The Data Science Process

DAPT 631

Intro to Data Mining
Intro to Python
Intro to Jupyter Notebook

Intro to *pandas*

pandas EDA

Neural Networks
Clustering

Intro to Python (Caesar Cipher)
Data Science Process

Decision Trees
Random Forests

Gradient Boosting
Classifier Accuracy
Neural Networks

Data Wrangling
Association Analysis
Wrap-up

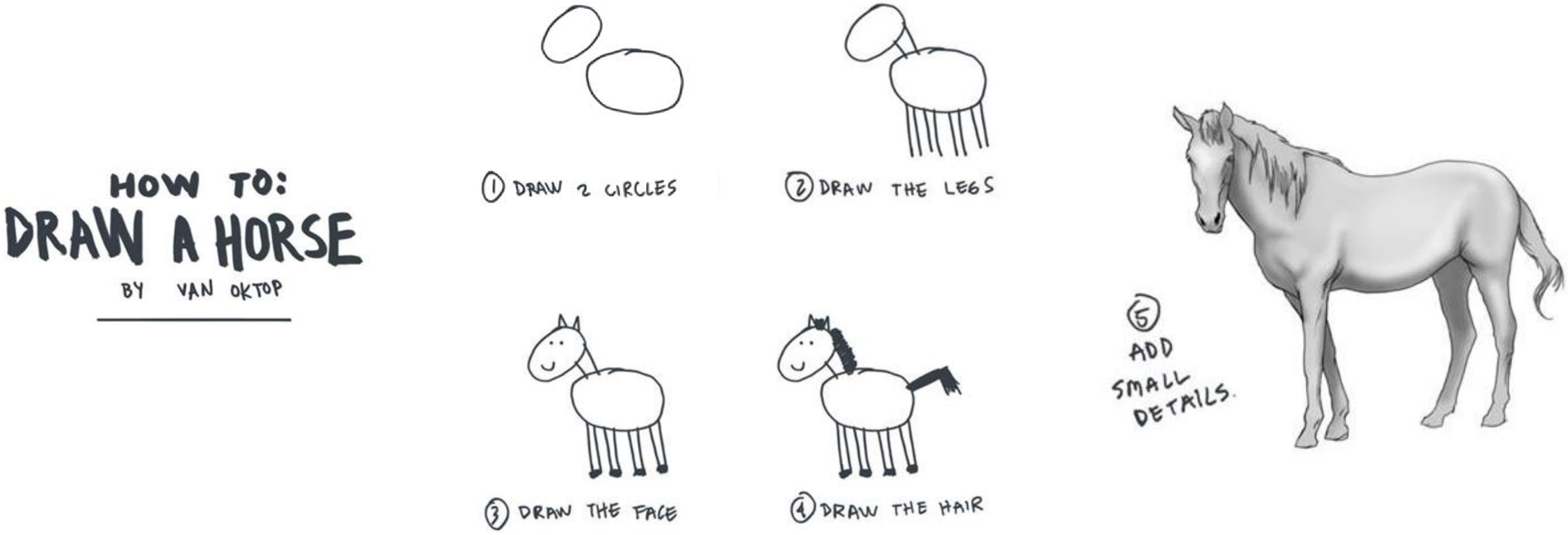
			HyFlex		HyFlex		HyFlex		HyFlex
		Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
	Friday					6-Mar			Apri l17
Session 1	12:30 - 2:15					Data Mining			
Session 2	2:30 - 4:15					Data Mining			
Session 3	4:30 - 6:15								Data Mining
	Saturday	10-Jan	24-Jan	7-Feb	21-Feb	7-Mar	21-Mar		18-Apr
Session 4	8:00 - 9:45	Data Mining	Data Mining	Python	Python	Python	Data Mining		Data Mining
Session 5	10:00 - 11:45	Data Mining	Data Mining	Python	Python	Python	Data Mining		Data Mining

1

BUILD
A MACHINE LEARNING MODEL
IN JUST THREE
QUICK AND EASY STEPS
USING [...]!!!

– Most tutorials

How to Become a Data Scientist?



2

MIT report: 95% of generative AI pilots at companies are failing

By **Sheryl Estrada**
Senior Writer And Author Of CFO Daily

August 18, 2025, 6:54 AM ET

Key Reasons for ML Project Failure

Strategic Misalignment

Unrealistic Expectations

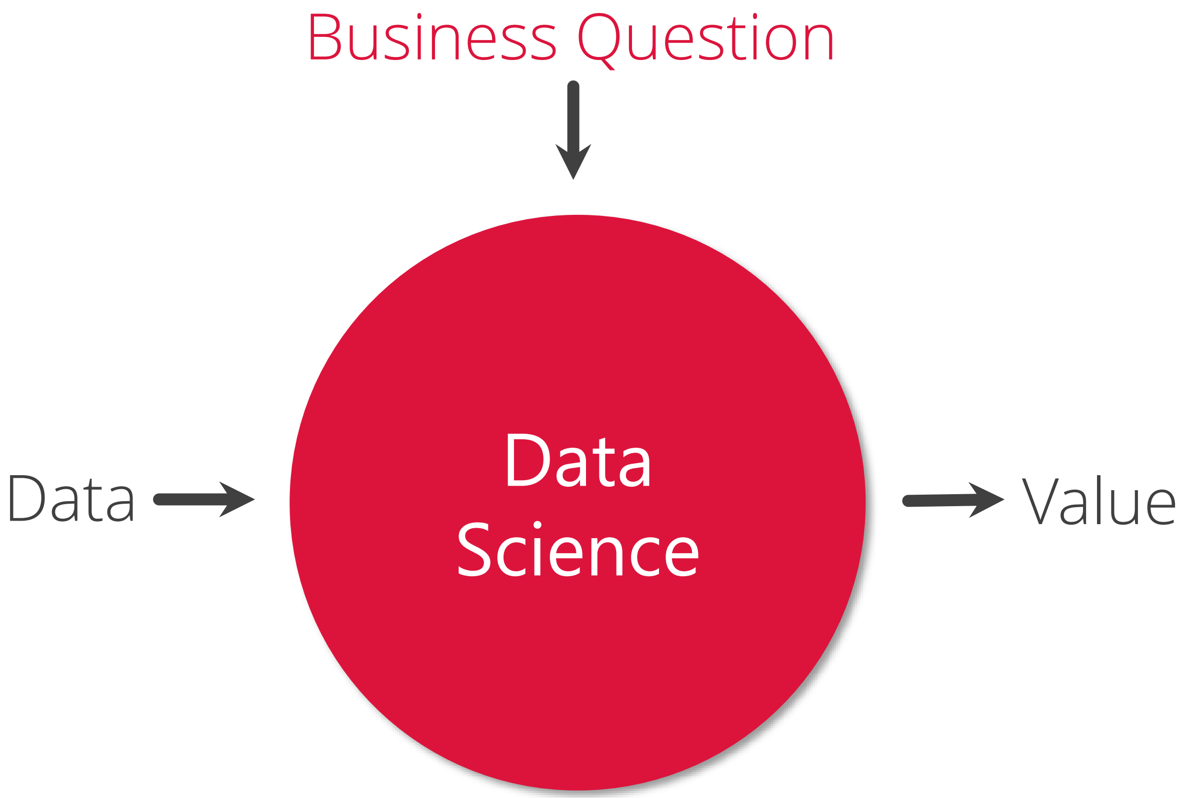
Focus on Technical Metrics

Integration Challenges

Process & People Gaps

How to Avoid Failure?

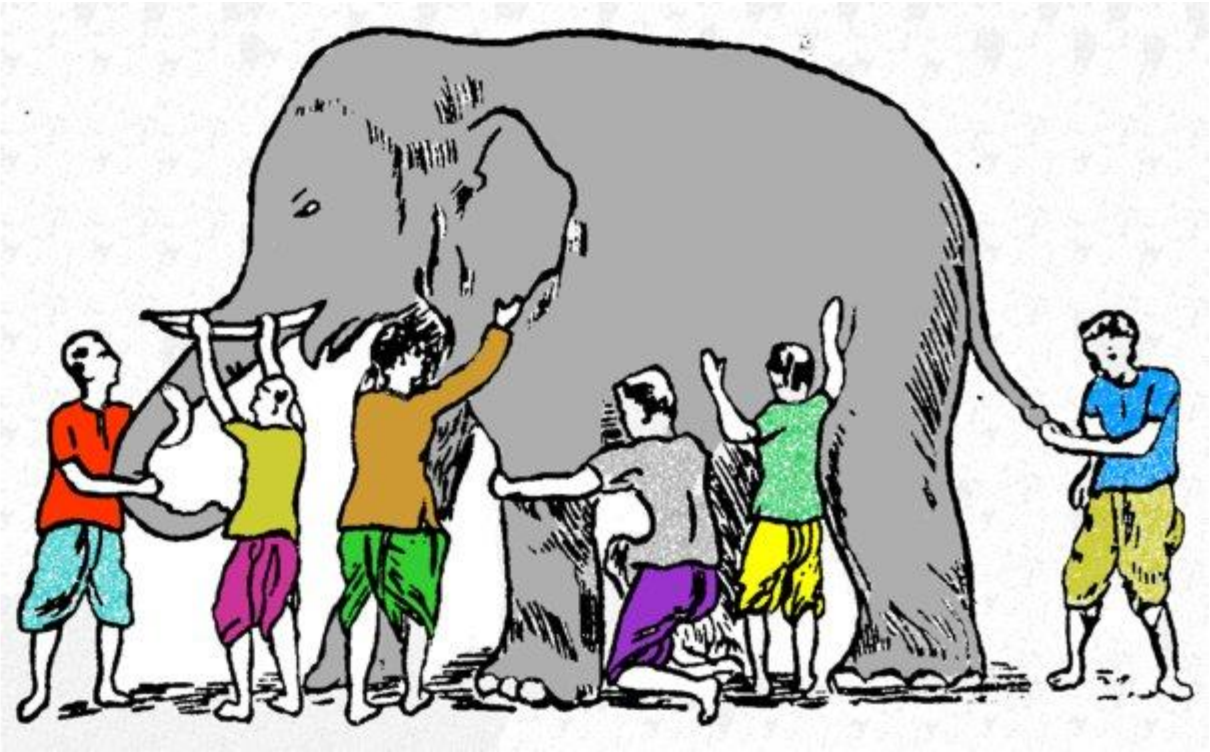
1. Build with Organizational Buy-in
2. Build with End In Mind
3. Build with a Structured Approach


Business Question
Data
Data Science
Value

"The beginning of wisdom is to call things by their proper name."

– Confucius

The Blind Men and the Elephant

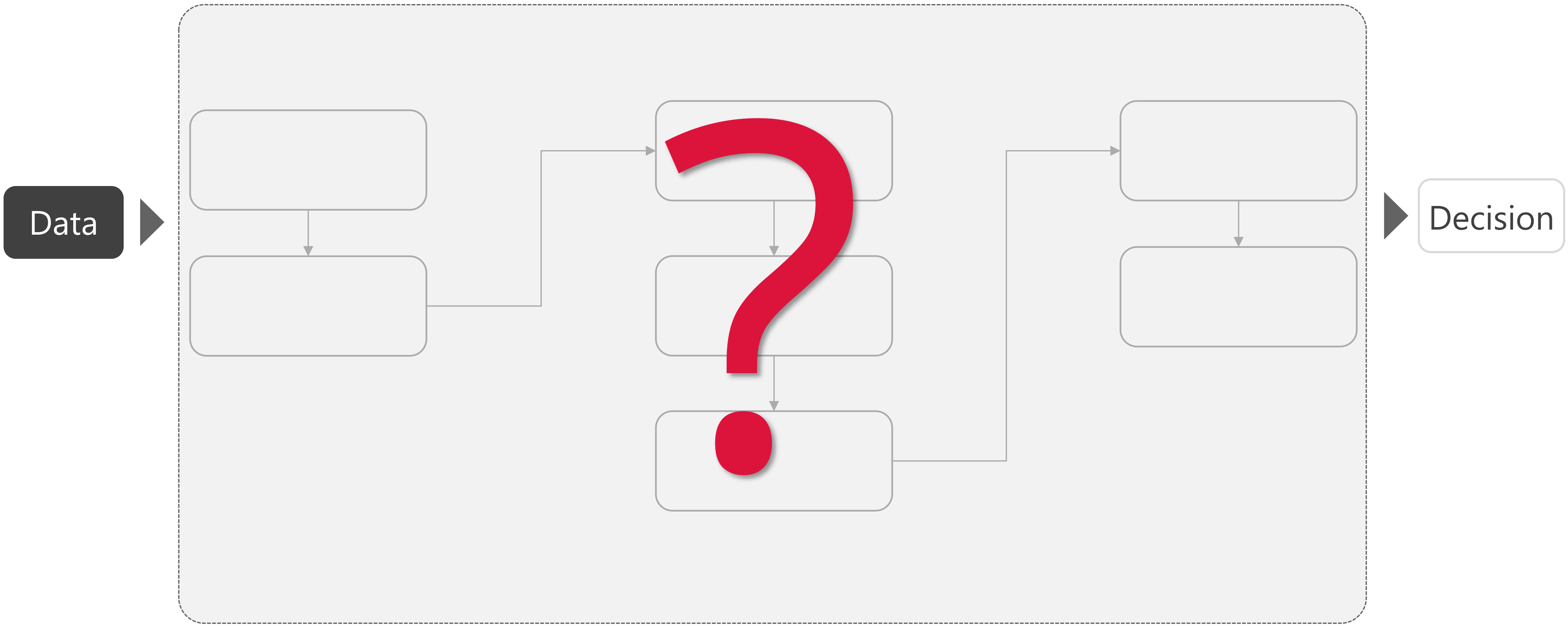


It was six men of Indostan
To learning much inclined,
Who went to see the Elephant
(Though all of them were blind),
That each by observation
Might satisfy his mind.

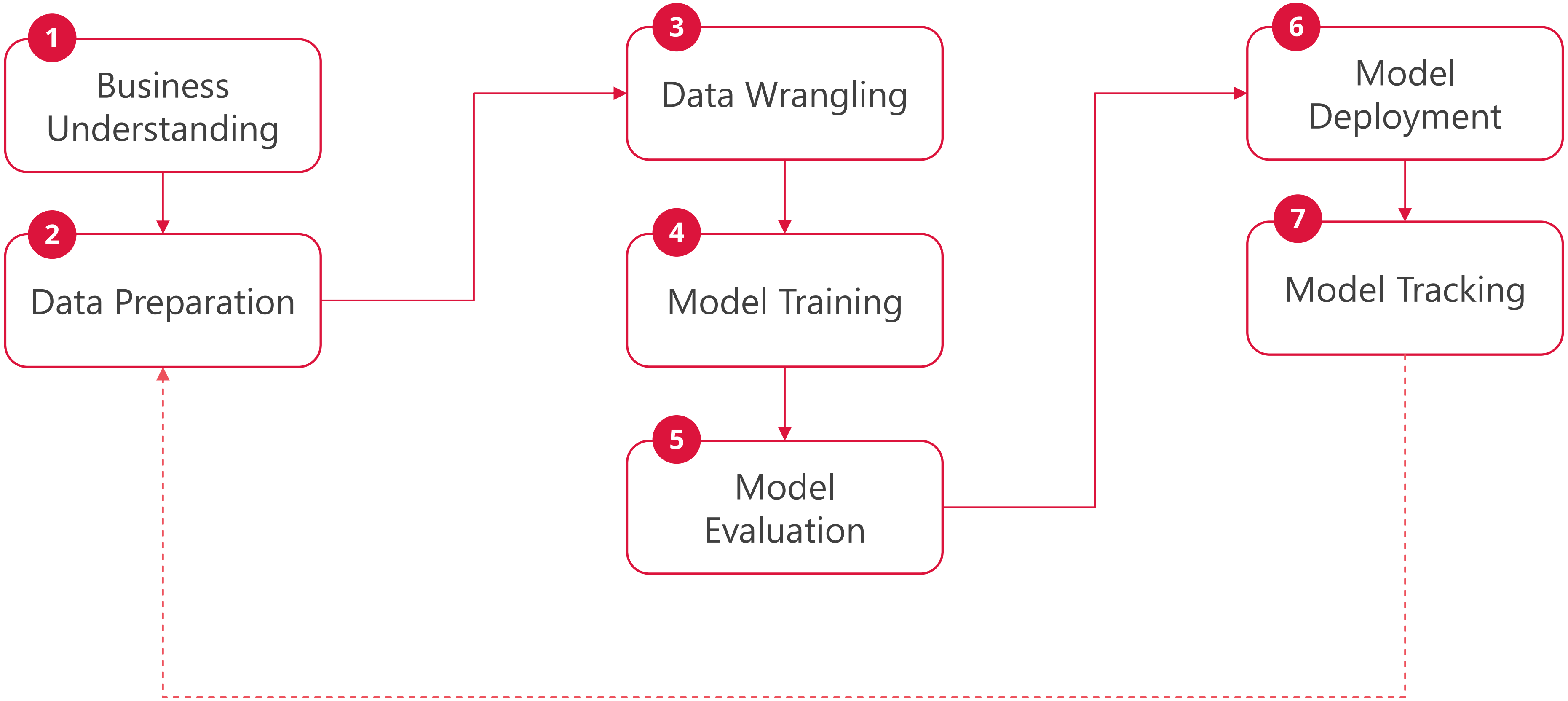
And so these men of Indostan
Disputed loud and long,
Each in his own opinion
Exceeding stiff and strong,
Though each was partly in the right
And all were in the wrong!

– John Godfrey Saxe

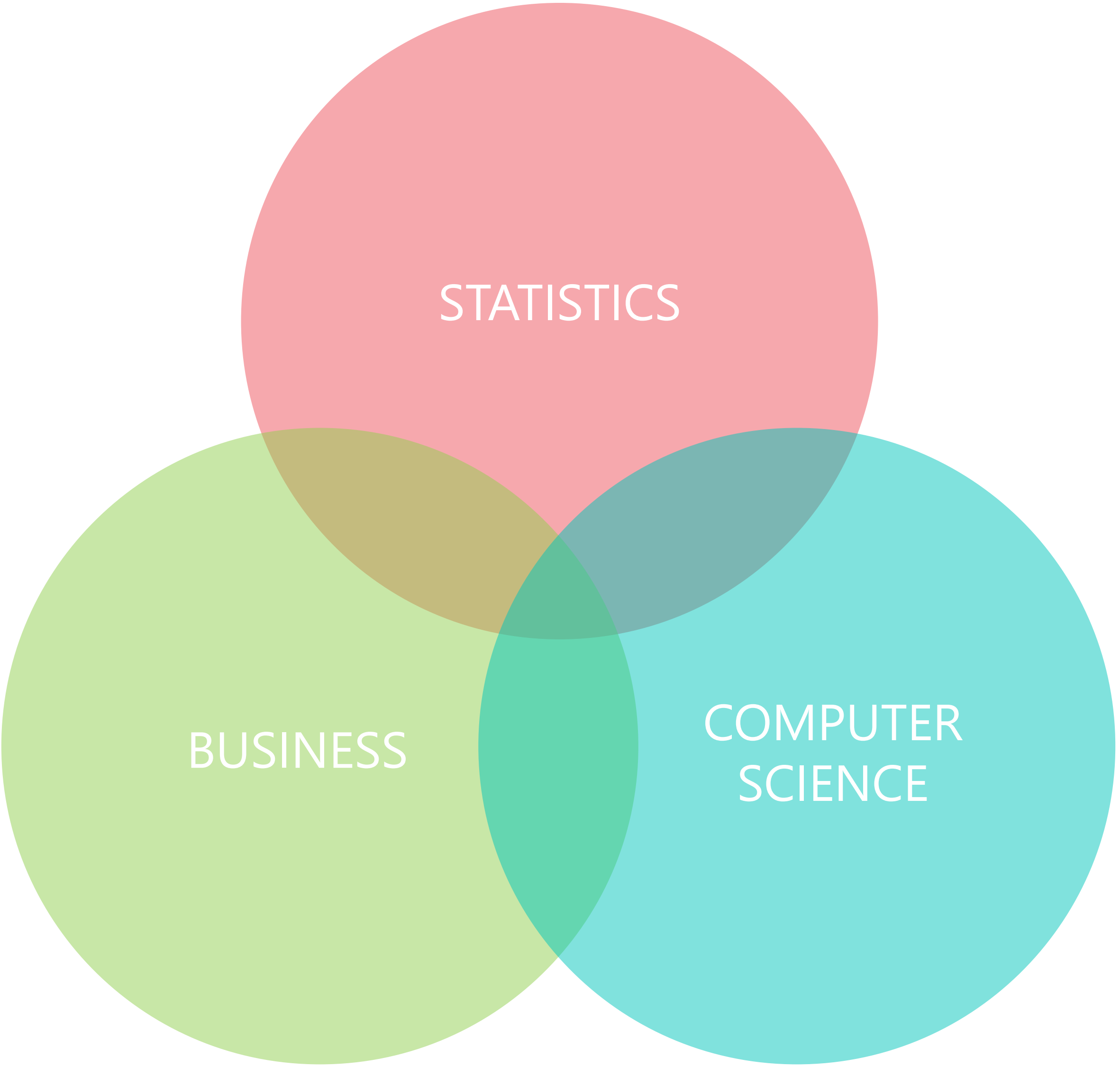

Data
Data Science
Decision
Past
Future


Data
Decision

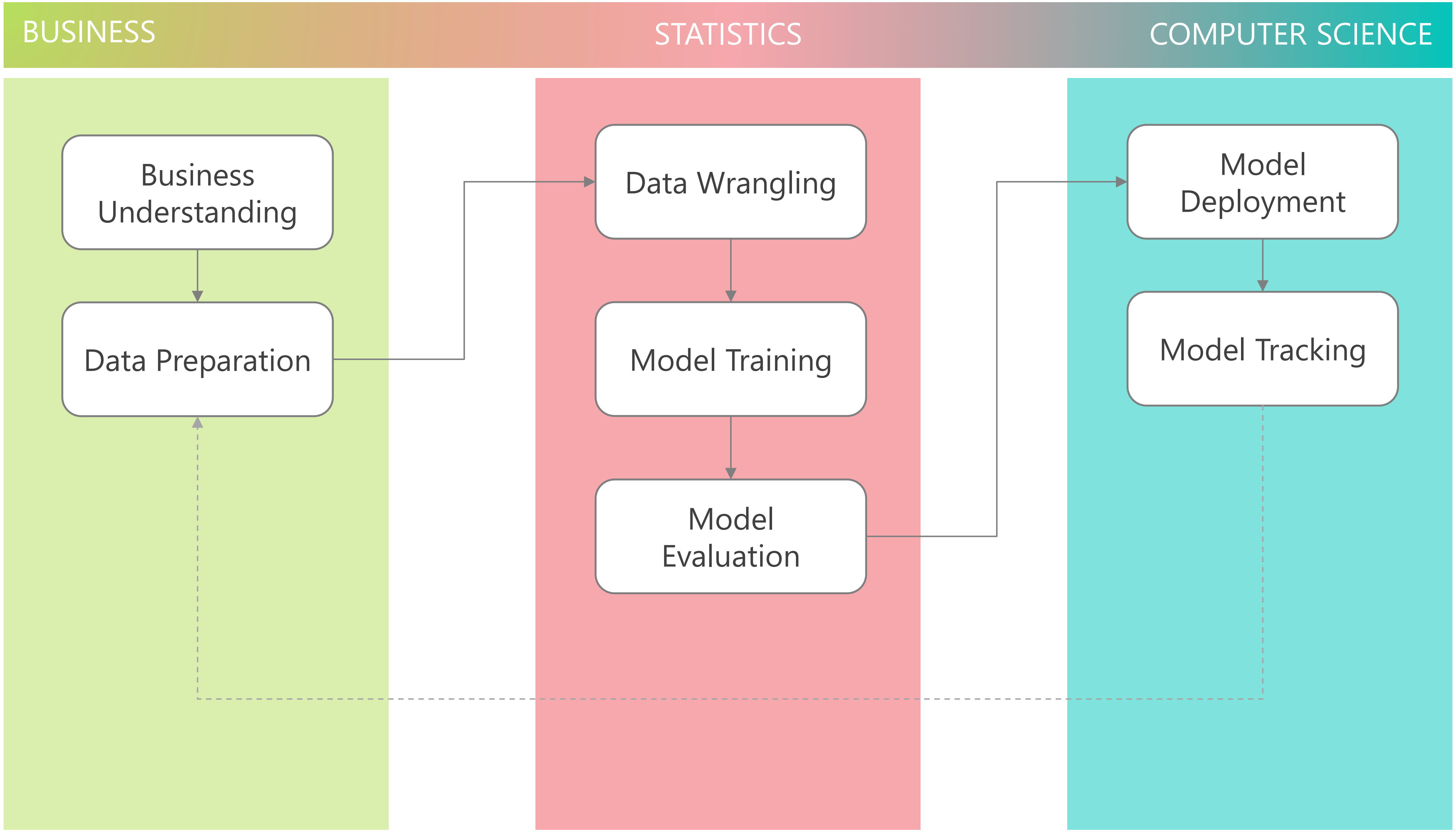
Data Science Process



Data Science



The Data Science Process



The Data Science Process

Business Understanding	Data Preparation	Data Wrangling	Model Training	Model Evaluation	Model Deployment	Model Tracking
Determine	Identify	Impute	Train	Evaluate	Document	Monitor
Understand	Collect	Transform	Assess	Peer Review	Deploy	Maintain
Map	Assess	Reduce	Select	Present		Test
	Vectorize					

Business Understanding	Data Preparation	Data Wrangling	Model Training	Model Evaluation	Model Deployment	Model Tracking

Far better
an approximate answer to the right question
than
an exact answer to the wrong question.

– John Tukey

1 DETERMINE

2 UNDERSTAND

3 MAP

What does the client want to achieve?

1 **DETERMINE**

2 UNDERSTAND

3 MAP

Primary Objective

- Reduce attrition
- Customized targeting
- Plan future media spend
- Prevent fraud
- Recommend Products

1 DETERMINE

2 **UNDERSTAND**

- Understand **success criteria**
  - Specific, measurable, time-bound
- List **assumptions, constraints,** and **important factors**
- Identify **secondary or competing objectives**
- Study **existing solutions** (if any)

3 MAP

1 DETERMINE

2 UNDERSTAND

3 MAP

Business Objective → Technical Objective

- State the **project objective(s) in technical terms**
- Describe how the data science project will **help solve the business problem**
- Explore **successful scenarios**

A problem well stated

is a problem half-solved.

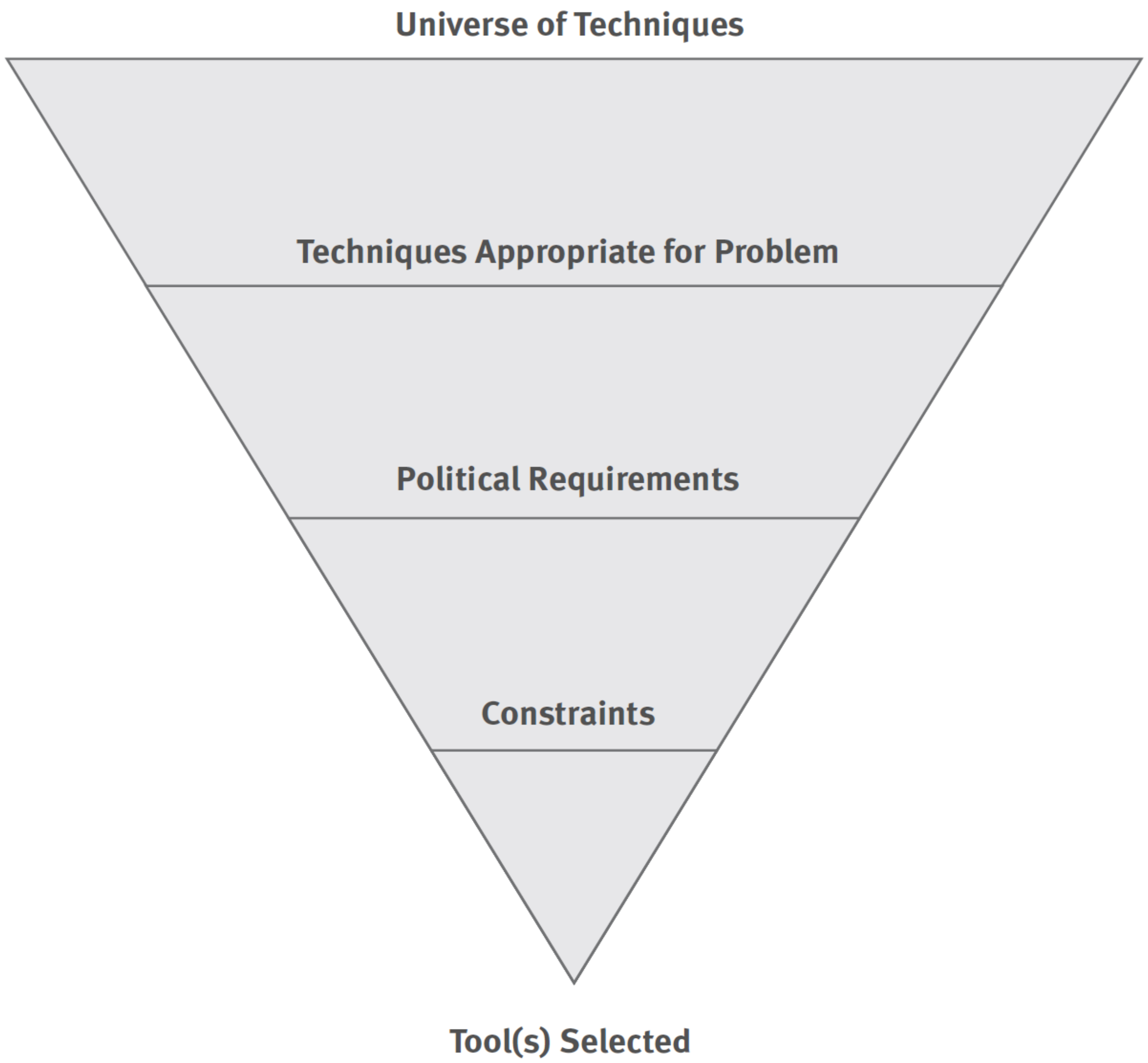
– CF Kettering

1 DETERMINE

2 UNDERSTAND

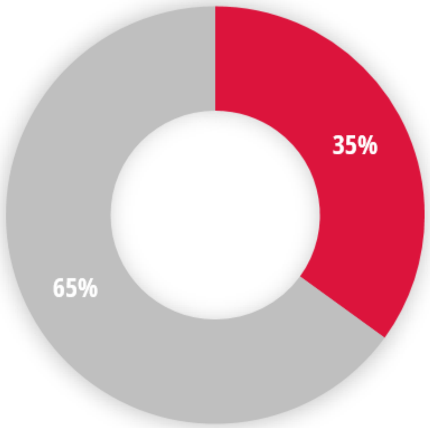
3 **MAP**

OBJECTIVE →	TECHNIQUE →	EXAMPLES
Predict Values	Regression	Linear regression, Bayesian regression, Decision Trees
Predict Categories	Classification	Logistic regression, SVM, Decision Trees
Predict Preference	Recommender System	Collaborative / Content-based filtering
Discover groups	Clustering	k-means, Hierarchical clustering
Identify unusual data points	Anomaly Detection	k-NN, One-class SVM
…		


Universe of Techniques
Techniques Appropriate for Problem
Political Requirements
Constraints
Tool(s) Selected

If all you have is a hammer
then everything looks like a nail.

- **Primary Objective:** Prevent attrition → Increase subscription renewals
- **Competing Objective:** High value customers are also targeted for up-sell
- **Constraints:** Avoid targeting customers too close to their contract expiration
- **Success Criteria:** Current renewal rate = 65% → Improve by 8%
- **Existing Solution:** Business-rule-based targeting
- **Data Science Objective:** Build a binary classification model to identify customers who are not likely to renew their subscriptions three months in advance of their contract expiration.
- **Success Scenario:** The model correctly identifies 80% of the future attritors, a promotional campaign targets all likely attritors, and successfully converts 19% of them into non-attritors.

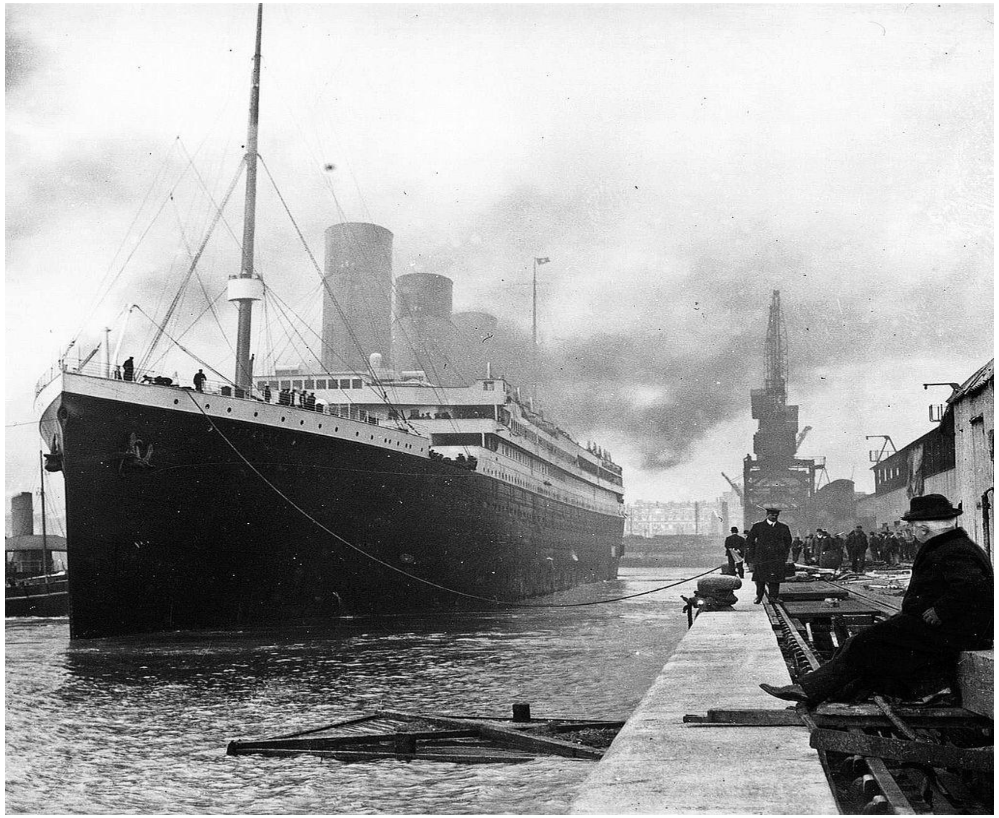


Project Plan

- Duration
- Inventory of resources
- Tools and techniques
- Risks and contingencies
- Costs and benefits
- Milestones

The thought that disaster is impossible often leads to an unthinkable disaster.

– Gerald Weinberg



Titanic at Southampton docks, prior to departure

1 **IDENTIFY**

2 **COLLECT**

3 **ASSESS**

4 **VECTORIZE**

1 **IDENTIFY**

2 COLLECT

3 ASSESS

4 VECTORIZE

- **Data sources, formats**
  - Database, Streaming API's, Logs, Excel files, Websites, etc.
- **Entity Relationship Diagram** (ERD)
- Identify **additional data sources**
  - Demographics data appends,
  - Geographical data,
  - Census data, etc.
- Identify **relevant data**
- Record **unavailable data**
- How long a history is available, and how much of it should be used?

1 IDENTIFY

2 COLLECT

- Access or acquire all relevant data in **a central location**
- **Quality control checks and tests**
  - File formats, delimiters
  - Number of records, columns
  - Primary keys

3 ASSESS

4 VECTORIZE

1 IDENTIFY

2 COLLECT

3 **ASSESS**

4 VECTORIZE

First look at the data

- **Get familiar** with the data
- Study **seasonality**
  - Monthly/weekly/daily patterns
  - Unexplained gaps or spikes in the historical data
- Detect **mistakes**
  - Extreme or outlier values
  - Unusual values
  - Special missing values
- Check **assumptions**
- Review **distributions**

tableau SOFTWARE

alteryx

ggplot2

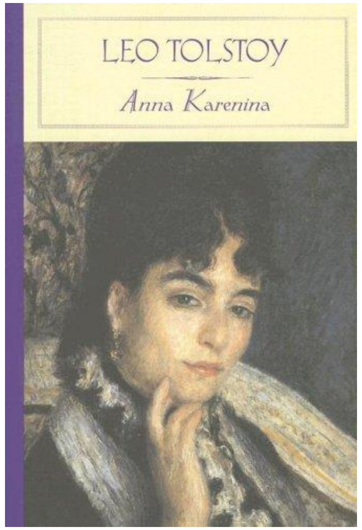
matplotlib

seaborn

Tidy dataset are all alike;

Every messy dataset is messy in its own way.

- Hadley Wickham



There is no substitute for getting to know your data.

– Witten and Frank

GOAL: Create the Analysis Dataset

1 IDENTIFY

2 COLLECT

3 ASSESS

4 **VECTORIZE**

$$y = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ . \\ . \\ . \\ y_n \end{pmatrix} \qquad X = \begin{pmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1j} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2j} \\ x_{31} & x_{32} & x_{33} & \dots & x_{3j} \\ . & . & . & & . \\ . & . & . & & . \\ . & . & . & & . \\ x_{n1} & x_{n2} & x_{n3} & \dots & x_{nj} \end{pmatrix}$$

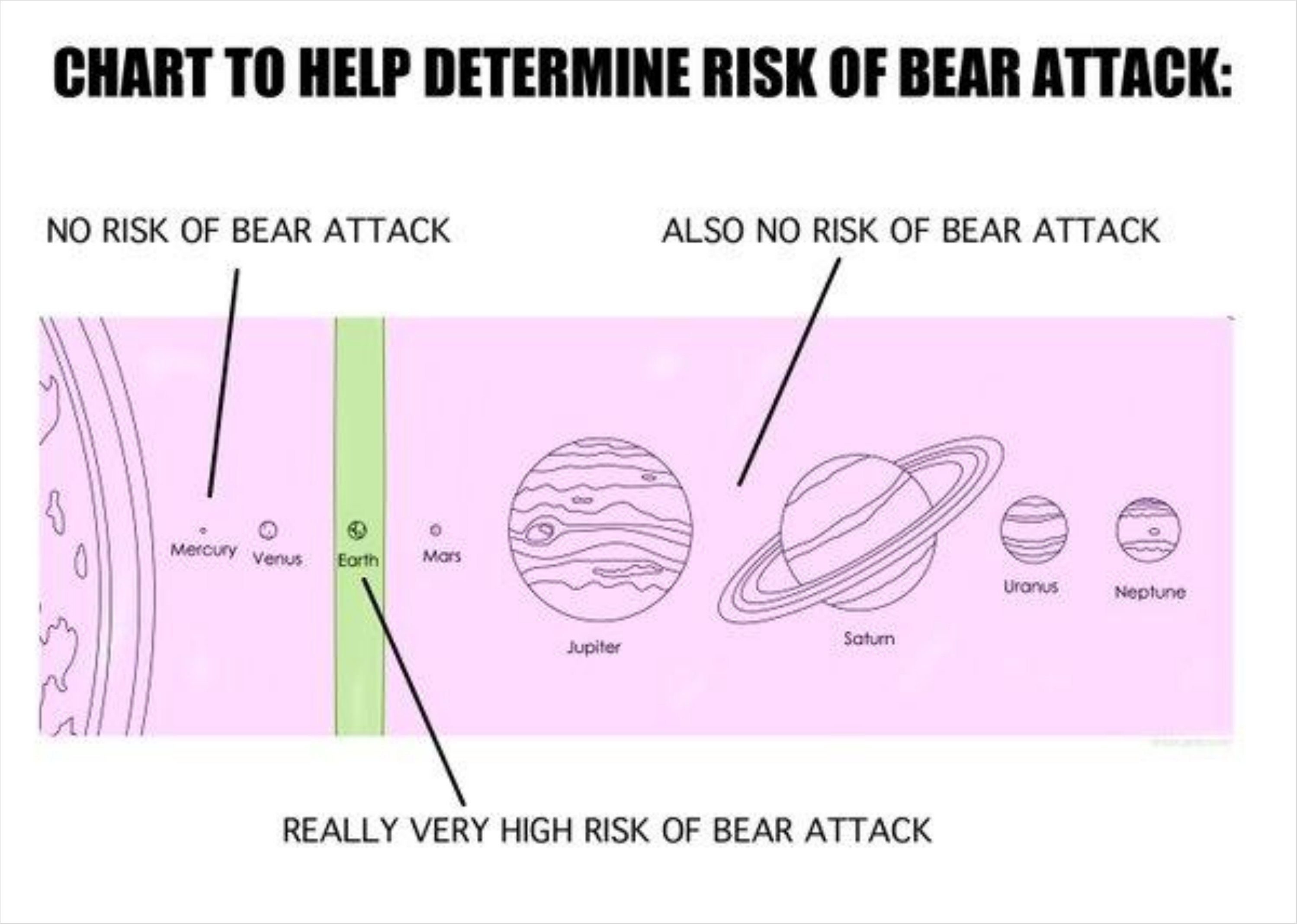
Outcome
Target
Independent Variable

Inputs
Features / Attributes
Dependent Variables

Target Definition

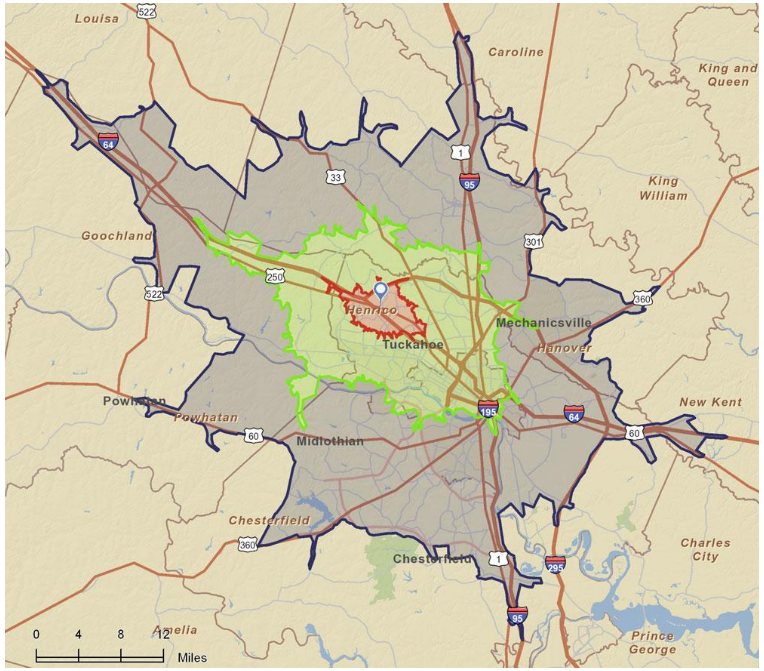
- **Churn = 90 days of consecutive inactivity** (for a pre-paid telecom customer)
- What's **inactivity**?
  - Incoming and outgoing calls
  - Data usage
  - Incoming text
  - Promotional texts
  - Voicemail usage
  - Call forwarding
  - Etc.
- Customers may **change their device** or phone number.
  - Churn at the individual (person) level, or at the device (phone) level?
- Customers may return (become active again) after 90 days of inactivity?
- Prediction window
  - Predict 90 days of consecutive inactivity?
  - Would 10 days of consecutive inactivity suffice?
  - How many customers return after *x* days of inactivity?
- Fraud, Involuntary churn
- …

Accurate but not Precise

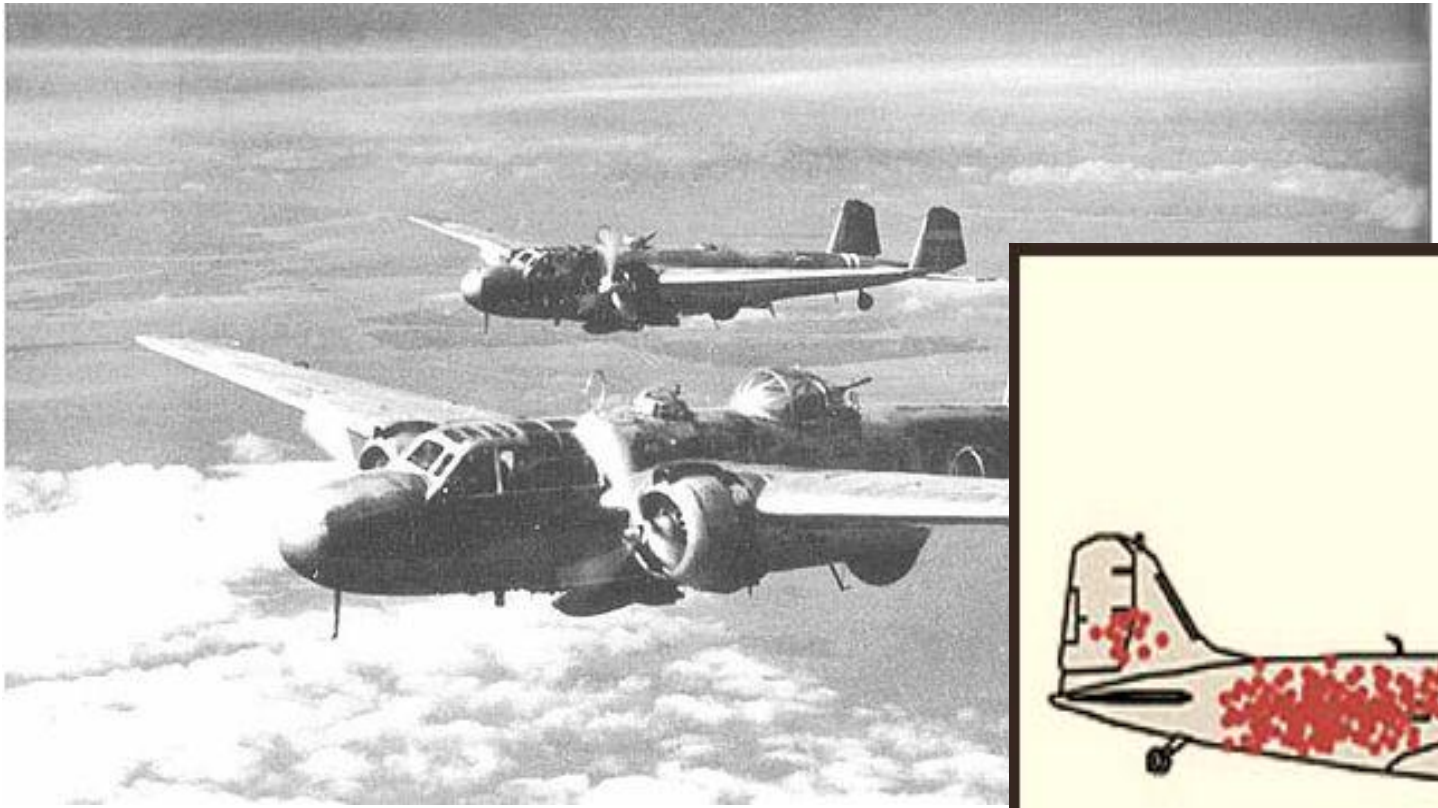


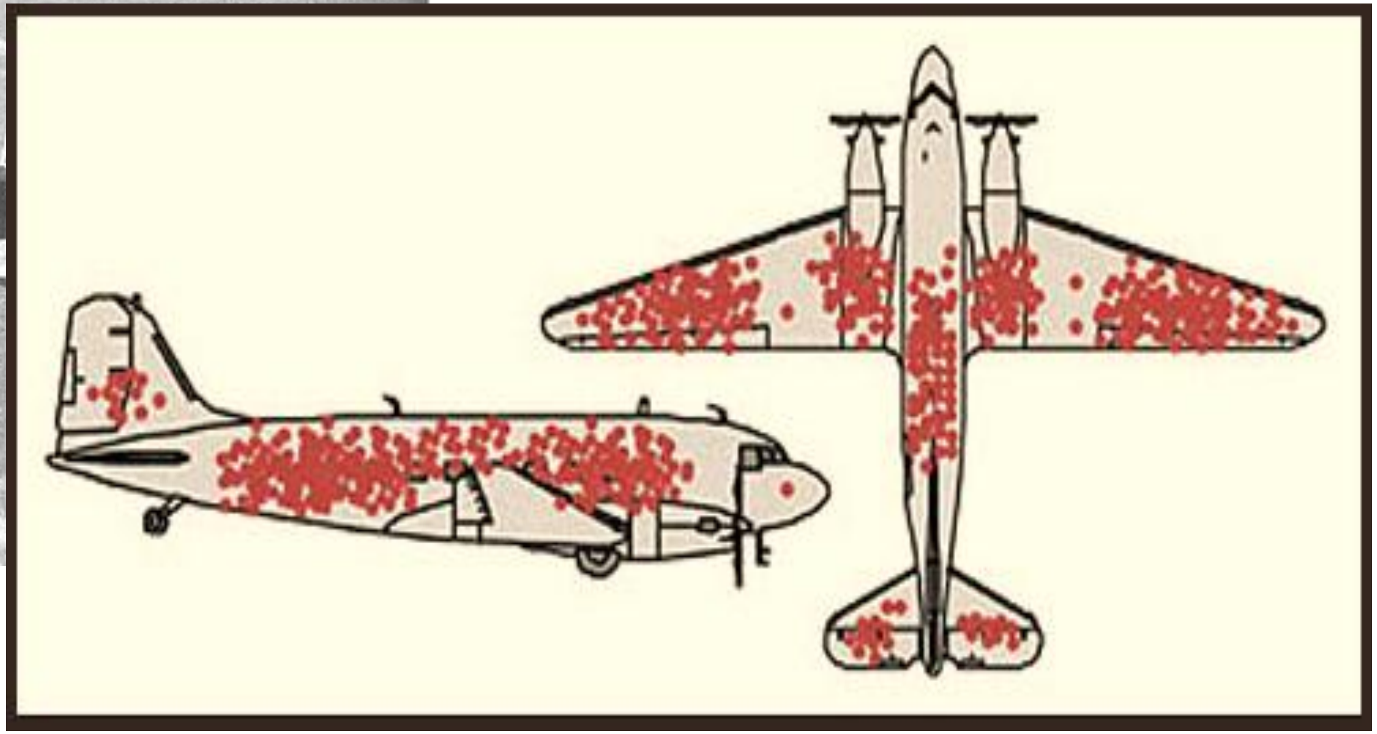
Modeling Sample

- **Historical trends and seasonality**
  - Are there certain timeframes that should be discarded?
  - The model should be generalizable
- **Eligible, relevant population**
  - Must align with the business goals
- **Eligible, relevant markets**
  - Must align with the business goals
  - E.g., within a certain drive-time distance
- **Outdated products or events**



Selection Bias





Abraham Wald's Work on Aircraft Survivability
Journal of the American Statistical Association Vol. 79, No. 386 (June, 1984)

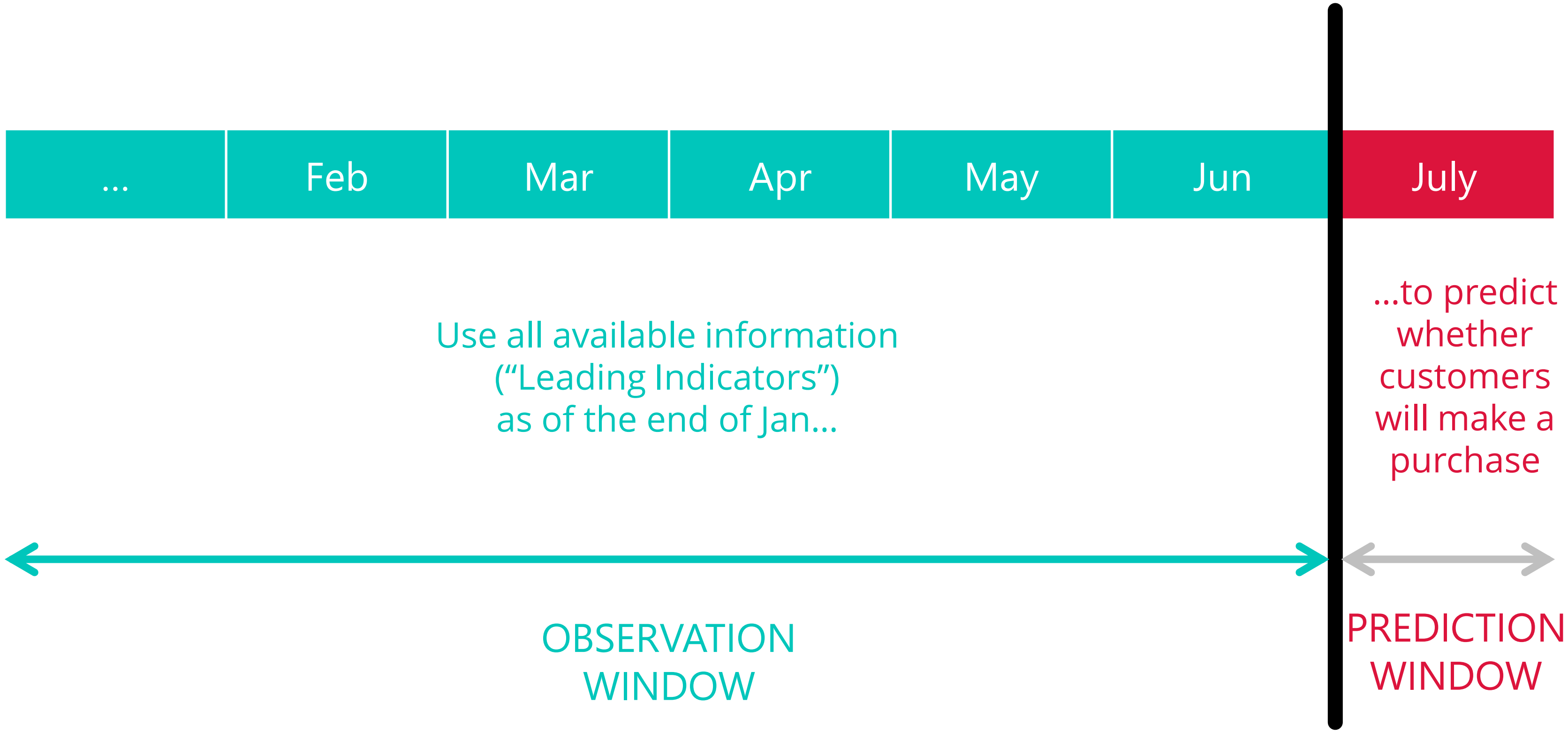
Making Prediction about the Future

Dog or muffin?

vs.

Who is likely to churn?

Information Leakage



- The leading indicators must be calculated from the timeframe *leading up to* the event – it must not overlap with the prediction window.
- Beware of proxy events, e.g., future bookings

Data Aggregation

- **Attribute creation**
  - Derived attributes: Household income / Number of adults = Income per adult
- **Brainstorm with team members** (both technical and non-technical)

$$X = \begin{pmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1j} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2j} \\ x_{31} & x_{32} & x_{33} & \dots & x_{3j} \\ . & . & . & & . \\ . & . & . & & . \\ . & . & . & & . \\ x_{n1} & x_{n2} & x_{n3} & \dots & x_{nj} \end{pmatrix}$$

CUSTOMER ID	PURCHASE DATE
1001	02-12-2015:05:20:39
1001	05-13-2015:12:18:09
1001	12-20-2016:00:15:59
1002	01-19-2014:04:28:54
1003	01-12-2015:09:20:36
1003	05-31-2015:10:10:02
…	…

CUSTOMER ID	x_1	x_2	…	x_j
1001	…	…		…
1002	…	…		…
1003	…	…		…
…	…	…	…	…

1. Number of transactions (Frequency)
2. Days since the last transaction (Recency)
3. Days since the earliest transaction (Tenure)
4. Avg. days between transaction
5. # of transactions during weekends
6. % of transactions during weekends
7. # of transactions by day-part (breakfast, lunch, etc.)
8. % of transactions by day-part
9. Days since last transaction / Avg. days between transactions
10. …

OUTPUT: The Analysis Dataset

1 IDENTIFY

2 COLLECT

3 ASSESS

4 **VECTORIZE**

$$y = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ . \\ . \\ . \\ y_n \end{pmatrix}$$

Outcome
Target
Independent Variable

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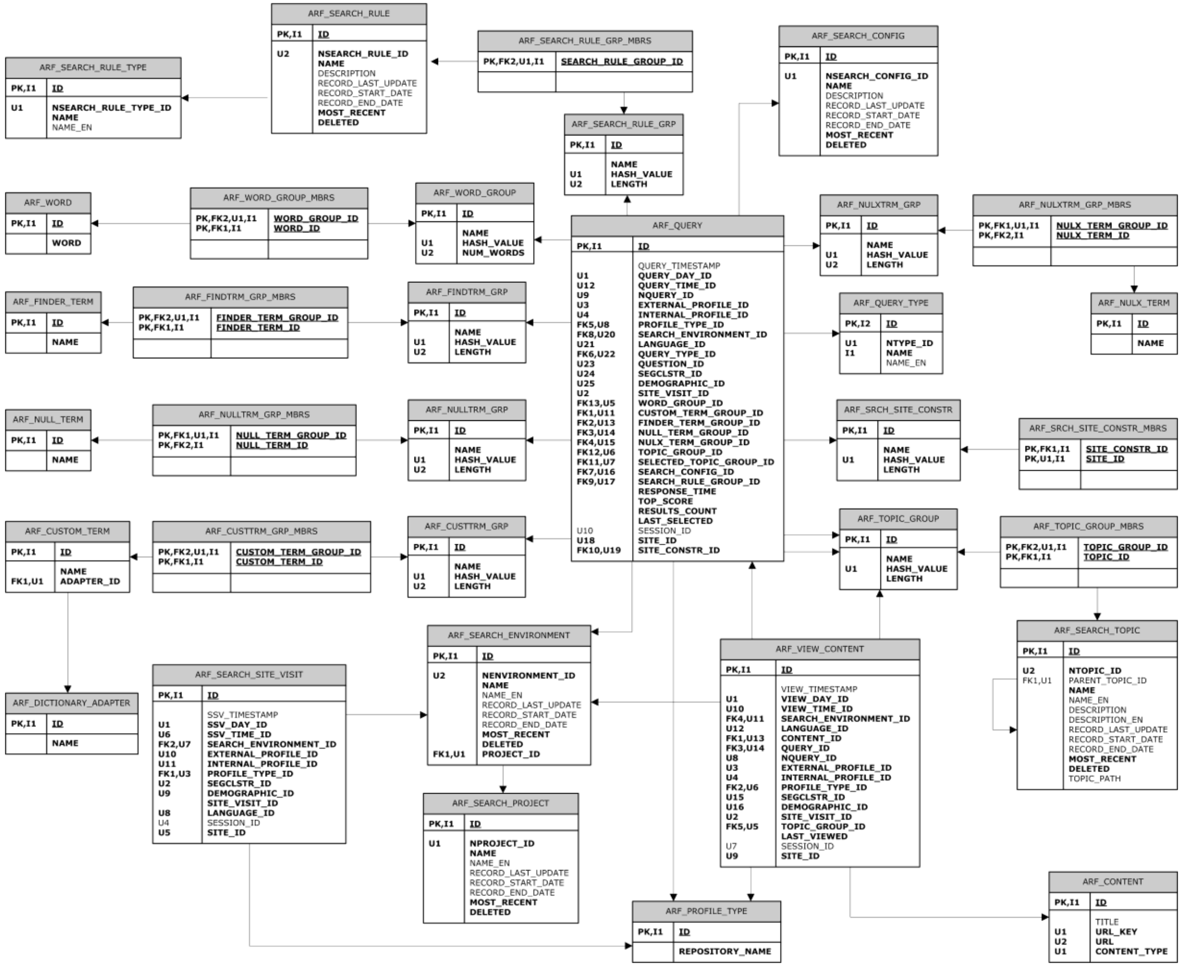
Inputs
Features / Attributes
Dependent Variables


ARF_SEARCH_RULE
ARF_SEARCH_RULE_TYPE
ARF_SEARCH_RULE_GRP_MBRS
ARF_SEARCH_CONFIG
ARF_SEARCH_RULE_GRP
ARF_WORD
ARF_WORD_GROUP_MBRS
ARF_WORD_GROUP
ARF_QUERY
ARF_NULXTRM_GRP
ARF_NULXTRM_GRP_MBRS
ARF_FINDER_TERM
ARF_FINDTRM_GRP_MBRS
ARF_FINDTRM_GRP
ARF_QUERY_TYPE
ARF_NULX_TERM
ARF_NULL_TERM
ARF_NULLTRM_GRP_MBRS
ARF_NULLTRM_GRP
ARF_SRCH_SITE_CONSTR
ARF_SRCH_SITE_CONSTR_MBRS
ARF_CUSTOM_TERM
ARF_CUSTTRM_GRP_MBRS
ARF_CUSTTRM_GRP
ARF_TOPIC_GROUP
ARF_TOPIC_GROUP_MBRS
ARF_SEARCH_ENVIRONMENT
ARF_SEARCH_TOPIC
ARF_DICTIONARY_ADAPTER
ARF_SEARCH_SITE_VISIT
ARF_VIEW_CONTENT
ARF_SEARCH_PROJECT
ARF_CONTENT
ARF_PROFILE_TYPE

Business Understanding | Data Preparation | **Data Wrangling** | **Model Training** | **Model Evaluation** | Model Deployment | Model Tracking

Time Spent

Data Wrangling

Model Building

Give me six hours to chop down a tree

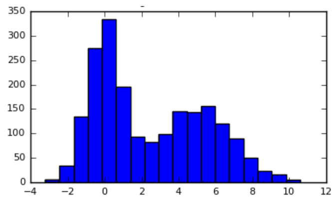
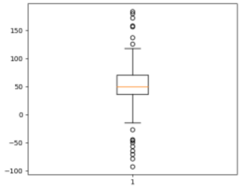
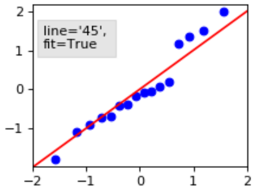
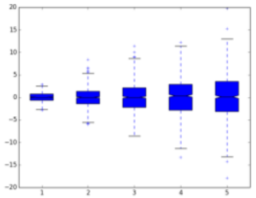
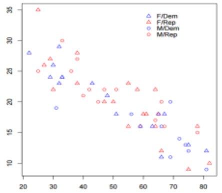
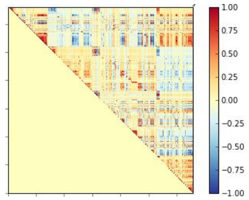
and I will spend the first four sharpening the axe.

— Abraham Lincoln (?)

- **Descriptive statistics**
  - Review with the client
- **Correlation analysis**
  - Review with the client
  - Watch out for data leakage
- **Missing value imputation**
- **Trim extreme values**
- **Process categorical attributes**
- **Transformations** (square, log, etc.)
  - Binning / variable smoothing
- **Multicollinearity**
  - Reduce redundancy
- **Additional feature** (derived variables)
- **Interactions**
- **Normalization** (scaling)

	Univariate	Multivariate

Non-Graphical	○ Categorical: Tabulated frequencies
	○ Quantitative:
	    ○ Central tendency: mean, median, mode
	    ○ Spread: Standard deviation, inter-quartile range
	    ○ Skewness and kurtosis
		○ Cross-tabulation
		○ Univariate statistics by category
		○ Correlation matrices

Graphical	○ Histograms ○ Box plots, stem-and-leaf plots ○ Quantile-normal plots   	○ Univariate graphs by category (e.g., side-by-side box-plots) ○ Scatterplots ○ Correlation matrix plots   

- **Feature Reduction:** The process of selecting a subset of features for use in model construction
  - Useful for both supervised and unsupervised learning problems

Art is the elimination of the unnecessary.

– Pablo Picasso

Feature Reduction: Why

- **True dimensionality <<< Observed dimensionality**
  - The abundance of redundant and irrelevant features
- **Curse of dimensionality**
  - With a fixed number of training samples, the predictive power reduces as the dimensionality increases. [Hughes phenomenon]
  - With d binary variables, the number of possible combinations is $O(2^d)$.
- **Goal of the Analysis**
  - Descriptive → Diagnostic → Predictive → Prescriptive

Hindsight	Insight	Foresight

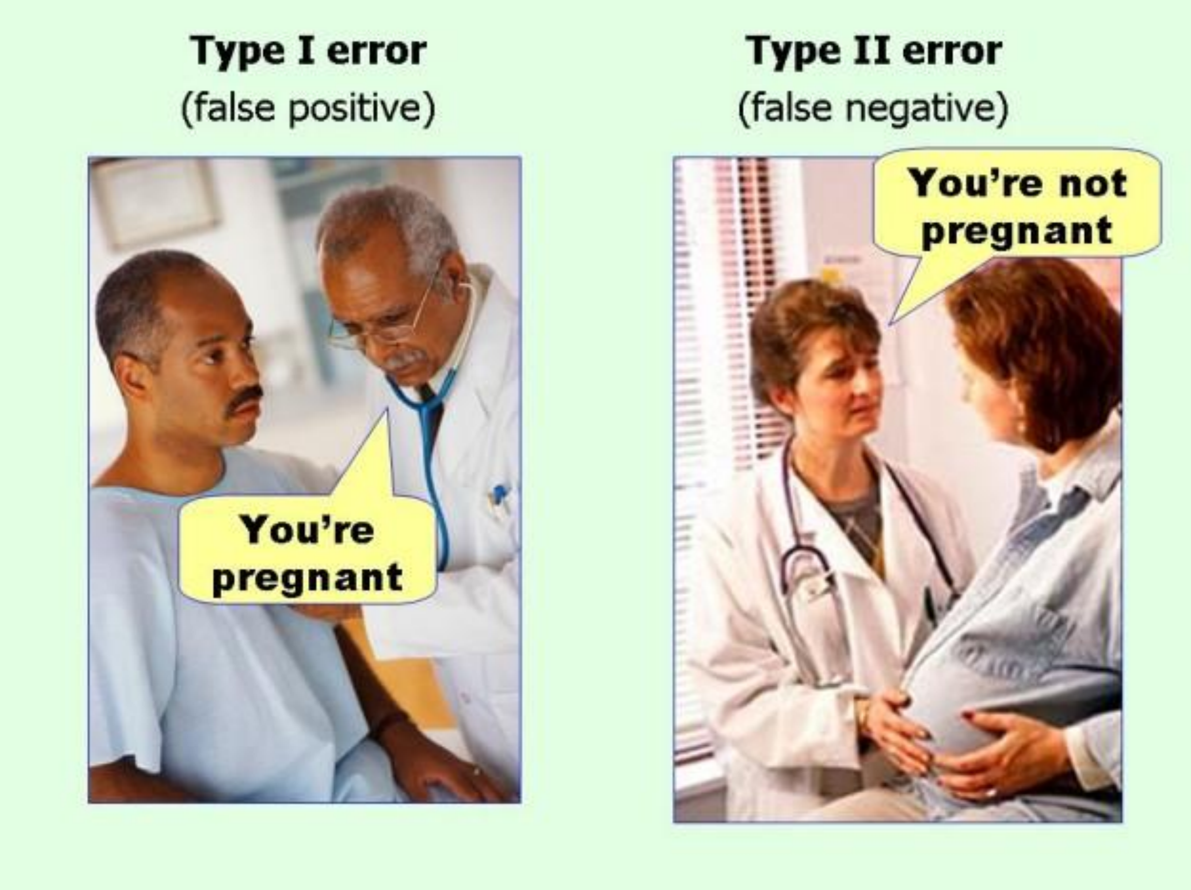
- **Law of Parsimony** [Occam's Razor]
  - Other things being equal, simpler explanations are generally better than complex ones.
- **Overfitting**
- **Execution time** **(Algorithm and data processing)**

Feature Reduction Techniques

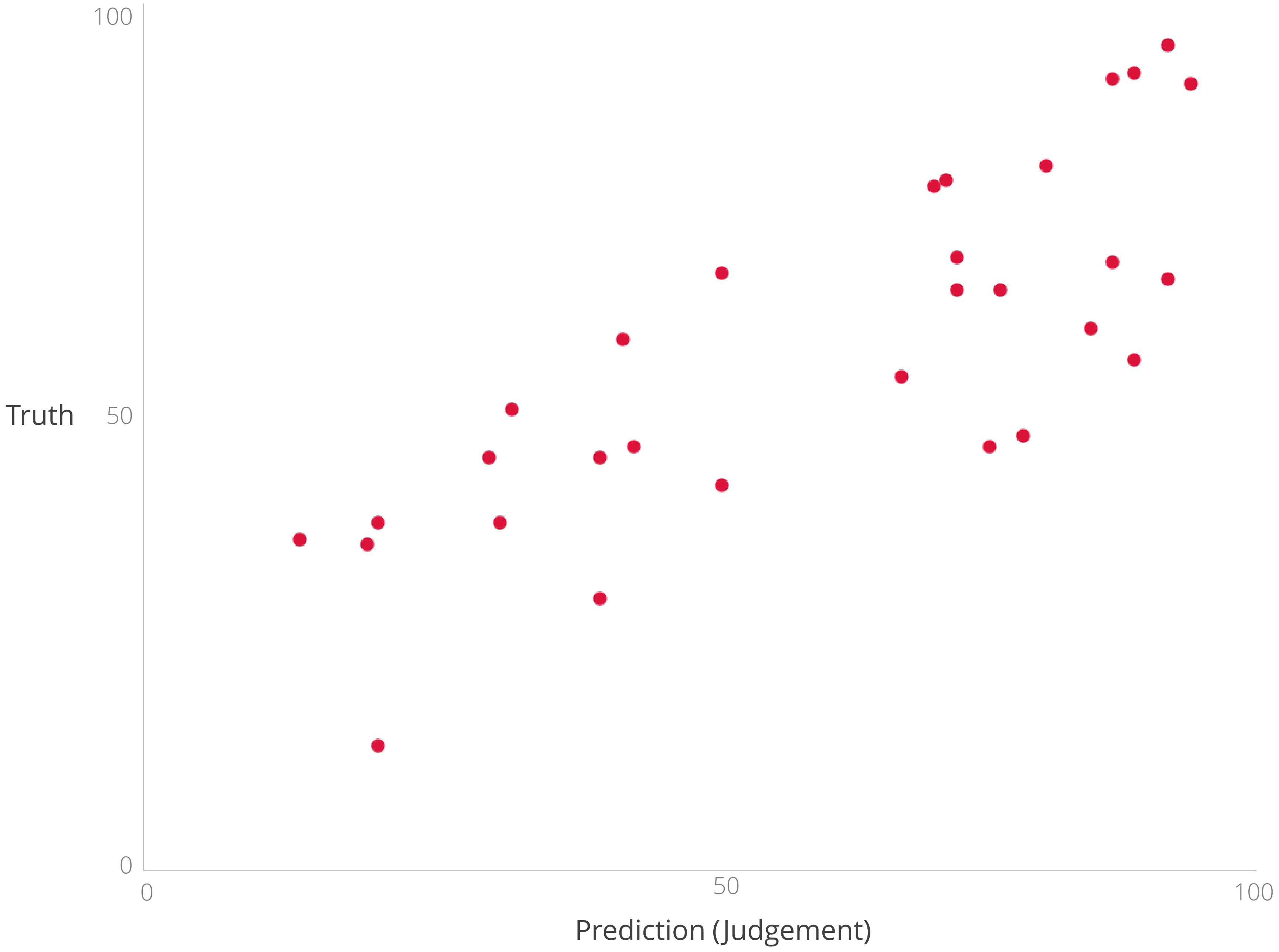
1. Percent missing values
2. Amount of variation
3. Pairwise correlation
4. Multicolinearity
5. Principal Component Analysis (PCA)
6. Cluster analysis
7. Correlation (with the target)
8. Forward selection
9. Backward elimination
10. Stepwise selection
11. LASSO
12. Tree-based selection

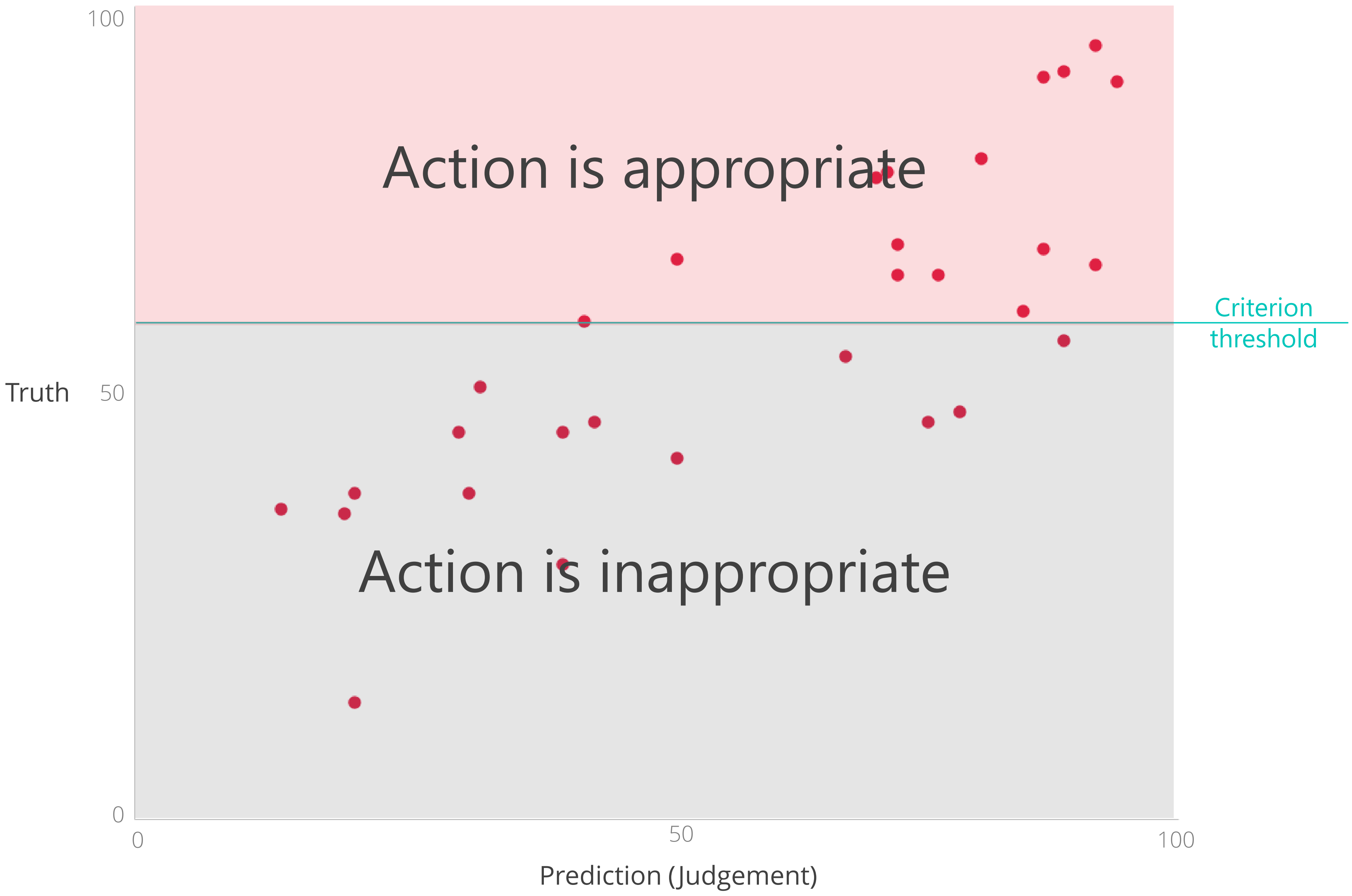
- Try **more than one machine learning technique**
- Fine-tune **parameters** and **hyper-parameters**
- Assess **model performance**
- Avoid **Over-fitting**

Assess Model Performance

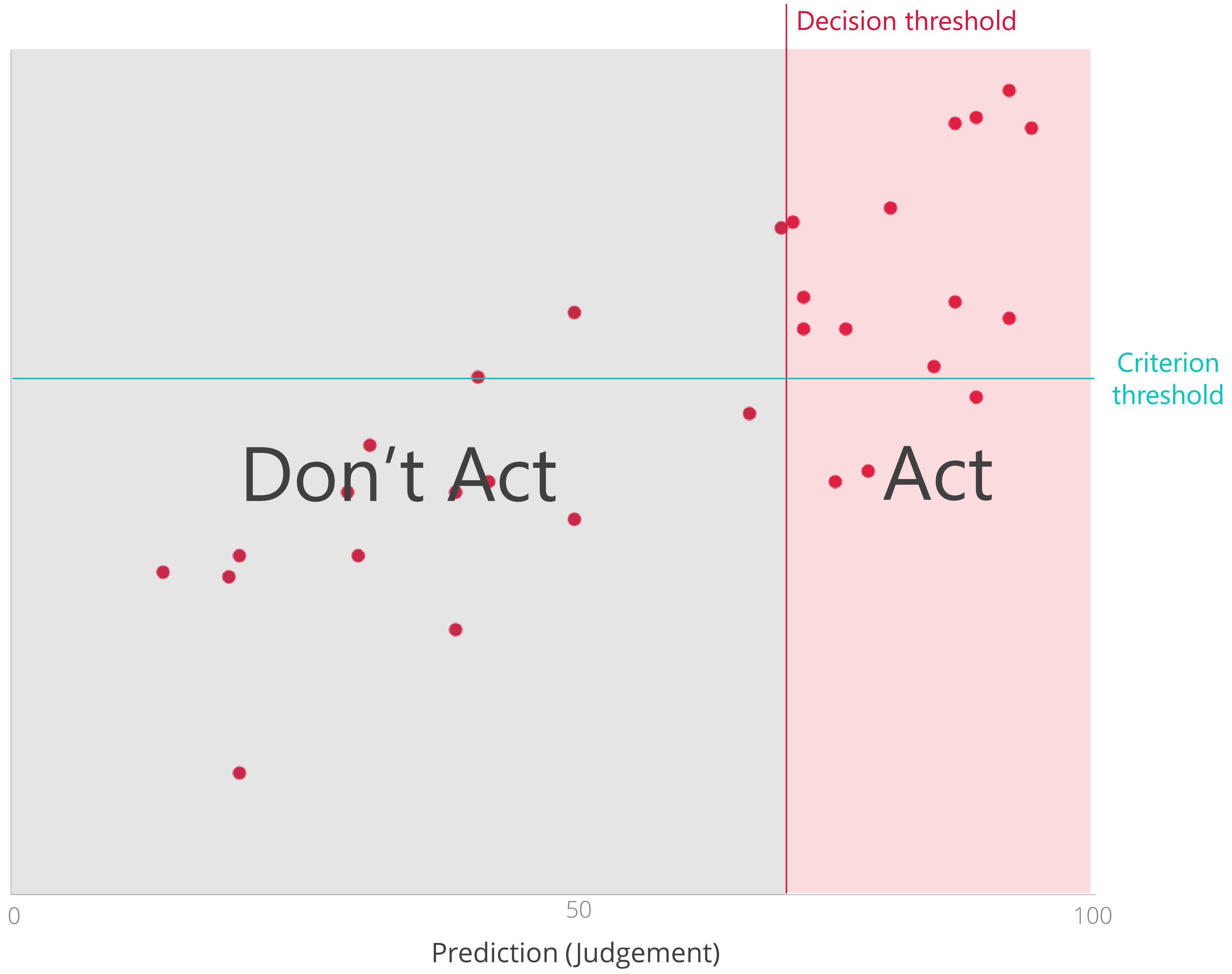


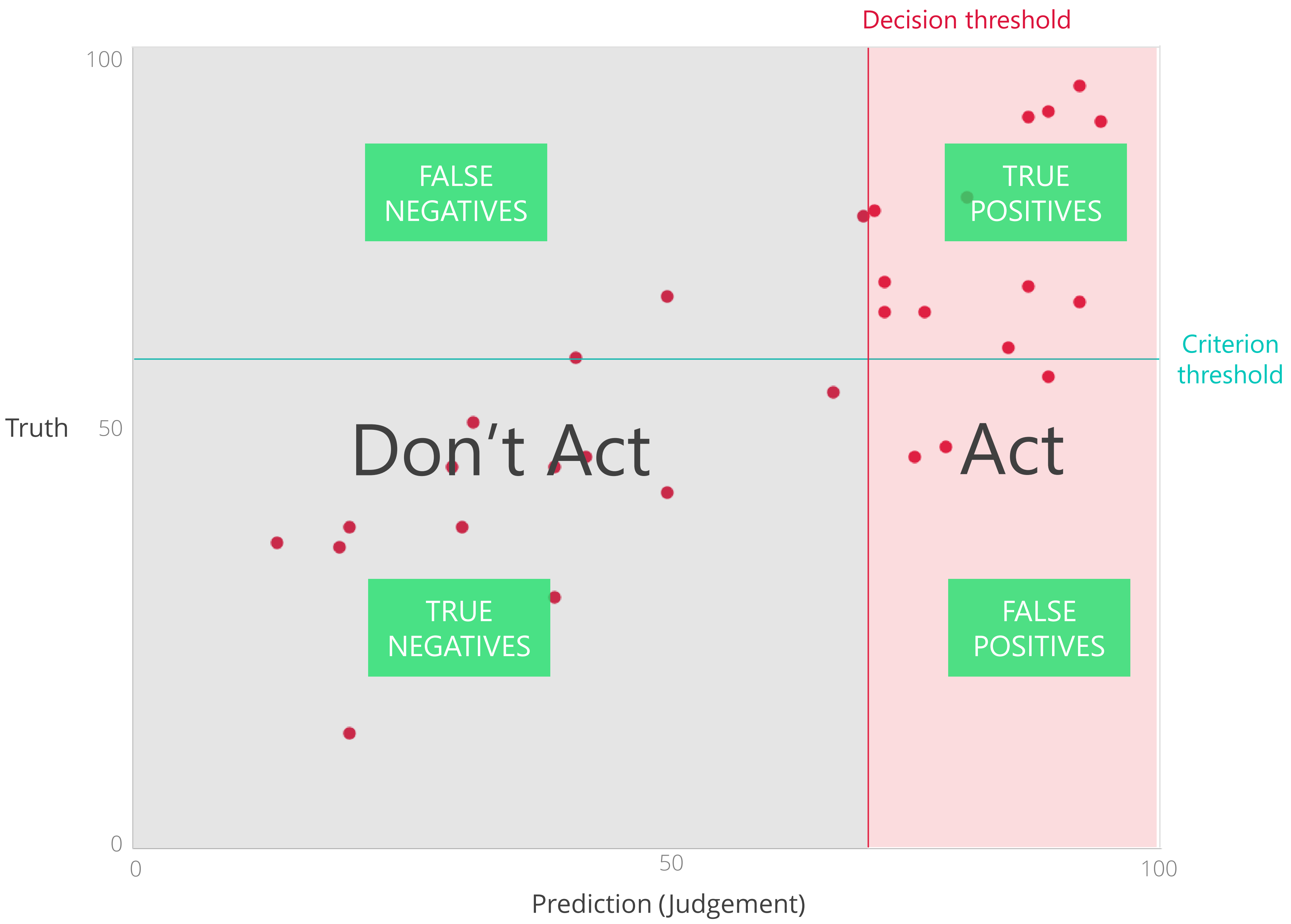
- Area Under the ROC Curve (AUC), Confusion Matrix, Precision, Recall, Log-loss
- Model Lift, Model Gains, Kolmogorov-Smirnov (KS), etc.


100
Truth
50
0
0
50
100
Prediction (Judgement)

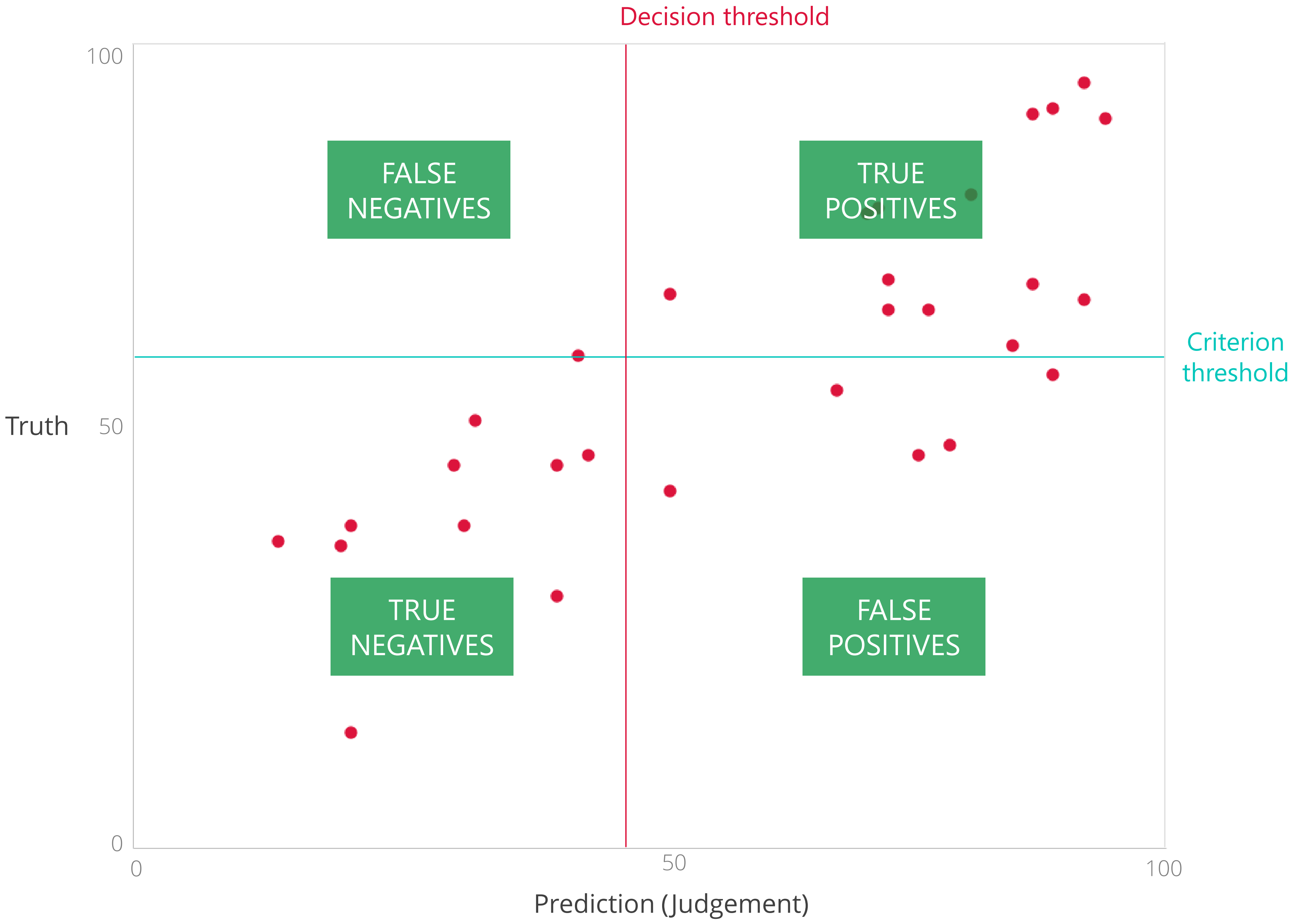


100
Action is appropriate
Criterion
threshold
Truth
50
Action is inappropriate
0
0
50
100
Prediction (Judgement)

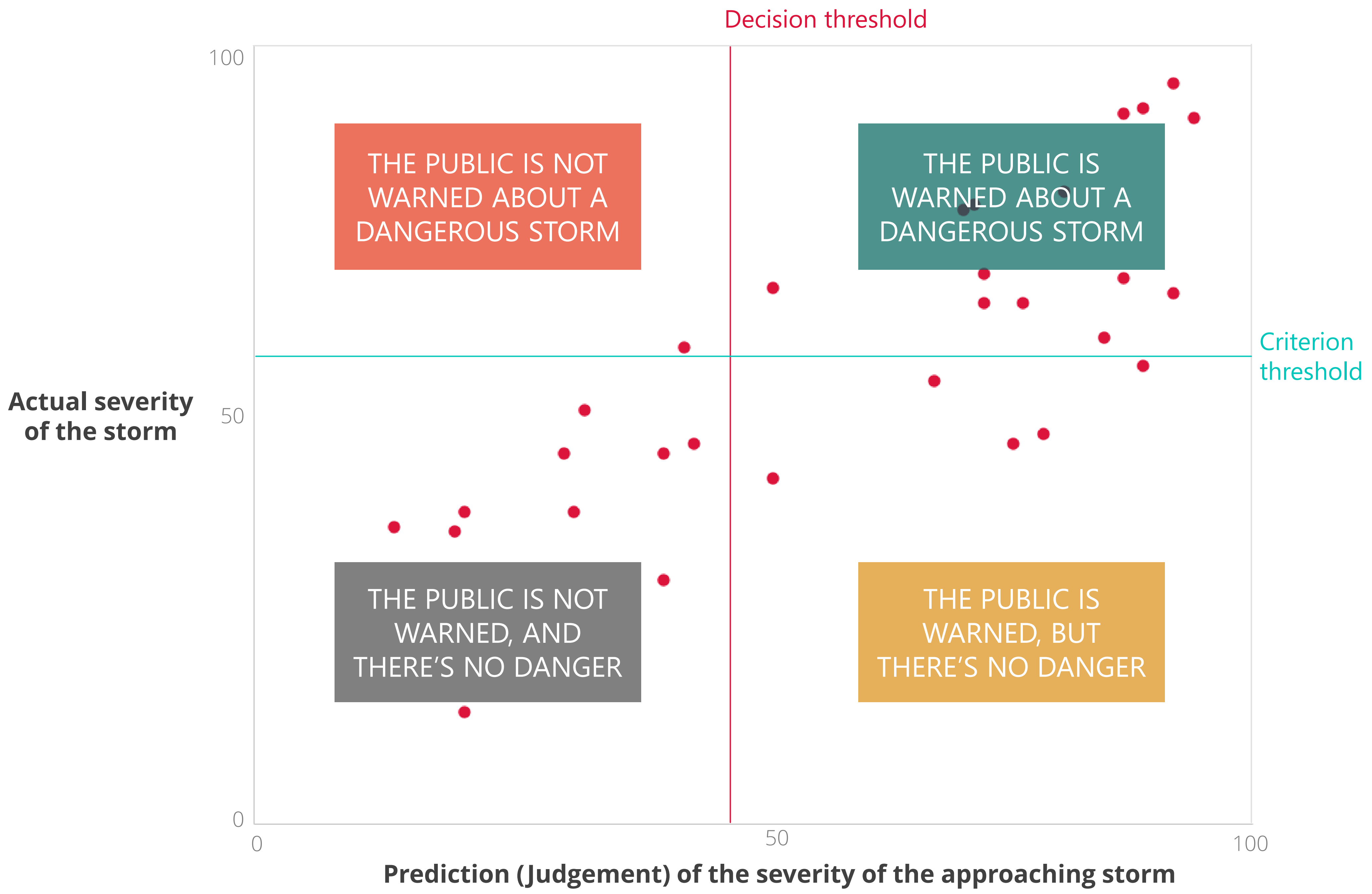

Decision threshold
Criterion threshold
Don't Act
Act
0
50
100
Prediction (Judgement)



Decision threshold
100
50
0
Truth
FALSE NEGATIVES
TRUE POSITIVES
Criterion threshold
Don't Act
Act
TRUE NEGATIVES
FALSE POSITIVES
0
50
100
Prediction (Judgement)



Decision threshold
100
FALSE NEGATIVES
TRUE POSITIVES
Criterion threshold
Truth
50
TRUE NEGATIVES
FALSE POSITIVES
0
0
50
100
Prediction (Judgement)



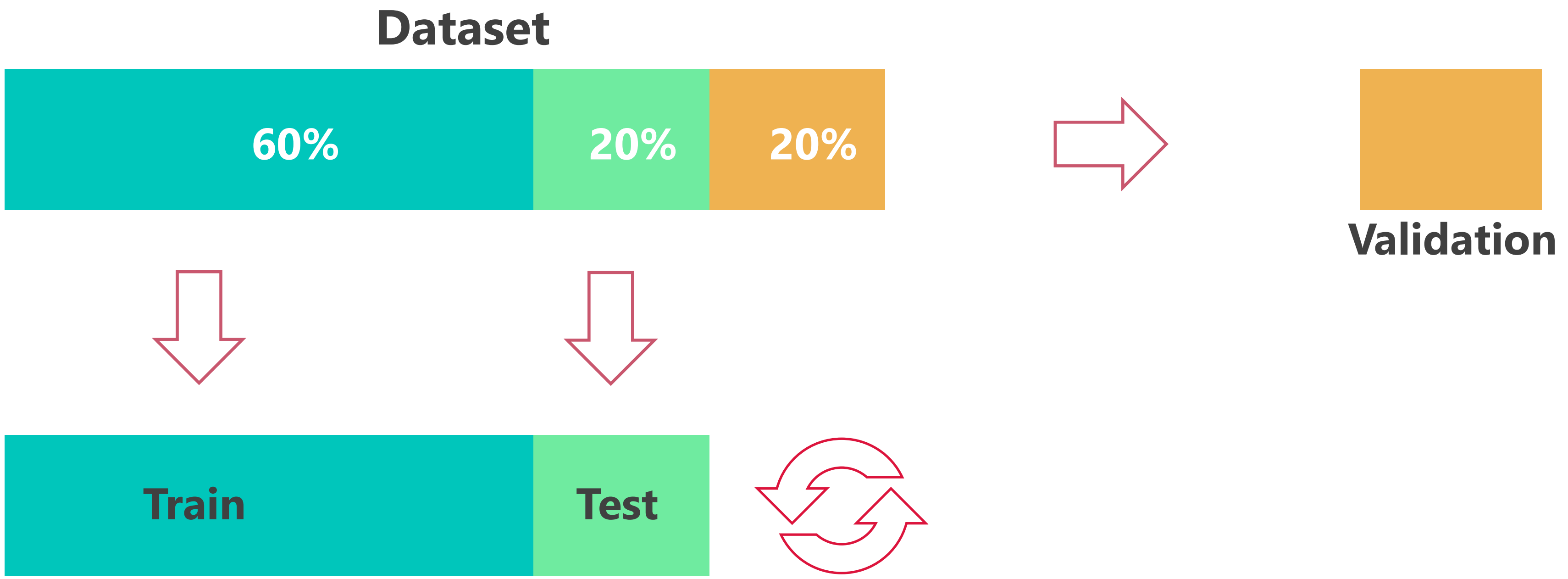
Decision threshold
100
50
0
THE PUBLIC IS NOT WARNED ABOUT A DANGEROUS STORM
THE PUBLIC IS WARNED ABOUT A DANGEROUS STORM
Criterion threshold
Actual severity of the storm
THE PUBLIC IS NOT WARNED, AND THERE'S NO DANGER
THE PUBLIC IS WARNED, BUT THERE'S NO DANGER
0
50
100
Prediction (Judgement) of the severity of the approaching storm

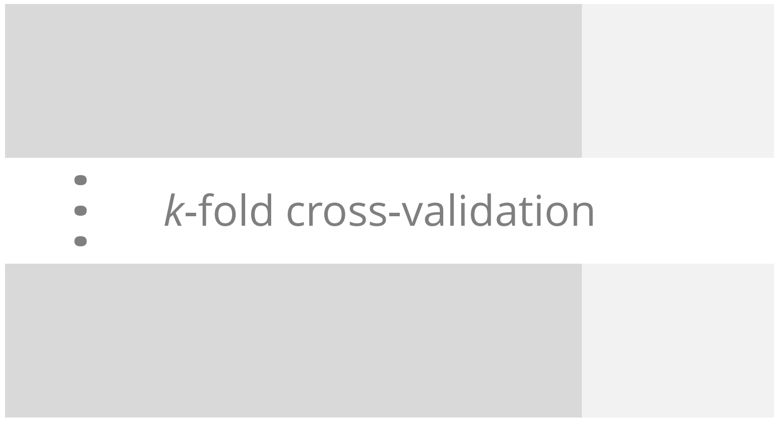
When a measure becomes a target,

it ceases to be a good measure.

Goodhart's law

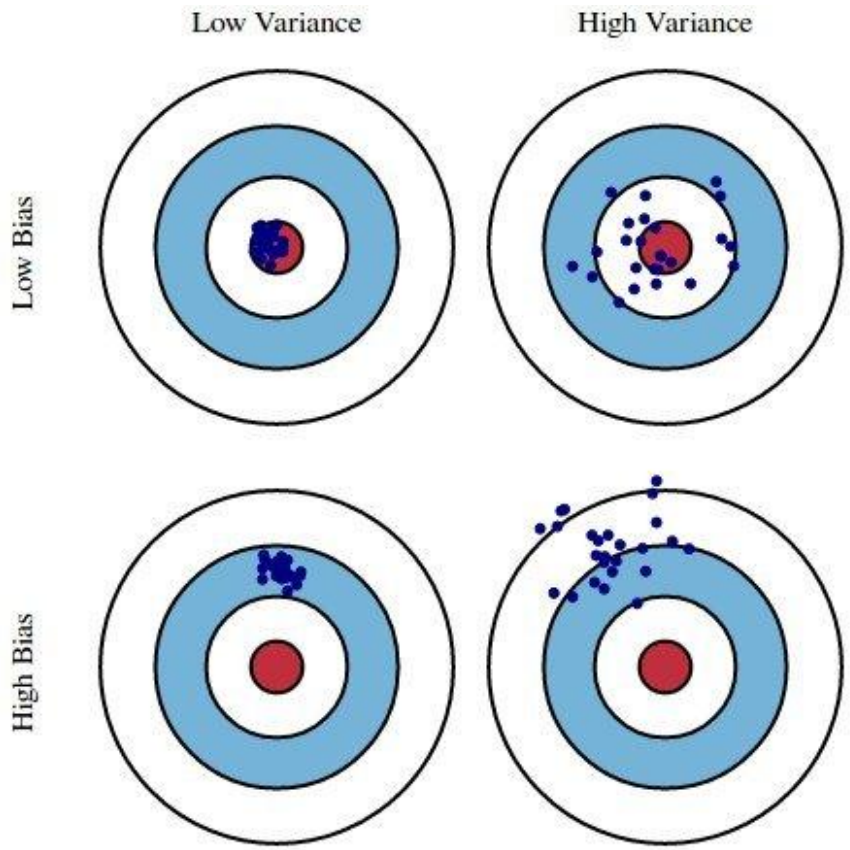
Tri-fold Partition

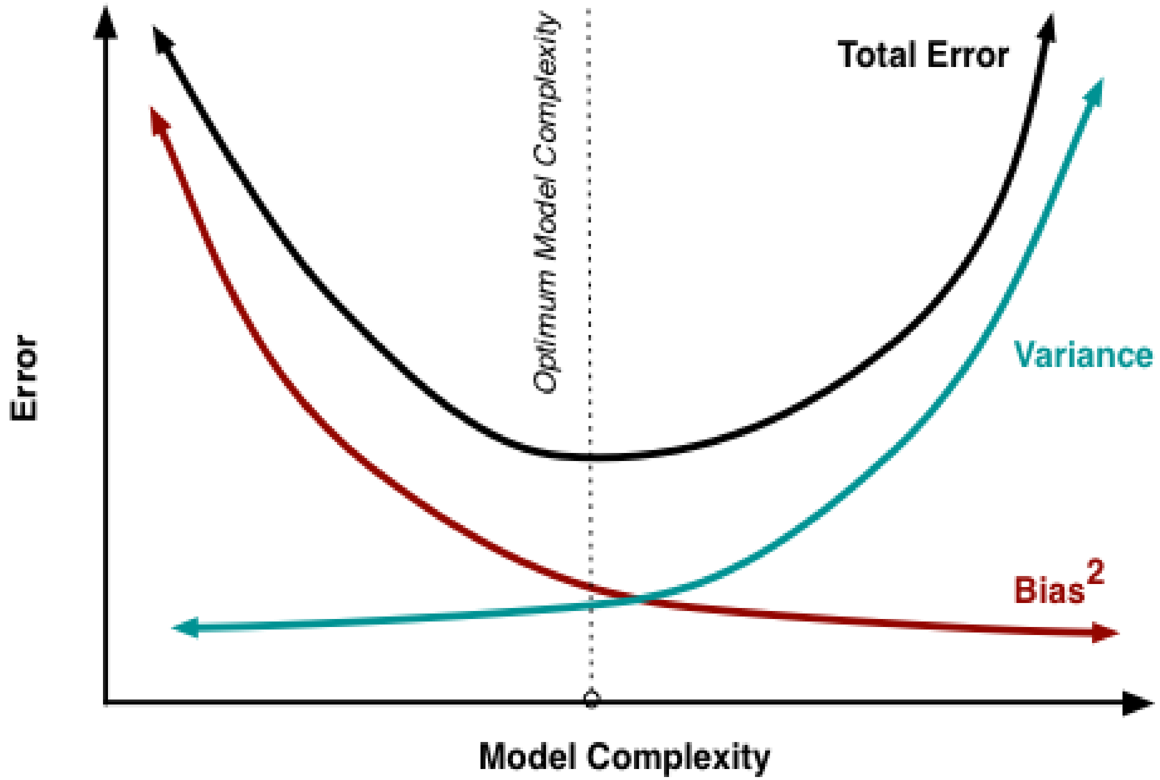




- **Fine-tune** and **select** the best model based on Train + Test sets.
- **Evaluate** the chosen algorithm on the Validation set (previously unseen data).

Bias-Variance Tradeoff





With four parameters I can fit an elephant,

and with five I can make him wiggle his trunk.

– John von Neumann

1. MODEL SELECTION
2. ASSESSMENT
3. PRESENTATION

1 **MODEL SELECTION**

2 ASSESSMENT

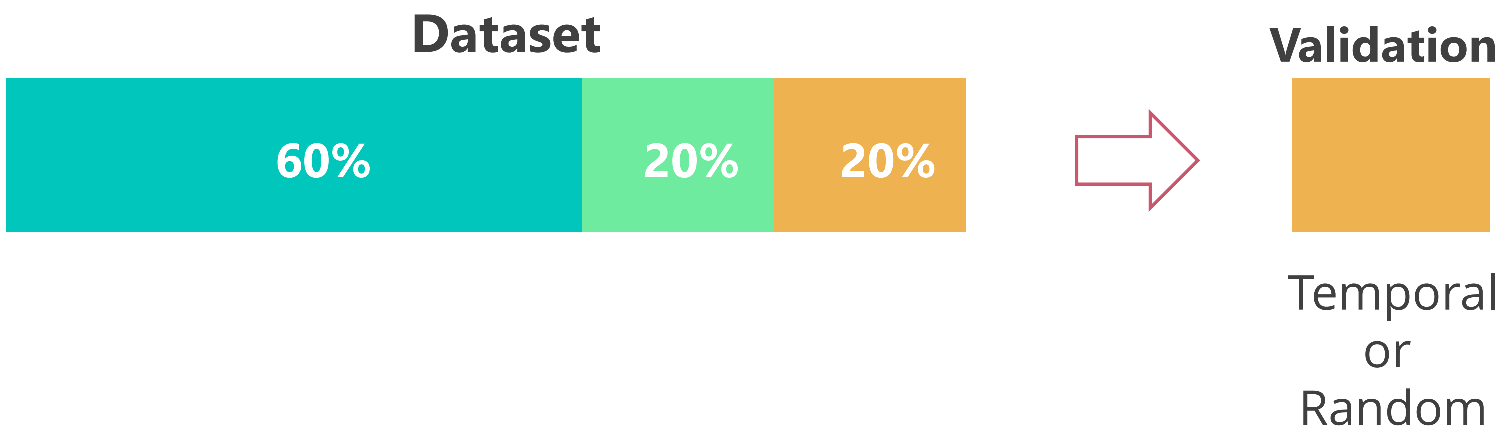
3 PRESENTATION

- **Law of Parsimony** (Occam’s Razor)
- **Model execution time**
- **Deployment complexity**

Build the simplest solution that can adequately answer the question.

1 MODEL SELECTION

2 **ASSESSMENT**



3 PRESENTATION

1 MODEL SELECTION

2 ASSESSMENT

3 PRESENTATION

- **AUC, Somer's D, etc.**
- **Cumulative Gains Chart / Lift Chart**
- **Predictor Importance**
- **Each predictor's relationship with the target**
- **Model usage recommendations**
  - Decile reports
  - How many deciles should be targeted?
- **Personify**
- **Compare against existing business rules/model**
- **Model peer-review** (Quality Control)

Interpret results as they relate to the business application.

Model Comparisons

Size (column %s)

XGB Deciles (↑ Good, ↓ Bad) × FICO Deciles (← Good, Bad →)

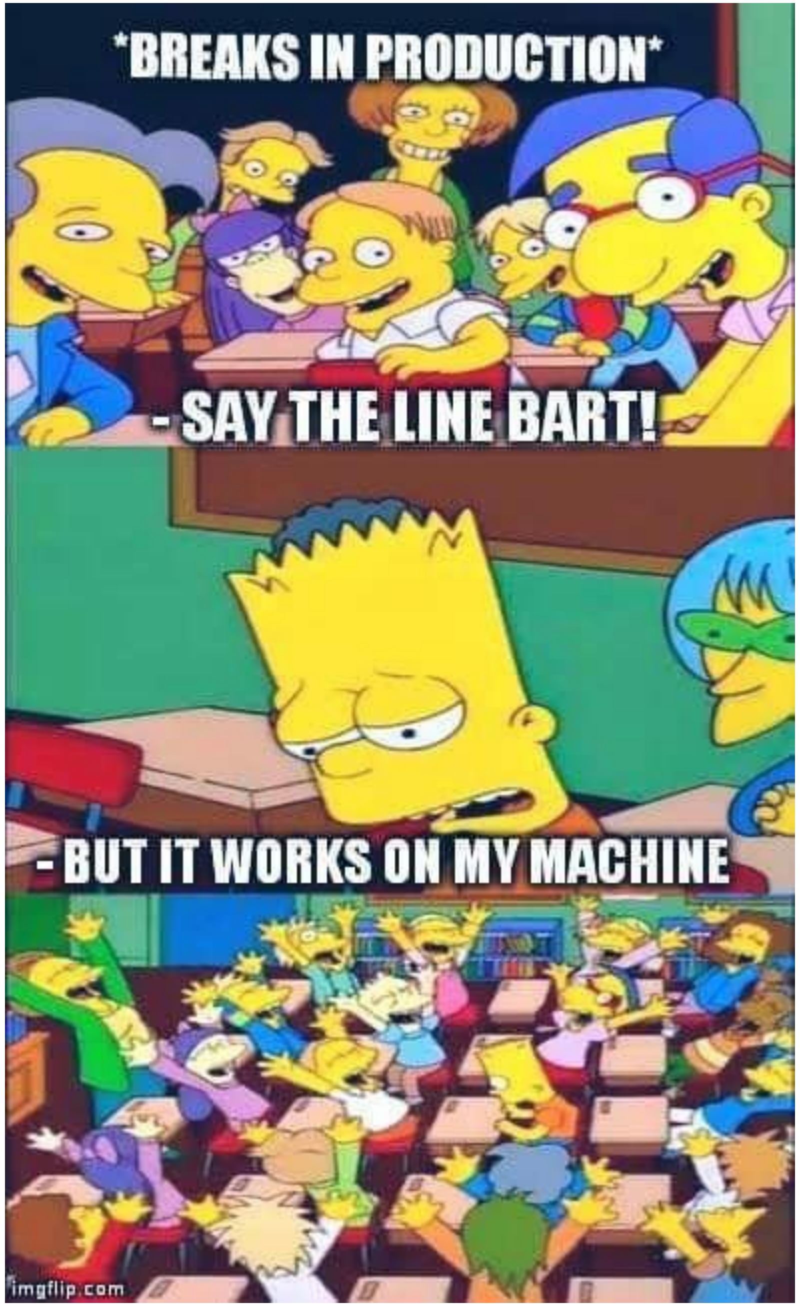
XGB \ FICO	0	1	2	3	4	5	6	7	8	9
0	44%	26%	13%	7%	4%	2%	2%	1%	1%	0%
1	22%	24%	17%	12%	9%	6%	4%	3%	2%	1%
2	13%	16%	18%	16%	12%	9%	7%	4%	3%	2%
3	8%	12%	16%	15%	14%	12%	9%	7%	4%	3%
4	4%	8%	12%	15%	14%	14%	13%	9%	7%	4%
5	3%	6%	9%	12%	14%	15%	15%	13%	9%	6%
6	2%	4%	7%	10%	13%	14%	15%	15%	12%	9%
7	1%	2%	4%	7%	10%	13%	14%	16%	16%	14%
8	2%	1%	3%	5%	6%	10%	13%	17%	21%	22%
9	2%	1%	1%	2%	4%	5%	8%	15%	25%	39%

Bad Rate

XGB Deciles (↑ Good, ↓ Bad) × FICO Deciles (← Good, Bad →)

XGB \ FICO	0	1	2	3	4	5	6	7	8	9
0	0%	1%	1%	2%	4%	3%	5%	8%	23%	31%
1	1%	1%	1%	2%	3%	6%	9%	12%	18%	19%
2	1%	1%	2%	2%	3%	6%	7%	11%	14%	32%
3	1%	2%	2%	4%	5%	6%	6%	9%	18%	29%
4	1%	1%	4%	4%	6%	7%	9%	12%	18%	32%
5	1%	2%	4%	6%	6%	7%	10%	12%	18%	28%
6	3%	3%	4%	4%	9%	11%	13%	15%	18%	29%
7	20%	3%	5%	8%	9%	9%	14%	15%	19%	30%
8	26%	6%	5%	8%	11%	14%	16%	20%	24%	35%
9	49%	10%	12%	20%	24%	29%	33%	39%	46%	59%

- **Model production cycle**
  - Weekly, monthly, live?
- **Scoring code, or publish model as a web service**
- **Model Documentation** (Technical Specifications)
  - Data preparation, transformations, imputations, parameter settings, etc.
- **Reproducibility**
  - `requirements.txt`, Docker containers


BREAKS IN PRODUCTION
- SAY THE LINE BART!
- BUT IT WORKS ON MY MACHINE
imgflip.com

1 **MONITOR**

2 **MAINTAIN**

3 **TEST**

1 MONITOR

2 MAINTAIN

3 TEST

- **Model decay tracking (monitoring) plan**
  - Model performance over time
  - Predictor distribution
  - Probability Stability Index (PSI)

1 MONITOR

2 **MAINTAIN**

- Model maintenance plan
- Plan for adding new data sources
- Version control
  - GitHub, DVC

3 TEST

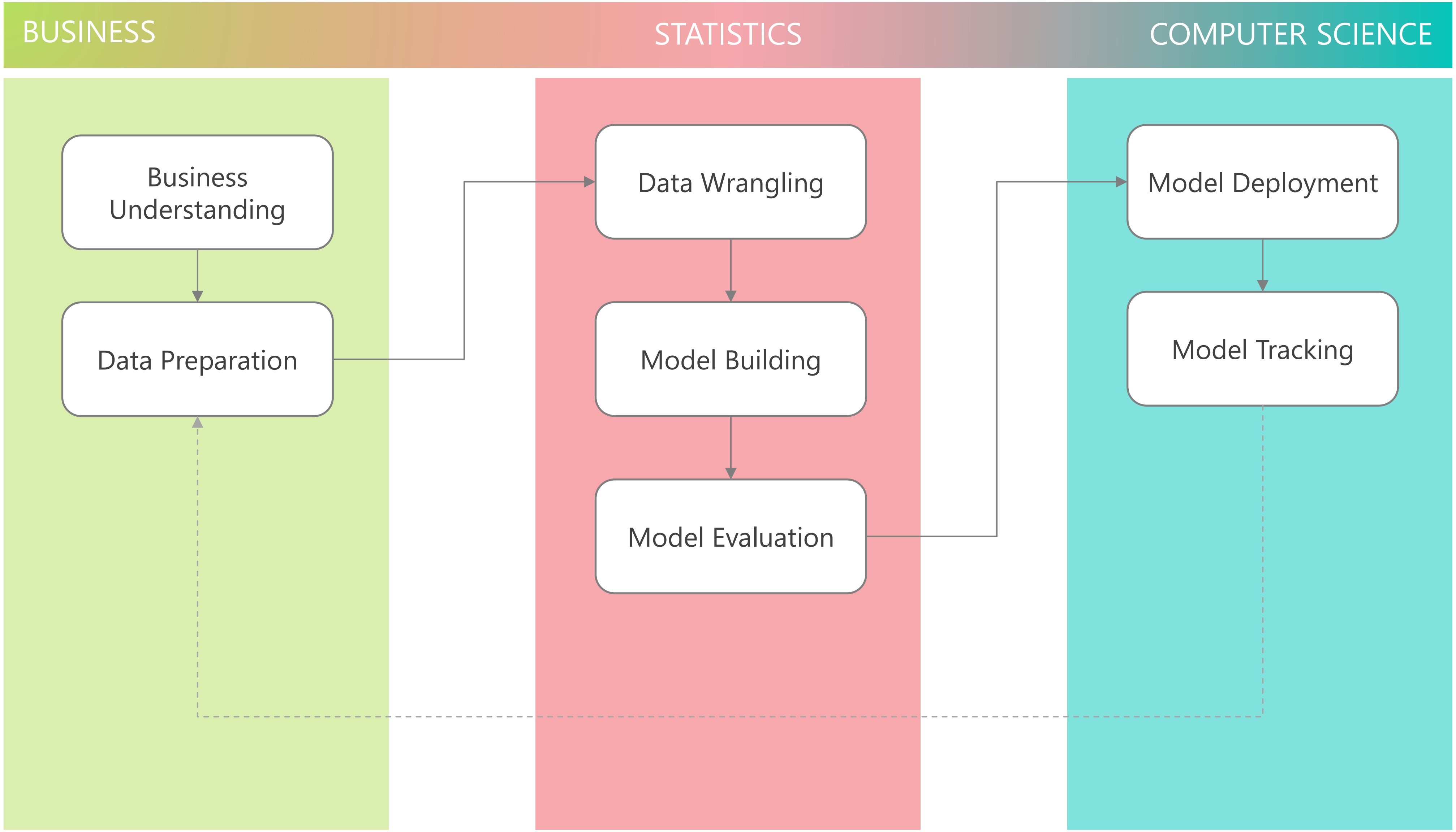
1 MONITOR

2 MAINTAIN

3 TEST

- **Campaign Set-up and Execution**
  - Experimental Design (A/B, Fractional Factorial)

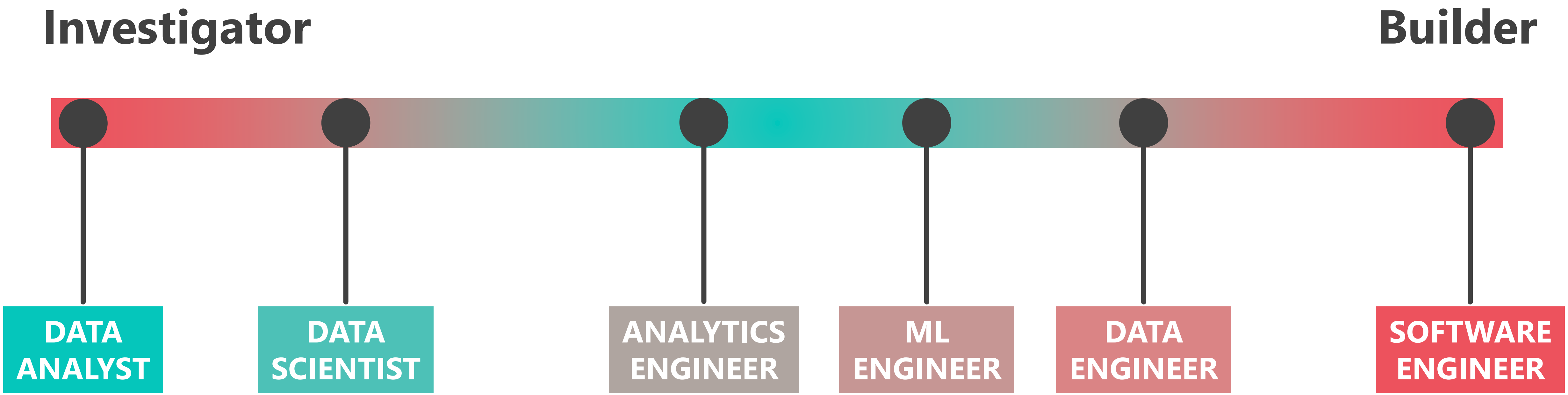
Data Science Process: Recap



Data Science Process: Recap

Business Understanding	Data Preparation	Data Wrangling	Model Training	Model Evaluation	Model Deployment	Model Tracking
Determine	Identify	Impute	Train	Evaluate	Document	Monitor
Understand	Collect	Transform	Assess	Peer Review	Deploy	Maintain
Map	Assess	Reduce	Select	Present		Test
	Vectorize					
DISCUSS	**COLLATE**	**WRANGLE**	**PERFORM**	**COMMUNICATE**	**EXECUTE**	**TRACK**

Data Roles


Investigator
Builder
DATA ANALYST
DATA SCIENTIST
ANALYTICS ENGINEER
ML ENGINEER
DATA ENGINEER
SOFTWARE ENGINEER

DAPT 631

Assignment #1 (Individual Assignment)

Due by10-FEB-2026

1. From the following five aspects of a Data Science project, which one do you think is the most important? Please provide a rationale for your answer.
    a. Understanding the business question,
    b. Quality of data,
    c. Statistical rigor and accuracy,
    d. Using the correct tools/techniques, and
    e. Communicating results back to stakeholders.
2. From the following aspects of Data Science, which one are you most interested in? Please elaborate your answer.
    a. Business Requirements,
    b. Exploratory Data analysis (EDA),
    c. Feature Engineering and data pipelines,
    d. Model Building,
    e. Putting the model into production (automation),
    f. Explain model results to non-technical audience,
    g. Develop and implement strategies based on model results,
    h. Other.
3. With the rapid growth in AI technologies, there's an ongoing debate about the future role of data analysts and data scientists.

    Do you think data scientists/analysts will become obsolete in the coming years? Why or why not? Support your answer with specific examples of tasks or roles where data scientists/analysts might be replaced or enhanced by AI and discuss areas where human expertise might still be essential.

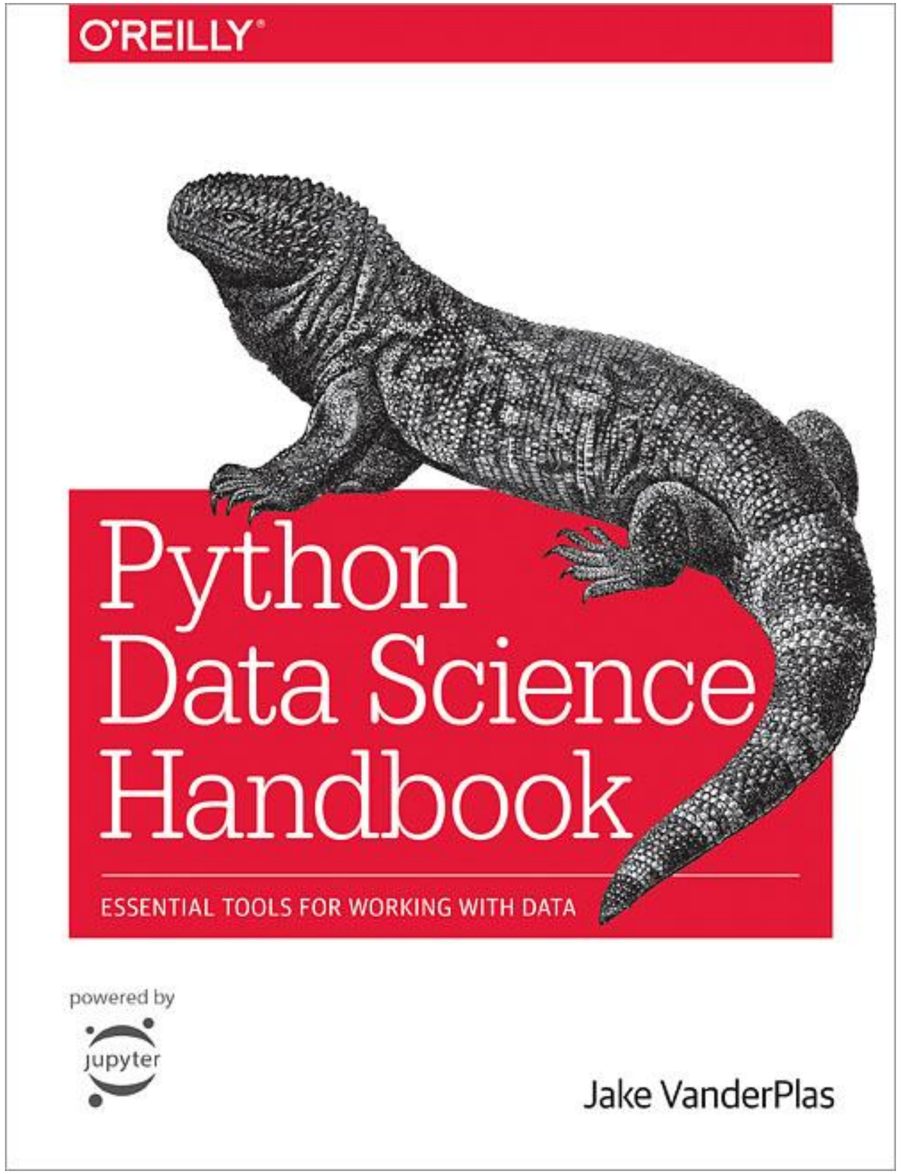
Next Up

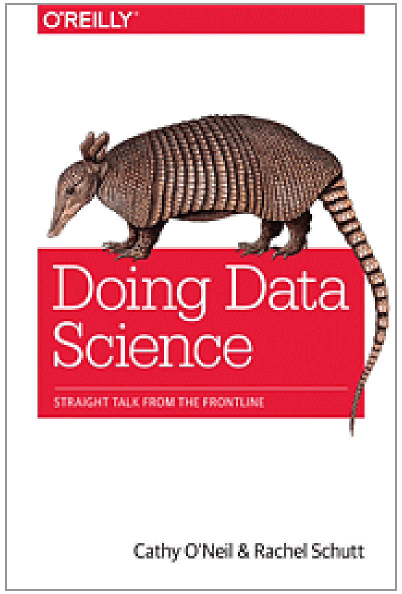
1. ~~Introduction~~
2. ~~The Data Science Process~~
3. **Supervised Learning**
4. Unsupervised Learning

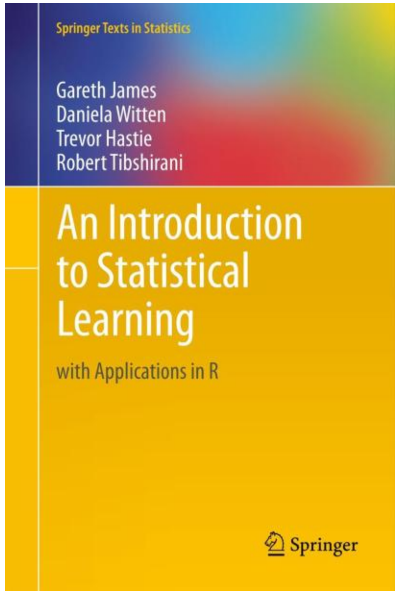
Data Mining Algorithms

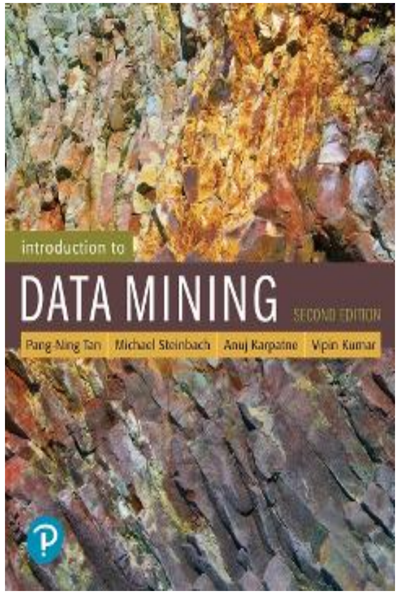
5. The Grunt Work
6. Wrap Up

Linear Regression → Decision Trees → Random Forests → Gradient Boosting → ...









- Chapter 3. **Classification**: *Basic Concepts and Techniques*
- Chapter 5. **Association Analysis**: *Basic Concepts and Algorithms*
- Chapter 7. **Cluster Analysis**: *Basic Concepts and Algorithms*

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100+ Free Data Science Books

Chapter 5: Machine Learning