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Analysis of the Scalability of a Deep-Learning Network for Steganography "Into the Wild" $\hfill \hfill \h$

Outline

Introduction

Our test bench to assess scalability for DL-based steganalysis Choice of the network for JPEG steganalysis Choice of the database Choice of the payload

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Empirical security measurement:

Steganalysis empirical security measurement ingredients:

- A few state-of-the art CNN networks,
- A database,
- A scenario such as the clairvoyant:
 - = Laboratory scenario,
 - = Worst case attack for Alice.

Empirical security measurement:

Steganalysis empirical security measurement ingredients:

A few state-of-the art CNN networks, → Minimum size required?

- ► to face to database ↗,
- ► to face to diversity Z,

to be in the over-parameterized region.

 \rightarrow Accuracy ranking if database is larger?

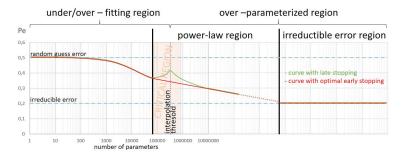
A database,

 \rightarrow Minimum size to be better than a random guesser?

 \rightarrow CNNs collapse or not if the training is larger?

(1) Macroscopic black-box first observations:

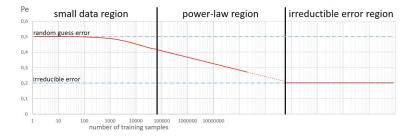
Model scaling general behavior:



 \rightarrow It is beneficial using over-parameterized networks, i.e. with **millions of parameters i.e** $\geq 10^6.$

(2) Macroscopic black-box first observations:

Data scaling general behavior:



 \rightarrow In the power-law region, the more data, the better results, \rightarrow Power-law region seems to start between 10^4 to 10^5 images.

General model for those 2 behaviors:

The test error (noted $\tilde{\epsilon}$) can be simplified¹ in [*]:

$$\widetilde{\epsilon}(m,n) = \underbrace{an^{-lpha}}_{dataset \ power-law} + \underbrace{bm^{-eta}}_{model \ power-law} + c_{\infty}$$

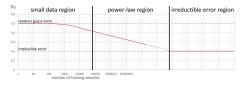
• a, b,
$$\alpha$$
, β , c_{∞} real positive constants,

- α and β control the exponential decreasing,
- \triangleright c_{∞} the irreducible error.

[*] Rosenfeld, J.S., Rosenfeld, A., Belinkov, Y., Shavit, N. <u>A constructive prediction of the generalization error across scales</u> ICLR'2020, Apr 2020.

¹ in the power-law regions.

Effect of increasing the dataset size:



In this paper, we use only one CNN

and study the effect of database scaling.

In the dataset power-law region,

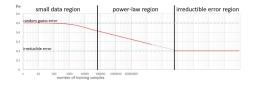
we should observe the exponential decreasing [*]:

$$\epsilon(n) = a'n^{-\alpha'} + c'_{\infty}$$



[*] Hestness, J., Narang, S., Ardalani, N., Diamos, G., Jun, H., Kianinejad, H., Patwary, M.M.A., Yang, Y., Zhou, Y. <u>Deep Learning Scaling is Predictable, Empirically</u> <u>Unpublished - ArXiv 1712.00409, 2017.</u>

Why studying the effect of increasing the dataset size?



Why studying this?

ML community observed this power-law. What about steganalysis?

Database scaling;

An important ingredient for empirical security analysis?

Model scaling in steganalysis = future work².

 $^{^2 \}rm First$ observations have been made during JPEG steganalysis Alaska#2 competition, when using the scalable modified EfficientNet network, which is based on the principle of building gradually larger/scalable EfficientNet networks.

Analysis of the Scalability of a Deep-Learning Network for Steganography "Into the Wild" — Our test bench to assess scalability for DL-based steganalysis

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Our test bench to assess scalability for DL-based steganalysis

Choice of the network for JPEG steganalysis

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Choice of the network for JPEG steganalysis

Choice of the network for JPEG steganalysis:

Low Complexity network (LC-Net) [*]:

- One of the state-of-the-art CNN until mid-2020,
- 20 times fewer parameters than SRNet,
- Faster learning than other networks,
- ▶ Medium size model (3.10⁵ parameters),
 - \rightarrow WARNING: model size close to the *interpolation threshold*.
 - \rightarrow early stopping during learning.



^[*] Huang, J., Ni, J., Wan, L., Yan, J.

A Customized Convolutional Neural Network with Low Model Complexity for JPEG Steganalysis ACM IH&MMSec'2019. Jul 2019.

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Choice of the database

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Choice of the database

Choice related to the database:

Requirements:

ISSD

- Grey level images (color steganalysis is not enough understood),
- More than one million images (needs large dataset),
- ► A controlled database (easier to analysis and generate),
- A diverse database (more realistic),
- A quality factor 75:
 - \rightarrow Robustness to quantization diversity is not enough understood,
 - \rightarrow Will facilitate future comparison with uncontrolled databases;
- Small size images (256×256; memory budget).

The LSSD database is available at:

http://www.lirmm.fr/~chaumont/LSSD.html.

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Choice of the payload

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Choice of the payload

Choice of the payload:

Objectives:

- ► Accuracy ∈ [60%, 70%] for a small database (≃ 20,000 images) i.e. being sufficiently far from the *random-guess* region,
- \blacktriangleright \rightarrow Large progression margin (when dataset is scaled),
- \blacktriangleright \rightarrow Room for future works (using better networks).

 \rightarrow JUNIWARD at 0.2 bpnzacs for grey-level JPEG 256 $\times 256$ images from LSSD database with a QF=75.

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Experimental protocol

Essential points:

- 4 learning sets: 20k, 100k, 200k, 1 million (cover+stego) JPEG images,
- ▶ 5 models for each learning set (std < to 0.8% for 20k),
- 1 unique test set: 200k (cover+stego) JPEG images,
- LC-Net hyper-parameters are almost the same as the paper,
- ▶ Use of an IBM container having access to 2 Tesla V100 GPU.

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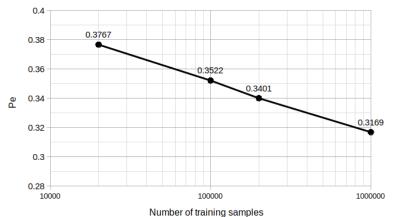


Figure: Average probability of error with respect to the learning database size. Notice that the abscissa scale is logarithmic.

Analysis of the Scalability of a Deep-Learning Network for Steganography "Into the Wild" ${\cap}{\cap$

Analysis

Essential points:

- Accuracy improved by 6% from 20k to 1M images,
- LC-Net does not have its performance collapsing,
- ► Standard deviation is getting smaller and smaller, → learning process is more and more stable.

Other facts:

- Time consumption:
 - ▶ 20k ≈ 2h
 - ▶ 1 million pprox 10 days
- Memory consumption:
 - 20k \approx 10 GB (MAT file in double precision)
 - 1 million \approx 500 GB (MAT file in double precision)

Analysis of the Scalability of a Deep-Learning Network for Steganography "Into the Wild" ${\cap}{\cap$

What about power-law?

Using a non-linear regression with Lagrange multipliers:

$$\epsilon(n) = 0.492415n^{-0.086236} + 0.168059$$

- Erroneous to affirm that the irreducible $P_E = 16.8\%$,
- but without much error on the prediction, probability of error for 20M images should be close to 28%,
- For 2k images it was 37%,

 \rightarrow 9% increase which is a considerable improvement in steganalysis domain.

Analysis of the Scalability of a Deep-Learning Network for Steganography "Into the Wild" Conclusions and perspectives

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Conclusions (1)

Error power-law is also observed for steganalysis:

- Even with a medium-size model $(3 \times 10^5 \text{ parameters})$,
- Even starting with a medium-size database $(2 \times 10^4 \text{ images})$.

Take away message:

Increasing a lot (20 million images) will make you win almost 10% in accuracy Analysis of the Scalability of a Deep-Learning Network for Steganography "Into the Wild" Conclusions and perspectives

Conclusions (2)

Future work:

- Evaluate with more diversity (quality factors, payload sizes, embedding algorithms, colour, less controlled database),
- Evaluate with other networks,
- Reduce learning time and optimize memory management,
- Find a more precise irreducible error value,
- Study the slope of the power-law depending on the starting point of the CNN (use of transfer, use of curriculum, use of data-augmentation such as pixels-off),
- Find innovative techniques when the database is not huge in order to increase the performances.

Slides downloadable here: http://www.lirmm.fr/~chaumont/LSSD.html.