Network Traffic Classification Using Apache Spark

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Bachelor Thesis
October 16, 2017
Bachelor's Degree in Informatics Engineering
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Abstract

Apache Spark's capabilites offer new possibilities to make software systems more scalable and reliable. The framework can be used to improve old network visibility platforms. Previously, these systems used to be run in a single node, and used Deep Packet Inspection (DPI) techniques to classify the network flows. Deep Packet Inspection methods have a high computational cost so this limited the systems to a lower performance. Classifiers were forced to sample the input data in order to be able to process it in realtime, which caused important loss of information.

This project makes use of Spark's innovative features to create a distributed and fault tolerant platform that can analyse much more flows per second using Machine Learning to achieve a high precision and accuracy at a low computational cost.

Acknowledgements

I would first like to thank my thesis advisor, professor Pere Barlet Ros for giving me the opportunity to work on this project.

I would also like to mention my coworkers and classmates and their constant help and advice.

Finally, I would like thank my family and friends for their support and encouragement during the months of working on this project, and specially Maria and her tables.

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1.1 Introduction

1.1.1 Context and formulation of the problem

Internet Service Providers and Mobile Network Operators are facing enormous amounts of traffic on their networks from the proliferation of smart devices and applications, as well as IoT. The "always connected" lifestyle is making the traffic levels grow exponentially. Service providers cannot meet the demands of network performance and provide a good customer experience, and are under increasing pressures to move to "smart pipe" business models. With the help of network classification tools like the one developed in this project, network visibility is achieved, and large amounts of detailed information from IP addresses and application is collected. Analysing this data can help understand customer demand. User behavior analysis leads to customer segmentation and personalized services, that add extra value to the services provided and help ISPs and MNOs reduce costs and find new revenue opportunities [2]. This project comes from the need to take different innovative technologies and merge and apply them to the field of traffic classification, in order to obtain a product that has more features that add extra value where the other market options lack. Such features are real-time data analysis, a fault-tolerant distributed system, and traffic classification based on machine learning algorithms.

1.1.2 Objectives

To achieve the aforementioned objectives, the following specific goals will have to be accomplished:

- Implementation of the machine learning algorithm that will classify the network traffic.
- Design the distributed system architecture.
- Implement a real time analysis module for the system.
- Design tests to check the system performance under different circumstances.

1.1.3 Stakeholders

In this section the main stakeholders of this project will be defined.

- **Internet Service Providers and Mobile Network Operators:** One of the main interested agent in this projects are Internet Service Providers and Mobile Network Operators. Customer metrics are very important for telecommunication companies that aim to understand consumer behaviors in order to create personalized services, as well as manage network usage once the personalized plans are deployed.

- **Private and public organisations:** Private and public organisations need to manage their networks in order to ensure that they are used correctly according to their usage rules. The best way to achieve it is to use a network visibility tool that classifies network traffic and lets the administrators enforce a correct and fair usage of the network.

- **System and Network Administrators:** System and Network Administrators, and IT Management in general, are another interested agent in this project, as they are the ones that will personally use the developed system.

1.1.4 State of the art

Some time ago, when Network visibility technologies were just starting, they used Packet Capture and Deep Packet Inspection to identify protocols and extract packet content and metadata for analysis and communication patterns recognition.

Nowadays the standard of the industry is Netflow[1]. Netflow is a protocol developed by Cisco Systems to run on Cisco IOS that collects IP traffic information. It gets information on the applications used in the network and how the bandwidth is consumed.

In the area of machine learning, recent studies suggest working with specific algorithms, such as the C4.5 [4]. This project is not the only product in the market that provides network visibility through traffic classification. Some of the most important solutions offered by other vendors are brocade[2] and gigamon[3]. The technologies used by these products are unknown, as the companies that sell them don't want to disclosure the inner workings of their systems. As a result, instead of developing a system that competes with the other products in the market, the goal of this project is to test the viability of a network traffic classification tool using Apache Spark technology.

1.2 Scope

1.2.1 Project boundaries and requirements

To achieve the final goals, the project has to accomplish some requirements:

- **The system has to be distributed and fault tolerant:** Networks can produce large amounts of traffic. To be able to process all this data and offer a high availability under big workloads the system needs to work over a distributed network of servers that share all the computing load. Moreover, this design allows the system to be fault tolerant and to keep operating while suffering failures. All this will happen under the hood, the clients won't notice the current state of the system.

- **The system has to be able to process real time data:** In order to be a useful tool to the System and Network Administrators, the project has to be able to analyse network traffic in real time making it possible to know how the network bandwidth is used.

- **The system has to use Machine Learning:**In order to identify and classify network traffic, the system has to use Machine Learning algorithms to be able to keep improving its performance and accuracy.

1.2.2 Possible problems

- **Problems with the datasets:**the datasets may not be good to train the algorithm. A bad use of the dataset may also take place. Special atention to the preparation and division of the dataset.

- **Difficulties to test the distributed system in a real environment:** in order to test the distributed system in a real scenario, a lot of physical machines and a complex network structure are needed. Obtaining this resources can become a challenge.

- **Limited Time:** this is a complex project, and the fact that it is developed under time restrictions can force the initial goals to be modified in order to obtain a good result.

1.3 Methodology and rigor

1.3.1 Methodoly

To develop the project the Waterfall methodology will be used.

Waterfall projects go through different sequential phases. Theses phases define the development process of the project. They are: Requirements, Design, Implementation, Verification and Maintenance.

In this project we won't go through the Maintenance phase, as it falls out of the scope of the project.

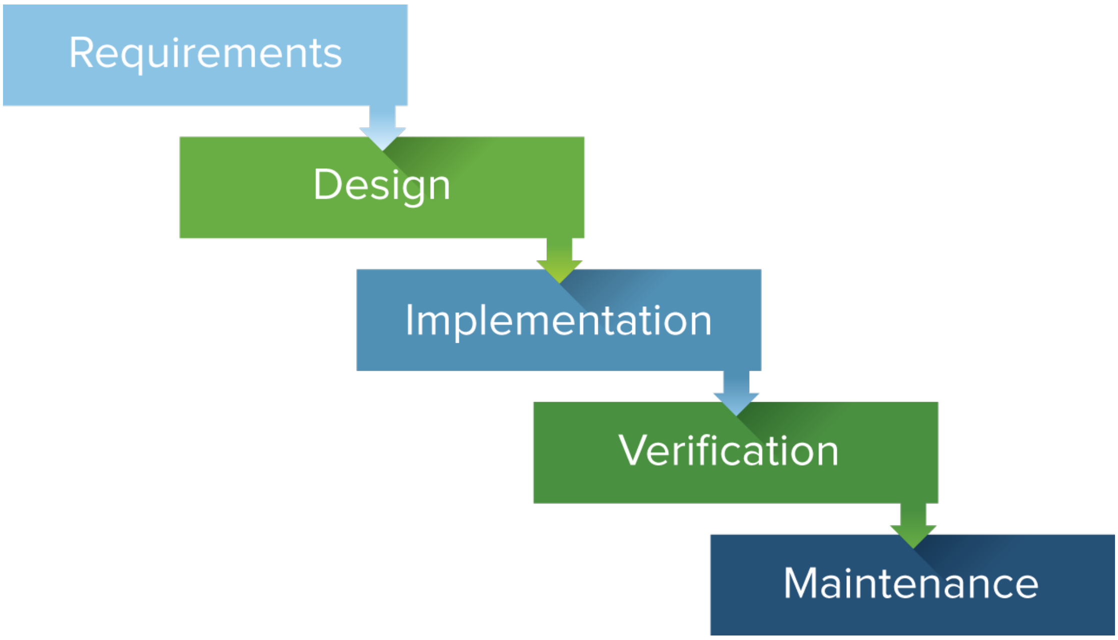


Figure 1: Process of the Waterfall Methodology

Source: https://d2myx53yhj7u4b.cloudfront.net/sites/default/files/waterfall%402x.png

The Waterfall methodology has been chosen as it is the model that suits better the needs of a single developer project [5].

1.3.2 Tools

During the development of the system all the tests will be done in an emulated environment with virtual machines and networks. Once the project is in a more advanced stage, the possibility of testing it in a real environment with real machines to test the ability of the system to recover and keep working in case of a failure of one of its components will be studied.

While implementing the code, a version control software called Git will be used. An online service called Github will be used in order to be able to access the code from any computer.

A version control methodology called Git Flow will be used. However, in a more advanced stage of the project, if it were to be commercialized, it probably would be sold as Software as a Service (SaaS) and a different methodology would fit the new model better. In this kind of projects a different version control methodology is normally used: github-flow. This new workflow would fit more the new stage of the project. [6][7]

To make the reports latex and LibreOffice will be used.

1.3.3 Validation

Periodic meetings with the director will be made, and the progress of the project will be checked. The results of the tests of the Machine Learning algorithms will be will be checked to be in the expected range, and if negative, the algorithms will be tweaked to improve their accuracy.

To evaluate the tolerance to failures and the capacity of the system to work in a distributed architecture, some tests will be designed and measurements of different parameters will be made.

1.4 Project calendar

The project has an approximate duration of four months, starting on February and ending on June. The estimated workload that it will have is around 455 hours. In case unexpected incidents occur and prevent the project from advancing, there is the possibility to extend the project four months.

The project will be done by only one person, and as a result all the tasks will be performed sequentially, even if there are no dependencies between them.

1.4.1 Tasks duration estimation

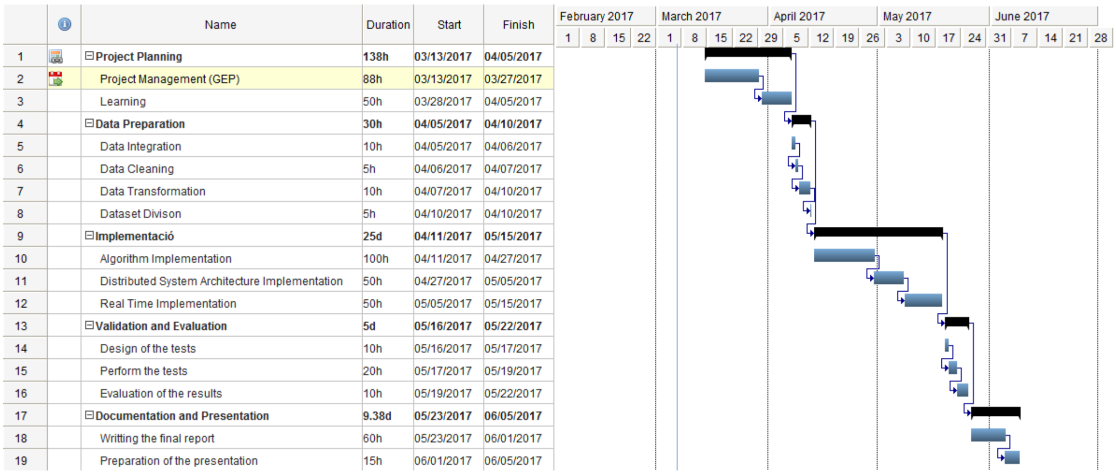
The project will be divided in different tasks and subtasks:

Task	Hours
1. Project Planning	130
1.1 Project Management (GEP)	80
1.2 Learning	50
2. Data Preparation	30
2.1 Data Integration	10
2.2 Data Cleaning	5
2.3 Data Transformation	10
2.4 Dataset Division	5
3. Implementation	180
3.1 Algorithm Implementation	80
3.2 Distributed System Architecture Implementation	50
3.3 Real Time Implementation	50
4. Validation and Evaluation	40
4.1 Design of the tests	10
4.2 Perform the tests	20
4.3 Evaluation of the results	10
5. Documentation and Presentation	75
5.1 Writting the final report	60
5.2 Preparation of the presentation	15
TOTAL	455

Table 1: Task duration estimation

1.4.2 Gantt chart

The following Gantt Chart is the result of the estimation of hours that each task will take.



	Name	Duration	Start	Finish
1	Project Planning	138h	03/13/2017	04/05/2017
2	Project Management (GEP)	88h	03/13/2017	03/27/2017
3	Learning	50h	03/28/2017	04/05/2017
4	Data Preparation	30h	04/05/2017	04/10/2017
5	Data Integration	10h	04/05/2017	04/06/2017
6	Data Cleaning	5h	04/06/2017	04/07/2017
7	Data Transformation	10h	04/07/2017	04/10/2017
8	Dataset Divison	5h	04/10/2017	04/10/2017
9	Implementació	25d	04/11/2017	05/15/2017
10	Algorithm Implementation	100h	04/11/2017	04/27/2017
11	Distributed System Architecture Implementation	50h	04/27/2017	05/05/2017
12	Real Time Implementation	50h	05/05/2017	05/15/2017
13	Validation and Evaluation	5d	05/16/2017	05/22/2017
14	Design of the tests	10h	05/16/2017	05/17/2017
15	Perform the tests	20h	05/17/2017	05/19/2017
16	Evaluation of the results	10h	05/19/2017	05/22/2017
17	Documentation and Presentation	9.38d	05/23/2017	06/05/2017
18	Writting the final report	60h	05/23/2017	06/01/2017
19	Preparation of the presentation	15h	06/01/2017	06/05/2017

Figure 2: Gantt chart

1.4.3 Tasks and dependencies

Project planning

In this first phase, the scope and the objectives of the project are defined.

In the Project Planning phase there are two tasks. In theory they are independent, but due to the large workload that the Project Management (GEP) task creates, the two tasks are done mostly one after the other.

Data preparation

In this phase of the project the datasets will be prepared for their future usage. The tasks that constitute this stage have to be performed in order, as they are dependent on each other.

In the first one, the different datasets will be merged into a single dataset. In the Data Cleaning and Data Transformation tasks, the dataset will be processed in order to fill the missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies.

In the last task of this stage, the dataset will be divided into the Training dataset, the Evaluation dataset and the Testing dataset.

Implementation

In this development phase there are three main tasks. They have been planned to be done sequentially, one after the other.

This stage represents the main part of the development process, and during this period all the features of the final system will be implemented.

Validation and evaluation

In this stage the tests will be designed and performed in order to check that the system works as expected.

With the help of the tests' results, the system performance will be evaluated and analysed.

Documentation and presentation

This last stage of the project consists in writing the final report and preparing the oral presentation of the project, that will be done in front of a tribunal that will evaluate the work done.

1.5 Resources

1.5.1 Human resources

The only human resource that will be available during the project will be a single developer, that will perform the different roles necessary to complete the project. The dedication to the project will be around 30 hours per week. This is an approximation that can change depending on the workload of each week.

1.5.2 Material resources

During the project, different resources will be used.

1. **Custom Desktop Computer (CPU i7 2700k, GPU nvidia GeForce GTX 560 Ti, 8GB RAM)**. Hardware tool used in the development of the project. The code of the project will be written with it, as well as reports.

2. **Lenovo ThinkPad t450s laptop.** It will be used with the same purposes as the Desktop compter.

3. **Git and GitHub.** Version control system for tracking changes in the project codes. GitHub online services will be used.

4. **Sublime Text 2.** Text editor used to write the code of the project.

5. **Apache Spark.** Open-source cluster-computing framework in which the system will be developed.

6. **Gantter.** Online tool to make Gantt Charts.

7. **Asana.** Online tool to keep track of the project state.

1.6 Risks and alternatives

The project is expected to be presented between the 26th and the 30th of June. Due to the fact that there will be a lot of work involving technologies yet to learn for the developer, it is possible that the development will take more time than estimated and the project won't be finished in time. In case this scenario happens, the project would be presented in October.

The stage where more problems are bound to happen is the implementation phase, as the developer has to learn and use new technologies.

Another possible problem that can arise during the development of the project is the lack of any physical infrastructure to test the system. In this case, virtualisation should be considered to evaluate the system. This should be considered when analysing the performance results.

In the most optimistic scenario the project would be finished sooner than expected. In this case, there would be the possibility to talk with the director to discuss new features for the project.

A more realistic estimation would be finishing the project with all its planned features just in time, or even having to extend it four months and finishing it on October.

The worst case scenario would be having to extend the duration of the project and having to reduce the expected features of the system in order to finish the development in time.

1.7 Economical management of the project

1.7.1 Estimation of costs

Human resources costs

Only one worker will be working on this project, and he will have to perform all the tasks. However, to estimate human costs, it has been taken into consideration that the different roles performed entail different costs. The cost/hour of a project manager should be around 50€/hour. Contrarily, the developer's wage should be around 25€/hour. The salary of the engineer is estimated to be 35€/hour.

Task	Hours	Resources	Salary (€/h)	Cost
1. Project Planning	130			5250
1.1 Project Management (GEP)	80	Project Manager	50	4000
1.2 Learning	50	Developer	25	1250
2. Data Preparation	30			750
2.1 Data Integration	10	Developer	25	250
2.2 Data Cleaning	5	Developer	25	125
2.3 Data Transformation	10	Developer	25	250
2.4 Dataset Division	5	Developer	25	125
3. Implementation	180			4500
3.1 Algorithm Implementation	80	Developer	25	2000
3.2 Distributed System Architecture Implementation	50	Developer	25	1250
3.3 Real Time Implementation	50	Developer	25	1250
4. Validation and Evaluation	40			1400
4.1 Design of the tests	10	QA Engineer	35	350
4.2 Perform the tests	20	QA Engineer	35	700
4.3 Evaluation of the results	10	QA Engineer	35	350
5. Documentation and Presentation	75			3750
5.1 Writting the final report	60	Project Manager	50	3000
5.2 Preparation of the presentation	15	Project Manager	50	750
TOTAL	455			15650

Table 2: Direct costs by activity according to the Gantt Chart

Task	Hours	Salary (€/h)	Estimated Cost (€
Project manager	155	50	7750
Developer	260	25	6500
QA Engineer	40	35	1400
TOTAL			**15650**

Table 3: Human resources costs

Material resources costs

In this section the costs of the material resources have been calculated.

It has been considered that the desktop computer will be used for 80% of the hours, and the laptop for the remaining 20%.

To calculate the amortization, it has been considered that a year has 250 laborable days, and each laborable day has 8 hours of worktime.

Finally I have included the cost of printing the TFG. The price is estimated to be around 50€ per copy. Four copies will be needed: three for each member of the tribunal and one for the director of the project.

The material costs are equally distributed among the different tasks of the project.

Resource	Price (€)	Units	Useful life (years)	Amortization/h (€/h)	Hours	Amortization (€)
Desktop Computer	1100	1	6	0.09	2912	267.9
Lenovo ThinkPad t450s laptop	710	1	5	0.07	728	51.69
TFG printed on paper	50	4				200
TOTAL						**519.59**

Table 4: Indirect costs for material resources

Indirect costs

In this section all the indirect costs will be specified. The cost of the electricity, water, Internet and workplace will be my monthly housing costs, as my home will be the place where the project will be developed most of the time.

As well as with the material costs, the indirect costs are equally distributed among the different tasks of the project.

Product	Price (€/month)	Estimated Cost (€
Internet	20	80
Workplace	375	1500
Electricity bill	37.5	150
Water bill	20	80
T-jove 1 zona	35	140
TOTAL		**1950**

Table 5: General indirect costs

Cost contingency

The following costs will cover any possible problem that increases the real cost of the project. A percentage of 15% will be reserved for this purpose.

Product	Percentage	Price (€)	Cost (€)
Human resources	15%	15650	2347.5
Material resources	15%	519.59	77.94
General resources	15%	1950	292.5
TOTAL			**2717.94**

Table 6: Cost contingency table

Unforeseen events

In this section possible unexpected events are taken into consideration:

1. Desktop computer failure. In case of failure of the desktop computer, it will have to be repaired or substituted for a new one. Due to the time constrains of the project, the best option would be to buy a new computer. In this case, 1100€ would be added to the cost of the project. However, the possibility of this failure happening is very low (we decide it is around 5%).

2. In case of a failure in the laptop, the same scenario would take place, increasing the final cost in 710€.

Product	Probability	Units	Price (€)	Cost (€)
Desktop computer failure	5%	1	1100	55
Laptop failure	5%	1	710	35.5
TOTAL				**90.5**

Table 7: Unforeseen events costs.

Final Cost

The final cost of the project is shown in the table below.

Concept	Cost (€)
Human resources	15650
Material resources	519.59
Indirect costs	1950
Cost contingency	2717.94
Unforeseen events	90.5
TOTAL	**20928.03**

Table 8: Final cost of the project

In this calculation the costs of the taxes have been omitted. They should be taken into consideration as they might increase significantly the cost of the project.

1.7.2 Control management

There are very few factors that can be controlled in this project, as the material resources were bought time ago, and the indirect costs will exist even if nothing is developed. The only thing that can be controlled are human resources.

In case unexpected incidents occur and the project has to be extended four months, the cost would increase 1950 euros from the indirect general costs, and an unkown amount from the human resources costs, as more hours of work would be needed to end the project .

At the end of each phase of the project, the number of hours dedicated to its completion will be computed and compared with the estimated hours, in order to control possible deviations.

1.8 Sustainability

1.8.1 Economic dimension

In the cost study carried out previously, it has been shown that most of the costs of the project come from the human resources expenses. The remaining costs are inevitable, and would exist even if there wasn't any project in development. This low production and development costs make the project economically viable.

The strength of this project lies in the savings that this product would have for ISPs and MNOs, and the ability to create personal internet plans that it would give them. It would also be an economic benefit for companies and organizations that use this product to gain visibility in their networks.

1.8.2 Social Dimension

The social dimension of this project is very limited, and probably it won't improve anybody's life quality.

However, a positive social aspect of this project that might happen, is that thanks to the ISPs and MNOs being able to create and promote new and personalized services, prices could drop and make everybody able to afford an Internet plan.

A negative aspect of this project might be the loss of privacy, as this product will increase network visibility for network managers. Despite the sensation of privacy loss, this is a relatively insignificant problem, as network users will still be anonymous and only the type of traffic they are generating will be known.

1.8.3 Environmental dimension

Zero material resources have been specifically bought for this project. All the resources used where bought time ago for other purposes and will continue to be used after the end of this project, so no waste and pollution have been generated for the developement of this project.

Although the enviromental impact of this project is very small, in the real implementation of the final product there will be a server or a network of servers always working, analysing the network traffic sent to them.

1.8.4 Sustainability Matrix

In the following table the sustainability of the project is evaluated. Environmental, economic and social categories have a score between 0 and 10, and the global score is between 0 and 30.

Sustainability	Environmental	Economic	Social	**Total**
Score	3	10	4	17

Table 9: Sustainability Matrix

Apache Spark Framework

Apache Spark[8] is a general-purpose cluster computing system. The Spark project was born in 2009 at UC Berkeley's AMPLab and made open source in 2010 under the BSD license. Later, in 2013, it was donated to the Apache Software Foundation, which changed its license to Apache 2.0.

Version	Original release date	Last version	Release date
0.5	2012-06-12	0.5.1	2012-10-07
0.6	2012-10-14	0.6.2	2013-02-07
0.7	2013-02-27	0.7.3	2013-07-16
0.8	2013-09-25	0.8.1	2013-12-19
0.9	2014-02-02	0.9.2	2014-07-23
1.0	2014-05-30	1.0.2	2014-08-05
1.1	2014-09-11	1.1.1	2014-11-26
1.2	2014-12-18	1.2.2	2015-04-17
1.3	2015-03-13	1.3.1	2015-04-17
1.4	2015-06-11	1.4.1	2015-07-15
1.5	2015-09-09	1.5.2	2015-11-09
1.6	2016-01-04	1.6.3	2016-11-07
2.0	2016-07-26	2.0.2	2016-11-14
2.1	2016-12-28	2.1.1	2017-05-02
2.2	2017-07-11	2.2.0	2017-07-11

Table 10: Spark versions.

Legend
- Old version
- Older version, still supported
- Latest version

Source: https://en.wikipedia.org/wiki/Apache_Spark

In 2015 Spark had more than 1000 contributors, making it one of the most active projects of the Apache Software Foundation.

It provides high-level APIs in Java, Scala, Python and R, and can be integrated with Hadoop and can process existing Hadoop HDFS data.

In the big data industry there was the need for a general purpose cluster computing tool that solved the existing tools' limitations. Hadoop MapReduced could only perform batch processing, Apache Storm could only perform stream processing, Apache Impala could only perform interactive processing, and Neo4j could only perform graph processing.

Apache Spark provided real-time stream processing, interactive processing, graph processing, and very fast in-memory batch processing.

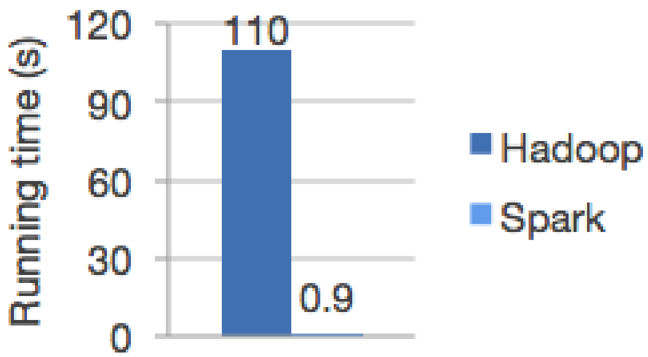


Figure 3: Logistic regression in Hadoop and Spark.

Source: https://spark.apache.org/

When a Spark application is excuted, the first step is to create the SparkContext object. This element is a logic connection with the cluster. This element is usually created within the main function, that is executed by the Spark Driver.

The Spark Driver is the program that declares the transformations and actions on the RDDs and submits such requests to the master. Its location is independent of the master and slaves.

The DAG Scheduler is the high-level scheduling layer that implements stage-oriented scheduling. It divides each job in different stages and computes DAG (Direct Acyclic Graph) with these stages. It also keeps track of which RDDs and stage outputs are materialized, and finds a schedule to run the job.

In addition to creating a DAG of stages, the DAG Scheduler also determines the best locations to run each task on, based on the current cache status. Furthermore, it handles failure.

Once the DAG Scheduler has sent the Direct Acyclic Graph to the Cluster Manager, the later creates tasks out of it and submits them to the workers, coordinating the different job stages. The workers are where the tasks are actually executed.

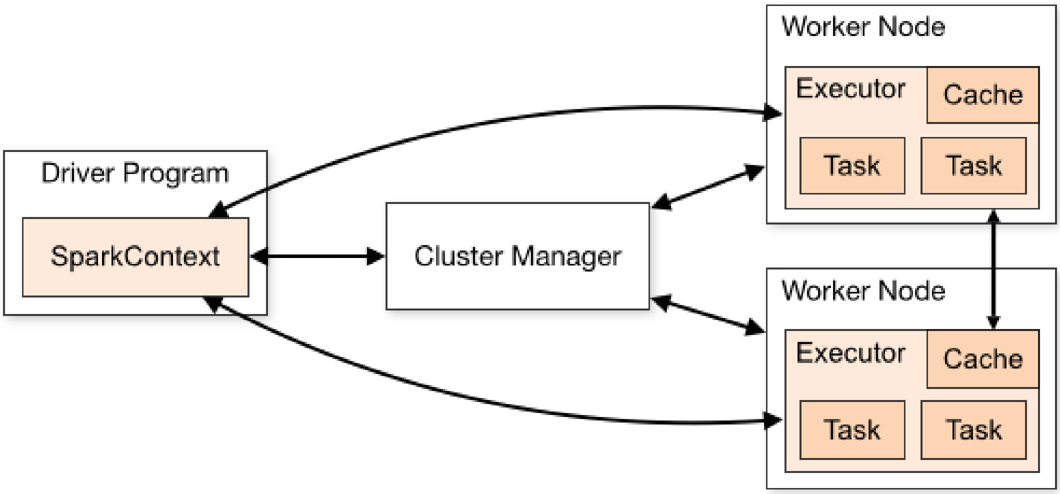


Figure 4: Spark cluster mode overview.

Source: http://spark.apache.org/docs/latest/img/cluster-overview.png

2.1 RDDs

The Resilient Distributed Dataset (RDD) is the fundamental data unit in Apache Spark. An RDD is an immutable distributed collection of elements of data, partitioned across nodes in a cluster that can be operated in parallel. RDDs can't be changed, but new RDDs can be generated by transforming existing ones.

Each dataset in RDD is divided into logical partitions, which may be computed on different nodes of the cluster.

RDDs are fault tolerant. That means that in case of losing data in a calculation of an RDD, it can be recalculated from the original data. This is possible because RDDs are only readable. The system saves all the operations that the RDDs go through, and in case data needs to be recovered, the operations can be applied again to the original data.

RDDs are distributed in the different cluster nodes. Using the operation RDD.partition the granularity of the data can be configured. There are two types of basic operations: transformations and actions. The transformations create a new RDD from a set of data or from another RDD. The actions calculate a result based on the data of one or more RDDs.

Below are the most commonly used operations on RDDs, both transformations and actions. The complete list of operations can be dound in the programming guide published by Apache Spark [1].

Transformation	Description
map(func)	Returns a new distributed dataset, formed by passing each element of the source through a function func.
filter(func)	Returns a new dataset formed by selecting those elements of the source on which func returns true.
flatMap(func)	Similar to map, but each input item can be mapped to 0 or more output items (so func should return a Seq rather than a single item).
union(otherDataset)	Returns a new dataset that contains the union of the elements in the source dataset and the argument.
intersection(otherDataset)	Returns a new RDD that contains the intersection of elements in the source dataset and the argument.
distinct([numTasks])	Returns a new dataset that contains the distinct elements of the source dataset.
join(otherDataset, [numTasks])	When called on datasets of type (K, V) and (K, W), returns a dataset of (K, (V, W)) pairs with all pairs of elements for each key. Outer joins are supported through leftOuterJoin, rightOuterJoin, and fullOuterJoin.

Table 11: RDD transformations

Source: http://spark.apache.org/docs/2.1.1/programming-guide.html

Spark uses a lazy evaluation approach. This means Spark does not evaluate each transformation on the data right away, the execution will not start until an action is triggered. The transformations are added to the DAG, and only when the Driver requests some data, the DAG actually gets executed.

Some advantages of lazy evaluation are increased manageability, less computation time and

[1] http://spark.apache.org/docs/2.1.1/programming-guide.html

Actions	Description
reduce(func	Aggregate the elements of the dataset using a function func (which takes two arguments and returns one). The function should be commutative and associative so that it can be computed correctly in parallel.
Collect()	Returns all the elements of the dataset as an array at the driver program. This is usually useful after a filter or other operation that returns a sufficiently small subset of the data.
Count()	Returns the number of elements in the dataset.
First()	Returns the first element of the dataset (similar to take (1)).
take(n)	Returns an array with the first n elements of the dataset.
CountByKey()	Only available on RDDs of type (K, V). Returns a hashmap of (K, Int) pairs with the count of each key.
foreach(func)	Runs a function func on each element of the dataset. This is usually, done for side effects such as updating an Accumulator or interacting with external storage systems.
foreach(func)	Runs a function func on each element of the dataset. This is usually, done for side effects such as updating an Accumulator or interacting with external storage systems.

Table 12: RDD actions

Source: http://spark.apache.org/docs/2.1.1/programming-guide.html

increased speed, reduced complexity and optimized excution.

With lazy evaluation, Apache Spark programs can be organized into smaller operations. It reduces the number of passes on data by grouping operations. Since only necessary values get computed, the trip between the driver and the cluster is saved, speeding up the process.

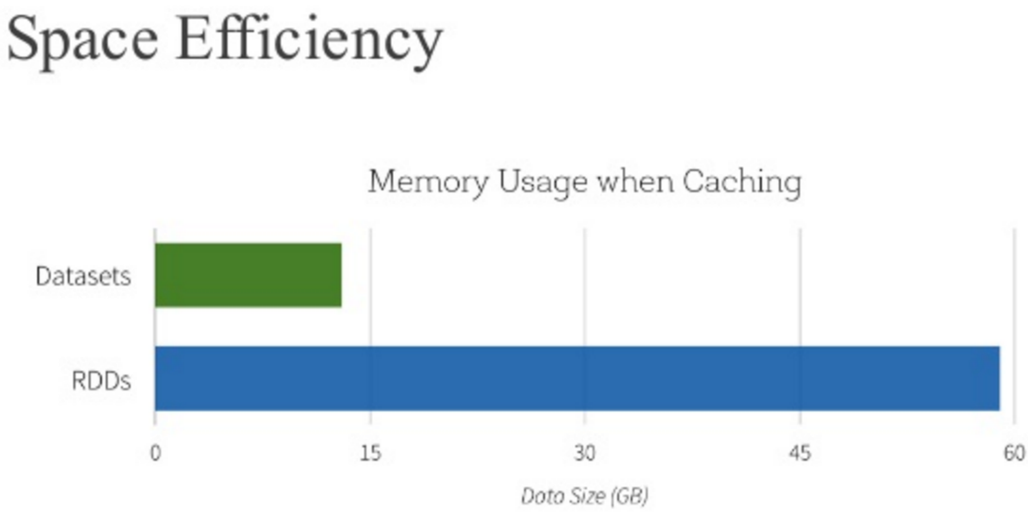


Figure 5: Space Efficiency: Datasets vs RDDs.

Source: https://databricks.com/blog/2016/07/14/a-tale-of-three-apache-spark-apis-rdds-dataframes-a
html

After Spark 2.0, RDDs are replaced by Dataset, which is strongly-typed like an RDD, but with richer optimizations under the hood. The RDD interface is still supported, however, is highly recommend to switch to use Dataset, which has better performance than RDD.

2.2 Datasets and dataframes

A **Dataset** is a collection of data distributed over different cluster nodes. Datasets were introduced in Spark 1.6 and provided the benefits of RDDS, like strong typing and the ability to use lambda functions, with the benefits of Sparks SQL's optimized execution engine.

A **DataFrame** is a Dataset organized into named columns. Conceptually, it is equivalent to a table in a relation database or a data frame in python, but with better optimizations under the hood.

2.3 Spark Components

Spark Core is the underlying general execution engine for the Spark platform. It comes with a set of high-livel libraries that provided increased functionalities, like support for SQL, streaming data and machine learning. These libraries can be combined to create complex workflows.

Next, the different modules that create the Apache Spark Ecosystem will be explained.

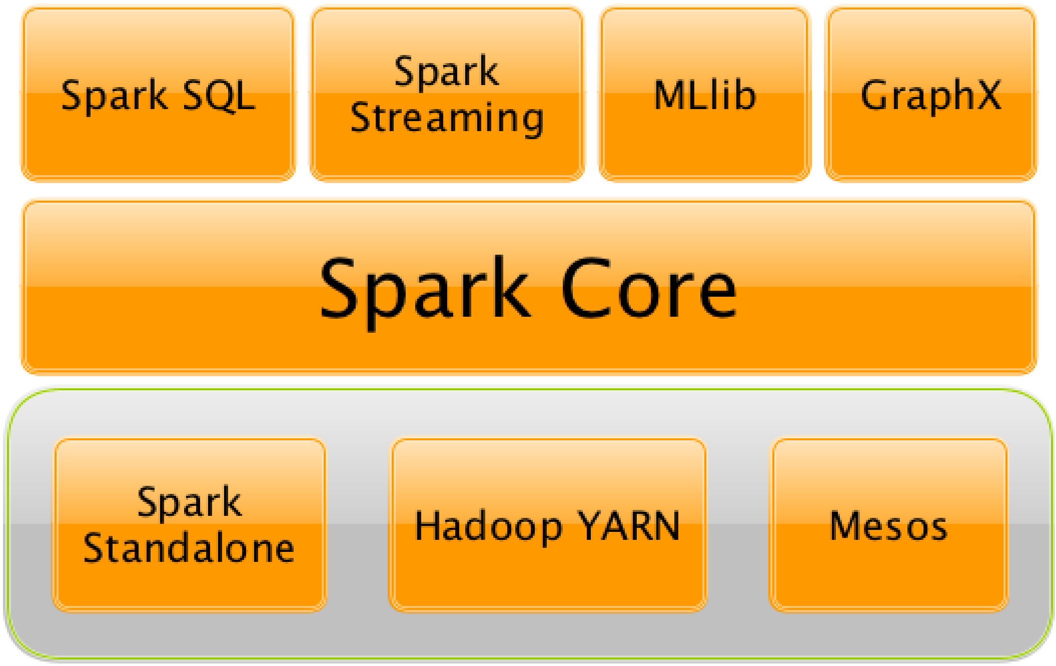


Figure 6: The Spark Platform.

Source: https://jaceklaskowski.gitbooks.io/mastering-apache-spark/spark-overview.html

2.3.1 Spark Streaming

Spark Streaming[9] is an extension of the Spark core. It is an stream processing engine that enables high-throughput, scalable and fault-tolerant processing of live data streams.

To ingest data in the system many sources can be used, like Flume, Kafka, Kinesis or TCP sockets. This data can then be processed using algorithms and high level functions, like map, reduce and join. You can apply Spark's machine learning and graph processing algorithms on these data streams. After the data has been processed, it can be sent out to filesystems, live dashboards and databases.

Figure 7: Streaming architecture.

Source: https://spark.apache.org/docs/latest/streaming-programming-guide.html

Internally, Spark Streaming ingests live input data streams divided into mini batches. RDD transformations are applied to the batches by the Spark engine to generate the final result.

Figure 8: Spark Streaming flow of data.

Source: https://spark.apache.org/docs/latest/streaming-programming-guide.html

This structure allows the same code to be used for offline data processing and live stream analytics. This comes at the price of having a latency equal to the duration of the batch.

Discretized Streams

Discretized Streams, also known as Dstreams, are an abstraction of a continous flow of data provided by Spark Streaming. DStreams are actually series of RDDs, each one containing data from an specific time interval.

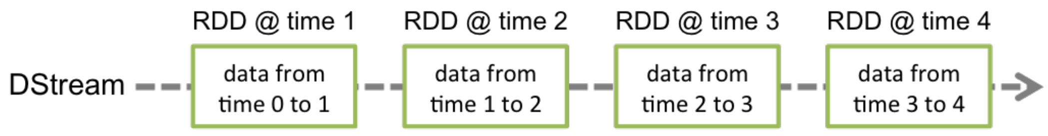


Figure 9: DStreams internal structure.

Source: https://spark.apache.org/docs/latest/streaming-programming-guide.html

The operations on a DStream are internally applied to all the RDDs that compose the stream. Spark Streaming has two categories of streaming sources built-in.

- **Basic sources:** Sources directly available in the StreamingContext API, like sockets and filesystems.

- **Advanced sources:** Sources available through external libraries, like Flume, Kafka and Kinesis.

Applications that use Spark Streaming need to be run on more than one core, or thread when running locally, as one core is needed to run the receiver, and another to process the received data.

Structured Streaming

Structured Streaming[10] was introduced in Spark 2.0. It is a collection of additions to Spark Streaming rather than a huge change to Spark itself. This leads to a new stream processing model that is very similar to a batch processing model.

The main idea behing Structured Streaming is to have a table that is constantly having new entries added to it. This new model, while being more optimized, has a resemblance to the old batch processing model.

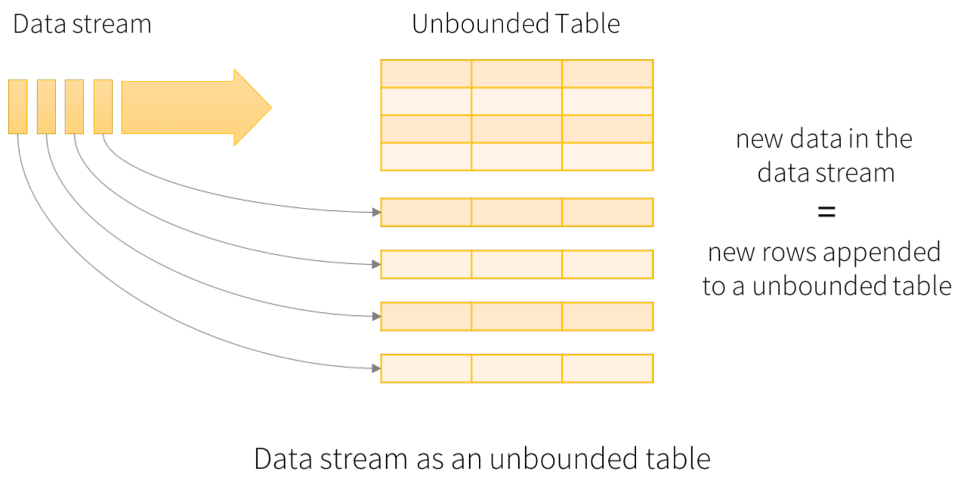


Figure 10: Input Table in Structure Streaming.

Source: https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html

Every data element arrived on the stream is like a new row being appended to the table.

A transformation on the input table will generate the "Result Table". Every ≪trigger interval≫ (for example, every 1 second), new rows are appended to the input table, which results in updates in the Result Table.

There are different modes to decide what gets pushed out to the external storage:

- **Complete Mode:** The entire table with the processed data is pushed out to the external storage. Is the storage connector that has to decide if it writes the entire table or filters it.

- **Append Mode:** Only the new rows appended in the table since the last trigger are pushed out to the external storage. This mode is only useful when the existing rows on the results table are not expected to change.

- **Update Mode:** The rows that were updated since the last trigger will be written to the external storage. Note that this is different from the Complete Mode in that this mode only outputs the rows that have changed since the last trigger.

2.3.2 Spark SQL

Spark SQL is a Spark module that introduces a new data abstraction, SchemaRDD, that provides support for semi-structured and sructured data. One of the main characteristic is that it provides relational processing with Spark functional programming. Unlike the basic Spark RDD API, the interfaces of Spark SQL provides Spark with more information about the structure of the data and the computation when are being performed. Internally, this extra information is used to perform extra optimizations.

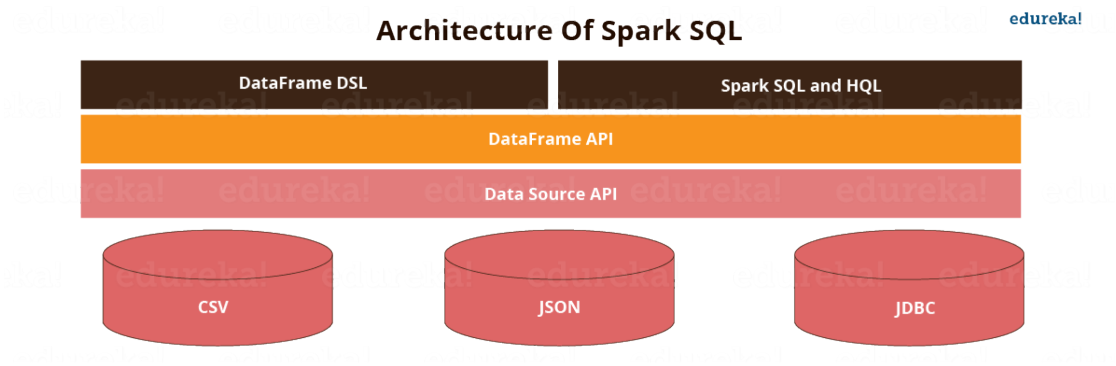


Figure 11: Architecture of Spark SQL.

Source: https://www.edureka.co/blog/spark-sql-tutorial/

The main capabilities of Spark SQL in terms of using structured and semi-structured data are:

1. Provides a DataFrame abstraction in Python, Scala and Java. This integration simplifies working with structured datasets and makes it easy to run SQL queries alongside complex analytic algorithms.

2. Unifies Data Acces by reading and writting data from a variety of structured formats as JSON, Hive Tables and Parquet (providing a single interface for an efficient work.)

3. Allows to query data from other structured formats as JSON, HIve Tables, etc; using SQL.

2.3.3 GraphX

GraphX is a Spark's API extension for graphs and graph-parallel computation. It includes ready-to-use graph algorithms to simplify analytics tasks. Some of this algorithms are PageRank, Connected Components and Triangle Counting.

2.3.4 MLlib

MLlib[7] is Spark's machine learning library. It helps deploy applications that use machine learning algorithms in a practical and easy way, taking advantage of the scalability the cluster offers.

Machine learning is the field of computer science that has the goal to make computers learn without being explicitly programmed.

It provides high level tools, such as:

- Machine learning algorithms for classification, regression and clustering.
- Featurization: attem iribute selection, dimensionality reduction, transformation and feature extraction.
- ML Pipelines.
- Persistence: loading and saving models, Pipelines and algorithms.

The available algorithms and functionalities can be consulted at the Machine Learning Library (MLlib) Guide [2].

With the realease of Spark 2.0, the RDD-based APIs in the spark.mllib package have entered maintenance mode. Now, the primary Machine Learning API for Spark is the DataFrame-based API in the spark.ml package.

2.3.5 Cluster Deployment

To take profit of the full potential of Apache Spark it needs to be run on a cluster. To do so, a cluster manager and a distributed storage system are needed.

Spark can use a wide variety of distributed storage systems, including Hadoop Distributed File System (HDFS), MapR File System (MapR-FS), Cassandra, OpenStack Swift, Amazon S3 or Kudu. It also allows a custom solution to be implemented.

Spark can connecto to several types of cluster managers. The cluster manager is responsible allocating resources for applications across the cluster. Once the cluster is up and running, Spark acquires executors on the cluster nodes, which are processes that run computations and

[2] http://spark.apache.org/docs/2.1.1/ml-guide.html

store data. When the executors are ready, it sends the code to them. Finally, SparkContext sends different tasks to the executors.

This architecture provides isolation to the applications, making them independent at scheduling and execution level. However this makes sharing data between applications impossible without writing it to an external storage system. Spark is indifferent to the cluster manager, as long as it an acquire executors, and these can communicate with each other.

The latest Spark release (version 2.2.0) suports three different cluster managers:

1. **Standalone:** a simple cluster manager included with Spark.

2. **Apache Mesos:** an open-source cluster manager developed ad University of California, Berkeley.

3. **Hadoop YARN:** the resource manager in Hadoop 2.

4. **Kubernetes:** Kubernetes is an open-source platform for providing container-centric infrastructure. Currently the support is only experimental.

By default, standalone scheduling clusters are resilient to Worker failures (insofar as Spark itself is resilient to losing work by moving it to other workers). However, the scheduler uses a Master to make scheduling decisions, and this (by default) creates a single point of failure: if the Master crashes, no new applications can be created. In order to circumvent this, we have two high availability schemes, detailed below.

Standby masters with ZooKeeper ZooKeeper is a service that using it allows to provide a leader election and state storage mantainig the configuration information, naming, providing distributed syncronization and group services. With this service you can launch multiple masters in your cluster by being connected to the same ZooKeeper's instance; one of them will be elected as "leader" and the other will remain in standby mode. In case that the "leader" dies, another master will be choosen, recovering the old master's state, and the resume scheduling. This entire recovering process, since the first moment that the first leader goes down, should take beween one or two minutes. Note that the delay only affects to the programation of new applications, the applications that were already running during the failover remain unaffected.

Single-Node Recovery with Local File System The best way to go for the high availability of the production level is ZooKeeper. However. when the master crushes, there is enough registered information in the filesystem to be able to recovr the status of the master. There is enough state written in the directory to recover the master process when the applications and workers are regustered.

Implementation

In this chapter, I provide details and explanations about the implementation of my project. The codes are available at https://github.com/marccode/tfg.

3.1 Project Structure

It was decided that the scope of the project wouldn't include developing a connector to put real data from Cisco routers into Spark, so an *instance generator* was created, in order to simulate input data. It was programmed with Bash, and can be adjusted to send data at different rates of flows/second.

To ingest data directly into Spark, Apache Kafka has been used. It provides a distributed platform to stream data in real time, from any number of sources to any number of listeners, through any number of topics.

THe *instage generator* outputs the simulated network traffic into a Kafka producer.

Our Apache Spark cluster uses a Kafka consumer to receive data from the producer. Once the network flows arrive at the Spark receiver running in a cluster node, they are divided into RDDs, each RDD containing data from a specific time window. These series of RDDs are feed into the Spark Mllib Pipeline containing the required preprocessing steps and the actual classifier model.

After being classified by the machine learning model, the data instances are saved into a MariaDB SQL Server. The database contains information about all the features of each flow, the result of its classification, and the date and time it was received by Spark.

This database can be queried by a live dashboard, which displays in real time the results of the classification of the incoming data instances in dynamic charts.

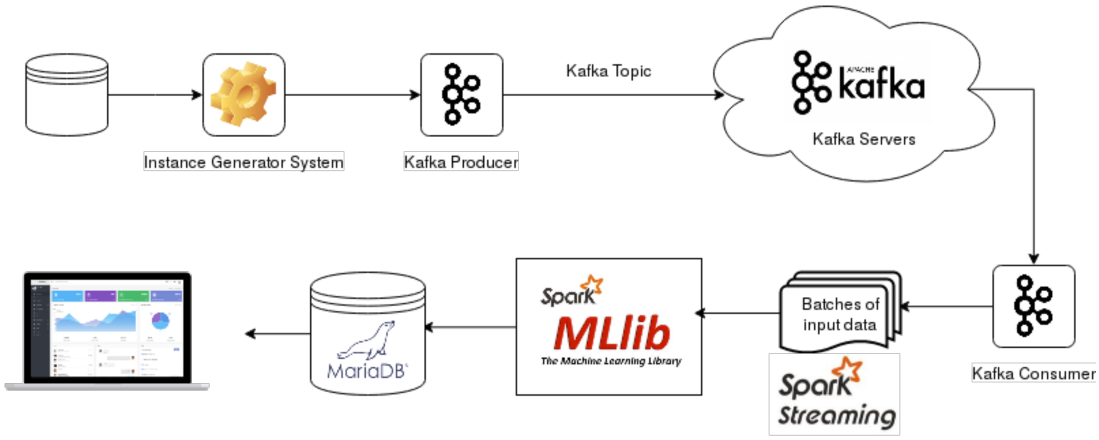


Figure 12: Architecture of project.

3.2 Dataset

The dataset used to train and evaluate teh developed system was provided by the director of the thesis[1]. It contains a vector of features of each traffic flow, along with the application that generated it. The vector consists of features obtained from the NetFlow feature in Cisco Routers. Netflow is a network protocol designed by Cisco Systems to collect network traffic going through an interface.

The datasets consisted originally of 7 different archives, collected at the UPC Gigabit acess link.

Each traffic set was registered at different hours, with the objective of collecting flows as much different as possible. For example, we can expect the networks at night to be full of backup applications traffic, or to collect more skype calls during the day than at night. Following the same logic, the traffic on the weekend won't be the same as the traffic during a week day.

The days and hours were the datasets were collected can be seen on the table below.

Once the traffic was captured, the flows had to be classified in order to obtain a trainning dataset and an evaluation dataset. This process was done with an automatic tool based on the L7-filter[5], as explained on [X: article del Pere]. As it is explained in the referred article, the accuracy of the tool was probably not as agood as a manual inspection. However, millions of flows had to be classified, thus it was impossible to do the classification manually.

This stablished the "base truth" upon which the classification of flows would be based.

Name	Date	Day	Start Time	Duration	Packets	Bytes
UPC-I	11-12-08	Thursday	10:00	15 minutes	95 M	53 G
UPC-II	11-12-08	Thursday	12:00	15 minutes	114 M	63 G
UPC-III	12-12-08	Friday	16:00	15 minutes	102 M	55 G
UPC-IV	12-12-08	Friday	18:30	15 minutes	90 M	48 G
UPC-V	21-12-08	Sunday	16:00	1 hour	167 M	123 G
UPC-VI	22-12-08	Monday	12:30	1 hour	345 M	256 G
UPC-VII	10-03-09	Tuesday	03:00	1 hour	114 M	78 G

Table 13: Information of the datasets

The dataset had 57 different classes and 32071325 instances. However, not all the flows were classified and some of them had an unknown origin/application. The 21057548 unkown instances were removed from dataset, leaving us with 11013777 instances.

The distribution of instances among each class can be seen in the figure 12.

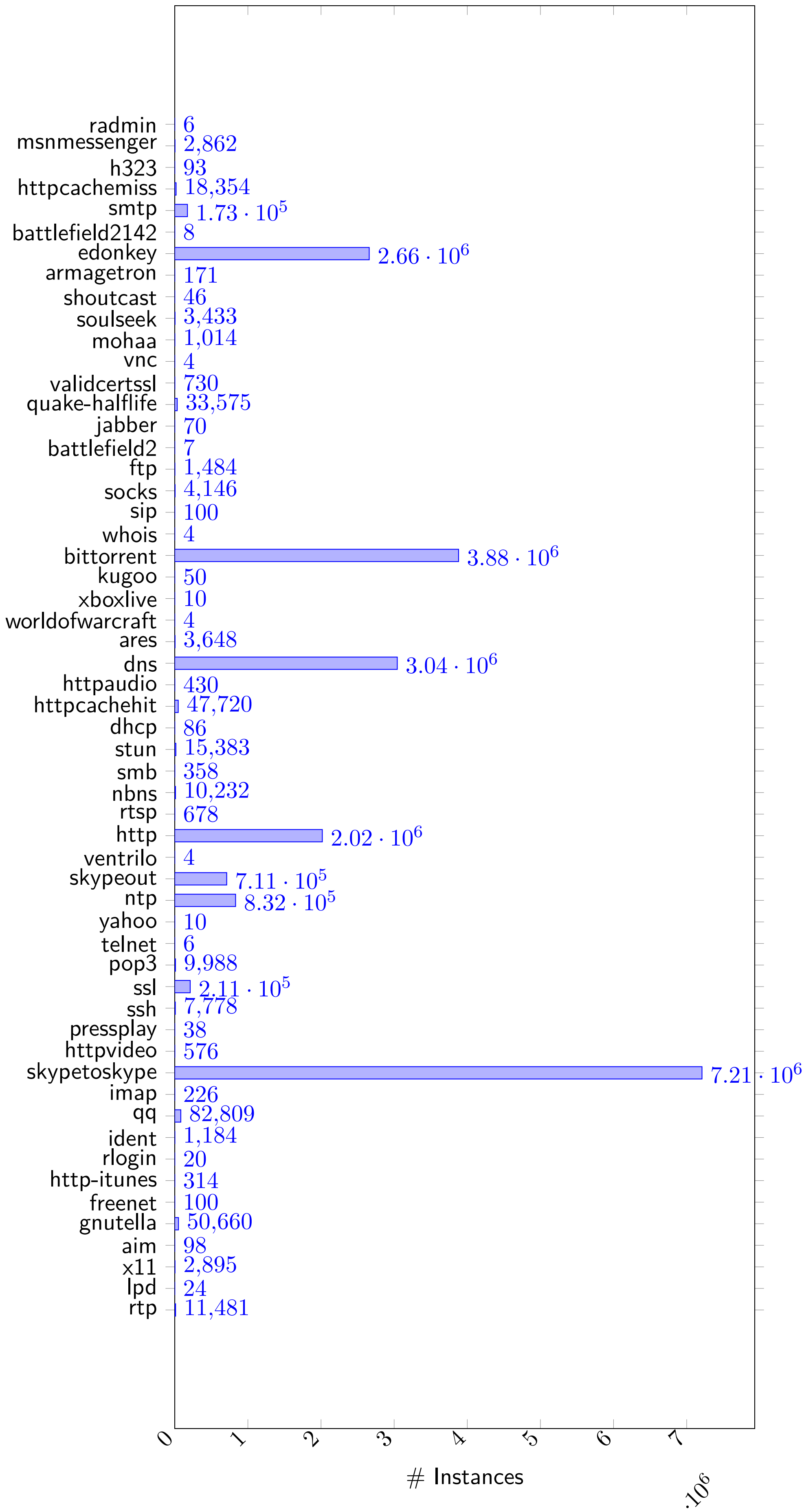


Figure 13: Distribution of the instances over different classes

Next, each class of the dataset is briefly explained[5]:

- **radmin:** Remote control software.
- **msnmessenger:** Instant messaging client.
- **h323:** Standard from the ITU Telecommunication Standardization Sector that defines the protocols to provide audio-visual communication sessions on any packet network.
- **httpcachemiss:** Proxy Cache miss for HTTP.
- **Smtp:** Simple Mail Transfer Protocol.
- **battlefield2142:** Traffic generated by Battlefield 2142 online video game.
- **edonkey:** Decentralized, server-based, peer-topeer file sharing network.
- **armagetron:** Multiplayer game.
- **shoutcast:** Software for streaming media over the Internet.
- **soulseek:** Peer-to-peer file sharing network and application.
- **mohaa:** Traffic generated by Medal of Honor: Allied Assault videogame.
- **vnc:** Virtual Network Computing traffic.
- **validcertssl:** Valid certificate SSL.
- **quake-halflife:** Half Life 1 engine games.
- **jabber:** Open instant messenger protocol.
- **battlefield2:** EA videogame Battelfield 2.
- **ftp:** File Transfer Protocol.
- **socks:** Firewall traversal protocol.
- **sip:** Session Initiaion Protocol.
- **whois:** Query/response protocol used for domain name info.
- **bittorrent:** Peer-to-peer file sharing tool.
- **kugoo:** Chinese peer-to-peer program.
- **xboxlive:** Console.

- **worldofwarcraft:** World of Warcraft online game.
- **ares:** Peer-to-peer file sharing program.
- **dns:** Domain Name System.
- **httpaudio:** Audio over HTTP.
- **httpcachehit:** Proxy Cache hit for HTTP.
- **dhcp:** Dynamic Host Configuration Protocol.
- **stun:** Simple Traversal of UDP through Nat.
- **smb:** Samba. Server Message Block. Microsoft Windows file sharing.
- **nbns:** NetBIOS name service.
- **rtsp:** Real Time Streaming Protocol.
- **http:** HyperText Transfer Protocol.
- **ventrilo:** VoIP.
- **skypeout:** Skype to phone.
- **ntp:** Network Time Protocol.
- **yahoo:** Yahoo messenger. Instant messenger protocol.
- **telnet:** Insecure remote login.
- **pop3:** Post Office Protocol version 3. Application-layer Internet standard protocol used by local e-mail clients to retrieve e-mails form a remote server.
- **ssl:** Secure Socket Layer.
- **ssh:** Secure Shell.
- **pressplay:** Legal music distribution site.
- **httpvideo:** Video over HTTP.
- **skypetoskype:** Skype to Skype voice call.
- **imap:** Internet Message Access Protocol (E-mail).
- **qq:** Chinese instant messenger protocol.

- **ident:** Identification Protocol.
- **rlogin:** Remote login.
- **http-itunes:** iTunes traffic.
- **freenet:** Peer-to-peer platform for censorship-resistan communication.
- **gnutella:** Peer-to-peer file sharing.
- **aim:** AOL instant messenger.
- **x11:** X Windows Version 11. Networked GUI system used in Unix.
- **lpd:** Line Printer Daemon Protocol
- **rtp:** Real-time Transport Protocol.

With the dataset cleaned, some operations to enrich it have been carried out. For example, the duration of the flow has been obtained from the initial and final time and the average packet size of the flow has been computed.

All the fields of the feature vector can be seen at table 14 on page 43.

In order to have single dataset from which to obtain the training dataset and evaluation dataset all the datasets were merged in a single one. Next, to avoid problems with the date and time of creation of each flow when training the model, all the flows have been shuffled and randomly selected to constitute the two datasets.

No information about IP adresses is included nor used in this dataset. This can affect the overhall system classification performance negatively, however what could be seen at first as a limitation comes with two positives aspects: it makes the trained model less dependent on the network it has been trained on, and it doesn't violate the privacy of the users of the networks were it is used, as it is not known which computers have created the flows.

Feature	Description
protocol	IP protocol value
src_port	Source port of the flow
dest_port	Destination port of the flow
packets	Total number of packets in the flow
bytes	Flow length in bytes
start_time	Time stamp of the first packet of the flow
end_time	Time stamp of the last packet of the flow.
duration	Duration of the flow in nanoseconds precision
bytes_per_packet	Average packet size of the flow
ToS	Type of Service from the first packet
urg	TCP flag
ack	TCP flag
psh	TCP flag
rst	TCP flag
syn	TCP flag
fin	TCP flag

Table 14: Description of the features of the dataset

3.3 Classification Model

For this work, three classifiers have been selected for its evaluation. Next, a brief description of each one is presented.

3.3.1 Studied Classifiers

Naive Bayes

The Naive Bayes classifier is based on the Bayes Theorem and predits the outcome of a classification using the conditional a posteriori probability of a categorical class variable given independent predictor variables probabilities.

It assumes that all the features are independent and equally important. This is not always true in real-world escenarios.

Decision Tree

Decision trees are supervised learning models used for classifcation and regression. They have a flowchart structure where each internal node represents an evaluation or test on an attribute and each branch represents the outcome of the evaluation. Finally, each leaf (final node) represents a class label.

To construct a decision tree all the features are considered and different split points are tested using a cost function. The split with the best cost is selected. Different algorithms use different metrics for evaluating the splits. This method is recursive, as the formed subtrees can be subdivided using the same technique.

In this work the decision tree that has been used is the famous C4.5, specifically its weka implementation J48.

K-nearest Neighbours

K-nearest neighbours is a classification algorithm that uses the class of the nearest neighbours of an instance to determine its class. In order to calculate which are the nearest neighbours, a distance concept has to be defined. This classifier has only one parameter, K, that specifies the number of neighbouring instances to be taken into consideration.

The main disavadvantage of this model is that it won't perform well if the distance function is not correctly selected.

The implementation used is the one provided with the Weka software.

3.3.2 Classifier training and evaluation

Usually, 70% of the classified instances were used to train the model, leaving the remaining 30% for evaluation and testing. This was the traditional split of the dataset done in the majority of the machine learning projects, however there is no formal justification for it.

In the particular case of this project, as millions of classified instances were available, there was no need to use a high percentage of the dataset to train the model. To decide how many instances were to be used for training purposes, a model was trained initially with 30% of the data (1717440 instances). Then, another model was trained with 10% less of instances. The performance metrics of the second model were the same as the first one, so another model was trained with 10% less instances than the second model. This process was followed until the performance metrics of the model decreased.

This method helped to reduce overfitting, a phenomenon produced by the over specialisation of the model in a specific dataset.

Validation

In order to compare classifiers and decide which one is better we need stablish how we are going to evaluate them. After processing the testing dataset with a classifier we obtain a *confusion matrix*.

		True Class	
	Total population	valid	not valid
Predicted class	valid	True positive (Tp)	False Positive (Fp)
	not valid	False negative (Fn)	True negative (Tn)

Table 15: Confusion matrix

The *confusion matrix* represents the intersection between the classifier results and the actual classes of the dataset. A classified data instance can be one of four types:

- *True Positive (Tp):* A positive element classified as positive.
- *True Negative (Tn):* A negative element classified as negative.
- *False Positive (Fp):* A negative element classified as positive.
- *False Negative (Fn):* A positive element classified as negative.

From the confusion matrix we can obtain the metrics we will be using to evaluate the models.

- *Accuracy:* Represents the proportion of correctly classified elements.

$$Accuracy = \frac{Tp + Tn}{Tp + Fp + Tn + Fn}$$

- *Precision:* Considering the elements classified as a certain class, the precision represents the proportion of elements that are in fact from that class.

$$Precision = \frac{Tp}{Tp + Fp}$$

- *Recall:* ARepresents the proportion of valid elements selected.

$$Recall = \frac{Tp}{Tp + Fn}$$

- *F-measure (F1):* F-measure considers both the precision and the recall in a proportion that can be adjusted. In this project the same proportion has been used. This is called harmonic mean.

$$F - measure(F1) = \frac{2 * Precision * Recall}{Precison + Recall}$$

Evaluation

The full confusion matrices are available at the appendix A.

Naive Bayes
The software Weka has been used to evaluate this algorithm. As the results below show, it doesn't perform well in this case.

Correctly Classified Instances **15.7776%**
Incorrectly Classified Instances **84.2224%**

Weighted Avg.
TP Rate: **0.158**
FP Rate: **0.039**
Precision: **0.441**
Recall: **0.158**
F-Measure: **0.174**

K-nearest Neighbours
The implementation of K-Nearest Neighbours of Weka Ibk has been used with a parameter k, neighbours to use, of 1. The results are shown below.

Correctly Classified Instances **86.6485%**
Incorrectly Classified Instances **13.3515%**

Weighted Avg.
TP Rate: **0.866**
FP Rate: **0.033**
Precision: **0.859**
Recall: **0.866**
F-Measure: **0.861**

Decision Tree
Decision Trees can create biased trees if some classes dominate, and therefore it is recommended to balance the dataset before training the decision tree.

In our case, eventhough the dataset has some imbalances, the classes with less weight have nearly no appearances at all compared to the other classes. Consequently, balancing the dataset will increase the accuracy and precision of the classifier on these classes, but this will have little effect on the total accuracy and precision, as instances of these classes won't appear very often. This, however, will cause the global False Positive rate to increase, as more instance will be classified as if they were of these minoritary classes.

Correctly Classified Instances **93.1931%**
Incorrectly Classified Instances **6.8069%**

Weighted Avg.
TP Rate: **0.932**
FP Rate: **0.018**
Precision: **0.929**
Recall: **0.932**
F-Measure: **0.930**

After getting the results of the previous tests it was decided to use the Decision Tree classifier, as it provided the best performance metris and it was known that it had the best computational cost.

3.3.3 Optimizations

After deciding which classifier to use a few changes were made to improve the system performance.

Optimization 1: PCA

The Principal Component Analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated [1].

Doing a Principal Compenent Analysis on the dataset we get the following results:

[1] https://en.wikipedia.org/wiki/Principal_component_analysis

Ranked attributes:

0.6186 1 0.429protocol-0.429ack-0.429fin-0.429syn-0.426psh
0.4736 2 -0.654start_time-0.653end_time+0.281packets+0.243bytes+0.062bytes_pkts
0.3417 3 -0.655bytes-0.63packets-0.268end_time-0.268start_time-0.153bytes_pkts
0.2696 4 -0.71bytes_pkts-0.589dest_port+0.275tos+0.215src_port+0.114packets
0.1982 5 -0.958tos-0.209dest_port-0.192bytes_pkts+0.031packets+0.024bytes
0.1304 6 -0.823src_port-0.43dest_port-0.329duration+0.102bytes_pkts+0.081tos
0.0682 7 0.553bytes_pkts-0.548dest_port+0.501src_port-0.373duration-0.052packets
0.0113 8 0.839duration+0.328bytes_pkts-0.328dest_port-0.114syn-0.114ack

If we now use the dataset obtained from the PCA to evaluate the classifier model we get the results shown below:

Correctly Classified Instances **84.507%**
Incorrectly Classified Instances **15.493%**

Weighted Avg.
TP Rate: **0.845**
FP Rate: **0.042**
Precision: **0.837**
Recall: **0.845**
F-Measure: **0.840**

As we can see, after applying the results of the Principal Component Analysis and reducing to eight the features used by the Decision Tree the results are slighty worse. Nonetheless, the results are still good, and if the performance of the system is low, PCA could be an interesting option, as it could help to process huge volums of data in real time by reducing the number of features, making the classifier simple, and thus reducing the computational cost.

Optimization 2: Dataset modifications

After observing the resuls of the classification model, some changes on the dataset classes can be purposed.

First of all, it has to be noted that this system's goal would be to be a tool for network and system administrators to help classify the traffic on their networks. This can lead to diverse interpretations of what classes of traffic the system has to differentiate. The modifications shown below don't diminish the information provided by this system to its users, but improves its performance.

In all the following tables the white rows are the results before the modification, and the grey rows the results after the modification.

Skype
The TP rate of skypeout is not very high because its instances usually are classified as bittorrent and edonkey. A possible reason for this is that skype uses a peer-to-peer protocol, as well as bittorrent and edonkey.

	TP Rate	FP Rate	Precision	Recall	F-Measure
Weighted Avg.	0.932	0.018	0.929	0.932	0.930
Skypeout	0.499	0.011	0.622	0.499	0.554
Skypetoskype	0.962	0.037	0.931	0.962	0.946
Skype	0.930	0.051	0.916	0.930	0.923
Weighted Avg.	0.935	0.024	0.934	0.935	0.934

Table 16: Skype Metrics

After the modification, the metrics of the new category skype are a bit lower than the ones that skypetoskype used to have, however they are still good results, and the new weighted average is higher than before. Moreover, there are more true positive instances of the new class skype than the sum of the true positive instances of the old skypeout and skypetoskype classes.

HTTP
All the metrics of the http-itunes and httpaudio classes were 0 because non of the instances were classified correctly. There were 3 instances of both http-itunes and httpaudio classes, and in both cases 2 of them were classified as http. The classifier also had problems separating httpcachemiss from httpcachehit, and both were also usually classified as http.

After the modification on the dataset all the metrics of the class http improve, and so does the weighted average.

Torrents
The biggest problem the classifier had with traffic generated by torrents applications was to differentiate it from skype traffic. This could be due to the fact that skype uses p2p to communicate, like torrents filesharing applications do.

In the confusion matrix we can see that the total instances of torrent applications' flows classified as skype class where a total of 4982, but after the modification the misclasification were reduced to 4791 instances.

Games
All the games unless quake-halflife and mohaa were classified very poorly, but this happened

	TP Rate	FP Rate	Precision	Recall	F-Measure
Weighted Avg.	0.932	0.018	0.929	0.932	0.930
http	0.954	0.010	0.913	0.954	0.933
httpcachemiss	0.455	0.000	0.568	0.455	0.505
httpcachehit	0.758	0.000	0.831	0.758	0.793
httpaudio	0.000	0.000	0.000	0.000	0.000
httpvideo	0.200	0.000	0.200	0.200	0.200
http-itunes	0.000	0.000	0.000	0.000	0.000
http	0.957	0.010	0.915	0.957	0.936
Weighted Avg.	0.935	0.024	0.935	0.935	0.935

Table 17: HTTP Metrics

because they nearly never appeared on the dataset. After the modification, the new category has lightly lower performance metrics than quake-halflife had. However we improve enormously the other game categories. In the confusion matrix can be seen how nearly all the instances of the games category are classified correctly.

	TP Rate	FP Rate	Precision	Recall	F-Measure
Weighted Avg.	0.932	0.018	0.929	0.932	0.930
edonkey	0.802	0.016	0.879	0.802	0.839
soulseek	0.742	0.000	0.767	0.742	0.754
bittorrent	0.974	0.008	0.966	0.974	0.970
kugoo	0.000	0.000	0.000	0.000	0.000
ares	0.813	0.000	0.867	0.813	0.839
gnutella	0.949	0.000	0.913	0.949	0.931
torrents	0.915	0.026	0.941	0.915	0.928
Weighted Avg.	0.939	0.028	0.940	0.939	0.939

Table 18: Torrents Metrics

3.4 Real-time Streaming

One of the initial requirements of the projecte was that it had to be able to process data in real time. To fulfill it, the module Spark Streaming has been used.

As it has been explained, Spark can take data into the system from a diverse range of systems. In this project two of the available options have been used. First, during the development phase, tcp sockets were used to ingest the data. A custom script was created in order to control the ammount of data sent to the Spark Streaming receiver.

Later in the implementation phase, it was decided to change the data ingestion mechanism in order to provide more reliability to the system. Apache Kafka was choosen.

3.4.1 Apache Kafka

Kafka[4] is a distributed streaming platform for moving data in real time. It works like a publish-subscribe system, and its architecture makes it fault tolerant and scalable.

Kafka stores messages that come from many processes called *producers*. *Producers* push the data into *topics*, which are simply a stream of messages. Another type of processes called *consumers* query Kafka and get the messages published to the *topics* they are subscribed to.

	TP Rate	FP Rate	Precision	Recall	F-Measure
Weighted Avg.	0.932	0.018	0.929	0.929	0.930
battlefield2142	0.000	0.000	0.000	0.000	0.000
battlefield2	0.000	0.000	0.000	0.000	0.000
armagetron	0.000	0.000	0.000	0.000	0.000
mohaa	0.556	0.000	0.714	0.556	0.625
quake-halflife	0.957	0.000	0.993	0.957	0.975
worldofwarcraft	0.000	0.000	0.000	0.000	0.000
games	0.952	0.000	0.980	0.952	0.966
Weighted Avg.	0.940	0.028	0.940	0.940	0.939

Table 19: Games Metrics

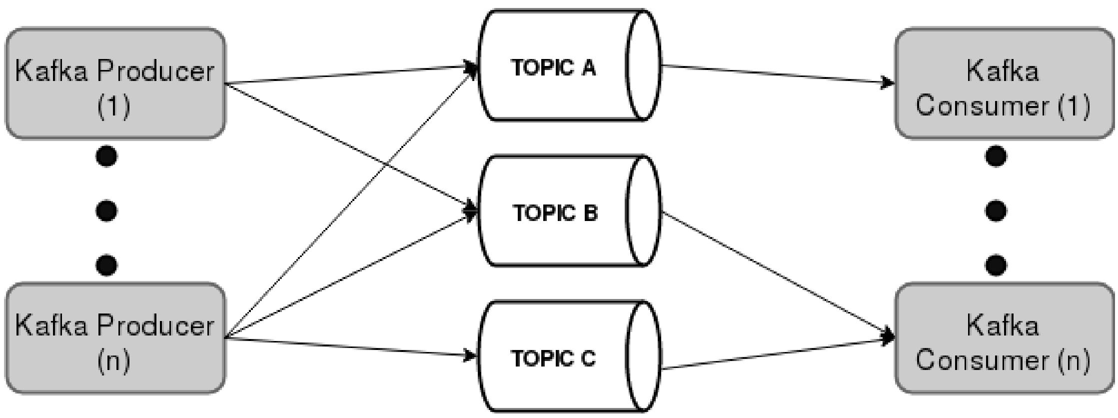


Figure 14: Architecture of Apache Kafka

Kafka lets us to receive data from different sources simultaniously and to have more than one consumer at the same time. This allows spark to have multiple receivers and ingest quicker so the ingest system doesn't become the bottleneck.

Spark has a package to help integrate Kafka with Spark Streaming. For this project Kafka 0.10 has been used.

As it has been explained, Spark Streaming works with time windows. The size of the windows can be chosen by the developer. Every time the batches of a time window are processed by the Spark engine entails a fixed overhead, independent of the number of flows that have to be classified. For this reason, after trying different values for the size of the window, it has been choosen the value of 5 seconds, that allows analysis of the network in real time with an acceptable delay, and doesn't overload the system.

3.5 Persistence

MariaDB is an open source relational database management system. Its developement is led by a team of original developers of MySQL, who forked it after the acquisiton by Oracle. MariaDB has been choosen to store the received data instances in realtim and the result of its classification thanks to its high availability, scalability and performance beyond MySQL and other databases[2]. The structure of the database table where the received data is stored is similar to the structure of the feature vector of the dataset itself, and can be seen in table 20.

Field name	Variable type
id	Int
protocol	Int
src_port	Int
dest_port	Int
packets	Int
bytes	Int
start_time	Double
end_time	Double
duration	Double
bytes_pkts	Int
tos	Int
urg	Int
ack	Int
psh	Int
rst	Int
syn	Int
fin	Int
application	Varchar
received_time	Datetime
prediction	Varchar

Table 20: Structure of the database table

[2] https://mariadb.com/kb/en/library/mariadb-vs-mysql-features/

3.6 Life dashboard

In order to make the system usable and make a useful tool out of it, there was the need to visualize the results of the classification of flows. To make the system more versatile it was decided to make the dashboard as a webpage. This way it could be possible to monitor the state of a network from a range of different devices, like smartphones, computers, smart TVs...

The dashboard had to provide information about the state of the network in real time. However, it was thought to be a useful feature to also show information about the historical use of the network since the beginning of the classification in the network.

Even if the system developed in this project classifies network flows, from the point of view of a system or network administrator is equally useful or even better to monitor the use of the bandwidth by bytes rather than flows, as they are the ones that reflect the real effect of a certain application on a network. To solve this potential issue, the dashboard also shows the information in bytes. This is possible because each flow received has information about its size in bytes.

The charts are created using the library ECharts 3[3], and the ones that show real time data are automatically updated without the need to refresh the browser using AJAX and a custom API.

Echarts 3 provides a set of functionalities that enriches the UI of the dashboard. For example, when hovering the mouse over a slice of a pie chart, or a line of a line chart it shows a summary of the data in this section. It also allows the user the choose what data to show on the chart by clicking on the items of the legend and enabling or disabling classes of traffic.

The backend has been coded using Flask[6]. Flask is a microframework for Python based web applications. Microframework doesn't mean it laks any functionality, it means that Flask aims to keep the core simple and add features using extensions. There are two main sections on the dashboard: live data and historical data.

3.6.1 Live data section

In this section of the dashboard we can see a dynamic line chart where each line represents the traffic generated by a specific application. This type of chart was selected because it helps visualize the pass of time and compare all the different classes of traffic simultaneously and its evolution. Every five seconds new data is appended to the chart and the oldest data is removed, leaving a one minute sliding window.

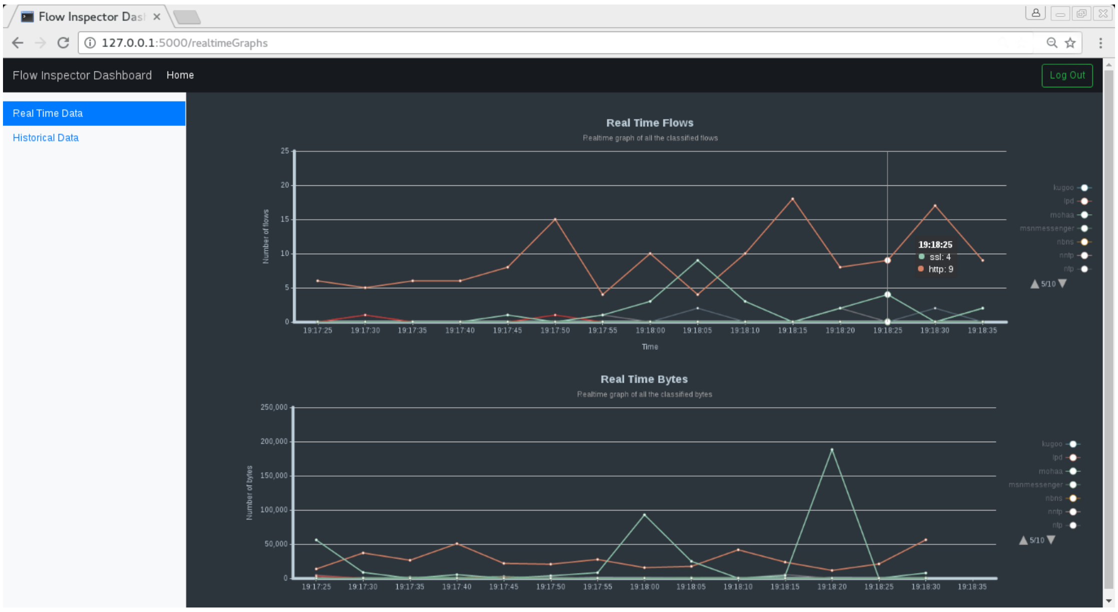


Figure 15: Screenshot of the realtime section of the dashboard

The first chart shows the data based on the flows each application generates. The second chart uses the number of bytes instead.

3.6.2 Historical data section

In this section of the dashboard we can see a two pie charts where each slice represents the traffic generated by a specific application. This type of chart was selected because it helps visualize the proportions and the percentage each class represents.

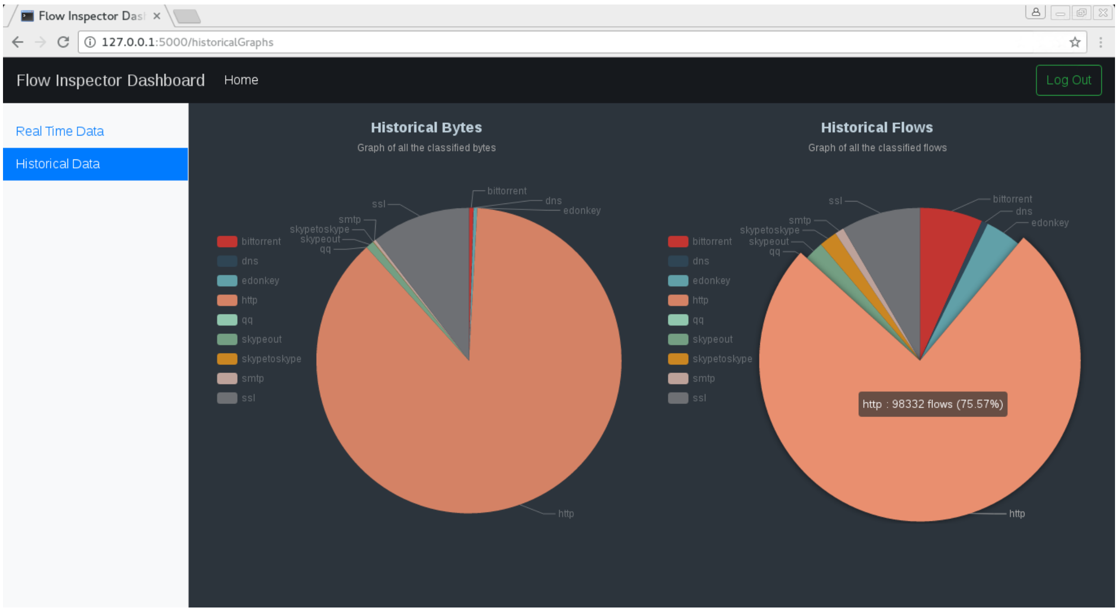


Figure 16: Screenshot of the historical data section of the dashboard

The chart on the right shows the proportions based on the bytes each application generates. The chart on the left uses the number of flows instead.

Validation and evaluation

To test the performance of the system and validate it, it has been deployed in a real-world scenario where tests have been run.

4.1 Environment

The enviromnet choosen to perform the tests is Amazon Web Services (AWS).

Amazone Web Services is a subsidiary of Amazon that provides cloud computing platforms.

Using AWS we can test the system in a realistic environment and using as many nodes for the Spark Cluster as desired.

A series of AWS EC2 instances have been launched in order to create a structure like the one shown in the *Implementation* chapter.

Two more services of AWS have also been used:

- *AWS S3* for the online storage, to upload .jar files and other archives required to run the tests.
- *AWS RDS* to create a MariaSQL server, in order to have all the system integrated in the cloud.

Three different types of EC2 instances have been used:

- t2.micro
  - vCPU: 1
  - Mem (GiB): 1
  - Storage: GP2 SSD 8GB 3000 IOPS.
  - Operative System: Ubuntu Server 16.04 LTS

- t2.small
  - vCPU: 1
  - Mem (GiB): 2
  - Storage: GP2 SSD 8GB 3000 IOPS.
  - Operative System: Ubuntu Server 16.04 LTS
- t2.medium
  - vCPU: 2
  - Mem (GiB): 4
  - Storage: GP2 SSD 8GB 3000 IOPS.
  - Operative System: Ubuntu Server 16.04 LTS

A t2.micro instance has been used to execute a Kafka Producer and feed data into Spark.

The Kafka cluster is composed for only a t2.medium instance running Zookeeper and the kafka server.

For the nodes of the Spark cluster t2.medium instances have been used, as two CPUs per node were required by Spark Streaming in order to be able to process the data received.

Name	Instance ID	Instance Type	Availability Zone	Instance State
Kafka_Producer	i-01576ffe1a73bc62c	t2.micro	eu-west-2a	running
Spark_Master	i-0142b43248a4a470c	t2.medium	eu-west-2a	running
Spark_Slave_1	i-0a2ed0d1a46bf0430	t2.medium	eu-west-2a	running
Spark_Slave_2	i-06ed4236e2904124a	t2.medium	eu-west-2a	running
Spark_Slave_3	i-048b35b4d3cb02f1b	t2.medium	eu-west-2a	running
Zookeper_Kafka_Server	i-0c47db9f237a22395	t2.small	eu-west-2a	running

Figure 17: AWS Console showing the running instances

4.2 Test

The goal of the validation and evaluation phase is to perform a test or tests to find out the performance of the developed system in a real world scenario.

I want to check if the performance of Spark running an application more complex than a simple benchmark is as good as it is advertised by its developers.

I also want to learn its real capability to scale up. According to theory it should scale linearly, we will see if this holds up in practise.

To ask all these questions, Spark will be deployed in the environment described before and will execute the developed application against a stream of data constantly getting bigger. The goal is to try to find the maximum number of data instances that Spark is able to process per second, running in a certain number of nodes. In other words, we want to find out the maximum throughput for a given cluster.

To monitor the state of the cluster nodes and the application, as well as the executors and the driver, the web UI integrated with Spark will be used[2].

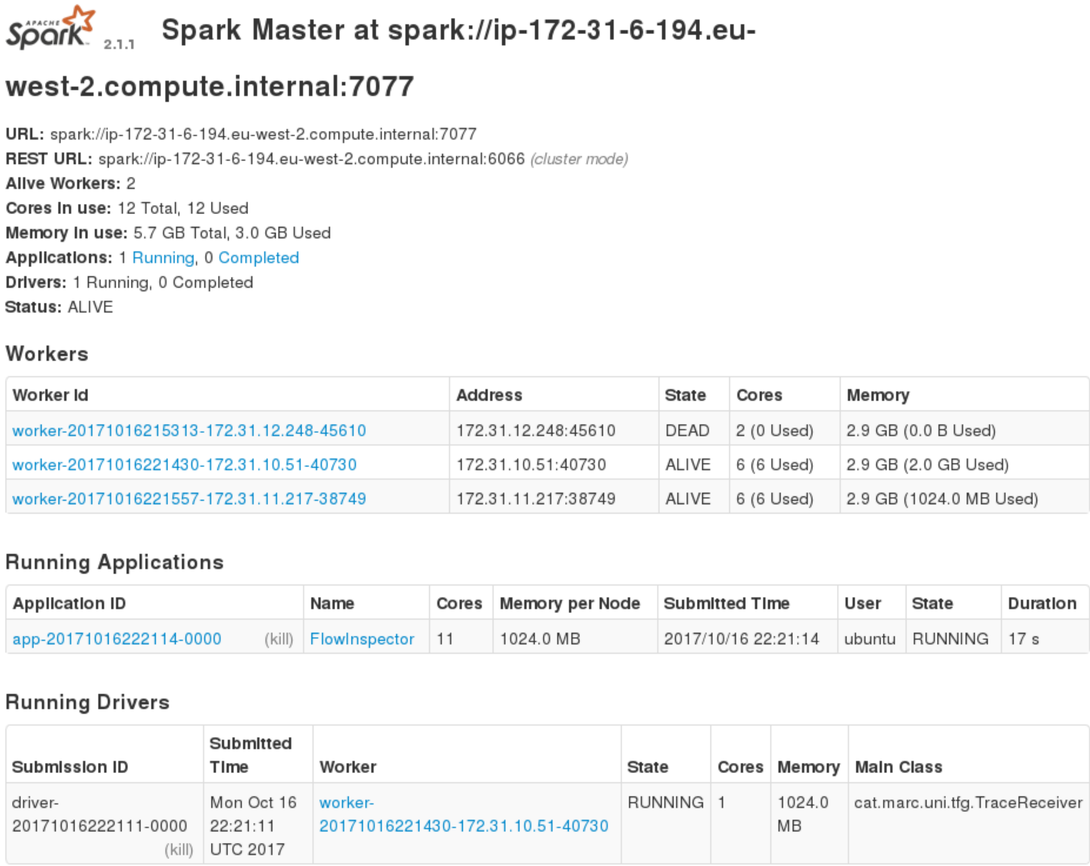


Figure 18: Spark Web UI.

4.3 Results

- **Maximum Throughput with one node**: 200000 flows/second
- **Maximum Throughput with two nodes**: 280000 flows/second
- **Maximum Throughput with three nodes**: 350000 flows/second

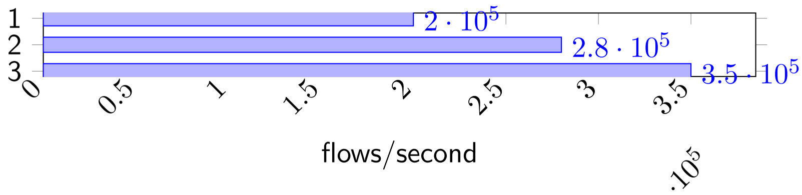


Figure 19: Maximum Throughput on different number of nodes

Eventhough we don't have any other performance data to compare from other frameworks, we have seen that Spark is in fact very fast processing data in memory. This makes it even when running in a single node.

This have caused problems when trying to find the maxium throughput, because so many flows had to be sent per second that the Kafka Producer reached its maximum, or the Spark node crashed because the Garbage Collector of Java wasn't was enough.

Another problem encountered during the test was the difficulty to generate data instances at a faster pace than they were consumed, and to known precisely the rate at which they were created.

Increasing parallellism in a micro batch system like Spark is simpler said than done. Spark performs a reshuffle operation that introduces a considerable overhead itself. Moreover, Sparks not always uses parallelism. As it receives the data on a single node, the one running the Kafka receiver, it has to send to data to the other nodes on the cluster before they can actually process it. This makes parallelism even harder to exploit. As we have seen Spark is so fast even in a single node that it considers that is faster to process the data on the same node where it is received.

In order to force Spark to use parallelism we can set the option *spark.locality.wait* to 0. This parameter is the seconds that Spark waits to launch a data-local task before giving up and launching it on another node of the cluster. We have used this option on the tests in order to observe the effects of parallelism and this might be one of the reasons why the system didn't scale up linearly, because we introduced some unnecessary overhead.

All these factors have increased considerably the difficulty to find the maximum throughput with precision, so the results presented have to be seen as aproximations.

Future Work

This project, having accomplished all of its purposed goals, has stablished a solid base from where to develop a more complet project with more functionalities and overall improved performance. Eventhough all the used frameworks and technologies have proved to be perfectly capable of accomplishing the needs of this project, right now it is still closer to a proof of concept than a fully working system ready to be deployed on production. As such, it has a great potential and there are many ares for improvemnt. Some of the possible ways to continue its developement are :

- **Anomaly detection**
  Right now, the developed platform just classfies the incoming traces and displays the results of the classifications on the live dashboard. Future work could modify the existent classifier or create new ones to try to detect anomaliels on the network, like wrong use by a user, or a cyber attack.

- **New versions of Apache Spark**
  Apache Spark is in constant developement and currently is one of the Apache projects with more collaborators. Since the begining of this project, new versions with updates and new features have been released. It could be interesting to adapt the current project to the new versions and take advantage of the latests incorporations, like Structured Streaming.

- **Connector for Cisco routers**
  As of now, the developed system ingests data with Apache Kafka, data feeded through a Kafak Producer. However, the data that's put into the Kafka Producer is create "artificially" with an instance generator from the available dataset. Another way to improve the project would be to develop a connector to be able to send real Netflow data from a Cisco router to Spark Streaming.

- **Improve storage**
  The storage part of the project hasn't received special attention to improve its performance. Currently it performs well, but if the overall performance of the system increases it could become a bottleneck. Future work could improve MariaDB performances

- **DashBoard**
  More features could be added to the dashboard. For example, it could show more information about the probability of a dataset instance being from one class or another, not just the decision of the classifier. It could also provide information about the performance of the servers were the system is running.

- **Security**
  Currently, all the communications between the different machines are in plain text. For security reasons, if the project is intended to be deployed to a production environment, SSL shoud be used.

As one can see, there are many possibilities for improvement, and due to the modular nature of Apache Spark and consequently of this project, many of these improvements can be done gradually and independently.

Conclusions

The objectives of this projecte were the development of a network traffic classification platform that acould work in realtime, that integrated machine learning and that could run over a distributed cluster in order to be highly available and fault tolerant. To achieve these goals the decision to use the Apache Spark framework was made, and it has been demostrated that Spark is in fact capable of running a high demmanding application.

However, in my personal experience, the learning curve of Apache Spark is very step and it often forces you to learn other, at first simingly unrelated tools, in order to be able to fully profit from its capabilities.

The efficency of Spark and its ease to adapt an application to run it in clusters with different structures has been confirmed. Moreover, this process of adaptation is very transparent and goes nearly unnoticed by the user. However, the integration between different nodes and libraries of Spark hasn't been as seaslessly as it was suposed to be according to Spark's developers.

During the project, the waterfall methodology has been used as it was previously decided. Also, the stages of the project have been followed as planned. Thanks to this plannification, all the obstacles found and the unforeseen events have been sorted out. This has reaffirmed the good management of the project.

As explained in chapter 5 (Future work), there is still a lot of room for improvements in the project. Serà interessant veure com evoluciona el framework Spark i com aplicar les novetats que presenta per millor el rendiment del sistema desenvolupat.

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Appendices

Results of the evaluated classifiers

A.1 Detailed Accuracy by class for the evaluated classifiers

A.1.1 Naive Bayes

A.1.2 K-Nearest Neighbours

A.1.3 Decision Tree

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
0.473	0.029	0.141	0.473	0.217	ssl
0.039	0.004	0.524	0.039	0.072	http
0.011	0.002	0.191	0.011	0.021	skypeout
0.800	0.003	0.012	0.800	0.024	ident
0.050	0.001	0.218	0.050	0.081	smtp
0.003	0.001	0.412	0.003	0.005	bittorrent
0.039	0.000	0.333	0.039	0.070	rtp
0.005	0.002	0.285	0.005	0.009	edonkey
0.022	0.005	0.002	0.022	0.004	pop3
0.000	0.003	0.000	0.000	0.000	stun
0.053	0.019	0.007	0.053	0.012	gnutella
0.184	0.019	0.022	0.184	0.039	httpcachehit
0.000	0.003	0.000	0.000	0.000	rtsp
0.000	0.000	0.000	0.000	0.000	imap
0.000	0.029	0.000	0.000	0.000	msnmessenger
0.938	0.014	0.011	0.938	0.023	ares
0.158	0.062	0.571	0.158	0.248	skypetoskype
0.797	0.021	0.014	0.797	0.027	ssh
0.385	0.002	0.011	0.385	0.022	ftp
0.800	0.000	0.061	0.800	0.113	httpvideo
0.018	0.001	0.013	0.018	0.015	httpcachemiss
0.677	0.030	0.004	0.677	0.007	soulseek
0.000	0.000	0.000	0.000	0.000	nbns
0.000	0.000	0.000	0.000	0.000	http-itunes
0.959	0.062	0.388	0.959	0.552	ntp
0.350	0.089	0.399	0.350	0.373	dns
0.774	0.296	0.010	0.774	0.020	qq
0.252	0.009	0.042	0.252	0.072	quake-halflife
0.081	0.000	0.188	0.081	0.113	socks
0.556	0.152	0.000	0.556	0.000	mohaa

Table 21: Naive Vayes - Detailed Accuracy By Class - Part One

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
0.200	0.016	0.002	0.200	0.003	x11
0.333	0.000	1.000	0.333	0.500	smb
0.000	0.000	0.000	0.000	0.000	armagetron
0.000	0.000	0.000	0.000	0.000	freenet
0.000	0.000	0.000	0.000	0.000	kugoo
1.000	0.000	0.176	1.000	0.300	validcertssl
0.000	0.000	0.000	0.000	0.000	ventrilo
0.000	0.000	0.000	0.000	0.000	sip
0.000	0.000	0.000	0.000	0.000	rlogin
0.000	0.000	0.000	0.000	0.000	jabber
0.000	0.000	0.000	0.000	0.000	h323
0.000	0.000	0.000	0.000	0.000	dhcp
0.000	0.000	0.000	0.000	0.000	httpaudio
0.000	0.000	0.000	0.000	0.000	pressplay
0.000	0.000	0.000	0.000	0.000	aim
0.000	0.000	0.000	0.000	0.000	vnc
0.000	0.000	0.000	0.000	0.000	whois
0.000	0.000	0.000	0.000	0.000	radmin
0.000	0.000	0.000	0.000	0.000	lpd
0.000	0.000	0.000	0.000	0.000	battlefield2142
0.000	0.000	0.000	0.000	0.000	yahoo
0.000	0.000	0.000	0.000	0.000	xboxlive
0.000	0.000	0.000	0.000	0.000	worldofcraft
0.000	0.000	0.000	0.000	0.000	telnet
0.000	0.000	0.000	0.000	0.000	shoutcats
0.000	0.000	0.000	0.000	0.000	battlefield2
0.158	0.039	0.441	0.158	0.174	Weighted Avg.

Table 22: Naive Vayes - Detailed Accuracy By Class - Part Two

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
0.765	0.002	0.808	0.765	0.786	ssl
0.890	0.013	0.881	0.890	0.886	http
0.394	0.019	0.415	0.394	0.404	skypeout
0.500	0.000	0.556	0.500	0.526	ident
0.792	0.002	0.790	0.792	0.791	smtp
0.913	0.024	0.895	0.913	0.904	bittorrent
0.126	0.000	0.146	0.126	0.135	rtp
0.675	0.042	0.698	0.675	0.686	edonkey
0.281	0.000	0.368	0.281	0.318	pop3
0.500	0.000	0.527	0.500	0.513	stun
0.897	0.000	0.821	0.897	0.857	gnutella
0.639	0.001	0.670	0.639	0.654	httpcachehit
0.800	0.000	0.800	0.800	0.800	rtsp
0.000	0.000	0.000	0.000	0.000	imap
0.520	0.000	0.722	0.520	0.605	msnmessenger
0.500	0.000	0.640	0.500	0.561	ares
0.891	0.058	0.889	0.891	0.890	skypetoskype
0.696	0.000	0.706	0.696	0.701	ssh
0.385	0.000	0.556	0.385	0.455	ftp
0.000	0.000	0.000	0.000	0.000	httpvideo
0.309	0.000	0.443	0.309	0.364	httpcachemiss
0.677	0.000	0.808	0.677	0.737	soulseek
0.239	0.000	0.293	0.239	0.263	nbns
0.333	0.000	0.167	0.333	0.222	http-itunes
0.967	0.001	0.970	0.967	0.969	ntp
0.986	0.004	0.977	0.986	0.982	dns
0.352	0.003	0.348	0.352	0.350	qq
0.967	0.000	0.954	0.967	0.961	quake-halflife
0.784	0.000	0.853	0.784	0.817	socks
0.556	0.000	0.714	0.556	0.625	mohaa

Table 23: K-nearest Neighbours - Detailed Accuracy By Class - Part One

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
0.160	0.000	0.167	0.160	0.163	x11
0.667	0.000	0.500	0.667	0.571	smb
0.000	0.000	0.000	0.000	0.000	armagetron
0.000	0.000	0.000	0.000	0.000	freenet
0.000	0.000	0.000	0.000	0.000	kugoo
1.000	0.000	0.667	1.000	0.800	validcertssl
0.000	0.000	0.000	0.000	0.000	ventrilo
0.000	0.000	0.000	0.000	0.000	sip
0.000	0.000	0.000	0.000	0.000	rlogin
0.000	0.000	0.000	0.000	0.000	jabber
0.000	0.000	0.000	0.000	0.000	h323
0.000	0.000	0.000	0.000	0.000	dhcp
0.000	0.000	0.000	0.000	0.000	httpaudio
0.000	0.000	0.000	0.000	0.000	pressplay
0.000	0.000	0.000	0.000	0.000	aim
0.000	0.000	0.000	0.000	0.000	vnc
0.000	0.000	0.000	0.000	0.000	whois
0.000	0.000	0.000	0.000	0.000	radmin
0.000	0.000	0.000	0.000	0.000	lpd
0.000	0.000	0.000	0.000	0.000	battlefield2142
0.000	0.000	0.000	0.000	0.000	yahoo
0.000	0.000	0.000	0.000	0.000	xboxlive
0.000	0.000	0.000	0.000	0.000	worldofcraft
0.000	0.000	0.000	0.000	0.000	telnet
0.000	0.000	0.000	0.000	0.000	shoutcats
0.000	0.000	0.000	0.000	0.000	battlefield2
0.861	0.032	0.859	0.861	0.860	Weighted Avg.

Table 24: K-nearest Neighbours - Detailed Accuracy By Class - Part Two

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
0.975	0.000	0.954	0.975	0.964	ssl
0.954	0.010	0.913	0.954	0.933	http
0.499	0.011	0.622	0.499	0.554	skypeout
0.900	0.000	0.900	0.900	0.900	ident
0.983	0.000	0.971	0.983	0.977	smtp
0.974	0.008	0.966	0.974	0.970	bittorrent
0.398	0.000	0.672	0.398	0.500	rtp
0.802	0.016	0.879	0.802	0.839	edonkey
0.888	0.000	1.000	0.888	0.940	pop3
0.565	0.000	.765	0.565	0.650	stun
0.758	0.000	0.831	0.758	0.793	httpcachehit
0.000	0.000	0.000	0.000	0.000	rtsp
0.000	0.000	0.000	0.000	0.000	imap
0.600	0.000	0.517	0.600	0.556	msnmessenger
0.813	0.000	0.867	0.813	0.839	ares
0.962	0.037	0.931	0.962	0.946	skypetoskype
1.000	0.000	1.000	1.000	1.000	ssh
0.692	0.000	1.000	0.692	0.818	ftp
0.200	0.000	0.200	0.200	0.200	httpvideo
0.455	0.000	0.568	0.455	0.505	httpcachemiss
0.742	0.000	0.767	0.742	0.754	soulseek
0.272	0.000	0.714	0.272	0.394	nbns
0.000	0.000	0.000	0.000	0.000	http-itunes
0.999	0.001	0.982	0.999	0.990	ntp
1.000	0.000	0.998	1.000	0.999	dns
0.811	0.001	0.731	0.811	0.769	qq
0.957	0.000	0.993	0.957	0.975	quake-halflife
0.838	0.000	0.861	0.838	0.849	socks
0.556	0.000	0.714	0.556	0.625	mohaa

Table 25: Decision Tree - Detailed Accuracy By Class - Part One

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
0.160	0.000	1.000	0.160	0.276	x11
0.000	0.000	0.000	0.000	0.000	smb
0.000	0.000	0.000	0.000	0.000	armagetron
0.000	0.000	0.000	0.000	0.000	freenet
0.000	0.000	0.000	0.000	0.000	kugoo
1.000	0.000	0.667	1.000	0.800	validcertssl
0.000	0.000	0.000	0.000	0.000	ventrilo
0.000	0.000	0.000	0.000	0.000	sip
0.000	0.000	0.000	0.000	0.000	rlogin
0.000	0.000	0.000	0.000	0.000	jabber
0.000	0.000	0.000	0.000	0.000	h323
0.000	0.000	0.000	0.000	0.000	dhcp
0.000	0.000	0.000	0.000	0.000	httpaudio
0.000	0.000	0.000	0.000	0.000	pressplay
0.000	0.000	0.000	0.000	0.000	aim
0.000	0.000	0.000	0.000	0.000	vnc
0.000	0.000	0.000	0.000	0.000	whois
0.000	0.000	0.000	0.000	0.000	radmin
0.000	0.000	0.000	0.000	0.000	lpd
0.000	0.000	0.000	0.000	0.000	battlefield2142
0.000	0.000	0.000	0.000	0.000	yahoo
0.000	0.000	0.000	0.000	0.000	xboxlive
0.000	0.000	0.000	0.000	0.000	worldofcraft
0.000	0.000	0.000	0.000	0.000	telnet
0.000	0.000	0.000	0.000	0.000	shoutcats
0.000	0.000	0.000	0.000	0.000	battlefield2
0.932	0.018	0.929	0.932	0.930	Weighted Avg.

Table 26: Decision Tree - Detailed Accuracy By Class - Part Two