Exploring Unsupervised Learning Methods for Automated Protocol Analysis

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***Abstract*—The ability to analyse and differentiate network protocol traffic is crucial for network resource management to provide differentiated services by Telcos. Automated Protocol Analysis (APA) is crucial to significantly improve efficiency and reduce reliance on human experts. There are numerous automated state-of-the-art unsupervised methods for clustering unknown protocols in APA. However, many such methods have not been sufficiently explored using diverse test data-sets. Thus failing to demonstrate their robustness to generalise across diverse unknown protocols.**

This study proposed a comprehensive framework to evaluate various combinations of feature extraction and clustering methods in APA. It also proposed a novel approach to automate selection of model parameters for feature extraction, thus significantly reducing hyper-parameter space. Promising results of a novel field-based tokenisation approach also led to our proposal of a novel automated hybrid approach for feature extraction and clustering of unknown protocols in APA.

Our proposed hybrid approach performed the best in 7 out of 9 of the diverse test data-sets, thus displaying the robustness to generalise across diverse unknown protocols. It also outperformed the unsupervised clustering technique in state-of-the-art open-source APA tool, NETZOB in all test data-sets.

***Index Terms*—unsupervised learning, automated protocol analysis, protocol feature extraction and clustering.**

I. Introduction

Communication protocols are a predefined set of rules that multiple parties use at different OSI layers to communicate consistently. Despite there being many open-standards protocols (e.g. TCP, IP & 802.11), there are still numerous proprietary unknown protocols owned by companies & organizations. Therefore, there is the need for Protocol Analysis (PA) to infer detailed specifications of unknown protocols for network resource management, IoT interoperability, network protocol security audit, simulation and conformance testing [1]. Furthermore, the ability to analyse and differentiate network protocol traffic at routers (especially those of unknown protocols) is vital for effective network resource management by Telcos for differentiated Quality of Service (QoS).

This paper focuses on PA via Static Traffic Analysis based on analysis of captured network traffic of unknown protocols. This is a two stage process, where: 1) Vocabulary inference involves understanding the protocol messages, and 2) Grammar inference involves understanding the protocol predefined set of rules. Vocabulary inference involves clustering protocol messages into smaller and similar groups for subsequent inference of protocol field boundaries, relationships and semantics.

Traditionally, PA is done manually by experts and is very time-consuming, taking months or even years and it is challenging to recruit, train and retain such experts. Therefore, the need for APA was first raised in [2], with approaches inspired by disciplines like Bioinformatics, Natural Language Processing (NLP) and Machine Learning (ML) being proposed [3]–[5], so as to significantly improve efficiency and reduce reliance on human experts. Today, NETZOB [5] is the most comprehensive open-source APA framework that utilizes a bioinformatics-inspired method for protocol message clustering [6] and is our baseline for comparison.

This paper focuses on automated feature extraction and clustering of protocol messages in the Vocabulary inference stage. This is a crucial and early step affecting subsequent APA stages. We assume no prior knowledge and explore various unsupervised methods. Our key contributions are:

1) Developed a comprehensive APA framework for evaluation of various combinations of state-of-the-art unsupervised feature extraction & clustering methods.
2) Proposed novel methods for automated model optimisation for APA and developed greater insights into techniques for automatic field-based tokenization.
3) Comprehensive experimentation of unsupervised automated features extraction and unknown protocol message clustering for APA, leading to an improved hybrid approach over state-of-the-art open-source APA tool, NETZOB and other related works.

Section II presents related works, Section III presents our proposed APA framework and methods, Section IV describes the experiment methodology, Section V discusses our experiment results and finally Section VI concludes the paper.

II. Related Works

Related works have typically focused on inferring message format types from packets of a single unknown protocol [5] - [7], using feature extraction and clustering techniques such as sequence alignment [5] and information bottleneck [8]. Today, there are hundreds of different protocols and it is naive and limiting to assume that a stream of unknown packets belong to a single protocol. Hence, our proposed framework (in Section III) aims to automatically differentiate both unknown protocol and message format types via distinguishing features to facilitate further analysis in later APA stages.

Previous works have also typically used information from the entire packet for feature extraction [5] - [7]. However, only the header of protocol packets usually contain information with relevance to the protocol's operation. Hence, it is desirable to perform feature extraction on only the packet header. Faced with an unknown protocol, there is no information on the length of this header portion. Therefore, our framework introduces a novel method that aims to infer the header length of the unknown protocol that yields the most amount of useful information for differentiating unknown protocols.

To extract features of an unknown protocol, techniques from bioinformatics and NLP have been employed. Bossert et al proposed NETZOB [5], which uses Needleman-Wunsch Sequence Alignment (NWSA) from bioinformatics to infer message formats and cluster protocols & message types, while Discoverer [2] uses tokenisation, recursive clustering and merging clusters to do so. Both techniques require expert knowledge on common delimiters in the protocol. The global sequence alignment technique NWSA used by NETZOB is also computationally time expensive ($\mathcal{O}(n^2)$, where n is the number of data packets), and makes use of only observable literal information, ignoring semantic information. Luo et al [7] proposed using Latent Dirichlet Allocation (LDA) from NLP to study the type distributions derived from the statistics of message N-grams to infer protocol message formats of different types. However, the study did not perform an extensive hyper-parameter tuning of the α & β that control the Dirichlet distribution or to select the size of LDA topics.

Kleber et al proposed NEMESYS [9] that uses the delta of the congruence in bit values of consecutive bytes to identify field boundaries in a packet using its intrinsic message structure. For text-based protocols with longer fields, this intrinsic structure-aware approach of obtaining field boundaries is able to produce more meaningful tokens than n-grams. NEMESYS is used by our novel field-based tokenisation approach.

III. Proposed APA Framework

The proposed APA framework comprises steps shown in Fig 1. It does not strictly mandate a linear application of methods, but rather encapsulates a set of unsupervised methods to be potentially used in combination. Section IV-B lists the combination of methods that we evaluated. Methods in each step of the framework are described as follows:

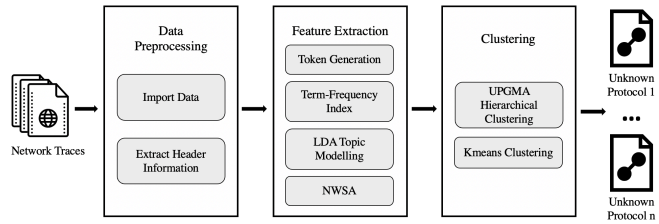


Fig. 1: Overview of Proposed APA Framework

A. Data Pre-Processing

Network traces in PCAP format are imported using the Python SCAPY library as binary or hexadecimal packets to facilitate feature extraction. We assumed that all protocols at OSI layers below the unknown protocol are known and their headers stripped from the packet. Finally, the header of the unknown protocol can be extracted from the remaining packet using the inferred header length from Section III-B5.

B. Feature Extraction

The framework proceeds to extract distinguishing features, from the header of the unknown protocol, that will be utilized in subsequent clustering stage to differentiate packets from different protocols and message format types.

1) Tokens Generation: In NLP's N-grams tokenisation [8], one gram is a single word and adjacent words in a text string are combined to form tokens. In contrast, protocol headers are typically parsed as binary strings, one gram is represented by a single byte and consecutive bytes combined to form a N-grams token. Alternatively for text-based protocols with longer fields, a novel field-based tokenisation approach is proposed where NEMESYS [9] is used to infer field boundaries within a protocol header and tokenisation performed along these boundaries. The resultant corpus of tokens generated for each protocol header packet can be further analysed by advanced statistical methods like LDA in Section III-B3 to generate distinguishing features for subsequent clustering.

2) Term-Frequency (TF) Index: With a generated corpus of tokens per protocol packet, the next step is to generate an appropriate feature representation that is distinct for different protocols and message formats. First, we explored using the TF index for feature extraction. By recording the raw count of unique tokens in each corpus, a TF matrix of size $p \times n$ is generated (where p is number of protocols and n is number of unique tokens). Despite its intuitive representation, the generated matrix is often sparse, making computational storage unnecessarily expensive. Furthermore, the high dimensionality of the matrix meant that the application of dimensional reduction methods such as Principal Component Analysis (PCA) would often be required as clustering performance generally depreciates with higher dimensions.

3) Latent Dirichlet Allocation (LDA): Due to the limitations of the TF index discussed above, we sought a more efficient alternative. Next, we explored the use of LDA from NLP for feature extraction. LDA is an unsupervised topic modelling approach that allocates the generated tokens to a set of predefined number of LDA topics, based on the statistical extent of dissimilarity in which each individual token shared with other tokens in the corpus. Using the structured topic modelling (stm) package in R [10], a vector representation for each protocol packet in the data set is generated. This vector represents the posterior probability of the packet belonging to a particular LDA topic, given the corpus of tokens.

4) Optimising LDA Topic Size: The topic size is a key LDA hyper-parameter that determines not only the size, but also the generated feature representation that will be used to represent each protocol packet of a data-set. As such, it is crucial for practical deployment to automate and optimise the selection of this key LDA hyper-parameter, as optimising the topic size results in better clustering performance, with the optimised value being specific to the individual data-set. However despite its importance, such hyper-parameter tuning has not been explored in previous works.

By utilising the mean semantic coherence and exclusivity scores of a LDA topic size [10] as unsupervised metrics, the LDA topic size hyper-parameter can be automatically optimised for a given data-set, thus resulting in better clustering performance. The FREX metric [11] is used as a measure to quantify the degree of exclusivity of a given topic in a way that balances the word frequency, with $\mathrm{FREX}_{\mathrm{k,v}}$ being the weighted harmonic mean of the rank of token v in topic k (Equation 1). While the exclusivity score provides a quantity of measure for the degree of dissimilarity between LDA topics generated from a specific size, the semantic coherence score measures the extent in which tokens in the same topic co-occur together in the same communication protocol (Equation 2).

$$FREX_{\mathrm{k,v}} = \left(\frac{\omega}{ECDF(\beta_{k,v} / \sum_{j=1}^{K} \beta_{j,v})} + \frac{1-\omega}{ECDF(\beta_{k,v})} \right)^{-1} \quad (1)$$

where ECDF is the empirical CDF, $\beta_{k,v}$ is the topic-specific frequency of token v in topic k and ω is the weight set to 0.7 to favor exclusivity.

$$C_{\mathrm{k}} = \sum_{i=2}^{M} \sum_{j=1}^{i-1} log \left(\frac{D(v_{\mathrm{i}}, v_{\mathrm{j}}) + 1)}{D(v_{\mathrm{j}})} \right) \quad (2)$$

where $\mathrm{C_k}$ is the semantic coherence for topic k, $\mathrm{D(v_i,v_j)}$ is the number of times tokens $\mathrm{v_i}$ and $\mathrm{v_j}$ appear together in the same protocol and $\mathrm{D(v_j)}$ is the total number of times the token $\mathrm{v_j}$ appears in the data set.

With the derivation of the exclusivity and semantic coherence scores for each LDA topic in a given size of generated topics, the mean values of the topics in each size were used as a measure for the overall quality of the topics generated from that specific topic size. With the vast difference in scales of the mean exclusivity and semantic coherence scores, the values were normalised to between 0 and 1. The optimum topic size can then be determined graphically by the data point with the greatest Euclidean distance from the origin. This data point will correspond to the selected optimised LDA topic size hyper-parameter. For example, in Figure 2, it is observed that the optimum number of LDA topics selected for the Link Layer data-set (described in Section IV-A) was 6.

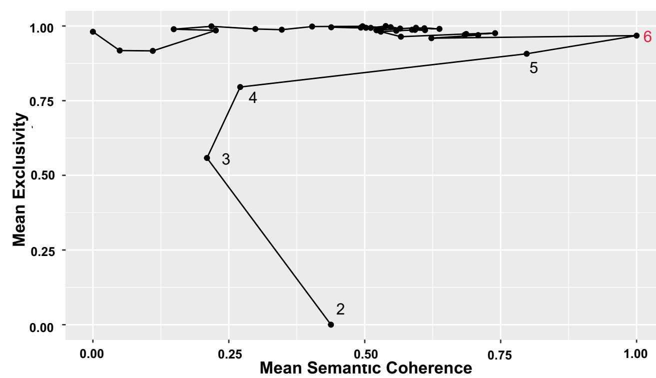


Fig. 2: Mean Exclusivity against Mean Semantic Coherence for Link Layer data-set. Points represent mean values for a topic size, with topic size increasing along the trace.

5) Optimising Extracted Protocol Header Length: In the data pre-processing stage (Section III-A), we would require the length of the unknown protocol header to be accurately estimated, as this would result in the right amount of features to be extracted, in order to obtain good clustering results. Similar to optimising the LDA topic size hyper-parameter (Section III-B4), optimising the extracted header length in the pre-processing is also crucial for practical deployment that has not yet been explored in previous works.

Based on our analysis, key features found in the header of the protocol packets are often sufficient in distinguishing between the different protocol and message format types. Conversely, using the entire protocol packet for feature extraction and clustering would often introduce a significant amount of stochastic noise into the data, thus adversely affecting the quality of LDA topics generated and subsequently clustering performance. Therefore, it is crucial to be able to accurately estimate the appropriate protocol header length to be extracted, and used for subsequent feature extraction and clustering stages. Just like the LDA topic size, it was observed that the extracted header length was also a hyper-parameter value that was specific to the individual data set.

We extend the approach to optimise the LDA topic size hyper-parameter (Section III-B4) by varying the header length, and produced different iterations of the plot in Figure 2. The goal is to determine the appropriate header length to be used for a data-set, given the various plots generated. A novel approach proposed, is to select the header length that generated the plot with the most isolated optimal data point (i.e. highest euclidean distance from origin). Consequently, the optimised header length selected would generate the optimised LDA topic size with greatest difference in exclusivity and semantic coherence scores. Mathematically, the degree of isolation is measured by mean difference in Euclidean distance between the optimum data point and its two adjacent neighbours.

6) Needleman-Wunsch Sequence Alignment (NWSA): NSWA from bioinformatics is used by NETZOB [12] to compute the alignment score, by comparing the similarity between packet sequences via global sequence alignment. Iterating over each data-set, a matrix of alignment scores can be generated for clustering. It is more expensive computationally and thus unsuitable for clustering of large data-sets.

C. Unsupervised Clustering

The framework proceeds to cluster packets of the same protocol or message format into disjoint sets using the set of representative features extracted via methods in Section III-B in an unsupervised manner via a similarity metric.

1) Similarity Metric: Conventionally, determining the degree of similarity between data points has often been through the use of Euclidean distance in the N-dimensional subspace. However, given that the dimension of the set of representative features increases with LDA topic size, the degree of sparseness also increases exponentially. Therefore, the curse of dimensionality [13] makes Euclidean distance a poor similarity metric candidate for protocols clustering. Alternatively, the Cosine similarity metric is often a better choice for high-dimensional data that considers each data point to be represented by a single vector and scores the similarity between pairwise vectors based on the angle between them.

2) UPGMA Hierarchical Clustering: The unweighted pair group method with arithmetic mean (UPGMA) algorithm is an agglomerative hierarchical clustering algorithm that regards each protocol packet as first belonging to a single cluster and then proceeds to combine the 2 most similar clusters to form a larger overarching cluster in an iterative manner using the cosine similarity metric. This is repeated until the threshold to indicate the minimum degree of dissimilarity between the clusters is exceeded. We use a static threshold of 0.5 and this results in a tree-like dendrogram as shown in Figure 3.

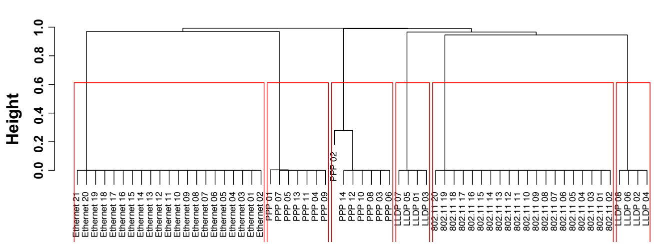


Fig. 3: Dendrogram of Clustering Link Layer Protocols with 6 disjoint clusters formed.

3) K-Means Clustering: Alternatively, the K-Means clustering algorithm is an unsupervised learning algorithm that first assigns the data points randomly into K distinct and disjoint clusters, and then iteratively shifts the K centroids based on the class association of the data points to the nearest centroid. In each step, the algorithm assigns the data points to new clusters, such that the within sum of squares of the clusters are reduced in each iteration, eventually converging to a global minimum at some point. The number of predefined centroids, K, can be determined through the ”elbow method”, which is automated with the use of the Kneedle algorithm [14]. The stochastic nature of the clustering output is due to the random initialisation of the K centroids that may not be desirable.

IV. Experiments

A. Data-sets

This study aims to differentiate unknown protocols at different OSI layers, and different message format types of an unknown protocol. Hence, a wide variety of protocol and message format types is necessary to test the framework extensively. Therefore, the diversity with and within our 9 data-sets in total, comprehensively evaluates the robustness and the ability to generalise for unknown protocols of our proposed framework. Each data-set comprises 200 protocol packets sourced from open-source.

The 5 protocols used for fine-grain type clustering are ICMP, TCP, SCTP, DNS and HTTP and the aim is to cluster the message format types in each protocol (e.g. ICMP 8, ICMP 0 & TCP ACK, TCP SYN etc.). Additionally, we have 4 OSI layers-based data-sets, with each data-set containing protocols from the respective OSI layers, where the aim is to cluster the protocols types in each layer. Note that all message format types in the single protocol-based data-sets and all protocols in the OSI layers-based data-sets are assumed to be unknown. Table I describes the unknown protocols at each OSI layer for the 4 OSI layers-based data-sets.

OSI Layer	Unknown Protocols
Link	Point to Point Protocol (PPP), Link Layer Discovery Protocol (LLDP), IEEE 802.11, Ethernet
Transport	Internet Control Message Protocol (ICMP), Transmission Control Protocol (TCP), User Datagram Protocol (UDP), Stream Control Transmission Protocol (SCTP)
Application (Binary Protocols)	Domain Name Server (DNS), Routing Information Protocol (RIP), Transport Layer Security (TLS)
Application (Text-based protocols)	Trivial File Transfer Protocol (TFTP), Hypertext Transfer Protocol (HTTP), Simple Mail Transfer Protocol (SMTP)

TABLE I: Protocols used for each OSI Layer Data-set

B. Experimental Setup

Our experiments have three objectives. First, to compare the different tokenisation methods of proposed framework, which is done by comparing N-grams and NEMESYS [9] across the 9 data-sets. Second, to evaluate both the proposed LDA topic size and extracted protocol header length optimisation methods. This is done by varying the LDA topic sizes and header lengths to observe how the chosen topic size and header length compare with the actual best-performing topic size and header length. And finally, to compare the overall clustering performance across 5 different combinations of feature extraction & clustering methods of the proposed framework. The first approach is to use the open source APA tool, NETZOB that utilizes NWSA feature extraction and UPGMA clustering. The second approach combines LDA features extraction with K-MEANS clustering. The third approach combines LDA features extraction with UPGMA clustering. The fourth approach uses TF index feature extraction with UPGMA clustering. N-grams tokenisation is used with all feature extraction methods, with the exception of NWSA. Finally, the fifth approach is our proposed hybrid approach that automatically selects the best feature extraction method based on our findings from the previous four approaches. By default, TF index feature extraction is used with UPGMA clustering. However, for application layer binary protocols, LDA feature extraction is used, and for application layer textual protocols, our proposed field-based tokenisation based on NEMESYS is used instead. The detection of binary or textual protocols can be achieved automatically via suitable predefined rules.

We repeat the entire process of proposed APA framework (in Section III) for all 9 data-sets. The header length for each data-set is determined using the proposed method in the Section III-B4 for all feature extraction methods in the proposed framework. Before starting our experiments, a comprehensive hyper-parameter tuning process was done. For NEMESYS, the σ value for bit congruence was optimal at 0.5 and that no tokens should be kept longer than 40 bytes. For N-grams tokenisation, hexadecimal packet representation was more efficient than binary for all feature extraction methods. Moreover, a gram size of 3 bytes was determined to be optimal. Optimal values for all tuned hyper-parameters will be used across all data-set. Due to space constraints, we are unable to present the detailed tuning results in this paper.

V. Results and Discussion

A. Evaluation Metric

To quantify overall clustering performance, the evaluation metric used is the Adjusted Rand Index (ARI). It is a modified version of the rand index which is commonly used as an extrinsic indicator of unsupervised clustering performance based on the deviation from the ground truth [15]. We deem ARI > 0.4 as satisfactory clustering performance. Ground truth labels extracted from well-known protocols in the 9 data-sets are used strictly for performance evaluation only.

B. Results Analysis

Our first objective is to compare the tokenisation methods (Section IV-B). Figure 4 shows the ARI for NEMESYS and N-grams tokenisation across the 9 data-sets. There is no clear winner and NEMESYS out-performs in 5 out of 9 data-sets. Closer analysis shows that NEMESYS performs significantly better than N-grams tokenisation for both application layer textual protocols and HTTP protocol data-sets, which is also an application layer textual protocol. Our results suggest that NEMESYS tokenization is more effective for application layer textual protocols. This leads us to propose a novel field-based tokenisation based on NEMESYS for application layer textual protocols in our proposed hybrid approach (Section IV-B).

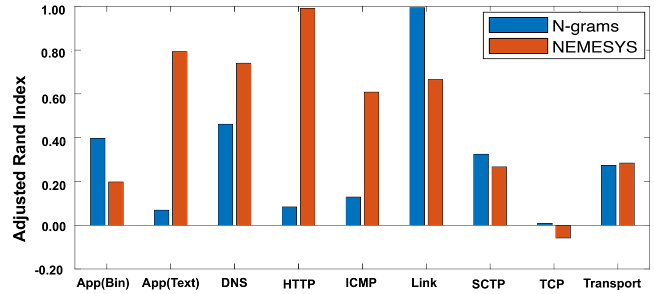


Fig. 4: ARI of NEMESYS vs. N-grams tokenisation across 9 data-sets

Our second objective is to evaluate both the proposed LDA topic size and extracted protocol header length optimisations. Figure 2 shows that the optimised LDA topic size for the link layer data-set was chosen to be 6. For validation, we plotted how ARI varies with changing topic size (Figure 5) and observed that performance was poor (i.e. low ARI) with small topic sizes, but improves until ARI peaks with optimal topic size 6. Similarly, the LDA topic sizes selected using proposed optimisation method in Section III-B4 are either optimal or near-optimal for the other data-sets.

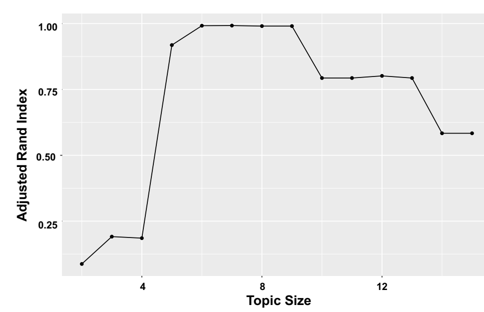
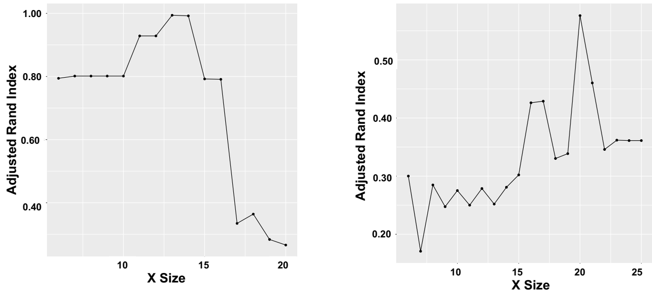


Fig. 5: ARI of LDA feature extraction for Link Layer data-set against topic size

For optimising the extracted protocol header length needed in pre-processing stage (Section III-A), Figures 6a & 6b show that the optimised protocol header lengths for link layer and transport layer data-sets were chosen to be at 14 and 20 bytes respectively, which corresponded to highest ARI scores. Similarly, the header lengths selected using proposed optimisation method in Section III-B5 were either optimal or near-optimal for the other data-sets. Therefore, both proposed LDA topic size and extracted protocol header length optimisations have been validated and are deemed crucial for practical deployment, which has not yet been previously explored.

Figure 7 compares final clustering performance results of the 5 approaches (Section IV-B) across all 9 data-sets. Results show that our proposed hybrid approach is best performing in 7 out of 9 data-sets, with ARI $>$ 0.4 for 6 data-sets. Unfortu-



(a) Link Layer data-set (b) Transport Layer data-set

Fig. 6: ARI of LDA feature extraction against protocol header length for Link and Transport data-sets

nately, all approaches did not achieve satisfactory performance (ARI $<$ 0.4) for the STCP, TCP and Transport layer data-sets. Upon further investigation, we realised that these 3 data-sets comprised of more protocols and message format types to differentiate with less distinct features, thus making effective clustering challenging. However, after further analysis of the UPGMA dendrograms generated from our proposed approach, we observed that by optimising the static UPGMA threshold of 0.5 (Section III-C2), it is possible to significantly improve the performance, which we leave for future works.

Finally, due to the extensive coverage of our 9 data-sets across all the OSI layers with diverse protocols and message format types, we have proven the robustness of our proposed hybrid approach to generalise for unknown protocols, which is crucial for practical deployment and has not been adequately addressed in previous works.

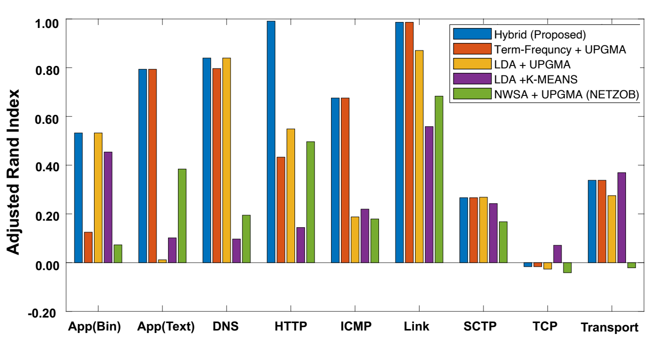


Fig. 7: Comparing ARIs of 5 approaches across 9 data-sets

VI. Conclusion

In conclusion, we proposed a comprehensive APA framework and evaluated various combinations of feature extraction and clustering methods, including those used by NETZOB [5]. Our proposed hybrid approach, that utilizes a novel field-based tokenisation based on NEMESYS for application layer textual protocols, is best performing in 7 out of 9 data-sets with ARI $>$ 0.4 for 6 data-sets. This result proves the robustness and generalising ability of our proposed hybrid approach. We also validated our proposed automated optimisation methods, for both LDA topic size and extracted protocol header length, that is crucial for practical deployment.

We hope that our works contributed as crucial foundation stones for future APA works to be built upon. With recent advances in Deep Learning, like Deep Auto-Encoders for automated features extraction, it will be exciting to explore the application of these advanced Machine Learning (ML) methods for unsupervised learning in APA. Finally, we have only explored the tip of the APA iceberg and in the future, we hope to build upon our proposed APA framework to explore application of advanced ML methods in more areas of APA.

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