

Efficient algorithms for checking avoiding sure loss

Nawapon Nakharutai

Joint work with

Matthias C. M. Troffaes and Camila C. S. Caiado

Durham University

July 12, 2017

Outline

- Avoiding sure loss
- Results and contributions
 - Linear programs
 - Size reduction
 - Methods for solving linear programs
 - Degeneracy and stalling
 - Early stopping
 - Closed form for initial feasible points
- Improve three methods: simplex, affine scaling and primal-dual
- Benchmarking

Desirability axioms

- A possibility space Ω
- A gamble $f : \Omega \rightarrow \mathbb{R}$

Q: How should we reason with desirable gambles?

Suppose we are offered:

Outcomes	A	B	C
f_1	-5	-1	-2
f_2	30	20	0
f_3	-1	2	-1
f_4	-50	100	-50
$f_2 + f_4$	-20	120	-50

Desirability axioms

- (D1) Do not accept sure loss.
- (D2) Accept sure gain.
- (D3) Accept positive scaled invariance.
- (D4) Accept positive combination of desirable gambles. [2]

Avoiding sure loss

Definition 1

A set of desirable gambles \mathcal{D} is said to *avoid sure loss* if for all $n \in \mathbb{N}$, $\lambda_1, \dots, \lambda_n \geq 0$ and $f_1, \dots, f_n \in \mathcal{D}$ [5]:

$$\sup_{\omega \in \Omega} \left(\sum_{i=1}^n \lambda_i f_i(\omega) \right) \geq 0. \quad (1)$$

Linear programs

Theorem 2

A set of desirable gambles \mathcal{D} avoids sure loss if and only if the optimal value of (P1) is zero, or if the dual problem has feasible solutions [7].

$$\begin{aligned}
 \text{(P1)} \quad & \min \quad \alpha \\
 \text{subject to} \quad & \forall \omega \in \Omega : \sum_{i=1}^n \lambda_i f_i(\omega) - \alpha \leq 0 \\
 \text{where} \quad & \lambda_i \geq 0 \quad (\alpha \text{ free}).
 \end{aligned}$$

$$\begin{aligned}
 \text{(D1)} \quad & \max \quad 0 \\
 \text{subject to} \quad & \forall f_i : \sum_{\omega \in \Omega} f_i(\omega) p(\omega) \geq 0 \\
 & \sum_{\omega \in \Omega} p(\omega) = 1 \\
 \text{where} \quad & p(\omega) \geq 0.
 \end{aligned}$$

Size reduction

An alternative linear program is slightly smaller in size and has only non-negative variables:

Theorem 3

Choose any $\omega^ \in \Omega$. A set \mathcal{D} avoids sure loss if and only if the optimal value of (P2) is zero, or if (D2) has feasible solutions [3].*

$$(P2) \quad \min \sum_{i=1}^n \lambda_i f_i(\omega^*) + \alpha$$

$$\text{subject to } \forall \omega \neq \omega^* : \sum_{i=1}^n \lambda_i (f_i(\omega^*) - f_i(\omega)) + \alpha \geq 0$$

where $\lambda_i, \alpha \geq 0$.

$$(D2) \quad \max \quad 0$$

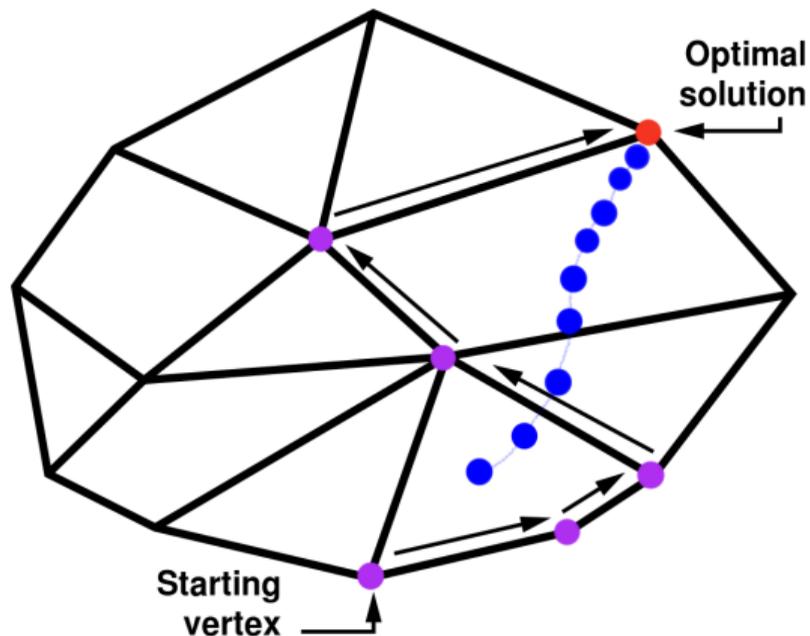
$$\text{subject to } \forall f_i \in \mathcal{D} : \sum_{\omega \neq \omega^*} (f_i(\omega^*) - f_i(\omega)) p(\omega) \leq f_i(\omega^*)$$

$$\sum_{\omega \neq \omega^*} p(\omega) \leq 1$$

where $p(\omega) \geq 0$.

Algorithms for solving linear programs

- Simplex
- Affine scaling
- Primal-dual



Degeneracy

- Simplex
 - Cycling: infinite iterations and no convergence.
 - Stalling: finite iterations, but in exponential time [1].
- Affine scaling
 - A restriction on a step-size [4].
- Primal-dual
 - Affecting numerical performance [1].

Early stopping

Lemma 4

(Adapted from [6]) The linear programming problem

$$\min \quad c^\top x \quad (2)$$

$$\text{subject to} \quad Ax \geq 0 \quad (3)$$

either has an optimal value that is zero, or is unbounded.

- Can stop when a current value is negative.
- Extra stopping for affine scaling and primal-dual.

Starting points

- To start those methods, we need an initial point.
- Simplex and Affine scaling
 - Closed form for both primal and dual problems.
- Primal-dual
 - Closed form for primal problem.

Overall comparison among improved methods

Comparison	simplex	affine scaling	primal-dual
Stalling	−	+	+
Stop early	−	+	+
Starting points	+	+	±
Convergence speed	−	+	++
Complexity per step	++	−	−

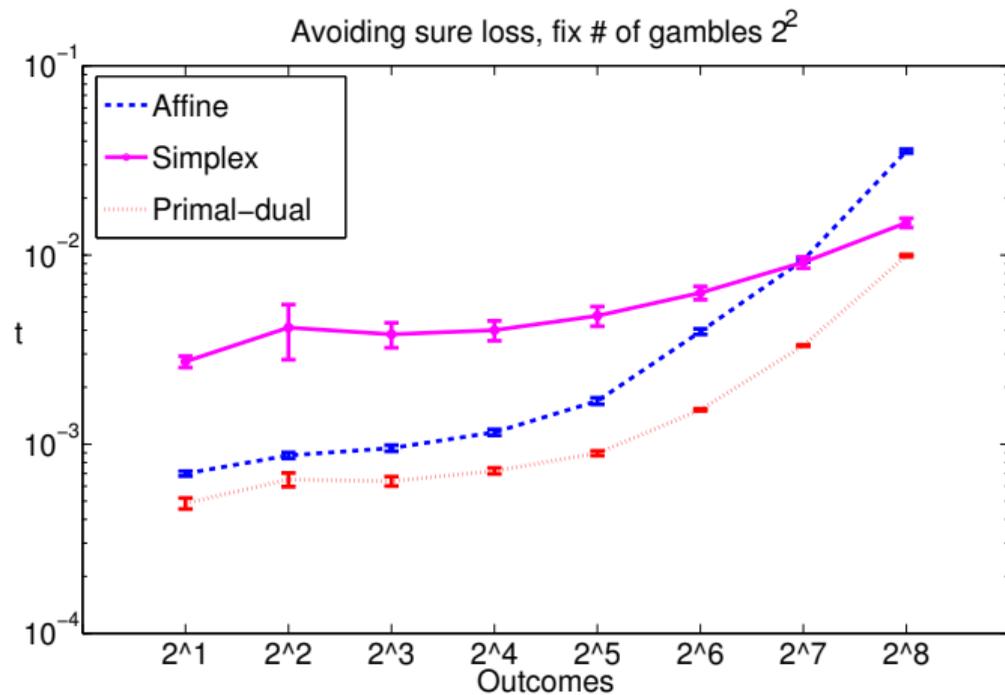
Conclusion

- Simplex is not normally efficient for checking avoiding sure loss due to degeneracy.
- Because of early stopping rules, affine scaling and primal-dual are much more efficient, especially when sets of desirable gambles do not avoid sure loss.
- Overall performance for checking avoiding sure loss:
primal-dual > affine scaling > simplex.

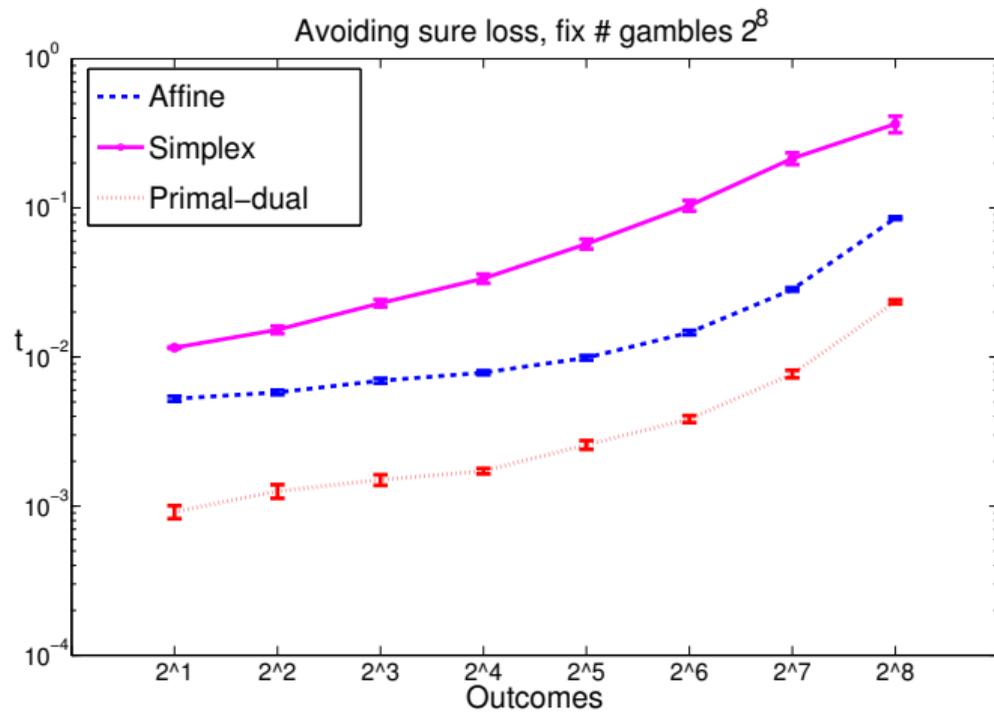
References

- [1] Christodoulos A. Floudas and Panos M. Pardalos, editors. *Encyclopedia of Optimization, Second Edition*. Springer, 2009.
- [2] Enrique Miranda and Gert de Cooman. *Introduction to Imprecise Probabilities*, chapter Lower prevision, pages 28–55. Wiley, 2014.
- [3] Nawapon Nakharutai. Computing with lower previsions using linear programming. Master's thesis, Durham University, 2015. unpublished thesis.
- [4] Romesh Saigal. *Linear programming : a modern integrated analysis*. Springer Science+Business Media New York, 1995.
- [5] Matthias C. M. Troffaes and Gert de Cooman. *Lower Previsions*. Wiley Series in Probability and Statistics. Wiley, 2014.
- [6] Robert J. Vanderbei. *Linear Programming: Foundations and Extensions, Second edition*. Springer, 2001.
- [7] Peter Walley. *Statistical Reasoning with Imprecise Probabilities*. Chapman and Hall, London, 1991.

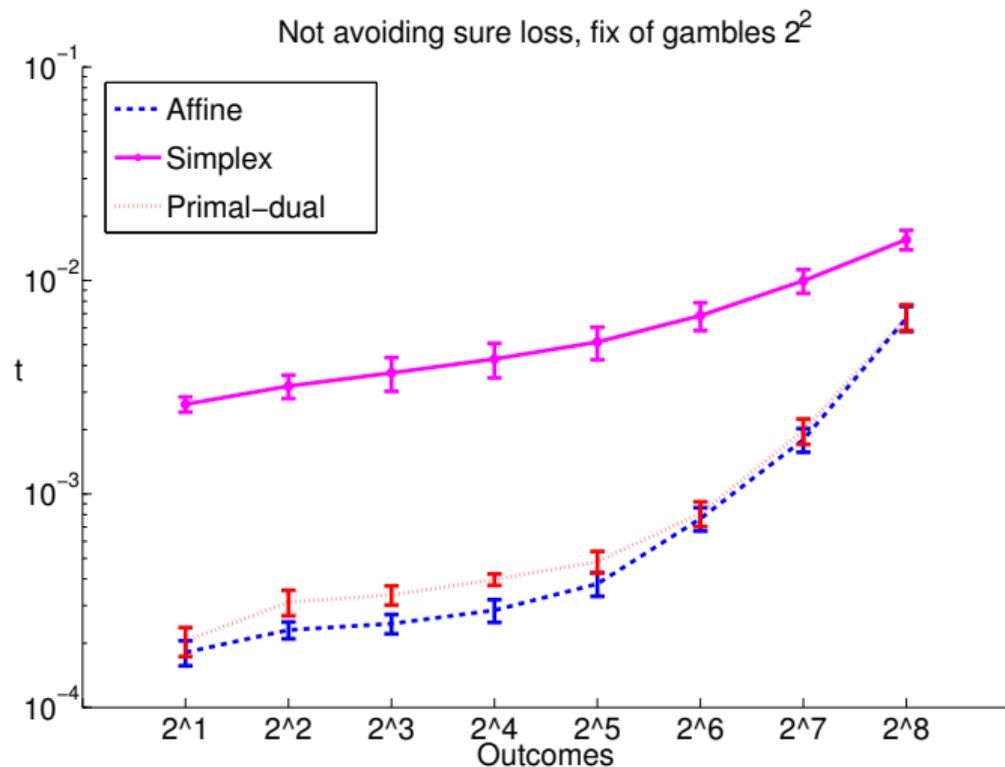
Benchmarking improved methods



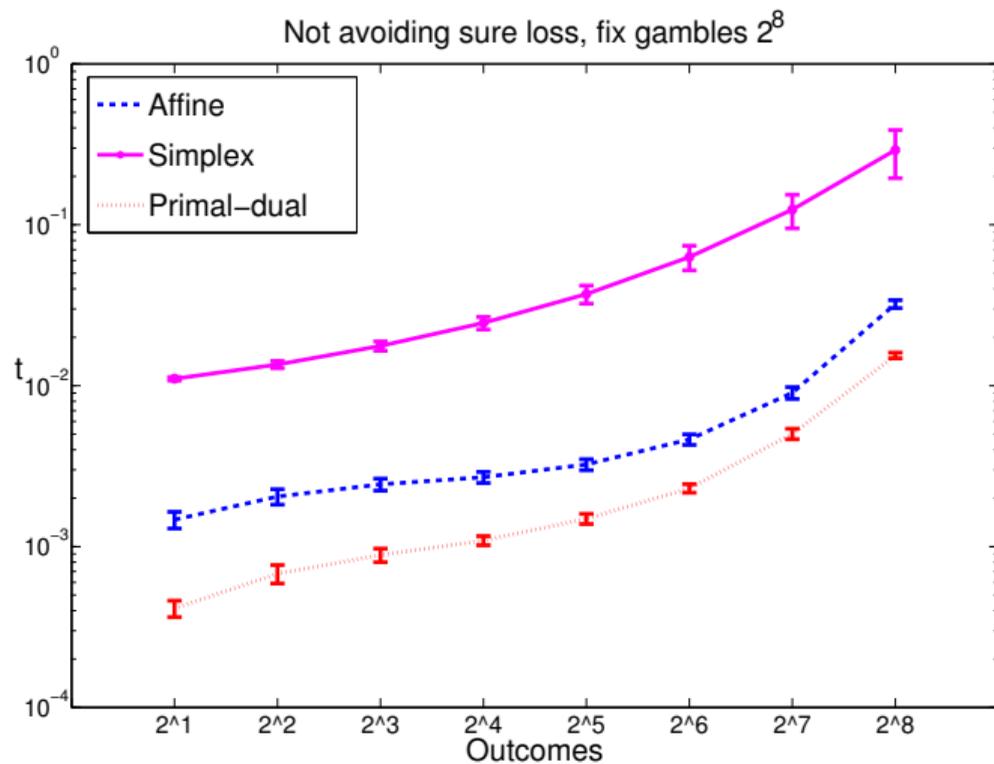
Benchmarking improved methods



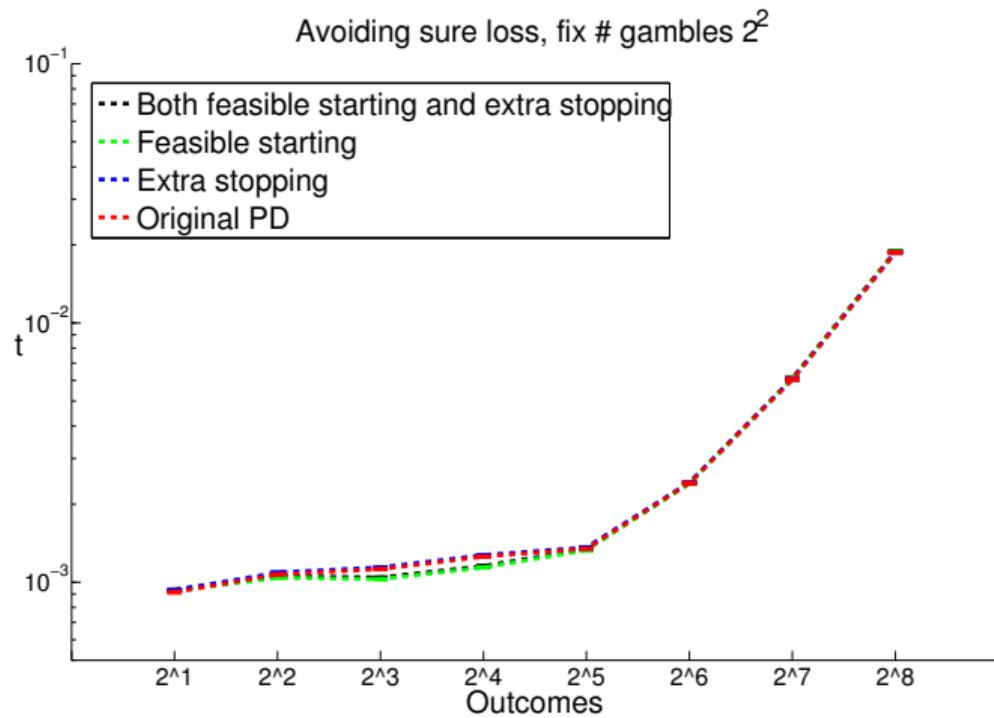
Benchmarking improved methods



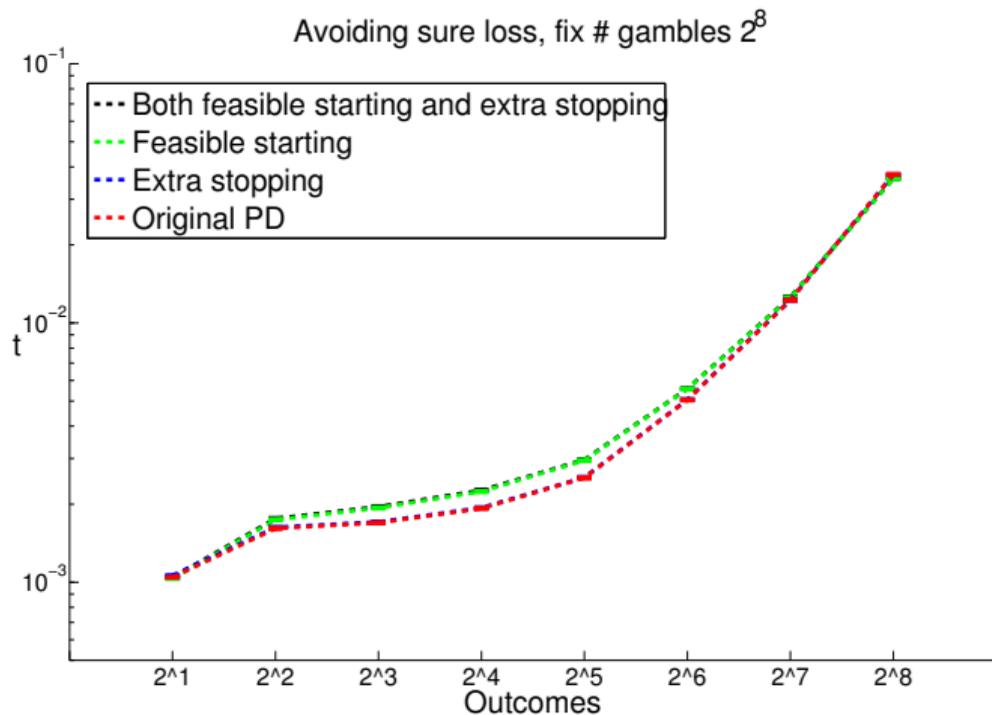
Benchmarking improved methods



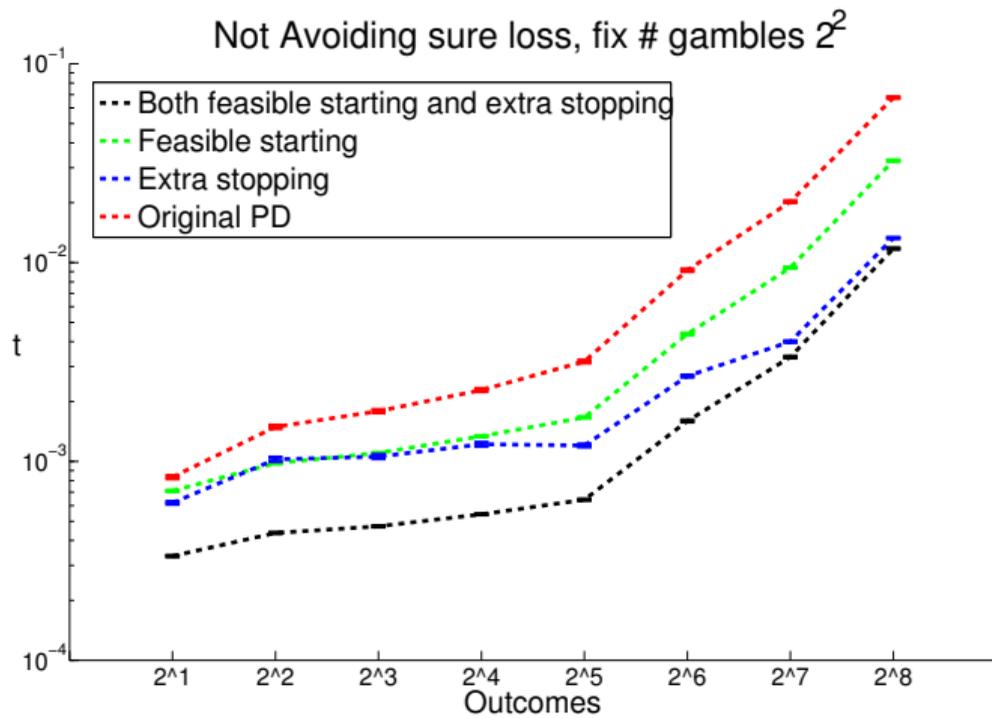
Different improved primal-dual methods



Different improved primal-dual methods



Different improved primal-dual methods



Different improved primal-dual methods

