Chapter 6: Understanding Machine Learning-Based Malware Detectors

DATA SCIENCE IN SECURITY

Introduction

- With the open source machine learning tools available today
  - you can build custom malware detection tools
    - whether as your primary detection tool
    - or to supplement commercial solutions.

Introduction

- why build your own machine learning tools?
  - can allow you to catch new examples of threats
    - commercial antivirus engines might miss them
  - Commercial tools are “closed books”
    - we don’t necessarily know how they work
    - we have limited ability to tune them
  - we know how our own detection tools work
    - can tune them to our liking to reduce
      - false positives
      - or false negatives

Steps for Building a Machine learning–Based Detector

- fundamental difference between machine learning and other kinds of computer algorithms.
  - traditional algorithms tell the computer what to do
  - machine-learning systems learn how to solve a problem by example
    - they automate the work of creating security signatures
    - they have the potential to perform more accurately than signature-based approaches
      - especially on new, previously unseen malware.

Steps for Building a Machine learning–Based Detector

- workflow to build machine learning-based detector
  1. Collect examples of malware and benignware.
     - called training examples to train the machine learning system to recognize malware.
  2. Extract features from each training example
     - to represent the example as an array of numbers
     - also includes research to design good features
  3. Train the machine learning system
     - using the features we have extracted.
  4. Test the approach on some data
     - not included in our training examples

Gathering Training Examples

- ability to recognize suspicious binaries depends heavily on the
  - quantity of training examples
    - the more examples you feed your system, the more accurate it's likely to be
  - quality of training examples you provide.
    - samples you collect should mirror the kind of malware and benignware you expect your detector to see

Extracting Features

- we train machine learning systems by showing them features of software binaries
  - file attributes that will help the system distinguish between good and bad files e.g.
    - Whether it’s digitally signed
    - The presence of malformed headers
    - The presence of encrypted data
    - Whether it has been seen on more than 100 network workstations

Designing Good Features

- choose features that represent your best guess to distinguish bad files from good files.
  - E.g. “contains encrypted data”
    - benignware will contain encrypted data more rarely.
- don’t use set of features too large relative to the number of training examples
  - not enough training examples to teach your system what each feature actually says (probably)
  - Statistics tells us that it’s better to
    - give your system a few features relative to the training examples
    - Let it form well-founded beliefs about which features truly indicate malware.

Designing Good Features

- make sure features represent a range of hypotheses
  - E.g.
    - you may choose features related to encryption
    - but make sure to also use features unrelated to encryption
      - if system fails to detect malware based on one type of feature, it might still detect it using other features.

Training Machine Learning Systems

- depends on the machine learning approach you're using
  - E.g.
    - training a decision tree approach involves a different learning algorithm than training a logistic regression approach
- Fortunately
  - all machine learning detectors provide the same basic interface
    - You provide them with training data that contains
      - features from sample binaries
      - corresponding labels
    - the algorithms learn to determine
      - a new unseen binaries are malicious or benign.

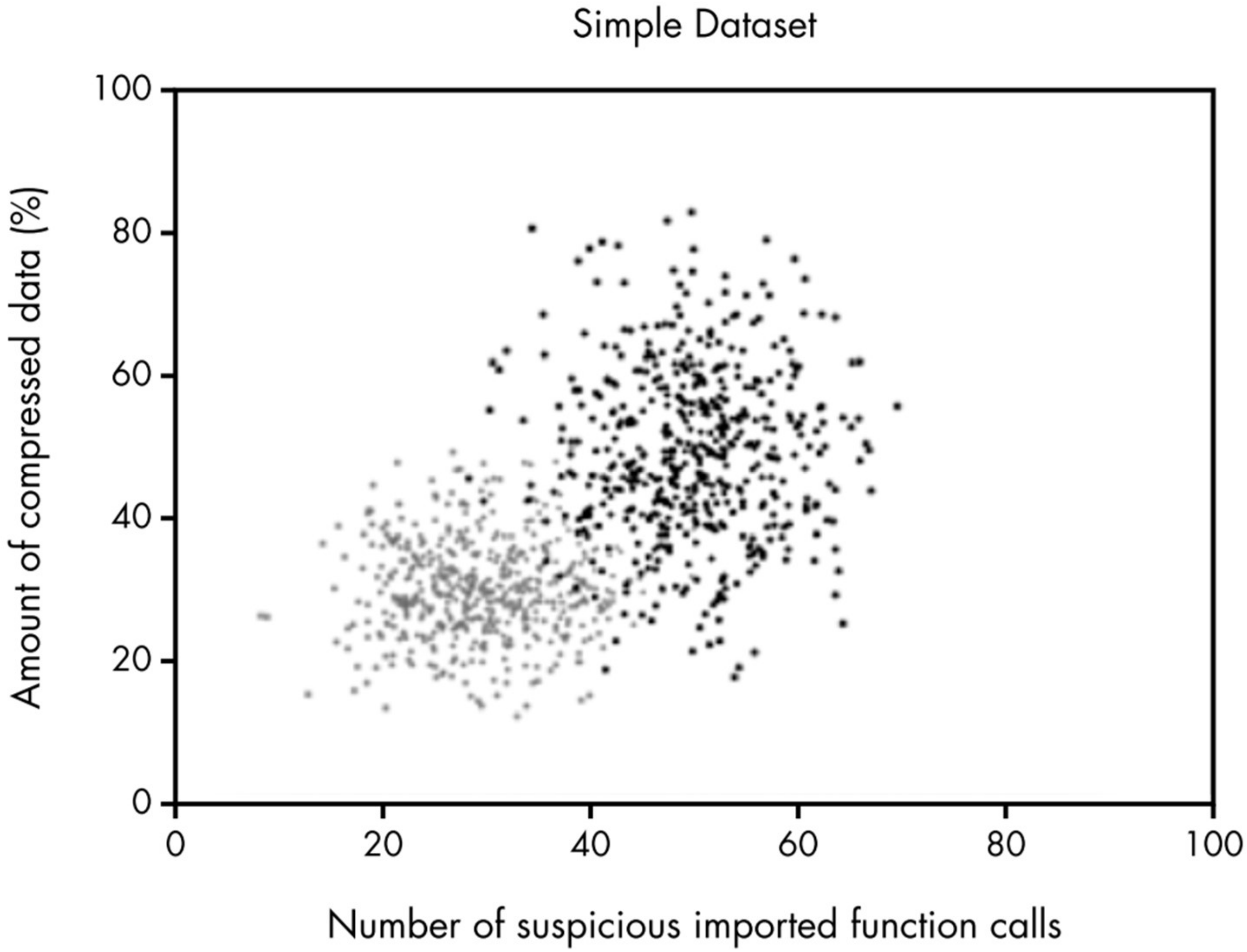
Testing Machine Learning Systems

- you need to check how accurate it is.
  - running the trained system on data that you didn’t train it on and seeing
    - how well our systems will detect new malware
    - how well our systems will avoid producing false positives on new benignware.

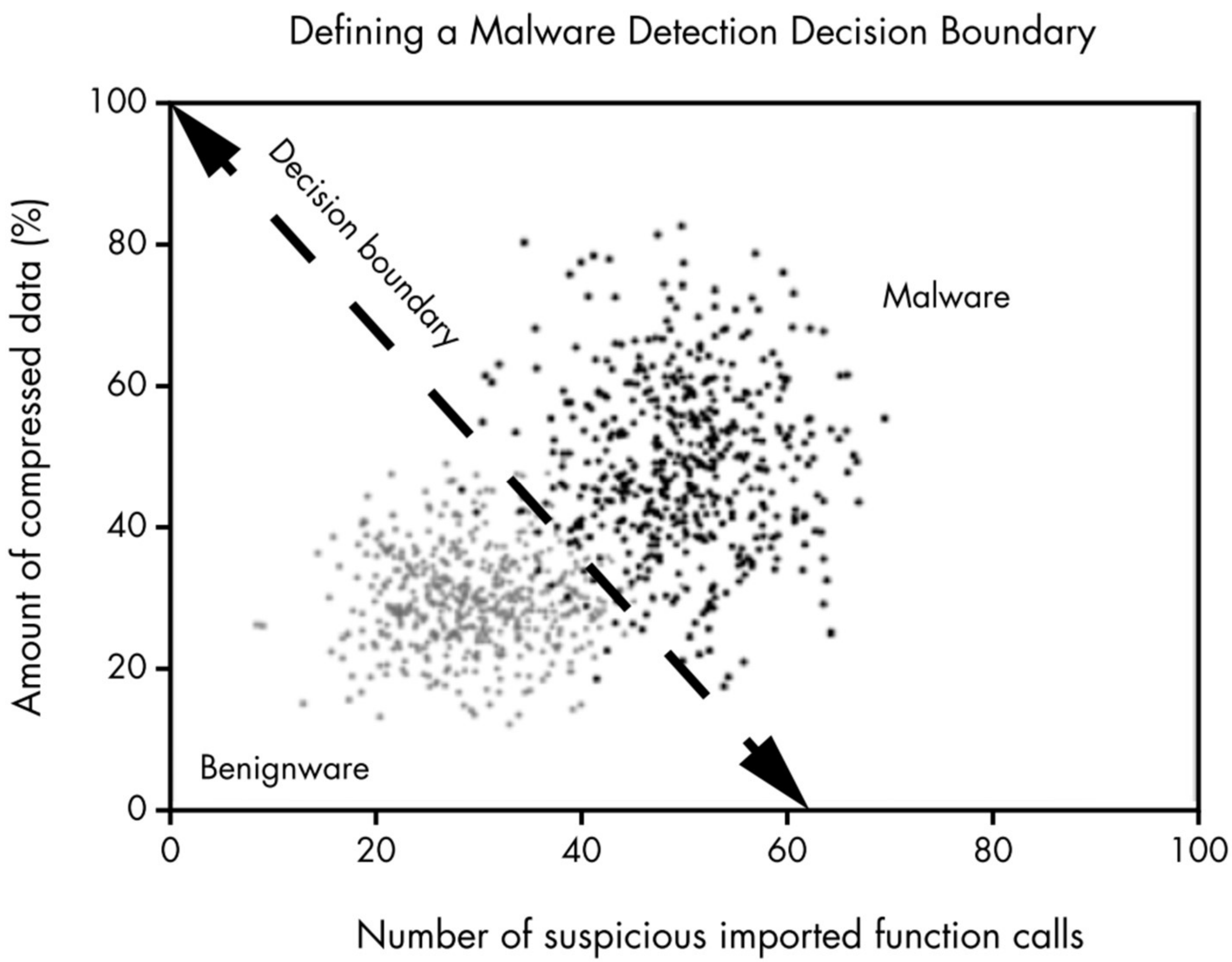
understanding Feature Spaces and Decision Boundaries

- Two simple geometric ideas can help you understand all machine learning-based detection algorithms:
  - the idea of a geometrical feature space
    - geometrical space defined by the features you've selected
  - the idea of a decision boundary.
    - geometrical structure running through feature space such that
      - binaries on one side are defined as malware
      - binaries on the other side are defined as benignwareSS

understanding Feature Spaces and Decision Boundaries



understanding Feature Spaces and Decision Boundaries



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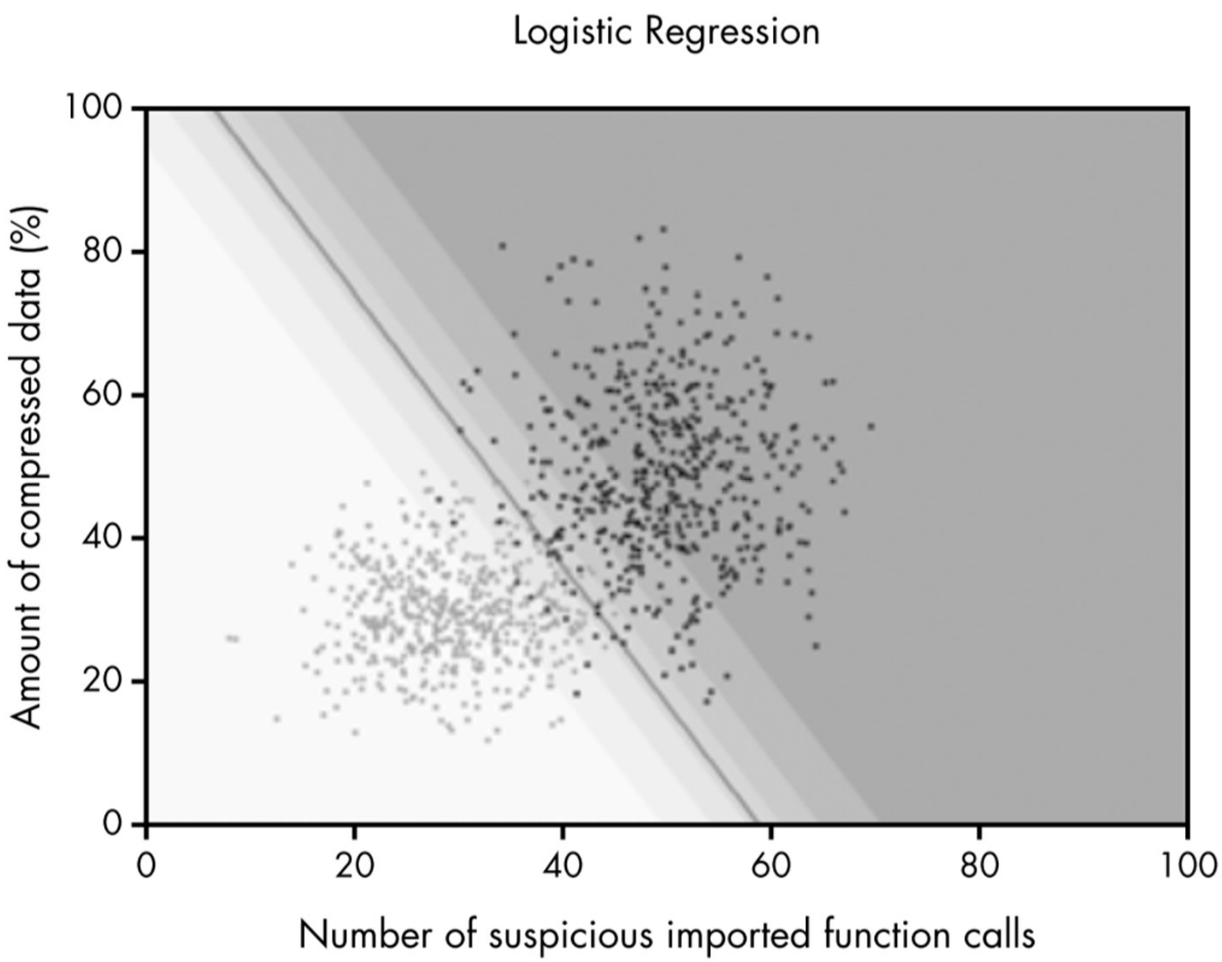

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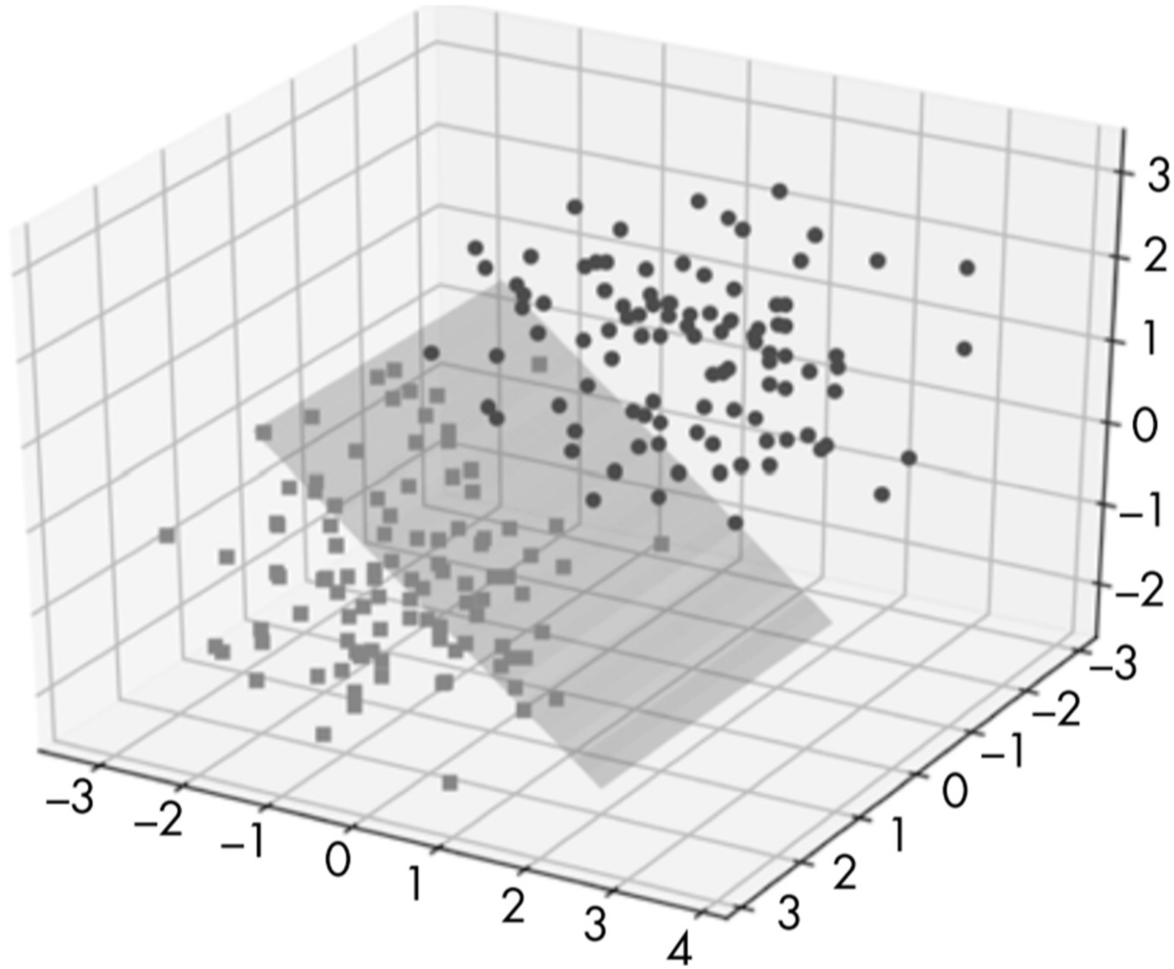

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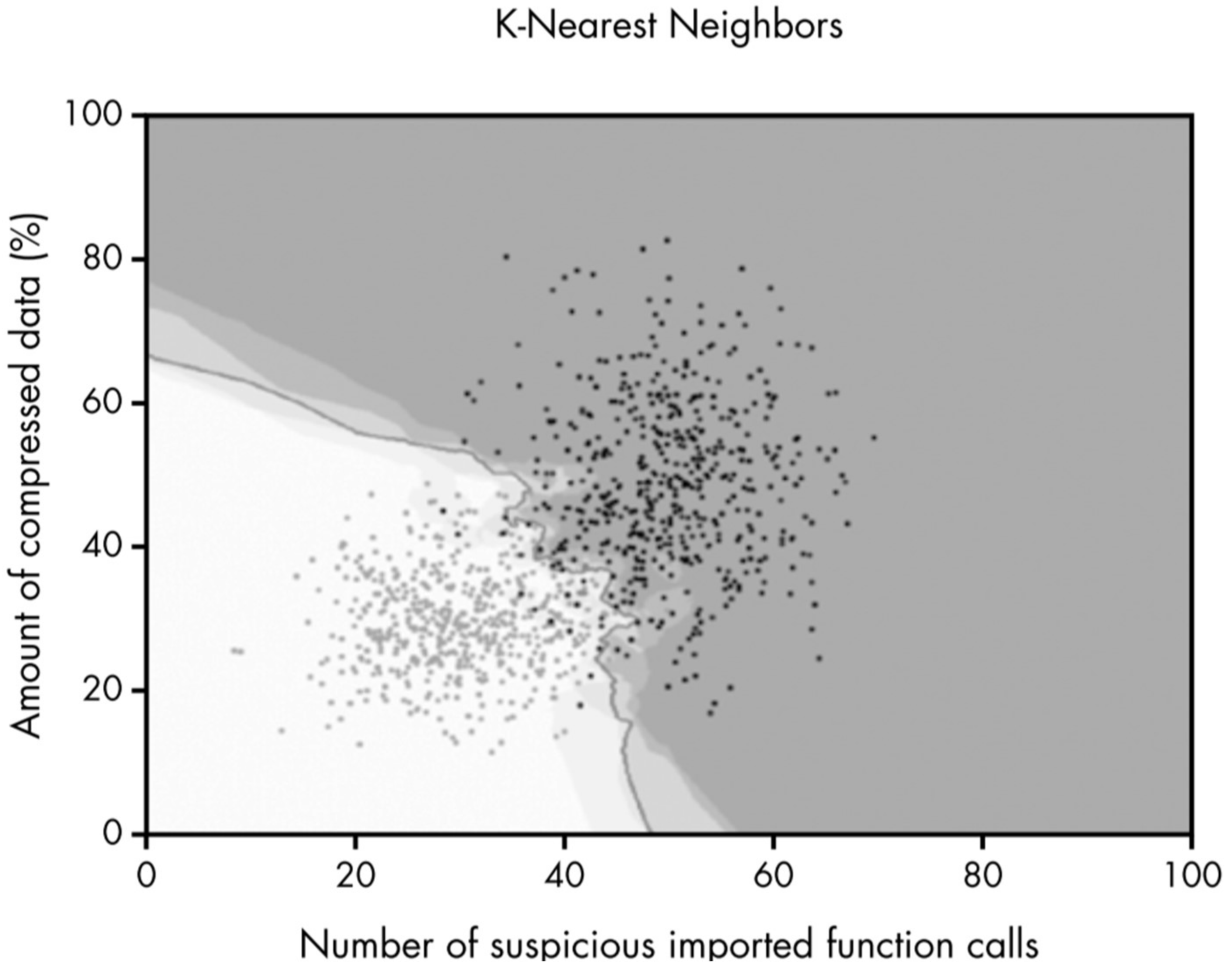

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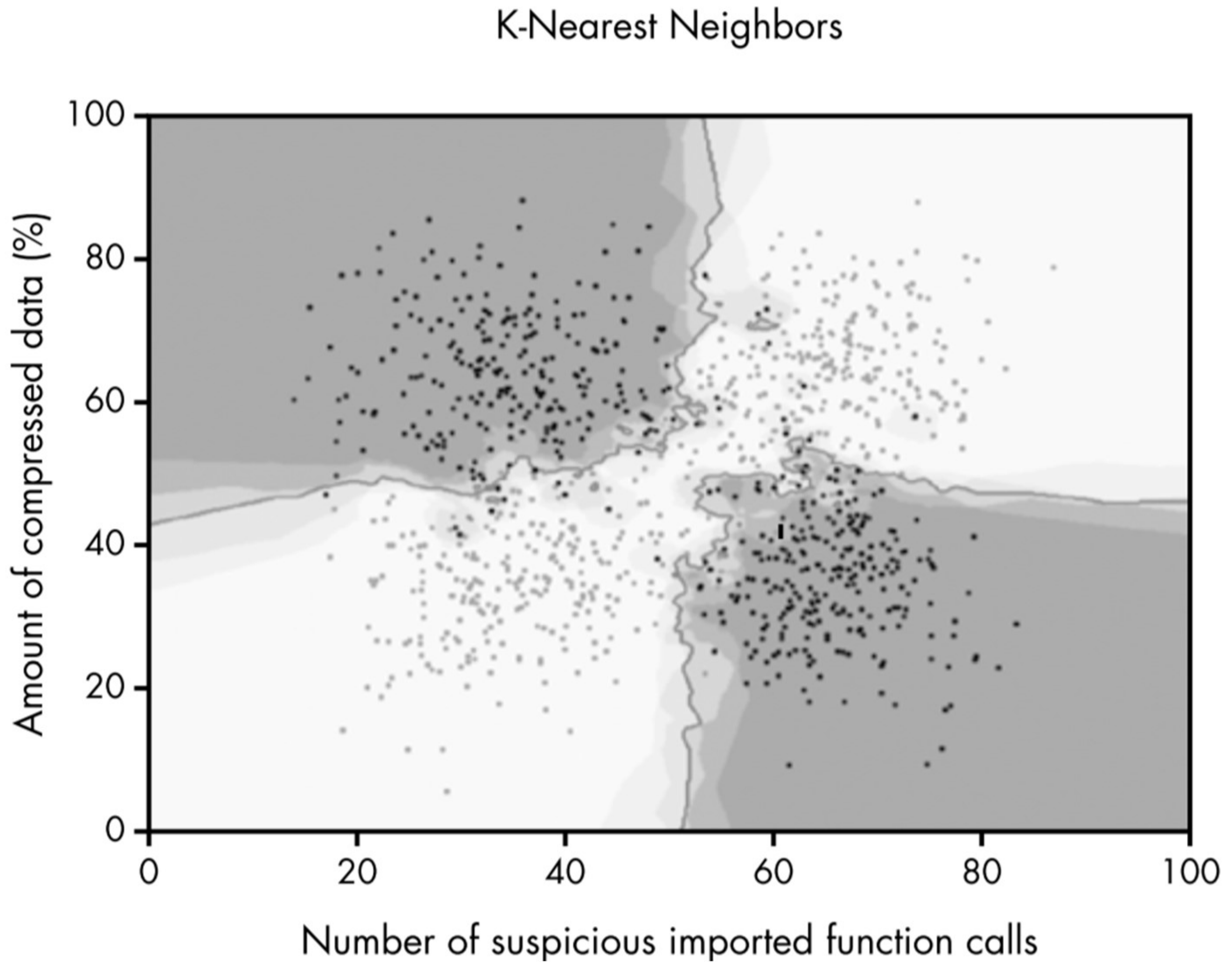
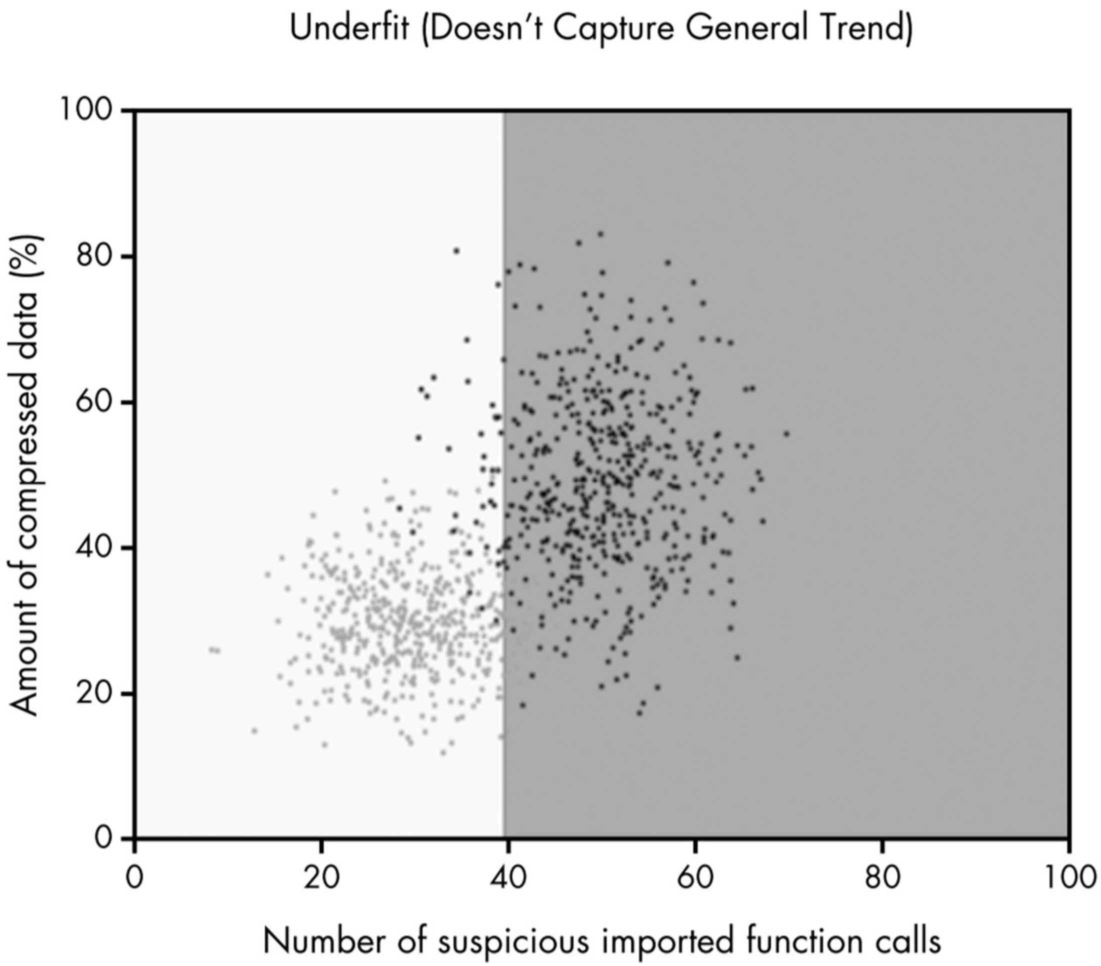


what Makes Models Good or Bad: overfitting and underfitting

- Good, accurate detection models
  - capture the general trend in what the training data says
  - without getting distracted by the outliers or the exceptions
- Underfit models
  - ignore outliers
  - but fail to capture the general trend
  - resulting in poor accuracy on unseen binaries
- Overfit models
  - get distracted by outliers
  - don’t reflect the general trend
  - yield poor accuracy on unseen binaries.

what Makes Models Good or Bad: overfitting and underfitting



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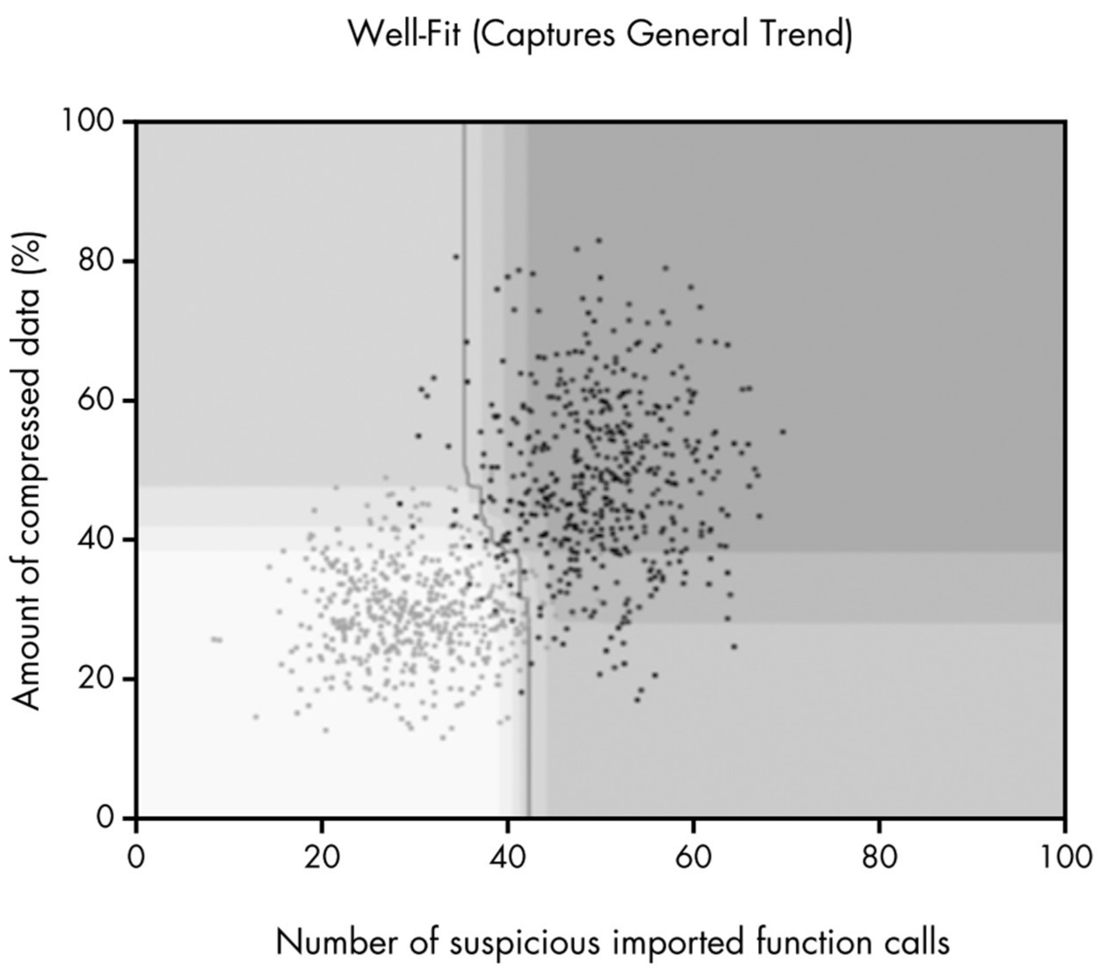

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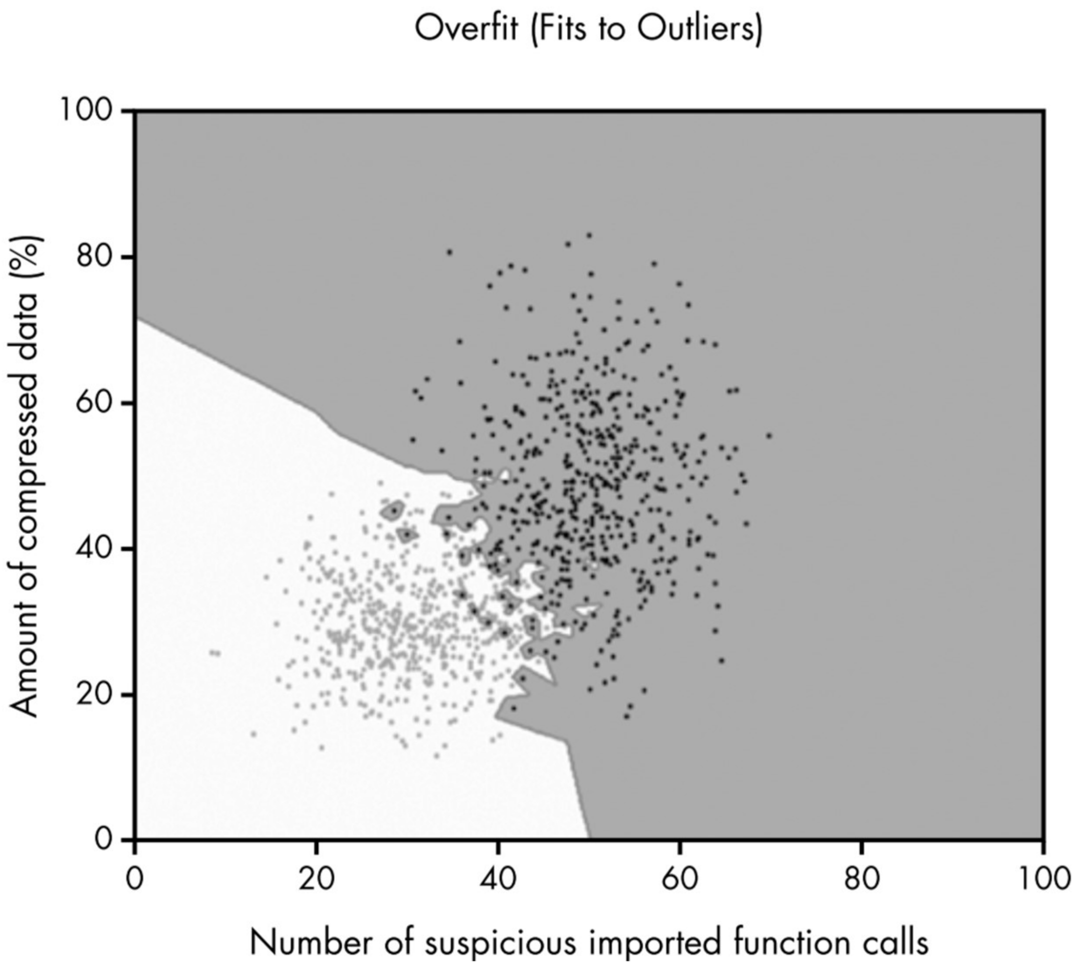
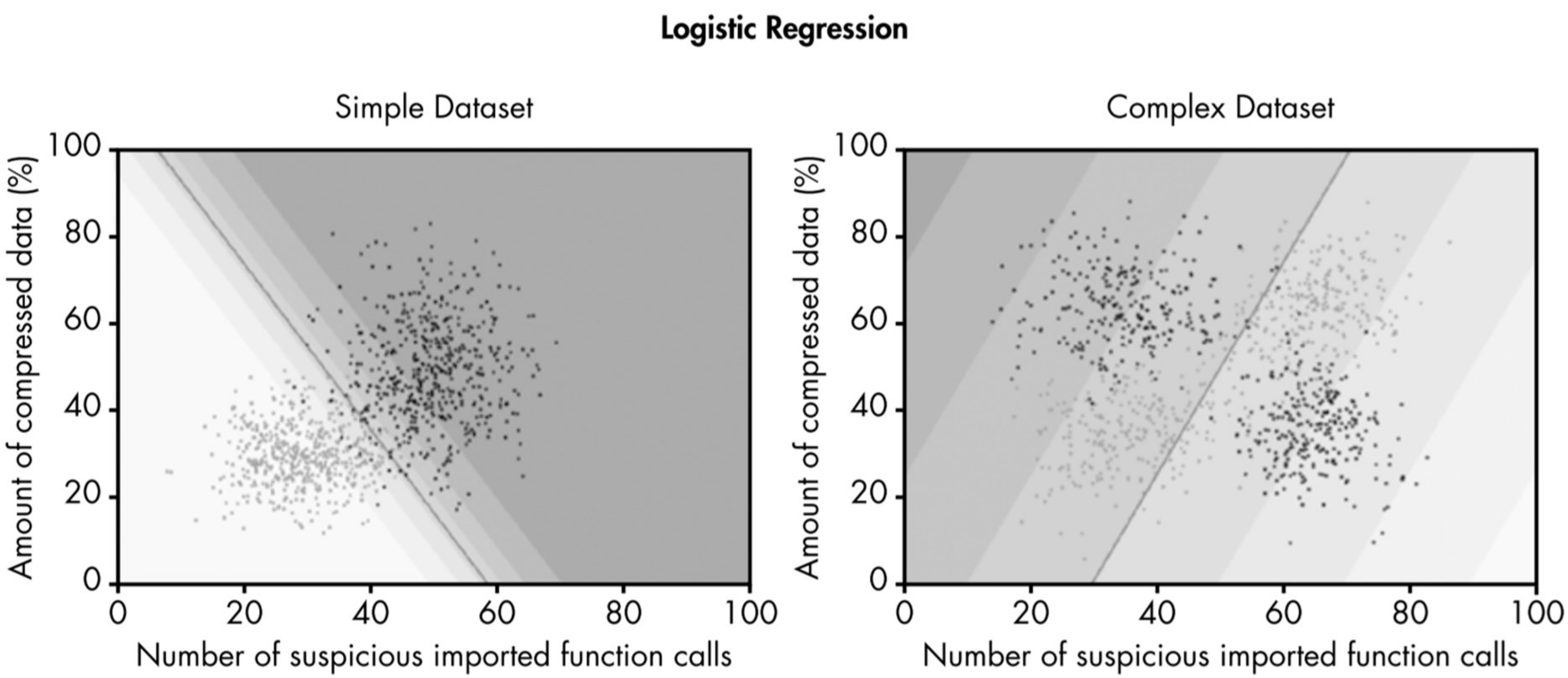


Major types of Machine learning algorithms

- Logistic Regression
  - Linear machine learning algorithm



Major types of Machine learning algorithms

- Logistic Regression

```
def logistic_regression(compressed_data, suspicious_calls, learned_parameters): ❶
compressed_data = compressed_data * learned_parameters["compressed_data_weight"] ❷
    suspicious_calls = suspicious_calls * learned_parameters["suspicious_calls_weight"]
score = compressed_data + suspicious_calls + bias ❸
    return logistic_function(score)

def logistic_function(score): ❹
    return 1/(1.0+math.e**(-score))
```

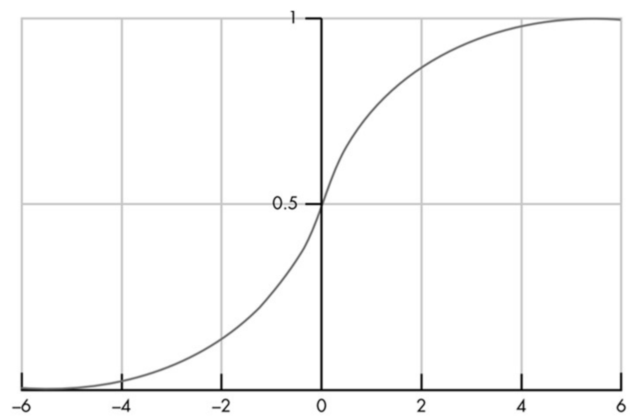


Figure 6-12: A plot of the logistic function used in logistic regression

Major types of Machine learning algorithms

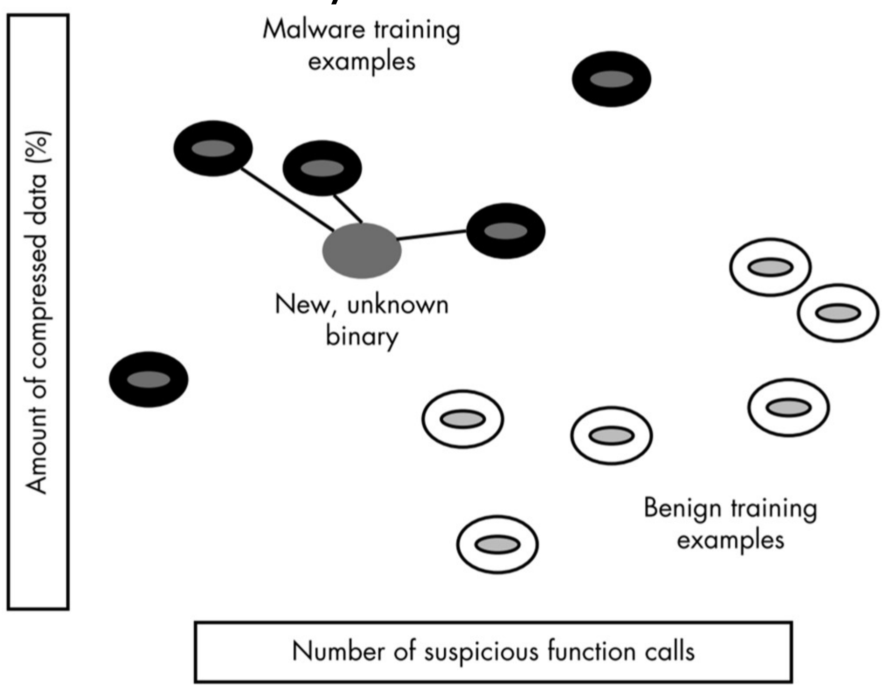
- Logistic Regression
  - how exactly does learn based on the training data?
    - It uses an iterative, calculus-based approach called gradient descent.
    - We won’t get into the details

Major types of Machine learning algorithms

- When to Use Logistic Regression
  - has distinct advantages and disadvantages
    - advantage is that one can easily interpret it
      - Features that have high weight are those the model interprets as malicious
      - Features with negative weight are those the model believes are benignware
      - is a fairly simple approach
    - Disadvantage
      - when the data is complex, logistic regression often fails.

Major types of Machine learning algorithms

- K-Nearest Neighbors
  - the file is malicious
    - if the majority of the k closest binaries to an unknown binary are malicious



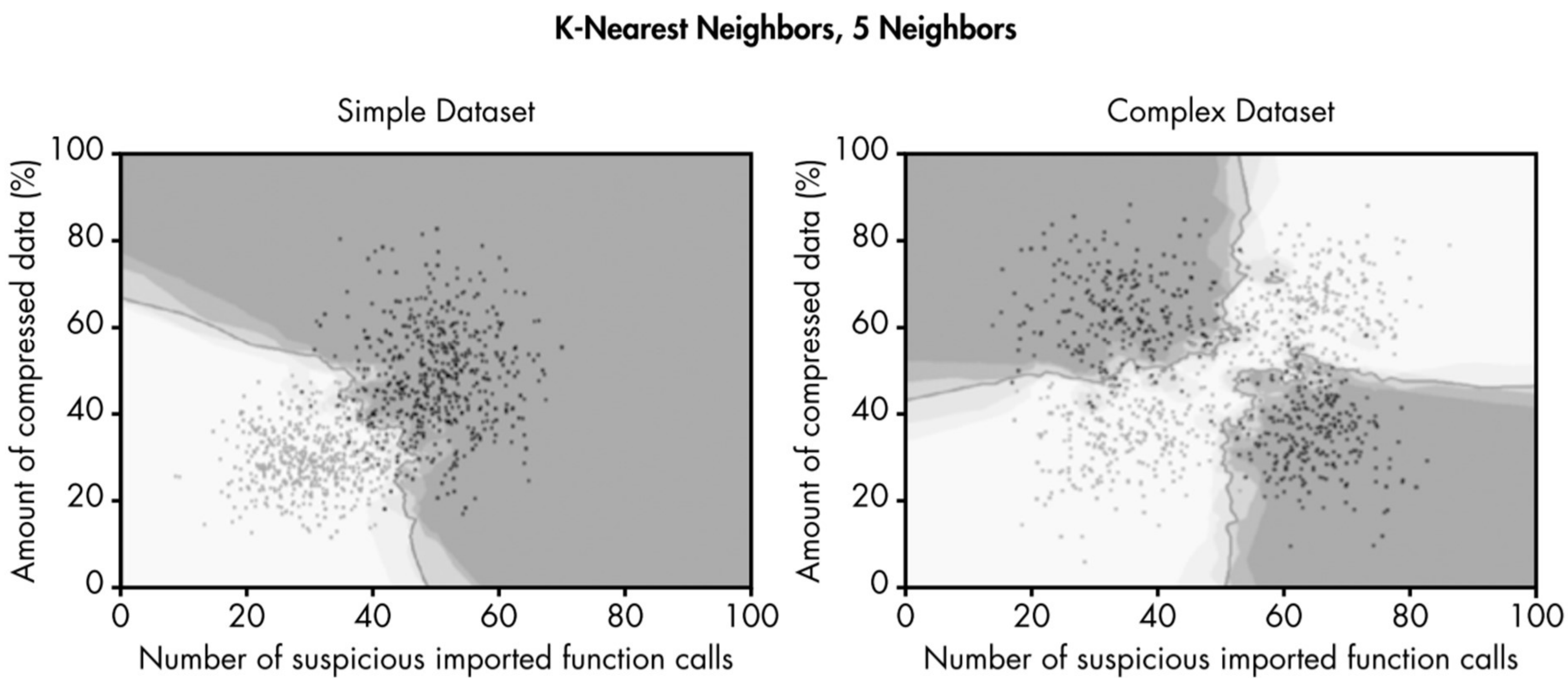
Major types of Machine learning algorithms

- K-Nearest Neighbors
  - most common distance function

```
import math
def euclidean_distance(compression1,suspicious_calls1, compression2, suspicious_calls2): ❶
    comp_distance = (compression1-compression2)**2 ❷
    call_distance = (suspicious_calls1-suspicious_calls2)**2 ❸
    return math.sqrt(comp_distance + call_distance) ❹
```

Major types of Machine learning algorithms

- K-Nearest Neighbors
  - Choosing the Number of Neighbors That Vote



Major types of Machine learning algorithms

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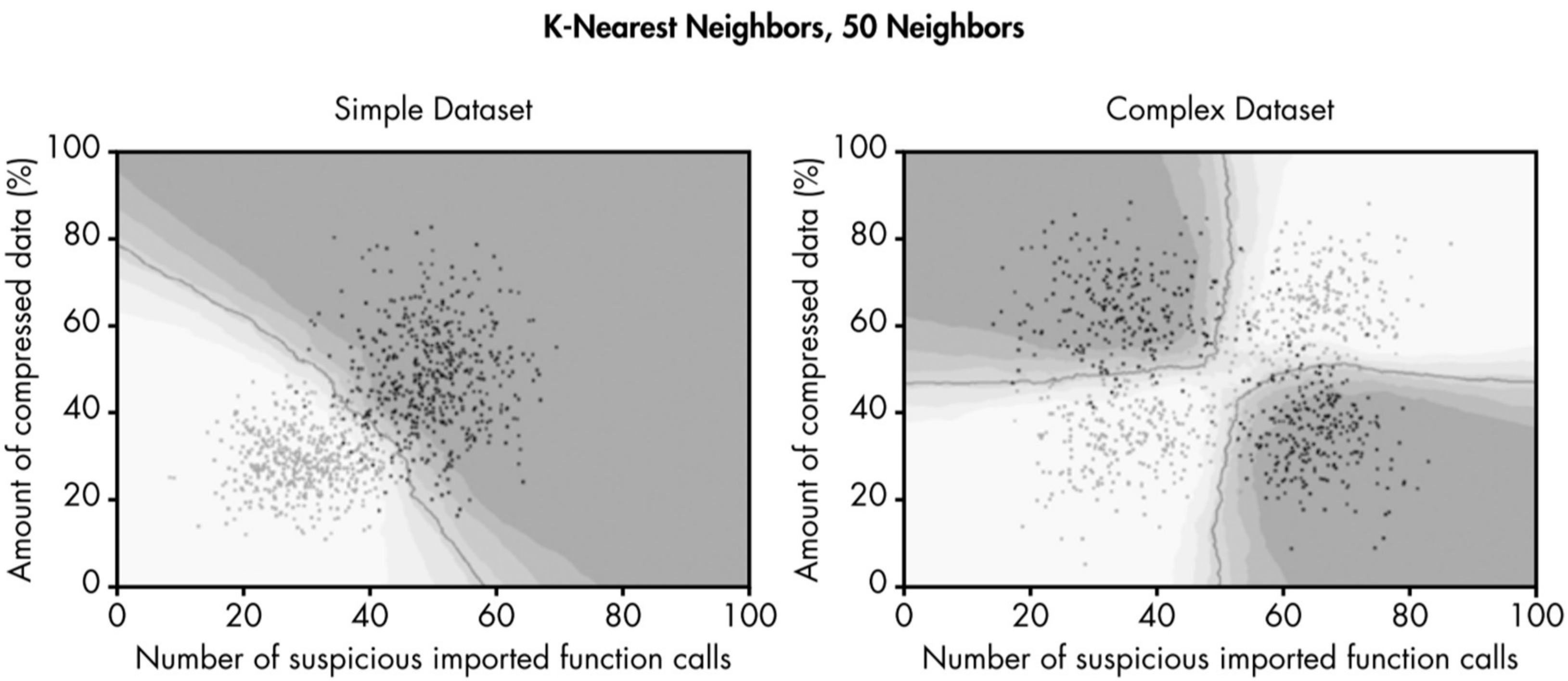
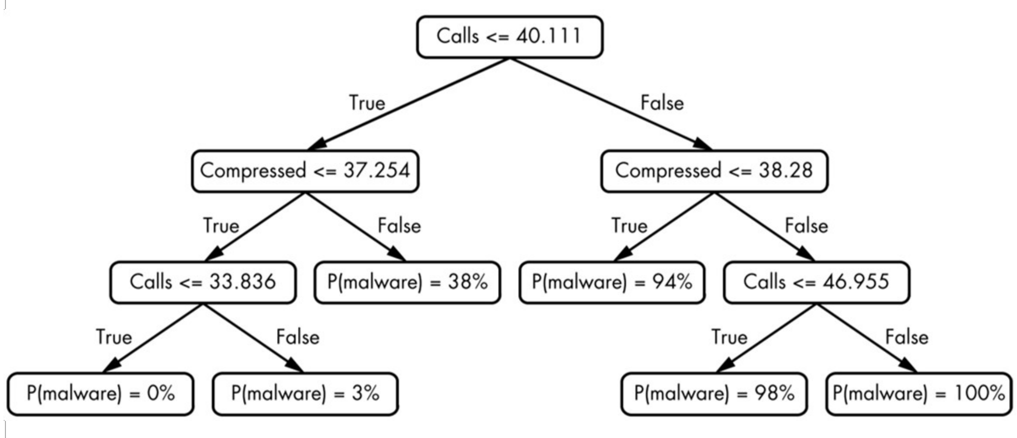


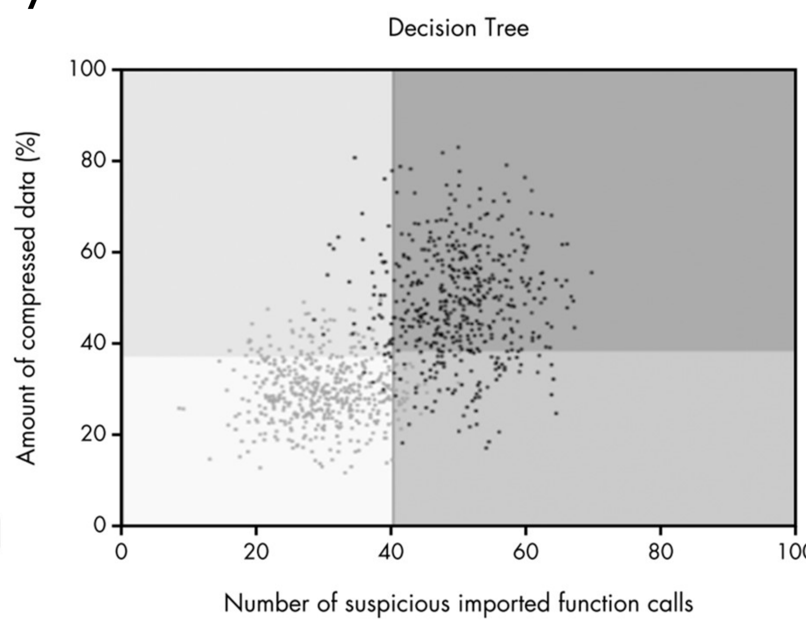
Major types of Machine learning algorithms

- When to Use K-Nearest Neighbors
  - good algorithm when
    - you have data where features don’t map cleanly onto the concept of suspiciousness
    - but closeness to malicious samples is a strong indicator of maliciousness.
  - E.g. when classifying malware families that share code
    - KNN might be a good algorithm to try
  - Another advantage
    - it provides clear explanations of why it has made a given classification decision

Major types of Machine learning algorithms

- Decision Trees
  - automatically generate a series of questions to decide whether or not a given binary is malware
  - similar to the game Twenty Questions





Major types of Machine learning algorithms

- Decision Trees
  - Choosing a Good Root Node
    - best root node is the one for which we get
      - a “yes” answer for most if not all samples of one type
      - a “no” answer for most if not all samples of the other type
  - Picking Follow-Up Questions
    - similar to the root node

Major types of Machine learning algorithms

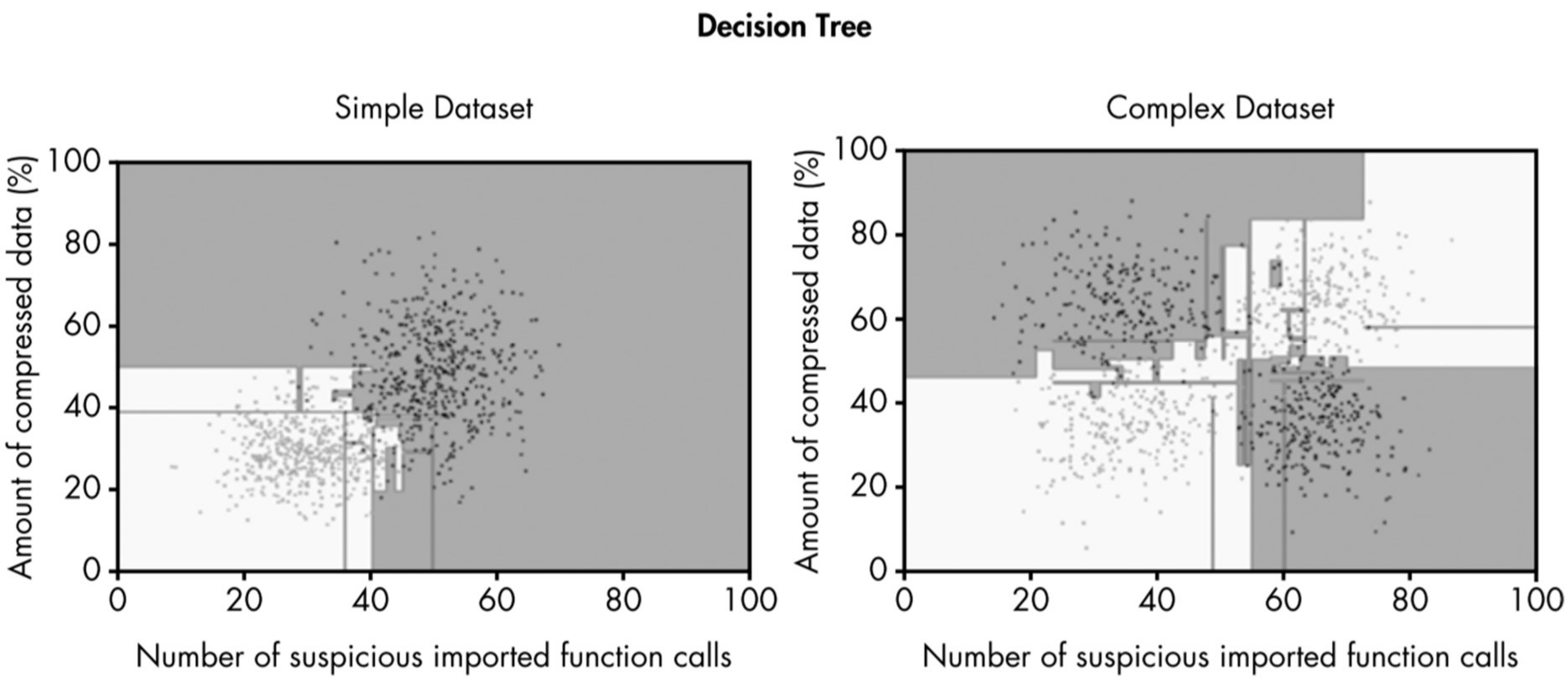
- Decision Trees
  - When to Stop Asking Questions
    - limit the number of questions
    - limit tree depth
    - allow tree to keep growing until it is certain about every example in training set

Major types of Machine learning algorithms

- Decision Trees
  - When to Stop Asking Questions
    - constraining the size of the tree prevents overfitting
    - allowing the tree to grow increases the complexity of the decision boundary
    - Practitioners usually try multiple depths

Major types of Machine learning algorithms

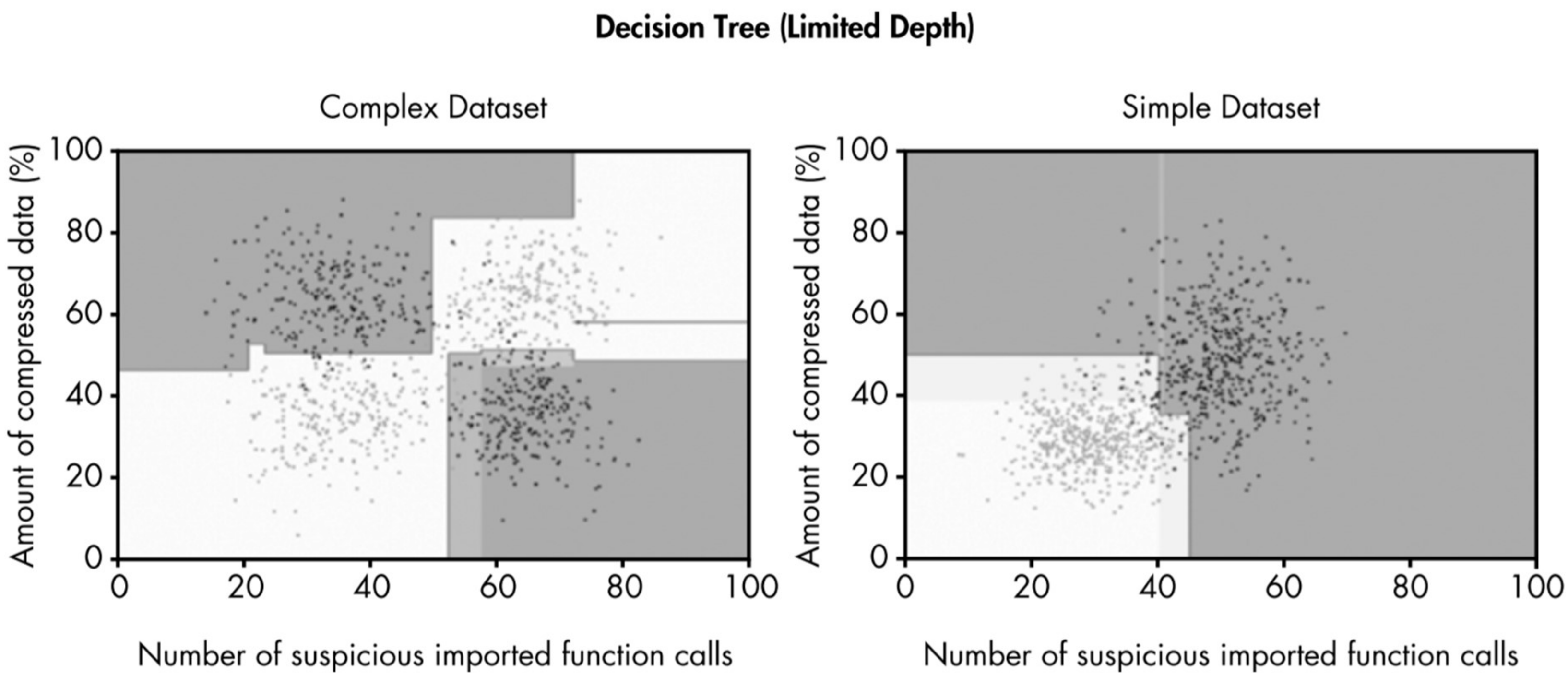
- Decision Trees



No maximum depth

Major types of Machine learning algorithms

- Decision Trees



Depth limited to 5

Major types of Machine learning algorithms

- When to Use Decision Trees
  - they often do not result in very accurate models.
    - The reason is related to their jagged decision boundaries
  - don’t usually learn accurate probabilities around their decision boundaries

Major types of Machine learning algorithms

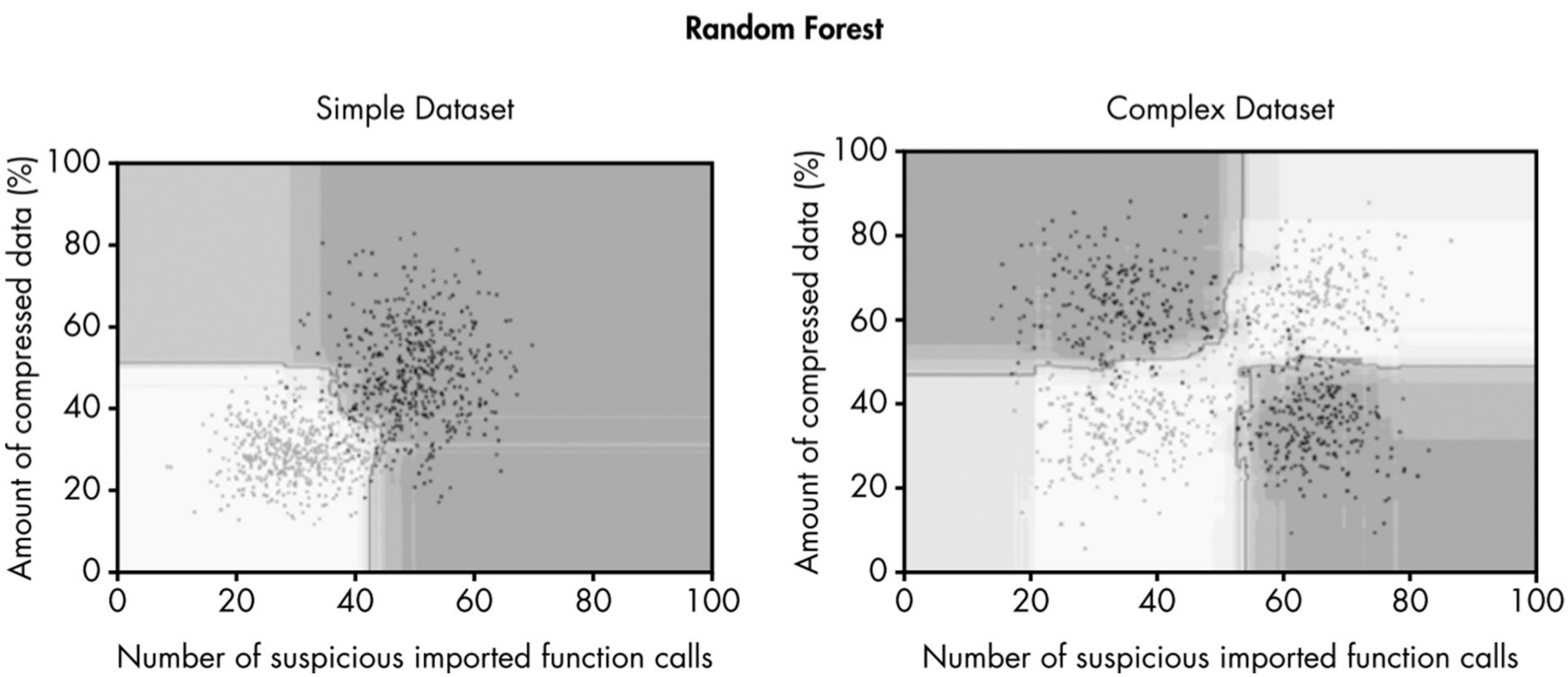
- Random Forest
  - Use hundreds or thousands of decision trees in concert
    - decision trees to vote to decide for a new binary
    - decision trees should be diverse
      - have different perspectives

Major types of Machine learning algorithms

- Random Forest
  - Training for each tree:
    - Randomly choose some examples from training set.
    - Build a decision tree from the random sample.
      - each time ask a question of only a handful of features
      - and disregard the other features.
  - Detection on a previously unseen binary
    - Run detection for each individual tree on the binary.
    - Decide based on the number of trees that voted "yes."

Major types of Machine learning algorithms

- Random Forest



Using 100 decision trees