Constructing and Machine Learning Calabi-Yau Five-Folds

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joint with

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Online Machine Learning Seminar, March 13, 2024

Construction 00000000000 Statistics

Machine Learning

Calabi-Yau manifolds



"A lot of mathematicians like to solve problems that finish off work on a particular subject," Chen said. "Calabi was someone who liked to start a subject."

Construction

Cohomology

Statistics

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Calabi-Yau manifolds

between Mathematics...

Definition

A *Calabi-Yau n-fold* is a compact Kähler manifold X^n with trivial canonical bundle.

Cohomology

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Calabi-Yau manifolds

between Mathematics...

Definition

A *Calabi-Yau n-fold* is a compact Kähler manifold X^n with trivial canonical bundle.

Xⁿ compact Kähler:

$$\begin{array}{c} \begin{pmatrix} & \mathcal{K}_{X} \simeq \mathcal{O}_{X} \\ & \uparrow \\ \exists \Omega \in H^{0}(X; \Omega_{X}^{n}) \text{ s.t. } \Omega(x) \neq 0 \\ & \uparrow \\ \text{ struct group } \mathcal{T}X \text{ red to } \mathrm{SU}(n) \\ & \uparrow \\ \exists g \text{ K\"ahler s.t. } \mathrm{Hol}(g) \subseteq \mathrm{SU}(n) \end{array} \right) \Rightarrow \begin{pmatrix} \mathcal{C}_{1}(X) = 0 \\ & \uparrow \\ \exists g \text{ K\"ahler s.t. } \mathrm{Ric}(g) = 0 \\ & \uparrow \\ \exists g \text{ K\"ahler s.t. } \mathrm{Ric}(g) \subseteq 0 \\ & \uparrow \\ \exists g \text{ K\"ahler s.t. } \mathrm{Hol}^{0}(g) \subseteq \mathrm{SU}(n) \\ & \uparrow \\ \exists m \text{ s.t. } m\mathcal{K}_{X} \simeq \mathcal{O}_{X} \\ & \uparrow \\ \exists X' \xrightarrow{m:1} X \text{ with } \mathcal{K}_{X'} \simeq \mathcal{O}_{X'} \end{pmatrix}$$

(converse if $\pi_1(X) = 0$)

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Calabi-Yau manifolds

between Mathematics...





D. Examples

0.23. Despite the simplicity of the condition $r = \lambda g$ the reader should not imagine that examples are easy to find. If you are not convinced, try to find one yourself which is not in our book. And if you succeed, please write to us immediately. Ricci flat compact manifolds are even harder to come by. The author will be happy to stand you a meal in a starred restaurant in exchange of one of these!

Cohomology

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Calabi-Yau manifolds ... and Physics

Calabi-Yau manifolds are the most promising candidates for internal spaces in the compactification mechanism. Their geometry affects the properties of the subsequent 4-dim theory.

$\mathbb{R}^{1,3} imes X^6$

and Hull-Strominger are necessary and sufficient for spacetime supersymmetry:

- (X,g) complex Hermitian with Plank-scale, (V, h) Hermitian vector bundle, Ω holomorphic 3-form never vanishing,
- $\partial \overline{\partial} g = \sqrt{-1} \operatorname{tr} F_h \wedge F_h \sqrt{-1} \operatorname{tr} R_g \wedge R_g$,
- $d^*g = \sqrt{-1} \left(\partial \overline{\partial}\right) \lg \|\Omega\|$,
- F Yang-Mills.

P. Candelas, G. T. Horowitz, A. Strominger, E. Witten, Vacuum configurations for superstrings, *Nucl. Phys. B* 258 (1985) 46–74.

Machine Learning











Cohomology

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CY manifolds in dim 1 and 2 $\,$

$\mathsf{dim} = 1$

Calabi-Yau onefold is the torus. It is a complex elliptic curve, in particular, algebraic:

$$y^2 z = x^3 + axz^2 + bz^3$$

(where $4a^3 + 27b^2 \neq 0$).

$\dim = 2$

Simply-connected Calabi-Yau twofolds are K3 surfaces. They are quartic surfaces in \mathbb{P}^3 :

$$x^4 + y^4 + z^4 + w^4 = 0.$$

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CY manifolds in dim 3

$\mathsf{dim}=\mathsf{3}$

- Yau conjectures finitely many topological types of CY in each dim
- at least 2590 distinct diffeom classes of CICY
- over 473 million toric embeddings of CY
- Reid's fantasy: there is only one CY threefold, all CY threefolds are connected through conifold transitions
 - M. Reid, The moduli space of 3-folds with K = 0 may nevertheless be irreducible, *Math. Ann.* 278 (1987), 329–334.
 - S. T. Yau, A survey of Calabi-Yau manifolds, Adv. Lect. Math. (ALM), 18, International Press, 2011, 521–563.

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CY manifolds in dim 3



A. Ashmore, Y.-H. He, Calabi-Yau three-folds: Poincaré polynomials and fractals, in *Strings, gauge fields, and the geometry behind*, 173–186, World Scientific, 2013

Construction

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Introduction

$$X^{n-1} = \{x \in \mathbb{P}^n : p(x) = 0\}$$

Cohomology

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where $p(x) \in \mathbb{C}[x_0, \ldots, x_n]$ homogeneous polynomial of degree d

Construction

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•
$$0 o T_X o T_{\mathbb{P}^n}|_X o N_{X|\mathbb{P}^n} o 0 \rightsquigarrow K_X = K_{\mathbb{P}^n}|_X \otimes N_{X|\mathbb{P}^n}$$

Construction

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Statistics

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• 0
$$\rightarrow$$
 $T_X \rightarrow$ $T_{\mathbb{P}^n}|_X \rightarrow$ $N_{X|\mathbb{P}^n} \rightarrow$ 0 \rightsquigarrow $K_X = K_{\mathbb{P}^n}|_X \otimes$ $N_{X|\mathbb{P}^n}$

•
$$\mathcal{K}_{\mathbb{P}^n}|_X = \mathcal{O}_X(-n-1)$$

•
$$N_{X|\mathbb{P}^n} = \mathcal{O}_X(d)$$

Construction

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Introduction

$$X^{n-1} = \{x \in \mathbb{P}^n : p(x) = 0\}$$

Statistics

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Cohomology

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$$\mathcal{K}_{\mathbb{P}^n}|_X = \mathcal{O}_X(-n-1)$$

•
$$N_{X|\mathbb{P}^n} = \mathcal{O}_X(d)$$

• $\rightsquigarrow K_X = \mathcal{O}_X(-n-1+d)$

Construction

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Introduction

$$X^{n-1} = \{x \in \mathbb{P}^n : p(x) = 0\}$$

Statistics

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where $p(x) \in \mathbb{C}[x_0, \dots, x_n]$ homogeneous polynomial of degree d

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$$0 \to T_X \to T_{\mathbb{P}^n}|_X \to N_{X|\mathbb{P}^n} \to 0 \rightsquigarrow K_X = K_{\mathbb{P}^n}|_X \otimes N_{X|\mathbb{P}^n}$$

Cohomology

•
$$\mathcal{K}_{\mathbb{P}^n}|_X = \mathcal{O}_X(-n-1)$$

•
$$N_{X|\mathbb{P}^n} = \mathcal{O}_X(d)$$

•
$$\rightsquigarrow K_X = \mathcal{O}_X(-n-1+d)$$

Proposition

X Calabi-Yau
$$\Leftrightarrow$$
 $d = n + 1$



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Fermat quintic threefold

$$X^3 = \left\{ [x_0: \dots: x_4] \in \mathbb{P}^4 \ : \ x_0^5 + x_1^5 + x_2^5 + x_3^5 + x_4^5 = 0 \right\}$$



• $c(T_X) = 1 + 10H^2 - 40H^3$, where H is hyperplane div class $\mathbb{P}^{n-1} \hookrightarrow \mathbb{P}^n$

•
$$\chi(X) = -40 \int_X H^3 = -200$$
 by Bézout

•
$$h^{1,1}(X) = 1, h^{2,1}(X) = 101$$

Construction

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CICY

Complete Intersection Calabi-Yau

$$X^n := \{p_1 = \cdots = p_K = 0\} \subseteq \mathcal{A}$$

- $\mathcal{A} := \mathbb{P}^{n_1} \times \cdots \times \mathbb{P}^{n_m}$ ambient space
- p_1, \ldots, p_K polyn depending on m sets of homogeneous coord
- q_{α}^{r} the homog degree of p_{α} in the coord of the *r*th proj space

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CICY

Complete Intersection Calabi-Yau

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- p_1, \ldots, p_K polyn depending on m sets of homogeneous coord
- q_{α}^{r} the homog degree of p_{α} in the coord of the *r*th proj space such that:
 - X smooth
 - dim $X = \dim \mathcal{A} \mathcal{K} = \sum^{m} n_{r} \mathcal{K}$
 - $K_X = \mathcal{O}_X$

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CICY

Complete Intersection Calabi-Yau

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 - X smooth
 - dim $X = \dim \mathcal{A} \mathcal{K} = \sum^m n_r \mathcal{K}$

•
$$\mathcal{K}_X = \mathcal{O}_X$$
, i.e. for any $r, \sum^K q_{lpha}^r = n_r + 1$

P. Candelas, A. Dale, C. Lütken, R. Schimmrigk, Complete intersection Calabi-Yau manifolds, *Nucl. Phys. B* 298 (1988), 493.

Construction

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CICY : configuration matrix

Cohomological invariants of X only depends on q_{lpha}^r

$$X \quad \rightsquigarrow \quad \left(\begin{array}{cccc} n_1 & q_1^1 & \cdots & q_K^1 \\ \vdots & \vdots & \ddots & \vdots \\ n_m & q_1^m & \cdots & q_K^m \end{array}\right)$$

•
$$K = \sum^{m} n_r - n$$

• for any r , $\sum^{K} q_{\alpha}^r = n_r + 1$

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CICY : configuration matrix

Cohomological invariants of X only depends on q_{lpha}^r

$$X \quad \rightsquigarrow \quad \left(\begin{array}{cccc} n_1 & q_1^1 & \cdots & q_K^1 \\ \vdots & \vdots & \ddots & \vdots \\ n_m & q_1^m & \cdots & q_K^m \end{array}\right)$$

where

•
$$K = \sum^{m} n_r - n$$

• for any r , $\sum^{K} q_{\alpha}^r = n_r + 1$

Remark

There are redundancies!

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CICY : finiteness

*X*⁵



$$X^5 \quad \hookrightarrow \quad \mathcal{A} = (\mathbb{P}^1)^f \times \mathbb{P}^{n_1} \times \cdots \times \mathbb{P}^{n_F}$$

• assume
$$\sum_{r=1}^{f+F} q_{\alpha}^r \ge 2$$
 for any α , since $(1 | 1) = pt$

• then
$$f + F + 5 \ge K$$

- then $F \leq 10$
- assume bilin constraint involving \mathbb{P}^1 also involves \mathbb{P}^{n_j} , since $\begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} = \mathbb{P}^1$
- assume $\sum_{r=1}^{f} q_{\alpha}^{r} > 2$ for any α , otherwise product
- ... then $f \leq 15$

• then
$$K = f + \sum_{r=1}^{f+F} n_r - 5 \le 30$$

maximum size for a configuration matrix for CICY fivefold is

 $\mathbf{25}\times\mathbf{30}$

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CICY : configuration matrix' redundancies

• permutations of rows and columns (lexicographic order, Gray-Haupt-Lukas algorithm, brute force)



- permutations of rows and columns (lexicographic order, Gray-Haupt-Lukas algorithm, brute force)
- ineffective splittings

$$\left(\begin{array}{c|c}n \mid \sum_{a=1}^{n+1} u_a & q\end{array}\right) \quad \rightsquigarrow \quad \left(\begin{array}{c|c}n \mid 1 & 1 & \cdots & 1 & 0\\n \mid u_1 & u_2 & \cdots & u_{n+1} & q\end{array}\right)$$

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CICY : configuration matrix' redundancies

- permutations of rows and columns (lexicographic order, Gray-Haupt-Lukas algorithm, brute force)
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accidental identities

$$\begin{pmatrix} 2 & 2 & a \\ n & 0 & q \end{pmatrix} = \begin{pmatrix} 1 & | & 2a \\ n & | & q \end{pmatrix}, \qquad \begin{pmatrix} 1 & | & 1 & a \\ 1 & | & 1 & b \\ n & | & 0 & q \end{pmatrix} = \begin{pmatrix} 1 & | & a + b \\ n & | & q \end{pmatrix}, \qquad \begin{pmatrix} 3 & | & 2 & a \\ n & 0 & q \end{pmatrix} = \begin{pmatrix} 1 & | & a \\ 1 & a \\ n & | & q \end{pmatrix},$$
$$\begin{pmatrix} 1 & | & 2 & 0 \\ 2 & 1 & 1 & a \\ n & | & 0 & q \end{pmatrix} = \begin{pmatrix} 1 & | & a \\ 1 & a \\ n & | & q \end{pmatrix}, \qquad \begin{pmatrix} 2 & | & 2 & 1 & 0 \\ 2 & 1 & 1 & a \\ n & 0 & 0 & q \end{pmatrix} = \begin{pmatrix} 1 & | & 2 & 0 \\ 1 & 2 & a \\ n & | & 0 & q \end{pmatrix}, \qquad \dots$$



- n = 3 7890 spaces, 265 distinct Hodge diamonds
- n = 4 921 497 spaces, 4 417 distinct Hodge diamonds
- n = 5 expected $\sim 10^8$ spaces, we constructed 27068 configuration matrices of dimensions up to 4 \times 4, up to permutations, 2375 distinct Hodge diamonds



The list of complete intersection Calabi-Yau three-folds, http://www-thphys.physics.ox.ac.uk/projects/CalabiYau/cicylist/.



Complete intersection Calabi-Yau four-folds, http://www-thphys.physics.ox.ac.uk/projects/CalabiYau/Cicy4folds/index.html.



R. Alawadhi, D. A., A. Leonardo, T. Schettini Gherardini, Constructing and Machine Learning Calabi-Yau Five-folds, *Fortschr. Phys.* (arXiv:2310.15966).



Complete intersection Calabi-Yau five-folds, https: //www.dropbox.com/scl/fo/z7ii5idt6qxu36e0b8azq/h?rlkey=0qfhx3tykytduobpld510gsfy&dl=0



M. Kreuzer, H. Skarke, Calabi-Yau data, http://hep.itp.tuwien.ac.at/~kreuzer/CY/.

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CY fivefolds : Hodge numbers



•
$$h^{0,0} = h^{5,5} = 1$$
 (compact, connected)

• $h^{p,q} = h^{5-p,5-q}$ (Serre duality)

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$$h^{p,0} = 0$$
 for $p \notin \{0,5\}$ (Bochner)

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•
$$b_k = \sum_{p+q=k} h^{p,q}$$
 (Frölicher)

•
$$\chi = \sum_{k} (-1)^{k} b_{k} = 2h^{1,1} - 4h^{1,2} + 4h^{1,3} + 2h^{2,2} - 2h^{1,4} - 2h^{2,3}$$
 (Euler)

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 (Euler)

•
$$11h^{1,1} - 10h^{1,2} - h^{2,2} + h^{2,3} + 10h^{1,3} - 11h^{1,4} = 0$$
 (Atiyah-Singer)

Construction

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Construction

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Example CICY threefold in \mathbb{P}^5 : Hodge numbers

$$X^3 = \left(\begin{array}{ccc} 5 & 2 & 4 \end{array}\right)$$


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Example CICY threefold in \mathbb{P}^5 : Hodge numbers

$$X^3 = \left(\begin{array}{ccc} 5 & 2 & 4 \end{array}\right)$$

 $p(x) \in H^0(\mathbb{P}^5; \mathcal{O}_{\mathbb{P}^5}(2)), q(x) \in H^0(\mathbb{P}^5; \mathcal{O}_{\mathbb{P}^5}(4)),$ generic

$$X^3 = \{x \in \mathbb{P}^5 : p(x) = q(x) = 0\}$$

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$$X^{3} = \{x \in \mathbb{P}^{5} : p(x) = q(x) = 0\}$$
$$= \{x \in Y^{4} := \{y \in \mathbb{P}^{5} : q(x) = 0\} : p(x) = 0\}$$

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$$X^{3} = \{x \in \mathbb{P}^{5} : p(x) = q(x) = 0\}$$

=
$$\{x \in Y^{4} := \{y \in \mathbb{P}^{5} : q(x) = 0\} : p(x) = 0\}$$

$$\begin{bmatrix} 0 & h^{1,1}(X) & 0 & 0\\ 1 & 0 & h^{2,1}(X) & h^{1,1}(X) & 0\\ 0 & 0 & 1 & 0 \end{bmatrix}$$

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CY threefolds in \mathbb{P}^5 : Hodge numbers



Remark

- $H^{1,1}(X)$ Kähler class parameters
- $H^{2,1}(X) = H^{1,2}(X) = H^2(X; \Omega^1_X) = H^1(X; T_X)$ cplx struct param
- P. Green, T. Hübsch, Polynomial deformations and cohomology of Calabi-Yau manifolds, *Comm. Math. Phys.* 113 (1987), no. 3, 505–528.
- T. Hübsch, Calabi-Yau manifolds. A bestiary for physicists, World Scientific, 1992.

Example CICY threefold in \mathbb{P}^5 : cohomology of \mathcal{O}_X

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Construction

 $X = \left(\begin{array}{cc} 5 & 2 & 4 \end{array} \right)$

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By Dolbeault-Grothendieck: $h^{p,q}(X) = H^q(X; \mathcal{O}_X)$, then

$$h(\mathcal{O}_X) = (h^{0,0}(X), h^{0,1}(X), h^{0,2}(X), h^{0,3}(X), \cdots)$$

Example CICY threefold in \mathbb{P}^5 : cohomology of \mathcal{O}_X

Introduction

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Machine Learning

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$$\begin{array}{l} 0 \rightarrow \mathcal{O}_{\mathbb{P}^{5}}(-2) \rightarrow \mathcal{O}_{\mathbb{P}^{5}} \rightarrow \mathcal{O}_{Y} \rightarrow 0 \\ 0 \rightarrow \mathcal{O}_{Y}(-4) \rightarrow \mathcal{O}_{Y} \rightarrow \mathcal{O}_{X} \rightarrow 0 \end{array}$$

Example CICY threefold in \mathbb{P}^5 : cohomology of \mathcal{O}_X

Cohomology

 $X = \left(\begin{array}{ccc} 5 & 2 & 4 \end{array}\right)$

Machine Learning

Statistics

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Theorem

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Construction

$$\dim H^0(\mathbb{P}^n;\mathcal{O}_{\mathbb{P}^n}(d)) \ = \ egin{pmatrix} n+d \ d \end{pmatrix} \quad if \quad d\geq 0$$

$$\dim H^n(\mathbb{P}^n;\mathcal{O}_{\mathbb{P}^n}(d)) \ = \ inom{-d-1}{-n-d-1} \quad ext{ if } \quad d\leq -n-1$$

dim $H^i(\mathbb{P}^n; \mathcal{O}_{\mathbb{P}^n}(d)) = 0$ otherwise

Example CICY threefold in \mathbb{P}^5 : cohomology of \mathcal{O}_X

 $X = \left(\begin{array}{cc} 5 & 2 & 4 \end{array} \right)$

Apply long exact seq in cohomology to $0 \to \mathcal{O}_{\mathbb{P}^5}(-2) \to \mathcal{O}_{\mathbb{P}^5} \to \mathcal{O}_Y \to 0$:

$$\begin{split} h(\mathcal{O}_{\mathbb{P}^5}) &= (1, 0, 0, 0, 0, 0) \\ h(\mathcal{O}_{\mathbb{P}^5}(-2)) &= (0, 0, 0, 0, 0, 0) \\ & \rightsquigarrow h(\mathcal{O}_Y) &= (1, 0, 0, 0, 0) \end{split}$$

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Example CICY threefold in \mathbb{P}^5 : cohomology of \mathcal{O}_X

 $X = \left(\begin{array}{cc} 5 & 2 & 4 \end{array} \right)$

Apply long exact seq in cohomology to $0 \to \mathcal{O}_{\mathbb{P}^5}(-2) \to \mathcal{O}_{\mathbb{P}^5} \to \mathcal{O}_Y \to 0$:

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Apply long exact seq in cohomology to $0 \to \mathcal{O}_{\mathbb{P}^5}(-6) \to \mathcal{O}_{\mathbb{P}^5}(-4) \to \mathcal{O}_Y(-4) \to 0$:

$$h(\mathcal{O}_{\mathbb{P}^{5}})(-4) = (0, 0, 0, 0, 0, 0)$$
$$h(\mathcal{O}_{\mathbb{P}^{5}}(-6)) = (0, 0, 0, 0, 0, 1)$$
$$\rightsquigarrow h(\mathcal{O}_{Y}(-4)) = (0, 0, 0, 0, 1)$$

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Example CICY threefold in \mathbb{P}^5 : cohomology of \mathcal{O}_X

 $X = \left(\begin{array}{cc} 5 & 2 & 4 \end{array} \right)$

Apply long exact seq in cohomology to $0 \to \mathcal{O}_{\mathbb{P}^5}(-2) \to \mathcal{O}_{\mathbb{P}^5} \to \mathcal{O}_Y \to 0$:

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Apply long exact seq in cohomology to $0 \to \mathcal{O}_{\mathbb{P}^5}(-6) \to \mathcal{O}_{\mathbb{P}^5}(-4) \to \mathcal{O}_Y(-4) \to 0$:

$$h(\mathcal{O}_{\mathbb{P}^{5}})(-4) = (0, 0, 0, 0, 0, 0)$$
$$h(\mathcal{O}_{\mathbb{P}^{5}}(-6)) = (0, 0, 0, 0, 0, 1)$$
$$\rightsquigarrow h(\mathcal{O}_{Y}(-4)) = (0, 0, 0, 0, 1)$$

Apply long exact seq in cohomology to $0 \to \mathcal{O}_Y(-4) \to \mathcal{O}_Y \to \mathcal{O}_X \to 0$:

$$h(\mathcal{O}_Y) = (1, 0, 0, 0, 0)$$
$$h(\mathcal{O}_Y(-4)) = (0, 0, 0, 0, 1)$$
$$\rightsquigarrow h(\mathcal{O}_X) = (1, 0, 0, 1)$$



 $X = \left(\begin{array}{cc} 5 & 2 & 4 \end{array} \right)$

$$h(\Omega^{1}_{X}) = (h^{1,0}(X), h^{1,1}(X), h^{1,2}(X), h^{1,3}(X), \cdots)$$



 $X = \left(\begin{array}{cc} 5 & 2 & 4 \end{array} \right)$

$$h(\Omega^{1}_{X}) = \left(h^{1,0}(X), h^{1,1}(X), h^{1,2}(X), h^{1,3}(X), \cdots\right)$$

$$0 o T_X o T_{\mathbb{P}^5}|_X o N_{X|\mathbb{P}^5} o 0$$

$\begin{array}{ccc} \mbox{Introduction} & \mbox{Construction} & \mbox{Cohomology} & \mbox{Cohomology} & \mbox{Statistics} & \mbox{Machine Learning} & \mbox{Cohomology} & \mbox{Statistics} & \mbox{Machine Learning} & \mbox{Cohomology} & \$

 $X = \left(\begin{array}{cc} 5 & 2 & 4 \end{array} \right)$

$$h(\Omega^{1}_{X}) = \left(h^{1,0}(X), h^{1,1}(X), h^{1,2}(X), h^{1,3}(X), \cdots\right)$$

$$0
ightarrow T_X
ightarrow T_{\mathbb{P}^5}|_X
ightarrow N_{X|\mathbb{P}^5}
ightarrow 0$$

$$0 \to \underbrace{N_{X|\mathbb{P}^{5}}^{\vee}}_{=\mathcal{O}_{X}(-2) \oplus \mathcal{O}_{X}(-4)} \to \Omega^{1}_{\mathbb{P}^{5}}|_{X} \to \Omega^{1}_{X} \to 0$$

Example CICY threefold in \mathbb{P}^5 : cohomology of Ω^1_X

 $X = \left(\begin{array}{cc} 5 & 2 & 4 \end{array} \right)$

Machine Learning

Statistics

$$h(\Omega^{1}_{X}) = \left(h^{1,0}(X), h^{1,1}(X), h^{1,2}(X), h^{1,3}(X), \cdots\right)$$

$$0 \to T_X \to T_{\mathbb{P}^5}|_X \to N_{X|\mathbb{P}^5} \to 0$$

$$0 \to \underbrace{N_{X|\mathbb{P}^{5}}^{\vee}}_{=\mathcal{O}_{X}(-2) \oplus \mathcal{O}_{X}(-4)} \to \Omega^{1}_{\mathbb{P}^{5}}|_{X} \to \Omega^{1}_{X} \to 0$$

Theorem (Euler sequence)

Construction

Introduction

$$0 o \Omega^1_{\mathbb{P}^n} o \mathcal{O}_{\mathbb{P}^n}(-1)^{\oplus (n+1)} o \mathcal{O}_{\mathbb{P}^n} o 0$$

$$\stackrel{\otimes \mathcal{O}_X}{\leadsto} 0 o \Omega^1_{\mathbb{P}^5}|_X o \mathcal{O}_X(-1)^{\oplus 6} o \mathcal{O}_X o 0$$



 $X = \left(\begin{array}{ccc} 5 & 2 & 4 \end{array}\right)$

•
$$h(\mathcal{O}_X(-2)) = (0, 0, 0, 20),$$

 $h(\mathcal{O}_X(-4)) = (0, 0, 0, 104)$

 $\rightsquigarrow h(N_{X|\mathbb{P}^{5}}^{\vee}) = h(\mathcal{O}_{X}(-2)) + h(\mathcal{O}_{X}(-4)) = (0,0,0,124)$

•
$$h(\mathcal{O}_X(-1)^{\oplus 6}) = (0,0,0,6)^{\oplus 6} = (0,0,0,36),$$

 $h(\mathcal{O}_X) = (1,0,0,1)$

$$\rightsquigarrow h(\Omega^1_{\mathbb{P}^5}|_X) = (0, 1, 0, 35)$$

•
$$h(N_{X|\mathbb{P}^5}^{\vee}) = (0, 0, 0, 124),$$

 $h(\Omega_{\mathbb{P}^5}^1|_X) = (0, 1, 0, 35)$

 $\rightsquigarrow h(\Omega^1_X) = (0, 1, 89, 0)$





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Example CICY threefold in \mathbb{P}^5 : cohomology of Ω^1_X

 $X = \left(\begin{array}{ccc} 5 & 2 & 4 \end{array}\right)$



Construction

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Example CICY threefold in \mathbb{P}^5 : Hodge diamond

$X^{3} =$	(5	2	4
-----------	----	---	---

			1				$b_0 = 1$	
		0		0			$b_1 = 0$	
	0		1		0		$b_2 = 1$	
1		89		89		1	$b_{3} = 180$	
	0		1		0		$b_4 = 1$	
		0		0			$b_{5} = 0$	
			1				$b_6 = 1$	
$\chi = -176$								

Construction

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CICY : Koszul sequence

Koszul complex

Let
$$X = \{\xi = 0\}$$
 for $\xi \in H^0(\mathbb{P}^n; \mathcal{E})$, where $\mathcal{E} := \mathcal{O}_{\mathbb{P}^n}(d_1) \oplus \cdots \oplus \mathcal{O}_{\mathbb{P}^n}(d_k)$,

$$0 \to \wedge^k \xi^{\vee} \to \wedge^{k-1} \xi^{\vee} \to \dots \to \wedge^2 \xi^{\vee} \to \xi^{\vee} \to \mathcal{O}_{\mathbb{P}^n} \to \mathcal{O}_X \to 0$$

Then

$$E_0^{q,k} = H^q(\mathbb{P}^n; \wedge^k \xi^{\vee}) \Rightarrow H^q(X; \mathcal{O}_X)$$

$$X = \left(\begin{array}{ccc} 5 & 2 & 4 \end{array}\right) \qquad \rightsquigarrow \qquad 0 \rightarrow \mathcal{O}_{\mathbb{P}^{5}}(-6) \rightarrow \mathcal{O}_{\mathbb{P}^{5}}(-2) \oplus \mathcal{O}_{\mathbb{P}^{5}}(-4) \rightarrow \mathcal{O}_{\mathbb{P}^{5}} \rightarrow \mathcal{O}_{X} \rightarrow 0$$

 $E_0^{q,k} = H^q(\mathbb{P}^n; \wedge^k \xi^{\vee}) \qquad k = 2 \qquad k = 1 \qquad k = 0 \qquad H^q(X; \mathcal{O}_X)$



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Example CICY threefold in \mathbb{P}^5 : Koszul sequence

$$X = \left(\begin{array}{ccc} 5 & 2 & 4 \end{array}\right) \xrightarrow{\otimes \Omega^{1}_{\mathbb{P}^{5}}} 0 \to \Omega^{1}_{\mathbb{P}^{5}}(-6) \to \Omega^{1}_{\mathbb{P}^{5}}(-2) \oplus \Omega^{1}_{\mathbb{P}^{5}}(-4) \to \Omega^{1}_{\mathbb{P}^{5}} \to \Omega^{1}_{\mathbb{P}^{5}}|_{X} \to 0$$

Bott formula \rightsquigarrow

Introduction

 $E_0^{q,k} = H^q(\mathbb{P}^n; \Omega^1_{\mathbb{P}^5} \otimes \wedge^k \xi^{\vee}) \qquad k = 2 \qquad k = 1 \qquad k = 0 \qquad H^q(X; \Omega^1_{\mathbb{P}^5}|_X)$

$$q = 0 \qquad 0 \longrightarrow 0 + 0 \longrightarrow 0 - - - - - 0$$

$$q = 1 \qquad 0 \longrightarrow 0 + 0 \longrightarrow 1 - - - - 1$$

$$q = 2 \qquad 0 \longrightarrow 0 + 0 \longrightarrow 0 - - - - 0$$

$$q = 3 \qquad 0 \longrightarrow 0 + 0 \longrightarrow 0 - - - - 35$$

$$q = 4 \qquad 0 \longrightarrow 0 + 0 \longrightarrow 0$$

$$q = 5 \qquad 35 \longrightarrow 0 + 0 \longrightarrow 0$$

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CICY : Bott formula

$$\dim H^q(\mathbb{P}^n; \wedge^p T_{\mathbb{P}^n} \otimes \mathcal{O}_{\mathbb{P}^n}(k)) = \begin{cases} \binom{(k+n+1+p)}{p} \cdot \binom{(k+n)}{n-p} & \text{if } q = 0, \quad k \ge -p \\ 1 & \text{if } q = n-p, \quad k = -(n+1) \\ \binom{(-k-n-2)}{p} \cdot \binom{(-k-p-1)}{n-p} & \text{if } q = n, \quad k \le -(n+p+2) \\ 0 & \text{if } \text{ otherwise} \end{cases}$$

Construction

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 $H^q(X; \Omega^1_X)$

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Example CICY threefold in \mathbb{P}^5 : Koszul sequence

$$X = \left(\begin{array}{ccc} \mathbf{5} & \mathbf{2} & \mathbf{4} \end{array}\right) \quad \rightsquigarrow \quad \mathbf{0} \to \mathcal{N}_{X|\mathbb{P}^{\mathbf{5}}}^{\vee} \to \Omega_{\mathbb{P}^{\mathbf{5}}}^{\mathbf{1}}|_{X} \to \Omega_{X}^{\mathbf{1}} \to \mathbf{0}$$

 $H^q(X; \mathcal{O}_X(-2) \oplus \mathcal{O}_X(-4)) \qquad H^q(X; \Omega^1_{\mathbb{P}^5}|_X)$



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Example CICY threefold in \mathbb{P}^5 : Koszul sequence

$$X = \begin{pmatrix} 5 & 2 & 4 \end{pmatrix} \xrightarrow{\otimes \Omega_{\mathbb{P}^{5}}^{2}} 0 \to \Omega_{\mathbb{P}^{5}}^{2}(-6) \to \Omega_{\mathbb{P}^{5}}^{2}(-2) \oplus \Omega_{\mathbb{P}^{5}}^{2}(-4) \to \Omega_{\mathbb{P}^{5}}^{2} \to \Omega_{\mathbb{P}^{5}}^{2}|_{X} \to 0$$

 $E_0^{q,k} = H^q(\mathbb{P}^n; \Omega^2_{\mathbb{P}^5} \otimes \wedge^k \xi^{\vee}) \qquad k = 2 \qquad k = 1 \qquad k = 0 \qquad H^q(X; \Omega^2_{\mathbb{P}^5}|_X)$





$$X = \left(\begin{array}{ccc} 5 & 2 & 4 \end{array}\right)$$



where

$$\operatorname{Sym}^2(N_{X|\mathbb{P}^5}^{\vee}) = \mathcal{O}_X(-4) \oplus \mathcal{O}_X(-6) \oplus \mathcal{O}_X(-8)$$

Example CICY fivefold in
$$\mathbb{P}^5$$
 : Hodge diamond

Construction

$$X = \left(\begin{array}{ccc} 2 & 1 & 1 & 1 \\ 6 & 0 & 0 & 7 \end{array}\right)$$

Cohomology 000000000000000000000000



$$\chi = -39984$$

Machine Learning

Statistics

Cohomology

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CICY fivefolds : summary

Problems and (possible) solutions:

- supplementary variables required
- if they decouple, solution is unique in the Hodge numbers
- otherwise, consider ineffective splitting
- limited computational resources

Results:

- $\bullet~27\,068$ configuration matrices of dimensions up to 4 \times 4, up to permutations
- ignoring 3 909 of them which are products
- $\bullet\,$ full Hodge diamond computed for 12433 manifolds, $\sim 53,7\%$
- 2375 distinct Hodge diamonds

Statistics •00000000 Machine Learning



2 Construction







Construction

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CICY fivefolds : distribution of Euler number

$$\langle \chi
angle = -11154, 59^{-1296}_{-39984}$$



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CICY fivefolds : distribution of Hodge number $h^{1,1}$

$$\langle h^{1,1}\rangle = 3,57_0^{15}$$



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CICY fivefolds : distribution of Hodge number $h^{1,2}$

$$\langle h^{1,2}
angle = 0,46_0^{66}$$



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CICY fivefolds : distribution of Hodge number $h^{1,3}$

 $\langle h^{1,3} \rangle = 0,84_0^{35}$



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CICY fivefolds : distribution of Hodge number $h^{1,4}$

$$\langle h^{1,4} \rangle = 468,72_{52}^{1667}$$



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CICY fivefolds : distribution of Hodge number $h^{2,2}$

 $\langle h^{2,2} \rangle = 8,9^{510}_0$



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CICY fivefolds : distribution of Hodge number $h^{2,3}$




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CY cohomology : asymptotic behaviour





2 Construction







Introduction	Construction	Cohomology	Statistics	Machine Learning
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Neural net	work			

Input vector



(e.g. $\sigma(x) = \lg(1 + e^x)$ softplus)



Statistics

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Neural network

$$f_i^n = f(W_{ij}^n f_j^{n-1} + b_i^n).$$



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Universal approximation theorem

THEOREM 12 (Universal Approximation Theorem) We have the following approximations by feed-forward NNs:

Arbitrary Width For every continuous function $f : \mathbb{R}^d \to \mathbb{R}^D$, every compact subset $K \subset \mathbb{R}^d$, and every $\epsilon > 0$, there exists [347] a continuous function $f_\epsilon : \mathbb{R}^d \to \mathbb{R}^D$ such that $f_\epsilon = W_2(\sigma(W_1))$, where σ is a fixed continuous function, $W_{1,2}$ affine transformations and composition appropriately defined, so that $\sup_{x \in K} |f(x) - f_\epsilon(x)| < \epsilon$.

Arbitrary Depth Consider a feed-forward NN with n input neurons, m output neuron and an arbitrary number of hidden layers each with n +m + 2 neurons, such that every hidden neuron has activation function φ and every output neuron has activation function the identity ⁸ Then [348], given any vector-valued function f from a compact subset $K \subset$ \mathbb{R}^{m} , and any e > 0, one can find an F, a NN of the above type, so that |F(x) - f(x)| < e for all $x \in K$.



G. Cybenko, Approximation by superpositions of a sigmoidal function, Math. of Control, Signals, and Systems 2 (1989), no. 4, 303–314.



P. Kidger, T. Lyons, Universal Approximation with Deep Narrow Networks, Conference on Learning Theory, arXiv:1905.08539.

⁸Here $\varphi : \mathbb{R} \to \mathbb{R}$ is any non-affine continuous function which is continuously differentiable at least at one point and with non-zero derivative at that point.

Cohomology

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Machine Learning CICY : literature

CICY 3fold	dense	convolutional	convolutional	inception
h ^{1,1}	84%	90%	94%	99%
$h^{2,1}$	-	-	37%	50%

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- L. Rubini, Coomologia di varietà Calabi-Yau ad intersezione completa tramite techiche di machine learning, Tesi di Laurea Magistrale, Università di Firenze, 2023. https://github.com/LapoRubini/ML_CICY3
- E. Hirst, T. Schettini Gherardini, Calabi-Yau four/five/six-folds as \mathbb{P}^n_w hypersurfaces: Machine learning, approximation, and generation, arXiv:2311.17146.

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Machine Learning CICY fivefolds : architectures

• classifier:

 $h^{1,1}$: $N_{4*4}(512, \sigma, \delta_{0.4}, 256, \sigma, \delta_{0.3}, 256, \sigma, 16, S)$,

other: $N_{4*4}(512, \sigma, \delta_{0.4}, 512, \sigma, \delta_{0.3}, 512, \sigma, \delta_{0.3}, 256, \sigma, N_H, S)$

• linear regressor:

 $h^{1,1}$: $N_{4*4}(512, s, 256, s, 128, s, 32, s, 8, s, 1)$

other: N_{4*4}(1024, s, 1024, s, 512, s, 64, s, 16, s, 1)

• convolutional regressor:

 $N_{\textbf{4}*\textbf{4}}(C_{\textbf{5}*\textbf{5}}\textbf{180}, r, BN_{\textbf{0}.\textbf{99}}, C_{\textbf{5}*\textbf{5}}\textbf{100}, r, BN_{\textbf{0}.\textbf{99}}, C_{\textbf{5}*\textbf{5}}\textbf{40}, r, BN_{\textbf{0}.\textbf{99}}, C_{\textbf{5}*\textbf{5}}\textbf{20}, r, BN_{\textbf{0}.\textbf{99}}, \delta_{\textbf{0}.\textbf{4}}, f, \textbf{1}, r)$



H. Erbin, R. Finotello, Machine learning for complete intersection Calabi-Yau manifolds: A methodological study, *Phys. Rev. D* 103 (2021).

Construction

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Machine Learning CICY fivefolds : $h^{1,1}$

$h^{1,1}$	R^2	Accuracy
Classifier	n/a	88%
Linear Regressor	85%	93%
Convolutional Regressor	91%	96%

- For four-folds, accuracy 96%, 93%, 94% respectively
- Number of values of $h^{1,1}$: 12

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Machine Learning CICY fivefolds : $h^{1,2}$

$h^{1,2}$	R^2	Accuracy
Classifier	n/a	98%
Linear Regressor	-ve	83%
Convolutional Regressor	-ve	97%

- Number of values of h^{1,2}: 33
- $h^{1,2} = 0$ for 97, 7%

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Machine Learning CICY fivefolds : $h^{1,3}$

$h^{1,3}$	R^2	Accuracy
Classifier	n/a	96%
Linear Regressor	61%	93%
Convolutional Regressor	79%	95%

- Number of values of h^{1,3}: 34
- $h^{1,2} = 0$ for 95, 7%

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Machine Learning CICY fivefolds : $h^{1,4}$

h ^{1,4}	R^2	Accuracy	Acc w/ 10% Toler
Classifier	n/a	3%	n/a
Linear Regressor	98%	3%	86%
Convolutional Regressor	98%	2%	86%

- Number of values of h^{1,4}: 642 Range: 52 ≤ h^{1,4} ≤ 1667
- Very high R² score

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Machine Learning CICY fivefolds : $h^{2,2}$

h ^{2,2}	R^2	Accuracy
Classifier	n/a	22%
Linear Regressor	26%	25%
Convolutional Regressor	16%	27%

- Wide range
- Most values close to 0

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Machine Learning CICY fivefolds : $h^{2,3}$

h ^{2,3}	R^2	Accuracy	Acc w/ 10% Toler
Classifier	n/a	2.7%	n/a
Linear Regressor	97%	0.2%	77%
Convolutional Regressor	98%	0.1%	85%

- Wide range: $598 \le h^{2,3} \le 18327$
- Very high R² score

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Machine Learning CICY fivefolds : χ

χ	R^2	Accuracy	Acc w/ 10% Toler
Classifier	n/a	3%	n/a
Linear Regressor	50%	0%	0%
Convolutional Regressor	98%	0.04%	83%

- Wide range: $-39984 \le \chi \le -1296$
- Very high R² score



Machine Learning CICY fivefolds : conclusions

- very good results for $h^{1,1}$
- probably guessing $h^{1,2} = 0$ and $h^{1,3} = 0$
- very poor performance for $h^{2,2}$
- ullet regressors are good approximator for $\mathit{h^{1,4}}$, $\mathit{h^{2,3}}$, and χ

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Work in progress...

- construct complete dataset
- extrapolate predictions from low to high Hodge numbers
- investigation across different complex dimensions
- unobserved clustering behaviour
- hints for unknown formulas
- include other topological properties
- approximation methods
- toric CY fivefolds
- non-Kähler CY

• . . .

Thank you!

