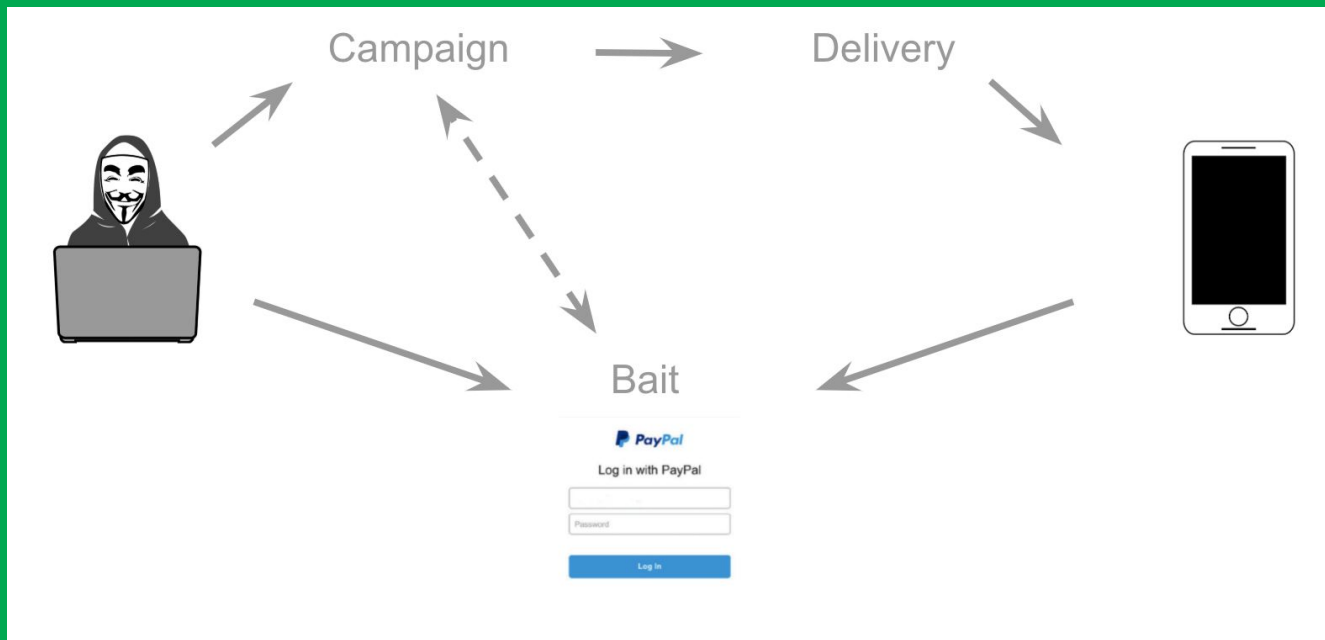


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# 0-day Security Detections at Scale

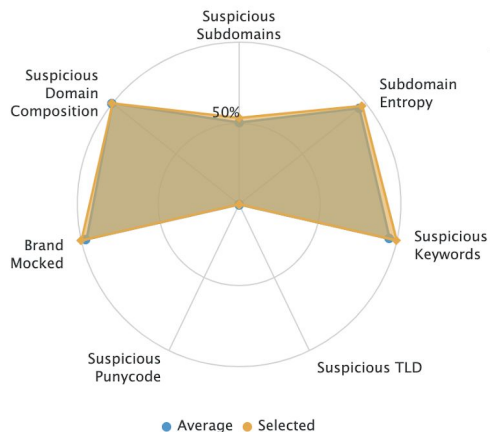
Zdenek Letko

# Motivation



# Motivation

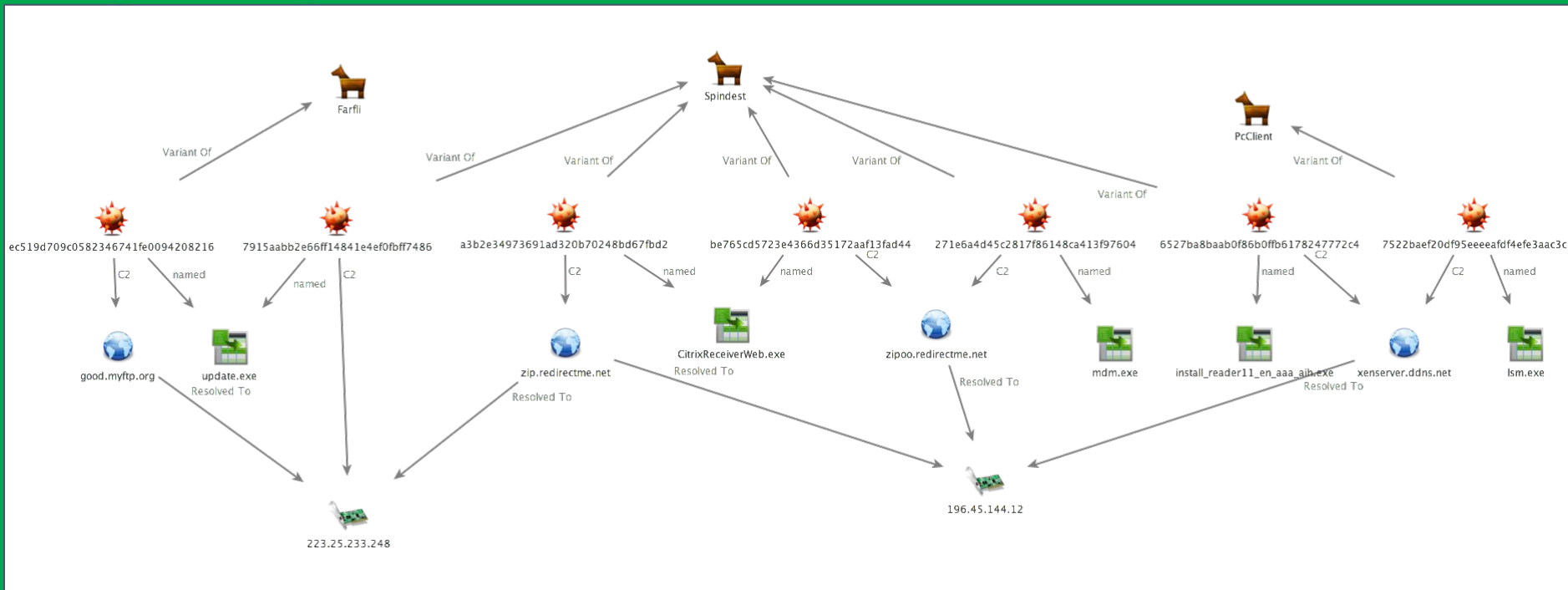
## ZERO-DAY PHISHING



Timestamp	URL	Phishing Score
11:32 28 Oct 2019	<a href="https://1572258739062.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk">1572258739062.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk</a>	83%
08:15 28 Oct 2019	<a href="https://1572246900960.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk">1572246900960.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk</a>	86%
03:18 27 Oct 2019	<a href="https://1572142714769.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk">1572142714769.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk</a>	86%
04:09 26 Oct 2019	<a href="https://1572055763891.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk">1572055763891.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk</a>	82%
09:32 25 Oct 2019	<a href="https://1572031958595.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk">1572031958595.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk</a>	86%
06:23 25 Oct 2019	<a href="https://1572020625896.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk">1572020625896.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk</a>	83%
03:29 25 Oct 2019	<a href="https://1572010171199.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk">1572010171199.billing.facebook.com-user----account----overview----new----terms8eb493ef.4061151572247010552.1528986948509.snappli.co.uk</a>	86%



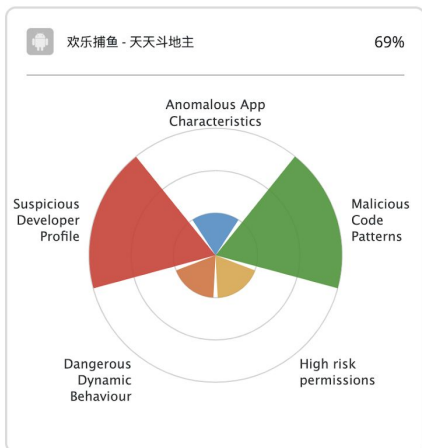
# Motivation











Source: [researchcenter.paloaltonetworks.com](http://researchcenter.paloaltonetworks.com)

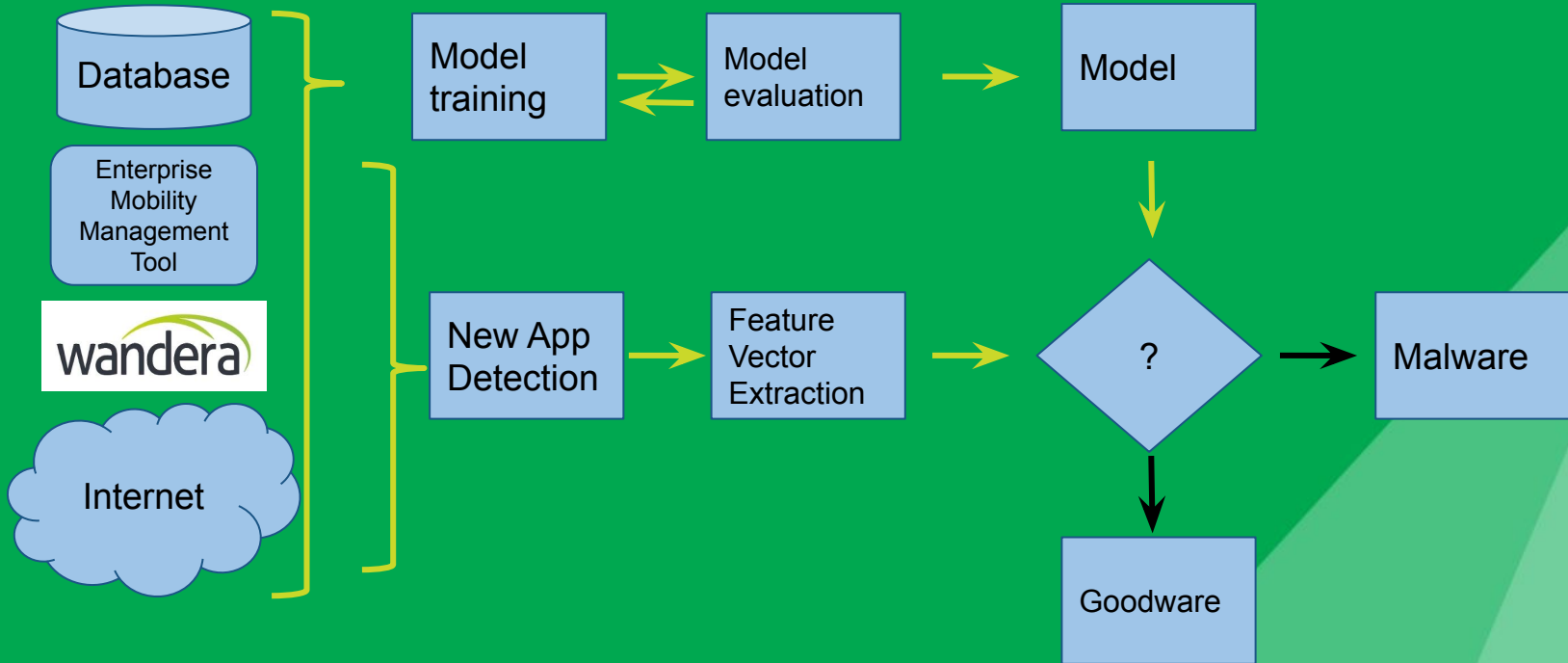
# Motivation

## RISKY APPS



App	Risk Score
▼  欢乐捕鱼 - 天天斗地主	69%
▼  SuperX Phone Cleaner	69%
▼  Totally TABS 2019 : Accurate Battle Simulator	60%
▼  Master of Spin - Daily Reward Link	54%
▼  Call On Duty Mobile Free Games: Offline Game	52%
▼  Manga Geek - Free Manga Reader App	71%
▼  QR Scanner Pro - Scan All QR Codes & Barcodes	62%
▼  Video Editor Pro - Music, Vlog, Effect, Filter	62%

# Detection Process



# Agenda

Malware

ML-based Detection

ML-based Detection as a Service

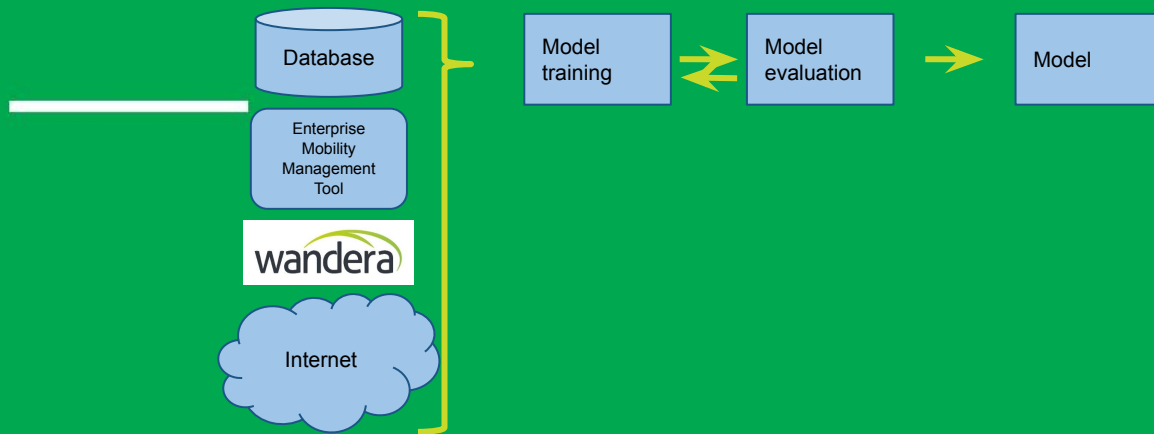


# Malware



# Types of Mobile Malware

- Ransomware
- Spyware
- Adware
- Trojan
- Rooting
- SMS-fraud
- Cryptojacking
- Banker



# Training

# Possible Data Sources

---

- Static analysis
  - App code (API calls, strings, domains, obfuscation, patterns, ...)
  - App packaging (author, source, certificates, permissions, ...)
- Dynamic analysis
  - Communication destinations IP/domain
  - Communication security / content / patterns
  - Device behaviour (battery drain, ...)
- Manual inspection by threat ops team -- **possible trusted labels for training data**
- Internet databases and providers (free or paid = various quality)
  - IP/Domain blacklists
  - App analyses results, researches reports, ... -- **possible labels for the training data**

# Feature Vector Encoding

- Unique app identifiers -- SHA / MD5 hashes
- Feature vector
  - Very sparse binary vector (over million of elements and growing)
- Categorical features
- Sparse feature domain

Q. Shi, J. Petterson, G. Dror, J. Langford, A. Smola, and S. Vishwanathan:  
Hash kernels for structured data. Journal of Machine Learning Research, 10(Nov):2615–2637, 2009

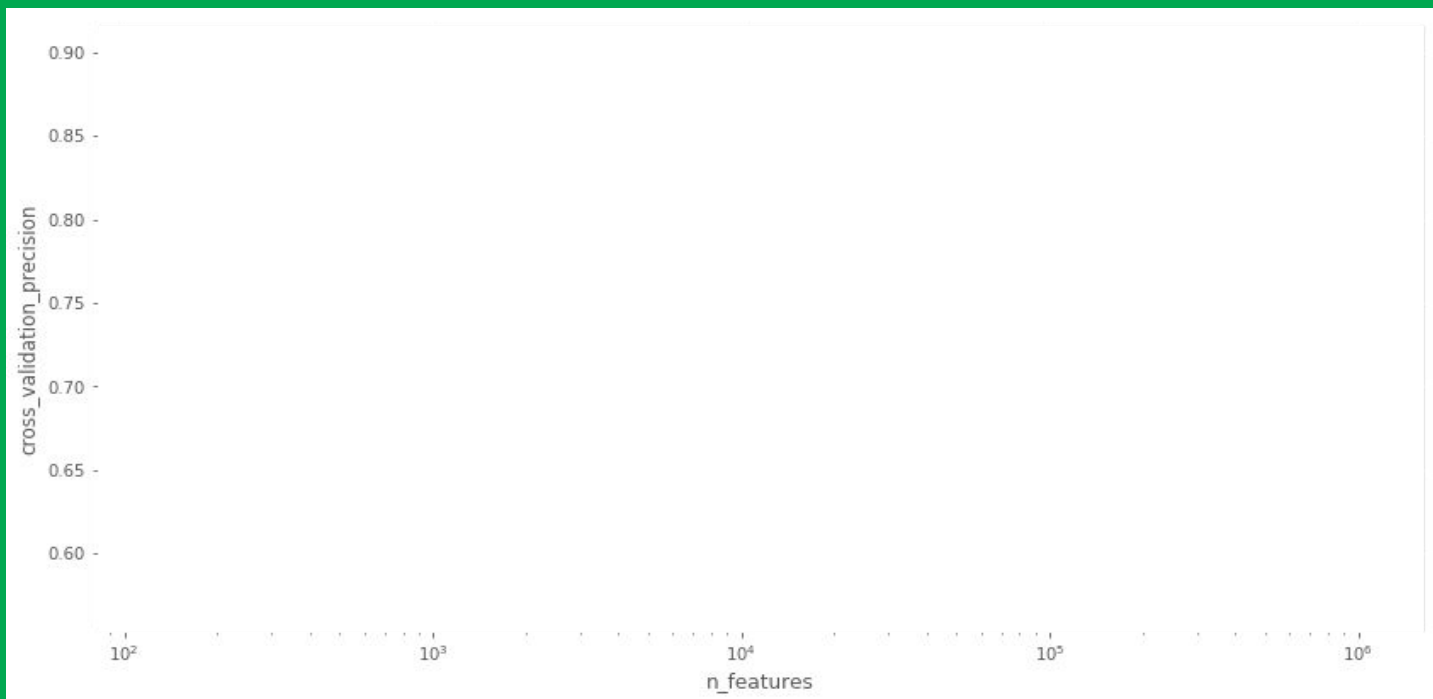
# Feature Hashing

---

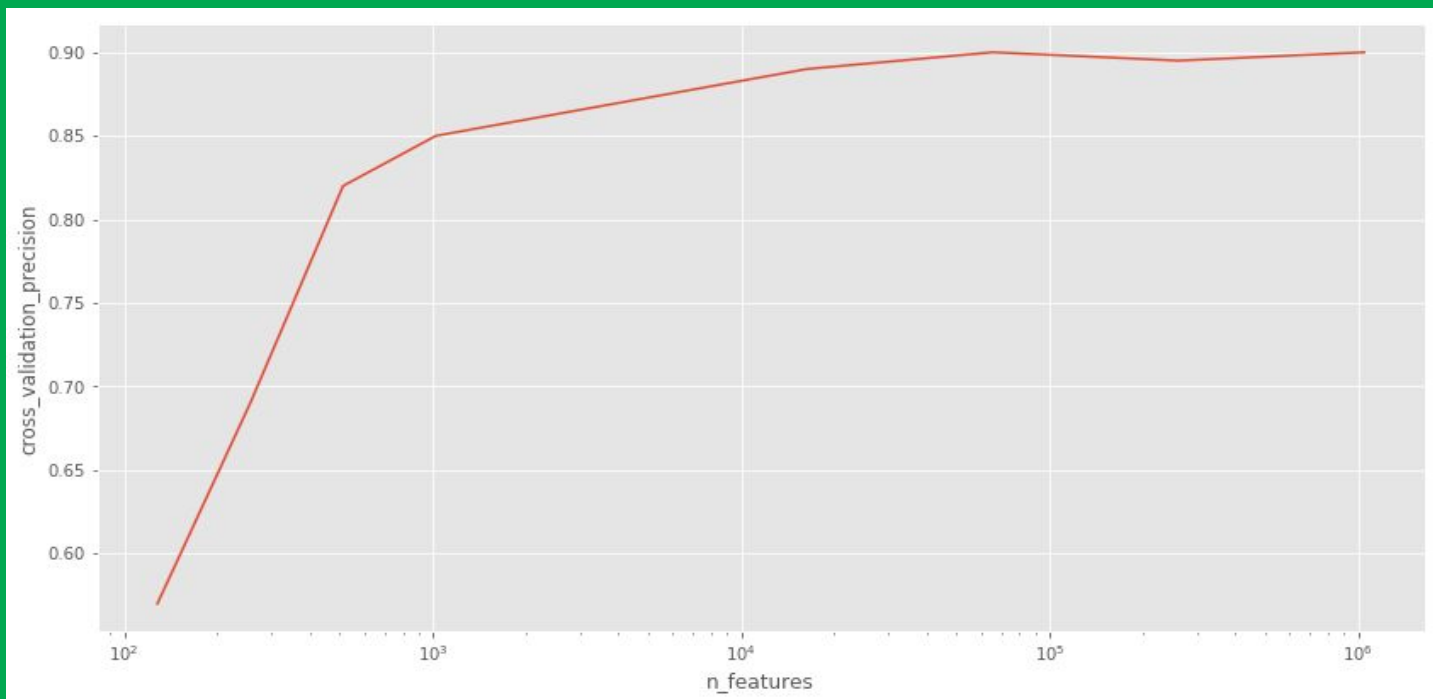
- Effective representation and encoding -- Feature Hashing
  - Handles increasing size of the binary vector
  - Fixed size of final feature vector
- Pros
  - No dictionary (mapping)
  - Preserves sparsity
- Cons
  - No inverse mapping
  - Hash collisions

# Hashing function - Number of Features after Hashing

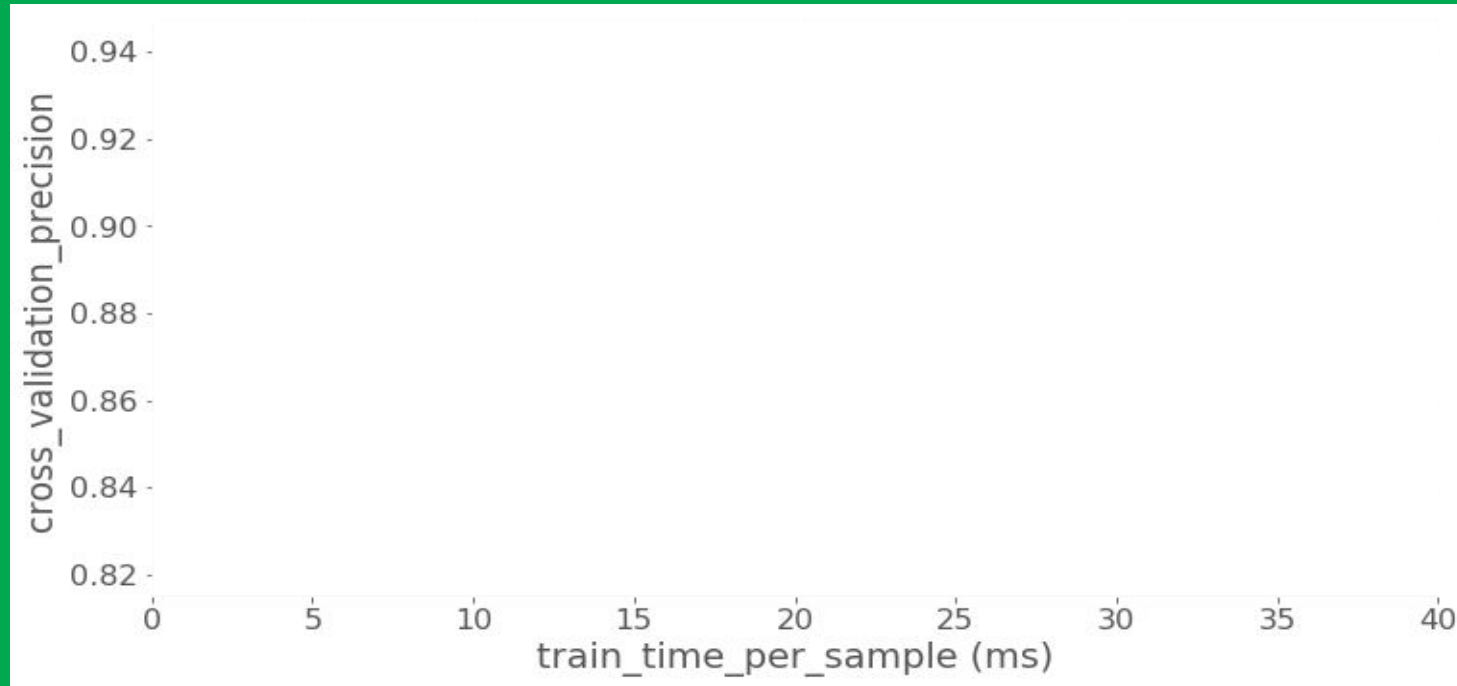
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# Hashing function - Number of Features after Hashing

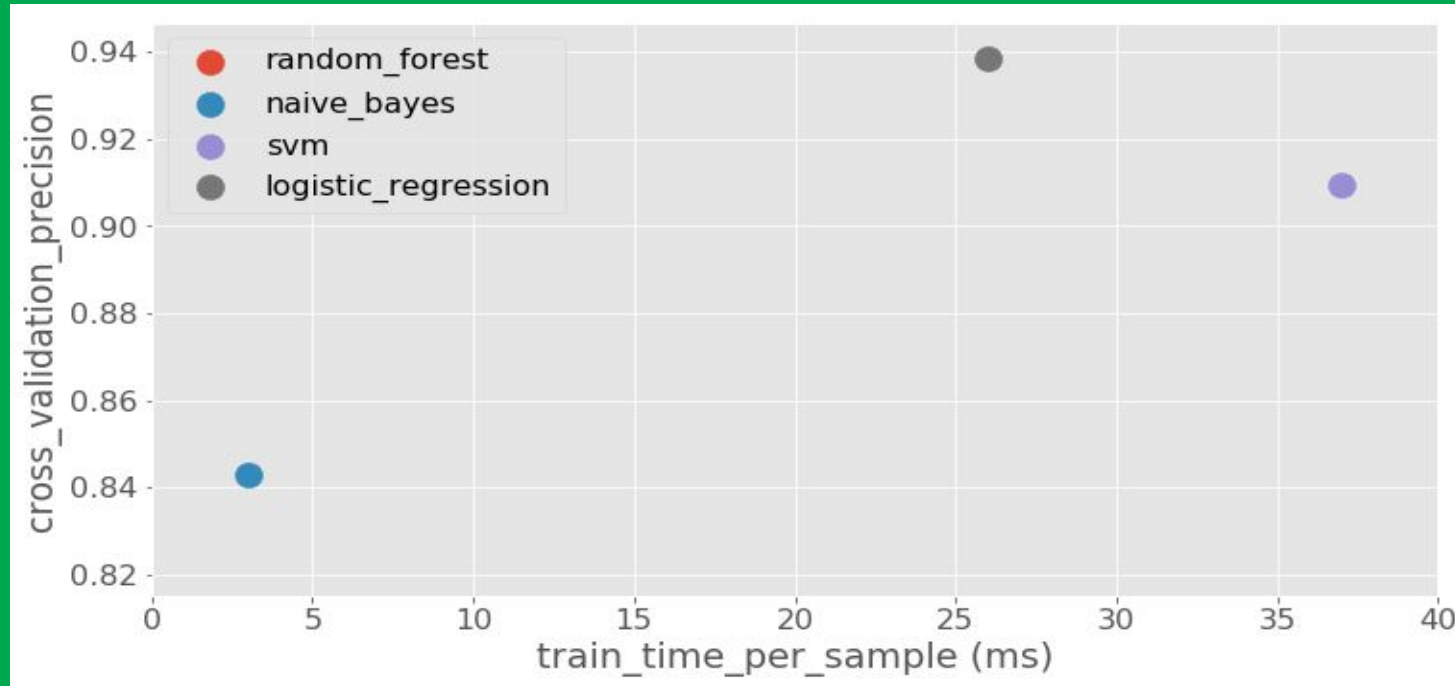


# Classification Algorithms



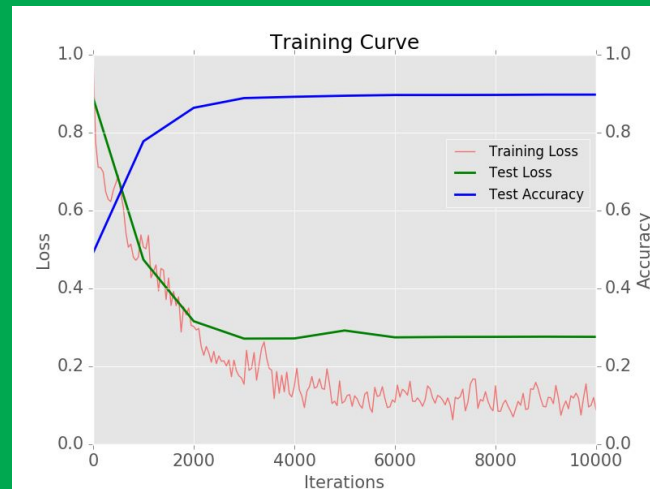


# Classification Algorithms



# Model Training Loop

- Supervised learning
  - Balanced training set
- Logistic regression
  - Limited memory Broyden–Fletcher–Goldfarb–Shanno (LBFGS) algorithm
- Training Process & Termination
  - No improvement in recent iterations
  - Training loss stabilised
  - Overfitting
  - Test loss increases
  - Number of iteration



# Trained Model Evaluation -- QA

- Cross validation -- accuracy, precision, recall, ...
- Impact estimation -- validation on all previously classified samples
- Top 50 -- manually crafted sample set

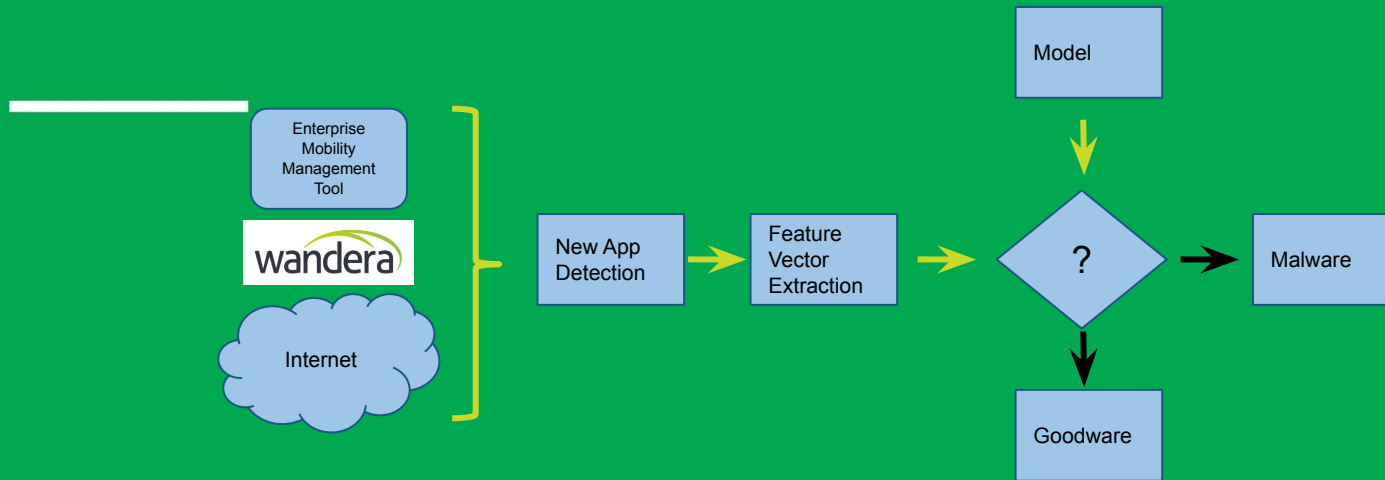
		True condition			
		Condition positive	Condition negative	Prevalence = $\frac{\Sigma \text{Condition positive}}{\Sigma \text{Total population}}$	Accuracy (ACC) = $\frac{\Sigma \text{True positive} + \Sigma \text{True negative}}{\Sigma \text{Total population}}$
Predicted condition	Predicted condition positive	<b>True positive,</b> Power	<b>False positive,</b> Type I error	Positive predictive value (PPV), Precision = $\frac{\Sigma \text{True positive}}{\Sigma \text{Predicted condition positive}}$	False discovery rate (FDR) = $\frac{\Sigma \text{False positive}}{\Sigma \text{Predicted condition positive}}$
	Predicted condition negative	<b>False negative,</b> Type II error	<b>True negative</b>	False omission rate (FOR) = $\frac{\Sigma \text{False negative}}{\Sigma \text{Predicted condition negative}}$	Negative predictive value (NPV) = $\frac{\Sigma \text{True negative}}{\Sigma \text{Predicted condition negative}}$
		True positive rate (TPR), Recall, Sensitivity, probability of detection = $\frac{\Sigma \text{True positive}}{\Sigma \text{Condition positive}}$	False positive rate (FPR), Fall-out, probability of false alarm = $\frac{\Sigma \text{False positive}}{\Sigma \text{Condition negative}}$	Positive likelihood ratio (LR+) = $\frac{\text{TPR}}{\text{FPR}}$	Diagnostic odds ratio (DOR) = $\frac{\text{LR+}}{\text{LR-}}$
		False negative rate (FNR), Miss rate = $\frac{\Sigma \text{False negative}}{\Sigma \text{Condition positive}}$	True negative rate (TNR), Specificity (SPC) = $\frac{\Sigma \text{True negative}}{\Sigma \text{Condition negative}}$	Negative likelihood ratio (LR-) = $\frac{\text{FNR}}{\text{TNR}}$	
				F <sub>1</sub> score = $\frac{2}{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}}$	

Source: wikipedia

# Online vs. Offline Learning

Online learning is still challenging in our environment

Offline learning with possibly high frequency of training

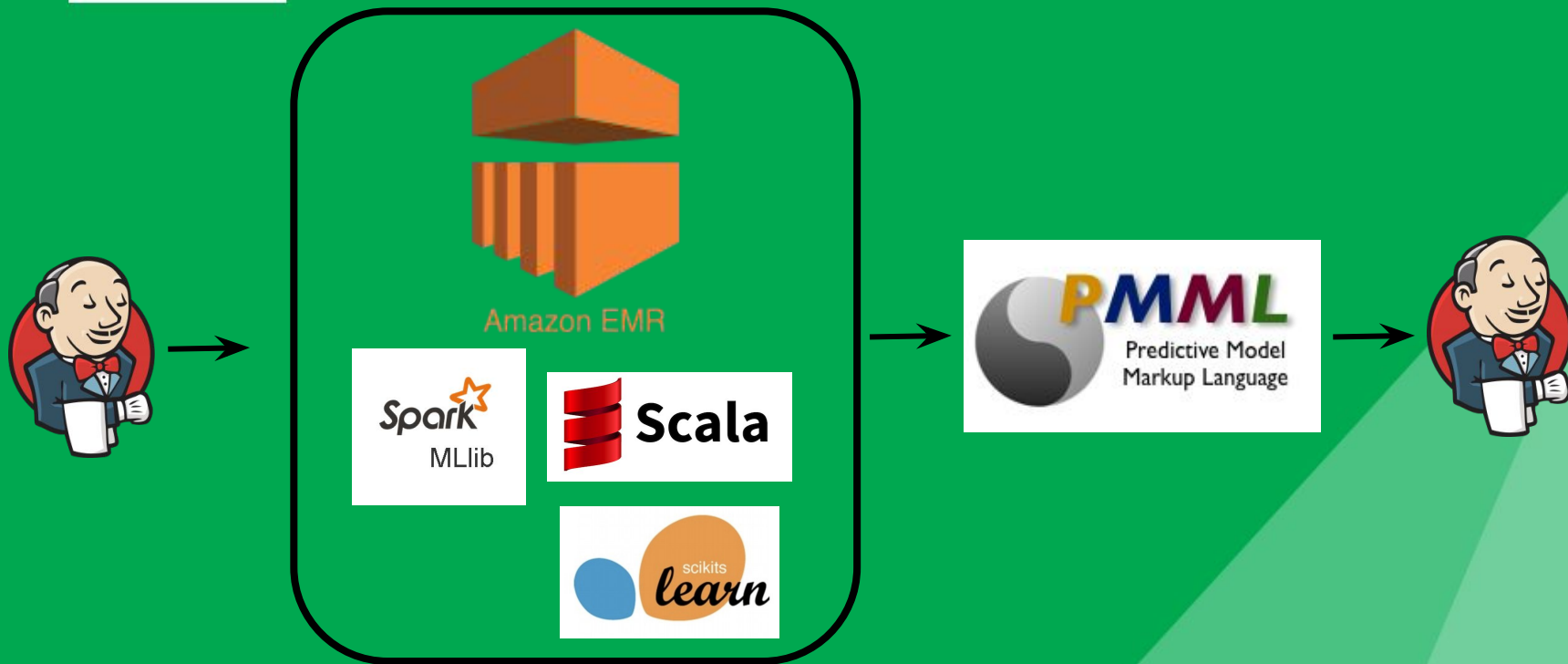


# Malware Detection as a Service

# Clear Separation of ML & Production



# Technical Background - Full Automation



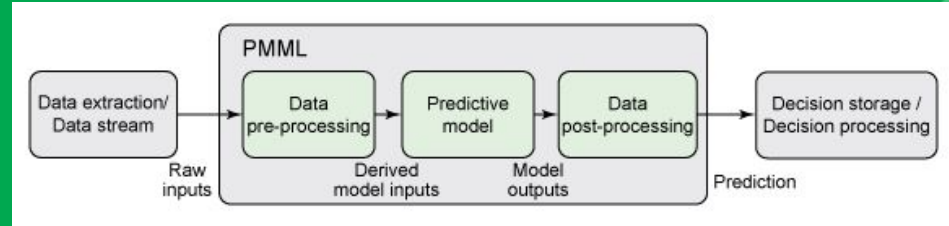
# PMML



- Header
- Data Dictionary
- Mining Schema
- Data Transformations
- Model
- Targets
- Output
- Model Explanation
- Model verification

Pre-processing

Post-processing



<http://dmg.org/pmml/>

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  <Neuron id="3" bias="-3.1808306946637">
    <Con from="0" weight="0.119477686963504" />
    <Con from="1" weight="-1.97301278112877" />
    <Con from="2" weight="3.04381251760906" />
  </Neuron>
  <Neuron id="4" bias="0.743161353729323">
    <Con from="0" weight="-0.49411146396721" />
    <Con from="1" weight="2.18588757615864" />
    <Con from="2" weight="-2.01213331163562" />
  </Neuron>
</NeuralLayer>
```



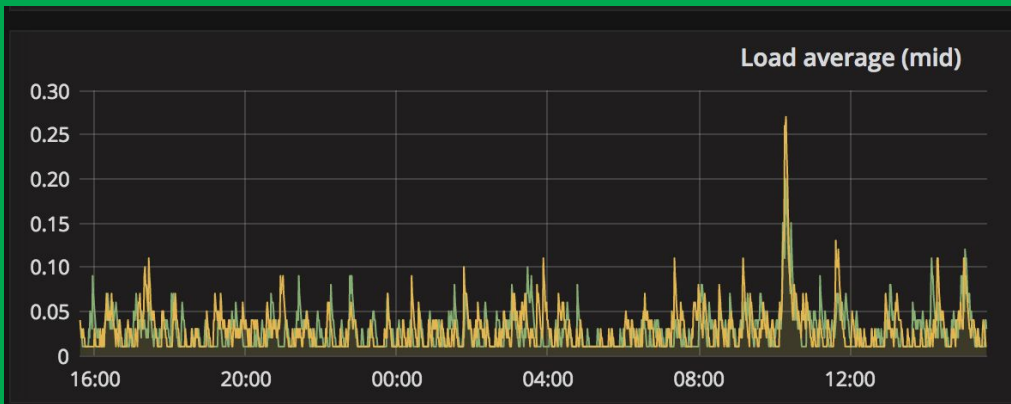
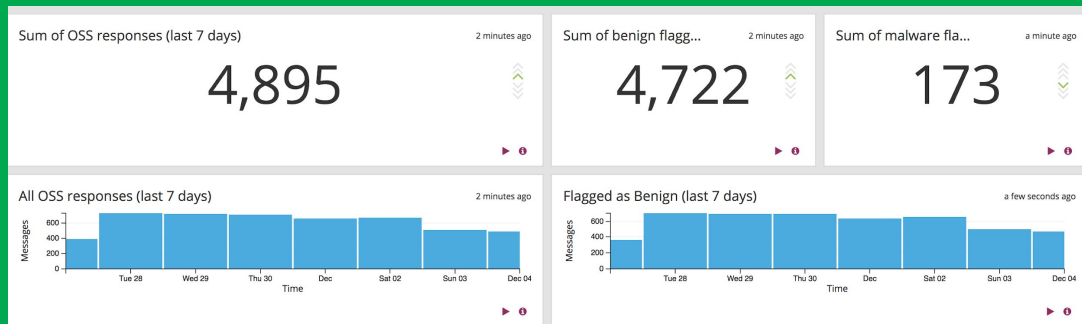
# Scoring Service

- Model agnostic micro-service written in Java
  - Loads PMML (XML) and executes the model for given inputs
- “Low” resources requirements
- Super fast for small models
- Work distribution (data science vs. engineering)



# Monitoring

- Metrics
- Logs
- Is it enough for DS?



# Lesson Learnt: Overfitting Investigation 1/2

- Problem: Discrepancy between cross validation results and production results (accuracy, precision, recall)
- Contributing factors
  - Duplicates in training data (different app identifiers)
  - Size of feature space (hashing setting or model)
  - Data distribution 50/50 (goodware/malware)

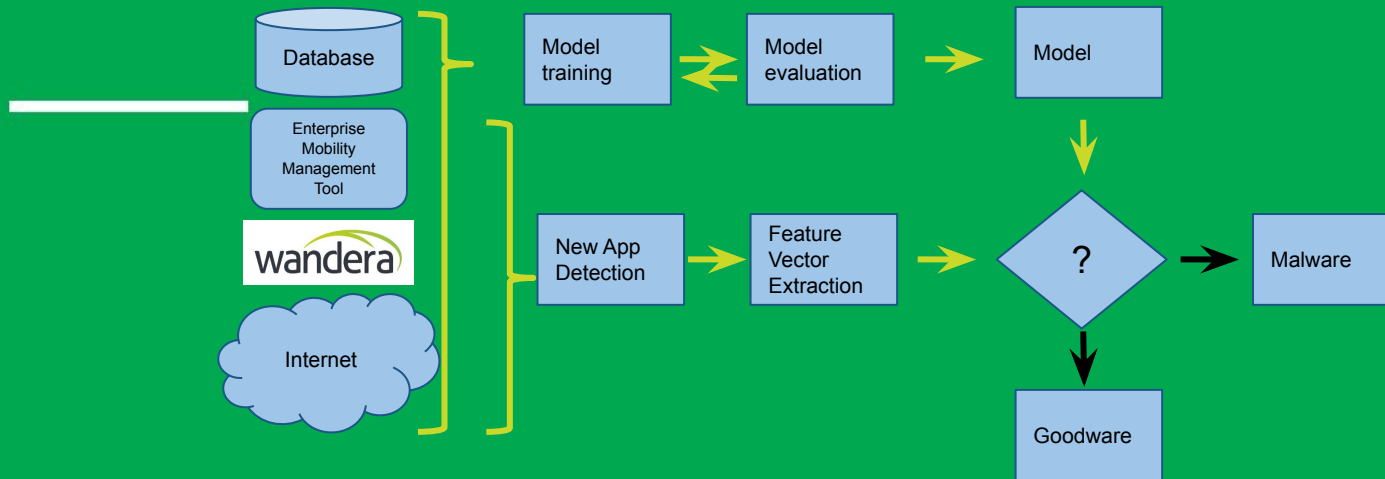
# Lesson Learnt: Overfitting Investigation 2/2

- Actions
  - Remove duplicates after hashing
  - Increased regularisation parameter (gradient descent parameter of logistic regression)
  - Data distribution reflects production

# Other Lessons Learnt

---

- Hashing is super useful
- Overfitting / Underfitting -- Check accuracy, precision, recall, ...
- Data can become really huge
- Check Openscoring vs. Spark results -- Look for implementation bugs
- Automate everything and document your decisions
- Data scientists and threat ops like to see context in logs and they like to query those data  
(marketing and users love stories and visualisations)



Thank You

# Wandera Ecosystem

