

Managing Data Science | Lessons from the Field

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PARIVEDA

What You'll Learn Today

GOALS

What is the bar for data science teams

PITFALLS

What are common data science struggles

DIAGNOSES

Why so many of our efforts fail to deliver value

RECOMMENDATIONS

How to address these struggles with best practices

Lots of Legitimate Promises



Saved \$40M

In claims with predictive analytics



35% of Sales

Come from product recommendations



Saved \$450M

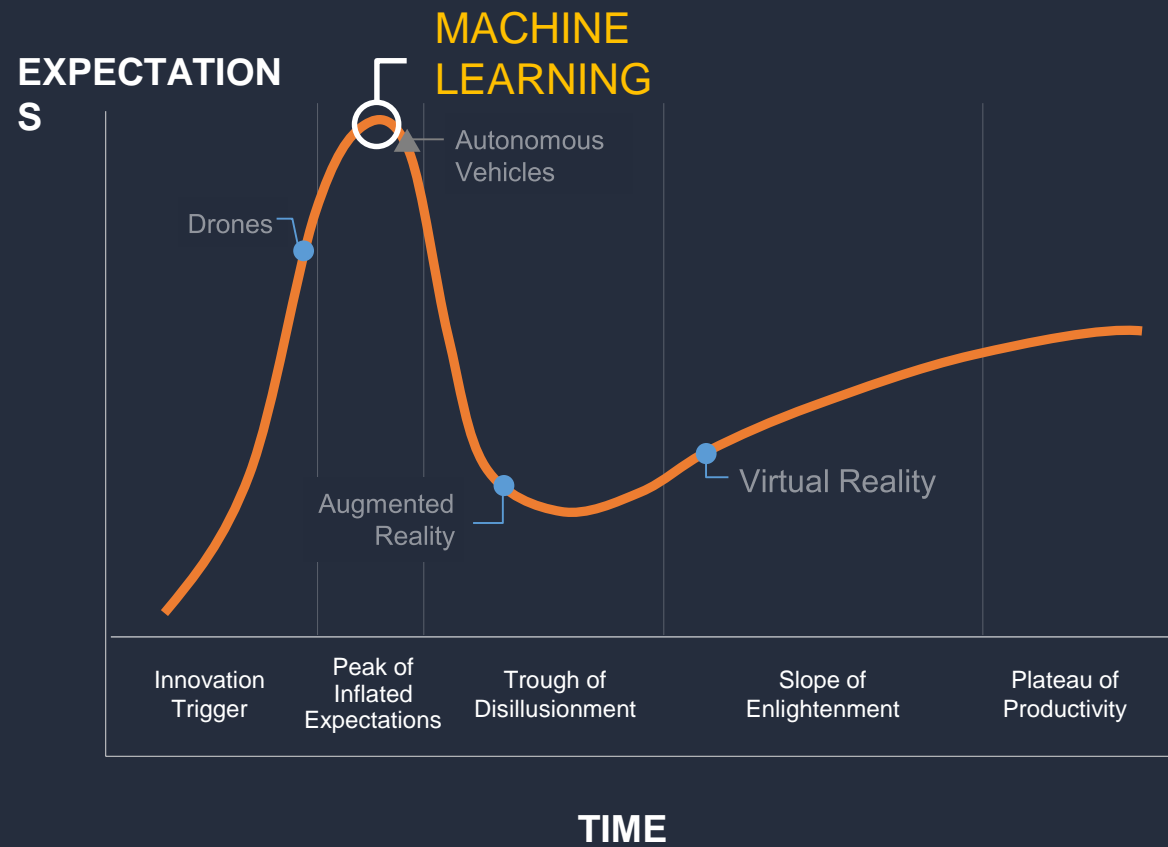
By detecting fraudulent tax returns

Lots of Hype

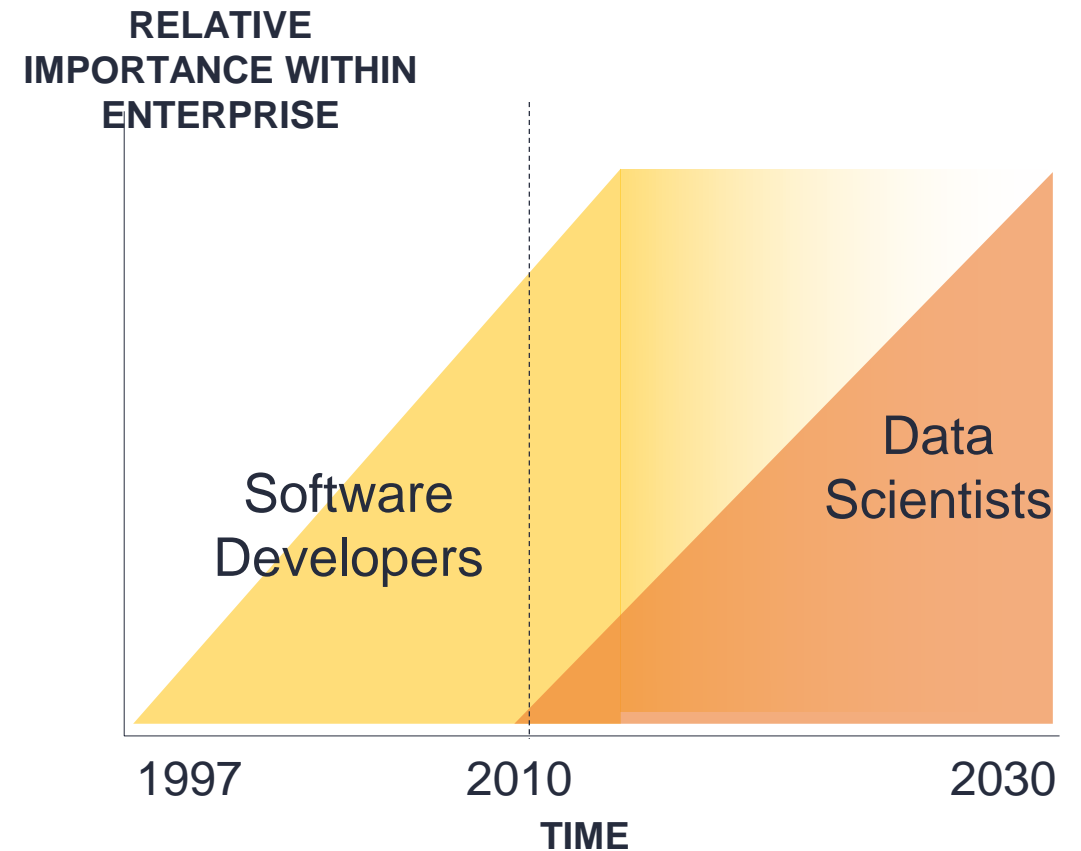
Companies Mentioning
'Artificial Intelligence'
On Earnings Calls



Lots of Risk of Disappointment



This Sounds Eerily Familiar



What is the Goal?

Measurable

Your “quality” indicator.

Reliable

Your “hit rate.”

Scalable

Your “throughput.”



DATA SCIENCE PITFALLS



It was the
wrong problem



Oops, already
solved by
someone else



Have the wrong
tools for this problem



Too slow for it
to matter

I SOLVED THE PROBLEM BUT...



Solved the
wrong way

Results used
Wrong way



World changes
while solving
problem

Problems multiply,
can't tackle all
at once



DIAGNOSES



Data Science is Different from Software Development



- Research versus development focus
- No answer is a valid answer
- Traditional testing is insufficient given non-deterministic nature
- No generally accepted process metrics (e.g. story points)
- Data must be tracked

Forget About Other Stakeholders in the Process



For Data Science Managers

- Accelerate project delivery through reuse, knowledge management
- Mitigate key-man risk / accelerate onboarding
- Hire & retain top talent



For Business Leaders

- Understand real-world impact
- Reliable, predictable insights
- Minimize change to existing workflows



For Data Scientists

Access powerful infrastructure & preferred tools



For IT Leaders

- Ensure stability & security
- Leverage existing infrastructure
- Minimize operational burden

Fixation on Tools at the Expense of People and Process



Moonshot vs. Laps Around the Track

- Perfection as enemy of shipped
- Muddle “pure research” and “applied templates”



Disconnected from the Business

- Little familiarity with practical business constraints
- Limited ability to drive *adoption*



Missing Some Key Personnel Muscles

- The full stack data scientist is a myth
- Gap in "soft" skills training



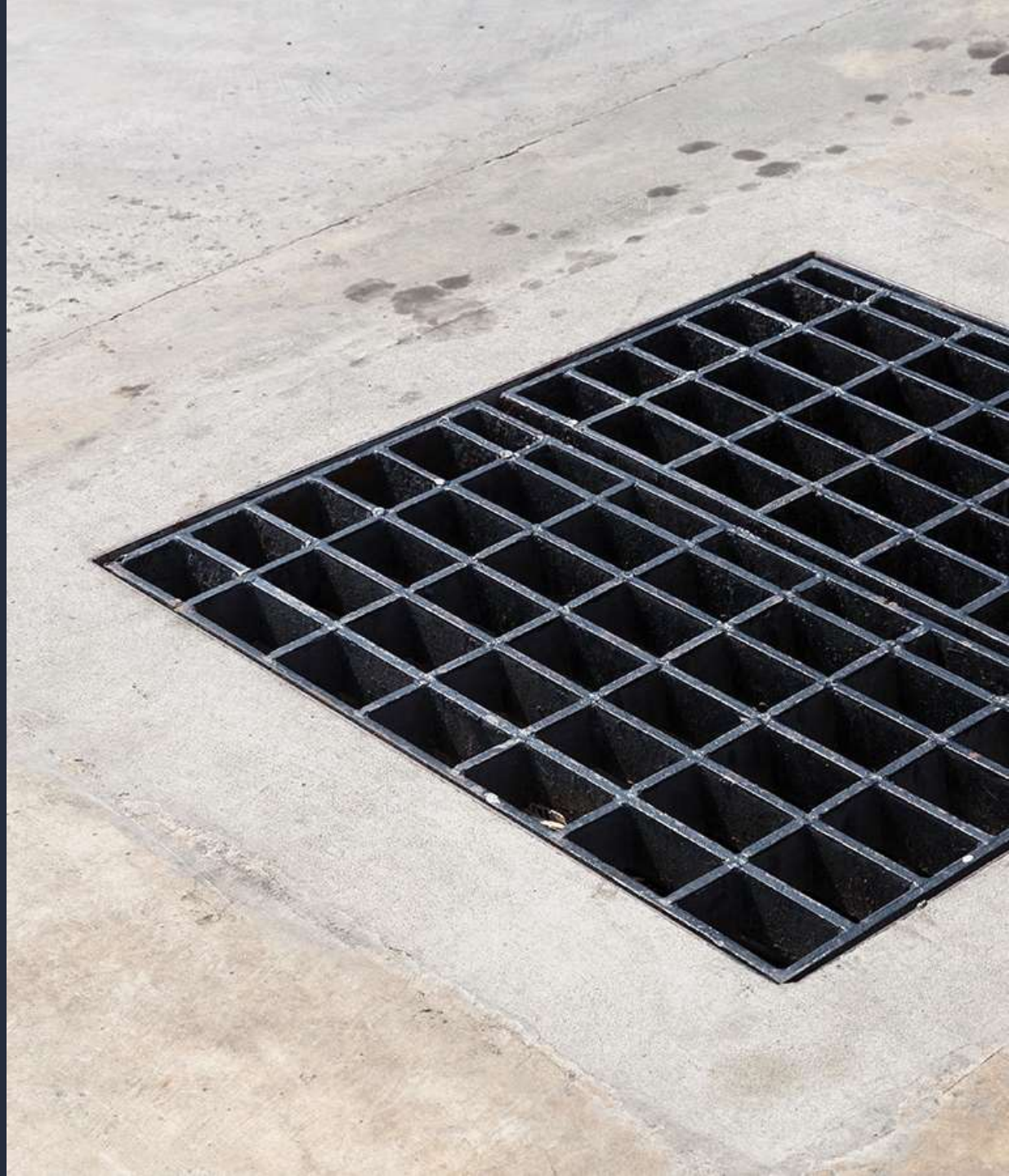
Artisan Thinking vs. Modular System Thinking

- Limited culture of re-use and compounding
- Not planning for future iterations (e.g., no reproducibility / documentation)



Bad Incentive Structures

- Key responsibilities fall between gaps
- Significant information loss in project transitions



RECOMMENDATIONS



Best Practices Take Many Forms

Process

Both a *single* project and *portfolio* of projects

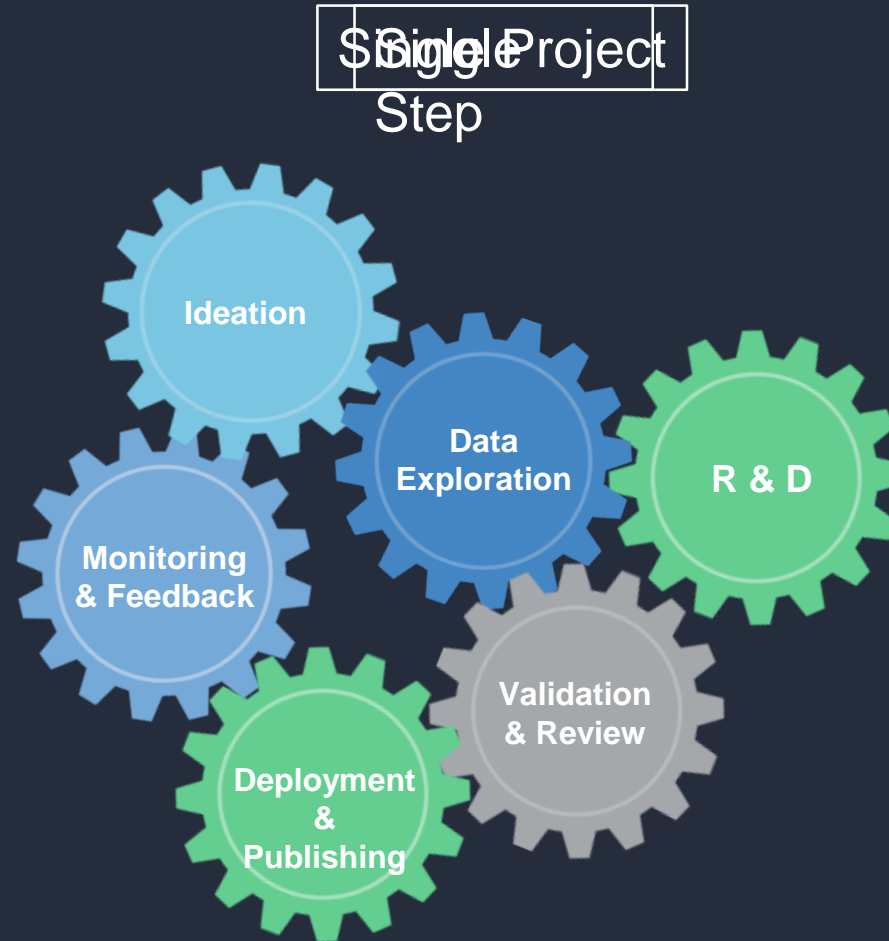
People

Types of capabilities and org design

Technology

Flexible infrastructure and tooling without the
wild west

Data science system at many levels

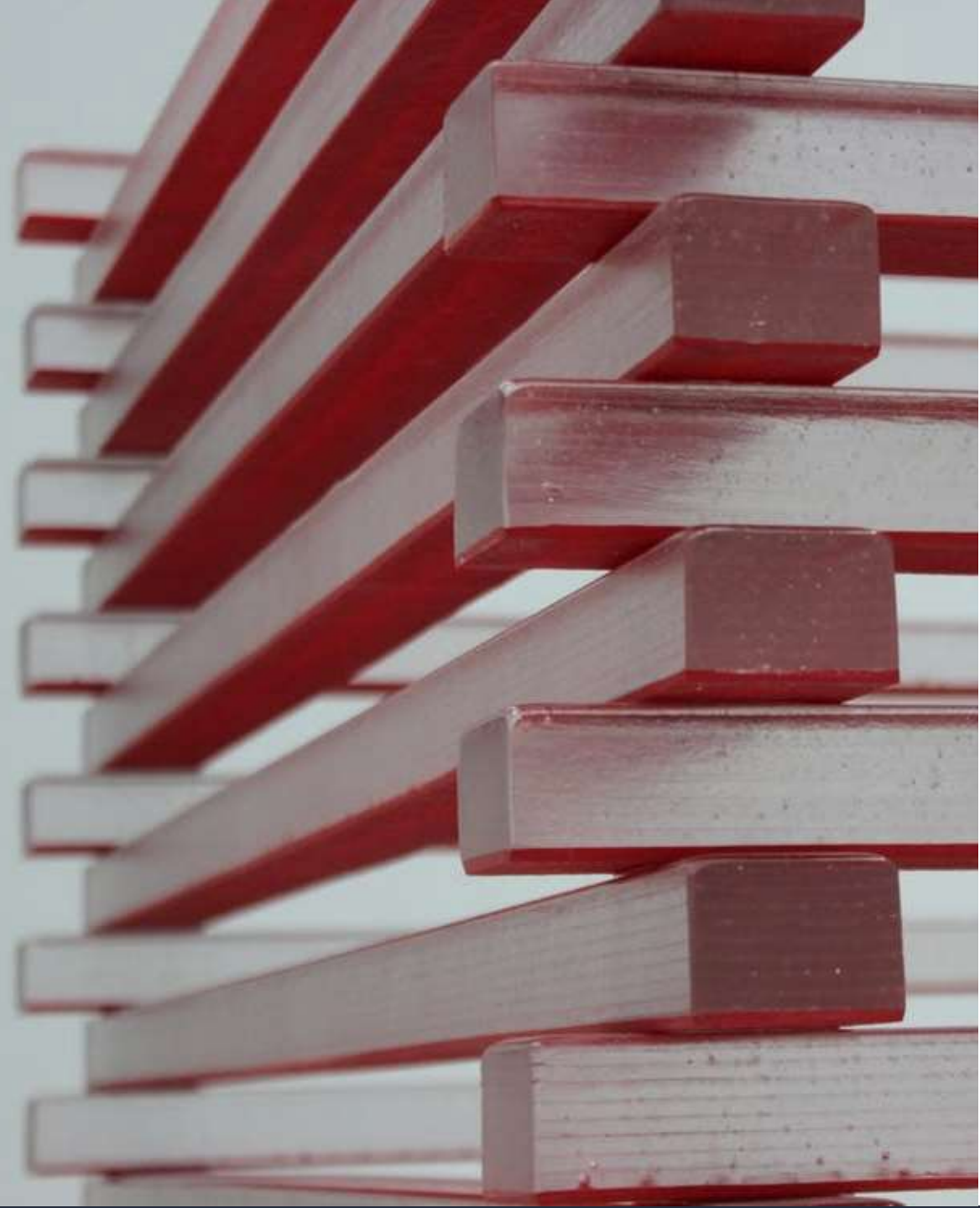




Portfolio of Projects

Managing the lifecycle

- Expect and embrace iteration
- Enable compounding collaboration
- Ensure auditability and reproducibility, even if you're not regulated (yet)



Ideation

- Problem first, not data first
- Practice and master order of magnitude ROI math
- Maintain repo of past work
- Create and enforce templates for MRDs
- Maintain a stakeholder-driven backlog



Artifact Selection

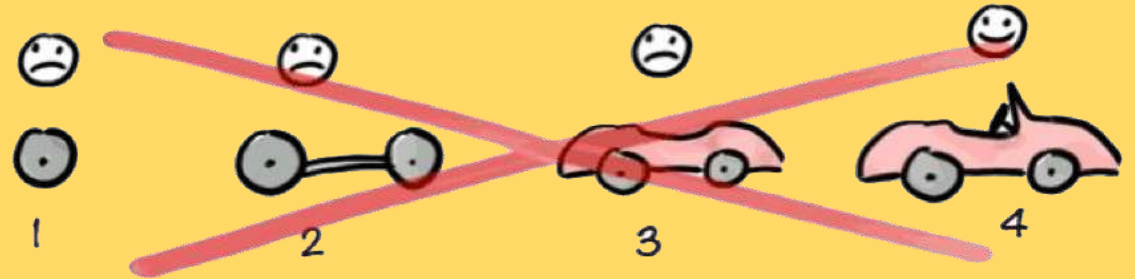
- Leverage rapid prototyping and design sprint methodology
- Create multiple mock-ups of different deliverable types
- Consider creating synthetic data with baseline models



Research & Development

- Establish standard software configurations, but give flexibility to experiment
- Abstract away compute provisioning
- Build simple models first
- Set a cadence for delivering insights
- Ensure business KPI tracked consistently over time

Not like this...



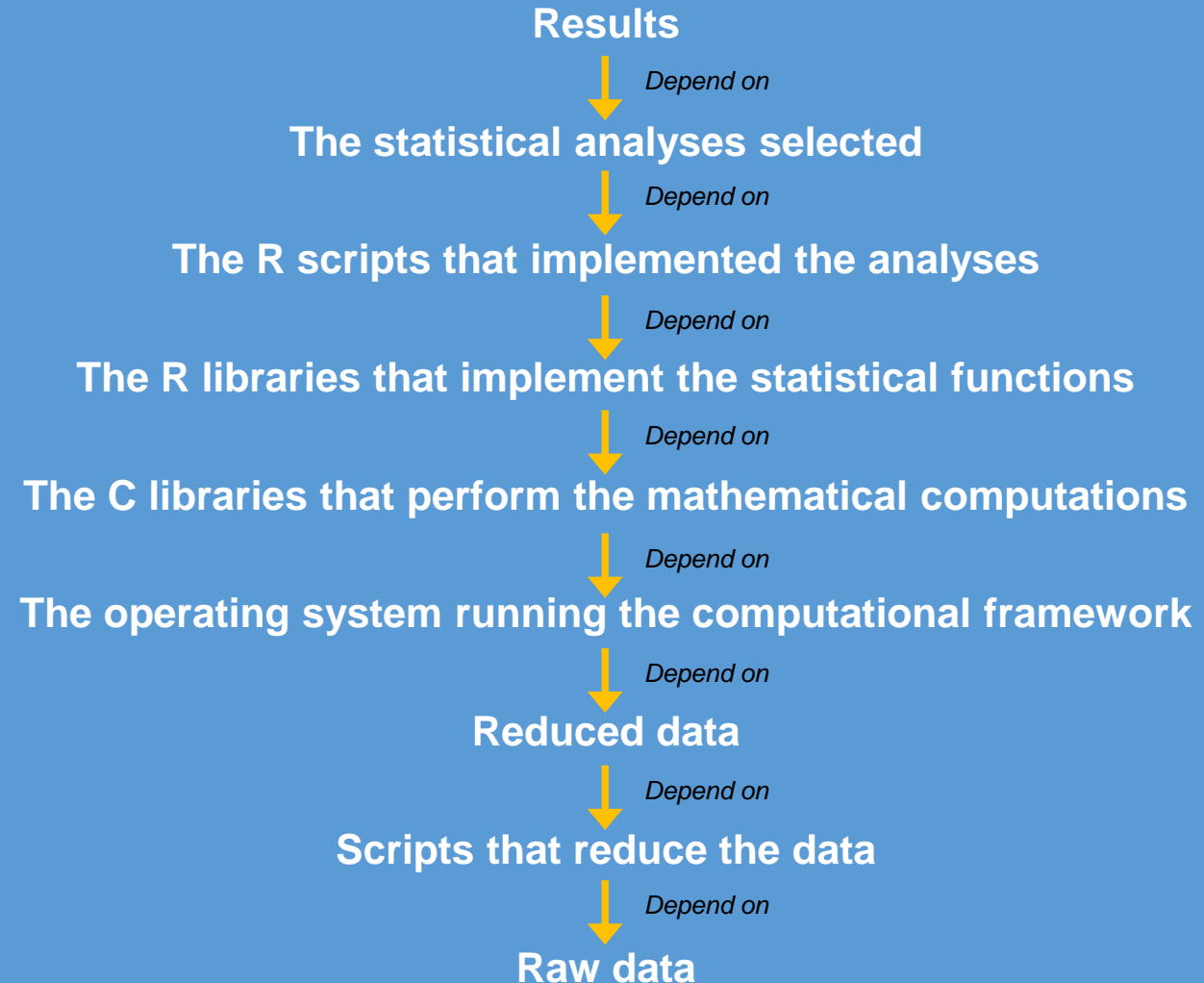
Like this!



Validation

- More than just code review, get stakeholder and IT sign-off
- Ensure reproducibility and clear lineage
- Use automated validation checks to support human inspection
- Preserve results (even nulls) to central repo

WHAT INFLUENCES A RESULT?



Delivery

- Support for many deliverable artifacts (reports, dashboards, apps, batch APIs, real-time APIs)
- Define a promote-to-production workflow
- Flag upstream and downstream dependencies



Monitoring

- Build ROI testing into all major deliverables
- Require monitoring plans before considering “done”
- Integrate with tools where people spend most of their time (e.g., email / Slack)
- Anticipate risk and change management burdens



Keeping all the balls in the air

- Measure everything, including yourself
- Focus on reducing time to iterate
- Socialize aggregate portfolio impact



The many hats of data science

	ROLE	PRIORITIES	PITTFALLS WITHOUT THEM
	Data Scientist	Generating and communicating insights, understanding the strengths and risks	Naïve or low power insights
	Data Infrastructure Engineer	Building scalable pipelines and infrastructure that make it possible to do the higher levels of needs.	Insight generation is slow, because DS is spending their time doing infrastructure work
	Data Product Manager	Articulating the business problem, translating to day-to-day work, ensuring ongoing engagement.	Projects miss the mark, don't translate into tangible business value
	Business Stakeholder	Vetting the prioritization and ROI, providing ongoing feedback	ROI decisions aren't made sensibly, not knowing when to pull the plug
	Data Storyteller	Creating engaging visual and narrative journeys for analytical solutions	Low engagement and adoption from end users

Organizational Design Dilemmas

- False centralization / decentralization dichotomy
- Most evolve as they scale and as business demands shift
- Technology can help bridge the gap

Pros

CENTRALIZATION

- Community and mentorship
- easier transparency for managers and IT
- More passive technical knowledge sharing

DECENTRALIZATION

- Deeper understanding of business processes and priorities
- Easier change management

Cons

- Isolation on data science island
- Loss of credibility with business
- Frustrated data scientists

- Less technical knowledge compounding
- Harder to codify best practices
- Risk of shadow IT

What We Covered Today

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QUESTIONS?

Check out dominodatalab.com or find us
in the [AWS Marketplace](#)

WELCOME TO THE DATA SCIENCE INNOVATION SUMMIT

9:15	Coffee & Light Breakfast
9:30	Welcome, Carlos Escapa, AWS
9:40	Joe Spisak, AWS
10:15	Mac Steele, Domino Data Lab
11:15	Break
11:30	Sean Beard, Pariveda
12:30	Lunch
1:15	Panel Discussion/Q&A
2:00	Connect with others



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