Automated Detection of Fronts using a Convolutional Neural Network

James C. Biard, Kenneth E. Kunkel, and Evan Racah

A deeper understanding of climate model simulations and the future effects of global warming on extreme weather can be attained through direct analysis of the phenomena that produce weather. Realistically, this requires procedures that automatically identify such phenomena in an unbiased and comprehensive way. Atmospheric fronts are one centrally important weather phenomenon because of the variety of significant weather events associated directly with them, including severe thunderstorms and a wide spectrum of precipitation types and amounts. In operational meteorology to this day, fronts are identified and drawn visually based on the approximate spatial coincidence of a number of quasi-linear localized features - a trough (relative minimum) in air pressure in combination with gradients in air temperature and/or humidity and a shift in wind. Fronts are categorized as cold, warm, stationary, or occluded, with each type exhibiting somewhat different characteristics. Fronts are extended in space with one dimension much larger than the other, thus requiring representation at a minimum as a line, but that line can have a complex shape, posing a unique challenge for automated approaches. A Deep Learning Convolutional Neural Network (CNN) algorithm was implemented to automatically identify and classify fronts. The CNN was trained using a “truth” dataset of front locations determined by National Weather Service meteorologists as part of operational 3-hourly surface analyses. The input to the CNN is a set of 5 gridded fields of surface atmospheric variables, including 2m temperature, 2m specific humidity, surface pressure, and the two components of the 10m horizontal wind velocity vector at 3-hr resolution. The output is 5 feature maps containing the probabilities of the 4 front types plus no-front.

The algorithm was trained on ~~one~~ multiple years, and then used to produce front probabilities for each 3-hr time snapshot over a 14-year period covering the continental United States and some adjacent areas. The total probabilities of fronts derived from the CNN matches very well with the manual truth dataset. There is a slight underestimate in total numbers in the CNN results but the spatial pattern is a close match. The categorization of front types by CNN is best for cold and occluded and worst for warm. Further development of the algorithm is being pursued but these results highlight the great promise of this technology for application to the large number of climate simulations that continues to grow.