PyConf HYDERABAD 2019

scribble Data

# Managing Production Data Prep Pipelines

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Scribble Data

Anecdotally only **2%** of models* are **productionized**!

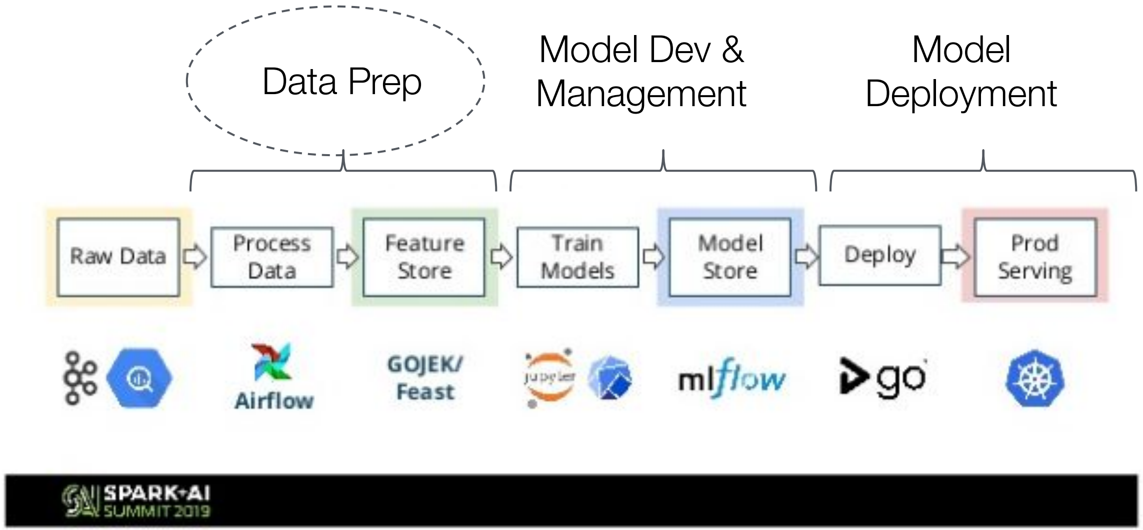
* Most of these are in Python

# Outline

- ML Infrastructure Overview
  - Why data prep is important
- Pipeline Structure and Challenges
- Where Does Time & Effort Go
- Required Capabilities

# ML Infrastructure Overview

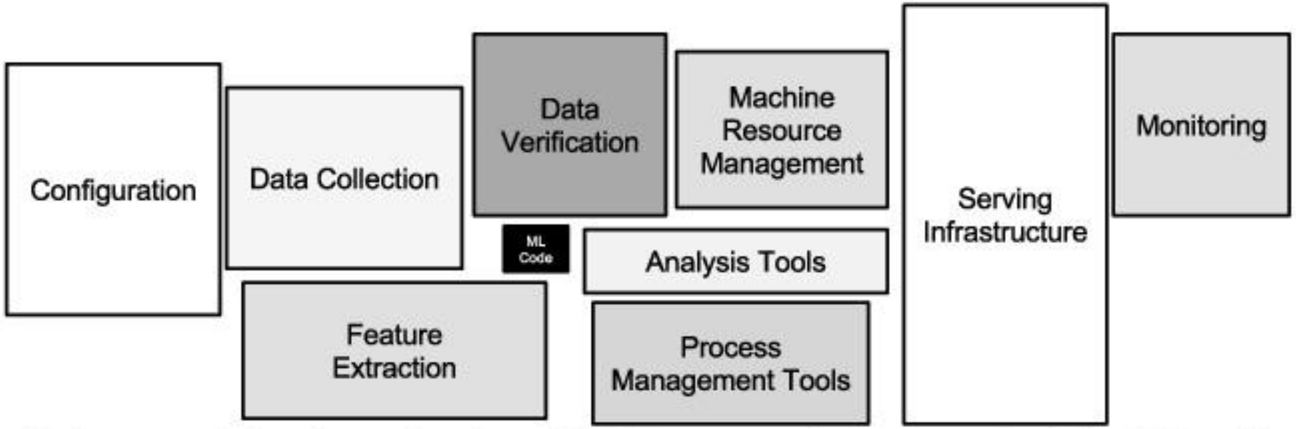
# Production ML - Emerging Generic Architecture




GoJEK @ Spark AI Summit, April 2019

https://databricks.com/session/scaling-ride-hailing-with-machine-learning-on-mlflow

# Data Prep - Significance




*"Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex."*

Paper from Google - NeurIPS 2015

https://papers.nips.cc/paper/5656-hidden-technical-debt-in-machine-learning-systems.pdf

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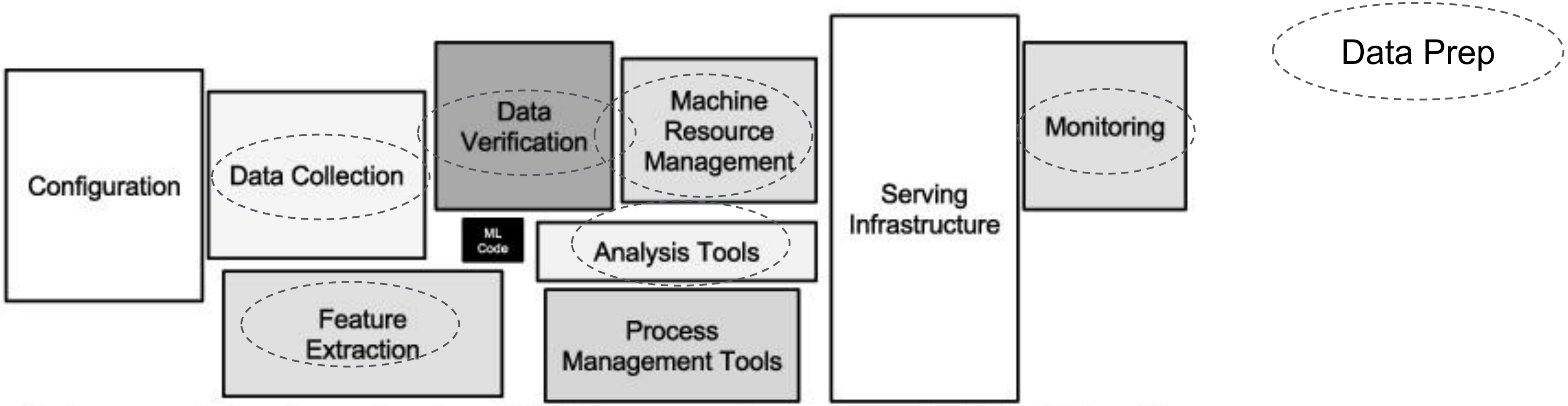


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Implement, Operate, Audit, Access, Monitor Model Input and Output

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# Data Prep for Models - Nature

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- Also called Feature Engineering
- Features are variables generated from data
    - Continuous process (Batch + Near Realtime + Realtime)
- Large in number (‘00s to ‘000s) & evolving
- Frequently executed

| Customer | SKU | Name |
| --- | --- | --- |
| 17826162 | 0293192 | Thai Dragon Fruit |

Retail Customer
(X GB)

→

| Customer | Premium | Imported |
| --- | --- | --- |
| 17826162 | 15% of txns | 5% of spend |

Features
(~X/1000)

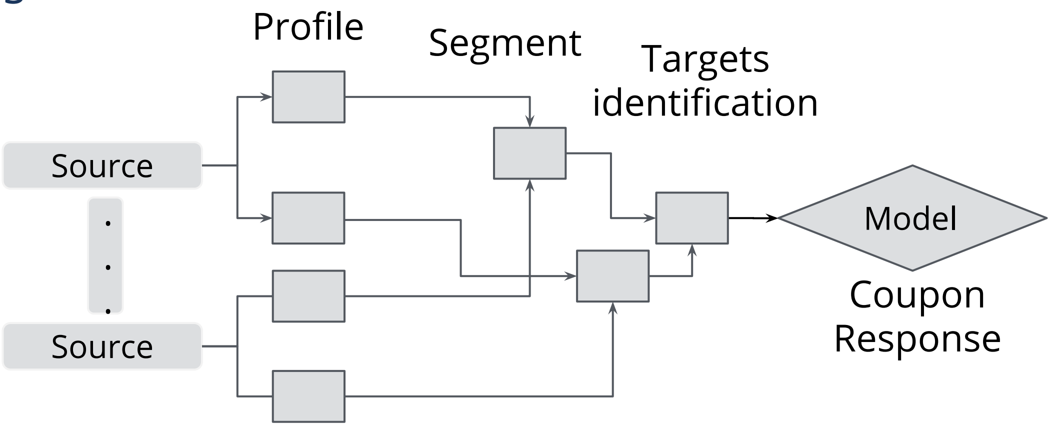
# Data Prep Pipeline  Consumers

| Nature | Example | Timing | Users |
|---|---|---|---|
| Models | Prediction | Batch or Realtime | Data savvy (python etc)<br>Understand scale & contracts |
| Automation | Reordering | Typically batch | Application developers (Java)<br>Less flexibility & More Contracts |
| Analysis | Segmentation | Adhoc | SQL-based tooling<br>Explainability critical<br>Availability and access focus<br>Completeness nice to have |

# Nature of the Problem

# Data Prep Pipelines - Structure

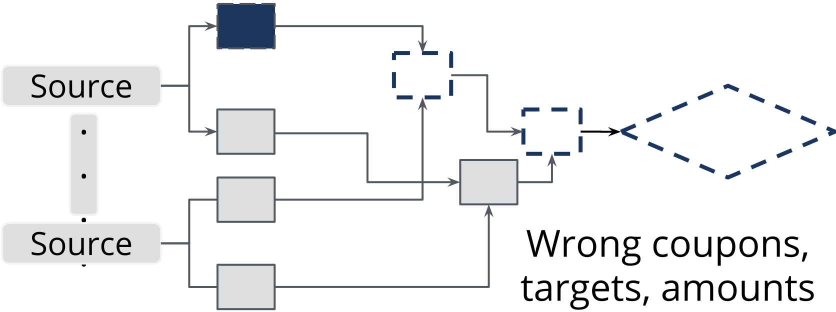
- Multiple, intersecting DAGs
- Can be broad and deep
- Continuous change
- Compute intensive
- Long execution times
- High volume of data




Sample: 50GB/day, 2M customers, 200 features, 10 pipelines, 4 hours execution time

# Network+Time Makes Everything Hard

- Fluid systems that evolve over time
- Change propagates thru network
- Validation is always incomplete
- Hidden dependencies
- Impact can't be undone




Sample: 6TB recompute and unknown $$ cost when profile is wrong!

# Where does time go?

# Where does time go? Stitching Systems

- Data sources, semantics, transformations span large space
- Rapid change in business need
- Natural fit for Python
- Flexibility and speed critical
    - Quick movement from test to prod
- Limited organizational resources
    - Robustness and productivity is critical

Python's advantage: Interfacing (sqlalchemy,REST etc), computation (pandas etc), application framework (django etc)

# Where does time go? xData

- Explanation for each feature & value
  - Three different languages/tests/contracts
  - Business/application consumers want to know
- Everyday, for every output
  - Many combinations - versions x runs x dependencies
- Reproducibility is a requirement
  - No explanation is credible without one

xData will enter conversations soon

# Where does time go? Changes

- Changes - Involuntary (bugs) and Voluntary (functionality)
    - Different classes of features with different behaviors
- Thousands of lines of dense code
    - Corner cases + large volumes of data
- Correctness issues can be **very** expensive
    - Embarrassment and $$$
    - Laborious investigation, fixing code and data

Expect Python data management layer!

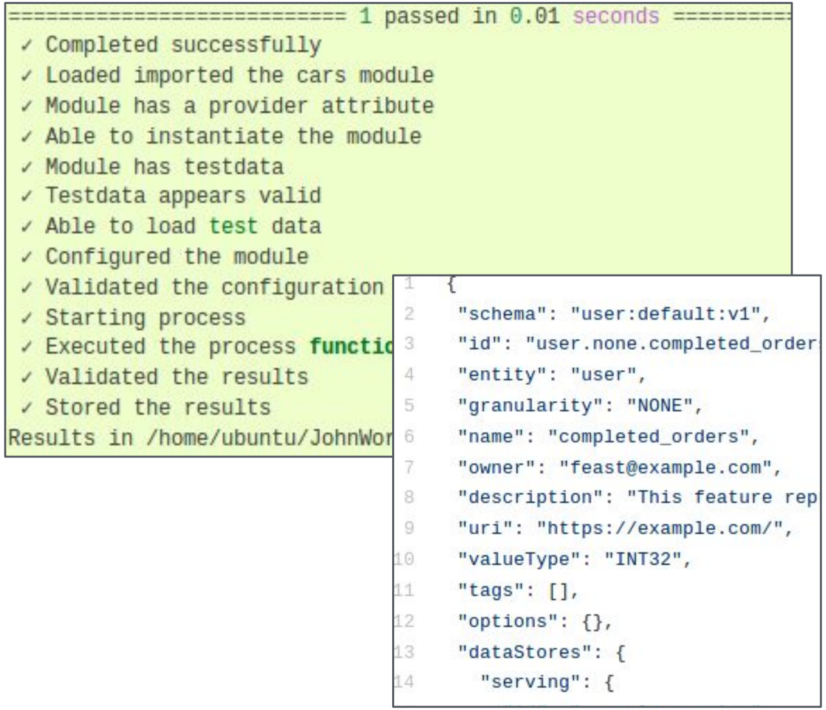
# Where does time go? Resource Management

- Pandas is memory intensive: 5x rule
  - Continuous optimization and careful coding
  - Explicit memory management
- Implementing tradeoffs
  - Dev speed (D), Ops cost (O), Scalability (S)
- Need more high perf data structures (lists, dicts)
- Hidden Gem - Itertoolz

# Required Capabilities

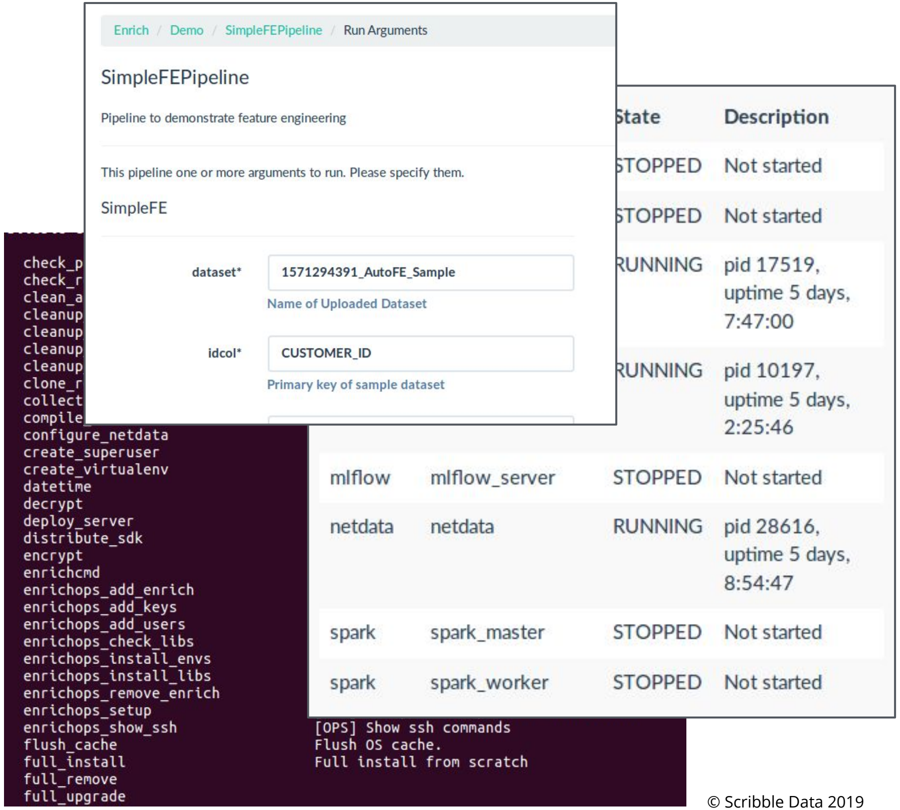
# Implement: Provide Structure to Development

- Modular class structure
  - Flexible configuration
  - Pre/post exec validation
  - Pytest integration
  - Automatic documentation
  - Data quality checking
- Productivity enhancers
  - Feature specification DSL
  - Query/other templates



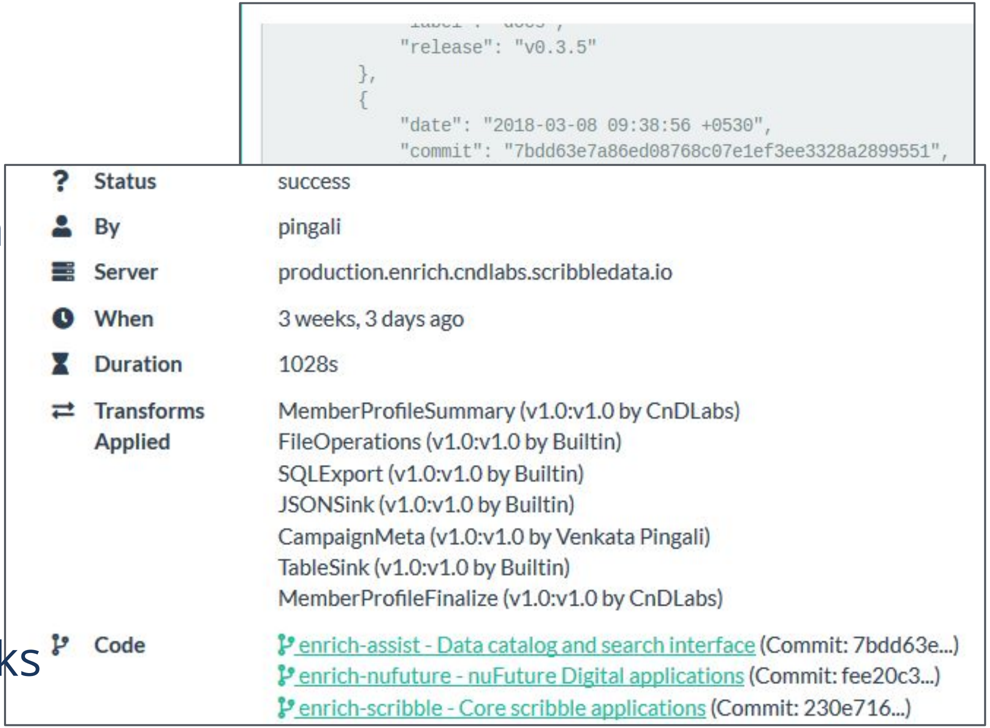
# Operate: Flexible & Controlled Execution Management

- Parameterization
  - Easily extensible
  - Dynamic defaults
- Notifications w/ callouts
- Automated deployment
  - Coordinated across modules
  - Impact analysis of changes
- Service integration
  - Prefect, Netdata, Supervisor



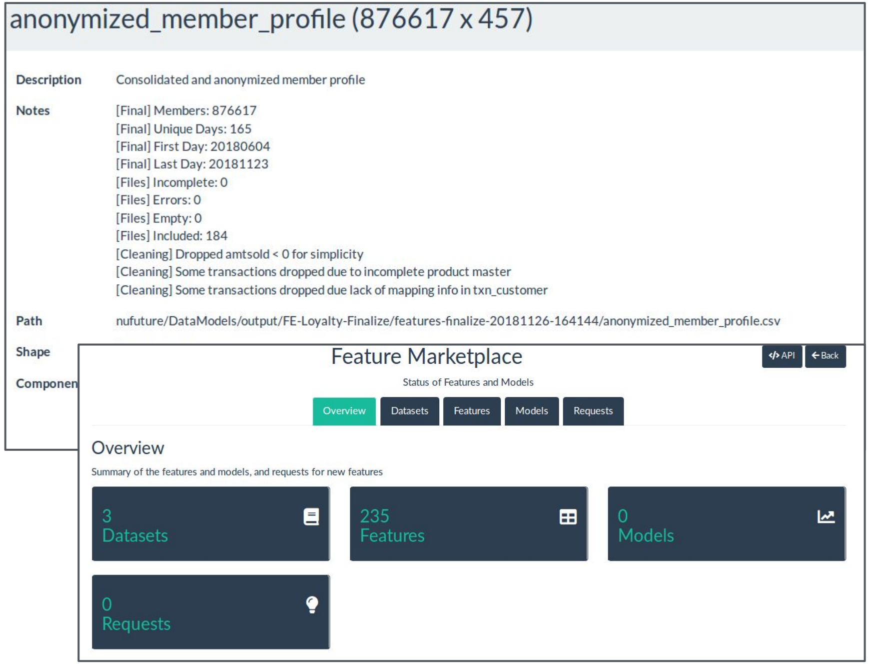
# Audit: Use and Manage Metadata Extensively

- Knowing what changes your data goes through
- End-to-end auditability
    - All data and all runs
    - Metadata standardization
- Discovery and reuse
    - Pipelines, modules
    - Lineage search
- Early warning systems
    - Input/output quality checks
    - Note critical decisions



# Access: Stable, Safe, Continuous Consumption

- Marketplace for data discovery
- Data contracts
- Isolation: Multi-tenant namespaces
  - File system, tables, S3
- Time: Versioned namespaces
  - Storage locations
  - Metadata
- Linked data and code



# Takeaways

- Data prep required for all ML
  - Costly, cumbersome, error prone
  - Structure of the problem makes it hard
- Provide support in all stages of lifecycle
  - Implement, operate, audit, and consume
- xData will grow
  - Model correctness q’s are often data correctness q’s

# THANK YOU
# FOR YOUR TIME

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