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Recognising structural patterns in code

A k-means clustering approach

Bachelor Thesis

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Abstract

For the Computer to use and understand data it is necessary to parse it into computer readable format. For building a parser a model of the grammar and structure of the data must be known or created. For many new programming language dialects and also for log files of new software these models are normally not available. For creating a model, the structure and grammar information must therefore be inferred from the source code which is a time consuming process. The goal of this project is helping developers find structure of software code automatically. For this, the thesis introduces a clustering approach with k-means. Through different vector representations, structural information should be exploited and assigned accordingly in different clusters. This should help developers get a better overview of the data and in a perfect case be able to create parser rules per cluster.

The used approach had some promising results, assigning different patterns into different clusters. We used overall 24 different possible combinations of representation. Of these 24 representation, there were four representations with good results, having a v-measure score equal or higher than 0.66 from a maximum of one for Java, and another 4 with satisfying results having equal or better results than 0.4, also for Java. The Representors with good scores in Java, also did a good job, clustering C Sharp, XML and ABACUS log files, with at leas one representation scoring higher than 0.66. For C++, Python the scores were satisfying. Only for the language Brainfuck, the clustering with these Representors did not work well.

Unfortunately our approach for using the k-means implementation for calculating a precision value for how closely languages are related, did not perform well.

Contents

1 Introduction

1.1 Motivation

Writing software means reading software code. For developers it is crucial to understand the state of the system in order to carry out development and software evolution tasks. As a consequence, developers often use as much time reading and understanding the written code as actually writing new code. Analysing tolls for integrated development environments can help developers understanding code and reduce time for assessing software code.[4] For that such tools can be created a software model of the used language must exist in form of a parser. For many dialects of programming language these models do not exists. Aside from programming languages log files are a very important part of software applications. Many current software applications do produce auxiliary text files as output. These log files are used various ways for example in debugging and profiling purposes. While generating log files is a very simple and straightforward process, the understanding of log files can be quite hard, as these can be very large files with complex structure.[7] If a model of the grammar und underlying structure does not exist, it is necessary to infer these properties from the source code. The inferring of a software model and the building of a custom parser is a complex task that can take several people several months to accomplish. In this bachelors project we tried to build a tool that can help distinguish different pattern and structures automatically from software code or log files.[2]

1.2 Goal and Focus

The goal of this thesis is to develop a software tool that can atomically find structure in software code od unknown software code or log files and to generate different sets consisting of related pattern so that a parser rule can be inferred. The process of creating the software tool manifested three different sub-problems that had to be addressed:

1. **Statement creation.** Structure manifests itself in an ordered sequence of different tokens. For finding different patterns, a smallest statement had to be found, which is able to hold structural information. For this thesis it is assumed, that carriage returns are a natural and often used way which indicates the beginning of a new pattern. A statement is then split into tokens. A token consists of one or more Symbols and in is defined through first the encapsulating of blank spaces and second in a change of symbols.

2. **Representation and differentiation.** For algorithmically deciding and quantifying the difference between statements a way for mathematically representing needs to be introduced. The approaches used in these methods differ from creating a vector out of defining features. but instead focuses on the type of symbols used in a token.

3. **Clustering.** A programming language consists of a finite number of different pattern that are used for describing a Software. These pattern are therefore used multiple times only differing in the used variables and parameters. Patterns that are similar or differ only in used variables must be filtered. Filtering is achieved through k-means clustering. Patterns should be clustered according to their similarity.

To achieve a solution to these sub-problems, certain assumptions about the commonalities of languages and log files had to be made. We tried to keep these assumptions as minimal as possible so that a wide variety of programming languages and log files could be analysed:

- A Language consists of a finite number of patterns that differ only in used variables and parameters.

- Software Code contains indents and carriage returns as is best practice for many programming languages amongst developers.

2
Methods

In this chapter we describe in detail the used methods for creating and tokenizing token and put forward the different representations used in the created tool. In our context a method is defined as a process, which if replaced, would result in a different output of the tool. For visualising our methods, we use the following simplified Java example:

```
if (x > 1) {return 0;}
if (x <= 0) {return 1;}
else {return v1;}
```

Listing 1: Simplified Java Code

2.1 Statements and Tokens

To be able to cluster the data, it first needs to be processed into smaller instances that are comparable to each other. As mentioned in the introduction, we used in this project different levels of instances called: Statements and tokens, where a Statement consists of tokens. A statement can be created in different ways. Because the main effort of this thesis lies in the structural clustering with the k-means algorithm, the creation of statements is simplified.

A statement is a line of code. Carriage retunes and line feeds are a very important way to make software code readable, creating a structure the human eye can perceive more easily. The way of using carriage returns and line feeds for defining a statements tries to exploit the way we make software code and log files more readable for humans.

In our example before, each new line, would become a statement, creating three different statements from this code snippet:

```
if (x > 1) {return 0;}
if (x <= 0) {return 1;}
else {return v1;}
```

Listing 2: Statements in Java example

A token is a single word, numeral or punctuation. A statement is further processed into tokens. The smallest instance. Words are a sequence of at least one letter and can contain numerals. **Words** cannot contain punctuation. **Numerals** are a sequence of at least one digit. A Numeral cannot contain letters or punctuation. **Punctuation** is one special character which cannot be a letter nor a digit.

In our example tokens would be made as follows:

```
if ( x > 1) {return 0;}
if (x <= 0) {return 1;}
else {return v1;}
```

Listing 3: Tokens in statements

In this example the words are marked in orange, numerals are in green and punctuation is in blue. Tokens are divided by spaces. Punctuation that is not encapsulated by spaces will still be tokenized as an individual special. This means as seen in the example, that a "<=" will be tokenized into two tokens: "<" and "=". Variables such as "v1" are tokenized as a word.

2.2 Representors

As mentioned in the introduction, vector representation is needed for clustering statements. A Representor adds or modifies representation to a statement. There are three different categories of Representors: Type Representors, Distance Representors and Weight Representors.

1. **Type Representor.** Type Representors create vector representations according to the characteristics of the tokens of the statement and assign numbers to the vector accordingly.

2. **Distance Representor.** Distance Representors calculate distance information from the given representation of a Type Representor.

3. **Weight Representor.** Weight Representors function as noise cancelling or filtering and can weight specific parts of a representation more or less.

Representors can be concatenated in the order above. A Type Representor is always needed, but can optionally be followed by a Distance Representor or a Weight Representor or both.

2.2.1 Type Structure Representor

The first Type Representor to be looked at, is the Type Structure Representor. It assigns a strict value according to the type of the token.

Example: In our implementation we assigned the values 0 for words, 1 for numerals and 2 for Punctuation. For our previous used Java snippet in Listing 2

```
if (x > 1) {return 0;}
if (x <= 0) {return 1;}
else {return v1;}
```

Listing 4: Simplified Java snippet

Type Structure Representor gives us the vector representations:

```
(0 2 0 2 1 2 2 0 1 2 2)
(0 2 0 2 2 1 2 2 0 1 2 2)
(0 2 0 0 2 2)
```

Listing 5: Type Structure Representation example as vectors

2.2.2 Type Specific Representor

The Type Specific Representor uses the same structural information for calculating the vector representation as the Type Structure Representor. But instead of assigning a single value per type, the Type Specific Representor assigns a value per encountered unique token, with the exception of bracket symbols, for which opening and closing brackets are treated as one unique token. To maintain the structural information, the assigned value of the token is then normed by the type of the token. A vector element therefore is defined as:

$$vector\_element = \frac{1}{assigned\_token\_value} + type\_value.$$

Example: Same as in the Type Structure Representor we assigned the values 0 for words, 1 for numerals and 2 for Punctuation. A punctuation token therefore would always be in the interval $(2, 3]$.

For our previous used Java snippet in Listing 2

```
if (x > 1) {return 0;}
if (x <= 0) {return 1;}
else {return v1;}
```

Listing 6: Type Specific Representation example

this gives us the vector representations:

$$(\tfrac{1}{1}+0\ \ \tfrac{1}{2}+2\ \ \tfrac{1}{3}+0\ \ \tfrac{1}{4}+2\ \ \tfrac{1}{5}+1\ \ \tfrac{1}{2}+2\ \ \tfrac{1}{6}+2\ \ \tfrac{1}{7}+0\ \ \tfrac{1}{8}+1\ \ \tfrac{1}{9}+2\ \ \tfrac{1}{6}+2)$$
$$(\tfrac{1}{1}+0\ \ \tfrac{1}{2}+2\ \ \tfrac{1}{3}+0\ \ \tfrac{1}{4}+2\ \ \tfrac{1}{10}+2\ \ \tfrac{1}{8}+1\ \ \tfrac{1}{2}+2\ \ \tfrac{1}{6}+2\ \ \tfrac{1}{7}+0\ \ \tfrac{1}{8}+2\ \ \tfrac{1}{9}+2\ \ \tfrac{1}{6}+2)$$
$$(\tfrac{1}{11}+0\ \ \tfrac{1}{6}+2\ \ \tfrac{1}{7}+0\ \ \tfrac{1}{12}+0\ \ \tfrac{1}{9}+2\ \ \tfrac{1}{6}+2)$$

Listing 7: Type Specific Representation as vectors example

2.2.3 Distance Zero Representor

For exploiting distance information, the Distance Zero Representor measures the distance between the occurrences of the same values given by the used Type Representor. Measurement starts with zero as a new value is first encountered. If the same value is encountered after that, the new vector element will be the distance between the first encounter and the current position of the vector element. Example: For simplifying the example, Type Structure Representor is used for assigning type values.

```
(0 2 0 2 1 2 2 0 1 2 2)
(0 2 0 2 2 1 2 2 0 1 2 2)
(0 2 0 0 2 2)
```

Listing 8: Type Representation as calculated in Listing 5

Applying Distance Zero Representation to the above Java snippet gives:

```
(0 0 0 2 4 4 5 5 8 8 9)
(0 0 0 2 3 5 5 6 6 9 9 10)
(0 0 2 3 3 4)
```

Listing 9: Distance Zero Representation of Type Structure Representation on Listing 14

2.2.4 Distance All Representor

The Distance All Representor calculates the maximal distance between to previously assigned type values given by a Type Representor. It then sets the calculated distance for all values of the same previously assigned type value.

Example: Type Structure Representor is used for assigning type values

```
(0 2 0 2 1 2 2 0 1 2 2)
(0 2 0 2 2 1 2 2 0 1 2 2)
(0 2 0 0 2 2)
```

Listing 10: Type Representation as calculated in Listing 5

Applying Distance All Representor gives the following representations:

```
(4 3 5 3 4 3 3 5 4 3 3)
(5 3 6 3 3 5 3 3 6 5 3 3)
(2 3 2 2 3 3)
```

Listing 11: Distance All Representation vector representation example

2.2.5 Weight Summary Representor

The Weight Summary Representor is used as noise reduction. Multiple subsequent occurrences of the same type value are summarized into one vector element. Example: In the following example the use of this technique can be seen in the reducing the difference between line 1 and line 2:

```
(0 2 0 2 1 2 2 0 1 2 2)
(0 2 0 2 2 1 2 2 0 1 2 2)
(0 2 0 0 2 2)
```

Listing 12: Type Representation as calculated in Listing 5

Applying Weight Summary Representor gives the following representations:

```
(0 2 0 2 1 2 0 1 2)
(0 2 0 2 1 2 0 1 2)
(0 2 0 2)
```

Listing 13: Weight Summary Representation vector representation example

2.2.6 Weight Sum First Representor

In code important information such as keywords can often be found in the beginning of a line of code. Weight Sum First Representor adds all values following to currently

assigned values as new vector element, giving vector elements in the beginning a higher weight.
Example: For our previously used Java snippet in Listing 5, applying Weight Sum First Representor gives the following representations.

```
(14 14 12 12 10 9 7 5 5 4 2)
(16 16 14 14 12 10 9 7 5 5 4 2)
(6 6 4 4 2 2)
```

Listing 14: Weight Sum Representation vector representation example

2.2.7 Weight Inverse Representor

The Weight Inverse Representor inverses every vector element. This reduces the variance of the data and inverses the weighting of the data. Example: The representation of the Type Structure Representor as shown in Listing 5 inverted. A Zero value as possible in Type Structure Representation is not affected:

$$(0\ \ \tfrac{1}{2}\ \ 0\ \ \tfrac{1}{2}\ \ \tfrac{1}{1}\ \ \tfrac{1}{2}\ \ \tfrac{1}{2}\ \ 0\ \ \tfrac{1}{1}\ \ \tfrac{1}{2}\ \ \tfrac{1}{2})$$
$$(0\ \ \tfrac{1}{2}\ \ 0\ \ \tfrac{1}{2}\ \ \tfrac{1}{2}\ \ \tfrac{1}{1}\ \ \tfrac{1}{2}\ \ \tfrac{1}{2}\ \ \tfrac{1}{1}\ \ \tfrac{1}{1}\ \ \tfrac{1}{2}\ \ \tfrac{1}{2})$$
$$(0\ \ \tfrac{1}{2}\ \ 0\ \ 0\ \ \tfrac{1}{2}\ \ \tfrac{1}{2})$$

Listing 15: Type Specific Representation as vectors example

2.3 K-Means

K-means is an unsupervised clustering algorithm. It clusters the given data in k different clusters, with k being a known parameter, according to the vector representation of the data. For clustering the data k different centroids are randomly initialized and the algorithm labels the data according to the nearest centroid. At the end of the algorithm the centroids will have minimal distance to its assigned data points. It achieves this by moving the centroids to mathematical mean of all the assigned data points. The mathematical expression, given the trainings set $\{x^{(1)}, ..., x^{(m)}\}$ and $x^{(i)} \in \mathbb{R}$ of the k-means algorithm is as follows:

```
1. Initialize cluster centroids $\mu_1, \mu_2, \ldots, \mu_k \in \mathbb{R}^n$ randomly.
2. Repeat until convergence: {
       For every $i$, set
           $c^{(i)} := \arg\min_j ||x^{(i)} - \mu_j||^2.$
       For each $j$, set
           $\mu_j := \frac{\sum_{i=1}^m 1\{c^{(i)} = j\} x^{(i)}}{\sum_{i=1}^m 1\{c^{(i)} = j\}}.$
   }
```

Figure 2.1: Mathematical expression of k-means [3]

A practical example of the k-means algorithm:

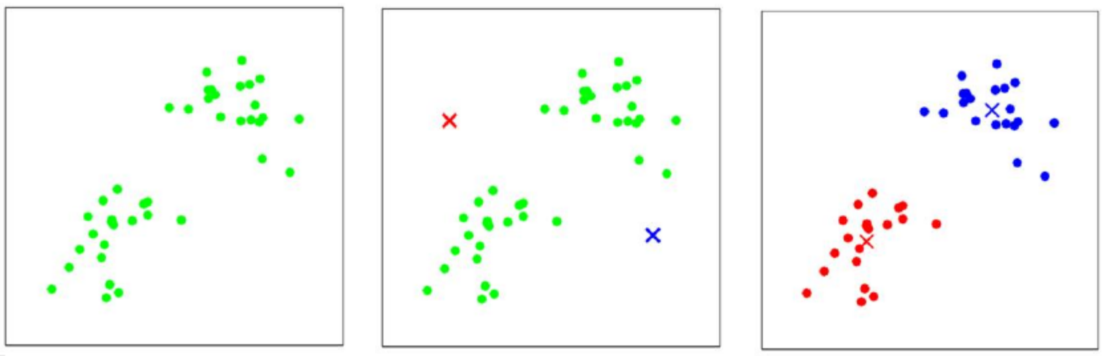


Figure 2.2: Example of k-means iteration [3]

The red and blue cross are the centroids and are initialized randomly. The centroids will then gradually move nearer to the mean of the final clusters for each iteration, minimizing the cost or distortion function:

$$J(c, \mu) = \sum_{i=1}^{m} ||x^{(i)} - \mu_{c^{(i)}}||^2.$$

J measures the sum of squared distances between each training example $x^{(i)}$ and the centroid of the cluster $\mu_{c^{(i)}}$ to which it has been assigned.

2.4 The Elbow Method

One problem of the k-means algorithm is that the parameter k must be known. In our case the parameter k is not known. K is dependent on the given input; on which we want to limit our assumptions. Therefore, a way to algorithmically calculate k is needed. The idea behind the Elbow Method is to find the number of centroids, so that you have the maximal number of centroids, which is k, for which the fit of the centroids to the data - measured by the cost function J- does not improve significantly any more. In the case of k equals one, the position of the centroid would be the mean of all data point and in the case of k equals the number of date point the centroids would be the points themselves, giving for k equals one the worst fit and for k equals the number of data points a perfect fit. This can be illustrated by the following example where we normed J by k:

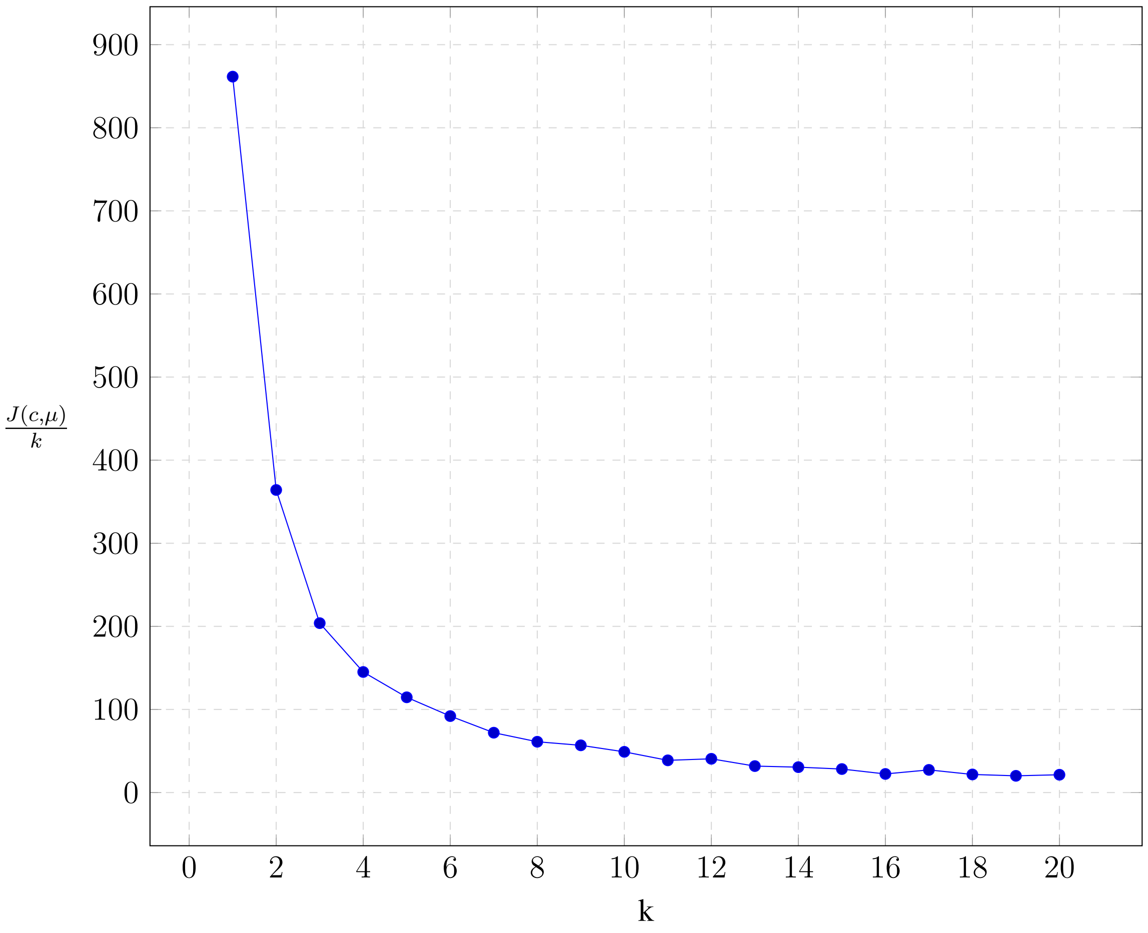


Figure 2.3: Average Fit per centroid per k

As seen in the figure above, the improvement in the data modelling decreases as k becomes larger. By calculating the partial derivative $\frac{c_{i-1} - c_{i+1}}{k_{i-1} - k_{i+1}}$, this decrease can be measured. For getting the value for k, the partial derivative is maximized until it reaches a threshold α, with $\alpha \in \mathbb{R}^{-}$.

In a two dimensional case the visual interpretation looks as follows:

2.5 Language Differentiation

This thesis also provides a method to calculate a precision value of how closely related two languages are based on the representation based k-means clustering. For this, one language is clustered with the k-means algorithm. For each cluster the radius is calculated ranging from the coordinate of the centroid to the assigned data point which is furthest away from the centroid. For comparing a second language to the first it is enough to only calculate the representation. For each represented data point of the second language it is then checked if it is inside any circle spanned from the previously calculated radii. It is calculated as follows:

$$language\_relation = 1 - \frac{number\_of\_data\_points\_in\_radius}{number\_of\_datapoints}$$

This means, that for any given two languages the result 1 means that the two languages are related closely and 0 means that the languages are completely different. The two dimensional visualisation looks as follows, with the red and blue crosses being the data points of the clusters of the clustered language, with the centroid as the centre and the green crosses being the data points of the second language:

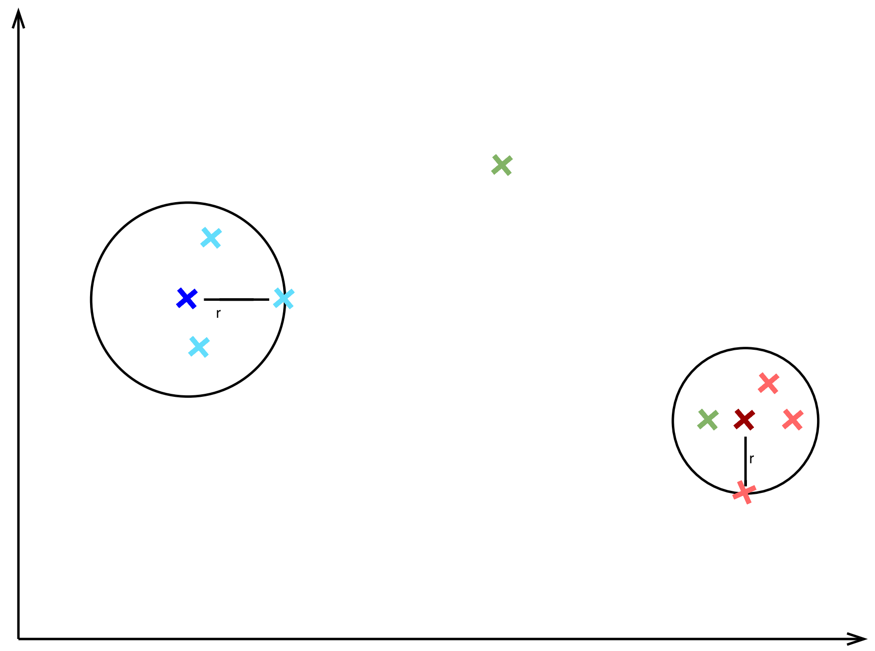


Figure 2.4: Two dimensional example of Language Differentiation

3 Implementation

This chapter gives an overview of the implementation of the k-means clustering tool. First we look at used resources. After that we look at the k-means and Language Differentiator pipeline and how the data is processed.

3.1 Technology

The k-means clustering tool is developed in Pharo 4.0. Statements and tokens are separated with Petit Parser [1] and is also used for recognizing the types of the tokens.

3.2 K-Means Pipeline

The first implementation to verify our ideas of clustering statements of software code was a simple k-means clustering algorithm with a single static k as a parameter.

Known k. The implementation of the k-means clustering tool for calculating a single cluster is quite straightforward. A code file is loaded by a File Handler object. With the help of Petit Parser the loaded code file is then split into statements and tokens by the New Line Statementmaker. A Representor Runner is responsible for handling the different representation methods and calls to the loaded Representors. The Representors then successively create the vector representation. This representations get clustered by the implemented k-means algorithm. The processed clusters are sent back to File

Handler, which saves each cluster in a separate file, containing the assigned statements to the clusters. To initialize the centroids in a reasonable range of values, the range is determined by the Representors used. This is to minimize the risk of getting centroids without any data assigned to them, so called empty centroids. The data flow can be seen in the following figure:

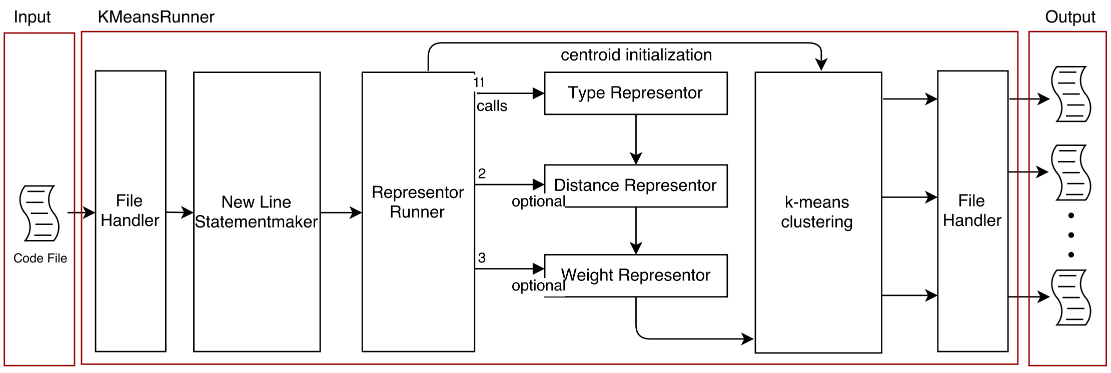


Figure 3.1: Simplified data flow in the single k k-means pipeline

As discussed before, assumptions on the structure of the input, should be minimal. Therefore we don't wont to make assumptions about k, but to have a algorithm to calculate the optimal number of clusters.

Interval. If the optimal number of clusters is not known, it is needed to calculate different clusterings withdifferent numbers of clusters and compare them. For this we implemented a way to create different clusters for a given interval. For each natural number in this interval, a set of clusters is calculated and then compared according to the elbow method discussed in section 2.4. Each calculated set of clusters is given to the File Handler and output is created for each set of clusters in the same way as in the implementation above. All results from the distortion function, as well as the used representation and the optimal value of k is saved in log file. The expansion results in this updated data flow:

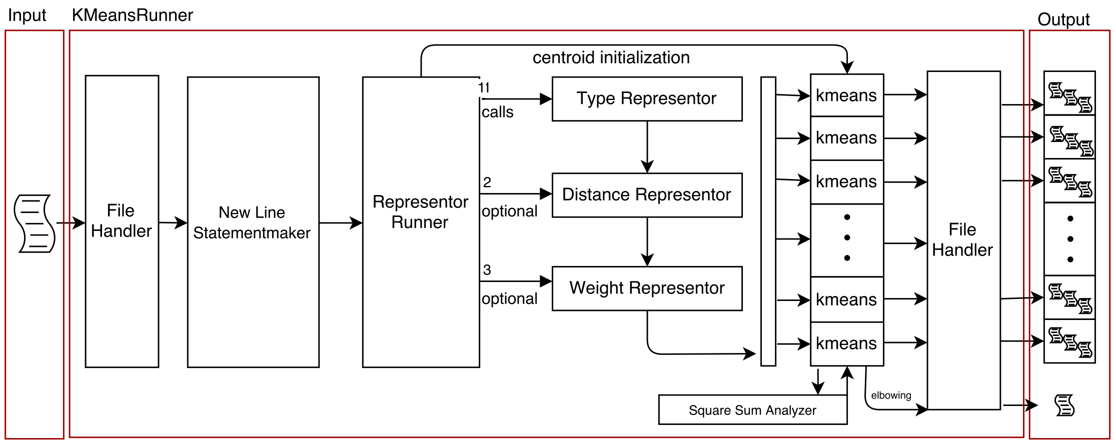


Figure 3.2: Simplified data flow in the expanded k-means pipeline

Square Sum Analyser calculates the distortion function for the elbowing of the k-means clusterings.

3.3 Language Differentiation Pipeline

As in section 2.5 discussed it is possible to use the implementation of the k-means clustering to use for calculating a precision value for how closely related different languages are. The implementation is expanded by adding an control object for the language differentiation. The data flow of the Language Differentiation looks accordingly:

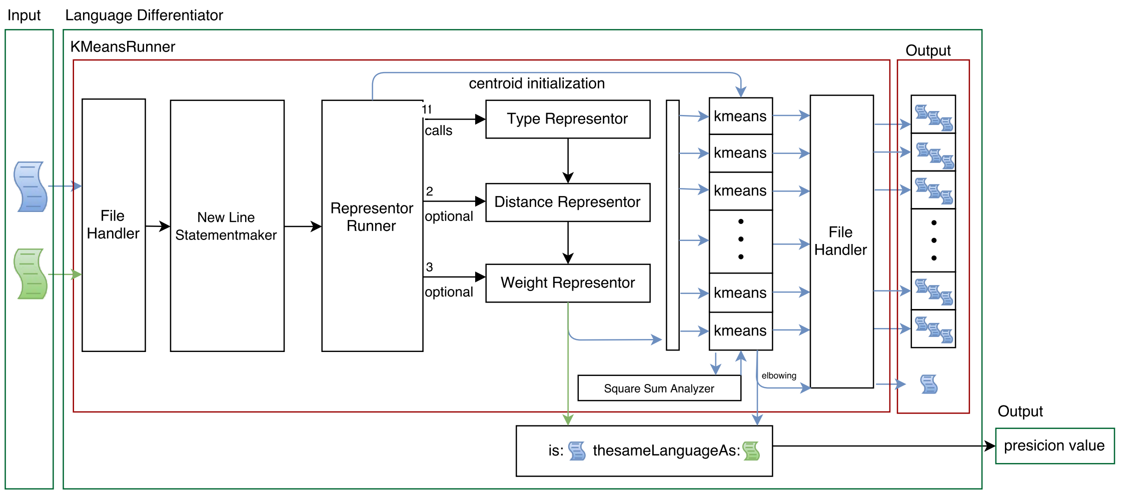


Figure 3.3: Simplified data flow in the Language Differentiator pipeline

3.4 Runtime

The runtime of the developed tool is dependent on different parameters of the input and configuration. The parameters it depends on are the number of iteration, the size of the trainings data and the numbers of clusters, as well as the number of attributes, meaning the lengths of the vector representations. While running the algorithm we experienced slow downs for calculating the clustering using Type Structure Representor and calculations with Weight Inverse Representor. This two Representations are the only one using float calculation instead of integer calculations. Because there are lot of vector calculations involved, it leads to the conclusion that floating point calculation is the cause of the slow downs.

3.5 Testing

Testing is done in SUnit, which is integrated in Pharo 4.0. A test suite was implemented testing vector calculations and the correct functioning of the creation of the representation.

4 Evaluation

In this chapter we are going to evaluate how well the ideas implemented in this thesis work. For this we look at the different methods and first discuss how we can evaluate them and then we look at how they perform on an Example. For this evaluation we concentrate on Java. In the next chapter other languages will be evaluated. Evaluating an unsupervised learning algorithm does have the problem, that there is no labelled data to test against. But because we know what the goal of the algorithm is supposed to be, we were able to manually cluster the Java file into a reference clustering, to test our methods against.

4.1 The Elbow Method

The elbow method, as seen in Section 2.4, is a heuristic for finding a good value for the parameter k. In our manually clustered Java data, we were able to cluster it into 13 different clusters, making this our desired output of the elbow method. For the Type Structure and the Type Specific Representor we run the elbow methods with different parameter α on Java data:

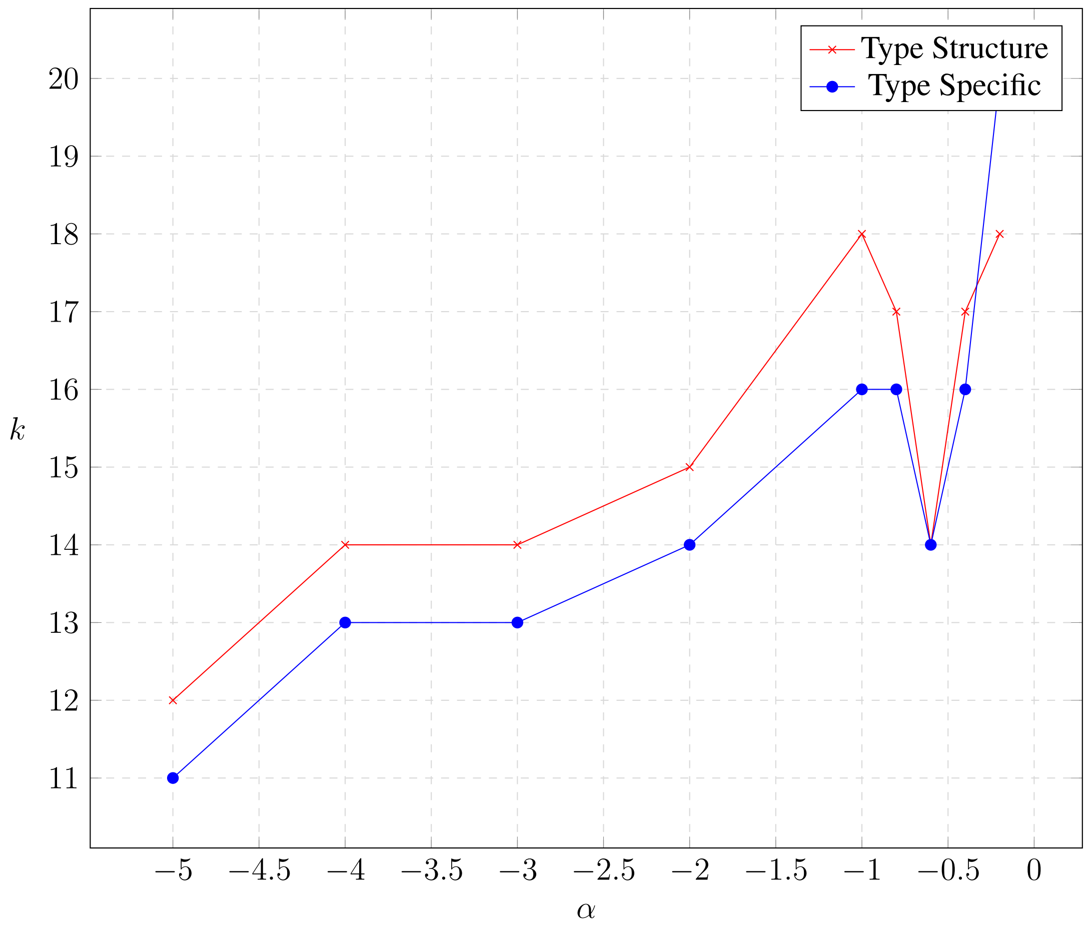


Figure 4.1: Plot of elbow method. Heuristic value of k, given α

The the smaller α, the smaller k is. This two plots show, that to get near the desired value for k, a value of α equal to -4 is desirable, and will be used for further calculations. It is important to notice that the calculated k differs for the same value for α for the two different used representation methods. Also we have to address the problem of statistical outliers, as can be seen in this graph at around $\alpha = -0.5$. Given that the underlying k-means algorithm is statistical outliers are expected. Problems related to the k-means implementation well be discussed in section 4.2.

4.2 Evaluating the Representations

Evaluating the performance of the clustering for the different representations, needs a distinct evaluation method, which giving us a value to compare. We introduce V-

Measures for measuring the performance of our tool.

4.2.1 V-Measures

Given the knowledge of the ground truth class assignments of the samples, which we manually created, it is possible to define some a metric using conditional entropy analysis. In particular Rosenberg and Hirschberg (2007) [6] define the following two desirable objectives for any cluster assignment:

- **homogeneity:** each cluster contains only members of a single class.
- **completeness:** all members of a given class are assigned to the same cluster.

Homogeneity and completeness scores are formally given by:

$$h = 1 - \frac{H(C|K)}{H(C)}$$
$$c = 1 - \frac{H(K|C)}{H(K)}$$

with the conditional entropy of the classes given the cluster assignments $H(C|K)$ being defined as:

$$H(C|K) = -\sum_{c=1}^{|C|}\sum_{k=1}^{|K|}\frac{n_{c,k}}{n}log\Big(\frac{n_{c,k}}{n_k}\Big)$$

and the conditional entropy of the classes is given by:

$H(C) = -\sum_{c=1}^{|C|}\frac{n_c}{n}log\Big(\frac{n_c}{n}\Big)$ where n_k is the number of samples in cluster k and $n_{c,k}$ is the number of samples from class c assigned to cluster k.
The conditional entropy of clusters given class $H(K|C)$ and the entropy of clusters $H(K)$ are defined in a symmetric manner.

V-Measure is defined as the harmonic mean of homogeneity and completeness:

$$v = 2\frac{h * c}{h + c}$$

This gives us values for h, c and v ranging from $[0, 1]$. This values can be used as a score to compare how well our representations performed, with 1 being a perfect score and 0 being the lowest score. [6]

4.2.2 V-Measure scores

With this we can calculate two tables, containing all the possible representations introduced in this thesis. The first table is clustered using the Type Structure representation and second table is calculated using Type Specific representation. The two tables are structured, that first all the Representors are evaluated with the respective Type Representor and in an additional step, the Weight Representors are concatenated with the Distance Representors.

Table 4.1: Java v-measures of all possible representations with Type Structure Representor

Representor	homogenity	completeness	v-measure	perfect k	empty centroids
Type Structure	0,61	0,9	0,73	13	0
Dist Zero	0,47	0,35	0,4	14	4
Dist All	0,89	0,53	0,66	13	4
Wheight Summary	0,25	0,23	0,24	14	8
Weight Sum First	0,21	0,27	0,24	11	5
Weight Inverse	0,77	0,56	0,65	11	0
Dist Zero					
Wheight Summary	0,22	0,42	0,29	16	5
Weight Sum First	0,14	0,11	0,12	12	7
Weight Inverse	0,72	0	0	11	9
Dist All					
Wheight Summary	0,08	0,29	0,13	13	6
Weight Sum First	0,1	0	0	20	13
Weight Inverse	0,57	0	0	11	5

Table 4.2: Java v-measures of all possible representations with Type Specific Representor

Representor	homogenity	completeness	v-measure	perfect k	empty centroids
Type Specific	0,68	0,91	0,77	11	0
Dist Zero	0,56	0	0	13	6
Dist All	0,36	0	0	14	9
Wheight Summary	0,62	0,95	0,75	14	0
Weight Sum First	0,27	0	0	15	9
Weight Inverse	0,47	0,73	0,58	20	6
Dist Zero					
Wheight Summary	0,45	0	0	15	8
Weight Sum First	0,12	0	0	20	10
Weight Inverse	0,65	0,65	0,62	11	6
Dist All					
Wheight Summary	0,6	0	0	13	8
Weight Sum First	0,1	0	0	20	9
Weight Inverse	0,87	0	0	11	9

All the calculations in the two tables were made with clusterings for the interval $[10, 25]$ and with $\alpha = -3$. Aside from the calculations of the scores for homogeneity, completeness and v-measures, the tables also feature the elbowed value for k as "perfect k". In k-means clustering it is possible for centroids, to not be assigned to any data points. Because of this, the number of empty centroids encountered in the clustering, is featured as well. While computing the v-measure scores there was a problem with the range of the values computed. Under the condition of empty centroids present, there was a possibility for the scores be lower than zero. Fortunately this was only the case if there were many centroids without assigned data points. For simplicity, these values were rounded to zero.

4.2.3 Explaining the Results

The best results were achieved by using only the two Type Representors. They scored extremely well in completeness with values up to 0.91, if used without any other representation. The best scores however were achieved by adding the Weight Summary Representor, which as discussed in section 2.2 serves as noise reduction. With the addition of Weight Summary representation, the algorithm scores up to 0.95 and works extremely well if used with the Type Specific representation, but not as good with the Type Structure representation. Overall the v-measures scores of the Type Structure table have a mean of 0.28, which is slightly better as the mean of all the v-measure scores of the Type Specific Representation as basic representation, which is 0.2. But if we look at the highest scores, Type Structure Representation is the better choice having both the highest score with the representation that uses only Type Representation and the highest score overall with the use of Type Specific Representation and the Weight Summary Representor.

The heuristic guess for k does extremely well. As mentioned before, $\alpha = -3$ was used for the calculations of the elbow method. Interesting are above all the combination of Representors that do not result in empty centroids. For those representations the guessed k maximally varies by 2 from the manually created example. For the best combination, being composed of the Type Specific and the Weight Summary, it only differs by one additional clustering.

While there are pretty good results from our tool, most of them have only low scores. This section tries to find an explanation, as to why.

Assumptions. The main goal of the thesis was to find structural patterns in software code files or log files, while keeping the assumptions about the structure of this files as minimal as possible. One of the problems of using a clustering algorithm is, that said algorithm does make assumptions about the data it is clustering. For k-means this assumption lies in the goal of the algorithm to minimize the squared sum of the distances, from the data points to centroids. This means that it always tries to find clusters that are circular in shape. This must not be the case for the representations we created in this theses, as the representations were created, as seen fit for representing certain characteristics of structures.

Variance. If we look in the scores table, it stands out, that representations do poor, that create a big variance in the data. This is the case for all the Distance Representors, as well as for representations such as Weight Sum First. It is interesting to see, that the Distance Representors do better, if we lower the variance of the data, which is the case, if we additionally use the Weight Inverse Representor. This could be the case, again, because the k-means algorithm tries to minimize the squared sum distances from data points to centroids. With a big variance in the data, this can cause the k-means algorithm to give more weight to clusters that are more dense and thus neglecting smaller clusters with lower density. [5]

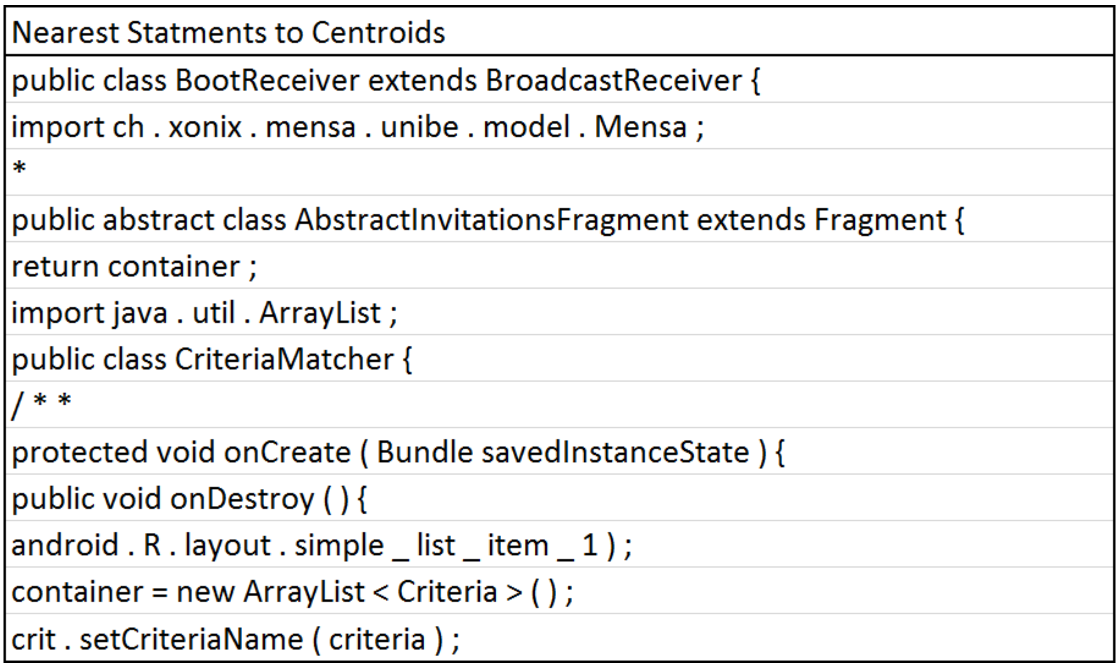
Empty Centroid. In the results, we needed to feature a column for empty centroids, as this is a big problem, that needs to be addressed. Centroids are randomly initialized uniformly over all dimensions of the vector, scaled to the highest vector element found in the data. In contrast to featurization, representations allows for vectors of different sizes.

For vector calculations this means that smaller vectors need to be padded with zeros to compare them. This also means that more relevant data lies in the lower dimensions of a vector. If the centroids are uniformly initialised over every dimension, initialized centroids can be further away from the data points as any other centroid. We can see this in Weight Sum First, were we have high values at the beginning and low values at the end. So Weight Sum First increases this phenomena. A problem in this explanation lies therein, that empty centroids are not a problem for all representations the same way. This means that there needs be another problem causing this. Another look into the scores table reveals, that empty centroids are more common for Representors, that have higher variance in the data.

Convergence. Scores rely on the convergence of the k-means algorithm. For the algorithm to be guaranteed to converge to the optimal result, certain assumptions of the data must be met. These assumptions are discussed above. So if these assumptions are not met, it is possible that the algorithm converges to local instead of global optimums. In our thesis it is unfortunately the case, that these assumptions are not met. This can result in different results as in the tables above. This does not necessarily mean that are calculated data is not valid. If the Representors are run multiple times, the algorithm that did well in the scores in the tables above, were actually to be the most robust ones, having the lowest variance in the scores and the distortion function. This can be traced back to the robustness in relation to the empty centroids, meaning that if a representation is more likely to have empty centroids, it is also be expected to have higher variance of the v-measures and the results of the distortion function.

4.2.4 Nearest statement sample

The output of the implemented clustering tool is described in section 3.2. In evaluating our tool, we wanted to know, what the nearest statements of each centroid is.



Nearest Statments to Centroids
public class BootReceiver extends BroadcastReceiver {
import ch . xonix . mensa . unibe . model . Mensa ;
*
public abstract class AbstractInvitationsFragment extends Fragment {
return container ;
import java . util . ArrayList ;
public class CriteriaMatcher {
/ * *
protected void onCreate (Bundle savedInstanceState) {
public void onDestroy ( ) {
android . R . layout . simple _ list _ item _ 1) ;
container = new ArrayList < Criteria > ( ) ;
crit . setCriteriaName (criteria) ;

Figure 4.2: Nearest statements per centroids, created witch Type Structure Representor

The first thing that stands out is that we have here to different lines that are related to commenting. It is clear that comments are problematic in out clustering approach, because the beginning of the statements defines to which cluster it should be assigned to, and not the representation of the whole information. Also there are two almost identical statements on line 1 and line 4, with the difference being in the length. This means that the length of the representation does play a big role in the assignments of the statements to clusters. It is to note here, that this would be the same statement, if Weight Summary Representor would have been used with the Type Structure Representor.

Nearest Statments to Centroids
import ch . xonix . mensa . unibe . model . Mensa ;
Intent intent = new Intent (this , DrawerMenuActivity . class) ;
public class BootReceiver extends BroadcastReceiver {
public abstract class AbstractInvitationsFragment extends Fragment {
container = new ArrayList < Criteria > ( ) ;
import java . util . Set ;
tenOClock . set (Calendar . YEAR , Calendar . MONTH , Calendar . DAY _ OF _ MONTH , 10 , 0 , 0) ;
else {
}) ;
if (LoginService . isLoggedIn ( ))
adapter = createAdapter ( ) ;
public class CriteriaMatcher {
* This simple abstract class has the functionality which is common for both

Figure 4.3: Nearest statements per centroids, created witch Type Specific Representor

Type Structure Representor does a better job, assigning the comments to the same clusters. We still have the problem here, that we have to nearly identical patterns, starting with the import statements. It would be desired, to have them in the same cluster. The only difference of those two structures lies in the lengths of the statement, and further more only in a series of a repeating pattern. This is a huge draw back of our implemented approaches. Also we have the same problem as in figure 8.3 above, here in line 3 and 4, with statements that only differ in one word.

5 Evaluating other languages

The evaluation in for the k-means algorithm were done in Java. From this evaluation we can now discard certain representations as not usable. That these representations do well for other languages than Java can be concluded from the evaluation part. For this we will now take a look at the performance of the representations for other languages and also we will run our algorithm on an Abacus log file. All the files contain source code randomly selected from Github. Each file contains roughly about 300 lines of code or more.

5.1 C Sharp / C#

Table 5.1: C Sharp v-measures

Representor	homogeneity	completeness	v-measure	perfect k	empty centroid
Type Structure	0,86	0,75	0,8	13	2
WeightSummary	0,23	0,61	0,34	12	5
Type Specific	0,61	1	0,75	15	2
WeightSummary	0,9	0,15	0,26	11	4

If we look at the taxonomy of programming languages, we see that C Sharp is a very close descended of Java. This means that many structural elements are the same. It does not surprise than that the results of our methods are not that different. The heuristic for k is in this example not as good as for Java, as we manually classified C Sharp into 17 clusters, making for C Sharp the use of $\alpha = -3$ not the best choice. Nevertheless are the scores for the single use of the Type Representors very satisfying, with the best v-measure around 0.8. But it stands out, that the Weight Summary Representor -our noise reduction- does not perform as good as in Java. This is surprising, given the close relation between Java and C Sharp. While it resulted in good scores for Java -giving the best score with Type Specific respresenation- , the scores for C Sharp are remarkably low. Differences can lie in the composition of the used data. For this thesis around 300 lines of code for each languages were used in the clustering of the language. A big challenge in clustering is the correct assignment of comments. If a code contains lots of comments in different ways or software code that is commented out, this will be clustered differently as intended, as we all comments to be assigned to the same cluster. The C Sharp code used for clustering shows indeed lots of different comments, that were not clustered as intended.

It is also surprising that we have way more empty centroids than in Java. The clustering of Java resulted in neither of the used representations in empty centroid. It is not clear as to why this happens. One things that seems to be standing out, is that the use of the noise reduction, either improves the result, or makes causes it to have more empty centroids. This can be the case, because reducing noise also means that information is removed, lowering the dimension of the vectors. If too much information is removed, the clustering can not work properly, as variance of the data may becomes to low, so that data points can be distinguished well enough.

5.2 C++

Table 5.2: C++ v-measures

Representor	homogeneity	completeness	v-measure	perfect k	empty centroid
Type Structure	0,35	0,84	0,5	16	0
WeightSummary	0,67	0,27	0,39	12	3
Type Specific	0,4	0,65	0,5	16	4
WeightSummary	0,15	0,41	0,22	17	7

C++, like C Sharp, is very closely related to Java. So similar results are to be expected. With Type Structure and Type Specific representation this is the case, even though they score lower. It is suspected that there are the same problems in clustering as in C Sharp. C++ does also contain different ways for commenting, that are difficult to handle. The scores of C++ are similar to C Sharp than to those calculated for Java.

Like C Sharp, the manual clustered example contained 17 clusters. The number of clusters, was guessed better than for C Sharp. With Type Structure and Type Specific only missing one cluster and Type Specific with applied Weight Summary guessing the correct k.

5.3 Phyton

Table 5.3: Phyton v-measures

Representor	homogeneity	completeness	v-measure	perfect k	empty centroid
Type Structure	0,47	0,76	0,58	13	0
WeightSummary	0,66	0,41	0,5	13	3
Type Specific	0,51	0,8	0,62	16	2
WeightSummary	0,27	0,53	0,37	18	1

Python does have similar constructs as Java, but is not as closely related to it like C++ or C#. The evaluation of Python shows reasonable clusterings for Type Structure and Type Specific, but does also not well, if Weight Summary representation is applied. If we include the guessed value for k and the number of centroids, Type Structure does better than Type Specific representation, even tough the Type Specific alone does have a higher score, but it does not guess k as good. The number of clusters in our manually created clustering is 12. Elbowing does achieve a good value for the Type Structure Representor, with our without the application of Weight Summary Representor, creating only one extra cluster. For Type Specific, k is guessed witch a difference of 4, respectively 6 extra centroids. If we take a look at the used code, we see lots of different statements, that begin with "print" and should be assigned to the same cluster. Having just one word at the beginning of the statement characterising the whole statement works the same way as comments do. This makes it hard for the clustering algorithm to assign them properly.

5.4 XML

Table 5.4: XML v-measures

Representor	homogeneity	completeness	v-measure	perfect k	empty centroid
Type Structure	0,7	0,86	0,77	11	0
WeightSummary	0,6	0,45	0,51	11	5
Type Specific	0,58	0,38	0,46	13	5
WeightSummary	0,83	0,51	0,63	11	2

All the previously evaluated programming languages have similar contracts. This cannot be said about XML, as it is a hierarchical markup language. The best results were scored with the Type Structure Representor, scoring high in homogeneity and completeness. The other results are not absolutely conclusive, because it can be determined, if noise reduction does help or not.

The manually clustered example contains 15 clusters. This means, that for XML $\alpha = -3$ does not seem to be the best choice, as the guess for k is too low over all the evaluated representations.

5.5 ABACUS log file

Table 5.5: ABACUS log v-measures

Representor	homogeneity	completeness	v-measure	perfect k	empty centroid
Type Structure	0,84	0,48	0,61	14	6
WeightSummary	0,37	0,33	0,35	14	7
Type Specific	0,77	0,41	0,54	12	3
WeightSummary	0,89	0,65	0,75	11	7

The ABACUS log files does achieve good scores, even though there are many empty centroids in the clustering process. Because the empty centroids can just be discarded, the v-measures are the more important part of the analysis and only one representation methods has a score lower than 0.5. In the scores gathered, it stands out, that Weight

Summary representation only improves the score, if used with Type Specific representation. For Type Structure Representor this does not apply. The number of clusters would have been guessed pretty good by the elbow method. But if we subtract the empty centroids from it, we get to few different clusters.

It is not certain, why the clustering of the ABACUS log files results in this many empty centroids, but it could mean that there is lots of the same data types in one part of the statements, causing the problem with the initialization of the centroids, as was discussed before. The problem with this explanation is, that Type Structure with Weight Summary does no perform better, which should be expected in that case.

5.6 Brainfuck

Table 5.6: Brainfuck v-measures

Representor	homogeneity	completeness	v-measure	perfect k	empty centroid
Type Structure	0,5	0	0	12	5
WeightSummary	0,2	0,04	0,07	11	8
Type Specific	0,62	0,01	0,21	13	5
WeightSummary	0,28	0	0	11	6

Brainfuck differs from any other programming language evaluated in this thesis. Brainfuck uses only aight different special characters as instructions, with everything else being treated as comments. This makes clustering the statements very hard, as there is very little difference between statements. Even tough we remarked in the evaluation of Java that fewer variance can result in better scores, it is clear that to few variance cannot be clusters correctly into different clusters, as all data gathers around the same points. Because we initialize centroids uniformly over all dimensions, this results with Brainfuck in many empty centroids. Also it is important to see, that noise reduction goes awry as well, reducing the dimension of the data remarkably, because Brainfuck only uses one type for all instructions. Reducing dimensions, does also mean that we loose information. This may work well for Java, as it really reduces noise, but in Brainfuck, it looses too much information.

5.7 General Problems

The approach introduced in this thesis does have a few key points, that seem to cause problems in clustering:

Comments. Comments are hard to find. In programming languages there is often times, more than one way defining a comment, ranging from single-line to multi-line comments. A comments is defined by the first tokens in a statement, with the rest of the statement containing arbitrary information, even out-commented structure, making them very hard to cluster correctly.

Formatting. Our approach for creating statements -taking every new line- is depended on the correct formatting of the software code. Not correctly formatted code can cause structure not being statementized correctly.

Dimensionality. There are different dimensions in the data that need to be looked at: vector dimension, number of clusters expected, and number of lines in the input. If one of those mentioned dimension is to low, it can result in not proper clustering by the k-means algorithm, because it does not have enough difference in the data, to assign them to different enough clusters. One thing we do to have this work better, is that we scale the centroids to the range of values that are possible in the used representation.

6 Language Differentiation

After evaluation the k-means algorithm, we now take a look at the performance of our expansion for calculating a precision value for how close languages are related.

Table 6.1: Cross Language Differentiation

languages	Brainfuck	C Sharp	C++	Java	Abacus log	Python	Xml
Brainfuck	0,002	0	0,002	0	0,004	0	0
C Sharp	0	0	0	0	0,003	0	0
C++	0,005	0	0,106	0	0,003	0	0
Java	0,35	0,028	0,19	0,002	0,157	$6.5 \cdot 10^{-2}$	0.13
Abacus log	0,002	0	0	0	0,001	0	0
Phyton	0,12	0	0,053	0	0,075	0	$3.3 \cdot 10^{-2}$
Xml	0,48	0,043	0,505	0,11	0,38	0.11	0.12

The results of the Language Differentiator are unfortunately not as expected. It was be expected that languages, like Java and C Sharp would be similar, because they both are a C type language as is C++ and to Python. But it was not expected, that nearly all values calculated, resulted near or are zero. This applies also to the abacus log file, which is not even a language. It would not suffice to just relate to the problems mentioned in section 4.2.3. There must be a general flaw in the idea.

The underlying idea of the Language Differentiator was, that if we can cluster statements in a satisfying way, clusters of different statements in a single language would need to be further apart from statements of other clusters than from statements of the same cluster. The conclusion from this was, that different languages would result in different clusterings, with different centroids.

Overlap. While it is not possible in k-means, that clusters overlap, it is possible for clusters of other languages, because they are created independently. If the variance of the data is small, that all the clusters of different languages are located in the same space, but with different cluster assignments. This means that if they overlap, our way of calculating language differentiation would not be able to find differences between the languages, because they would still count as positive findings in our calculations.

7
Conclusion and Future Work

Finding structural patterns in code or log files can help infer grammar rules, as an important part of building a parser. In this thesis we introduced pattern recognition, using the unsupervised learning algorithm k-means and presented ways for representing the data for the used algorithm. Our goal was to minimize assumptions on the input, therefore allowing our tool to work on any given code or log files. We evaluated these method to see if they would perform as expected.

Representations were calculated using different representation, witch can be chained to gather, using one Representor of each category, categorized in Type Representors, Distance Representors and Weight Representors.

The evaluation of the representations indicate, that using Type Representations without any other representation performs for all input the best. Using Weight Summary Representation for noise reduction can further improve the results on some languages, but is not guaranteed to perform better. If we take a better look at the Type Representors, Type Specific does perform slightly better for any tested language.

Apart from the results given by the Type Representors and/or Weight Summary representation, the other representations did not well in the evaluation, having low scores and a problem in the robustness regarding their computations, giving high variance in multiple runs and resulting in empty centroids.

Using k-means for clustering structural patterns in code clearly has limitations, as k-means itself does make assumptions on the data while clustering, always trying to find circular shaped clusters.

7.1 Future Work

Regarding the Problems of k-means, different unsupervised learning algorithms, using single linkage or hierarchical clustering could be implemented and evaluated, as they make different assumptions their input.

The run time of the k-means implementation is quite high for big data sets and first of all, if vectors contain floating point numbers. Better implementation of vector computations could certainly improve the run time of our tool.

In this thesis, the main focus lied on the different representations and the implementation of the k-means pipeline. The statements were created as single lines, as we wanted to limit our assumptions. Most programming languages have block structures, allow for encapsulating other statements. The new line approach does not allow for encapsulation. Improvement on the creation of statements could improve the output of our tool.

With the knowledge about the assumption made by the k-means algorithm, we could also try to make more representations, which could exploit those assumptions more.

It would also be interesting to see, how the results could be improved, if we add heuristics for finding Keywords. Keywords are a very important construct of programming languages, that cannot be found with our representation approach. Comments or print statements can add different structure after a Keyword, but should be assigned to the same cluster. Adding information about keywords, for example as a forth type for tokens, could improve the clusterings.

List of Tables

Listings

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Bibliography

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8 Anleitung zu wissenschaftlichen Arbeiten

This chapter contains additional documentation to the created tool implemented in Pharo 4.0 and does also consist of a users guide to get the data used in this thesis.

8.1 Introduction

The main effort in this bachelor thesis lies in the implementation of the clustering and representation mechanics. There our three different parts in our finished tool.

- **StructureFinder** calculates clusters for given input.
- **StructureAnaylizer** calculates the clusters and returns additional information about how well it performed.
- **LanguageDifferentiator** Calculates a precision value for two input languages or can additional be used for cross comparison of different languages.

8.2 Getting Started

For replicating the results of this thesis or to play around with the clustering mechanics Pharo 4.0 and the used Image File in this thesis.

Pharo 4.0 with a standard Pharo 4.0 Image can be downloaded from:

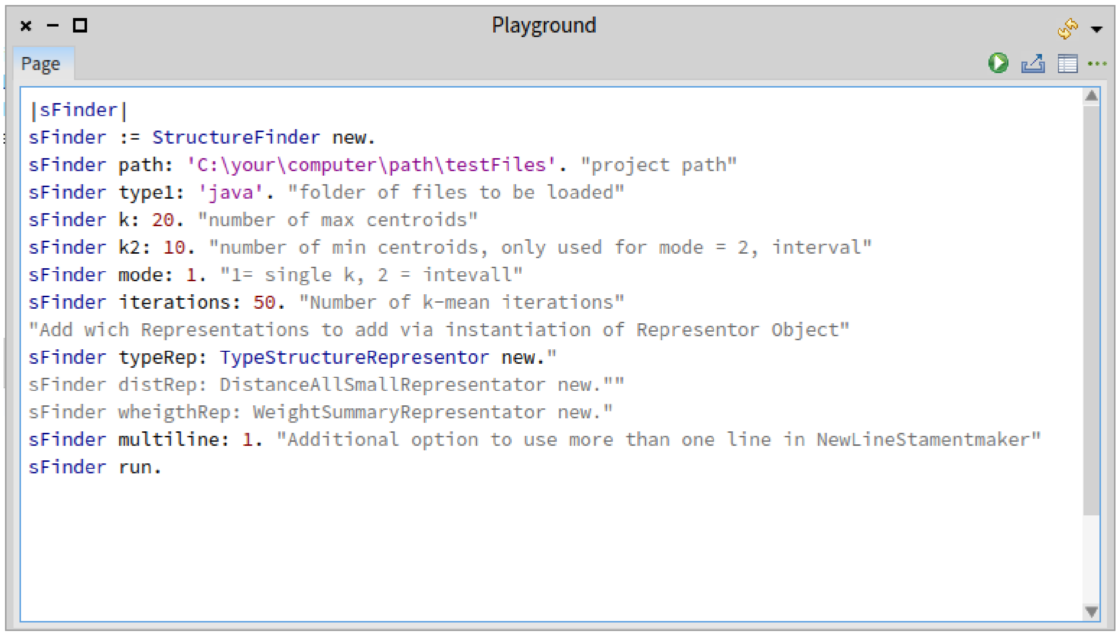
The Image you need, containing the source code of this thesis is stored on a git repository and can be cloned using the git command: clone...

8.3 Structure Finder

For the following execution of our tool, a folder structure is to be created, containing the input and folders for the output files.

For proper use of tool the folder structure needs to look like this. The StructureFinder is the implemented k-means clustering tool. In the uploaded Image there should be preconfigured Playgrounds. If there is no playground open, one needs to be opened.

The Playground for the StructureFinder contains all necessary parameters for running the clustering algrorithm.



```
|sFinder|
sFinder := StructureFinder new.
sFinder path: 'C:\your\computer\path\testFiles'. "project path"
sFinder type1: 'java'. "folder of files to be loaded"
sFinder k: 20. "number of max centroids"
sFinder k2: 10. "number of min centroids, only used for mode = 2, interval"
sFinder mode: 1. "1= single k, 2 = intevall"
sFinder iterations: 50. "Number of k-mean iterations"
"Add wich Representations to add via instantiation of Representor Object"
sFinder typeRep: TypeStructureRepresentor new."
sFinder distRep: DistanceAllSmallRepresentator new.""
sFinder wheigthRep: WeightSummaryRepresentator new."
sFinder multiline: 1. "Additional option to use more than one line in NewLineStamentmaker"
sFinder run.
```

Figure 8.1: Pharo 4.0 playground for configuring and running StrucureFinder

For simplicity, the preconfigured playgrounds contains information on the parameters, that can be set. We now take a closer look at the parameters that can be set.

- **Path** This parameter is necessary for correct loading and storing of the input respectively the output files. The path should point to the root of the folder structure as defined above.

- **mode** It is possible to run two different modes of StructureFinder. Parameter 1 creates a single run of the clustering for input k. Paramter 2 runs the clustering for every natural number between k2 and k.

- **type1** It is possible to have different folders containing different languages in your project root folder. Type is the name of the Folder containing the input. Output will be saved in the same folder, under results.

- **k** number of clusters for single clustering.
- **k2**
- **iteration**
- **typeRep**
- **distRep**
- **WieghtRep**

Output. Insert picutre single mode output screenshot

8.4 Structure Analyzer

8.5 Language Differentiator