Carnegie Mellon University
Software Engineering Institute

Data Science for Cybersecurity Workshop

INFOSEC WORLD

INFOSECWORLDUSA.COM

This material is based upon work funded and supported by the Department of Defense under Contract No. FA8702-15-D-0002 with Carnegie Mellon University for the operation of the Software Engineering Institute, a federally funded research and development center. The view, opinions, and/or findings contained in this material are those of the author(s) and should not be construed as an official Government position, policy, or decision, unless designated by other documentation.

DM22-0810

[DISTRIBUTION STATEMENT A] This material has been approved for public release and unlimited distribution. Please see Copyright notice for non-US Government use and distribution.

Carnegie Mellon University
Software Engineering Institute

Thomas Scanlon

Technical Manager – CERT Data Science

Software Engineering Institute

Carnegie Mellon University

Clarence Worrell

Senior Data Scientist

Software Engineering Institute

Carnegie Mellon University

Carnegie Mellon University (CMU)

Pioneering discoveries that enrich the lives of people on a global scale

- Turning disruptive ideas into success through leading-edge research
- 2021 *U.S. News and World Report* rankings
  - #1 in computer engineering, artificial intelligence (AI), cybersecurity, and software engineering
  - #2 in overall computer science
  - #3 in data analytics/science

CMU Software Engineering Institute (SEI)

Carnegie Mellon University
Software Engineering Institute

Bringing innovation to the U.S. Government

- A Federally Funded Research and Development Center (FFRDC) chartered in 1984 and sponsored by the Department of Defense (DoD)
- Leader in researching complex software engineering, cyber security, and AI engineering solutions
- Critical to the U.S. Government's ability to acquire, develop, operate, and sustain software systems that are innovative, affordable, trustworthy, and enduring

The CERT Division: The Birthplace of Cybersecurity

- **Trusted**
  Conducting research for the U.S. Government in a non-profit, public-private partnership
- **Valued**
  Collaborating with military, industry, and academia globally to innovate solutions
- **Relevant**
  Achieving technology and talent results for our mission partners

CERT Applied Data Science for Cybersecurity Professional Certificate

	Classroom	eLearning	Onsite
Fundamentals of Statistics Applied to Cybersecurity		✔	
Advanced Analytics: Netflow		✔	
Advanced Analytics: Malware		✔	
Advanced Analytics: Digital Forensics		✔	
CERT Applied Data Science for Cybersecurity Certificate Examination		✔	

https://www.sei.cmu.edu/education-outreach/credentials/credential.cfm?customel_datapageid_14047=348770

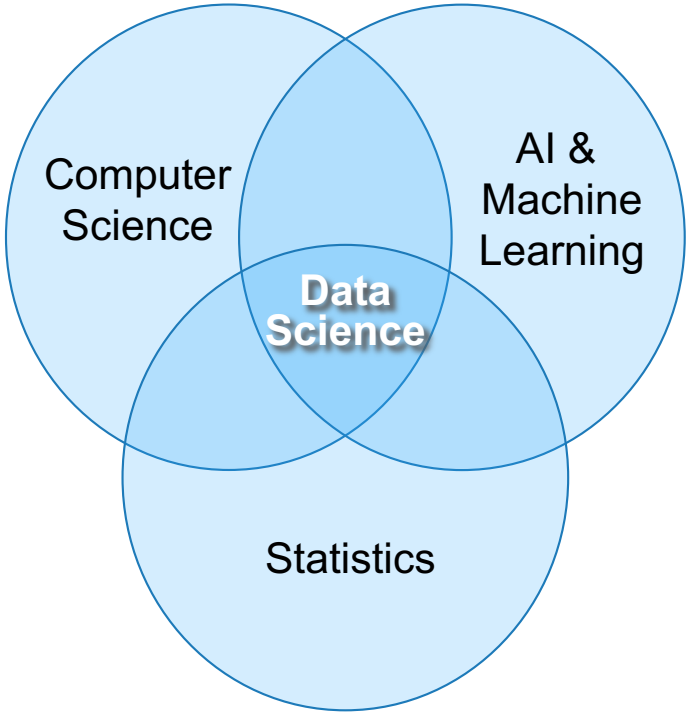
Carnegie Mellon University
Software Engineering Institute

Data Science for Cybersecurity Overview

INFOSEC WORLD

INFOSECWORLDUSA.COM

Data Science



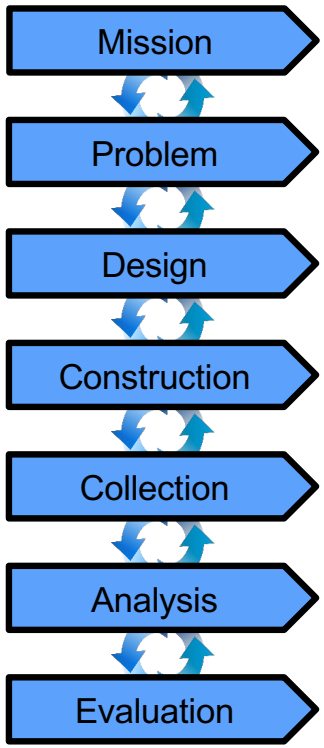
Analysis Techniques

- Prediction
- Classification
- Deep Learning
- "Big Data"
- Outlier detection
- Feature extraction

Methods:

- Regression
- Neural nets
- Bayesian networks
- Structural equation modeling
- Latent Dirichlet allocation
- Hidden Markov models
- Gradient boosting
- …

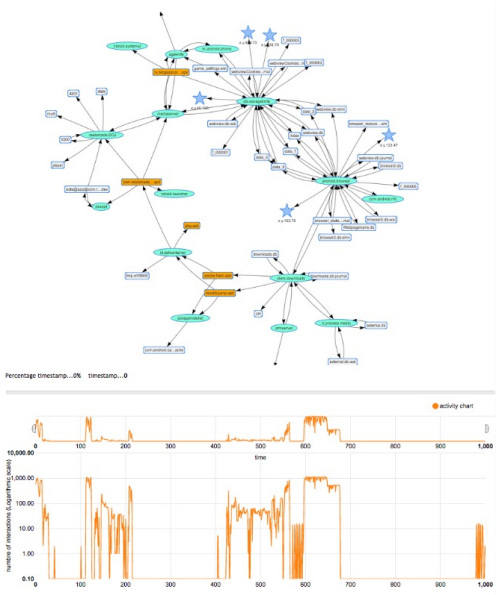
Data Analytics



Data Types

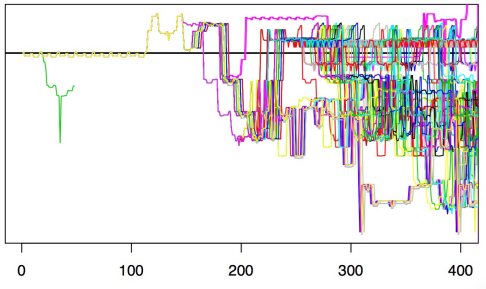
Image	Static Video
Time series	Financial data Event counts
Network data	Netflow PCAP DNS BGP
Structured text	Web forms Structured data (JSON, XML) Source code
Free text	News Tweets Email
many more…	

Malware family classification

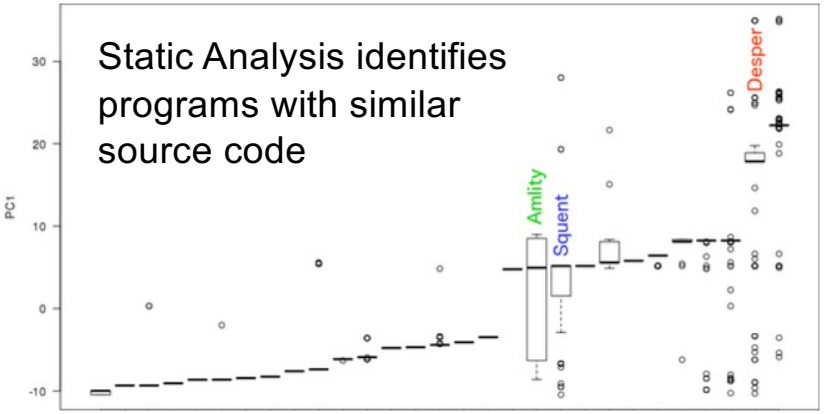


Signal Flow graph highlights behavior relating different malware families

Program instruction analysis shows similarity and diversion of behavior

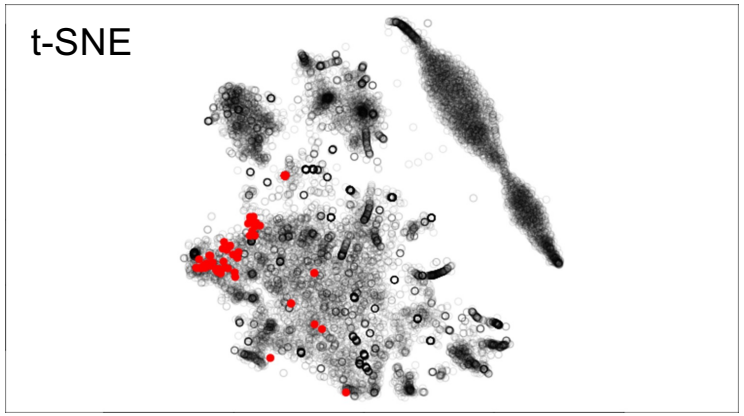


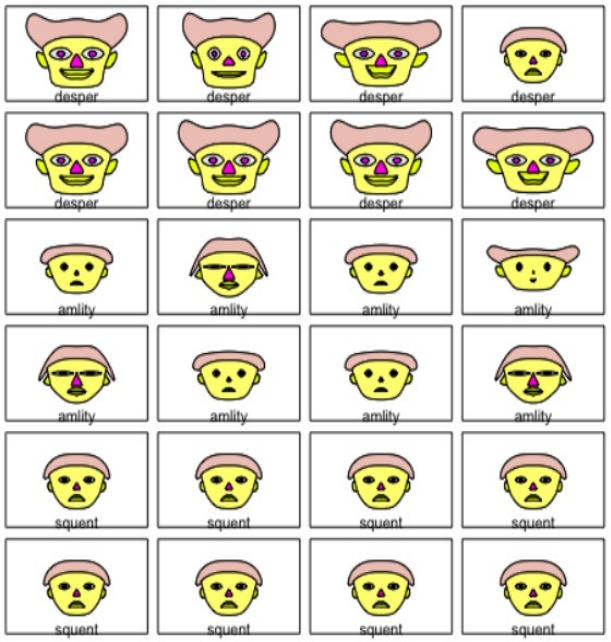
Static Analysis identifies programs with similar source code



Malware family classification – Visualization

Simplify visualization of extremely complex data through the use of dimensionality reduction and associated visualization techniques

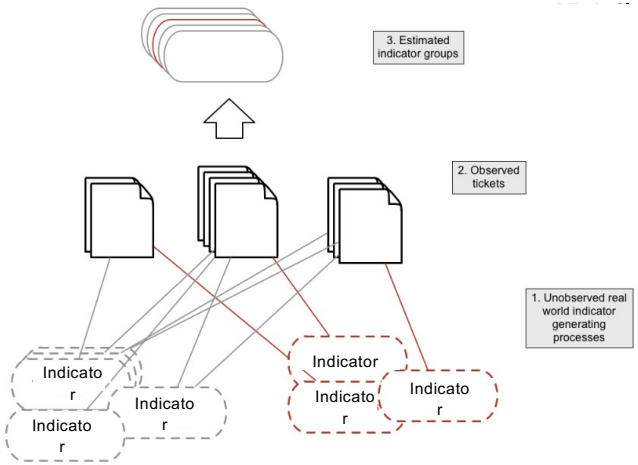


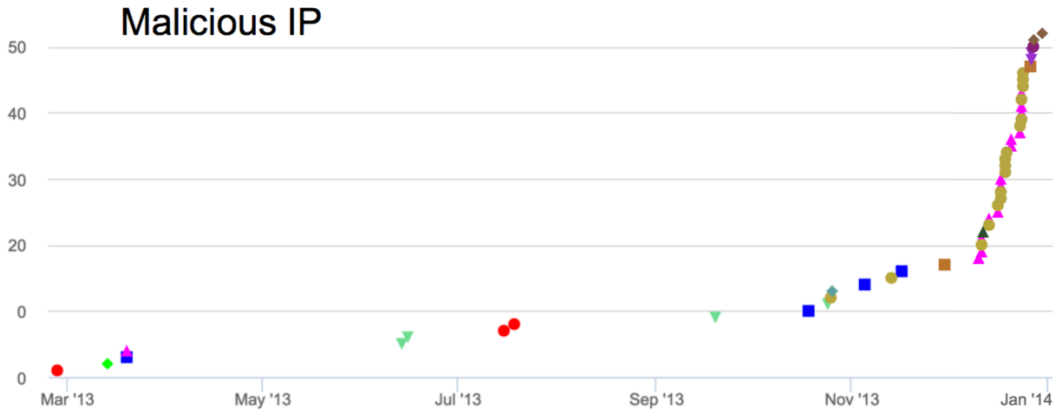


Chernoff face experiment

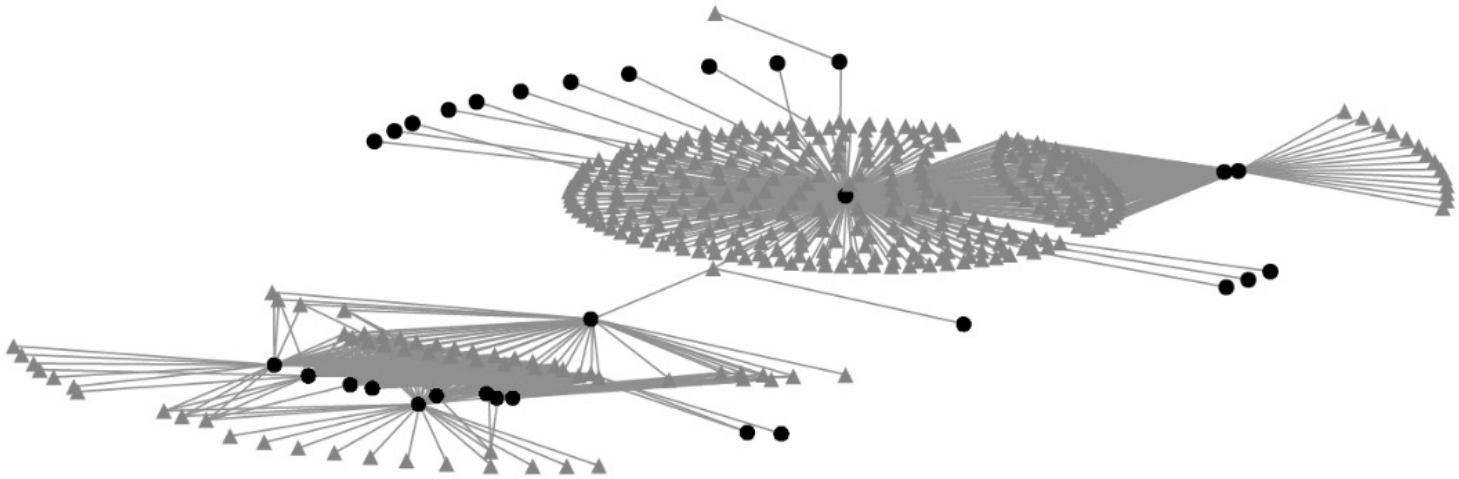
Incident Ticket analysis

Collections of incident tickets often contain hidden trends, revealing attacker methods and techniques that are invisible in individual tickets. Natural Language Processing helps find these trends.





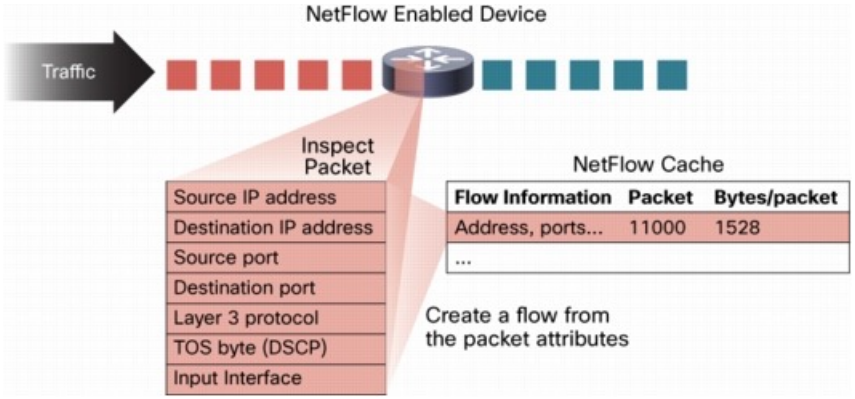
Incident Ticket analysis – Visualization



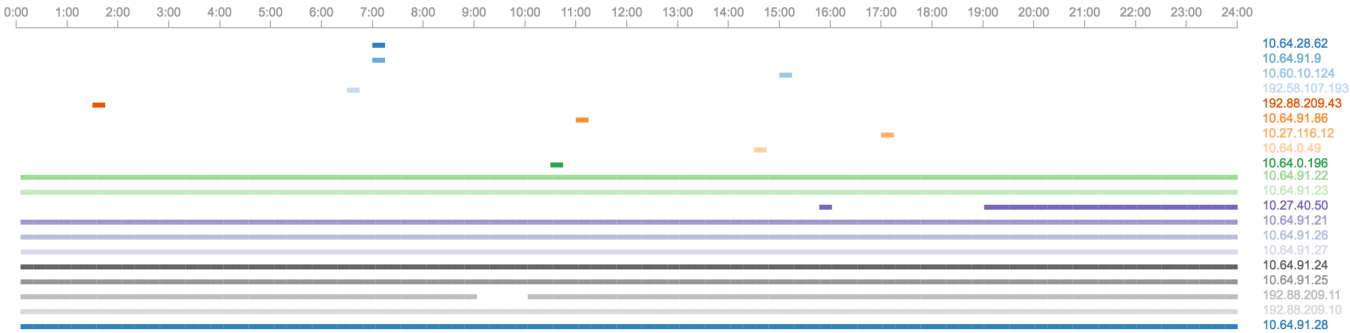
A subset of the ticket-indicator graph
(for a small set of selected indicators)

- Tickets are grey triangles
- Indicators are black circles
- Edges connect tickets to the indicators they contain

Network traffic classification



Netflow data summarizes network traffic, losing significant information. Numerous techniques exist to infer information from the flows themselves.



Other Applications

- APT Defense
- Trust Modeling
- Deepfakes
- Automated forecasting and detection of cyber-attacks
- Static code analyzer behavior
- Technical debt estimation
- Cognitive support for assurance using Watson
- Email sentiment analysis
- IoT based search-and-rescue

Data Science Dos and Don'ts

Do

- Have a question in mind
- Utilize your subject experts
- Think of what data you **need** vs. **have**
- Interrogate your data
- Document all collection, cleaning, and transformation steps
- Justify models used
- Interrogate your model(s)
- Be ready for 'negative' results

Don't

- Force your data to fit your hypothesis
- Forsake model interpretability to do a 'machine learning / AI model'
- Overfit
- Overinterpret

Carnegie Mellon University
Software Engineering Institute

AI/ML Overview

INFOSEC WORLD

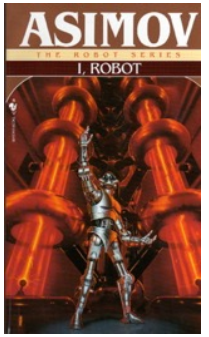
INFOSECWORLDUSA.COM

When People Say "AI," They Might be Referring to Either a Narrow AI or a General AI

- **Narrow AI (Hard)**
- An algorithm to carry out one particular task.

- *Examples:*
- Google Translate
- Autonomous Vehicles
- Spam Filters

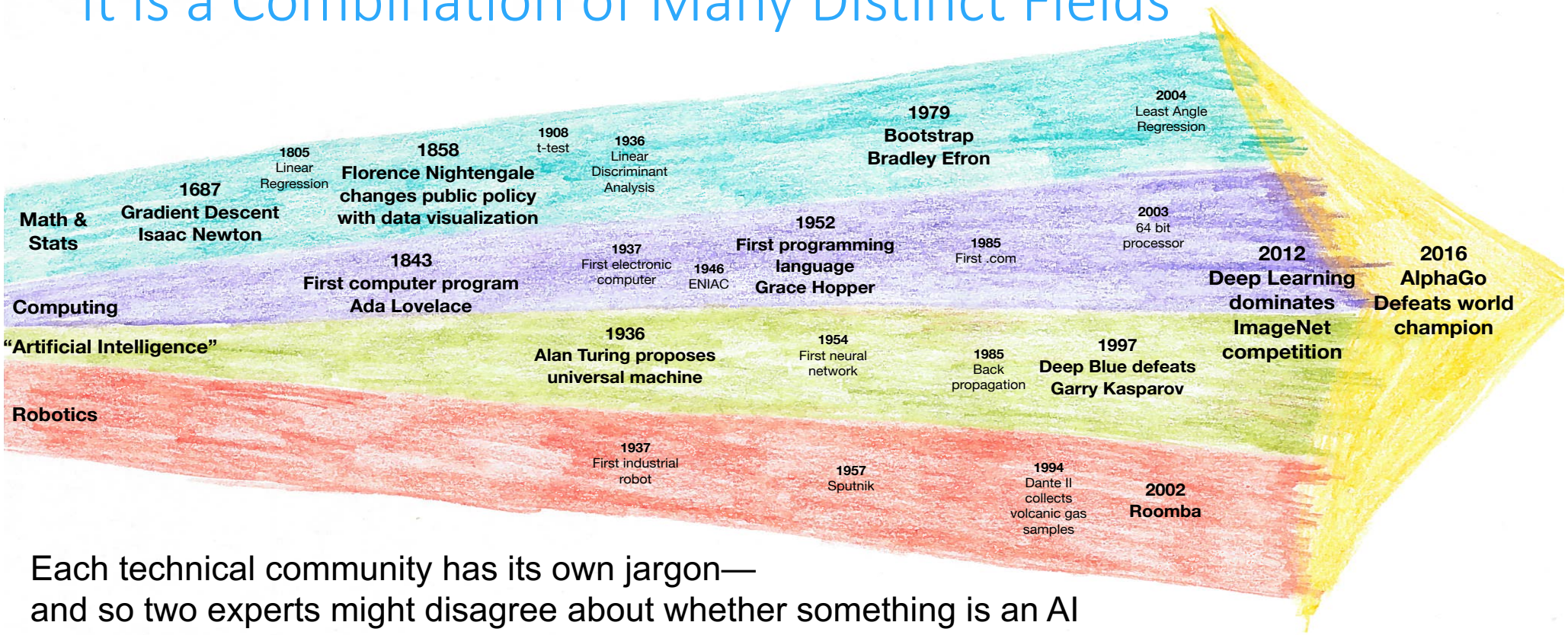
- **General AI (Soft)**
- A machine that exhibits human intelligence.



- *Examples:*
- Doesn't exist yet.
- e.g., one goal should be to be able to monitor the understanding of its audience and make adjustments. This is something human children can generally do by the age of 5.

Modern Artificial Intelligence is not a Monolith, it is a Combination of Many Distinct Fields

Carnegie Mellon University
Software Engineering Institute



Each technical community has its own jargon—
and so two experts might disagree about whether something is an AI

Example of Language Confusion

- **"I want to use _____ to build a speech recognition algorithm."**
- Different people would fill in the blank differently, and mean the same thing:

"Artificial Intelligence" – In this example, probably refers to using ML to set up a narrow AI

"Machine Learning" – A large set of methods for extracting information from data, including neural networks

"Neural Network" – one type of machine learning algorithm, originally patterned after how humans were thought to think

"Deep Learning" – A strategy for building neural networks that are easy to write down and can model complex behavior

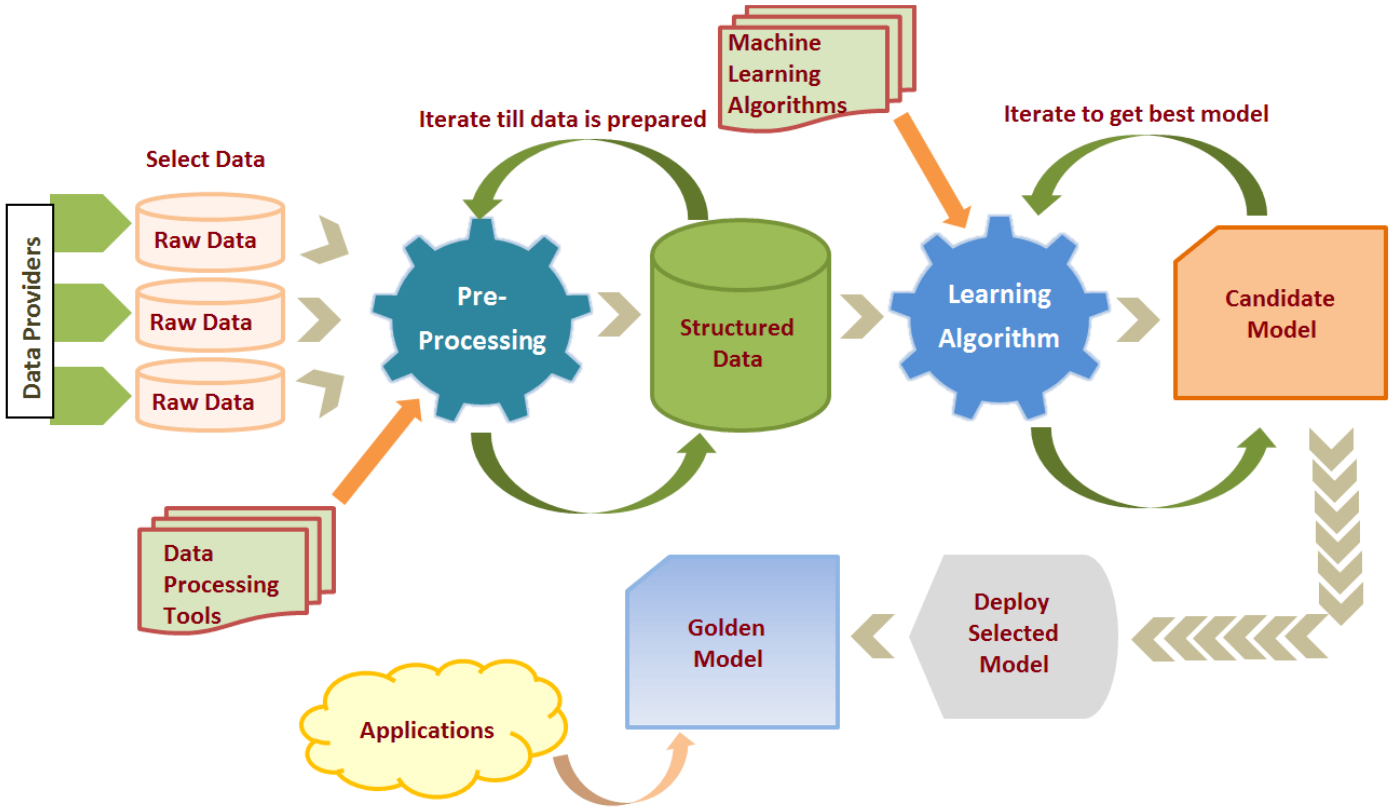
Recommendation: When somebody says AI, ask them to be more specific and define what they mean.

ML and AI

- These could all be considered narrow AI, but do not use any ML:
  - Navigation (Google Maps) – Calculates optimum path based on an algorithm
  - Roomba – uses sensors to map the room, then follows a pre-programmed algorithm to most efficiently cover it
  - Non-Player Characters (NPCs) in video games – dialog and interactions between player characters and NPCs are pre-programmed and constrained for game play.

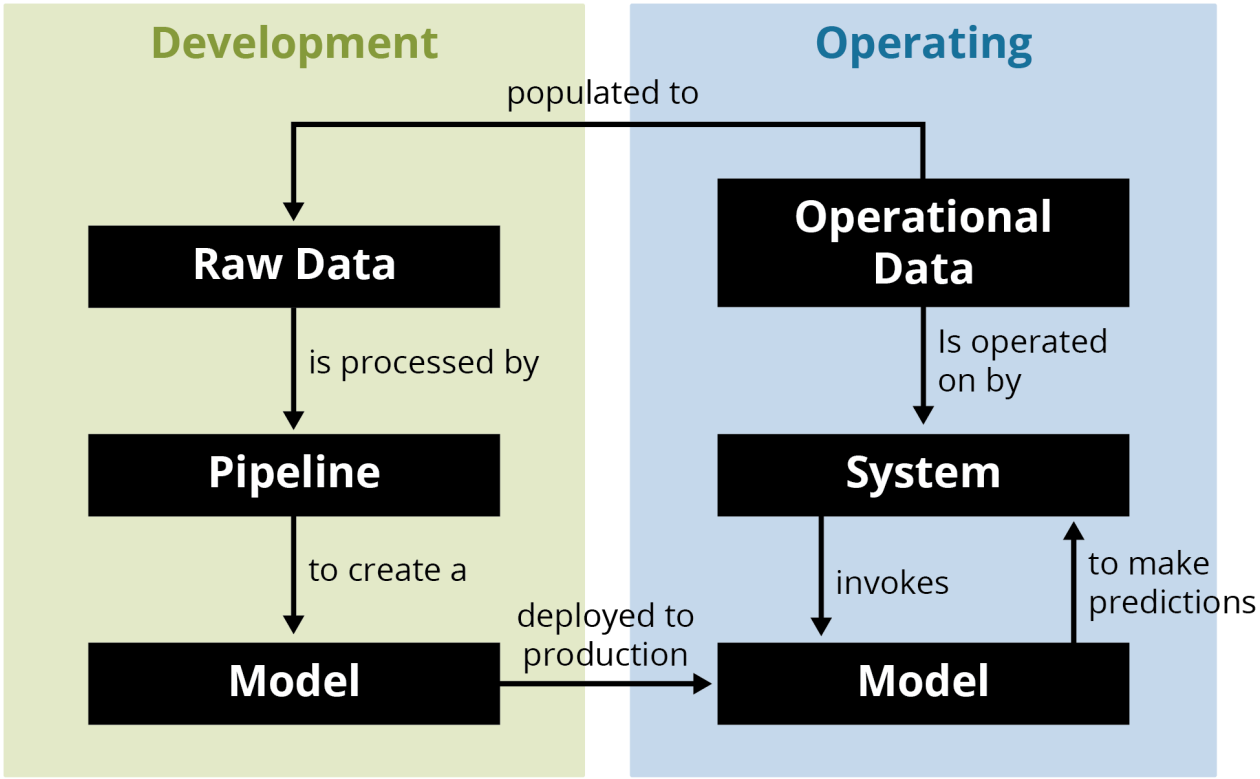
- ***ML is currently one of the best ways to create a successful narrow AI from data:***
  - Image recognition (used in autonomous vehicles)
  - Speech recognition (used in Alexa, Siri, and Echo)
  - Recommendation engines (used by Netflix and Amazon)

ML Process

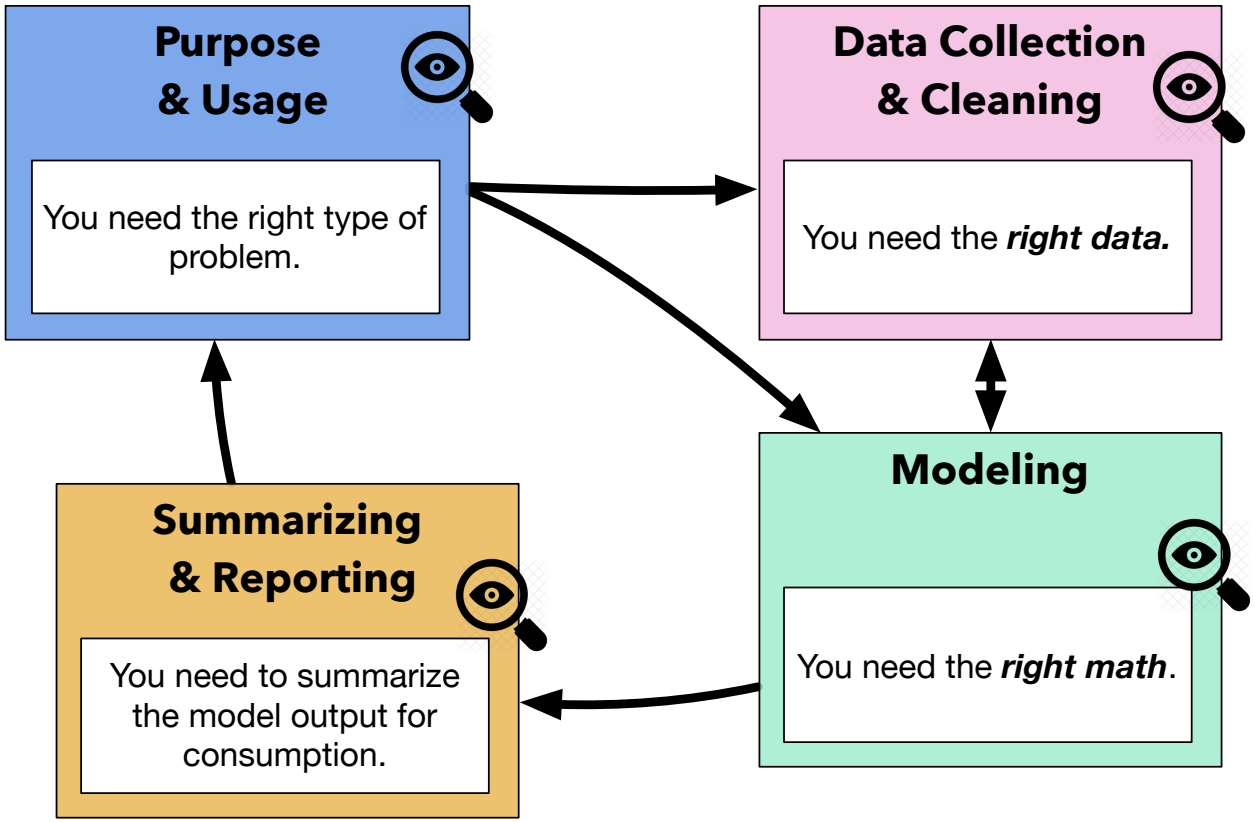


https://elearningindustry.com/machine-learning-process-and-scenarios/

Notional ML Pipeline

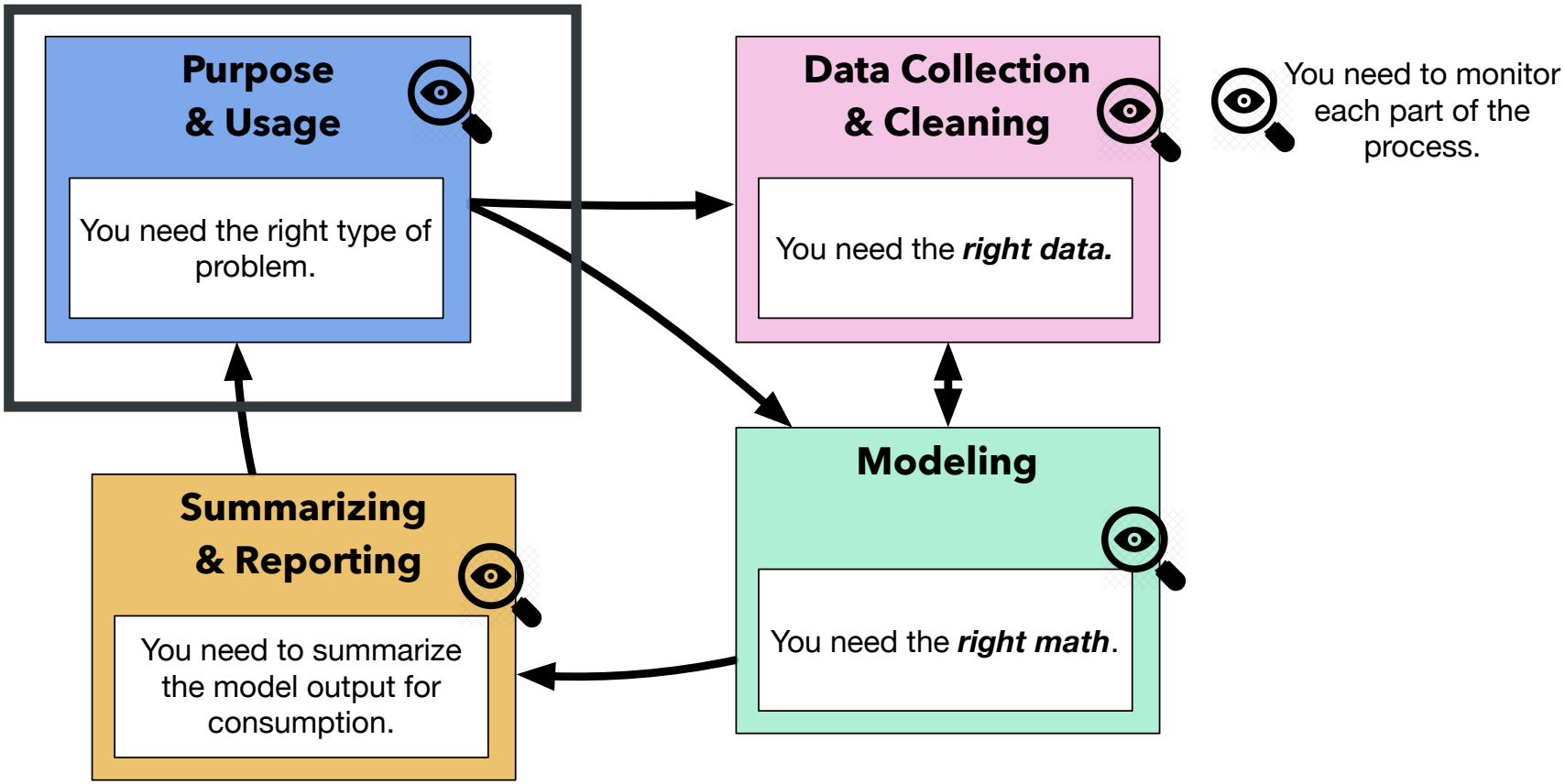


Process for an ML/Data Science Project



For many projects, data collection and cleaning require a majority of the time and effort.

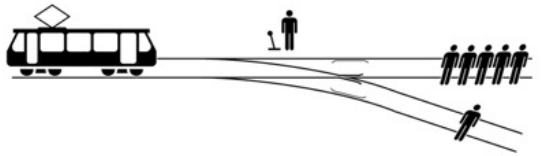
Purpose and Usage



Not all Problems can be Solved with AI (or ML)

- AI cannot solve the trolley problem.

- AI can help optimize a chosen criteria.
- It cannot tell you what criteria to optimize.



You have two options:

1. Do nothing and allow the trolley to kill the five people on the main track.
2. Pull the lever, diverting the trolley onto the side track where it will kill one person.

Moreover: To implement an automatic system (like a self-driving car), we must make these choices ahead of time.

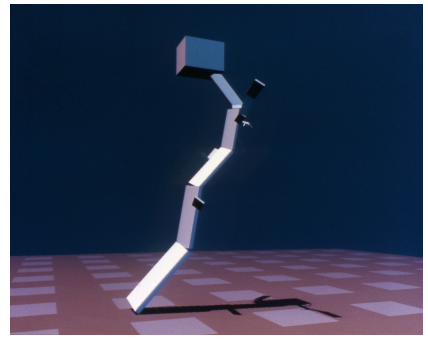
https://www.technologyreview.com/s/612341/a-global-ethics-study-aims-to-help-ai-solve-the-self-driving-trolley-problem/

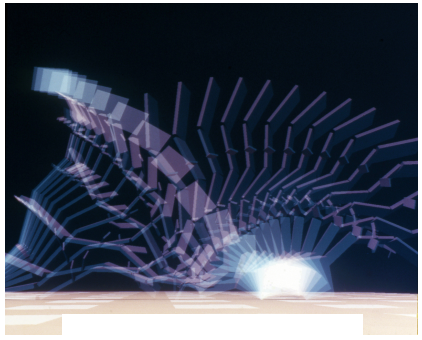
Translating a Real World Problem into Something Tractable is not Always Straightforward

- Example: What does it mean to “jump”?
- Researchers were trying to have an AI design creatures that were optimized for “jumping”

When they defined jumping as “maximum elevation reached by the center of gravity of the creature during the test,” They got tall skinny creatures with enormous heads (top).

When they defined jumping as "furthest distance from the ground of the block that was originally closest to the ground” they got tall skinny creatures that flipped over (bottom).





arXiv:1803.03453

Usability, Interpretability and Explainability

Cautionary Tale:

Flint, Michigan developed an ML system to predict which homes had lead pipes that needed to be replaced.

Overall, performance was reasonably good, with about 80% accuracy.

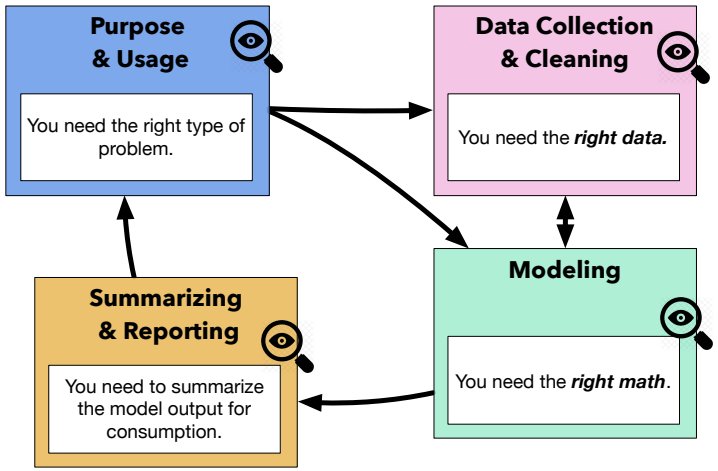
The city scrapped the system. One of the primary reasons was that they could not convey to the public how the algorithm worked, and why some houses were prioritized over others.

"When we started this, people would say, 'You did my neighbor's house and you didn't do mine,'" [Mayor] Weaver said.

- **Recommendation: Usability, interpretability and explainability must be designed into an ML/AI system. It cannot be added as an afterthought.**

https://www.theatlantic.com/technology/archive/2019/01/how-machine-learning-found-flints-lead-pipes/578692/

If Your Use-Case Changes…



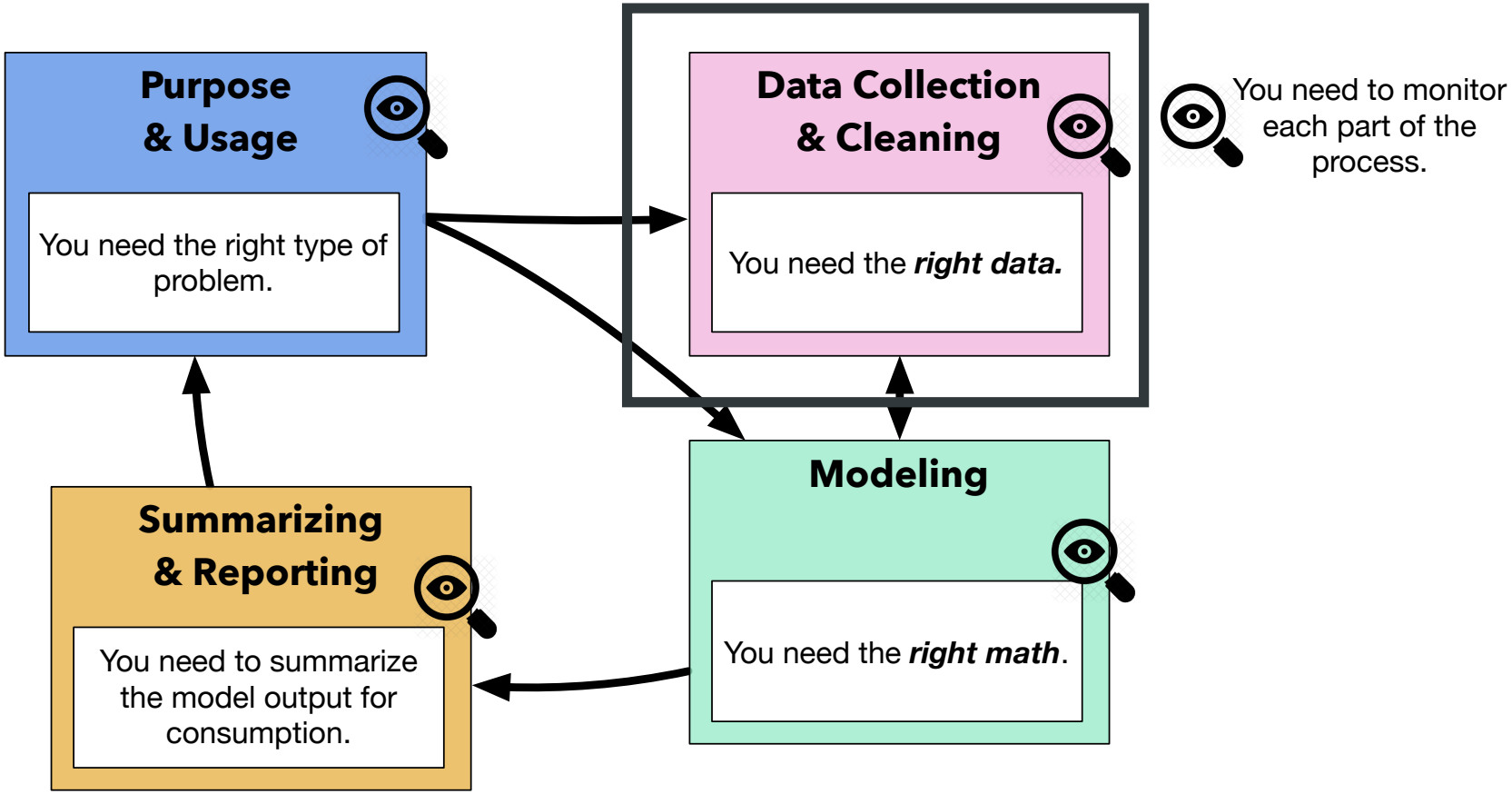
- You definitely need a new model.
- Because the math must match the use.

- You very likely need new data.
- Because the data must match the use.

Possible mitigations:

- Get end user involved from the beginning.
- Do feasibility studies.
- Collect extra data.

Data Collection and Cleaning



Your Data has to Contain the Right Information, Otherwise, It Doesn't Matter how Much You Have

- If you want to be able to input a pile of financial documents and detect fraud, that's a supervised learning problem.
- You need to train your model on financial documents that have been labeled
-  contains fraud  no identified fraud

- Without this labeled data you cannot do ***this*** analysis.
- (There are other analyses that can still move you towards that goal, but they're more complex and less certain to produce useful results.)

Data Collection Must Reflect Usage Conditions

- ML algorithms learn what's in the data.
- ***So, "what's in the data" must match the conditions where the results will be used.***

- Train (your model) the way you fight.

• Google Flu Trends

- Designed to predict severity of flu outbreak, during real time.
- ***In 2008***, it worked very well, correctly predicting the CDC results weeks earlier.
- ***In 2013***, the predictions were off by 140%.
- The application conditions changed over time, reducing the accuracy of predictions.
- Project was discontinued.

https://www.wired.com/2015/10/can-learn-epic-failure-google-flu-trends/

• Dog/Wolf Images

(a) Husky classified as wolf (b) Explanation

Figure 11: Raw data and explanation of a bad model's prediction in the "Husky vs Wolf" task.

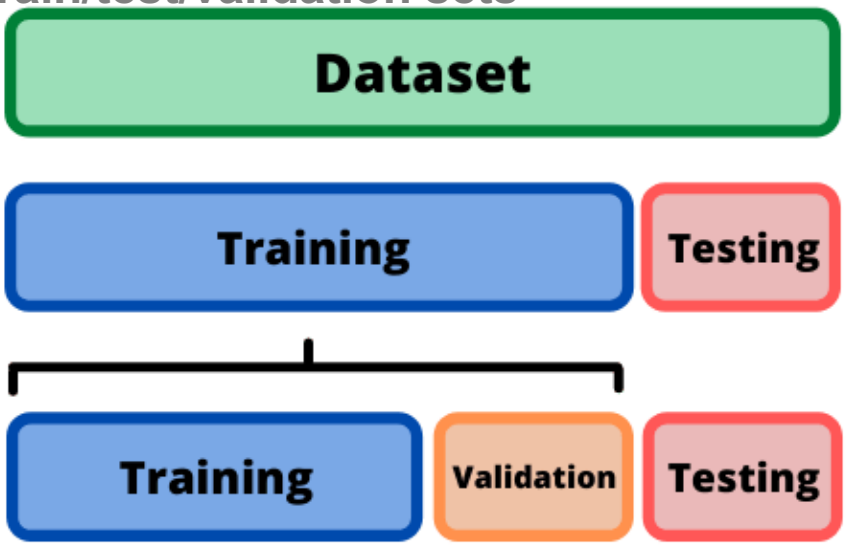
- This model learned to distinguish between wolves and dogs by looking at the background, because a snow background indicated "wolf."

https://arxiv.org/pdf/1602.04938.pdf

Split data into training/test/validation sets

- Defense against bias
- Sacrifice some ‘power’
- Depends on your ‘n’
- 50/50 splits often common
- Sometimes 70/30, 80/20, 90/10

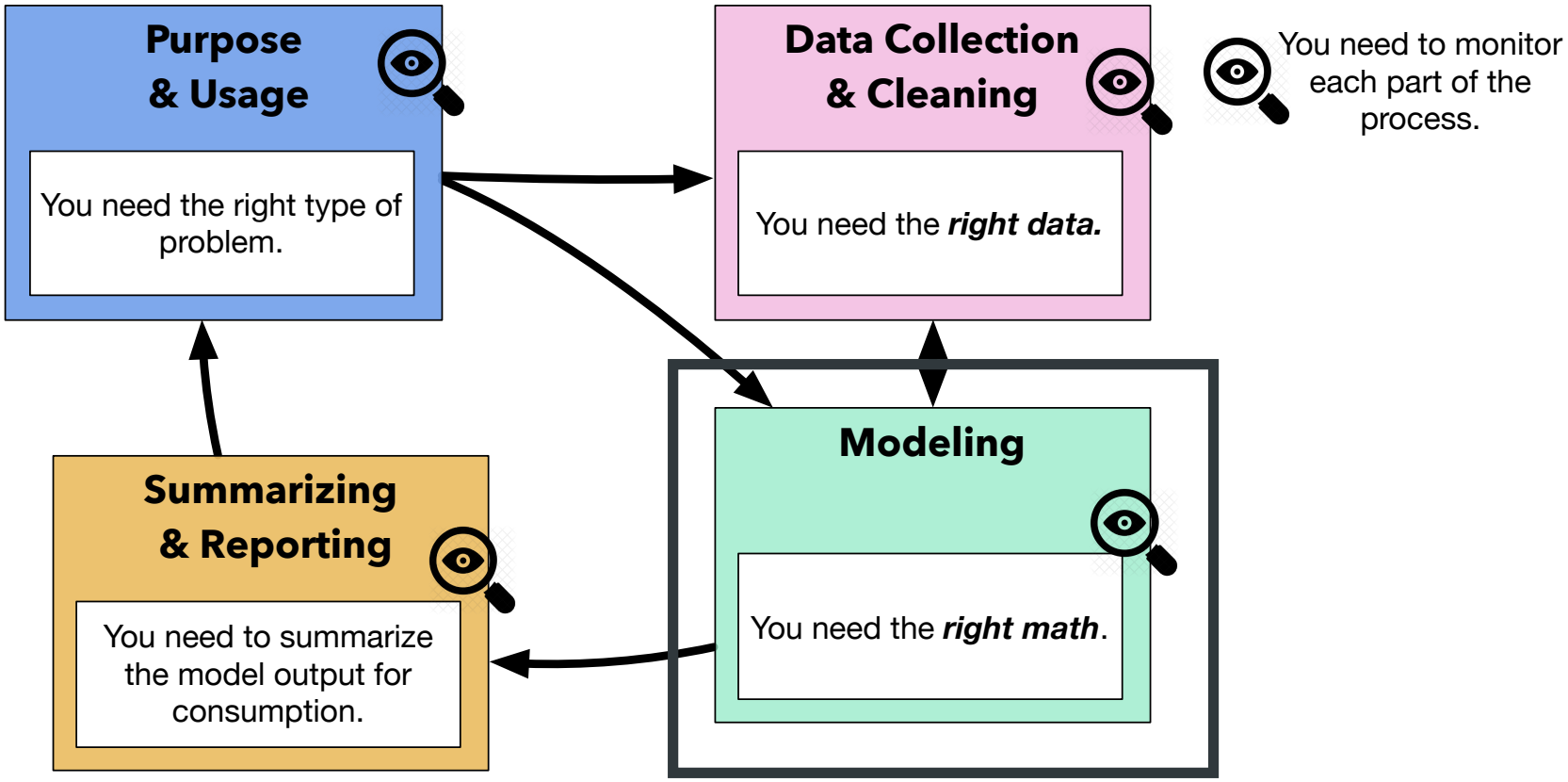
If possible, randomly split data into train/test/validation sets



Synthetic Data

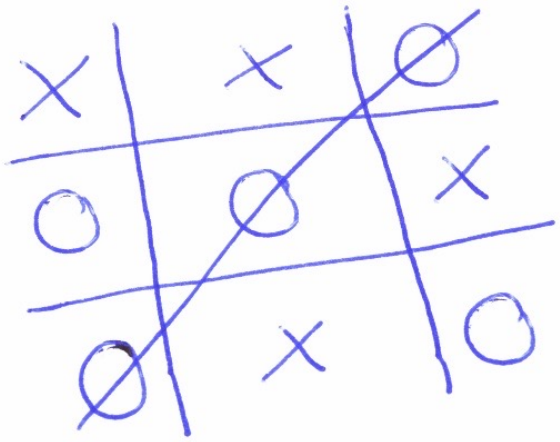
- Data that is generated artificially, usually algorithmically/programmatically
- Common approach in ML for creating large enough data sets
- Must be careful that data is representative
- Must be careful that models don't train on artificial properties

Modeling



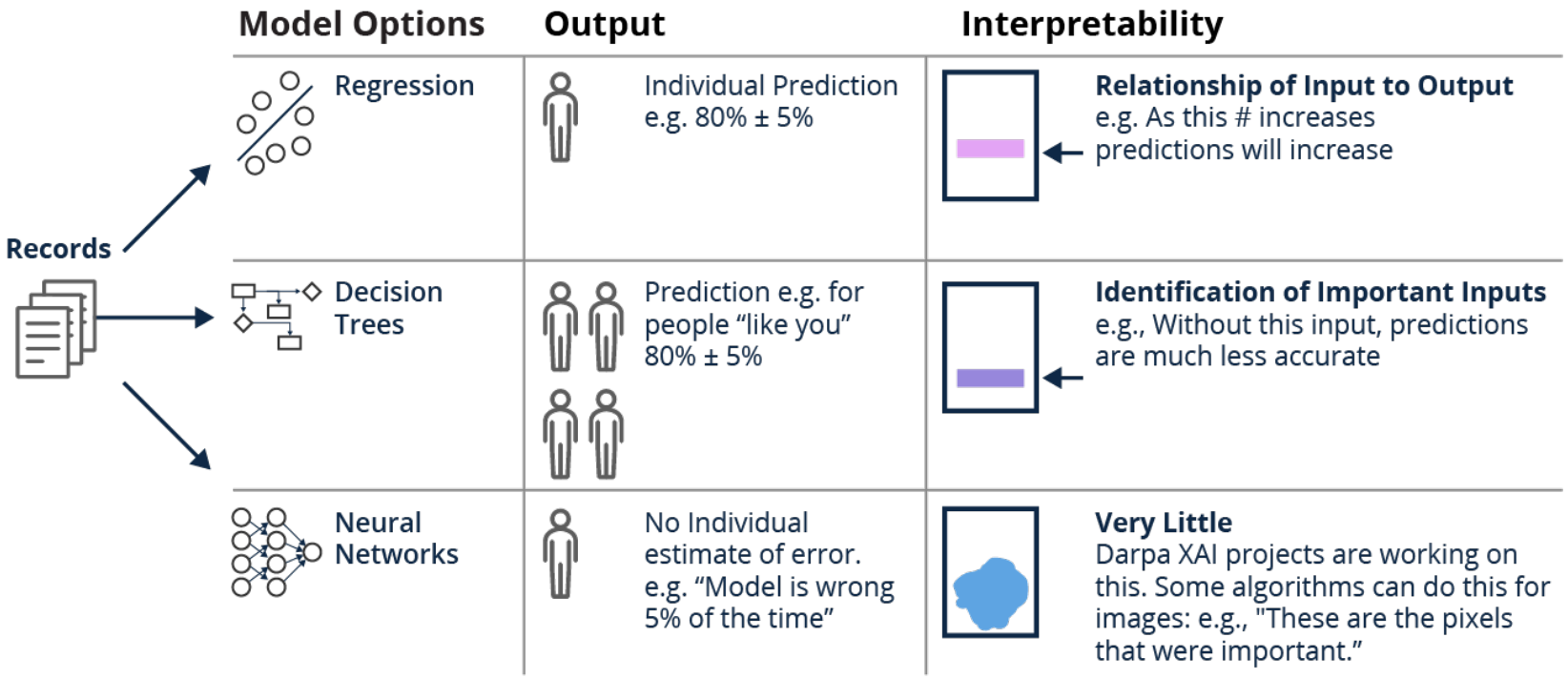
If You use the Wrong Math, You can get Pure Nonsense

- An algorithm that always takes the “best” move on the next turn will never lose at ***tic-tac-toe.*** It will either win or draw.



- An algorithm that always takes the next “best” move in ***chess***, will always fall into any trap set by its opponent. In order to see the trap and avoid it, the algorithm must be able to consider more than one move ahead.

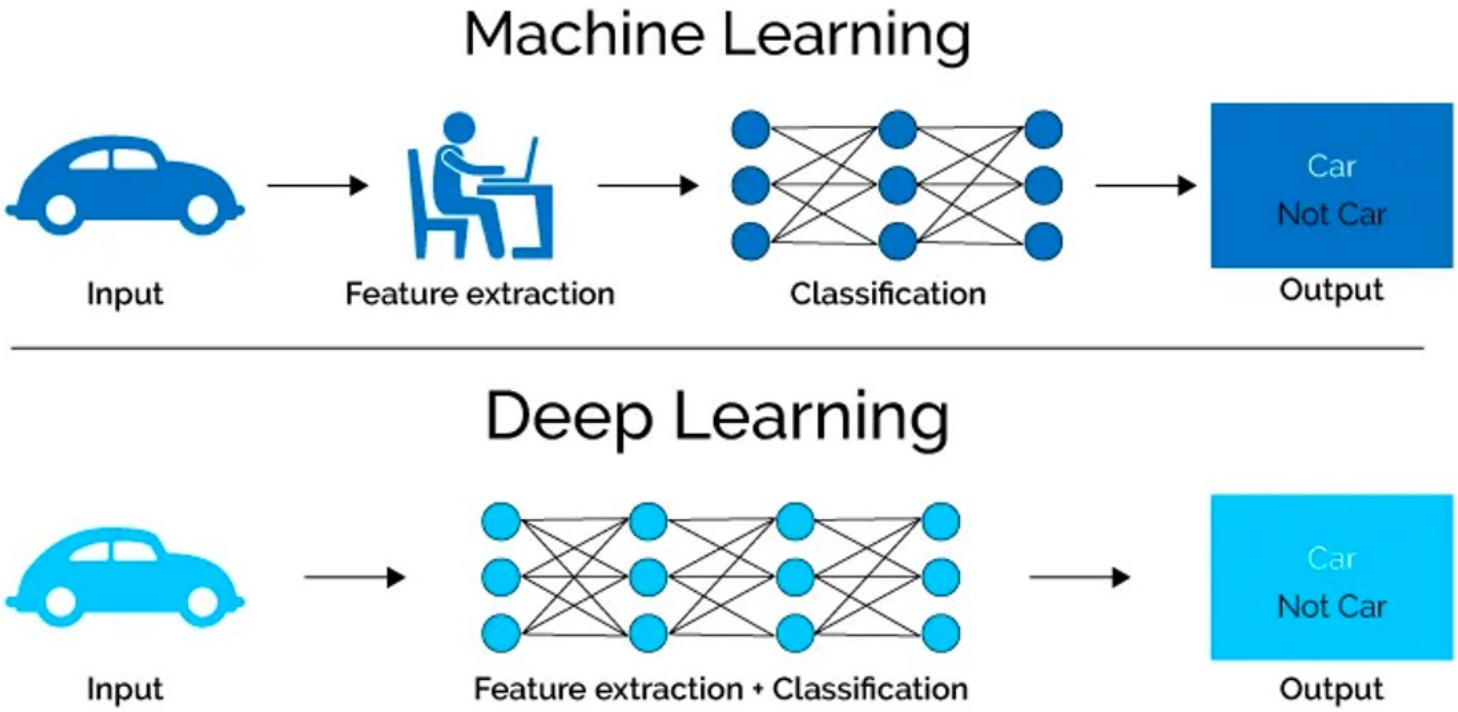
There are Usually Several Options of "Right Math," but Only Some of Them will give you the Summary You Need



There are Different Types of ML

	Supervised Machine Learning	Unsupervised Machine Learning	Reinforcement Learning
Useful for	Making A->B predictions	Discovering previously unknown patterns in data	Optimization in complex, but constrained tasks
Example Uses	Determine whether an image contains a ship. Determine whether a set of financial documents indicate fraud. From a baseball player's prior performance, predict performance in the next game.	Discover customer profiles Identify clusters of malware Identify anomalous network activity	Optimizing logistics chain management Optimizing strategy in a game
Common Methods	**Regression** (Linear, Regression Trees, Kernel Regression, …) **Classification** (Support Vector Machines, Logistic Regression, Discriminant Analysis) Neural Networks, Ensemble Methods…	**Clustering** (K-means, DBSCAN, Mixture modeling) Association Rule Mining Anomaly Detection Neural Networks	Q-Learning Policy Optimization State-Action-Reward-State-Action Deep Deterministic Policy Gradient
Notes	By far the most common	Data widely available, implementation and verification are tricky	Only beginning to move into commercial space, still largely academic.

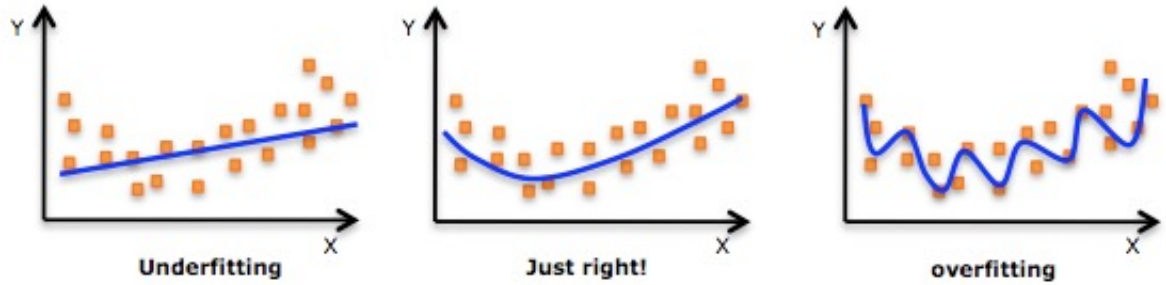
Machine Learning & Deep Learning



Deep learning is machine learning using a neural network.

https://semiengineering.com/deep-learning-spreads/

Underfitting and Overfitting



Lots of Performance Metrics can seem Similar, Even if They're Quite Different

Different kinds of errors may have different kinds of implications.

Metric	What it measures
Error Rate	How often is the algorithm wrong?
False Positive	Algorithm predicted "yes," But the truth is "no"
False Negative	Algorithm predicted "no," But the truth is "yes"
Positive Predictive Value	Of the "yes's" that were predicted, How many are actually "yes"

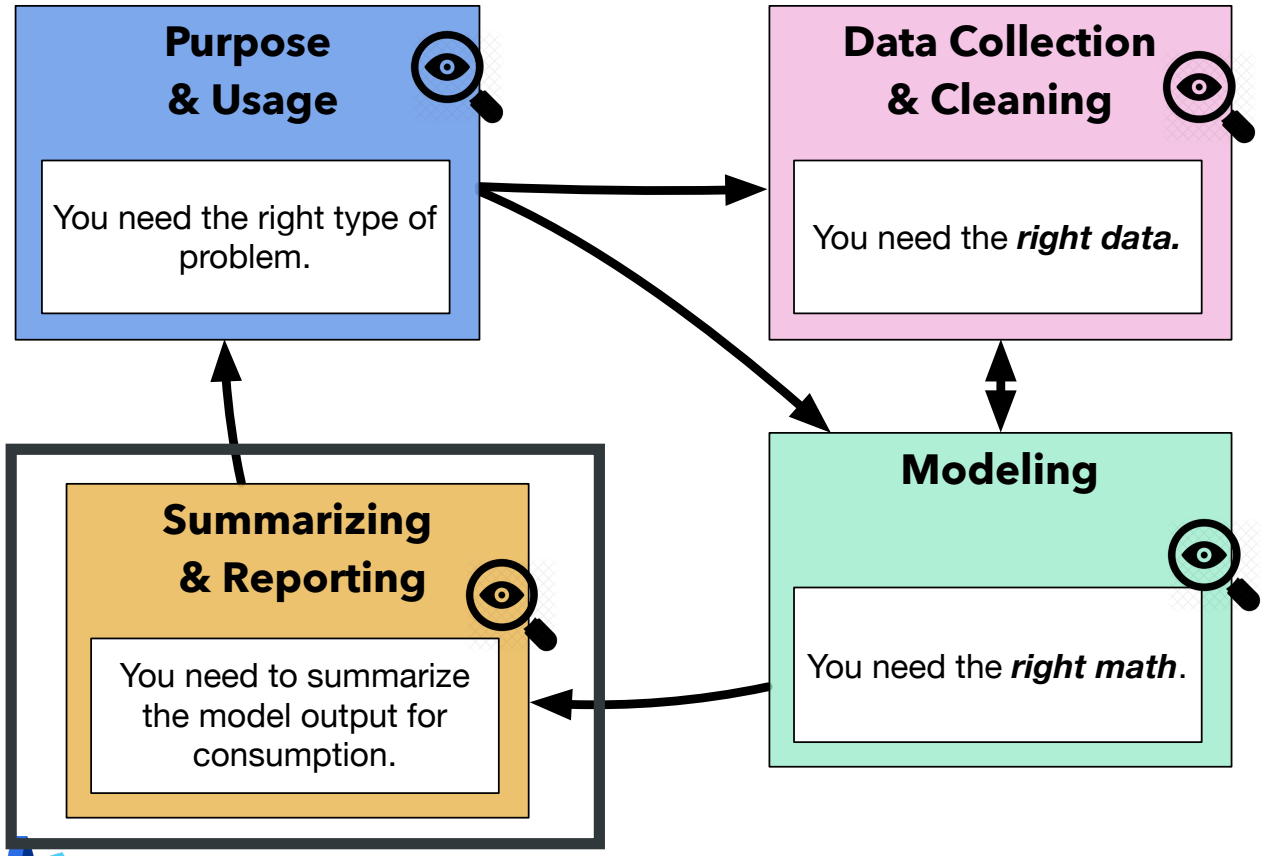
The metrics you choose for an ML project are a policy statement about what kind of systematic errors are acceptable, and which should be minimized.

https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

A Note on Transfer Learning

Using model weights trained for a particular task or set of inputs, removing the first and last layers, and training new input and output layers while holding the middle layers fixed; Purpose to encourage model re-use, such as using a pretrained model.

Summarizing & Reporting



ML System User Interfaces Must Communicate Inherent Uncertainty

- ***ML systems are based on probability.***
- ***There is inherent uncertainty in any probabilistic system.***
- ***Output from an ML system must communicate this uncertainty to the users***.

Hypothetical:
Her mom is 5’10” and her dad is 6’1”. Can you predict how tall she will be as an adult?
You can make a good guess, but with some uncertainty.
e.g., *She’ll probably be about 5’10”*

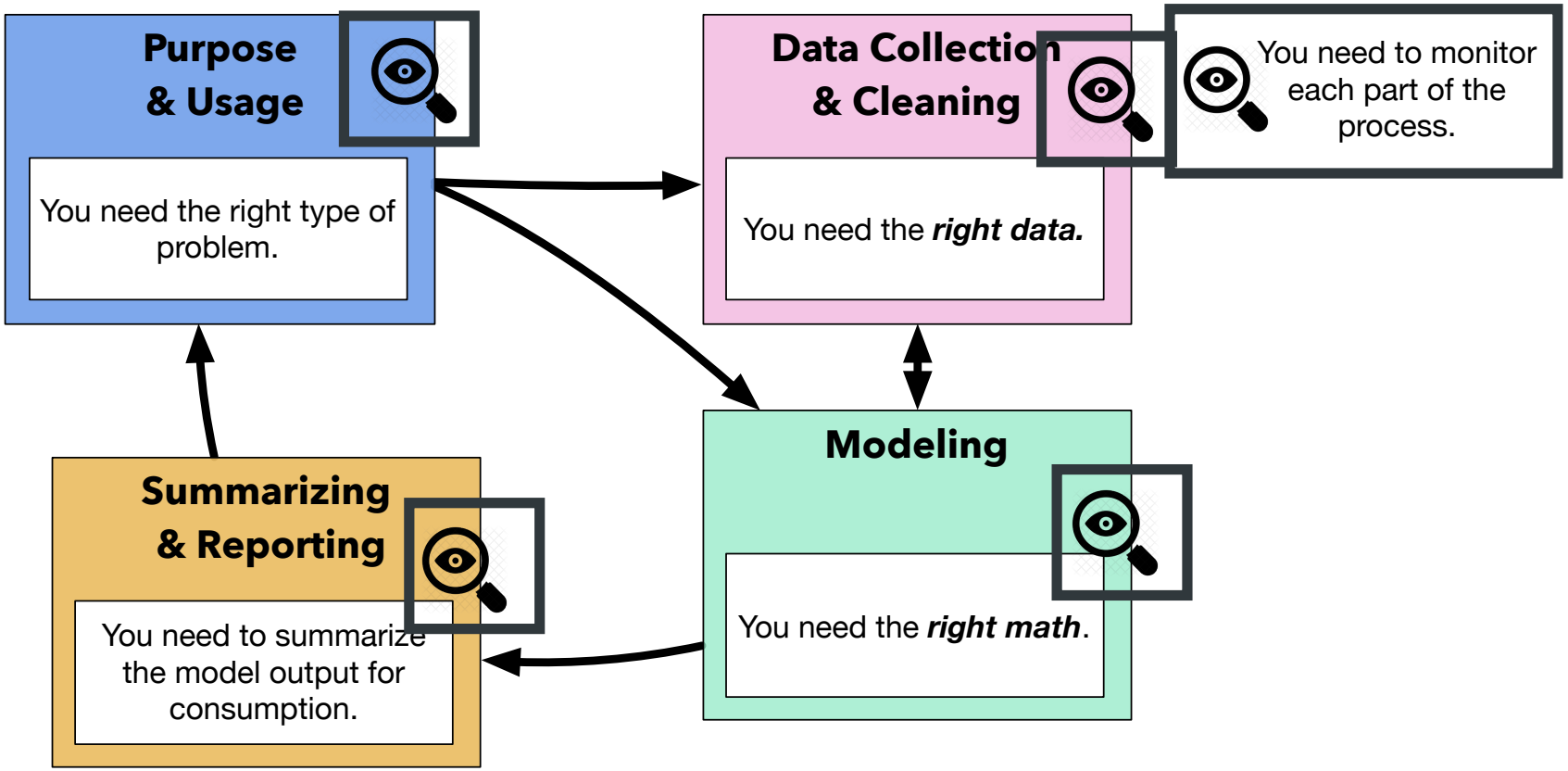
This is the kind of prediction (supervised) ML is doing. It’s doing it faster, with more data, and more precise math. So there’s (usually) less uncertainty than a human prediction.

e.g., *There’s an 80% probability she’ll be between 5’8” and 5’10”.*

ML Systems Must be Designed to Work Within a Larger System

- Risks are different in different contexts.
  - Low risk: An ML system makes an error in predicting which new movie you will like.
  - Medium risk: An ML system makes an error in predicting whether an individual is an insider threat.
- Risk evaluations should be considered in system design.
  - Performance metrics must be chosen to measure context-dependent risks.
  - If the risks are acceptable, an autonomous system might be appropriate.
  - If the risks of an autonomous system are too high, then there need to be appropriate procedures in place to verify a decision and escalate as appropriate (checks and balances) .
- Tactics, techniques and procedures must be carefully designed to mitigate risk.
  - A human-in-the-loop is often suggested as one way to mitigate risk, but this may not be sufficient if there are incentives to “just go with what the algorithm says”

Monitoring



AI/ML Implement Policy

- Examples of where algorithms are implementing policy:
  - Determining whether applicants are eligible for Medicare.
  - Identifying and locating men delinquent in paying child support.
  - Identifying and removing citizens registered to vote in multiple locations.
  - Predicting whether an individual is a threat and should be detained.

- In each of these examples (and many more), we must be able to verify that the algorithm is implementing policy as intended, and that policy is not being set by software developers.

Danielle Keats Citron, Technological Due Process, 85 Wash. U. L. Rev. 1249 (2008).

Any Deployed AI/ML System Needs Checks and Balances

- In the same way that we require inspections for food safety, automobile safety, and aviation safety, we must be able to determine whether a deployed AI/ML system is functioning as designed.
- We must be able to validate and adjust:
  - Training data
  - Model choice
  - Model implementation
  - The data pipeline for the deployed model
  - Performance in the field

Anybody can download Tensorflow and throw a pile of data at it. That does not mean the output is useful or correct.

Validation metrics don't really exist right now. This is one place to invest in research.

- Good monitoring and validation practices help ensure good performance, making the system more secure against both adversaries and poor implementation.

Useful Questions to Begin an Oversight Discussion

- What policy is this algorithm implementing?
  - What are the intended consequences of a policy?
  - What unintended consequences can be anticipated?
- What checks and balances are in place?
  - How will field performance be evaluated?
  - What is the procedure for monitoring and validation? Who will be doing the monitoring?
  - Are there historic problems (e.g., racial bias) in this area that could be perpetuated?
- What procedures are in place for handling inherent uncertainty?
  - How is uncertainty communicated to the end user?
  - How can the end user check or verify a prediction? (e.g., If you're uncertain about a rain forecast, you might look at a radar map.)
  - How does the end user make a decision when told a prediction has low confidence? (e.g., the ML system only has 60% confidence in its prediction.)

Checklist to Identify Good Candidates for ML Projects

- Can you state your problem as either:
  - I would like to use ___ data to predict ___.
  - I would like to understand the structure of the features recorded in ___ data.
  - I would like to optimize ____ well defined process.
- Is it a large scale problem?
- Have you already done exploratory analysis on available data?
- Have you considered the broader context?

Carnegie Mellon University
Software Engineering Institute

Thank you!

INFOSEC WORLD

INFOSECWORLDUSA.COM