Adversarial Attacks Against Linear and Deep-Learning Regressions in Astronomy

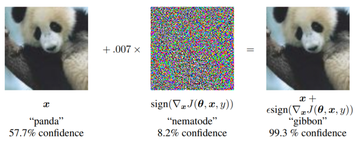
Members: Teresa Huang, Zacharie Martin, Greg Scanlon, Eva Wang

Mentors: Soledad Villar, David W. Hogg

Abstract

Recent work has shown that neural networks are susceptible to adversarial attacks, but what about simpler machine learning models? In this paper we investigate adversarial attacks to popular machine learning models for regressions in astronomical data. Namely, AstroNN (a Bayesian Neural Network), The Cannon (a quadratic generative model), and a simple linear regression. We suggest a few approaches to measuring the strength of adversarial attacks that take into consideration the physical properties of predictions. Our results suggest that generative (or causal) models are more robust to adversarial attacks than discriminative models.

Introduction



Adversarial attack in image classification: a small amount of noise added to a data point that results in the model assigning the incorrect class label with high confidence

- In physical sciences, deep learning as well as other classical methods are being successfully used for regressions
- A method's vulnerability to attack may be indicative of some kind of deficiency in the size or coverage of the training data
- Our work investigates the susceptibility of different classes of astronomical regression models to adversarial attacks

Methodology

- **Data**:
  - Our data are stars which are described by their spectra and derived labels from the APOGEE Data Release (DR14)
  - 1,000 spectra are randomly selected using the same pre-processing as targeted models to ensure compatibility
- **Models**: There are many different kinds of regressions in the field of astrophysics that could be targets for attack.
  - Linear discriminative regressions
  - Generative regressions
  - Discriminate neural networks
- **How to find an attack**:
  - Adversarial attack at the data point x is a perturbation $\Delta x \in S$ that maximizes the loss

$$\max_{s \in S} \ell(x + s, y, f_\theta)$$

  - There exist different strategies for finding the optimal perturbations. In our paper we focus on the Fast Gradient Sign Method (FGSM) from Goodfellow et al. (2014), which consists of one gradient step for the optimization function

$$\Delta_x = \epsilon \text{sign}(\nabla_x \ell(x, y; f_\theta))$$

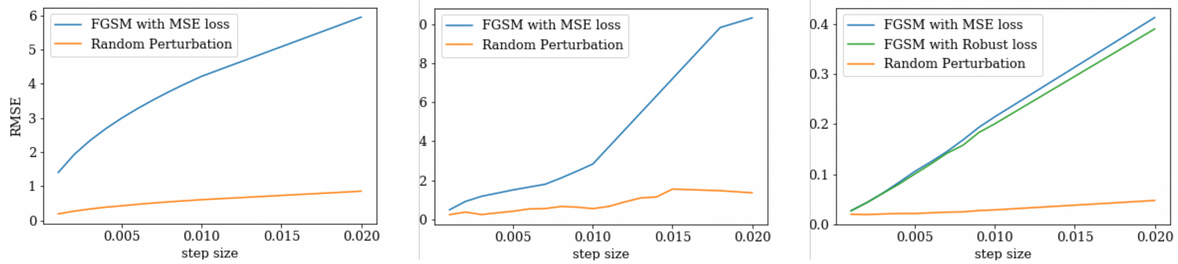
- **How to evaluate its success**:
  - Comparison between attacks and random perturbations

$$A(\Delta_x, x; f_\theta) = \frac{\ell(x + \Delta_x, f_\theta(x); f_\theta)}{\mathbb{E}_{s \in S} \ell(x + s, f_\theta(x); f_\theta)}$$

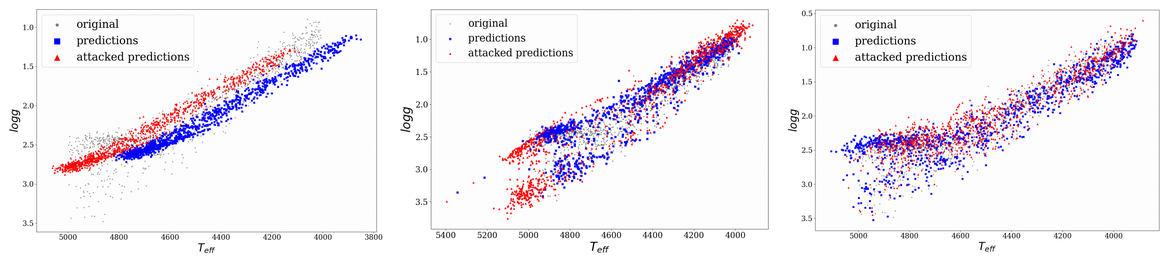
Results

Linear Model | The Cannon | AstroNN

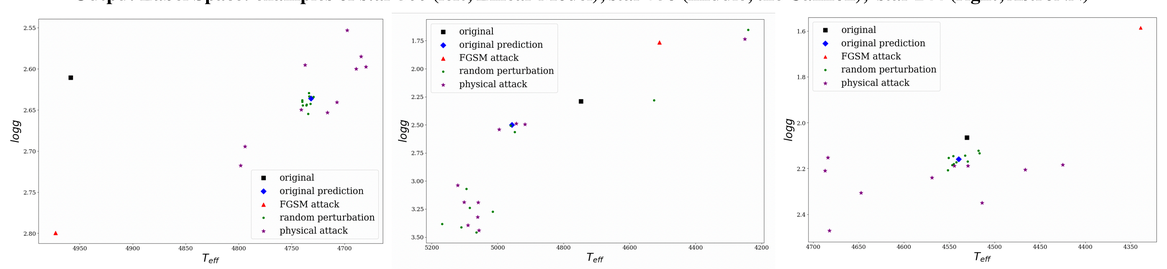
Root Mean Square Error (RMSE) loss between model output given random perturbations versus optimal FGSM perturbations



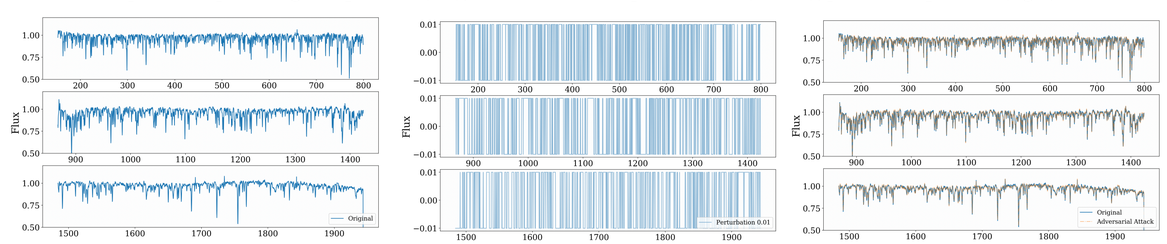
Model Predicted Labels, Attacked Labels and Ground Truth Labels



Output Label Space: examples of star 500 (left, Linear Model), star 758 (middle, the Cannon), star 244 (right, AstroNN)



Input Flux Space: original spectrum (left), added adversarial perturbation (middle), perturbed spectrum (right)



Discussion

In our experiments, we use the FGSM method with step size ranging from 0.001 to 0.02 and step value 0.01 (11 points in total). All three models use MSE as loss objective to calculate gradient direction for attacks.

- The first row of plots shows the RMSE loss for each model
- The second row of plots compares two labels predicted by the models without attack, predicted under attack and ground truth
- Highlights of attacks to individual stars are shown in the third row: points illustrate attacked predictions, random perturbations, original predictions, ground truth labels, and physical model attacks
- To confirm the adversarial attacks are small and uninformative, the fourth row shows one example flux spectrum. We can see the perturbation is adding random small noises to each flux pixel, almost imperceptible for human eyes

To compare the susceptibility of each model to adversarial attacks we measure each model's sensitivity quotient, defined as:

$$\text{SQ}(f) = \frac{\text{RMSE of Optimal Attack}}{\text{RMSE of Random Attack}}$$

At the step size of interest 0.01, we observe the linear model's sensitivity quotient is 6.92, The Cannon is 4.50 and AstroNN is 6.93. The Cannon is therefore more robust to adversarial attacks than the linear model and AstroNN as measured by the SQ.

Conclusion

In this paper we have only scratched the surface of what we believe is a fundamental question in natural sciences: to what extent are popular machine learning models vulnerable to adversarial attacks. We only consider the simplest FGSM attack but we intend to look at single pixel attacks, and l_2 attacks for future work. In the results we obtained, the order of models from least to most robust is: the Bayesian Neural Network, the linear model, and The Cannon. However, the attacks we found were not incredibly successful (definitely not as successful as the known attacks for image classification). We don't consider this question settled because there are many other possible attacks that we haven't explored. These results are mostly aligned with the intuition that higher capacity models are more vulnerable to attacks, and that generative models may be less vulnerable to attacks than discriminative models due to their causal structure.

Acknowledgements

We would like to sincerely thank David W. Hogg and Soledad Villar whose guidance, inspiration and leadership made this project possible. We would also like to thank Elena Sizikova, Milan Brandovic, and Anastasios Noulas for their hard work in facilitating this iteration of the CDS Capstone Course.

MSML 2020

This project was submitted to the Mathematical and Scientific Machine Learning 2020 Conference, Princeton University