Deep Learning Models for Ionospheric Electron Density Time Sequence Prediction

DATA-17

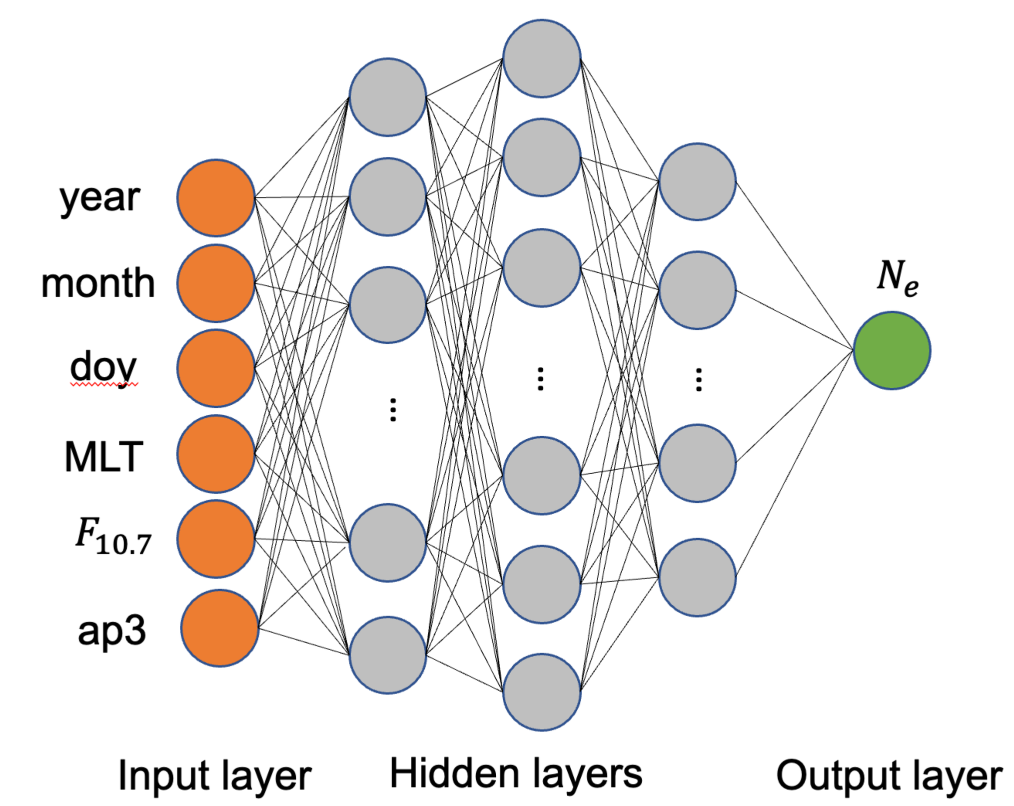
Yang Pan[1]; Mingwu Jin[1]; Shunrong Zhang[2]; Yue Deng[1];

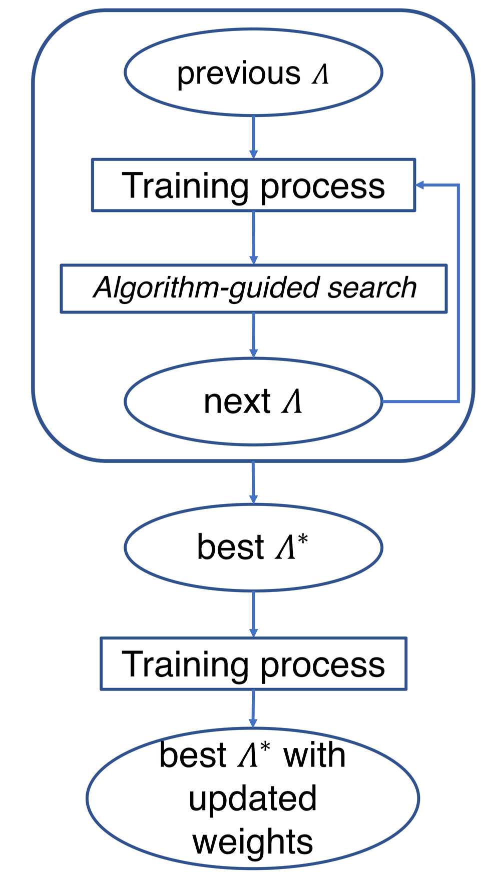
[1]Physics, University of Texas at Arlington, TX; [2]Haystack Observatory, MIT, Westford, MA;

Abstract

- We developed electron density (*NeI*) prediction models using neural network (NN) with aid of neural architecture search (NAS).
- Incoherent scatter radar (ISR) at Millstone Hill observatory (MLH) serves as the database.
- *NeI* at the height of 350km of our interest exhibits variations in different temporal scale.
- NAS finds the optimal NN architecture, and the improvement is associated with the network complexity.
- Deep NN (DNN) with NAS (DNN-NAS) shows an improvement more than 10% over single layer NN (SLNN).

Methodologies

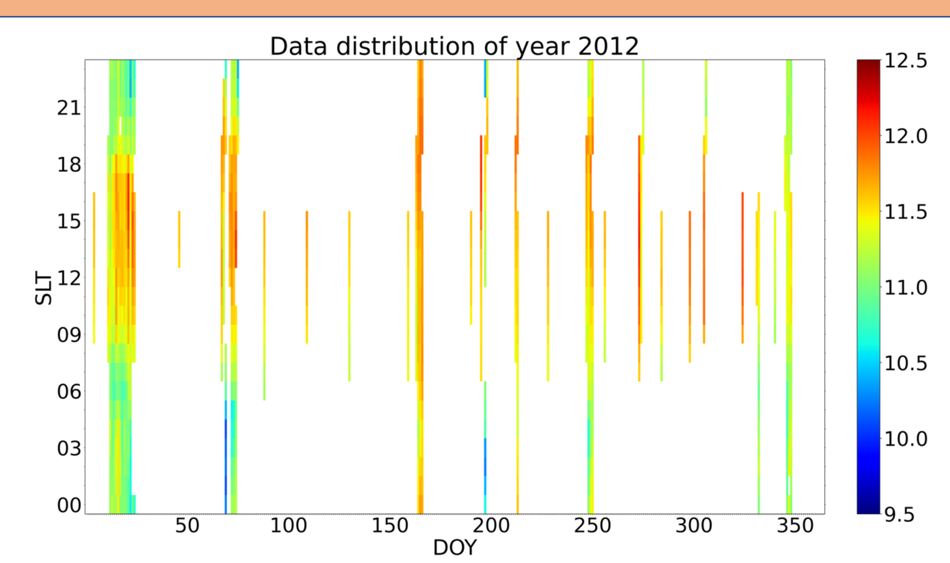




Term	Definition	Elements
Hyper-parameters (Λ)	Network structure and training conditions	Layer numbers Neuron number at each layer Optimizer Learning rate
parameters (θ)	Network trainables	Weights Biases

- A typical neural network architecture forms the tree-like structure with many tunable parameters shown in the table.
- Consider hyperparameters the nodes of the hierarchical tree structure. Leaves are nodes without any child node.
- Different search algorithms of NAS:
  - Random: the next hyper-parameter is totally random.
  - Greedy: larger number of leaves has a less chance of being next hyper-parameter.
  - Bayesian: Gaussian process-based update of network structures.

Objective



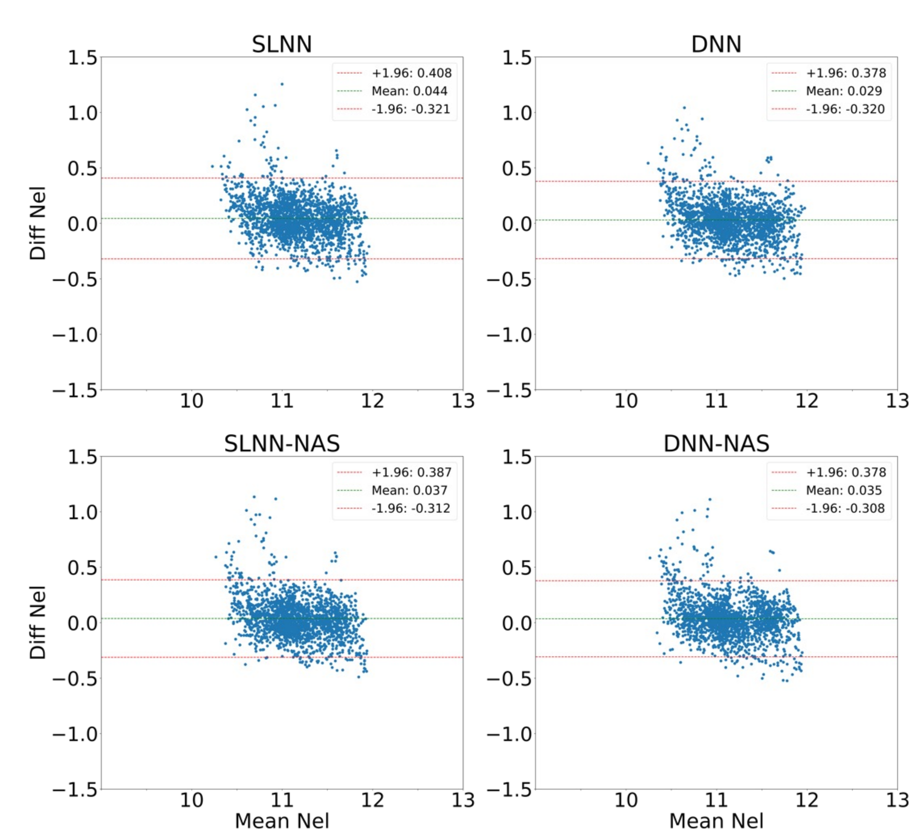
- The operation of Incoherent Scatter Radar (ISR) is limited, leaving data gaps.
- The electron densities (*NeI*) depend on various parameters.
- We aim to build different deep learning models to predict *NeI* with the aid of neural architecture search (NAS) technique within ISR parameters.

Experiments

	Description
Purge condition	F10.7≤300, Ap3≤80, $\log_{10} Nel \in [\log_{10} 5\times10^9, \log_{10} 3\times10^{12}]$
Input parameters	year, cyclic DOY, cyclic SLT, F10.7, Ap3
Dataset	ISR MLH data [2003-2018] Val: [2010, 2015] Test: [2007, 2012]

- ISR MLH data with altitude at the height of 350km were used.
- The one-hour length bin is applied to the data, which improves the data quality.
- The purge conditions rule out cases when geophysical indices are high.
- The cyclic (sine and cosine) is applied to day of year (DOY) and solar local time (SLT) to reflect the periodic changes.

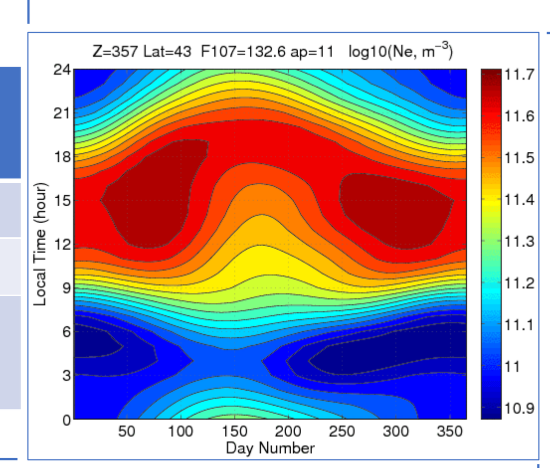
Results



The BA-plots of four models on the test set, averaged difference is in green line and the 95% limits of agreements are between red lines.

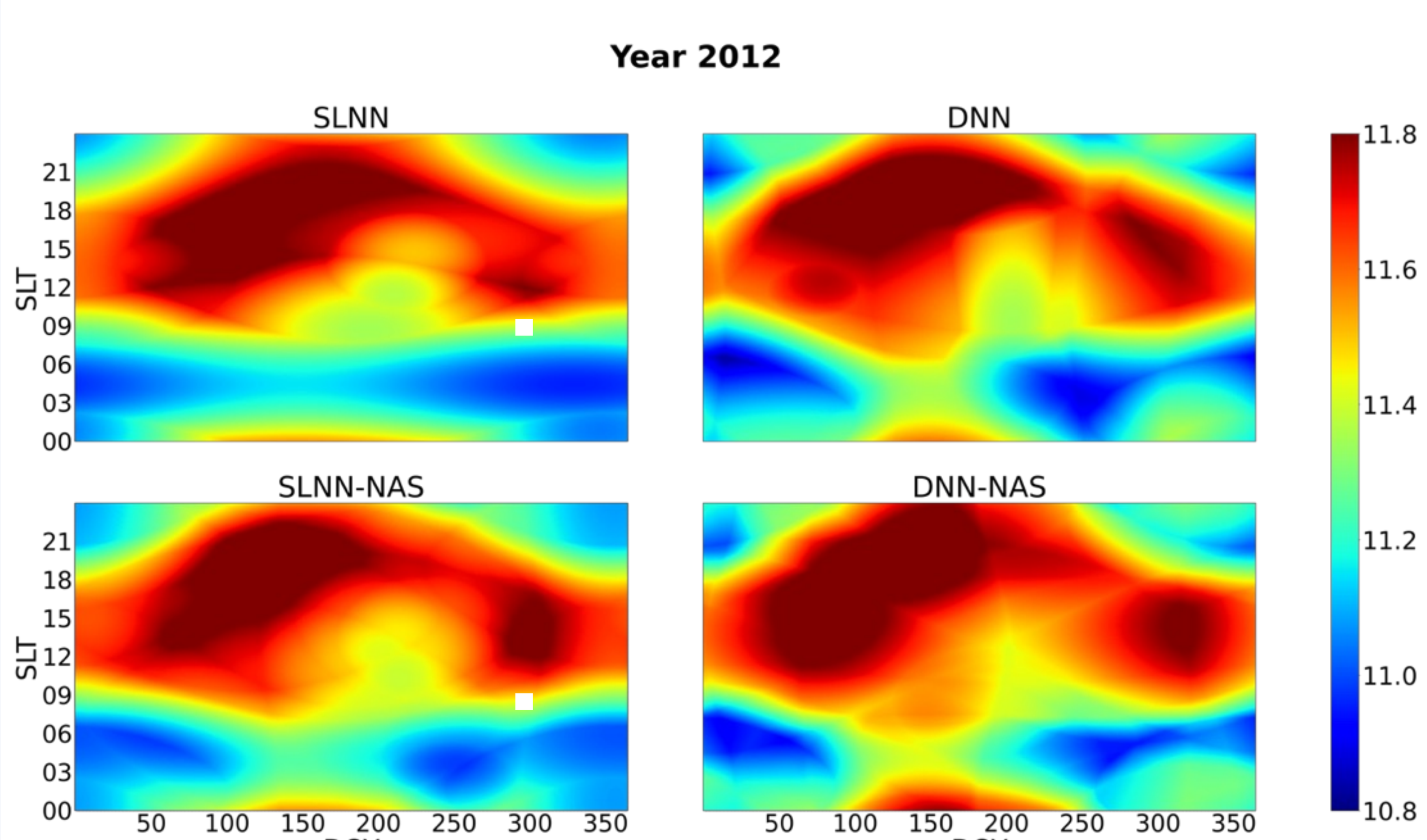
- SLNN shows the large bias and wide limits of agreement.
- DNN-NAS owns the narrowest limits of agreement.

	SLNN	DNN	SLNN-NAS	DNN-NAS
MAE	0.1399	0.1312	0.1307	0.1250
RMSE	0.1908	0.1805	0.1821	0.1784
RE (%)	1.2667	1.1872	1.1844	1.1327



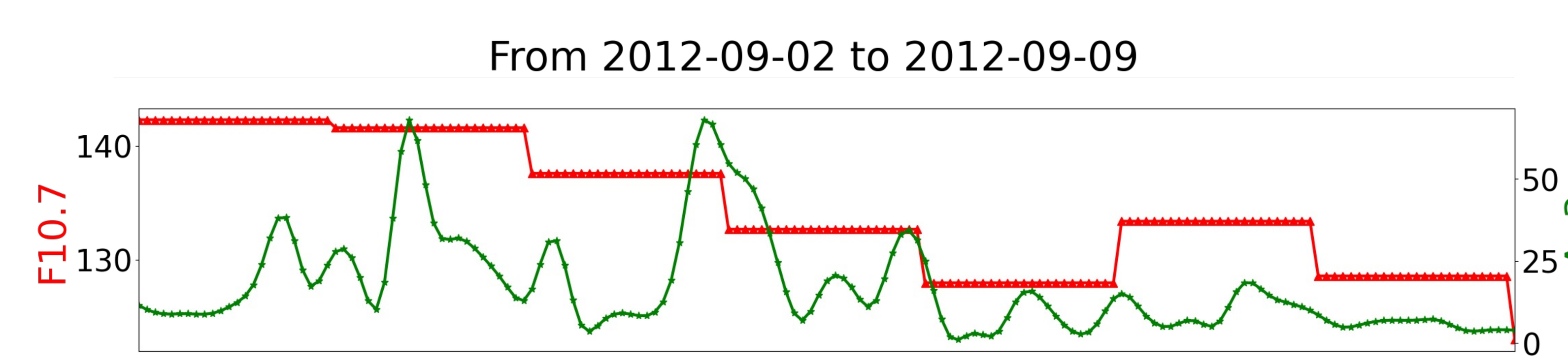
Annual *NeI* pattern of year 2012 from ISR empirical model (ISRIM) and four model predictions on fixed F10.7 and Ap3.

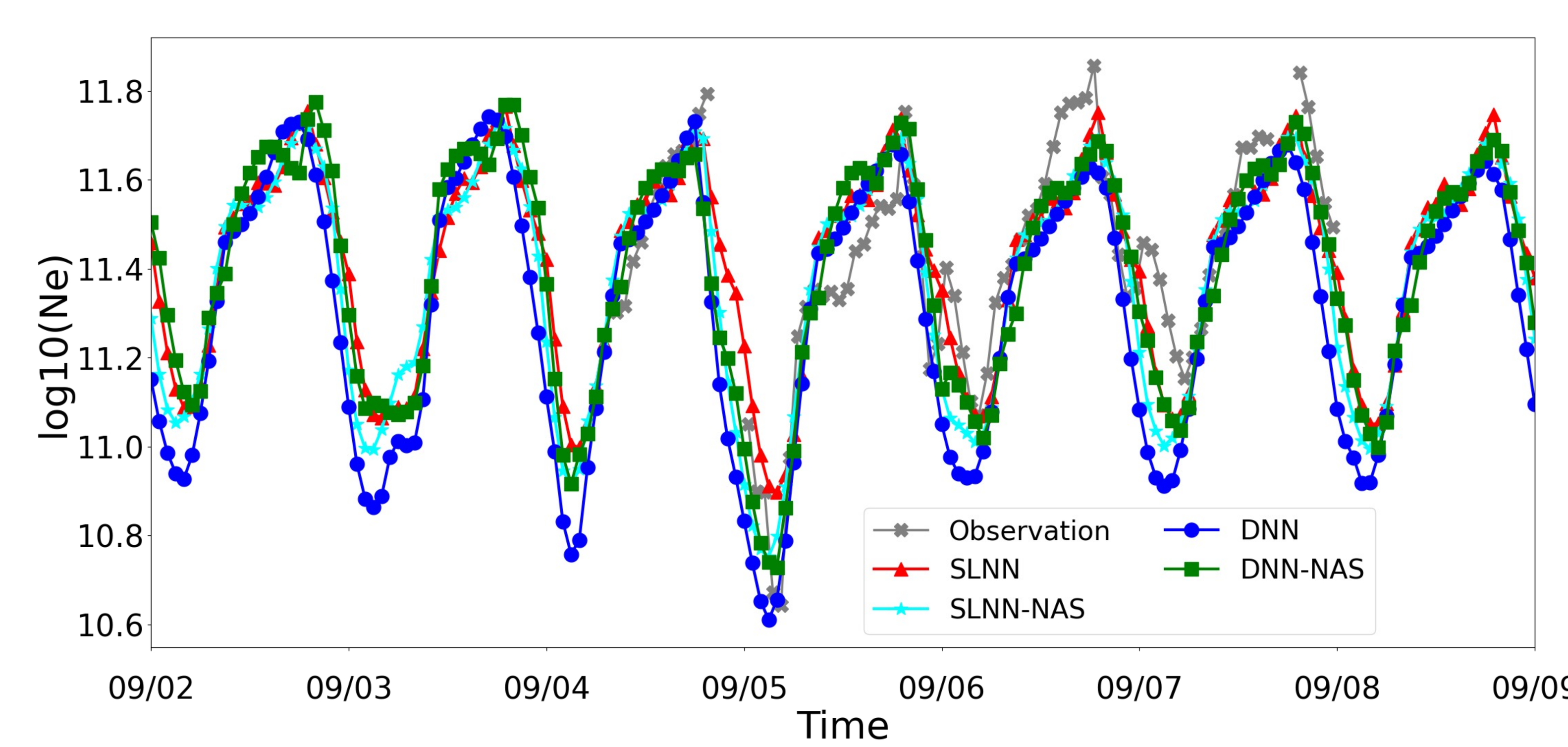
- Fixed geophysical indices as input for NNs.
- The typical saddle-shaped semi-annual patterns are visible among all NN results.
- Appealing crest in DNN-NAS result.



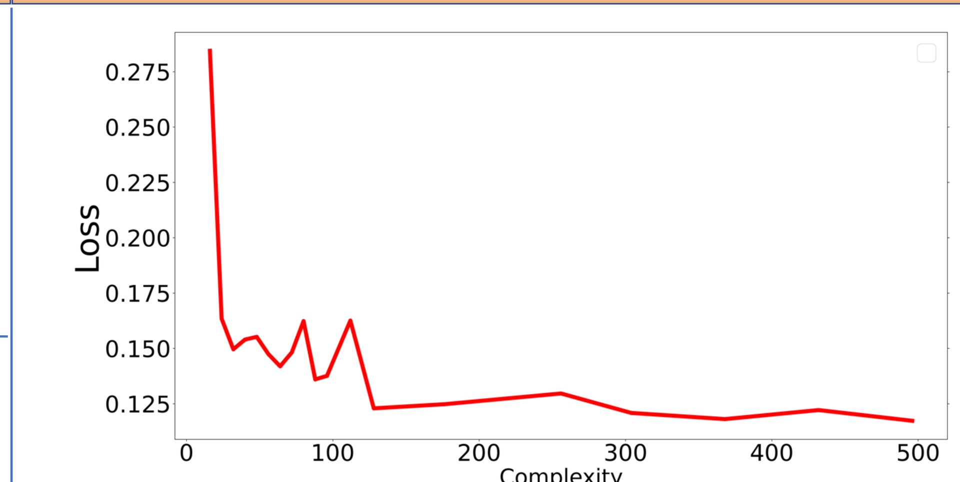
NeI patterns of decent coverage during 2012-09-02 to 2012-09-09. Four model outputs are marked in different shapes and colors.

- All the models track the patterns well.
- DNN tends to have undershoot predicted Nel before dawn.
- DNN-NAS has the overall best predictions.





Conlusion



- The Loss (MAE) decreases in a logarithmic-like way when the network complexity increases.
- The performance of NAS saturates beyond certain complexity.
- DNN-NAS outperforms SLNN in both fitting and prediction with a reduction more than 10%.
- All models can reproduce the semi-annual *NeI* pattern, similar to the empirical model (ISRIM).
- The daily *NeI* patterns shows the potential of NN models in predicting *NeI* in a resolved variation.

Acknowledgment

AFOSR, MURI Award FA9559-16-1-0364
NASA GDC-IDS

Contacts

Yang Pan: yang.pan@mavs.uta.edu
Mingwu Jin: mingwu@uta.edu
Shunrong Zhang: shunrong@mit.edu
Yue Deng: yuedeng@uta.edu