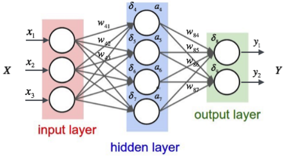
Tuning and extending artificial neural networks used in automatic phase identification of detections at 3-component seismic stations of the International Monitoring System

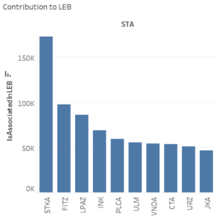
Radek Hofman, Elena Tomuta, Ronan Le Bras

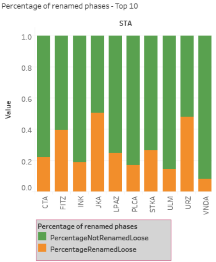
International Data Centre
Preparatory Commission for the Comprehensive Nuclear-Test-Ban Treaty Organization



- Initial wave type (iwt) is determined using StaPro (Station Processing) software for all IMS arrivals detected at IDC
  - iwt∈{noise, regional S, regional P, teleseismic}
  - initial wave type is further refined to more specific wave types
- For 3-component stations the system relies on a cascade of three binary classifiers implemented as neural networks (NNs)
- Current NN weights were derived in 2002 using data from a single station (STKA) and are applied to all 3-component stations worldwide
- We now have much more station specific data reviewed by analysts
- Our goal is to investigate if the classification performance of 3-component seismic stations can be improved by re-training using more station-specific data

- Performance of 3-component stations varies:





- We did re-training of URZ (a highly contributing station with above average iwt classification error) using data up to 2017
- New weights were tested against 2017 data with results:

	Correct classification rate				
iwt class	regional S	regional P	teleseismic	noise	TOTAL
old (left)	50.4%	76.82%	43.77%	49.73%	49.89%
new (right)	**74.35%**	**77.92%**	**50.07%**	**67.84%**	**67.13%**

Presentation outline

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- Neural networks in StaPro
- Algorithm and its inputs
- Why re-tunig effort?
- Ingredients needed
- Dataset
- Re-training details
- Results on validation set
- Results on test set (Jan-Nov 2017)
- Conclusions and future plans

Neural networks in StaPro

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- Neural networks (NNs) are used in StaPro for initial wave type (iwt) determination for three-component (3C) stations
- The purpose is to assign an initial wave type to each arrival: noise (**N**), regional S (**regS**), regional P (**regP**) or teleseismic (**tele**)
- Given iwt, StaPro further refines the wave type using a Bayesian model:

iwt	sub-categories
noise	—
regional S	Sn, Lg, Rg, Sx
regional P	Pn, Pg, Px
teleseismic	P, tx

- This gets saved into IDC database and is used in further processing

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- The system comprises of a cascade of three binary classifiers
  - Step 1: the system tries to distinguish between noise **N** and a signal {**regS**, **regP**, **tele**}
  - Step 2: if signal: is it **regS** or {**regP**, **tele**}?
  - Step 3: if {**regP**, **tele**}: is it **regP** or **tele**?
- All three classifiers are implemented as a multilayer perceptron (neural network)

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1. SERENO, T. and PATNAIK, G., Initial Wave-type Identification with Neural Networks and its Contribution to Automated Processing in IMS Version 3.0, Technical Report, SAIC-93/1219, 1993
2. WANG, J., Adaptive training of neural networks for automatic seismic phase identification. Monitoring the Comprehensive Nuclear-Test-Bant Treaty: Data Processing and Infrasound (2002): 1021-1041.

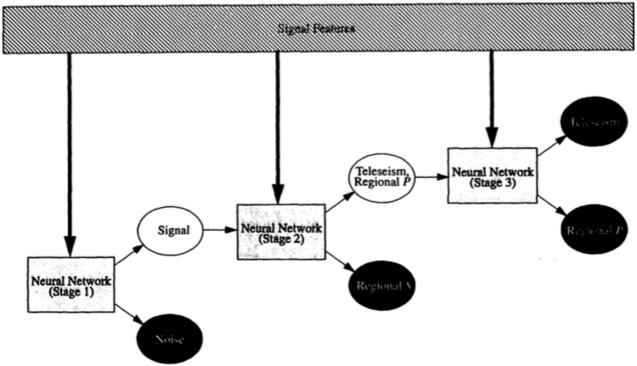

Figure 19. A schematic representation of our neural network approach to solving the 4-class initial wave-type identification problem is shown.

*Figure from (Sereno and Patnaik, 1993)

All three NNs in the cascade have the same topology: input layer of size 15, hidden layer of size 6, output layer of size 2, all dense with sigmoid activation (total 110 tunable weights)

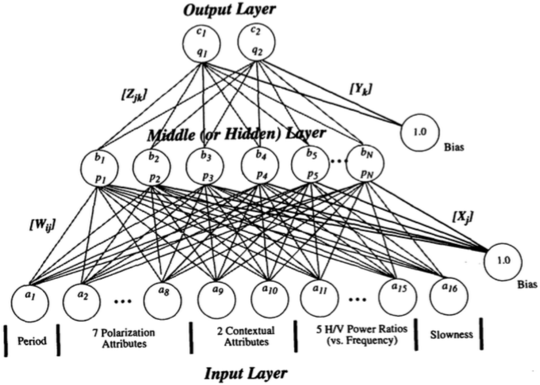

*Figure from (Sereno and Patnaik, 1993)

Inputs (classification features)

Initial wave type is determined using a set of features computed along with detection of arrivals:

#	Feature	Description	Source	Norm.
1	*period*	Dominant period of the detected phase	ARRIVAL	
2	*rect*	Signal rectilinearity	APMA	
3	*plans*	Signal planarity	APMA	
4	$inang_1$	Long-axis incidence angle	APMA	$/90$
5	$inang_3$	Short-axis incidence angle	APMA	$/90$
6	*hmxmn*	Ratio of the maximum to minimum horizontal amplitude	APMA	$\log_{10}$
7	*hvratp*	Ratio of horizontal-to-vertical power	APMA	$\log_{10}$
8	*hvrat*	Similar to *hvratp*, measured at the time of the maximum 3C amplitude	APMA	$\log_{10}$
9	$N_{after} - N_{before}$	Difference between the no. of arrivals before and after within $\pm 60s$	on the fly	$/10$
10	$T_{after} - T_{before}$	Mean time difference between arrivals before and after within $\pm 60s$	on the fly	$/100$
11	$htov_1$	Horiz. to vert. power ratio in octave freq. band centered at 0.25 Hz	AMP3C	$\log_{10}$
12	$htov_2$	Horiz. to vert. power ratio in octave freq. band centered at 0.5 Hz	AMP3C	$\log_{10}$
13	$htov_3$	Horiz. to vert. power ratio in octave freq. band centered at 1.0 Hz	AMP3C	$\log_{10}$
14	$htov_4$	Horiz. to vert. power ratio in octave freq. band centered at 2.0 Hz	AMP3C	$\log_{10}$
15	$htov_5$	Horiz. to vert. power ratio in octave freq. band centered at 4.0 Hz	AMP3C	$\log_{10}$

A brief history

- According to *Sereno and Patnaik, (1993*), the iwt classification system was created in early 1990s (as en extension of a two class system P vs. S) and became part of IMS v3 (IMS stands here for *Intelligent Monitoring System*)
- Station-specific weights were trained using analyst-reviewed data for two 3C stations which had enough data
- For the rest of stations "average" weights yielded by training using data from multiple stations were produced
- Around 2002 the weights have been re-trained using data from STKA station, see *(J. Wang, 2002)*
- Since then, these weights are used as weights for all 3C stations in IMS (IMS stands here for *International Monitoring System*)

Why re-training effort?

- Is it correct to use weights derived using a single station data globally?
- Can we do better if the weights were derived for each station individually using station specific data?
- Nowadays, there is much more analyst-reviewed data than before ($\sim$ 20 years)
- Re-training means just a change in configuration of StaPro – if we keep the original topology of NNs then no code changes are needed

Ingredients needed for successful re-training

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1. **Training data** - For neural network it holds true the more, the better
2. **Back-propagation algorithm** - The algorithm for NN training
   - Unfortunately, the original C code used for training we do not have. However, the generic nature of NNs and a domain knowledge allows us to use an arbitrary NN library for the training
3. **A way to translate weights from re-training into StaPro configuration files**
   - We need to produce and alternate weights file and replace with it the original one in StaPro
4. **A simulated pipeline which can be run with the alternate weight file**
   - This gives us an alternate iwt classification which we can evaluate against analyst-reviewed data in a test set

Ingredients needed for successful re-training

1. **Training data** - We chose to start with URZ station
   - It is one of the most data rich stations and its current iwt classification performance is around 50%
2. **Back-propagation algorithm** - We use Python library Keras backed by Theano
3. **A way to translate weights from re-training into StaPro configuration files**
   - We analyzed the C code and created a script putting the new weights into a weights file template in the right order
4. **A simulated pipeline which can be run with the alternate weight file**
   - We are able to run StaPro using the Station Tuning framework

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- **Training dataset:** analyst reviewed URZ arrivals **2003-2016**
  - Signal phases are selected randomly from all automatic arrivals associated to LEB
  - Noise phases are selected randomly from all automatic arrivals classified as noise and not associated to LEB
  - Training data is split on training and validation data in ratio 9:1 (22982 arrivals to 2554)
  - 25536 noise phases, 8512 regS phases, 8512 regP phases and 8512 tele phases (we aimed for ratio 3:1:1:1 in order to have a balanced dataset)
- **Test dateset:** analyst reviewed URZ arrivals **Jan-Nov 2017**
- Dataset used by *Wang, (2002)* comprised of $\sim$ 1500 phases for all 4 classes

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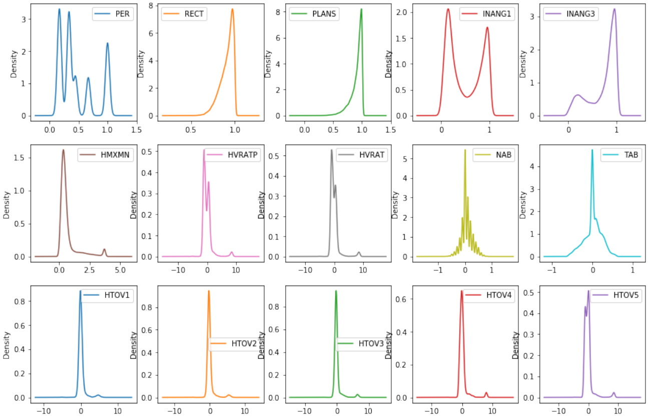
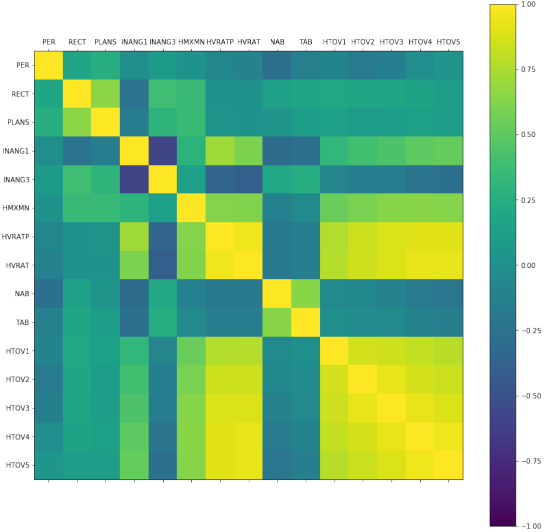
Density plot of all features in training dataset. Some densities are multimodal.




PER
RECT
PLANS
INANG1
INANG3
HMXMN
HVRATP
HVRAT
NAB
TAB
HTOV1
HTOV2
HTOV3
HTOV4
HTOV5
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

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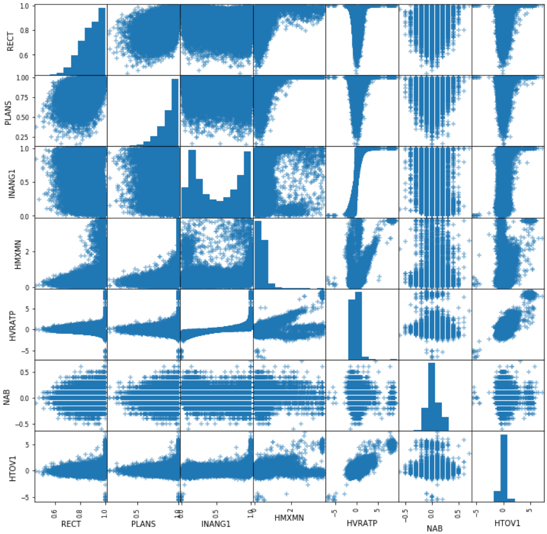
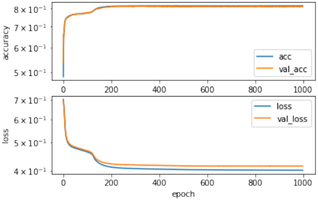
Correlation matrix for selected features. Only selected representatives from groups of highly correlated features (e.g. HTOV1-HTOV5) are included.



- For re-training we used a Python-based stack (Jupyter Notebook, Keras, Numpy, Pandas)
- Training took several minutes on a commodity HW
- Trained weights were exported in the format corresponding with the original weight file ingested by StaPro

- Training parameters for all three networks:
  - **batch size:** 512
  - **number of epochs:** 1000
  - **loss:** binary cross-entropy
  - **optimizer:** adam



Comparison of confusion matrices for old and new weights

Old weights				
		true phase		
		P	S	T
iwt	N	140	297	133
	P	**565**	64	203
	S	26	**509**	155
	T	72	17	**373**
accuracy: **56.65%**				

New weights				
		true phase		
		P	S	T
iwt	N	39	67	43
	P	**601**	1	143
	S	5	**735**	158
	T	158	84	**520**
accuracy: **72.67**%				

Test set: URZ arrivals 2017/01/01 - 2017/11/30

	phase class (associated)				TOTAL
	reg S	reg P	tele	N	
#	581	643	1997	32525	35746

Evaluation metrics:

Correct classification rate

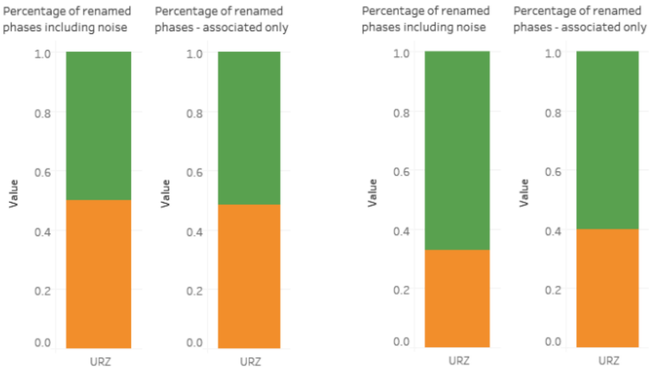
Ratio of the correctly classified phases to the total number of phases (the higher the better).

N-phase rate

Percentage of associated phases incorrectly identified as noise in the automatic bulletin (the lower the better).

Test set results – summary

Old weights (left): associated phases **51.56%**, including noise **49.89%**
New weights (right): associated phases **60.01%**, including noise **67.13%**



Results by iwt sub-category (associated)

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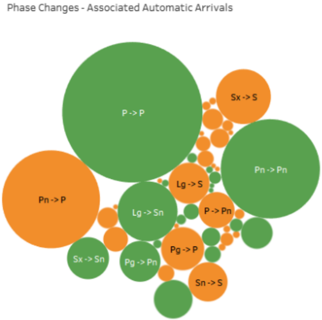
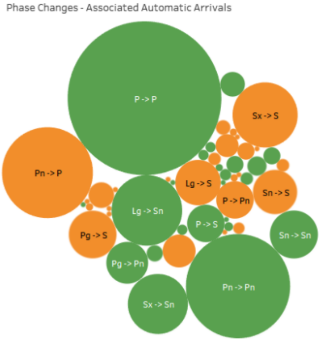
	Correct classification rate			
iwt class	regional S	regional P	teleseismic	TOTAL
old weights (left)	50.4%	76.82%	43.77%	51.56%
new weights (right)	**74.35%**	**77.92%**	**50.07%**	**60.01%**





Results by iwt sub-category (including noise)

	Correct classification rate				
iwt class	regional S	regional P	teleseismic	noise	TOTAL
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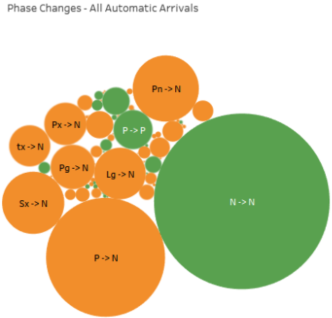

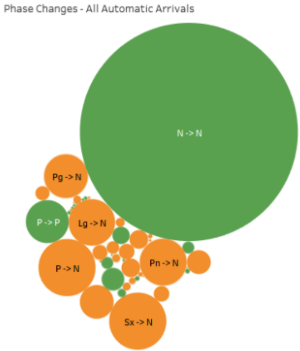

Results – N-phase rate

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N-phase rate

Percentage of associated phases incorrectly identified as noise in the automatic bulletin.

- N phases in the automatic bulletin would not be associated to form and locate events by the automatic system $\Rightarrow$ reducing the number of N phases that must be renamed and associated in the final analyst bulletin would reduce the load of analysts

	N-phase rate			
	regional S	regional P	teleseismic	TOTAL
old weights	39.41%	12.60%	16.68%	19.96%
new weights	**13.94%**	**12.60%**	**11.37%**	**12.08%**

Conclusion and future plans

- The re-training using more data looks promising so far, classification accuracy on test data set is higher than with the old weights
- Our goals is to create a re-training software which would enable us to easily create new station-specific weight files for all 3C stations
- In the next phase we want to evaluate if the performance can be increased using a classifier
  - Replace the cascade of three NNs with a single classifier for all four classes
  - Do not use precomputed features but classify on the level of samples using recurrent or convolution networks