

2019

Machine Learning vs Conventional Analysis Techniques for the Earth's Magnetic Field Study

Sheri Loftin

Southern Methodist University, sloftin@mail.smu.edu

Sarah J. Fite

Southern Methodist University, fites@mail.smu.edu

Laura V. Bishop

Southern Methodist University, lvbishop@mail.smu.edu

Stavros Kotsiaros

University of Maryland, stavros.kotsiaros@nasa.gov

Follow this and additional works at: <https://scholar.smu.edu/datasciencereview>

 Part of the [Categorical Data Analysis Commons](#), and the [Other Earth Sciences Commons](#)

Recommended Citation

Loftin, Sheri; Fite, Sarah J.; Bishop, Laura V.; and Kotsiaros, Stavros (2019) "Machine Learning vs Conventional Analysis Techniques for the Earth's Magnetic Field Study," *SMU Data Science Review*: Vol. 2 : No. 1 , Article 7.

Available at: <https://scholar.smu.edu/datasciencereview/vol2/iss1/7>

This Article is brought to you for free and open access by SMU Scholar. It has been accepted for inclusion in SMU Data Science Review by an authorized administrator of SMU Scholar. For more information, please visit <http://digitalrepository.smu.edu>.

Machine Learning vs Conventional Analysis Techniques for the Earth's Magnetic Field Study

Sheri Loftin¹, Sarah Fite², Laura Bishop³, Stavros Kotsiaros⁴

¹ Master of Science in Data Science, Southern Methodist University,
Dallas, TX 75275 USA

²National Aeronautics and Space Administration, Goddard Space Flight Center,
8800 Greenbelt Drive, Greenbelt, MD 20771 USA
{sloftin, fites, lvbishop}@smu.edu
Stavros.Kotsiaros@nasa.gov

Abstract. Current techniques for calculating and generating models used for analyzing the Earth's magnetic field are laborious and time-consuming. We assert that machine learning can have a significant impact on building magnetic field models more quickly and on various levels of complexity, specifically as it pertains to data cleansing and sorting. Our approach to this problem uses a reverse iterative multi-phase process for data cleansing, in which, initially, the CHAOS-6 model data is examined to determine if machine learning can be used to differentiate between useful data components for spherical harmonics, versus data noise. During this phase, six different machine learning techniques are used and compared: two classification techniques (Convolutional Neural Network (CNN) and Support Vector Classification (SVC)) and four regression techniques (Random Forest Regression (RFR), Support Vector Regression (SVR), Logistic Regression, and Linear Regression). During this initial phase, the focus is on understanding the accuracy of machine learning for model selection and uses relatively clean data. Future phases should include machine learning relevance as it pertains to the massive volume of data received from satellites. Exploring the machine learning capabilities for magnetic field datasets accomplishes 1) faster and more efficient computation when there are millions of rows of data in any given 30-day period, and 2) lowers the propagation of errors that cause some data to be useless in the spherical harmonics computations used in the model generation.

¹ Sheri Loftin is completing her MS in Data Science at SMU. She is the Planetary Data Systems Database Training and Communications Coordinator at Goddard Space Flight Center, contracted through Adnet Systems.

² Sarah Fite is completing her MS in Data Science at SMU. She is a Business Analyst at iHeartMedia, Inc.

³ Laura Bishop is completing her MS in Data Science at SMU. She is a Technical Sales Manager in Cybersecurity at IBM.

⁴ Dr. Stavros Kotsiaros is the advisor for this project. He is a research scientist at the University of Maryland and a visiting collaborator at NASA-Goddard Space Flight Center.

1 Introduction

The European Space Agency's (ESA) Living Planet Programme launched a trio of satellites on 22 November 2013 called *Swarm*, which is the fourth Earth Explorer mission [5].

Two years of magnetic data from the *Swarm* mission and monthly means from 160 ground observatories were used in the paper by Finlay et al., *Recent geomagnetic secular variation from Swarm and ground observatories as estimated in the CHAOS-6 geomagnetic field model*, (2016) [19].

The Earth's magnetic field is effectively a 'super shield' that protects the planet from cosmic radiation and charged particles in the solar wind [6]. Earth's magnetic field is created by sources both internal and external to our planet. The largest field is created by electric currents flowing in the Earth's liquid outer core which is known as the "core field". The core field together with a small contribution from the magnetized rocks in the Earth's lithosphere producing what is known as the lithospheric or crustal field, encompass the so-called internal magnetic field. The external field is produced by electric currents flowing in the Earth's ionosphere and magnetosphere.

Low Earth Orbiting (LEO) satellites measure the Earth's large scale lithospheric magnetic field. LEO satellites provide a statistical homogeneity of measurement on a world-wide scale. In reality, the lithospheric magnetic signal is masked by the dominant core field signal as well as by the "time-varying external fields" that contaminate the lithospheric signal along the satellite's orbit [5]. There are ways to minimize the contamination by suppressing the undesired signals with 'along-satellite-track' analysis [7][8] or using magnetic field gradients [29]. Specifically, the configuration of the *Swarm* trio can be used to estimate the East-West (EW) magnetic field gradient from differences between measurements of the two lower satellites, and the North-South gradient from differences between successive vector measurements along the satellite tracks [5]. A major statistical and data challenge is extracting weak lithospheric signals from the total magnetic field observations [5]. Modeling the magnetic field due to both the internal and external sources is essential for a more complete and more accurate estimation of the Earth's total magnetic field. The CHAOS-6 [19] model incorporates lithospheric, core and external field sources.

Even with the most accurate satellite measurements, developing a precise model for the Earth's magnetic field is difficult from a few perspectives: field of study, statistical, and data. It requires expertise in a number of different scientific disciplines, including magnetometry, spacecraft measurements, planetary physics, geology, etc. As in many complex scientific fields of study, the more professional experience gained, the better the results. A benefit of studying the Earth's magnetic field is the plethora of data collected. For example, in this study, 31 days of satellite data generated over 2.6 million rows of cleaned collection data representing 2.6 million data points of magnetic field readings. Current methods struggle to handle the amount of data produced. Another limitation of the current methods lies in a shortcoming within spherical harmonic computations. "Dirty data" entered into the spherical harmonic computation creates errors that do not only affect the region of the Earth where the

contamination originated but globally. Therefore, the errors propagate throughout the model and may affect the usefulness of the model in specific regions of interest. With spherical harmonics, the errors cannot be all filtered out, and some of the data rendered useless as the propagation of such errors may become significant and affect the weaker signals to be modelled. With more modern machine learning techniques, these errors can be detected and filtered out earlier, thereby allowing more of the data to be used and lowering the overall error leakage in the model. These techniques are how tools, technology, and processing of Data Science and Machine Learning can improve the generation of geomagnetic field models better for all scientists.

2 Background

The goal for studying the Earth's magnetic field is two-fold: 1) to better understand the magnetic shield and 2) to study the interior of our planet. Pragmatic applications for this research include understanding of tectonic dynamics, drilling for natural resources, planetary science, and better navigation systems. While the theoretical perspective paints a dire picture of a weakening magnetic shield, the more that is known and understood, the better our advances to understand the implications of such change.

The objective for applying Data Science approaches and Machine Learning techniques to creating geomagnetic models is to reduce the complexity of generating hi-resolution models to be used in the study of the Earth's magnetic field and to utilize the enormous amount of collected data, thereby allowing for a more accurate view of the geomagnetic field. Today, hi-resolution models require extensive computations with several iterations making the model generation an expensive process.

The design of this project is to improve the management of the data volume by reducing the compilation time by at least 30%. Additionally, we aim to improve the error propagation and leakage in the analysis and estimation due to the entanglement of the various magnetic field sources. Finally, another goal is to use more of the data collected to provide a more thorough model.

2.1 Definition of Terms

The Swarm satellite configuration consists of two satellites which orbit 450-Kilometers above the Earth and a third satellite which orbits at 530-Kilometers above the Earth. At the core of each Swarm satellite is an instrument, the Vector Field Magnetometer (VFM), which is pertinent to this study:

Vector Field Magnetometer (VFM) – Located at the tip of the optical bench on the boom, the VFM measures magnetic field vector. The VFM contains a 3-axis Compact Spherical Coil (CSC) sensor with a 3-axis Compact Detector Coil (CDC) sensor inside that acts as a closed loop system. It achieves a null field at the detector coils in the sphere by adjusting the compensating CSC currents. The raw data is the current level in the CSC coils.

The geomagnetic field is modelled in terms of Spherical Harmonics. A model of the Earth's magnetic field is therefore a set of spherical harmonic coefficients which aim to represent as accurate a picture as possible of the current state of the geomagnetic field of Earth.

3 Dataset and Data Exploration

The data we are using consists of 2,678,400 rows of cleaned, magnetic data produced by the CHAOS-6 model. This “dummy” data will allow the model to be trained for “best fit” in the Crustal data model.

There are 19 variables collected as shown in Table 1.

Table 1 CHAOS-6 Model Data used for comparison

Variable Name	Meaning	Minimum	Maximum
T [md2000]	Time in units of decimal DAYS from 1/1/2000 midnight.	5844	5875
r [km]	Coordinate distance from the center of Earth measurements – radius in kilometers (km)	6814	6835
theta [degrees]	Position coordinate angle from x-axis – in degrees(Longitude)	2.648	177.352
phi [degrees]	Position coordinate angle from z- axis – in degrees(Latitude)	-180.0000	179.9995
B_r1 [nano Tesla]	Radial Internal Field (I)	-48793	52931
B_theta1 [nano Tesla]	Co-latitudinal Internal Field (I)	-32958	11531
B_phi1 [nano Tesla]	Azimuthal Internal Field (I)	-12785.80	12282.23
B_r2 [nano Tesla]	Radial core Field (C)	-48792	52934
B_theta2 [nano Tesla]	Co-latitudinal core Field (C)	-32957	11528
B_phi2 [nano Tesla]	Azimuthal core Field (C)	-12786.330	12281.600
B_r3 [nano Tesla]	Radial crustal Field (L)	-15.34000	12.67000
B_theta3 [nano Tesla]	Co-latitudinal crustal Field (L)	-7.73000	11.38000
B_phi3 [nano Tesla]	Azimuthal crustal Field (L)	-10.62000	7.83000
B_r4 [nano Tesla]	Radial external Field (E)	-55.1600	54.960
B_theta4 [nano Tesla]	Co-latitudinal external Field (E)	-12.39	114.08
B_phi4 [nano Tesla]	Azimuthal external Field (E)	-27.0000	24.6300
B_r5 [nano Tesla]	Radial total Field (T)	-48824.1	52963.3
B_theta5 [nano Tesla]	Co-latitudinal total Field (T)	-32952	11540
B_phi5 [nano Tesla]	Azimuthal total Field (T)	-12793.780	12281.430

Formula background- Magnitude of the magnetic field is computing using a 3D variation of the Pythagorean Theorem:

$$B = \sqrt{x * x + y * y + z * z}$$

$$\begin{aligned} \text{Internal Field} &= \text{Core Field} + \text{Crustal Field} \\ \text{Internal Field} &= [B_r2, B_theta2, B_phi2] + [B_r3, B_theta3, B_phi3] \end{aligned}$$

$$\begin{aligned} \text{Total Field} &= \text{Internal Field} + \text{External Field} \\ \text{Total Field} &= \text{Internal Field} + [B_r4, B_theta4, B_phi4] \end{aligned}$$

The design is based on using the crustal field variables, r $theta$ phi , to represent the position of the measurement and the strength of the magnetic field at that position. A machine learning model is created to yield the same or statistically similar enough results for the crustal field variables in data columns 11-14.

As shown in figures 1 and 2 (below), each magnetic field source has its own "signature" and varies significantly in strength, as compared to the other. In each figure the x-axis represents longitude, and the y-axis represents latitude, while the color bar represents the strength of the magnetic field at each location. The unit for the color bar is nanoTesla. Also, in each figure, North is 0 on the y-axis and South is 180; thus the Earth appears upside down.

The total magnetic field has definite features, especially around the polar regions of the Earth. This is dominated by the most robust magnetic field source of the Earth and is created by the dynamo action of our solid core rotating at a slightly different speed than the surrounding liquid mantle.

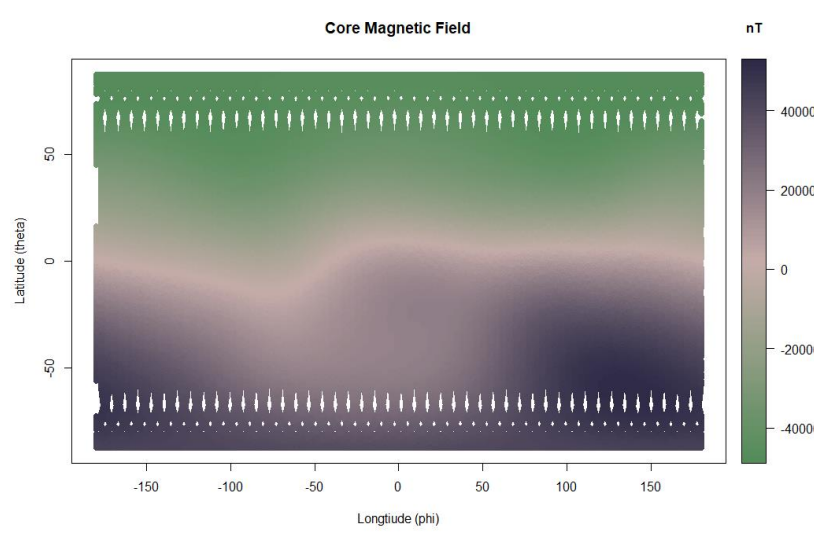


Fig. 1. 2D rendering of the core magnetic field with the 'x' axis for longitude and 'y' axis for latitude.

Within the data of the crustal field, the continental outlines are subtle but present. The strength of the magnetic field at each point is significantly lower than the strength of the core field. Because of this vast difference, the signal of the crustal field can easily get lost within the data of the total magnetic field, which includes the core field, the crustal field, and the external field.

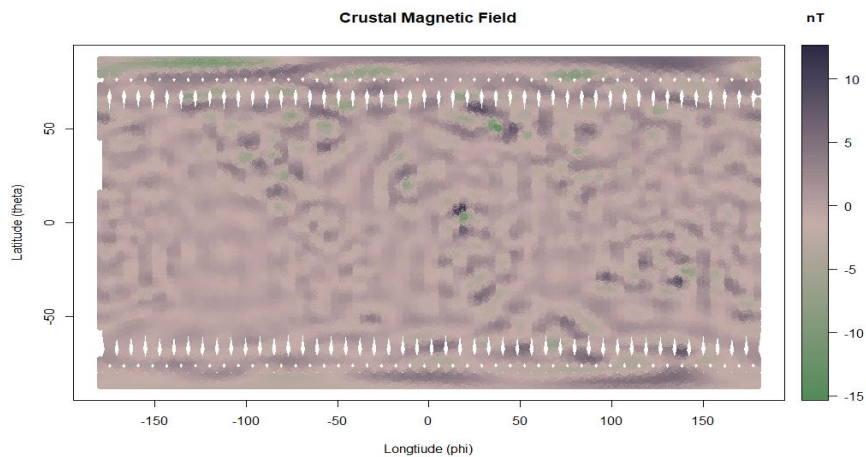


Fig. 2. 2D rendering of the crustal magnetic field with the 'x' axis for longitude and 'y' axis for latitude.

Since the core field is so much stronger than the crustal field (the signature we are looking to model with this project), we have chosen to use the combination of the external field and the crustal field as our dataset. The goal is to be able to search through this dataset and have the machine learning tool find the signature of the crustal magnetic field.

The external field is produced in the ionosphere and the magnetosphere of the Earth and is only one factor stronger than the crustal field. On the contrary, in comparison, the core field is three factors stronger. The external field also lacks the variety of anomalies that exist within the crustal field.

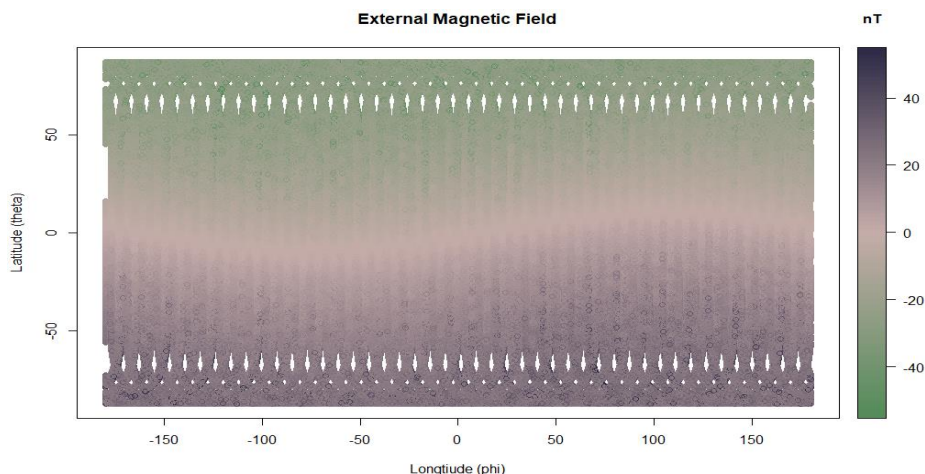


Fig. 3. 2D rendering of the external magnetic field data with the 'x' axis for longitude and 'y' axis for latitude.

4 Methodology

4.1 Model Comparison

Initially, the model is trained using the variables related to time, position and the positional components of the total magnetic field. These variables correspond to columns 1-4 and 17-19 and are labeled t , r , θ , ϕ , and B_r5 , $B_\theta5$, and $B_\phi5$. Columns 1-4 feeds the algorithm and resulting in Columns 17-19. This is the proof of concept to justify using *Swarm* mission data to test the applicability of a machine learning dataset for magnetic field modeling.

4.2 CHAOS-6 Analysis Techniques

The CHAOS-6 model uses a method called spherical harmonics. The model itself is a series of coefficients that when entered into the spherical harmonic formula produce a description of the magnetic field of the Earth.⁵

The crustal field is represented by the coefficients corresponding to 21 – 110 degrees. There are 11,880 coefficients in the CHAOS-6 model. Given the complexity of the process and the vast number of coefficients, it becomes easy to see why this process would take so long to compute values.

⁵ An introduction to spherical harmonics by Wojciech Jarosz, Assistant Professor at Dartmouth University is found at <https://cs.dartmouth.edu/wjarosz/publications/dissertation/appendixB.pdf>

4.3 Machine Learning Methods

As previously mentioned, this paper examines six (6) machine learning approaches to determine which method best predicts the data most useful for the crustal data model. The approach taken is an inverse data analysis. That is, instead of starting the process with the dirtiest data imported directly from the source (satellite data), then struggling with cleansing and clustering that data, then spending a great deal of time determining if errors and challenges encountered during that process are the result of the premise or a challenge in the data, we chose to start with a clean, known dataset (crustal model). This dataset is then mixed with the external model data to create our initial phase of 'dirty data.' Our premise is that if the crustal model data is successfully predicted amongst the "dirty data" of the external model data, success is achieved at this initial phase (Phase 1). Following this, the next step is to use the dataset in a dirtier, earlier revision from the satellite. The number of backward iterations of the data from clean to dirtier is not known at this time but is estimated to be at least four (4) to confidently know this approach is statistically successful and useable by NASA Goddard.

We review both classification and regression methods. Phase 1 is looking at predicting 'in or out' of the crustal dataset, which is standard classification. Due to the highly linear nature of the data, and unknown characteristics of the data in following Phases (closer to the raw data from the satellite), the requirement exists to have a strong machine learning foundation by which to evaluate the best method.

Classification Approaches. Classification approaches are essential in systematically structuring the data.

Convolutional Neural Networks. Research into previous machine learning techniques used to improve upon spherical harmonics shows that Convolutional Neural Networks (CNN) have potential. While no previous research has been discovered discussing this from a planetary magnetic field perspective, there have been attempts to replace spherical harmonics in other realms. Two papers listed below have used CNN to replace spherical harmonics in the realms of particle physics [21] and heart MRIs [22].

By design, the CNN technique is the starting point because of its ability to handle image data, before any data analysis had been conducted. SVC, RFR, SVR, Logistic Regression, and Linear Regression act as comparison techniques to determine which method yields the best statistical result of accuracy.

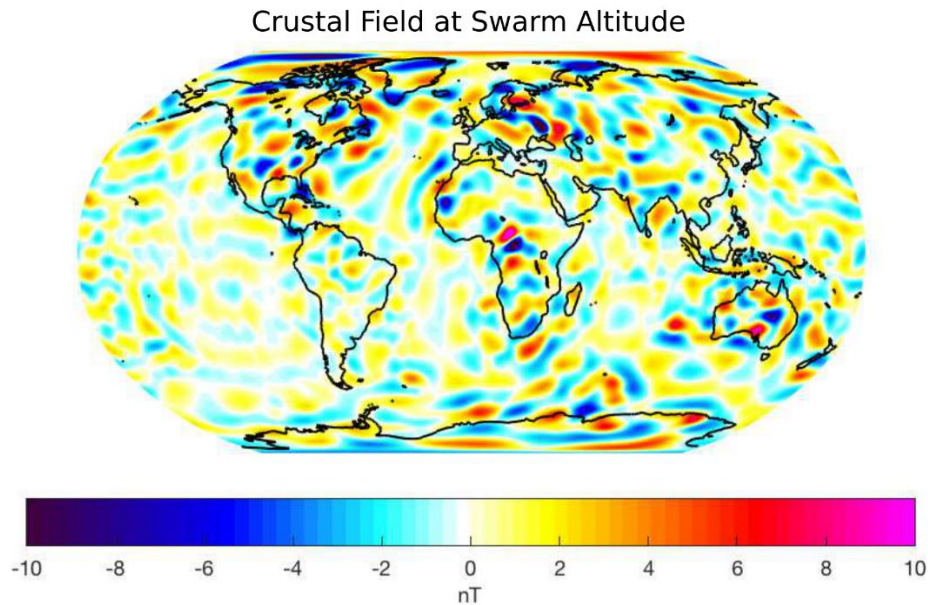


Fig 4: Outline of continents overlaid on the crustal field model data. Courtesy of Stavros Kotsiaros.

CNN's primary use is image analysis. In this case, CNN treats the magnetic field of the Earth as an image with certain distinctive features. As seen in *Figure 4* above, the outlines of the continents are somewhat visible to a trained eye. This feature could be used to distinguish the image of the crustal model from the image of the core or the external model. A CNN should be able to separate this signature feature.

Support Vector Classification. Given the linear nature of the data, SVC is as a secondary approach for comparison of CNN.

Regression Approaches. For each regression approach, the measure of a proper machine learning technique is its error rate. The top three (3) error techniques according to Botchkarev survey [27] are used in this paper to evaluate the distance between estimates and predictions during cross-validation:

- 1) Mean Absolute Error (MAE) – Average of absolute distance between data and prediction. The proportional weight of the error. Less sensitive to outliers.
- 2) Root Mean Square Error (RMSE) – Measures average magnitude of error. Gives weight to larger errors and makes them more pronounced in the model; useful to compare to MAE to understand the distribution of the larger errors. When MAE = RMSE, the distribution of errors is consistent.
- 3) Mean Absolute Percentage Error (MAPE) – This measurement shows a small relative error and shows the precision of the models. This works best with medium and large datasets.

The model analysis Python code used was built by Dr. Jacob Drew of Southern Methodist University and his work for the State of North Carolina Education [23]. The model analysis code builds regression models that are evaluated using cross-validation and a random seed. This is accomplished using parameters of Python's `sklearn.model_selection`'s `cross_validate` function, which performs the cross-validation for regression estimators. The random seed ensures that all regression estimators are tested on the same randomly selected data rows for each cross-validation fold. Dr. Drew created custom scorers for MAE, RMSE, and MAPE using the three chosen mean error scores. Thus, all three scores are calculated using a single call to `cross_validate()`. All of this functionality lies in a custom function `'EvaluateRegressionEstimator()'`, which allows multiple regression models to be tested using the same test/train cv data and consistently produces the evaluation scores for each model.

The same regression model function was used to evaluate each approach outside of CNN and SVC. A five (5) fold cross validation is used, along with passing the three (3) mean error scores into the cross-validation in one (1) call.

`GridSearchCV` "exhaustively" searches for the best parameters used in the regression methods for the four (4) non-CNN regression approaches. `GridSearchCV` is passed as a regression algorithm (one of the 4), a parameter grid based on the regression, and a number of cross-validation folds. Using `GridSearchCV` improves the accuracy of nested cross-validation, thereby improving the accuracy of the model prediction.

Linear Regression models the behavior between dependent response (label of 'in crustal model' - 1 or not - 0) and explanatory variables of 'theta', 'phi' and 'mag' (magnitude).

For these approaches, a sample size from the 2.6 million *Swarm* satellite model data was used totaling 26,784 rows and five (5) folds. The training set is 21,427 rows, and the test set is 5,357 rows. This smaller dataset was chosen to allow for decent processing time on a 2016 MacBook Pro running macOS Mojave v 10.14.2 with a 3.3GHz Intel Core i7 processor and 16 GB 2133 MHz LPDDR3 memory. With this smaller dataset, RFR takes at least 24 hours to run.

Linear Regression. In this multi-linear regression, the value is capped between 0 and 100. Two options are analyzed: 1) normalize with `'fit_intercept'` set to True; and 2) no normalization when `'fit_intercept'` set to False.

Random Forest Regression. An RFR is a comprehensive supervised machine learning approach that randomly selects features and builds a collection of base models or decision trees from different subsamples of the training data; then sums up the result for the final mode or decision tree. We pulled subsamples from the 21,427-row training data and built 500 decision trees. The minimum size for leaves is a set of [10, 25, 50], which will help reduce noise in the training data. RFR is good for the following: numerical features; smaller set of categorical features; and capturing non-linear relationships in the data [24]. All three of these features apply to the dataset.

Support Vector Regression. SVR determines the distance of the data point from the boundary or hyperplane. The error is the tolerance or margin of distance from the hyperplane. Broader margins between the data points indicate better classifiers, as the categories are more distinct. SVR is suitable for use on many features and low noise datasets. While the crustal field and external field dataset being modeled does not have many features, it is reasonably low in noise for our Phase 1. By keeping SVR in the regression comparison, a baseline creates future Phases where the data is not as clean and orderly as in Phase 1.

The SVR parameters include the 'kernel' parameter, which looks at both linear and non-linear hyperplanes. For the non-linear, 'rbf,' the gamma is set at a default of '1/number of columns in the dataset, which is three (3)' and 0.1. The penalty parameter 'C' is the cost or error tolerance. Too high a 'C' value can lead to overfitting. GridSearchCV is used to optimize these hyper-parameters for the SVR.

Logistic Regression. Logistic Regression is a binary classification approach based on the 'Label' variable for the model. In this case, GridSearchCV is used to generate the best parameters using the three (3) scoring measures mentioned above.

5 Results

5.1 Support Vector Classification

The result of using an SVC approach yielded a 99% accuracy. In subsequent phases, using dirtier data, closer to the raw data from the satellite, we believe the linearity of the data will not be as strong.

Table 2. Results from SVC analysis, demonstrating 99% accuracy

	Prediction Accuracy	0.99914
Prediction label	0	1
0	13373	6
1	17	13388

5.2 Convolutional Neural Networks

Using a training and testing set of the data from the crustal field combined with the external field, the CNN has picked out the crustal field with 54.3% accuracy.

Table 3. Prediction table output from CNN.

	Prediction Accuracy	54.3%
Prediction Label	0	1
0	521678	518725
1	147922	150875

In hindsight, this result is not too surprising. CNN's primary use is with large feature datasets for visual and text processing, neither of which we had. However, it does set the foundation of comparison in later phases of the project.

The Error Comparisons for Regression Approaches [25][26]. To evaluate the success of our model, we compare the following regression metrics for performance.

Table 4. Regression technique results for MAE, RMSE, and MAPE

	MAE	RMSE	MAPE	Difference RMSE - MAE
Linear Regression	0.175272	0.21355	14.3907	0.038278
Support Vector Regression	0.103333 0.0009178	0.137702	8.74311	0.034369
Logistic Regression	1	0.0025938	10.114 0.18560	0.00167599
Random Forest Regressor	0.002995	0.0438683	5	0.0408733

MAE. Using absolute numbers with no indication of the magnitude of the error, the Logistic Regression has the smallest MAE at .0009. The RFR also has a small MAE at .003. The largest MAE comes from Linear Regression at .175. The difference or distance between high to low MAE is .172.

RMSE. Looking at the impact and frequency of error, Logistic Regression is the smallest at .0025. RFR also has a small RMSE at .04.

The most significant difference between RMSE and MAE is .04 for Linear Regression and RFR, indicating larger distributions of error in these approaches. The smallest difference between MAE and RMSE is Logistic Regression with a difference of 0.001.

MAPE. Although considerable effort is made to create equality among the methods by using GridSearchCV, etc., the percentage comparison between approaches varies by 14.2%. Leading to greater model accuracy, by a noticeable amount, in the RFR at .186%. Logistic Regression and SVR are within 1.3% range of each other from 8.7-10%. Linear Regression has the highest model percentage error at 14%.

6 Conclusions and Recommendation

Given the reverse, iterative approach to finding the best machine learning method, it is not unexpected to receive the highly accurate results and the linearity of the dirty data (Crustal + External model). For Classification, the SVC outperformed the CNN due to the SVC's and the data's linear nature. From an approach perspective, and not a NASA productivity or efficiency needs perspective; a future attempt would take the Earth's magnetic image, as shown in Fig.4, and map that through a CNN. This approach more closely aligns to successful CNN attempts with visual images. The test would be for the ability of CNN to predict changes in the Earth's magnetic crust based on the image, which results from raw satellite data.

For Phase 1 of our analysis, Linear Regression and SVR performed the least favorably in MAE and RMSE. These results are somewhat surprising given the linearity of the data. Logistic Regression and RFR have strengths in MAE and RMSE. RFR performed well across the board based on MAE, MAPE, and RMSE. Following phases of analyses will determine if RFR or Logistic Regression remain preferable approaches with dirtier data.

An adjacent approach is to 'one-hot encode' the data and maintain a history of magnetic data based on the spherical harmonics' triangulation of the spot on the Earth. Then, with a sufficient dataset for each spot captured, use that data to predict the change in magnetism.

Phase 1's foundation of regression and classification results create a solid foundation to find the optimum point of data condition by which machine learning is applied.

7 Ethics

Ethics in data collection, usage and retention are always important. The ethical considerations for this dataset and this paper are not significant. The *Swarm* data used falls under the ESA Data Policy for ERS, Envisat and Earth Explorer missions. The Policy's goal is to provide access in a nondiscriminatory way and allow the use of all primary and processed data (up to level 2) for scientific procedures, commercial practices, or for the public good [11]. Specifically, the ESA Data Policy is to encourage the following:

- continued Earth science activities;
- encourage technology innovation and instruments to observe the Earth;
- support operational applications and new applications being developed;
- support the private sector to invest in derived products and services;
- support global Earth Observation industry in the ESA Member States.

Since *Swarm* is part of the Earth mission, it is covered under the category of the policy outlining 'Free dataset,' which includes full, and open, online access at no cost, abiding by the ESA terms and conditions. This dataset is also one-way, in which no data is uploaded to the ESA site. There is no private information in the dataset in which security needs must be taken into consideration. There are no ethical collection issues.

References

1. Sabaka, T.J. et al.: Extending comprehensive models of the Earth's magnetic field with Ørsted and CHAMP data. *Geophysical Journal International*. 159, 2, 521–547 (2004).
2. Sabaka, T.J. et al.: CM5, a pre-Swarm comprehensive geomagnetic field model derived from over 12 yr of CHAMP, Ørsted, SAC-C and observatory data. *Geophysical Journal International*. 200, 3, 1596–1626 (2015).
3. Lesur, V. et al.: GRIMM: the GFZ Reference Internal Magnetic Model based on vector satellite and observatory data. *Geophysical Journal International*. 173, 2, 382–394 (2008).
4. Lesur, V. et al.: Parent magnetic field models for the IGRF-12GFZ-candidates. *Earth, Planets and Space*. 67, 1, (2015).
5. Olsen, N. et al.: LCS-1: a high-resolution global model of the lithospheric magnetic field derived from CHAMP and Swarm satellite observations. *Geophysical Journal International*. 211, 3, 1461–1477 (2017).
6. Lithospheric magnetic field, http://www.esa.int/spaceinvideos/Videos/2017/03/Lithospheric_magnetic_field.
7. Maus, S. et al.: Resolution of direction of oceanic magnetic lineations by the sixth-generation lithospheric magnetic field model from CHAMP satellite magnetic measurements. *Geochemistry, Geophysics, Geosystems*. 9, 7, (2008).
8. Thébaud, E. et al.: The satellite along-track analysis in planetary magnetism. *Geophysical Journal International*. 188, 3, 891–907 (2011).
9. Kotsiaros, S., Olsen, N.: The geomagnetic field gradient tensor. *GEM - International Journal on Geomathematics*. 3, 2, 297–314 (2012).
10. Random Forest vs Logistic Regression: Binary Classification for Heterogeneous Datasets, K. Kirasich, T. Smith, B. Sadler. <https://scholar.smu.edu/cgi/viewcontent.cgi?article=1041&context=datasciencereview>
11. ESA Data Policy for ERS, Envisat and Earth Explorer missions, October 2012. https://earth.esa.int/c/document_library/get_file?folderId=296006&name=DLFE-3602.pdf
12. United Nations Resolution A/RES/41/65 dated 3 December 1986 on Principles relating to Remote Sensing of the Earth from Space.
13. Lithographic Magnetic Field. Richard Holm. <https://www.liverpool.ac.uk/~holme/lith.html>
15. Wikipedia - Lithosphere <https://en.wikipedia.org/wiki/Lithosphere>.
15. Wikipedia – Subduction <https://en.wikipedia.org/wiki/Subduction>.
16. ESA Earth Online – Magnetic lithosphere detailed.

https://earth.esa.int/web/guest/news/-/asset_publisher/G2mU/content/magnetic-lithosphere-detailed;jsessionid=0F5F7E6A634EB99B3912C9EC80BD0534.jvm1?redirect=https%3A%2F%2Fearth.esa.int%2Fweb%2Fguest%2Fnews%3Bjsessionid%3D0F5F7E6A634EB99B3912C9EC80BD0534.jvm1%3Fp_p_id%3D101_INSTANCE_G2mU%26p_p_lifecycle%3D0%26p_p_state%3Dnormal%26p_p_mode%3Dview%26p_p_col_id%3Dcolumn-1%26p_p_col_pos%3D1%26p_p_col_count%3D2%26_101_INSTANCE_G2mU_cur%3D2%26_101_INSTANCE_G2mU_keywords%3D%26_101_INSTANCE_G2mU_advancedSearch%3Dfalse%26_101_INSTANCE_G2mU_delta%3D10%26_101_INSTANCE_G2mU_andOperator%3Dtrue

17. Thébault, Purucker, Whaler, Langlais, Sabaka : The Magnetic Field of the Earth's Lithosphere, Dec 2009.

18. Swarm, <https://earth.esa.int/web/sppa/mission-performance/esa-missions/swarm>

19. Finlay, C.C., Olsen, N., Kotsiaros, S., Gillet, N. and Toffner-Clausen, L., (2016) Recent geomagnetic secular variation from Swarm and ground observatories as estimated in the CHAOS-6 geomagnetic field model. *Earth, Planets, Space*, 68, 112, doi: 10.1186/s40623-016-0486-1

20. Elagin, Andrey. (2018). Comparing Spherical Harmonics Analysis and Machine Learning Techniques for Double-Beta Decay Identification in a Large Liquid Scintillator Detector. Zenodo. <http://doi.org/10.5281/zenodo.1345691>

21. Wojciech Jarosz. *Efficient Monte Carlo Methods for Light Transport in Scattering Media*. Ph.D. dissertation, UC San Diego, September 2008. <https://cs.dartmouth.edu/wjarosz/publications/dissertation/appendixB.pdf>

22. Leila Cristina C. Bergamasco, Carlos E. Rochitte, and Fátima L. S. Nunes. 2018. 3D medical objects processing and retrieval using Spherical Harmonics: a case study with Congestive Heart Failure MRI exams. In *Proceedings of ACM SAC Conference, Pau, France, April 9-13, 2018 (SAC'18)*, 8 pages. DOI: 10.1145/3167132.3167168

23. Drew J., The Belk Endowment Educational Attainment Data Repository for North Carolina Public Schools, (2018), GitHub repository, <https://github.com/jakendrew/EducationDataNC>

24. Turi Machine Learning Platform User Guide, https://turi.com/learn/userguide/supervised-learning/random_forest_regression.html.

25. Jj, Jj: MAE and RMSE - Which Metric is Better? – Human in a Machine World – Medium, <https://medium.com/human-in-a-machine-world/mae-and-rmse-which-metric-is-better-e60ac3bde13d>.

26. Using Mean Absolute Error to Forecast Accuracy, <http://canworksmart.com/using-mean-absolute-error-forecast-accuracy/>.

27. Botchkarev, Alexei. Performance Metrics (Error Measures) in Machine Learning Regression, Forecasting and Prognostics: Properties and Typology. Sep 2018. <https://arxiv.org/pdf/1809.03006.pdf>

28. Alvira Swalin. Choosing the Right Metric for Machine Learning Models.

<https://medium.com/usf-msds/choosing-the-right-metric-for-machine-learning-models-part-1-a99d7d7414e4>

29. Kotsiaros, S.: Toward more complete magnetic gradiometry with the Swarm mission. *Earth, Planets and Space*. 68, 1, (2016).

Appendix A

1. R Code

```
R version 3.5.1 (2018-07-02) -- "Feather Spray"
Copyright (C) 2018 The R Foundation for Statistical
Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)
```

```
R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain
conditions.
```

```
Type 'license()' or 'licence()' for distribution details.
```

```
R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.
```

```
Type 'demo()' for some demos, 'help()' for on-line help,
or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.
```

```
> # The header contained extra information. This was
removed using WordPad. The file was originally save as a
.dat file and so was converted to a .txt
> # The file is then read in as tab delimited file into a
dataframe named data1
> setwd("C:/Users/Sheri/Documents/Data Science/Thesis/")
> data1 <- read.delim(file="C:/Users/sheri/Documents/Data
Science/Thesis/CHAOS_preds_SWC_20160101-
20160131_mod.txt",header=FALSE, sep = '|')
> cran <- getOption("repos")
> cran["dmlc"] <- "https://apache-mxnet.s3-
accelerate.dualstack.amazonaws.com/R/CRAN/"
> options(repos = cran)
> install.packages("mxnet")
Installing package into 'C:/Users/sheri/Documents/R/win-
library/3.5'
(as 'lib' is unspecified)
```

```

trying                                URL                'https://apache-mxnet.s3-
accelerate.dualstack.amazonaws.com/R/CRAN/bin/windows/con
trib/3.5/mxnet_1.3.0.zip'
Content type 'application/zip' length 30443134 bytes (29.0
MB)
downloaded 29.0 MB

```

package 'mxnet' successfully unpacked and MD5 sums checked

```

The downloaded binary packages are in
      C:\Users\sheri\AppData\Local\Temp\Rtmp8mNdR9\downlo
aded_packages
> require("mxnet")
Loading required package: mxnet
> install.packages("mlbench")
Installing package into 'C:/Users/sheri/Documents/R/win-
library/3.5'
(as 'lib' is unspecified)
trying                                URL
'https://cran.rstudio.com/bin/windows/contrib/3.5/mlbench
_2.1-1.zip'
Content type 'application/zip' length 1058987 bytes (1.0
MB)
downloaded 1.0 MB

```

package 'mlbench' successfully unpacked and MD5 sums checked

```

The downloaded binary packages are in
      C:\Users\sheri\AppData\Local\Temp\Rtmp8mNdR9\downlo
aded_packages
> library("mlbench")
Warning message:
package 'mlbench' was built under R version 3.5.2
> install.packages("plot3D")
Installing package into 'C:/Users/sheri/Documents/R/win-
library/3.5'
(as 'lib' is unspecified)
trying                                URL
'https://cran.rstudio.com/bin/windows/contrib/3.5/plot3D_
1.1.1.zip'
Content type 'application/zip' length 2944559 bytes (2.8
MB)
downloaded 2.8 MB

```

package 'plot3D' successfully unpacked and MD5 sums checked

The downloaded binary packages are in

```

C:\Users\sheri\AppData\Local\Temp\Rtmp8mNdR9\downloaded_packages
> library("plot3D")
Warning message:
package 'plot3D' was built under R version 3.5.2
> # Inspecting the data
> head(data1)
      V1      V2      V3      V4      V5      V6      V7
V8     V9     V10    V11    V12    V13    V14
1  5844  6833.886  162.8708  94.39791  45904.40  1960.22 -
10062.76 45900.66 1958.78 -10066.81 3.73 1.44 4.05 53.51
2  5844  6833.887  162.9339  94.42800  45900.36  1986.93 -
10060.42 45896.68 1985.38 -10064.46 3.68 1.55 4.05 53.52
3  5844  6833.888  162.9970  94.45834  45896.30  2013.66 -
10058.01 45892.67 2012.00 -10062.05 3.63 1.66 4.04 53.53
4  5844  6833.889  163.0602  94.48893  45892.20  2040.43 -
10055.54 45888.63 2038.65 -10059.58 3.56 1.77 4.04 53.54
5  5844  6833.891  163.1233  94.51977  45888.04  2067.22 -
10053.01 45884.55 2065.34 -10057.03 3.50 1.88 4.03 53.55
6  5844  6833.892  163.1864  94.55087  45883.88  2094.04 -
10050.41 45880.46 2092.06 -10054.43 3.42 1.98 4.01 53.56
      V15     V16     V17     V18     V19
1  15.39 -4.41 45957.91 1975.62 -10067.17
2  15.28 -4.42 45953.88 2002.20 -10064.84
3  15.16 -4.43 45949.83 2028.82 -10062.44
4  15.04 -4.44 45945.74 2055.47 -10059.98
5  14.93 -4.45 45941.59 2082.15 -10057.45
6  14.81 -4.46 45937.44 2108.85 -10054.87
> tail(data1)
      V1      V2      V3      V4      V5      V6
V7     V8     V9     V10    V11    V12
2678395 5875 6834.278 170.7456 60.46576 40567.10 -2509.88
-12739.08 40569.44 -2508.29 -12739.39 -2.34 -1.59
2678396 5875 6834.279 170.8068 60.57665 40593.18 -2466.66
-12738.00 40595.49 -2465.03 -12738.28 -2.31 -1.63
2678397 5875 6834.280 170.8679 60.68907 40619.22 -2423.05
-12736.82 40621.50 -2421.38 -12737.08 -2.28 -1.67
2678398 5875 6834.281 170.9291 60.80305 40645.23 -2379.06
-12735.54 40647.48 -2377.35 -12735.79 -2.25 -1.71
2678399 5875 6834.282 170.9902 60.91861 40671.21 -2334.67
-12734.18 40673.43 -2332.92 -12734.40 -2.22 -1.75
2678400 5875 6834.283 171.0512 61.03580 40697.15 -2289.88
-12732.71 40699.34 -2288.09 -12732.91 -2.19 -1.79
      V13     V14     V15     V16     V17     V18     V19
2678395 0.30 33.06 -1.87 -1.96 40600.16 -2511.76 -12741.05
2678396 0.28 33.06 -1.92 -1.98 40626.24 -2468.58 -12739.98
2678397 0.26 33.06 -1.97 -2.00 40652.28 -2425.02 -12738.82
2678398 0.24 33.06 -2.02 -2.02 40678.29 -2381.07 -12737.56

```

```

2678399 0.22 33.06 -2.06 -2.04 40704.27 -2336.73 -12736.22
2678400 0.20 33.06 -2.11 -2.06 40730.22 -2291.99 -12734.77
> summary(data1)
      V1          V2          V3          V4
V5
  Min.   :5844   Min.   :6814   Min.    :  2.648   Min.   :-
180.0000   Min.   :-48793   Min.   :-32958
  1st Qu.:5852   1st Qu.:6820   1st Qu.: 45.169   1st Qu.: -
90.2879   1st Qu.: -36730   1st Qu.: -22016
  Median :5860   Median :6828   Median :  90.163   Median :
-0.1035   Median :  2937   Median : -14929
  Mean   :5860   Mean    :6826   Mean    :  90.104   Mean    :
0.2425   Mean    : -981   Mean    : -14734
  3rd Qu.:5867   3rd Qu.:6833   3rd Qu.:135.064   3rd Qu.:
89.8413   3rd Qu.: 29694   3rd Qu.: -8611
  Max.   :5875   Max.    :6835   Max.    :177.352   Max.    :
179.9995   Max.    :52931   Max.    :11531
      V7          V8          V9          V10
V11
  Min.   :-12785.80   Min.   :-48792   Min.   :-32957   Min.
:-12786.330   Min.   :-15.34000
  1st Qu.: -2939.43   1st Qu.: -36730   1st Qu.: -22016   1st
Qu.: -2939.580   1st Qu.: -1.01000
  Median :          90.12   Median :  2936   Median : -14929
Median :  89.770   Median :  0.01000
  Mean   :          1.64   Mean    : -981   Mean    : -14734   Mean
:  1.638   Mean    :  0.01122
  3rd Qu.: 3166.59   3rd Qu.: 29695   3rd Qu.: -8612   3rd
Qu.: 3166.815   3rd Qu.: 1.07000
  Max.   :12282.23   Max.    :52934   Max.    :11528   Max.
:12281.600   Max.    :12.67000
      V12          V13          V14
V15          V16
  Min.   :-7.73000   Min.   :-10.620000   Min.   :-55.1600
Min.   :-12.39   Min.   :-27.0000
  1st Qu.: -0.69000   1st Qu.: -0.670000   1st Qu.: -18.3200
1st Qu.:  8.36   1st Qu.: -6.9925
  Median :  0.07000   Median : -0.020000   Median :  0.0900
Median : 14.54   Median :  0.2300
  Mean   :  0.07041   Mean    :  0.001557   Mean    : -0.2081
Mean   :17.07   Mean    : -0.1829
  3rd Qu.:  0.85000   3rd Qu.:  0.610000   3rd Qu.: 17.8400
3rd Qu.:22.39   3rd Qu.:  6.2500
  Max.   :11.38000   Max.    :  7.830000   Max.    : 54.9600
Max.   :114.08   Max.    :24.6300
      V17          V18          V19
  Min.   :-48824.1   Min.   :-32952   Min.   :-12793.780
  1st Qu.: -36749.6   1st Qu.: -21992   1st Qu.: -2938.403

```

```

Median : 2937.3   Median :-14912   Median :    91.105
Mean   : -981.2   Mean    :-14716   Mean    :    1.457
3rd Qu.: 29713.3 3rd Qu.: -8597   3rd Qu.: 3164.323
Max.   : 52963.3 Max.    : 11540   Max.    : 12281.430
> ncol(data1)
[1] 19
> nrow(data1)
[1] 2678400
> any(is.na(data1))
[1] FALSE
> # So the columns represent the measurements from the five
types of magnetometers
> # To do: Follow up with Stavros on which r, theta, phi
group identifies with which magnetometer so we can label
the columns appropriately
> data_header <-
c("t", "r", "theta", "phi", "B_r1", "B_theta1", "B_phi1", "B_r2",
"B_theta2", "B_phi2", "B_r3", "B_theta3", "B_phi3", "B_r4", "B
_theta4", "B_phi4", "B_r5", "B_theta5", "B_phi5")
> colnames(data1) <- data_header
> head(data1)
      t      r      theta      phi      B_r1 B_theta1      B_phi1
B_r2 B_theta2      B_phi2 B_r3 B_theta3 B_phi3
1 5844 6833.886 162.8708 94.39791 45904.40 1960.22 -
10062.76 45900.66 1958.78 -10066.81 3.73 1.44 4.05
2 5844 6833.887 162.9339 94.42800 45900.36 1986.93 -
10060.42 45896.68 1985.38 -10064.46 3.68 1.55 4.05
3 5844 6833.888 162.9970 94.45834 45896.30 2013.66 -
10058.01 45892.67 2012.00 -10062.05 3.63 1.66 4.04
4 5844 6833.889 163.0602 94.48893 45892.20 2040.43 -
10055.54 45888.63 2038.65 -10059.58 3.56 1.77 4.04
5 5844 6833.891 163.1233 94.51977 45888.04 2067.22 -
10053.01 45884.55 2065.34 -10057.03 3.50 1.88 4.03
6 5844 6833.892 163.1864 94.55087 45883.88 2094.04 -
10050.41 45880.46 2092.06 -10054.43 3.42 1.98 4.01
      B_r4 B_theta4 B_phi4      B_r5 B_theta5      B_phi5
1 53.51 15.39 -4.41 45957.91 1975.62 -10067.17
2 53.52 15.28 -4.42 45953.88 2002.20 -10064.84
3 53.53 15.16 -4.43 45949.83 2028.82 -10062.44
4 53.54 15.04 -4.44 45945.74 2055.47 -10059.98
5 53.55 14.93 -4.45 45941.59 2082.15 -10057.45
6 53.56 14.81 -4.46 45937.44 2108.85 -10054.87
> # Convolutional Neural Network
> # Create training and test datasets
> # source code:
https://stackoverflow.com/questions/17200114/how-to-split-data-into-training-testing-sets-using-sample-function

```

```

> ## 75% of the sample size
> smp_size <- floor(0.75 * nrow(data1))
> ## set the seed to make your partition reproducible
> set.seed(123)
> train_ind <- sample(seq_len(nrow(data1)), size =
smp_size)
> train <- data1[train_ind, ]
> test <- data1[-train_ind, ]
> summary(train)

```

t	r	theta	phi
B_r1	B_theta1		
Min. :5844	Min. :6814	Min. : 2.648	Min. :-179.99999
1st Qu.:5852	1st Qu.:6820	1st Qu.: 45.096	1st Qu.: -90.24108
Median :5860	Median :6828	Median : 90.098	Median : -0.06814
Mean :5860	Mean :6826	Mean : 90.053	Mean : 0.25613
3rd Qu.:5867	3rd Qu.:6833	3rd Qu.:135.019	3rd Qu.: 89.81388
Max. :5875	Max. :6835	Max. :177.352	Max. :179.99950
B_phi1	B_r2	B_theta2	
B_phi2	B_r3		
Min. :-12785.80	Min. :-48792	Min. :-32957	Min. :-12786.330
1st Qu.: -2941.46	1st Qu.: -36775	1st Qu.: -22013	1st Qu.: -2941.460
Median : 89.31	Median : 2888	Median : -14927	Median : 89.020
Mean : -0.291	Mean : -1011	Mean : -14733	Mean : -0.291
3rd Qu.: 3161.29	3rd Qu.: 29654	3rd Qu.: -8612	3rd Qu.: 3161.110
Max. : 12282.23	Max. : 52934	Max. : 11528	Max. : 12281.600
B_theta3	B_phi3	B_r4	
B_theta4	B_phi4		
Min. :-7.72000	Min. :-10.620000	Min. :-55.1600	Min. :-12.39
1st Qu.: -0.69000	1st Qu.: -0.670000	1st Qu.: -18.3500	1st Qu.: 8.36
Median : 0.07000	Median : -0.020000	Median : 0.0600	Median : 14.54
Mean : 0.07092	Mean : 0.001272	Mean : -0.2241	Mean : 17.07
			Mean : -0.1766

```

3rd Qu.: 0.85000 3rd Qu.: 0.610000 3rd Qu.: 17.8300
3rd Qu.: 22.38 3rd Qu.: 6.2500
Max. :11.38000 Max. : 7.830000 Max. : 54.9600
Max. :114.08 Max. : 24.6300
  B_r5      B_theta5      B_phi5
Min. :-48824 Min. :-32952 Min. :-12793.780
1st Qu.: -36794 1st Qu.: -21989 1st Qu.: -2940.325
Median : 2888 Median : -14911 Median : 90.330
Mean : -1011 Mean : -14716 Mean : -0.466
3rd Qu.: 29672 3rd Qu.: -8598 3rd Qu.: 3158.400
Max. : 52963 Max. : 11540 Max. : 12281.430
> summary(test)
      t              r              theta              phi
B_r1      B_theta1
Min. :5844 Min. :6814 Min. : 2.648 Min. :-
179.9996 Min. :-48792.1 Min. :-32958
1st Qu.:5852 1st Qu.:6820 1st Qu.: 45.383 1st Qu.: -
90.4274 1st Qu.: -36595.9 1st Qu.: -22025
Median :5859 Median :6828 Median : 90.365 Median :
-0.1717 Median : 3091.0 Median : -14933
Mean :5859 Mean :6826 Mean : 90.255 Mean :
0.2018 Mean : -891.5 Mean : -14736
3rd Qu.:5867 3rd Qu.:6833 3rd Qu.:135.201 3rd Qu.:
89.9404 3rd Qu.: 29811.1 3rd Qu.: -8609
Max. :5875 Max. :6835 Max. :177.352 Max. :
179.9989 Max. : 52931.3 Max. : 11531
  B_phi1      B_r2      B_theta2
B_phi2      B_r3
Min. :-12785.780 Min. :-48791.3 Min. :-32957
Min. :-12786.300 Min. :-15.310000
1st Qu.: -2934.210 1st Qu.: -36595.6 1st Qu.: -22026
1st Qu.: -2934.445 1st Qu.: -1.010000
Median : 92.695 Median : 3090.9 Median : -14932
Median : 92.140 Median : 0.010000
Mean : 7.429 Mean : -891.5 Mean : -14736
Mean : 7.427 Mean : 0.008176
3rd Qu.: 3183.505 3rd Qu.: 29811.2 3rd Qu.: -8609
3rd Qu.: 3183.633 3rd Qu.: 1.070000
Max. : 12281.690 Max. : 52933.8 Max. : 11528
Max. : 12281.060 Max. : 12.650000
  B_theta3      B_phi3      B_r4
B_theta4      B_phi4
Min. :-7.7300 Min. :-10.610000 Min. :-55.1600
Min. :-12.39 Min. :-27.0000
1st Qu.: -0.6900 1st Qu.: -0.670000 1st Qu.: -18.2425
1st Qu.: 8.37 1st Qu.: -7.0200
Median : 0.0700 Median : -0.010000 Median : 0.1800
Median : 14.55 Median : 0.1900

```

```

Mean      : 0.0689      Mean      : 0.002412      Mean      : -0.1602
Mean      : 17.08      Mean      : -0.2018
3rd Qu.: 0.8500      3rd Qu.: 0.610000      3rd Qu.: 17.8900
3rd Qu.: 22.41      3rd Qu.: 6.2500
Max.      :11.3600      Max.      : 7.820000      Max.      : 54.9600
Max.      :114.08      Max.      : 24.6300

      B_r5          B_theta5          B_phi5
Min.    :-48824.1   Min.    :-32952    Min.    :-12793.660
1st Qu. :-36616.1   1st Qu. :-22002    1st Qu. :-2933.012
Median  : 3091.3    Median  :-14916    Median  : 93.355
Mean    : -891.7    Mean    :-14719    Mean    : 7.227
3rd Qu. : 29831.0   3rd Qu. :-8595    3rd Qu. : 3180.102
Max.    : 52963.2   Max.    : 11540     Max.    : 12278.980
> # removing negative values from the coordinates
> # Add the absolute value of the lowest x and y to shift
the origin to the bottom left corner
> i <- min(train$phi)
> j <- min(train$theta)
> train$phi <- train$phi + abs(i)
> train$theta <- train$theta + abs(j)
> # Creating initial plots
> # Using the B_r value to provide more variation in the
plot and show more detail
> core_2D <- scatter2D(train$phi, train$theta, colvar =
train$B_r2, col = ramp.col(c("blue", "yellow", "red")))
> crust_2D <- scatter2D(train$phi, train$theta, colvar =
train$B_r3, col = ramp.col(c("blue", "yellow", "red")))
> ext_2D <- scatter2D(train$phi, train$theta, colvar =
train$B_r4, col = ramp.col(c("blue", "yellow", "red")))
> # Separating the crustal field
>          crust_train          <-
train[,c("t", "r", "theta", "phi", "B_r3", "B_theta3", "B_phi3"
)]
>          crust_train$mag      <-          sqrt(crust_train$B_r3      *
crust_train$B_r3          +          crust_train$B_theta3          *
crust_train$B_theta3          +          crust_train$B_phi3          *
crust_train$B_phi3)
> crust_train$label <- 1
>          c_train      <-          crust_train[,c("phi", "theta", "mag",
"label")]
> head(c_train)
      phi      theta      mag label
770248 101.7547 137.00533 0.7772387 1
2111396 104.8607 177.28091 2.9830354 1
1095403 172.9893 169.54833 2.6161231 1
2365072 272.8674 121.94003 5.0093313 1
2518944 165.6680 29.88937 5.2148058 1
122019 114.2449 68.62554 1.5667163 1

```



```

> nrow(c_train)
[1] 2008800
>
>          crust_test
test[,c("t","r","theta","phi","B_r3","B_theta3","B_phi3")
]
> crust_test$mag <- sqrt(crust_test$B_r3 * crust_test$B_r3
+   crust_test$B_theta3 *   crust_test$B_theta3 +
crust_test$B_phi3 * crust_test$B_phi3)
> crust_test$label <- 1
> c_test <- crust_test[,c("phi", "theta", "mag", "label")]
> head(c_test)
      phi   theta   mag label
10 94.67786 163.4388 5.538447    1
16 94.87651 163.8172 5.320357    1
18 94.94501 163.9433 5.227332    1
19 94.97970 164.0063 5.181477    1
29 95.34367 164.6362 4.650387    1
32 95.45927 164.8250 4.489822    1
> nrow(c_test)
[1] 669600
> # Separating the external field
>
>          external_train
train[,c("t","r","theta","phi","B_r4","B_theta4","B_phi4"
)]
> external_train$mag <- sqrt(external_train$B_r4 *
external_train$B_r4 + external_train$B_theta4 *
external_train$B_theta4 + external_train$B_phi4 *
external_train$B_phi4)
> external_train$label <- 0
> e_train <- external_train[,c("phi", "theta", "mag",
"label")]
> head(e_train)
      phi   theta   mag label
770248 101.7547 137.00533 17.46832    0
2111396 104.8607 177.28091 26.42282    0
1095403 172.9893 169.54833 29.87461    0
2365072 272.8674 121.94003 24.36782    0
2518944 165.6680 29.88937 22.51942    0
122019 114.2449 68.62554 30.99013    0
> nrow(e_train)
[1] 2008800
>
>          external_test
test[,c("t","r","theta","phi","B_r4","B_theta4","B_phi4")
]
> external_test$mag <- sqrt(external_test$B_r4 *
external_test$B_r4 + external_test$B_theta4 *
external_test$B_theta4 + external_test$B_phi4 *
external_test$B_phi4)

```

```

> external_test$label <- 0
> e_test <- external_test[,c("phi", "theta", "mag",
"label")]
> head(e_test)
      phi    theta    mag label
10 94.67786 163.4388 55.66985    0
16 94.87651 163.8172 55.54672    0
18 94.94501 163.9433 55.51164    0
19 94.97970 164.0063 55.48357    0
29 95.34367 164.6362 55.31372    0
32 95.45927 164.8250 55.26211    0
> nrow(e_test)
[1] 669600
> # Combining the external and crustal field to provide a
realistic dataset in which to search for the crustal field
> # Also normalizing the data for more clarity in the CNN
run
> combined_train <- rbind(c_train, e_train)
> com_train_scaled <- combined_train
> com_train_scaled$mag <- scale(combined_train$mag)
> head(com_train_scaled)
      phi    theta    mag label
770248 101.7547 137.00533 -0.9489097    1
2111396 104.8607 177.28091 -0.8035846    1
1095403 172.9893 169.54833 -0.8277580    1
2365072 272.8674 121.94003 -0.6700856    1
2518944 165.6680 29.88937 -0.6565482    1
122019 114.2449 68.62554 -0.8968963    1
> nrow(com_train_scaled)
[1] 4017600
> combined_test <- rbind(c_test, e_test)
> com_test_scaled <- combined_test
> com_test_scaled$mag <- scale(combined_test$mag)
> head(com_test_scaled)
      phi    theta    mag label
10 94.67786 163.4388 -0.6353813    1
16 94.87651 163.8172 -0.6497494    1
18 94.94501 163.9433 -0.6558781    1
19 94.97970 164.0063 -0.6588991    1
29 95.34367 164.6362 -0.6938882    1
32 95.45927 164.8250 -0.7044665    1
> nrow(com_test_scaled)
[1] 1339200
> dim(com_train_scaled)
[1] 4017600      4
> train.x <- data.matrix(com_train_scaled[,1:3])
> train.y <- com_train_scaled[,4]
> mx.set.seed(0)

```

```

> model <- mx.mlp(train.x, train.y, hidden_node=5,
out_node=2, out_activation="softmax",
+ num.round=5, array.batch.size=15,
learning.rate=0.07, momentum=0.9,
+ eval.metric=mx.metric.accuracy,
array.layout = "rowmajor")
Start training with 1 devices
[1] Train-accuracy=0.499977364318179
[2] Train-accuracy=0.499971639507076
[3] Train-accuracy=0.499971639507076
[4] Train-accuracy=0.499971639507076
[5] Train-accuracy=0.499971639507076
> test.x <- data.matrix(combined_test[,1:3])
> test.y <- combined_test[,4]
> preds = predict(model, test.x)
Warning message:
In mx.model.select.layout.predict(X, model) :
  Auto detect layout of input matrix, use rowmajor..

> sqrt(mean((preds-test.y)^2))
[1] 0.54394
> pred.label = max.col(t(preds))-1
> table(pred.label, test.y)
      test.y
pred.label  0     1
           0 521678 518725
           1 147922 150875

```

2. Python Code

```

# coding: utf-8
# Code from Dr Jake Drew, SMU
#
https://github.com/jakemdrew/EducationDataNC/blob/master/2017/Models/2017GraduationRates4yr.ipynb
#and SMU Data Mining Class

# ## Data Setup - r, theta, phi, magnitude

# In[2]:

import pandas as pd
import numpy as np

df_trainSM = pd.read_csv('/Users/laurabishop/Documents/R
Repositories/Capstone Magnetic Field/combined_all_SM.csv')

```

```

df_trainSM.columns = ['Unnamed', 'theta', 'phi', 'mag',
'label']
df_trainSM = df_trainSM.drop('Unnamed', 1)
print("Training data for small data frame")
print ('Size of the dataset:', df_trainSM.shape)
print ('Information about dataset: ', df_trainSM.info())
print ('Head: ', df_trainSM.head())

# ## Data Exploration - r, theta, phi, magnitude

# In[2]:

import matplotlib.pyplot as plt
plt.plot(df_trainSM)
plt.show()

# In[3]:
plt.plot(df_trainSM)
plt.savefig('rThetaPhiMagPLOT.pdf',
orientation='portrait', papertype='letter')
plt.close()

# In[4]:

#From SMU Data Mining Class
import seaborn as sns
import matplotlib.pyplot as plt
#sns.pairplot(df_testSM, vars=['B_r3',
# 'B_theta3',
# 'B_phi3'], hue='B_r3')
sns.pairplot(df_trainSM)
#plt.title ('Pair Plot for External Training Split')
plt.show()

# In[5]:

sns.pairplot(df_trainSM)
plt.savefig('rThetaPhiMagPAIRPLOT.pdf',
orientation='portrait', papertype='letter')
plt.close()

# In[22]:

```

```

#From SMU Data Mining Class
#theta & phi
import matplotlib.pyplot as plt
N=50
#mag & phi
y = np.array (df_trainSM.mag)
x = np.array (df_trainSM.phi)
area = np.pi * (3 * np.random.rand(N))**2 # 0 to 3 point
radii
plt.scatter(x, y, color='g', s=5, linewidths=0, alpha=0.5)
plt.title('Scatter for mag compared to phi')
plt.show()

#mag and theta
y = np.array (df_trainSM.mag)
x = np.array (df_trainSM.theta)
area = np.pi * (3 * np.random.rand(N))**2 # 0 to 3 point
radii

plt.scatter(x, y, color='r', s=5, linewidths=0, alpha=0.5)
plt.title('Scatter for mag compared to theta')
plt.show()

# In[5]:

#From SMU Data Mining Class
#theta & phi

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
N=50
x = []
y = []
for i in range(len(df_trainSM)) :
    if df_trainSM.label[i] == 0:
        x.append(i)
    else: y.append(i)
for j in range (13379,13405):
    x.append(j) == np.nan

df = pd.DataFrame({'x':x, 'y':y})
df.columns = ['External', 'Crustal']
df.plot(kind='scatter',x='External',y='Crustal',
color='red')

```

```

plt.show()
plt.scatter(x, y, color='g', s=5, linewidths=0, alpha=0.5)
plt.title('Scatter Crustal Field Data v External Field
Data')
plt.xlabel("External Field Data (Noise) - Number of Rows")
plt.ylabel("Crustal Field Data - Number of Rows")
plt.savefig('PLOTExternalCrustal.pdf',
orientation='portrait', papertype='letter')
plt.close()
plt.show()

```

```
# In[56]:
```

```

print (np.shape(x))
print (np.shape(y))
print (type(x))
#for i in range(len(x)) :
#   if x[i] == 0 or x[i] == 1:
#       print("hi")
#   else:
#       print (i)
#       #x[i] == np.nan

print (np.shape(x))
# ## Create Linear Regression Variables

```

```
# In[6]:
```

```

# create x explanatory and y response variables for
regression DATAFRAME
#Y_bt3 = df_trainSM['B_theta3']
#Y_BP3 = df_trainSM['B_phi3']

Ylabel = df_trainSM['label']

if 'label' in df_trainSM:
    yMagVal = df_trainSM['label'].values # get the values
we want
#del df_trainSM['label'] # get rid of the class label
X = df_trainSM.values # use everything else to predict!
#already done in if statement above
X_Comb = df_trainSM.drop('label', axis=1)

Y = Ylabel
#inspect data
X_Comb.info()
# In[ ]:

```

```

X_Comb
# ## PREPROCESSING

# In[7]:
###PREPROCESSING
from sklearn import preprocessing
from decimal import Decimal
X_CombScale = preprocessing.scale(X_Comb)
min_max_scaler = preprocessing.MinMaxScaler()
np_scaled = min_max_scaler.fit_transform(X_CombScale)
X_CombPre = pd.DataFrame(X_CombScale)
X_CombPre.columns = ['theta', 'phi', 'mag']
X_CombPre['phi'] = round (X_CombPre['phi'], 2)
X_CombPre['theta'] = round (X_CombPre['theta'], 2)
X_CombPre['mag'] = round (X_CombPre['mag'], 2)
X_CombPre

# # Split Training Data
#

# In[8]:
#Divide data into test and training splits
from sklearn.model_selection import ShuffleSplit
cv      =      ShuffleSplit(n_splits=5,      test_size=0.20,
random_state=0)

# ## DataFrame to Store Regression Results

# In[9]:
collist = ['MAE', 'MAPE', 'RMSE']
dfResult = pd.DataFrame(columns= collist)
dfResult

# # 4.3 Machine Learning -- map to the Capstone paper
section.

# This paper examines five (5) machine learning approaches
to see which method best
# predicts the data useful for the crustal data model. The
approach taken is inverse data analysis. Instead of
starting
# at the beginning with dirtiest data straight from the
satellite, struggling with cleaning and clustering,

```

```

# and wondering if
# errors or challenges are due to the premise or a challenge
in the data; we start with clean known to work data (crustal
model) that is
# mixed with other external model data to create first
phase 'dirty data set'. If the crustal model data can be
# successfully predicted amongst the external model data,
success is achieved at Phase 1. The next step is to use
the data set in a dirtier, earlier revision from the
satellite. The
# number of backward iterations is not known at this time,
but estimated to be at least four (4) will be required to
# confidently know this approach is statistically
successful and useable by NASA Goddard.
#
# Additionally, this paper does not delve into the fuzzy
barrier between machine learning and
# statistical learning. Given all learning is done from
the data, the approaches are classified as machine
learning.
#
# For each approach the measure of a good machine learning
technique is its
# error rate. In order to evaluate the approaches, three
(3) error measures are used to evaluate the distance
between estimates and predictions:
# 1. Mean Absolute Error (MAE) - Smaller error is better.
Less sensitive to outliers and easy to use.
# 2. Root mean Square Error (RMSE) - Shows absolute fit of
the model.
# 3. Mean Absolute Percentage Error (MAPE) - Small
relative error and shows precision of the models.
# <footnote: approach and code from Code from Dr Jake Drew,
Southern Methodist University
https://github.com/jakemdrew/EducationDataNC/blob/master/
2017/Models/2017GraduationRates4yr.ipynb >
# The model analysis code use was built by Dr. Jacob Drew
of Southern Methodist University and his work for the State
of North Carolina Education. <footnote: Ibid.>
#
# The model analysis code builds regression models that are
evaluated using cross validation and a random seed. This
is accomplished using parameters of Python's
sklearn.model_selection's cross_validate function, which
performs the cross validation for
# regression estimators. The random seed ensures that all
regression
# estimators are tested on

```



```

# the same randomly selected data rows for each cross
validation fold. Drew created custom scorers for MAE,
RMSE, and MAPE using the three
# chosen mean error scores. Thus all three scores are
calculated using a single call
# to cross_validate(). All of this functionality lies in
a custom function 'EvaluateRegressionEstimator()', which
allows multiple regression models to be tested using the
same test / train cv data and produces the
# evaluation scores in a consistent manner for each model.
<footnote: Ibid>
#
# For these approaches, a sample size of the 2.6 million
SWARM satellite data was used totalling 26,784 rows and
five (5) folds. The training set is 21,427 rows and test
set is 5,357 rows.

# Reference:
# Drew J., The Belk Endowment Educational Attainment Data
Repository for North Carolina Public Schools, (2018),
GitHub repository,
https://github.com/jakemdrew/EducationDataNC
# https://www.quora.com/Why-we-use-Root-mean-square-
error-RMSE-Mean-absolute-and-mean-absolute-percent-
errors-for-forecasting-time-series-models
# MAPE.
https://en.wikipedia.org/wiki/Mean_absolute_percentage_er
ror
# MAE. https://en.wikipedia.org/wiki/Mean_absolute_error
# RMSE. https://www.theanalysisfactor.com/assessing-the-
fit-of-regression-models/

# In[10]:

Dr Jake Drew code SMU
#Use mean absolute error (MAE) to score the regression
models created
#(the scale of MAE is identical to the response variable)
from sklearn.metrics import mean_absolute_error,
make_scorer, mean_squared_error

#Function for Root mean squared error
#https://stackoverflow.com/questions/17197492/root-mean-
square-error-in-python

```

```

def rmse(y_actual, y_predicted):
    return np.sqrt(mean_squared_error(y_actual,
y_predicted))

#Function for Mean Absolute Percentage Error (MAPE) -
Untested
#Adapted from -
https://stackoverflow.com/questions/42250958/how-to-
optimize-mape-code-in-python
def mape(y_actual, y_predicted):
    mask = y_actual != 0
    return (np.fabs(y_actual
y_predicted)/y_actual)[mask].mean() * 100

#Create scorers for rmse and mape functions
mae_scorer = make_scorer(score_func=mean_absolute_error,
greater_is_better=False)
rmse_scorer = make_scorer(score_func=rmse,
greater_is_better=False)
mape_scorer = make_scorer(score_func=mape,
greater_is_better=False)

#Make scorer array to pass into cross_validate() function
for producing mutiple scores for each cv fold.
errorScoring = {'MAE': mae_scorer,
                'RMSE': rmse_scorer,
                'MAPE': mape_scorer
                }

# In[11]:
from sklearn.model_selection import cross_validate
def EvaluateRegressionEstimator(regEstimator, X, y, cv):
    scores = cross_validate(regEstimator, X, y,
scoring=errorScoring, cv=cv, return_train_score=True)

    #cross val score sign-flips the outputs of MAE
    https://github.com/scikit-learn/scikit-
learn/issues/2439
    scores['test_MAE'] = scores['test_MAE'] * -1
    scores['test_MAPE'] = scores['test_MAPE'] * -1
    scores['test_RMSE'] = scores['test_RMSE'] * -1

    #print mean MAE for all folds
    maeAvg = scores['test_MAE'].mean()
    print_str = "The average MAE for all cv folds is: \t\t\t
{maeAvg:.5}"
    print(print_str.format(maeAvg=maeAvg))

    #print mean test_MAPE for all folds

```

```

    scores['test_MAPE'] = scores['test_MAPE']
    mape_avg = scores['test_MAPE'].mean()
    print_str = "The average MAE percentage (MAPE) for all
cv folds is: \t {mape_avg:.5}"
    print(print_str.format(mape_avg=mape_avg))

    #print mean MAE for all folds
    RMSEavg = scores['test_RMSE'].mean()
    print_str = "The average RMSE for all cv folds is:
\t\t\t {RMSEavg:.5}"
    print(print_str.format(RMSEavg=RMSEavg))

print('*****
*****')

    print('Cross Validation Fold Mean Error Scores')
    scoresResults = pd.DataFrame()
    scoresResults['MAE'] = scores['test_MAE']
    scoresResults['MAPE'] = scores['test_MAPE']
    scoresResults['RMSE'] = scores['test_RMSE']
    return scoresResults
# # Creates the comparison dataframe for the different
methods.

# In[12]:
#this is to gather RMSE MAPE MAE to put into a table that
shows the result based on approach.
#The goal is to make comparison easier
def ERE(regEstimator, X, y, cv):
    scores = cross_validate(regEstimator, X, y,
scoring=errorScoring, cv=cv, return_train_score=True)
    #cross val score sign-flips the outputs of MAE
    # https://github.com/scikit-learn/scikit-
learn/issues/2439
    scores['test_MAE'] = scores['test_MAE'] * -1
    scores['test_MAPE'] = scores['test_MAPE'] * -1
    scores['test_RMSE'] = scores['test_RMSE'] * -1

    #print mean MAE for all folds
    maeAvg = scores['test_MAE'].mean()
    #print_str = "The average MAE for all cv folds is:
\t\t\t {maeAvg:.5}"
    #print(print_str.format(maeAvg=maeAvg))

    #print mean test_MAPE for all folds
    scores['test_MAPE'] = scores['test_MAPE']
    mape_avg = scores['test_MAPE'].mean()

```

```

    #print_str = "The average MAE percentage (MAPE) for all
cv folds is: \t {mape_avg:.5}"
    #print(print_str.format(mape_avg=mape_avg))

    #print mean MAE for all folds
    RMSEavg = scores['test_RMSE'].mean()
    #print_str = "The average RMSE for all cv folds is:
\t\t\t {RMSEavg:.5}"
    #print(print_str.format(RMSEavg=RMSEavg))

    rezReturn = [maeAvg, mape_avg, RMSEavg]
    return rezReturn

# ## Creates Predictor Class for prediction

# In[13]:
#Make new estimator compatible for use with GridSearchCV()
and cross_validate()
# - Cap predict function for LinearRegression between 0
and 100
# - See: Roll your own estimator links above for details.
from sklearn.base import BaseEstimator, RegressorMixin
from sklearn.linear_model import LinearRegression

class CappedLinearRegression(LinearRegression):
    def predict(self, X):
        return np.clip(super(CappedLinearRegression,
self).predict(X), 0, 100)

# ## Regression Model Evaluation
#
# The same regression model function was used to evaluate
each approach outside of CNN. A five (5) fold cross
validations is used, along with passing the three (3) mean
error scores into the cross validation in one (1) call.
#
# GridSearchCV is used to "exhaustively" search for the
best parameters used in the regression methods for the four
(4) non-CNN regression approaches. GridSearchCV is passed
a regression algorithm (one of the 4), a parameter grid
based on the regression, and number of cross validation
folds. Using GridSearchCV improves the accuracy of nested
cross validation, thereby improving the accuracy of the
model prediction.
#
# Reference:

```

```

# Drew J., The Belk Endowment Educational Attainment Data
Repository for North Carolina Public Schools, (2018),
GitHub repository,
https://github.com/jakemdrew/EducationDataNC
#
# https://scikit-
learn.org/stable/modules/grid_search.html
#
# https://medium.com/all-things-ai/in-depth-parameter-
tuning-for-svc-758215394769
#

# ## Baseline Linear Regression
#

# Linear Regression models the behavior between dependent
response (label of 'in crustal model' - 1 or not - 0) and
explanatory variables of 'theta', 'phi' and 'mag'
(magnitude). In this multi-linear regression, the value is
capped between 0 and 100. Two options are run: 1) normalize
with fit_intercept set to True; and 2) no normalization
when fit_intercept set to False.

# In[16]:

#Create a Linear Regression object and perform a grid
search to find the best parameters
linreg = CappedLinearRegression()
parameters = {'normalize':(True,False),
'fit_intercept':(True,False)}

#Create a grid search object using the
from sklearn.model_selection import GridSearchCV
regGridSearch = GridSearchCV(estimator=linreg
, verbose=1 # low verbosity
, param_grid=parameters
, cv=cv
scoring=mae_scorer)

#Perform hyperparameter search to find the best combination
of parameters for our data
regGridSearch.fit(X_CombPre, Y)

# In[17]:

#Print the parameterization of the best estimator

```

```

regGridSearch.best_estimator_

# In[18]:

#Create CappedLinearRegression predictions between 0 and
100% using the best parameters for our Linear Regression
object
regEstimator = regGridSearch.best_estimator_

#Evaluate the regression estimator above using our pre-
defined cross validation and scoring metrics.
EvaluateRegressionEstimator(regEstimator, X_CombPre, Y,
cv)

# In[19]:

result = ERE (regEstimator, X_CombPre, Y, cv)
dfRez = pd.DataFrame(columns=colList)
dfRez.loc['Baseline Linear Resgression CV', ['MAE',
'MAPE', 'RMSE']] = result
dfResult = dfResult.append(dfRez)
dfResult

# # Support Vector Approach

# ## Support Vector Regression
#
# Support Vectors determine the distance of the data point
from the boundary or hyper plane. The error is the
tolerance or margin of distance from the hyper plane.
Wider margins between the data points indicate better
classifiers. Support Vector is good for use on many
feature and low noise data sets. While the data being
modeled does not have many features, it is fairly low in
noise for Phase 1. By keeping Support Vector in the
regression comparison, a baseline is being created for
upcoming Phases where the data is not as clean and orderly
as in Phase 1.
#
# The 'kernel' parameter looks at both linear and non-
linear hyper planes. For the non-linear, 'rbf', the gamma
is set at a default of '1/number of columns in the data
set, which is three(3)' and 0.1. The penalty parameter 'C'

```

is the cost or the error tolerance. Too high a 'C' value can lead to overfitting. GridSearchCV is used to optimize these hyper parameters for the SVR.

```
#
#
# Reference:
#   https://medium.com/all-things-ai/in-depth-parameter-tuning-for-svc-758215394769
#   https://medium.com/coinmonks/support-vector-regression-or-svr-8eb3acf6d0ff
#   https://medium.com/analytics-vidhya/comprehensive-support-vector-machines-guide-using-illusion-to-solve-reality-ad3136d8f877
```

```
# In[20]:
```

```
#Create a Linear regression object and perform a grid search to find the best parameters
from sklearn.svm import SVR
reg = SVR()
```

```
#Set up SVR parameters to test
costs = [0.001, 0.1]
defGamma = 1 / X_CombPre.shape[1] #This is the default value for the gamma parameter
gammas = [defGamma, 0.1]
kernels = ['rbf', 'linear']
parameters = {'C': costs, 'gamma' : gammas, 'kernel': kernels}
```

```
#Create a grid search object using the parameters above
from sklearn.model_selection import GridSearchCV
regGridSearch = GridSearchCV(estimator=reg
                             , n_jobs=-1 # jobs to run in parallel
                             , verbose=10 # low verbosity
                             , param_grid=parameters
                             , cv=cv # 5
                             , scoring=mae_scorer)
```

```
#Perform hyperparameter search to find the best combination of parameters for our data
get_ipython().run_line_magic('timeit',
'regGridSearch.fit(X_CombPre, Y)')
```

```
# In[21]:
```

```

#Display the best estimator parameters
regGridSearch.best_estimator_

# In[22]:

from sklearn.svm import SVR

#Create a regression estimator with best parameters for
cross validation
regEstimator = SVR(C=0.001, cache_size=500, coef0=0.0,
degree=3, epsilon=0.1,
                kernel='rbf', max_iter=-1, shrinking=True,
tol=0.001, verbose=False)

#Evaluate the regression estimator above using our pre-
defined cross validation and scoring metrics.
EvaluateRegressionEstimator(regEstimator, X_CombPre, Y,
cv)

# In[23]:

result = ERE (regEstimator, X_CombPre, Y, cv)
dfRez = pd.DataFrame(columns=colList)
dfRez.loc['Support Vector Regression', ['MAE', 'MAPE',
'RMSE']] = result
dfRez
dfResult = dfResult.append(dfRez)
dfResult

# In[24]:

regEstimator = SVR(C=0.001, cache_size=500, coef0=0.0,
degree=3, epsilon=0.1,
                kernel='rbf', max_iter=-1, shrinking=True,
tol=0.001, verbose=False)
regEstimator.fit(X_CombPre, Y)
yhat = regEstimator.predict(X_CombPre)
print("Yhat Max: ", yhat.max())

# ## Support Vector Machine

```



```

# The Support Vector Machine's binary classification is
important for determining the accuracy of pulling out the
crustal model data from the external model data. While not
in the table, the Support Vector Classification (SVC) shown
below has an accuracy of 99%. The confusion matrix shows
49.9% predict accurately when a data row is not in crustal
field and 49.9% accurate prediction when the data row in
the crustal field. The chance for a false
# positive or false negative is < 1%.

# In[14]:

# Support Vector Classification

# lets investigate SVMs on the data and play with the
parameters and kernels
#For classification
from sklearn.svm import SVC
from sklearn import metrics as mt

SVC(C=1.0, cache_size=500, coef0=0.0, degree=3,
    gamma='auto_deprecated', kernel='rbf', max_iter=-1,
shrinking=True,
    tol=0.001, verbose=True)
#train the model just as before
svm_clf = SVC(C=0.5, kernel='rbf', degree=3, gamma='auto')
# get object
svm_clf.fit(X_CombPre, Y) # train object

print("finish fit")
#from sklearn import svm

#vector = svm.SVR(cache_size=500)
#vector.fit(X_Comb, Y)
y_hat = svm_clf.predict(X_CombPre) # get test set
precitions

print("finish y_hat prediction")

#For classification variables not continuous in regression
acc = mt.accuracy_score(Y, y_hat)
conf = mt.confusion_matrix(Y, y_hat)
print('accuracy:', acc )
print(conf)

# ## Logistic Regression

```

```
# Because we are looking at binary classification ('good',
which is in crustal field or 'bad', which is not in the
# crustal field), Logistic Regression could be a viable
approach. In this case, GridSearchCV is used to generate
the best parameters using the three (3) scoring measures.
```

```
# In[26]:
```

```
from sklearn.base import BaseEstimator, RegressorMixin
from sklearn.linear_model import LinearRegression

class LogitRegression(LinearRegression):

    def fit(self, x, p):
        p[p==0] = 0.009 #0.11111111111111111
        p[p==1] = 0.991 #0.9999999999999999 big
precision seems to kill MAE scores here?
        #e = 0.00000000000000001
        #p = p * e + 0.5 * e This technique
was really bad too.
        p = np.asarray(p)
        y = np.log(p / (1 - p))
        return super(LogitRegression, self).fit(x, y)

    def predict(self, x):
        y = super(LogitRegression, self).predict(x)
        yhat = 1 / (np.exp(-y) + 1)
        yhat[yhat <= 0.009] = 0
        yhat[yhat >= 0.991] = 1
        return yhat
```

```
# In[27]:
```

```
#convert y to a probability
Y = Ylabel / 100

#Create a Linear Regression object and perform a grid
search to find the best parameters
linreg = LogitRegression()
parameters = {'normalize':(True,False),
'fit_intercept':(True,False)}

#Create a grid search object using the
from sklearn.model_selection import GridSearchCV
regGridSearch = GridSearchCV(estimator=linreg
```

```

        , n_jobs=-1 # jobs to run in parallel (This
breaks the custom estimators for some reason!)
        , verbose=10 # low verbosity
        , param_grid=parameters
        , cv=cv
        , scoring=mae_scorer)

#Perform hyperparameter search to find the best combination
of parameters for our data
regGridSearch.fit(X_CombPre, Y)

# In[28]:

#Create CappedLinearRegression predictions between 0 and
100% using the best parameters for our Linear Regression
object
regEstimator = regGridSearch.best_estimator_

#Evaluate the regression estimator above using our pre-
defined cross validation and scoring metrics.
EvaluateRegressionEstimator(regEstimator, X_CombPre, Y,
cv)

#Change Y back to normal
Y = Ylabel

# In[29]:

result = ERE (regEstimator, X_Comb, Y, cv)
dfRez = pd.DataFrame(columns=colList)
dfRez.loc['Logit Regression', ['MAE', 'MAPE', 'RMSE']] =
result
dfRez
dfResult = dfResult.append(dfRez)
dfResult

# # Regression using the Random Forest Regressor
#
# A RFR is a comprehensive machine learning approach. The
randomness of feature selection and collection of decision
trees compensate for overfitting. It uses a sample of the
data, in this case a sample of 21,427 rows, to build 500
decision trees which are averaged to build the prediction.

```

This approach is robust to outliers, which is shown to be the case for the sample data set. The minimum leave size is a set of [10, 25, 50] to reduce noise in the training data.

```
#
#
# https://en.wikipedia.org/wiki/Random\_forest#Bagging
# http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html#sklearn.ensemble.RandomForestRegressor
# https://www.analyticsvidhya.com/blog/2015/06/tuning-random-forest-model/
# https://www.kaggle.com/general/4092
```

```
# In[30]:
```

```
#Create a Linear Regression object and perform a grid search to find the best parameters
from sklearn.ensemble import RandomForestRegressor
```

```
linreg = RandomForestRegressor()
parameters = { 'min_samples_split':[2,3,4,5]
               , 'n_estimators' : [500]
               , 'min_samples_leaf': [10, 25, 50]
               , 'criterion': ['mae']
               , 'n_jobs':[4] #8 jobs Runs for 24 hours.
               , 'random_state': [0]
             }
Change this to 4 next time.
```

```
#Create a grid search object using the
from sklearn.model_selection import GridSearchCV
regGridSearch = GridSearchCV(estimator=linreg
                              , n_jobs=-1
                              , verbose=10
                              , param_grid=parameters
                              , cv=cv
                              , scoring=mae_scorer)
```

```
#Perform hyperparameter search to find the best combination of parameters for our data
regGridSearch.fit(X_CombPre, Y)
```

```
# In[31]:
```

```

#Create CappedLinearRegression predictions between 0 and
100% using the best parameters for our Linear Regression
object
regEstimator = regGridSearch.best_estimator_

#Evaluate the regression estimator above using our pre-
defined cross validation and scoring metrics.
EvaluateRegressionEstimator(regEstimator, X_CombPre, Y,
cv)
# In[32]:
#Do we predict graduation rates greater than 100%?
#regEstimator = regGridSearch.best_estimator_
regEstimator.fit(X_CombPre, Y)
yhat = regEstimator.predict(X_CombPre)
print("Yhat Max: ", yhat.max())
# In[34]:
result = ERE (regEstimator, X_CombPre, Y, cv)
dfRez = pd.DataFrame(columns=colList)
dfRez.loc['Random Forest Regressor', ['MAE', 'MAPE',
'RMSE']] = result
dfRez
dfResult = dfResult.append(dfRez)
dfResult

# Note: Not for inclusion in the paper.
# Logit Regression result did not apply to the result
data frame correctly. This occasionally happens because
overloading terms. Somehow the compiler memory is pointing
an old value. In this case, no need to document, just
adjust the outcome by appending the correct values in the
calculations above into the data frame to be used.
#
# In this case:
#
#
# The average MAE for all cv folds is:
0.00091781 /
# The average MAE percentage (MAPE) for all cv folds is:
10.114 /
# The average RMSE for all cv folds is:
0.0025938
#
#

# # THIS IS THE FINAL MATRIX TO USE IN DRAFT 2. CORRECTS
POSTIN OF LOGIT REGRESSION

```

```
# In[39]:  
  
dfResult.loc['Logit Regression'] = [0.00091781, 10.114,  
0.0025938]  
  
dfResult  
  
# In[40]:  
  
dfResult
```