On the importance of tests

BUILDING DATA ENGINEERING PIPELINES IN PYTHON

Oliver Willekens
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Software tends to change

Common reasons for change:

- new functionality desired
- bugs need to get squashed
- performance needs to be improved

Core functionality rarely evolves

How to ensure stability in light of changes?

Rationale behind testing

- **improves chance of code being correct in the *future***
  - prevent introducing breaking changes

- **raises *confidence* (not a guarantee) that code is correct *now***
  - assert actuals match expectations

- **most up-to-date documentation**
  - form of documentation that is always in sync with what's running

The test pyramid: where to invest your efforts

Testing takes time

- thinking what to test
- writing tests
- running tests

Testing has a high return on investment

- when targeted at the correct layer
- when testing the non-trivial parts, e.g. distance between 2 coordinates ? uppercasing a first name

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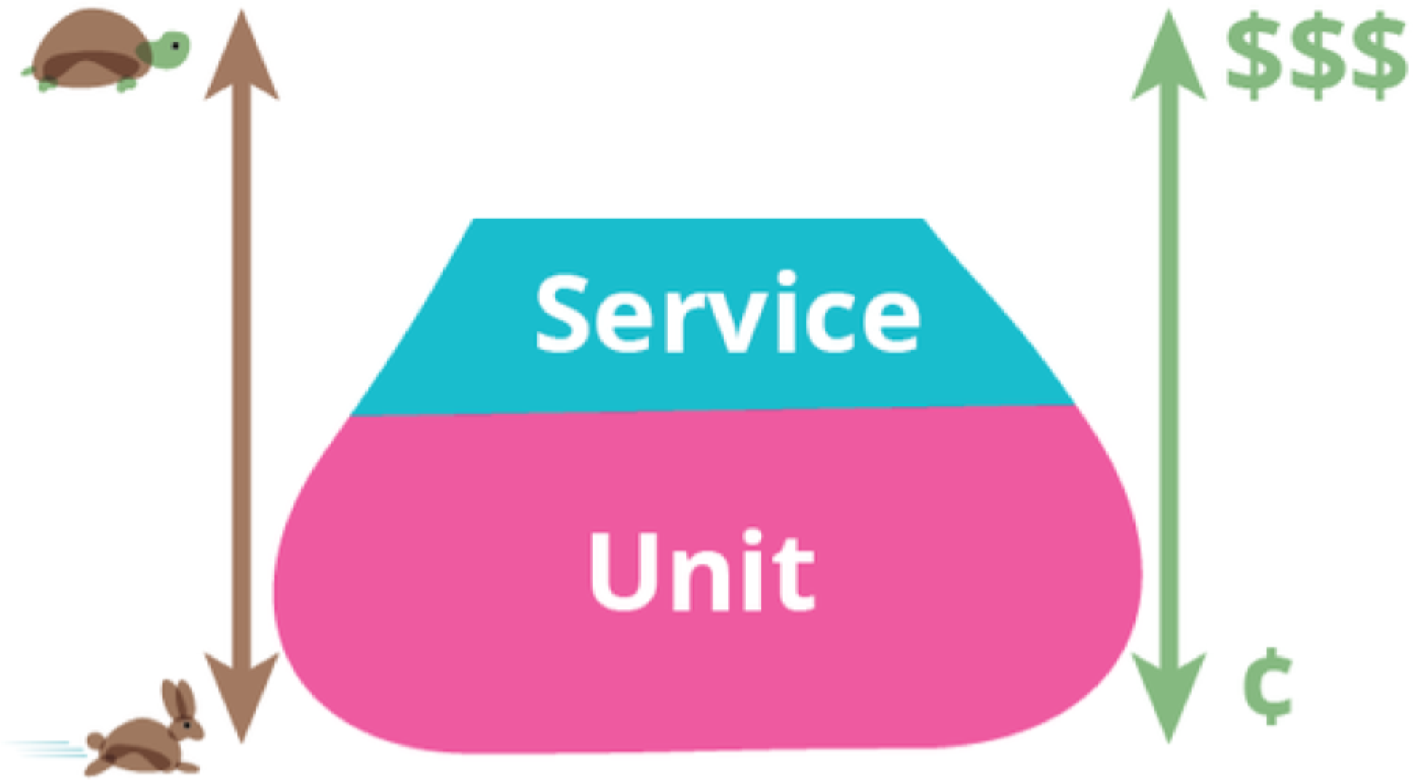

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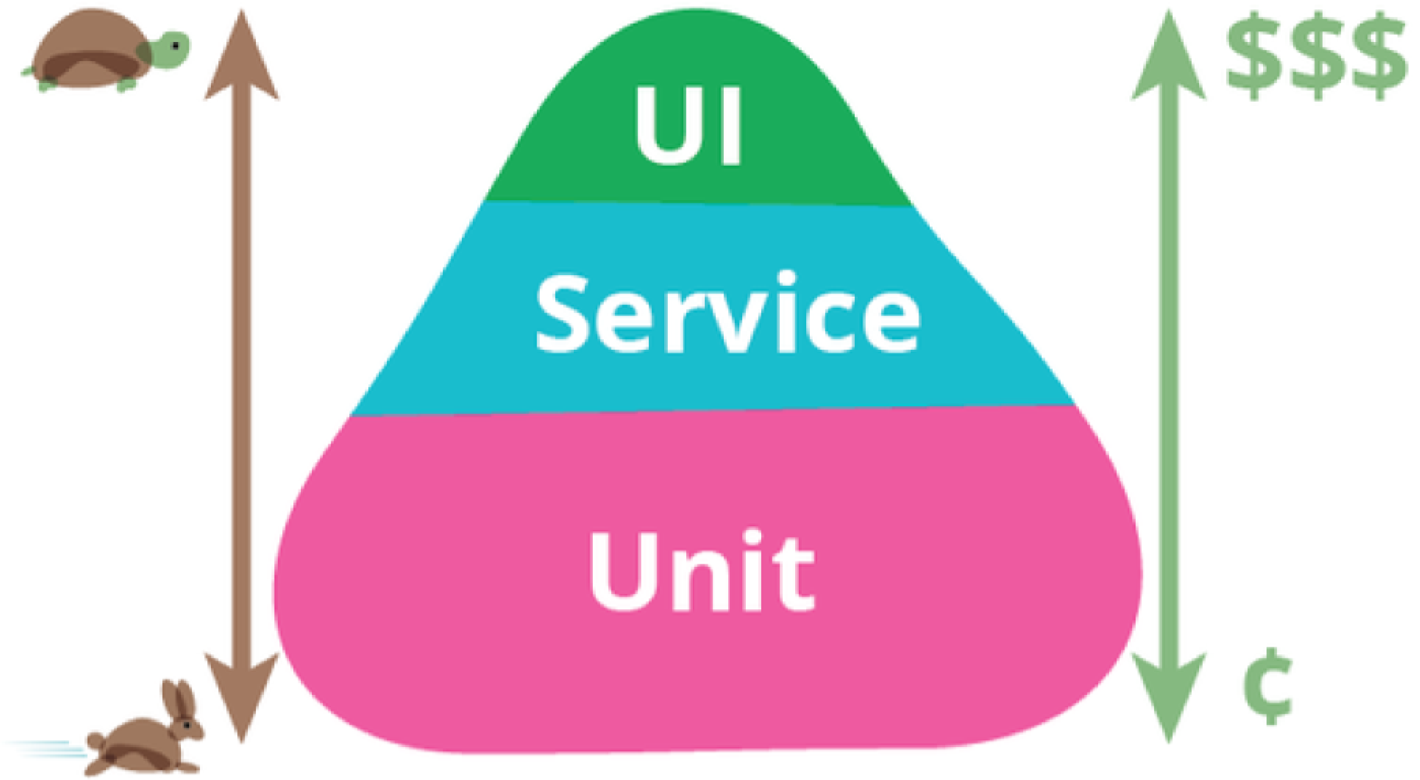

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Let's have this sink in!

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Writing unit tests for PySpark

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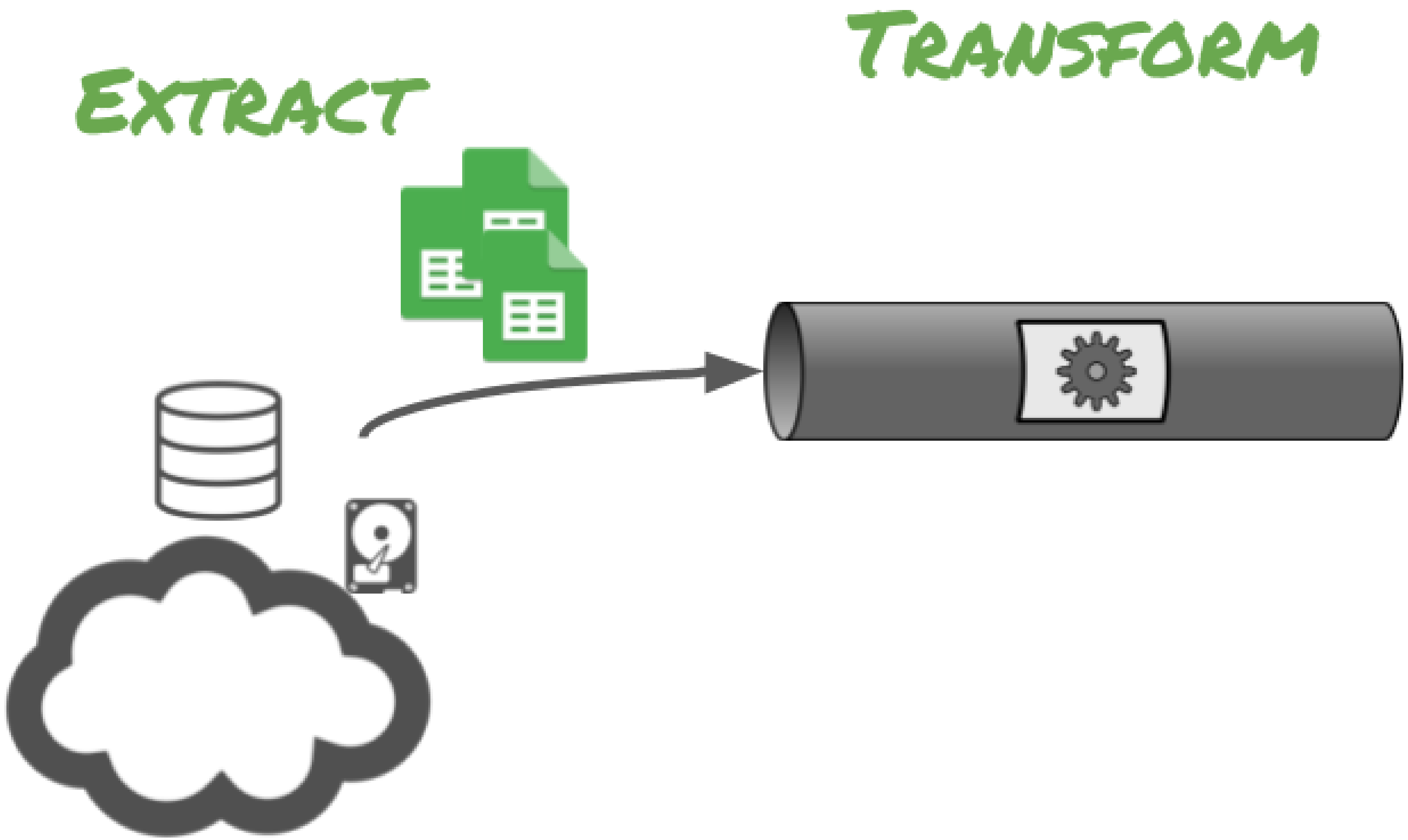

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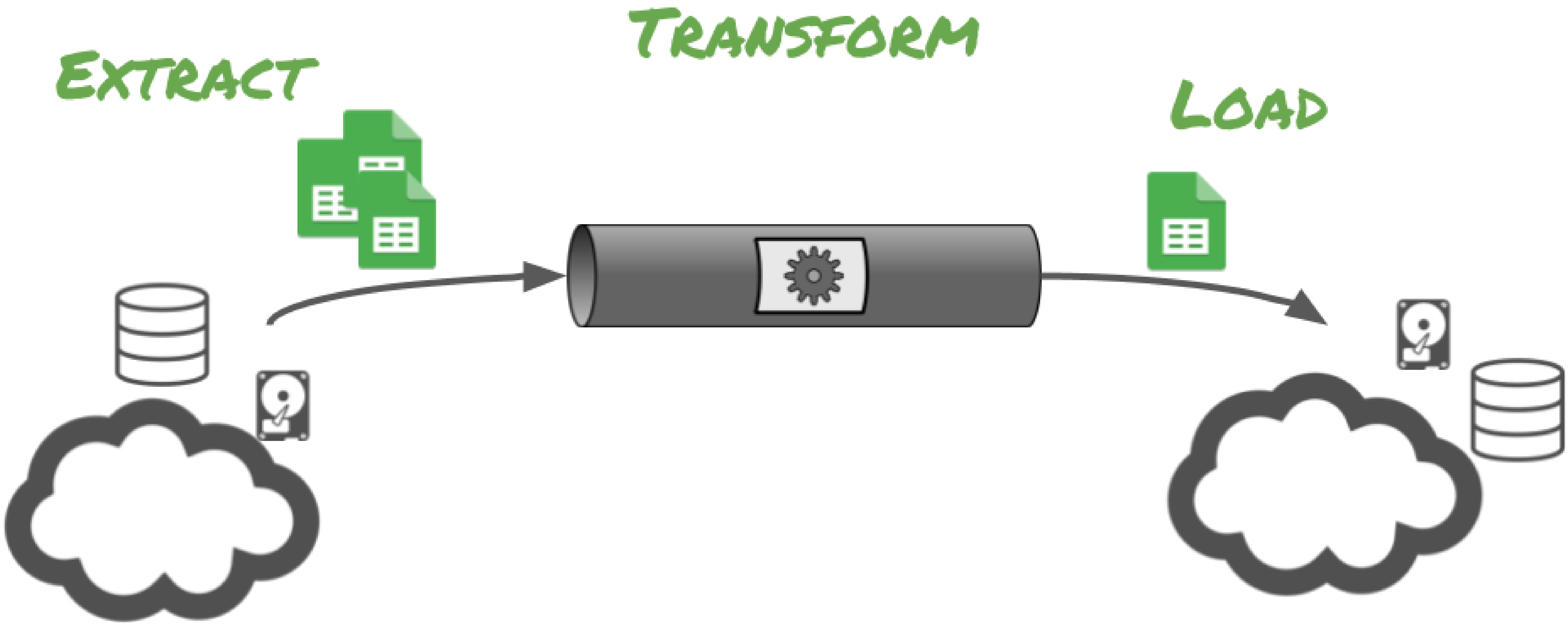
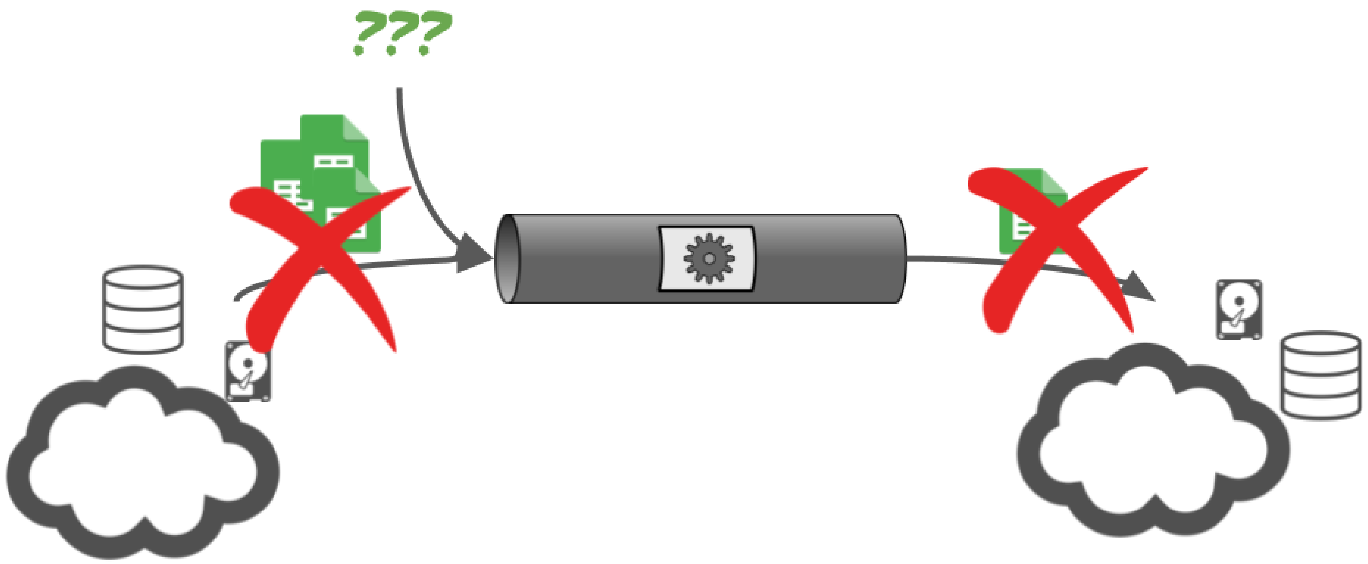


Separate transform from extract and load

```
prices_with_ratings = spark.read.csv(…)  # extract
exchange_rates = spark.read.csv(…)  # extract

unit_prices_with_ratings = (prices_with_ratings
                            .join(…) # transform
                            .withColumn(…))  # transform
```



Solution: construct DataFrames in-memory

```
# Extract the data
df = spark.read.csv(path_to_file)
```

- depends on input/output (network access, filesystem permissions, ...)
- unclear how big the data is
- unclear what data goes in

```
from pyspark.sql import Row
purchase = Row("price",
               "quantity",
               "product")
record = purchase(12.99, 1, "cake")
df = spark.createDataFrame((record,))
```

+ inputs are clear
+ data is close to where it is being used ("code-proximity")

Create small, reusable and well-named functions

```
unit_prices_with_ratings = (prices_with_ratings
                            .join(exchange_rates, ["currency", "date"])
                            .withColumn("unit_price_in_euro",
                                        col("price") / col("quantity")
                                        * col("exchange_rate_to_euro"))
```

```
def link_with_exchange_rates(prices, rates):
    return prices.join(rates, ["currency", "date"])

def calculate_unit_price_in_euro(df):
    return df.withColumn(
        "unit_price_in_euro",
        col("price") / col("quantity") * col("exchange_rate_to_euro"))
```

Create small, reusable and well-named functions

```python
def link_with_exchange_rates(prices, rates):
    return prices.join(rates, ["currency", "date"])

def calculate_unit_price_in_euro(df):
    return df.withColumn(
        "unit_price_in_euro",
        col("price") / col("quantity") * col("exchange_rate_to_euro"))
```

```python
unit_prices_with_ratings = (
  calculate_unit_price_in_euro(
    link_with_exchange_rates(prices, exchange_rates)
  )
)
```

Testing a single unit

```
def test_calculate_unit_price_in_euro():
    record = dict(price=10,
                  quantity=5,
                  exchange_rate_to_euro=2.)
    df = spark.createDataFrame([Row(**record)])
```

Testing a single unit

```
def test_calculate_unit_price_in_euro():
    record = dict(price=10,
                  quantity=5,
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    df = spark.createDataFrame([Row(**record)])
    result = calculate_unit_price_in_euro(df)
```

Testing a single unit

```python
def test_calculate_unit_price_in_euro():
    record = dict(price=10,
                  quantity=5,
                  exchange_rate_to_euro=2.)
    df = spark.createDataFrame([Row(**record)])
    result = calculate_unit_price_in_euro(df)

    expected_record = Row(**record, unit_price_in_euro=4.)
    expected = spark.createDataFrame([expected_record])
```

Testing a single unit

```
def test_calculate_unit_price_in_euro():
    record = dict(price=10,
                  quantity=5,
                  exchange_rate_to_euro=2.)
    df = spark.createDataFrame([Row(**record)])
    result = calculate_unit_price_in_euro(df)

    expected_record = Row(**record, unit_price_in_euro=4.)
    expected = spark.createDataFrame([expected_record])

    assertDataFrameEqual(result, expected)
```

Take home messages

1. Interacting with external data sources is costly
2. Creating in-memory DataFrames makes testing easier
   - the data is in plain sight,
   - focus is on just a small number of examples.
3. Creating small and well-named functions leads to more reusability and easier testing.

Let's practice!

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Continuous testing

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Running a test suite

Execute tests in Python, with one of:

in stdlib	3rd party
unittest	pytest
doctest	nose

Core task: **assert** or raise

Examples:

```
assert computed == expected
with pytest.raises(ValueError):  # pytest specific
```

Manually triggering tests

In a Unix shell:

```
cd ~/workspace/my_good_python_project
pytest .
# Lots of output…
== 19 passed, 2 warnings in 36.80 seconds ==
```

```
cd ~/workspace/my_bad_python_project
pytest .
# Lots of output…
== 3 failed, 1 passed in 6.72 seconds ==
```

Note: Spark increases time to run unit tests.

Automating tests

Problem:

- forget to run unit tests when making changes

Solution:

- Automation

How:

- Git -> configure hooks
- Configure CI/CD pipeline to run tests automatically

CI/CD

Continuous Integration:

- get code changes integrated with the master branch regularly.

Continuous Delivery:

- Create “artifacts” (deliverables like documentation, but also programs) that can be deployed into production without breaking things.

Configuring a CI/CD tool

CircleCI looks for *.circleci/config.yml*.

Example:

```
jobs:
  test:
    docker:
      - image: circleci/python:3.6.4
    steps:
      - checkout
      - run: pip install -r requirements.txt
      - run: pytest .
```

Often:

1. checkout code
2. install test & build requirements
3. run tests
4. package/build the software artefacts
5. deploy the artefacts (update docs / install app / ...)

Let's practice!

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