

# Invariants, polytopes, and optimization

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based on joint work with [Peter Bürgisser](#), [Cole Franks](#), Ankit Garg,  
Rafael Oliveira, Avi Wigderson (ITCS'18, FOCS'18, FOCS'19)

# Overview

There are **algebraic** and **geometric** problems in invariant theory that are amenable to **numerical** optimization algorithms over noncommut. groups.



These capture a wide range of surprising applications – from algebra and analysis to computer science and even quantum information.

Plan for today:

- 1 Introduction to framework
- 2 Panorama of applications
- 3 Geodesic first-order algorithms

*'Computational invariant theory without computing invariants'*

# Symmetries and group actions

Group actions mathematically model *symmetries* and *equivalence*.



**Problem:** How can we algorithmically and efficiently determine when two objects are equivalent?

- ▶ computing *normal forms*, describing *moduli spaces* and *invariants*...

Interesting (and often difficult) problems with many applications:

- ▶ no polynomial-time algorithms are known for **graph isomorphism**.
- ▶ matrices equivalent under **left-right action** iff equal rank; but **tensor rank** is NP-hard.

We will see many more examples in a moment...

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## General setup

$G \subseteq GL_n$  complex reductive group, e.g.,  $GL_n$ ,  $SL_n$ , or  $T_n = (\mathbb{C}^*)^n$

$\pi: G \rightarrow GL(V)$  regular representation on f.d. complex vector space

- ▶ **orbits**  $Gv = \{\pi(g)v : g \in G\}$  and their closures  $\overline{Gv}$

*Orbit equality problem:* Given  $v_1$  and  $v_2$ , is  $Gv_1 = Gv_2$ ? *Robust version:*

*Orbit closure intersection problem:* Given  $v_1$  and  $v_2$ , is  $\overline{Gv_1} \cap \overline{Gv_2} \neq \emptyset$ ?

- ▶ equivalently,  $p(v_1) = p(v_2)$  for all  $G$ -invariant polynomials  $p$
- ▶ captures equality in Mumford's *GIT quotient*

**Null cone membership problem:** Given  $v$ , is  $0 \in \overline{Gv}$ ?

[Hilbert]

- ▶  $v$  is called *unstable* if yes, *semistable* if no
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## Example: Conjugation

$$G = \mathrm{GL}_n, V = \mathrm{Mat}_n, \pi(g)X = gXg^{-1}$$

$$\begin{pmatrix} \lambda_1 & 1 & & \\ & \lambda_1 & 1 & \\ & & \lambda_1 & \ddots \\ & & & \ddots \end{pmatrix}$$

- ▶  $X, Y$  are in *same orbit* iff same Jordan normal form
- ▶  $X, Y$  have *intersecting orbit closures* iff same **eigenvalues** (counted with algebraic multiplicity)
- ▶  $X$  is in *null cone* iff **nilpotent**

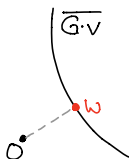
NB: The last two problems have a meaningful approximate version!

## Null cone and norm minimization

We can characterize the null cone  $\mathcal{N} = \{v \in V : 0 \in \overline{Gv}\}$  by an optimization problem. **Capacity** of  $v$ :

$$\text{cap}(v) := \min_{u \in \overline{Gv}} \|u\| = \inf_{g \in G} \|\pi(g)v\|$$

- ▶  $v$  in null cone iff  $\text{cap}(v) = 0$



$$\|w\| = \min \{ \|u\| : u \in \overline{G.v} \}$$

**Norm minimization problem:** Given  $v$ , find  $g \in G$  s. th.  $\|\pi(g)v\| \approx \text{cap}(v)$ .



## Norm minimization and its dual

Use  $K$ -invariant inner product, where  $K = G \cap U_n$  is maximal compact.  
We want to minimize the function:

$$F_v: G \rightarrow \mathbb{R}, \quad F_v(g) := \log \|\pi(g)v\|$$

Its gradient at  $g = I$  defines the **moment map**:

$$\mu: V \setminus \{0\} \rightarrow i \operatorname{Lie}(K), \quad \operatorname{tr}(\mu(v)H) = \partial_{t=0} F_v(e^{Ht}) \quad \forall H \in i \operatorname{Lie}(K)$$

( $F_v$  should really be defined on  $K \backslash G$ ; then  $T_I \cong i \operatorname{Lie}(K)$ ;  $\mu$  should be defined on  $\mathbb{P}(V)$ )

**Kempf-Ness:** Let  $0 \neq w \in \overline{Gv}$ . Then,  $\mu(w) = 0$  iff  $w$  has minimal norm.

Thus we are led to:

**Scaling problem:** Given  $v$ , find  $g \in G$  such that  $\mu(\pi(g)v) \approx 0$ .

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## Summary so far

$G \subseteq GL_n$  complex reductive,  $\pi: G \rightarrow GL(V)$  regular representation  
 $K \subseteq G$  maximally compact,  $\mu: V \setminus \{0\} \rightarrow i \text{Lie}(K)$  moment map

**Null cone membership problem:** Given  $v$ , is  $0 \in \overline{Gv}$ ?

... and its relaxations:

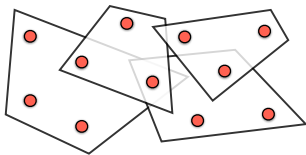
**Norm minimization problem:** Given  $v$ , find  $g \in G$  s. th.  $\|\pi(g)v\| \approx \text{cap}(v)$ .

**Scaling problem:** Given  $v \in V$ , find  $g \in G$  s. th.  $\mu(\pi(g)v) \approx 0$ .

The last two problems are dual to each other, and either can be used to solve null cone membership!

Let us look at some examples...

## A panorama of applications



## Example: Matrix scaling (raking, IPFP, ...)

Let  $X$  be matrix with nonnegative entries. A *scaling* of  $X$  is a matrix

$$Y = \begin{pmatrix} a_1 & & \\ & \ddots & \\ & & a_n \end{pmatrix} X \begin{pmatrix} b_1 & & \\ & \ddots & \\ & & b_n \end{pmatrix} \quad (a_1, \dots, b_n > 0).$$

A matrix is called *doubly stochastic (d.s.)* if **row & column sums** are 1.

**Matrix scaling** (Geometry): Given  $X$ ,  $\exists$  (approximately) **d.s.** scalings?

**Permanent** (Invariant Theory): ... iff  $\text{per}(X) > 0!$

- ▶ ... iff  $\exists$  bipartite perfect matching in support of  $X$
- ▶ can be decided in **polynomial time**
- ▶ find scalings by alternately fixing rows & columns ☺
- ▶ convergence controlled by permanent

[Sinkhorn]

[Linial et al]

Connections to statistics, complexity, combinatorics, geometry, numerics, ...

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Pe  $V = \text{Mat}_n$ ,  $G = T_n \times T_n$ ,  $\pi(g, h)v = gvh$ .

$\mu: V \setminus \{0\} \rightarrow \mathbb{R}^n \oplus \mathbb{R}^n$

$\mu(v) = (\text{row sums, column sums})$  of  $X_{i,j} = \frac{|v_{i,j}|^2}{\|v\|}$

Connections to statistics, complexity, combinatorics, geometry, numerics, ...



## Example: Schur-Horn theorem

Let  $\lambda_1 \geq \dots \geq \lambda_n$  and  $\delta_1, \dots, \delta_n$  be integers.

Given  $\lambda$  and  $\delta$ ,  $\exists$  Hermitian matrix with spectrum  $\lambda$  and **diagonal**  $\delta$ ?

$$U \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix} U^* = \begin{pmatrix} \delta_1 & \star & \star \\ \star & \ddots & \star \\ \star & \star & \delta_n \end{pmatrix}$$

**Schur-Horn theorem:** ... iff  $\delta$  in  $\text{conv}(S_n \cdot \lambda)$ !

**Kostka numbers** (Representation Theory): ... iff branching multiplicity  $K_\delta^\lambda$  for  $T_n \subset GL_n$  is nonzero.

Starting point for convexity results in symplectic geometry [Kostant, Atiyah, Guillemin-Sternberg, Duistermaat-Heckman, Mumford, Kirwan, ...]

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$K_C$   $V = V_\lambda$  Weyl module of  $GL_n$ , restricted to  $G = T_n$ .

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$\langle \lambda, \delta \rangle$

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# Torus actions

Any representation of  $G = T_n = (\mathbb{C}^*)^n$  decomposes as  $V = \bigoplus_{\omega \in \Omega} V_\omega$  for weights  $\Omega \subseteq \mathbb{Z}^n$ . If  $v = \sum_{\omega \in \Omega} v_\omega$  then  $\pi(z)v = \sum_{\omega} z^\omega v_\omega$ .

Capacity:

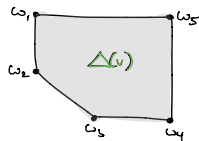
$$\text{cap}(v)^2 = \inf_{z \in T_n} \sum_{\omega} |z^\omega|^2 \|v_\omega\|^2 = \inf_{x \in \mathbb{R}^n} \sum_{\omega} e^{x \cdot \omega} \|v_\omega\|^2$$

- ▶ norm minimization is **geometric programming** (log-convexity in  $x$ )
- ▶  $\text{cap}(v) = 0$  iff  $0 \notin \Delta(v) := \text{conv} \{\omega : v_\omega \neq 0\}$ ; **linear programming**

Moment map:

$$\mu: V \setminus \{0\} \rightarrow \mathbb{R}^n, \quad \mu(v) = \frac{\sum_{\omega} \omega \|v_\omega\|^2}{\sum_{\omega} \|v_\omega\|^2}$$

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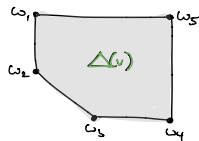
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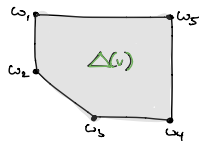
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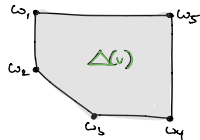
# Moment polytopes

It is often interesting to characterize the image of the moment map:

- ▶ For  $G = T_n$ , we saw on the previous slide that

$$\Delta(v) = \overline{\{\mu(w) : w \in Gv\}} \subseteq \mathbb{R}^n$$

is a convex polytope.



- ▶ If  $G$  non-commutative? For  $G = GL_n$ ,  $\mu(w) \in \text{Herm}_n$  and

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[Mumford, Kirwan]

These are moment polytopes of  $G$ -orbit closures in  $\mathbb{P}(V)$ .

**Moment polytope membership problem:** Given  $v$  and  $\lambda$ , is  $\lambda \in \Delta(v)$ ?

Often even interesting when *not* restricted to orbits. We will denote the corresponding polytope by  $\Delta$ . It coincides with  $\Delta(v)$  for generic  $v$ .

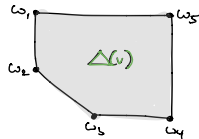
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## Example: Horn problem

Let  $\alpha_1 \geq \dots \geq \alpha_n \geq 0$ ,  $\beta_1 \geq \dots \geq \beta_n \geq 0$ ,  $\gamma_1 \geq \dots \geq \gamma_n \geq 0$  be integers.

**Horn problem** (Geometry): When  $\exists$  Hermitian  $n \times n$  matrices  $A, B, C$  with spectrum  $\alpha, \beta, \gamma$  such that  $A + B = C$ ?

- ▶ Horn conjectured linear inequalities on  $\alpha, \beta, \gamma$ .

**Saturation property** (Invariant theory): ... iff *Littlewood-Richardson coefficient*  $c_{\alpha, \beta}^{\gamma} > 0$

[Knutson-Tao]

- ▶ Horn inequalities sufficient
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|  $\mu: V \setminus \{0\} \rightarrow \text{Herm}_n^3$   
|  $\mu(X, Y) = (XX^*, YY^*, -X^*X - Y^*Y)$

|  $\Delta = \{(\alpha, \beta, -\gamma) : A \geq 0, B \geq 0, \text{tr}(A) + \text{tr}(B) = 1\}$

so]

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## Example: Left-right action and noncommutative PIT

Let  $X = (X_1, \dots, X_d)$  be a tuple of matrices. A *scaling* of  $X$  is a tuple

$$Y = (gX_1h^{-1}, \dots, gX_dh^{-1}) \quad (g, h \in \text{GL}_n)$$

Say  $X$  is *quantum doubly stochastic (q.d.s.)* if  $\sum_k X_k X_k^* = \sum_k X_k^* X_k = I$ .

**Operator scaling** (Geometry): Given  $X$ ,  $\exists$  (approx.) **q.d.s** scalings?

**Polynomial identity testing** (Invariant Theory): ... iff  $\exists$  matrices  $Y_k$  such that  $\sum_k Y_k \otimes X_k$  is invertible.

- ▶ numerical algorithms can solve this in **deterministic polynomial time**

[Garg et al, cf. Ivanyos et al]

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Many further connections (Brascamp-Lieb inequalities, Paulsen problem, ...).

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Pc

th.  $V = \mathrm{Mat}_n^d$ ,  $G = \mathrm{GL}_n \times \mathrm{GL}_n$ ,  $\pi(g, h)$  as above.

$\mu: V \setminus \{0\} \rightarrow \mathrm{Herm}_n \oplus \mathrm{Herm}_n$

$\mu(X_1, \dots, X_d) = (\sum_k X_k X_k^*, -\sum_k X_k^* X_k)$

Many further connections (Brascamp-Lieb inequalities, Paulsen problem, ...).

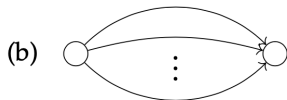
## Example: Quivers

**Quiver:** Directed graph with vertex set  $Q_0$  and edge set  $Q_1$ .

Given *dimension vector*  $(n_x)_{x \in Q_0}$ , consider natural action of

$$G = \prod_{x \in Q_0} \mathrm{GL}(n_x) \quad \text{on} \quad V = \bigoplus_{x \rightarrow y \in Q_1} \mathrm{Mat}_{n_y \times n_x}$$

- ▶ generalizes Horn and left-right action:



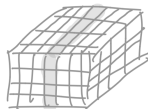
Many structural results known:

- ▶ semi-invariants characterized by [King, Derksen-Weyman, Schofield-Van den Bergh, ...]
  - ▶ moment polytopes characterized by Horn-like inequalities [Baldoni-Vergne-W]
- ... but efficient algorithms only in special cases.

## Example: Tensors and quantum marginals

Let  $X \in \mathbb{C}^{n_1} \otimes \dots \otimes \mathbb{C}^{n_d}$  be a tensor. A *scaling* of  $X$  is a tensor of the form

$$Y = (g_1 \otimes \dots \otimes g_d)X \quad (g_k \in \text{GL}_{n_k})$$



Consider  $\rho_k = X_k X_k^*$ , where  $X_k$  is  $k$ -th principal flattening of  $X$ .

(In quantum mechanics,  $X$  describes joint state of  $d$  particles and  $\rho_k$  marginal of  $k$ -th particle.)

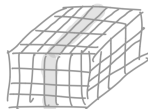
**Tensor scaling problem:** Given  $X$ , which  $(\rho_1, \dots, \rho_d)$  can be obtained by scaling?

- ▶ eigenvalues form **convex polytopes** (moment polytopes)
- ▶ exponentially many vertices, faces [Berenstein-Sjamaar, Klyachko, Ressayre, Vergne-W]
- ▶ related to asymptotic support of *Kronecker coefficients*
- ▶ can we find efficient **algorithmic** description?

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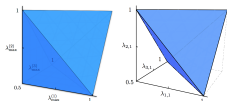
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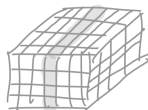
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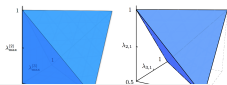
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$$V = \mathbb{C}^{n_1} \otimes \dots \otimes \mathbb{C}^{n_d}, \quad G = \text{GL}_{n_1} \times \dots \times \text{GL}_{n_d}, \quad \pi \text{ as above.}$$

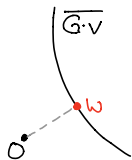
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$$\Delta(v) = \{(\text{spec } \rho_1, \dots, \text{spec } \rho_d)\}$$

-W]

# Geodesic first-order algorithms for norm minimization and scaling



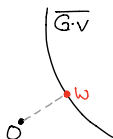
# Non-commutative optimization duality

Recall  $F_v(g) = \log \|\pi(g)v\|$  and  $\mu(v)$  is its gradient at  $g = I$ . By Kempf-Ness, the following *optimization problems* are equivalent:

$$\boxed{\inf_{g \in G} F_v(g)} \iff \boxed{\inf_{g \in G} \|\mu(\pi(g)v)\|}$$

[Kempf-Ness]

- ▶ primal: **norm minimization**, dual: **scaling problem**
- ▶ non-commutative version of linear programming duality



We developed **quantitative** duality theory and 1st & 2nd order methods.

Why does the duality hold at all?  $F_v$  is **convex along geodesics** of  $K \setminus G$ !

## Geodesic convexity and smoothness

Homogeneous space  $K \backslash G$  has geodesics  $\gamma(t) = e^{tH}g$  for  $H \in i\text{Lie}(K)$ .

**Proposition:**  $F_v$  satisfies the following properties along these geodesics:

- 1 convexity:  $\partial_{t=0}^2 F_v(\gamma(t)) \geq 0$
- 2 smoothness:  $\partial_{t=0}^2 F_v(\gamma(t)) \leq 2N(\pi)^2 \|H\|^2$

$N(\pi)$  is the *weight norm*, defined as the maximal norm of all weights in  $\pi$ .

- ▶ typically small (e.g., upper-bounded by degree for  $G = \text{GL}_n$ )

Smoothness implies that

$$F_v(e^H g) \leq F_v(g) + \text{tr}(\mu(v)H) + N(\pi)^2 \|H\|^2.$$

Thus, gradient descent with sufficiently small step size makes progress!

# First-order algorithm: geodesic gradient descent

Given  $v$ , want to find  $w = \pi(g)v$  with  $\|\mu(w)\| \leq \varepsilon$ .

**Algorithm:** Start with  $g = I$ . For  $t = 1, \dots, T$ :

Compute moment map  $\mu(w)$  of  $w = \pi(g)v$ . If norm  $\varepsilon$ -small, **stop**.

Otherwise, replace  $g$  by  $e^{-\eta\mu(w)}g$ .

$\eta > 0$  suitable step size

## Theorem

Let  $v \in V$  be a vector with  $\text{cap}(v) > 0$ . Then the algorithm outputs  $g \in G$  such that  $\|\mu(w)\| \leq \varepsilon$  within  $T = \frac{4N(\pi)^2}{\varepsilon^2} \log \frac{\|v\|}{\text{cap}(v)}$  iterations.

▶ Algorithm runs in time  $\text{poly}(\frac{1}{\varepsilon}, \text{input size})$ .

Can use constructive invariant theory to lower-bound capacity.

▶ Algorithm solves **null cone membership problem** if  $\varepsilon$  sufficiently small!

Moment polytopes are rigid thanks to geometric invariant theory.

Peter Bürgisser will explain this in more detail tomorrow.

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## Analysis of algorithm

“Unless moment map  $\varepsilon$ -small, replace  $g$  by  $e^{-\eta\mu(w)}g$ .”

To obtain rigorous algorithm, need to show *progress in each step*:

$$F_v(g_{\text{new}}) \leq F_v(g) - c$$

Then,  $\log\|v\| - Tc \geq \log \text{cap}(v)$  bounds the number of steps  $T$ .

Progress follows from **smoothness**:

$$F_v(e^H g) \leq F_v(g) + \text{tr}(\mu(v)H) + N(\pi)^2 \|H\|^2$$

If we plug in  $H = -\eta\mu(w)$  then

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Thus, if we choose  $\eta = 1/2N(\pi)^2$  then we obtain

$$F_v(g_{\text{new}}) \leq F_v(g) - \frac{1}{4N(\pi)^2}\|\mu(w)\|^2 \leq F_v(g) - \frac{\varepsilon^2}{4N(\pi)^2}. \quad \square$$

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□

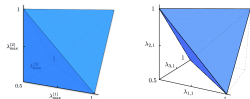


# How about moment polytopes?

Recall:

**Moment polytope membership problem:** Given  $\nu$  and  $\lambda$ , is  $\lambda \in \Delta(\nu)$ ?

- ▶  $\nu$  in null cone  $\Leftrightarrow 0 \notin \Delta(\nu)$
- ▶ can we reduce to  $\lambda = 0$ ?



*Shifting trick:*

- ▶ for simplicity, assume  $\lambda$  integral
- ▶ replace  $V$  by  $W = V \otimes V_{\lambda^*}$  if  $G$  commutative, shifts all weights by  $-\lambda$
- ▶  $\lambda \in \Delta(\nu)$  iff  $0 \in \Delta(w)$  for *generic*  $w \in \nu \otimes \pi(G)v_{\lambda^*}$  ☺ [Mumford, Brion, ...]

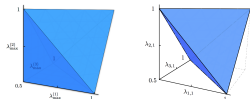
*Result:* **Randomized first-order algorithm** for moment polytopes.

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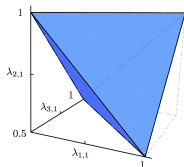


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# Summary and outlook



Null cone & moment polytopes

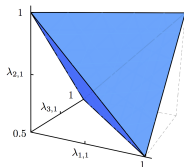
↕ duality

Norm minimization

Effective numerical algorithms for **null cone** and **moment polytope** problems, based on **geometric invariant theory** and **geodesic convex optimization**, with a wide range of applications.

On Tuesday, Peter Bürgisser will discuss the **noncommutative duality theory** in more detail and explain how to design **second-order algorithms**.

# Summary and outlook



Null cone & moment polytopes

↕ duality

Norm minimization

Effective numerical algorithms for **null cone** and **moment polytope** problems, based on **geometric invariant theory** and **geodesic convex optimization**, with a wide range of applications. *Many exciting directions:*

- ▶ Polynomial-time algorithms in all cases?
- ▶ In commutative case, poly-time algorithms known and can beat our geodesic algorithms! Can we design geodesic interior point methods?
- ▶ Tensors in applications are often structured. Implications?
- ▶ **What are the tractable problems in invariant theory?**  $\mathbb{C} \rightsquigarrow \mathbb{F}$ ? 🐘

*Thank you for your attention!*

## A general equivalence

$$\mathcal{V} \subseteq \mathbb{P}(V)$$

All points in  $\Delta(\mathcal{V})$  can be described via invariant theory:

$$V_\lambda \subseteq \mathbb{C}[\mathcal{V}]_{(k)} \quad \Rightarrow \quad \frac{\lambda}{k} \in \Delta(\mathcal{V})$$

( $\lambda$  highest weight,  $k$  degree)

- ▶ Can also study **multiplicities**  $g(\lambda, k) := \# V_\lambda \subseteq \mathbb{C}[\mathcal{V}]_{(k)}$ .
- ▶ This leads to interesting computational problems:

$$g = ?$$

(#-hard)

$$g > 0?$$

(NP-hard)

$$\exists s > 0 : g(s\lambda, sk) > 0?$$

(our problem!)

Completely unlike Horn's problem: *Knutson-Tao saturation property does not hold, and hence we can hope for efficient algorithms!*