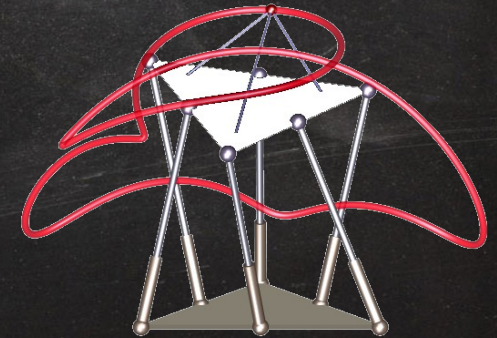
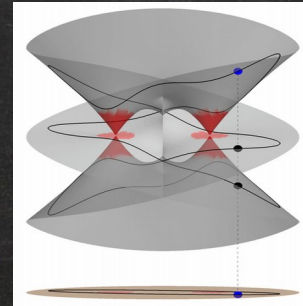
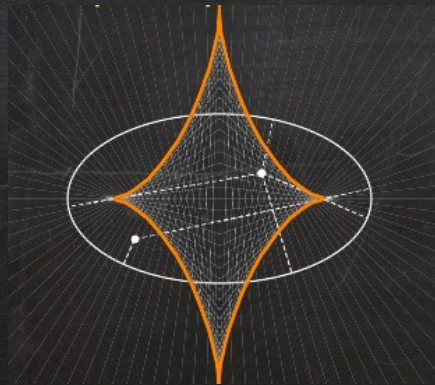
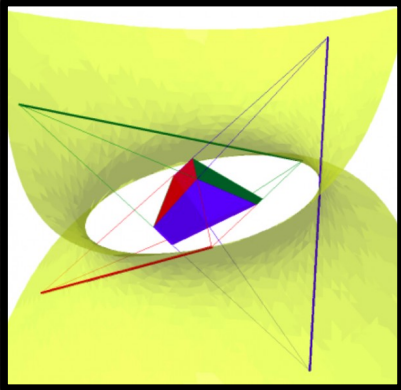


# Nonlinear Algebra of Data Science & AI



Kathlén Kohn

WASP | WALLENBERG  
AUTONOMOUS SYSTEMS  
AND SOFTWARE PROGRAM



# Linear algebra

All undergraduate students learn about **Gaussian elimination**, a general method for solving linear systems of algebraic equations:

**Input:**

$$\begin{aligned}x + 2y + 3z &= 5 \\7x + 11y + 13z &= 17 \\19x + 23y + 29z &= 31\end{aligned}$$

**Output:**

$$\begin{aligned}x &= -35/18 \\y &= 2/9 \\z &= 13/6\end{aligned}$$

**Solving very large linear systems is central to applied mathematics.**



# Nonlinear algebra

Lucky students also learn about **Gröbner bases**, a general method for non-linear systems of algebraic equations:

**Input:**

$$x^2 + y^2 + z^2 = 2$$

$$x^3 + y^3 + z^3 = 3$$

$$x^4 + y^4 + z^4 = 4$$

**Output:**

$$3z^{12} - 12z^{10} - 12z^9 + 12z^8 + 72z^7 - 66z^6 - 12z^4 + 12z^3 - 1 = 0$$

$$\begin{aligned} 4y^2 + (36z^{11} + 54z^{10} - 69z^9 - 252z^8 - 216z^7 + 573z^6 + 72z^5 \\ - 12z^4 - 99z^3 + 10z + 3) y + 36z^{11} + 48z^{10} - 72z^9 \\ - 234z^8 - 192z^7 + 564z^6 - 48z^5 + 96z^4 - 96z^3 + 10z^2 + 8 = 0 \end{aligned}$$

$$\begin{aligned} 4x + 4y + 36z^{11} + 54z^{10} - 69z^9 - 252z^8 - 216z^7 \\ + 573z^6 + 72z^5 - 12z^4 - 99z^3 + 10z + 3 = 0 \end{aligned}$$

This is very hard for large systems, but . . .

# The world is non-linear!

Many models in the sciences and engineering are characterized by polynomial equations. Such a set is an **algebraic variety**.

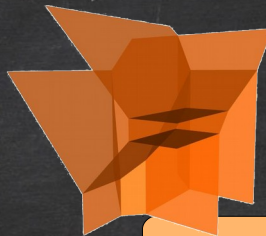
- ♦ Algebraic statistics
- ♦ Machine learning
- ♦ Optimization
- ♦ Computer vision
- ♦ Robotics
- ♦ Complexity theory
- ♦ Cryptography
- ♦ Biology
- ♦ Economics
- ♦ ...





# Nonlinear Algebra

Algebraic Geometry

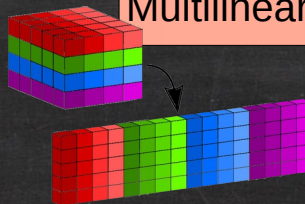


Combinatorics

Discrete Geometry

Tropical Geometry

Multilinear Algebra



Convex Geometry

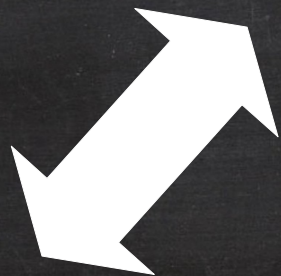
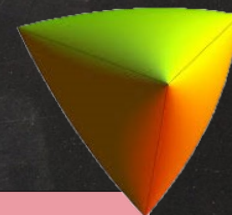
Algebraic Topology

Representation Theory

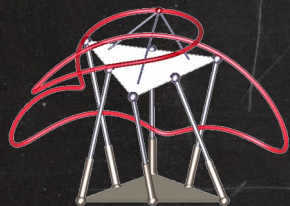
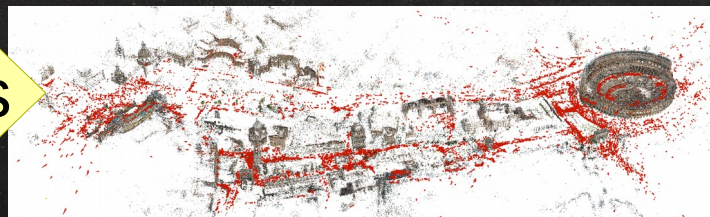
Numerics

Number Theory

...



Applications





# Algebraic Statistics

*Invariant theory and scaling algorithms for maximum likelihood estimation*

arXiv: 2003.13662

joint work with



Carlos Améndola  
(TU Munich / Univ. Ulm)

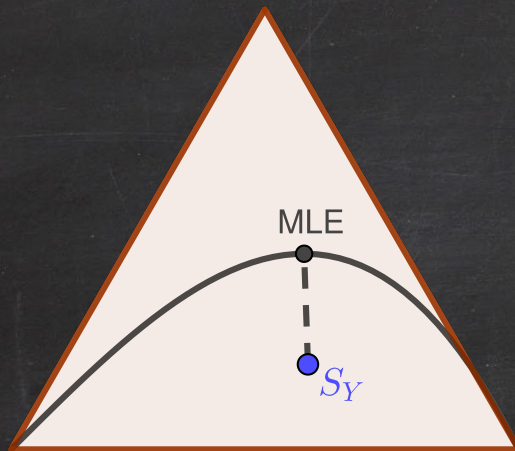


Philipp Reichenbach  
(TU Berlin)



Anna Seigal  
(University of Oxford)

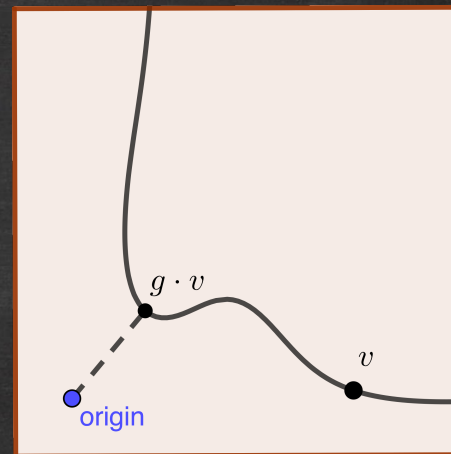
## Statistics



**Given:** statistical model  
sample data  $S_Y$

**Task:** find **maximum likelihood estimate**  
(MLE)  
= distribution in model that best fits  $S_Y$

## Invariant theory

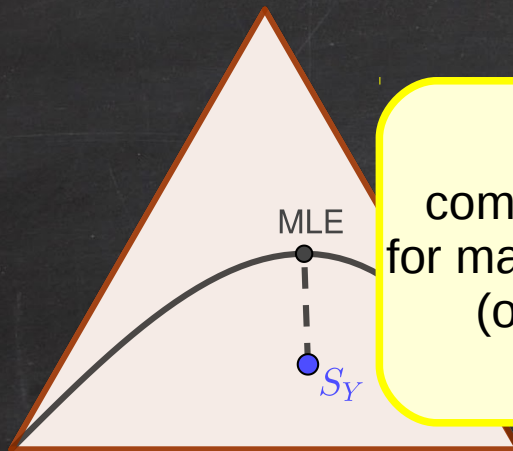


**Given:** orbit  $G \cdot v = \{g \cdot v \mid g \in G\}$   
of a group  $G$  acting on vector  $v$

**Task:** compute **capacity**  
= closest distance of orbit to origin



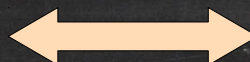
## Statistics



## Invariant theory

H. Derksen, V. Makam:  
computed maximum likelihood thresholds  
for matrix normal models using our dictionary!  
(open question due to Mathias Drton)  
arXiv: 2007.10206

Convergence analysis



Null cone (Hilbert, 1893);  
Stability notions



Algorithms to find MLE  
(1940)



Algorithms for capacity /  
null cone membership testing  
(2017 – now)



# Algebraic Statistics

*Projective geometry of Wachspress coordinates*

arXiv: 1904.02123

*Moment Varieties of Measures on Polytopes*

arXiv: 1807.10258

joint works with



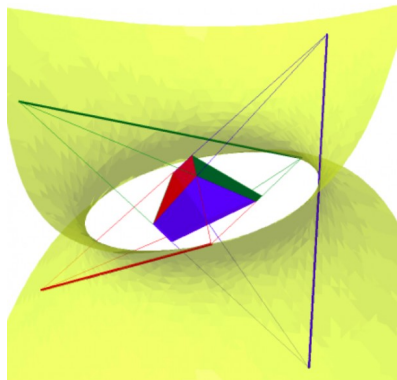
Kristian Ranestad  
(University of Oslo)



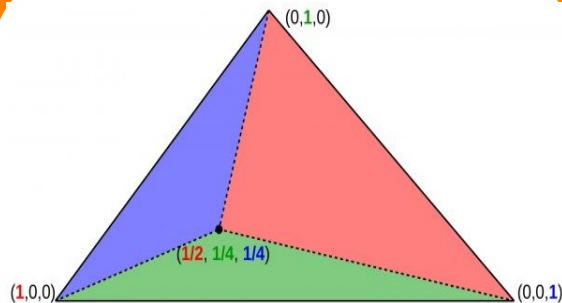
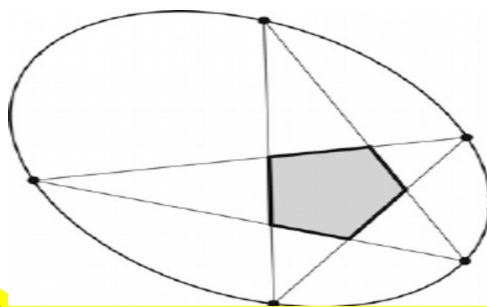
Boris Shapiro  
(Stockholm University)



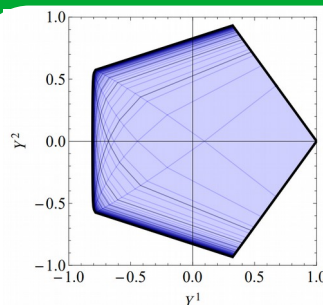
Bernd Sturmfels  
(MPI MiS Leipzig / UC Berkeley)



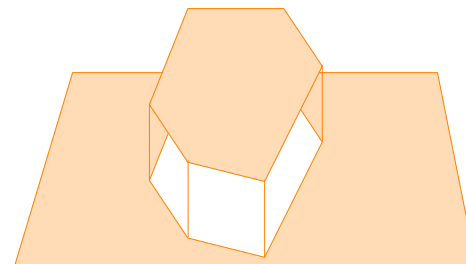
**classical algebraic geometry**  
adjoint hypersurfaces



**geometric modeling**  
barycentric coordinates  
for arbitrary polytopes



**physics**  
scattering amplitudes



**algebraic statistics:**  
moments of uniform distributions  
on polytopes

$$\begin{array}{ccc}
 x_2^6 & & \\
 x_2^5 & x_1 x_2^5 & \\
 x_2^4 & x_1 x_2^4 & x_1^2 x_2^4 \\
 x_2^3 & x_1 x_2^3 & x_1^2 x_2^3 \\
 x_2^2 & x_1 x_2^2 & x_1^2 x_2^2 \\
 x_2 & x_1 x_2 & x_1^2 x_2 \\
 1 & x_1 & x_1^2
 \end{array}$$

**intersection  
theory:**  
Segre classes of  
monomial schemes



# Machine Learning

*Pure and Spurious Critical Points: a Geometric Study of Linear Networks*

arXiv: 1910.01671

joint work with

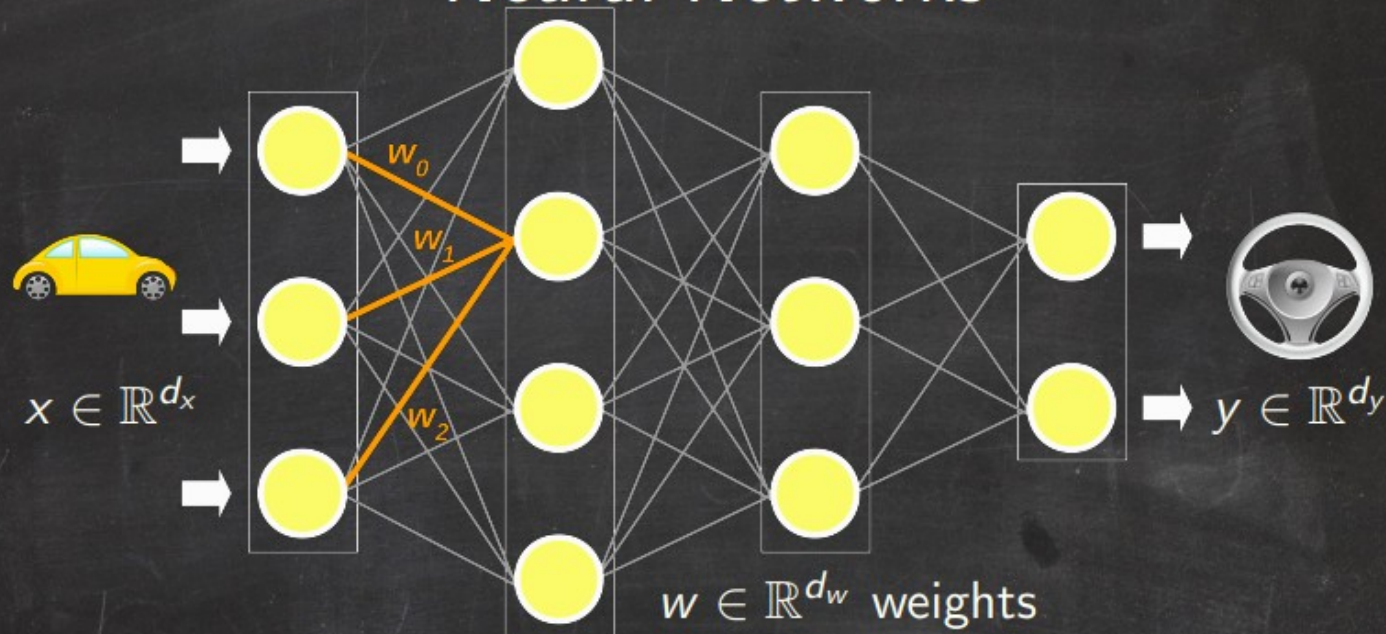


Matthew Trager  
(Amazon AI)



Joan Bruna  
(Courant Institute NYU)

# Neural Networks



A neural network is defined by a continuous mapping  $\Phi : \mathbb{R}^{d_w} \times \mathbb{R}^{d_x} \longrightarrow \mathbb{R}^{d_y}$ .

**Definition**  $\mathcal{M}_\Phi := \left\{ \Phi(w, \cdot) : \mathbb{R}^{d_x} \rightarrow \mathbb{R}^{d_y} \mid w \in \mathbb{R}^{d_w} \right\} \subset C(\mathbb{R}^{d_x}, \mathbb{R}^{d_y})$

is called the **neuromanifold** of  $\Phi$ .

**Observation** 1.  $\Phi$  piecewise smooth  $\Rightarrow \mathcal{M}_\Phi$  manifold with singularities

2.  $\dim \mathcal{M}_\Phi \leq d_w$

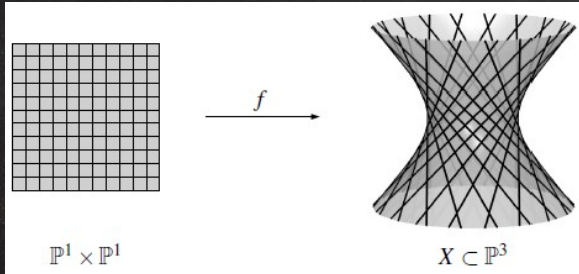


The neuromanifold of the linear network  $\Phi$  is

$$\mathcal{M}_\Phi = \left\{ M \in \mathbb{R}^{d_h \times d_0} \mid \text{rk}(M) \leq \underbrace{\min\{d_0, d_1, \dots, d_h\}}_{=: r} \right\}.$$

width of layers

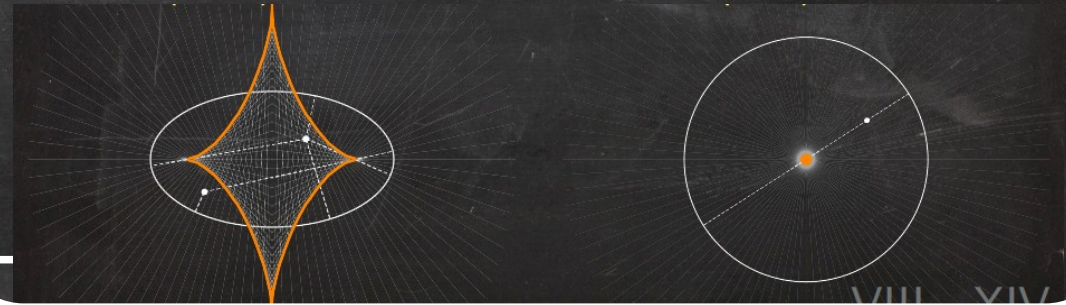
This is a **determinantal variety**!



machine learning with quadratic loss



**minimizing Euclidean distance to determinantal variety**



for linear networks with smooth convex losses:

	quadratic loss	other loss
$r = \min\{d_0, d_h\}$	no bad min.	no bad min.
$r < \min\{d_0, d_h\}$	no bad min.	bad min.

convex optimization  
on vector space

special embedding of  
determinantal varieties



# Computer Vision

*PL1P – Point-line Minimal Problems under Partial Visibility in Three Views*

arXiv: 2003.05015

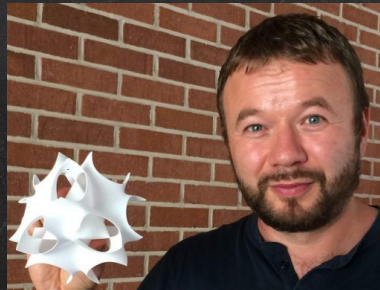
*PLMP – Point-Line Minimal Problems in Complete Multi-View Visibility*

arXiv: 1903.10008

joint works with



Timothy Duff  
(Georgia Tech)



Anton Leykin  
(Georgia Tech)

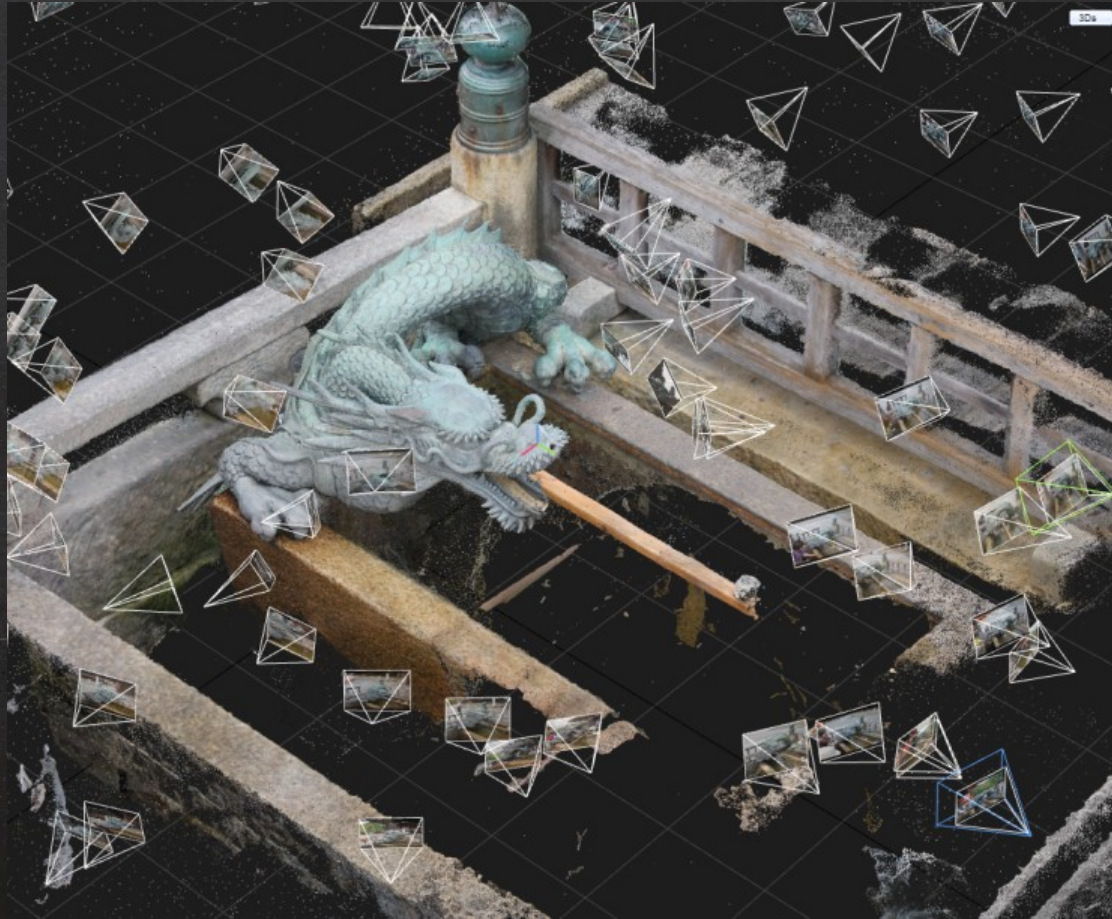


Tomas Pajdla  
(CIIRC CTU in Prague)



# Goal:

Reconstruct 3D scenes and camera poses from 2D images





# 3D Reconstruction Pipeline

Input images

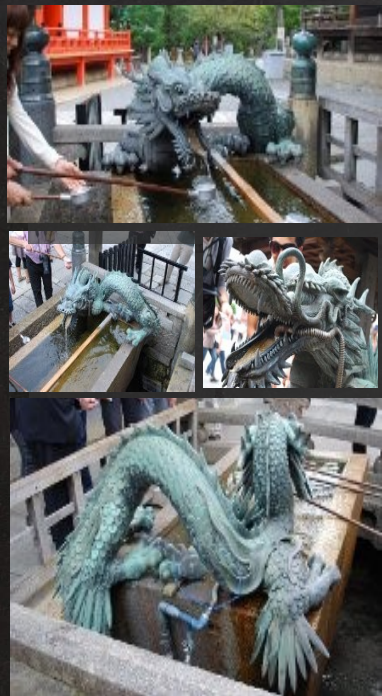
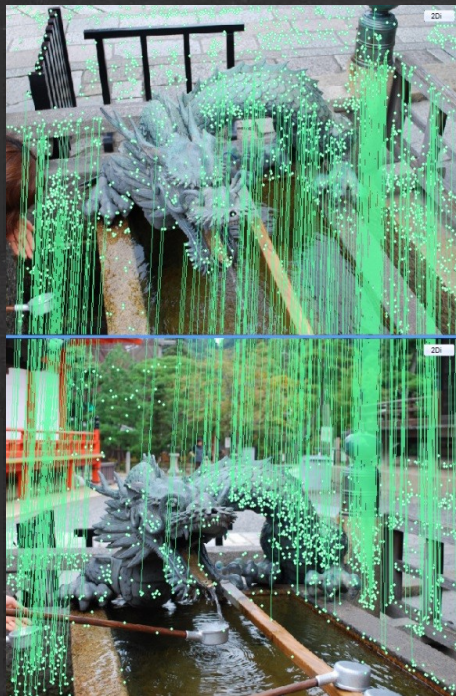
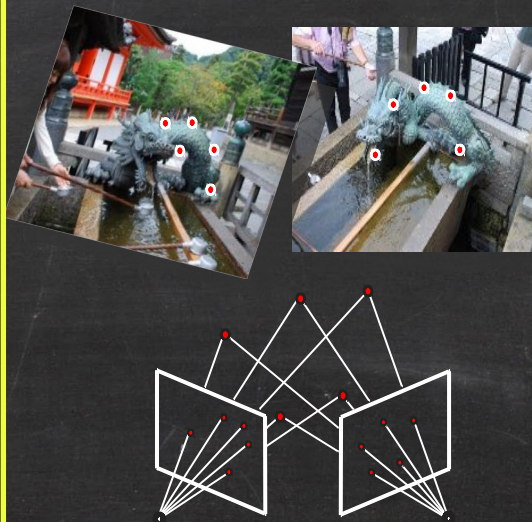


Image Matching



Identify common points and lines on given images

Camera Geometry



Reconstruct 3D points and lines as well as camera poses

Cameras & points

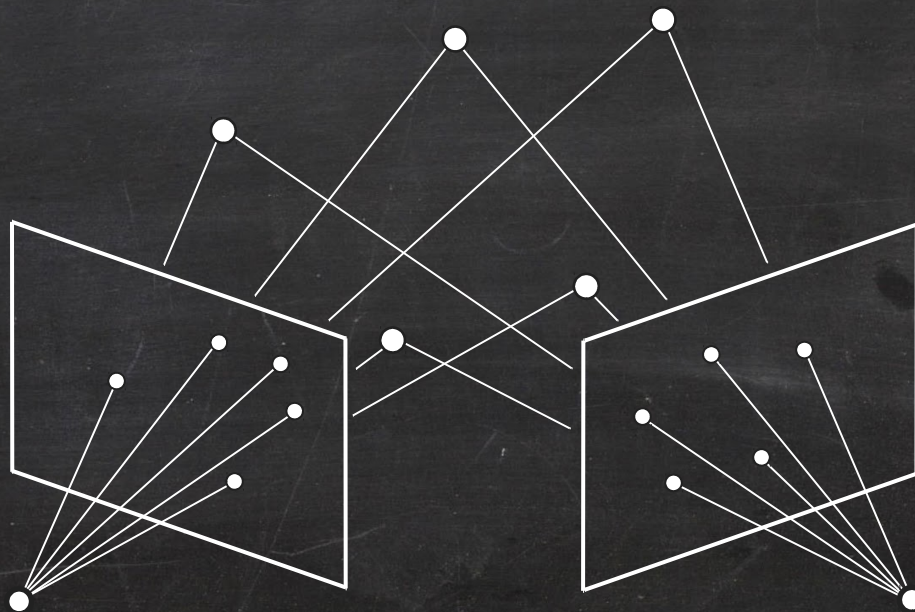


This is an **algebraic** problem!



# Example: The 5-Point Problem

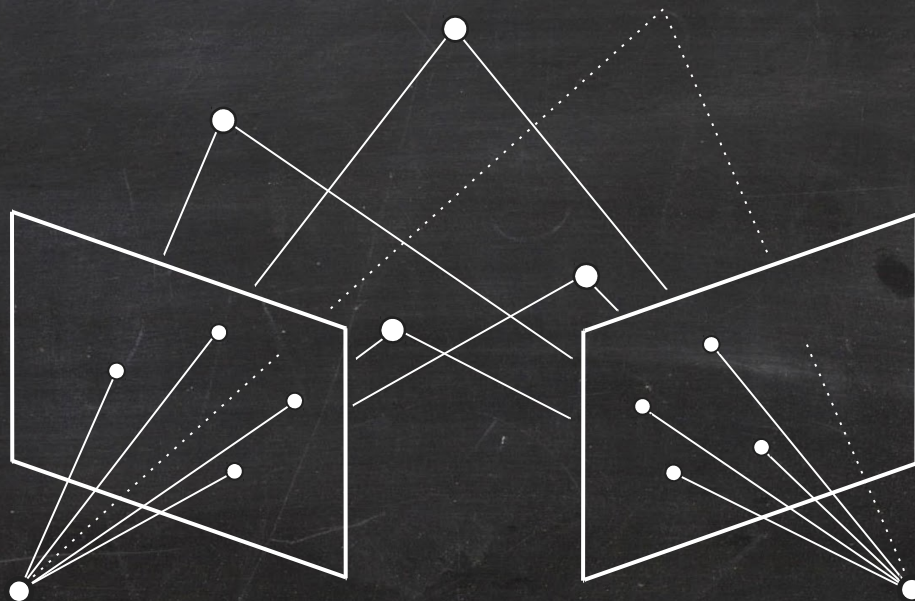
- Given: 2 images showing **5** points
- Goal: recover **5** points in 3D, and both (relative) camera poses



**This problem has 20 solutions for generic input images**  
(counted over the complex numbers).

# An Underconstrained Problem

- Given: 2 images showing **4** points
- Goal: recover **4** points in 3D, and both (relative) camera poses

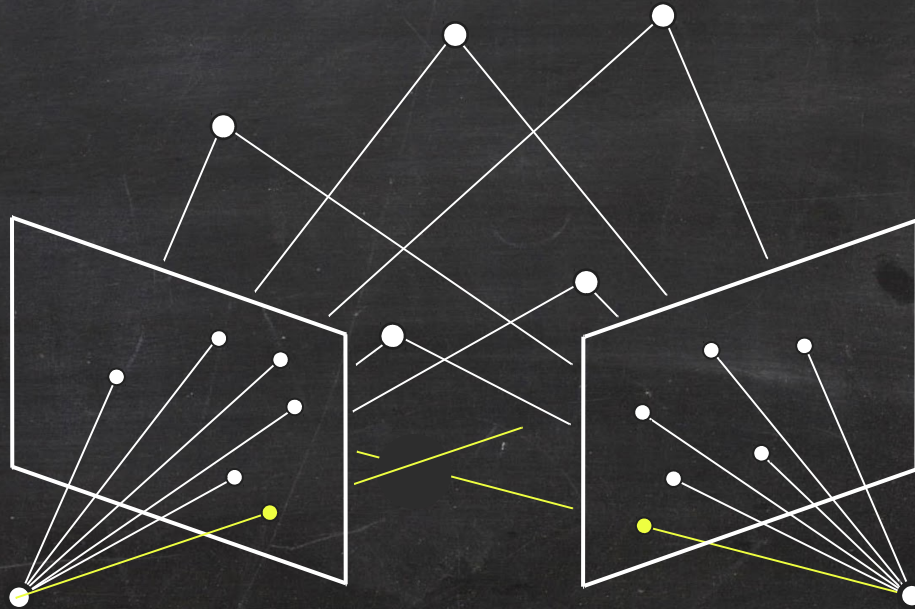


This problem has **infinitely many** solutions for generic input images.



# An Overconstrained Problem

- Given: 2 images showing **6** points
- Goal: recover **6** points in 3D, and both (relative) camera poses



**This problem has 0 solutions for generic input images.**

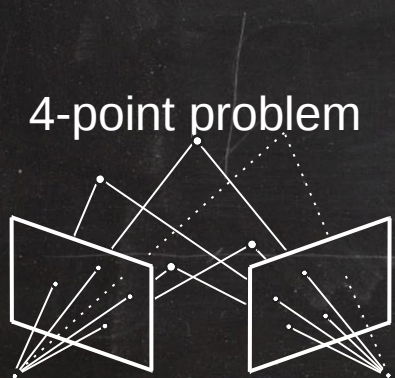
Some input images have solutions, but they are **not stable under noise** in the input images!

# Minimal Problems

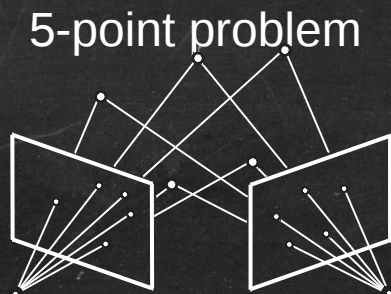
*Definition:* A 3D reconstruction problem is **minimal** if

$$0 < \# \text{ solutions} < \infty$$

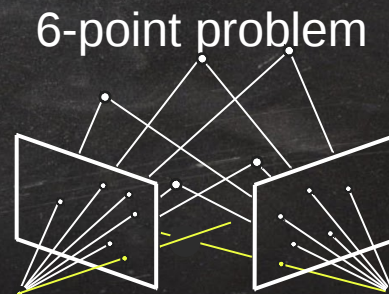
for **generic (random)** input images.



$\infty$  solutions  
**not minimal**



20 solutions  
**minimal**



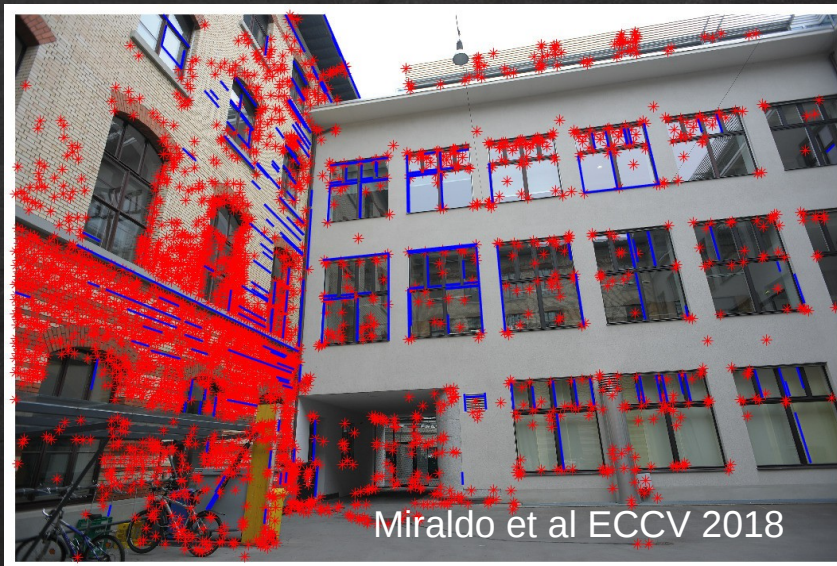
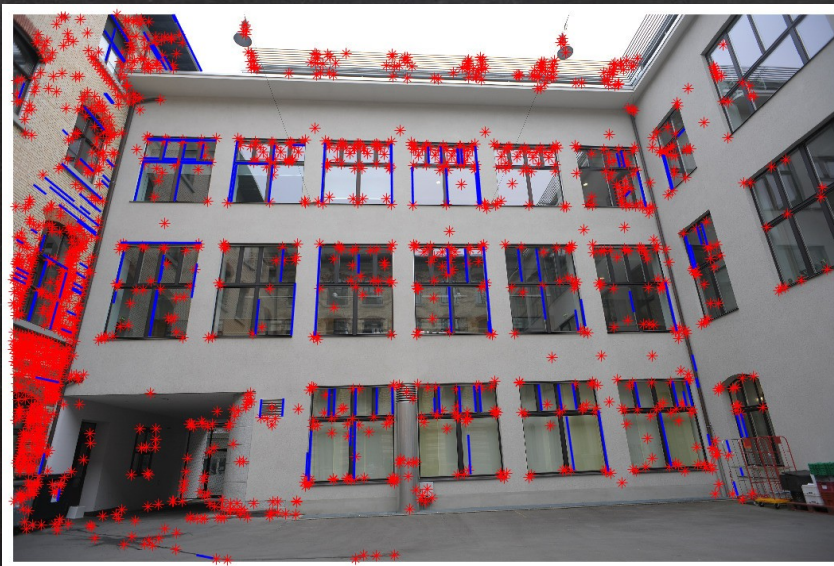
0 solutions  
**not minimal**



# Fundamental Research Questions

1. Can we list **all** minimal problems?
2. How many solutions do they have?

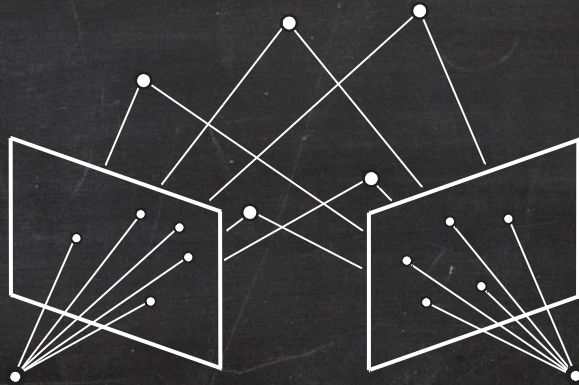
We do not only want to work with **points**,  
but also with **lines** and their incidences!





# Our Result

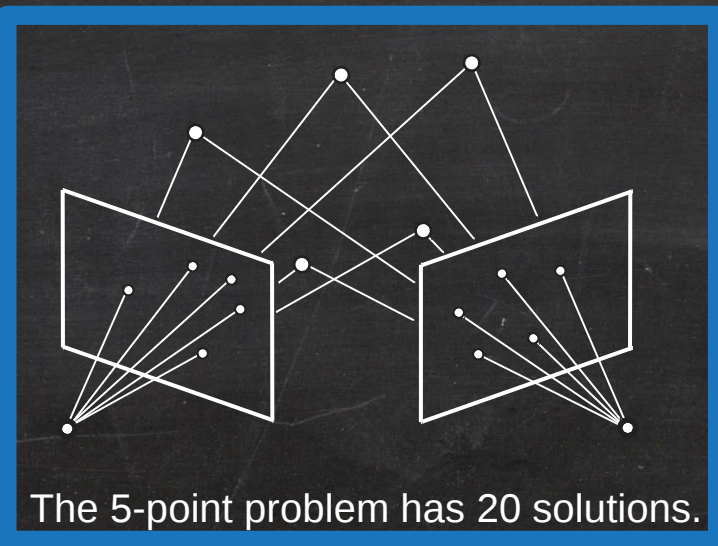
We provide the **first complete classification of all minimal problems** when all points and lines are visible in each given image.





# Our Result

We provide the **first complete classification of all minimal problems** when all points and lines are visible in each given image.



## RESULT

There are **exactly 30 minimal problems** for *complete multi-view visibility* (modulo extra lines in 2 views).

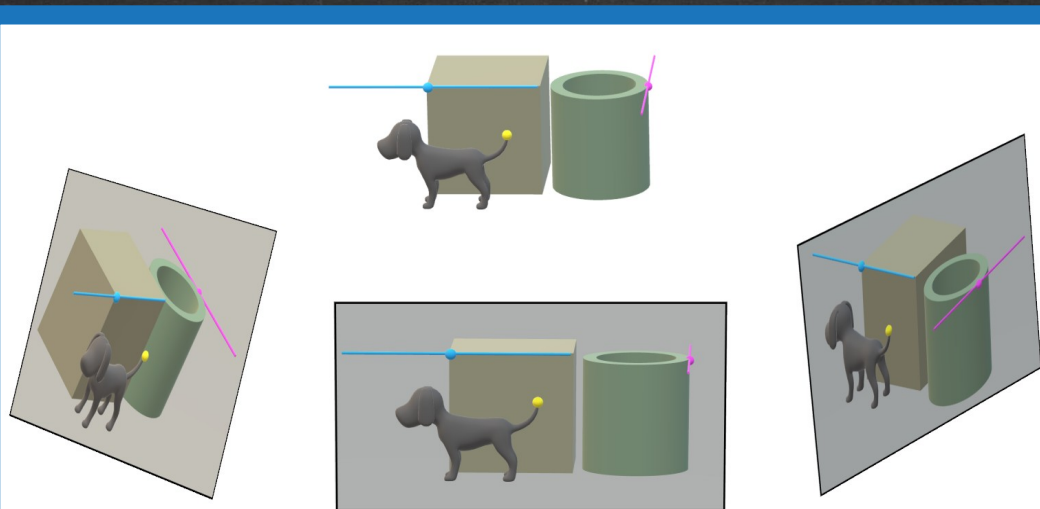
# views	6	5	5	5	4
# sols	$\approx 10^6$	11296	26240	11008	3040
# views	4	4	4	4	4
# sols	4512	1728	32	544	544
# views	3	3	3	3	3
# sols	360	552	480	264	432
# views	3	3	3	3	3
# sols	328	480	240	64	216
# views	3	3	3	3	3
# sols	212	224	40	144	144
# views	3	3	2	2	2
# sols	144	64	20	16	12

# Our Result

We provide the **first complete classification of all minimal problems** when all points and lines are visible in each given image.

First solver for  
such a high-  
degree problem  
based on state-of-  
the-art algorithms  
from **numerical  
algebraic  
geometry:**































TRPLP – Trifocal  
Relative Pose from  
Lines at Points,  
Fabbri et. al.,  
CVPR 2020



This problem has 312 solutions  
(counted over the complex numbers).

## RESULT

There are **exactly 30 minimal problems** for *complete multi-view visibility* (modulo extra lines in 2 views).

# views	6	5	5	5	4
					
# sols	$\approx 10^6$	11296	26240	11008	3040
# views	4	4	4	4	4
					
# sols	4512	1728	32	544	544
# views	3	3	3	3	3
					
# sols	360	552	480	264	432
# views	3	3	3	3	3
					
# sols	228	480	240	64	216
# views	3	3	3	3	3
					
# sols	312	224	40	144	144
# views	3	3	2	2	2
					
# sols	144	64	20	16	12



# Our Result

We provide the **first complete classification of all minimal problems** when all points and lines are visible in each given image.

We **measure the complexity of each minimal problem** by computing its number of solutions (counted over the complex numbers).

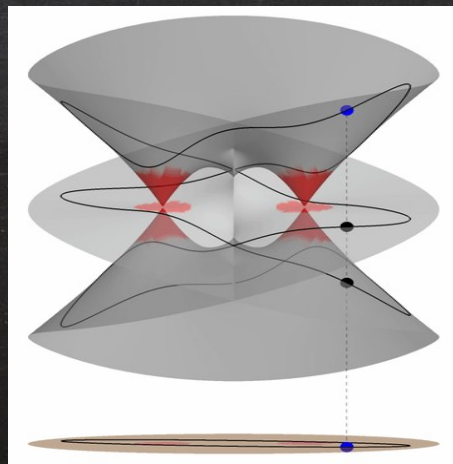
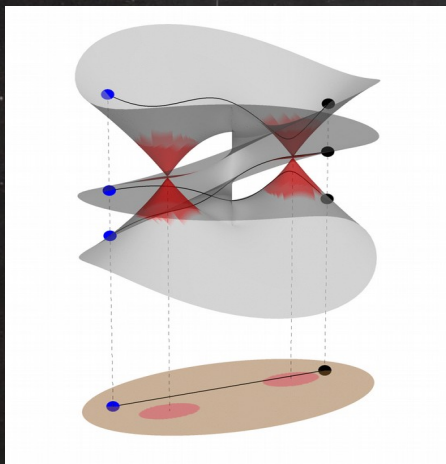
## RESULT

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# views	6	5	5	5	4
# sols	$\approx 10^6$	11296	26240	11008	3040
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# views	3	3	3	3	3
# sols	360	552	480	264	432
# views	3	3	3	3	3
# sols	328	480	240	64	216
# views	3	3	3	3	3
# sols	312	224	40	144	144
# views	3	3	2	2	2
# sols	144	64	20	16	12

# Our Tools: Nonlinear Algebra

- **Algebraic geometry**  
for proof of classification
- **Gröbner bases**  
symbolic computation of #sols  
for 2 & 3 views
- **Homotopy continuation & monodromy**  
numerical computation of #sols  
for 4, 5 & 6 views



## RESULT

There are **exactly 30 minimal problems** for *complete multi-view visibility* (modulo extra lines in 2 views).

# views	6	5	5	5	4
# sols	$\approx 10^6$	11296	26240	11008	3040
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# sols	360	552	480	264	432
# views	3	3	3	3	3
# sols	328	480	240	64	216
# views	3	3	2	2	2
# sols	144	64	20	16	12



# What about partial visibility?

There can be missing data / occlusions in the given images.



Image 1

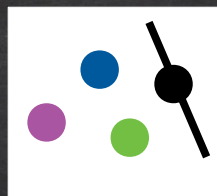


Image 2

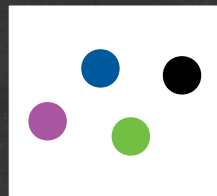


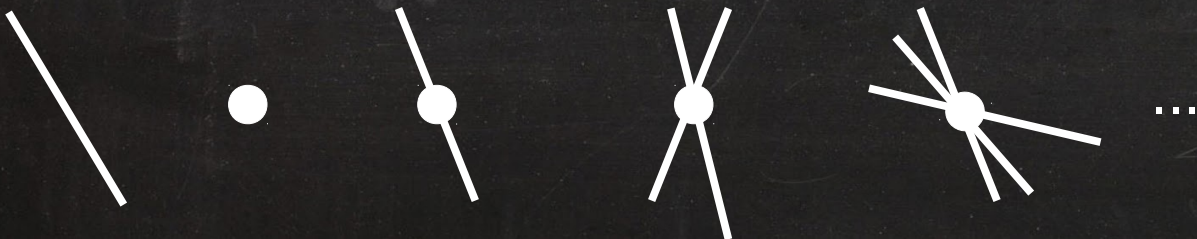
Image 3

- Minimal problems with complete visibility have at most 6 views.  
**Minimal problems with partial visibility exists for arbitrarily many views!**

⇒ Assume: **3 views**

- There are still  $\infty$  minimal problems, and their classification is hard!

⇒ Assume: **each line is adjacent to at most 1 point**



There are still  $\infty$  minimal problems!

# Our Result

We **completely classify all minimal problems for 3 views** when each line is adjacent to at most 1 point:

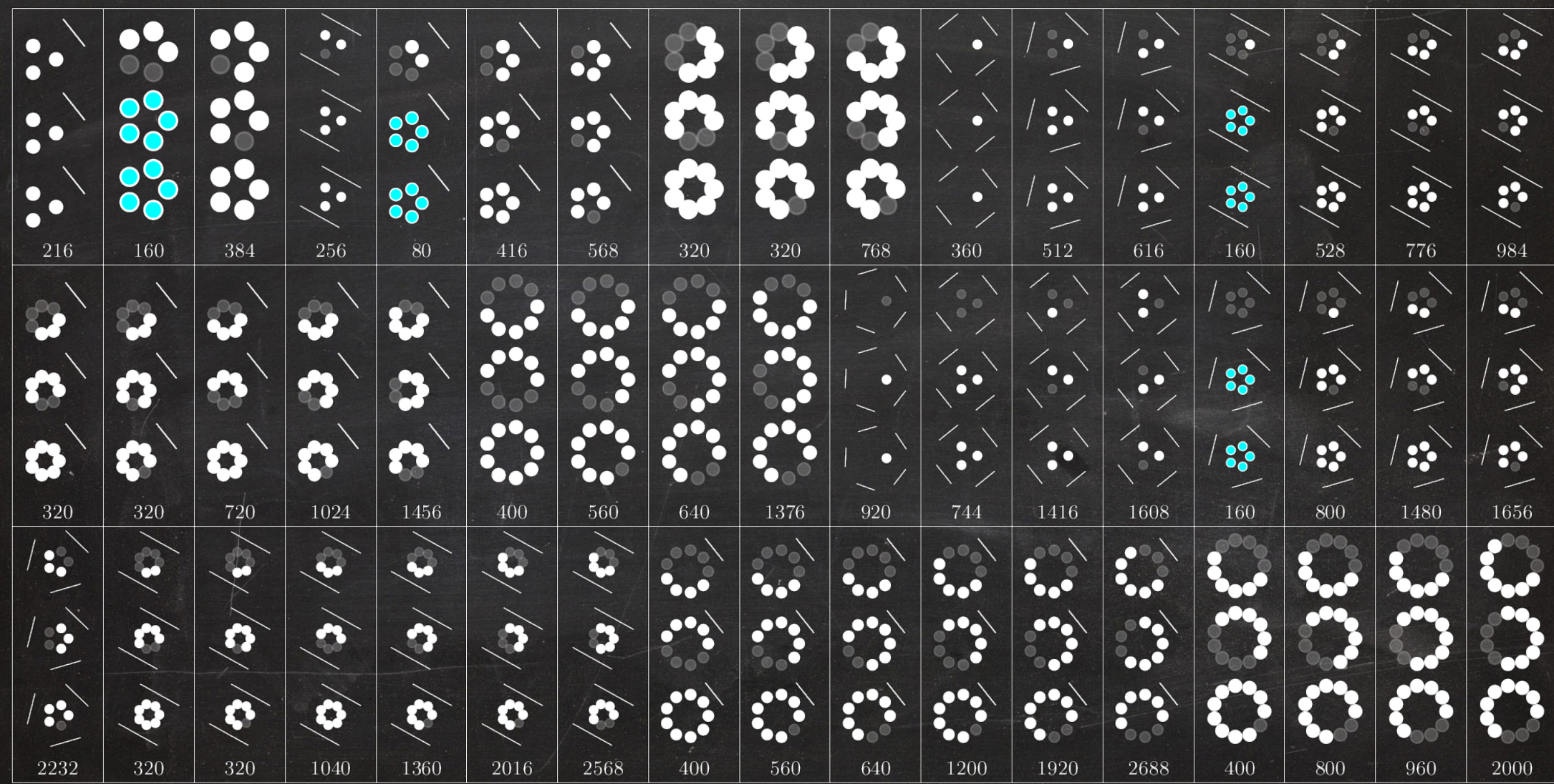
There are **74575** equivalence classes of minimal problems.

Among them, **759** have **less than 300** solutions.

# solutions	64	80	144	160	216	224	240	256	264	272	288
# problems	13	9	3	547	7	2	159	2	2	11	4

There are **51** equivalence classes of minimal problems without incidences.





**Final comment: Interaction between different sciences is key!**

**Thanks for  
your attention!**