

# Non-negative matrix factorization (NMF)

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# Especificação

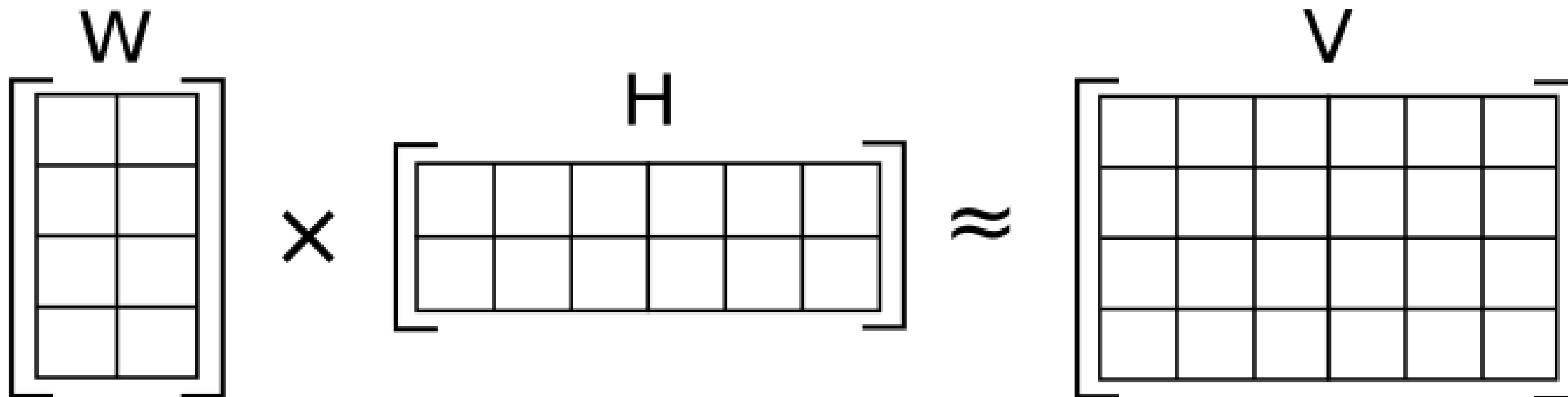
# Matrizes não-negativas

$$V_{ij} \geq 0, \forall i, j$$

$$V \in \mathbb{R}_+^{m \times n}$$

$$V \geq 0$$

# Fatoração<sub>3</sub>



# Problema aproximado

$$[W H] = \arg \min_{W \geq 0, H \geq 0} f(W, H) = \frac{1}{2} ||V - WH||_F^2$$

# Algoritmo

# Gradiente Descendente Alternado

$$x^{(k+1)} = x^{(k)} - \alpha^{(k)} \nabla_x f(x^{(k)})$$

- $k \in \mathbb{N}$  o número da iteração
- $x^{(k)}$  é a variável na iteração  $k$
- $x^{(k+1)}$  é a variável na iteração  $k + 1$
- $\alpha^{(k)} \geq 0$  é o tamanho do passo na iteração  $k$
- $\nabla_x f(x^{(k)})$  é o gradiente da função  $f$  com respeito à  $x$

# Gradiente Descendente Alternado

$$W^{(k+1)} = W^{(k)} - \alpha_W^{(k)} \nabla_W f(W^{(k)}, H^{(k)})$$

$$H^{(k+1)} = H^{(k)} - \alpha_H^{(k)} \nabla_H f(W^{(k+1)}, H^{(k)})$$

$$f(W^{(k+1)}, H^{(k+1)}) \leq f(W^{(k)}, H^{(k)})$$



# Propriedades base

$$\nabla_{\mathbf{X}} \operatorname{tr}(\mathbf{A}\mathbf{X}) = \mathbf{A}^T$$

$$\nabla_{\mathbf{X}} \operatorname{tr}(\mathbf{X}^T \mathbf{A}) = \mathbf{A}$$

$$\nabla_{\mathbf{X}} \operatorname{tr}(\mathbf{X}^T \mathbf{A} \mathbf{X}) = (\mathbf{A} + \mathbf{A}^T) \mathbf{X}$$

$$\nabla_{\mathbf{X}} \operatorname{tr}(\mathbf{X} \mathbf{A} \mathbf{X}^T) = \mathbf{X} (\mathbf{A}^T + \mathbf{A})$$

# Propriedades utilizadas

$$||X||_F^2 = \text{tr}(X^T X) \quad (1)$$

$$\text{tr}(X) = \text{tr}(X^T) \quad (2)$$

$$\nabla_x \text{tr}(AXB) = A^T B^T \quad (3)$$

$$\nabla_x \text{tr}(X^T AX) = (A + A^T)X \quad (4)$$

$$\nabla_x \text{tr}(B^T X^T XB) = 2XB B^T \quad (5)$$

# Desenvolvendo a função objetivo

$$\begin{aligned} \|V - WH\|_F^2 &\stackrel{(1)}{=} \text{tr} \left\{ (V - WH)^T (V - WH) \right\} \\ &= \text{tr} \left\{ V^T V - V^T WH - (WH)^T V + (WH)^T WH \right\} \\ &\stackrel{(2)}{=} \text{tr} \left\{ V^T V - 2W^T H^T V + H^T W^T WH \right\} \\ &\stackrel{(1)}{=} \|V\|_F^2 - 2\text{tr}(W^T H^T V) + \text{tr}(H^T W^T WH) \end{aligned}$$

# Desenvolvendo a função objetivo

$$f(W, H) = \frac{1}{2} ||V - WH||_F^2 = ||V||_F^2 - tr(W^T H^T V) + \frac{1}{2} tr(H^T W^T W H)$$

# Cálculo do gradiente

$$\nabla_W f \stackrel{(3,5)}{=} (WH - V)H^T$$

$$\nabla_H f \stackrel{(3,4)}{=} W^T(WH - V)$$

$$\nabla_x \text{tr}(AXB) = A^T B^T \quad (3)$$

$$\|V\|_F^2 - 2\text{tr}(W^T H^T V) + \text{tr}(H^T W^T W H) \quad \nabla_x \text{tr}(X^T A X) = (A + A^T)X \quad (4)$$

$$\nabla_x \text{tr}(B^T X^T X B) = 2X B B^T \quad (5)$$

# Fórmula de atualização

$$\begin{aligned} W^{(k+1)} &= W^{(k)} - \alpha_W^{(k)} (WH - V) H^T \\ H^{(k+1)} &= H^{(k)} - \alpha_H^{(k)} W^T (WH - V) \end{aligned}$$

# Tamanho do passo

Lee e Seung 2001

$$[\alpha_W]_{ij} = \frac{W_{ij}}{[WHH^T]_{ij}}, [\alpha_H]_{ij} = \frac{H_{ij}}{[W^TW H]_{ij}}$$

$$\begin{aligned}
W_{ij} &= W_{ij} - [\alpha_W]_{ij} [(WH - V)H^T]_{ij} \\
&= W_{ij} - \frac{W_{ij}}{[WHH^T]_{ij}} [(WH - V)H^T]_{ij} \\
&= W_{ij} - \frac{[W(WH - V)H^T]_{ij}}{[WHH^T]_{ij}} \\
&= W_{ij} \left( 1 - \frac{[(WH - V)H^T]_{ij}}{[WHH^T]_{ij}} \right) \\
&= W_{ij} \left( \frac{[WHH^T]_{ij}}{[WHH^T]_{ij}} - \frac{[(WH - V)H^T]_{ij}}{[WHH^T]_{ij}} \right) \\
&= W_{ij} \frac{[VH^T]_{ij}}{[WHH^T]_{ij}}
\end{aligned}$$



$$\begin{aligned}
H_{ij} &= H_{ij} - [\alpha_H]_{ij} [W^T (WH - V)]_{ij} \\
&= H_{ij} - \frac{H_{ij}}{[W^T WH]_{ij}} [W^T (WH - V)]_{ij} \\
&= H_{ij} \left( 1 - \frac{[W^T (WH - V)]_{ij}}{[W^T WH]_{ij}} \right) \\
&= H_{ij} \left( \frac{[W^T WH]_{ij}}{[W^T WH]_{ij}} - \frac{[W^T (WH - V)]_{ij}}{[W^T WH]_{ij}} \right) \\
&= H_{ij} \frac{[W^T V]_{ij}}{[W^T WH]_{ij}}
\end{aligned}$$

# Fórmula de atualização

- A cada iteração a função objetivo não aumenta seu valor
- O algoritmo não garante a convergência para um mínimo global
- Para manter a não-negatividade, o tamanho do passo realiza operações elemento a elemento com valores não-negativos

$$W^{(k+1)} = W^{(k)} \circ \frac{V H^{(k)T}}{W H^{(k)} H^{(k)T}}$$

$$H^{(k+1)} = H^{(k)} \circ \frac{W^{(k)T} V}{W^{(k)T} W^{(k)} H^{(k)}}$$

# Convergência

# Teorema

Lee e Seung 2001

$$\frac{1}{2} ||V - WH||_F \qquad f(W^{(k+1)}, H^{(k+1)}) \leq f(W^{(k)}, H^{(k)})$$

$$W^{(k+1)} = W^{(k)} \circ \frac{V H^{(k)T}}{W H^{(k)} H^{(k)T}}$$

$$H^{(k+1)} = H^{(k)} \circ \frac{W^{(k)T} V}{W^{(k)T} W^{(k)} H^{(k)}}$$

# Função objetivo

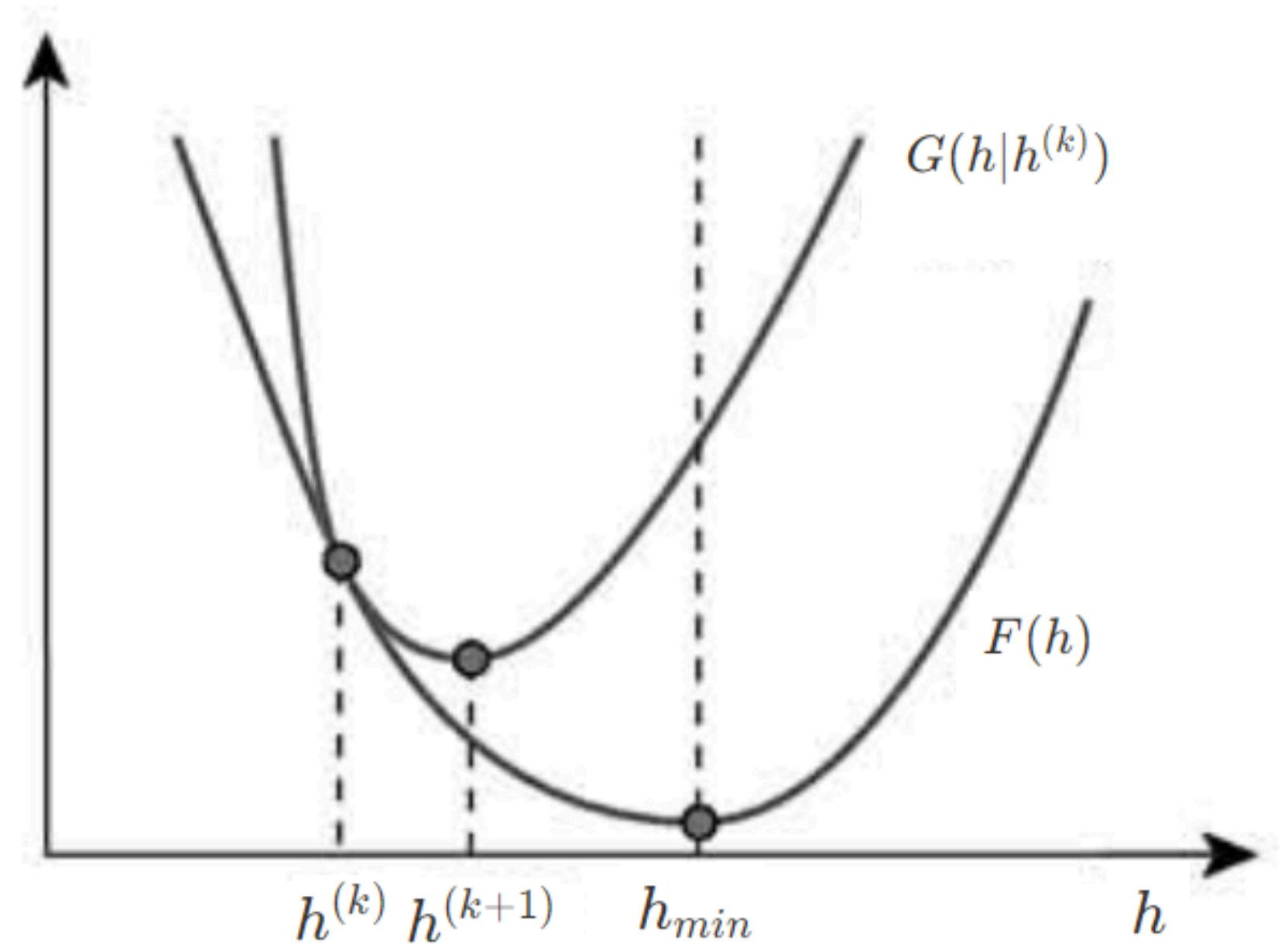
$$f(h) = \frac{1}{2} ||Wh - v||_2^2$$

$$F(h) = f(h^{(k)}) + \nabla f(h^{(k)})^T (h - h^{(k)}) + \frac{1}{2} (h - h^{(k)})^T \nabla^2 f(h^{(k)}) (h - h^{(k)})$$

# Técnica de otimização

- Majorization Minimization
- Minimização de uma função auxiliar (limite superior)

$$G(h|h^{(k)}) \geq F(h), G(h|h) = F(h)$$



# Lema 1

Se ***G*** é uma função auxiliar, então o valor de ***F*** não cresce quando a seguinte atualização for feita:

$$h^{(k+1)} = \arg \min_h G(h|h^{(k)})$$

$$F(h^{(k)}) = G(h^{(k)}|h^{(k)}) \geq G(h^{(k+1)}|h^{(k)}) \geq F(h^{(k+1)})$$

# Definição de $G$

$$\begin{aligned}\frac{1}{2}||Wh - v||_2^2 &= \frac{1}{2}(Wh - v)^T(Wh - v) \\ &= \frac{1}{2}(h^T W^T - v^T)(Wh - v) \\ &= \frac{1}{2}(h^T W^T Wh - h^T W^T v - v^T Wh - v^T v) \\ &= \frac{1}{2}(h^T W^T Wh - 2h^T W^T v + v^T v)\end{aligned}$$

$$\nabla_h f(h) = W^T Wh - W^T v \qquad \nabla_h^2 f(h) = W^T W$$



# Definição de $G$

$$G(h|h^{(k)}) = f(h^{(k)}) + \nabla f(h^{(k)})^T (h - h^{(k)}) + \frac{1}{2} (h - h^{(k)})^T K(h^{(k)}) (h - h^{(k)})$$

$$K(h^{(k)}) \geq \nabla^2 f(h^{(k)})$$

$$K_{ab}(h^{(k)}) = \text{Diag} \left( \frac{[W^T W h^{(k)}]_a}{[h^{(k)}]_a} \right)_{ab}$$

# Definição de $G$

$$\begin{aligned} \text{Diag}\left(\frac{[Ax]_i}{[x]_i}\right) &= \text{Diag}\left(\frac{[y]_i}{[x]_i}\right) \\ &= \frac{\text{Diag}(y)}{\text{Diag}(x)} \\ &= D_x^{-1} D_y \\ &= \begin{bmatrix} \frac{y_1}{x_1} & 0 & \dots & 0 \\ 0 & \frac{y_1}{x_1} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \frac{y_d}{x_d} \end{bmatrix} \end{aligned}$$

# Condição de função auxiliar

$$F(h) = f(h^{(k)}) + \nabla f(h^{(k)})^T (h - h^{(k)}) + \frac{1}{2} (h - h^{(k)})^T W^T W (h - h^{(k)})$$

$$G(h|h^{(k)}) = f(h^{(k)}) + \dots + \frac{1}{2} (h - h^{(k)})^T \text{Diag} \left( \frac{[W^T W h^{(k)}]_i}{[h^{(k)}]_i} \right) (h - h^{(k)})$$

$$G(h|h^{(k)}) \geq F(h)$$

$$(h - h^{(k)})^T \left( \text{Diag} \left( \frac{[W^T W h^{(k)}]_i}{[h^{(k)}]_i} \right) - W^T W \right) (h - h^{(k)}) \geq 0$$

# Condição de função auxiliar

$$L_{ab}(h^{(k)}) = h_a^{(k)} \left( K(h^{(k)}) - W^T W \right)_{ab} h_b^{(k)}$$

$$\begin{aligned} v^T L v &= \sum_{ab} v_a L_{ab} v_b \\ &= \sum_{ab} v_a h_a^{(k)} \left( \text{Diag} \left( \frac{[W^T W h^{(k)}]_a}{[h^{(k)}]_a} \right)_{ab} - W^T W_{ab} \right) h_b^{(k)} v_b \\ &= \sum_{ab} h_a^{(k)} (W^T W)_{ab} h_b^{(k)} v_a^2 - v_a h_a^{(k)} (W^T W)_{ab} h_b^{(k)} v_b \\ &= \sum_{ab} (W^T W)_{ab} h_a^{(k)} h_b^{(k)} \left[ \frac{1}{2} v_a^2 + \frac{1}{2} v_b^2 - v_a v_b \right] \\ &= \frac{1}{2} \sum_{ab} (W^T W)_{ab} h_a^{(k)} h_b^{(k)} (v_a - v_b)^2 \\ &\geq 0 \end{aligned}$$

# Tamanho do passo

$$\frac{\partial G(h|h^{(k)})}{\partial h} = \nabla f(h^{(k)}) + K(h - h^{(k)}) \quad \frac{\partial G(h|h^{(k)})}{\partial h} = 0$$

$$h = h^{(k)} - K^{-1} \nabla f(h^{(k)})$$

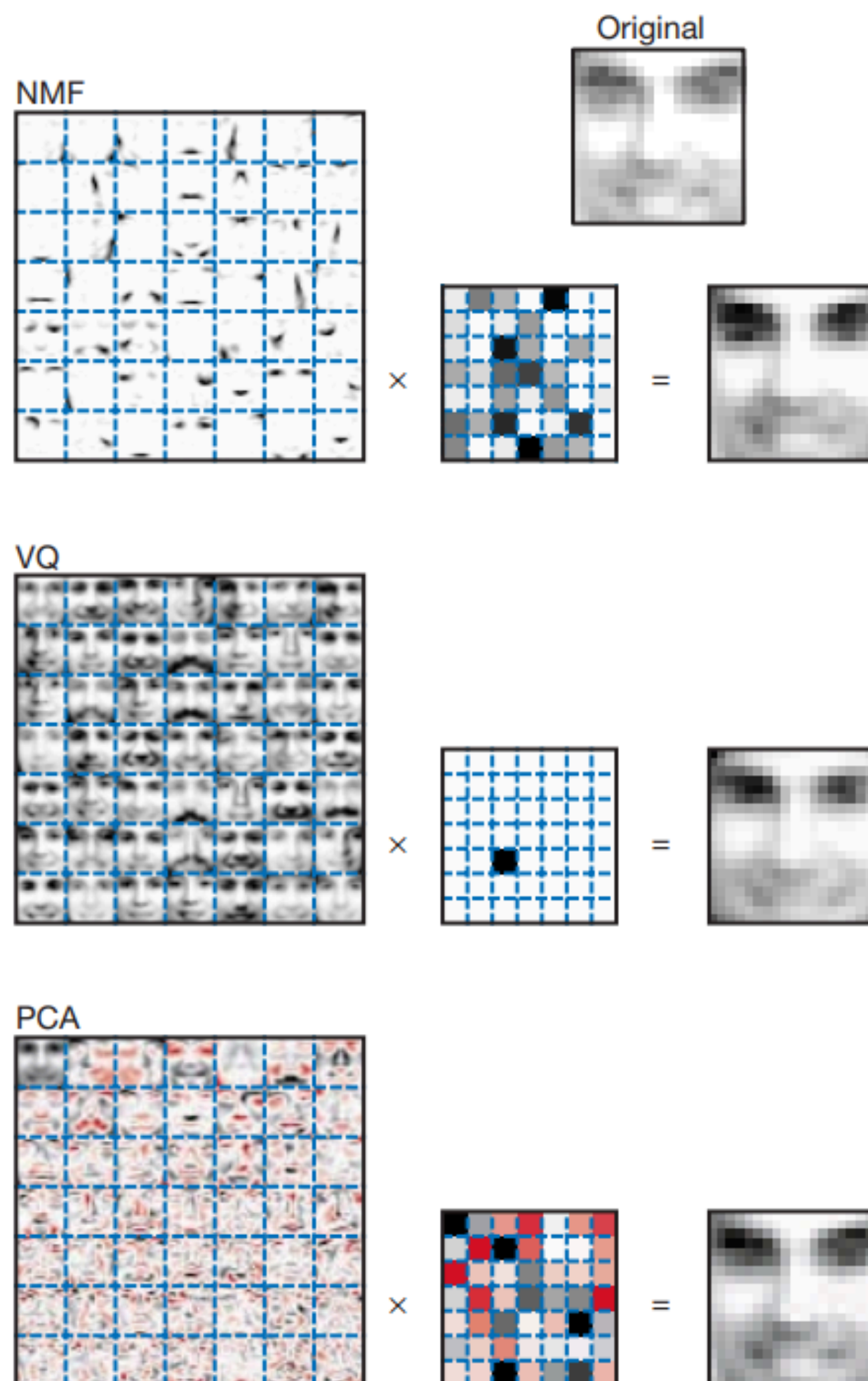
# Tamanho do passo

$$\begin{aligned}h &= h^{(k)} - K^{-1} \nabla f(h^{(k)}) \\&= h^{(k)} - \text{Diag} \left( \frac{[h^{(k)}]_i}{[W^T W h^{(k)}]_i} \right) W^T (W h^{(k)} - v) \\&= h^{(k)} - h^{(k)} \otimes \frac{[W^T (W h^{(k)} - v)]_{ij}}{[W^T W h^{(k)}]_{ij}} \\&= \frac{h^{(k)} W^T W h^{(k)}}{W^T W h^{(k)}} - \frac{h^{(k)} (W^T W h^{(k)} + W^T v)}{W^T W h^{(k)}} \\&= h^{(k)} \otimes \frac{[W^T v]_{ij}}{[W^T W h^{(k)}]_{ij}}\end{aligned}$$

Aplicações

# Imagem

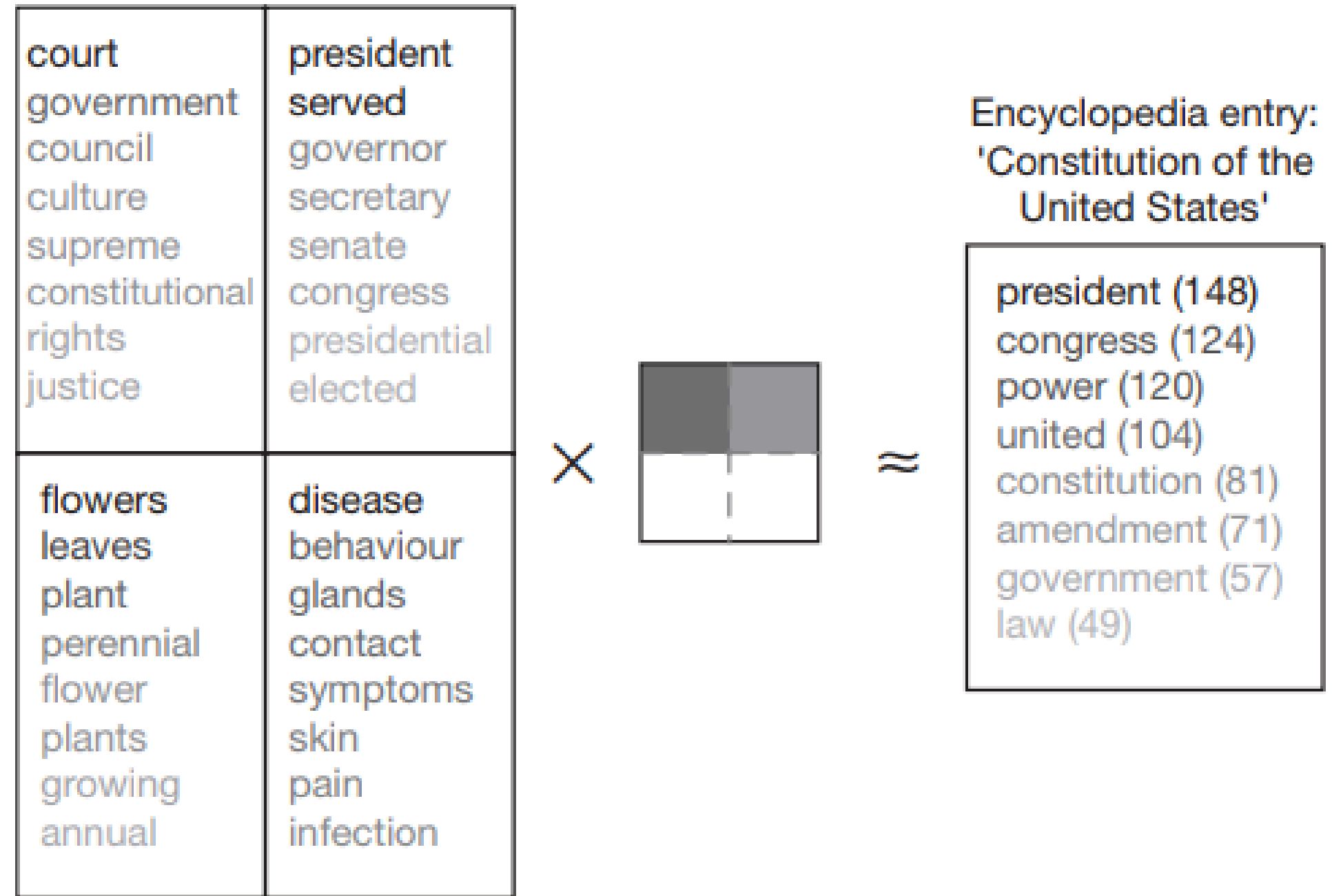
- Imagens de rostos
- 2429 imagens
- 19 X 19 pixels
- Aproximação de posto 49
- Preto e branco





# Texto

- Artigos do Grolier
- 30991 artigos
- Vocabulário de 15276 palavras
- Aproximação de posto 200
- Vetorização por frequência



metal process method paper ... glass copper lead steel

person example time people ... rules lead leads law

# Referências

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