DAGWORKS

# Hamilton: Natively bringing SWE best practice to Python data transformations

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# whoami

**Stefan** Krawczyk
Co-creator of **Hamilton** &&
CEO **DAGWorks** Inc.

## 12+ years in ML & Data platforms

# Why do SWE principles matter?

# Why do SWE principles matter?

It helps scale/amplify human efforts; & humans are $$$.

# Agenda

1. **Motivating pain**
2. Hamilton
3. General Usage
4. Native SWE
5. Summary

# A story of motivating pain

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# Example: Creating a dataframe (e.g. for ML training)

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```

😬 Now picture the passage of time: personnel Δ, sophistication ⬆️, etc

# Problem: unit & integration testing; data quality 👎

```
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save_df(df, "some_location")
```

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# Problem: code readability & documentation 🧐

```
df = loader.load_actuals(dates) # e.g. spend, signups
if config['region'] == 'UK':
    df['holidays'] = is_uk_holiday(df['year'], df[' week'])
else:
    df['holidays'] = is_holiday(df['year'], df['week'])
df['avg_3wk_spend'] = df['spend'].rolling(3).mean()
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df['spend_b'] = multiply_columns(df['acquisition_cost'], df['B'])
save_df(df, "some_location")
```

?

😬 Now picture the passage of time: personnel Δ, sophistication ⬆️, etc

# Problem: difficulty in tracing lineage 🤯

```
df = loader.load_actuals(dates) # e.g. spend, signups
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   df['holidays'] = is_uk_holiday(df['year'], df[' week'])
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   df['holidays'] = is_holiday(df['year'], df['week'])
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df['spend_b'] = multiply_columns(df['acquisition_cost'], df['B'])
save_df(df, "some_location")
```

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# Problem: code reuse and duplication

```
df = loader.load_actuals(dates) # e.g. spend, signups
if config['region'] == 'UK':
    df['holidays'] = is_uk_holiday(df['year'], df[' week'])
else:
    df['holidays'] = is_holiday(df['year'], df['week'])
df['avg_3wk_spend'] = df['spend'].rolling(3).mean()
df['acquisition_cost'] = df['spend'] / df['signups']
df['spend_shift_3weeks'] = df['spend'].shift(3)
df['special_feature1'] = compute_bespoke_feature(df)
df['spend_b'] = multiply_columns(df['acquisition_cost'], df['B'])
save_df(df, "some_location")
```

😬 Now picture the passage of time: personnel Δ, sophistication ⬆️, etc

# Problem: onboarding 📈 & debugging 📈

```
df = loader.load_actuals(dates) # e.g. spend, signups
if config['region'] == 'UK':
   df['holidays'] = is_uk_holiday(df['year'], df[' week'])
else:
   df['holidays'] = is_holiday(df['year'], df['week'])
df['avg_3wk_spend'] = df['spend'].rolling(3).mean()
df['acquisition_cost'] = df['spend'] / df['signups']
df['spend_shift_3weeks'] = df['spend'].shift(3)
df['special_feature1'] = compute_bespoke_feature(df)
df['spend_b'] = multiply_columns(df['acquisition_cost'], df['B'])
save_df(df, "some_location")
```

😬 Now picture the passage of time: personnel Δ, sophistication ⬆️, etc

# Question for you!

1. Are any of these pains familiar to you? If so, which ones?
2. Do you have some other pains related to pipelines/modeling?

✋ Raise hand | ~~Unmute~~ !

# Agenda

1. ~~Motivating pain~~
2. **Hamilton**
3. General Usage
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# Hamilton

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# What is Hamilton?

## Micro-orchestration framework
## for defining dataflows
## using declarative functions

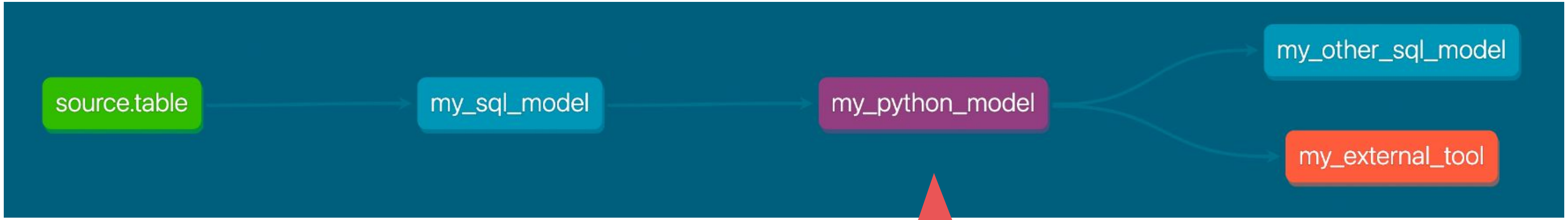
SWE best practices: ☑️ testing ☑️ documentation ☑️ modularity/reuse

`pip install sf-hamilton [came from Stitch Fix]`

**[www.tryhamilton.dev](http://www.tryhamilton.dev) ← uses pyodide!**

# Mirco-orchestration vs Macro-orchestration

## Macro-orchestration is handling this whole thing:




## Micro-orchestration is handling what happens within this step

# What's a dataflow?

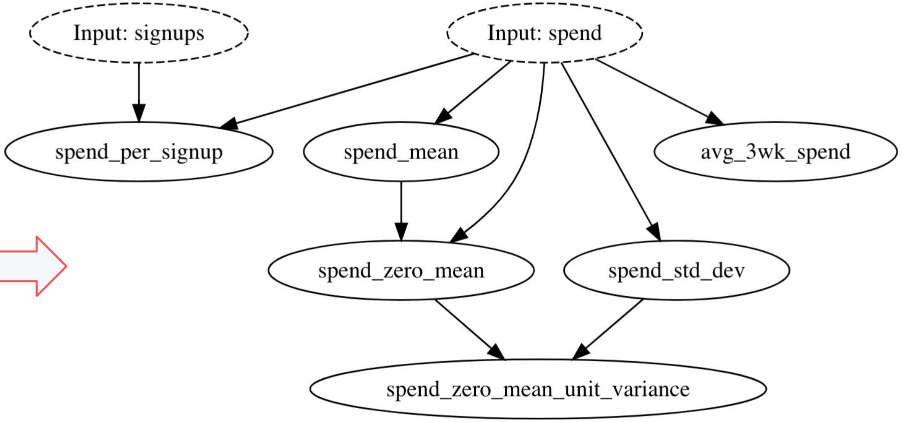
**Fancy way of saying:**

## How data + computation "flow"

## Can be expressed as a directed acyclic graph (DAG).

e.g., this is a dataflow:

```
df['avg_3wk_spend'] = df['spend'].rolling
df['spend_per_signup'] = df['spend']/df['
spend_mean = df['spend'].mean()
df['spend_zero_mean'] = df['spend']   spe
spend_std_dev = df['spend'].std()
df['spend_zero_mean_unit_variance'] = df[
```



# Declarative functions?

**Functions *declare:***

- What they create in the dataflow.
- What dependencies are required for computation.
- You don’t run the functions directly.

> When you read the function, you’ll understand what it does and what it needs.

# A-ha moment: debugging a dataframe

**Idea:** What if every output (column) corresponded to exactly one Python fn?

**Addendum:** What if you could determine the dependencies from the way that function was written?

In Hamilton, the **output** (e.g., column)

is determined by the **name of the function**.

The **dependencies** are determined by the **input parameters**.

# Old Way vs. Hamilton Way:

Instead of

```python
df['c'] = df['a'] + df['b']
df['d'] = transform(df['c'])
```

**Outputs == Function Name**   **Inputs == Function Arguments**

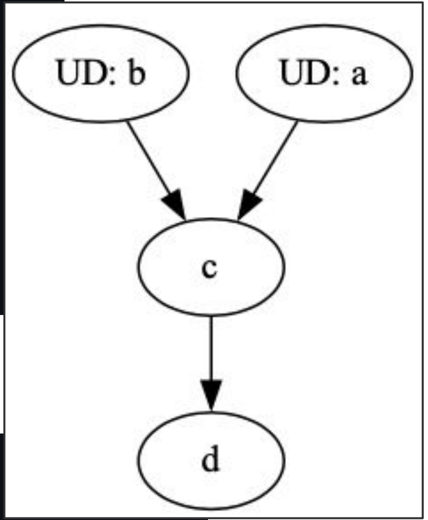
You declare

```python
def c(a: pd.Series, b: pd.Series) -> pd.Series:
    """Sums a with b"""
    return a + b

def d(c: pd.Series) -> pd.Series:
    """Transforms C to ..."""
    new_column = _transform_logic(c)
    return new_column
```

# Full Hello World (Note: works for any python object type)

Functions

```
# feature_logic.py
def c(a: pd.Series, b: pd.Series) -> pd.Series:
    """Sums a with b"""
    return a + b

def d(c: pd.Series) -> pd.Series:
    """Transforms C to ..."""
    new_column = _transform_logic(c)
    return new_column
```




Driver says what/when to execute

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

# Things to mention, but I won't cover:

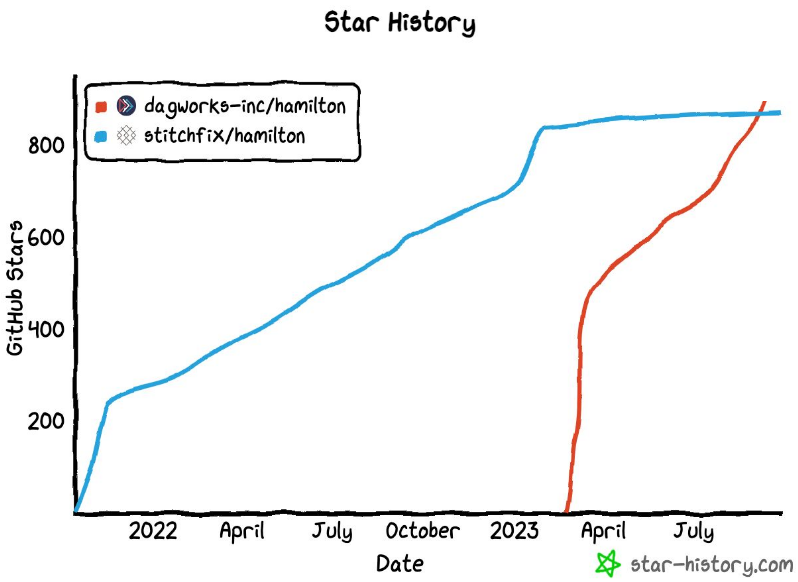
We also have decorators that you add to functions that...

```
● @tag                 # attach metadata
● @parameterize        # curry + repeat a function
● @extract_columns     # one dataframe -> multiple series
● @extract_outputs     # one dict -> multiple outputs
● @check_output        # data validation; very lightweight
● @config.when         # conditional transforms
● @subdag              # parameterize parts of your DAG
```

& more... Hamilton code is **portable** & runs **& scales** anywhere python runs.

# Some Hamilton stats

~1.6K Unique Stargazers
200+ slack members
100K+ downloads




Note: dbt took 3.5 years to get to 600 stars

## Hamilton is used by many, including:

STITCH FIX
Joby AVIATION
BRITISH CYCLING
AXIOM CLOUD
IBM
ascena RETAIL GROUP INC.
Government Digital Service
veriff
HABITAT ENERGY
Opendoor
Pacific Northwest NATIONAL LABORATORY
LexisNexis RISK SOLUTIONS

# Agenda

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# Hamilton: General Usage

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# When should I <u>not</u> consider Hamilton?

You **can't draw** a flowchart (DAG)...

Or if you have code that depends on inspecting the value output of a transform, e.g.

```
output_1 = transform_1(a, b)
if output_1 < 0.5:
  output_2 = transform_2(output_1)
else:
  output_2 = transform_3(output_1
```

If it's minor, you can break this up into separate DAGs ... otherwise not a fit.

*[though we can build this capability in...]*

# When ***should I*** consider Hamilton?

If you can draw a flowchart (DAG), you can put it into Hamilton:

- Time-series feature engineering (origin)
- Tired of managing scripts that do transformations...
- Describing E2E ML Pipelines + MLOps integrations
- Web request flows.
- LLM Workflows!

Code & software best practices enthusiasts:

- Hamilton ⬇️ Code Complexity

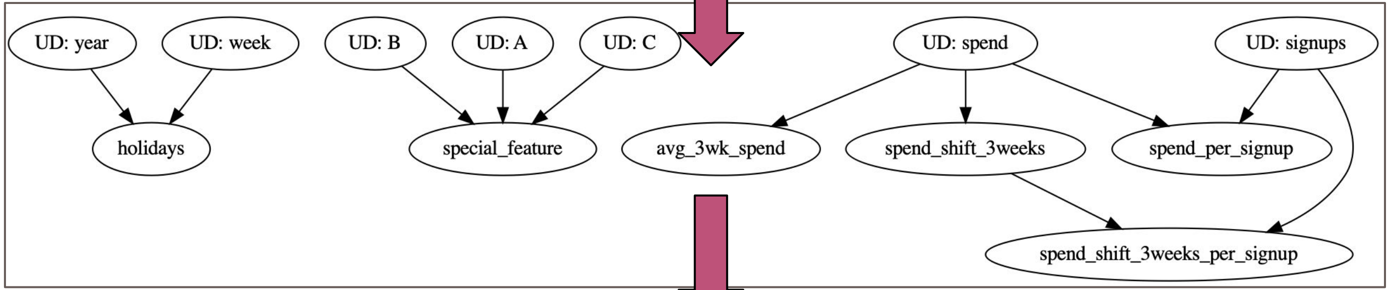
# Example Hamilton use case: Feature Engineering

Data loading & Feature code:

```python
def holidays(year: pd.Series, week: pd.Series) -> pd.Series:
    """Some docs"""
    return some_library(year, week)
def avg_3wk_spend(spend: pd.Series) -> pd.Series:
    """Some docs"""
    return spend.rolling(3).mean()
def spend_per_signup(spend: pd.Series, signups: pd.Series) -> pd.Series:
    """Some docs"""
    return spend / signups
def spend_shift_3weeks(spend: pd.Series) -> pd.Series:
    """Some docs"""
    return spend.shift(3)
def spend_shift_3weeks_per_signup(spend_shift_3weeks: pd.Series, signups: pd.Series) -> pd.Series:
    """Some docs"""
    return spend_shift_3weeks / signups
```

features.py

Via Driver:




Feature Dataframe:

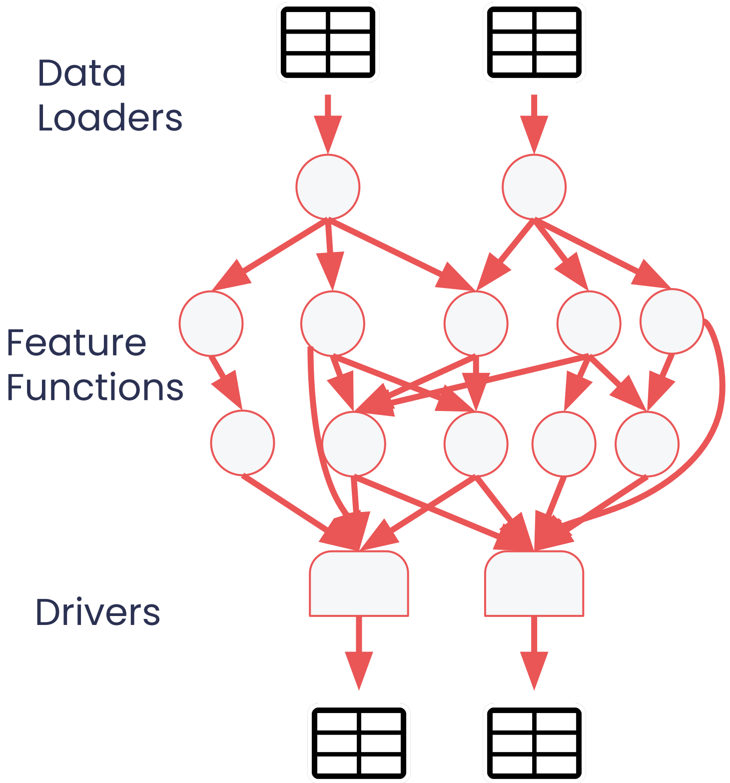
| Year | Week | Sign ups | ... | Spend | Holiday |
|---|---|---|---|---|---|
| 2015 | 2 | 57 | ... | 123 | 0 |
| 2015 | 3 | 58 | ... | 123 | 0 |
| 2015 | 4 | 59 | ... | 123 | 1 |
| 2015 | 5 | 59 | ... | 123 | 1 |
| ... | ... | ... | ... | ... | ... |
| ... | ... | ... | ... | ... | ... |
| ... | ... | ... | ... | ... | ... |
| ... | ... | ... | ... | ... | ... |
| 2021 | 16 | 1000 | ... | 1234 | 0 |

run.py

# Example Hamilton use case: Feature Engineering

Code that needs to be written:

1. Functions to load data
   a. normalize/create common index to join on
2. Feature functions
   a. Unit test these easily!
   b. Optional: model functions.
3. Drivers materialize data
   a. DAG is walked for only what's needed.
   b. E.g. place this code in wherever you run your python.



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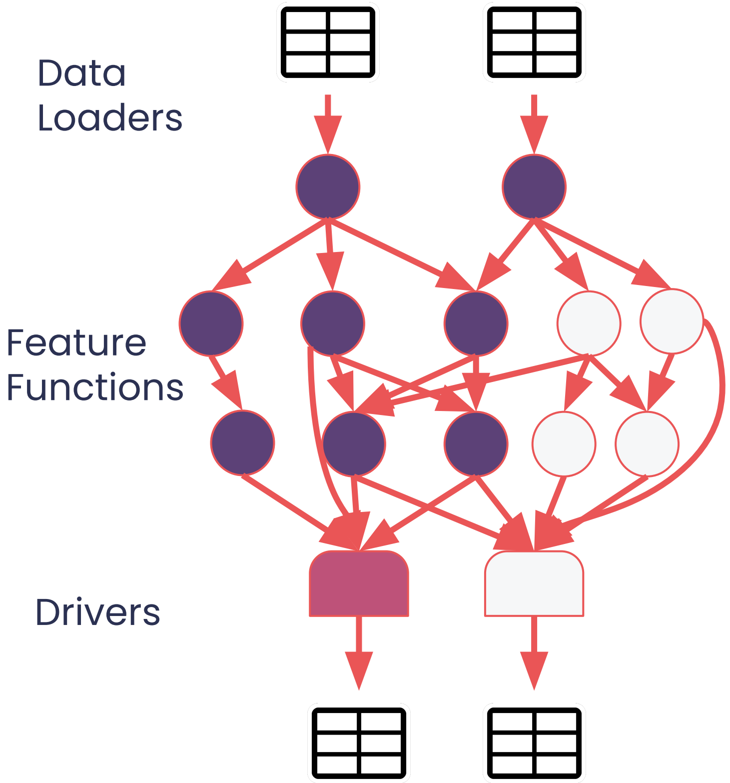

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# Hamilton: Native SWE

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# Native SWE

5 Common Ideals

- General: Testing & Docs.
- KISS
- YAGNI
- DRY
- SOLID

# General: Testing & Documentation

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```python
# client_features.py

def height_zero_mean_unit_variance(height_zero_mean: pd.Series,
                                   height_std_dev: float) -> pd.Series:
    return height_zero_mean / height_std_dev
```

**Testing**: easier to unit & integration test.

```python
# test_client_features.py

def test_height_zero_mean_unit_variance():
    actual = height_zero_mean_unit_variance(pd.Series([1,2,3]), 2.0)
    expected = pd.Series([0.5,1.0, 1.5])
    assert actual == expected
```

# General: Testing & Documentation

```python
# client_features.py

@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,
                                   height_std_dev: float) -> pd.Series:
   return height_zero_mean / height_std_dev
```

**Testing**: easier to unit & integration test.

**Data Quality Tests:** runtime checks via annotation*.

# General: Testing & Documentation

```python
# 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,
                                   height_std_dev: float) -> pd.Series:
    """Zero mean unit variance value of height"""
    return height_zero_mean / height_std_dev
```

**Testing**: easier to unit & integration test.

**Data Quality Tests:** runtime checks via annotation*.

**Self-documenting**: naming, doc strings, annotations, & visualization

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**Testing**: easier to unit & integration test.

**Data Quality Tests:** runtime checks via annotation*.

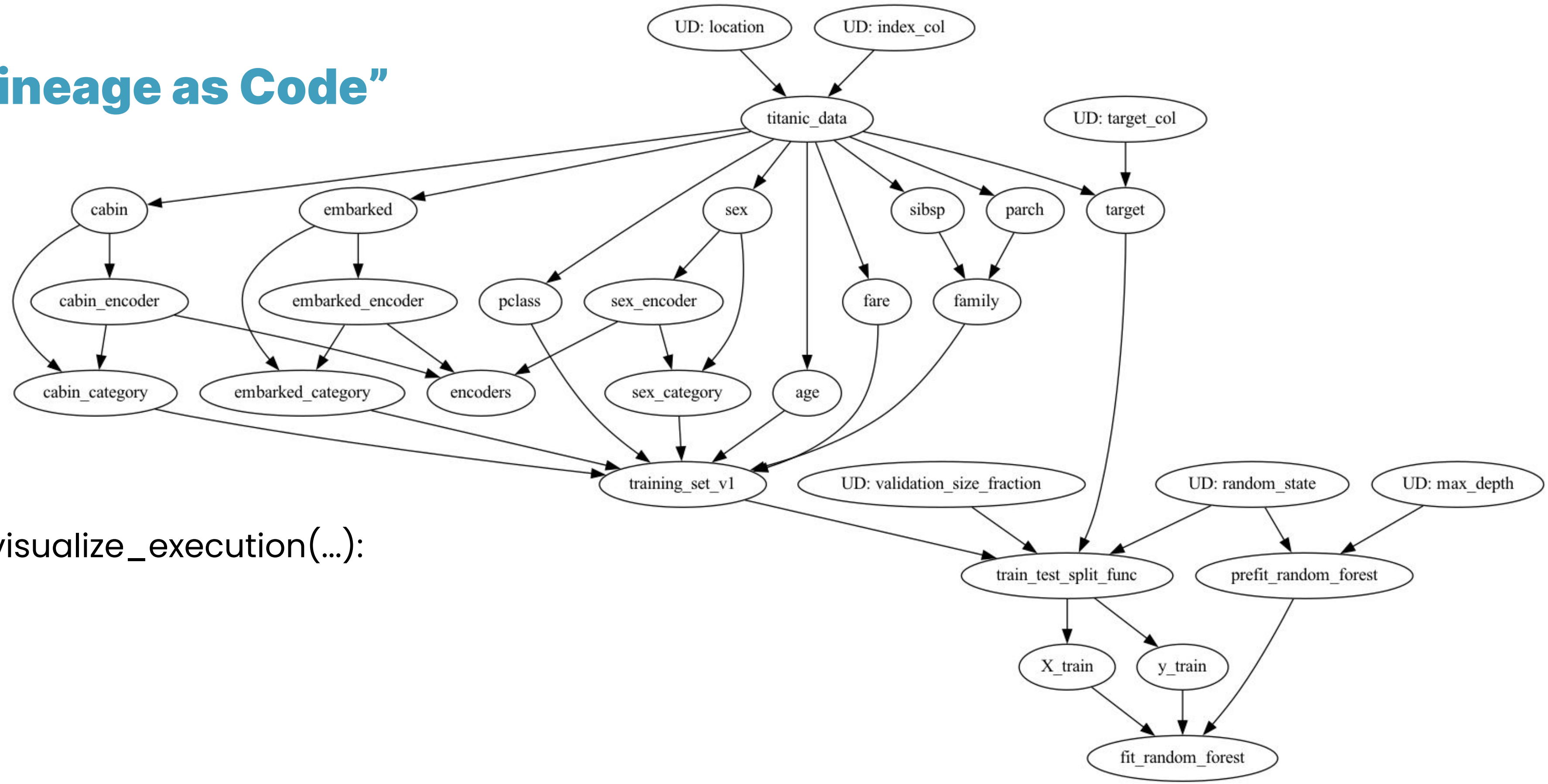
**Self-documenting**: naming, doc strings, annotations, & visualization

**Scale:** all these enable you to scale the team & code.

# Visualization is first class

## "Lineage as Code"

dr.visualize_execution(…):



# Native SWE

5 Common Ideals

- ~~General: Testing & Docs.~~
- **KISS**
- **YAGNI**
- DRY
- SOLID

# KISS (keep it simple, stupid)

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```
data['hzmuv'] = data['height_zero_mean'] / height_std_dev
```

**vs**

```
def height_zero_mean_unit_variance(height_zero_mean: pd.Series,
                                   height_std_dev: float) -> pd.Series:
    """Zero mean unit variance value of height"""
    return height_zero_mean / height_std_dev
```

**No object-oriented code**: don’t need to learn much to write a function.

**Testing story:** can change with confidence.

**Complexity is contained**: function, including naming, defines the boundaries

# YAGNI (You Aren’t Gonna Need It)

*“Premature optimization is the root of all evil” - Donald Knuth*

# YAGNI (You Aren't Gonna Need It)

```python
def height_zero_mean_unit_variance(height_zero_mean: pd.Series,
                                   height_std_dev: float) -> pd.Series:
    """Zero mean unit variance value of height"""
    return height_zero_mean / height_std_dev
```

**Hard to over engineer**: functions force simplicity.

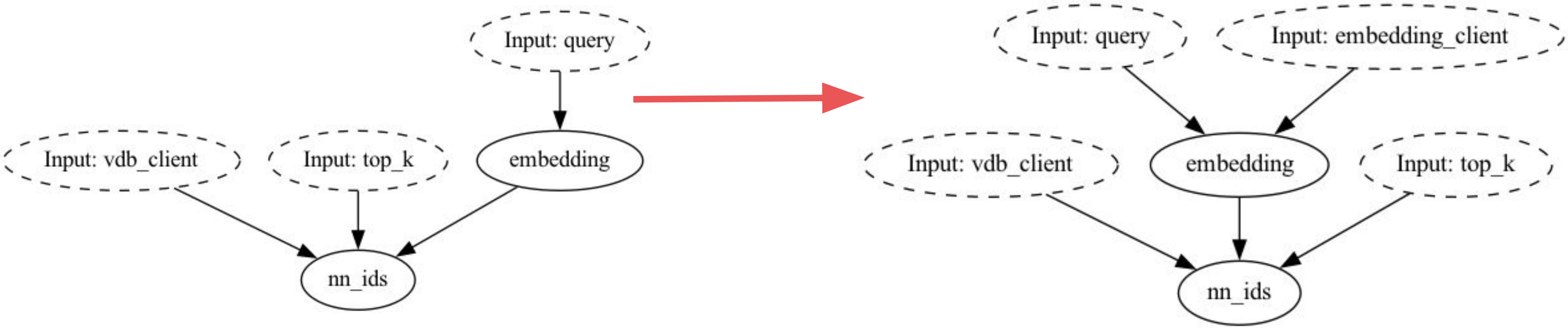
**Declarative structure:** easy to modify when needed.

# YAGNI (You Aren’t Gonna Need It)

## E.g. easy to refactor when needed:

```python
def embedding(query: str) -> List[float]:
  response = openai.Embedding.create(input=query, model="HARDCODED")
  return response["data"][0]["embedding"]
```

```python
def embedding(query: str, embedding_client: object) -> List[float]:
  return embedding_client.get_embedding(query)
```



# Native SWE

5 Common Ideals

- ~~General: Testing & Docs.~~
- ~~KISS~~
- ~~YAGNI~~
- **DRY**
- **SOLID**

# DRY (don’t repeat yourself)

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```
data['avg_3wk_spend'] = data['spend'].rolling(3).mean()
data['spend_per_signup'] = data['spend']/data['signups']
spend_mean = data['spend'].mean()
data['spend_zero_mean'] = data['spend'] - spend_mean
spend_std_dev = data['spend'].std()
data['szmuv'] = data['spend_zero_mean']/spend_std_dev
```

**VS**

```
def spend_zero_mean(spend: pd.Series, spend_mean: float) -> pd.Series:
  """Shows function that takes a scalar. In this case to zero mean spend."""
  return spend - spend_mean

def spend_std_dev(spend: pd.Series) -> float:
  """Function that computes the standard deviation of the spend column."""
  return spend.std()

def spend_zero_mean_unit_variance(spend_zero_mean: pd.Series, spend_std_dev: float)
-> pd.Series:
  """Function showing one way to make spend have zero mean and unit variance."""
  return spend_zero_mean / spend_std_dev
```

# SOLID Principles:
# Single Responsibility Principle

# Single Responsibility Principle

## Functions: single task; “named piece of business logic”

```
def embedding(query: str) -> List[float]:
  response = openai.Embedding.create(input=query, model="HARDCODED")
  return response["data"][0]["embedding"]
```

## Driver: no logic; just handling context of what & where

```
dr = driver.Driver(config, module1, module2)
outputs = ["spend", "signups", ...]
result = dr.execute(outputs,inputs=input_data)
```

# SOLID Principles: Open Closed Principle

# Open for Extension

## Can use @config to modify; adding new functions is straightforward.

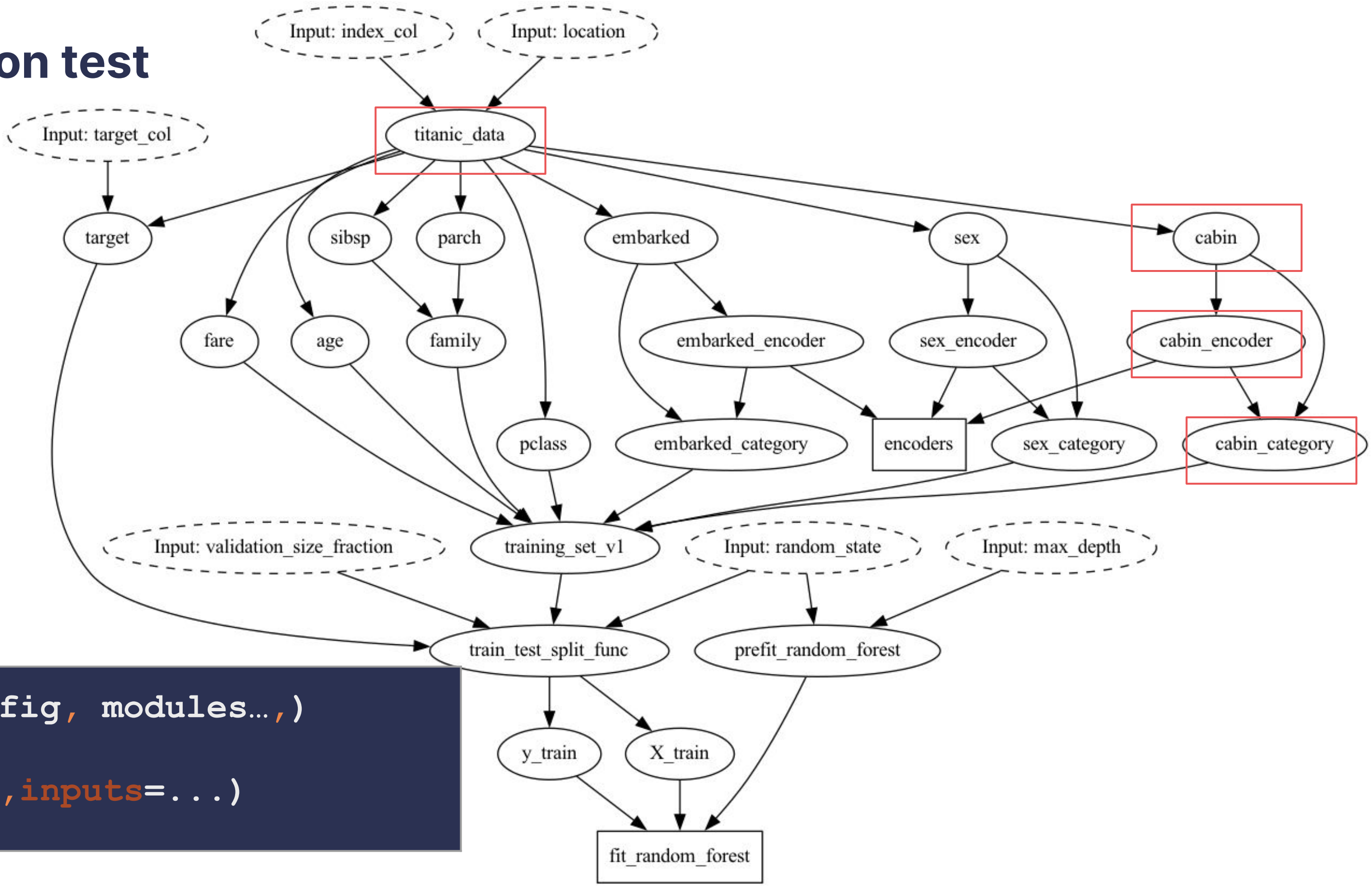
```python
def embedding(query: str) -> List[float]:
  response = openai.Embedding.create(input=query, model="HARDCODED")
  return response["data"][0]["embedding"]
```

```python
@config.when(provider="anthropic")
def embedding__anthropic(query: str) -> List[float]:
  response = antropic_api.get_embedding(input=query)
  return response["data"]["embedding"]
```

```python
def nn_ids(
 embedding: List[float], vectordb_client: Client, top_k: int) -> List[int]:
  results = vectordb_client.search(embedding=embedding, top_k=top_k)
  return results
```

# Open for Extension

## Can easily integration test a distinct path




```
dr = driver.Driver(config, modules…,)
result = dr.execute(
    ["cabin_category"],inputs=...)
```

# Closed for Modification

## Hard to break existing logic; or if you do, it’s clear why.

```python
def height_zero_mean_unit_variance(height_zero_mean: pd.Series,
                                   height_std_dev: float) -> pd.Series:
    """Zero mean unit variance value of height"""
    return height_zero_mean / height_std_dev
```

## Things Hamilton  checks:

- Type annotations match
- You have the right inputs for the outputs you want
- Can add runtime data quality checks via `@check_output`
  - e.g. with Pandera

# SOLID Principles:
# Liskov Substitution Principle

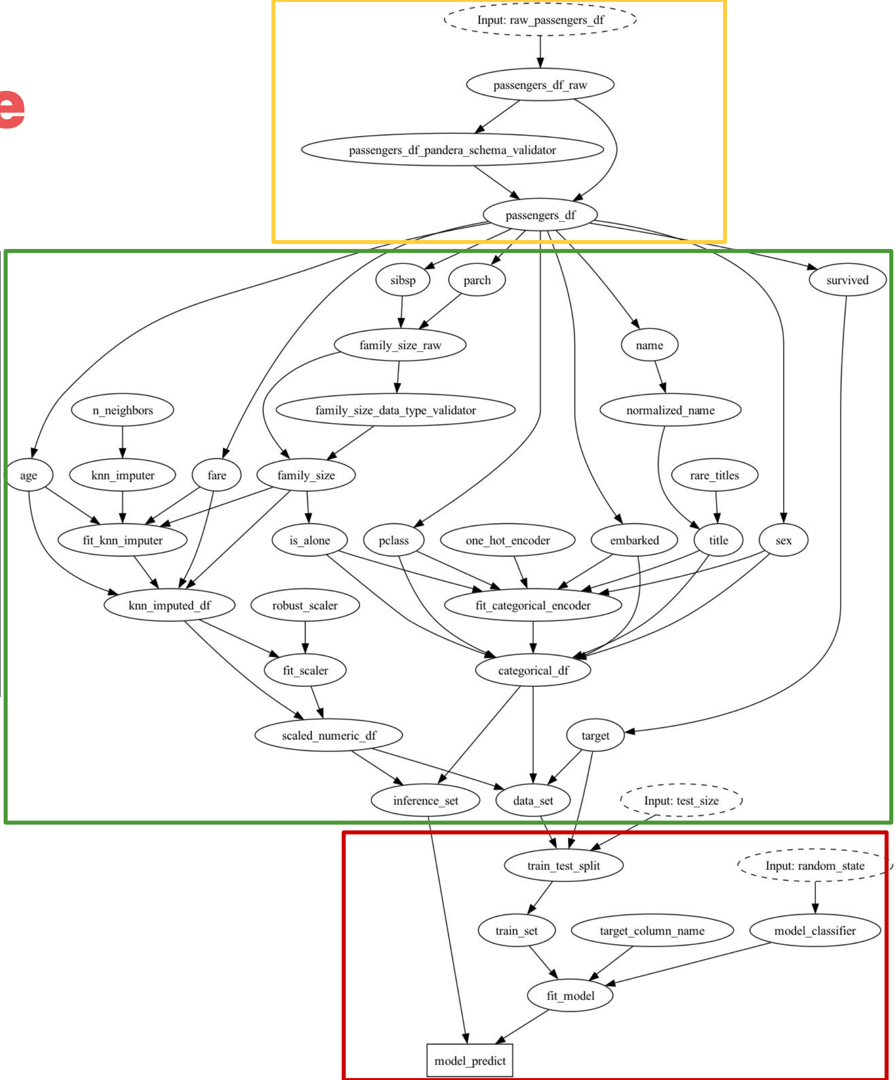
# Liskov Substitution Principle

```python
import data_loader, feature_transforms, model_pipeline

# DAG for training/inferring on titanic data
titanic_dag = driver.Driver(config,
  data_loader, feature_transforms, model_pipeline,
  adapter=base.DefaultAdapter(),
)
# execute & get output
result = titanic_dag.execute(["model_predict"],
      inputs={"raw_passengers_df": raw_passengers_df}
  )
```

## Options to swap:

- @config.when
- module swap
- swap where this code runs



# SOLID Principles:
# Interface Segregation Principle

"clients can choose to depend only on the functionalities they need."

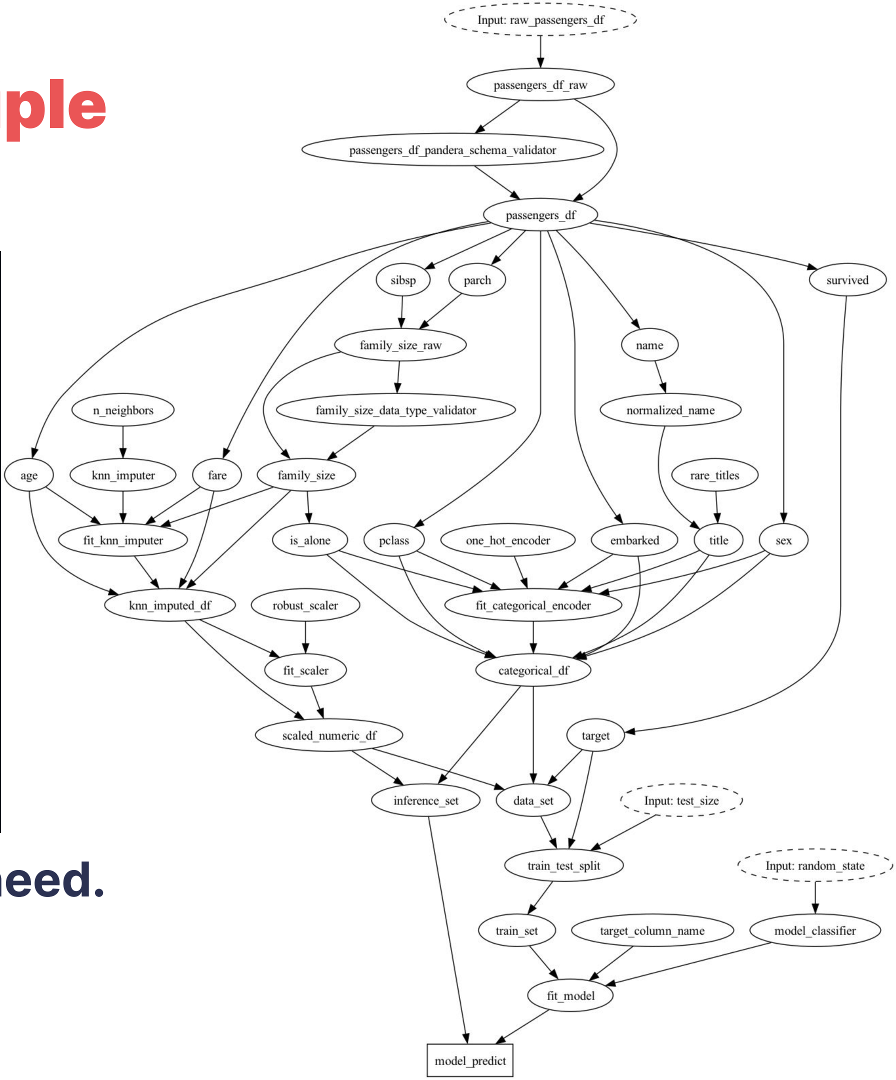
# Interface Segregation Principle

```python
import data_loader, feature_transforms, model_pipeline

# DAG for training/inferring on titanic data
titanic_dag = driver.Driver(config,
  data_loader, feature_transforms, model_pipeline,
  adapter=base.DefaultAdapter(),
)
# execute & get output full pipeline
result = titanic_dag.execute(["model_predict"],
      inputs={"raw_passengers_df": raw_passengers_df}
)

# execute & get output just data_set
result = titanic_dag.execute(["data_set"],
      inputs={"raw_passengers_df": raw_passengers_df}
)
```

1. Functions only depend on what they need.
2. Don’t  need it? Don’t run it.



# SOLID Principles:
# Dependency Inversion Principle

“use interfaces instead of concrete implementations wherever possible”
“avoid tight coupling between software modules”

# Dependency Inversion Principle

## Hamilton does this by definition.

Functions & parameters have type annotations.

```python
import data_loader, feature_transforms, model_pipeline

# DAG for training/inferring on titanic data
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# execute & get output
result = titanic_dag.execute(["model_predict"],
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  )
```
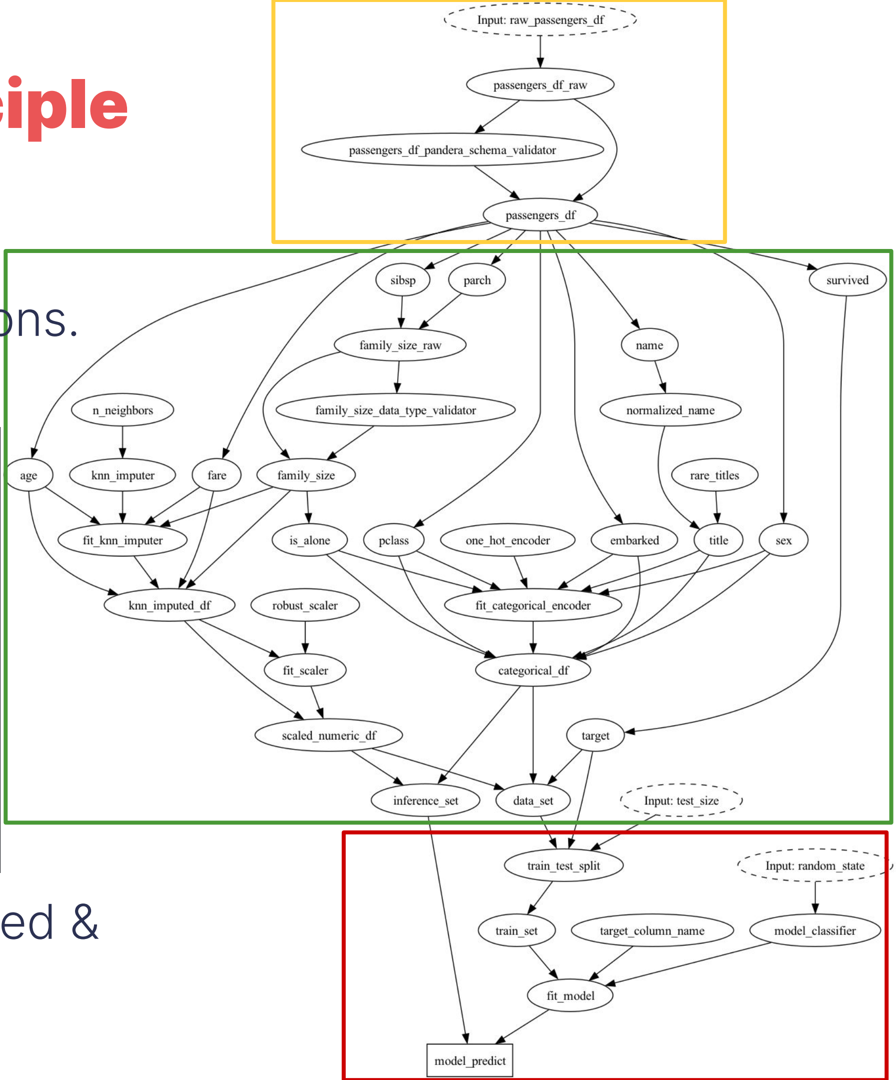

The driver requests what should be computed & delegates to underlying functions.



# Agenda

1. ~~Motivating pain~~
2. ~~Hamilton~~
3. ~~General Usage~~
4. ~~Native SWE~~
5. **Summary**

# Summary

DAGWORKS

# TL;DR: Summary

1. Hamilton is a micro-orchestration framework for dataflows in Python.
2. Good SWE practices improve the value of your (human) work and Hamilton promotes them by design:
   - ✅ General: Testing & Docs.
   - ✅ KISS
   - ✅ YAGNI
   - ✅ DRY
   - ✅ SOLID
3. You'll get more value with Hamilton because:
   - It's straightforward to test & document.
   - It's hard to do bad things when adding/removing/adjusting dataflows.
   - It fosters reuse so you can move faster.
   - Standardizes the way to iterate and add to the code base.

# TL;DR: Summary

Good SWE practices improve the value of human work hours, and Hamilton promotes them by design.

**Hamilton** is a micro-orchestration framework for dataflows in Python.

- It was created to tame a code base (& therefore process).
- It's opinionated (e.g. dbt for Python).
    - Use it for data processing, ML, to LLM workflows.
- SWE best practices come natively, without really thinking about it.

# Sneak peek - sharing dataflows:

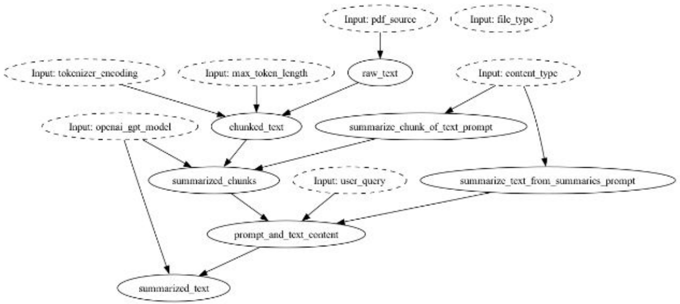
[hub.dagworks.io](hub.dagworks.io)

Hamilton Dataflow Hub  Dataflows  Changelog  DAGWorks Blog  GitHub

- Introduction
- Users
  - Example Template
  - zilto
    - text_summarization
- Official

Users > zilto > text_summarization

# text_summarization




## To get started:

### Dynamically pull and run

```
from hamilton import dataflow, driver
# downloads into ~/.hamilton/dataflows and loads the module -- WARN
text_summarization = dataflow.import_module("text_summarization", "
dr = (
    driver.Builder()
    .with_config({})  # replace with configuration as appropriate
    .with_modules(text_summarization)
    .build()
)
# execute the dataflow, specifying what you want back. Will return
result = dr.execute(
    [text_summarization.CHANGE_ME, ...],  # this specifies what you
    inputs={...}  # pass in inputs as appropriate
)
```

To get started:
- Dynamically pull and run
- Use published library version

Purpose of this module
Configuration Options
Limitations
Source code
Requirements

# Fin. Thanks for listening!

`> pip install sf-hamilton` or ⌨️ on tryhamilon.dev

**Questions**?

📣 join us on on Slack or subscribe to blog.dagworks.io!

📚 documentation: hamilton.dagworks.io

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Star ⭐: https://github.com/dagworks-inc/hamilton

https://www.dagworks.io (sign up! We're building on top of Hamilton!)

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