Reinforcement Learning

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Lecture 3: Linear Programming

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License Information for Reinforcement Learning (EE-568)

Recall: Reinforcement learning setup

- Reinforcement Learning: Sequential decision making in an unknown environment
- Markov decision process: $M = (\mathcal{S}, \mathcal{A}, \mathsf{P}, r, \mu, \gamma)$
- Stationary stochastic policy $\pi : \mathcal{S} \to \Delta(\mathcal{A})$, $a_t \sim \pi(\cdot|s_t)$
- State-value function: $V^\pi(s) := \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) | s_0 = s, \pi\right]$
- Performance objective: $\max_\pi (1-\gamma) \sum_{s \in \mathcal{S}} \mu(s) V^\pi(s)$

Challenges:

- Infer long-term consequences based on limited, noisy short-term feedback.
- Unknown transition dynamics P: knowledge only through sampled experience.
- Large state- and action-spaces.
- Non-convex performance objective as a function of π.

Motivation

- Approximate dynamic programming (previous lecture)
  - Attempts to find approximate fixed-point solutions to the (nonlinear) Bellman equation.
  - Pros:
    - + Well-studied setting for tabular MDPs that comes with theoretical convergence guarantees.
      - See Lecture 2.
    - + Deep-learning variants (e.g., DQN [20]) are powerful.
  - Cons:
    - − Does not leverage classical machine-learning tools rooted in *convex* optimization.

Motivation (cont'd)

◦ The linear programming approach (this lecture)

- Introduces the linear programming (LP) approach, i.e., an alternative convex viewpoint.
- Overviews recent scalable algorithms with theoretical guarantees rooted in the LP approach.
- Highlights how historical key limitations have been eliminated.

Revisiting Bellman optimality equation

- We denote $V^\star(s) = \max_{\pi \in \Pi} \ V^\pi(s)$.
- $V^\star$ satisfies the Bellman optimality equation, which can be written as a feasibility problem:

$$
\begin{aligned}
&\min_{V} \ 0 \\
&\text{s.t.} \ \ V(s) = (\mathcal{T}V)(s) := \max_{a \in \mathcal{A}} \left[r(s,a) + \gamma \sum_{s' \in \mathcal{S}} \mathsf{P}(s'|s,a) V(s') \right], \quad \forall\, s \in \mathcal{S}.
\end{aligned}
$$

  - $\mathcal{T}$ is the so-called Bellman operator
  - The only feasible assignment is $V^\star$
  - The above equality constraints are nonlinear in V due to the maximization over $\mathcal{A}$

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- $\mathcal{T}$ is the so-called Bellman operator
- The only feasible assignment is $V^\star$
- The above equality constraints are nonlinear in V due to the maximization over $\mathcal{A}$

Remarks: ◦ The Bellman optimality operator is a γ-contraction mapping w.r.t. ℓ_∞-norm:

$$\left\| \mathcal{T}V' - \mathcal{T}V \right\|_\infty \leq \gamma \left\| V' - V \right\|_\infty.$$

◦ The Bellman operator is also monotonic (component-wise): $V' \leq V \;\Rightarrow\; \mathcal{T}V' \leq \mathcal{T}V$.

Solving MDPs via LPs: Primal LP formulation (cont'd)

Derivation:

- We will derive LP to reach the unique solution of $V^\star$.
- Recall: Bellman optimality opterator $[\mathcal{T}V](s) = \max_{a\in\mathcal{A}} \left(r(s,a) + \gamma \sum_{s'\in\mathcal{S}} \mathsf{P}(s'|s,a)V(s') \right)$.
- $V^\star$ is feasible as

$$V^\star(s) = [\mathcal{T}V^\star](s) \geq r(s,a) + \gamma \sum_{s'\in\mathcal{S}} \mathsf{P}(s'|s,a)V^\star(s'),\ \forall (s,a) \in \mathcal{S}\times\mathcal{A}.$$

- For any feasible V, we have $V \geq \mathcal{T}V$. Component-wise monotonicity ($V_1 \geq V_2 \Rightarrow \mathcal{T}V_1 \geq \mathcal{T}V_2$)

$$V \geq \mathcal{T}V \geq \mathcal{T}^2 V \geq \cdots \geq \mathcal{T}^\infty V = V^\star,$$

  implies optimality of $V^\star$.
- Uniqueness follows as $\mathcal{T}$ is contractive.

Relaxation of Bellman optimality condition

- The Bellman optimality $\Rightarrow V^\star$ is the function with the lowest values $V(s)$ among all $V \in \mathbb{R}^{|\mathcal{S}|}$ satisfying

$$V(s) \geq \; r(s,a) + \gamma \sum_{s' \in \mathcal{S}} \mathsf{P}(s'|s,a)V(s'), \quad \forall \; s \in \mathcal{S}, \; a \in \mathcal{A}. \qquad \text{(Bellman inequality)}$$

- Note that the Bellman inequality constraint is linear in V $\quad \Longrightarrow \quad$ Linear Programming (LP)

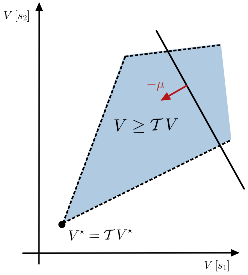


Figure: Graphical interpretation of Bellman inequality

Solving MDPs via LPs: Primal LP formulation

◦ The previous derivation motivates the following LP.

Primal LP

Let $\mu(s) > 0, s \in \mathcal{S}$ be the initial distribution (or any positive weights). Then, the primal LP is given by

$$\begin{aligned} \min_{V} \quad & (1-\gamma) \sum_{s \in \mathcal{S}} \mu(s) V(s) \\ \text{s.t.} \quad & V(s) \geq \; r(s,a) + \gamma \sum_{s' \in \mathcal{S}} \mathsf{P}(s'|s,a) V(s'), \quad \forall\, s \in \mathcal{S},\; a \in \mathcal{A}. \end{aligned} \tag{P}$$

Remarks:

- ◦ The number of decision variables is $|\mathcal{S}|$, and the number of constraints is $|\mathcal{S}||\mathcal{A}|$.
- ◦ Given $V^\star$, we can determine an optimal (deterministic) policy greedily

$$\pi^\star(s) \in \arg\max_{a \in \mathcal{A}} \left[r(s,a) + \gamma \sum_{s' \in \mathcal{S}} \mathsf{P}(s'|s,a) V^\star(s) \right]. \tag{1}$$

- ◦ The factor $(1-\gamma)$ in the objective will ensure that the dual variables are in the simplex.

Solving MDPs via LPs: Primal LP formulation (cont'd)

Recall: Primal LP

Let $\mu(s) > 0, s \in \mathcal{S}$ be the initial distribution (or any positive weights). The primal LP formulation is given by

$$\begin{aligned} \min_{V} \quad & (1-\gamma)\sum_{s\in\mathcal{S}} \mu(s)V(s) \\ \text{s.t.} \quad & V(s) \geq r(s,a) + \gamma \sum_{s'\in\mathcal{S}} \mathsf{P}(s'|s,a)V(s'), \quad \forall\, s \in \mathcal{S},\ a \in \mathcal{A}. \end{aligned} \tag{P}$$

Lemma (LP Formulation and $V^\star$)

$V^\star$ is the unique optimal solution to the above LP formulation for any positive weights $\{\mu(s)\}$.

Remark:

- The unique optimizer does not depend on the positive weights $\{\mu(s)\}$.

Solving MDPs via LPs: Dual LP formulation

- From linear programming, we know that the dual LP of (P) is given by the following.
  - See supplementary material, Slide 8. We refer to [19] for a comprehensive treatment.

Dual LP

$$
\begin{aligned}
\max_{\lambda} \quad & \sum_{s\in\mathcal{S}} \sum_{a\in\mathcal{A}} r(s,a)\lambda(s,a) \\
\text{s.t.} \quad & \sum_{a\in\mathcal{A}} \lambda(s,a) = (1-\gamma)\mu(s) + \gamma \sum_{s'\in\mathcal{S},a'\in\mathcal{A}} \mathsf{P}(s|s',a')\lambda(s',a'), \quad \forall\, s\in\mathcal{S}, \\
& \lambda(s,a) \geq 0, \quad \forall\, s\in\mathcal{S}, a\in\mathcal{A}.
\end{aligned} \tag{D}
$$

Remarks:

- The number of decision variables is given by $|\mathcal{S}||\mathcal{A}|$.
- The number of constraints is given by $|\mathcal{S}| + |\mathcal{S}||\mathcal{A}|$.
- The constraints imply the decision variables are probabilities: $\lambda \in \Delta([|\mathcal{S}||\mathcal{A}|])$.
- The solution to the dual LP $\lambda^\star$ corresponds to the state-action *occupancy* of $\pi^\star$.

Occupancy measure

Definition (Occupancy measure)

The occupancy measure for an initial distribution μ and a policy π is defined as follows:

$$\lambda_\mu^\pi(s,a) = (1-\gamma)\sum_{t=0}^{\infty}\gamma^t \mathbb{P}[s_t = s, a_t = a \mid s_0 \sim \mu,\ \pi],$$

where $\mathbb{P}[\cdot \mid s_0 \sim \mu,\ \pi]$ denotes the probability of an event when following policy π starting from $s_0 \sim \mu$.

Interpretation:

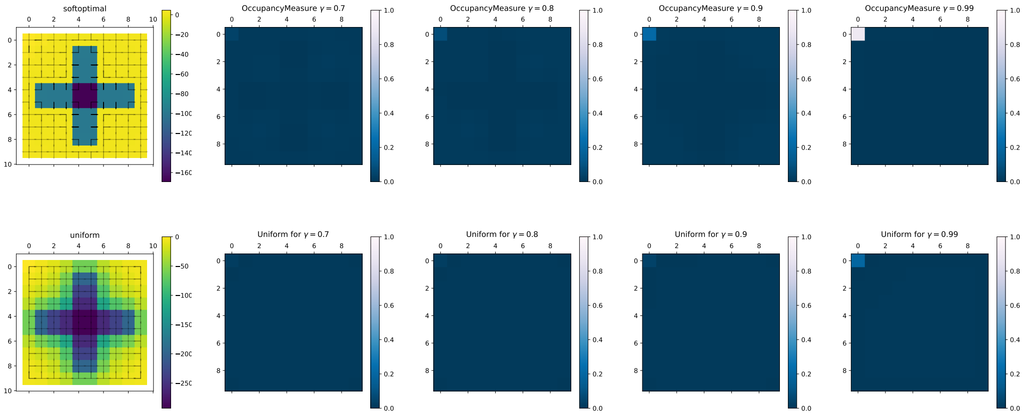
- $\lambda_\mu^\pi(s,a)$ is the normalized discounted visitation frequency of the pair (s,a) when π is played:

$$\lambda_\mu^\pi(s,a) = (1-\gamma)\mathbb{E}\left[\sum_{t=0}^{\infty}\gamma^t \mathbb{1}(s_t = s, a_t = a)\ \middle|\ s_0 \sim \mu,\ \pi\right]$$

- We sometimes drop the subscript μ after specifying a fixed initial distribution.

Visualize an occupancy measure

- Let us consider the policies represented by the arrows in the leftmost column.
- The corresponding occupancy measures varying the discounted factor are depicted just below.
- Notice that increasing γ makes the effect of the initial distribution less and less prominent.



A closer look at the dual LP

- For any policy π and $s_0 \sim \mu$, we defined the occupancy measure $\lambda^\pi(s,a)$ as

$$\lambda^\pi(s,a) := (1-\gamma)\sum_{t=0}^{\infty}\gamma^t \mathbb{P}[s_t = s, a_t = a \,|\, s_0 \sim \mu, \pi].$$

- We can write

$$\begin{aligned}
&(1-\gamma)\mathbb{E}_{s\sim\mu}[V^\pi(s)] && \Rightarrow \text{ primal objective (P)} \\
&= (1-\gamma)\,\mathbb{E}\left[\sum\nolimits_{t=0}^{\infty}\gamma^t r(s_t,a_t) \mid s_0 \sim \mu,\ \pi\right] \\
&= (1-\gamma)\,\mathbb{E}\left[\sum\nolimits_{t=0}^{\infty}\sum_{s\in\mathcal{S},a\in\mathcal{A}}\gamma^t \mathbb{1}(s_t = s, a_t = a) r(s,a) \mid s_0 \sim \mu,\ \pi\right] \\
&= (1-\gamma)\sum_{s\in\mathcal{S},a\in\mathcal{A}}\sum_{t=0}^{\infty}\gamma^t \mathbb{P}[s_t = s, a_t = a \,|\, s_0 \sim \mu,\ \pi]\, r(s,a) \\
&= \sum_{s\in\mathcal{S}}\sum_{a\in\mathcal{A}}\lambda^\pi(s,a) r(s,a) && \Rightarrow \text{ dual objective (D)}
\end{aligned}$$

A closer look at the dual LP (cont'd)

Recall: Dual LP

$$\begin{aligned}
\max_{\lambda} \quad & \sum_{s\in\mathcal{S}}\sum_{a\in\mathcal{A}} r(s,a)\lambda(s,a) \\
\text{s.t.} \quad & \sum_{a\in\mathcal{A}} \lambda(s,a) = (1-\gamma)\mu(s) + \gamma \sum_{s'\in\mathcal{S},a'\in\mathcal{A}} \mathsf{P}(s|s',a')\lambda(s',a'), \quad \forall\, s\in\mathcal{S}, \\
& \lambda(s,a) \geq 0, \quad \forall\, s\in\mathcal{S}, a\in\mathcal{A}.
\end{aligned} \tag{D}$$

Observations:

- The occupancy measure $\lambda^{\pi}(s,a)$ satisfies the constraints in the dual LP.
- By the Markov property, we have (see the supplementary material, Slide 14 for details)

$$\lambda^{\pi}(s,a) = (1-\gamma)\mu(s)\pi(a|s) + \gamma \sum_{s',a'} \pi(a|s)\mathsf{P}(s|s',a')\lambda^{\pi}(s',a').$$

- Summing over a implies feasibility.

A closer look at the dual LP (cont'd)

Recall: Dual LP

$$\begin{aligned} \max_{\lambda} \quad & \sum_{s\in\mathcal{S}}\sum_{a\in\mathcal{A}} r(s,a)\lambda(s,a) \\ \text{s.t.} \quad & \sum_{a\in\mathcal{A}} \lambda(s,a) = (1-\gamma)\mu(s) + \gamma \sum_{s'\in\mathcal{S},a'\in\mathcal{A}} \mathsf{P}(s|s',a')\lambda(s',a'), \quad \forall\, s\in\mathcal{S}, \\ & \lambda(s,a) \geq 0, \quad \forall\, s\in\mathcal{S}, a\in\mathcal{A}. \end{aligned} \tag{D}$$

Observations:

- For any λ feasible to the dual LP, we can define a policy

$$\pi_\lambda(a\,|\,s) = \frac{\lambda(s,a)}{\sum_{a\in\mathcal{A}}\lambda(s,a)},$$

  where we set $\pi_\lambda(\cdot|s)$ arbitrarily when $\sum_{a\in\mathcal{A}}\lambda(s,a) = 0$. Then, $\lambda^{\pi_\lambda} = \lambda$.

- Note that λ is optimal for (D) iff π_λ is an optimal policy [30]. (self-study)

- Optimality of policies does not depend on μ. (LP sensitivity analysis)

Finding the optimal policy

- Primal LP approach:
  - Solve primal LP to obtain for the optimal value function $V^\star$
  - Then construct an optimal policy (deterministic) as the greedy policy

$$\pi^\star(s) \in \arg\max_{a \in \mathcal{A}} \left[r(s,a) + \gamma \sum\nolimits_{s' \in \mathcal{S}} \mathsf{P}(s'|s,a) V^\star(s') \right].$$

- Dual LP approach:
  - Solve the dual LP to obtain an optimal state-action occupancy $\lambda^\star$
  - Then construct the optimal policy (randomized) by

$$\pi^\star(a \mid s) = \frac{\lambda^\star(s,a)}{\sum_{a \in \mathcal{A}} \lambda^\star(s,a)}.$$

- For further reading: See [30] (Section 6.9)

Occupancy measure and value function

Pop quiz: ◦ What is the relation between the occupancy measure and the value function?

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Answer:

$$(1-\gamma)V^{\pi}(\mu) = \langle \lambda_{\mu}^{\pi}, r \rangle.$$

Occupancy measure and value function

Pop quiz: ◦ What is the relation between the occupancy measure and the value function?

Answer:

$$(1-\gamma)V^\pi(\mu) = \langle \lambda_\mu^\pi, r \rangle.$$

Remark: ◦ It holds that

$$V^\pi(\mu) = \langle \mu, V^\pi \rangle = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \mid s_0 \sim \mu,\ \pi\right].$$

Occupancy measure and value function (cont'd)

Derivation:

$$
\begin{aligned}
V^{\pi}(\mu) &= \mathbb{E}\left[\sum_{t=0}^{\infty}\gamma^t r(s_t,a_t) \mid s_0\sim\mu,\ \pi\right] \\
&= \mathbb{E}\left[\sum_{t=0}^{\infty}\gamma^t \sum_{s,a} r(s,a)\mathbb{1}(s_t=s, a_t=a) \mid s_0\sim\mu,\ \pi\right]
\end{aligned}
$$

Occupancy measure and value function (cont'd)

Derivation:

$$
\begin{aligned}
V^\pi(\mu) &= \mathbb{E}\left[\sum_{t=0}^{\infty}\gamma^t r(s_t,a_t) \mid s_0\sim\mu,\ \pi\right] \\
&= \mathbb{E}\left[\sum_{t=0}^{\infty}\gamma^t \sum_{s,a} r(s,a)\mathbb{1}(s_t=s,a_t=a) \mid s_0\sim\mu,\ \pi\right] \\
&= \sum_{s,a} r(s,a)\ \mathbb{E}\left[\sum_{t=0}^{\infty}\gamma^t \mathbb{1}(s_t=s,a_t=a) \mid s_0\sim\mu,\ \pi\right] \qquad \text{(Linearity of expectation)}
\end{aligned}
$$

Occupancy measure and value function (cont'd)

Derivation:

$$\begin{aligned}
V^\pi(\mu) &= \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \mid s_0 \sim \mu,\ \pi\right] \\
&= \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \sum_{s,a} r(s,a) \mathbb{1}(s_t = s, a_t = a) \mid s_0 \sim \mu,\ \pi\right] \\
&= \sum_{s,a} r(s,a)\ \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \mathbb{1}(s_t = s, a_t = a) \mid s_0 \sim \mu,\ \pi\right] && \text{(Linearity of expectation)} \\
&= \sum_{s,a} r(s,a) \sum_{t=0}^{\infty} \gamma^t\ \mathbb{P}[s_t = s, a_t = a \mid s_0 \sim \mu,\ \pi] && \text{(Dominated convergence theorem)}
\end{aligned}$$

◦ For more details on the dominated convergence theorem, see Slide 11 in the supplementary material.

Occupancy measure and value function (cont'd)

Derivation:

$$\begin{aligned}
V^{\pi}(\mu) &= \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \mid s_0 \sim \mu,\ \pi\right] \\
&= \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \sum_{s,a} r(s,a) \mathbb{1}(s_t = s, a_t = a) \mid s_0 \sim \mu,\ \pi\right] \\
&= \sum_{s,a} r(s,a)\ \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \mathbb{1}(s_t = s, a_t = a) \mid s_0 \sim \mu,\ \pi\right] && \text{(Linearity of expectation)} \\
&= \sum_{s,a} r(s,a) \sum_{t=0}^{\infty} \gamma^t\ \mathbb{P}[s_t = s, a_t = a \mid s_0 \sim \mu,\ \pi] && \text{(Dominated convergence theorem)} \\
&= \frac{\sum_{s,a} r(s,a) \lambda_{\mu}^{\pi}(s,a)}{1-\gamma} = \frac{\langle \lambda_{\mu}^{\pi}, r\rangle}{1-\gamma}. \quad \square
\end{aligned}$$

◦ For more details on the dominated convergence theorem, see Slide 11 in the supplementary material.

Some more compact notation

- With the following definitions, we can compactly write the primal and dual LP in matrix form.
- We will use the following matrix notation.
  - Write the transitions P in matrix form, i.e., P is a $(|S||A| \times |S|)$-matrix and the entry in row $(s,a) \in \mathcal{S} \times \mathcal{A}$ and column $s' \in \mathcal{S}$ is given by

$$P_{(s,a),s'} \triangleq \mathsf{P}(s'|s,a).$$

  - E is a binary matrix of dimensions $|S||A| \times |S|$, defined by

$$E_{(s,a),s'} \triangleq \begin{cases} 1 & (\text{if } s = s'), \\ 0 & (\text{else}). \end{cases}$$

  - Write $r, \ \lambda \in \mathbb{R}^{|S||A|}$ for the (column) vectors with entries $r(s,a)$, $\lambda(s,a)$ at index $(s,a) \in \mathcal{S} \times \mathcal{A}$, respectively.
  - Write $\mu, \ V \in \mathbb{R}^{S}$ for the vectors with entries $\mu(s), \ V(s)$ at index $s \in \mathcal{S}$, respectively.

Some more compact notation - Visualization

- To simplify the notation, recall the matrices defined on slide 20:
  - $E \in \mathbb{R}^{|\mathcal{S}||\mathcal{A}|\times|\mathcal{S}|}$ such that $(EV)(s,a) = V(s)$ (copying $|\mathcal{A}|$ times),
  - $P \in \mathbb{R}^{|\mathcal{S}||\mathcal{A}|\times|\mathcal{S}|}$ such that $(PV)(s,a) = \sum_{s'} \mathsf{P}(s'|s,a)V(s')$ (expectation over $s'|s,a$).
  - E is a block matrix, with the $|\mathcal{S}| \times |\mathcal{S}|$ identity matrix vertically stacked $|\mathcal{A}|$ times:

$$E = \begin{bmatrix} I_{|\mathcal{S}|} \\ \vdots \\ I_{|\mathcal{S}|} \end{bmatrix}.$$

  - P is a block matrix, with the $(|\mathcal{S}| \times |\mathcal{S}|)$-matrices P_{a_i}

$$P_{a_i} = \begin{pmatrix} \mathsf{P}(s_1|s_1,a_i) & \cdots & \mathsf{P}(s_{|\mathcal{S}|}|s_1,a_i) \\ \vdots & & \vdots \\ \mathsf{P}(s_1|s_{|\mathcal{S}|},a_i) & \cdots & \mathsf{P}(s_{|\mathcal{S}|}|s_{|\mathcal{S}|},a_i) \end{pmatrix},$$

vertically stacked for $i = 1, \ldots, |\mathcal{A}|$:

$$P = \begin{bmatrix} P_{a_1} \\ \vdots \\ P_{a_{|\mathcal{A}|}} \end{bmatrix}.$$

Some more compact notation - Visualization (cont'd)

- Their adjoints are given by
  - $E^T \in \mathbb{R}^{|\mathcal{S}|\times|\mathcal{S}||\mathcal{A}|}$ such that $(E^T\lambda)(s) = \sum_a \lambda(s,a)$ (sum over all a),
  - $P^T \in \mathbb{R}^{|\mathcal{S}|\times|\mathcal{S}||\mathcal{A}|}$ such that $(P^T\lambda)(s') = \sum_{s,a} \mathsf{P}(s'|s,a)\lambda(s,a)$ (total expectation for s' w.r.t. λ).

  - E^T is a block matrix, with the $|\mathcal{S}| \times |\mathcal{S}|$ identity matrix horizontally stacked $|\mathcal{A}|$ times:

$$E^T = \begin{bmatrix} I_{|\mathcal{S}|} & \cdots & I_{|\mathcal{S}|} \end{bmatrix}.$$

  - P^T is a block matrix, with the $(|\mathcal{S}| \times |\mathcal{S}|)$-matrices $P^T_{a_i}$

$$P^T_{a_i} = \begin{pmatrix} \mathsf{P}(s_1|s_1,a_i) & \cdots & \mathsf{P}(s_1|s_{|\mathcal{S}|},a_i) \\ \vdots & & \vdots \\ \mathsf{P}(s_{|\mathcal{S}|}|s_1,a_i) & \cdots & \mathsf{P}(s_{|\mathcal{S}|}|s_{|\mathcal{S}|},a_i) \end{pmatrix},$$

horizontally stacked for $i = 1, \ldots, |\mathcal{A}|$:

$$P^T = \begin{bmatrix} P^T_{a_1} & \cdots & P^T_{a_{|\mathcal{A}|}} \end{bmatrix}.$$

Linear Programming - Summary

Primal LP:

$$\min_{V\in\mathbb{R}^{|\mathcal{S}|}} \quad (1-\gamma)\langle \mu, V\rangle \qquad \text{s.t.} \quad EV \geq r + \gamma P V. \tag{P}$$

- Primal LP over value functions
- $|\mathcal{S}|$ decision variables and $|\mathcal{S}||\mathcal{A}|$ constraints
- $\forall\ V$ primal feasible $\quad \Rightarrow\ V^\star \leq V$
- Optimal value function $V^\star$ is the optimizer
- Optimal policy is the associated greedy policy

Dual LP

$$\max_{\lambda\in\mathbb{R}^{|\mathcal{S}||\mathcal{A}|}} \quad \langle \lambda, r\rangle \qquad \text{s.t.} \quad E^\top\lambda = (1-\gamma)\mu + \gamma P^\top \lambda, \quad \lambda \geq 0. \tag{D}$$

- Dual LP over occupancy measures
- $|\mathcal{S}||\mathcal{A}|$ variables and $|\mathcal{S}| + |\mathcal{S}||\mathcal{A}|$ constraints
- $\forall$ policy π, the induced λ^π is dual feasible
- $\forall$ feasible $\lambda \Rightarrow \pi_\lambda$ has occupancy measure λ
- Optimal policy is the associated random policy $\pi_{\lambda^\star}$

Dynamic programming vs linear programming (exact solutions)

Algorithm	Component	Output
Value Iteration (VI)	Bellman Optimality Operator $\mathcal{T}$	$V^\star$ (control)
Policy Iteration (PI)	(Multiple) Bellman Operator $\mathcal{T}^\pi$ + Greedy Policy	$\pi^\star$ (control)
Linear Programming (LP)	LP solver (Simplex, Interior Point Method)	$V^\star, \pi^\star$ (control)

Dynamic Programming:

- Simple iterative updates.
- Polynomial complexity in $|\mathcal{S}|$ and $|\mathcal{A}|$ and $(1-\gamma)^{-1}$.
- Works better for short horizon problems.

Linear Programming:

- Rich library of fast LP solvers.
- Polynomial complexity in $|\mathcal{S}|$ and $|\mathcal{A}|$ **but not** on $(1-\gamma)^{-1}$.
- Works better for long horizon problems.

The LP approach - Pros and Cons

◦ Why is this useful?

- Defining optimality is simple: no value functions, no fixed-point equations, just the numerical objective.
- Easily comprehensible with an optimization background.
- A disciplined convex optimization template with a rich set of algorithms.

◦ End User License Agreement:

- Number of variables is large.
- Intractable number of constraints.
- Constraints may not be satisfied when working with function approximators.

Beyond exact solutions - A bit of history of approximate linear programming (ALP)

- [Manne 1960] [18]
  - Formulated the primal LP over value functions and showed equivalence to Bellman equations.
- [Borkar 1988] [3] and [Hérnandez-Lerma & Lasserre 1996, 1999] [10, 11]
  - Studied the LP approach to MDPs with continuous state and action spaces.
  - The corresponding LPs are infinite-dimensional.
- [Schweitzer & Seidman 1982] [34]
  - Proposed linear function approximators to reduce the number of decision variables
  - Proposed a relaxation to reduce the number of constraints.
- [De Farias & Van Roy 2003, 2004] [6, 7]
  - Analyzed the reduction [Schweitzer & Seidman 1982] [34].
  - Inspired some follow-up work in RL [Petrik et al. 2009,2010] [28, 27], [Desai et al. 2012] [8], [Abbasi-Yadkori et al. 2014] [1], [Lakshminarayanan et al. 2018] [16].
- We refer to Slide 36 in the supplementary material for more details.

Towards the Lagrangian

- Instead of working solely with the primal or dual LP formulation, we work with an expression combining them.
- Introducing the Lagrangian multipliers vector $\lambda \in \mathbb{R}^{|\mathcal{S}||\mathcal{A}|}$, we can write the Lagrangian as follows:

Primal LP:

$$\begin{aligned} \min_{V \in \mathbb{R}^{|\mathcal{S}|}} \quad & (1-\gamma)\langle \mu, V \rangle \\ \text{s.t.} \quad & EV \geq r + \gamma P V. \end{aligned} \tag{P}$$

Dual LP

$$\begin{aligned} \max_{\lambda \in \mathbb{R}^{|\mathcal{S}||\mathcal{A}|}} \quad & \langle \lambda, r \rangle \\ \text{s.t.} \quad & E^\top \lambda = (1-\gamma)\mu + \gamma P^\top \lambda, \quad \lambda \geq 0. \end{aligned} \tag{D}$$

$$\Updownarrow$$

Saddle point formulation

$$\min_{V} \max_{\lambda \geq 0} (1-\gamma)\langle \mu , V \rangle + \langle \lambda , r + \gamma P V - E V \rangle. \tag{Saddle-point problem}$$

Minimax optimization

∘ We recap some minimax optimization background in preparation for the so-called REPS algorithm.

Bilinear min-max template

$$\min_{\mathbf{x}\in\mathcal{X}} \max_{\mathbf{y}\in\mathcal{Y}} f(\mathbf{x}) + \langle \mathbf{A}\mathbf{x}, \mathbf{y}\rangle - h(\mathbf{y}),$$

where $\mathcal{X} \subseteq R^p$ and $\mathcal{Y} \subseteq \mathbb{R}^n$.

- $f : \mathcal{X} \to \mathbb{R}$ is convex.
- $h : \mathcal{Y} \to \mathbb{R}$ is convex.

Convex-concave min-max template

$$\min_{\mathbf{x}\in\mathcal{X}} \max_{\mathbf{y}\in\mathcal{Y}} \Phi(\mathbf{x}, \mathbf{y}), \tag{2}$$

where $\Phi(\mathbf{x}, \mathbf{y})$ is convex in $\mathbf{x}$ and concave in $\mathbf{y}$.

Basic algorithms for minimax

◦ Given $\min_{\mathbf{x}\in\mathcal{X}} \max_{\mathbf{y}\in\mathcal{Y}} \Phi(\mathbf{x},\mathbf{y})$, define $V(\mathbf{z}) = [\nabla_{\mathbf{x}}\Phi(\mathbf{x},\mathbf{y}), -\nabla_{\mathbf{y}}\Phi(\mathbf{x},\mathbf{y})]$ with $\mathbf{z} = [\mathbf{x},\mathbf{y}]$.

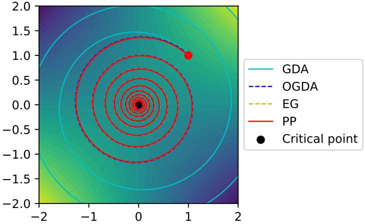

Figure: Trajectory of different algorithms for a simple bilinear game $\min_x \max_y xy$.

◦ (In)Famous algorithms
- Gradient Descent Ascent (GDA)
- Proximal point method (PPM) [33]
- Extra-gradient (EG) [15]
- Optimistic Gradient Descent Ascent (OGDA) [21]
- Reflected-Forward-Backward-Splitting (RFBS) [4]

◦ EG and OGDA are approximations of the PPM
- $\mathbf{z}^{k+1} = \mathbf{z}^k - \eta V(\mathbf{z}^k)$.
- $\mathbf{z}^{k+1} = \mathbf{z}^k - \eta V(\mathbf{z}^{k+1})$.
- $\mathbf{z}^{k+1} = \mathbf{z}^k - \eta V(\mathbf{z}^k - \alpha V(\mathbf{z}^{k-1}))$
- $\mathbf{z}^{k+1} = \mathbf{z}^k - \eta[2V(\mathbf{z}^k) - V(\mathbf{z}^{k-1})]$
- $\mathbf{z}^{k+1} = \mathbf{z}^k - \eta V(2\mathbf{z}^k - \mathbf{z}^{k-1})$

Proximal point method (PPM)

◦ Consider the following smooth unconstrained optimization problem: $\min_{\mathbf{x}\in\mathbb{R}^p} f(\mathbf{x})$

Proximal point method for convex minimization.

For a step-size $\tau > 0$, PPM can be written as follows

$$\boxed{\mathbf{x}^{k+1} = \arg\min_{\mathbf{x}\in\mathbb{R}^p}\left\{f(\mathbf{x}) + \frac{1}{2\tau}\|\mathbf{x}-\mathbf{x}^k\|^2\right\} := \mathrm{prox}_{\tau f}(\mathbf{x}^k)} \tag{3}$$

Observations: ◦ The optimality condition of (3) reveals a simpler PPM recursion for smooth f:

$$\boxed{\mathbf{x}^{k+1} = \mathbf{x}^k - \tau\nabla f(\mathbf{x}^{k+1}).}$$

◦ PPM is an **implicit**, non-practical algorithm since we need the point $\mathbf{x}^{k+1}$ for its update.

◦ Each step of PPM can be as hard as solving the original problem.

◦ Convergence properties are well understood due to Rockafellar [33].

PPM and minimax optimization

PPM applied to the minimax template: $\min_{\mathbf{x}\in\mathbb{R}^d} \max_{\mathbf{y}\in\mathbb{R}^n} \Phi(\mathbf{x},\mathbf{y})$

Define $\mathbf{z} = [\mathbf{x},\mathbf{y}]^\top$ and $\mathbf{V}(\mathbf{z}) = [\nabla_{\mathbf{x}}\Phi(\mathbf{x},\mathbf{y}), -\nabla_{\mathbf{y}}\Phi(\mathbf{x},\mathbf{y})]^\top$. PPM iterations with a step-size $\tau > 0$ is given by

$$\mathbf{z}^{k+1} = \mathbf{z}^k - \tau\mathbf{V}(\mathbf{z}^{k+1}).$$

Derivation:

- For $\tau > 0$, $(\mathbf{x}^{k+1},\mathbf{y}^{k+1})$ is the unique solution to the saddle point problem,

$$\boxed{\min_{\mathbf{x}\in\mathbb{R}^d} \max_{\mathbf{y}\in\mathbb{R}^n} \Phi(\mathbf{x},\mathbf{y}) + \frac{1}{2\tau}\|\mathbf{x}-\mathbf{x}^k\|^2 - \frac{1}{2\tau}\|\mathbf{y}-\mathbf{y}^k\|^2} \tag{4}$$

- Writing the optimality condition of the update in (4)

$$\boxed{\mathbf{x}^{k+1} = \mathbf{x}^k - \tau\nabla_{\mathbf{x}}\Phi(\mathbf{x}^{k+1},\mathbf{y}^{k+1}), \qquad \mathbf{y}^{k+1} = \mathbf{y}^k + \tau\nabla_{\mathbf{y}}\Phi(\mathbf{x}^{k+1},\mathbf{y}^{k+1})} \tag{5}$$

Observation:

- **PPM is an implicit algorithm.**
- For the bilinear problem, PPM is implementable!

Proximal point methods in the Bregman setup

Definition: Bregman distance

Let $\omega : \mathcal{X} \to \mathbb{R}$ be a distance generating function where ω is $1-$strongly convex w.r.t. some norm $\|\cdot\|$ on the underlying space and is continuously differentiable. The Bregman distance induced by $\omega(\cdot)$ is given by

$$D_\omega(\mathbf{z}, \mathbf{z}') = \omega(\mathbf{z}) - \omega(\mathbf{z}') - \nabla\omega(\mathbf{z}')^\top(\mathbf{z} - \mathbf{z}').$$

- The proximal point method in the Bregman setup reads as follows:

$$\boxed{\mathbf{x}^{k+1} = \arg\min_{\mathbf{x}\in\mathbb{R}^p} \left\{ f(\mathbf{x}) + \frac{1}{\tau} D_\omega(\mathbf{x}, \mathbf{x}^k) \right\}}$$

Remarks:

- Choosing the negative entropy as a generating function $\omega(\mathbf{x}) = \langle \mathbf{x}, \log \mathbf{x} \rangle$, we obtain the KL divergence. Such $\omega(\mathbf{x})$ is 1-strongly convex in $\|\cdot\|_1$ norm.
- This choice will allow to avoid projection in the simplex constraints and it improves the dependence on the domain dimension.
- Now, we will see PPM in action on the Lagrangian.

Detour: Primal-dual π-learning given the model

Saddle point formulation

$$\min_{V} \max_{\lambda \in \Delta_{\mathcal{S}\times\mathcal{A}}} (1-\gamma)\langle \mu \,, V\rangle + \langle \lambda \,, r + \gamma PV - EV\rangle. \qquad \text{(Saddle-point problem)}$$

◦ For known dynamics, it can be solved via primal-dual gradient updates:

- $V_{k+1} = V_k - \eta\Big((\gamma P - E)^\top \lambda_k + (1-\gamma)\mu\Big).$
- $\lambda_{k+1} \propto \lambda_k \odot e^{\eta(r+\gamma PV_k - EV_k)}$, where $\odot$ denotes entry wise multiplication.

Detour: Primal-dual π-learning given the model

Saddle point formulation

$$\min_{V} \max_{\lambda \in \Delta_{\mathcal{S}\times\mathcal{A}}} (1-\gamma)\langle \mu \,, V\rangle + \langle \lambda \,, r + \gamma PV - EV\rangle. \qquad \text{(Saddle-point problem)}$$

- For known dynamics, it can be solved via primal-dual gradient updates:
  - $V_{k+1} = V_k - \eta\Big((\gamma P - E)^\top \lambda_k + (1-\gamma)\mu\Big)$.
  - $\lambda_{k+1} \propto \lambda_k \odot e^{\eta(r+\gamma PV_k - EV_k)}$, where $\odot$ denotes entry wise multiplication.
- The second update is known as *mirror descent* over the simplex (see 22 for details). It is defined by

$$\lambda_{k+1} := \arg\max_{\lambda \in \Delta_{\mathcal{S}\times\mathcal{A}}} \left(\langle \lambda, r + \gamma PV_k - EV_k\rangle - \frac{1}{\eta}\mathsf{KL}\left(\lambda || \lambda_k\right)\right),$$

where $\mathsf{KL}\left(p||q\right) = \sum_i p_i \log\left(\frac{p_i}{q_i}\right)$ is the Kullback-Leibler divergence.

- The mirror descent update can be explicitely written as

$$\lambda_{k+1}(s,a) = \frac{\lambda_k(s,a)\exp(\eta[r+\gamma PV_k - EV_k](s,a))}{\sum_{s',a'}\lambda_k(s',a')\exp(\eta[r+\gamma PV_k - EV_k](s',a'))}.$$

Detour: Primal-dual π-learning given the model

Saddle point formulation

$$\min_{V} \max_{\lambda \in \Delta_{\mathcal{S}\times\mathcal{A}}} (1-\gamma)\langle \mu\,, V\rangle + \langle \lambda\,, r + \gamma PV - EV\rangle. \qquad \text{(Saddle-point problem)}$$

- For known dynamics, it can be solved via primal-dual gradient updates:
  - $V_{k+1} = V_k - \eta\Big((\gamma P - E)^\intercal \lambda_k + (1-\gamma)\mu\Big)$.
  - $\lambda_{k+1} \propto \lambda_k \odot e^{\eta(r+\gamma PV_k - EV_k)}$, where $\odot$ denotes entry wise multiplication.
- Gradients are expectations under the occupancy measure iterates λ_k and the transition law P

$\Rightarrow$ efficient stochastic implementation [Chen et al. 2018] [5], [Jin & Sidford. 2018] [12].

  - State-of-the-art sample complexity for solving small MDPs.
  - $\mathcal{O}\left(\frac{|\mathcal{S}||\mathcal{A}|\log(\frac{1}{\delta})}{(1-\gamma)^4\varepsilon^2}\right)$ samples for finding an ε-optimal policy with probability at least $1-\delta$.

REPS: A success story

- REPS is widely popular in the robotics community.
- It applies proximal point to the Dual LP.
- A robot trained with REPS manages to play table tennis.

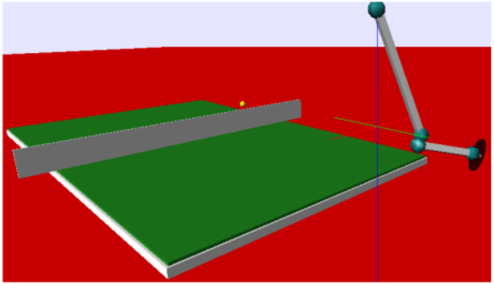

Figure: Source: Relative Entropy Policy Search [26]

Towards REPS: Proximal point on the dual LP

- Recall: Proximal point is generally an implicit method.
- However, for a linear objective PPM can be implemented.
- Hence, we can apply proximal point updates on the Lagrangian, which is just a bilinear form.

Recall: Dual LP

$$\begin{aligned}\lambda_k &= \operatorname{argmax}_{\lambda \in \Delta} \langle \lambda, r \rangle \\ &\qquad \text{s.t.} \quad E^T \lambda = \gamma P^T \lambda + (1-\gamma)\mu.\end{aligned}$$

Remarks:

- The problem in the current form suffers from $|\mathcal{S}|$ many constraints.

The Lagrangian: Towards an unconstrained problem.

◦ The corresponding Lagrangian is:

$$\max_{\lambda \in \Delta} \min_{V} \; \langle \lambda, r \rangle + \langle V, \gamma P^T \lambda - E^T \lambda \rangle + (1-\gamma)\langle V, \mu \rangle.$$

◦ Applying proximal point we obtain the following update:

$$\lambda_k = \operatorname{argmax}_{\lambda \in \Delta} \underbrace{\min_{V} \; \langle \lambda, r \rangle + \langle V, \gamma P^T \lambda - E^T \lambda \rangle + (1-\gamma)\langle V, \mu \rangle}_{:= f(\lambda)} - \frac{1}{\eta} D_{\mathsf{KL}}(\lambda, \lambda_{k-1}).$$

KKT conditions on the Lagrangian update.

Derivation:

- We notice by convexity of the Bregman divergence that the update is convex in λ.
- We introduce an auxiliary problem for any V as follows:

$$\lambda_k^V = \operatorname{argmax}_{\lambda \in \Delta} \langle \lambda, r \rangle + \langle V, \gamma P^T \lambda - E^T \lambda \rangle + (1-\gamma)\langle V, \mu \rangle - \frac{1}{\eta} D_{\mathsf{KL}}(\lambda, \lambda_{k-1}).$$

- By optimality conditions, it must hold

$$r + \gamma PV - EV - \frac{1}{\eta} \nabla_\lambda D_{\mathsf{KL}}(\lambda_k^V, \lambda_{k-1}) = 0.$$

- Thus, λ_k^V can be computed in closed form for any V

$$\lambda_k^V(s,a) = \frac{\lambda_{k-1}(s,a) e^{\eta(r(s,a)+\gamma(PV)(s,a)-(EV)(s,a))}}{\sum_{s',a'} \lambda_{k-1}(s',a') e^{\eta(r(s',a')+\gamma(PV)(s',a')-(EV)(s',a'))}}.$$

The unconstrained problem

◦ We can leverage the KKT conditions to write an unconstrained problem where the only decision variable is V:

$$\min_V \langle \lambda_k^V, r\rangle + \langle V, \gamma P^T \lambda_k^V - E^T \lambda_k^V \rangle + (1-\gamma)\langle V, \mu\rangle - \frac{1}{\eta} D_{\mathsf{KL}}(\lambda_k^V, \lambda_{k-1}).$$

◦ With some calculus, we have the following compact form.

Unconstrained problem (REPS)

$$V_k = \min_V (1-\gamma)\langle \mu, V\rangle + \frac{1}{\eta}\log \sum_{s,a} \lambda_{k-1}(s,a) e^{\eta(r(s,a)+\gamma(PV)(s,a)-(EV)(s,a))}.$$

Remarks:

◦ The decision variable V has dimension $|\mathcal{S}|$.

◦ The objective is convex and smooth with Lipschitz continuous gradient.

The REPS algorithm [26]

Algorithm: REPS

Initialize λ_0 (for example uniform)

for each iteration $k = 1, \ldots, K$ **do**

Solve the problem

$$V_k = \min_V (1-\gamma)\langle \mu, V \rangle + \frac{1}{\eta} \log \sum_{s,a} \lambda_{k-1}(s,a) e^{\eta(r(s,a)+\gamma(PV)(s,a)-(EV)(s,a))}$$

Update the occupancy measure:

$$\lambda_k(s,a) \propto \lambda_{k-1}(s,a) e^{\eta(r(s,a)+\gamma(PV_k)(s,a)-(EV_k)(s,a))}$$

end for

Sample complexity of REPS [25]

Algorithm	Oracle	Output
REPS	Exact gradient	$\mathcal{O}\left(\frac{\lvert\mathcal{S}\rvert^{3/2}}{(1-\gamma)^2\epsilon^2}\right)$
REPS	Stochastic Biased Gradients	$\mathcal{O}\left(\frac{\lvert\mathcal{S}\rvert^{3/2}}{(1-\gamma)^8\beta^2\epsilon^8}\right)$

Remarks:

- The exact gradient case achieves the best-known sample complexity
  - e.g., comparable to NPG (see Lecture 5)
- The sample complexity with stochastic gradients degrades.
- For the stochastic gradient case, one needs to assume that $\lambda_k(s,a) \geq \beta > 0$.
  - it solves the exploration problem by assumption.

Wrap Up

- The LP approach allows us to formulate RL as a convex optimization problem.
- The primal and dual LP are equivalent formulations of the RL objective.
- The saddle point formulation combines the primal and dual viewpoint.
- Applying the proximal point algorithm to the dual program yields the celebrated REPS algorithm.
- Offline policy evaluation and optimization are needed when we only learn from previously collected data.
  - see supplementary material at the end!

- Next lecture: Policy gradient methods (Part 1)!

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Supplementary

Mathematical background

Supplementary Material: Linear Programming Basics

Definition (LP)

A linear program in inequality form is an optimization problem of the form

$$\begin{aligned} \max_{\mathbf{x}\in\mathbb{R}^n} \quad & \mathbf{c}^T\mathbf{x} \\ \textit{s.t.} \quad & \mathbf{A}\mathbf{x} \leq \mathbf{b}, \end{aligned} \tag{6}$$

where $\mathbf{c}\in\mathbb{R}^n$, $\mathbf{b}\in\mathbb{R}^m$, *and* $\mathbf{A}\in\mathbb{R}^{m\times n}$.

Definition (Dual LP)

The dual LP of the LP in (6) *is*

$$\begin{aligned} \min_{\mathbf{y}\in\mathbb{R}^m} \quad & \mathbf{b}^T\mathbf{y} \\ \textit{s.t.} \quad & \mathbf{A}^T\mathbf{y} = \mathbf{c}, \\ & \mathbf{y} \geq \mathbf{0}. \end{aligned} \tag{7}$$

Supplementary Material: Linear Programming Basics (cont'd)

∘ We say that an LP has a *feasible solution* if there is an assignment satisfying its constraints. Formally, for 6 this means that here exists $\mathbf{x} \in \mathbb{R}^n$ such that $\mathbf{A}\mathbf{x} \leq \mathbf{b}$.

∘ We say that an LP is *bounded* if its objective is uniformly bounded across all feasible solutions. Formally, for 6 this means that $\sup \left\{ \mathbf{c}^T \mathbf{x} \mid \mathbf{A}\mathbf{x} \leq \mathbf{b} \right\} < \infty$.

Theorem (Strong duality)

Suppose that the primal LP in (6) *has a feasible solution and is bounded. Then both 6 and 7 attain optimal solutions* $\mathbf{x}^\star$ *and* $\mathbf{y}^\star$*, and they satisfy*

$$\mathbf{c}^T \mathbf{x}^\star = \mathbf{b}^T \mathbf{y}^\star.$$

∘ Self-study: Prove that in the LP formulation of MDPs, (D) is indeed the dual program of (P).

Supplementary Material: Dominated convergence

∘ To understand why we can swap limit and expectation, recall the dominated convergence theorem from real analysis.

Theorem (Dominated convergence, DCT)

Let $(f_n)_{n\in\mathbb{N}}$ be a sequence of real-valued measurable functions on some measure space (Ω, Σ, ν). Suppose f_n converges pointwise to f ($\lim_{n\to\infty} f_n(\omega) = f(\omega)$ for all $\omega \in \Omega$). Suppose further that $(f_n)_n$ is dominated by some integrable function g ($|f_n(\omega)| \le g(\omega)$ and $\int_\Omega |g_n| d\nu < \infty$). Then

$$\int_\Omega f d\nu = \lim_{n\to\infty} \int_\Omega f_n d\nu.$$

Supplementary Material: Dominated convergence (cont'd)

◦ On Slide 19, we used the DCT with

- (Ω, Σ, ν) the probability space over the trajectories $\tau = (s_0, a_0, s_1, a_1, s_2, \dots)$ under policy π
- $f_n(\tau) = \sum_{t=0}^{n} \gamma^t \mathbb{1} s_t = s, a_t = a$, which converge to $f(\tau) = \sum_{t=0}^{\infty} \gamma^t \mathbb{1} s_t = s, a_t = a$ pointwise
- $g(\tau) = \sum_{t=0}^{\infty} \gamma^t 1 = \frac{1}{1-\gamma}$.

Applying the DCT, we confirm

$$
\begin{aligned}
\mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \mathbb{1} s_t = s, a_t = a \mid s_0 \sim \mu,\ \pi\right] &= \int_{\Omega} f d\nu \\
&= \lim_{n\to\infty} \int_{\Omega} f_n d\nu \\
&= \lim_{n\to\infty} \mathbb{E}\left[\sum_{t=0}^{n} \gamma^t \mathbb{1} s_t = s, a_t = a \mid s_0 \sim \mu,\ \pi\right] \\
&= \sum_{t=0}^{\infty} \gamma^t\ \mathbb{P}[s_t = s, a_t = a \mid s_0 \sim \mu,\ \pi],
\end{aligned}
$$

where the last step holds by linearity of expectation.

Supplementary

LP and optimization

Supplementary Material: Bellman Equation for State-action Visitation Distribution

Recall the definition

$$\lambda^\pi(s,a) := \sum_{t=0}^{\infty} \gamma^t \mathbb{P}[s_t = s, a_t = a \,|\, \pi, s_0 \sim \mu].$$

Bellman Equation for λ^π

$$\lambda^\pi(s,a) = \mu(s)\pi(a|s) + \gamma \sum_{s',a'} \pi(a|s)\mathsf{P}(s|s',a')\lambda^\pi(s',a').$$

Supplementary Material: Bellman Equation for State-action Visitation Distribution

Proof.

$$
\begin{aligned}
&\lambda^\pi(s,a)\\
=&\mathbb{P}[s_0=s,a_0=a]+\sum_{t=1}^{\infty}\gamma^t\mathbb{P}[s_t=s,a_t=a|\pi,s_0\sim\mu]\\
=&\mu(s)\pi(a|s)+\sum_{t=1}^{\infty}\gamma^t\sum_{s',a'}\mathbb{P}\Big[s_t=s,a_t=a|s_{t-1}=s',a_{t-1}=a',\pi,s_0\sim\mu\Big]\mathbb{P}\Big[s_{t-1}=s',a_{t-1}=a'|\pi,s_0\sim\mu\Big]\\
=&\mu(s)\pi(a|s)+\gamma\sum_{t=1}^{\infty}\mathbb{P}\Big[s_t=s,a_t=a|s_{t-1}=s',a_{t-1}=a'\Big]\mathbb{P}\Big[s_{t-1}=s',a_{t-1}=a'|\pi,s_0\sim\mu\Big]\\
=&\mu(s)\pi(a|s)+\gamma\sum_{t=1}^{\infty}\pi(a|s)\mathsf{P}(s|s',a')\sum_{t=1}^{\infty}\gamma^{t-1}\mathbb{P}\Big[s_{t-1}=s',a_{t-1}=a'|\pi,s_0\sim\mu\Big]\\
=&\mu(s)\pi(a|s)+\gamma\sum_{s',a'}\pi(a|s)\mathsf{P}(s|s',a')\lambda^\pi(s',a')
\end{aligned}
$$

where the third equality is due to Markov property. □

PPM guarantees for minimax optimization

Theorem (Convergence of PPM [33])

Suppose $(\mathbf{x}^k, \mathbf{y}^k)$ *be the iterates generated by PPM (i.e., (5)), then for the averaged iterates, it holds that*

$$\left| \Phi\left(\frac{1}{K}\sum_{k=1}^{K}\mathbf{x}^k, \frac{1}{K}\sum_{k=1}^{K}\mathbf{y}^k \right) - \Phi(\mathbf{x}^\star, \mathbf{y}^\star) \right| \leq \frac{\|\mathbf{x}^0 - \mathbf{x}^\star\|^2 + \|\mathbf{y}^0 - \mathbf{y}^\star\|^2}{\tau K}.$$

Theorem (Linear convergence [33])

Suppose $(\mathbf{x}^k, \mathbf{y}^k)$ *be the iterates generated by* (5), $\Phi(\cdot,\cdot)$ *is* μ_x*−strongly convex in* $\mathbf{x}$ *and* μ_y*−strongly concave in* $\mathbf{y}$. *Let* $\mu = \max\{\mu_x, \mu_y\}$. *Then, for any* $\tau > 0$, $(\mathbf{x}^k, \mathbf{y}^k)$ *satisfies the following*

$$r^{k+1} \leq \frac{1}{1+\mu\tau} r^k,$$

where $r^k = \|\mathbf{x}^k - \mathbf{x}^\star\|^2 + \|\mathbf{y}^k - \mathbf{y}^\star\|^2$.

Remark:
- Still need an implementable and convergent algorithm beyond the stylized bilinear case.
- Note what happens when $\tau \to \infty$.

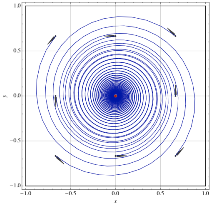
Extra-gradient algorithm (EG) [14]

EG method for saddle point problems

1. Choose $\mathbf{x}^0, \mathbf{y}^0$ and τ.

2. For $k = 0, 1, \cdots,$ perform:

$$\begin{aligned}
\tilde{\mathbf{x}}^k &:= \mathbf{x}^k - \tau \nabla_{\mathbf{x}} \Phi(\mathbf{x}^k, \mathbf{y}^k), \\
\tilde{\mathbf{y}}^k &:= \mathbf{y}^k + \tau \nabla_{\mathbf{y}} \Phi(\mathbf{x}^k, \mathbf{y}^k). \\
\mathbf{x}^{k+1} &:= \mathbf{x}^k - \tau \nabla_{\mathbf{x}} \Phi(\tilde{\mathbf{x}}^k, \tilde{\mathbf{y}}^k). \\
\mathbf{y}^{k+1} &:= \mathbf{y}^k + \tau \nabla_{\mathbf{y}} \Phi(\tilde{\mathbf{x}}^k, \tilde{\mathbf{y}}^k).
\end{aligned}$$



◦ Idea: Predict the gradient at the next point

$$\boxed{\mathbf{z}^{k+1} = \mathbf{z}^k - \tau \mathbf{V}\big(\underbrace{\mathbf{z}^k - \tau \mathbf{V}(\mathbf{z}^k)}_{\text{prediction of } \mathbf{z}^{k+1}} \big)} \tag{EG}$$

Remark: ◦ 1-extra-gradient computation per iteration

Extra-gradient algorithm: Convergence

Theorem (General case [9])

Let $0 < \tau \leq \frac{1}{L}$. It holds that

- *Iterates $(\mathbf{x}^k, \mathbf{y}^k)$ remains bounded in a convex compact set.*
- *Primal-dual gap reduces:* $\mathrm{Gap}\left(\frac{1}{K}\sum_{k=1}^{K}\mathbf{x}^k, \frac{1}{K}\sum_{k=1}^{K}\mathbf{y}^k\right) \leq \mathcal{O}\left(\frac{1}{K}\right)$.

Theorem (Linear convergence [21])

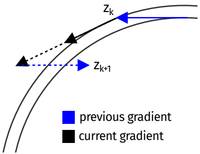
Suppose $(\mathbf{x}^k, \mathbf{y}^k)$ be the iterates generated by Extra-gradient algorithm, $\Phi(\cdot,\cdot)$ is μ_x-strongly convex in $\mathbf{x}$ and μ_y-strongly concave in $\mathbf{y}$. Let $\mu = \max\{\mu_x, \mu_y\}$. Then, for $\tau = \frac{1}{4L}$, $(\mathbf{x}^k, \mathbf{y}^k)$ satisfies,

$$r^{k+1} \leq \left(1 - \frac{1}{c\kappa}\right)^k r^0,$$

where $r^k = \|\mathbf{x}^k - \mathbf{x}^\star\|^2 + \|\mathbf{y}^k - \mathbf{y}^\star\|^2$, $\kappa = \frac{L}{\mu}$ is the condition number of the problem, and c is a constant which is independent of the problem parameters.

Optimistic gradient descent ascent algorithm (OGDA) [31]

OGDA for saddle point problems
1. Choose $\mathbf{x}^0, \mathbf{y}^0, \mathbf{x}^1, \mathbf{y}^1$ and τ.
2. For $k = 1, \cdots,$ perform:
$\mathbf{x}^{k+1} := \mathbf{x}^k - 2\tau\nabla_\mathbf{x}\Phi(\mathbf{x}^k, \mathbf{y}^k) + \tau\nabla_\mathbf{x}\Phi(\mathbf{x}^{k-1}, \mathbf{y}^{k-1}).$
$\mathbf{y}^{k+1} := \mathbf{y}^k + 2\tau\nabla_\mathbf{y}\Phi(\mathbf{x}^k, \mathbf{y}^k) - \tau\nabla_\mathbf{y}\Phi(\mathbf{x}^{k-1}, \mathbf{y}^{k-1}).$



- Main difference from the GDA: Add a "momentum" or "reflection" term to the updates

$$\boxed{\mathbf{z}^{k+1} = \mathbf{z}^k - \tau\left[\mathbf{V}(\mathbf{z}^k) + \underbrace{(\mathbf{V}(\mathbf{z}^k) - \mathbf{V}(\mathbf{z}^{k-1}))}_{\text{momentum}}\right].} \tag{OGDA}$$

- Known as Popov's method [29], it is also a special case of the Forward-Reflected-Backward method [17].
- It has ties to the Reflected-Forward-Backward Splitting (RFBS) method [4]:

$$\boxed{\mathbf{z}^{k+1} = \mathbf{z}^k - \tau\mathbf{V}(2\mathbf{z}^k - \mathbf{z}^{k-1}).} \tag{RFBS}$$

Remark: ◦ Advanced material at the end: OGDA is an approximation of PPM for bilinear problems.

OGDA: Convergence

Theorem (General case [9])

Let $0 < \tau \leq \frac{1}{2L}$, $\mathbf{x}^1 = \mathbf{x}^0, \mathbf{y}^1 = y^0$. It holds that

- *Iterates $(\mathbf{x}^k, \mathbf{y}^k)$ remains bounded in a convex compact set.*
- *Primal-dual gap reduces:* $\mathrm{Gap}\left(\frac{1}{K}\sum_{k=1}^K \mathbf{x}^k, \frac{1}{K}\sum_{k=1}^K \mathbf{y}^k\right) \leq \mathcal{O}\left(\frac{1}{K}\right)$.

Theorem (Linear convergence [21])

Suppose $(\mathbf{x}^k, \mathbf{y}^k)$ be the iterates generated by OGDA, $\Phi(\cdot,\cdot)$ is μ_x-strongly convex in $\mathbf{x}$ and μ_y-strongly concave in $\mathbf{y}$. Let $\mu = \max\{\mu_x, \mu_y\}$. Then, for $\tau = \frac{1}{4L}$, $(\mathbf{x}^k, \mathbf{y}^k)$ satisfies,

$$r^{k+1} \leq \left(1 - \frac{1}{c\kappa}\right)^k r^0,$$

where $r^k = \|\mathbf{x}^k - \mathbf{x}^\star\|^2 + \|\mathbf{y}^k - \mathbf{y}^\star\|^2$, $\kappa = \frac{L}{\mu}$ is the condition number of the problem, and c is a constant which is independent of the problem parameters.

*Bregman divergences

Table: **Bregman functions** $\psi(\mathbf{x})$ & corresponding Bregman divergences/distances $d_\psi(\mathbf{x},\mathbf{y})^a$.

Name (or Loss)	**Domain**[b]	$\psi(\mathbf{x})$	$d_\psi(\mathbf{x},\mathbf{y})$
Squared loss	$\mathbb{R}$	x^2	$(x-y)^2$
Itakura-Saito divergence	$\mathbb{R}_{++}$	$-\log x$	$\frac{x}{y} - \log\left(\frac{x}{y}\right) - 1$
Squared Euclidean distance	$\mathbb{R}^p$	$\\|\mathbf{x}\\|_2^2$	$\\|\mathbf{x}-\mathbf{y}\\|_2^2$
Squared Mahalanobis distance	$\mathbb{R}^p$	$\langle \mathbf{x}, \mathbf{A}\mathbf{x}\rangle$	$\langle (\mathbf{x}-\mathbf{y}), \mathbf{A}(\mathbf{x}-\mathbf{y})\rangle^c$
Entropy distance	p-simplex[d]	$\sum_i x_i \log x_i$	$\sum_i x_i \log\left(\frac{x_i}{y_i}\right)$
Generalized I-divergence	$\mathbb{R}^p_+$	$\sum_i x_i \log x_i$	$\sum_i \left(\log\left(\frac{x_i}{y_i}\right) - (x_i - y_i)\right)$
von Neumann divergence	$\mathbb{S}^{p\times p}_+$	$\mathbf{X}\log\mathbf{X} - \mathbf{X}$	$\mathrm{tr}\left(\mathbf{X}(\log\mathbf{X} - \log\mathbf{Y}) - \mathbf{X} + \mathbf{Y}\right)^e$
logdet divergence	$\mathbb{S}^{p\times p}_+$	$-\log\det\mathbf{X}$	$\mathrm{tr}\left(\mathbf{X}\mathbf{Y}^{-1}\right) - \log\det\left(\mathbf{X}\mathbf{Y}^{-1}\right) - p$

[a] $x, y \in \mathbb{R}$, $\mathbf{x},\mathbf{y} \in \mathbb{R}^p$ and $\mathbf{X},\mathbf{Y} \in \mathbb{R}^{p\times p}$.
[b] $\mathbb{R}_+$ and $\mathbb{R}_{++}$ denote non-negative and positive real numbers respectively.
[c] $\mathbf{A} \in \mathbb{S}^{p\times p}_+$, the set of symmetric positive semidefinite matrix.
[d] p-simplex:= $\{\mathbf{x}\in\mathbb{R}^p : \sum_{i=1}^p x_i = 1, x_i \geq 0, i = 1,\dots,p\}$
[e] $\mathrm{tr}(\mathbf{A})$ is the trace of $\mathbf{A}$.

*Mirror descent [2]

What happens if we use a Bregman distance d_ψ in gradient descent?

Let $\psi : \mathbb{R}^p \to \mathbb{R}$ be a μ-strongly convex and continuously differentiable function and let the associated Bregman distance be $d_\psi(\mathbf{x}, \mathbf{y}) = \psi(\mathbf{x}) - \psi(\mathbf{y}) - \langle \mathbf{x} - \mathbf{y}, \nabla\psi(\mathbf{y})\rangle$.
Assume that the inverse mapping $\psi^\star$ of ψ is easily computable (i.e., its convex conjugate).

- **Majorize**: Find α_k such that

$$f(\mathbf{x}) \leq f(\mathbf{x}^k) + \langle \nabla f(\mathbf{x}^k), \mathbf{x} - \mathbf{x}^k\rangle + \frac{1}{\alpha_k} d_\psi(\mathbf{x}, \mathbf{x}^k) := Q_\psi^k(\mathbf{x}, \mathbf{x}^k)$$

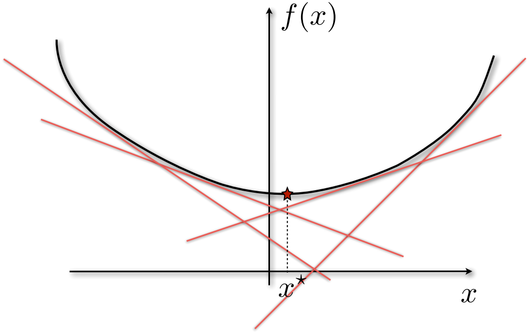
- **Minimize**

$$\begin{aligned}
\mathbf{x}^{k+1} &= \arg\min_{\mathbf{x}} Q_\psi^k(\mathbf{x}, \mathbf{x}^k) \Rightarrow \nabla f(\mathbf{x}^k) + \frac{1}{\alpha_k}\left(\nabla\psi(\mathbf{x}^{k+1}) - \nabla\psi(\mathbf{x}^k)\right) = 0 \\
\nabla\psi(\mathbf{x}^{k+1}) &= \nabla\psi(\mathbf{x}^k) - \alpha_k \nabla f(\mathbf{x}^k) \\
\mathbf{x}^{k+1} &= \nabla\psi^\star(\nabla\psi(\mathbf{x}^k) - \alpha_k\nabla f(\mathbf{x}^k)) \qquad (\nabla\psi(\cdot))^{-1} = \nabla\psi^\star(\cdot)[32].
\end{aligned}$$

- Mirror descent is a **generalization** of gradient descent for functions that are Lipschitz-gradient in norms other than the Euclidean.
- MD allows to deal with some **constraints** via a proper choice of ψ.

*What to keep in mind about mirror descent?

- Approximates the optimum by lower bounding the function via hyperplanes at $\mathbf{x}_t$



- The smaller the gradients, the better the approximation!

*Mirror descent example

How can we minimize a convex function over the unit simplex?

$$\min_{\mathbf{x}\in\Delta} f(\mathbf{x}),$$

where

- $\Delta := \{\mathbf{x}\in\mathbb{R}^p \ : \ \sum_{j=1}^p x_j = 1, \mathbf{x}\geq 0\}$ is the **unit simplex**;
- f is convex L_f-Lipschitz continuous with respect to some norm $\|\cdot\|$. (not necessarily *L-Lipschitz gradient*)

Entropy function

- Define the entropy function

$$\psi_e(\mathbf{x}) = \sum_{j=1}^p x_j \ln x_j \quad \text{if } \mathbf{x}\in\Delta, \quad +\infty \text{ otherwise.}$$

- ψ_e is 1-strongly convex over $\mathrm{int}\Delta$ with respect to $\|\cdot\|_1$.
- $\psi_e^\star(\mathbf{z}) = \ln\sum_{j=1}^p e^{z_j}$ and $\|\nabla\psi_e(\mathbf{x})\|\to\infty$ as $\mathbf{x}\to\tilde{\mathbf{x}}\in\Delta$.
- Let $\mathbf{x}^0 = p^{-1}\mathbf{1}$, then $d_\psi(\mathbf{x},\mathbf{x}^0)\leq \ln p$ for all $\mathbf{x}\in\Delta$.

⋆Entropic descent algorithm [2]

Entropic descent algorithm (EDA)

Let $\mathbf{x}^0 = p^{-1}\mathbf{1}$ and generate the following sequence

$$x_j^{k+1} = \frac{x_j^k e^{-t_k f_j'(\mathbf{x}^k)}}{\sum_{j=1}^p x_j^k e^{-t_k f_j'(\mathbf{x}^k)}}, \quad t_k = \frac{\sqrt{2 \ln p}}{L_f} \frac{1}{\sqrt{k}},$$

where $f'(\mathbf{x}) = (f_1(\mathbf{x})', \ldots, f_p(\mathbf{x})')^T \in \partial f(\mathbf{x})$, which is the **subdifferential** of f at $\mathbf{x}$.

- This is an example of **non-smooth** and **constrained** optimization;
- The updates are multiplicative.

*Convergence of mirror descent

Problem

$$\min_{\mathbf{x}\in\mathcal{X}} f(\mathbf{x}) \tag{8}$$

where

- $\mathcal{X}$ *is a closed convex subset of* $\mathbb{R}^p$;
- f *is convex* L_f*-Lipschitz continuous with respect to some norm* $\|\cdot\|$.

Theorem ([2])

Let $\{\mathbf{x}^k\}$ *be the sequence generated by mirror descent with* $\mathbf{x}^0 \in \mathrm{int}\mathcal{X}$.
If the step-sizes are chosen as

$$\alpha_k = \frac{\sqrt{2\mu d_\psi(\mathbf{x}^\star, \mathbf{x}^0)}}{L_f}\frac{1}{\sqrt{k}}$$

the following convergence rate holds

$$\min_{0\leq s\leq k} f(\mathbf{x}^s) - f^\star \leq L_f\sqrt{\frac{2d_\psi(\mathbf{x}^\star, \mathbf{x}^0)}{\mu}}\frac{1}{\sqrt{k}}$$

- *This convergence rate is* **optimal** *for solving* (8) *with a first-order method.*

Supplementary material

Offline policy evaluation

A primal LP for policy evaluation.

◦ Recall that $Q^\pi(s,a)$ is a fixed point for the expectation Bellman operator $\mathcal{T}^\pi$.

$$Q^\pi(s,a) = (\mathcal{T}^\pi Q^\pi)(s,a) = r(s,a) + \gamma \sum_{s',a'} \mathsf{P}(s'|s,a)\pi(a'|s')Q^\pi(s',a')$$

Derivation:

◦ It follows that Q^π belongs to the set given by

$$\left\{ Q \in \mathbb{R}^{|\mathcal{S}||\mathcal{A}|} : Q^\pi(s,a) \geq r(s,a) + \gamma \sum_{s',a'} \mathsf{P}(s'|s,a)\pi(a'|s')Q^\pi(s',a') \right\}$$

◦ Therefore, we can write the following program for Q^π:

$$\begin{aligned} Q^\pi &= \operatorname{argmin}_Q \langle c, Q \rangle \\ &\quad \text{s.t.} Q(s,a) \geq r(s,a) + \gamma \sum_{s',a'} \mathsf{P}(s'|s,a)\pi(a'|s')Q(s',a') \quad \forall s,a \in \mathcal{S} \times \mathcal{A} \end{aligned}$$

◦ The variable c is a vector of dimension $|\mathcal{S}||\mathcal{A}|$ defined as $c(s,a) = (1-\gamma)\pi(a|s)\mu(s)$.

The corresponding dual LP.

◦ With standard techniques we can derive the following dual formulation over the occupancy measure.

$$\lambda^\pi = \operatorname{argmax}_{\lambda \geq 0} \langle r, \lambda \rangle$$

$$\text{s.t.} \lambda(s,a) = \gamma \sum_{s',a'} \mathsf{P}(s|s',a')\pi(a|s)\lambda(s',a') + c(s,a) \quad \forall s,a \in \mathcal{S} \times \mathcal{A}$$

Remark:

◦ The only feasible point is λ^π [22].

◦ We can change the objective without affecting the maximizer.

◦ However, we change the objective value.

◦ Several recent works proposed to add an f-divergence to the objective. [22, 24, 23]

A modified Dual LP

Dual LP with f-divergences

$$\lambda^\pi = \text{argmax}_{\lambda \geq 0} \langle r, \lambda \rangle - \frac{1}{\eta} D_f(\lambda, \widetilde{\lambda^\pi})$$

$$\text{s.t.}\lambda(s,a) = \gamma \sum_{s',a'} \mathsf{P}(s|s',a')\pi(a|s)\lambda(s',a') + c(s,a) \quad \forall s,a \in \mathcal{S} \times \mathcal{A}$$

Remarks:

- ∘ Notice that the constraints are different from the one used in the LP formulation for REPS.
- ∘ We use more general f-divergences D_f instead than KL divergence.
- ∘ The center point is $\widetilde{\lambda^\pi}$ as opposed to λ_{k-1}.

Conjugation of functions

∘ Idea: Represent a convex function in $\max$-form:

Definition

Let $\mathcal{Q}$ be a Euclidean space and $\mathcal{Q}^*$ be its dual space. Given a proper, closed and convex function $f : \mathcal{Q} \to \mathbb{R} \cup \{+\infty\}$, the function $f^* : \mathcal{Q}^* \to \mathbb{R} \cup \{+\infty\}$ such that

$$f^*(\mathbf{y}) = \sup_{\mathbf{x} \in \mathrm{dom}(f)} \left\{ \mathbf{y}^T \mathbf{x} - f(\mathbf{x}) \right\}$$

is called the Fenchel conjugate (or conjugate) of f.

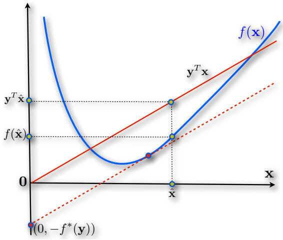


Figure: The conjugate function $f^*(\mathbf{y})$ is the maximum gap between the linear function $\mathbf{x}^T\mathbf{y}$ (red line) and $f(\mathbf{x})$.

Observations:
∘ $\mathbf{y}$: slope of the hyperplane
∘ $-f^*(\mathbf{y})$: intercept of the hyperplane

Conjugation of functions

Definition

Given a proper, closed and convex function $f : \mathcal{Q} \to \mathbb{R} \cup \{+\infty\}$, the function $f^* : Q^* \to \mathbb{R} \cup \{+\infty\}$ such that

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$$f^*(\mathbf{y}) = \sup_{\mathbf{x} \in \mathrm{dom}(f)} \left\{ \mathbf{y}^T \mathbf{x} - f(\mathbf{x}) \right\}$$

is called the Fenchel conjugate (or conjugate) of f.

Properties

- f^* is a convex and lower semicontinuous function by construction as the supremum of affine functions of $\mathbf{y}$.
- The conjugate of the conjugate of a convex function f is the same function f; i.e., $f^{**} = f$ for $f \in \mathcal{F}(\mathcal{Q})$.
- The conjugate of the conjugate of a non-convex function f is its lower convex envelope when $\mathcal{Q}$ is compact:
  - $f^{**}(\mathbf{x}) = \sup\{g(\mathbf{x}) : g$ is convex and $g \leq f, \forall \mathbf{x} \in \mathcal{Q}\}$.
- For closed convex f, μ-strong convexity w.r.t. $\|\cdot\|$ is equivalent to $\frac{1}{\mu}$ smoothness of f^* w.r.t. $\|\cdot\|_*$.
  - Recall dual norm: $\|\mathbf{y}\|_* = \sup_{\mathbf{x}}\{\langle \mathbf{x}, \mathbf{y} \rangle : \|\mathbf{x}\| \leq 1\}$.
  - See for example Theorem 3 in [13].

Fenchel duality of f-divergence

∘ Using Fenchel conjugation, we can rewrite an f-divergence as follows:

$$D_f(\lambda, \widetilde{\lambda^\pi}) = \sum_{s,a} \widetilde{\lambda^\pi}(s,a) f\left(\frac{\lambda(s,a)}{\widetilde{\lambda^\pi}(s,a)}\right) = \max_u \sum_{s,a} \lambda(s,a)u(s,a) - \widetilde{\lambda^\pi}(s,a) f^\star\left(u(s,a)\right)$$

where we used the dual function $u : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$.

Remark:

∘ When seeing $D_f(\lambda, \widetilde{\lambda^\pi})$ as a function of λ, we have that its Fenchel conjugate is given by the following expression $(D_f(\cdot, \widetilde{\lambda^\pi}))^* = \langle \widetilde{\lambda^\pi}, f^*(\cdot)\rangle$

Some additional operators towards the Lagrangian

- For compacteness we will consider the Bellman evaluation operator $\mathcal{L}_\pi : \mathbb{R}^{\mathcal{S}\times\mathcal{A}} \rightarrow \mathbb{R}^{\mathcal{S}\times\mathcal{A}}$
- The action on $Q(s,a)$ is

$$(\mathcal{L}^\pi Q)(s,a) = Q(s,a) - \gamma \sum_{s',a'} \mathsf{P}(s'|s,a)\pi(a'|s')Q(s',a')$$

- The adjoint operator $\mathcal{L}_\pi^* : \mathbb{R}^{\mathcal{S}\times\mathcal{A}} \rightarrow \mathbb{R}^{\mathcal{S}\times\mathcal{A}}$
- The action on $\lambda(s,a)$ is

$$(\mathcal{L}_\pi^* \lambda)(s,a) = \lambda(s,a) - \gamma \sum_{s',a'} \mathsf{P}(s|s',a')\pi(a|s)\lambda(s',a')$$

The Lagrangian

Derivation:

- Thanks to the Bellman evaluation operator we have that

$$\lambda^{\pi} \;=\; \mathrm{argmax}_{\lambda\geq 0} \min_{Q} \langle r, \lambda\rangle - \frac{1}{\eta} D_f(\lambda, \widetilde{\lambda^{\pi}}) - \langle Q, \mathcal{L}_{\pi}^{*}\lambda\rangle + \langle Q, c\rangle$$

- Rearranging the terms:

$$\lambda^{\pi} \;=\; \mathrm{argmax}_{\lambda\geq 0} \min_{Q} \langle r - \mathcal{L}_{\pi} Q, \lambda\rangle - \frac{1}{\eta} D_f(\lambda, \widetilde{\lambda^{\pi}}) + \langle Q, c\rangle$$

- Exchanging $\max$ and $\min$ by strong duality:

$$Q^{\pi} \;=\; \mathrm{argmin}_{Q} \max_{\lambda\geq 0} \langle r - \mathcal{L}_{\pi} Q, \lambda\rangle - \frac{1}{\eta} D_f(\lambda, \widetilde{\lambda^{\pi}}) + \langle Q, c\rangle$$

- Recognizing the Fenchel dual:

$$Q^{\pi} \;=\; \mathrm{argmin}_{Q} \langle \widetilde{\lambda^{\pi}}, f^{*}(\eta(r - \mathcal{L}_{\pi} Q))\rangle + \langle Q, c\rangle$$

- We derived the formulation used in AlgaeDICE for policy evaluation.

LP with function approximation

a.k.a. Approximate Linear Programming (ALP)

Scaling up primal-dual π-learning

Large-scale MDPs $\Rightarrow$ Large-scale optimization

◦ Parameterize λ and V via linear functions

- $\lambda_\nu = \Psi\nu$, for some feature matrix $\Psi \in \mathbb{R}^{|\mathcal{S}||\mathcal{A}|\times n}$
- $V_\theta = \Phi\theta$, for some feature matrix $\Phi \in \mathbb{R}^{|\mathcal{S}|\times m}$

Assumption: The columns of Ψ are probability distributions.

Relaxed saddle point formulation

$$\min_{\theta} \max_{\nu \in \Delta_{[n]}} (1-\gamma)\langle \mu , \Phi\theta\rangle + \langle \nu , \Psi^\top (r + \gamma P\Phi\theta - E\Phi\theta)\rangle$$

Scaling up primal-dual π-learning(cont'd)

Relaxed saddle point formulation

$$\min_{\theta} \max_{\nu \in \Delta_{[n]}} (1-\gamma)\langle \mu \,,\, \Phi\theta \rangle + \langle \nu \,,\, \Psi^\top (r + \gamma P \Phi\theta - E\Phi\theta) \rangle$$

- Primal-dual updates:
  - $\theta_{k+1} = \theta_k - \eta\Big((\gamma P\Phi - E\Phi)^\top \Psi \nu_k + \Phi^\top \mu\Big)$,
  - $\nu_{k+1} \propto \nu_k \odot e^{\eta \Psi^\top (r + \gamma P \Phi \theta_k - E\Phi\theta_k)}$.
- Implementable with only sample access to the columns of Ψ and the transition law P [Chen et al. 2018] [5].
  - $\mathcal{O}\left(\frac{n\, m \log(\frac{1}{\delta})}{(1-\gamma)^4 \varepsilon^2}\right)$ samples for finding an $\varepsilon + \varepsilon_{\text{approx}}$-optimal policy with probability at least $1-\delta$.
  - $\varepsilon_{\text{approx}}$ captures the expressivity of the approximation architecture.

Prior works in ALP - Linear function approximation

Large-scale MDPs $\Rightarrow$ Large-scale optimization

- Reduce the number of decision variables by projecting onto a lower-dimensional subspace.
  - Let $\phi_1, \ldots, \phi_k : \mathcal{S} \to \mathbb{R}$ be k basis functions (or features).
  - $\Phi := \begin{bmatrix} \phi_1 & \ldots & \phi_k \end{bmatrix} \in \mathbb{R}^{|\mathcal{S}| \times k}$ is the corresponding feature matrix.
  - The (ALP) is obtained by adding the linear constraint $V = \Phi\theta = \sum_{i=1}^{k} \theta_i \phi_i$ to the original primal LP (P).

Approximate linear program [Schweitzer & Seidman 1982] [34]

$$
\begin{aligned}
\min_{\theta \in \mathbb{R}^k} \quad & (1-\gamma) \sum_{s \in \mathcal{S}} \mu(s)(\Phi\theta)(s) \\
\text{s.t.} \quad & (\Phi\theta)(s) \geq \; r(s,a) + \gamma \sum_{s' \in \mathcal{S}} \mathrm{P}(s'|s,a)(\Phi\theta)(s'), \quad \forall\; s \in \mathcal{S},\; a \in \mathcal{A}.
\end{aligned}
\tag{ALP}
$$

Prior works in ALP - Linear function approximation (cont'd)

Assumptions:

- The set $\{\phi_1, \ldots, \phi_k\}$ is linearly independent.
- $\mathbf{1} \in \operatorname{span}\big(\{\phi_1, \ldots, \phi_k\}\big) := \{\Phi\theta \mid \theta \in \mathbb{R}^k\}$. This ensures that (ALP) is feasible [6] .
- The values $\sum_{s' \in \mathcal{S}} \mathsf{P}(s'|s,a)\phi_i(s')$ and $\mu^\top \phi_i$, $i = 1, \ldots, k$, can be accessed in $\mathcal{O}(1)$ time.

Quality of the approximate solution (Th.2 in [De Farias & Van Roy 2003] [6])

$$\|V^\star - V^\star_{\text{ALP}}\|_{1,\mu} \le \frac{2}{1-\gamma} \underbrace{\min_\theta \|V^\star - \Phi\theta\|_\infty}_{\varepsilon_{\text{approx}}:\ \text{approximation error}}.$$

Notation:

- $\theta^\star_{\text{ALP}}$ is optimal to (ALP) and $V^\star_{\text{ALP}} = \Phi\theta^\star_{\text{ALP}}$ is the approximate value function.
- $\|V\|_{1,\mu} := \sum_{s \in \mathcal{S}} \mu(s)|V(s)|$ is the μ-weighted ℓ_1-norm, where $\mu > 0$.
- $\Phi\theta^\star$ is the $\|\cdot\|_\infty$-norm projection of $V^\star$ to the subspace $V = \Phi\theta$.
- $\varepsilon_{\text{approx}} := \min_\theta \|V^\star - \Phi\theta\|_\infty = \|V^\star - \Phi\theta^\star\|_\infty$ is called the approximation error.

Prior works in ALP - Linear function approximation (cont'd)

Quality of the approximate solution

$$\|V^\star - V^\star_{\text{ALP}}\|_{1,\mu} \leq \frac{2}{1-\gamma}\varepsilon_{\text{approx}}.$$

Remarks:

- $\varepsilon_{\text{approx}} = \min_\theta \|V^\star - \Phi\theta\|_\infty$ captures the approximation power of the feature map.
- If $V^\star \in \text{span}\big(\phi_1, \ldots, \phi_k\big)$, then $V^\star = \Phi\theta^\star_{\text{ALP}}$.
- In general, $\|V^\star - V^\star_{\text{ALP}}\|_{1,\mu} = \mathcal{O}(\varepsilon_{\text{approx}})$.
- Focus on finding a good basis, leaving the search of the "right" weights to an LP solver.

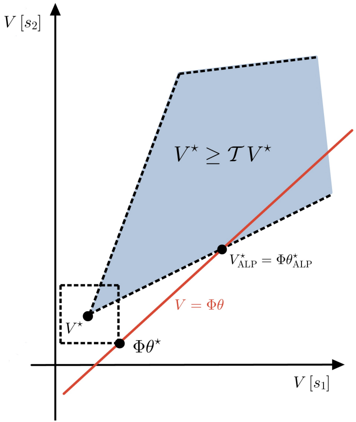

Figure: Graphical interpretation of ALP [6]

Prior works in ALP - Constraint sampling

∘ Reduce the number of constraints by constraint sampling.

- (x, a) is treated as an uncertainty parameter.
- $\mathcal{S} \times \mathcal{A}$ is the uncertainty space.
- $\mathbb{P}$ is a probability distribution on $\mathcal{S} \times \mathcal{A}$.
- $\{(s_i, a_i)\}_{i=1}^N$ i.i.d. samples on $(\mathcal{S} \times \mathcal{A}, \mathbb{P})$.
- $\mathcal{N} \subset \mathbb{R}^k$ is a bounding set.
- The relaxed LP (RLP) is obtained from (ALP) by restricting $\theta \in \mathcal{N}$ with N sampled constraints.

Relaxed linear program [De Farias & Van Roy 2001] [7]

$$\begin{aligned} \min_{\theta \in \mathcal{N}} \quad & (1-\gamma) \sum_{s \in \mathcal{S}} \mu(s)(\Phi\theta)(s) \\ \text{s.t.} \quad & (\Phi\theta)(s_i) \geq r(s_i, a_i) + \gamma \sum_{s' \in \mathcal{S}} \mathsf{P}(s'|s_i, a_i)(\Phi\theta)(s'), \quad \forall\, i = 1, \ldots, N. \end{aligned} \tag{RLP}$$

Prior works in ALP - Constraint sampling (cont'd)

Assumptions:

- The set $\mathcal{N} \subset \mathbb{R}^k$ is compact, i.e., bounded and closed.
- The optimal solution $\theta^\star_{\text{ALP}}$ to (ALP) is in $\mathcal{N}$.
- The sampling probability distribution is $\mathbb{P} \propto \lambda^{\pi^\star}$, i.e., the state-action visitation distribution induced by an optimal policy $\pi^\star$.

How many samples give a good solution (Th.3.1 in [De Farias & Van Roy 2004] [7])

Let $\varepsilon, \delta \in (0,1)$. If $N \geq \tilde{\mathcal{O}}\Big(\frac{4k\log(\frac{1}{\delta})}{(1-\gamma)\varepsilon}\frac{\sup_{\theta\in\mathcal{N}}\|V^\star-\Phi\theta\|_\infty}{\mu^\top V^\star}\Big)$, then with probability at least $1-\delta$, we have

$$\|V^\star - V^\star_{\text{RLP}}\|_{1,\mu} \leq \|V^\star - V^\star_{\text{ALP}}\|_{1,\mu} + \varepsilon\|V^\star\|_{1,\mu},$$

where the probability is taken over the random sampling of constraints.

Notation:

- $\theta^\star_{\text{RLP}}$ is optimal to (RLP) and $V^\star_{\text{RLP}} = \Phi\theta^\star_{\text{RLP}}$ is the approximate value function.
- $\varepsilon \in (0,1)$ is the desired approximation accuracy.
- $\delta \in (0,1)$ is the desired confidence level.

Prior works in ALP - Constraint sampling (cont'd)

Remarks:

- (RLP) is a relaxation of (ALP).
- The constraint $\theta \in \mathcal{N}$ ensures that the optimal value of (RLP) is bounded.
- The relaxed linear program (RLP) is random.
- $\theta^\star_{\text{RLP}}$ and $V^\star_{\text{RLP}} = \Phi\theta^\star_{\text{RLP}}$ are random variables.
- A lower bound on the number of samples needed to achieve an ε-accurate solution with probability at least $1-\delta$, is called the sample complexity of the problem.
- The sample complexity bound depends on the choice of the bounding set $\mathcal{N}$.
- The sample complexity bound requires access to samples from the optimal state-action visitation distribution (which is not known a priori).

Common theme of all prior ALP works

- Reduce the number of decision variables by projecting on a low-dimensional subspace.
- Reduce the number of constraints (e.g., by constraint sampling).
- Solve the resulted LP with generic solver.
- Analyze the quality of the approximate solution.
- Either scale badly with the size of the state-action spaces or
- Require access to samples from a distribution that depends on the optimal policy.
- Require knowledge of dynamics or access to a simulator.
- Focus mainly on the approximation of the optimal value function but not so much on extracting a nearly optimal policy.

Off-policy reinforcement learning (aka batch reinforcement learning)

◦ Learn to control from a previously collected dataset.

◦ Important for safety-critical applications, where deploying a suboptimal policy during learning is impossible.

- Think about drug testing.

Remarks:

◦ This setting is distinct from IRL, where the data is given by an "expert" policy.

◦ In this setting, we do have access to a reward signal from previous experience.

◦ We assume that the data covers the state-action space sufficiently well.

Off-policy reinforcement learning: The formalism

◦ In off-policy RL, we focus on the usual objective, which is:

$$J(\pi) = \mathbb{E}_{s\sim\mu}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \,|\, s_0 = s,\, \pi\right].$$

◦ However, we assume access only to samples from a fixed policy $\widetilde{\pi}$.

Remarks: ◦ The policy $\widetilde{\pi}$ represents the policy previously used to collect the experience dataset.

◦ In drug testing, $\widetilde{\pi}$ may represent the policy used by the human doctors (not necessarily optimal).

A useful subproblem: Offline policy evaluation

◦ We saw that often we find an optimal policy via learning the state-action value function:

$$Q^\pi(s,a) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t,a_t) \,|\, s_0 = s,\, a_0 = a,\, \pi\right].$$

◦ However, we assume access only to samples from a fixed policy $\widetilde{\pi}$.

◦ Estimating $Q^\pi(s,a)$ using samples from $\widetilde{\pi}$ is known as **offline policy evaluation**.

◦ Next, we derive a convex programming approach to compute $Q^\pi(s,a)$.

Self-study: ◦ Compare to the derivation of the Primal LP to compute $V^\star$.

An offline policy evaluation (OPE) approach

OPE via f-divergences

Let g be the convex conjugate of an f-divergence. [22] proposes to use the following formulation via Q^π:

$$Q^\pi \;=\; \text{argmin}_Q \mathbb{E}_{\lambda^{\tilde{\pi}}} g(r - \mathcal{L}_\pi Q) + (1-\gamma)\langle Q, c\rangle, \tag{OPE}$$

where $c(s,a) = \pi(a|s)\mu(s)$ is the joint state-action distribution.

Remarks:

- Recall the operator $\mathcal{L}^\pi$:

$$(\mathcal{L}^\pi Q)(s,a) = Q(s,a) - \gamma \sum_{s',a'} \mathsf{P}(s'|s,a)\pi(a'|s')Q(s',a').$$

- The problem (OPE) is convex and smooth in Q because g is convex.
- The problem (OPE) is unconstrained and g acts like a loss function.
- A biased objective estimate can be obtained by sampling from c and $\widetilde{\lambda^\pi}$.
- The name *offline* comes from not needing samples from λ^π.

From policy evaluation to policy optimization

AlgaeDICE [24]

Maximizing (OPE) objective over π gives us a policy optimization objective, dubbed as AlgaeDICE:

$$\pi^\star \in \operatorname{argmax}_\pi \min_Q \; (1-\gamma)\langle c, Q\rangle + \mathbb{E}_{\lambda^{\tilde{\pi}}} g\left(r - \mathcal{L}_\pi Q\right).$$

Remarks:

- We only need to sample from the initial distribution μ, the policy π, and the offline policy $\tilde{\pi}$.
- We only interact with the environment via $\tilde{\pi}$.

An alternative offline policy evaluation from the Lagrangian perspective [35]

- The approach in [35] *PRO-RL* exploits the Lagrangian of (LP) formulation.
- It has the same underpinnings of REPS adapted for the offline RL.

PRO-RL [35]

Let h be a strongly convex function. The PRO-RL approach uses the following formulation:

$$\max_{\lambda \in \Delta} \min_{V} \; \langle \lambda, r + \gamma PV - V \rangle + (1-\gamma)\langle \mu, V \rangle - \frac{1}{\eta} \mathbb{E}_{(s,a)\sim\lambda^{\tilde{\pi}}} \left(h\Big(\frac{\lambda(s,a)}{\lambda^{\tilde{\pi}}(s,a)} \Big) \right).$$

Remarks:

- The inner product with λ are equivalent to expectations with samples drawn from λ:

$$\langle \lambda, r + \gamma PV - V \rangle = \mathbb{E}_{(s,a)\sim\lambda} \left[r(s,a) + \gamma PV(s,a) - V(s) \right].$$

- [35] proposes to optimize an empirical objective obtained from samples.
- AlgaeDICE is a Q-based offline RL approach, whereas PRO-RL is value-based.

Guarantees for PRO-RL

Algorithm	Main assumptions	Samples for ϵ-optimal policy
PRO-RL	$\frac{\lambda^\star(s,a)}{\lambda^{\tilde{\pi}}(s,a)} \leq B < \infty$, $h(\cdot)$ is M_h-strongly convex	$\mathcal{O}\left(\frac{B\|\mathcal{S}\|}{(1-\gamma)^4 \epsilon^6 M_f}\right)$

Remarks:

- The assumption $\frac{\lambda^\star(s,a)}{\lambda^{\tilde{\pi}}(s,a)} < \infty$ has the interpretation that the occupancy measure $\lambda^{\tilde{\pi}}$ has support larger than the support of the optimal occupancy measure $\lambda^\star$.
- The sample complexity gurantees worsen as B increases.
- That means that the more "different" $\lambda^{\tilde{\pi}}$ and $\lambda^\star$ are, the more samples are required.