# Threats to Machine Learning Applications

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August 18, 2020

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DM20-0594

# Carnegie Mellon Leads an Ecosystem of Innovation for Cybersecurity


## CMU Campus – Global Research University

- Global research university known for its world-class, interdisciplinary programs in computer science, machine learning/artificial intelligence, engineering, business, arts, policy, and science
- Ranked #1 for Computer Science, #1 for Artificial Intelligence, #6 in Engineering (*U.S. News and World Report*)
- 1,442 total faculty and 130 research centers
- CyLab, CMU's security and privacy research institute, brings together experts from all schools across the university


## CMU Software Engineering Institute (SEI)

- Founded in 1984 by the DoD as a Federally-Funded Research and Development Center (FFRDC) focused on software engineering
- Leader in software engineering, cybersecurity, and artificial intelligence research
- Established CERT in 1988
- About $145M annual funding (~$23M DoD Line)
- Critical to the DoD ability to acquire, develop, operate, and sustain software systems that are innovative, affordable, trustworthy, and enduring *(CMU SEI Sponsoring Agreement)*

# CERT Division


Founded on a unique combination of experiential understanding of DoD missions, the cyber warfighter, the operational domain, and constantly changing technology

Adapts the best science to impact operational missions, increase the trustworthiness of technology, and develop cyber talent

Partners with DoD, non-DoD agencies, and the private sector enable CERT to maintain technical depth, attract top talent, amplify DoD financial investment, reduce the risk to DoD missions, and scale the research

Strengthens the resilience of critical national functions, increases the cybersecurity and resilience of DoD systems and Defense Industrial Base, and develops the cyber capacity of allies and partners

# Outline

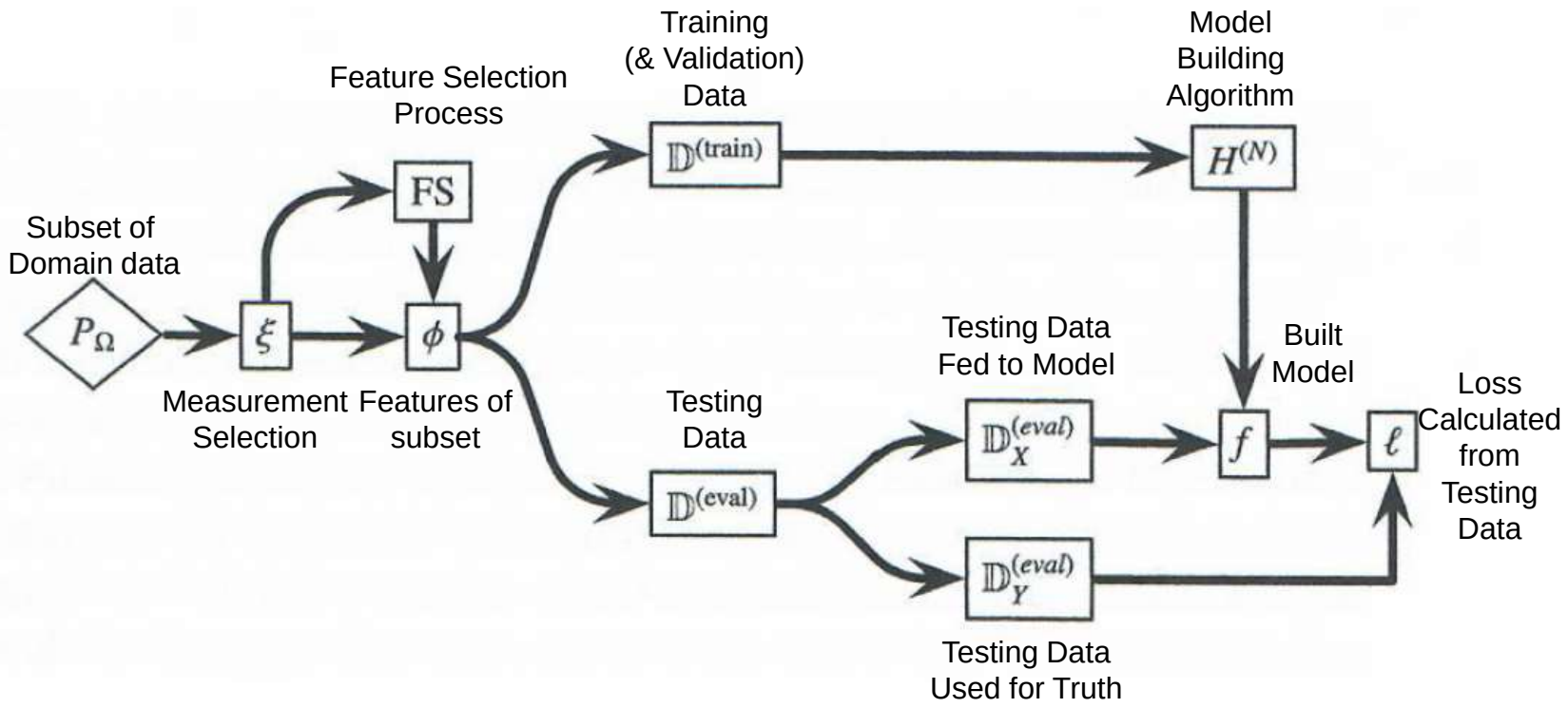
**Understanding the ML Attack Surface**

**Understanding Risks of Transfer Learning**

**Remedies and Limitations**

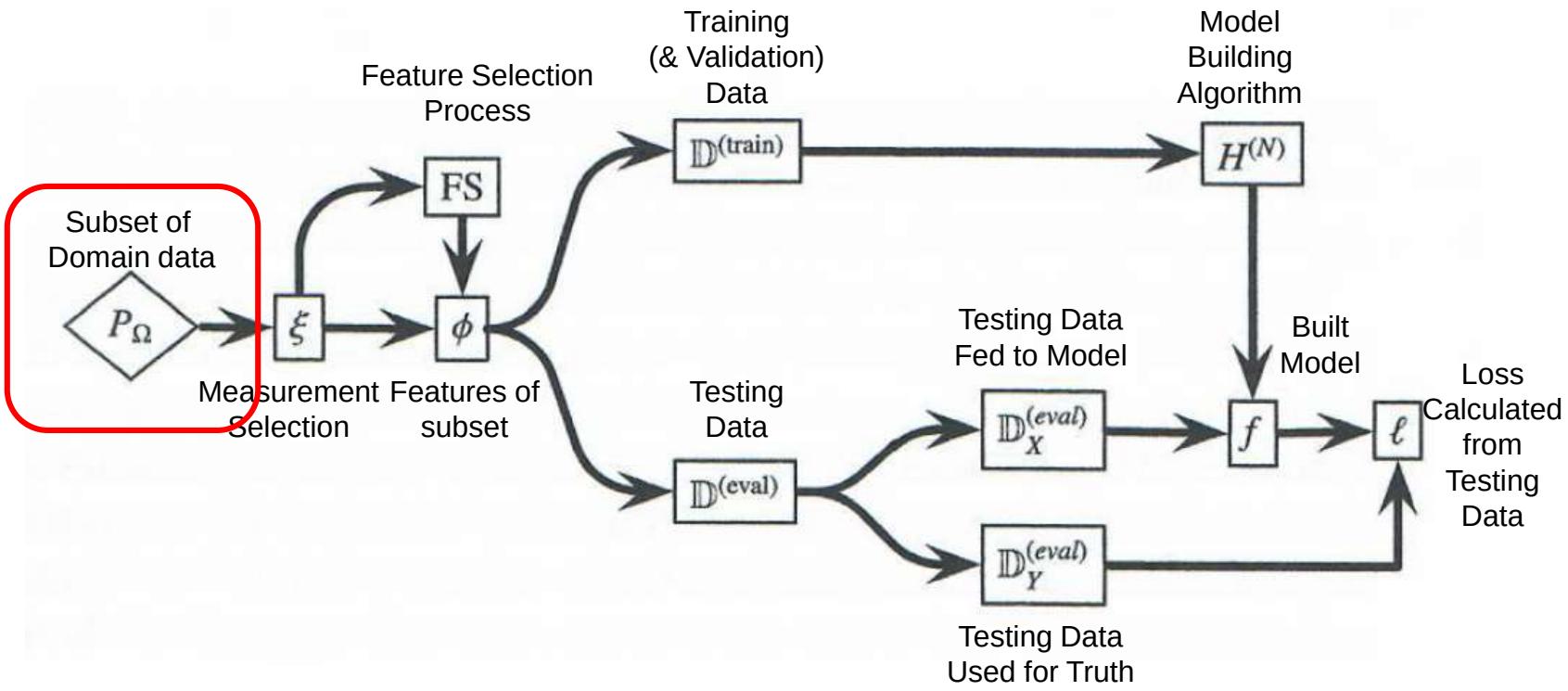
**Conventional Threats to Machine Learning**

# Developing a Machine Learning Application




Adapted from Joseph, Nelson, Rubinstein, Tygar; Adversarial Machine Learning, Cambridge University Press, 2019

# Data Attacks – Selected Domain Subset

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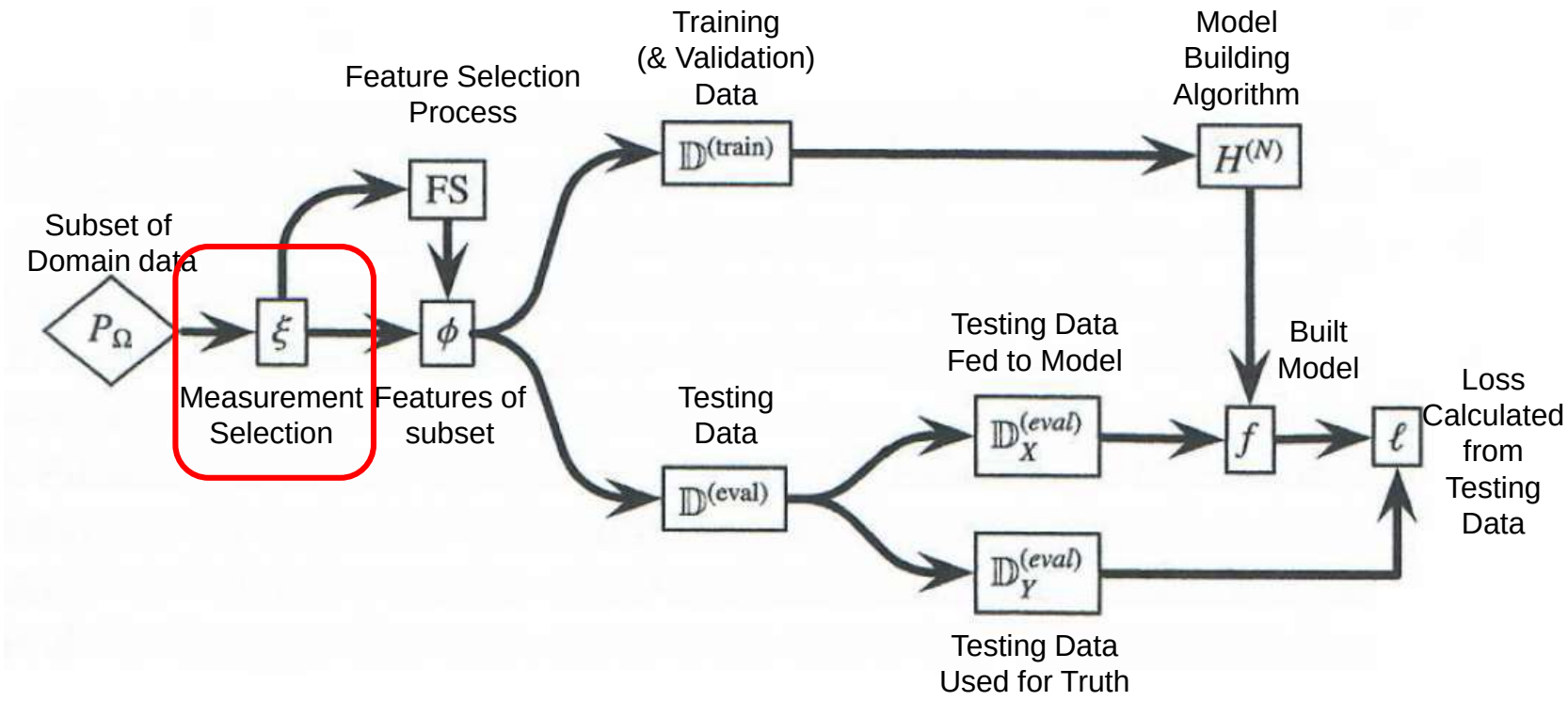
# Data Attacks – Measurements

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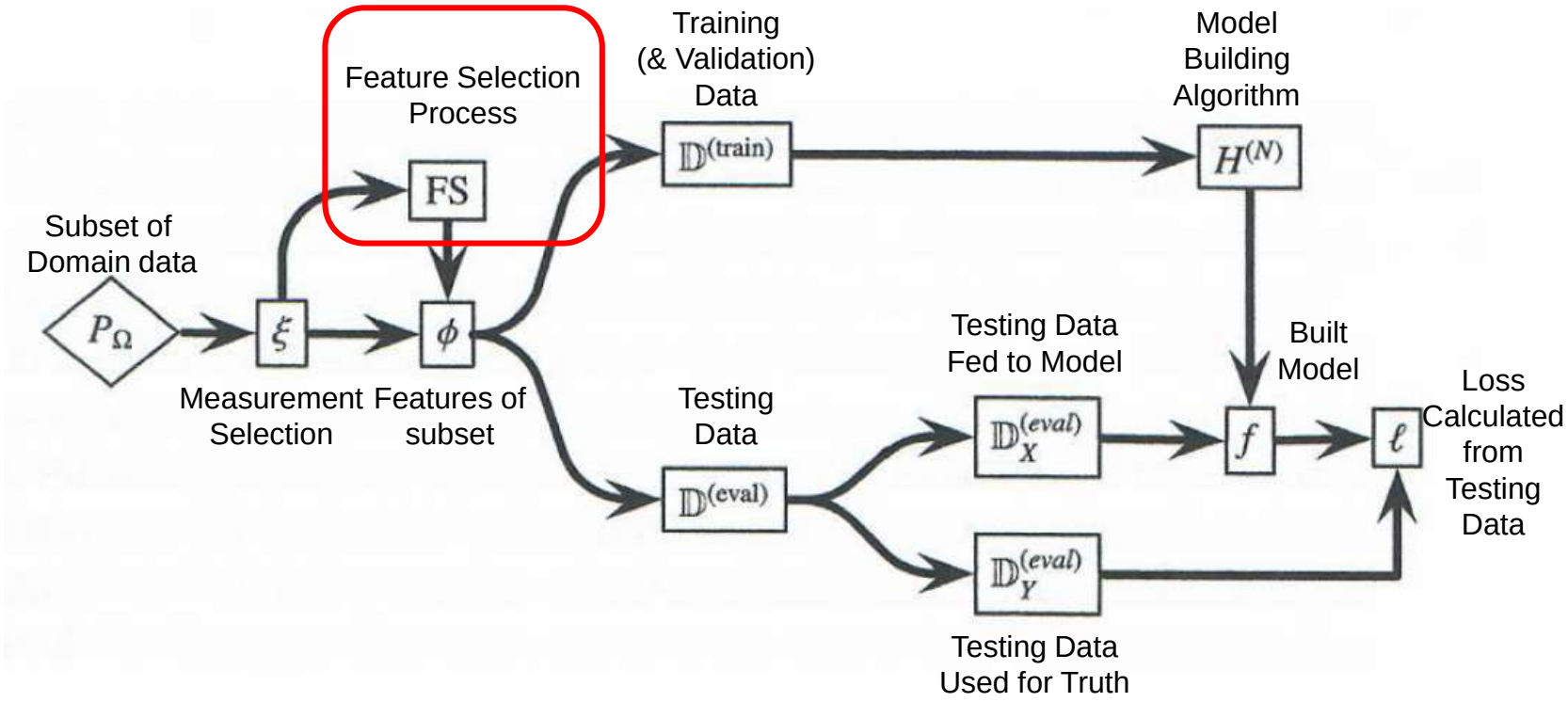
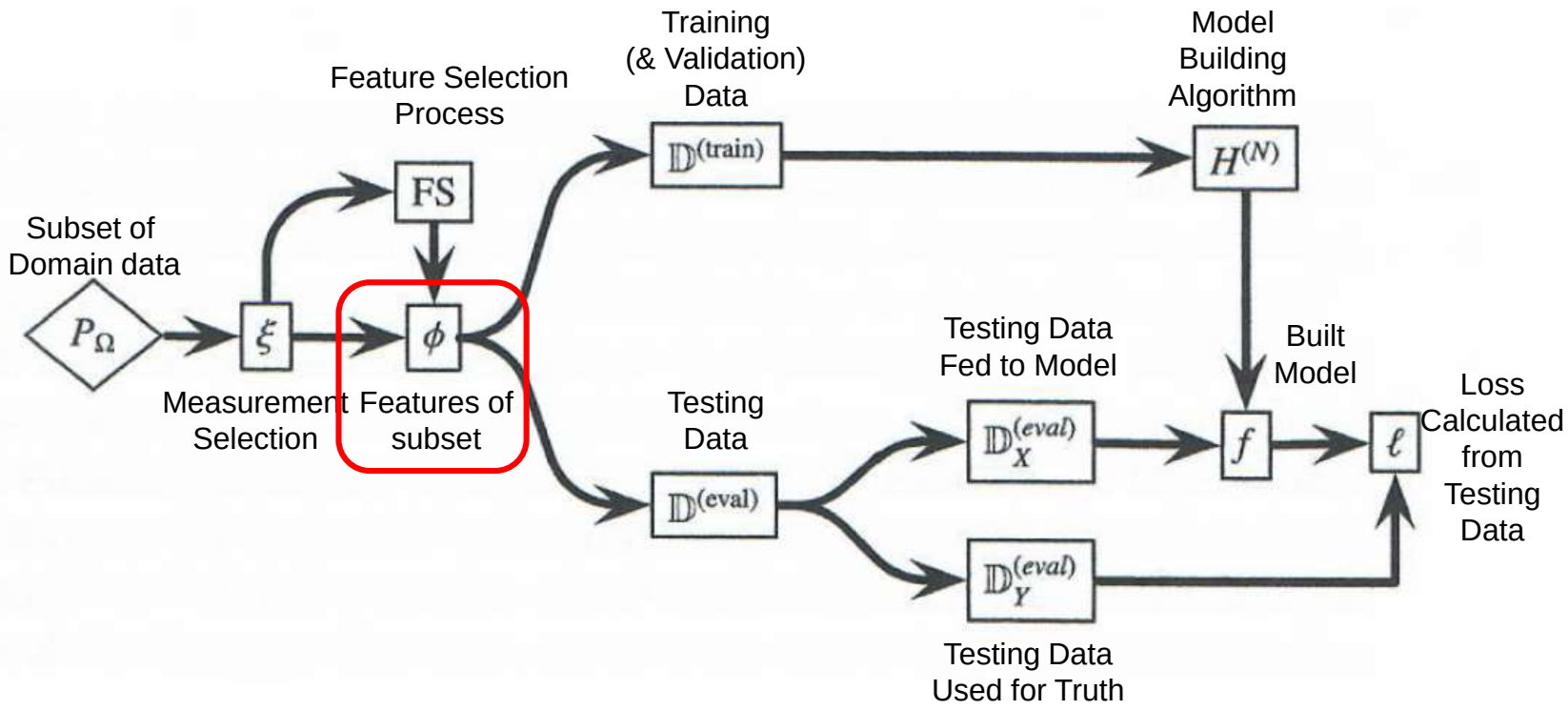
# Algorithm Attacks – Feature Selection




Adapted from Joseph, Nelson, Rubinstein, Tygar; Adversarial Machine Learning, Cambridge University Press, 2019

# Data Attacks – Features

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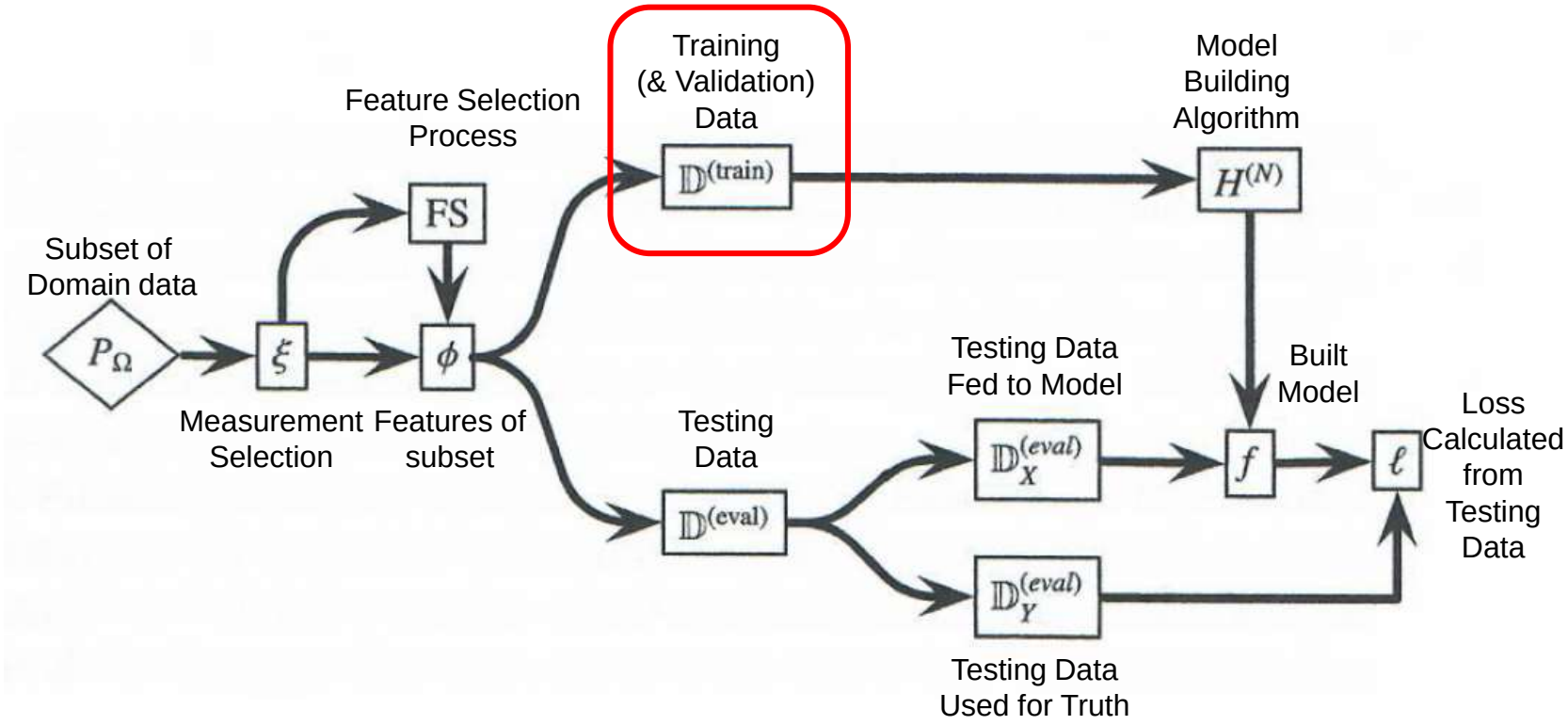
# Data Attacks – Training Data

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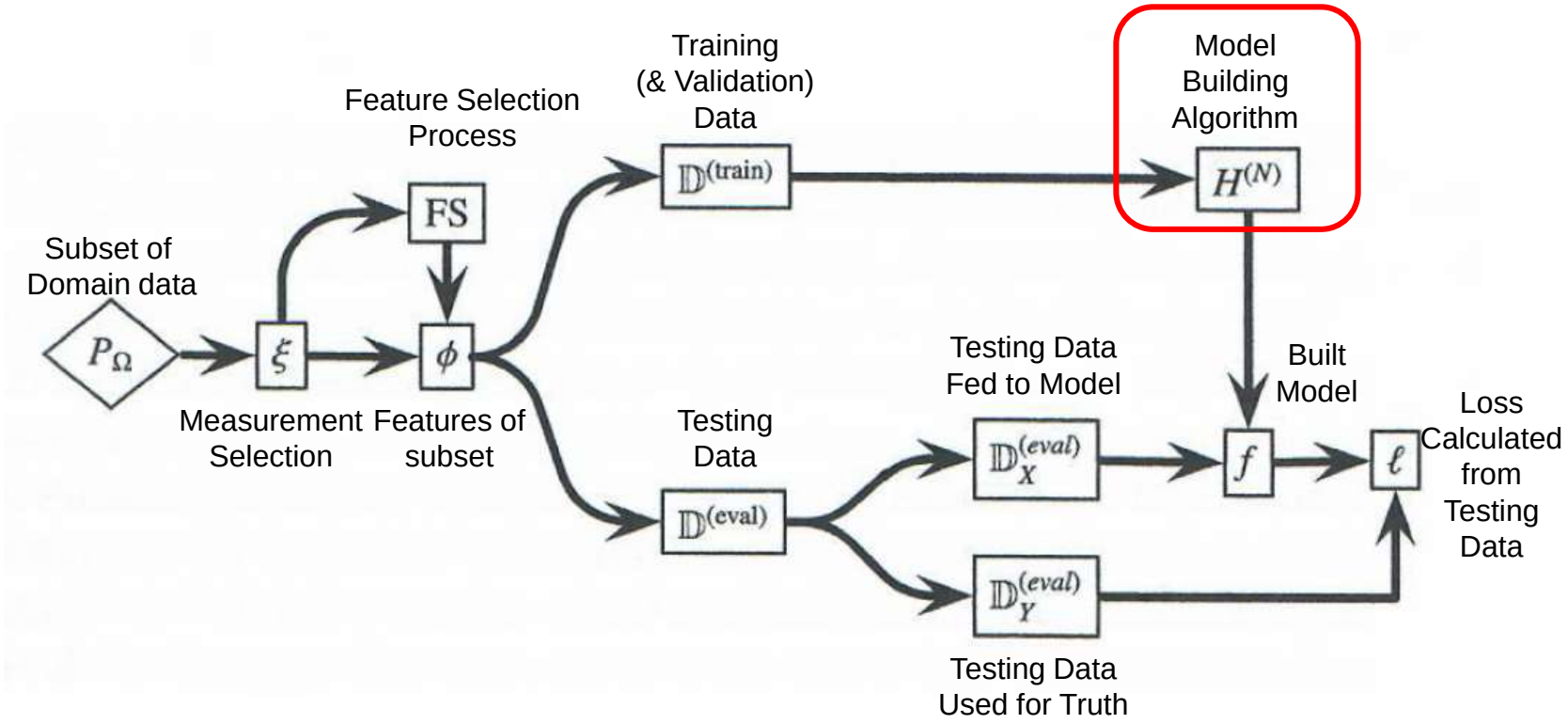
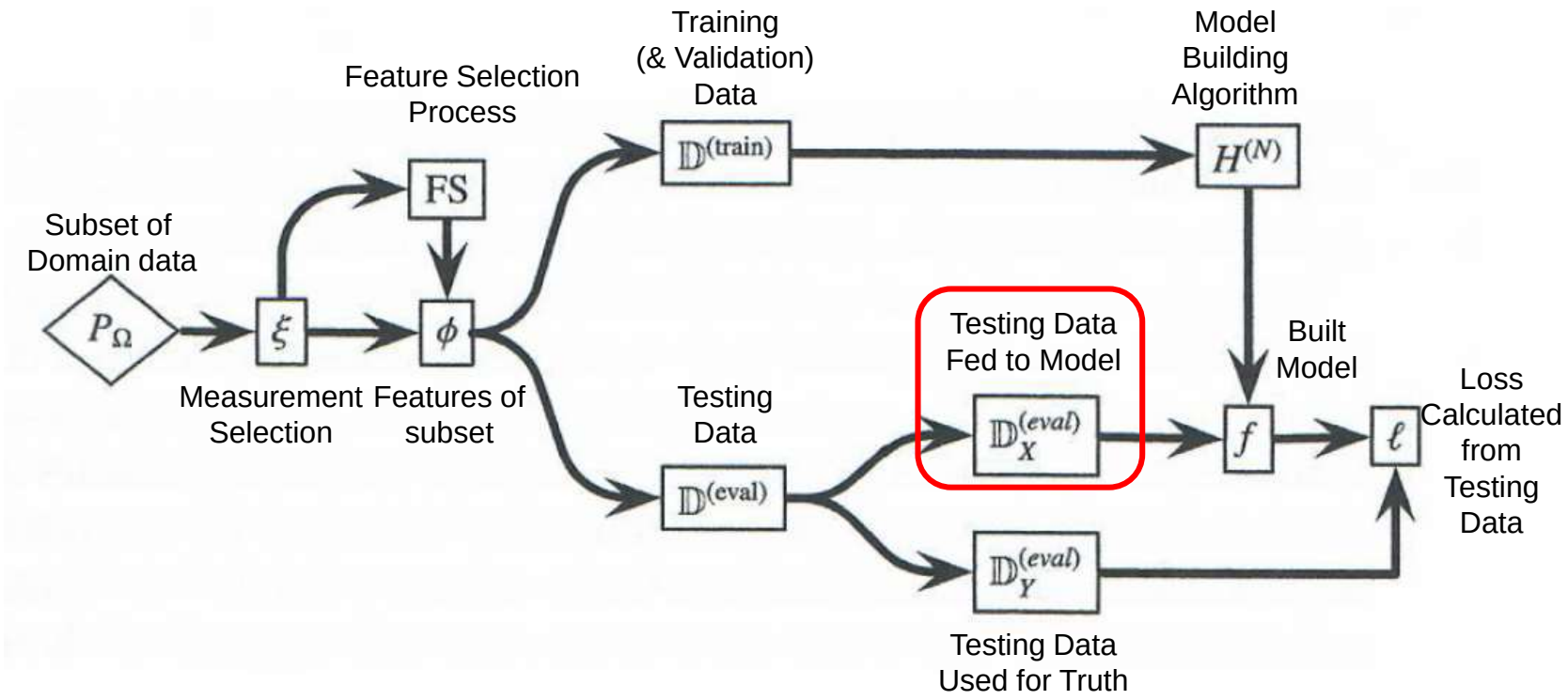
# Algorithm Attacks – Model Construction




Adapted from Joseph, Nelson, Rubinstein, Tygar; Adversarial Machine Learning, Cambridge University Press, 2019

# Data Attacks – Model Testing Data

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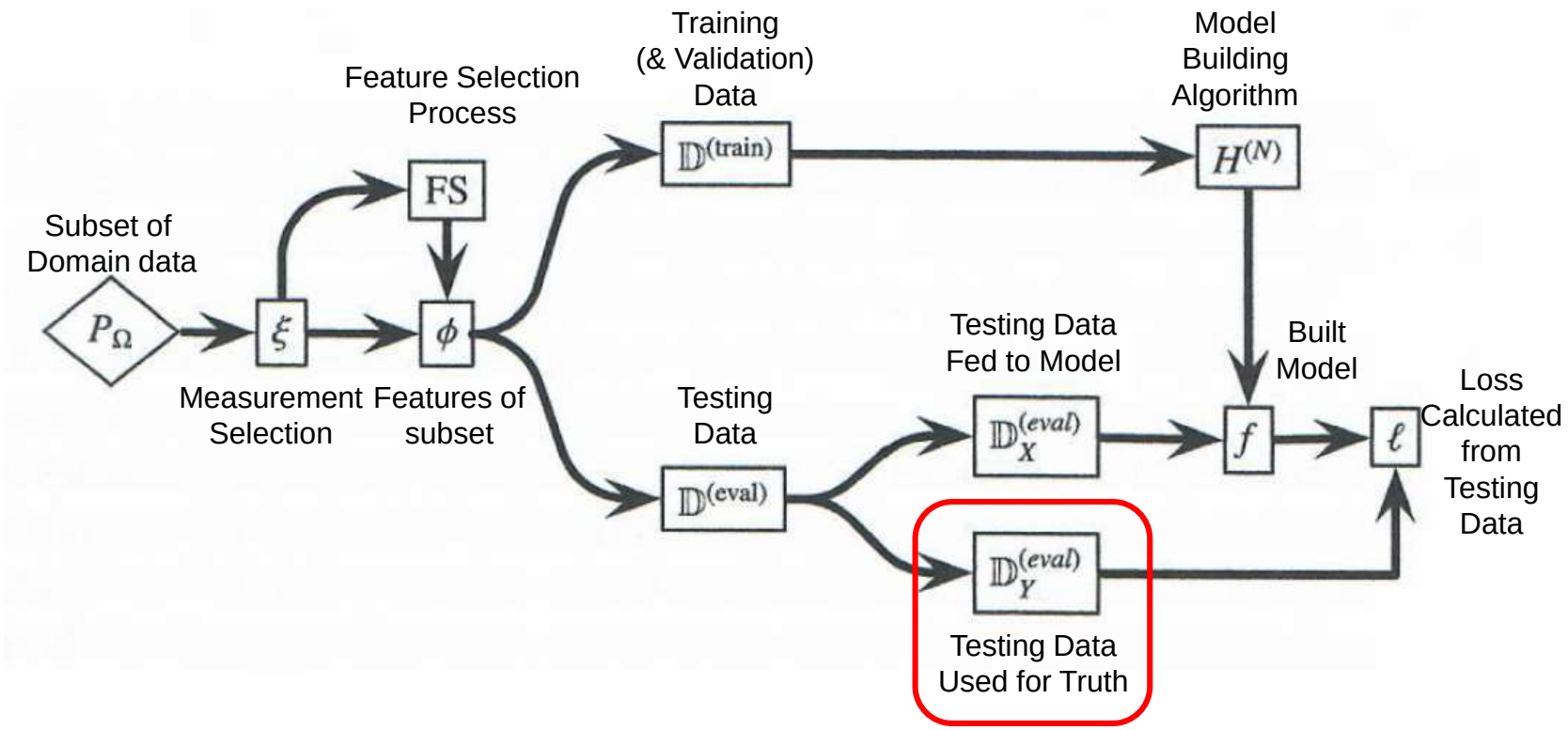
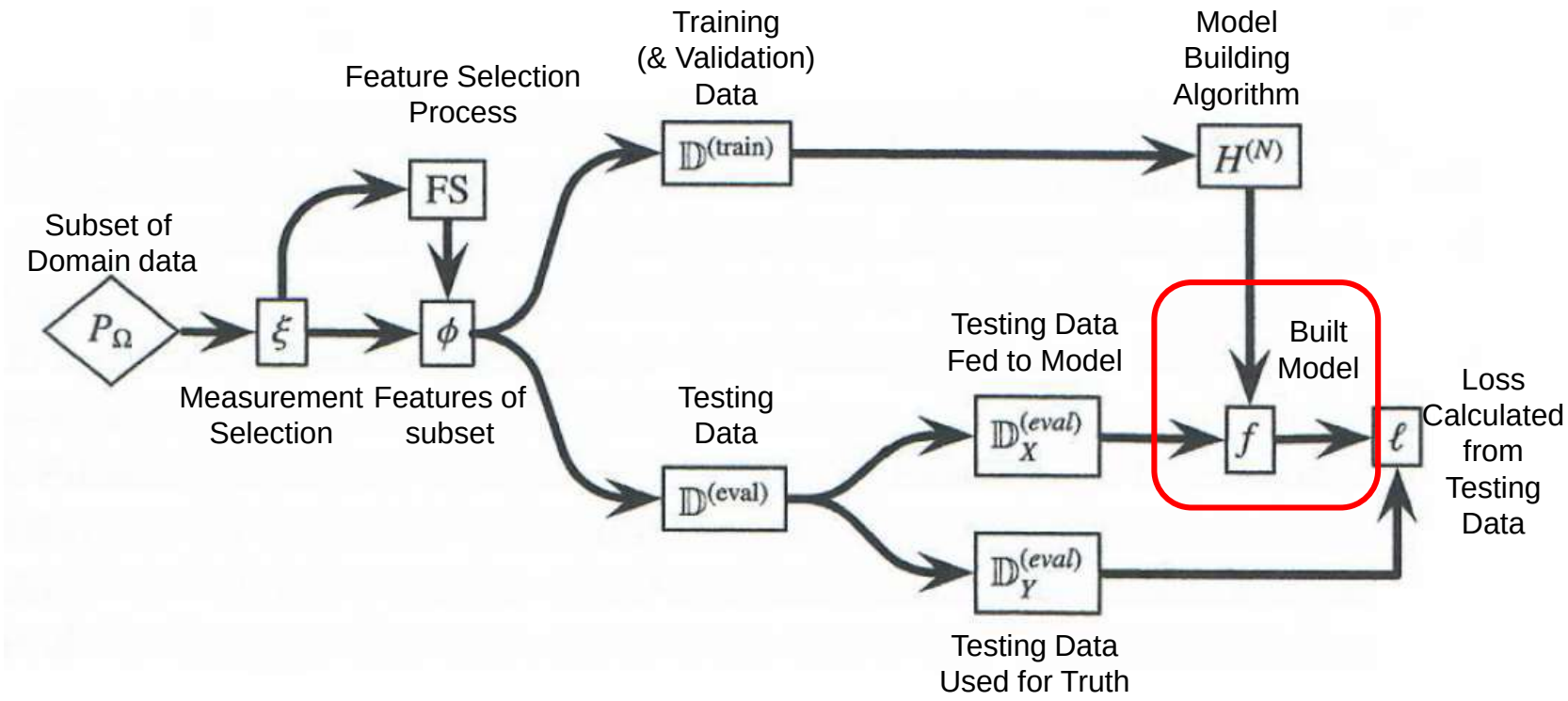
# Data Attacks – Ground Truth




Adapted from Joseph, Nelson, Rubinstein, Tygar; Adversarial Machine Learning, Cambridge University Press, 2019

# Algorithm Attacks – Model

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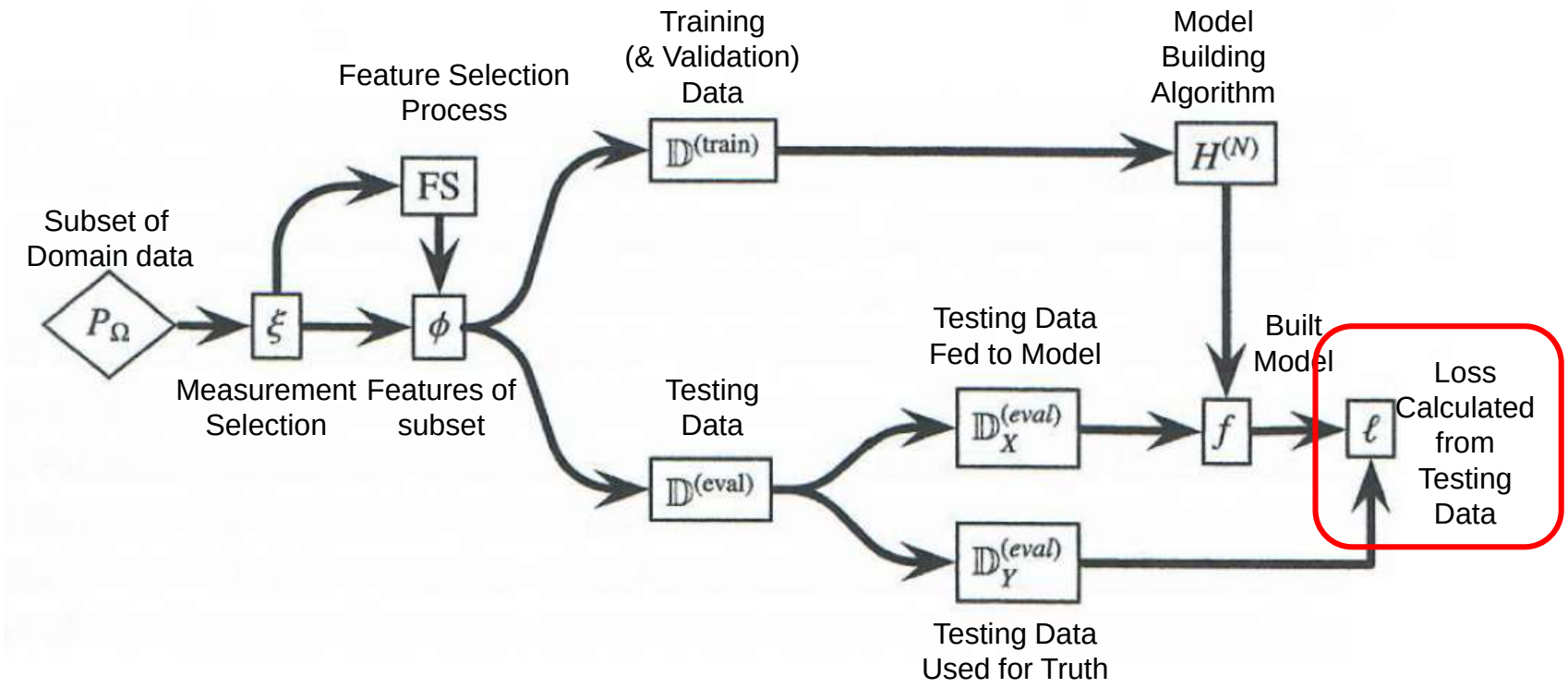
# Data Attack – Loss Measurements

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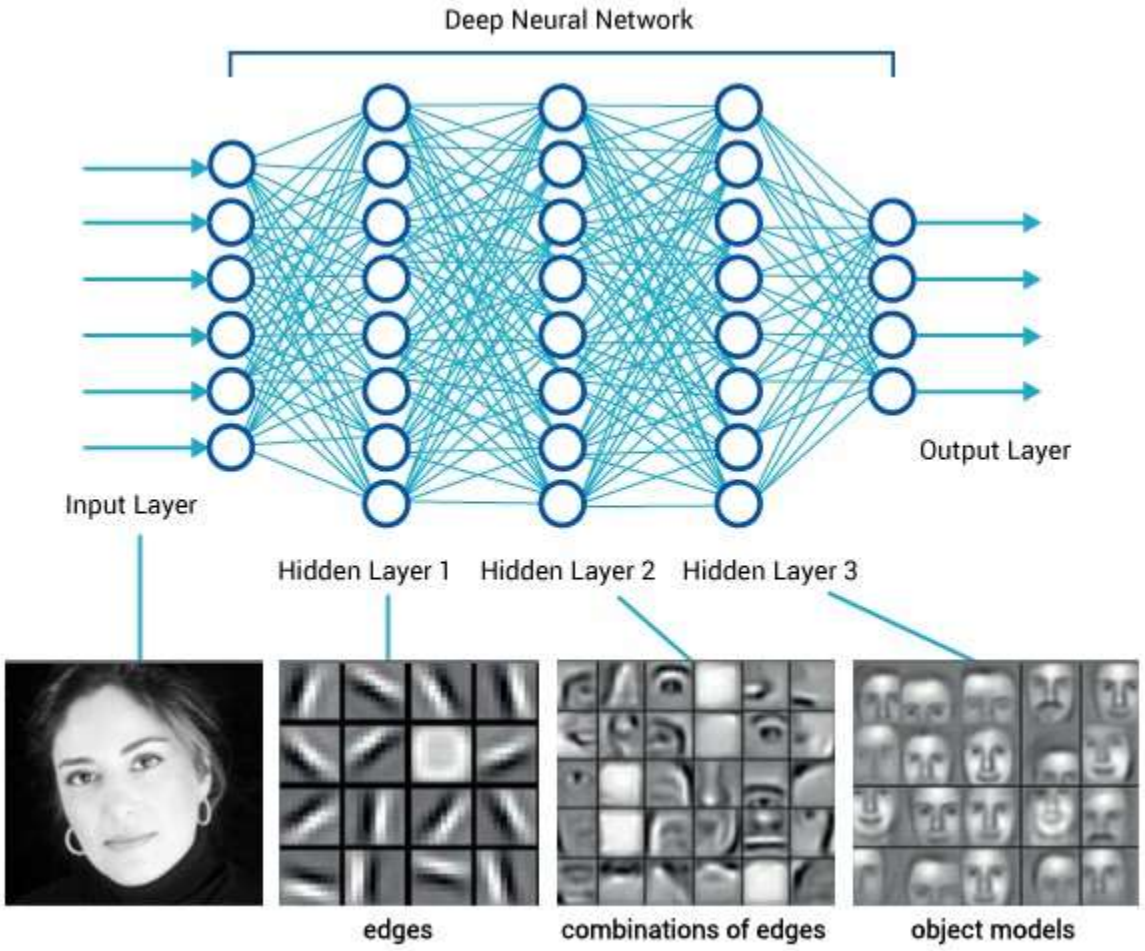
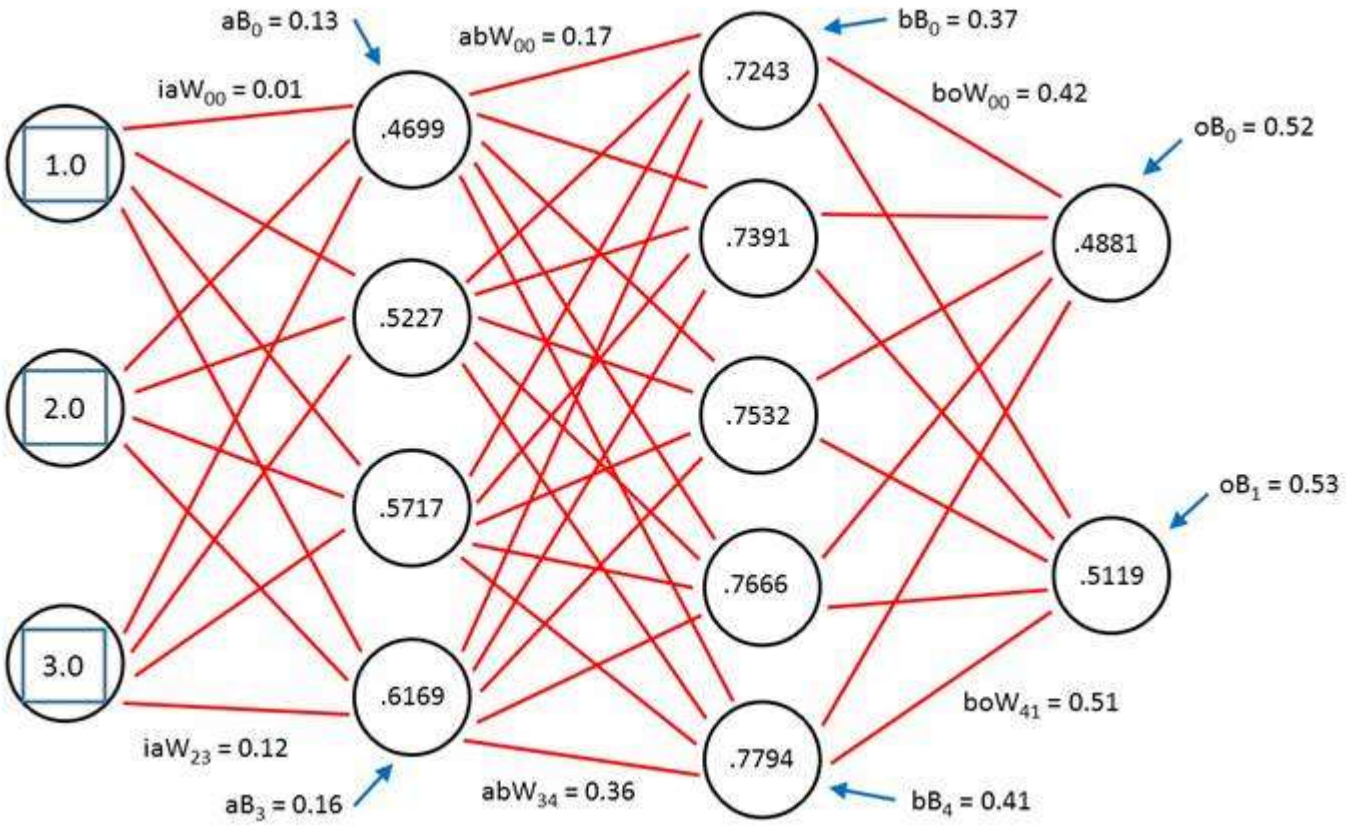
# Deep Neural Network Structure



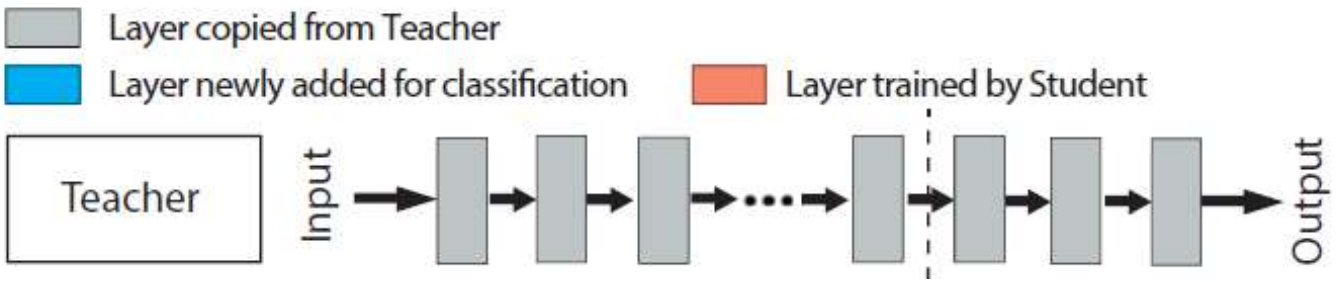

Aashay Sachdeva, Deep Learning for Computer Vision for the average person, Mar 6, 2017, https://medium.com/diaryofawannapreneur/deep-learning-for-computer-vision-for-the-average-person-861661d8aa61

# Trained Deep Neural Network




Sergey Golubev, Deep Neural Networks: A Getting Started Tutorial, Part #1, 30 June 2014, https://www.mql5.com/en/blogs/post/203

# Overview of Transferring Learning




Bolun Wang, Yuanshun Yao, Bimal Viswanath, Haitao Zheng, Ben Y. Zhao; "With Great Training Comes Great Vulnerability: Practical Attacks Against Transfer Learning ," 27th USENIX Security Symposium; Aug 15-17, 2018; pg 1281

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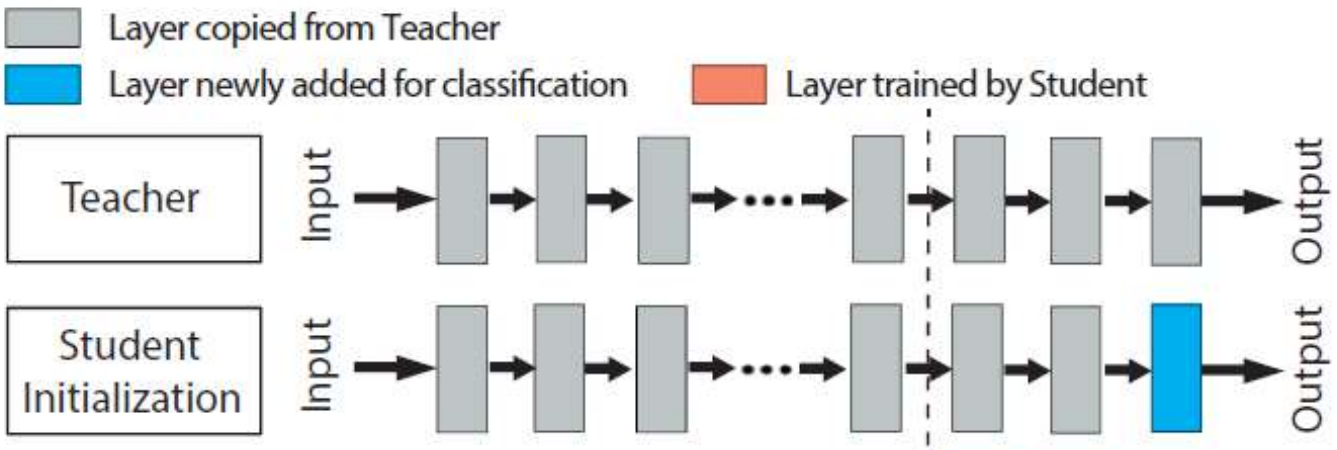


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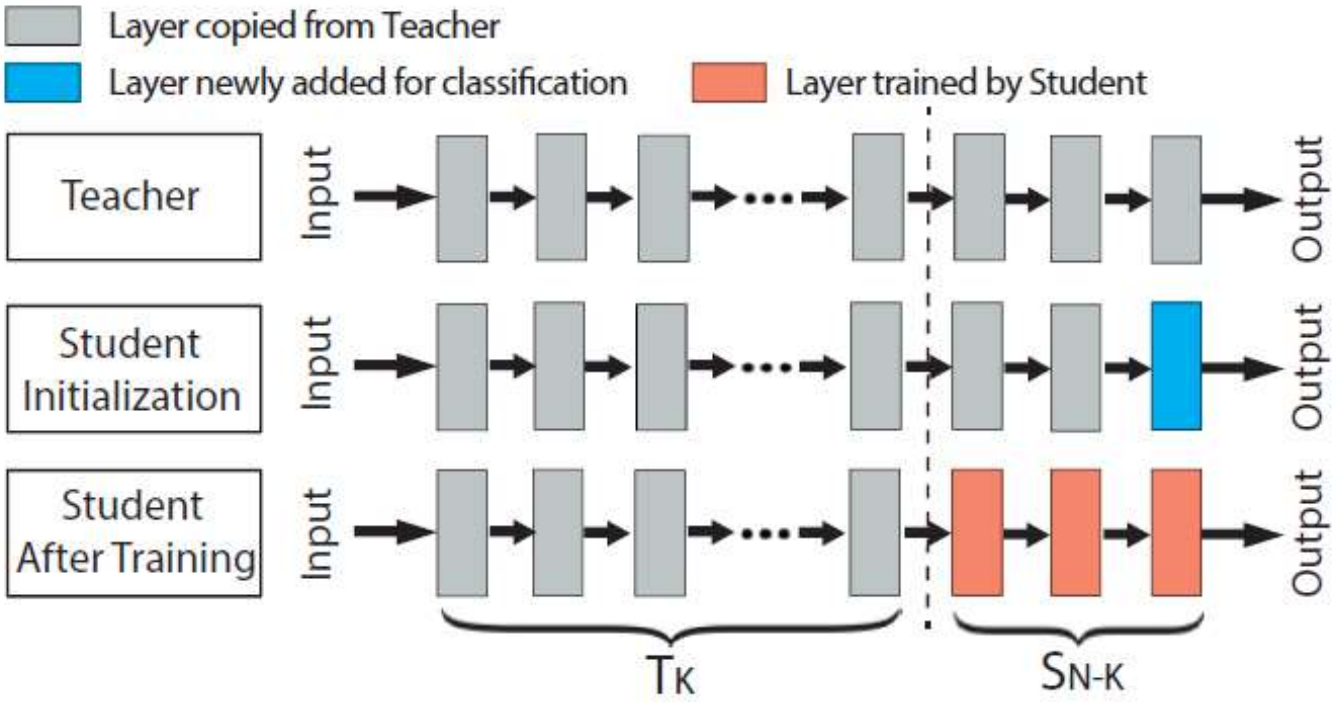


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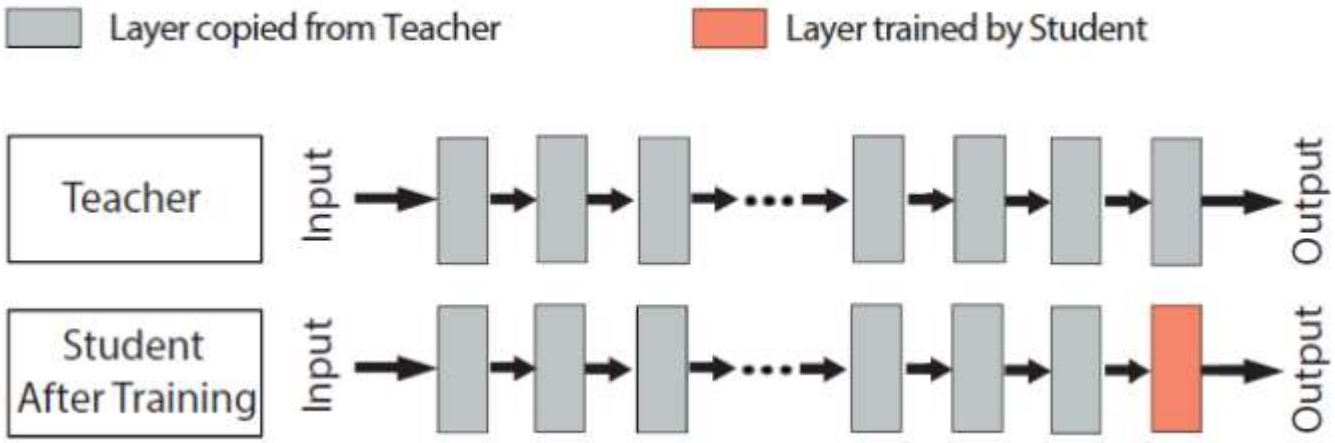
# Deep Layer Feature Extraction



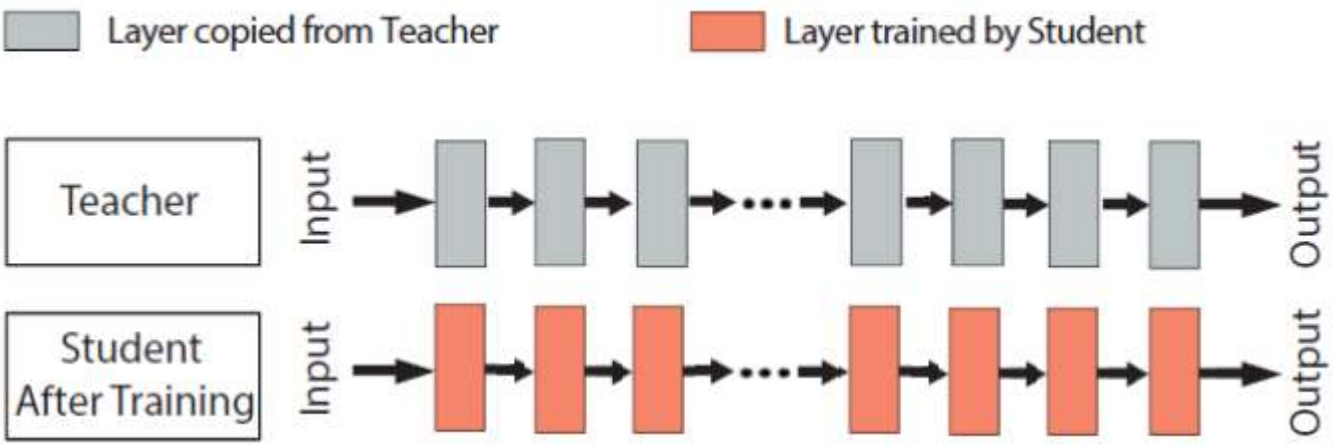

Used when domains are close

Pro: Cheap training; good accuracy

Con: Adversary has deep knowledge of teacher
Easier to exfiltrate model
Easier to create adversarial input

Bolun Wang, Yuanshun Yao, Bimal Viswanath, Haitao Zheng, Ben Y. Zhao; "With Great Training Comes Great Vulnerability: Practical Attacks Against Transfer Learning ," 27th USENIX Security Symposium; Aug 15-17, 2018; pg 1281

# Full model fine tuning



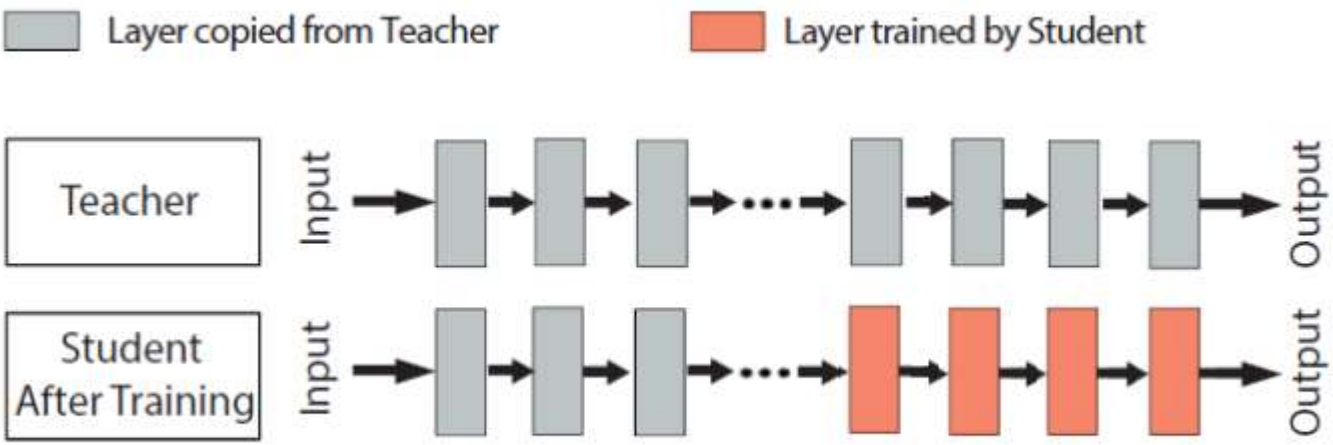

Used when domains are not close

Pro: Better accuracy than deep layer feature extraction
Resilient to teacher-specific attacks

Con: Costly to train

Bolun Wang, Yuanshun Yao, Bimal Viswanath, Haitao Zheng, Ben Y. Zhao; "With Great Training Comes Great Vulnerability: Practical Attacks Against Transfer Learning ," 27th USENIX Security Symposium; Aug 15-17, 2018; pg 1281

# Mid-Layer Feature Extraction




Compromise choice

- Accuracy depends on relationship between student and teacher domains
- Better resiliency than deep, not as good as full
- More costly to train than deep, cheaper than full

Bolun Wang, Yuanshun Yao, Bimal Viswanath, Haitao Zheng, Ben Y. Zhao; "With Great Training Comes Great Vulnerability: Practical Attacks Against Transfer Learning ," 27th USENIX Security Symposium; Aug 15-17, 2018; pg 1281

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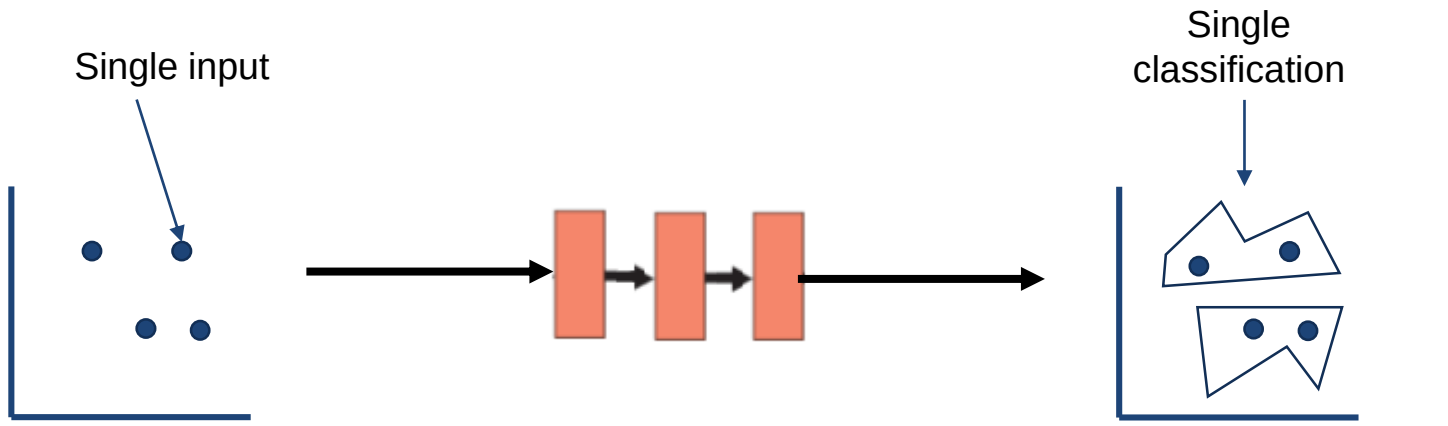
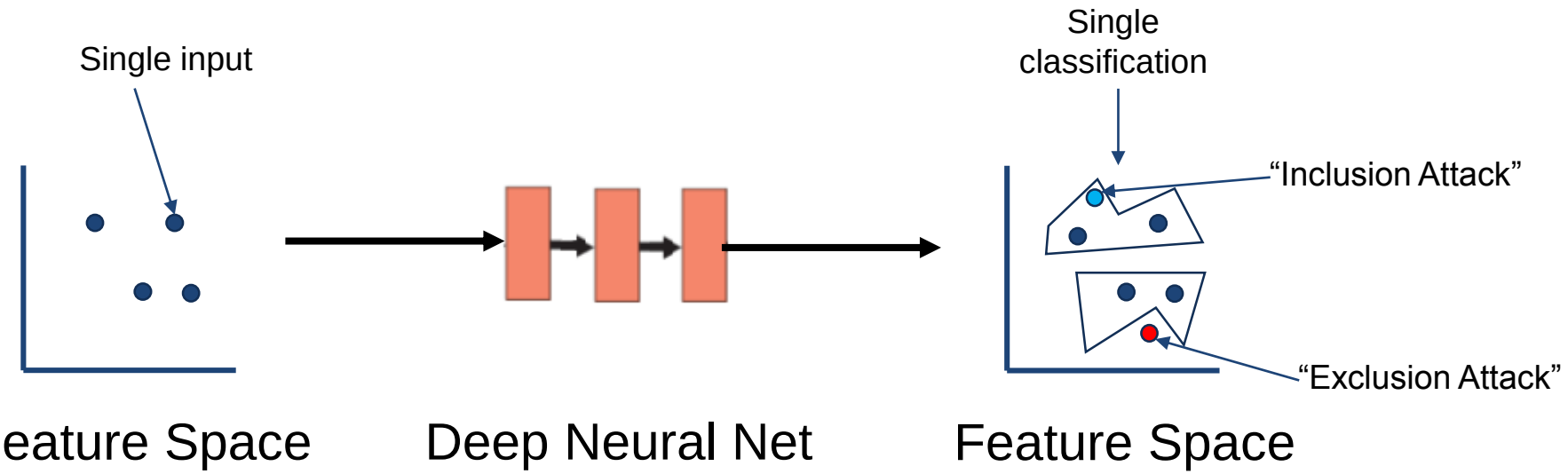
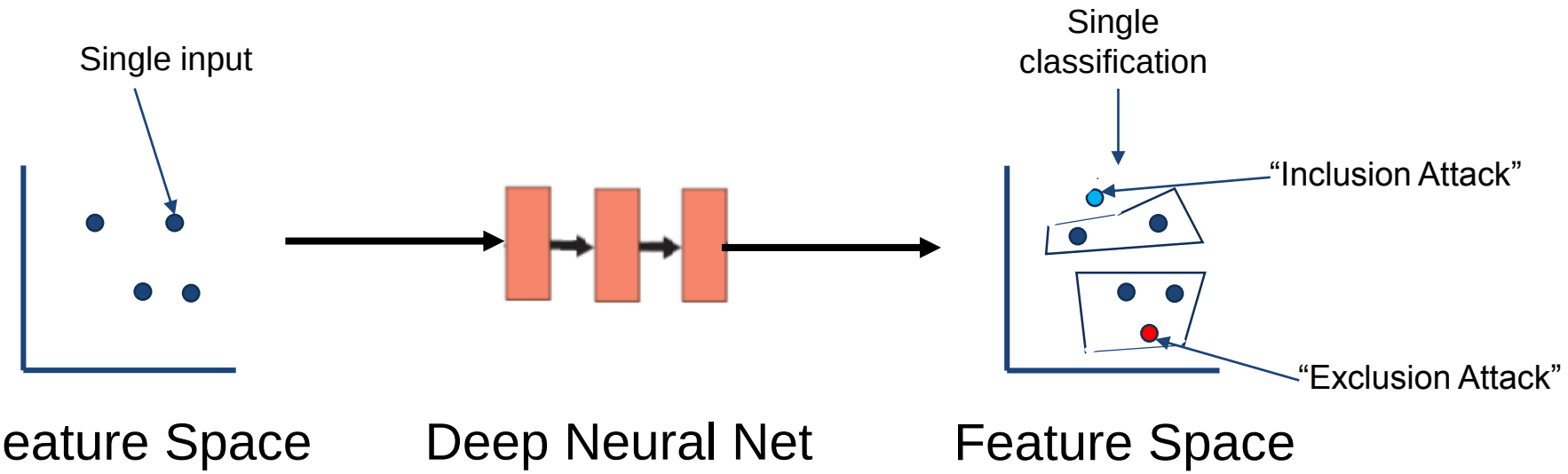
# Creating Classifications



# Adversarial Input



# Adding Resiliency




- Cutting off spikes mitigates undesired "inclusions"
- Enclosing spikes mitigates undesired "exclusions"

# Training for resilience

Methods to improve model resiliency

- Add adversarial examples in training
- Train with larger domain subset
- Calculate convex hull of classification boundary
- Apply statistical robust regression

All of these methods trade resiliency for accuracy

- Adversarial examples are noisy
- Overfitting creates raggedy boundaries
- Concave boundaries could be legitimate – should be excluded
- Looser boundaries could be legitimate – should be included

Redundancy is an alternative strategy – at a cost

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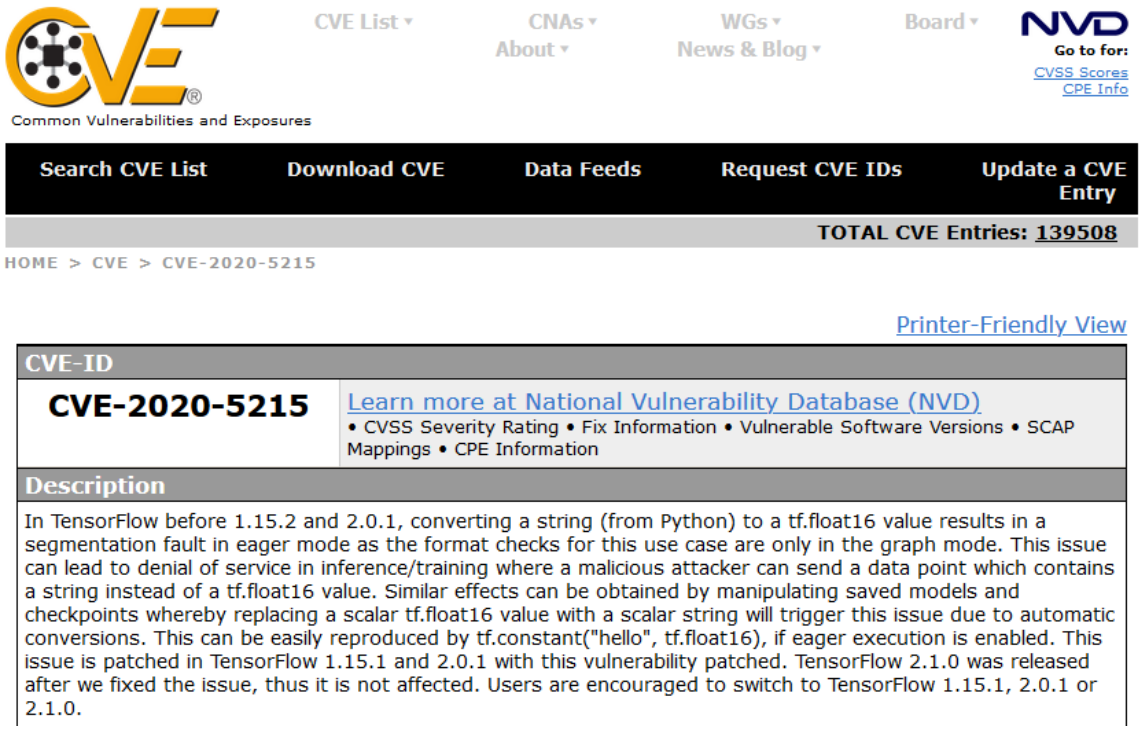
# Coding Hygiene



CVE List ▾ CNAs ▾ About ▾ WGs ▾ News & Blog ▾ Board ▾ NVD Go to for: CVSS Scores CPE Info

Common Vulnerabilities and Exposures

Search CVE List | Download CVE | Data Feeds | Request CVE IDs | Update a CVE Entry

TOTAL CVE Entries: 139508

HOME > CVE > CVE-2020-5215

Printer-Friendly View

| CVE-ID | |
|---|---|
| CVE-2020-5215 | Learn more at National Vulnerability Database (NVD) • CVSS Severity Rating • Fix Information • Vulnerable Software Versions • SCAP Mappings • CPE Information |

**Description**

In TensorFlow before 1.15.2 and 2.0.1, converting a string (from Python) to a tf.float16 value results in a segmentation fault in eager mode as the format checks for this use case are only in the graph mode. This issue can lead to denial of service in inference/training where a malicious attacker can send a data point which contains a string instead of a tf.float16 value. Similar effects can be obtained by manipulating saved models and checkpoints whereby replacing a scalar tf.float16 value with a scalar string will trigger this issue due to automatic conversions. This can be easily reproduced by tf.constant("hello", tf.float16), if eager execution is enabled. This issue is patched in TensorFlow 1.15.1 and 2.0.1 with this vulnerability patched. TensorFlow 2.1.0 was released after we fixed the issue, thus it is not affected. Users are encouraged to switch to TensorFlow 1.15.1, 2.0.1 or 2.1.0.

https://cve.mitre.org/cgi-bin/cvename.cgi?name=CVE-2020-5215

Any of the algorithms in creating the application or in the generated application could have coding weaknesses leading to vulnerabilities

Mitigation: Good cyber hygiene

# Software supply chain for assembled software

Machine learning depends on frameworks and data sets
Relatively less is known about the security of these “supplies”

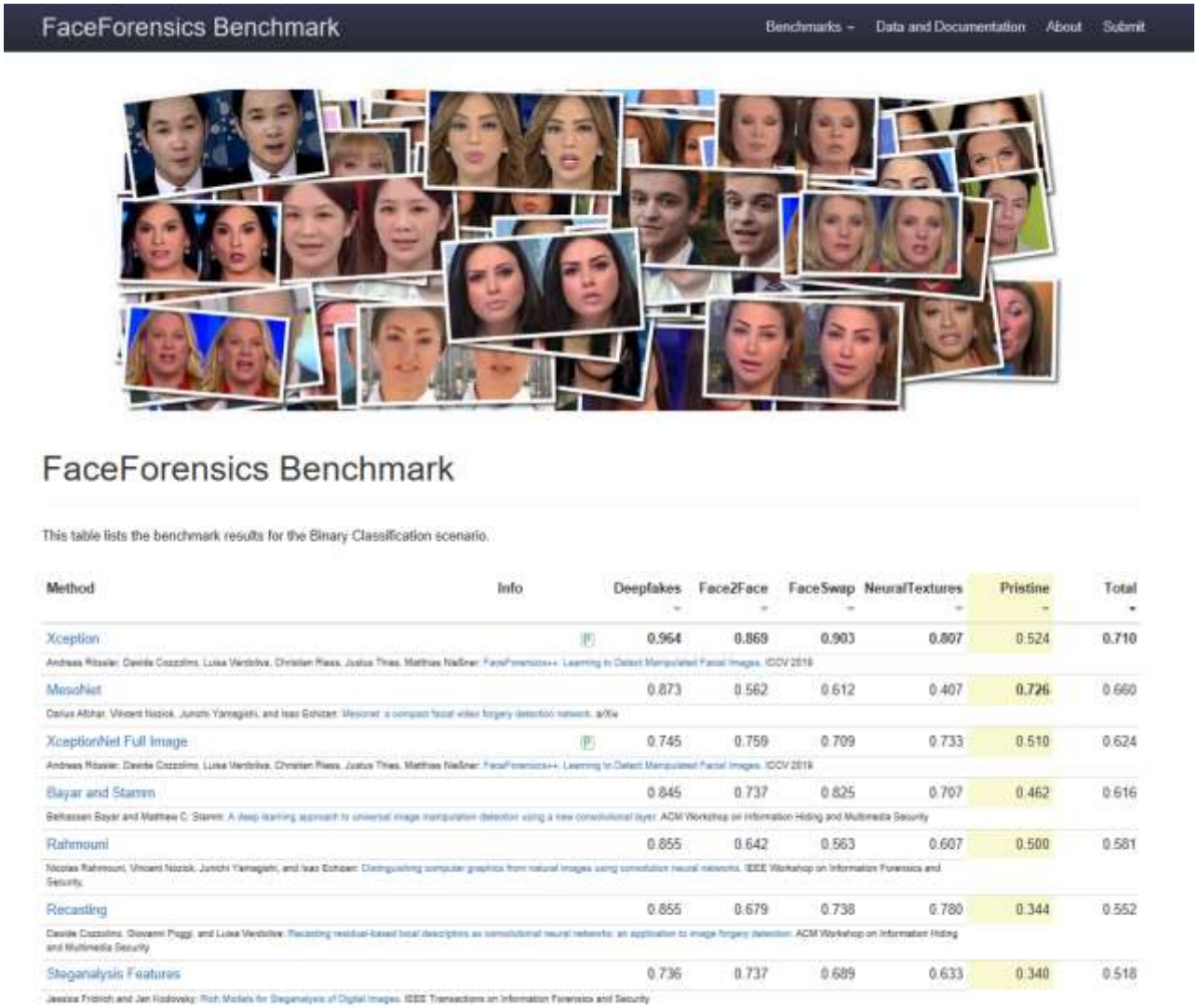
| Machine Learning Frameworks | Data Sources |
| --- | --- |
| • Pandas<br>• Numpy<br>• Scikit-learn<br>• Matplotlib<br>• TensorFlow<br>• Keras<br>• Seaborn<br>• Pytorch & Torch | • Kaggle<br>• UCI Machine Learning Repository<br>• Find Datasets<br>• Data.gov<br>• xView<br>• ImageNet<br>• Google’s Open Images |

# Machine learning system face training data supply challenges

Rich supplies of “deep fakes” are readily accessible

Source: https://ai.googleblog.com/2019/09/contributing-data-to-deepfake-detection.html

# Poor detection of deep fakes

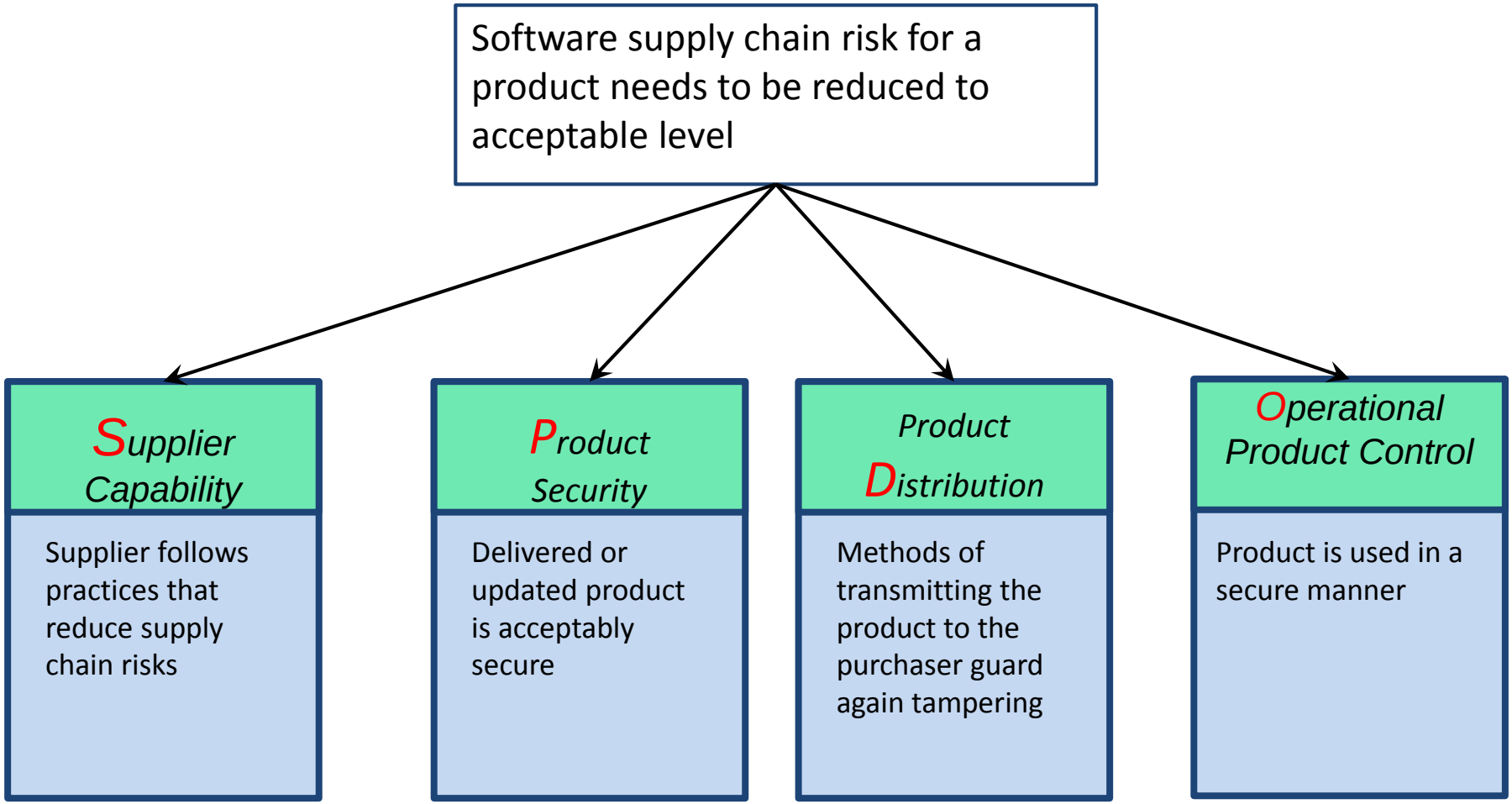



Cannot reliable verify that training data obtained through a supply chain

Preconfigured machine learning (i.e., teacher) systems provide a vehicle to distribute bad training data

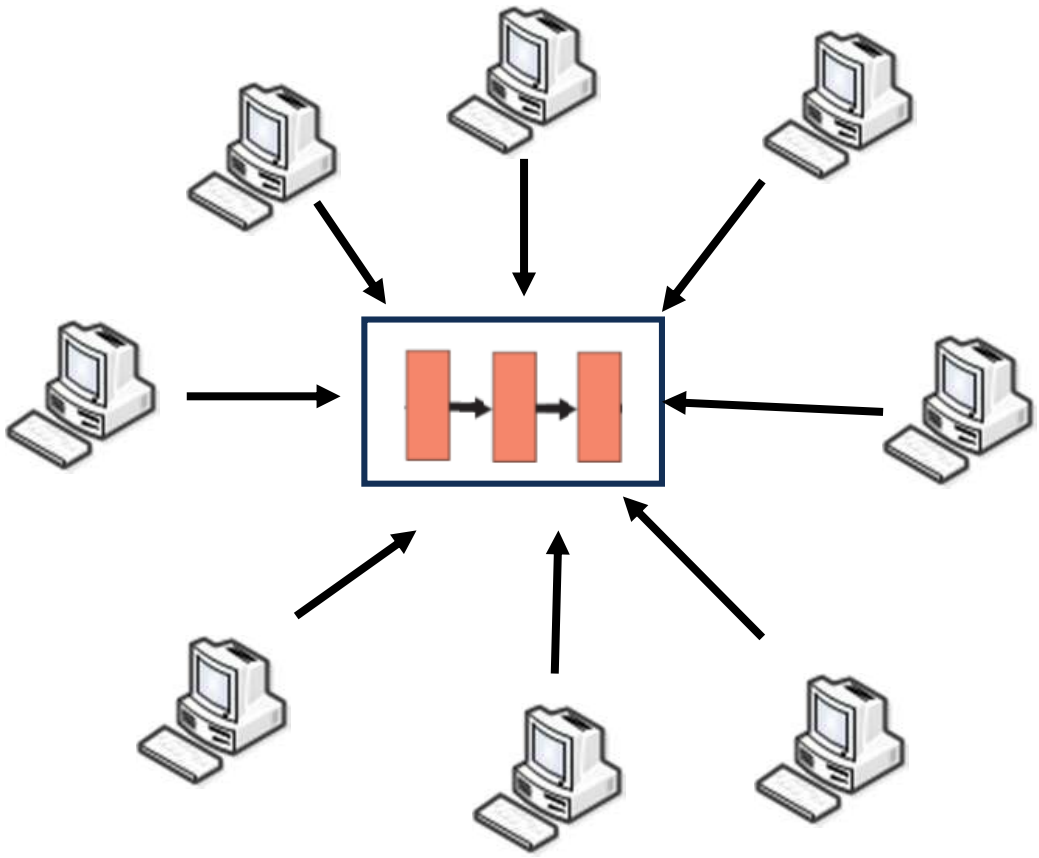
Source: http://kaldir.vc.in.tum.de/faceforensics_benchmark/index.php (as of 9/25/19)

# Reducing software supply chain risk factors




Ellison, Alberts, Creel, Dorofee, Woody, "Software Supply Chain Risk Management: From Products to Systems of Systems," 2010, https://resources.sei.cmu.edu/asset_files/TechnicalNote/2010_004_001_15194.pdf

# Denial of Service Attack



Remediation: Network hygiene

(https://us-cert.cisa.gov/ncas/tips/ST04-015)

# Integration Points are Typically Weak

Machine learning applications are part of a system

New operating environments, i.e., interconnections between system parts, are a major cause of vulnerabilities

Extra-ML parts of the application are routes to ML attacks

Clark, Frei, Blaze, Smith, "Familiarity Breeds Contempt: The Honeymoon Effect and the Role of Legacy Code in Zero-Day Vulnerabilities," ACSAC '10 Dec. 6-10, 2010, p. 251-260."

# Insider Threat

Easy vector for data attacks

Remediations:

- Organizational evaluation
- Organizational processes
- Tools
- Training

https://www.sei.cmu.edu/education-outreach/courses/course.cfm?coursecode=V26

# “Fake News” and AI Untrustworthiness

People ultimately use output from ML systems

Reasoning from ML systems is generally opaque

Parties can amplify potential misgivings

“Through 2021, 80% of line of business (LOB) leaders will override business decisions made by AI,” Gartner survey*

Remediations:

- Technical: Improved explanations and expectations
- Social: Education and experience

Recognize: Machine Learning is Statistics

*Graham Peters, Alan D. Duncan, Gartner Group, “100 Data and Analytics Predictions Through 2024,” March 20, 2020, pg 4

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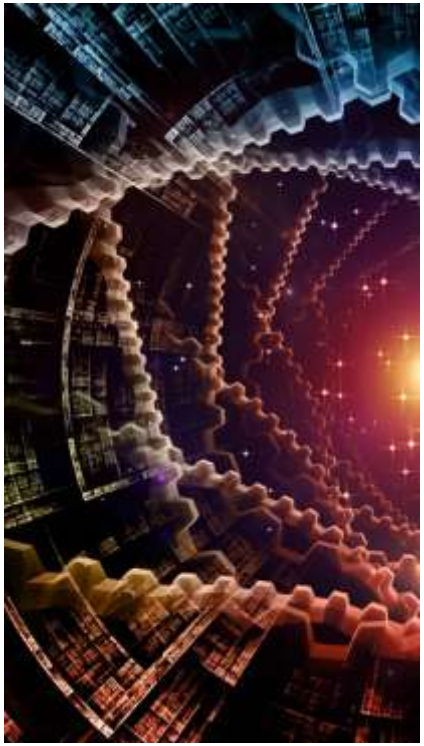
# Ways to Engage with Us



- **Download software and tools**
- **Explore research and capabilities**
- **Participate in education offerings**
- **Attend an event**
- **Search the digital library**
- **Read the SEI Year in Review**
- **Collaborate with the SEI on a new project**

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