https://github.com/pyladiesams/kedro-prod-ready-ds-pipelines-aug2025

kedro

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Data science that ships: production-ready pipelines with Kedro

Merel Theisen for PyLadies Amsterdam

26th of August 2025

Agenda

1. About me
2. Common challenges for data practitioners
3. Intro to Kedro
4. Modularity
5. Separation of concerns
6. Maintainability
7. Q&A

About me

- Pronouns: she/her ⭐
- I’m from the Netherlands NL

- I’ve been working as a Software Engineer for 9 years 👩‍💻
- Currently Principal Software Engineer at QuantumBlack ✨
- I’ve been the tech lead for Kedro for over 3 years 🚀

Contact
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01

Common challenges for data practitioners

Under-engineering refers to building with reduced complexity resulting in a less robust, efficient and capable product. It happens because of tight deadlines or because of a lack of expertise.

We under-engineer data science experiments & create code with a lot of technical debt

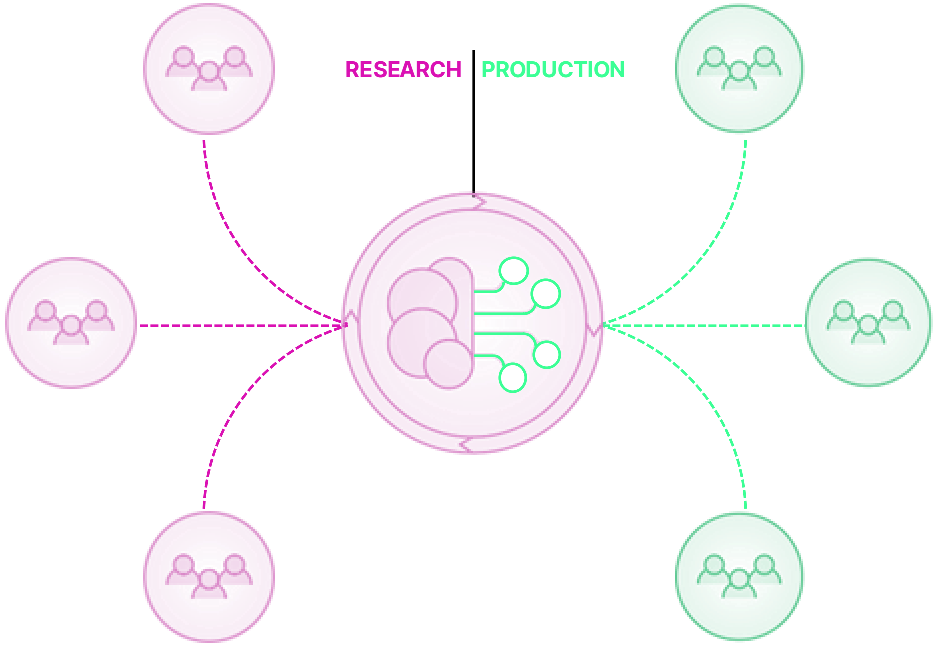
Technical debt is intentional or accidental decisions that make code difficult to understand, maintain, extend and fix. Much like a loan, you pay a higher cost later, because it decreases the team's agility as the project matures.

How do we *usually* pay off this technical debt?

Data scientists handover code to data & machine-learning engineers

> “Part of the context is that I may fall slightly on the less technical side, so I have been mainly working out of notebooks and relying on data engineers to productionalise code.”

DATA SCIENTIST AT A MAJOR PHARMACEUTICAL COMPANY



Data Scientists

Anyone that gets to create data science experiments in the research phase

Data & ML Engineers

Anyone that must overhaul data science experiments produced in the research phase

LF AI & DATA

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The challenges of creating machine learning products

A workflow beyond notebooks
still has challenges

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"Data scientists have to learn so many tools to create high-quality code."

"I have to think about Sphinx, flake8, isort, black, Cookiecutter Data Science, Docker, Python Logging, virtual environments, Pytest, configuration and more ."

"I spend a lot of time trying to understand a codebase that I didn't write."

"It's tedious to always setup documentation and code quality tooling my project."

"Everyone works in different ways."

"It takes really long to put code in production and we have to rewrite and restructure large parts of it."

"My code will not run on another person's machine."

"No one wants to use the framework I created."

"We all have different levels of exposure to software engineering best-practice."

"It's an approach or process that's understood to help build software that's superior in terms of speed of execution, shipping with higher quality, or building more maintainable code."

GERGELY OROSZ,
AUTHOR OF THE PRAGMATIC ENGINEER

02

Intro to Kedro

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Kedro

An open-source Python toolbox that applies software engineering principles to data science code, making it easier to transition from prototype to production.

FOUNDED IN

2017

STATUS

LF AI & DATA
GRADUATE PROJECT

Benefits

Reduces the time spent rewriting data science experiments so that they are fit for production.

Encourage **harmonious team collaboration** and improve productivity.

Upskills all collaborators on how to apply software engineering principles to data science code.

+10,000
GITHUB STARS

+500,000
MONTHLY DOWNLOADS

+29,000,000
PIPELINE RUNS IN 2023

Enterprise adoption

tomtom

Johnson & Johnson

Santander

Rabobank

Telkomsel

Beamery

AXA NASA Roche

Developed by

QuantumBlack AI by McKinsey

Printify

dagster

SOCIETE GENERALE

ING

We built Kedro to reduce technical debt in data science experiments, making an easier transition from experimentation to production

What does Kedro give you?

Project Template

Inspired by Cookiecutter Data Science

Data Catalog

Our core declarative IO abstraction layer

Nodes + Pipelines

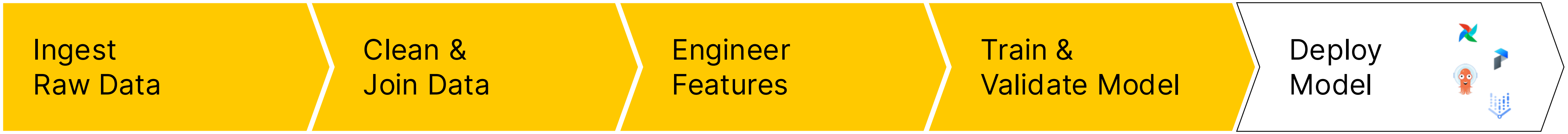
Constructs which enable data-centric workflows

Run status visualisation

Constructs to facilitate debugging

Extensibility

Inherit, hook in or plug-in to make Kedro work for you



ZONE OF INFLUENCE

03

The workshop project

https://github.com/pyladiesams/kedro-prod-ready-ds-pipelines-aug2025

Example project

Scenario

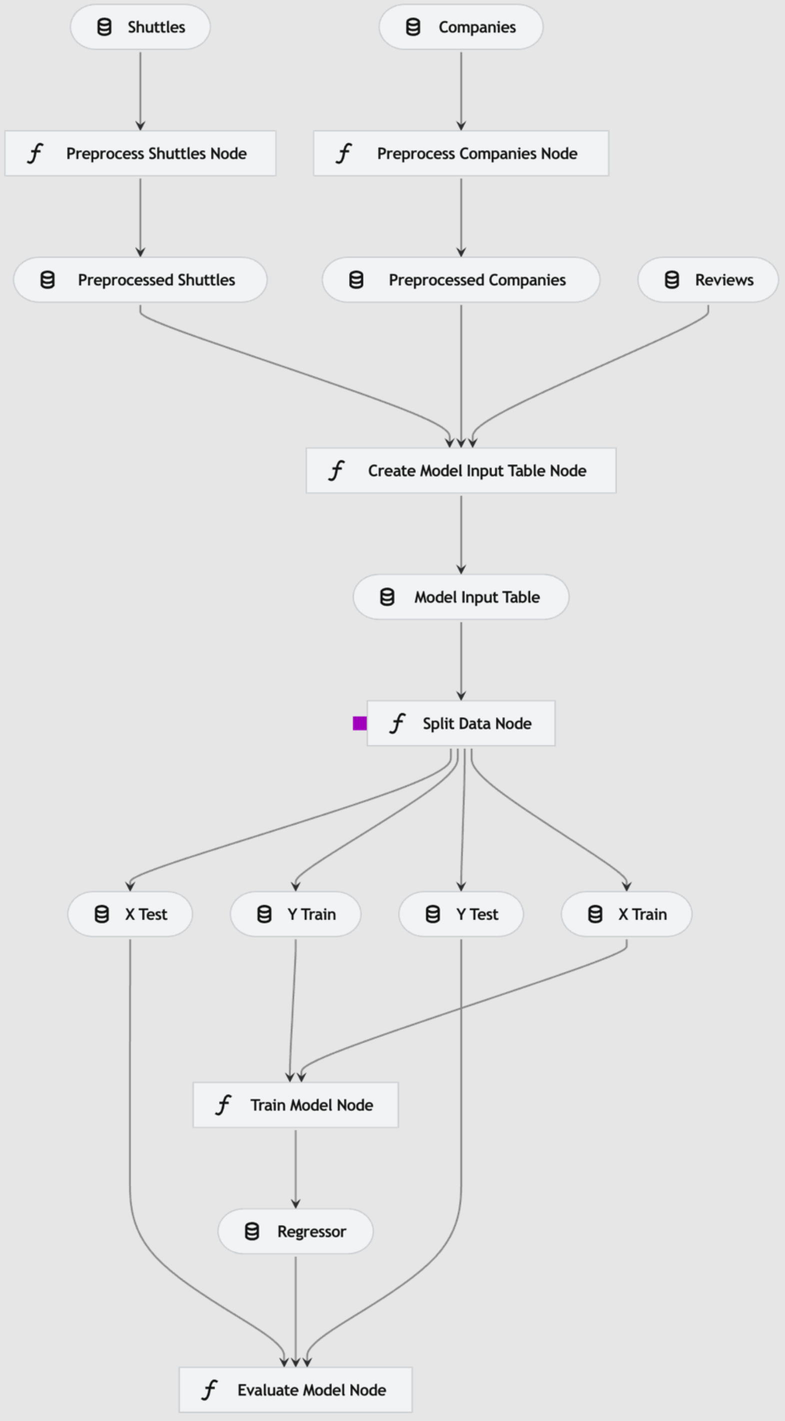
The year is 2160 and the space tourism industry is booming.

There are thousands of space shuttle companies taking tourists to the Moon and back.

You have been able to source amenities offered in each space shuttle, customer reviews and company information.

Goal

Build a model to estimate the price of a return trip.



04

Modularity

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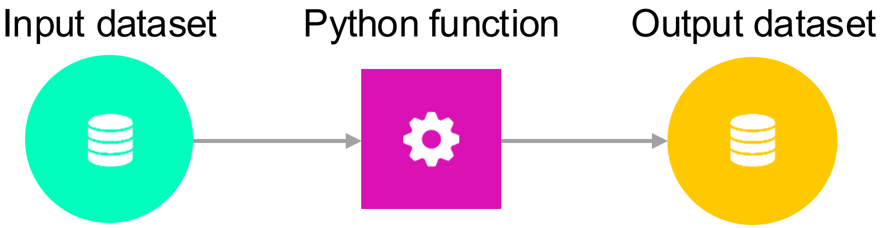
Modularity

- Breaking down a complex software system into smaller, independent modules.
- Each module is responsible for a specific function or feature and operates independently.
- Modules should be loosely coupled, meaning that they should not depend on each other too much.
- Enhanced readability and understandability of the system
- Allows for reusability
- Easier collaboration
- Makes it easier to test smaller chunks, which can be faster and help find bugs

Nodes & Pipelines

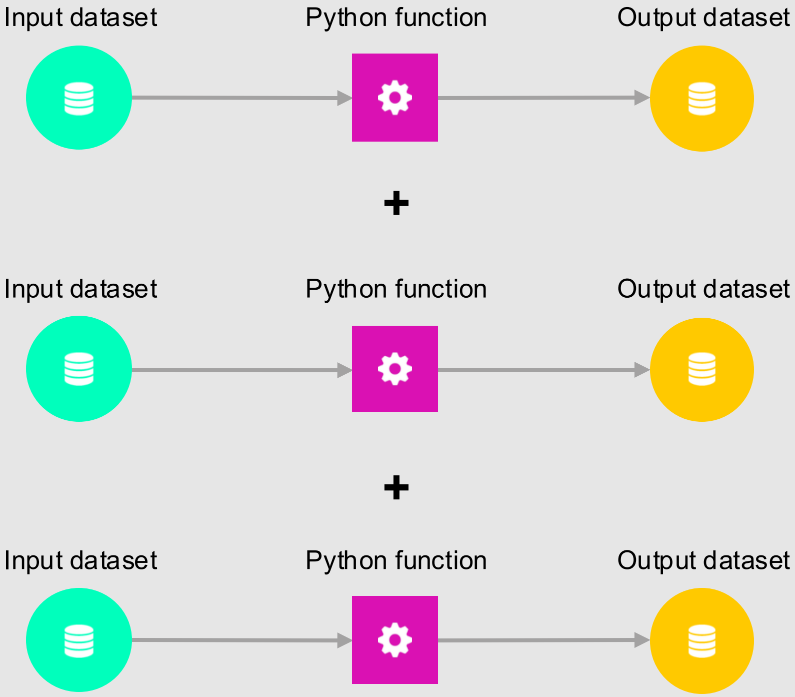
What is a node?

- A pure Python function that has an input and an output.
- Node definition supports multiple inputs for things like table joins and multiple outputs for things like producing a train/test split.



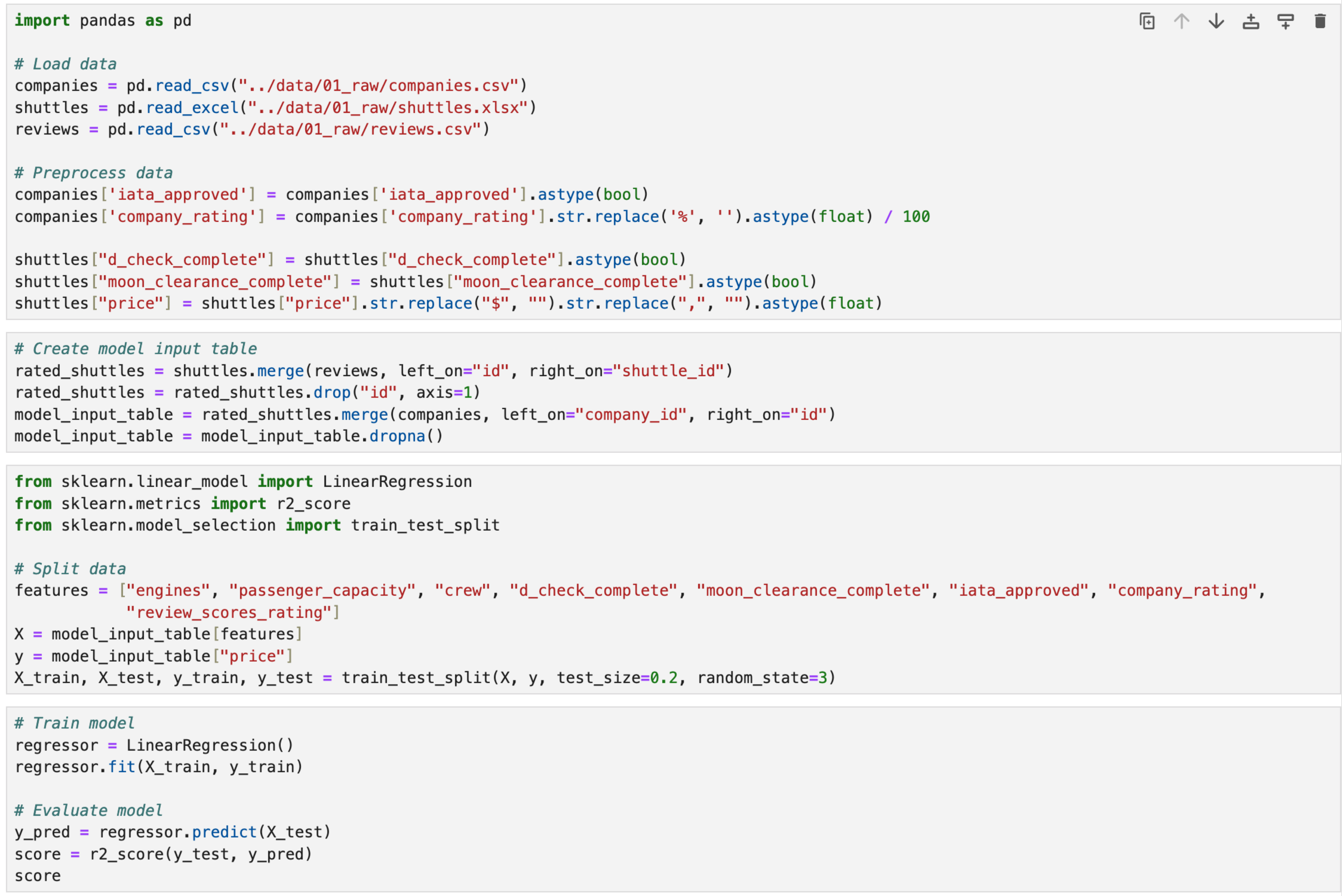
What is a pipeline?

- It is a directed acyclic graph.
- A collection of nodes with defined relationships and dependencies.



Example data science project

Before refactoring



```python
import pandas as pd

# Load data
companies = pd.read_csv("../data/01_raw/companies.csv")
shuttles = pd.read_excel("../data/01_raw/shuttles.xlsx")
reviews = pd.read_csv("../data/01_raw/reviews.csv")

# Preprocess data
companies['iata_approved'] = companies['iata_approved'].astype(bool)
companies['company_rating'] = companies['company_rating'].str.replace('%', '').astype(float) / 100

shuttles["d_check_complete"] = shuttles["d_check_complete"].astype(bool)
shuttles["moon_clearance_complete"] = shuttles["moon_clearance_complete"].astype(bool)
shuttles["price"] = shuttles["price"].str.replace("$", "").str.replace(",", "").astype(float)
```

```python
# Create model input table
rated_shuttles = shuttles.merge(reviews, left_on="id", right_on="shuttle_id")
rated_shuttles = rated_shuttles.drop("id", axis=1)
model_input_table = rated_shuttles.merge(companies, left_on="company_id", right_on="id")
model_input_table = model_input_table.dropna()
```

```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split

# Split data
features = ["engines", "passenger_capacity", "crew", "d_check_complete", "moon_clearance_complete", "iata_approved", "company_rating",
            "review_scores_rating"]
X = model_input_table[features]
y = model_input_table["price"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=3)
```

```python
# Train model
regressor = LinearRegression()
regressor.fit(X_train, y_train)

# Evaluate model
y_pred = regressor.predict(X_test)
score = r2_score(y_test, y_pred)
score
```

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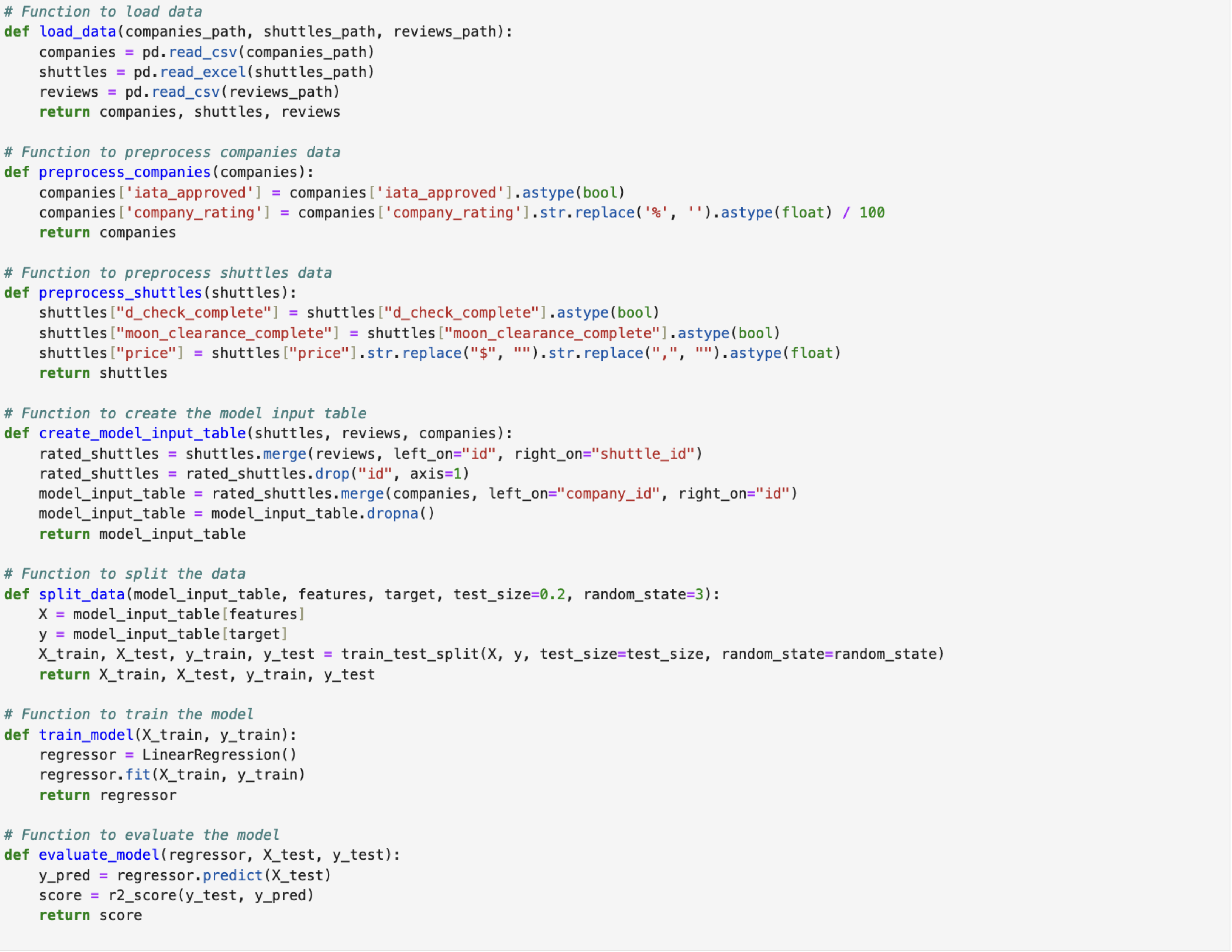
Example with modularity

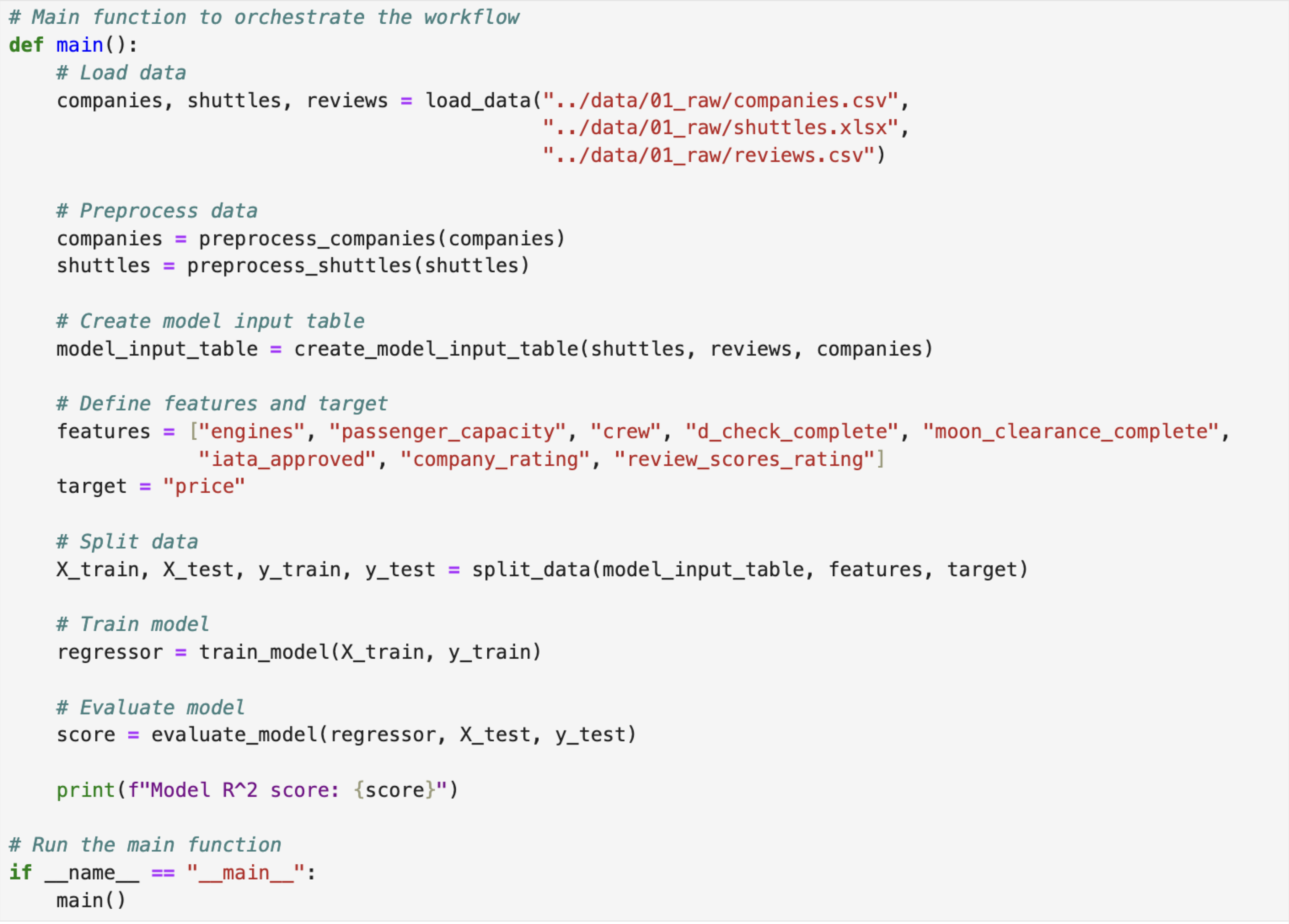
Code separated into functions



```python
# Function to load data
def load_data(companies_path, shuttles_path, reviews_path):
    companies = pd.read_csv(companies_path)
    shuttles = pd.read_excel(shuttles_path)
    reviews = pd.read_csv(reviews_path)
    return companies, shuttles, reviews

# Function to preprocess companies data
def preprocess_companies(companies):
    companies['iata_approved'] = companies['iata_approved'].astype(bool)
    companies['company_rating'] = companies['company_rating'].str.replace('%', '').astype(float) / 100
    return companies

# Function to preprocess shuttles data
def preprocess_shuttles(shuttles):
    shuttles["d_check_complete"] = shuttles["d_check_complete"].astype(bool)
    shuttles["moon_clearance_complete"] = shuttles["moon_clearance_complete"].astype(bool)
    shuttles["price"] = shuttles["price"].str.replace("$", "").str.replace(",", "").astype(float)
    return shuttles

# Function to create the model input table
def create_model_input_table(shuttles, reviews, companies):
    rated_shuttles = shuttles.merge(reviews, left_on="id", right_on="shuttle_id")
    rated_shuttles = rated_shuttles.drop("id", axis=1)
    model_input_table = rated_shuttles.merge(companies, left_on="company_id", right_on="id")
    model_input_table = model_input_table.dropna()
    return model_input_table

# Function to split the data
def split_data(model_input_table, features, target, test_size=0.2, random_state=3):
    X = model_input_table[features]
    y = model_input_table[target]
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size, random_state=random_state)
    return X_train, X_test, y_train, y_test

# Function to train the model
def train_model(X_train, y_train):
    regressor = LinearRegression()
    regressor.fit(X_train, y_train)
    return regressor

# Function to evaluate the model
def evaluate_model(regressor, X_test, y_test):
    y_pred = regressor.predict(X_test)
    score = r2_score(y_test, y_pred)
    return score
```

Example with modularity

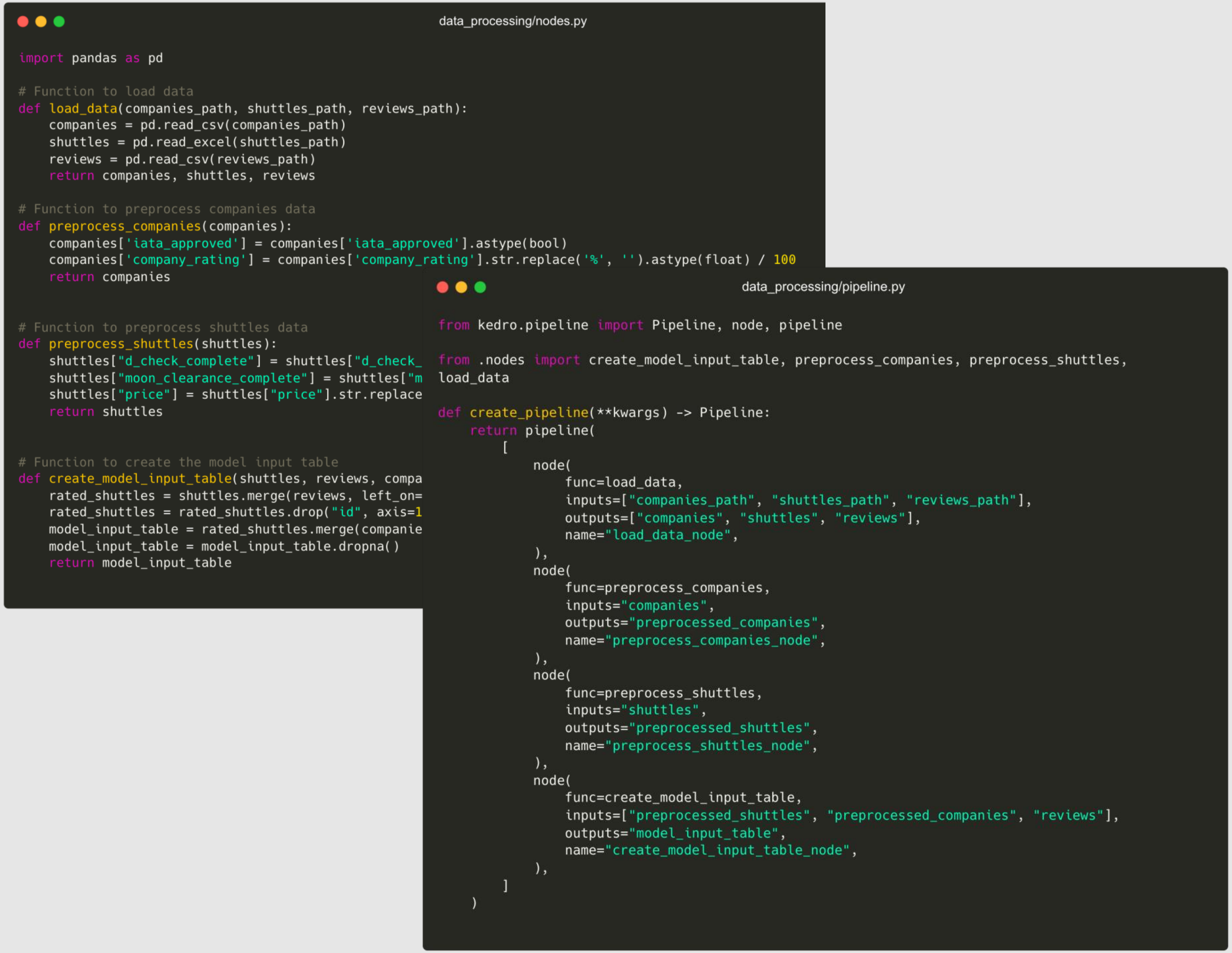
Main method that calls all functions



```python
# Main function to orchestrate the workflow
def main():
    # Load data
    companies, shuttles, reviews = load_data("../data/01_raw/companies.csv",
                                             "../data/01_raw/shuttles.xlsx",
                                             "../data/01_raw/reviews.csv")

    # Preprocess data
    companies = preprocess_companies(companies)
    shuttles = preprocess_shuttles(shuttles)

    # Create model input table
    model_input_table = create_model_input_table(shuttles, reviews, companies)

    # Define features and target
    features = ["engines", "passenger_capacity", "crew", "d_check_complete", "moon_clearance_complete",
                "iata_approved", "company_rating", "review_scores_rating"]
    target = "price"

    # Split data
    X_train, X_test, y_train, y_test = split_data(model_input_table, features, target)

    # Train model
    regressor = train_model(X_train, y_train)

    # Evaluate model
    score = evaluate_model(regressor, X_test, y_test)

    print(f"Model R^2 score: {score}")

# Run the main function
if __name__ == "__main__":
    main()
```

Example with modularity in Kedro

Using nodes and pipeline to structure the functions



data_processing/nodes.py

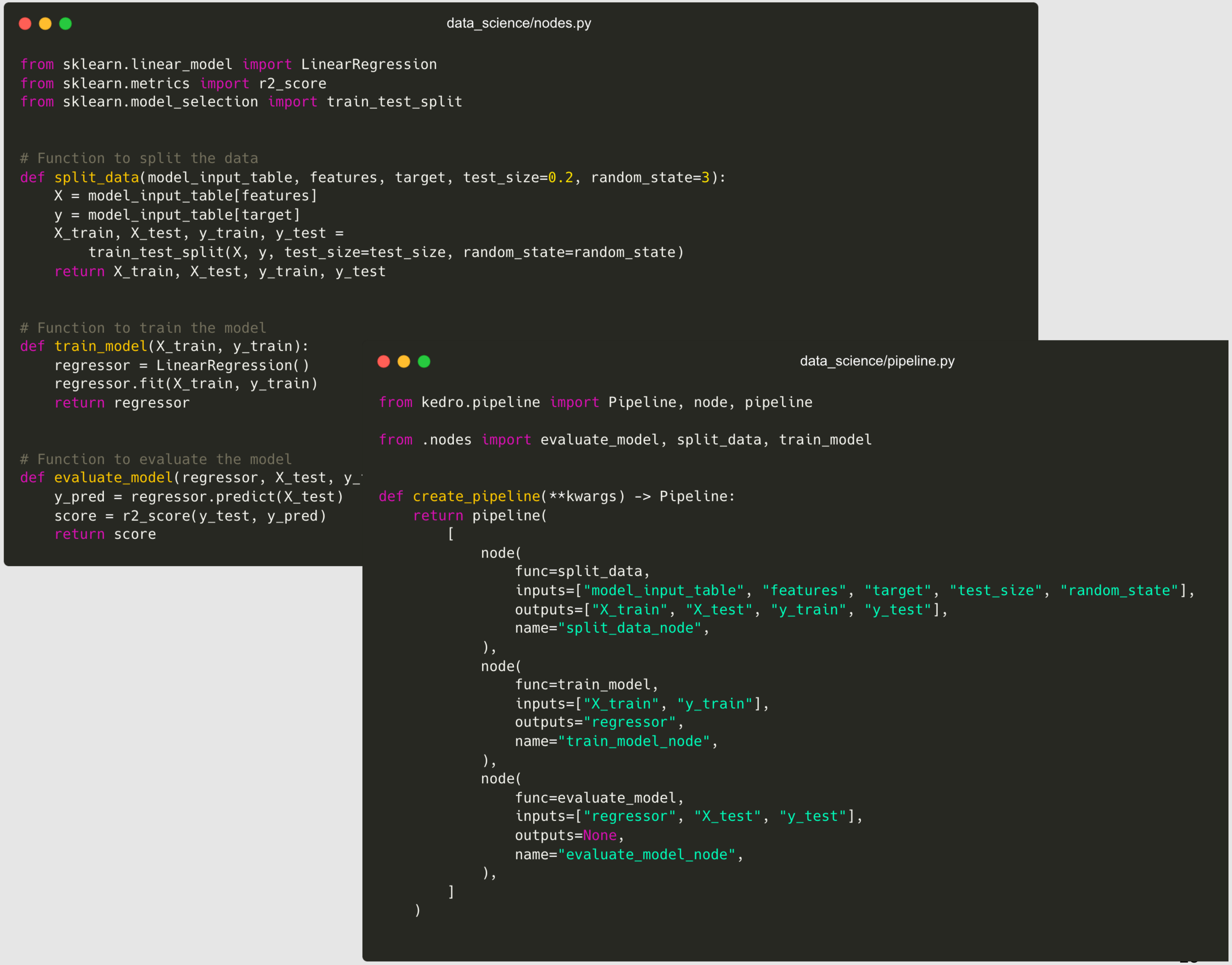
```python
import pandas as pd

# Function to load data
def load_data(companies_path, shuttles_path, reviews_path):
    companies = pd.read_csv(companies_path)
    shuttles = pd.read_excel(shuttles_path)
    reviews = pd.read_csv(reviews_path)
    return companies, shuttles, reviews

# Function to preprocess companies data
def preprocess_companies(companies):
    companies['iata_approved'] = companies['iata_approved'].astype(bool)
    companies['company_rating'] = companies['company_rating'].str.replace('%', '').astype(float) / 100
    return companies


# Function to preprocess shuttles data
def preprocess_shuttles(shuttles):
    shuttles["d_check_complete"] = shuttles["d_check_
    shuttles["moon_clearance_complete"] = shuttles["m
    shuttles["price"] = shuttles["price"].str.replace
    return shuttles


# Function to create the model input table
def create_model_input_table(shuttles, reviews, compa
    rated_shuttles = shuttles.merge(reviews, left_on=
    rated_shuttles = rated_shuttles.drop("id", axis=1
    model_input_table = rated_shuttles.merge(companie
    model_input_table = model_input_table.dropna()
    return model_input_table
```

data_processing/pipeline.py

```python
from kedro.pipeline import Pipeline, node, pipeline

from .nodes import create_model_input_table, preprocess_companies, preprocess_shuttles,
load_data

def create_pipeline(**kwargs) -> Pipeline:
    return pipeline(
        [
            node(
                func=load_data,
                inputs=["companies_path", "shuttles_path", "reviews_path"],
                outputs=["companies", "shuttles", "reviews"],
                name="load_data_node",
            ),
            node(
                func=preprocess_companies,
                inputs="companies",
                outputs="preprocessed_companies",
                name="preprocess_companies_node",
            ),
            node(
                func=preprocess_shuttles,
                inputs="shuttles",
                outputs="preprocessed_shuttles",
                name="preprocess_shuttles_node",
            ),
            node(
                func=create_model_input_table,
                inputs=["preprocessed_shuttles", "preprocessed_companies", "reviews"],
                outputs="model_input_table",
                name="create_model_input_table_node",
            ),
        ]
    )
```

Example with modularity in Kedro

Using nodes and pipeline to structure the functions



data_science/nodes.py

```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split


# Function to split the data
def split_data(model_input_table, features, target, test_size=0.2, random_state=3):
    X = model_input_table[features]
    y = model_input_table[target]
    X_train, X_test, y_train, y_test =
        train_test_split(X, y, test_size=test_size, random_state=random_state)
    return X_train, X_test, y_train, y_test


# Function to train the model
def train_model(X_train, y_train):
    regressor = LinearRegression()
    regressor.fit(X_train, y_train)
    return regressor


# Function to evaluate the model
def evaluate_model(regressor, X_test, y_
    y_pred = regressor.predict(X_test)
    score = r2_score(y_test, y_pred)
    return score
```

data_science/pipeline.py

```python
from kedro.pipeline import Pipeline, node, pipeline

from .nodes import evaluate_model, split_data, train_model


def create_pipeline(**kwargs) -> Pipeline:
    return pipeline(
        [
            node(
                func=split_data,
                inputs=["model_input_table", "features", "target", "test_size", "random_state"],
                outputs=["X_train", "X_test", "y_train", "y_test"],
                name="split_data_node",
            ),
            node(
                func=train_model,
                inputs=["X_train", "y_train"],
                outputs="regressor",
                name="train_model_node",
            ),
            node(
                func=evaluate_model,
                inputs=["regressor", "X_test", "y_test"],
                outputs=None,
                name="evaluate_model_node",
            ),
        ]
    )
```

05

Separation of concerns

Separation of concerns

- Different parts of software system should be designed to address different concerns
  - E.g. separate user interaction layer, data access layer and business logic layer
- Separation of concerns helps to improve the readability, understandability, and maintainability of software systems.
- It also makes it easier to change and evolve the system over time.

Configuration

Parameters

Parameters for machine learning models, such as learning rate, number of iterations and train/test split.

Hyperparameters

Hyperparameters for deep learning models, such as number of layers and number of neurons.

Experiment

Experiment configuration, such as the number of trials, the random seed, and the logging level.

Location of Input Data

Paths to files and directories, so the code knows where to find the data it needs. Also specify required columns or filters.

Credentials

Connection information for databases and other data sources, such as server address and credentials.

Location of Output Results

Output settings, such as the directory for saving the results, file format, and level of verbosity.

What is configuration?

- “Settings” for your machine-learning code
- A way to define requirements for data, logging and parameters in different environments
- Helps keep credentials out of your code base
- Keep all parameters in one place

What does configuration help you do?

- Machine learning code that transitions from prototype to production with little effort
- Makes it possible to write generalisable and reusable analytics code that does not require significant modification to be used

🟪 **EXPERIMENT OR MODEL**

🟩 **DATA ACCESS**

Data catalog

What is the Catalog?

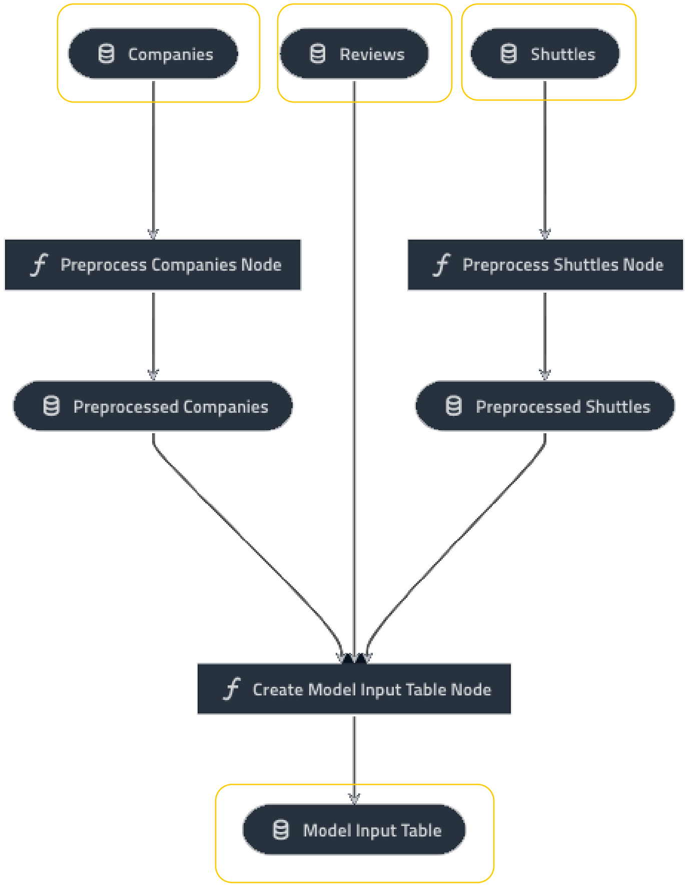
- Manages the loading and saving of your data
- Available as a code or YAML API
- Versioning is available for file-based systems every time the pipeline runs

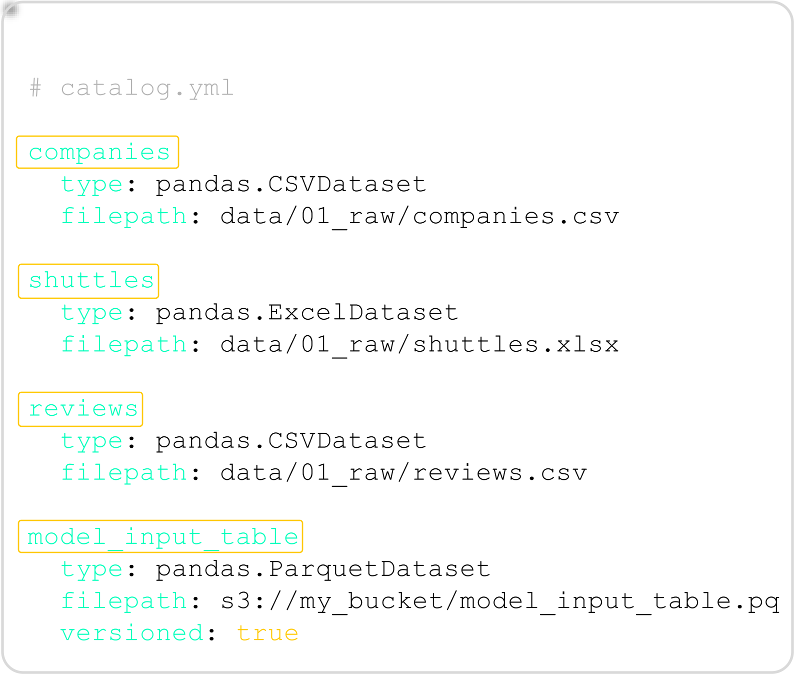
What does the Catalog help you do?

- Never write a single line of code that would read or write to a file, database or storage system
- Makes it possible to write generalisable and reusable analytics code that does not require significant modification to be used
- Access data without leaking credentials

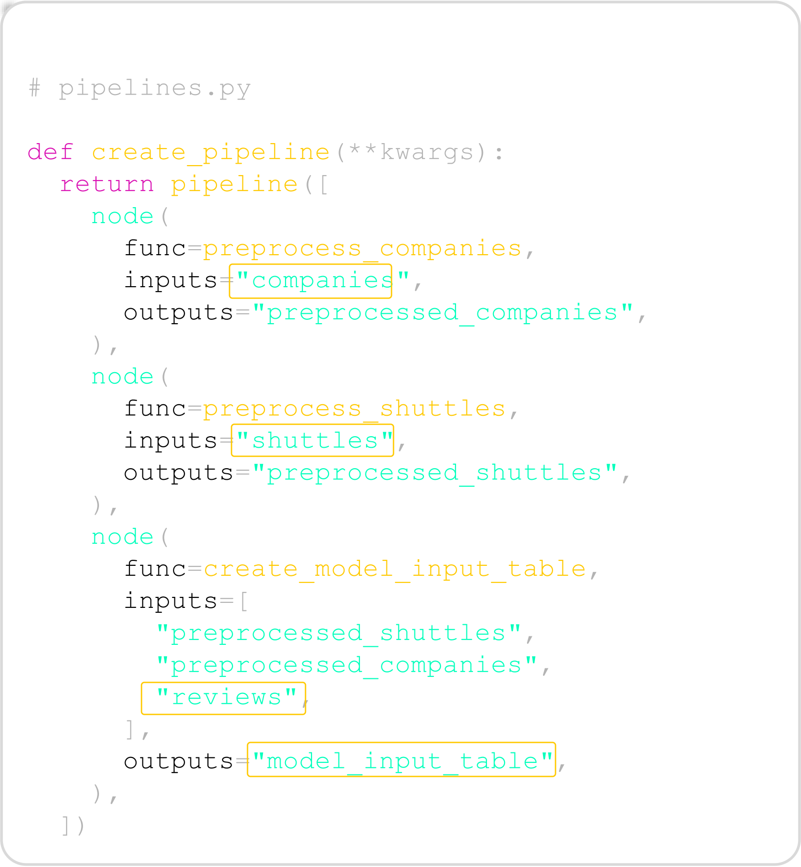
Kedro connects datasets and nodes through pipelines

Nodes are normal Python functions and datasets are declared in YAML





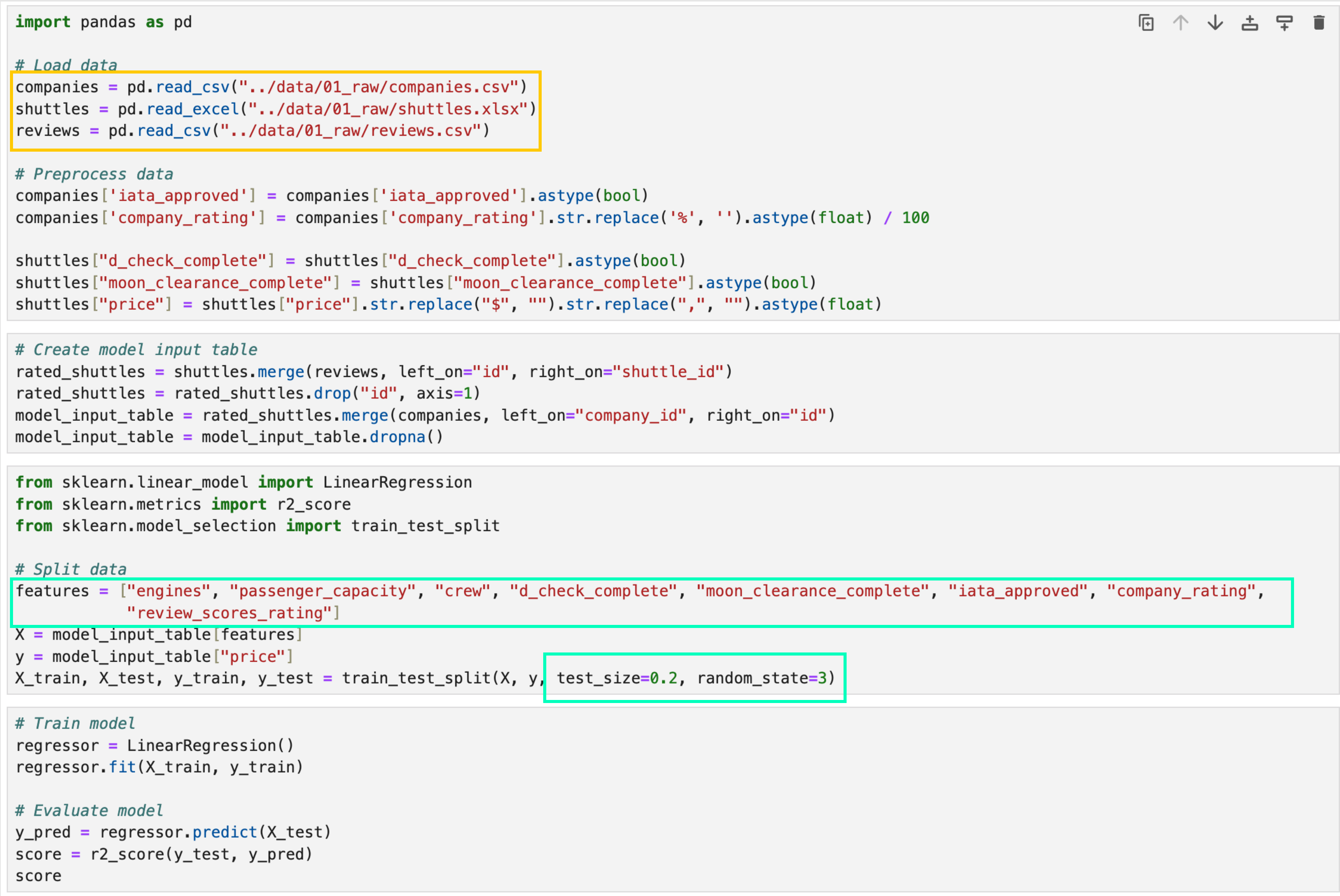
```yaml
# catalog.yml

companies
  type: pandas.CSVDataset
  filepath: data/01_raw/companies.csv

shuttles
  type: pandas.ExcelDataset
  filepath: data/01_raw/shuttles.xlsx

reviews
  type: pandas.CSVDataset
  filepath: data/01_raw/reviews.csv

model_input_table
  type: pandas.ParquetDataset
  filepath: s3://my_bucket/model_input_table.pq
  versioned: true
```



```python
# pipelines.py

def create_pipeline(**kwargs):
  return pipeline([
    node(
      func=preprocess_companies,
      inputs="companies",
      outputs="preprocessed_companies",
    ),
    node(
      func=preprocess_shuttles,
      inputs="shuttles",
      outputs="preprocessed_shuttles",
    ),
    node(
      func=create_model_input_table,
      inputs=[
        "preprocessed_shuttles",
        "preprocessed_companies",
        "reviews",
      ],
      outputs="model_input_table",
    ),
  ])
```

Example data science project

Before refactoring



```
import pandas as pd

# Load data
companies = pd.read_csv("../data/01_raw/companies.csv")
shuttles = pd.read_excel("../data/01_raw/shuttles.xlsx")
reviews = pd.read_csv("../data/01_raw/reviews.csv")

# Preprocess data
companies['iata_approved'] = companies['iata_approved'].astype(bool)
companies['company_rating'] = companies['company_rating'].str.replace('%', '').astype(float) / 100

shuttles["d_check_complete"] = shuttles["d_check_complete"].astype(bool)
shuttles["moon_clearance_complete"] = shuttles["moon_clearance_complete"].astype(bool)
shuttles["price"] = shuttles["price"].str.replace("$", "").str.replace(",", "").astype(float)
```

```
# Create model input table
rated_shuttles = shuttles.merge(reviews, left_on="id", right_on="shuttle_id")
rated_shuttles = rated_shuttles.drop("id", axis=1)
model_input_table = rated_shuttles.merge(companies, left_on="company_id", right_on="id")
model_input_table = model_input_table.dropna()
```

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split

# Split data
features = ["engines", "passenger_capacity", "crew", "d_check_complete", "moon_clearance_complete", "iata_approved", "company_rating",
            "review_scores_rating"]
X = model_input_table[features]
y = model_input_table["price"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=3)
```

```
# Train model
regressor = LinearRegression()
regressor.fit(X_train, y_train)

# Evaluate model
y_pred = regressor.predict(X_test)
score = r2_score(y_test, y_pred)
score
```

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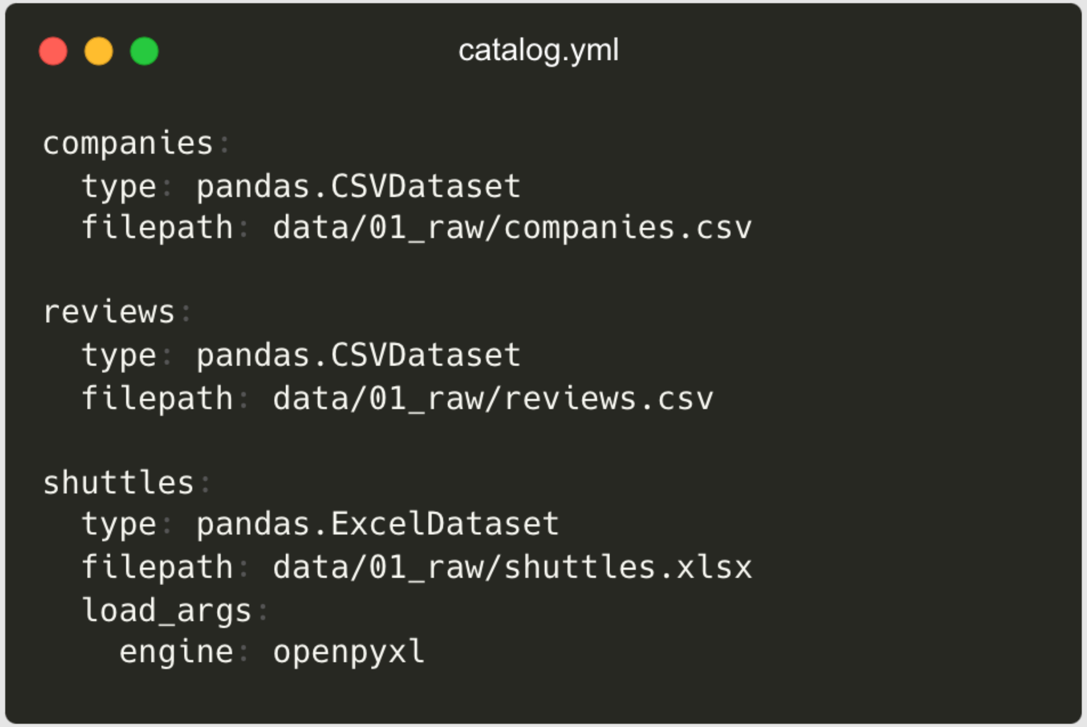
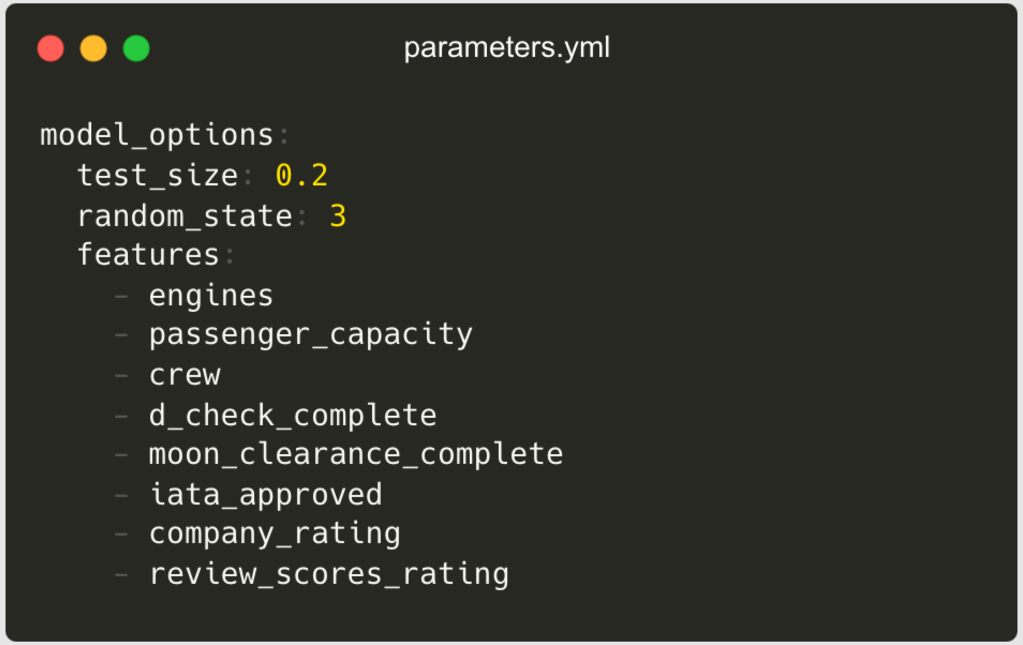
Separate data I/O and configuration

Put I/O information and parameters in configuration


catalog.yml

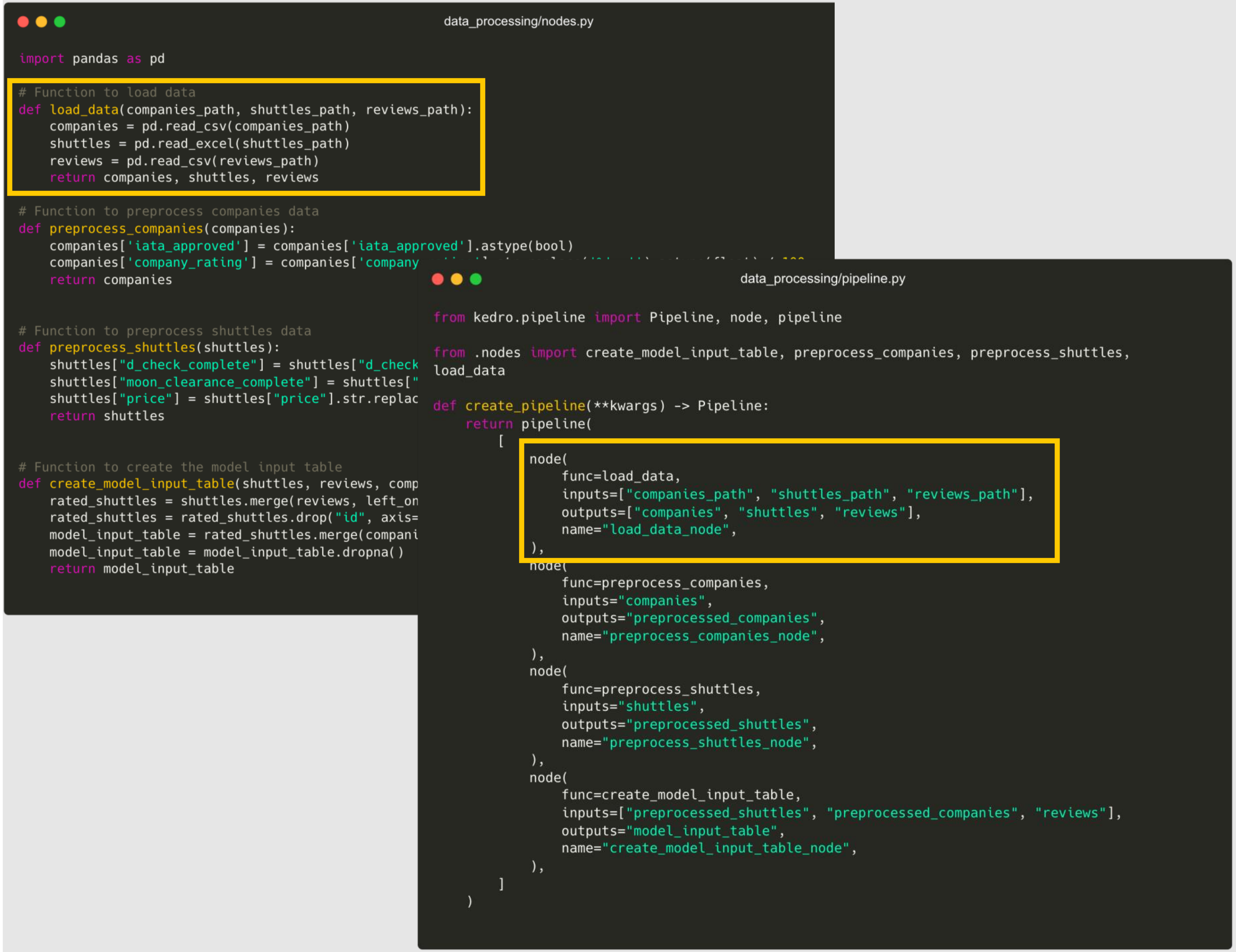
```yaml
companies:
  type: pandas.CSVDataset
  filepath: data/01_raw/companies.csv

reviews:
  type: pandas.CSVDataset
  filepath: data/01_raw/reviews.csv

shuttles:
  type: pandas.ExcelDataset
  filepath: data/01_raw/shuttles.xlsx
  load_args:
    engine: openpyxl
```


parameters.yml

```yaml
model_options:
  test_size: 0.2
  random_state: 3
  features:
    - engines
    - passenger_capacity
    - crew
    - d_check_complete
    - moon_clearance_complete
    - iata_approved
    - company_rating
    - review_scores_rating
```

Data I/O handled by the DataCatalog

No longer need code to read or save data



data_processing/nodes.py

```python
import pandas as pd

# Function to load data
def load_data(companies_path, shuttles_path, reviews_path):
    companies = pd.read_csv(companies_path)
    shuttles = pd.read_excel(shuttles_path)
    reviews = pd.read_csv(reviews_path)
    return companies, shuttles, reviews

# Function to preprocess companies data
def preprocess_companies(companies):
    companies['iata_approved'] = companies['iata_approved'].astype(bool)
    companies['company_rating'] = companies['company
    return companies


# Function to preprocess shuttles data
def preprocess_shuttles(shuttles):
    shuttles["d_check_complete"] = shuttles["d_check
    shuttles["moon_clearance_complete"] = shuttles["
    shuttles["price"] = shuttles["price"].str.replac
    return shuttles


# Function to create the model input table
def create_model_input_table(shuttles, reviews, comp
    rated_shuttles = shuttles.merge(reviews, left_on
    rated_shuttles = rated_shuttles.drop("id", axis=
    model_input_table = rated_shuttles.merge(compani
    model_input_table = model_input_table.dropna()
    return model_input_table
```

data_processing/pipeline.py

```python
from kedro.pipeline import Pipeline, node, pipeline

from .nodes import create_model_input_table, preprocess_companies, preprocess_shuttles,
load_data

def create_pipeline(**kwargs) -> Pipeline:
    return pipeline(
        [
            node(
                func=load_data,
                inputs=["companies_path", "shuttles_path", "reviews_path"],
                outputs=["companies", "shuttles", "reviews"],
                name="load_data_node",
            ),
            node(
                func=preprocess_companies,
                inputs="companies",
                outputs="preprocessed_companies",
                name="preprocess_companies_node",
            ),
            node(
                func=preprocess_shuttles,
                inputs="shuttles",
                outputs="preprocessed_shuttles",
                name="preprocess_shuttles_node",
            ),
            node(
                func=create_model_input_table,
                inputs=["preprocessed_shuttles", "preprocessed_companies", "reviews"],
                outputs="model_input_table",
                name="create_model_input_table_node",
            ),
        ]
    )
```

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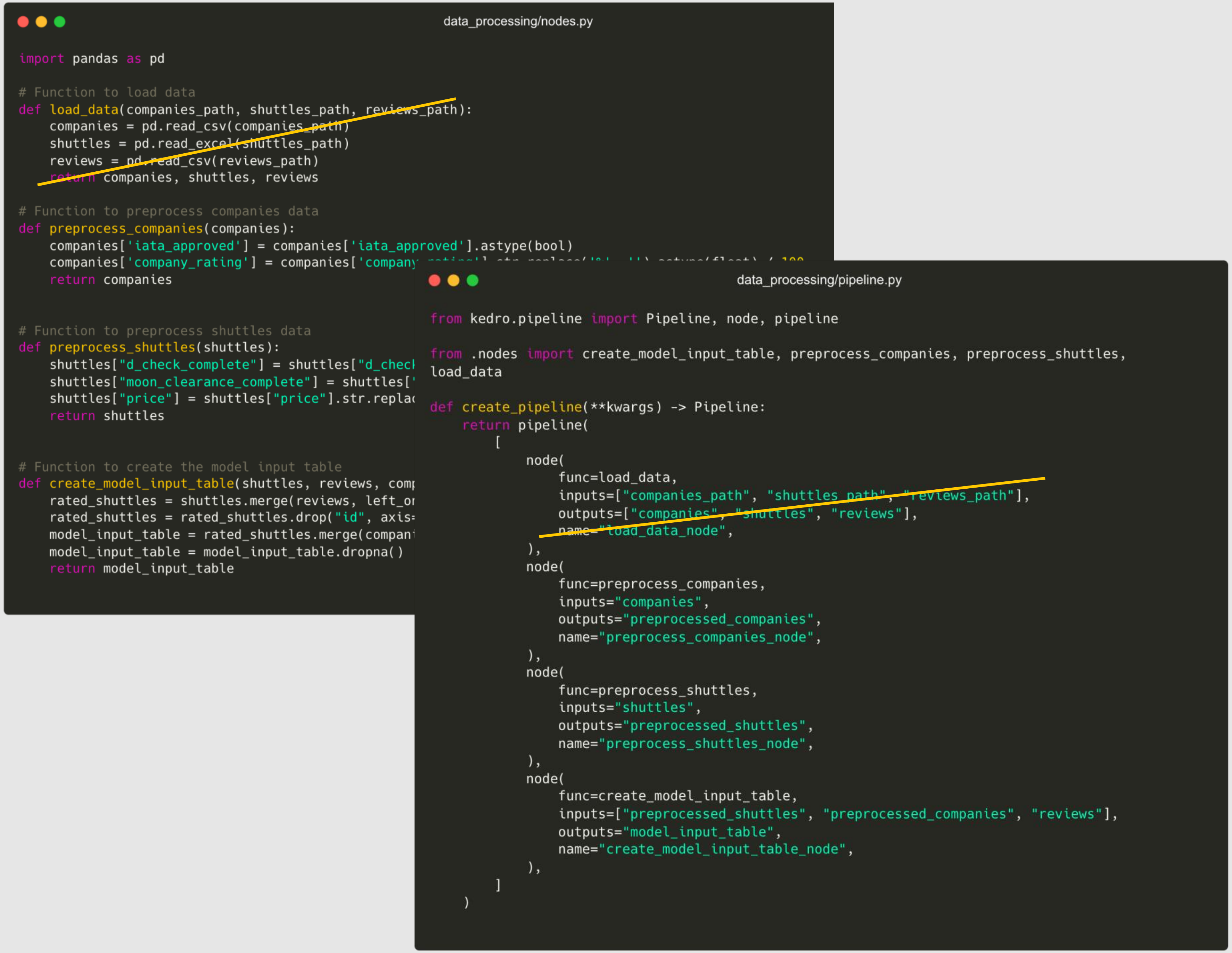
Data I/O handled by the DataCatalog

No longer need code to read or save data



data_processing/nodes.py

```
import pandas as pd

# Function to load data
~~def load_data(companies_path, shuttles_path, reviews_path):~~
~~    companies = pd.read_csv(companies_path)~~
~~    shuttles = pd.read_excel(shuttles_path)~~
~~    reviews = pd.read_csv(reviews_path)~~
~~    return companies, shuttles, reviews~~

# Function to preprocess companies data
def preprocess_companies(companies):
    companies['iata_approved'] = companies['iata_approved'].astype(bool)
    companies['company_rating'] = companies['company
    return companies


# Function to preprocess shuttles data
def preprocess_shuttles(shuttles):
    shuttles["d_check_complete"] = shuttles["d_chec
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    shuttles["price"] = shuttles["price"].str.repla
    return shuttles


# Function to create the model input table
def create_model_input_table(shuttles, reviews, com
    rated_shuttles = shuttles.merge(reviews, left_o
    rated_shuttles = rated_shuttles.drop("id", axis=
    model_input_table = rated_shuttles.merge(compan
    model_input_table = model_input_table.dropna()
    return model_input_table
```

data_processing/pipeline.py

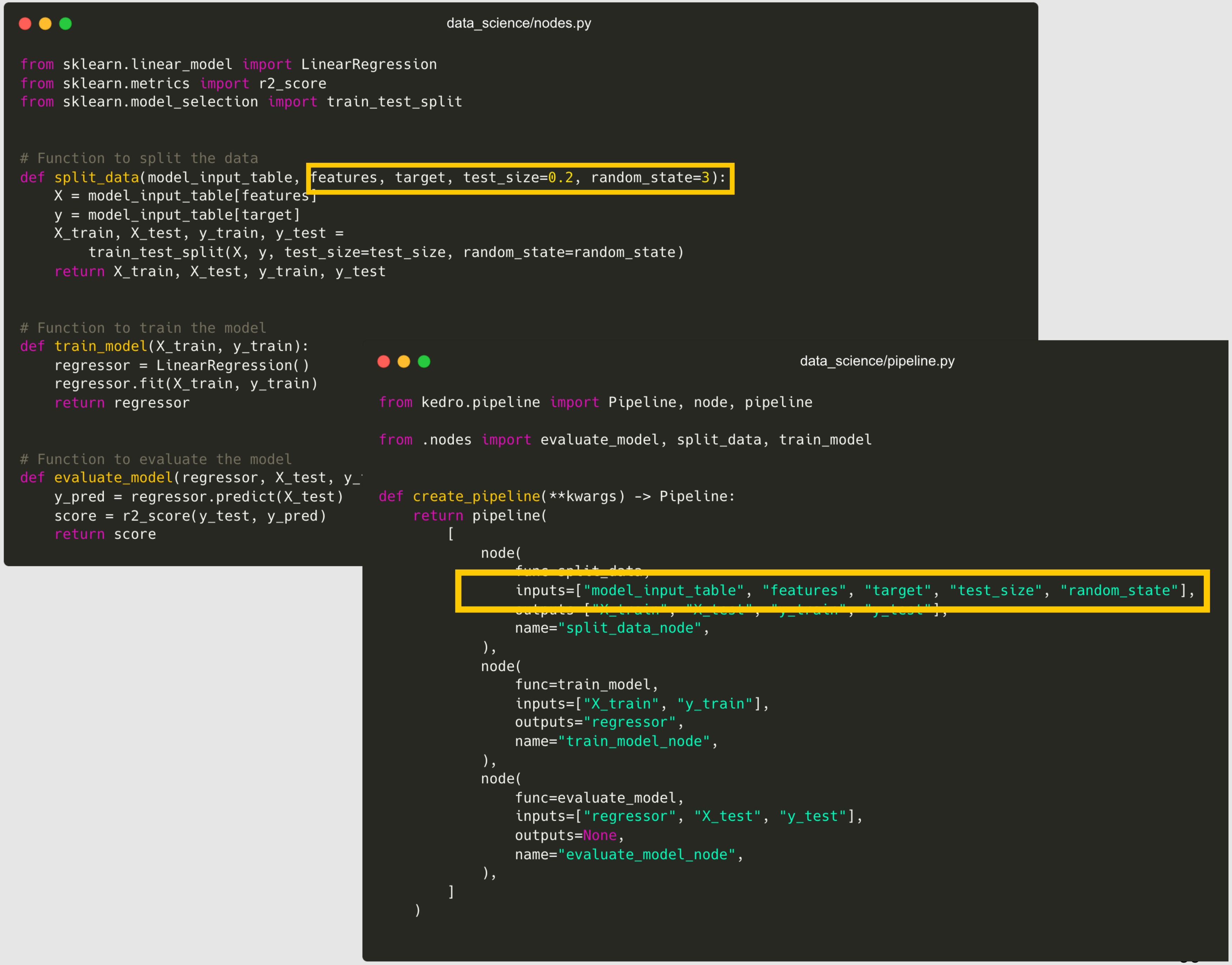
```
from kedro.pipeline import Pipeline, node, pipeline

from .nodes import create_model_input_table, preprocess_companies, preprocess_shuttles,
load_data

def create_pipeline(**kwargs) -> Pipeline:
    return pipeline(
        [
            node(
                func=load_data,
                ~~inputs=["companies_path", "shuttles_path", "reviews_path"],~~
                ~~outputs=["companies", "shuttles", "reviews"],~~
                ~~name="load_data_node",~~
            ),
            node(
                func=preprocess_companies,
                inputs="companies",
                outputs="preprocessed_companies",
                name="preprocess_companies_node",
            ),
            node(
                func=preprocess_shuttles,
                inputs="shuttles",
                outputs="preprocessed_shuttles",
                name="preprocess_shuttles_node",
            ),
            node(
                func=create_model_input_table,
                inputs=["preprocessed_shuttles", "preprocessed_companies", "reviews"],
                outputs="model_input_table",
                name="create_model_input_table_node",
            ),
        ]
    )
```

“Settings” put into configuration

Use parameters from config



data_science/nodes.py

```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split


# Function to split the data
def split_data(model_input_table, features, target, test_size=0.2, random_state=3):
    X = model_input_table[features]
    y = model_input_table[target]
    X_train, X_test, y_train, y_test =
        train_test_split(X, y, test_size=test_size, random_state=random_state)
    return X_train, X_test, y_train, y_test


# Function to train the model
def train_model(X_train, y_train):
    regressor = LinearRegression()
    regressor.fit(X_train, y_train)
    return regressor


# Function to evaluate the model
def evaluate_model(regressor, X_test, y_
    y_pred = regressor.predict(X_test)
    score = r2_score(y_test, y_pred)
    return score
```

data_science/pipeline.py

```python
from kedro.pipeline import Pipeline, node, pipeline

from .nodes import evaluate_model, split_data, train_model


def create_pipeline(**kwargs) -> Pipeline:
    return pipeline(
        [
            node(
                func=split_data,
                inputs=["model_input_table", "features", "target", "test_size", "random_state"],
                outputs=["X_train", "X_test", "y_train", "y_test"],
                name="split_data_node",
            ),
            node(
                func=train_model,
                inputs=["X_train", "y_train"],
                outputs="regressor",
                name="train_model_node",
            ),
            node(
                func=evaluate_model,
                inputs=["regressor", "X_test", "y_test"],
                outputs=None,
                name="evaluate_model_node",
            ),
        ]
    )
```

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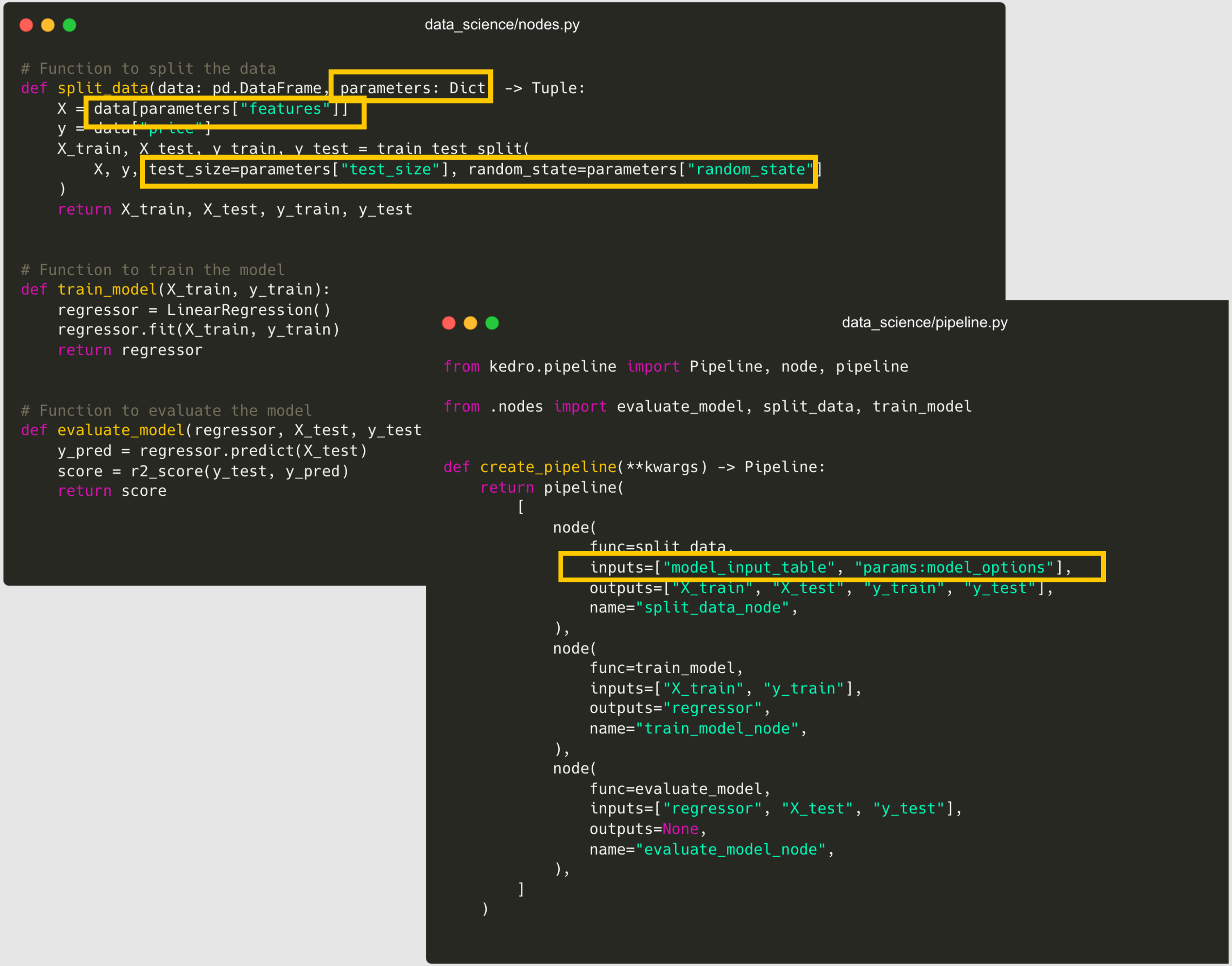
“Settings” put into configuration

Use parameters from config



data_science/nodes.py

```python
# Function to split the data
def split_data(data: pd.DataFrame, parameters: Dict) -> Tuple:
    X = data[parameters["features"]]
    y = data["price"]
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=parameters["test_size"], random_state=parameters["random_state"]
    )
    return X_train, X_test, y_train, y_test


# Function to train the model
def train_model(X_train, y_train):
    regressor = LinearRegression()
    regressor.fit(X_train, y_train)
    return regressor


# Function to evaluate the model
def evaluate_model(regressor, X_test, y_test
    y_pred = regressor.predict(X_test)
    score = r2_score(y_test, y_pred)
    return score
```

data_science/pipeline.py

```python
from kedro.pipeline import Pipeline, node, pipeline

from .nodes import evaluate_model, split_data, train_model


def create_pipeline(**kwargs) -> Pipeline:
    return pipeline(
        [
            node(
                func=split_data,
                inputs=["model_input_table", "params:model_options"],
                outputs=["X_train", "X_test", "y_train", "y_test"],
                name="split_data_node",
            ),
            node(
                func=train_model,
                inputs=["X_train", "y_train"],
                outputs="regressor",
                name="train_model_node",
            ),
            node(
                func=evaluate_model,
                inputs=["regressor", "X_test", "y_test"],
                outputs=None,
                name="evaluate_model_node",
            ),
        ]
    )
```

06

Maintainability

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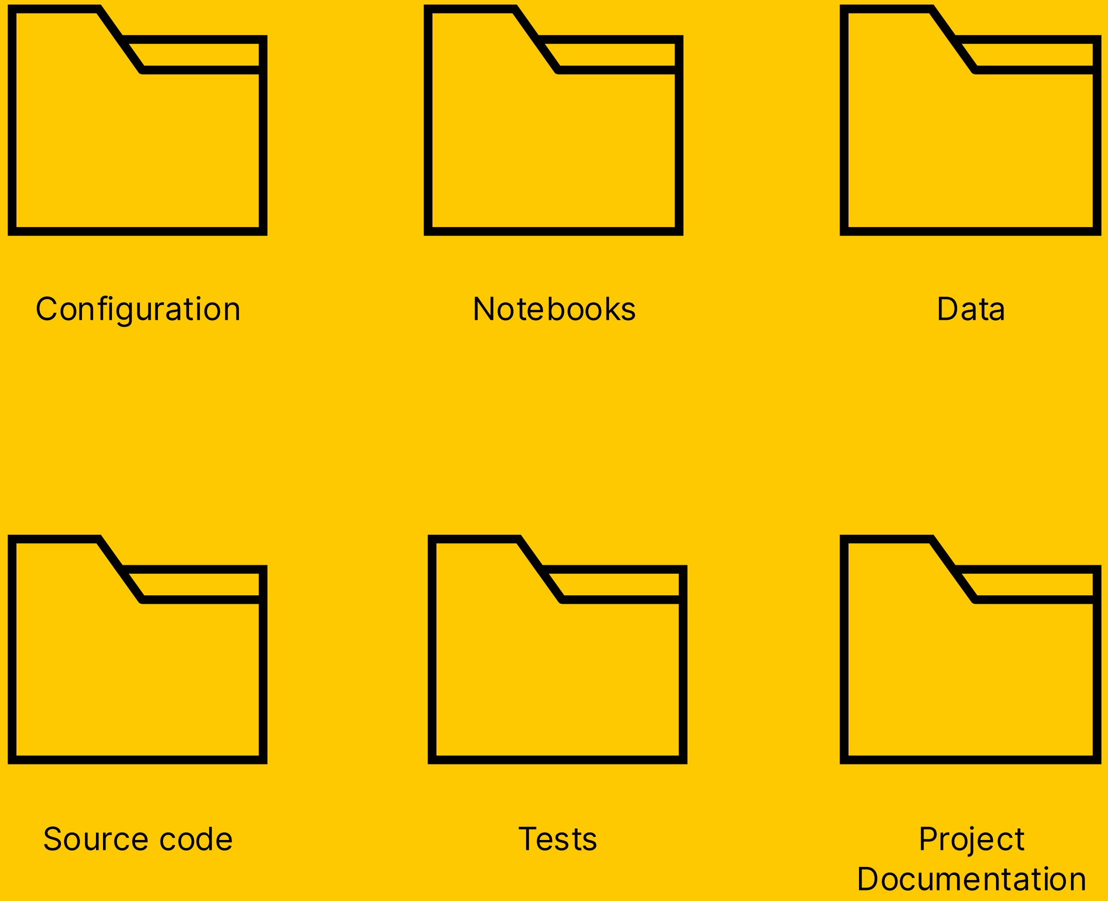
Maintainability

- A measure of how easy it is to understand, modify, and improve software.
- Testability: verifies that your code meets different requirements (functional, business, performance, reliability, etc..)
- Readability: linted, formatted and documented code
- Findability: structure and organisation of code

Project template



Configuration

Notebooks

Data

Source code

Tests

Project Documentation

What is the project template?

- Standard and customisable project structure
- Built-in support for Python logging, Pytest for unit tests and Sphinx for documentation

What does the project template help you do?

- Establish standardisation across your organisation
- You spend less time digging around in previous projects for useful code
- Makes it easier for collaborators to work with you

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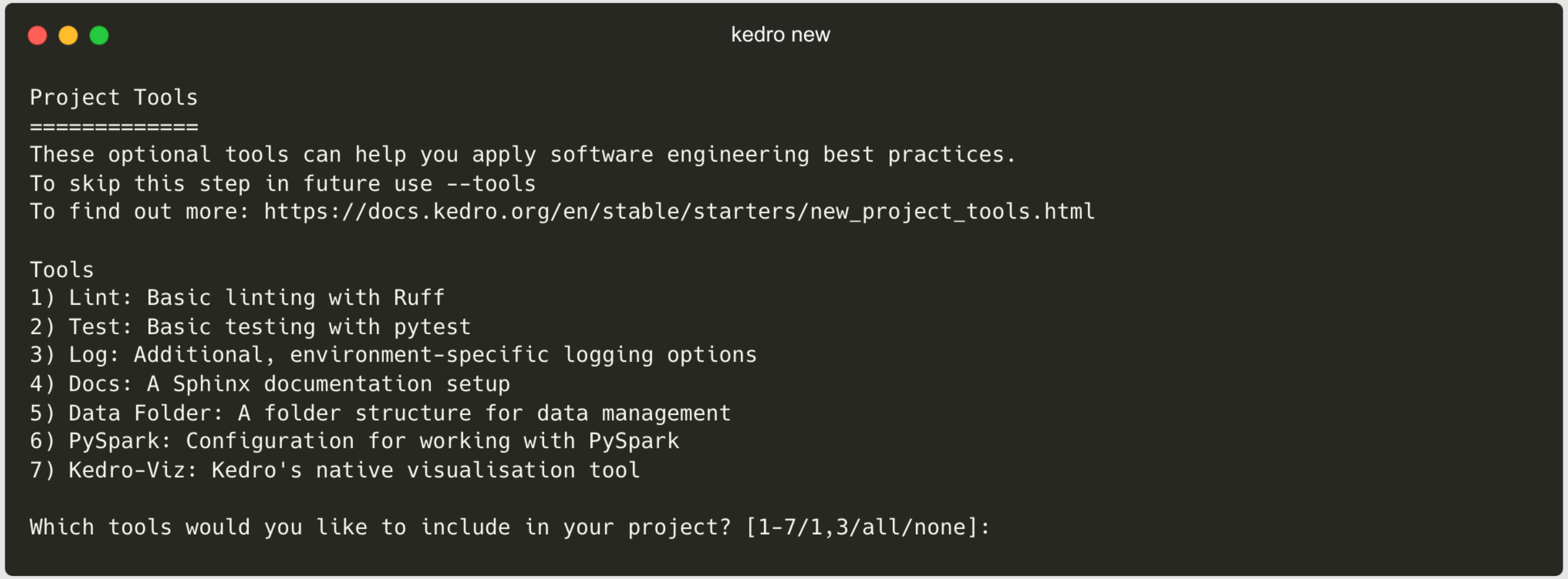
Project creation options

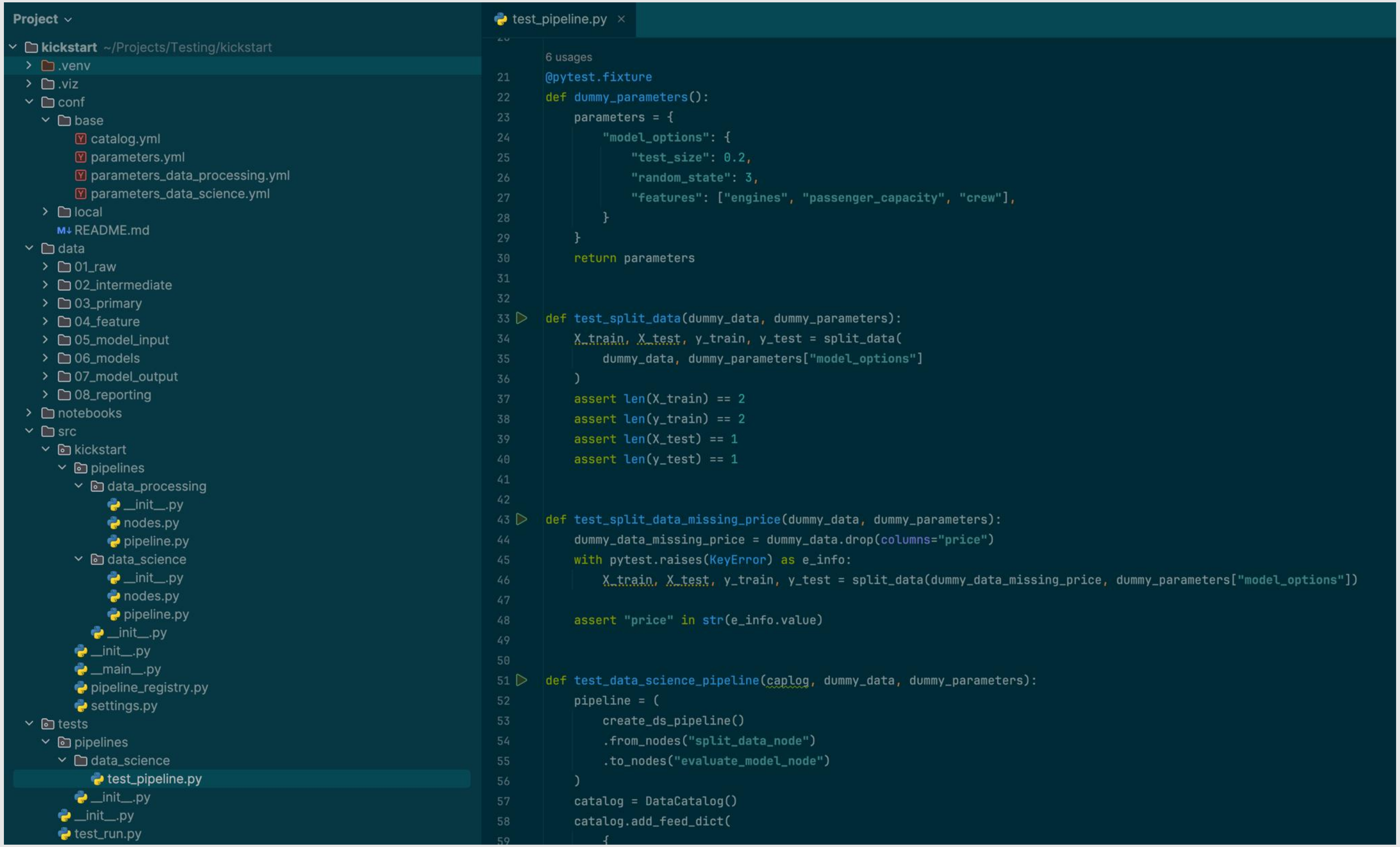
Include linting, testing, logging and documentation setup



```
Project Tools
=============
These optional tools can help you apply software engineering best practices.
To skip this step in future use --tools
To find out more: https://docs.kedro.org/en/stable/starters/new_project_tools.html

Tools
1) Lint: Basic linting with Ruff
2) Test: Basic testing with pytest
3) Log: Additional, environment-specific logging options
4) Docs: A Sphinx documentation setup
5) Data Folder: A folder structure for data management
6) PySpark: Configuration for working with PySpark
7) Kedro-Viz: Kedro's native visualisation tool

Which tools would you like to include in your project? [1-7/1,3/all/none]:
```

Example Kedro project structure

Including test setup & examples



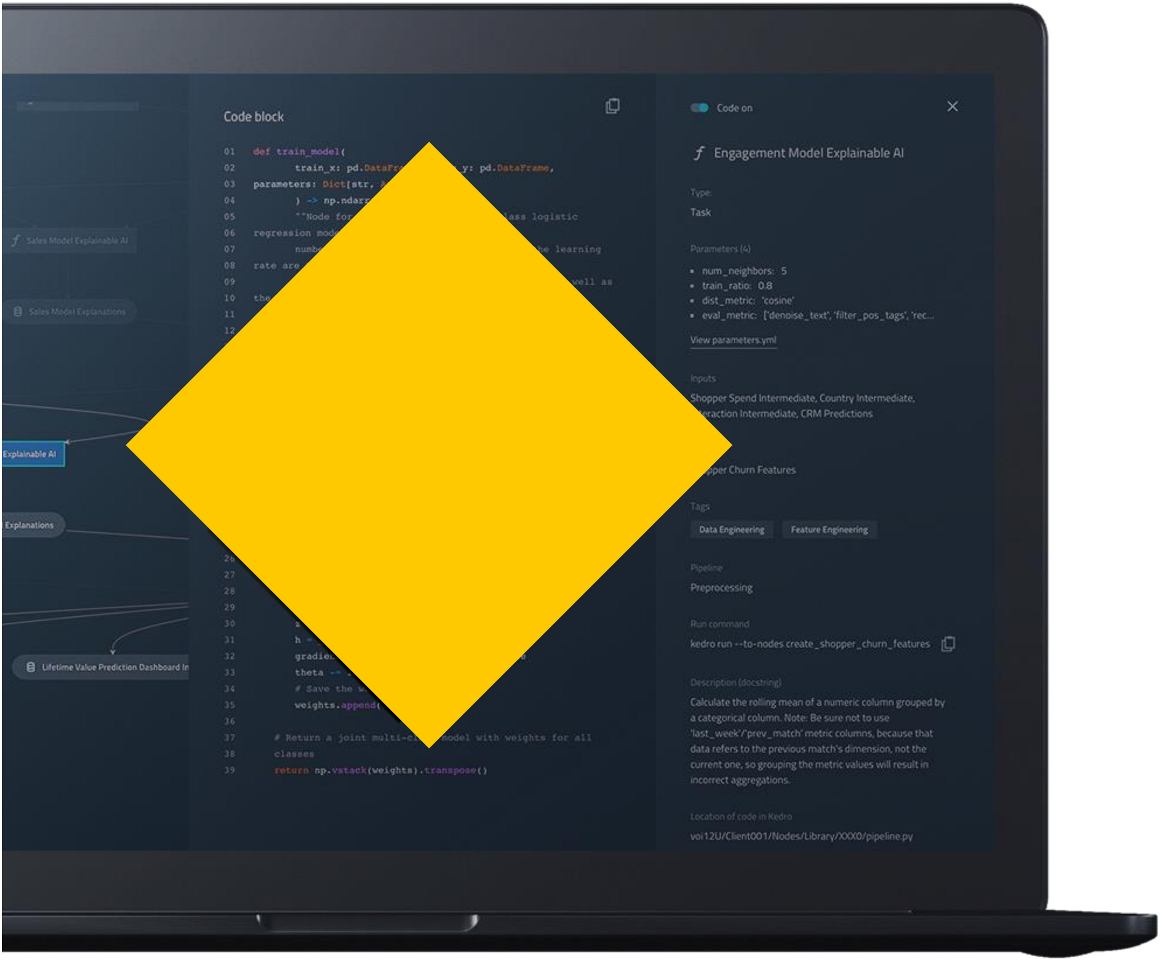
```
kickstart ~/Projects/Testing/kickstart
  .venv
  .viz
  conf
    base
      catalog.yml
      parameters.yml
      parameters_data_processing.yml
      parameters_data_science.yml
    local
    README.md
  data
    01_raw
    02_intermediate
    03_primary
    04_feature
    05_model_input
    06_models
    07_model_output
    08_reporting
  notebooks
  src
    kickstart
      pipelines
        data_processing
          __init__.py
          nodes.py
          pipeline.py
        data_science
          __init__.py
          nodes.py
          pipeline.py
        __init__.py
      __init__.py
      __main__.py
      pipeline_registry.py
      settings.py
  tests
    pipelines
      data_science
        test_pipeline.py
      __init__.py
    __init__.py
    test_run.py
```

```python
@pytest.fixture
def dummy_parameters():
    parameters = {
        "model_options": {
            "test_size": 0.2,
            "random_state": 3,
            "features": ["engines", "passenger_capacity", "crew"],
        }
    }
    return parameters


def test_split_data(dummy_data, dummy_parameters):
    X_train, X_test, y_train, y_test = split_data(
        dummy_data, dummy_parameters["model_options"]
    )
    assert len(X_train) == 2
    assert len(y_train) == 2
    assert len(X_test) == 1
    assert len(y_test) == 1


def test_split_data_missing_price(dummy_data, dummy_parameters):
    dummy_data_missing_price = dummy_data.drop(columns="price")
    with pytest.raises(KeyError) as e_info:
        X_train, X_test, y_train, y_test = split_data(dummy_data_missing_price, dummy_parameters["model_options"])

    assert "price" in str(e_info.value)


def test_data_science_pipeline(caplog, dummy_data, dummy_parameters):
    pipeline = (
        create_ds_pipeline()
        .from_nodes("split_data_node")
        .to_nodes("evaluate_model_node")
    )
    catalog = DataCatalog()
    catalog.add_feed_dict(
        {
```

Summary

- Software Engineering principles can elevate the quality and usability of your data science projects, even when experimental
- Kedro makes it easy to embed modularity, separation of concerns and maintainability
- It’s possible to establish and embed best practices without any tools

Kedro Resources


Sales Model Explainable AI
Sales Model Explanations
Explainable AI
Explanations
Lifetime Value Prediction Dashboard In

Code block

```
def train_model(
        train_x: pd.DataFr          y: pd.DataFrame,
parameters: Dict[str, A
        ) -> np.ndarr
        """Node for                    lass logistic
regression mode
        numbe                            he learning
rate are
                                          well as
the


        h
        gradie
        theta -=
        # Save the w
        weights.append(

    # Return a joint multi-cl    model with weights for all
    classes
    return np.vstack(weights).transpose()
```

Code on

ƒ Engagement Model Explainable AI

Type:
Task

Parameters (4)

- num_neighbors: 5
- train_ratio: 0.8
- dist_metric: 'cosine'
- eval_metric: ['denoise_text', 'filter_pos_tags', 'rec...

View parameters.yml

Inputs
Shopper Spend Intermediate, Country Intermediate, teraction Intermediate, CRM Predictions

pper Churn Features

Tags
Data Engineering Feature Engineering

Pipeline
Preprocessing

Run command
`kedro run --to-nodes create_shopper_churn_features`

Description (docstring)
Calculate the rolling mean of a numeric column grouped by a categorical column. Note: Be sure not to use 'last_week'/'prev_match' metric columns, because that data refers to the previous match's dimension, not the current one, so grouping the metric values will result in incorrect aggregations.

Location of code in Kedro
voi12U/Client001/Nodes/Library/XXX0/pipeline.py

There are many resources to get started using Kedro; here is a list of resources you can access.

Convert existing work into a Kedro project
We support workflows that take you from Jupyter notebooks and glue code scripts into a Kedro project.
blog.kedro.org

View demo
Interact with pipeline visualisation and experiment tracking with Kedro-Viz.
demo.kedro.org

Learn Kedro
Walk through our spaceflights tutorial and get up to speed on beginner-to-intermediate functionality.
docs.kedro.org

Join the community
Join a friendly and growing community of Kedroids waiting for your questions.
slack.kedro.org

Q&A

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Thank you!

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