RoCELib

Robust Counterfactual Explanation Library

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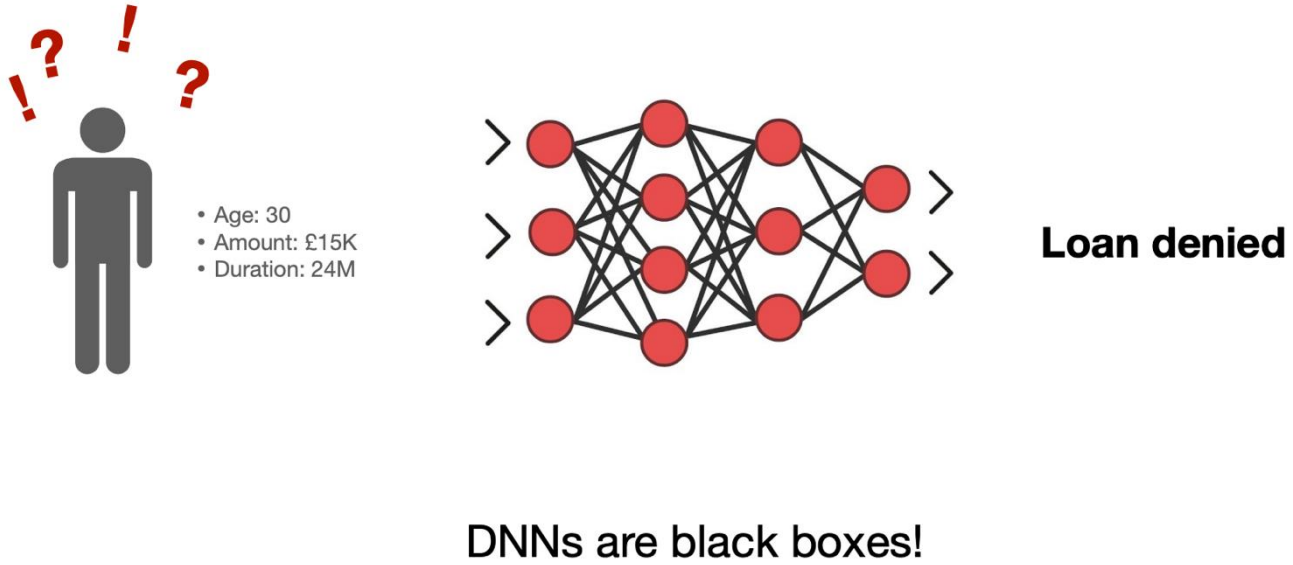
Group 6

What is a Counterfactual Explanation? (CE)

Why do we need counterfactual explanations?

- Explainable AI = problem
- Difficult to explain the outcomes of Neural Networks



- User wants to know why loan has been denied so they can try change the outcome
- GDPR regulations – require meaningful explanations for automated decision making

https://fraleo.github.io/misc/leofante_tutorial_ecai23.pdf

What is a counterfactual explanation?

Original instance

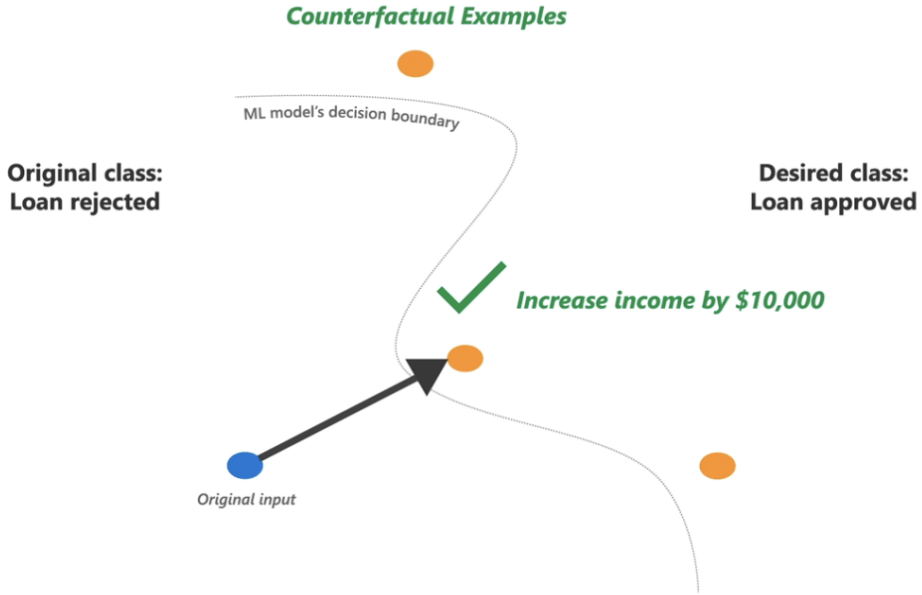
- Age: 30
- Amount: £15K
- Duration: 24M

Loan denied

Counterfactual explanation

- Age: 30
- Amount: **£10K**
- Duration: 24M

The application would have been accepted
had you asked for £10K instead of £15K



- Counterfactual explanation: a what-if scenario that describes how a different outcome could have occurred, had the input been different.
- We can use Counterfactual Explanations to help explain the outcome of these black box models

https://fraleo.github.io/misc/leofante_tutorial_ecai23.pdf

Importance of Robustness of CEs

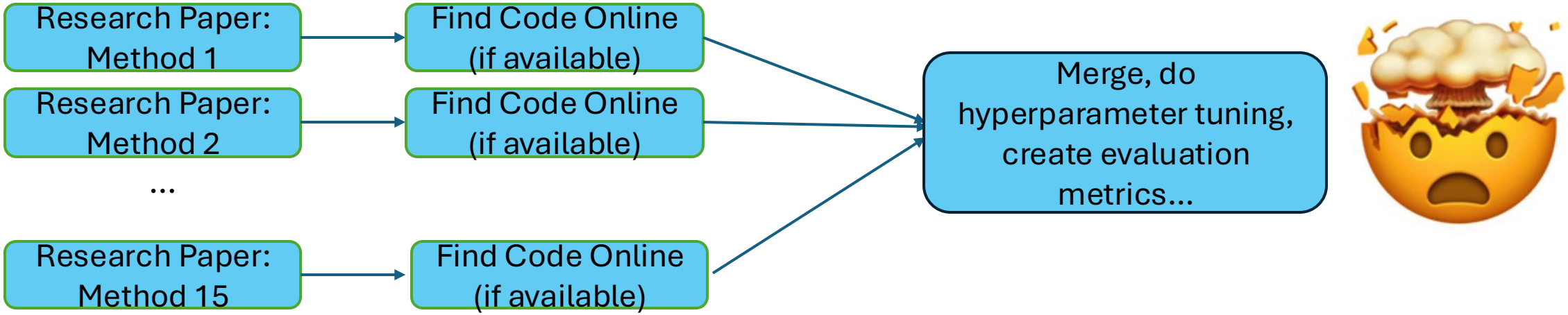
- Many **methods** for generating CEs
- Lots of ways to evaluate how 'good' these Counterfactual Explanations are
- Distance commonly used
- One way is measuring the **Robustness** of CEs
- Robustness = explanation remains consistent and reliable even when small changes are made to the input data
- Evaluating robustness is important:
  - Trustworthy interpretation
  - Fairness

Different Notions of Robustness

1. Input perturbations
2. Model perturbations
3. Model multiplicity
4. Noisy execution

Problem: Counterfactual Explanation research

- Many papers outlining different ways to generate CEs
- Very painful process to compare even 2 methods let alone the whole research space



- Very few ways to benchmark these methods currently
- Most libraries that do exist focus purely on evaluating the distance of CEs produced
- There is very little emphasis on evaluating the **Robustness** of Counterfactual Explanations

Introducing...

RoCELib!

- Open-Source Python Library
- Covers 15+ CE generation methods
- Focus on robustness evaluation – 8+ metrics
- Easy to extend

Glossary

A generation method is an algorithm used to produce counterfactual explanations

Robustness evaluation assesses the stability and reliability of counterfactual explanations

Initial Codebase

- The result of a UROP - bare bones implementation
- Issues included:
  - Very hard to understand how the library works and to use it
  - Filled with bugs
  - Not enough robustness metrics for evaluation

User Requirement Gathering

- Discussed with our supervisors about their needs, created a list of key features to add
- We were able to categorise the list of features into the desires of 3 potential stakeholders:

ML Engineer

- Ability to import trained models
- Generating Counterfactual explanations easily
- Digestible way of comparing methods

CE Researcher

- Extensibility: Adding own recourse method & evaluation metric

Library Maintainer

- Code Maintainability
- CI/CD
- Testing

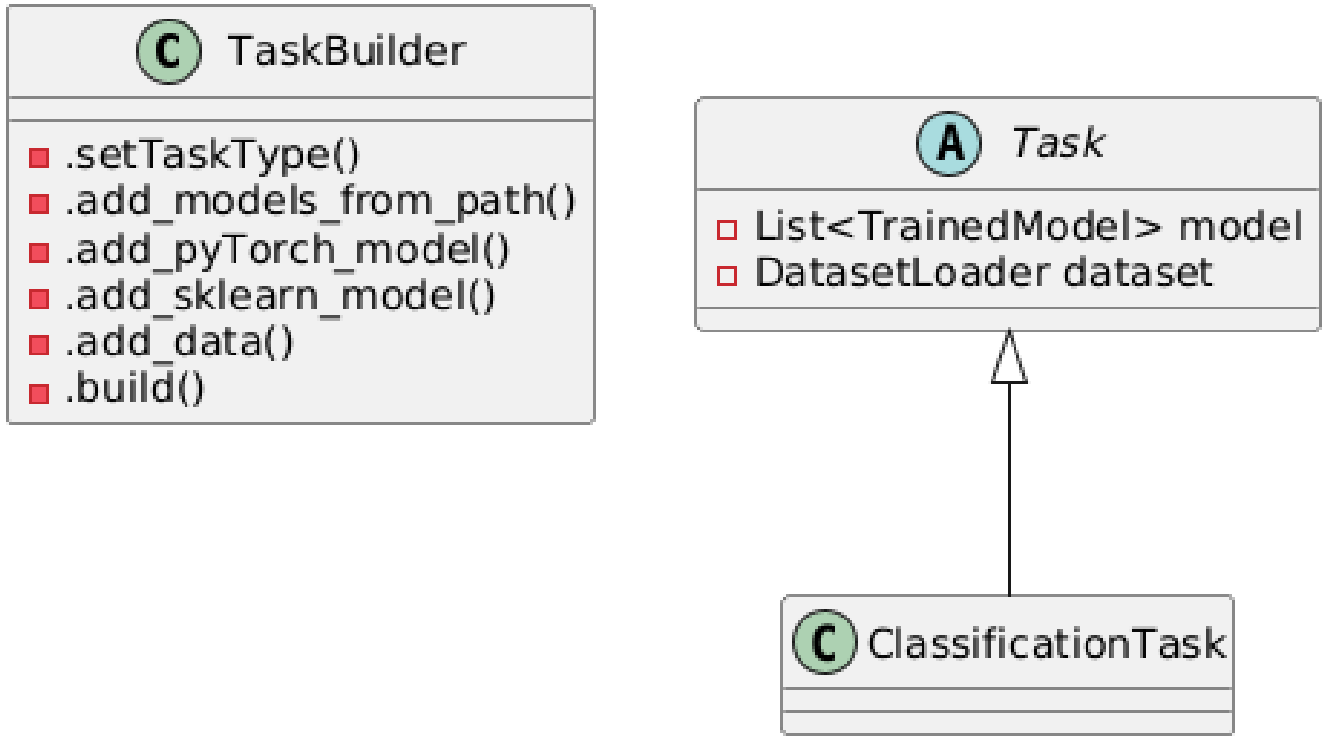
Meet Sarah…

- Researcher who has developed a model for predicting outcomes of loan applications
- Needs to ensure robustness of her counterfactual explanations
- Rather than spending weeks cloning researchers' code and testing her model, she uses RoCELib…

Sarah's Need 1: Ability to import trained models

- Sarah wants to assess CE robustness across a set of models
- So needs to add multiple models to the library

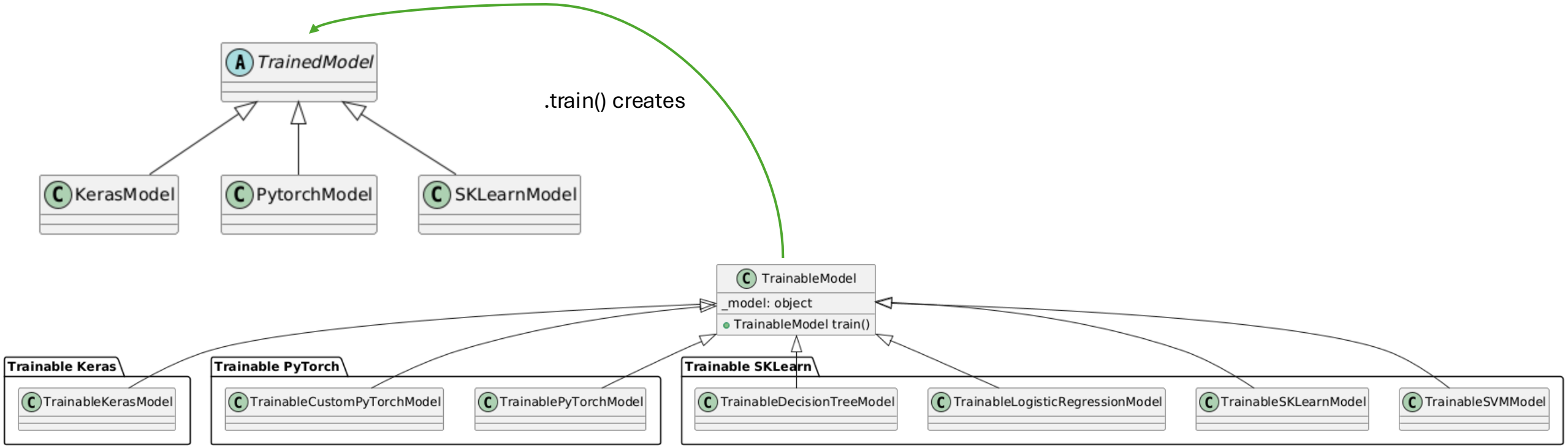
Task Redesign



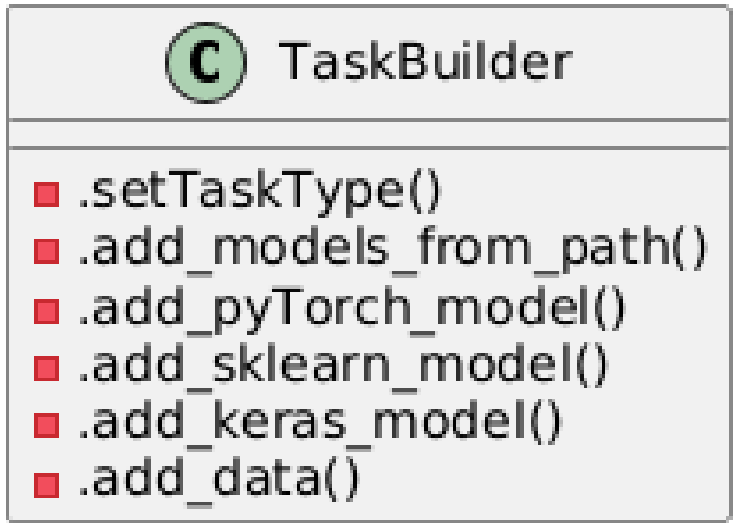
Model Redesign

TrainedModel = Trained Model Imported from Sarah's computer

TrainableModel = Model we create explicitly within the library



Task Builder




```
ct = (TaskBuilder()
        .add_model_from_path("model.pkl")
        .add_pytorch_model(34, [8], 1, dl)
        .add_sklearn_model("svm")
        .add_data(dl).build()
)
```

- Makes Tasks **configurable**
- Allows the addition of **multiple models**
- Task creation in one line **(simplified user interaction)**

Sarah's Need 2: Generating Counterfactual explanations easily

Sarah wants to:

- **Generate CEs easily**, in a single line
- Evaluate CE generation methods using a **combination of metrics**

Original code:

- required you to **instantiate multiple classes** for each recourse method and evaluation metric
- **restricted data to Pandas** data frames only

Easy Generation of CEs

- Can now generate in one line with **any combination** of recourse methods and evaluation metrics using **strings**

```
ces = ct.generate(["MCE", "BinaryLinearSearch", "RNCE"])
evals = ct.evaluate(["MCE", "RNCE"], ["DeltaRobustnessEvaluator", "Distance", "Validity"])
```

- Can **specify preferred datatype**

```
ces = ct.generate(["MCE"], "Tensor")
```

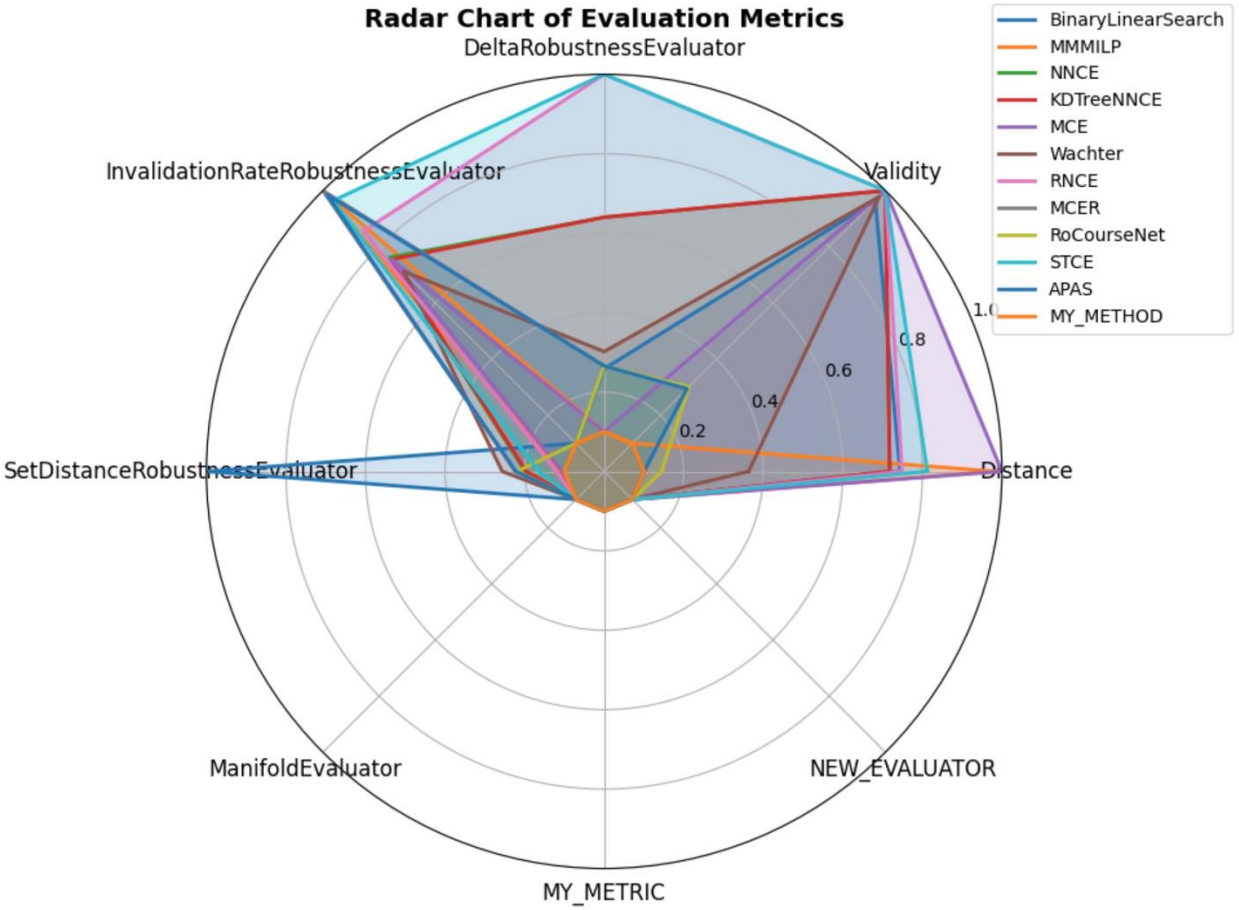
Sarah’s need 3: Digestible way of comparing methods

Dosent have complete understanding of arbitrary metric values

Need to quickly choose the best one

Visualisation + exportation

- Radar graph allows quick comparison of metrics you compare about more
- Can quickly digest the method comparisons
- Results get exported to a .zip folder
- Cares about DeltaRobustness, STCE most well-rounded



Sarah’s requirements

- Importing trained models 
- Easy counterfactual generation 
- Availability of visual methods comparison 

Meet Kevin...

- Researcher who has an idea for a new counterfactual generation method
- He wants to evaluate the validity and robustness of his method against other generators in the research space
- He decides to use RoCELib...

Kevin's Need: Library Extensibility

Kevin **requires** the library to be **extensible** so that he can add his own:

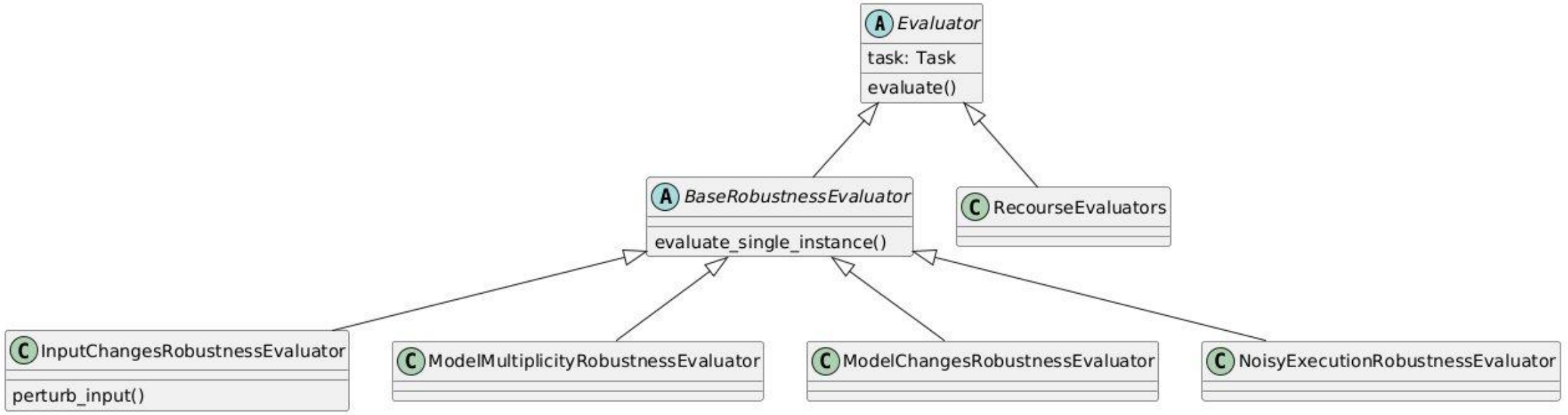
- recourse methods
- evaluation metric

However, the old codebase:

- Contains **tight coupling**
- Requires changes to underlying library to add recourse methods & metrics

Extensibility: Easy Addition of New Recourse Methods & Evaluation Metrics

- Can now easily add a new recourse method without changing the library
- User simply implements a single abstract method



Kevin’s requirements

- Adding CE generation methods 
- Adding evaluation metric 

Deployment

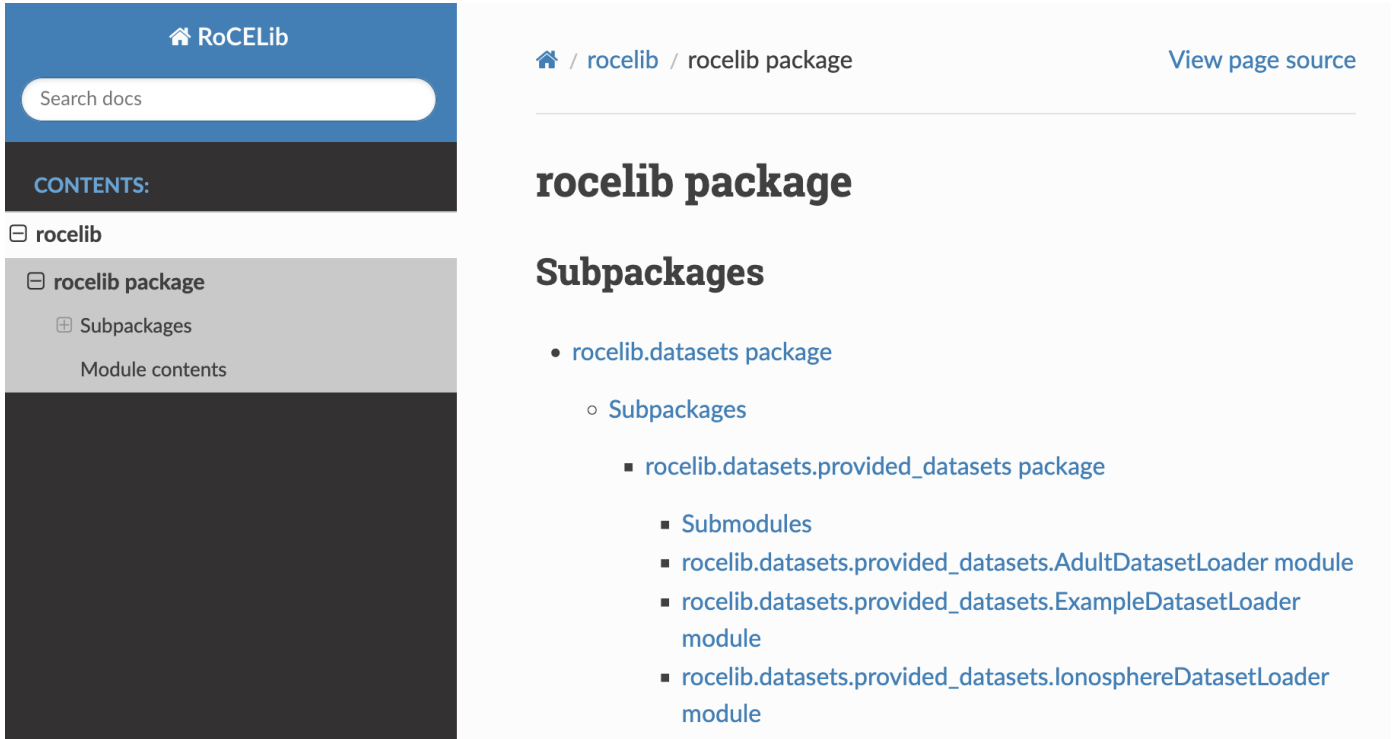
User Need: Being able to set-up library

- Little emphasis on usability
  - Lack of documentation
  - No packaging
- Difficult adding to existing project and understanding codebase

Documentation

https://jstadl.github.io/RoCELib/rocelib.html

- All functions documented
- Exhaustive Notebooks explaining how to use library, hosted on Google Colab

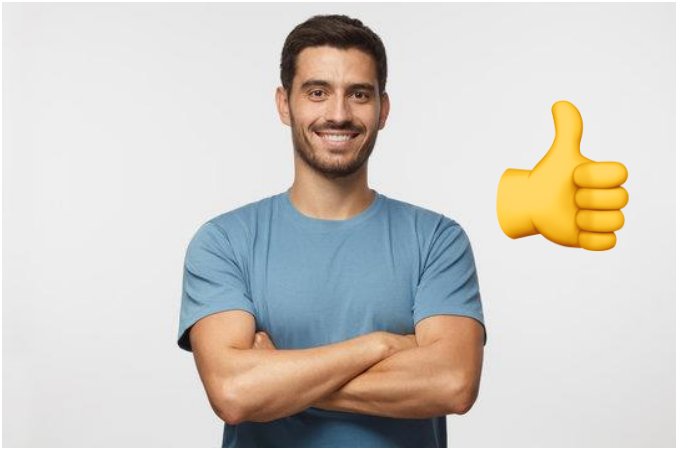


Packaging


```
pip install RoCELib
```

Packaging and deployment automated through GitHub actions

Evaluation: Deployment



Maintainability

Meet Howard...

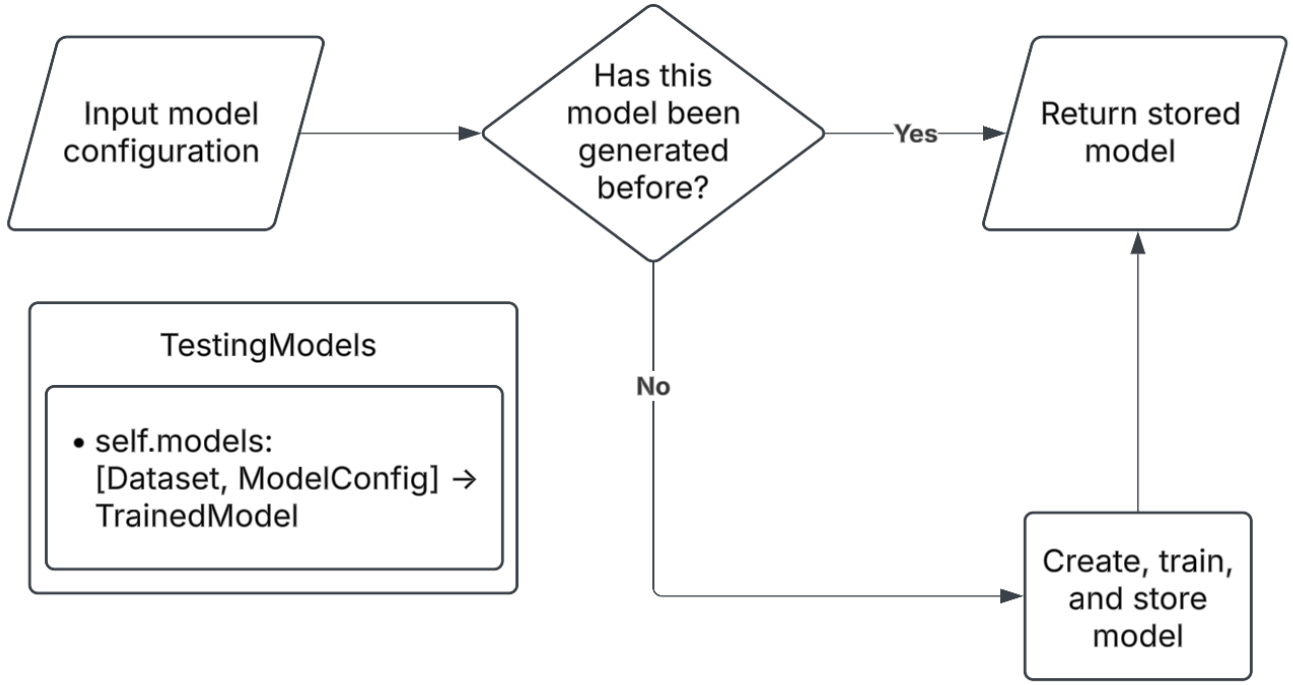
- Maintainer/Contributor of library
- He wants to be able to contribute some new research he has made to the library for others to use
- Needs good developer ecosystem

Problem: Code Maintainability

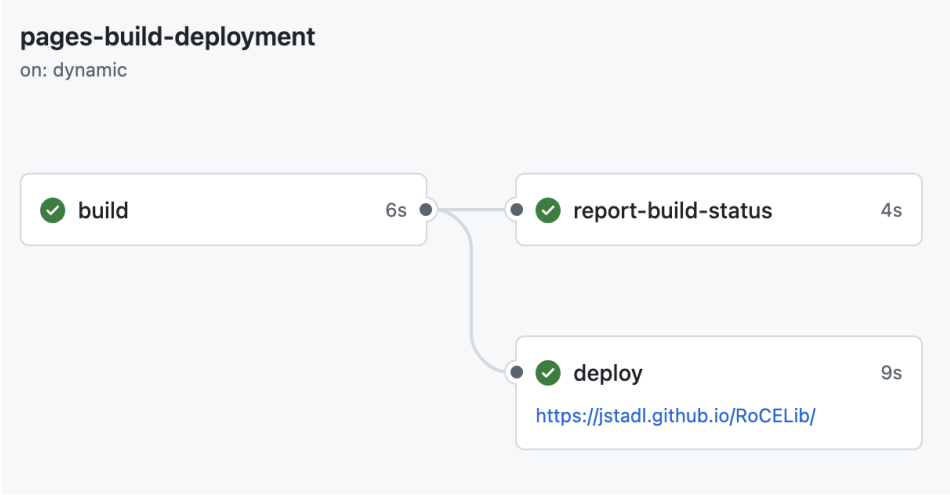
- Software engineering best practices not followed in original codebase
  - Poor testing
  - No CI/CD Pipeline
- Needs good automation to prevent keeping package updated becoming a chore

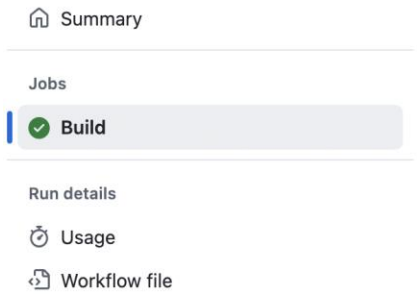
Testing

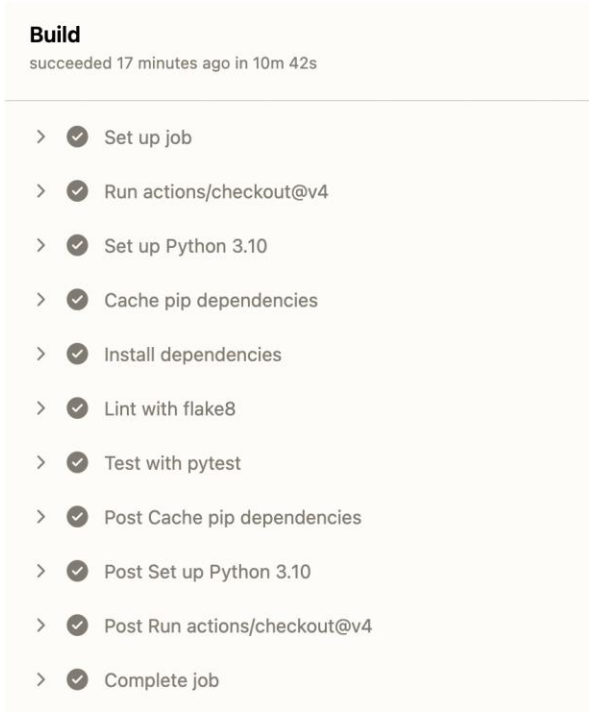
- Original tests were slow, and often not testing the right thing
- Singleton testing infrastructure for efficiency gains
- Original code: 33 tests, 13:05 to run, 66% coverage
- Our code: 75 tests, 8:09 to run, 78% coverage

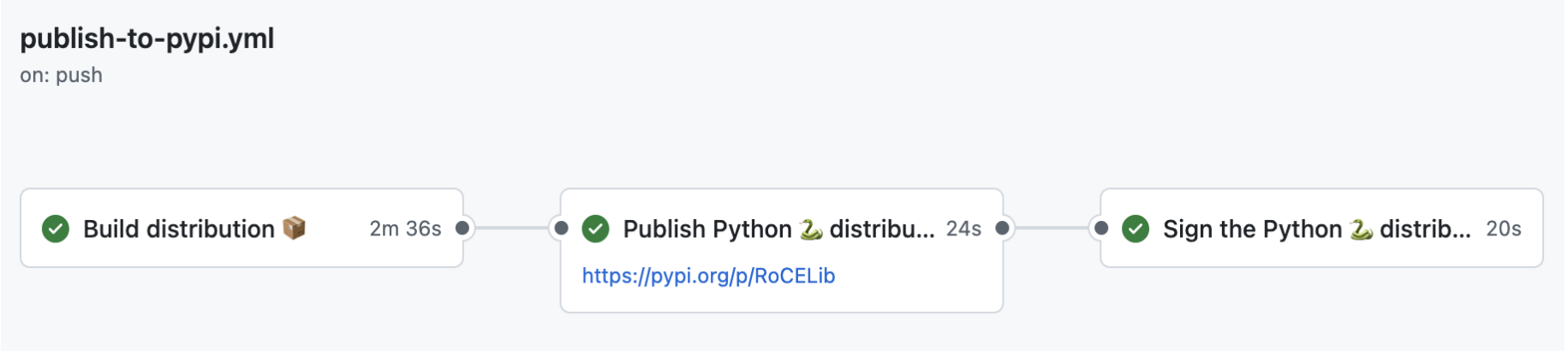


CI/CD setup


pages-build-deployment
on: dynamic
build 6s
report-build-status 4s
deploy 9s
https://jstadl.github.io/RoCELib/


Summary
Jobs
Build
Run details
Usage
Workflow file


Build
succeeded 17 minutes ago in 10m 42s
Set up job
Run actions/checkout@v4
Set up Python 3.10
Cache pip dependencies
Install dependencies
Lint with flake8
Test with pytest
Post Cache pip dependencies
Post Set up Python 3.10
Post Run actions/checkout@v4
Complete job

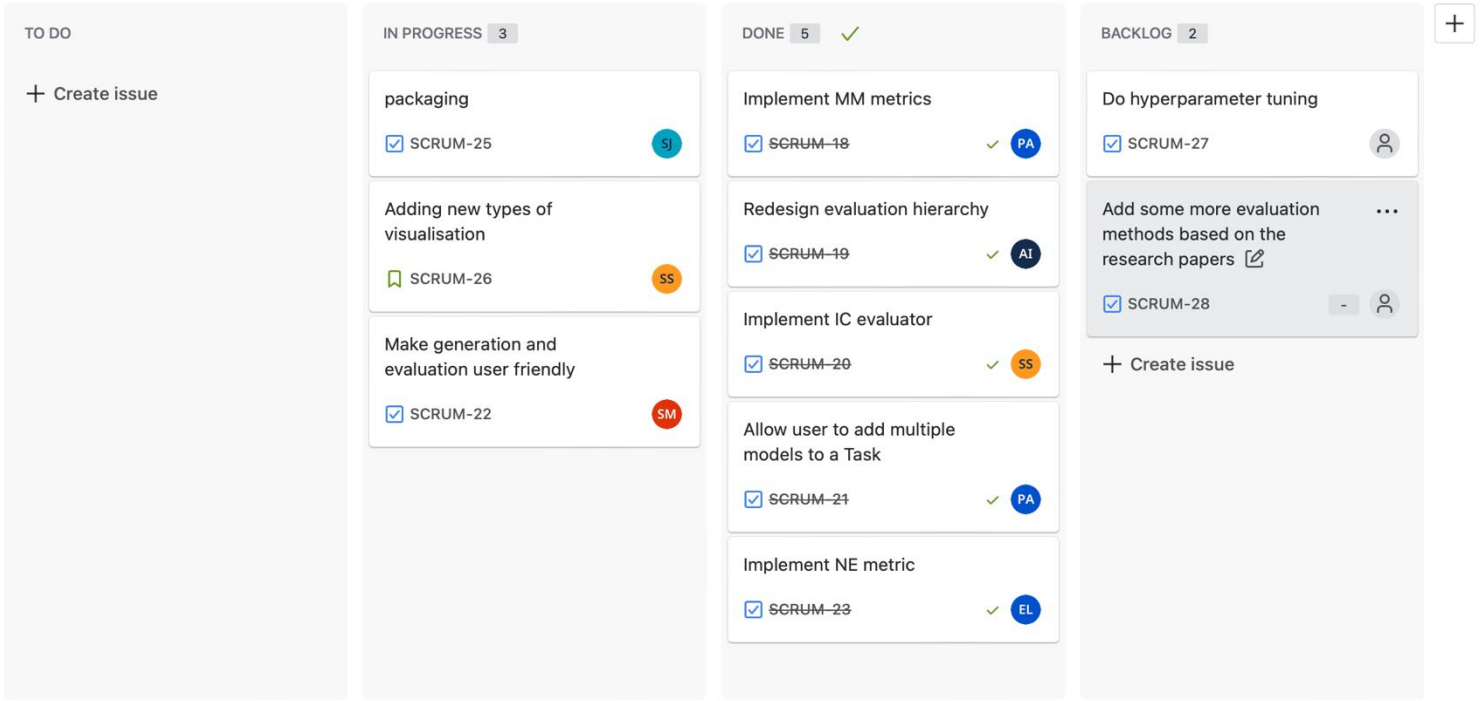

publish-to-pypi.yml
on: push
Build distribution 📦 2m 36s
Publish Python 🐍 distribu... 24s
https://pypi.org/p/RoCELib
Sign the Python 🐍 distrib... 20s

Evaluation: Maintainability

Project Management

Project Management

- Four 2-week sprints
- Bi-weekly meetings
- Scrum Master
- Feedback → pivot (classification task)
- At the end of each sprint we created a backlog



Project Evaluation

Overall evaluation

Redesigned Architecture
- Simpler and more intuitive structure
- More extensible

Added Key Features
- Importing models
- Easy CE generation
- More robust metrics
- Visualisations and output

Much More Maintainable
- Solid CI/CD and actions set up
- Much improved testing

Easier for Users to Use
- Tutorial notebooks
- Auto-deployed documentation

RoCELib

Robust Counterfactual Explanation Library

Questions?

Metrics Implemented

- Problem: Doesn't have enough robustness metrics to evaluate on
  - Noisy Execution robustness metric: Invalidation Rate Robustness
  - Input change robustness metric: VaR robustness
  - Very quick to add a new metric due to redesigned classes

Error Handling

- Original code: User exposed to low level errors
- SS of pandas dimension error

Fixes Implemented:

- Improved exception handling in PyTorch, Keras and SkLearn model imports.
- Clearer error messages for file format mismatches and missing files.
- Validation to ensure only supported model structures are loaded.

Result: Faster debugging and troubleshooting.

- More robust and user-friendly library.