Malware Detection in PDF Files and Evasion Attacks

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Under supervision of

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Context

- A PDF file can contain
  - JavaScript Code
  - Flash objects
  - Binary Programs
  - ...
- All PDF readers have weaknesses
- Many attack vectors used by malwares

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Our Work

- Use machine learning to detect infected PDF
- Modify infected PDF to lure the classifier
- Find efficient counter-measures to this attack

1. Malware Detection using Machine Learning
2. Evasion Attacks
3. Counter-Measures

PDF Structure

In a Nutshell

- PDF: set of objects identified by tags (features)
- Several tools for PDF analysis (e.g. PDFiD)
- 21 features are frequently used by malwares
  - *based on Didier Stevens security expert's work: https://blog.didierstevens.com/programs/pdf-tools/*

Supervised Learning

Definition

- Inferring a function from labeled training data

In our case

Dataset:

- 10 000 clean PDF
- 10 000 PDF with Malware (Contagio)

Feature vector = [Tag1 occ., Tag2 occ., ...]

For a given PDF

Function: $class(X) = y$

- $X \in \mathbb{Z}^n$: feature vector
- y: label

$$\begin{array}{rl} 1 & \text{if the PDF is clean} \\ -1 & \text{if the PDF contains a malware} \end{array}$$

Example

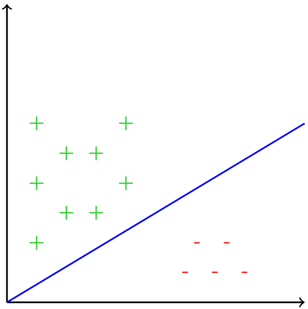
```
PDFiD 0.2.1 CLEAN_PDF_9000_files/rr-07-58.pdf
 PDF Header: %PDF-1.4
 obj                     23
 endobj                  23
 stream                   6
 endstream                6
 xref                     2
 trailer                  2
 startxref                2
 /Page                    4
 /Encrypt                 0
 /ObjStm                  0
 /JS                      0
 /JavaScript              0
 /AA                      0
 /OpenAction              0
 /AcroForm                0
 /JBIG2Decode             0
 /RichMedia               0
 /Launch                  0
 /EmbeddedFile            0
 /XFA                     0
 /Colors > 2^24           0
```


```
{'name': 'CLEAN_PDF_9000_files/rr-07-58.pdf',
 'label': 1,
 'features': array([23, 23, 6, 6, 2, 2, 2, 4, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])}
```


$$f(23, 23, \ldots, 0) = 1$$

SVM (Support Vector Machine)

- One scatterplots per label
- Find a hyperplan to delimit them



Training our SVM

- 60% of our data set used for training
- 40% used for testing

Description

- Get the feature vectors and labels for the training dataset
- Normalize independently each feature
- Create the SVM (use scikit-learn python module)
- Test with the remaining PDF

First Results

- Accuracy: 99.62 %
- Malwares detected as clean: 0,34% (28/8087)
- Clean detected as malware: 0,03% (3/8087)

Model Improvements

Change the Training and Testing Sets

- Modify the splitting ratio
  - 80%/20% $\rightarrow$ better accuracy
- Use X-validation

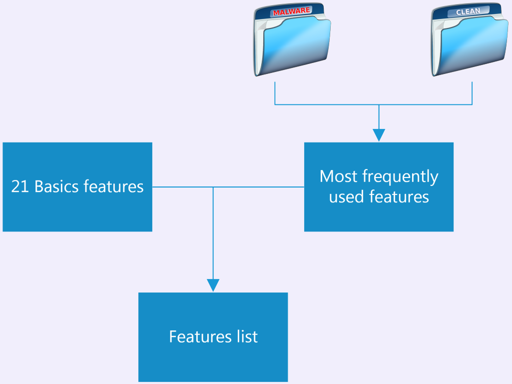
Change the Chosen Features

- Select discriminating feature with respect to our dataset

Features Selection (Frequency)

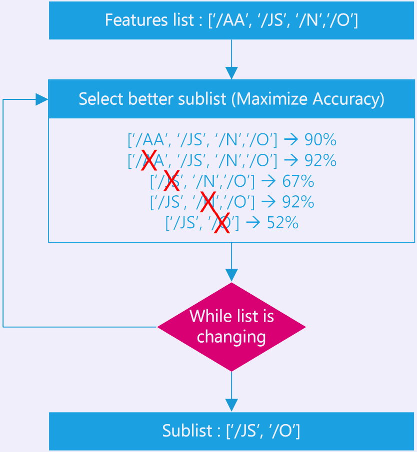
Use every features
⇒ Too many features (computing break)

1st Method : Frequency Selection



Features Selection (Sublist)

2nd Method : Select Best Sublist



Results

Features selection comparison

Features selection	Accuracy (x-validation)	Nb of features
No features selection (21 basics features)	99,48%	21
Sublist from 21 basis features	99,68%	12
Frequency + Sublist from all features	99,59%	18

Other results

- Apparently no overfitting issue

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Adversary Model

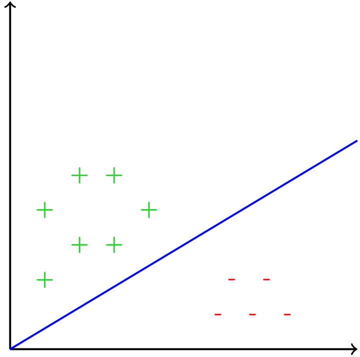
White Box Adversary

- The training dataset
- The used classification algorithm
- PDF files with malware that are detected by the SVM

Goal

Append objects to the PDF to evade the detection

Naive Attack: Increase the Value of One Component



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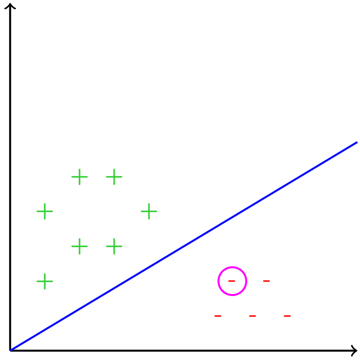

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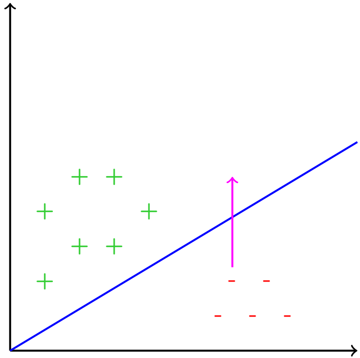

- Increase a well chosen component to cross the border

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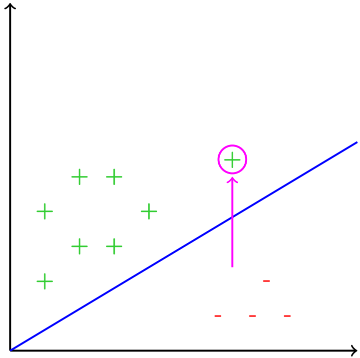

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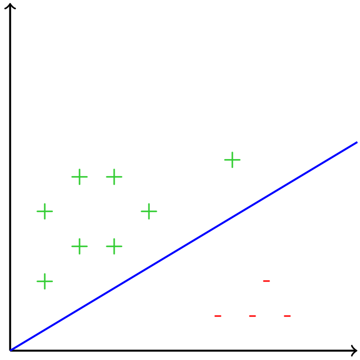

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- Add a lot of “non suspicious” objects (e.g. 50)

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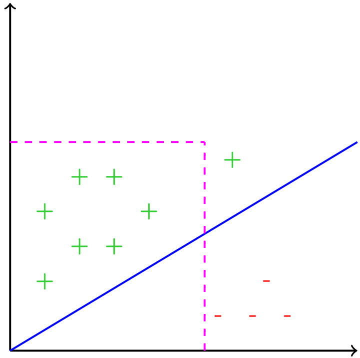

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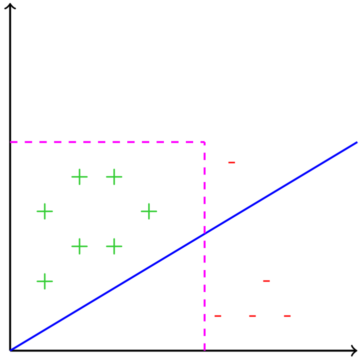

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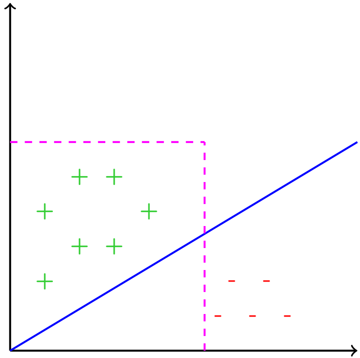
Second Attack: Gradient Descent



- Step by step approach (iterations)
- More components are modified
- Less objects added on the whole

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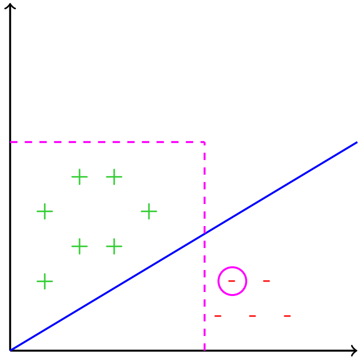

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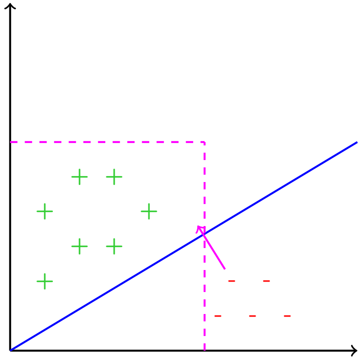

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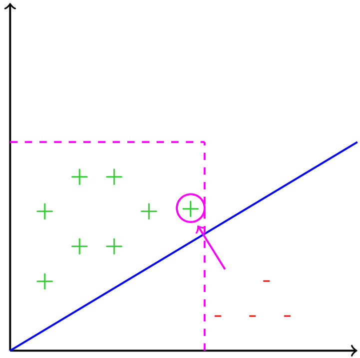

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Test and Result of the Attack

Theoretical Attack

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In Practice

- Forge new PDF files from gradient-descent-computed vectors
- Rounding is required $\Rightarrow$ precision issues
- 97.5% of the newly forged PDF were detected as clean

Vector Component Threshold

Threshold Computation

Threshold $\in \mathbb{N}^*$ because PDF objects number is discrete

1. Arbitrarily choose a threshold
2. Apply this threshold on each vector component independently
3. Check success rate of gradient descent
4. If success rate not low enough reduce threshold and go to 2)

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Results

- 5 $\rightarrow$ reduce attacks by 35%
- 4 $\rightarrow$ reduce attacks by 36%
- 3 $\rightarrow$ reduce attacks by 38%
- 2 $\rightarrow$ reduce attacks by 40%
- 1 $\rightarrow$ reduce attacks by 94%

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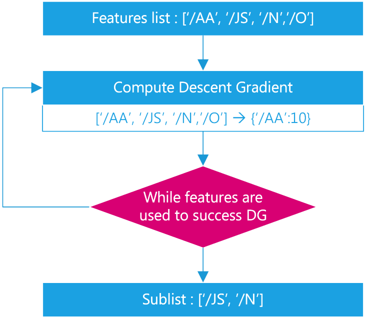
$\Rightarrow$ Cannot perform better only with threshold

Features Selection (Remove GD)

Removing Features

- Gradient descent: only some features used
- Idea: remove features used by GD
- Work with various initial choices of features (not only the 21 from PDFiD)



Features Selection (Remove GD)

Results

	Attack prevention	Accuracy	Nb of features
Treshold only	94,00%	99,81%	20
Remove GD only	99,97%	98,05%	2 (/JS and /XFA)
Threshold + Remove GD	99,99%	99,22%	9

Adversarial Learning

Principle

Supervised learning:

- Feed SVM by labeling gradient-descent-forged PDFs
- Relaunch the learning step
- Rounds until attack reduction is stable
- No need of feature selection

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Results

- labeled forged PDF between each rounds
- Iterations of GD = hardness of the attack

Round	SV	Accuracy (%)	Iterations of GD	Success rate of GD (%)
0	293	99,70	800	100
1	308	99,68	1800	90
2	312	99,67	3000	0

$\Rightarrow$ 3 iterations is enough for SVM to be fully resistant to GD attacks

Conclusion and Perspectives

Conclusion

- Naive SVM: easy to trick with gradient descent
- Usage of threshold: stops almost every GD attack
- Optimal features computation reduces even more the attack surface
- But reduce a bit the accuracy of the SVM

Perspectives

- Change adversary model:
  - Attacker has no knowledge of used classifier
  - Attacker uses another classifier for gradient descent
- Use deep learning like GAN (Generative Adversarial Network)
- Attack classifier with Monte-Carlo Markov Chains (MCMC) techniques

Thank you for your time !
Questions?

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