

Malware mining

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Agenda



- What makes a great AV product
- What is data-mining?
- Data-mining methods
 - Decision trees
 - Support Vector Machines
 - ROCs



- Data-mining as a heuristic/generic method
- Extracting features
- Practical uses of malware data-mining
- Conclusions and questions

What would make a great AV product?

- Proactively detects as many threats as possible
- Creates a very low number of false alarms
- Requires as little maintenance as possible
- Runs quickly and introduces little overhead



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But how can this be done?

- Traditional (specific) detection methods (strings, hashes)
- Generic detection methods
- Heuristic detection methods
- Cloud-based methods
- Reputation methods
- Behavioural methods

Detection method	Proactive capability	Cost to update	Available for
Specific (manual)	None	Medium	Many years
Specific (automated)	None	Low	Many years
Generic (manual)	High	High	Many years
Generic (automated)	Medium	Medium	Many years
Heuristic (manual)	Medium	High	Many years
Heuristic (automated)	Medium	Low	???



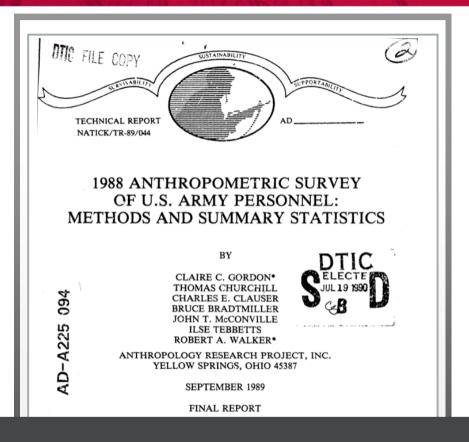




What is data-mining?

Data Mining—An Example

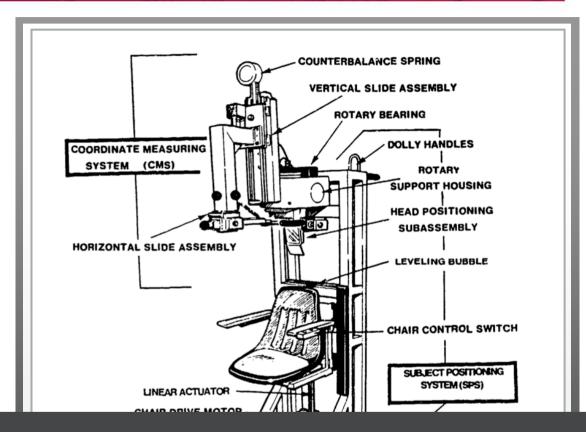
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Source: http://mreed.umtri.umich.edu/mreed/downloads.html#anthro, http://www.dtic.mil/dticasd/docs-a/anthro_military.html

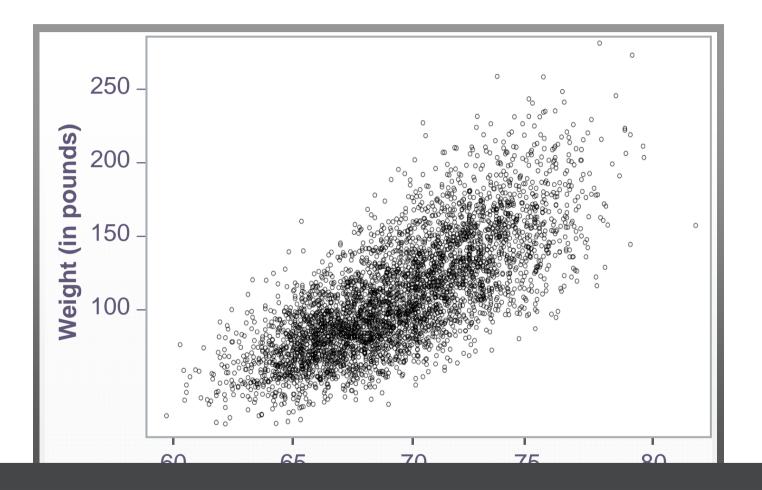
Measurements





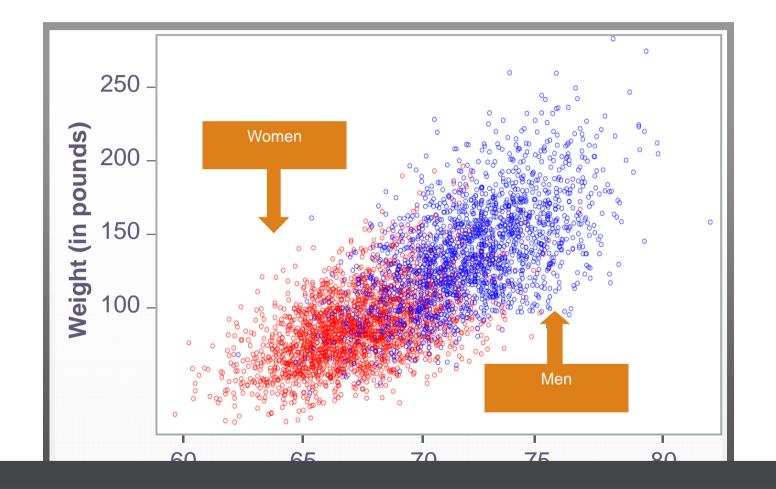
Height Versus Weight



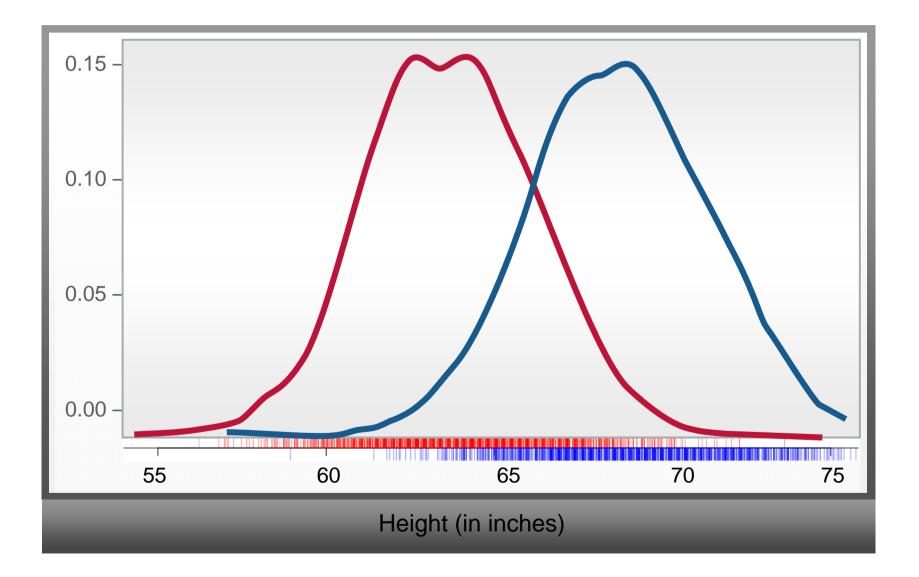


Height Versus Weight + 1 Boolean feature



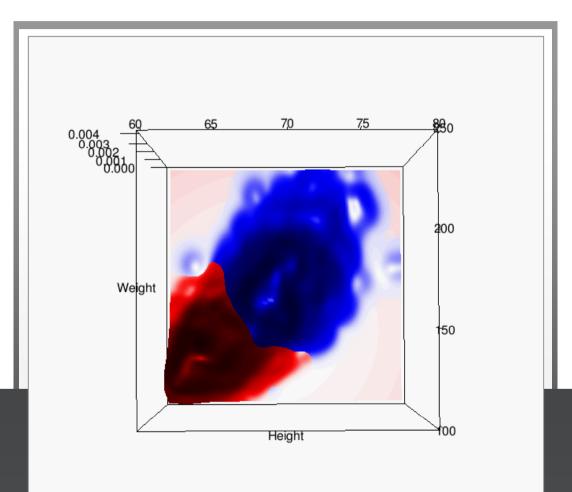


One Dimension Only (1 feature)

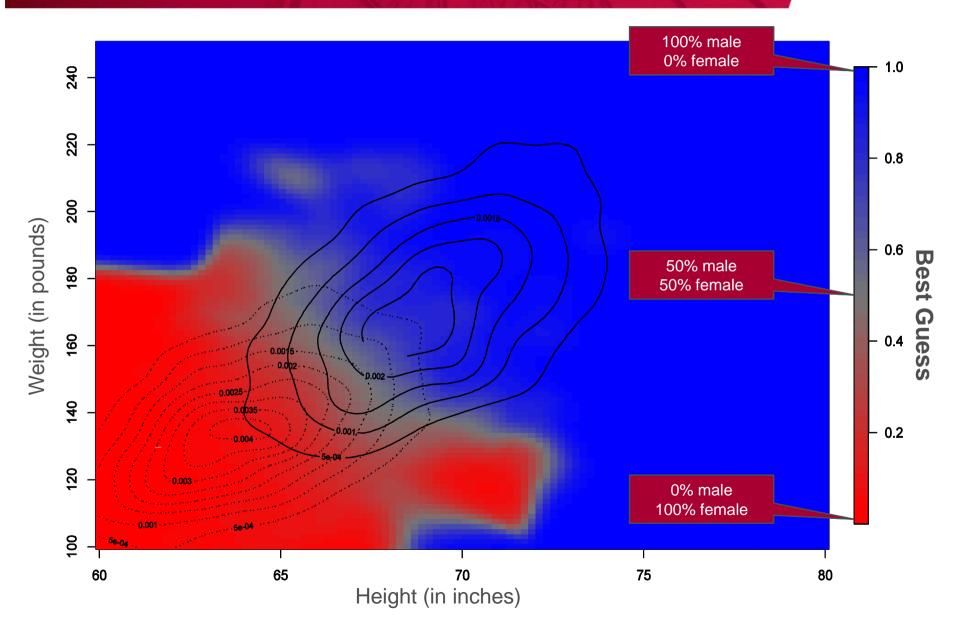


Putting Weight and Height Into Perspective



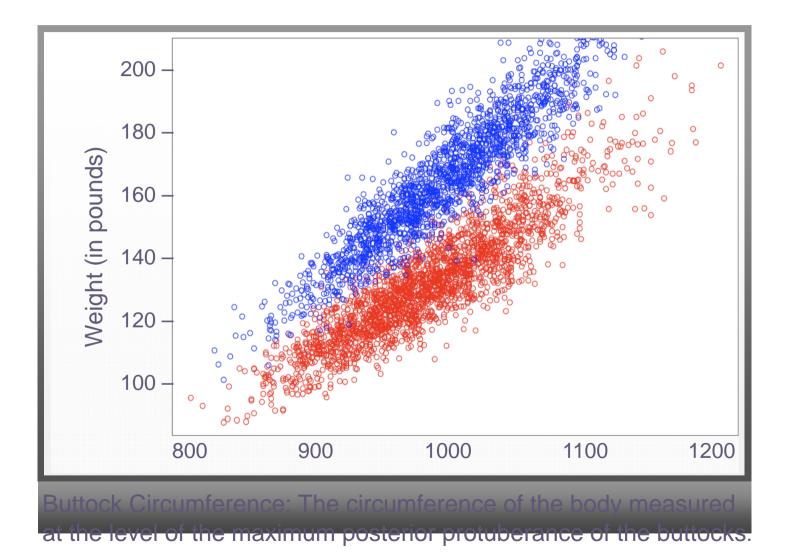


Best Guess for Gender

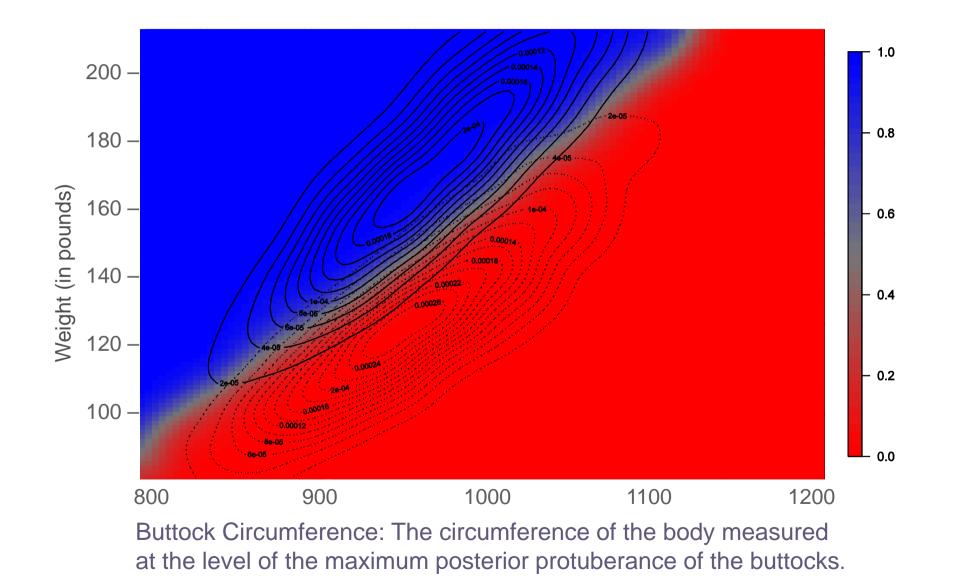


Better Features





Best Guess for Revised Features



Further Improving the Separation

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Signal to Noise

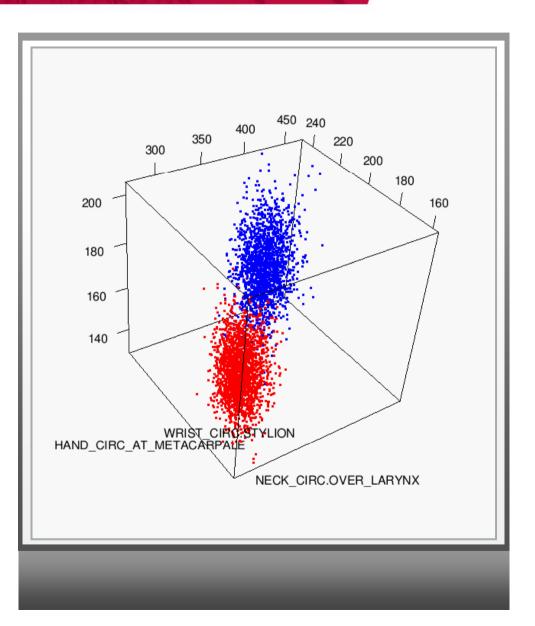
Features with very different distribution per class

Correlation

Features with low correlation

Dimensionality

Consider more features at the same time

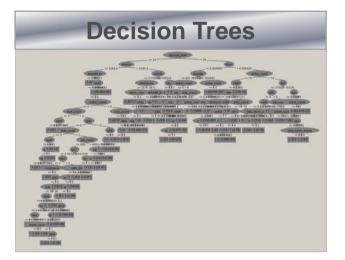


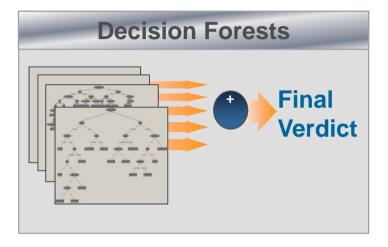


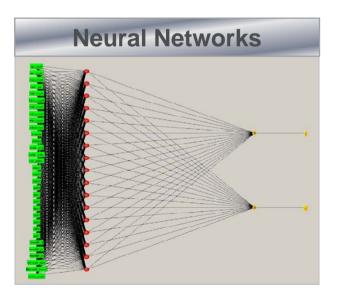


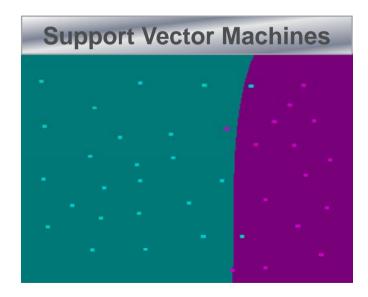
Data-mining methods

Classification Algorithms



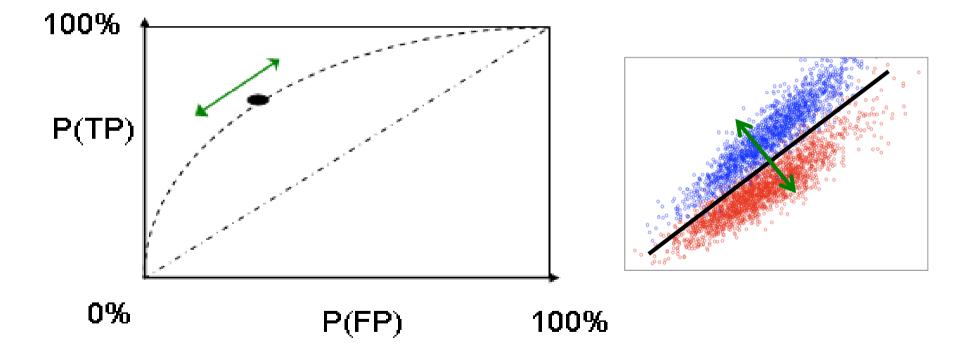




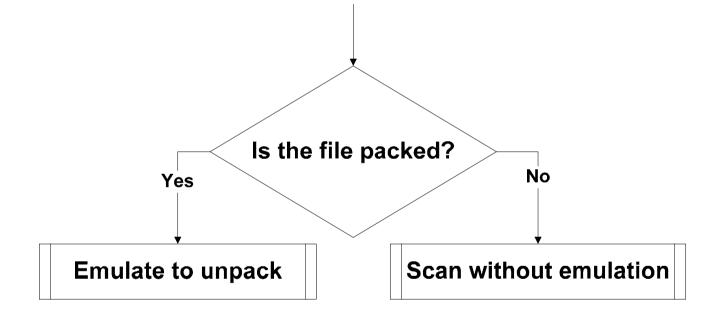




ROCs graphically represent the quality of separation achieved by data-mining

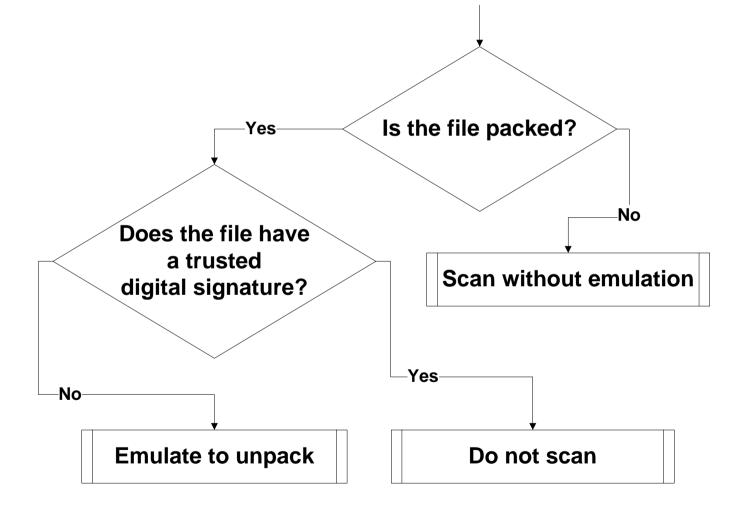


Primitive decision tree



Manually-constructed decision tree (logic)





Feature extraction for PE files

- Is file packed = Boolean
- Is file a DLL = Boolean
- HLL language = Integer {1=VB, 2=MSVC, 3=Delphi, 4=.NET, 5=...}
- How many PE sections = Integer
- Are section names standard = Boolean
- Are characteristics of sections standard = Boolean
- Is entry point in the 1st section = Boolean
- Is file digitally signed = Boolean
- Is DOS header standard = Boolean
- Is PE timestamp old = Boolean
- How many resources = Integer
- How many languages in resources = Integer
- Do timestamps in PE header/resources/digisig match = Boolean
- Number of imports = Integer
- Number of exports = Integer
- Number of bound imports = Integer
- Number of imports from WSOCK32.DLL

Steps to build a decision tree

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Build collections

- Build two TP and FP sets (training sets)
- Setting aside collections for testing (e.g. 10-25%)

Extract features

- From TP set
- From FP set

Model

- Can be expensive for large collections and lots of features
- Pruning (if there is overfitting)

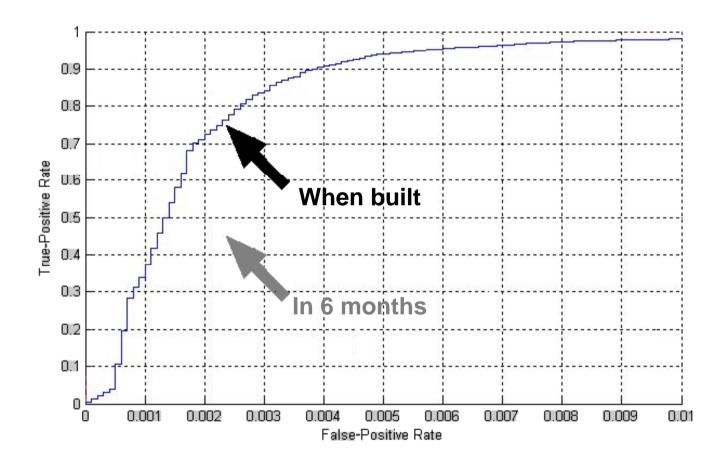
Test

- If the result is not good – make changes and repeat

Convert into usable form

Decision tree logic into C or C++

Decision tree (DT) for PE files with 20 features



Converting logic into code

Tree View

DT visualized in Weka

- Ieaf 1 (1)
 Ieaf 2 (1)
 Ieaf 3 (1)
 Ieaf 4 (1)
 Ieaf 5 (1)
 node 6 (13)
 node
 node</
- DT as C code

```
if (LSEX <= 0) {
if (PACK \leq 0) {
  if (TIME <= 1174454487) {
    if (TIME <= 708992669) {
       if (DLLB <= 0) {
         if (SIZE <= 1043955) {
           if (CONS <= 0) {
             if (RESD <= 40) {confidence=9892; }
             else {
                if (URLD <= 0) {
                  if (WNET <= 0) {
                    if (OVLY <= 905728) {
                       if (SECS <= 8) {
                         if (WSCK \leq 0) {
                           if (IMSZ <= 212)
                             if (OVLY <= 399050) {
  if (SIZE <= 66240) {confidence=-5500;}</pre>
                               else { confidence=9255;}
                                • • •
```

👙 Weka Classifier Tree Visualizer: 04:27:00 - Cobweb (departments_string-weka.filters.unsupervised.attribute.StringToNominal-C1-weka.filters.unsup... 📃 🗖 🗙

eaf 23 (1)

leaf 20 (1)



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Practical uses of malware data-mining

Practical uses

- To prioritize and de-prioritize samples in research queues
- To drive the depth of the sample analysis on the endpoint, gateway or a server
- To check the most suspicious samples using cloudbased security
- To exclude less suspicious samples from cloud communication
- Applies to anti-malware, anti-spam
- It is an automatic heuristic!

Conclusions

- Data-mining is very useful in malware analysis
- Easy to automate
- Can be used for both "strong" and "weak" heuristic verdicts
 - Detections
 - Limiting
 - Prioritization



Questions



