# Manually testing a data pipeline

ETL AND ELT IN PYTHON



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# Testing data pipelines

#### Data pipelines should be thoroughly tested

 Validate that data is extracted, transformed, and loaded as expected

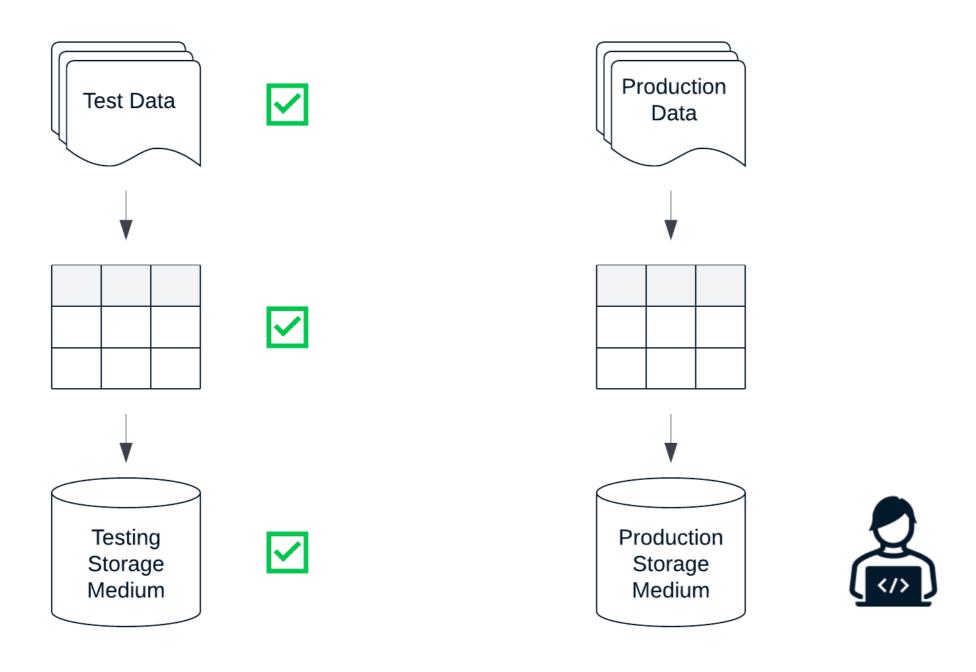
# Validating pipelines' limits maintenance efforts after deployment

- Identify and fix data quality issues
- Improves data reliability

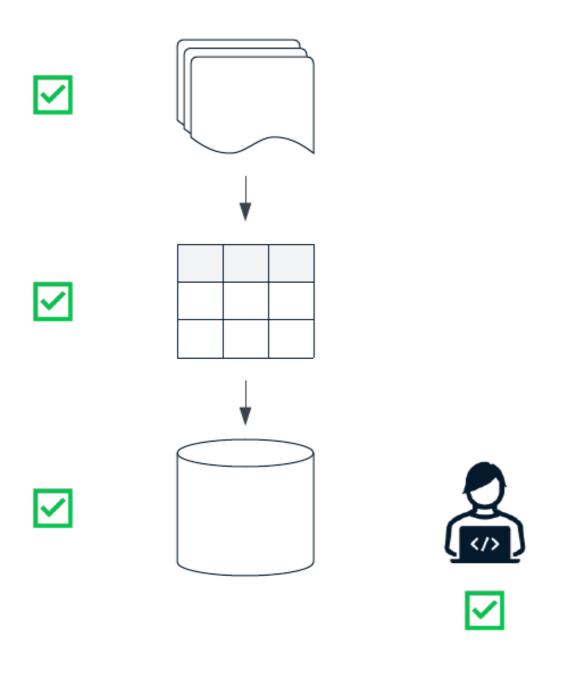
#### Tools and techniques to test data pipelines

- End-to-end testing
- Validating data at "checkpoints"
- Unit testing

# Testing and production environments



# Testing a pipeline end-to-end



#### **End-to-end testing**

- Confirm that pipeline runs on repeated attempts
- Validate data at pipeline checkpoints
- Engage in peer review, incorporate feedback
- Ensure consumer access and satisfaction with solution

# Validating pipeline checkpoints

```
# Extract, transform, and load data as part of a pipeline
...

# Take a look at the data made available in a Postgres database
loaded_data = pd.read_sql("SELECT * FROM clean_stock_data", con=db_engine)
print(loaded_data.shape)
```

```
(6438, 4)
```

```
print(loaded_data.head())
```

```
timestamps volume open close
1997-05-15 13:30:00 1443120000 0.121875 0.097917
1997-05-16 13:30:00 294000000 0.098438 0.086458
1997-05-19 13:30:00 122136000 0.088021 0.085417
```



# Validating DataFrames

```
# Extract, transform, and load data, as part of a pipeline
...

# Take a look at the data made available in a Postgres database
loaded_data = pd.read_sql("SELECT * FROM clean_stock_data", con=db_engine)

# Compare the two DataFrames.
print(clean_stock_data.equals(loaded_data))
```

True

# Let's practice!

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# Unit-testing a data pipeline

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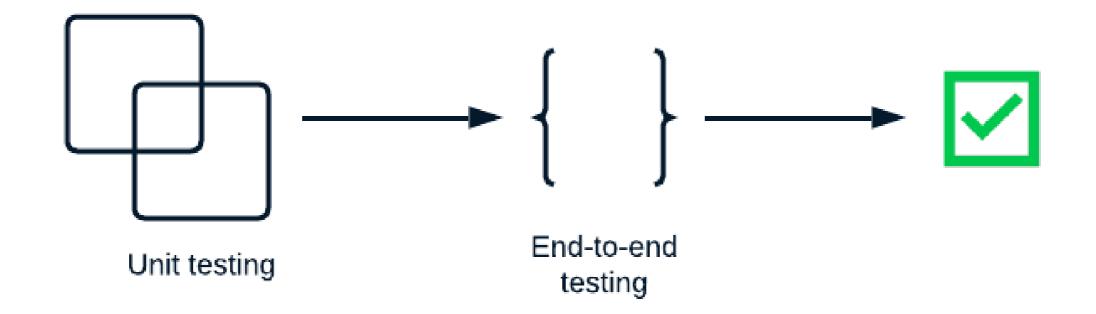
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# Validating a data pipeline with unit tests

#### Unit tests:

- Commonly used in software engineering workflows
- Ensure code works as expected
- Help to validate data



# pytest for unit testing

```
from pipeline import extract, transform, load

# Build a unit test, asserting the type of clean_stock_data
def test_transformed_data():
    raw_stock_data = extract("raw_stock_data.csv")
    clean_stock_data = transform(raw_data)
    assert isinstance(clean_stock_data, pd.DataFrame)
```

#### assert and isinstance

```
pipeline_type = "ETL"

# Check if pipeline_type is an instance of a str
isinstance(pipeline_type, str)
```

#### True

```
# Assert that the pipeline does indeed take value "ETL"

assert pipeline_type == "ETL"

# Combine assert and isinstance
assert isinstance(pipeline_type, str)
```

#### AssertionError

```
pipeline_type = "ETL"

# Create an AssertionError
assert isinstance(pipeline_type, float)
```

```
Traceback (most recent call last):
   File "<stdin>", line 4, in <module>
AssertionError
```

# Mocking data pipeline components with fixtures

```
import pytest
@pytest.fixture()
def clean_data():
    raw_stock_data = extract("raw_stock_data.csv")
    clean_stock_data = transform(raw_data)
    return clean_stock_data
def test_transformed_data(clean_data):
    assert isinstance(clean_data, pd.DataFrame)
```

# Unit testing DataFrames

```
def test_transformed_data(clean_data):
    # Include other assert statements here
    # Check number of columns
    assert len(clean_data.columns) == 4
    # Check the lower bound of a column
    assert clean_data["open"].min() >= 0
    # Check the range of a column by chaining statements with "and"
    assert clean_data["open"].min() >= 0 and clean_data["open"].max() <= 1000</pre>
```

# Let's practice!

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# Running a data pipeline in production

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### Data pipeline architecture patterns

```
# Define ETL function
...

def load(clean_data):
...

# Run the data pipeline
raw_stock_data = extract("raw_stock_data.csv")
clean_stock_data = transform(raw_stock_data)
load(clean_stock_data)
```

```
> ls
etl_pipeline.py
```

```
# Import extract, transform, and load functions
from pipeline_utils import extract, transform, load

# Run the data pipeline
raw_stock_data = extract("raw_stock_data.csv")
clean_stock_data = transform(raw_stock_data)
load(clean_stock_data)
```

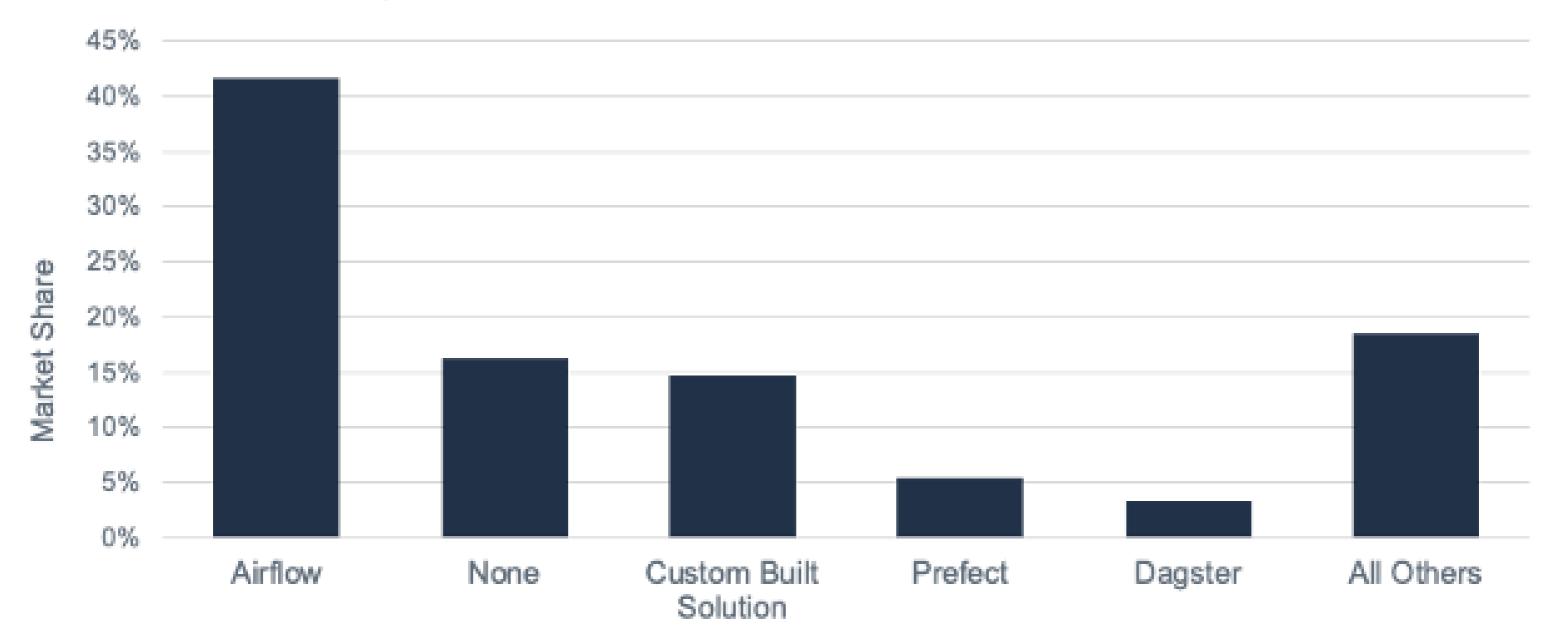
```
> ls
  etl_pipeline.py
  pipeline_utils.py
```

# Running a data pipeline end-to-end

```
import logging
from pipeline_utils import extract, transform, load
logging.basicConfig(format='%(levelname)s: %(message)s', level=logging.DEBUG)
try:
   # Extract, transform, and load data
    raw_stock_data = extract("raw_stock_data.csv")
    clean_stock_data = transform(raw_stock_data)
    load(clean stock data)
    logging.info("Successfully extracted, transformed and loaded data.") # Log success message
# Handle exceptions, log messages
except Exception as e:
    logging.error(f"Pipeline failed with error: {e}")
```



# Orchestrating data pipelines in production



<sup>&</sup>lt;sup>1</sup> https://open.substack.com/pub/seattledataguy/p/the-state-of-data-engineering-part? r=1po78c&utm\_campaign=post&utm\_medium=web



# Let's practice!

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# Congratulations!

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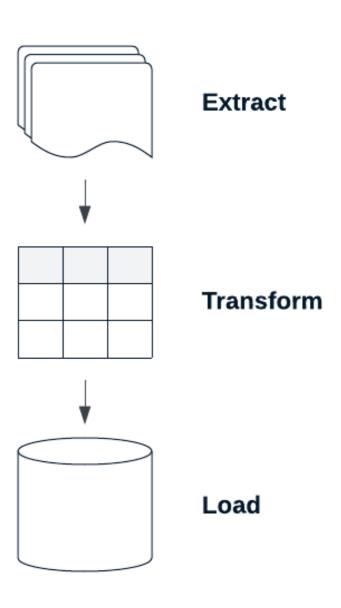


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# Designing and building data pipelines

- Designing sound data pipelines
- Extract, transform, and load architecture
- Exception handling and logging



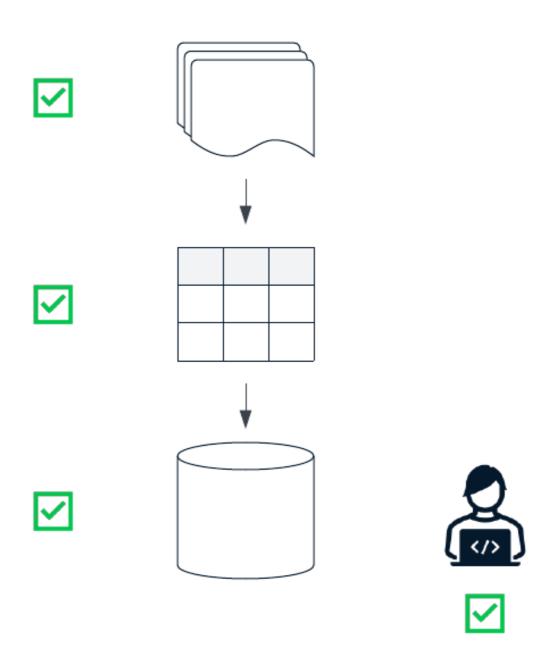
## Advanced ETL techniques

- Handling nested JSON
- Advanced transformation logic
- Persisting data to SQL databases

```
{
    "863703000": {
        "volume": 1443120000,
        "price": {
             "close": 0.09791,
             "open": 0.12187
        }
    },
    ...
}
```

# Deploying and maintaining data pipelines

- Validate and test data pipelines
- Running a pipeline in a production setting
- Orchestration tools



## Next steps









- Introduction to Airflow in Python Course
- Data Engineer Career Track
- Associate Data Engineer Certification

- Apache Airflow
- Astronomer
- Snowflake

# Thank you! ETL AND ELT IN PYTHON

