WHY GOOD MODELS FAIL

HOW AMBIGUITY, UNCERTAINTY, AND BAD SCIENCE
CAUSE MOST DATA SCIENCE PROJECTS TO FAIL

87%

OF ALL DATA SCIENCE PROJECTS FAIL
-VENTUREBEAT

REASON ONE: **AMBIGUITY**

WHEN REQUIREMENTS ARE HARD TO DEFINE

AMBIGUITY OCCURS WHEN WE DON'T KNOW WHAT QUESTIONS TO ASK

HOW TO NAVIGATE **AMBIGUITY** IN DATA SCIENCE?

1. FILL KNOWLEDGE GAPS

BECOME A SUBJECT MATTER EXPERT

2. ITERATE QUICKLY

RESEARCH, PRESENT, GET FEEDBACK

3. DEFER TO THE EXPERTS

LET THEM DRIVE THE RESEARCH

4. EXPLORE WITHOUT BUILDING

UNDERSTAND THE PROBLEM FULLY, THEN START DESIGNING

REASON TWO: **UNCERTAINTY**

WHEN SUCCESS IS HARD TO DEFINE

HOW TO NAVIGATE **UNCERTAINTY** IN DATA SCIENCE?

1. UNDERSTAND THE PROCESS

THE FULL LIFECYCLE OF A RECORD

2. UNDERSTAND THE KPIS

THE SOURCE, TARGET, CALCULATION, STAKEHOLDERS

3. UNDERSTAND THE DOLLARS

SAVINGS/REVENUE CALCULATIONS MUST BE DONE METHODICALLY

THE **PROCESS** IMPACTS THE **KPIS** WHICH IMPACT THE **DOLLARS**

REASON THREE: **BAD SCIENCE**

WHEN VALUE IS MIS-MEASURED

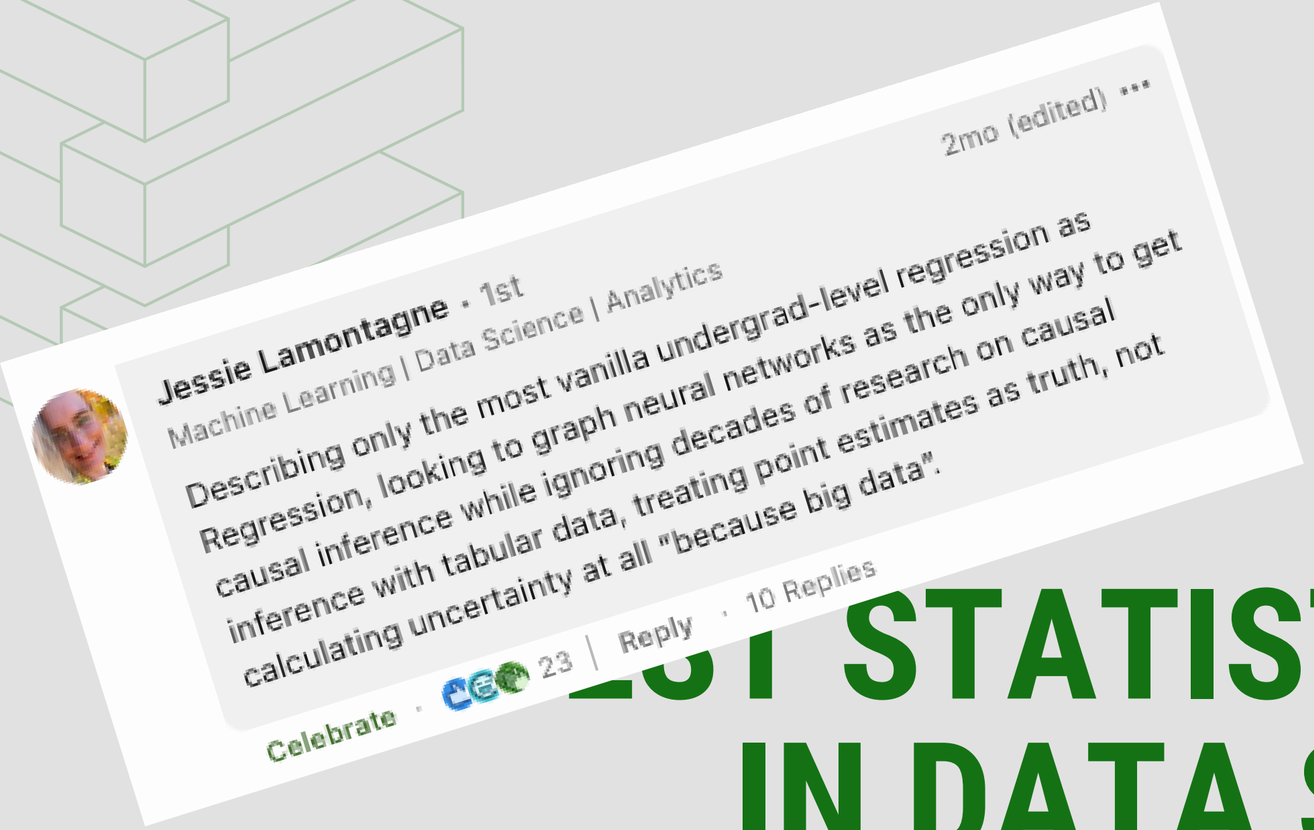
1. INCORRECT METRICS

INAPPROPRIATE METRICS ARE THE HALLMARK OF BAD SCIENCE

2. BAD STATISTICS

THE MOST UNDER-APPRECIATED ASPECT OF DATA SCIENCE

BIGGEST STATISTICS MISTAKES IN DATA SCIENCE



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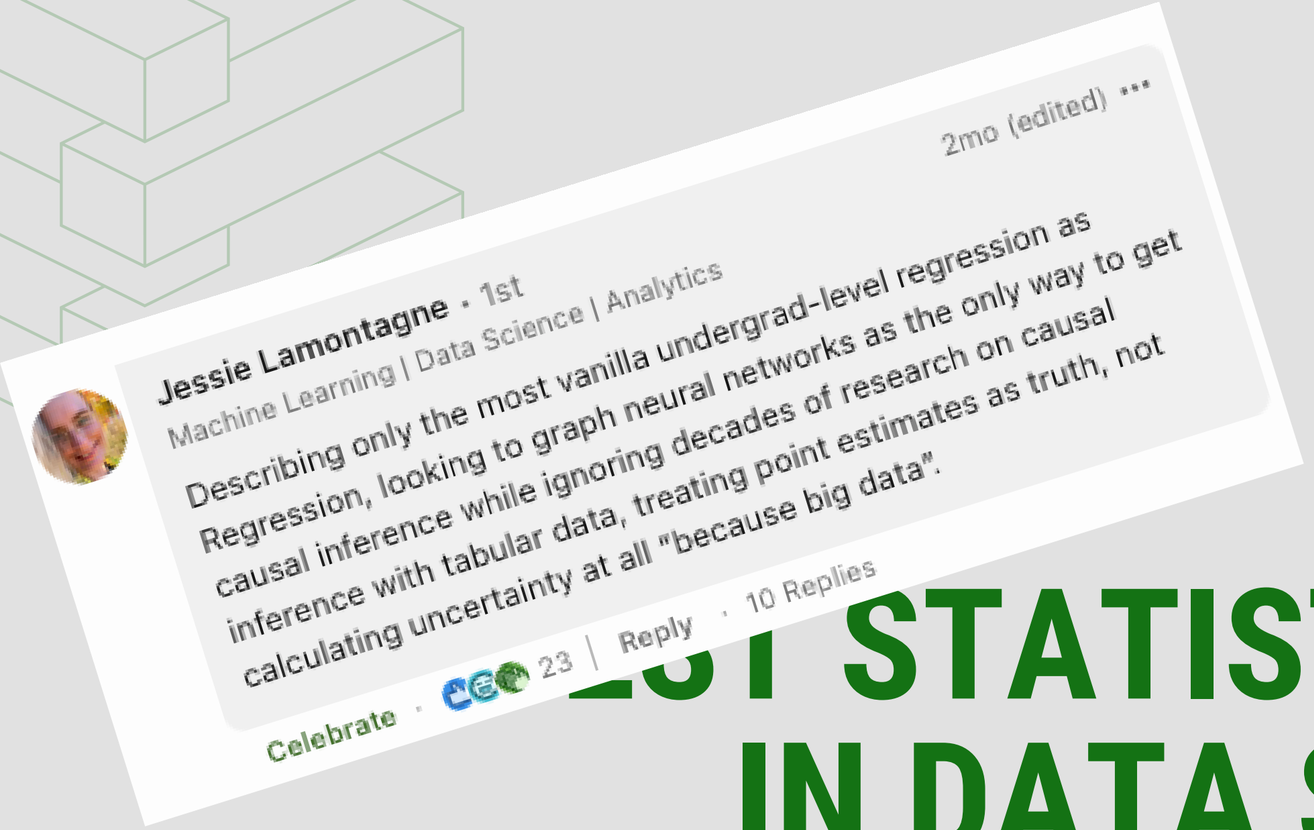

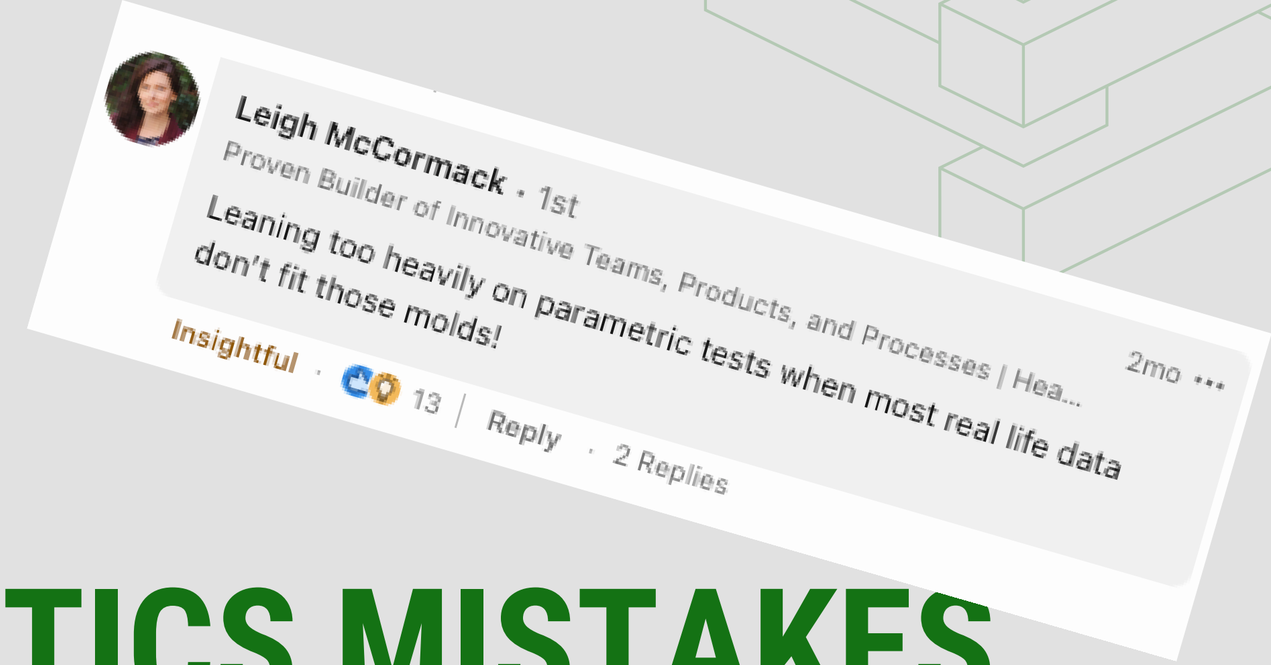

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2mo (edited)

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Statistical tests and models assume a priori that you have a theory of how the system your are studying works. They simply estimate the quantitative bounds of your theory. Not generally whether it is right or wrong. This is even true of classical hypothesis testing.

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Jessie Lamontagne · 1st
Machine Learning | Data Science | Analytics
Describing only the most vanilla

Thomas Speidel · 2nd
Statistician and Data Scientist
1. The independent/predictor variables have to be normally distributed

Aaron Sheldon · Following
VP of Engineering at Genstate
In general across all scienti
strong limitatio

Justyn Hornor (He/Him) · 2nd
Fractional CTO/CPO. Polymath. Inventor. Technolo
Not recognizing Type 1 vs Type 2 errors as needs.
Like · 3 | Reply
right or wrong. This is even true of cl
Celebrate · 34 | Reply · 4 Replie

Kristen Kehrer (She/Her) · 1st
Data Scientist | Developer Advocate
Not so much fellow stat
"correlation is not caus
stakeholders after shar
Like · 9 | Reply

Timothy Dobbins · You
Building data products @ Gridsearch | Principal DS @ Trilliant Health
2mo · Edited

Statistics is the biggest skills gap in data science right now. I thought it was software engineering but having seen how data science is done in many organizations and hearing from statisticians yesterday about the common mistakes data scientists make, I'm convinced that the coding gaps are nothing compared to the stats gaps.

My stats friends really showed up yesterday.

Mary van Valkenburg and 414 others
63 comments · 31 reposts

Like · 13 | Reply · 2 Replies

Joe Wyer (He/Him) · 1st
Head of Economics and Applied Science @ Haus | We're Hiring!
1mo
Thinking statistical significance should be the filter for go/no go of business decisions.
Like · 4 | Reply · 2 Replies

Leigh McCorm
Proven
Insig

Jeff Bean · 2nd
Senior Consultant at Deloitte
2mo
Failing to recognize the difference between "significant" (i.e., P<0.05, not likely due to chance, etc.) and "meaningful" (i.e., Cohen's delta, worthwhile, cost-effective, etc.). You need both.
2 | Reply

Peter Mancini (He/Him) · 1st
Principal at Stealth Startup
1. Not knowing what distribution their data is and using tools that depend upon a specific distribution, usually the normal distribution.
2mo

uffington, PhD · 1st
ta Scientist
derstanding decision analysis and value of information example, building an extremely complicated model when alysis is sufficient to guide the business to the correct
2mo
nderstand that underpowered experiments are even if the result is statistically significant.
Insightful · 6 | Reply · 2 Replies

Rodrigo Rivera · 1st
Data Products for Business Users Builder | Enabling Anyone t...
around the p-value
3 Replies

REQUIREMENTS ARE HARD TO DEFINE BECAUSE OF **AMBIGUITY**

SUCCESS IS HARD TO DEFINE BECAUSE OF **UNCERTAINTY**

VALUE IS MIS-MEASURED BECAUSE OF **BAD SCIENCE**

AMBIGUITY OCCURS WHEN WE DON’T KNOW WHAT QUESTIONS TO ASK

UNCERTAINTY OCCURS WHEN WE DON’T KNOW HOW TO VALIDATE THE ANSWERS

BAD SCIENCE OCCURS WHEN WE INCORRECTLY VALIDATE THE ANSWERS.

THANK YOU!

LET'S CONNECT