Deep Learning for Digital Typhoon

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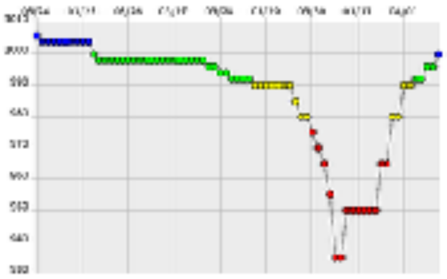
Digital Typhoon
Project

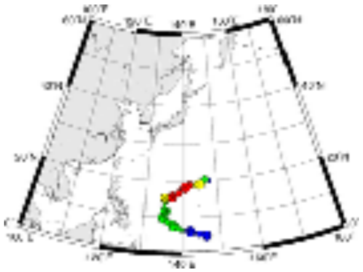
Outline

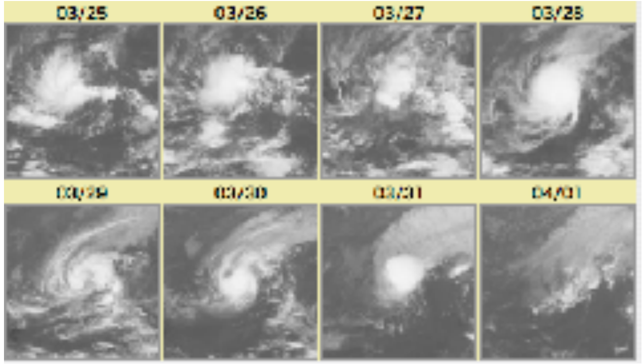
1. Digital Typhoon
2. Deep Learning
3. Data
4. Application Examples
    1. Nonlinear frames interpolation
    2. *Tropical cyclone* vs *Extratropical cyclone* classifier
    3. *Tropical cyclone* intensity categorisation
    4. Centre pressure regression model
    5. Motion estimation
5. Conclusions & Future

1. Digital Typhoon

Online: http://digital-typhoon.org







1. Digital Typhoon

Online: http://digital-typhoon.org

Basin	Sequences	Images
W.N. Pacific	974	165,132
W.S. Pacific	402	54,188
Total	1,376	219,320

1. Digital Typhoon

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Basin	Sequences	Images
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2. Deep Learning

"Learn from data"

Supervised Learning

Learn mapping between **input** and a **target**.

E.g. Regression, classification…

Unsupervised Learning

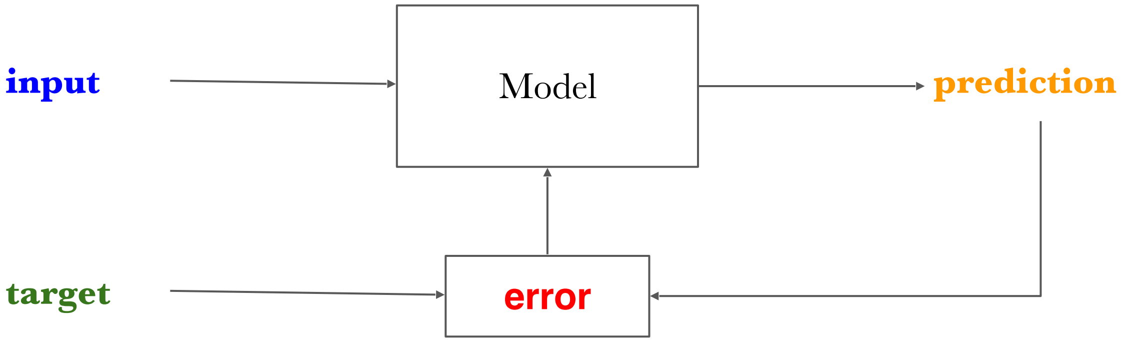
Try to extract relevant patterns from the data.

E.g. Clustering…

2. Deep Learning

Supervised learning

- Obtain **prediction** for **input**.
- Update the model using **error** $= f($**prediction**, **target**$)$.



2. Deep Learning

Training vs Evaluation

- Split dataset in **training** and **test** datasets.
    - Training: Used for **learning** a model.
    - Test: Used to **evaluate** if what has been learnt also applies to new data. Typical metrics: accuracy, ROC etc.

2. Deep Learning

Training vs Evaluation

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Worst enemy of deep learning

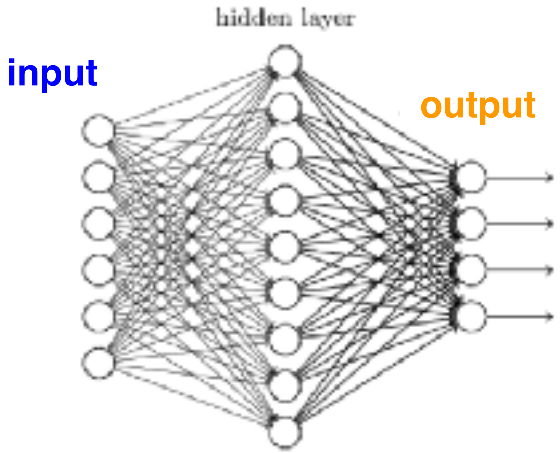
- **Overfitting**: Model performs good on training data but does poorly on test data.
- We want our model to be able to **generalise** to unseen data.

2. Deep Learning

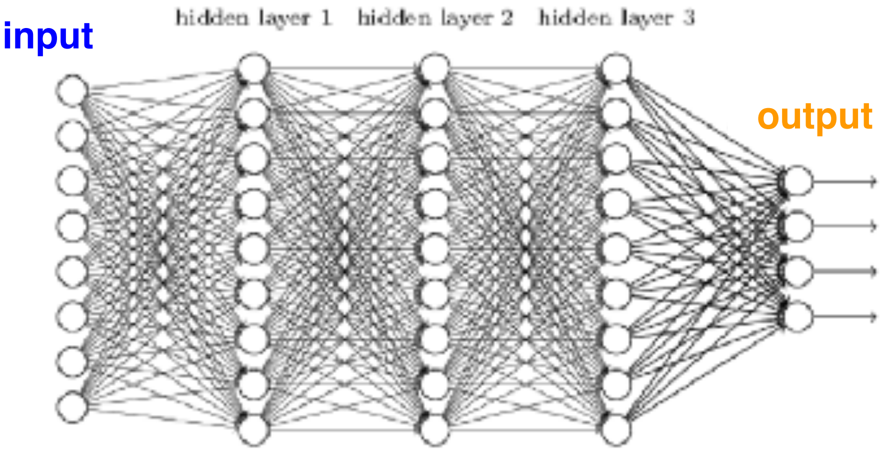
Use of Artificial Neural Networks

Inspired by how the brain work.

Non-deep neural network

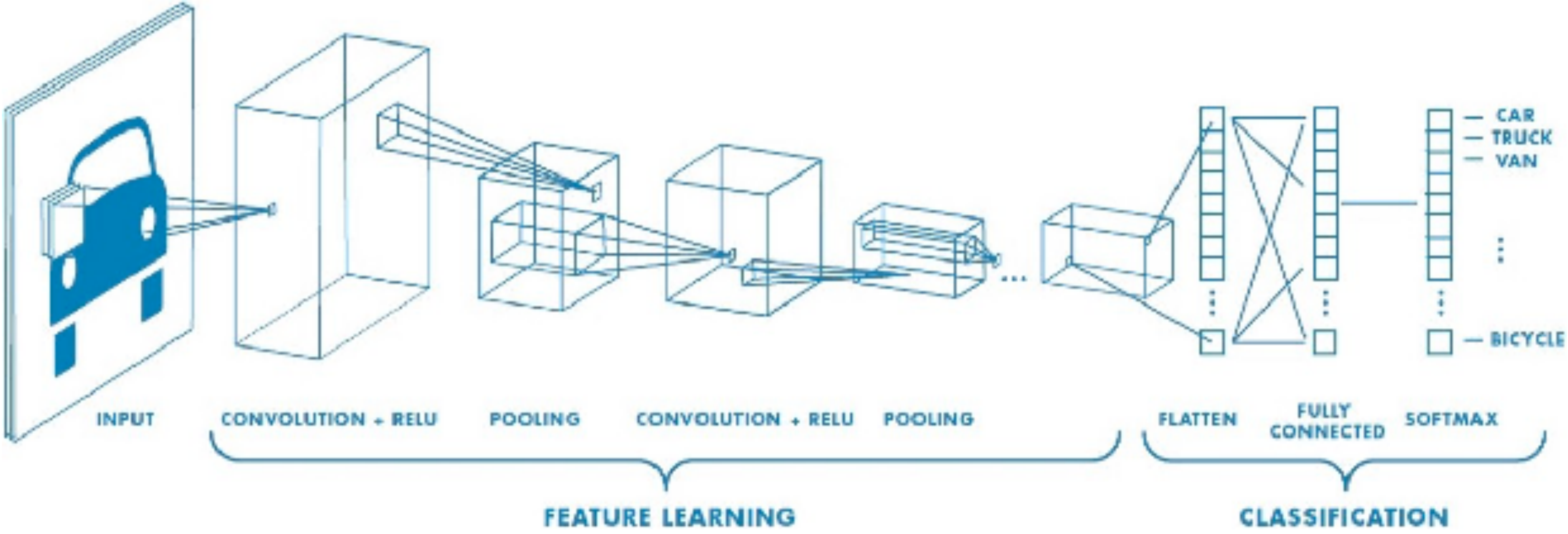


Deep neural network



2. Deep Learning

Convolutional Network



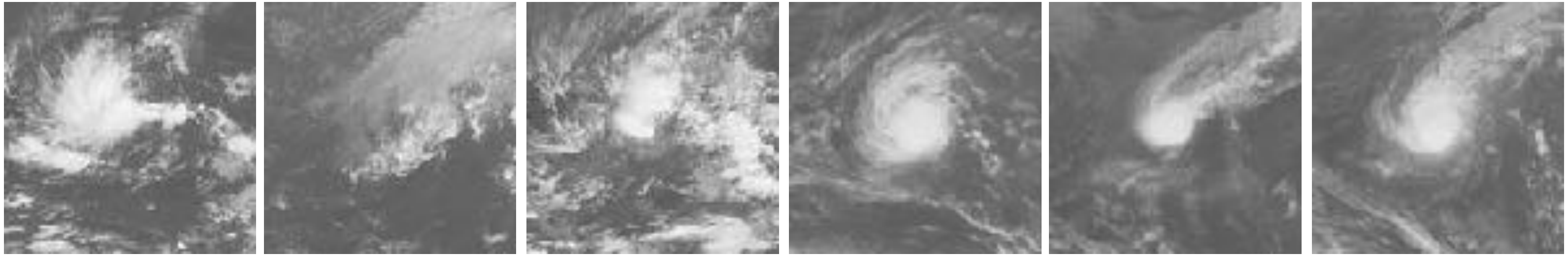
Ref: https://medium.com/@rohanthomas.me/convolutional-networks-for-everyone-1d0699de1a9d

3. Data

Satellite Imagery

More than 160k images since 1978, infrared 512x512 images

…

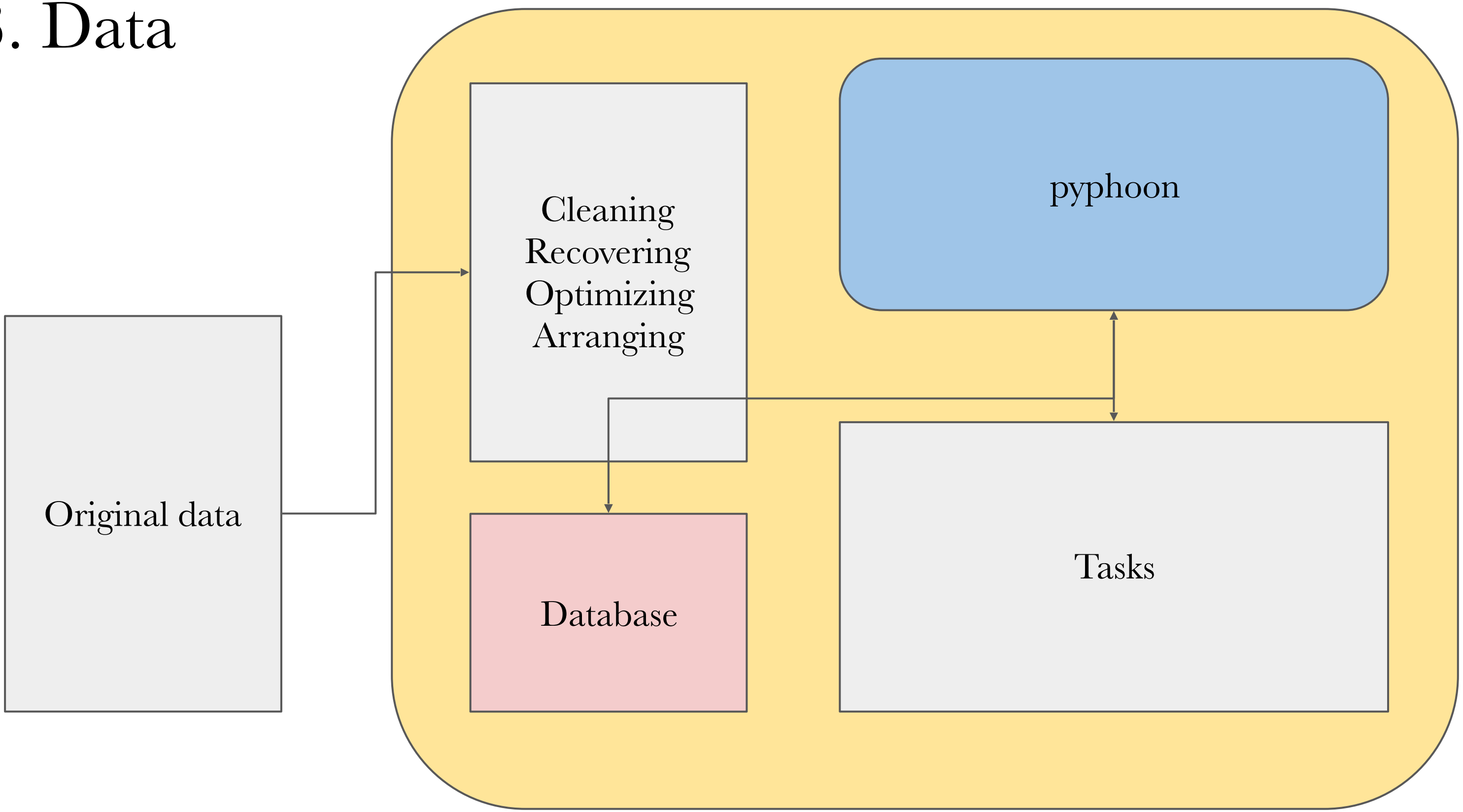


…

Best Track (JMA)

Wind speed, centre pressure, typhoon category…

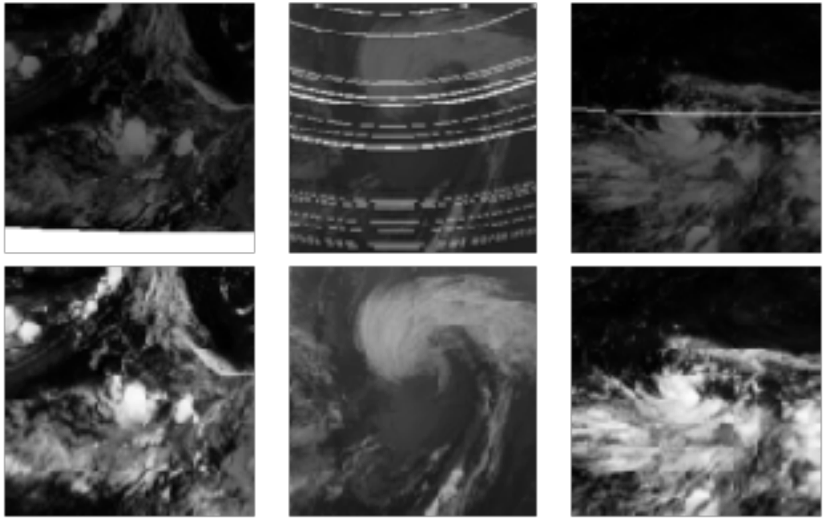
3. Data


Original data
Cleaning
Recovering
Optimizing
Arranging
pyphoon
Database
Tasks

3. Data

Cleaning

- Detecting corrupted images
- Valid values range (K): [160, 310]
- Recovering corrupted pixels
- Corrected images: 4.8k of 164k



(a) 26th of June 1987 at 14:00 PST (from Typhoon Sequence 198704).

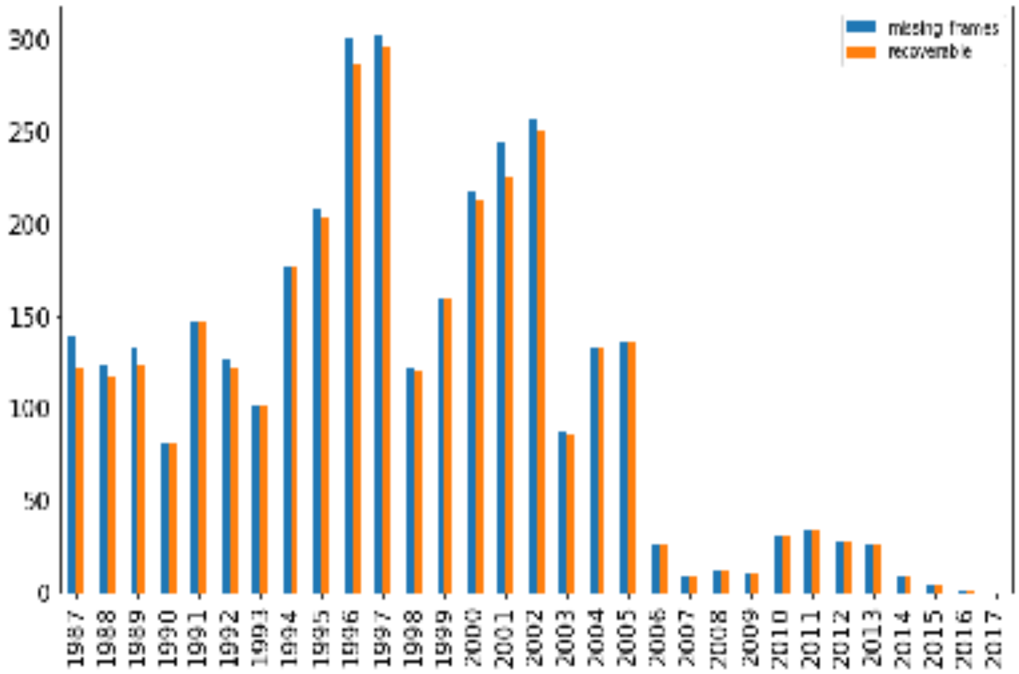
(b) 6th of September 1982 at 21:00 PST (from Typhoon Sequence 198215).

(c) 20th of June 1982 at 03:00 PST (from Typhoon Sequence 198205).

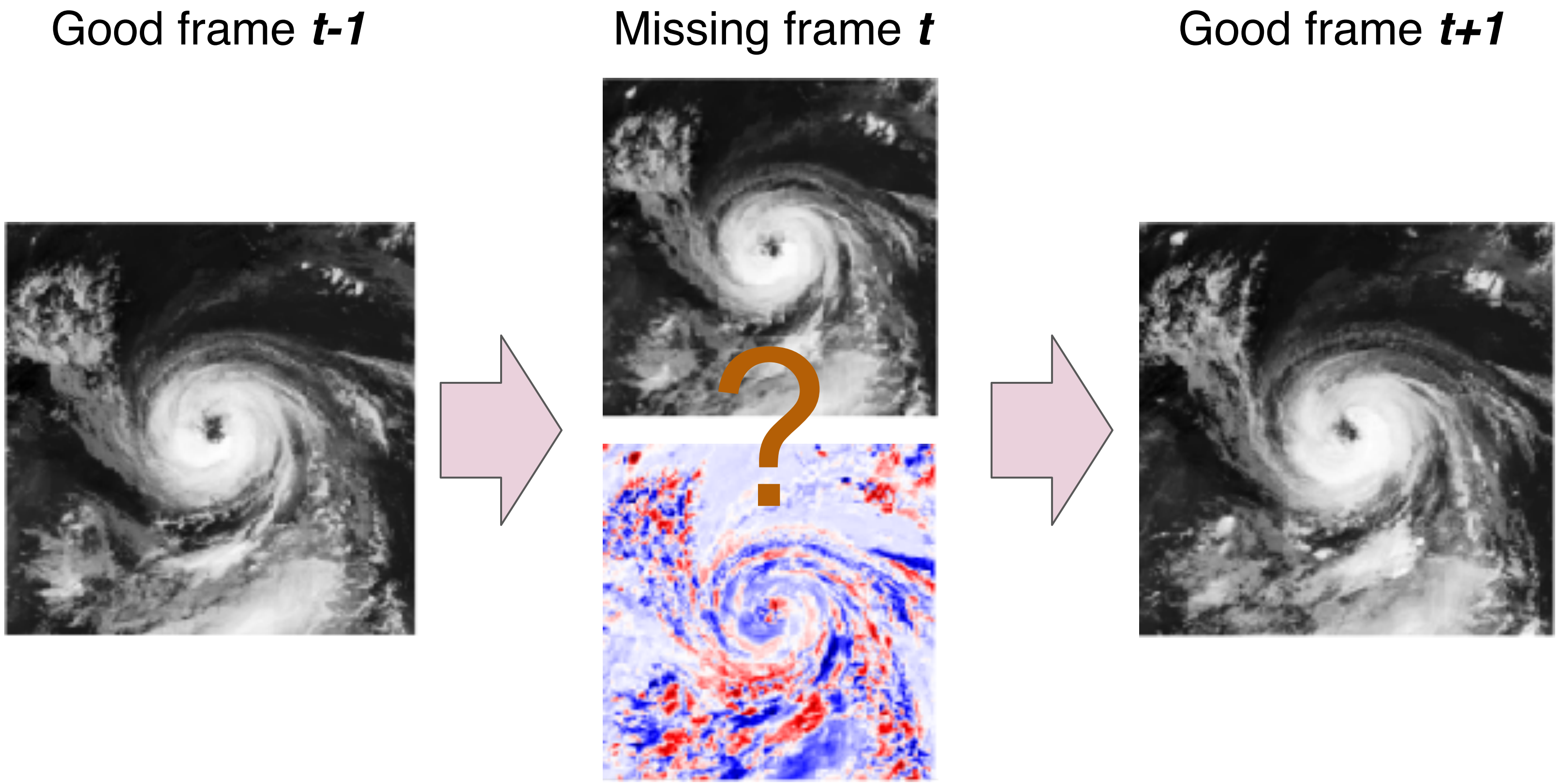
3. Data

Recovering

- Detecting missing frames
- Recovering from neighbours
- Years 1987 - 2017
- Total missing frames: 3.4k
-    Recoverable: 3.3k

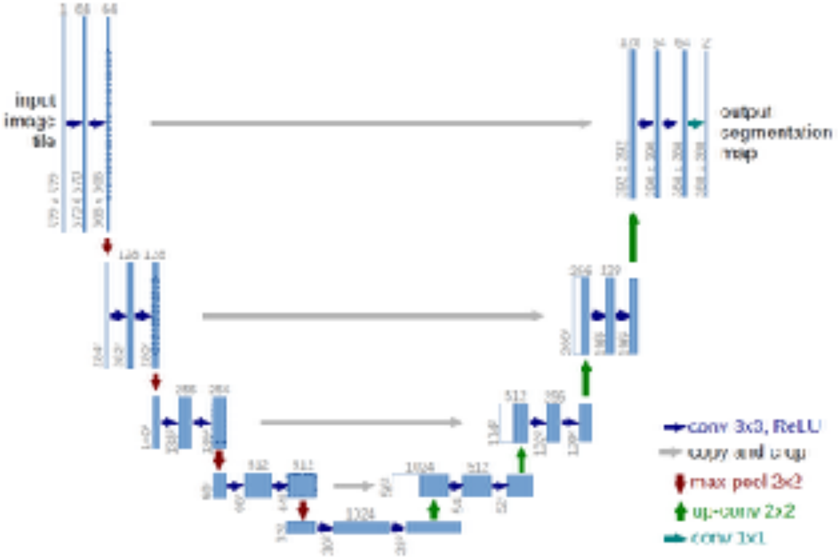


4.1 Nonlinear frames interpolation



4.1 Nonlinear frames interpolation

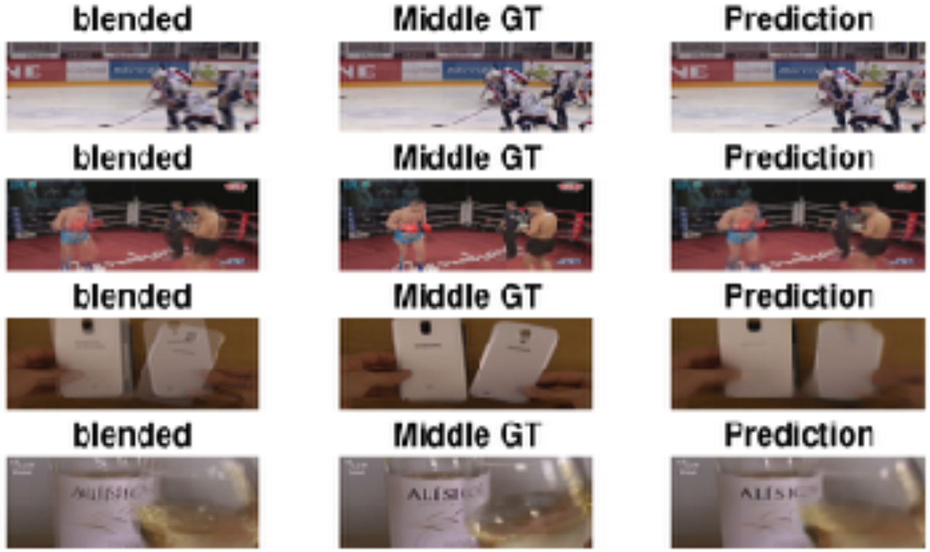
Method: Machine learning



Deep Motion: A Convolutional Neural Network for Frame Interpolation

Neil Joshi, Duncan Woodbury

January 25, 2017



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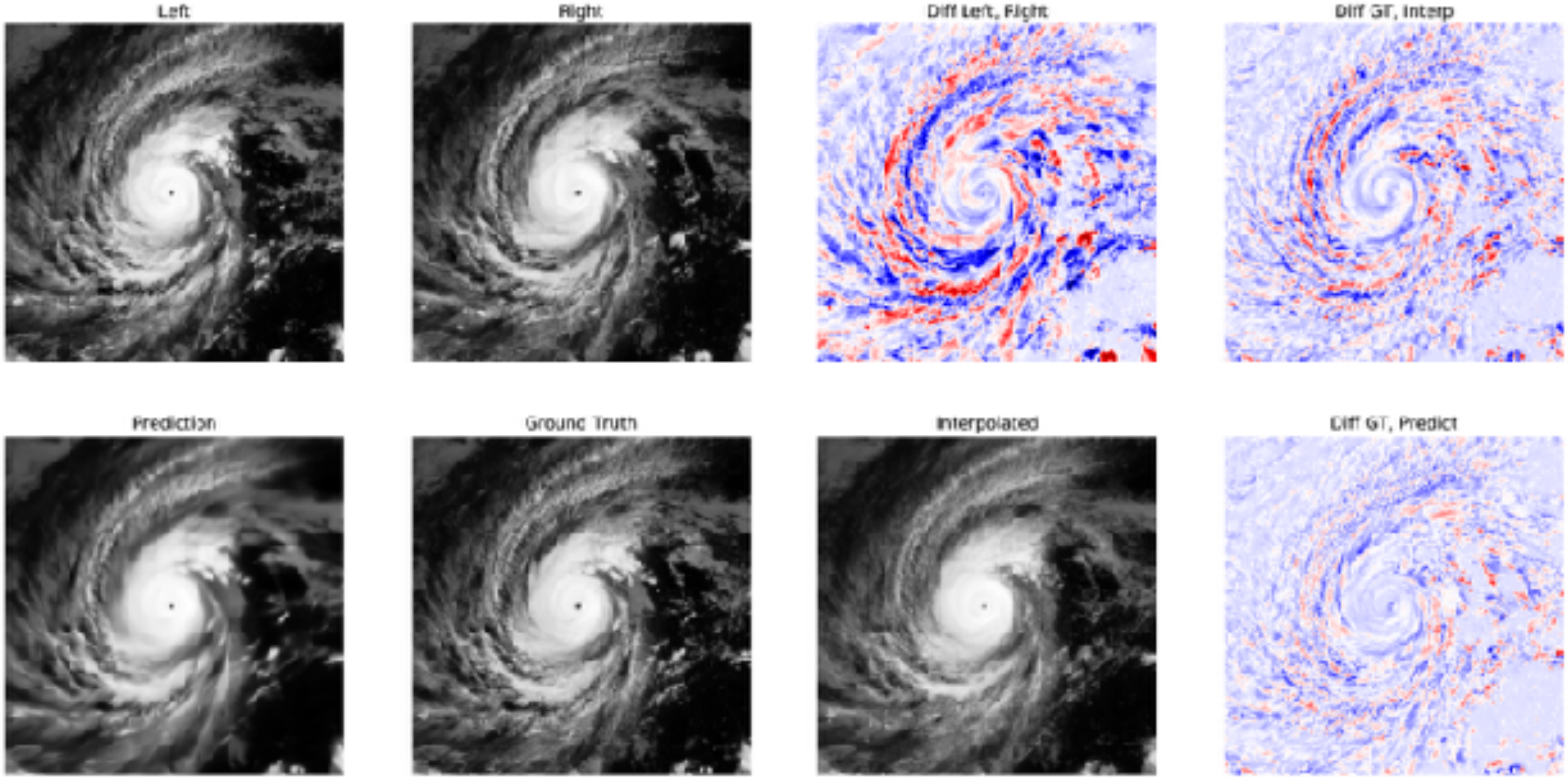

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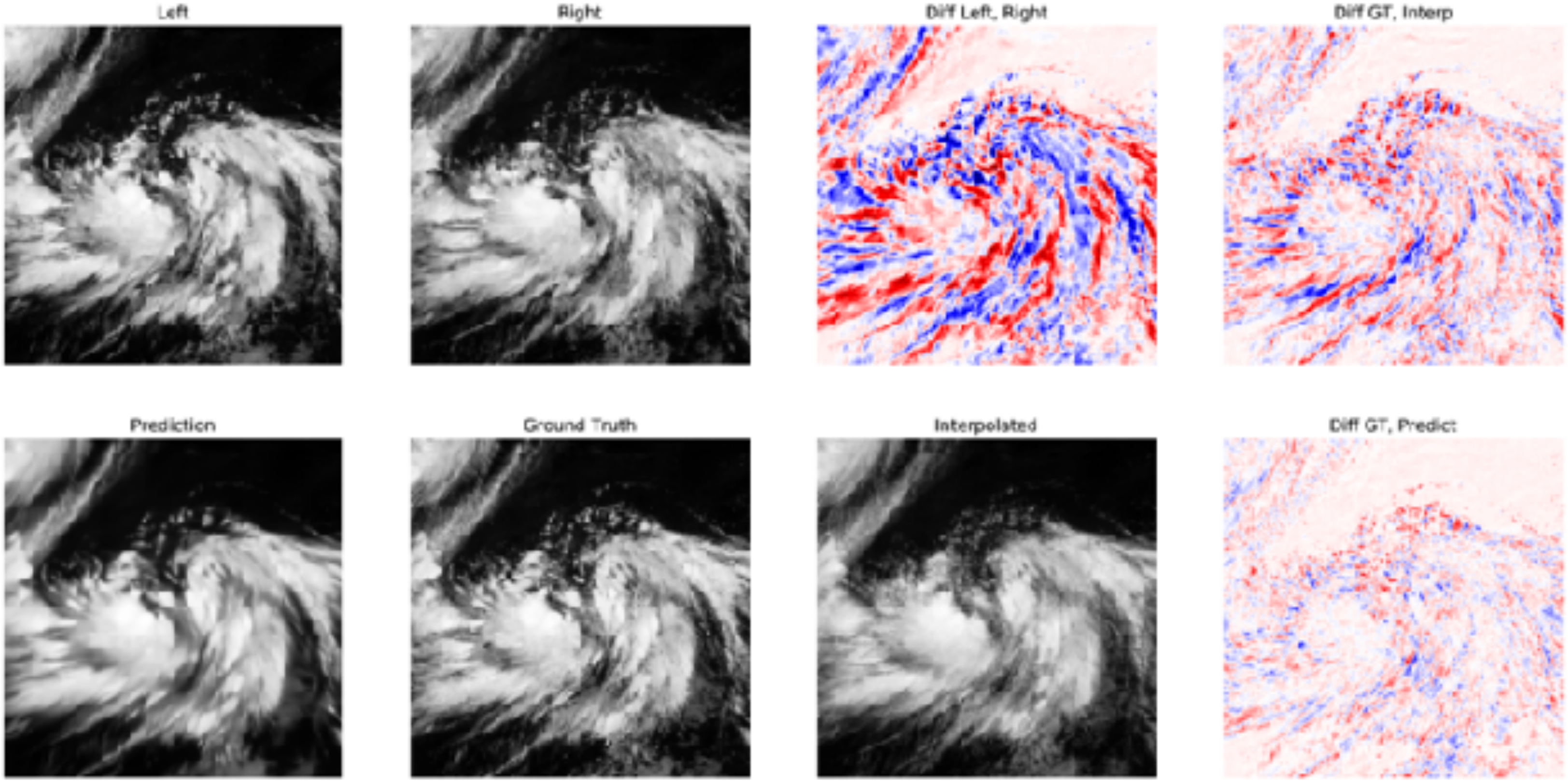
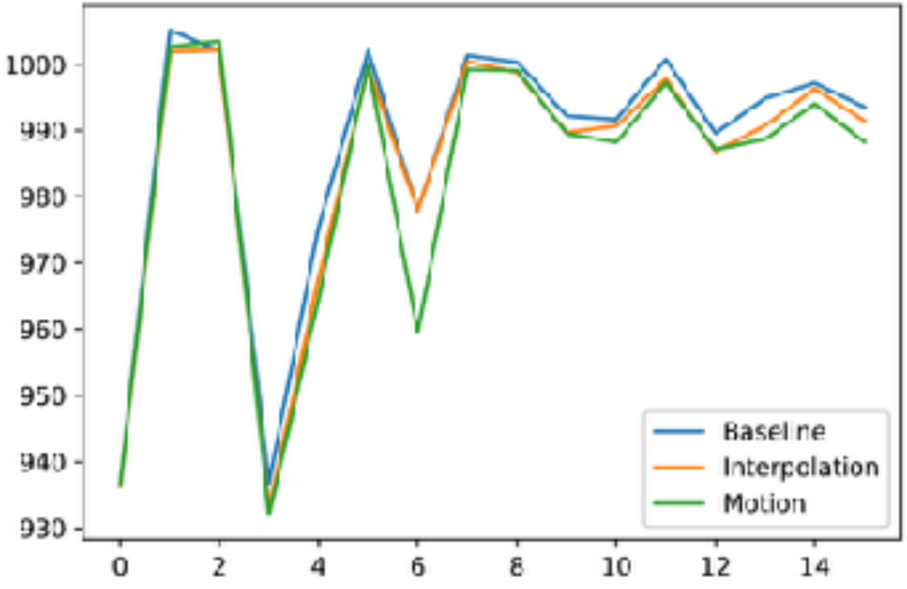


4.1 Nonlinear frames interpolation

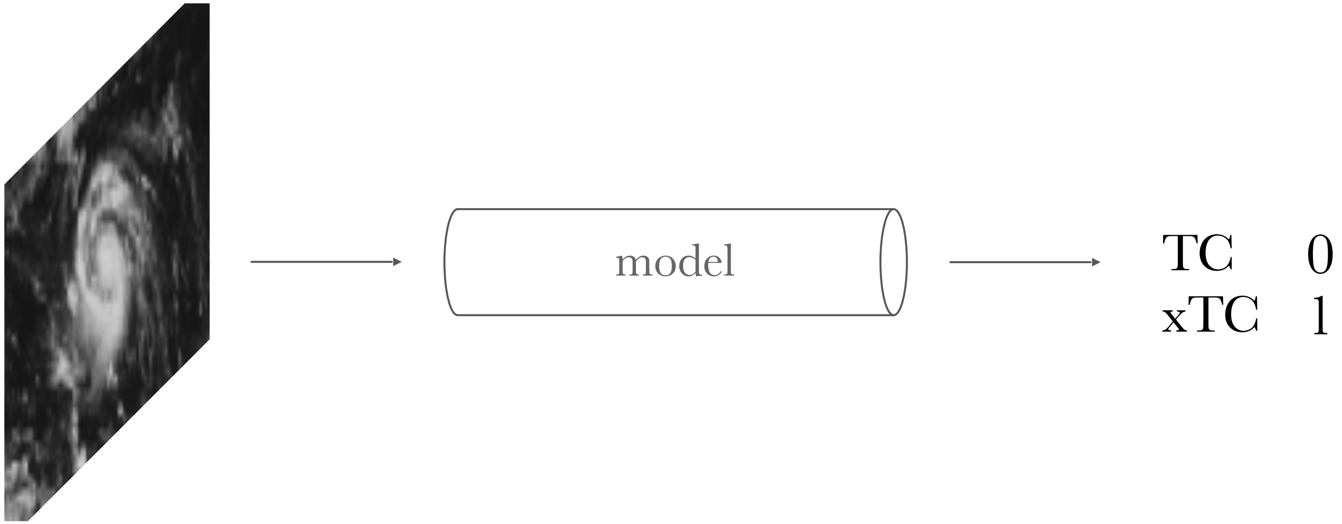
Evaluating results:

- **Random sequence of frames from the test dataset**
- **Testing on estimation of pressure task**
- **Baseline** - original image
- **Interpolation** - linear interpolation
- **Motion** - nonlinear interpolation



4.2 Tropical cyclone / Extratropical cyclone

Given a satellite image from Digital Typhoon dataset, estimate whether that image belongs to a ***Tropical Cyclone*** (**TC**) or an ***Extratropical Cyclone*** (**xTC**).

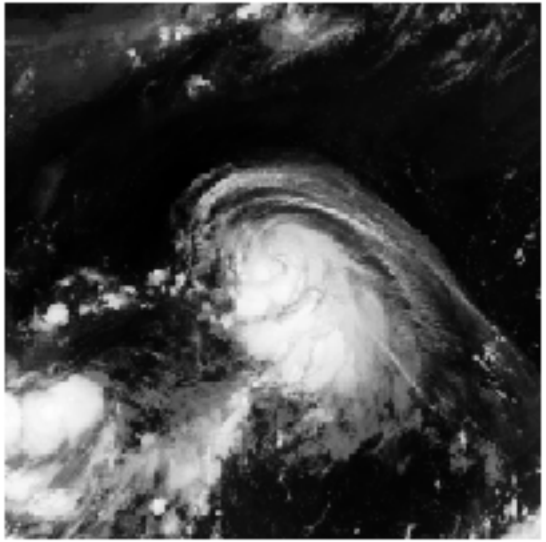


4.2 Tropical cyclone / Extratropical cyclone

Is this task possible at all?

Tropical Cyclone

201718



Extra-Tropical Cyclone

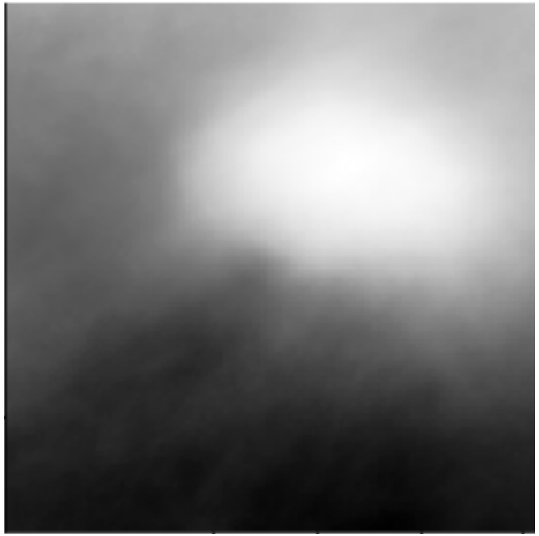
201711

4.2 Tropical cyclone / Extratropical cyclone

Mean image for each class

Tropical Cyclone

Extra-Tropical Cyclone

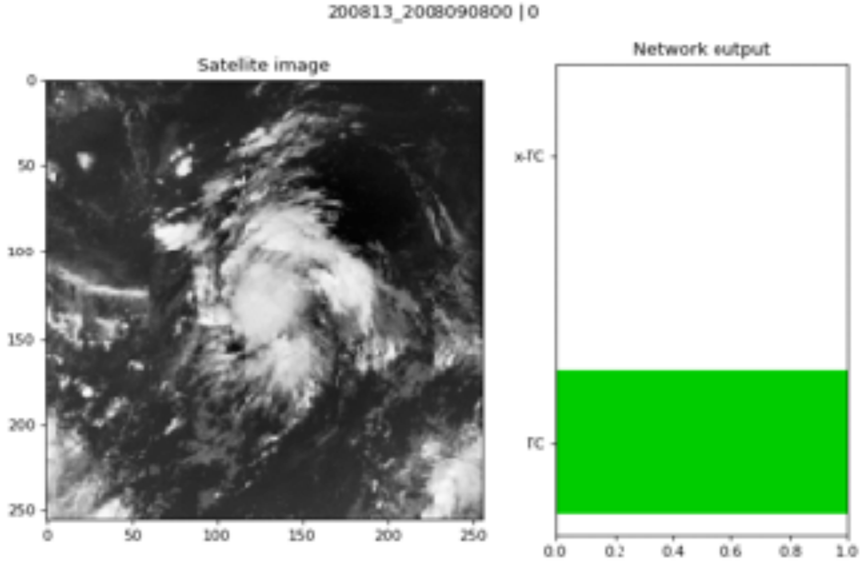


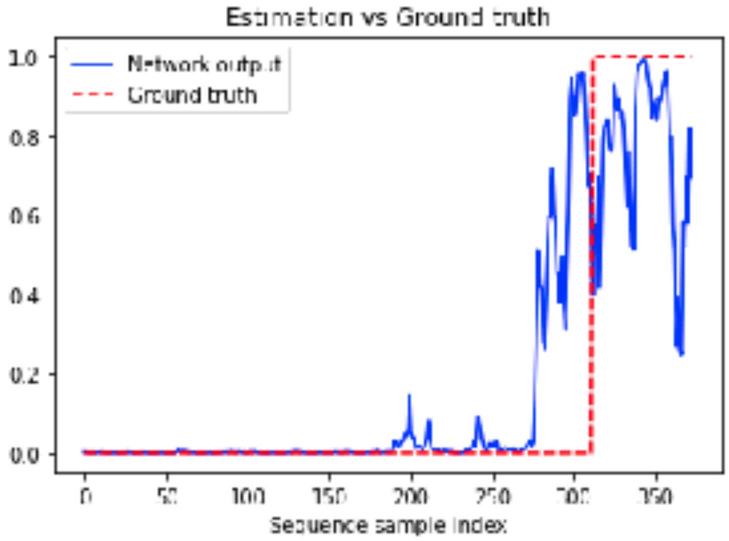
4.2 Tropical cyclone / Extratropical cyclone

~95% accuracy

4.2 Tropical cyclone / Extratropical cyclone

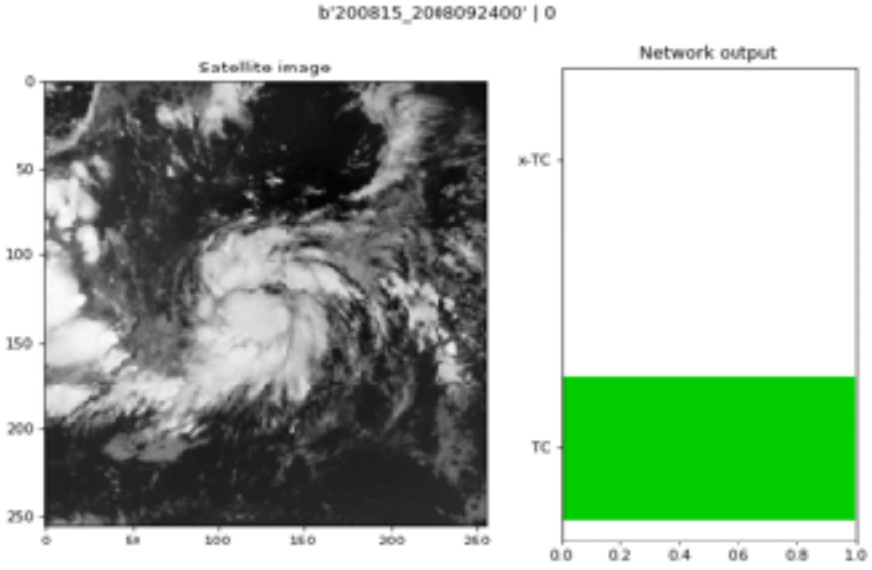
Example: **200813**

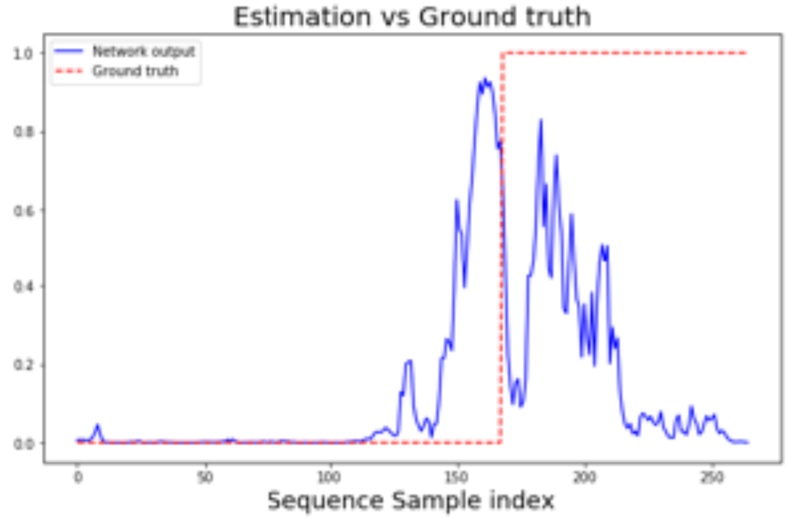




4.2 Tropical cyclone / Extratropical cyclone

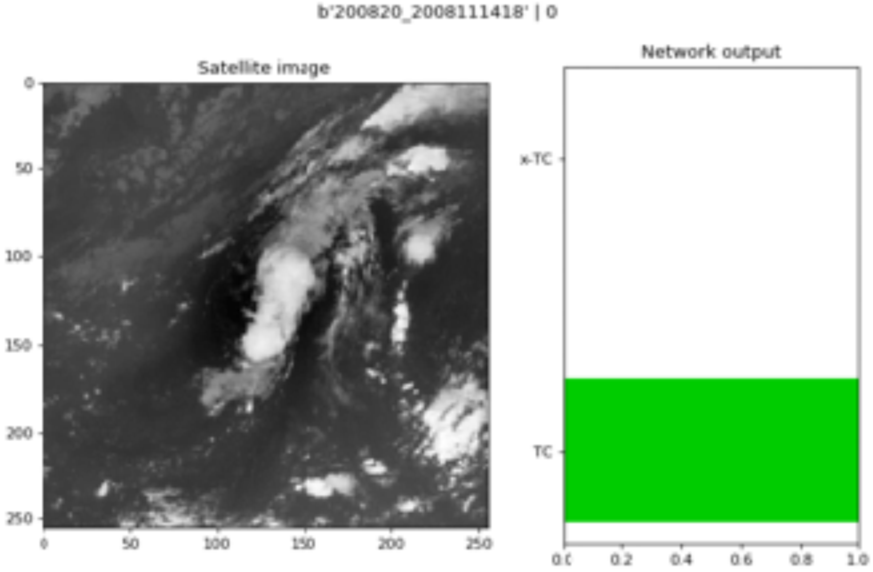
Example: **200815**

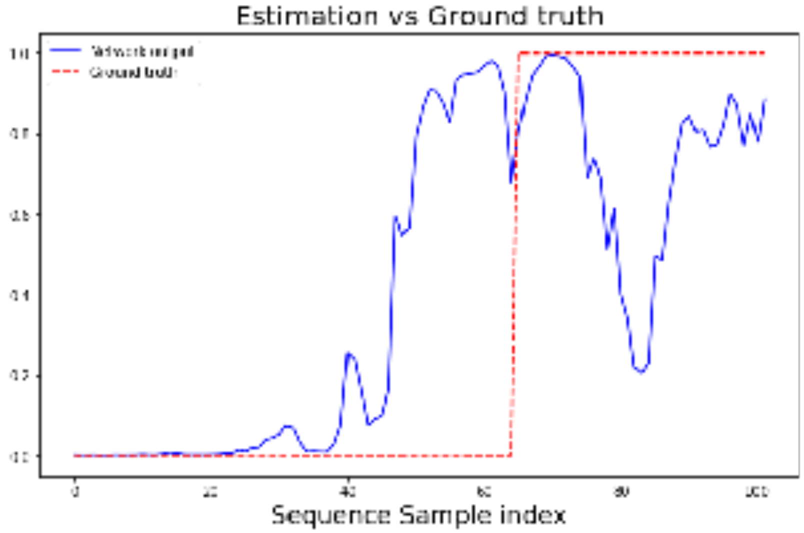




4.2 Tropical cyclone / Extratropical cyclone

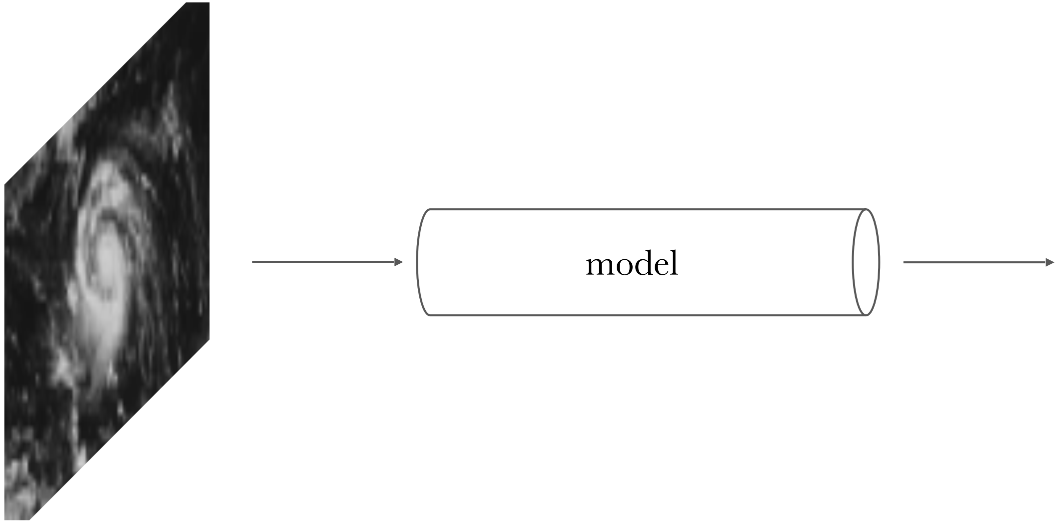
Example: **200820**





4.3 Tropical cyclone: Categorisation

Given a satellite image from Digital Typhoon dataset, estimate its **intensity category**.

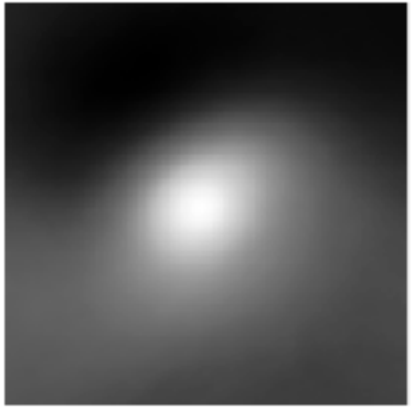


Tropical Depression	2
Tropical Storm	3
Severe Tropical Storm	4
Typhoon	5

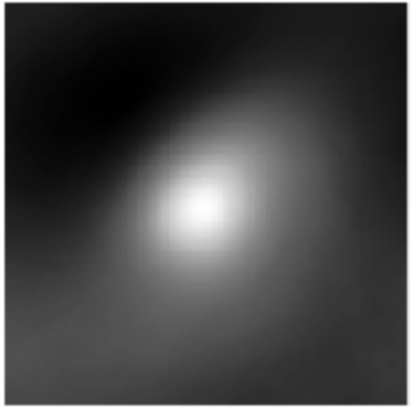
4.3 Tropical cyclone: categorisation

Mean image for each class

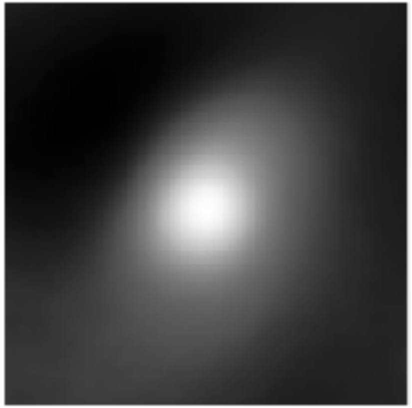
Tropical Depression



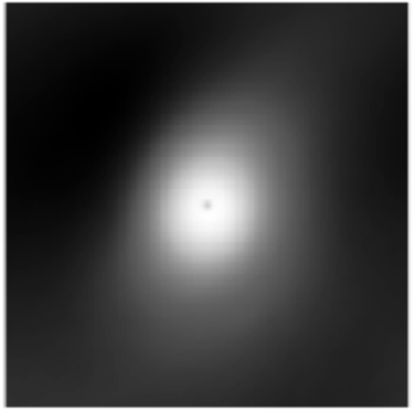
Tropical Storm



Severe Tropical Storm



Typhoon



4.3 Tropical cyclone: categorisation

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Why?

- Different network topology
- Model trained from scratch
- More data has been used (3x)

Room for improvement

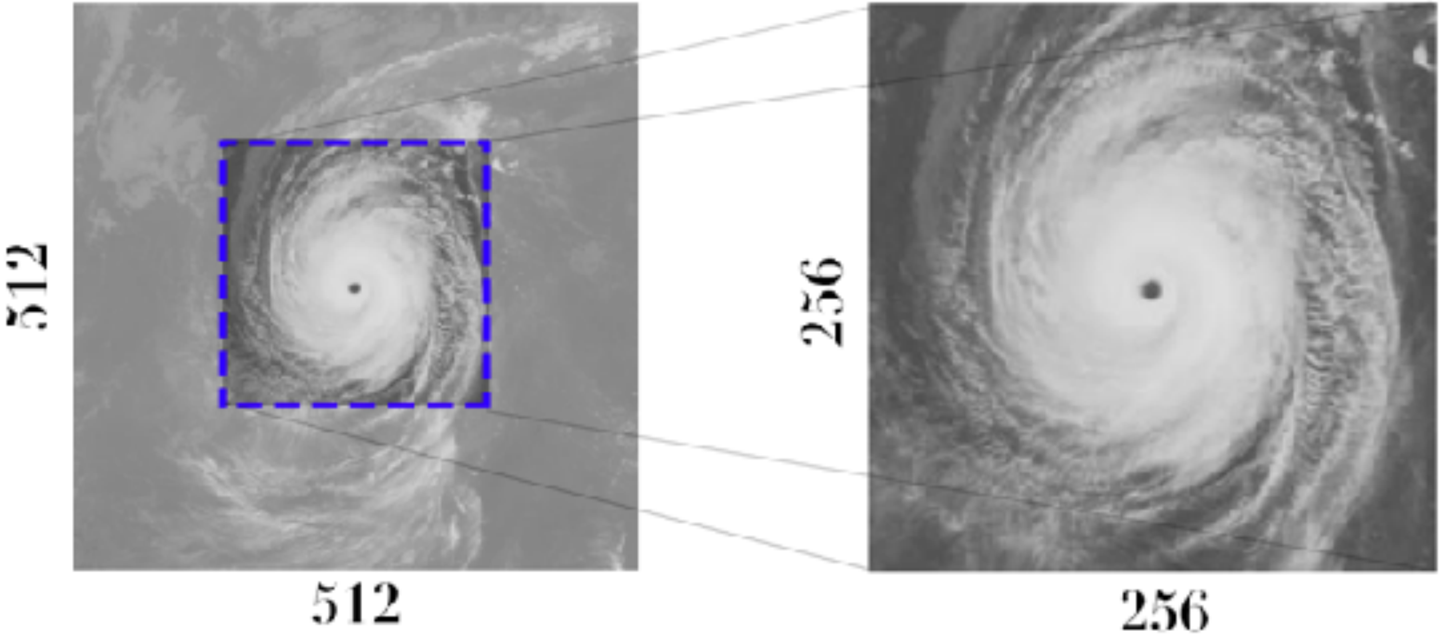
- Time series models: RNNs.

4.3 Tropical cyclone: categorisation

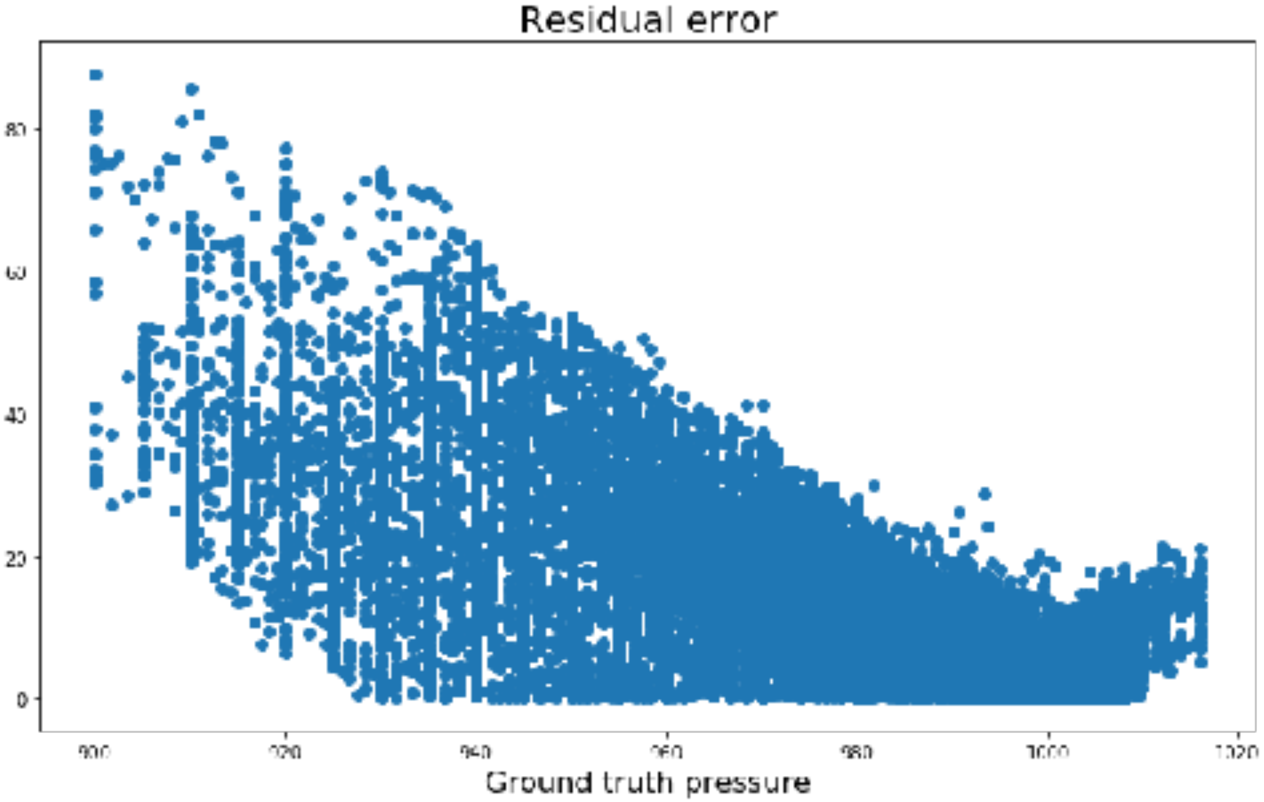
If training/test data split done randomly…

- State of the art (Pradhan *et al.*): **80% accuracy**, 8 classes, 43m parameters
- Ours: **90% accuracy**, 4 classes, ~5m parameters

4.4 Tropical cyclone: centre pressure regression



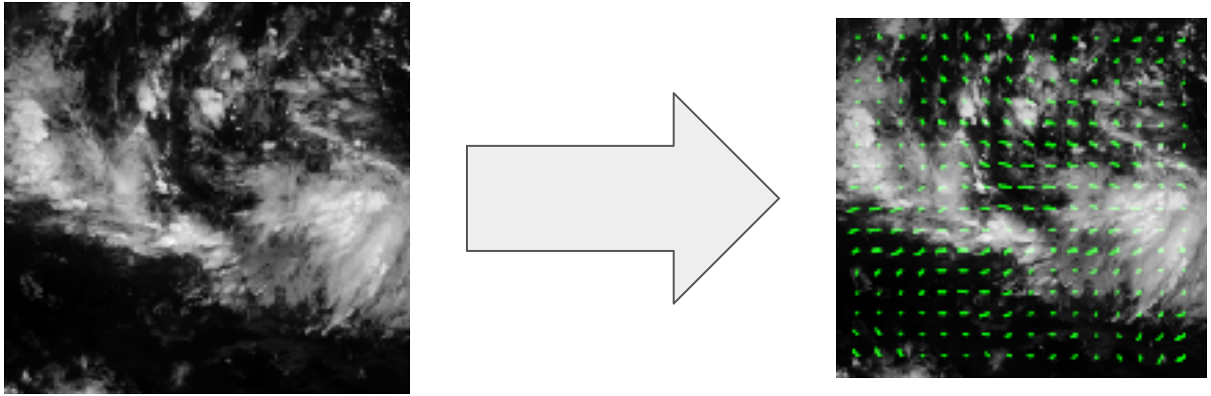
4.4 Tropical cyclone: centre pressure regression



Mean residual error
8 hPa

4.5 Motion Estimation

- **Extract motion from images**
  - **Extra data dimension for classification and regression tasks**
  - **Warp images for better nonlinear interpolation**



4.5 Motion Estimation

- **Method:**
  - **Pretrained SPyNet**

Optical Flow Estimation using a Spatial Pyramid Network

Anurag Ranjan   Michael J. Black
Max Planck Institute for Intelligent Systems, Tübingen, Germany
{anurag.ranjan, black}@tuebingen.mpg.de

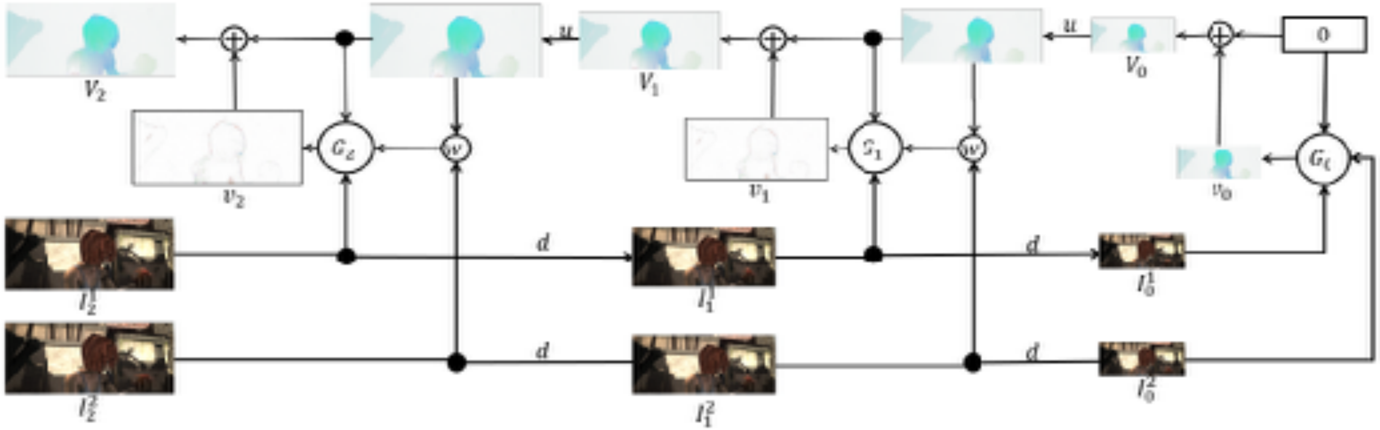
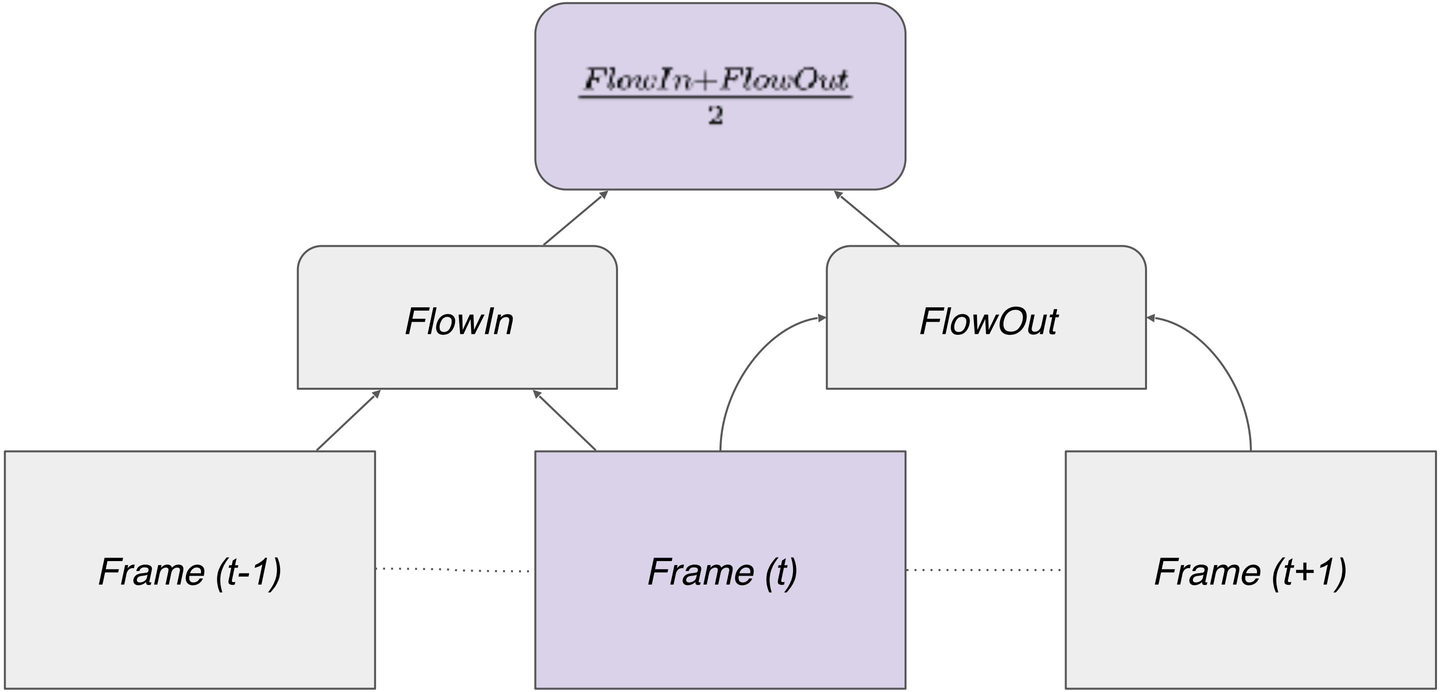


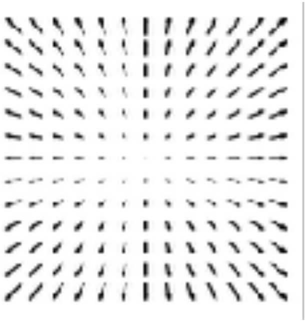
Figure 1. Inference in a 3-Level Pyramid Network [15]: The network G_0 computes the residual flow v_0 at the highest level of the pyramid (smallest image) using the low resolution images $[I_0^1, I_0^2]$. At each pyramid level, the network G_k computes a residual flow v_k which propagates to each of the next lower levels of the pyramid in turn, to finally obtain the flow V_2 at the highest resolution.

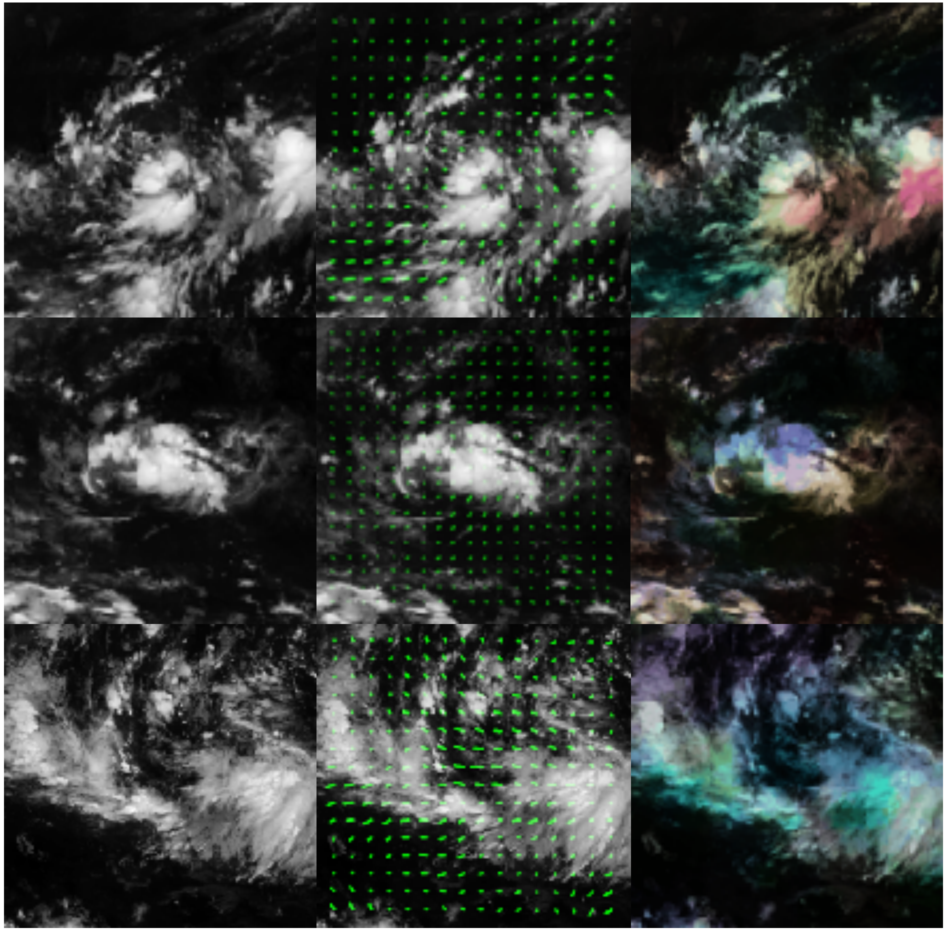
4.5 Motion Estimation



4.5 Motion Estimation

- **Dense optical flow visualisation**
  - Motion vectors on a regular grid
  - Per-pixel color coding





5. Conclusions & Future

- Deep Learning as a powerful and versatile toolkit.
- **Limitations**: unbalanced dataset, corrupted/missing image frames, best track sometimes relative…
- Time-series information.

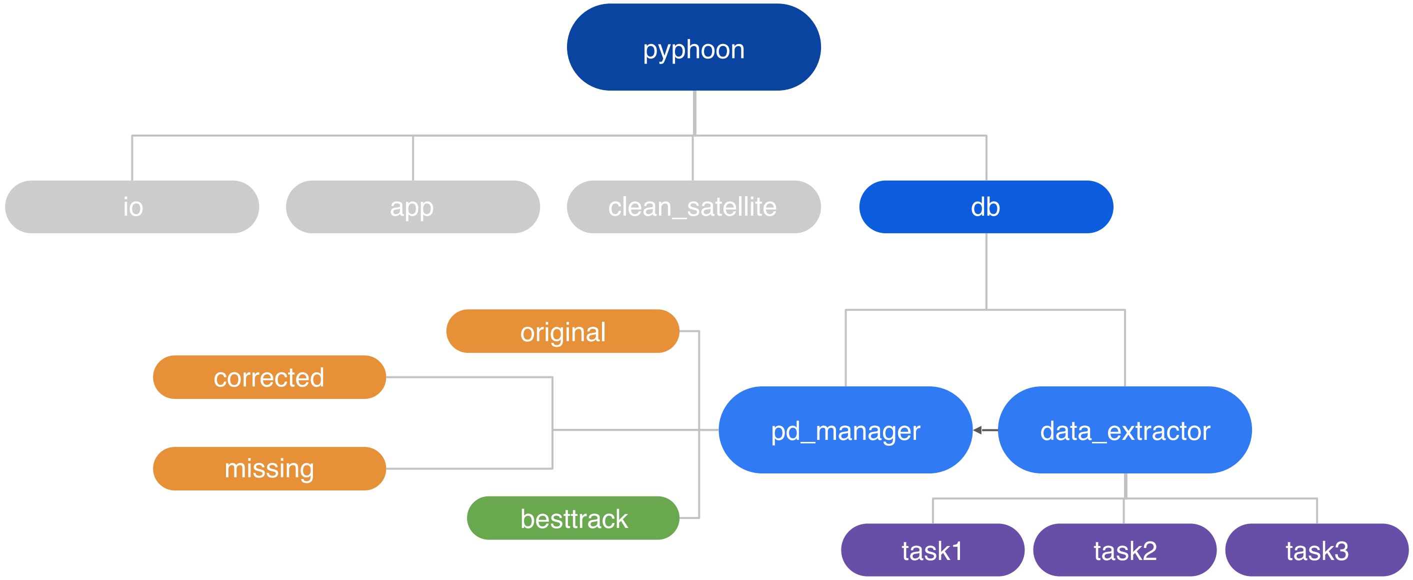
6. Code

- Python library **pyphoon** in development: http://lcsrg.me/pyphoon.
- Keras+Tensorflow to build our deep learning models.
- Release of pretrained models soon at http://github.com/lucasrodes/pyphoon.

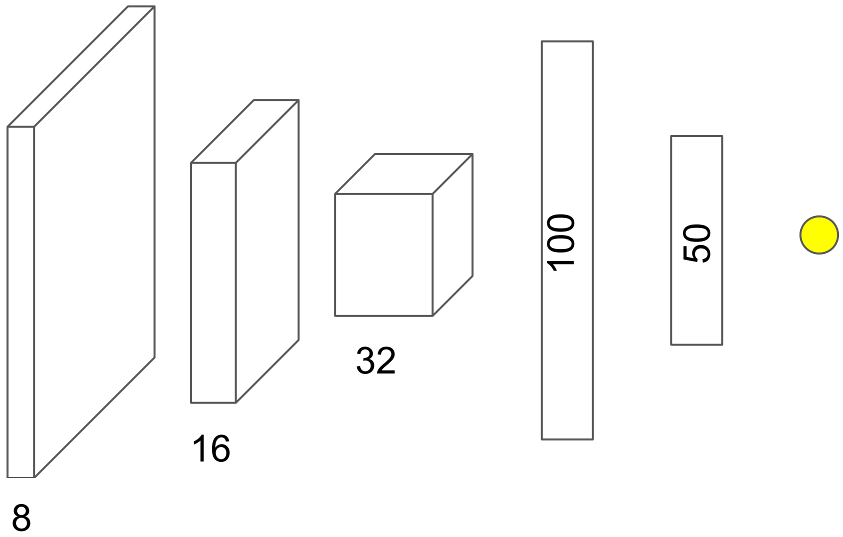
appendix

3. Data

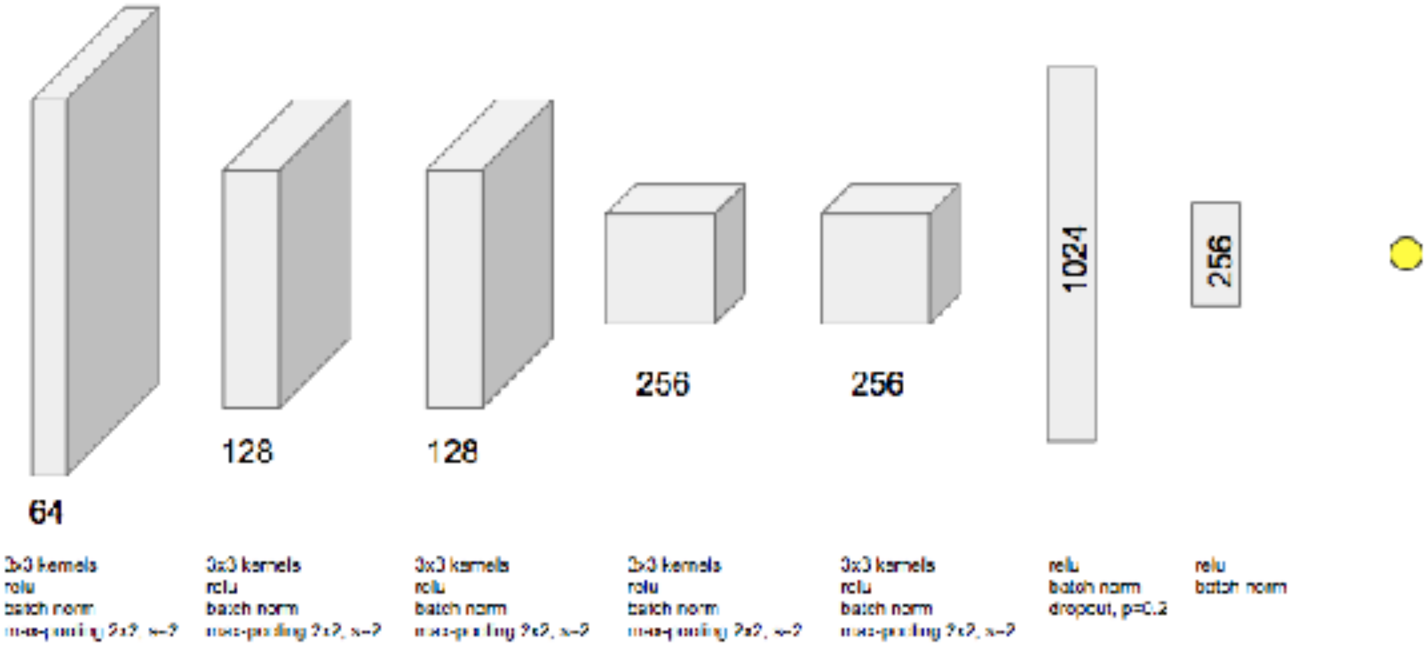
Data management



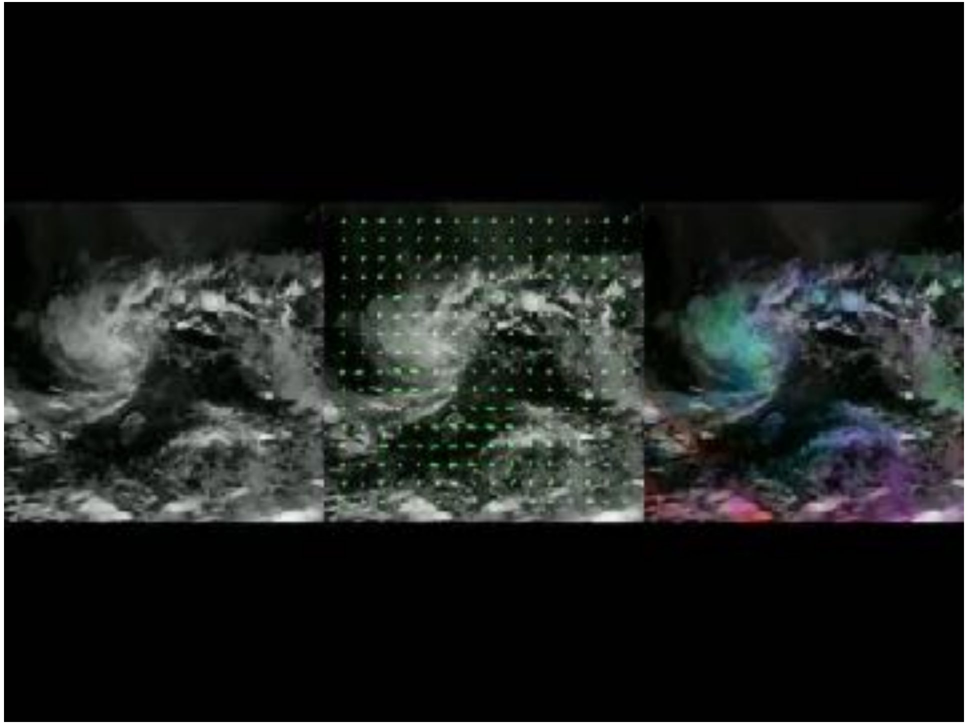
TC/xTC Network



Centre Pressure Regression Net



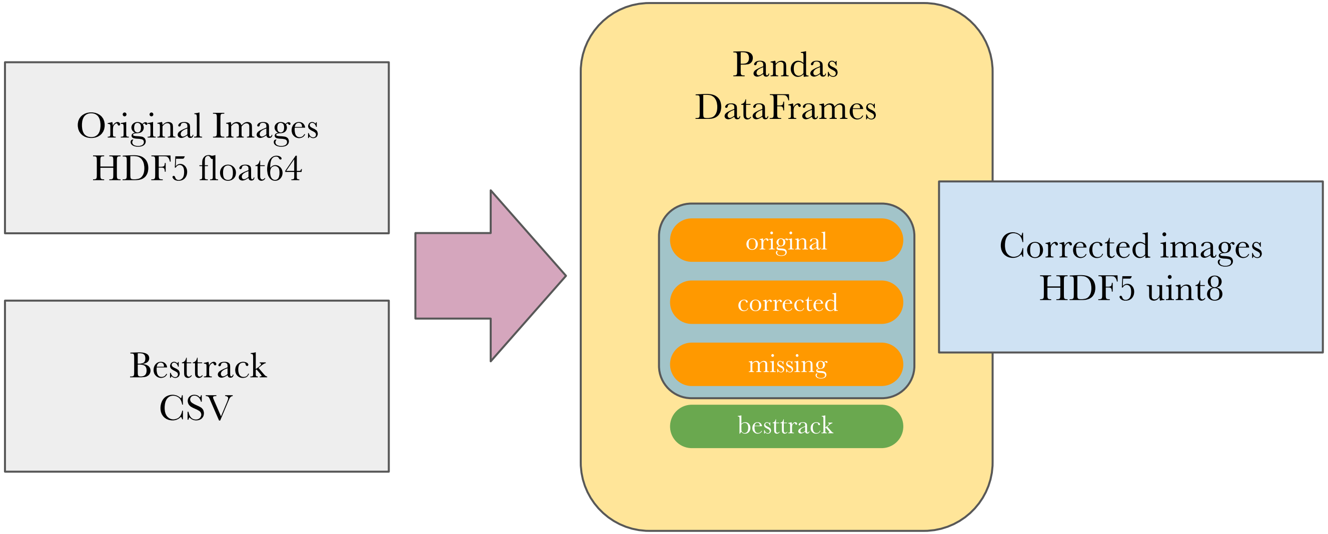
4.5 Motion Estimation



3. Data

New data format

- **Better memory utilisation**
- **Easier to manage**
- **Flexibility and scalability**



3. Data

Remark: Data split

Unless stated otherwise, throughout this project, we split the data such that images belonging to the same typhoon sequence are all contained in the same set (either training or test).

Training	**Test**
1978,	2011,
1979,	2012,
…	...
2011	2017