# Offline Reinforcement Learning with In-Sample Tsallis Regularized Policy

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## Abstract

Offline reinforcement learning methods learn from a fixed dataset collected by some behavior policy without further interaction with the environment. Such datasets often contain only a subset of the state and action spaces. Standard off-policy algorithms suffer from the extrapolation error known as the unrealistic action values for the actions not present in the dataset. The inaccurate value estimate can in turn cause out-of-distribution actions to be preferred in the policy improvement stage, leading to poor performance. Many methods propose to enforce the closedness between the learned policy and the behavior policy. In this paper, we propose to learn a in-sample Tsallis regularized policy that has support strictly within the dataset support. Our method also generalizes the in-sample softmax as a special case of the Tsallis policy where the support of the learned policy remains the same to the behavior policy. Moreover, if we assume the dataset is generated by Tsallis policies such that the absent actions are truncated, then we can guarantee the learned Tsallis policy is sufficiently similar to the behavior policy by showing bounded KL distance. This is the firs application of Tsallis regularization to offline RL to the best of our knowledge, where insufficient exploration as one of the main drawbacks of Tsallis regularized policies vanishes.

## 1 Introduction

## 2 Background

### 2.1 Reinforcement Learning

RL problems are usually modelled by Markov Decision Processes (MDPs) expressed by the tuple $(\mathcal{S}, \mathcal{A}, P, r, \gamma)$, where $\mathcal{S}$ and $\mathcal{A}$ respectively denote state space and action space. $P(\cdot|s,a)$ denotes transition probability over the state space given state-action pair $(s,a)$, and $r(s,a)$ defines the reward associated with that transition. $\gamma \in (0,1)$ is the discount factor. A policy $\pi(\cdot|s)$ is a mapping from the state space to distributions over actions. The state-action value function starting from $(s,a)$ following policy $\pi$ is defined as $Q_\pi(s,a) = \mathbb{E}_\pi\left[\sum_{t=0}^{\infty}\gamma^t r(s_t,a_t)|s_0=s,a_0=a\right]$. It is a classic result that there exists a stationary optimal policy that maximizes the cumulative return [20]. Its fixed point $Q_*(s,a)$ satisfies the Bellman optimality equation $Q_*(s,a) = r(s,a) + \gamma\mathbb{E}_{s'\sim P(\cdot|s,a)}[\max_{a'} Q_*(s',a')]$. Therefore, in practice it is common to update the action value function by acting greedily with respect to the current estimate.

We are interested in the MDPs that are *entropy-regularized*: the reward function is augmented with an additional entropic penality (or bonus). For example, the Shannon entropy $\mathcal{H}\left(\pi(\cdot|s)\right) := -\sum_a \pi(a|s)\ln\pi(a|s)$ is often added as a bonus to encourage the policy to be stochastic. The maximum Shannon entropy action value function satisfies $\tilde{Q}_\pi(s,a) = r(s,a) +$

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$\gamma \mathbb{E}_{s' \sim P(\cdot|s,a)} \mathbb{E}_{a \sim \pi(\cdot|s)} \left[ \tilde{Q}_\pi(s,a) - \tau \mathcal{H}\left(\pi(\cdot|s)\right) \right]$, where $\tau$ denotes a coefficient. The maximum $r(s,a) + \gamma \mathbb{E}_{s' \sim P(\cdot|s,a)} \left[ \tau \ln \sum_a \exp\left(\tau^{-1} Q_\pi(s,a)\right) \right]$ is attained when the policy is the well-known Boltzmann softmax $\pi(a|s) \propto \exp\left(\tau^{-1} Q_\pi(s,a)\right)$, where $\propto$ denotes proportional to up to a constant not depending on actions. KL divergence $D_{KL}(\pi(\cdot|s) \,||\, \mu(\cdot|s)) := \sum_a \pi(a|s) \ln \frac{\pi(a|s)}{\mu(a|s)}$ is another popular choice, where $\mu$ is some baseline policy [2, 21, 25]. Unlike Shannon entropy, KL divergence is often added as a penalty to penalize large deviation from $\mu$. The KL-regularized optimal policy takes the form $\pi(a|s) \propto \mu(a|s) \exp\left(\tau^{-1} Q_\pi(s,a)\right)$, where we overloaded the coefficient $\tau$ for Shannon entropy.

## 2.2 $q$-statistics and Tsallis regularization

In this paper we consider a broad class of less studied entropic regularizer known as the Tsallis entropy $S_q(\pi(\cdot|s)) := \frac{1}{q-1}\left(1 - \sum_a \pi^q(a|s)\right)$, where $q \in \mathbb{R}_+$. It is also called generalized entropy since it generalizes the Shannon entropy [23, 24]. Tsallis entropy can also be defined by the $q$-logarithm in a similar manner to the standard logarithm defining Shannon entropy, hence eases the notation and derivation. $q$-logarithm and its unique inverse function $q$-exponential are defined by [24]:

$$\ln_q x = \frac{x^{q-1} - 1}{q-1}, \quad \exp_q x = \left[1 + (q-1)x\right]_+^{\frac{1}{q-1}}, \quad S_q(\pi(\cdot|s)) = -\sum_a \pi(a|s) \ln_q \pi(a|s), \quad (1)$$

where $[\cdot]_+ = \max\{\cdot, 0\}$. When $q \to 1$, the $q$-logarithm (resp. $q$-exponential) recovers the standard logarithm (resp. exponential) and hence Tsallis entropy degenerates to Shannon entropy. When $q = 2$, we arrive at the Tsallis sparse entropy $S_2(\pi(\cdot|s)) := \pi(a|s)\left(1 - \pi(a|s)\right)$ [5, 16]. The name sparse entropy comes from the fact that the regularizer leads to sparse support for the resulting *sparsemax* policy [3, 18]. When $q = \infty$, the regularizer vanishes. In this paper, we call the regularized policy sparsemax for all $q$ , and express them using the $q$-exponential[1]:

$$\pi(a|s) = \exp_q\left(\frac{Q(s,a)}{\tau} - \psi\left(\frac{Q(s,\cdot)}{\tau}\right)\right), \; \psi\left(\frac{Q(s,\cdot)}{\tau}\right) \doteq \frac{\sum_{a \in K(s)} \frac{Q(s,a)}{\tau} - 1}{|K(s)|} + \frac{1}{q-1}. \quad (2)$$

$K(s)$ is the set of highest-value actions satisfying $1 + i\frac{Q(s,a_{(i)})}{\tau} > \sum_{j=1}^{i} \frac{Q(s,a_{(j)})}{\tau}$, with $a_{(j)}$ denotes the $j$-th largest action. Intuitively, the policy first sorts actions by $a_{(1)}, \ldots, a_{(|\mathcal{A}|)}$ and then compute the threshold $\psi$. Suppose $Q(s, a_{(j+1)}) \le \psi \le Q(s, a_{(j)})$, then actions from $a_{(j+1)}, \ldots, a_{(|\mathcal{A}|)}$ are truncated and have zero probability of being selected. The actions $a_{(1)}, \ldots, a_{(j)}$ are called allowable actions and collected in the set $K(s)$. The degree of truncation and the size of $K(s)$ can be controlled by $\tau$. The truncation is visualized in Figure 1.

Note that for $q \neq 1, 2, \infty$ the policy does not have a closed-form solution. Nonetheless we can resort to the Taylor's expansion to obtain approximate sparsemax policies, see Appendix A for details. For those cases Eq. (2) still holds, but may need an additional renormalization step to guarantee a valid probability distribution. Therefore, in the rest of the paper, we write $\pi(a|s) \propto \exp_q\left(\frac{Q(s,a)}{\tau}\right)$. The effect of $q$ lies in defining the range of the acceptable actions in $K(s)$ or extent of action truncation. Indeed, we can show that as $q \to \infty$, the unnormalized Taylor's expansion for the policy $\pi(a|s) \to 1, \forall a$, that is, after normalization it becomes a uniform distribution. We compare argmax, softmax, sparsemax and plot the behavior of sparsemax truncation in Figure 1. We focus on Gaussian policies which are common for continuous-action algorithms.

Very recently Zhu et al. [29] proposed in RL to exploit Tsallis KL divergence [9] which generalizes Tsallis entropy. They proved that the regularized optimal policy takes a similar form to the optimal KL-regularized policy:

$$D^q_{KL}(\pi(\cdot|s) \,||\, \mu(\cdot|s)) = -\sum_a \pi(a|s) \ln_q \frac{\mu(a|s)}{\pi(a|s)}, \; \pi(a|s) = \mu(a|s) \exp_q\left(\frac{Q_\pi(s,a)}{\tau} - \psi\left(\frac{Q_\pi(s,a)}{\tau}\right)\right). \quad (3)$$

We also write the policy as $\pi(a|s) \propto \mu(a|s) \exp_q\left(\frac{Q_\pi(s,a)}{\tau}\right)$. It is worth noting that unlike the KL divergence, the Tsallis KL divergence cannot be decomposed as $\ln_q \frac{\pi(a|s)}{\mu(a|s)} \neq \ln_q \pi(a|s) - \ln_q \mu(a|s)$.

[1]Different to prior works [16, 5], our definition of $\psi$ has an additional $\frac{1}{q-1}$ term to accommodate the $q$-exponential policy, see Appendix A for derivation.

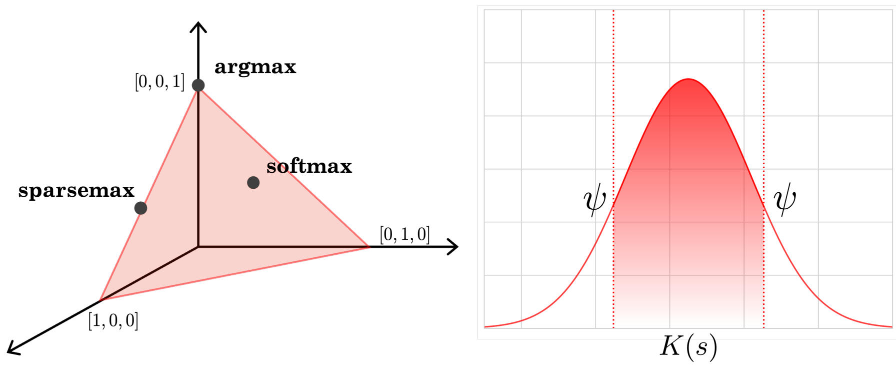


Figure 1: (Left) Comparison between argmax, softmax and sparsemax on the probability simplex. Argmax produces a deterministic policy residing on the vertices, while a softmax policy lies inside the simplex. By contrast, a sparsemax policy lives on the border. (Right) Sparsemax operator acting on a Gaussian policy by truncating actions with value below the threshold $\psi$. Actions with value larger than $\psi$ are collected in the set $K(s)$.

### 2.3 Offline Reinforcement Learning

We consider the problem of offline RL, where the agent cannot interact with the environment and instead learn from a fixed dataset $\mathcal{D} = \{(s, a, r, s')_{1:N}\}$ collected by some unknown behavior policy $\pi_{\mathcal{D}}$. The dataset $\mathcal{D}$ typically contains only a small subset of the $\mathcal{S} \times \mathcal{A}$ space. Standard off-policy algorithms are known to suffer from the extrapolation error referring to the function approximator erroneously estimate action values for those out-of-distribution (OOD) actions not present in the dataset. Extrapolation error can happen as a result of e.g. the smoothness of neural networks when the update is around some low sample region [11]. In the policy improvement step, the unrealistic high values of the OOD actions lead to target values that are further in favor of sampling OOD actions, causing a vicious loop.

It is worth noting that unlike for online RL, where the OOD actions can lead to sampling more around the low sample region and eventually correction of the values, in offline RL this is impossible. Instead, many of the existing works propose to force the learned policy to be close to the behavior policy [6, 8, 7, 19]. This is often achieved by adding a regularizer in the policy update penalizing deviating from the behavior policy [10, 15, 12, 26], e.g. by incorporating KL divergence $\max_\pi \mathbb{E}_{s\sim\mathcal{D}}\left[\mathbb{E}_{a\sim\pi(\cdot|s)}\left[Q(s,a)\right] - \tau D_{KL}(\pi(\cdot|s)\,||\,\pi_{\mathcal{D}}(\cdot|s))\right]$. The critic is typically updated by minimizing the loss $\mathbb{E}_{(s,a,s')\sim\mathcal{D}}\mathbb{E}_{a\sim\pi(\cdot|s)}\left[\left(r(s,a) + \gamma Q(s',a') - Q(s,a)\right)^2\right]$. The regularization leads to the policy form $\pi(a|s) \propto \pi_{\mathcal{D}}(a|s)\exp\left(\tau^{-1}Q_\pi(s,a)\right)$ where the learned policy must have the same support of the behavior policy. This idea is shared by the *in-sample* methods that enforce the support of the learned policy to be within the behavior policy $\pi \preceq \pi_{\mathcal{D}}$ [8, 14, 27], which is achieved by only updating for the actions in the dataset.

## 3 Method

### 3.1 In-Sample Softmax for Offline RL

To alleviate the OOD error, Fujimoto et al. [8] proposed the in-sample Bellman optimality equation to update only for actions present in the dataset:

$$Q_{*,\pi_{\mathcal{D}}}(s,a) = r(s,a) + \gamma\mathbb{E}_{s'\sim P(\cdot|s,a)}\left[\max_{a':\pi_{\mathcal{D}}(a'|s')>0} Q_{*,\pi_{\mathcal{D}}}(s',a')\right]. \tag{4}$$

Later, Xiao et al. [27] proposed in-sample softmax to better estimate the policy inside the bracket since in the continuous case the hard max operator might be difficult to solve for. By regularizing with the Shannon entropy $\tau\mathcal{H}(\pi)$ and imposing the dataset support constraint, the in-sample softmax

Bellman optimality equation has the following evaluation step:

$$Q_{*,\pi_{\mathcal{D}}}(s,a) = r(s,a) + \gamma \mathbb{E}_{s' \sim P(\cdot|s,a)} \left[ \tau \ln \sum_{a' : \pi_{\mathcal{D}}(a'|s') > 0} \exp\left(\tau^{-1} Q_{*,\pi_{\mathcal{D}}}(s',a')\right) \right]. \tag{5}$$

As the dataset support constraint poses a challenge to implementation, Xiao et al. [27] proposed to transform the summation into an expectation to avoid directly computing the constraint:

$$\begin{aligned} \sum_{a' : \pi_{\mathcal{D}}(a'|s') > 0} \exp\left(\tau^{-1} Q_{*,\pi_{\mathcal{D}}}(s',a')\right) &= \sum_{a' : \pi_{\mathcal{D}}(a'|s') > 0} \frac{\pi_{\mathcal{D}}(a'|s')}{\pi_{\mathcal{D}}(a'|s')} \exp\left(\tau^{-1} Q_{*,\pi_{\mathcal{D}}}(s',a')\right) \\ &= \mathbb{E}_{a' \sim \pi_{\mathcal{D}}(\cdot|s')} \left[\exp\left(\tau^{-1} Q_{*,\pi_{\mathcal{D}}}(s',a') - \ln \pi_{\mathcal{D}}(a'|s')\right)\right]. \end{aligned} \tag{6}$$

The expectation can be approximated by Monte-Carlo sampling actions from the dataset. Since the term $\exp\left(\tau^{-1} Q_{*,\pi_{\mathcal{D}}}(s',a')\right)$ appears also in the regularized softmax policy, in-sample softmax updates the policy towards

$$\pi_{t+1,\pi_{\mathcal{D}}} \propto \pi_{\mathcal{D}}(a|s) \exp\left(\frac{Q_{t,\pi_{\mathcal{D}}}(s,a)}{\tau} - \ln \hat{\pi}_{\mathcal{D}}(a|s)\right), \tag{7}$$

where $\hat{\pi}_{\mathcal{D}}$ inside the exponential function is learned to imitate the behavior policy to avoid $\pi_{\mathcal{D}} = 0$ leading to an unbounded log-policy.

The benefits of the in-sample softmax can be interpreted as (1) softmax is easier to compute than hard max in the continuous action setting; (2) the in-sample softmax policy Eq. (7) can be seen as a KL-regularized policy and hence the dataset support constraint is satisfied. In fact, the support of $\pi_{\pi_{\mathcal{D}},k+1}$ should be exactly the same as $\pi_{\mathcal{D}}$ since $\exp(\frac{\cdot}{\tau}) > 0$ as long as $\tau \neq \infty$. We now explain why Eq. (7) can be regarded as a KL-regularized policy: it can be decomposed into two terms: the first term $\pi_{\mathcal{D}}(a|s)\exp\left(\frac{Q_{t,\pi_{\mathcal{D}}}(s,a)}{\tau}\right)$ acts as a KL-regularized policy with respect to the behavior policy; the second term $\exp\left(-\ln \hat{\pi}_{\mathcal{D}}(a|s)\right)$ can be seen as induced by another regularization $-\sum_a \pi(a|s) \ln \hat{\pi}_{\mathcal{D}}(a|s)$, which is the cross entropy between the in-sample softmax policy and the (learned) behavior policy.

However, the fact that the softmax policies always have full support indicates there is a persistent gap to Eq. (4). Since we want to improve upon the behavior policy, it is expected that action candidates should gradually narrow down to the maximizer. Furthermore, since Eq. (7) is only implicitly regularizing the policy and no explicit KL regularization for the value estimation [26], there is no guarantee that the learned policy should be close to the behavior policy.

### 3.2 In-Sample Tsallis Regularization

We propose to replace the Shannon entropy in in-sample softmax to the Tsallis entropy. The seemingly simple replacement, however, leads to drastically different behavior of the policy. Indeed, since we can control the truncation effect of the Tsallis regularized policies, we have the support of $\pi^{\text{Tsallis}}_{\pi_{\mathcal{D}},k+1} \preceq \pi_{\mathcal{D}}$, i.e. the support of the learned policy is either equal or within the dataset support.

Furthermore, Tsallis policies provide an means to formulate the common assumption that actions not present in the dataset are with low probability of being selected [13]. If we assume the behavior policy is also a Tsallis policy, then the support constraint $a : \pi_{\mathcal{D}}(a|s) > 0$ can be naturally replaced to the truncation criterion $a \in K(s)$; i.e.,

$$\pi_{\mathcal{D}}(a|s) \propto \exp_q\left(\frac{Q_{\pi_{\mathcal{D}}}(s,a)}{\tau_{\mathcal{D}}}\right), \quad \sum_{a \in K_{\mathcal{D}}(s)} \pi_{\mathcal{D}}(a|s) = 1, \tag{8}$$

where $\tau_{\mathcal{D}}$ is an unknown coefficient and $K_{\mathcal{D}}(s)$ denotes the set of actions present in the dataset. Under the Tsallis behavior policy assumption, the dataset support constraint $a : \pi_{\mathcal{D}}(a|s) > 0$ coincides with the condition $a \in K_{\mathcal{D}}(s)$. Revisiting the in-sample hard-max Bellman equation Eq. (4):

$$Q_{*,\pi_{\mathcal{D}}}(s,a) = r(s,a) + \gamma \mathbb{E}_{s' \sim P(\cdot|s,a)} \left[\max_{a' \in K_{\mathcal{D}}(s)} Q_{*,\pi_{\mathcal{D}}}(s',a')\right].$$

However, the assumption of the Tsallis behavior policy alone is not useful. The power of the assumption manifests when we use also Tsallis regularized policy learning:

$$\pi_{t+1,\pi_{\mathcal{D}}}(a|s) \propto \exp_q\left(\frac{Q_{t,\pi_{\mathcal{D}}}(s,a)}{\tau}\right), \quad \sum_{a\in K_{\mathcal{D}}(s)} \pi_{t+1,\pi_{\mathcal{D}}}(a|s) = 1. \tag{9}$$

$$Q_{t+1,\pi_{\mathcal{D}}}(s,a) = r(s,a) + \gamma\mathbb{E}_{s'\sim P(\cdot|s,a)}\left[\sum_{a'\in K_{\mathcal{D}}(s)} \pi_{t+1}(a'|s')\left(Q_{t,\pi_{\mathcal{D}}}(s',a') - \tau S_q(\pi_{t+1}(\cdot|s'))\right)\right]. \tag{10}$$

The term inside the bracket is known as $q$-maximum [17]. Similar to the softmax operators [1, 2], $q$-maximum is an approximation to the maximum with degree controlled by $q$.

More importantly, the support constraint is naturally satisfied since the learned Tsallis policy learns a new set of allowable actions $K_{t,q}$ from $K_{\mathcal{D}}(s)$ depending on $q$ and iteration $t$. The set satisfies the condition $K_{t,q} \preceq K_{\mathcal{D}}$: i.e. $|K_{t,q}| \leq |K_{\mathcal{D}}|$ and support constraint $\pi_t \preceq \pi_{\mathcal{D}}$. Let us take $q = 2$ for example:

$$\begin{aligned}
Q_{t+1,\pi_{\mathcal{D}}}(s,a) &= r(s,a) + \gamma\mathbb{E}_{s'\sim P(\cdot|s,a)}\left[\sum_{a'\in K_{\mathcal{D}}(s)} \pi_{t+1}(a'|s')\left(Q_{t,\pi_{\mathcal{D}}}(s',a') - \tau S_2(\pi_{t+1}(\cdot|s'))\right)\right] \\
&= r(s,a) + \gamma\mathbb{E}_{s'\sim P(\cdot|s,a)}\left[\tau \sum_{a'\in K_{\mathcal{D}}(s)} \left(\frac{Q_{t,\pi_{\mathcal{D}}}(s',a')}{\tau}\right)^2 - \left(\psi\left(\frac{Q_{t,\pi_{\mathcal{D}}}(s',a')}{\tau}\right) - 1\right)^2 + \tau\right] \\
&= r(s,a) + \gamma\mathbb{E}_{s'\sim P(\cdot|s,a)}\left[\tau \sum_{a'\in K_{t,q}(s)} \left(\frac{Q_{t,\pi_{\mathcal{D}}}(s',a')}{\tau}\right)^2 - \left(\psi\left(\frac{Q_{t,\pi_{\mathcal{D}}}(s',a')}{\tau}\right) - 1\right)^2 + \tau\right].
\end{aligned} \tag{11}$$

The second equation is because $\max_{\pi} \sum_{a\in\pi(\cdot|s)} \pi(a|s)Q(s,a) + \tau S_2(\pi(\cdot|s))$ attains its maximum at $\tau\sum_{a\in K(s)}\left(\frac{Q(s,a)}{\tau}\right)^2 - \psi\left(\frac{Q(s,\cdot)}{\tau}\right)^2 + \tau$ [16, 18], and the last equation is due to $K_{t,q} \preceq K_{\mathcal{D}}$. Eq. (11) states that, one needs not to explicitly enforce the support constraint since it is automatically fulfilled by learning a new subset of allowable actions.

We now show that, if the Tsallis behavior policy assumption holds and we use Tsallis regularized policy learning, then the learned policy is guaranteed to stay close to the behavior policy in the sense that their KL divergence is uppper-bounded.

**Theorem 1.** *Suppose the dataset $\mathcal{D}$ is generated by a Tsallis behavior policy of entropic index $q$. Let $K_{t,q}(s) \preceq K_{\mathcal{D}}(s)$ denote the set of allowable actions at $t$-th iteration whose cardinality is smaller than $K_{\mathcal{D}}(s)$. Also let $\pi_t(a|s) \propto \exp_q\left(\frac{Q_{t-1}(s,a)}{\tau}\right)$ denote the learned policy. Then the KL divergence between $\pi_t$ and the behavior policy can be upper bounded:*

$$D_{KL}(\pi_t(\cdot|s)\,||\,\pi_{\mathcal{D}}(\cdot|s)) \leq |K_{t,q}(s)|\left[\pi_t^q(a|s) - \pi_t^{q-1}(a|s) + \pi_t(a|s) - \frac{q-3}{q-1} + \pi_{\mathcal{D}}^{q-2}(a|s) - \pi_{\mathcal{D}}^{q-1}(a|s)\right]. \tag{12}$$

The bound is suggestive. For $q = 1$ (the in-sample softmax case) the bound is not useful and simply states the KL divergence may be unbounded. On the other hand, choosing any $q > 1$ brings an upper bound of at most $4|K_{t,q}(s)|$. When $q = 2$, the in-sample sparsemax has KL divergence to the behavior policy bounded by $|K_{t,q}(s)|\,(\pi_t(a|s) - \pi_{\mathcal{D}}(a|s) + 2)$. However, it should be noted that there is a trade-off between the power of policies $\pi^q$ and the cardinality of $K_{t,q}(s)$: $K_{t,q}(s)$ tends to collect all actions when $q \to \infty$.

*Proof.* We first prove the following lemma:

**Lemma 1.** *The difference between the standard logarithm and q-logarithm can be expressed by:*

$$\ln x - \ln_q x = (q-1)\left[\frac{d}{dq}\ln_q x - \ln x \ln_q x\right].$$

*Proof.* Let us begin with the right hand side

$$
\begin{aligned}
&(q-1)\left[\frac{d}{dq}\ln_q x - \ln x \ln_q x\right] = (q-1)\left[\frac{d}{dq}\frac{x^{q-1}-1}{q-1} - \ln x \ln_q x\right] \\
&= (q-1)\left[\frac{(x^{q-1}-1)'(q-1) - (x^{q-1}-1)(q-1)'}{(q-1)^2} - \ln x \ln_q x\right] \\
&= (q-1)\left[\frac{(q-1)x^{q-1}\ln x - (x^{q-1}-1)}{(q-1)^2} - \ln x \ln_q x\right] \\
&= x^{q-1}\ln x - \ln_q x - (q-1)\ln x \ln_q x = ((q-1)\ln_q x + 1)\ln x - \ln_q x - (q-1)\ln x \ln_q x \\
&= \ln x - \ln_q x.
\end{aligned}
$$

□

With the lemma, we have the following theorem indicating the Tsallis backward learning policies have bounded distance to the behavior policy: We decompose the KL divergence into three terms and apply Lemma 1:

$$
\begin{aligned}
&D_{KL}(\pi_t(\cdot|s)\,||\,\pi_{\mathcal{D}}(\cdot|s)) = \mathbb{E}_{a\sim\pi_t(\cdot|s)}\left[\ln \pi_t(a|s) - \ln \pi_{\mathcal{D}}(a|s)\right] \\
&= \mathbb{E}_{a\sim\pi_t(\cdot|s)}\left[\underbrace{\ln \pi_t(a|s) - \ln_q \pi_t(a|s)}_{(1)} + \underbrace{\ln_q \pi_t(a|s) - \ln_q \pi_{\mathcal{D}}(a|s)}_{(2)} + \underbrace{\ln_q \pi_{\mathcal{D}}(a|s) - \ln \pi_{\mathcal{D}}(a|s)}_{(3)}\right].
\end{aligned}
\tag{13}
$$

Let us now respectively bound the three terms:

$$
\begin{aligned}
(1): \ln \pi_t(a|s) - \ln_q \pi_t(a|s) &= (q-1)\left[\frac{d}{dq}\ln_q \pi_t(a|s) - \ln_q \pi_t(a|s)\ln \pi_t(a|s)\right] \\
&= \pi_t^{q-1}(a|s)\ln \pi_t(a|s) - \ln_q \pi_t(a|s) - (q-1)\ln_q \pi_t(a|s)\ln \pi_t(a|s) \\
&\le \pi_t^{q-1}(a|s)\ln \pi_t(a|s) + \frac{1}{q-1} + \ln \pi_t(a|s) \\
&\le \left(\pi_t^{q}(a|s) - \pi_t^{q-1}(a|s)\right) + \pi_t(a|s) - \frac{q-2}{q-1},
\end{aligned}
\tag{14}
$$

where we leveraged $\ln x \le x-1$ and $\ln_q \exp_q(x) = x$ both when $x>0$. Considering the definition of $\pi_t(a|s) \propto \exp_q\left(\frac{Q_{t-1}(s,a)}{\tau} - \psi\left(\frac{Q_{t-1}(s,\cdot)}{\tau}\right)\right)$ and $\exp_q(x) = [1+(q-1)x]_+^{\frac{1}{q-1}}$, we must have $\pi_t(a|s) > 0 \Leftrightarrow a \in K_{t-1,q}(s) \Leftrightarrow -\frac{1}{q-1} \le \frac{Q_{t-1}(s,a)}{\tau} - \psi\left(\frac{Q_{t-1}(s,\cdot)}{\tau}\right) \le 0$. If $a \notin K_{t-1,q}(s)$, then $\ln \pi_t(a|s) = -\infty$ and the KL term is unbounded. The same fact is exploited to yield an upper bound $\frac{1}{q-1}$ for (2). We now work with (3):

$$
\begin{aligned}
&(3): \ln_q \pi_{\mathcal{D}}(a|s) - \ln \pi_{\mathcal{D}}(a|s) = -(q-1)\left[\frac{d}{dq}\ln_q \pi_{\mathcal{D}}(a|s) - \ln_q \pi_{\mathcal{D}}(a|s)\ln \pi_{\mathcal{D}}(a|s)\right] \\
&\le -\pi_{\mathcal{D}}^{q-1}(a|s)\ln \pi_{\mathcal{D}}(a|s) \le -\pi_{\mathcal{D}}^{q-1}(a|s)\left(1 - \frac{1}{\pi_{\mathcal{D}}(a|s)}\right) = \pi_{\mathcal{D}}^{q-2}(a|s) - \pi_{\mathcal{D}}^{q-1}(a|s).
\end{aligned}
\tag{15}
$$

Putting all terms together, we arrive at the upper bound that

$$
\begin{aligned}
D_{KL}(\pi_t(\cdot|s)\,||\,\pi_{\mathcal{D}}(\cdot|s)) &\le \sum_{a\in K_{t,q}(s)} \pi_t(a|s)\left[\pi_t^{q}(a|s) - \pi_t^{q-1}(a|s) + \pi_t(a|s) - \frac{q-3}{q-1} + \pi_{\mathcal{D}}^{q-2}(a|s) - \pi_{\mathcal{D}}^{q-1}(a|s)\right] \\
&\le K_{t,q}(s)\left[\pi_t^{q}(a|s) - \pi_t^{q-1}(a|s) + \pi_t(a|s) - \frac{q-3}{q-1} + \pi_{\mathcal{D}}^{q-2}(a|s) - \pi_{\mathcal{D}}^{q-1}(a|s)\right].
\end{aligned}
$$

□

The assumption of Tsallis behavior policy is not restrictive. If all actions present, then it corresponds to the case of $q = 1$ where the policy has full support. On the other hand, different levels of missingness can be simulated by both $q$ and $\tau$.

Another advantage of Eq. (10) is that for $q > 1$, the policy is a variant of categorical distributions which is less susceptible to numerical issues than exponential functions [22]. Furthermore, Eq. (10) can switch between greedy policy and multimodal policy. The former is achieved when all but one action have values lower than the threshold; while vice versa for the latter.

**In-sample Tsallis Policy Estimation** Similar to [27], we want to directly use the actions from the dataset to estimate our policy. We do a similar step to Eq. (7):

$$\begin{aligned}
&\pi_{t+1,\pi_{\mathcal{D}}}(a|s) \propto \exp_q\left(\frac{1}{\tau}Q_{t,\pi_{\mathcal{D}}}(s,a)\right) = \pi_{\mathcal{D}}(a|s)\pi_{\mathcal{D}}(a|s)^{-1}\exp_q\left(\frac{1}{\tau}Q_{t,\pi_{\mathcal{D}}}(s,a)\right)\\
&= \pi_{\mathcal{D}}(a|s)\exp_q\left(\ln_q\frac{1}{\pi_{\mathcal{D}}(a|s)}\right)\exp_q\left(\frac{1}{\tau}Q_{t,\pi_{\mathcal{D}}}(s,a)\right)\\
&= \pi_{\mathcal{D}}(a|s)\left(\exp_q\left(\frac{1}{\tau}Q_{t,\pi_{\mathcal{D}}}(s,a) + \ln_q\frac{1}{\pi_{\mathcal{D}}(a|s)}\right)^{q-1} - (q-1)^2\frac{1}{\tau}Q_{t,\pi_{\mathcal{D}}}(s,a)\ln_q\frac{1}{\pi_{\mathcal{D}}(a|s)}\right)^{\frac{1}{q-1}}.
\end{aligned} \tag{16}$$

In the last step we made use of the relationship $\left(\exp_q x \cdot \exp_q y\right)^{q-1} = \exp_q(x+y)^{q-1} + (q-1)^2 xy$ [28].

**Remark.** *Tsallis entropy regularization has not been popular since its proposal in RL [16]. One of the main reasons is the sparsemax policies are not suitable for online RL since the exploration is handicapped resulted from the action truncation. However, in offline RL this drawback vanishes, and theoretically it allows for bounding the distance to the behavior policy, guaranteeing less OOD actions.*

## 4 Implementation

Let $\theta, \phi, \omega$ denote the parametrization of networks for $Q$, $\pi_{\pi_{\mathcal{D}}}$, $\pi_{\mathcal{D}}$, respectively. In-sample softmax updates the policy towards

$$\pi_{\pi_{\mathcal{D}},Q_\theta}(a|s) = \pi_{\mathcal{D}}(a|s)\exp\left(\frac{Q_\theta(s,a) - Z(s)}{\tau} - \ln\pi_\omega(a|s)\right), \tag{17}$$

where $Z(s)$ denotes the normalization constant and is necessary since the policy is updated by minimizing KL divergence:

$$\begin{aligned}
&D_{KL}(\pi_{\pi_{\mathcal{D}},Q_\theta}(\cdot|s)\,||\,\pi_\phi(\cdot|s)) = \mathbb{E}_{a\sim\pi_{\pi_{\mathcal{D}},Q_\theta}(\cdot|s)}\left[\ln\pi_{\pi_{\mathcal{D}},Q_\theta}(a|s) - \ln\pi_\phi(a|s)\right]\\
&= \mathbb{E}_{a\sim\pi_{\mathcal{D}}(\cdot|s)}\left[-\exp\left(\frac{Q_\theta(s,a)-Z(s)}{\tau} - \ln\pi_\omega(a|s)\right)\ln\pi_\phi(a|s)\right],
\end{aligned}$$

where the $\pi_{\mathcal{D}}$ term in $\pi_{\pi_{\mathcal{D}},Q_\theta}$ is absorbed into the expectation, so the KL divergence loss can be minimized by sampling actions from the offline dataset.

We follow the same setup here, but replacing every appearance of $\ln, \exp$ to their $q$-logarithm and $q$-exponential counterpart. Similar to the discussion after Eq. (7), the Tsallis policy we derived here can be seen as the result from Tsallis KL regularization, plus another regularization that gives rise to the additional term inside the $\exp_q$ function. In the implementation, we choose the sparsemax parametrization $q = 2$, which gives the following Tsallis in-sample sparsemax actor-critic update rule:

$$\mathcal{L}_{\text{actor}}(\phi) = -\mathbb{E}_{s,a\sim\mathcal{D}}\left[\left(\exp_2\left(\frac{1}{\tau}Q_\theta(s,a) + \ln_2\frac{1}{\pi_\omega(a|s)}\right) - \frac{1}{\tau}Q_\theta(s,a)\ln_q\frac{1}{\pi_\omega(a|s)}\right)\ln\pi_\phi(a|s)\right], \tag{18}$$

$$\mathcal{L}_{\text{baseline}}(\zeta) = \mathbb{E}_{s\sim\mathcal{D},a\sim\pi_\phi(s)}\left[\left(v_\zeta(s) - Q_\theta(s,a) - \tau\ln_2\pi_\phi(a|s)\right)^2\right], \tag{19}$$

$$\mathcal{L}_{\text{critic}}(\theta) = \mathbb{E}_{s,a,r,s'\sim\mathcal{D}}\left[\left(r + \gamma v_\zeta(s') - Q_\theta(s,a)\right)^2\right]. \tag{20}$$

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# A Derivation

It is worth noting that, for $q \neq 1$ the regularized policy is given by

$$\pi^*(a|s) = \sqrt[q-1]{\left[\frac{Q_\pi(s,a)}{q\tau} - \psi\left(\frac{Q_\pi(s,\cdot)}{\tau}\right)\right]_+ (q-1)}, \tag{21}$$

the normalization function $\psi$ can only be analytically solved when $q = 2, \infty$. When $q \neq 1, 2$, the closed-form expression of $\pi, \psi$ might not exist. Following [4], we leverage the first order Taylor expansion $f(z) + f'(z)(x - z)$ on the policy Eq. (21), where we let $z = 1$, $x = \left[\frac{Q_\pi(s,a)}{q\tau} - \psi\left(\frac{Q_\pi(s,\cdot)}{q\tau}\right)\right]_+ \frac{q-1}{p}$, $f(x) = x^{\frac{1}{q-1}}$, $f'(x) = \frac{1}{q-1} x^{\frac{2-q}{q-1}}$. So that

$$\begin{aligned} \tilde{\pi}^*(a|s) &\approx f(z) + f'(z)(x - z) \\ &= 1 + \frac{1}{q-1}\left(\left(\frac{Q_\pi(s,a)}{q\tau} - \tilde{\psi}\left(\frac{Q_\pi(s,\cdot)}{q\tau}\right)\right)\frac{q-1}{p} - 1\right). \end{aligned} \tag{22}$$