- We would like to thank all reviewers for insightful comments. In the response below, we address the main concern of
- 2 Reviewer 2. Due to the space limit, we cannot address other comments, which are indeed interesting and helpful. All
- 3 typos and suggestions related to the presentation and the writing of the paper will be fixed/included in the final version.
- 4 Response to Reviewer 2. The main concern is whether there is a bug in the proof of the online stochastic mirror
- 5 descent, specifically the inequality between line 254 and line 255 in the supplementary material.
- 6 In fact, there is **no** bug in the proof.
- 7 Let's consider first the given example (copy below).
- 8 take Phi to be 0.5\*ell\_2^2
- 9 take all norms to be ell\_2
- $t_0$  take theta\_t=y\_{t}=(0,1)
- $take theta_{t+1}=y_{t+1} = (0,0)$
- 12 set K to be half plane where first coordinate is bigger than say 1
- $13 thus x_t = (1,1)$
- $^{14}$  the inequality does not hold, as you would need 1 >= 2
- By the choice of  $\Phi(\cdot) = \frac{1}{2} \|\cdot\|_2^2$ , we have  $\nabla \Phi(x^t) = x^t$ . By our notation,  $\theta^t = \nabla \Phi(x^t)$ , so  $\theta^t = x^t$ . Consequently,
- we do not understand why in the example,  $\theta^t$  is taken to be (0,1) and  $x^t$  can be (1,1).
- Besides, between line 254 and line 255 (in the supplementary material, i.e., full paper),  $\theta^{t+1}$  does not involve so we do
- not understand the role of  $\theta^{t+1}$  in the example here. We try to guess whether the reviewer meant  $\theta^{t+1}$ . However, even
- with that guess, we do not see any contradiction.
- In the following, we give the proof of the inequality between line 254 and 255 with very detail explanation. Recall that  $\Psi^t = \frac{1}{n} D_{\Phi}(\boldsymbol{x}^* || \boldsymbol{x}^t)$ . First, we observe that

$$\eta \left( \Psi^{t+1} - \Psi^t \right) = D_{\Phi}(\mathbf{x}^* \| \mathbf{x}^{t+1}) - D_{\Phi}(\mathbf{x}^* \| \mathbf{x}^t) \tag{1}$$

$$\leq D_{\Phi}(x^* || y^{t+1}) - D_{\Phi}(x^* || x^t) \tag{2}$$

$$= \Phi(\boldsymbol{x}^*) - \Phi(\boldsymbol{y}^{t+1}) - \langle \underbrace{\nabla \Phi(\boldsymbol{y}^{t+1})}_{\boldsymbol{\vartheta}^{t+1}}, \boldsymbol{x}^* - \boldsymbol{y}^{t+1} \rangle - \Phi(\boldsymbol{x}^*) + \Phi(\boldsymbol{x}^t) + \langle \underbrace{\nabla \Phi(\boldsymbol{x}^t)}_{\boldsymbol{\theta}^t}, \boldsymbol{x}^* - \boldsymbol{x}^t \rangle$$
(3)

$$= \Phi(\boldsymbol{x}^{t}) - \Phi(\boldsymbol{y}^{t+1}) - \langle \boldsymbol{\vartheta}^{t+1}, \boldsymbol{x}^{t} - \boldsymbol{y}^{t+1} \rangle - \langle \boldsymbol{\vartheta}^{t+1} - \boldsymbol{\theta}^{t}, \boldsymbol{x}^{*} - \boldsymbol{x}^{t} \rangle$$

$$(4)$$

$$= \Phi(\boldsymbol{x}^{t}) - \Phi(\boldsymbol{y}^{t+1}) - \langle \boldsymbol{\theta}^{t}, \boldsymbol{x}^{t} - \boldsymbol{y}^{t+1} \rangle + \langle \eta \boldsymbol{g}^{t}, \boldsymbol{x}^{t} - \boldsymbol{y}^{t+1} \rangle + \langle \eta \boldsymbol{g}^{t}, \boldsymbol{x}^{*} - \boldsymbol{x}^{t} \rangle$$
(5)

$$\leq -\frac{\alpha_{\Phi}}{2} \| \boldsymbol{y}^{t+1} - \boldsymbol{x}^{t} \|^{2} + \eta \langle \boldsymbol{g}^{t}, \boldsymbol{x}^{t} - \boldsymbol{y}^{t+1} \rangle + \eta \langle \boldsymbol{g}^{t}, \boldsymbol{x}^{*} - \boldsymbol{x}^{t} \rangle$$

$$(6)$$

$$\leq \frac{\eta^2}{2\alpha_{\Phi}} \|\boldsymbol{g}^t\|_*^2 + \eta \langle \boldsymbol{g}^t, \boldsymbol{x}^* - \boldsymbol{x}^t \rangle \tag{7}$$

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- 23 (1) by definition of  $\Psi^t$ ;
  - (2) by the generalized Pythagorean property (Lemma 1);
    - (3) by the definition of the Bregman divergence;
- 26 (4) by notation  $\vartheta^{t+1} = \nabla \Phi(\boldsymbol{y}^{t+1})$  and  $\boldsymbol{\theta}^t = \nabla \Phi(\boldsymbol{x}^t)$ ;
  - (5) using  $\boldsymbol{\vartheta}^{t+1} = \boldsymbol{\theta}^t \eta \cdot \boldsymbol{g}^t$  by the algorithm;
  - (6) using the  $\alpha_{\Phi}$ -strong convexity of  $\Phi$ , specifically,  $\Phi(\boldsymbol{x}^t) \Phi(\boldsymbol{y}^{t+1}) \langle \boldsymbol{\theta}^t, \boldsymbol{x}^t \boldsymbol{y}^{t+1} \rangle \leq -\frac{\alpha_{\Phi}}{2} \| \boldsymbol{y}^{t+1} \boldsymbol{x}^t \|^2$  since  $\Phi(\boldsymbol{y}^{t+1}) \geq \Phi(\boldsymbol{x}^t) + \langle \boldsymbol{\theta}^t, \boldsymbol{y}^{t+1} \boldsymbol{x}^t \rangle + \frac{\alpha_{\Phi}}{2} \| \boldsymbol{y}^{t+1} \boldsymbol{x}^t \|^2$  where recall  $\boldsymbol{\theta}^t = \nabla \Phi(\boldsymbol{x}^t)$  and  $-\langle \boldsymbol{\theta}^t, \boldsymbol{x}^t \boldsymbol{y}^{t+1} \rangle = \langle \boldsymbol{\theta}^t, \boldsymbol{y}^{t+1} \boldsymbol{x}^t \rangle$ ;
  - (7) using Cauchy-Schwarz inequality  $\langle \boldsymbol{a}, \boldsymbol{b} \rangle \leq \|\boldsymbol{b}\| \|\boldsymbol{a}\|_* \leq \|\boldsymbol{b}\|^2/2 + \|\boldsymbol{a}\|_*^2/2$ , specifically  $\langle \eta \boldsymbol{g}^t, (\boldsymbol{x}^t \boldsymbol{y}^{t+1}) \rangle \leq \frac{\alpha_{\Phi}}{2} \|\boldsymbol{y}^{t+1} \boldsymbol{x}^t\|^2 + \frac{\eta^2}{2\alpha_{\Phi}} \|\boldsymbol{g}^t\|_*^2$ .
- Remark that, as mentioned in the paper, our approach follows the potential argument of Bansal et Gupta [4], which has been appeared recently in *Theory of Computing*, pp. 1-32, vol 15, 2019. In particular, the part related to the concern is proved in their paper (page 19, paragraph "Potential change", https://theoryofcomputing.org/articles/v015a004/v015a004.pdf). Note that they considered convex functions.
- In conclusion, we believe that our proof is correct.