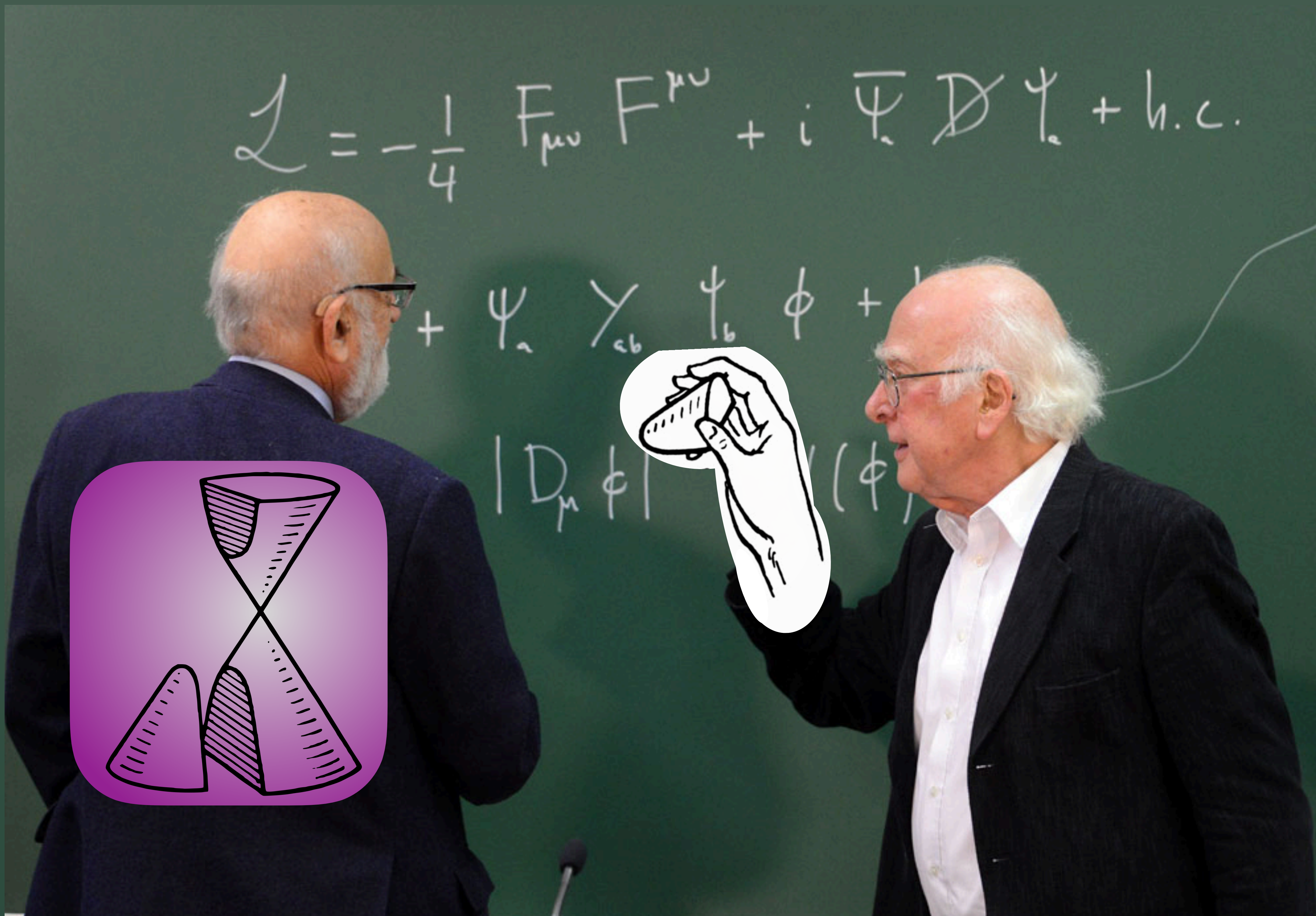
TWO FOR THE PRICE OF ONE

Tim Cohen

University of Oregon

UC Davis Joint Theory Seminar
April 16, 2018

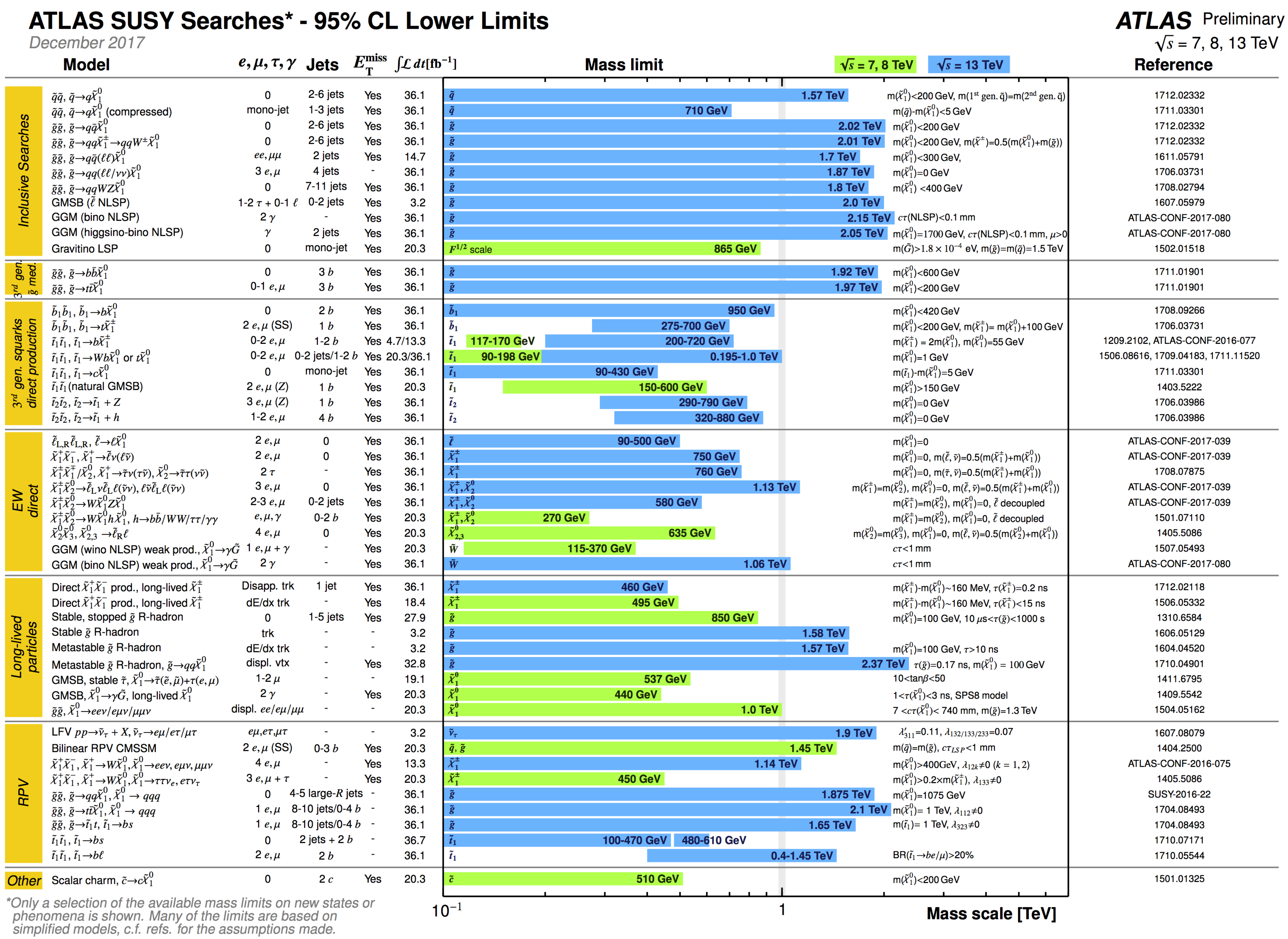
THE HYPERBOLIC HIGGS



with Nathaniel Craig, Gian Giudice, and Matthew McCullough

arXiv:1803.03647

WHERE'S THE NEW PHYSICS?!?

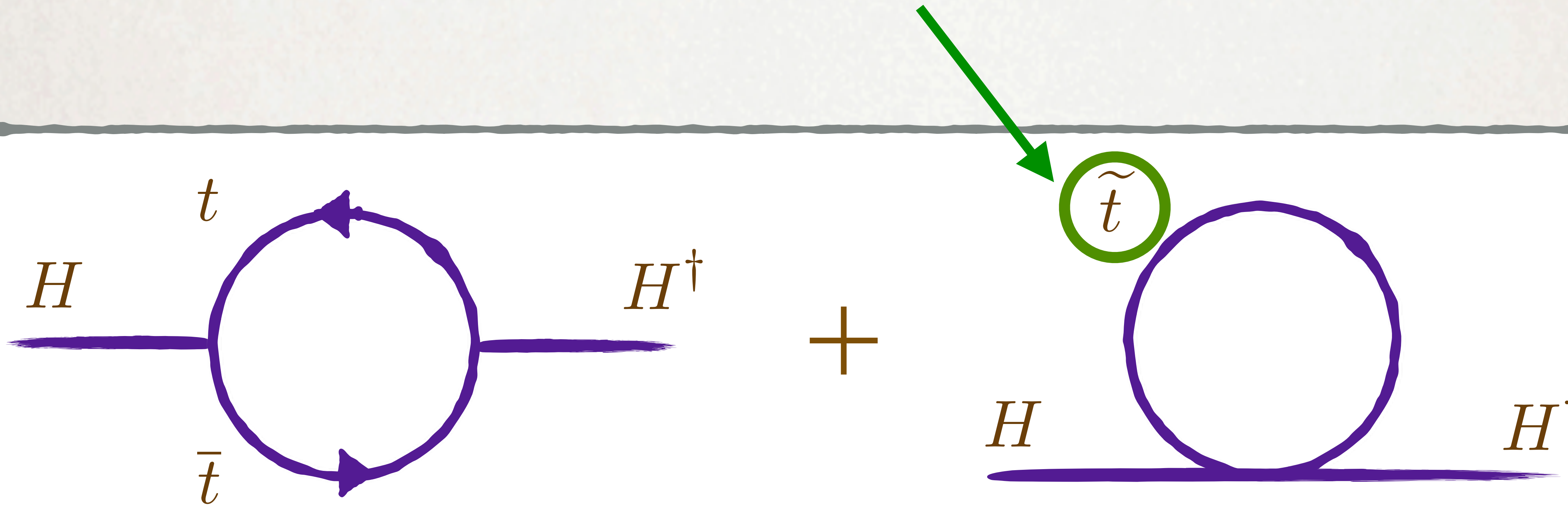


GUIDANCE FROM NATURALNESS

GUIDANCE FROM NATURALNESS

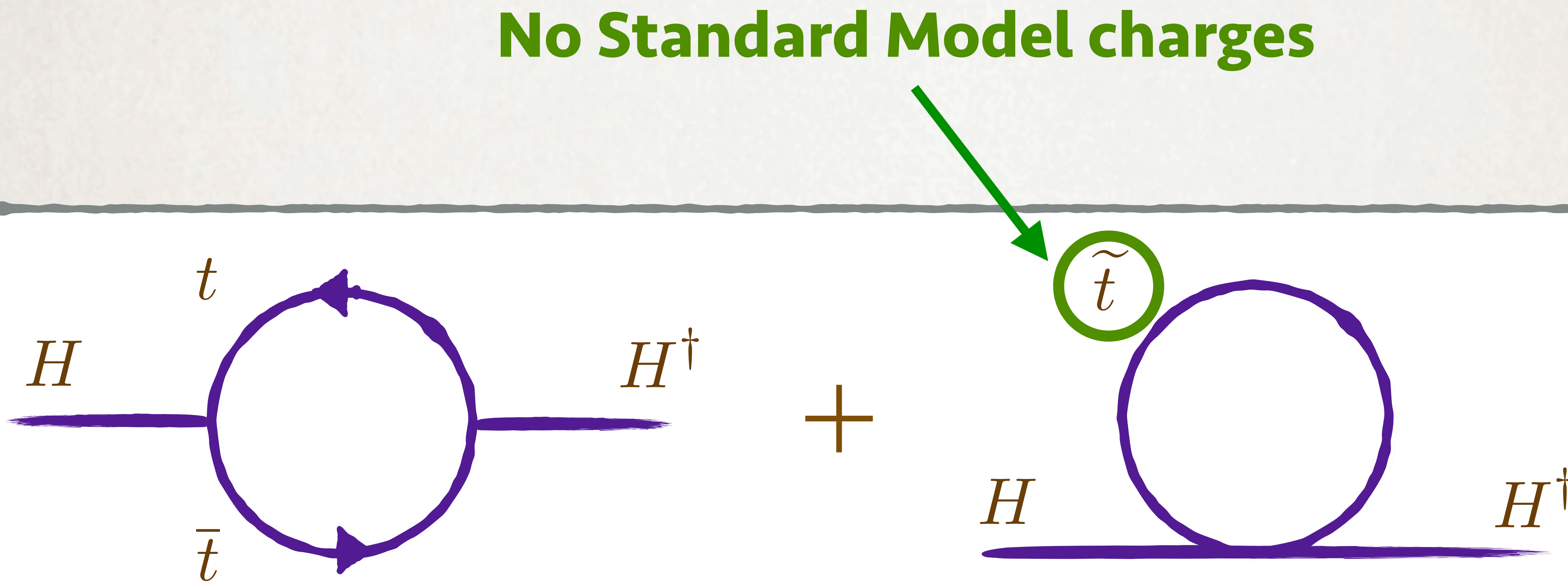
NORMAL NATURALNESS

Same charge as the top



$=$ UV insensitive

~~NORMAL~~ NATURALNESS
NEUTRAL



$= \text{UV insensitive (at one-loop)}$

STATE OF THE ART

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

Mirror Glueballs
Higgs portal observables

Higgs coupling shifts
$\sim$ tuning

Curtin and Varhaaren [arXiv:1506.06141]

STATE OF THE ART

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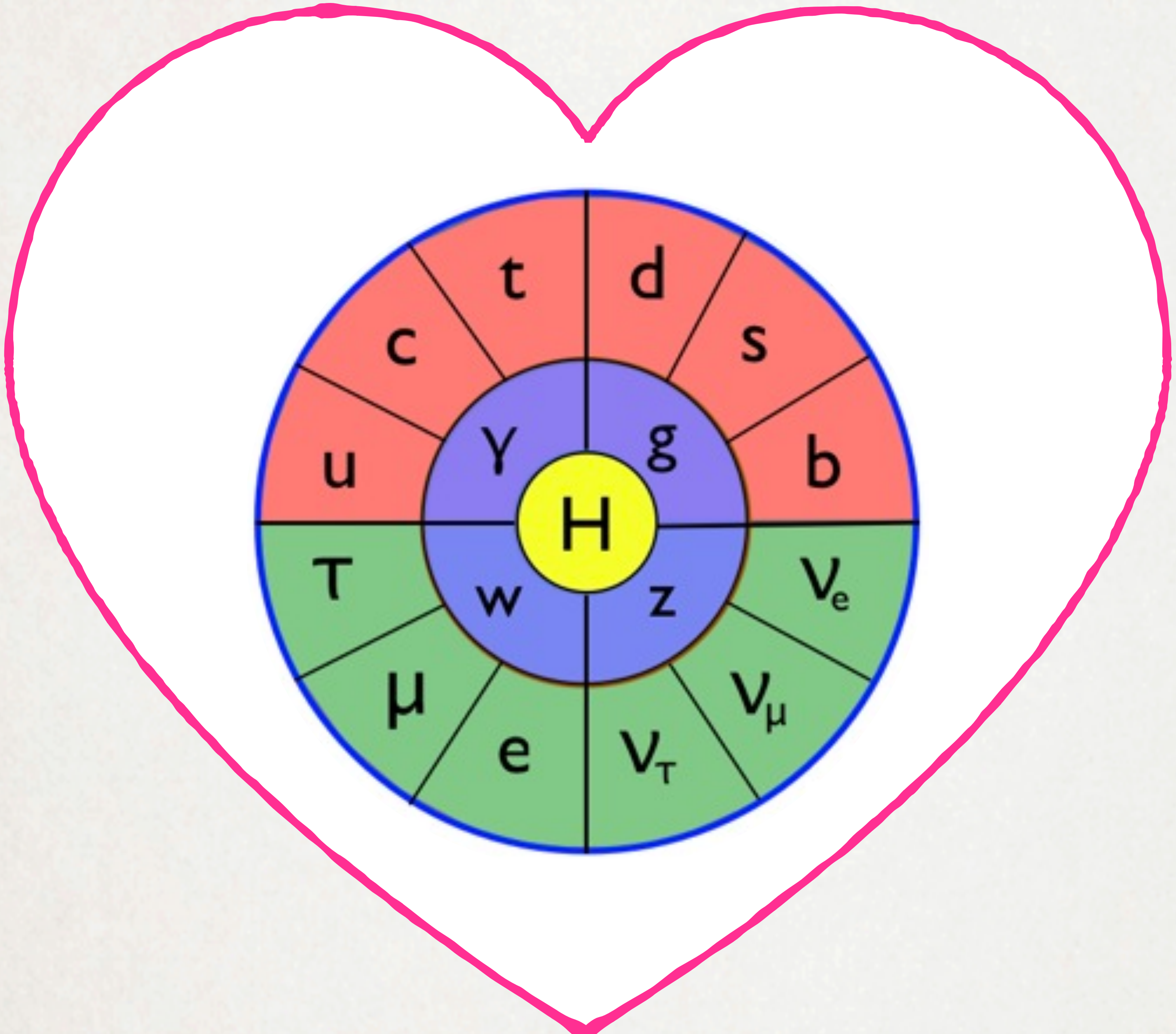
This talk!!

DOUBLE DOWN!



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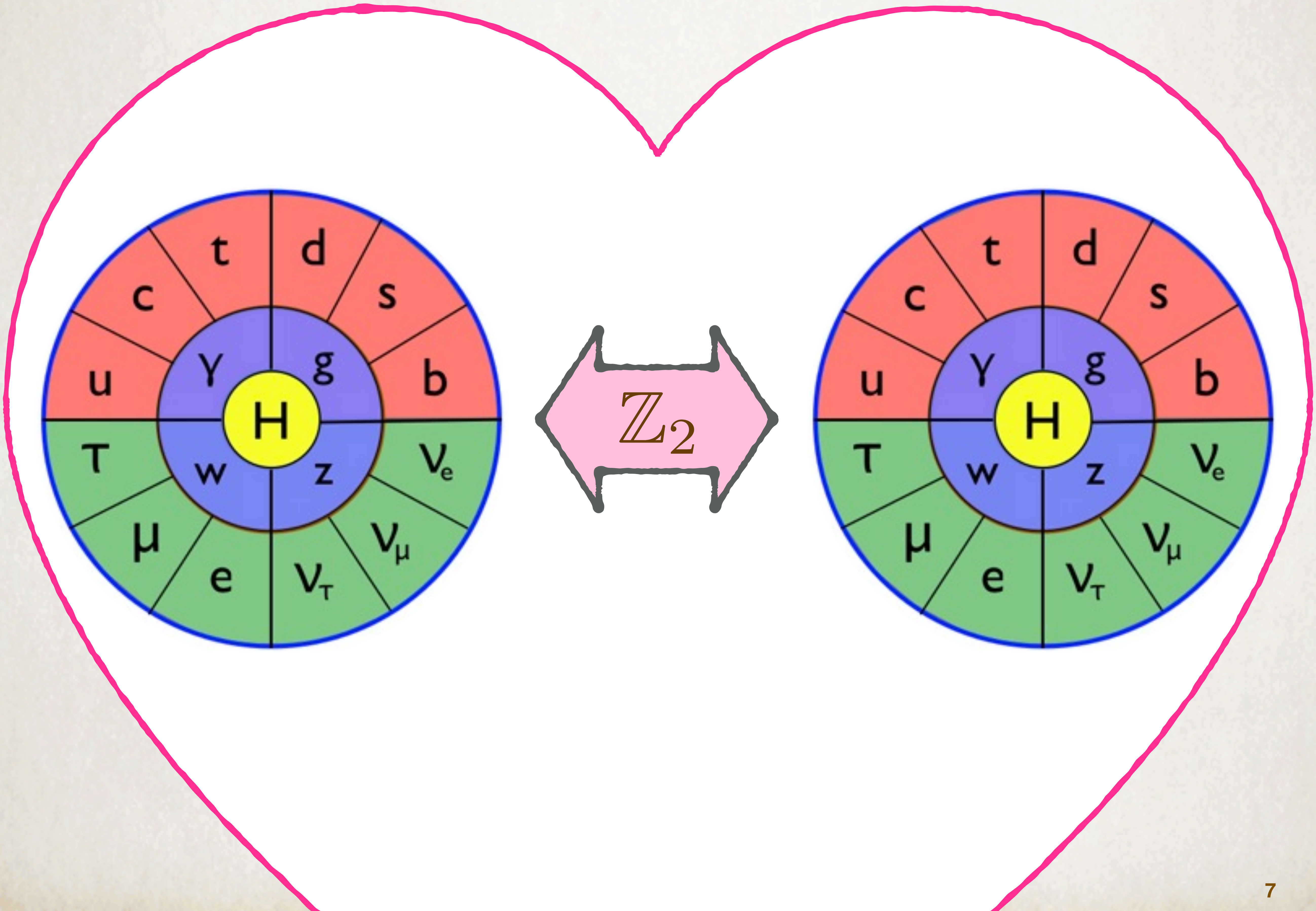

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TWIN HIGGS

Accidental $\mathrm{SU}(4)$

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

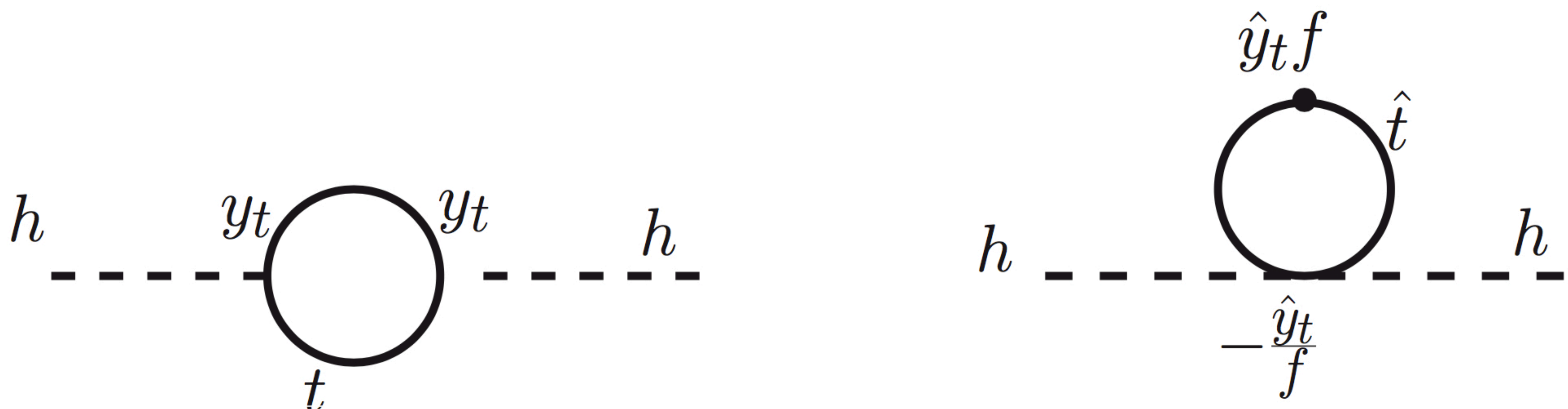
$$f^2 = v^2 + v_T^2$$

$$\mathrm{SU}(4) \to \mathrm{SU}(3)$$

7 Goldstones: 6 eaten ➡ 1 light scalar

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

TWIN QUADRATIC CORRECTIONS



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

THE HYPERBOLIC HIGGS

Accidental $\mathrm{U}(2,2)$

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

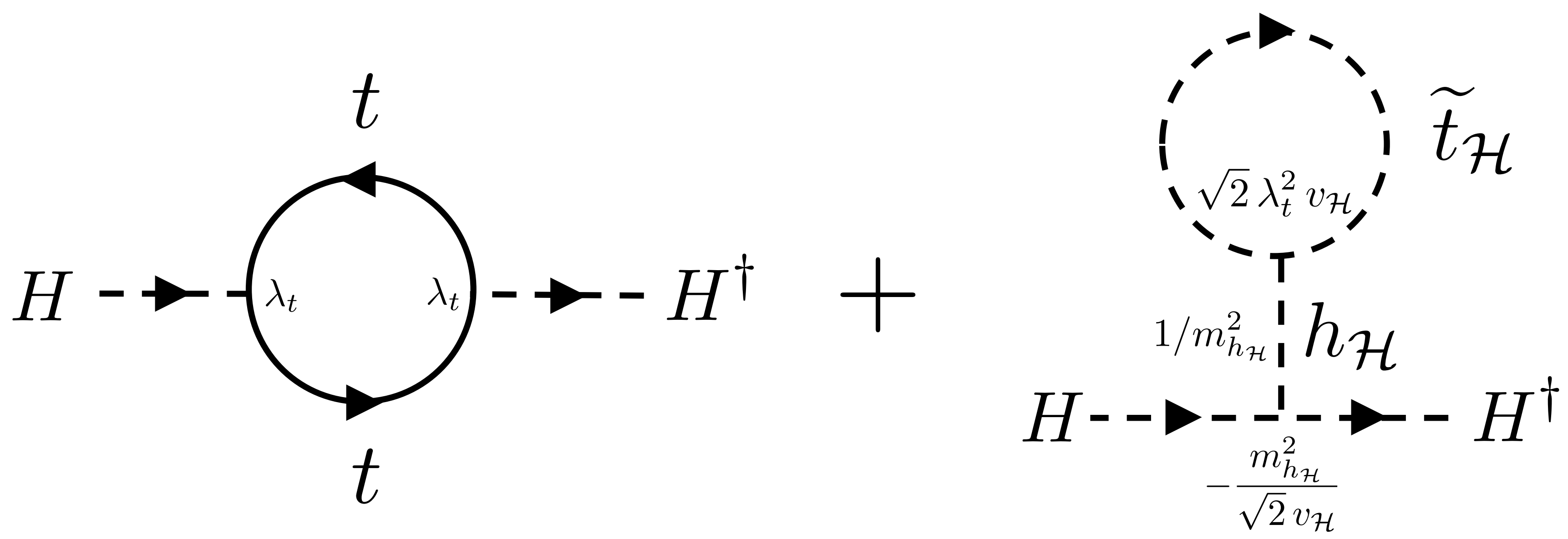
$$\big|H_{\mathcal{H}}\big|^2 - \big|H\big|^2 = \frac{m^2}{\lambda}$$

Flat-direction

QUADRATIC CORRECTIONS

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

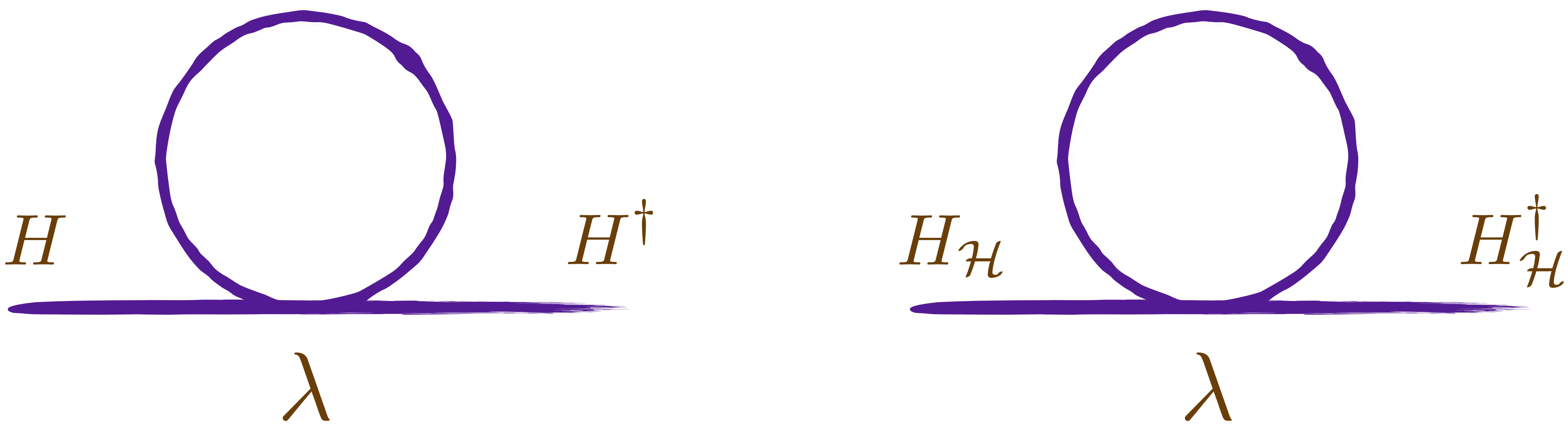
$$\mathcal{L} = \left(\lambda_t\, H\, \psi_Q\, \psi_{U^c} + \text{h.c.}\right) + \lambda_t^2 \left|H\right|^2 \left(\left|\widetilde{Q}_\mathcal{H}\right|^2 + \left|\widetilde{U}^c_\mathcal{H}\right|^2 \right)$$



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

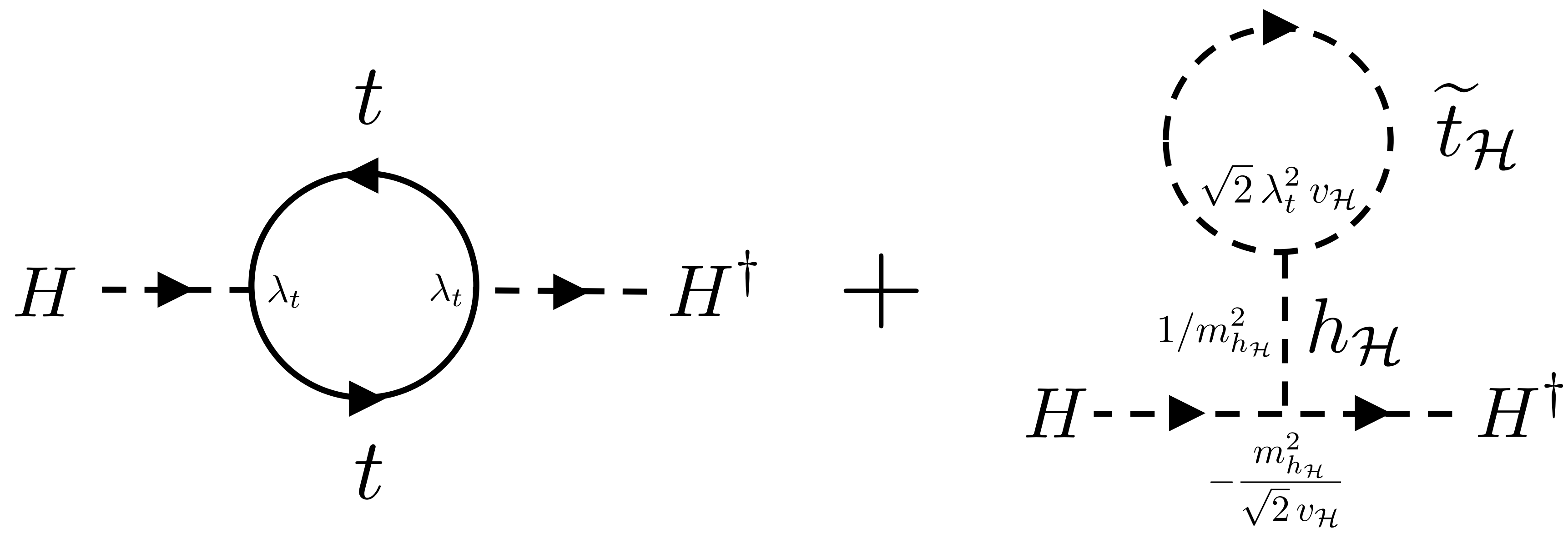
IR ISSUES - I

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



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

IR ISSUES - II



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

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

PHENOMENOLOGY

Higgs portal

Top partner vevs

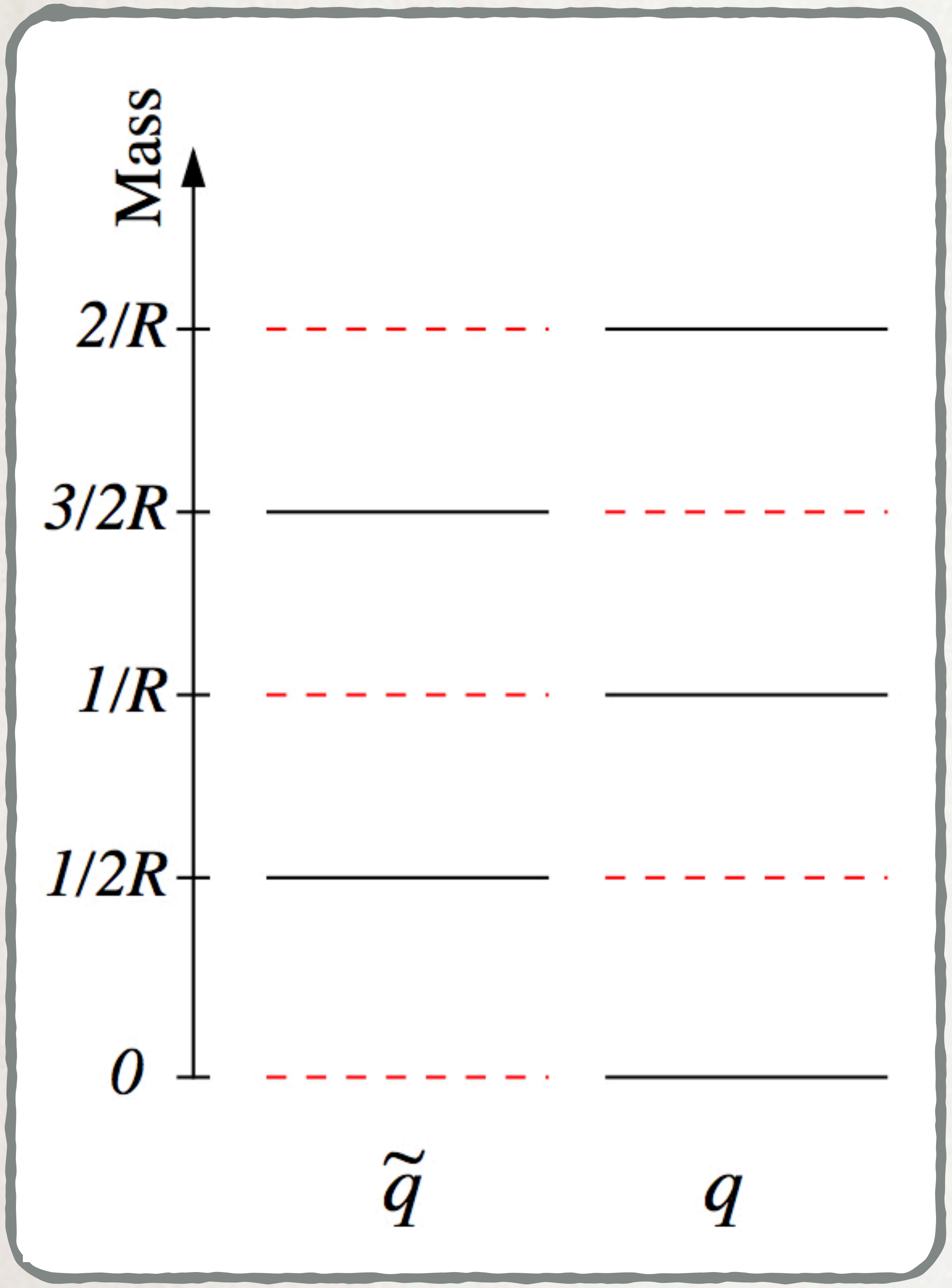
Higgs-top partner mixing

Eaten top partners

Modified dark shower phenomenology

UV COMPLETION

ASIDE: FOLDED SUSY



Uncolored stops

5D SUSY

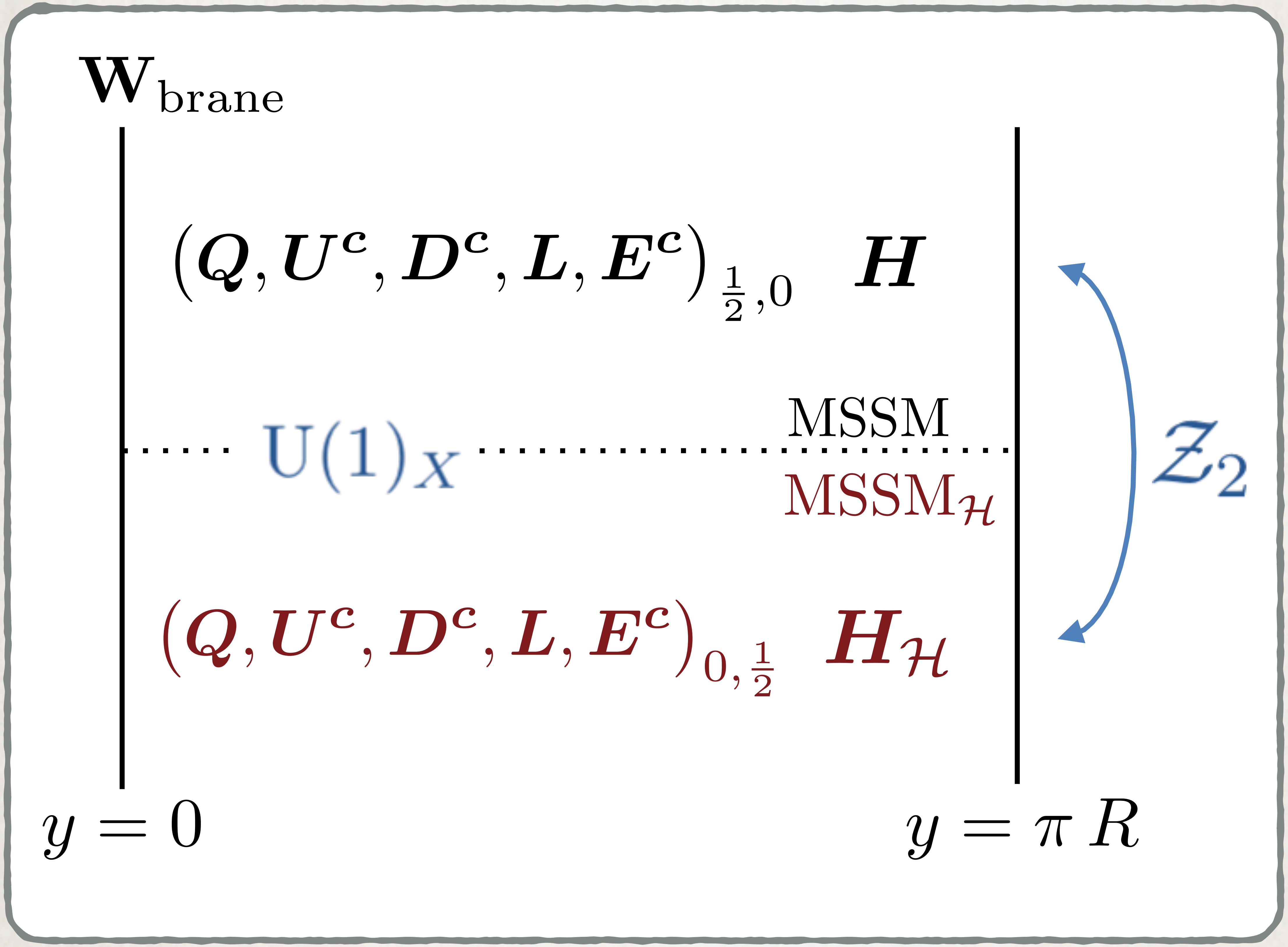
Double the MSSM

Boundary conditions lift colored stops

Electroweak charged

Burdman, Chacko, Goh, Harnik [arXiv:hep-ph/0609152]

A MODEL



$\mathbf{W}_{\text{brane}}$
$(\boldsymbol{Q}, \boldsymbol{U^c}, \boldsymbol{D^c}, \boldsymbol{L}, \boldsymbol{E^c})_{\frac{1}{2},0}$ $\boldsymbol{H}$
MSSM
$\mathrm{U}(1)_X$
$\mathrm{MSSM}_{\mathcal{H}}$
$\mathcal{Z}_2$
$(\boldsymbol{Q}, \boldsymbol{U^c}, \boldsymbol{D^c}, \boldsymbol{L}, \boldsymbol{E^c})_{0,\frac{1}{2}}$ $\boldsymbol{H}_{\mathcal{H}}$
$y = 0$
$y = \pi R$

TOP YUKAWA LOOPS

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

$$\omega^{\pm}_{B,F} = q_{B,F} \pm R\,m_t(H)$$

Boundary conditions

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

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

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

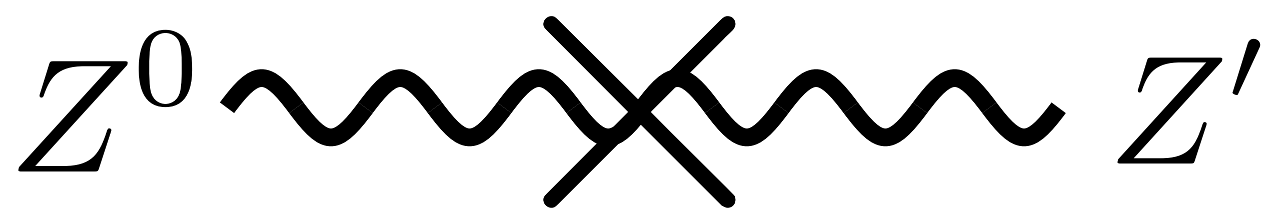
$\mathbf{U(1)}_{\boldsymbol{X}}$

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

Hyperbolic quartic!

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

Non-decoupling *D*-term

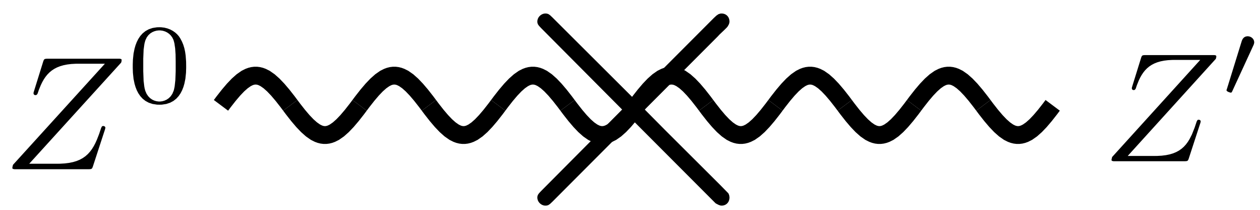


$$\Delta\rho = \frac{4\,g_X^2\,M_W^2}{g^2\,M_X^2} \quad\longrightarrow\quad \frac{M_X}{g_X} > 8.6\ \mathrm{TeV}$$

TENSION

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

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



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

MINIMIZE

Conditions for vevs

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

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

Physical Higgs mass

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

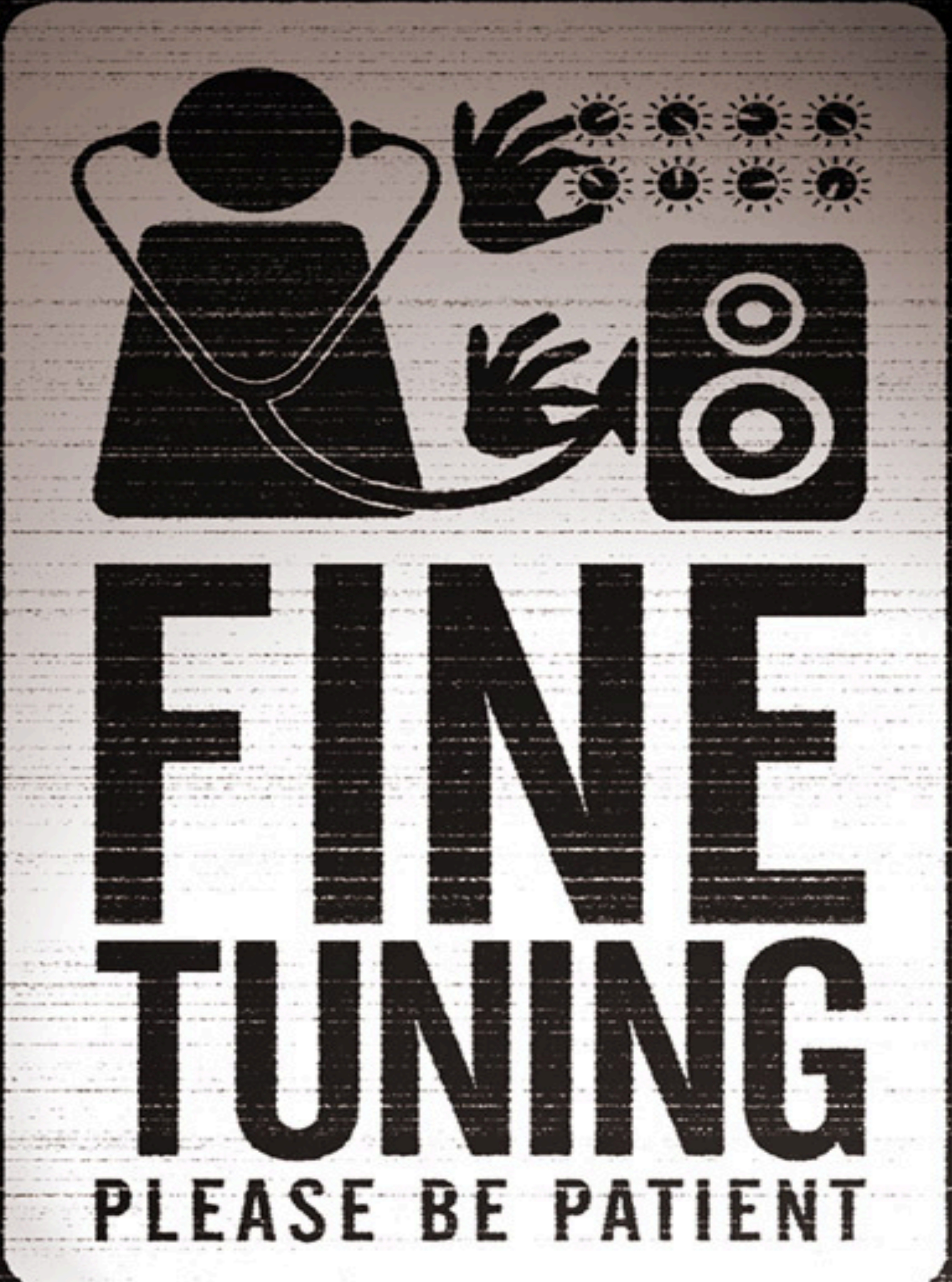
$$m_h^2 \simeq \left(2\, M_Z^2 + \frac{N_c\, \lambda_t^4}{2\, \pi^2}\, v^2 \log \frac{v_{\mathcal{H}}}{v} \right) \frac{v_{\mathcal{H}}^2}{v_{\mathcal{H}}^2 + v^2}$$

Mixing

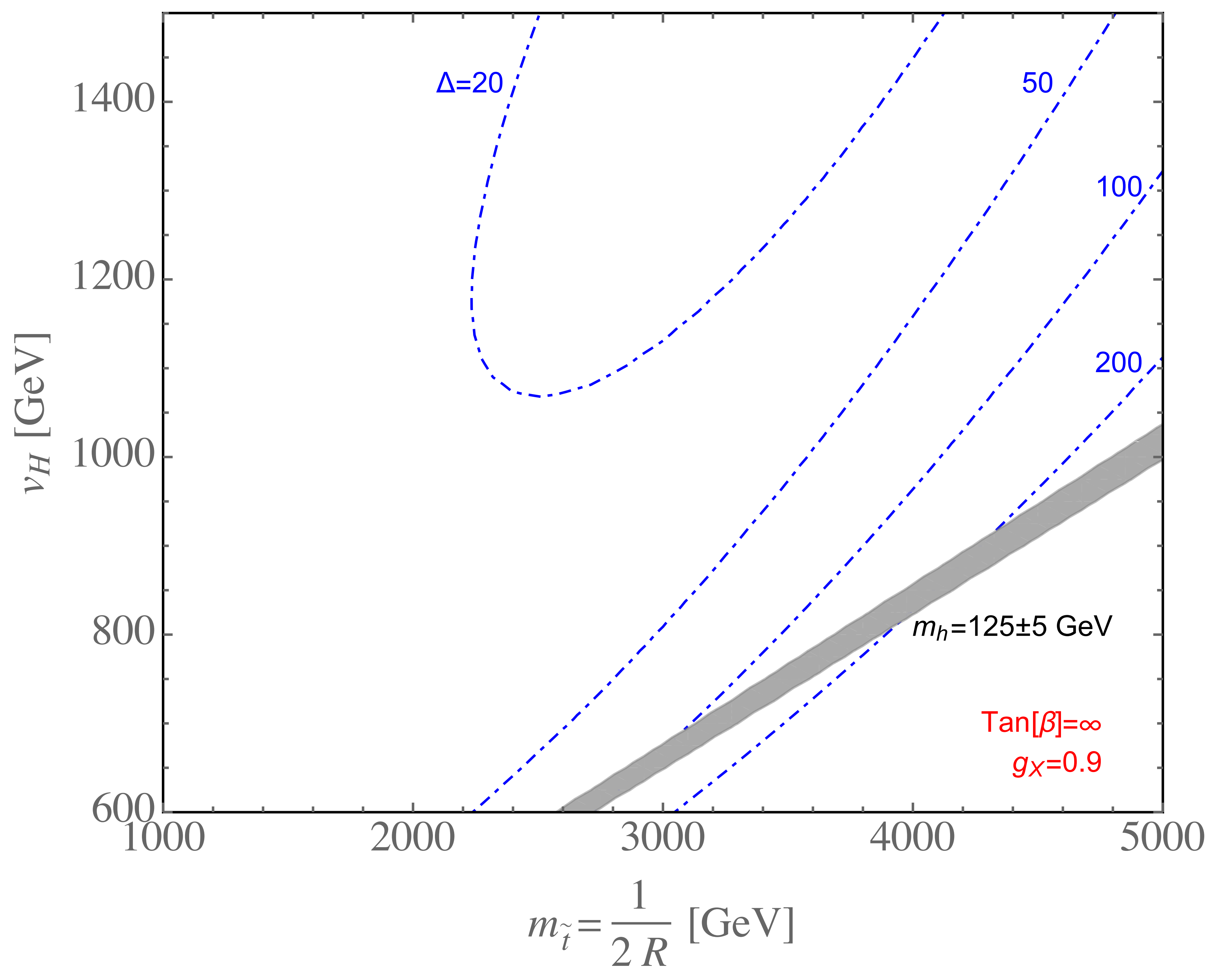
Factor of 2 bigger than MSSM

SCALES

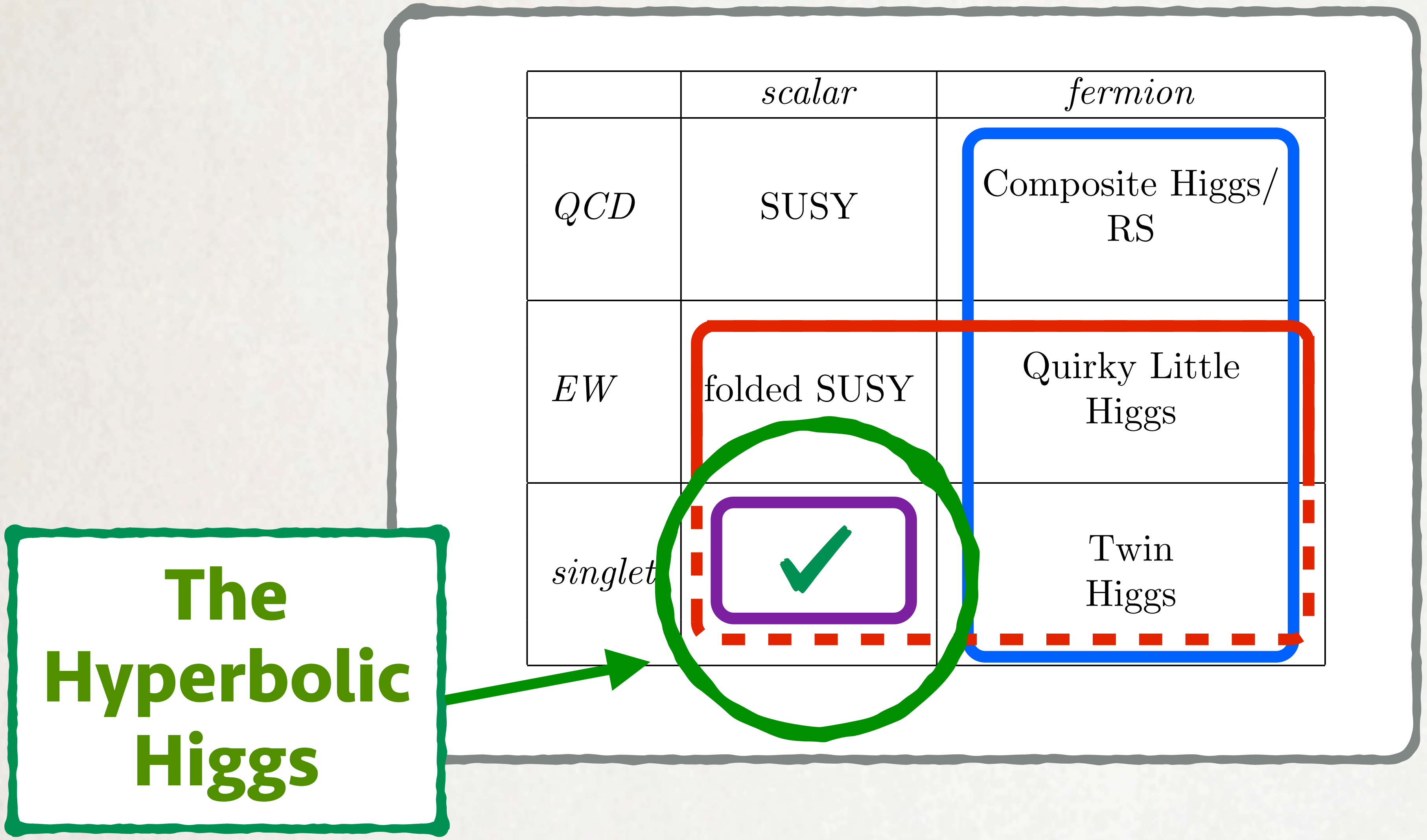
Cutoff	Λ	—	$\dfrac{1}{2R}$
Hyperbolic	$m_{h_{\mathcal{H}}}$	—	$\sqrt{2\,\xi}\,g_X\,v_{\mathcal{H}}$
Weak	m_h	—	$\sqrt{2\,M_Z^2 + \dfrac{N_c\,\lambda_t^4}{2\,\pi^2}\,v^2 \log\dfrac{v_{\mathcal{H}}}{v}}$


FINE
TUNING
PLEASE BE PATIENT

PARAMETER SPACE



OUTLOOK



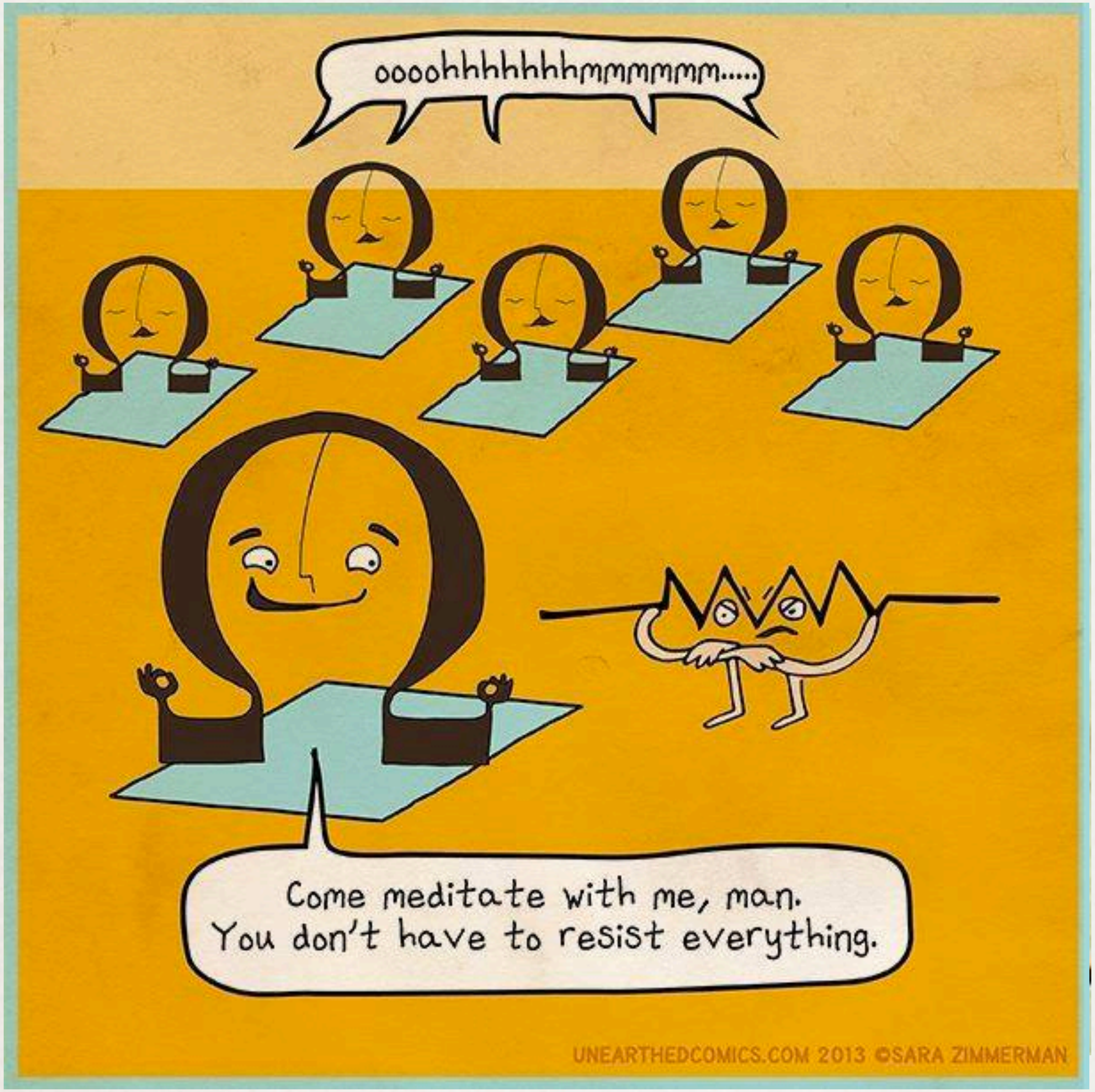
Accidental $\mathrm{U}(2,2)$ global symmetry

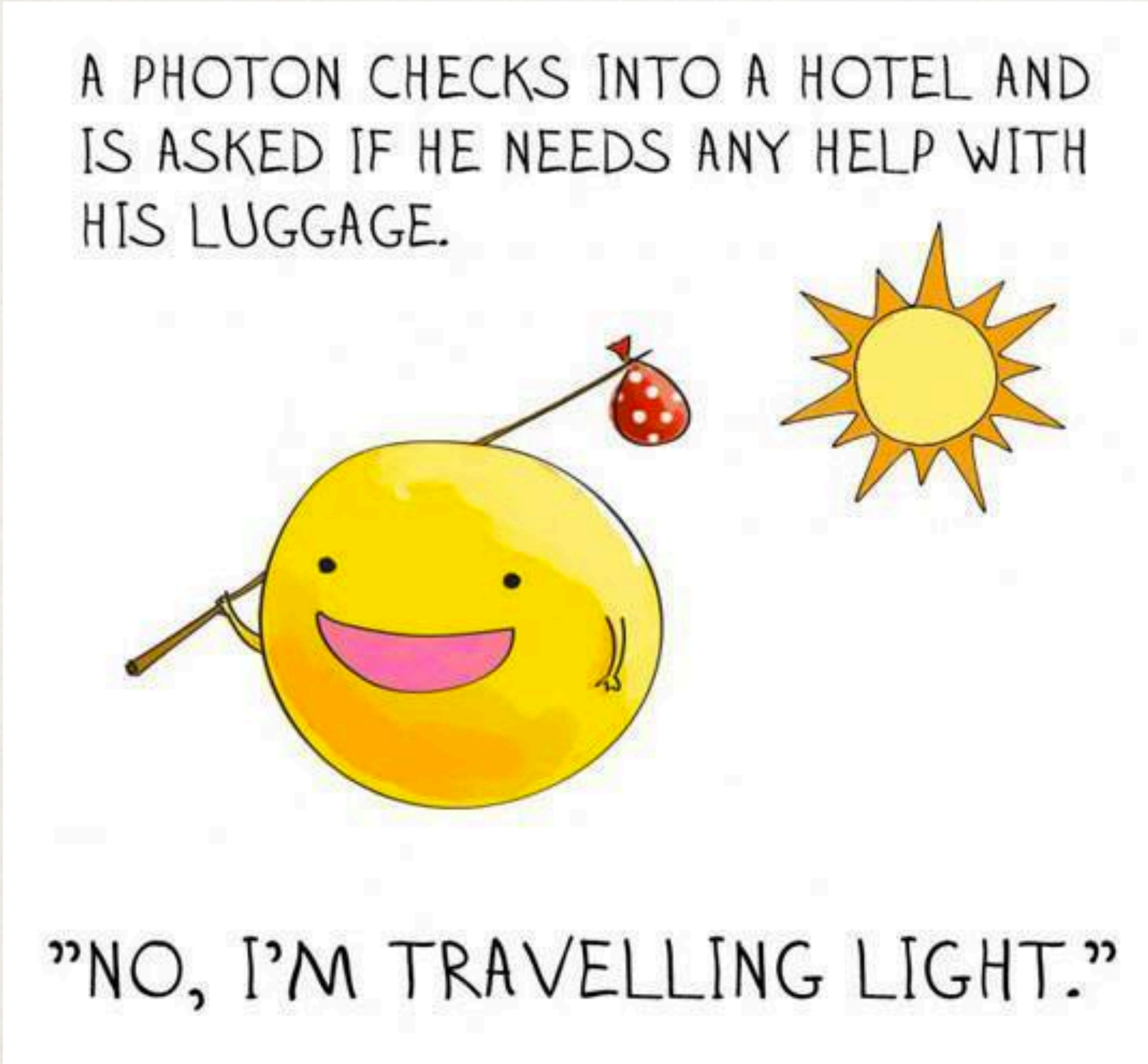
SM neutral scalar top partners

5D SUSY UV completion

Top partner vevs!


And now
for something
completely different...


oooohhhhhhhmmmmmm.....
Come meditate with me, man.
You don't have to resist everything.
UNEARTHEDCOMICS.COM 2013 ©SARA ZIMMERMAN


A PHOTON CHECKS INTO A HOTEL AND IS ASKED IF HE NEEDS ANY HELP WITH HIS LUGGAGE.
"NO, I'M TRAVELLING LIGHT."

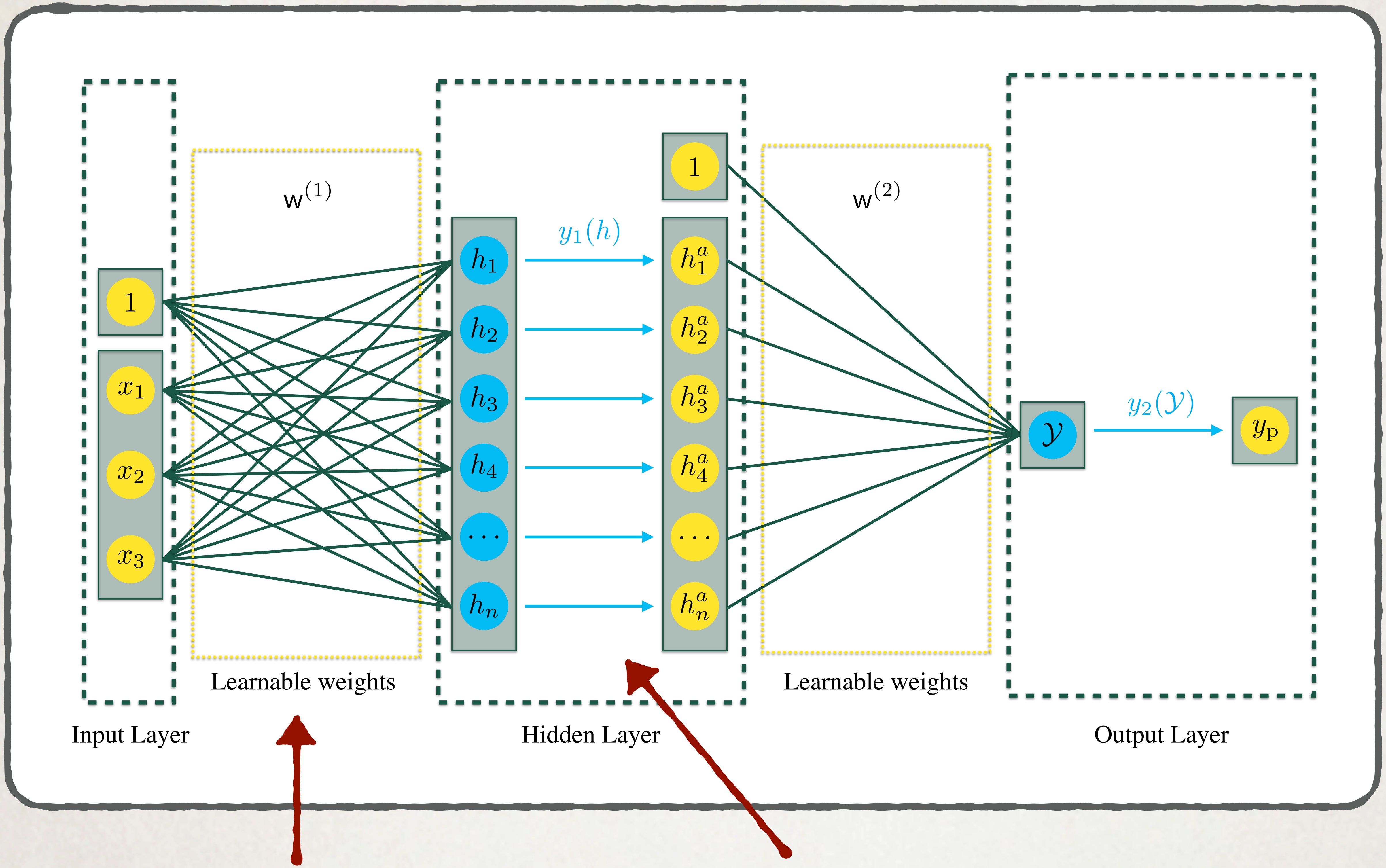
WHAT IS THE MACHINE LEARNING?

with Spencer Chang and Bryan Ostdiek

arXiv:1709.10106

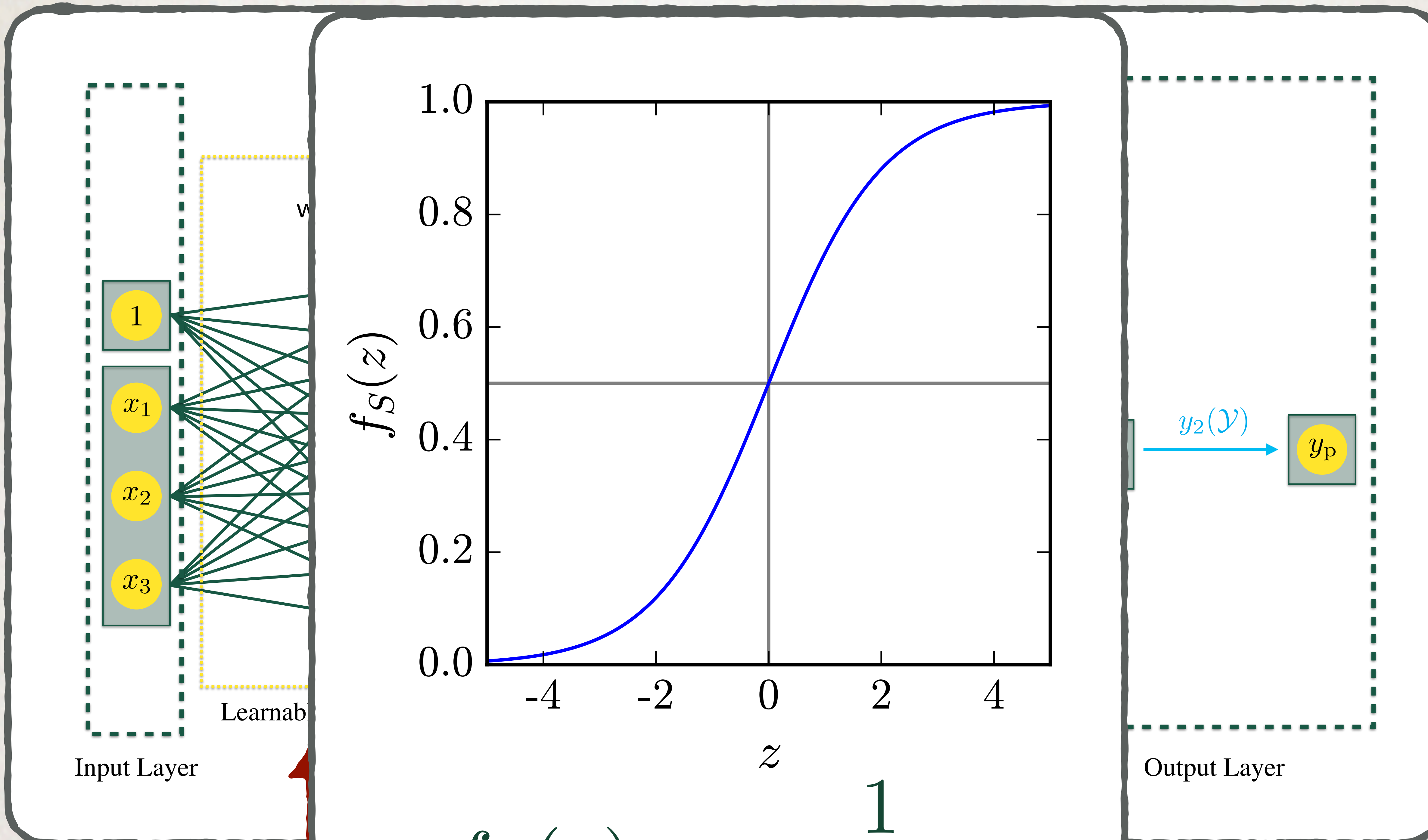
RISE OF THE MACHINES

(DEEP) NEURAL NETWORKS



Matrix multiplication. Activation function.

(DEEP) NEURAL NETWORKS

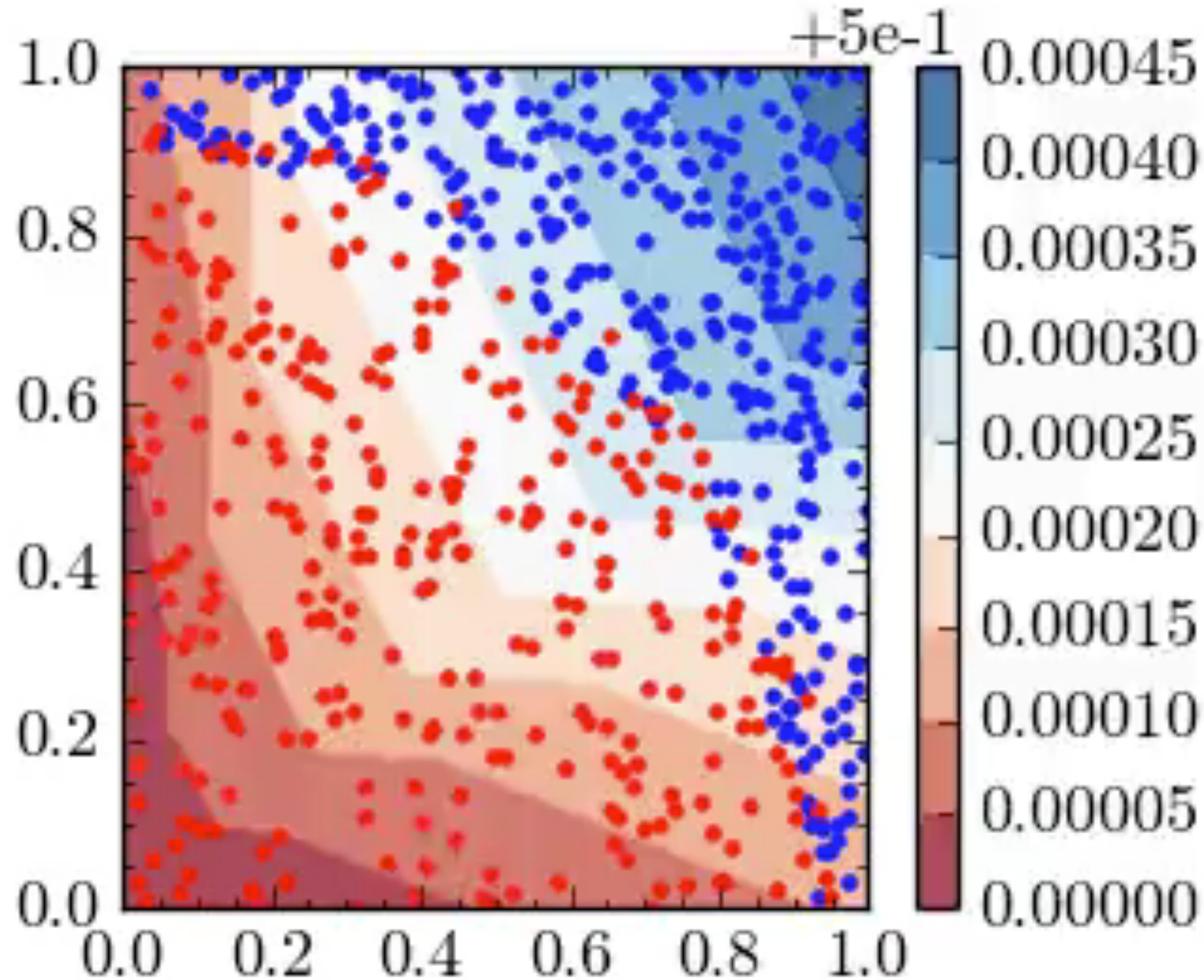


$$f_S(z) = \frac{1}{1 + e^{-z}}$$

Matrix mu

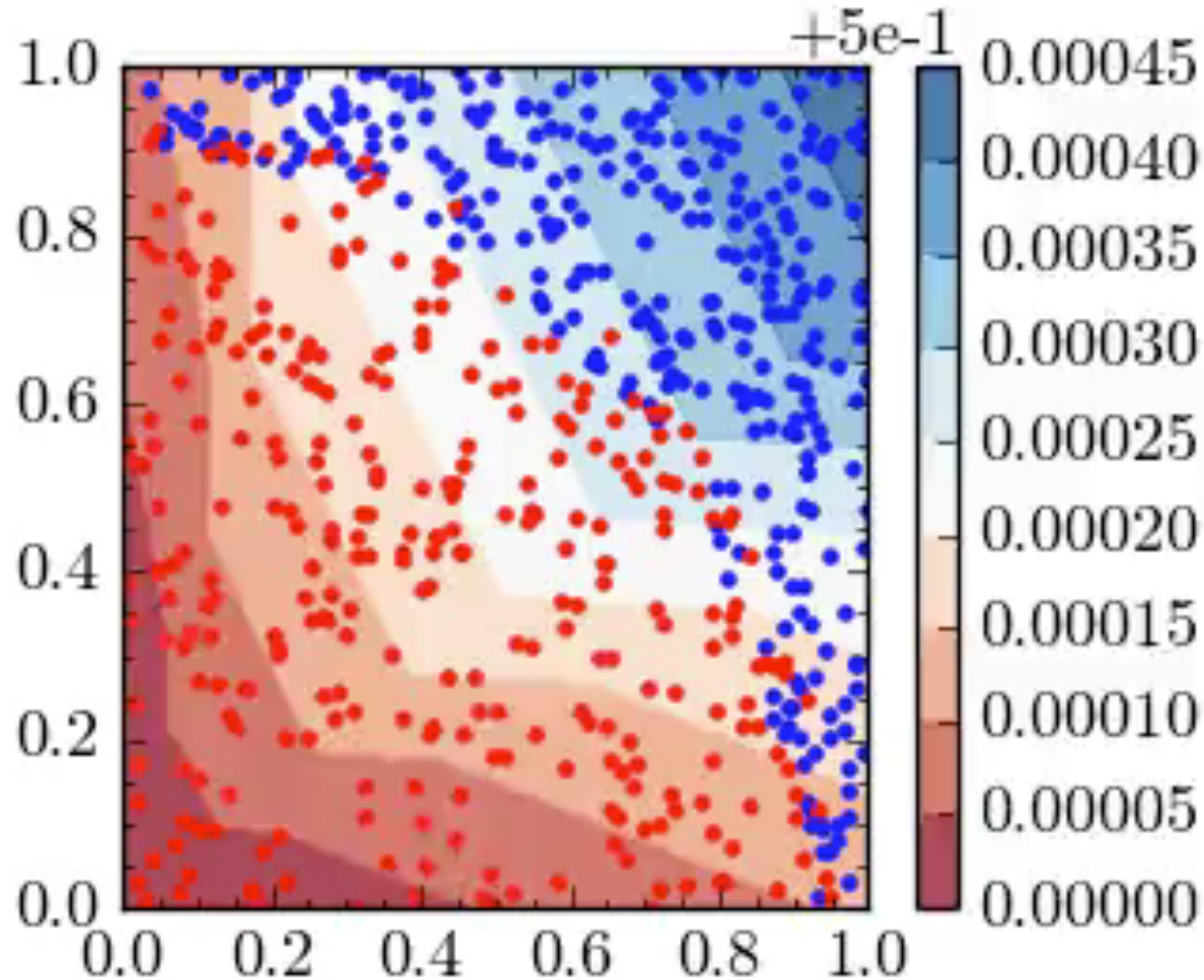
TRAINING

Loss function: minimize comparison between network output and input labels



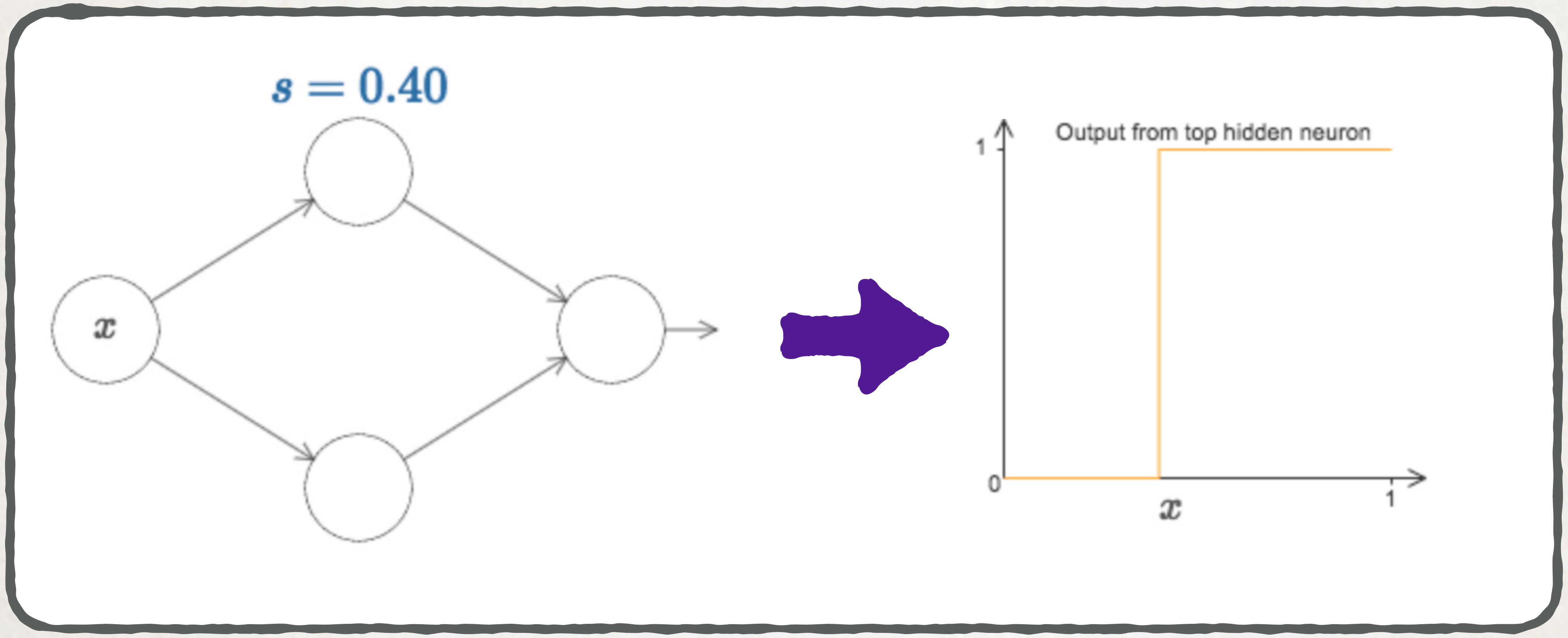
TRAINING

Loss function: minimize comparison between network output and input labels



UNIVERSAL APPROXIMATORS

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



Early important papers:
George Cybenko, Aproximation by superpositions of a sigmoidal function [1989];
Kurt Hornik, Maxwell Stinchcobe, and Halbert White, Multilayer Feedforward Networks are Universal Approximators [1989].

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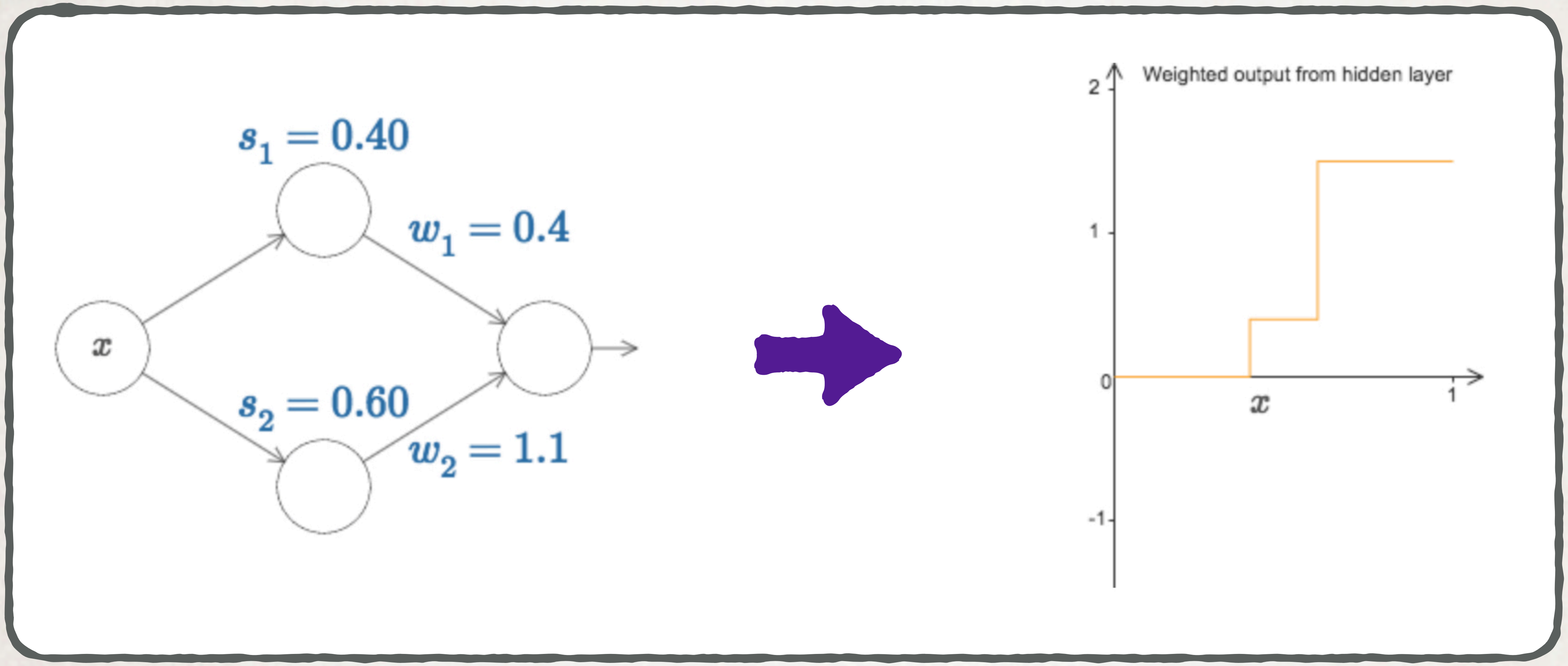

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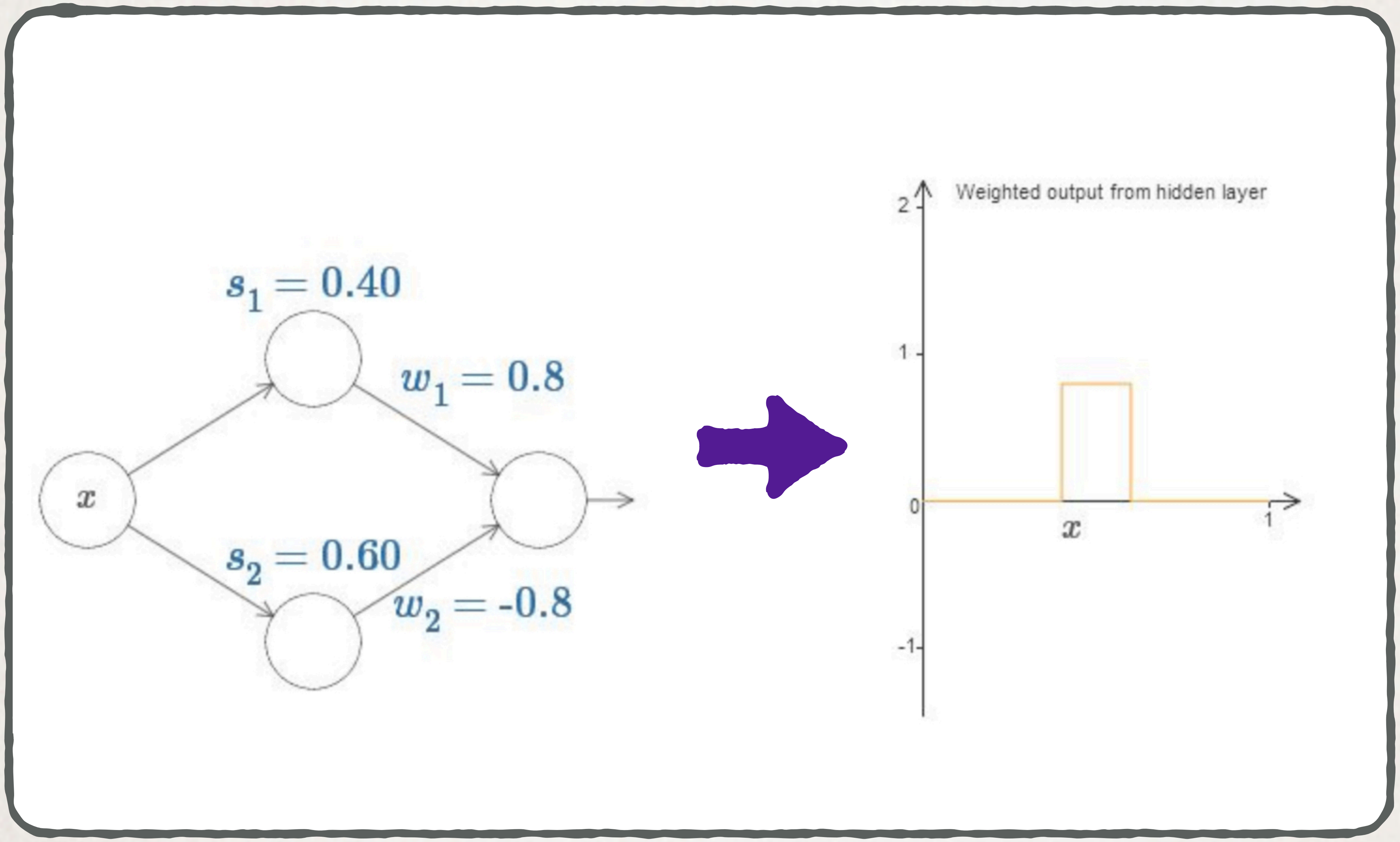

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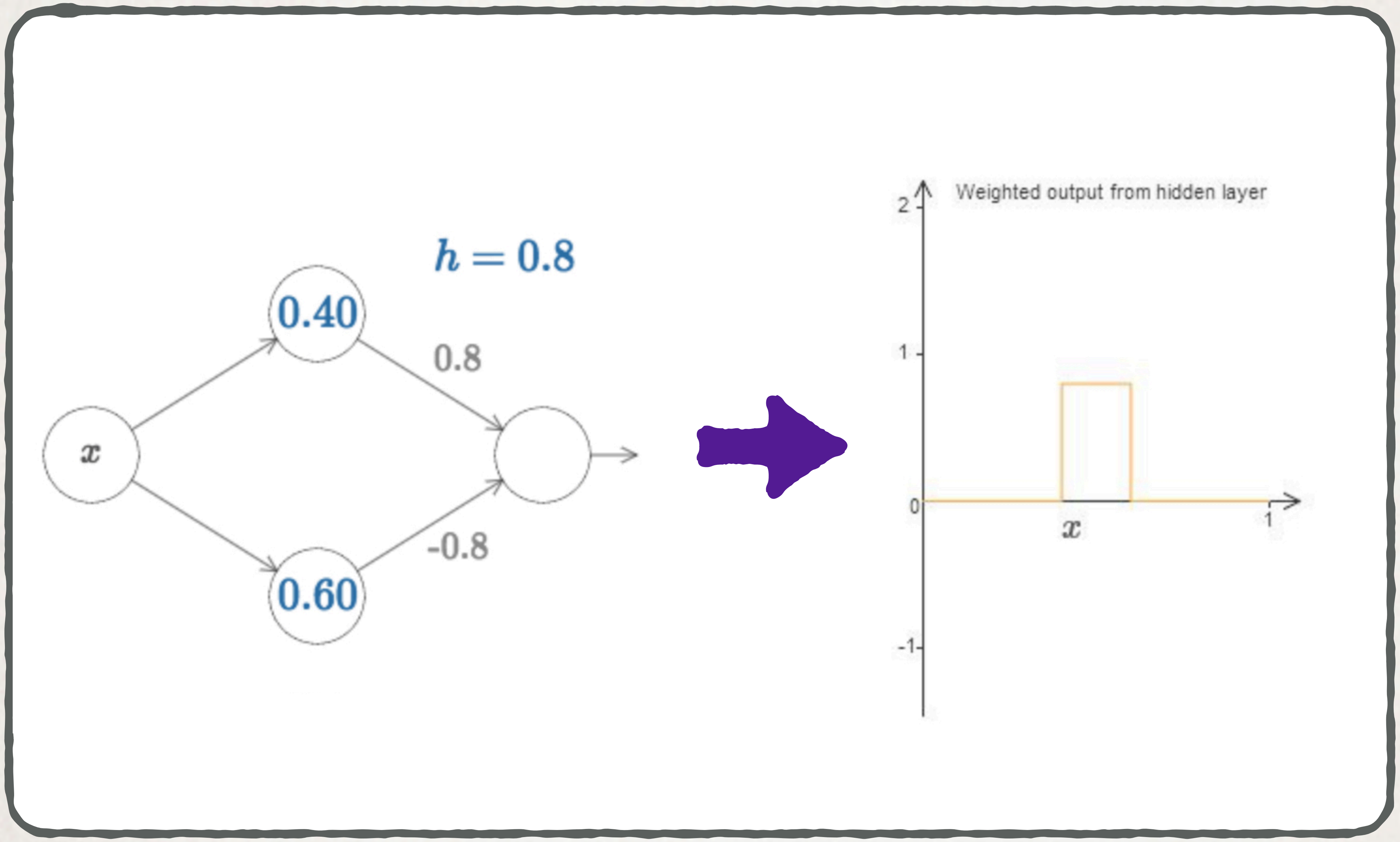

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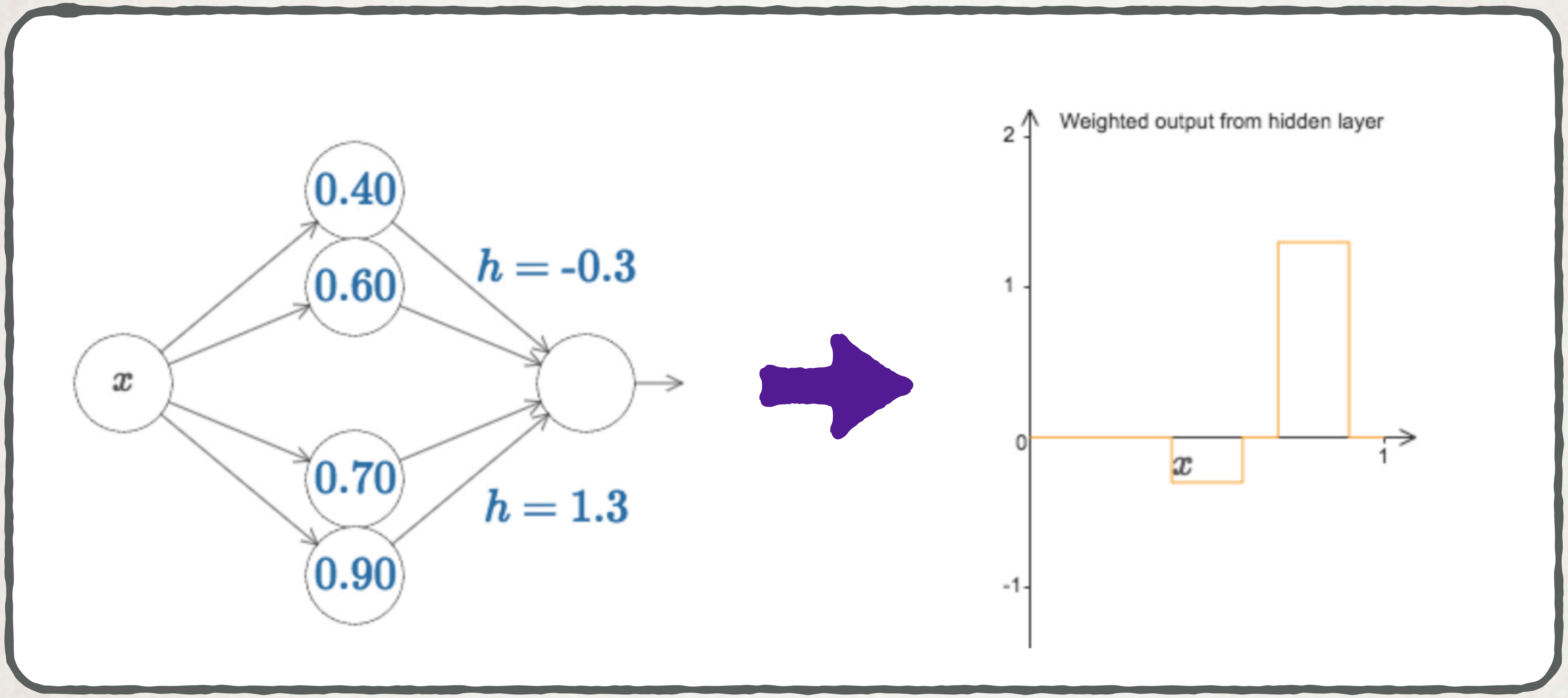

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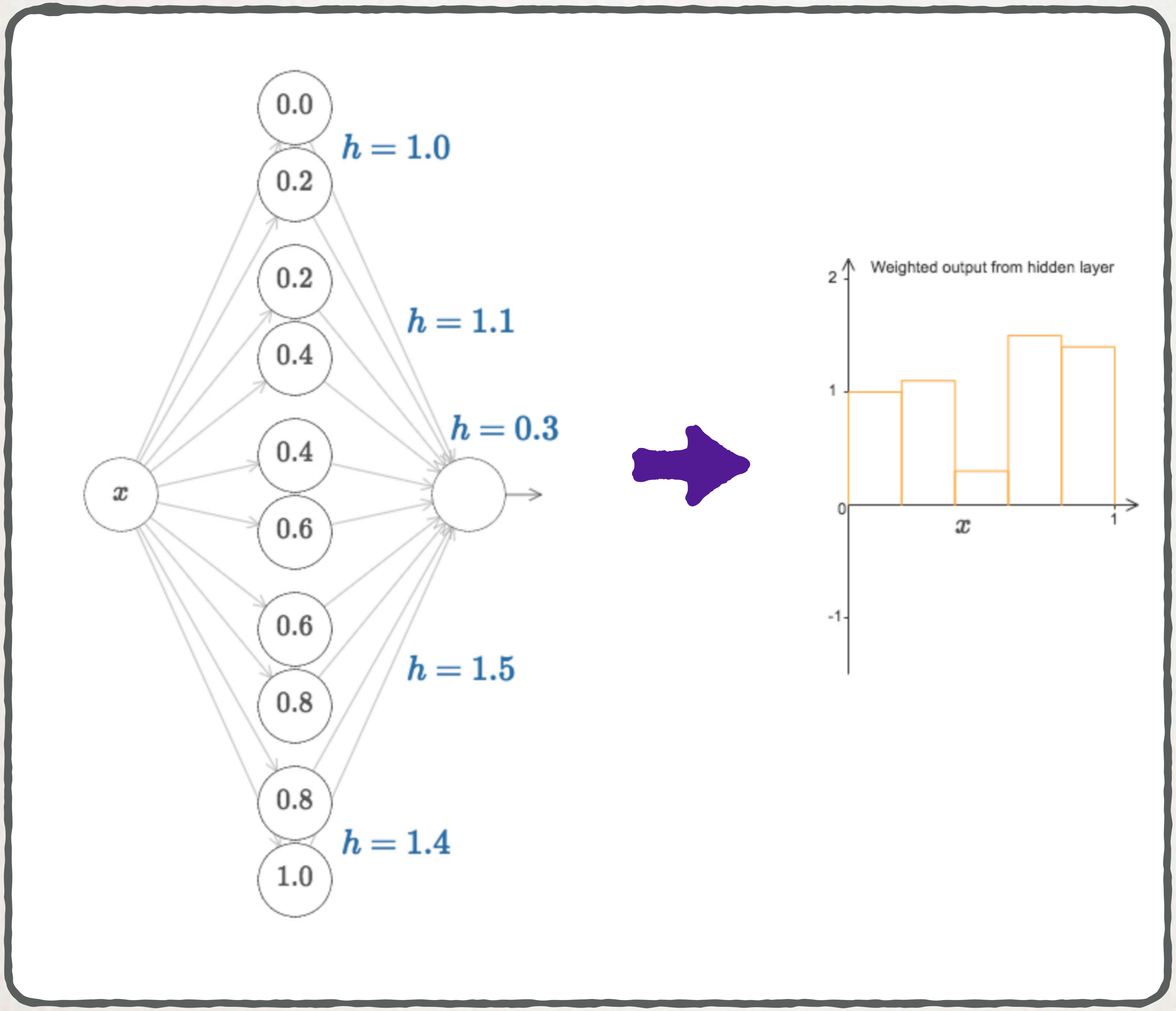


PREMISE

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

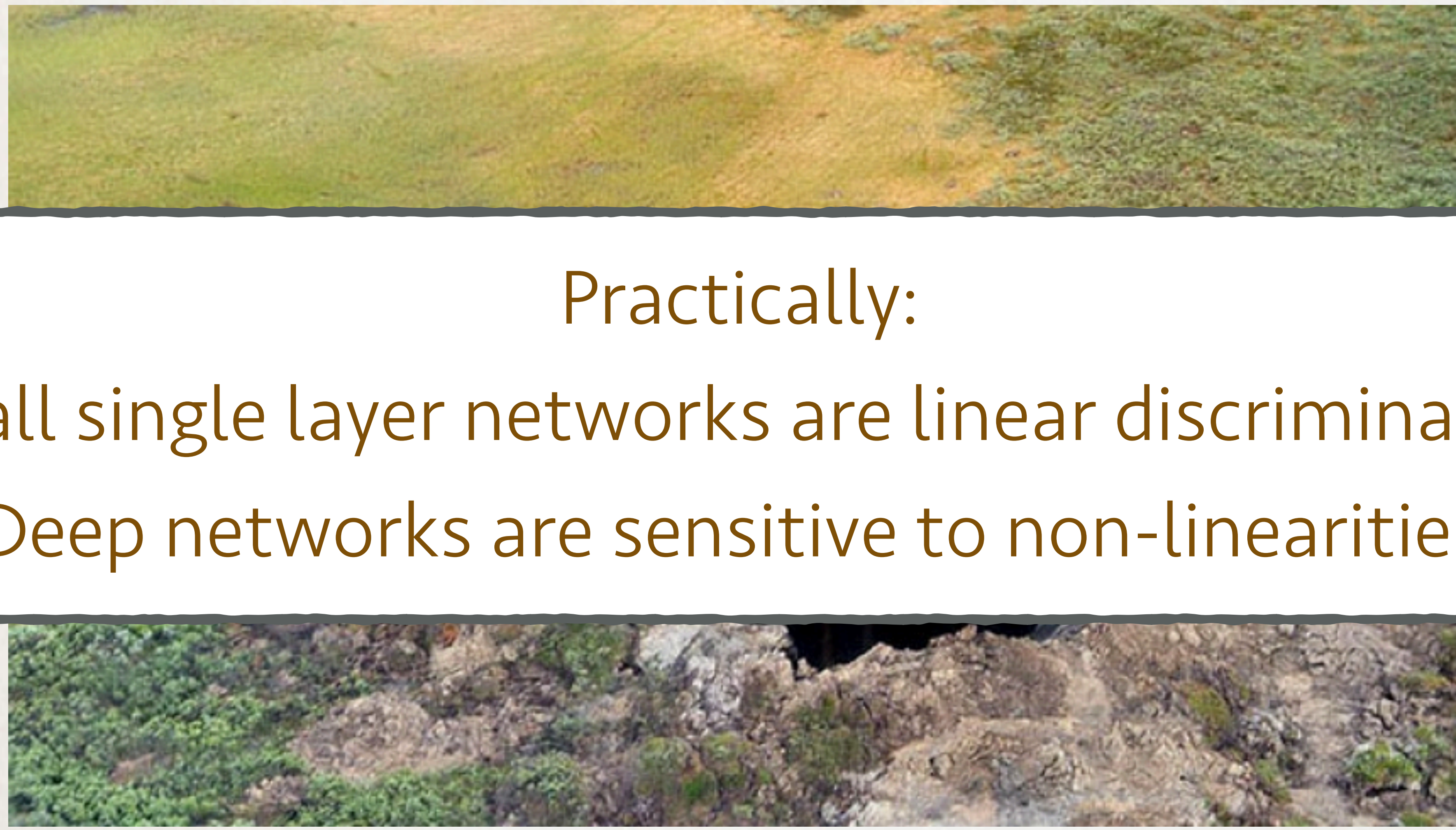
GOING DEEPER

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;

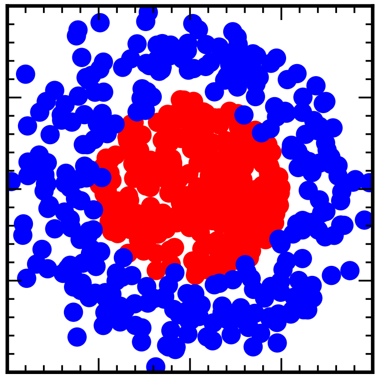
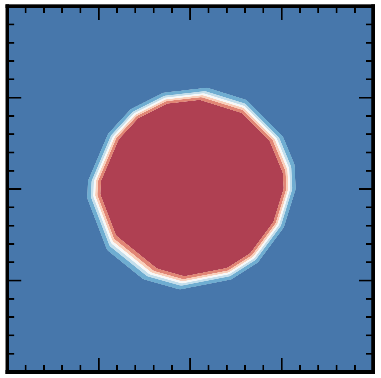
Deep networks are sensitive to non-linearities.

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

WHAT IS THE MACHINE LEARNING?

Spencer Chang, TC, Bryan Ostdiek [arXiv:1709.10106]

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?*

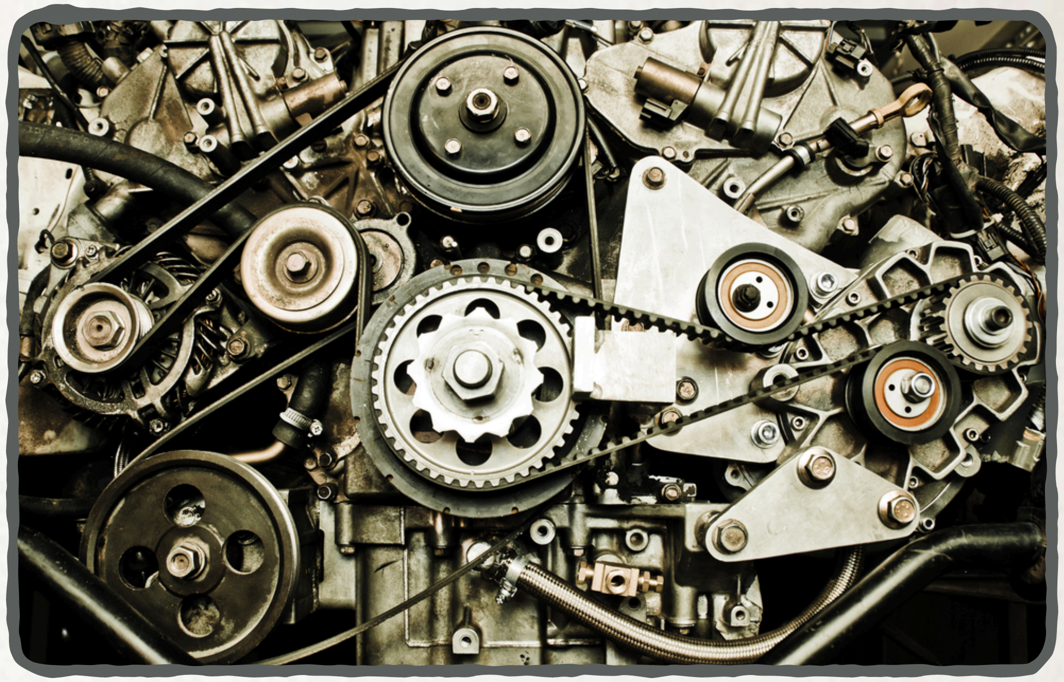
(a) Train network on low level data
(b) Compute low level AUC
(c) Choose a high level variable
(d) Train new machine using low + high level variables
(e) Compute low/high hybrid AUC
(f) No performance change implies network has saturated

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.

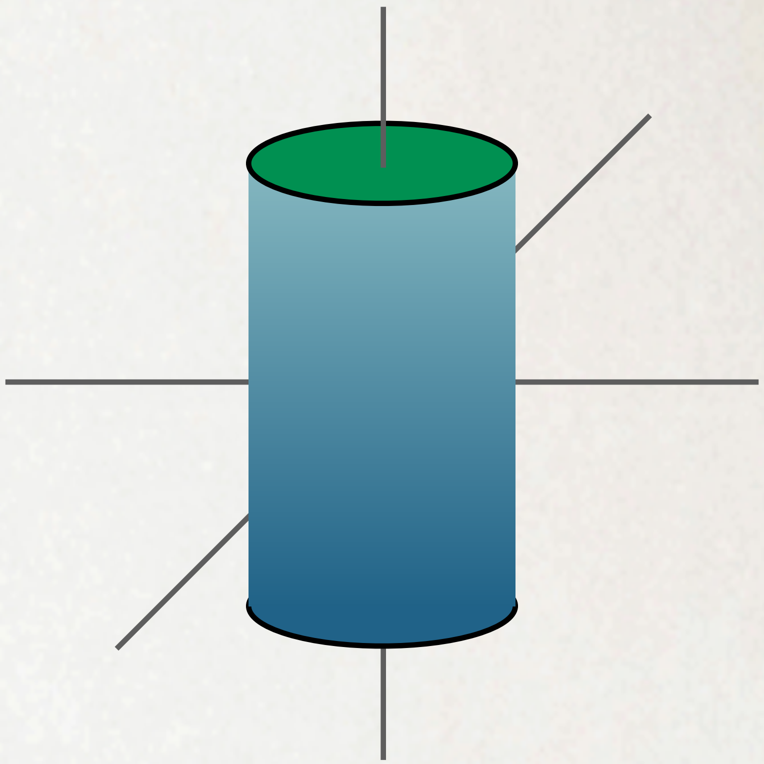
Metrics computed on test set using scikit-learn.

DATA PLANING: TOY MODEL

Signal

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

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.

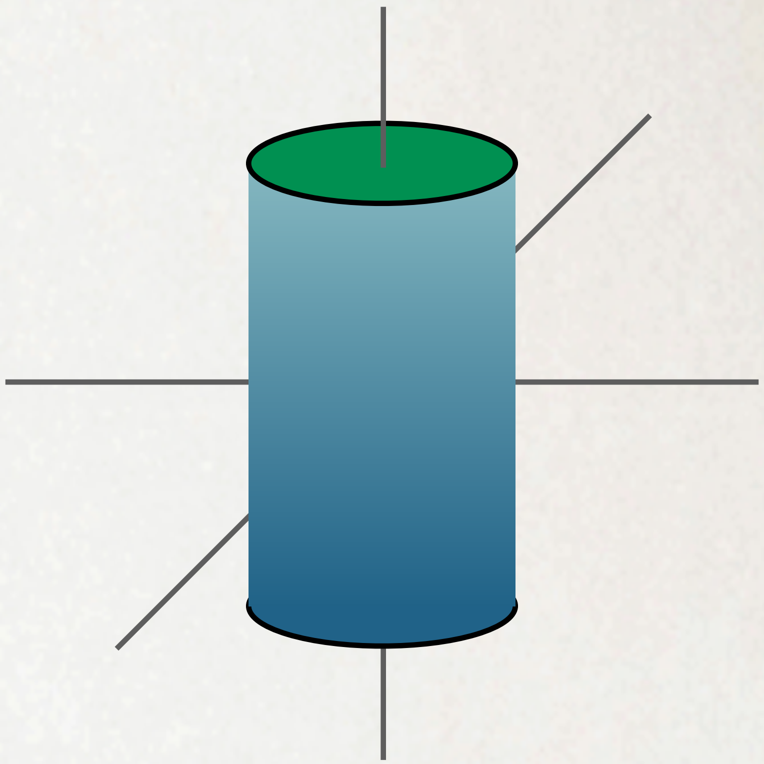
No remaining ability to discriminate.

DATA PLANING: TOY MODEL

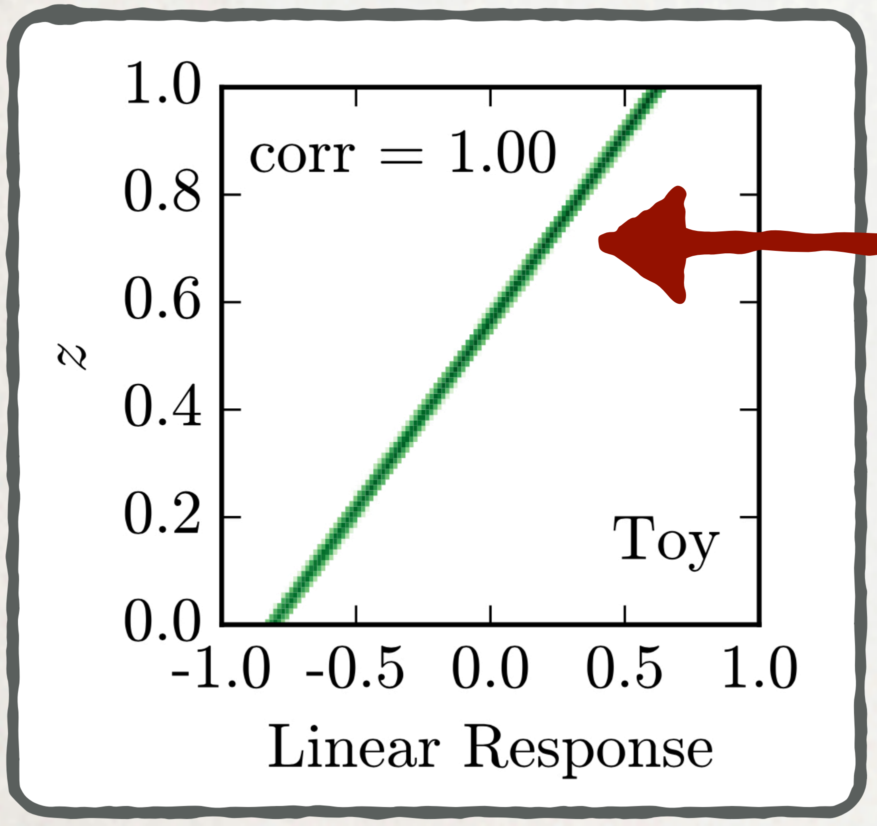
Signal

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

constants



Background is uniform.

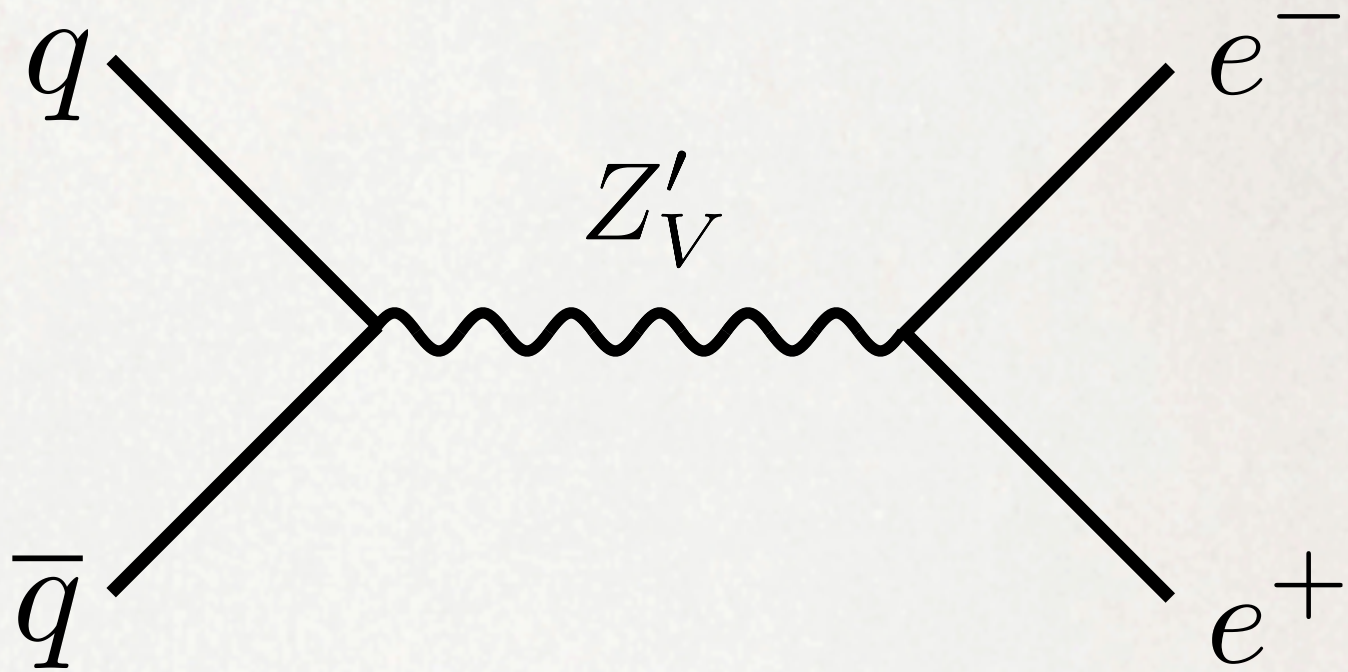


Linear discriminant

BSM MODELS

I) vector couplings

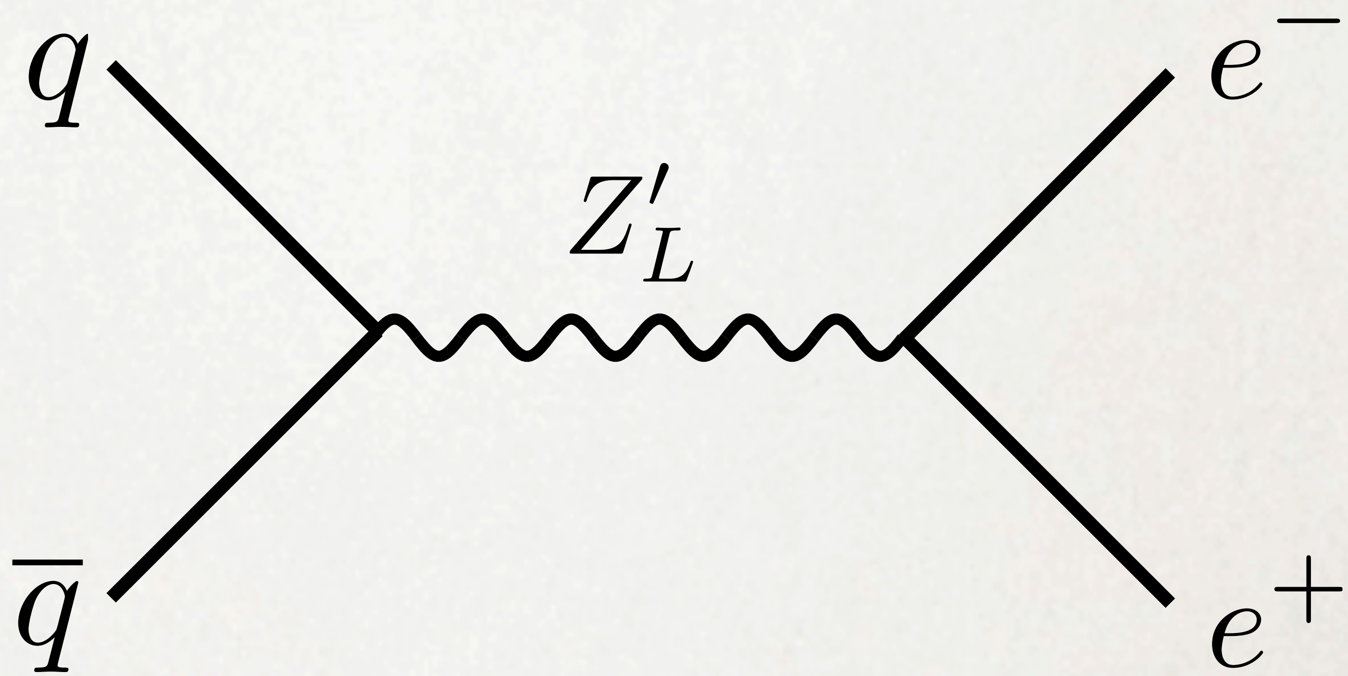
$g_L = g_R$



or

II) left-handed couplings

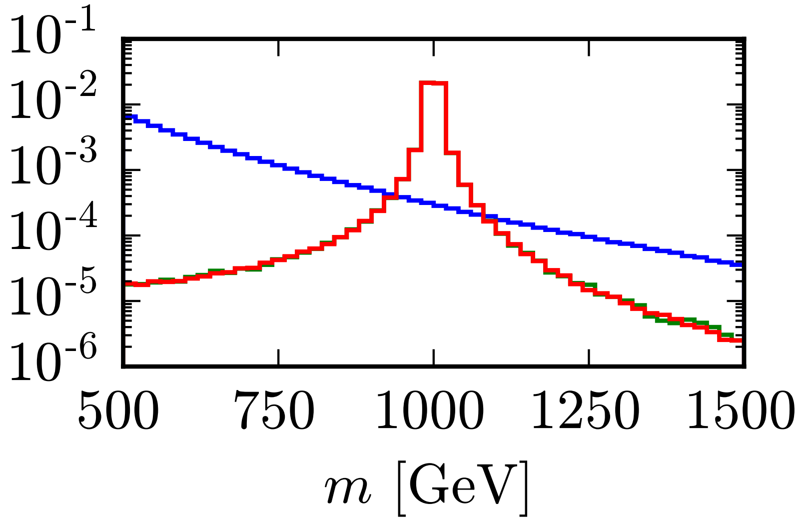
$g_R = 0$



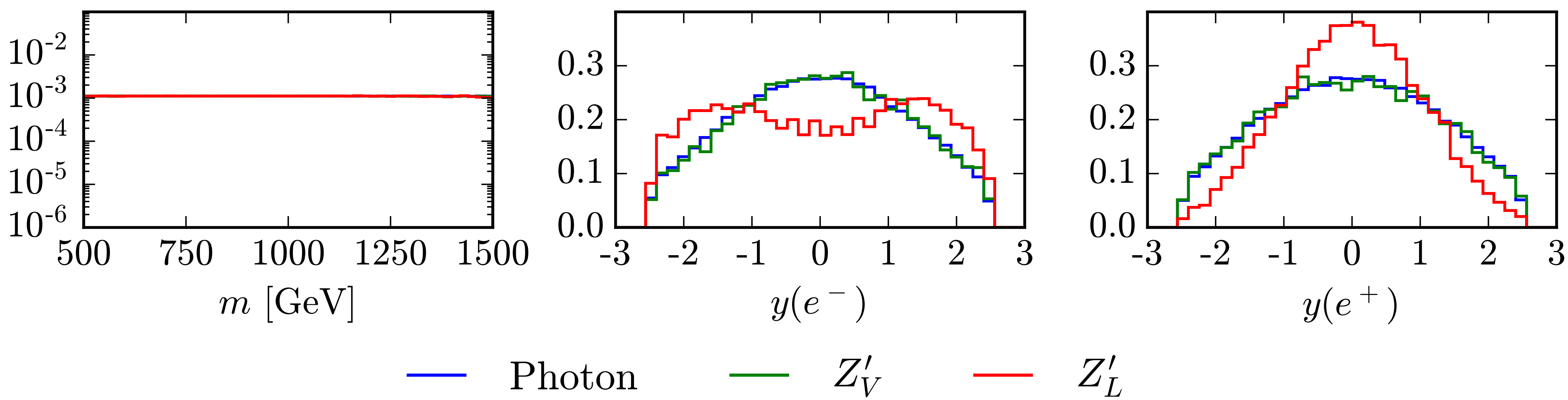
$$\mathcal{L} \supset Z'_\mu \sum_f Q_f \left(g_L \overline{f} \gamma^\mu P_L f + g_R \overline{f} \gamma^\mu P_R f \right)$$

BSM DISTRIBUTIONS

Kinematics



After planing in mass



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

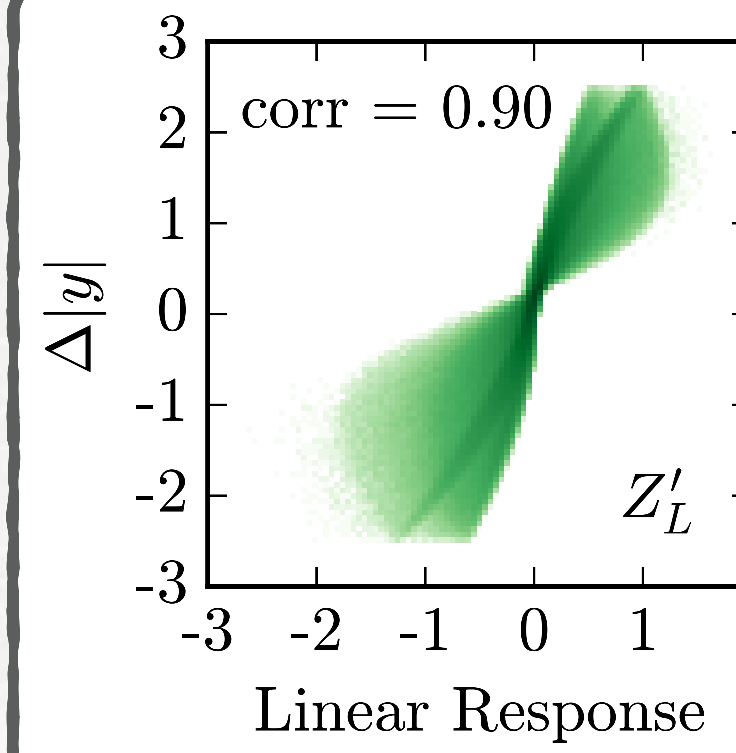
$(E,\vec{p})$	m	Planed	Linear AUC	Deep AUC
✓	✗	✗	0.763280(05)	0.989353(59)
✓	✓	✗	0.942004(02)	0.989826(10)
✓	✗	m	0.626648(28)	0.6258(24)
✓	✗	$(m, \Delta\lvert y\rvert)$	0.52421(15)	0.5320(25)

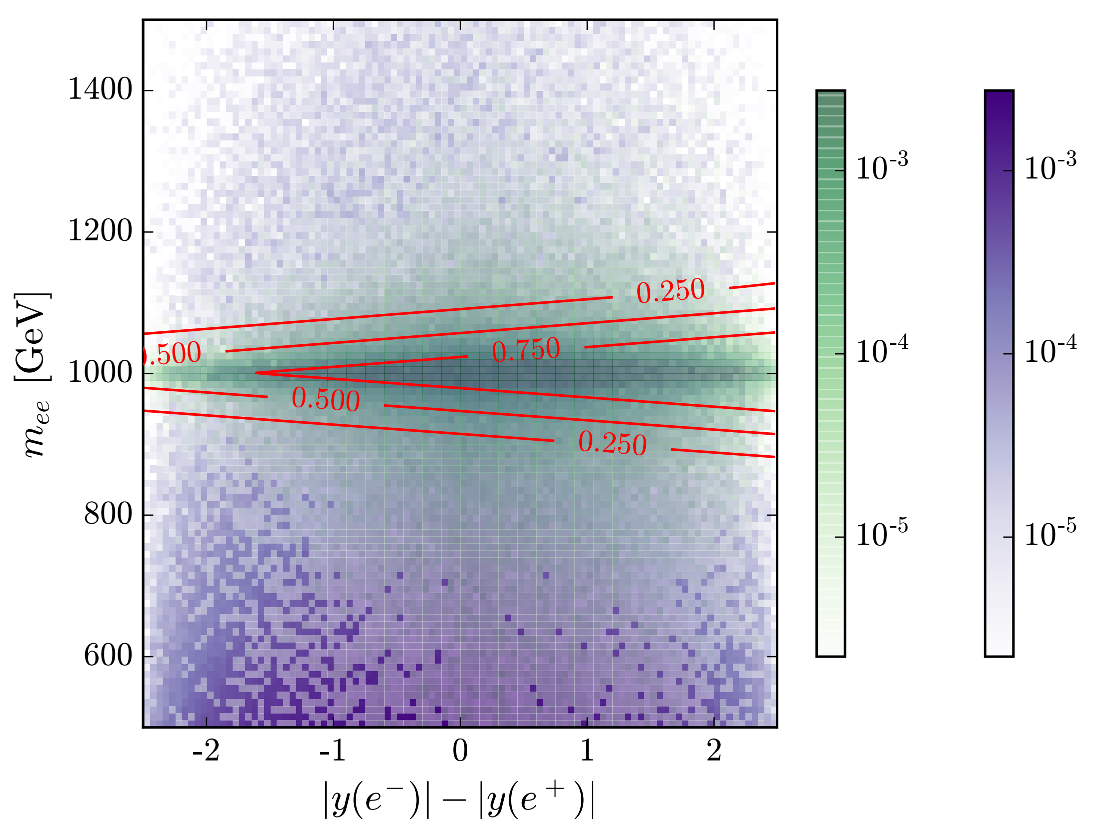
$$\Delta|y| = |y(e^+)| - |y(e^-)|$$

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) neutral 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.