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**

<table>
<thead>
<tr>
<th>Model</th>
<th>Parameters</th>
<th>$E_T^{miss}$</th>
<th>$\sum E_T^{miss}$</th>
<th>Mass Limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{g} \to q\tilde{q}$</td>
<td>mono-jet</td>
<td>Yes</td>
<td>36.1</td>
<td>710 GeV</td>
</tr>
<tr>
<td>$\tilde{t} \to t\tilde{q}$</td>
<td>mono-jet</td>
<td>Yes</td>
<td>36.1</td>
<td>2.02 TeV</td>
</tr>
<tr>
<td>$\tilde{g} \to q\tilde{q}$ (compressed)</td>
<td>mono-jet</td>
<td>Yes</td>
<td>36.1</td>
<td>1.7 TeV</td>
</tr>
<tr>
<td>$\tilde{t} \to t\tilde{q}$</td>
<td>mono-jet</td>
<td>Yes</td>
<td>36.1</td>
<td>1.7 TeV</td>
</tr>
</tbody>
</table>

**Gluino (ino NLSP)**

- $\tilde{g}$ | 2 jets | Yes | 3.2 | 2.0 TeV | $m_{\tilde{g}} > 200$ GeV |
- $\tilde{g}$ | 2 jets | Yes | 3.2 | 2.05 TeV | $m_{\tilde{g}} > 200$ GeV |

**Chargino/LSP**

- $\tilde{\chi}_1^\pm$ | 0 | mono-jet | 20.3 | 36.1 | $m_{\tilde{\chi}_1^\pm} > 1.8 \times 10^{-3}$ GeV |
- $\tilde{\chi}_1^0$ | 0 | mono-jet | 20.3 | 36.1 | $m_{\tilde{\chi}_1^0} > 1.8 \times 10^{-3}$ GeV |

**Other**

- $\tilde{c}$ | 0 | 2 $c$ | 20.3 | 36.1 | $m_{\tilde{c}} > 100$ GeV |

**Reference**

- 1712.0332
- 1712.0332
- 1712.0332
- 1611.0058
- 1706.0731
- 1708.0274
- 1607.0379
- 1502.0151
- 1711.0191
- 1711.0191
- 1708.0206
- 1708.0201
- 1209.21226
- 1506.03459
- 1711.11203
- 1711.0331
- 1403.0222
- 1709.0398
- 1709.0396
- 1709.0396
- 1709.0396

*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.
GUIDANCE FROM NATURALNESS

DO THIS
NOT THAT
This talk
NORMAL NATURALNESS

\[ H \quad t \quad H^\dagger \quad + \quad H \quad \tilde{t} \quad H^\dagger \]

Same charge as the top

= UV insensitive
No Standard Model charges

\[ H \rightarrow \tilde{t} \rightarrow H^\dagger \rightarrow \tilde{t} \rightarrow H \rightarrow H^\dagger \]

= UV insensitive (at one-loop)
### STATE OF THE ART

<table>
<thead>
<tr>
<th>strong direct production</th>
<th>scalar</th>
<th>fermion</th>
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<tbody>
<tr>
<td>$QCD$</td>
<td>SUSY</td>
<td>Composite Higgs/RS</td>
</tr>
<tr>
<td>$EW$</td>
<td>folded SUSY</td>
<td>Quirky Little Higgs</td>
</tr>
<tr>
<td>$singlet$</td>
<td>?</td>
<td>Twin Higgs</td>
</tr>
<tr>
<td><strong>Mirror Glueballs</strong></td>
<td><strong>Higgs coupling shifts</strong></td>
<td>~ tuning</td>
</tr>
<tr>
<td><strong>Higgs portal direct production</strong></td>
<td><strong>Higgs portal observables</strong></td>
<td></td>
</tr>
</tbody>
</table>

Curtin and Varhaaren [arXiv:1506.06141]
Table 1. The "theory space" of solutions to the hierarchy problem with top partners, organized by SM gauge charge and spin, with a representative model example in each field. The gauge charge dictates the direct top partner production mode, which makes the LHC suitable for discovery of colored top partners. For uncolored top partners, mirror glueballs are highly favored for EW-charged mirror sectors, and possible for singlet top partners. Higgs coupling shifts of same order as tuning are present in all known fermionic top partner theories. Together, these two signatures allow discovery of all known uncolored top partner theories. A hypothetical "singlet-stop" theory is indicated with a question mark, and would have to be discovered by either probing the UV completion or, for partner masses of a few 100 GeV, with Higgs portal observables (see text).

As exciting as this experimental signature is, it is not a requirement for generic Twin-Higgs type models—the SM-singlet sector could easily have relatively light quarks, making for a hadron spectrum more like that of the visible sector. On the other hand, mirror glueballs, and their associated signals, are a requirement for uncolored naturalness theories with EW-charged mirror sectors, like Folded SUSY or Quirky Little Higgs. This is due to LEP limits forbidding BSM particles with EW charge lighter than about 100 GeV [59]. If the structure of the mirror sector is based on our own, it cannot contain very light strongly interacting matter, resulting in glueballs at the bottom of the mirror-QCD spectrum. Crucially, this makes mirror glueball signals the smoking-gun discovery signal for Folded-SUSY type theories.

It is interesting to think about the empty square in Table 1. So far, no explicit theory with SM-singlet scalar top partners has been proposed. If such a theory existed, and there were no other SM-charged states required near the weak scale, discovery could be quite difficult. In a Folded-SUSY like spectrum with weak-scale soft masses we might again expect the existence of mirror glueballs, with their accompanying experimental signatures. If, however, the mirror sector contains light matter or mirror-QCD was broken, discovery would have to proceed through Higgs-portal observables: invisible direct top partner production $h \to \tilde{t}\tilde{t}$ [60, 61], Higgs cubic coupling shifts [60, 62] at a 100–4–...
DOUBLE DOWN!
**Accidental SU(4)**

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

\[ f^2 = \nu^2 + \nu_T^2 \]

**SU(4) \rightarrow SU(3)**

7 Goldstones: 6 eaten \[\rightarrow\] 1 light scalar


Tim Cohen [University of Oregon]
TWIN QUADRATIC CORRECTIONS

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

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

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

Flat-direction
\[ \mathcal{L} = (\lambda_t H \psi_Q \psi_{U^c} + \text{h.c.}) + \lambda_t^2 \left( |H_H \cdot \tilde{Q}_H|^2 + |H_H|^2 |\tilde{U}_H^c|^2 \right) \]

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

\[ \delta V \propto \lambda_t^2 \Lambda^2 \left( |H_H|^2 - |H|^2 \right) \]
IR ISSUES - 1

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

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

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

\[ W_{\text{brane}} \]

\[ (Q, U^c, D^c, L, E^c)_{1/2, 0}^{1/2, 0} \quad H \]

\[ U(1)_X \quad \text{MSSM} \quad \text{MSSM}_H \]

\[ (Q, U^c, D^c, L, E^c)_{0, 1/2}^{0, 1/2} \quad H_H \]

\[ y = 0 \quad y = \pi R \]
**TOP YUKAWA LOOPS**

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

\[ \omega_{B,F}^\pm = q_{B,F} \pm R m_t(H) \]

**Boundary conditions**

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

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

\[ V_{\text{CW}} = -\frac{21 \zeta(3) \lambda_t^2}{32 \pi^2 (\pi R)^2} \left\{ N_c \left( |H|^2 - |H_H|^2 \right) - |\tilde{Q}_H|^2 - 2 |\tilde{U}_H^c|^2 \right\} \]
\[ V_{\text{U}(1)X} = \frac{g_X^2}{2} \xi \left( |H_H|^2 - |H|^2 - f_X^2 \right)^2 \]

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

---

Non-decoupling \( D \)-term

Hyperbolic quartic!

\[ Z^0 \not\sim Z' \]

\[ \Delta \rho = \frac{4 g_X^2 M_W^2}{g^2 M_X^2} \quad \rightarrow \quad \frac{M_X}{g_X} > 8.6 \text{ TeV} \]
TENSION

\[ V_{U(2,2)} = (\tilde{m}^2 + \tilde{m}^2_X)\left( |H|^2 + |H_H|^2 \right) + \frac{g_Z^2}{2} \left( |H|^4 + |H_H|^4 \right) \]

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

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

Conditions for vevs

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

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

Physical Higgs mass

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

Factor of 2 bigger than MSSM

Mixing

$t - \tilde{t}_H$ loop
SCALES

Cutoff \( \Lambda = \frac{1}{2R} \)

Hyperbolic \( m_{h_H} = \sqrt{2} \xi g_X v_H \)

Weak \( m_h = \sqrt{2 M_Z^2 + \frac{N_c \lambda_t^4}{2 \pi^2} v^2 \log \frac{v_H}{v}} \)
FINE TUNING
PLEASE BE PATIENT
$\Delta = 20$

$m_t = \frac{1}{2R} [\text{GeV}]$

$m_H = 125 \pm 5 \text{ GeV}$

$\tan \beta = \infty$

$g_X = 0.9$
Accidental $U(2, 2)$ global symmetry

SM neutral scalar top partners

5D SUSY UV completion

Top partner vevs!

The Hyperbolic Higgs
And now for something completely different...
Come meditate with me, man. You don’t have to resist everything.
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
Matrix multiplication. Activation function.
(DEEP) NEURAL NETWORKS

Input Layer

Learnable weights

$$w^{(1)}$$

$$w^{(2)}$$

$$y_1(h)$$

$$y_2(Y)$$

Output Layer

Learnable weights

$$h_1$$

$$h_2$$

$$h_3$$

$$h_4$$

Matrix multiplication.

Activation function.

$$f_S(z) = \frac{1}{1 + e^{-z}}$$
Loss function: minimize comparison between network output and input labels
TRAINING

Loss function: minimize comparison between network output and input labels
Early important papers:
George Cybenko, Aproximation by superpositions of a sigmoidal function [1989];
Kurt Hornik, Maxwell Stinchcombe, and Halbert White, Multilayer Feedforward Networks are Universal Approximators [1989].
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UNIVERSAL APPROXIMATORS

Michael Nielsen [http://neuralnetworksanddeeplearning.com/]
Machine learning algorithm finds all available features for discriminating signal from background.
Shallow networks require exponential nodes to model functions to arbitrary accuracy.

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


“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.
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

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

Background is uniform.

RESULTS

<table>
<thead>
<tr>
<th>( (x, y, z) )</th>
<th>( r )</th>
<th>PLANED</th>
<th>LINEAR AUC</th>
<th>DEEP AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>✓</td>
<td>x</td>
<td>x</td>
<td>0.61275(01)</td>
<td>0.81243(45)</td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>x</td>
<td>0.79672(01)</td>
<td>0.81388(23)</td>
</tr>
<tr>
<td>✓</td>
<td>x</td>
<td>r</td>
<td>0.61030(01)</td>
<td>0.61026(02)</td>
</tr>
<tr>
<td>✓</td>
<td>x</td>
<td>(r, z)</td>
<td>0.5081(16)</td>
<td>0.49998(03)</td>
</tr>
</tbody>
</table>

Check saturation.

No remaining ability to discriminate.
Signal

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

Background is uniform.

Linear discriminant
BSM MODELS

I) vector couplings

\[ g_L = g_R \]

or

II) left-handed couplings

\[ g_R = 0 \]

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

After planing in mass

Note: highly idealized.
### DATA PLANING: BSM

#### Vector Couplings

<table>
<thead>
<tr>
<th>$(E, \bar{p})$</th>
<th>$m$</th>
<th>Planned</th>
<th>Linear AUC</th>
<th>Deep AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>✓</td>
<td>✗</td>
<td>✗</td>
<td>0.746221(01)</td>
<td>0.988510(98)</td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✗</td>
<td>0.938967(01)</td>
<td>0.989007(03)</td>
</tr>
<tr>
<td>✓</td>
<td>✗</td>
<td>$m$</td>
<td>0.50550(29)</td>
<td>0.4942(48)</td>
</tr>
</tbody>
</table>

No remaining ability to discriminate.

#### Left-Handed Couplings

<table>
<thead>
<tr>
<th>$(E, \bar{p})$</th>
<th>$m$</th>
<th>Planned</th>
<th>Linear AUC</th>
<th>Deep AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>✓</td>
<td>✗</td>
<td>✗</td>
<td>0.763280(05)</td>
<td>0.989353(59)</td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✗</td>
<td>0.942004(02)</td>
<td>0.989826(10)</td>
</tr>
<tr>
<td>✓</td>
<td>✗</td>
<td>$m$</td>
<td>0.626648(28)</td>
<td>0.6258(24)</td>
</tr>
<tr>
<td>✓</td>
<td>✗</td>
<td>$(m, \Delta</td>
<td>y</td>
<td>)$</td>
</tr>
</tbody>
</table>

\[ \Delta |y| = |y(e^+)| - |y(e^-)| \]

TIM COHEN [UNIVERSITY OF OREGON]
left-handed couplings

<table>
<thead>
<tr>
<th>$(E, p')$</th>
<th>Planed</th>
<th>Linear AUC</th>
<th>Deep AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>✓ ×</td>
<td>✓</td>
<td>0.763280(05)</td>
<td>0.989353(59)</td>
</tr>
<tr>
<td>✓ ✓</td>
<td>✓</td>
<td>0.942004(02)</td>
<td>0.989826(10)</td>
</tr>
<tr>
<td>✓ ×</td>
<td>m</td>
<td>0.626648(28)</td>
<td>0.6258(24)</td>
</tr>
<tr>
<td>✓ ×</td>
<td>$(m, \Delta</td>
<td>y</td>
<td>)$</td>
</tr>
</tbody>
</table>

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.