Incorporating Multiple Cluster Models for Network Traffic Classification

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***Abstract*—Network traffic classification is one of essential functions for local and ISP networks for quality of service, network usage statistics, resource provisioning, and security. With its importance, a substantial number of previous studies have explored various machine learning techniques based on network flow statistics to improve the accuracy of classification and reported promising results with fairly high classification accuracy. However, what we observed from previously proposed network traffic classification techniques with our own data set recently collected are somewhat unacceptable results. In particular, we observed that simply combining flow attributes for classification may lead to unexpectedly poor accuracy in classification (less than xx%). In this paper, we propose a new traffic classification method based on attribute groups, each of which consists of a set of attributes belonging to a single parameter (e.g., packet size, inter-arrival time, etc). Our method then incorporates multiple cluster models obtained from individual attribute groups to reach the final classification decision based on the population of candidate protocols (or applications). From our extensive experiments, we observed that our proposed technique significantly outperforms existing cluster-based classification techniques, showing up to yy% better accuracy.**

I. Introduction

Accurately identifying network-based applications is of major interest for local and ISP networks for various purposes, including quality of service, network usage statistics, resource provisioning, and security [1], [3], [6]. Earlier, network protocols/applications were identified simply based on TCP/UDP port numbers. However, the traditional technique based on port-numbers are proved to be ineffective where accuracy is less than 70% [4] since network applications using random port numbers or non-standard port numbers are increasing day-by-day and also usage of tunneling makes identification of applications more difficult just based on port numbers. Due to this reason, a substantial body of research has been conducted to replace or complement the port-based identification.

One approach to overcome the limitation of the port-based identification is to inspect the packet payload information with template signature sets [7], [5] or machine learning techniques [4]. While highly accurate, drawbacks of the deep packet inspection-based approach include encrypted traffic transformed with cryptographic keys and privacy concerns as many countries do not permit the extraction of full payload information from packets with increasing privacy requirements.

The limitations of the traditional port-based identification and the payload inspection-based classification suggested to utilize transport layer characteristics of the application as the differentiator. From previously proposed techniques [], we can see the combination of transport layer characteristics with machine learning techniques would be an effective alternative for network traffic classification. Several techniques were proposed based on supervised learning [], while some other techniques utilized unsupervised or semi-supervised clustering techniques [], reporting promising accuracy for network traffic classification. However, what we actually observed from previously proposed network traffic classification techniques with our own data set recently collected are somewhat unacceptable results. In particular, one important observation is that simply combining flow attributes for classification leads to unexpectedly poor accuracy in classification (less than xx%), which motivates us to thoroughly examine the impact of flow attributes in this work.[1]

To evaluate the significance of flow attributes to classification accuracy, we use a notion of attribute groups. An attribute group consists of a set of attributes that are derived from a single communication characteristic. For example, the packet size group includes the minimum packet size, maximum packet size, average packet size, standard deviation of packet sizes observed from a single flow. We consider four attribute groups of flow information group, packet size group, packet inter-arrival time group, and relative packet inter-arrival time group, as will be discussed in the Section III in detail. From our preliminary experiments, we observed that some combinations of attributes work quite better than the other combinations. Moreover, simply applying a subset of attributes selected based on the evaluation to supervised techniques significantly improves performance compared to using the entire attributes without selection. With the initial observations, we developed a new semi-supervised learning technique based on the attribute groups. A key challenge for this approach is how to use multiple attribute groups to make a single classification decision. To address this, we establish independent cluster models based on individual attribute groups and incorporate the results

[1]A (network) flow is defined as a set of packets for a single session of communication with the five tuples of source IP address, destination IP address, source port number, destination port number, and protocol type.

collected from multiple cluster models. Although it is known that clustering techniques generally work poorly compared to supervised learning techniques [6], we will present that the proposed technique using multiple cluster models yield comparable classification accuracy.

The key contributions of this paper can be summarized as follows:

- We evaluate the significance of flow attributes to classification accuracy with a notion of attribute group. We used 18 flow attributes in total and four groups are formed, which are flow information group, packet size group, packet inter-arrival time group, and relative packet inter-arrival time group.
- From the evaluation results with the attribute groups, we examine classification accuracy with the entire attributes and with the selected ones using supervised learning methods, to ensure validity of the selection.
- We present a new clustering technique for network traffic classification that utilizes multiple cluster models developed from the attribute groups. A set of heuristic algorithms are also presented to incorporate multiple cluster models.
- We also present experimental results for evaluating the proposed traffic classification technique. Experiments for sensitivity study are also conducted to see the impact of configurable parameters.

The paper organization is as follows. We provide a summary of related studies in Section II. In Section III, we examine the significance of attribute groups to classification accuracy and performance with selected attributes with supervised learning methods. We then present the new clustering technique incorporating multiple cluster models in Section IV and evaluation results are presented in Section V. Finally we conclude our presentation with a summary and future direction in Section VI.

II. Related Work and Motivation

A substantial body of research has been conducted for network traffic classification with machine learning techniques. The work can broadly be divided into the following three categories:

- *Un-supervised* []: Labeling information of the training data is not available at the time of training. We use various clustering algorithms for the classification of unlabeled data[].
- *Supervised* []: We provide the labels for the flows when we train the model and then use this model to test each incoming flow whether it belongs to any of the application which is provided at the time of training[].
- *Semi-supervised* []: We provide partial labeling information at the time of training and we use clustering algorithms to cluster the training data. We use the partially available labeling information to label each cluster. Heuristics have been proposed on how to label the cluster from partial training information[]

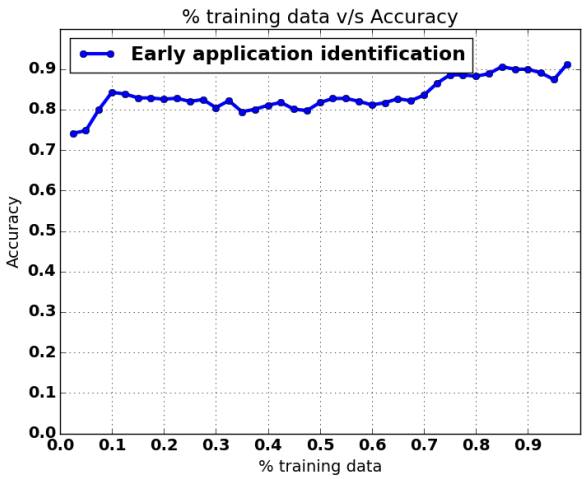

Fig. 1: % of training data v/s Accuracy with only average packet size as attribute. We have considered Average Packet Size as the only attribute for K-Means algorithm. We observe that accuracy reaches around 90% when we have around 95% of training data

ACAS[4]: In paper[4], they explored the problem of network traffic classification by *automatically developing signatures* for various network based applications. ACAS encodes initial*n-bytes*of the payload into space and uses supervised machine learning algorithm as the classification algorithm. They did experiments with various settings of the initial *n-bytes* and observed accuracies more than 99% for both settings of the initial bytes. We observe this technique is effective in identifying applications with very high accuracy with our data set ($\approx$ 99%). Drawback of this technique is it requires completely labeled data. Which means we should know prior to the start classification it should know all the applications that classifier may encounter in future (which is not a feasible solution). It also As mentioned, however, it requires the access to the payload, which could be limited by laws due to privacy concerns. In addition, encryption plays an important role in classification, which may significantly lower the accuracy.

K-Means classification technique[2]. Main idea of the paper[2] is using of K-Means and DBSCAN clustering algorithms which were not used earlier for network traffic classification. They identified DBSCAN algorithm is the only algorithm which labeled traffic as noise.The time of building the models is very low for K-Means algorithm. They claim K-Means accuracy on an average is around 84%. We ran the K-Means classification technique across by varying the number of clusters from 10 to 140, and Figure 2 show the result. As can be seen from the figure, classification performance is largely not acceptable with quite less than 70% accuracy.

Early Application Identification.[1] In the paper[1], they described new technique by which identification of the application can be achieved at the earliest. They discussed the usage of only first *4 packets* in the classification, by which we can identify the application as soon as possible. They propose

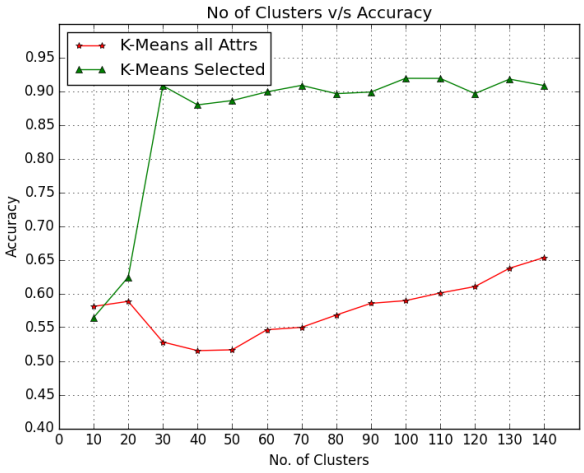

Fig. 2: Number of clusters v/s Accuracy for K-Means algorithm with All and Selected attributes

that by using only Average Packet size of the flow is enough to get desired classification accuracy.They claim the accuracy of 98% can be achieved by using only Average Packet Size as the attribute for machine learning algorithms. We also evaluated this technique. Rather than considering only the first 4 packets in a flow as suggested in the paper, we considered the whole packets to see the maximum performance. Although this technique is based on clustering as the above technique and uses only the average packet size attribute, it yielded quite enhanced results as shown in Figure **??** across diverse ratios between training data set and testing data set.

III. Grouping of Attributes

Total attributes considered for the study are 18.

A. Preliminary Results

Our experiments results for each group of attributes are as following:

We observe from Table.II, Table.III, Table.V and Table.IV that accuracy is not very good when we consider all the attributes of flow in the classification. When subset of attributes in a group is considered then the accuracy is better than when all attributes in the group are considered. From Table.II, Table.III accuracy is very low, this group doesn't make much difference in the accuracy when considered in the classification. From Table.V and Table.IV we observe accuracy when considering all the attributes is not as good as when we consider subset of them. Table.IV we observe combination of *Avg Pkt Size* and *Std Div Pkt Size* gives the best accuracy of the group, similarly combination of *Min Pkt Size*, *Max Pkt Size* and *Avg Pkt Size* gives second best accuracy of the group. Similarly from Table.V combination of *Total Pkt Size*, *Payload Size* and also combination of *Payload size*, *Number of Packets in the flow* gives better accuracy in the group. From fig.3, we observe with only subset (7 out 18 attributes) is giving almost same accuracy(at some points even more), as when

TABLE II: Accuracy based on IAT group

Avg IAT	Min IAT	Max IAT	Std Div IAT	Final Accuracy
✓	×	×	×	47.29%
×	✓	×	×	49.34%
×	×	✓	×	39.20%
×	×	×	✓	42.82%
✓	✓	×	×	45.86%
✓	×	✓	×	44.25%
✓	×	×	✓	47.78%
×	✓	✓	×	39.64%
×	✓	×	✓	42.91%
×	×	✓	✓	40.54%
✓	✓	✓	×	45.20%
✓	✓	×	✓	47.18%
✓	×	✓	✓	42.70%
×	✓	✓	✓	40.10%
✓	✓	✓	✓	42.75%

TABLE III: Accuracy based on RIAT group

Avg RIAT	Max RIAT	Std Div RIAT	Final Accuracy
✓	×	×	55.86%
×	✓	×	54.08%
×	×	✓	53.41%
✓	✓	×	55.21%
✓	×	✓	54.28%
×	✓	✓	55.25%
✓	✓	✓	56.41%

TABLE IV: Accuracy based on Packet Size group

Avg Pkt Size	Min Pkt Size	Max Pkt Size	Std Div Pkt Size	Final Accuracy
✓	×	×	×	92.43%
×	✓	×	×	75.95%
×	×	✓	×	92.22%
×	×	×	✓	91.82%
✓	✓	×	×	91.46%
✓	×	✓	×	92.98%
✓	×	×	✓	93.96%
×	✓	✓	×	91.46%
×	✓	×	✓	92.69%
×	×	✓	✓	92.76%
✓	✓	✓	×	93.98%
✓	✓	×	✓	93.62%
✓	×	✓	✓	92.76%
×	✓	✓	✓	91.73%
✓	✓	✓	✓	93.75%

TABLE I: Attributes used in out studies

Name	Description	Related Attributes
IAT	Inter Arrival Time, time difference between i^{th} and $i+1^{th}$ packets	Standard Deviation IAT Minimum IAT Maximum IAT Average IAT
RIAT	Relative Inter Arrival Time, IAT of the the packet divided my mimimum of IAT	Average RIAT Standard Deviation of RIAT Minimum RIAT Maximum of RIAT
Packet Size	Size of the packet in the flow including headers	Average Packet Size Standard Deviation of Packet Size Minimum Packet Size Maximum Packet Size
Flow Duration	Duration of the entire flow from initiation to termination	Flow Duration
Total Packet Size	Summation of the packet sizes of all the packets inside the flow	Total Packet Size
Number of Packets	Total number of packets inside the flow	Number of Packets
Packets per Second	$\frac{NumberofPackets}{FlowDuration}$	Average Packets Per Second
Bytes Per Second	$\frac{TotalPacketSize}{FlowDuration}$	Average Bytes Per Second
Payload Size	$Size_{PaloadSize} = Size_{Total} - Size_{header}$	Payload Size

TABLE V: Accuracy based on Flow attribute group

Total Pkt Size	Flow Duration	Number of Packets	Avg Pkts Per Sec	Avg Bytes Per Sec	Payload Size	Accuracy
✓	✓	×	×	×	×	92.92%
✓	×	✓	×	×	×	91.66%
✓	×	×	✓	×	×	91.12%
✓	×	×	×	×	✓	94.53%
×	✓	×	×	×	✓	92.58%
×	×	✓	×	×	✓	93.80%
✓	✓	×	✓	×	×	92.31%
×	✓	✓	×	×	✓	92.02%
✓	✓	✓	✓	×	×	91.86%

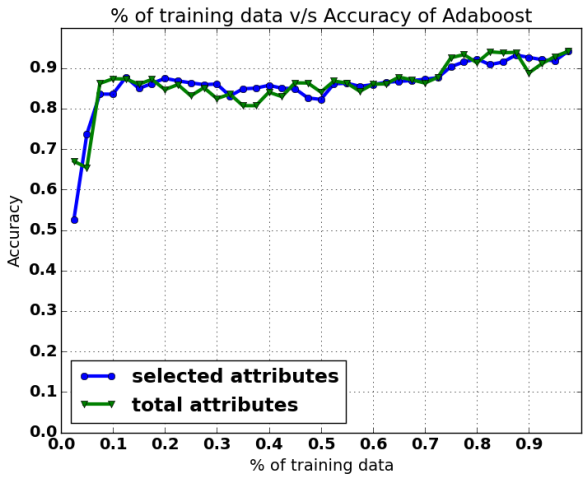

Fig. 3: Percentage of Training data v/s Accuracy for Adaboost

we consider total 18 attributes with Adaboost (Supervised) Algorithm[]. Extra attributes is not increasing accuracy at all. With less attributes we have faster classifier. From fig.2 we observe selection of subset of attributes increases accuracy dramatically.

IV. Multiple Cluster Models

A. Population Fraction

In this paper, we introduced new term called population fraction, which stands for percentage of dominant application (application with most number of flows in the cluster in consideration.) flows to total flows in a cluster

$$P_{clus} = (\frac{flows_{dominant}}{flows_{total}})_{clus} \quad (1)$$

B. Description of the technique used for classification

Based on V and IV we can observe particular combination of attributes results in better accuracy(like *Average Pkt Size* and *Std Div Pkt Size*). From fig.2 it can be observed that the accuracy of selected attributes is around 90%, which can be further improved by considering multiple trained models(with different combination of attributes) than with one

trained model(which has superset of combination of attributes used in multiple models). In a single classifier, supervised or unsupervised, we cannot consider combination of attributes as we have to put every attribute to be considered through training model. So, we advised usage of four different models, each with particular combination of attributes.

- *Model 1* In this model we considered attributes, Average Pkt Size and Standard Pkt Size.
- *Model 2* We considered Average, Minimum, Maximum Packet size attributes in this model.
- *Model 3* Considered Total Flow Size, Payload Size as the attributes for this model
- *Model 4* Considered Number of Packets, Payload Size as the attributes for this model.

We use results from four models in determining the final classified result of the incoming flow. We tested different hypothesis. Following are the explanation of hypothesis considered in deciding the final classification result. *Considered Strategies*

- *Random* Select classification of any of the results from the four models as the final classification result
- *Greatest* Select classification result from model with highest population fraction as the final classification result
- *Quorum* Select the majority result from trained models. If we have 3 models resulted in one classification result and other resulted in other application then we consider result of 3 as the final classification result. In case of tie we select application randomly
- *Unanimous* Select the final classification only when all the results from the four models exactly results in the same result. Otherwise mark it as unknown
- *Unanimous Greatest* Similar to unanimous but fallback hypothesis is greatest.
- *Unanimous Random* Similar to unanimous but fallback hypothesis is random
- *Unanimous Quorum* Unanimous with fallback hypothesis as Quorum

V. Evaluation

A. Datasets

Data had been collected with full payload in early-2014. It has been gathered on various interfaces 1) Wired 2) WIFI 3) 3G and LTE. Data had been collected for individual application in isolation, by generating requests intentionally and capturing bidirectional data. Considered five tuples (i.e., Source IP, destination IP, source port, destination port and protocol). Used TCP flags to mark the start and end of flow(flow started before the capture, or flows terminating after the capture are not considered in construction of flows).

We selected 5 protocols (Skype, Bittorrent, Http, Edonkey and Gnutella) for further study, criteria for the selection of this protocols is number of flows.

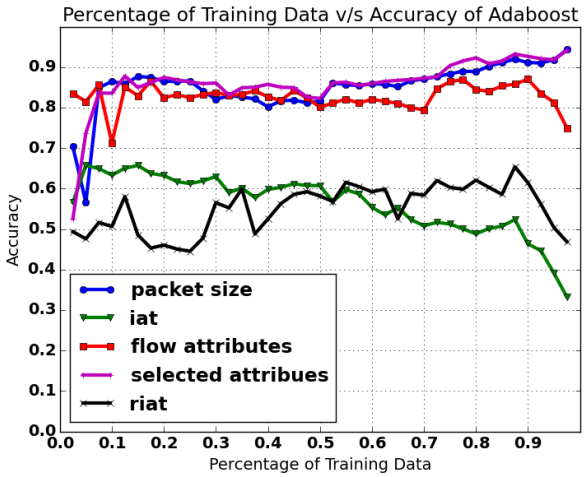

Fig. 4: Percent of training data v/s Accuracy for Adaboost with Groups of Attributes.Plotting Adaboost with each group of attributes.

B. Cleaning

We constructed flows from packets, which we read from *pcap* files using *scapy* a python library. Used community maintained signatures[] available for this protocols from L7 filters. We matched payload of each constructed flow with corresponding signatures from L7, if we find an unmatched flow then it is discarded otherwise labeled as the matched signature.

C. Experimental Setup

We used *sklearn* a python library for machine learning algorithms in our study. *sklearn* is the most used python library for data analysis in python. Used *Numpy* for numerical computations, it is a python library to handle numerical computation in efficient way. Used *Matplotlib* for plotting the results, it is a python library which lets us plot the results.

We divide our data into training and testing partitions. We used training data to train the model and testing data to test the accuracy of the trained model in correctly classifying protocols. During training phase we label clusters in each model(we have 4 of them) based on population fraction(majority based). Each test flow is fed into the trained model and we get the label for that test flow which is compared with the actual label for that flow. Finally

$$Accuracy = \frac{TP}{TotalFlows} \tag{2}$$

Where TP stands for True positive, meaning correctly identified flow during testing. Total flows are the total number of flows in the testing set.

D. Results

From fig.4 we notice classification with highest accuracy at almost all the ratios of training set is observed for Adaboost. Accuracy for Naive Bayes[] from fig.5 is very low when

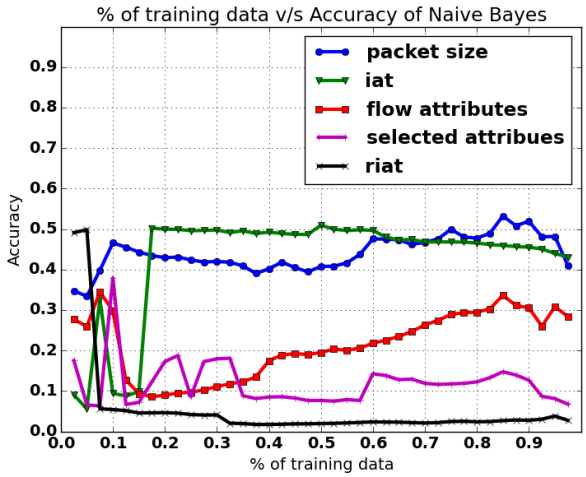

Fig. 5: % of training data v/s Accuracy for Naive Bayes with Groups of Attributes. Plotting Naive Bayes with each group of attributes.

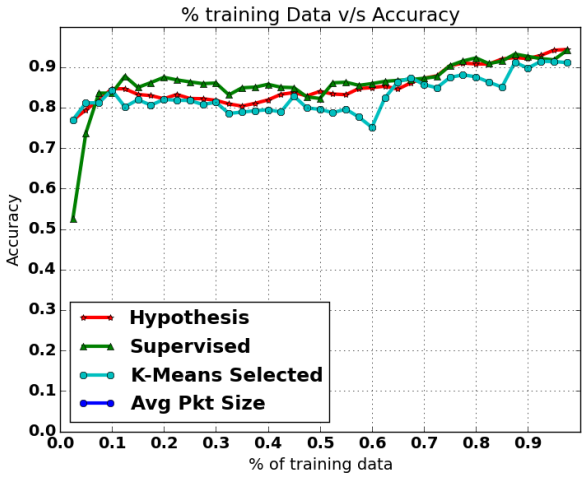

Fig. 7: Percent of training data v/s Accuracy Comparing all the existing and proposed technique

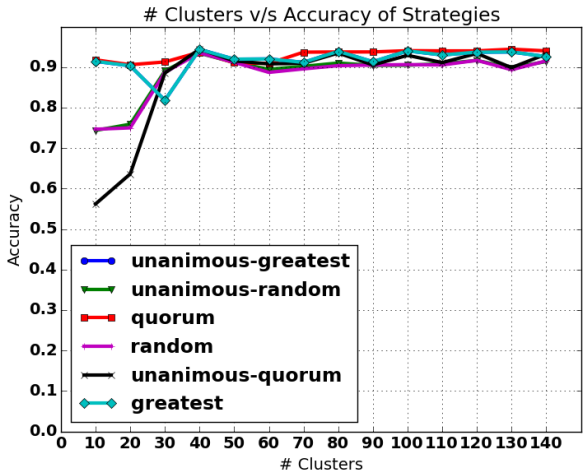

Fig. 6: # Clusters v/s Accuracy of various strategies

compared with Adaboost, it is not very effective in classifying the protocols.

From fig.6, it can noticed that accuracies are very high for *Quorum*, *Greatest* and *Unanimous Greatest* strategies.

We chose *Unanimous Greatest* for further study. Results for proposed classification technique, Supervised(Adaboost) and K-Means are used for comparison. From fig.7 we notice that the accuracy is higher than traditional K-Means clustering algorithm at almost all the ratios of the training set. Proposed technique accuracy is comparable to that of the supervised(Adaboost) technique, at times it is higher than supervised too.

VI. Conclusion

By considering all the attributes of flow in classifying the application doesn't give better results. Selected attributes with combinations gives better accuracy. Accuracy doesn't continually increases along with number of clusters, as we get better accuracy when we are around 40 clusters.

Considering IAT and RIAT for classification gives us the least accuracy when compared with other attributes of the flow. Even considering all attributes of packet size and flow also doesn't give better accuracy.

Population fraction will be very good parameter in classification of flow using clustering techniques.

Acknowledgment

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References

[1] L. Bernaille, R. Teixeira, and K. Salamatian, "Early application identification," in *Proceedings of the 2006 ACM CoNEXT Conference*, ser. CoNEXT '06. New York, NY, USA: ACM, 2006, pp. 6:1–6:12. [Online]. Available: http://doi.acm.org/10.1145/1368436.1368445

[2] J. Erman, M. Arlitt, and A. Mahanti, "Traffic classification using clustering algorithms," in *Proceedings of the 2006 SIGCOMM Workshop on Mining Network Data*, ser. MineNet '06. New York, NY, USA: ACM, 2006, pp. 281–286. [Online]. Available: http://doi.acm.org/10.1145/1162678.1162679

[3] L. Grimaudo, M. Mellia, and E. Baralis, "Hierarchical learning for fine grained internet traffic classification," in *8th International Wireless Communications and Mobile Computing Conference, IWCMC 2012, Limassol, Cyprus, August 27-31, 2012*, 2012, pp. 463–468. [Online]. Available: http://dx.doi.org/10.1109/IWCMC.2012.6314248

[4] P. Haffner, S. Sen, O. Spatscheck, and D. Wang, "Acas: automated construction of application signatures," in *Proceedings of the 2005 ACM SIGCOMM workshop on Mining network data*, ser. MineNet '05. New York, NY, USA: ACM, 2005, pp. 197–202. [Online]. Available: http://doi.acm.org/10.1145/1080173.1080183

[5] B. Park, Y. J. Won, M. Kim, and J. W. Hong, "Towards automated application signature generation for traffic identification," in *IEEE/IFIP Network Operations and Management Symposium: Pervasive Management for Ubioquitous Networks and Services, NOMS 2008, 7-11 April 2008, Salvador, Bahia, Brazil*, 2008, pp. 160–167. [Online]. Available: http://dx.doi.org/10.1109/NOMS.2008.4575130

[6] G. Xie, M. Iliofotou, R. Keralapura, M. Faloutsos, and A. Nucci, "Subflow: Towards practical flow-level traffic classification," in *Proceedings of the IEEE INFOCOM 2012, Orlando, FL, USA, March 25-30, 2012*, 2012, pp. 2541–2545. [Online]. Available: http://dx.doi.org/10.1109/INFCOM.2012.6195649

[7] M. Ye, K. Xu, J. Wu, and H. Po, "Autosig-automatically generating signatures for applications." in *CIT (2)*. IEEE Computer Society, 2009, pp. 104–109.