# Using Machine Learning Tools To Estimate Photospheric Velocity Fields Prior to the Formation of Active Regions


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## Introduction

Active regions are home to highly energetic events on the Sun. They form as a result of magnetic flux evolving under the forces present below the solar surface. When the magnetic flux density is large enough these events can lead further into solar flares and coronal mass ejections, which can have catastrophic consequences here on Earth due to the interaction with our magnetic field. Predicting these events is a key problem in protecting technologies and ourselves. In order to predict these events we need to understand what signs on the surface of the Sun indicate the oncoming of their appearance.

One indicator could be revealed in the topology of flows on the surface. Hence, accurately recovering these flows is key in studying the topology. Machine learning provides an opportunity to reproduce the velocity field from observations by training a neural network (e.g. DeepVel [1]) on data from high resolution simulations. Work done has already showed that, on granular scales on the quiet Sun, there is sufficient evidence to explore DeepVel further as a tool to use alongside existing flow recovery methodologies such as FLCT [4].

## Project Aims

Done:

- Retrieve simulation data [2], which includes full velocity vector prior to flux emergence;
- Train DeepVel with single output to recover 3-Dimensional velocity field;
- Compare predicted outputs with simulation;

Next:

- Study appearance and change in Lagrangian coherent structures (LCSs) in flows;
- Compare results with other methodologies show in flow diagram;

## Methods

Collect data from simulation

Train neural network on sample of data

Produce and study success of output

Study flow topology by finding LCSs

Compare results with flow recovery methodologies e.g. FLCT, balltracking [3]

Apply methodology to observations

## Conclusions

- DeepVel shows a good performance in recovering flow topology around active regions.
- With access to current data sets DeepVel can be modified for making predictions from most observational data sets.
- The application of DeepVel on active regions shows evidence of success to warrant further testing.
- DeepVel is model based. It cannot recover flows for data that is higher resolution than the input—other neural networks exist which may be able to enhance existing data.
- Complex structures and sharp patterns in flows are still hard to detect fully.
- DeepVel can suffer from generalisation which remains to be tested.

## Future Work

- Understand the relationship between Deepvel, training time/samples and prediction success to account for overfitting and optimise overall performance.
- Compare the success of DeepVel with other methodologies, on active regions.
- Compare how different models affect the success of predictions and recovering topology.
- Test DeepVel on observational data, from both low and high resolution images.
- Search for observable features using LCSs from the finite time Lyapunov exponent, which indicate where the appearance of an active region will occur.

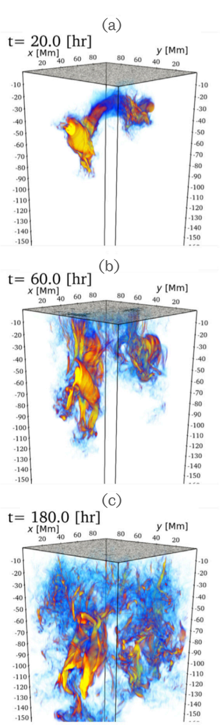


Fig 1. (Left) Plots showing evolution of force-free flux tube placed at 50Mm below surface of convective zone at different time stamps (a) t=20hr, (b) t=60hr, (c) t=60hr.

Plots courtesy of R2D2 simulation run by H. Hotta and H. Iijima [2].

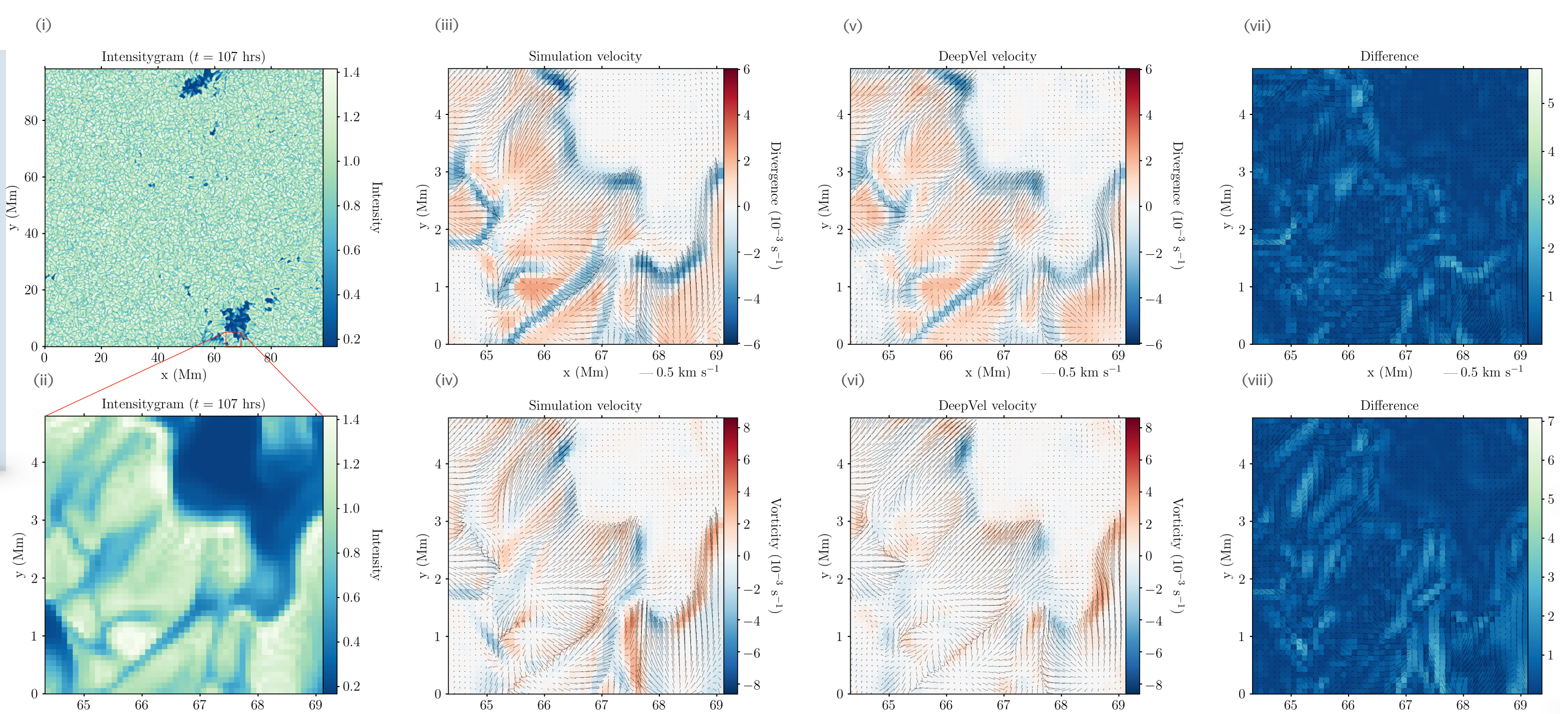


Fig 2. (Left) (i) Intensitygram from simulation data at optical depth $\tau = 1$, (ii) close up of area with complex structure, (iii) simulated velocity field superimposed on the divergence field, (iv) simulated velocity field superimposed on the vorticity field, (v) DeepVel recovered velocity field superimposed on the recovered divergence field, (vi) DeepVel recovered velocity field superimposed on the recovered vorticity field, (vii) absolute error between simulated and recovered velocity field, (viii) absolute errors between simulated and recovered velocity fields.

## Results

| Metric | Velocity | Divergence | Vorticity |
|---|---|---|---|
| Pearson Correlation | 0.937 | 0.937 | 0.755 |
| Mean Absolute Error | 0.991 | 3.43 | 4.02 |
| Median Absolute Error | 0.830 | 2.332 | 2.248 |
| Mean Relative Error | 0.494 | 2.474 | 6.733 |
| Median Relative error | 0.305 | 0.238 | 0.920 |
| Cosine Similarity | 0.885 | - | - |

Table 1. Results for success of DeepVel, after 100 epochs of training on 2000 training samples and 500 validation samples, on a single prediction on domain containing active region at optical depth $\tau = 1$.


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