Language Agnostic Botnet Detection based on ESOM and DNS

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botconf
30.11.2016

Contents

Introduction

Motivation:

- Bots are using DNS protocol as a communication channel:
  - such as covert channel
  - to transport commands or information
- In many cases DNS names are generated via "Domain Generation Algorithm" (DGA)
- Example: Tinba, Pisloader, PadCrypt, ...

Goal:

- Botnet detection via DGA identification with
  - Emergent Self-Organizing Maps (ESOMs)
  - language independent features from domain names

Introduction

Our requirement is

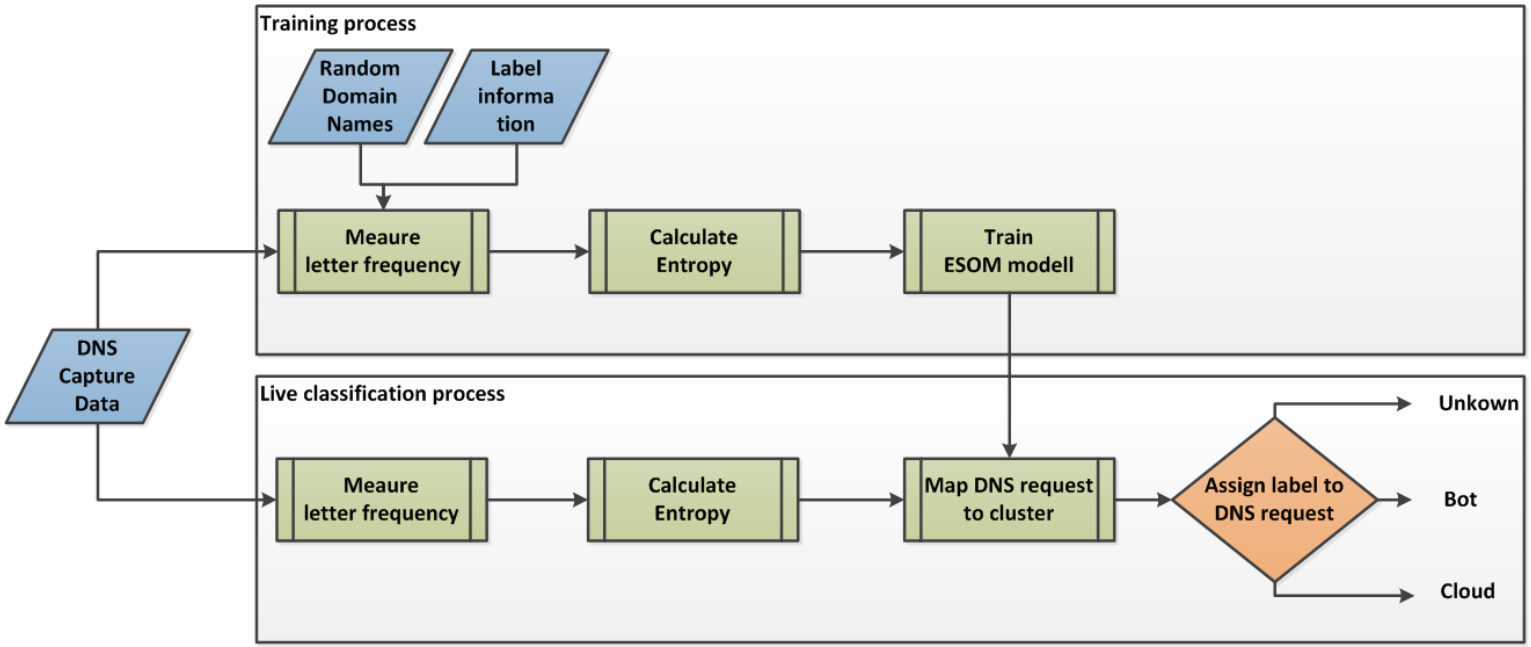
- to be language independent
- a distinction between cloud and malware DGAs

Emergent Self-organizing Maps

- Self Organizing Map (SOM) is an artifcial neural network (ANN), based on an unsupervised learning algorithm
  - NN are used to estimate or approximate function
  - unsupervised learning: type of algorithms that try to find correlations in and / or representations of the input data without any external informations (e.g. a classification) than the data itself
- Method of mapping high-dimensional input to low dimensional output such as (mostly) 2-D or 3-D
- Similar inputs are mapped to close locations on the low dimensional map such that the local topology is preserved.
- Large SOMs are called Emergent Self-Organizing Maps to emphasize the distinction.

Analysis Strategy

1. Extract language features from domain names in data samples
2. Run ESOM training with compiled feature set
3. Categorize domain names from real live traffic with ESOM map



Training data

- For training we used benign DNS
  and domain names from different malware DGAs

Benign DNS

- is taken from real network data
- contains only requests for
  - "standard domain names"
  - (auto generated) domain cloud names

- DNS could be contaminated with auto generated domains.
- An analysis with Alexa domain list and cloud domain names
  in separate training data samples is published in our paper.

Training Data

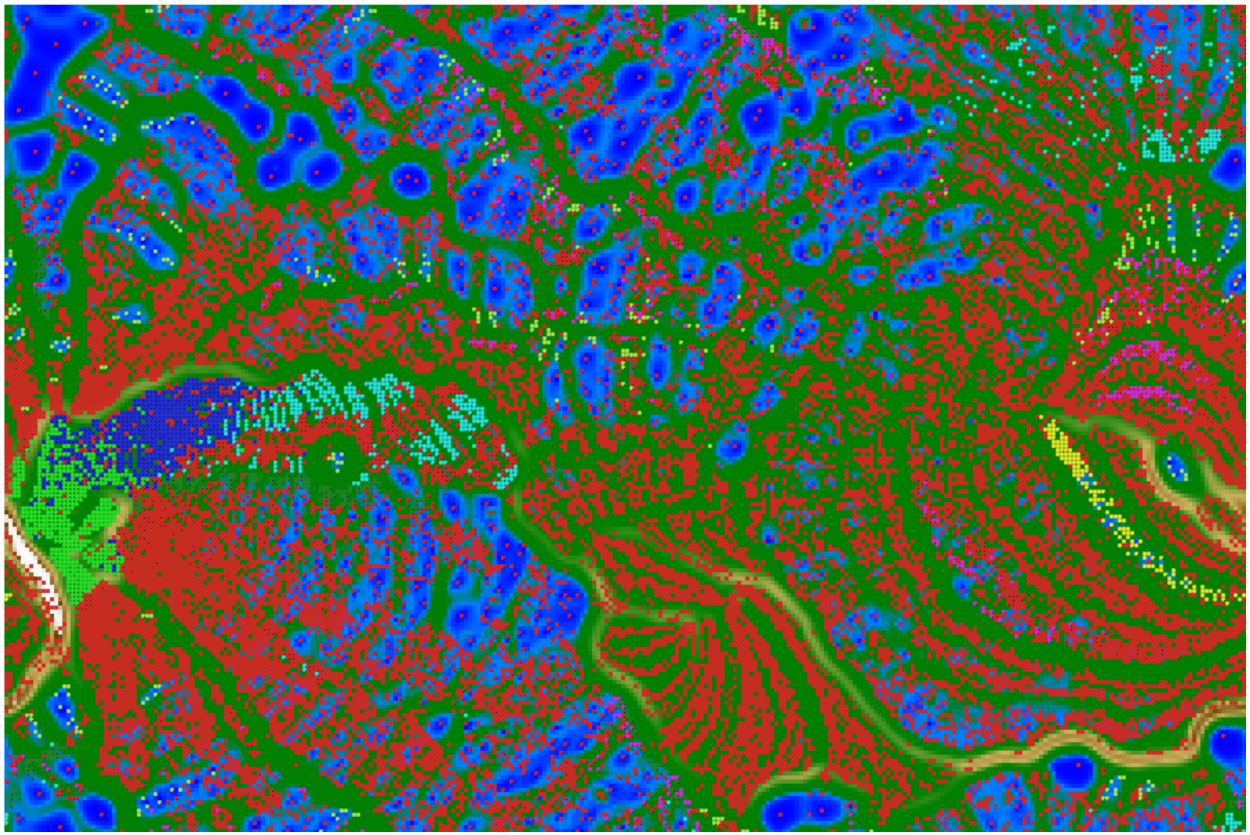
- Malware DGAs with different characteristics among each other

sample	**characteristics**
newgoz	doamin usually start with 1
ramnit	all letters except 'z'
shiotob	only digits 1,2,3,4,5,9
symmi	count sub-domains $>$ 2 and all letters except 'zyj'
tinba	double counts of letters,e.g. 'jj'
murofet v3	numbers between 10 and 69
padcrypt	only letters: a,b,c,d,e,f,n,o,l,m,k

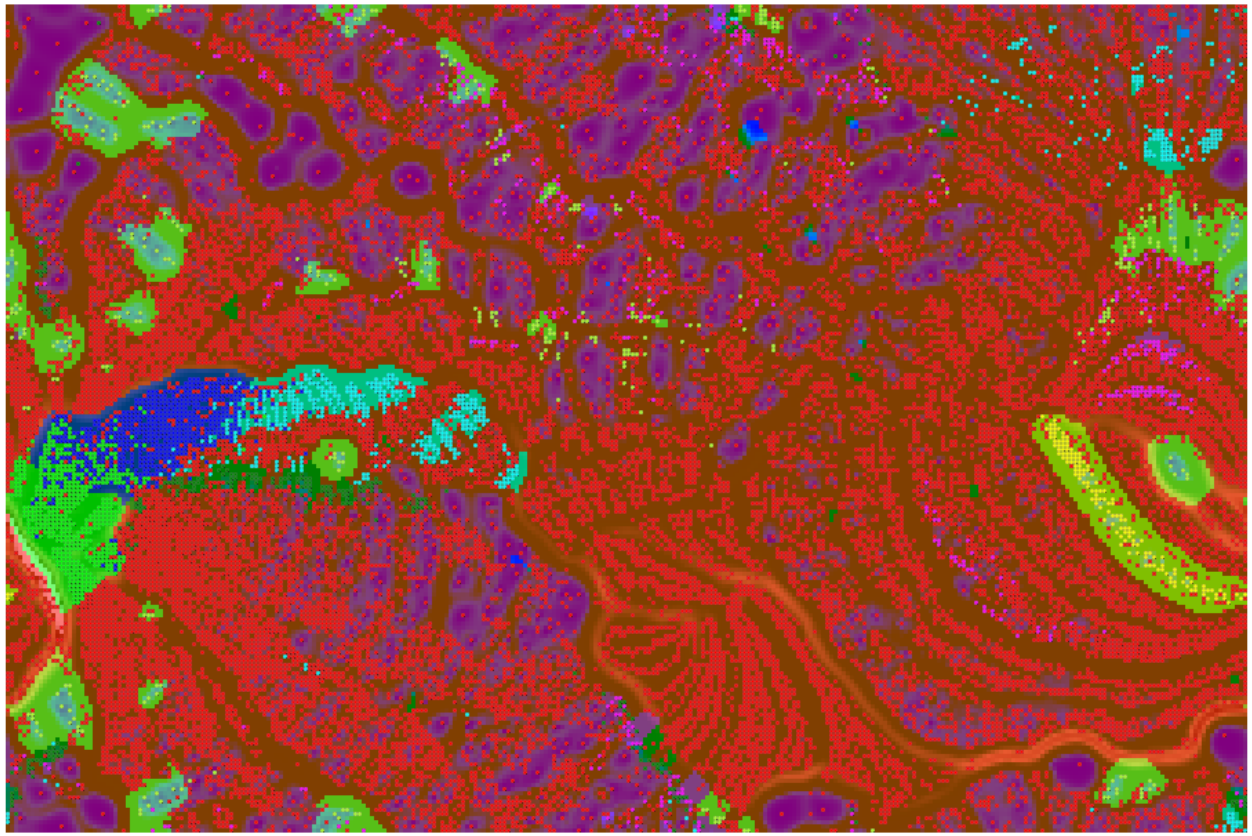
Extracted features from domain names

language feature	third-level domain	second-level domain	top-level domain
letter frequency	×	×	×
digit frequency	×	×	×
vowel frequency	×	×	×
consonant frequency	×	×	×
Shannon entropy	×	×	×
bi-gram frequency	×	×	–
tri-gram frequency	×	×	–

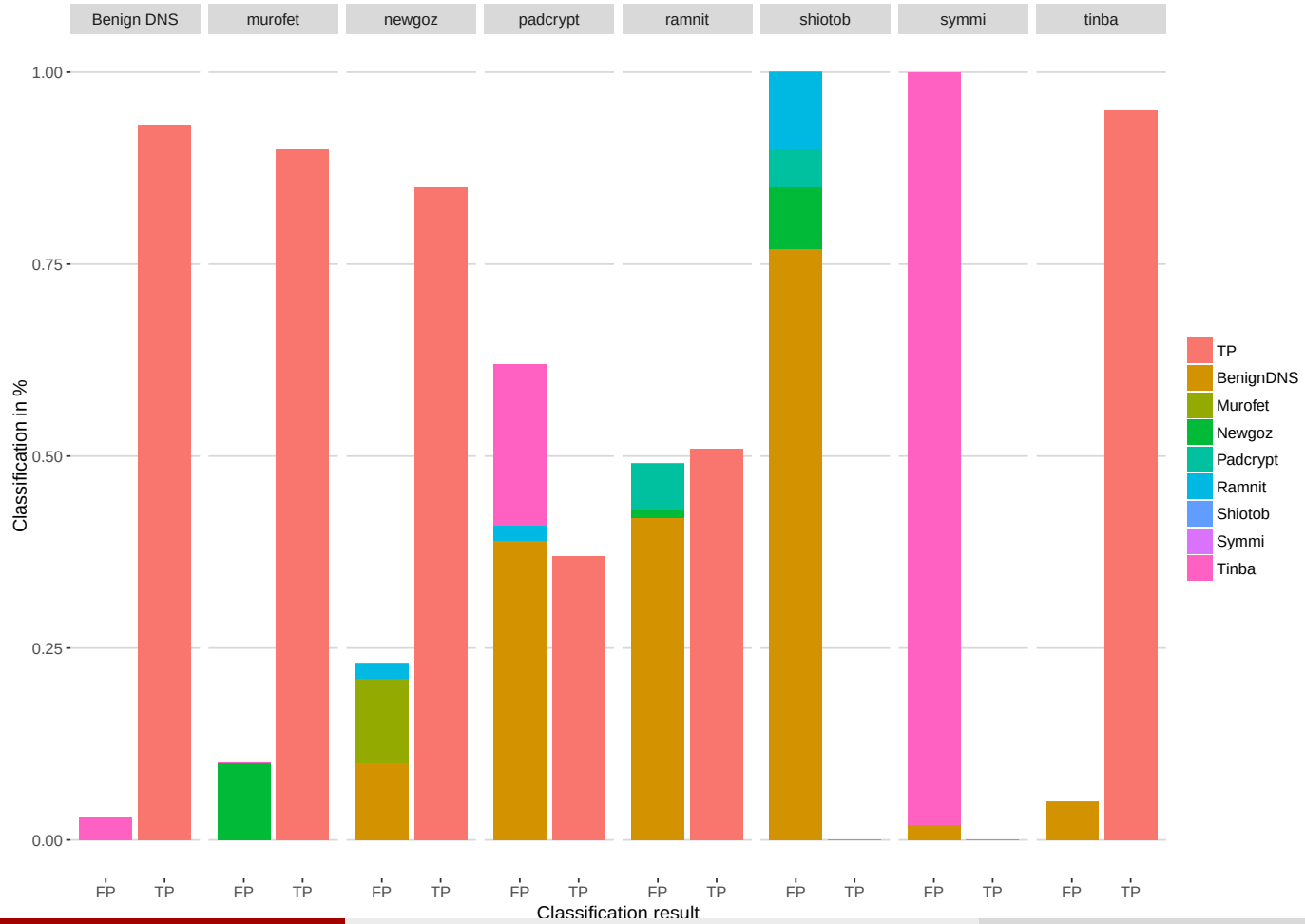
- Calculated map with size 200×300
- Every color stands for a data set
- Color gradient map: Earth
  - green (and then brown): low similarities between data points
  - blue: many similarities between data points



- Calculated surface of map
- Algorithm: gradient calculation between local minimas and maximas
- Color of area is dominated by color of most occurred data points
- Colored areas are used for domain name classification



- Compare results of every domain name in validation data set with every data point in map
- "False Positive" (FP) and "True Positive" (TP) classification rate for surface validation



Calculating Detection Rate

- Compare results of every domain name in data set with every data point in map
- Rate $\widehat{=}$ domain names identified in a category divided by the total number of domains in a data sample

- Sample names in columns are the categories
- Rows are presenting the malware sample, which we want to detect

	benign dns	newgoz	padcrypt	ramnit	tinba
banjori	-	0.20	-	0.8	-
corebot	0.02	-	-	-	-
dircrypt	0.39	0.03	0.04	0.54	-
fobber	0.48	-	0.03	0.49	-
gozi	0.67	-	0.09	0.24	-
kraken	0.62	-	0.03	0.13	0.22
locky	0.36	-	0.03	0.13	0.47
necurs	0.5	0.04	0.02	0.07	0.36
nymain	0.66	-	0.03	0.17	0.14
proslikefan	0.63	-	0.05	0.09	0.24
pykspa	0.63	-	0.05	0.09	0.24
qadars	0.87	-	0.07	0.06	-
qakbot	0.23	0.1	0.03	0.53	0.09
ranbyus	0.44	0.01	-	0.19	0.35
simba	1	-	-	-	-
vawtrak	0.74	-	0.02	0.24	-

Summary and Conclusion

- Presented a novel approach of detecting Botnets based on ESOMs.
- Method is language feature independent
- Our approach can classify between benign and botnet DGA domains.
- Next steps:
  - Evaluating uncertainties
  - Tune training parameters
  - Running long-term validation in real live networks

Thank you!