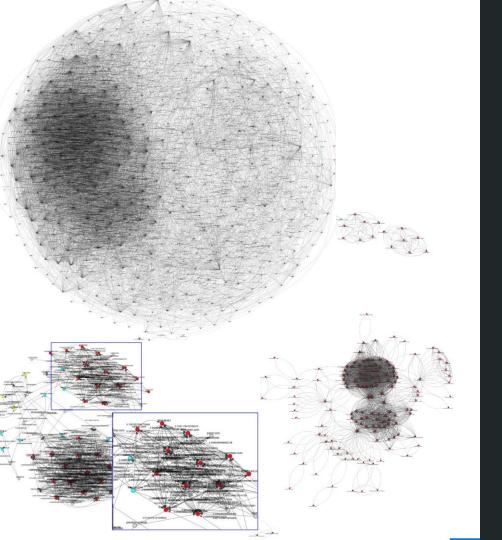


Development of novel algorithms for fraud detection in online advertising

Olaya García Fernández Master Thesis Cybersecurity 18-19



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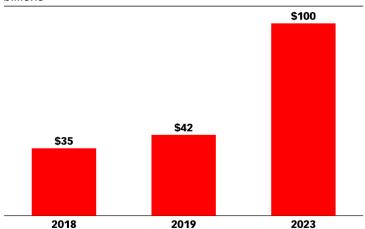
## Introduction

#### Web Advertising makes money

Fraud Losses increasing

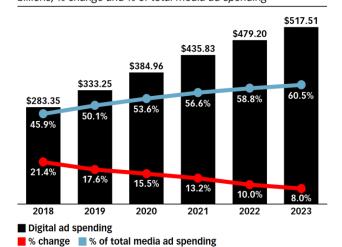
#### Ad Spending Lost to Ad Fraud Worldwide, 2018, 2019 & 2023

billions



Note: includes fraudulent activities via in-app advertising, mobile and online; 2019 dollars lost to fraud=21% increase vs. 2018
Source: Juniper Research, "Future Digital Advertising: Artificial Intelligence & Advertising Fraud 2019-2023" as cited in press release, May 21, 2019

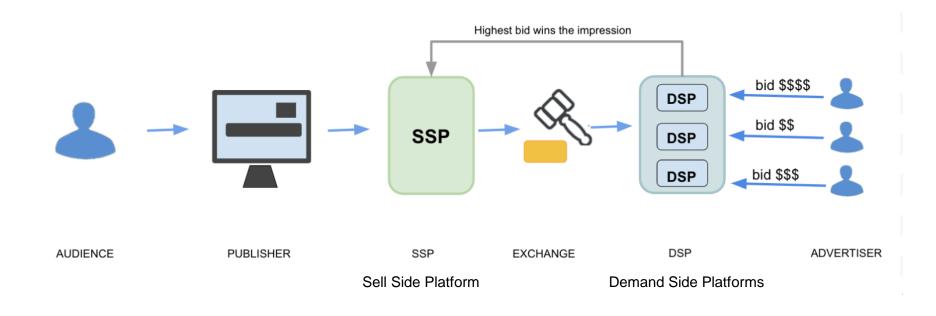
Digital Ad Spending Worldwide, 2018-2023 billions, % change and % of total media ad spending



Note: includes advertising that appears on desktop and laptop computers as well as mobile phones, tablets and other internet-connected devices, and includes all the various formats of advertising on those platforms; excludes SMS, MMS and P2P messaging-based advertising Source: eMarketer, February 2019

247511 www.eMarketer.com T10016 www.eMarketer.com

# Lifecycle of an Ad



# The fraud problem

#### What is fraud?

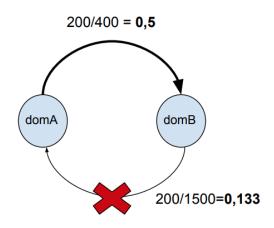
#### **Focus:**

- Programmatic Advertising
- Invalid Traffic
- Non Intentional Traffic (NIT)

#### Why?

- open ecosystem
- Ad Fraud is not illegal
- monetary reward based on the volume of transactions

# Co-visitation Networks



$${}_{d}^{n}G = (V_{d} \subseteq D, E = \{(domA, domB) : domA, domB \in D, | [\Gamma_{G}(domA) \cap \Gamma_{G}(domB)] / \Gamma_{G}(domA) \}$$

### Using Co-Visitation Networks For Detecting Large Scale Online Display Advertising Exchange Fraud

Ori Stitelman, Claudia Perlich m6d Research 37 E. 18th Street New York, NY claudia@m6d.com Brian Dalessandro, Rod Hook, Troy Raeder m6d Research 37 E. 18th Street New York, NY Foster Provost NYU/Stern School & m6d Research 44 W. 4th Street New York, NY

# Algorithm

## **Dataset**

Logs from incoming requests that the DSPs exchange with the AdEchange.



user\_ip : IP addr of the user that creates de Ad-request.

**referrer\_domain**: publishers ad-request referrer domain.

300 logs/200MB per day csv.gzip format; 13000000 TOTAL rows /per log

# Solution

Development Framework

- Apache Spark
- Python
- GraphFrames
- Jupyter Notebook

Why use these technologies?

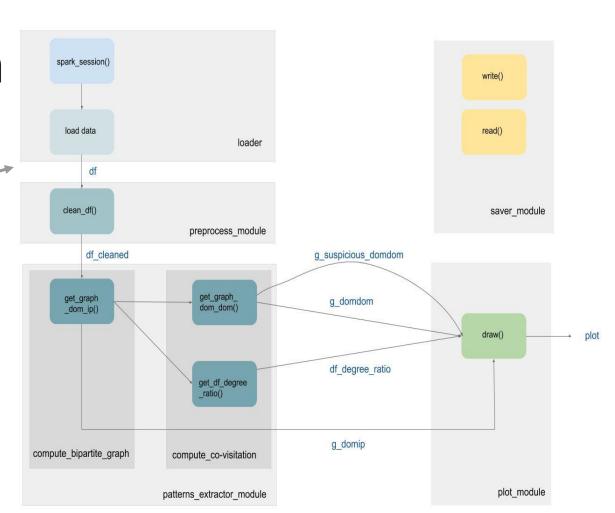
- most popular framework for bigdata
- high speed cluster computation
- data parallelism
- distributed environment

# Implementation Design

Flow Chart

**Utils library** 

df\_utils.py gf\_utils.py row\_cleaner\_utils.py read\_write\_utils.py draw\_utils.py spark\_utils.py



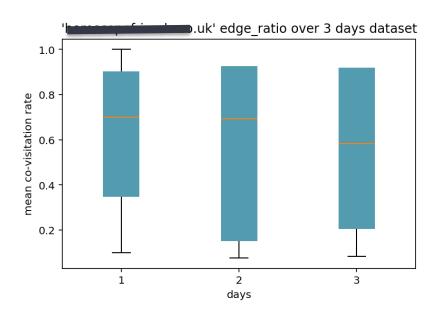
## Results

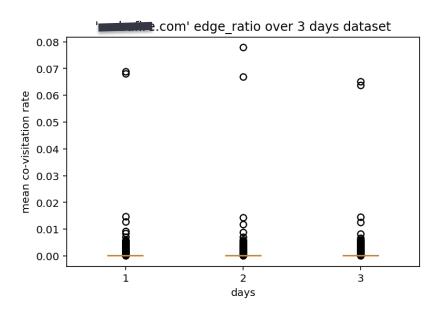
Comparing domains.

		day 1			day 2			day 3		
		outDegree	co-visitation	common_ips	outDegree	co-visitation	common_ips	outDegree	co-visitation	common_ips
Suspicious Domains	com	279	0.652	3.907	419	0.436	13.9476	320	0.610	7.0
	haraspefriends.co.uk	147	0.605	6.054	152	0.5706	7.4146	155	0.566	6.794
	portalpoptime.com.br	90	0.529	3.7	87	0.513	4.103	66	0.677	9.485
Worthy Domains	iter.com	2815	1.873E-4	9.390	2945	2.008E-4	7.962	2626	2.2996E-4	8.006
	<u>00</u>	4999	7.533E-5	13.146	5002	8.194E-5	14.357	4900	7.559E-5	12.391
	r.J.com	3775	2.109E-4	13.957	3737	1.987E-4	14.066	3884	1.941E-4	13.525



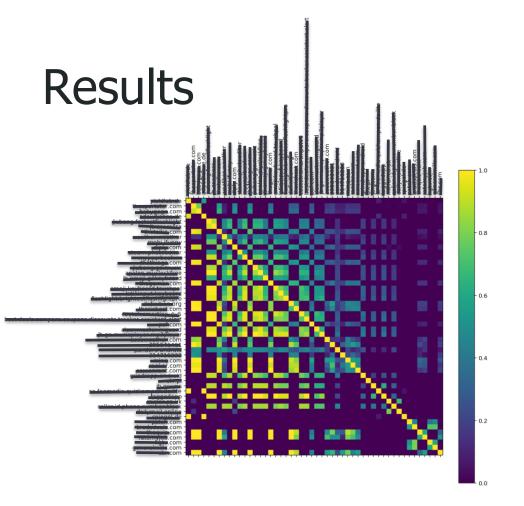
# Results

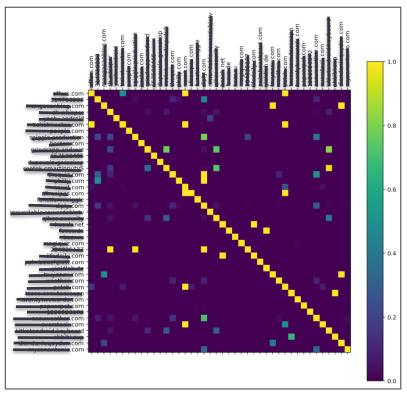




suspicious domain

legal domain





# Conclusion

 Algorithm implementation for automatic detection of malicious domains in large datasets with Pyspark.

Utils library design: scalability, easiness of use, adaptability

(Graph analysis: Graphframes + Distributed Environment: Pyspark)

Validation of results Stitelman's paper even on small sample datasets

## **Future Work**

Graph Embedding

 Evaluate the algorithm threshold over the time and train IA model.

# Acknowledgments

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