Convolutional neural networks with dynamic convolution for time series classification

Krisztian Buza, Margit Antal Department of Mathematics-Informatics Sapientia Hungarian University of Transylvania Targu Mures, Romania buza@biointelligence.hu, manyi@ms.sapientia.ro

Introduction: time series classification

Example: Signature Verification



Image: https://commons.wikimedia.org/wiki/File:Online signture.jpg

Introduction: time series classification

Example: Signature Verification



Image: https://commons.wikimedia.org/wiki/File:Online signture.jpg

Introduction: time series classification

Example: Signature Verification



Buza, Antal: Convolutional neural networks with dynamic convolution for time series classification buza@biointelligence.hu

Time series classification methods

Fawaz, H.I., Forestier, G., Weber, J., Idoumghar, L., Muller, P.A.: Deep learning for time series classication: a review. Data Mining and Knowledge Discovery 33(4), pp. 917 – 963 (2019)

Buza, K.: Time series classification and its applications. In: Proceedings of the 8th International Conference on Web Intelligence, Mining and Semantics, pp. 1 - 4 (2018)

Convolution with max pooling





translations of local patterns: irregular robustness

Dynamic convolution



Our contribution

- Dynamic convolution
 - Replace dot product in convolution by dynamic time warping calculations
- Neural networks with dynamic convolution
 - Replace the first convolutional layer by a *dynamic* convolutional layer

Experimental evaluation

- Data: real-world time series datasets from "The UEA & UCR Time Series Classification Repository" – www.timeseriesclassification.com
- Two convolutional neural network architectures: Net1 and Net2
- Two version of both Net1 and Net2:
 - (a) with conventional convolution
 - (b) with dynamic convolution
- 10-fold cross-validation, t-test
- Codes: https://github.com/kr7/DCNN

Results

Dataset	Net1		Net2	
	CNN	DCNN	CNN	DCNN
Adiac	0.506 ± 0.061	$0.575 {\pm} 0.046 \bullet$	0.558 ± 0.052	$0.640 {\pm} 0.055 \bullet$
ArrowHead	0.886 ± 0.064	$0.896{\pm}0.083$ \circ	$0.900{\pm}0.062$	$0.887 {\pm} 0.082$ \circ
Beef	0.733 ± 0.170	$0.800 {\pm} 0.163 \bullet$	0.700 ± 0.180	$0.783 {\pm} 0.130 \bullet$
EarthQuakes	$0.725 {\pm} 0.042$	$0.733{\pm}0.069$ \circ	0.699 ± 0.072	$0.731{\pm}0.063$ \circ
ECG200	$0.870 {\pm} 0.050$	$0.890{\pm}0.044{\rm ~\circ}$	0.865 ± 0.084	$0.870{\pm}0.064$ \circ
FiftyWords	0.702 ± 0.033	$0.714{\pm}0.045$ \circ	0.686 ± 0.034	$0.715 {\pm} 0.027 \bullet$
Plane	$0.981 {\pm} 0.032$	$0.990{\pm}0.029$ \circ	0.976 ± 0.032	$0.995{\pm}0.014$ •
SwedishLeaf	$0.864{\pm}0.041$	$0.883 {\pm} 0.027 \bullet$	0.862 ± 0.036	$0.881{\pm}0.033$ \circ
WordSynonyms	$0.682 {\pm} 0.031$	$0.714{\pm}0.050$ •	0.681 ± 0.049	$0.727 {\pm} 0.047 \bullet$
Yoga	$0.951 {\pm} 0.013$	$0.960 {\pm} 0.012 \bullet$	0.945 ± 0.022	$0.959{\pm}0.008$ \circ
	1			

Conclusions

- Dynamic convolution: dynamic time warping calculations instead of dot product
- Our experimental evaluation shows that neural networks with dynamic convolution outperform "usual" convolutional neural networks in case of various time series classification tasks
- Codes: https://github.com/kr7/DCNN