SPARK+AI
SUMMIT EUROPE

Detecting Mobile Malware with Apache Spark

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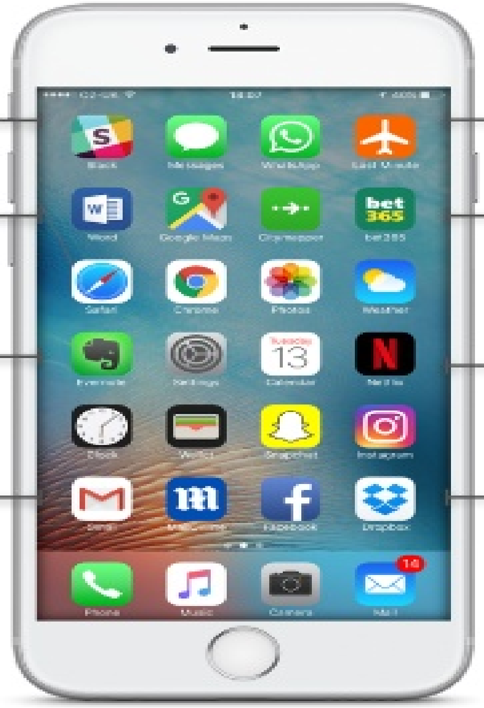
#SAISDev9

Summary

- The problem: Mobile-first malware detection
- The data and features
- The Machine Learning (ML) model
- Why Apache Spark?
- Making it production ready
- Data Science @ Wandera

The power of enterprise mobility



- ✓ Seamless internal communication
- ✓ Added flexibility to working hours
- ✓ Access to more apps and productivity tools
- ✓ E-mail and other services available anywhere

- ! Devices are prone to security threats
- ! Concerns around appropriate usage
- ! Data usage costs are opaque and spiraling
- ! Potentially exposing sensitive data

Happy hunting ground for attackers

435%

High severity threats (CVSS) growth in 2016

80%

of organizations experienced mobile phishing attack

38%

of hackers bypass endpoint defense using social engineering

100%

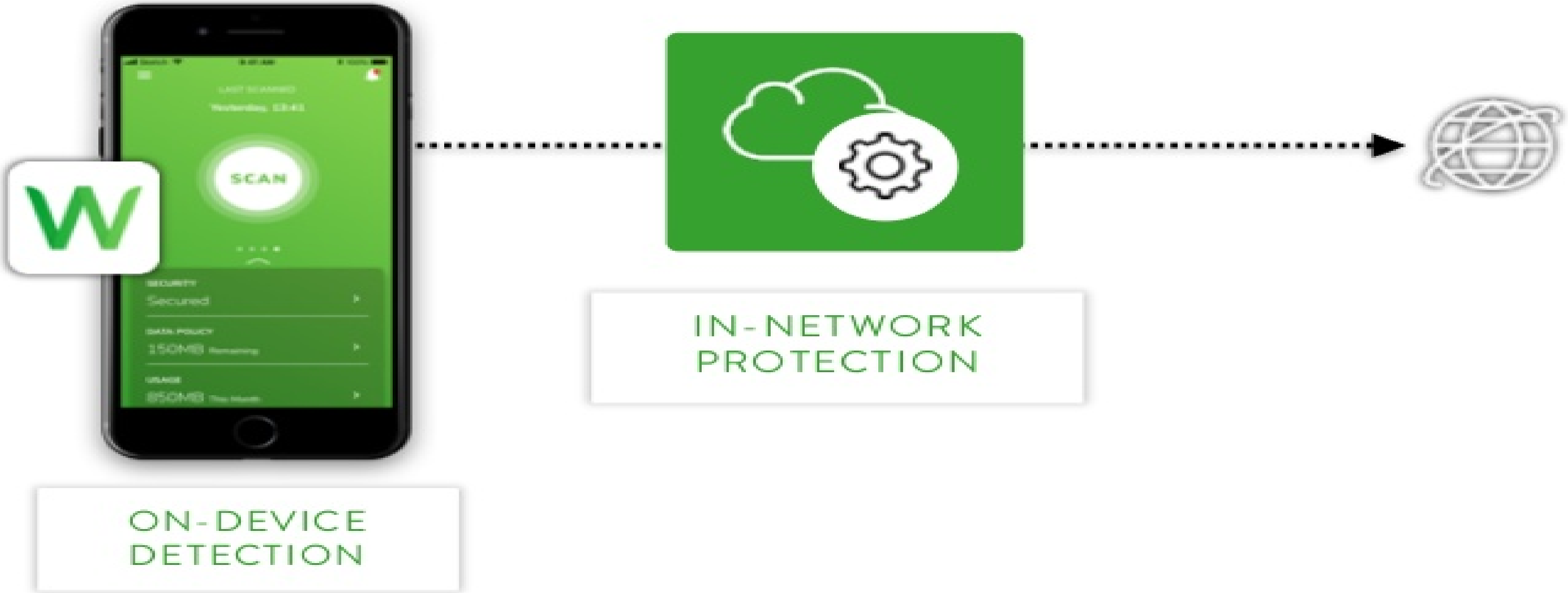
Mobile malware growth in 2016

Gartner

“Mobile threats can no longer be ignored”

- AUGUST 2017 - GARTNER MARKET GUIDE TO MOBILE THREAT DEFENSE

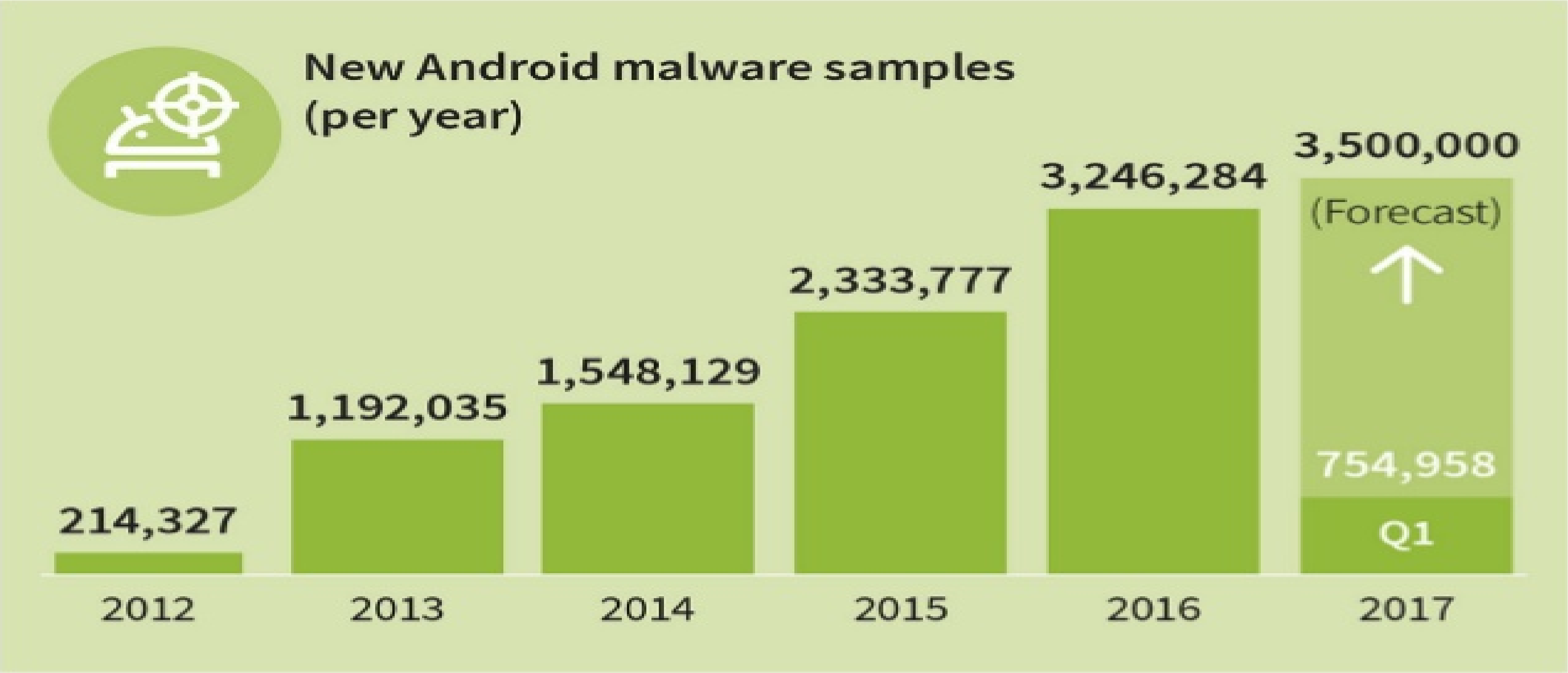
Secure Mobile Gateway



ON-DEVICE DETECTION

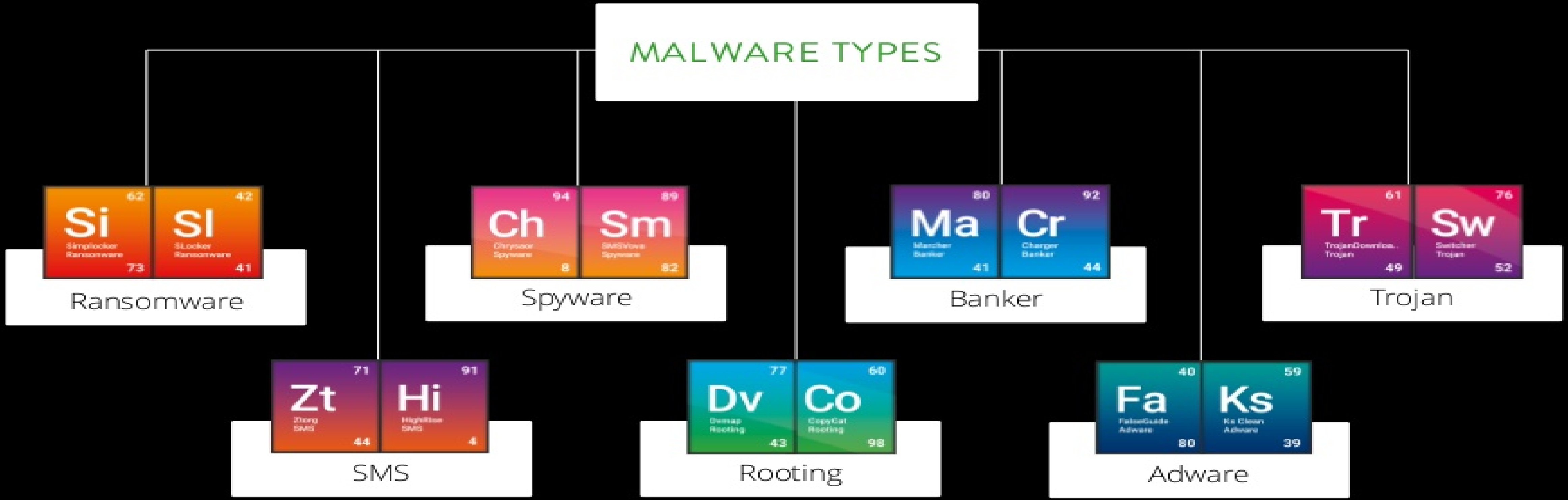
IN-NETWORK PROTECTION

The Rise of Mobile Malware



Credit: GData 2017

Our objectives: Identify <u>and</u> Classify



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Why is this a novel problem?

- Mobile malware is on the rise
- Signature based detection is no longer scalable or effective
- We needed a solution that could
  - work across both known and unknown threats;
  - effectively protect our customers; and
  - enable threat research to quickly identify new outbreaks
- First solution = signatures and lists
- Our solution = machine learning!

The data …

Good and bad apps

- Source 1: official app stores
- Source 2: seen in our devices
- Source 3: seen by our gateway

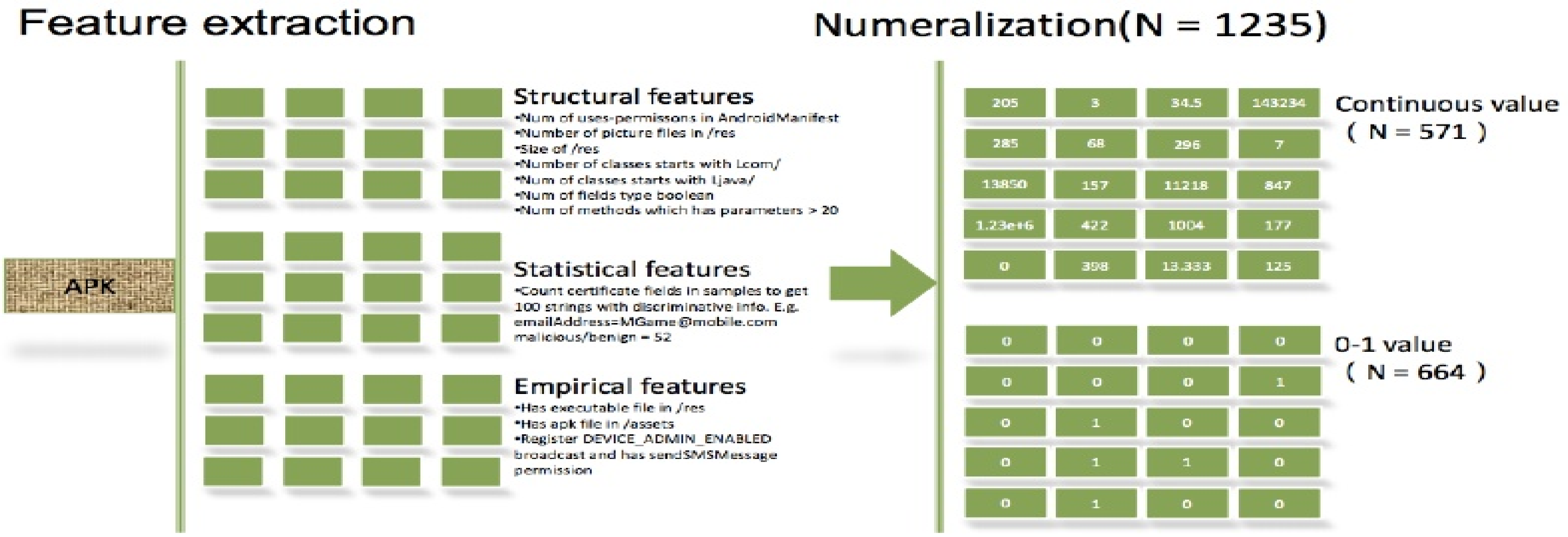
+

3rd-party threat intelligence

External input verified for labels (supervised learning)

Currently storing: ~2 million labelled apps

… the features …



Feature extraction

Numeralization(N = 1235)

Structural features

- Num of uses-permissons in AndroidManifest
- Number of picture files in /res
- Size of /res
- Number of classes starts with Lcom/
- Num of classes starts with Ljava/
- Num of fields type boolean
- Num of methods which has parameters > 20

Statistical features

- Count certificate fields in samples to get 100 strings with discriminative info. E.g. emailAddress=MGame@mobile.com malicious/benign = 52

Empirical features

- Has executable file in /res
- Has apk file in /assets
- Register DEVICE_ADMIN_ENABLED broadcast and has sendSMSMessage permission

Continuous value
（ N = 571 ）

205	3	34.5	143234
285	68	296	7
13850	157	11218	847
1.23e+6	422	1004	177
0	398	13.333	125

0-1 value
（ N = 664 ）

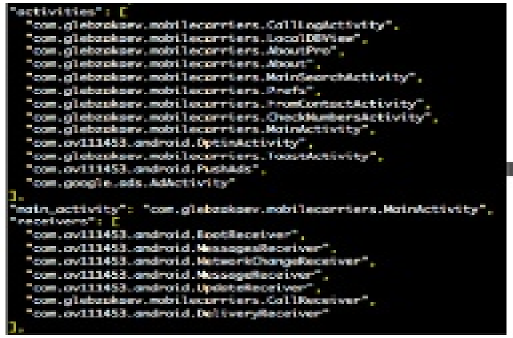
0	0	0	0
0	0	0	1
0	1	0	0
0	1	1	0
0	1	0	0

Baidu 2016

… how we extract them

Direct metadata extraction
- Total unique fields for all apps ~ 500,000
- A typical app ~ 10+ fields
- SPARSE VECTOR

Solution:
- Hashing function (vector to indices)
- Allows for fast retrieval
- With big enough map (2^20) to avoid clashes
- DENSE VECTOR

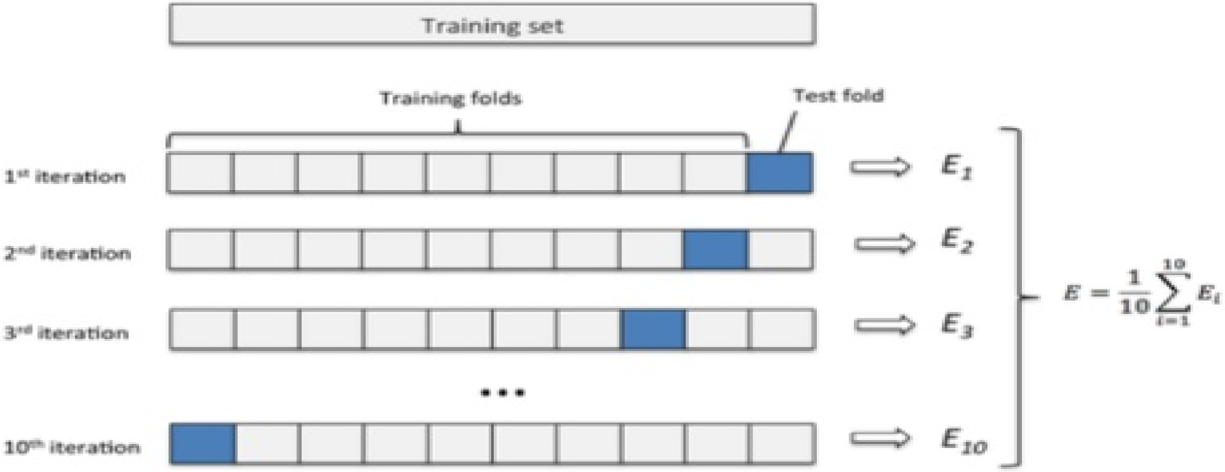


```
"activities": [
   "com.glebzakaev.mobilecarriers.CallLogActivity",
   "com.glebzakaev.mobilecarriers.LocalDBView",
   "com.glebzakaev.mobilecarriers.AboutPro",
   "com.glebzakaev.mobilecarriers.About",
   "com.glebzakaev.mobilecarriers.MainSearchActivity",
   "com.glebzakaev.mobilecarriers.Prefs",
   "com.glebzakaev.mobilecarriers.FromContactActivity",
   "com.glebzakaev.mobilecarriers.CheckNumbersActivity",
   "com.glebzakaev.mobilecarriers.MainActivity",
   "com.avl11453.android.OptinActivity",
   "com.glebzakaev.mobilecarriers.ToastActivity",
   "com.avl11453.android.PushAds",
   "com.google.ads.AdActivity"
],
"main_activity": "com.glebzakaev.mobilecarriers.MainActivity",
"receivers": [
   "com.avl11453.android.BootReceiver",
   "com.avl11453.android.MessagesReceiver",
   "com.avl11453.android.NetworkChangeReceiver",
   "com.avl11453.android.MessageReceiver",
   "com.avl11453.android.UpdateReceiver",
   "com.glebzakaev.mobilecarriers.CallReceiver",
   "com.avl11453.android.DeliveryReceiver"
],
```

$$\begin{pmatrix} feature_1 \\ \cdots \\ \cdots \\ \cdots \\ feature_n \end{pmatrix}$$

... and how the Machine Learns

- Selected model = Logistic Regression
    - Models tried = (LogReg, SVM, Decision Tree)
- K-fold cross validation to select best parameters
- Accuracy: 0.96



Why Apache Spark?

Truly big data

Millions of data points, millions of fields

Ease of use

Fast, easy and iterative. From EDA to app in days. Scala and python API.

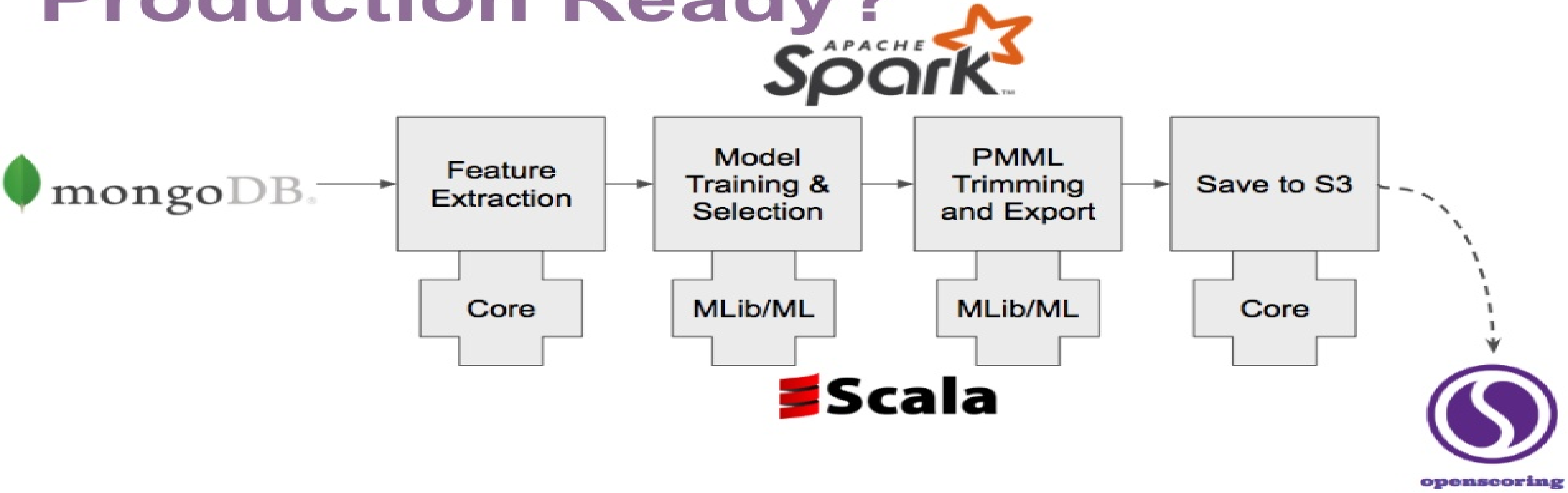
Deployment and Scale

From local to cluster is easy!

Model persistence

PMML paradigm already integrated

Production Ready?



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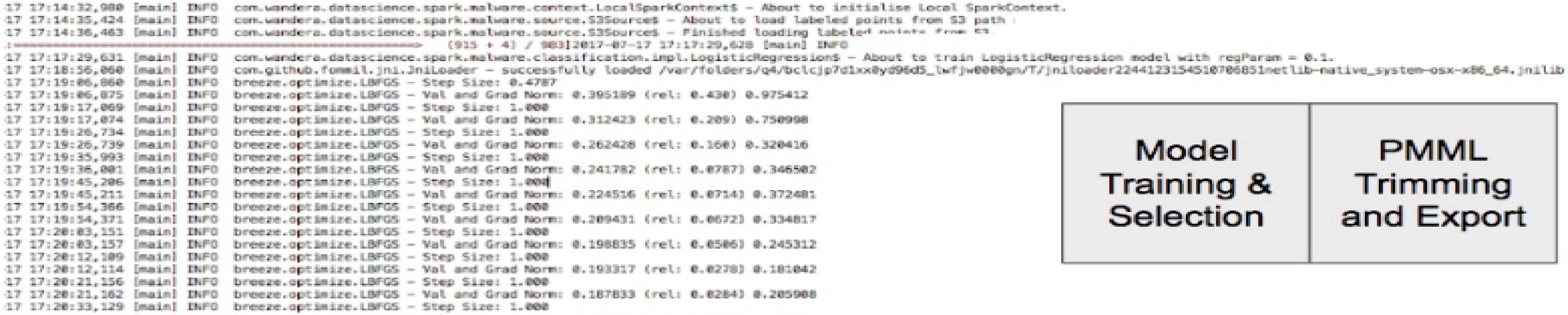
P.M.M.L

- Predictive Model Markup Language
- Industry standard
- Pro: Language agnostic, REST API, good algo coverage
- Con: large file size

Production Ready?



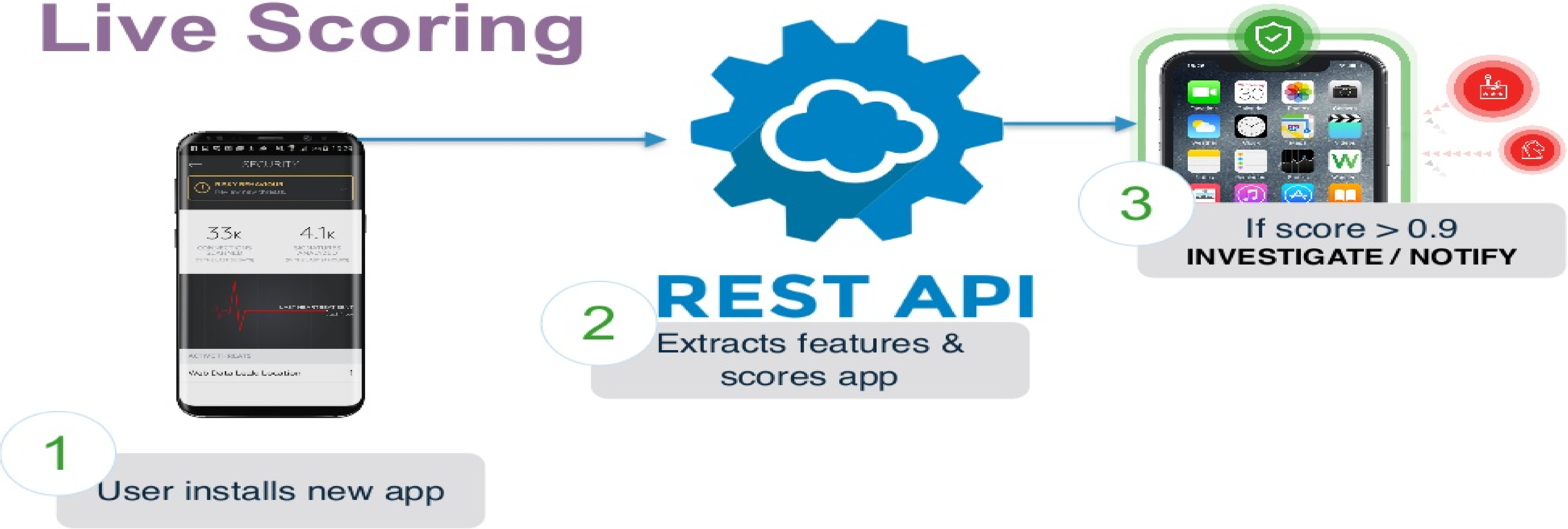
```
17 17:14:32,980 [main] INFO  com.wandera.datascience.spark.malware.context.LocalSparkContext$ - About to initialise Local SparkContext.
17 17:14:35,424 [main] INFO  com.wandera.datascience.spark.malware.source.S3Source$ - About to load labeled points from S3 path :
17 17:14:36,463 [main] INFO  com.wandera.datascience.spark.malware.source.S3Source$ - Finished loading labeled points from S3.
:=================================================================>   (915 + 4) / 983]2017-07-17 17:17:29,628 [main] INFO
17 17:17:29,631 [main] INFO  com.wandera.datascience.spark.malware.classification.impl.LogisticRegression$ - About to train LogisticRegression model with regParam = 0.1.
17 17:18:56,060 [main] INFO  com.github.fommil.jni.JniLoader - successfully loaded /var/folders/q4/bclcjp7d1xx0yd96d5_lwfjw0000gn/T/jniloader2244123154510706851netlib-native_system-osx-x86_64.jnilib
17 17:19:06,860 [main] INFO  breeze.optimize.LBFGS - Step Size: 0.4787
17 17:19:06,875 [main] INFO  breeze.optimize.LBFGS - Val and Grad Norm: 0.395189 (rel: 0.430) 0.975412
17 17:19:17,069 [main] INFO  breeze.optimize.LBFGS - Step Size: 1.000
17 17:19:17,074 [main] INFO  breeze.optimize.LBFGS - Val and Grad Norm: 0.312423 (rel: 0.209) 0.750998
17 17:19:26,734 [main] INFO  breeze.optimize.LBFGS - Step Size: 1.000
17 17:19:26,739 [main] INFO  breeze.optimize.LBFGS - Val and Grad Norm: 0.262428 (rel: 0.160) 0.320416
17 17:19:35,993 [main] INFO  breeze.optimize.LBFGS - Step Size: 1.000
17 17:19:36,001 [main] INFO  breeze.optimize.LBFGS - Val and Grad Norm: 0.241782 (rel: 0.0787) 0.346502
17 17:19:45,206 [main] INFO  breeze.optimize.LBFGS - Step Size: 1.000
17 17:19:45,211 [main] INFO  breeze.optimize.LBFGS - Val and Grad Norm: 0.224516 (rel: 0.0714) 0.372481
17 17:19:54,366 [main] INFO  breeze.optimize.LBFGS - Step Size: 1.000
17 17:19:54,371 [main] INFO  breeze.optimize.LBFGS - Val and Grad Norm: 0.209431 (rel: 0.0672) 0.334817
17 17:20:03,151 [main] INFO  breeze.optimize.LBFGS - Step Size: 1.000
17 17:20:03,157 [main] INFO  breeze.optimize.LBFGS - Val and Grad Norm: 0.198835 (rel: 0.0506) 0.245312
17 17:20:12,109 [main] INFO  breeze.optimize.LBFGS - Step Size: 1.000
17 17:20:12,114 [main] INFO  breeze.optimize.LBFGS - Val and Grad Norm: 0.193317 (rel: 0.0278) 0.181042
17 17:20:21,156 [main] INFO  breeze.optimize.LBFGS - Step Size: 1.000
17 17:20:21,162 [main] INFO  breeze.optimize.LBFGS - Val and Grad Norm: 0.187833 (rel: 0.0284) 0.205908
17 17:20:33,129 [main] INFO  breeze.optimize.LBFGS - Step Size: 1.000
```

Model Training & Selection

PMML Trimming and Export

- Saving to PMML (ML vs MLlib / DF vs RDD)
  - DataFrame API - doesn’t have PMML functionality (yet)
  - Hacked PMML to get probabilities for predictions
  - Size of model ~ 20Mb (compressed)
- Overall time to train: less than 2 hours on a big enough cluster

Live Scoring



1 User installs new app

2 Extracts features & scores app

3 If score > 0.9
INVESTIGATE / NOTIFY

Data Science @ Wandera

= Innovative Research + Scalable Architecture + Efficient Feature Delivery

Stanford University

Imperial College London

UCL

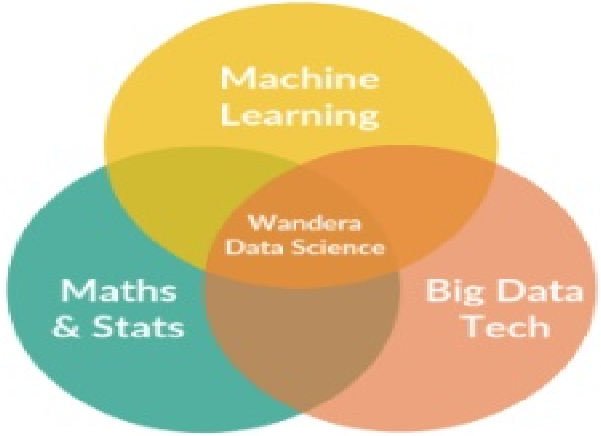
UNIVERSITY OF CAMBRIDGE

VYSOKÉ UČENÍ TECHNICKÉ V BRNĚ

UNIVERSITY OF OXFORD

Carnegie Mellon University

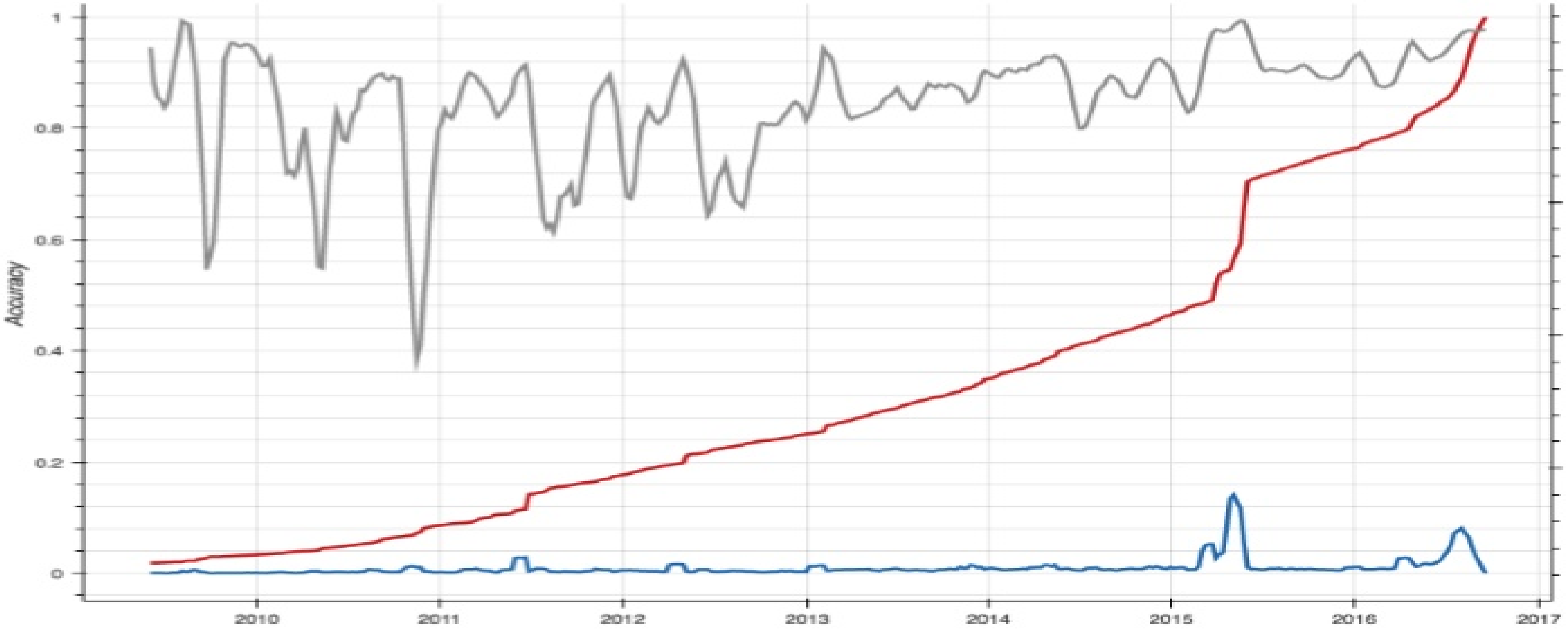
Universitatea de Stat din Moldova



- Cross-disciplinary team of scientists, analysts & developers
- Focus on solving real-world problems in a real-time, distributed network
- Global team with presence in USA, London, UK and Czech Republic

Thanks for listening

Appendix 1: model testing results



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