6. Positive polynomials

Problem: given a set $X \leq \mathbb{R}^{n}$ and a polynomial $f \in \mathbb{R}\left[x_{1}, \ldots, x_{n}\right]$ find $f_{\text {min }}=\inf _{x \in X} f(x)$
$Q_{\text {connected to many optimization problems }}$ ese., MaxCut:
$X=\{0,1\}^{n}$, G weighted graph with edge weights $W_{i j}$ $f(x)=-\sum_{(i, j) \in E} w_{i j}\left(x_{i}-x_{j}\right)^{2}$
$\xi$ then $f_{\text {min }}=-\operatorname{MaxCut}(G)$
Reformulation: $f_{\text {min }}=\sup \{\lambda \in \mathbb{R} \mid f-\lambda$ is nonnegative on $X\}$
$\Rightarrow$ being able to cheat algorithmically whether a polynomial is nonnegative would allow us to solve many opt. problems

Two main players: 1. $\left\{f \in \mathbb{R}\left[x_{1}, \ldots, x_{n}\right] \mid f(x) \geqslant 0 \forall x\right\}=P$ the convex cone of nonnegative poly
2. $\left\{f \in \mathbb{R}\left[x_{1}, \ldots, x_{n}\right] \mid f(x)=\sum g_{2}^{2}(x)\right.$ for some $\left.g_{i} \in \mathbb{R}\left[x_{1}, \ldots, x_{n}\right]\right\}=: \Sigma$
The univariate case:
Theorem: a univariate polynomial $f \in \mathbb{R}[x]$ is nonnegative if and only if it is a sum of squares.
$\measuredangle$ a nonnegative polynomial must have even degree
There are similar results for nonnegative polynomials on $[a, b]$

The general case: Hilbert
Minkowski conjectured that nonnegative $\neq$ sum of square
Let's work now with homogeneous polynomials
$\rightarrow$ homogenize and dehomogenize does not change $\geqslant 0$ or sos.
We will denote by $P_{n, d}=\left\{f \in \mathbb{R}\left[x_{1}, \ldots, x_{n}\right]_{d} \mid f \geqslant 0\right\}$

$$
\Sigma_{n, d}=\left\{f \in \mathbb{R}\left[x_{1}, \ldots, x_{n}\right]_{d} \mid f \text { is sos }\right\}
$$

Theorem (Hilbert 1888): Let $n \geqslant 2$ and $d$ even. Then $\Sigma_{n, d}=P_{n, d}$ iff
(i) $n=2$
(ii) $d=2$
(iii) $n=3, d=4$ "the Hilbert cases"

Proof: (partial)
(i) dehomogenization gives univariste polynomials
(ii) $f(x)=x^{\top} A x$ with $A$ symmetric. $f \geqslant 0 \Leftrightarrow A \geqslant 0$

$$
\begin{aligned}
& \Leftrightarrow A=B^{\top} B \\
& \Leftrightarrow f(x)=x^{\top} B^{\top} B x=\|B x\|^{2} \\
& \Leftrightarrow f \text { sos }
\end{aligned}
$$

(iasi) technical proof, based on the fact that for any nonnegative ternary quartic \& there exists $g$ st. $\operatorname{deg} g=2$ and $f-g^{2} \geqslant 0$.
The remaining cases?

- $n \geqslant 3, d \geqslant 6$ the counterexample is based on the Motzkin polynomial

$$
f(x, y, z)=z^{6}-3 x^{2} y^{2} z^{2}+x^{2} y^{4}+x^{4} y^{2}
$$

- $n \geqslant 4$ the counterexample is based on the polynomial

$$
f(w, x, y, z)=w^{4}+x^{2} y^{2}+x^{2} z^{2}+y^{2} z^{2}-4 w x y z
$$

However, Hilbert's $17^{\text {th }}$ problem ask if we can write every nonnegative polynomial as a sum of rational functions.
Theorem: Any nonnegative polynomial can be written as a sum of squares of rational functions.

We can prove it using a version of the Positivstellensatz
Theorem: $g_{1}, \ldots, g_{k} \in \mathbb{R}\left[x_{1}, \ldots, x_{n}\right], S=\left\{x \in \mathbb{R}^{n} \mid g_{i}(x) \geqslant 0 \quad \forall i=1, \ldots, k\right\}$, $P=\left\{\sum_{i \in\left\{0, j^{i}\right.} \sigma_{i} g_{i}^{i_{2}} \cdots \cdot g_{k}^{i_{k}} \mid \sigma_{i} \in \mathbb{R}\left[x_{1}, \ldots, x_{n}\right] \operatorname{sos}\right\}, f \in \mathbb{R}\left[x_{1}, \ldots, x_{n}\right]$. Then
(i) $f>0$ on $S \Leftrightarrow \exists g, h \in P$ with $f g=1+h$
(ii) $f \geqslant 0$ on $S \Leftrightarrow \exists g, h \in P, m \geqslant 0$ with $f g=f^{2 m}+h$
(iii) $f=0$ on $S \Leftrightarrow \exists g \in P, m \geqslant 0$ with $f^{2 m}+g=0$

Using this we can prove Hilbert $17^{\text {th }}$ problem:
$\rightarrow$ we have $K=0$, so $f \geqslant 0$ on $\mathbb{R}^{n} \Leftrightarrow \exists g, h$ sos, $m \geqslant 0$ such that

$$
f g=f^{2 x}+h
$$

un s $f=\left(\frac{1}{g}\right)^{2} \quad g\left(f^{2 k}+h\right)$ is a rational sos
Theorem (Schniudgen) $f \in \mathbb{R}\left[x_{1}, \ldots, x_{n}\right]$ such that $f>0$ on $S$, then $f \in P$, namely

$$
f=\sum_{i \in\{0,1\}^{k}} \sigma_{i} g_{2}^{i_{1}} \cdot \ldots \cdot g_{k}^{i_{k}} \text { with } \sigma_{i} \text { sos }
$$

7. SOS cone and optimization

Back to the beginning: $f_{\text {min }}=\sup \{\lambda \in \mathbb{R} \mid f-\lambda \geqslant 0\}$ $m f_{\text {sos }}=\sup \{\lambda \in \mathbb{R} \mid f-\lambda$ is sos $\}$
Since $\{\operatorname{sos}\} \nsubseteq\{\geqslant 0\}$, then $f_{\text {sos }} \leqslant f_{\text {min }}$ BUT we can compute $f_{\text {sos }}$ !

A polynomial $f \in \mathbb{R}\left[x_{1}, \ldots, x_{n}\right]$ is sos if and only if $t=m^{\top} A m, A \geqslant 0$
\& vector of
monomials
Example: $t=y^{4}-x y^{2}+x^{2}+1$
then $m=\left\{1, x, y, x^{2}, x y, y^{2}\right\}$
$\rightarrow$ I can also just take a

$$
A=\left[\begin{array}{cccccc}
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & -\frac{1}{2} \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & -\frac{1}{2} & 0 & 0 & 0 & 1
\end{array}\right]
$$ subset of monomial, if that's enough: $\tilde{m}=\left\{1, x, y^{2}\right\}$

$$
A=\left[\begin{array}{ccc}
1 & 0 & 0 \\
0 & 1 & -\frac{1}{2} \\
0 & -\frac{1}{2} & 1
\end{array}\right]
$$

$A \succcurlyeq 0$ and in fact $f=\frac{3}{4}\left(x-y^{2}\right)^{2}+\frac{1}{4}(x+y)^{2}+1$

Using this remark we can compute $f_{\text {see }}$ via a semidefinite program We look for a decomposition

$$
f-\lambda=m^{\top} A_{m} \quad, \quad \lambda \in \mathbb{R}, \quad A \geqslant 0 .
$$

${ }^{2}$ depends on $\lambda$
Then

$$
f_{\text {sos }}=\text { sup } \lambda
$$

subject to $A \succcurlyeq 0$ $f-\lambda=m^{\top} A m \leftarrow$ linear conditions

Example: $f-\lambda=m^{\top} A_{m}$ with $\{A\}_{i, j}=\partial_{i j}$

$$
\begin{aligned}
& x^{4}-x y^{2}+x^{2}+(1-\lambda)=a_{11}+\left(a_{22}+a_{14}+a_{41}\right) x^{2}+\ldots+a_{66} y^{4} \\
\Rightarrow f_{\text {Ios }}= & \text { sup } 1-a_{11} \\
& \text { subject to }\left\{\begin{array}{l}
A \succcurlyeq 0 \\
a_{22}+a_{14}+a_{41}=1, \ldots, a_{66}=1
\end{array}\right.
\end{aligned}
$$

What is in general an SDP?
Let $A$ be a matrix with unknown entries, such as

$$
A=\left[\begin{array}{llll}
1 & 0 & x & 0 \\
0 & 1 & 0 & z \\
x & 0 & 2 & y \\
0 & z & y & y
\end{array}\right]
$$

Then the associated SDP is
maximize $l(x, y, z)$
subject to $A \geqslant 0$
the points satisfying this constraint form the "feasible set"
What is the feasible set?
Def: a spectrahedron is the intersection of the cone of positive semidefinite matrices with a linear space.
Equivalently, it is a set with the following shape

$$
\left\{\left(x_{1}, \ldots, x_{n}\right) \in \mathbb{R}^{n} \mid \sum_{i=1}^{n} x_{i} A_{i}+A_{0} \succcurlyeq 0\right\} .
$$

Example: the spectrahedron associated to $A=\left[\begin{array}{llll}1 & 0 & x & 0 \\ 0 & 1 & 0 & z \\ x & 0 & 2 & y \\ 0 & z & y & y\end{array}\right]$ is:
(1) the cone $\sum$ of PSD $4 \times 4$ symmetric matrices $\left(\partial_{i j}\right)_{i j}$ intersected with the linear space

$$
\left\{a_{11}=a_{22}=1, a_{33}=2, a_{12}=a_{14}=a_{23}=0, a_{34}=a_{44}\right\}
$$


then the spectrahedron is $\left\{x A_{1}+y A_{2}+z A_{3}+A_{0} \succcurlyeq 0\right\}$
$\frac{1}{v}$
Semialgebraic, convex sets $\rightarrow$ NICE!
$\triangle$ many properties: see exercises

