Machine Learning and Algebraic Approaches towards Complete Matter Spectra in 4d F-theory

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With M. Cvetič, R. Donagi, L. Lin, M. Liu, F. Rühle - 2007.00009

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 - describes strongly (in g_S) coupled IIB-string theory
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- Global F-theory compactifications: vector-like spectrum hard as non-topological
- $\Rightarrow\,$ How can we control the vector-like spectrum in F-theory?

Motivation and outline

Counting vector-like pairs in F-theory Learning control over the vector-like spectra Summary and Outlook

Outline and strategy

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Revision: Chiral and vector-like spectra in F-theory

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 $\begin{aligned} & \text{Curve} \leftrightarrow \mathcal{C}\left(\mathbf{c}\right) = V\left(\mathcal{P}(\mathbf{c})\right) \text{ hypersurface in } dP_3\\ & \text{Line bundle} \leftrightarrow \mathcal{L}(\mathbf{c}) = \left.\mathcal{O}_{dP_3}(D_L)\right|_{\mathcal{C}(\mathbf{c})} \end{aligned}$

• with machine learning (decision trees)

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- Revision: Chiral and vector-like spectra in F-theory
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- Summary and conclusion

Chiral and vector-like spectra – generalities Chiral and vector-like spectra – in F-theory

Recipe for the Standard Model constructions

• Gauge group $SU(3) \times SU(2) \times U(1)$

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Chiral excess

- Fields: (co)kernel of operator (e.g. $\Delta \phi = 0$)
- Chiral excess: $\chi = ind(D)$ with D a Dirac operator:

 $\ker(D): n imes ext{chiral fields } \phi, \qquad \operatorname{coker}(D): \overline{n} imes ext{anti-chiral fields } \overline{\phi}$

 $\Rightarrow~\chi=n-\overline{n}$ [Atiyah-Singer index theorem]

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String theory (MS)SM constructions with exact chiral spectrum

- $E_8 \times E_8$ [Candelas Horowitz Strominger Witten '85], [Greene Kirklin Miron Ross '86], [Braun He Ovrut Pantev '05], [Bouchard Donagi '05], [Anderson Gray He Lukas '10], ...
- Type II [Berkooz Douglas Leigh '96], [Aldazabal Franco Ibanez Rabadan Uranga '00], [Ibanez Marchesano Rabadan '00], [Blumenhagen Kors Lust Ott '01], [Cvetič Shiu Uranga '01], ...
- F-theory [Krause Mayrhofer Weigand '12], [Cvetič Klevers Mayorga Oehlmann Reuter '15], [Lin Weigand '16], [Cvetič Lin Liu Oehlmann '18], [Cvetič Halverson Lin Liu Tian '19], [Taylor Turner '19], [Raghuram Taylor Turner '19], ...

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Chiral vs. vector-like spectrum

• Higgs doublet ϕ_H corresponds to pair $(\phi, \overline{\phi})$:

Irrep of G_{SM} (n, \overline{n}) χ | Decomposition: Leptons + Higgs

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Elliptic 4-fold Y_4 , gauge group G and irreps R of G

- IIB: Identify profile of axio-dilaton $au = C_0 + e^{i\phi}$ in presence of D7-branes
- $\bullet\,$ Backreaction: Treat τ as complex structure modulus of elliptic curve
- \Rightarrow Singular 4-fold π : $Y_4 \twoheadrightarrow B_3$:
 - Gauge group G: Singularities of Y_4
 - Fields in irrep **R**: Localize on curves $C_{\mathbf{R}} \subseteq B_3$
 - Irrep. **R** of $G: \mathbb{P}^1$ -fibration over C_R matter surface S_R

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Chiral spectrum of irrep R (more recently [Taylor Turner '19], [Raghuram Taylor Turner '19], ...

- Pick flux background $G_4 \in H^{2,2}(Y_4)$
- $\Rightarrow~\chi=\int_{\mathcal{S}_{\mathsf{R}}}\mathcal{G}_{\mathsf{4}}.$ [Donagi/Wijnholt, 09],[Braun/Collinucci/Valandro, 11], [Marsano/Schaefer-Nameki, 11],

[Krause/Mayrhofer/Weigand,11,12], [Grimm/Hayashi, 11], [Cvetič/Grimm/Klevers, 12], [Braun/Grimm/Keitel, 13],

[Cvetič/Grassi/Klevers/Piragua,13], [Borchmann/Mayrhofer/Palti/Weigand, 13], [Lin/Mayrhofer/Till/Weigand, 15], . . .

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Vector-like spectra in F-theory

Gauge potential for field strength G_4

• $\mathcal{G}_4 o \mathcal{A}_3 \in \mathrm{CH}^2(Y_4) \subseteq H^2_D(Y_4,\mathbb{Z}(2))$ [Curio/Donagi, 98], [Donagi/Wijnholt,12,13],

[Anderson/Heckman/Katz, 13], [Intriligator, Jockers, Mayr, Morrison, Plesser '12]

• Consider $\mathcal{L}_{\mathsf{R}} = \pi^*(A_3 \cdot S_{\mathsf{R}}) \otimes \mathcal{O}_{C_{\mathsf{R}},\mathsf{spin}} \in \operatorname{Pic}(C_{\mathsf{R}})$

 $\Rightarrow \mathcal{L}_{\mathsf{R}} \text{ counts vector-like spectra [M.B. Mayrhofer Pehle Weigand '14], [M.B. Mayrhofer Weigand '17], [M.B. '18]}$ chiral fields $\leftrightarrow H^0(\mathcal{C}_{\mathsf{R}}, \mathcal{L}_{\mathsf{R}})$, anti-chiral fields $\leftrightarrow H^1(\mathcal{C}_{\mathsf{R}}, \mathcal{L}_{\mathsf{R}})$.

Typically, $h^i(C_{\mathbf{R}}, \mathcal{L}_{\mathbf{R}})$ hard to determine:

• Non-topological, i.e. deformation $C_{\mathbf{R}} o C'_{\mathbf{R}}$ can lead to jumps

$$h^{i}(\mathcal{C}_{\mathsf{R}},\mathcal{L}_{\mathsf{R}})=(h^{0},h^{1})
ightarrow h^{i}(\mathcal{C}_{\mathsf{R}}^{\prime},\mathcal{L}_{\mathsf{R}}^{\prime})=(h^{0}+a,h^{1}+a)$$

 \Rightarrow Higgs pairs/exotic matter

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Example: Line bundles in F-theory (MS)SM

curve	g	\mathcal{L}	d	d BN-theory		
$C_{(3,2)_{1/6}} = V(s_3, s_9)$	10	$\mathcal{L}_{(3,2)_{1/6}}^{\otimes 36} = \mathcal{K}_{\mathcal{C}_{(3,2)_{1/6}}}^{\otimes 24}$	12	h ⁰ 3	<i>h</i> ¹ 0	ho10
				4 5	1 2	6 0
$C_{(1,2)_{-1/2}} =$	82	$\mathcal{L}_{(1,2)_{-1/2}}^{\otimes 36} = \mathcal{K}_{\mathcal{C}_{(1,2)_{-1/2}}}^{\otimes 22} \otimes \mathcal{O}_{\mathcal{C}_{(1,2)_{-1/2}}}(-30 \cdot Y_1)$	84	h ⁰	h^1	ρ
				3	0	82
				4	1	78
$V(s_3, s_2s_5^2 + s_1(s_1s_9 - s_5s_6))$				÷	÷	÷
				10	7	12
$C_{(\overline{3},1)_{-2/3}} = V(s_5,s_9)$						
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Machine learning approach Analytic approach

F-theory and heterotic challenges with vector-like spectra

- In heterotic compactifications [Anderson Gray Lukas Palti '10 & '11 and subsequent works]
 - X is (favourable) CICY 3-fold with known Pic(X)
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- Too ambitious to solve all at the same time.

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 - ⇒ Model as coherent sheaf and compute vector-like spectrum by Ext-groups [M.B., 17], [M.B./Posur, 19]
 - In practice very challenging to tell if divisors give isomorphic line bundles.
 - **5** Deformations of $C_{\mathbf{R}}$ and $L_{\mathbf{R}}$ can change vector-like spectrum.
 - **(**In many (MS)SM constructions: L_R is root bundle (~ generalized spin-bundle).
- Too ambitious to solve all at the same time.
- \Rightarrow Focus on simpler situation first, then apply these lessons to involved scenarios.

Machine learning approach Analytic approach

Strategy

- Ignore root and non-pullback issues.
- Investigate how deformations of $C_{\mathbf{R}}$ changes vector-like spectrum.

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Tasks:

- Find $h^0(C(\mathbf{c}), \mathcal{L}(\mathbf{c})) \equiv h^0(\mathbf{c})$ as function of the parameters \mathbf{c} .
- Identify curve geometries for which $h^0(C(\mathbf{c}), \mathcal{L}(\mathbf{c}))$ jumps.

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- Approaches:
 - Use software to compute h⁰(c) and interpret the results with machine learning. (Surge of similar works, but mostly suited for heterotic ST [Ruehle, 17], [Klaewer/Schlechter, 18], [Larfors/Schneider, 19,20], [Brodie/Constantin/Deen/Lukas, 19])
 - **2** Find $h^0(\mathbf{c})$ from Koszul resolutions and interpret it with Brill-Noether theory.

Machine learning approach Analytic approach

Machine learning approach Analytic approach

Generating the data set

• Use software to compute $h^0(C(\mathbf{c}), \mathcal{L})$ for different parameters \mathbf{c} :

Machine learning approach Analytic approach

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- Interpret results with binary decision trees.

Machine learning approach Analytic approach

Decision trees

- Decision tree: directed, connected graph with unique root node.
- Binary tree: each node has either 0 or 2 sub-nodes.
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Machine learning approach Analytic approach

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$$c_j \leq \kappa_j^{(n)}$$
: input assigned to left sub-node,
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- For training: minimize Gini impurity for given training data.



Machine learning approach Analytic approach

The data, features and classes

- Data:
 - Hypersurface curves $C(\mathbf{c}) = V(P(\mathbf{c}))$ in dP_3 with $1 \le g \le 6$.
 - Coefficients $\mathbf{c} = \{c_k\}$ with $c_k \in \{0, 1\}$.
 - For each $C(\mathbf{c})$, consider 13 line bundles $L \in \operatorname{Pic}(dP_3)$ and compute $h^0(C(\mathbf{c}), L|_{C(\mathbf{c})})$
 - g = 1: Only 127 data points per bundle *L*.
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 \Rightarrow Train tree to make implication 'feature' \Rightarrow 'class' (training-testing ratio: 90:10).

Machine learning approach Analytic approach

Example of tree trained on split-type (g = 3, d = 3)



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Average accuracy



Average accuracy vs genus for different features

Machine learning approach Analytic approach

Interpretation

- Training on coefficients:
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Machine learning approach Analytic approach

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 - work surprisingly well,
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 - $\Rightarrow\,$ Intuitive understanding and extrapologication to higher genus possible!
 - Lesson: $h^0(C(\mathbf{c}), L|_{C(\mathbf{c})})$ more likely to jump if $C(\mathbf{c}) = \widetilde{C}(\mathbf{c}) \cup \mathbb{P}^1$.

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- Failure of topological criteria:
 - Other sources/origins of jumps in cohomology.
 - Most likely under-represented due to bias in data set ($\leftrightarrow c_i \in \{0,1\}$).

Machine learning approach Analytic approach

Application to F-theory GUT model

- Geometry of 4-fold:
 - SU(5) supported on $S\cong dP_3\subseteq B_3$ [Beasley Heckman Vafa I&II '09]
 - U(1)-restricted Tate model Grimm/Weigand, '10]
 - \Rightarrow Explicit fourfold $Y_4 \twoheadrightarrow B_3$ with SU(5) imes U(1) gauge symmetry in [M.B., '17]
- Chiral spectrum:

$$\chi(\mathbf{10}_1) = 3$$
, $\chi(\mathbf{5}_{-2}) = -18$, $\chi(\mathbf{5}_3) = 15$.

• Focus on $C_{\mathbf{5}_3} \equiv C$:

$$g = 24$$
, $\deg(\mathcal{L}_{\mathbf{5}_3}) = 38$, 44 coefficients c_i .

- Study splittings $C \to \widetilde{C} \cup \mathbb{P}^1$ where \mathbb{P}^1 is one of the 6 rigid divisors in dP_3 .
 - $E_{1,2}$ lead to jumps. They satisfy $L \cdot E_{1,2} < -1$.
 - Splitting off combinations of $E_{1,2}$ gives $h^0 \in \{15, 17, 18, 19, 20, 21\}$.
 - Cannot get $h^0 = 16$ in this way!

Machine learning approach Analytic approach

Rational from machine learning approach:

- What we did learn:
 - Oftentimes, topological criteria sufficient to engineer jumps.
 - In particular: $C \to \widetilde{C} \cup \mathbb{P}^1$ with $\deg(L|_{\mathbb{P}^1}) < -1$ likely to give jump.
 - $\Rightarrow\,$ Quick and easy application to high genus curves.
 - Example: Splits of g = 24 curve in F-theory toy model: $h^0 \in \{15, 17, 18, 19, 20, 21\}$.

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 - Example: Splits of g = 24 curve in F-theory toy model: $h^0 \in \{15, 17, 18, 19, 20, 21\}$.
- What we did **not** learn why does that work?
 - Why do the splittings $C \to \widetilde{C} \cup \mathbb{P}^1$ lead to jumps?
 - Why can we not reach $h^0 = 16$ in the previous example?
 - Do other splittings $C \rightarrow C_1 \cup C_2$ lead to jumps?
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 \Rightarrow Answers follow from Koszul resolution, h^0 -stratifications and Brill-Noether theory.

Machine learning approach Analytic approach

How to find $h^0(C(\mathbf{c}), \mathcal{L}) \equiv h^0(\mathbf{c})$ in theory?

• Pullback line bundle admits Koszul resolution:

$$0 \to \mathcal{O}_{dP_3}(D_L - D_C) \xrightarrow{P(\mathbf{c})} \mathcal{O}_{dP_3}(D_L) \to \mathcal{L} \to 0$$

2 Obtain long exact sequence in sheaf cohomology:

$$0 \longrightarrow H^{0}(D_{L} - D_{C}) \longrightarrow H^{0}(D_{L}) \longrightarrow H^{0}(\mathcal{L})$$

$$(H^{1}(D_{L} - D_{C}) \longrightarrow H^{1}(D_{L}) \longrightarrow H^{1}(\mathcal{L}))$$

$$(H^{2}(D_{L} - D_{C}) \longrightarrow H^{2}(D_{L}) \longrightarrow 0 \longrightarrow 0$$

Sometimes: $0 \to H^0(\mathcal{L}) \to H^1(D_L - D_C) \xrightarrow{M_{\varphi}(\mathbf{c})} H^1(D_L) \to H^1(\mathcal{L}) \to 0$ By exactness: $h^0(\mathcal{L}) = \ker(M_{\varphi}(\mathbf{c}))$ Study ker $(M_{\omega}(\mathbf{c}))$ as function of complex structure \mathbf{c}

Machine learning approach Analytic approach

Example: g = 3, $\chi = 1$ (d = 3)

•
$$C(\mathbf{c}) = V(P(\mathbf{c}))$$
 and $P(\mathbf{c}) = c_1 x_1^3 x_2^3 x_3^2 x_4 + \dots + c_{12} x_3^2 x_4 x_5^3 x_6^3$
• For $D_L = H + 2E_1 - 2E_2 - E_3$ find

$$0 o H^0(\mathcal{L}) o \mathbb{C}^3 \xrightarrow{M_{\varphi}(\mathbf{c})} \mathbb{C}^2 o H^1(\mathcal{L}) o 0 \,, \quad M_{\varphi} = \left(\begin{smallmatrix} c_3 & c_2 & c_1 \\ 0 & c_{12} & c_{11} \end{smallmatrix}
ight)$$

h⁰(L) = 3 - rk(M_φ(c)) & stratification of curve geometries:

$\operatorname{rk}(M_\varphi)$	explicit condition	curve splitting
2	$(c_3c_{11}, c_3c_{12}, c_2c_{11} - c_1c_{12}) \neq 0$	C^1
1	$c_3 = 0, \ c_2 c_{11} - c_1 c_{12} = 0$	<i>C</i> ²
1	$c_1=c_2=c_3=0$	$B_2 \cup \mathbb{P}^1_b$
1	$c_{11} = c_{12} = 0$	$\mathbb{P}^1_{a}\cup \ddot{B_1}$
0	$c_1 = c_2 = c_3 = c_{11} = c_{12} = 0$	$\mathbb{P}^1_a \cup A \cup \mathbb{P}^1_b$

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Machine learning approach Analytic approach

Stratification diagram



Types of jumps

- Brill-Noether theory: C^2 smooth, irreducible but line bundle divisor special
- Curve splittings: Factoring off \mathbb{P}^1_a , \mathbb{P}^1_b leads to jump

Machine learning approach Analytic approach

Example 2:
$$g = 5$$
, $\chi = 0$ ($d = 4$)

•
$$P(\mathbf{c}) = c_1 x_1^3 x_2^4 x_3^2 x_4^2 + \dots + c_{16} x_3^3 x_4 x_5^4 x_6^3$$

- $D_L = H + E_1 4E_2 + E_3$
- Koszul resolution gives

$$egin{aligned} & h^0(\mathcal{L}) = 7 - \mathrm{rk}(\mathcal{M}_arphi(\mathbf{c})) \ & \mathcal{M}_arphi = \left(egin{aligned} & c_{15} & c_{11} & c_7 & 0 & 0 & 0 & 0 \ & 0 & c_{10} & c_6 & c_3 & c_{11} & c_7 & 0 \ & c_{12} & c_6 & c_3 & 0 & c_7 & 0 & 0 \ & 0 & c_5 & c_2 & 0 & c_6 & c_3 & c_7 \ & c_8 & c_2 & 0 & 0 & c_3 & 0 & 0 \ & 0 & c_{14} & c_{11} & c_7 & 0 & 0 & 0 \ & 0 & c_1 & 0 & 0 & c_2 & 0 & c_3 \end{array}
ight) \end{aligned}$$

 \Rightarrow Study $\operatorname{rk}(M_{\varphi}(\mathbf{c}))$ as function of \mathbf{c}



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Machine learning approach Analytic approach

Brill-Noether theory [1874 Brill, Noether] - more modern exposition in [Mumford '75], [Griffiths, Harris '94] ...

Example on torus $C_1 \cong \mathbb{C}/\Lambda = \operatorname{Jac}(C_1)$



$$h^0(\mathcal{O}_{C_1}(p-q)) = 0 \quad \to \quad h^0(\mathcal{O}_{C_1}(0)) = 1$$

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General picture

• Abel-Jacobi map gives $\varphi_d \colon \operatorname{Div}_d(\mathcal{C}) \to \operatorname{Jac}(\mathcal{C}) \cong \mathbb{C}^g / \Lambda$

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$$G_d^n = \{ \varphi_d(\mathcal{L}), h^0(\mathcal{C}, \mathcal{L}) = n \} \subseteq \operatorname{Jac}(\mathcal{C})$$

- dim $G_d^n \ge \rho(d, n, g) = g n \cdot (n + \chi)$
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eq 0\}\ &G_0^1 &= \{\mathcal{L} \;,\; d=0,\; n=1\}\ &\cong \{q=0\in \mathbb{C}/\Lambda\} \end{aligned}$$

General picture

• Abel-Jacobi map gives $\varphi_d \colon \operatorname{Div}_d(\mathcal{C}) \to \operatorname{Jac}(\mathcal{C}) \cong \mathbb{C}^g / \Lambda$

•
$$G_d^n = \{\varphi_d(\mathcal{L}), h^0(\mathcal{C}, \mathcal{L}) = n\} \subseteq \operatorname{Jac}(\mathcal{C})$$

- dim $G_d^n \ge \rho(d, n, g) = g n \cdot (n + \chi)$
- $\dim G_d^n =
 ho$ for generic curves [1980 Griffiths, Harris]
- \Rightarrow Upper bound for h^0 on generic curves [Watari, 16]

$$\begin{array}{c|c|c} h^0 & h^1 & \rho \\ \hline 0 & 0 & 1 \\ 1 & 1 & 0 \\ 2 & 2 & -3 \\ \end{array}$$

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Machine learning approach Analytic approach

Gluing *local* sections



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Gluing *local* sections II



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 - Lead-offs:
 - Sufficient criteria for jumps
 - **2** Algorithmic h^0 -spectrum estimate

Machine learning approach Analytic approach

Sufficient criteria for jumps

Let S be a smooth surface, $L \in Pic(S)$ a line bundle, and |C| a linear system of curves on S with smooth general member C. Consider a special member $C_1 \cup C_2$ s.t. C_1 , C_2 meet transversely in $C_1 \cdot C_2 > 0$ distinct points.

Machine learning approach Analytic approach

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• Let $N_i = h^0(C_i, \mathcal{L}|_{C_i})$. Then

$$h^{0}(C_{1} \cup C_{2}, L|_{C_{1} \cup C_{2}}) \geq N_{1} + N_{2} - C_{1} \cdot C_{2}.$$

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• Assume that C_1 , C_2 are smooth curves of genus g_1 , g_2 , $h^1(C, L|_C) = 0$, $\deg(L|_{C_2}) > 2g_2 - 2$ and $\deg(L|_{C_1}) < \min\{0, g_1 - 1\}$. Then

$$h^0\left(\left. C_1 \cup C_2, \left. L \right|_{C_1 \cup C_2}
ight) - h^0\left(\left. C, \left. L \right|_C
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Machine learning approach Analytic approach



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Algorithmic estimate for h^0 -spectrum



https://github.com/homalg-project/ToricVarieties_project

- Estimate *h*⁰-spectrum from lower bounds at **subset of nodes**.
- Implemented in package H0Approximator with M. Liu.

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- Caveat: Check that \widetilde{C} is irreducible.

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- Insights from simplified analysis of pullback bundles in dP_3 :
 - Jumps originate from interplay between curve splittings and Brill-Noether theory
 - Formulate sufficient conditions for jumps to happen
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- Take away message:

Recipe for additional vector-like pair: Factor $C \to \widetilde{C} \cup \mathbb{P}^1$ with $\deg(L|_{\mathbb{P}^1}) < -1$.

curve	g	\mathcal{L}	d	BN-theory		
$C_{(3,2)_{1/6}} = V(s_3, s_9)$	10	$\mathcal{L}_{(3,2)_{1/6}}^{\otimes 36} = \mathcal{K}_{\mathcal{C}_{(3,2)_{1/6}}}^{\otimes 24}$	12	h ⁰ 3 4 5	<i>h</i> ¹ 0 1 2	ρ 10 6 0
$C_{(1,2)_{-1/2}} = V\left(s_3, s_2s_5^2 + s_1(s_1s_9 - s_5s_6)\right)$	82	$\mathcal{L}_{(1,2)_{-1/2}}^{\otimes 36} = \mathcal{K}_{\mathcal{C}_{(1,2)_{-1/2}}}^{\otimes 22} \otimes \mathcal{O}_{\mathcal{C}_{(1,2)_{-1/2}}}(-30 \cdot Y_1)$	84	<i>h</i> ⁰ 3 4 ⋮ 10	<i>h</i> ¹ 0 1 ∶ 7	ho ho ho ho ho ho ho ho ho ho
$C_{(\overline{3},1)_{-2/3}} = V(s_5,s_9)$						
:	•					

Outlook: Back to F-theory (MS)SM constructions II

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- Origin of root bundles:
 - $G_4 \in H^{2,2}_{\mathbb{Q}}(Y_4)$: Associated 'gauge field' $A_{\mathbb{Q}} \in \mathrm{CH}^2_{\mathbb{Q}}(Y_4)$.
 - \Rightarrow $A_{\mathbb{Q}}$ does not uniquely fix vector-like spectrum.
 - \Rightarrow Wilson line(s) in intermediate Jacobian of Y₄ as additional datum?

Broader outlook

- Current technical extensions for (MS)SM model building:
 - non-pullback/root bundles
 - stratification for several curves in one global F-theory model
- Conceptual:
 - Vector-like spectra for pseudo-real representations
 - Non-vertical G₄ (flux moduli dependence!)
 - (Geometric) symmetries protecting vector-like pairs
- Further applications:
 - (S)CFTs
 - swampland program

Thank you for your attention!

