Hamilton

enabling software engineering best practices for data transformations via generalized dataflow graphs

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@ Stitch Fix
CDMS Workshop VLDB 2022

Introduction

Introduction

Context:

- Stitch Fix is a business where “machine learning” is core to the product
- Stitch Fix has 100+ Data Scientists (DS)
  - No hand-off; DS responsible for productionization*
  - DS own ETLs on top of a data lakehouse
- Data platform team goals:
  - Capabilities
  - Iteration speed
  - Maintenance

*https://multithreaded.stitchfix.com/blog/2019/03/11/FullStackDS-Generalists/

Introduction

Connection with Data ecosystems:

- ML Industry perspective
- Code is metadata to be managed
    - Feeds into data management processes
        - Code produces/augments data; impacts developer productivity.
        - Want granular traceability/lineage? Code is the best source.
        - Code and data quality (DQ) are coupled.
    - Code [& data] only grows
        - additions + modifications >> deletions.

Software Engineering Pain Points with Data Transformations

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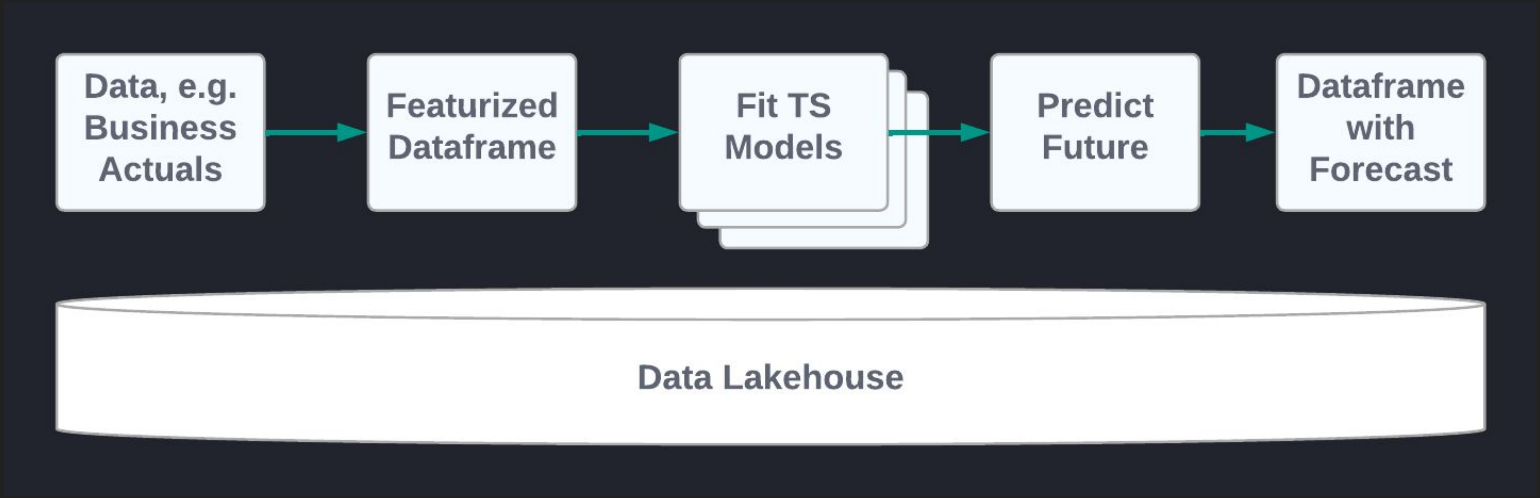

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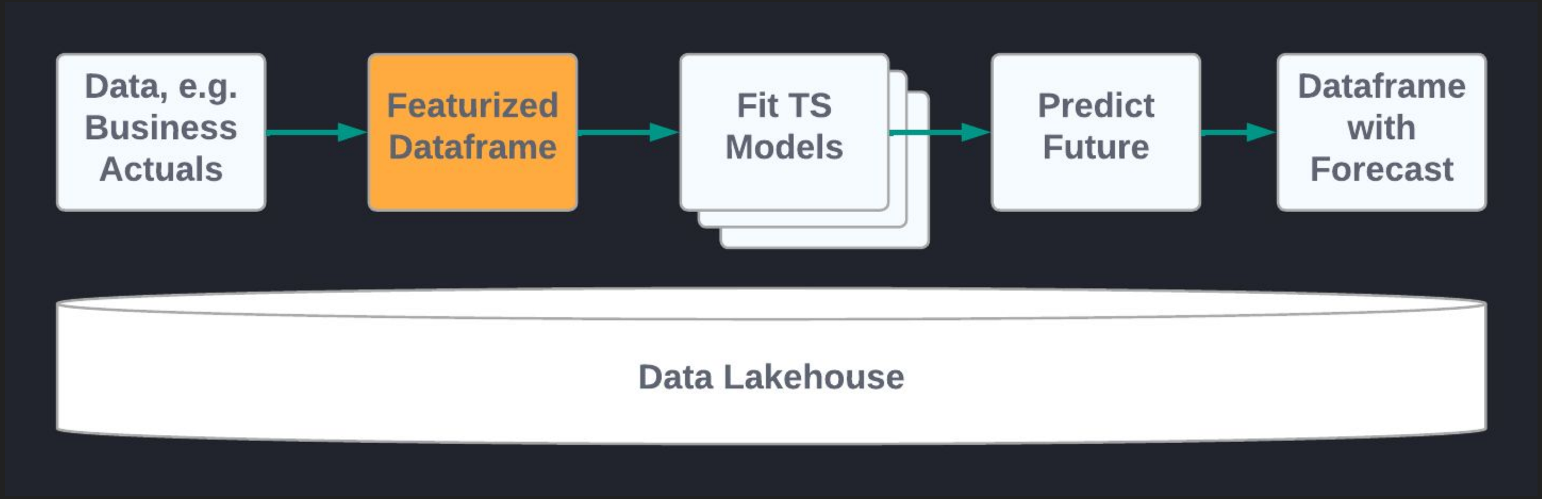

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Now scale this code to 1000+ columns & a growing team 😬

Problem: unit testing & integration testing 👎

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Problem: code readability & documentation 🧐

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Problem: difficulty in tracing lineage 🤯

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Problem: code reuse and duplication

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Hamilton

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    """Some docs"""
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def spend_per_signup(spend: pd.Series, signups: pd.Series) -> pd.Series:
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def spend_shift_3weeks(spend: pd.Series) -> pd.Series:
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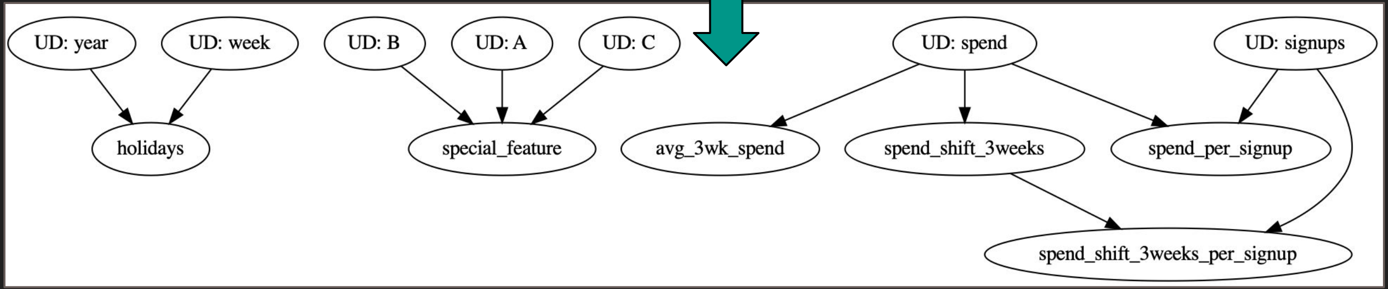

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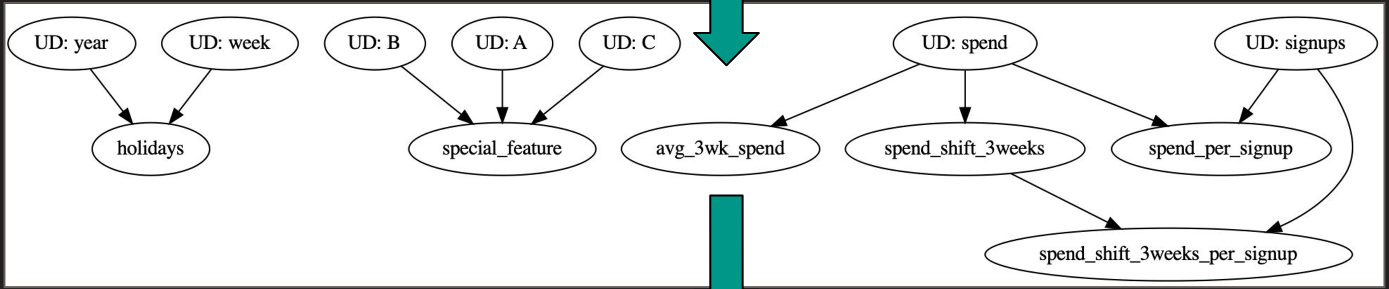

Hamilton

Object(s) (e.g. Dataframe, ML Model):

Year	Week	Sign ups	...	Spend	Holiday
2015	2	57	...	123	0
2015	3	58	...	123	0
2015	4	59	...	123	1
2015	5	59	...	123	1
...	...	...	...	...	...
...	...	...	...	...	...
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Python Modules

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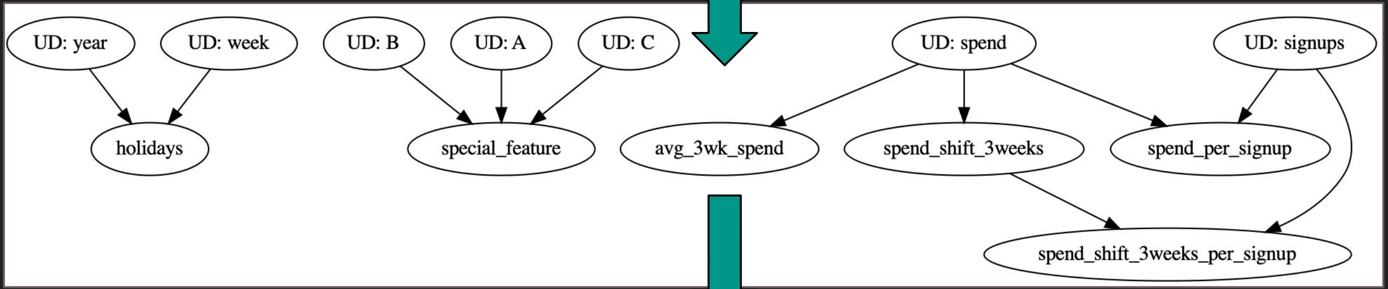

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"Driver" Code

Hamilton Paradigm: declaring a dataflow

Instead of:

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df['c'] = df['a'] + df['b']
df['d'] = transform(df['c'])
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You declare:

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def c(a: pd.Series, b: pd.Series) -> pd.Series:
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+ some driver code (not shown)

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Outputs == Function Name

Inputs == Function Arguments

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Full Hello World

Functions:

```python
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“Driver” - this actually says what and when to execute:

```python
# run.py
from hamilton import driver
import feature_logic
dr = driver.Driver({'a': ..., 'b': ...}, feature_logic)
df_result = dr.execute(['c', 'd'])
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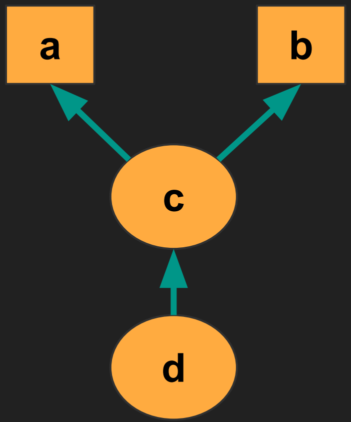

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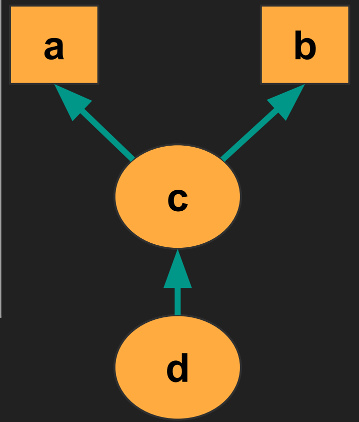

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Enabling software engineering best practices & then some

Software engineering best practices & then some:

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# located in client_features.py
@tag(owner='Data-Science', pii='False')
@check_output(data_type=np.float64, range=(-5.0, 5.0), allow_nans=False)
def height_zero_mean_unit_variance(height_zero_mean: pd.Series,
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- Documentation ✅ function doc, visualization, `@tag`
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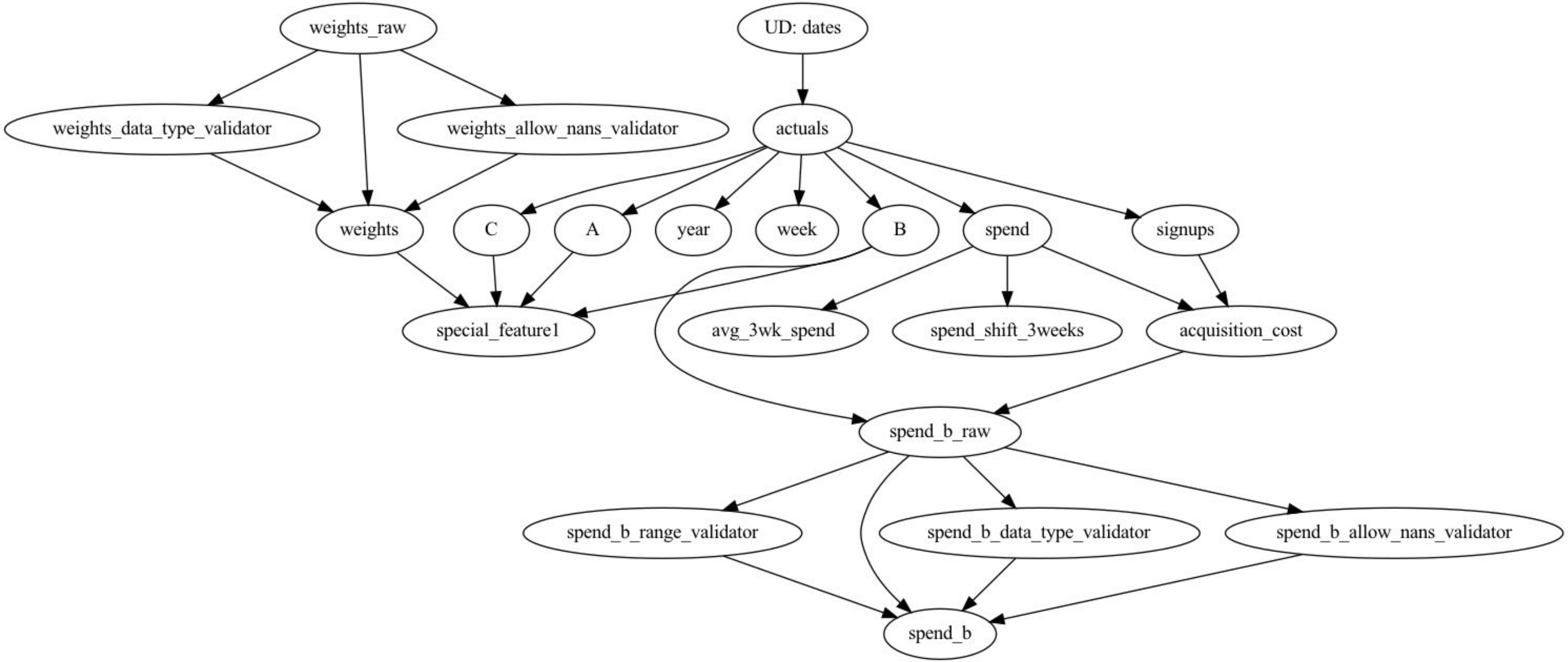
- Documentation ✅ function doc, visualization, `@tag`
- Modularity/reuse ✅ module curation & drivers
- Data quality ✅ `@check_output` runtime checks
- Lineage ✅ DAG, versioning, `@tag`

… more in the paper!

Example Dataflow Visualization



Evaluation

Hamilton @ Stitch Fix

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- FED team manages 4000+ feature definitions
  - All feature definitions are:
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    - Documentation friendly
    - Centrally curated, stored, and versioned in git.
- Data Science teams ❤️ it:
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    - Most willing to pay migration cost.
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WORK IN PROGRESS

Summary & Future Work

Summary:

- A declarative dataflow paradigm in python
- Functions, via naming, encode a dataflow
- Software engineering best practices come from:
  - Encapsulation of transform logic within functions.
  - Decoupling transform logic from materialization.

Future Work:

- Source code based governance
  - How do we integrate it further?
- Compiling to an orchestration framework
- Modeling your entire data lakehouse independently of materialization concerns

Hamilton is Open Source Code

```
> pip install sf-hamilton
```

Get started in <15 minutes!

Star ⭐ on github:

https://github.com/stitchfix/hamilton

Documentation

https://hamilton-docs.gitbook.io/

Various examples:

https://github.com/stitchfix/hamilton/tree/main/examples

Thank you.

Questions?

https://twitter.com/stefkrawczyk

https://www.linkedin.com/in/skrawczyk/

https://github.com/stitchfix/hamilton