Improving feedback for a web-based marking system

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Abstract

This thesis will discuss the work done towards improving the feedback provided supplied to users of the Infandango system. By applying machine learning methods to submission data from a previous year a model is created which can provide a single score to the user, representing their progress so far. A discussion of the efficacy of different machine learning methods will provide reasons for choosing one model over the others. This will then be integrated with the Infandango system, providing a visual mechanism to display the score.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

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Chapter 1

Introduction

Infandango is an open source web-based system for automated grading of Java code submitted by students[10]. The aim of this project is to improve the feedback provided to students by using machine learning methods to display a visual representation of their current progress. In chapter 3 the design process will be discussed, justifying primary aspects of the design. Chapter 4 will be reserved for discussing the process through which the final model was chosen, documenting the results of various analyses. Implementation of the feedback device with the current Infandango system will be explained in Chapter 5 and the report will end with a conclusion and summary of the work.

Chapter 2

Background

2.1 Infandango

Infandango is an automated web-based marking system for student submitted programming exercises. A student can view the list of warm-up, optional and core exercises and choose to submit a file for one of them. This file is then compiled and tested by Jester in a sandbox. Between the web frontend and Jester there is a PostgresSQL database which stores stores the source code of each submission and the score information for each marked submission. Each question has a label: **warmup** questions are simple questions which can be skipped if the user feels confident, **core** questions are questions which the user is highly encouraged to try and may affect the end coursework mark, and **optional** questions are provided for particularly interested students.

2.1.1 Current feedback

The primary source of feedback in Infandango is displayed in Figure 2.1. Each submission is marked with a set of JUnit tests and the fraction of these tests which are correct is displayed. This fraction is converted into a percentage and displayed on a red (0 - 40%), orange (40%-70%) or green (70%-100%) background. More general feedback is also available which displays similar information but the results are displayed by week rather than by question.

2.1.2 Current data

The system has been used with the first year Java programming course at the University of Edinburgh, for a few years. The database information for these years has been kept and retains all the information about submissions: marks, submission time, number of resubmissions. This information for one year has been anonymised and made available for use. This has only happened for one year because the questions have changed since previous years and therefore the data would be inconsistent with the current questions.

2.2 Literature

Khan Academy[4] is a website which provides users with online education material:

> Our online materials cover subjects ranging from math and finance to history and art. With thousands of bite-sized videos, step-by-step problems and instant data[1]

A blog post[8] written by David Hu about Khan Academy demonstrates that different feedback measures can affect user performance significantly. Khan Academy gives users certain kinds of exercises, for example choosing the approriate position on a number scale. It can then generate endless variations of this problem for the user to continue attempting until they are deemed proficient[1]. The original Khan Academy system required a user to get 10 consecutive exercises of a certain type correct before they can be deemed proficient at that type of exercise. In an attempt to improve this system, a logistic regression model is used to calculate the probability that a user passes the next exercise successfully, with a threshold of 94% representing the new proficieny level. Over a 6 day period 10% of users tested the new method. Users of the new system earned 20.8% more proficiences, attempted 15.7% more exercises and required 26% less exercises per proficiency. Hu summarises by saying the boost seems to come from allowing users to move on from exercises which they already proficient at, without requiring them to complete their streak thus wasting time on something they already understand. Although the current system does not require perfection like Khan Academy did, it is possible that users are more reluctant to move on from exercises in which they get a minor error, and have just less than 100%. Providing encouragement for the user to move on is one aim of this feedback design.

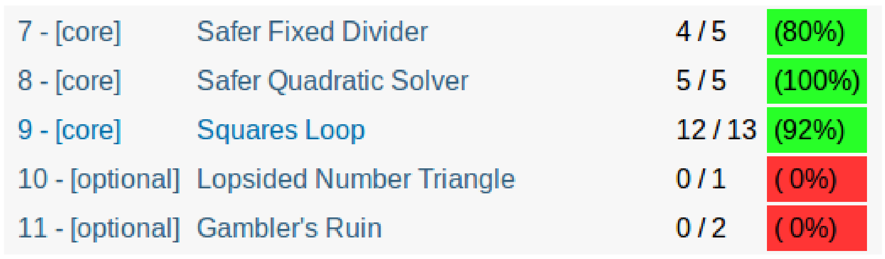
2.2.1 Programming Assessment

In *Automated Evaluation of Programming Assignments*[9], Kaushal and Singh describe various measures used as part of an automated marking system: regularity, efficiency,

[1]A proficiency is earned when a user is deemed to be ”proficient” at a certain kind of exercise

integrity and accuracy. Notably, Infandango only gives feedback on one of these areas, accuracy. The paper tracks the change in these measures as students use the system and find that there is a general improvement on all categories when feedback is based on these measurements. This shows that accuracy is not the only measurement that should be used to provide feedback and these are possibilities to be considered for Infandango.

2.2.2 Machine Learning



7 - [core]	Safer Fixed Divider	4 / 5	(80%)
8 - [core]	Safer Quadratic Solver	5 / 5	(100%)
9 - [core]	Squares Loop	12 / 13	(92%)
10 - [optional]	Lopsided Number Triangle	0 / 1	(0%)
11 - [optional]	Gambler's Ruin	0 / 2	(0%)

Figure 2.1: This is a crop of what will be displayed to the user for a given week

Chapter 3

Design

The literature has shown us that machine learning methods can be useful in generating feedback for students, and this can be combined with a visual display for intuitive understanding. The first design decision to be made is the language and libraries to be used when writing the program.

3.1 Language and Tools

Two languages are immediate possibilities for implementation: Java[5] and Python[6]. Java because I had the most experience with it and some parts of Infandango are written in Java. Most of Infandango was, however, written in Python with which I also had experience. Due to the emphasis the project has on machine learning, R[7] was another approriate language. The final decision was to use Python with scikit-learn[3] and pybrain[2] libraries: this provides the simplest integration with Infandango (since the parts with which this will need to be integrated are written in Python) and the libraries provide a variety of machine learning methods.

3.2 Proposed Design

Using the data from a previous year a model will be trained using machine learning methods. The model output a value which will be displayed somewhere in the Infandango system.

3.2.1 Model

The Infandango system is similar to the Khan Academy system and so the method Khan Academy uses is an approriate starting point. Infandango allows a user to submit many solutions for an exercise, and so does Khan Academy. However, there are two properties that distinguish Khan Academy from Infandango:

- For each exercise, the next solution submitted is for the same kind of question but the details are randomly generated
- A solution is a binary feature: correct or incorrect

This means a user can keep submitting solutions to an exercise even after they get one solution correct. However, in Infandango once a user gets 100% there is no reason for the user to submit another solution because they have already perfected that exercise. The second difference means our data will be numerical instead of binary and this needs to be considered when designing the model. The first difference is significant, and requires a change in granularity of the data: instead of measuring progress on a submission by submission basis, the focus should be on the final mark a user will achieve for an exercise. So instead of trying to predict the score for the next *submission*, try to predict the final score for the next *question*.

With an idea of how the model was going to work, some exploratory work was done on the data. Although users are encouraged to answer all questions, the do not receive marks directly for each question. This makes missing data a potential problem. Figure 3.1 shows the submission rates for all the questions. It shows that submission rates can get as low as around 10% for some questions. Figure 3.2 shows the submission rates for only core questions. The submission rates are on average higher than for non-core questions. Combined with the fact that users are likely to have more motivation for core questions (since they potentially count towards their final mark) data from now on will only be considering core questions.

With the amount of missing data still being significant changing to yet another level of granularity was considered: predicting on a week by week basis. Using this method there could be a lot less missing data: take the average of all the questions for a week to get the score for that week. This means there will still be a data point for a student if they miss one question, and they would have to have no solutions for all questions in a week to get no score for a week. Comparing Figure 3.3 to Figure 3.2 a rise in the amount of data points can be seen. On average there is about BLAH data points for a given week, and about BLAH data points for a given question.

- The semester has 8 weeks worth of exercises. If all 7 weeks are used as a fea-

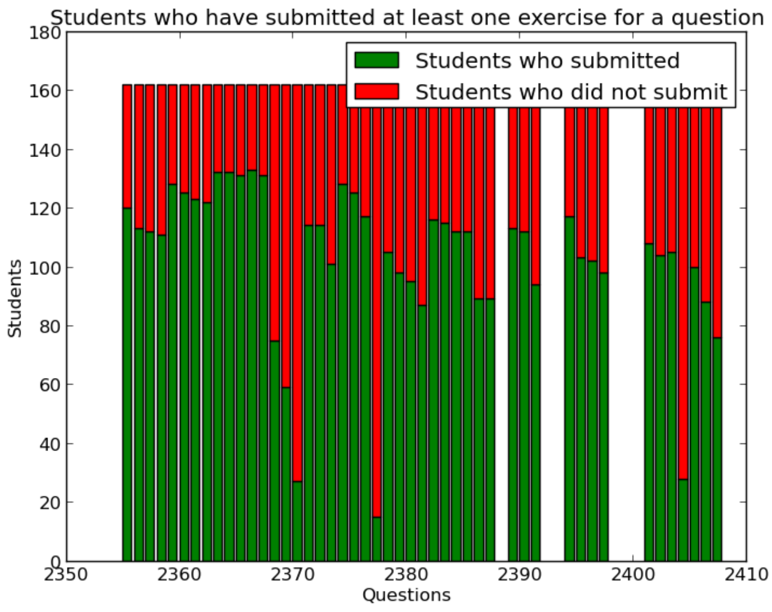


Figure 3.1: Submission rates for all questions

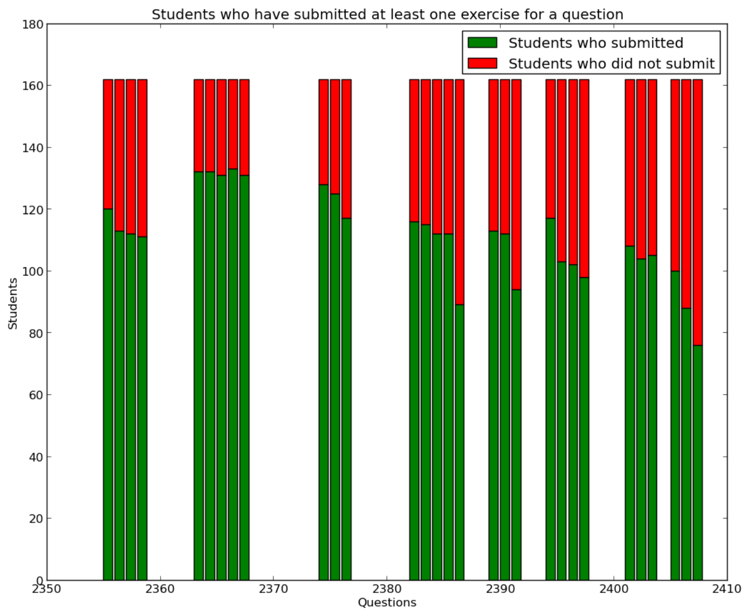


Figure 3.2: Submission rates for only core questions

ture and the score for week 8 is predicted then the user would not receive any feedback until the last week. If feedback is to be generated for each week then a separate model needs to be trained for each week: one model where there is only 1 week of evidence and week 2 is predicted, another where there are 2 weeks of evidence and week 3 is predicted and so on. Neither of these options are desirable.

- Even after 3-5 weeks there would only just be enough data to start getting reasonable results CITE HERE

- Grouping data like this means we have a lot less training examples

A similar alternative to this model is to treat each question within a week separately, giving the model a much larger dimensionality. Although this does remove the latter two problems, the first problem still remains. This also raises the likelihood of data being missing for a feature (it is more common for a student to miss one exercise within a week than the whole week).
Both of these models have been working with the assumption that we want to learn something about *specific* questions. So if, for example, a question was particularly hard then the model might be able to learn that it should predict lower scores for that question. However, we have seen the difficulties that these models incur. For this rea-

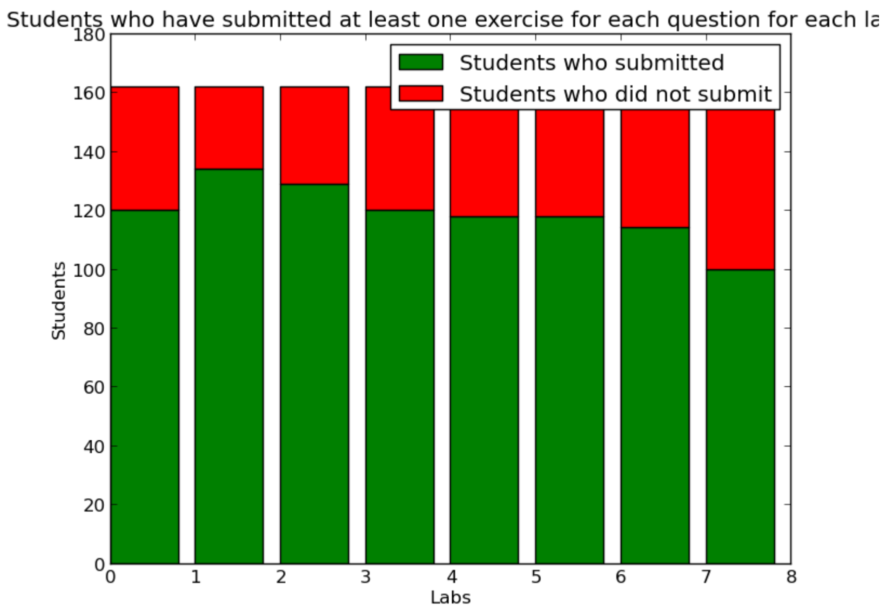


Figure 3.3: Submission rates for at least one question per week

son a much simpler model was created. The model has ***N*** features, each a percentage. Each feature represents a score from the corresponding previous question. The class is the score for the ***N+1*** problem, so when a user is using the system it will try to predict their next score given their previous ***N*** scores. This creates a moving window of previous scores, with each feature simply being *a question* rather than, for example *week 3, question 2b*.

3.2.1.1 Unexplored Alternatives

There are many unexplored possibilities for other features like a weighted moving average or the number of problems unfinished. With this project it was important to complete the system quickly so that user tests can be done over a period of weeks. Other possibilities for features and other learning methods can be explored in later projects.

3.2.1.2 Training the model

Django is used to retrieve the training data from the anonymised data from a previous year. This data is filtered into groups of ***N+1*** consecutive results, with the final result being the class. For each set of ***K*** results ***K-N*** sets of results are created. This provides the machine learning methods with a lot more training data than alternative models.
In order to decide which learning method to use sci-kit learn's cross validation method splits the data into training and testing sets, with a testing size of 20%. Different machine learning methods were then trained on this data and tested by comparing their R2 scores. In Figure 3.4 it can also be seen that these tests are done multiple times over different values of ***N***. The highest accuracy is obtained by Logistic Regression at ***N*** = 4. Logistic Regression is also the most consitent of the methods, thus making it the most appropriate choice.

3.2.2 Visualising the results

3.3 Integration with Infandango

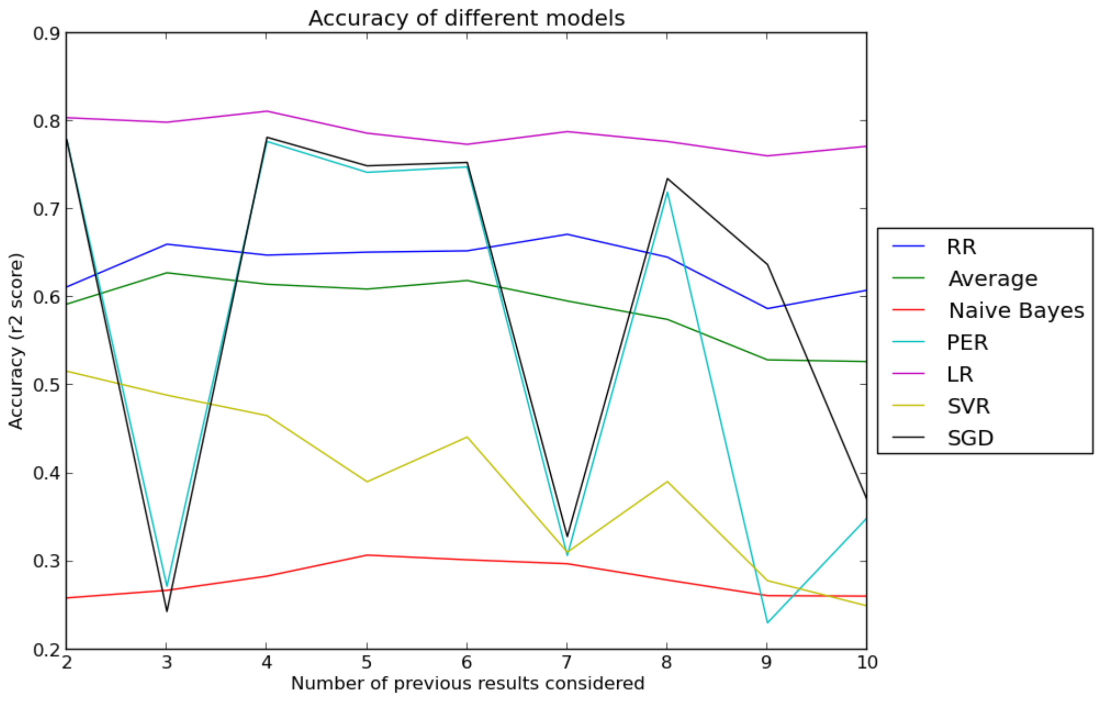


Figure 3.4: Comparison of different machine learning methods comparing their accuracy against the number of previous exercises considered

Chapter 4

Choosing a model

There are many aspects to choosing a model and these choices greatly impact on the final performance of the model. Unlike the Khan Academy example, these questions do not have a binary PASS or FAIL quality, they only have a percentage correct. For this reason the problem is treated as a regression problem (predicting the percentage score of the next question) opposed to a classification problem (predicting if the next submission will PASS or FAIL).

4.1 Feature selection

The Khan Academy model is built based on one assumption: a user can always *generate another example* and it will be of the *same type*. These are two qualities which Infandango does not share. Infandango has a preset number of manually written exercises and they are not grouped *strictly* by similarity. The first set of features used was the average mark for each week, giving 8 features: one for each week). The first reason this is, theoretically, a good set of features is that for every training example the features represent the same questions. This means the model has the potential to learn about each individual week (this will not hold true for some later feature sets). Also by using the average mark the problem of missing data is much less common. However these features are not suitable for a number of reasons:

- The semester has 8 weeks worth of exercises. If all 7 weeks are used as a feature and the score for week 8 is predicted then the user would not receive any feedback until the last week which would be too late for the user to change their learning habits accordingly. If new feedback is to be generated each week then a separate model needs to be trained for each week (since the number of features would be changing): one model where there is only one week of evidence and week 2 is predicted, another where there are two weeks of evidence and week 3 is predicted and so on. This would be needlessly complicated and would only update the feedback weekly

- Even after 3-5 weeks there would only just be enough data to start getting reasonable results CITE HERE

- Grouping data like this means we have a lot less training examples

A similar alternative to these features is to treat each question within a week separately, increasing the dimensionality considerably. Although this does remove the latter two problems, the first problem still remains: we would need to train separate models in order to continually update feedback. This also raises the likelihood of data being missing for a feature (it is more common for a student to miss one exercise within a week than miss the whole week).
Both of these models have been working with the assumption that we want to learn something about *specific* questions. So if, for example, a question was particularly hard then the model might be able to learn that it should predict lower scores for that question. However, it is not desirable to train a model to predict each question. For this reason a much simpler model was created. The model has ***N*** features, each a percentage. Each feature represents a score from a question. The model attempts to predict the score for the ***N+1*** problem. So when a user is using the system it will try to predict their next score given their previous ***N*** scores. This creates a moving window of previous scores, with each feature being an *anonymous* question rather than, for example *week 3, question 2b*.
A final feature was created to utilise the rest of the data not included in the preceding ***N*** exercises: The average. This will allow a model to take into account the overall performance of a student, rather than just their recent performance.

4.2 Selection of preliminary models

The package being used for the majority of the machine learning is scikit-learn (SKL): a general-purpose machine learning library for python. Since the purpose of this project is not to implement machine learning methods, but to explore the problem using machine learning methods, it is quicker and simpler to use a pre-existing library.

Using this library makes choosing the preliminary models a much less difficult decision: use lots of models. With the relatively low dimensionality of the problem it is very quick to train and test models so there is little reason to exclude a model from the test set. The following are the models from SKL which are used:

- Support Vector Machine
- Logistic Regression
- Linear Regression
- Ridge Regression
- Lasso
- Elastic Net

An interesting non-linear model which is missing from this list is Neural Networks. SKL does not have the capability of creating and training a Neural Network but a python library that specialises in Neural Networks is pybrain. Although using a Neural Network required learning and using another library it is useful to have multiple non-linear models.

4.2.1 Training the models

The baseline to test against is quite simple: the average of all the features. Although simple this model has given better results than some of the machine learning models.
To compare the models a python script was created which split the data into a training and test set. The models are trained on the training data and the mean square error is calculated using the testing data. However, since the value for N is not fixed this test is performed for values of N ranging from 2 to 9. The errors can then be plotted against N to show how the accuracy changes with the number of features but also how each model performs against the others.
The problem with testing like this is the results can vary quite a bit by chance since the amount of data is not particularly large. To remove some of this variance k-fold cross validation is performed. In k-fold cross validation the original data set is split into k subsets, each of roughly equivalent size. The procedure above is performed with k-1 sets as training data and 1 set as testing data. This is performed k times, each time

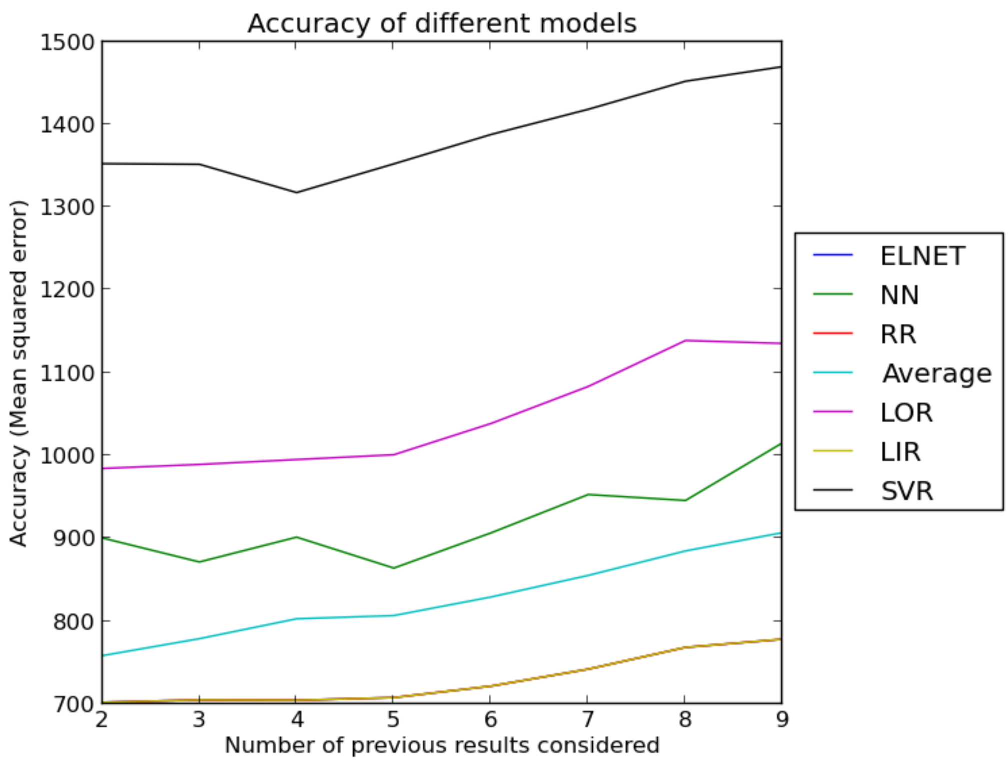


Figure 4.1: Comparison of different machine learning methods comparing their accuracy against the number of previous exercises considered

alternating which set is used as the testing set so that by the end each set has been used as the testing set. This provides more robust results which are less prone to variance.

Figure 4.1 appears to tell us that LIR (Linear Regression) performs the best. However, it also seems that RR (Ridge Regression), ELNET (Elastic Net) and Lasso are missing from the graph. However, if the graph is magnified on the Linear Regression line we get Figure 4.2

This graph shows that the linear models all perform very similarly with their maximum variance being displayed in Figure 4.2 as roughly 0.06. Although not visible in the previous figure, it can be seen in Figure 4.3 that Ridge Regression follows Linear Regression very closely.

4.3 Final model

4.3.1 Optimisation

4.4 Testing the model

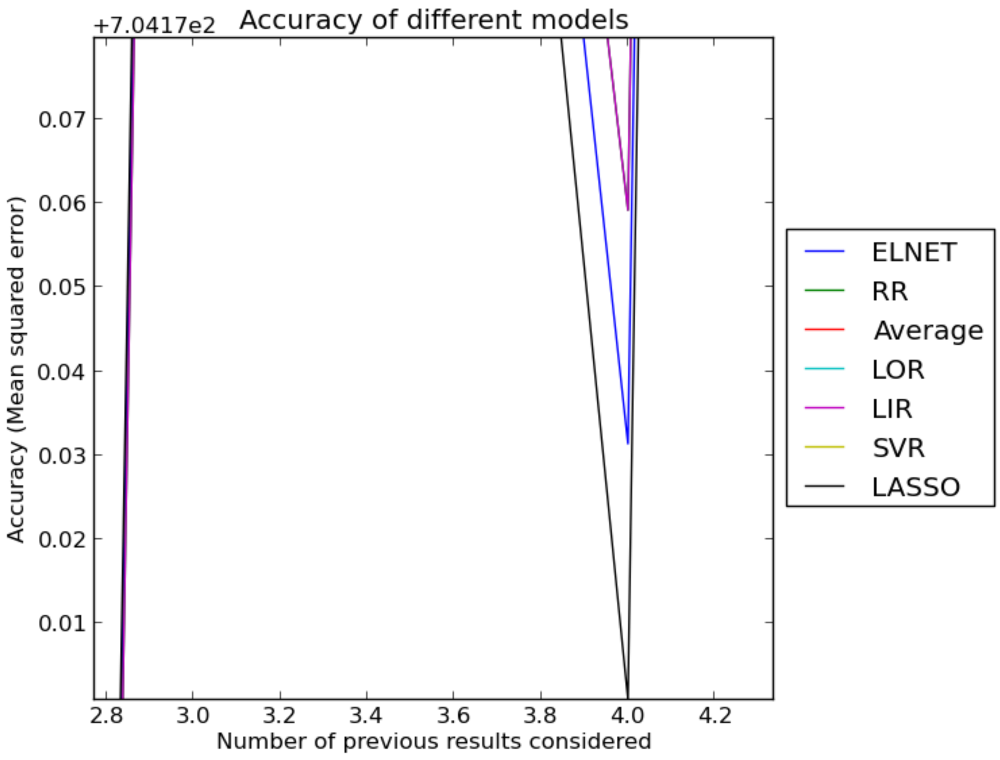


Figure 4.2: Similarity of the linear models

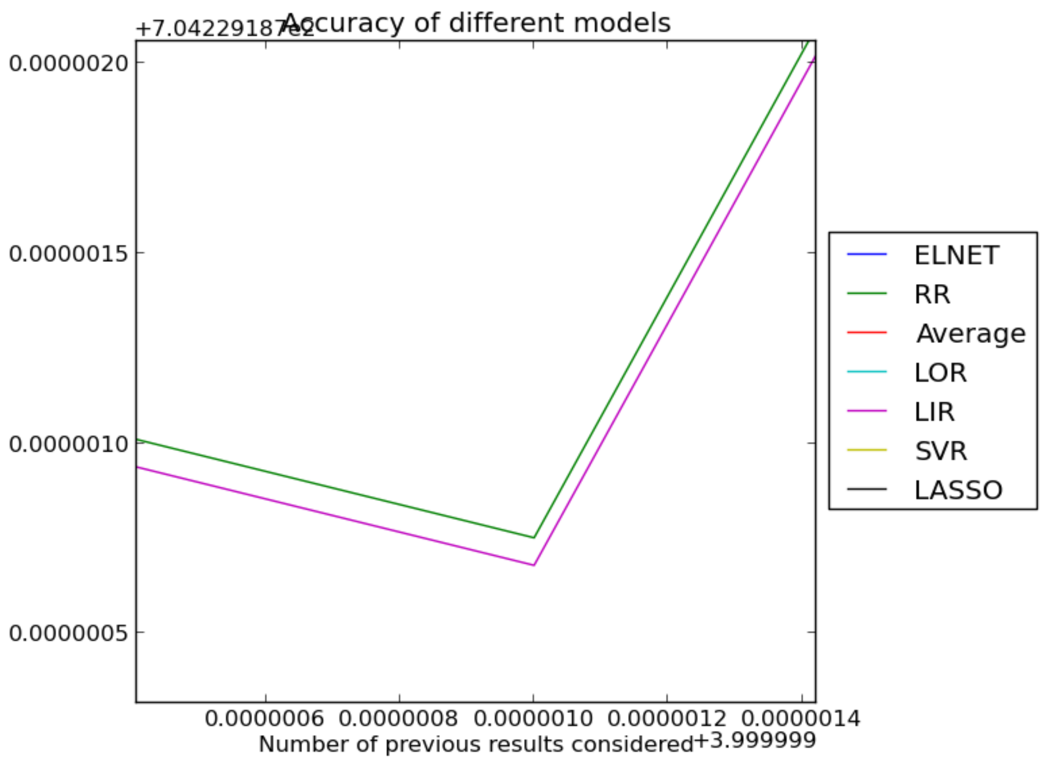


Figure 4.3: Ridge regression follows extremely closely to linear regression

Chapter 5

Implementation

Chapter 6

Evaluation

Chapter 7

Conclusion

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