MLOps Engineering Machine Learning Operations V2.0.0 Sessions 6 - 7

MsC in Business Analytics and Data Science Madrid, May 2025





main.py

Orchestrate the full ML pipeline from config, logging every action for traceability and robust error handling

Config drives the pipeline

- Loads config.yaml and .env for all parameters
- Pipeline logic is never hardcoded

Support modular stages

- Choose to run full, data, or train pipeline
- Enables rapid debugging and development

Centralize all logging

- Configure and initialize logging once
- Logs are consistent across all modules

Explicit error handling

- Catch, log, and exit on all critical errors
- Never allow silent failures

Pass data between steps

- Each step hands off to the next via clear variables
- Enables flexible pipeline rearrangement

Log every pipeline event

- Logs all key steps, actions, and errors
- All pipeline runs are fully traceable



data_loader.py

Load and validate all data using config, preserving raw files and logging every detail for auditability

Config controls all loading

- All paths, types, and file options set in config.yaml
- No hardcoded values used

Validate every config value

- Check for missing or invalid paths before loading
- Fail fast if config has errors

Never overwrite raw data

- Always read, never mutate raw input files
- Protect original source for full reproducibility

Flexible format support

- Load CSV, Excel, or future formats with config switch
- Adapt quickly to data changes

Log every step and file

- Log data paths, file types, and load status
- Always log file shape and success/failure

Fail safe and clearly

- Raise clear errors on missing files or wrong formats
- Log every error with actionable detail



data_validation.py

Validate and enforce data schema, types, and completeness before entering the pipeline (GIGO) at every critical data entry point

Schema defined in config

- Column types and expectations set in config.yaml
- Data validation logic is versioncontrolled and easy to update

Check for missing fields

- Warn or fail on missing required columns
- Never proceed with incomplete schema

Validate data types

- Ensure each column matches expected type
- Raise clear error if mismatch

Handle missing values explicitly

- Identify, log, and optionally impute or reject rows
- Prevent silent data loss

Fail fast on errors

- Action (raise/warn)
 is configurable from
 config.yaml
- Stop pipeline or log warning as per project phase

Log all validation results

- Store full validation report as JSON for audit and reproducibility
- Log all checks, issues, and summary for traceability



preprocessing.py

Fit preprocessing only on the train split and drive all logic from config for leakageproof, reproducible ML

Config controls all transforms

- All preprocessing steps set in config.yaml
- Reproducible experiments every run

Always fit on train split only

- Never use test data for fitting
- Prevents all data leakage

Never overwrite raw data

- Keep raw, processed data separate
- Maintain full audit trail

Each function does one job

- Split, rename, scale, encode steps modular
- Enables easy testing

Log every transformation

- Log each step, shape, and file path
- All logs controlled by config

Validate config before use

- Check config keys, warn if missing
- Fail fast on config errors



features.py

Create, transform, and select features modularly and track all changes for reproducibility

Config controls feature logic

- All engineering steps defined in config.yaml
- Supports easy iteration and audit

Modular feature functions

- Each transformation in a dedicated function
- Enables isolated testing

Enable feature selection

- Select features by config or method (e.g. importance)
- No hardcoded lists

Track all feature changes

- Log every new or modified feature
- Maintain full audit trail

Preserve original columns

- Never overwrite raw features
- Keep raw, engineered, and selected features separate

Log every feature step

- Log creation, selection, and dropping of features
- Store feature list for reproducibility



model.py

Centralize model pipeline control in config.yaml and always split data before preprocessing to guarantee robust results

All pipeline settings in config

- Models, splits, metrics set in config
- No hardcoding anywhere

Split before preprocessing

- Raw data split first, never after
- Strictly prevents leakage

Switch models via config

- Change model type with model.active
- Params per model in config

Keep all data stages separate

- Raw and processed files always distinct
- Easy to trace lineage

Log every pipeline stage

- Log data load, split, train, eval
- Paths and shapes always logged

Modular and testable code

- Every function takes clear inputs
- All parts unit testable



evaluation.py

Evaluate model using configurable metrics and log all results for transparent model comparison

Config lists all metrics

- Metrics set in config.yaml, not hardcoded
- Enables flexible evaluation

Calculate each metric modularly

- Each metric in its own function
- Easily add or remove metrics

Log every result

- Log every metric, split, and model version
- Store results for each run

Support multiple splits

- Evaluate and log metrics for each split (train/val/test)
- Enables fair, transparent model comparison

Enable model comparison

- Store metrics for multiple models
- Track changes across experiments

Fail safe on metric errors

- Catch and log errors, never crash
- Continue evaluating all metrics and splits



inference.py

Serve predictions using the trained pipeline and log all inference for reproducibility

Load pipeline from artifacts

- Always load model and transformer from saved files
- No training logic in inference

Validate input data

- Check new data matches expected schema
- Warn or fail on mismatch

Apply full preprocessing

- Transform input exactly as in training
- Prevent feature drift

Return predictions and probabilities

- Output both class and probability if available
- Flexible output options

Log all inference events

- Log input shape, prediction output, and time
- Store all requests for audit

Fail safe and trace errors

- Catch and log prediction errors
- Never serve incomplete predictions

Unit tests ensure code quality before deployment, while production monitoring safeguards reliability and performance with real data

DEV

- Uses only mock or synthetic data
- Validates code logic in isolation
- Covers both success and failure scenarios
- Fast, repeatable, and deterministic
- Never touches production systems or data
- Automated and run frequently (CI/CD)
- Focuses on small, isolated functions or modules
- Can use monkeypatching or mocks
- Designed for debugging and fast feedback
- Ensures functions handle edge cases robustly

PROD

- Uses real, live production data
- Monitors model and pipeline behaviour continuously
- Detects data drift and schema changes
- Validates live predictions for outliers
- Runs in parallel to actual production workloads
- Utilizes shadow or canary deployments
- Relies on alerts, dashboards, and logging
- Focuses on performance and reliability
- Ensures rapid rollback if failures are detected

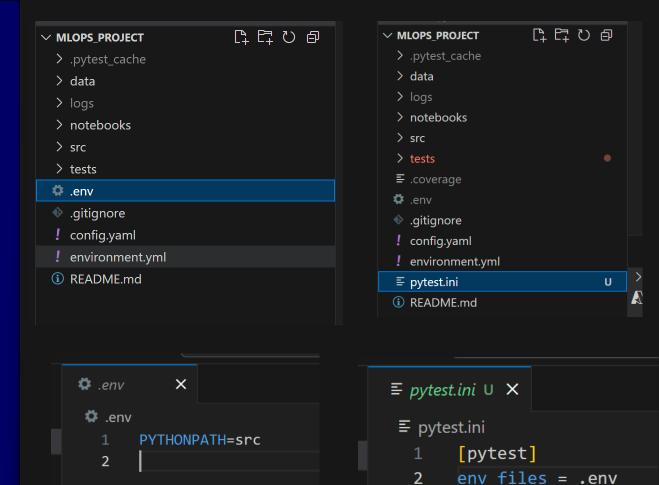
Running robust tests:

1. Install pytest-dotenv

2. pytest.ini:
[pytest]
env_files = .env

3..env:
PYTHONPATH=src

Ensure all project code is discoverable by pytest





From your root folder:

Most common pytest calls

```
pytest
pytest -q
pytest -v
pytest tests/test_file_name.py
pytest tests/test_file_name.py::test_function_name

pytest --cov=src
pytest --cov=src --cov-report=term-missing
```

(mlops_project) PS C:\Users\idiaz\OneDrive - IE University\00. IE Courses\01. 2025_H1\4. MLOps\mlops_project> [