Challenges – Data Quality

- Good quality data is **critical**
  - bad data → bad model
  - Some models need large amount of training data
- Data have insufficient quantity / variability for context
  - Especially problematic for models finding less common patterns (e.g., disease screening, anomaly detection)
  - Underrepresented populations → non-generalizable rules (socioeconomic, gender, race, ethnic and other disparities)
- Data labels represent human bias / false beliefs
  - e.g., court sentences, hiring / firing decisions
  - Can promulgate or exacerbate inequality
- Data have incomplete, inaccurate and/or variable labels
  - Different terms or metrics for same label due to human inconsistency
- Critical input data may be missing
  - **Polanyi's Paradox**:
    - Human decision-making beyond explicit understanding or description
  - Human may not realize which data contributed to human decision
  - Critical inputs may not be represented in AI training data

Challenges – ML Model Problems

- Models can be brittle
  - Small changes in input → big changes in output
  - Unable to see the forest for the trees (double-edged sword)
  - Humans are BETTER at generalization and situational awareness
- Small changes to input introduced by hackers (**adversarial examples**) led to wrong output [https://www.nature.com/articles/d41586-019-03013-5]
- Models can also degrade over time
  - Similar concept for laboratory tests (drift, shift)

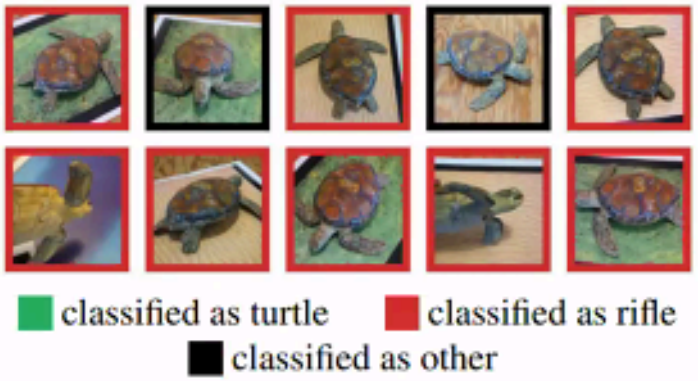


Figure 1. Randomly sampled poses of a 3D-printed turtle adversarially perturbed to classify as a rifle at every viewpoint[2]. An unperturbed model is classified correctly as a turtle nearly 100% of the time.

Athalye et al. 2018.
https://arxiv.org/pdf/1707.07397.pdf

Challenges - Cybersecurity

- AI can be hacked just like any other software
  - Robotic surgical systems (https://www.ncbi.nlm.nih.gov/pubmed/30397993)
- Hacked systems have potential for unauthorized disclosure, patient harm
- Human autonomy ("human-in-the-loop") may help detect malfunctions
- US national efforts for AI cybersecurity
  - National Security Commission on Artificial Intelligence (https://www.nscai.gov/)
    - Established 2018 by John S. McCain National Defense Authorization Act (Public Law 115-232)

Challenges - Transparency

- Definitions (multiple)
  - For AI developers: Reasons for model's performance are **known** and **understood**
  - For end-users (ethics): Sufficient information is published such that model's performance can be audited [https://www.who.int/publications/i/item/9789240029200]
- Lack of transparency (**Black box problem**)
  - Rules developed by the AI algorithm
    - May be indecipherable after model is trained, even to the developer(s)
    - May not be able to determine why algorithm generated certain output
    - May generally work well but some output may be inexplicably wrong

Challenges - Ethics

- Hot topic because of some noted failures
  - https://georgetownsecuritystudiesreview.org/2021/05/06/racism-is-systemic-in-artificial-intelligence-systems-too/
  - https://technologyandsociety.org/bias-and-discrimination-in-ai-a-cross-disciplinary-perspective/
  - https://www.technologyreview.com/2019/01/21/137783/algorithms-criminal-justice-ai/
- **Beneficence:** Maximize benefits; minimize risks and harms
  - AI can propagate and exacerbate human bias
  - Protect human autonomy in decisions (**"human-in-the-loop"**)
    - ACR and RSNA recommendation → do not approve autonomous AI until sufficient human-supervised AI experience obtained
- **Auditability**: Audit the tool to verify performance, ensure ethics followed
- **Accountability**: Who or what is accountable when something goes wrong
  - Medicolegal liability
    - AI is not standard of care
    - Regulations not yet developed in US
    - EU paper (https://pubmed.ncbi.nlm.nih.gov/33489979/) that discusses that liability is based on physician using standard of care

Challenges – Ethics (cont.)

- **Intelligibility**
  - Achieved through Transparency and eXplainability
    - https://nvlpubs.nist.gov/nistpubs/ir/2020/NIST.IR.8312-draft.pdf
  - **Transparency** [https://www.who.int/publications/i/item/9789240029200]
    - Sufficient information **published** before the design or deployment of an AI technology
      - Describes how technology is designed, intended use, data used, etc.
    - Also means that a person knows when AI is being used on them
  - **eXplainability** (XAI)
    - Providing the human user an explanation of how the AI tool works

Other Challenges

Personnel

- Medicine lacks sufficient data scientists
- Many data scientists lack expertise in medicine and/or healthcare environment

Organizational

- Lack AI strategies
  - Right tasks
  - Right data
  - Right evidence standard(s)
  - Right approaches for integration
- Deploying models in clinical environments is challenging (patient safety, population differences between locations)

Financial

- Lack of reimbursement mechanisms
- Harder to define returns on investment

Technical

- Lack of adequate computational infrastructure
- Introduces new cybersecurity threats that aren't yet addressed

Response to Challenges → Guidelines

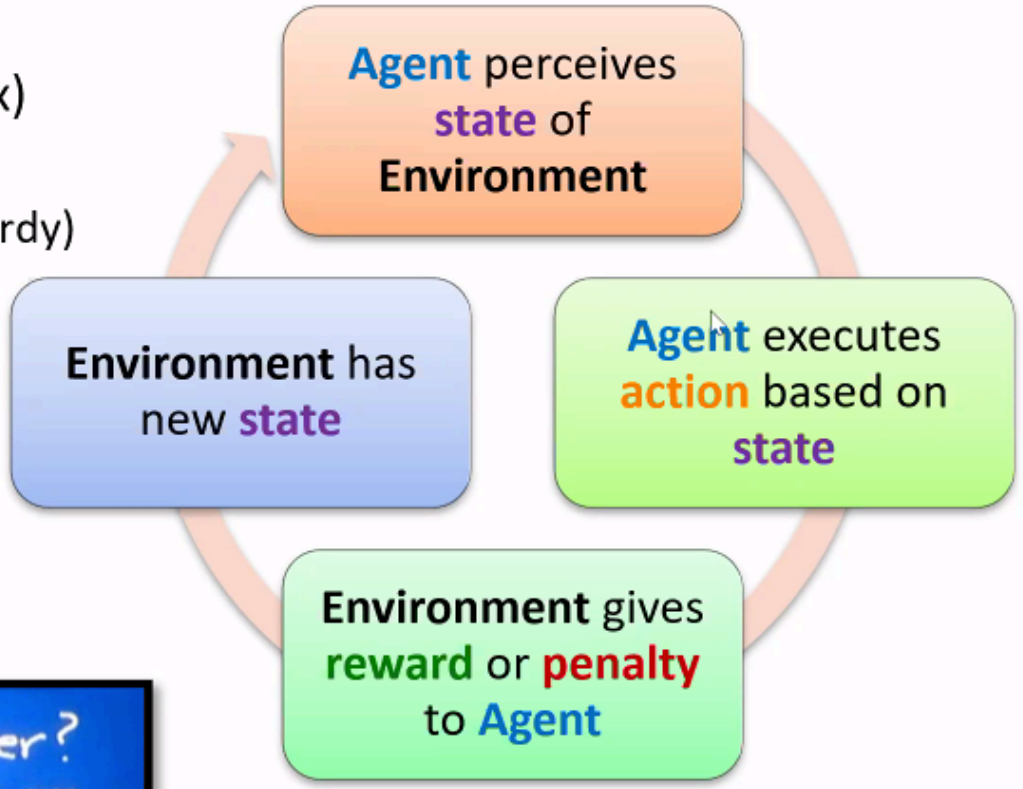
- Guideline for machine learning model development (US, Canada, UK Guideline – Oct 2021)
  - https://www.fda.gov/medical-devices/software-medical-device-samd/good-machine-learning-practice-medical-device-development-guiding-principles
  - Multidisciplinary expertise throughout
  - Good software/security practices
  - Data representative of intended patient population
  - Training data independent of testing data
  - Reference data is well characterized
  - Model design tailored to available data and reflects intended use
  - Focus on keeping the human in the loop (human AI team)
  - Testing demonstrates performance during clinically relevant conditions
  - Users provided clear essential information for use
  - Deployed models are monitored for performance in the real world
- AI Ethics Guidelines and White Papers
  - WHO Ethics Guidelines for AI https://www.who.int/publications/i/item/9789240029200
  - UNESCO https://unesdoc.unesco.org/ark:/48223/pf0000379920.page=14
  - EU guidelines https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai
  - https://www.intelligence.gov/artificial-intelligence-ethics-framework-for-the-intelligence-community

ML Definitions – Types of Learning

Supervised learning	Trains on classified and/or labeled data • Goal → train model to generate **known** answers, patterns or relationships
Fully supervised	All data labeled to same extent (degree of detail)
Semi-supervised	Some data are labeled while other data are not • Unlabeled data may be auto-labeled to match patterns on labeled data
Weakly supervised	Small amount of data have detailed labels; rest of data have fewer labels
Unsupervised learning	Data which have **not** been classified or labeled • Goal → model discovers **new** (previously **unknown**) patterns or relationships

ML Definitions – Types of Learning

- **Reinforcement learning**
  - Used to learn how to reach a (complex) goal
    - Game playing (IBM Watson and Jeopardy)
    - Speech to text, financial trading



ML Definitions – Types of Learning

- **Transfer learning**
  - Separate category vs. subtype of supervised learning
  - Data used for training the model are transferred from a different related domain
    - Data were developed for use in a domain different than the one intended for the model
    - Example: Using natural images from ImageNet (https://image-net.org/) to train a models for medical images [Alzubaidi et al 2021 https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8036379/]
  - Coarse training done on transferred data
  - Fine tune training with smaller data directly related to domain of use
  - Reasons
    - Data are expensive
    - Higher quality and quantity data may be more available, cheaper in another domain

ML Definitions - Data

- **Instance**
  - Single event in a data set
  - # instances required to train a model depends on the problem and model used
  - **Outlier**
    - Instance which is significantly different from the remaining instances in the population
    - Can skew results
    - Different models have different sensitivities to outliers
- **Label** – observed value for a feature of an individual instance
- **Feature**
  - An aspect (variable) of the training data
  - Called a **dimension** in unsupervised learning

	Feature 1	Feature 2	Feature 3
Instance 1	Red	Slow	Yes
Instance 2	Red	Fast	No
Instance 3	Green	Medium	No

Red, Green, Slow, Fast, Medium, Yes and No are all **labels** in this data set.

ML Definitions - Models

- **Algorithm**
  - Repeatable process used to train a model from a given set of training data
- **Parameter**
  - Internal values inside machine learning that the model derives based on training data
  - e.g., weights, bias values
- **Model** = algorithm + parameters
  - When a model is used for classification, it is called a **classifier** [https://towardsdatascience.com/machine-learning-classifiers-a5cc4e1b0623]
  - **Weak learner (weak model):** model whose performance only slightly > random chance
  - Good model: model that **generalizes well** (it performs the same on new data as it did on the training (and test) data)
- **Epoch**
  - 1 epoch = 1 pass through the training data

ML Definitions – Model Evaluation

Signal

The true underlying pattern you are trying to learn from the data

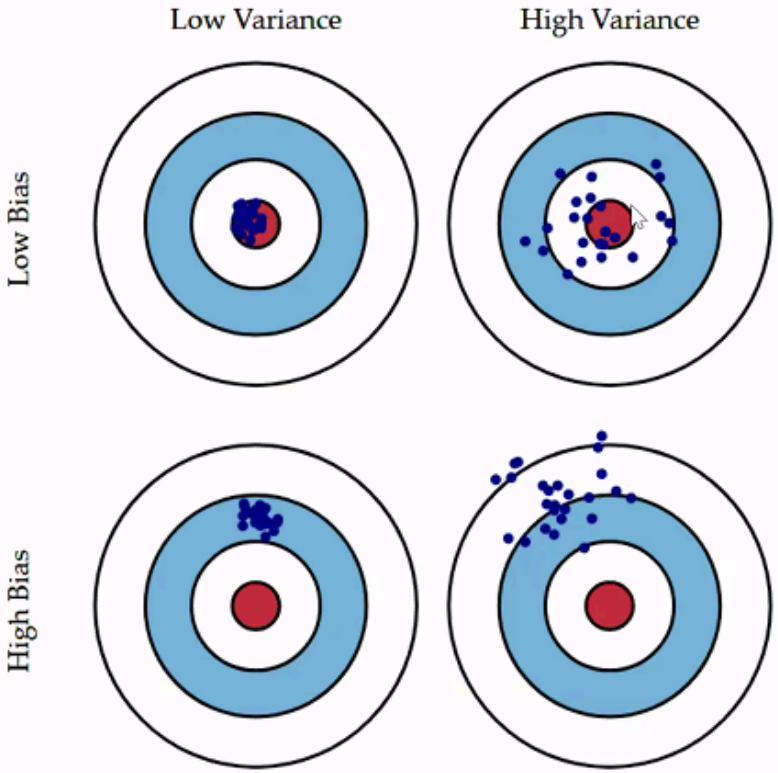
Well designed machine learning separates signal from noise

Noise

Irrelevant information or randomness in a data set

Irreducible error

Bias	Variance	Irreducible error
• Measure of inaccuracy • High bias + low variance ➔ consistently inaccurate results	• Measure of imprecision (lack of reproducibility) • High variance + low bias ➔ inconsistently accurate results	• Noise that cannot be reduced by optimizing algorithms



https://devopedia.org/bias-variance-trade-off

ML Definitions – Model Evaluation

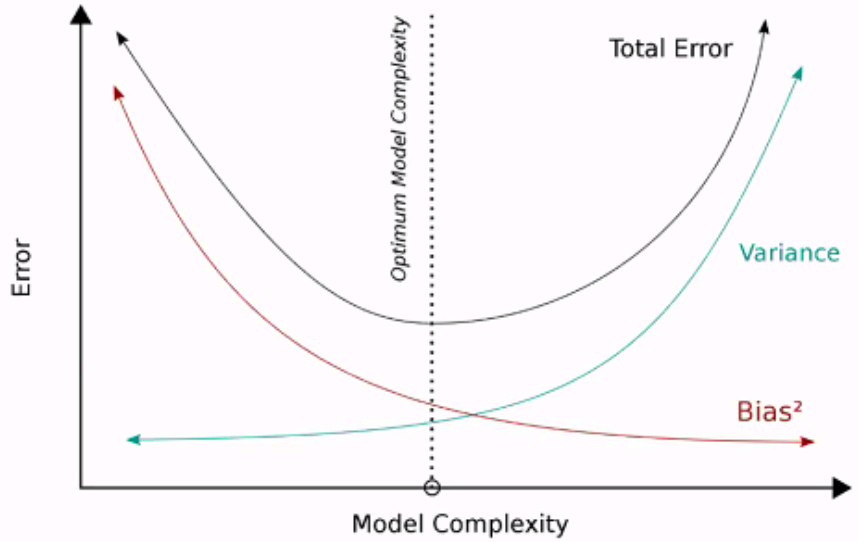
Bias

- *Not just an ethical term…*
- Amount of **inaccuracy** in the model's performance after training
- High bias → model is inaccurate (underfit)
- Low bias → model is accurate (but may be overfit)

Variance

- Amount of **imprecision** (square of standard deviation (σ) → σ^2)
- Due to model's sensitivity to small fluctuations in the training set
- High variance → model is imprecise (and likely overfit)
- Low variance → model is precise (but may not be accurate and may be underfit)

ML Definitions – Model Evaluation



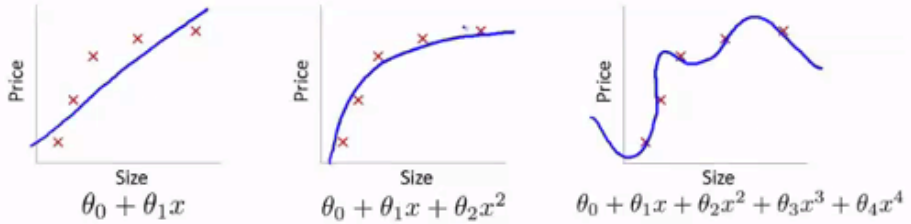
- **Bias-Variance Trade-Off**
  - Things that reduce variance increase bias
  - Things that reduce bias increase variance

$$Total\ error = (bias^2) + variance + irreducible\ error$$

https://en.wikipedia.org/wiki/Bias%E2%80%93variance_tradeoff
https://towardsdatascience.com/understanding-the-bias-variance-tradeoff-165e6942b229

ML Definitions – Model Evaluation

- **Goodness of fit**
  - How closely a model's output values match the observed (true) values
- **Underfitting**
  - Model does not accurately predict output for the data fed to it
    - high bias, low or high variance



High bias (underfit) | "Just right" | High variance (overfit)

https://datascience.stackexchange.com/questions/361/when-is-a-model-underfitted

- **Overfitting**
  - Occurs when statistical model exactly fits training data BUT…
    - Does not fit new data well (test or production data)
  - Training set has low error rate but test set has high error rate = high variance
  - **Most common problem** for any statistical model using a training set

ML Definitions – Model Evaluation

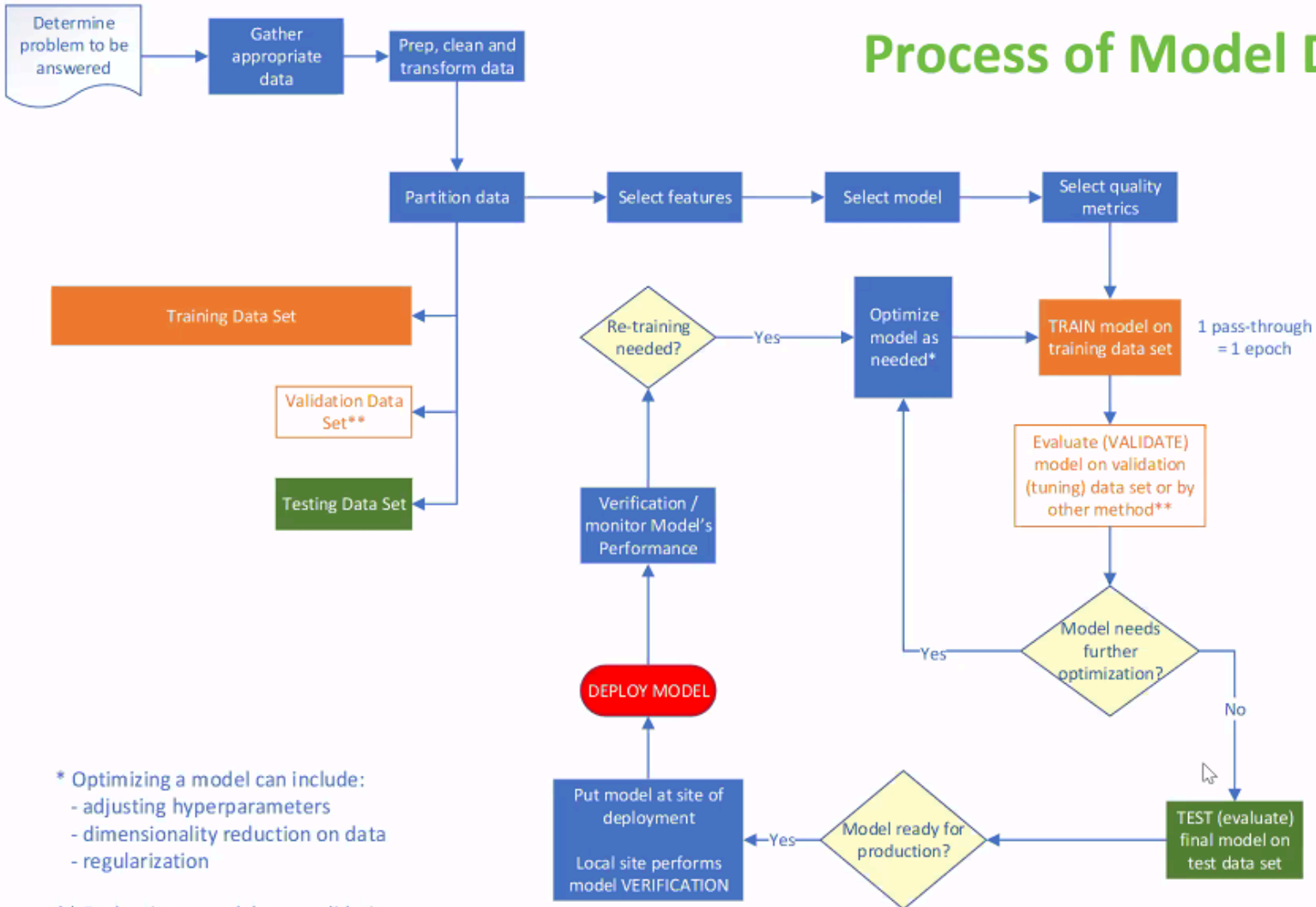
- **Null error rate**
  - For classification methods, rate of being wrong if you ALWAYS pick the majority class
  - If the majority class has 105 instances out of 165 total instances
    - Null error rate = (165 – 105)/165 = 36%
  - **Accuracy paradox**
    - Best classifier for the intended use may have a higher error rate than the null error rate
    - Occurs when condition or outcome is very low percentage of overall data set (e.g., 1%)
    - Model can correctly predict absence of the condition in 99% of cases – hooray! BUT…
    - May completely fail to detect the condition being sought
      - 100% failure of detecting the condition (but null error rate is only 1%)
    - Take home point → Use different statistical methods when trying to screen for low incidence conditions

Process of ML Model Development

- Many ways that a model can be trained → tested → deployed
  - Depends on model, amount of data, and other factors
- Phases of model development have variable nomenclature between authors
  - E.g., learning phase, inference phase
- A few definitions to resolve possible confusion

	What it means in machine learning…	**What it means in a hospital laboratory…**
Validation	Evaluating preliminary (non-final) *model* • Results of evaluation lead to tweaking (tuning) the model	Final evaluation of a *laboratory test* where no further changes to the test procedure are expected
Testing	Final evaluation of a *machine learning model* where no further changes to the model are expected	Evaluating preliminary (non-final) *laboratory test* OR Performing live clinical testing

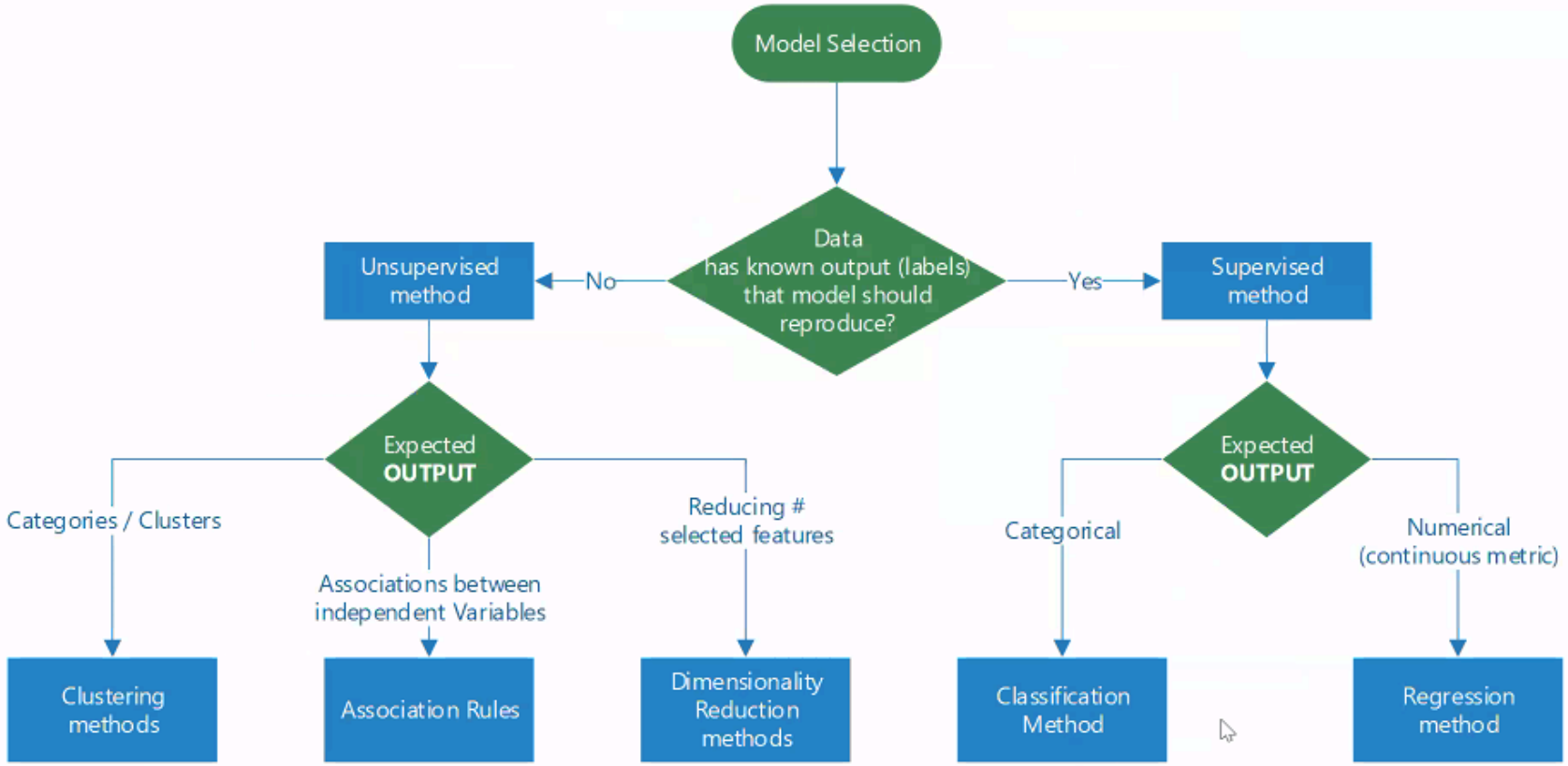
Process of Model Development



* Optimizing a model can include:
- adjusting hyperparameters
- dimensionality reduction on data
- regularization

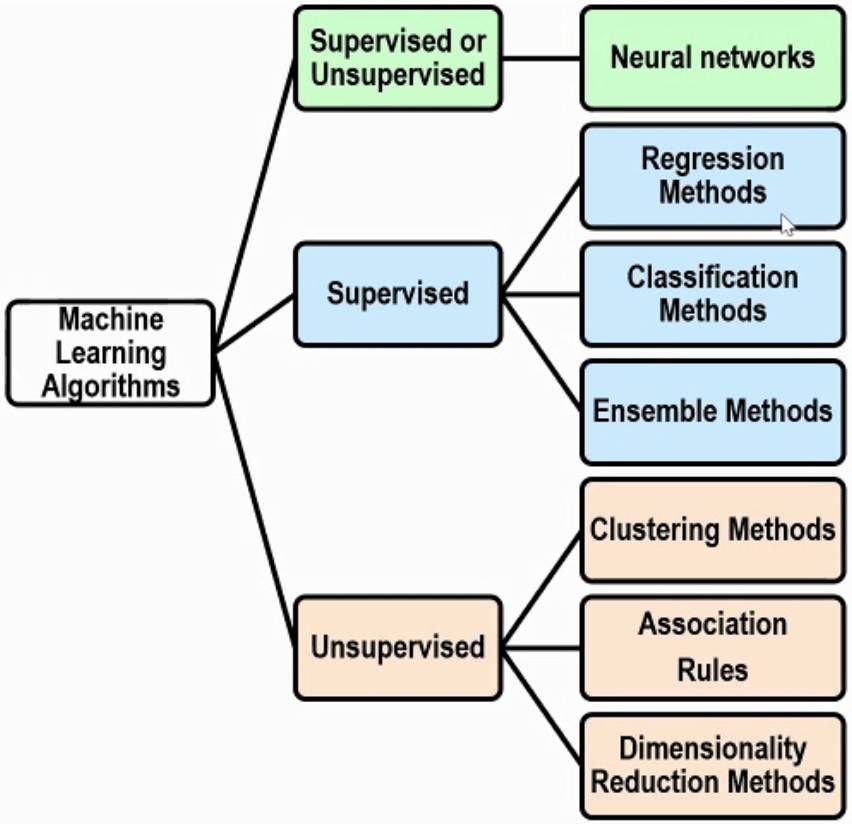
** Evaluating a model on a validation data set may not always be needed.

Process of Model Development



Machine Learning Algorithms

- Each category has algorithms that are primarily used for that purpose
- However, classification algorithms may sometimes be used for regression and vice versa
- Unsupervised algorithms may sometimes be used with supervised learning



Artificial Neural Networks (ANNs)

- Goal: Solve problems like a human
- Operate via flow through neural nets, akin to biological networks
  - Handles large amounts of complex data
  - Computationally intensive
  - Unraveling the pathways after training is completed can be difficult to impossible → **Black Box Problem**
- **Nodes** (akin to neurons) → transfer functions
- **Connections** (akin to synapses, a.k.a. edges)
- **Back-propagation** (nice YouTube (https://www.youtube.com/watch?v=llg3gGewQ5U) video)
  - Learns mistakes based on output
- Layers (nodes in each layer *usually* have same activation function)
  - **Input layer**: # nodes = # features selected in data
  - **Output layer**: # nodes = # output categories of data
  - **Hidden layer(s): Shallow networks** usually have 1; **Deep networks** have >3