# Detecting client-side e-banking fraud using a heuristic model

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- E-banking malware;
- Man-in-the-browser attack;
  - "Owns" the browser;
  - Not possible to detect malware with web techniques, i.e JavaScript.

## Normal banking web page

	Betalen	Sparen	Inkomen voor later	Beleggen	Lenen	Hypotheken	Verzekeren	Contact		
edede	elingen	1					Goedemorgen Bf laatste bezoek: woensdag 20 mr 2 Bankma	t'13, 11:25 uur	Litlogge	n
								🔞 He	lp	
	Veil	ig Bankieren								
		op telefonische verzoek regelmatig vanuit servi	-							
			Hetzelfde geldt voor e- gevraagd wordt om coo codes. Controleer of het slotje slotje niet direct zichtba beveiligingsinformatie.	mail. Ga nooit i les te verstrekl in uw browser	n op verzoe ken. ABN A aanwezig i	sken per e-mail o MRO zal nooit per s en u <u>verbinding</u>	m op een link te e-mail vragen o hebt met ABN A	klikken waarbij u im persoonlijke MRO. Soms is het		

#### Figure 1: Normal banking web page

### Servicemelding:

Geachte klant!



Tot onze spijt zijn momenteel alle servers van het Internetbankieren overbelast, waardoor u een kleine vertraging bij de toegang tot uw account en zijn functies kunt oplopen.

Wacht totdat het systeem uw aanvraag volledig uitgevoerd heeft, zodat u toegang kunt krijgen tot uw account.

Opmerking:

Het proces kan enkele minuten in beslag nemen afhankelijk van de mate van belastbaarheid van de servers van de bank.

Wij bieden u onze excuses aan voor dit tijdelijke ongemak!



#### Figure 2: Malicious banking web page

To what extend is it possible to detect maliciously injected code into a web page using a heuristic model in order to counteract fraud and what is the performance of such technique in terms of accuracy and execution time?

- Pattern recognition;
- Cannot detect injections from unknown malware.

- CaffeineMonkey: a method to analyse and detect malicious JavaScript (Feinstein et. al.);
- Prophiler: a filter to examine millions of web pages for malicious content (Canali, Davide, et al.);
- Zozzle: a low-overhead solution that applies Bayesian analysis to detect JavaScript malware in the browser (Curtsinger, Charlie, et al.).

- Supervised machine learning;
  - Labeling of benign and malicious pages
- Server-side detection mechanism;

**Goal**: detect injections from unknown malware and difficult to bypass.

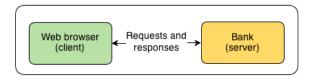


Figure 3: Normal interaction with an e-banking web site.

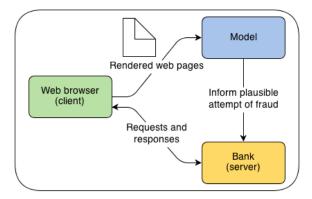


Figure 4: Overview of fraud detection implementation.

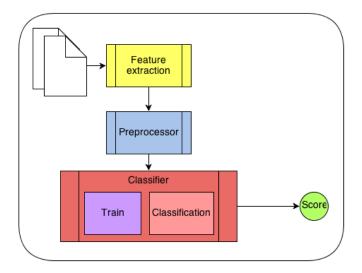


Figure 5: Overview of the fraud detection model.

Brief selection of features that are identified:

- iframes;
- inline styles;
- hidden elements;
- input fields;
- (obfuscated) Javascript;
- external Javascript, stylesheets and images.

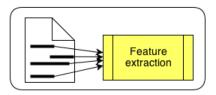


Figure 6: Feature extraction component

A total of 26 relevant features are identified from HTML, Javascript and URLs

- Transforms the feature data to a vector as input for the classifier;
- Assigns a maliciousness score based on the extracted URL features.

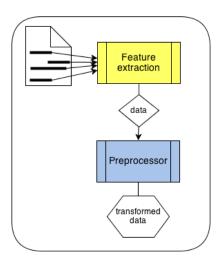


Figure 7: Preprocessor component

- Naïve Bayes learning algorithm
- Two components
  - Trainer;
  - Classification.

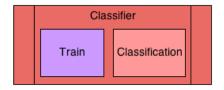


Figure 8: Classifier components

Train the classifier on manual labeled malicious and benign pages.

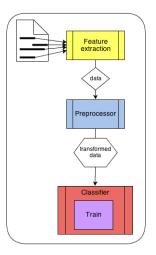


Figure 9: Classifier - trainer component

## Classifier: classification

- Classifies an unknown page against the training set using the Bayes' theorem;
- Result consists of a probability between 0 and 100% for each class.

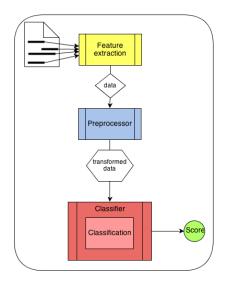


Figure 10: Classifier - classification

## Results: performance

Mean execution time to classify an unknown page: 0.176 seconds.

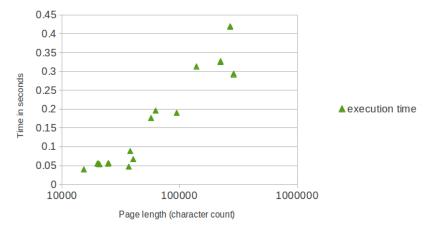


Figure 11: Execution time performance

## Results: accuracy

90% accuracy reached with  ${\sim}32.000$  instances in the training set.

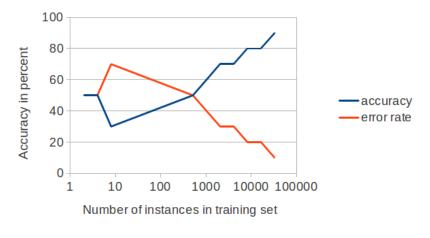


Figure 12: Accuracy measurements

Experiment to validate the developed model:

- Train classifier on page adapter by Zeus malware;
- Classify a page adapted by Citadel malware.

Result: classified as malicious with a probability of 100%.

- Classifier reaches an accuracy of 90% given the used dataset (needs validation with more complete set);
- The developed model is able to counteract fraud, caused by (unknown) malware;
- Classification process of a web page is performed with a mean of 0.176 seconds;
- Improvement of the model may lower impact on resources and optimizing executing time.

- Feinstein, Ben, Daniel Peck, and I. SecureWorks. "Caffeine monkey: Automated collection, detection and analysis of malicious javascript." Black Hat USA 2007 (2007).
- Canali, Davide, et al. "Prophiler: a fast filter for the large-scale detection of malicious web pages." Proceedings of the 20th international conference on World wide web. ACM, 2011.
- Curtsinger, Charlie, et al. "ZOZZLE: Fast and Precise In-Browser JavaScript Malware Detection." USENIX Security Symposium. 2011.