# A numerical toolkit for the likelihood correspondence

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  - https://sites.google.com/wisc.edu/jose/
- Workshop on Computational and Applied Enumerative Geometry (The Fields Institute)
  - June 3 7, 2024

#### Organizers

- Taylor Brysiewicz Western University
- Luis Garcia Puente Colorado College
- Nickolas Hein Benedictine College
- Jordy Lopez Garcia Texas A&M University
- Kevin Purbhoo University of Waterloo
- Goal: Discuss our main character (likelihood correspondence) as a multiprojective variety with a (long term) view towards understanding biology (long branch attraction)

#### Outline

- Algebraic statistics: Invitation, ML degrees, likelihood geometry and maximum likelihood estimation
- Numerical toolkit for a biprojective variety (bidegree geometrically)
- Applications



### Who are you, what do you do?

Little did we realize ...

#### MR4297926 - Solving decomposable sparse systems

Brysiewicz, Taylor; Rodriguez, Jose Israel; Sottile, Frank; Yahl, **Thomas** 

Numer. Algorithms 88 (2021), no. 1, 453-474.

#### MR4285764 - Decomposable sparse polynomial systems

Brysiewicz, Taylor; Rodriguez, Jose Israel; Sottile, Frank; Yahl, Thomas

J. Softw. Algebra Geom. **11** (2021), no. 1, 53–59.

#### MR3810571 - Trace test

Leykin, Anton; Rodriguez, Jose Israel; Sottile, Frank Arnold Math. J. 4 (2018), no. 1, 113–125.

#### **MR**4166467 - A numerical toolkit for multiprojective varieties

Hauenstein, Jonathan D.; Leykin, Anton; Rodriguez, Jose Israel; Sottile, Frank

Math. Comp. **90** (2021), no. 327, 413–440.

(Reviewer: Dayton, Barry H.)

#### MR3833644 - Numerical computation of Galois groups

Hauenstein, Jonathan D.; Rodriguez, Jose Israel; Sottile, Frank Found. Comput. Math. 18 (2018), no. 4, 867–890.

(Reviewer: Dayton, Barry H.)



### Algebraic Statistics

Interdisciplinary field with applications

- **Textbooks**: multiple to choose from
  - Algebraic geometry
  - Combinatorics
  - Commutative algebra
  - More geometry
- Dictionary between algebra and statistics
  - Computation drives these connections
    - Symbolic and numerical

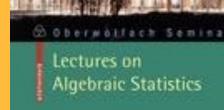
Satoshi Aoki
Hisayuki Hara
Akimichi Takemura

Markov Bases in Algebraic Statistics Copplighted Martinets
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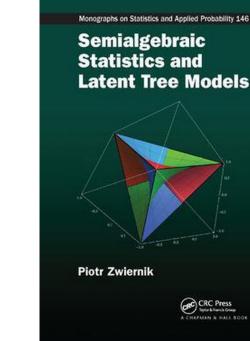
Algebraic Statistics Seth Sullivant



Matthias Drigor Bernd Sturmfers Sett Suttivent





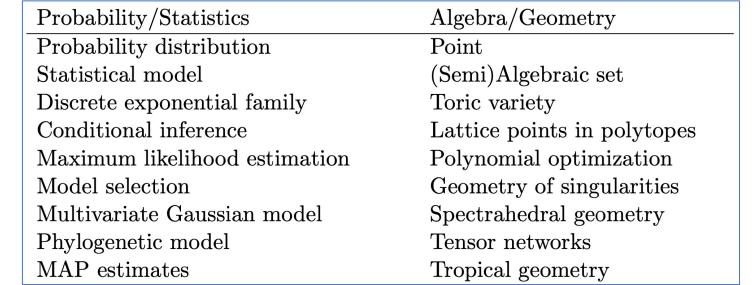


#### ALGEBRAIC STATISTICS FOR COMPUTATIONAL BIOLOGY



EDITED BY
LIOR PACHTER
BERND STURMFELS

CAMBRIDGE



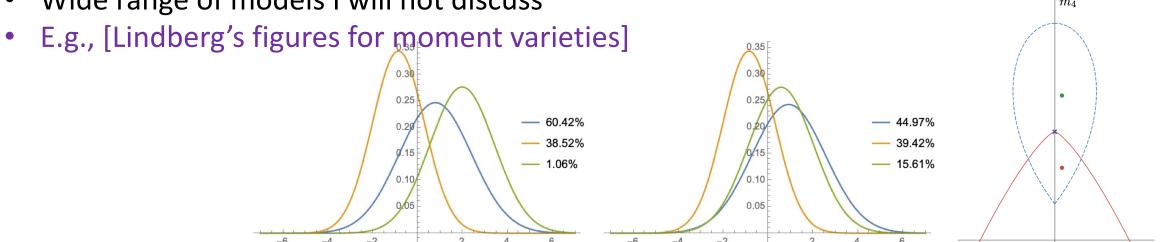


### Algebraic Statistical Model (Discrete models)

A variety restricted to a probability simplex

- Probability simplex  $\Delta_n$ 
  - Set of points with nonnegative coordinates summing to one
  - i-th coordinate is the probability of observing event i
- From a variety **construct** an algebraic statistical model:
  - Restrict an affine variety to  $\Delta_n$
  - For a projective variety, the hyperplane at infinity is given by the sum of coordinates
- Often: the models have a parametric description
  - Finding an implicit description is phrased as an elimination problem
- Remark: we take a narrow notion of an algebraic statistical model today

Wide range of models I will not discuss



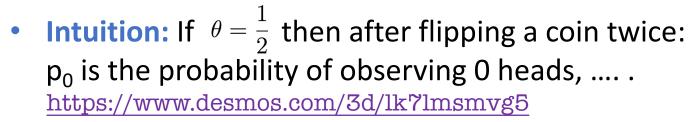


### An Example: Hardy-Weinberg Curve

Algebraic statistical model: Restricting a curve X to the probability simplex using elimination.

Algebraic curve X parameterized by

$$\mathbb{R} \to \mathbb{R}^3$$
,  $\theta \mapsto (p_0, p_1, p_2) = ((1 - \theta)^2, 2\theta(1 - \theta), \theta^2)$ 



- Implicit relations:
  - Find algebraic constraints on  $(p_0, p_1, p_2)$
- Inspection: [board]





•(Sept 18-22, 2023): "Invitation to algebraic statistics and applications"

•Jose Rodriguez, Serkan Hosten, Kaie Kubjas, Thomas Kahle, Fatemeh Mohammadi, Guillaume A. Pouliot.

•(Oct 9-13, 2023) Alg Stat for Ecological and Biological Systems

•Elizabeth Gross, Elina Robeva, Seth Sullivant, Eliana Duarte.

•(Nov 6-10, 2023) Algebraic Economics

•Sonja Petrović, Piotr Zwiernik, Ngoc Tran, Mladen Kolar.

•(Dec 11-15) New directions in algebraic statistics:

Statistical Learning, Neural networks, Bayesian statistics

•Mathias Drton, Lek-Heng Lim, Jonathan Hauenstein, Debdeep Pati.

Data & Information •

**Uncertainty Quantification** 

# Algebraic Statistics and Our Changing World

## **New Methods for New Challenges**

September 18 — December 15, 2023



#### **Mathias Drton**

Technical University of Munich



#### **Elizabeth Gross**

University of Hawai'i at Mānoa



**Lek-Heng Lim**University of Chicago

**BACKGROUND:** 

**Invitation To Alg Stat recordings:** 

https://www.imsi.institute/activities/invitationto-algebraic-statistics-and-applications/



#### Sonja Petrović

Illinois Institute of Technology



#### Elina Robeva

University of British Columbia



#### Jose Rodriguez University of Wisconsin –

Madison



#### Piotr Zwiernik

University of Toronto & Pompeu Fabra University



#### **Bernd Sturmfels**

MPI Leipzig & UC Berkeley



Models + Data = Likelihood correspondence



### An Example: Hardy-Weinberg Curve

Continuing on with the example: maximum likelihood estimation

Algebraic curve X parameterized by

$$\mathbb{R} \to \mathbb{R}^3$$
,  $\theta \mapsto (p_0, p_1, p_2) = ((1 - \theta)^2, 2\theta(1 - \theta), \theta^2)$ 

- Intuition: If  $\theta = \frac{1}{2}$  then after flipping a coin twice:  $p_0$  is the probability of observing 0 heads, .... . https://www.desmos.com/3d/lk?lmsmvg5
- Implicit relations:

Find algebraic constraints on  $(p_0, p_1, p_2)$ 

- Inspection: [board]
- Biased coin is flipped two times
  - Unknown: the probability of a heads  $\theta$ .
- Aim: Recover (1) the parameter θ and
  (2) probability of observing k=0,1,2 heads
- Approach: Maximum likelihood estimation



- Data is iid: (Sample size N=10)
   HH, HH, HT, TH, TT, TT, HT, TT, TT
- Summarize as the data vector: (5,3,2)
- For generic data, this likelihood function [board] has a unique critical point
- ML degree of the model
  - counts critical points
  - # of solutions to likelihood eqs
  - Upper bound on the algebraic complexity of MLE
- ML degree one example

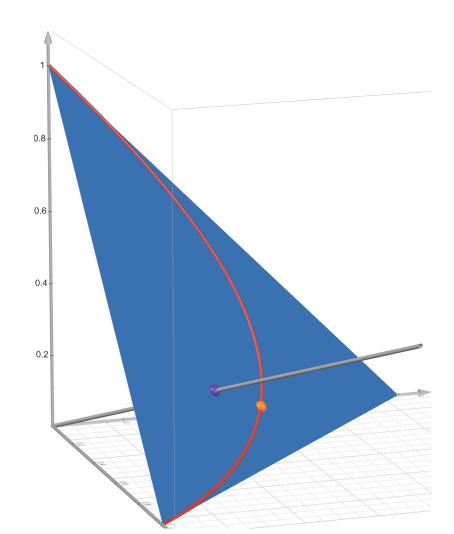
https://www.desmos.com/3d/cjidlbag?r



### Likelihood correspondence

Capture the geometry of maximum likelihood estimation

- Likelihood correspondence: encapsulates the geometry of mle (optimization problem)
  - Remark: although subtleties for boundary components and singular locus
- The likelihood correspondence is a biprojective variety
  - I.e., a multiprojective variety
- In equations: [see blackboard]



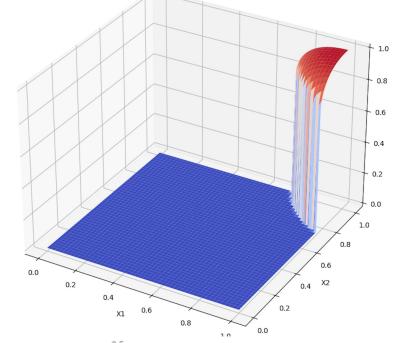


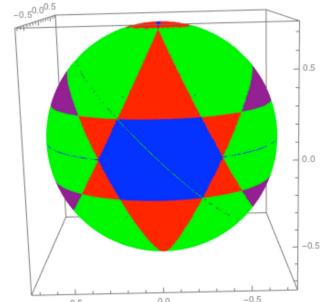
Multidegrees through a geometric lens

# **/**

Multiprojective applications + projective (starter) toolkit

- Broader Impactful Applications
  - Computer vision
  - Power systems
  - Economics
- Numerical Toolkit (Projective starter pack) [Blackboard]
  - Idea (Bertini's Thm): intersect with a general linear space of complimentary dimension
    - Read off invariants like degree and dimension
    - Sampling
    - Component membership test
- Trust building: a trace test for completeness
  - Irreducible curve in the plane (on an affine chart) [Blackboard]
- Trace Test Thm: The sums are a linear function in t.
   If we only use continuation on a proper subset of intersection points,
  - the resulting sums are **not** a linear function in *t*.
    - Irreducibility of the curve is crucial, as is genericity of linear's.





# **//**

### Multidegrees

- Recall projective setting:
  - **Input**: integer *c*
  - Construct a general c dimensional linear space
  - Output: the number of isolated points in intersection
  - **Idea**: The degree of the union of irreducible codimension *c* components
- Biprojective setting:
  - Input (a,b) integers such that a+b=c
  - Construct (A,B) general linear spaces with dimension (a,b)=(dim(A), dim(B))
  - Output: the number of isolated points in intersection
  - Convenient multidegree notation:
    - polynomial with integer coefficients counting intersection points

$$d_{(c,0)} \cdot \mathbf{p}^c + d_{(c-1,1)} \cdot \mathbf{p}^{c-1}\mathbf{u} + \dots + d_{(1,c-1)} \cdot \mathbf{p}\mathbf{u}^{c-1} + d_{(0,c)} \cdot \mathbf{u}^c$$

Example: Irreducible curve [Blackboard]

$$V(xu^2 - 36)$$





### A trace test by example

- Consider  $\mathbb{C} \times \mathbb{C}$  as an affine chart of  $\mathbb{P}^1 \times \mathbb{P}^1$
- For t=0, three points of intersection:

$$\mathbb{V}(xu^2 - 36) \cap \mathbb{V}((x-1)(u-3) + 3t)$$

- Irreducible curve  $V(xu^2-36)$
- Union of linear's:  $\mathbb{V}(x-1) \cup \mathbb{V}(u-3)$
- For  $(x,u) \in \mathbb{C} \times \mathbb{C}$  construct the

rank 1 matrix 
$$\begin{bmatrix} x \\ 2+3x \end{bmatrix} \begin{bmatrix} u \\ 5+7u \end{bmatrix}^T \in \mathbb{P}^3$$

The points give matrices that we sum:

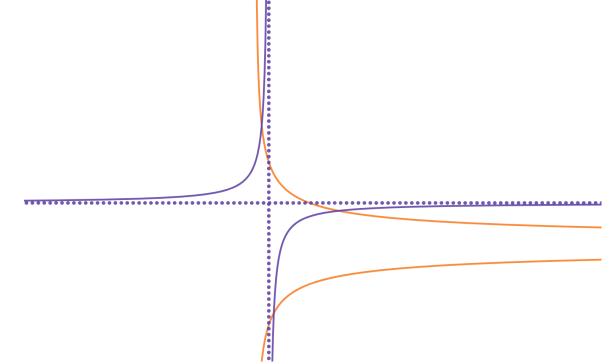
$$\begin{bmatrix} 1 \\ 5 \end{bmatrix} \begin{bmatrix} 6 \\ 47 \end{bmatrix}^T + \begin{bmatrix} 1 \\ 5 \end{bmatrix} \begin{bmatrix} -6 \\ -37 \end{bmatrix}^T + \begin{bmatrix} 4 \\ 14 \end{bmatrix} \begin{bmatrix} 3 \\ 26 \end{bmatrix}^T = \begin{bmatrix} 12 & 114 \\ 42 & 414 \end{bmatrix}$$

- Continuation: vary t from 0 to an integer.
  - Get three new points; Get three new matrices; Get their sum.

$$t = 0$$

$$12 \quad 114$$

$$\begin{bmatrix} 12 & 124 \\ 48 & 486 \end{bmatrix}$$



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- Thm: The sums are a linear function in t.
- If we only use continuation on a proper subset of intersection points, the resulting sums are **not** a linear function in t.
  - Irreducibility of the curve is crucial, as is genericity of linear's.
- Takeaway: verifies completeness of a pair of multidegrees.
  - Generalizes so long as you can restrict your positive dimensional variety to the curve case
    - Issue: Cartesian products of curves

# Likelihood correspondence

Bidegrees for polynomial optimization



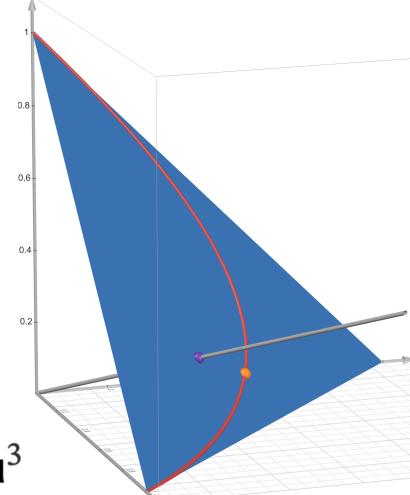
### Likelihood correspondence (Continued)

Capture the geometry of maximum likelihood estimation

- **Likelihood correspondence**: encapsulates the geometry of mle (optimization problem)
  - **Remark**: although subtleties for boundary components and singular locus
- The likelihood correspondence is a biprojective variety
  - I.e., a multiprojective variety
- In equations: [see blackboard]
- What is the multidegree of our red curve example?
  - ML degree is 1
  - IVIL degree is 1  $p^2 + 2pu$  The model's degree is 2.
- 2x2x2 rank one tensors: ML degree one; Degree of model is 6
  - Bidegree of likelihood correspondence

$$p^7 + 3p^6u + 6p^5u^2 + 6p^4u^3$$

- Restricted to a general hyperplane: ML degree is 15
  - Further restricted to another hyperplane: ML degree is 18
- **Sectional ML degree**  $p^7 + 15p^6u + 18p^5u^2 + 6p^4u^3$





### Huh-Sturmfels Involution

[HS] Assuming the model is smooth, given the bidegree of the likelihood correspondence
 produce the sectional ML degrees and vice versa

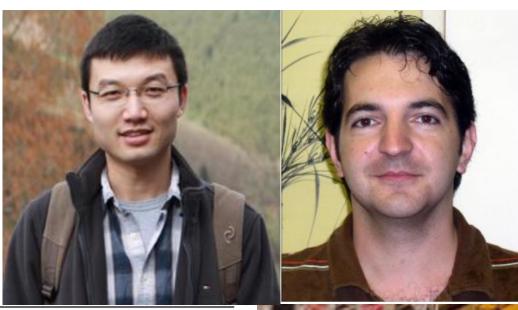
$$B_Y(\mathsf{p},\mathsf{u}) = \frac{\mathsf{u} \cdot S_Y(\mathsf{p},\mathsf{u}-\mathsf{p}) - \mathsf{p} \cdot S_Y(\mathsf{p},0)}{\mathsf{u}-\mathsf{p}}$$

$$S_Y(p, u) = \frac{u \cdot B_Y(p, u + p) + p \cdot B_Y(p, 0)}{u + p}$$

• Our contribution: extend to singular situation

**TABLE 2** ML Bidegree for rank one tensors.

$k = \dim(Y_k)$	$n = 2^k - 1$	$oldsymbol{B}_{Y_k}$ and $oldsymbol{S}_{Y_k}$
2	3	$p^3 + 2 p^2 u + 2 p u^2$
		$p^3 + 4 p^2 u + 2 p u^2$
3	7	$p^7 + 3p^6u + 6p^5u^2 + 6p^4u^3$
		$p^7 + 15p^6u + 18p^5u^2 + 6p^4u^3$
4	15	$p^{15} + 4p^{14}u + 12p^{13}u^2 + 24p^{12}u^3 + 24p^{11}u^4$
		$p^{15} + 64p^{14}u + 132p^{13}u^2 + 96p^{12}u^3 + 24p^{11}u^4$





#### **Program Co-Chairs:** Sonja Petrović Carina Curto





#### **SIAM Activity Group on Algebraic Geometry**

This activity group brings together researchers who use algebraic geometry in industrial and applied mathematics. We welcome participation from theoretical mathematical areas and those areas falling under the broadly interpreted notion of algebraic geometry and its applications.

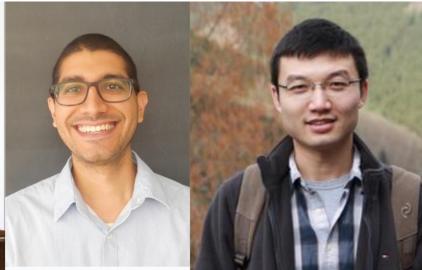
### SIAM AG25 at University of Wisconsin --- Madison

July 7 - 11, 2025

#### **Local Organizers:**

Gheorghe Craciun, Laurentiu Maxim, Jose Israel Rodriguez, **Botong Wang** 







### 3x3 Matrices with rank at most two

These correspond to a mixture model from statistics

- The ML degree is 10
  - Given a generic 3x3 data matrix, the respective likelihood function has 10 critical points
- The ML bidegree is

$$(10p^8 + 24p^7u + \cdots) = (6p^8 + 12p^7u + \cdots) + (4p^8 + 12p^7u + \cdots)$$

- Symmetrize the data matrix to pass to the right hand side.
- Idea: Use coefficient parameter homotopy to test
  - Take data to a generic subvariety and see how many (if any!) critical points follow suit
- Elizabeth Gross and taking data to zero

ML ta	ble o	$f 4 \times 4$	rank 2 m	atrices	ML ta	ble o	$f 4 \times 4$	rank 3 m	atrices
$R \backslash \backslash S$	{}	{11}	$\{11, 44\}$	$\{11, 22, 44\}$	$R \backslash \backslash S$	{}	{11}	$\{11, 44\}$	$\{11, 22, 44\}$
{}	191	118	76	51	{}	191	73	31	14
{11}		73	42	25	{11}		118	42	17
$\{22\}$				25	$\{22\}$				17
$\{44\}$			42	25	$\{44\}$			42	17
$\{11, 22\}$				17	$\{11, 22\}$				25
$\{11, 44\}$			31	17	$\{11, 44\}$			76	25
$\{22, 44\}$				17	$\{22,44\}$				25
$\{11, 22, 44\}$				14	$\{11, 22, 44\}$				51

# **/**

### Offshoots and new directions

- Putting into practice
  - U-generation (Tim Duff and Anton Leykin)
    - Implementation: Equation by equation methods for solving polynomial systems
- Polynomial rings in infinitely many variables
- Conormal varieties are dimension n
  - Equation by equation method?
- Applications:
  - Long branch attraction (Max Hill, Wisconsin -> UC Riverside -> ICERM -> U of Hawaii)
    - Coefficient parameter homotopy and semi-algebraic descriptions
    - Software to solve these problems
    - Given generic data we can recover a phylogenetic tree(s) with four leaves
    - What does non-generic data mean?
  - Economic fragility in supply chains

