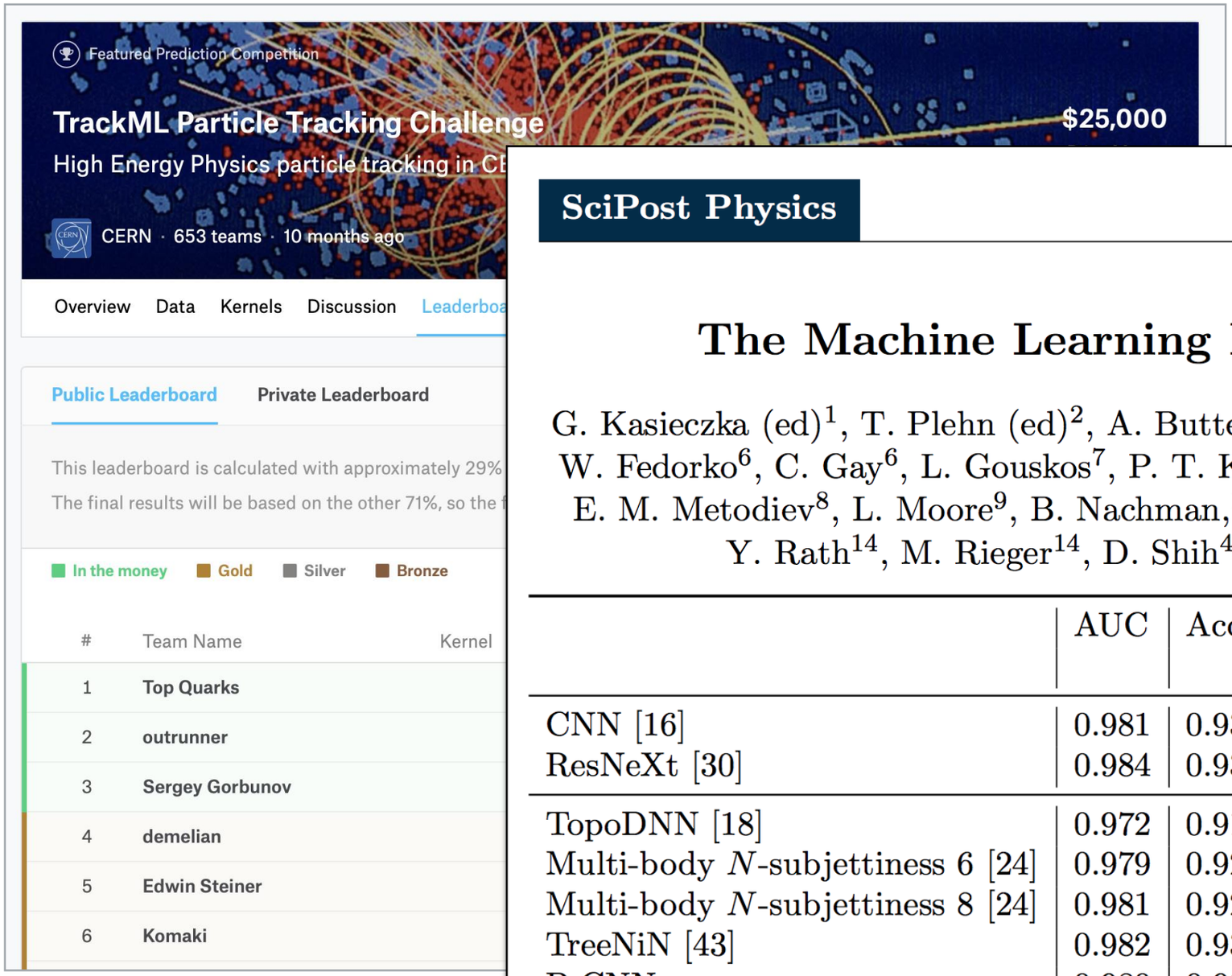
Reproducible Open Benchmarks for Data Analysis Platform

Kyle Cranmer, Irina Espejo,
Sebastian Macaluso, **Heiko Mueller**
New York University

Shih-Chieh Hsu, Aaron Maritz,
Ajay Rawat, Cha Suaysom
University of Washington



SciPost Physics Submission

The Machine Learning Landscape of Top Taggers

G. Kasieczka (ed)[1], T. Plehn (ed)[2], A. Butter[2], K. Cranmer[3], D. Debnath[4], M. Fairbairn[5], W. Fedorko[6], C. Gay[6], L. Gouskos[7], P. T. Komiske[8], S. Leiss[1], A. Lister[6], S. Macaluso[3,4], E. M. Metodiev[8], L. Moore[9], B. Nachman,[10,11], K. Nordström[12,13], J. Pearkes[6], H. Qu[7], Y. Rath[14], M. Rieger[14], D. Shih[4], J. M. Thompson[2], and S. Varma[5]

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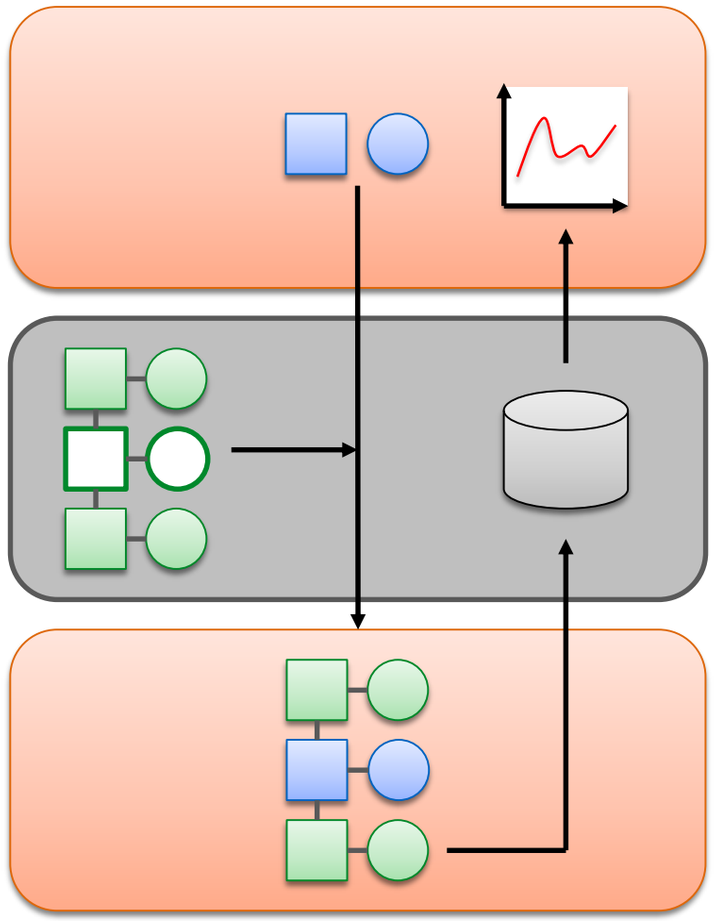
Reproducible Open Benchmarks Platform

Exploratory work for enabling such community benchmarks.

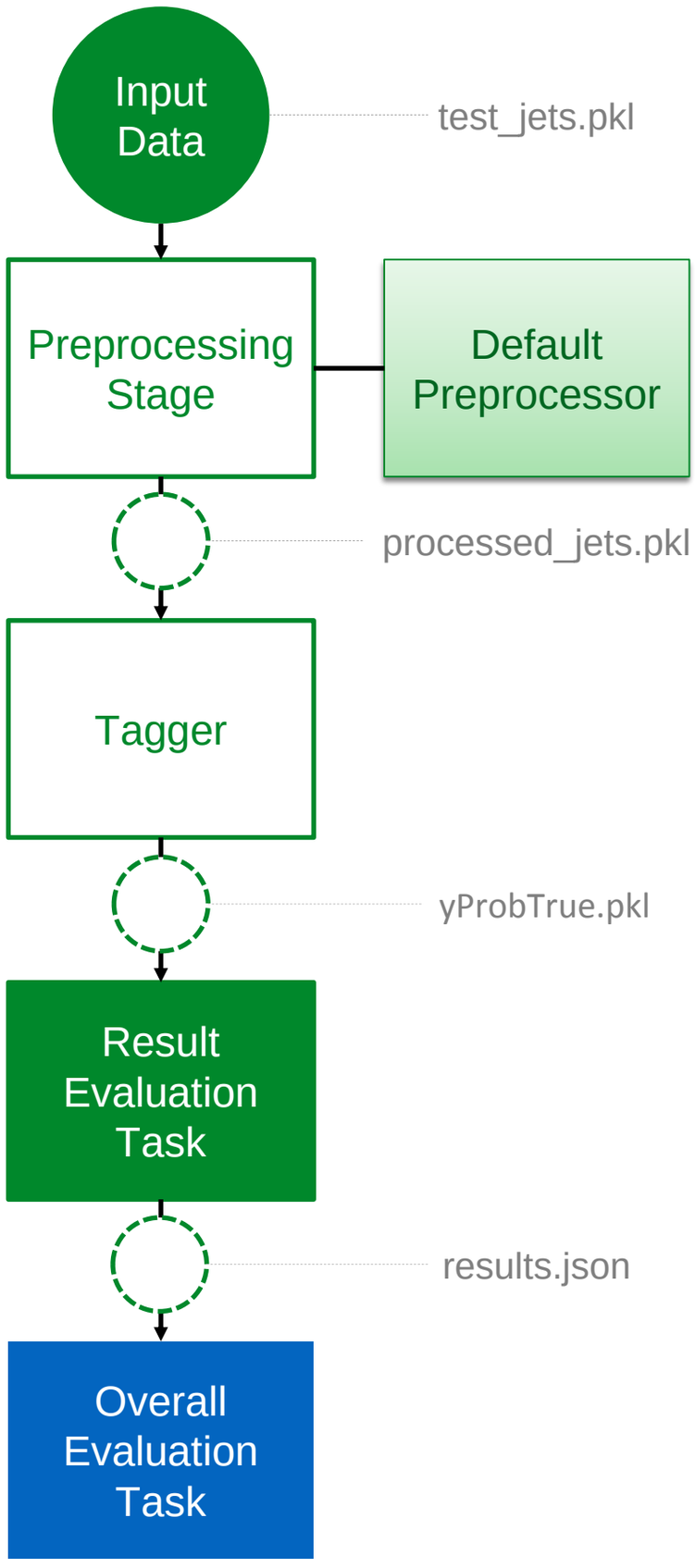
Components and Actors in ROB

1. Benchmark workflow defined by **coordinator** along with input data.
2. **Users** provide code (e.g. docker containers) that satisfy workflow stages, input parameters, and input data (file upload).
3. **Back-end** processes workflows and evaluates metrics (powered for example by REANA).
4. **Front-end** to collect input and display results.



Reproducible research data analysis platform

Benchmark Workflow Example

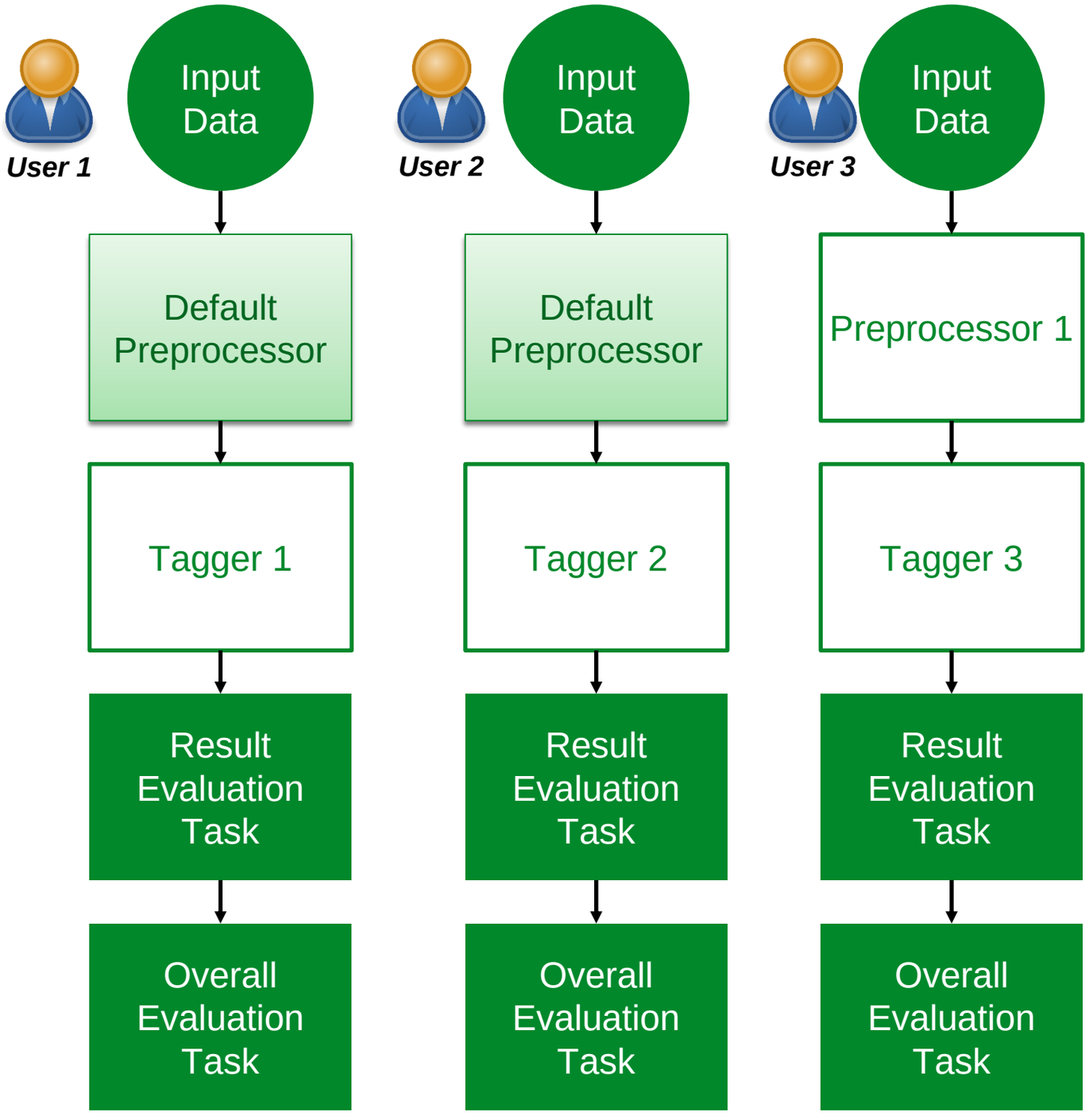


Workflow Templates

Coordinator defines structure of the workflow:

- Static input data
- User-provided input data
- Intermediate output data
- Implementation for static workflow stages
- Default implementation for variable workflow stages
- Variable (user-provided) workflow stages

Benchmark Workflow Example (cont.)



Benchmark Participants

Users create different instances of the workflow by providing **implementation for variable workflow stages** (and variable input data).

Workflow Templates

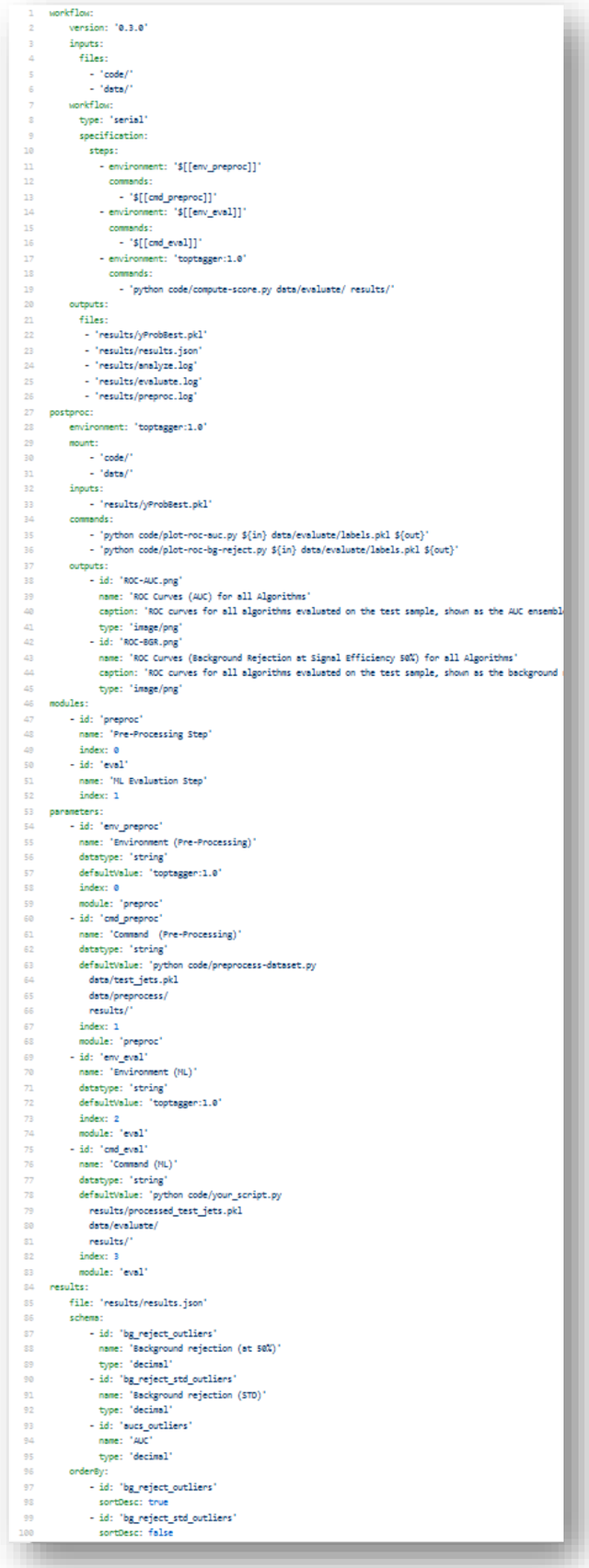
Components of Workflow Templates

1. Workflow specification (e.g. REANA serial workflow) with optional references to template parameters

2. Post-processing steps to evaluate overall performance (e.g. REANA serial workflow)

3. Declaration of template parameters (used by front-end for data input)

4. Specification of result schema to generate '*leader board*'.



```yaml
workflow:
  version: '0.3.0'
  inputs:
    files:
      - 'code/'
      - 'data/'
  workflow:
    type: 'serial'
    specification:
      steps:
        - environment: '$[[env_preproc]]'
          commands:
            - '$[[cmd_preproc]]'
        - environment: '$[[env_eval]]'
          commands:
            - '$[[cmd_eval]]'
        - environment: 'toptagger:1.0'
          commands:
            - 'python code/compute-score.py data/evaluate/ results/'
  outputs:
    files:
      - 'results/yProbBest.pkl'
      - 'results/results.json'
      - 'results/analyze.log'
      - 'results/evaluate.log'
      - 'results/preproc.log'
postproc:
  environment: 'toptagger:1.0'
  mount:
      - 'code/'
      - 'data/'
  inputs:
      - 'results/yProbBest.pkl'
  commands:
      - 'python code/plot-roc-auc.py ${in} data/evaluate/labels.pkl ${out}'
      - 'python code/plot-roc-bg-reject.py ${in} data/evaluate/labels.pkl ${out}'
  outputs:
      - id: 'ROC-AUC.png'
        name: 'ROC Curves (AUC) for all Algorithms'
        caption: 'ROC curves for all algorithms evaluated on the test sample, shown as the AUC ensembl
        type: 'image/png'
      - id: 'ROC-BGR.png'
        name: 'ROC Curves (Background Rejection at Signal Efficiency 50%) for all Algorithms'
        caption: 'ROC curves for all algorithms evaluated on the test sample, shown as the background
        type: 'image/png'
modules:
  - id: 'preproc'
    name: 'Pre-Processing Step'
    index: 0
  - id: 'eval'
    name: 'ML Evaluation Step'
    index: 1
parameters:
  - id: 'env_preproc'
    name: 'Environment (Pre-Processing)'
    datatype: 'string'
    defaultValue: 'toptagger:1.0'
    index: 0
    module: 'preproc'
  - id: 'cmd_preproc'
    name: 'Command  (Pre-Processing)'
    datatype: 'string'
    defaultValue: 'python code/preprocess-dataset.py
      data/test_jets.pkl
      data/preprocess/
      results/'
    index: 1
    module: 'preproc'
  - id: 'env_eval'
    name: 'Environment (ML)'
    datatype: 'string'
    defaultValue: 'toptagger:1.0'
    index: 2
    module: 'eval'
  - id: 'cmd_eval'
    name: 'Command (ML)'
    datatype: 'string'
    defaultValue: 'python code/your_script.py
      results/processed_test_jets.pkl
      data/evaluate/
      results/'
    index: 3
    module: 'eval'
results:
  file: 'results/results.json'
  schema:
      - id: 'bg_reject_outliers'
        name: 'Background rejection (at 50%)'
        type: 'decimal'
      - id: 'bg_reject_std_outliers'
        name: 'Background rejection (STD)'
        type: 'decimal'
      - id: 'aucs_outliers'
        name: 'AUC'
        type: 'decimal'
  orderBy:
      - id: 'bg_reject_outliers'
        sortDesc: true
      - id: 'bg_reject_std_outliers'
        sortDesc: false
```

Workflow Templates (cont.)

```yaml
workflow:
    version: '0.3.0'
    inputs:
      files:
        - 'code/'
        - 'data/'
    workflow:
      type: 'serial'
      specification:
        steps:
          - environment: '$[[env_preproc]]'
            commands:
              - '$[[cmd_preproc]]'
          - environment: '$[[env_eval]]'
            commands:
              - '$[[cmd_eval]]'
          - environment: 'toptagger:1.0'
            commands:
              - 'python code/compute-score.py data/evaluate/ results/'
    outputs:
      files:
       - 'results/yProbBest.pkl'
       - 'results/results.json'
       - 'results/analyze.log'
       - 'results/evaluate.log'
       - 'results/preproc.log'
```

Workflow Templates (cont.)

```yaml
workflow:
    version: '0.3.0'
    inputs:
      files:
        - 'code/'
        - 'data/'
    workflow:
      type: 'serial'
      specification:
        steps:
          - environment: '$[[env_preproc]]'
            commands:
              - '$[[cmd_preproc]]'
          - environment: '$[[env_eval]]'
            commands:
              - '$[[cmd_eval]]'
          - environment: 'toptagger:1.0'
            commands:
              - 'python code/compute-score.py data/evaluate/ results/'
    outputs:
      files:
        - 'results/yProbBest.pkl'
        - 'results/results.json'
        - 'results/analyze.log'
        - 'results/evaluate.log'
        - 'results/preproc.log'
```

```yaml
parameters:
  - id: 'env_preproc'
    name: 'Environment (Pre-Processing)'
    datatype: 'string'
    defaultValue: 'toptagger:1.0'
    index: 0
    module: 'preproc'
  - id: 'cmd_preproc'
    name: 'Command  (Pre-Processing)'
    datatype: 'string'
    defaultValue: 'python code/preprocess-dataset.py
      data/test_jets.pkl
      data/preprocess/
      results/'
    index: 1
    module: 'preproc'
```

Workflow Templates (cont.)

```yaml
workflow:
    version: '0.3.0'
    inputs:
      files:
        - 'code/'
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    workflow:
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```

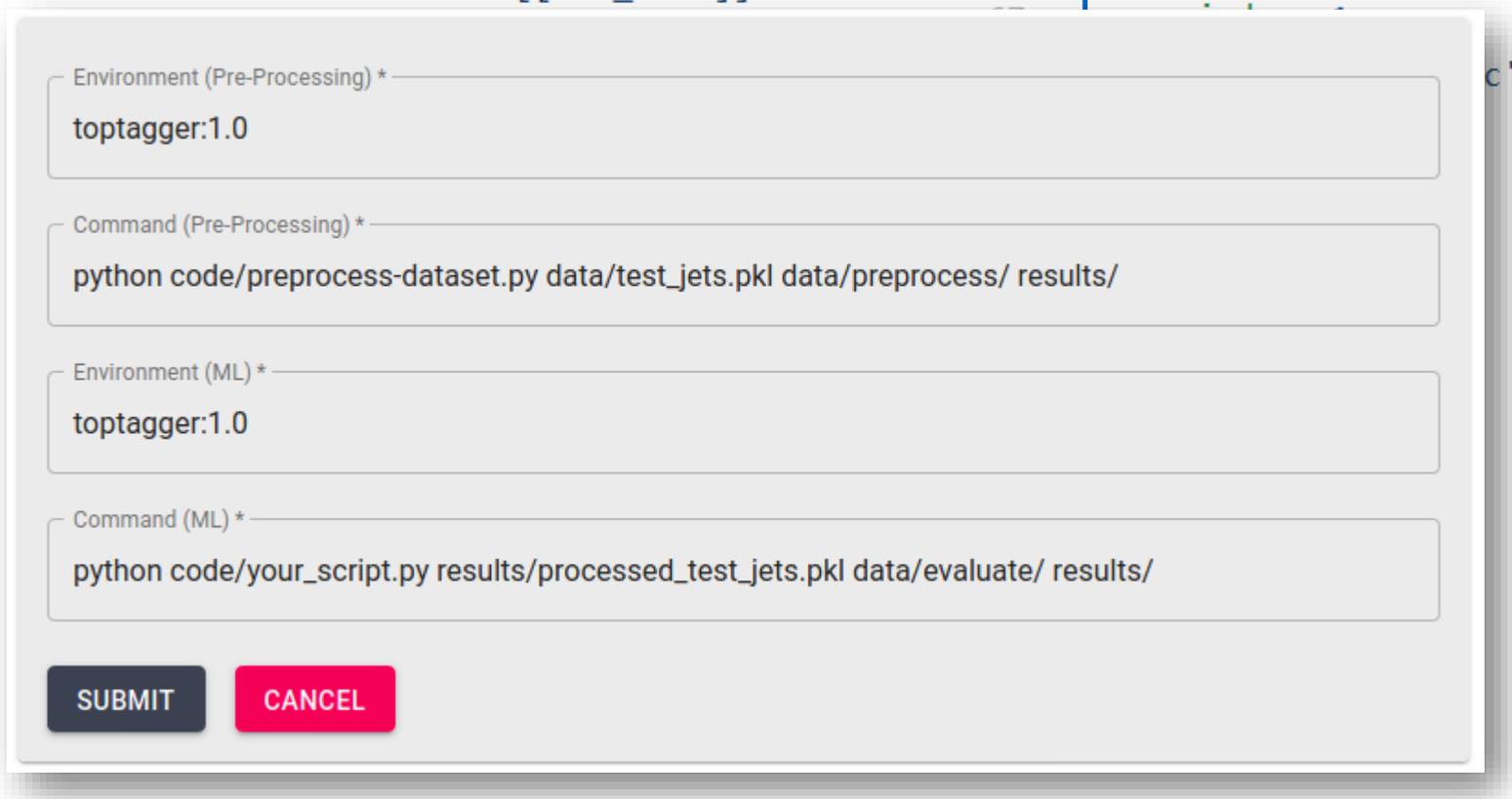

Workflow Templates (cont.)

Post-processing workflow to summarize overall results (e.g., generate plots)

```
postproc:
    environment: 'toptagger:1.0'
    mount:
        - 'code/'
        - 'data/'
    inputs:
        - 'results/yProbBest.pkl'
    commands:
        - 'python code/plot-roc-auc.py ${in} data/evaluate/labels.pkl ${out}'
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          type: 'image/png'
```
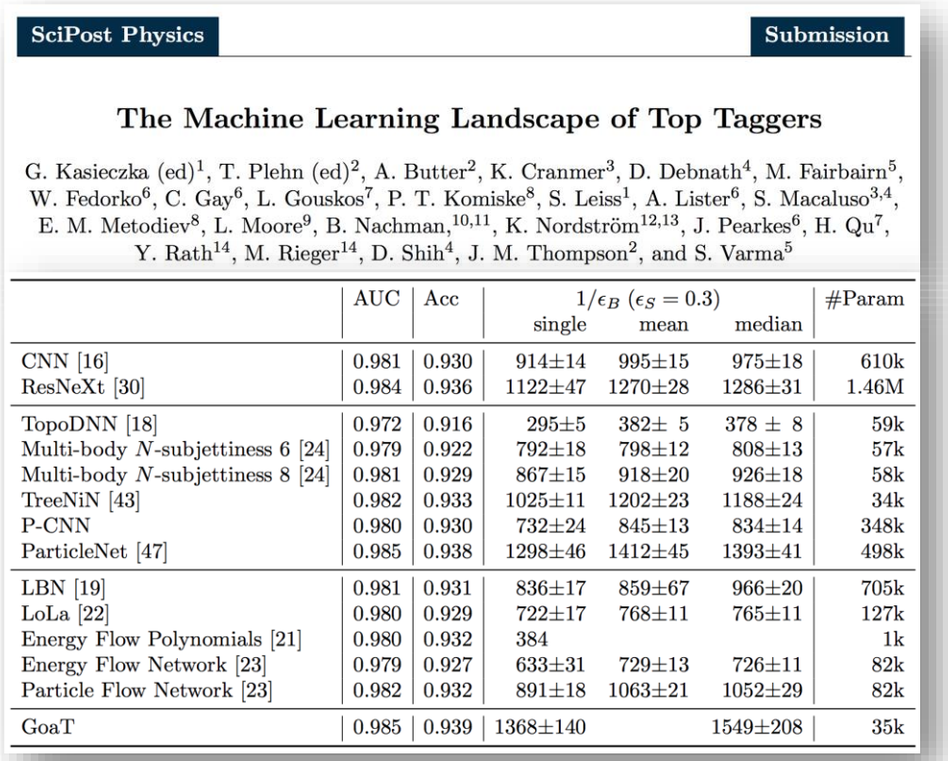

Workflow Templates (cont.)

Result schema to store benchmark results in database and to generate ranking

```yaml
results:
    file: 'results/results.json'
    schema:
        - id: 'bg_reject'
          name: 'Background rejection (at 50%)'
          type: 'decimal'
        - id: 'bg_reject_std'
          name: 'Background rejection (STD)'
          type: 'decimal'
        - id: 'auc'
          name: 'AUC'
          type: 'decimal'
    orderBy:
        - id: 'bg_reject'
          sortDesc: true
        - id: 'bg_reject_std'
          sortDesc: false
```



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Demo

The **Reproducible Open Benchmarks for Data Analysis Platform (ROB)** is an experimental prototype for enabling community benchmarks of data analysis algorithms. The goal of ROB is to allow user communities to evaluate the performance of their different data analysis algorithms in a controlled competition-style format.

Participate in Community Benchmarks

- Hello World
  Simple Hello World Demo
- ML4Jets - Top Tagger Comparison
  The Machine Learning Landscape of Top Taggers
- Number Predictor
  Simple Number Predictor Demo

The Machine Learning Landscape of Top Taggers

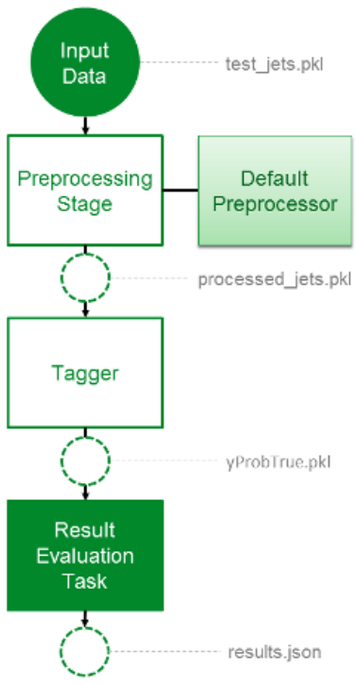
Benchmark Goals

Based on the established task of identifying boosted, hadronically decaying top quarks, this benchmark compares a wide range of modern machine learning approaches (see The Machine Learning Landscape of Top Taggers paper for more details).

The goal of this study is to see how well different neutral network setups can classify jets based on calorimeter information. While initially it was not clear if any of the machine learning methods applied to toptagging would be able to significantly exceed the performance of the multi-variate tools,later studies have consistently showed that we can expect great performance improvement from most modern tools. This turns around the question into which of the tagging approaches have the best performance (also relative to their training effort), and if the leading taggers make use of the same, hence complete set of information.

How to Participate

The benchmark workflow consists of three main steps.



Participants are given a test dataset consisting of 200k signal and 200k background jets. The top signal and mixed quark-gluon background jets are produced with using Pythia8 with its default tune for a center-of-mass energy of 14 TeV and ignoring multiple interactions and pile-up. For a simplified detector simulation we use Delphes with the default ATLAS detector card.

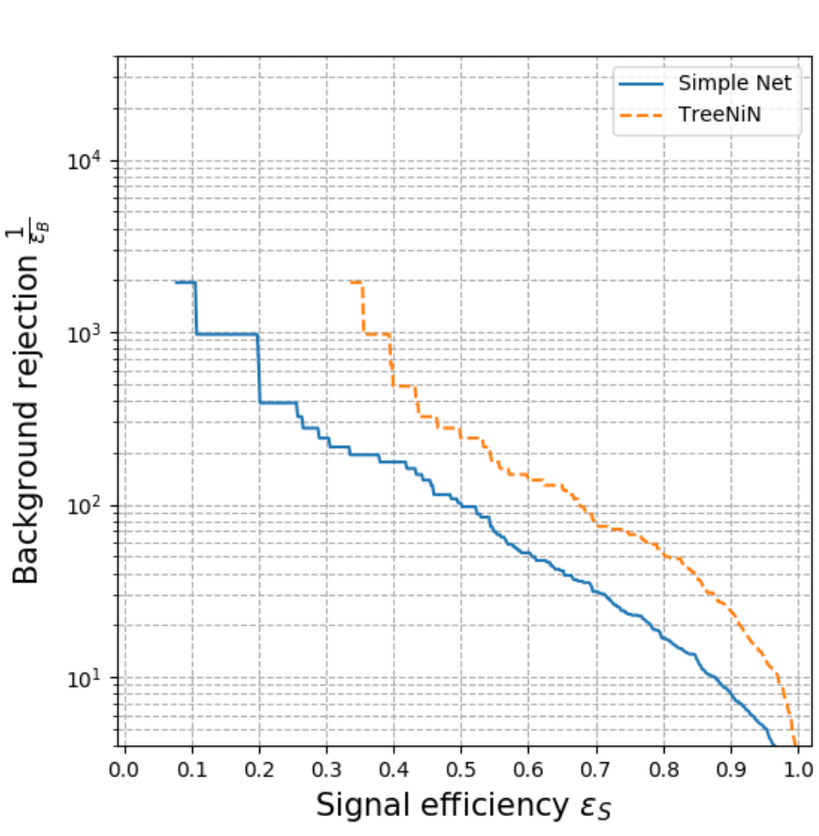
The produced results should contain classification results for each jet to measure the performance of the network and test which jets are correctly classified in each approach. Overall results are sorted in decreasing order by the background rejection as signal efficiency at 50%.

The Machine Learning Landscape of Top Taggers

Performance Metrics

	Background rejection (at 50%)	Background rejection (STD)	AUC
TreeNiN	242.500000	13.857100	0.983987
Simple Net	99.552600	9.379710	0.958746

ROC Curves (Background Rejection at Signal Efficiency 50%) for all Algorithms



ROC curves for all algorithms evaluated on the test sample, shown as the background rejection ensemble median of multiple trainings.

ML4Jets - Top Tagger Comparison

The Machine Learning Landscape of Top Taggers

OVERVIEW CURRENT RESULTS MY SUBMISSIONS

TreeNiN

Submit New Run ...

Upload Files ...

New Submission ...

Runs (TreeNiN)

Started at 16-Jan-2020 12:03:23
Finished at 16-Jan-2020 12:03:41

Inputs

Environment (Pre-Processing): toptagger:1.0
Command (Pre-Processing): python code/preprocess-dataset.py data/test_jets.pkl data/preprocess/ results/
Environment (ML): toptagger:1.0
Command (ML): python code/TreeNiN.py results/processed_test_jets.pkl data/evaluate/ results/

Outputs

results/yProbBest.pkl (16-Jan-2020 12:03:57)

results/results.json (16-Jan-2020 12:03:57)


```
{
    "bg_reject": 242.5,
    "bg_reject_std": 13.857142857142843,
    "auc": 0.9839870883795416,
    "auc_std": 0.00024491250326624716
}
```


results/analyze.log (16-Jan-2020 12:03:57)

results/evaluate.log (16-Jan-2020 12:03:57)

results/preproc.log (16-Jan-2020 12:03:57)

ML4Jets - Top Tagger Comparison

The Machine Learning Landscape of Top Taggers

OVERVIEW CURRENT RESULTS MY SUBMISSIONS

TreeNiN

Submit New Run ...

Upload Files ...

New Submission ...

Submit New Run (TreeNiN)

Environment (Pre-Processing) *
toptagger:1.0

Command (Pre-Processing) *
python code/preprocess-dataset.py data/test_jets.pkl data/preprocess/ results/

Environment (ML) *
toptagger:1.0

Command (ML) *
python code/your_script.py results/processed_test_jets.pkl data/evaluate/ results/

SUBMIT CANCEL

ML4Jets - Top Tagger Comparison

The Machine Learning Landscape of Top Taggers

OVERVIEW CURRENT RESULTS MY SUBMISSIONS

TreeNiN

Submit New Run ...

Upload Files ...

New Submission ...

Runs (TreeNiN)

Started at 16-Jan-2020 12:03:23

Inputs

Environment (Pre-Processing): toptagger:1.0
Command (Pre-Processing): python code/preprocess-dataset.py data/test_jets.pkl data/preprocess/ results/
Environment (ML): toptagger:1.0
Command (ML): python code/TreeNiN.py results/processed_test_jets.pkl data/evaluate/ results/

CANCEL

Continue …

Ongoing and Future Work

(Re-)run competition using REANA as the backend

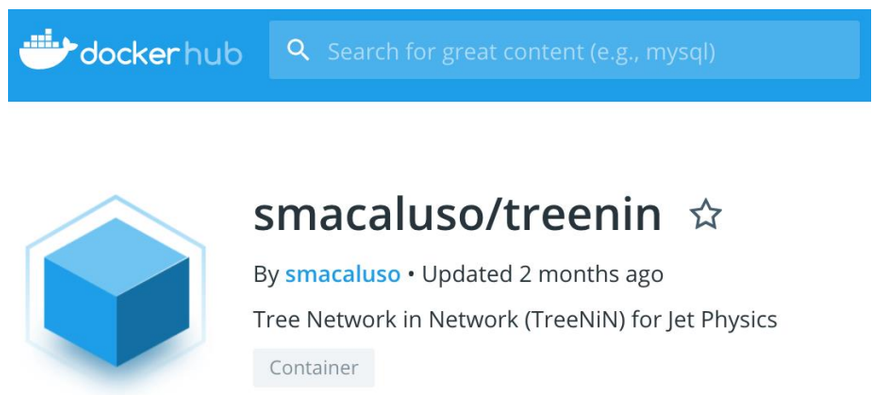
Full Yadage Workflow for TreeNiN

https://github.com/cha-suaysom/reana-demo-treenin

Docker Container

https://github.com/diana-hep/TreeNiN

https://hub.docker.com/r/smacaluso/treenin



Anyone else interested?

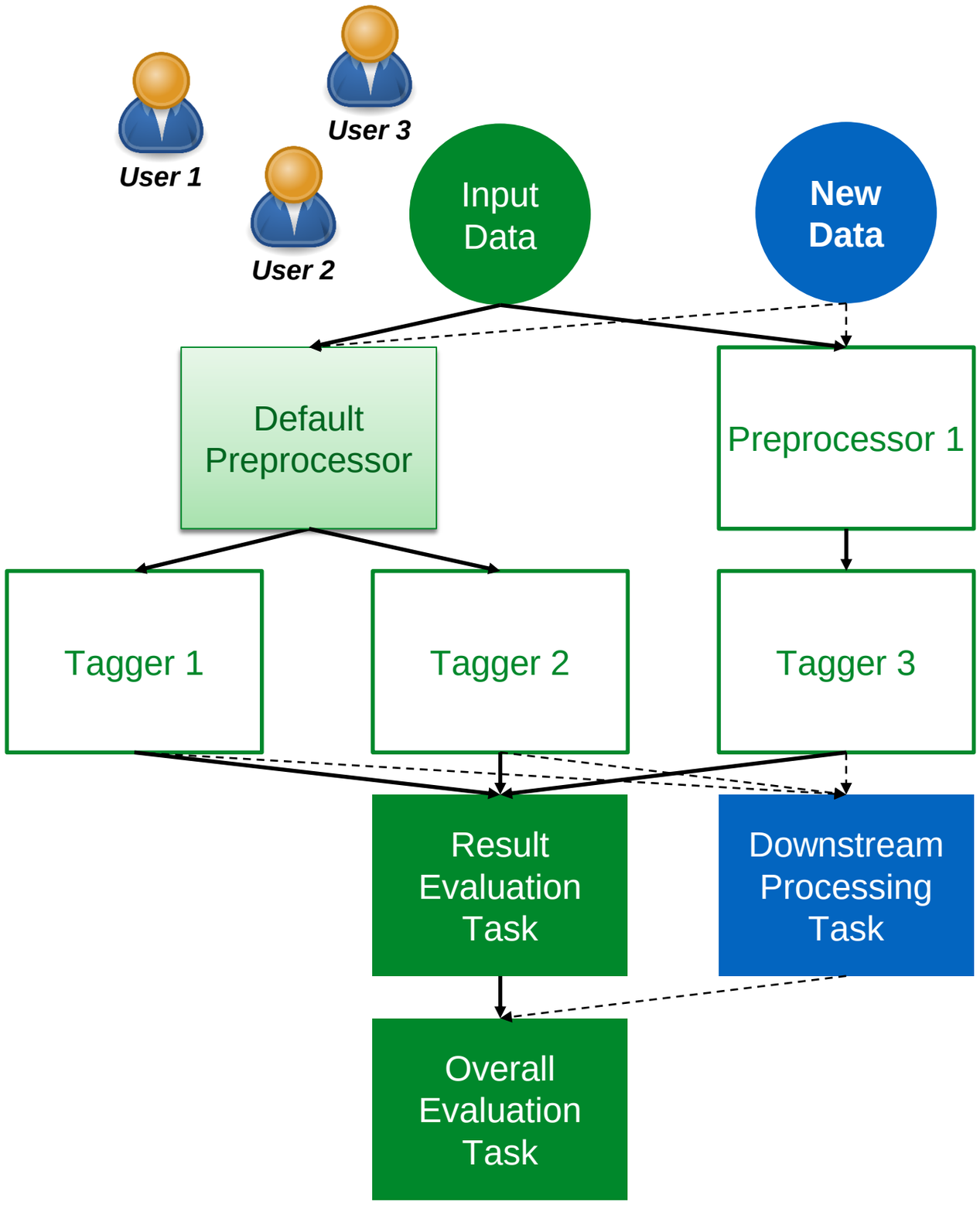
Code Repositories for ROB

https://github.com/scailfin/rob-core

https://github.com/scailfin/rob-webapi-flask

https://github.com/scailfin/rob-ui

Ongoing and Future Work (cont.)



Other applications …

Run provided model with different input data.

Compare different input dataset and models against each other (e.g. **Standard Cortical Observer**).

Apply different/additional downstream processing tasks to the model results.