15-859 Algorithms for Big Data Assignment 1

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1: Scratcy Scratch

$$T = \left\{ (x, \sin \frac{1}{x}) : x \in (0, 1] \right\} \cup \{(0, 0)\}$$

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$$\left(\frac{1}{x} \right)$$
$$\left[\frac{1}{x} \right]$$
$$\left\{ \frac{1}{x} \right\}$$
$$\left\| \frac{1}{x} \right\|$$
$$|\frac{1}{x}|$$
$$\left\| \frac{1}{x} \right\|$$
$$\left\lceil \frac{1}{x} \right\rceil$$

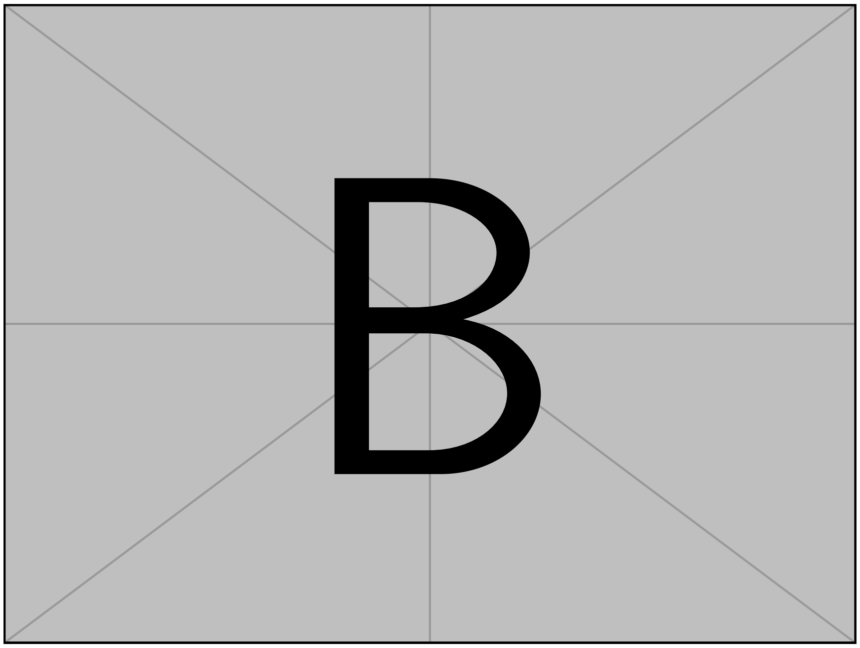

Figure 1: Landing/Login Page Example

We denote the historical trajectory as $\tau = (s_1, a_1, \ldots, a_{t-1}, s_t)$ and action-observation history (AOH) for player i as $\tau^i = \left(\Omega^i\left(s_1\right), a_1, \ldots, a_{t-1}, \Omega^i\left(s_t\right)\right)$, which encodes the trajectory from player i 's point of view.

We evaluated the policy periodically during training by testing it without exploration noise. Figure 2 shows the performance curve for a selection of environments. We also report results with components of our algorithm.

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$$X = (X_1, ..., X_n) \qquad \text{(using “...”)}$$
$$X = (X_1, \ldots, X_n) \qquad \text{(using “\textbackslash dots”)}$$

“Hello World!”

Problem: Show that if $(x_n)_n$ *converges to* x *in the usual sense, then* $\lim_{n\to\infty} x_n = \lim_{\mathcal{F}} x_n$.

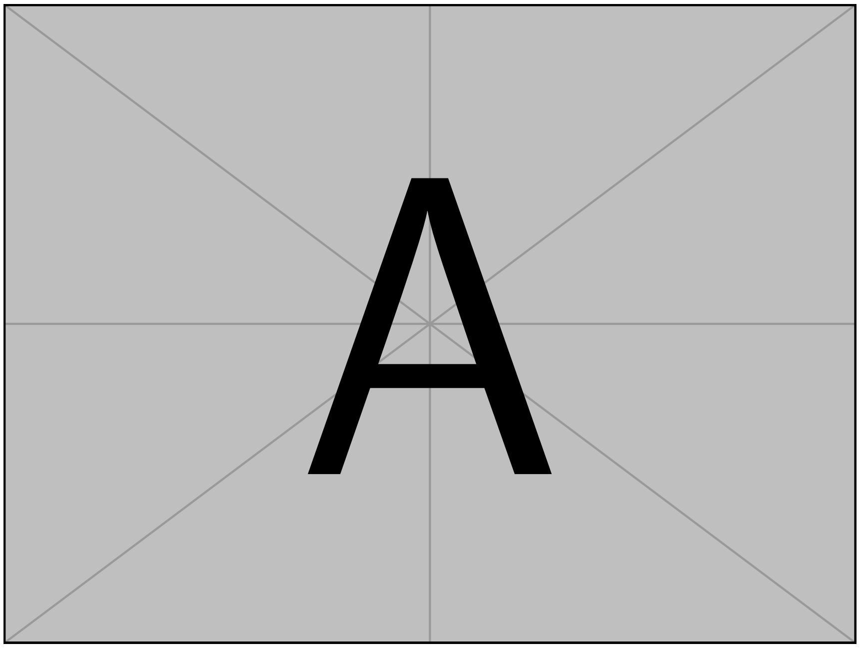

Figure 2: Landing/Login Page Example

Suppose that $(x_n)_n$ converges to x. We show that this x is also the $\mathcal{F}$-limit of $(x_n)_n$.

Proof. Take any ε. Then we know that for some large enough N, if $n \geq N$, then $x_n \in B_\varepsilon(x)$. Since every non-principal ultrafilter on $\mathbb{N}$ contains $\mathcal{F}_\infty$, then $\mathcal{F}$ also contains $\{n : n \geq N\}$, since the complement is finite. Therefore since filters are closed upwards, any sequence items x_n with $n < N$ that happen to fall in the ball around x, i.e, $x_n \in B_\varepsilon(x)$ is also contained in some filter element, so $\{n \in \mathbb{N} : |x_n - x| < \varepsilon\} \in \mathcal{F}$, as desired. □

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$$P(X) = \int P(X \mid z; \theta) P(z) dz.$$

$$P(X) = \int xyz dx.$$

1 A

Definition 1.1 (Using *)**.** A distribution on matrices $\boldsymbol{S} \in \mathbb{R}^{k \times n}$ has the $(\varepsilon, \delta, \ell)$-JL moment property if for all $x \in \mathbb{R}^n$ with $|x|_2 = 1$,

$$\mathop{\mathbf{E}}_{\boldsymbol{S}} \left| |\boldsymbol{S}x|_2^2 - 1 \right|^\ell \leq \varepsilon^\ell * \delta.$$

Definition 1.2 (Using \cdot)**.** A distribution on matrices $\boldsymbol{S} \in \mathbb{R}^{k \times n}$ has the $(\varepsilon, \delta, \ell)$-JL moment property if for all $x \in \mathbb{R}^n$ with $|x|_2 = 1$,

$$\mathop{\mathbf{E}}_{\boldsymbol{S}} \left| |\boldsymbol{S}x|_2^2 - 1 \right|^\ell \leq \varepsilon^\ell \cdot \delta.$$

$\mathbf{Pr}\left[X \geq a\right] \leq \frac{\mathbf{E}[X]}{a}$

$x \, \mathbf{Pr}_X \left[X \geq a\right] \leq \frac{\mathbf{E}[X]}{a}$

$x\mathbf{Pr}_X \left[X \geq a\right] \leq \frac{\mathbf{E}[X]}{a}$

$\mathbf{E}_{X\sim} \left[X \geq a\right] \leq \frac{\mathbf{E}[X]}{a}$

$p(\boldsymbol{z}, \boldsymbol{x}) = p(\boldsymbol{z})p(\boldsymbol{x} \mid \boldsymbol{z})$

$p(\boldsymbol{z}, \boldsymbol{x}) = p(\boldsymbol{z})p(\boldsymbol{x}|\boldsymbol{z})$

$KL\left(P \parallel Q\right)$

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We evaluated the policy periodically during training by testing it without exploration noise. Figure 2 shows the performance curve for a selection of environments.

$$\sum_{i=1}^{n}$$

$$\begin{aligned}
\nabla_\mu(\mathbb{E}_{x\sim q_\mu} f(x)) &= \nabla_\mu \int_x f(x) q_\mu(x) dx \\
&= \int_x f(x)(\nabla_\mu \log q_\mu(x)) q_\mu(x) dx \\
&= \mathbb{E}_{x\sim q_\mu} \left(f(x) \nabla_\mu \log q_\mu(x)\right)
\end{aligned}$$

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\end{aligned}$$

$\mathbf{Pr}\left[X \geq a\right] \leq \frac{\mathbf{E}[X]}{a}$

$$\phi, \Phi, \varphi$$

,

Theorem 1.3 (Gibbs Variational Principle)**.** *Let $p(\mathbf{z}, \mathbf{x})$ be a joint distribution over latent variables and observables. Then,*

$$p(\mathbf{z} \mid \mathbf{x}) = \mathop{\arg\max}_{q(\mathbf{z}|\mathbf{x}):\ \textit{distribution over } \mathbf{z}}$$

$$\min_x |\boldsymbol{A}x - b|_2^2$$

$$\boldsymbol{M}$$

$$|\langle \boldsymbol{u}, \boldsymbol{v} \rangle|^2 \leq \langle \boldsymbol{u}, \boldsymbol{u} \rangle \cdot \langle \boldsymbol{v}, \boldsymbol{v} \rangle$$

$$\begin{aligned} p(\text{Disease} \mid \text{Symptoms}) &= \frac{p(\text{Disease}, \text{Symptoms})}{p(\text{Symptoms})} \\ &= \frac{p(\text{Disease}, \text{Symptoms})}{\sum_{\text{Disease}' \in \text{Diseases}} p(\text{Disease}', \text{Symptoms})} \end{aligned}$$

$$\frac{1}{\mathcal{Z}(\theta)} \exp\left(\sum_{\substack{i,j \in [n] \\ i \neq j}} x_i x_j \theta_{ij} + \sum_{i \in [n]} x_i \theta_i \right),$$

$$\mathcal{Z}(\theta) = \sum_{\boldsymbol{x} \in \{\pm 1\}^n} p(\theta, \boldsymbol{x})$$

Let $p(\boldsymbol{z}, \boldsymbol{x})$ be a joint distribution ovre latent variables $\boldsymbol{z}$ and observables $\boldsymbol{x}$. Then

$$p(\boldsymbol{z} \mid \boldsymbol{x}) = \operatorname*{arg\,max}_{q(\boldsymbol{z}|\boldsymbol{x}):\text{distribution over } \boldsymbol{z}}$$