Decision Science

2. Business context and strategy

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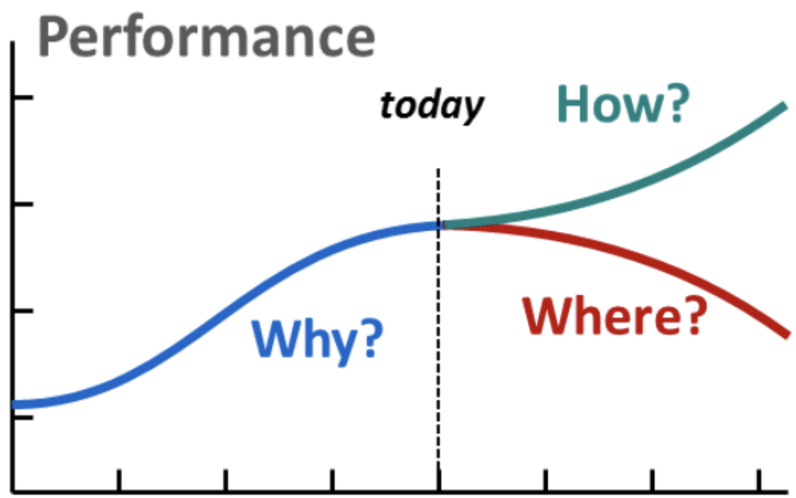
Three critical questions



Source: Kim Warren, Strategic Management Dynamics – Status Quo, Desired and Feared Trajectories

- **What** happened (data / facts) and **Why** (inference)
- **Where** are we likely going if we do things as before?
  - Is it a feared scenario?
  - What contributes to it?
- **How** to achieve the desired trajectory? Is it realistic?

Remember VUCA? Complex Systems?

Trajectories and good ol' SWOT

Ecommerce selling apparel. What do they want? What should they do?

$\max$ **Top line** (revenue) | **bottom line** (EBITDA) | customer **satisfaction**.

- Status Quo: what is most likely trajectory? What contributes to it?
  - looks good $\implies$ strengths
  - looks bad or unsatisfactory $\implies$ weaknesses
- Feared trajectory (shocks, risks, macro environment, competition):
  - scenario looks bad $\implies$ threats
- Desired trajectory. Is it reasonable and realistically achievable?
  - if yes $\implies$ opportunities

Tradeoffs: it depends

- What if it's a startup that received big funding?
- What if it wants to capture market share?
- What if the goal is to have sustainable profitability?
- What if they position themselves as luxury?

> The question we asked is too generic. We need a **strategy** and possible decisions, constraints in their **value chain**

What is the optimal tradeoff between objectives? In which part of value chain should they

Principle nr. 8

What is true and how should I act?

You should have those questions in mind not just at the job

More nuanced: likely, plausible, with convergent evidence. “Seeing clearly”

What is a strategy anyways?

NOT just **aspiration** towards goal or a **vision** or a **target**.

Step	Outcome	Characteristics
Honest diagnosis	Identify obstacles	Few critical, relevant aspects
Guiding policy	General approach to overcome	Focused on key aspects
Coherent actions	Support policy with action plan	Coordinated and focused

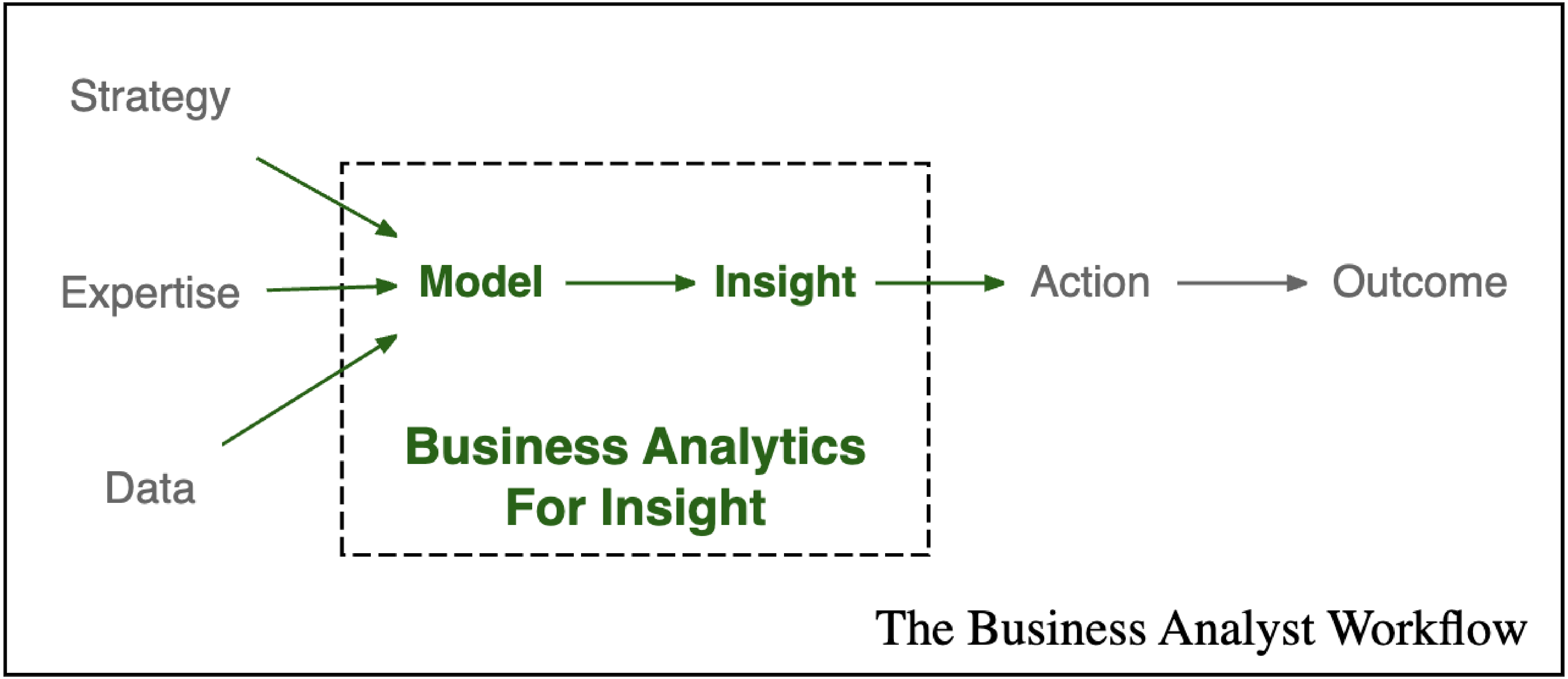
When it comes to setting good goals, you might've heard of SMART

Principle nr. 9

Know your firm's strategy. Call out bad strategy.

First ask, understand, contribute. Challenge if situation allows.

Business Analysts' Workflow



Source: Adam Fleischhacker; This process is highly iterative and depends on having good feedback and collaboration

Characteristics of this process

- **Outcome-focused**: What's the point otherwise?
- **Strategically-aligned**: Not all outcomes are equal!
- **Action-oriented**: Biggest pitfall of any AI/ML initiative – when it's not actionable!
  - Needs clear and persuasive communication
- **Computationally rigorous**:
  - Correctness, reproducibility and maintainability
  - Accesible: idealy in an app which users explore

Principle nr. 10

Don’t get too enamored with exploratory data analysis

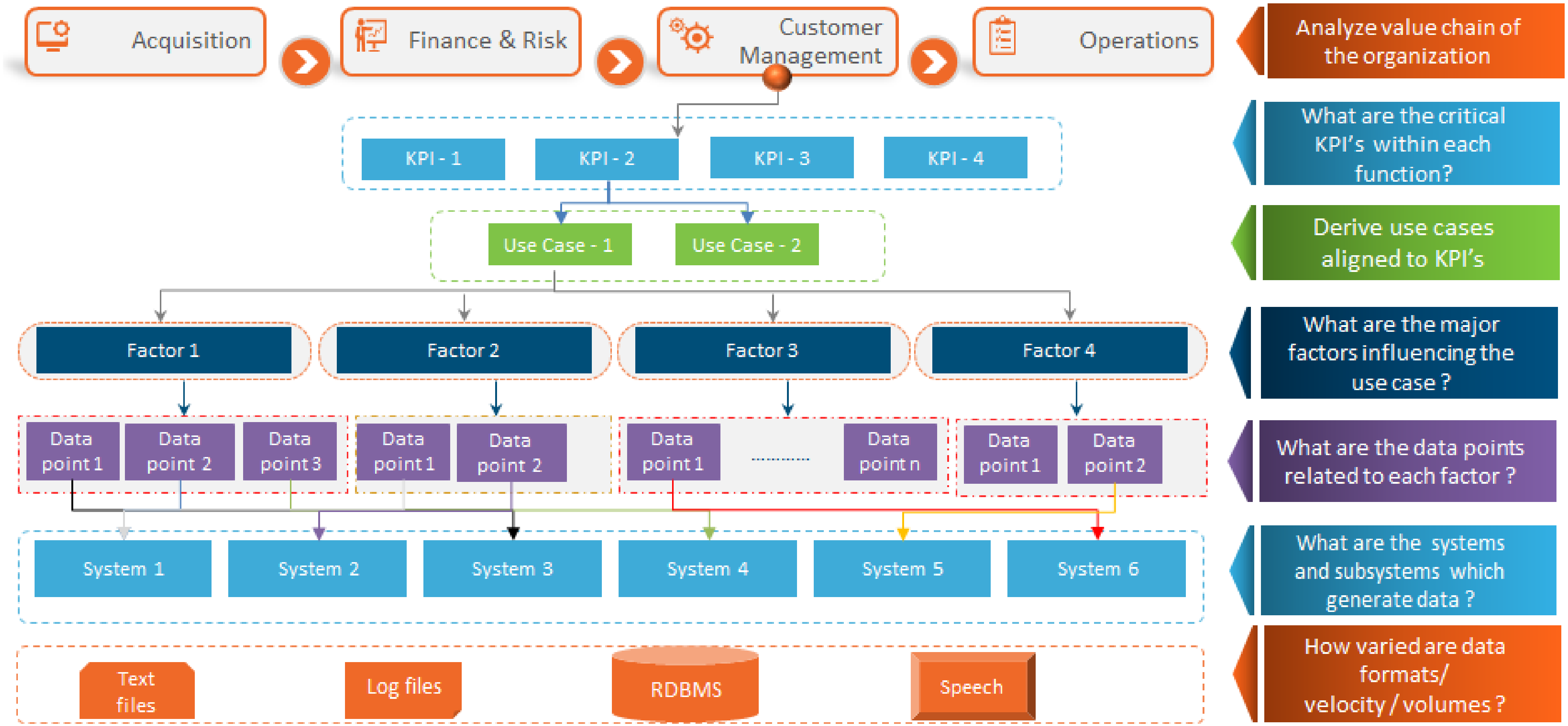
EDA is essential, but do it mindfully – don’t jump to conclusions

Data Scientists often forget about outcomes and actions / interventions

Other processes to be aware of

- Scientific process (it’s not “the science says …”)
    - Statistics and experiment design (12 steps)
    - Causal inference
- Machine Learning (12 steps)
- CRISP-DM, Tuckey’s EDA
- Software Development, Product Management
    - Algorithmic/computational problem-solving

Value Chain meets Decision Science



Source: bayesianquest – Data Science Strategy Safari. This framework was useful in my role as the Head of Data Science

Principle nr. 11

Understand what thy buzzwords mean

AI, Analytics, Big Data, Generative AI, Deep Learning, Machine Learning, Cybernetics

Weak AI

Decision-Making Under Uncertainty at Scale

- domain-specific (medicine vs finance vs automotive ...)
- data-driven (key idea of learning from data)
- varying, limited degrees of autonomy
- sometimes concerned with networks of agents

AGI (Artificial General Intelligence). Michael Jordan - Stop calling everything AI

Cybernetics is the OG AI

The science of *general regularities* of *control* and *information processing* in animal, machine and human

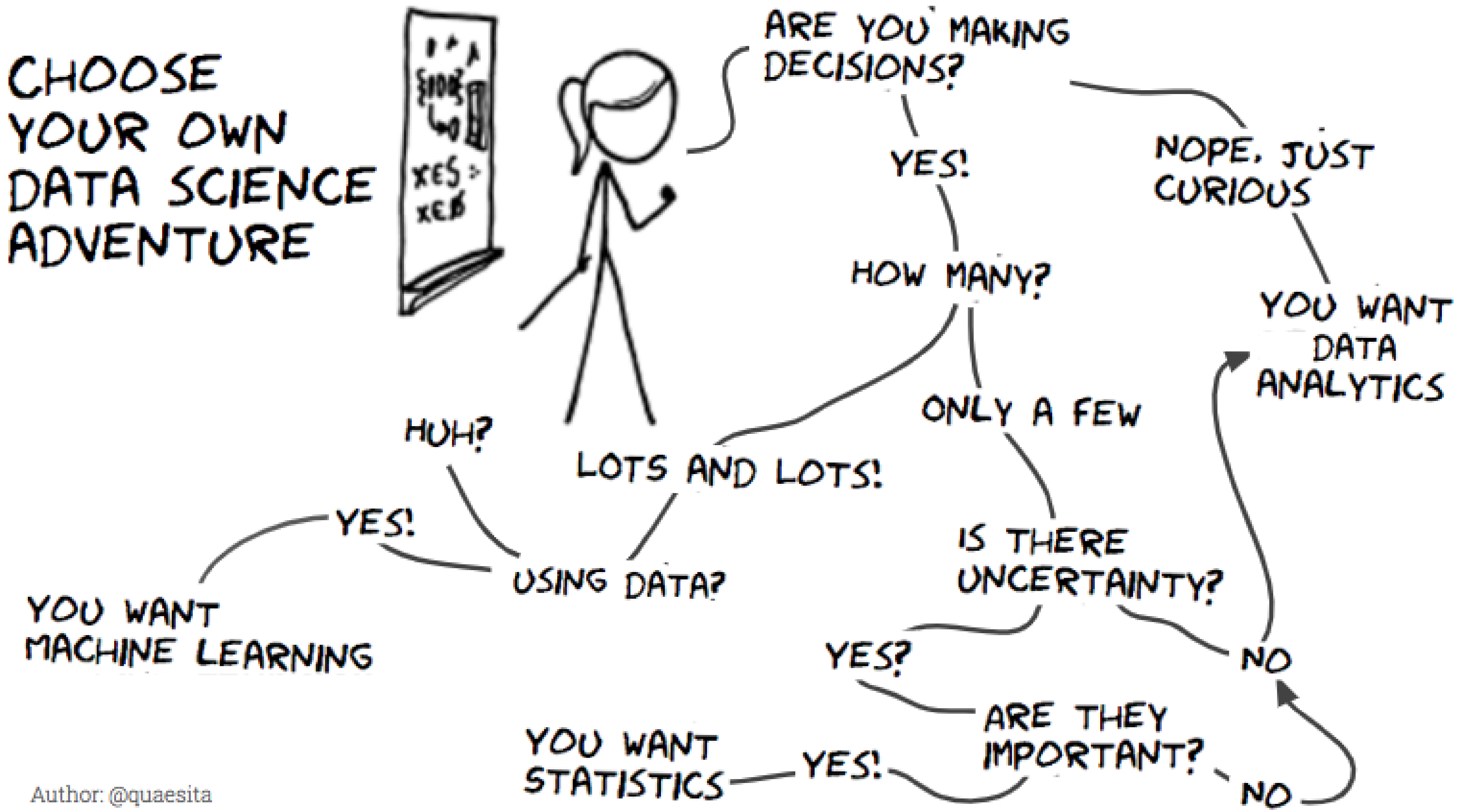
What? Let's unpack this

Unpacking Cybernetics

- **Control** $\implies$ **goal-directedness**. Action to steer to a trajectory or autopoesis (perserve $(\mathrm{S}-\mathrm{f}\,)_{\mathrm{org}}$)
- **Information Processing** $\implies$ pattern recoginition, perception, modeling & inference
- **General regularities** $\implies$ plausible of control and information processing across fields and CAS
- Animal refers to applications in biology, machine – in engineering, and human – in our society and behavior.

In economic cybernetics, we're concerned with economics, society and human behavior,

Analytics vs ML vs Stats



Source: xkcd; Instead of Stats, I would say we want Causal Inference

Principle nr. 12

Analytics is for inspiration. Formulating a hypothesis is a science and art

Think of a good analyst, as a detective. One can also model, but still do analytics

Principle nr. 13

When doing ML, split your damn data

- is there a pattern to be found?
- do we have relevant data?
- $\implies$ we're in business of ML!

Many ML and Statistical models are like a geocentic model – good at prediction, but the

Principle nr. 14

Often in ML, you use predictions for optimization

- make sure loss function is aligned with the business cost
- make sure you're not over/under-fitting

In business applications, it's not enough just to predict. What do you do about it?

Principle nr. 15

You can’t derive a theory using data alone

- Causal Inference is harder than ML
- You want to know the consequences of your intervention
- Theory $\longrightarrow \ldots$ Causal Model + Data $\longrightarrow$ New insight

Causal inference can also be seen as a problem of inferring/predicting missing data

Principle nr. 16

Statistics is about changing your action and mind under evidence

- Under what circumstances would I change my default action?
    - Does the evidence make my H_0 ridiculous?
    - Is it due to chance?

Roles in firms: Stuff data people do

- Data Engineering – pipelines and infrastructure
- Data Analysts – detectives, decision support
- BI – infrastructure for reporting, clean, modeled data
- ML Engineer – builds ML models and deploys them
- Data Scientist – jack of all trades, often lots of stats
- Product Analyst – cares about experiments
- Decision Makers & Domain Experts are usually the clients

Everyone deals with data, even BE, FE, Decision-Makers, QA, DevOPS, domain experts

At some point, we'll discuss

- AI product management:
  - PAIR: People+AI research (Google)
  - Event Storming
  - Ethics and controversies of AI
- Full Stack data apps
  - ML Systems and technical debt
  - Computational Reproducibility
- Replication crisis
  - Media and Bullshit

More on course philosophy

- Motivation for why is something important (method, idea, model, process, …)
- Develop conceptual understanding and intuition
  - Theoretical rigor only where necessary
- Use simulations as a safe playground
- Practical and realistic applications
  - problem formulation: focus on decision-making
  - start with simplest models
  - deal with messy data and introduce more realism

Learning is never linear

We circle and come back to an idea until it really makes sense

There is no shame in going back to basics – there is so much to appreciate

The danger of thinking in buckets

Here is R. Sapolsky's argument about studying different aspects of human behavior:

- Our brains think about stuff in buckets / boundaries
- These buckets influence our memory, language, behavior
- We stop seeing the big picture:
    - Bad at differentiating facts within buckets
    - Exagerrate differences between buckets
- Tempting to claim that a bucket is the only, true explanation
- Some of the most influential scientists fell into this trap

We’ll walk across many buckets

- **Problem space**: the CAS of a firm, but not only
- **Cognitive science**: intelligence, rationality, foolishness
- **Probability Theory**: Reason under uncertainty, DAGs, DGPs
- **Statistics**: formulating hypotheses, experiment design
- **Machine Learning**: next year we focus on predictions
- **Computer Science**: how to make the stuff usable
- **Philosophy**: ethics, epistemiology, phil. science
- **Mathematics**: elegant abstractions and tools

And take short trips and detours

- Pedagogical
- Industrial
- Always come back home to problem-solving