# Practical application of artificial neural networks for seismic event detection

J. Doubravová and J. Horálek

Institute of Geophysics, Dpt. of Seismology

CzechGeo Workshop, 5.12.2018

# Outline



- 2 SLRNN and training
  - WEBNET
  - Single Layer Recurrent Neural Network
  - SLRNN training

# 3 Results

- False detections
- Undetected events

## 4 Application

- Application to Webnet
- Application to Reykjanet

# Motivation

### continual data produced by dense seismic networks must be reduced

• detection of seismic events should:

- minimize false detections
- detect also weak events.
- neural networks can extract useful information, forward problem is solved fast

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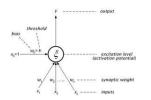
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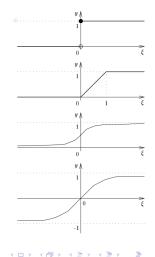
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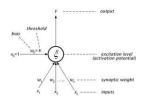
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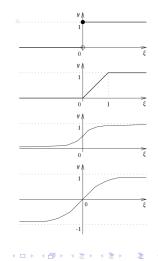




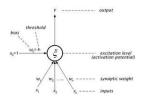
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- weights w = synaptic weights, bias w<sub>0</sub> = -h threshold
- activation potential  $\xi = \sum_{i=0}^{n} w_i x_i$
- activation function  $y = \sigma(\xi) = \begin{cases} 1, & \xi \ge 0 \\ 0, & \xi < 0 \end{cases}$

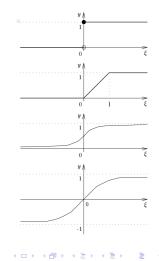


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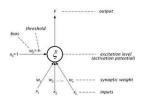


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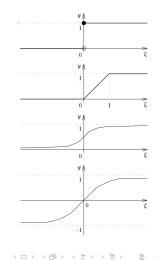
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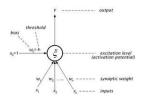


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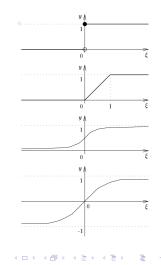
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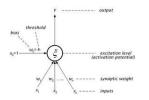
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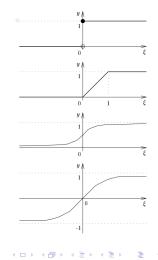


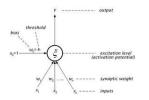
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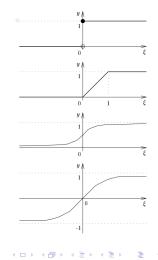


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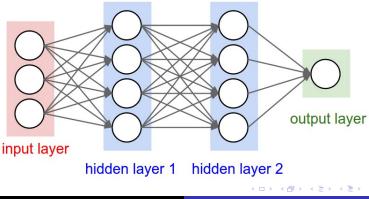


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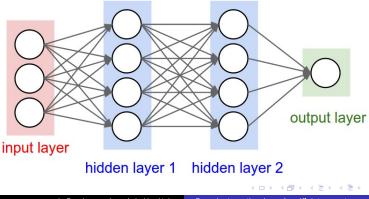
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- typical tasks: classification, pattern recognition, regression



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WEBNET Single Layer Recurrent Neural Network SLRNN training

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### WEBNET

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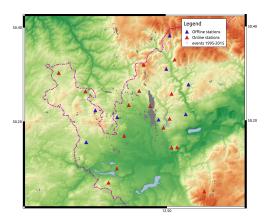
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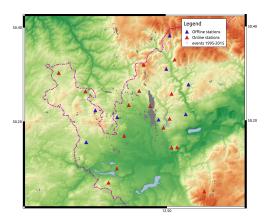
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- 250Hz, 3C velocity records

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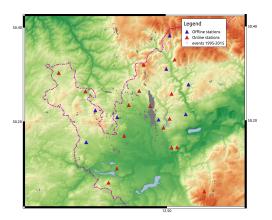
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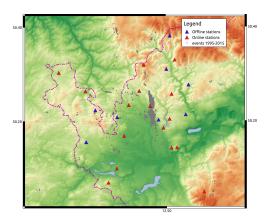


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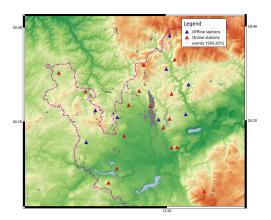


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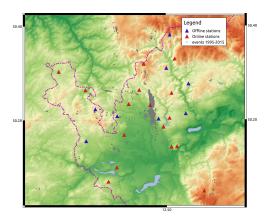


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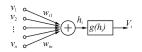
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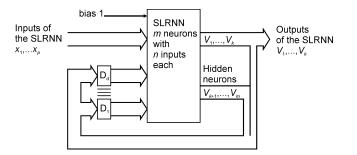
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- outputs fed back as inputs = recurrence, memory
- variable delay  $D_1...D_d$





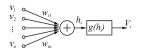
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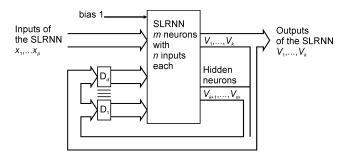
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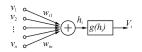


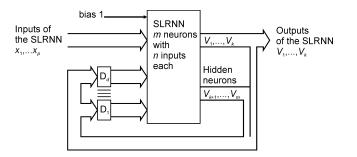
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WEBNET Single Layer Recurrent Neural Network SLRNN training

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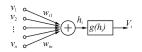


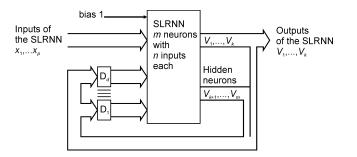
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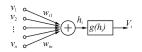


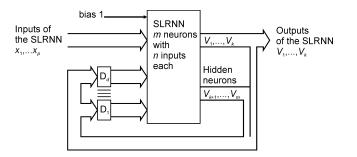


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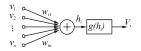


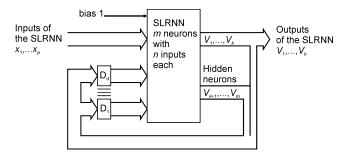


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# SLRNN - architecture

- 8 neurons, 18 inputs, 3 outputs (event, P, S)
- delays 1, 2, 4, and 8 samples 4x8=32 feedbacks





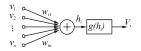
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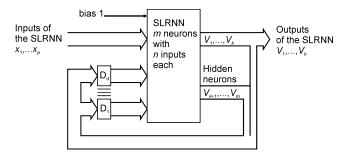
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WEBNET Single Layer Recurrent Neural Network SLRNN training

# SLRNN - architecture

- 8 neurons, 18 inputs, 3 outputs (event, P, S)
- delays 1, 2, 4, and 8 samples 4x8=32 feedbacks



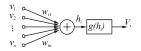


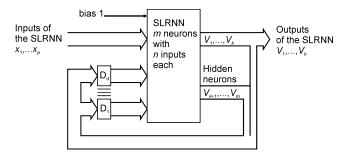
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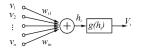


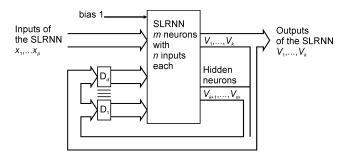
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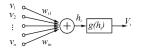


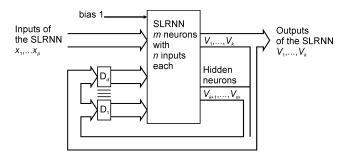


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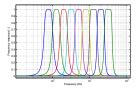




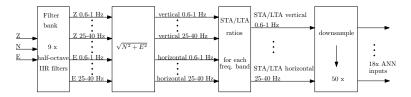
WEBNET Single Layer Recurrent Neural Network SLRNN training

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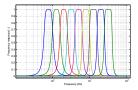
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WEBNET Single Layer Recurrent Neural Network SLRNN training

# SLRNN - data preprocessing

- STA/LTA in 9 narrow-band filtered velocity records
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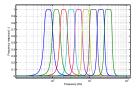


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WEBNET Single Layer Recurrent Neural Network SLRNN training

# SLRNN - data preprocessing

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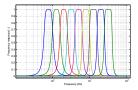




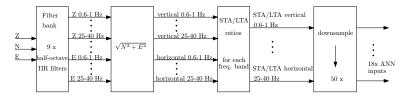
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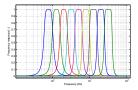


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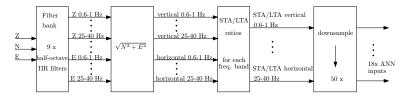
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WEBNET Single Layer Recurrent Neural Network SLRNN training

# Outline

#### Artificial neural networks

#### 2 SLRNN and training

- WEBNET
- Single Layer Recurrent Neural Network
- SLRNN training

#### 3 Results

- False detections
- Undetected events

#### Application

- Application to Webnet
- Application to Reykjanet

WEBNET Single Layer Recurrent Neural Network SLRNN training

# Training

- supervised learning: searching w<sub>ij</sub> to fit required outputs for training set
- cost function minimization by Back Propagation Through Time (gradient based method, back propagation of error modification for recurrent networks)

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#### Data

- seismic swarm 2008 (events) and calm year 2010 (disturbances) WEBNET (West Bohemia)
- events of various magnitudes, locations, mechanisms...
- disturbances of different nature -blasts, regional and teleseismic ev., wind, stroms...
- training set divided (randomly)
  - actual training data (80%)
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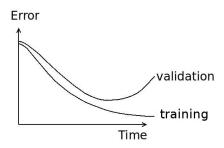
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WEBNET Single Layer Recurrent Neural Network SLRNN training

# Training and overtraining

#### • training continues until the validation set error decreases

 cost function strongly nelinear! = more attempts from randomly selected starting point

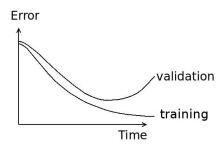


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False detections Undetected events

#### False detections ?

#### • tested on swarm 2011, single station detection

- many false detections
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Undetected events

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- 3

#### Results

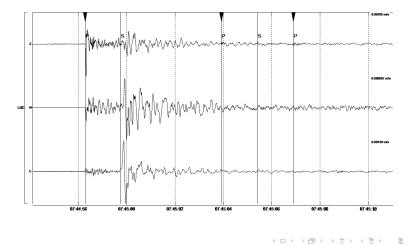
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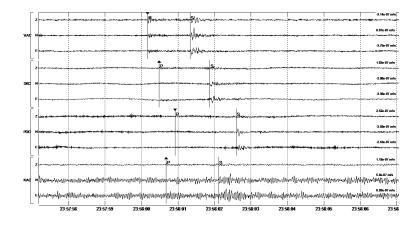
#### Undetected events Ev. $M_L = 2.3$ and $M_L = 2.2$ in coda of $M_L = 3.8$



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False detections Undetected events

# Undetected events $M_L = -0.3$ noisy record on KAC



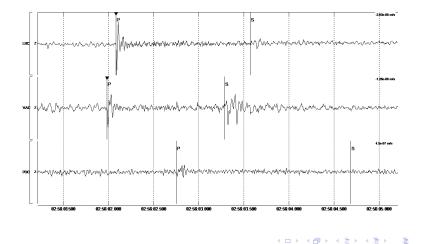
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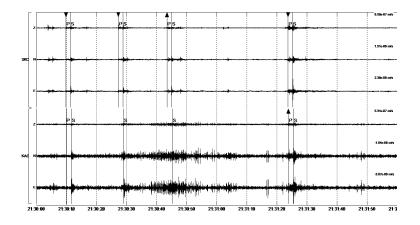
#### Undetected events weak amplitudes on POC $M_L = 0.2$



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False detections Undetected events

# Undetected events disturbances on KAC



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False detections Undetected events

#### How to solve it?

- we have high number of false detections / or very weak events
  - too much events to process
- few undetected events really unacceptable
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False detections Undetected events

#### How to solve it?

- we have high number of false detections / or very weak events
  too much events to process
- few undetected events really unacceptable
- => WE MUST USE COINCIDENCE IN THE NETWORK

Application to Webnet Application to Reykjanet

# Coincidence

- when a human processes waveforms, he takes into account all the stations at once
- let the machine see detection outputs of the stations at once
- for each detection we look for sufficient number of detections on other stations in certain time window

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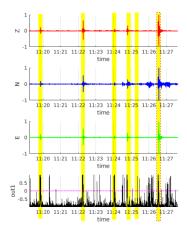
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Application to Webnet Application to Reykjanet

# Coincidence



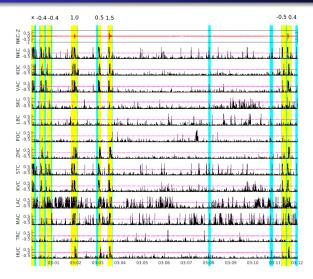
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# Coincidence 4 vs. 6



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## Concidence 4 vs. 6

- six stations seems to be enough for reasonable minimum magnitude
- time window to search for coincidence was 0.8s

Artificial neural networks SLRNN and training Results Application to Webnet Application to Reykjanet

### Concidence 4 vs. 6

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# Outline

- Artificial neural networks
- 2 SLRNN and training
  - WEBNET
  - Single Layer Recurrent Neural Network
  - SLRNN training
- 3 Results
  - False detections
  - Undetected events

#### Application

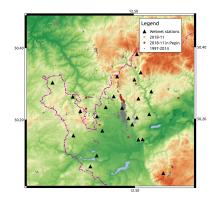
- Application to Webnet
- Application to Reykjanet

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Application to Webnet Application to Reykjanet

#### Webnet

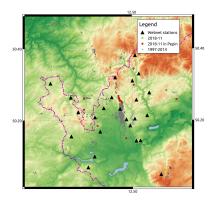
- even there is a good detection and location provided by PEPIN, there are some limitations
- especially events outside the NK focal zone could be missing



Application to Webnet Application to Reykjanet

#### Webnet

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Application to Webnet Application to Reykjanet

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#### Application

- Application to Webnet
- Application to Reykjanet

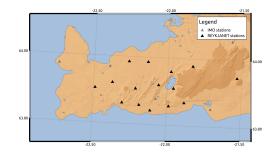
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Application to Webnet Application to Reykjanet

#### Reykjanet network

#### • south-west Iceland, Reykjanes peninsula

- 15 off-line stations
- size of the network, number of stations, earthquake swarm activity similar to WB



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Application to Webnet Application to Reykjanet

#### Reykjanet network

- south-west Iceland, Reykjanes peninsula
- 15 off-line stations
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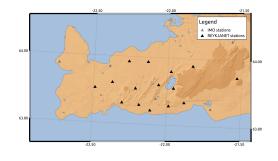


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Application to Webnet Application to Reykjanet

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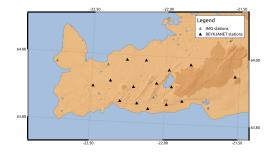


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#### Neural network

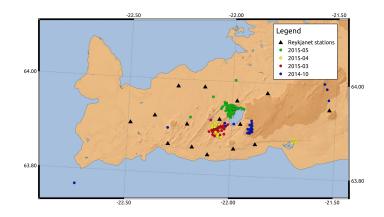
#### • the best SLRNN network trained for WEBNET



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#### Data: 4 small swarms 2014-2015



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Application to Webnet Application to Reykjanet

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Application to Webnet Application to Reykjanet

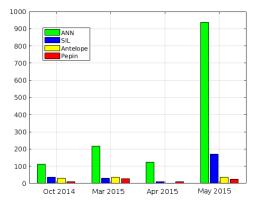
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#### Number of events



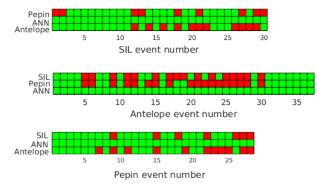
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Application to Webnet Application to Reykjanet

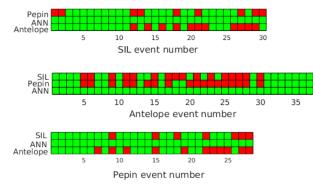
#### Porovnání jednotlivých jevů - březen 2015



- Pepin and SIL sorted by magnitude
- Antelope sorted in time

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### Porovnání jednotlivých jevů - březen 2015



- Pepin and SIL sorted by magnitude
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#### Weakest event

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### Conclusion

#### • SLRNN detector is fast and effective

- coincidence within a network solves undetected events
- coincidence reduces reasonably number of false detections
- further processing will reveal weak events as they can't be successfully localized
- the neural network trained for West Bohemia works well for Reykjanet

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# Thank you for your attention !

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