



Annual Computer Security Applications Conference

SpacePhish: The Evasion-space of Adversarial Attacks against Phishing Website Detectors using Machine Learning

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SPRITZ Security & Privacy Research Group

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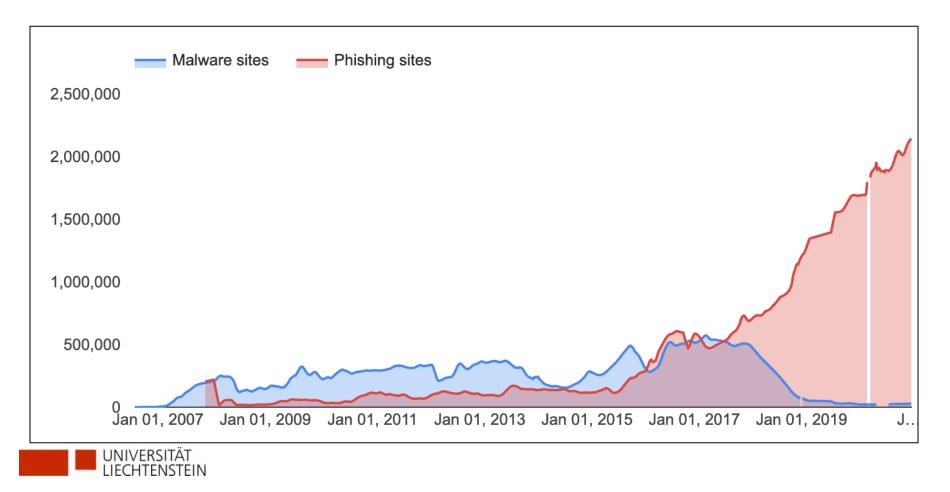
Spoiler?

In the adversarial ML domain, have you ever read a research paper showing an attack that has an effectiveness of 3%?



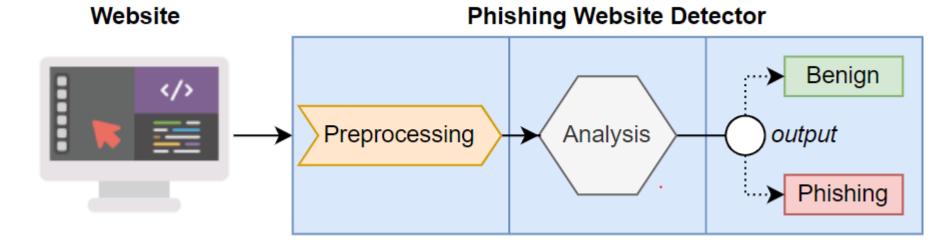
Current Landscape of Phishing

- Phishing attacks are continuously increasing
- Most detection methods still rely on *blocklists* of malicious URLs
 - These detection techniques can be <u>evaded easily</u> by "squatting" phishing websites!



Current Landscape of Phishing – Countermeasures

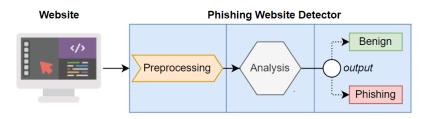
• Countering such simple (but effective) strategies can be done via *data-driven* methods



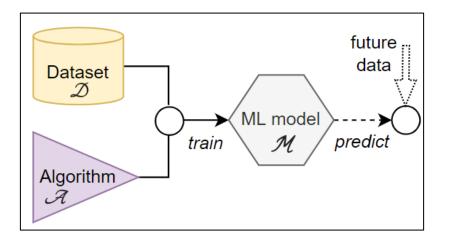


Current Landscape of Phishing – Countermeasures (ML)

• Countering such simple (but effective) strategies can be done via *data-driven* methods



• Such methods (obviously ⁽ⁱⁱⁱ⁾) include (also) Machine Learning techniques:



• Machine Learning-based Phishing Website Detectors (ML-PWD) are very effective [1]

• Even popular products and web-browsers (e.g., Google Chrome) use them! [2]



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[1]: Tian, Ke, et al. "Needle in a haystack: Tracking down elite phishing domains in the wild." Internet Measurement Conference 2018.
[2]: El Kouari, Oumaima, Hafssa Benaboud, and Saiida Lazaar. "Using machine learning to deal with Phishing and Spam Detection: An overview."
International Conference on Networking, Information Systems & Security. 2020.

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Phishing in a nutshell

- Phishing websites are taken down quickly
 - The moment they are reported in a blocklist, they become useless
- Even if a victim lands on a phishing website, the phishing attempt is not complete
 - The victim may be "hooked", but they are not "phished" yet!

Most phishing attacks end up in failure [3]



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Phishing in a nutshell (cont'd)

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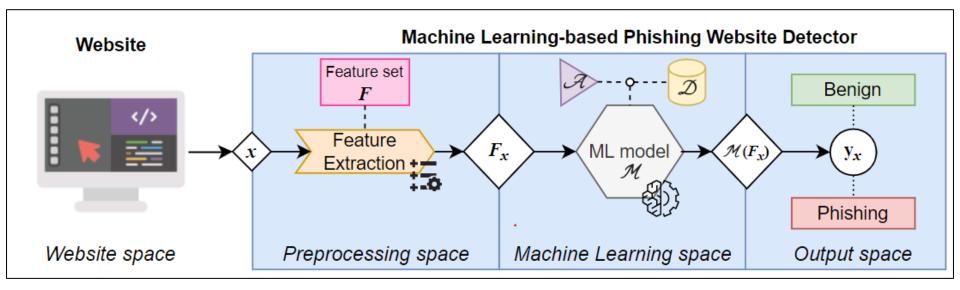
- Phishers are well aware of this fact... but they (clearly) keep doing it
 - Hence, they "have to" evade detection mechanisms

(Remember: Real attackers operate with a cost/benefit mindset [4])



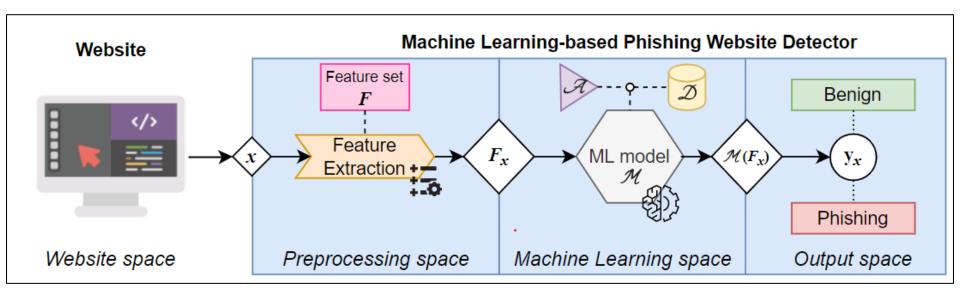
- ML-PWD are good but...
- o ...the detection of ML methods *can* be bypassed via (adversarial) *evasion* attacks!
- Adversarial Attacks exploit a **perturbation**, ε , that induces an ML model, \mathcal{M} , to misclassify a given input, F_x , by producing an incorrect output (y_x^{ε} instead of y_x)

find
$$\varepsilon$$
 s.t. $\mathcal{M}(F_{\mathbf{X}}) = y_{\mathbf{X}}^{\varepsilon} \neq y_{\mathbf{X}}$





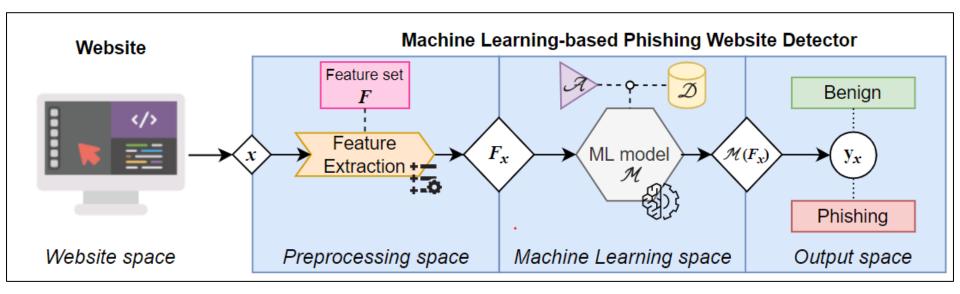
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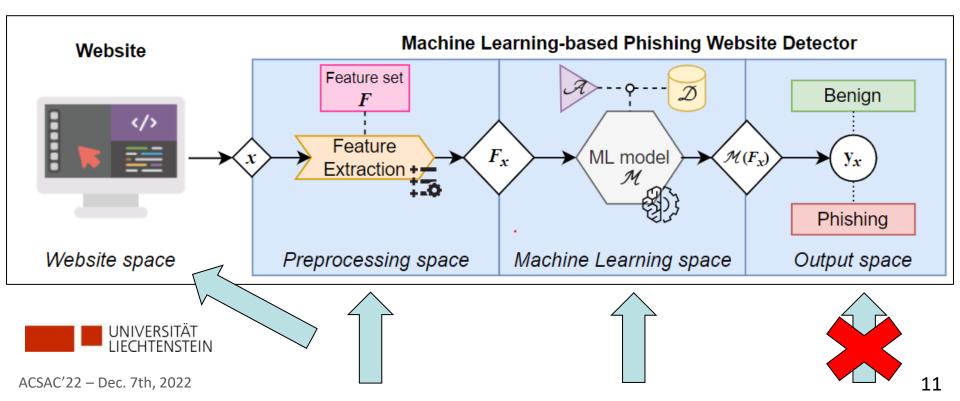
• In the context of a ML-PWD, such **perturbation** can be introduced in three 'spaces':





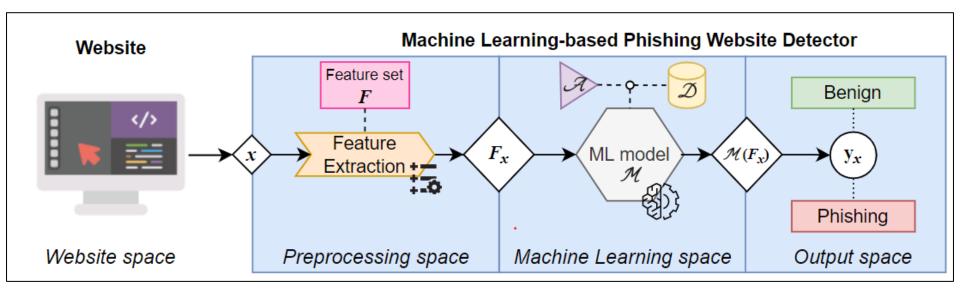
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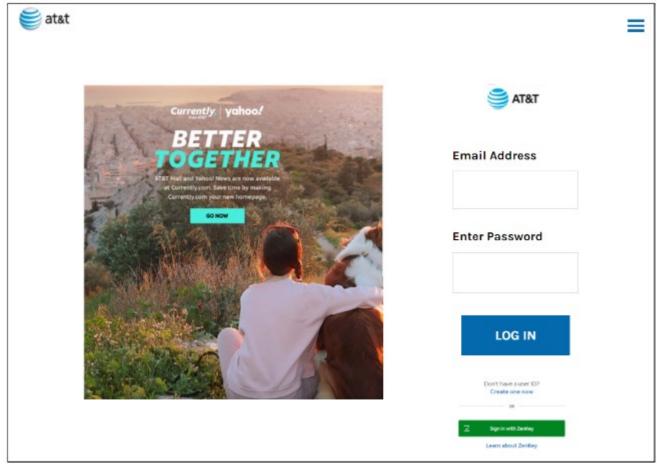
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UN Question: Which 'space' do you think an *attacker* is **most likely** to use?

Website-space Perturbations (WsP) in practice – original example

Figure 4: An exemplary (and true) Phishing website, whose URL is https://www.63y3hfh-fj39f30-f30if0f-f392.weebly.com/.





Website-space Perturbations (WsP) in practice – changing the URL

https://www.63y3hfh-fj39f30-f30if0f-f392.weebly.com/

https://www.legitimate123.weebly.com/



Website-space Perturbations (WsP) in practice – changing the HTML





Website-space Perturbations (WsP) in practice – changing URL+HTML

https://www.63y3hfh-fj39f30-f30if0f-f392.weebly.com/



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Why do we need all of this anyway? (first reason)

2020 IEEE Symposium on Security and Privacy

Intriguing Properties of Adversarial ML Attacks in the Problem Space

Fabio Pierazzi^{*†}, Feargus Pendlebury^{*†‡§}, Jacopo Cortellazzi[†], Lorenzo Cavallaro[†] [†] King's College London, [‡] Royal Holloway, University of London, [§] The Alan Turing Institute

"This paper focuses on test-time evasion attacks in the so-called **problem space**, where the challenge lies in modifying real input-space objects that correspond to an adversarial feature vector. The main challenge resides in the **inverse feature-mapping** problem since in many settings it is not possible to convert a feature vector into a problem-space object because the feature mapping function is neither invertible nor differentiable."



Why do we need all of this anyway? (first reason) [cont'd]

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- This observation is well-founded, however...
- ... if the attacker has access to the feature space, then such "problem" does not apply.

Perturbations in the feature space are **not unrealistic**: they simply require the attacker to compromise the ML system.

- This is possible [5], but it has <u>a high cost!</u>
- All past work considering "feature space" perturbations can be made valuable by assuming that the attack has a higher cost!

Why do we need all of this anyway? (second reason)

- Most existing work in the ML-PWD domain has shortcomings, among which:
 - Some craft perturbations in the "feature" space (not impossible, but costly!)
 - Others assume strong attackers (full knowledge, or massive queries)
 - Liang et al. [57] took days!
 - No statistical validation (crucial for a fair evaluation!)

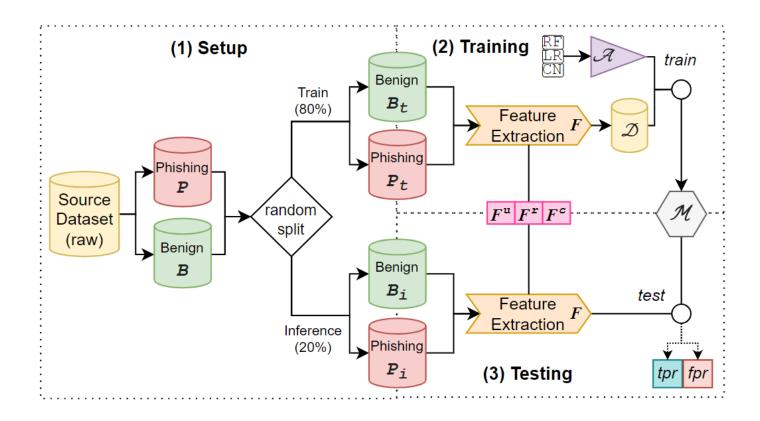
Paper (1st Author)	Year	Evasion space	ML-PWD types (F)	ML Algorithms	Defense	Datasets (reprod.)	Stat. Val.
Liang [57]	2016	Problem	F ^c	SL	×	1 (🗡)	×
Corona [30]	2017	Feature	F^r, F^c	SL	 ✓ 	1 🗸	×
Bahnsen [20]	2018	Problem	$F^{\boldsymbol{u}}$	DL	×	1 (🗡)	×
Shirazi [79]	2019	Feature	F^{c}	SL	×	4 🗸	✓*
Sabir [77]	2020	Problem	$F^{\boldsymbol{u}}$	SL, DL	 ✓ 	1 (🗡)	×
Lee [55]	2020	Feature	F^{c}	SL	 ✓ 	1 🗸	×
Abdelnabi [8]	2020	Problem	F^{r}	DL	 ✓ 	1 🗸	×
Aleroud [11]	2020	Both	$F^{\boldsymbol{u}}$	SL	×	2 🗸	×
Song [81]	2021	Problem	F^{c}	SL	 ✓ 	1 🚺	×
Bac [18]	2021	Feature	$F^{\boldsymbol{u}}$	SL, DL	×	1 (🗡)	×
Lin [59]	2021	Feature	F^{c}	DL	 ✓ 	1 🖌	×
O'Mara [67]	2021	Feature	F^{r}	SL	×	1 🖌	×
Al-Qurashi [10]	2021	Feature	F^{u}, F^{c}	SL, DL	×	4 🗸	×
Gressel [36]	2021	Feature	F^{c}	SL, DL	 ✓ 	1 (🗡)	×
Ours		Both	F^u, F^r, F^c	DL, SL	 ✓ 	2 🗸	 Image: A start of the start of

ACSAC'2 What is the true impact of realistic adversarial attacks against ML-PWD?

Evaluation – Workflow



- Are "cheap" perturbations (i.e., blind WsP) effective? Let's assess their impact!
- First, we develop proficient ML-PWD (high *tpr*, low *fpr*)





Evaluation – Baseline



- Are "cheap" perturbations (i.e., blind WsP) effective? Let's assess their impact!
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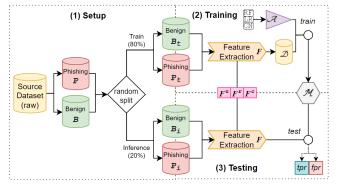


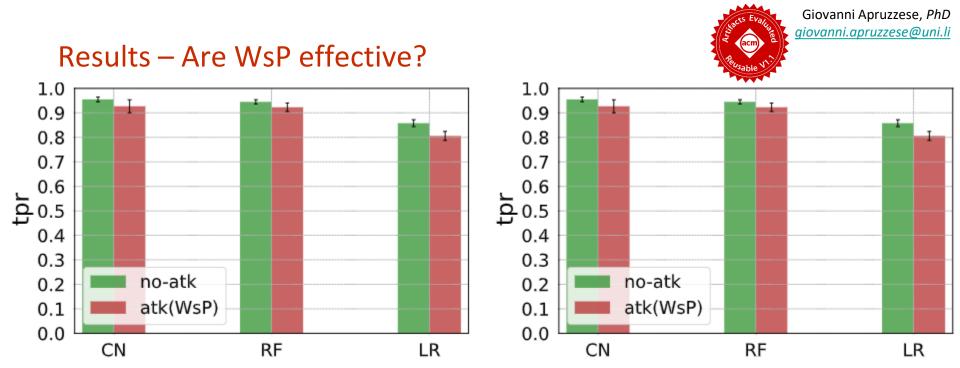
Table 3: Performance in non-adversarial settings, reported as theaverage (and std. dev.) tpr and fpr over the 50 trials.

- Results comparable to the state-of-the-art ^(C)
- Let's attack such ML-PWD
 - The *tpr* will decrease!



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$\mathcal{A} \mid F$		Ze	nodo	$\delta _{ m phish}$		
Я		tpr	f pr	tpr	fpr	
	F^{u}	0.96±0.008	0.021±0.0077	0.55±0.030	0.037 ± 0.0076	
CN	$F^{\boldsymbol{r}}$	0.88±0.018	0.155±0.0165	0.81±0.019	0.008 ± 0.0020	
	F^{c}	0.97 ± 0.006	$0.018{\scriptstyle \pm 0.0088}$	0.93±0.013	$0.005{\scriptstyle \pm 0.0025}$	
	F^{u}	0.98 ± 0.004	0.007±0.0055	0.45±0.022	0.003±0.0014	
RF	F^{r}	0.93 ± 0.013	0.025±0.0118	0.94 ± 0.016	0.006 ± 0.0025	
	F^{c}	$0.98{\scriptstyle \pm 0.006}$	$0.007{\scriptstyle\pm0.0046}$	0.97±0.007	$0.001{\scriptstyle \pm 0.0011}$	
	F^{u}	0.95±0.009	0.037±0.0100	0.24±0.017	0.011 ± 0.0026	
LR	F ^{<i>r</i>}	0.82±0.017	0.144±0.0171	0.74±0.025	0.018 ± 0.0036	
	<i>F</i> ^{<i>c</i>}	0.96±0.007	0.025 ± 0.0077	0.81±0.020	$0.013{\scriptstyle \pm 0.0037}$	



(a) Zenodo. The plot shows the *tpr* before and after our WsP attack. The WsP entail invisible manipulations of the HTML. We repeat the experiments 50 times.

(b) δ Phish. The plot shows the tpr before and after our WsP attack. The WsP entail invisible manipulations of the HTML. We repeat the experiments 50 times.

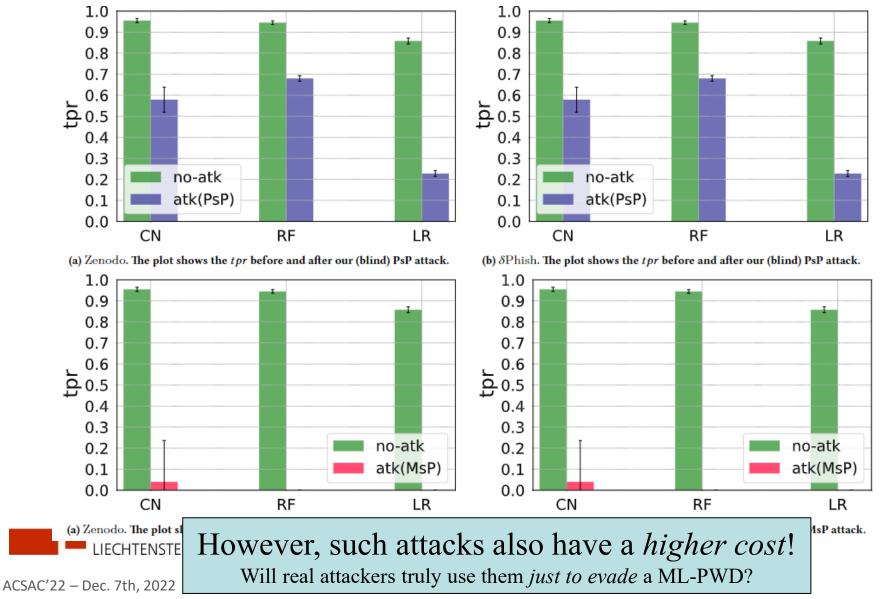
- o In some cases, NO
 - This is *significant* because most past studies show ML-PWD being bypassed "regularly"!
- In some cases, VERY LITTLE
 - This is also significant, because even a 3% decrease in detection rate can be problematic when dealing with *thousands of samples*!
- In other cases (not shown here), YES
 - This is very significant, because WsP are cheap and are likely to be exploited by attackers



Results – What about attacks in the other spaces?



In general, attacks in the other spaces (via PsP and MsP) are more disruptive...





<u>https://spacephish.github.io</u> (<u>https://tinyurl.com/spacephish-demo</u>)





- https://spacephish.github.io (https://tinyurl.com/spacephish-demo) Ο
- https://nbviewer.org/github/hihey54/acsac22 spacephish/blob/main/mlsec folder/mlsec artifact-manipulate.ipynb 0

```
def websiteAttacks_html(in_html,string,num):
    ind=in_html.find('</body>')
    content=""
   for i in range(0, num):
        content=content+string
    out_html=in_html[:ind]+content+in_html[ind:]
    return out html
```

	In [6]:	# TEST ORIGINAL	In [8]:	# TEST ADVERSARIAL
		<pre>with open(original_fil</pre>		<pre>with open(output_file,</pre>
UNIVERSITÄT LIECHTENSTEIN		<pre>{ "n_models": 8, "p_mod_00": 0.891, "p_mod_01": 0.811, "p_mod_02": 0.891, "p_mod_03": 0.811, "p_mod_04": 0.806, "p_mod_05": 0.741, "p_mod_06": 0.806, "p_mod_07": 0.741 }</pre>		<pre>{ "n_models": 8, "p_mod_00": 0.426, "p_mod_01": 0.794, "p_mod_02": 0.426, "p_mod_03": 0.794, "p_mod_04": 0.864, "p_mod_05": 0.774, "p_mod_06": 0.794, "p_mod_06": 0.794, "p_mod_07": 0.741 }</pre>
Dec. 7th, 2022		-		-





- <u>https://spacephish.github.io</u> (<u>https://tinyurl.com/spacephish-demo</u>)
- o https://nbviewer.org/github/hihey54/acsac22_spacephish/blob/main/mlsec_folder/mlsec_artifact-manipulate.ipynb

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Review #6C	2 Oct 2022	
Overall merit 3. Reusable		

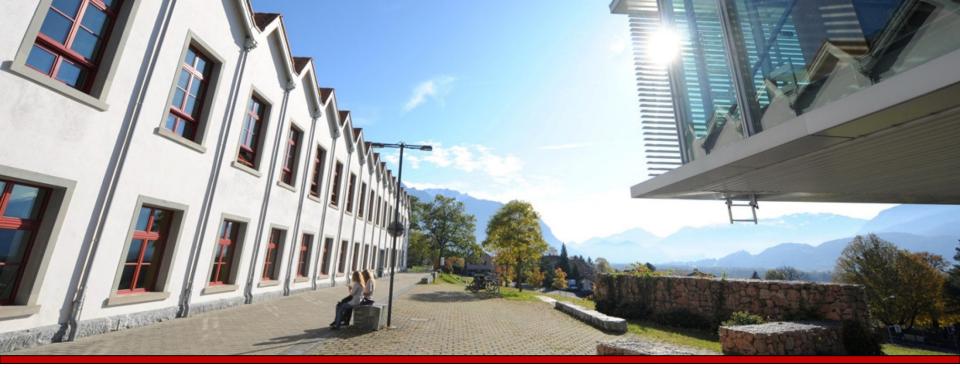
Comments

The code and dataset are well documented in the repo. The scripts and dataset are easily reused. All the questions are included in the repo. The results are consistent with the paper, the supplementary file, and the repo's result files.

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