

An Efficient Network Traffic Classification Based on Vital Random Forest for High Dimensional Dataset

by

ALHAMZA MUNTHER WARDI ALALOUSI

(1340211014)

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

School of Computer and Communication Engineering UNIVERSITI MALAYSIA PERLIS

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The favor, above all, before all, and after all, is entirely Allah's (SWT), to whom my neverending thanks and praise are humbly due.

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LIST OF ABBREVIATIONS

ABRF Active Build-model Random Forest

BFW Broadband Fixed Wireless

CBMG Customer Behavior Model Graph

Chi2 Chi-Squared

CPU Central Processing Unit

DCCP Datagram Congestion Control Protocol

DNS Domain Name System

DoS Denial of Service

DPI Deep-Packet Inspection

DR Data Reduction

DSL Digital Subscriber Line

EM Expectation Maximization

FCBF Fast Correlation-Based Filter

FSCGRV Fast correlation based filter, Significance feature

evaluator, Chi-squared and Gain ratio: and Ranking and

Borda Count Voting

FTP File Transfer Protocol

GR Gain Ratio

HMM Hidden Markov Model

HTTP Hypertext Transfer Protocol

IANA Internet Assigned Numbers Authority

IBL Instance-Based Learning

ID3 Iterative Dichotomiser 3

IDS Intrusion Detection System

IETF Internet Engineering Task Force

IG Information Gain

IP Internet Protocol

IPTs Inter-Arrival Time Packets

IRC Internet Relay Chat

ISP Internet service providers

KNN K-Nearest Neighbors

ML Machine Learning

MySQL My Structured Query Language

NAT Network Address Translation

NB Naïve Bayes

NBKE Naïve Bayes Kernel Estimation

OAA One-Against-All

OAO One-Against-One

P2P Peer-to-Peer

PDF Probability Density Function

PNN Probabilistic Neural Network

POP3 Post Office Protocol 3

PS Packet Size

QoS Quality of Service

RF Random Forest

SCTP Stream Control Transmission Protocol

SFE Significance Feature Evaluator

SMTP Simple Mail Transfer Protocol

SSH Secure Shell

Symmetrical Uncertainty SU

Support Vector Machine **SVM**

TCP Transmission Control Protocol

User Datagram Protocol UDP

VoIP Voice over Internet Protocol

This item is protected by original copyright VPN Virtual Private Network

Pengelasan Trafik Rangkaian Berkesan berdasarkan Vital Random Forest bagi Set Data Dimensi Tinggi

ABSTRAK

Tesis ini mencadangkan serta melaksanakan satu kaedah pengelasan trafik rangkaian yang berkesan berdasarkan vital random forest (VRF) baru bagi pemeriksaan data berdimensi tinggi. Kejuruteraan trafik rangkaian merupakan satu daripada teknologi penting yang memaparkan pertumbuhan yang pantas dalam revolusi teknologi seantero dunia. Pengelasan trafik rangkaian memberikan faedah yang boleh dipertimbangkan sebagai suatu wadah kejuruteraan rangkaian yang penting bagi sekuriti rangkaian, reka bentuk rangkaian dan juga bagi pemantauan dan pengurusan rangkaian. Ia memberikan perkhidmatan yang berbeza seperti mengenal pasti aplikasi yang paling banyak menggunakan sumber rangkaian, ia mewakili bahagian teras daripada sistem pengesanan instrusi secara automatik, ia membantu mengesan aplikasi anomali, dan ia juga membantu mengenali aplikasi yang digunakan di seantero dunia bagi tujuan penawaran produk baru. Dalam kata lain, pelbagai cabaran yang dihadapi oleh para jurutera rangkaian dalam usaha mereka mengelaskan trafik. Yang paling biasa adalah pertambahan jenis aplikasi dan saiz data trafik yang besar. Oleh itu, berdasarkan kajian lepas, ramai penyelidik berlumba-lumba memperkenalkan kaedah kaedah yang berkesan bagi pengelasan trafik. Keberkesanan pengelasan trafik bergantung pada beberapa faktor penting seperti ketepatan pengelasan, penggunaan memori dan masa pemprosesan Tesis ini mencadangkan vital random forest VRF sebagai pengelasan trafik rangkaian yang berkesan, yang merupakan satu pakej yang memperkenalkan teknik pemilihan penapis baru, pengurangan input data dan model binaan baru bagi kaedah random forest baru untuk mengelaskan trafik rangkaian bagi set data yang besar. VRF juga bermatlamat mengurangkan masa pemprosesan, meningkatkan ketepatan pengelasan, serta mengurangkan penggunaan memori. Rangka kerja VRF yang dicadangkan memberikan tiga sumbangan, pertama, reka bentuk teknik pemilihan penapis baru berdasarkan penggunaan teknik empat dan dua penapis bagi memilih set penapis yang paling signifikan. Kedua, pengurangan input data yang bertujuan menyingkirkan semua input rekod yang berlebihan dengan pengkatogerian kelas. Ketiga, mereka bentuk model binaan baru bagi random forest standard, yang dikenali sebagai ABRF (Active Build model Random Forest). ABRF dibina berdasarkan pokok aktif (pengelas), sebaliknya, pokok pasif didiagnosis, dikeluarkan dan diganti dengan pokok aktif. Keputusan eksperimen adalah berdasarkan beberapa daripada set data tanda aras (data set global). Data ini dikumpul daripada beberapa rangkaian bagi mencapai semua paket yang berkaitan dengan TCP, UDP dan IP dalam kedua-dua arah. Keputusan menunjukkan penambahbaikan yang ketara dari segi faktor yang signifikan, iaitu ketepatan pengelasan, masa pemprosesan dan penggunaan memori. Secara purata, keputusan VRF berhubung dengan faktor ini dijalankan berdasarkan. 16 set data tanda aras, ketepatan keseluruhan VRF meningkat sebanyak 6% berbanding dengan hutan rawak asal untuk mencapai 99.58%, masa pemprosesan telah menurun dengan perbezaan 62% manakala VRF menggunakan hanya 38% daripada jumlah purata masa dan purata penggunaan memori dikurangkan sebanyak 40%. Selanjutnya, VRF telah disahkan melalui perbandingan keputusan daripada faktor yang dinyatakan di atas dengan penyelidikan terdahulu.

An Efficient Network Traffic Classification Based on Vital Random Forest for High Dimensional Dataset

ABSTRACT

This thesis proposes and implements an efficient network traffic classification method based on a new vital random forest for high dimensional data. Network traffic engineering is one of the most important technologies that have witnessed a rapid growth in the revolution of worldwide technologies. Network traffic classification has added considerable interest as an important network engineering tool for network security, network design, as well as network monitoring and management. It can introduce different services such as identifying the applications which are most consuming for network resources, it represents the core part of automated intrusion detection systems, it helps to detect anomaly applications and it helps to know the widely-used applications for the intention of offering new products. On the other hand, several challenges faced by network engineers on their course to classify traffic. The most common of which are increasing application types and the huge size of data traffics. Therefore, many researchers have been competing in literature to introduce an efficient method for traffic classification. The efficiency is dependent on important factors such as classification accuracy, memory consumption and processing time. This thesis presents a Vital Random Forest (VRF) as efficient network traffic classification which is a one package that introduces a new features-selection technique, data inputs reduction and a new build model for original random forest method to classify network traffic for huge datasets. VRF aims to reduce processing time, increase classification accuracy and decrease memory consumption. The proposed framework of VRF consists of three contributions; first one is design of a new features-selection technique based on adopting four techniques and two filters for selecting most significant features set. Second is a data input reduction aiming to remove all redundant record inputs with class categorization. Third is to design a new build model for standard random forest called Active Build model Random Forest (ABRF). ABRF is built based on active trees (classifiers) while the passive trees are diagnosed, omitted and replaced with active trees. The results from the experiments conducted are based on several benchmark datasets (global dataset). These data were collected from the edge of a network to access all packets associated with a TCP, UDP and IP connections in both directions. The results exhibit noticeable improvement in terms of three significant factors, namely; classification accuracy, processing time and memory consumption. The averaging results of VRF with regard to these factors were conducted based on 16 benchmark datasets where the classification accuracy of VRF is increased by 6% compared with original random forest to reach 99.58%, the processing time was decreased down with difference 62% while VRF consumed only 38% from the total average time and the averaging memory consumption is reduced by 40%. Furthermore, VRF has been validated by comparing the results for the above-mentioned factors with previous works.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Network traffic engineering is one of the most important technologies that have witnessed a rapid growth in the revolution of global technologies. Network traffic identification and classification have recently gained considerable interest as an important network engineering tool for network security, network design, as well as network monitoring and management (Dainotti, Pescape, & Claffy, 2012).

Network traffic classification is a process that categorizes network traffic according to various parameters (e.g. port number, arrival time, type of protocol, packet length, etc) into a number of application classes such as (P2P, WWW, Mail, etc.). This method introduces multi-beneficial solutions in different avenues, such as network security, network management, network measurement and quality-of-service (QoS) (Callado et al., 2009). Many of network engineers have had started to inspect and analyze network traffic but they faced several novel challenges the most significant of which are the huge amount of classified data traffic and the variety of applications. As a result, numerous studies have been proposed to face the above mentioned challenges and they started competing in terms of different factors such as accuracy of classification, memory consumption, CPU consumption and time consumption of processing (Dainotti, Pescapé, & Sansone, 2011; Nguyen & Armitage, 2008). The studies introduced various solutions that involved two major types: First, representing traditional solutions that include well-known port number, deep packet inspection and behavior-based approach. Second is Machine Learning (ML): there was a considerable interest in several disciplines such as

philosophical, logical and conceptual issues, and then research interest shifted to computational and algorithmic aspects of ML that is driven mainly by practical application. That's why many studies were rerouted towards ML. This thesis focuses on supervised machine learning method and its contribution in the area of network traffic classification.

1.2 Background

This section provides a general background to the work presented in this thesis. It briefly introduces the principal technologies referenced throughout this thesis as network traffic engineering, Machine Learning and Random Forest.

1.2.1 Network Traffic Engineering

First and foremost, to understand the network traffic engineering we need to define the network engineering, it's a method of manipulating your network to suit your traffic. Network traffic engineering is defined as that aspect of network engineering of dealing with the issue of performance evaluation and performance optimization of operational IP networks (Calfado et al., 2009). Traffic Engineering encompasses the application of technology and scientific principles to the measurement, characterization, modeling, and control of network traffic. The enhancement of the network is achieved at both levels: traffic and resources, with regard to different performance requirements and utilizing network resources economically and reliably. The performance is measured in terms of delay, jitter, packet loss and throughput. The main purpose of network traffic engineering is to facilitate reliable network operations. This is accomplished using policies to keep network survivability and minimizing the vulnerability of the network to service outages