



Threat Detection based on Deep Learning at Scale

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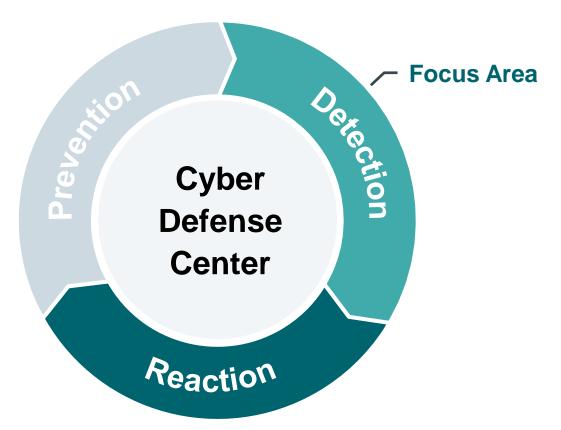


Cyber Defense Center

Globally distributed Team

Mission

- Monitoring of Siemens infrastructure worldwide
- Identify and analyze security threats

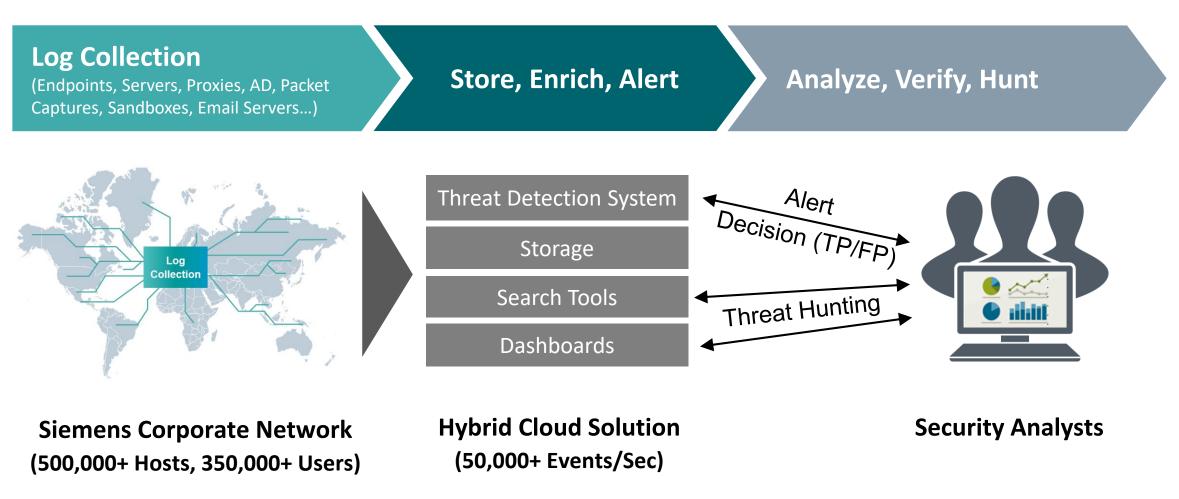




Cyber Defense Center

Mission: Threat Detection

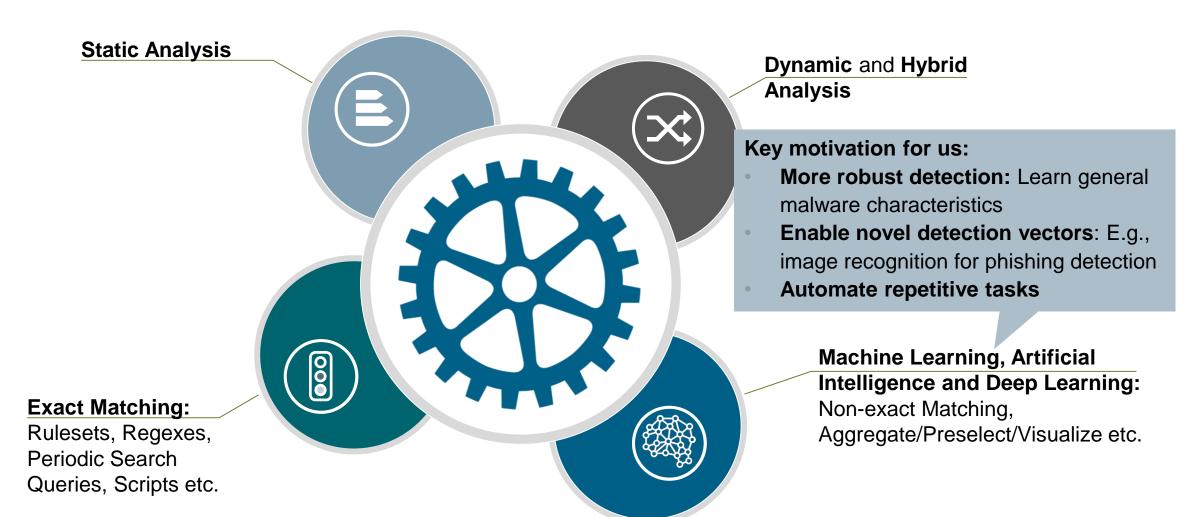




Cyber Defense Center

Main Detection Components





2019

Al and Deep Learning on the Rise

High expectations due to success stories





Self-driving Cars



Translation



Cancer Detection

Al and Deep Learning on the Rise



How about Security?



Dedicated Workshops



Large amount of new Papers



Numerous (Open Source) Tools and Implementations

Al and Deep Learning on the Rise

Key Challenges (in Large Environments):

 \rightarrow Huge gap between research and practice



Limited Generalizability



Limited Scalability



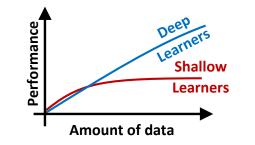


Accuracy (TPs, FPs etc)



No Standard Architectures

2019



Not enough (labeled) Data



Technical Challenges



Use Case: DGA Detection



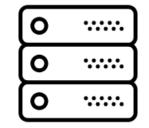


Malware: attempt to communicate with Attackers' server





Infected Host

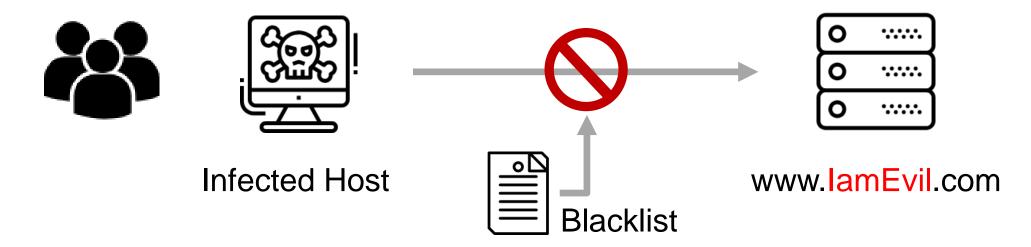




What is a DGA doing?



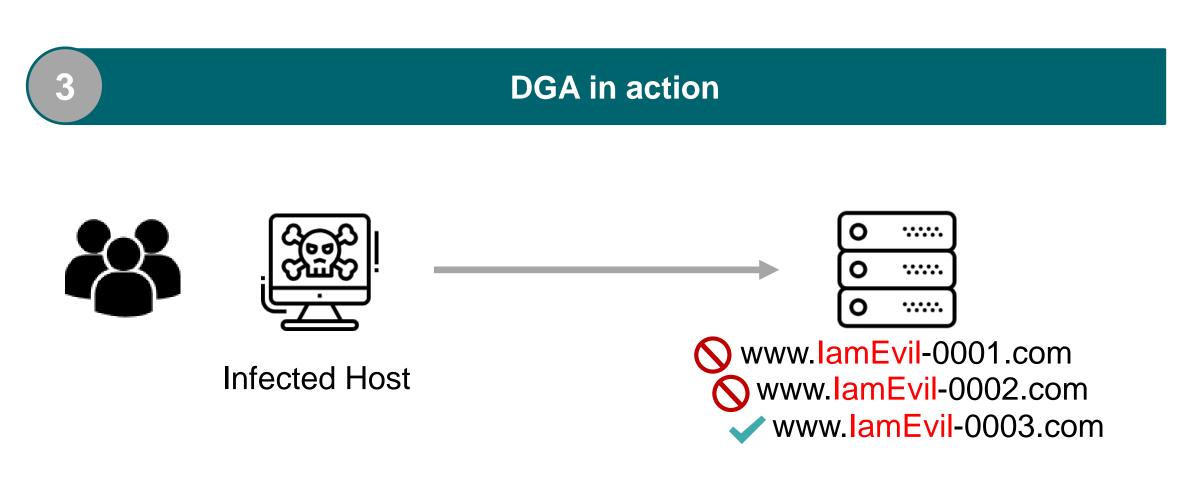
Defenses Up: blacklist stops the communication



2

What is a DGA doing?









Simply blocking domains does not scale anymore





Infected host



www.lamEvil-0001.com
www.lamEvil-0002.com
www.lamEvil-0003.com

A Simple DGA Example



2	॑def	<pre>generate_domain(year, month, day):</pre>
3		"""Generates a domain name for the given date."""
4		domain = ""
5		
6		for i in range(16):
7		year = ((year ^ 8 * year) >> 11) ^ ((year & 0xFFFFFFF0) << 17)
8		<pre>month = ((month ^ 4 * month) >> 25) ^ 16 * (month & 0xFFFFFF8)</pre>
9		day = ((day ^ (day << 13)) >> 19) ^ ((day & 0xFFFFFFE) << 12)
10		domain += chr(((year ^ month ^ day) % 25) + 97)
11		
12	Ŷ	return domain + ".com"

print(generate_domain(2019, 5, 7))
print(generate_domain(2019, 6, 19))



konsbolyfadifehn.com myycvfoqtcpbbypd.com

2019

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[CryptoLocker DGA]

Quiz: Can you distinguish Legitimate Domains from Malicious ones?



edkowalczyk.com

abcdefgtfddf2223.com

xjpakmdcfuqe.nl

b9qmjjys3z.com

skhhtcss.edu.hkreqblcsh.net

watdoejijbijbrand.nl

blkdmnds.com

lkckclckl1i1i.com

oqjiwef12egre6erg6qwefg312qrgqretg132.com

kdnlrklb.com cilavocofer.eu

hzmksreiuojy.in

llanfairpwllgwyngyllgogerychwyrndrobwll-llantysiliogogogoch.com

Quiz: Can you distinguish Legitimate Domains from Malicious ones?







Name of a town in Wales

[https://www.youtube.com/watch?v=fHxO0UdpoxM]



Detecting DGAs with Deep Learners

Detecting DGAs with Al



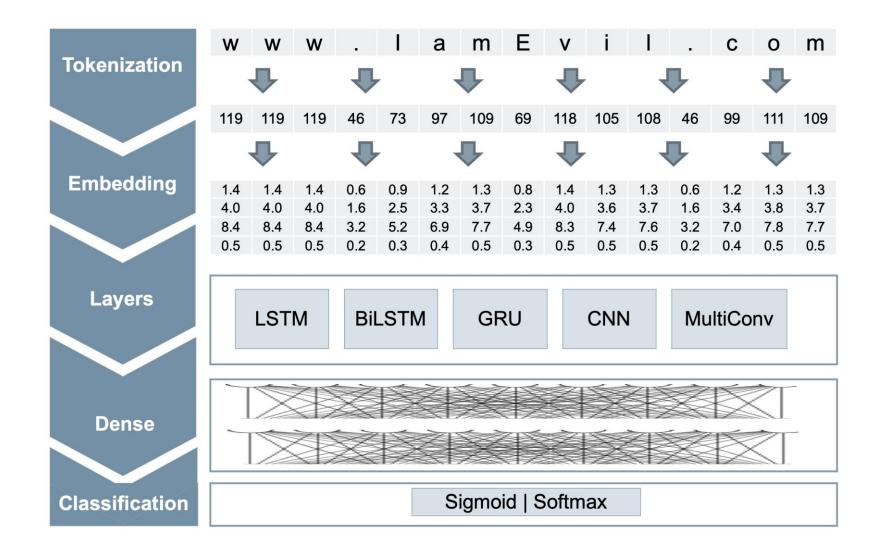
1. Characters are converted to ASCII tokens

2. Tokens are embedded into multi-dimensional vectors

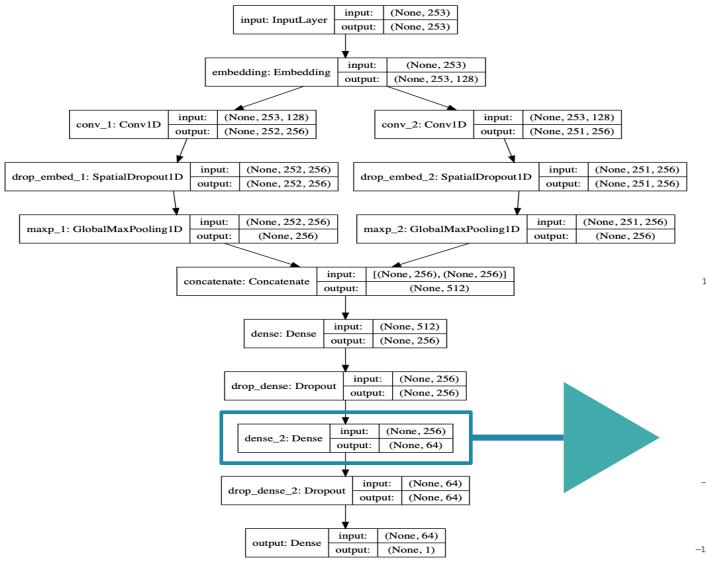
3. Forward layers or Recurrent layers can be utilized to generate features

4. Fully connected layers can be used to increase the model depth

5. A suspiciousness score is assigned based on the output of sigmoid output neuron or softmax layer



Example CNN Layer with UMAP

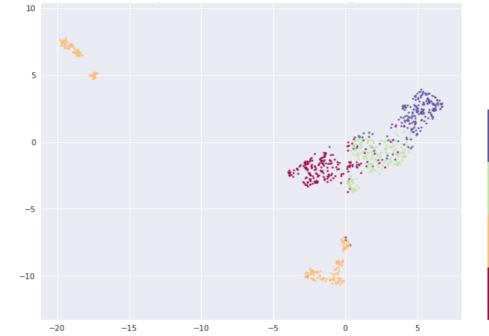


label	domain
1	simonettecaileigh.net
1	kimberleedonaldson.net
2	savingdrivetechnology.com
3	durforcogivprasufor.ru
normal-traffic	kokkoku-anime.com
2	personpermitmountain.com

3

2

isil



Results



Deep Learning Approach						Shallow Learner Approach (
Accuracy (%)	TPR (%)	FPR (%)	TNR (%)	FNR (%)		Accuracy (%)	TPR (%)	FPR (%)	TNR (%)	FNR (%)		
98.64	98.08	0.77	99.23	1.02		84.36	96.78	31.56	68.43	3.21		



Design Platform and Operationalize

Operational Challenge



500,000+ Hosts 50,000+ Events per second 6+ TBs of data per day 24/7 Operations Highly Volatile Loads (20x)

2019

Operationalize Smart!



500,000+ Hosts 50,000+ Events per second 6+ TBs of data per day 24/7 Operations Highly Volatile Loads (20x) Don't burden your team with

Auto Scaling (Elasticity) Auto Failover Server Patching Backups

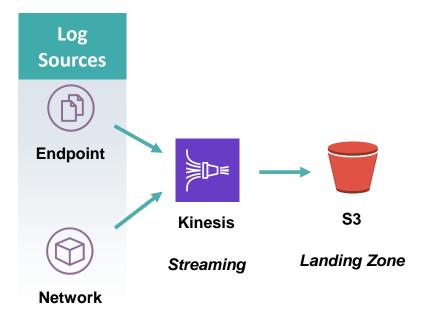
Go Serverless

2019

Ingest and Inference



Ingest Pipeline: Store AD- Proxy- Email-Logs into the S3

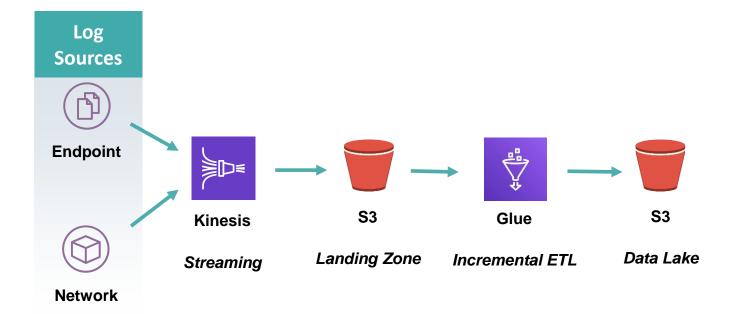


Ingest and Inference

2



ETL: Cleaning and Transforming Data

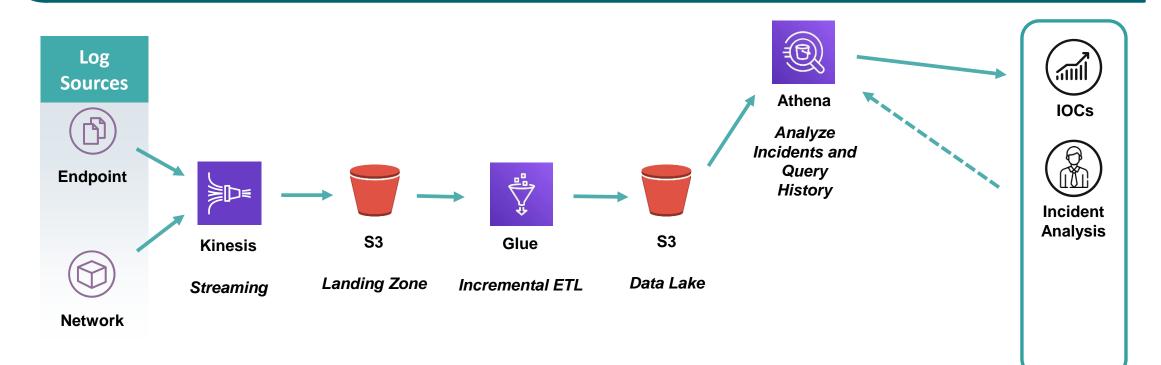


Ingest and Inference

3



Presentation: Create Statistics, Provide Data to Analysts

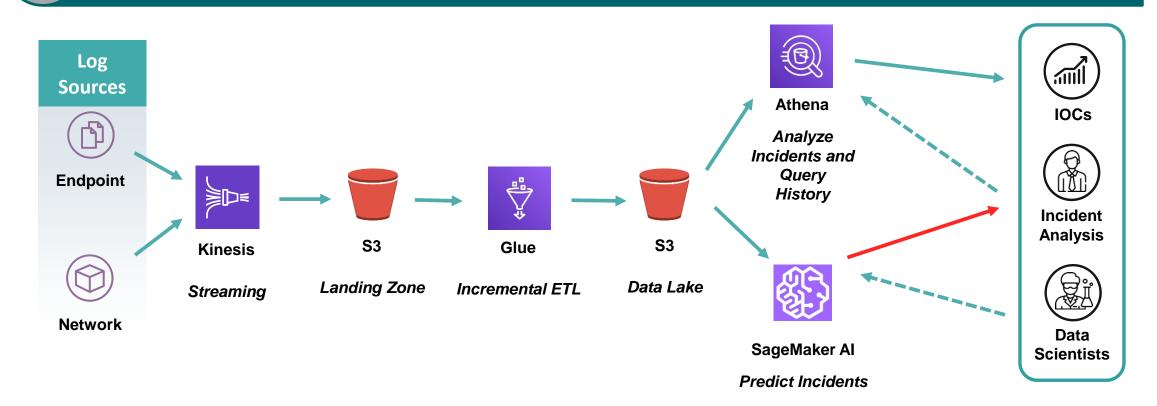


Ingest and Inference

4

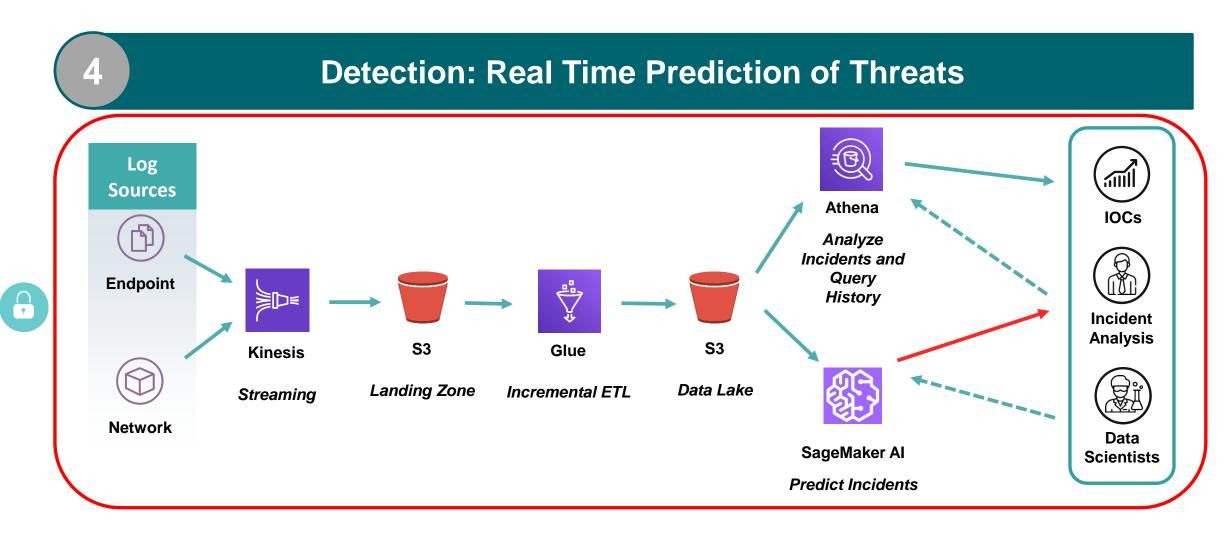


Detection: Real Time Prediction of Threats



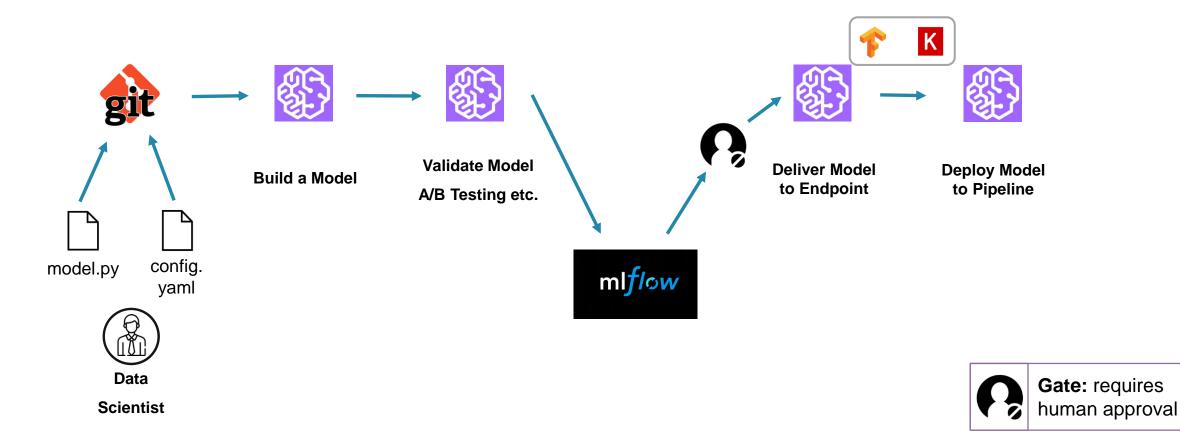
Ingest and Inference





AI Model Generation and Deployment



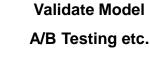


git — 💱

config.

yaml

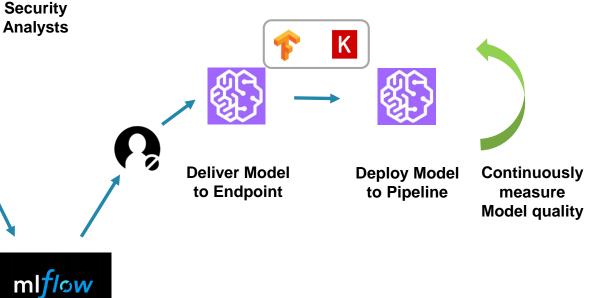
Build a Model



Constantly improve Models

with TPs/FPs from

Security Analysts





Karl Peter Fuchs and Jan Pospisil

Important Pipelines

AI Feedback Loop

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Data

Scientist

model.py

Ingenuity for life

SIEMENS



