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Question analysis of coding questions on StackOverflow

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Preface

This is my Master thesis concluding the two years spent at NTNU Gjøvik: Master Applied Computer Science - Web, Mobile, Games track. The thesis was carried out during the spring semester 2016, from January to the end of May.

The main concept for the thesis was based on discussions with supervisor. The original plan was to create a Chat Agent that could answers students questions and give feedback to their question quality, by using StackOverflow as a knowledge base. However, during the Master thesis project presentation, other professors noted that the scope of the project was to large for a Master thesis. The thesis were therefore narrowed down to focus on coding questions posted on StackOverflow, in an attempt to evaluate question quality and predict the future votes for a given question.

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Acknowledgement

Abstract

Stack Overflow (SO) is today for many developers a well known Question-Answering (QA) system. However, SO has a high requirement to the questions and answers posted, which is reflected through their voting and reputation system. This peer-review processes can be used as an indicator to a questions quality, where questions with high up-votes can be defined as good questions. In this thesis, a system has been developed using Machine Learning (ML) and Support Vector Machines (SVM) to see if it is possible to predict whether or not a new question will be considered as a good or bad question.

This was achieved by using the Stack Exchange (SE) data set, specifically using the one for SO. Questions were dived into two classes, where bad questions was question with a vote score below zero, and good questions were those above zero. Based on content in the various questions, a set of feature detectors was developed and tested against the raw data set. Surprisingly, the features actually lowered the overall score (the raw data set had a score of 0.804, and the ones using all the feature detectors had a score of 0.793).

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1 Introduction

Today, many uses the Internet as a resource to find answers to their questions and problems. In the past, one were often restricted to only use keywords and not being able to pose the problem as you would when asking another human being. Most search engines today can handle natural language queries, which makes it easier to find the answer you are looking for. The Internet offers a wide range of resources to acquire new knowledge, everything from encyclopaedias to blogs, forums and Question-Answering (QA) communities. One well known QA community is the Stack Exchange (SE) community, which is built upon the same model as Stack Overflow (SO) [1]. SE has grown large since its release in 2009, and now contains 154 different communities.

As a developer, one often find oneself in the situation that a part of the code does not work, you get weird error messages, or you are simply stuck. This is were SO comes in. SO is a part of the SE community, although SO was actually released before SE. Jeff Atwood and Joel Spolsky wanted to offer programmers a QA site where they could get the answer they wanted without having to read through a lot of text, see others posting "I also have the same issue" or having to subscribe and pay to see the solution [55]. Question (and answer) quality is maintained through the use of a peer-reviewed gamification system, where users are awarded with votes, reputation and badges for their participation [37, 51, 55, 67]. One of the requirements is that the questions should be of good quality [58, 63, 62]. If a question is bad, users can vote to close or delete it (in which the question will be put on hold). A question can be put on hold or closed if they meet any of the following criterias: Exact duplicate (same question has been asked before), off-topic (not related to SO), unclear what is being asked, too broad (e.g. could write a book about question being asked) or primarily opinion-based [8, 60].

1.1 Problem description

Most of the systems that have been developed so far focuses on finding the best answer to a question asked by the user. Few, if any, focuses on the quality of the question being asked. What defines a good question, and can we in anyway predict whether or not a new question posted on SO will be considered good or bad by the community? There are many users who has either a negative view or relationship in regards to SO. Many experience that their questions gets down-voted, closed or even deleted. For some, they simply do not know how to ask an acceptable question. Questions related to homework are one example of questions that

add examples here

are not accepted on SO. There is even a post on Meta.StackExchange discussing whether or not it should be acceptable to use greetings and sentiments in posts [7]. Therefore, the question becomes: What is and is not a valid question on SO?

1.2 Research questions

- What defines a good (coding) question on SO?
- Can we predict a questions quality by using Support Vector Machines (SVM)?
- What type of features increases the accuracy of the SVM?

1.3 Methodology to be used

The theoretical background in this thesis is mainly focused on Question Classification (QC) and similar research in relation to SO. What has been the focus of other researchers, and in what way did they proceed to solve their questions? The analysis of the questions are done by using the publicly available database dump, which is available via SE archive[1] [56]. There are several others who have used the same dataset [1, 2, 18, 37, 40, 52, 64, 73]. Taking into consideration that SO was released in 2008, it means that it now contains approximately 8 years of peer-reviewed data. Because of the size of the data set, and the total amount of posted questions, going through all questions manually would be too time-consumings. Therefore only a select few were studied too see if it was possible to identify what separated the highly up and down-voted questions.

The goal was to develop a Machine Learning (ML) learning system which was based on SVM, since many papers document that this has the best classification accuracy for text classification. The methodology therefore also includes a documentation on the development process, and how and why the given features used were selected.

For the sake of replicability, and also be able to undo potential errors, the system is available in a a GitHub repository[2]. In addition to the source code, the repository also contains both the samples that was used (stored in CSV files), and the models that was created.

1.4 Justification, Motivation and Benefits

Many systems focuses only on finding a good answer, and does not ask if it is a good question. As a famous Norwegian saying goes[3]: "A fool may ask more than ten wise men can answer". This means that new research possibilities could be opened up in relation to researching question quality by expanding the system.

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[1]StackExchange dataset: https://archive.org/details/stackexchange (Downloaded 30. March 2016).

[2] GitHub repository: https://github.com/klAndersen/IMT4904_MasterThesis_Code

[3] Although its origin comes from a Danish word collection from 1682: https://snl.no/En_d%C3%A5re_kan_sp%C3%B8rre_mer_enn_ti_vise_kan_svare.

Since all the communities within SE is based on the same model, few modifications would be needed to scale the program to be used within the other communities. As noted in several papers [37, 38, 40, 51, 67, 73], question quality is measured based on the amount of votes given. Which can also be compared against the peer-review process in academia, and given that SO targets professionals and experts, using SO as a scientific reference is not that far-fetched[4]. SE has also been the focus of various researchers these past years [69]. Improving ones own ability to ask better questions can also have a pedagogical effect, which means that this system could be implemented in education.

1.5 Limitations

The greatest limitation is the time available. A large amount of time was spent on setting up the database, and retrieving the questions (the Posts table contains both questions and answers). Only a selection of the questions were selected (a total of 20,000 questions), and training the SVM over one sample set can easily take several hours. This also has an impact on classification accuracy, since in some cases there is only a small amount of the questions that contains a given feature (e.g. the hexadecimal feature, which only was present in 160 of 20,000 questions). A limitation is also that the focus is only on SO, which means that one would need to make additional adjustments and add more filtering to account for the differences that may occur in each community.

1.6 Thesis contribution

This thesis contribution can be summarized as to the following: Predicting (programming) question quality by using Artificial Intelligence (AI) and ML to improve the questions quality. Instead of posting bad questions that can get downvoted or closed, the developed system could be able to give feedback to the questions quality. Furthermore, the research presented could open up for new research in relation to how we ask questions online, and in what ways these best can be analysed. It can also be used for educational purposes, e.g. having questions iteratively improve their question quality by asking the system questions.

1.7 Thesis structure

The following is the structure of this thesis:

- Chapter 2: State of the art and relevant research
- Chapter 3: Methodology
- Chapter 4: Discussion on development, the thesis and limitations
- Chapter 5: Conclusion and suggestions for further work

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[4] Posnett et al. [40, p. 1] noted that SO "ranked 2nd among reference sites, 4th among computer science sites, and 97th overall among all websites".

2   Related work

2.1   Stack Overflow (SO)

2.1.1   Stack Overflows (SO) Design

The following list shows the design used in SO (based on Sewak et al. [51, p. 6-7] and Treude et al. [67, p. 805]):

1. Votes: Questions and answers which are considered good (or bad) by the community can be given a score. This gives a filtering mechanisms, which allows users to ignore answers that are bad or wrong. Furthermore, answers are sorted by votes, and you can also sort questions on SO by vote score (see Figure 1).
2. Accepted answer: If the user asking a question gets an answer that they find satisfactory, they can select it as the "accepted answer". This answer will be the first displayed of the answers, and is also viewable when searching for questions (see Figure 1 and 2).
3. Tags: Each question is associated with a tag[1], which can be a topic, a programming language, a methodology, etc.
4. Badges: Similar to achievements in games, Badges are used to reward the user for their participation.
5. Reputation and Bounty: Currency system for user participation. E.g. voting for questions, getting your answer selected as the accepted one, etc. Bounty is a trade, where if your question goes unanswered for too long, you offer up parts of your reputation to receive an answer.
6. Data dump: Available data dump containing all content available within the SE community [56]. You can either download single files, or everything by using a Torrent client.
7. Pre-Search: Encouraging users to check that their question is not already posted by presenting a search bar when asking a new question.
8. URL keywords and Google: The questions title is included in the URL, allowing it to be processed by search engines. In addition, Google uses their crawlers every 10 second to have the latest updates from in their search engine [15].
9. Critical mass: Before Atwood and Spoolsky launched SO, they invited developers and programmers to participate to have some domain experts available.

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[1] A full list can be seen here: http://stackoverflow.com/tags/
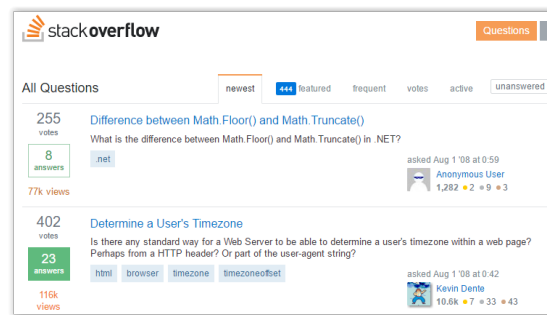
Figure 1: List of questions, where one can see those with an accepted answers are marked with a green background.
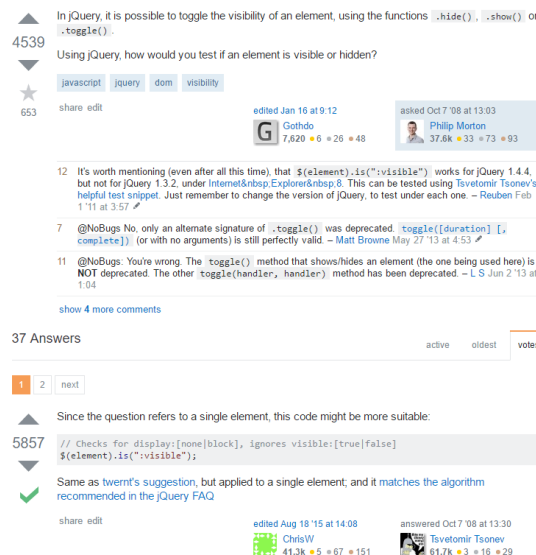
Figure 2: Example of a question on Stack Overflow[2]

2.1.2 Stack Overflow (SO) and Gamification

Deterding et al. [9] defines Gamification as "the use of game design elements in non-game contexts", and is the definition this section will be based on. Several papers make notes of the pedagogical and educational aspect of SO [38, 40, 73], and [38, 73] use the term gamification in their paper. One of the founders, Jeff Atwood said in an interview that he wanted users to not just give good answers, but also trick them into improving their communication skills [40][3]. In

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[2]Source: http://stackoverflow.com/questions/178325/checking-if-an-element-is-hidden
[3] From this interview:
http://www.wired.com/2012/07/stackoverflow-jeff-atwood/2012.

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the course IMT4007 Serious Games Simon McCallum and Marius Nowostawski, presented their game GoRad, which was based on us students reading articles and posting questions which were voted on. The SO system awards users based their activity by using votes, reputation and badges [51, 37, 67, 57, 61]. In relation to gaming, there are four player types: Achievers, Explorers, Socializers and Killers [32, p. 3].

These player types can be used as a representation[4] for the various users of SO. Achievers are there for the reputation and badges, socializers are to interact, discuss and share knowledge. Explorers might find joy in looking at various topics, or searching for unanswered questions. The only exception would be the "Killer" type. Killers are those ". . . who always want to create trouble/problems for other participants" [32, p. 3]. In an online QA system (or Internet in general), these are what are commonly referred to as "Trolls" [13, 4]. However, due to the system used in SO, Trolls would not be able to survive, simply because the reputation controls what you have access to [59]. If you down-vote a post, you lose reputation. If your post gets down-voted, you also lose reputation. Users who are not willing to follow the guidelines can be locked out of SO [3]. However, today there is a lot of blogs complaining about the current structure of SO, who claims that a lot of the moderators are trolls[5].

2.1.3 Stack Overflow (SO) and reputation

Many QA sites includes domain experts to ensure some quality is upheld, and uses voting and reputation as a quality measurement [2]. Furthermore, questions topics, page views and votes can be used by search engines as a ranking mechanism, and it helps users to find the answers they are looking for. Anderson et al. [2] identifies two principles for the answer process. This process starts with the question being filtered down through the users, starting with domain experts. If the domain experts does not answer, it goes further down the chain, until it in the end either gets an answer, or is not answered at all. Both Anderson et al. [2] and Treude et al. [67] defines an unanswered question to be a question where no accepted answer is chosen[6]. The second principle is that a questions activity level does not just indicate the interest for the question, but could also be an indicator for quality (because a question can have multiple answers).

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[4] Yang et al. [73] characterised users as "Sparrows" and "Owls", where sparrows answers question for reputation and owls answers the difficult ones (domain experts).
Ahmed et al. [1, p. 2] defined users as "lurkers, help-seekers (askers) and givers (responders)".
[5] https://www.reddit.com/r/programming/comments/3cafkp/is_stack_overflow_overrun_by_trolls/.
https://medium.com/@johnslegers/the-decline-of-stack-overflow-7cb69faa575d
Last accessed 23.05.2016.
[6] However, they do not take into considerations users who find a solution on their own, or simply forget or neglect to mark a an answer as accepted.

Since users can only gain 200 reputation points daily, the only way to earn more is by having your answer marked as accepted or through bounties [61]. Movshovitz-Attias et al. [37] found that users earn more reputation by providing good answers rather than good questions[7]. Most questions was asked by the users with a low reputation, but on average users with high reputation asked more questions. This indicates that reputation could be used as a measurement for expertise. Ahmed et al. [1] also found that there was a correlation between amount of answers given and the users reputation.

Yang et al. [73] found that the activity level of a user is not equal to knowledge, and divided users into two groups; "Sparrows" and "Owls". The sparrows are the basic users who earns reputation and badges by answering the easy questions, and has a greater interest in the gamification element. They found that the sparrows usually has a low average score and targets questions that are easy, or non-relevant. Nonetheless, they are still important since they are able to provide quick feedback. As for the owls, they are considered to be the domain experts. The owls earn reputation by asking more advanced questions, providing better answers (i.e. getting their answer accepted) and answering popular and difficult[8] questions.

Posnett et al. [40] views SE and SO as a learning community, since users help each gain new knowledge, and motivates learning. They wanted to see if the quality of the users answers improved over time. By constructing a posting history for each user, they found that the overall answer score decreased, and that the answer quality was static.

Nasehi et al. [38] did a qualitative analysis of code examples posted on SO. Their focus was on questions related to Java programming, with the requirements that the question should at least have a score of +4 and the answer +7. In addition, a code example should be included (by checking for <code> in the post). They found that the code explanation was just as important as the code examples (but you are still restricted to the quality of that example). For the code to be considered good, they listed the following attributes:

1. Concise code: Code samples should not be too long. They should be simple, and only focus on the parts that are relevant to the topic. Additional or non-relevant parts should instead be documented by using descriptive comments.

[7] However, as stated in Movshovitz-Attias et al. [37, p. 3], the reputation system was changed at one point. Originally, up-votes on questions and answers gave users a +10, but this was later changed into up-votes on questions only giving +5.

[8] Popularity was measured based on page views and the time between a question was posted until an answer was selected as accepted. The popularity can also therefore be seen as a measurement for difficulty. The longer it takes to answer, the more difficult the question is [73, p. 273].

2. Question context: If the code is not working properly, suggestions for improvement should be added. One could also explain best practices and suggestions for improved readability. This will also have a pedagogical benefit, since the user asking the questions will learn to write better code.
3. Highlighting important elements: "Straight to the point", clearing up misunderstandings, pointing to relevant resources, etc.
4. Step-by-step solution: Splitting code into chunks, and explaining each chunk and its functionality. Comparison of languages; e.g. "How can I do X in C#, when I'm used to Java?"
5. Providing links to extra resources: Answers can be kept short by adding links to external resources, but a short summary should still be added.

2.2 Asking questions

2.2.1 What is the definition of a question?

The context of a question varies within the setting it is used. A question can be broad, where multiple answers can all be correct, or they can be factual, having only one right answer. When you are asking someone a question, you ask because you want to either find a solution to a problem, or learn something new. In the context of learning, questions are used for evaluating the students knowledge, or help them learn something new Nielsen et al. [39].

When doing research, you need research questions and hypotheses to decide what the goal of your research is. What questions are you trying to find an answer to, and what does that answer tell you? Slowiaczek et al. [53] defines asking a question as information selection and the answer(s) to a question as information usage. If you are working with statistical data, and you just post the numbers, this will not inform anyone. You need to explain what the numbers mean, and how you got them. The quality of an answer is also restricted to the quality of the question you ask. One can therefore assume that if you ask a good question, you will get a good answer [53].

2.2.2 Question Classification (QC)

QC is the process of categorizing a question into a class or category based on its structure, usually to decide what the expected answer type is [29, 30, 31]. To classify a question, it is important to select only those features that helps you identify the class it belongs to. To get a classification results, you use what is known as a classifier. The quality of a classifier can be measured by its accuracy and precision (see Equation 2.1 and 2.1; taken from [29, p. 13]).

$$\text{Accuracy} = \frac{\text{\# of correct predictions}}{\text{\# of predictions}} \tag{2.1}$$

$$\text{Precison}[c] = \frac{\text{\# of correct predictions of class } c}{\text{\# of prediction of class } c} \tag{2.2}$$

WH-words

WH-words are mostly found in factoid questions [31]. Huang et al. [21] listed eight different WH-words: What, which, when, where, who, how, why, and rest (rest being the type does not belong to any of the previous type). Letovsky [27] also listed "Whether" and "Discrepancy"[9]. However, not all are equally easy to use for classification, because even if the questions ask for the same answer, wording and syntactic structures can make it difficult to classify. Question containing words like "What", "Why", "How" and "Which", can be harder to classify due to the lack of limitation in regards to answer types[10] [21, 31].

Bag of Words (BOW) and N-grams

N-gram is a model that is used for splitting text into either characters (character model) or word frequencies (word model). The Bag of Words (BOW) model (or unigram) only looks at singular words, ignoring the order and relies only on the frequency for each word [34, 42]. Bi-grams takes dual values, tri-gram takes three, etc.

One problem with N-grams is that the dimension of the feature space is equal to the amount of words in the vocabulary [42, 30] When using categorization, there can be issues with mapping new words that does not exist in the vocabulary [74]. The impact of N-gram is also related to the size of the text being analysed. Zhang and Lee [75] found that there was not a big difference when using between bag-of-ngrams (all continuous word sequences in the question) and BOW as features.

Word mapping and processing: Case-sensitivity, Stemming, Stop words and Tokenization

To reduce the amount of words used, there are more steps that can be taken. By removing the case-sensitivity, all words will be equal (e.g. is the word 'Hello' equal to the word 'hello'?). [21] includes case-sensitivity under a definition called word shape, consisting of five elements: upper case, all lower case, mixed case, all digits, and other.

Semantics can be used for word filtering, e.g. removal of duplicate words or words with same meaning. WordNet has a built in function called synsets() which removes synonyms (words having the same meaning). You can also look for hypernyms (words belonging to a category with a parent-child relationship) or use stemming. Stemming reduces the word to its base-form, e.g. crying would be converted into the word cry. Word separation is also possible through tokenization, which splits the text into an array based on a set delimiter. There is also usage of stop words for removal of frequently used words in a given lan-

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[9] "Questions that reflect confusion over a perceived inconsistency." [27, p. 5]

[10] An answer type (or named entity) is the expected type of the answer to a given question (e.g. a Location, Organization, Person, Date, etc) [19, 31, 43, 74].

guage.

Grammatical properties can be extracted by using Part of Speech (POS), e.g. by using Natural Language Toolkit (NLTK)[11], which can be helpful in reducing ambiguities [5]. Li and Roth [29] uses the word head chunks to identify what the question is asking for when multiple types are introduced (avoid ambiguity). The same concept is used in [21] and [30], but there it is referred to as headwords.

2.2.3 Text classification

The goal of text classification (or text categorization) is to be able to process multiple documents or large amounts of text into categories. It shares similarities with question classification, although an obvious difference would be the size of the text that is processed. Some examples are spam filtering [42, 24], to identify languages, or filing documents based on content [24]. Documents can belong in more then category, and since categories can overlap they must be treated as a binary classification problem [23] . Text classification starts with retrieval of the documents, usually by using Information Retrieval (IR) methods, and then transforming the text into features for the classification. When you have a large amount of text, you can easily get a feature space that is very high dimensional, and that is why feature selection is important. Feature selection is the selection of features (or attributes) that are important for the classification. E.g. if you were classifying documents based on colour description, then hypernyms for colour would be an important feature.

2.2.4 Question-Answering (QA)

QA is mostly used as a method for finding the answer to a question from an unknown amount of documents. When using a search engine, one can accept that there are several results that are listed because at least one of the search terms exists. However, when using a QA system, users wants the answer straight away instead of having to read through several documents. In addition, QA sites allows users to search for questions in the same way they would ask another human (natural language[12]), and there are also different types of QA sites. Domain specific QA focuses on a specific topic (e.g. SO) and open domain where everything goes. QA sites can also function as an archive or a knowledge base, since all the posts are available even years after they were posted.

Yen et al. [74] found that it was more efficient searching for answers in a small dataset, then the document as a whole. By using a passage retriever, the documents were split into paragraphs and ranked by using evaluation metrics. Isozaki [22] could not use TF-IDF based paragraph retrieval, because the paragraphs

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[11] NLTK includes in their POS tagger the following grammatical properties: Adjective, adposition, adverb, conjuction, determiner, article, noun, numeral, particle, pronoun, verb, punctuation mark and others [65, See Section 2.3].

[12] However, there is a problem with linguistics in natural language systems [31].

were too short to cover all query terms. If the terms that were used were too short or too long, the passage scores would not reflect the density distribution. Xu et al. [72] built an online QA system for tourism, which consisted of question analysis, information retrieval and answer extraction. Since rule-based approach requires expert knowledge, creating features that are domain specific can improve accuracy (what they called "domain term concept hierarchy"). To validate the classification, they tested the results by using 5-fold cross-validation.

Li and Roth [29] used semantics to categorize questions based on the possible semantic answer type. One issue with questions are that since they can be very short, they contain little text. However, the lack of long text improves both the accuracy and analysis.

Zhang and Lee [75] says that QC is important, and simply looking for WH-words is not enough. By using WH-words, headwords, WordNet semantics, N-grams and word shapes as features, and a linear SVM and Maximum Entropy model, they reached an 89.2% and 89.0% over a standard benchmark dataset. They also experimented with four other algorithms, Nearest Neighbours (simplified version of k-NN), Naive Bayes and Decision Tree and Sparse Network of Winnows (SNoW). However, these were outperformed by the SVM.

2.3 Support Vector Machines (SVM)

SVMs are good for solving regression and classification problems, and attempts to solve a linearly separable problem by using hyperplanes [10, 26, 42]. It is usually used for binary classifications, where classes are represented as either +1 or -1 [34, 42]. The hyperplane is the plane which separates the two classes:

$$\vec{w}^{\top}\vec{x} = \text{-}b \tag{2.3}$$

where b is the intercept term and $\vec{w}$ is the weight vector (or decision hyperplane normal vector). The data set can be represented as $\mathbb{D} = \{(\vec{x}_i, y_i)\}$ where $\vec{x}_i$ is a data point, and y_i is its belonging class label. The linear classifier is represented in Equation 2.4 [34, p. 295-296].

$$f(\vec{x}) = \text{sign}(\vec{w}^{\top}\vec{x} + b) \tag{2.4}$$

In addition to using a hyperplane, the SVM has an additional separation known as support vectors. Support vectors are the training points closest to the margin (the margin is the distance from the hyperplane) [10, 34]. Which then gives that the optimal hyperplane is the furthest from the support vectors [26]. SVM has four different kernels, but a limitation is that there is no way to select the best kernel function. Therefore, SVM often uses hyper-parameters and select the classifier based on the best results [66]. Equation 2.5 - 2.7 shows the kernel functions (K) for polynomial, radial basis function (RBF) and sigmoid (taken

from [26, p. 273]).

Polynomial - for a given polynomial degree d, the following is used:

$$K(\mathbf{x_j}, \mathbf{x}) = [(\mathbf{x} \cdot \mathbf{x_j}) + 1]^d \tag{2.5}$$

Radial - for a given γ value, the following is used:

$$K(\mathbf{x_j}, \mathbf{x}) = e^{-\gamma |\mathbf{x} - \mathbf{x_j}|^2} \tag{2.6}$$

Sigmoid - for a given sigmoid function S, we get a kernel function of parameters v and c:

$$K(\mathbf{x_j}, \mathbf{x}) = S(v(\mathbf{x} \cdot \mathbf{x_j}) + c) \tag{2.7}$$

For text classification, in most cases it will be non-linearly separable. One can therefore allow the SVM to do some mistakes. However, there is a cost for misclassifications, represented by what is called a slack variable ξ_i. If ξ_i is set (not zero), then the vector can miss the margin requirement at the cost of ξ_i. Equations are shown in Equation 2.8 - 2.10 (taken from [34, p. 301]).

Find

$$\vec{w}, b \ and \ \xi_i \geq 0 \tag{2.8}$$

so that we can minimize the optimization problem

$$\frac{1}{2}\vec{w}^\mathsf{T}\vec{w} \ + \ C \sum_i \xi_i \tag{2.9}$$

and for all

$$\{(x_i, y_i)\}, \ y_i(\vec{w}^\mathsf{T}\vec{x} \ + \ b) \geq 1 - \xi_i \tag{2.10}$$

However, this gives a trade-off between the size of the margin and how much the data points can be adjusted. To avoid overfitting, the parameter C is used for regularization, where the size of C decides how much flexibility you get from the slack variable [34]. SVM neither suffer from the Curse of dimensionality, because the computational complexity is independent of the kernels dimensional space [66].

Joachims [23] found that SVM consistently achieved good performance during text categorization. Since SVM could generalize in high dimensional feature space, the need for feature selection was removed, and SVM was also robust. Since SVM does not require parameter tuning, they could find good parameter settings automatically. Loni et al. [30] found that SVM are successful on high dimensional data when it is sparse, but they still suffer from redundant features.

2.4 Dataset

short about the datasets, others who has used it, and datasets in general, e.g. [25, 54, 71]

12

2.5 undefined

Stanley and Byrne [64] - Predicting Tags for StackOverflow Posts

Short et al. [52] - Tag Recommendations in StackOverflow

Wang et al. [70] - An Empirical Study on Developer Interactions in StackOverflow

3   Methodology

3.1   Dataset and MySQL Database

3.1.1   Dataset

The dataset contains all information that is currently available in the SE community (at the time the dataset was created). The following is a list of the tables found in the dataset:

- Badges: Badges awarded to users.
- Comments: Comments given either to a question or an answer.
- Posts: Posts on SE, this contains both questions and answers.
- Posthistory: The history of a given post (e.g. edits, reason for closing, etc.).
- Postlinks: Link to other Posts (e.g. duplicates).
- Users: Information about the given user registered at the given community.
- Votes: Type of vote given to a Post (e.g. up/down, vote to close, etc.).

In the beginning, the dataset that was used was downloaded in August 2015. However, since this turned out to be outdated, the latest dataset was downloaded from (https://archive.org/details/stackexchange) on 30. March 2016. The dataset comes in zip-files, where each zip-file contains all the rows found in the given table. These rows are presented in an XML file, as shown in Listing 3.1.

Listing 3.1: Content in stackoverflow.com-Tags.xml

```
<?xml version="1.0" encoding="utf-8"?>
<tags>
<row Id="1" TagName=".net" Count="227675"
ExcerptPostId="3624959" WikiPostId="3607476" />
<row Id="2" TagName="html" Count="511091"
ExcerptPostId="3673183" WikiPostId="3673182" />
...
</tags>
```

3.1.2   MySQL Database

In the beginning, the issue was getting access to the file and see how it looked like. Since most of these XML files had a large file size (ranging from 3,9 MB to 71,9 GB) none of the editors could open them. Attempting to open them through Python code also failed, since there was not enough memory to process everything. The only solution was therefore to create a MySQL database that could contain all the data.

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Setting up the MySQL database was not a straight forward process. The operative system I was running was Arch Linux, where they had switched from using Oracle's MySQL to MariaDB[1]. One of the main problems was the available storage space[2] and the varying file sizes. Some of the issues were mainly connection timeout, no more disk space and connection loss (e.g. "Error Code: 2013. Lost connection to MySQL server during query"). To avoid losing the connection to the database, the timeout values had to be changed in MySQL Workbench (shown in Figure 3).
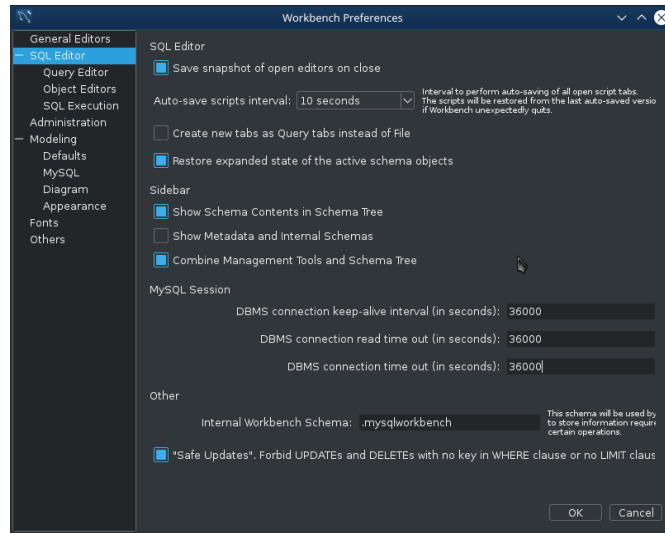

Figure 3: MySQL Workbench: Setting timeout values to avoid connection loss

The next problem was the lack of disk space. MySQL by default stores all databases and belonging tables in /var/lib/mysql/, and it also creates temporary backup files (where the file size is equal to the size of the current database). Since the default folder for temporary files was on /root, the disk space was used up in less than 30 minutes. Therefore, two things needed to be done. First, disable the storage of temporary files, and secondly change the storage location for the database. The problem when tinkering with the configuration file is that things easily break. Which is what happened, and a clean install was needed for both MariaDB and MySQL (the changed settings can be seen in Listing 3.2). The final step was to create symbolic links that linked the database to the location where the tables were stored (this has to be done before creating the tables, if not MySQL Workbench will store the tables in /var/lib/mysql/)[3].

---

[1] See https://wiki.archlinux.org/index.php/MySQL.

[2] The HDD with Arch Linux installed had a disk size of 500 GB, with four partitions; root, var, swap and home. 40 GB was used for /root and /var, 12 GB was used for swap and the remainder was used for /home.

[3] It should be noted that after an upgrade of MariaDB, MySQL and MariaDB could no longer

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Listing 3.2: Changes made to config file: /etc/mysql/my.cnf

```
# disable storage of temporary files
#tmpdir = /tmp/
# disable storage of log files
#log-bin = mysql-bin

# set directory for storing database files
datadir = /home/mysql
```

Listing 3.3: Load XML file into a table in the MySQL database

```
LOAD XML LOCAL INFILE
path_to_xml_file
INTO TABLE db_table
ROWS IDENTIFIED BY '<row>';
```

Listing 3.3 shows how the files were loaded into the tables, and the complete database can be seen in Appendix A.2, p. 42. Since the Posts table is large (~29,5 million rows) and it contains both questions and answers, two new tables were created; "posvote_Posts"[4] and "negvote_Posts". posvote_Posts contains questions with a score higher then zero (score > 0) and negvote_Posts contains all questions with a score lower then zero (score < 0).

3.2 Development process

When starting the development, the focus was on retrieving the data from the database, and processing it for text analysis. To be able to store all the retrieved columns and the belonging rows without creating object classes, the pandas.DataFrame[5] was used.

The questions retrieved needed to be processed before any analysis could be done. The reason for this is because the questions was written as HTML (including HTML entities). An example is shown in Listing 3.4. Every question starts with the <p> tag, and if the question contains code samples, these are wrapped with a <code> tag. To convert the HTML text into readable text, a HTML parser class was created (based on answer by [12]).

---

find the tables, even if they still were in the /home/mysql/ folder. It is therefore advisable to dump the database after inserting all the tables, since it goes a lot faster to restore the database from dump rather than insertion from XML files.

[4] The Posts table has a file size of ~43,6 GB, whereas posvote_Posts file size is ~11,2 GB. negvote_Posts has a file size of ~1,33 GB.

[5] Pandas: http://pandas.pydata.org/.

Listing 3.4: Question before HTML is removed (Question ID: 941156)

```
<p>
Why do we need callbacks in ASP.NET or any server side technology?
</p>&#xA;&#xA;<p>One answer can be, to achieve asynchronous calls.
</p>&#xA;&#xA;<p>But I am not satisfied with this answer.</p>
&#xA;&#xA;<p>Please explain it in a different way.
</p>
&#xA;
```

To process the questions, CountVectorizer from scikit-learn was used. CountVectorizer uses the vocabulary found in the text and counts the frequency of each word [49] [45, see 4.2.3]. When looking at this vocabulary, a lot of of unimportant words was found (a lot which came from the code samples) in some of the questions. At first all code samples were removed from the text, but later on they were replaced with the value 'has_codeblock', indicating that this question contained one or more code samples. This was achieved by using a combination of lxml[6] and bs4[7] (BeatifulSoup). lxml was used to construct an XML tree containing all the tags (to be able to retrieve the content by searching for a given tag), and bs4 was used for beautifying the HTML (since in some cases an error was thrown complaining about "Missing end tag").

However, for some questions, part of the text was lost, and for others, some <code> tags was not removed. On inspection, it was found that the trailing text following the <code> samples was stored in a .tail attribute. Since the <code> was removed, the .tail attribute was also removed. This was fixed by storing the the content of the <code> .tail attribute into its <parent>[8] (where <parent> is the tag that contained the given <code></code>) .tail attribute. As for the non-complete removal of <code> tags, this error mostly occurred for code samples that contained XML or HTML code[9], because the lxml parser failed. The solution was to replace the lxml parser with bs4 and just change the content of the <code> tag to the value 'has_codeblock'.

Considering the size of the dataset, and that the source code was hosted on GitHub, I was hesitant to store the training data in a separate file. However, when loading 20,000 samples from the database with a 'WHERE' parameter, things tend to go more slow. At this point, it was decided to try to dump the loaded data from the database to a file. This was achieved by using pandas.DataFrame.to_csv[10].

---

[6]lxml: http://lxml.de/

[7]BeatifulSoup: https://www.crummy.com/software/BeautifulSoup/

[8] It was also necessary to check if the <parent> had a .tail, if not, the .tail attribute had to be set for the <parent> to avoid the error: "NoneType + str: TypeError".

[9] One example is this question:
http://stackoverflow.com/questions/19535331/print-page-specific-area-or-element.

[10] pandas.DataFrame.to_csv:

At a later point, the unprocessed dataset was also dumped to a CSV file for replicability.

Further examination showed that the vocabulary contained a lot of numerical and hexadecimal values, but also a lot of non-English words. The numerical and hexadecimal values were replaced using regular expressions to 'has_hexadecimal' and 'has_numeric'. The non-English words were a bit more troublesome to handle, since these were mainly used to prove a point or show an example of the issue they were having[11]. Attempts were made to filter them out by using corpus.words.words() and corpus.wordnet.synset() from NLTK[12], and PyEnchant[13]. However, WordNet does not have a complete database of all English words, and they all claimed some words were not English even though they were. The solution turned out to be a lot simpler. Instead of creating filters, the CountVectorizer already had one built in. By adjusting the minimum document frequency (min_df) and setting it to 0.01, words that appeared in less 1% of all documents were ignored.

To be able to run the system without relying on an Integrated Development Environment (IDE), making it run from the Terminal using basic command setup seemed like a good idea. At first optparse was used, which ironically turned out to be deprecated and replaced by argparse. However, the problem was that you could only run one command at a time, whereas I wanted the program to be able to run until exited. The reason for this was because it needs to load a model before it can make a prediction, in addition the user might want to predict multiple questions. This was therefore replaced with a basic while loop that runs until the users enters the exit command. The setup used for argparse was kept, so users from *nix system might be more familiar with similar commands (shown in Listing 3.5). At the end, there were some commands that were not added to the menu, since these were mostly used for testing.

Listing 3.5: System menu

```
Menu:
d: Loads default model (if exists) from ./pickle_models
e: Exit the program
h: Displays this help menu
l: Load user created model. Arguments:
        path: Path to directory with model(s) (e.g. /home/user/my_models/)
        filename: The models filename
        suffix: File type − Optional (default: '.pkl')
```

---

http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.to_csv.html.

[11] http://stackoverflow.com/questions/856307/wordwrap-a-very-long-string.

[12] http://www.nltk.org/

[13] http://pythonhosted.org/pyenchant/

p: Predict the quality of the entered question. Arguments:

      question: Question to predict quality of

t: Train a new model based on an existing (or new) data set. Arguments:

      path: Path to directory with training data (e.g. /home/user/my_data/)

      filename: Filename for data set (model name will be the same as this)

      db_load: Load from database (Enter 0: No, 1: Yes)

      limit: Limit for database row retrieval (integer) − Optional unless 'db_load' is '1'

u: Create an unprocessed data set based on database content (from database set in dbconfig.py). Arguments:

      filename: Filename for data set (model name will be the same as this)

      limit: Limit for database row retrieval (integer)

      feature_detectors: Create singular feature detectors based on data set? (Enter 0: No, 1: Yes)

      create_model: Create classifier model(s) based on data set?

      0: No, 1: Unprocessed model, 2: Feature detector model(s) 3: Both (1 and 2)

3.3 Feature sets, attributes and processing

When retrieving the questions from the database, the vote score was set to less than -10 for bad question and greater than 50 for good questions (retrieval limit set to 10,000; 20,000 total). However, the vote score was set too low for the bad questions, since only 683 rows was returned. Therefore, the score was then set to less than -5. What was also found when using pandas.Categorical to get an overview (code snippet in Listing 3.7 and result in Table 1), one can see that for the 10,000 bad questions, the average vote score was -7. This could be an indicator that when a question has a vote score below -5, they are ignored.

Class	Statistics	AnswerCount	Score	Question length
-1	mean	2.0483	-7.0275	319.226
	std	1.3129	2.676	382.115
	min	0.0	-147.0	13.0
	25%	1.0	-7.0	153.0
	50%	2.0	-6.0	239.0
	75%	3.0	-6.0	379.0
	max	20.0	-6.0	13673.0
1	mean	11.9379	182.5483	459.329
	std	13.707824	317.47217	531.187559
	min	0.0	51.0	13.0
	25%	6.0	67.0	189.0
	50%	9.0	96.0	328.0
	75%	14.0	173.0	558.0
	max	518.0	9432.0	18867.0

Table 1: Results from pandas.DataFrame and pandas.Categorical. -1 is for bad questions (votes < -5), and 1 are for good questions (votes > 50).

Listing 3.6: Getting Categorical data from pandas.DataFrame

```
from pandas import DataFrame, Categorical

# get statistics from pandas.DataFrame
temp_df = __so_dataframe.loc[:, ("Score", "Body", "Title",
        "AnswerCount", "length")]
temp_df.loc[:, CLASS_LABEL_KEY] = Categorical(__so_dataframe.loc[:,
                                        "label"])


# prints out the questions AnswerCount, Score and length
print(temp_df.groupby("label").describe())
# prints all selected columns
print(temp_df.groupby("label").describe(include='all'))
```

To be able to develop some theories on what the difference between good and bad questions was, a total of 200 questions were reviewed (by sorting questions based on votes[14]). It was easier to see certain patterns in down-voted questions rather than those that were up-voted. A repetitive pattern was that many had either no code example, or poorly written code. These questions could also show

---
[14]http://stackoverflow.com/questions?sort=votes

Step	Text processing	Vocabulary count	CountVectorizer
1	None	69766	analyzer="word"
2	Stop words	69462	analyzer="word", stop_words="english"
3	Removal of code, hexadecimal and numerical values	27624	analyzer="word", stop_words="english"
4	Minimum document frequency	440	analyzer="word", min_df=0.01, stop_words="english"

Table 2: Feature reduction steps before and after text was processed.

indications of not having tried anything, or that they were based on either homework or school assignments. This in turn lead to a hypothesis that if a question contains indicator of word synonyms for homework[15], it would be considered a bad question. In addition, some code examples had syntax errors, which made the minimum working example (MWE) not executable. Some questions also contained links, either to external resources or indicators of potential duplicates. Therefore links was also considered a potentially useful feature. Tags was also considered as a feature, which was divided into two: Attached and External tag. Attached tags are tags which the user has linked to the question, whereas external tags are all the tags available on SO. Version numbering was also considered, but this was not included due to the complexity of writing a proper filtering method to account for all possible variations.

Features were added in the same manner as was done for code samples, numerical and hexadecimal values. However, there were some issues when attempting to replace the tags and the synonyms for homework. At first, WordNet was used for synonyms (using wordnet.synset()). The only problem was that for the word 'homework', wordnet.synset() only returns ['homework', 'prep', 'preparation']. Whereas Thesaurus[16] had a lot more suggestions, and was therefore used instead. Words were selected based on whether or not it was plausible that they could be used in programming related question setting. A new problem now arose, namely the issue that the word "assignment" did not necessarily need to occur in a homework setting, since it could also be used as a programming word (e.g. assignment operator[17]). Therefore features for homework were split into two types: 'has_homework' and 'has_assignment'.

Tags were without a doubt one of the most annoying features to detect and replace. Site tags (or external) are single text values in the database, whereas the question can have up to five tags attached. Those attached tags are then

---

[15] http://www.thesaurus.com/browse/homework
[16] http://www.thesaurus.com/browse/homework
[17] http://stackoverflow.com/questions/5368258/the-copy-constructor-and-assignment-operator

separated in the following format: "<c><multi-threading>", which had to be processed by removing the '<' and the '>'. After the removal, each tag value was added to a list, so that all attached tags was indexed based on the question they belonged to. Furthermore, a combination of string replacement and regular expression was needed. The regular expression was used for single character tags (e.g. 'C'), and word replacement for longer words. The reason for this was that when using string replacement, single character tags replaced occurrences even if they appeared in the middle of a word. If the tags contained characters that could be interpreted as a regular expression (e.g. C++), it would give error about multiple repetitions. In addition, the tags needed to be sorted based on their length, since for questions that contained tags which included both <C> and <C++>, if <C> came first, it replaced the <C++> with 'has_*_tag'++. The text also had to be converted to lower-case to ensure proper tag matching.

Listing 3.7: Replacing tags in the question

```
for word in word_set:
        if len(word) == 1:
                # if its only one character (e.g. 'C'), ensure that it is a singular word by using regex
                text = re.sub(r"\b%s\b" % word, replacement_text, text, flags=re.IGNORECASE)
        else:
                text = text.replace(word, replacement_text)
```

4 Discussions

for now this chapter is a bit messy due to the tables appearing all over the place. please ignore the "readability" issues these causes for now

chapter 4.1 is temporarily done, the same goes for 4.2 (might add more to that later on)

4.1 Data set and Question selection

The dataset was retrieved from Stack Exchange Archive [56], and contains all the data posted from the beginning. In this thesis, only the data for SO was used, specifically only the posted questions. A simplified overview is shown in Table 3, which lists questions based on score.

	Amount	Oldest	Newest	Vote (lowest)	Vote (highest)
Votes < 0	659,955	06.08.2008	06.03.2016	-147	-1
Votes = 0	5,256,105	06.08.2008	06.03.2016	0	0
Votes > 0	5,286,971	31.07.2008	06.03.2016	1	13845
All questions	11,203,031	31.07.2008	06.03.2016	-147	13845

Table 3: Overview of the Stack Overflow dataset.

As previously mentioned in Section 3.3, the value used to extract the questions was set to -5 and +50. The problem with these values are that they were simply selected. Originally, the value for bad questions was -10, which were then changed to -5 because -10 only retrieved 683 rows (and I wanted 10,000 samples for both question types). However, as can be seen from Table 3, +50 is most likely a to low value for the good questions. To get better results based on desired quality, there are three options to consider which could improve this.

The first is the easiest. If you are only interested in a set sample size, then you could simply retrieve the amount sorted by score. If you then want 10,000 of each, you would then get the 10,000 that are scored highest (or lowest). The second option would be to get a set limit based on the actual score, by using the mean or average. For all the questions of a given type, retrieve the average and then select questions which has a score higher (or lower) than the average. The third option would be to use quartiles. Quartiles is measured by a given percentage of the observations, where each quartile represents 25%: Q_1 (25%), M

(median, 50%) and Q_3 (75%) [17]. The equation to calculate the quartiles are shown in Equation 4.1 - 4.3.

$$Q_1 = \frac{(n+1)}{4} \tag{4.1}$$

$$M = \frac{(n+1)}{2} \tag{4.2}$$

$$Q_3 = \frac{3 \cdot (n+1)}{4} \tag{4.3}$$

As previously mentioned in Section 3.3, there was no clear indicator for the good questions. Some consisted only of two sentences, e.g. "I committed the wrong files to Git. How can I undo this commit?"[1]. Common for most of the top-voted are that they are mostly short, however you also have those that are long[2]. There is also what I would call a bias factor. If enough people have the same problem, then it will automatically become a good question. Not because of the questions quality, but simply because many will encounter it (e.g. Bugs, IDE behaviour, tweaks, etc). The same can be said for bad questions. In many cases, a question is bad not because of the question that is asked, but simply because it does not follow the guidelines. If a question is a duplicate, it is automatically voted for closure, and will in most cases receive multiple down-votes. Questions which gives a hint of being school related will also receive down-votes, mainly because SO targets professionals and experts. SO is neither a fan of unnecessary text like greetings and gratefulness [7, 20].

Is SO fit for measuring question quality? In a closed domain setting, the answer is yes. However, as mentioned, what type of quality being measured must be taken into consideration. As it is, the system would not be useful for an educational setting, because it bases its prediction on questions asked on SO. If a student were to ask the system a question, it might respond saying that this is a bad question (but the result may be based on the fact that it is a duplicate). For an educational setting, a better solution would be to develop a system similar to the one in [28]. With the current state of the system (if it were to be used), it would be more appropriate to use it as a measurement tool for new SO questions, rather then general question quality.

4.2 Development

There was a lot of back and forth during the development, with a lot of time being invested in properly understanding how to use Scikit-learn. The most use-

---

[1] This question currently have a score of 10,406:
http://stackoverflow.com/questions/927358/how-do-you-undo-the-last-commit.
[2] One example is this question, with a score of 3,009:
http://stackoverflow.com/questions/826782/css-rule-to-disable-text-selection-highlighting.

ful resource were of course Scikit-learns tutorials [48][3] and documentation [45, 50], but there were also two other tutorials that proved helpful ([41] and [11]). The main problem was that Scikit-learns documentation and most of the tutorials written by others is based on v0.17.1. Due to various problems with installation in regards to Numpy and Scipy, Scikit-learn had to be installed from GitHub (which is v0.18.dev0). In the development version, a lot of functions and modules had been re-written and moved, making many tutorials and examples outdated. One example is the code snippet in [41, "In [42]"], where *'cv=StratifiedKFold(label_train, n_folds=5)'* fails, because it expects the first argument to be n_folds[4].

Rehurek [41] used in his example Support Vector Classification (SVC) to train the SVM, but no explanation to why these parameter values[5], nor how he selected the best parameter from the printout[6] (mine is shown in Listing 4.1).

Listing 4.1: Output from SVC tutorial (testing with linear, rbf and sigmoid)

```
[mean: 0.80232, std: 0.01056, params: {'classifier__kernel': 'linear', 'classifier__C': 1},
mean: 0.78451, std: 0.01750, params: {'classifier__kernel': 'linear', 'classifier__C': 10},
...(15 lines removed)...
mean: 0.71416, std: 0.00101, params: {'classifier__gamma': 0.0001, 'classifier__kernel':
'sigmoid', 'classifier__C': 1000}]
```

4.3 Parameter selection for GridSearchCV and the results

There were two different classifiers that were used on the training data, SVC (parameters shown in Listing 4.2) and Stochastic Gradient Descent (SGD) (parameters shown in Listing 4.3). The values for the SVC are based on the example from Scikit-learn [44], the same goes for the values for the SGD Scikit-learn [47] ([21, 33, 75] used the default values when training their system). The reason that these two were used were because of the "roadmap", shown in the Appendix A.3, Figure 5 on p. 43. The reason for including SGD was partially

---

[3] The examples that were worked through can be seen here (as stated in ReadMe, the only thing I have altered is comments and adjustments for v0.18.dev0):
https://github.com/klAndersen/scikit-learn_tutorials.
[4] Documentation for v0.17.1:
http://scikit-learn.org/stable/modules/generated/sklearn.cross_validation.StratifiedKFold.html.
Documentation for v0.18.dev0:
http://scikit-learn.org/dev/modules/generated/sklearn.model_selection.StratifiedKFold.html.
[5] I later found that these were just the basic numbers used in one of their examples for the grid search: http://scikit-learn.org/stable/auto_examples/model_selection/grid_search_digits.html.
[6] The score, parameters and estimator can be found by using these attributes: *'best_score_'*, *'best_params_'* and *'best_estimator_'*.

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because I misread a zero, but also because if one were to extend the sample size, SGD could potentially get better results.

Listing 4.2: Parameters for SVC

```
param_svm = [
{'clf__C': [1, 10, 100, 1000], 'clf__kernel': ['linear']},
{'clf__C': [1, 10, 100, 1000], 'clf__gamma': [0.001, 0.0001], 'clf__kernel': ['rbf']},
{'clf__C': [1, 10, 100, 1000], 'clf__gamma': [0.001, 0.0001], 'clf__kernel': ['sigmoid']},
]
```

Listing 4.3: Parameters for SGD

```
grid_parameters = {
'vect__min_df': (0.01, 0.025, 0.05, 0.075, 0.1),
'vect__max_df': (0.25, 0.5, 0.75, 0.95, 1.0),
'tfidf__use_idf': (True, False),
'tfidf__norm': ('l1', 'l2'),
'clf__alpha': (0.00001, 0.000001),
'clf__penalty': ('l1', 'l2', 'elasticnet'),
'clf__n_iter': (10, 50, 75, 100),
# 'clf__loss': ('hinge', 'log', 'modified_huber', 'squared_hinge', 'perceptron'),
}
```

Only 20,000 questions were selected, and it would probably had been better to have selected more than this. However, one need to take in consideration the time available, and the time it takes to process and train all the classifiers. When using exhaustive search it matches all the parameters against each other, to see which one has the best combination. This means that if you have 30 different parameters, and a cross-validation of 10, then the total amount of fits is 300 [36]. The fit count is shown in Equation 4.4 for SVC and in Equation 4.5 for SGD.

$$
\text{count(C)} + (\text{count(C)} \cdot \text{count(gamma)}) + (\text{count(C)} \cdot \text{count(gamma)})
$$
$$
\implies \text{result} \cdot \text{cross-validation} = \text{fit\_amount} \quad (4.4)
$$
$$
\implies 4 + (4 \cdot 2) + (4 \cdot 2) = 20 \cdot 5 = 100
$$

$$
\text{count(min\_df)} \cdot \text{count(max\_df)} \cdot \text{count(use\_idf)} \cdot \text{count(norm)} \cdot \text{count(alpha)}
$$
$$
\cdot \text{count(penalty)} \cdot \text{count(n\_iter)} \cdot \text{count(loss)} \implies result \cdot \text{cross-validation} = \text{fit\_amount}
$$
$$
\implies 5 \cdot 5 \cdot 2 \cdot 2 \cdot 2 \cdot 3 \cdot 4 = 2400 \cdot 5 = 12,000
$$
$$
(4.5)
$$

A faster alternative to GridSearchCV would be RandomizedSearchCV, but as stated in [36], it may give lower scores. His suggestion is to start with Grid-SearchCV, and then compare the results against RandomizedSearchCV. This was

not done in this thesis, as it did not seem relevant for thesis. However, for the process of fine-tuning the parameters, RandomizedSearchCV would perhaps have been a better option. One could then have started with a high spread of values to then narrow it down, and finally get the optimal ones using GridSearchCV.

> will add discussions on features and results after all new models have been created - Issue: Unprocessed was trained with HTML in text

To be written:

1. Discussion on features
2. Classifier and features; none, singular, all
3. Classifier and features; none, singular, all - for questions that contain the given feature
4. Classifier and estimator
5. Site tags and "assignment": Excluded from training set using "all" features
6. SO dataset vs. tex.stackexhange
7. Stemming - did this improve or worsen the results? Regardless of results, why?
8. Stemming - Porter vs. Lancaster (e.g. issue with certain words not being stemmed, vs. too much stemming (non-related words))
9. The cost of probability (i.e. SGD)
10. Presumption that max_df=95% was a smart move (was it really when comparing to SGD using all?)

> these tables and listings are temporarily placed here and might be moved into Appendix at a later point.

	Unprocessed	Features
Score	0.993	0.993
C	1	1
Kernel	Linear	Linear

Table 4: Comparison of raw data set (unprocessed) and singular feature detectors for Tex.StackExhange (August 2015 data set).

	Score
Code samples	0.783
Numerical	0.796
Hexadecimal	0.793
Homework	0.794
Link	0.795
Tags	0.757
Unprocessed	0.804

Table 5: Comparison of raw data set (unprocessed) and singular feature detectors. Using SVC, with Kernel=RBF, C=1000 and Gamma=(γ) 0.001

	Unprocessed (SVC)	All features	All features (no stemming)
Score	0.804	0.793	0.784
C	1000	1000	1000
Gamma (γ)	0.001	0.001	0.001
Kernel	RBF	RBF	RBF

Table 6: Comparison of raw data set (unprocessed) and all feature detectors (SVC)

	Unprocessed	Unprocessed (loss='log')	All features (loss='log')
Score	0.8073125	0.8071875	0.79325
Min DF	0.01	0.01	0.01
Max DF	1.0	1.0	0.75
Use IDF	False	True	True
Alpha	1e-05	1e-05	1e-05
Normalization	l1	l2	l2
Penalty	l1	l2	l2
Iteration	100	75	100
Loss	hinge	log	log

Table 7: Comparison of raw data set (unprocessed) and all feature detectors (SGD)

	Unprocessed	FEATURE	C	Gamma (γ)	Kernel	Amount
Code samples	Score: 0.802	Score: 0.784	1000	0.001	RBF	9,855
Numerical	Score: 0.834	Score: 0.815	1	N/A	Linear	9,024
Hexadecimal	Score: 0.859	Score: 0.883	1000	0.001	RBF	160
Homework	Score: 0.873	Score: 0.859	1000	0.001	RBF	374
Link	Score: 0.885	Score: 0.838	1	N/A	Linear	2,575
Tags	Score: 0.806	Score: 0.757	1000	0.001	Sigmoid	19,967
All features	Score: 0.808	Score: 0.788	1000	0.001	RBF	17,558

Table 8: Comparison of raw data set (unprocessed) and singular features, for questions that had it.

4.4   Artificial Intelligence (AI) Methods

main goal is to write about alternative methods and potential limitations with using svm, etc.

4.5   Limitations and other issues

One of the major issues was the fact that the latest development version was used instead of the stable one. The question became at one point whether or not a switch should be made from using the development version into the stable version. There were two things that needed to be taken into consideration. First of all, it was unknown when this development version would become the next stable one. If the development version became the new stable version, a lot of alterations would have to be made to the source code. Furthermore, for the long term, if this system would become successful, it would be easier to maintain in the future if it relied on the latest version.

Time was also a major limitation for the development. When you are only one person with only one computer there is a certain limitation to how much work can be done simultaneously. A lot of time were spent having to rebuild the database and processing the data (e.g. finding features, replacing it, training classifiers). To ensure expandability (for the SE community) and ensuring replicability (having a unprocessed data set), more than once code had to be updated or re-written. This easily caused a lot of unforeseen issues. The worst one was the realization that after the update of the unprocessed data set (changing it to contain HTML like in the database), the HTML was not removed from the text. The impact was that all the models that were created using the parameters and data from the unprocessed had to be re-trained to get correct results.

One of the more peculiar issues (which I do not have an explanation for), was when the real training started (using the SVC and GridSearchCV). The reason that this issue cannot be explained, is because I do not know what caused it to happen. What happened was that when the training was started, no verbose was printed at all (which was weird considering I had used the same values before and it then gave a verbose output). The program ran for hours, without giving any feedback, errors or output.

It took almost three days to find a solution, where part of the solution was switching to Windows (which had its own issues, since x64 is not supported by Numpy). The main difference was that in Windows, at least verbose was printed, although it only printed verbose once[7]. There were two things that were changed, which finally made it both print verbose and complete the training. The first part was changing the n_jobs value to something else than -1. By setting n_jobs=-1, Grid-SearchCV will run all jobs in parallel, using all logical cores (e.g. on a CPU with 4 physical cores, it will use all 8 logical cores). However, multi-threading is not supported in Windows [16]. To ensure that progress was made, and that the program had not frozen again, the verbose level was increased. By increasing

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[7] Verbose was printed once, sometime twice between the first 20 - 60 minutes, then nothing. The longest run time that was registered was around 12 hours without any verbose printed.

the verbose level, you can force the algorithm to print more information about progress, but with an increase in the time it takes to finish [35, 68]. The most fascinating part was that after increasing the verbose level, it not only printed out continuously, but it even finished training in less than 3 hours! It has not been tested in Linux, but the reason nothing happened may have been the same which happened for Windows, that it could not utilize all cores[8].

---

[8] My assumption is that when all the logical cores are used, there is no processing power left for the Operative System (OS). This in turn would then cause an infinite deadlock, since by using all the cores, there is no processing power left for the OS. There is also a known issue with parallelization in Linux, see: https://pythonhosted.org/joblib/parallel.html#bad-interaction-of-multiprocessing-and-third-party-libraries.

5   Conclusion/Summary

5.1   Overview of main results

- short about SO today
- short about the work that was done
- short about the results and what they indicate

5.2   Further work

- syntax errors/Lint check, e.g. http://esprima.org/demo/validate.html
- SO as an IDE - https://emilschutte.com/stackoverflow-autocomplete/
- sentiment analysis
- symbol usage, e.g. '?', '!', emoticons, etc
- use of greetings, thanks, etc.
- version numbering
- fine tuning of parameters (e.g. RandomizedSearchCV)
- using N-grams

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A   Appendix

A.1   Acronyms

AI Artificial Intelligence. 3

BOW Bag of Words. 9

IDE Integrated Development Environment. 18, 24, 32

IR Information Retrieval. 10

ML Machine Learning. iii, 2, 3

NLTK Natural Language Toolkit. 10, 18, 45

POS Part of Speech. 10

QA Question-Answering. iii, 1, 6, 10, 11

QC Question Classification. 2, 8, 11

SE Stack Exchange. iii, 1–4, 7, 14, 30

SGD Stochastic Gradient Descent. 25–27

SO Stack Overflow. iii, 1–7, 10, 21, 23, 24, 27, 32

SVC Support Vector Classification. 25, 26, 30

SVM Support Vector Machines. ii, iii, 2, 3, 11, 12, 25

A.2   MySQL Database

Figure 4: MySQL Database used for dataset

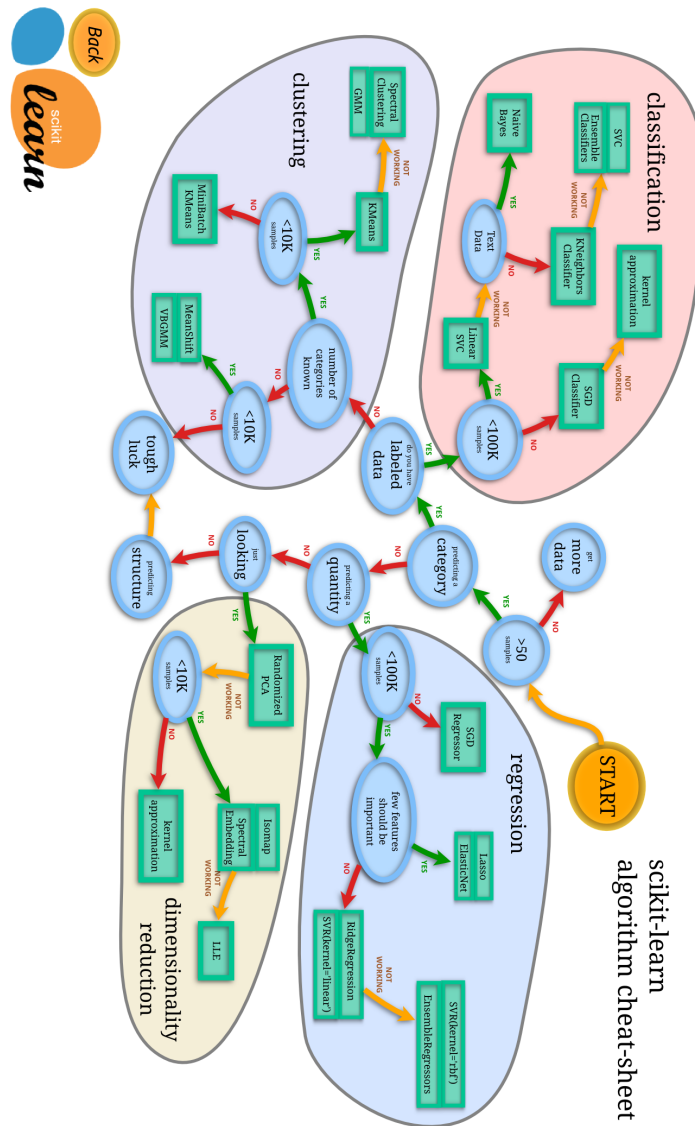## A.3 Scikit-learns roadmap - Choosing the right estimator

Figure 5: Choosing the right estimator [46].

A.4 Quick installation guide for Windows x64

Since Python is much more adapted to *nix systems then Windows, I decided to write a short guide on how to install Python 3.5 and Scikit-learn on Windows. This guide is provided as-is, and I make no guarantees that this will result in a functioning installation, but it should at least reduce the problems. A presumption here is that the operative system is Windows x64 (if you have x86, you can ignore all the x64 settings). Before installing anything, download the following:

- Python: https://www.python.org/downloads/windows/.
  Select the Python version with "Windows x86-64" in its name.
- CygWin: https://cygwin.com/
- MinGW: http://www.mingw.org/
- MySQL connector for Python (Git; only needed for running this project):
  https://github.com/mysql/mysql-connector-python.
- x64 version of Numpy and Scipy [6, 14]:
  http://www.lfd.uci.edu/~gohlke/pythonlibs/.
  The latest available versions at the time of writing is "*numpy-1.11.1rc1+mkl-cp35-cp35m-win_amd64.whl*" and "*scipy-0.17.1-cp35-cp35m-win_amd64.whl*".
- Scikit-learn (Git): https://github.com/scikit-learn/scikit-learn
- If you do not have a version of Microsoft Visual Studio installed, you need to install Visual Studio 2013 or newer (because compiler requires it)[1].

1. Install Python, update pip, and install these packages:
   pip install -U bs4 pandas nltk matplotlib cython nose nosetests
2. Install MinGW. Thereafter select "mingw32-base" under "MinGW Base System". In addition, under "MinGW Base System", select all belonging to Class "bin" and "dll"
3. Install CygWin. During installation, you will be asked what you want to install. Select all entries that contains "gcc", "mingw64", "make", "automake", "lapack" and "openblas". The GCC-compilers are used in combination with MinGW, because Scikit-learn needs Fortran, Lapack and OpenBlas for *make* to succeed.
4. Change to folder with the x64 version of Numpy and Scipy, and install them [6, 14]:
   pip install "numpy-1.11.1rc1+mkl-cp35-cp35m-win_amd64.whl"
   Verify installation: 1. *python*, 2. *import numpy*, 3. *numpy.__version__*.
   pip install "scipy-0.17.1-cp35-cp35m-win_amd64.whl" and verify using the same steps, swapping numpy with scipy.
5. Start CygWin (run as administrator), change to directory containing Scikit-learn and run the following commands:
   python setup.py build and *python setup.py install*.

---

[1] "vcvarsall.bat needed for python to compile missing from visual studio 2015":
http://stackoverflow.com/q/33323172

6. If you want to use NLTK, you need to run *python*, *import nltk* and *ntlk.download()* to download the corpus.