# Activity Detection from Encrypted Remote Desktop Protocol Traffic

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Abstract—An increasing amount of Internet traffic has its content encrypted. We address the question of whether it is possible to predict the activities taking place over an encrypted channel, in particular Microsoft's Remote Desktop Protocol. We show that the presence of five typical activities can be detected with precision greater than 97% and recall greater than 94% in 30-second traces. We also show that the design of the protocol exposes fine-grained actions such as keystrokes and mouse movements which may be leveraged to reveal properties such as lengths of passwords.

## I. INTRODUCTION

One response to the obvious security weaknesses of networks is to encrypt the payloads of packet traffic. It was estimated in 2018 that encryption was used in more than 70% of network communications [21] but the rate of penetration is quite variable because of the cost and complexity of public key infrastructure, particularly for small enterprises. We explore the question of how much can be detected about interactions, even when payloads are encrypted. In particular, we are concerned with activity detection: what is a user doing?

There are some legitimate reasons to be able to answer this question: determining usage to insure adequate provisioning, for example. It is also important to know how much an adversary could infer [34]. We focus on the Microsoft Remote Desktop Protocol (RDP), a popular protocol that provides an encrypted channel between a client and a host, allowing remote work on the host [10]. Five major interactions occur between client and host: file download, browsing on the host (i.e. a mixture of viewing, typing, and using the mouse), using an editor on the host, watching a video, and copying content from host to client or *vice versa* using the clipboard.

We show that, even though all traffic is encrypted, it is possible to detect which of these activities is underway from the traffic properties, even if two or more simultaneous activities are occurring. A heterogeneous ensemble classifier achieves precision greater than 97% and recall greater than 94%. We also discover that there are markers in the protocol that are directly related to fine-grained user actions.

## II. RELATED WORK

Traffic inspection and classification has two main purposes: security (detecting malicious activity [25]), and quality of service management (insuring resources are appropriate for

traffic [23]). Traffic analysis can be done using: port structure (services being used) [9], deep packet inspection (signatures in payloads) [9], data analytics (per-packet or per-flow) [5], or behavioral classification (communication pattern graphs) [5].

To overcome the weaknesses associated with the portbased and payload-based approaches, data analytics has been proposed as a solution for network traffic classification [2], [13]. In particular, data-analytic approaches can detect novel traffic using anomaly detection [33].

Draper-Gil et al. [11] generated a dataset used by several researchers to predict traffic classes. It contains browsing, email, chat, streaming, file transfer, VoIP, and P2P traffic; each inside and outside of a VPN tunnel. However, each window contains only a single kind of traffic. Draper-Gil used k-Nearest Neighbor and decision tree predictors; Saber et al. [26] used under- and over-sampling, PCA, SVMs; Lotfollahi et al. [19] used stacked autoencoders and convolutional neural networks; and Vu et al. [30] used LSTMs. The best models on this dataset achieve F1 scores up to 0.98 on the single-class prediction problem.

Zhang et al. [32], in the closest work to ours, classify categories of seven types of activities: Browsing, Chat, Online Gaming, Downloading, Uploading, Online Video, and BitTorrent, using windows of different sizes. However, each window contains at most two simultaneous kinds of traffic. They achieve around 80% prediction accuracy for 5-second windows and over 90% accuracy for 1-minute traffic windows for the single class problem. Their accuracy decreases for some classes when there are two concurrent activities.

A finer-grained, and harder, version of the problem is to detect not only the kind of traffic but which application is being used. Taylor et al. [28] create an "Appscanner" tool to recognize smartphone apps in encrypted traffic. Their work was later improved by Taylor et al. [29] using bursts, packets grouped within a time window. They analyze one second bursts to deliver near real-time prediction for 110 out of 200 most popular free Google Play applications. Alan and Kaur [1] reduce computational complexity by analyzing only the first 64 packets to identify the application. Saltaformaggio et al. [27] achieve an average of 78% precision and 76% recall using KMeans and multi-class SVM and properties that could be captured by eavesdropping. In addition, they also

paid attention to how easy it was to discover user properties from the traffic, and revealed some major privacy issues. Application identification is also possible in encrypted tunnels. Lotfollahi et al. [19] and Yamansavascilar et al. [31] run their experiments on the same VPN dataset by Draper-Gil et al. [11] to detect application instead of the broad traffic category.

A related problem is to detect what actions users are doing on their devices, that is behavioral detection. Conti et al. [7] analyze encrypted traffic from Android devices to discover user behaviors such as sending a new message with Gmail or opening the Dropbox app. Their study included seven Android applications: Facebook, Gmail, Twitter, Tumblr, Dropbox, Google+ and Evernote and they simulated user actions to obtain signatures of flows generated by use of these apps. Coull and Dyer analyze user behaviors in Apple iMessage [8] and showed that users' actions, as well as language and length of messages exchanged, can be predicted. Park and Kim [24] predict KakaoTalk's eleven behaviors in encrypted traffic. Liu et al. [18] predict whether a user is using Wechat, WhatsApp and Facebook and behaviors such as voice calling, video calling or picture sharing. Dubin et al. [12] trained a classifier to predict the most popular YouTube videos titles, basing on encrypted traffic statistics, notably the bits per peak.

#### III. APPROACH

A real-world system was used to collect RDP traffic data about five classes of traffic. Derived data were computed from the base traffic data using Discrete Cosine Transform, singular value decomposition, and independent component analysis. A series of predictive models were then built and their performance assessed using standard measures as well as a custom measure designed for the problem.

# A. System setup

The Remote Desktop Protocol is designed to let a user at a client interact with a host as if sitting at that host. It provides the full interactivity of using the mouse, viewing the screen, and using the keyboard.

The client workstation, called Workstation01, is a 6-core Intel Xeon processor, 36 GB memory, 2 TB storage and Network Interface Card connected to a Local Area Network with an Internet gateway, running Microsoft Windows 10 Professional. For data analysis, Java Runtime Environment 1.8 was installed to run CIC FlowMeter v4.0 for attribute extraction, and Wireshark to capture RDP network traffic into .pcap files. As a Remote Desktop client, Workstation01 is configured to mount local drives, allow clipboard and runs in resolution 1366x768 with full user desktop experience.

Hyper-V service is enabled on Workstation01 for virtualization and there are two virtual machines running on it: Win01 and Centos-Miner. Win01 VM is a plain installation of a Windows 10 Professional 1809 virtual machine that acts as a Remote Desktop host. The VM is configured with 4 virtual cores and 8 GB of RAM. It has a static IP, Network Level Authentication, and a Windows firewall with an exception

allowing incoming RDP traffic. This setup ensures that Workstation01 can connect freely to Win01 VM over both TCP and UDP protocols on port 3389.

CentOS-Miner is a CentOS 7.5 VM running on top of Workstation-01 Hyper-V. This Linux virtual machine has a Bash environment and Tshark installed and it is used for data exploration and additional attribute extraction.

A physically remote VM, CAC01, is hosted at Queen's University's Centre for Advanced Computing. The configuration is exactly the same as for Win01 VM except that it runs Windows 10 Education, and resides behind a firewall with NAT. CAC-01 has 4 virtual cores and 4 GB of RAM.

Traffic to Win01 is on the same IP subnet as the client, and only encounters the built-in Windows firewall on Win01 itself. Traffic to CAC01 passes through an Internet connection, the Queen's University campus network, and a physical firewall that accepts connections on port 13389 and forwards them to CAC01 on port 3389. RDP uses TCP only for traffic outside a subnet, and a mixture of TCP and UDP for traffic within a subnet, so two different predictive models had to be developed.

Figure 1 shows the network setup with all the Virtual Machines used for data generation. The red path shows the traffic path for the local subnet scenario and the green path represents the distant scenario, traversing the Internet.

#### B. Data Collection

The Remote Desktop traffic attributes were captured for 30 second windows of one or more of the following activity classes:

- Download file download from host to client;
- Browsing using a browser (Firefox and Chrome) on the host, driven from the client;
- Notepad editing on the host from the client (typing for more than 80% of the time window);
- YouTube playing a video on the host (Youtube or mp4s), viewed on the client; and
- Clipboard copying content from remote system to local using the clipboard mechanism.

Samples may be pure – a single activity for 30 seconds – or mixed, with up to four activities simultaneously in a 30-second window.

Attribute collection is performed by CIC Flow Meter and Tshark. The former is a tool developed by University of New Brunswick's Canadian Institute for Cybersecurity [16]. CIC Flow Meter extracts a predefined number of attributes for each network traffic conversation from a .pcap file. There will be one conversation for TCP only traffic samples, and two conversations for TCP and UDP traffic samples. Predictive attributes include properties such as packet lengths, interarrival times and TCP SYN flag counts.

A Bash script extracts additional meaningful predictive attributes from the packet-level attributes of Tshark. The additional attributes include Packet Length Statistics from Wireshark, as shown in Figure 2, and include attributes discovered during exploratory data analysis. All of the data is preprocessed to insure that forward always refers to traffic

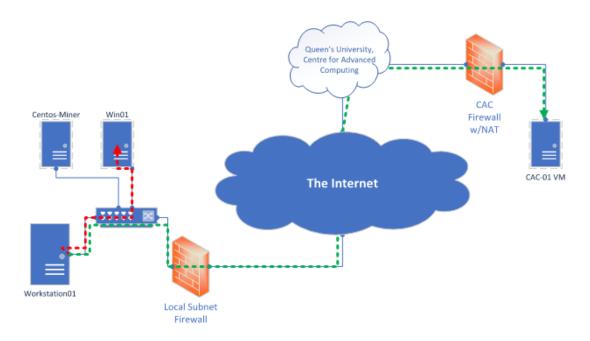


Fig. 1. Network architecture diagram

Topic / Item	Count	Average	Min val	Max val	Rate (ms)	Percent	Burst rate	Burst start		
✓ Packet Lengths	833	88.22	52	295	0.0283	100%	0.1100	23.574		
0-19	0	-	-	-	0.0000	0.00%				
20-39	0				0.0000	0.00%				
40-79	316	53.72	52	56	0.0107	37.94%	0.0300	1.109		
80-159	491	102.58	92	153	0.0167	58.94%	0.0800	23.574		
160-319	26	236.35	171	295	0.0009	3.12%	0.0200	8.472		
320-639	0				0.0000	0.00%	-			
640-1279	0	-	-	-	0.0000	0.00%				
1280-2559	0	-	-	-	0.0000	0.00%				
2560-5119	0				0.0000	0.00%				
5120 and greate	r 0	-	-	-	0.0000	0.00%	-			
isplay filter: Enter a disp	lay filter								App	olv

Fig. 2. Wireshark - packet length statistics

from local to remote, and backward the converse, based on IP addresses.

Several derived attributes of the measured traffic attributes were also computed. The Discrete Cosine Transform expresses a sequence as a sum of cosine functions. It has often been observed that a single component of the DCT integrates the variability within a sequence [22]. We compute this value for each row of the dataset, that is for the collected traffic attributes of each traffic flow.

Singular Value Decomposition is an affine transformation of a vector space into a form where the greatest variability is captured by the first few axes of the transformed space. Truncation of the SVD amounts to a projection of a high-dimensional space into a low-dimensional one in a way that preserves maximal variation. We apply SVD to the matrix of windows  $\times$  traffic attributes and keep the first 20 columns of the left singular vector matrix.

Independent Component Analysis (ICA) [15] is another matrix transformation that decomposes a matrix into statistically independent components. We apply ICA to the windows

TABLE I ATTRIBUTES

Attributes							
ACK Flag Cnt	Fwd Blk Rate Avg	Subflow Bwd Byts	svd8				
Active Max	Fwd Byts/b Avg	Subflow Bwd Pkts	svd9				
Active Mean	Fwd Header Len	Subflow Fwd Byts	svd10				
Active Min	Fwd IAT Max	Subflow Fwd Pkts	svd11				
Active Std	Fwd IAT Mean	Tot Bwd Pkts	svd12				
Bwd Blk Rate Avg	Fwd IAT Min	Tot Fwd Pkts	svd13				
Bwd Byts/b Avg	Fwd IAT Std	TotLen Bwd Pkts	svd14				
Bwd Header Len	Fwd IAT Tot	TotLen Fwd Pkts	svd15				
Bwd IAT Max	Fwd PSH Flags	URG Flag Cnt	svd16				
Bwd IAT Mean	Fwd Pkt Len Max	FwdFrame91-93	svd17				
Bwd IAT Min	Fwd Pkt Len Mean	FwdFrame80-91	svd18				
Bwd IAT Std	Fwd Pkt Len Min	FwdFrame90-94	svd19				
Bwd IAT Tot	Fwd Pkt Len Std	FwdFrame96-98	ica0				
Bwd PSH Flags	Fwd Pkts/b Avg	FwdFrame103-105	ica1				
Bwd Pkt Len Max	Fwd Pkts/s	FwdFrame1280-2559	ica2				
Bwd Pkt Len Mean	Fwd Seg Size Avg	BwdFrame40-79	ica3				
Bwd Pkt Len Min	Fwd URG Flags	BwdFrame80-159	ica4				
Bwd Pkt Len Std	Idle Max	BwdFrame160-319	ica5				
Bwd Pkts/b Avg	Idle Mean	BwdFrame320-639	ica6				
Bwd Pkts/s	Idle Min	BwdFrame640-1279	ica7				
Bwd Seg Size Avg	Idle Std	BwdFrame1280-2559	ica8				
Bwd URG Flags	Init Bwd Win Byts	BwdPUSH	ica9				
CWE Flag Count	Init Fwd Win Byts	FwdPUSH	ica10				
ECE Flag Cnt	PSH Flag Cnt	dct_col	ica11				
FIN Flag Cnt	Pkt Len Max	svd0	ica12				
Flow Byts/s	Pkt Len Mean	svd1	ica13				
Flow Duration	Pkt Len Min	svd2	ica14				
Flow IAT Max	Pkt Len Std	svd3	ica15				
Flow IAT Mean	Pkt Len Var	svd4	ica16				
Flow IAT Min	Pkt Size Avg	svd5	ica17				
Flow IAT Std	RST Flag Cnt	svd6	ica18				
Flow Pkts/s	SYN Flag Cnt	svd7	ica19				

 $\times$  traffic attributes and select the 20 columns of the left decomposition matrix  $^{1}$ .

The final predictive attribute set is shown in Table I. Shapley Values calculate the contributions to a final result

<sup>&</sup>lt;sup>1</sup>There are a number of sophisticated ways to select the most important columns, for example those with maximal kurtosis, but we retain the first 20 and leave it to attribute selection to find the best.

made by individual players in a game theory context [17]. They have been successfully applied to attribute selection in predictors because of the development of fast approximation algorithms that avoid the implicit exponential number of attribute combinations to be evaluated. The two most popular Shapley value explainers are TreeExplainer [20], for tree-based predictors, and DeepExplainer, for neural networks predictors.

We use Shapley values for attribute selection. The selection process is run independently five times, each time for a different class. Shapley Values were computed with two different classification techniques as the backend: Neural Network (Deep Explainer) and Extreme Gradient Boosting (XGBoost).

# C. Individual Techniques and the Ensemble Predictor

For predictors, we use k-Nearest Neighbors, Support Vector Machines [3], decision trees, random forests [4], Adaboost [14], XGBoost [6], and multilayer perceptrons.

Each of the prediction techniques was run with 10-fold cross validation, with binary class labels (traffic class present or not). The final ensemble model consists of the top three most effective classifiers for each traffic class, chosen to maximize the precision, so that the ensemble classifier can determine with a high degree of certainty whenever a specific kind of traffic is present. A specific sample is predicted to contain a specific class of traffic when at least two of the three classifiers predict that class.

The output of the ensemble classifier is 5 binary values, predicting the presence of each of the 5 kinds of traffic in the sample. Three different performance measures are calculated:

- The precision, recall and F1 score for each class;
- A confusion matrix for each class;
- An ensemble score function designed for the problem domain.

The ensemble score function assigns points to each record as follows:

- For a true negative, no points;
- For a true positive, add one point;
- For a false positive, subtract two points;
- For a false negative, no points.

For instance, if the model predicts download and clipboard, where the traffic actually contained download and browsing, it will assign +1 point for download, 0 points for browsing as it was a false negative, 0 points for Notepad and YouTube as they were true negatives, and -2 for false positive on clipboard. The aggregate of scores calculated on all test set rows is divided by the sum of all positive labels in the test set and multiplied by 100. The scoring function severely penalizes the ensemble whenever it predicts a traffic class that is not actually present. This insures that the model is reliable for predicting behavior.

#### D. Dataset

The dataset consists of 2160 30-second data samples. The information relating to number of samples is summarized in Table II for the CAC-01 (Remote VM, TCP transport) and Table III for Win01 (Local subnet VM, TCP and UDP

transport) traffic respectively. For simplicity, we will refer to the first kind of traffic as TCP and to the latter as UDP.

When TCP is the only protocol used, it is easier to make accurate predictions. When UDP is added, the problem complexity grows because there are at least two conversations – one for the TCP stream and one for the UDP stream, in the same Remote Desktop session. UDP seems to be used for bulk transfers while TCP is used to send user inputs, such as keystrokes and mouse movements, and perhaps RDP session management details.

Every keystroke that is sent from local system to the remote system over Remote Desktop is carried by two 92-byte TCP frames in the forward direction. As a result, the total number of 92-byte frames in a window reveals how many keystrokes have been sent (except that actions such as pressing and holding a Shift key generates 92-byte frames, until the key is released).

The remote system also responds with packets that are revealing. 92-byte upward packets produce PSH-flagged packets whose payload size correlates with the visual change to the screen of the character echo – the more pixels changed, the larger the payload<sup>2</sup>. This suggests a potential attack against passwords, since the echoed character is typically not the character sent but a filler character. As a result, entering a password may produce an easily detectable signature.

Mouse movements generate packets of either 97 or 104 bytes, with 97-byte packets associated with mouse clicks. Observing the number of such packets allows mouse activity to be estimated; and the mixing with 92-byte packets allows even finer grained estimates – for example, the size of form data might be estimated by observing how many characters are typed in between mouse clicks and small mouse movements.

### IV. RESULTS

Attribute ranking is computed for ten cases: 5 TCP activities and 5 UDP activities, and for each both the tree-based and neural-net based Shapley value computation. This results in twenty ranked lists of attribute significance. Tree based Shapley values also provide information about whether an attribute is associated with one class label or the other, and how strongly. These are shown as red and blue points in plots.

The most predictive attributes are fairly consistent using both the tree-based and network-based Shapley values. The 92- and 104-byte attributes rank highly, as do many of the SVD components, suggesting that the original attributes tend to capture traffic properties that are strongly correlated.

Table IV shows the best attributes for the TCP traffic classes and Table V shows the best attributes for the UDP traffic classes.

Table VI shows the performance summary for the predictors run on the TCP traffic and Table VII summarizes performance for the UDP traffic. Accuracies are over 10-fold cross validation.

<sup>&</sup>lt;sup>2</sup>There are hints that what is being returned is the delta of the character being displayed.

TABLE II
TOTAL TCP SAMPLES COUNT

Num samples	Download?	Browsing?	Notepad?	YouTube?	Clipboard?
240	1	0	0	0	0
240	0	1	0	0	0
239	0	0	1	0	0
243	0	0	0	1	0
120	0	0	0	0	1
74	0	1	0	0	1
43	1	1	0	0	0
25	1	0	1	0	1
22	1	0	1	0	0
62	0	0	1	1	0
27	1	0	0	1	0
63	0	1	0	1	0
22	0	0	1	0	1
15	1	1	0	0	1
21	1	0	1	1	1
1456	TOTAL				

TABLE III
TOTAL UDP SAMPLES COUNT

Num samples	Download?	Browsing?	Notepad?	YouTube?	Clipboard?
103	1	0	0	0	0
92	0	1	0	0	0
100	0	0	1	0	0
105	0	0	0	1	0
100	0	0	0	0	1
42	0	1	0	0	1
44	0	1	0	1	0
42	1	0	1	0	0
37	1	0	1	0	1
39	1	0	0	1	0
704	TOTAL				

TABLE IV SELECTED ATTRIBUTE SETS FOR TCP CLASSES

TCP Download	TCP Browsing	TCP Notepad	TCP YouTube	TCP Clipboard
svd0	FwdFrame103-105	svd2	BwdFrame320-639	FwdPUSH
BwdFrame80-159	BwdFrame320-639	FwdFrame91-93	svd1	svd1
BwdFrame320-639	Fwd Pkt Len Mean	svd0	svd6	svd0
Init Fwd Win Byts	Fwd Seg Size Avg	FwdPUSH	svd0	Subflow Bwd Byts
Tot Fwd Pkts	svd8	BwdFrame80-159	svd9	ica7
BwdFrame640-1279	BwdPUSH		FwdPUSH	FwdFrame91-93
Fwd IAT Mean	FwdFrame96-98		TotLen Fwd Pkts	FwdFrame103-105
Pkt Len Std	FwdPUSH		Flow IAT Std	svd6
Bwd IAT Max	BwdFrame1280-2559		BwdFrame640-1279	ica11
ica19	ica7			svd11
Bwd Pkt Len Mean	FwdFrame91-93			ica5
Flow Byts/s	Init Fwd Win Byts			Fwd Pkt Len Mean
	Bwd Pkt Len Mean			BwdFrame320-639
				svd8
				Pkt Len Std

For each TCP and UDP traffic class we select the top three best performing cross-validated predictors to build two ensemble predictors – the TCP Ensemble and the UDP Ensemble, shown in Figures 7 and 8.

Table VIII provides the True Positives, False Positives, True Negatives, and False Negatives with five-fold cross-validation for the ensemble predictors. We then calculate Accuracy, Precision, Recall and F1 score.

Table IX, summarizes the single ensemble scores obtained for each fold of the TCP and UDP models, along with the average. Voting makes a significant contribution towards reducing false positives.

For both UDP and TCP traffic, there are similarities when it comes to the most commonly misclassified traffic classes. For both TCP and UDP traffic, the most common misclassification misses the Clipboard class. This is reflected in the recall scores for the UDP Clipboard at only 94.97% and the TCP Clipboard at 95.67%, while other classes all have recall higher than 98%.

The most common error in TCP traffic is a mixture of Browsing and Clipboard being classified as Browsing only. Both Browsing and Clipboard involve mouse movements and mouse clicks, both right- and left-clicks, but it seems slightly

TABLE V
SELECTED ATTRIBUTE SETS FOR UDP CLASSES

UDP Download	UDP Browsing	UDP Notepad	UDP YouTube	UDP Clipboard
svd0	svd1	FwdFrame91-93	svd1	svd2
svd1	Fwd Pkt Len Std	BwdFrame40-79	svd0	Bwd IAT Std
svd2	FwdFrame96-98	svd2	svd3	Fwd IAT Mean
Fwd Pkt Len Std	svd0	Fwd IAT Min	svd5	FwdFrame103-105
Bwd Header Len	svd5	svd1	BwdFrame80-159	Flow IAT Mean
	FwdFrame90-94	Bwd IAT Mean	FwdFrame91-93	Flow IAT Std
	BwdFrame320-639		Flow IAT Max	BwdFrame40-79
			Bwd IAT Max	BwdFrame320-639
			Fwd Pkt Len Mean	Bwd IAT Mean
			Fwd Seg Size Avg	FwdFrame91-93
			BwdFrame320-639	Pkt Len Mean
			Bwd IAT Std	FwdFrame90-94
			Fwd IAT Max	Fwd IAT Min
			svd4	
			Bwd Header Len	
			ica8	
			Bwd Pkt Len Max	
			Fwd IAT Tot	
			Bwd IAT Tot	

TABLE VI
TCP TRAFFIC INDIVIDUAL TECHNIQUES – ACCURACY AND STANDARD DEVIATION

Technique	Download	Browsing	Notepad	YouTube	Clipboard
NN	99.66%	98.62%	99.66%	99.59%	95.88%
1111	$(\pm 0.46\%)$	$(\pm 1.27\%)$	$(\pm 0.46\%)$	$(\pm 0.46\%)$	$(\pm 1.23\%)$
RF	99.18%	99.38%	99.86%	99.59%	98.69%
Kr	$(\pm 0.79\%)$	$(\pm 0.57\%)$	$(\pm 0.27\%)$	$(\pm 0.46\%)$	$(\pm 0.84\%)$
XGB	99.52%	99.59%	99.72%	99.59%	98.56%
AGD	$(\pm 0.69\%)$	$(\pm 0.62\%)$	$(\pm 0.46\%)$	$(\pm 0.45\%)$	$(\pm 1.12\%)$
SVM	99.73%	99.24%	99.86%	99.59%	95.47%
SVIVI	$(\pm 0.34\%)$	$(\pm 0.72\%)$	$(\pm 0.28\%)$	$(\pm 0.45\%)$	$(\pm 2.60\%)$
Ada	99.66%	99.25%	99.86%	99.52%	98.49%
Aua	$(\pm 0.46\%)$	$(\pm 0.57\%)$	$(\pm 0.28\%)$	$(\pm 0.81\%)$	$(\pm 0.67\%)$
KNN	99.45%	99.04%	99.79%	99.31%	94.71%
KININ	$(\pm 0.51\%)$	$(\pm 0.70\%)$	$(\pm 0.31\%)$	$(\pm 0.68\%)$	$(\pm 1.81\%)$
DTC	98.63%	98.83%	99.93%	99.52%	96.91%
DIC	$(\pm 0.86\%)$	$(\pm 0.75\%)$	$(\pm 0.21\%)$	$(\pm 0.69\%)$	$(\pm 1.20\%)$

surprising that these are difficult to distinguish.

The second most common error occurs when Browsing traffic is classified as Browsing and Clipboard, generating a false positive prediction for Clipboard. The third most common is for the combination of Download, Browsing and Clipboard where the Clipboard traffic is missed. The fourth most common is when a Download and YouTube mixture is classified as Download only. Misclassifications are rare the other way – mixtures of the two rarely get classified as YouTube only. Download has a potential to dominate YouTube, apparently because it generates significantly more and faster traffic; and it is possible that backward (remote to local) packet lengths could vary, especially when traversing the Internet. This could be caused by TCP adjusting the window size for transfers. Interestingly, there were no misclassifications relating to the 4-class TCP traffic.

For UDP traffic, the most common misclassification is again a False negative for the Clipboard class. Most often, this happens in the mixture of Download, Notepad and Clipboard, where Clipboard is missed and traffic is classified as Download and Notepad. Both Download and Notepad have many more visible traffic attributes than Clipboard does – the total number of backward bytes for Download and 92-byte frames for Notepad. There were some other misclassifications such as Browsing and Clipboard being identified as Browsing alone and Clipboard or Browsing being classified as none of the five classes.

We wondered if Browsing samples from web sites with lots of video and dynamic content would tend to get misclassified as the YouTube class. Such misclassifications are rare and the predictive model is apparently resilient to audio and video contents embedded in websites.

# V. Conclusions

We have shown that, for an encrypted protocol such as RDP, it is still possible to infer five common categories of activities with high reliability from traffic properties that cannot be concealed by encryption. It is conceivable that some of these predictions could be defeated by obfuscation in the protocol but protocol designers are caught between the need to conceal activity and the need to provide responsiveness. As we have shown, this has led to a design in which keystrokes, mouse

TABLE VII
UDP TRAFFIC INDIVIDUAL TECHNIQUES – ACCURACY AND STANDARD DEVIATION

Technique	Download	Browsing	Notepad	YouTube	Clipboard
NN	99.86%	97.72%	99.71%	99.86%	96.02%
ININ	$(\pm 0.42\%)$	$(\pm 1.93\%)$	$(\pm 0.57\%)$	$(\pm 0.42\%)$	$(\pm 2.09\%)$
RF	99.86%	99.29%	99.43%	100.00%	98.15%
Kr	$(\pm 0.42\%)$	$(\pm 0.71\%)$	$(\pm 0.69\%)$	$(\pm 0.00\%)$	$(\pm 1.28\%)$
XGB	99.57%	99.01%	98.72%	99.15%	97.87%
AGB	$(\pm 0.91\%)$	$(\pm 0.90\%)$	$(\pm 1.34\%)$	$(\pm 0.95\%)$	$(\pm 1.30\%)$
SVM	99.71%	98.29%	99.72%	99.43%	95.03%
SVIVI	$(\pm 0.57\%)$	$(\pm 1.39\%)$	$(\pm 0.57\%)$	$(\pm 0.69\%)$	$(\pm 2.73\%)$
Ada	99.57%	99.01%	99.57%	99.71%	98.44%
Aua	$(\pm 0.65\%)$	$(\pm 0.91\%)$	$(\pm 0.65\%)$	$(\pm 0.86\%)$	$(\pm 1.00\%)$
KNN	99.86%	98.01%	99.72%	99.01%	94.45%
KININ	$(\pm 0.42\%)$	$(\pm 1.45\%)$	$(\pm 0.56\%)$	$(\pm 1.11\%)$	$(\pm 2.17\%)$
DTC	99.86%	98.87%	99.58%	98.86%	96.60%
БІС	$(\pm 0.42\%)$	$(\pm 1.76\%)$	$(\pm 0.65\%)$	$(\pm 1.06\%)$	$(\pm 1.69\%)$

 ${\bf TABLE~VIII}\\ {\bf SUMMARY~of~Each~TCP~and~UDP~Traffic~Class~Results~over~5-fold~cross-validation}$ 

Class	FP	TP	FN	TN	Accu.	Prec.	Rec.	F1
TCP Download	1	391	2	1062	99.79	99.74	99.49	99.62
TCP Browsing	3	434	1	1018	99.73	99.31	99.77	99.54
TCP Notepad	0	390	1	1065	99.93	100.00	99.74	99.87
TCP YouTube	2	413	3	1038	99.66	99.52	99.28	99.40
TCP Clipboard	5	265	12	1174	98.83	98.15	95.67	96.89
UDP Download	0	221	0	483	100.00	100.00	100.00	100.00
UDP Browsing	2	175	3	524	99.29	98.87	98.31	98.59
UDP Notepad	1	178	1	524	99.72	99.44	99.44	99.44
UDP YouTube	0	188	0	516	100.00	100.00	100.00	100.00
UDP Clipboard	4	170	9	521	98.15	97.70	94.97	96.32

TABLE IX
SINGLE ENSEMBLE SCORE RESULTS

Fold	TCP Ensemble Score	UDP Ensemble Score
1	98.18	95.36
2	97.86	97.47
3	97.19	97.85
4	97.95	96.22
5	98.13	98.90
Average	97.86	97.16

activity, and visual rendering all leave traces in the encrypted traffic which could potentially be used for attacks.

A limitation of this model is that it only used traffic between Windows 10 systems. Different systems, and RDP updates, could conceivably change traffic structure in a macroscopic way, although the proof of concept here suggests that only model retraining would be needed. Other kinds of traffic were not examined: for example, two-way video such as Zoom or Skype might induce quite different traffic structure.

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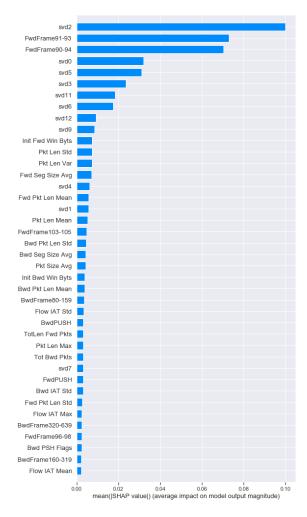


Fig. 3. TCP Attribute Ranking - Notepad, Deep Explainer

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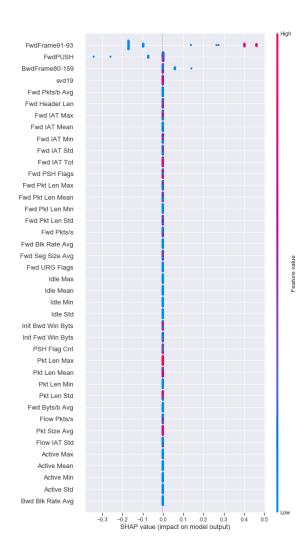


Fig. 4. TCP Attribute Ranking - Notepad, XGBoost Explainer

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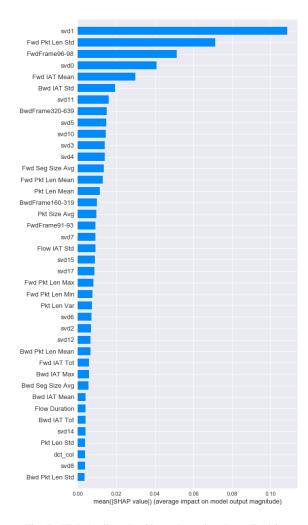


Fig. 5. UDP Attribute Ranking - Browsing, Deep Explainer

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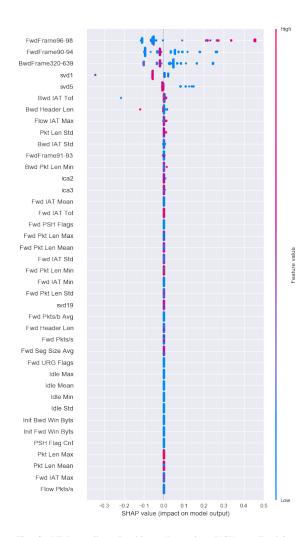


Fig. 6. UDP Attribute Ranking - Browsing, XGBoost Explainer

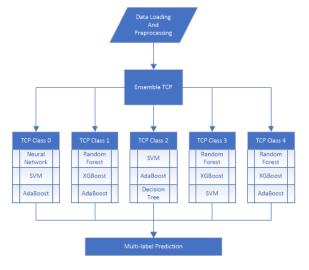


Fig. 7. TCP Ensemble Model

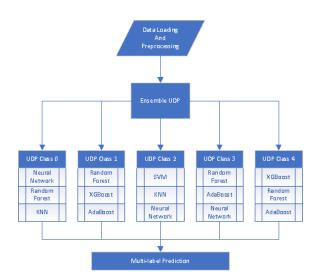


Fig. 8. UDP Ensemble Model