



**Garbage Data =
Garbage AI:**
An Open Source Data
Quality & Observability
For Teams With No Time

Agenda

Perspective: Life is an unproductive mess in data and analytics teams

Fix: principles of DataOps: agile, lean, devops

Problem: AI is awesome and it will make the mess so much worse

Part 1: AI – new use case: data + LLMs to give insight

Part 2: AI – more people creating insight: vibe data engineering

Conclusion

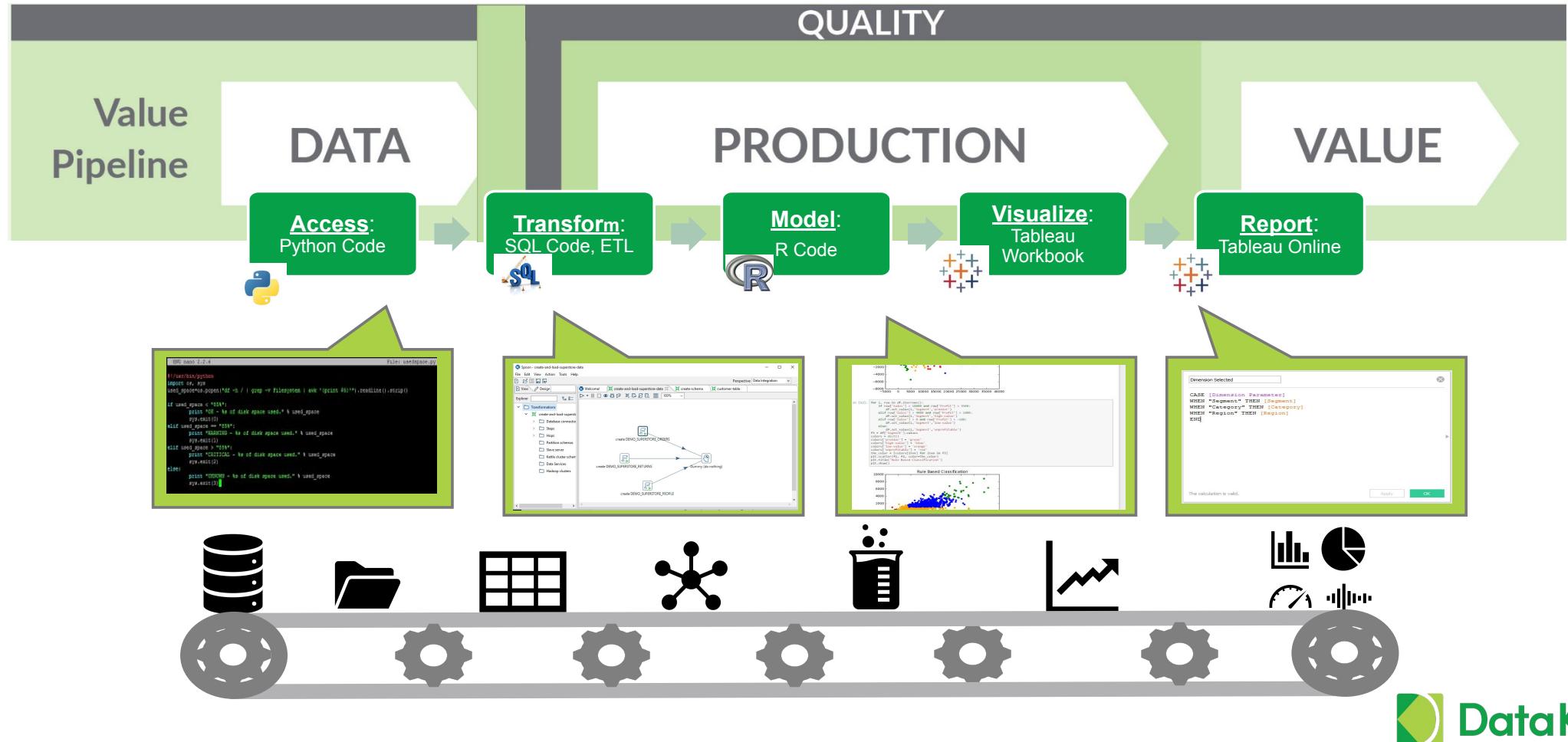
My Background & Focus

- 15 years software & AI: NASA, MIT, startups, Microsoft, then 20 years in data
- I learned three things
 - You get crappy data and shit breaks.
 - Your customers don't know what they want until they see it.
 - You always have too much to do.
- **Data and Analytics have a crisis of productivity**

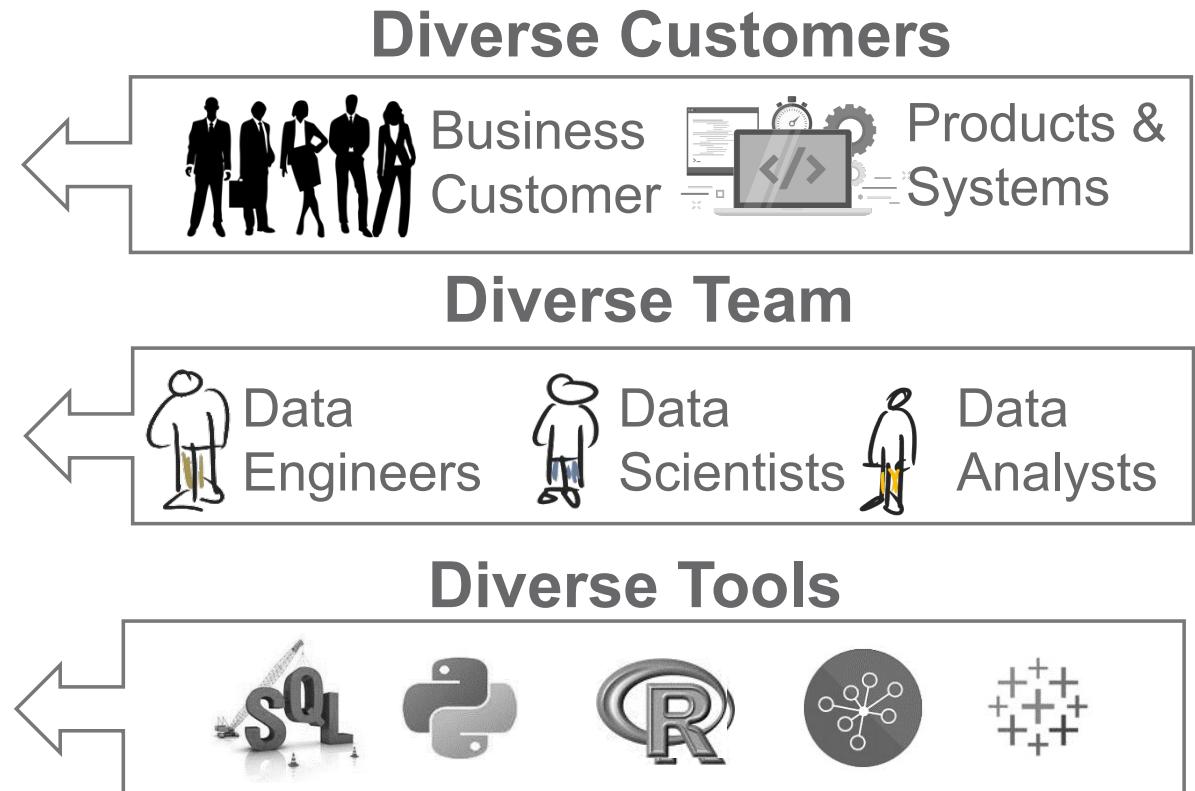
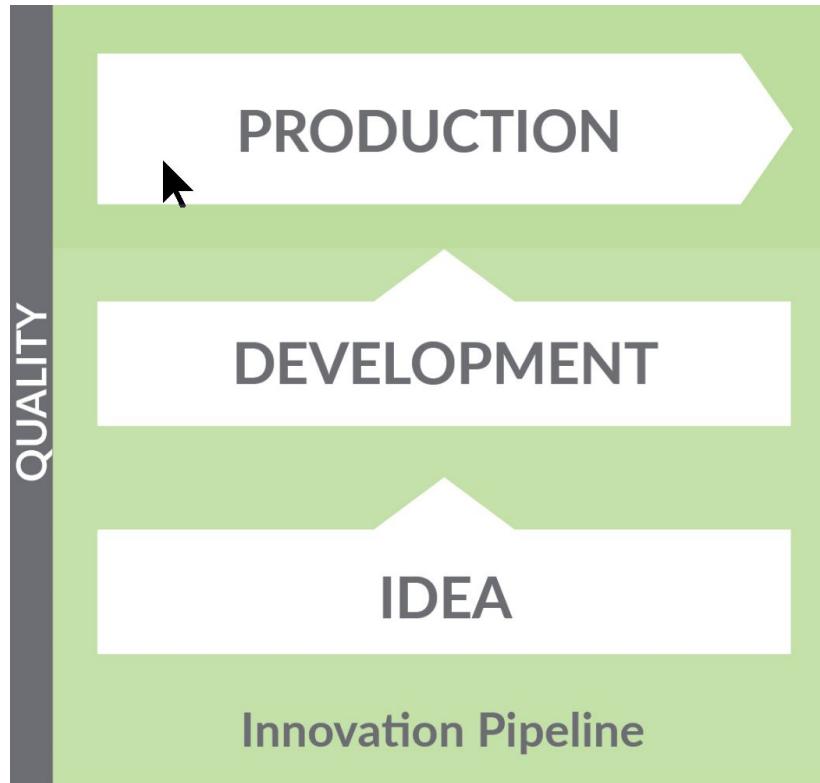
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- **Data and Analytics have a crisis of productivity**
- **For the last dozen years we (DataKitchen) are trying to fix this problem: 'DataOps'**
 - We have run a profitable, independent business
 - Data engineering with our software based on DataOps practices
 - Books, trainings, conferences, management consulting, writing, podcasts.
 - Top down software sales to CDOs (ugh)
 - Last few years open source open source data quality & observability to drive DataOps adoption

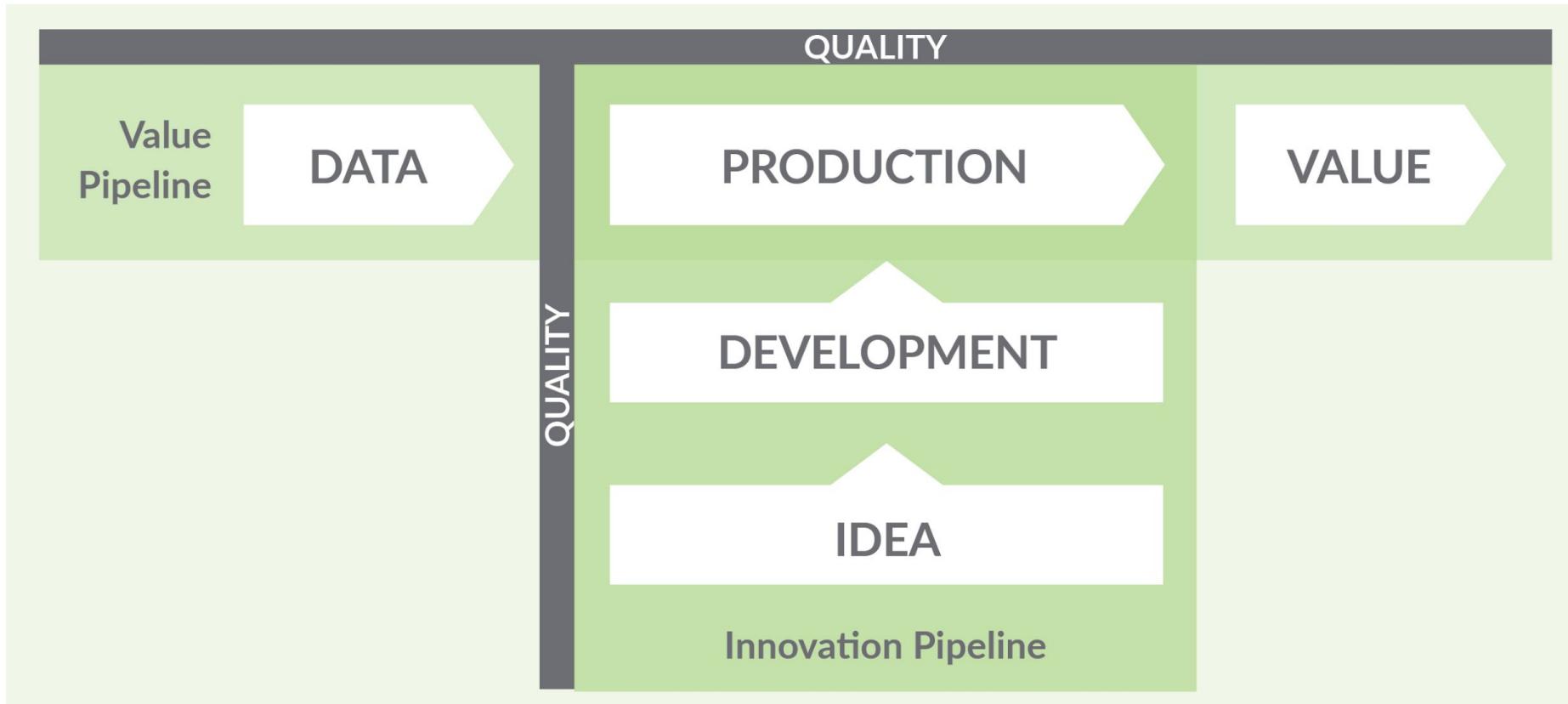
Analytic process are like manufacturing: materials (data) and production outputs (refined data, charts, graphs, model)



Analytic processes are like software development:
code continually move from development to
production

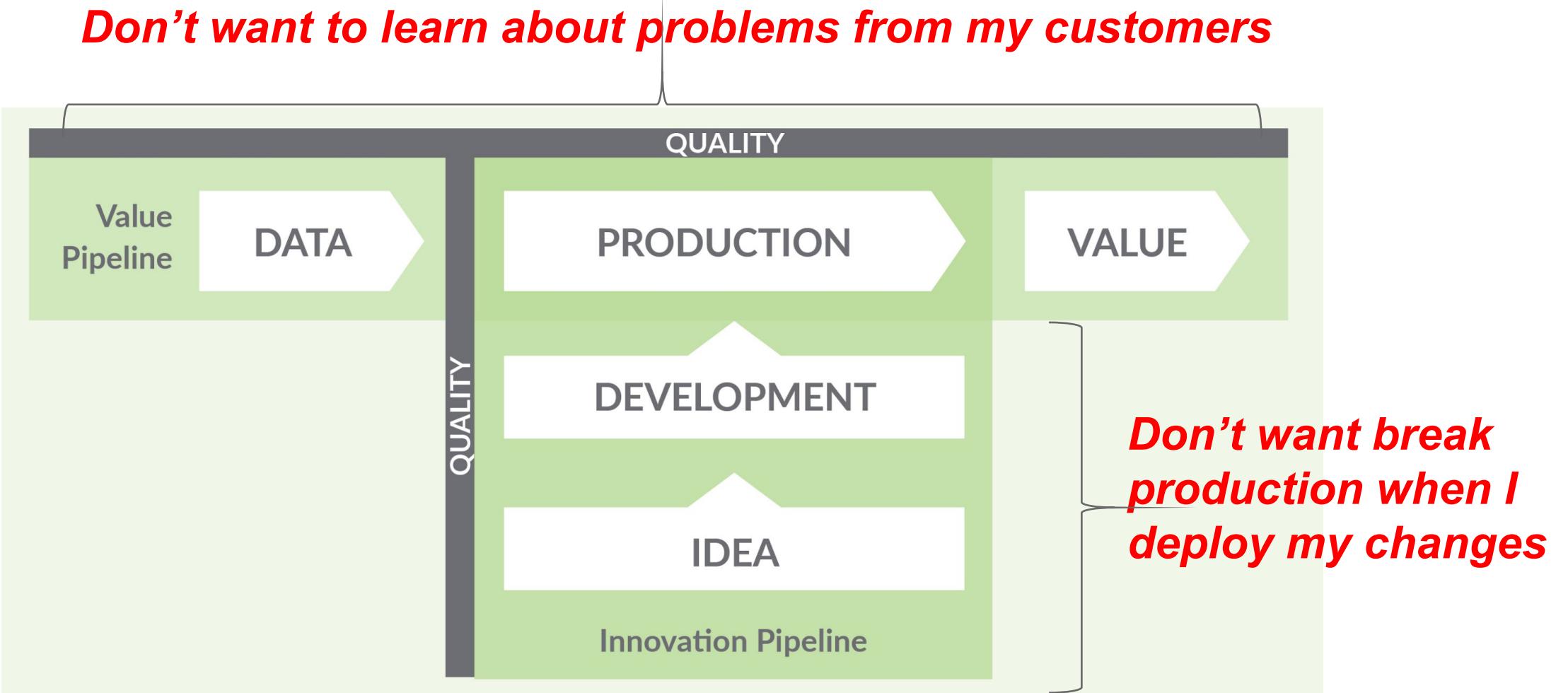


Two Key DataOps Pipelines: Value & Innovation



What DataOps Helps You Avoid

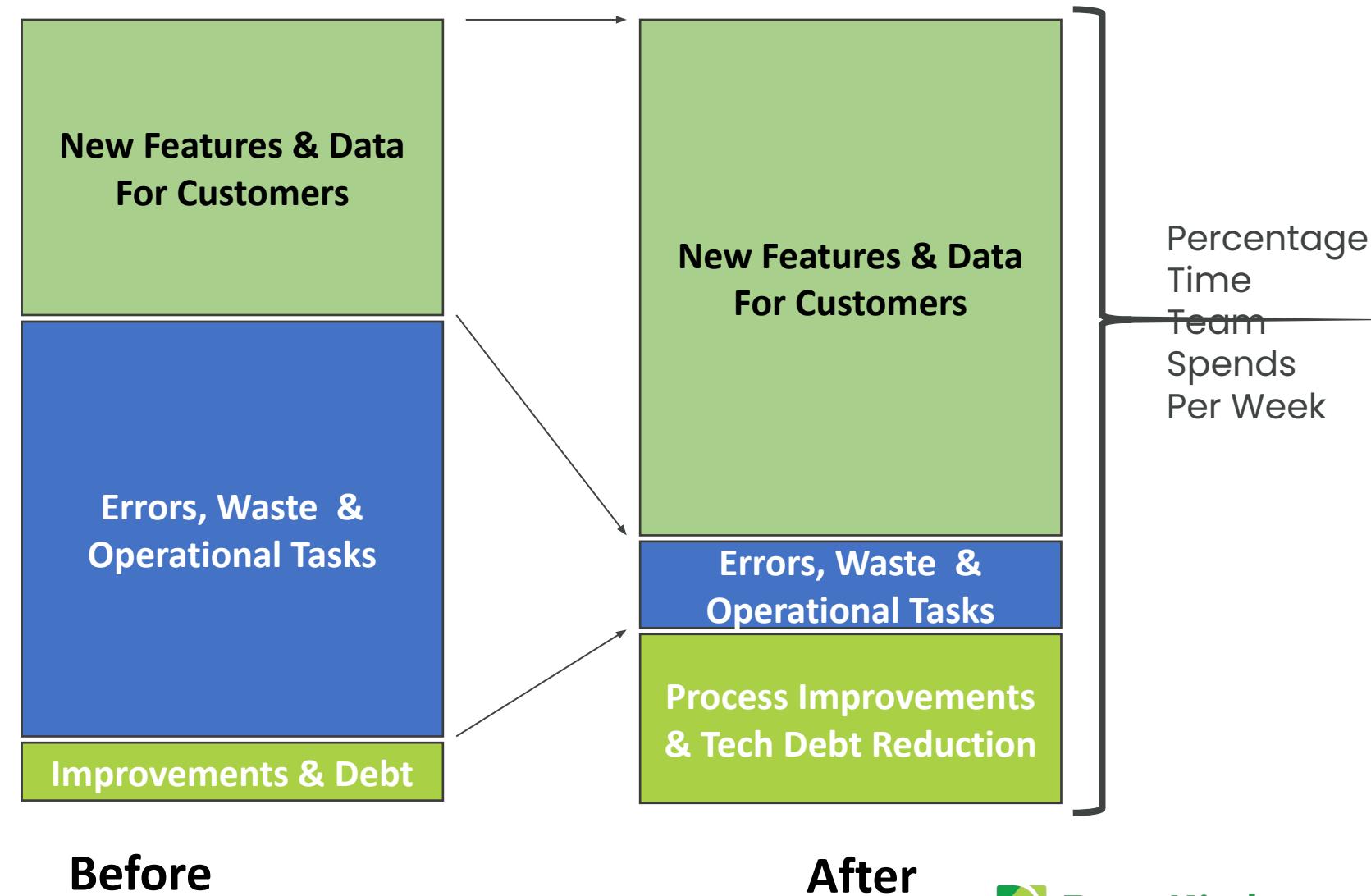
Don't want to learn about problems from my customers



DataOps Benefit: Improves Productivity

Only **22%** of time is spent on innovation;
78% on errors and manual execution.

– Gartner (2020)



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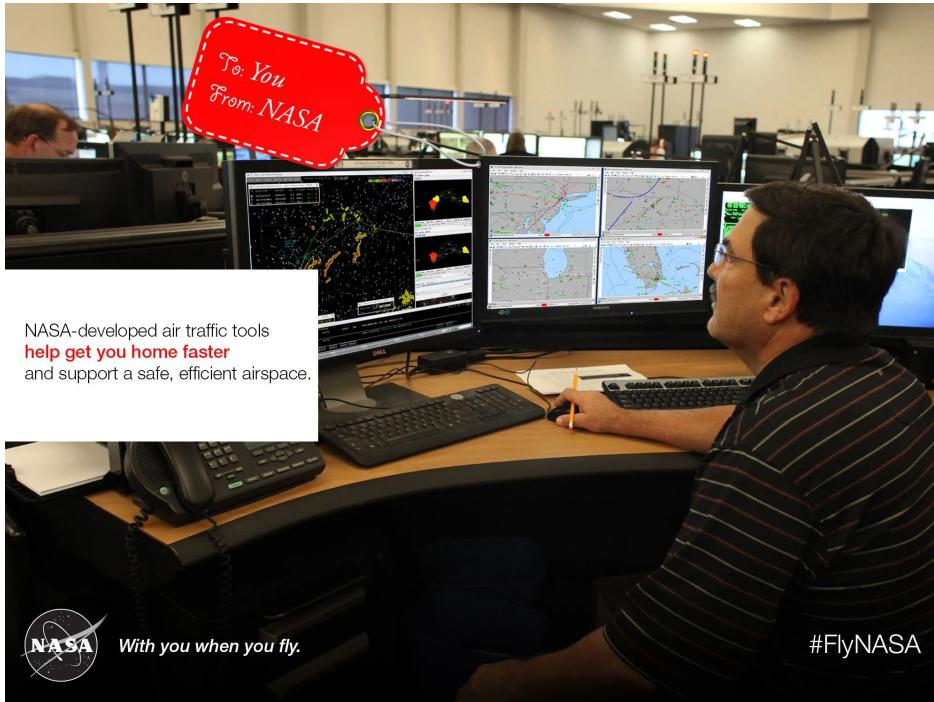
AI Is Invading The Data Team



AI (really Large Language Models or LLMs) reality:

- Your analytic engineers are vibing, coding tables late into the night.
- Your standard reports—people are using Claude to analyze data directly
- Your LLMs are confidently serving up garbage, sometimes.
- Your predictive models—once your pride and joy—are degrading faster than you can debug them.
- More stakeholders are screaming for AI magic.

LLMs (Or Any Model) Will Never Get 100% Perfect Results.



Embrace The Imperfection

- LLMs are somewhere from 10% - 50% **inaccurate.**
- Improving accuracy is getting asymptotically harder.
- LLMs will **ALWAYS** deliver imperfect results

Yet LLMs have a huge potential to **assist** users and make them more productive

AI Is Expanding The World Of Data Analytics

LLMs as an Analytics Interface:

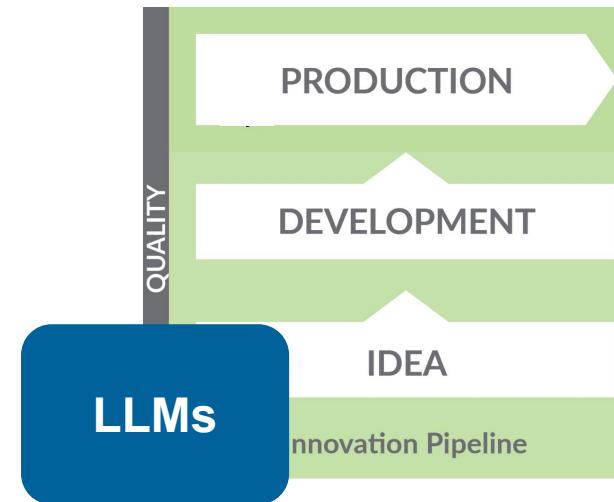
More data being used to make predictions, in new use cases, by utilizing LLMs



AI Is Expanding The World Of Data Analytics

LLM are expanding the pool of users

More code is being created and put into production by many more people



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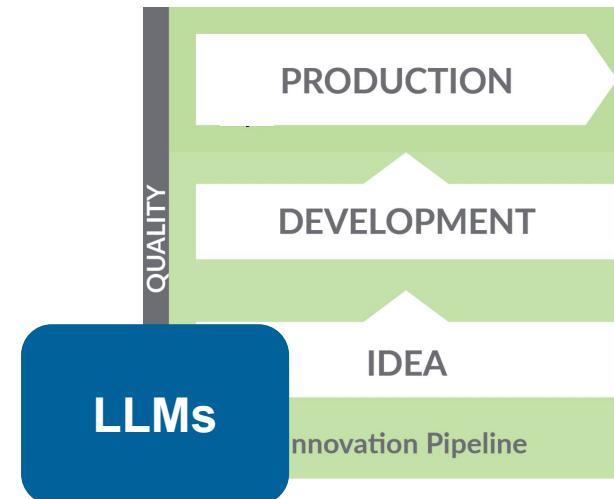
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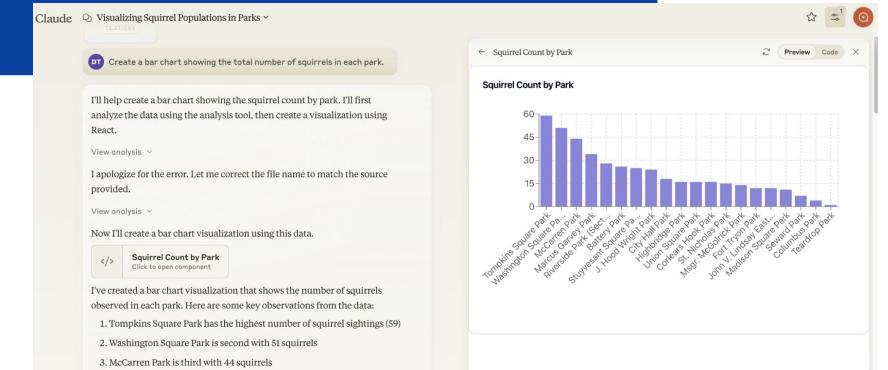
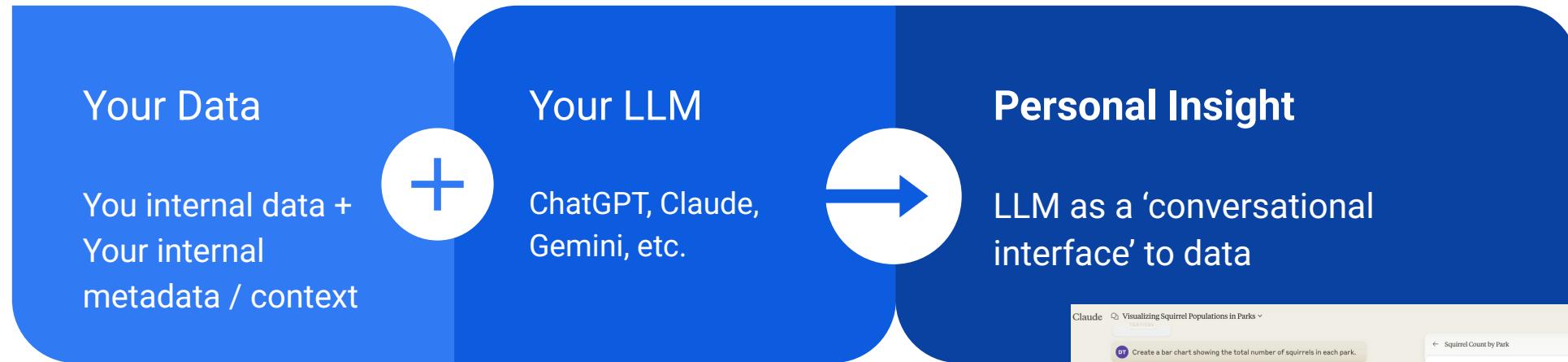


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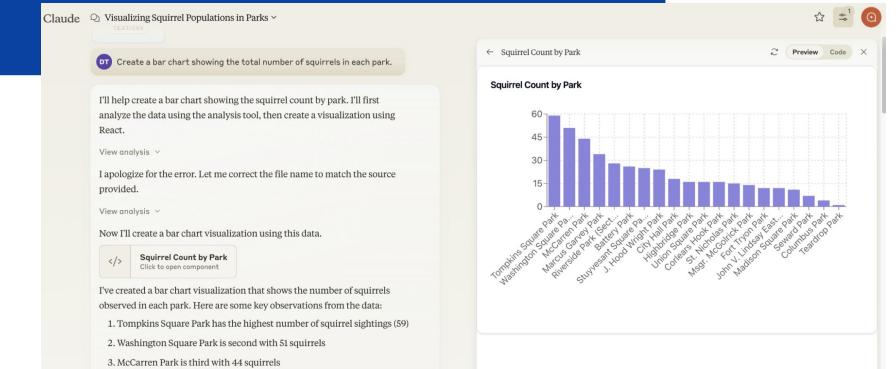
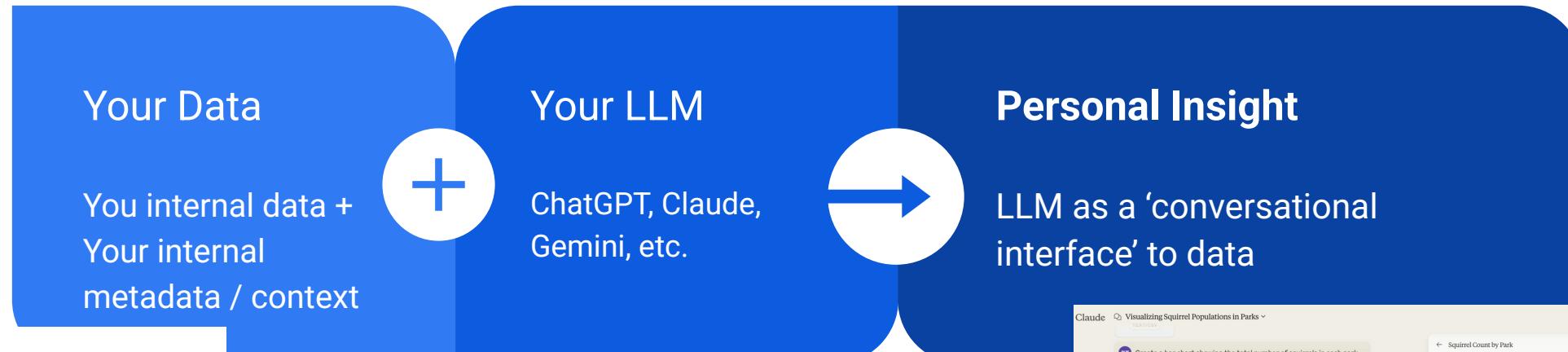
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New Use Case: LLM as an Analytics Interface



LLMs Drive More Data Usage, Faster



Bad Data Compounds LLMs Error

Your Data

Your Model (e.g. LLM)

Your Insight

For Example

**Data Is 80%
Correct**

For Example

**Model 80%
Accurate**

Expected Value

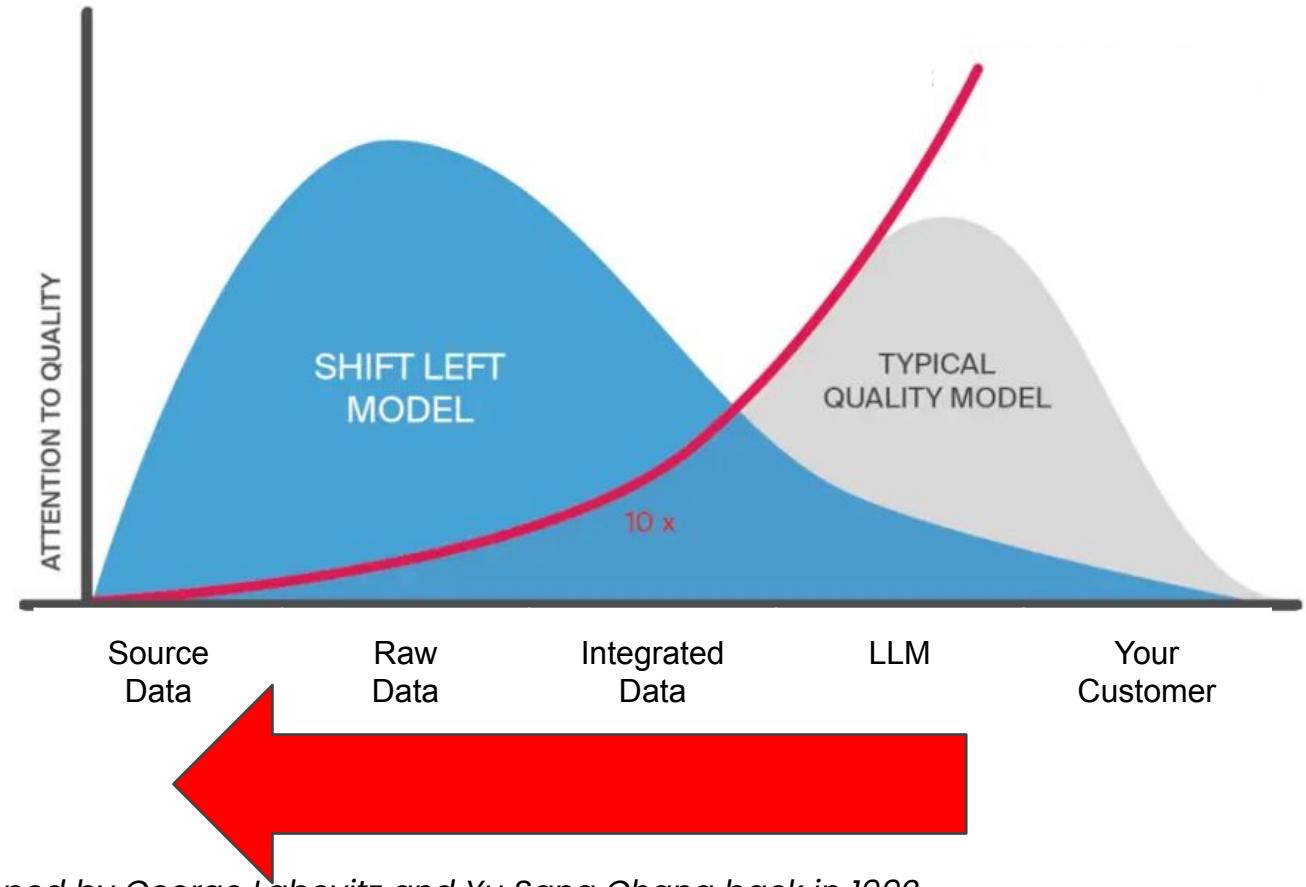
64% Accuracy

Shift Left Data Quality Saves Big Time

It is 10x cheaper to find a problem in data at the source or raw layer.

Apply the 1:10:100 rule*:

- Cost of preventing poor data quality at source is \$1 per record
- Cost of remediation after it is created is \$10 per record
- Cost of failure (i.e. doing nothing) is \$100 per record



**developed by George Labovitz and Yu Sang Chang back in 1992*

AI / LLMs Needs Test Coverage

**AI are using more data ... therefore you need to check data, automatically
... mean you need to improve automated test coverage**

In All Levels/Zones In Your Database/Data Lake

- Every Table Should Have Tests
- Every Column In Every Table Should Have Tests
- Every Significant Business/Domain Specific Metric Should Have Tests

Every Tool That Uses Data Should Be Checked For Errors and Timing

Types of Tests in Test Coverage

What Types Of Automated Tests?

- Every Table Should Have Tests
 - **Consistency Tests: Volume, Freshness, Schema**
- Every Column In Every Table Should Have Tests
 - **Consistency Tests: Volume, Freshness, Schema, Drift**
- Every Significant Business Metric Should Have Tests
 - **Domain Specific: Custom, Domain Specific Testing**

Every Tool That Uses Data Should Be Checked For Errors and Timing

- **Check Logs For Errors**
- **Check Metrics**
- **Check Task Status and Substatus Results**
- **Check Timing and Duration**

How to Measure Test Coverage

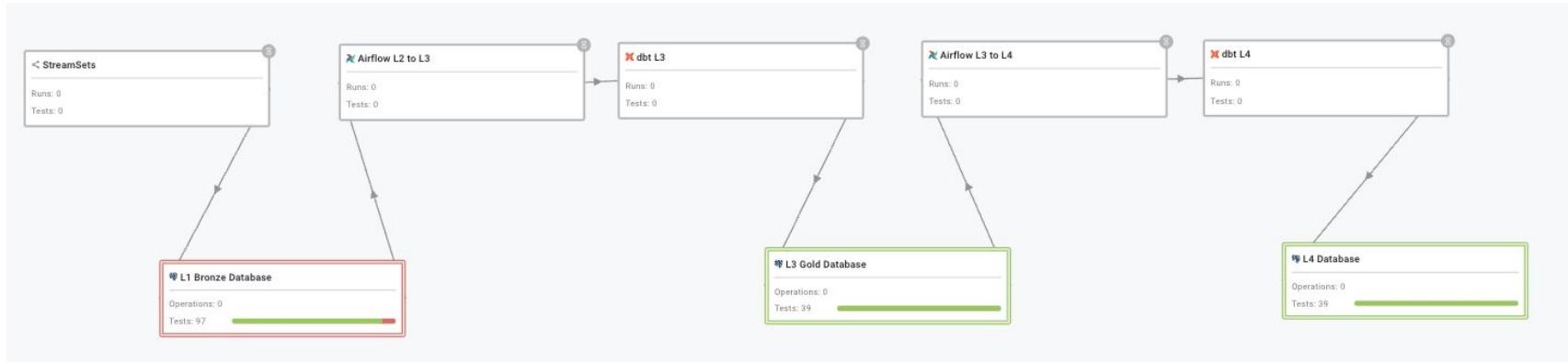
In All Levels/Zones In Your Database/Data Lake

- Every Table Should Have Tests
 - **Minimum 2 Test Per Table**
- Every Column In Every Table Should Have Tests
 - **Minimum 2 Tests Per Column**
- Every Significant Business Metric Should Have Tests
 - **Minimum 1 Custom Test Per Metric**

Every Tool That Uses Data Should Be Checked For Errors and Timing

- **Minimum 1 Check Per Tool:** Logs For Errors
- **Optional:** Check Metrics
- **Minimum 1 Check Per Tool Per Job:** Task Status and Substatus Results
- **Minimum 1 Check Per Tool Per Job:** Timing and Duration

Example: Test Coverage Counts Medallion



This Medallion Architecture Has **Three Database Levels** (L1, L2, L3), **Three Tools** (Streamsets, Airflow, dbt), And **Five Jobs/Workflows** to Monitor

- *L1 – 100 tables + 10 Columns*: Minimum 200 Table Tests and 2000 Column Tests
- *L2 – 100 tables + 10 Columns*: Minimum 200 Table Tests and 2000 Column Tests
- *L3 – 10 tables + 30 Columns*: Minimum 20 Table Tests and 600 Column Tests, Plus a handful of Domain Specific Business Metric Tests
- *3 Tools*: 3 Checks For Errors
- *6 Jobs*: 12 Checks For Problems

Writing Data Test Manually Does Not Scale

An example

- With TestGen, a junior operator can generate 2,500 tests with **two steps** (profile, generate tests)
- It would take a trained Data Engineer **7.2 months** to achieve the same results – with no time for meetings, breaks, or vacations

Number of Tests	2,500	
Number of Tables	20	
Number of Columns	1,000	
Minutes per Test	30	
Hours	1,250	
Days	156	8 hours/day
Weeks	31	5 days/week
Months	7.2	4.35 weeks/month
TestGen	2 steps	

*How long does it take to write one data quality test?
Do you engineers know what tests to write?*

Need AI to fight AI



DataKitchen Data Quality TestGen Software:

80% of the data tests you need automatically

- **One-Click Data Quality** – Instantly generate and run automated tests.
- **Data Profiling** – 51 column-level insights.
- **In-Database Execution** – Fast, secure testing in your own database.
- **120+ AI-Generated & Custom Tests** – Comprehensive data validation coverage.
- **Anomaly Detection** – Automatic alerts for freshness, volume, schema, and drift.
- **Data Catalog** – Unified view of metadata, hygiene issues, PII, and test results.
- **Quality Scoring Dashboards** – Custom scorecards with drill-downs to drive improvement.

AI Is Expanding The World Of Data Analytics

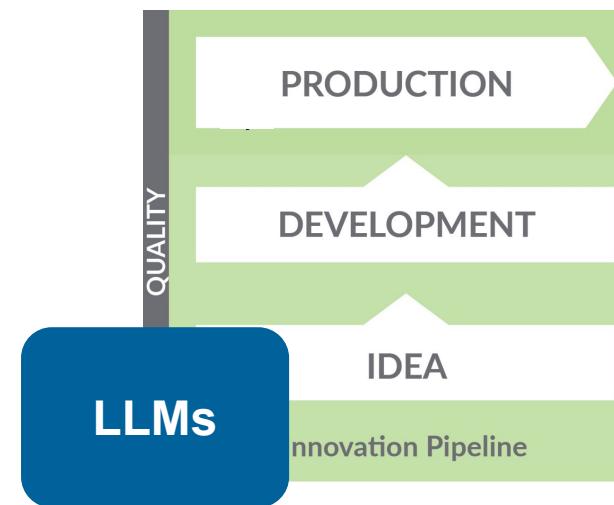
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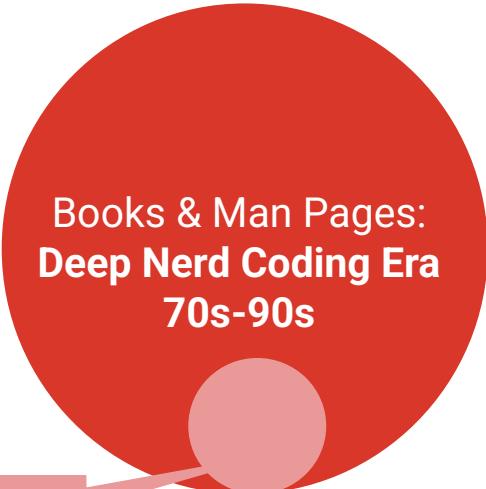


LLM are expanding the pool of users

More code is being created and put into production by many more people



Coding: A New Era of Data Teams

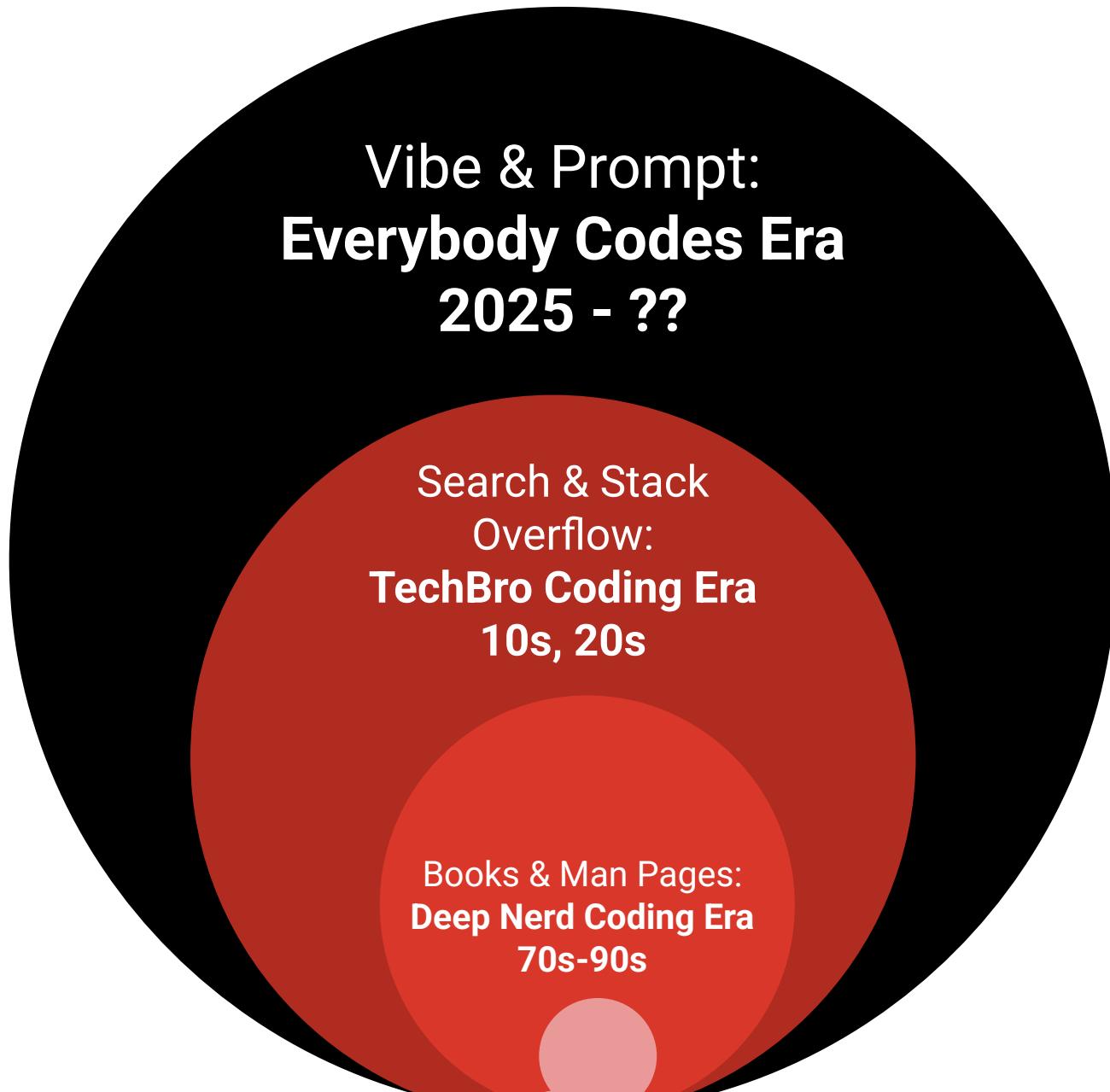


Books & Man Pages:
Deep Nerd Coding Era
70s-90s

Originally: 'Women's Work'

Coding: A New Era of Data Teams





Coding: A New Era of Data Teams

LLMs increase the production of Analytics

More people will be building

- new tables
- new reports
- new models
- new use cases
- and lots of SQL

It's a vibe coding extravaganza!

AI Is Expanding the World Of Data

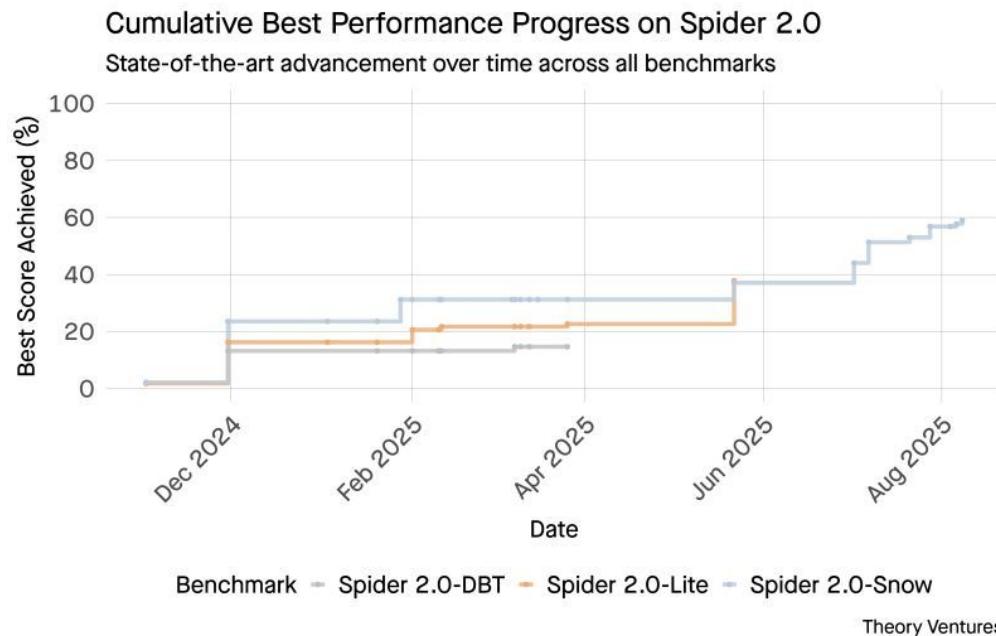
More code being created in data analytics systems, by more types of people, due to LLMs. For example:

- Using Claude Desktop to help write SQL
- Using the 'AI Assistant' in your favorite ETL or orchestration tool help write YAML configuration
- Using Claude Code to write some Python model code.

You boss, your customer are all doing these kinds of actions today

There are more and more people coding ... and more coming!

LLMs Struggle With Writing SQL



- GPT-5 excels at math but struggles with databases
- Spider 2.0 benchmarks expose the gap
- Performance remains poor across all variants:
 - Spider 2.0-Snow peaks at 59.05% accuracy, Spider 2.0-DBT tops out at 39.71%
 - 56 submissions from 12 model families since November 2024.
- Business context is the real challenge
- Human judgment remains irreplaceable

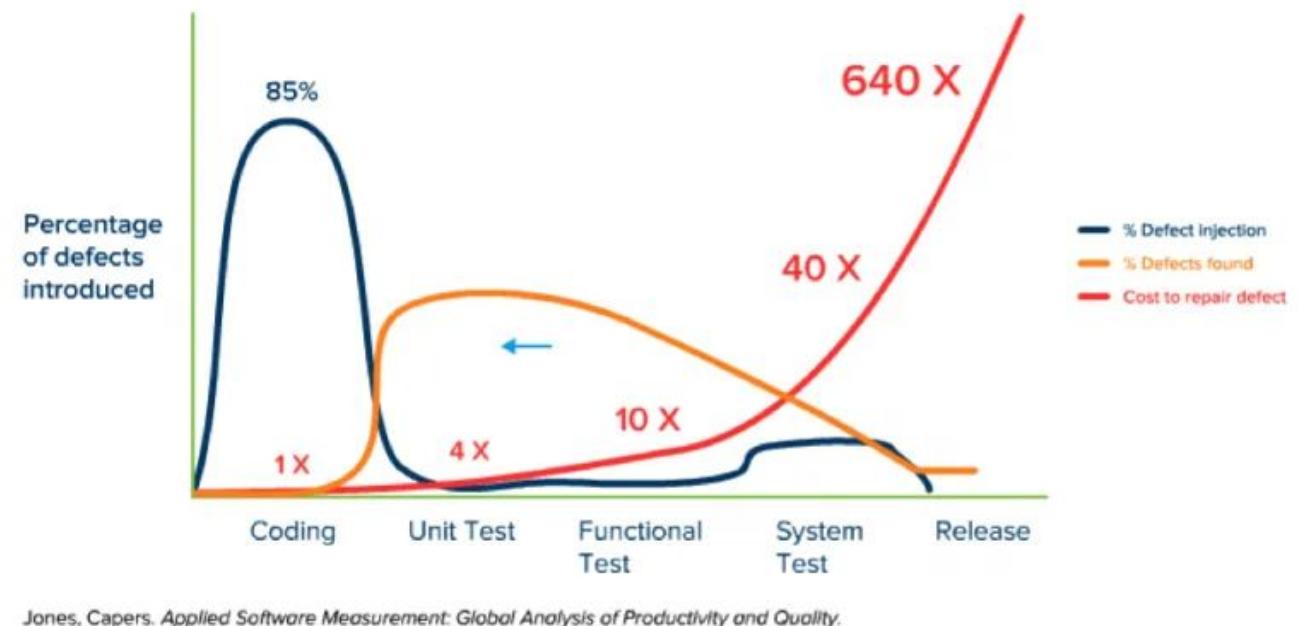
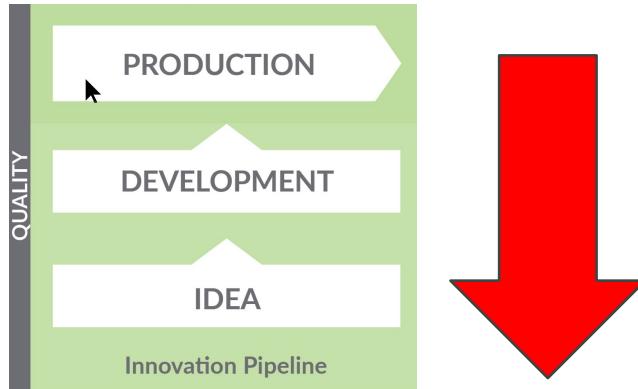
Context Helps LLM Improve Accuracy

- AI generates code that looks right but fails
- For example, it produces syntactically correct SQL but doesn't understand your actual data, creating solutions that break in practice.
- Why?
 - Real data is messy
 - Data engineering needs context, not just code
 - "Data Context" formalizes hidden knowledge
 - Context enables AI to reason better
 - Data Profiling, Data Catalog, Data Quality Test Results, Etc.

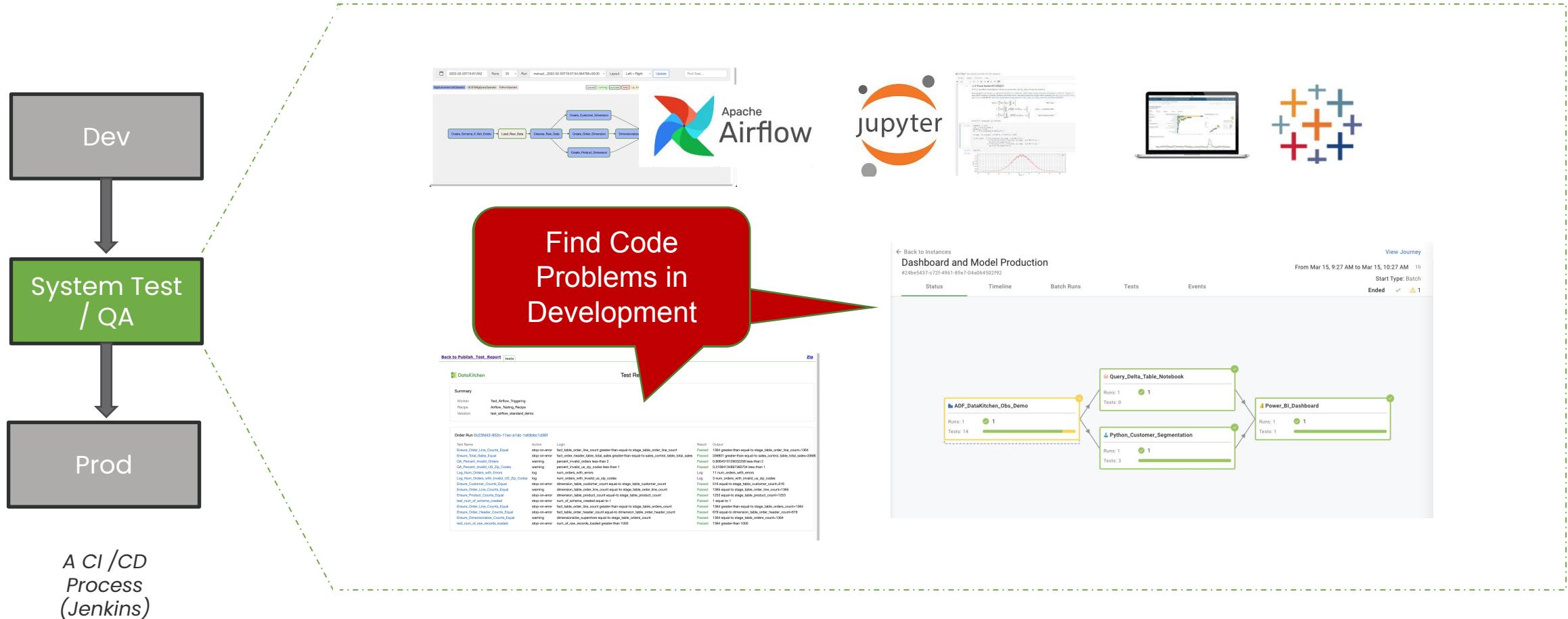
Context Is Not A Miracle Cure: Expect More Code, Worse Quality

Shift Down Test Coverage Saves Costs

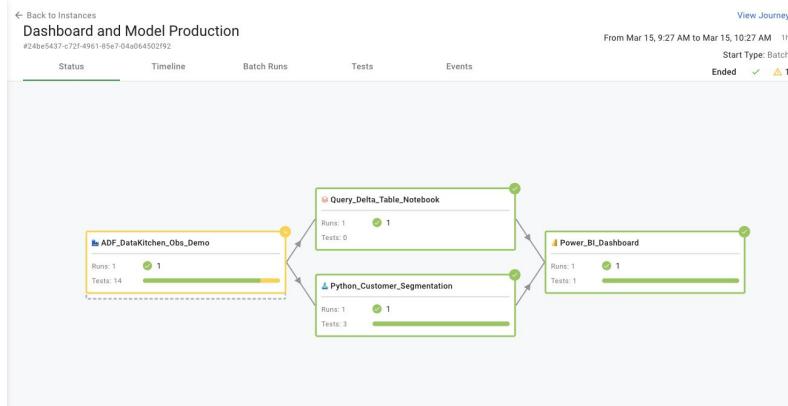
The earlier your tests find a problem in development, the lower the cost and hassle



Regression Needs Full Coverage of Tools & Data



DataOps Observability: Data Observability Tool



DataOps Observability:

- Open Source, Full Featured, Data Observability Tool. All Features, One User
- Enterprise Version Starts At \$100 Per User Per Month
- Extensive Connectors

It Does Five Tasks:

1. Single Pane Of Glass Across Your Entire Data Production State
2. Process Lineage Graph – Data Journey
3. Collects Logs, Metrics, Runs Status, Schedules, And Test Result
4. Production Dashboard And Alerts
5. Enables Full Regression Testing And Production Monitors and Andons



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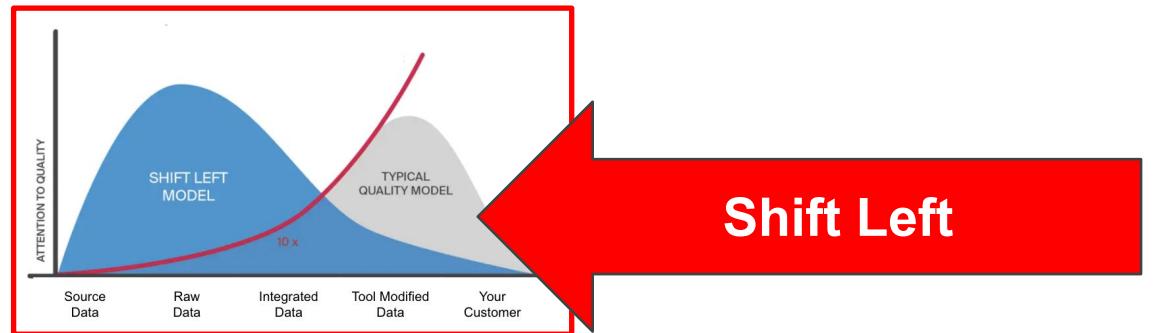
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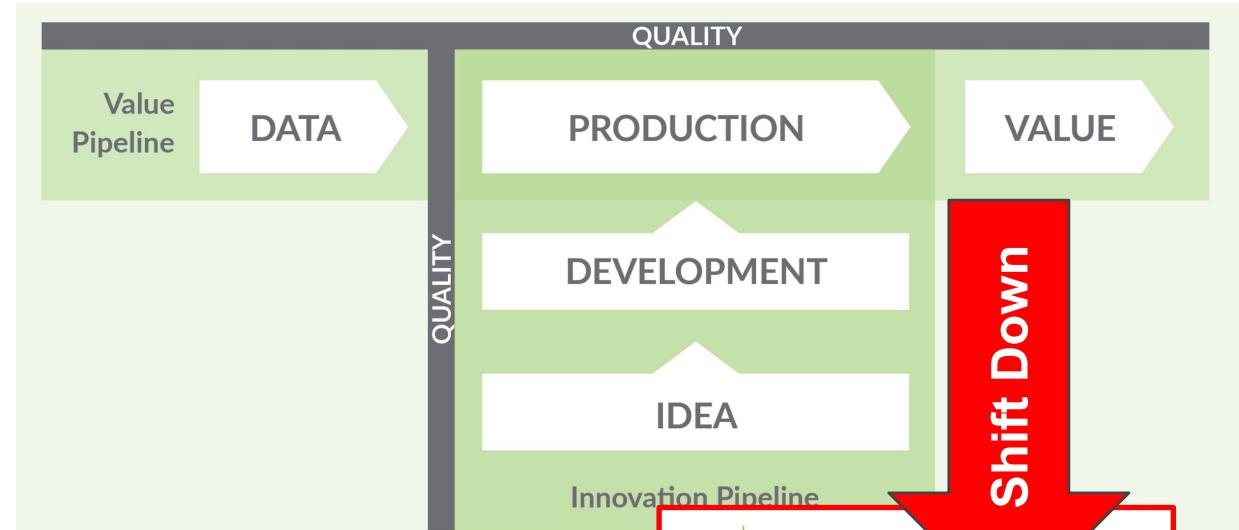
Conclusion

Data Quality and Observability for Small Data Teams

- Low Code
- AI to fight AI
- Full Featured Open Source
- White Glove User Experience
- Enterprise: Fixed-Fee Pricing. Unlimited Usage.



Shift Left



Shift Down



dataKitchen

Learn More About DataOps & Data Observability



Install Open Source TestGen

<https://info.datakitchen.io/testgen>

Install Open Source DataOps Observability

<https://docs.datakitchen.io/articles/#!open-source-data-observability/install-data-observability-products-open-source>

Sign The DataOps Manifesto

<http://dataopsmanifesto.org>

Free DataOps Cookbook

<https://datakitchen.io/the-dataops-cookbook/>

Free DataOps Certification

<https://info.datakitchen.io/training-certification-dataops-fundamentals>

Free Data Quality & Observability Certification

<https://info.datakitchen.io/data-observability-and-data-quality-testing-certification>