# CS 780 MMs Class Project

## Preliminary Report

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## Motivation

This project is intended to explore opitons for automating a key part of the ongoing Magnetospheric Multiscale Mission - the selection of which detailed datapoints ought to be downloaded from the sattelite. This job is crrently done by a Scientist in the Loop, who must spend time each day evaluating the data observed by the satelite to decide how to spend bandwidth resources.

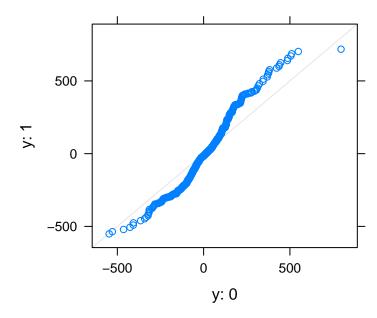
Automating the selection of interesting data would free up valuable human time on the project. To do this, we have explored several methods for determining what data points might be interested, as detailed below.

#### Related work

(papers describing machine learning methods or their applications)

#### Evaluation criteria

We found that the data was not identically and independently distributed, as demonstrated by the exemplary QQ plot below.



In fact the data is a time series. Therefore, we could not use the usual method of keeping some test data out to evaluate the performance of our model, because it would have left discontinuities in the data used for training our model.

Therefore, we are using one of the two data sets as a validation set, while using the other data set in full to train our model. We hypothesise that adding time-delayed factors (i.e. factors which contain values from previous samples) will significantly improve the performance of many machine learning models on the validation set. See below for details.

#### Methods

We compared our time series models against the basic feature set with no consideration for time, using multiple machine learning methods.

Our first time series model, which we will call time shifting, involves adding n columns to the data that contain each feature shifted n=5 points in the past. The second time series model, which we will call time difference, involves adding a column which takes the average difference between the current data point x and the past n=20 data points.

## Logistic Regression

```
## Basic MMS data
## -----
## Test set of 302 SITL points - Found: 143 Missed: 159
## Training set of 932 SITL points - Found: 444 Missed: 488
## Total set of 1234 SITL points - Found: 589 Missed: 645
## Classificaton Error - Test: 0.1367742 Training: 0.1399885 Total: 0.1387544
## Time Shift data
## -----
## Test set of 296 SITL points - Found: 136 Missed: 160
## Training set of 938 SITL points - Found: 494 Missed: 444
## Total set of 1234 SITL points - Found: 629 Missed: 605
## Classificaton Error - Test: 0.1377529 Training: 0.1274214 Total: 0.1302195
## Time Diference data
## -----
## Test set of 302 SITL points - Found: 154 Missed: 148
## Training set of 932 SITL points - Found: 475 Missed: 457
## Total set of 1234 SITL points - Found: 631 Missed: 603
## Classificaton Error - Test: 0.1273118 Training: 0.1310958 Total: 0.1297193
```

### **Bagging**

Using 16 splits (number of features).

```
## Basic MMS data Set

## ------

## Test set of 302 SITL points - Found: 236 Missed: 66

## Training set of 932 SITL points - Found: 932 Missed: 0

## Total set of 1234 SITL points - Found: 1168 Missed: 66

## Classificaton Error - Test: 0.05677419 Training: 0 Total: 0.01419813
```

```
## Time Shift data
## ------
## Test set of 296 SITL points - Found: 229 Missed: 67
## Training set of 938 SITL points - Found: 938 Missed: 0
## Total set of 1234 SITL points - Found: 1167 Missed: 67
## Classificaton Error - Test: 0.05768403 Training: 0 Total: 0.01442101
## Time Difference data
## -------
## Test set of 302 SITL points - Found: 241 Missed: 61
## Training set of 932 SITL points - Found: 932 Missed: 0
## Total set of 1234 SITL points - Found: 1173 Missed: 61
## Classificaton Error - Test: 0.05247312 Training: 0 Total: 0.01312251
```

#### Random Forests

Using 4 splits (square root of number of features).

```
## Basic MMS data Set
## -----
## Test set of 302 SITL points - Found: 239 Missed: 63
## Training set of 932 SITL points - Found: 932 Missed: 0
## Total set of 1234 SITL points - Found: 1170 Missed: 64
## Classificaton Error - Test: 0.05419355 Training: 0 Total: 0.01376788
## Time Shift data
## -----
## Test set of 296 SITL points - Found: 229 Missed: 67
## Training set of 938 SITL points - Found: 938 Missed: 0
## Total set of 1234 SITL points - Found: 1167 Missed: 67
## Classificaton Error - Test: 0.05768403 Training: 0 Total: 0.01442101
## Time Difference data
## -----
## Test set of 302 SITL points - Found: 239 Missed: 63
## Training set of 932 SITL points - Found: 932 Missed: 0
## Total set of 1234 SITL points - Found: 1171 Missed: 63
## Classificaton Error - Test: 0.05419355 Training: 0 Total: 0.01355276
```

## Radial SVM

```
## Time Difference data
## ------
## Test set of 932 SITL points - Found: 692 Missed: 240
## Training set of 302 SITL points - Found: 210 Missed: 92
## Total set of 1234 SITL points - Found: 903 Missed: 331
## Classificaton Error - Test: 0.06884682 Training: 0.07913978 Total: 0.07120577
```

#### Validation

Since, during training, the version of each model using the time difference did significantly better for all models, we will compare those methods' performance on our validation set. Since none of the models perform exceptionally well here, it is likely that they have overfit. We suspect this may be an artifact of the different different SITLs on different weeks, or of our comparatively sparse training data. Regardless, the algorithm's performance on this validation set is a good indicator of its likely performance on the hidden test that you have for us, professor.

Also: Since Logistic Regression did so poorly, we've chosen to omit it here for brevity.

#### **Bagging**

#### Recommendations

## Classificaton Error - Total: 0.1625786

Random Forests with Time Difference data did best on our validation set out of all tested methods. With a classification error of 12.73%, they are not as accurate as we might hope, but since we tested each of the methods on a validation set which is similar to the set we will be tested on, we hope that it will have a similar classification error there.

## Analysis

Since Random Forests did less well on our training data, but better on our validation set, it seems likely that other methods overfit. This can be solved in a few ways, not least of which will be to acquire more data. Overfitting is evidence that our methods are too flexible - so another way to reduce their flexibility would be to use bagging or boosting in combination with another method, or to use cross-validation to choose such parameters as the amount of time-shift to use.