

# Threats to Machine Learning Applications

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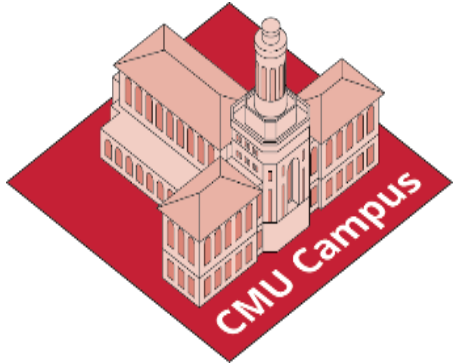
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DM20-0594

# 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

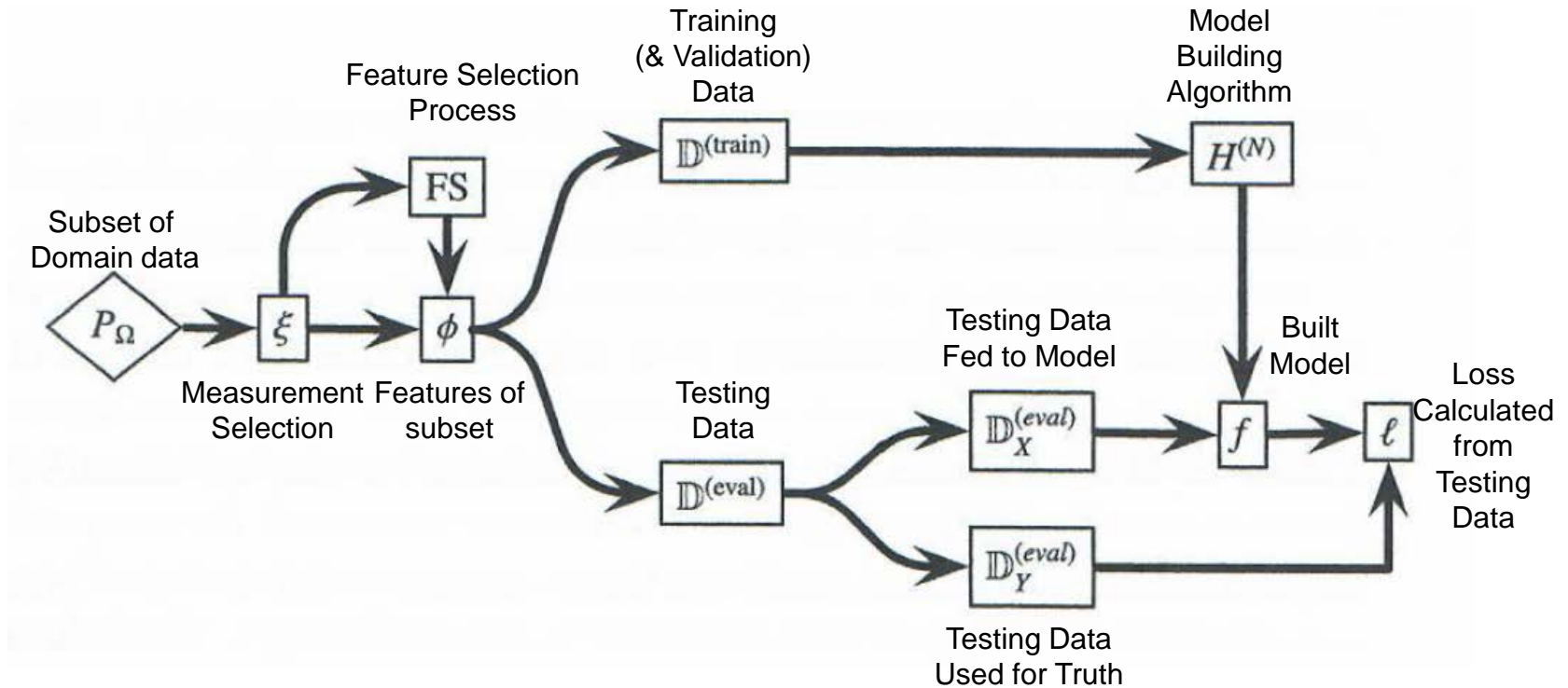
**Understanding the ML Attack Surface**

**Understanding Risks of Transfer Learning**

**Remedies and Limitations**

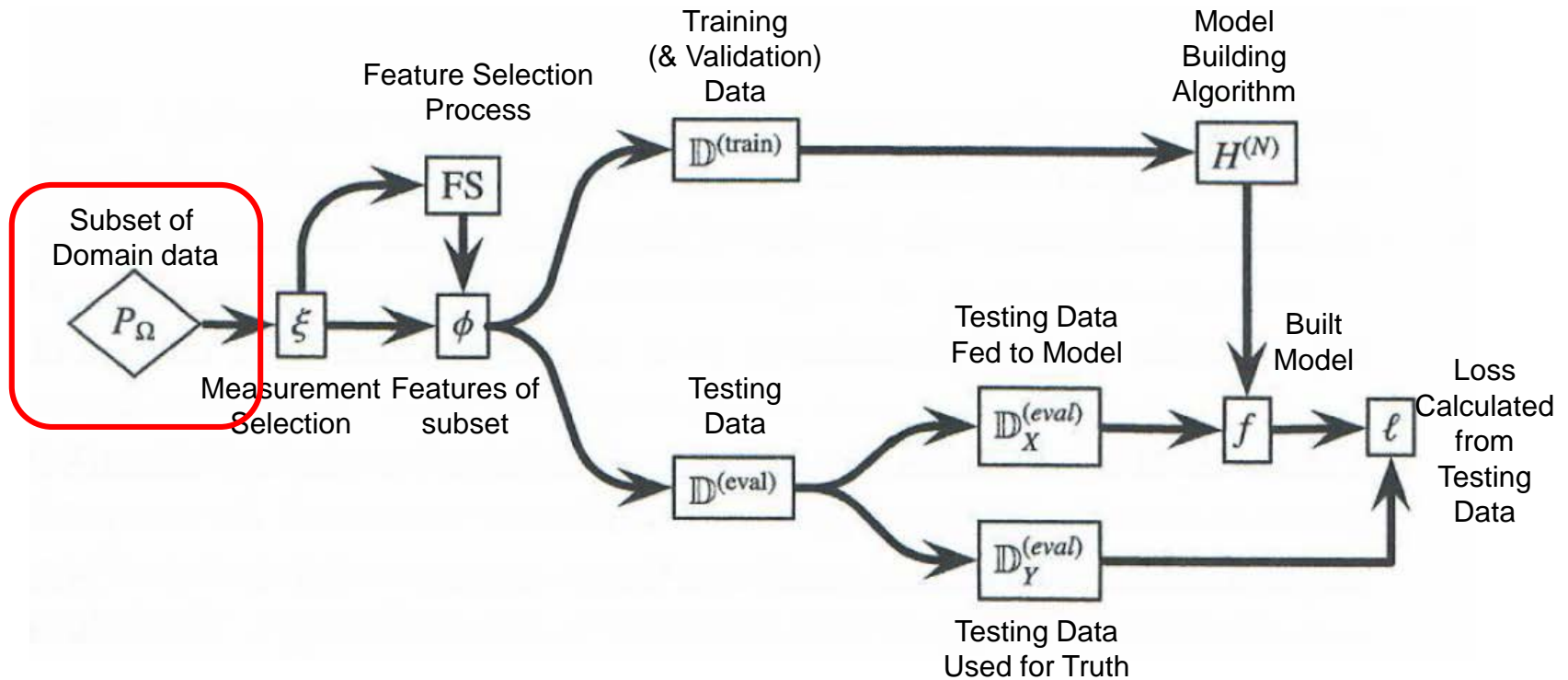
**Conventional Threats to Machine Learning**

# Developing a Machine Learning Application



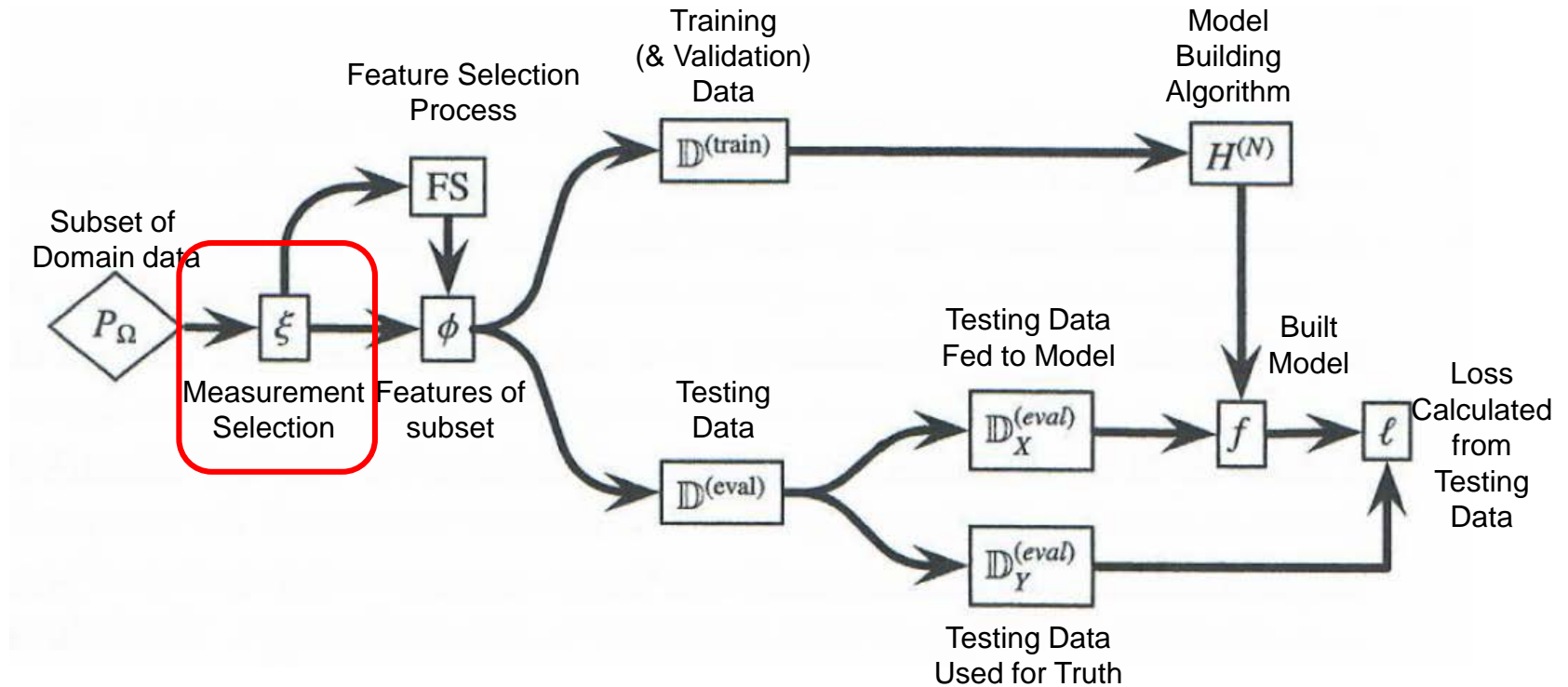
Adapted from Joseph, Nelson, Rubinstein, Tygar; Adversarial Machine Learning, Cambridge University Press, 2019

# Data Attacks – Selected Domain Subset



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

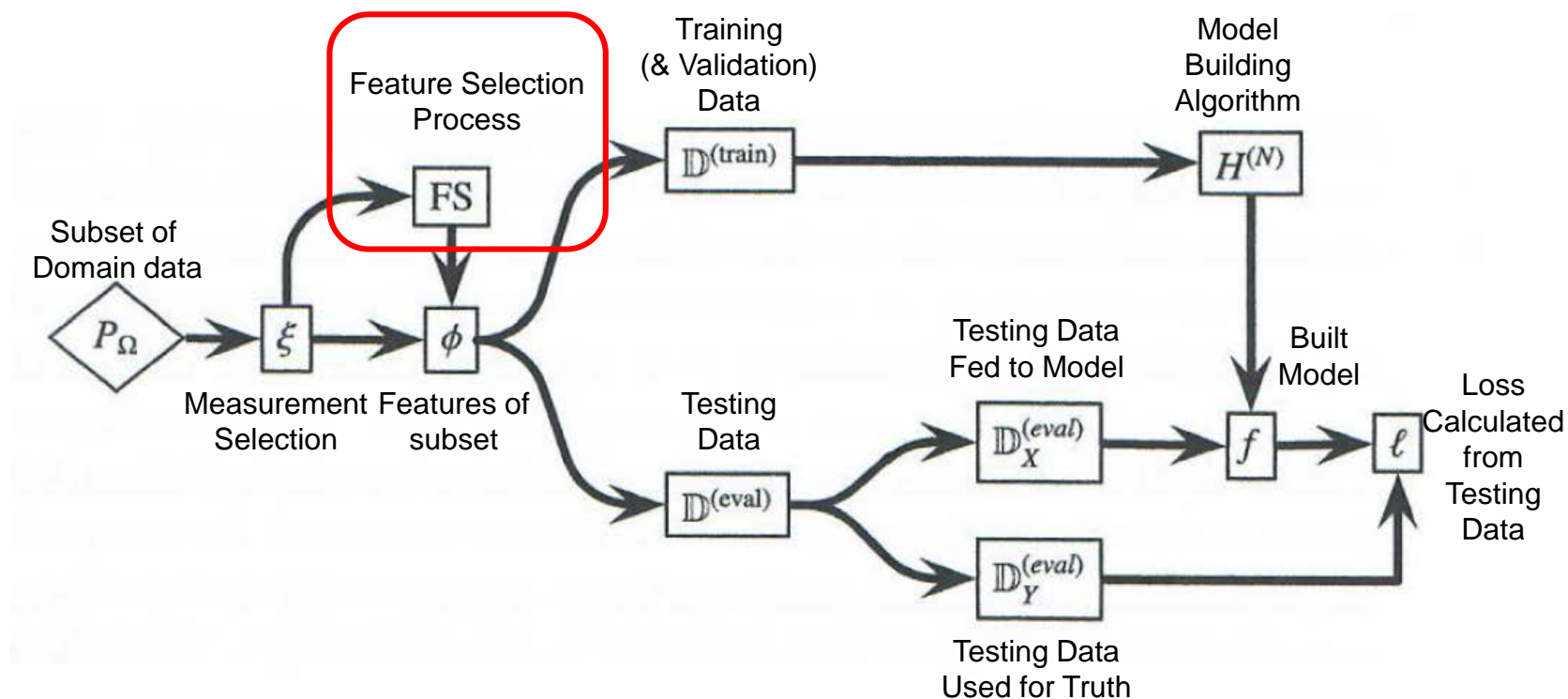
# Data Attacks – Measurements



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

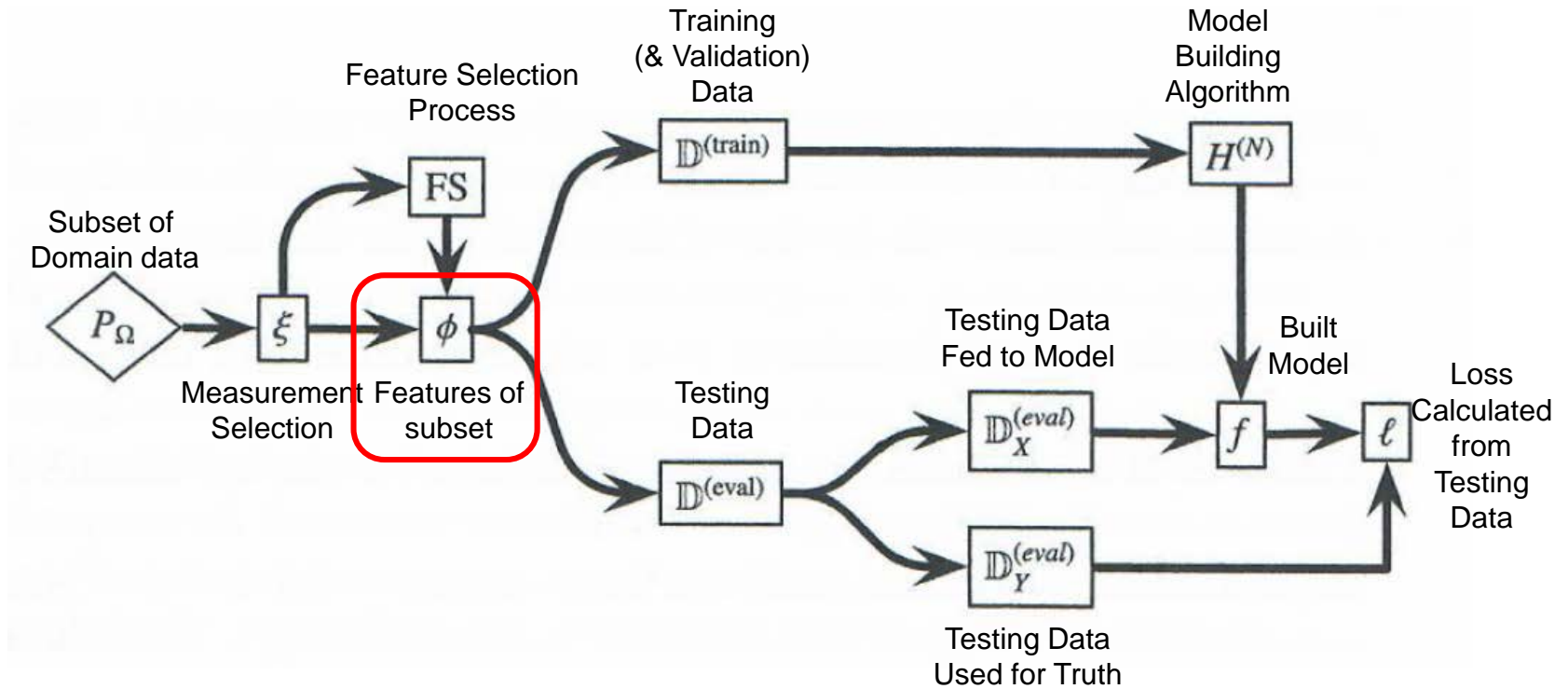


# Algorithm Attacks – Feature Selection



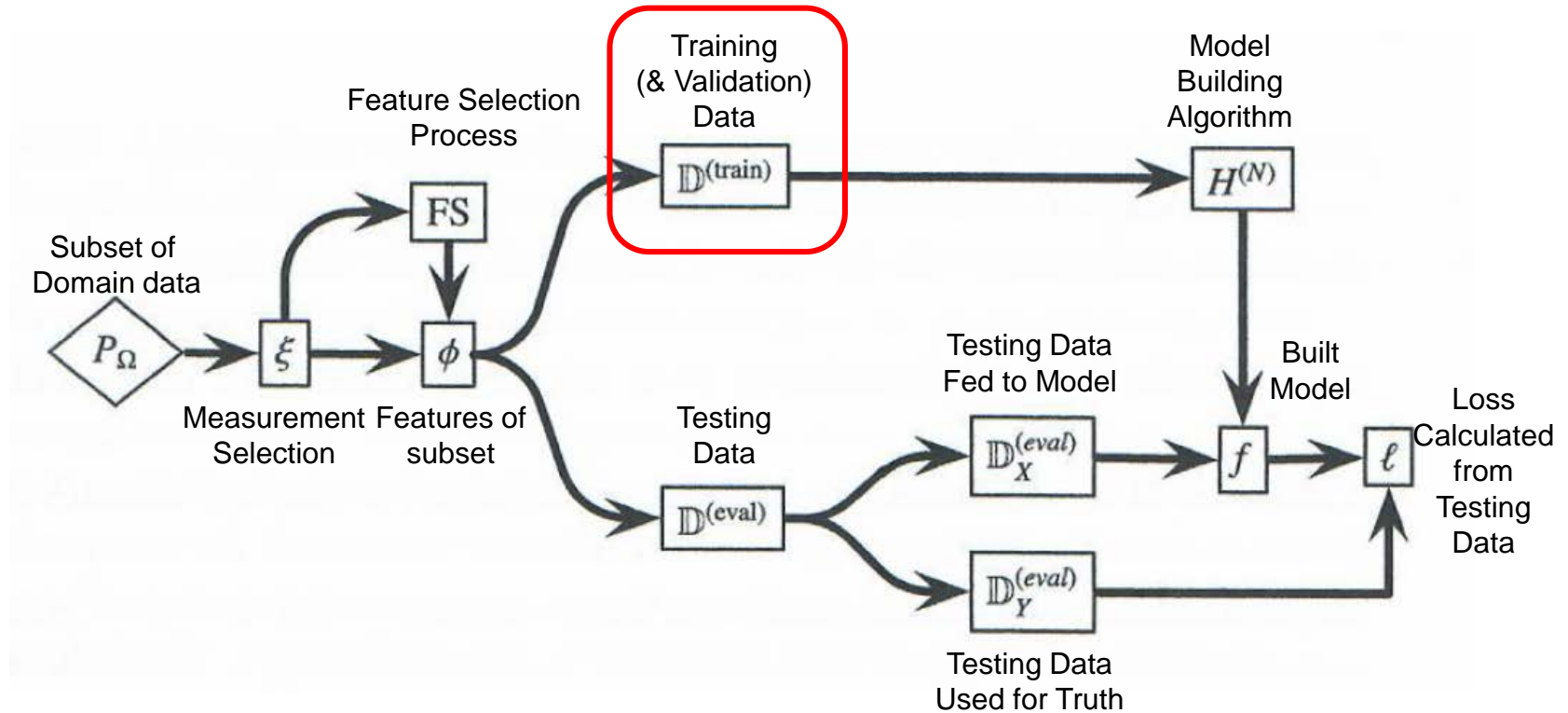
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# Data Attacks – Features



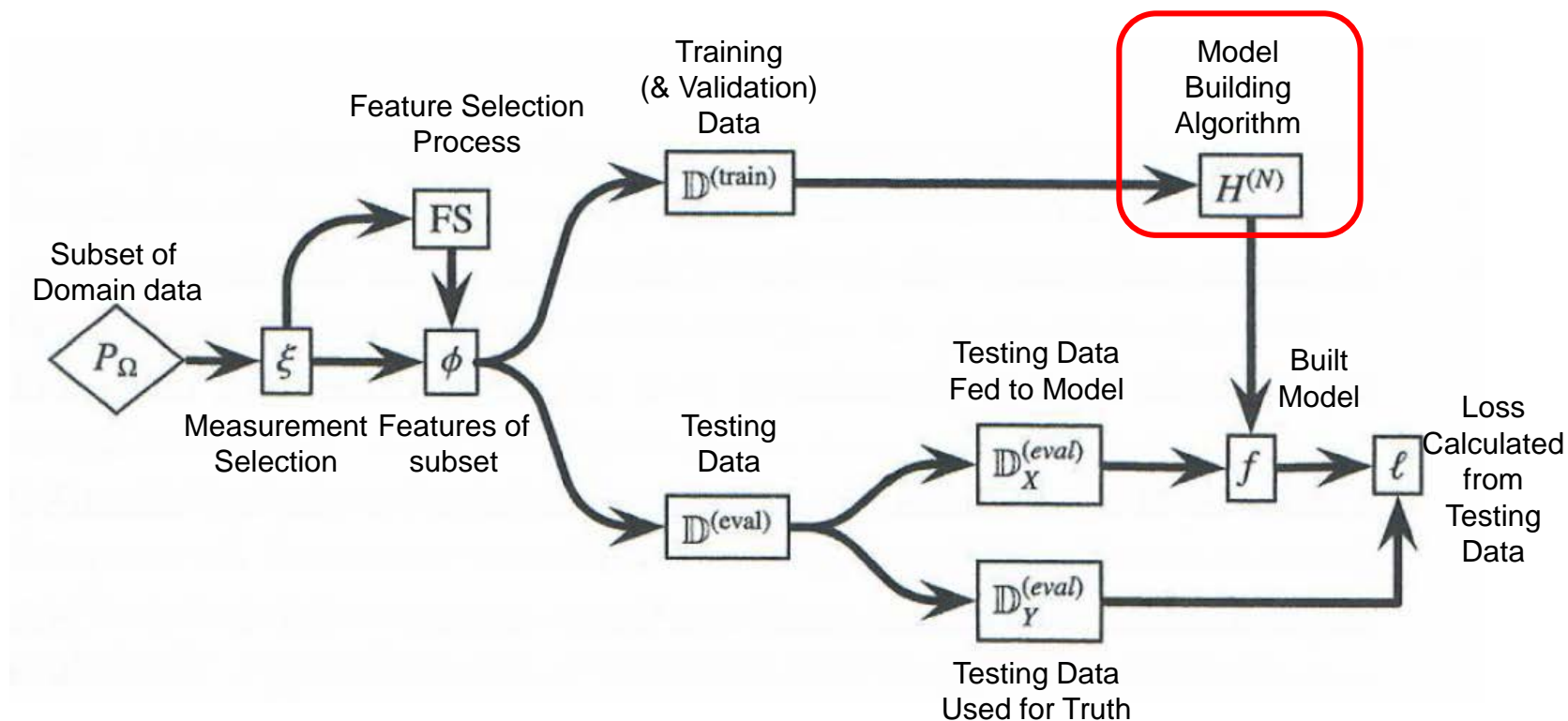
Adapted from Joseph, Nelson, Rubinstein, Tygar; Adversarial Machine Learning, Cambridge University Press, 2019

# Data Attacks – Training Data



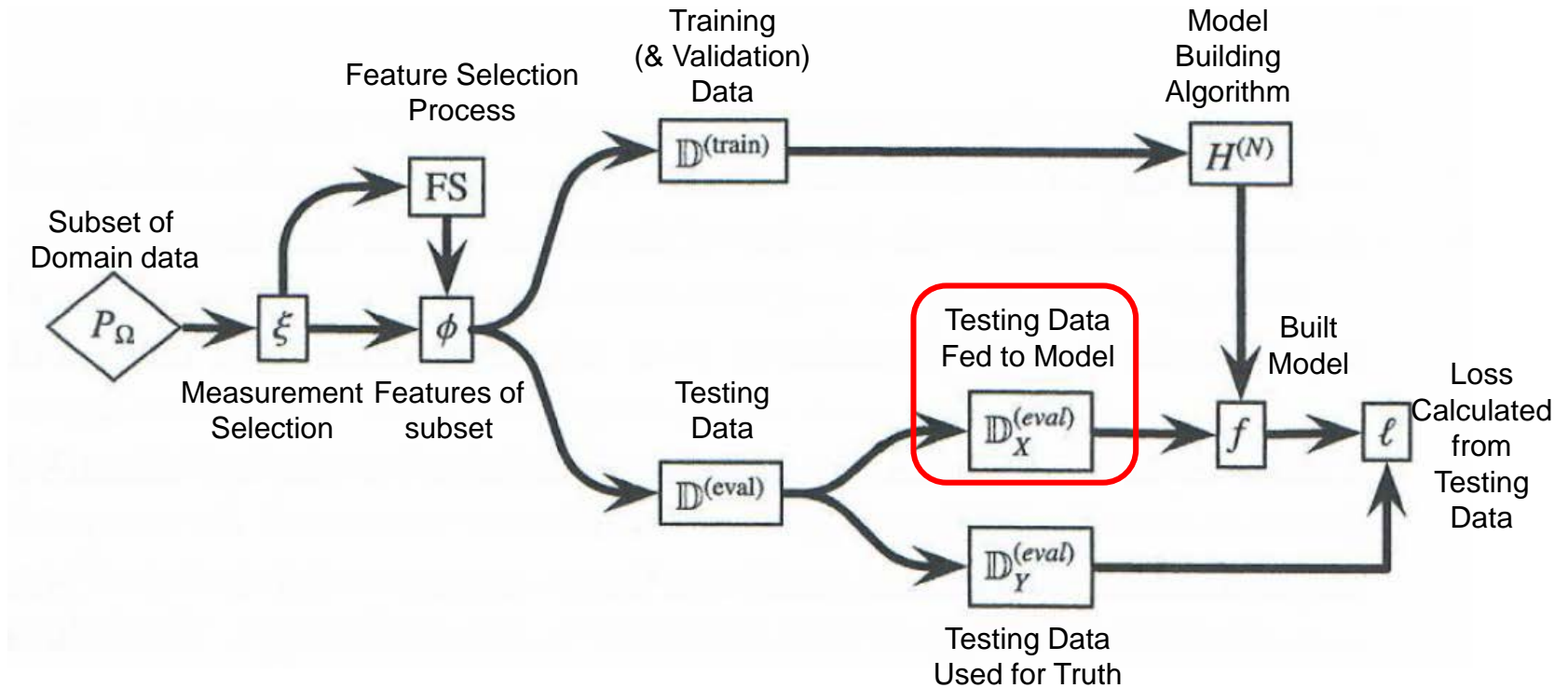
Adapted from Joseph, Nelson, Rubinstein, Tygar; Adversarial Machine Learning, Cambridge University Press, 2019

# Algorithm Attacks – Model Construction



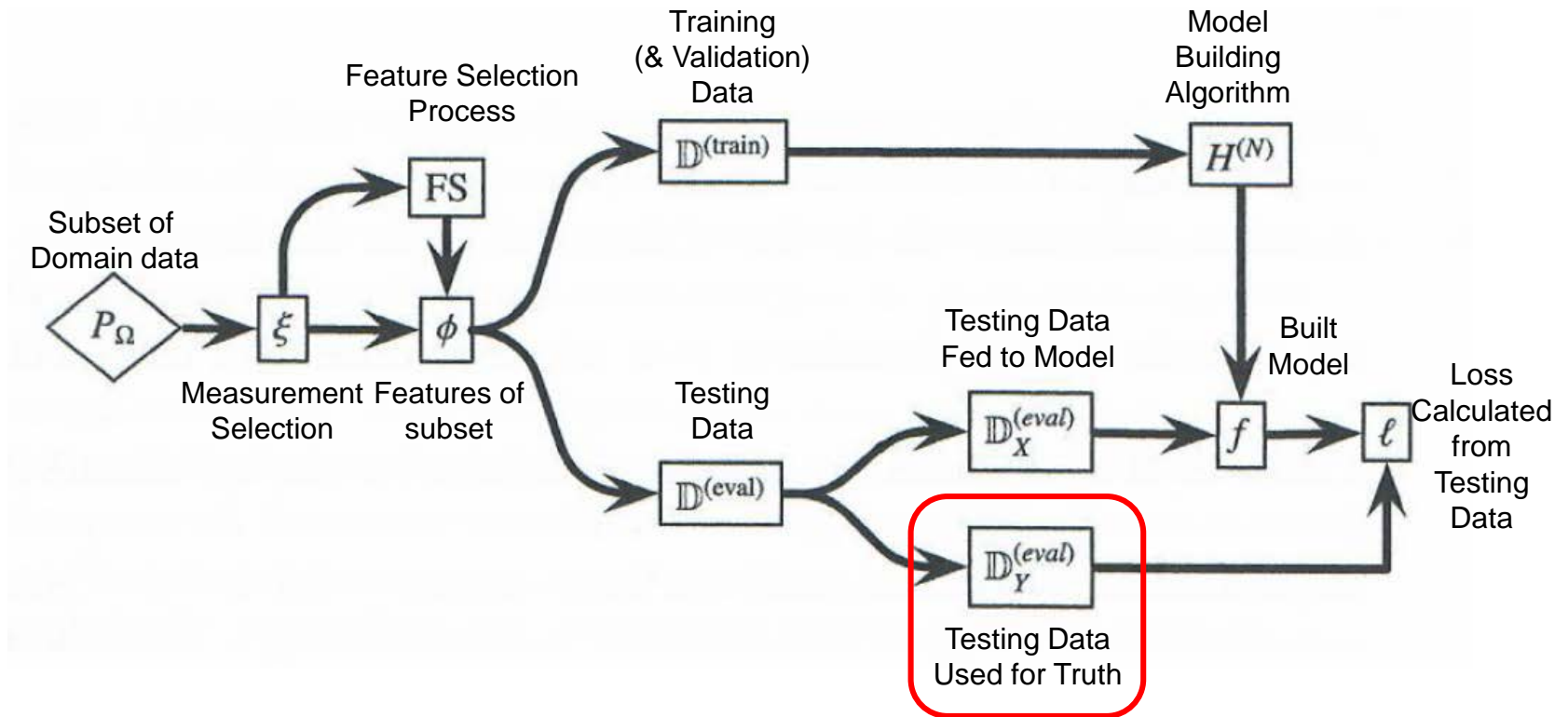
Adapted from Joseph, Nelson, Rubinstein, Tygar; Adversarial Machine Learning, Cambridge University Press, 2019

# Data Attacks – Model Testing Data



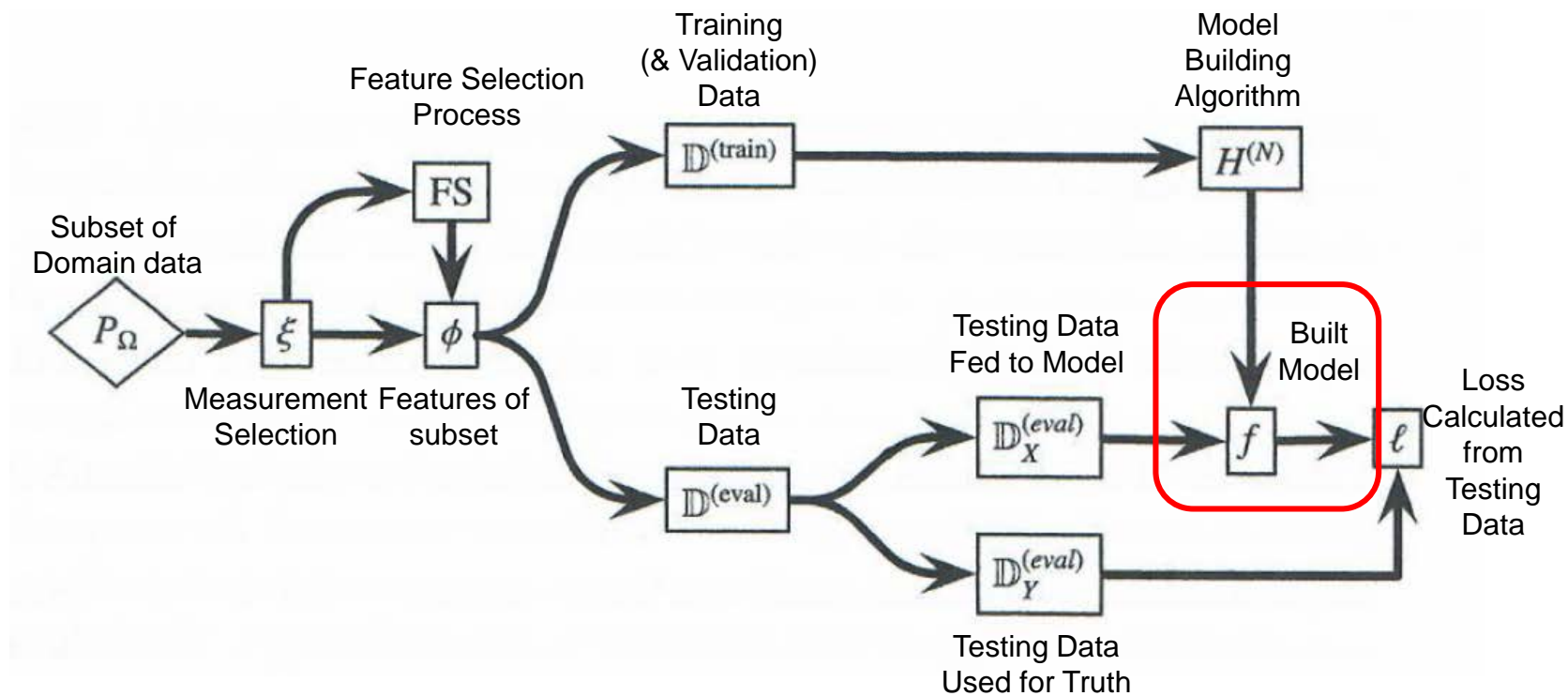
Adapted from Joseph, Nelson, Rubinstein, Tygar; Adversarial Machine Learning, Cambridge University Press, 2019

# Data Attacks – Ground Truth



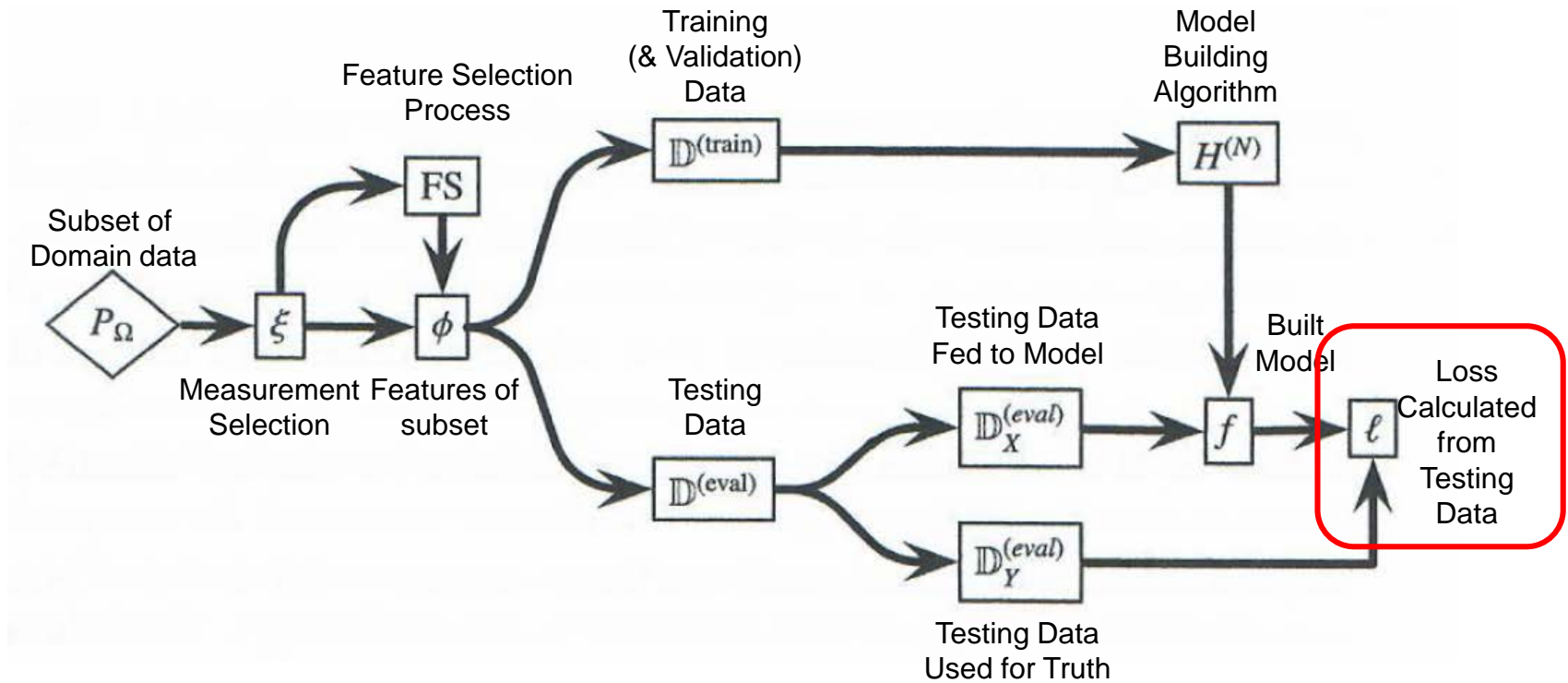
Adapted from Joseph, Nelson, Rubinstein, Tygar; Adversarial Machine Learning, Cambridge University Press, 2019

# Algorithm Attacks – Model



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

# Data Attack – Loss Measurements



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



# Outline

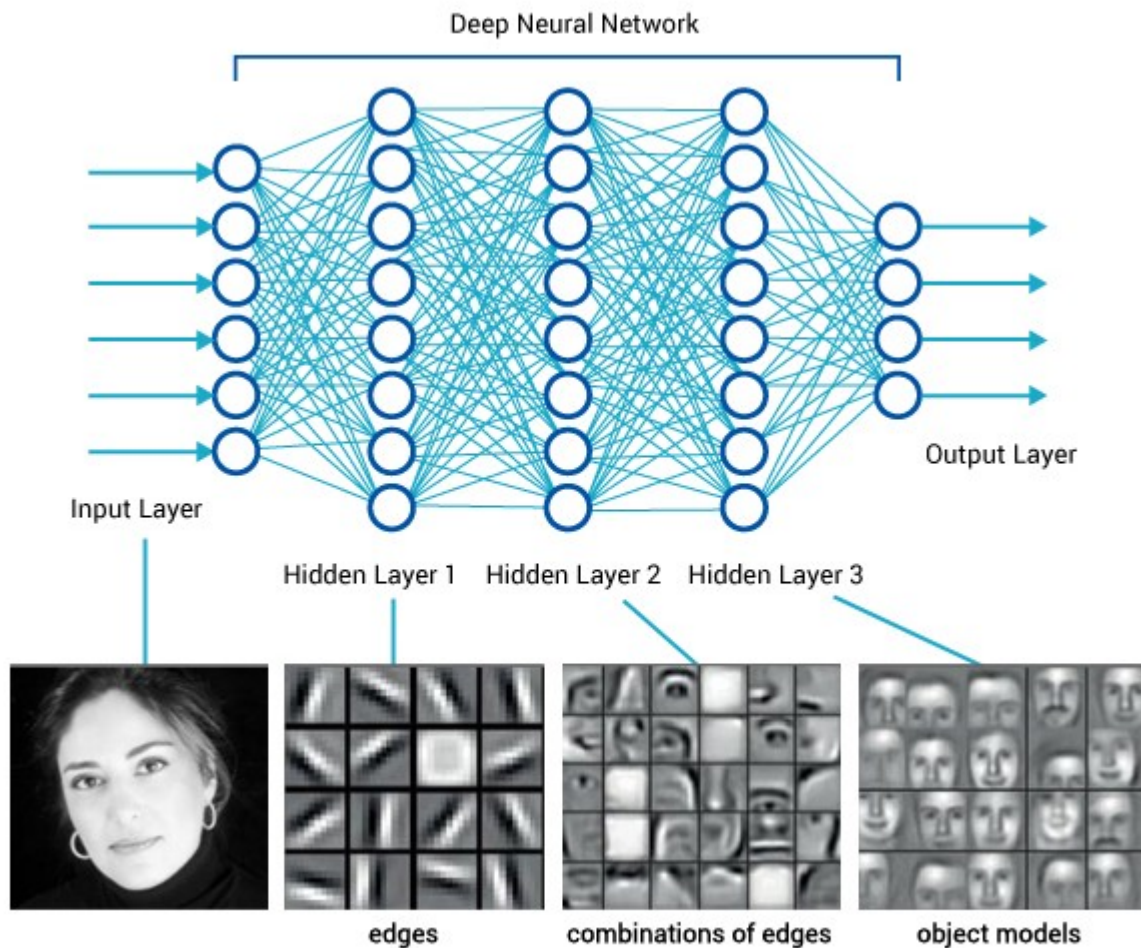
**Understanding the ML Attack Surface**

**Understanding Risks of Transfer Learning**

**Remedies and Limitations**

**Conventional Threats to Machine Learning**

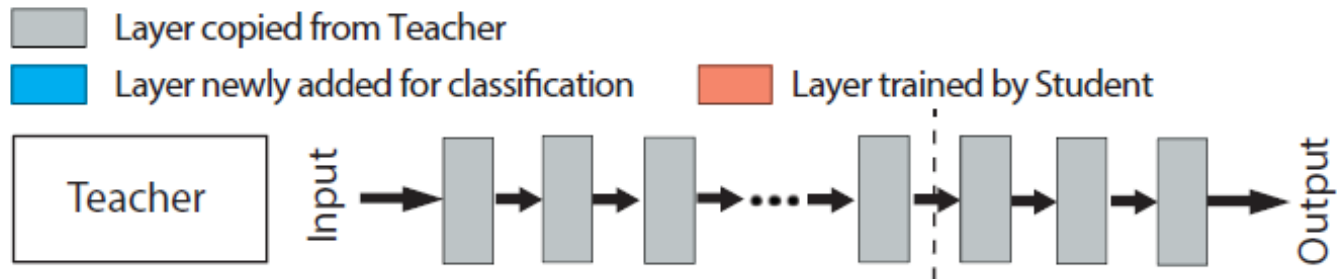
# Deep Neural Network Structure



[Aashay Sachdeva](https://medium.com/diaryofawannapreneur/deep-learning-for-computer-vision-for-the-average-person-861661d8aa61), 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>

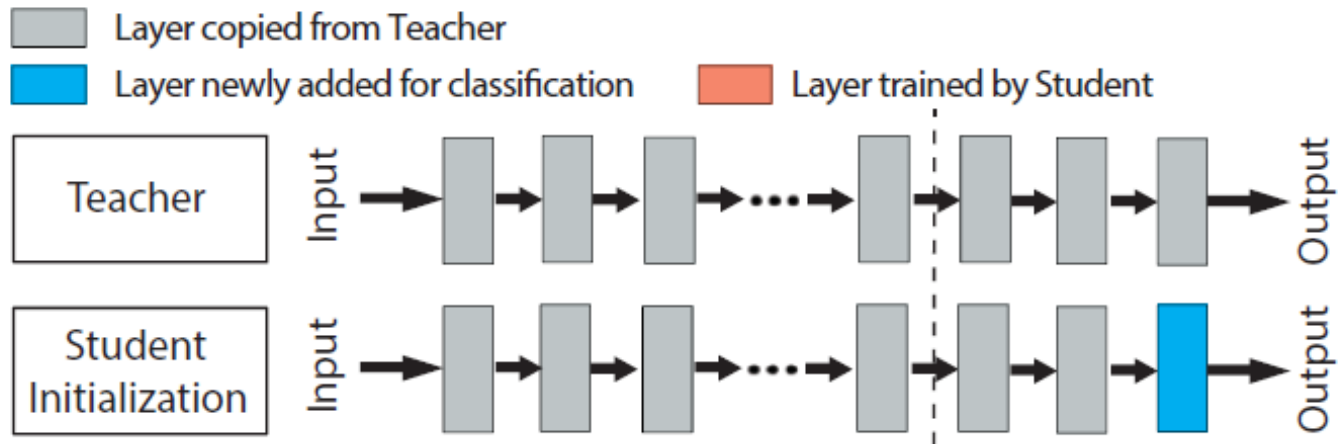


# Overview of Transferring Learning



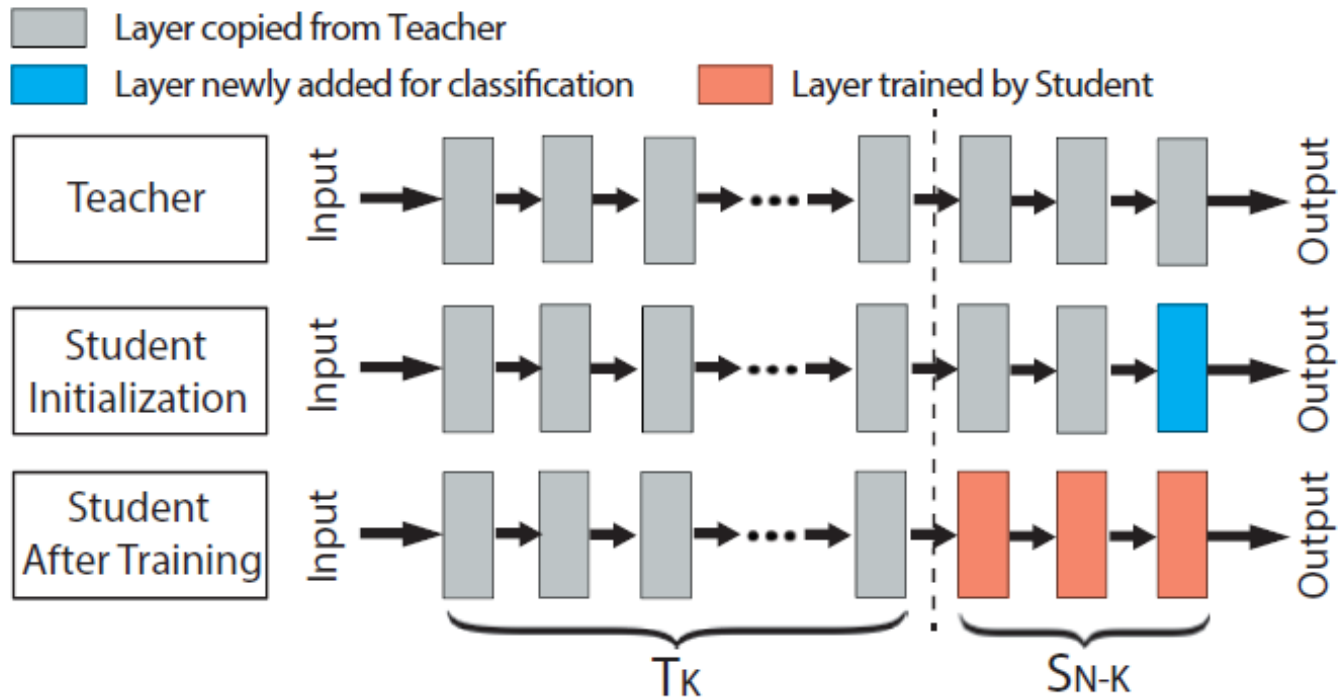
Bolun Wang, Yuanshun Yao, Bimal Viswanath, Haitao Zheng, Ben Y. Zhao; "With Great Training Comes Great Vulnerability: Practical Attacks Against Transfer Learning," 27th USENIX Security Symposium; Aug 15-17, 2018; pg 1281

# Overview of Transferring Learning



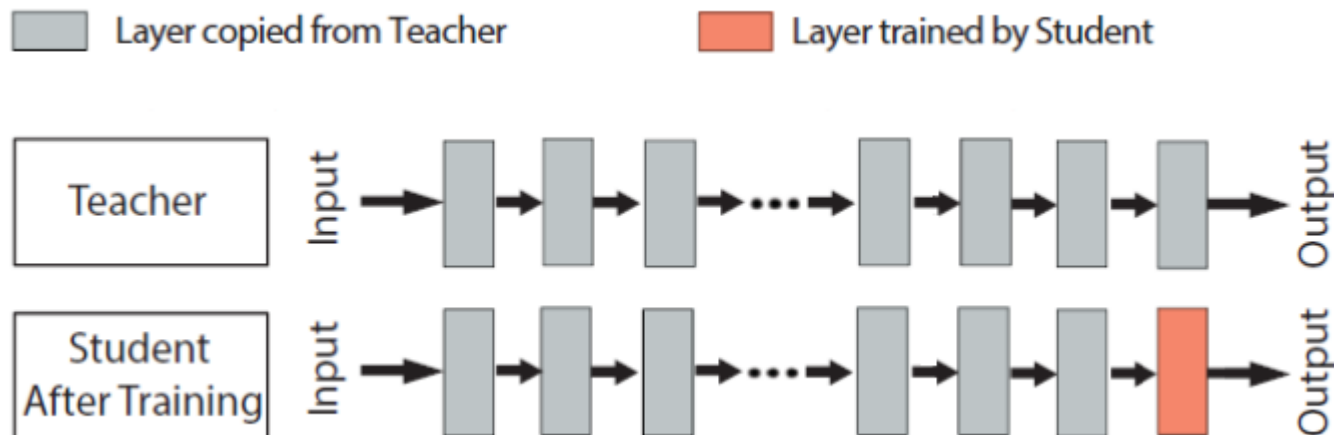
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# Overview of Transferring Learning



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# Deep Layer Feature Extraction



Used when domains are close

Pro: Cheap training; good accuracy

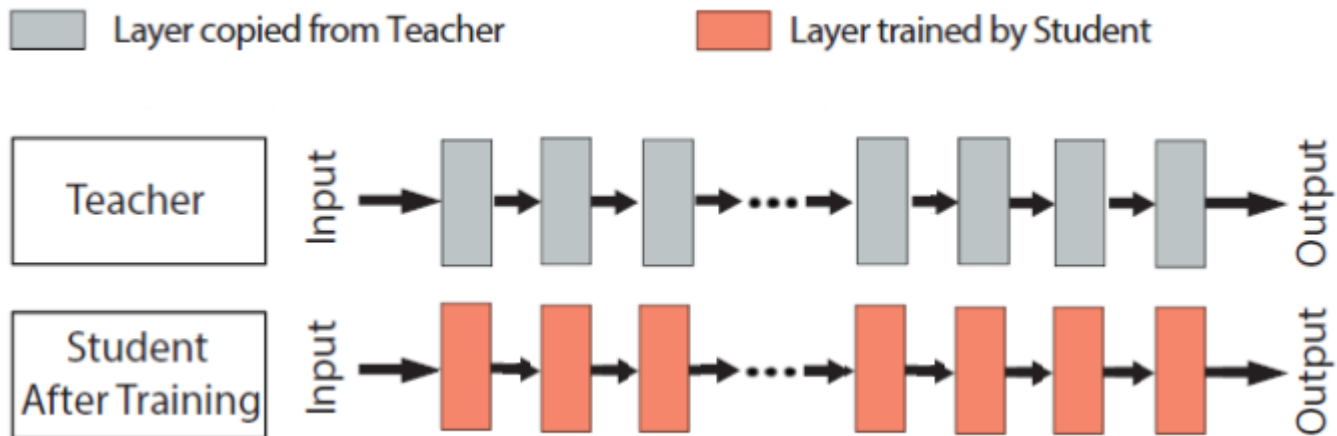
Con: Adversary has deep knowledge of teacher

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

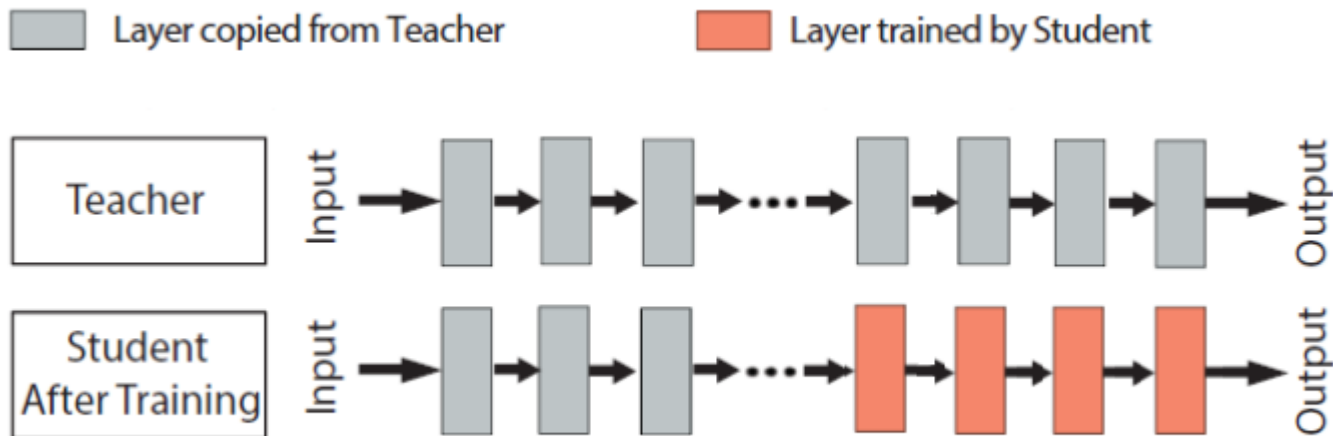
Pro: Better accuracy than deep layer feature extraction  
Resilient to teacher-specific attacks

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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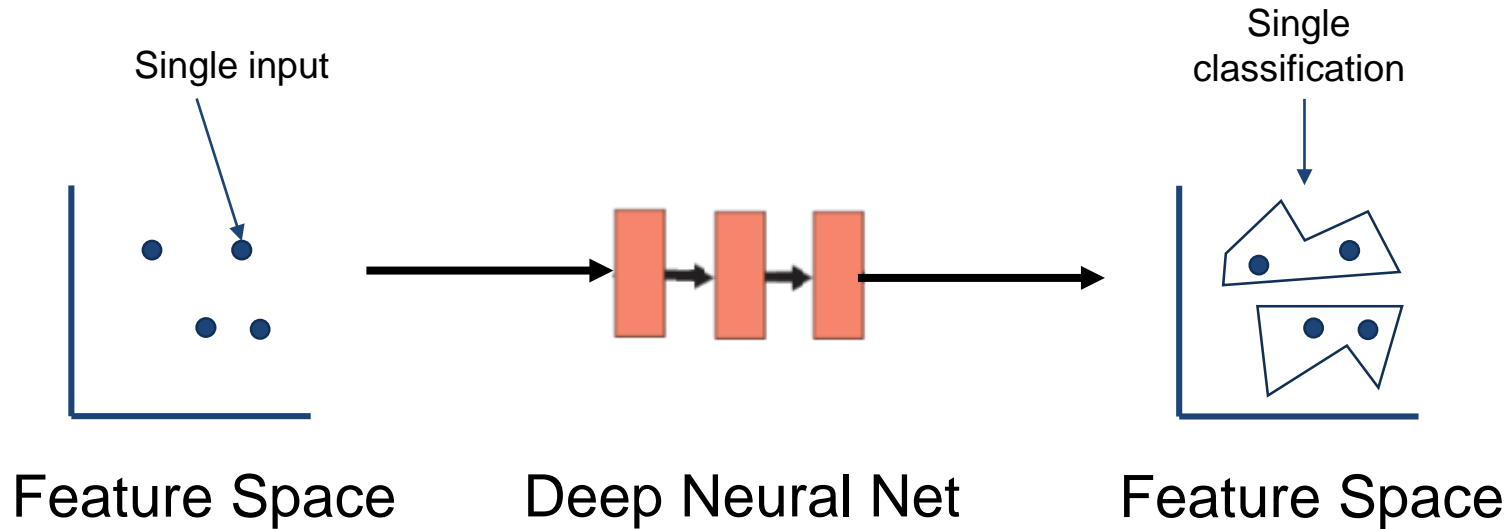
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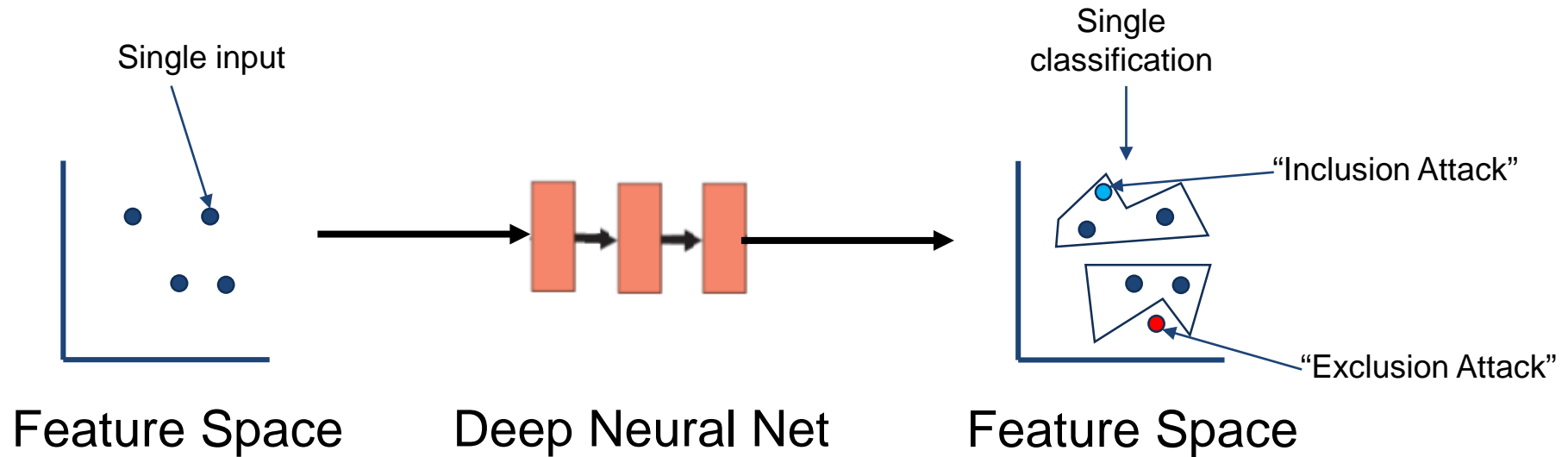
**Remedies and Limitations**

**Conventional Threats to Machine Learning**

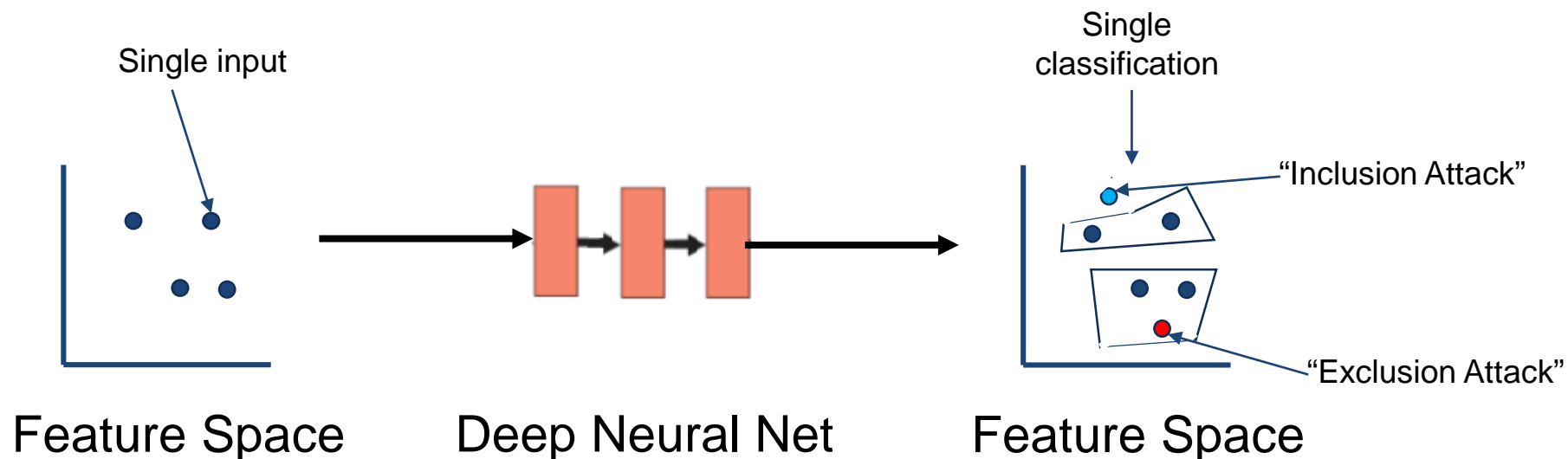
# Creating Classifications



# 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

# Outline


**Understanding the ML Attack Surface**

**Understanding Risks of Transfer Learning**

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**Conventional Threats to Machine Learning**

# Coding Hygiene



Common Vulnerabilities and Exposures

CVE List ▾    CNAs ▾ About ▾    WGs ▾ News & Blog ▾    Board ▾    **NVD**  
Go to for:  
[CVSS Scores](#)  
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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	
<b>CVE-2020-5215</b>	<a href="#">Learn more at National Vulnerability Database (NVD)</a> • 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 <code>tf.constant("hello", tf.float16)</code> , 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”

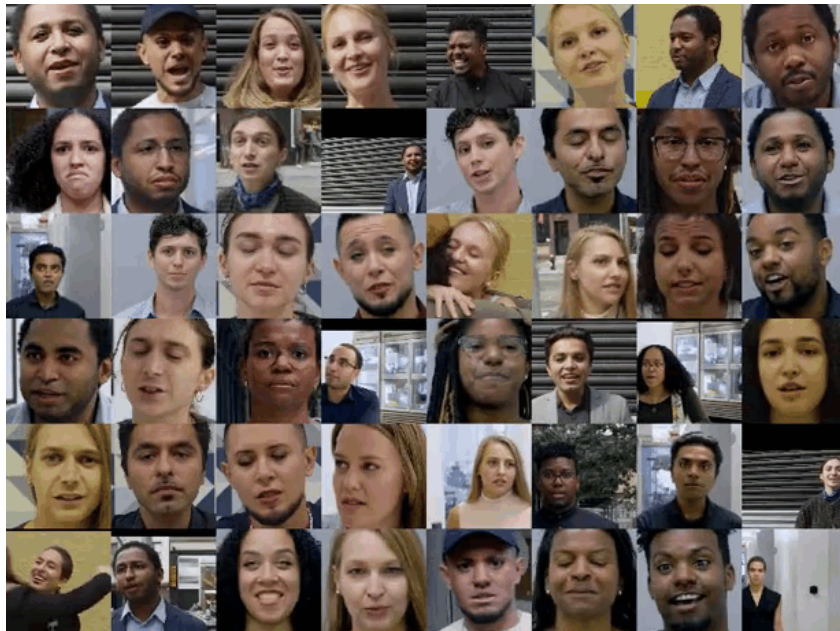
## Machine Learning Frameworks

- Pandas
- Numpy
- Scikit-learn
- Matplotlib
- TensorFlow
- Keras
- Seaborn
- Pytorch & Torch

## Data Sources

- Kaggle
- UCI Machine Learning Repository
- Find Datasets
- Data.gov
- xView
- ImageNet
- 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 reliably verify that training data obtained through a supply chain

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

## FaceForensics Benchmark

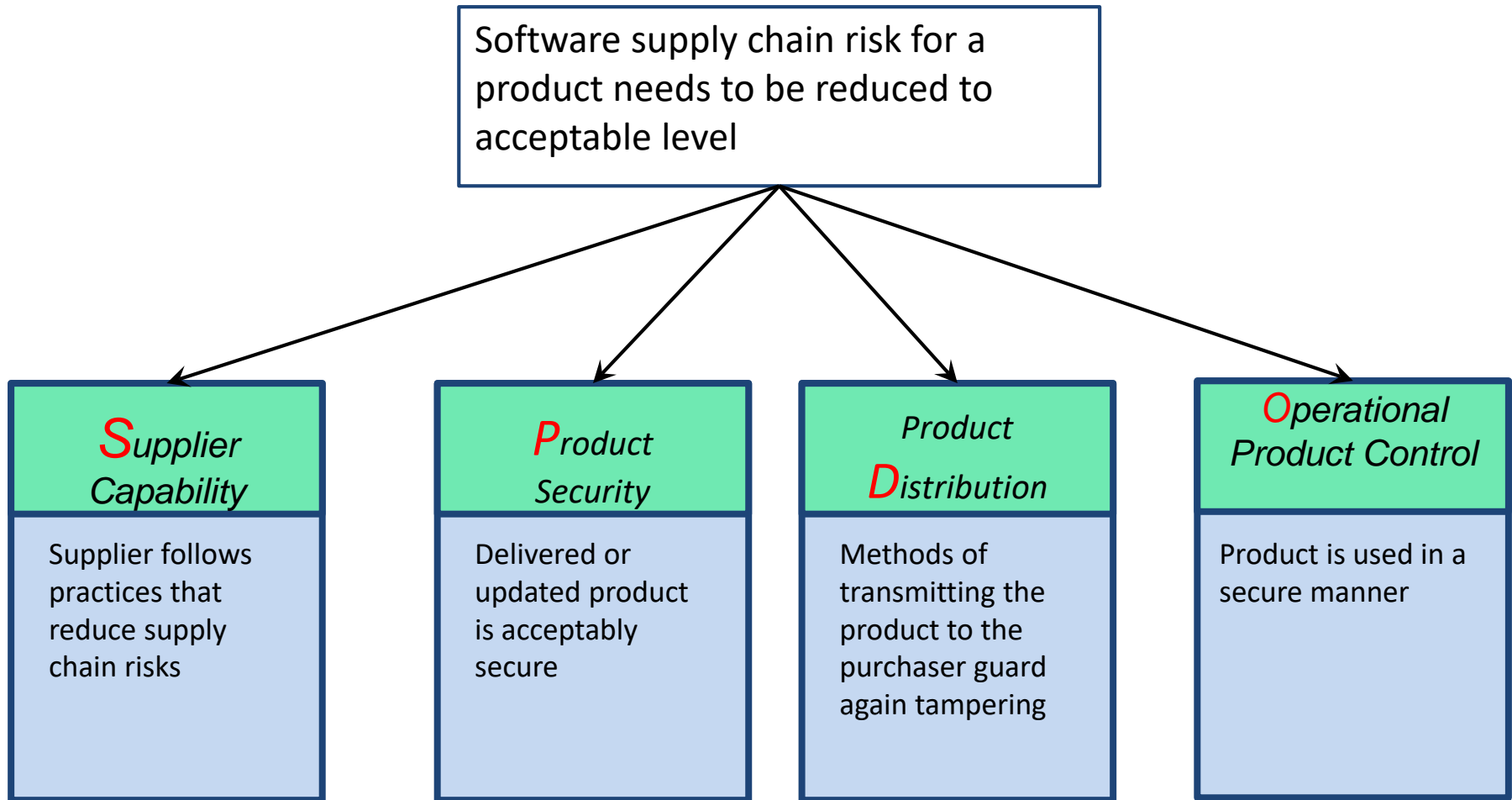
This table lists the benchmark results for the Binary Classification scenario.

Method	Info	Deepfakes	Face2Face	FaceSwap	NeuralTextures	Pristine	Total
<a href="#">Xception</a>	Andreas Rössler, Davide Cozzolino, Luisa Verdoliva, Christian Riess, Justus Thies, Matthias Nießner: <a href="#">FaceForensics++: Learning to Detect Manipulated Facial Images</a> . ICCV 2019	0.964	0.869	0.903	0.807	0.524	0.710
<a href="#">MesoNet</a>	Darius Afchar, Vincent Nozick, Junichi Yamagishi, and Isao Echizen: <a href="#">MesoNet: a compact facial video forgery detection network</a> . arXiv	0.873	0.562	0.612	0.407	0.726	0.660
<a href="#">XceptionNet Full Image</a>	Andreas Rössler, Davide Cozzolino, Luisa Verdoliva, Christian Riess, Justus Thies, Matthias Nießner: <a href="#">FaceForensics++: Learning to Detect Manipulated Facial Images</a> . ICCV 2019	0.745	0.759	0.709	0.733	0.510	0.624
<a href="#">Bayar and Stamm</a>	Belhassen Bayar and Matthew C. Stamm: <a href="#">A deep learning approach to universal image manipulation detection using a new convolutional layer</a> . ACM Workshop on Information Hiding and Multimedia Security	0.845	0.737	0.825	0.707	0.462	0.616
<a href="#">Rahmouni</a>	Nicolas Rahmouni, Vincent Nozick, Junichi Yamagishi, and Isao Echizen: <a href="#">Distinguishing computer graphics from natural images using convolution neural networks</a> . IEEE Workshop on Information Forensics and Security.	0.855	0.642	0.563	0.607	0.500	0.581
<a href="#">Recasting</a>	Davide Cozzolino, Giovanni Poggi, and Luisa Verdoliva: <a href="#">Recasting residual-based local descriptors as convolutional neural networks: an application to image forgery detection</a> . ACM Workshop on Information Hiding and Multimedia Security	0.855	0.679	0.738	0.780	0.344	0.552
<a href="#">Steganalysis Features</a>	Jessica Fridrich and Jan Kodovsky: <a href="#">Rich Models for Steganalysis of Digital Images</a> . IEEE Transactions on Information Forensics and Security.	0.736	0.737	0.689	0.633	0.340	0.518

Source:

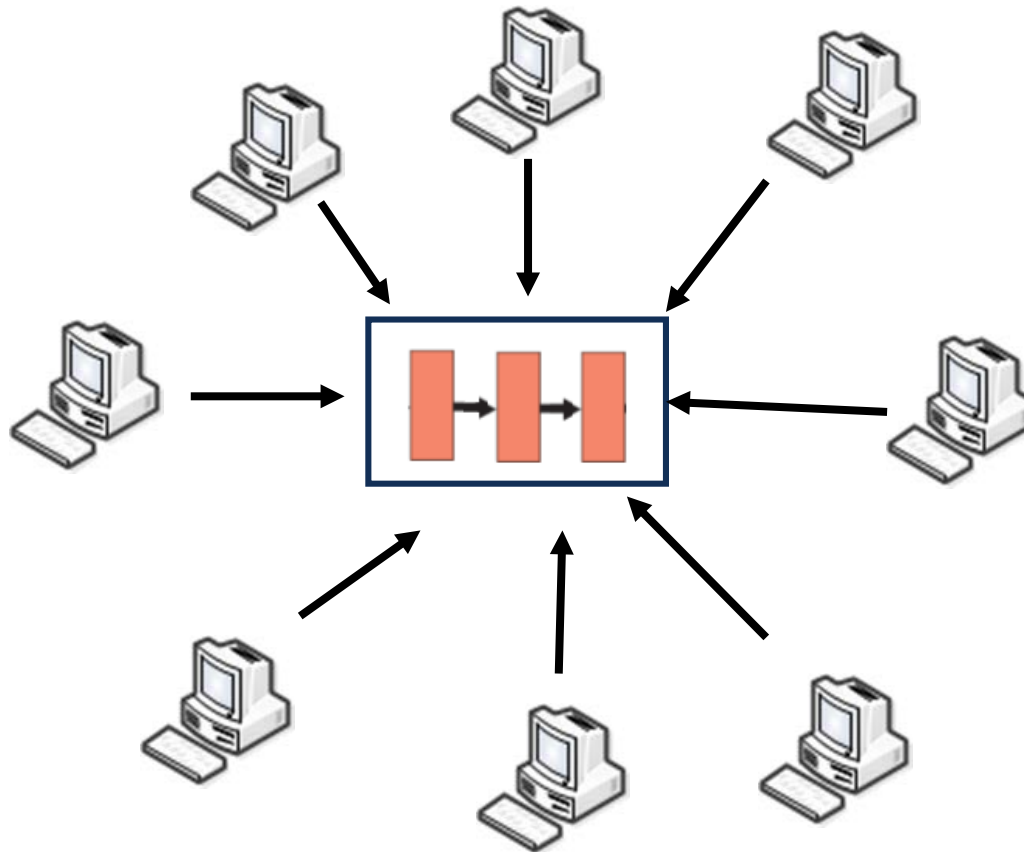
[http://kaldir.vc.in.tum.de/faceforensics\\_benchmark/index.php](http://kaldir.vc.in.tum.de/faceforensics_benchmark/index.php) (as of 9/25/19)

# 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](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



# Outline

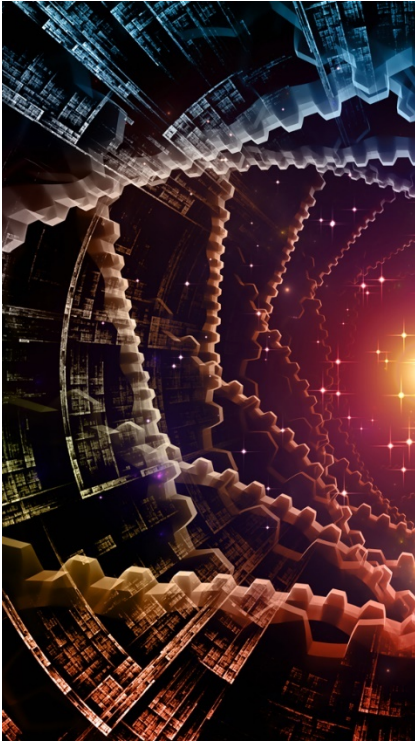
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# Ways to Engage with Us



- 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

## Software Engineering Institute

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