# Automatic detection of volcanic eruptions in Doppler radar observations using a neural network approach

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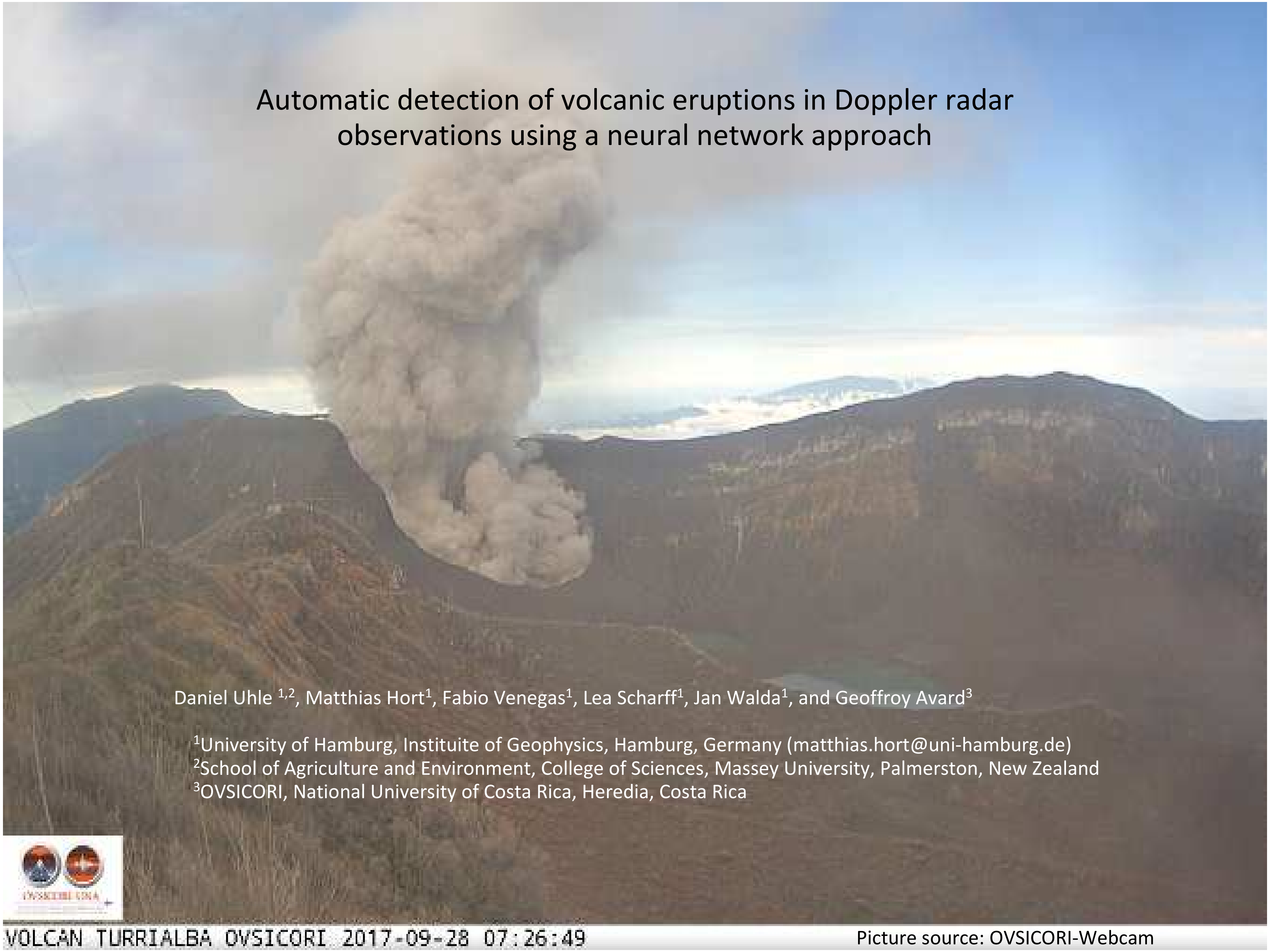


Picture source: OVSICORI-Webcam

## Idea behind the project:

- Automatically detect ash emissions of volcanoes independent of weather conditions and daylight
- Process Data at the station to minimize data transmission
- Transmit this information to local authorities

## Task

- Develop a neural network that is capable of detecting eruptions automatically

## Requirement

- a network architecture with low computational cost.
- the ability to classify data from a live stream

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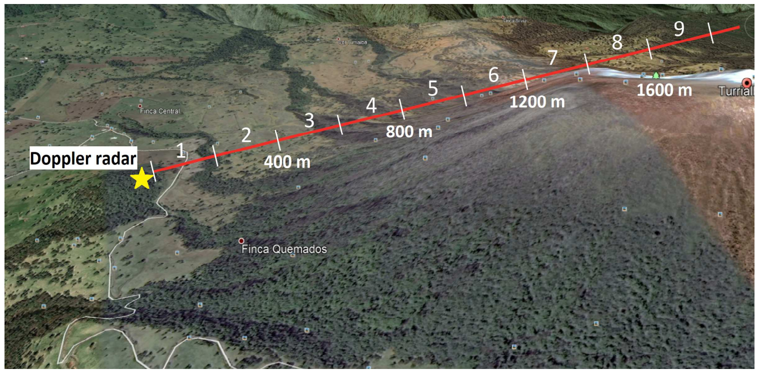
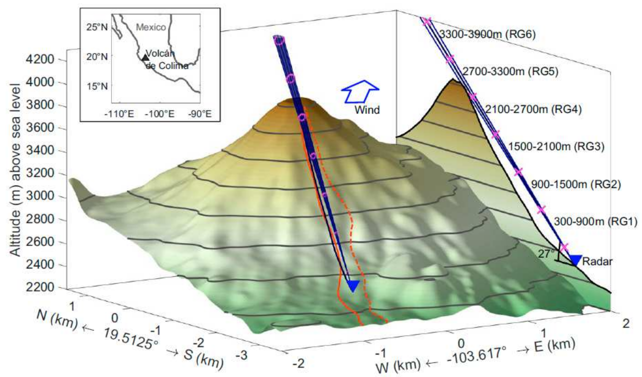
# Station setup

Turrialba, Costa Rica

Volcan de Colima, Mexico

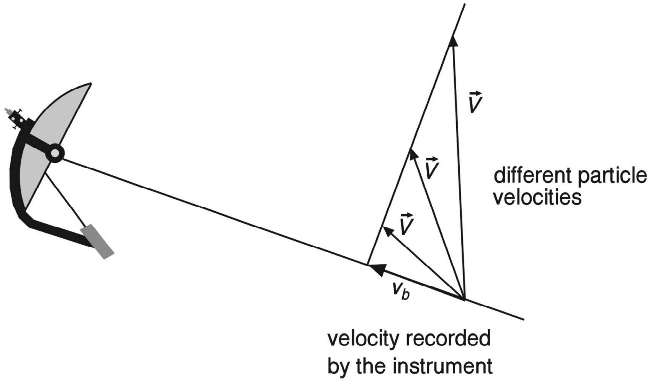


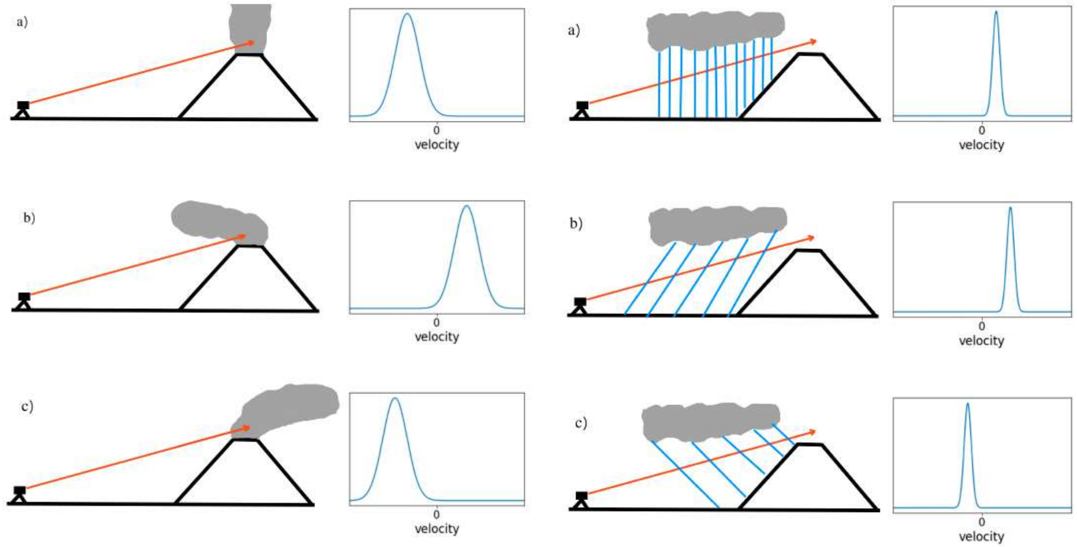



For recording the data we use a Frequency Modulated Continous Wave Radar. Range Gate resolution in case of Turrialba was 200 m and range gates RG5, RG9-RG11 were recorded . In case of Volcan de Colima we used a range gate length of 600 m and range gates RG1-RG6 were recorded. Data at Volcan de Colima were recorded in 2014/2015 and at Turrialba volcano data was recorded between July 2017 and Jan 2019.

# Difficulties involved in radar data




Radars can only measure velocities along the radar beam thereby mapping a 3D process onto the 1D radar beam.

Radars detect any moving object inside a radar beam and therefore discriminating between an eruption and rain is not that straight forward. On the left side we show three schematic drawings of an eruption column and the associated velocity measured by the radar. On the right side three different rain scenarios are depicted along with the associated velocities recorded by a radar. Note that objects moving away from the radar are recorded with negative velocities and objects moving towards the radar are assigned positive velocities.

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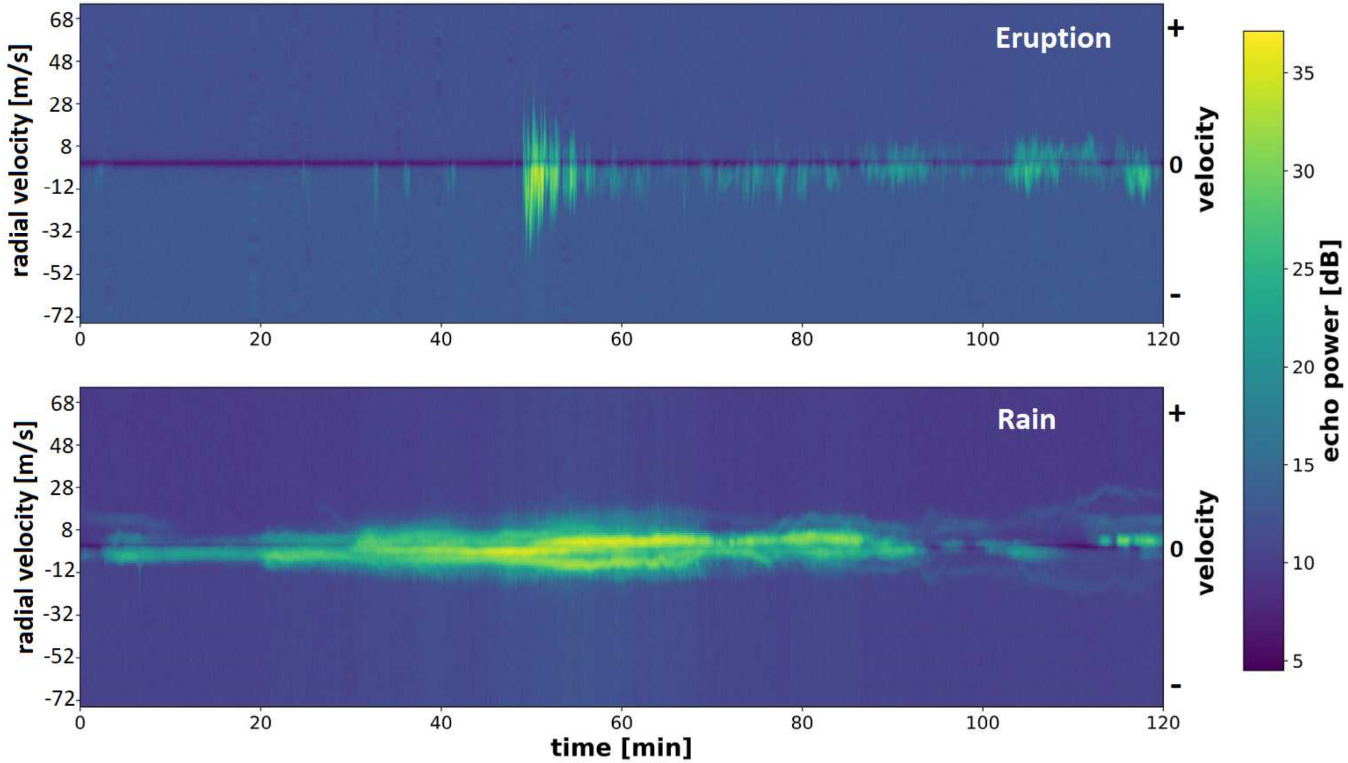
# Typical Doppler radar recording of an eruption and rain




This figure shows a typical velocigram. It shows the temporal evolution of energy reflected by objects inside the radar beam moving at different velocities.

The data shown above was recorded at Turrialba volcano. The upper plot shows the data from the 10th range gate, where a typical pattern for eruptions can be seen. The bottom plot shows data from the 5th range gate which is located in between the instrument and the vent. It shows a typical rain signal.

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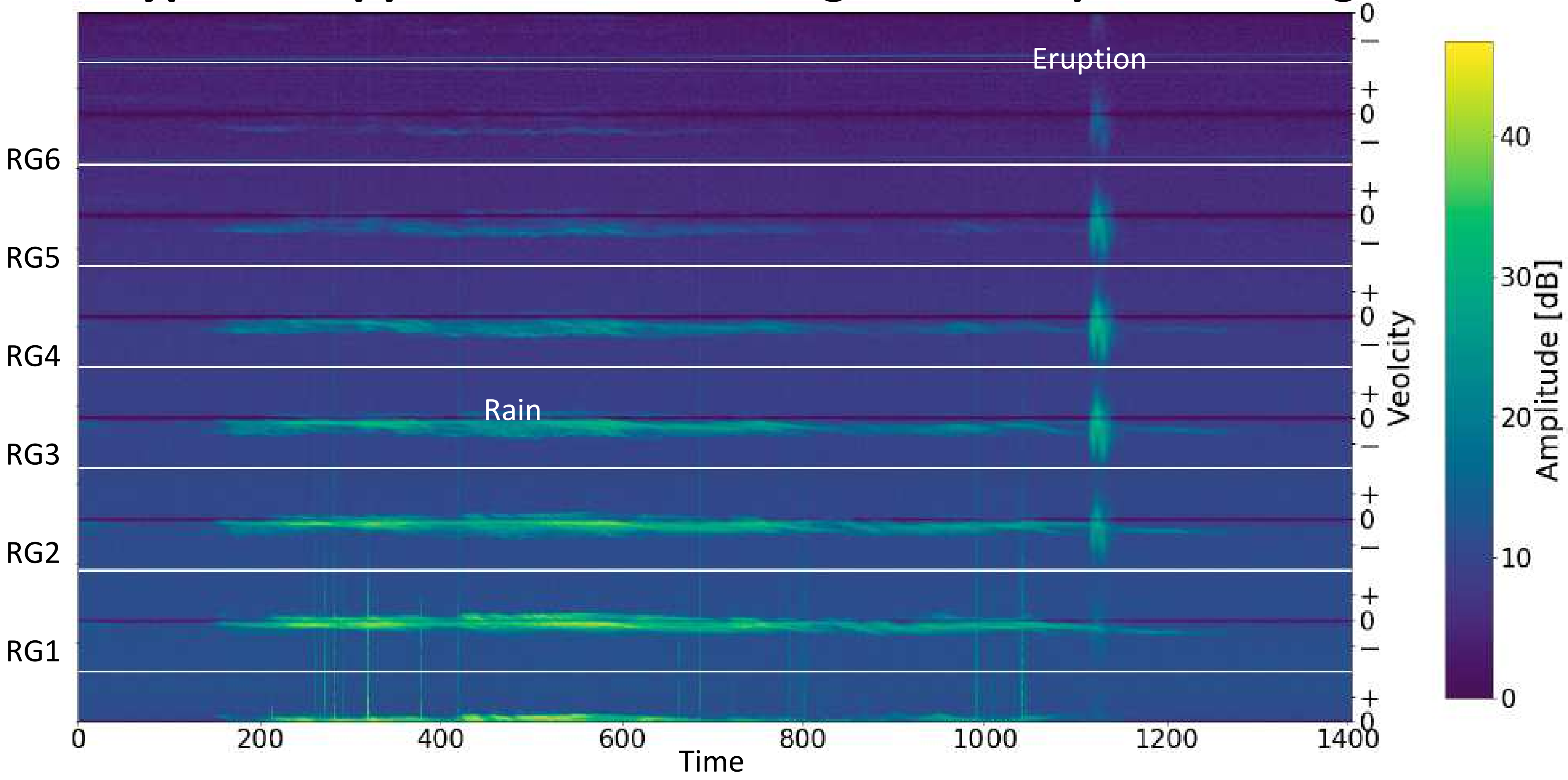
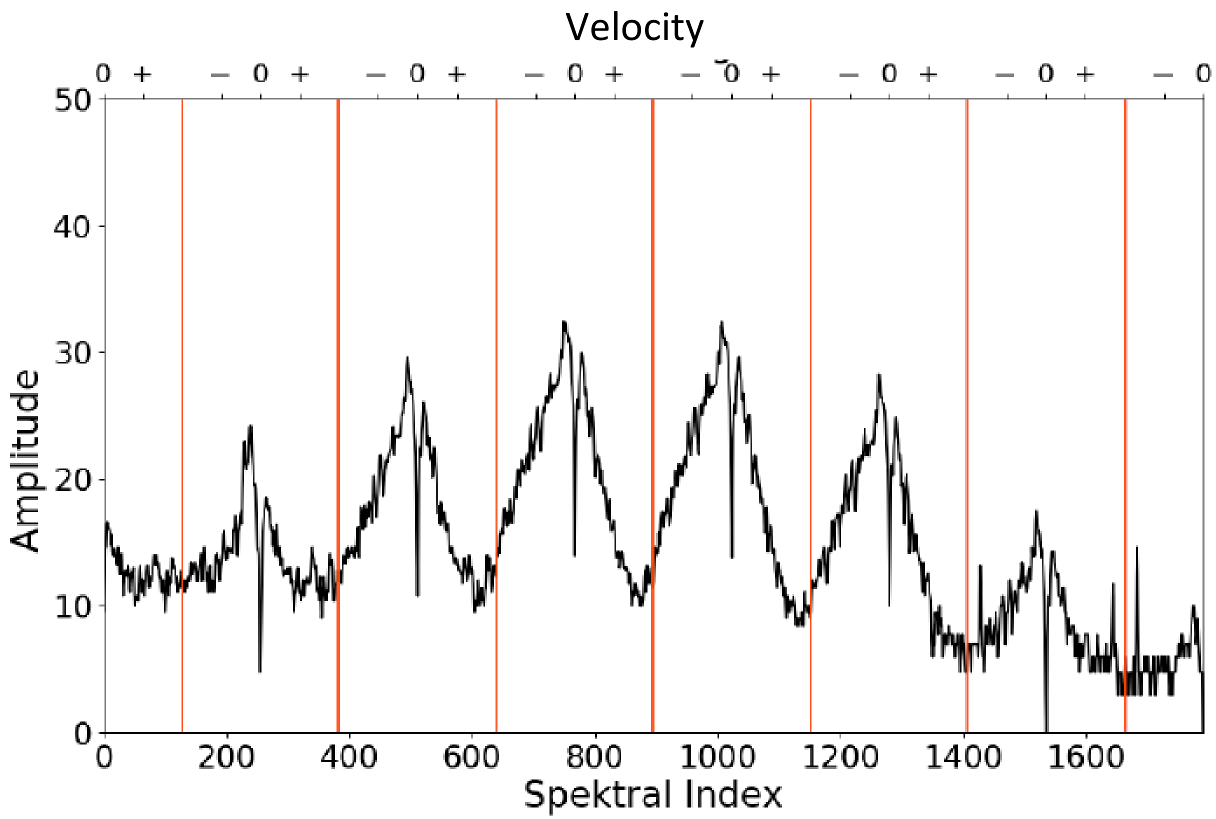
# Typical Doppler radar recording of an eruption during rain




Recording of an eruption at Volcan de Colima volcano during rain. Shown is the full set of data recorded by the radar (Range Gates 1-6). They are separated by the white horizontal lines. Due to spectral leaking in the radar during data processing the eruption (occurred in Range Gate 5) is also visible in range gates 3, 4, and 6.

While rain occurs closer to the instrument (RG1-RG4), the eruption is clearly visible in RG5.

# Data input into neural network




Each velocigram consists of many single Spectra recorded by the radar. One of those spectra is shown above. It was recorded at Colima volcano and the vertical red lines are the different range gates. If rotated by 90° clockwise and then color coding the amplitude we get one vertical line of a velocigram.

# Network design

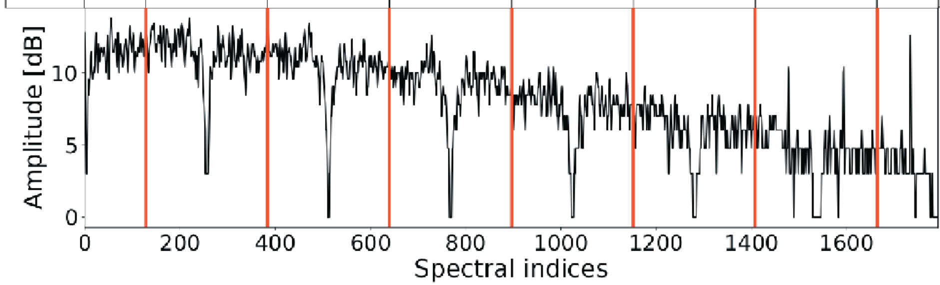
- fully connected feed forward network
- one hidden layer was found to be sufficient
- Following Heaton (Introduction to Neural Networks with Java, 2008) we use

$$N_{input} > N_{hidden} > N_{output}$$
$$N_{hidden} = 2/3 x N_{input} + N_{output}$$
$$N_{hidden} < 2x N_{input}$$

We have tested different network architectures in case of the Colima data, to explore which amount of data is sufficient for the classification process.

Single Spectrum recorded at Colima volcano. We have tested three different network with different amounts of input data. FullNet includes all data, 2RGTNet only two range gates and 1RGTNet only the range gate above the active dome.

| | RGT 0 | RGT 1 | RGT 2 | RGT 3 | RGT 4 | RGT 5 | RGT 6 | RGT 7 | $N_{input}$ | $N_{hidden}$ | $N_{output}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| FullNet | x | x | x | x | x | x | x | x | 1792 | 1197 | 3 |
| 2RGTNet | | x | | | x | | | | 512 | 344 | 3 |
| 1RGTNet | | | | | x | | | | 256 | 173 | 3 |



# Training and Test Data for Colima

We use data recorded at Volcan de Colima during the month of February and March 2015 for training. The data is divided into three datasets: the training data and two sets of test data. Training data and the first set of test data (test-1 data) were derived from data recorded in February 2015 and the second set of test data (test-2 data) was derived from data recorded in March 2015. The training data and test-1 data was manually labeled multiple times to achieve the highest possible quality in labels. For the data recorded in February 2015, eruptions as well as rain were picked. The second set of test data, Test-2 data, was picked only once. This allows a comparison between human (as in monitoring) and machine performance.

## Colima data

| Data set | Noise | Rain | Eruption | Total |
|---|---|---|---|---|
| Training data | 76913 | 59080 | 11336 | 147329 |
| Test-1 data | 17864 | 16284 | 2685 | 36833 |
| Test-2 data | 71937 | Not labeled | 10530 | 82467 |

Composition of the data sets used to train and analyze the neural networks. For the test-2 data set only eruptions where picked.

# Training and Test Data for Turrialba

We use data recorded at Turrialba volcano from July 2017 until Jan 2019.

## Turrialba data

| Data set | Noise | Rain | Eruption | Total |
|---|---|---|---|---|
| Training data | 38161 | 38015 | 38097 | 114273 |
| Validation data | 4726 | 4800 | 4758 | 14284 |
| Test data | 4727 | 4799 | 4759 | 14285 |

The Training and Validation data sets were used to train the neural network.
The Test data set was not used while training.

# Training results

## Colima data

| | FullNet | 2RGTNet | 1RGTNet |
|---|---|---|---|
| Accuracy training data | 99.3% | 97.2% | 90.6% |
| Loss training data | 0.026 | 0.082 | 0.246 |
| Accuracy test-1 data | 98.9% | 96.9% | 90.4% |
| Loss test-1 data | 0.038 | 0.089 | 0.252 |

## Turrialba data

| | |
|---|---|
| Accuracy training data | 98.67 % |
| Loss training data | 0.045 |
| Accuracy validation data | 98.57 % |
| Loss validation data | 0.047 |
| Accuracy test data | 98.48 % |
| Loss test data | 0.053 |

Measuring the performance of the different networks. A categorical cross-entropy (Goodfellow et al., 2016) is used as a loss function. All classes (noise, rain, eruption) have been taken into account, to calculate those values.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). Deep Learning. MIT Press. http://www.deeplearningbook.org

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# Confusion matrices for Colima

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| | | | Noise | Rain | Eruption |
|---|---|---|---|---|---|
| FullNet | Training data | Noise | **76302 (99.2%)** | 222 (0.4%) | 102 (0.9%) |
| | | Rain | 571 (0.7%) | **58846 (99.6%)** | 85 (0.7%) |
| | | Eruption | 40 (0.05%) | 12 (0.02%) | **11149 (98.5%)** |
| | Test-1 data | Noise | **17616 (98.6%)** | 82 (0.5%) | 30 (1.1%) |
| | | Rain | 240 (1.3%) | **16199 (99.5%)** | 30 (1.1%) |
| | | Eruption | 8 (0.04%) | 3 (0.02%) | **2625 (97.8%)** |
| 2RGTNet | Training data | Noise | **75748 (98.5%)** | 2080 (3.5%) | 534 (4.7%) |
| | | Rain | 809 (1.1%) | **56881 (96.3%)** | 165 (1.5%) |
| | | Eruption | 356 (0.5%) | 119 (0.2%) | **10637 (93.8%)** |
| | Test-1 data | Noise | **17511 (98%)** | 565 (3.5%) | 134 (5%) |
| | | Rain | 253 (1.4%) | **15674 (96.3%)** | 46 (1.7%) |
| | | Eruption | 100 (0.6%) | 45 (0.3%) | **2505 (93.3%)** |

Confusion matrices for the FullNet and 2RGTNet network, for the training data and Test-1 data. The columns show what has been picked and the rows the prediction of the neural network. Along the main diagonal, human interpretation and the neural networks prediction match. The off-diagonal elements show the differences between human interpretation and network prediction, e.g. the top right value shows the number of samples where eruption was assigned by a human and the network predicted noise.

# Confusion matrices for Turrialba

| | | Noise | Rain | Eruption |
|---|---|---|---|---|
| Training data | Noise | **38142 (99.9%)** | 23 (0.1%) | 1339 (3.5%) |
| | Rain | 0 (0.0%) | **38063 (99.9%)** | 131 (0.4%) |
| | Eruption | 19 (0.1%) | 11 (0.0%) | **36545 (96.1%)** |
| Test & validation data | Noise | **9448 (99.9%)** | 7 (0.1%) | 360 (3.8%) |
| | Rain | 0 (0.0%) | **9501 (99.8%)** | 40 (0.4%) |
| | Eruption | 5 (0.1%) | 9 (0.1%) | **9199 (95.8%)** |

The columns show what has been picked and the rows the prediction of the neural network. Along the main diagonal, human interpretation and the neural networks prediction match. The off-diagonal elements show the differences between human interpretation and network prediction, e.g. the top right value shows the number of samples where eruption was assigned by a human and the network predicted noise.

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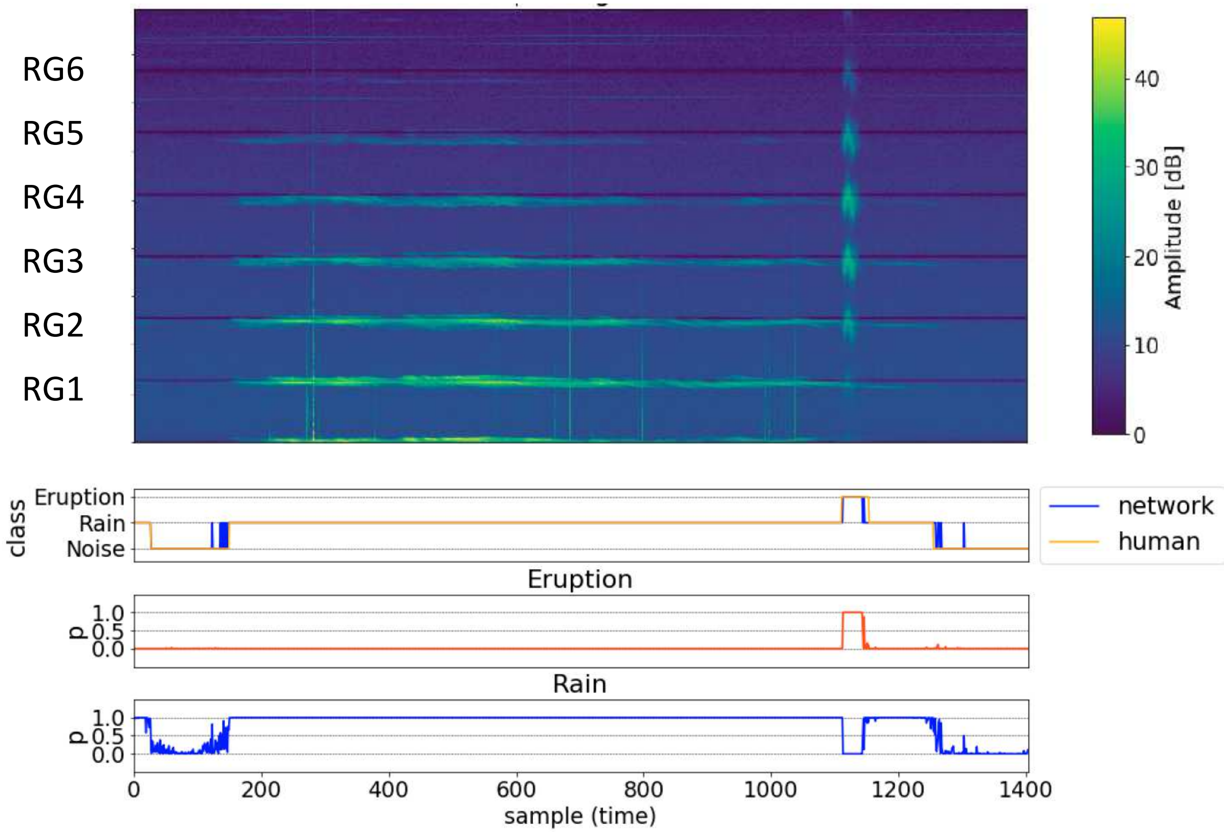
# Runtime perfomance

| Laptop i7-7500 CPU | FullNet | 2RGTNet | 1RGTNet |
|---|---|---|---|
| mean | 8.2 s | 1.45 s | 0.76 s |
| standard deviation | 0.025 s | 0.024 s | 0.01 s |
| classification frequency | 10 kHz | 56 kHz | 108 kHz |

| Rasberry PI 4/B 4Gb | FullNet | 2RGTNet | 1RGTNet |
|---|---|---|---|
| mean | 20.43 s | 6.87 s | 3.41 s |
| standard deviation | 0.34 s | 0.56 s | 0.06 s |
| classification frequency | 2 kHz | 5 kHz | 11 kHz |

Comparison of time measurements for the different networks classifying about 82500 spectra. The classification rate corresponds to the number of spectra the networks classify per second. Comparison time refers to the time of the FullNet running on the Laptop with a i7-7500 CPU. Also note that in the case of the Rasberry PI only Test-1 Data were classified as the 82500 Spectra of the Test-2 did not fit into its memory.

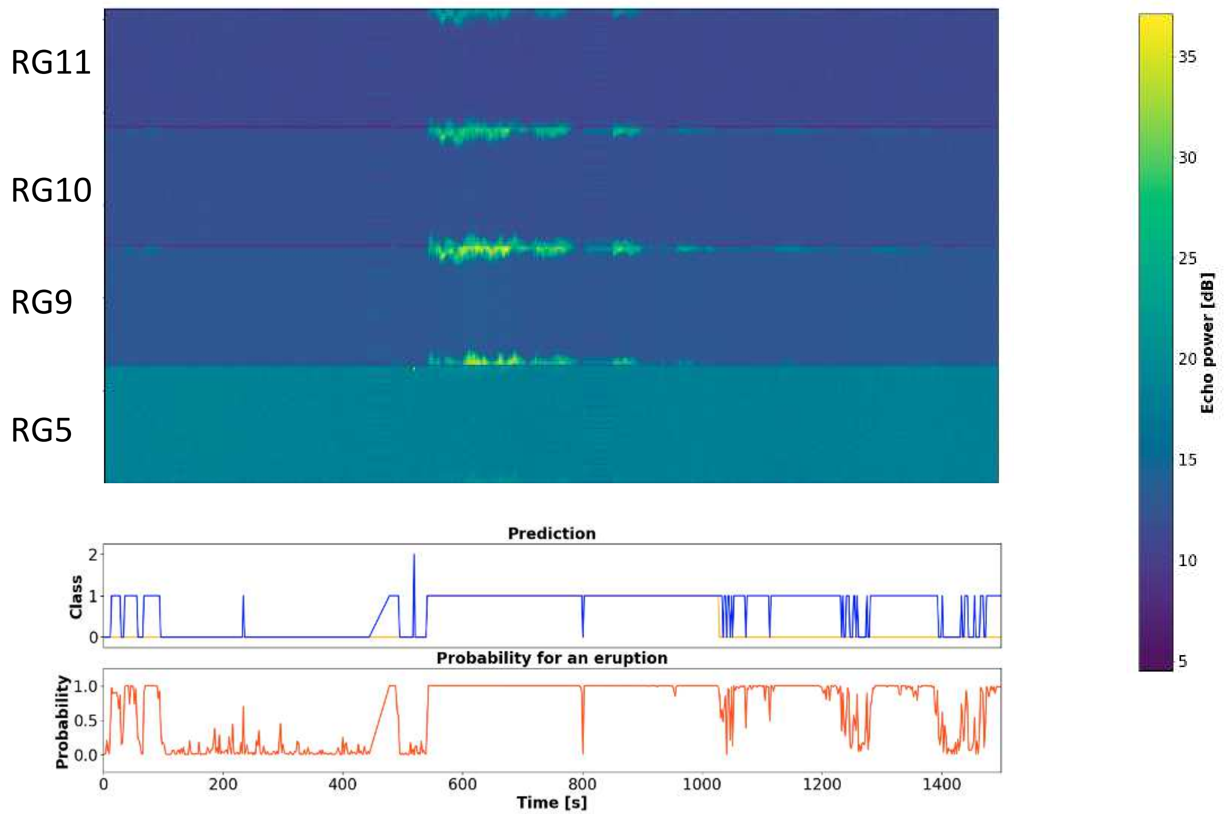
# Data classification example from Volcan de Colima




Here we show a data example presented already earlier in the slides, this time however with the classification of the data using FullNet. The figure is composed of four subplots. The first subplot shows the velocigram of the radar data. The x-axis shows the temporal evolution of the signal.

The second subplot shows the class for every spectrum: orange indicates the class picked by a human and blue the class assigned by the neural network. The third subplot shows the probability (as determined by the neural network) of the spectrum being associated with an eruption. This gives us more information about the network output than only the predicted class. The last subplot shows the probability of the spectra being rain.

# Data classification example from Turrialba volcano




Similar to the example shown in the last slide here we show a classification example from our Turrialba data set. Class 0 is noise, class 1 is eruption, class 2 is rain. One can see clearly that the network has difficulties to determine the exact end of an eruption (usually dominated by ash falling back onto the ground) or even finds more eruptions than human-picked.

# Conclusions

- Using two different data sets we have shown that a reliable automatic classification of eruptions, rain and noise in the data is possible with an accuracy of at least 98 **%**
- Even a very simple network is capable of performing the classification task and can run on a minicomputer having a low power consumption
- Classification on site is possible allowing automatic notification of authorities without transmitting huge amounts of data. Nevertheless, manual validation is recommended to minimize false positives.
- Even though distinguishing between very light rain and small eruptions is still a problem, major eruptions are clearly detected.