A Deep Learning Neural Network for Voigt Profile Fitting Quasar Absorption Lines

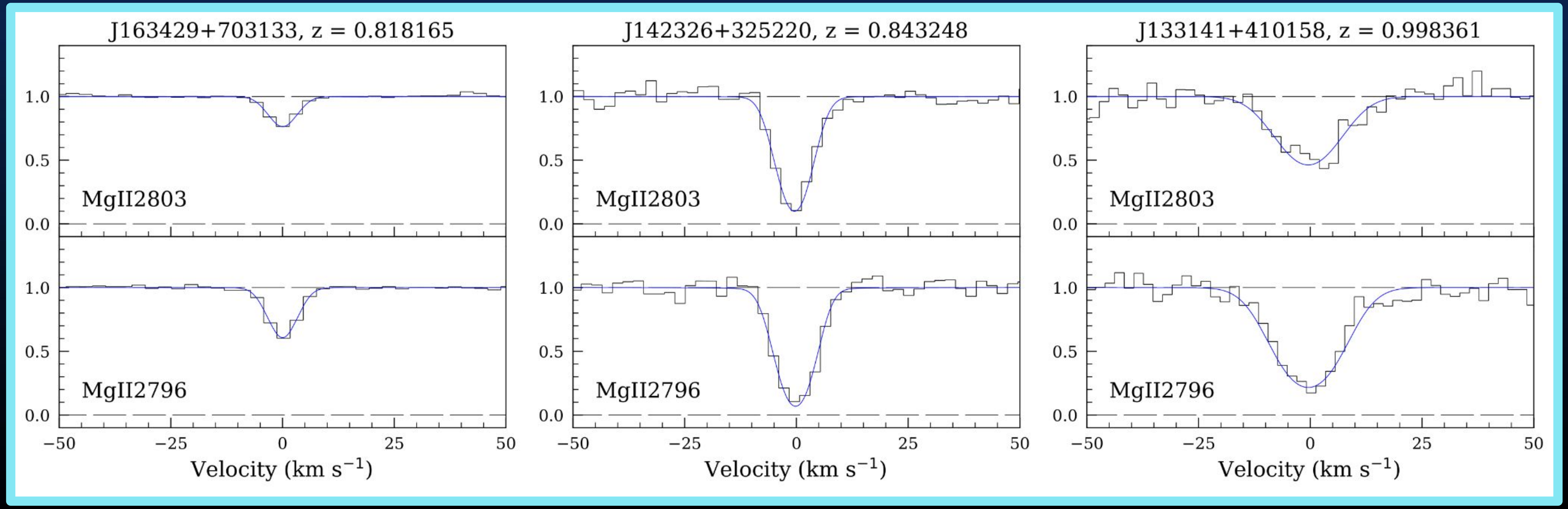
Bryson Stemock (bstemock@nmsu.edu), New Mexico State University

Motivation

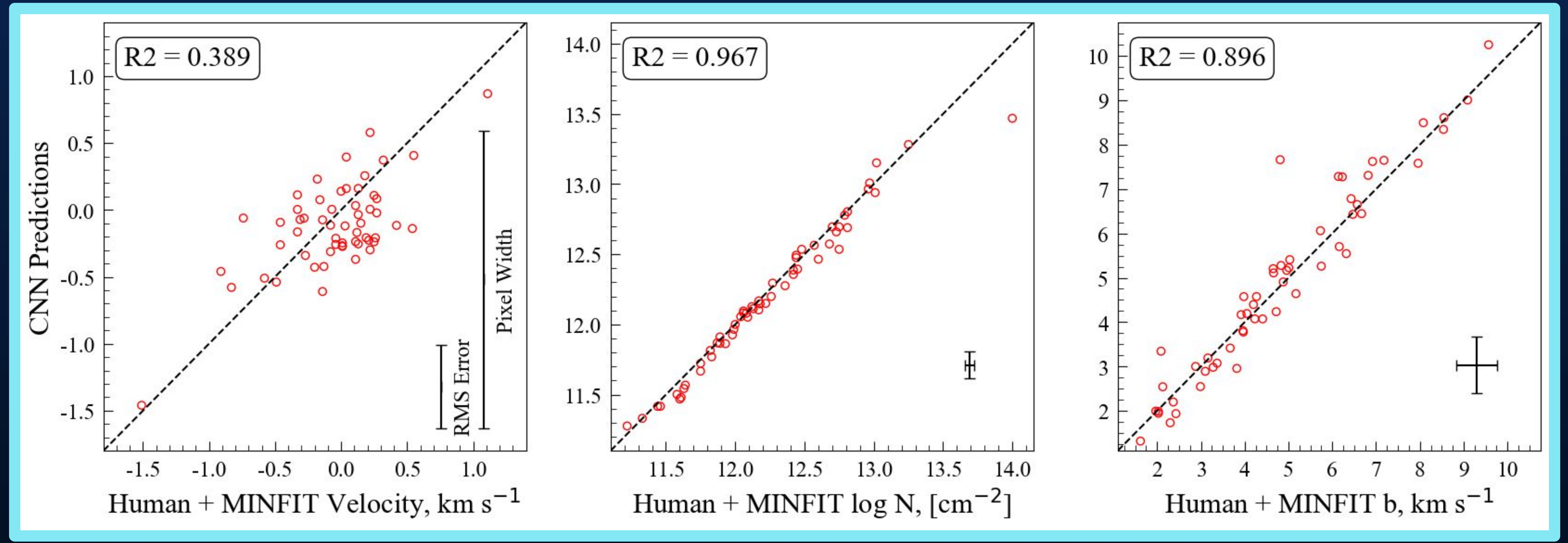
Voigt Profile (VP) fitting complex kinematic QSO absorption line systems is extremely time consuming and, based on current expert human efficiency, I estimate that it would take roughly 70 years to VP fit only the 3500 CIV absorption systems we have on disk. If these human-intensive methods aren't replaced by more efficient methods, the field of quasar absorption line spectroscopy will struggle to progress alongside the rest of astronomical research as a whole.

Voigt Profile fitting a system is a way of using forward modeling to obtain the rest frame velocity, v, column density, logN, and Doppler parameter, b, of the absorbing gas structures, which exist in the Circumgalactic Medium (CGM) and Intergalactic Medium (IGM). This information is an important part of understanding the Baryon Cycle: how baryons cycle in and out of galaxies and what they do while they're within galaxies.

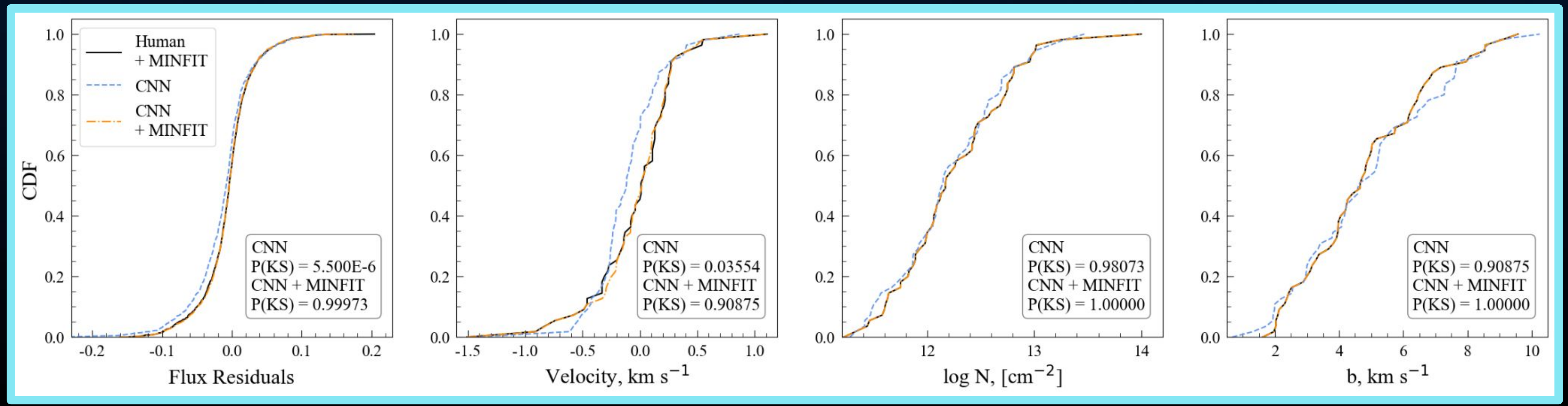
Right: Examples of absorption line systems (black) with Voigt Profiles overplotted (blue)



Training and Testing a Convolutional Neural Network (CNN)



We trained a CNN on 10^6 simulated single cloud MgII absorption systems with varying v, logN, b, and signal-to-noise ratios. Once we achieved satisfactory learning, the CNN was given 56 single cloud systems previously fit by Churchill et al. (2020) using a deterministic chi-square minimization routine, MINFIT, and an initial model provided by a human expert. The results are shown on the left (top).



Top Left: Results from 56 observed systems. CNN predictions (y-axis) for each parameter vs. the MINFIT results that required human effort (x-axis). Characteristic error bars are given.

Bottom Left: CDFs and K-S test results for residuals between models and data, v, logN, and b for the observed systems (left to right).

Human vs. Machine

For each observed system, the CNN was tested in two ways against the original human + MINFIT results. The CNN's predictions for each parameter are fairly close to the original results. Although there seems to be significant spread in velocity, each pixel is 2.22 km s^{-1} wide, meaning that these are subpixel deviations. However, when comparing the residuals between CNN models and data, we see a discrepancy between the CNN and the original fits. This is due to recurring simultaneous underpredictions of logN and overpredictions of b by the CNN.

With this in mind, we rerun the deterministic routine MINFIT using the CNN's predicted parameters as an initial model. Doing so recovers the original results without significant deviation. Therefore, while the CNN is unable to replicate the results of classical deterministic VP fitting, it is in fact able to provide the initial models typically provided by humans to a more sophisticated VP fitter, deterministic or otherwise. Thus, in the case of single cloud systems, we find that a CNN is able to replace a human expert, therefore expediting the VP fitting process. Future work will involve multicloud systems, absorption from multiple ions, and more.

Collaborators: Christopher Churchill, Caitlin Doughty, Rogelio Ochoa, Sultan Hassan,