SIA - TP4

Grupo 7

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Red de Kohonen

Datos (x28):

Country
Area
GDP
Inflation
Life Expectancy
Military Expense
People Growth
Unemployment

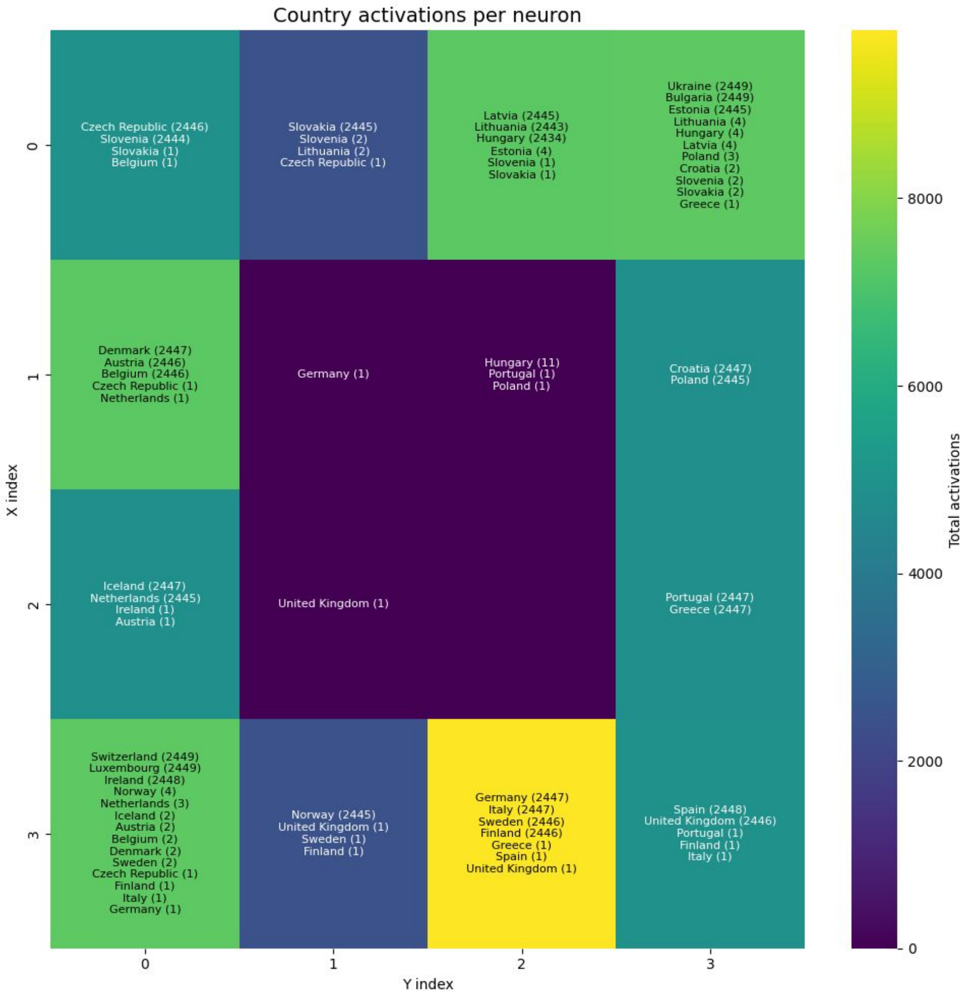
Variables:

Epochs (Factor)
R0
R constante o variable
S: Euclídea o Exponencial
K

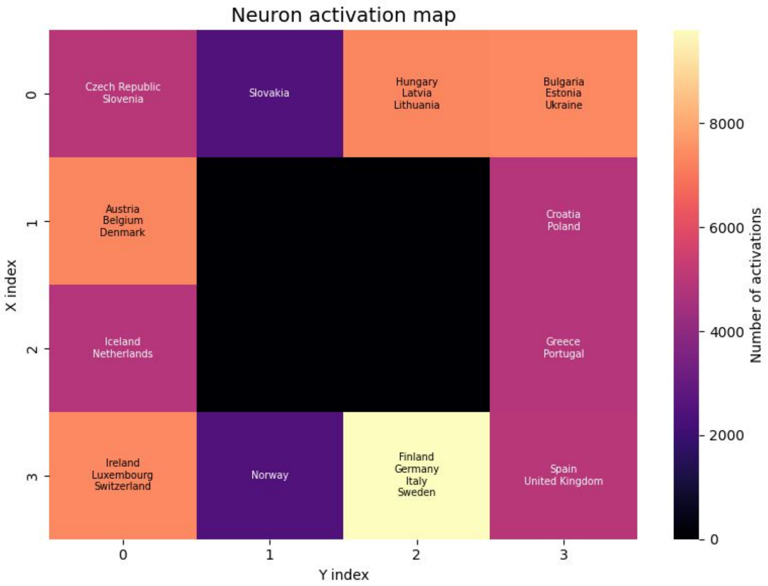
*Learning Rate fijo en 1

Parámetros:

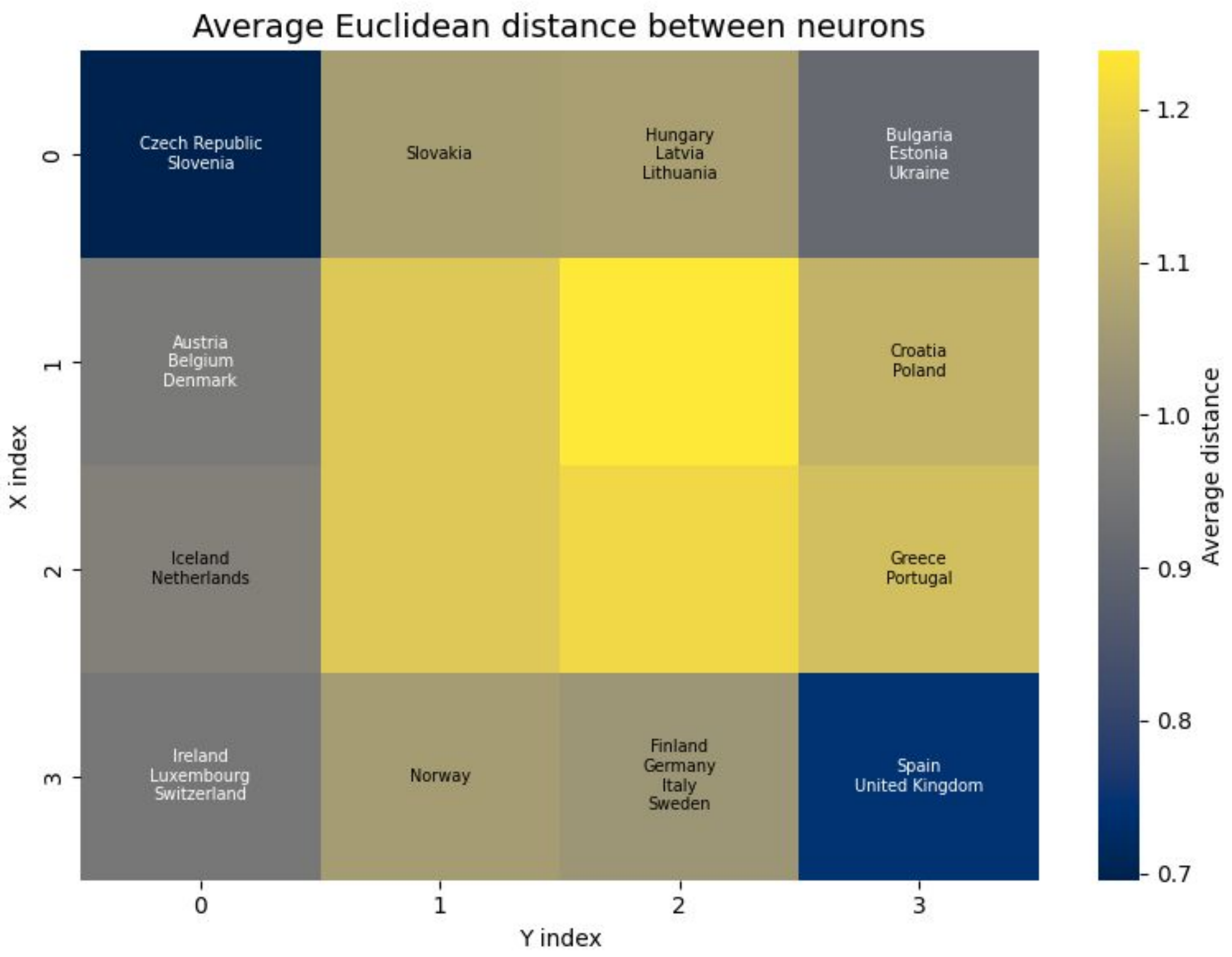
- Epochs factor: 350
- R0: 6
- R variable
- Distancia Euclídea
- K: 4



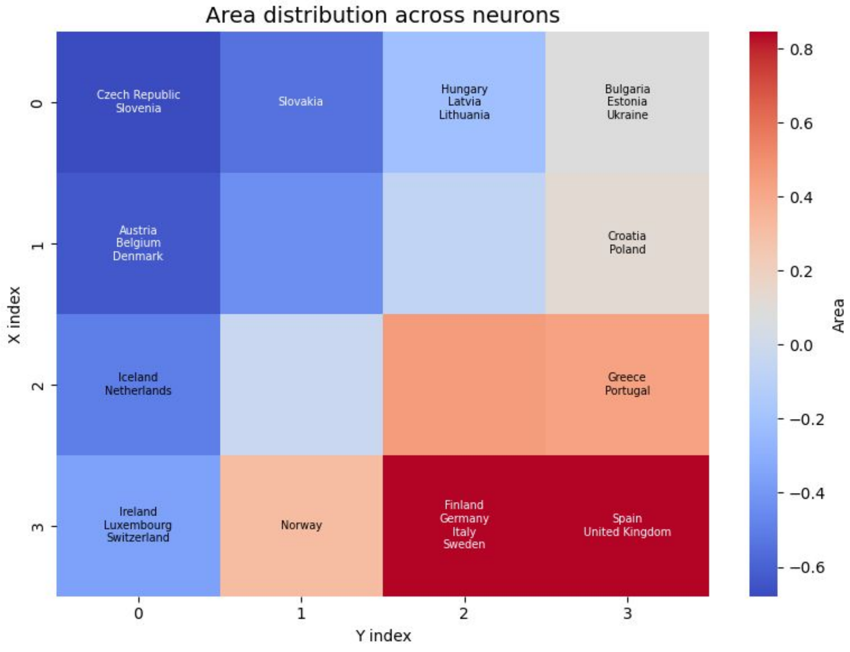
Country activations per neuron
Czech Republic (2446)
Slovenia (2444)
Slovakia (1)
Belgium (1)
Slovakia (2445)
Slovenia (2)
Lithuania (2)
Czech Republic (1)
Latvia (2445)
Lithuania (2443)
Hungary (2434)
Estonia (4)
Slovenia (1)
Slovakia (1)
Ukraine (2449)
Bulgaria (2449)
Estonia (2445)
Lithuania (4)
Hungary (4)
Latvia (4)
Poland (3)
Croatia (2)
Slovenia (2)
Slovakia (2)
Greece (1)
Denmark (2447)
Austria (2446)
Belgium (2446)
Czech Republic (1)
Netherlands (1)
Germany (1)
Hungary (11)
Portugal (1)
Poland (1)
Croatia (2447)
Poland (2445)
Iceland (2447)
Netherlands (2445)
Ireland (1)
Austria (1)
United Kingdom (1)
Portugal (2447)
Greece (2447)
Switzerland (2449)
Luxembourg (2449)
Ireland (2448)
Norway (4)
Netherlands (3)
Iceland (2)
Austria (2)
Belgium (2)
Denmark (2)
Sweden (2)
Czech Republic (1)
Finland (1)
Italy (1)
Germany (1)
Norway (2445)
United Kingdom (1)
Sweden (1)
Finland (1)
Germany (2447)
Italy (2447)
Sweden (2446)
Finland (2446)
Greece (1)
Spain (1)
United Kingdom (1)
Spain (2448)
United Kingdom (2446)
Portugal (1)
Finland (1)
Italy (1)
X index
Y index
Total activations
0
2000
4000
6000
8000

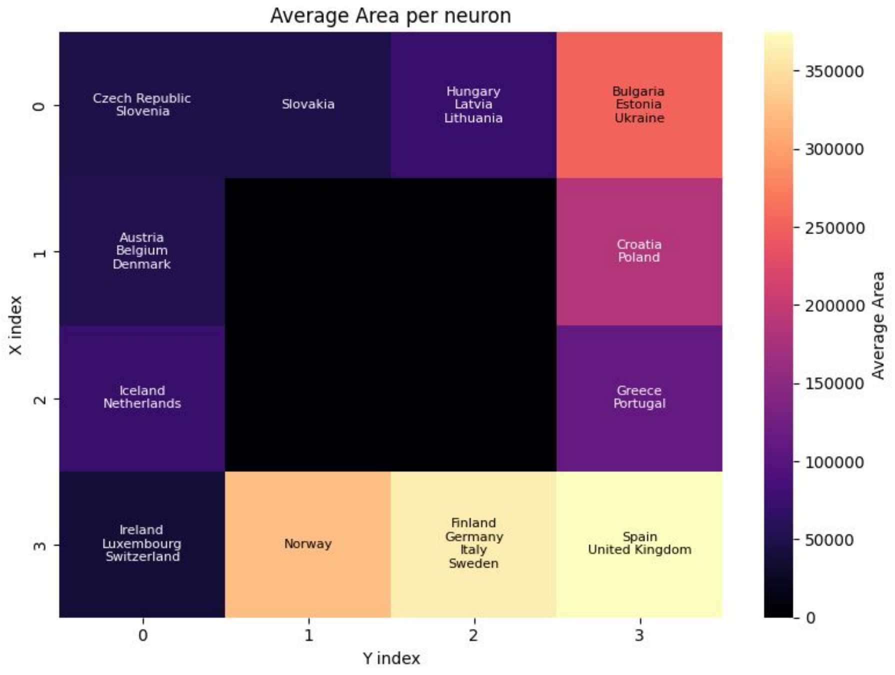


Neuron activation map
Czech Republic
Slovenia
Slovakia
Hungary
Latvia
Lithuania
Bulgaria
Estonia
Ukraine
Austria
Belgium
Denmark
Croatia
Poland
Iceland
Netherlands
Greece
Portugal
Ireland
Luxembourg
Switzerland
Norway
Finland
Germany
Italy
Sweden
Spain
United Kingdom
X index
Y index
Number of activations
0
2000
4000
6000
8000

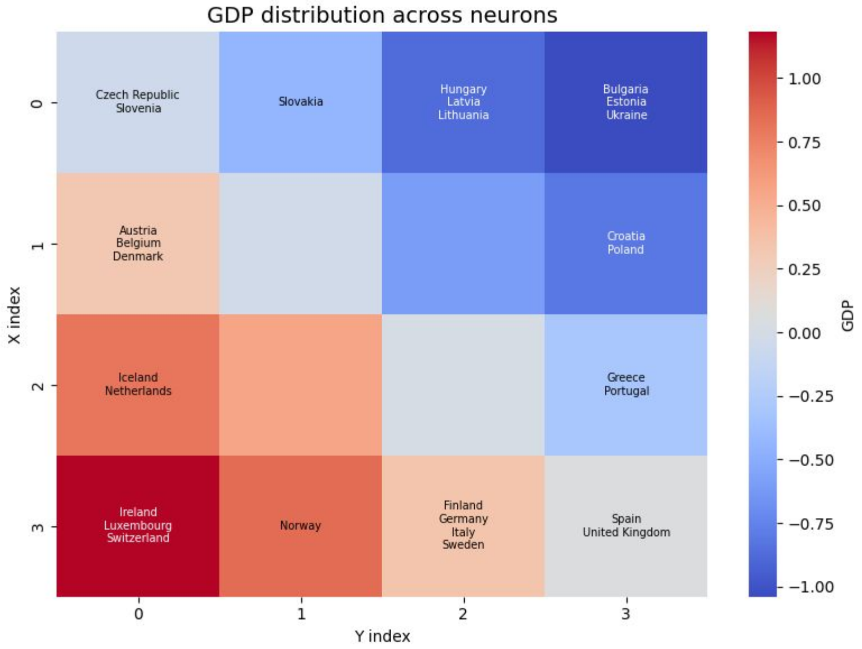

Average Euclidean distance between neurons
Czech Republic
Slovenia
Slovakia
Hungary
Latvia
Lithuania
Bulgaria
Estonia
Ukraine
Austria
Belgium
Denmark
Croatia
Poland
Iceland
Netherlands
Greece
Portugal
Ireland
Luxembourg
Switzerland
Norway
Finland
Germany
Italy
Sweden
Spain
United Kingdom
X index
Y index
0
1
2
3
Average distance
1.2
1.1
1.0
0.9
0.8
0.7

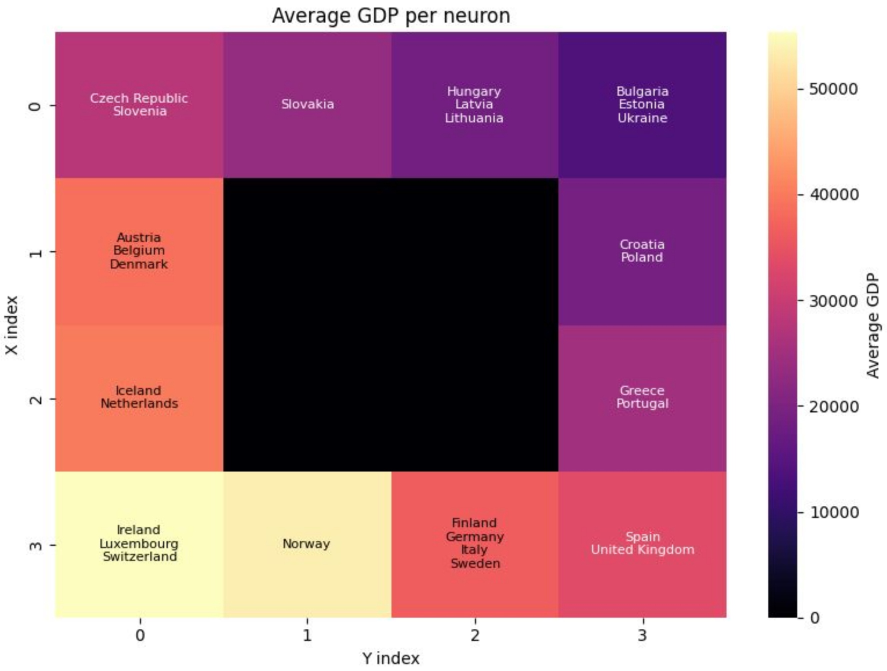
Representación Pesos de Variable vs Promedio de la variable



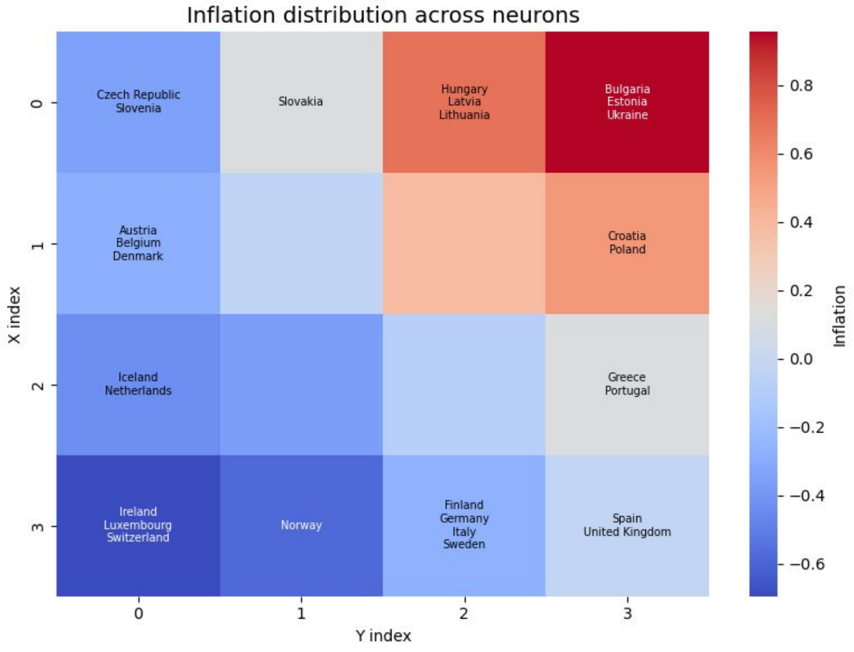


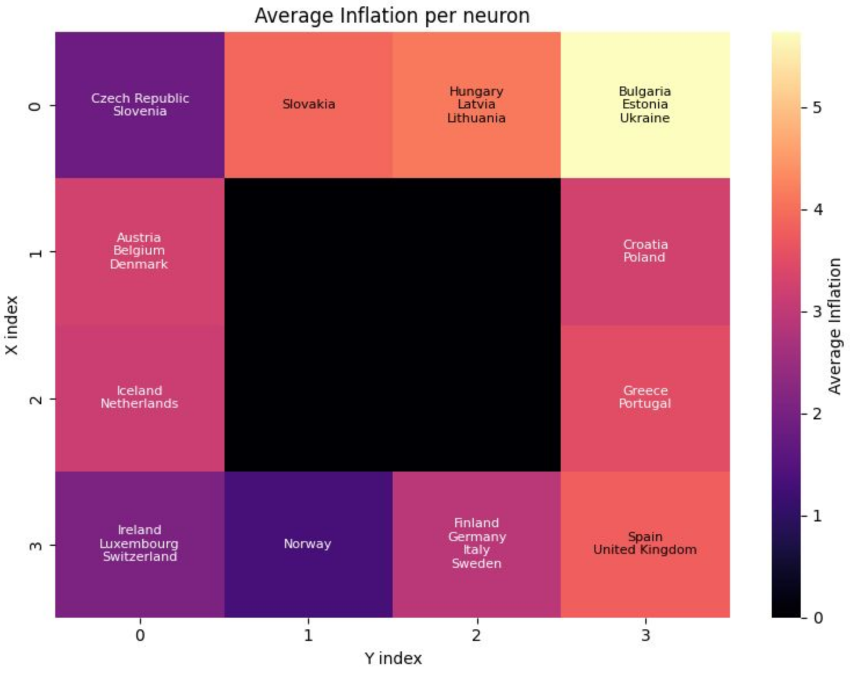
Representación Pesos de Variable vs Promedio de la variable



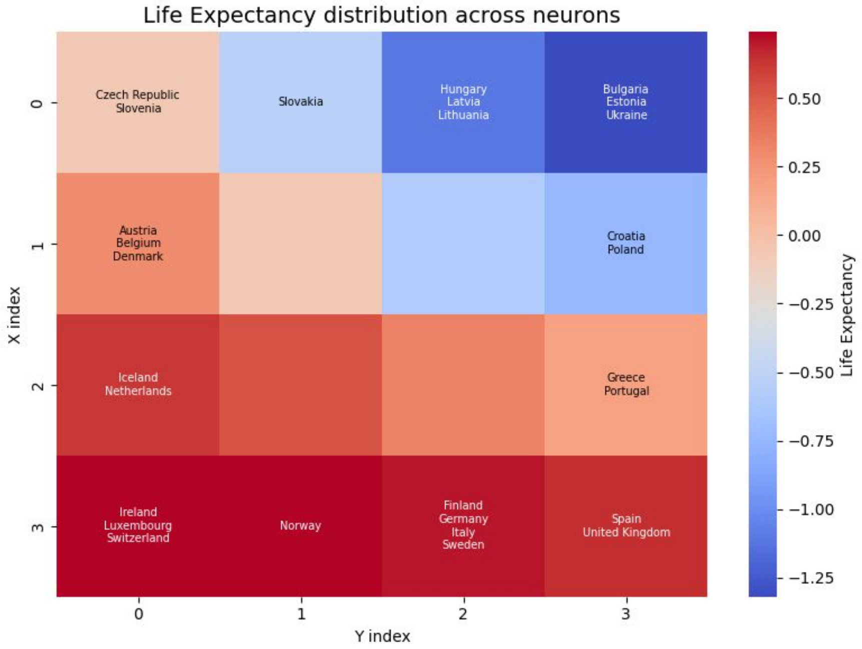


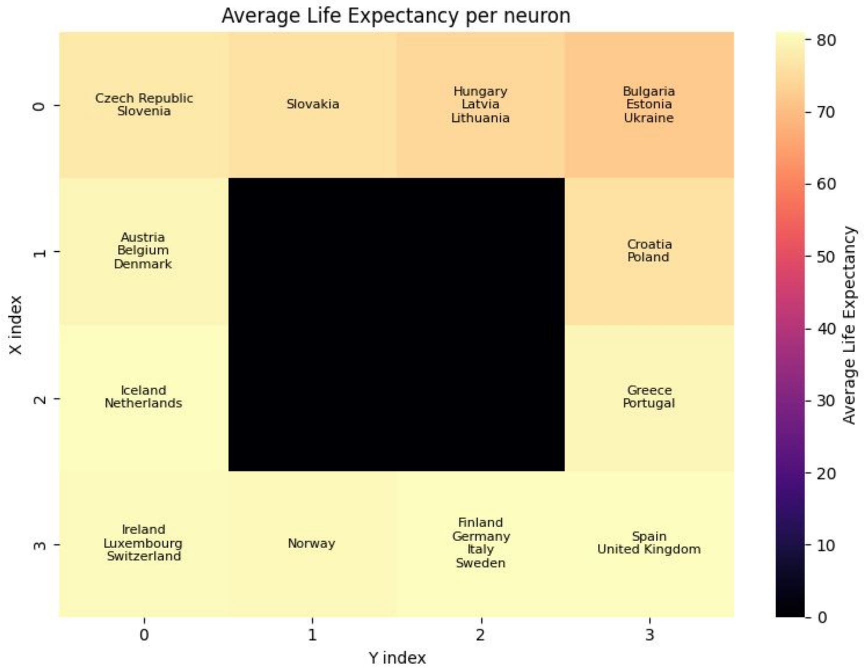
Representación Pesos de Variable vs Promedio de la variable



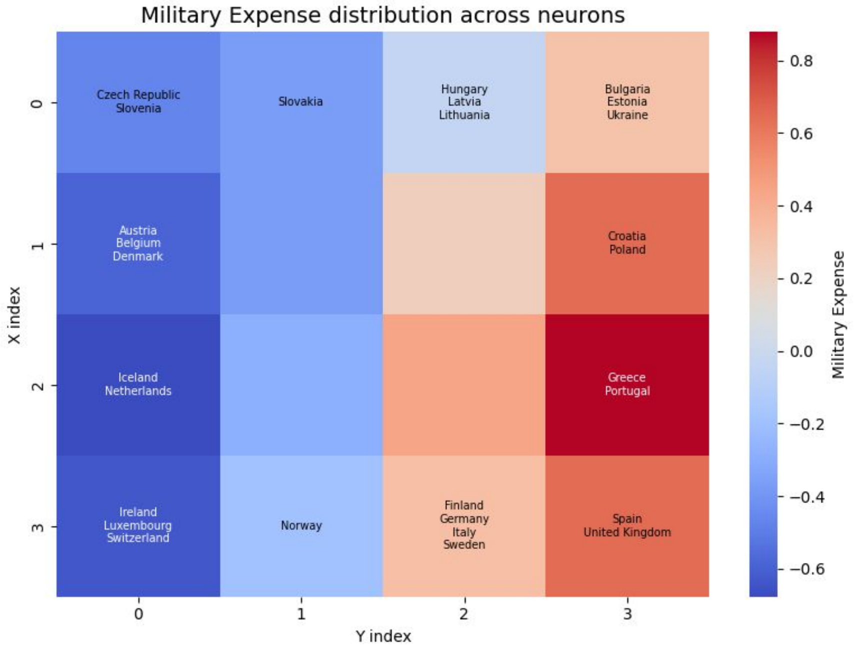


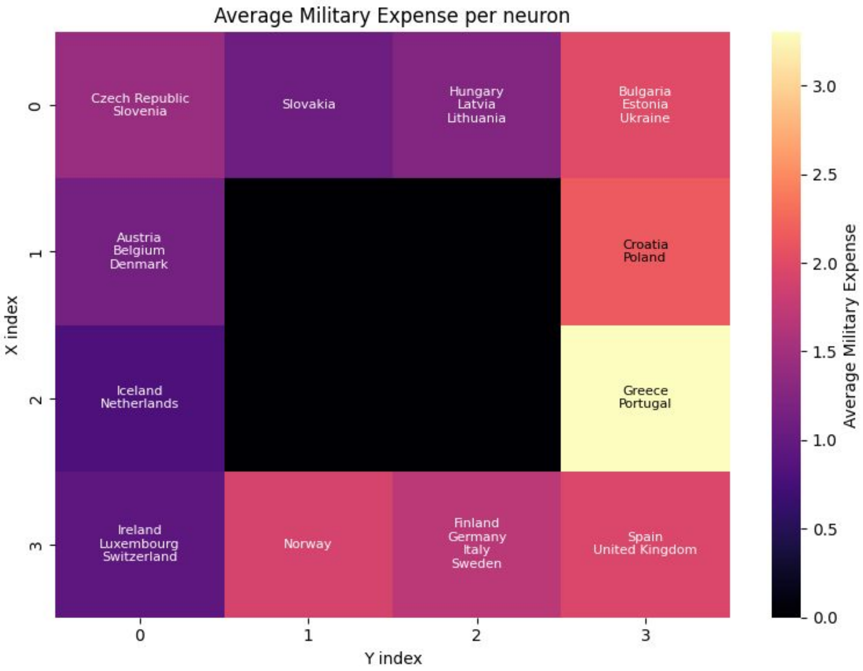
Representación Pesos de Variable vs Promedio de la variable



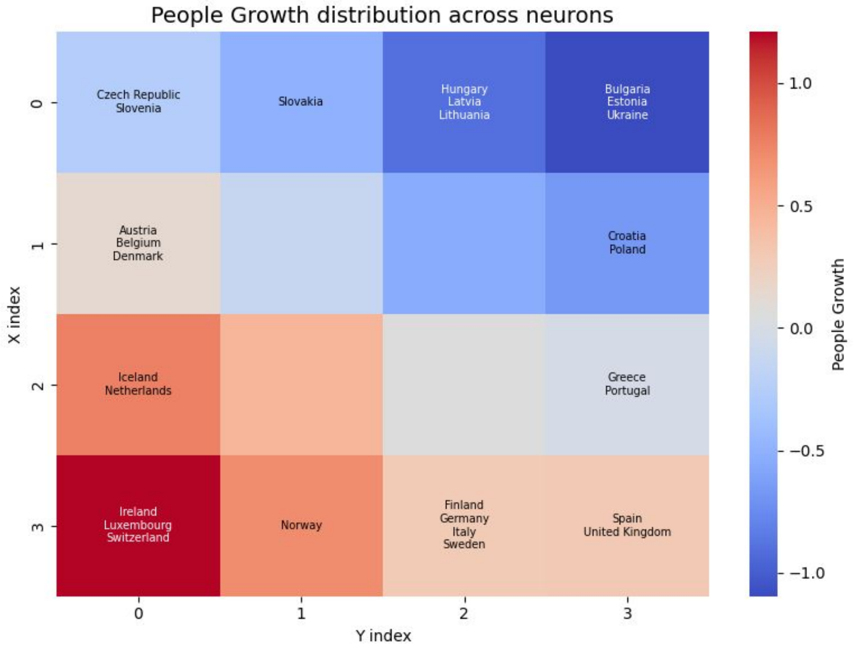


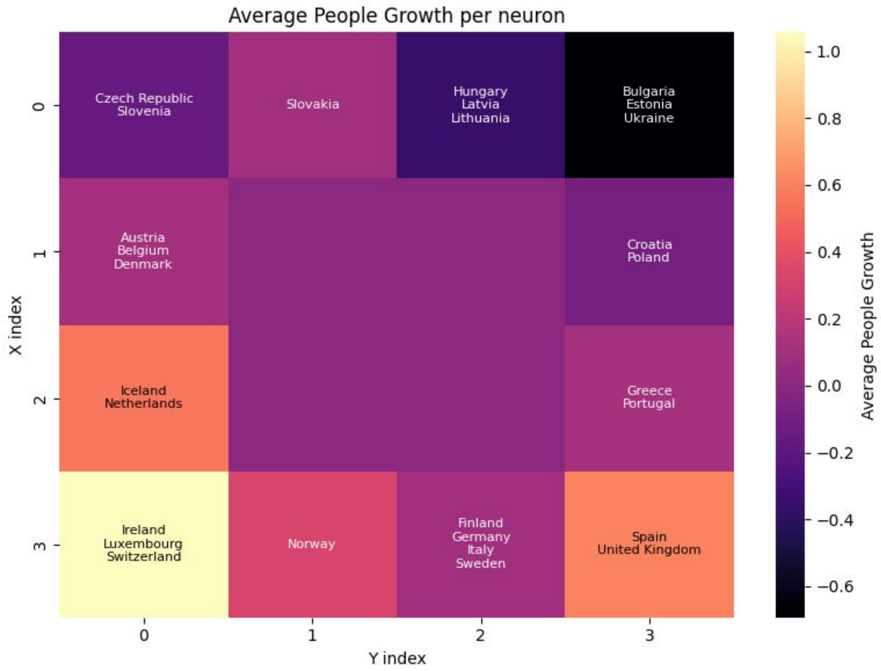
Representación Pesos de Variable vs Promedio de la variable



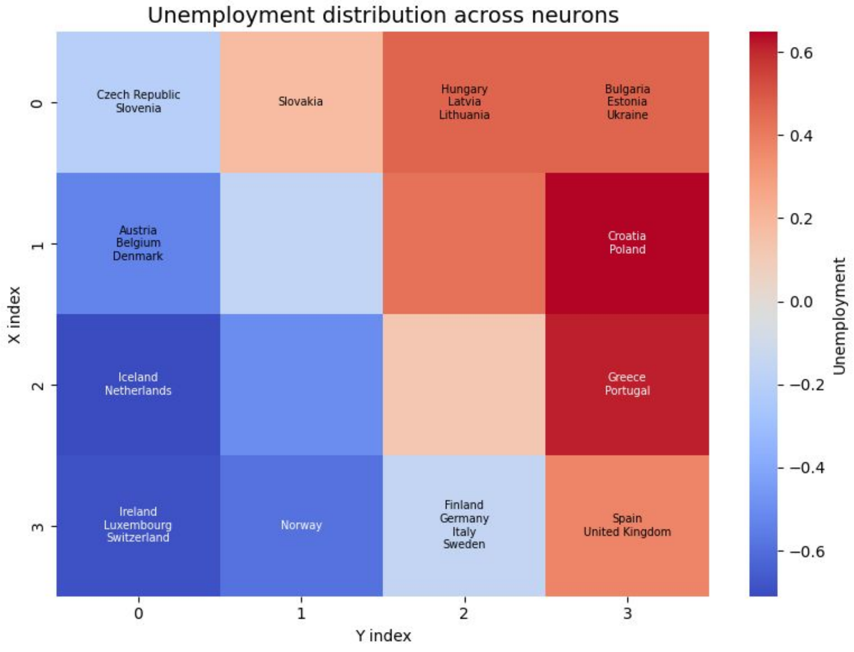


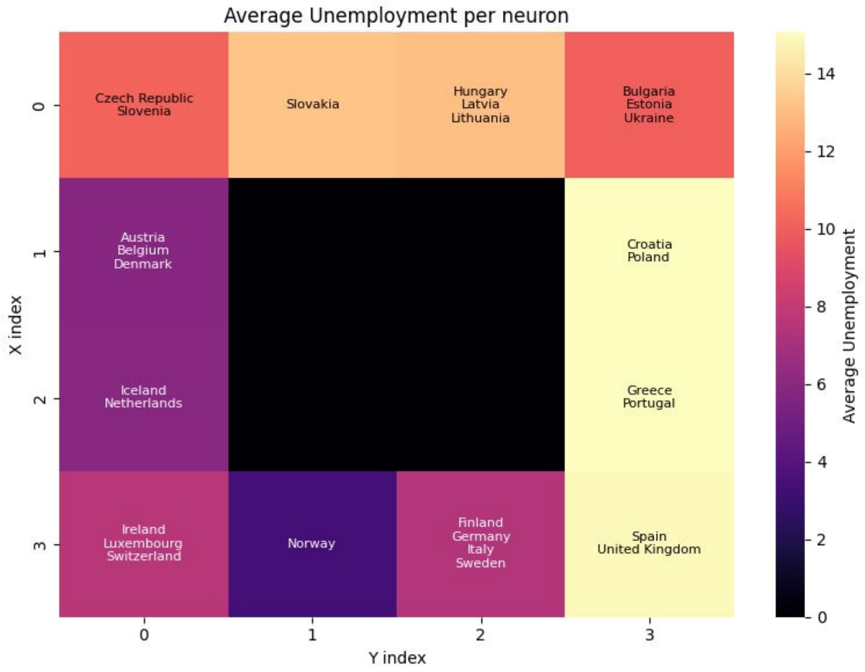
Representación Pesos de Variable vs Promedio de la variable



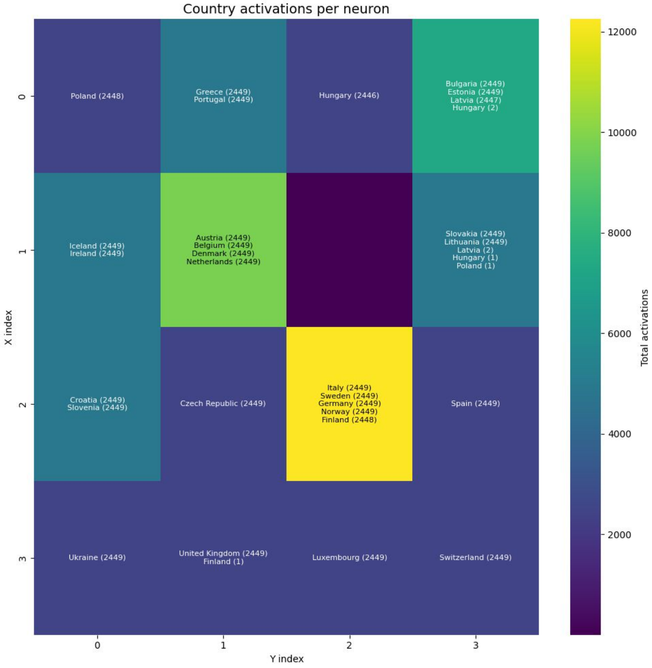


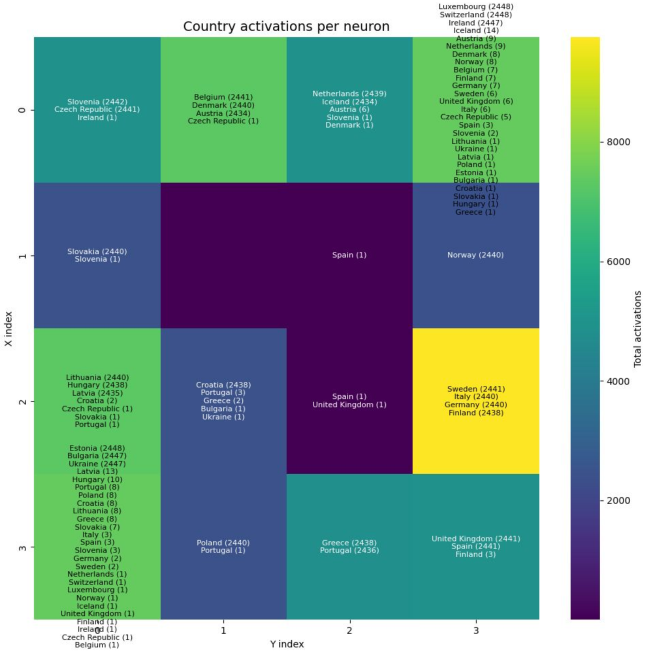
Representación Pesos de Variable vs Promedio de la variable





Elección de Radio Inicial: 1.5 vs 12

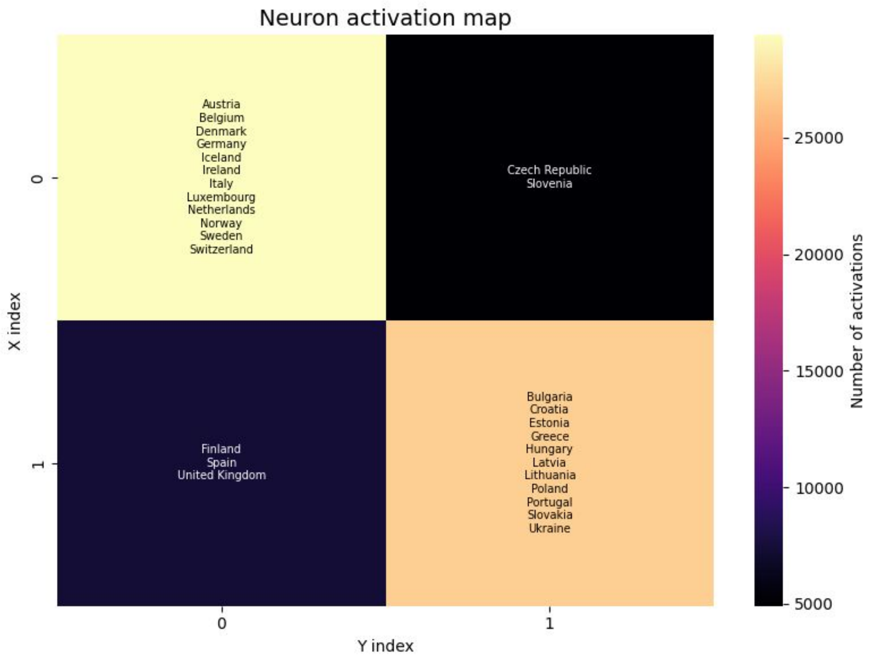


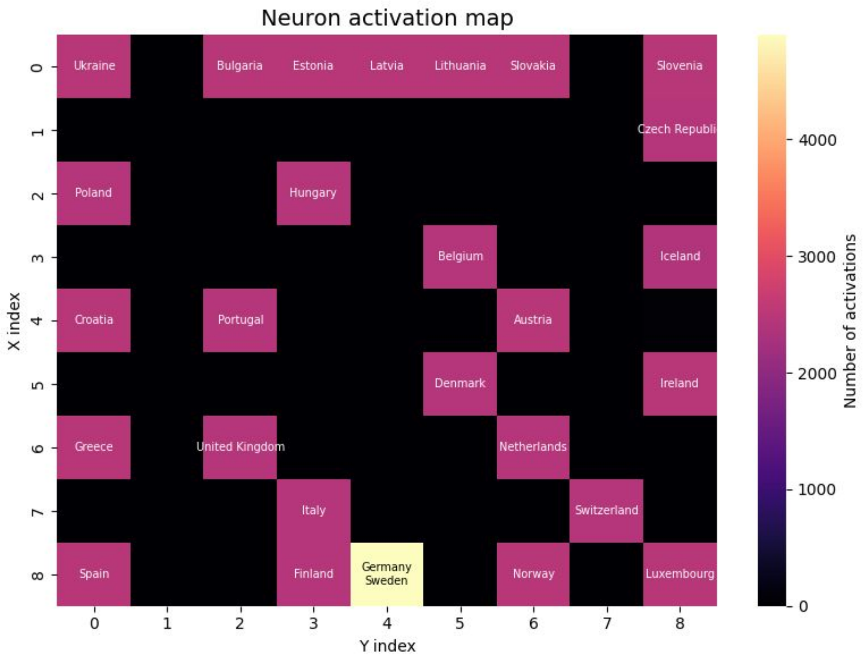


Características encontradas con R0 chico:

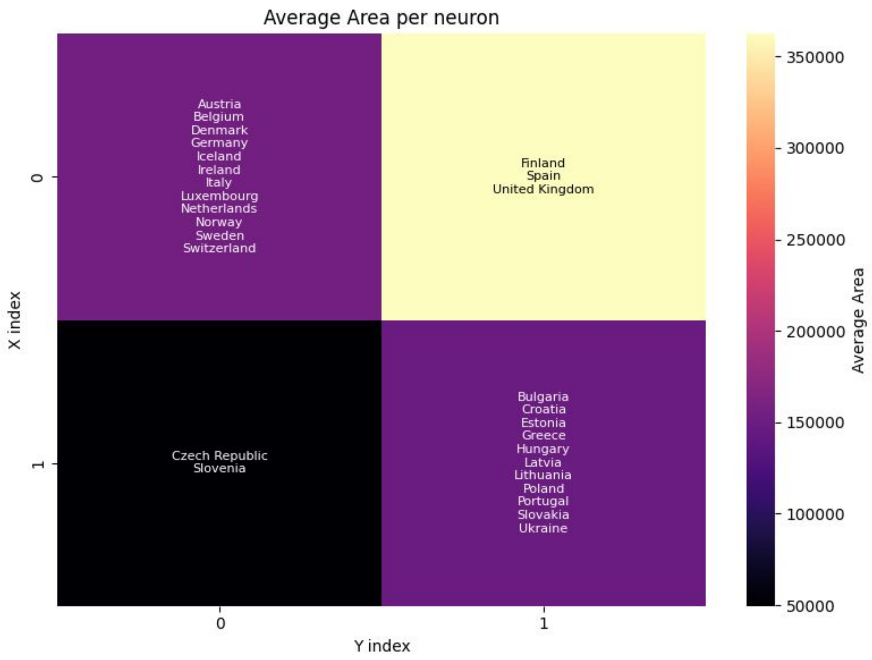
- Convergencia más rápida pero menos generalización
- Los pesos de las neuronas no se ajustan gradualmente
- Aprendizaje local

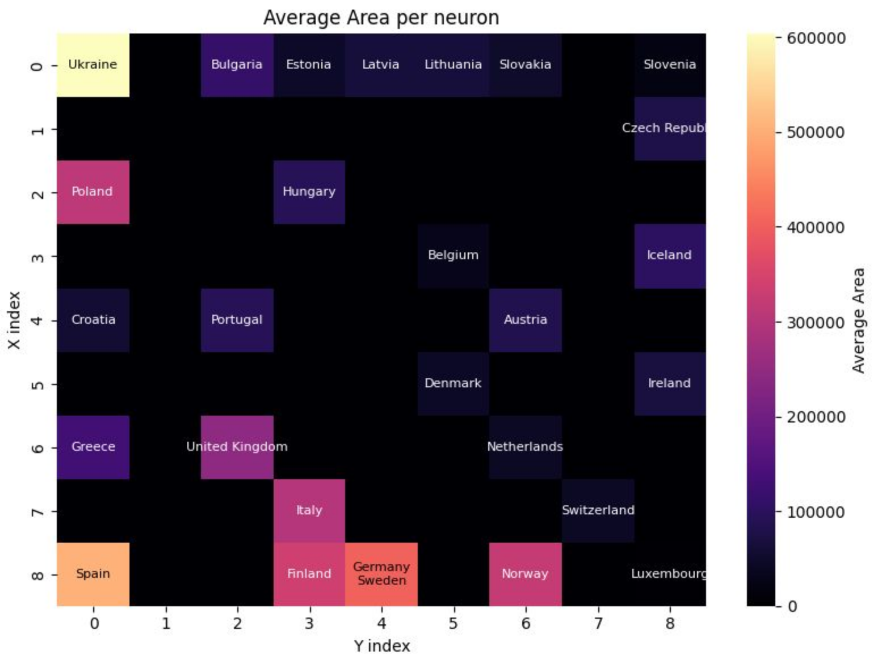
Elección de K: 2 vs 9





Elección de K: 2 vs 9 (Comparando Var.)





Con K chico:

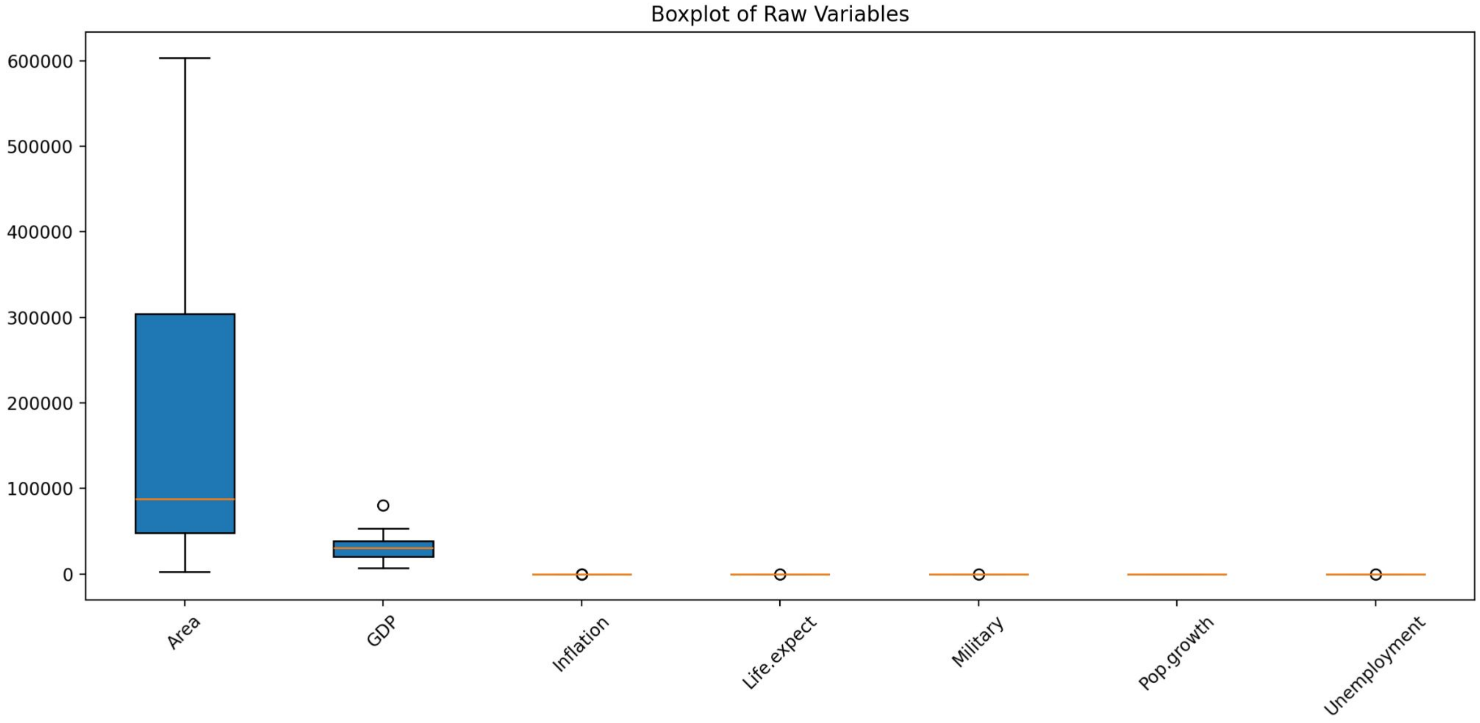
Existe una menor capacidad de discriminación y queda un mapa muy general

Con K grande:

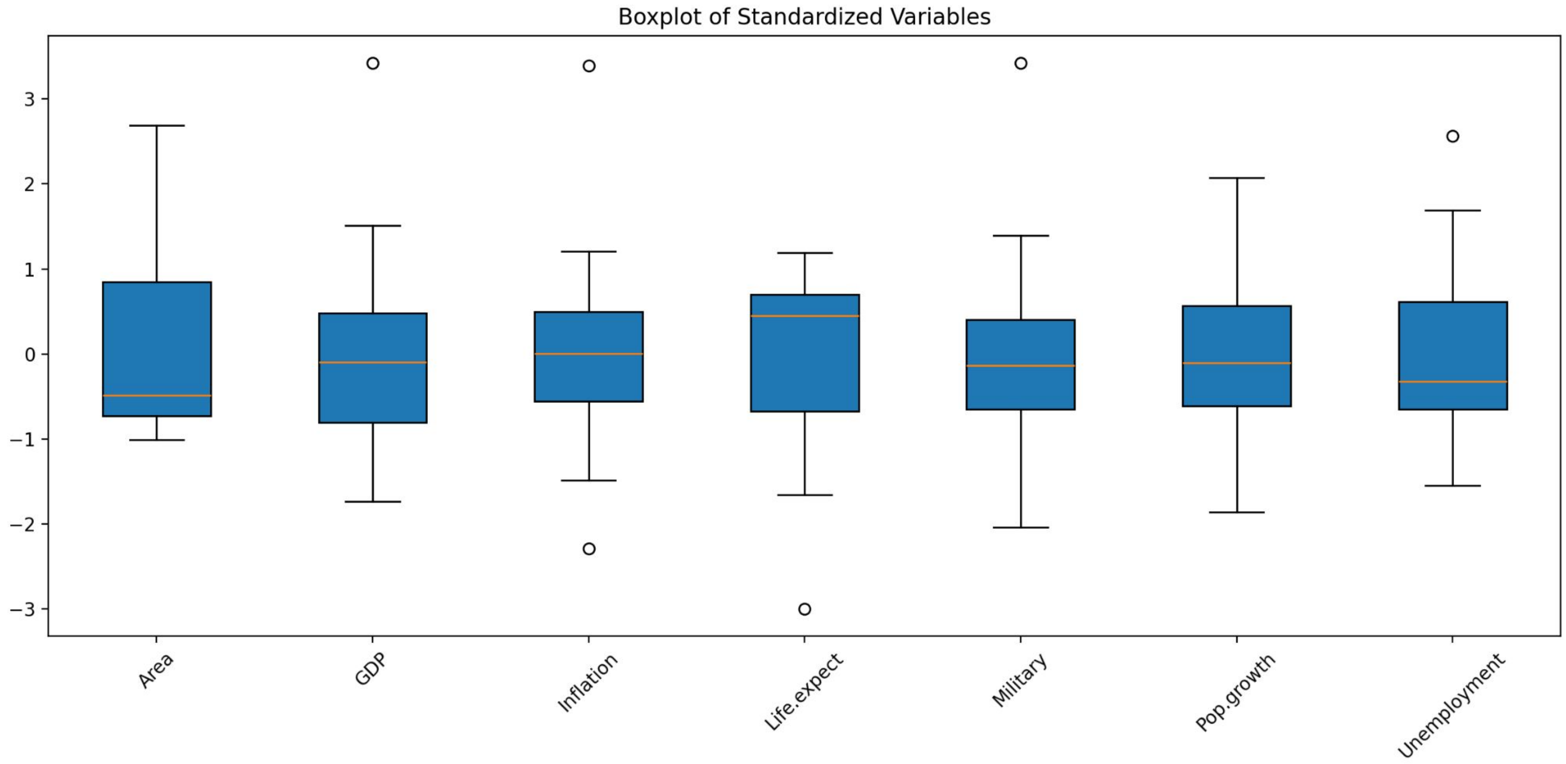
Hay más neuronas muertas y suele memorizar ejemplos individuales

Modelo de Oja

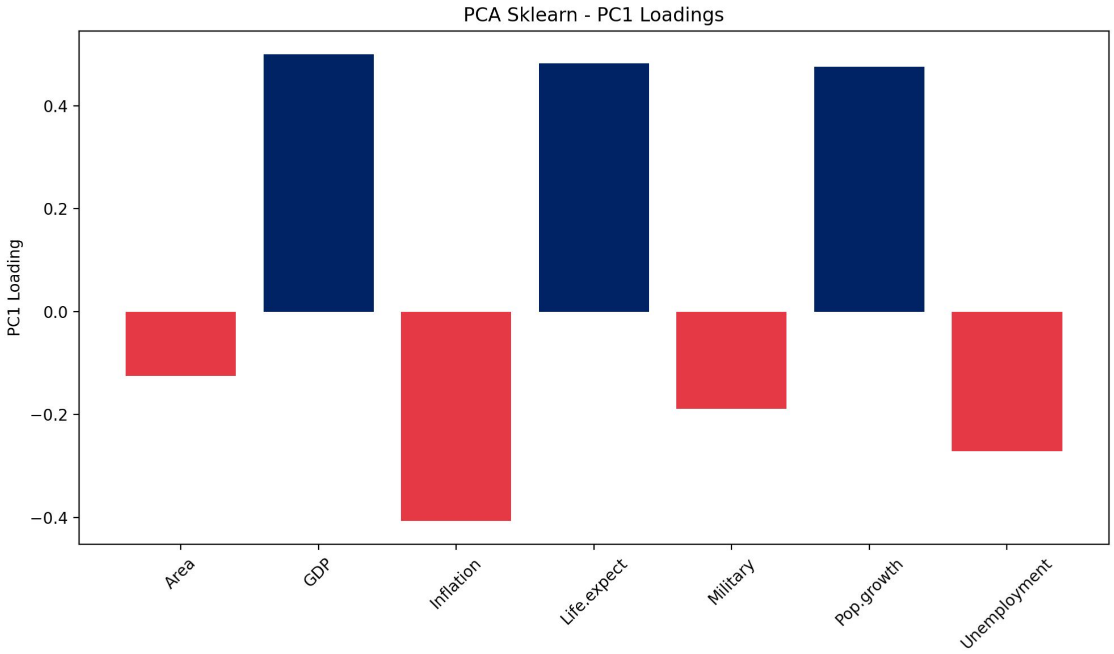
Variables sin estandarizar



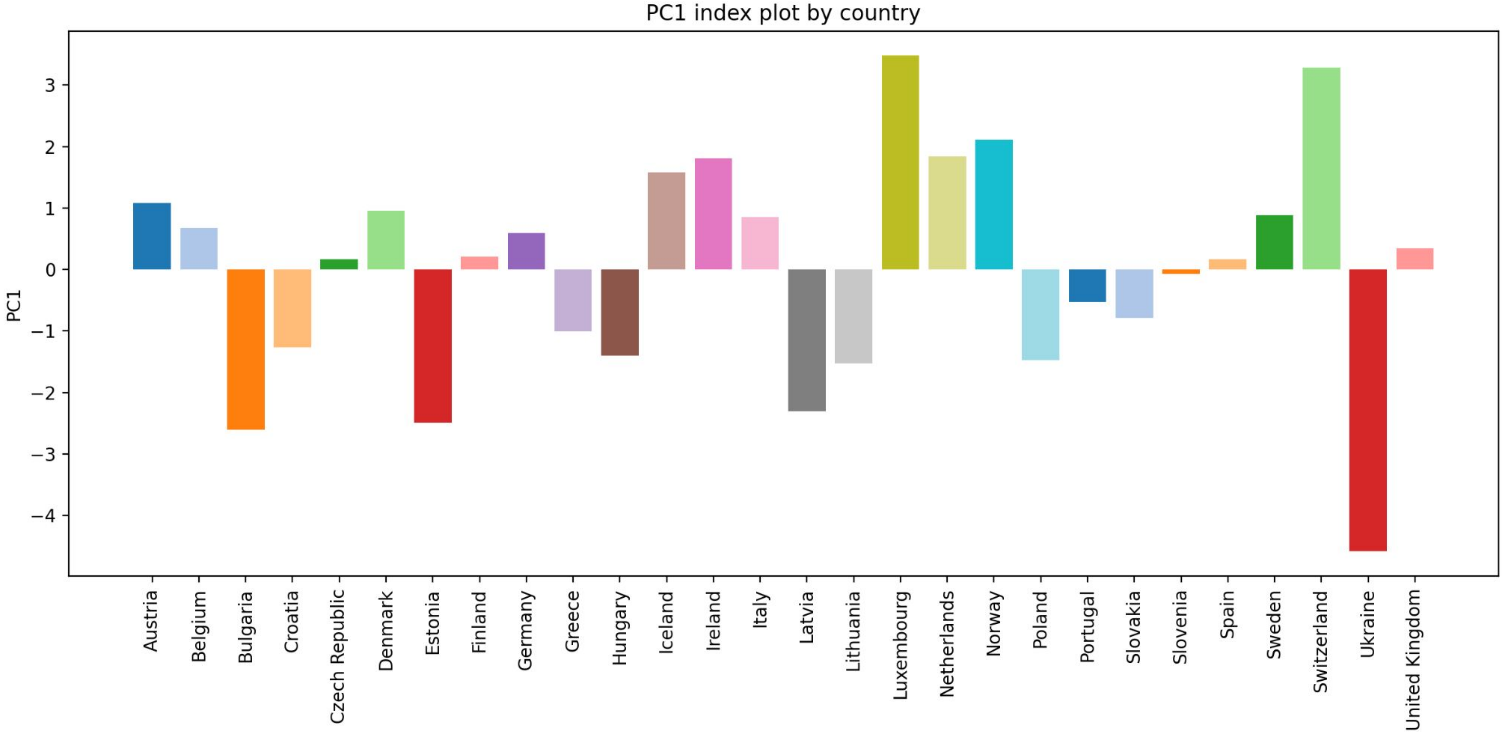
Variables estandarizadas



Interpretación de PC1 (SKlearn)

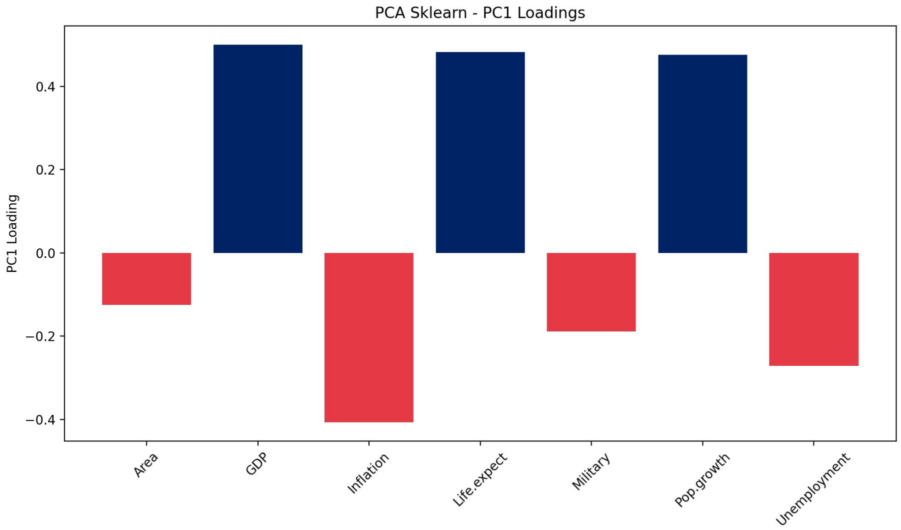


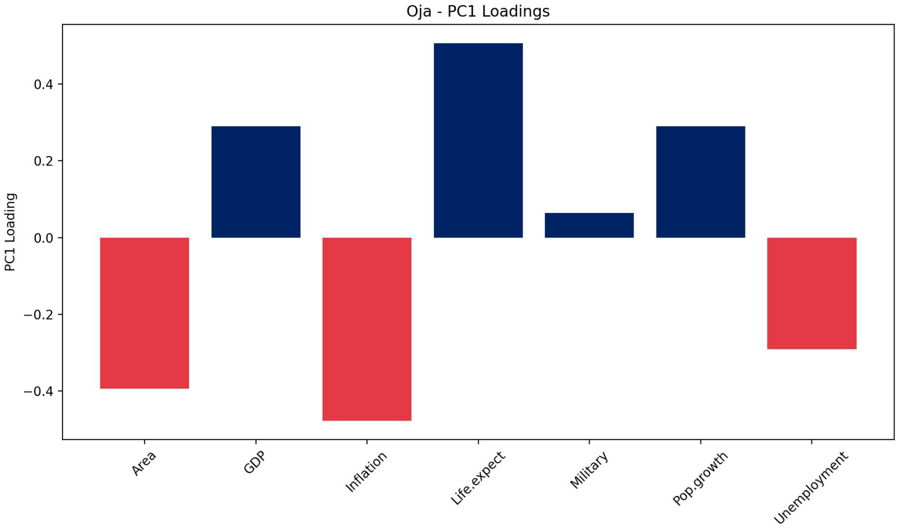
Índice



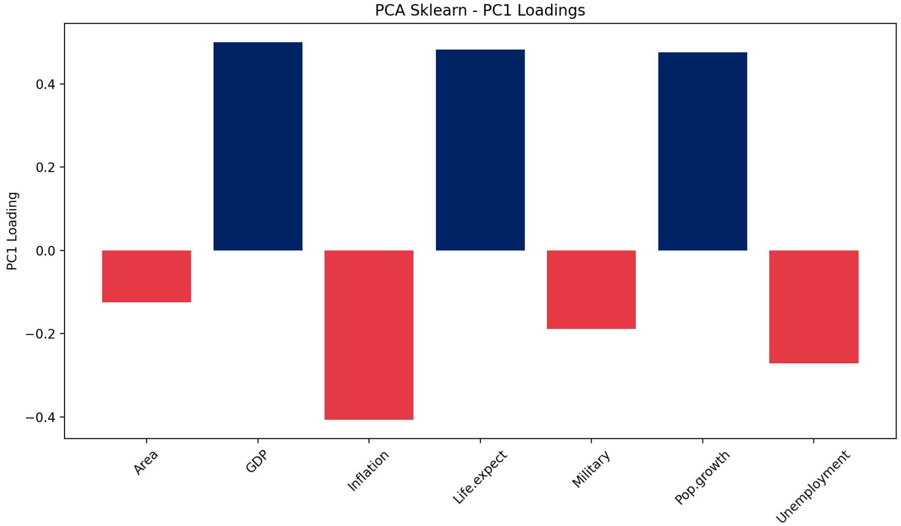
PC1 index plot by country
PC1
3
2
1
0
−1
−2
−3
−4
Austria
Belgium
Bulgaria
Croatia
Czech Republic
Denmark
Estonia
Finland
Germany
Greece
Hungary
Iceland
Ireland
Italy
Latvia
Lithuania
Luxembourg
Netherlands
Norway
Poland
Portugal
Slovakia
Slovenia
Spain
Sweden
Switzerland
Ukraine
United Kingdom

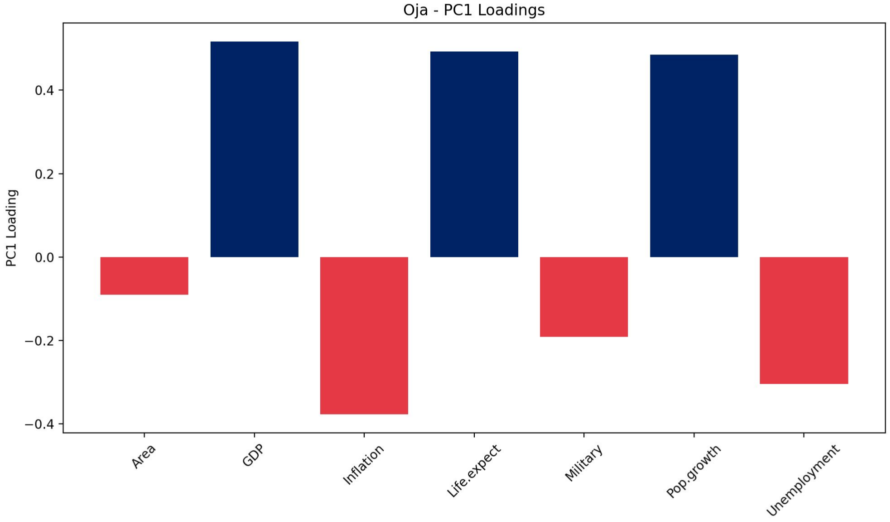
η=0.1 Epochs=100 E=0.22



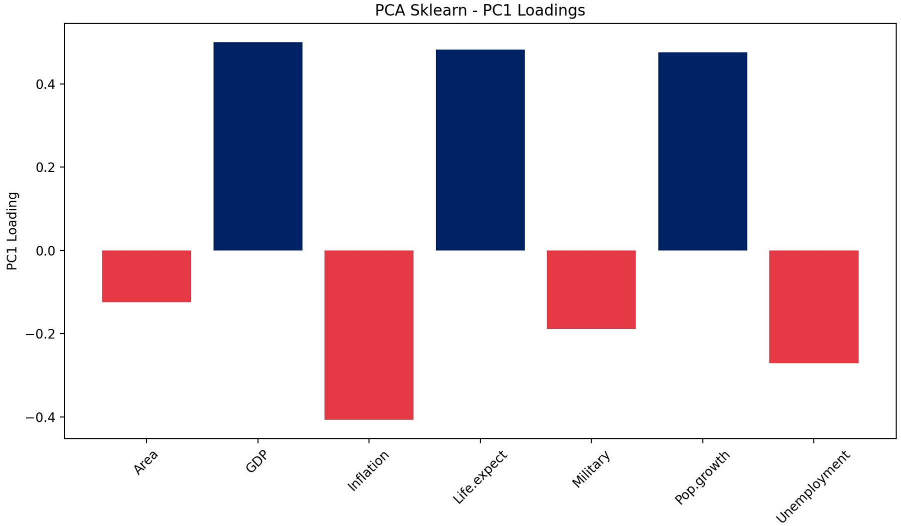


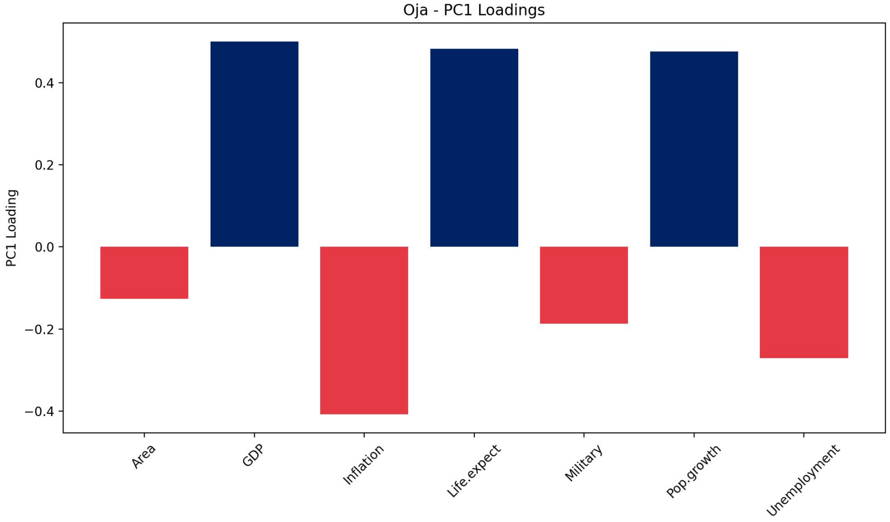
η=0.01 Epochs=1000 E=0.003675



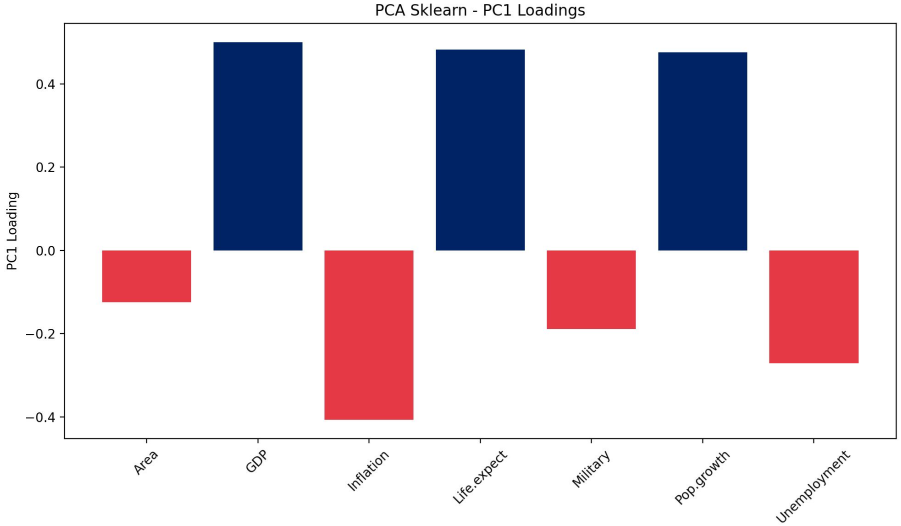


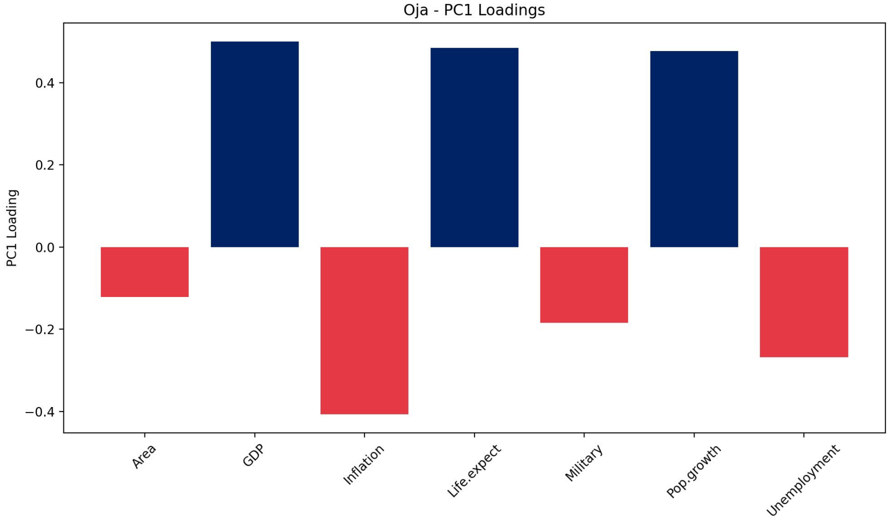
η=0.001 Epochs=1000 E=0.000004





η=0.0001 Epochs=1000 E=0.00004



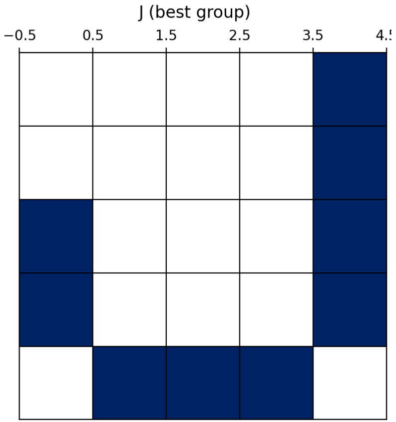


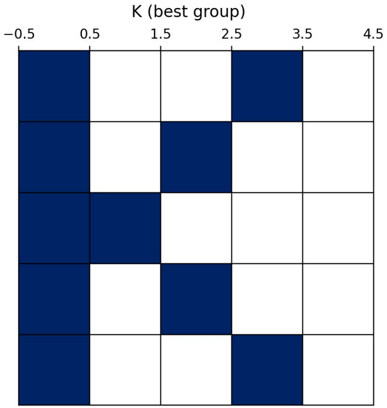
Conclusiones

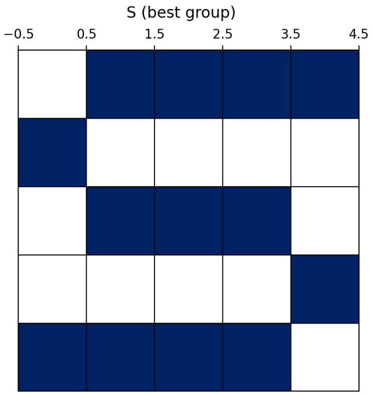
- El PC1 puede ser considerado una medida del bienestar social.
- Las variables que más impactan de forma positiva son el GDP, la expectativa de vida y la tasa de crecimiento poblacional.
- La variable negativa con mayor magnitud es la inflación, mientras que la variable con menor magnitud es el área.
- Oja aproxima el PC1 de mejor forma con valores menores de η.
- Con valores muy altos de η Oja puede no converger nunca.
- Con valores muy bajos de η tarda mucho en converger.

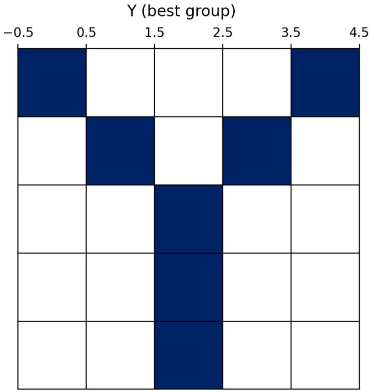
Red de Hopfield

Mejor grupo de 4 letras
$|<,>|$medio = 1.333

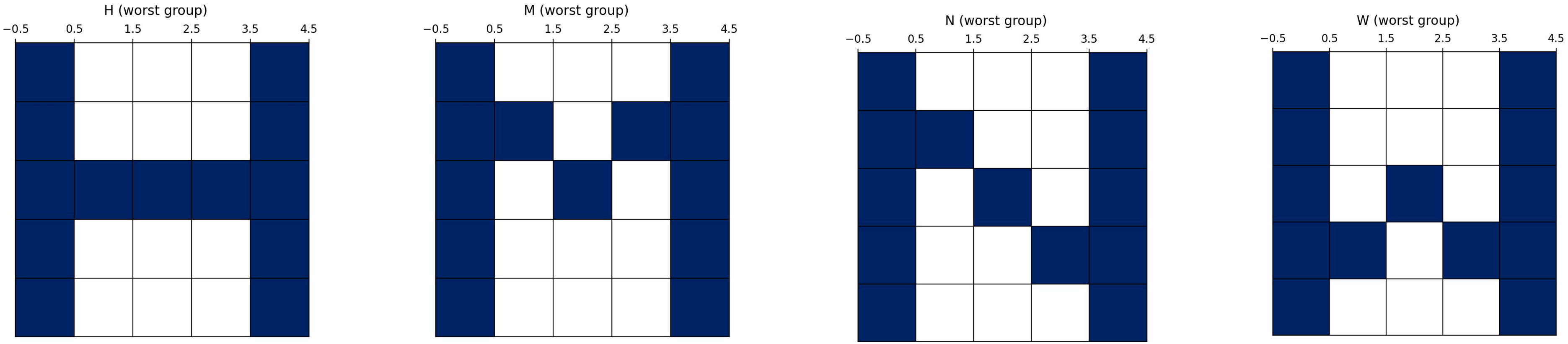






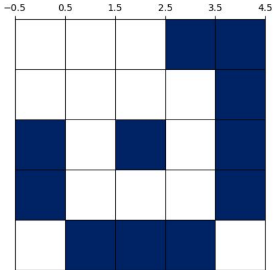


Peor grupo de 4 letras
|<,>|medio = 18.333

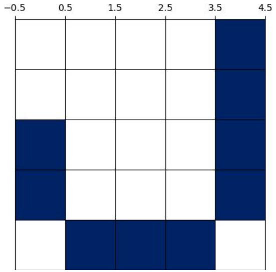


Análisis de convergencia según el ruido

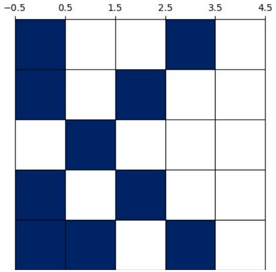
μ = 0.1



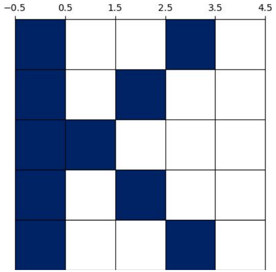
H(w) = -7.36



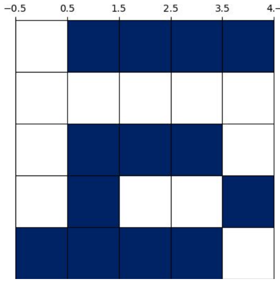
H(w) = -10.56



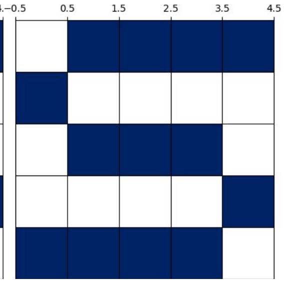
H(w) = -7.04



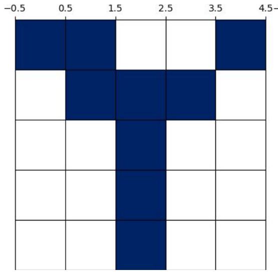
H(w) = -10.56



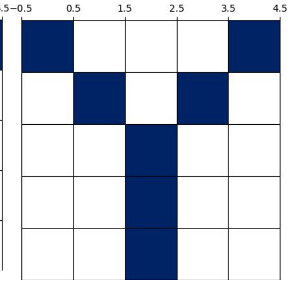
H(w) =-7.52



H(w) = -10.72



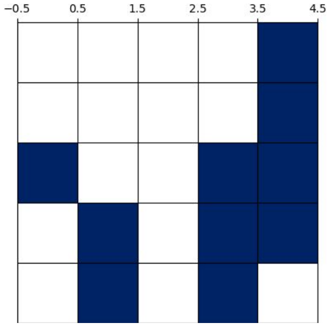
H(w) = -7.2



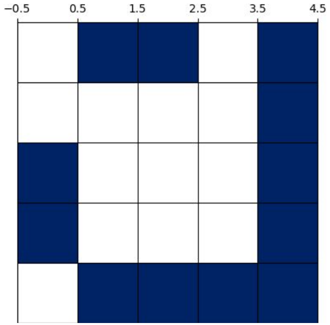
H(w) = -10.72

Análisis de convergencia según el ruido

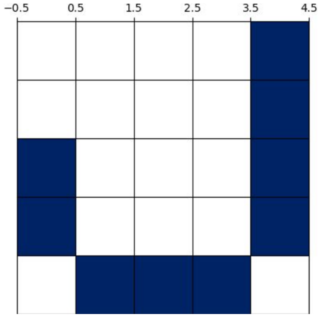
$\mu = 0.2$



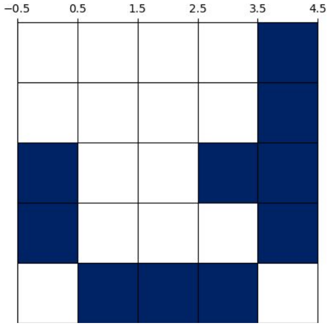
H(w) = -4.00



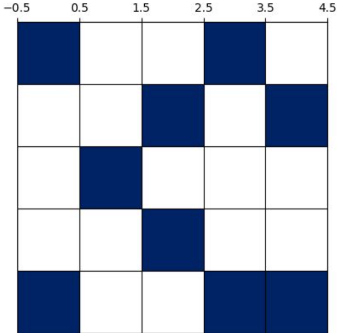
H(w) = -6.88

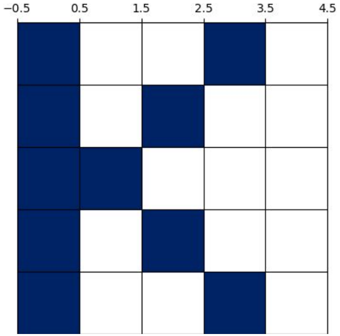


H(w) = -8.96



H(w) =-10.56

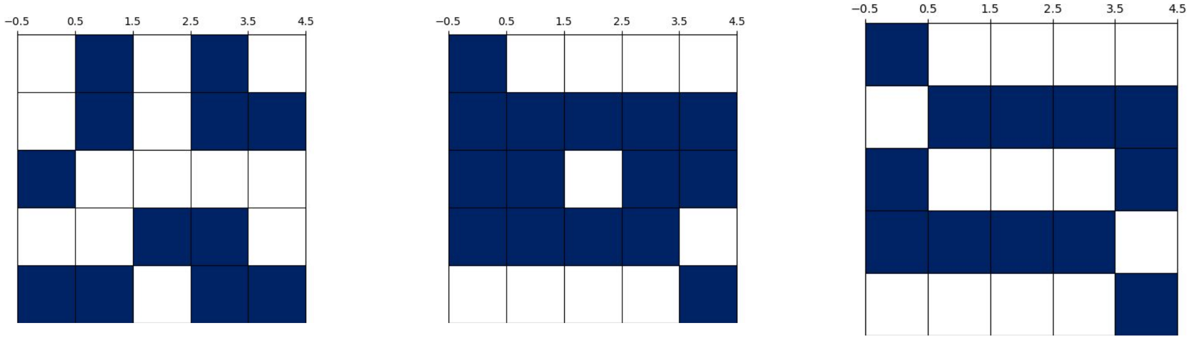




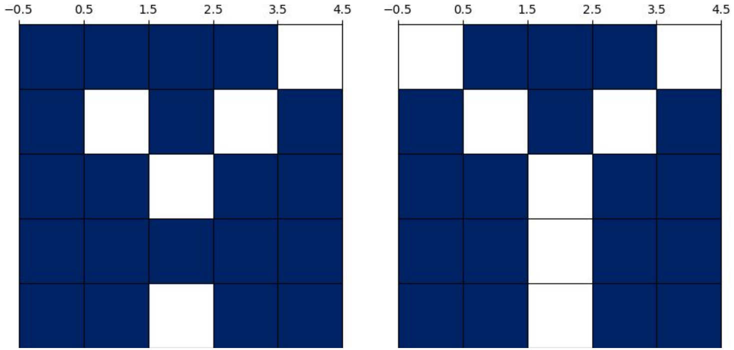
Análisis de convergencia según el ruido

$\mu = 0.6$

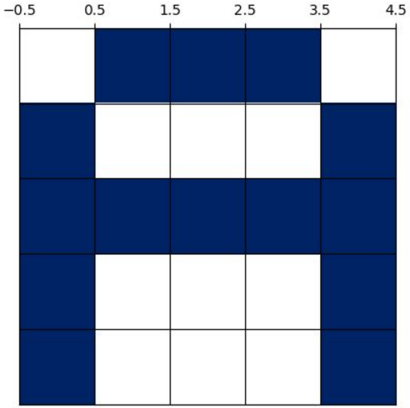
S



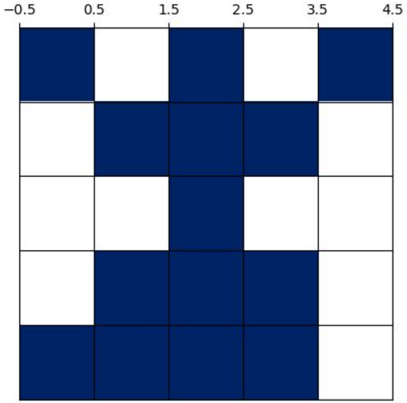
Y



Análisis de mínimos locales y complementos de los patrones almacenados

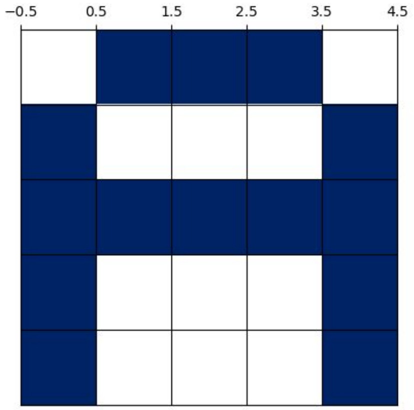


patrón almacenado



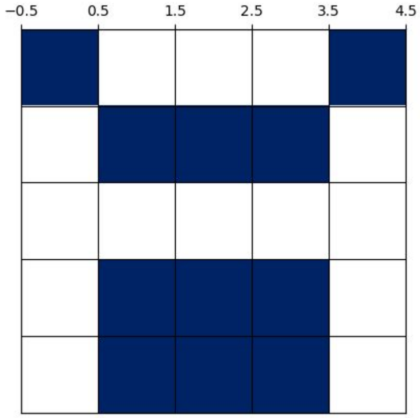
noise = 0.9

Análisis de mínimos locales y complementos de los patrones almacenados



patrón almacenado

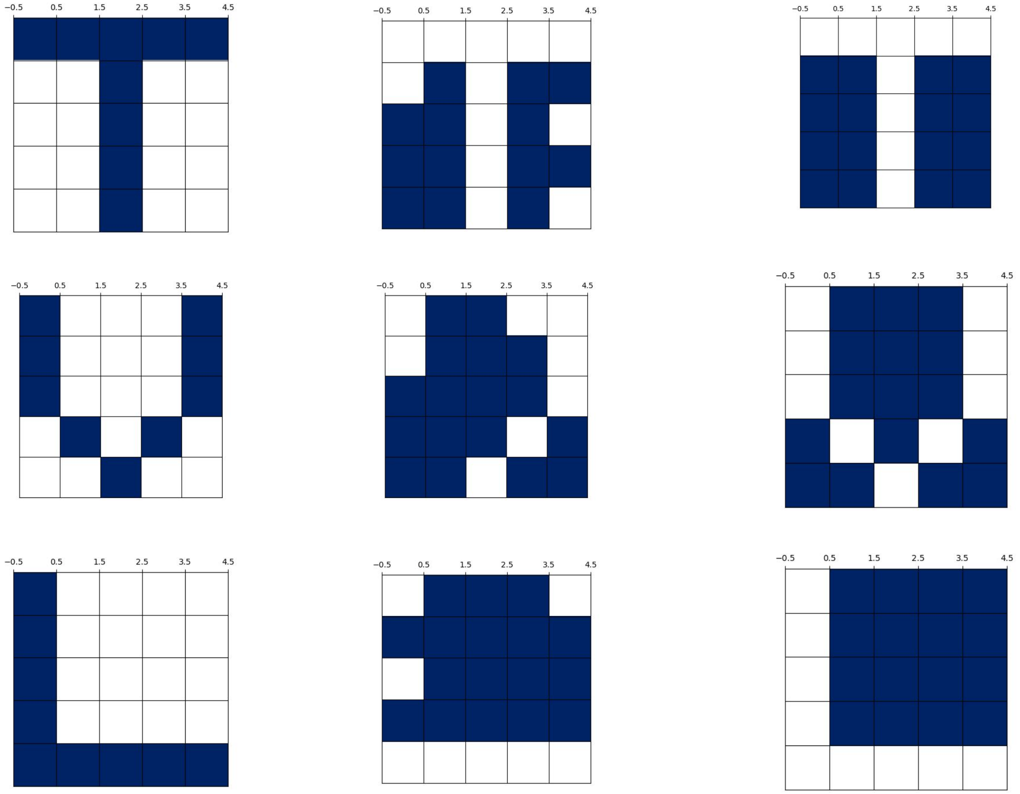
H(w) = -11.52



patrón espurio obtenido

H(w) = -11.52

Análisis de mínimos locales y complementos de los patrones almacenados



Análisis de mínimos locales y complementos de los patrones almacenados

$$sign(h_i^\nu) = \xi_i^\nu$$

$$h_i^\nu = \sum_j w_{ij}\xi_j^\nu = \frac{1}{N}\sum_j\sum_\mu \xi_i^\mu\xi_j^\mu\xi_j^\nu$$

$$h_i^\nu = \frac{1}{N}\sum_j\sum_{\mu\neq\nu}\xi_i^\mu\xi_j^\mu\xi_j^\nu + \frac{1}{N}\sum_j \xi_i^\nu\xi_j^\nu\xi_j^\nu h_i^\nu = \frac{1}{N}\sum_j\sum_{\mu\neq\nu}\xi_i^\mu\xi_j^\mu\xi_j^\nu + \frac{1}{N}\xi_i^\nu$$

$$sign(h_i^\nu) = \xi_i^\nu$$

Análisis de mínimos locales y complementos de los patrones almacenados

$$-\xi^{\nu} = (-\xi_1^{\nu}, -\xi_2^{\nu}, ..., -\xi_n^{\nu})$$

$$\boxed{sign(h_i) = -\xi_i^{\nu}}$$

$$h_i = \sum_j w_{ij}(-\xi_j^{\nu}) = \frac{1}{N}\sum_j \sum_\mu \xi_i^{\mu}\xi_j^{\mu}(-\xi_j^{\nu})$$

$$h_i = -\frac{1}{N}\sum_j \sum_\mu \xi_i^{\mu}\xi_j^{\mu}\xi_j^{\nu}$$

Análisis de mínimos locales y complementos de los patrones almacenados

$$h_i = -\frac{1}{N}\sum_j \sum_\mu \xi_i^\mu \xi_j^\mu \xi_j^\nu$$

$$h_i = -(\frac{1}{N}\sum_j \sum_{\mu \neq \nu} \xi_i^\mu \xi_j^\mu \xi_j^\nu + \frac{1}{N}\sum_j \xi_i^\nu \xi_j^\nu \xi_j^\nu)$$

$$h_i = -(\frac{1}{N}\boxed{\sum_j \sum_{\mu \neq \nu} \xi_i^\mu \xi_j^\mu \xi_j^\nu} + \frac{1}{N}\xi_i^\nu)$$

$$sign(h_i) = -\xi_i^\nu$$