Automated Traffic Classification and Application Identification using Machine Learning

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Supported by Cisco Systems, Inc. under the URP program

Outline

- Motivation
- Current Solutions & Shortfalls
- Machine Learning Approach
- Experimental Results
- Conclusions & Future Work

Motivation

- Different areas greatly benefit from classifying network traffic flows according to their creating applications
  - Application-based traffic trend analysis
  - Adaptive, network-based QoS mapping
  - Dynamic application-based access control
  - Lawful interception
  - Detection of malicious traffic

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Current Solutions & Shortfalls 1/2

- Use port numbers for identification
  - Well-known and registered ports (IANA)
  - Known default ports (e.g. http://www.portsdb.org)
- Ambiguous default ports
- Applications use different or unknown ports
  - Multiple servers/clients on same IP address
  - Dynamically allocated ports (e.g. passive FTP)
  - Users deliberately using different ports (hide use of applications or bypass port-based filters)

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Current Solutions & Shortfalls 2/2

- Stateful reconstruction of session and application information
  - Inspecting packet payload and decoding protocol
  - Resource intensive, must know the protocol (or reverse engineer), fails with encryption, privacy?
- Signature-based approach
  - Pattern search in packet payload
  - More efficient than protocol decoding but decreased accuracy, finding signatures can be difficult, fails with encryption, privacy?

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Machine Learning Approach 1/4

- Use protocol independent flow attributes (features)
  - Packet-level: e.g. packet length
  - Flow-level: e.g. inter-arrival times, duration, volume
  - Multi-flow-level: e.g. number of concurrent flows
- Use Machine Learning (ML) to classify flows using these features
  - Train algorithm on representative set of flows
  - Classify/predict classes for new unseen flows
- Idea is not completely new but lots of open questions
  - What algorithm? What (set of) features?
  - Accuracy? Performance?

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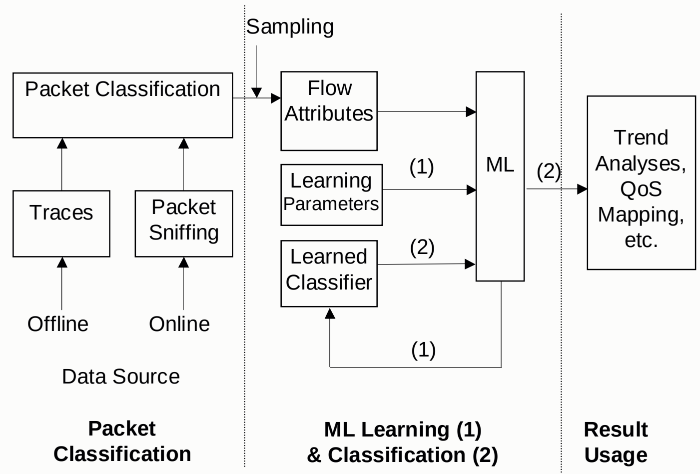
Machine Learning Approach 2/4



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Machine Learning Approach 3/4

- Machine Learning Algorithm
  - Autoclass (http://ic.arc.nasa.gov/ic/projects/bayes-group/autoclass/)
  - Unsupervised learning (clustering)
- Feature selection
  - Sequential forward search (greedy algorithm)
    - Start with empty feature set
    - Each step add new feature that maximally increases goodness metric
  - Wrapper model (execute actual ML algorithm)
  - Goodness Metric: Intra-Class Homogeneity (H)
    - Percentage of instances of majority application in class

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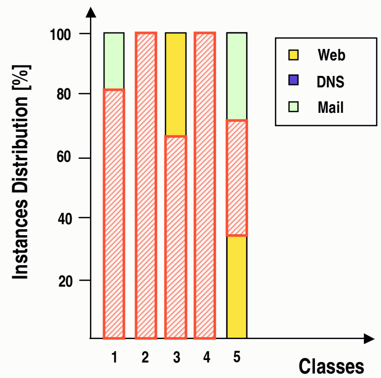
Machine Learning Approach 4/4

Example Homogeneity (H) computation

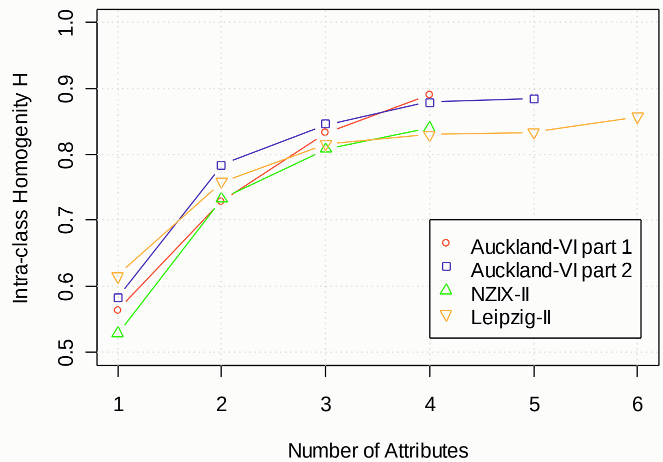


Class	App	H [%]
1	Web	82
2	DNS	100
3	Mail	67
4	Web	100
5	DNS	38
Total Average H		**77.4**

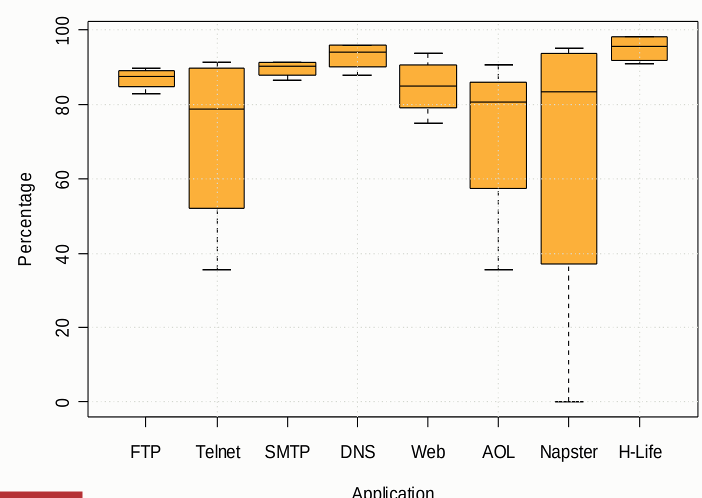
Dataset

- Packet traces from NLANR (http://www.nlanr.net)
  - Auckland VI (2 days), Leipzig II, NZIX II
  - 8 different applications: FTP Data, Telnet, Mail (SMTP), DNS, Web, AOL Messenger, Napster, Half-life
  - 1000 randomly sampled flows for each application
  - No payload in public traces
    - Select flows based on application default ports
    - Assume most flows are of expected application
    - Some ‘wrong’ flows decrease homogeneity
- Flow Attributes (Features)
  - Packet length (mean/variance), inter-arrival times (mean/variance), volume (bytes), duration
  - Bidirectional (except duration)

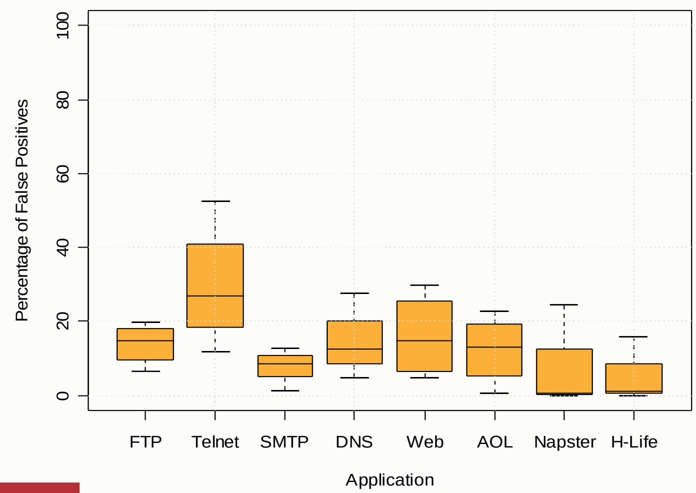
Results – Average Homogeneity



Results – Accuracy



Results – False Positives



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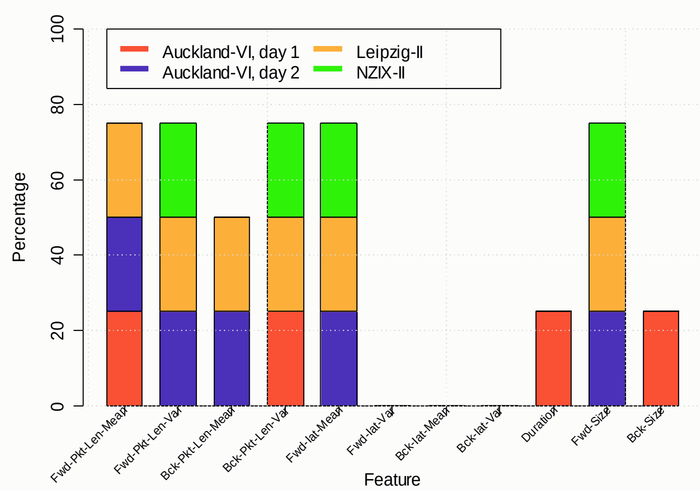
Results – Best Features



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Conclusions

- Some separation of applications can be achieved
  - Average accuracy 86.5%
- Features
  - Packet length, volume favoured over inter-arrival times, duration (biased by our set of applications!)
- Performance (2.4GHz Celeron)
  - Learning very slow (~8.5 hours with full feature set)
  - Classification fast (~6,300 flows/second)
- Disadvantages of current ML technique
  - Classes need to be mapped to applications
  - Many parameters to be tuned

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Future Work

- Compared different ML algorithms (especially supervised techniques)
- Compare different feature selection methods
- Investigate new features
- For verification use traces where real application 'is known' (payload analysis)
- Investigate how quickly flows can be classified
- Investigate influence of flow sampling
- Investigate different application (e.g. peer-to-peer)
- Develop prototype software

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The End

Questions, Comments?