

Calabi-Yau metrics, machine learning and the spectrum of the Laplace operator

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Does string theory describe our universe?

- **Heterotic string** on Calabi–Yau comes closest to realistic MSSM models

Usually focus on getting correct gauge group, matter spectrum, superpotential, etc.

- Do not need details of **metric** for these

How many of these string vacua are physically reasonable?

Problem: a ‘theory of everything’ should give particle masses, couplings, supersymmetry breaking patterns

- Need Kähler potential of theory and zero modes – depend on the metric on the internal space
- No **explicitly** known (compact) Calabi–Yau metrics!

This talk: computing these metrics numerically and progress on zero modes

Review of $\mathcal{N} = 1$ compactifications

Numerical Calabi–Yau metrics

Application: the spectrum of the Laplace operator

Review of $\mathcal{N} = 1$ compactifications

Low-energy limit is 10d supergravity coupled to Yang–Mills

Want **Minkowski** compactifications that preserve some supersymmetry

$$M_{10} = \mathbb{R}^{1,3} \times X$$

X is 6d and compact with vector bundle V

- Metric g
- Dilaton ϕ
- Gauge fields A with $G \subseteq E_8 \times E_8$
- 3-form flux H

Compactification

Minimal ($N = 1$) SUSY in 4d requires $SU(3)$ holonomy [Candelas et al. '85]

- No H flux
- X is **Calabi–Yau**

Physics in 4d determined by geometry of X – Kaluza–Klein reduction fixes 4d modes

- e.g. for scalars, masses in 4d c.f. eigenvalues of **Laplacian** in 6d

$$\square_{10}(\zeta_4 \otimes \phi_6) = 0 \equiv \square_4 \zeta_4 \otimes \phi_6 - \zeta_4 \otimes \Delta_6 \phi_6$$

$$\Delta_6 \phi_6 = \lambda \phi_6 \quad \Rightarrow \quad \square_4 \zeta_4 = \lambda \zeta_4 \equiv m^2 \zeta_4$$

Zero modes ($\lambda = 0$) determine low-energy physics

Particle content comes from choice of X and V , e.g.

- $SU(3)$ bundle gives E_6 gauge group in 4d, further broken to SM group by flat bundle
- $\frac{1}{2}\chi(X) = 3$ gives correct number of particle generations
- Many top-down models with promising MSSM-like spectrums

Masses of quarks and leptons from cubic Yukawa couplings

- Come from triple overlap of zero modes on X coupled to gauge field

$$C_{abc} = \int_X \psi_a \cdot \psi_b \cdot \psi_c \sqrt{g} d^6x$$

- Often cohomological calculations but need ψ_a to be **normalised** zero modes

A wish list

Zero modes $\lambda = 0$ give light particles in 4d ✓

- Zero modes reduce to cohomology

Yukawa couplings ✗

- Cohomology calculation but missing **normalisation** $\int_X |\psi_a|^2 \sqrt{g} d^6x = 1$

Supersymmetry breaking ✗

- Soft masses and couplings c.f. $N = 1$ Kähler potential and normalised zero modes [Kaplunovsky, Louis '93; Blumenhagen et al. '09; ...]

Massive modes $\lambda > 0$ ✗

- Extra low-lying modes? At what scale? **Swampland** distance conjecture

Numerical Calabi–Yau metrics

What is a Calabi–Yau?

Calabi–Yau manifolds are (complex) Kähler manifolds with a **Ricci-flat** metric

- Kähler with $c_1(X) = 0 \Rightarrow$ there exists a Ricci-flat metric [Yau '77]
- **Existence** but no explicit constructions

Kähler \Rightarrow **Kähler potential** K gives (real) two-form $J = \partial\bar{\partial}K$ s.t.

$$J^3 = \text{vol}_J \quad \text{and} \quad dJ = 0$$

$c_1(X) = 0 \Rightarrow$ (complex) nowhere-vanishing $(3, 0)$ -form Ω s.t.

$$|\Omega|^2 = \text{vol}_\Omega \quad \text{and} \quad d\Omega = 0$$

Example: Fermat quintics

Quintic hypersurface X in \mathbb{P}^4 with $(z_0, \dots, z_4) \sim t(z_0, \dots, z_4)$

$$Q(z) = z_0^5 + z_1^5 + z_2^5 + z_3^5 + z_4^5 - 5\psi z_0 z_1 z_2 z_3 z_4 = 0$$

$c_1(X) = 0 \Rightarrow$ three-form Ω fixed by $Q(z)$, e.g. in $z_0 = 1$ patch

$$\Omega = \frac{dz_2 \wedge dz_3 \wedge dz_4}{\partial Q / \partial z_1}$$

Metric (and J) completely determined by Kähler potential

$$g_{i\bar{j}}(z, \bar{z}) = \partial_i \bar{\partial}_{\bar{j}} K(z, \bar{z}), \quad \text{vol}_J \sim \det g_{i\bar{j}} d^6 z$$

How do we measure accuracy?

How do we know whether some $g_{i\bar{j}}$ is the Calabi–Yau metric?

The Ricci-flat metric is given by a K that satisfies (c.f. Monge–Ampère)

$$\frac{\text{vol}_J}{\text{vol}_\Omega} \Big|_p = \text{constant} \quad \Rightarrow \quad R_{i\bar{j}} = 0$$

The volumes are easier to calculate than the Ricci tensor. Normalising the volumes we define a **functional** of K

$$\sigma(K) = \int_X \left| 1 - \frac{\text{vol}_\Omega}{\text{vol}_J} \right| \text{vol}_\Omega$$

The exact CY metric has $\sigma = 0$

The problem of finding the Ricci-flat metric on a Calabi–Yau then reduces to finding a single function $K(z, \bar{z})$ that **minimises** σ

There are many approaches to this problem:

- Position space methods [Headrick, Wiseman '05]
- Spectral methods [Donaldson '05; Douglas et al. '06; Brauner et al. '07; Headrick, Nassar '09]
- Regression methods [AA et al. '19]
- Neural networks [Douglas et al. 20; Anderson et al. '20]

One can also try to find $g_{i\bar{j}}(z, \bar{z})$ **directly** (but need to impose Kähler, overlap conditions, etc.) [Anderson et al. '20; Jejjala '20]

Natural Kähler metric on \mathbb{P}^4 given by

$$K_{\text{FS}} = \log \sum_{i=0}^4 z_i \bar{z}_i$$

Can generalise this with a **hermitian matrix** $h^{\bar{j}}$

$$K(h) = \log \sum_{i, \bar{j}=0}^4 z_i h^{\bar{j}} \bar{z}_j$$

Restricting to $X \subset \mathbb{P}^4$ (defined by $Q(z) = 0$) gives a Kähler metric but **not** Ricci-flat

- **25 real parameters** in $h^{\bar{j}}$ that we can vary
- Need more parameters to better approximate the Ricci-flat metric

Generalise by replacing coordinates z_i with **homogeneous polynomials s_α** of degree k

$$\text{e.g. } k = 2 : \quad s_\alpha = (z_0^2, z_0z_1, z_0z_2, \dots)$$

Kähler potential is then

$$K(h) = \log \sum_{\alpha, \bar{\beta}=0}^{14} s_\alpha h^{\alpha\bar{\beta}} \bar{s}_{\bar{\beta}}, \quad h^{\alpha\bar{\beta}} \sim 225 \text{ parameters}$$

At degree k have $N_k \sim \mathcal{O}(k^3)$ parameters, so can approximate the Ricci-flat metric to **arbitrary precision!**

- **'Algebraic metrics'** – higher k allows better precision (smaller σ)
- **Spectral method** as $s_\alpha \bar{s}_{\bar{\beta}}$ give a basis for eigenspaces of Laplacian on \mathbb{P}^4 (U(1)-invariant spherical harmonics on S^9)

How to fix $h^{\alpha\bar{\beta}}$?

Finding the 'best' approximation to the Ricci-flat metric on X amounts to finding $h^{\alpha\bar{\beta}}$ so that σ is minimised

Three approaches:

- Iterative procedure [Donaldson '05; Douglas '06; Braun '07]
- Minimise σ directly (Mathematica) [Headrick, Nassar '09]
- Treat σ as a loss function for a neural network [Douglas et al. 20; Anderson et al. '20]

In all cases, numerical integrals carried out by **Monte Carlo**

Approximate the Ricci-flat metric by the 'balanced' metric on X

- Define the T operator as

$$T(h)_{\alpha\bar{\beta}} = \int \text{vol}_\Omega \frac{s_\alpha \bar{s}_\beta}{\sum_{\gamma, \bar{\delta}} s_\gamma h^{\gamma\bar{\delta}} \bar{s}_\delta},$$

- $h^{\alpha\bar{\beta}}$ is 'balanced' when $h^{\alpha\bar{\beta}} = [T(h)_{\alpha\bar{\beta}}]^{-1}$

As $k \rightarrow \infty$, the balanced metrics $K(k)$ converge to the exact Calabi–Yau metric (also works for Einstein metrics $R_{i\bar{j}} \propto g_{i\bar{j}}$).

- How do you solve for the balanced $h^{\alpha\bar{\beta}}$? Iterate using

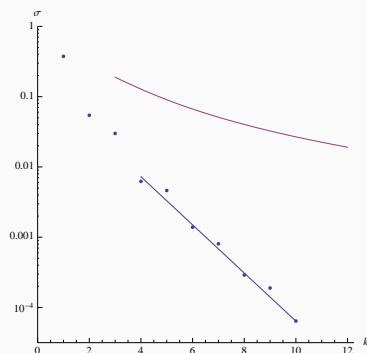
$$h_{(n+1)}^{\alpha\bar{\beta}} = [T(h_{(n)})_{\alpha\bar{\beta}}]^{-1}$$

The fixed point is the balanced metric (**guaranteed convergence!**)

Optimal metrics [Headrick, Nassar '09]

The 'optimal metrics' are the most precise. For Fermat quintic

$$\sigma_{\text{Donaldson}} \sim k^{-2}, \quad \sigma_{\text{optimal}} \sim 2.2^k$$



(c.f. [Headrick, Nassar '09])

Problem: number of parameters grows as k^6 – 'curse of dimensionality' – and exponentially slower

- The optimal metrics work well only for small k or where there is a **large symmetry** that reduces the number of independent parameters

Solution: machine learning is well suited to these kinds of problems

Initial question: is the **data** of a Calabi–Yau metric ‘learnable’? [Ashmore et al. ‘19]

Consider trying to learn $\det g_{\bar{i}\bar{j}}$ via **supervised learning**

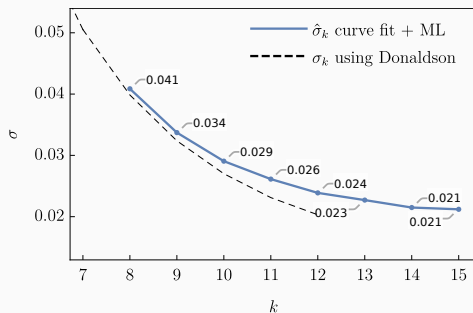
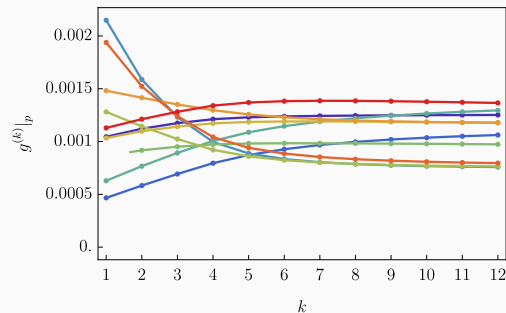
- Compute $\det g_{\bar{i}\bar{j}}^{(k)}$ for 10,000 points on X at degrees $k = (4, 5, 6, 7)$
- Extrapolate to $\det g_{\bar{i}\bar{j}}^{(k)}$ for larger k , e.g. $k = 12$

We then have labelled data {Inputs \rightarrow Outputs} of the form

$$\text{Inputs} = \left\{ p = (z_0, \dots, z_4), \det g_{\bar{i}\bar{j}}^{(4)} \Big|_p, \dots, \det g_{\bar{i}\bar{j}}^{(7)} \Big|_p \right\}, \quad \text{Outputs} = \left\{ \det g_{\bar{i}\bar{j}}^{(k)} \Big|_p \right\}$$

Feed this into a 'gradient-boosted decision tree' – result is a function that takes inputs from an **unseen point** on X and gives the predicted value of $\det \hat{g}_{ij}^{(k)} \Big|_p$

- We can then compare the σ accuracy to test how well we are doing



Similar σ values – but approx. **two orders of magnitude** quicker than direct $k = 12$ calculation!

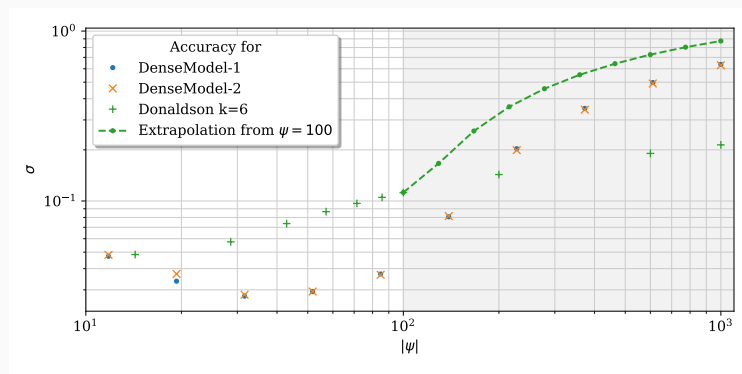
Learning $h^{\alpha\bar{\beta}}$ including dependence on **complex structure** ψ using neural network

- For phenomenology, want to be able to scan over values of moduli / understand how couplings and masses depend on moduli
- **Loss function** is $\sigma(K)$ – minimise by stochastic gradient descent
- Uses ψ as input feature
- Single dense hidden layer of width $\dim\{s_\alpha\}$ or $(\dim\{s_\alpha\})^2$ (computing K at degree k)

$$\psi \rightarrow \text{Model} \rightarrow h^{\alpha\bar{\beta}} \rightarrow K(z, \bar{z}) \rightarrow g_{i\bar{j}}$$

\uparrow
 z_i

Results when trained on $\psi \in (0, 100)$ at $k = 6$ (c.f. [Anderson et al. '20])



Gives precision comparable to Donaldson at $k = 12$

- Donaldson at $k = 12$ takes **days** to run over the range $\psi = 0, \dots, 100$ – neural network trained in **minutes** for same range
- Gives full dependence on complex structure moduli!

Recall that the CY metric is determined by K via

$$K = \log(s_\alpha h^{\alpha\bar{\beta}} \bar{s}_\beta),$$

where s_α are homogeneous, degree- k polynomials of the z_j

Replace this with a **feed-forward network** $F(z, \bar{z})$ such that $K = \log F$

$$(\operatorname{re} z_j \bar{z}_j, \operatorname{im} z_j \bar{z}_j) \mapsto F(z, \bar{z})$$

$$F = \theta_d \circ W^{(d)} \dots \circ \theta_1 \circ W^{(1)}$$

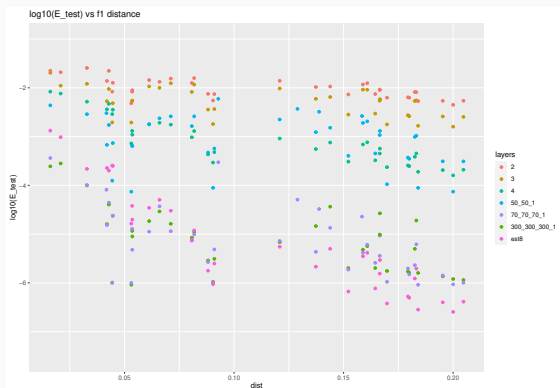
where $W^{(n)}$ are linear maps (weights) and $\theta_n(x) = x^2$ are non-linear homogeneous activation functions

- Number of parameters = $25 \times \text{width}_1 + \text{width}_1 \times \text{width}_2 + \dots + \text{width}_d \times 1$

Has the advantage that you do not fill out the space of metrics at degree k

- Can resolve features at scales k^{-1} with degree k polynomial basis
- Use a network with smaller width but more layers (depth) \Rightarrow higher effective k – 11,620 parameters for (70, 70, 70) network vs 245,025 for $k = 8$

σ values for $k = 2, 3, 4$ optimal and various networks (c.f. [Douglas et al. 20])



Application: the spectrum of the Laplace operator

Important phenomenological details of models determined by **harmonic modes** on CY

Ignoring gauge sector, harmonic modes are (p, q) -eigenforms of the Laplace operator

$$\Delta = d\delta + \delta d, \quad \Delta|\phi_n\rangle = \lambda_n|\phi_n\rangle$$

where λ_n are **real** and **non-negative** and appear with multiplicity μ_n (c.f. continuous or finite **symmetries**)

- Need some way of finding both the spectrum and the harmonic modes themselves
- Scalar case done [Braun et al. '08]

The Laplace operator

For each (p, q) , given a (non-orthonormal) basis of (p, q) -forms $\{\alpha_A\}$ we can expand the eigenmodes as

$$|\phi\rangle = \sum_A \langle \alpha_A | \tilde{\phi} \rangle |\alpha_A\rangle$$

so that

$$\begin{aligned} \Delta|\phi\rangle &= \lambda|\phi\rangle \\ \sum_B \langle \alpha_A | \Delta | \alpha_B \rangle \langle \alpha_B | \tilde{\phi} \rangle &= \sum_B \lambda \langle \alpha_A | \alpha_B \rangle \langle \alpha_B | \tilde{\phi} \rangle \\ \Rightarrow \Delta_{AB} \tilde{\phi}_B &= \lambda O_{AB} \tilde{\phi}_B \end{aligned}$$

Generalised eigenvalue problem for λ and $\tilde{\phi}_A$

The Laplace operator

Basis $\{\alpha_A\}$ is infinite dimensional – truncate to a **finite approximate basis** at degree k_ϕ in z_i

$$\frac{(\text{degree } k_\phi (p, 0)\text{-form})(\text{degree } k_\phi (0, q)\text{-form})}{(|z_0|^2 + \dots + |z_4|^2)^{k_\phi}}$$

where we have (c.f. harmonic forms on \mathbb{P}^4)

{degree $k_\phi (0, 0)$ -form} = degree k_ϕ polynomials

{degree 2 (1, 0)-form} = $\{z_0 dz_1 - z_1 dz_0, z_0 dz_2 - z_2 dz_0\}$

$\vdots = \vdots$

1. Hodge star and complex conjugation \Rightarrow

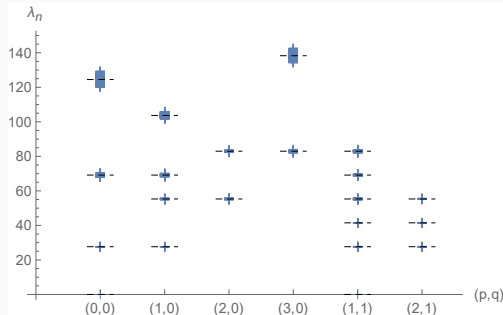
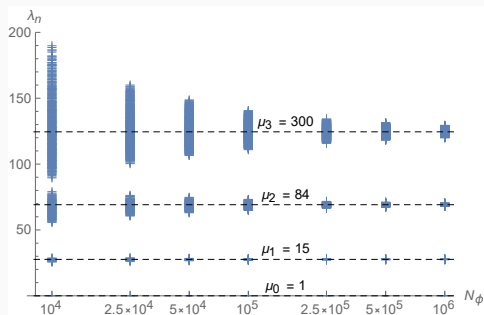
$$\lambda_n^{(p,q)} = \lambda_n^{(q,p)} = \lambda_n^{(3-p,3-q)} = \lambda_n^{(3-q,3-p)}$$

2. Compute matrices Δ_{AB} and O_{AB} **numerically** for independent choices of (p, q)

3. Find eigenvalues and eigenvectors

Example: \mathbb{P}^3 [Ikeda, Taniguchi '78]

Numeric results: spectrum on \mathbb{P}^3 at $k_\phi = 3$ with 10^6 points for numerical integrals, use exact metric on $\mathbb{P}^3 - (0, 0)$ spectrum for varying number of points and (p, q) spectrum



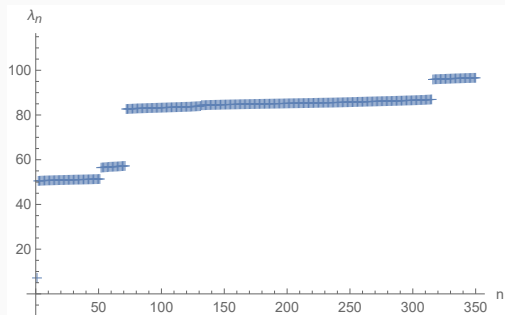
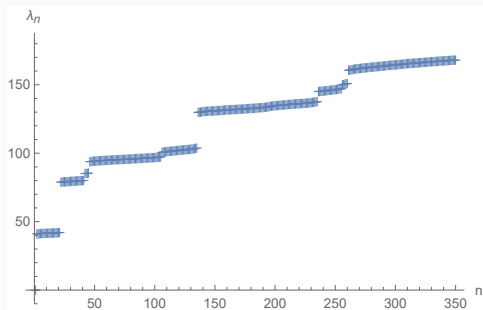
- Eigenvalues and multiplicities determined by **SU(4) representations** (set $\text{Vol} = 1$)
- Degeneracy of eigenvalues recovered as number of integration points $\rightarrow \infty$ (restores SU(4) symmetry)

Fermat quintic

On CY we don't have the exact metric:

1. Specify the CY (e.g. Fermat quintic) and compute metric numerically
2. Pick a finite basis for (p, q) -forms at some degree
3. Solve numerically for eigenvalues and eigenvectors of Laplace operator (for each choice of (p, q))

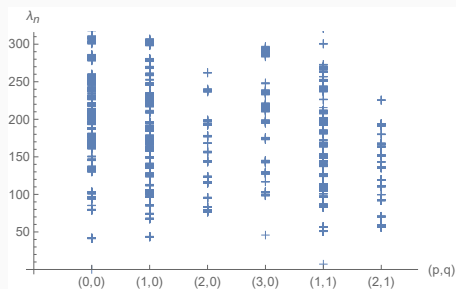
Spectrum for $(0, 0)$ - and $(1, 1)$ -forms



Fermat quintic

(p, q)	(0, 0)		(1, 0)		(2, 0)	
$\dim\{\alpha_A\}$	1225		1400		350	
n	λ_n	μ_n	λ_n	μ_n	λ_n	μ_n
0	0.00	1	43.7 ± 0.2	20	77.0 ± 0.3	30
1	41.5 ± 0.3	20	67.7 ± 0.3	30	79.0 ± 0.4	30
2	79.4 ± 0.4	20	74.1 ± 0.3	30	83.1 ± 0.3	20
3	85.3 ± 0.2	4	85.4 ± 0.4	34*	95.5 ± 0.3	20
4	95.5 ± 0.9	60	96.8 ± 0.4	20	116 ± 1	40
5	102 ± 1	30	101 ± 1	60	123 ± 1	30

(p, q)	(3, 0)		(1, 1)		(2, 1)	
$\dim\{\alpha_A\}$	350		1600		400	
n	λ_n	μ_n	λ_n	μ_n	λ_n	μ_n
0	45.8	1	7.13	1	56.4 ± 0.1	20
1	98.9 ± 0.4	20	50.8 ± 0.2	30	59.2 ± 0.2	20
2	103 ± 0.4	20	51.2 ± 0.1	20	70.5 ± 0.2	30
3	117 ± 0.2	4	56.9 ± 0.2	20	92.3 ± 0.4	60
4	128 ± 1	30	83.3 ± 0.4	60	99.7 ± 0.2	4
5	144 ± 1	30	85.5 ± 0.7	184*	111 ± 0.4	40



Ω and J should give $\lambda = 0$ eigenmodes for (3, 0) and (1, 1) – improves as size of approximate basis is increased

Multiplicities = dimension of irreps of $(S_5 \times \mathbb{Z}_2) \times (\mathbb{Z}_5)^4$

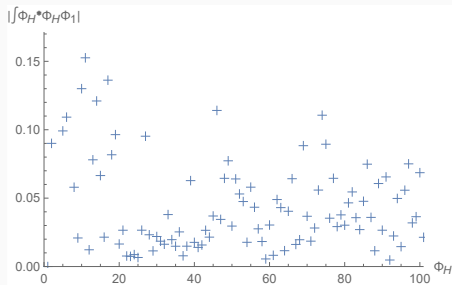
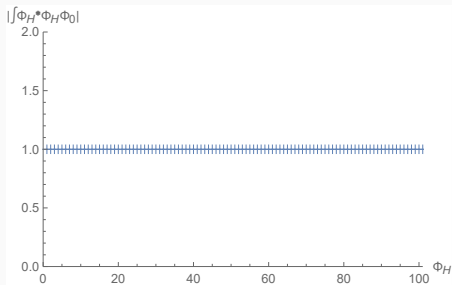
Yukawa couplings

Honest Yukawa couplings computed by $(0, q)$ -forms valued in gauge bundle V

$$W = \dots + \lambda_u QHu + \dots, \quad \lambda_u = \int_X \Omega \wedge \text{tr}(\Psi_Q \wedge \Psi_H \wedge \Psi_u)$$

Toy example: **triple overlap** of a light scalar mode with two heavy scalar modes

$$\left| \int_X \bar{\Phi}_H \Phi_H \Phi_L \right| = |Y_{\bar{H}HL}| \quad \text{where } \Phi_m = \frac{\phi_m}{\sqrt{\langle \phi_m | \phi_m \rangle}}$$



Summary

- Calabi–Yau metrics are important for getting real predictions from string theory
- Analytic metrics not known (and may never be) so must rely on numerical results
- Many methods to compute metrics – ML looks extremely promising for this!
- With the ‘data’ of the metric, one can compute eigenmodes of the Laplace operator

Outlook

- Include vector bundles (gauge fields)
 - Donaldson works for bundles too [Douglas et al. ‘06] – can diagnose **stability**
 - ML for gauge connections? Harmonic modes?
- CY threefolds appear as target spaces for $N = (2, 2)$ SCFTs with $c = 9$
 - Spectrum of CY \subset spectrum of CFT **operators**
 - Overlap integrals \equiv OPEs in CFT
- SYZ conjecture? F-theory?

Thank you!