

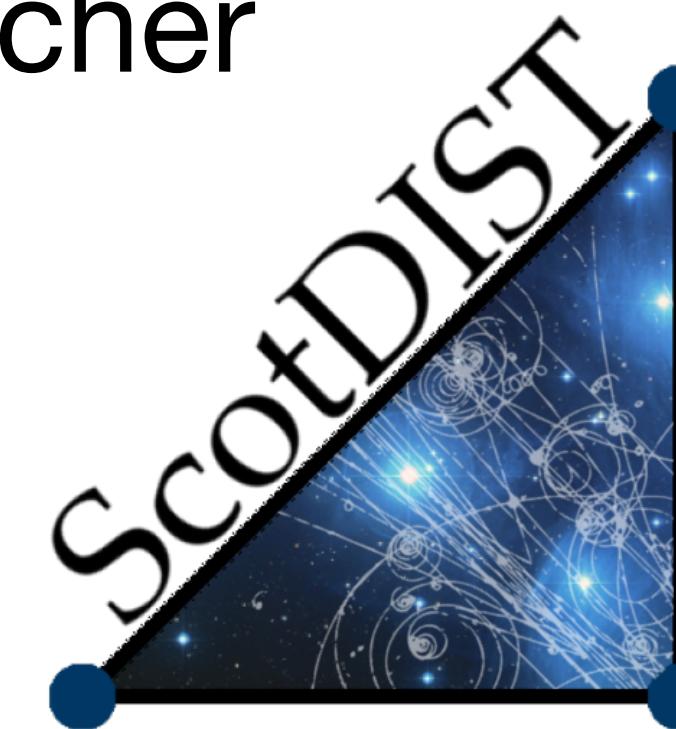
RADYNVERSION: Learning to Invert a Solar Flare Atmosphere Using Invertible Neural Networks

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with: C. Osborne and L. Fletcher

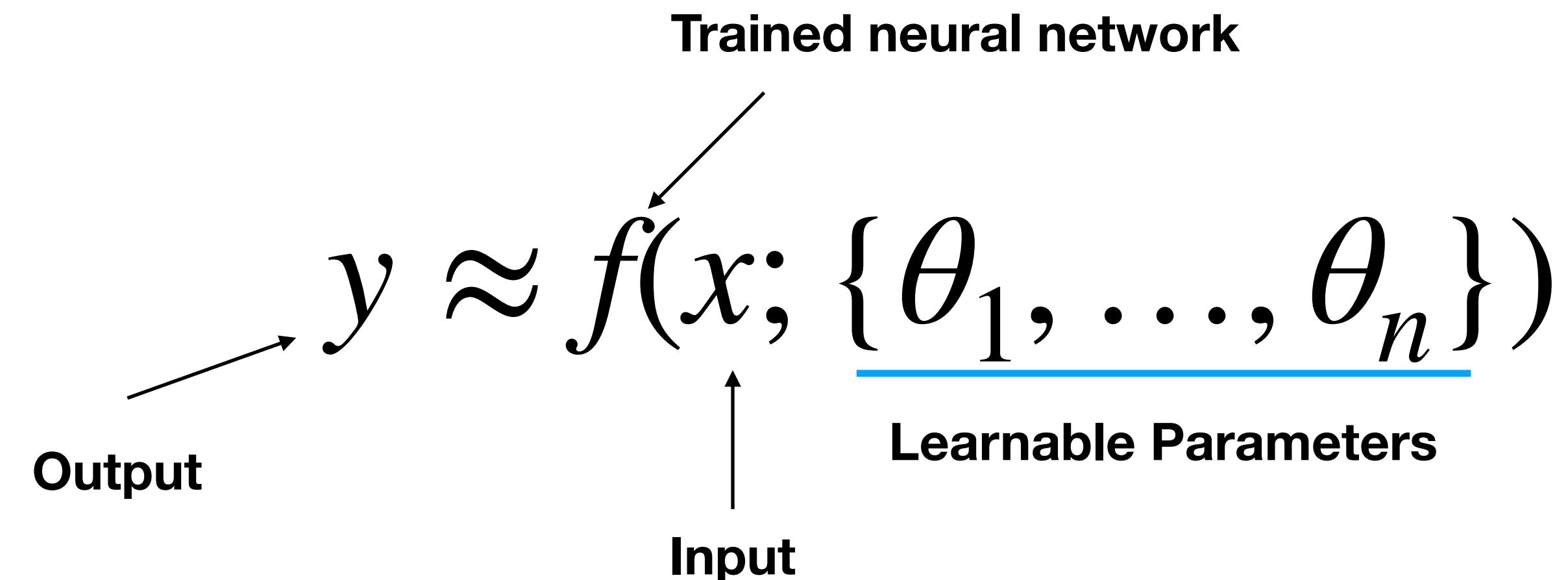


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What can we learn?

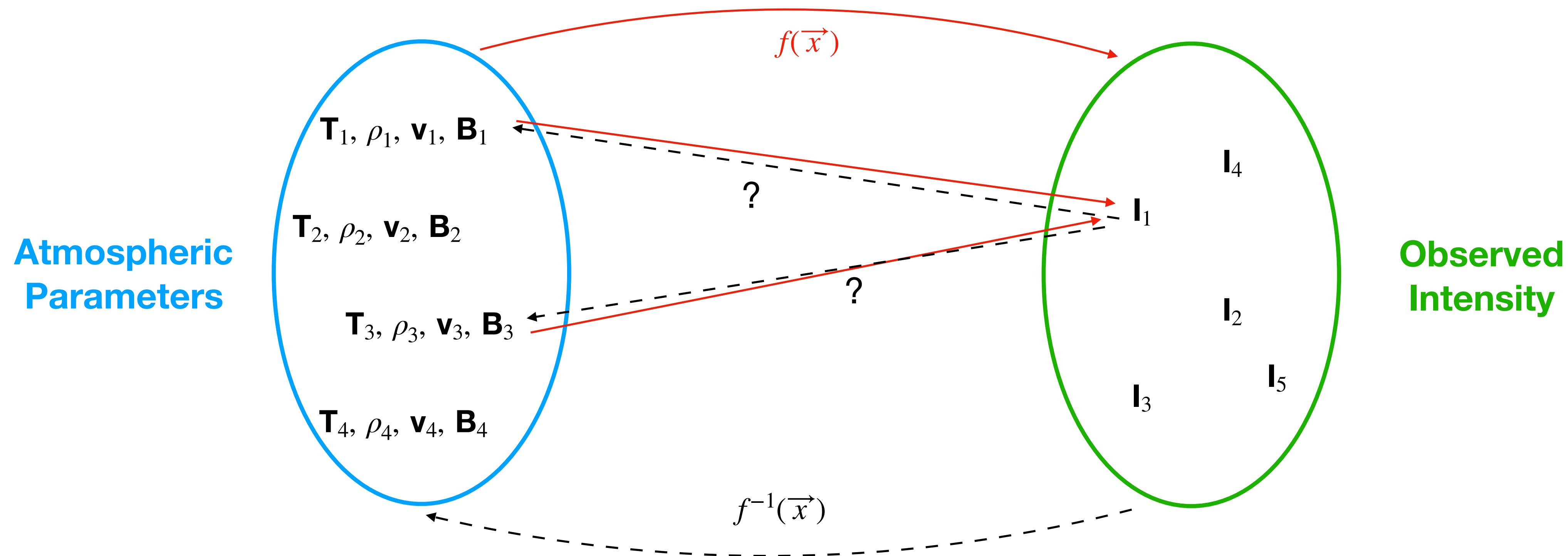
- Machine learning is the process of using statistical techniques to give computers the ability to learn how to perform a specific task *without* being explicitly programmed
- Deep neural networks are very good function approximators (Cybenko 1989, Lu+ 2017)
 - processes that can be expressed by **well-defined functions** can be learned by a deep neural network





The Problem with Inversions

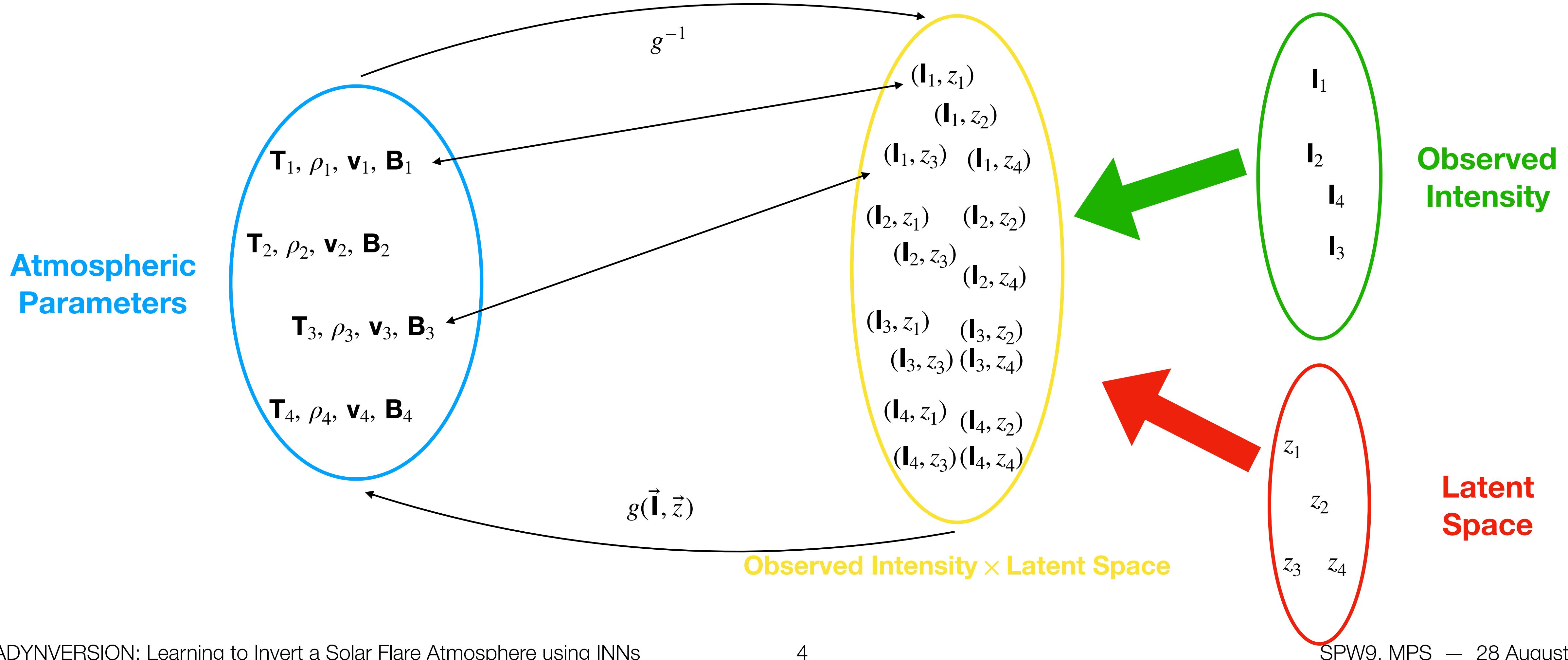
- **Inversions, however, are not well-defined functions**
 - there are many combinations of atmospheric parameters that can produce the same line profiles
 - there is information lost about the physics in the forward process



Cannot be modelled with traditional deep learning*

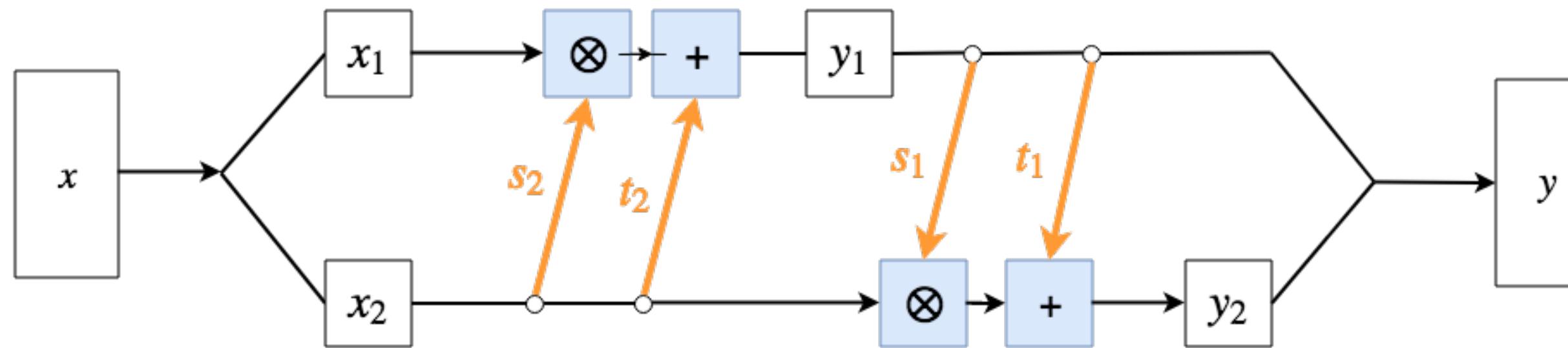
Fixing the Problem

- How do we formulate the inverse process in such a way as to make it well-defined?
 - Introduce a latent space, z , which contains the information lost in the forward process



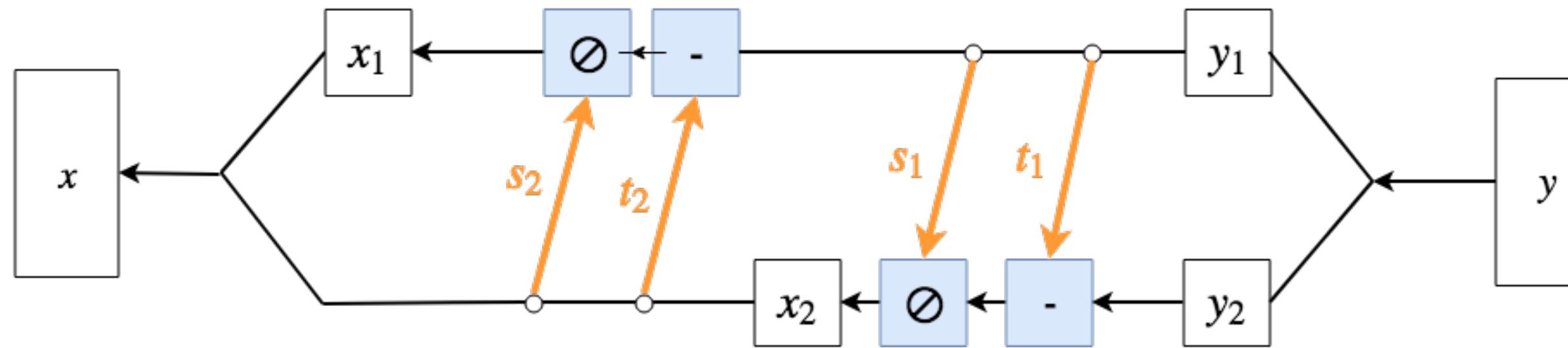
Invertible Neural Networks (INNs)

- The layers we stack in INNs are known as **affine-coupling blocks**:



$$y_1 = x_1 \otimes \exp(s_2(x_2)) + t_2(x_2)$$

$$y_2 = x_2 \otimes \exp(s_1(y_1)) + t_1(y_1)$$

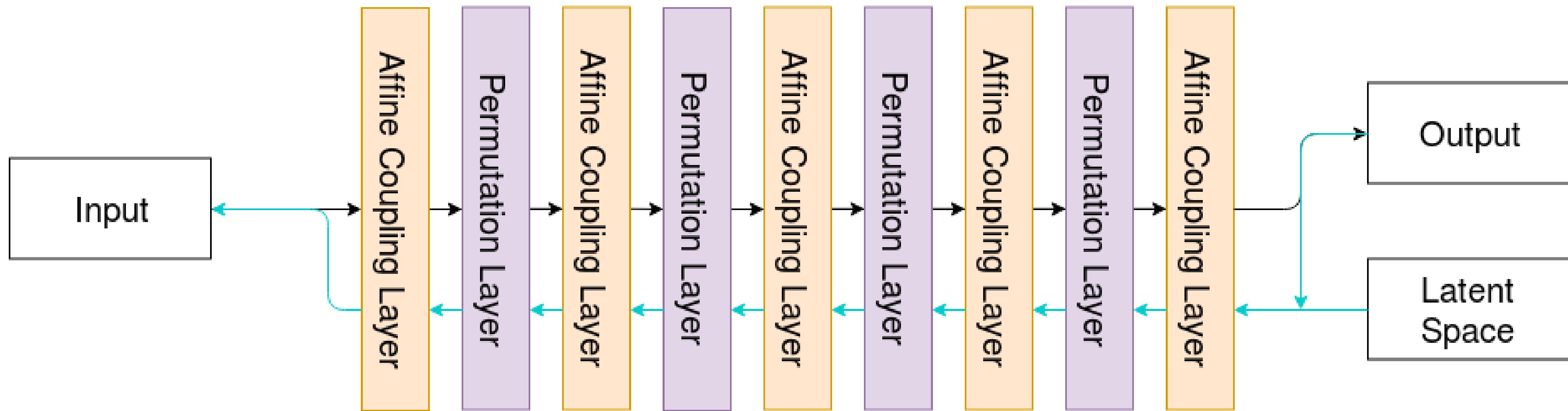


$$x_2 = (y_2 - t_1(y_1)) \otimes \exp(s_1(y_1))$$

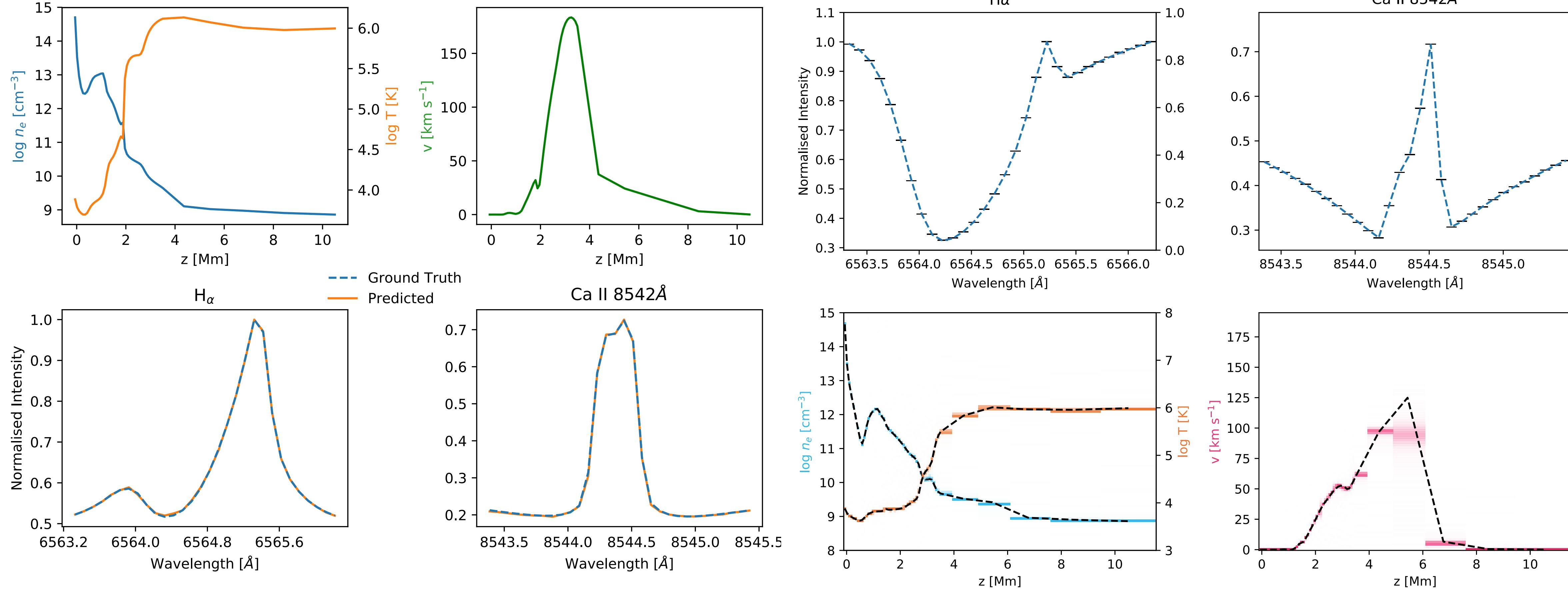
$$x_1 = (y_1 - t_2(x_2)) \otimes \exp(s_2(x_2))$$

See Dinh+ 2014, 2017 & Ardizzone+ 2018 for more details

Invertible Neural Networks (INNs)



- **We use the F-CHROMA RADYN grid for training data**
 - available here: <https://star.pst.qub.ac.uk/wiki/doku.php/public/solarmodels/start>
- **Each simulation has 500 timesteps**
- **All electron beams, range of cutoff energies: 10–25keV, range of spectral index: 3–8 and range of total energy deposited**
- **We extract H α and Ca II λ 8542 line profiles as well as temperature, velocity and density profiles from each timestep of each simulation**
- **This gives us >40000 pairs of spectral lines to learn our inversions from**
- **Each pair of lines has corresponding atmospheric parameters**
- **Using any less than 2 lines doesn't work**



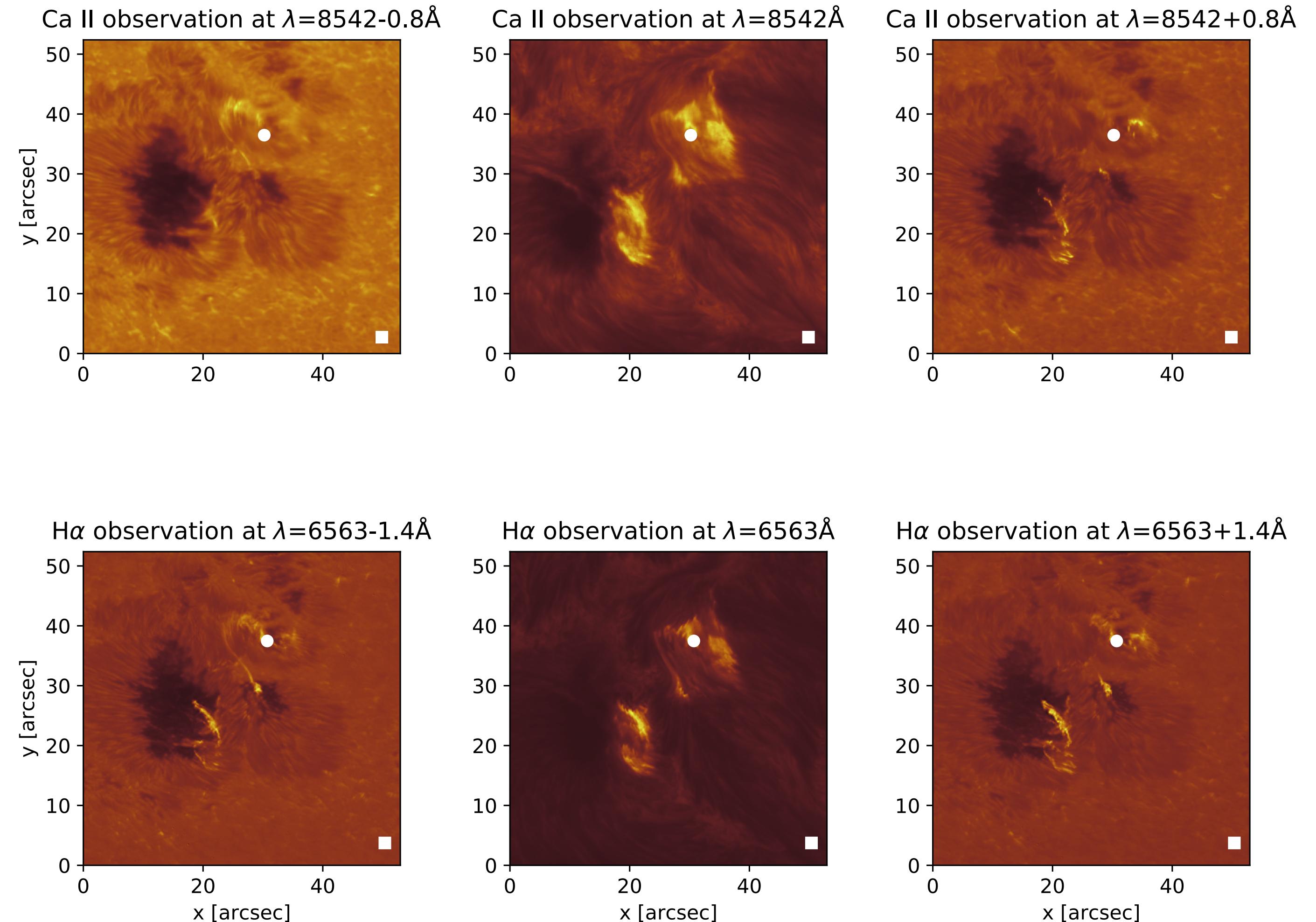
Forward Model Test

Inversion Test

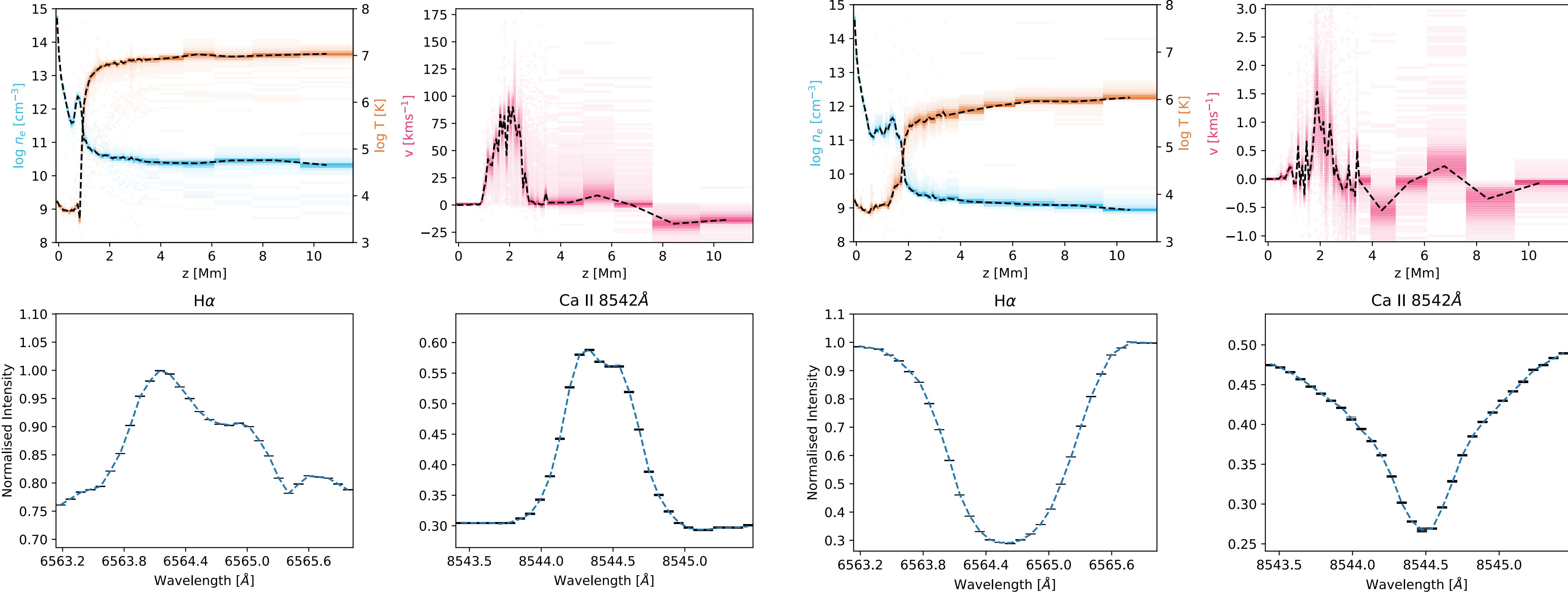
Inversion of Real Data

- **M1.1 flare SOL20140906T17:09**
NOAA AR12157
- **Observed by SST/CRISP in H α**
and Ca II λ 8542
- **Wavelength sampling: 15 points**
for H α , 25 for Ca II

Figure: Observations in both wavelengths just after the flare onset. The circular point is a point on the flare ribbon. The square point is a point off the flare ribbon.



Single-pixel Inversions



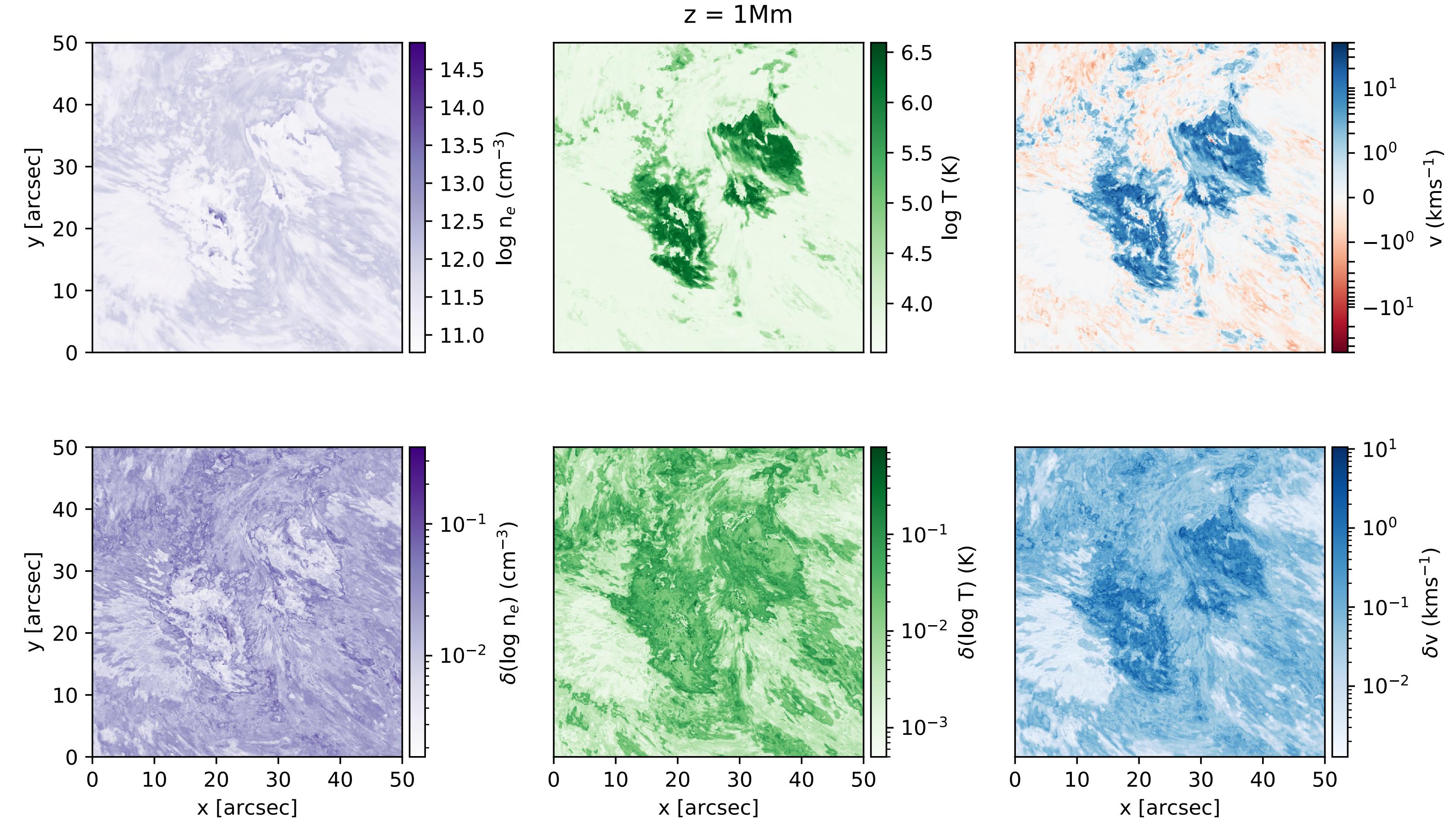
Inversion of circular point

See Osborne, Armstrong & Fletcher, 2019

Inversion of square point

Whole Image Inversions

- Can do a whole image inversion in ~30 minutes (50 nodes in each of the three atmospheric parameters, for ~100s of inversions on 1k x 1k FOV)
- Includes errors by calculating standard error on median solution
- ~1.5TB of inverted data (largest inversion ever done?)
- Figure shows whole image inversions at heights where Ca II core forms in flares according to Kerr+ 2016



Armstrong, Osborne and Fletcher (in prep.)

- Analyse whole image inversions and see what our inversions say about the flaring chromosphere
- Apply RADYNVERSION to 6 September 2017 X9.3 flare data (and see how much it breaks)
- RADYNVERSION using a log τ grid is in prep for more insights into analysis
- Add more spectral lines (Mg II, Ca II H&K,...)
- Ideally add polarimetry once a forward model is available (see Osborne thesis)

Useful links:

- Paper: https://bit.ly/radynversion_paper
- Code: https://bit.ly/radynversion_code