## Last Iterate Convergence in No-regret Learning: Constrained Min-max Optimization for Convex-concave Landscapes

## 1 Equations of the Jacobian of OMWU

$$\begin{split} &\frac{\partial g_{1,i}}{\partial x_i} = \frac{e^{-2\eta \frac{\partial f_{si}}{\partial x_i} + \eta \frac{\partial f_{si}}{\partial x_i}}}{S_x} + x_i \frac{1}{S_x^2} \left( e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} (-2\eta \frac{\partial^2 f}{\partial x_i^2}) S_x - e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} \frac{\partial S_x}{\partial x_i} \right) \\ & \text{where} \quad &\frac{\partial S_x}{\partial x_i} = e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} - 2\eta \sum_k x_k e^{-2\eta \frac{\partial f}{\partial x_k} + \eta \frac{\partial f}{\partial x_k}} \frac{\partial^2 f}{\partial x_i^2} \\ &\frac{\partial g_{1,i}}{\partial x_j} = x_i \frac{1}{S_x^2} \left( e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} (-2\eta \frac{\partial^2 f}{\partial x_i \partial x_j}) S_x - e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} \frac{\partial S_x}{\partial x_j} \right) \\ & \text{where} \quad &\frac{\partial S_x}{\partial x_j} = e^{-2\eta \frac{\partial f}{\partial x_j} + \eta \frac{\partial f}{\partial x_j}} (-2\eta \frac{\partial^2 f}{\partial x_i \partial y_j}) S_x - e^{-2\eta \frac{\partial f}{\partial x_k} + \eta \frac{\partial f}{\partial x_i}} \frac{\partial^2 f}{\partial x_j \partial x_k} \\ &\frac{\partial g_{1,i}}{\partial y_j} = x_i \frac{1}{S_x^2} \left( e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} (-2\eta \frac{\partial^2 f}{\partial x_i \partial y_j}) S_x - e^{-2\eta \frac{\partial f}{\partial x_k} + \eta \frac{\partial f}{\partial x_i}} \frac{\partial S_x}{\partial y_j} \right) \\ & \text{where} \quad &\frac{\partial S_x}{\partial y_j} = \sum_k x_k e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} (-2\eta \frac{\partial^2 f}{\partial x_i \partial y_j}) S_x - e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} \frac{\partial S_x}{\partial y_j} \right) \\ & \text{where} \quad &\frac{\partial S_x}{\partial y_j} = \sum_k x_k e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} \frac{\partial^2 f}{\partial x_k \partial y_j} \\ & \text{where} \quad &\frac{\partial S_x}{\partial z_j} = \eta \sum_k x_k e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} \frac{\partial^2 f}{\partial x_k \partial z_j} \\ & \text{where} \quad &\frac{\partial S_x}{\partial z_j} = \eta \sum_k x_k e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} \frac{\partial^2 f}{\partial x_k \partial z_j} \\ & \text{where} \quad &\frac{\partial S_x}{\partial x_j} = \sum_k x_k e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} \frac{\partial^2 f}{\partial x_k \partial y_j} \\ & \text{where} \quad &\frac{\partial S_x}{\partial x_j} = \sum_k x_k e^{-2\eta \frac{\partial f}{\partial x_i} + \eta \frac{\partial f}{\partial x_i}} \frac{\partial f}{\partial x_i} \\ & \frac{\partial f}{\partial x_i} = y_i \frac{1}{S_x^2} \left( e^{-2\eta \frac{\partial f}{\partial y_i} + \eta \frac{\partial f}{\partial x_i}} \frac{\partial f}{\partial x_i} \frac{\partial f}{\partial x_i} \right) \\ & \text{where} \quad &\frac{\partial S_x}{\partial x_j} = \sum_k y_k e^{2\eta \frac{\partial f}{\partial y_i} - \eta \frac{\partial f}{\partial y_i}} 2\eta \frac{\partial f}{\partial y_i} \\ & y_i = e^{-2\eta \frac{\partial f}{\partial y_i} - \eta \frac{\partial f}{\partial y_i}} - \eta \frac{\partial f}{\partial y_i} - \eta \frac{\partial f}{\partial y_i} \frac{\partial f}{\partial y_i} \\ & \frac{\partial g_{2,i}}{\partial x_j} = y_i \frac{1}{S_y^2} \left( e^{2\eta \frac{\partial f}{\partial y_i} - \eta \frac{\partial f}{\partial y_i}} - \eta \frac{\partial f}{\partial y_i} - \eta \frac{\partial f}{\partial y_i} - \eta \frac{\partial f}{\partial y_i} - \eta \frac$$

$$\frac{\partial g_{2,i}}{\partial w_j} = y_i \frac{1}{S_y^2} \left( e^{2\eta \frac{\partial f}{\partial y_i} - \eta \frac{\partial f}{\partial w_i}} (-\eta \frac{\partial^2 f}{\partial w_i \partial w_j}) - e^{2\eta \frac{\partial f}{\partial y_i} - \eta \frac{\partial f}{\partial w_i}} \frac{\partial S_y}{\partial w_j} \right)$$
where 
$$\frac{\partial S_y}{\partial w_j} = \sum_k y_k e^{2\eta \frac{\partial f}{\partial y_i} - \eta \frac{\partial f}{\partial w_i}} (-\eta \frac{\partial^2 f}{\partial w_k \partial w_j})$$

## 1.1 Jacobian matrix at $(x^*, y^*, z^*, w^*)$

This section serves for the "Spectral Analysis" of Section 3. The Jacobian matrix of g at the fixed point is obtained based on the calculations above. We refer the main article for the subscript indicating the size of each block matrix.

$$J = \begin{bmatrix} \mathbf{I} - D_{\mathbf{x}^*} \mathbf{1} \mathbf{1}^\top - 2\eta D_{\mathbf{x}^*} (\mathbf{I} - \mathbf{1} \mathbf{x}^{*\top}) \nabla_{\mathbf{x}\mathbf{x}}^2 f & -2\eta D_{\mathbf{x}^*} (\mathbf{I} - \mathbf{1} \mathbf{x}^{*\top}) \nabla_{\mathbf{x}\mathbf{y}}^2 f & \eta D_{\mathbf{x}^*} (\mathbf{I} - \mathbf{1} \mathbf{x}^{*\top}) \nabla_{\mathbf{x}\mathbf{x}}^2 f & \eta D_{\mathbf{x}^*} (\mathbf{I} - \mathbf{1} \mathbf{x}^{*\top}) \nabla_{\mathbf{x}\mathbf{y}}^2 f \\ 2\eta D_{\mathbf{y}^*\top} (\mathbf{I} - \mathbf{1} \mathbf{y}^*) \nabla_{\mathbf{y}\mathbf{x}}^2 f & \mathbf{I} - D_{\mathbf{y}^*} \mathbf{1} \mathbf{1}^\top + 2\eta D_{\mathbf{y}^*} (\mathbf{I} - \mathbf{1} \mathbf{y}^{*\top}) \nabla_{\mathbf{y}\mathbf{y}}^2 f & -\eta D_{\mathbf{y}^*} (\mathbf{I} - \mathbf{1} \mathbf{y}^{*\top}) \nabla_{\mathbf{y}\mathbf{x}}^2 f & -\eta D_{\mathbf{y}^*} (\mathbf{I} - \mathbf{1} \mathbf{y}^{*\top}) \nabla_{\mathbf{y}\mathbf{y}}^2 f \\ \mathbf{I} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} & \mathbf{0} & \mathbf{0} \end{bmatrix}$$

By acting on the tangent space of each simplex, we observe that  $D_{\mathbf{x}^*} \mathbf{1} \mathbf{1}^\top \mathbf{v} = 0$  for  $\sum_k v_k = 0$ , so each eigenvalue of matrix J is an eigenvalue of the following matrix

$$J_{\text{new}} = \begin{bmatrix} \mathbf{I} - 2\eta D_{\mathbf{x}^*} (\mathbf{I} - \mathbf{1}\mathbf{x}^{*\top}) \nabla_{\mathbf{x}\mathbf{x}}^2 f & -2\eta D_{\mathbf{x}^*} (\mathbf{I} - \mathbf{1}\mathbf{x}^{*\top}) \nabla_{\mathbf{x}\mathbf{y}}^2 f & \eta D_{\mathbf{x}^*} (\mathbf{I} - \mathbf{1}\mathbf{x}^{*\top}) \nabla_{\mathbf{x}\mathbf{x}}^2 f & \eta D_{\mathbf{x}^*} (\mathbf{I} - \mathbf{1}\mathbf{x}^{*\top}) \nabla_{\mathbf{x}\mathbf{y}}^2 f \\ 2\eta D_{\mathbf{y}^*} (\mathbf{I} - \mathbf{1}\mathbf{y}^{*\top}) \nabla_{\mathbf{y}\mathbf{x}}^2 f & \mathbf{I} + 2\eta D_{\mathbf{y}^*} (\mathbf{I} - \mathbf{1}\mathbf{y}^{*\top}) \nabla_{\mathbf{y}\mathbf{y}}^2 f & -\eta D_{\mathbf{y}^*} (\mathbf{I} - \mathbf{1}\mathbf{y}^{*\top}) \nabla_{\mathbf{y}\mathbf{x}}^2 f & -\eta D_{\mathbf{y}^*} (\mathbf{I} - \mathbf{1}\mathbf{y}^{*\top}) \nabla_{\mathbf{y}\mathbf{y}}^2 f \\ \mathbf{I} & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}$$

The characteristic polynomial of  $J_{\text{new}}$  is  $\det(J_{new} - \lambda I)$  that can be computed as the determinant of the following matrix:

$$\begin{bmatrix} (1-\lambda)\mathbf{I} + (\frac{1}{\lambda} - 2)\eta D_{\mathbf{x}^*}(\mathbf{I} - \mathbf{1}\mathbf{x}^{*\top})\nabla_{\mathbf{x}\mathbf{x}}^2 f & (\frac{1}{\lambda} - 2)\eta D_{\mathbf{x}^*}(\mathbf{I} - \mathbf{1}\mathbf{x}^{*\top})\nabla_{\mathbf{x}\mathbf{y}}^2 f \\ (2 - \frac{1}{\lambda})\eta D_{\mathbf{y}^*}(\mathbf{I} - \mathbf{1}\mathbf{y}^{*\top})\nabla_{\mathbf{y}\mathbf{x}}^2 f & (1 - \lambda)\mathbf{I} + (2 - \frac{1}{\lambda})\eta D_{\mathbf{y}^*}(\mathbf{I} - \mathbf{1}\mathbf{y}^{*\top})\nabla_{\mathbf{y}\mathbf{y}}^2 f \end{bmatrix}$$
(1)