Smoothing for non-smooth optimization, lecture 4

Last time: *Smoothing techniques*

- *•* A "fixed" smoothing approach
- *•* Excessive gap technique

Today: *Applications*

- *•* Game theory: computation of Nash equilibrium
- *•* Sparse principal component analysis

Recap $P(y)$ $f(x)$ Consider min $\max_{y \in Q_2} {\{\langle c, x \rangle - \langle b, y \rangle + \langle Ax, y \rangle\}} = \max_{y \in Q_2}$ max $\min_{x \in Q_1} {\langle \langle c, x \rangle - \langle b, y \rangle + \langle Ax, y \rangle}.$ min *x*∈*Q*¹

Write these problems as

min
$$
\{f(x) : x \in Q_1\}
$$
 = max $\{\phi(y) : y \in Q_2\}$

for

$$
f(x) = \langle c, x \rangle + \max_{y \in Q_2} \{ \langle Ax, y \rangle - \langle b, y \rangle \}
$$

and

$$
\phi(y) = -\langle b, y \rangle + \min_{x \in Q_1} \left\{ \langle c, x \rangle + \langle Ax, y \rangle \right\}.
$$

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Smoothing techniques

- Assume d_i is a prox-function for Q_i with modulus ρ_i and max value *Di*.
- In *N* iterations get $x^N \in Q_1$, $y^N \in Q_2$ such that

$$
0 \le f(\mathbf{x}^{N}) - \phi(\mathbf{y}^{N}) \le \frac{4||A||}{N+1} \sqrt{\frac{D_1 D_2}{\rho_1 \rho_2}}
$$

• Each iteration requires elementary operations and the solution of three problems of the form

$$
\min\left\{d_i(z) - \langle g, z \rangle : z \in Q_i\right\}
$$

• All of this holds for any choice of norms in *Ei*, not necessarily the Euclidean norm.

Matrix games

Games in strategic form:

- *•* Each player has a finite set of pure strategies
- *•* A simultaneous choice of strategies determines the payoff of each player

Equilibrium: choice of strategies for each player so that no player wishes to deviate

Theorem 1 (Nash, 1950) *Under suitable circumstances such an equilibrium exists (may involve randomization).*

Consider a two-person, zero-sum game:

- *• ^A* [∈] IR*m*×*ⁿ* : Player 2's payoff matrix
- $x \in \Delta_n$: set of mixed strategies of Player 1.
- *• y* ∈ ∆*m*: set of mixed strategies of Player 2.

Player 1's problem: min max $(Ax)_j$
 $x \in \Delta_n$ *j*

Player 2's problem: $\max_{y \in \Delta_m} \min_i (A^{\mathsf{T}} y)_i$

Nash equilibrium problem:

 $\min_{x \in \Delta_n} \max_{y \in \Delta_m} \langle Ax, y \rangle = \max_{y \in \Delta_m} \min_{x \in \Delta_n} \langle Ax, y \rangle.$

To apply smoothing techniques need prox-functions for $Q_1 = \Delta_n, Q_2 = \Delta_m.$

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Euclidean distance:

$$
d_1(x) := \frac{1}{2} \sum_{i=1}^n \left(x_i - \frac{1}{n} \right)^2, \ \ d_2(x) := \frac{1}{2} \sum_{j=1}^m \left(y_j - \frac{1}{m} \right)^2.
$$

It is easy to see that

$$
D_1 = \frac{1}{2} - \frac{1}{2n} \le \frac{1}{2}, \ D_2 = \frac{1}{2} - \frac{1}{m} \le \frac{1}{2}.
$$

Also, for the Euclidean norms in $\mathbb{R}^n, \mathbb{R}^m$ we have

$$
\rho_1=\rho_2=1,
$$

and

$$
||A|| = \sigma_{\max}(A) = \sqrt{\lambda_{\max}(A^{\mathsf{T}}A)}.
$$

So in *N* iterations get $x^N \in \Delta_n$, $y^N \in \Delta_m$ such that

$$
0 \le f(\mathbf{x}^N) - \phi(\mathbf{y}^N) \le \frac{\sqrt{\lambda_{\max}(A^\mathsf{T} A)}}{N+1}
$$

Entropy:

$$
d_1(x) := \sum_{i=1}^n x_i \log x_i + \log n, \ \ d_2(x) := \sum_{j=1}^m y_j \log y_j + \log m.
$$

It is easy to see that

$$
D_1 = \log n, \ D_2 = \log m.
$$

Also, for the 1-norms in $\mathbb{R}^n, \mathbb{R}^m$ we have

$$
\quad\text{and}\quad
$$

 $\rho_1 = \rho_2 = 1,$ $\left| \mathbf{A} \mathbf{.} \mathbf{.} \right|$ $||A|| = \max \{|A|_{ij}\}.$

So in *N* iterations get $x^N \in \Delta_n$, $y^N \in \Delta_m$ such that

$$
0 \le f(\mathbf{x}^N) - \phi(\mathbf{y}^N) \le \frac{4\sqrt{\log n \log m} \max |A_{ij}|}{N+1}
$$

What about the subproblems at each iteration? Need to solve

$$
\min\left\{d_1(x) - \langle g, x \rangle : x \in \Delta_n\right\}.
$$

For the entropy $d_1(x) = \sum^{n}$ *i*=1 x_i log x_i + log n , get a closed-form solution

$$
x_i = \frac{e^{g_i}}{\sum\limits_{k=1}^n e^{g_k}}, i = 1, \dots, n
$$

For the Euclidean distance $d_1(x) = \frac{1}{2} \sum^{n} {(x_i - 1/n)^2}$, it follows from the KKT conditions that the solution is

$$
x_i = (g_i - \lambda)^+, \ i = 1, \dots, n
$$

for $\lambda \in \mathbb{R}$ such that $\sum_{i=1}^n (g_i - \lambda)^+ = 1$.

Can find λ by sorting g_i , $i = 1, \ldots, n$.

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Sequential games

Games that involve turn-taking, chance moves, and imperfect information.

Example 2 (Simplified poker)

- Opening: players bet 1 each
- *•* One card is dealt to each player
- *•* Player 1 can check or raise
	- If Player 1 checks then Player 2 can check or raise
	- If Player 2 checks there is a showdown (higher wins)
	- If Player 2 raises then Player 1 can fold, or call (showdown)
- If Player 1 raises then Player 2 can fold, or call (showdown)

Game tree representation

The sequence form

- *•* With perfect recall, can formulate the Nash equilibrium problem in terms of sequences of moves.
- Strategies ↔ set of realization plans

Example 3 (simplified poker)

Player 1's sequences:

sequences:
\n
$$
S = \left\{ \emptyset, k^J, r^J, k^Q, r^Q, k^J f^J, k^J c^J, k^Q f^Q, k^Q c^Q \right\}
$$

Set of realization plans: $\{x : Ex = e, x \ge 0\}$, for

alization plans:
$$
\{x : Ex = e, x \ge 0\}
$$
, for
\n
$$
E = \begin{bmatrix} 1 & & & \\ -1 & 1 & 1 & \\ -1 & & 1 & 1 \\ & -1 & & 1 & 1 \\ & & -1 & & 1 & 1 \end{bmatrix}, e = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \leftarrow \qquad \sum_{k=0}^{3} \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}
$$

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 χ = $(1, \frac{1}{3}, \frac{2}{3}, \frac{1}{2}, \frac{1}{2}, \frac{1}{3})$

Nash equilibrium via sequence form

Assume

- *• Q*1*, Q*2: realization plans of Players 1 and 2
- *• A*: Player 2's payoff matrix

Nash equilibrium

$$
\min_{x\in Q_1}\max_{y\in Q_2}\langle Ax,y\rangle=\max_{y\in Q_2}\min_{x\in Q_1}\langle Ax,y\rangle.
$$

- In matrix games Q_1 , Q_2 are simplices
- *•* In sequential games *Q*1, *Q*² are complexes

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Rhode Island Hold'em: created for AI research

- *•* Each player pays an ante of 5 chips.
- *•* Each player is dealt a single card, placed face down.
- *•* First betting round: Each player may check, or bet if no bets have been placed. If a bet has been placed, then the player may fold, call, or raise. The players are limited to 3 raises per betting round. In this betting round, the bets are 10 chips.
- *•* A community card is dealt face up and a second betting round take place with bets equal to 20 chips.
- *•* Another community card is dealt face up and a final betting round takes place at this point, with bets equal to 20 chips.

Texas Hold'em Poker (with limits):

Game tree has $\sim 10^{18}$ nodes.

• Gilpin and Sandholm (2005–):

Can approximate by solving abstractions (simpler sequential games)

• The closer the abstraction, the better

If neither player folds, then the showdown takes place. Both players turn over their cards. The player who has the best 3-card poker hand takes the pot. In the event of a draw, the pot is split evenly. The ranking of hands is given below.

Hands

- *•* Straight flush: e.g., *J, Q, K* of spades
- *•* Three of a kind: e.g., 8*,* 8*,* 8 of spades, hearts, diamonds
- *•* Straight: e.g., *J, Q, K*
- *•* Flush: e.g., 2*,* 5*,* 7 diamonds
- *•* Pair: e.g., 2*,* 2*,* 8
- *•* High card

Hoda, Gilpin, Sandholm, P. (2006–):

Apply smoothing techniques to solve large sequential games.

Theorem 4 (HGP 2006) *Any prox-function for the simplex yields a prox-function for any complex.*

Remarks

- *•* Provide estimates of relevant ρ*, D*
- *•* Subproblem (for *Q* complex):

$$
\min\left\{d(z)-\langle g,z\rangle:z\in Q\right\}.
$$

can be recursively solved via solving subproblems over simplices

• Most expensive work per iteration: matrix-vector products

$$
x \mapsto Ax, \ y \mapsto A^{\mathsf{T}} y
$$

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Complexity results

From Smoothing and HGP Theorem get:

Theorem 5

.

• For the entropy induced prox-function:

$$
\left[(4G^2/\epsilon) \max |A_{ij}| \right] \text{ itns } \sim (\bar{x}, \bar{y}) \in Q_1 \times Q_2 \text{ such that}
$$

$$
\max_{y \in Q_2} \langle Ay, \bar{x} \rangle - \min_{x \in Q_1} \langle A\bar{y}, x \rangle \le \epsilon
$$

- *G: size of the game tree*
- *• For the Euclidean induced prox-function:*

$$
\left[(4G/\epsilon)\lambda_{\max}^{1/2}(A^{\mathsf{T}}A) \right] \text{ itns} \sim (\bar{x}, \bar{y}) \in Q_1 \times Q_2 \text{ such that}
$$

$$
\max_{y \in Q_2} \langle Ay, \bar{x} \rangle - \min_{x \in Q_1} \langle A\bar{y}, x \rangle \le \epsilon
$$

Computational experience

Test problems, size of *A*

- *•* Rhode Island Hold'em poker, 1*M* × 1*M*.
- *•* Abstractions of Texas Hold'em poker:

 $81 \times 81, 1041 \times 1041,$ $10421 \times 10421, 160k \times 160k$ $13M \times 13M$, $100M \times 100M$

About the $160K \times 160K$ instance

Efficient matrix representation

• Payoff matrix in poker games admits a concise representation. For example, for a three-round game

$$
A = \begin{bmatrix} A_1 & & \\ & A_2 & \\ & & A_3 \end{bmatrix}
$$

where $A_i = F_i \otimes B_i$, $i = 1, 2$ and $A_3 = F_3 \otimes B_3 + S \otimes W$ for
smaller matrices F_i, B_i, S, W .

- *•* Do not need to form *A* explicitly.
- Instead have subroutines that compute $x \mapsto A^Tx$, $y \mapsto Ay$.

Matrix *A*

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Upper-left blocks of *E*

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Path of the iterates' gap

$$
\max_{y \in Q_2} \langle y, Ax^k \rangle - \min_{x \in Q_1} \langle y^k, Ax \rangle
$$

Largest instance attempted so far:

A : 101*,* 192*,* 201 × 101*,* 192*,* 221

E : 40*,* 476*,* 881 × 101*,* 192*,* 201

F : 40*,* 476*,* 881 × 101*,* 192*,* 221

number of non-zeros in *A*: 2*,* 927*,* 336*,* 725*,* 318

Implementation

- *•* Based on EGT technique
- *•* Machine: 1.65GHz IBM eServer p5 570 with 64 gigabytes of RAM
- *•* Concise representation requires only 2.49 GB of RAM.
- *•* Entire algorithm uses about 30 GB of RAM.
- *•* Each iteration takes a few hours (it has run for months)

Matrix *F*

Poker players

Poker is a central challenge problem in AI. Some reasons:

- *•* Imperfect information: the other players' cards are hidden, future events
- *•* Bluffing and other deceptive strategies are needed in a good player
- *•* Interest in developing automatic poker players

Gilpin, Sandholm, Sorensen 2007

- *•* A poker player based on the four-round abstraction.
- *•* Use the approximate equilibrium found by our algorithm.

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Principal component analysis

Suppose $C \in \mathbf{S}^n$ is a covariance matrix. Then there exist $P \in \mathbb{R}^{n \times n}$ orthogonal such that

$$
C = Q \text{Diag}(\lambda(C))Q^{\mathsf{T}} = \sum_{i=1}^{n} \lambda_i(C) p_i p_i^{\mathsf{T}}
$$

Principal components: p_1, \ldots, p_n

Can find first principal component by solving:

 $X: = 7^{2^k}$

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Sparse first principal component:

$$
\begin{array}{ll}\n\max & x^{\top}Cx\\ \n\text{s.t.} & x^{\top}x = 1\\ \n\text{card}(x) \le k\n\end{array}
$$

SDP relaxation

 \max *C* • $X - \delta 1$ • $|X|$ s.t. $I \bullet X = 1$ $X \succ 0$.

For simplicity assume $\delta = 1$.

Then the SDP

$$
\begin{array}{ll}\n\max & C \bullet X - 1 \bullet |X| \\
\text{s.t.} & I \bullet X = 1 \\
& X \succeq 0\n\end{array}
$$

can be written as

$$
\max_{X \in Q_1} \min_{Y \in Q_2} \{ \langle C, X \rangle - \langle X, Y \rangle \}
$$

where

$$
Q_1 = \{ X \in \mathbf{S}^n : X \succeq 0, \langle I, X \rangle = 1 \}, \quad Q_2 = \left\{ Y \in \mathbf{S}^n : |Y_{ij}| \le 1 \right\},\
$$

and $\langle \cdot, \cdot \rangle$ is the trace inner product: $\langle X, S \rangle = \text{trace}(XS) = X \bullet S.$

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Prox-function for *Q*1:

$$
d_1(X) = \sum_{i=1}^{n} \lambda_i(X) \log \lambda_i(X) + \log n
$$

Prox-function for *Q*2:

$$
d_2(Y) = \frac{1}{2} \langle Y, Y \rangle
$$

It is easy to see that $D_1 = \log n$, $D_2 = n^2/2$.

For suitable norms we get $\rho_1 = \rho_2 = 1$ and $||A|| = 1$.

Thus in *N* iterations get $\bar{X} \in Q_1$ such that $C \cdot \bar{X} - 1 \cdot |\bar{X}|$ is within

$$
\frac{2\sqrt{2}n\sqrt{\log n}}{N+1}
$$

of the optimal SDP value.

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Subproblems at each iteration:

\n- $$
\min\left\{\sum_{i=1}^{n} \lambda_i(X) \log \lambda_i(X) + \log n - G \cdot X : X \geq 0, I \cdot X = 1\right\}
$$
\n- $$
\min\left\{\frac{1}{2}U \cdot U - \langle G, U \rangle : |U_{ij}| \leq 1\right\}
$$
\n

Solution to second one:

$$
U_{ij} = \text{sign}(G_{ij}) \min \left\{ |G_{ij}|, 1 \right\}.
$$

Solution to the first one (similar to entropy):

• Compute eigenvalue decomposition: $G = V \text{Diag}(\lambda(G)) V^\top$

• Let
$$
h_i := \frac{e^{\lambda_i(G)}}{\sum_{k=1}^n e^{\lambda_k(G)}}
$$
, $i = 1, ..., n$

• Let
$$
X = V \text{Diag}(h) V^{\top}
$$

References for today's material

- S. Hoda, A. Gilpin, J. Peña, and T. Sandholm, "A gradient-based algorithm for finding Nash equilibria in extensive form games," In preparation.
- *•* A. D'Aspremont, L. El Ghaoui, M. Jordan, and G. Lankcriet, "A direct formulation for sparse PCA using semidefinite programming," To appear in SIAM Review.