

Sum of squares generalizations for conic sets

Numerical example

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For each cone ($K_{\text{SOSPSD}}, K_{\text{SOS } \ell_2}, K_{\text{SOS } \ell_1}$) we compare the computational time to solve a simple example with its SOS formulation. We use an example analogous to the polynomial envelope problem from [4, Section 7.2], but replace the nonnegativity constraint by a conic inequality. Let $q_{i \in [2..m]}(\mathbf{x})$ be randomly generated polynomials in $\mathbb{R}_{n,2d_r}[\mathbf{x}]$. We seek a polynomial that gives the tightest approximation to the ℓ_1 or ℓ_2 norm of $(q_2(\mathbf{x}), \dots, q_m(\mathbf{x}))$ for all $\mathbf{x} \in [-1, 1]^n$:

$$\min_{q_1(\mathbf{x}) \in \mathbb{R}_{n,2d}[\mathbf{x}]} \int_{[-1,1]^n} q_1(\mathbf{x}) d\mathbf{x} : \quad (1a)$$

$$q_1(\mathbf{x}) \geq \|(q_2(\mathbf{x}), \dots, q_m(\mathbf{x}))\|_p \quad \forall \mathbf{x} \in [-1, 1]^n, \quad (1b)$$

with $p \in \{1, 2\}$ in Equation (1b).

To restrict Equation (1b) over $[-1, 1]^n$, we use *weighted sum of squares* (WSOS) formulations. A polynomial $q(\mathbf{x})$ is WSOS with respect to weights $g_{i \in [1..K]}(\mathbf{x})$ if it can be expressed in the form of $q(\mathbf{x}) = \sum_{i \in [1..K]} g_i(\mathbf{x}) p_i(\mathbf{x})$, where $p_{i \in [1..K]}(\mathbf{x})$ are SOS. Papp and Yildiz [4, Section 6] show that the dual WSOS cone (we will write K_{WSOS}^*) may be represented by an intersection of K_{SOS}^* cones. We represent the dual *weighted* cones K_{WSOSPSD}^* , $K_{\text{WSOS } \ell_2}^*$ and $K_{\text{WSOS } \ell_1}^*$ analogously using intersections of K_{SOSPSD}^* , $K_{\text{SOS } \ell_2}^*$ and $K_{\text{SOS } \ell_1}^*$ respectively.

Let $\mathbf{f}_{i \in [1..m]}$ denote the coefficients of $q_{i \in [1..m]}(\mathbf{x})$ and let $\mathbf{w} \in \mathbb{R}^U$ be a vector of quadrature weights on $[-1, 1]^n$. A low dimensional representation of Equation (1) may be written as:

$$\min_{\mathbf{f}_1 \in \mathbb{R}^U} \mathbf{w}^\top \mathbf{f}_1 : \quad (\mathbf{f}_1, \dots, \mathbf{f}_m) \in K, \quad (2)$$

where K is $K_{\text{WSOS } \ell_2}$ or $K_{\text{WSOS } \ell_1}$. If $p = 2$, we compare the $K_{\text{WSOS } \ell_2}$ formulation with two alternative formulations involving $K_{\text{Arw SOSPSD}}$. We use either K_{WSOSPSD} to model $K_{\text{Arw SOSPSD}}$, or K_{WSOS} . For $p = 1$, we build an SOS formulation by replacing (2) with:

$$\min_{\mathbf{f}_1, \mathbf{g}_2, \dots, \mathbf{g}_m, \mathbf{h}_2, \dots, \mathbf{h}_m \in \mathbb{R}^U} \mathbf{w}^\top \mathbf{f}_1 : \quad (3a)$$

$$\mathbf{f}_1 - \sum_{i \in [2..m]} (\mathbf{g}_i + \mathbf{h}_i) \in K_{\text{WSOS}}, \quad (3b)$$

$$\mathbf{f}_i - \mathbf{g}_i + \mathbf{h}_i = 0, \quad \mathbf{g}_i, \mathbf{h}_i \in K_{\text{WSOS}} \quad \forall i \in [2..m]. \quad (3c)$$

We select interpolation points using a heuristic adapted from [4, 5]. We uniformly sample N interpolation points, where $N \gg U$. We form a Vandermonde matrix of the same structure as the matrix \mathbf{P} used to

construct the lifting operator, but using the N sampled points for rows. We perform a QR factorization and use the first U indices from the permutation vector of the factorization to select U out of N rows to keep.

All experiments are performed on hardware with an AMD Ryzen 9 3950X 16-Core Processor (32 threads) and 128GB of RAM, running Ubuntu 20.10, and Julia 1.8 [1]. Optimization models are built using JuMP [3] and solved with Hypatia 0.5.3 [2] using our specialized, predefined cones. Scripts we use to run our experiments and raw results are available in the Hypatia repository.¹ We use default settings in Hypatia and set relative optimality and feasibility tolerances to 10^{-7} .

In Tables 1 and 2, we show Hypatia’s termination status, number of iterations, and solve times for $n \in \{1, 4\}$ and varying values of d_r and m . The termination status (*st*) columns of Tables 1 and 2 use the following codes to classify solve runs:

co the solver claims the primal-dual certificate returned is optimal given its numerical tolerances,

tl a limit of 1800 seconds is reached,

rl a limit of approximately 120GB of RAM is reached,

sp the solver terminates due to slow progress during iterations,

er the solver reports a different numerical error,

sk we skip the instance because the solver reached a time or RAM limit on a smaller instance.

If $p = 1$, we let $d = d_r$, where the maximum degree of $q_1(\mathbf{x})$ is $2d$. If $p = 2$, we vary $d \in \{d_r, 2d_r\}$ and add an additional column *obj* in Table 1 to show the ratio of the objective value under the K_{WSOS} (or equivalently K_{WSOSPSD}) formulation divided by the objective value under the $K_{\text{WSOS}\ell_2}$ formulation. Note that in our setup, the dimension of $K_{\text{WSOS}\ell_2}$ only depends on d . A more flexible implementation could allow polynomial components to have different degrees in $K_{\text{WSOS}\ell_2}$ for the $d = 2d_r$ case.

For $p = 2$ and $d = 2d_r$, the difference in objective values between $K_{\text{WSOS}\ell_2}$ and alternative formulations is less than 1% across all converged instances. For $p = 2$ and $d = d_r$, the difference in the objective values is around 10–43% across converged instances. However, the solve times for $K_{\text{WSOS}\ell_2}$ with $d = 2d_r$ are sometimes faster than the solve times of alternative formulations with $d = d_r$ and equal values of n , m , and d_r . This suggests that it may be beneficial to use $K_{\text{WSOS}\ell_2}$ in place of SOS formulations, but with higher maximum degree in the $K_{\text{WSOS}\ell_2}$ cone. The solve times using K_{WSOSPSD} are slightly faster than the solve times using K_{WSOS} . For the case where $p = 1$, the $K_{\text{WSOS}\ell_1}$ formulation is faster than the K_{WSOS} formulation, particularly for larger values of m . We also observe that the number of iterations the algorithm takes for $K_{\text{WSOS}\ell_2}$ compared to alternative formulations varies, but larger for $K_{\text{WSOS}\ell_1}$ compared to the alternative SOS formulation.

¹Instructions and scripts for reproducing our experiments are available at <https://github.com/chriscoey/Hypatia.jl/tree/master/benchmarks/natvsext>.

n	d_r	m	d	$K_{\text{SOS } \ell_2}$			K_{SOS}			K_{SOSPSD}			obj	
				st	iter	time	st	iter	time	st	iter	time		
1	20	4	20	co	13	0.1	co	17	0.4	co	13	0.2	0.89	
			40	co	16	0.2	co	19	1.8	co	15	1.1	0.99	
		8	20	co	13	0.1	co	17	2.9	co	14	2.1	0.85	
			40	co	19	0.7	co	21	18.0	co	16	10.0	1.00	
		16	20	co	14	0.4	co	19	48.0	co	14	27.0	0.80	
			40	co	21	2.4	co	20	264.0	co	17	188.0	1.00	
		32	20	co	15	1.6	co	22	1189.0	co	17	843.0	0.78	
			40	co	23	13.0	tl	3	2033.0	tl	7	2075.0	0.03	
	64	20	co	17	8.5	rl	*	*	rl	*	*	*		
		40	co	20	59.0	sk	*	*	sk	*	*	*		
	40	4	40	co	14	0.2	co	17	1.4	co	14	1.0	0.89	
			80	co	19	1.0	co	19	7.7	co	17	6.2	0.99	
			8	40	co	16	0.6	co	19	15.0	co	15	9.1	0.82
				80	co	21	3.1	co	21	93.0	co	17	62.0	1.00
		16	40	co	17	2.0	co	20	246.0	co	16	152.0	0.79	
			80	co	27	13.0	co	21	1737.0	co	18	1206.0	1.00	
32		40	co	18	7.6	tl	3	2031.0	tl	8	1803.0	0.02		
		80	co	27	53.0	rl	*	*	rl	*	*	*		
64		40	co	19	36.0	sk	*	*	sk	*	*	*		
		80	co	26	226.0	sk	*	*	sk	*	*	*		
2		4	2	co	13	0.2	co	18	0.9	co	15	0.6	0.75	
			4	co	21	33.0	co	43	133.0	co	37	97.0	1.00	
	8		2	co	13	0.4	co	21	11.0	co	18	7.7	0.64	
			4	co	21	102.0	tl	49	1816.0	tl	60	1811.0	1.00	
	16	2	co	15	2.3	co	30	242.0	co	25	203.0	0.59		
		4	co	21	437.0	sk	*	*	sk	*	*	*		
	32	2	co	15	10.0	tl	6	1848.0	tl	10	1972.0	15.00		
		4	co	22	1707.0	sk	*	*	sk	*	*	*		
	64	2	co	15	46.0	sk	*	*	sk	*	*	*		
		4	tl	10	1935.0	sk	*	*	sk	*	*	*		
	4	4	4	co	17	11.0	co	30	114.0	co	27	93.0	0.69	
			8	tl	10	1840.0	rl	*	*	tl	*	*	*	
8		4	co	18	42.0	co	34	1494.0	co	29	1111.0	0.58		
		16	4	co	18	174.0	rl	*	*	tl	*	*	*	
32		4	co	16	580.0	sk	*	*	sk	*	*	*		
		64	4	tl	10	1853.0	sk	*	*	sk	*	*	*	

Table 1: Solve time in seconds and number of iterations (iter) for instances with $p = 2$.

n	d	m	$K_{\text{SOS } \ell_1}$			K_{SOS}		
			st	iter	time	st	iter	time
1	40	8	co	17	0.5	co	15	0.5
		16	co	21	1.3	co	15	1.9
		32	co	25	3.2	co	15	11.0
		64	co	29	7.6	co	17	87.0
		128	co	32	17.0	co	18	610.0
	80	8	co	21	2.6	co	18	2.6
		16	co	24	5.6	co	17	13.0
		32	co	27	13.0	co	18	89.0
		64	co	31	31.0	co	18	600.0
		128	co	38	83.0	tl	*	*
4	2	8	co	17	0.5	co	17	0.4
		16	co	18	1.0	co	16	1.3
		32	co	24	2.8	co	17	7.8
		64	co	27	6.4	co	17	57.0
		128	co	30	14.0	co	17	400.0
	4	8	co	25	28.0	co	21	54.0
		16	co	28	86.0	co	22	318.0
		32	co	29	198.0	tl	9	1823.0
		64	co	31	423.0	sk	*	*
		128	co	42	1210.0	sk	*	*

Table 2: Solve time in seconds and number of iterations (iter) for instances with $p = 1$.

References

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