

# Computing Nash equilibria and best response strategies in two-person zero-sum sequential games

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## Abstract

In this manuscript, we consider the problem of computing a best response against an opponent's realization plan in two-person sequential games. The proposed algorithm for solving the corresponding constrained convex-optimization problem, derives from the primal-dual scheme of A. Chambolle and T. Pock. Our algorithm is simple: all resolvent operators can be effectively computed in closed-form, using only elementary algebraic operations.

## Index Terms

game theory; two-person sequential game; Nash equilibria; best response; convex-optimization; constraint; primal-dual scheme

## I. INTRODUCTION

### A. Notation and Terminology

To begin, let us introduce some technical notation and terminology we will be using in this paper. The reader should lookup any standard textbook (for example [1]) on convex optimization for a tutorial introduction to these notions. Viz,

- $\mathcal{P}(S)$ : set of all the subsets of  $S$ ;
- $\mathcal{P}_k(S)$ : set of all the subsets of  $S$  which have exactly  $k$  elements;
- $\mathbb{R}^{m \times n}$ : space of all  $m$ -by- $n$  real matrices;
- $E^{-1}(U)$ : pre-image of  $U \subset \mathbb{R}^n$  under a matrix  $E \in \mathbb{R}^{p,n}$ , namely the set  $\{x \in \mathbb{R}^n \mid Ex \in U\}$ ;
- $A^T$ : transpose of a matrix  $A$ ;
- $\begin{bmatrix} A \\ B \end{bmatrix}$ : vertical stacking of two matrices  $A$  and  $B$ ;
- $v_j$ :  $j$ th component of a vector  $v$ ;
- $u^T v$ : dot product of two vectors  $u$  and  $v$ ;
- $\mathbb{R}_+^n$ : the  $n$ -dimensional nonnegative orthant;
- $(x)_+$ : component-wise maximum of a vector  $x$  and 0;
- $i_C$ : indicator function of a convex set  $C$ ;
- $\Pi_C$ : euclidean projector onto a convex set  $C$ ;
- $\|K\|_2$ : matrix 2-norm of a matrix  $K$ ;
- *l.s.c.p.c.*: acronym for adjective *lower semi-continuous proper convex*;
- $f^*$ : Fenchel transform (a.k.a convex conjugate) of a *l.s.c.p.c* function  $f$ ;
- $(1 + \sigma \partial f)^{-1}$ : resolvent (a.k.a proximal) operator of a *l.s.c.p.c* function  $f$ , for a given stepsize  $\sigma > 0$

### B. Generating the Texas Hold'em Poker game tree

Let  $a := (a_1, a_2, a_3, a_4) \in \mathbb{R} \times \mathbb{R} \times \mathbb{R}^2 \times \mathbb{R}^2$  hold the accounting info, where:

- $a_1 \in \mathbb{R}$  is the running bet size,
- $a_2 \in \mathbb{R}$  is the running total amount in the pot,
- $a_3 \in \mathbb{R}^2$  is a vector showing what each player has put into the pot sofar, and
- $a_4 \in \mathbb{R}^2$  is a vector showing running capital of each player.

Let  $ok(a, L)$  be a flag which is true iff the bet size  $a_1$  has not exceeded the limit  $L$  and each player's running credit is nonnegative. For any round  $t \in \mathbb{N}$ , let  $p(t)$  be the player to begin and  $\Sigma(t)$  be the set of all signals that can be emitted by the chance player.

**Definition 1.** A signal is simply any part of the information needed at shutdown to score the player's hands.

**Remark 1.** An emitted signal can be fully observable (for example, community cards), or only partially observable (for example when private / hole / pocket cards are delt, players can only see their own hole cards given to them; they can't see another player's hole cards).

$$\gamma(t, T, a, L) = \begin{cases} \mathcal{P}_1(\Sigma(t)), & \text{if } (t < T) \wedge ok(a, L) \wedge (p(t) = 0); \\ \{\mathbf{F}_{p(t)}\} \cup \mathbf{C}_{p(t)} \gamma(t+1, T, a, L) \cup \mathbf{K}_{p(t)} \lambda(t, T, g(a, \mathbf{K}_{p(t)}), L), & \text{if } (t < T) \wedge ok(a, L) \wedge (p(t) > 0); \\ \emptyset, & \text{if } t \geq T \vee \neg ok(a, L). \end{cases} \quad (1)$$

where the auxiliary function  $\lambda$  is defined by:

$$\left. \begin{aligned} \lambda(t, T, a, L) &:= \cup_{n=0}^{\infty} \alpha_1^{(n)}(t, T, a, L) \cup \cup_{n=0}^{\infty} \alpha_2^{(n)}(t, T, a, L) \\ \alpha_1^{(n)}(t, T, a, L) &:= (\mathbf{R}_{p(t)}' \mathbf{R}_{p(t)})^n \mathcal{P}_1(\{\mathbf{F}_{p(t)}', \mathbf{K}_{p(t)}'\}) \gamma(t+1, T, g(a, (\mathbf{R}_{p(t)}' \mathbf{R}_{p(t)})^n \mathcal{P}_1(\{\mathbf{F}_{p(t)}', \mathbf{K}_{p(t)}'\})), L) \\ \alpha_2^{(n)}(t, T, a, L) &:= (\mathbf{R}_{p(t)}' \mathbf{R}_{p(t)})^n \mathbf{R}_{p(t)}' \mathcal{P}_1(\{\mathbf{F}_{p(t)}', \mathbf{K}_{p(t)}'\}) \gamma(t+1, T, g(a, (\mathbf{R}_{p(t)}' \mathbf{R}_{p(t)})^n \mathbf{R}_{p(t)}' \mathcal{P}_1(\{\mathbf{F}_{p(t)}', \mathbf{K}_{p(t)}'\})), L) \end{aligned} \right\} \quad (2)$$

### C. Statement of the problem

Consider a two-person sequential game<sup>1</sup> in sequential-form (See for example, [2] and [3] for theory on sequential-form representation), and let  $A \in \mathbb{R}^{m,n}$  be our payoff matrix. We will be referring to the other player as “the opponent”. We are interested in the problem of finding a best response strategy  $x^* \in \mathbb{R}_+^n \cap E^{-1}(\{e\})$ , given a fixed behavioral strategy  $y_0$  for the opponent, where  $E$  is a sparse  $p$ -by- $n$  matrix whose entries are  $-1$ ,  $0$ , or  $+1$ , and  $(1, 0, 0, \dots, 0) =: e \in \mathbb{R}^p$ . Recall that  $E$  and  $e$  encode linear constraints on our “admissible” realization plans<sup>2</sup>  $x$ , in the sequential form representation of the game. In the language of convex-optimization, one can readily give the following saddle-point formulation for this problem. Viz,

$$\min_{x \in \mathbb{R}_+^n \cap E^{-1}(\{e\})} -y_0^T A x \quad (3)$$

**Definition 2.** A solution  $x^*$  to problem (3) is called a best response strategy against the opponent’s fixed strategy  $y_0$ .

**Remark 2.** Of course  $y_0$  is not necessarily an optimal strategy for the opponent. In case it is, the pair  $(x^*, y_0)$  is a Nash equilibrium for the game.

**Remark 3.** In practice,  $A$ ,  $E$ , and  $F$  are very sparse. This sparsity should be thoroughly exploited<sup>3</sup> by a solver for problem (3).

In section II, we give a brief overview of existing methods for solving (3). We elaborate our proposed algorithm in section III.

## II. RELATED WORK

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## III. THE PROPOSED ALGORITHM

In this section we present the algorithm which is the purpose of this paper, namely an algorithm for solving (3). Our algorithm (Alg.1) is a use-case of the generic primal-dual algorithm of A. Chambolle and T. Pock, namely Algorithm 1 of [4].

### A. Derivation of the algorithm

First observe that (1) can be re-written in the form:

$$\min_{x \in \mathbb{R}^n} f(-Ax) + g(x) \quad (4)$$

where:

$$\left. \begin{aligned} g &:= i_{E^{-1}(\{e\})} + i_{\mathbb{R}_+^n} \\ f &: z \mapsto y_0^T z \end{aligned} \right\} \quad (5)$$

Finally, the primal-dual formulation of this problem (which can be easily obtained using Fenchel-Rockafellar duality, for example) is:

$$\min_{x \in \mathbb{R}^n} \max_{y \in \mathbb{R}^m} y^T (-A)x_0 + g(x) - f^*(y) \quad (6)$$

Now, let’s observe that  $i_{E^{-1}(\{e\})}(x) = \max_{\zeta \in \mathbb{R}^p} \zeta^T (e - Ex)$ , and so one can re-write (2) as:

$$\min_{x \in \mathbb{R}^n} \max_{y \in \mathbb{R}^m, \zeta \in \mathbb{R}^p} \begin{bmatrix} y \\ \zeta \end{bmatrix}^T Kx + G(x) - F^*(y, \zeta) \quad (7)$$

where we’ve defined:

$$\left. \begin{aligned} K &:= - \begin{bmatrix} A \\ E \end{bmatrix} \\ G &:= g - i_{E^{-1}(\{e\})} = i_{\mathbb{R}_+^n} \\ F^* &: (y, \zeta) \mapsto (f^*(y) - \zeta^T e) = (i_{\{y_0\}}(y) - e^T \zeta) \end{aligned} \right\} \quad (8)$$

Furthermore, one easily checks that  $F^*$  and  $G$  are l.s.c.p.c with resolvent (a.k.a proximity) operators given by the simple formulae:

$$\left. \begin{aligned} (1 + \tau \partial G)^{-1} &= \Pi_{\mathbb{R}_+^n} : x \mapsto (x)_+ \\ (1 + \sigma \partial F^*)^{-1} &: (y, \zeta) \mapsto (y_0, \zeta + \sigma e) \end{aligned} \right\} \quad (9)$$

Using these ingredients, we derive the primal-dual algorithm given in Alg.1, for solving (7), and thus (3).

**Remark 4.** Equation (7) is in the form of equation (2) in [4] if we take  $X := \mathbb{R}^n$  and  $Y := \mathbb{R}^m \times \mathbb{R}^p$ .

**Remark 5.** Neither  $G$  nor  $F^*$  is strongly convex and so Alg.1 cannot be accelerated in the sense of algorithm 39 of [4].

<sup>1</sup>In a sequential game, players take turns in play, one after the other, as opposed to simultaneous play.

<sup>2</sup>In games in sequential form, the terms “strategy” and “realization plan” mean the same thing.

<sup>3</sup>For example when multiplying vectors with these matrices.

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**Algorithm 1:** Primal-dual algorithm for computing best response against opponent's fixed realization plan  $y_0$ 

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**Given** Tolerance  $\epsilon > 0$ .

**Initialize**  $\tilde{x}^{(0)} = x^{(0)} \in \mathbb{R}^n$ ;  $\zeta^{(0)} \in \mathbb{R}^q$ ;  $\tau, \sigma > 0$  s.t.  $\tau\sigma\|K\|_2^2 < 1$ ;  $k = 0$ .

**Precompute**  $\eta_0 \leftarrow \tau A^T y_0$

**repeat**

$$\begin{aligned}\zeta^{(k+1)} &\leftarrow \zeta^{(k)} - \sigma(e - E\tilde{x}^{(k)}) \\ x^{(k+1)} &\leftarrow (x^{(k)} + \eta_0 + E^T \zeta^{(k+1)})_+ \\ \tilde{x}^{(k+1)} &\leftarrow 2x^{(k+1)} - x^{(k)} \\ k &\leftarrow k + 1\end{aligned}$$

**until**  $\frac{\|x^{(k+1)} - x^{(k)}\|_2^2}{2\tau} + \frac{\|\zeta^{(k+1)} - \zeta^{(k)}\|_2^2}{2\sigma} < \epsilon$  ;

**return**  $x^{(k)}$ ,  $-y_0^T A x^{(k)}$

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### B. Convergence analysis of the algorithm

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**Remark 6.** The derivation above reveals that in equation (3) above, if the constraint " $x \geq 0$ " is replaced by a constraint " $x \in C$ " (thus obtaining a new problem) where  $C$  is a convex set, then we simply need to replace the operator " $(\cdot)_+$ " with " $\Pi_C$ " in the equations to obtain a corresponding algorithm. Of course, this is because  $i_C^* = \Pi_C$ .

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### REFERENCES

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