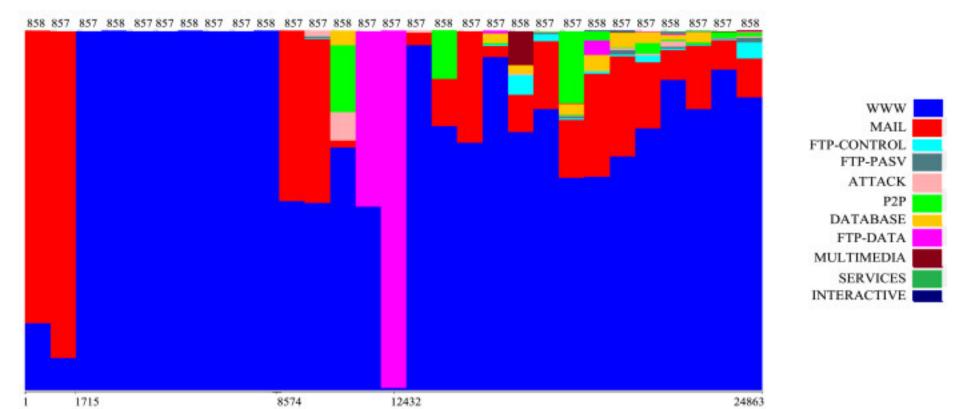
Superviz Plenary Meeting WP4-PO4.1

Yufei Han @ INRIA PIRAT

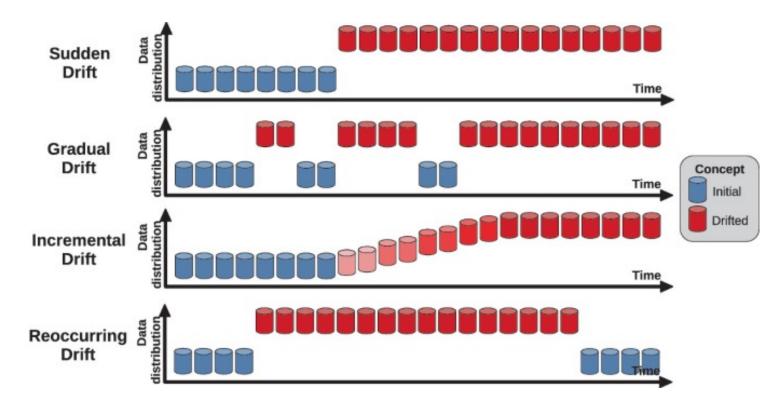
March 11, 2025

@Campus Cyber

- What is the bottleneck for ML-based IDS
 - Concept drift of attack behaviours: attackers may change attack techniques to evade detection or exploit new attack surfaces



- What is the bottleneck for ML-based IDS
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• Theoretically, every ML model has a significantly deteriorated prediction accuracy over concept drifted inputs

Theorem 1 Let $\theta \in \mathcal{H}$ be a hypothesis, $\epsilon_s(\theta)$ and $\epsilon_t(\theta)$ be the expected risks of source and target respectively, then

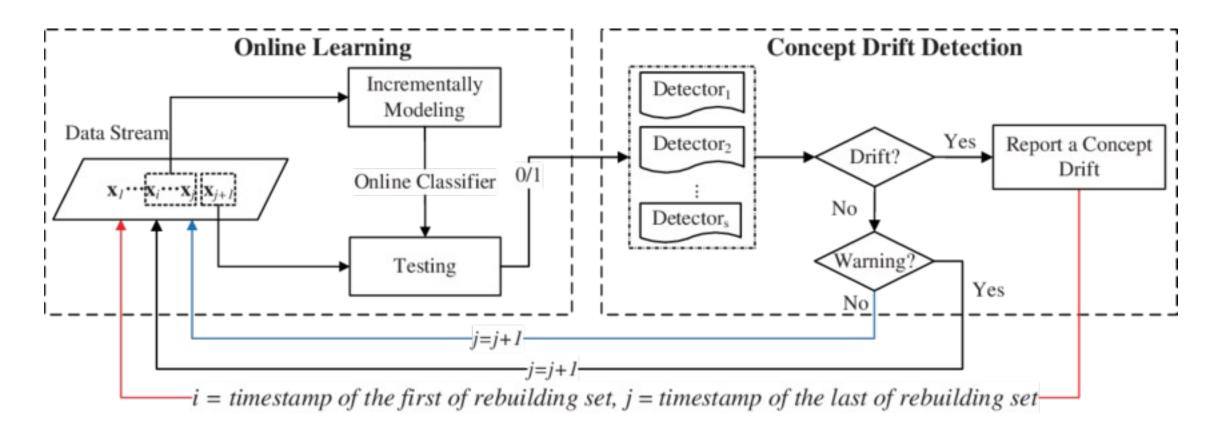
$$\epsilon_t(\theta) \leqslant \epsilon_s(\theta) + 2d_k(p,q) + C, \tag{9}$$

where C is a constant for the complexity of hypothesis space and the risk of an ideal hypothesis for both domains.

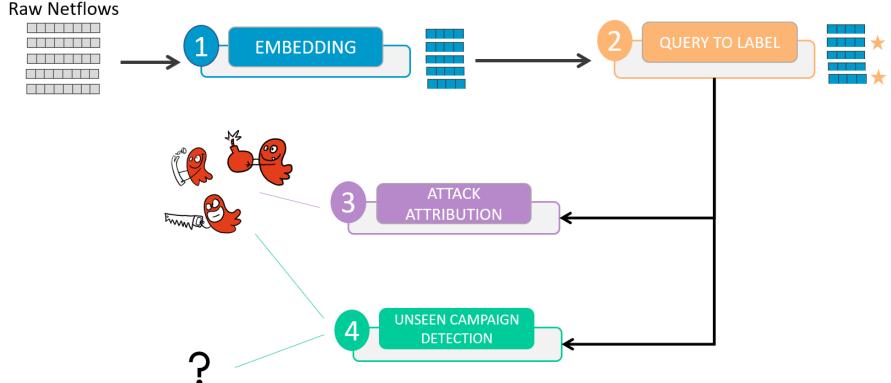
Distribution gap between training and testing data

Michel. I. Jordan et al, Learning Transferable Features with Deep Adaption Networks, ICML 2015

• How to reach this goal ?

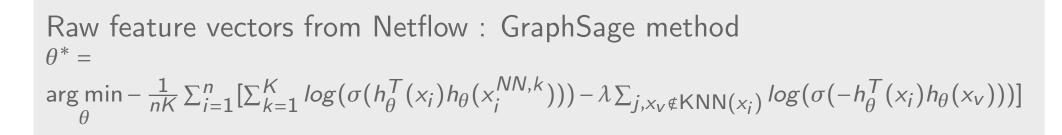


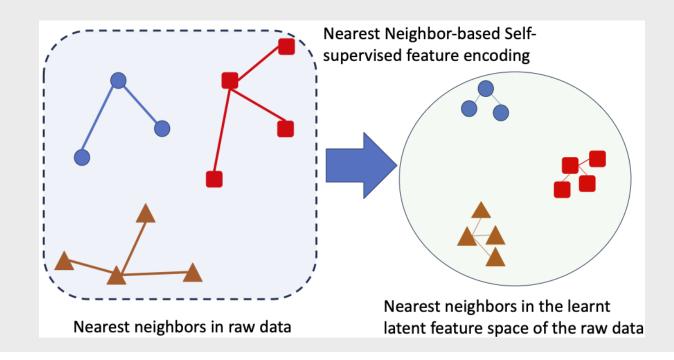
• Active Learning as a protocol for incrementally update the knoweldge for network attack classification

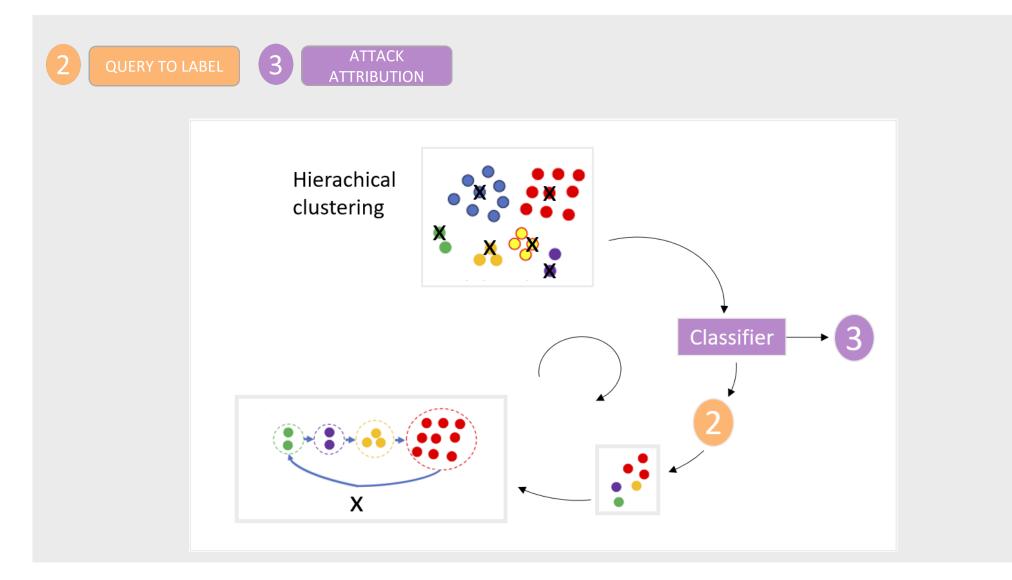


Helene Orsini and Yufei Han, DYNAMO: Towards Network Attack Campaign Attribution via Density-Aware Active Learning, https://hal-emse.ccsd.cnrs.fr/UNIV-UBS/hal-04877620v1

EMBEDDING







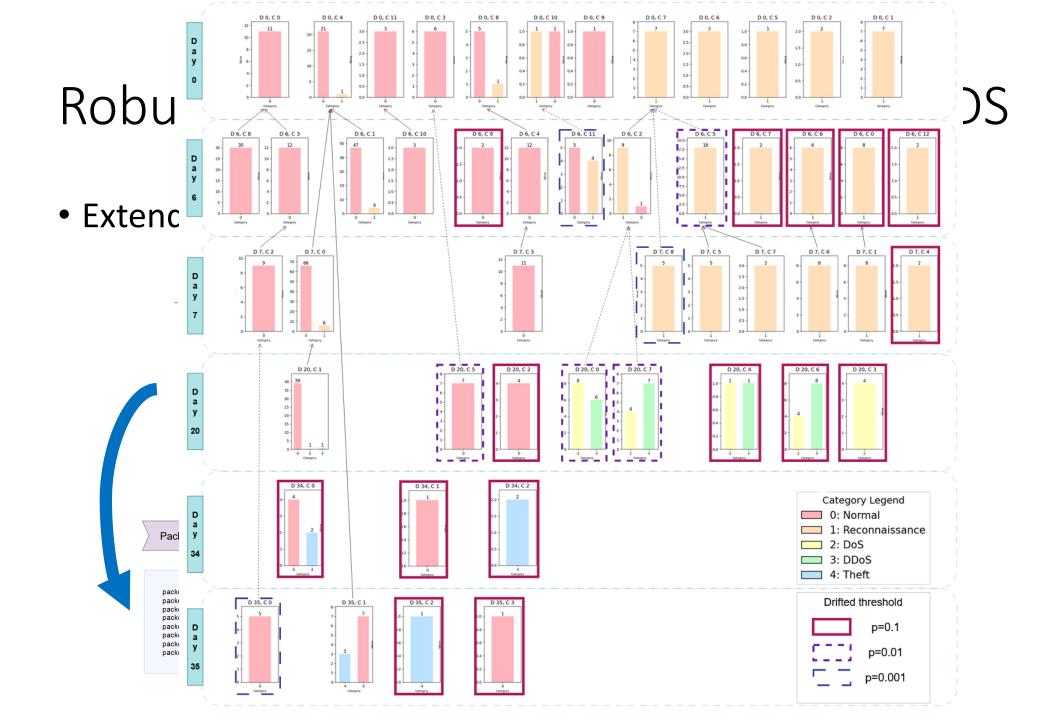
4 DETECTION

UNSEEN CAMPAIGN

Pu learning

Train a classifier to distinguish between positive and negative. Learning phase: **Positive and Unlabelled** (*only some of the positive examples in the training data are labeled and none of the negative examples are*)

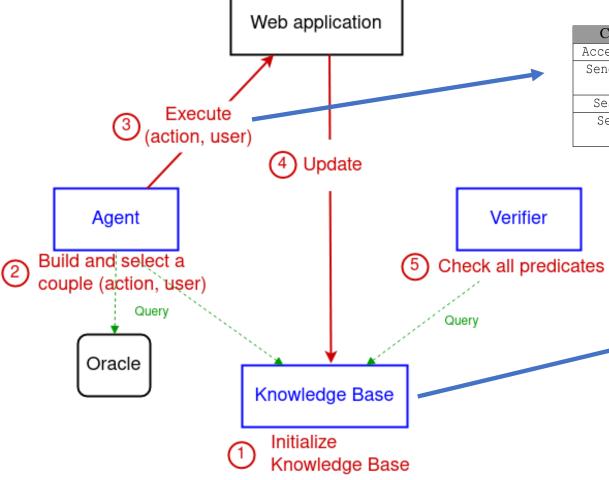
$$g_{\phi}^{pu} = \arg\min_{\phi} \frac{\pi}{n_p} \sum_{x_i \in S} \left[\ell(g_{\phi}^{pu}(h_{\theta}(x_i)), y_i = +1) - \ell(g_{\phi}^{pu}(h_{\theta}(x_i)), y_i = -1) \right] + \frac{1}{n_u} \sum_{x_i \in X_{unlabeled}} \ell(g_{\phi}^{pu}(h_{\theta}(x_i)), y_i = -1)$$



- Back to the question "How to reach a robust IDS facing concept drift ?"
- Can we predict the attack behaviour ?
- Natan Talon et al, SCWAD: Automated Pentesting of Web Applications, <u>https://inria.hal.science/hal-04874868v1/document</u>

Vulnerabilities, e.g. Broken Access Control and

Reflected Cross-Site Scripting.



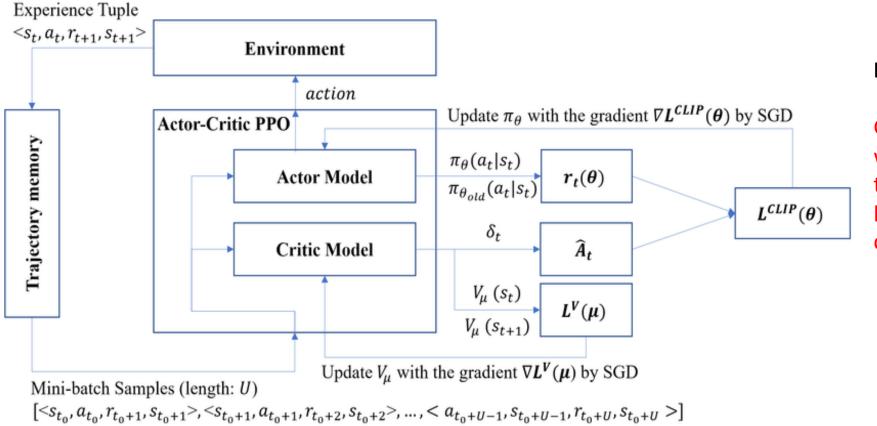
Action set

Command	Parameters	Expected behavior on the Web application
AccessWebPage	u: <i>url</i>	change current page for the current user
SendHttpForm	x: $xpath$, input: $dict \ \{ \ key:$	send the form identified by x and filled with input to
	value }	the web application
SearchData	data: <i>string</i>	return true if data has been found in the current page
SetCookie	cookie: dict { key: value }	add cookie to user's cookies if this cookie doesn't
		exists and replace it otherwise

User login: user name

User credentials: The credentials for the application User cookies: The set of cookies, active or not User pages: The pages visited by the user and/or those to which the user has a link User current page: The current page visited by the user User allowed paths: All the links to the pages reachable by the user

Learn an attack policy with reinforcement learning



Key question to answer:

Given the current staste of the target web application and the vulnerability to explore, what shall be the most likely action that an attack can take to compromise the application ?

Thanks !