Prevention of occurrence of dead units in self-organizing maps

Student: Bc. Jakub Novák Supervisor: doc. RNDr. Martin Takáč, PhD.

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Goals

- review existing approaches
- suggest SOM modifications
- implement simulations
- analyze to what extent the proposed modifications succeed in eliminating dead units

Self-organizing map

- model of artificial neural network
 trained using unsupervised learning
- preserves topology
- two-dimensional representation of the input space
- neighbourhood function
 - adapts neighbourhood of winning neuron
 - neighbourhood shrinks with time



Self-organizing map

- SOM algorithm has 2 steps
 - \circ competition
 - learning
- competition
 - neurons compete, which one has weights the closest to the input
- learning
 - neurons adapt weights within the neighbourhood
 - SOM parameters update (learning rate, neighbourhood size, ...)

Motivation

- neurons remember information about available data in their weights
- small map forces neurons to represent more different data
- bigger map can represent data more precisely
 - unused neurons, called dead units, might occur

Dead units problem

- common
- as a result, network capacity is not being fully utilized
- usually caused by badly initialized weights in the SOM
 - some neurons have weights far from any data
- rich get richer
- losers adapt too little

Dead units problem



8	1	8	8	2	2	2	2	2	2	2	3	6	6	5	6	6	6	6	6
1	1	8	8	2	2	2	2	2	2	2	2	6	3	1	6	6	6	6	6
8	8	1	8	2	2	2	2	2	2	2	2	6	8	6	6	6	6	4	6
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9	3	5	5	5	5	9	9	9	3	3	3	3	3	3	3	7	7	7	7
4	4	4	5	5	9	3	9	9	3	3	3	3	3	1	7	7	7	7	7
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4	4	4	4	9	8	9	9	3	8	8	8	9	8	9	8	5	5	5	9
4	4	4	4	9	9	9	9	5	8	9	8	8	8	8	8	5	9	5	5
4	4	4	4	4	3	9	9	9	8	8	8	8	8	8	8	5	3	5	5

(3) 20x20 SOM without dead units

General setup

- SOM of size 20x20
- scikit-learn digit dataset
 - 1797 hand written 8x8 digits
- 30 epochs
- Gaussian neighborhood size

Method

- neighbourhood size and learning rate annealing
- training random dead unit
- training dead units for novel inputs

Neighbourhood size and learning rate annealing

- standard approach
- two phases
 - initial organization phase
 - start off with big neighbourhood size and quickly (within few epochs) get to small neighbourhood size
 - fine-tuning phase
 - fine-tuning neuron weights
 - (xA, yA) starting point
 (xB, yB) breaking point
 (xC, yC) end point



Neighbourhood size and learning rate annealing

- explored all combinations for
 - breaking points in 1st, 3rd, 7th and 12th epoch
 - breaking point learning rates: 0.1, 0.2, 0.5
 - initial neighbourhood sizes: 2, 5, 10, 20, 50, 100
- hypothesis
 - starting with larger neighbourhood sizes can help minimize the number of dead units

Neighbourhood size and learning rate annealing

Breakir	ng point	Initial sigma										
alpha: 0.2		2.0	<mark>5.0</mark>	10.0	20.0	50.0	100.0					
int	1	13.00%	11.25%	9.50%	12.75%	12.00%	11.75%					
pod	3	10.50%	9.00%	13.50%	7.50%	13.25%	11.75%					
ing	7	10.50%	13.00%	7.00%	10.50%	11.30%	10.50%					
eak	12	12.25%	8.75%	9.50%	11.25%	7.75%	9.00%					
B	20	10.00%	10.50%	9.75%	10.00%	10.75%	9.75%					

(5) Percentage of dead units for each parameter combination using first method.

Breakin	ig point	Initial sigma										
alpha	a: 0.5	2.0	5.0	10.0	20.0	50.0	100.0					
int	1	8.75%	9.50%	9.75%	11.25%	9.75%	9.25%					
bod	3	10.25%	8.50%	11.00%	9.25%	11.00%	11.25%					
ing	7	11.00%	12.00%	11.50%	12.50%	11.50%	10.50%					
eak	12	10.00%	8.50%	9.50%	10.00%	10.75%	10.00%					
B	20	11.50%	12.00%	11.25%	9.75%	12.25%	12.50%					

- extra step after each epoch
- randomly choose dead unit
- find closest input datum
- adapt dead units weights and weights of its neighbourhood with this datum

- two variants
 - remove dead unit from map of dead units
 - keep dead unit in map of dead units
- hypothesis
 - \circ ~ eliminate dead neurons by forcing them to adapt

• keeping the dead unit in map of dead units achieved better results (8.25-13.75% vs 7-13% of dead units)

Breaking point alpha: 0.2				Initial	sigma			Breakin	g point	Initial sigma						
		2.0	5.0	10.0	20.0	50.0	100.0	alpha: 0.2		2.0	5.0	10.0	20.0	50.0	100.0	
point	1	11.75%	10.25%	11.50%	10.50%	11.00%	11.50%	nt	1	11.75%	9.75%	13.00%	8.00%	11.00%	10.50%	
	3	10.25%	11.00%	12.25%	9.50%	11.75%	11.25%	ing poi	3	12.75%	11.50%	11.50%	11.25%	12.25%	10.00%	
ing	7	11.00%	9.00%	11.50%	10.75%	10.25%	11.50%		7	13.00%	10.25%	10.00%	13.00%	13.25%	12.50%	
eak	12	9.00%	10.00%	9.00%	10.00%	9.25%	9.25%	eak	12	7.00%	11.25%	11.00%	10.00%	12.00%	9.25%	
Ā	20	11.75%	11.00%	10.25%	9.75%	12.50%	10.25%	D	20	11.00%	12.50%	11.25%	11.00%	9.50%	12.50%	

(6) Results for variant that removed dead unit from the map of dead units.

(7) Results for variant that kept dead unit in the map of dead units.

Training dead units for novel inputs

- are neurons weights similar enough to the input datum?
- threshold variable
 - some digits are not clearly separable

- choosing threshold
 - calculate mean Euclidean distance for inputs of the same category
 - calculate cross-category Euclidean distances

Training dead units for novel inputs

- two variants
 - dead units are adapted with learning rate according to annealing scheme
 - dead units are adapted with constant learning rate (1.0)
- hypothesis
 - potential better clusterization
 - novelty inputs mapped to unused neurons

• using decayed learning rate according to annealing scheme achieved slightly better results

Breaking point alpha: 0.1				Initial	sigma			Breaking po	oint	Initial sigma						
		2.0	5.0	10.0	20.0	50.0	100.0	alpha: 0.1		2.0	5.0	10.0	20.0	50.0	100.0	
Breaking point	1	11.00%	11.50%	8.50%	10.00%	10.50%	11.50%	Ĕ	1	13.80%	13.30%	13.50%	14.30%	15.00%	9.80%	
	3	13.25%	13.00%	10.50%	10.50%	10.75%	9.25%	poi	3	11.50%	12.00%	13.30%	15.30%	12.30%	12.50%	
	7	10.00%	7.50%	10.50%	10.50%	9.75%	11.00%	ing	7	10.80%	12.30%	12.00%	14.00%	10.00%	13.80%	
	12	13.25%	9.50%	12.25%	8.00%	11.50%	10.75%	eak	12	10.30%	11.30%	10.00%	10.80%	13.50%	15.50%	
	20	10.50%	12.75%	9.00%	12.25%	12.25%	12.75%	B	20	11.30%	9.00%	9.80%	14.00%	13.30%	15.00%	

(8) Results for variant that used decayed learning rate.

(9) Results for variant that used constant 1.0 learning rate.

1. Big neighborhood size (baseline)	2. Remove DU from dead_units list after adapting it	2. Keep DU in dead_units list after adapting it	3. Threshold = 0.4, Learning rate depends on decay	3. Threshold = 0.5, Learning rate depends on decay
Breaking point Initial sigma alpha: 0.1 2.0 5.0 10.0 20.0 50.0 100.0 ਦ 1 13.50% 11.50% 10.50% 11.75% 12.25% 10.50% 2 1 3.50% 11.75% 12.25% 10.50%	Breaking point Initial sigma alpha: 0.1 2.0 5.0 10.0 20.0 50.0 100.0 E 1 13.75% 12.00% 12.75% 12.50% 100.0% J 0.00% 0.75% 0.75% 0.75% 10.0% 0.75% 10.76%	Breaking point Initial sigma alpha: 0.1 2.0 5.0 10.0 20.0 50.0 100.0 Ξ 1 11.75% 11.50% 12.25% 10.75% 11.00% 10.75% Ξ 1 0.75% 11.50% 12.55% 10.75% 11.00% 10.75%	Breaking point Initial sigma alpha: 0.1 2.0 5.0 10.0 20.0 50.0 100.0 Ξ 1 11.00% 11.50% 8.50% 10.00% 15.0% 11.50% Ξ 2 12.55% 0.50% 10.00% 10.50% 15.0%	Breaking point alpha: 0.1 Initial sigma 12.00% 10.0 20.0 50.0 100.0 1 12.00% 11.75% 11.25% 11.05% 12.5% 11.25% 1 21.00% 11.72% 11.26% 0.76% 10.0% 12.5% 11.05%
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Neighborhood size and learning rate annealing
 Training random dead unit
 Training dead units for novel inputs

Neighborhood size and learning rate annealing
 Training random dead unit
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0.313

(10) Average percentage of dead units across methods.

(11) Average quantization error across methods.





(12) Quantization error convergence across methods.

- what could be improved based on results
- first method
 - values of neighbourhood size seems to depend on the size of SOM
- second method
 - no significant dependencies
- third method
 - not reliable in current state
 - correct threshold is extremely data dependent

- third method bonus experiment
 - for each neuron, remember how much training it got
 - if threshold not satisfied, choose neuron with least training received
 - \circ $\,$ early results not good for SOM $\,$
 - under-trained neurons disrupt clustering property of SOM

Future work

- different SOM sizes
 - with more neurons than training examples
- train on more datasets
- finer exploration of threshold variable
- criterion function

Thank you for your attention

Questions

- Akým spôsobom získané výsledky závisia od konkrétneho datasetu a konkrétnej veľkosti mapy?
 - o priamo
 - problém separability
 - neuróny nútené reprezentovať viac kategórií dát
 - väčšia mapa by nám mohla pomôcť vidieť väčšie rozdiely medzi navrhnutými metódami
- Ktoré parametre by bolo treba upraviť, keby bola SOM oveľa väčšia?
 - veľkosť okolia v štartovacom bode
 - veľkosť okolia v "breaking" bode
 - ostatné parametre nie sú závislé od veľkosti SOM

Questions

- Aký všeobecný záver resp. odporúčania by ste vyvodili?
 - vyskúšať viac veľkostí SOM
 - vyskúšať viac rôznych datasetov