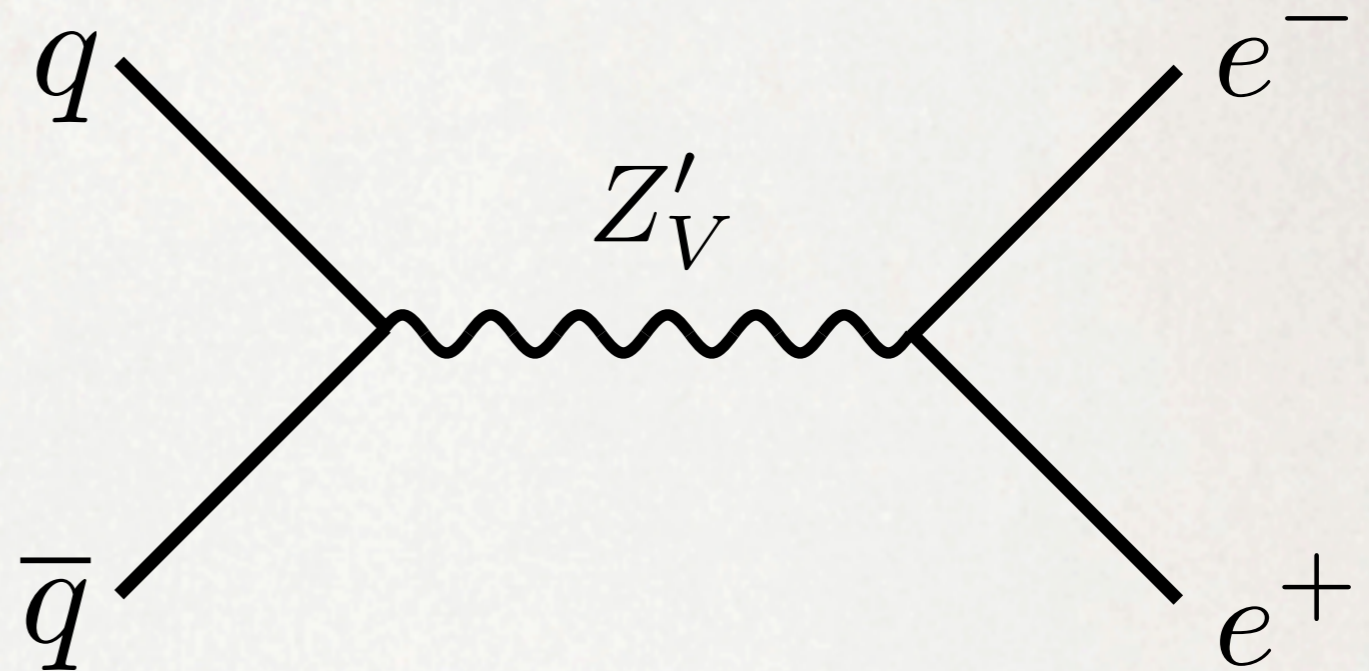


Linear discriminant

BSM MODELS

I) vector couplings

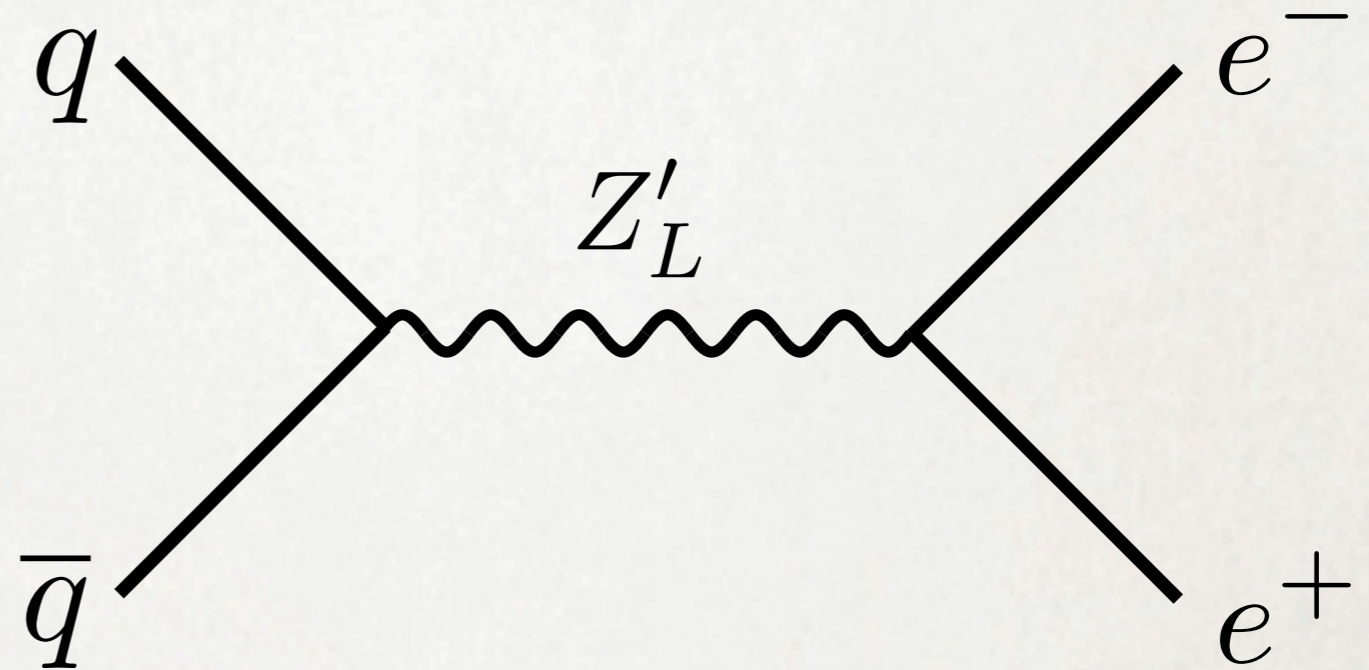
$$g_L = g_R$$



or

II) left-handed couplings

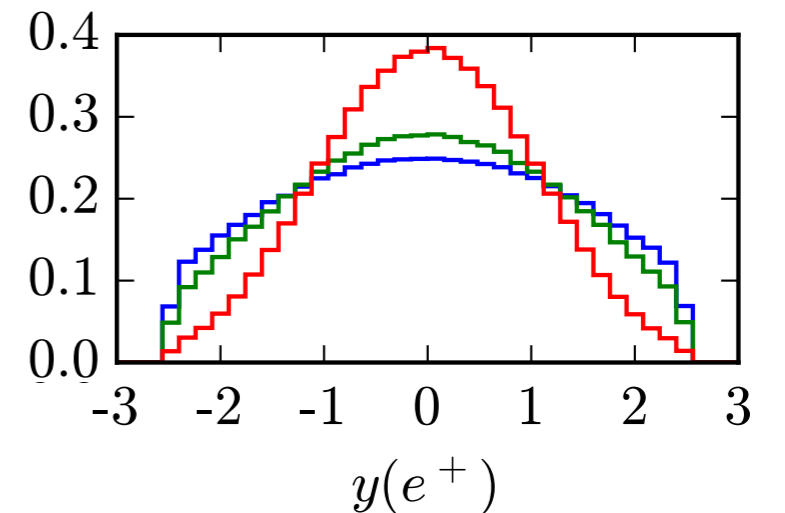
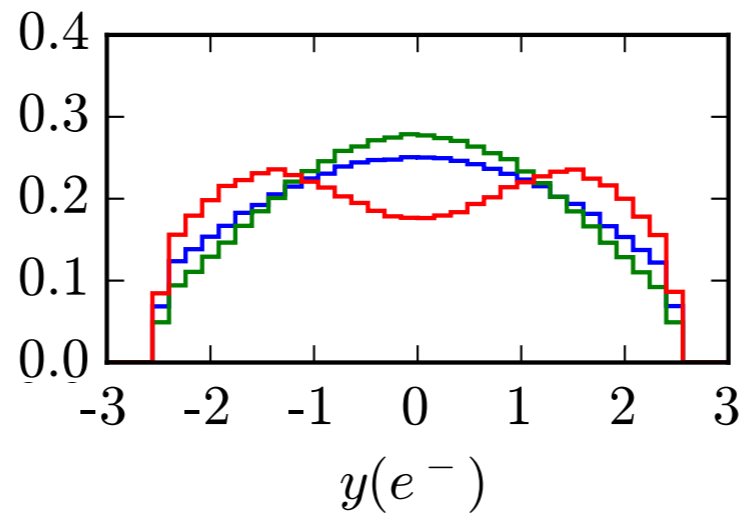
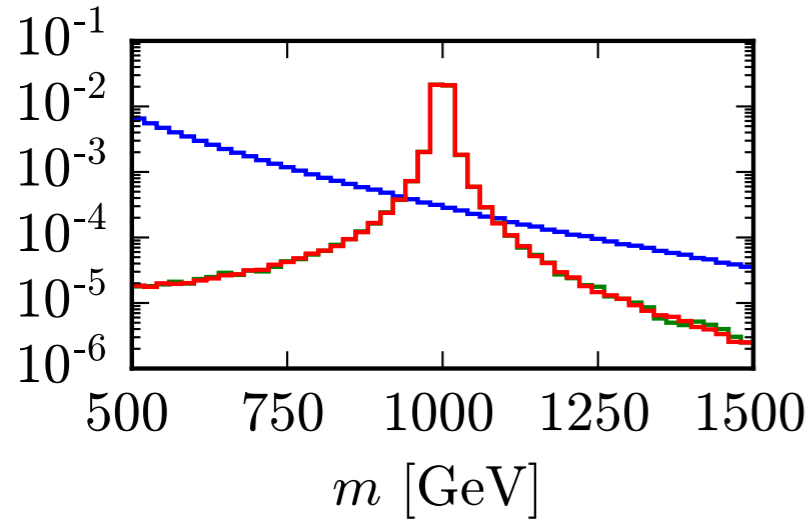
$$g_R = 0$$



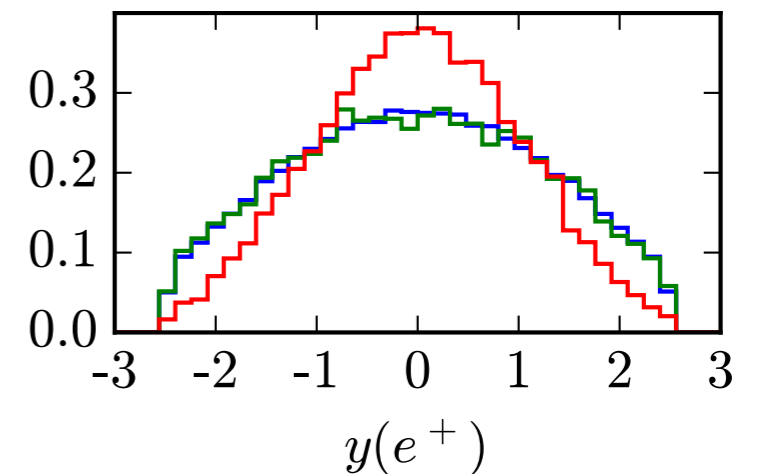
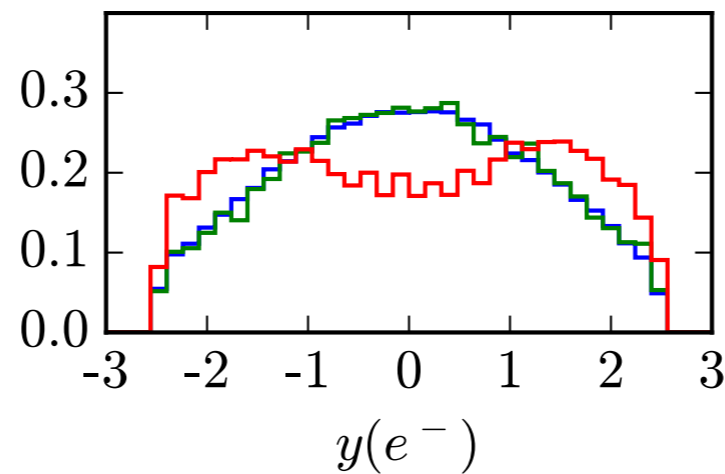
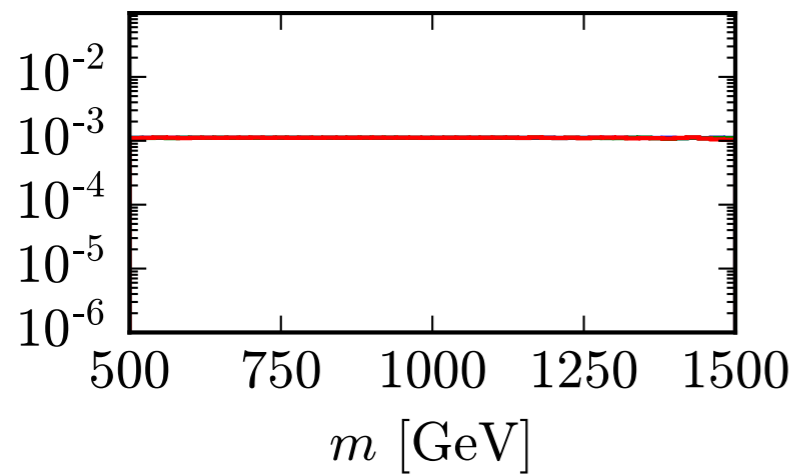
$$\mathcal{L} \supset Z'_\mu \sum_f Q_f \left(g_L \bar{f} \gamma^\mu P_L f + g_R \bar{f} \gamma^\mu P_R f \right)$$

BSM DISTRIBUTIONS

Kinematics



After planing in mass



— Photon — Z'_V — Z'_L

Note: highly idealized.

DATA PLANING: BSM

vector couplings

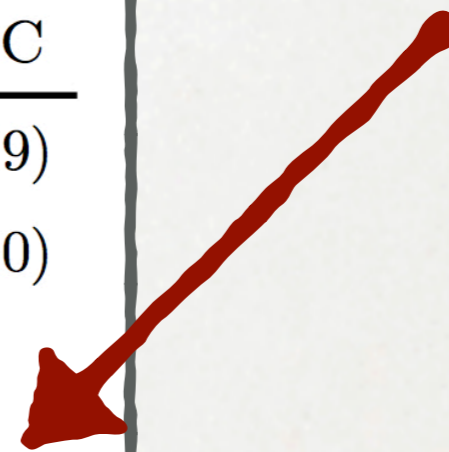
(E, \vec{p})	m	PLANED	LINEAR AUC	DEEP AUC
✓	✗	✗	0.746221(01)	0.988510(98)
✓	✓	✗	0.938967(01)	0.989007(03)
✓	✗	m	0.50550(29)	0.4942(48)



No remaining ability to discriminate.

left-handed couplings

(E, \vec{p})	m	PLANED	LINEAR AUC	DEEP AUC
✓	✗	✗	0.763280(05)	0.989353(59)
✓	✓	✗	0.942004(02)	0.989826(10)
✓	✗	m	0.626648(28)	0.6258(24)
✓	✗	$(m, \Delta y)$	0.52421(15)	0.5320(25)

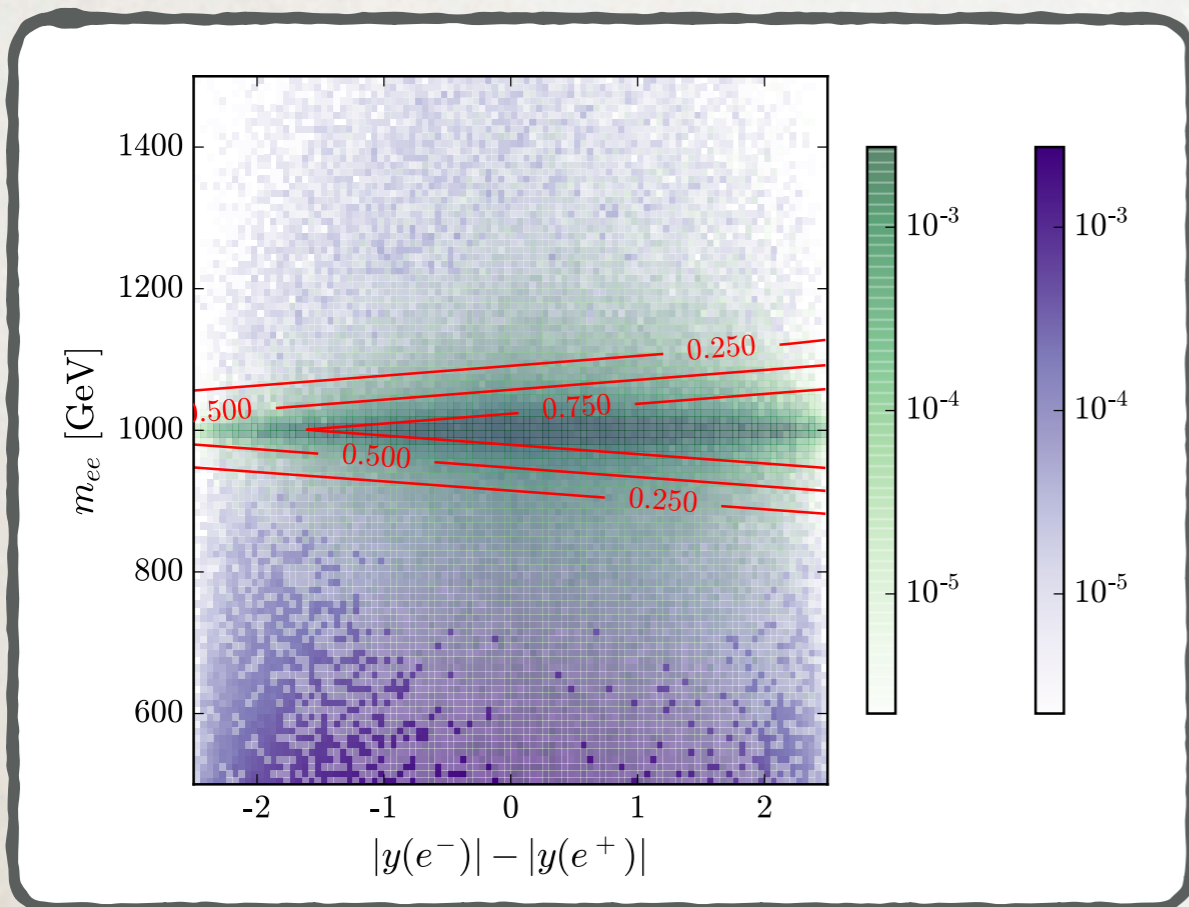
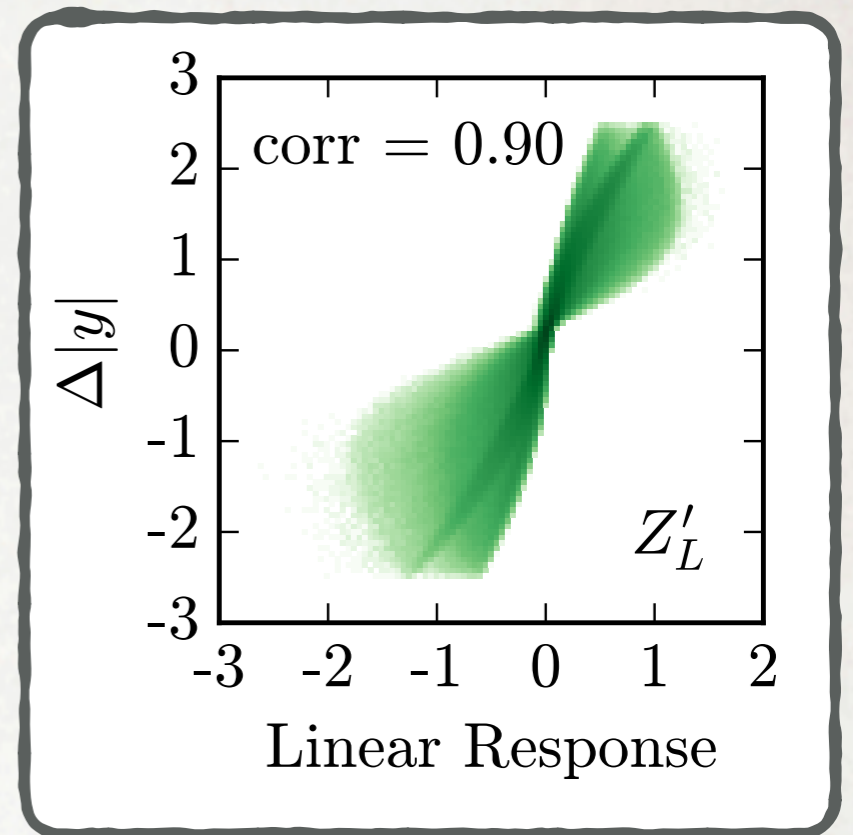


$$\Delta|y| = |y(e^+)| - |y(e^-)|$$

A CLOSER LOOK

left-handed couplings

(E, \vec{p})	m	PLANED	LINEAR AUC	DEEP AUC
✓	✗	✗	0.763280(05)	0.989353(59)
✓	✓	✗	0.942004(02)	0.989826(10)
✓	✗	m	0.626648(28)	0.6258(24)
✓	✗	$(m, \Delta y)$	0.52421(15)	0.5320(25)



- Train a network using
- (a) only mass: AUC = 0.939
 - (b) both: AUC = 0.989

$$\Delta|y| = |y(e^+)| - |y(e^-)|$$

OUTLOOK

OUTLOOK

(Deep) neural network is universal fitter.

Train to distinguish signal from background.

But what is the machine learning?

Data planing procedure unpacks discriminating power.

Future work: Apply to more realistic setting.

Future work: Apply when best variables are unknown.