

# Defining success

DEMYSTIFYING DECISION SCIENCE



Akshay Swaminathan

PD Soros Fellow at Stanford University  
School of Medicine

# Success in Decision Science

Great models aren't enough without impact

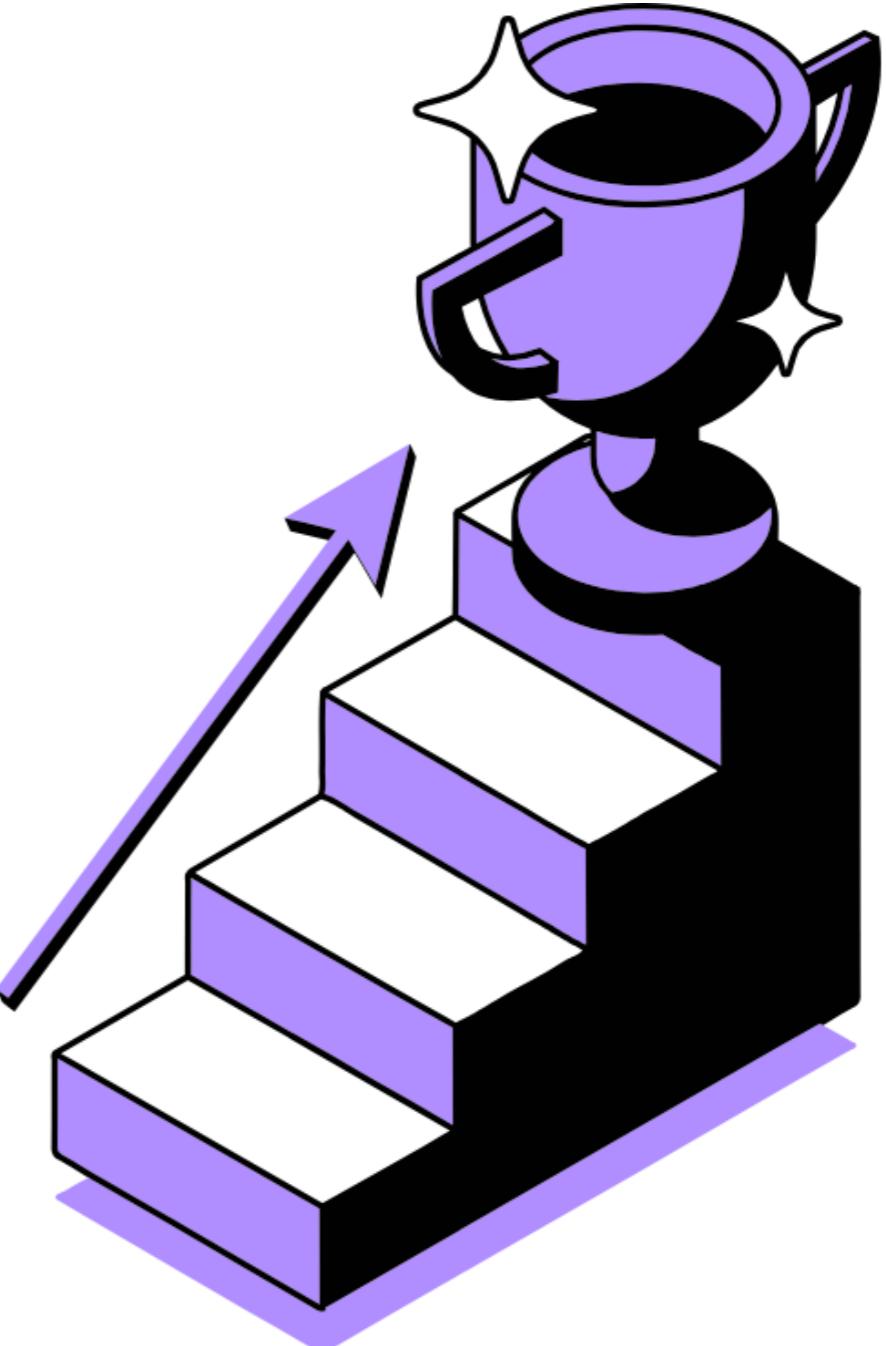
- Sophisticated analysis is only valuable if it's used and acted upon

Undefined success leads to wasted effort

- Without shared goals, insights may be ignored, misunderstood, or go unused

Success must be agreed upon

- Align with your stakeholder or customer on what a "successful outcome" looks like - *before* the work begins



# Understand what success looks like to your customer

## Be customer-focused

- Focus on the problems they need solved
- Clarify what outcomes would be considered a win

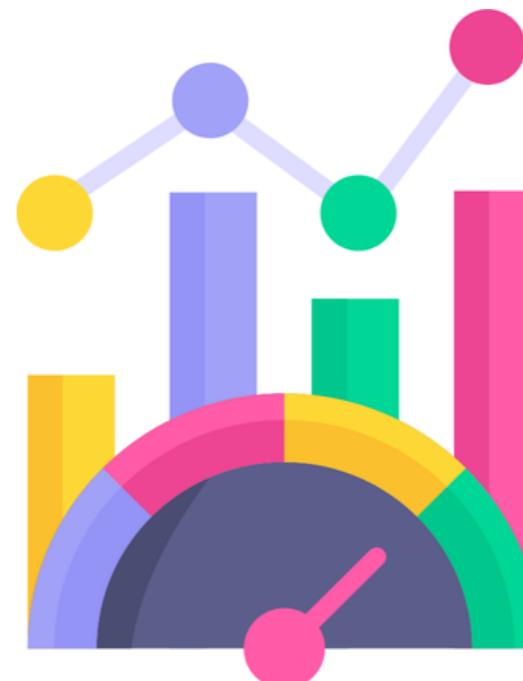
## Success is not just about accuracy

- The real value lies in how the model supports better decisions
- A restaurant chain may care more about reducing waste and targeting marketing than about model precision



# Measures of success

- **Performance:** Model accuracy, precision, recall, or other technical indicators
- **Time:** Whether the project was delivered when it was needed
- **Cost:** Whether you stayed within budget
- **Business impact:** Did the project contribute to strategic goals or measurable improvement?
- **Quality:** Code clarity, documentation, and reproducibility
- **Stakeholder satisfaction:** Was the work well-communicated and useful to the audience?



# Minimum Viable Product (MVP)

## Start simple

- The MVP is the simplest version of your solution that delivers core value
- Answer one key question and be ready to implement

## Use MVPs to build momentum and trust

- Agree on success metrics at the beginning
- Communicate, track, and report progress
- Demonstrate early wins and build support



# **Let's practice!**

**DEMYSTIFYING DECISION SCIENCE**

# Databases and quality checks

DEMYSTIFYING DECISION SCIENCE



Howard Friedman

Adjunct Professor at Columbia  
University

# Triaging data sources

## Not all data is equally useful

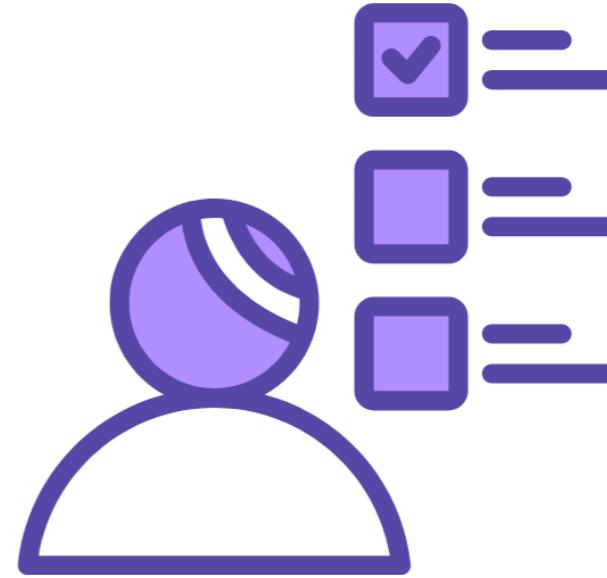
- Some datasets require heavy cleaning or lack meaningful features
- Others may not be worth the effort at all

## Data triaging helps prioritize quickly

- Assess whether a dataset is viable before investing time and resources

## Start with availability

- Is the data easy to access or behind a paywall
- Are there permission or security barriers
- Sorting this out early helps avoid wasted effort



# Key checks

## Consider costs

- Are there licensing or access fees
- Will you need to pay for storage or specialized tools

## Evaluate utility

- Does the dataset contain what you need for your analysis
- Check the scope, detail, completeness, and feature relevance

## Check update frequency

- Real-time predictions need real-time or regularly updated data
- Mismatched update cycles can render data unusable

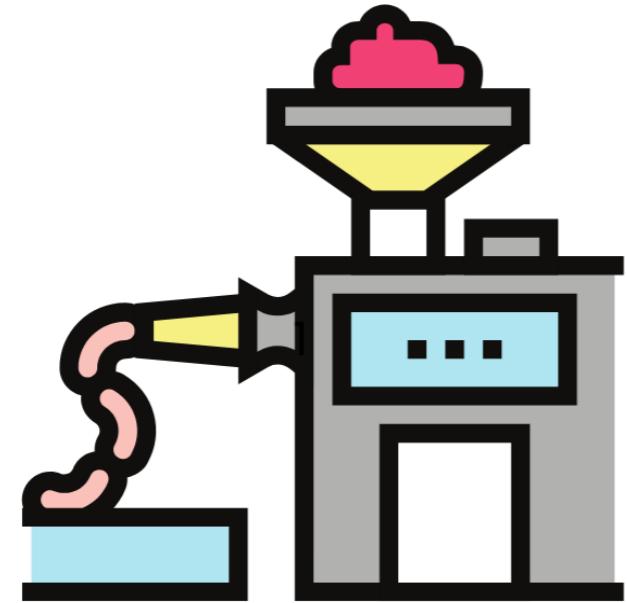
## Assess geographic resolution

- Does the data align with the spatial level your analysis requires
- National-level data won't help if you need zip-code granularity

# Data quality checks

## Data quality matters

- Bad data can ruin models and lead to bad decisions
- "Garbage in, garbage out" is a real risk in decision science



## Watch for missingness

- Percentage of missing values in each column
- Patterns that suggest deeper data collection issues

## Do basic range checks

- Are there values that don't make sense for your context
- Examples: age = 450 or price = -\$10
- Use checks to flag major issues early

# More checks

## Review outliers

- Use histograms or boxplots to visualize
- Discuss with stakeholders before excluding anything

## Assess timeliness

- Ask whether your data is recent enough to be relevant
- Fast-moving contexts need frequently updated data

## Ensure formatting consistency

- Look for inconsistent date formats, spelling issues, or column naming mismatches
- Clean and standardize to avoid problems during analysis



# **Let's practice!**

**DEMYSTIFYING DECISION SCIENCE**

# Model prioritization

DEMYSTIFYING DECISION SCIENCE



Howard Friedman

Adjunct Professor at Columbia  
University

# Starting simple with linear regression

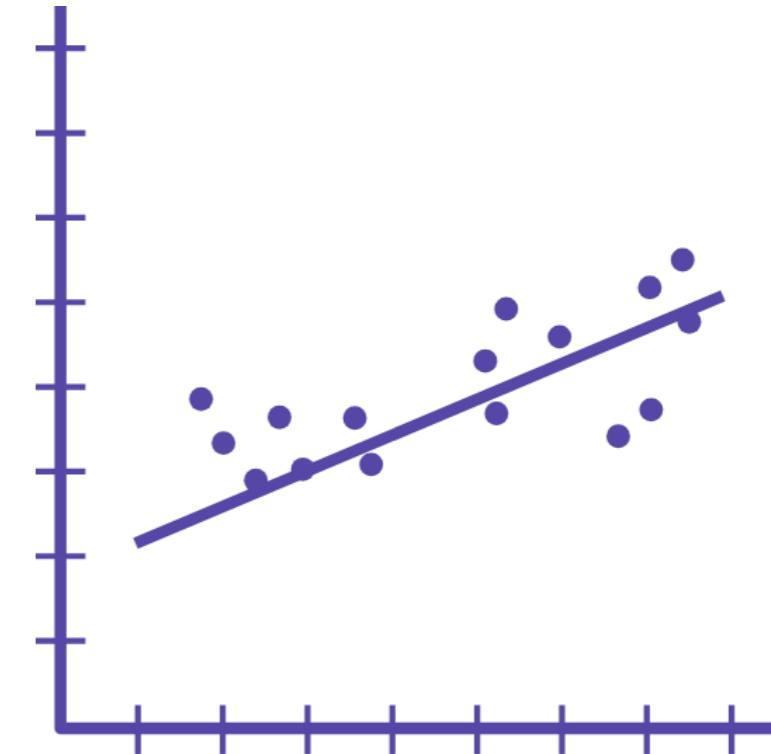
- Effective for continuous outcomes when assumptions are met
- 200+ years of proven usefulness in real-world analysis

## Simplicity has power

- Linear regression finds the best-fit line through your data
- With transformations, it can model complex non-linear relationships too

## Interpretability matters

- Coefficients help with alignment
- Quick to compute - easy to explain



# Logistic regression

Many real-world problems involve binary or categorical predictions:

- Fraud detection, churn prediction, and healthcare risk models



**Logistic regression is highly versatile**

- Suitable for binary outcomes, multiple categories, or even ordered outcomes

**Probabilities support decision-making**

**Easy to interpret and implement**

- Coefficients show how each feature influences the outcome
- Great as a baseline for more complex classifiers

# Feature transformations

## Start with a strong baseline model

- Build a functional version first, then assess the value of more advanced models

## Feature transformations can boost performance

- Transformations like log or square can increase variance explained
- They can also improve how well your model fits the data

## Match model assumptions to the data

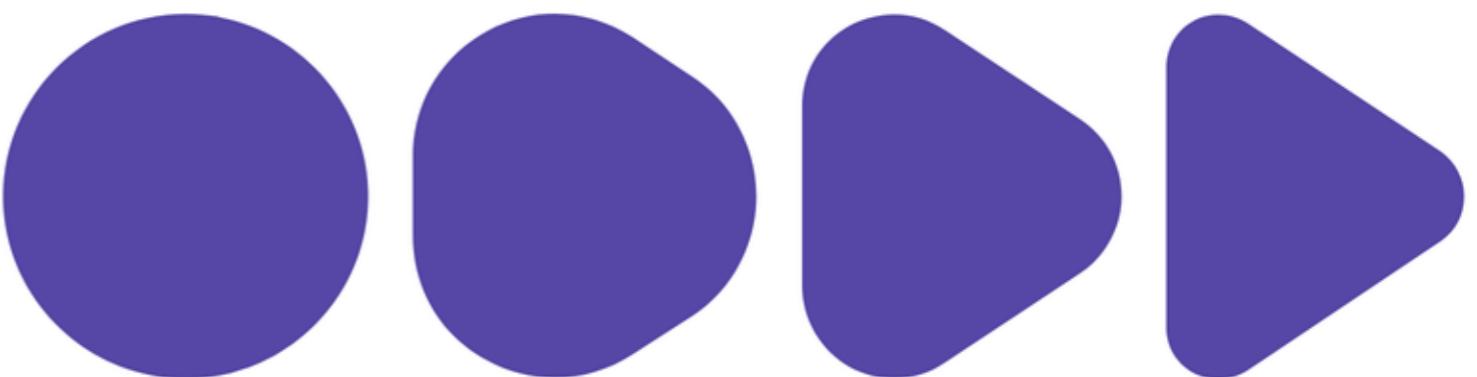
- Some models, like linear regression, perform best when residuals are normally distributed



# Common transformations

- **Log and square root transformations** compress wide ranges and reduce outlier impact
- **Standardization and normalization** bring features to similar ranges, especially useful when units vary
- **Polynomial terms** such as squared and cubic terms can represent complex, non-linear relationships with minimal effort

*Use transformations to improve early models before jumping to complex ones*



# **Let's practice!**

**DEMYSTIFYING DECISION SCIENCE**

# Tracking performance

DEMYSTIFYING DECISION SCIENCE



Akshay Swaminathan

PD Soros Fellow at Stanford University  
School of Medicine

# Model performance

## Different models, different strengths

- One model is better at identifying who is likely to default
- The other is better at estimating how much they might default by



## Which model is better? It depends on the goal

- Do you care more about flagging risky customers
- Or estimating the financial impact of default

# Model metrics

Different metrics shine a light on different aspects of performance

## Commonly used evaluation metrics:

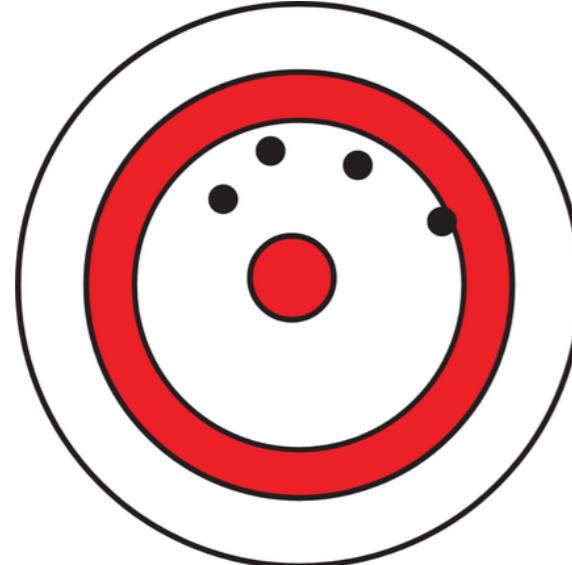
- Accuracy
- Precision
- Recall
- F1-Score
- Area Under the Curve (AUC)
- Mean Absolute Error (MAE)
- Mean Absolute Percent Error (MAPE)



# Accuracy

Broad overview of correctness

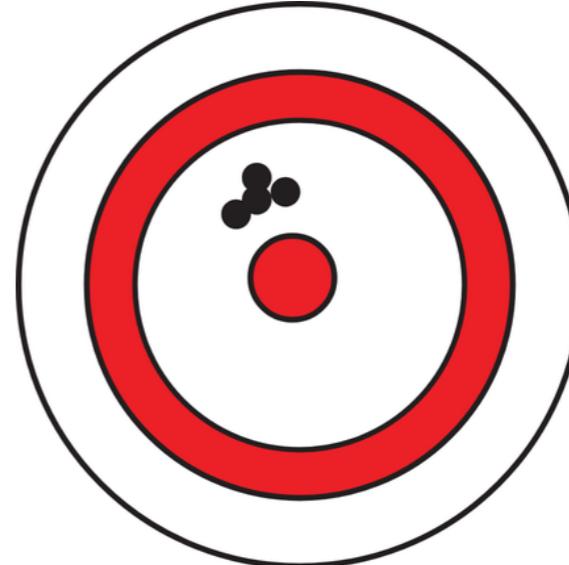
- Measures the percentage of all predictions the model got right
- Works well when classes are balanced, like spam vs not spam



# Precision

How many predicted positives are actually correct

- Important when false positives are costly
- Low precision = flagging many legitimate transactions as fraudulent



# More metrics

## Recall: catch the true positives

- Measures how well the model finds actual positives
- Important when missing a case has high cost (e.g., fraud, disease)

## Area under the curve (AUC): measure of class separation

- Evaluates how well the model distinguishes classes
- Not tied to a specific threshold

## Regression metrics: measuring prediction error

- Mean Absolute Error (MAE): average size of prediction errors
- Mean Percentage Error (MPE): how far off predictions are in percentage terms



# Dashboards are critical

Dashboards transform complex analyses into clear, actionable insights, making it easier to drive decisions.



# Basic principles

## Know your audience

- Executives want summaries
- Analysts need detail

## Highlight key metrics

- Show only what matters most
- Avoid clutter and noise

## Use clear visualizations

- Bar charts for comparisons, line charts for trends over time
- Simple visuals often work best



# More principles

## Track change over time

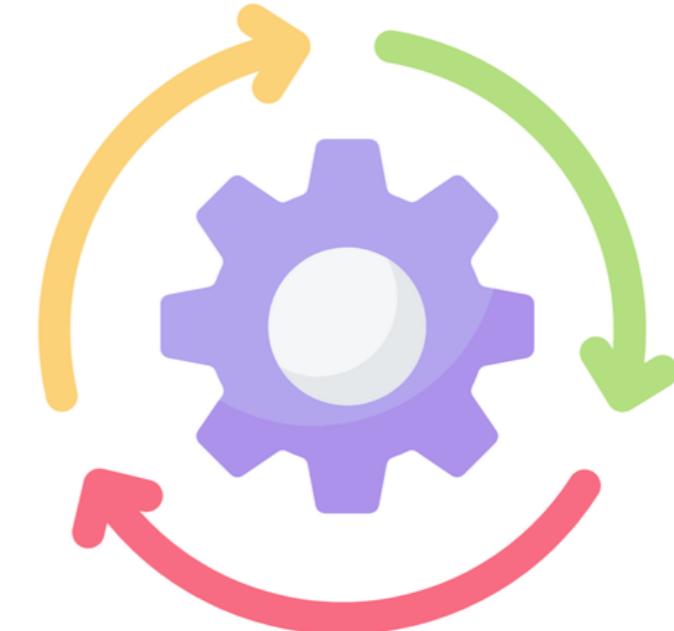
- Monitor model performance and feature drift
- Trends give context to metrics

## Add context, not just numbers

- Use brief annotations to explain key shifts
- Help users understand what's happening and why

## Test and iterate

- Share early and gather feedback
- Update dashboards as models and needs evolve



# **Let's practice!**

**DEMYSTIFYING DECISION SCIENCE**