Democratizing machine learning research with OpenML

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Infinite range of possibilities, tacit experience



Infinite range of possibilities, tacit experience

collection, cleaning, preprocessing, featurization, selection,...



Infinite range of possibilities, tacit experience





Model selection





Infinite range of possibilities, tacit experience

Model selection







Neural architecture search

Infinite range of possibilities, tacit experience





Model selection



Infinite range of possibilities, tacit experience

Model selection





Hyperparameter tuning



Transfer / continual / meta learning





People run millions of experiments every day

What if we could capture, organise and learn from them?



Human experts

People run millions of experiments every day

What if we could capture, organise and learn from them?











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What if... we could organize the world's machine learning information

and make it universally accessible and useful?









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mapping the universe









uniform meta-data

models

1000s of papers





Citizen Science projects



Democratizing data How can we generalize this idea?



Citizen Science projects





Well-organized data, easily accessible, uniform meta-data







Machine learning models

(Assuming we have these)





Data from various sources

What format? What meta-data? Can we automate this?

?



Well-organized data, easily accessible, uniform meta-data







Machine learning models

(Assuming we have these)





Data from various sources

Most ML data is (at some point) represented as dataframe/matrix Well-organized data, easily accessible, uniform meta-data

(Required anyway for many ML models)

(Can be a data loading script for large and remotely hosted data)







Machine learning models





(Required anyway for many ML models)

(Can be a data loading script for large and remotely hosted data)







Machine learning models





(Required anyway for many ML models)

(Can be a data loading script for large and remotely hosted data)







Machine learning models





various sources



ML tasks (e.g. classification) Semi-automatically extracts metadata, converts to uniform formats

easily accessible, uniform meta-data







Machine learning models





Data from various sources



ML tasks (e.g. classification)





Data from various sources



ML tasks (e.g. classification)





Data from various sources



ML tasks (e.g. classification)



An open platform for discovering and sharing ML datasets, algorithms, experiments



(scripts, notebooks, apps, cloud jobs)

OpenML



Website (new.openml.org)

OpenML web interface

| OpenML web | Search Search | Datasets | Dataset analys | is | | | |
|--|--|--|--|--|-----------------------|-----------------|--|
| 🂰 OpenML | Q covertype | | | | | | Sign In |
| Search | 7 datasets found verified 😢 | | | | | 2 ⁷⁸ | |
| Tasks | Sylva_prior Datasets from the Agnostic Learning vs. Prior Knowledge Challenge | Data Detail | Analysis | Tasks | | | |
| Flows | (http://www.agnostic.inf.ethz.ch) ▲ 486 🚯 14 🖽 14.4k x 109 🖪 1040 🕲 7 years ago v.1 🗸 | covertype data | aset | | | | |
| Collections | covertype | Choose one or more attri | butes for distribution plot (first 1k attri | butes listed) Missing values | ≑ # categories | \$Target | \$Entroj |
| Benchmarks | Normalized version of the Forest Covertype dataset (see version 1), so that the numerical values are between 0 and 1. Contains the forest cover type for | | filter data | 0 | 7 | true | 13 |
| Task Types | Ä 342 ♥ 1 🔥 40 ☶ 581k x 55 🖪 150 ⓑ 8 years ago v.3 ✔ | soil_type_28 | nominal | 0 | 2 | | 0.01 |
| Learn | CovPokElec Dataset created to study concept drift in stream mining. It is constructed by | soil_type_17 soil_type_18 soil_type_19 | nominal nominal | 0 0 0 | 2 2 2 2 | | 0.04 |
| Documentation [©] | combining the Covertype, Poker-Hand, and Electricity datasets. More details | soil_type_20 | nominal | 0 | 2 | | 0.08 |
| Blog 🖻 | V.1 🗸 | Distribution plot | | | | | |
| API's Contribute Meet up | covertype Predicting forest cover type from cartographic variables only (no remotely sensed data). The actual forest cover type for a given observation (30 x 30 216 11 10k x 55 18 180 38 years ago v.1 | Choose if the color cod Target based distr Stack Oun-stack | e is based on target or not ibution O Individual distribution | | | | Spruce_ |
| Terms & Citation | covertype This is the famous covertype dataset in its binary version, retrieved 2013-11- 13 from the libSVM site (called covtype.binary there). Additional to the | class | 10k 5k | | | | Lodgepo Pondero Cottonw Aspen |
| 🕻 Minify 🕻 Dark | 📕 22 🚯 9 🖽 581k x 55 🖪 293 🕲 7 years ago | | 0 Spr | Lodge Ponde | Cotton Aspen | Dougi Krum | |







OpenML web interface

Tasks

| (| OpenML | | Q Search datasets | | |
|----------|-------------------|-------|---|--|-----------------------------------|
| Disco | over | | 90172 tasks found | × ↓7 ▼ | Detail |
| | Data sets | | 🌼 96.2k 💙 0 🔥 0 | ්ටු2 years ago | Top 1000 rui |
| | Tasks | 90.2k | eeg-eye-state | | sklearn.pipelin |
| \$ | Flows | | Supervised Classification: pred evaluate with 10-fold Crossval | dict 'Class', idation | |
| ¢ | Runs | | 🌼 95.5k 💙 0 🔥 0 | [™] 34 years ago | sklearn.model_se |
| Д | Collections | | hill-valley Supervised Classification: pred | dict 'Class', | sklearn.pipelin |
| Þ | Task Types | | evaluate with 10-fold Crossval 🌼 92.4k 💙 0 📤 0 | idation う2 years ago | sklearn.nei |
| <u></u> | Measures | | ozone-level-8hr | | |
| *** | People | | Supervised Classification: pred evaluate with 10-fold Crossval | dict 'Class', idation | sklearn.pipel |
| Learr | n more | | 🏟 90.8k 🔎 0 🔥 0 | Ŋ4 years ago | sklearn.pipel |
| | Documentation | | ozone-level-8hr | | WERd.RI.Att |
| 2 | Get involved | | Supervised Classification: pred evaluate with 10-fold Crossval | dict 'Class', idation う2 years ago | sklearn.pipelin sklearn.pipeli |
| 5 | OpenML Foundation | | • | | |
| • | Terms & Citation | | banknote-authenticatio | n dict 'Class', idation | weka.FilteredC |
| . | Our team | | | 34 years ago | |











from sklearn import ensemble from openml import tasks, runs



task = tasks.get task(3954)run.publish()



- model = ensemble.RandomForestClassifier() run = runs.run model on task(model, task)



from torch.nn from openml import tasks, runs

task = tasks.get task(3954)run = runs.run model on task(clf, task) run.publish()





- model = torch.nn.Sequential(processing net, features net, results net)



Benchmarking suites

- How can we build better, more general benchmarks?
 - Start with a large set of datasets (e.g. OpenML)
 - Define strict set of constraints
 - Retrieve and test models on all matching datasets
 - Gather results from different researchers in a central place (e.g. OpenML)
- Offers a way to really use benchmark suites and converge to well-defined accepted suites
- Are meant to be dynamic: evolve with new datasets joining over time



Benchmarking suites

All results can be streamed, organized, downloaded to/from OpenML

| « | OpenML | Q Search collections | |
|---------|----------------------------|---|--------|
| Searc | :h | 130 collections found run 😢 | |
| 8 | Datasets | | |
| | Tasks | A large-scale comparison of classification algorithms We investigate the performance of a wide range of classification algorithms on | Ru |
| ٠ | Flows | a wide range of datasets to better understand when they perform well and | Shows |
| д | Runs | 🥃 512 📁 514 📫 63 📕 91.4k 📔 1 🕲 6 years ago | Predic |
| \$ | Collections | Source Selection Improve Classification? Feature selection can be of value to classification for a variety of reasons. Real | Show |
| Та | sks | world data sets can be rife with irrelevant features, especially if the data was | |
| Ru | ins 13 | = 374 ⊨ 374 ¥ 24 ▲ 7.45k ⊨ 15 5/3 years ago | |
| Þ | Task Types | Search Study | An |
| <u></u> | Measures | Run results of the ongoing AutoML benchmark, see https://openml.github.io/automlbenchmark/.The benchmark includes both | b |
| Learr | า | 🛢 19 📁 19 🌼 6 👗 117 🖪 226 🕲 2 years ago | aset |
| | Documentation ^면 | Section CC18-Example | Dati |
| ۳ | Blog 🖻 | Soon plant Soon pla | |
| > | API's | | |
| 2 | Get involved | Prefetching for SPARQL endopints Data prefetching is a standard technique used to accelerate the access to data | |

| | | | | 2 |
|---|---|-------------|--|--------|
| n Collection | Analysis | Tasks | Runs | |
| scatter plot of r | esults | | | |
| tive Accuracy | | | | |
| results for eac | h fold (can be slow) | | | |
| adult | automlbenchmark_autosklearn(1) automlbenchmark_h2oautoml(1) automlbenchmark_tpot(1) | • • • | automlbenchmark_autoweka(1) automlbenchmark_randomforest(1) automlbenchmark_tunedrandomfor | est(1) |
| APSFailure APSFailure oank-marketing connect-4 ashion-MNIST guillermo helena higgs | • • • | | | |
| jannis jungle_chess DCup09_app MiniBooNE nomao numerai28.6 riccardo robert | • | • | • | |
| shuttle volkert | | | *** * | * |

0.4

0.6

0.8

0.2



Sign In

Benchmarking suites

- Example: OpenML-CC18
 - 3.8 million results
- Classification only
- 72 datasets
- Contain missing values and categorical features
- Medium-sized (500-100000 observations, <5000 features after one-hot-encoding)
- Not unbalanced
- No groups/block/time dependencies
- No sparse data
- Some more subjective criteria (see paper)

| analcatdat |
|--------------|
| dresses-sa |
| madelon |
| jm1 |
| cmc |
| pc3 |
| ilpd |
| blood-trans |
| first-order- |
| GesturePha |
| pc1 |
| credit-g |
| connect-4 |
| Biorespons |
| kc2 |
| churn |
| kc1 |
| eucalyptus |
| electricity |
| cylinder-ba |
| diabetes |
| phoneme |
| adult |
| jungle_ches |
| CIFAR_10 |
| sick |
| bank-mark |
| steel-plate |
| mfeat-mor |
| vehicle |
| wall-robot- |
| ozone-leve |
| credit-appr |
| Internet-Ac |
| pc4 |
| 0.0 |



AUC score distribution

| climate-me | odel-simulation- | crashe | s | |
|-------------|------------------|--------|--------------|-----|
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| mfeat-pixe | el | | | |
| car | | | | |
| kr-vs-kp | | | | |
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| texture | | | | |
| mnist_784 | | | | |
| analcatdat | a_authorship | | | |
| MiceProte | in | | | |
| 0.0 | 0.2 | 0.4 | 0.6 score | 0.8 |



OpenML Community

250000+ yearly users 13000+ registered contributors 900+ publications

15,581

20000+ datasets 8000+ flows 10.000.000+ runs



OpenML Architecture



Democratizing machine learning itself





ML tasks (e.g. classification)

Now that we have data on millions of experiments, can we automate the building and tuning of machine learning models?

Automatic Machine Learning (AutoML)

Replace manual trial and error with automated search (based on prior experience)





Automatic Machine Learning (AutoML)

Replace manual trial and error with automated search (based on prior experience)





memory

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OpenML as a global memory

Machine-readable repository of machine learning results



Structure of AutoML systems





Structure of AutoML systems



Structure of AutoML systems



Structure of learning AutoML systems



Automating machine learning

auto-sklearn: uses OpenML to warm-start the search for the best pipelines



ABLR (Amazon): uses OpenML to learn how to search hyperparameters



Feurer et al. 2020

Perrrone et al. 2018

Automating machine learning

ProbMF (Microsoft): uses OpenML to recommend the best algorithms



GAMA (TU/e): modular AutoML system, handles wide range of tasks



Fusi et al. 2018



Gijsbers et al. 2018 - 2022

Automating machine learning

OptFormer (DeepMind): uses OpenML to train a transformer model, predict the next models to try









Chen et al. 2022





Human-Al interaction Algorithms learn from models shared by humans Humans learn from models built by bots



Join us! (and change the world) Active open source community - Hackathons 2-3x a year **OpenML** Foundation - Sponsorship, science OpenML spin-off: PortML - Services, projects

We're hiring! **2** Research Engineer positions at TU Eindhoven



















Thanks to the entire OpenML star team



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Pieter Gijsbers



Matthias Feurer

Andreas Müller





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Jan van Rijn



Sebastian Fischer



Prabhant Singh



Marcel Wever





Bernd Bischl

Heidi Seibold

×

Guiseppe Casalicchio

Sahithya Ravi



Erin Ledell



Bilge Celik



Neil Lawrence





Janek Thomas

















Thank you! 谢谢













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