# Detecting Convective Clouds in Geostationary Satellite data with Convolutional Neural Networks

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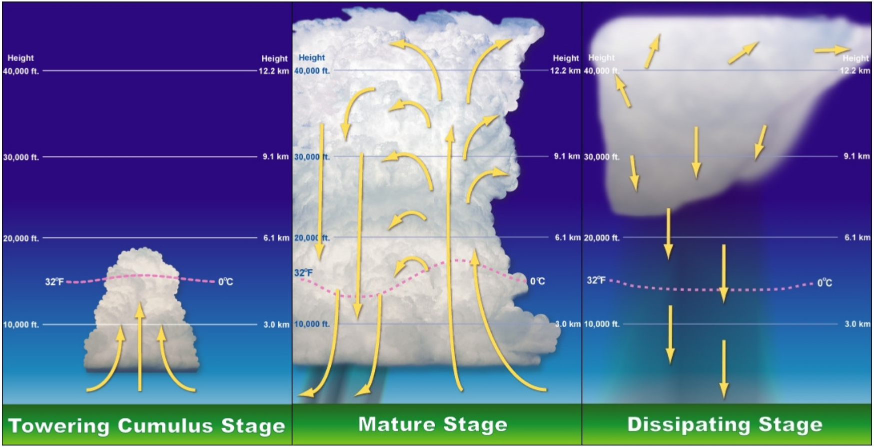
27, January 2020

# Overview

- Problem
- Methodology
- Results
- Conclusions and potential future work

# Problem

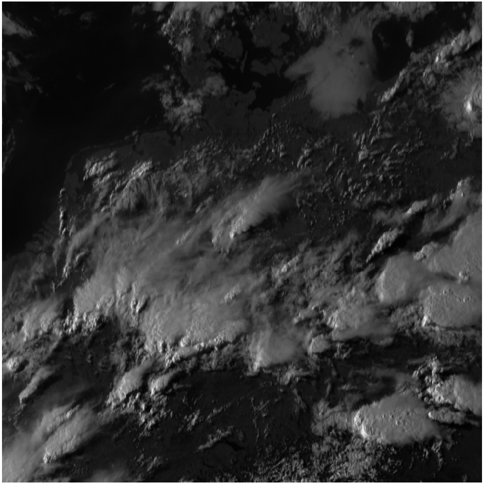
# What are Convective Clouds?




Source: Wikipedia / NOAA

# Meteosat Second Generation

- Geostationary satellites that take very high temporal resolution (5min or 15min) but low spatial resolution images (∼1km or ∼3km).



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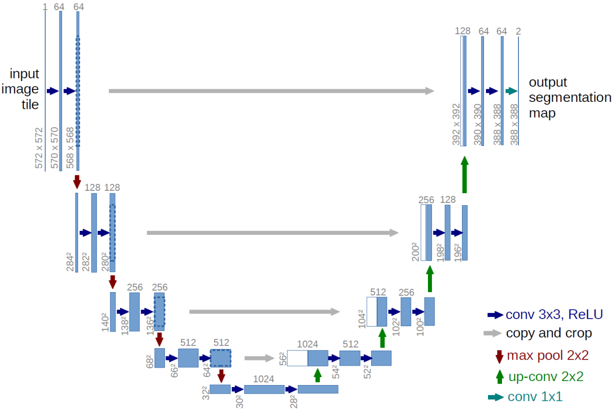


arXiv:1505.04597

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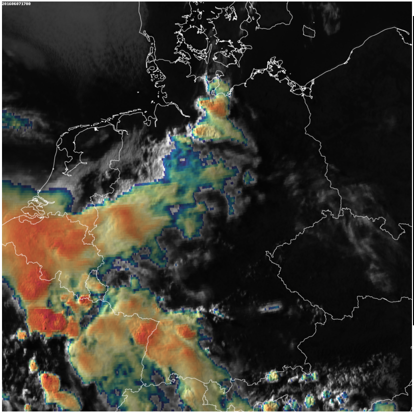
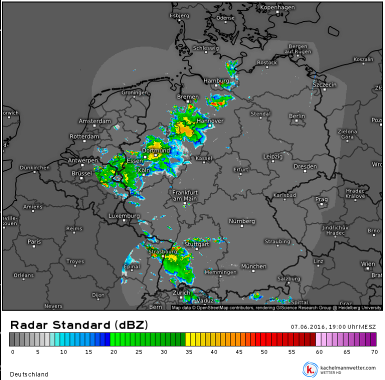
- We present the labellers with a false colour image that combines the HRV and one IR channel as well as a radar image and ground observations.





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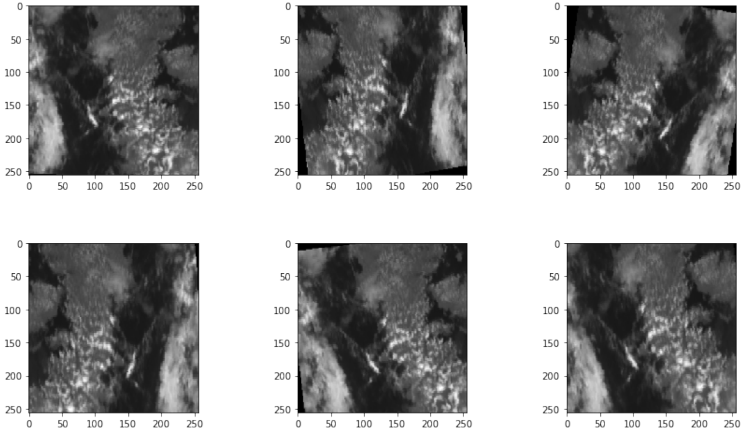
- We need to make the most of what we have.
- Make random transformations to the data and labels and feed them to the network.



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- $$1 - \frac{2\sum y_t y_p + 1}{\sum y_t + \sum y_p + 1} \tag{1}$$
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- This leads to better convergence in this case than the more common binary cross entropy.

# Hyperparameters

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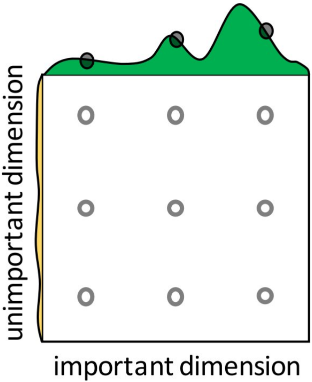
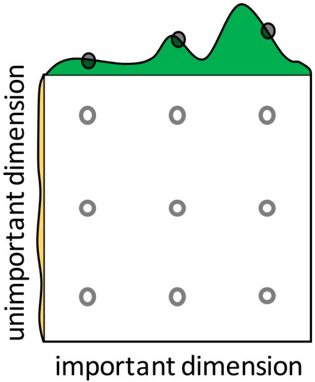
| Hyperparameters | Possible values |
|---|---|
| Data Augmentation | flips, maximum angles, maximum zoom... |
| Number of "recursions" for the UNET | 1, 2, 3, 4, 5... |
| Nonlinearity | ReLU, ELU, CELU... |
| Method of upsampling | Transposed convolution, pixel shuffle |
| Optimisation algorithm | RMSProp, Adam... |
| Dropout percentage | 0, 0.2, 0.5... |
| Batch size | 4, 8, .... |
| Learning rate | 0.001, 0.005 ... |
| Learning rate annealing | none, one cycle, cosine... |




Source: Yao, Quanming et al. (2018).

- The solution is to do a hyperparameter search.

# Hyperparameter optimisation



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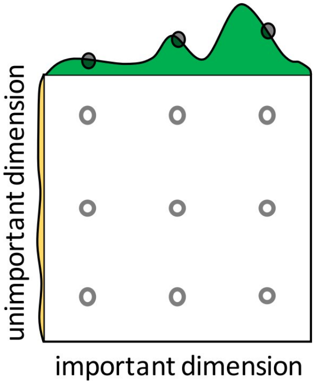


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- We NEED to have a separate validation dataset here.

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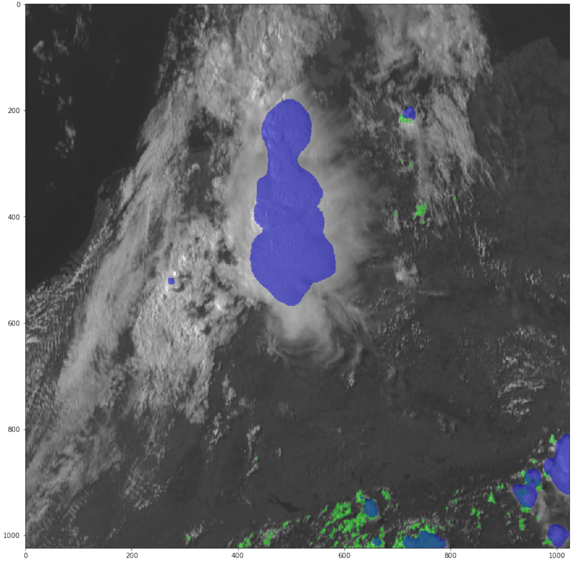


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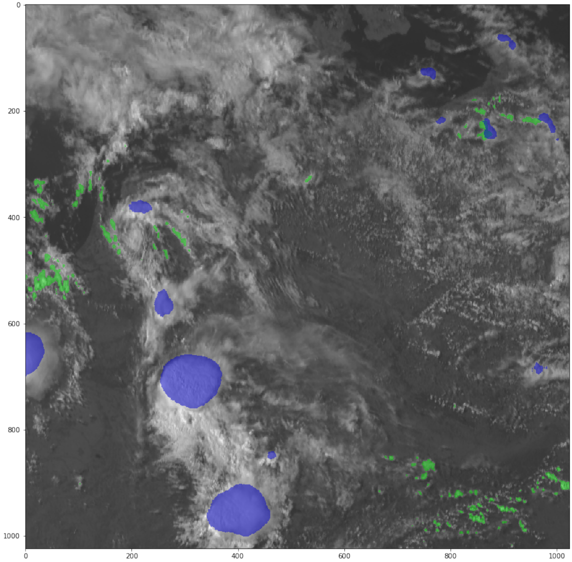


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- We perform very well against a test set drawn from the labels ( 98% accuracy)
- However assessing the performance of the labels themselves is not trivial. (No real ground truth.)

# Extensions and Conclusion

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