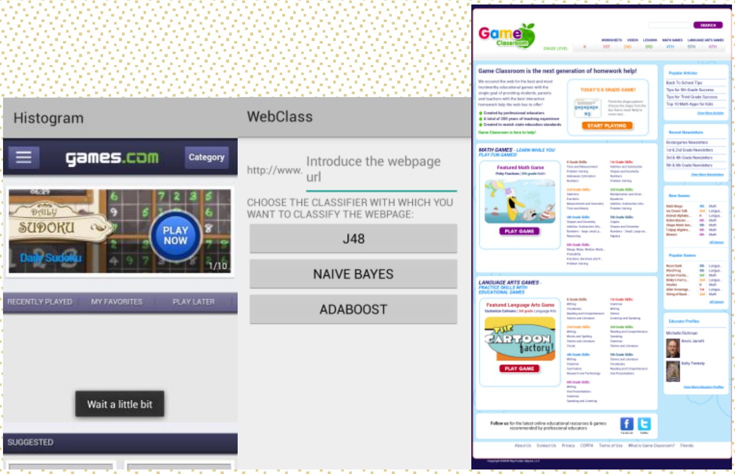

Diego Salas Ugalde

Android app for Automatic Web Page Classification
Analysis of Text and Visual Features

July 2015

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UNIVERSIDADE DE COIMBRA

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Departamento de Engenharia Electrotécnica e de Computadores
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For Graduate Study in MSc Program
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Android app for Automatic Web Page Classification

Analysis of Text and Visual Features

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Abstract

Internet keeps growing everyday and with that, the creation of new web pages. Due to this fact, web pages of many different categories can be found such as News, Sports or Business. This issue has made investigators think about one innovative concept: Webpage Classification. This new approach implies the categorization of web pages to one or more category labels. Some research has been done during the last years using text and visual content extracted from the web pages to be able to classify. However, the need of being able to do such a thing in an Android app has not been investigated yet, to the best of our knowledge.

Consequently, this thesis is focused in the development of an Android app which is able to classify web pages. First of all, text and visual features have to be extracted from each webpage.

Four types of visual features were extracted from each web page to construct a visual features vector of 160 attributes. Concerning to the text features, a text features vector was also built for each of the webpage with 160 attributes. To do so, a “Bag-Of-Words” of one hundred and sixty words was set up from the HTML code already extracted and filtered. Thus, we end up having a full vector of 320 attributes for each webpage. A binary classification was performed trying to distinguish web pages for Adults and for Kids.

Good results were obtained especially when using AdaBoost classifier with text and visual features where a 94.44% of accuracy of correct classifications was achieved.

Keywords: Web page classification, feature extraction, Adults, Kids, term frequency-inverse document frequency, Android.

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Chapter 1

Introduction

It is known that nowadays, the field of Information Technology is constantly evolving. In this big field of study, many operating systems are emerging and new are also appearing. Besides, the World Wide Web is invariably growing and with that, the number of web pages is increasing significantly as it is clearly shown in Figure 1.1.

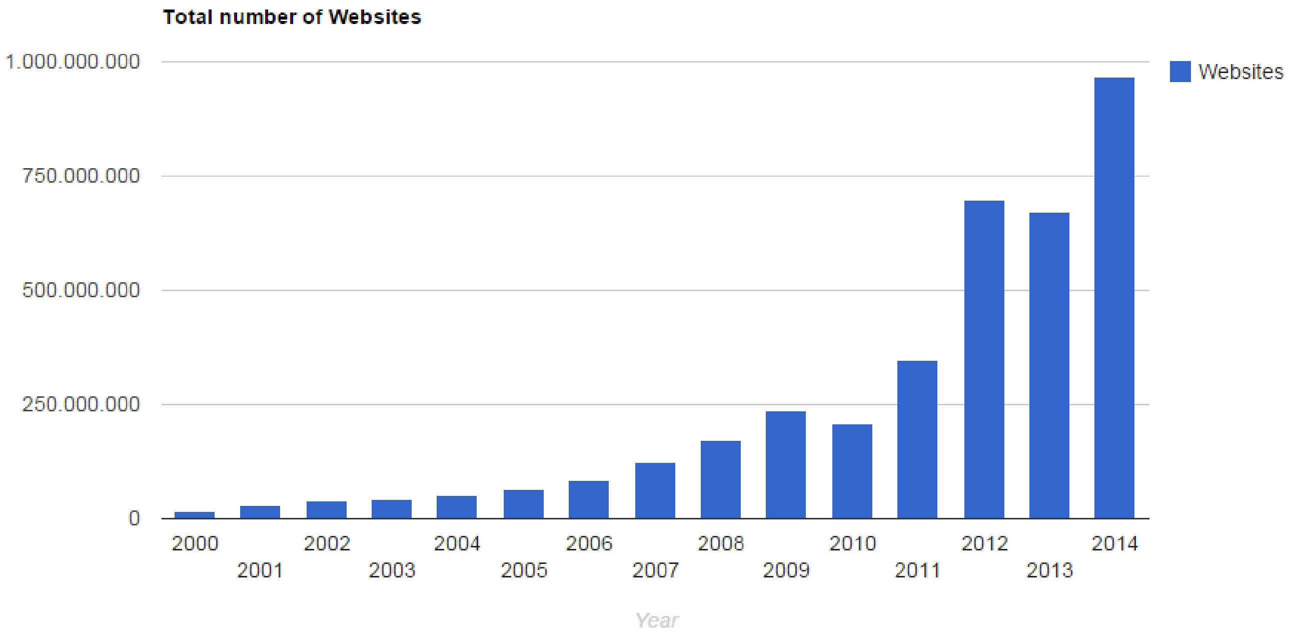


Figure 1.1: Grow of the number of websites in this century. [1]

A web page is a document commonly written in Hyper Text Markup Language (HTML) that is accessible through the Internet or other network using a browser. Due to this fact, the concept of web pages classification has been released and deeply investigated. Web page classification is essential for many tasks such as focused crawling, which is a software application that systematically browses the World Wide Web by collecting web pages that satisfy some definite property; assistance in the development of web directories; quality improvement of web search; aid in the analysis of the topical structure of the web; spam avoidance or web filtering.

Web pages have improved significantly their appearance since the first web pages were created 22 years ago. In the task of web pages classification some of their content is critical. Web pages need to attract the attention of the users to make them feel satisfying when using them. Thus, the design of a web page is really important. The visual structure of web pages of a particular subject or category tends to have similarities so that users feel familiar with them. Hence, the visual content of the web page contains important information and can help in web page classification.

A web page can contain various types of information, which is able to be seen, heard or interacted with by the end user. Textual, non-textual and interactive information can be directly perceived by the end user when using the web page. Examples of these can be static images, audio or video. Anyhow, not all of that information is crucial for web page classification. Visual features and text features were used in this thesis to do the classification.

A typical web page classification process consists in the following steps: extraction of visual and text features for the training web pages; creation of a feature vector for each web page, one based on visual features and the other in text features; reducing the dimensionality of the feature vectors if necessary; create a classifier by learning over the training feature vectors and finally, classify new web pages using that classifier.

As mentioned above, new operating systems are growing such as Android. Android powers more than a billion devices across the globe including mobile phones and tablets. This implies many users are familiarized with the world of apps. Combining this idea with the web page classification one, it is feasible to think about doing a web page classification application in Android. Based on this concept this thesis work was done.

1.1 Aims and objectives

The aim of this dissertation is to build an Android application which enables to perform web pages classification by analyzing the visual and text appearance of web pages. Concerning to the visual appearance, a screenshot of each web page is taken. That way we are able to get the web page as it appears to the user. Regarding to the text appearance, HTML code is used. Both visual and text are then used in this thesis to achieve the aim already mentioned above.

The motivation behind this dissertation is mainly based upon two works [2] [3]. In these papers, the authors confirmed that by using generic visual features, classifying web pages for several different types of tasks was viable. Using a binary classification, they classified web pages by two different subjective variables: their aesthetic value (whether one page is ugly or beautiful) and by their recency (whether one page have an old or a new design). They obtained good outcomes, mainly for the binary classification. This dissertation is also based on the WEKA toolkit [4] in which two classifiers are constructed: the Naive Bayes and a decision tree learning algorithm (J48). In this thesis, both binary classification and the WEKA toolkit were used.

The web page classification problem can be divided in a multi-label classification or in a binary classification problem, depending on the number of categories in which web pages are intended to be classified. In this work binary classification was implemented. The aim was to find out if a web page owned to Kids or Adults category.

1.2 State-of-the-art

The task of Web page classification has been deeply investigated in the last years, and many algorithms have been implemented to do such a process.

Web pages are text documents mostly written in HTML, which enclose supplementary information, such as HTML tags, hyperlinks and anchor texts. The features that are useful in web page classification can be classified into: on-page features, which are directly located on the page to be classified, and features of neighbors, which are located on the pages related in some way with the page which is going to be classified [5].

Nevertheless, web page classification presents some problems which can be divided into multiple sub-problems as they will be explained in this paragraph. Firstly, subject classification. It involves about the topic of a web page (i.e., news, blogs, kids, adults). Secondly, functional classification which implies which is the role the web page plays (e.g., personal home page, course page or admission page). Another sub-problem is sentiment classification. It is directed to the opinion that is cited in a web page, (i.e., the author's attitude about some particular topic). And the last sub-problem which is claimed could be referred as other types of classification. This includes genre classification (e.g., [6]), search engine spam classification (e.g., [7]) and much more.

Due to the fact we are interested in the words which are contained in the HTML code, web pages were preprocessed to discard the less important data such as HTML tags, stop words and rare words.

However, recent studies have revealed that the information contained in the HTML structure could also be useful in the web page classification. Besides, also the URL of the web pages has been proved to contain information that is useful to help in this task. This approach is investigated in M. Kan and H. Thi [8] and M.Kan [9]. This proposal is quicker than the traditional approaches by implying that full texts contained in the web pages are not needed to be analyzed. Their results show that this method is not clearly better than using full-text and links. On the other side, Riboni [10] exploits the information provided by the HTML structure and by the presence of hyperlinks. To exploit the HTML structure five different text sources were tested. These were the body, meta, title, mt (meta and title) and bmt (body, meta and title). With these tests, the meta tag and the title of the web page were found to be the most helpful sources to the categorization process.

Once the words from HTML code are extracted, it is known that not all of them have the same importance. To calculate the importance of a term, the frequency of a document containing that word and the specific tag of the HTML structure are used [11]. This weighting method was named as "Structure-oriented Weighting Technique (SWT)". To use the hyperlink information, in Riboni's paper a new method was developed in which downloading the web page was not necessary. It only used the anchor of the hyperlink, which is the text presented to the user to identify the link. A new method was also developed by combining the local and the hyperlink representation.

Using information derived from HTML tags can boost the classifiers performance as it can be shown in [12]. Golub and Ardö determined how significance indicators assigned to different web page elements (internal metadata, title, headings and main text), influence automated classification. They showed that the best results were achieved from a well-turned linear combination of those four elements of the web page.

S. Tice [13] proposed another approach of classifying web pages by using the Yioop search engine with active learning. Yioop search engine is a search engine similar to Google and Yahoo search engine but in which only a data set of web pages previously entered by the user was used. In this method a function to the Yioop search engine was developed to automatically assign labels to the web pages. The users could create multiple classifiers, which would be trained first in a small set of labeled documents and then improved after repeated rounds of active learning.

Vaghela et al. [14] approach the web page classification problem by using Term Frequency (tf). They built a method that calculated the tf of the stem of a term for each HTML tag. By combining the stemmed term frequency and each of the tag, a feature could be formed.

Gonçalves and Videira [3] developed a method of web page classification using visual features based in Boer et al. [2]. With features extracted from the visual content of a web page, they classified the web pages by their topic, aesthetic value and recency. Two different approaches were used. The first one consisted in the creation of a descriptor of the web page by using its low-level features extracted from a web page screenshot. Color and edge histograms, as well as Gabor and Tamura features were extracted. The second approach implied using a BoW (Bag Of Words) model to transform the SIFT local features and build a dictionary to represent each web page.

A web page classification approach based on the visual content was also implemented by Asirvatham et al. [15]. In this paper, a number of visual features, as well as textual features, were used. They proposed a method for automatic categorization of web pages into a few broad categories based on the structure of the web documents and the images presented on them.

Another approach was proposed by Kovacevic et al. [16], where a page is represented as a hierarchical structure, in which nodes represented simple HTML objects, texts and images while directed edges reflected spatial relations on the browser screen. Also using the visual information contained in that structure, heuristics rules are able to be defined. This implies they are applied to recognize multiple logical areas, which belong to different parts of the web page. These studies and [17] prove that the visual representation is useful and can be used in web page classification. It also implies and reinforces the idea that there is one big disadvantage when using only text features. This is that, if only text features are used, everything will depend on the language and nowadays, it is a huge problem due to the fact the majority of classifiers are built for the English Language.

1.3 Contribution

The first contribution is the construction of algorithms of feature extraction in Java programming language using the OpenCV library in Eclipse as well as Android Studio for the application. The extraction of well-known low-level features was done. These features are the Edge and Color Histogram, Gabor and Tamura Features. Also text features were extracted by taking the HTML code of each webpage and removing from there some characteristics by using the Jsoup library. Two datasets were created too in order to train and test the classifiers. Different classifiers are evaluated using the WEKA toolkit directly implemented in the Java code in Eclipse and also in Android Studio. Later on, the results will be exposed.

1.4 Thesis outline

This thesis is organized in the following chapters. In chapter 2 the entire theoretical basis behind the web classification process is explained including feature extraction of both visual and textual information, feature fusion in order to build a single vector for each web page, machine learning with WEKA toolkit and the train and test phase. In chapter 3, Android is introduced as a new task to this thesis. The construction of an Android application which is able to perform web pages classification is explained. Subsequently, in chapter 4, the results of the test phase after have trained the classifiers are exposed as well as the accuracy of the app performance. Finally, in chapter 5, conclusions to this thesis work are introduced as well as ideas to possible future work which could be done.

Chapter 2

Web Page Classification

This chapter presents the main theoretical idea in which this work is based. The fundamental concepts of web page classification will be deeply detailed. This involves the description of how all the features are extracted from each of the webpage and how the vectors are correctly built. Machine Learning will also be introduced in this chapter due to the fact that it is highly important in the classification process once the vectors are extracted and accurately produced. To conclude, train and test phases made with different classifiers will be analyzed.

2.1 Feature Extraction

Feature Extraction can be seen as the first step in the classification process. Two main features are considered in this dissertation. These are Visual and Text features. Thus, from each web page visual and text features will be extracted. After that, a vector of 320 attributes for each of the web page is built.

2.1.1 Visual Features

In [18] the concept of feature in computer vision and image processing is referred to a piece of information which is relevant and distinctive. As it was mentioned above, visual features are used in this thesis as one of the main differences from other previous works since visual features have been rarely applied when performing web page classification. In this dissertation, four different features were extracted from the visual content of the web pages. These are Color Histogram, Edge Histogram, Gabor Features and Tamura

Features. To achieve this, a screenshot of each of the webpage is needed. Therefore, those features already mentioned can be extracted using OpenCV library. A vector of a total of 160 attributes is built based only on these visual features.

- **Color Histogram**: It is a depiction of the distribution of the colors presented in an image. In this thesis, that image is the screenshot of each of the web pages. It can be built in any color space but the one used in this work was the RGB color space. 32 bins were extracted for this feature, what implies that 32 attributes of that 160-attribute-vector belong to this feature.

- **Edge Histogram**: An edge is a curve that follows a path of rapid change in image intensity. This Edge Histogram represents the distribution of edges orientations in the image. To extract it, the image is divided into a fixed number of sub-images and the local edge distribution for each sub image is represented by a histogram. The number of bins extracted was 80. In other words, 80 attributes of the vector correspond to Edge Histogram.

- **Gabor Features**: they are obtained by convolving the image with a Gabor filter. A Gabor filter is a linear band-pass filter whose impulse response is defined as a Gaussian function modulated with a complex sinusoid called the mother wavelet. It is used for edge and texture detection. Gabor features are sensitive to different scales and frequencies. These properties are useful when texture analysis is required. For the Gabor features 36 bins were extracted.

- **Tamura Features**: Tamura et al. [19] propose six types of features among Tamura. These were coarseness, contrast, directionality, line-likeness, regularity and roughness. After several tests, that work concluded that the first three mentioned above were the most significant ones. However, in this dissertation only contrast and directionality were used due to the fact coarseness dragged out the process. Contrast aims to capture the dynamic range of gray levels in the image together with the polarization of the distribution of black and white. Directionality is a global property over a region. It does not aim to differentiate between different orientations or patterns, but it measures the total degree of directionality. This is measured using the frequency distribution of oriented local edges against their directional angles. 6 bins of each Tamura feature were extracted which implies a total amount of 12 bins. These are reflected in 12 attributes in the final visual vector.

2.1.2 Text Features

Text features were also extracted from each of the web page. To calculate those attributes represented in the vector, some concepts have to be introduced. These concepts are TF-IDF [20], Bag Of Words (BoW) and Vector Space Model (VSM) [21].

TF-IDF stands for *term frequency-inverse document frequency*, and its weight is often used in information retrieval and text mining. This weight is a statistical measure used to evaluate how important a word is to a document in a collection. The importance rises equitably to the number of times a word appears in the document but it is offset by the frequency of the word in the corpus or collection of documents. Variations of the TF-IDF weighting scheme are often used by search engines as a central tool in scoring and ranking a document's relevance given a user query. One of the simplest ranking functions is computed by summing the TF-IDF for each query term; many more sophisticated ranking functions are variants of this simple model. TF-IDF can also be successfully used for stop-words filtering in various subject fields including text summarization and classification.

Typically, the TF-IDF weight is composed by two terms: the first computes the normalized Term Frequency (TF). This is the number of times a word appears in a document, divided by the total number of words present in that document. The second term is the Inverse Document Frequency (IDF), computed as the logarithm of the number of documents in the collection divided by the number of documents where the specific term appears.

- **TF: Term Frequency**, which measures how frequently a term occurs in a document. Since every document is different in length, it is possible that a term would appear more often in long documents than in shorter ones. Thus, the term frequency is often divided by the document length as a way of normalization:

$$TF(t) = \frac{NT_t}{T_t D} \qquad (2.1)$$

Being:

$NT_t = Number\ of\ times\ a\ term\ called\ t\ appears\ in\ a\ document$
$T_t D = Total\ number\ of\ terms\ in\ the\ document$

- **IDF: Inverse Document Frequency**, which measures how important a term is. While computing TF, all terms are considered equally important. However it is known that certain terms, such as "is", "of", and "that", may appear a lot of times but have little importance. Thus we need to weigh down the frequent terms while scale up the rare ones, by computing the following:

$$IDF(t) = \log \frac{TD}{ND_t} \qquad (2.2)$$

Being:

TD = Total number of documents.

$ND_t = Number\ of\ documents\ with\ the\ term\ t.$

In this work, words with less than 3 letters were removed to avoid this problem too.

Another important concept used in this thesis is Bag-Of-Words. It is a clarifying representation used in natural language processing and information retrieval. A text is then represented as a bag of its words, disregarding grammar and even word order but keeping multiplicity.

As the name suggests, a “bag” is created with the words that have more importance. Based on this “bag" (dictionary), the features are extracted. The dictionary of text words can be built in diverse ways, like the most repeated words of each category, the most repeated words in all the documents or even using a threshold for the IDF values. After the dictionary creation or the “bag”, the features are extracted from the documents. After that, the document is in the VSM. It is a vector that can represent the absolute frequency of the words (number of times), the presence or absence of the words (binary) and the importance of the word in the document or sentence that is being evaluated (TF-IDF). In this work absolute frequency of the terms is used. In other words, it is the number of times a term of the Bag-Of-Words is in the document which the vector is going to be extracted from.

The Vector Space Model (VSM) is an algebraic model to represent text information as a vector. In other words, it is a space where the text is represented as a vector of values instead of a text string. As it was explained in last paragraph, in this work, each of the attribute of the text features vector represent the absolute frequency of each word of the “bag” in the document.

These features are related to a single word and measure the importance of that word in the document.

2.2 Feature Fusion

One of the main objectives of this dissertation was to show that visual features have important information to help in the classification process. To accomplish this, the features fusion of different types needs to be considered. Once text features vectors as well as visual features were extracted, the fusion of those was executed. All the features extracted were normalized to the [0,1] scale.

Thus, a huge vector of 320 attributes for each web page was finally achieved when doing test with both visual and text information. Obviously, a vector only with text information will have 160 attributes and with visual information 160 attributes.

2.3 Machine Learning

Machine Learning is a huge field in computer science and a subfield of Artificial Intelligence (AI). It is devoted to the development of algorithms and techniques that allow the machine to learn to recognize patterns or predict future trends or behavior. At present, many machine learning algorithms are used without even knowing.

In 1959, Arthur Samuel [22] defined Machine Learning as:
”Field of study that gives computers the ability to learn without being explicitly programmed”. A recent and formal definition of Machine Learning was given by Tom Mitchell [23]. In that paper the following was stated:
”A computer program is set to learn from an experience E with respect to some task T and some performance measure P if its performance on T as measured by P improves with experience E”

There are many ML problems, but this work is focused on classification problems, which is the goal to categorize objects into a fixed set of categories (e.g., optical character recognition, face detection, spam filtering, topic spotting, medical diagnosis, weather prediction, webpage classification and much more).
The next sections approach the algorithm type of ML used in this work and some of the algorithms built to do classification.

There are too many ways to realize machine learning. Next, some of them are explained. There is supervising learning, where the computer is exposed to a set of examples that are previously labeled, to establish a set of characteristics or rules enabling it to later identify and classify new examples. Another approach of machine learning is the unsupervised learning. In this type of machine learning it is not given any type of indication to the computer about some type of grouping. All the examples are given to the classifiers, without any type of label. The classifier finds out common characteristics to group different types of data.

Machine learning algorithms, when conducting the training phase, are able to analyze the features and adjust their parameters to enhance their performance. This process of parameter adjustment is the goal of the term learning.
In this work, supervised learning was adopted. In this dissertation, WEKA toolkit was implemented which will be explained in section 2.4.

2.3.1 WEKA

WEKA is a collection of machine learning algorithms for data mining tasks. These algorithms, called Classifiers in WEKA, can either be applied directly to a dataset or called from your own Java code. In this thesis they are called form the Java code. WEKA also contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is well-suited for developing new machine learning schemes too.

WEKA (Waikato Environment for Knowledge Analysis) is also a popular suite of machine learning software written in Java, developed at the University of Waikato, New Zealand. WEKA is a free software available under the GNU General Public License which is a free, copy left license for software.

Moreover, WEKA can be also defined as a workbench that contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces for easy access to this functionality. The original non-Java version of WEKA was primarily designed as a tool for analyzing data from agricultural domains, but the more recent fully Java-based version (WEKA 3), for which development started in 1997, is now used in many different application areas, in particular for educational purposes and research. The main interface of WEKA toolkit is shown in Figure 2.1.

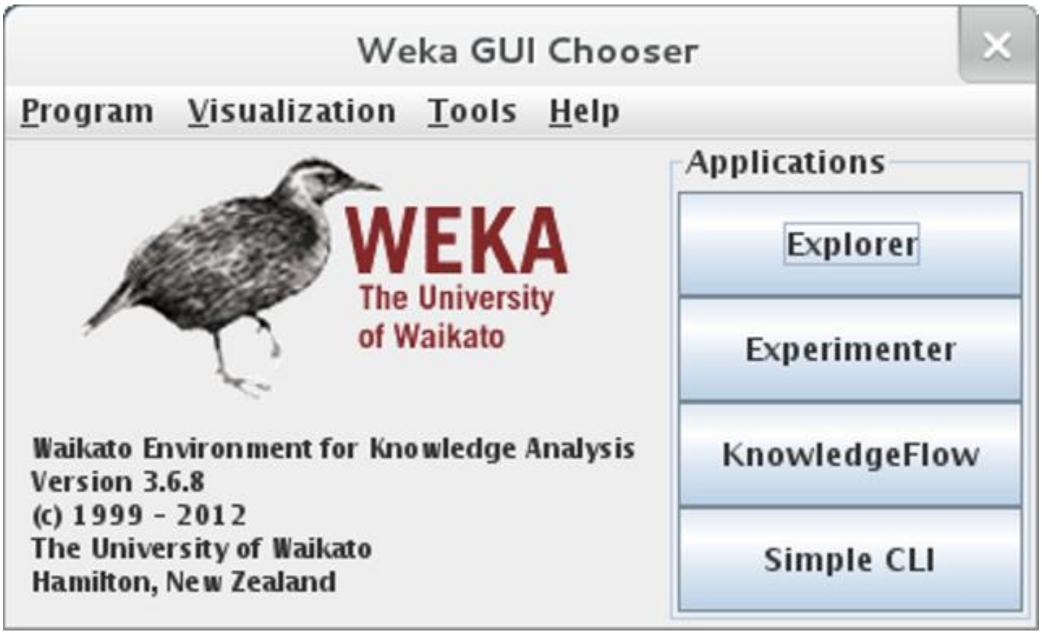
Advantages of WEKA include:

- Free availability under the GNU General Public License.
- Portability, since it is fully implemented in Java programming language and thus runs on almost any modern computing platform.
- A comprehensive collection of data preprocessing and modeling techniques.
- Ease of use due to its graphical user interfaces.
- It is available in platforms as Android Studio.

WEKA toolkit suppots several standard data mining tasks, more specifically, data preprocessing, clustering, regression, visualization and feature selection.

All of WEKA techniques are declared on the assumption that the data is available as a single flat file or relation, where each data point is described by a fixed number of attributes.

In this work, WEKA was directly implemented in Java code. To understand how this is developed, some basic concepts are needed to be described such as dataset, classifier, weka.filters and weka.classifiers.



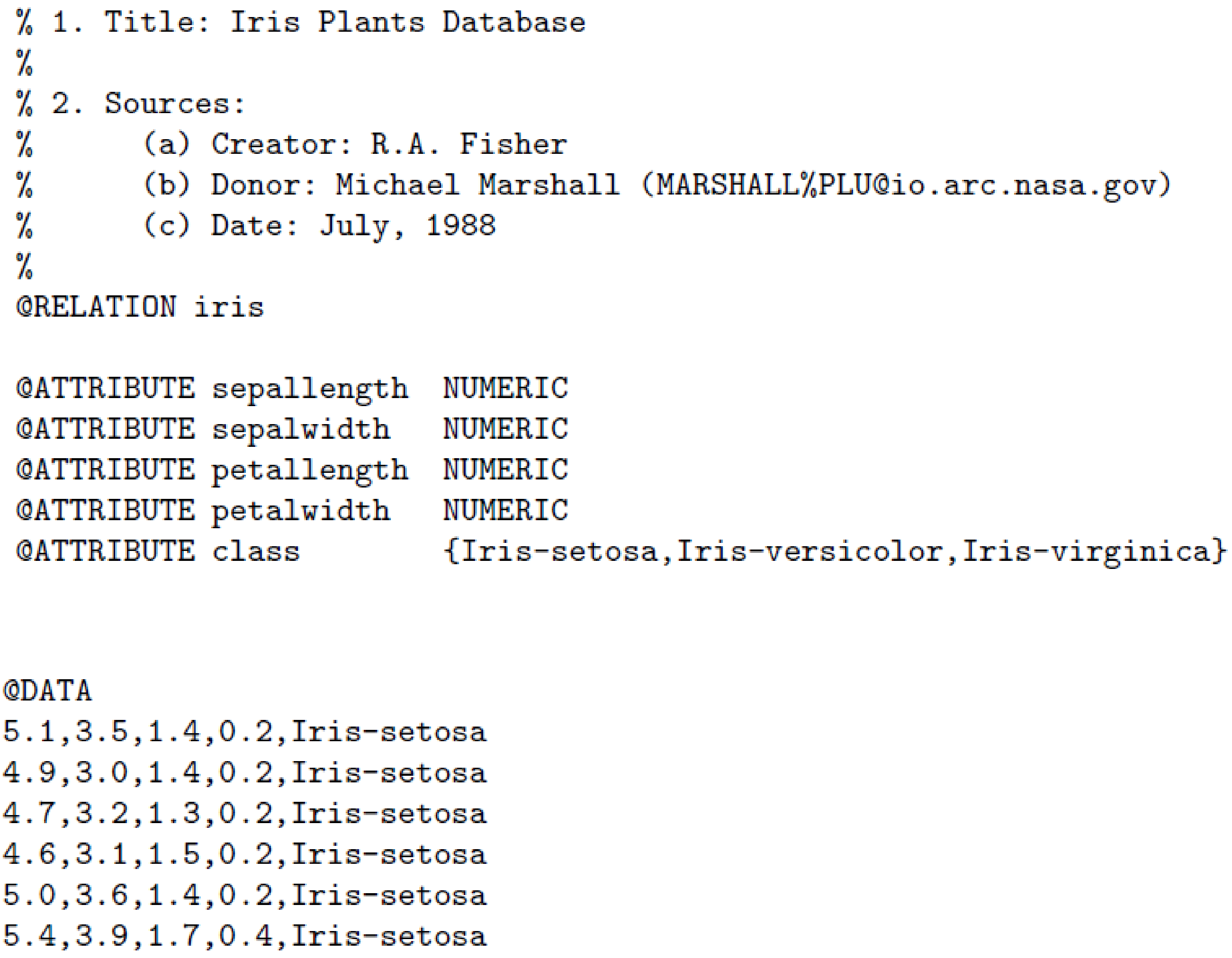
Waikato Environment for Knowledge Analysis
Version 3.6.8
(c) 1999 - 2012
The University of Waikato
Hamilton, New Zealand

Figure 2.1: WEKA interface. [24]

2.3.1.1 Dataset

A set of data items, the dataset, is a very basic concept of machine learning. In WEKA toolkit, it is implemented by the weka.core.Instances class. A dataset is a collection of examples, each one of the weka.core.Instance class. Each Instance consists of a number of attributes, any of which can be nominal, numeric or a string. Additional types are date and relational, which are not covered here but they will be explained later in this section when covering ARFF.

The external representation of an Instance class is an ARFF file, which consists of a header describing the attribute types and the data as comma-separated list. An ARFF (Attribute-Relation File Format) file is an ASCII text file that describes a list of instances sharing a set of attributes. ARFF files have two distinct sections. The first section is the Header information, which is followed by the Data information. The Header of the ARFF file contains the name of the relation, a list of the attributes (the columns in the data), and their types. An example header on the standard IRIS dataset looks as it is shown in Figure 2.2.



```
% 1. Title: Iris Plants Database
%
% 2. Sources:
%      (a) Creator: R.A. Fisher
%      (b) Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
%      (c) Date: July, 1988
%
@RELATION iris

@ATTRIBUTE sepallength  NUMERIC
@ATTRIBUTE sepalwidth   NUMERIC
@ATTRIBUTE petallength  NUMERIC
@ATTRIBUTE petalwidth   NUMERIC
@ATTRIBUTE class        {Iris-setosa,Iris-versicolor,Iris-virginica}


@DATA
5.1,3.5,1.4,0.2,Iris-setosa
4.9,3.0,1.4,0.2,Iris-setosa
4.7,3.2,1.3,0.2,Iris-setosa
4.6,3.1,1.5,0.2,Iris-setosa
5.0,3.6,1.4,0.2,Iris-setosa
5.4,3.9,1.7,0.4,Iris-setosa
```

Figure 2.2: Example of an ARFF file. [25]

Lines that begin with a %, are comments. The @RELATION, @ATTRIBUTE and @DATA declarations are case insensitive.

The ARFF Header sections of the file contain the relation declaration and attribute declarations. The relation name is defined as the first line in the ARFF file. The format is: @relation <relation-name> where <relation-name> is a string. The string must be quoted if the name includes spaces. In the case of attribute declarations, the form of an ordered sequence of @attribute statements is taken. Each attribute in the data set has its own @attribute statement which uniquely defines the name of that attribute and its data type.

The order the attributes are declared indicates the column position in the data section of the file. For example, if an attribute is the third one declared then Weka expects that all that attributes values will be found in the third comma delimited column. The format for the @attribute statement is: @attribute <attribute-name> <datatype>, where the <attribute-name> must start with an alphabetic character. If spaces are included in the name then the entire name must be quoted. The <datatype> can be any of the four types supported by Weka:

- numeric
    - integer is treated as numeric
    - real is treated as numeric
- <nominal-specification>
- string
- date [<date-format>]
- relational for multi-instance data (for future use)

<nominal-specification> and <date-format> are defined below.

The keywords numeric, real, integer, string and date are case insensitive. Numeric attributes can be real or integer numbers and nominal values are defined by providing a <nominal-specification> listing the possible values: <nominal-name1>, <nominal-name2>, <nominal-name3>. For example, the class value of the Iris dataset can be defined as follows:
@ATTRIBUTE class {Iris-setosa,Iris-versicolor,Iris-virginica}

2.3.1.2 Classifier

Any learning algorithm in WEKA is derived from the abstract weka.classifiers.Classifier class. Surprisingly, little is needed for a basic classifier: a routine which generates a classifier model from a training dataset (buildClassifier) and another routine which evaluates the generated model on an unseen test dataset (classifyInstance) or even generates a probability distribution for all classes (distributionForInstance).

A classifier model is an arbitrary complex mapping from all-but-one dataset attributes to the class attribute. The specific form and creation of this mapping, or model, differs from classifier to classifier. For example, ZeroR's (weka.classifiers.rules.ZeroR) model just consists of a single value: the most common class, or the median of all numeric values in case of predicting a numeric value (regression learning). ZeroR is a trivial classifier, but it gives a lower bound on the performance of a given dataset which should be significantly improved by more complex classifiers. As such it is a reasonable test on how well the class can be predicted without considering the other attributes.

2.3.1.3 weka.filters

The weka.filters package is concerned with classes that transform datasets by removing or adding attributes, resampling the dataset or removing examples. This package offers useful support for data preprocessing, which is an important step in machine learning.The weka.filters package is organized into supervised and unsupervised filtering, both of which are again subdivided into instance and attribute filtering.

2.3.1.4 weka.classifiers

Classifiers are at the core of WEKA. There are a lot of classifiers in WEKA. In this work three of them were used which are defined below. We used J48 tree, Naïve Bayes and AdaBoost which are explained as follows:

- **J48**: It is an open source Java implementation of the C4.5 algorithm in the WEKA data mining tool which is being explained in the current chapter. C4.5 builds decision trees from a set of training data using the concept of Information Entropy which basically is the expected value of the information contained in one sample. The training data is a set of already classified samples. At each node of the tree, C4.5 chooses the attribute of the data that most effectively splits its set of samples into subsets enriched in one class or the other. The splitting criterion is the normalized information gain (difference in entropy). The attribute with the highest normalized information gain is chosen to make the decision.

- **NAIVE BAYES**: It is a family of simple probabilistic classifiers based on Bayes' theorem with strong independence assumptions between the features. Bayes' theorem is stated mathematically as the following equation:

$$P(A|B) = \frac{P(B|A)*P(A)}{P(B)} \tag{2.3}$$

Where A and B are different events.

-P(A) and P(B) are the probabilities of A and B without regard to each other.

- P(A|B) is the probability of A given that B is true.
- P(B|A), is the probability of B given that A is true.

- **ADABOOST**: The word is an abbreviation of “Adaptive Boosting” and is a machine learning meta-algorithm. It is usually referred to as the best out-of-the-box classifier. It can also be used in combination with many other types of learning algorithms to improve their performance. The output of the other learning algorithms called weak learners, is combined into a weighted sum that represents the final output of the boosted classifier. AdaBoost is flexible in the sense that subsequent weak learners are modified in favor of those instances misclassified by previous classifiers.

Chapter 3

Android

This chapter discusses one relevant part of this thesis work: Android. Android is the name of a mobile operating system (OS) which is currently developed by Google and based on the Linux Kernel. It is installed in more than one billion devices in the whole world and it offers users access to Google’s own services like YouTube or Gmail.

In this thesis, the main idea was to build an application based on Android which is able to perform webpage classification with visual features. To do so, Android Studio was found as the main solution. Android Studio is an integrated development environment (IDE) for developing on the Android platform. It is also based on JetBrains' IntelliJ IDEA software, Android Studio is designed specifically for Android development. Besides, it is available for download on Windows, Mac OS X and Linux, and replaced Eclipse Android Development Tools (ADT) as Google's primary IDE for native Android application development. In this work Windows was used. Finally, it can be said that it is capable of building apps for Android phones, tablets, Android Wear, Android TV, Android Auto and Google Glass.

3.1 Android application

In this section the application will be introduced and explained. First of all, how the app was done and the tools needed to be applied in Android Studio are going to be explained. Secondly, how the app looks like and how it works will be described.

The name given to the application is WebClass and it weighs 47.08MB. As it was mentioned above, the app was done to achieve an Android application that performs web page classification. Three different classifiers have been used in this dissertation: J48, Naive Bayes and AdaBoost. They were obviously implemented in the application and each one is able to classify the webpage by using text features, visual features or both of them.

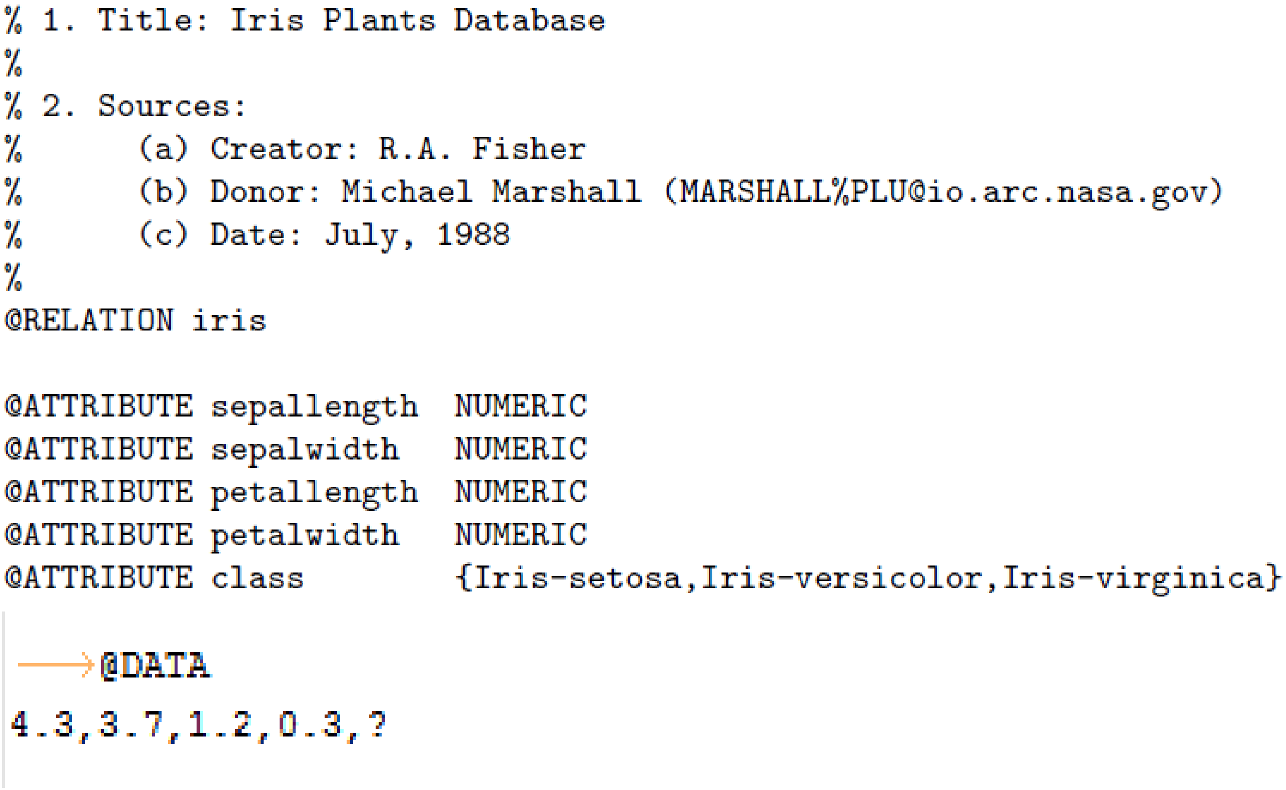
For implementing the classifiers in Android, WEKA toolkit was needed as it was explained in section 2.3.1. Thus, WEKA library was added to the Android project as well as OpenCV library to be able to extract visual features. OpenCV is a library of programming functions mainly aimed at real-time computer vision. The library is cross-platform and free for use under the open-source BSD license. Finally, for the text features Jsoup library was added. It is a Java library for working with HTML words. It provides a very convenient API for extracting and manipulating data, using the best of DOM, CSS and jquery-like methods. Jsoup also allows many things such as to scrape and parse HTML form a URL, file or string; find and extract data using DOM traversal or CSS selectors; manipulate the HTML elements, attributes and text; clean user-submitted content against a safe white-list to prevent XSS attacks or output tidy HTML. In summary, Jsoup is designed to deal with all varieties of HTML found in the wild.

To extract the visual features, the application takes a screenshot of the webpage. This is done using the concept of bitmap. That is to say, the app loads the webpage in a WebView and it gets a screenshot of it by creating a bitmap to get the height and weight of the screen. After this screenshot is taken, using OpenCV library the visual features (Color Histogram, Edge Histogram, Gabor and Tamura features) are extracted and therefore a 160 attribute-vector is built.

To extract the text features HTML code is extracted from the URL that is written by the user by using Jsoup library. After that, a filter is applied to be able to extract the words of the HTML code. Once those words are saved in one file, the 160 attribute-text-features-vector is built by using the BoW. This Bag Of Words or BoW is used to extract the vector by using the concept of absolute frequency. In other words, how many times a term, extracted from the html code of a webpage, is in the BoW. This way, the vector is built.

Once visual vector and/or text vector are/is extracted, this feature vector is included in the “@DATA” part of the ARFF extension test file used for classification as explained above. The last attribute added instead of being the name of the category is a “?” character letting WEKA “know” that this parameter want to be guessed based on the training values the classifiers has. This structure of the ARFF test file can be shown in Figure 3.1.

After this file is built and used to test the classifier selected by the user, another ARFF file is obtained with the labeled value of the “?” character written. So in that file, the result of the classification is shown. This value is showed to the user in an Android Toast (a pop-up window which shows the result to the user).



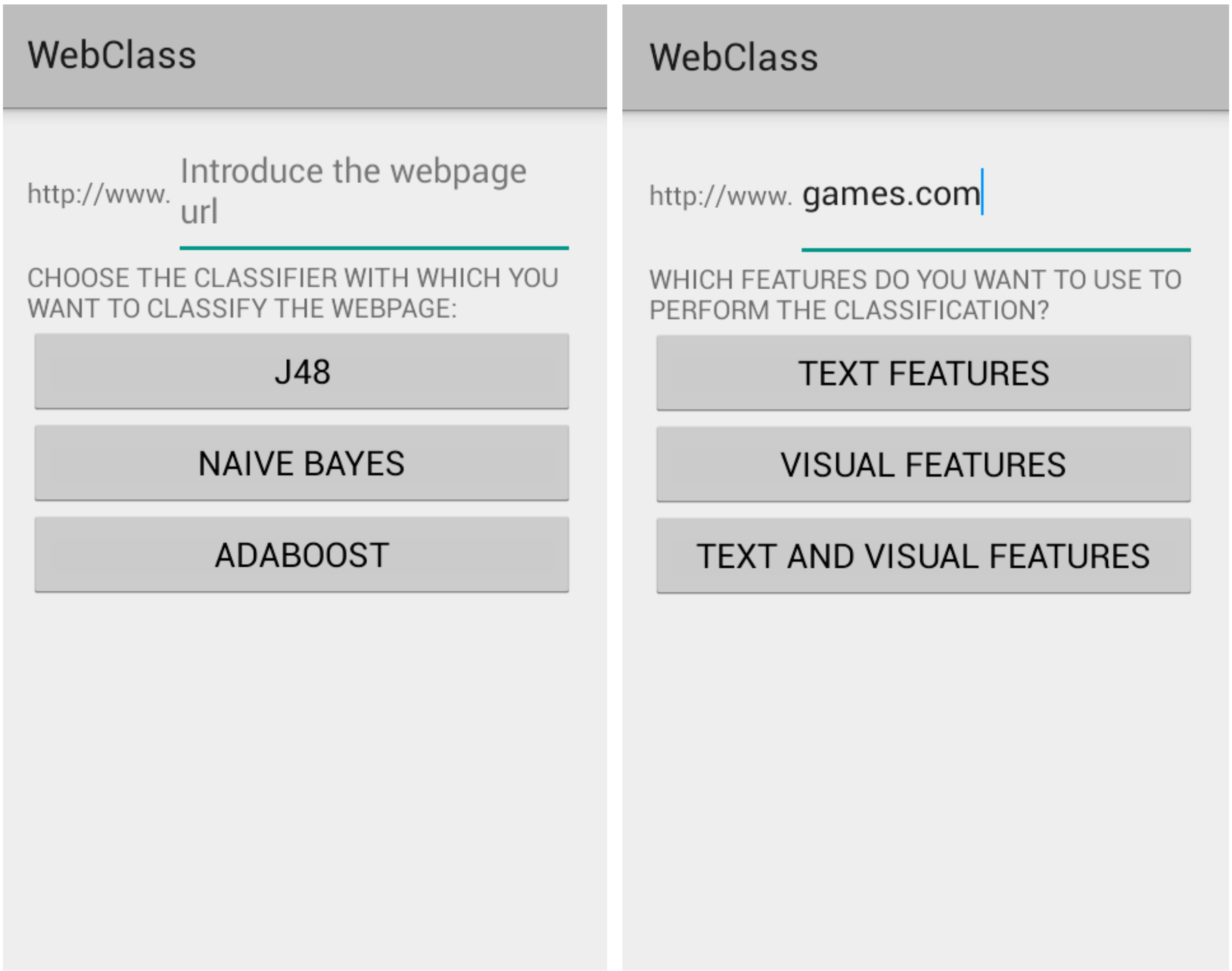
```
% 1. Title: Iris Plants Database
%
% 2. Sources:
%      (a) Creator: R.A. Fisher
%      (b) Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
%      (c) Date: July, 1988
%
@RELATION iris

@ATTRIBUTE sepallength  NUMERIC
@ATTRIBUTE sepalwidth   NUMERIC
@ATTRIBUTE petallength  NUMERIC
@ATTRIBUTE petalwidth   NUMERIC
@ATTRIBUTE class        {Iris-setosa,Iris-versicolor,Iris-virginica}

@DATA
4.3,3.7,1.2,0.3,?
```

Figure 3.1: Example of an .ARFF file used to test a classifier.

In Figure 3.2 we can see how the app is displayed to the user. In the left image, the front page that is displayed to the user when he enters into the application is exposed and how it is seen after deciding one classifier to classify the webpage the user introduces is shown in the image in the right side.



WebClass

http://www. Introduce the webpage url

CHOOSE THE CLASSIFIER WITH WHICH YOU WANT TO CLASSIFY THE WEBPAGE:

WebClass

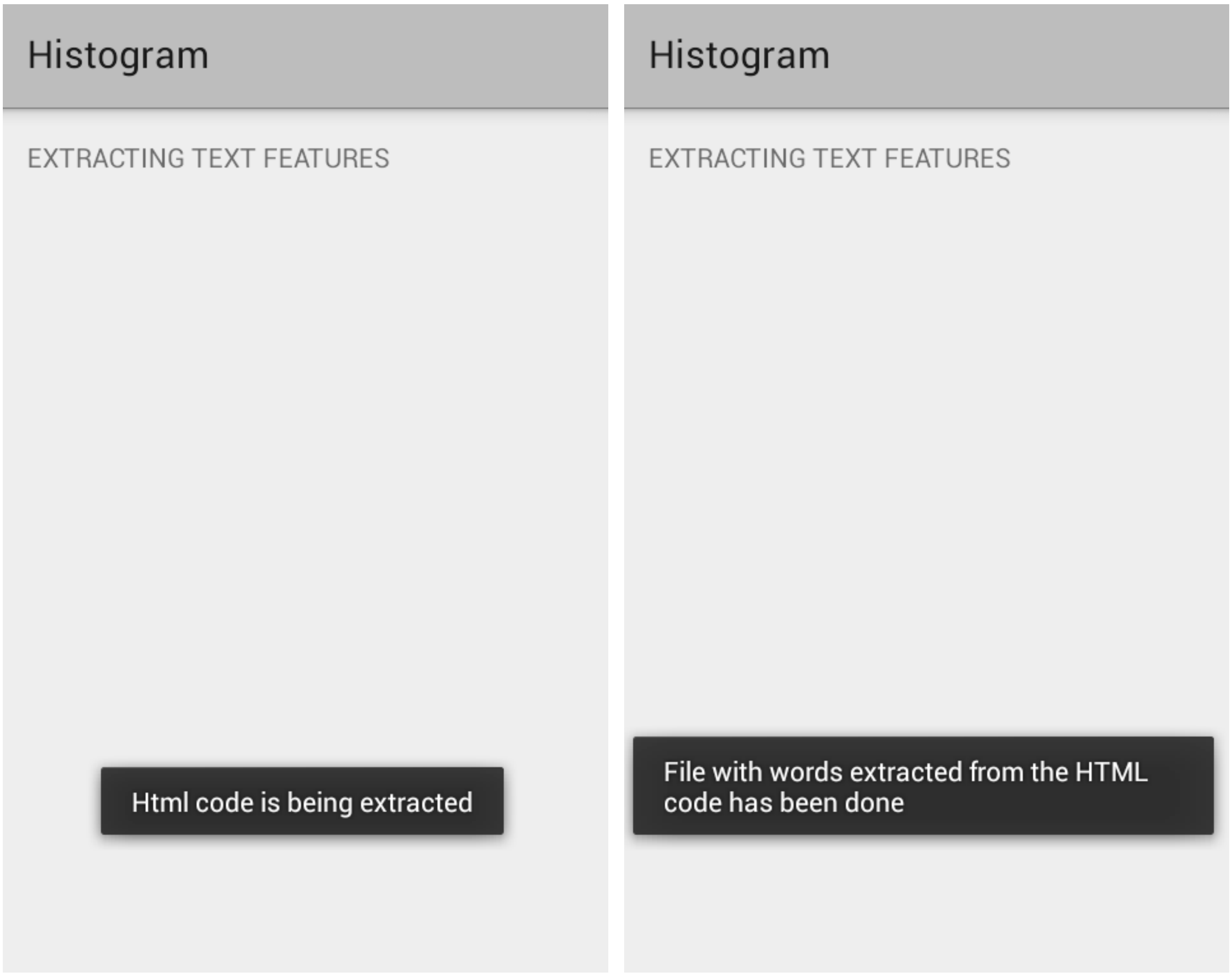
http://www. games.com

WHICH FEATURES DO YOU WANT TO USE TO PERFORM THE CLASSIFICATION?

Figure 3.2: Two screenshots taken from the app. The left image shows how the app is displayed to the user and the right one the screen the user can see after clicking in one of the classifiers.

Once the user has chosen one of the classifier and has introduced one URL in the field on the top of the screen; text features, visual features or even both can be used to perform the classification.

If text features are selected another screen will appear to the user as it is shown in Figure 3.3. There are two different toasts indicating and helping the user to know what the app is performing in the background, which is invisible for the user.



Histogram

EXTRACTING TEXT FEATURES

Html code is being extracted

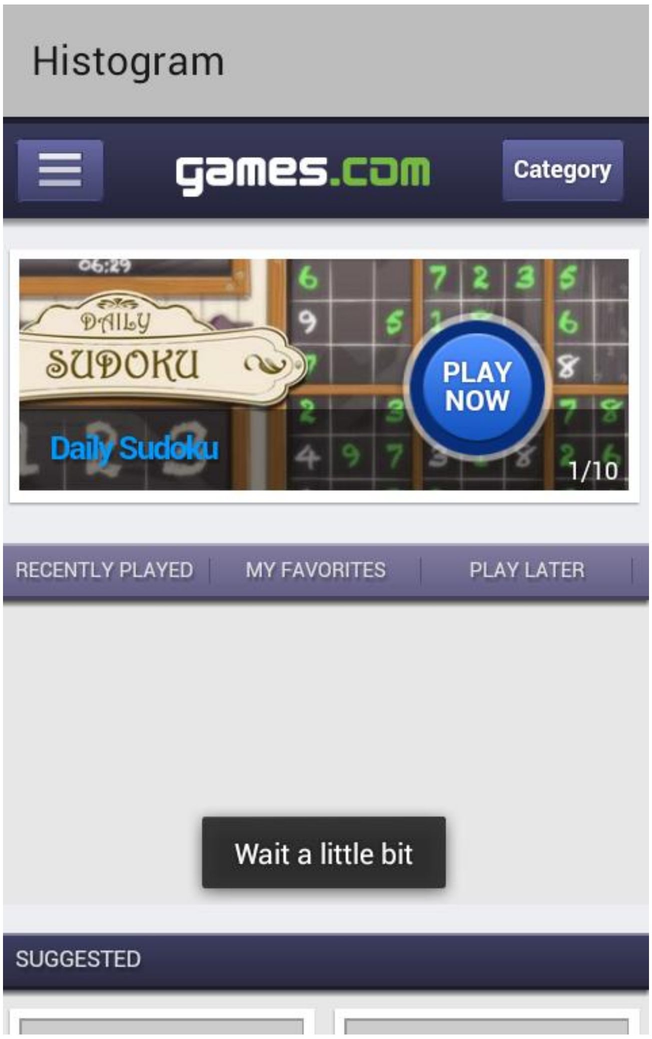
Histogram

EXTRACTING TEXT FEATURES

File with words extracted from the HTML code has been done

Figure 3.3: Screenshots taken from the app.

In case visual features are selected, and as it has been explained in this chapter, a screenshot of the webpage is taken. This is displayed in Figure 3.4 in which there is an example of the webpage “ww.games.com”.



Histogram

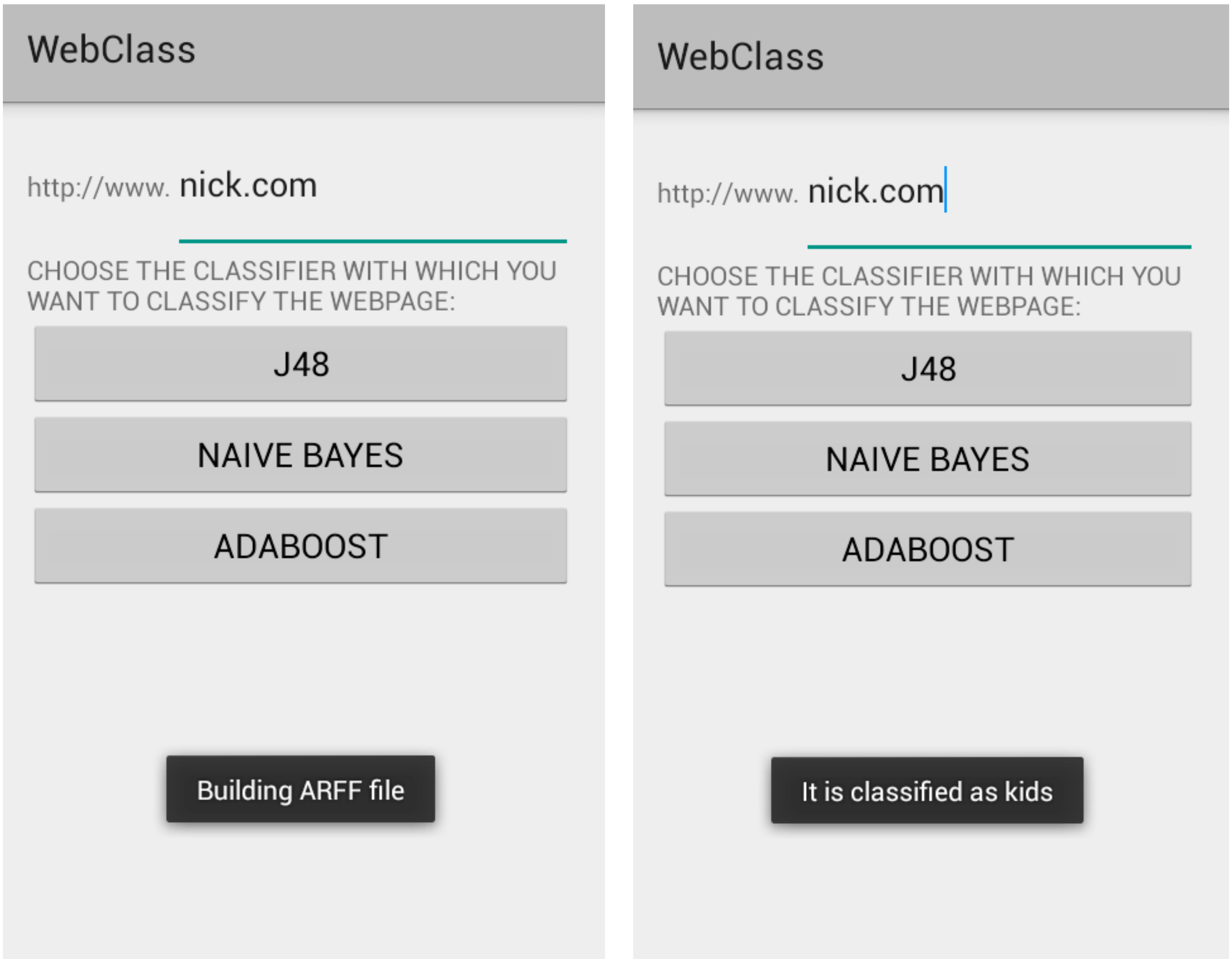
Wait a little bit

Figure 3.4: Screenshot of the app taken when getting the screenshot of the webpage.

As we can see in Figure 3.4, the app enters the webpage and displays it on the screen while advising the user with some Toast that he has to wait. This webpage cannot be accessed, it is just an image showed to the user. However, while extracting the visual features, the user can see the whole webpage due to the fact it is a scrollable screen.

After the screenshot is taken, the user still sees the screen showed in Figure 3.4 but with different toasts telling that the app is extracting the visual features. When this is done, the application goes back to the main screen already showed in Figure 3.2 and new different toasts appear as it is shown in Figure 3.5.

It also has to be said that, when selecting Visual and Text features option to classify, the visual part is performed before the text part. At the end, a result as shown in Figure 3.5 is obtained.



http://www. nick.com

CHOOSE THE CLASSIFIER WITH WHICH YOU WANT TO CLASSIFY THE WEBPAGE:

Building ARFF file

http://www. nick.com

CHOOSE THE CLASSIFIER WITH WHICH YOU WANT TO CLASSIFY THE WEBPAGE:

It is classified as kids

Figure 3.5: Screenshot taken once the features are extracted and the result is given to the user.

Those toasts indicate the last part of the classification process already mentioned above as well as the result of the classification performance. As we can see in Figure 3.5, www.nick.com has been classified as Kids (in a binary classification between Adults and Kids). This toast with the correspondent category will appear at the end of the classification.

Finally, in Figure 3.6, a flow chart of the app is shown to make it easier to understand how the different steps of the app created in this dissertation are.

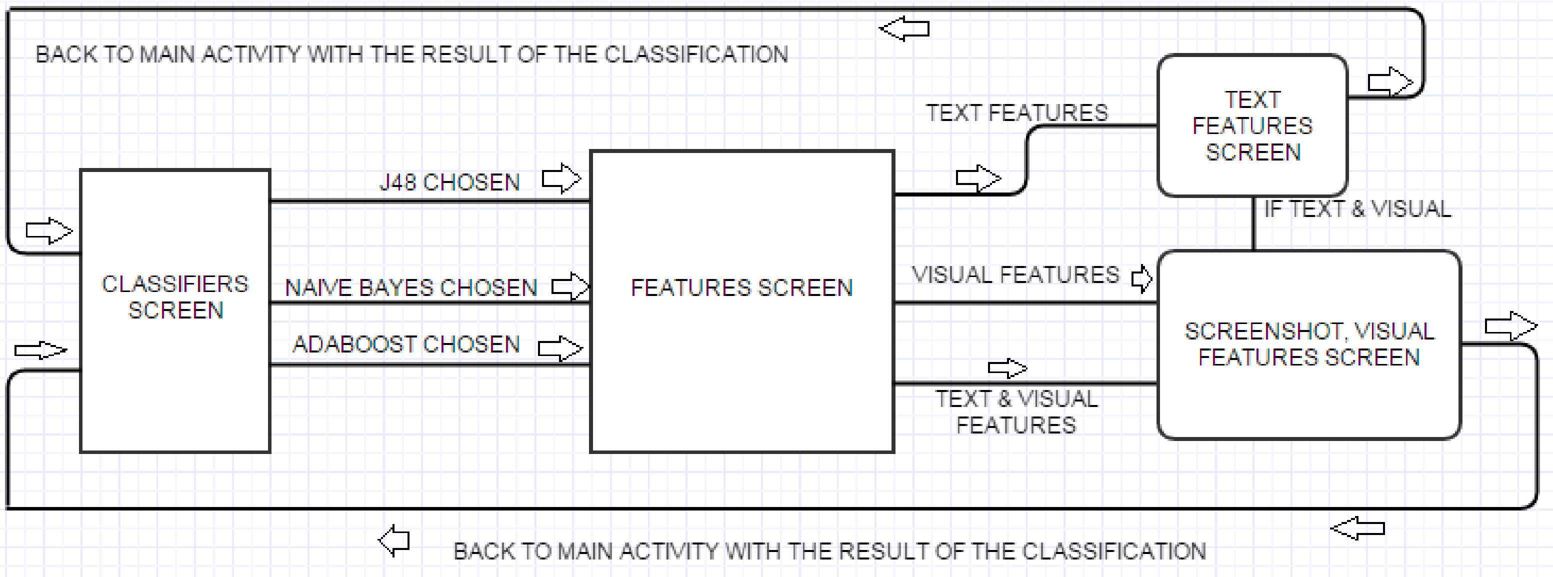


Figure 3.6: Flow chart of the application made.

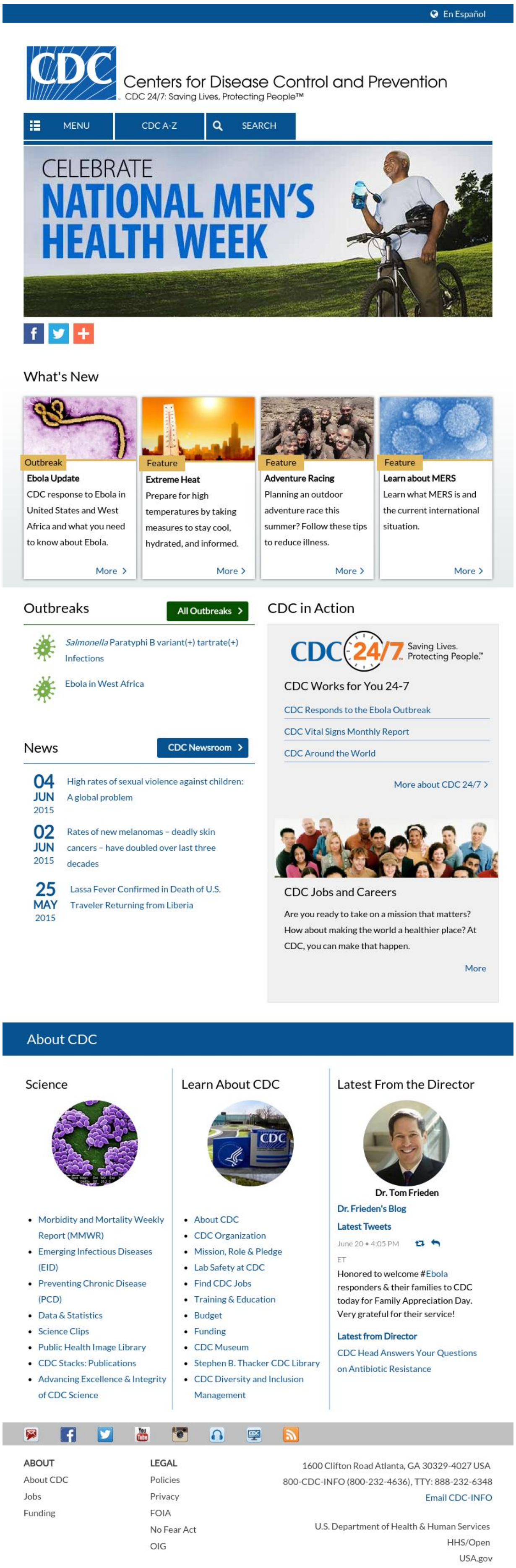
Chapter 4

Results

In this dissertation, we tested the application with a binary classification. This binary classification consists in distinguishing an Adult webpage from a Kid webpage. To achieve that, two main steps can be identified: train and test phase.

To perform this, a dataset is essential. To decide whether a webpage belongs to Adults or Kids category there is not a gist, so they were decided manually for the training dataset. It can be said that web pages for Adults were selected among categories (not porn) such as news, banks and universities due to the fact these web pages are not principally known to be for Kids.

In the other hand, Kids web pages were selected based on cartoons, TV series and learning for Kids websites. In Figure 4.1, it can be seen how an adult webpage looks like and in Figure 4.2 how a Kids webpage looks like. All of the web pages used for the training phase were in English, something which is very important for the classification to be more accurate and especially for the text features when building the Bag-Of-Words.



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HHS/Open
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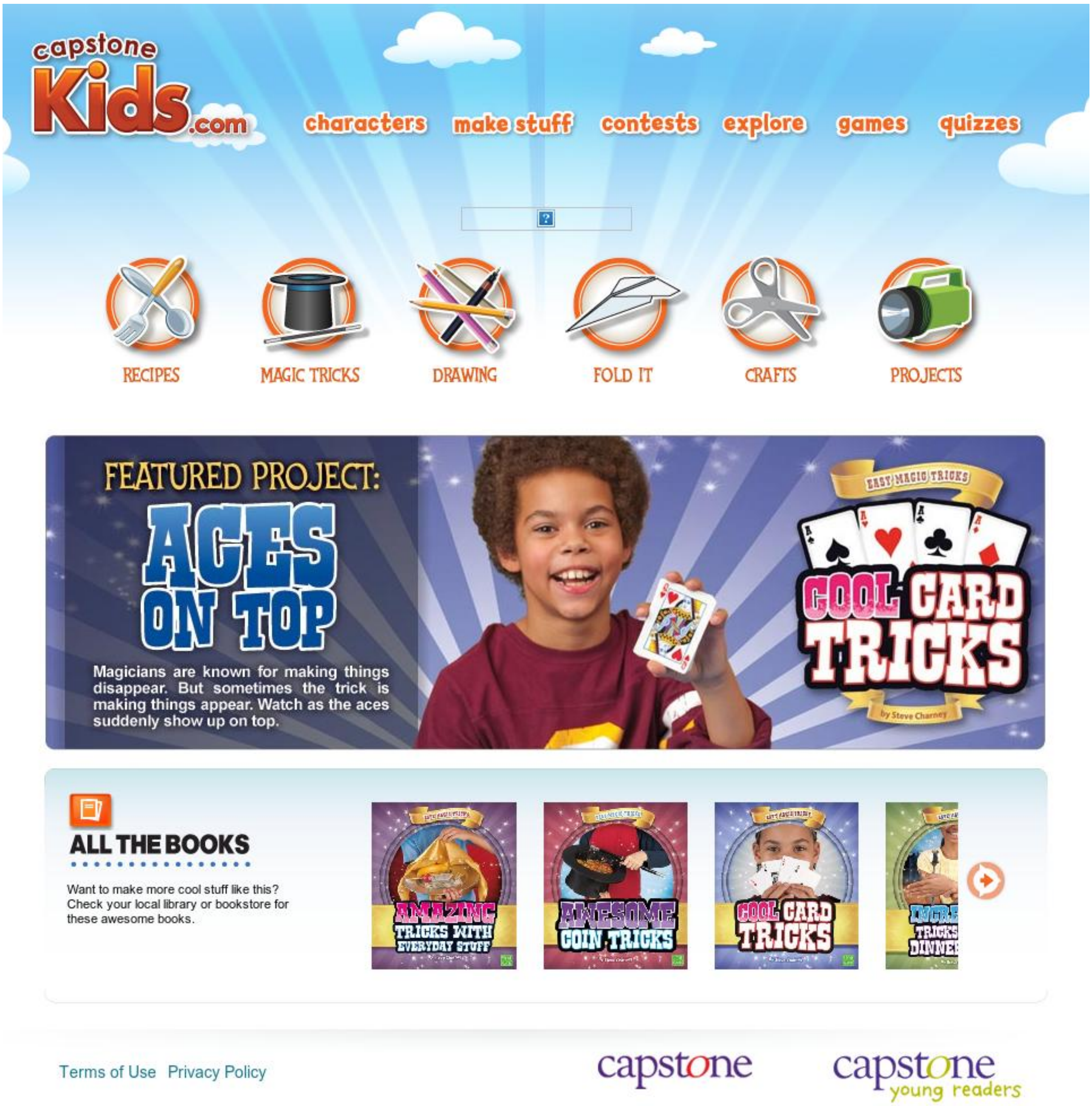
Figure 4.1: Screenshot taken with the app of an adult webpage called www.cdc.gov



Magicians are known for making things disappear. But sometimes the trick is making things appear. Watch as the aces suddenly show up on top.

Want to make more cool stuff like this? Check your local library or bookstore for these awesome books.

Figure 4.2: Screenshot taken with the Android app of the kids webpage www.capstonekids.com

On a first attempt, 208 web pages were used to train the classifier. 102 Kids web pages and 106 Adults web pages. Moreover, each one of the text-vector had 2000 attributes. As it was mentioned before, we used three different classifiers: J48, Naive Bayes and AdaBoost. After have trained the three classifiers, 48 web pages were used to test those classifiers: 26 adults and 22 kids web pages. Evidently, those pages used for the test phase had also 160 attributes in the visual vectors and 2000 attributes in the text vectors. After performing this, the results achieved were not good enough. As a solution, we decided to increase the number of web pages used for the training phase.

Therefore, after doing research of URLs for kids and adults 174 more web pages were added to train the classifiers. Thus, this second attempt consisted in training the classifiers with 382 web pages being 189 kids and 193 adults sites. The length of the vectors was not modified. The outcomes of this second attempt were better than the ones obtained in the first one but we were not satisfied.

A third attempt consisted in reducing the textual features to a total amount of 500. Once the features were reduced, we trained the classifiers again and test with the same test database. Once again, results were not what we expected so another approach was taken.

We decided then, that a good new solution could be reducing the amount of text features to the same quantity of visual attributes.

That way, the last and fourth attempt consisted in reducing the textual features to 160 so we had the same amount of features for visual and textual. After training again the classifiers and performing the test with the 44 web pages already mentioned, the results came up to be a little better than in previous attempts.

Nevertheless, it was found out that some of the web pages used in the test phase were not actually good to test and they were dragging out the final outcomes of the attempt. For that reason those web pages were eliminated from the test database having finally 36 web pages in the testing phase.

In summary, best results were achieved in this fourth attempt in which 36 web pages were used to test the classifiers being 18 of Adults and 18 of Kids. Besides 160 attributes were extracted in both visual and text and, as it was mentioned before, 382 web pages were used to train the classifiers being 189 from Kids and 193 from Adults category. Next, results are going to be described and evaluated.

As it was already stated, three classifiers were trained with text features, visual features and both of them together. We then tested with 36 web pages and the results are detailed in Figure 4.3.

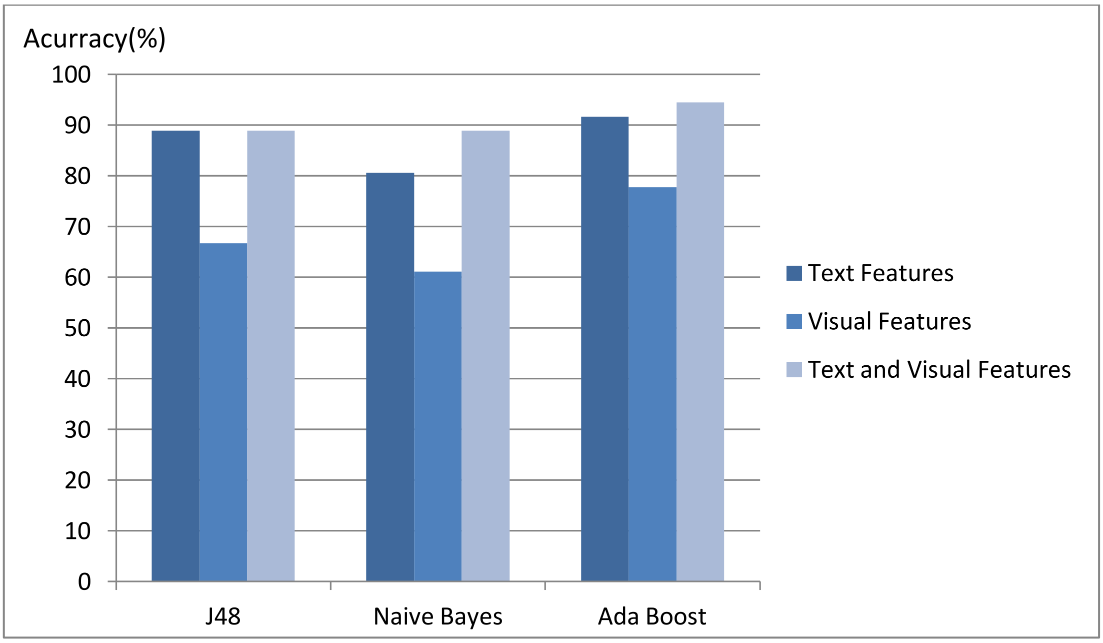


Figure 4.3: Graphic showing the results obtained when testing 36 web pages with the 3 classifiers and using text, visual or both features to classify.

In Figure 4.3 we can see the results obtained and some conclusions can be extracted from it. Next, we are going to evaluate the results independently for each of the three classifiers used.

In the case of J48, as it is shown in Figure 4.3, 88.89% of accuracy of well-classified web pages was obtained using text features. When using visual features itself, an accuracy of 66.67% was achieved. Nevertheless, when mixing both features 88.89% was got again. This is well represented in Table 4.1 where the three confusion matrices are shown. A confusion matrix is a specific table layout that allows visualization of the performance of an algorithm. Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. So all correct guesses are located in the diagonal of the table, and thus it is easy to visually inspect which web pages are correctly classified and which are not.

Table 4.1: The three confusion matrices obtained for the J48 classifier are displayed.

VISUAL FEATURES	Adults	Kids
Adults	14	4
Kids	8	10

TEXT FEATURES	Adults	Kids
Adults	17	1
Kids	3	15

VISUAL AND TEXT FEATURES	Adults	Kids
Adults	17	1
Kids	3	15

For this classifier, the classification did not improve when adding visual features to text features but, it did not get worse either so it is considered as a good result. As we can see in Table 4.1, in general, this classifier is better predicting Adults web pages than Kids web pages. In the case of using both visual and text features the results were pretty good only having 4 web pages bad classified. 1 from Adults category and 3 of them for Kids category.

On other hand and in the case of Naive Bayes classifier, the confusion matrices are exposed in Table 4.2. As we already could see in Figure 4.3, for this classifier, the accuracy improved an 8.33% when adding visual features to text features.

Table 4.2: The three confusion matrices for Naive Bayes classifier are shown.

VISUAL FEATURES	Adults	Kids
Adults	17	1
Kids	13	5

TEXT FEATURES	Adults	Kids
Adults	14	4
Kids	3	15

VISUAL AND TEXT FEATURES	Adults	Kids
Adults	17	1
Kids	3	15

For this classifier we also come to the conclusion that Adults web pages are better classified than Kids ones. As it is shown in Figure 4.2 and in Table 4.2 there is one improvement when comparing to J48 classifier. The classification improved when adding visual features to text features. Only using text features, the accuracy obtained of well classification was 80.56%, but once visual features were added, 88.89% was obtained. So, although the accuracy when using both features is the same for J48 and Naive Bayes classifiers, this classifier showed an improvement and reinforces the aim of the dissertation which is to show that visual features can help when performing web pages classification.

Finally, we are going to expose the outcomes obtained for AdaBoost classifier which were the best results obtained in this dissertation. In Table 4.3 we have the confusion matrices and with Figure 4.3, we can see that although the improvement of accuracy of well classification when adding visual to text features is 2.77% and therefore, less than the improvement obtained when using Naive Bayes classifier, the percentage of accuracy when using both features raises to 94.44% which is a very good result.

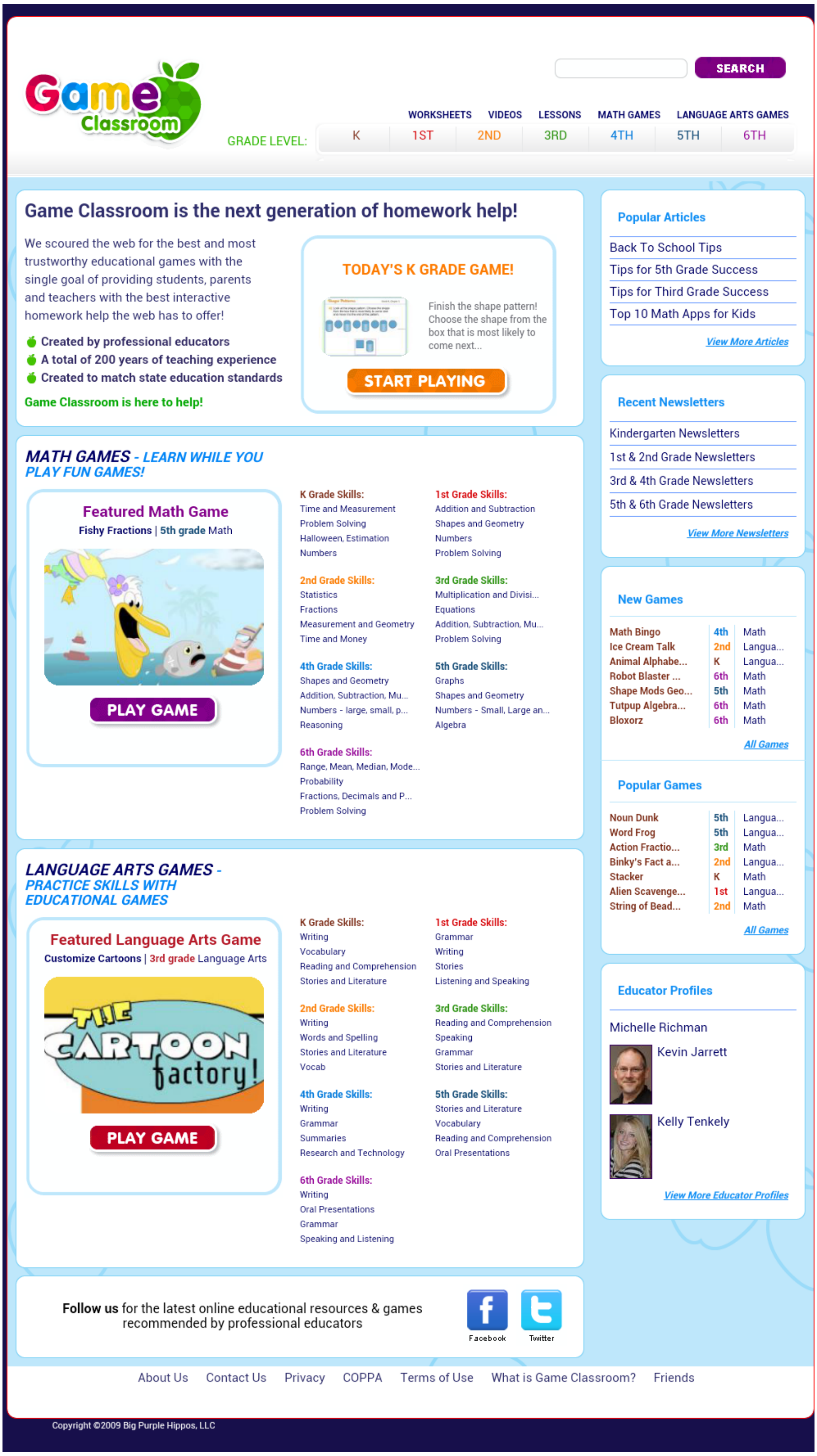
Table 4.3: The three confusion matrices obtained for AdaBoost classifier are shown in this table.

VISUAL FEATURES	Adults	Kids
Adults	16	2
Kids	6	12

TEXT FEATURES	Adults	Kids
Adults	17	1
Kids	2	16

VISUAL AND TEXT FEATURES	Adults	Kids
Adults	18	0
Kids	2	16

Once again, it can be concluded for this classifier also that Adults web pages are better classified than Kids ones. One of the possible reasons can be that there are more fields among Adults web pages than in Kids ones, so when testing a kid webpage can be classified as Adults. In other words, for Adults we can find News, Universities, Sports or Games web pages which imply a huge variety of colors in their pages. Nevertheless, for Kids web pages as we can say according to the research made in this dissertation, most of them are from cartoons or TV series and they are very colorful. But sometimes if they are less colorful they can be classified as Adults and that was one of the reasons why Adults web pages were better classified than Kids ones. There is an example in Figure 4.4 where a Kids webpage classified as Adults is shown.



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Addition, Subtraction, Mu...
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Writing
Stories
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2nd Grade Skills:
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Words and Spelling
Stories and Literature
Vocab

3rd Grade Skills:
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Speaking
Grammar
Stories and Literature

4th Grade Skills:
Writing
Grammar
Summaries
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5th Grade Skills:
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Bloxorz	6th	Math

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Alien Scavenge...	1st	Langua...
String of Bead...	2nd	Math

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Figure 4.4: Screenshot of a Kids webpage which was classified as Adults when using only visual features.

In summary, AdaBoost classifier was seen to be the best classifier with an accuracy of 94.44% when using both features. It has been shown in this chapter that although classifying only with visual features implies modest results, using both features to classify improved webpage classification than only using text features. This will be deeply discussed in chapter 5.

To end up this chapter, we will next show how the performance of the app is and how it works. In Table 4.4 this is clearly stated where three different web pages were tested. In that table, time of classification done by the app is shown depending on the features used to perform that classification. It is also displayed the weight of the web page's screenshot as well as the number of words extracted from the HTML code. It has to be said that it doesn't matter which classifier is chosen at the time of the performance. The only important issue is which features are used to perform the classification. That is why in Table 4.4 the time is considered to be the same for all classifiers. Some conclusions can be subtracted from that table and next they will be explained.

First of all, the main difference between that can be seen is the weight of the web pages' screenshot. As it is shown, a heavier screenshot implies a slow performance when using visual features and when using also text and visual features together.

Secondly we can also see the words extracted from the HTML code of each of the web page. It can be said that, in this case, how many words doesn't change a lot the time of the performance when using only text features.

Finally and as a conclusion, we can say that the only thing that matters for the time of execution of the app is how much the screenshot of the web page weighs.

Table 4.4: Performance of three different web pages in the application.

WEB PAGE	www.nick.com	www.games.com	www.su.se
CLASSIFICATION WITH TEXT FEATURES	25sec	26sec	26sec
CLASSIFICATION WITH VISUAL FEATURES	46sec	105sec	159sec
CLASSIFICATION WITH TEXT AND VISUAL FEATURES	61s	117sec	181sec

WEB PAGE	www.nick.com	www.games.com	www.su.se
WORDS EXTRACTED FROM THE HTML CODE	430	421	188
WEIGHT OF THE SCREENSHOT	1.61KB	91.5KB	375KB

Chapter 5

Conclusions

In this dissertation an approach for automatic web page classification by topic using the combination of text and visual features was described. A binary classification was performed, which aimed at distinguishing between Adults or Kids web pages. Good results were obtained which suggest that visual features from web pages improve the classification and they should not be ignored. To prove this and represented in a way it had not been represented yet, an Android application was done based on this classification process.

As it was explained in Chapter 4, three different classifiers were used in this work using text, visual or both features to perform classification. The results obtained in this work were very positive and they help to reaffirm that visual features complement the web page classification by topic that uses only text features. When visual features were used alone, these features are strong mainly for subjective variables, such as Gonçalves and Videira [3] already concluded. More types of subjective variables can also be developed, such as to distinguish if a web page transmits happiness or sadness for instance.

For future work about this thesis the main thing that could be said to do is to enhance the Android application. A deep study in the time of performance of classification could be made to reduce it and enhance the app to even be able to upload the app to PlayStore.

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