

Dynamics of Oja's rule:

$$\vec{w}_{t+1} = \vec{w}_t + \eta (y_t \vec{x}_t - y_t^2 \vec{w}_t), \text{ with } y_t = \vec{w}_t^T \vec{x}_t$$

An observation:

$$\vec{w}_{t+1}^2 = \vec{w}_t^2 + \underbrace{2\eta \vec{w}_t \cdot (y_t \vec{x}_t - y_t^2 \vec{w}_t)}_{2\eta y_t^2 (1 - \vec{w}_t^2)} + O(\eta^2)$$

Hence, if $\vec{w}_0 = \vec{0}$, we expect $|\vec{w}_t|$ to grow and reach one for large t .

Alternative rule with strict normalization enforcement:

• $\vec{w}_0$ such that $|\vec{w}_0| = 1$

$$\begin{aligned} \bullet \vec{w}_{t+1} &= \frac{\vec{w}_t + \eta y_t \vec{x}_t}{|\vec{w}_t + \eta y_t \vec{x}_t|} + O(\eta^2) \\ &= \frac{\vec{w}_t + \eta y_t \vec{x}_t}{|\vec{w}_t|} \left(1 + 2\eta \frac{y_t^2}{|\vec{w}_t|^2} \right)^{-1/2} \end{aligned}$$

$$|\vec{w}_t| = 1 = |\vec{w}_0| \quad \vec{w}_t + \eta (y_t \vec{x}_t - y_t^2 \vec{w}_t) : \text{Oja's rule}$$

Going to the diagonal basis of: $C_{ij} = \langle \vec{x}_i, \vec{x}_j \rangle_{\vec{x}}$

$$C = O \Lambda O^T, \text{ with } \Lambda = \text{diag}(d_1, \dots, d_n) \geq \dots \geq$$

orthogonal matrix

Change of variable: $\begin{cases} \vec{w} \rightarrow O^T \vec{w} = \vec{w}' \\ \vec{x} \rightarrow O^T \vec{x} = \vec{x}' \end{cases}, y = \vec{w}^T \vec{x} = y'$

Then, we clearly have by linearity:

$$\vec{w}_{t+1}' = \vec{w}_t' + \eta (y_t' \vec{x}_t' - (y_t')^2 \vec{w}_t')$$

with $\langle x_i' x_j' \rangle_{\vec{x}} = \lambda_i \delta_{ij}$ ←

I'll drop the "'" in the following.

Evolution of $\vec{w}_t$:

I assume $\vec{x}_1, \vec{x}_2, \dots, \vec{x}_t, \dots$ to be i.i.d from distribution with ~~zero~~ mean and ~~identity~~ covariance matrix. Then $\vec{w}_t$ obeys a Markovian dynamics:

$$\bullet \langle \vec{w}_{t+1} - \vec{w}_t \mid \vec{w}_t = \vec{w} \rangle_{\vec{x}} = \eta \langle (\vec{w} \cdot \vec{x}) \vec{x} - (\vec{w} \cdot \vec{x})^2 \vec{w} \rangle_{\vec{x}}$$

$$\langle (---)_i \mid --- \rangle_{\vec{x}} = \eta \left(\lambda_i w_i - \left(\sum_k \lambda_k w_k^2 \right) w_i \right)$$

$$\bullet \left| \vec{w}_{t+1} - \vec{w}_t \right|^2 = \eta^2 \left| y_t \vec{x}_t - y_t^2 \vec{w}_t \right|^2$$

$$= \eta^2 y_t^2 \left(\vec{x}_t^2 - 2 y_t \underbrace{\vec{x}_t \cdot \vec{w}_t}_{y_t} + y_t^2 \vec{w}_t^2 \right)$$

$$\underbrace{y_t^2 (\vec{w}_t^2 - 2)}_{\leq 0}$$

$$\leq \eta^2 (\vec{x}_t^2)^2 (\vec{w}_t^2) \leq 0$$

$$\Rightarrow \vec{w}_{t+1} - \vec{w}_t \leq \eta \vec{x}_t^2$$

assumed to be bounded from above by X_4

$$\Rightarrow \text{var}(\vec{w}_{t+1} - \vec{w}_t \mid \vec{w}_t = \vec{w}) \leq O(\eta^2)$$

I assume $\begin{cases} \eta \rightarrow 0 \\ t \rightarrow \infty \end{cases}$ with $\boxed{\tau = t\eta}$ fixed (3)

Consider evolution over time interval $[\tau, \tau + \varepsilon]$, i.e. from $t = \frac{\tau}{\eta}$ to $t' = \frac{\tau}{\eta} + \frac{\varepsilon}{\eta}$ (ε small, but first $\eta \rightarrow 0$)

$$\vec{w}_{t'} - \vec{w}_t = \sum_{t_0=t}^{t'-1} (\vec{w}_{t_0+1} - \vec{w}_{t_0})$$

Li, Wang, Zhang, NIPS2017

$$= \underbrace{\sum_{t_0=t}^{t'-1} \left\{ \underbrace{\langle \vec{w}_{t_0+1} - \vec{w}_{t_0} | \vec{w}_{t_0} \rangle}_{\text{order } \eta} + \vec{z}_{t_0} \right\}}_{\frac{\varepsilon}{\eta} \text{ terms}}$$

average = 0
 $|\vec{z}|^2 = O(\eta^2)$

[1]

$\text{var} \left(\sum_{t_0} \vec{z}_{t_0} \right) \sim O\left(\frac{\varepsilon}{\eta} \cdot \eta^2\right) \xrightarrow{\eta \rightarrow 0} 0$
 hence, negligible: CLT

[2]

$O(\varepsilon)$ small for small ε

Suggests that: $\vec{w}_{\frac{\tau}{\eta}} = \vec{W}(\tau = t\eta)$
 i.e. $\vec{W}$ varies on slow time scale

hence

$\langle \vec{w}_{t_0+1} - \vec{w}_{t_0} | \vec{w}_{t_0} \rangle$ does not vary by more than ε over $t_0 \in (t, t']$
 $\tau_0 \in [\tau, \tau + \varepsilon]$

Finally: (after division by ε)

$$\frac{d\vec{W}_i}{d\tau} = \lambda_i \vec{W}_i - \left(\sum_k \lambda_k \vec{W}_k^2 \right) \vec{W}_i$$

• Easy to check that, if $|\vec{w}(z=0)|=1$, then $|\vec{w}(z)|=1/\sqrt{c}$.

• Solution:

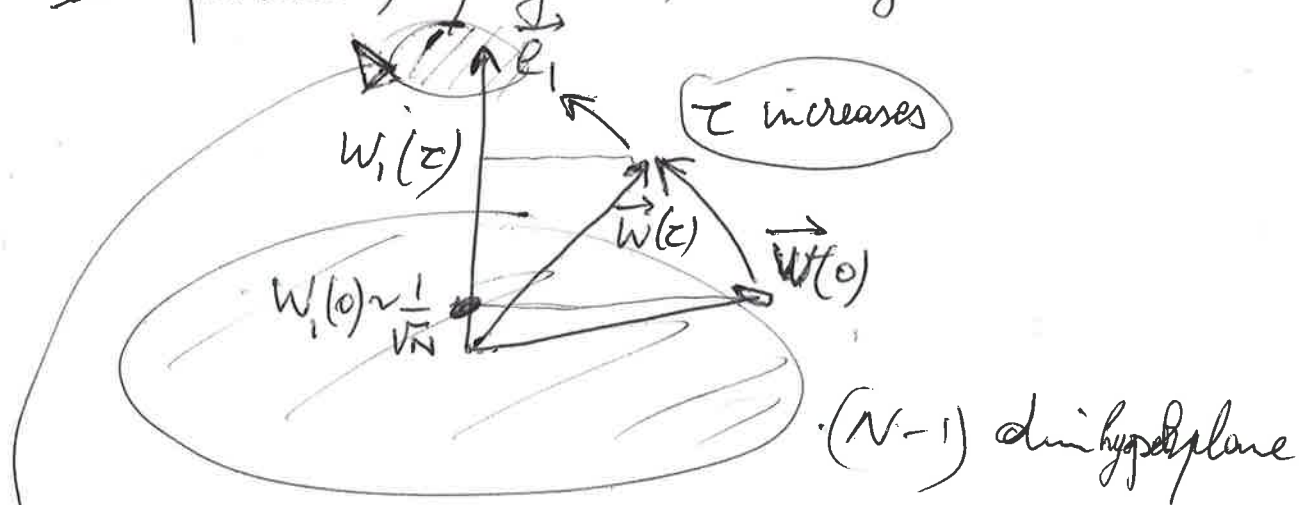
$$W_i(z) = \frac{W_i(0) e^{\lambda_i z}}{\left(\sum_k e^{2\lambda_k z} W_k(0)^2 \right)^{1/2}}$$

$\xrightarrow{\tau \rightarrow \infty}$ δ_{i1} : PCA !
(top component only so far)

Some remarks:

1. Here, $\eta \rightarrow 0$ & $t \rightarrow \infty$ with $t\eta = O(1)$

In practice, η fixed, t large



at large t , we will have fluctuations around $\vec{e}_1$, unless $\eta \rightarrow 0$, e.g. such as $\frac{1}{\sqrt{t}}$ ($\eta t \rightarrow \infty$)

2. Dependence on N ?

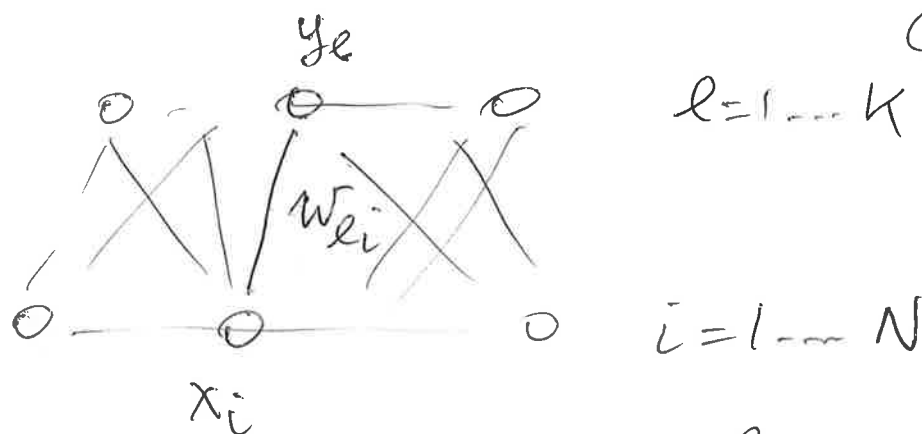
• escape from $\perp$ hyperplane;

$W_1(0) = \delta$ small requires $t \sim \frac{\log(\delta\sqrt{N})}{\eta(\lambda_1 - \lambda_2)}$ steps
($\approx \frac{1}{\sqrt{N}} e^{2(\lambda_1 - \lambda_2)z}$)

- in addition gap $d_1 - d_2$ may close as $N \rightarrow \infty$. (3)
- Theory here is in asymptotic setting: $\begin{cases} N \text{ fixed} \\ \text{many data} \dots \end{cases}$
 not high-dimensional setting, i.e. $N \approx t$

3. Extension to extraction of K top components:

(Sanger 1989)



$$\Delta w_{li} = \eta y_l \left(x_i - \sum_{k=1}^L y_k w_{ki} \right)$$

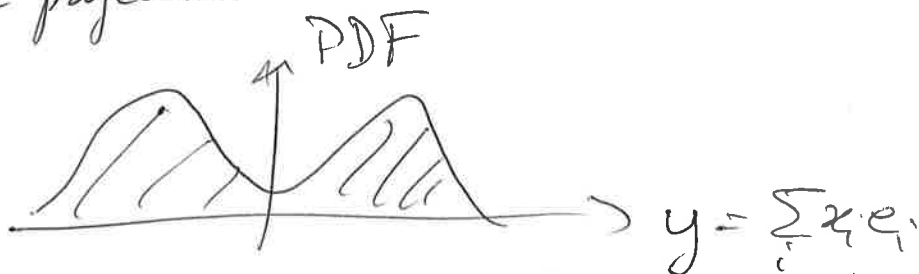
4. Other analysis, non quadratic:

PCA $\Leftrightarrow \max \left\langle \left(\sum_i e_i x_i \right)^2 \right\rangle_{\vec{x}}$, with $\sum_i e_i^2 = 1$

Non quadratic extensions

$\nabla \left(\sum_i e_i x_i \right)$, with $V(y) \neq y^2$

Example: $V(y) = y^4$: clustering, looks for large projections in absolute values



Modified
Oja's rule:

$$\vec{w}_{t+1} - \vec{w}_t = \eta A(y_t) (\vec{x}_t - y_t \vec{w}_t)$$

with $A(y) = \frac{dV}{dy}$