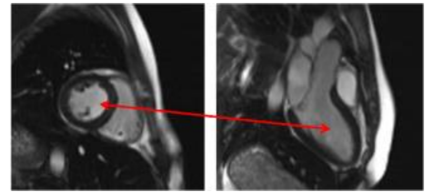
Characterizing shapes and motions

Some applications of AI to analysing physics and medical data

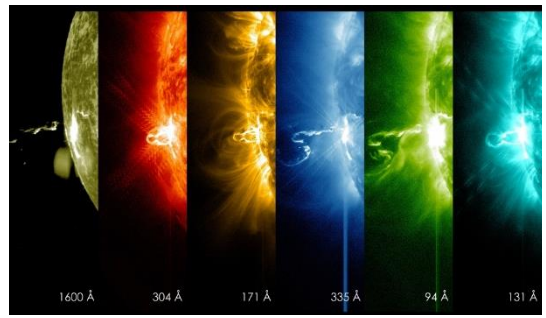
Adeline Paiement

My research domains



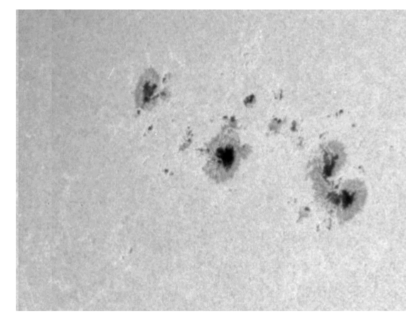
Visual perception

- Images
- Videos
- Multi-modal data



Modelling

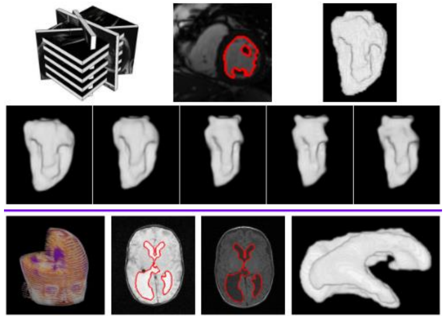
- Machine learning
- Deep learning
- ➢ Data-driven models
- ➢ Hybrid data- and knowledge-driven models

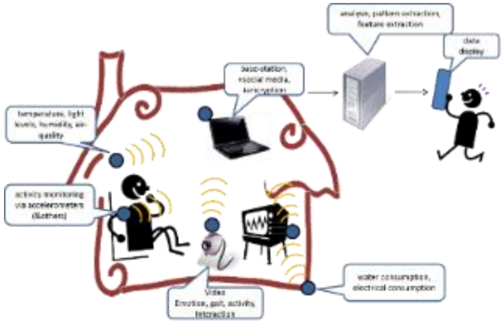


My research domains

Healthcare applications

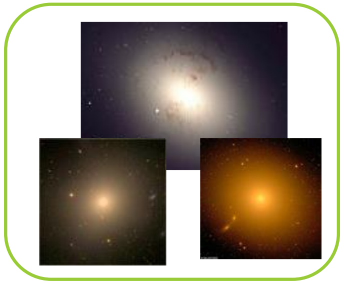
- Medical image analysis
- Diagnosis & assistive technologies

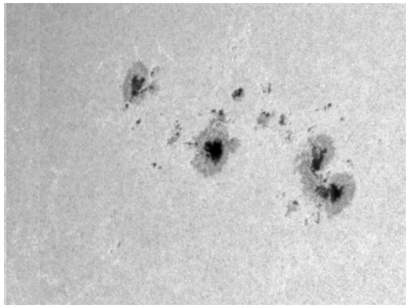




Astrophysics applications

- Catalogue generation from grand surveys
- Detection and monitoring of transient events

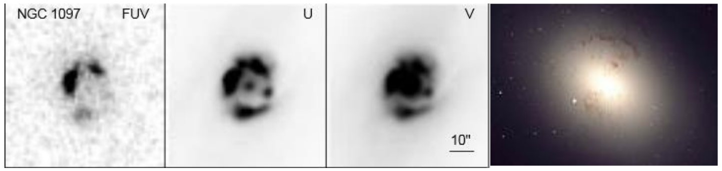


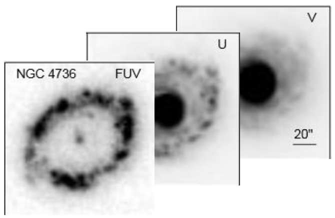


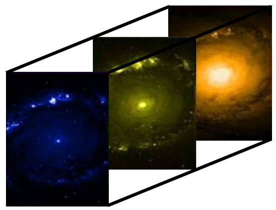
Similar tasks

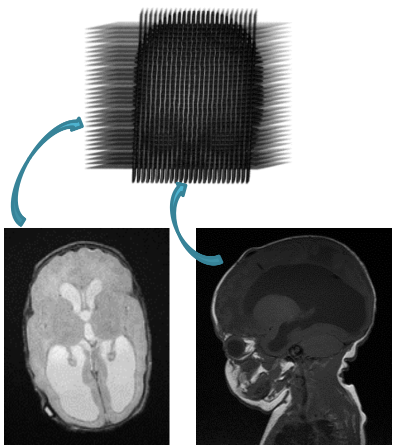
Characterising shapes

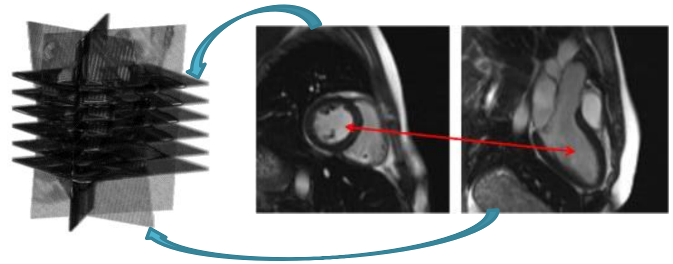
Characterising motions

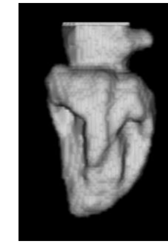


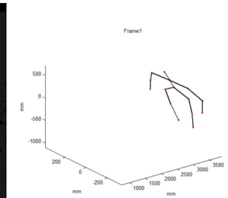


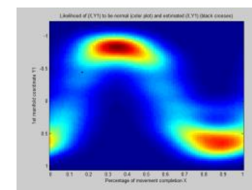


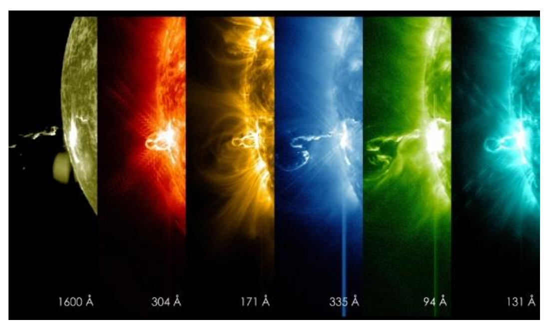


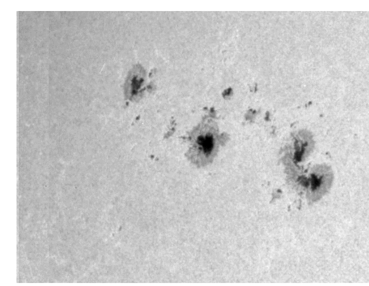










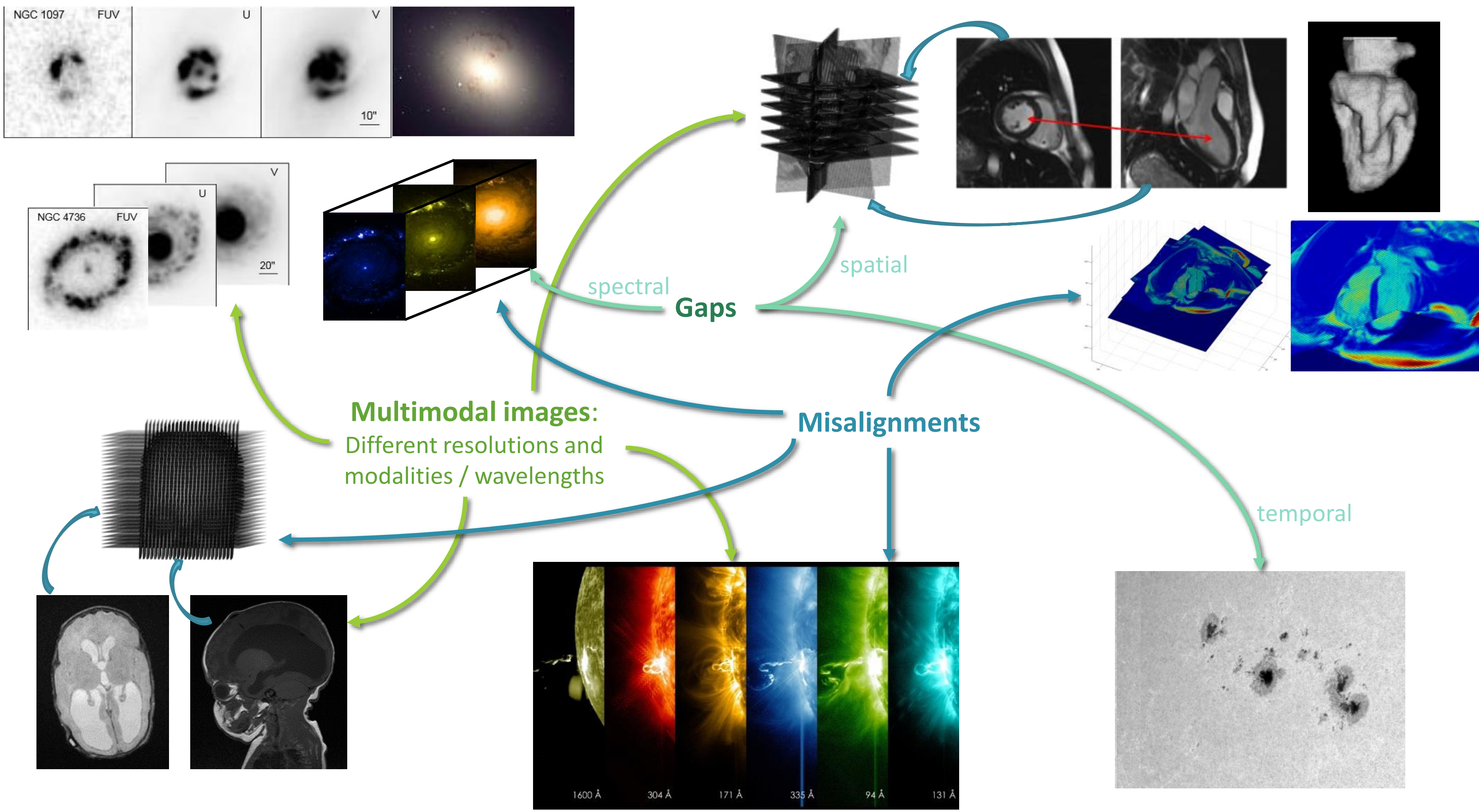


Similar challenges

Big data

Ground truth

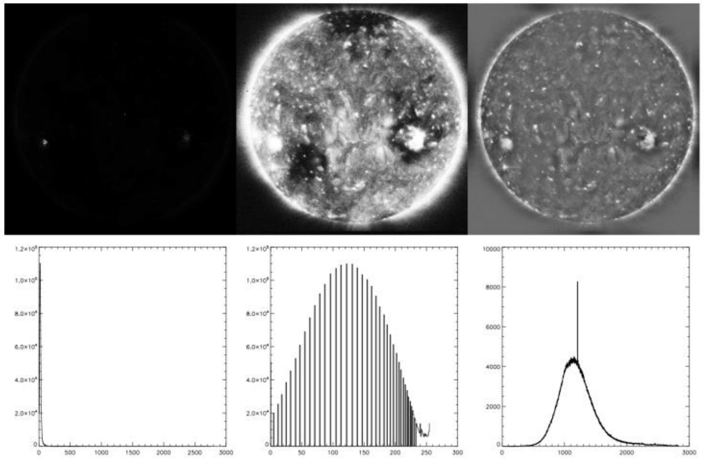
Interpretability



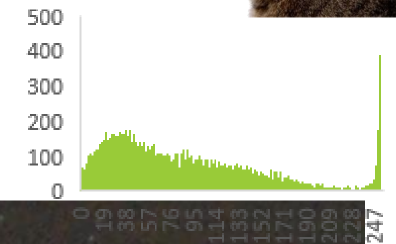
Peculiar image properties

Scientific vs natural images

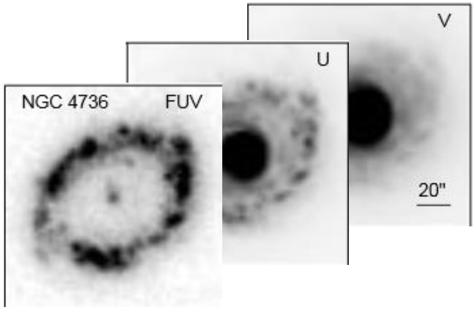
- High dynamic ranges, low contrasts



- Noise



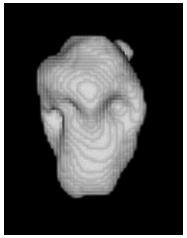
- Meaning of the intensity value

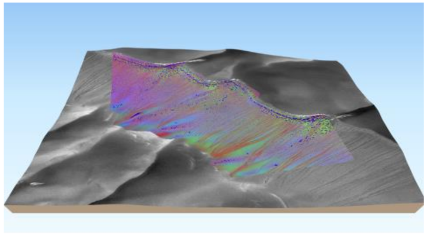


➢ Need specifically designed algorithms

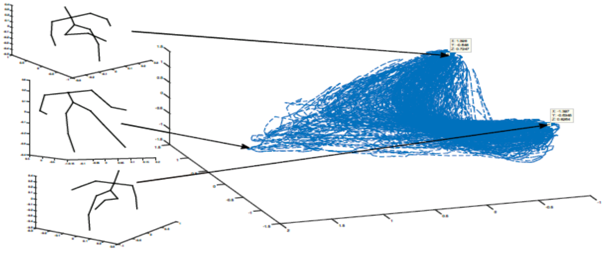
Overview: Characterising shapes and motions

Shape reconstruction

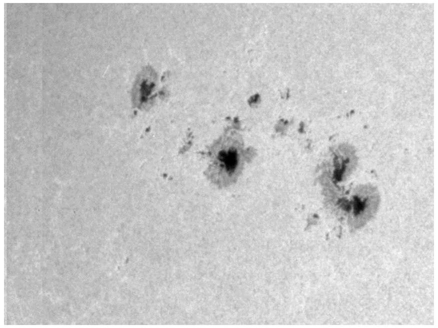




Shape analysis



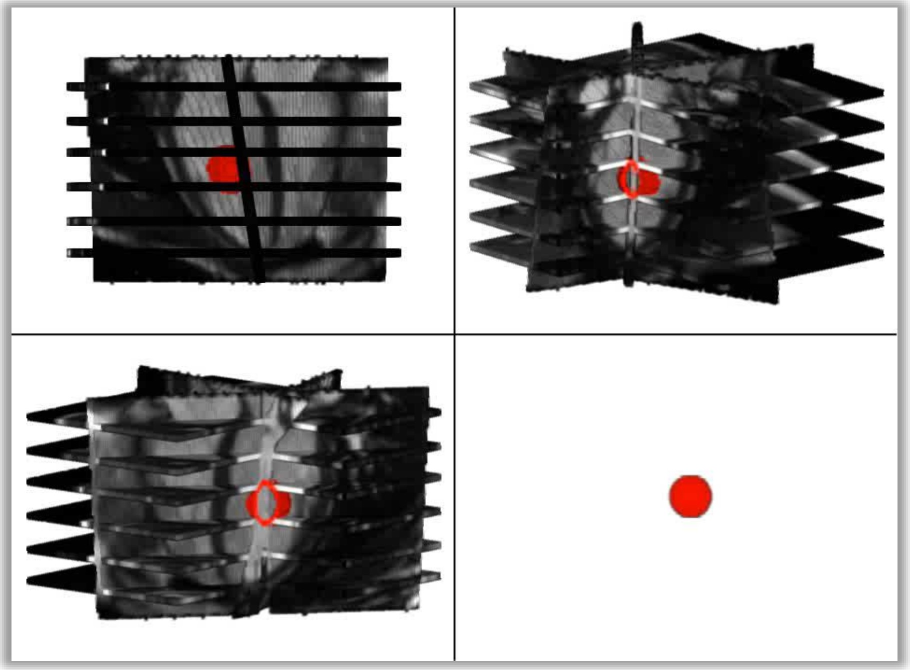
Motion analysis

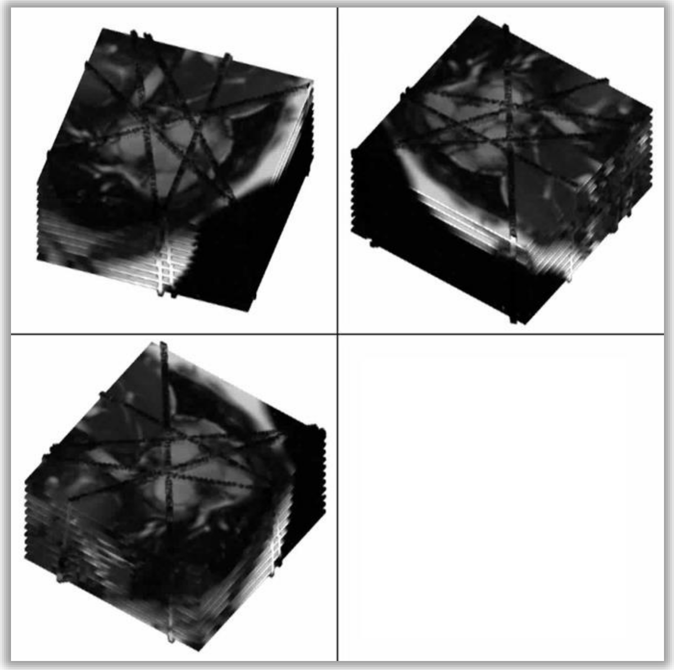


Trust issues

IReSISD: shape modelling for multimodal data

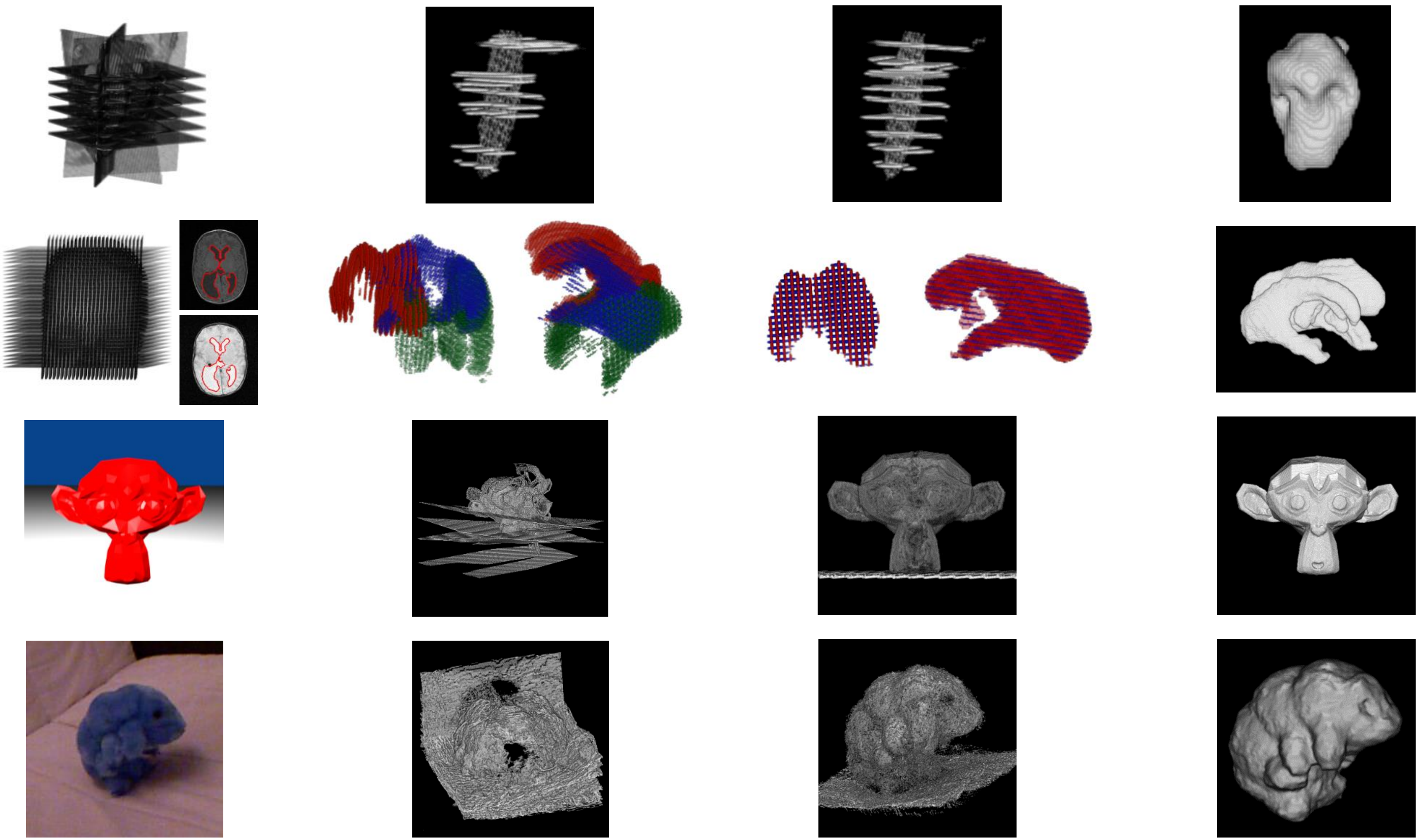
Modelling from multimodal data with heterogeneous resolutions, misalignments, and gaps





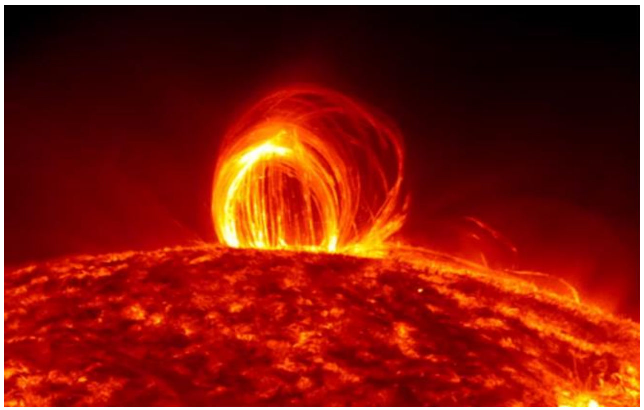
[1] Adeline Paiement, Majid Mirmehdi, Xianghua Xie, Mark Hamilton: **Registration and Modeling from Spaced and Misaligned Image Volumes**. *IEEE Transactions on Image Processing*, Vol. 25, Issue 9, 2016
[2] Adeline Paiement, Majid Mirmehdi, Xianghua Xie, Mark Hamilton: **Integrated Segmentation and Interpolation of Sparse Data**. *IEEE Transactions on Image Processing*, Vol. 23, Issue 1, 2014
[3] Adeline Paiement, Majid Mirmehdi, Xianghua Xie, Mark Hamilton: **Simultaneous Level Set interpolation and segmentation of short- and long-axis MRI**. *MIUA*, pp. 267-272, 2010

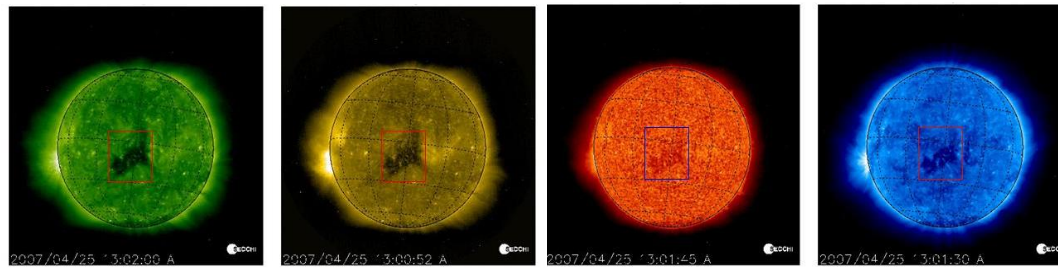
Some results on images and point clouds

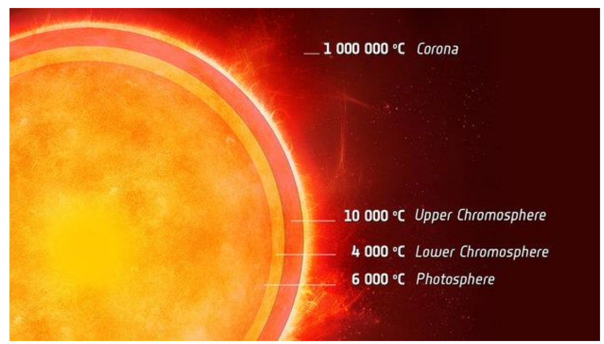


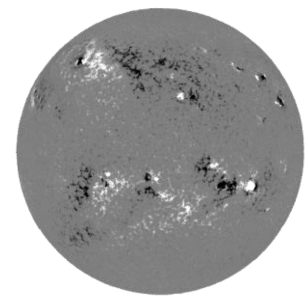
Some examples of applications in astrophysics

- Reconstruction of solar active regions from multispectral images









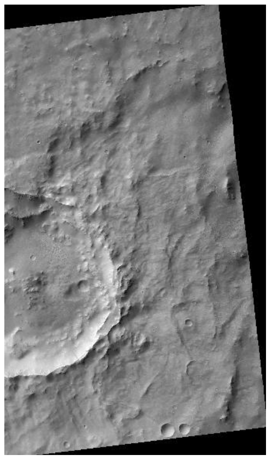
End goal:

- Understanding the mechanisms of the solar activity
- Predicting solar activity

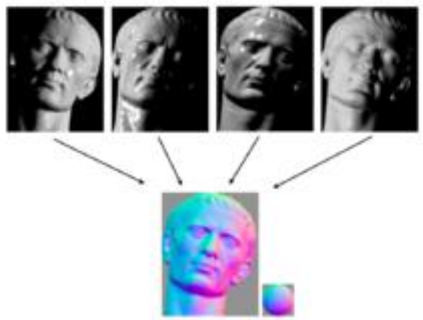
Collaboration with Paris-Meudon Observatory

Some examples of applications in astrophysics

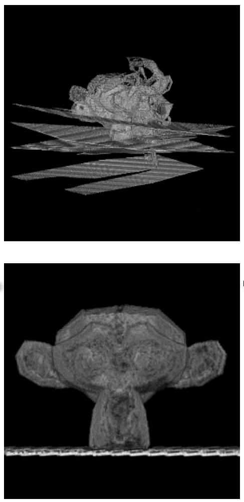
- Modelling of the Martian terrain from orbital multispectral images



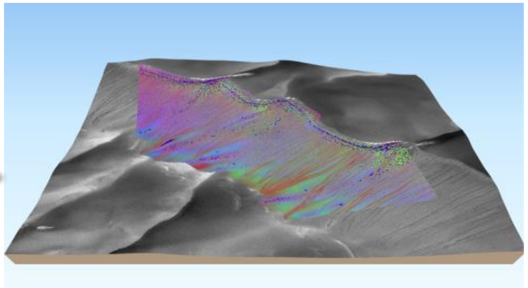
Raw image



Stereoscopic photometry – [image from Wikipedia]



Point cloud



Terrain model

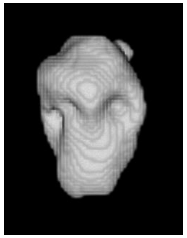
End goals:

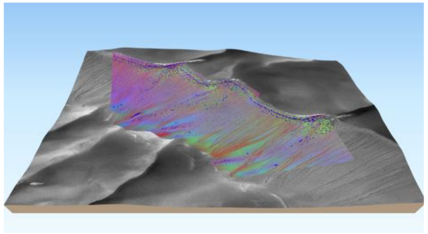
- Identification of typical and abnormal geological properties

Collaboration with Institut de Planétologie et d'Astrophysique de Grenoble (IPAG)

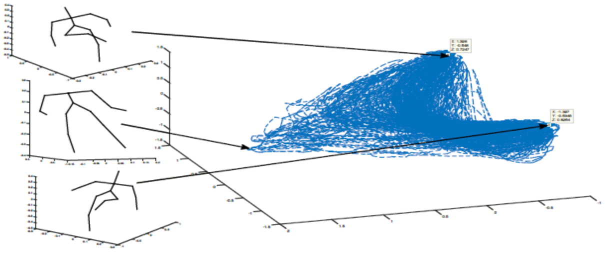
Overview: Characterising shapes and motions

Shape reconstruction

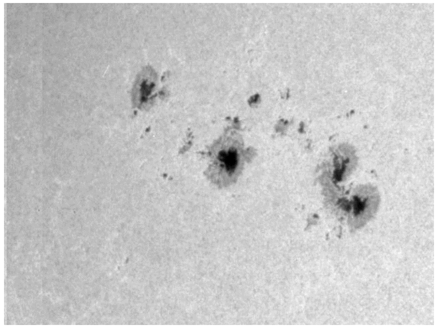




Shape analysis



Motion analysis

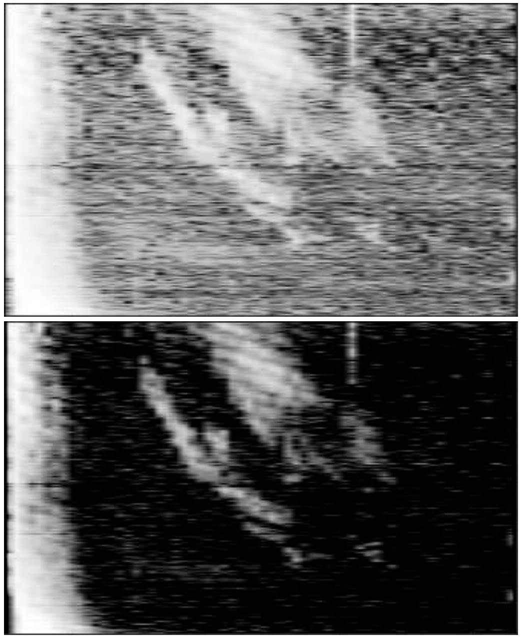


Trust issues

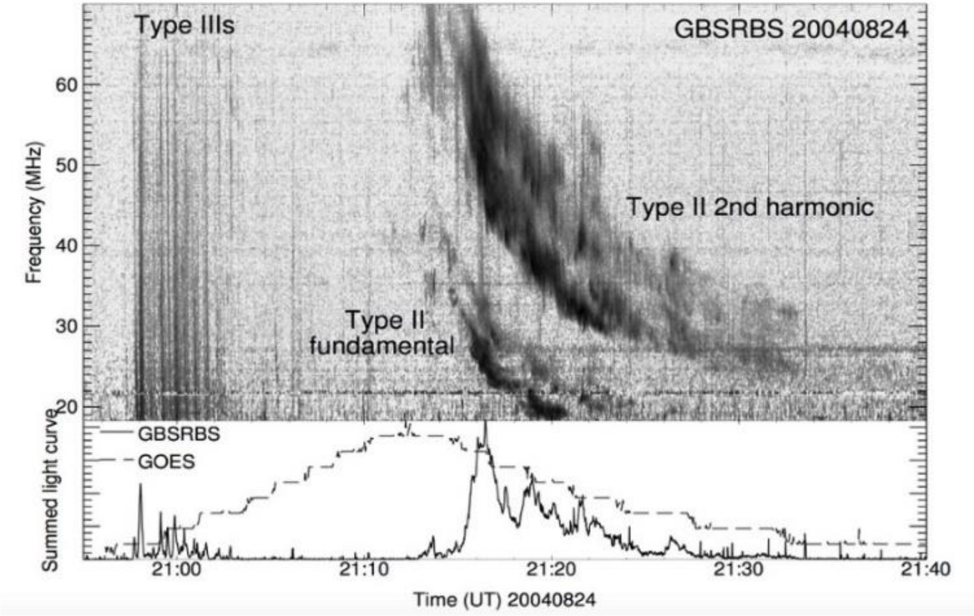
Joint solving of interdependent tasks

Solar radio bursts

- Detection
- Classification (types II and III)
- Regression of properties (duration, decrease rate, harmonic)



Truncated histogram

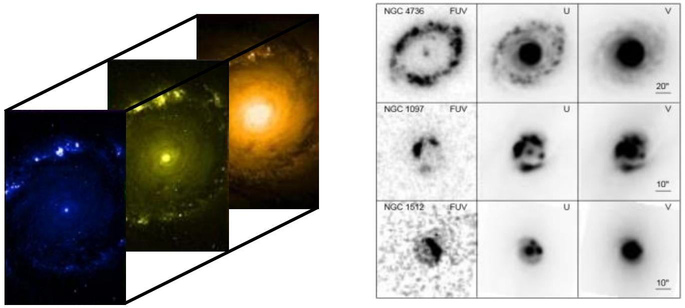


Collaboration with Paris-Meudon Observatory

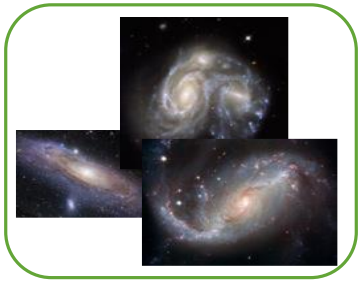
Joint solving of interdependent tasks

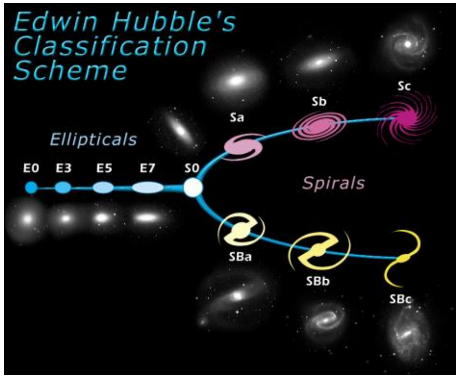
Galaxy morphology:

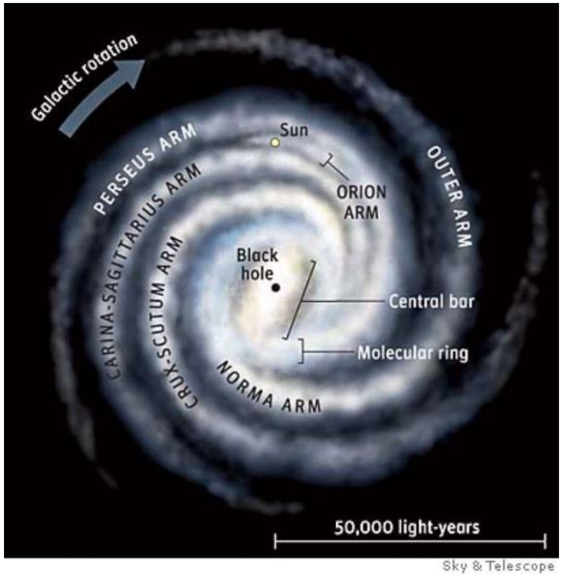
- Classification of morphology types
- Regression of morphology parameters
  - ➢ Including N/A params



Multispectral images





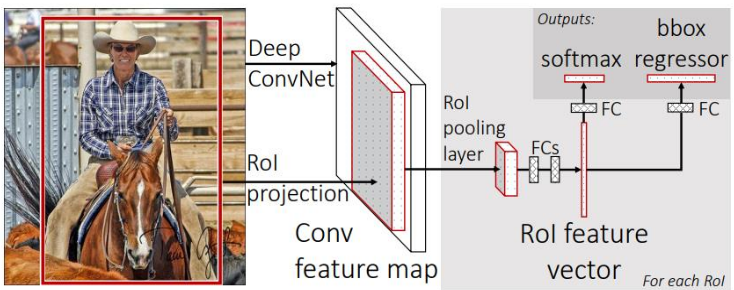


Collaboration with Strasbourg Observatory

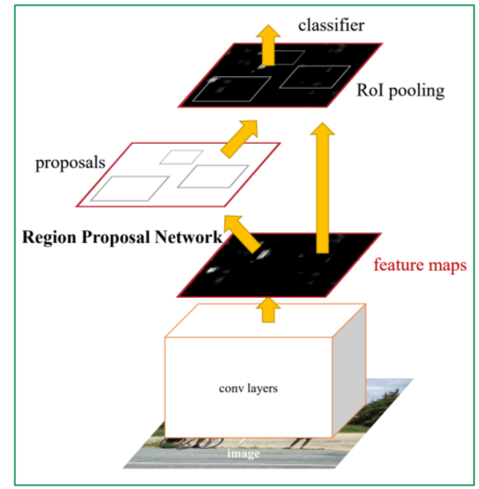
Joint solving of interdependent tasks

Typical answer nowadays: **Multi-branch deep neural network**

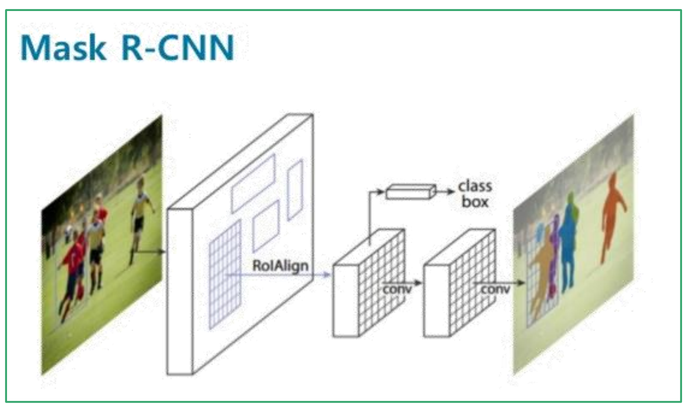
✓ Tasks share features



Fast R-CNN

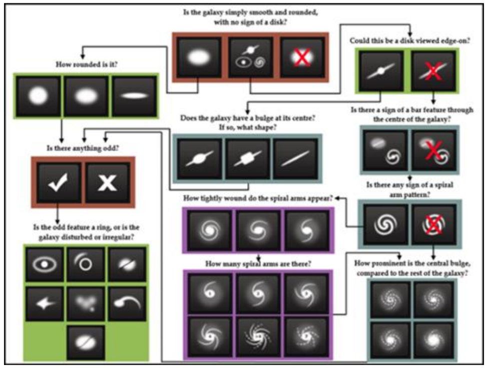


Faster R-CNN



Structured analysis that integrates *prior knowledge*

1. Characterisation as a simple multi-label classification problem [1]



Does not account for relations between parameters!

2. Hierarchical loss function [2]

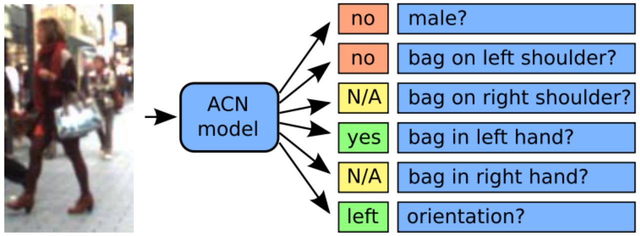
$$p(\mathrm{A},\mathrm{B}) = p(\mathrm{B}|\mathrm{A}) \cdot p(\mathrm{A})$$

Visible

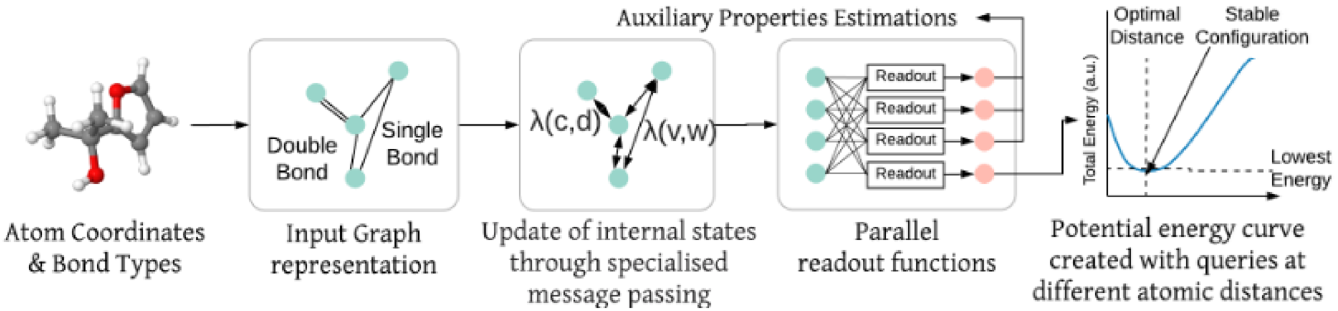
Value

Probability of the attribute value: softmax loss

Probability that attribute is visible: logistic loss



3. Architecture designed to match the problem's structure [3]



[1] S. Dieleman: **My solution for the Galaxy Zoo challenge**, 5 April 2014. [Online]

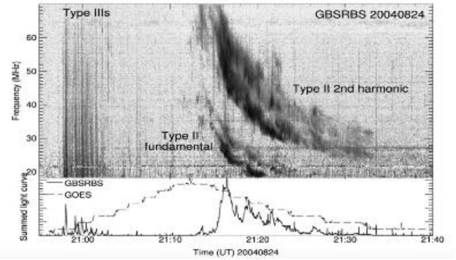
[2] P. Sudowe, H. Spitzer, B. Leibe: **Person Attribute Recognition with a Jointly-Trained Holistic CNN Model**. ICCV-W, 2015

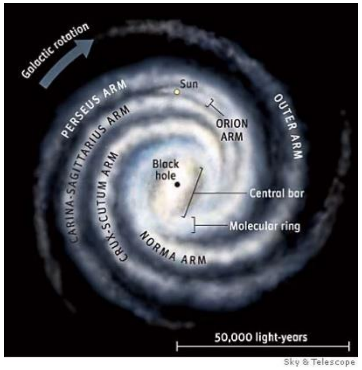
[3] J. Morgan, A. Paiement, C. Klinke: **VIMPNN: Physics informed DNN to estimate potential energies of unstable systems**. ICLR 2020

The question of representation

Parametric representation:

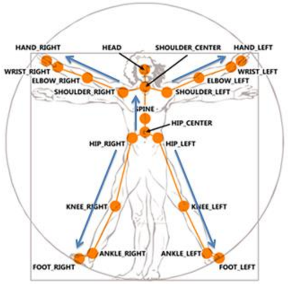
- Naturally defined:





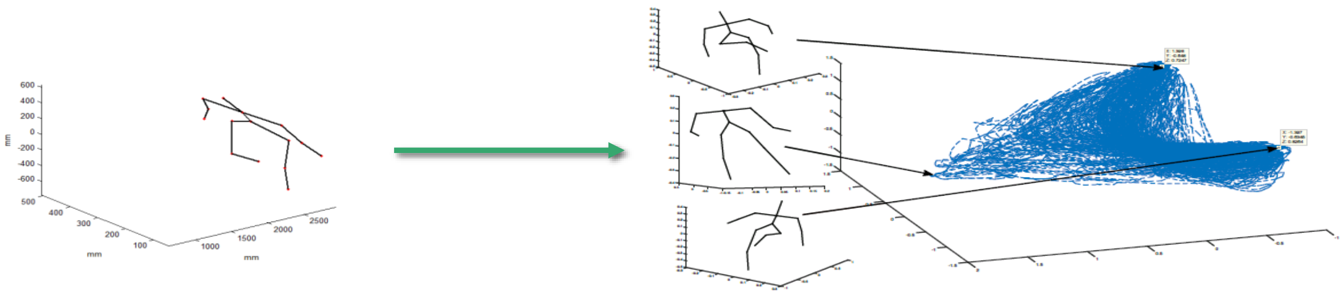
- Hard to define:

- Redundant:



The question of representation

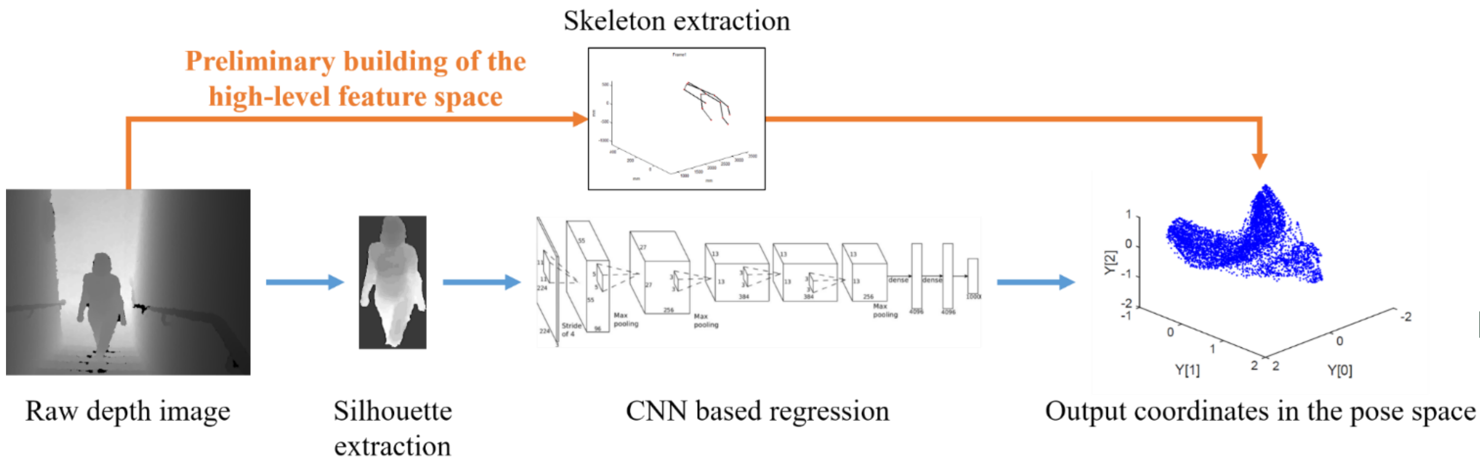
Learnt representation



Robust Diffusion Map Manifold

[1]

- … as a basis for deep learning analysis

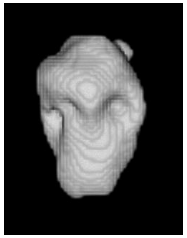


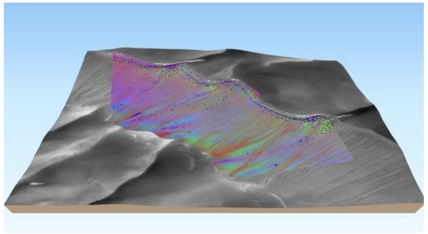
[2]

[1] A. Paiement, L. Tao, S. Hannuna, M. Camplani, D. Damen, M. Mirmehdi: **Online quality assessment of human movement from skeleton data**. *BMVC*, 2014
[2] B. Crabbe, A. Paiement, S. Hannuna, M. Mirmehdi: **Skeleton-free body pose estimation from depth images for movement analysis**. *ChaLearn Looking at People workshop at ICCV*, 2015

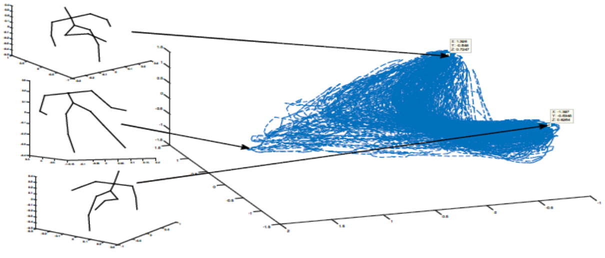
Overview: Characterising shapes and motions

Shape reconstruction

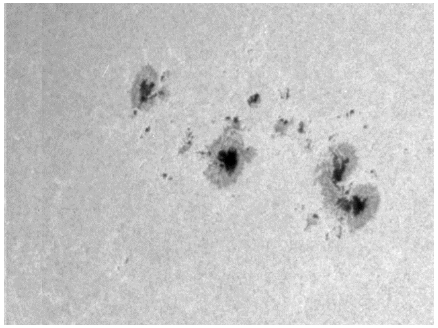




Shape analysis



Motion analysis

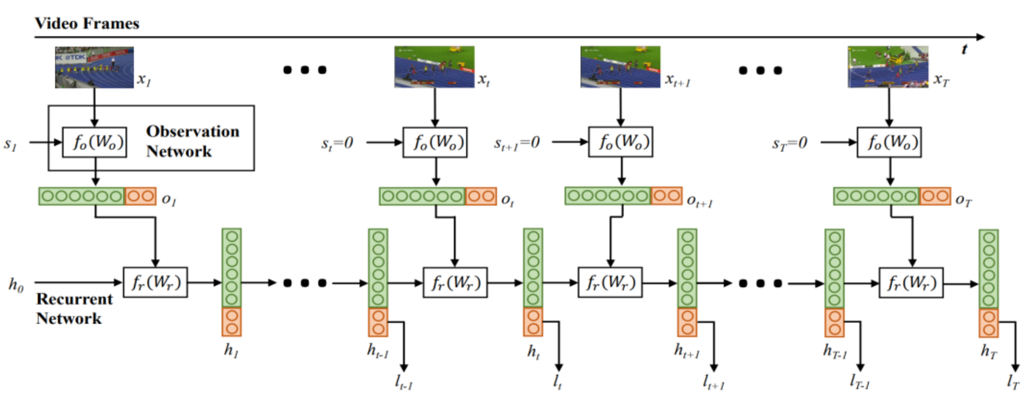


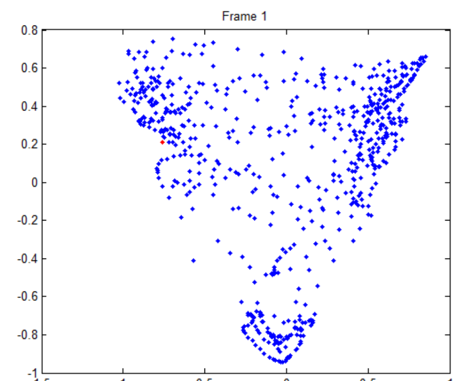
Trust issues

Joint tracking and characterization of near-Earth objects

Tracking in space...

... and in physical parameters' space



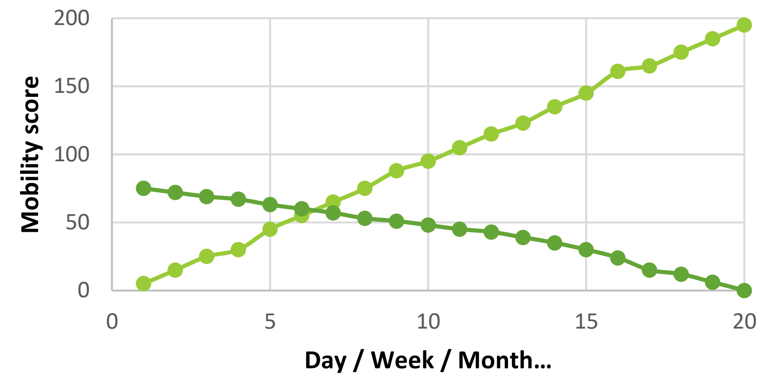


Collaboration with NASA/JPL

Mobility assessment from Kinect data

Scoring of movement quality

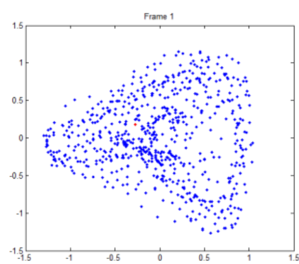
from depth images



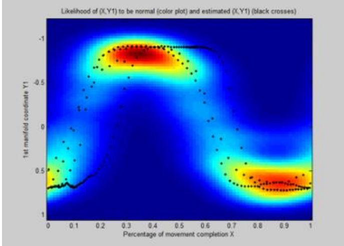
1. Model normal movements
2. Quantify deviations from the model

Kinect depth image

Pose representation



Statistical model of kinematics



Measure of kinematics' quality

Statistical model of pose

Measure of pose's quality

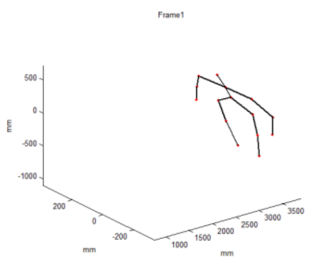
Collaboration with physiotherapy and orthopaedic experts at Bristol hospitals

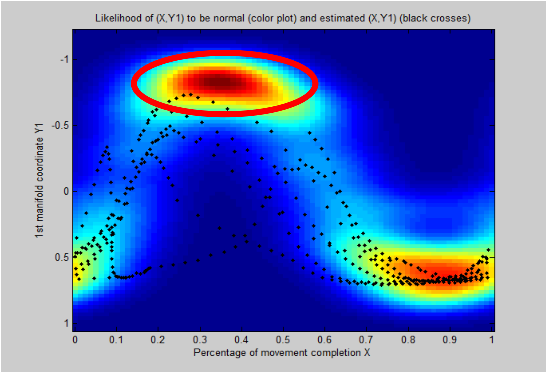
[1] A. Paiement, L. Tao, S. Hannuna, M. Camplani, D. Damen, M. Mirmehdi: **Online quality assessment of human movement from skeleton data**. *BMVC*, 2014

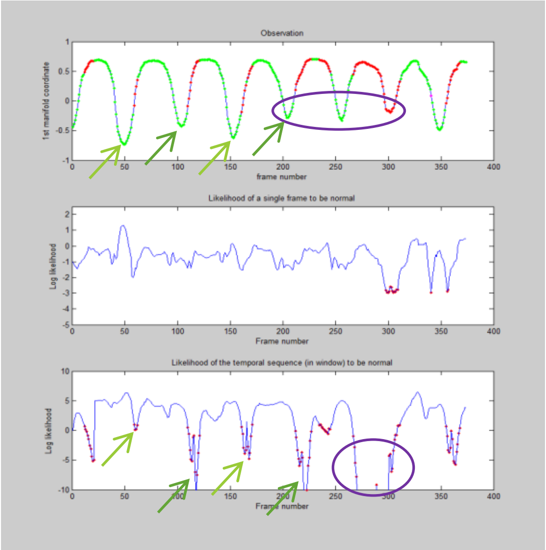
[2] L. Tao, A. Paiement, D. Damen, M. Mirmehdi, S. Hannuna, M. Camplani, T. Burghardt, I. Craddock: **A Comparative Study of Pose Representation and Dynamics Modelling for Online Motion Quality Assessment**. *Computer Vision and Image Understanding - SI: Assistive Computer Vision and Robotics*, Vol. 148, 2016

Some examples of abnormal movements

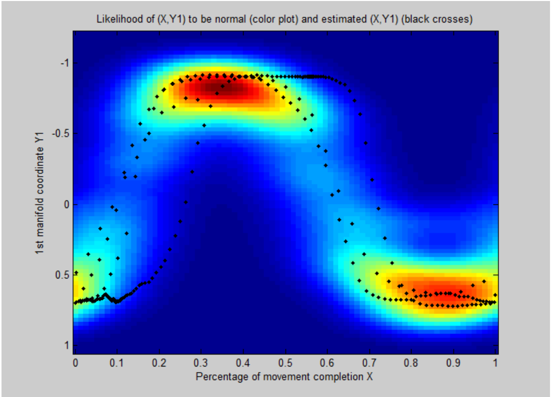
- Left leg lead

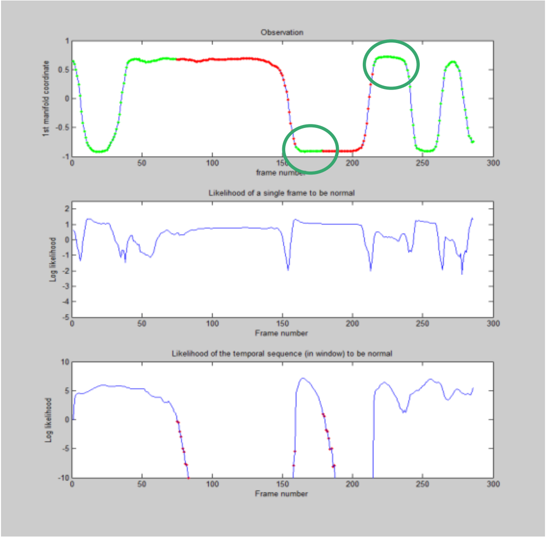






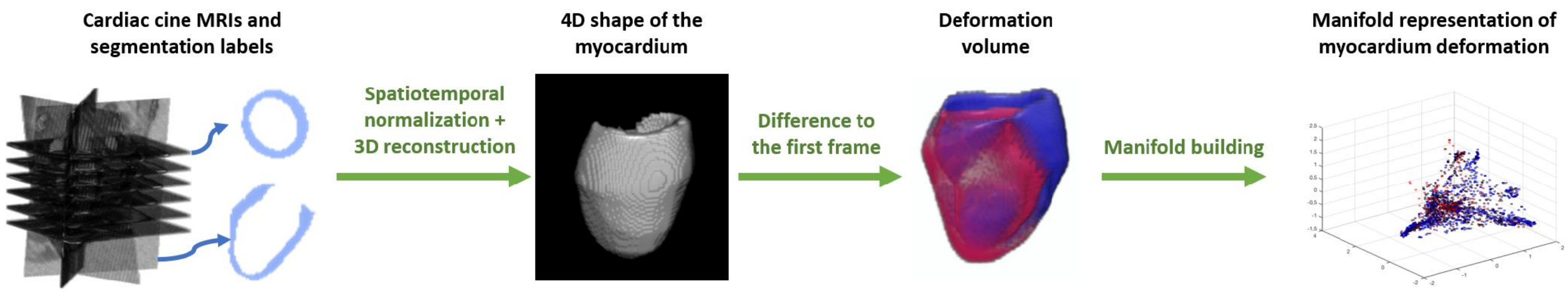
- Freeze





Heart function assessment

1. Manifold representation of heart deformations [1]



2. Modelling of a normal heart deformation sequence (in progress)

- Trust of clinicians:
  - Integration of, and mapping to, current proxy measures

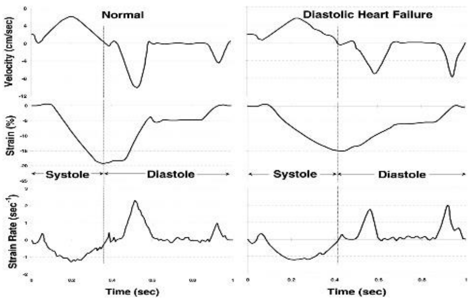


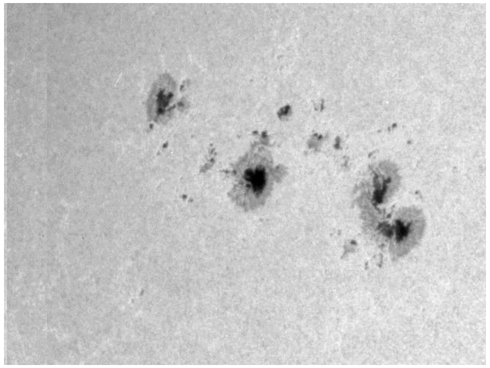
Image credit: Aurigemma et al. 2006

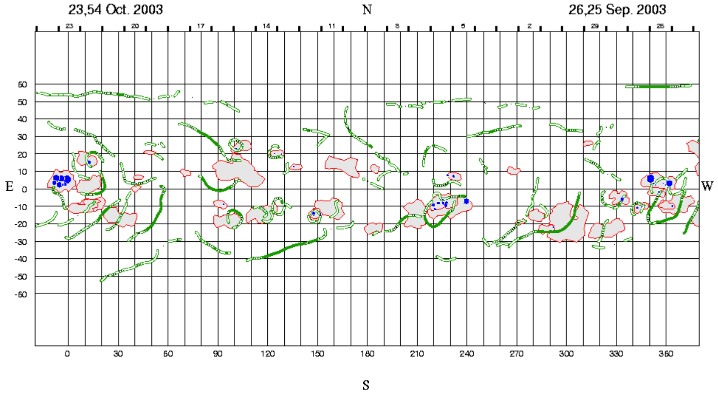
Collaboration with Bristol Heart Institute

[1] Paul Stroe, Xianghua Xie, Adeline Paiement: **Manifold modeling of the beating heart motion**. *Medical Image Understanding and Analysis (MIUA)*, 2018

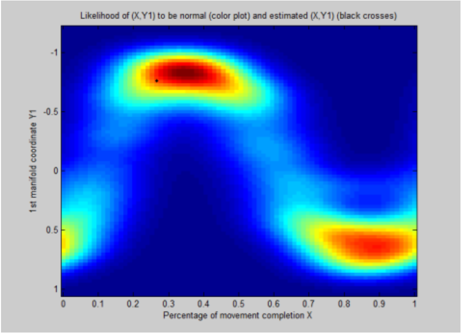
Predicting solar activity

1. Tracking of solar features and their interactions





2. Modelling of evolutions and behaviours

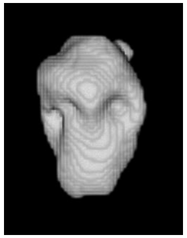


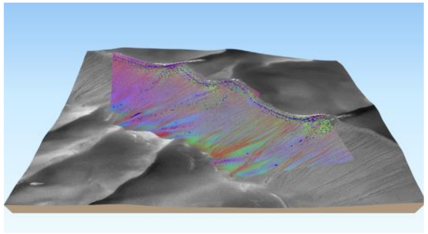
3. Prediction that integrates physics knowledge (e.g. magnetic properties)

Collaboration with solar physicist at Paris-Meudon Observatory

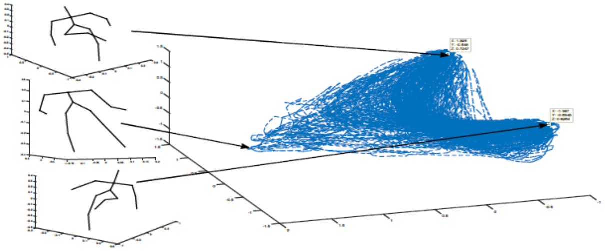
Summary: Characterising shapes and motions

Shape reconstruction

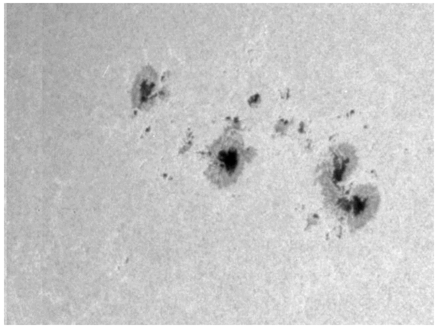




Shape analysis



Motion analysis

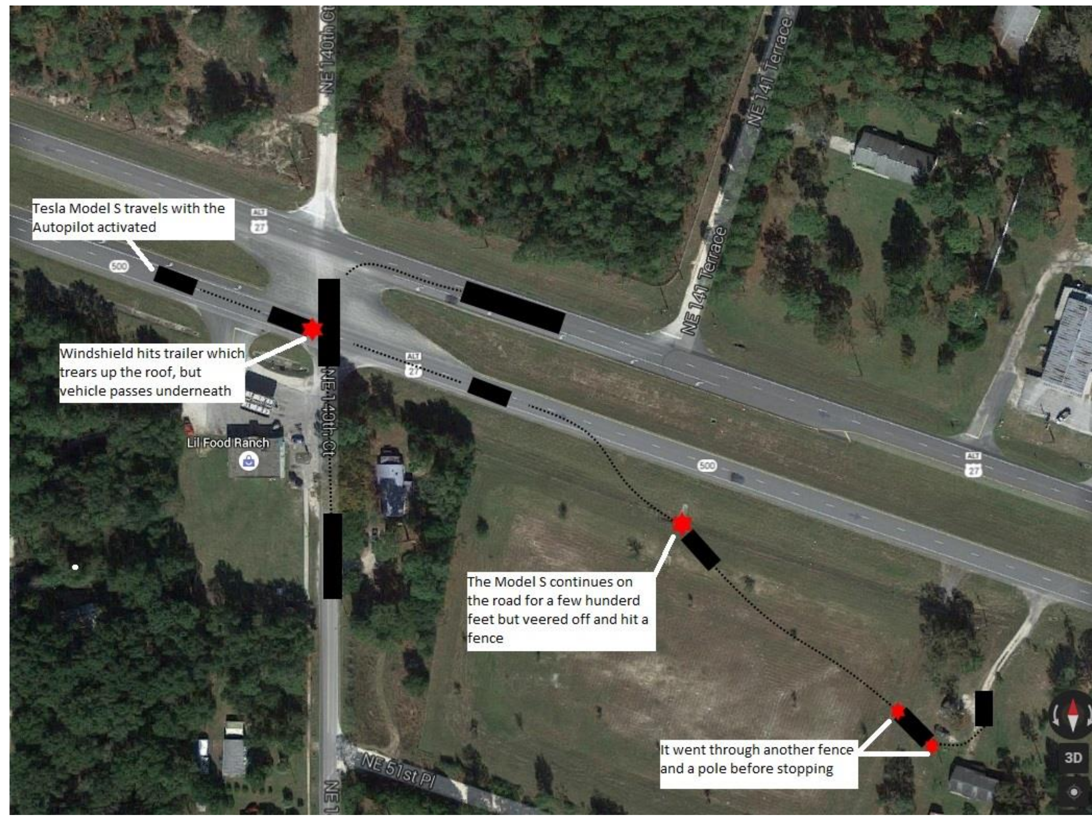


Trust issues

How much can we trust the models and their predictions?

Issue #1: we don't have all the possible data in the world

- Generalisation problem



How much can we trust the models and their predictions?

Issue #1: we don’t have all the possible data in the world

Issue #2: the data may be biased

- Biased data → biased models!

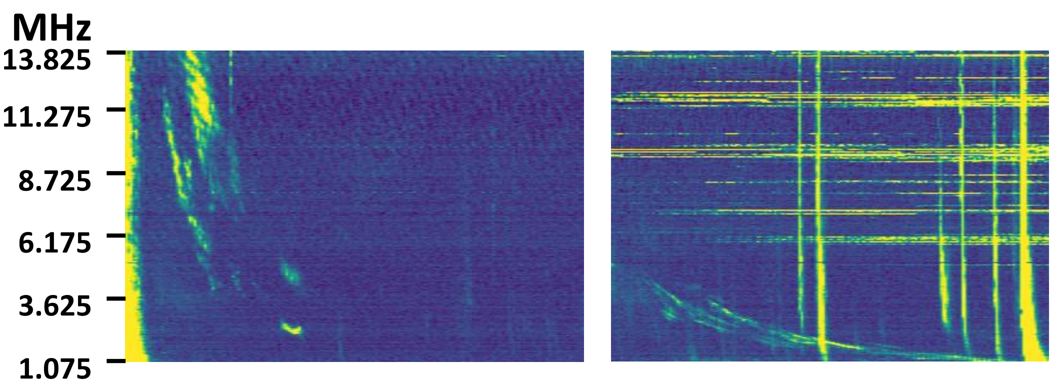
How much can we trust the models and their predictions?

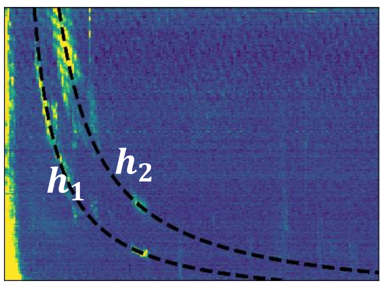
Issue #1: we don’t have all the possible data in the world

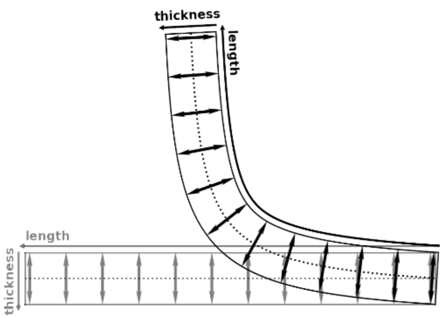
Issue #2: the data may be biased

Issue #3: supervised learning requires lots of expert annotated data

- constraints from prior knowledge (e.g. from physics) may:
  - reduce the model’s freedom
  - help its learning from fewer examples



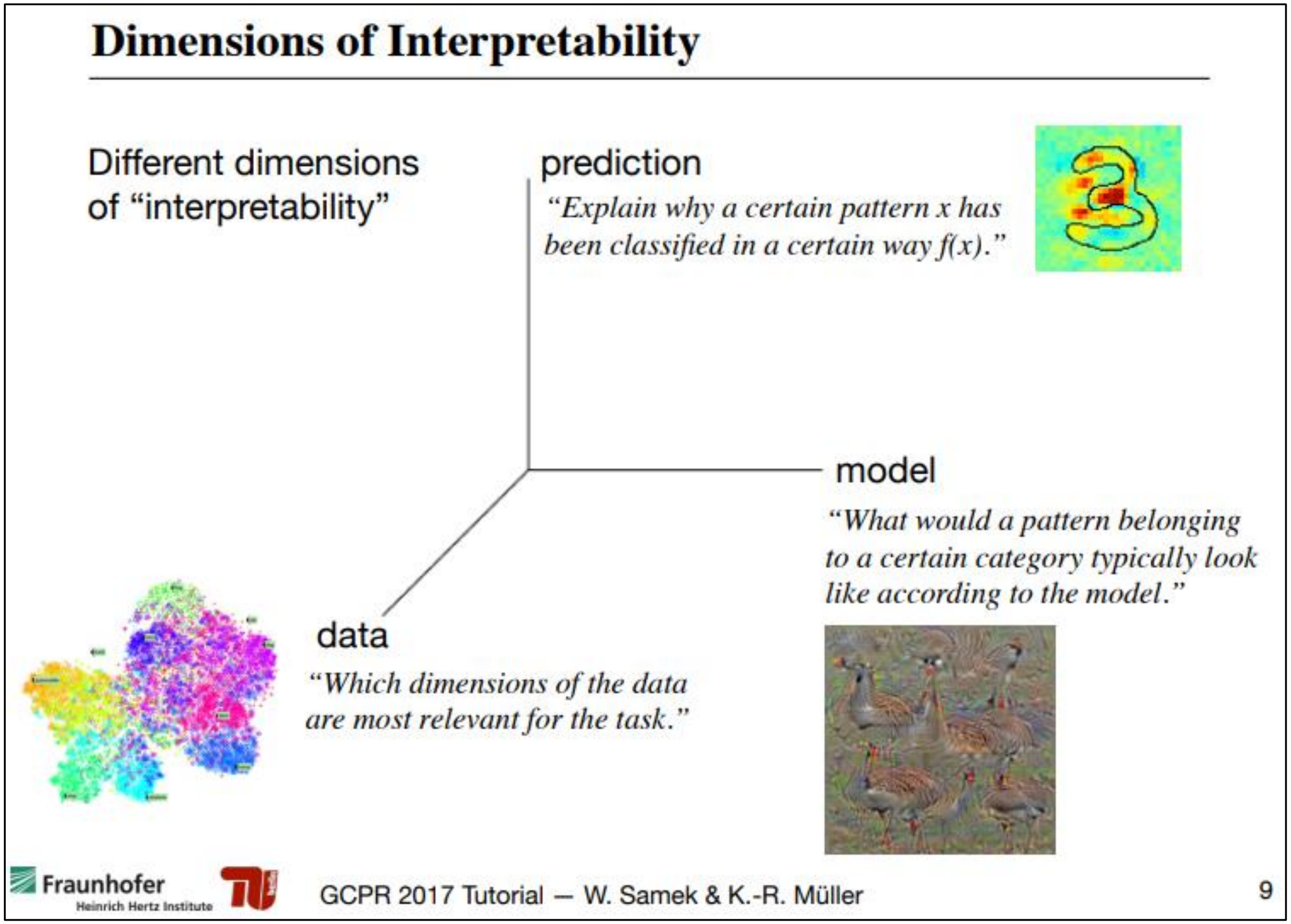




[1] Jenkins, Paiement, Xie, Aboudarham, Bonnin, Issautier: **Detection and parameter estimation of type II solar radio bursts**. HelioML 2019

How do we know what neural networks actually do?

Visualisation methods



The next (foreseeable) big developments in AI…

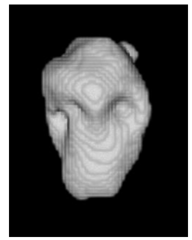
Explainable neural networks

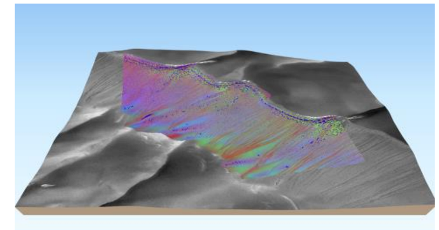


Hybrid **data**- and **knowledge**-driven models

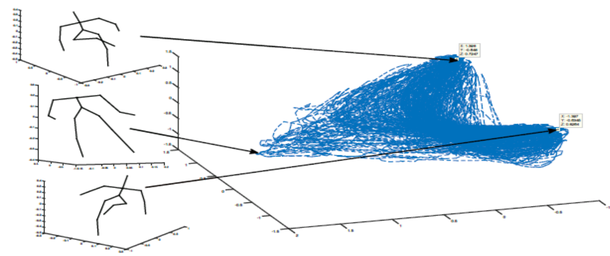
Summary: Characterising shapes and motions

Shape reconstruction

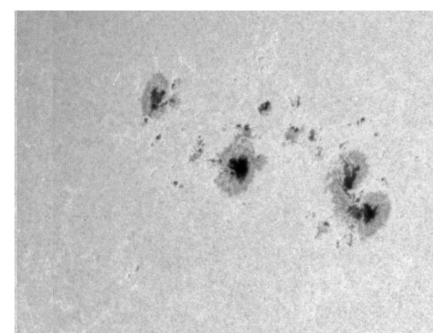




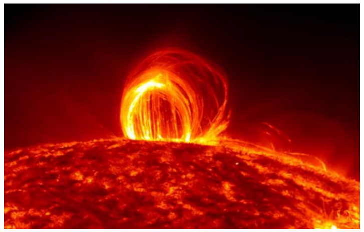
Shape analysis

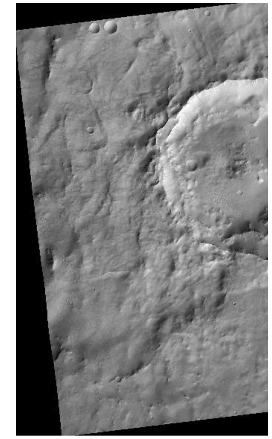


Motion analysis



Trust issues





Thank you for your attention