# Machine Learning in Security

CS463/ECE424

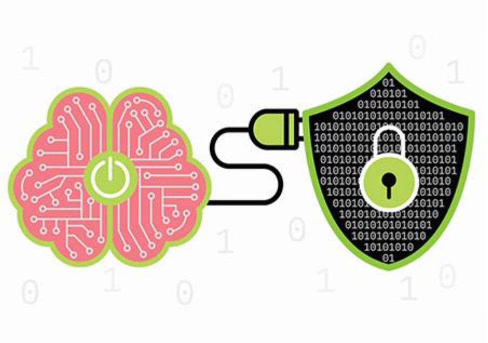
University of Illinois

Definitions

Spam Classification using Logistic Regression

Anomaly Detection through Deep Learning

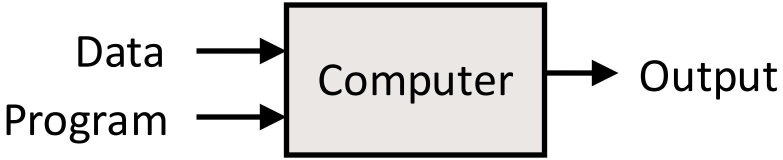
Challenges for Machine Learning in Security



# What is Machine Learning?

## **Traditional Programming**

When we know
how to do things




```
int addition (int a, int b)
{
        int r;
        r = a + b;
        return r;
}
```

# What is Machine Learning?

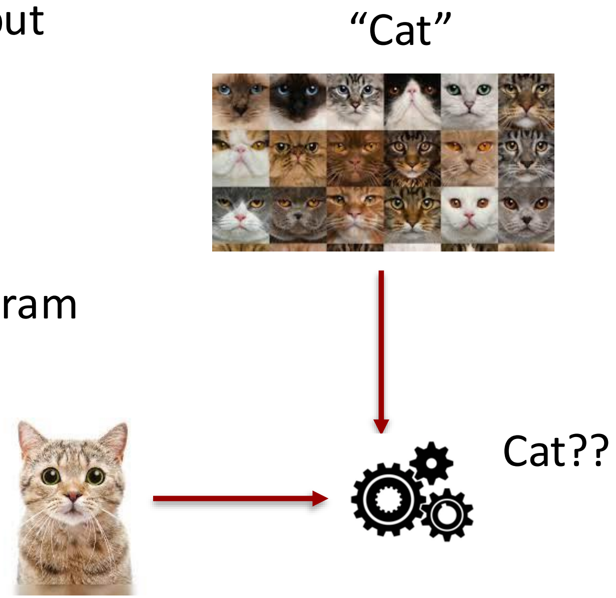
## Traditional Programming

Data, Program → Computer → Output

## Machine Learning

Data, Output → Computer → Program

When we don't know how to do it, but we have <u>some examples</u>




Credit to David Meyer

# What is Machine Learning?

A computer program is said to learn from **experience E**
with respect to some class of **tasks T** and **performance measure P**,
if its performance at tasks in T, as measured by P, improves with experience E.

-- Tom Mitchell, *Machine Learning*

Mitchell, T. (1997). *Machine Learning*, McGraw Hill. ISBN 0-07-042807-7, p.2.

# Steps towards Designing a ML System

- Step 1: Choosing the Training Experience (i.e., training dataset)
- Step 2: Modeling the Transformation
- Step 3: Choosing the Input & Output Representations
- Step 4: Choosing a Transformation Function Approximation
- Step 5: Evaluation

# When To Use Machine Learning?

- **When patterns exist in the data**
  - Even if we don't know what they are
- **When we cannot pin down the functional relationships mathematically (in-closed form)**
  - Else we would just code up the algorithm
- **When we have lots of data**
  - Labeled training sets are harder to come by than unlabeled data
  - Data is of high-dimension
- **When we want to discover lower-dimension representations**

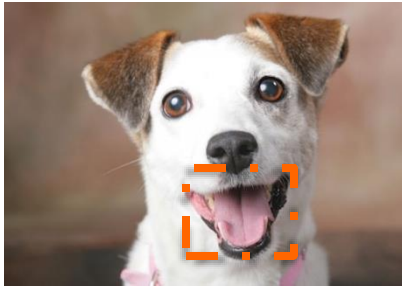
# Example: Spam Filtering

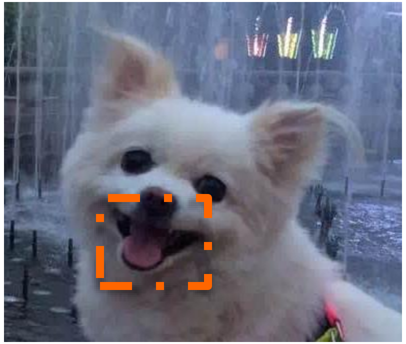

- **Task T**: classifying emails into two categories (spam, ham)
- **Performance measure P**: percent of emails correctly classified
- **Training Experience E**: a database of emails

# Step 1: Choosing the Training Dataset

- Training Dataset:
  - A database of emails
- What feedback can be provided to the learner?
  - A database of labeled emails
- How well does the training dataset represent the distribution of examples over which the final system performance P must be measured?
  - A database of labeled emails that represent the distribution of all the emails

# Step 1: Choosing the Training Experience

Cats v.s. Dogs

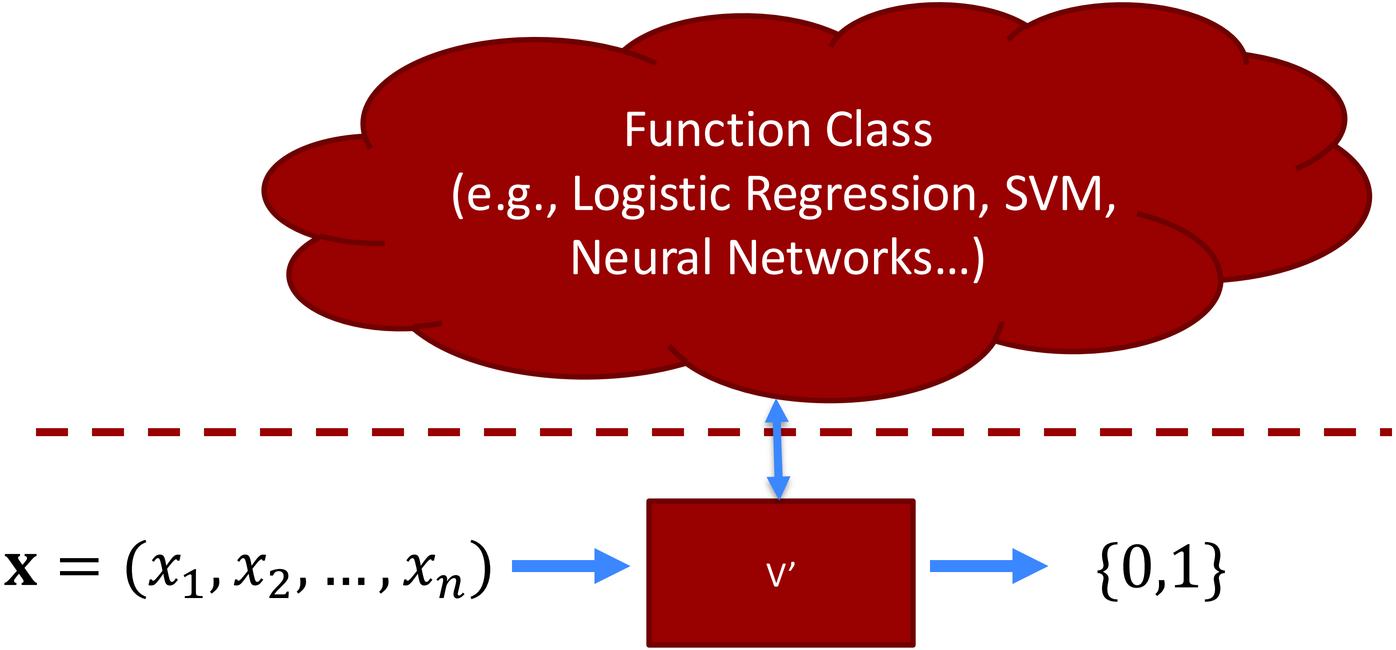
# Step 2: Modeling the Transformation

- **Task T:** classifying emails into 2 categories (Spam, Ham)
- Transformation (target) function $V: A \rightarrow B$
  - What's in the training examples?
    - A: Email contents (a collection of words)
  - What should be the output?
    - B: {Spam (1) , Ham (0)}

# Step 3: Choosing the Input & Output Representations

- How do we represent the model inputs and outputs?
  - Inputs could be categorical, numerical, binary, sequential …
  - We use code + math; they need “numbers“
- **Feature generation**
  - Abstract V: Email contents $\rightarrow \{0,1\}$
  - Realized V’: $\mathbf{x} = (x_1, x_2, \dots, x_n) \mapsto y \in \{0,1\}$
    - $x_i \in \{0,1\}$ represents whether a word $w_i$ is in the email
- **Feature selection**
  - To simplify the model (save time, avoid overfitting…)

# Step 4: Choosing the Transformation Function Approximation

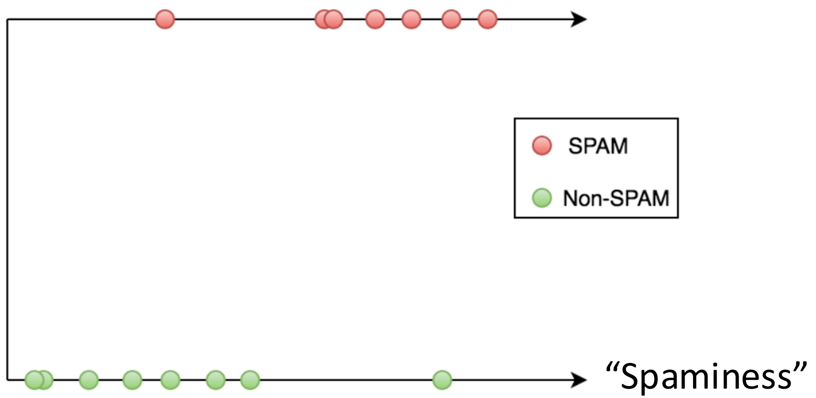


# Logistic Regression (1)

- V': $\mathbf{x} = (x_1, x_2, \ldots, x_n) \mapsto y \in \{0,1\}$
- How to design V'?
  - **Step 1**: Combine $x_1, x_2, \ldots, x_n$ to get a "spaminess" value
  - **Step 2**: Convert the "spaminess" value into a probability P(Spam)
    - Conversion enables the classification use-case; else it is useful for regression
  - **Step 3**: Make predictions on $y$ based on P(Spam)
    - e.g., $y = 1$ when P(Spam) > 0.5

# Logistic Regression (2)

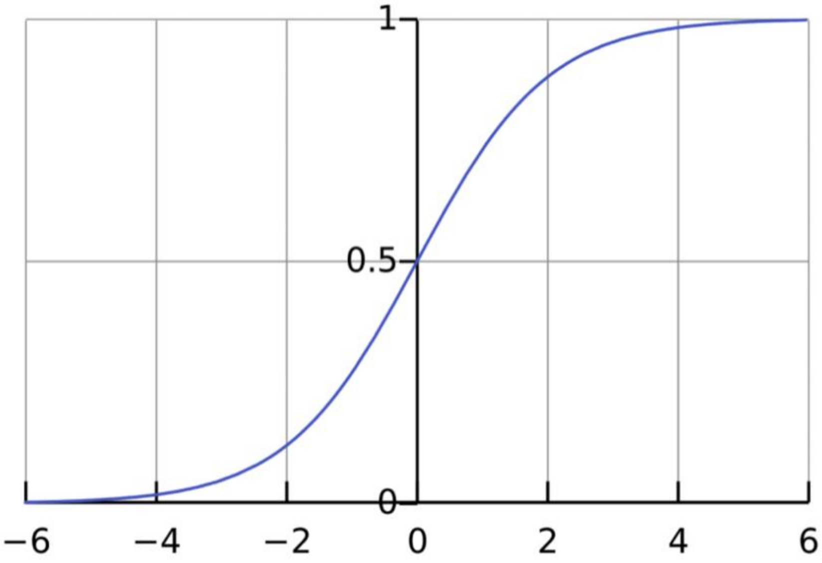
- Step 1: Combine $x_1, x_2, \ldots, x_n$ to get a "spaminess" value
  - Assume the existence of a weight vector $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_n)$
  - We define spaminess as the linear transformation $\boldsymbol{\theta}^{\mathbf{T}} \cdot \mathbf{x}$



# Logistic Regression (3)

- Step 2: Convert the “spaminess” value into a probability P(Spam)
  - Logistic function

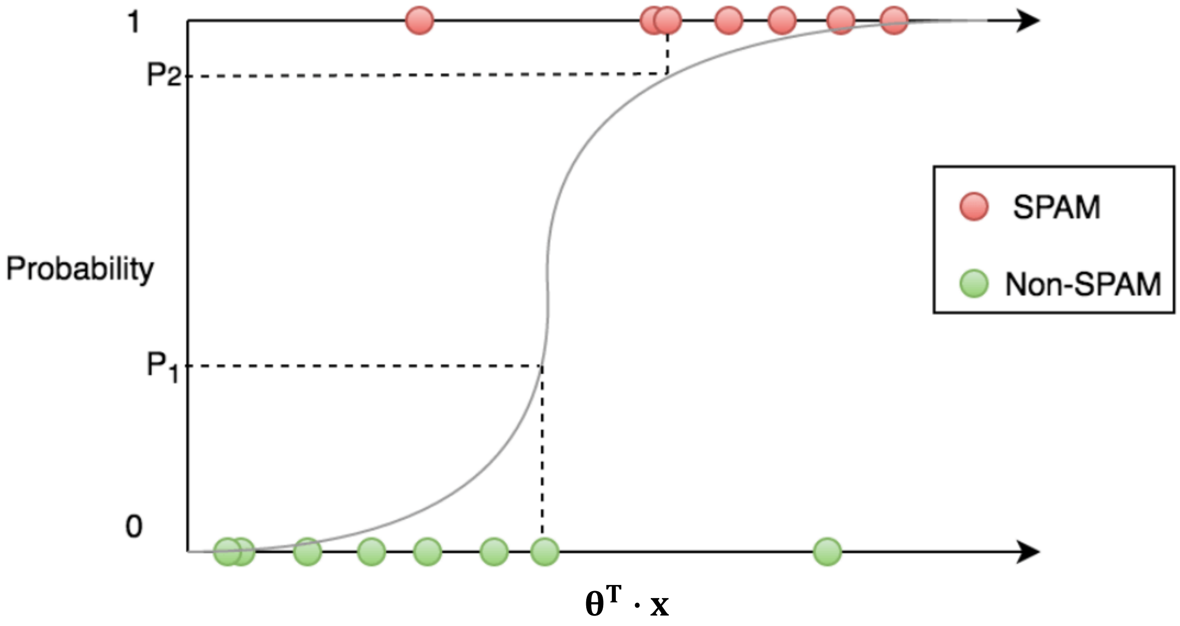
$$h_\theta(x) = g(\theta^T X) = \frac{1}{1+e^{-\theta^T x}}$$




Plot of logistic function $g$

# Logistic Regression (4)

- Step 3: Make predictions on y based on P(Spam)



# Logistic Regression: Training

- How do we determine the "best" value of $\boldsymbol{\theta}$?
  - For a given $\boldsymbol{\theta}$ and some labeled examples, how do we know whether $\boldsymbol{\theta}$ is good enough? i.e., is the best predictor of spam vs. ham?
- **Define a loss function** (e.g., log loss)

$$\text{Log Loss} = \sum_{(x,y)\in D} -y\log(y') - (1-y)\log(1-y')$$

where:

- $(x, y) \in D$ is the dataset containing many labeled examples, which are $(x, y)$ pairs.
- $y$ is the label in a labeled example. Since this is logistic regression, every value of $y$ must either be 0 or 1.
- $y'$ is your model's prediction (somewhere between 0 and 1), given the set of features in $x$.

# Logistic Regression: Training

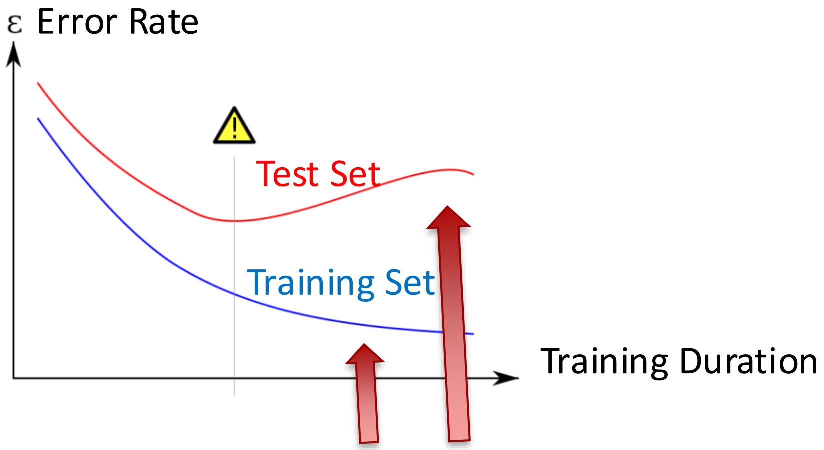
- How do we determine the “best” value of $\boldsymbol{\theta}$?
  - For a given $\boldsymbol{\theta}$ and some labeled examples, how do we know whether $\boldsymbol{\theta}$ is good enough? i.e., is the best predictor of spam vs. ham?
- **Define a loss function** (e.g., log loss)
  - Wrong predictions -> large loss
  - Correct predictions -> small loss
- Run **optimization algorithms** to find $\boldsymbol{\theta}$, minimize the loss
  - e.g., Stochastic Gradient Descent (SGD)

# Step 5: Evaluation

- Ground Truth
  - V: Email contents → $\{0,1\}$
- Hold out Method
  - Randomly partitioned data into two independent sets: a **test set,** a **training set**
  - Use **test set** instead of **training set** when assessing accuracy
- Cross-validation (k-fold)
  - Randomly partition the data into *k* **mutually exclusive** subsets, each approximately equal size
  - At *i*-th iteration, use **$D_i$ as test set** and **others as training set**

# Step 5: Evaluation

- Overfitting:

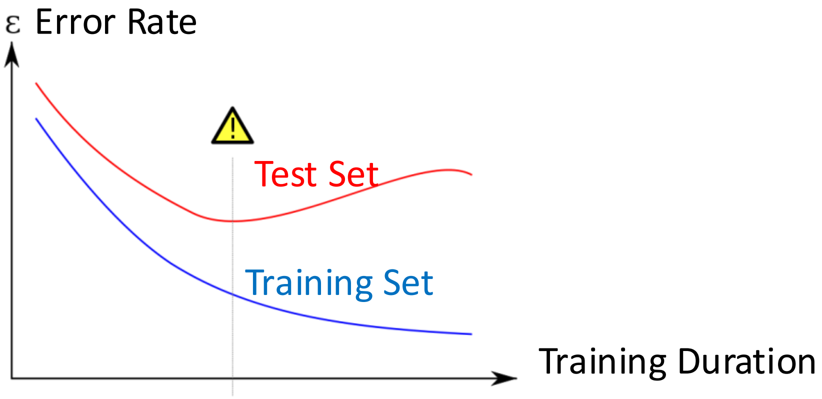


# Step 5: Evaluation

Cats v.s. Dogs

# Step 5: Evaluation

- Overfitting:




- Confusion Matrix:

| | Predicted Spam | Predicted Ham |
|---|---|---|
| **Spam** | True Positive (TP) | False Negative (FN) |
| **Ham** | False Positive (FP) | True Negative (TN) |

# Summary: Designing a ML System

- Step 1: Choosing the Training Experience (i.e., training dataset)
- Step 2: Modeling the Transformation
- Step 3: Choosing the Input & Output Representations
- Step 4: Choosing a Transformation Function Approximation
- Step 5: Evaluation

# DeepLog: Anomaly Detection through Deep Learning

- Anomaly Detection from System Logs
  - Identify **abnormal system behavior** from **large volume of system logs**
- Challenges
  - Large volume of data
  - Sequential data
  - Unstructured data
- Why deep learning?
  - Widely used for natural language processing (NLP)
  - *Log can be viewed as **a structured language**!*

# Step 1: Choosing the Training Data (1)

- What data do we have?
  - Large volume of log entries from normal system execution path
  - A few log entries of known attacks

# Step 1: Choosing the Training Data (2)

- What data should we use?
  - Training: normal logs
  - Testing: normal logs and attack logs
- **Advantages**:
  - Prevent overfitting
  - Test the system's behavior on <u>unseen attacks</u>
- **Disadvantages**:
  - May classify *any unseen behaviors as attacks* (i.e., false positives)

# Step 2: Modeling the Transformation

- **Outputs**: normal (-) v.s. abnormal (+)
- **Inputs**: Log entries from OpenStack VM deletion task (unstructured)
  - *t1* Deletion of file1 complete
  - *t2* Took 0.61 seconds to deallocate network …
  - *t3* VM Stopped (Lifecycle Event)
- Structured representation:
  - Log key
  - Parameter value (e.g., t1, file1)

# Step 3: Choosing the Input & Output Representations (1)

- The total number of **distinct log keys is constant**.
  - Log keys: $K = \{k_1, k_2, \ldots, k_n\}$
  - Parameter value vectors: (time interval, other parameter values)

| log message (log key underlined) | log key | parameter value vector |
|---|---|---|
| $t_1$ Deletion of **file1** complete | $k_1$ | $[t_1 - t_0, \text{file1Id}]$ |
| $t_2$ Took **0.61** seconds to deallocate network ... | $k_2$ | $[t_2 - t_1, 0.61]$ |
| $t_3$ VM Stopped (Lifecycle Event) | $k_3$ | $[t_3 - t_2]$ |
| ... | ... | ... |

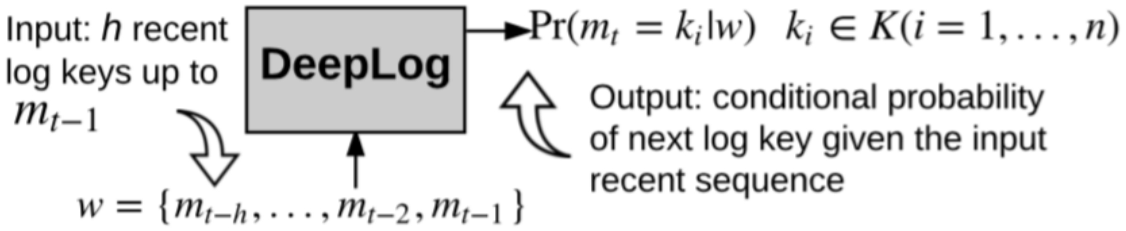
**Table 1: Log entries from OpenStack VM deletion task.**

# Step 3: Choosing the Input & Output Representations (2)

- Representation of Inputs:
  - **Log Keys:** structured, sequential, nominal
  - **Parameter Values:** structured, sequential, numerical (e.g., time, duration) or nominal (e.g., process id)
  - Different log keys have **different structures** for parameter values
- How to combine the inputs of different structures?
  - Train multiple models

# Step 3: Choosing the Input & Output Representations (3)

- Model 1: Log key anomaly detection model
  - Log keys: $K = \{k_1, k_2, \dots, k_n\}$
  - Input: A window $w$ of the $h$ most recent log keys $w = \{m_{t-h}, \dots, m_{t-2}, m_{t-1}\}$, where $m_i \in K$
  - Output: $\Pr[m_t = k_i \mid w]$ for each $k_i \in K, (i = 1, \dots, n)$



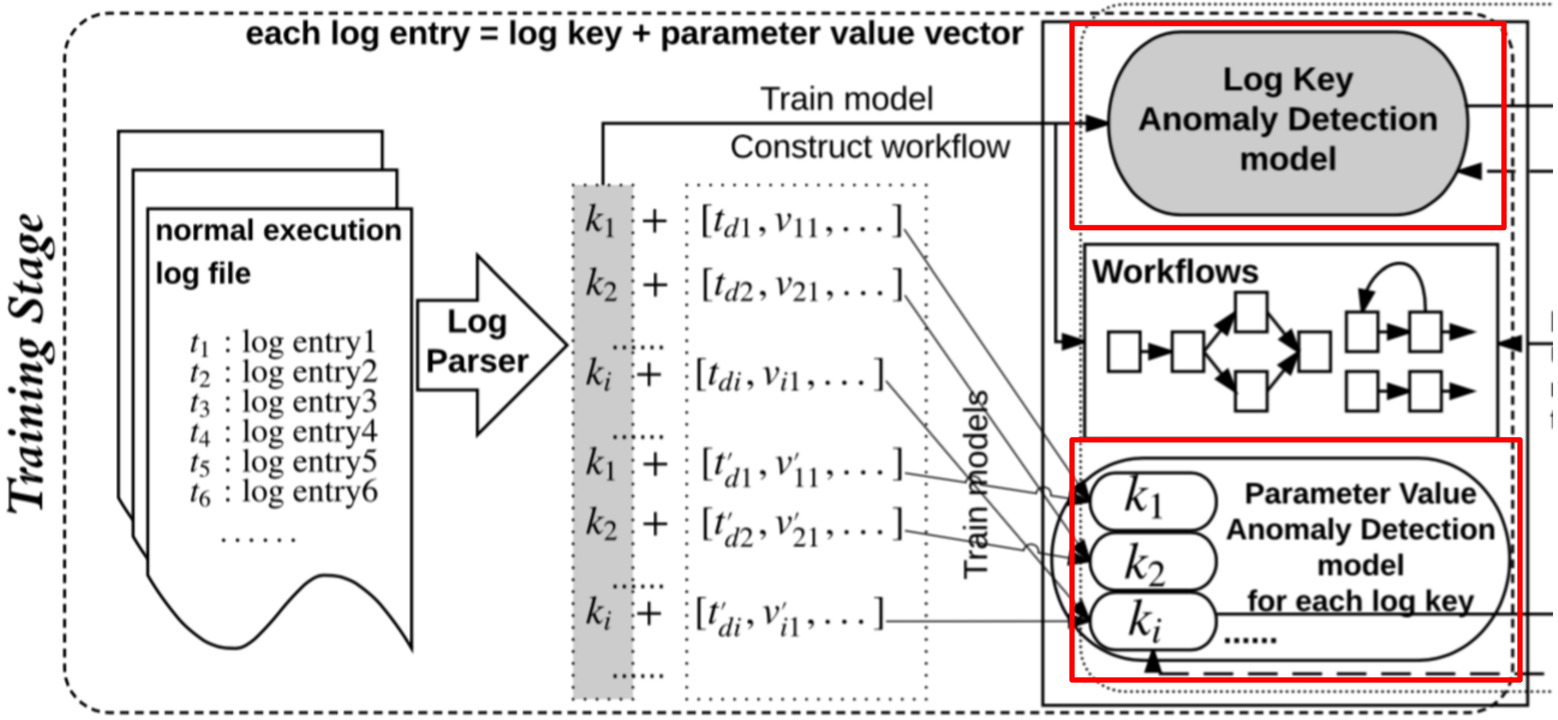
# Step 3: Choosing the Input & Output Representations (4)

- Model 2: Parameter value anomaly detection models
  - View each parameter value vector sequence (for a log key) as a separate time series
  - Train a separate model for each distinct log key value to predict the next parameter value
- Two steps of detecting anomaly
  - Predict the the next log key and parameter values
  - Compare the prediction against the observed log entry
    - Mark as anomaly if the probability for the observed log entry is low (not in the top $g$ candidates)

# Step 3: Choosing the Input & Output Representations (5)

- Two steps of detecting anomaly
  - Predict the the next log key and parameter values
  - Compare the prediction against the observed log entry
    - Mark as anomaly if the probability for the observed log entry is low (not in the top $g$ candidates)

# Step 3: Choosing the Input & Output Representations (6)



# Step 4: Choosing a Transformation Function Approximation

- Long Short-Term Memory (LSTM) Network
  - Has the capability of remembering previous inputs
  - Suitable for sequential data
  - A gentle walk through on LSTM networks (**optional**, 25 minutes): https://www.youtube.com/watch?v=WCUNPb-5EYI

# Step 5: Evaluation – Log Key Model (1)

- Hadoop-Distributed File System (HDFS) Dataset
  - System logs generated by map-reduce jobs on more than 200 Amazon's EC2 nodes
  - Labeled by domain experts
  - Log entries are grouped into sessions

| Log data set | Number of sessions | | $n$: Number of log keys |
|---|---|---|---|
| | Training data (if needed) | Test data | |
| HDFS | 4,855 normal;<br>1,638 abnormal | 553,366 normal;<br>15,200 abnormal | 29 |

- DeepLog **does not use the abnormal training data**

# Step 5: Evaluation – Log Key Model (2)

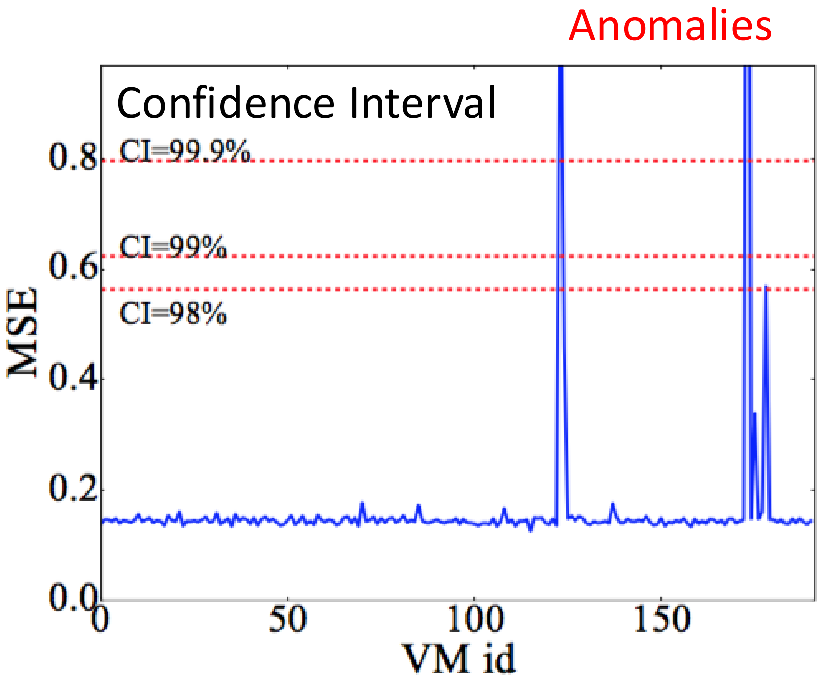
| | Predicted as Normal | Predicted as Abnormal |
|---|---|---|
| **Normal** | 552,533 (True Negative) | 833 (False Positive) |
| **Abnormal** | 619 (False Negative) | 14581 (True Positive) |

- Precision = True Positive / (True Positive + False Positive) = 94.60%
- Recall = True Positive / (True Positive + False Negative) = 95.93%

# Step 5: Evaluation – Parameter Value Model

- **OpenStack Log Dataset**
  - Run VM-related tasks
  - Inject anomalies at different execution points

- **Mean-squared error (MSE)** between the parameter value vector and the prediction output vector from DeepLog



# Challenges for Machine Learning in Security

- Outlier Detection
- High Cost of Errors
- Semantic Gap
- Diversity with Data
- Difficulties with Evaluations


Sommer, Robin, and Vern Paxson. "Outside the closed world: On using machine learning for network intrusion detection." *Security and Privacy (SP), 2010 IEEE Symposium on*. IEEE, 2010.

# Case Study: Outlier Detection

- ML needs large number of representatives for **each** class
  - What happens when $P(Spam)$ is very small?
- Not good at finding previously unknown malicious activities

# High Cost of Errors

S. Axelsson, "The Base-Rate Fallacy and Its Implications for the Difficulty of Intrusion Detection," in *Proc. ACM Conference on Computer and Communications Security*, 1999.


- **Example:** suppose a system generates
  - 1,000,000 audit records per day;
  - 10 audit records per intrusion;
  - Two intrusions per day.
- Intrusion: $I$, Alarm: $A$
- Detection rate: $P(A|I) = 99.9\%$
- False alarm rate: $P(A|\neg I) = 0.02\%$
- Given a detected record, what's the probability that the record represents a true intrusion?

$$P(I|A) = \frac{P(A|I)P(I)}{P(A|I)P(I) + P(A|\neg I)(1 - P(I))} = 9\%$$

# Semantic Gaps

- Difficult to transfer results into **actionable** report for the network operator
- Difficult to find the difference between “abnormal activity” and attacks
- Not interpretable! Unclear what the system learned
  - What do false positives and false negatives mean?
  - What features are used to produce correct results?

# Diversity with Data and Concept Drift

- Large variability in network traffic over short time intervals

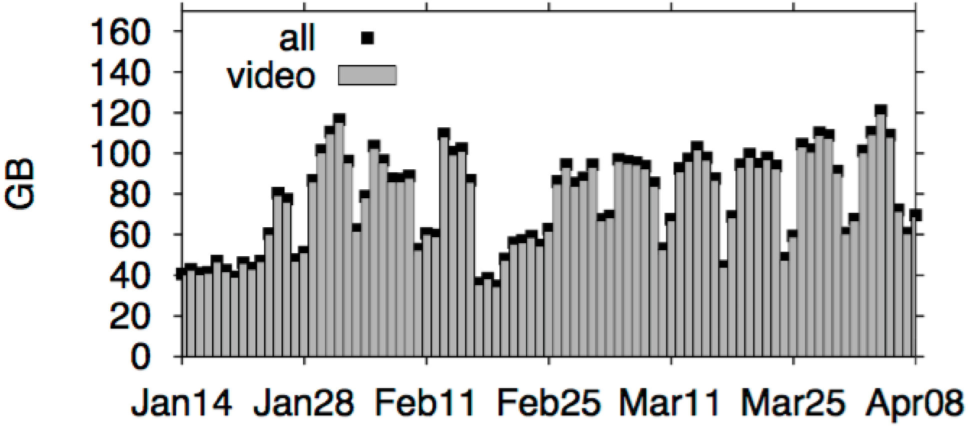



**Figure 5: Bytes Per Day**

P. Gill, M. Arlitt, Z. Li, and A. Mahanti, "YouTube Traffic Characterization: A View From the Edge," in *Proc. ACM SIGCOMM Internet Measurement Conference*, 2008.

# Difficulties with Evaluations

- Lack of (reliable) “ground truth”
- Outdated datasets
- Highly sensitive information (e.g., network traffic can include personal communications and business secrets)
- Difficulties with simulation and anonymization

# Reading


- [1] Androutsopoulos, Ion, et al. "An evaluation of naive bayesian anti-spam filtering." *arXiv preprint cs/0006013* (2000).

- [2] Du, Min, et al. "DeepLog: Anomaly Detection and Diagnosis from System Logs through Deep Learning." *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*. ACM, 2017.

- [3] Sommer, Robin, and Vern Paxson. "Outside the closed world: On using machine learning for network intrusion detection." *Security and Privacy (SP), 2010 IEEE Symposium on*. IEEE, 2010.

# Discussion Questions

- How can you attack the spam filtering model we discussed?
  - Can you get around the filtering and send a spam to a user's inbox?
  - Can you trick the algorithm to filter a ham email?

- Do you think ML will replace human analysts in detecting security threats? Why or why not?