Tuning and performance monitoring: Re-tuning artificial neural networks in StaPro

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Presentation outline

- Introduction — neural networks in StaPro
- Algorithm and its inputs
- Why re-tunnig effort?
- First results
- Conclusion 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 telesesmic (**tele**)
- Given iwt, StaPro further refines the wave type using a Bayesian model:

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

- This gets saved in IDCX.ARRIVAL table as IPHASE

Neural networks in StaPro

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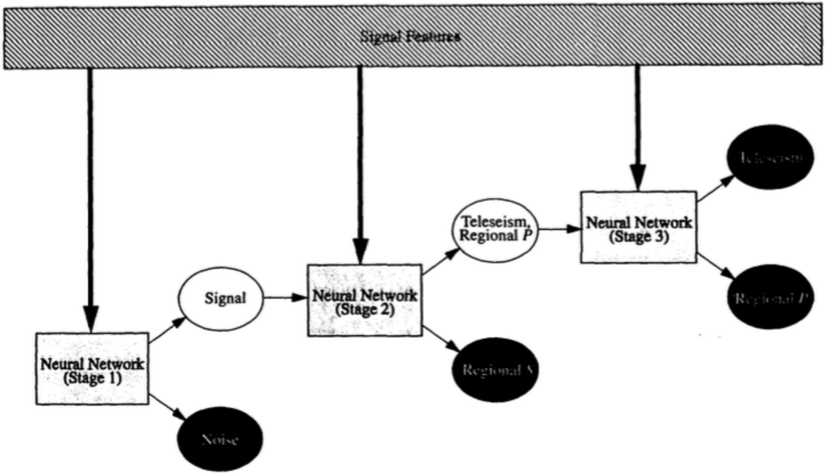
- The system comprises of a cascade of three binary classifiers
  - Step 1: the system tries to distinguish between noise **N** and a signal {**regS**, **regP**, **tele**}
  - Step 2: if signal: is it **regS** or {**regP**, **tele**}?
  - Step 3: if {**regP**, **tele**}: is it regional **P** or **tele**?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

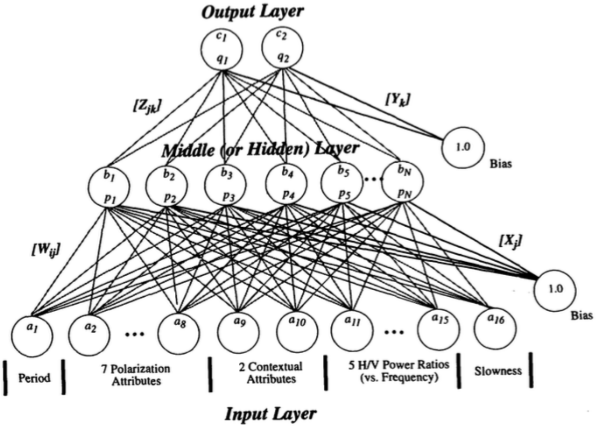
- WANG, J., Adaptive training of neural networks for automatic seismic phase identification. Monitoring the Comprehensive Nuclear-Test-Bant Treaty: Data Processing and Infrasound (2002): 1021-1041.
- SERENO, T. and PATNAIK, G., Initial Wave-type Identification with Neural Networks and its Contribution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

Cascade of three binary classifiers



Multilayer perceptron topology

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 (in total 110 parameters)



Inputs (classification features)

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#	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	$\log_{10}(\cdot)$
7	*hvratp*	Ratio of horizontal-to-vertical power	APMA	$\log_{10}(\cdot)$
8	*hvrat*	Similar to *hvratp*, measured at the time of the maximum 3C amplitude	APMA	$\log_{10}(\cdot)$
9	$N_{after} - N_{before}$	Difference between the number of arrivals before and after the arrival within $\pm 60s$	on the fly	$/ = 10$
10	$T_{after} - T_{before}$	Mean time difference between the arrivals before and after within $\pm 60s$	on the fly	$/ = 100$
11	$htov_1$	Horizontal-to-vertical power ratio in an octave frequency band centered at 0.25 Hz	AMP3C	$\log_{10}(\cdot)$
12	$htov_2$	Horizontal-to-vertical power ratio in an octave frequency band centered at 0.5 Hz	AMP3C	$\log_{10}(\cdot)$
13	$htov_3$	Horizontal-to-vertical power ratio in an octave frequency band centered at 1.0 Hz	AMP3C	$\log_{10}(\cdot)$
14	$htov_4$	Horizontal-to-vertical power ratio in an octave frequency band centered at 2.0 Hz	AMP3C	$\log_{10}(\cdot)$
15	$htov_5$	Horizontal-to-vertical power ratio in an octave frequency band centered at 4.0 Hz	AMP3C	$\log_{10}(\cdot)$

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

1. **Train/Test Datasets** - For neural network it holds true that the more, the better
2. **Back-propagation algorithm** - The algorithm for NN retraining
   - Unfortunately, the original C code used for training we do not have. However, the generic nature of NNs and a domain knowledge allows us (hopefully) 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 IDCX.ARRIVAL table with new IPHASE
5. **Evaluation script which compares the success rate of the new classification vs. the old one**

Ingredients needed for successful re-training

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1. **Train/Test Datasets** - We chose to start with URZ station
   - It is one of the most data rich stations and its current IWT 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 analysed the C code and created a script puting the new weights into the 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
5. **Evaluation script which compares the success rate of the new classification vs. the old one**
   - This still needs to be done but we plan to match arrivals in the new table with those in REB using proximity of arrival attributes

URZ dataset

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We also rely on analyst-reviewed data. Our URZ dataset is comprised of:

- 27399 noise phases, 9133 regS phases, 9133 regP phases and 9133 tele phases (we aimed for ratio 3:1:1:1 in order to have a balanced dataset)
  - In the dataset used by Wang, (2002) was $\sim$ 1500 phases for all 4 classes
- Signal phases are selected randomly from all automatic arrivals associated to REB
- Noise phases are selected randomly from all automatic arrivals classified as noise and not associated to REB
- The dataset is split on train and test data as 3:1

URZ — preliminary results

Confusion matrix of test data

Re-trained weights				
	N	P	S	T
N	**5687**	238	609	292
P	346	**1687**	14	473
S	653	5	**1651**	374
T	164	318	74	**1115**
accuracy **75%**				

URZ — preliminary results

- Comparison of classification capabilities of regS, regP and tele classes for original and new weights

Old weights				
	N	P	S	T
N	—	337	829	380
P	—	**1655**	170	540
S	—	45	**1312**	351
T	—	211	37	**983**
accuracy **57.66%**				

Re-trained weights				
	N	P	S	T
N	—	238	609	292
P	—	**1687**	14	473
S	—	5	**1651**	374
T	—	318	74	**1115**
accuracy **65.01%**				

Classification of noise phases

- We take all URZ noise phases we have and which were not used for training — 273972 noise phases

Re-trained weights				
	N	P	S	T
N	**226601**	—	—	—
P	14624	—	—	—
S	25745	—	—	—
T	7002	—	—	—
accuracy **82.71%**				

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
- If URZ re-training successful, 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