Karina Palyutina

Machine learning inference of existing search engine heuristics

Part II Project

St Catharine's College

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Proforma

Name:	**Karina Palyutina**
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Supervisor:	**Dr Jon Crowcroft**

Original Aims of the Project

Design and implementation of a framework that allows comparison of machine learning techniques. In order to gather data a toy search engine needs to be implemented together with two machine learners and an evaluation module. The search engine must take into account features of the pages that are likely to be found in real search engines, in particular, PageRank must be implemented. The search engine must support the use of various heuristic functions. Machine learners must be evaluated with respect to these heuristics and compared when possible.

Work Completed

The project has been successful: all objectives outlined in the proposal have been met and an effective evaluation framework has been implemented. The implemented search engine supports a variety features, including PageRank, term and image count. Two machine learning techniques – Naive Bayes and Support Vector Regression – have been implemented and evaluated with various heuristic functions. As an extension, a variety of kernels have been implemented for the Support Vector Machine.

Special Difficulties

No special difficulties have been encountered.

Declaration of Originality

I, Karina Palyutina of St Catharine's College, being a candidate for Part II of the Computer Science Tripos , hereby declare that this dissertation and the work described in it are my own work, unaided except as may be specified below, and that the dissertation does not contain material that has already been used to any substantial extent for a comparable purpose.

Signed

Date

Contents

1. Introduction

This project aims to explore the application of machine learning techniques to search engine heuristics. The goal of the project is not the correct classification of real search engine data, but identifying the means to correct classification. This chapter will outline the motivations and challenges in such a project as well as the work conducted in the area already.

1.1. Motivation

This project is inspired by increasing importance of search engine rankings. Today major search engines given a query return web pages in an order determined by secret algorithms. Such algorithms are believed to incorporate multiple unknown factors. For instance, Google claims to have over 200 unique factors that influence a position of a web page in the search results relative to a query[1]. Only a handful of these factors are disclosed to the webmasters in the form of very general guidelines. Moreover, the Google algorithm in particular is updated frequently. Despite the fact that it is possible to pass a vast number of queries through the black box of any existing search engine, the immensity of the search space and instability of such algorithms make them difficult to reverse engineer.

This project is concerned with application of machine learning techniques to search engines. The aim of the project, in particular, is to explore how machine learning techniques can be used effectively to infer algorithms from search engines. The result will be an extensible learner evaluation framework, which can be used to assess the feasibility of a machine learning approach to search engine heuristic inference. Even though this study does not attempt to reverse engineer any existing heuristics, the result can be applied to such an ambitious task.

1.2. Challenges

Machine learning is a natural approach to heuristic inference. However, applying such techniques to real search engines would likely be ineffective due to a number of factors. The

[1]http://www.google.com/competition/howgooglesearchworks.html

variability of the algorithms, the dynamic nature of the web and lack of meaningful feedback would prevent incremental improvement of the learner. For example, when there are as many as 200 features in question, false assumptions made by a learner may have an unpredictable effect on its performance. Moreover, a vast training set would be required to conduct the learning.

More generally, there are certain ambiguities associated with machine learning, which are 'problem-specific'. For example, it proves difficult to decide how much training data is necessary, as well as selecting it to avoid over/under-fitting[4]. Similarly, it is not straightforward as to which machine learning technique is best for a particular problem.

In order to circumvent the limitations imposed by using existing search engines, part of this project is to develop a toy search engine. This will allow me to run the machine learners with the features used by the search engine to deduce the weightings. Such transparency addresses the problems stated above and, more importantly, allows for useful evaluation of machine learning techniques by providing meaningful feedback.

1.3. Related Work

Machine learning has recently become very popular: it has a variety of applications among which is search engine design itself. Due to the vast applicability of the field, a lot of research has been done to improve the learning techniques and plenty of resources are available. For example, the Naive Bayesian classifier, used in this project, is one of the most well-known machine learners. Support Vector Regression, on the other hand, is an up-and-coming technique. As a consequence, fewer papers are available and these are prone to errors and typographical mistakes.

Despite the abundance of machine learning resources, I am not aware of any research aimed specifically at extracting search engine heuristics. There exist web site analytical tools, which claim to improve Google ranking[1]. Such tools are plentiful, but little is said about the methodology used.

Apart from the machine learning resources, the project relies on the availability of a variety of tools, among which are maths, indexing, natural language processing and html parsing tools. All of these are readily available in special purpose libraries, which are ubiquitous and well documented.

[1] 'SEOBook' and 'Woorank' are among the popular tools which offer website analysis to help improve ranking.

2. Preparation

The original aims of the project were defined very broadly, so some further structuring and planning was crucial at the early stages to make sure the goals were understood and subsequently achieved.

The beginning of this chapter introduces the principles of machine learning and the particular techniques implemented during this project in order to familiarise the reader with the field and the research I had conducted. The rest of the chapter describes the analyses undertaken before the development, in particular, formulating the goals and evaluating the relative importance of system components, as well as their associated risks.

2.1. Introduction to Machine Learning

Machine learning constitutes the central part of the project. Initially, the field was new to me, so research of different techniques was a big part of the preparation. To aid understanding of the upcoming sections, a few terms need to be defined:

Supervised learning	*Inferring a function from labeled training data.*
Unsupervised learning	*Inferring a function from unlabeled data.*
Learner	*An algorithm that has not seen any data yet.*
Classifier	*A learner that has been trained on the training data.*
Feature set	*A list of features describing the object to be learned (a web page).*
Training Set	*A list of labeled feature sets used to train a learner.*

Machine learning techniques can be broadly split into two categories: *supervised* and *unsupervised.* The supervised learners are typically quicker to train and are more reliable provided test data is available. The supervised approach is a better fit for this project, as training data can be labeled simply by performing queries on the search engine. Also, supervised learning is more widely used and offers a broader variety of techniques.

The Curse of Dimensionality is a well-known problem with machine learning: the amount of training data required to cover all possible combinations grows rapidly as features are added[1].

[1]The degrees of freedom are bounded by $O(pages^{features})$.

This phenomenon could negatively impact learning of the real search engines. An advantage of having a toy search engine, therefore, is that the number of features given to the machine learner can be limited to the features actually used by the search engine. This would not be possible in a real world scenario where the features are unknown.

Another major issue that is common to all machine learning methods is over- and under-fitting. These refer to the problem of finding balance between generalizing the model and closely fitting the training data. This is yet another source of interest to this project, as we can observe the behaviour of the learner when the control parameters are changed.

It is generally recommended that the simplest learners are tried first[4]. Of all learners Naive Bayesian is one of the most comprehensible. This in itself is a major advantage according to Occam's razor principle (which is a general guideline in machine learning). Hence, we start with describing the principles of the two machine learning techniques used - Naive Bayes and Support Vector Machines.

2.1.1. Naive Bayes

Naive Bayes is a probabilistic classifier based on Bayes Theorem. The posterior probability $P(C|\vec{F})$ denotes the probability that a sample page with a feature vector $\vec{F} = (F_1, F_2, \dots, F_n)$ belongs to class C. The posterior probability is computed from the prior probability $P(C)$ – the unconditional probability of a page belonging to the class C, the likelihood $P(\vec{F}|C)$ and the evidence $P(\vec{F})$:

$$P(C|\vec{F}) = \frac{P(C)P(\vec{F}|C)}{P(\vec{F})} \tag{2.1}$$

The right-hand side of the above equation is obtained from the training data.

The simplicity of the Bayesian approach is due to the conditional independence assumption: each F_i in $\vec{F}$ is assumed to be independent of every other to get $P(\vec{F}|C) = P(F_1|C) * P(F_2|C) * \dots * P(F_n|C)$. This leads to a concise classifier definition:

$$\hat{C} = argmax_C P(C) \prod_{i=1}^{n} P(F_i|C) \tag{2.2}$$

where $\hat{C}$ is the result of classification of a page with feature vector $F_1, F_2, \dots, F_n$.

In practice, the crude assumption rarely holds and is likely to be violated by our data, as we expect features of pages to be interdependent. However, it has been shown that Naive Bayes performs well under zero-one loss[1] in the presence of dependencies[6]. This has a few implications for the project, particularly, on evaluation methods.

[1]The zero-one loss function penalizes failure equally, but does not reward or penalize success.

As we have seen, Naive Bayes assigns probabilities to possible classifications in the process of classifying. Even though it generally performs well in classification tasks, these probability estimates are poor[5]. However, despite poor probability estimates, there exist several frameworks, which make use of Bayesian classification and achieve decent performance in ranking. For example, Zhang[12] experimentally found that Naive Bayes is locally optimal in ranking[1]. Another framework for ranking[8] is based on Placket-Luce model, which reconciles the concepts of score and rank[2]. Existence of such frameworks suggests that Naive Bayes is an adequate choice for a prototype learner.

In this project in particular, the web pages can be classified according to their discretized score or rank. This will be discussed further in Section 4.2.

Although classification is a useful technique to try, it feels more natural to represent score or rank as real numbers rather than classes. Regression is another approach to machine learning and the next learning technique I explored – Support Vector Regression – is non-probabilistic and has little in common with Naive Bayes.

2.1.2. ϵ-Support Vector Regression

While the binary classification problem has as its goal the maximization of the margin between the classes, regression is concerned with fitting a hyperplane through the given training sequence.

A great advantage of Support Vector machines is that they can perform non-linear classification or regression by using what is referred to as the *"Kernel Trick"* – an implicit mapping of features into a higher dimensional space, in which the data is linearly separable. The choice of a kernel function is problem specific and the best one is usually decided by trial and error.

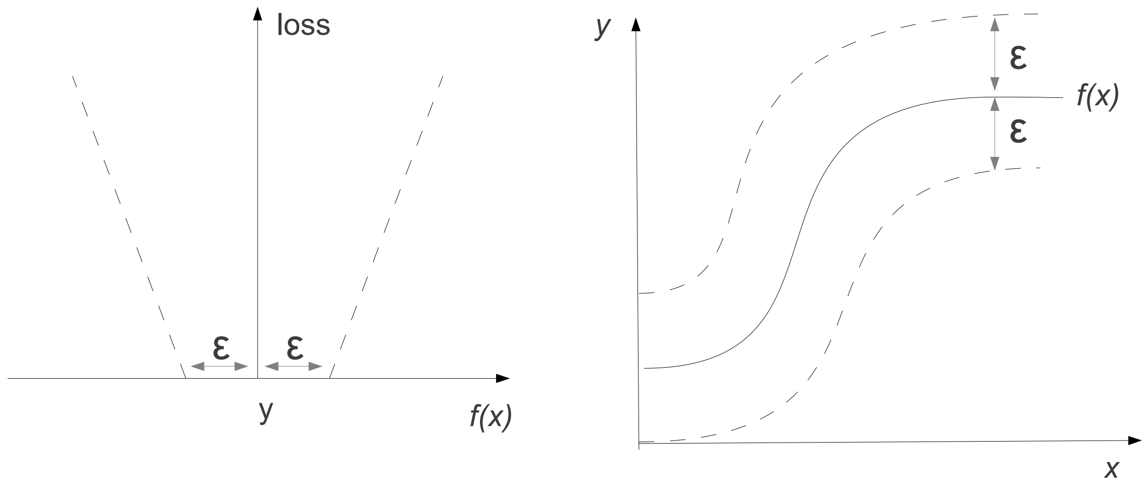
I begin by introducing the theoretical foundations of Support Vector Regression, which was first proposed by Vapnik[11].

Define a training sequence as a set of training points $D = \{(\mathbf{x_1}, t_1), (\mathbf{x_2}, t_2), ..., (\mathbf{x_l}, t_l)\}$ where $\mathbf{x_i} \in R^n$ is a feature vector holding features of pages and $\mathbf{t_i} \in R$ is the corresponding ranking of each page. The training sequence D is defined per query for a set of chosen queries.

In simple linear regression the aim is to minimize a regularized error function. I will be using an ϵ-insensitive error function (see Figure 2.1a).

[1]The paper defines a classifier as locally optimal in ranking a positive example E if there is no negative example ranked after E and vice versa for a negative example.

[2]Placket-Luce model is based on minimizing the Bayes risk over possible permutations.



(a) *ϵ-insensitive loss function* (b) *Predictions with ϵ-SVR*

Figure 2.1.

$$E(y(\mathbf{x}) - t)) = \begin{cases} 0 & \text{if } |y(\mathbf{x}) - t| < \epsilon \\ |y(\mathbf{x}) - t| - \epsilon & \text{otherwise} \end{cases}$$

where $y(\mathbf{x}) = \mathbf{w^T}\phi(\mathbf{x}) + b$ is the hyperplane equation (and so $y(\mathbf{x})$ is the predicted output) and t is the target (true) output.

The regression tube then contains all the points for which $y(\mathbf{x_n}) - \epsilon \leq t_n \leq y(\mathbf{x_n}) + \epsilon$ as shown in Figure 2.1(b).

To allow variables to lie outside of the tube, slack variables $\xi_n \geq 0$ and $\xi_n^* \geq 0$ are introduced. The standard formulation of the error function for support vector regression[7] can be written as follows:

$$E = C\sum_{n=1}^{N}(\xi_n + \xi_n^*) + \frac{1}{2}\|\mathbf{w}\|^2 \tag{2.3}$$

E must be minimized subject to four constraints:

$$\xi_n \geq 0, \tag{2.4}$$
$$\xi_n^* \geq 0, \tag{2.5}$$
$$t_n \leq y(\mathbf{x_n}) + \epsilon + \xi_n, \tag{2.6}$$
$$t_n \geq y(\mathbf{x_n}) - \epsilon - \xi_n^* \tag{2.7}$$

This constraint problem can be transformed into its dual form by introducing Lagrange multipliers $a_n \geq 0, a_n^* \geq 0$[1]. The dual problem involves maximizing:

$$L(\mathbf{a}, \mathbf{a}^*) = -\frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N}(a_n - a_n^*)(a_m - a_m^*)K(\mathbf{x_n}, \mathbf{x_m}) \tag{2.8}$$

$$-\epsilon\sum_{n=1}^{N}(a_n + a_n^*) + \sum_{n=1}^{N} t_n(a_n - a_n^*)$$

where $K(x_n, x_m)$ is the kernel function, t_n is the target output,

subject to constraints:

$$\sum_{n=1}^{N}(a_n - a_n^*) = 0, \tag{2.9}$$

$$0 \leq a_n,\ a_n^* \leq C, \quad n = 1, ..., l \tag{2.10}$$

I come back to these derivations again in Section 3.8 and further derivations will be constructed in order to implement the SVM.

2.2. Introduction to PageRank

The PageRank algorithm was originally described by Brin et al.[10]. It was first introduced as a way "to measure the relative importance of web pages". PageRank is interesting to include in this project not only because it is a defining feature of the Google search engine, but because it is a unique feature of its type, as it depends on the link structure of the whole web.

The basic idea is to capture the link structure of the web and provide a ranking of pages that is robust against manipulation. The importance is proportional to the number of links from other important pages. Thus, the importance 'flows' forward: the backlinks share their importance with the pages they link to. Such a simplified ranking of a set of pages can be expressed as an assignment

$$R(u) = c\sum_{v \in B_u}\frac{R(v)}{N_v} \tag{2.11}$$

An intuitive justification for such ranking is by analogy with a citation network: we are likely to find highly cited pages more important. The equation is recursive, so iterating until convergence results in a steady state distribution, which corresponds to the PageRank vector. The *Random Surfer Model* is only interested in a steady state distribution of a random walk on the web graph: at each step the surfer either follows a random link or "teleports" to a random page. Brin et al. justify ignoring the dangling links, as it does not have a significant effect on the ranking.

The teleportation vector determines whether the PageRank is "personalized". For the non-personalized version the teleportation vector holds equal probabilities for all pages in the web, whereas in a personalized approach the probabilities are distributed according the knowledge of the surfer's previous activity. In this project we are only concerned with non-personalized ranking, which is simpler and enough for the purposes of the project.

2.3. Requirements Analysis

The original aims of the project were very high level, so explicitly defining the goals in the early stages was central to the success of the project. The main project goals are summarized in Table 2.1.

Requirement description	Priority	Difficulty	Risk
Functional Requirements			
Implement a simple search engine	High	Low	Low
Ensure search engine can use both score and rank	Medium	Medium	Low
Implement two different machine learning techniques	High	High	High
Classifiers must achieve better than random results	High	Medium	High
Implement PageRank	Medium	Medium	Low
Non-Functional Requirements			
The search engine must be able to index a few thousand pages in reasonable[1] time	Medium	High	Medium
PageRank computation on a few thousand pages must complete in reasonable time	Medium	High	Medium
Machine learning modules must learn and classify within reasonable time	High	High	High
Clear interface definition between modules	High	Medium	Medium

Table 2.1.: *Project objectives*

Along with the stated requirements, it is important to note that in this project I regarded usability as a non-requirement. This decision was motivated by the fact that the project is result-oriented, therefore, quick implementation was prioritized over ease of use. The system is only meant to be used by me, hence there was no need for documentation and user interface.

2.3.1. Dependency analysis

To effectively plan the development, I also evaluated the dependencies of the core modules of the project(see Figure 2.2). It can be seen that there was a lot of freedom as to the order of implementation. It also became obvious that due to the apparent convergence of the modules, integration would be a complex exercise. As a result, a prototype had to be implemented very early on to see the design at work and to avoid surprises. This meant the implementation of Naive Bayes classifier, the parser and the indexer was on the high priority path.

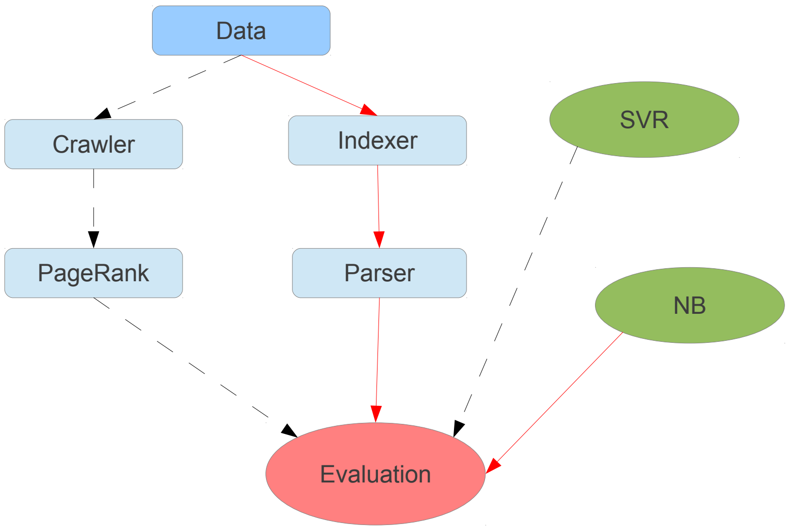


Figure 2.2.: *Summary of Main Dependencies. Colour groups functionally related modules, high priority paths are shown in red.*

2.4. Choice of Tools

The project made use of a lot of existing technologies to speed up development. This section discusses the most important choices made prior to development, such as the programming

[1]The project imposes no rigid speed requirements, however, it is highly desirable that the computing time does not slow the project down.

language and library choices.

2.4.1. Data Gathering

Data gathering is of major importance, as data decisions have tremendous impact on the rest of the implementation and the success of the project. The rest of the system assumes the existence of a pool of web pages available offline for fast indexing and parsing. Ideally the corpus of web pages would be "representative" of the whole web, to make generalisations more accurate. Originally, I was hoping to get such a collection from a resource, for example, the web corpus of the *Text Retrieval Conference* (TREC). However, such data is not easily available, so I had to retrieve pages using the *Wget* tool. In order to enhance the link structure of the downloaded pages, I restricted the corpus to one semantic area by only downloading websites related to construction materials[1]. This limitation of topic has certain advantages: relatively few pages need to be downloaded before the pages appear sufficiently interlinked, so the corpus has a distinct structure (as web pages similar in the field link to each other). All the links were converted, so that the link structure was preserved offline.

As for the size of the training data, Domingos[4] suggests that a primitive learner given more data performs better than a more complex one with less data. This, of course, is under certain assumptions of data quality, namely the assumption that the training data is a representative subset of all the possible data. Intuitively, provided there is no bias in data gathering, more data implies better generality. I have started with a training set spanning an order of a few thousands of pages, however, in practice, I found that there is no particular improvement beyond a thousand pages.

To conform with machine learning guidelines I separated data for testing and training at the very beginning. Different seed pages were used[2] and the web pages were downloaded into different directories. Each directory was estimated at around 3000 pages. In addition to this, I have taken the further precaution of setting aside small development and verification corpora to be used only during development to ensure no bias towards training data at the implementation stage. Also, their comparatively small size meant faster development.

2.4.2. Search Engine

The next important decision regarded the search engine. Originally, I considered using open source existing engines, in particular, *Lucene*. Even though I could freely modify it for the

[1]There is no particular reason to choose this topic, except that it had been used by the external project originator in his experiment trying to infer Google's ranking factors. This is described in the Proposal in more detail.

[2]Overlapping of pages is unlikely to occur due to shallow recursion depth.

purposes of the project, the complexity of it was unnecessary. I saw writing a simple search engine as a more beneficial exercise, as developing it in the first place potentially gives an insight into the problem.

Functionally, the search engine is a black box that takes a set of web pages and a set of queries and outputs an order. The order is determined by the features of the pages, which together make up a score. The score is the function that needs to be inferred using the ranking assigned by the search engine. However, we are only given the order as evidence. For most of this project I have assumed an existence of conversion between rank and score, and so the machine learners interact directly with scores.

In general, there are two aspects of information retrieval that have to be accounted for: precision and recall.

Precision	– *the fraction of retrieved pages that are relevant to the query.*
Recall	– *the fraction of relevant documents that are retrieved.*

Even though both are important to make a good search engine, in practice, the web is very large, and so precision, or even *precision at n*[1] has become more prominent in defining a good search engine: very rarely the user actually browses results ranked below the first ten pages. As a result, modern search engines tend to focus on high precision at the expense of recall[2]. Therefore, I will concentrate primarily on precision when designing a search engine.

2.4.3. Programming Language

When choosing a programming language, the main considerations amounted to library availability and simplicity. The project imposes no special requirements on the language, apart from, perhaps, library infrastructure for parsing web pages, maths and natural language processing. Python is a rapid development language with extensive library support. As for efficiency, all the mathematical operations in this project rely on Python math libraries, which are implemented in C. I have not programmed in Python before the project, so a slight overhead was caused by having to learn a new language.

2.4.4. Libraries

The project makes extensive use of libraries, Figure 2.3 shows an abstract diagram of the main libraries. As I mentioned earlier, library support was a major criterion when choosing a language and a lot of time was spent searching for and getting familiar with the relevant libraries. This section discusses some core libraries used in this project.

[1]"Precision at n" only evaluates precision with respect to n topmost returned pages.

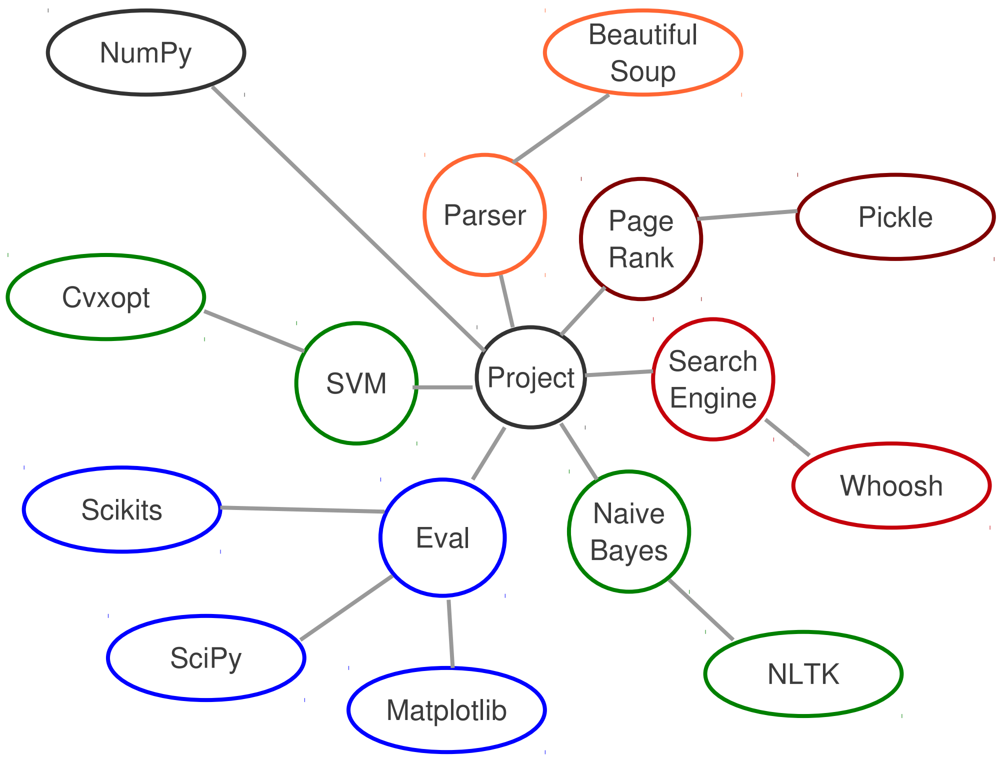


Figure 2.3.: *Libraries required in the project*

HTML parsing

Parsing HTML pages is crucial to the project and relies entirely on the library. Forgiving HTML parsing is a hard problem and I have chosen to use the **BeautifulSoup** library to build and navigate the parse tree. There are some simpler tools available for Python, however, they do not have such a diverse functionality. For example, the project made use of tag filtering and a variety of underlying parsers. The library was mainly used by the parsing module (when constructing feature sets) and the indexer.

Maths

NumPy is the most popular scientific Python library and was used throughout the project for various purposes including linear algebra, array and matrix manipulation, random number generation and others.

A library providing a Quadratic Programming Solver, required in order to implement the SVM, was the hardest to find. The **CvxOpt** library was one of very few with such functionality.

Other maths libraries, such as **SciPy** and **Scikits**, were of secondary importance to the project and were needed primarily during evaluation for tasks such as curve fitting and statistical bootstrapping.

Plotting

Adequate plotting capabilities were essential to the implementation and evaluation of the machine learners. **Matplotlib** is the de facto standard for plotting in Python. It has a simple API and importantly supports 3D plots, which were used extensively for the visual verification of SVM and Bayes.

Indexing

The choice of indexer was driven primarily by the ease of customisation. The **Whoosh** library is a powerful open source indexer with a purely Pythonic API and plentiful capabilities, a lot of which are highly customisable.

Object Serialization

This functionality was required mainly to allow for the pre-computing of the PageRank vector and other static page features. **Marshal** and **Pickle** were the two alternatives considered in the project. **Pickle** is more widely used and has proved more robust and portable, and so was preferred.

Naive Bayes

A Bayesian classifier is not hard to implement, so after some consideration I decided to use a library implementation, as a fast solution was desirable for the first prototype. There were surprisingly many implementations available, from which I chose the **Natural Language Toolkit Library (NLTK)**, as it had a concise and clear implementation as well as a simple input format.

2.4.5. Development Environment

All of the development was carried out on my personal machine running Ubuntu Linux 12.04. Code was written primarily in the *Vim* editor in concert with the Python shell for interactive development. Vim is a powerful editor which provides syntax highlighting, fast text navigation and manipulation as well as shell integration. I used the extended IPython shell due to its stored history and autocompletion features.

2.4.6. Version Control and Backup

I chose to use the Mercurial source control management tool for both version control and remote backup. The choice was motivated by its ease of use, simple setup and my own familiarity with it. In addition, it is integrated with the online repository hosting service BitBucket.

The backup of the code was twofold: every time a substantial change was made the remote repository was updated to hold the newest version. Regularly both the code and the data gathered during evaluation were also backed up onto an external hard drive.

2.5. Software Engineering Techniques

2.5.1. Iterative Development

While the set-up of Part II projects encourages a waterfall-like development model, the nature of this project required an iterative approach. The first iteration rendered a prototype: a primitive search engine with a Naive Bayesian baseline classifier. The next iteration modified each part of the system towards a more complex solution. Testing and debugging was performed at each iteration to ensure the system was improved. The main advantage of iterative development to this project was the ability to verify validity of the proposed design early on by means of the first working prototype.

2.5.2. Incremental Build Model

Within each iteration the development followed the evolved waterfall model, also known as the incremental build model. The system was split into components ('builds'), such that each represents a functionally separate unit of the system: a search engine, a learner, a parser and an assessment module. Increments were developed sequentially and were tested separately before integration at the end of the iteration. This approach allowed to decompose a complex system into manageable chunks, which eased the development.

2.5.3. Testing

Most functionality of the system developed in this project required some human analysis to be tested. Moreover, the system was frequently evolving, which made it difficult to write useful unit tests. Therefore, most testing was conducted manually. However, certain commonly reused functions were stable enough to easily unit test. I used Python's *Doctest* module for inline unit testing, which offers a lightweight solution with enough flexibility to provide the assurance required. Testing is discussed in more detail in Section 4.4.

2.6. Summary

In this chapter I have outlined the research and planning completed prior to the implementation stage. In particular, the chapter provided brief introductions to the machine learning techniques and the PageRank algorithm as well as shaping more detailed aims of the project. I also touched upon the development strategy followed during the project and the libraries used.

3. Implementation

This chapter describes the implementation of the system that was developed in this project. The outline of the overall architecture is followed by more detailed descriptions of the individual components: the search engine, the parser and the machine learners.

All components were implemented successfully and together form a working system.

3.1. System Architecture

To achieve the goal of the project, a machine learning techniques comparison framework was necessary. In the Introduction Chapter I mentioned the benefit of having a transparent system as the object to be learnt. To further justify this decision, it is worth mentioning that generalisation using machine learning is different from most optimization problems in that the function that is being optimized is out of our reach, and all that is visible to the machine learner is the training error. Because the goal of the project is not the correct classification of real data, but identifying the means to correct classification, it was important that informed choices were made towards the improvement of the learner. Taking this into account, knowing the function to be learned and having direct control over it, guided the improvement of the search engine.

Following this argument, a system in three parts was designed: a search engine, a machine learner and a parser to mediate between the two. Figure 3.1 illustrates the proposed learning system.

The Training Data is the web pages gathered as described in Section 2.4.1 and set aside at the beginning specifically for the training purposes. The Queries are implicitly part of the training data, as they determine which pages are returned by the search engine. The pages in the training directory are first indexed and the PageRank is computed for them. The queries are passed to the search engine, which outputs the returned pages in the order of importance. The parser computes feature sets for all the pages in the training directory and assigns a category to each page depending on the query and the output from the search engine. The feature sets are then used to train the learner. The trained learner is the output of the whole system.

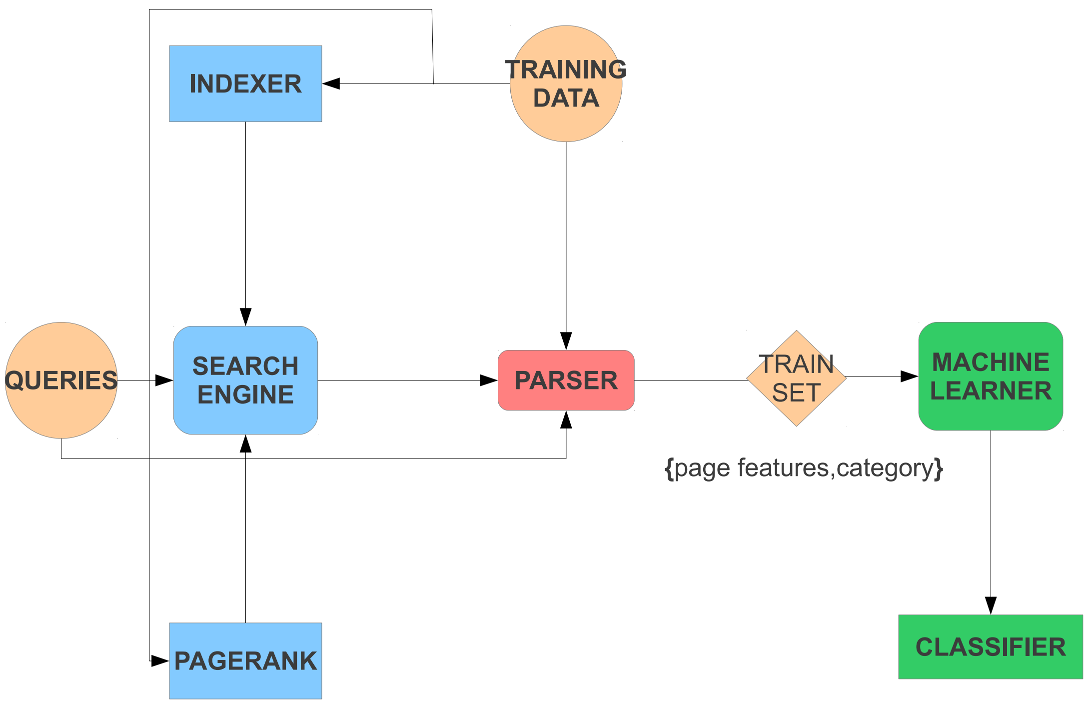


Figure 3.1.: *Overview of the system. Three major parts from left to right are search engine, parser and machine learner. The colour coding indicates belonging to the same component: green for the learner, blue for the search engine, pink for the parser and peach for the data.*

Apart from speed and informal correctness, another important aspect of the design was the non-interference between the data gathering modules (search engine and parser) and the machine learners to avoid biased results. In addition, these parts had to be sufficiently decoupled for the purposes of scalability and code reuse: both machine learners must communicate with the system via the same interface.

The evaluation module is also an essential part of the developed system, as it facilitates the feedback loop that would help assess the performance of the classifiers. Figure 3.2 shows a high level diagram of the evaluation process for a classifier. The Categorizer is a part of the parser that assigns true categories to the input pages. The search engine and the categorizer together are used to output the correct classification. This is then compared with the classifier's output. The classifier evaluation is further described in Section 4.2 as well as the methodology adopted.

The rest of this chapter outlines the implementation of the core parts of the system, the chal-

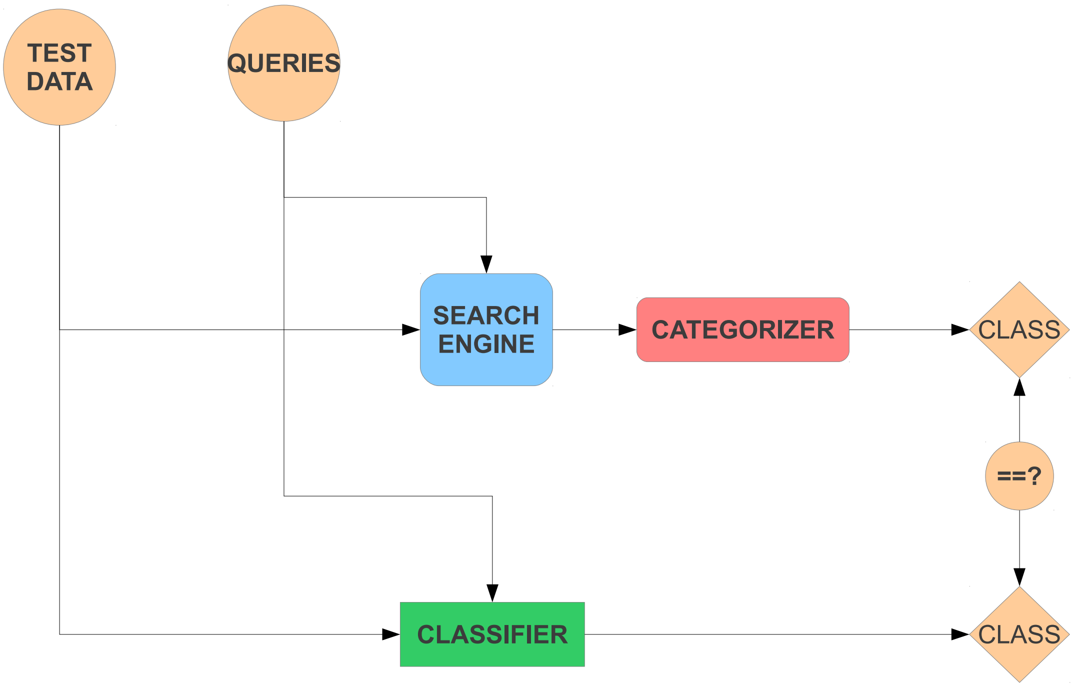


Figure 3.2.: *Evaluation process.*

lenges faced and the optimizations applied.

3.2. Search Engine

The existence of the search engine had twofold significance in the project: firstly, it gave me an insight into how search engines work and secondly, it was a way of gathering data for the machine learners. The first prototype of the system was heavily reliant on the engine ranking the pages. In the following iterations, however, its importance was diminishing: scores were computed for all pages, making the queries irrelevant.

Because I had decided to concentrate on precision, as discussed in Section 2.4.2 of the Preparation chapter, it was assumed for simplicity that all relevant documents were returned by the searcher. This assumption also emphasizes secondary importance of the search engine to the project: evaluation of the search engine itself could be ignored. The project swiftly moved on from the specifics of web pages towards the more general goal, which is concerned a lot more with the nature of the hidden score function than the features themselves.

Even though the search engine capabilities were not used to the extent I had envisaged, this section will elaborate further on the implementation of the indexer, as it helped me gain a useful insight into the field.

3.2.1. Indexer and Searcher

The module requirements featured flexibility, speed of indexing and retrieval as well as simplicity and usability. The *Whoosh* Python library provides all of these – it is an open source indexing library, so I had the option of modifying any part of it. It is built in pure Python, hence it has a clean Pythonic API. Its primary advantage is fast indexing and retrieval, although the project is mostly concerned with retrieval speed, as indexing is done rarely. The predecessors of Whoosh have served as the basis of well-known search engines such as *Lucene*, so it is also a powerful indexing tool, should I have needed more sophistication.

I have defined a very simple indexing schema. Perhaps, one notable detail is that Whoosh can store timestamps with the index, which enabled me to provide both clean and incremental index methods. The incremental indexing relies on the timestamp stored with the index and compares it to the last-modified time provided by the file system. The user can specify whether indexing has to be done from scratch or updated to accommodate some page changes or page addition/deletion. Even though I had not originally expected to need the incremental indexing capabilities, throughout the project it has provided significant speedups.

In the first prototype of the system, the search engine output the pages in the order of non-increasing PageRank. Subsequently, the sorting has been decoupled from retrieval and incorporated into the Parser module, which is described in detail in Section 3.6.

3.3. Computing PageRank

Section 2.2 of the Preparation Chapter explains the principles of the PageRank algorithm. In this section the PageRank algorithm is implemented using matrix inversion. This is the simplest method to compute PageRank for a few thousand pages and turned out to be reasonably fast. All matrix operations were performed using *NumPy* – the Python numerical library. The implementation is derived in the rest of the section.

First, a few variables need to be defined:

t	the teleportation probability
s	the probability of following a random link
$\boldsymbol{E}$	the teleportation matrix
$\boldsymbol{G}$	the matrix holding the link structure of the data

Matrix G can be defined as follows:

$$G_{i,j} = \begin{cases} 1/L & \text{if there is a link from i to j, where L = number of links from i} \\ 0 & \text{otherwise} \end{cases}$$

$\boldsymbol{G}$ is computed by traversing the data, which is described in more detail in the next section. $\boldsymbol{E}$ is chosen to be:

$$E_{i,j} = 1/N,$$

which corresponds to a non-personalised PageRank computation: the teleportation probabilities are identical for all surfers and all transitions are equiprobable. Both $\boldsymbol{G}$ and $\boldsymbol{E}$ are stochastic matrices: their entries are non-negative and their columns sum to one.

Probabilities s and $t = 1 - s$ are customizable and represent the willingness of the surfer to follow links as opposed to jump onto a random page. I used the values proposed in the original paper[10] with $s = 0.85$.

I defined a stochastic matrix $\boldsymbol{M}$ representing the web surfer activity, such that $M_{i,j}$ is the probability of going from page i to page j,

$$\boldsymbol{M} = s\boldsymbol{G} + t\boldsymbol{E} \tag{3.1}$$

In one step the new location of the surfer is described by the distribution $\boldsymbol{Mp}$. The objective is to find a stationary distribution $\boldsymbol{p}$, so by definition $\boldsymbol{p}$ is unchanged by surfer's activity:

$$\boldsymbol{p} = \boldsymbol{Mp} \tag{3.2}$$

Substituting 3.1 into 3.2

$$\boldsymbol{p} = (s\boldsymbol{G} + t\boldsymbol{E})\boldsymbol{p} = s\boldsymbol{Gp} + t\boldsymbol{Ep} \tag{3.3}$$

Rearranging equation 3.3 gives

$$(\boldsymbol{I} - s\boldsymbol{G})\boldsymbol{p} = t\boldsymbol{Ep} \tag{3.4}$$

where $\boldsymbol{I}$ is the identity matrix.

Because members of $\boldsymbol{p}$ must sum to one, $\boldsymbol{Ep}$ can be expressed as $\boldsymbol{P}$:

$$\boldsymbol{P} = [\overbrace{1/N, 1/N, \ldots, 1/N}^{N}]^T$$

So computing PageRank amounts to

$$\boldsymbol{p} = t(\boldsymbol{I} - s\boldsymbol{G})^{-1}\boldsymbol{P}, \tag{3.5}$$

where $(\boldsymbol{I} - s\boldsymbol{G})^{-1}$ denotes a matrix inverse operation.

This solution is simple at the expense of speed. Although computing inverse of a matrix is computationally expensive, the project does not require the computation to scale beyond a few thousand pages. The resultant performance was surprisingly pleasing, the time spent computing PageRank was insignificantly small in comparison to the time spent crawling the directory.

The PageRank vector computation happens within the `PageRank` class. The whole `PageRank` object is written to disk using the Python object serialization module *Pickle*. This allows the PageRank vector to be pre-computed and stored for each directory. The `load` class method is defined on the `PageRank` class to retrieve the relevant object for a given directory. The class is instantiated with an instance of the `Crawler` class, which embodies the link structure of a directory and is described in the next section.

3.4. Crawler

The `Crawler` abstracts away the underlying data directories and computes their link structures as matrices. The matrix $\boldsymbol{G}$, used for the PageRank computation, represents random link following activity. To obtain such a link structure each page has to be parsed, and all links recorded. Because the training and test data are obtained from a single source page by recursive link following, every page in a directory is guaranteed to be discovered by a spider.

The `Crawler` class recursively traverses the pages depth first starting with the seed page, the same as the seed page used for recursively downloading the pages from the web. To make sure each page is only explored once, a dictionary is used to hold pairs of absolute paths, which uniquely identify the page, and a numerical value corresponding to the timestamp when the page has been first discovered.

Although every page has a unique path, the links to other pages are relative. Such links need to be normalized to maintain consistency. A page object is used to encapsulate path complexity: all link paths are converted to absolute paths before addition to the dictionary. All outbound links are stored with the page in a Set data structure, such that no link is added more than once.

To produce the stochastic matrix $\boldsymbol{G}$, an empty $N \times N$ matrix is initialised, where N is the total number of pages. I also assume that whenever a surfer encounters a dangling page – a page that has no outbound links – a teleportation step occurs. Therefore, every dangling page links to every page in the pool including itself with equal probability $\frac{1}{N}$. For non-dangling pages, all

Page	A
A	0
B	1/2
C	1/2
D	0

Table 3.1.: *Illustration of non-dangling pages: B and C share A's 'importance' equally.*

links are assumed equiprobable and all pages that are not linked to have probability of 0. So if page A links to pages B and C, but not itself or D, its row in G is described by the Table 3.1.

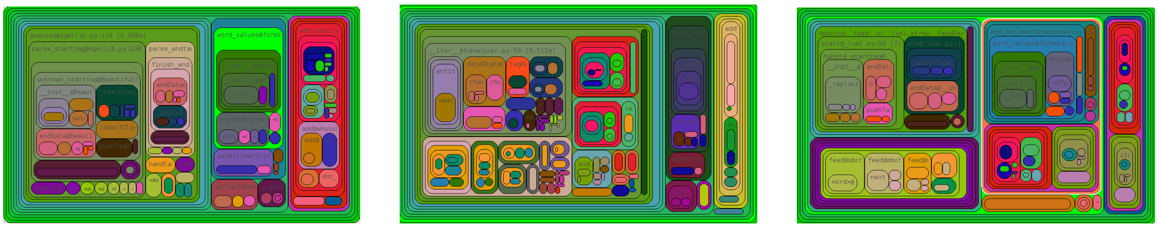
3.5. Optimizations

Even though speed is not a direct goal of the project, efficient implementation was desirable and so, optimization could not be overlooked. A significant amount of time was spent processing large quantities of data: indexing, PageRank and feature set computations all must complete in 'reasonable' time, i.e. in the final implementation the longest computation takes order of minutes and processes a few thousand pages. Various optimizations have been used to achieve this.

Both PageRank vector and the index are precomputed and kept in persistent storage. The incremental indexing feature allows us to edit parts of the index as opposed to recomputing the whole index from scratch. These precomputations provide certain speedups, but were not enough. Because the system is fairly complex and a lot of library code is used throughout, it was hard to determine which code most affects the speed. 'Blind' attempts at optimization did not work well, which motivated the use of a profiling tool.

Profiling the first prototype of the complete system revealed a surprising fact: most time was spent in the library code parsing pages. To mitigate this issue I have tried using custom parsers instead. Apart from speed, robustness was another important consideration, as a failure of a parser increases compute time. Two of the most renowned Python parsers are *Html5lib* and *Lxml*. Figure 3.3 below shows the visual representation for time profiling of 3 different runs obtained using *RunSnakeRun*, each exploiting a different parser. Despite *Html5lib* being quoted as the most robust and lenient, *Lxml* was sufficiently faster to be preferable.

Another limitation was discovered due to profiling: the PageRank vector was loaded into memory every time a page was parsed. The loading, therefore, happened once for each page, which is clearly undesirable. I used caching to ensure that each of the two possible PageRank vectors



(a) *Default* (b) *Html5lib* (c) *Lxml*

Figure 3.3.: *Visual profiles of three parsers from left to right: default Python HTML parser, Html5lib and Lxml. The internal boxes are sized in proportion to the time spent in each function. In all profiles three distinct major compartments can be seen, the leftmost being the compartment of interest: time spent in parsing. Taking into consideration that the other modules are unaffected by changing the parser implementation, it can be observed that Lxml (rightmost) is the fastest and Html5lib is the slowest.*

(corresponding to the test and train directories) is loaded from memory exactly once. This is achieved via a double singleton class, which loads the vectors lazily.

3.6. Parser

So far we have looked at the search engine. This section describes the parser – a functional unit, which provides an interface from the search engine to the machine learners. The search engine simply retrieves pages in response to a query and the machine learner expects as its input a set of labelled features for training and unlabelled features for classification/regression. The parser, therefore, must hide the nature of the data we are dealing with by translating it into the universal language of machine learners. Hence, the primary function of the parser is to compute feature vectors for pages. However, it is easy to outsource search engine heuristics into the Parser, too, as they require page parsing.

To accomplish these multiple goals, I have taken an object oriented approach to the design of the module. What I refer to as the parser is a few classes, which together perform a series of tasks related to page parsing. The module operates in two modes: rank and score; and handles both classification and regression. The most abstract interface to the module is through the two classes: a `TestFeatureSetCollection` and a `LabeledFeatureSetCollection`. Instances of these classes encapsulate all the data, so can be passed around to the machine learners, as well as the evaluation and plotting modules. These objects each operate within their own directories, to keep training and testing sufficiently separate.

Both category and rank are treated as page features and hence are part of the

LabeledFeatureSet class state. The LabeledFeatureSetCollection class is used for training the classifier, whereas the TestFeatureSetCollection class computes predicted category and is used for testing the classifier. Both, however, need to generate feature sets, one for the training data and the other for the test data. This common functionality is embodied in their abstract base class, FeatureSetCollection. Figure 3.4 shows a UML class diagram illustrating the main dependencies of the module.

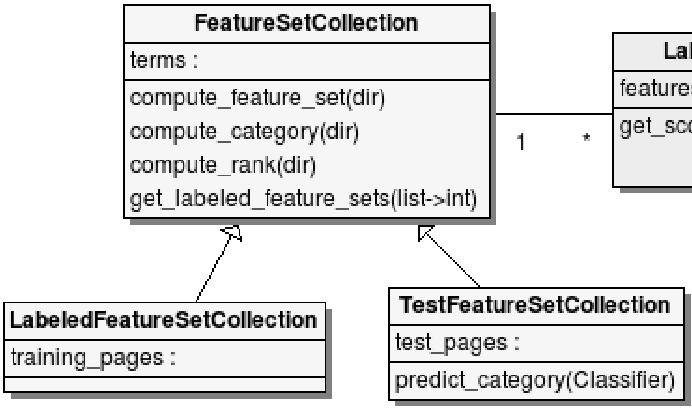


Figure 3.4.: *A UML class diagram illustrating the structure of the parser.*

The rest of this section talks about the specifics of the implementation, in particular, the features used and how HTML parsing is done.

3.6.1. Rank and Score

Conceptually a FeatureSetCollection is a dictionary of LabeledFeatureSet objects indexed by both page path and query term, as the features depend on both. After initialisation, all the features are computed and 'filled up' per page and per query term. In the original prototype the search engine used to output ranks (the ordinal representing the position of the page in results) as the target value for the machine learners to infer. This was fine for a prototype, however, there was an obvious flaw in this approach: the rank depends on the other web pages, which makes it impossible to infer from the features of a single page.

The later prototypes assumed the existence of conversion between rank and score and passed scores directly to the machine learners. The score function was implemented as a class method on the LabeledFeatureSet, so that the scores could be computed ad hoc for a variety of heuristics.

3.6.2. Features

The requirements analysis does not prescribe the use of any particular features. However, it states that both dynamic (query dependent) and static (query independent) features must be used. PageRank is a static feature that stands out above the others: it takes into account all the pages in the pool and reflects on the link structure hierarchy of the web pages. The parser loads the pre-computed PageRank vector indexed by the path to extract the PageRank for any page.

An example of a dynamic feature used in the project is query term count: the number of times the query term occurs on the page. This is obtained directly from the HTML files using the BeautifulSoup library. The HTML is parsed into clean text and the count is computed on the resultant string.

A related but different feature – stem count – is the number of times the stem of the word occurs in the text. This is obtained using the `PorterStemmer` module in the NLTK library.

Boolean features are another variety, which behave differently to the other features. Examples of boolean features include the presence of an image on a page, compliance of the page to an existing HTML standard and presence of advertisements.

The features have been added incrementally as the project progressed. All other features are similar to the ones described above and are obtained using the same methods.

3.7. Naive Bayes

In Section 2.1.1 it has been shown that the Naive Bayesian Classifier (NBC) is a good learner to implement as the first prototype, so a very quick implementation was preferred to make sure that the system can function as intended. Due to its simplicity and popularity, the NBC is widely available in libraries. Because the implementation of this module is straightforward and not central to the project, I decided to use one of many existing Python implementations.

The *NLTK* library implementation was particularly appealing as it offers a very concise interface. A classifier object is initialised by the `train` method on the `NaiveBayesClassifier` class. The format of the training set is defined as a list of tuples of featuresets and labels, e.g.

$$[(featureset_1, label_1), \cdots, (featureset_N, label_N)]$$

The `train` method simply computes the prior – the probability distribution over labels $P(label)$ and the likelihood – the conditional probability $P(featureset = f|label)$

by simply counting and recording the relevant instances. The method outputs a `NaiveBayesClassifier` instance parametrized by the two probability distributions. To avoid having to calculate $P(features)$ explicitly, a normalizing denominator 3.6 is used.

$$\sum_{l \in labels} (P(l)P(featureset_1|l) \cdots P(featureset_N|l)) \tag{3.6}$$

The `classify` method on the `NaiveBayesClassifier` object takes exactly one featureset and returns a label which maximizes the posterior probability $P(label|featureset)$ over all labels. Previously unseen features are ignored by the classifier, in order to avoid assigning zero probability to everything.

The only tangible difficulty with the implementation was the framework in which classification is done. This task is, however, achieved by the parser. To batch classify everything in the test directory, the classifier object is passed to the parser, where the featuresets for the test directories are computed, classified and recorded for the evaluation stage later. The particulars of this process were described in Section 3.6.

3.8. Support Vector Regression

In Section 2.1.2 I have introduced the theory of support vector machines. This section starts off with the implementation, which builds on the theory described in Section 2.1.2 and explains further transformations, which made up the essential part of the implementation. The section goes on to introduce some kernel functions and finishes off by explaining how hyperparameters might be tuned.

3.8.1. Implementation

To implement a support vector machine one must solve a problem of optimizing a quadratic function subject to linear constraints, usually referred to as the *Quadratic Programming* (QP) problem. Therefore, the first implementation task was to convert our existing optimization problem into a generic QP form to make use of the available solvers.

The maximization problem given in Equation 2.8 can be trivially expressed as the minimization problem in Equation 3.7.

$$min_{\boldsymbol{\alpha},\boldsymbol{\alpha}^*}\frac{1}{2}(\boldsymbol{\alpha}-\boldsymbol{\alpha}^*)^T P(\boldsymbol{\alpha}-\boldsymbol{\alpha}^*)+\epsilon\sum_{i=1}^{l}(\alpha_i+\alpha_i^*)-\sum_{i=1}^{l}t_i(\alpha_i-\alpha_i^*) \tag{3.7}$$

Subject to constraints 3.8 and 3.9 below. This derivation can be found in the LIBSVM paper[3], however, the version in the paper contains an error.

$$\mathbf{e}(\boldsymbol{\alpha}-\boldsymbol{\alpha}^*)=0 \tag{3.8}$$

$$0\le\alpha_i,\alpha_i^*\le C,\ i=1,...,l \tag{3.9}$$

where $\mathbf{e}=[1,...,1],\ P_{ij}=K(x_i,x_j),\ t_i$ is the target output, $C>0$ and $\epsilon>0$.

At this point in the implementation, for the first time, Python did not seem like the ideal choice of programming language. *CvxOpt* is one of the few Python libraries that implements a QP solver. The specification to the QP function is as follows: `cvxopt.solvers.qp(P,q,G,h,A,b)` solves a pair of primal and dual convex quadratic programs

$$\min\frac{1}{2}x^TPx+q^Tx \tag{3.10}$$

subject to

$$Gx\le h \tag{3.11}$$

$$Ax=b \tag{3.12}$$

Described in the next few pages are the transformations I devised to reconcile the minimization problem in Equation 3.7 and the library specification in Equation 3.10 and their respective constraints.
We take x to encode both $\boldsymbol{\alpha}$ and $\boldsymbol{\alpha}^*$ simultaneously, treating the upper half of x as $\boldsymbol{\alpha}$ and the lower half as $\boldsymbol{\alpha}^*$:

$$x=\begin{bmatrix}\boldsymbol{\alpha}\\ \boldsymbol{\alpha}^*\end{bmatrix}$$

We will see later how this definition allows for elegant representation of the problem (Equation 3.7).

First, we express the first term of Equation 3.10 to hold $(\boldsymbol{\alpha} - \boldsymbol{\alpha}^*)^T P(\boldsymbol{\alpha} - \boldsymbol{\alpha}^*)$. Take matrix P in Equation 3.10 as

$$P = \begin{bmatrix} K & -K \\ -K & K \end{bmatrix}$$

where $K_{ij} = K(x_i, x_j)$ is the kernel.
Observe that now

$$x^T Px = \begin{bmatrix} \boldsymbol{\alpha} \\ \boldsymbol{\alpha}^* \end{bmatrix} \begin{bmatrix} K & -K \\ -K & K \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha} \\ \boldsymbol{\alpha}^* \end{bmatrix}$$

and is equivalent to the first term of Equation 2.8:

$$\sum_{n=1}^{N} \sum_{m=1}^{N} (a_n - a_n^*)(a_m - a_m^*) K(x_n, x_m)$$

Now express the remaining two terms in Equation 3.7 by taking

$$q = \begin{bmatrix} \epsilon\mathbf{e} - t_0 \\ \vdots \\ \epsilon\mathbf{e} - t_{N-1} \\ \epsilon\mathbf{e} + t_0 \\ \vdots \\ \epsilon\mathbf{e} + t_{N-1} \end{bmatrix}$$

to achieve

$$q^T x = \epsilon \sum_{i=1}^{l} (\alpha_i + \alpha_i^*) - \sum_{i=1}^{l} t_i(\alpha_i - \alpha_i^*)$$

To encode constraint in Equation 3.9 consider the following pair of G and h.

$$G = \begin{array}{cc} \begin{array}{cc} \overbrace{\qquad\qquad\qquad}^{\text{N}} & \overbrace{\qquad\qquad\qquad}^{\text{N}} \end{array} & \\ \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & \cdots & \cdots & 0 \\ 0 & 0 & \ddots & 0 & \cdots & 0 \\ 0 & \cdots & 0 & \ddots & 0 & 0 \\ 0 & \cdots & \cdots & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & \cdots & \cdots & 0 \\ 0 & 0 & \ddots & 0 & \cdots & 0 \\ 0 & \cdots & 0 & \ddots & 0 & 0 \\ 0 & \cdots & \cdots & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} & \begin{array}{l} \left.\begin{matrix} \\ \\ \\ \\ \\ \\ \end{matrix}\right\} \text{2N} \\ \left.\begin{matrix} \\ \\ \\ \\ \\ \\ \end{matrix}\right\} \text{2N} \end{array} \end{array}$$

$$h = [\overbrace{0 \ldots 0}^{2N} \,|\, \overbrace{C \ldots C}^{2N}]^T$$

The final constraint in Equation 3.8 is trivial to adapt by simply taking

$$A = [\overbrace{1, \ldots, 1}^{N}, \overbrace{-1, \ldots, -1}^{N}]$$

and

$$b = 0$$

After the matrices were calculated, all that remained was to implement the transformations. The *Cvxopt* library has its own matrix constructor, however, has generally limited functionality when it comes to matrix operations, so *Numpy* was used much for matrix manipulation.

During the first implementation attempt, the solver gave mostly unintelligible error messages, so for the prototype of the SVM, I used the `Matlab` programming language. Matlab's `quadprog` function had an identical specification to the Python solver I intended to use. Matrices in Matlab are a lot more straightforward to manipulate, which was also a good reason for using it to check the correctness of my matrices before porting the code to Python.

3.8.2. SVM Kernel Functions

The kernel functions offer SVM great flexibility, however, it can be difficult to pick an appropriate one. If the expected pattern is well-defined, kernel selection might be intuitive. For example, a linear kernel is perfect for linear heuristics and the problem is reduced to fitting a hyperplane. Similarly, a radial basis kernel picks out hyperspheres. However, when we have no expectation of data, we need a most general kernel. In this section I examine a few kernels with various score functions. The kernels used in this section have been tuned as described in Section 3.8.3.

Name	$\boldsymbol{K(\vec{x}, \vec{y})}$
Linear	$ax \cdot y^T + c$
Gaussian	$\exp^{-\gamma\|\|x-y\|\|^2}$
Sigmoid	$\tanh(ax \cdot y^T + c)$
Polynomial	$a(x \cdot y^T)^d$
Weighted Sum	$a * Gaussian(x, y, \gamma) + (1 - a) * Linear(x, y)$
Product	$Linear(x, y) * Gaussian(x, y, \gamma)$

Table 3.2.: *Kernel Functions*

Kernel functions are the central component of SVM, and its choice is highly dependent on the application. I have considered a variety of kernel functions and experimented with their combinations to see how the performance differs. Table 3.2 shows the kernel functions I have used.

The simplest kernel function is the Linear kernel. It is simply a dot product of two vectors. Its generalized version is the Polynomial kernel, which takes degree as a parameter. Intuitively, the polynomial kernel is a lot more flexible than linear, but the larger the degree, the less 'smooth' it becomes, so it might overfit the training data.

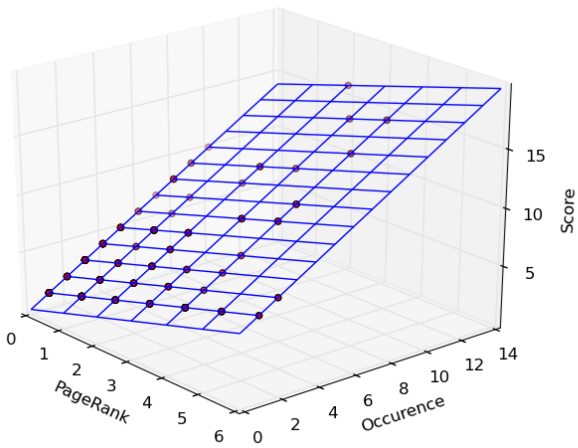
The Gaussian kernel is an example of a family of the Radial Basis Function kernels, which are most popular in SVM. $||x - y||$ denotes the Euclidean distance of the two feature vectors. The γ parameter is equivalent to $\frac{1}{2\sigma^2}$. The choice of γ has a major effect on the performance of the kernel and represents a trade-off between over- and underfitting.

The Sigmoid kernel is commonly used in neural networks and in combination with an SVM classifier forms a two layer perceptron network, where the scale parameter a is usually set to 1/N, where N is the number of dimensions (features)[9]. This kernel is different from the rest described here, as it only satisfies Mercer's conditions[1] for some values of its parameters, which means SVM can be constructed only for those values[11].

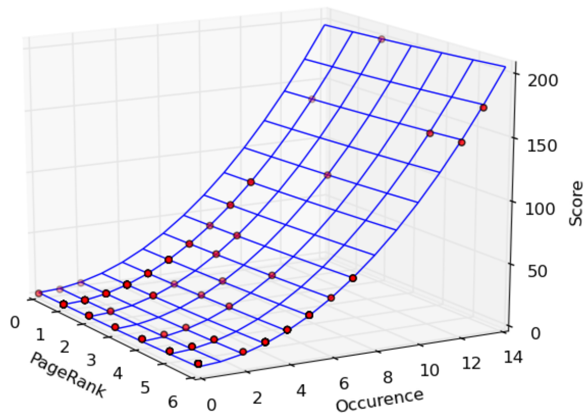
[1] A real-valued kernel K(x,y) satisfies Mercer's conditions if for all square integrable functions g(x) $\int\int K(x,y)g(x)g(y)dxdy \geq 0$.

The Sum and Product kernels are both an example of combination kernels, in this case a combination of the Linear and Gaussian kernels. I found that in situations where one kernel alone does not perform well, combination kernels might improve performance.

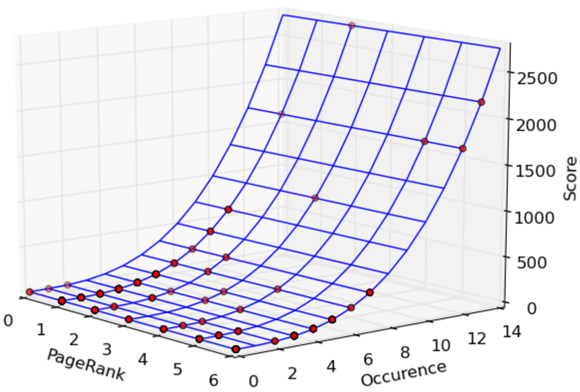
Figure 3.5 shows four different kernels (Linear, Polynomial of degrees 2 and 3 and Gaussian) applied to four distinct two dimensional heuristic functions (Linear, Quadratic, Cubic and Step). Clearly, the first three fits seem effortless, but fitting the step function with a Gaussian kernel was a lot more tricky. The Gaussian γ parameter was chosen by tuning as described in the next section.



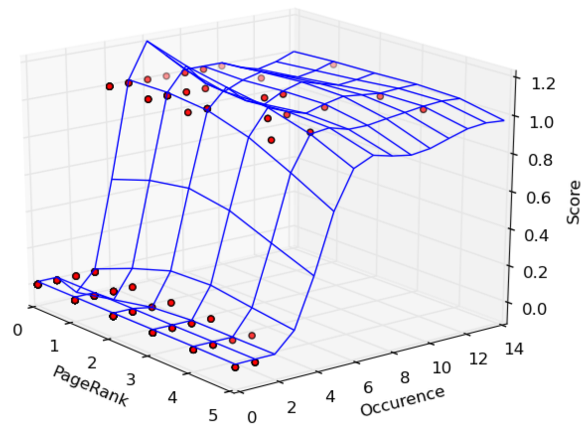
(a) *Linear*



(b) *Quadratic*



(c) *Cubic*



(d) *Step*

Figure 3.5.: *Four different two dimensional heuristic functions are fitted by SVR with four corresponding kernels: linear, polynomial degree 2, polynomial degree 3 and Gaussian.*

3.8.3. SVM Hyperparameter Tuning

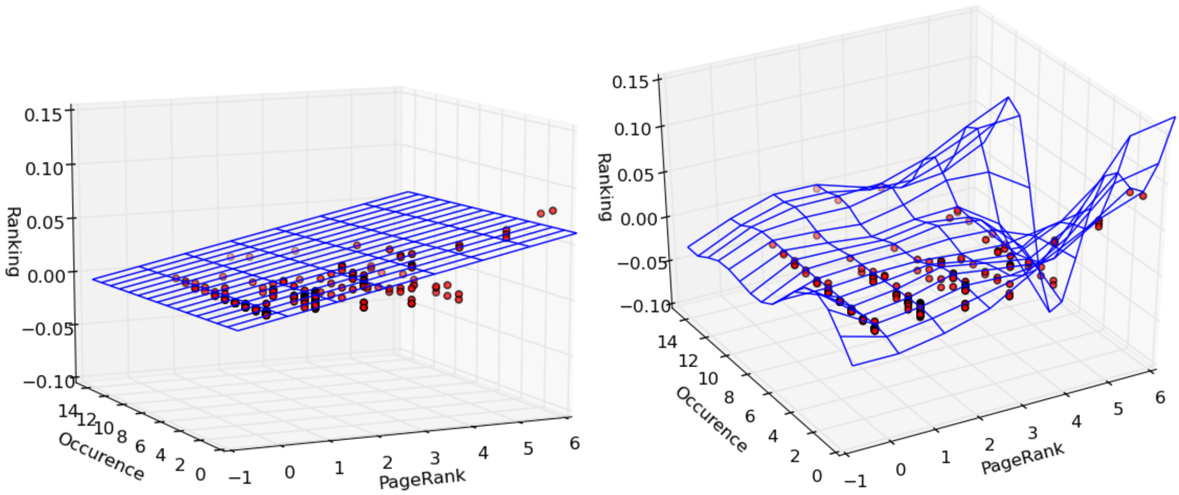
In comparison to Naive Bayes, SVM has a lot of degrees of freedom. The choice of kernel function was discussed in the previous section, however, each kernel has more adjustable parameters of its own. This section illustrates how kernel parameters might be tuned to minimize Mean Squared Error (MSE) to achieve a better fit.

Example: Given noisy data, find the hyperparameter values of the Product kernel which minimise MSE.

Recall the Product kernel definition from Section 3.8.2:

$$Product(x, y, \gamma) = Linear(x, y) * Gaussian(x, y, \gamma) = x \cdot y^T \exp^{-\gamma||x-y||^2}$$

The γ parameter determines how much effect the Gaussian component has: when γ is zero, the fit is purely linear. In this example I have chosen to use noisy non-injective data to show how complex fitting can be achieved. Two parameters γ and ϵ are varied until MSE is minimised. Figure 3.6 shows how the product kernel fit is improved by hyperparameter tuning. The rest of the section describes how this result was obtained.



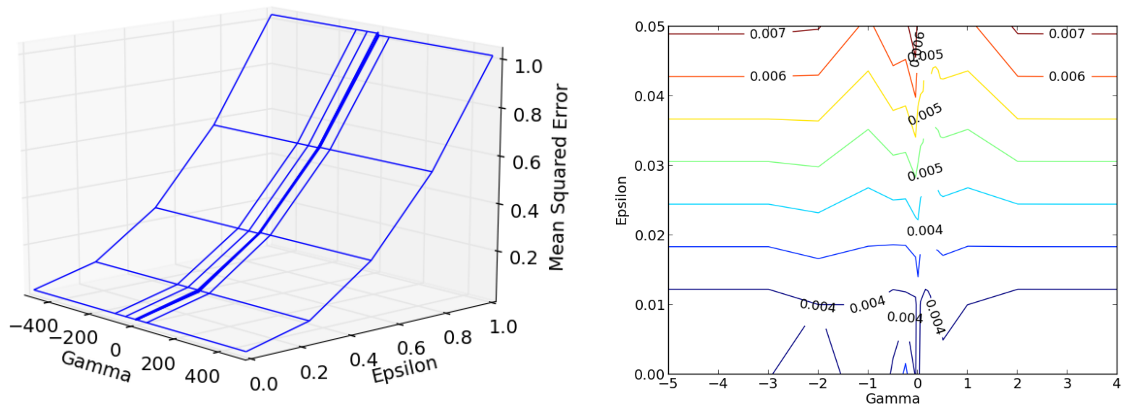
(a) $\gamma = 0$ (b) $\gamma = -0.23$

Figure 3.6.: *The same data is fit by the product kernel with different hyperparameters. Purely linear fit is improved by Gaussian: when γ is tuned, the hyperplane is perturbed to provide the best fit.*

Grid search

There are several ways of adjusting parameters, of which grid search is the simplest. In grid search a range of values for each parameter is specified and the MSE for each value is recorded. To choose the domain successfully, the analysis has to happen at different scales, starting from coarser (wider spread) parameter values, each time only choosing the best for finer tuning, so the algorithm works in a tournament fashion.

Figure 3.7 shows analyses at different scales on the training data: the coarsest and the finest (the intermediate results are omitted). Both ϵ and γ are varied, however, the ϵ parameter is expected to be best at 0. This is because we are fitting the training data directly, as opposed to learning from the training data and fitting previously unseen test data (recall that ϵ controls the degree of generalisation). At the coarsest scale (Figure 3.8a) it is observed that the contribution of the ϵ affects the error a lot more in comparison to γ: the plot appears constant with respect to γ. After a number of stages each time reducing the range of γ, it eventually becomes visible that the minima lie where γ is small (Figure 3.8b).

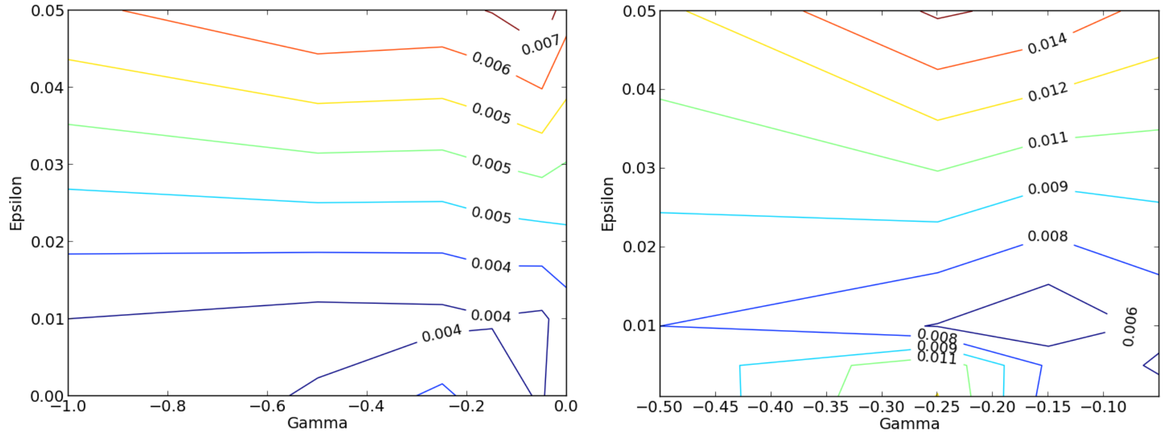


(a) *Coarse analysis* (b) *Fine analysis*

Figure 3.7.: *It is clear from (a), that increasing ϵ affects the fitting of the test data so greatly, that changing γ is insignificant in comparison. However, on the finer scale contour map (b), the minima can be found. As expected, MSE grows monotonically with ϵ in both plots.*

Overfitting

We have just found the best γ and ϵ, which fit training data directly. The values found, however, are not guaranteed to be optimal for the unseen test data due to possible overfitting. Figure 3.8 demonstrates that the minima for training and test data do not coincide. Whereas the training data is best fit with the ϵ approaching zero, the test data is fit better when the ϵ is non-zero, as it prevents sensitivity to the noise in the training data.



(a) *Training Data* (b) *Test Data*

Figure 3.8.: *Non-zero ϵ allows for better fit of the test data.*

Hyperparameter tuning was, perhaps, the hardest part of SVM, which required both very good understanding of the kernel functions, as well as the data used. Though in this section I described a primitive way of tuning, I would consider more advanced automated tuning schemes, perhaps, even using machine learning techniques to determine parameters.

3.9. Summary

In this chapter I have taken the reader from system architecture through the design and implementation of the various components which included the search engine, the parser as well as two machine learning modules.

Work was split between theoretical and pure software engineering. The theoretical work included derivations of the PageRank algorithm and support vector regression, which constituted essential part of the implementation. Some software engineering involved integrating libraries: a library implementation of the Naive Bayes classifier was used; the core of the search engine also relies on the existing indexing tools. Most of the work was in writing original code: implementing a crawler to explore the link structure of the pages; implementing the SVR and computing PageRank (using my derivations); implementing various kernel support for the SVR; designing and implementing a class-based structure to produce feature sets for both training and testing. Finally, the various components were optimized throughout.

4. Evaluation

This chapter presents an overview of the results of the work undertaken for the project and a comparison of these results to the initial goals. The results include both the evaluation of methods implemented as well as qualitative and quantitative assessment of the implementation itself. Furthermore, the chapter describes the measures undertaken to ensure a correct implementation.

4.1. Overall Results

The original success criteria for the project stated in the proposal (see Appendix A) are summarized below:

Criterion 1: *Implemented classifier can identify the importance of PageRank factor in the heuristic.*

The goal has been achieved as described in Section 4.2. Both classifiers were evaluated with PageRank being one of the features. Although PageRank is indistinguishable from any other feature as far as machine learning is concerned, it has been implemented as described in Section 3.3.

Criterion 2: *Various heuristics have been tried with different machine learners.*

This criterion constitutes the core part of the project and the evidence for it can be found in Sections 3.8.2, 3.6 and 4.2.

To achieve the original criteria the following modules have been implemented:

1. Search Engine
2. PageRank vector computation
3. Support Vector Regression and various kernels

4. Naive Bayes Classifier

5. Parser with a data structure supporting various heuristics

The project has been successful in achieving the goals stated in the original proposal. The result of the development is an extensible framework for classifier evaluation that can be used for further evaluation and analysis of machine learning techniques in general.

4.2. Classifier Evaluation

Two machine learning techniques explored in this project – regression and classification – are different in principle. The challenge in the evaluation is, therefore, to obtain results that can be compared despite the differences in implementation. To satisfy the comparability requirement, both SVM and Naive Bayes are run in the score mode: heuristic functions are used to output the score and the classifiers must predict it. The regression case is straightforward, however, there are obvious difficulties in the case of the classifier.

Classes can be used to approximate the score as shown in Figure 4.1. Suppose there are two classes separated by a threshold value T. Then for training all the scores are trivially mapped to the correct class depending whether they are greater or smaller than the threshold T. During evaluation the conversion has to be from the class to the score. Because information is lost during the quantization stage, every example classified into Class 1 is mapped to the median value of the scores – M1 – in the hope to minimize the error due to quantization.

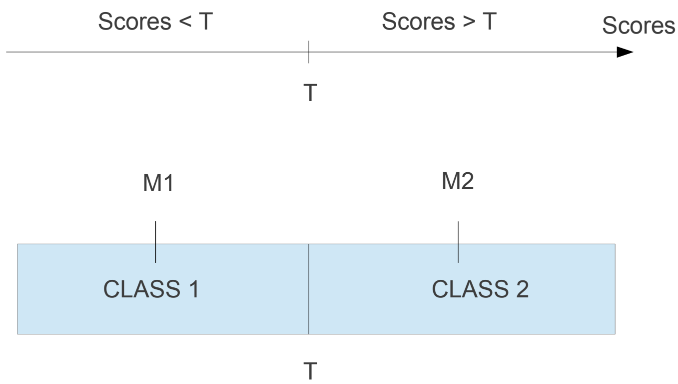


Figure 4.1.: *Quantization into two classes*

This section starts by describing general methodology used throughout the evaluation. The rest is structured in the form of hypothesis statements followed by their evaluations.

4.2.1. Methodology

Evaluation and comparison of classifiers is largely unprescribed: there is no method that applies well to every case. A lot of ambiguity is due to the fact that results obtained are ultimately dependent on the data used for training and testing. There are, however, generic guidelines to ensure adequate evaluation and comparison where possible. This section highlights several such aspects, which are then applied throughout the whole chapter.

Classification and Quantization Error

To compare classification and regression effectively, the error incurred in quantizing scores is tracked. In a two-class scenario there is one threshold score value that separates the two classes. This score value is computed as a median to have adequate class representation. When Bayes assigns a class to a feature set, it is perceived as assigning the mean value of the scores present in the class.

Data

To avoid biased results a development corpus was used during implementation, which was disjoint from the real test corpus and was of smaller size. The development corpus is further subdivided into the training corpus and the validation corpus to mirror the training and the test corpora, which were used to obtain all the results presented in this chapter. The evaluation was performed after the development of the whole system was complete and validated on the development corpus.

Mean Squared Error (MSE)

As a measure of classifier performance I have chosen to use mean squared error. It is computed as

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Actual_i - Predicted_i)^2$$

where $Actual$ is an array of true values of size N and $Predicted$ is the corresponding array of predictions made by the classifier. MSE is the second moment of the error and hence, incorporates both the variance and bias. Squaring penalizes large errors heavily, but small errors vanish, therefore, MSE is sensitive to outliers as opposed to Mean Absolute Error (MAE). On the other hand, MAE is more sensitive to noise, which we expect when predicting continuous scores. Altogether, MSE provides a good measure that is easily visualised.

Tolerance intervals

As MSE already captures the variance of the squared error, computing error bars to be the standard deviation of the squared error would offer no new information. However, the tolerance intervals for the mean error itself is a good measure of how spread the error is. In the best case, the interval is tight, indicating the stability of the seen error. If the error is spread, the classifier is making inconsistent mistakes. It is particularly important to include these in our evaluation due to the presence of quantization error. The mean error of the ceiling and its spread is a good indicator of the mean and variance introduced by quantization.

To compute confidence intervals one could repeat the measurement on different data subsets. The number of subsets would have to be around 20 or more for the Central Limit Theorem to apply. In practice, the data is scarce and recomputing the errors is time consuming, so a way to compute the intervals with just one error measurement is desirable. Bootstrapping achieves exactly that by sampling randomly from the array of squared errors to compute a new mean error. Even though bootstrapping might be less reliable, it provides a simple way to check the stability of the results. 95% confidence intervals were used throughout this chapter to compute error bars.

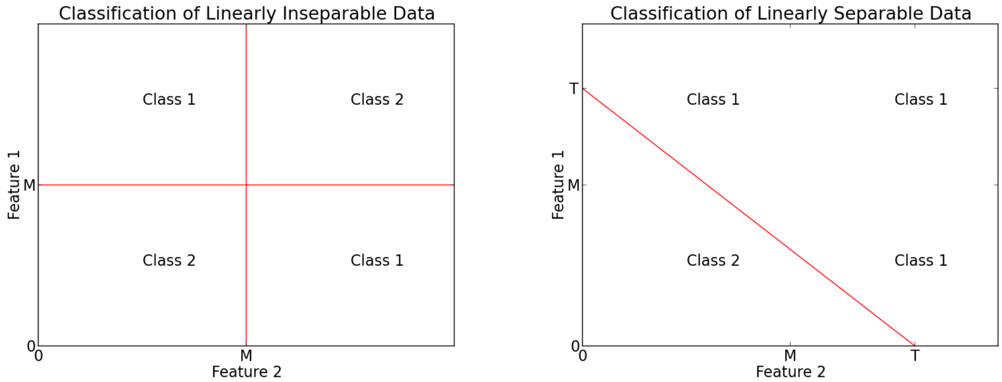
4.2.2. Linear and non-linear classification

Hypothesis: Naive Bayes performs better with linearly separable data.

Naive Bayes is a linear classifier and, therefore, linear separability of data is a premise of successful classification. To test this hypothesis, two minimal two-dimensional examples are constructed as shown in Figure 4.2 below. Example 4.2a cannot be solved by fitting a separating line between the classes, so Bayes is expected to fail in this case. Example 4.2b illustrates a 'cut-off sum' function and is trivially separable. Such a linear heuristic should be easy for Bayes to pick up on.

To evaluate the Bayes behaviour, the learner is run with both heuristics and mean squared errors are computed for both cases. Figure 4.3 shows the mean squared errors within their corresponding confidence intervals. Along with the actual Bayes classification error (denoted as 'Actual' on the y axes) the baseline and ceiling errors are plotted for comparison. The baseline performance is evaluated by randomly assigning classes, whereas the ceiling error illustrates the contribution of quantization error, inherent in classification of non-discrete scores.

The mean squared error in the inseparable case (Figure 4.3a) is significantly larger: in fact, its confidence interval overlaps with the one of the error in random classification (the baseline error). Similarly, the standard deviation of the error is similar in width to the baseline. This is



(a) *Linearly Inseparable Data* (b) *Linearly Separable Data*

Figure 4.2.: *On both plots M represents median points for corresponding features (this ensures adequate number of training examples for all quadrants). The red lines visualize the boundaries between the classes. In (b) the sum of features is equal to the threshold value T on the red line.*

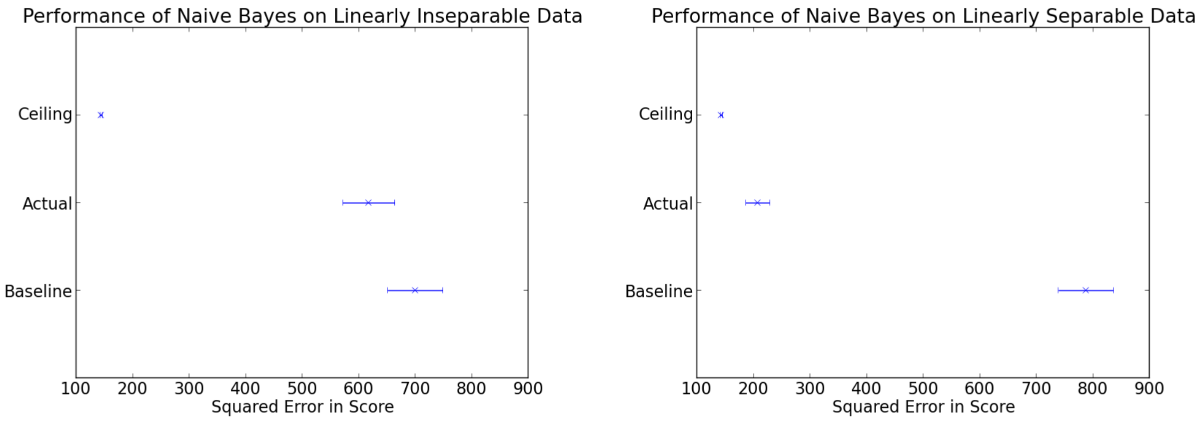
due to the fact that the classifier is making mistakes as frequently as random choice. In contrast, the separable data case (Figure 4.3b) shows a convincing improvement in classification error, however, the classifier is still not perfect. This might be a result of insufficient or unbalanced training data. In this particular case and in general, adding more training data improves the error up to a point when overfitting occurs. Nonetheless, it is rarely possible to gather a subset of training data that will have enough points very near to the class boundary to allow for perfect classification. Therefore, the result is consistent with the proposed hypothesis.

Hypothesis: SVM with linear kernel performs well for linear heuristics, but becomes unusable for non-linear ones.

For comparison, SVM with a linear kernel is tested for linearly separable and non-separable data. In this particular experiment the number of features used is fixed at 2 and the heuristics used are shown in the Table 4.1 below.

Name	Function
Linear	$x + y$
Quadratic	$x^2 + y$
Cubic	$x^3 + y$
Exponential	$exp(x) + y$

Table 4.1.: *Heuristic functions used to evaluate the performance of linear kernel.*



(a) *The mean error is near the baseline performance with similarly wide spread.*

(b) *The mean error approaches the goal performance.*

Figure 4.3.: *Naive Bayes Performance*

The SVM with a linear kernel is run with each of the heuristics shown above. The error parameter is tuned as described in Section 3.8.3. The value of ϵ that produces the best result is used in each case, for example, ϵ is zero in the case of a linear heuristic. The baseline performance is a hyperplane fitted through the mean score. The ceiling performance is computed as a least squares solution of an equation which has the form of the particular heuristic used. *Numpy* provides a *lstsq* function which finds the coefficients of a particular heuristic such that the squared error is minimal.

Figure 4.4 shows a failure of the linear kernel to fit non-linear data. The ceiling error id due to the numerical error in computation: this explains why the ceiling error in the exponential case is the largest of all.

Clearly, as in the Bayes case, the degradation is rapid. In the cubic and exponential cases the SVM seems to perform worse than the baseline, which can be explained by overfitting.

4.2.3. Bayes: Effects of Quantization

Hypothesis: Bayes classifies better when fewer classes are present.

It is intuitive that at a large number of classes, the more classes we introduce, the more precise the classifier has to be to perform equally well. However, taking into account the quantization error, non-linear behaviour might be expected: performance will improve due to the quantization error decreasing faster than precision up to a certain point. This experiment aims to determine the number of classes that minimizes the overall error of the classifier. In some

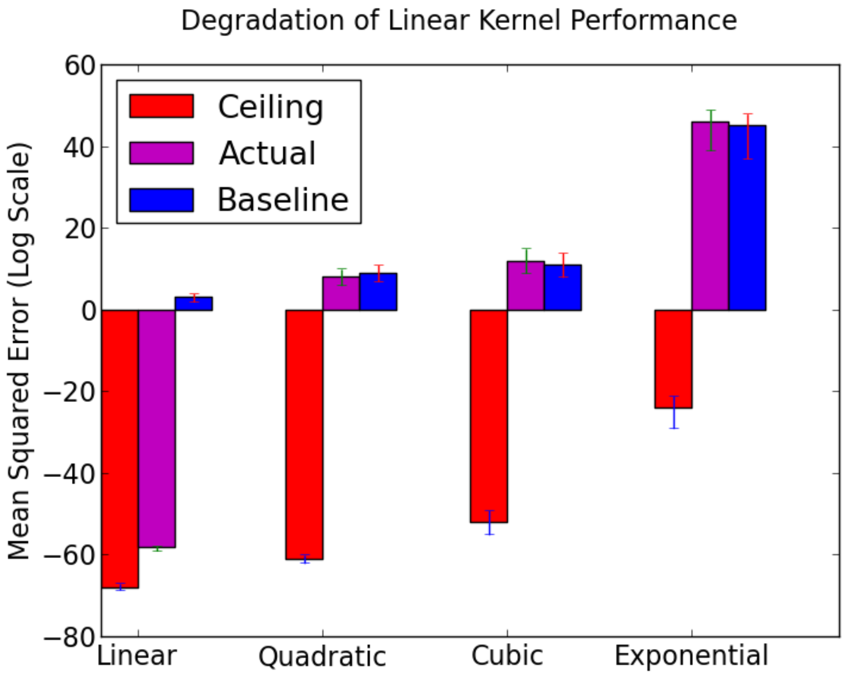


Figure 4.4.: *SVM with a linear kernel is evaluated against four different heuristics (x axis). Note that the MSE is in log scale. The error in the linear case is negligibly small, but is similar to the baseline case for all other heuristics.*

sense, quantization is akin to a hyperparameter: the results are specific to the heuristic and the data used.

In this experiment, a linear heuristic is used with two features as before. The number of classes is varied starting with two. Classes are added until the maximum possible number is reached – the number of distinct scores.

Figure 4.5 shows a result inconsistent with the proposed hypothesis: the error is diminishing as rapidly as the quantization error (ceiling). It is visible from Figure 4.6 that the data remains separable (as expected) independently of the number of classes. Clearly, Bayes is very effective at classification with the given heuristic. It is worth noting, that the actual performance is still worse than the ceiling and does not converge to zero as opposed to quantization error. It is possible that Bayes consistently misclassified a few particular examples, which lead to a gap in the plot.

The example chosen does not verify the hypothesis and proves the intuition wrong: the Bayes performance depends solely on whether the data is separable or not.

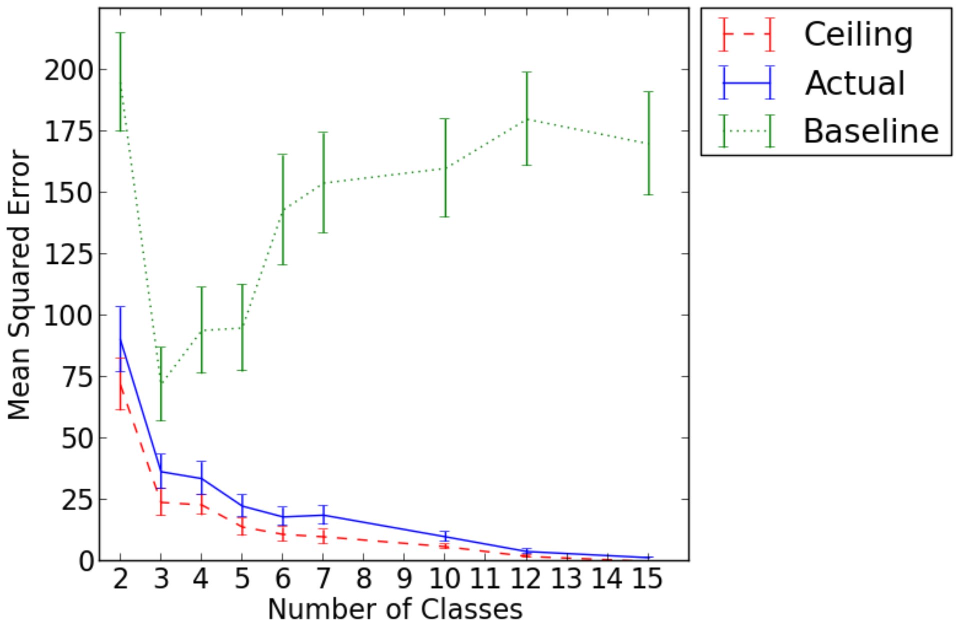
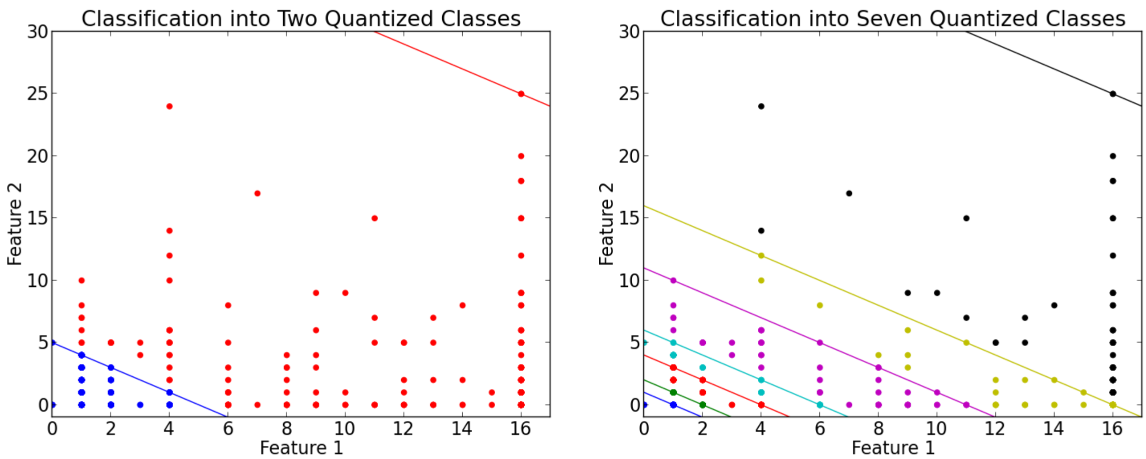


Figure 4.5.: *Bayes performance with varying number of classes.*



(a) *Two classes*

(b) *Seven classes*

Figure 4.6.: *Classification with different number of classes. The data is consistently separable.*

4.2.4. Curse of Dimensionality

Hypothesis: Bayes performance degrades rapidly as the number of features grows.

So far I have explored two dimensional cases where only two features were used for convenience of visualization. The Curse of Dimensionality is one of the well-known issues with classification: when new features are added, the size of the training set has to grow exponentially to cover all the new dimensions. Naive Bayes, however, lessens this problem a little due to the assumption of conditional independence. It is interesting to see how rapidly its performance degrades when more features are added while the training data is unchanged. It is important that all the features used are conditionally independent, as otherwise, the results would not be valid.

The number of classes is fixed at a value of seven, at which the performance is reasonable but still has some quantization error. We are only interested in relative performance, so it should not matter how many classes are used, however, it is important that the number of classes used produces a significantly better result than the baseline, to make sure a random guess could not produce a good result.

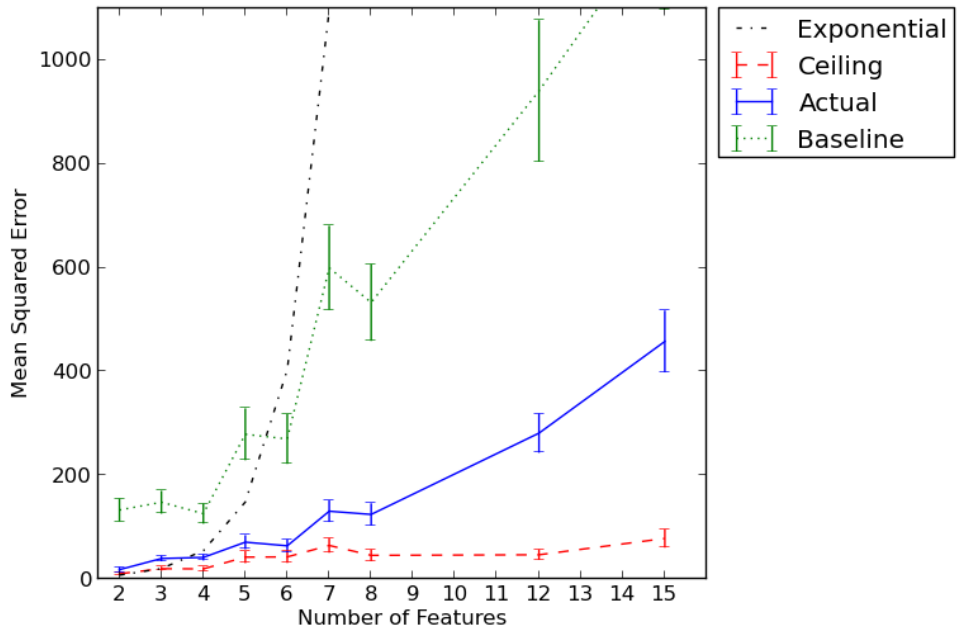


Figure 4.7.: *Bayes performancewith varying number of features.*

The result for a few linearly separable functions is computed and the average errors are plotted in Figure 4.7. The actual classification diverges from the ceiling when the number of features is about six. The rapid growth of the random classification curve is explained by the Curse of Dimensionality: degrees of freedom grow exponentially. The exponential growth is plotted in black for comparison: initially the baseline growth is near exponential, but less steep subsequently. This is due to the quality of training and test data: as the number of features grows, the number of training examples for each class is reduced, influencing the overall performance.

The ceiling and the actual curves are growing almost monotonically, as is expected. The flat regions at 5-6 and 7-8 are explained by the data specifics: the particular features added at those point appeared insignificant in the scores as they occurred infrequently and had small values.

It has proven hard to pick many conditionally independent features. Among the ones used were PageRank, image count, word count, frequency of search term occurrence, quality of HTML and alike.

The hypothesis is verified: the error grows as the number of features is increased. The growth, however, depends also on the quality of features – how much the addition of a new feature alters the classification, as well as on the training set – how many training examples are supplied.

Hypothesis: SVM performance does not degrade as the number of features grows.

As before, linear kernel is used in combination with a linear heuristic. Figure 4.8 supports the hypothesis: the error looks almost constant even in logarithmic scale. Hyperplane fitting is more resilient to more dimensions in the presence of linear heuristics.

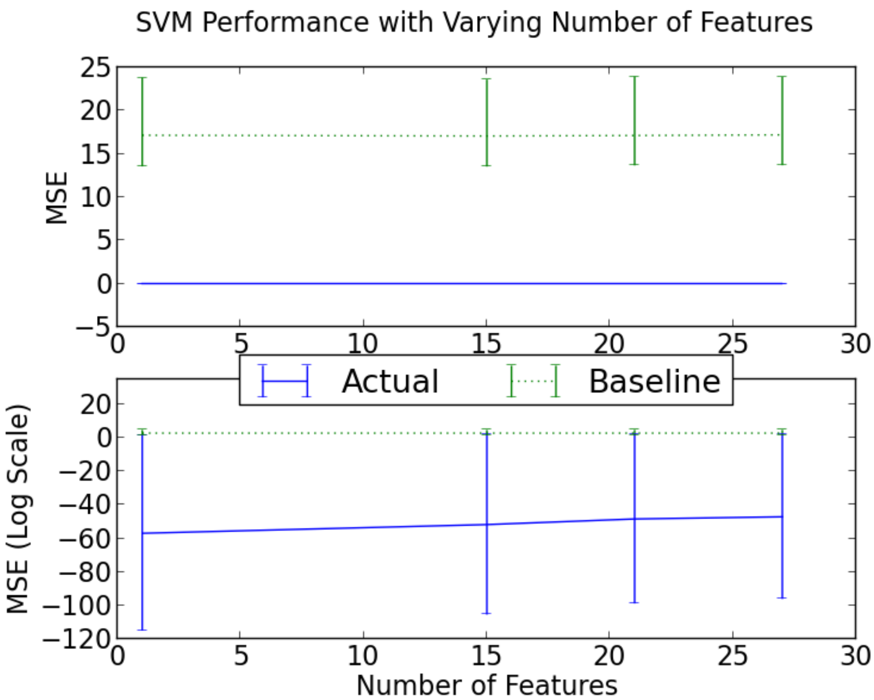


Figure 4.8.: *Both normal (upper figure) and logarithmic (lower figure) scales are shown. The error grows too slow for the growth to be noticeable without the logarithmic scale.*

4.3. Performance Evaluation

As stated in the Preparation chapter, the project does not have any hard timing requirements. PageRank computation, indexing and learning were envisaged as most time consuming. In the end, the time taken in learning and classifying was negligible and same can be said for the parser module. Throughout the implementation, it has become obvious that the most time was spent in indexing and PageRank computation. Therefore, in this section, I am looking in more detail at the timings and scalability of the two modules.

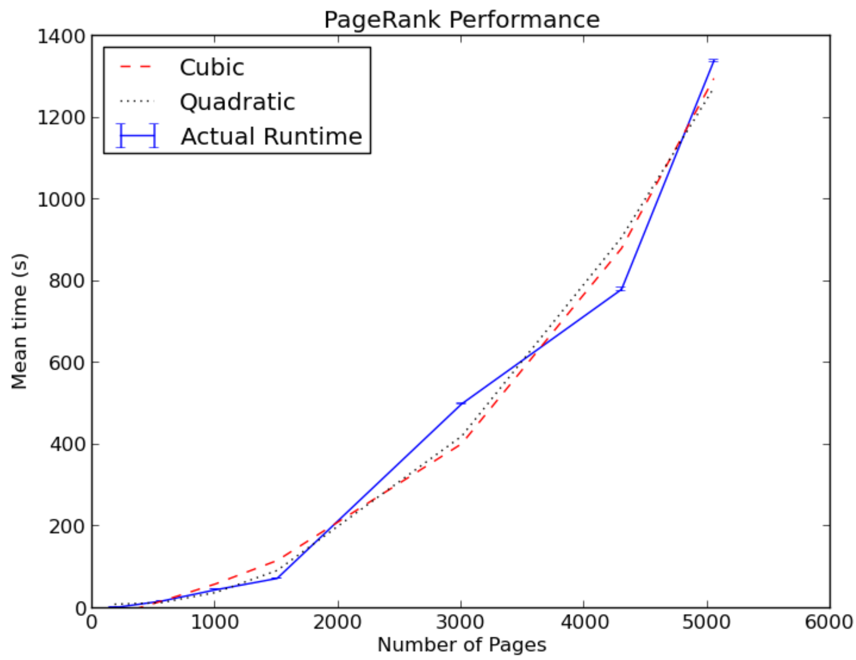


Figure 4.9.: *Time taken in computing PageRank for a growing set of pages. For convenience of comparison, cubic and quadratic curves are fitted.*

The plots were generated using a benchmark suite, which makes repeat measurements and calculates means and confidence intervals. I have configured the suite to take a hundred repeat measurements for a range of page numbers. 95% confidence intervals are represented by the error bars on the plots.

The benchmarks were performed on my personal computer with the following specifications:

Memory	1.7 GB
Cache Size	3072 KB
CPU	Intel Core2 Duo CPU
CPU Clock Frequency	2.26 GHz

Both plots also display fitted cubic and quadratic curves. The curves are fitted using the *Scipy* library curve fitting function, which uses the Levenburg-Marquardt algorithm[1]. Figure 4.9

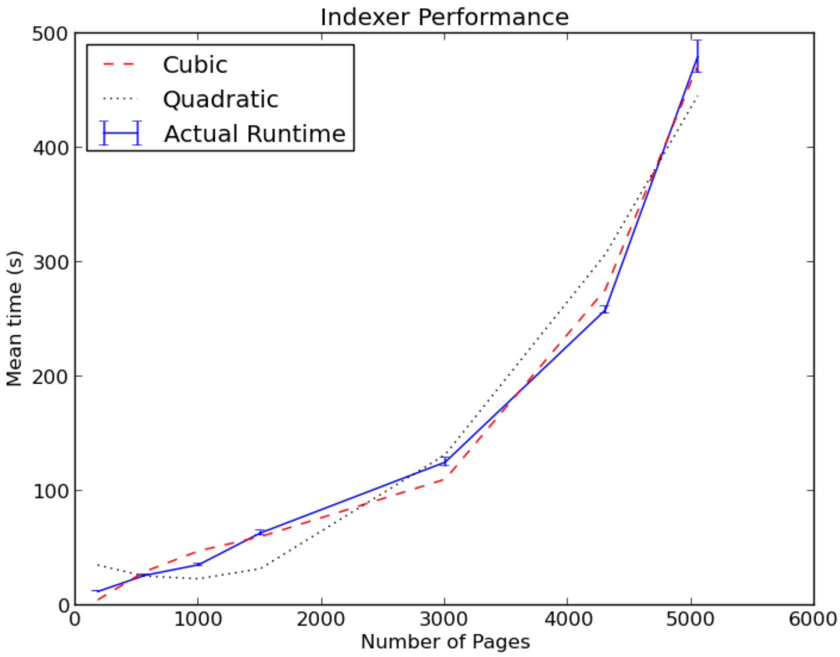


Figure 4.10.: *Time taken in indexing for a growing set of pages. For convenience of comparison, a cubic and a quadratic curves are fitted.*

shows how the performance of the PageRank computation degrades with the number of pages. Although both cubic and quadratic curves fit well, it can be said that up to around 5000 pages the growth is bound by $O(n^2)$. The average number of pages used in the project was around 3000 for each directory, which meant it took around seven minutes to crawl and generate the PageRank vector. However, it is expected that the growth is more rapid beyond the limit of 5000 pages. If dealing with more pages was within the scope of the project, the PageRank computation would have to be optimized further, as matrix inversion does not scale for a problem bigger than a few thousand pages.

Indexing shows similar behaviour, although it seems a lot smoother and unambiguously exhibits cubic behaviour. Indexing 300 pages (the size of the development and verification corpora) takes around two minutes, which is satisfactory considering that speed was not the primary objective of the project.

Altogether, both modules could potentially become a bottleneck. However, as development was carried out on a comparatively small development corpus (only around 500 pages), and

[1] Also known as Damped Least Squares method, the Levenburg-Marquardt algorithm works by minimizing a function over the space of its parameters.

the verified program was then run on the actual data only once, which means the slowest operating cases were infrequent. Both the index and the PageRank vector were stored and reused to avoid expensive recomputation. All things considered, it was not worth further optimizing the modules in question, as speed of implementation was prioritized over the speed of computation due to the infrequency of costly computations.

4.4. Testing

Formal correctness proofs are neither within the aims of the project, nor would they be feasible in the time given. Therefore, the main purpose of the testing is to gain a degree of certainty in the correctness of the program. The system developed is in a sense a prototype: it only gets used one time in order to obtain certain results. Therefore, tests did not need to be run as often as for a system that would be used in production. In addition, human analysis was often required to assess the quality of the programs. These aspects of the system motivate the decision to use manual testing, which is described further in this section.

4.4.1. High Level Test Plan

Table 4.2 summarizes the test plan used. Each of these tests was conducted at the end of module development and whenever a substantial change occurred that could potentially change the behaviour in the cases described.

Module	Test Objectives
Crawler	The output matrix accurately reflects the link structure of the pages
PageRank	The PageRank vector accurately reflects the hierarchy of the web pages
Indexer	Clean indexing overwrites existing index
Indexer	Incremental indexing adds/removes relevant index changes to reflect the changed web pages
Parser	Parser is robust in the face of bad formatting and encodings
Naive Bayes	Classification is better than random for separable data
SVM	The hyperplanes fit the data and change with the data to provide better fitting

Table 4.2.: *Summary of Test Objectives*

4.4.2. Example Test Cases

Crawler and PageRank

Both Crawler and PageRank were tested on artificially engineered small examples of link structure to verify the test objectives have been achieved.

Indexer

Indexing is heavily reliant on the library, so only the implemented parts required extensive testing – incremental and clean indexing capabilities. These were tested on the verification corpus. To test incremental indexing, pages were added, removed and altered and the relevant queries executed to verify that the changes have taken effect. The clean index was built both without an existing index – in which case a new index was created – and with an existing index – to verify that the old index is replaced by the new one.

Parser

The objective of the Parser testing was mainly its resilience to failure: examples of malformatted HTML and pages with special characters in the address were used to verify the robustness.

SVM and Bayes

Machine Learning modules both were tested with the visual aid of plotting in the two- and three-dimensional cases. The data was plotted alongside the hyperplane (SVM) or the separating line (Naive Bayes). The data was altered to provoke change in the hyperplane/separator and the subsequent change was verified.

4.5. Summary

In this chapter I assessed the performance of classifiers with different heuristics and drew some comparisons between them. I also benchmarked the performance of the slowest modules and illustrated the testing strategies adopted in this project.

5. Conclusions

The exploratory nature of the project allowed me to learn a lot both in the field of information retrieval and machine learning. I have started with very little insight in either field and thoroughly enjoyed the discoveries I made throughout.

5.1. Achievements

The project was successful in meeting all the requirements laid out both in the proposal and elaborated in the preparation stage. It is the first project to attempt to tackle search engine heuristics with a machine learning approach. The framework set in place can be used as a stepping stone in this previously unexplored area.

It is the largest project I have ever attempted and, perhaps, the most significant achievement has been the knowledge I have acquired during the process.

5.2. Lessons Learnt

The main lesson I have learnt from this project is that the importance of design cannot be underestimated. At the beginning I expected the programming to be the hardest part and, perhaps, rushed into implementation without having spent adequate time planning what should be done and how best to do it. This resulted in some redundant work that could have been avoided. If I were to do this project again, I would allocate more time to design at the beginning.

Another important observation that I am taking away is in tune with the previous point: writing loosely coupled and modular code pays off eventually. As code grew, refactoring often became unavoidable, but could have been made easier, had I programmed with re-usability in mind.

5.3. Future Work

Although the implementation is complete in the sense that it fulfills the success criteria for the project, the greater goal of the project is open ended. The framework developed can be used to further explore the machine learning techniques considered as well as to integrate the data from existing search engines. Also the machine learners can be used for a variety of different purposes unrelated to search engines.

The implementation can be enhanced by a user interface and made available on the internet for anyone to download, use and improve.

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A. Project Proposal

Introduction, The Problem To Be Addressed

PageRank (an algorithm which is used by Google to evaluate the 'importance' of a web page) is one of the most crucial factors which determine page performance in search returns. However, there are many more of such factors that are believed to become increasingly influential. Because Google's algorithm is frequently revised, changing page ranks cause web site owners to speculate about how their web pages 'deserved' an upgrade or a downgrade. Despite a large interest in this area, little research has been done to determine to what degree such factors affect the performance of a page. Certain tools[1] exist which attempt to advise web masters how to 'improve' their pages. However, heuristics used by such tools are not known and are possibly incomplete and no attempt has come close to accurately predicting Google rankings.

A problem of approximating algorithms which may be used by modern search engines is characterised by vast search space, which makes exhaustive search impossible and introduces the need for generalisation. Such a problem can be reduced to a classification problem, which is traditionally solved with the help of machine learning techniques. Even though machine learning finds natural application in this area, it is easy to see how it would be very hard to create a learner and apply it to, for example, Google's search engine. Naturally, one would need to have exhaustive resources to conduct such a study. Besides, machine learning has major drawbacks that would hinder such an ambitious experiment.

Firstly, there are little theoretical guarantees in this approach. Bounds, if any, referring to how much data needs to be processed to produce a 'correct' classifier are very imprecise and a classifier that performs well in practice may not be 'true'[2]. This means that if a machine learner was to be trained by the 'real world' data (Google search returns), little could be said about the performance of the obtained algorithm or, indeed, the 'truthfulness' of it. Not only would it give little insight into how successful the learning is, but also no guidance for improvement.

Another similar issue is referred to as 'overfitting': this describes a situation in which a classifier performs outstandingly on a particular set of data (often similar to training data), but given

[1] For example, Woorank or SEO are the most popular Chrome extensions to assess certain page qualities.
[2] A classifier is 'true' if it classifies data correctly for all inputs.

different data will perform as badly as random selection. This occurs when false connections between features and outputs have been made by the learner. Unfortunately, there is no single technique that will always avoid over/under-fitting[4].

Clearly, such limitations are hard to combat. Besides, machine learning techniques vary greatly, so clear and detailed feedback is essential to draw conclusions about the performance of a learner. Knowing how a particular technique copes with certain heuristics would be valuable, as it would allow to approach the original problem (approximating search engine heuristics reliably) in an informed way.

In this light, this project aspires to explore how machine learning techniques can be used to infer algorithms from search engines. To battle the constraints described above I will write my own simple search engine which will be used to observe the effectiveness of different machine learning techniques (see Figure A.1). The existence of such a search engine is vital to the project, as it offers ultimate control over the learning process. The heuristics used in the search engine will be transparent, which, for example, eliminates the dependency on continuously changing heuristics used by Google. Another advantage of this approach is the fact that only a minimal fraction of the web needs to be used. Such a 'mini-internet' will reside offline, which will speed up the indexing and also allow local modification of web pages.

Most importantly, this approach gives me straightforward ways to reason about the performance of learning techniques. The search engine can be evolved to incorporate various heuristics together with PageRank. Such heuristics need not match Google's actual heuristics, however must aim to improve browsing experience [1]. A lot of speculation has been done by web masters as to which qualities of a web page affect its ranking, these include compliance with web standards, number of words per page, frequency of occurrence of the search term on the page and alike. Because the goal of the project does not include 'reverse engineering' any particular existing algorithm, there is no harm in using such guesses as guidance.

Evolving the search engine and, hence, the learner iteratively will result in comprehensive conclusions about the effectiveness of the machine learning technique in question. Such conclusions can be used in the future as a guidance to learner design.

Starting Point

- A project[2] was undertaken by the proposer, which developed a primitive algorithm to predict, given six characteristics of a web page, its Google ranking. This project is mainly

[1] 'Precision and Recall' method can be used as a guide to evaluation of search engine complexity.
[2] http://www.scienceforsearch.com/project1.asp

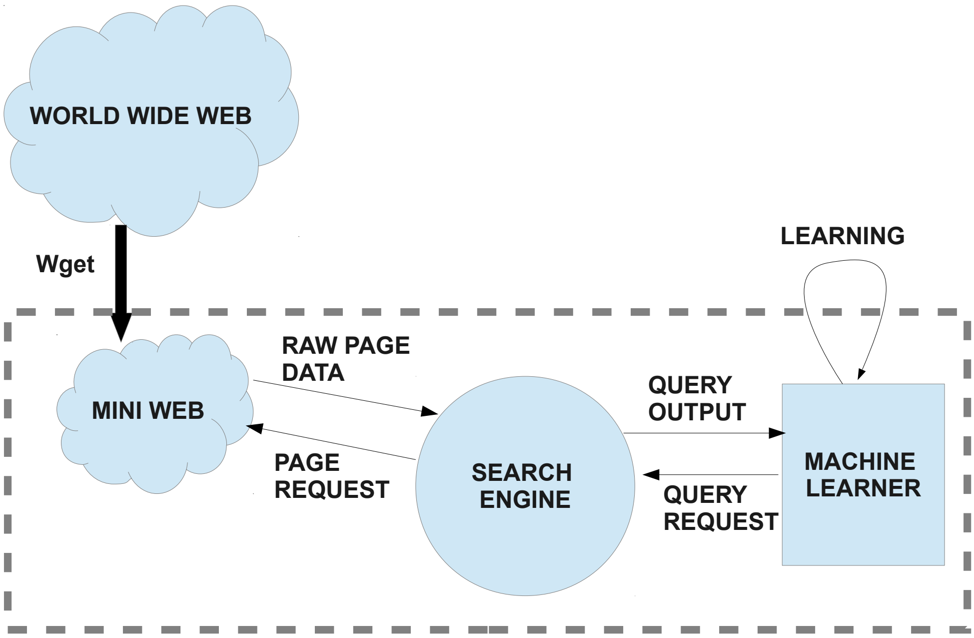

Figure A.1.: *The training of the learner. The system enclosed within the dotted box will be implemented in this project. The mini web is created by cloning web pages from the internet. The learner queries the search engine and gets back the results of the query as an input.*

an inspiration, however, the speculations about the Google page ranking factors can be useful for the search engine design.

- Python packages exist for manipulating web pages.
- Wget is a Linux open source utility that can be used to clone web pages.
- The paper describing PageRank is published and will be used to implement the algorithm.

Resources Required

- For this project I shall mainly use my own dual-core computer that runs Ubuntu Linux. I accept full responsibility for this machine and I have made contingency plans to protect myself against hardware and/or software failure.
- Backup will be to a BitBucket repository and/or an external hard drive.
- I will work on MCS computers should my main machine suddenly fail.

Work to be done

The project breaks down into the following sub-projects:

1. Decide on a category of search terms to explore in order to create a small network consisting of relevant web pages.
2. Implement PageRank within this network.
3. Write a simple search engine incorporating PageRank and few other features.
4. Decide on the representation of the input for the learner and set up the framework to format it.
5. In advance set aside training and test data: this is necessary to then justify the evaluation of the classifier.
6. Write a simple prototype for the learner[1] to test the grounds. Evaluate its performance to then set goals for the final learner.
7. Design, implement and test the learner.

[1]A Naive Bayesian would be a good prototype to use.

8. Attempt to evolve the search engine to be more usable and complex and observe how the learner copes with the changes of the search engine.

Success Criterion for the Main Result

The project will be a success if...

- The resulting classifier can identify the importance of the PageRank factor in the given search engine.
- The results of the experiment show how the chosen machine learning technique deals with various search engine heuristics. I would especially like to observe that certain heuristics are harder to pick up on than others and vice versa.

Possible Extensions

If I achieve my main result early I shall experiment with other machine learning techniques to see which perform better. I could also apply my learner to real search engines such as Google and Bing in the hope of discovering dependencies between features of the page and its success in ranking results.

Timetable: Work plan and Milestones to be achieved.

Planned starting date is 19/10/2011.

1. **9 Oct - 19 Oct**:
   - Do preliminary reading.
   - Familiarize myself with the field of machine learning.

   Milestone: Complete project proposal.
2. **Oct 20 - Nov 3**:
   - Decide which and how many websites should be cloned for use as the mini web.
   - Prepare some training data and, separately, test data. This includes queries to be run on the search engine and expected results.

3. **Nov 4 - Nov 15:**
   - Start writing a simple search engine and evaluate it on the test data.
4. **Nov 15 - Nov 25:**
   - Finish the search engine.
   - Start developing an early prototype for the learner.

   Milestone: Have a prototype of a complete system.
5. **Nov 25 - Dec 15:**
   - Evaluate the performance of the prototype learner.
   - Design and start implementing the final learner using the results obtained from the prototype as guidance.
6. **Dec 16 - Jan 1:** Finish the implementation of the learner.
7. **Jan 2 - Jan 16:** Evaluate the resulting classifier. Here is also good time to try a different design for the learner if the classifier does not perform as well as intended.
8. **Jan 17 - Feb 1:** Start working on progress report. Milestone: Write progress report.
9. **Feb 2 - Feb 20** Implement extensions.
10. **Feb 20 - Mar 5:** Evaluate extensions.
11. **Mar 5 - Mar 25:** Write dissertation main chapters.
12. **Mar 25 - April 10** Further evaluation and complete dissertation. Milestone: Dissertation final draft is finished.
13. **April 11 - April 20:** Proof reading and submission.