Analysis of Some Time-Series Metrics for Network Monitoring

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Introduction

- A method and metrics for Situational Awareness
- SA → Monitoring trends and changes in traffic
- Analysis over time → Time series models
- Metrics related to time series are key for SA
- Correlations over time → Autocorrelation Function
- Time window and time scale are important to understand the ACF

Background

- The ACF shows how one observation in time is related to other observations at other points in time
- The ACF and most metrics related to time series are dependent on the time window (W) and the time scale (b) over which they are computed
- Therefore W and b are important for interpreting T-S metrics
- Identify short-term & long-term dependencies
- Important for anomaly detection

References

Biersack, Callegari, and Matijasevic – Data Traffic Monitoring and Analysis

Box, Jenkins and Reinsel – Time Series Analysis: Forecasting and Control

Braun and Murdoch – A First Course in Statistical Programming with R

Brockwell and Davis – Time Series: Theory and Methods

Cowpertwait and Metcalfe - Introductory Time Series with R

Crovella and Krishnamurthy – Internet Measurement

Nucci and Papagiannaki – Design, Measurement and Management of Large-Scale IP Networks

Park and Willinger – Self-Similar Network Traffic and Performance Evaluation

Shumway and Stoffer - Time Series Analysis and its Applications

Method of Analysis

- Analysis of flow data to investigate this issue
- Construct an initial time series | W and b
- Estimate the autocorrelation function for this
- Vary the time scale (bin size) and estimate the ACF for each new time series
- Compare the ACFs across varying bin sizes
- Develop a metric to quantify the differences
- Vary time window (W)
- Compare ACFs across varying W |same bin size
- Metric can be tracked over time (successive Ws)

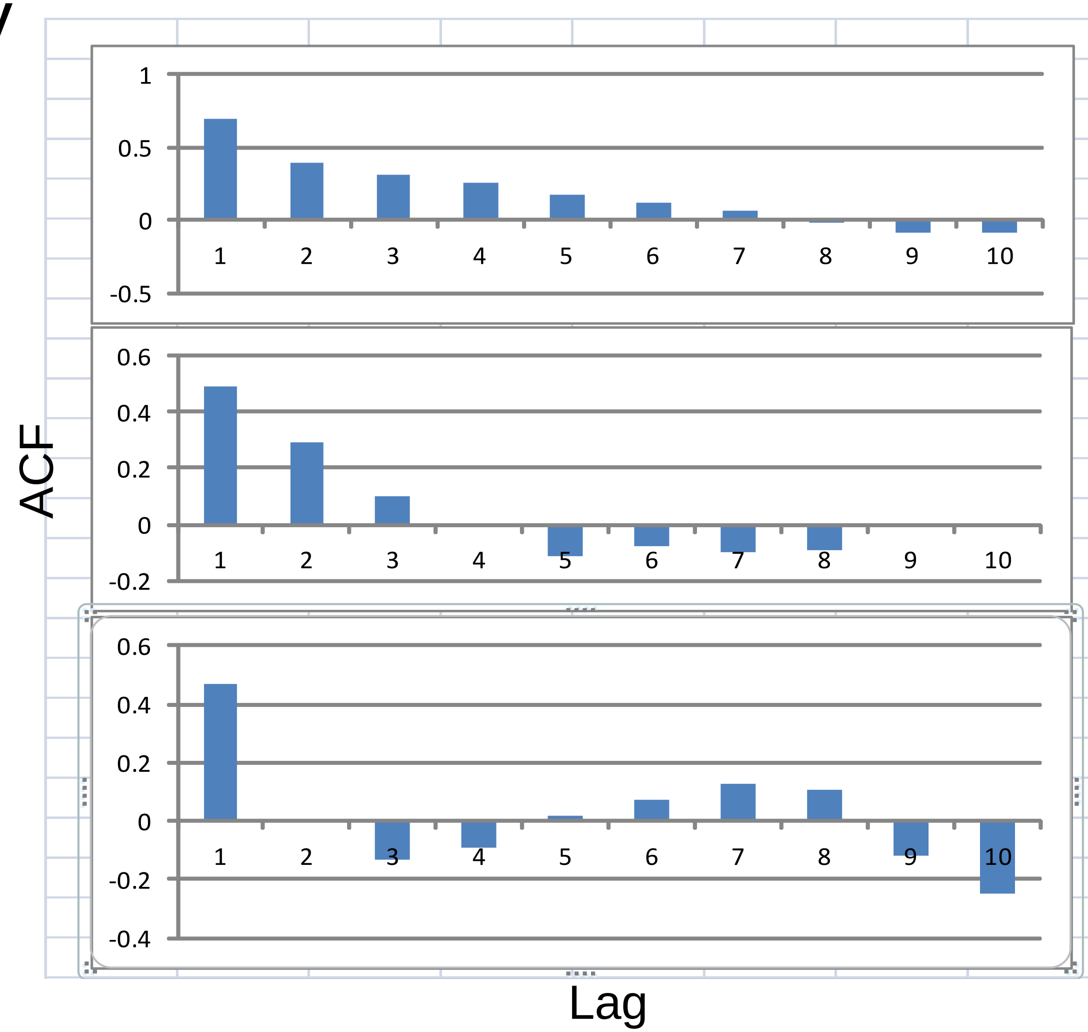
Data and Design

- Analysis reported here was done with publicly available data
- Three time windows (8 hours each)
- Three time scales (b=4,8,16 minutes)
- Analysis was done with SiLK and R
- Can be done with any flow data and scripts
- One set of comparisons shown (10 lags)
- One comparison of ACFs from two Ws
- Metric to investigate differences in ACFs:

  = Sum of absolute differences

Results

Autocorrelations by Time Scale – Lags one to ten.



Discussion

- ACF1 (bin size = 4min.) -> 0 at lag 8; low negative values after that till lag 17.
- ACF2 (bin size = 8 min.) -> sharper decrease
  - -> 0 at lag 4; then approximately cyclical
    - Less long-term effect
- ACF3 (bin size = 16 min.) -> 0 at lag 2 [~ MA(1)]
- ACFs across 2 time windows (bin size = 4min.)
  - Sum of absolute differences = 1
  - with mean = .1 (less than std. err.) >> ***Stable***

Conclusions

- An attack or intrusion usually implies some shift in traffic patterns
- One indicator of such shifts could be a change from a stable long-term dependency to a short-term dependency
- This methodology has the potential to detect such attacks at an early stage

Benefits

- This approach could detect attacks and intrusions that do not perturb the network traffic in other discernible ways
- Thus other techniques may not identify them early enough
- Early detection is important for effective mitigation

- This method also allows us to distinguish between short-term and long-term dependencies within traffic patterns
- This distinction is important for selecting the appropriate techniques for further analyzing network traffic
  - E.G. Short term → Traditional Poisson/Erlang Models
  - E.G. Long term → Complicated Self-Similar Models

Future Work

Implications of changes in the ACF wrt time scales

Predictions from attack/intrusion models

Alternative metrics to quantify differences in ACFs

Repeat the analysis: wide W & different networks

Test methodology with data with known attacks

Thank you!