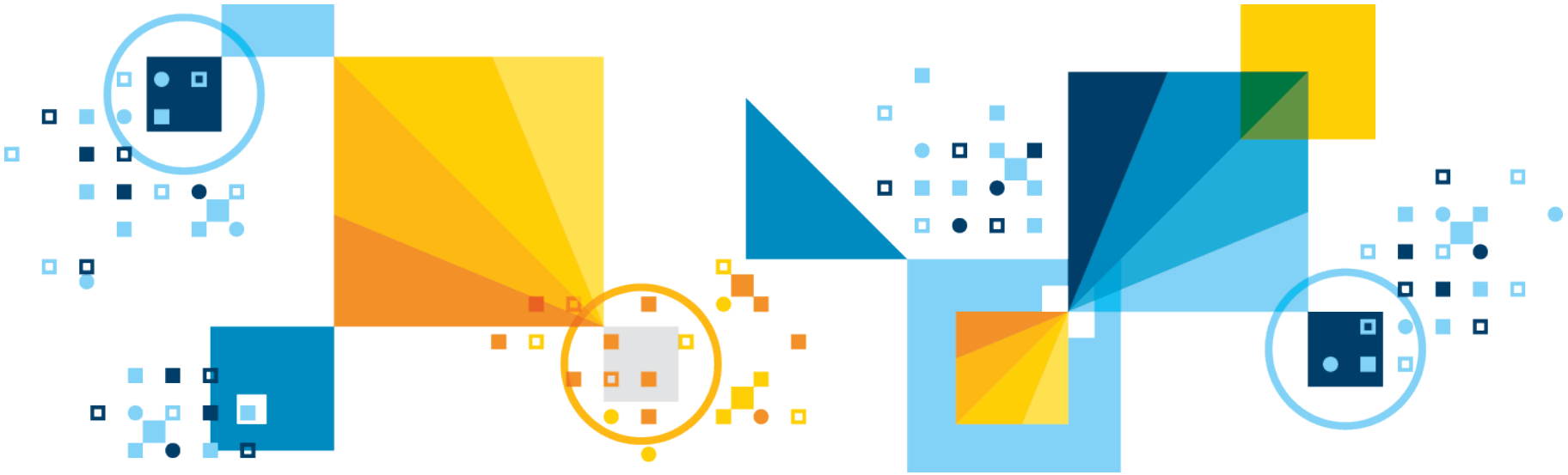
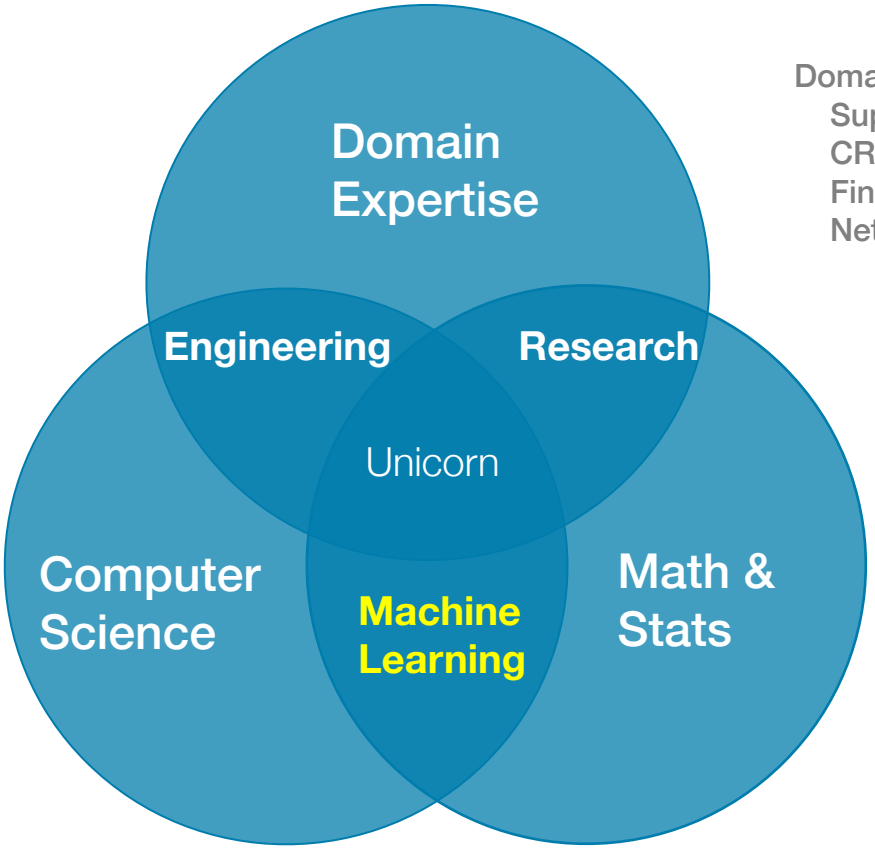
Introduction to Machine Learning



Introduction to Machine Learning - Agenda

8:30am - 9am	Breakfast, Socialize
9:00am – 10:00am	Kickoff, Overview of Machine Learning
10:00am – 10:15am	Break
10:15am – 12:00pm	Lab 1 - Machine Learning w/ Python & Spark pipeline
12:00 pm – 1pm	Lunch
1pm – 2:15pm	Lab 2 – Building an ML model w/ GUI
2:15pm – 2:30pm	Break
2:30pm – 3:45pm	Lab 3 - Intro to Principal Component Analysis w/ Spark
4pm – 4:30pm	Wrap up – Feedback from attendees

Machine Learning and Data Science….



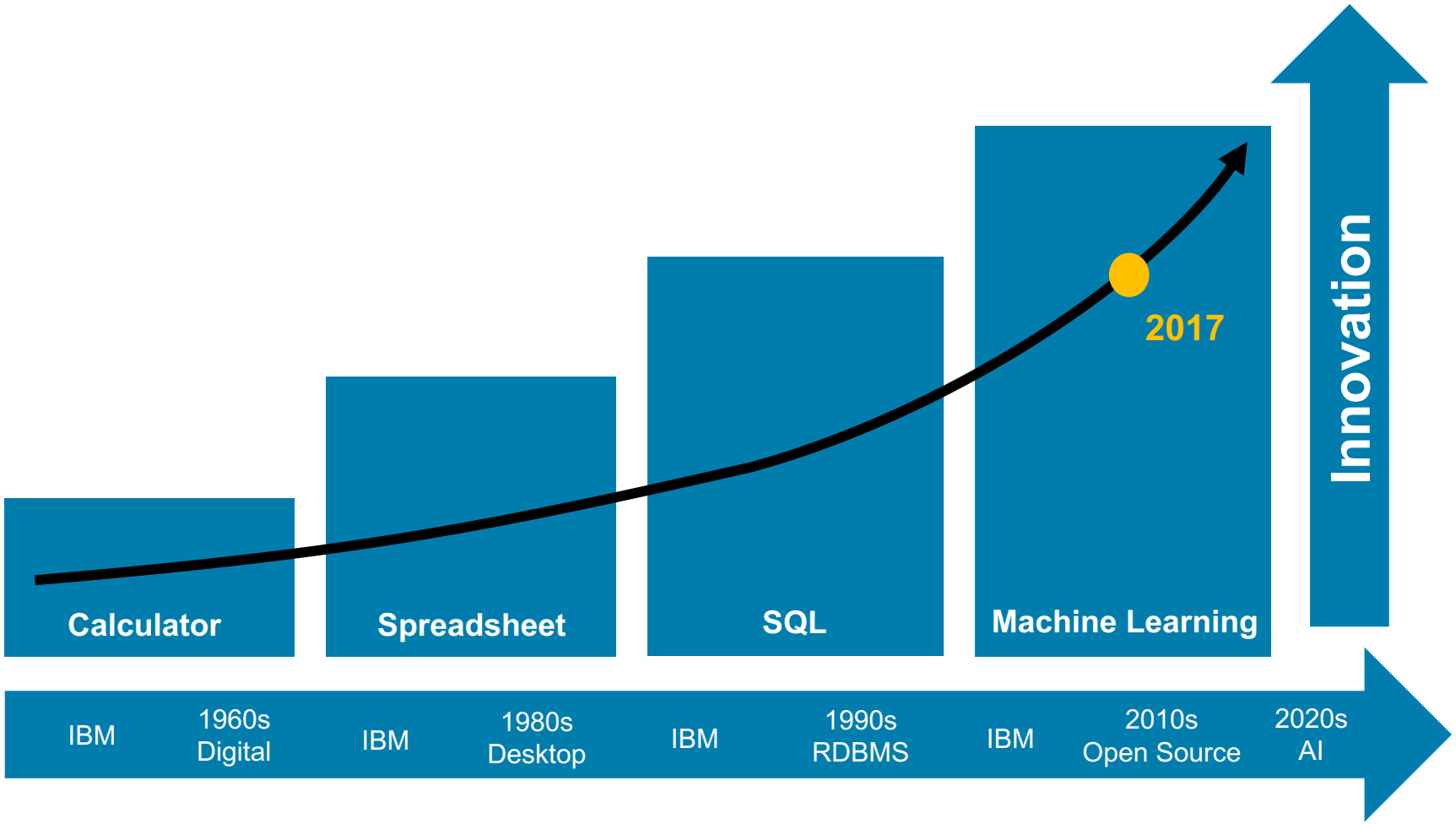
Domain Knowledge
- Supply Chain
- CRM
- Financials
- Networking

Scripting, SQL
Python, R Scala
Data Pipelines
Big Data/
Apache Spark

Mathematics
Computational

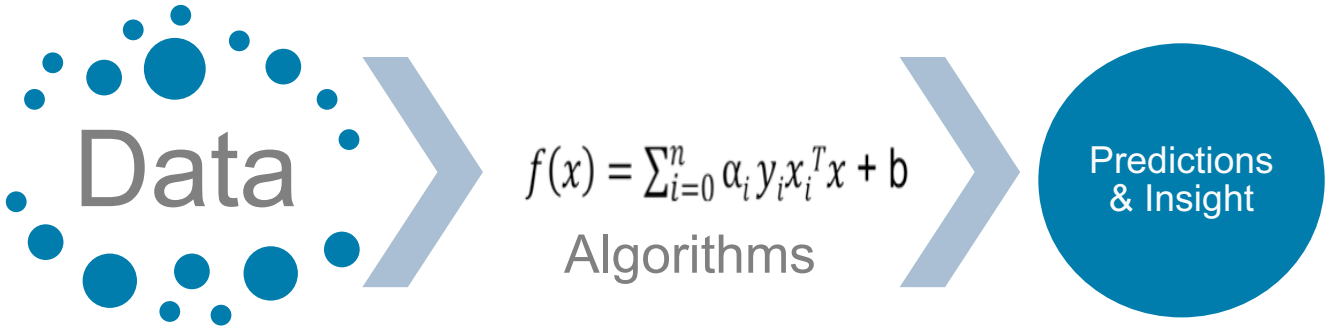
Data Science Projects Require multiple Skills

Future of Data Science is Democratizing Machine Learning..



But what is Machine Learning?

"Computers that learn without being explicitly programmed"
"Using algorithms to understand patterns in data"

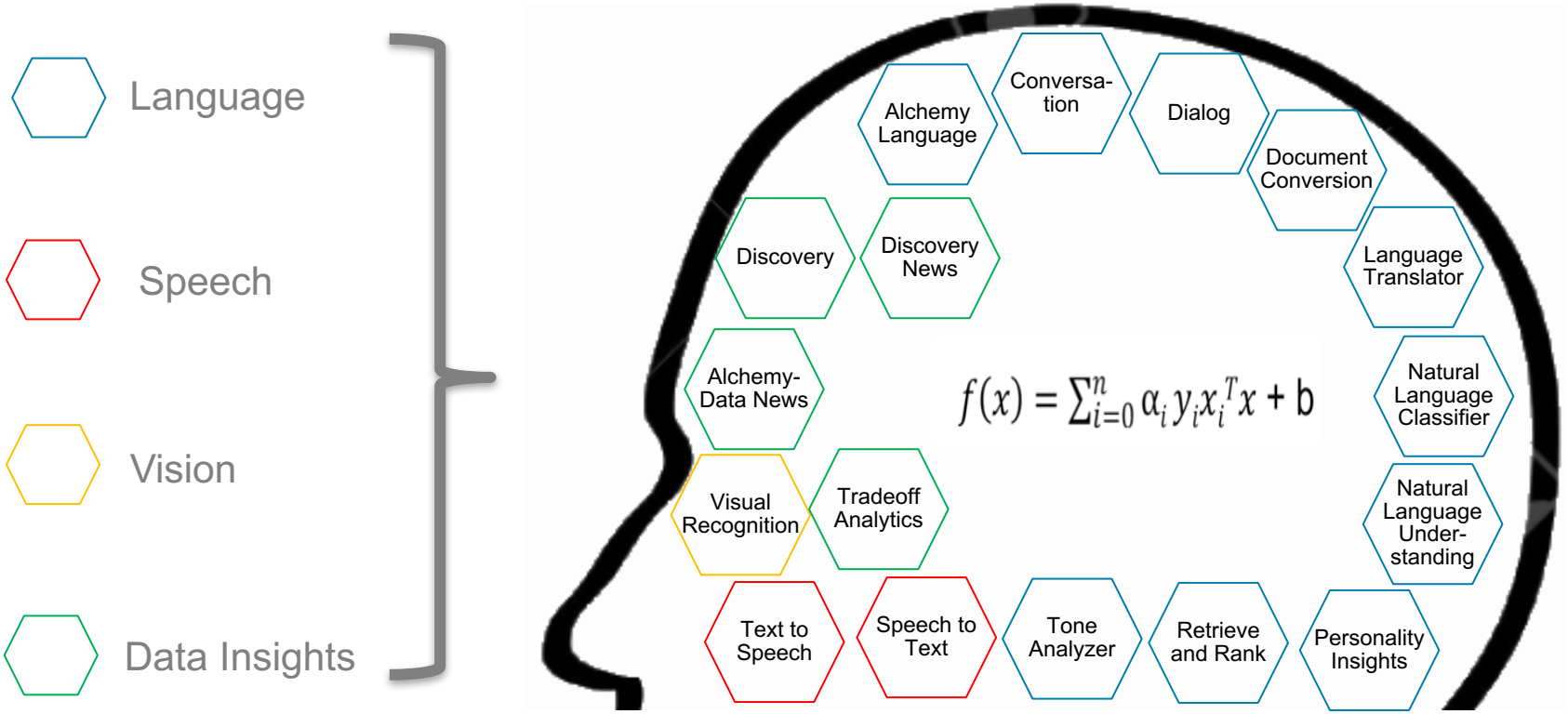


But what is Artificial Intelligence?

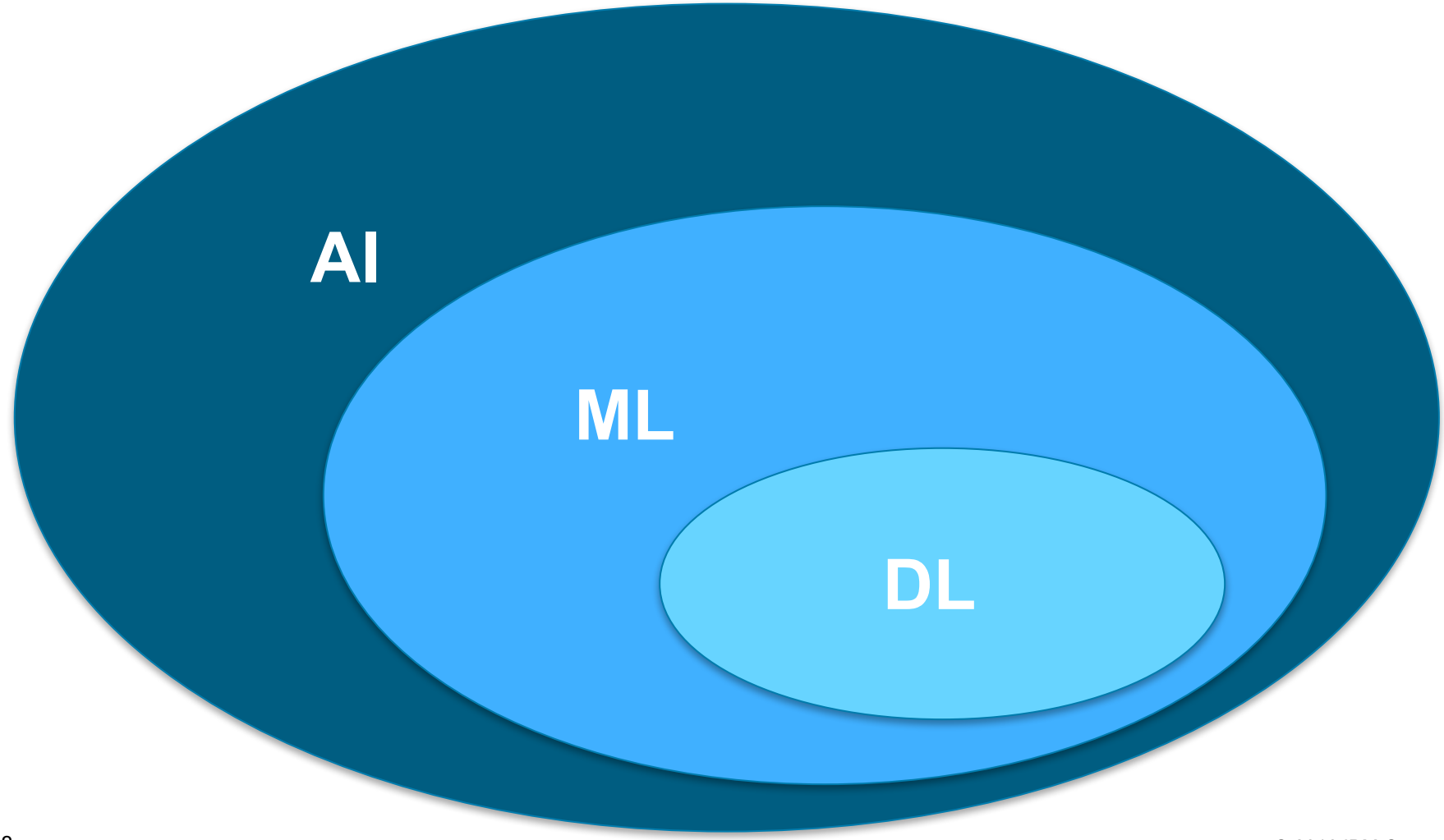
A theory and development of computer systems able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages..

Machine Learning = Artificial Intelligence???

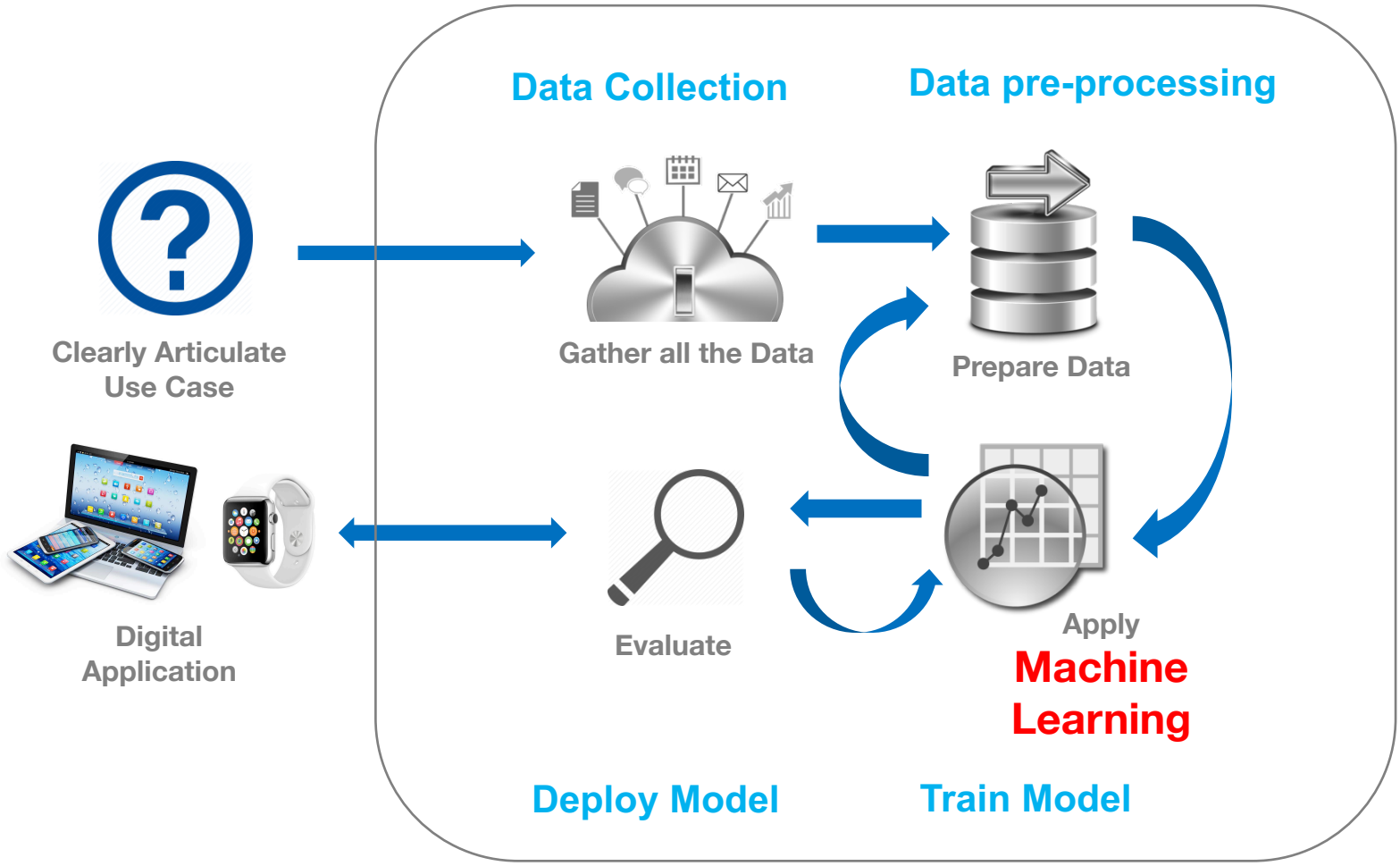
Data + Algorithms = Scored AI Models



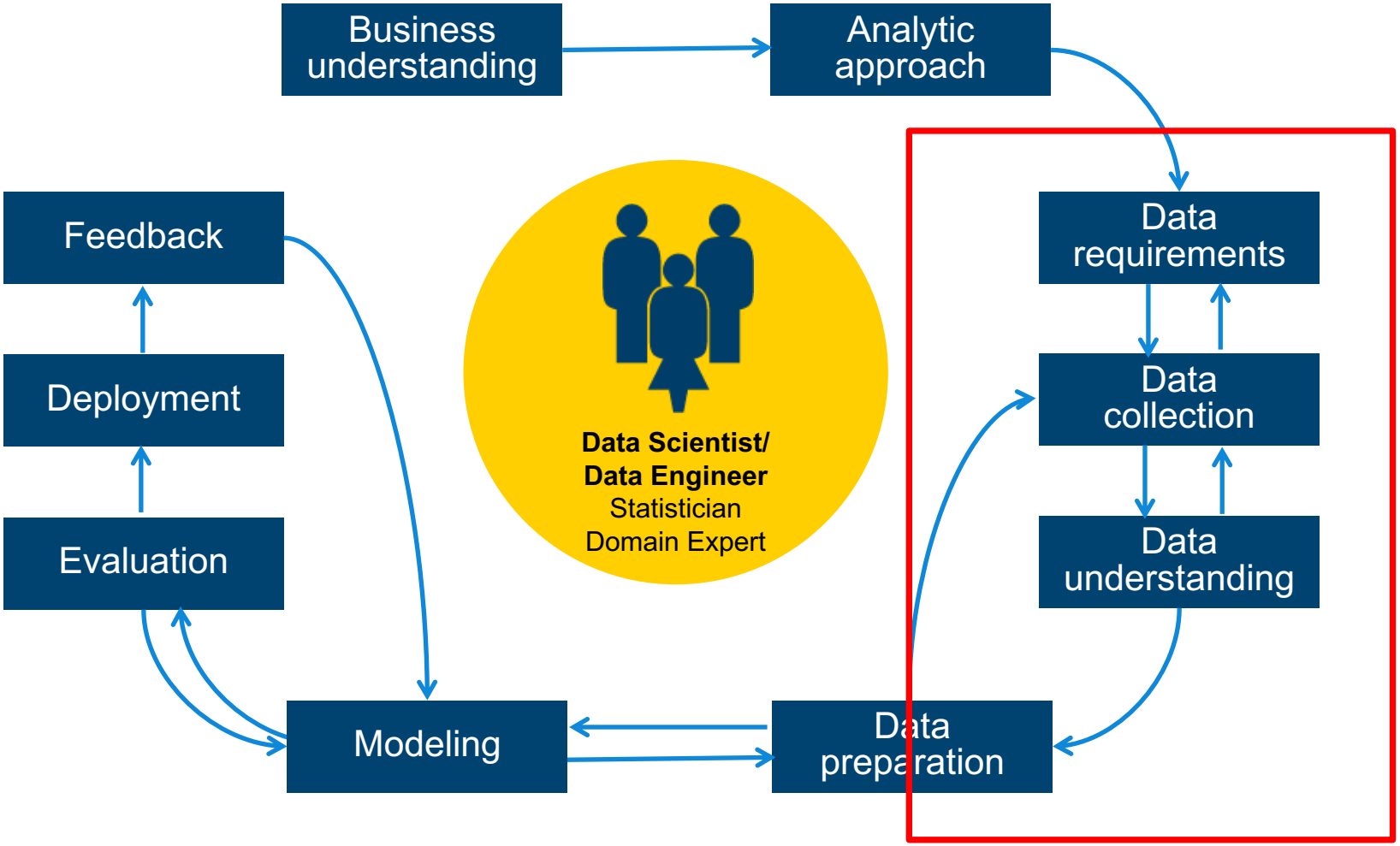
Plus Deep Learning is a deeper layer of ML…
Understanding AI, ML & DL Relationship…



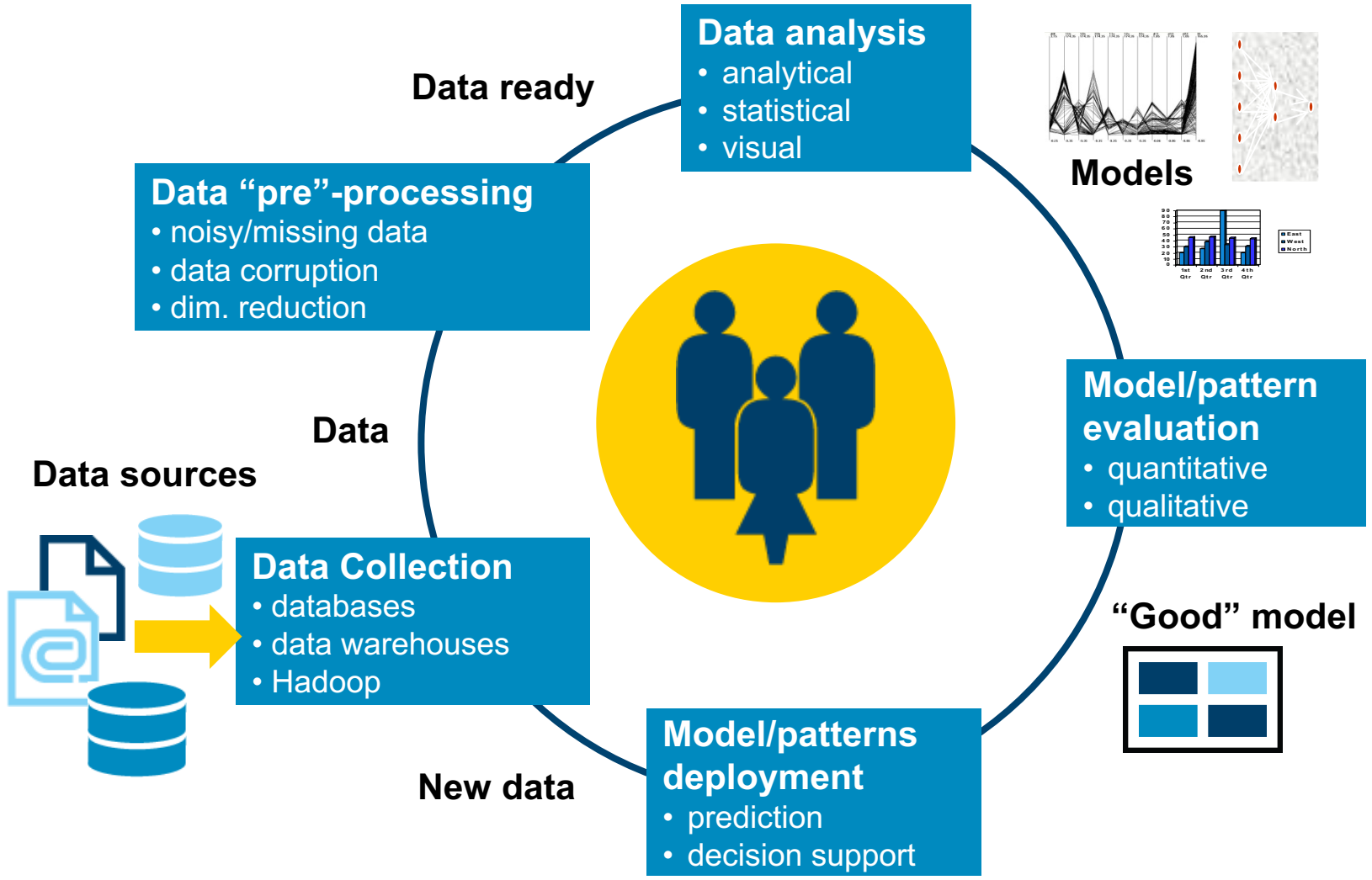
Steps to use Machine Learning for a use case…



Data Science Methodology



Data centric view of methodology

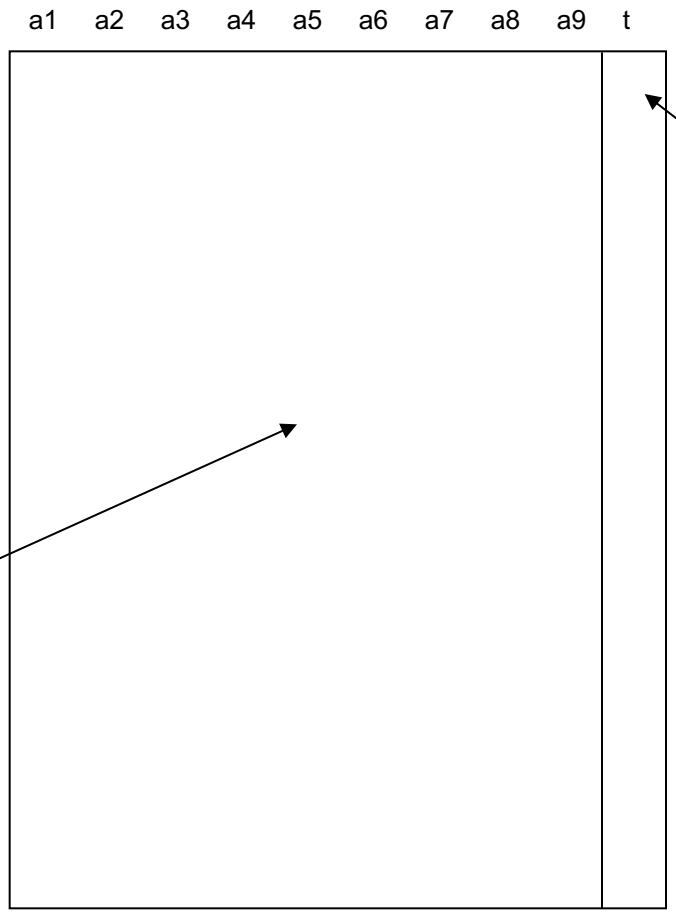


Preprocessing: Matrix for Machine Learning

Known as:
- Attributes
- Features
- Predictor variables
- Explanatory variables

Scale variables:
- Continuous variables, which can be measured on an interval scale or ratio scale
- ‘Weight’, ‘Temperature’, ‘Salary’, etc…

Categorical variables:
- Data with a limited number of distinct values or categories (nominal or ordinal)
- ‘Hair color’, ‘Gender’, ‘Grape varieties’, etc…



Known as:
- Label
- Target variable
- Dependent variable

Scale or Categorical

Data pre-processing (preparation)

- **Data preparation can be very time consuming depending on:**
  - The state of the original data
    - Data is typically collected in a “human” friendly format
  - The desired final state of the data (as required by the machine learning models and algorithms)
    - The desired final state is typically some “algorithm” friendly format
  - There may be a need for a (long) pipeline of transformations before the data is ready to be consumed by a model:
    - These transformations can be done manually (write code)
    - These transformations can be done through tools

Data pre-processing (preparation)

- **Data can be missing values:**
  - Blank fields
  - Fields with dummy values (9999)
  - Fields with “U” or “Unknown”

- **Data can be corrupt or incoherent:**
  - Data fields can be in the wrong place (strings where numbers are expected)
  - Spurious “End of Line” characters can chop original lines of data into several lines and cause data fields in the wrong place
  - Data entered in different formats: USA / US / United States

- **These aspects of data preparation are often referred to as:**
  - Data cleansing / wrangling

Data pre-processing (preparation)

- **Data dimensionality may need to be reduced:**

- **The idea behind reducing data dimensionality is that data raw data tends to have two subcomponents:**
  - "Useful features" (aka structure)
  - Noise (random and irrelevant)
  - Extracting the structure makes for better models

  - Examples of applications of dimensionality reduction
    - Extracting the important features in face/pattern recognition
    - Removing stop words when working on text classification
    - Stemming: fishing, fished, fisher ➔ fish

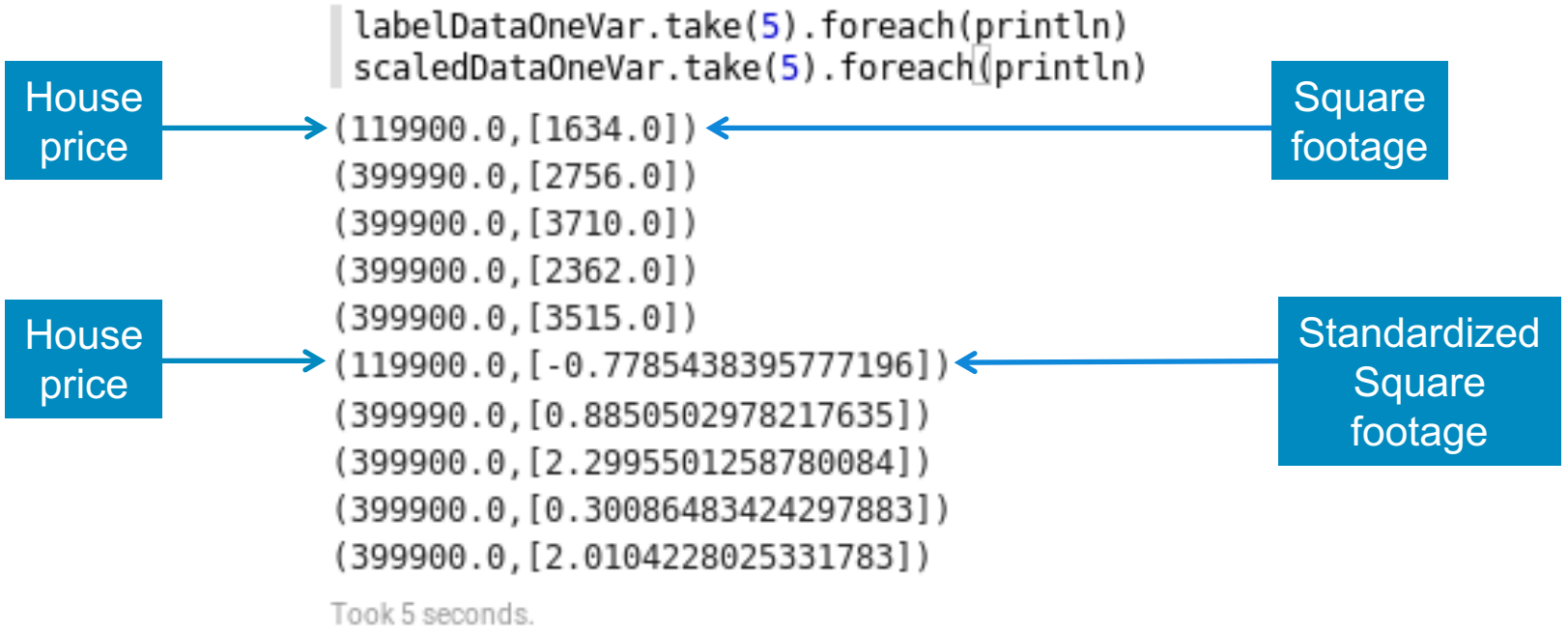
  - Examples methods of dimensionality reduction
    - Principal Component Analysis
    - Singular Value Decomposition

Data pre-processing (preparation)

- **Data may need to be transformed to match algorithms requirements:**
  - Tokenizing (typical in text processing)
  - Vectorizing (several algorithms in Spark MLlib require this)
    - Transform data into Vector arrays
    - Can be done manually (write Python or Scala code)
    - Can be done using tools (VectorAssembler in the new ML package)
      - (TF-IDF in text processing)
      - Word2Vec
  - Bucketizing
    - Transform a range of continuous values into a set of buckets

Data pre-processing (preparation)

- **Data may need to be transformed to match algorithms requirements:**
  - Standardization
    - Transform data to a set of Vector with Zero mean and Unit Standard deviation
    - Linear Regression with SGD in Spark MLlib requires this



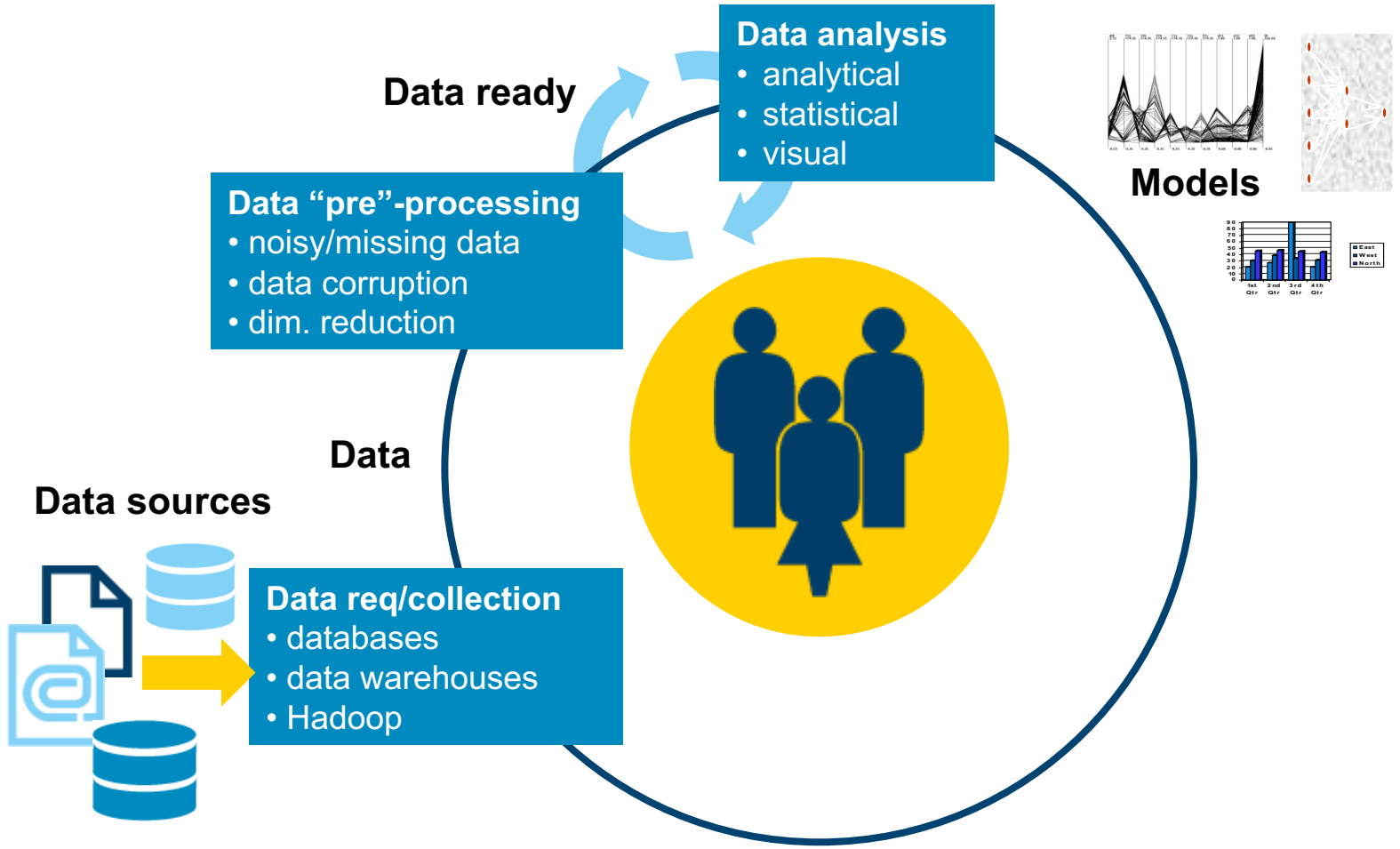
Data pre-processing (preparation)

- **Data may need to be transformed to match algorithms requirements:**
  - Normalization
    - Transform data so that each Vector has a Unit norm
  - Categorical values need to be converted to numbers
    - This is required by Spark MLlib classification trees
    - Marital Status: {“Widowed”, “Married”, “Divorced”, “Single”}
    - Marital Status: {0, 1, 2, 3}
    - You cannot do this if the algorithm could infer: Single = 3 X Married ☺

Data pre-processing (preparation)

- **Data may need to be transformed to match algorithms requirements:**
  - Dummy encoding
    - When categorical values cannot be converted to consecutive numbers
    - Marital Status: {“Single”, “Married”, “Divorced”, “Widowed”}
    - Marital Status: {“0001”, “0010”, “0100”, “1000”}
    - This is necessary if the algorithm could make some wrong inference from the numerical based categorical encoding:
      - Single = 3
      - Married = 2
      - Divorced = 1
      - Widowed = 0
        - > Single = Married + Divorced
        - > Single = Divorced x 3
        - > (this is a contrived example, but you get the idea ☺, replace marital status with colors…)

Data centric view of methodology

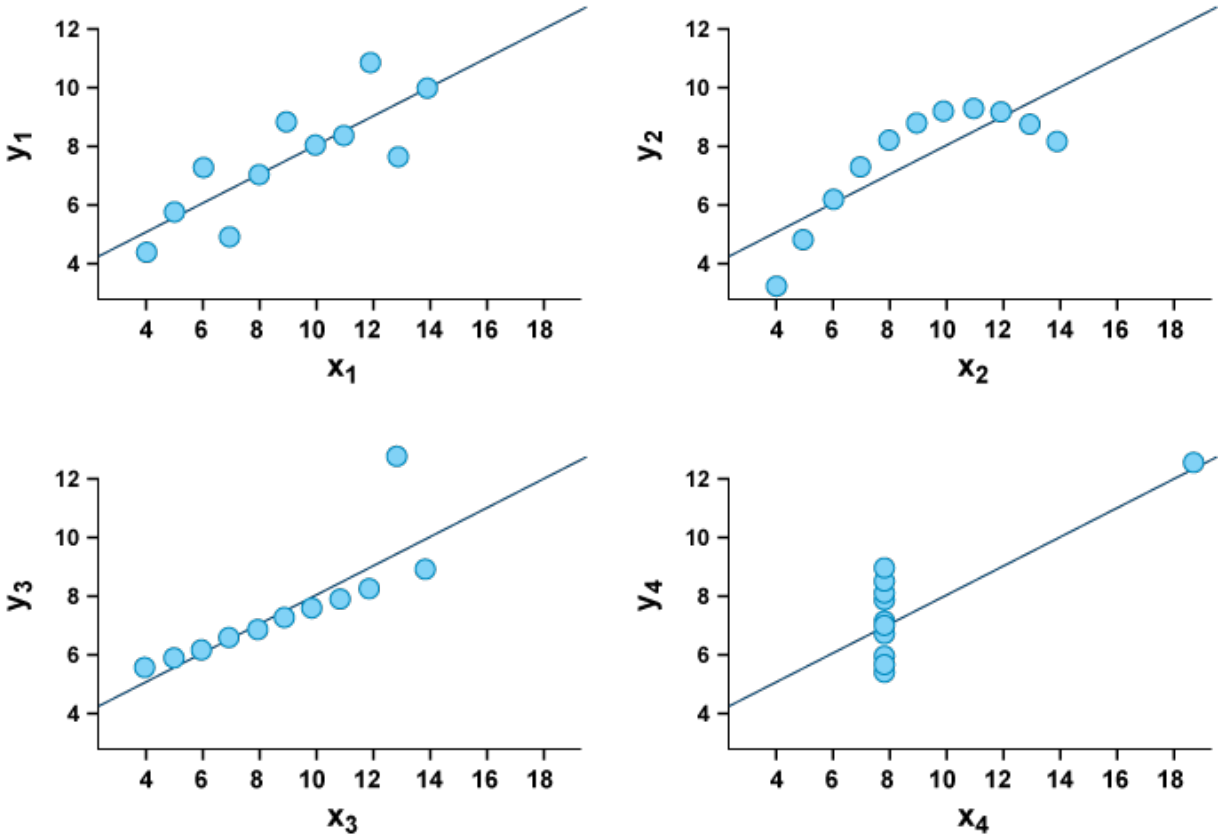


Data analysis:

- **The data analysis phase is very likely to be intertwined with the data preparation phase:**
  - It is not uncommon to use data analysis results to refine or drive the data preparation
    - In text classification: Group the tokens at hand and calculate the numbers in each group.
    - You most likely want to remove the most common and least common tokens as part of the analysis phase.

- **The data analysis phase should use:**
  - Mathematical tools (Statistics, correlations, Chi Square test of independence, etc…)
  - Visualizations

Data analysis: visualizations



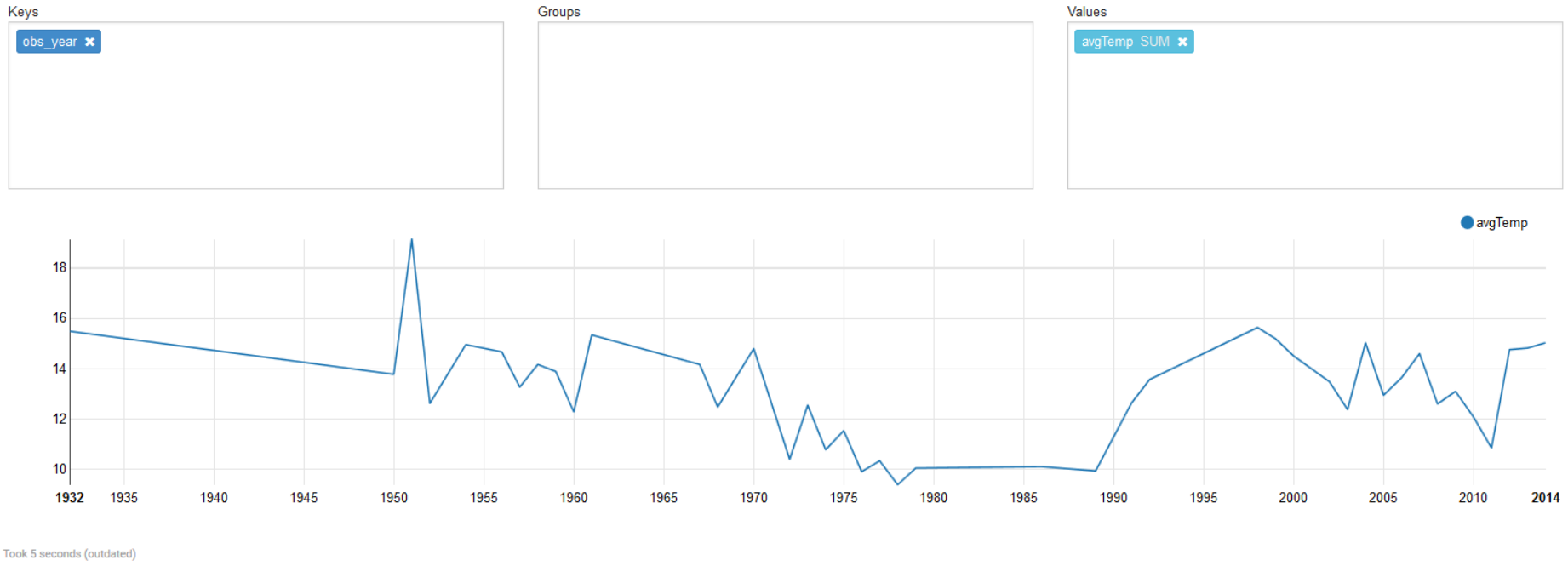
The four data sets have similar statistical properties:
- The mean of x is 9
- The variance of x is 11
- The mean of y is approx. 7.50
- The variance of y is approx. 4.12
- The correlation is 0.816

As shown the linear regression lines are approx. y=3.00+0.500x.

- **Anscombe's quartet**
  - The four datasets have nearly identical statistical properties (mean, variance, correlation), yet the differences are striking when looking at the simple visualization

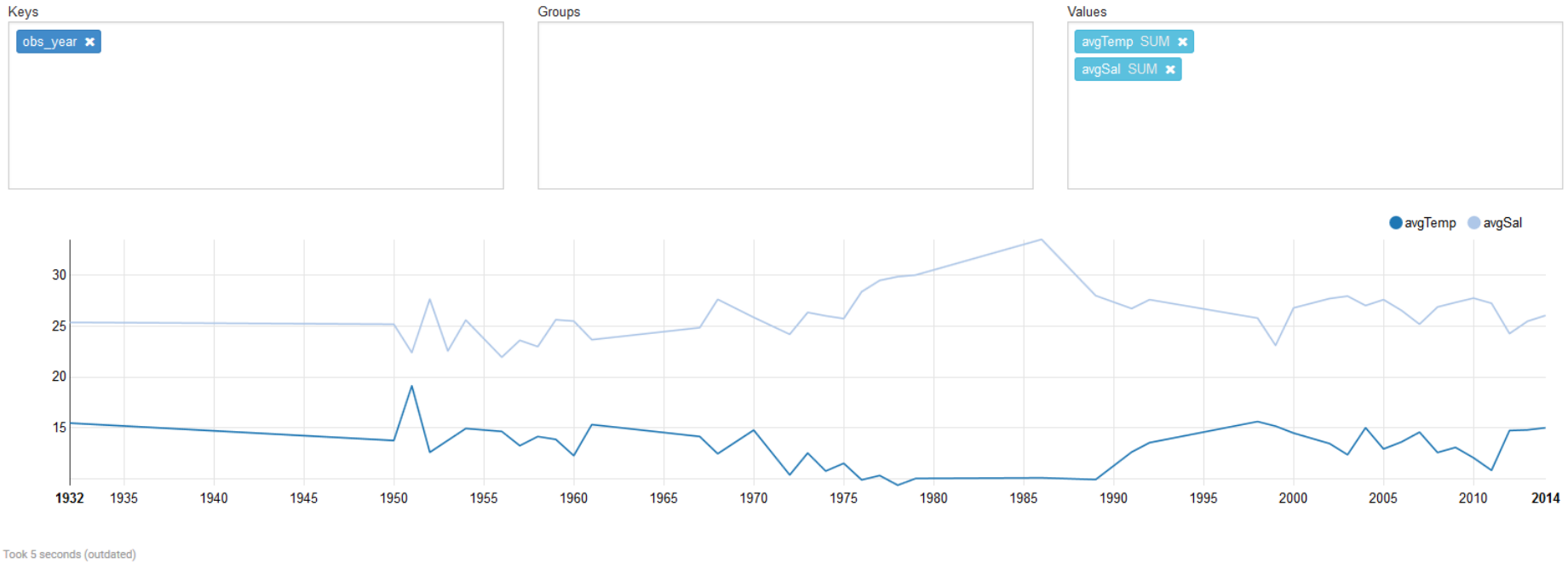
Data analysis: visualizations

- **Summer surface (depth < 10 meters) average temperature evolution in the archipelago…**



Data analysis: visualizations

- **Summer surface (depth < 10 meters) average temperature evolution in the archipelago + average salinity…**



Data analysis:

- **The data analysis phase can GUIDE you towards better and more relevant modeling:**
  - When you are building a classifier, it is important to understand the PREVALANCE of the condition that you are building a model for, i.e. how common or uncommon this condition effectively is…
  - Imagine you are working towards building a classifier for some medical condition and your training and testing data sets yield the following model

	Test positive	Test negative
Disease (100)	95 (True Positive)	5 (False Positive)
Normal (100)	5 (False Negative)	95 (True Negative)

- **With 95% sensitivity & specificity, this sounds like a great test…**

Data analysis:

- **What truly matters to the users of your new model / test (doctors, bankers, practitioners) is the PREDICTIVE VALUE of the test:**
  - If the test is positive, then what is the actual chance of being sick?
  - If the test is positive, then what is the actual chance of defaulting on the loan?
  - Is it 95% ?

- **Let's run the test on a population of 1,000,000 where 1% individuals (10,000) are actually suffering from this condition:**

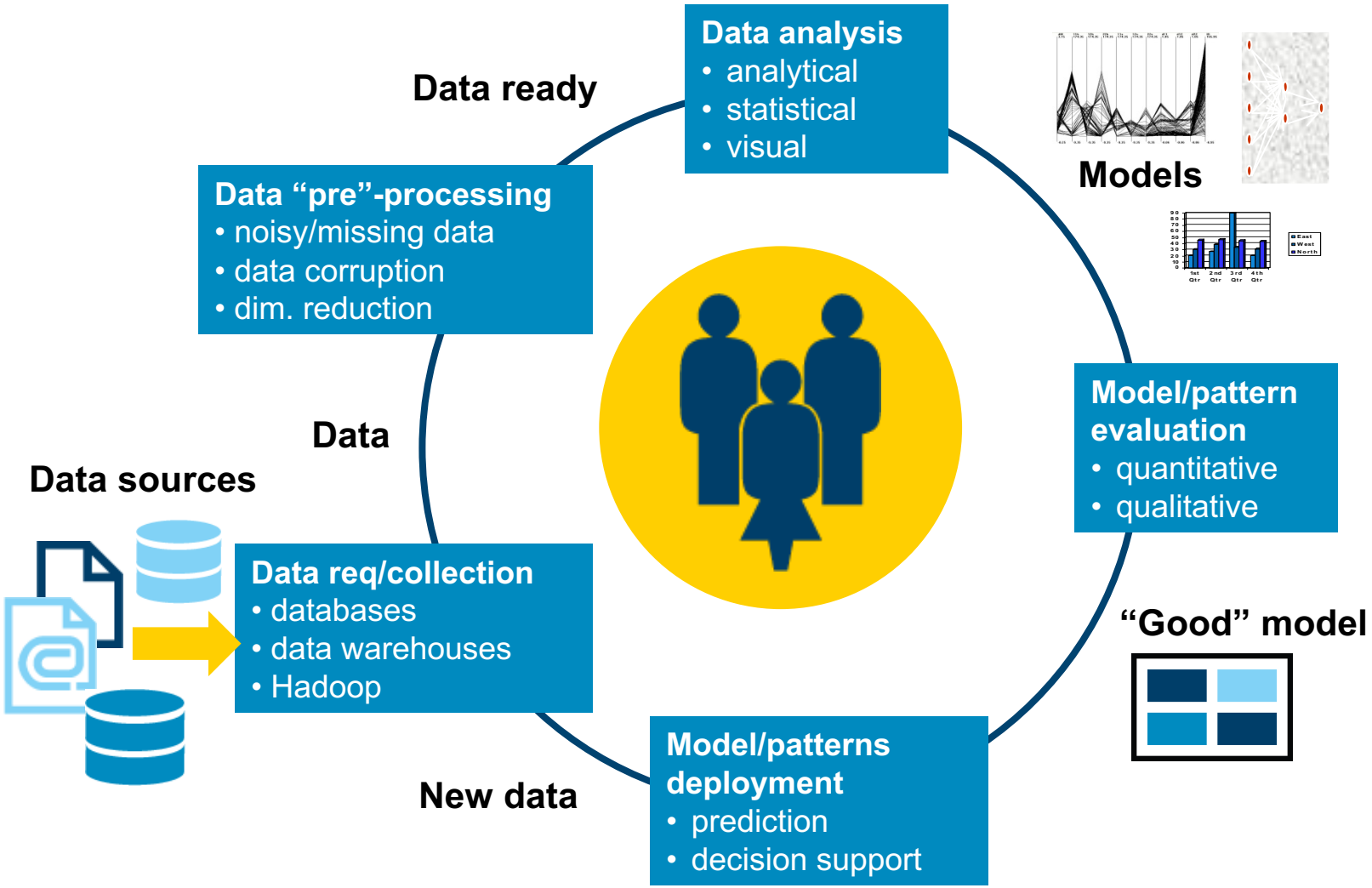
	Test positive	Test negative
Disease (10000)	9500 (95% True Positive)	500 (5% False Negative)
Normal (990000)	49500 (5% False Positive)	940500 (95% True Negative)

Data analysis:

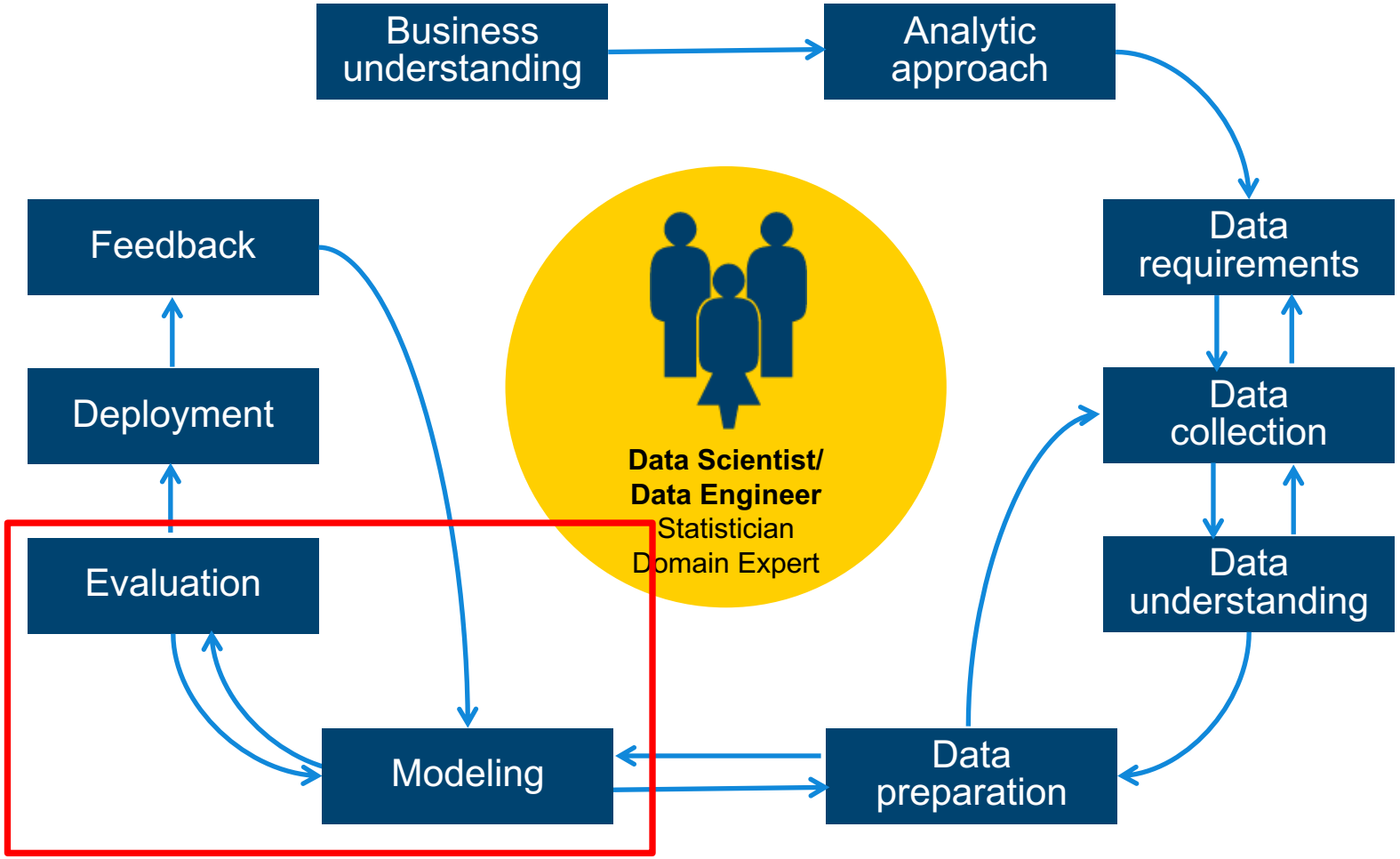
	Test positive	Test negative
Disease (10000)	9500 (95% True Positive)	500 (5% False Negative)
Normal (990000)	49500 (5% False Positive)	940500 (95% True Negative)

- **Probability of being sick if the test is positive:**
  - (# of people truly sick) / # positive result tests
  - 10000 / (49500 + 9500) = **16.9%**
  - What is happening here:
    - The condition is RARE and the 5% FALSE POSITIVES are still way higher in numbers than the true positives.
- **Data analysis of the prevalence of the condition tells us that a test with 99% or higher sensitivity / specificity would be needed.**

Data centric view of methodology



Data Science Methodology



Machine Learning – A more formal definition

Tom Mitchell of Carnegie Mellon University provides a widely quoted, more formal definition of 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"

Machine Learning vs Human Learning

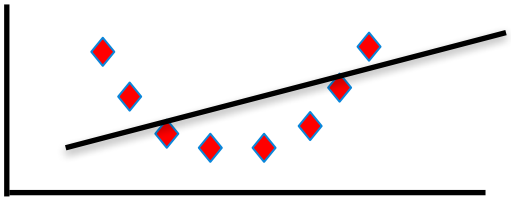
- **In many aspects, ML not fundamentally different from HL:**
  - Repeat the same task over and over again to gain experience.
  - Action of repeating the same task is referred to as “practice”
  - With practice and experience, we get better at learned tasks.

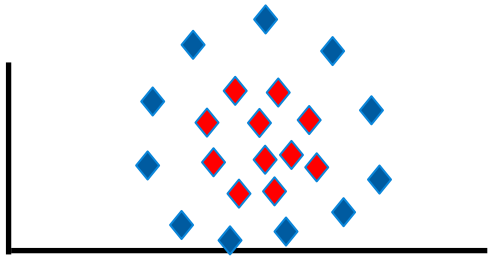
- **Examples:**
  - Learning how to play a music instrument
  - Learning how to play a sport (golf, tennis, etc…)
  - Practicing for a math exams doing exercises
  - A teacher or coach will measure performance to evaluate progress
  - Practice makes perfect

Learning challenges

- **Under fitting:**
  - Not knowing enough “basic” concepts, i.e. not being well-equipped enough to tackle learning at hand:
    - You can’t study calculus without knowing some algebra.
    - You can’t learn playing hockey without knowing how to skate.
    - You can’t learn polo without knowing how to ride.
  - This can lead to under fitting in Machine Learning: The chosen model is just not “sophisticated”, “rich”, enough to capture the concept.

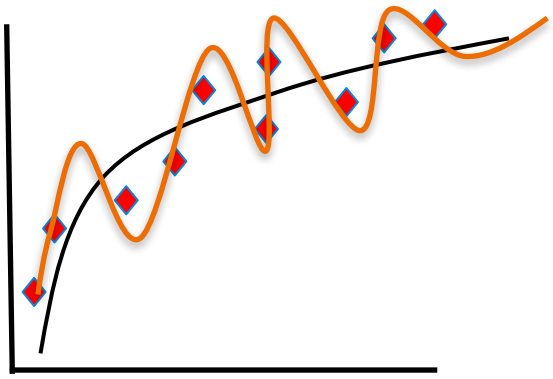
aX + BY + C



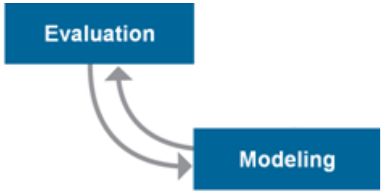


Learning challenges

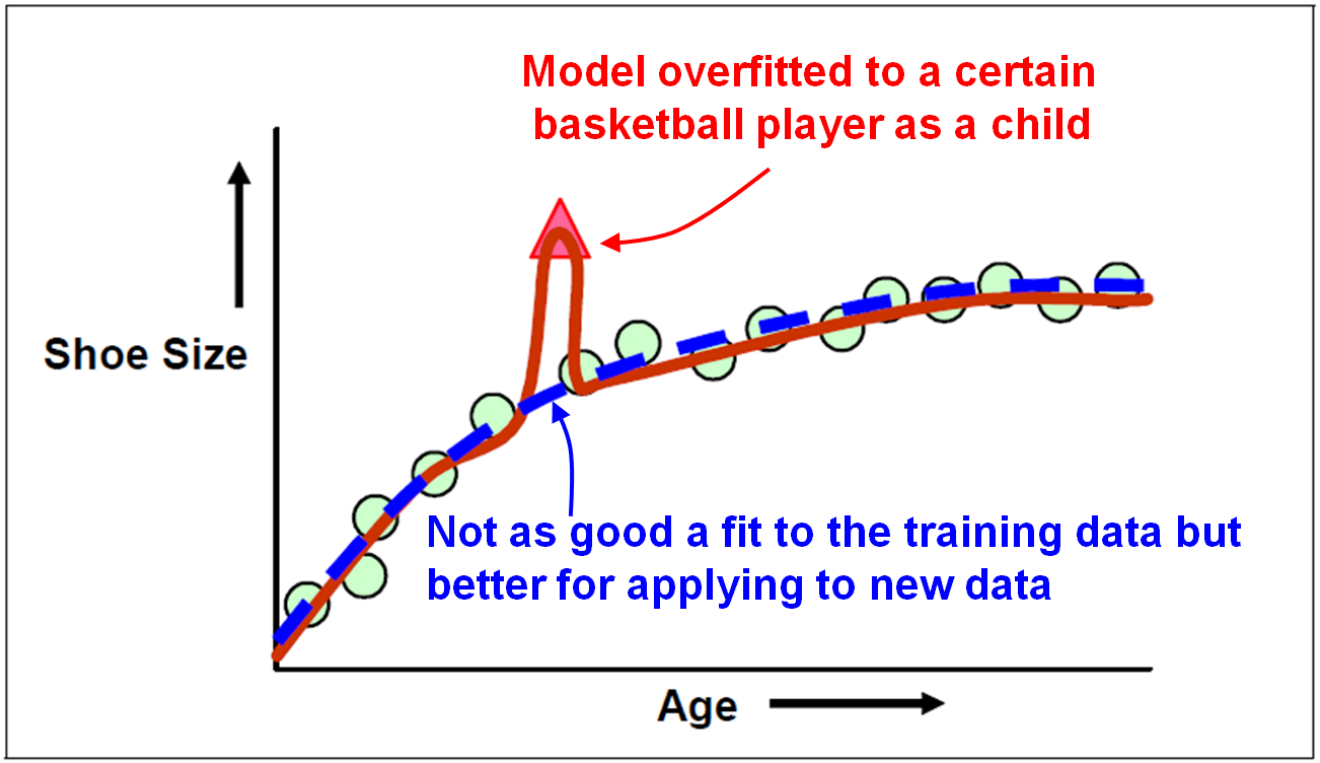
- **Over fitting:**
  - Hyper-sensitivity to minor fluctuations, ending up in modeling a lot of the unwanted noise in the data:
  - This can lead to over fitting in Machine Learning.



Model overfitting

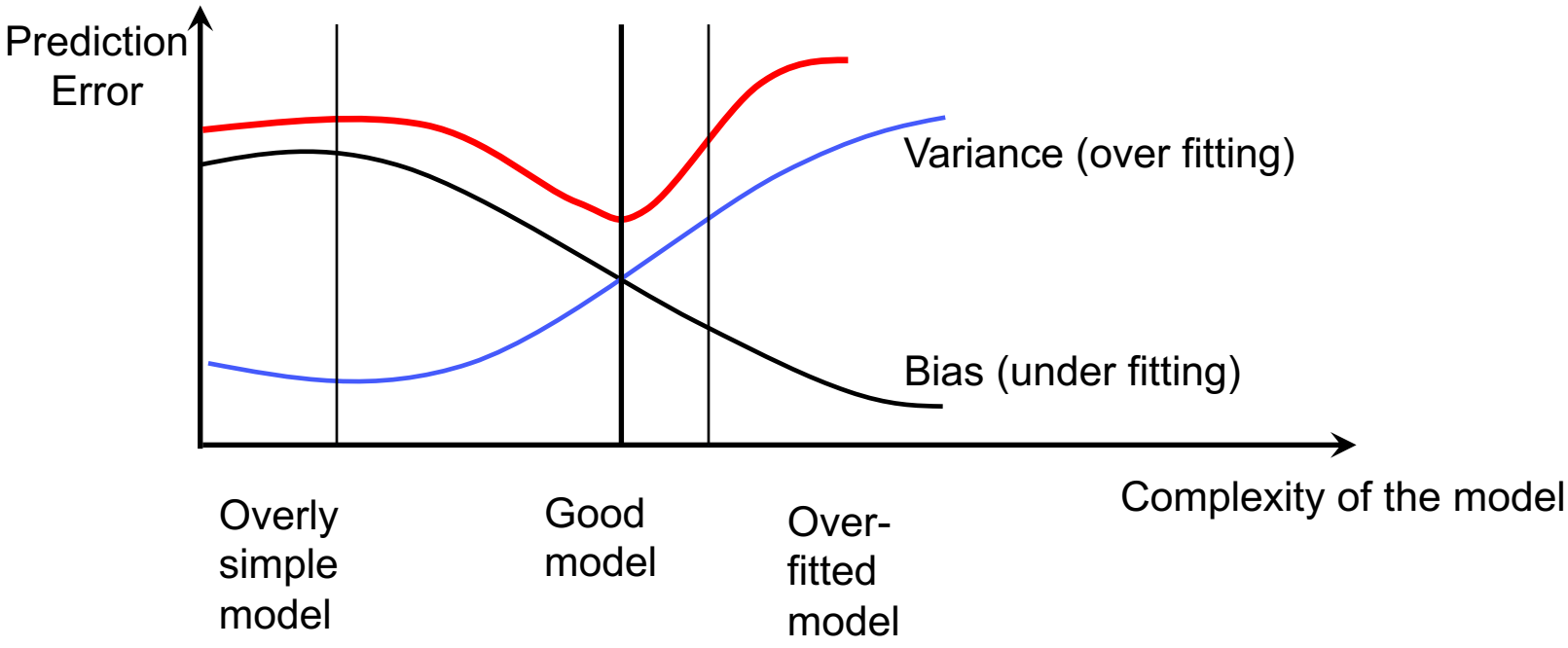


- When building a predictive model, there is a risk of overfitting the model to the training data.
- The model fits the training data very well, but it does not perform well when applied to new data.

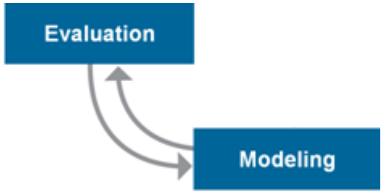


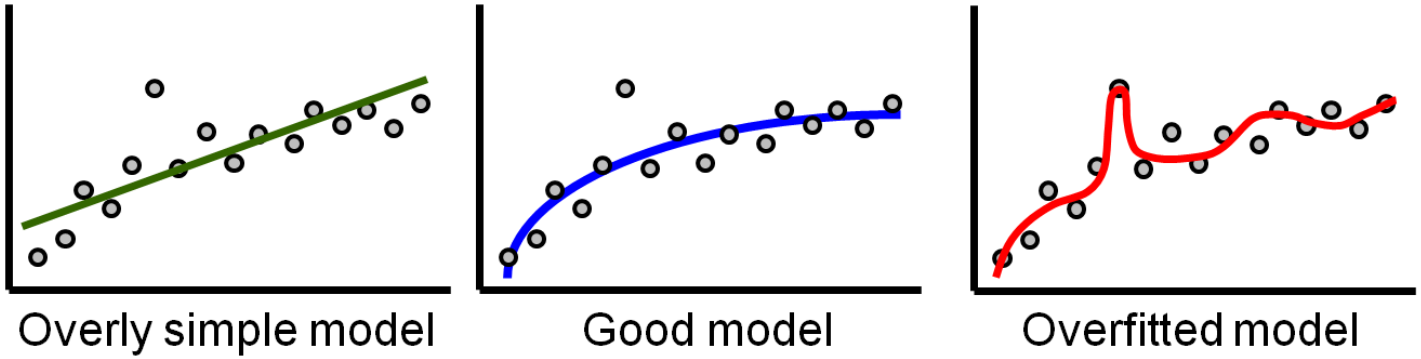
Learning challenges

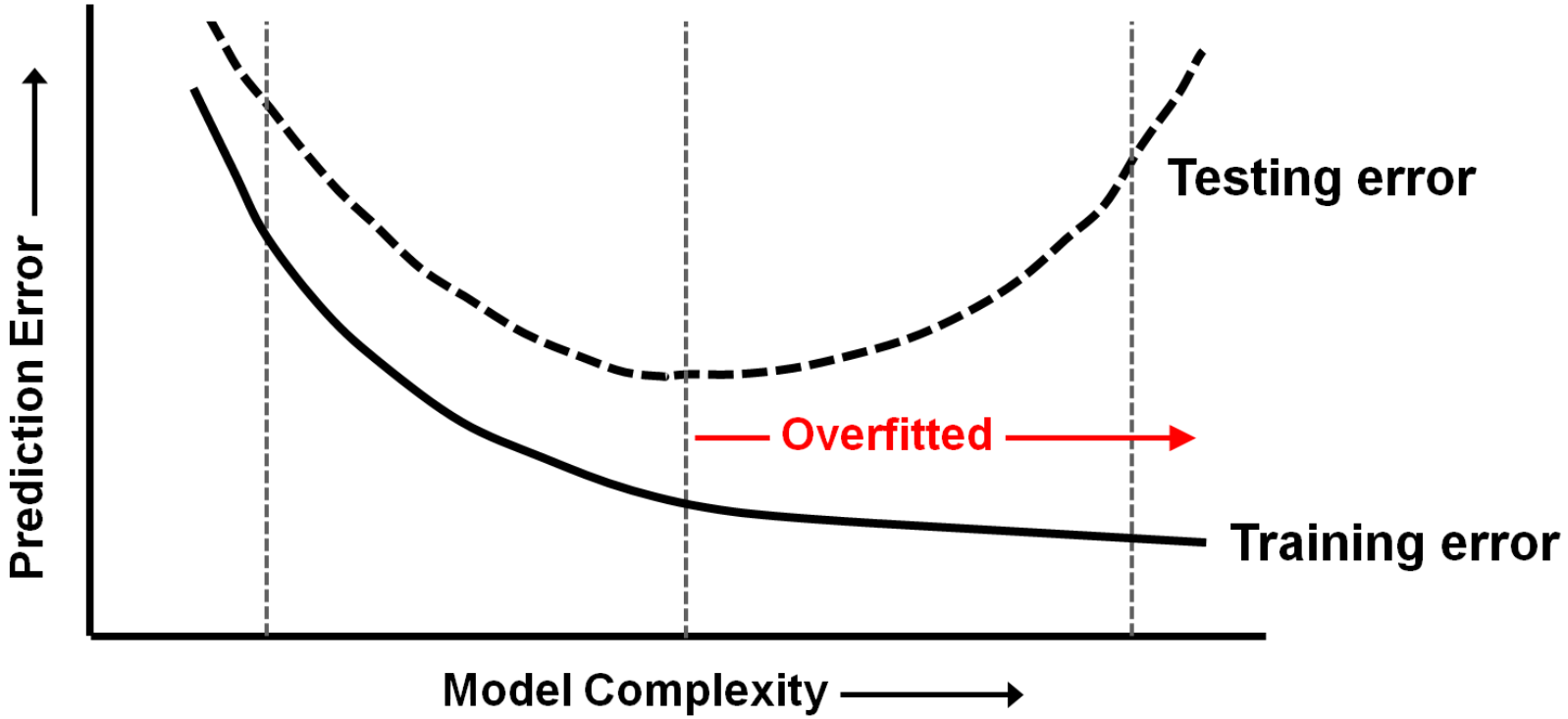
- **Compromise between bias and variance:**



When to stop training a model







Learning challenges

- **Diminishing returns:**
  - People can:
    - Have more or less talent
    - get bored or enthusiastic
  - Machines will not, however:
  - Making progress initially is usually more easy, but improving gets harder as we move along. We may need to try different learning methods, styles to keep going:
    - Machine learning algorithms have hyper-parameters which need to be tuned properly.
    - It may be necessary to use more than just one single method / algorithm to reach the goal.

Machine Learning Examples

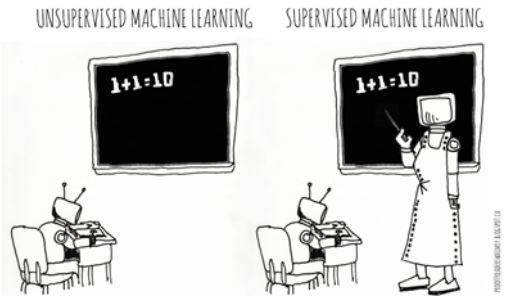
- Is this cancer ? (Medical diagnosis)
- Is this legitimate or fraud (spam) ?
- What is the market value of this house ?
- Which of these people are good friends with each other ?
- Will this engine fail (when) ?
- Will this person like this movie ?
- Who is this ?
- What did you say ? (Speech recognition)

Machine Learning solves problems that cannot be tackled by numerical means alone.

Categories of Machine Learning

- **Supervised learning**
  - The program is “trained” on a pre-defined set of “training examples”, which then facilitate its ability to reach an accurate conclusion when given new data
  - The algorithm is presented with example inputs and their desired outputs (correct results)
  - The goal is to learn a general rule that maps inputs to outputs

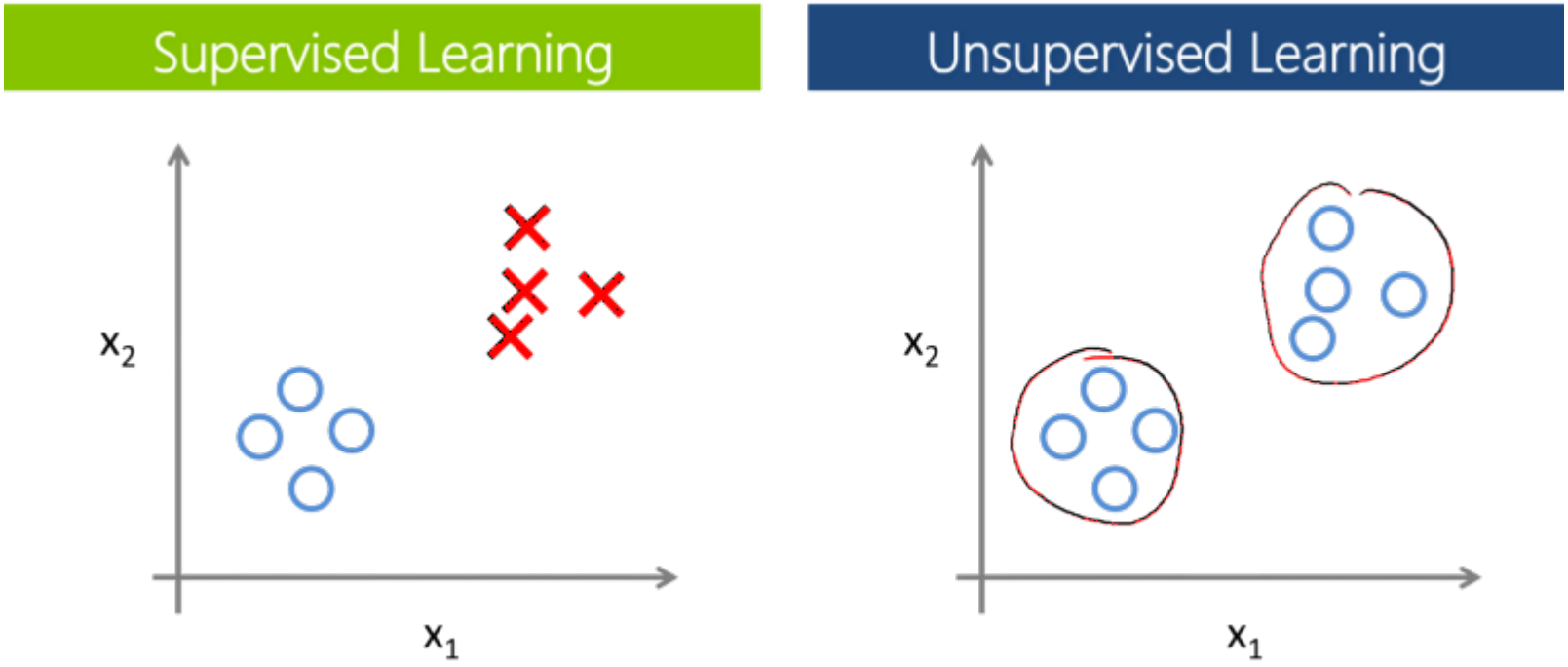
- **Unsupervised learning**
  - No labels are given to the learning algorithm, leaving it on its own to find structure (patterns and relationships) in its input
  - Unsupervised learning can be a goal in itself (discovering hidden patterns in data) or a means towards an end (feature learning)



Categories of Machine Learning

	Discrete Output	Continuous Output
Supervised Learning (require Ground-Truth)	• **Classification** (outcome is discrete) • Binary Classification • Linear Models (Logistic Regression) • Decision Trees • Naïve Bayes • Multi class Classification • Decision Trees • Naïve Bayes • K-NN	• **Regression** - Linear - Ridge - Lasso • **Decision Trees** • Random Forest • Gradient Boosted Trees
Unsupervised Learning (no Ground-Truth data required)	• Clustering - k-means • FP-Growth	• Clustering - k-means - Gaussian Mixture • Dimensionality Reduction - PCA - SVD

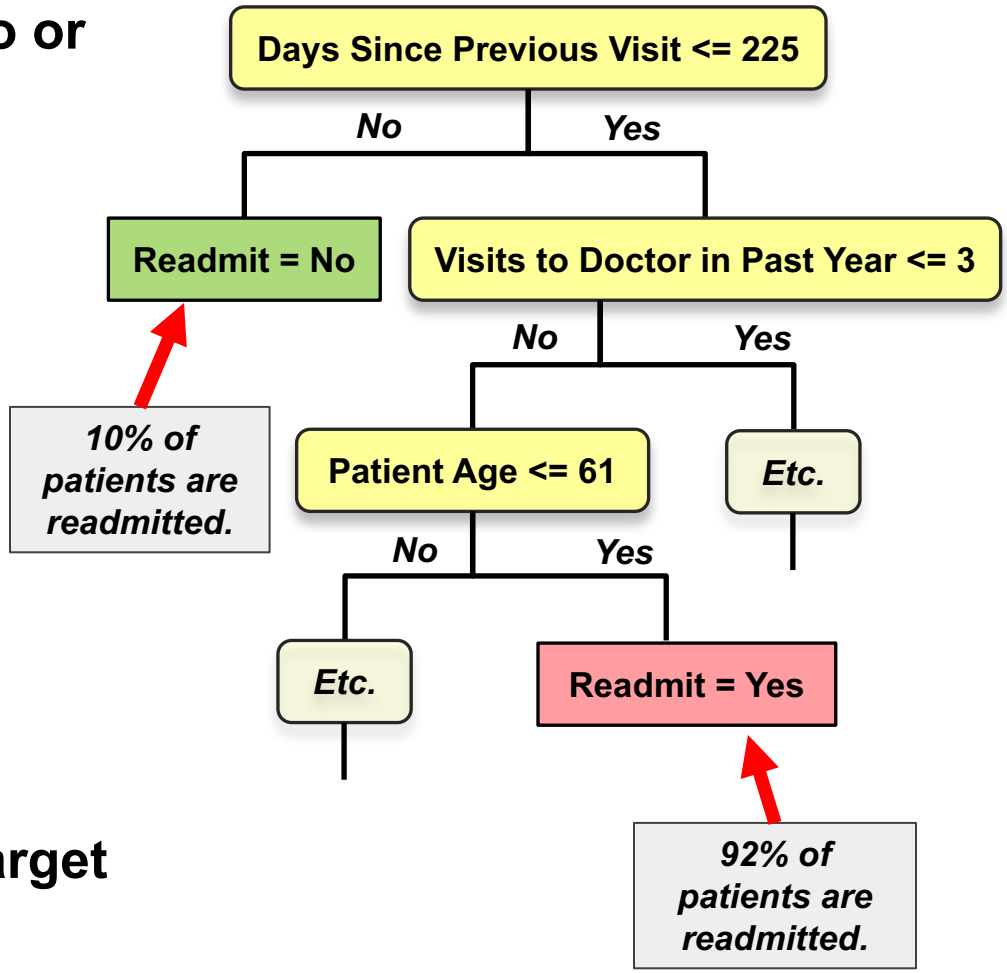
Supervised vs. Unsupervised Learning



Classification – Decision tree

Modeling

- **Class variable (target) with two or more outcomes.**
- **Splits records in a tree-like series of nodes along mutually-exclusive paths.**
  - Algorithm decides which variable and threshold value to use at each split
  - New records are predicted (classified) based on the leaf assignment
  - Accurate
  - Explicit decision paths
- **Can also handle continuous target ("regression tree").**



Classification – Naïve Bayes

Modeling

- **Two or more outcomes.**
- **Assumes independence among explanatory variables, which is rarely true (thus "naïve").**
- **Despite its simplicity, often performs very well… widely used.**
- **Significant use cases:**
  - Text categorization (spam vs. legitimate, sports or politics, etc.) using word frequencies as the features
  - Medical diagnosis (*e.g.*, automatic screening)

Classification – Naïve Bayes

Modeling

Outlook	Temp	Humidity	Windy	Play golf
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes
Rainy	Cool	Normal	False	Yes
Rainy	cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes
Sunny	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Rainy	Mild	High	True	No

Classification – Naïve Bayes

Modeling

Frequencies and probabilities for the weather data:

outlook			temperature			humidity			windy			play	
	yes	no		yes	no		yes	no		yes	no	yes	no
sunny	2	3	hot	2	2	high	3	4	false	6	2	9	5
overcast	4	0	mild	4	2	normal	6	1	true	3	3		
rainy	3	2	cool	3	1								
	yes	no		yes	no		yes	no		yes	no	yes	no
sunny	2/9	3/5	hot	2/9	2/5	high	3/9	4/5	false	6/9	2/5	9/14	5/14
overcast	4/9	0/5	mild	4/9	2/5	normal	6/9	1/5	true	3/9	3/5		
rainy	3/9	2/5	cool	3/9	1/5								

Classification – Naïve Bayes

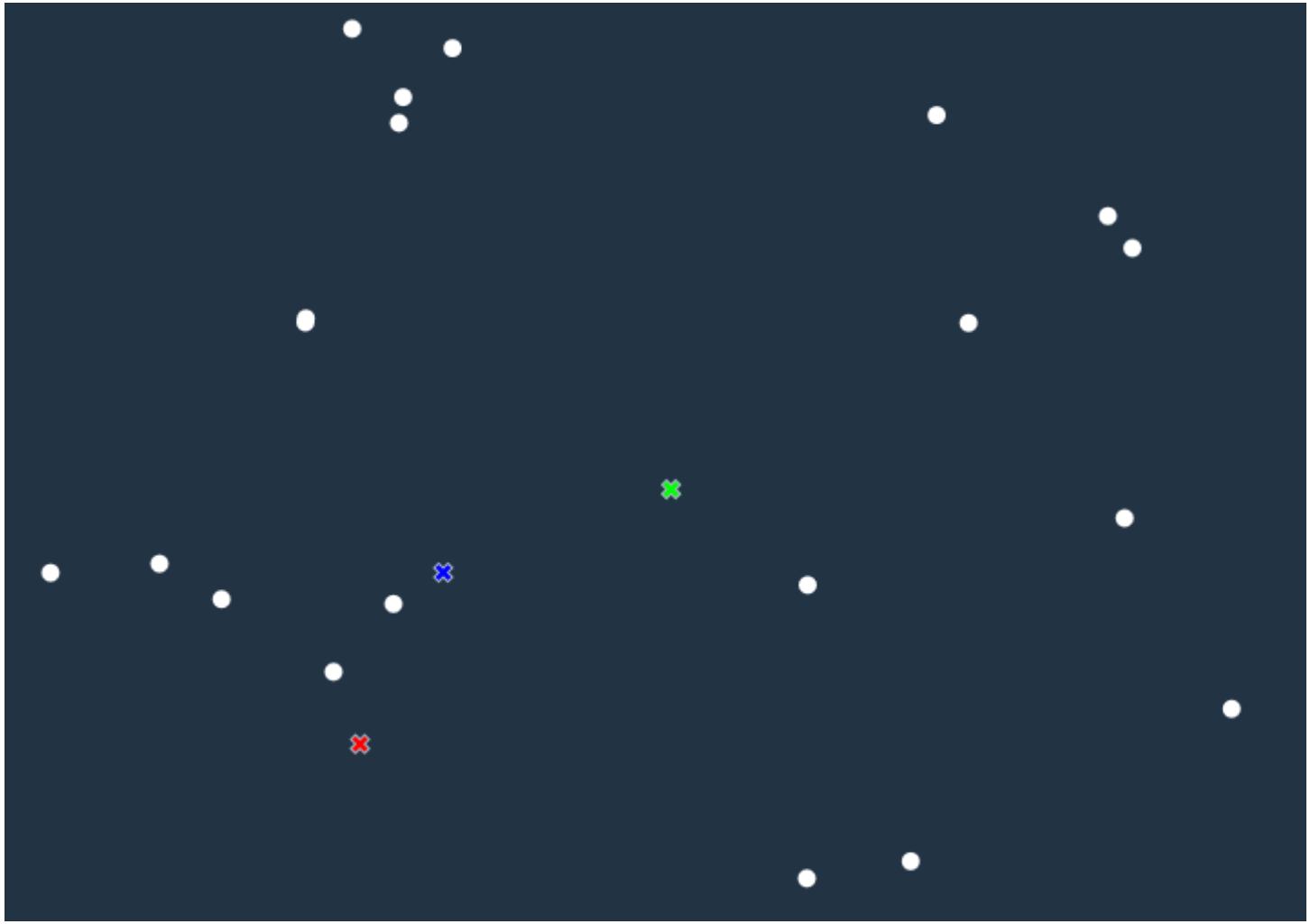
- L(yes) = 2/9 * 3/9 * 3/9 * 3/9 = 0.0082
- L(no) = 3/5 * 1/5 * 4/5 * 3/5 = 0.0577

- P(yes) = 0.0082 * 9/14 = 0.0053
- P(no) = 0.0577 * 5/14 = 0.0206

- The decision would be: NO.

Clustering – K-means method

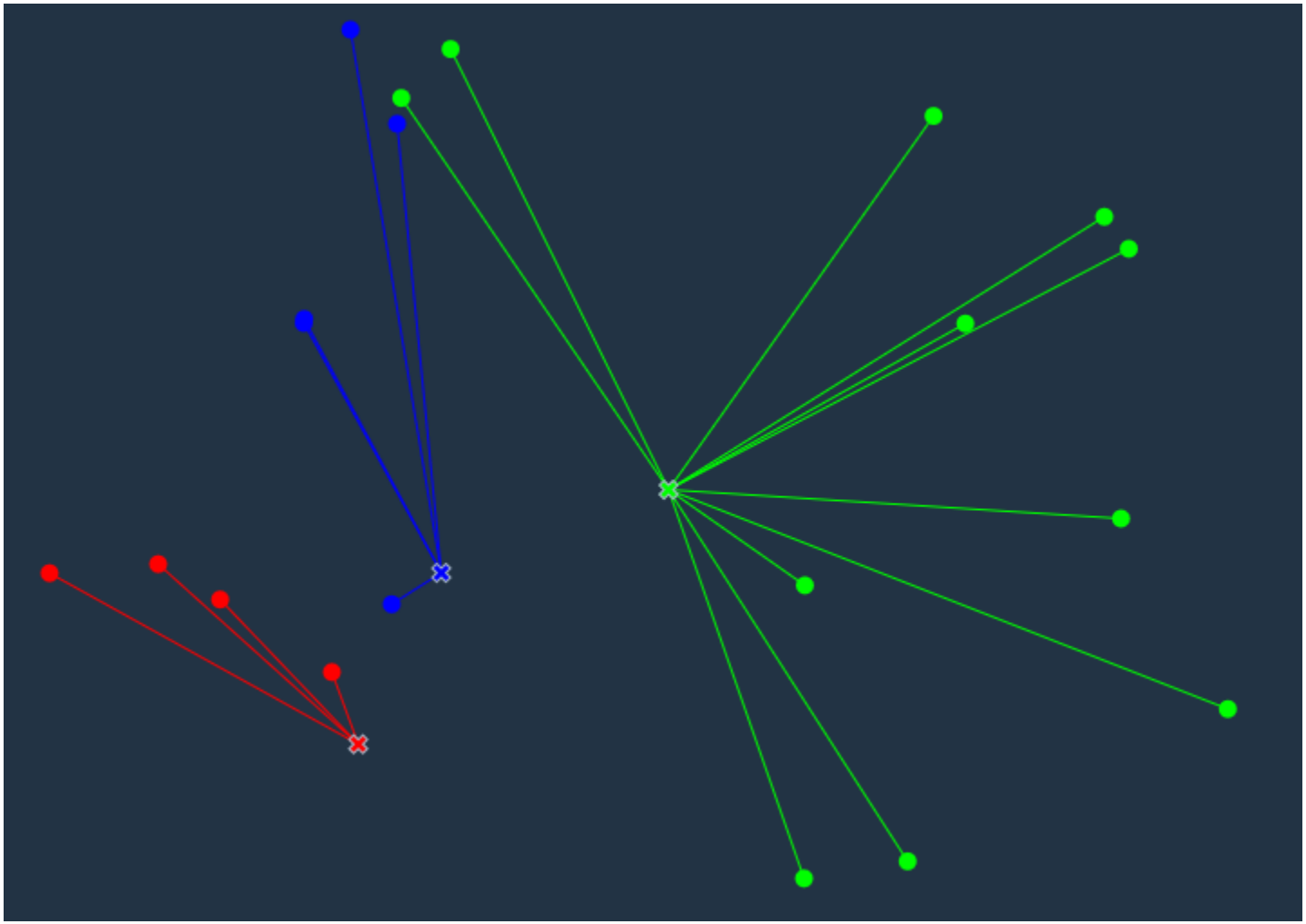
Modeling



Start with 20 data points and 3 clusters

Clustering – K-means method

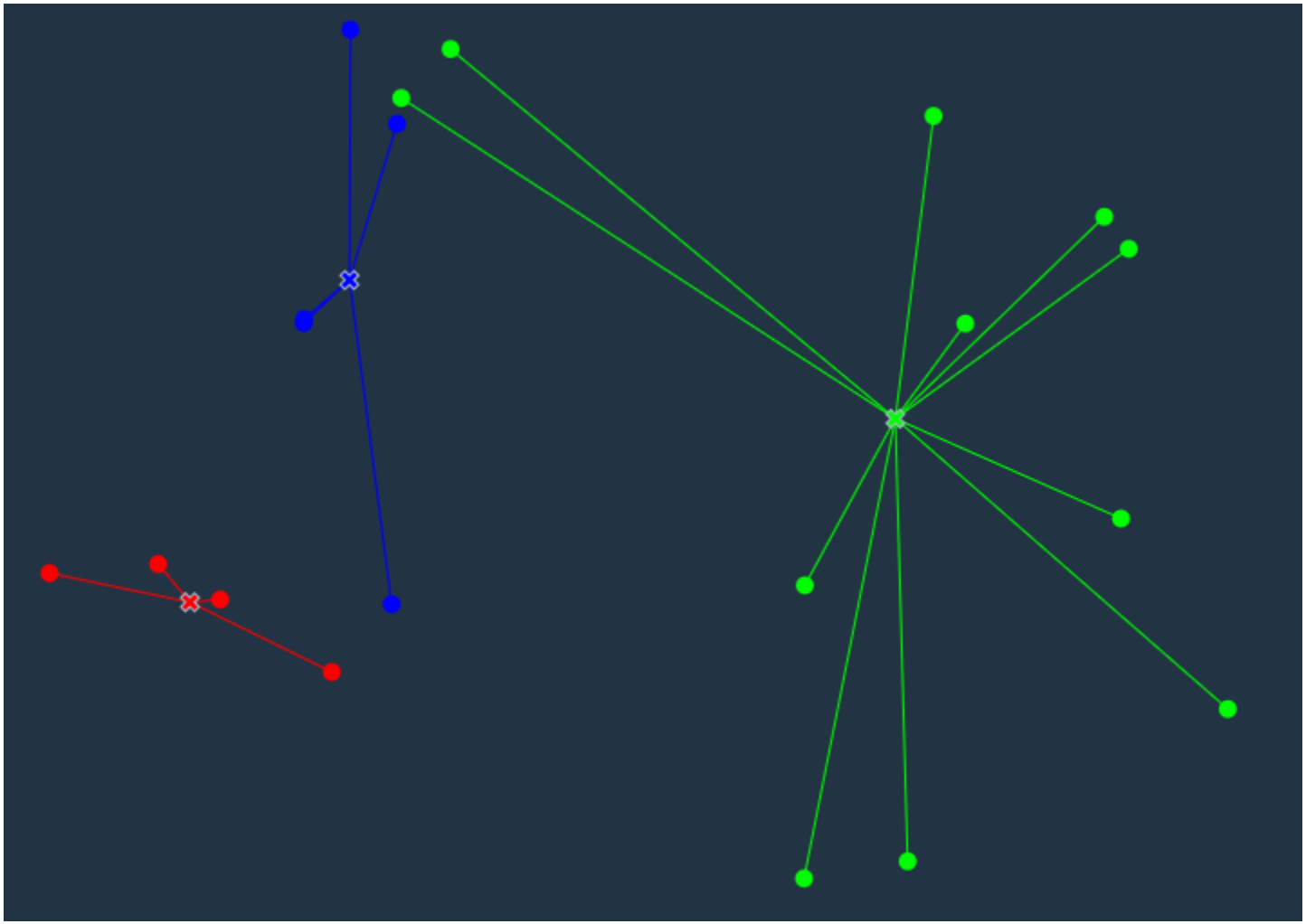
Modeling



Assign each data point to the nearest cluster

Clustering – K-means method

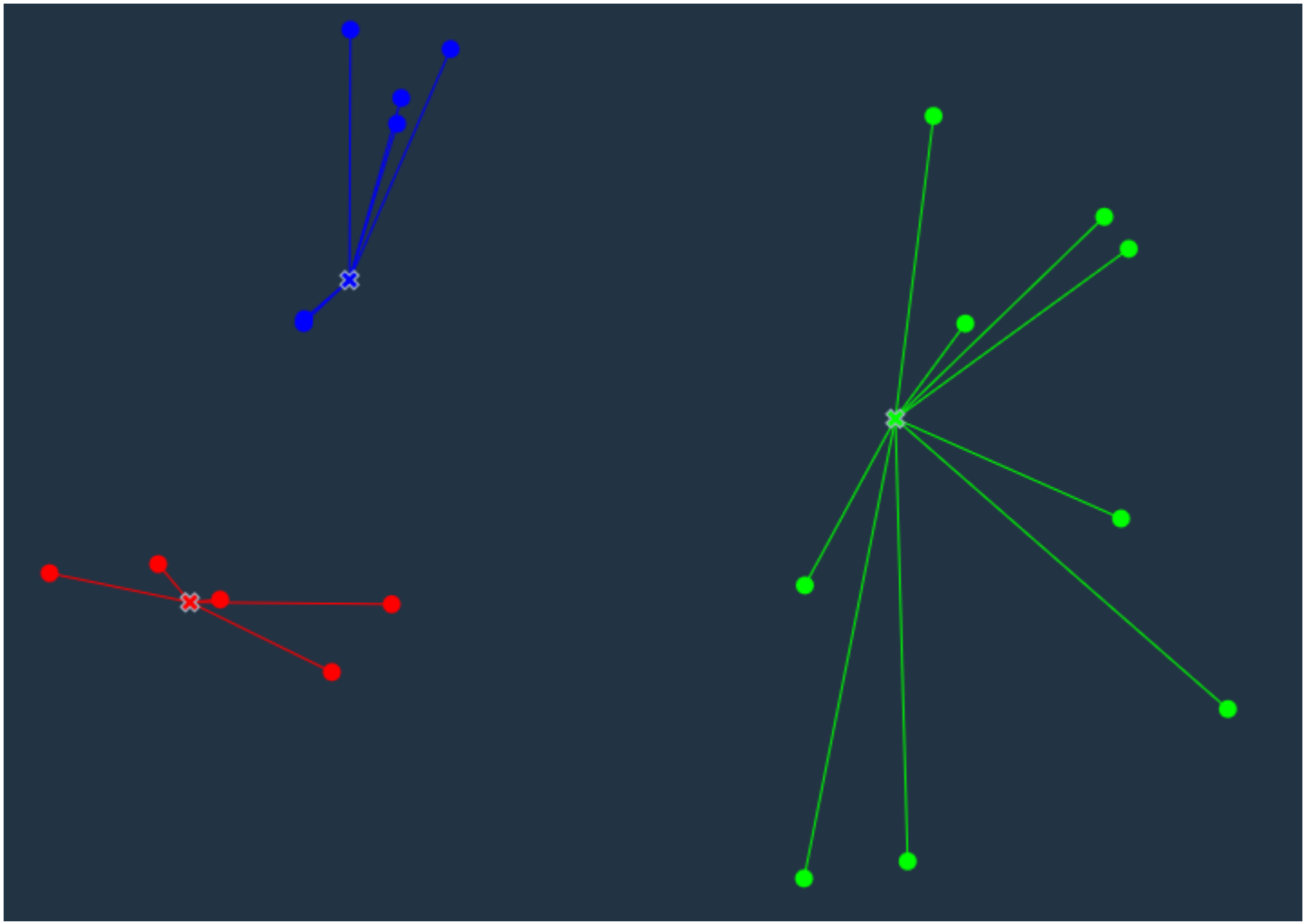
Modeling



Calculate centroids of new clusters

Clustering – K-means method

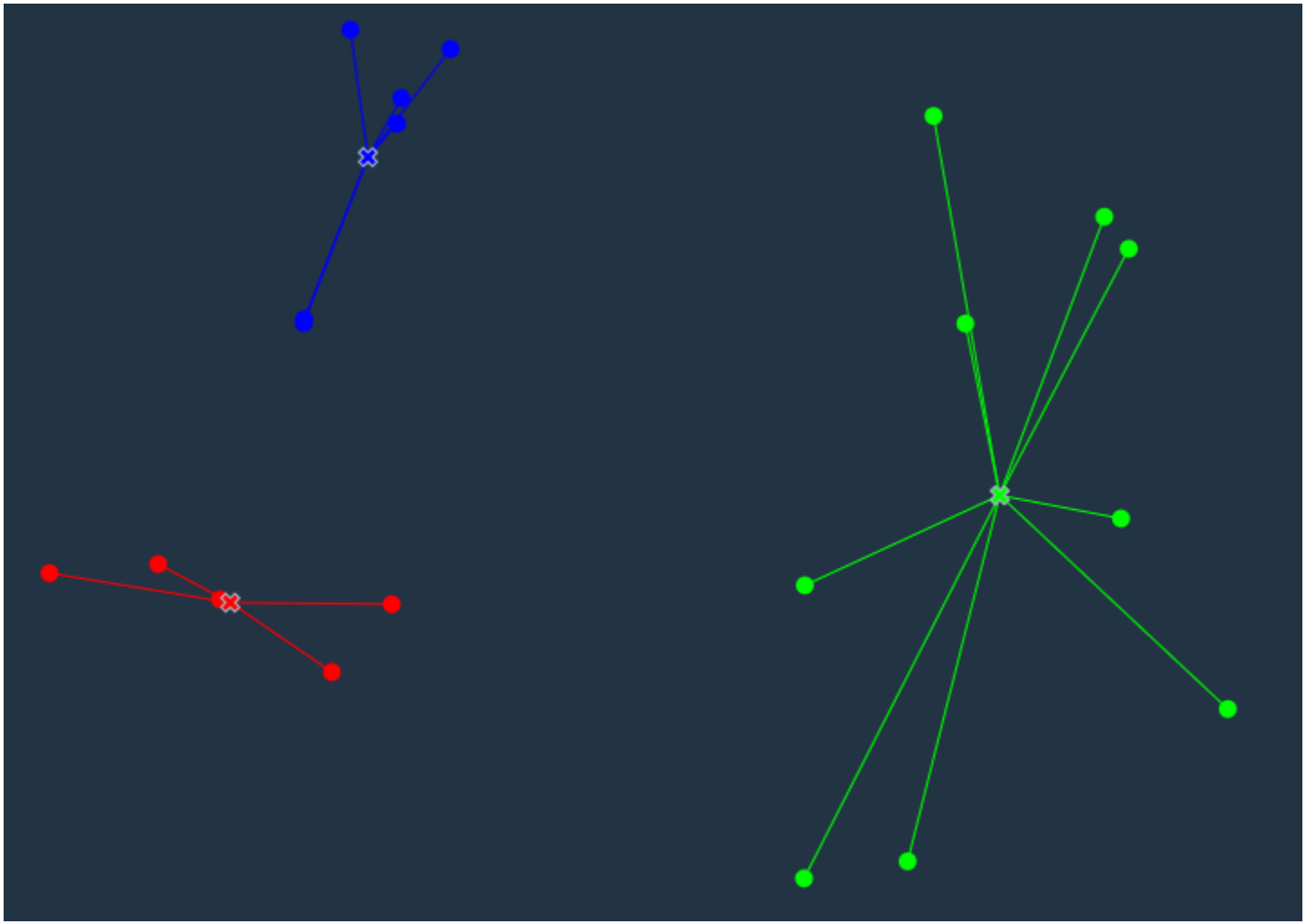
Modeling



Assign each data point to the nearest cluster

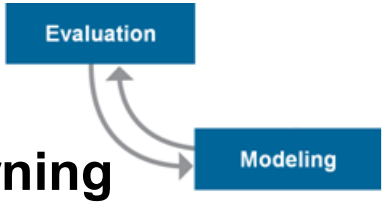
Clustering – K-means method

Modeling



Calculate centroids of new clusters…until convergence

Training, testing, & validation sets



- **During the model development process, supervised learning techniques employ training and testing sets and sometimes a validation set.**
  - Historical data with known outcome (*target*, *class*, *response*, or *dependent variable*)
  - Source data randomly split or sampled… mutually exclusive records
- **Why?**
  - Training set ➔ build the model (**iterative**)
  - Testing set ➔ tune the parameters & variables during model building (**iterative**)
    - Assess model quality during training process
    - Avoid overfitting the model to the training set
  - Validation set ➔ estimate accuracy or error rate of model (**once**)
    - Assess model's expected performance when applied to new data