Deep Learning Steganography

to Hide Malware in Web Content

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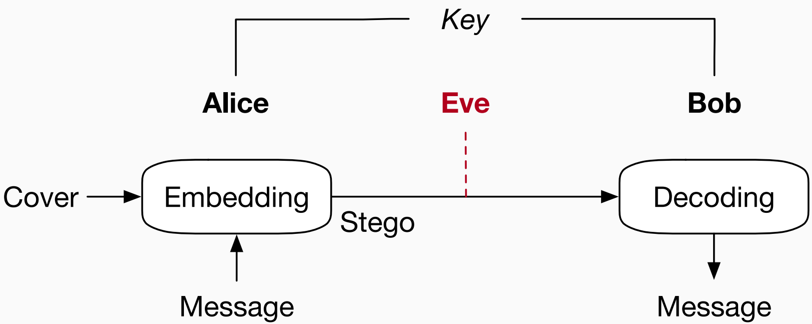
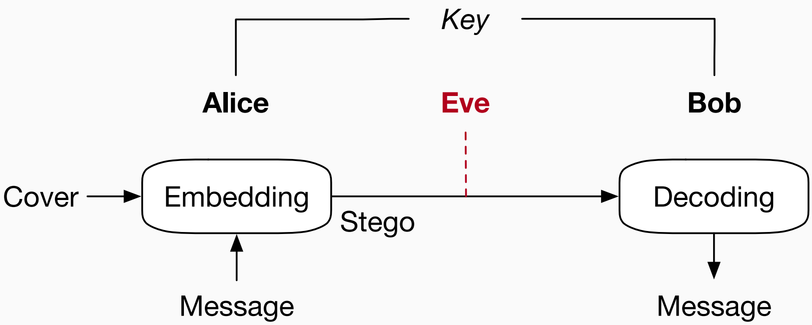
Steganography in a nutshell



Steganography in a nutshell

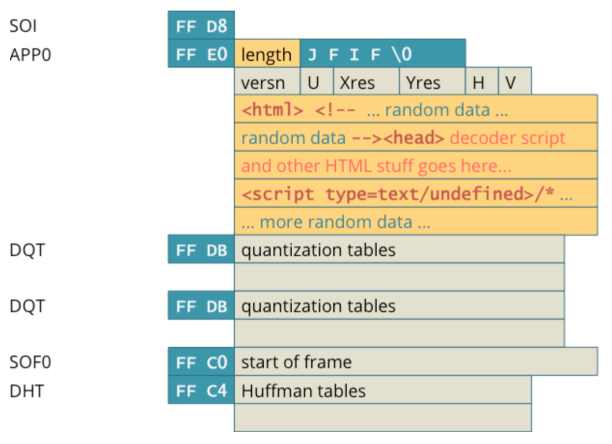


Message can be a malicious code

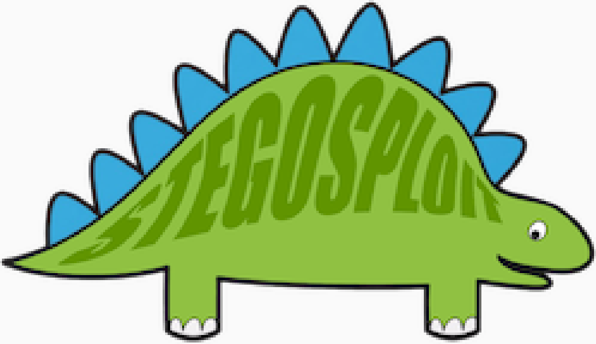
Polyglot file

Polyglot *(Noun)* :

a person who knows and is able to use several languages.

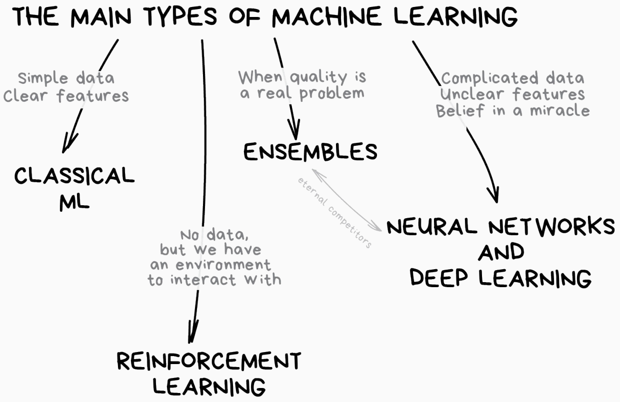


Stegosploit

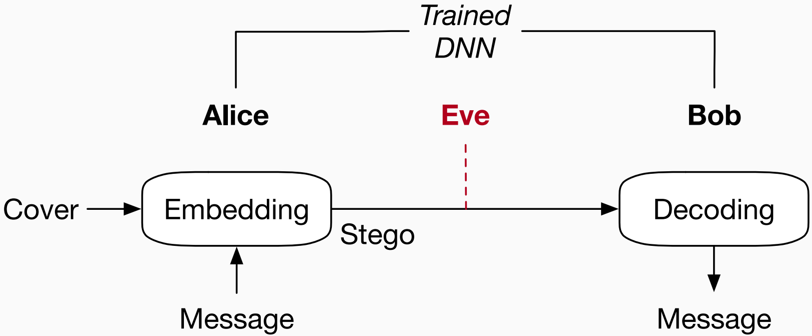


Machine Learning

source: *https://vas3k.com/blog/machine_learning/*



SteganoGAN's case



Huge claims about capacity & security

Can we implement a Machine Learning-based steganographic decoder using web technologies?

Disclaimer

- No GPUs in our laptops
- No Machine-Learning Background

Embedding decoder in a browser

SteganoGAN

- A Steganography algorithm from a Generative Adversarial Network
- Unpublished but public article
- Implementation Available
- Huge claims about capacity and security!

Output

(a) Original image

(b) Basic encoder

(c) Dense encoder

Zoom on basic one

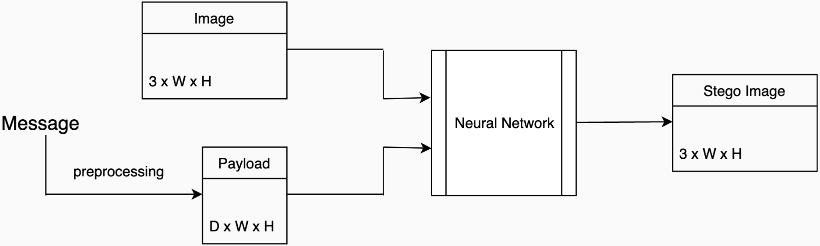
Goal

Adapt the SteganoGAN Decoder part to browser-compatible technologies

One candidate:

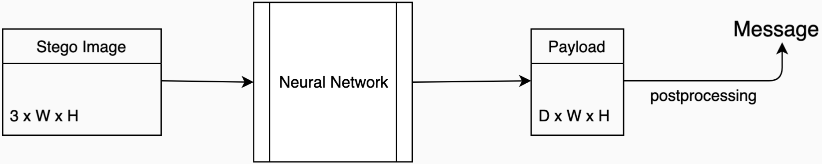
TensorFlow.js

SteganoGAN encoder



Three already trained versions of the Neural Network

SteganoGAN decoder



Essential components

Embed the decoding part *only*

Components:

- Tensor from Image: Python $\Rightarrow$ JavaScript
- Tensor manipulation: PyTorch $\Rightarrow$ TensorFlow
- Neural Network inference: PyTorch $\Rightarrow$ TensorFlow $\Rightarrow$ TensorFlow.js
- Message extraction: Python $\Rightarrow$ JavaScript

Payload construction

Before the encoding part:

RS_ECC(zlib_compression(utf-8_encoding(**Message**))) | 0x00000000

Repeated until no more space in a vector of size D x W x H

Message extraction

After the (decode) neural network inference:

How we improved it

- Define the separators as 4 bytes with a $hamming\_distance < n$
- Use the separators to deduce message length
- From message length, compute the most common bytes for every message character
    - zlib optional
    - Reed-Solomon ECC no longer needed
    - Much faster decoding for large images

How we improved it

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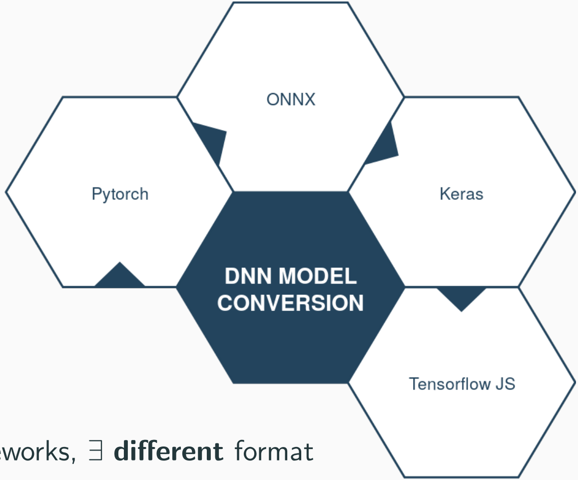
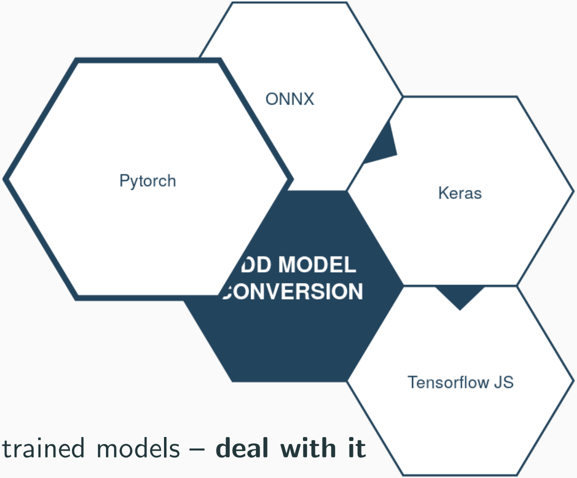
Easier to translate to JS

From Pytorch to Tensorflow JS...



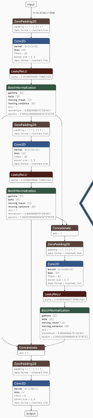
$\forall$ frameworks, $\exists$ **different** format

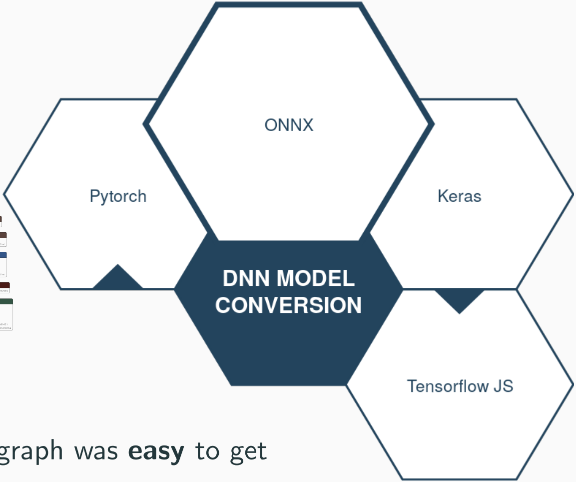
From Pytorch to Tensorflow JS...



Already trained models – **deal with it**

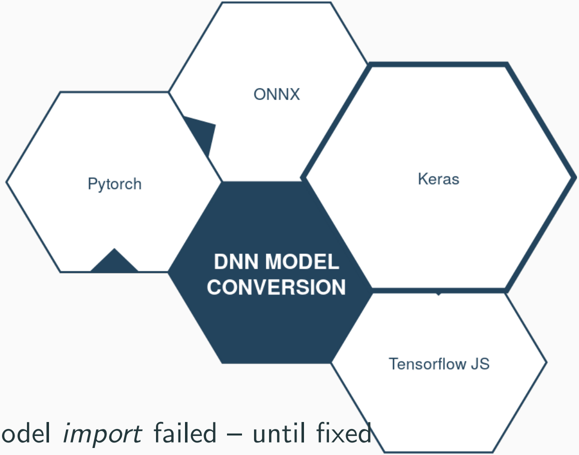
From Pytorch to Tensorflow JS...





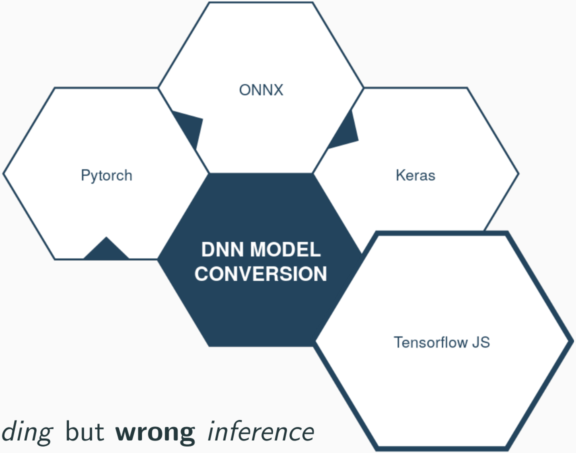
ONNX graph was **easy** to get

From Pytorch to Tensorflow JS...



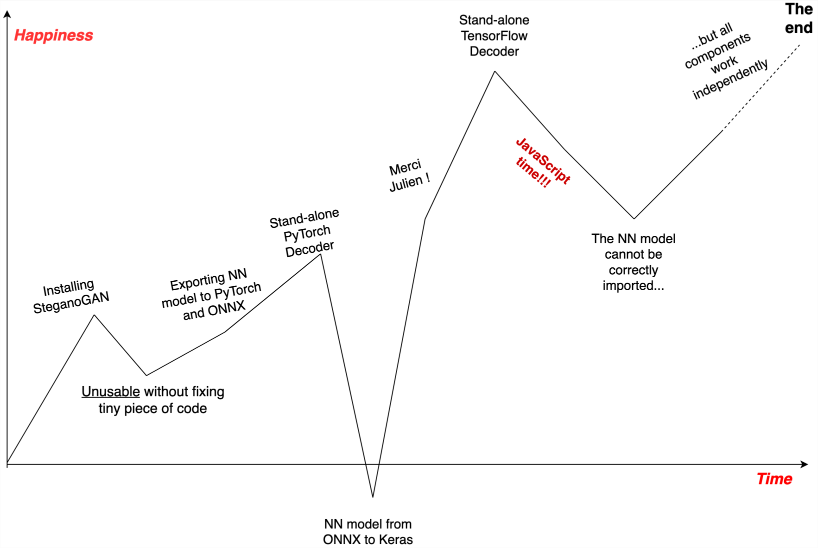
Keras model *import* failed – until fixed

From Pytorch to Tensorflow JS...



Fixed *loading* but **wrong** *inference*

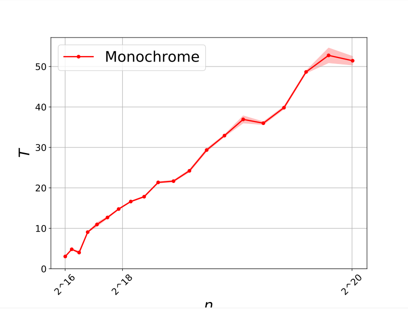
Our journey


Happiness
Installing SteganoGAN
Unusable without fixing tiny piece of code
Exporting NN model to PyTorch and ONNX
Stand-alone PyTorch Decoder
NN model from ONNX to Keras
Merci Julien !
Stand-alone TensorFlow Decoder
JavaScript time!!!
The NN model cannot be correctly imported...
...but all components work independently
The end
Time

Benchmarking SteganoGAN

Benchmark on CPU back-end (1/2)

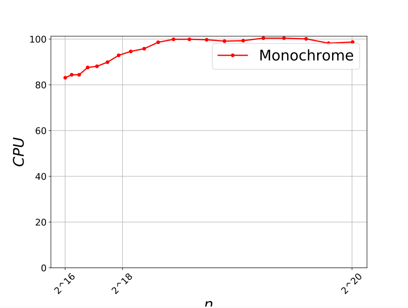
Decoding time as a function of image sizes



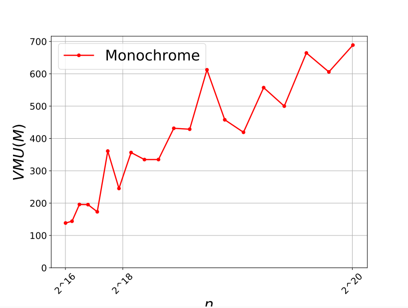
Stealthy decoding CPU implementation implies small images.

Benchmark on CPU back-end (2/2)

CPU usage as a function of image sizes



VRM usage as a function of image sizes



The footprint of CPU/VRM is not sneaky.

Size of javascript exploits

		mean size (B)	min size (B)	max size (B)
without compression (total: 179 exploits)		427.4	42	3871
`uglifyjs` (42 exploits)	compressed	263.8	40	2025
	not compressed	357.5	42	2839

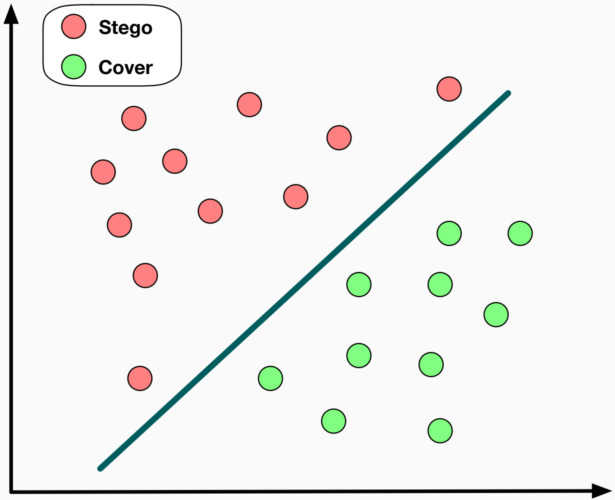
- average compression gain: 26.2%
- average compressed files size: 315.4 B

Steganalysis (1/2): Hand crafted features sets

	Dimensions	Domain
SRM	34671	Spatial
SRMQ1	12753	Spatial
maxSRM	34671	Spatial
DCTR	8000	JPEG
GFR	17000	JPEG
... + 20 others	...	...

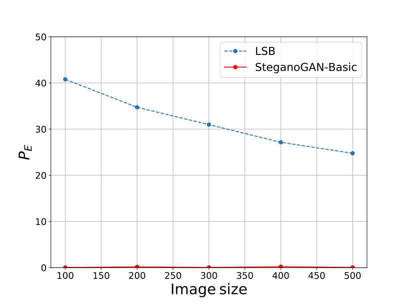
Available on *dde.binghamton.edu*

Steganalysis (2/2): (Low complexity) Linear Classifier

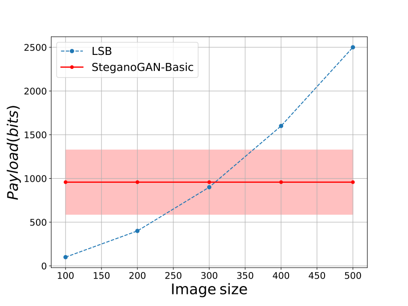


Steganalysis using trained adversary (SRMQ1 features set)

PE : Probability of error



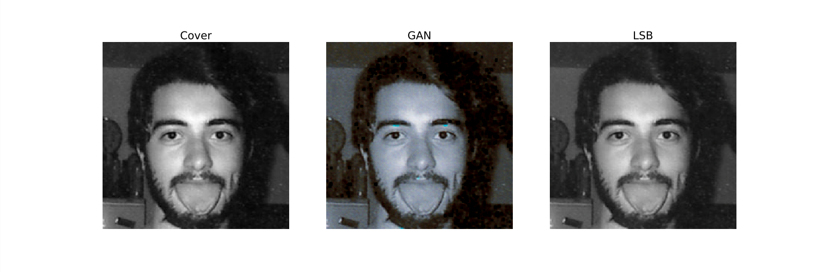
Message size

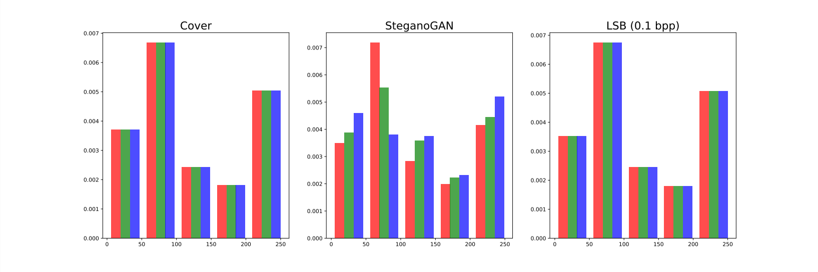


$$P_E = \frac{1}{2}(F_P + M_D)$$

Bonuses

SteganoGAN's weakness (one of them)





Stegosploit countermeasure (WebMaster POV)

If users are allow JPEG/PNG/... to upload file on the website :

- Place these assets on a separate domain.
- Rewrite the JPEG header to ensure no code is sneaked in there and remove all JPEG comments.
- Refuse requests whose type is "script" and source has a MIME type that starts match an image format

Literature about Steganography/Steganalysis

1. Traditional algorithms
    - Spatial-domain
    - Transform-domain
2. Deep learning-based algorithms

Discussion

- How to achieve a balance between security and capacity?
- How to improve the quality of steganographic image from the ML based large capacity steganography algorithm?
- How to consider complexity?

Conclusion

Already done

- one error away from full **POC**
- some clues about (SteganoGAN)
  - bad performance
  - bad security

Future works

- train a proper model for TensorFlow JS
- is steganography relevant for exploits?