

Impact of Packet Inter-arrival Time Features for Online Peer-to-Peer (P2P) Classification

Bushra Mohammed Ali Abdalla¹, Mosab Hamdan², Mohammed Sultan Mohammed³,
Joseph Stephen Bassi⁴, Ismahani Ismail⁵, Muhammad Nadzir Marsono⁶

^{1,2,3,5,6}Department of Electronic and Computer Engineering, Faculty of Electronic Engineering,
Universiti Teknologi Malaysia, 81310, Johor Bahru, Malaysia

⁴Department of Computer Engineering, Faculty of Engineering, University of Maiduguri, Borno state, Nigeria

Article Info

Article history:

Received Apr 12, 2018

Revised Jul 20, 2018

Accepted Jul 26, 2018

Keyword:

Features selection

Machine learning

Online features

P2P

ABSTRACT

Identification of bandwidth-heavy Internet traffic is important for network administrators to throttle high-bandwidth application traffic. Flow features based classification have been previously proposed as promising method to identify Internet traffic based on packet statistical features. The selection of statistical features plays an important role for accurate and timely classification. In this work, we investigate the impact of packet inter-arrival time feature for online P2P classification in terms of accuracy, Kappa statistic and time. Simulations were conducted using available traces from University of Brescia, University of Aalborg and University of Cambridge. Experimental results show that the inclusion of inter-arrival time (IAT) as an online feature increases simulation time and decreases classification accuracy and Kappa statistic.

*Copyright © 2018 Institute of Advanced Engineering and Science.
All rights reserved.*

Corresponding Author:

Muhammad Nadzir Marsono,
Department of Electronic and Computer Engineering,
Faculty of Electronic Engineering,
Universiti Teknologi Malaysia,
81310, Johor Bahru, Malaysia.
Email: nadzir@fke.utm.my

1. INTRODUCTION

Today, peer-to-peer (P2P) is as an architecture for sharing a wide range of media on the Internet. P2P traffic represents about 27% to 60% of the total Internet traffic, depending on geographic location [1], [2]. The high volume of P2P traffic is due to file sharing, video streaming, on-line gaming and other activities that client-server architecture cannot accomplish as fast or as efficient as the P2P architecture. Rapid progression of P2P traffic volume throughout the years have resulted in deteriorated network performance and congestion due to the high bandwidth consumption of P2P applications [3]. Therefore, traffic identification is required to improve traffic management.

First generation P2P application traffic were relatively easy to be identified due to the use of fixed ports numbers. However, current P2P applications are able to circumvent port-based identification by using anonymous port numbers or port disguise [4], [2]. Besides, methods that rely on inspecting application payload signatures have also been proposed [5]. For privacy and impractical reasons, this method is ineffective. The effectiveness of the port-based and payload-based methods prompted the use of flow statistics as features for traffic identification. These strategies offer flexibility to detect P2P traffic compared to using signature-based and port-based methods.

Several techniques have been proposed over the last two decades that focused on the attainable identification accuracy using several machine learning (ML) algorithms. However, the impact of exploring the effect of distinct sets of statistical features has not been researched in-depth. Work in [6] has reported that

feature selection is a vital task to improve the classification and identification performance compared to selection of the classification algorithm. Presently, several feature selection algorithms have been introduced, e.g., [7]-[11]. However, most of the introduced methods do not consider the impact of integrating online features with inter-arrival time (IAT) for online P2P classification.

This paper proposes an approach based on analytic methods one-way analysis of variance and incremental traffic classification algorithm. One-way analysis of variance is implemented using KNAME tool and Hoeffding Tree incremental machine learning algorithm is implemented using MOA (Massive On-line Analysis) tool in order to investigate the impact of packet IAT feature for online P2P classification.

The remainder of this paper is organized as follows. Section 2 introduces related works including ML concepts, traffic classification and feature selection. Section 3 discusses the methodology to investigate the impact of packet inter-arrival time feature for online P2P classification. The experimental setup, result and discussion are discussed in Section 4. Section 5 presents the conclusion.

2. RELATED WORK

Machine learning (ML) is a promising technique that has been used for data mining and knowledge discovery [12]. Unsupervised learning strategies basically clusters flows with similar pattern behaviour. Supervised learning needs a set of labeled data to train its model in advance for identification and classification of data [12].

Classification using flow features mainly deploys machine learning to perform training and classification. From the extracted flow features, the classifier predicts the class of new flow. This process is called a data mining problem. The first work using this technique was by [13]. Generally, classification can be performed in three steps, extracting the features, selection of feature and generating classifier [14].

Moore *et al.* [15] has suggested 249 features that can be potentially used in ML traffic identification. However most of these features can only be obtained in an off-line mode. Off-line features such as maximum and minimum bytes in packet only can be obtained with complete flows. Work in [16] employed all 249 features suggested in [15] derived from packet streams consisting of one or more packet headers. Most of these features cannot be extracted online from live traffic for online traffic identification.

Feature selection (FS) is used to select optimal subset features from the input which can efficiently describe the input data while reducing effects from irrelevant or noise features yet still provide good prediction of its class [7], [17]. Traffic identification can be improved with reference to computational performance and accuracy by using the most relevant features [18].

Loo *et al.* [8] proposed 12 online features without features related time. Monemi *et al.* [19] has proposed 35 real-time flow features that can be easily extracted from flow records. These flows include number of packets, port address, protocol, overall Transmission Control Protocol (TCP) flags, average volume in byte, volume in byte per packet, flow duration, payload volume in byte, flow duration, average number of packet per second, average volume in byte per second, average payload volume in byte per second, average payload volume in byte per packet, and average time interval. Erman *et al.* [16] has performed backward greedy search on various datasets and found that the use of time-related features such as duration, IAT and flow throughput are not useful in traffic classification.

Online features techniques have been proposed in [7], [20]. These works used Cambridge datasets and Naive Bayes to evaluate two feature selection algorithms named Bias Coefficient Results (BFS) and Selected Online Feature. These works achieved accuracy of 90.92% and 93.20%, respectively. Besides, the work in [7] has considered IAT as one of the proposed on-line features.

Most researches have focused on online features with IAT as suggested in [7], [11], [19], [21]. However, the impact of packet inter-arrival time feature for online P2P classification still plays an important role for accurate and timely classification.

3. OVERVIEW OF THE METHODS

Our proposed method to investigate the impact of packet IAT feature for online P2P classification consist of two main stages, test the significance of packet IAT feature and investigate the impact of packet IAT feature for online P2P identification with reference to accuracy, kappa statistic and time. The first stage one-way analysis of variance analytics using KNAME tool to test the significance of IAT. In the second stage, Hoeffding Tree incremental machine learning algorithm is implemented in MOA tool. All stages will be discussed in details in Section 3.1. Figure 1 shows the overview of the proposed method to investigate the impact of packet IAT feature for online P2P classification.

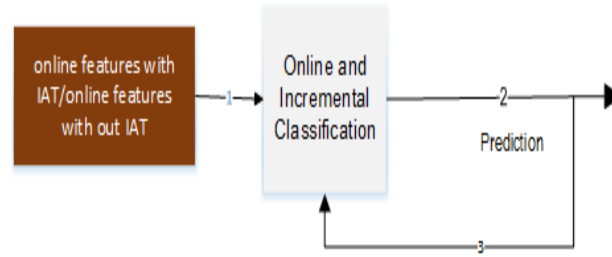


Figure 1. Proposed method

3.1. Techniques for analyzing features

Konstanz Information Miner (KNIME) is a recent open-source data analytics platform that allows for undertaking complete statistics and data mining analysis. One-way ANOVA is implemented in KNIME benchmark [22]. WEKA workspace tools also is used for classification [23]. One-way ANOVA is the most effective method available for analyzing the more complex data sets [24]. In this work, we computed the F-statistic using ANOVA. Equations (5) and (1) represents sum of square (SS) in ANOVA. While the sum of squares for Treatment (SST) is given by Equation (2). Sum of squares for Error (SSE) is computed using Equation (3). The Variance between Treatments (MST) is computed by Equation (4). The Variance Within Treatments (MSE) is computed using Equation (5). F-statistic is obtained by dividing MST to MSE is given by Equation (6). Using 95% confidence interval for mean difference, ANOVA is calculated as:

$$\begin{aligned} SS &= \sum_{j=1}^k \sum_{i=1}^{n_j} (y_{ij} - \bar{y})^2 & (1) \\ &= \sum_{j=1}^k \sum_{i=1}^{n_j} (\bar{y}_{ij} - \bar{y}_j + \bar{y}_j - \bar{y})^2 \\ &= \sum_{j=1}^k \sum_{i=1}^{n_j} (\bar{y}_{ij} - \bar{y}_j)^2 + \sum_{j=1}^k \sum_{i=1}^{n_j} (\bar{y}_j - \bar{y})^2 + 0 \end{aligned}$$

$$SST = \sum_{j=1}^k \sum_{i=1}^{n_j} (\bar{y}_j - \bar{y})^2 \quad (2)$$

$$SSE = \sum_{j=1}^k \sum_{i=1}^{n_j} (\bar{y}_{ij} - \bar{y}_j)^2 \quad (3)$$

Then

$$SS = SSE + SST \quad (4)$$

$$MS = \frac{SST}{K-1} \quad (5)$$

$$MSE = \frac{SSE}{K-1} \quad (6)$$

Thus, with ANOVA test null hypothesis (H_0): $\mu_1 = \mu_2 = \dots = \mu_k$, which means that there are no treatment effects. Where \bar{y} bar is the samples mean, n is the sample size, (\bar{y}_j) is the specified population mean.

Massive Online Analysis (MOA) [25]: MOA is a data stream mining suite that was written in Java. Users can use MOA using Graphic User Interface (GUI) or through command lines. Different from WEKA [23] which is for batch data mining, MOA specializes on processing and analyzing data streams. The suite includes evaluation tools such as concept drift evaluation, and interleaved-test-then-train evaluation. It is also built with a collection of data stream identification techniques such as Naive Bayes, Hoeffding Tree, Bagging and Boosting techniques. In this paper, MOA is used to analyze the impact of integrating online features with IAT for online P2P classification.

4. EXPERIMENTAL SETUP, RESULTS AND DISCUSSION

This section, presents and discusses the network traffic datasets used and the evaluation method used to evaluate the impact of integrating online features with inter-arrival time for online P2P classification.

4.1. Dataset

Network traces are used to validate the performance of the proposed technique. These datasets are PAM [26], UNIBS [27] and Cambridge [15]. Table 1 summarizes the used datasets, which the description of each dataset as follows:

- a. PAM traces was captured in Aalborg University from 25th February 2013 to 1st May 2013 and reported in [26]. The label of the dataset was collected using Volunteer-Based System (VBS). A total of 1,262,022 flows were captured, where 535,438 flows were labeled as reported in [26]. However, only 339,061 flows could be used as most flows have less than five packets and the netflow and feature extractor modules only extract flows that contain five packets or more. By using the provided information files, the flows are labeled into four classes: WEB, FTP, P2P, and Others.
- b. The UNIBS datasets [27] were obtained from a series of workstations at the University of Brescia from 30th September 2016 to 2nd October 2016. The traces are collected on edge router, where the traffic was generated by 20 workstations running GT toolset. In this work, the traces were processed using netflow and feature extractor based on 1 minutes timeout and flows with a minimum of five packets are extracted. A total of 77,303 flows are extracted and all flows features are extracted based on only the first five packets of each flow. The accompanied groundtruth labels, were use to classify flows into five classes, P2P, Skype, Web, Others, and Mail.
- c. The Cambridge datasets were obtained from traces captured on the Genome Campus network in August 2003 in the University of Cambridge [15]. There are ten different datasets each from a different period of the 24-hour day. These datasets consist of TCP flow. Furthermore, every flow sample is high dimensional since it contains 248 features. The dataset applications with negligible classes such as games and interactive were excluded as it is insufficient for training and testing. These include classes such as FTP-Pasv, Attack, P2P, Database, Multimedia, Web, Mail, FTP-Control, and Services.

Table 1. Datasets Statistics

	UNIBS	PAM	Cambridge
#Flow instances	77,303	339,061	397,030
#Classes	5	4	10
#Flow features extracted	9	9	9

4.1.1. Dataset preprocessing

Online features are extracted and online features with IAT and without IAT as suggested in our previous work [28] are selected. For the UNIBS and PAM datasets, the features are extracted based on the first five packets statistic of each flow. However, for the Cambridge dataset, the statistics of the first 5 packets are not available without access to the raw packets. Thus, for this dataset, the complete flow statistic is used (not only first 5 packets). In order to have a fair comparison of all datasets, the mean features in Cambridge dataset are modified to total features. Table 2 shows the list of feature that had been extracted.

Table 2. Online features with IAT

#	Name	Description
1	Port_a	Source port number
2	Port_b	Port b Destination port number
3	Ply_size_ba	Total byte in IP packet(Downlink)
4	Ply_size	Total byte in IP packet
5	Pck_size_ba	Total byte in Ethernet packet(Downlink)
6	Pck_size	Total byte in Ethernet packet
7	iat_ba	Total packet inter-arrival time(downlink)
8	Iat	Total packet inter-arrival time
9	Class	Protocol

4.1.2. Evaluation

Prequential evaluation using fading factors forgetting mechanism proposed by Gama *et al.* [29] is adopted as the evaluation method. This method is suitable for evaluating incremental learning algorithm. The prequential parameters used in our experiment are as stated below, unless specified otherwise:

- a. Classifier to train: Hoeffding Tree
- b. Stream to learn from: PAM, Cambridge and UNIBS dataset

- c. Training and testing on a total of 250,000 samples for PAM and Cambridge, while UNIBS 50000 samples.
- d. Testing every two hundred samples
- e. Instances between memory bound checks: 193,000 samples for PAM and Cambridge, while UNIBS 40000 samples
- f. Evaluate Prequential Parameters: Window Classification Performance Evaluator
- g. Size of sliding is 1,000

The performance indicators used in this research are classification time (T_c), Kappa statistic $K = 1$ and average accuracy (Acc). Average accuracy is the overall accuracy for a dataset. Let the total correct identification in a dataset with (N) flow instances is η . The performance indicators used in this paper are:

$$Acc = \frac{\eta}{N} \times 100\% \quad (7)$$

$$k = \frac{p_o - p_e}{1 - p_e} \quad (8)$$

while p_o : classifier's prequential accuracy p_e is: probability of correct prediction. Kappa has preferable properties such that value of 1 with perfect agreement ($p_o = 1$) is used. The value approximately zero when the observed agreement is almost the same as would be expected by chance ($p_o \approx p_e$). Furthermore, Kappa statistic does not assume marginal probabilities to be the same for different observers.

4.2. One-way ANOVA test results

This subsection explains the significant of selected features by using ANOVA test with 95% confidence interval for the mean difference. The result explains all selected features are significant because after tested with ANOVA the P-value less than 0.05. Also, this test explains the IAT features are less significant than other features as shown in Figure 2.

4.3. Online classification results

The experimental results presented in Figure 3 to Figure 8, illustrate the effect of IAT inclusion as an online feature for P2P identification. The result as presented in Table 3 indicates that packet IAT feature as online feature decreases identification accuracy and Kappa statistic. Furthermore, packet IAT feature increases the experimental evaluation time. This is as a result of packet IAT feature morphing which involves alternation on directional pattern which is dependent on network locations. Also these results prove previous offline studies that:

- a. Time-related features do not help to distinguish among applications [20], [30].
- b. The use and statistical features of application dependent only on inter-packet time is a challenging task due to the time required by an application to generate and transfer packets to the transport layer is masked by the fact that additional time is added due to the network conditions and the TCP layer [31].

Table 3. Classification Results

Cambridge	Online features without IAT	Online features with IAT
Accuracy mean	98.86	98.80
Kappa statistic mean	59.46	59.46
CPU total time per second mean	1.41	2.28
UNIBS dataset	Online features without IAT	Online features with IAT
Accuracy mean	94.13	93.15
Kappa statistic mean	87.87	86.16
CPU total time per second mean	0.51	0.74
PAM dataset	Online features without IAT	Online features with IAT
Accuracy mean	92.42	92.22
Kappa statistic mean	17.71	15.42
CPU total time per second mean	1.56	1.82

	Source	Sum of Squares	df	Mean Square	F	p-value
portA	Between Groups	9.26E12	3	3.09E12	5,668.7436	0.0
portA	Within Groups	1.85E14	339057	5.45E8		
portA	Total	1.94E14	339060			
portB	Between Groups	5.47E13	3	1.82E13	173,355.8736	0.0
portB	Within Groups	3.57E13	339057	1.05E8		
portB	Total	9.04E13	339060			
pck_size_ab	Between Groups	1.71E10	3	5.70E9	16,529.2872	0.0
pck_size_ab	Within Groups	1.17E11	339057	344,824,5912		
pck_size_ab	Total	1.34E11	339060			
pck_size_ba	Between Groups	1.84E9	3	6.15E8	10,702.6639	0.0
pck_size_ba	Within Groups	1.95E10	339057	57,435.3865		
pck_size_ba	Total	2.13E10	339060			
pck_size	Between Groups	1.99E10	3	6.64E9	17,676.6049	0.0
pck_size	Within Groups	1.27E11	339057	375,371.5113		
pck_size	Total	1.47E11	339060			
ply_size_ab	Between Groups	1.43E10	3	4.76E9	14,200.5108	0.0
ply_size_ab	Within Groups	1.13E11	339057	332,930.9074		
ply_size_ab	Total	1.27E11	339060			
ply_size_ba	Between Groups	1.95E9	3	6.49E8	11,378.5301	0.0
ply_size_ba	Within Groups	1.94E10	339057	57,073.045		
ply_size_ba	Total	2.13E10	339060			
ply_size	Between Groups	1.90E10	3	6.33E9	16,776.5031	0.0
ply_size	Within Groups	1.28E11	339057	377,416.4049		
ply_size	Total	1.47E11	339060			
iat_ab	Between Groups	2.00E11	3	6.68E10	554.798	0.0
iat_ab	Within Groups	4.08E13	339057	1.20E8		
iat_ab	Total	4.10E13	339060			
iat_ba	Between Groups	4.38E10	3	1.46E10	353.3253	0.0
iat_ba	Within Groups	1.40E13	339057	41,340,505.3144		
iat_ba	Total	1.41E13	339060			
iat	Between Groups	4.25E11	3	1.42E11	502.2179	0.0
iat	Within Groups	9.57E13	339057	2.82E8		
iat	Total	9.62E13	339060			

Figure 2. Screen shot of test statistic ANOVA

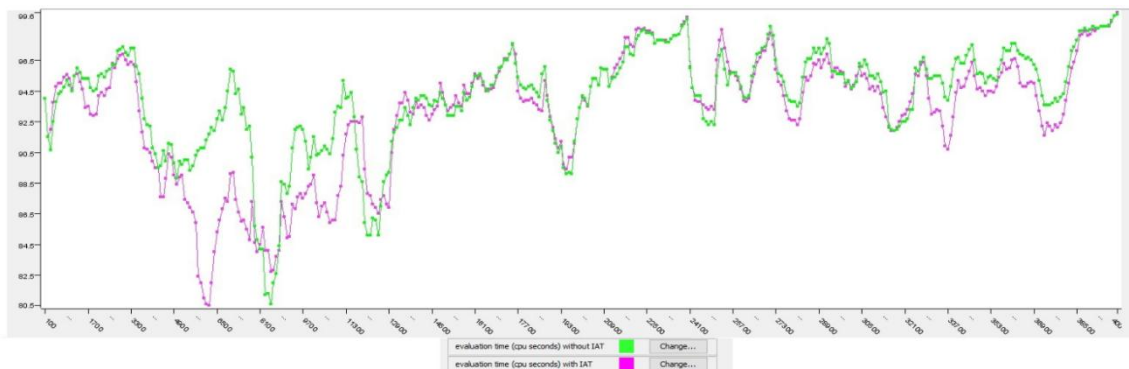


Figure 3. UNIBS dataset mean classification accuracy

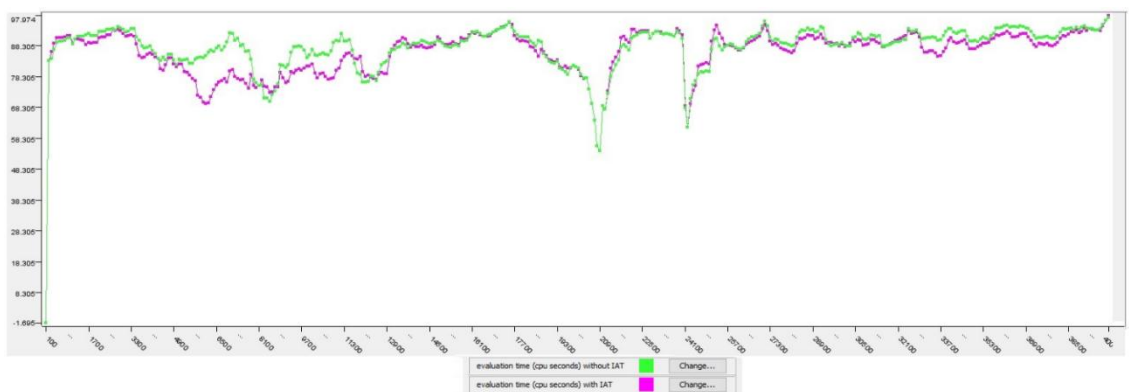


Figure 4. UNIBS dataset mean kappa statistic

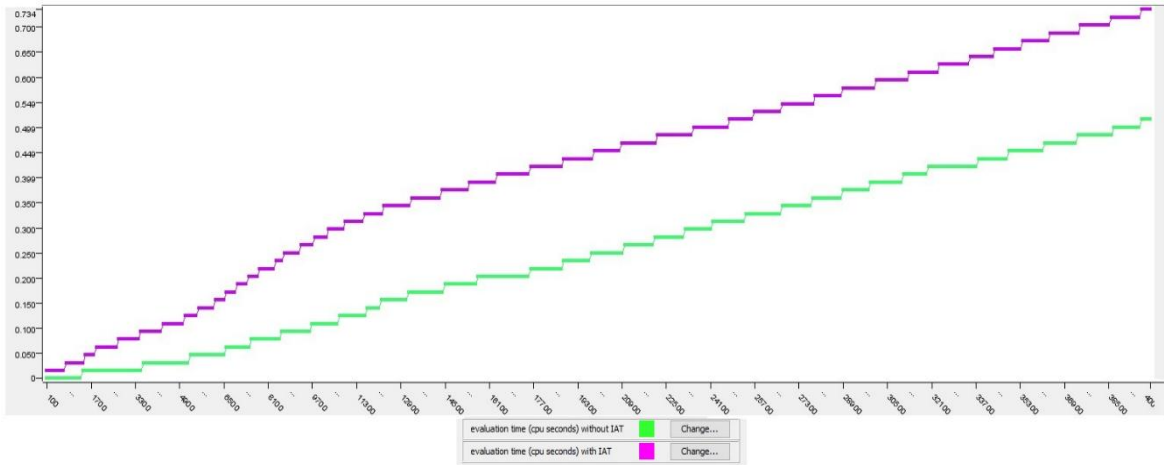


Figure 5. UNIBS dataset evaluation time

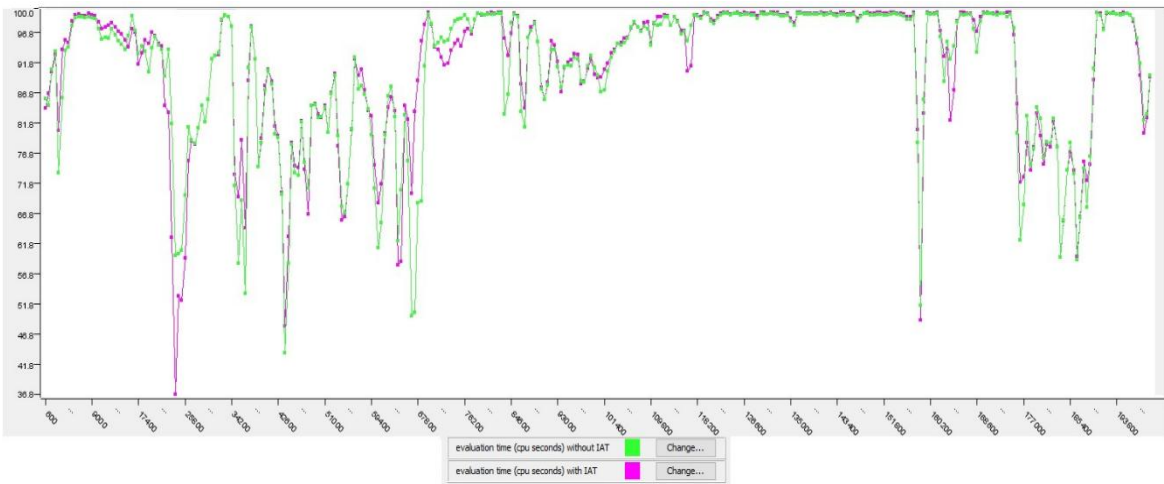


Figure 6. PAM dataset mean classification accuracy

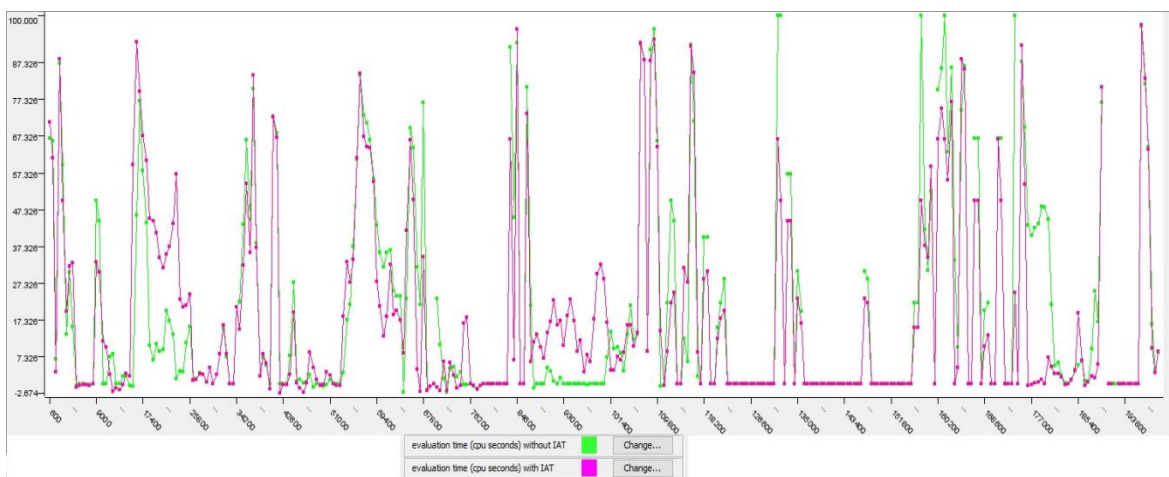


Figure 7. PAM dataset mean kapaa statistic

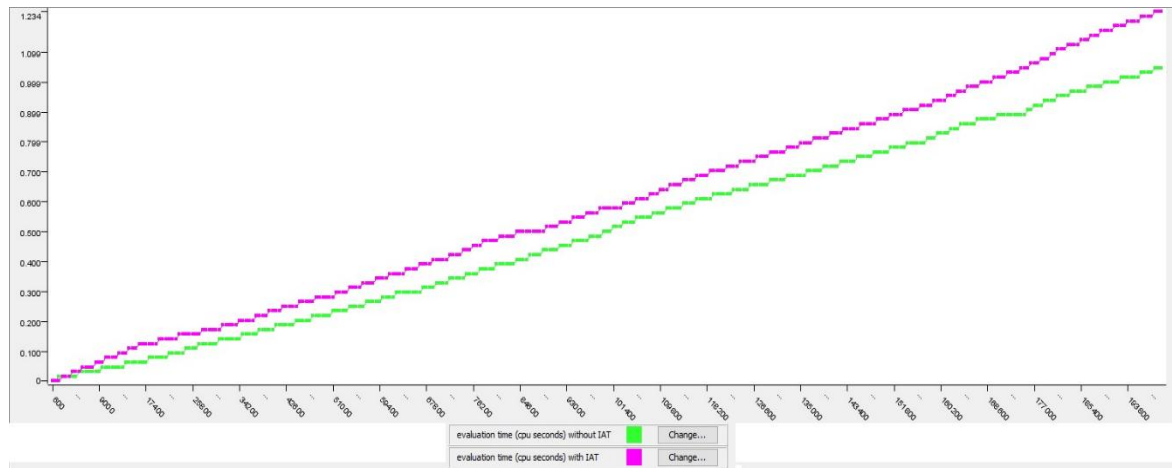


Figure 8. PAM dataset evaluation time

5. CONCLUSION

In this paper, we investigated the impact of packet IAT feature for online P2P classification with reference to accuracy, kappa statistic and evaluation time. The simulation results indicate that the packet IAT features for online P2P classification decrease accuracy and Kappa statistic, and also increase evaluation time. These results because IAT morphing usually involves alternation on direction pattern and depend on different network locations. The acknowledgment section is optional. The funding source of the research can be put here.

REFERENCES

- [1] D. L. Johnson, E. M. Belding, and G. Van Stam, "Network traffic locality in a rural african village," in *Proceedings of the fifth international conference on information and communication technologies and development*. ACM, 2012, pp. 268-277.
- [2] J. S. Bassi, L. H. Ru, I. Ismail, B. M. Khammas, and M. N. Marsono, "Online peer-to-peer traffic identification. based on complex events processing of traffic event signatures," *Journal TEKNOLOGI*, vol. 78, no. 7, pp. 9-16, 2016.
- [3] R. D. Torres, M. Y. Hajjat, S. G. Rao, M. Mellia, and M. M. Munafo, "Inferring undesirable behavior from p2p traffic analysis," booktitle is ACM SIGMETRICS Performance Evaluation Review, vol. 37, no. 1. ACM, 2009, pp. 25-36.
- [4] C. Wang, Z. Wang, Z. Ye, and H. Chen, "A p2p traffic identification approach based on svm and bfa," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 12, no. 4, pp. 2833-2842, 2014.
- [5] A. W. Moore and K. Papagiannaki, "Toward the accurate identification of network applications," in *International Workshop on Passive and Active Network Measurement*. Springer, 2005, pp. 41-54.
- [6] P. Van Der Putten and M. Van Someren, "A bias-variance analysis of a real world learning problem: The coil challenge 2000," *Journal of Machine Learning*, vol. 57, no. 1-2, pp. 177-195, 2004.
- [7] H. A. Jamil, A. Mohammed, A. Hamza, S. M. Nor, and M. N. Marsono, "Selection of on-line features for peer-to-peer network traffic classification," in *Recent Advances in Intelligent Informatics*. Springer, 2014, pp. 379-390.
- [8] H. R. Loo and M. N. Marsono, "Online network traffic classification with incremental learning," *Journal of Evolving Systems*, vol. 7, no. 2, pp. 129-143, 2016.
- [9] H. Zhang, *et al.*, "Feature selection for optimizing traffic classification," *Journal of Computer Communications*, vol. 35, no. 12, pp. 1457-1471, 2012.
- [10] S. Joseph, *et al.*, "Cooperative learning for distributed in-network traffic classification," in *IOP Conference Series: Materials Science and Engineering*, vol. 190, no. 1. IOP Publishing, 2017, p. 012010.
- [11] J.-j. Zhao, *et al.*, "Real-time feature selection in traffic classification," *Journal of China Universities of Posts and Telecommunications*, vol. 15, pp. 68-72, 2008.
- [12] T. T. Nguyen and G. Armitage, "A survey of techniques for internet traffic classification using machine learning," *Journal IEEE Communications Surveys & Tutorials*, vol. 10, no. 4, pp. 56-76, 2008.
- [13] M. G. Schultz, *et al.*, "Data mining methods for detection of new malicious executables," in *Security and Privacy, 2001. S&P 2001. Proceedings. 2001 IEEE Symposium on. IEEE, 2001*, pp. 38-49.
- [14] G. Tahan, *et al.*, "Mal-id: Automatic malware detection using common segment analysis and meta-features," *Journal of Machine Learning Research*, vol. 13, no. Apr, pp. 949-979, 2012.

- [15] A. Moore, et al., "Crogan, Discriminators for use in flow-based classification," *Queen Mary and Westfield College, Department of Computer Science, Technical Report*, 2005.
- [16] T. Auld, et al., "Bayesian neural networks for internet traffic classification," *Journal IEEE Transactions on neural networks*, vol. 18, no. 1, pp. 223-239, 2007.
- [17] A. Tjahyanto, et al., "Spectral-based features ranking for gamelan instruments identification using filter techniques," *Journal TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 11, no. 1, pp. 95-106, 2013.
- [18] O. Henchiri and N. Japkowicz, "A feature selection and evaluation scheme for computer virus detection," in *Data Mining, 2006. ICDM'06. Sixth International Conference on. IEEE, 2006*, pp. 891-895.
- [19] A. Monemi, et al., "Online netfpga decision tree statistical traffic classifier," *Journal of Computer Communications*, vol. 36, no. 12, pp. 1329-1340, 2013.
- [20] L. Zhen and L. Qiong, "A new feature selection method for internet traffic classification using ml," *Journal of Physics Procedia*, vol. 33, pp. 1338-1345, 2012.
- [21] Y. Zhao, et al., "Hierarchical real-time network traffic classification based on ecoc," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 12, no. 2, pp. 1551-1560, 2014.
- [22] h. KNIME, "," <https://tech.knime.org/forum/bioinformatics/>, "Acceced 22 Dec 2016".
- [23] h. WEKA, "," <http://www.cs.waikato.ac.nz/ml/weka/>, "Acceced 01 Dec 2016".
- [24] L. L. Kupper, "Applied regression analysis and other multivariate methods," *Duxbury Press, Boston, 1978*
- [25] A. Bifet and R. Kirkby, "Data stream mining a practical approach," *University of WAIKATO, Technical Report, 2009*.
- [26] V. Carela-Espanol, et al., "Is our ground-truth for traffic classification reliable?" in *International Conference on Passive and Active Network Measurement. Springer, 2014*, pp. 98-108.
- [27] F. Gringoli, et al., "Gt: picking up the truth from the ground for internet traffic," *Journal of ACM SIGCOMM Computer Communication Review*, vol. 39, no. 5, pp. 12-18, 2009.
- [28] B. M. A. Abdalla, et al., "Multi-stage feature selection for on-line flow peer-to-peer traffic identification," in *Asian Simulation Conference. Springer, 2017*, pp. 509-523.
- [29] J. Gama, et al., "On evaluating stream learning algorithms," *Journal of Machine learning*, vol. 90, no. 3, pp. 317-346, 2013.
- [30] J. Kögel, "One-way delay measurement based on flow data in large enterprise networks," *PhD thesis. Univ. Stuttgart, Inst. Für Kommunikationsnetze und Rechnersysteme, 2013*.
- [31] B. Qu, et al., "An empirical study of morphing on behavior-based network traffic classification," *Journal of Security and Communication Networks*, vol. 8, no. 1, pp. 68-79, 2015.

BIOGRAPHIES OF AUTHORS



Bushra Mohammed Ali, is a PhD candidate at the Faculty of Electrical Engineering Universiti Teknologi Malaysia. He obtained B.Sc. and M.Sc. in Computer Engineering and Networks-Faculty of Engineering and Technology, University of Gezira, Sudan. He is a lecturer at the faculty of Computer and Statistics Studies, University of Kordofan. His research interests include computer architecture, Network Traffic classification and control, Artificial Intelligence and optimization techniques.



Mosab Hamdan is a PhD student at Vecad research group in University Technology Malaysia (UTM). He obtained Bachelor degree in Electronic and Electrical engineering from University of Science and Technology (Sudan) in 2010, and Msc in computer architecture and networking at University of Khartoum (Sudan) in 2014. His current research interests are Software Defined Networking, Load Balancing, Traffic Classification, and Future Network.



Mohammed Sultan Mohammed received his BSc in Computer Engineering from Hodeidah University (Yemen) in 2005. He received the MSc in Computer Engineering and Networks from the University of Jordan (Jordan) in 2015. He is currently pursuing his Ph.D. study at Univesiti Teknologi Malaysia. His research interests are parallel processing, multi-core embedded systems, System-on-Chip (SoC).



Joseph Stephen Bassi received his Ph.D. degree in Electrical Engineering from the Universiti Teknologi Malaysia, in 2017, M.Eng. degree in Electrical & Electronics Engineering (Electronics) from University of Maiduguri, Nigeria in 2012 and B.Tech degree in Computer Science & Mathematics from Federal University of Technology Minna, Nigeria in 2000. He is currently a Lecturer with the Department of Computer Engineering, Faculty of Engineering, University of Maiduguri, Nigeria. His research interests are in Network algorithmic, Artificial Intelligence & optimization techniques and computer communication networks.



Ismahani Ismail received her PhD degree in Electrical and Computer Engineering from Universiti Teknologi Malaysia in 2013. She is a Senior Lecturer with the Faculty of Electrical Engineering, Universiti Teknologi Malaysia. Her fields are in digital systems and network algorithmic.



Muhammad Nadzir Bin Marsono received the PhD in Electrical and Computer Engineering. University of Victoria, Canada in 2007. He is now an Associate Professor at the Faculty of Electrical Engineering, Univeristi Teknologi Malaysia. His research interests in system level integration, working in multiple areas of embedded systems, specialized computer architectures, VLSI design, network algorithmic, network-on-chip, and network processor architectures.