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Probabilistic Graphical Models for Semi-Supervised Traffic Classification

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Traffic classification

- Traffic classification is the problem of defining the application class of a network flow by inspecting its packets.
- port-based → pattern match → statistical analysis.
- Useful in order to perform other network functions:
  - **Security**: Fine grain access control, valuable dimension for analysis
  - **Network Management**: network planning, QoS
  - **Performance measurement:** Performance dependence on traffic class

Problem Space

- So far research focuses on packet-level measurement with good results.
- But no systems implementations, because…
  - ➢ Required measurements are difficult
    - ✓ Focus on flow records.
    - ✓ Existing research exhibit encouraging results.
  - ➢ Inflexible and generic models
    - ✓ use modern ML techniques (Bayesian Modeling, Probabilistic graphical models)
    - ✓ Develop a problem specific ML-model with well defined parameters
    - ✓ Since records are sensitive to minor network changes, use semi-supervised learning

Outline

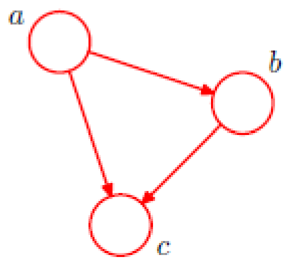
- **Model Presentation**
- Results
- Related work
- Further Development

Problem definition

- N flows extracted from a router each having M feauture.
- Each flow is represented by a vector x_i that has set of features x_{ij} with $0 < j \leq M$ and $0 < I \leq N$.
- Each flow has an application class c_i.
- Assume that we have L flows labeled and U flow unlabeled with $L+U = N$.
- Define f(.) such as , If $X_i \in U$, $f(X_i \mid C_L, L) = c_i$
- Assume that flow records are generated without any sampling applied and x_{ij} *are independent*.

Probabilistic Graphical Models

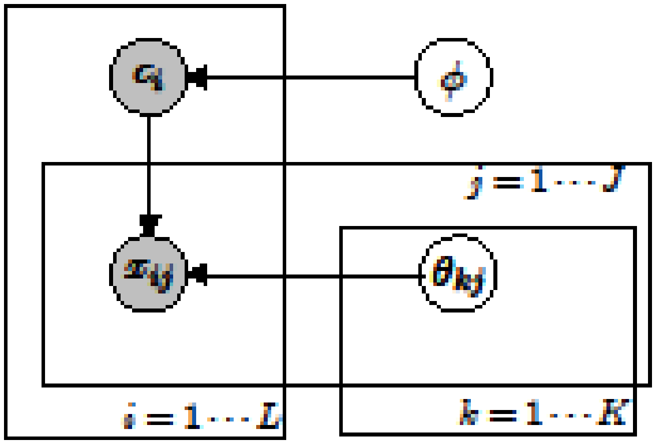
- Diagrammatic representations of probability distributions
- Directed acyclic graphs represent conditional dependence among R.V.
- Easy to perform inference $p(x) = \prod_{v \in V} p\big(x_v \,\big|\, x_{\mathrm{pa}(v)}\big)$



P(a,b,c) = P(a) P(b | a) P(c | a,b)

- Simple graph manipulation can give us complex distributions.
- Advantages:
  - Modularity
  - Iterative design
  - Unifying framework

Generative model



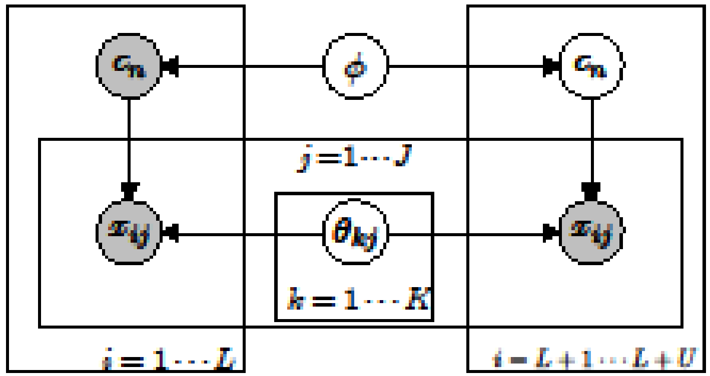
$$p(C_X, X, C_Y, Y \mid \phi, \theta) = \prod_{i=1}^{L+U} \left(p(c_i \mid \phi) \prod_j p(x_{ij} \mid \theta, c_i) \right)$$

- φ is the parameter of the class distribution and θ_{kj} is the parameter of the distribution of feature j for class k.
- Graph model similar to supervised Naïve Bayes Model.
- Assume $\theta_{kj} \sim \mathrm{Dir}(\alpha_\theta)$ and $\varphi \sim \mathrm{Dir}(\alpha_\varphi)$.
- Use bayesian approach to calculate parameter distribution.

Semi supervised learning

- Hybrid approach of supervised and unsupervised learning
- Train using a labeled dataset and extend model by integrating newly labelled datapoints.
- Advantages:
  - ✓ Reduced training dataset.
  - ✓ Increased accuracy when the model is correct.
  - ✓ Highly configurable when used with Bayesian modeling.
- Disadvantages
  - ✓ Computationally complex .

Semi supervised graphical model



- Calculating parameter increases exponentially as new unlabled datapoint are added. $p(\phi,\theta|X,Y,C_X) \propto \sum_{C_Y} p(C_X,X,C_Y,Y|\phi,\theta)p(\phi)p(\theta)$
- **Hard assignment**: Add newly labelled datapoint to the Cx with the highest posterior probability.
- **Soft assignment:** update the posterior for each parameter according to the predicted weight of the datapoint.
- Define class using: $f(x^*) = max_c(p(c|x^*))$

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Data

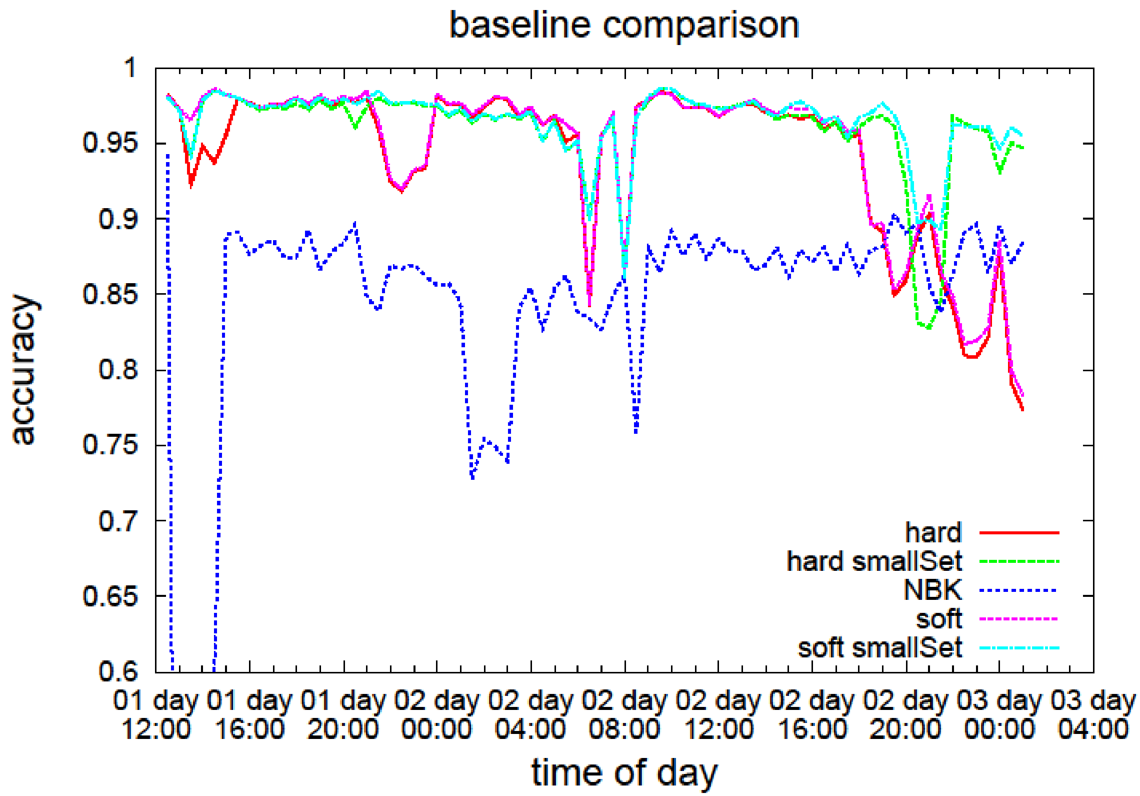
- 2 day trace from research facility [Li09]. Appr. 6 million tcp flows.
- Ground-truth using GTVS tool.
- Netflow records exported using nProbe. Settings similar to a Tier-1 ISP.
- Model implemented in C#. Also used the Naïve Bayes with kernel estimation implementation from the Weka Platform.
- Feature set:

srcIp/dstIP	srcPort/dstPort	ip tos	start/end time
tcpFlags	bytes	# packets	time length
avg. packet size	byte rate	packet rate	tcpF* (uniq. flag)

Application statistics

App	%	App	%	App	%
database	4.3	services	0.03	peer-to-peer	11.47
mail	2.5	Spam filter	0.48	web	72.33
ftp	6.25	streaming	0.31	vpn	0.1
im	0.6	voip	0.16	Remote access	0.61

Baseline comparison

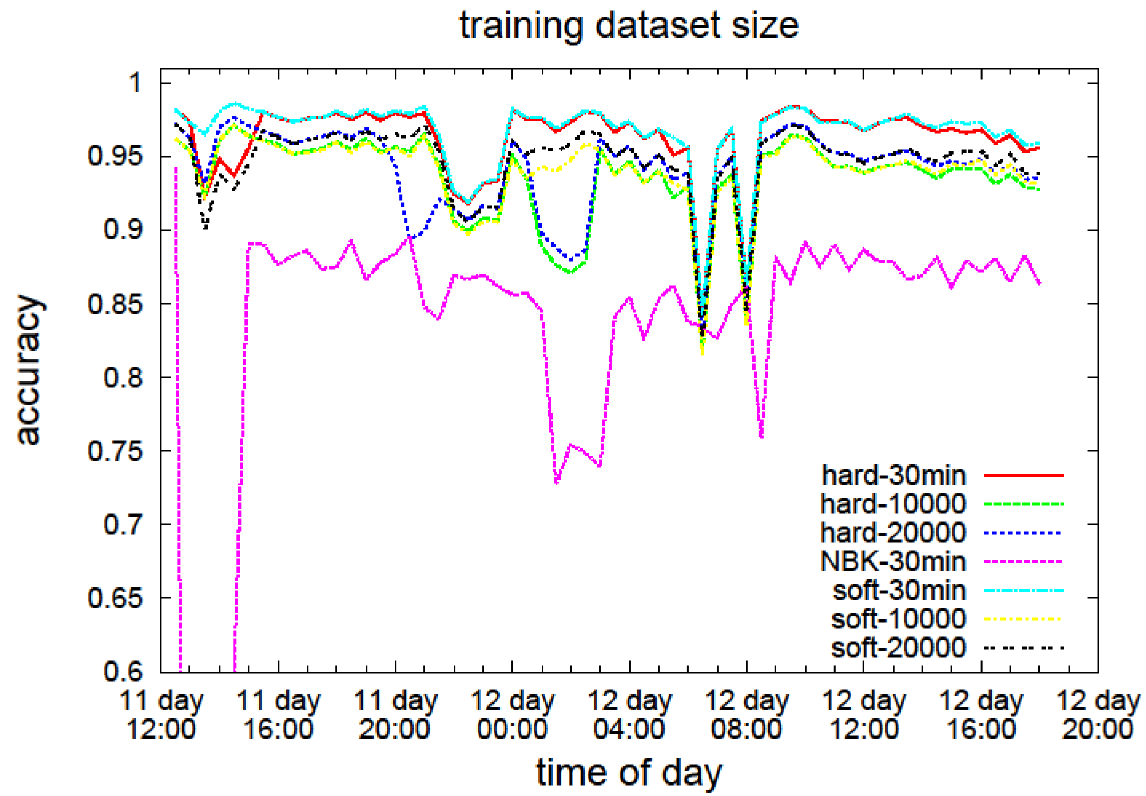


Baseline comparison – Class accuracy

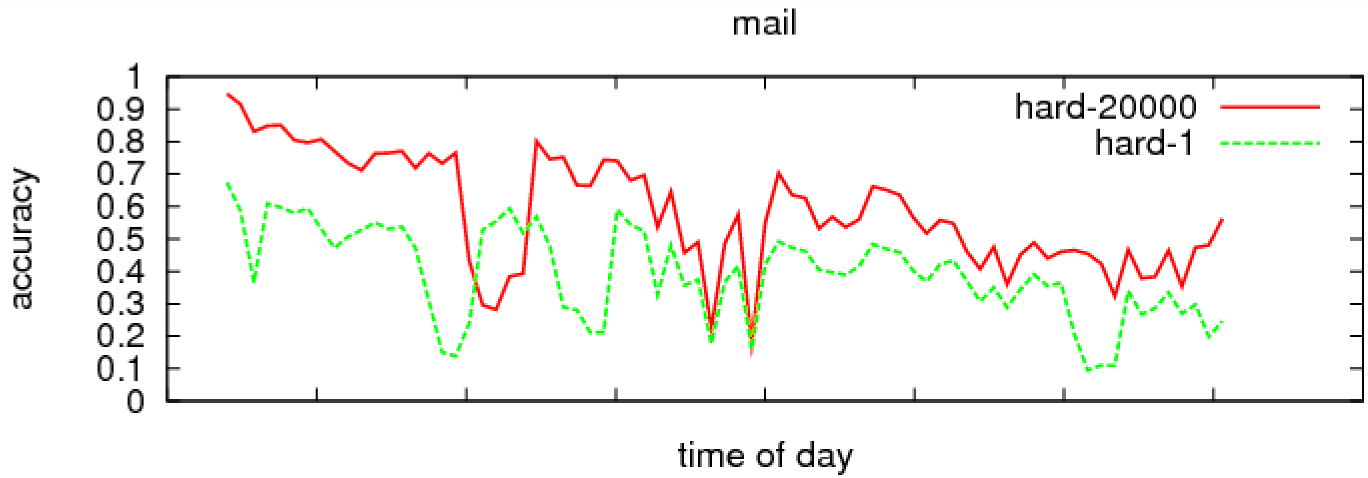
	DB	MAIL	FTP	IM	P2P	ACCESS
Hard	1	0.58	1	0.39	1	0.95
Hard-ss	1	0.59	1	0.82	1	0.77
Soft	1	0.55	1	0.42	1	0.96
Soft-ss	1	0.61	1	0.42	1	0.81
NBK	0.84	0.26	0.42	0.76	0.91	0.11

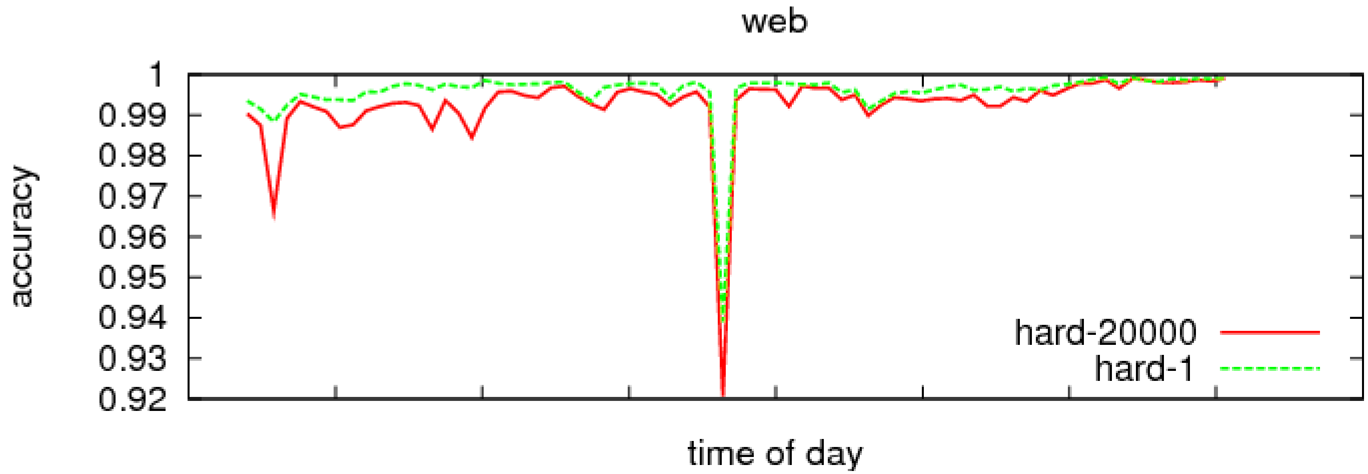
	SERV	SPAM	STREAM	WEB	VPN	VOIP
Hard	0	1	0.97	0.99	0.82	0.24
Hard-ss	0	1	0.91	0.99	0	0.44
Soft	0	1	0.96	0.99	1	0.77
Soft-ss	0	1	0.96	0.99	0.03	0.21
NBK	0.24	0.95	0.1	0.89	0.35	0.12

Dataset size



Model parameters





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Related work

- Lots of work on traffic classification using machine learning
  - Survey paper [Ngyen et al, IEEE CST 2008] and method comparison [Kim et al, Connext08]
- Semi-supervised learning used on packet-level measurements in [Erman et al, Sigmetrics07]
- Traffic classification using NetFlow data is quite recent
  - First attempt using a Naïve Bayes classifier introduced in [Jiang et al, INM07]
  - Approach to the problem using C4.5 classifier in [Carela-Espanol et al, Technical report 09]

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Further development

- Packet sampling
  - Difficult problem – multi view points could simplify the problem
- Adapt model for host characterization problem
  - Aggregate traffic on the host level and enrich data dimensions
- Incorporate graph level information in the model
  - Computer networks bares similarities with social networks

Conclusion

- Flow records may be a good data primitive for traffic classification.
- Modeling using probabilistic graphical model is not very difficult.
- Semi supervised learning is an effective concept, but is not a one-solves-all solution.
- Our model achieves 5-10% better performance than generic classifier and exhibits a good stability in short scale.
- Bayesian modeling and graphical models allow easy integration of domain knowledge and adaptation to the requirements of the user.
- Model can be extended to achieve better results.

Thank you!!!!