

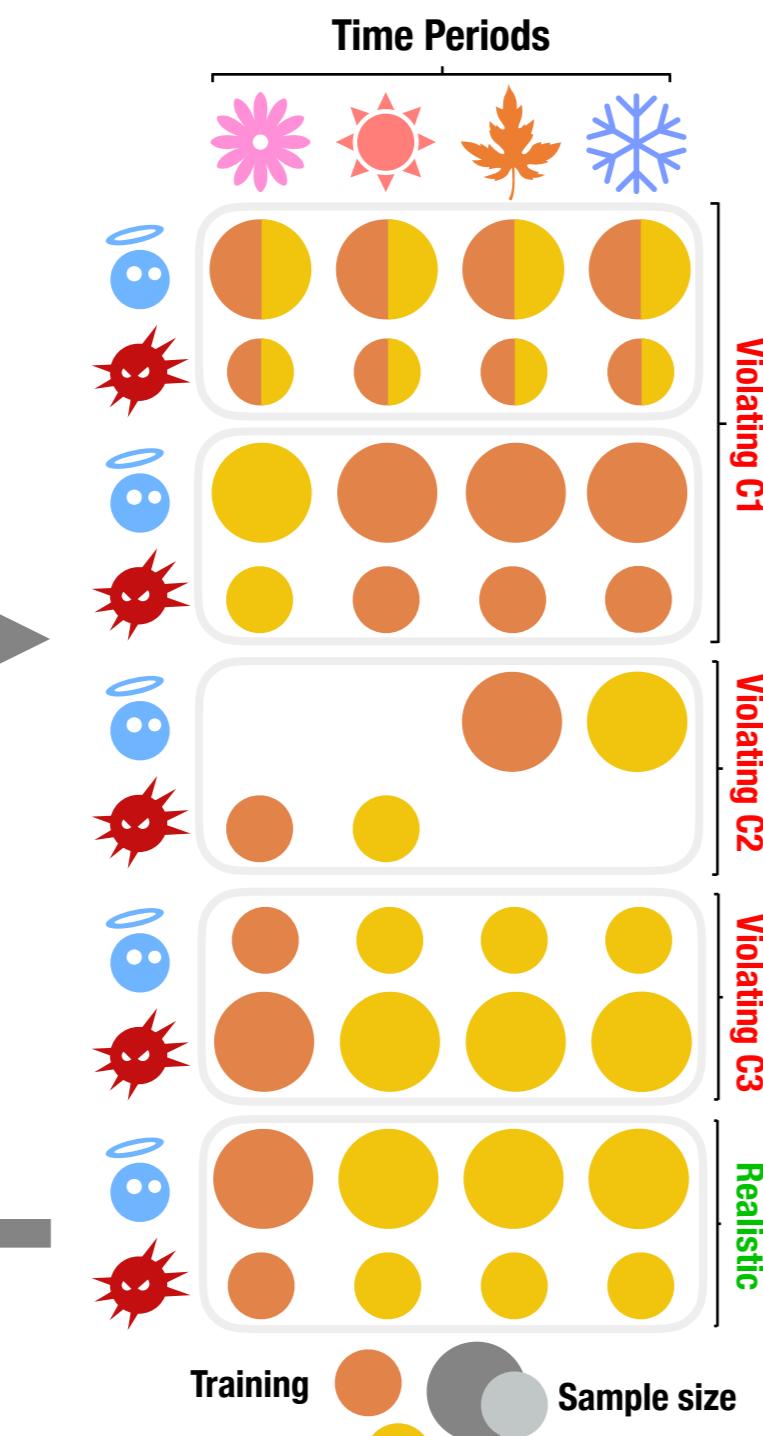


# Enabling Fair ML Evaluations for Security

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ML Security evaluations are flawed

Best practices for ML evaluations, such as k-fold CV, fail when i.i.d. assumptions do not hold, e.g., concept drift, adversarial ML.



## Temporal Experimental Bias

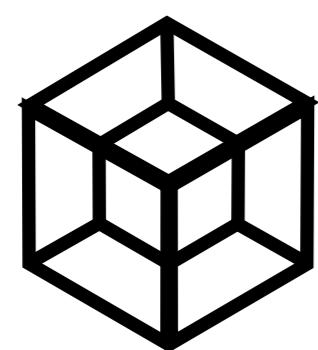
Caused by violating the temporal consistency of train and test sets.

## Spatial Experimental Bias

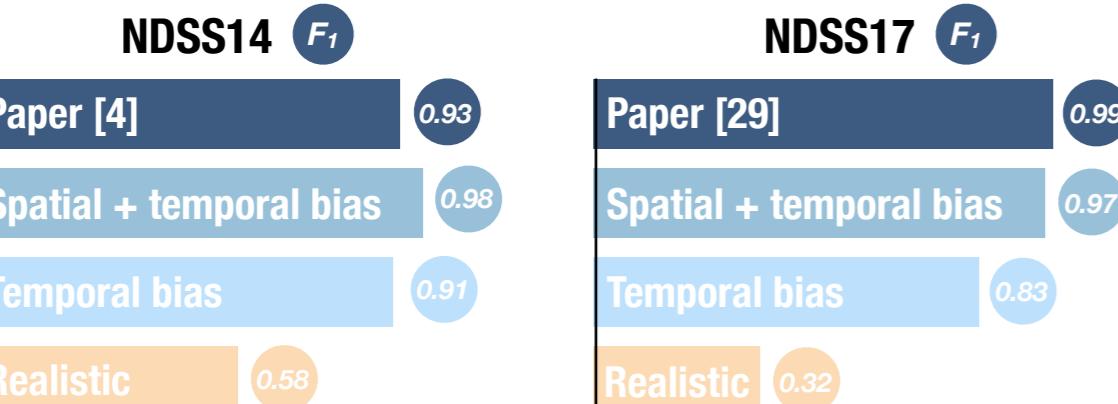
Caused by using unrealistic class ratios in the test set.

## TESSERACT

space-time bias-free evaluation framework

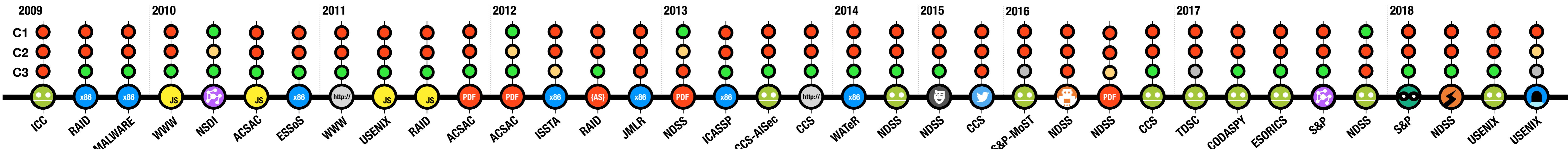


## Obscuring real performance



[NDSS14] bit vector features (APIs, metadata, strings, etc.), linear SVM, 66-34% holdout evaluation.

[NDSS17] Markov Chain-derived features (caller-callee APIs), RF, k-fold CV and (biased) timeline evaluation.



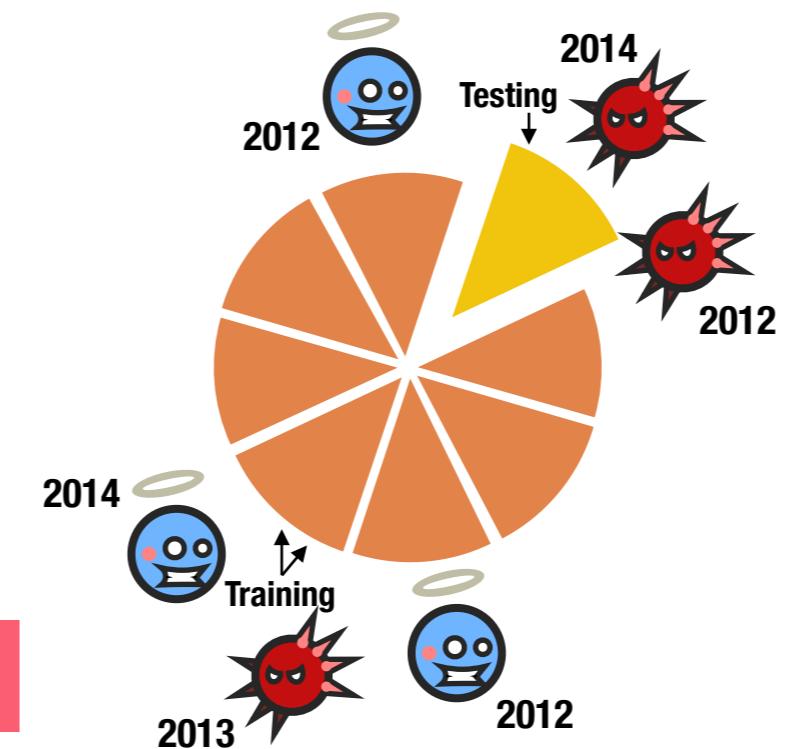
## C1 Temporal training consistency

All the objects in the training must be strictly temporally precedent to those in the testing.

### K-fold CV

K-fold cross-validation randomly samples objects in a time-agnostic manner which fails to model a real-world deployment.

**Violations** use future knowledge in training.



## C2 {good|mal}ware temporal consistency

In every testing period, all test objects must be from the same time window.



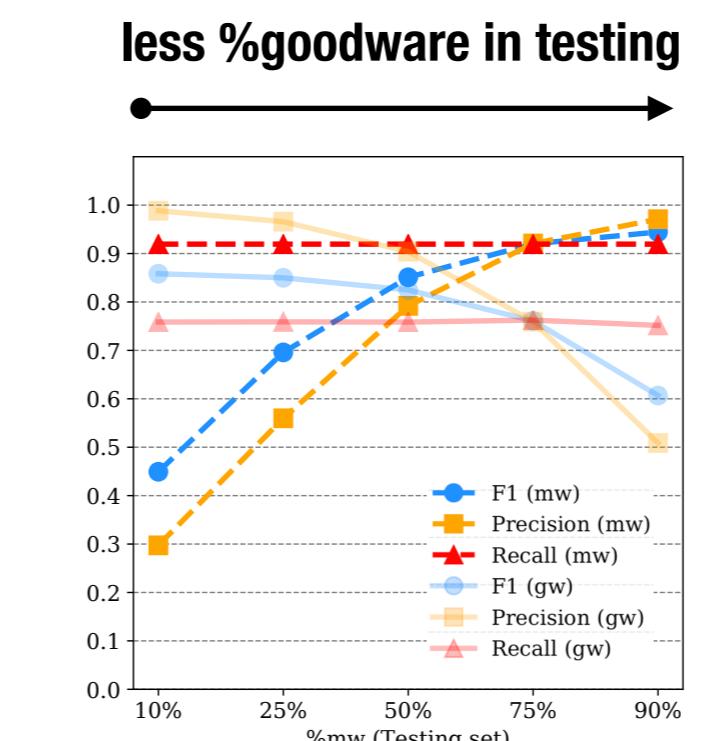
**Violations** may learn artifacts, such as old vs new APIs.

## C3 Realistic testing classes ratio

The testing distribution must reflect real-world objects ratios, such as malware-to-goodware percentages in a given context.

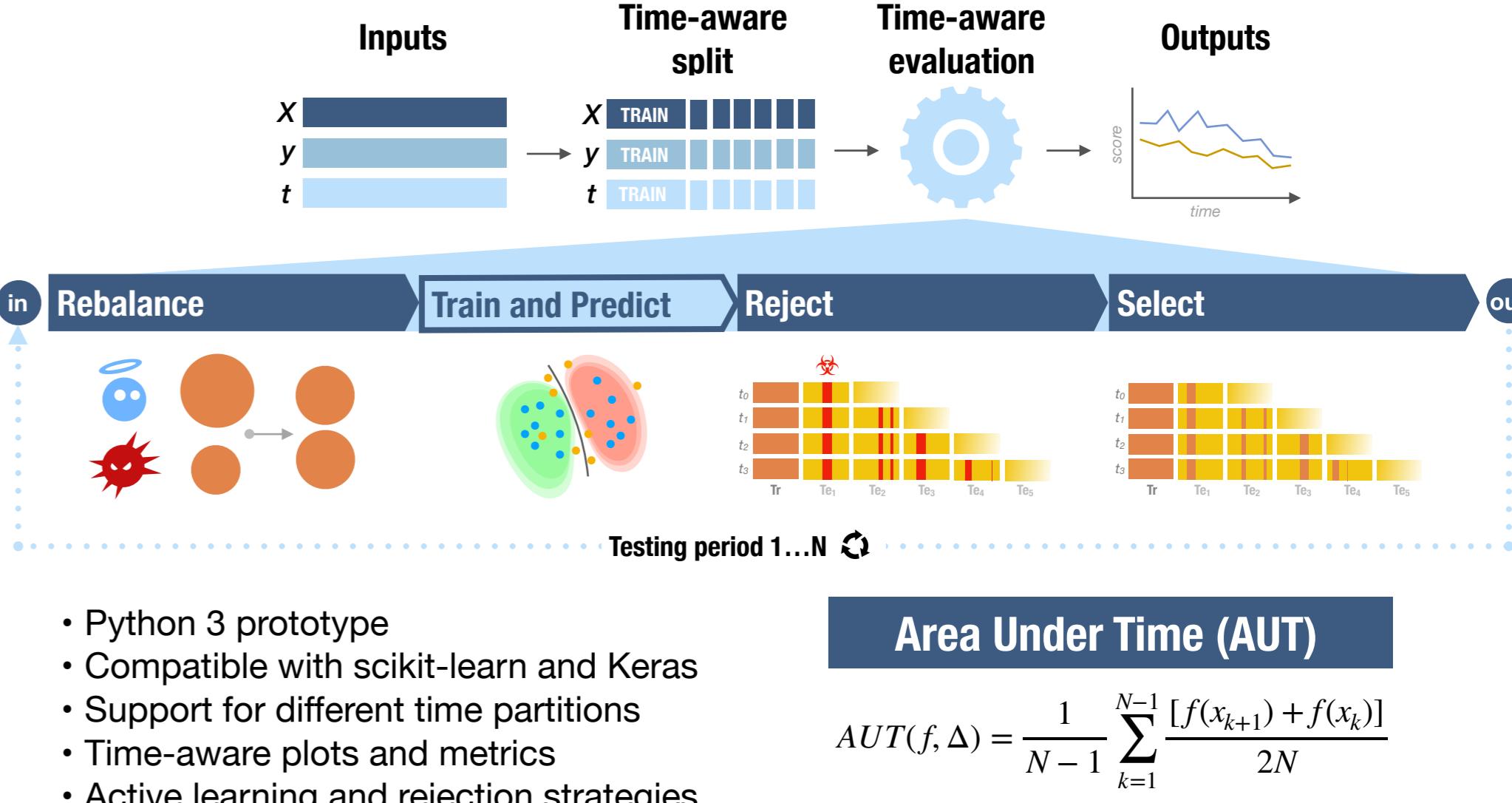
$$P_{mw}^* = \frac{TP}{TP + FP} \quad R_{mw}^* = \frac{TP}{TP + FN}$$

\* Undersampling goodware keeps  $R_{mw}^*$  steady and increases  $P_{mw}^*$



**Violations** produce unrealistic results.

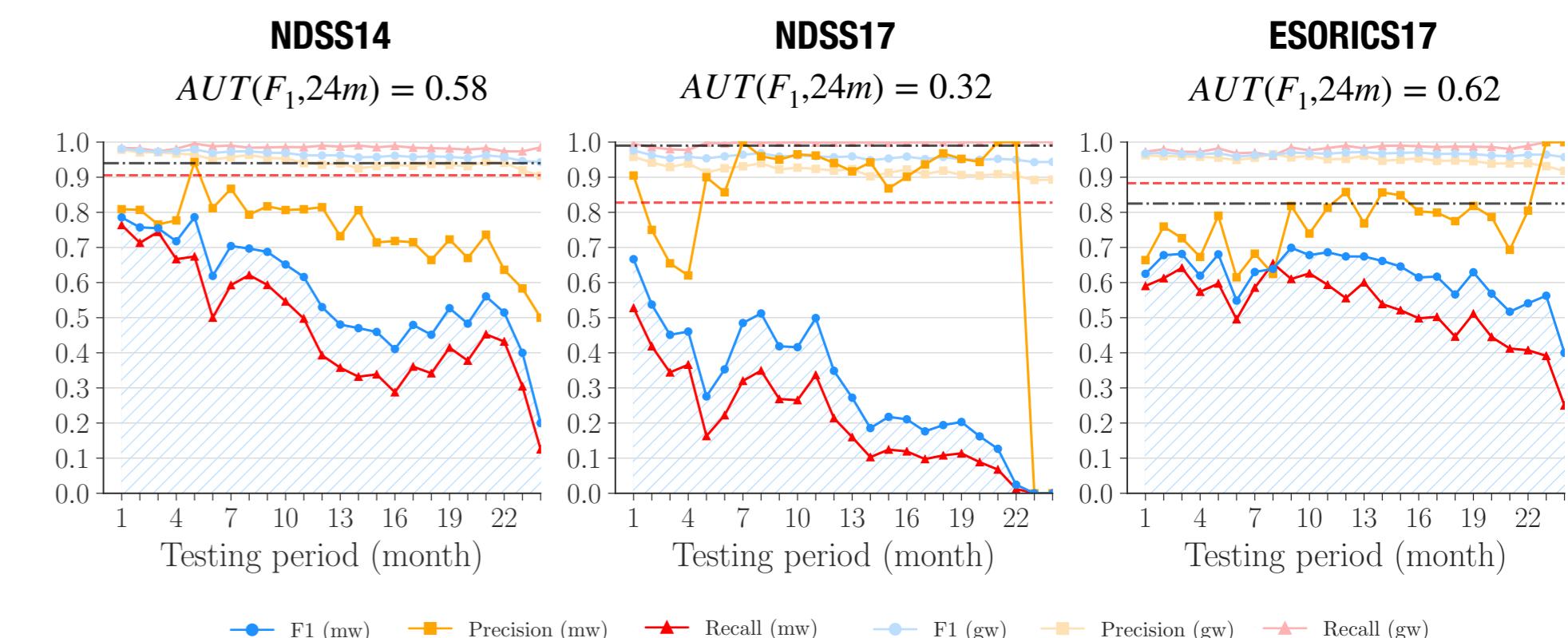
## TESSERACT: for when time matters!



- Python 3 prototype
- Compatible with scikit-learn and Keras
- Support for different time partitions
- Time-aware plots and metrics
- Active learning and rejection strategies

▼ Available at: [s2lab.kcl.ac.uk/projects/tesseract/](http://s2lab.kcl.ac.uk/projects/tesseract/)

## Revealing real performance



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- When the Magic Wears Off: Flaws in ML for Security Evaluations (and What to Do about It)—USENIX ENIGMA 2019
- POSTER: Enabling Fair ML Evaluations for Security—ACM CCS 2018
- TESSERACT: Eliminating Experimental Bias in Malware Classification across Space and Time—arXiv 2018

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