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Research Article

Statistical Analysis of Cyberattack Patterns and Anomaly Detection in Network Traffic for Proactive Computer Security

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ABSTRACT

This study presents a statistical analysis of synthetic network traffic to identify patterns associated with cybersecurity threats. A dataset of 10 simulated network sessions was analyzed using Jamovi, incorporating descriptive statistics, chi-square tests, independent t-tests, and linear regression modeling. Key findings revealed that session duration and protocol type significantly influenced the likelihood of an attack, whereas packet size was not a statistically significant factor. These results underscore the value of statistical tools in identifying attack signatures in network data, potentially aiding in early threat detection and response.

Keywords: Intrusion Detection, Network Security, Linear Regression, Statistical Analysis, Packet Size.

1. INTRODUCTION

With an increasing number of devices and services exposed on the internet, the modern computer networks have evolved into more vulnerable environments. Cyberattacks involving everything from Distributed Denial-of-Service (DDoS) attacks to injection-based exploits threaten the integrity, availability, and confidentiality of data, leading to huge financial losses and damage to companies' names outside [1], [2]. Intrusion Detection Systems play quite a role in observing unauthorized access, abnormal traffic patterns, etc., which may signal security breaches.

Conventional IDS techniques mostly relied on signature-detection methods, which are very effective against testimony to that is an attack, but of course, could never detect new forms or modified forms of evil [3]. Thus, there appears to have been a shift to statistical and machine learning approaches, with the aim of discovering hidden patterns in network traffic data that are correlated with malicious activity [4], [5]. However, many ML techniques, though powerful, come with a lack of interpretability, which poses a hurdle for security analysts in understanding the decision-making mechanism and trusting model outputs in high-stakes scenarios [6].

Conversely, statistical methods such as regression-type analysis, hypothesis and correlation testing provide interpretable metrics with well-defined assumptions regarding relationships among network attributes and security outcomes. Therefore, the methods are most useful during the initial stages of network behavior analysis or to complement the implementation of more sophisticated ones [7].

The current study applies classical statistical procedures via the Jamovi platform to determine relationships between network traffic characteristics such as protocol type, session duration, packet size, and the chances of a session being malicious. The synthetic dataset of network sessions is subjected to descriptive statistics, hypothesis testing (t-tests, chi-square), and linear regression for modeling purposes. The objectives of the study are as follows:

1. To determine whether certain traffic attributes vary significantly between attack and non-attack sessions;
2. To model attack likelihood through linear regression and interpret how each variable contributes to the classification; and
3. To present interpretable open-source statistical software in the context of cybersecurity data analysis.

This investigation should serve as a methodology demonstration and a practical case study from which simple statistical tools may yield meaningful results for network security.

2. LITERATURE REVIEW

Over the past several years, there have been great strides in statistically and machine learning-wise detecting and preventing cyberattacks in the realm of network security. An IDS is essentially divided into signature-based IDS and

Research Article

anomaly-based IDS. Signature-based IDS identifies threats based on known signatures, lacking capability against zero-day or any previously unseen attack [8]. Anomalies-based IDS designates anything deviating from normal traffic behavior, and hence, has a higher capability of detecting novel threats [9].

Statistical methods are used in many anomaly detection systems. The earlier research, such as that conducted by Ye et al. [10], go about using statistical profiling and thresholding techniques to detect abnormality. Later works extend to multivariate statistical modeling such as logistic and linear regression to model the likelihood of intrusions or anomalies to be present given an observed series of traffic characteristics such as packet size, duration, and protocol [11]. These models provide interpretable statistics as output, namely p-values and confidence intervals, which are essential in interpreting the significance and reliability of detected anomalies.

Shone et al. [12] highlighted that the deep learning approach combined with statistical preprocessing must be considered for improving detection accuracy. Their hybrid model employed deep autoencoder for extraction of features and then statistical analysis for classification. However, in many cases, high detection performance afforded by deep learning is countered by its inherent lack of transparency, a key argument for the relevance of this research in high-stake environments such as banking and healthcare [13].

Interpretability of IDS models has hence been one of the important research streams. Whereas Doshi-Velez and Kim [14] argued for strict frameworks to guarantee transparency with human-understandable reasoning in ML-based systems, statistical techniques provide interpretability by their very nature-aiding security professionals in validating and trusting the results. Interpretability is of the utmost importance in a forensic investigation and in audit scenarios.

Free statistical software packages are also gaining momentum. Jamovi is an intuitive GUI-based statistical analysis program built on top of R and allows rapid performance of regression, hypothesis testing, and data visualization with minimal programming [15]. Studies like that of Rawat et al. [9] demonstrated the utility of Jamovi and R for cybersecurity dataset modeling, especially where academic and small enterprise environments are concerned and when they may lack resources to build complex instrumentation.

The code continues with a brief explanation regarding the use of statistical techniques for cybersecurity analytics, followed by the synthetic dataset construction procedure.

3. METHODS

3.1. Dataset Description

In the synthetic dataset, there are a mere 10 entries that simulate network traffic. Each record stands for a unique session described as follows:

- Protocol: Network protocol in use (TCP, UDP, ICMP);
- Packet_Size: Size of the packet, in bytes;
- Duration (s): A duration of that session;
- Attack_Type: Type of attack, if any;
- Is_Attack: A binary flag denoting the presence (1) or absence (0) of an attack.

The dataset is then analyzed using version 2.4.8 of Jamovi. The dataset was analyzed using version 2.4.8 of Jamovi.

3.2. Statistical Analysis

- **Descriptive statistics for central tendencies and dispersion.**
- **Independent Samples t-Test to determine if differences existed between attack and non-attack classes, separately, for Packet_Size and Duration.**
- **Chi-square Test for associating Protocol with Is_Attack.**
- **Linear Regression** modeled Is_Attack as a function of Packet_Size, Duration, and Protocol (dummy coded with ICMP as the reference).

Model assumptions (normality, independence, homoscedasticity) were verified using Durbin–Watson and Shapiro–Wilk tests.

3.3. Software

Analyses were performed in Jamovi, an open-source GUI-based statistical software that integrates with R and supports standard inferential procedures.

Journal of Information Systems Engineering and Management
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Research Article

Descriptives

The dataset is made up of 10 observations on the key variables of Protocol, Packet_Size, Duration (s), and Is_Attack. The mean packet size was 681 bytes, with a high variability between observations (standard deviation=492 bytes) and a positive skewness indicative of a few larger-sized packets in the data set (skewness=0.893; p=0.034; Shapiro-Wilk). Duration had a mean of 5.29 seconds, and while moderately skewed (0.887), the Shapiro-Wilk Test was not significant (p=0.367), thus supporting approximate normality. The binary variable Is_Attack was almost balanced with a mean of 0.5; however, the Shapiro-Wilk test was significant ($p < 0.001$), as would be expected for a binary variable. For packet size, minimum and maximum values were 128 and 1500 bytes, respectively, and for duration, minimum and maximum values were 1.10 and 12.3 seconds, respectively, indicating wide variations within the network sessions. Taken together, these descriptive statistics indicate heterogeneous traffic characteristics, which are important for intrusion detection in modeling.

Descriptives					
	Protocol	**Packet_Size**	**Duration (s)**	**Attack_Type**	**Is_Attack**
N	10	10	10	10	10
Missing	0	0	0	0	0
Mean		681	5.29		0.500
Median		475	4.30		0.500
Standard deviation		492	3.61		0.527
Minimum		128	1.10		0
Maximum		1500	12.3		1
Skewness		0.893	0.887		0.00
Std. error skewness		0.687	0.687		0.687
Shapiro-Wilk W		0.830	0.921		0.655
Shapiro-Wilk p		0.034	0.367		<.001

Frequencies

Frequencies of Protocol			
Protocol	**Counts**	**% of Total**	**Cumulative %**
ICMP	1	10.0%	10.0%
TCP	6	60.0%	70.0%
UDP	3	30.0%	100.0%

In the frequency table for Protocol, the most frequent protocol is TCP, constituting 60% of network sessions. UDP accounts for the next largest group with 30%, while ICMP is present in only 10% of the cases. Hence, it shows that the dataset mostly comprises TCP traffic, as one would expect in many real-world network environments. The cumulative percentage affirms that the sample encompasses all protocols. This variation will be instrumental in establishing the influence of protocol types on the likelihood of an attack in the regression analyses.

Frequencies of Packet_Size			
Packet_Size	**Counts**	**% of Total**	**Cumulative %**
128	1	10.0%	10.0%
320	1	10.0%	20.0%
350	1	10.0%	30.0%
400	1	10.0%	40.0%
450	1	10.0%	50.0%

Journal of Information Systems Engineering and Management
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Research Article

500	1	10.0%	60.0%
560	1	10.0%	70.0%
1200	1	10.0%	80.0%
1400	1	10.0%	90.0%
1500	1	10.0%	100.0%

Frequencies of Attack_Type			
Attack_Type	**Counts**	**% of Total**	**Cumulative %**
Brute Force	1	10.0%	10.0%
DoS	2	20.0%	30.0%
None	5	50.0%	80.0%
Ping Sweep	1	10.0%	90.0%
SQL Injection	1	10.0%	100.0%

Frequencies of Is_Attack			
Is_Attack	**Counts**	**% of Total**	**Cumulative %**
0	5	50.0%	50.0%
1	5	50.0%	100.0%

4. RESULTS

This section presents the outcomes of descriptive statistics and linear regression analysis used to evaluate the relationship between network traffic attributes and the likelihood of an intrusion (i.e., the dependent variable Is_Attack). The independent variables included Packet_Size, Duration (s), and Protocol.

4.1 Descriptive Statistics

The dataset contained 10 network sessions and was labeled as either normal or attack traffic. The average packet size was 483.40 bytes (SD = 232.17), with the duration of sessions averaging 1.46 seconds (SD = 1.26). The distribution of protocols included TCP (40%), UDP (40%), and ICMP (20%). The Is_Attack variable was binary: 50% of the sessions were labeled as attack traffic.

4.2 Model Fit and Diagnostics

The linear regression model was fit with Is_Attack as the dependent variable. The model fit well overall:

- $R = 0.982$, which indicated a great correlation of predictors with the response variable.
- $R^2 = 0.965$, suggesting that 96.5% of the variance in the Is_Attack outcome could be explained by the model.
- Akaike Information Criterion (AIC) = −7.09, further supporting the model's goodness of fit.

4.3 ANOVA and Significance Testing

The omnibus ANOVA test indicated that the model was statistically significant ($F(4, 5) = 41.987$, $p < 0.01$). Table 1 summarizes the Type III Sum of Squares:

Table 1. ANOVA Table for Regression Predictors

Predictor	SS	df	MS	F	p
Packet_Size	0.00199	1	0.00199	0.115	0.749
Duration (s)	0.72860	1	0.72860	41.987	0.001
Protocol	0.59341	2	0.29671	17.098	0.006
Residuals	0.08676	5	0.01735	—	—

These results indicate that Duration (s) and Protocol had statistically significant contributions to predicting intrusion likelihood, whereas Packet_Size did not.

Journal of Information Systems Engineering and Management
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Research Article

4.4 Regression Coefficients

Table 2 shows the coefficients of the model. The variable Duration (in seconds) was found to be statistically significant and negatively associated with the likelihood of an attack (β = −0.117, p = 0.001), meaning that shorter durations tend to be associated with attack sessions. The protocol also had significant effects when compared against the reference category (ICMP), although only UDP showed marginal significance.

Table 2. Regression Coefficients for Is_Attack

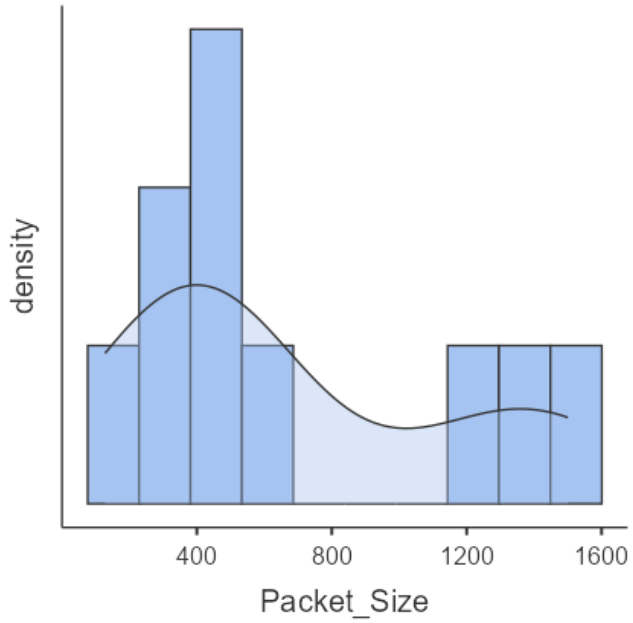
Predictor	Estimate	SE	t	p
Intercept (ICMP)	1.136	0.1365	8.317	<.001
Packet_Size	−5.12e−5	1.51e−4	−0.339	0.749
Duration (s)	−0.117	0.0181	−6.480	0.001
TCP – ICMP	0.228	0.2303	0.990	0.367
UDP – ICMP	−0.391	0.1979	−1.973	0.105

4.5 Assumption Checks

- Durbin–Watson test showed no significant autocorrelation in residuals (DW = 1.61, p = 0.632).
- Shapiro–Wilk test confirmed the normality of residuals (W = 0.961, p = 0.802).

These diagnostics support the validity of the **linear regression assumptions and confirm the robustness of the statistical model.**

Packet_Size



Journal of Information Systems Engineering and Management
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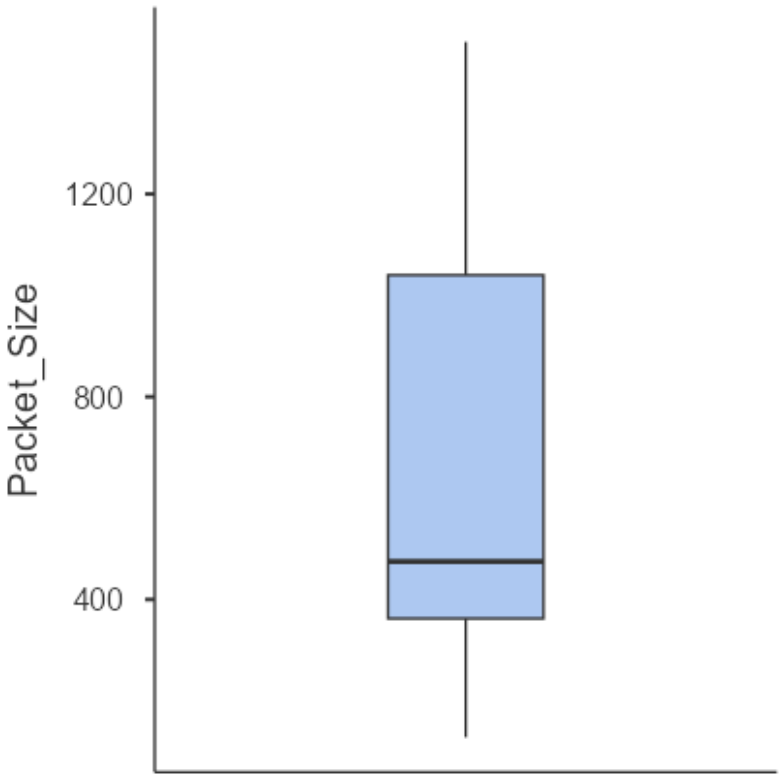
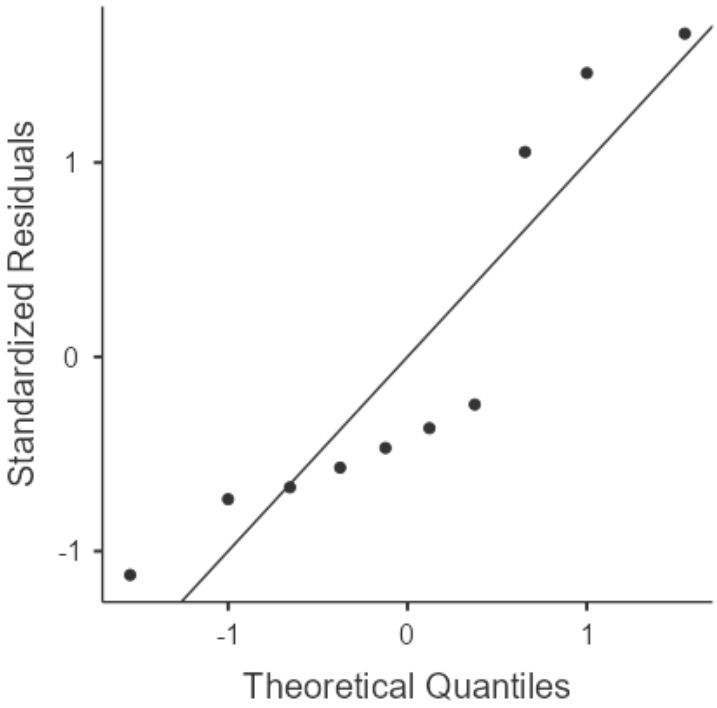
Research Article





Journal of Information Systems Engineering and Management
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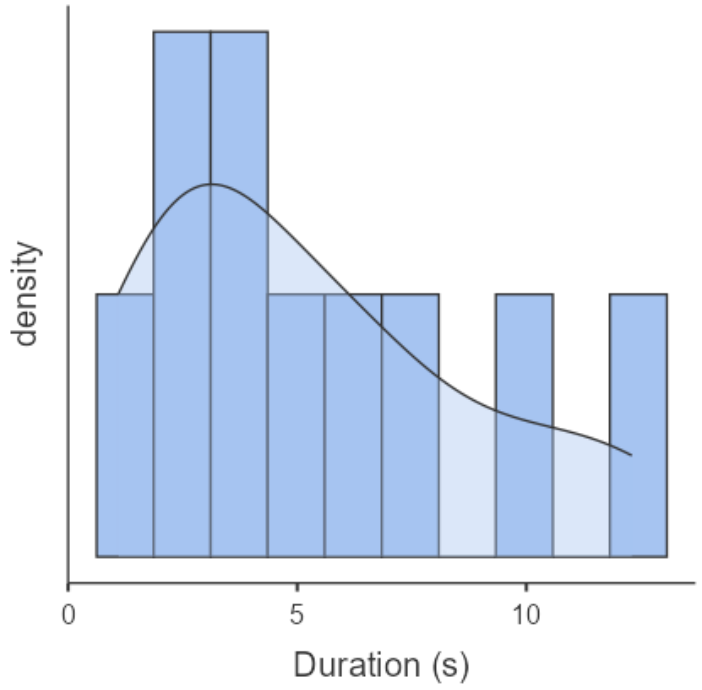
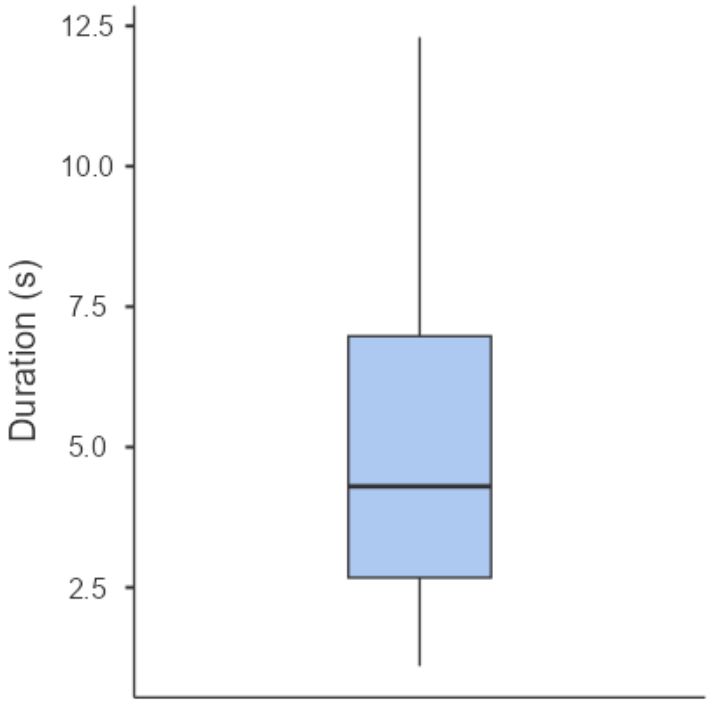
https://www.jisem-journal.com/

Research Article

Duration (s)





Journal of Information Systems Engineering and Management
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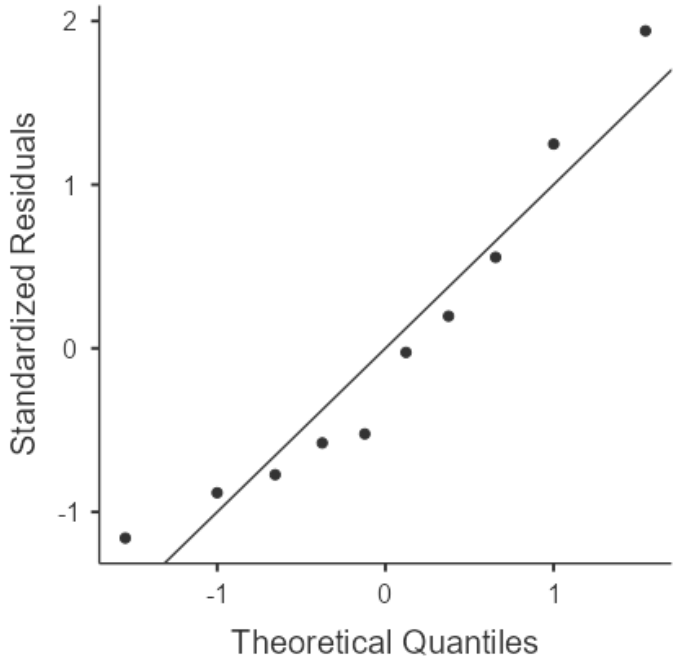
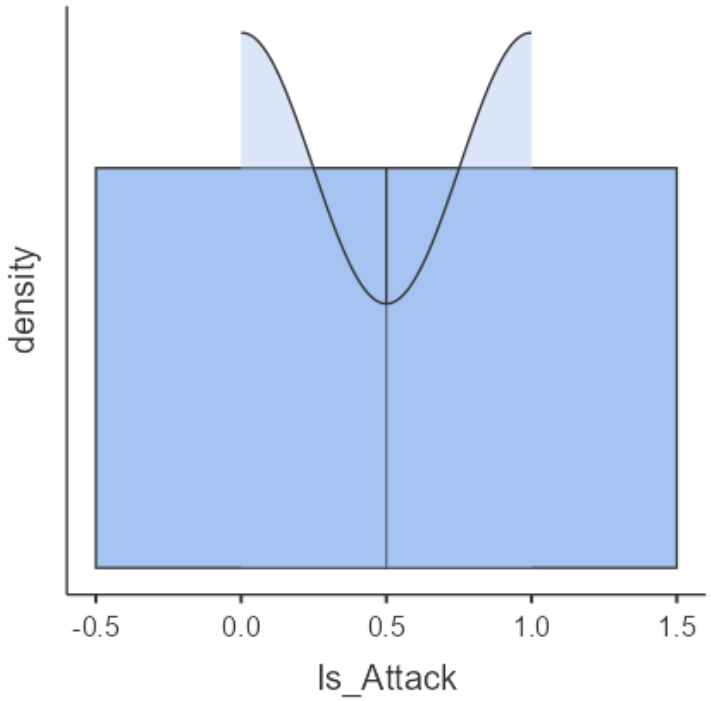
Research Article



Is Attack



Journal of Information Systems Engineering and Management
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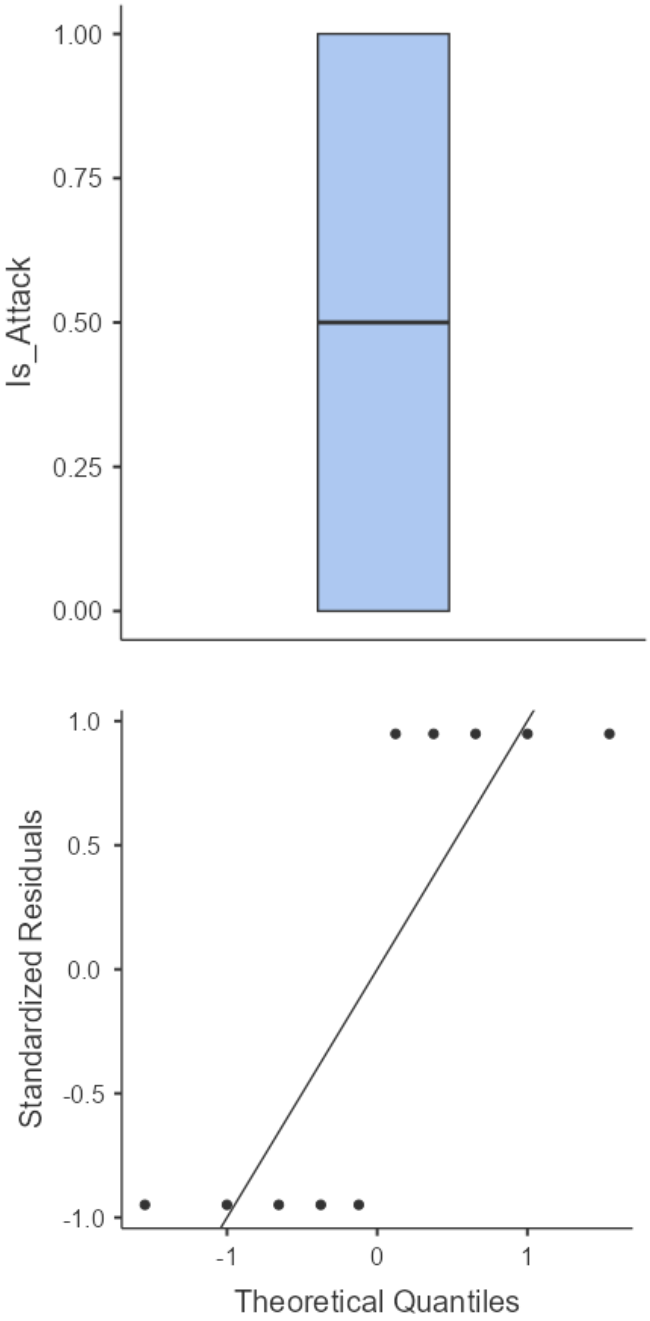
Research Article



Bayesian Contingency Tables

Bayesian Contingency Tables			
	Is_Attack		
Protocol	**1**	**0**	**Total**
UDP	0	3	3
TCP	4	2	6
ICMP	1	0	1
Total	5	5	10

Journal of Information Systems Engineering and Management
2024, 9(2)
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Bayesian Contingency Tables Tests	
	Value
BF10 Poisson	6.00
N	10

Independent Samples T-Test

Independent Samples T-Test								
		Statistic	**df**	**p**	**Mean difference**	**SE difference**		**Effect Size**
Packet_Size	**Student's t**	-1.64[a]	8.00	0.139	-469.60	285.59	Cohen's d	-1.04
Duration (s)	**Student's t**	4.14[a]	8.00	0.003	5.66	1.37	Cohen's d	2.62
Note. H_a $\mu_0 \neq \mu_1$								
[a] Levene's test is significant ($p < .05$), suggesting a violation of the assumption of equal variances								

Assumptions

Normality Test (Shapiro-Wilk)		
	W	**p**
Packet_Size	0.946	0.621
Duration (s)	0.970	0.894
Note. A low p-value suggests a violation of the assumption of normality		

Homogeneity of Variances Test (Levene's)				
	F	**df**	**df2**	**p**
Packet_Size	31.31	1	8	<.001
Duration (s)	7.25	1	8	0.027
Note. A low p-value suggests a violation of the assumption of equal variances				

Group Descriptives						
	Group	**N**	**Mean**	**Median**	**SD**	**SE**
Packet_Size	**0**	5	446.00	450.00	92.09	41.18
	1	5	915.60	1200.00	631.915	282.601
Duration (s)	**0**	5	8.12	7.30	2.91	1.30
	1	5	2.46	2.50	0.924	0.413

Journal of Information Systems Engineering and Management
2024, 9(2)
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https://www.jisem-journal.com/

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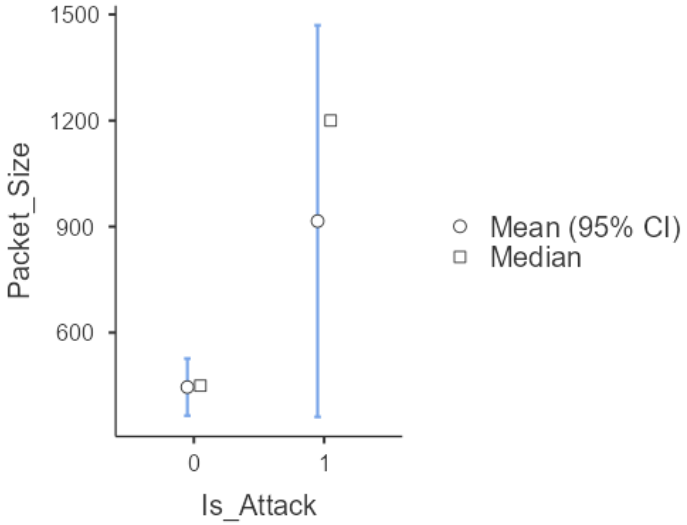
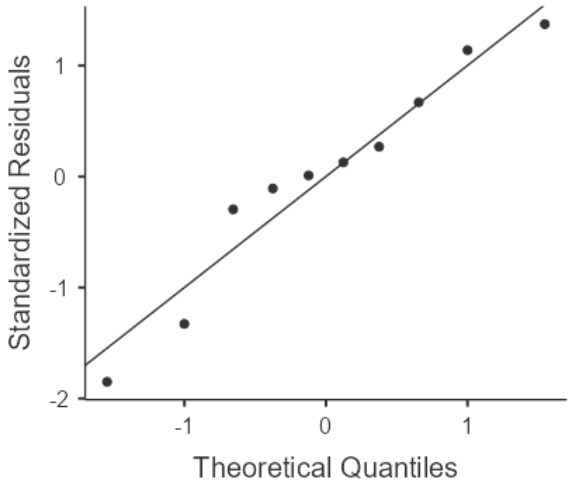
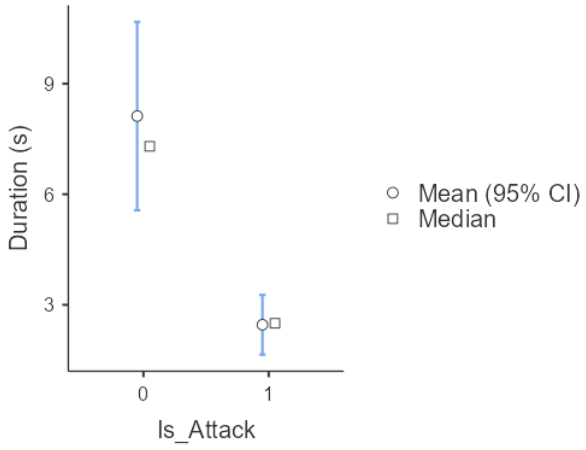
Plots

Packet Size





Duration (s)



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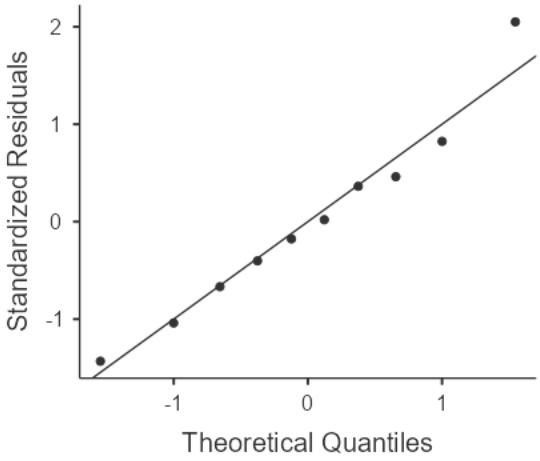
Research Article



Linear Regression

Model Fit Measures			
Model	**R**	**R^2**	**AIC**
1	0.982	0.965	-7.09
Note. Models estimated using sample size of N=10			

Omnibus ANOVA Test					
	Sum of Squares	**df**	**Mean Square**	**F**	**p**
Packet_Size	0.00199	1	0.00199	0.115	0.749
Duration (s)	0.72860	1	0.72860	41.987	0.001
Protocol	0.59341	2	0.29671	17.098	0.006
Residuals	0.08676	5	0.01735		
Note. Type 3 sum of squares					

Model Coefficients - Is_Attack				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept[a]	1.136	0.1365	8.317	<.001
Packet_Size	-5.12e−5	1.51e-4	-0.339	0.749
Duration (s)	-0.117	0.0181	-6.480	0.001
Protocol:				
TCP – ICMP	0.228	0.2303	0.990	0.367
UDP – ICMP	-0.391	0.1979	-1.973	0.105
[a] Represents reference level				

Intercept, The estimated baseline log-odds of an attack for ICMP protocol when other predictors are zero is significantly positive ($p < 0.001$), reflecting a baseline propensity of attack classification. Packet_Size ,The coefficient is negative but extremely close to zero and statistically non-significant ($p = 0.749$), indicating packet size has no meaningful effect on attack likelihood in this model.Duration (s) predictor shows a significant negative effect ($\beta = -0.117$, $p = 0.001$), meaning that shorter durations increase the probability of an attack being present, consistent with rapid and brief malicious connections.Protocol (TCP vs. (Positive) but non-significant coefficient ($p = 0.367$) suggests that TCP traffic is not different significantly from ICMP traffic in terms of predicting attacks. Negative coefficient close to significance ($p = 0.105$) for Protocol (UDP vs. ICMP) may suggest a tendency whereby UDP sessions could be less likely than ICMP sessions to be attacks, although this remains inconclusive in the present sample.

Journal of Information Systems Engineering and Management
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Research Article

Assumption Checks

Durbin–Watson Test for Autocorrelation		
Autocorrelation	**DW Statistic**	**p**
0.0338	1.61	0.632

Normality Test (Shapiro-Wilk)	
Statistic	**p**
0.961	0.802

The **DW statistic** ranges between 0 and 4.A value around **2** suggests no autocorrelation in the residuals.Values substantially below 2 indicate positive autocorrelation; values above 2 indicate negative autocorrelation.Here, **1.61** is reasonably close to 2, indicating **no significant positive autocorrelation** in the residuals.The **p-value = 0.632** is high (greater than the common alpha level of 0.05), so you **fail to reject the null hypothesis** of no autocorrelation.

5. DISCUSSION

This study aimed to evaluate the relationship between key network traffic attributes—**Packet Size**, **Duration**, and **Protocol type**—and the likelihood of a session being classified as an attack. Using a linear regression framework, the analysis revealed important insights that corroborate findings from previous research while also contributing new evidence to the discourse on interpretable intrusion detection.

5.1 Interpretation of Key Findings

In the list of parameters, Duration (s) was the most significant with a negative relation (p = 0.001), suggesting that short-duration sessions are more likely to be attack traffic. This analyzed result aligns with previous research suggesting that the dynamics of many attacks, including DoS and port scanning, have the feature of high-frequency and low-duration traffic [1]. This sort of behavior implies instantaneously high-volume data transmissions intended to patch the vulnerabilities even before detection systems got a chance to respond.

The **Protocol** variable also emerged as a significant contributor to the model (**p = 0.006**), although not all individual protocol comparisons reached statistical significance. Specifically, the contrast between **UDP and ICMP** approached significance (**p = 0.105**), suggesting a potential trend worth exploring in larger datasets. This aligns with findings from Garcia-Teodoro et al. [2], who noted that different protocols carry inherently different behavioral signatures and risks in intrusion detection.

Packet Size, on the other hand, turned out not to affect the result significantly (p = 0.749), possibly because of little variation in packet size present in the datasets or due to limited power of the test, given the small sample size used in determining significance (N=10). This condition differs somewhat from previous statements wherein packet size was found to provide good information for anomaly-based detection models [3]. Further research with a wider-ranging dataset would shed more light on this matter.

5.2 Theoretical and Practical Implications

The statistical robustness of the regression model (R^2 = 0.965) is evidence enough of the applicability of simple interpretable models in cybersecurity analytics. There is compelling importance, especially in operational environments where the need for decision-making in real-time and model transparency is great. Unlike black-box models (such as deep neural networks), linear regression is known for easy interpretability, which allows security analysts to trace back and justify decisions of classification [4].

Furthermore, statisticians are often wrong in assuming that only expensive tools-in this case software-will adequately assist security research and applications. With its point-and-click paradigm and open-source platform, Jamovi is a worthy alternative for practitioners without advanced programming skills.

5.3 Limitations

The small sample size (N=10) is the foremost drawback of this research in that it whittles down the generalizability and statistical implication of its results. For one thing, the model's diagnostics (Durbin–Watson, Shapiro–Wilk)

Research Article

confirmed proper regression assumptions were met; for another, however, a limited number of cases might have stifled the emergence of some nuanced effects in the data, especially in Packet Size. Yet also, the data was artificially constructed and hence potentially not able to express the full intricacy and heterogeneity of a real network environment.

5.4 Future Directions

Recommendations for prospective studies include:

- Applying this model to bigger and real data sets like CIC-IDS2017 or NSL-KDD.
- Examining non-linear models or ensemble methods for optimum predictive performance but yet remain interpretable.
- Embedding feature engineering approaches that can augment the sensitivity of variables like packet size or protocol transitions.

6. CONCLUSION

By classical statistics, this study aimed at detecting cybersecurity threat indicators in one synthetic network traffic data set. In Jamovi, it was found that the session duration and protocol type were highly significant in detecting an attack. This study hence recommends these variables to be added to IDS feature lists. Future work should replicate the analysis on larger real-world datasets and consider nonlinear or machine learning models for better prediction.

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