Adopting an MLOps mindset

DEVELOPING MACHINE LEARNING MODELS FOR PRODUCTION

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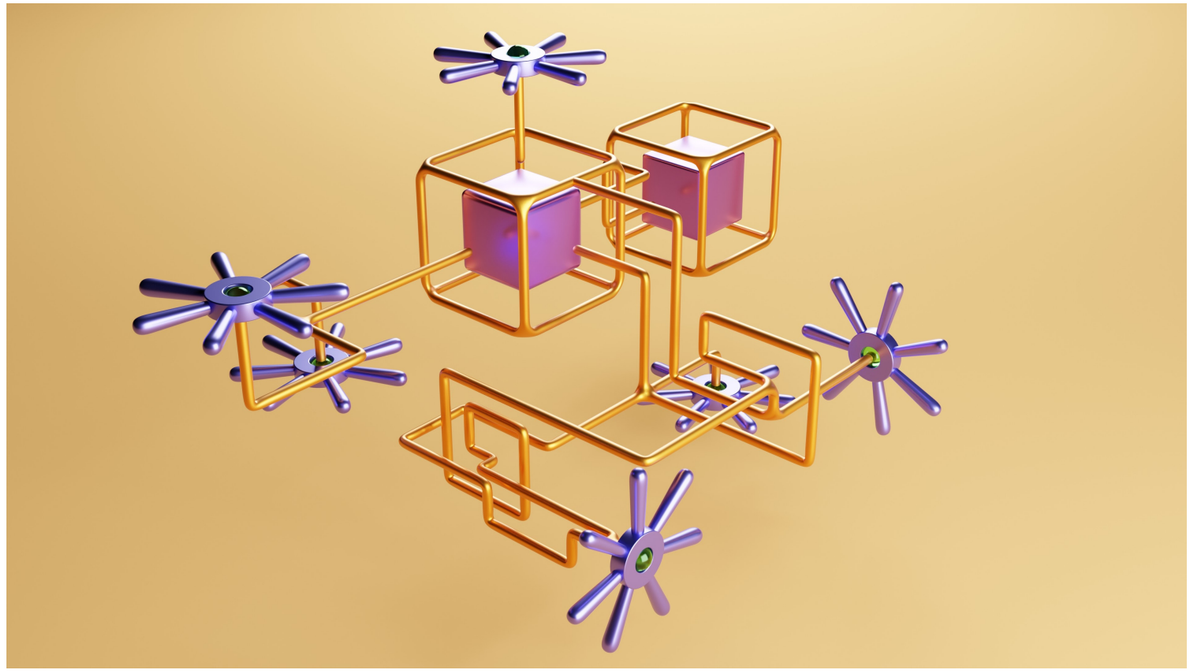
MLOps

- The process of automating and streamlining the ML workflow from experimentation to production
- Ensures that ML experiments are properly tested and ready to be deployed and scaled

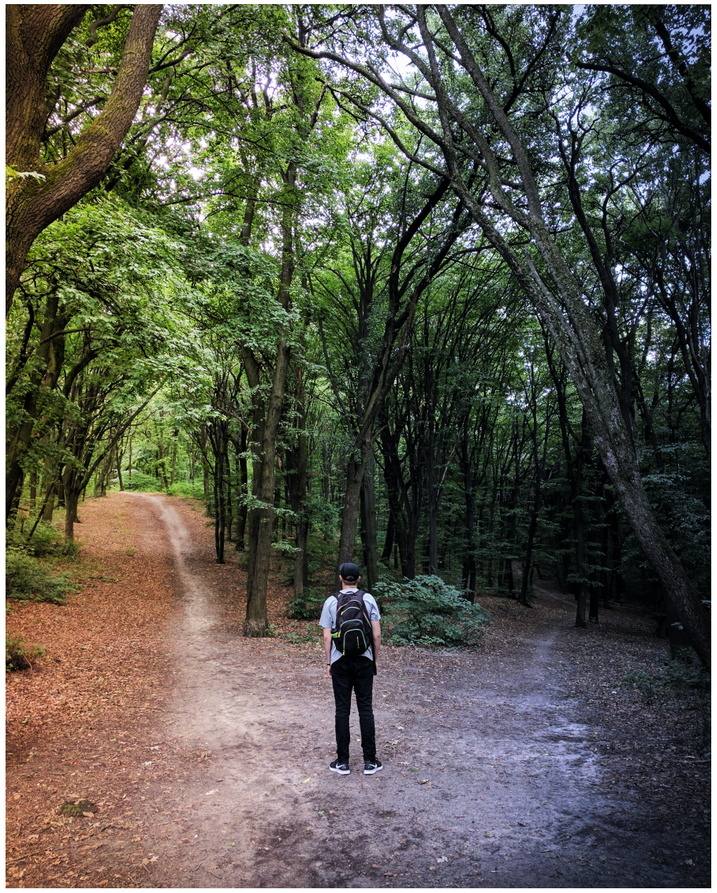


ML experiments

ML experiments involves testing models and determine which one is best

- MLOps includes model experimentation
- Evaluating models on different datasets
- Careful model selection essential
- Selection process may be time-consuming
- Ensures project success

From experiments to production



What Makes an ML Experiment Ready for Production?

- Tested and validated using appropriate metrics
- Proper documentation
- Performing monitoring is in place
- Production environment is secure and scalable

Why most ML experiments fail

There are many reasons why this might happen:

- Lack of clear goals and objectives
- Poor data quality
- Complex model architectures
- Insufficient training data
- Overfitting or underfitting

Technical debt

Code written in a hurry without proper testing or validation or missing/incomplete/out-of-date documenation

- Costly errors or bugs can occur if not addressed early on.
- Avoid technical debt by writing proper code and documentation from the start.

Let's practice!

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Writing maintainable ML code

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Project structuring

- Organize project files into a logical structure
- Group related files together
  - Organize data sets and ML models in separate folders
- Ensure files are properly named and labeled

Sample project structure

Sample project directory with a README file, requirements file and three subfolders: data, models, notebooks

```
├── README.md
├── data
|   ├── raw
|   ├── processed
|   └── interim
├── models
|   ├── model1.py
|   ├── model2.py
|   └── model3.py
├── notebooks
|   ├── data_exploration.ipynb
|   ├── model_training.ipynb
|   └── model_evaluation.ipynb
├── requirements.txt
```

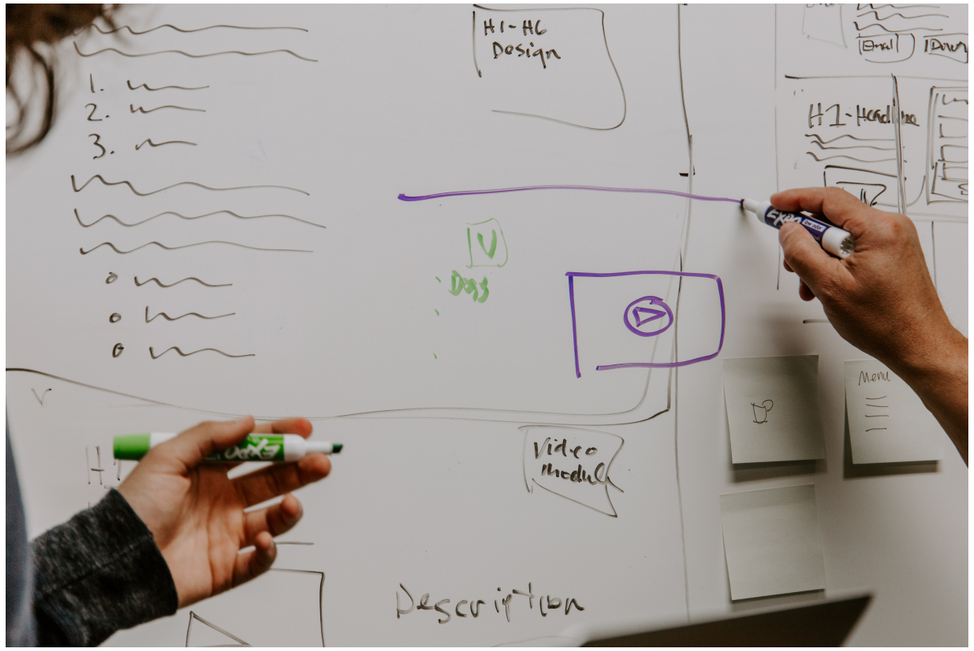
- README.md: Explains the purpose of the repository and how to use it.
- requirements.txt: Lists all dependencies
- data: contains data-related files, including raw data and processed data
- models: contains all model-related files, including scripts for creating models.
- notebooks: contains notebooks for data exploration, model training, and model evaluation.

Code versioning

- Use a version control system like git to keep track of changes to the code
- Allows for rollback of changes if necessary
- Can help identify the source of bugs and errors
- Allows for parallel work

Documentation

- Document code and project structure
- Explain the purpose of each file and function
- Describe how to use the code
- Include instructions on how to deploy the ML model



Adaptability of code

- Easier to understand, modify, and update
- Reduces the time and effort required to make changes to the codebase
- More easily adapt to data + code + requirements changes
- Less prone to bugs
- Easier to integrate new features or technologies as needed
- Essential for building ML applications that can evolve and adapt over time

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Writing effective ML documentation

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The components of excellent ML documentation

- Data sources
- Data schemas
- Labeling methods
- Model experimentation + selection
- Training environments
- Model pseudocode

Documenting data sources

Allows us to establish processes for evaluating the quality of our data.

This also offers other benefits:

- Keep track of where data comes from.
- Evaluate and iterate on the quality of data.

Data schemas

A structure that describes the organization of data.

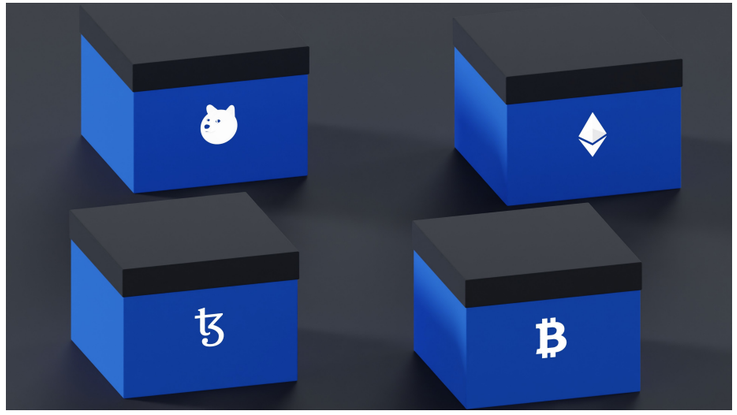
For a relational database schema:

Database key	Data type	Data order
`Person.name`	`string`	`nominal`
`Person.survey_score`	`integer`	`ordinal`

Labeling methods (for classification)

Documenting how we labeled our response variable enhances:

1. **Reproducibility** of the training pipeline.
2. **Model reliability** through label quality.
3. **Model performance** through label improvement.



Labeling methods can evolve over time.

Model pseudocode

A visual representation of the different steps involved in building your machine learning model.

This often includes:

- Feature engineering steps.
- Components of an ensemble pipeline.
- Example inputs and outputs of the model.

Model experimentation + selection

Documenting the process of experimentation and selection of the best model includes documenting:

- The model development process.
- The models considered.
- The metrics used.
- The hyperparameter combinations tried for each model.

Training environments

To document our training environment, we should include:

- Packages used with versions (eg. `scikit-learn==1.1.3`).
- Any random seeds used for non-deterministic training (eg. dimensionality reduction algorithms).

Why?

- Ability to reproduce the results of our machine learning models.
- Ensuring consistency between training and production deployments.

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