Awesome-META+: Meta-Learning Research and Learning Platform

Jingyao Wang $^{1}$, Chuyuan Zhang $^{1}$, Ye Ding $^{1}$, and Yuxuan Yang $^{1}$

$^{1}$Affiliation not available

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Abstract

Artificial intelligence technology has already had a profound impact in various fields such as economy, industry, and education, but still limited. Meta-learning, also known as “learning to learn”, provides an opportunity for general artificial intelligence, which can break through the current AI bottleneck. However, meta learning started late and there are fewer projects compare with CV, NLP etc. Each deployment requires a lot of experience to configure the environment, debug code or even rewrite, and the frameworks are isolated. Moreover, there are currently few platforms that focus exclusively on meta-learning, or provide learning materials for novices, for which the threshold is relatively high. Based on this, Awesome-META+, a meta-learning framework integration and learning platform is proposed to solve the above problems and provide a complete and reliable meta-learning framework application and learning platform. The project aims to promote the development of meta-learning and the expansion of the community, including but not limited to the following functions: 1) Complete and reliable meta-learning framework, which can adapt to multi-field tasks such as target detection, image classification, and reinforcement learning. 2) Convenient and simple model deployment scheme which provide convenient meta-learning transfer methods and usage methods to lower the threshold of meta-learning and improve efficiency. 3) Comprehensive researches for learning. 4) Objective and credible performance analysis and thinking.
Awesome-META+: Meta-Learning Research and Learning Platform

Jingyao Wang†‡, Chuyuan Zhang†‡, Ye Ding†‡, Yuxuan Yang§
*Institute of Software, Chinese Academy of Sciences, Beijing, China.
†University of Chinese Academy of Sciences, Beijing, China.
‡Shanghai Astronomical Observatory, Chinese Academy of Sciences, Shanghai, China.
§Suzhou University of Science and Technology, Suzhou, China.

Abstract—Artificial intelligence technology has already had a profound impact in various fields such as economy, industry, and education, but still limited. Meta-learning, also known as "learning to learn", provides an opportunity for general artificial intelligence, which can break through the current AI bottleneck. However, meta learning started late and there are fewer projects compare with CV, NLP etc. Each deployment requires a lot of experience to configure the environment, debug code or even rewrite, and the frameworks are isolated. Moreover, there are currently few platforms that focus exclusively on meta-learning, or provide learning materials for novices, for which the threshold is relatively high. Based on this, Awesome-META+, a meta-learning framework integration and learning platform is proposed to solve the above problems and provide a complete and reliable meta-learning framework application and learning platform. The project aims to promote the development of meta-learning and the expansion of the community, including but not limited to the following functions: 1) Complete and reliable meta-learning framework, which can adapt to multi-field tasks such as target detection, image classification, and reinforcement learning. 2) Convenient and simple model deployment scheme which provide convenient meta-learning transfer methods and usage methods to lower the threshold of meta-learning and improve efficiency. 3) Comprehensive researches for learning. 4) Objective and credible performance analysis and thinking.

Index Terms—System Design, Meta Learning, Software Development, Framework Integration

I. INTRODUCTION

With the vigorous development of the new global round of technological revolution and information technology, artificial intelligence (AI) technology has taken off and has had a profound impact on various fields such as the economy, society, industry, and education [1], [2], [3], [4]. AI technology has become the hottest topic in technology and the development of reliable, general AI has become a global consensus. However, current AI is still limited to specialized intelligence. Traditional machine learning paradigms, such as supervised learning based on labeled data or unsupervised learning represented by clustering, are specific to certain tasks and cannot provide effective feedback for unseen tasks or analyze unseen data [5], [5]. Meanwhile, specialized AI systems, due to their single task, clear demands, distinct application boundaries, rich domain knowledge, and relatively simple modeling, can surpass human intelligence in single item testing at the local intelligence level, forming a breakthrough in the field of AI. However, there is still a long way to go to meet the expectations of academic researchers for general AI, and it is difficult to overcome this limitation.

The emergence of meta-learning and related model research provides an opportunity for general AI. It can endow machine learning with the ability to adapt to new developments like humans, and complete multiple tasks that do not rely on human experience. Meta-learning [6], [7] can realize the idea of autonomous driving on roads with unknown conditions, or allow a robotic arm to handle various objects of different specifications and weights, achieving outstanding performance in multiple scenarios. This field is also one of the most promising areas currently [8], [9].

Although the current meta-learning frameworks in academia have superior performance in multiple fields, due to reasons such as numerous systems, wide application areas, narrow community, and high entry barriers, there are differences in the deployment of different models, or the application of the same model to different domain tasks [10], [11]. Moreover, there is a lack of relevant basic teaching resources. If we want to replicate and deploy multiple frameworks, it requires a lot of time, as meta-learning frameworks include optimization-based, model-based, and metric learning-based methods [12], [13], targeting areas such as reinforcement learning and few-shot learning [14], [15], [16]. In this condition, the deployment and application of multiple models are more complex. In addition, due to the narrow community of meta-learning compared to computer vision and other fields, and relatively high entry barriers, there are few summary platforms targeting newbies or comprehensive frameworks. Therefore, we decided to build a platform called Awesome-META+, which can provide various meta-learning framework optimization codes, deployment solutions, performance data, academic materials, and further expand to other fields, providing a standardized solution.

The goals and contributions of our system include:
- Providing a comprehensive and reliable meta-learning framework code that can adapt to multiple domains and improve academic research efficiency.
- Providing a convenient and simple model deployment solution to lower the threshold and promote the development of meta-learning and its transfer fields.
- Providing a comprehensive and complete information summary and learning platform for the meta-learning field to stimulate the vitality of the meta-learning community.
- Conducting objective and credible performance analysis and reflection to support framework selection and technology implementation.

Our work is shown in https://wangjingyao07.github.io/Awesome-Meta-Learning-Platform/. The Homepage is shown as Figure 1.

II. REQUIREMENTS ANALYSIS AND SYSTEM DESIGN

A. Audience groups

Awesome-META+ is a research and learning platform for meta-learning that is aimed at a wide range of Internet users. The target audience includes individuals who are interested in or working in the field of meta-learning. The platform is specifically divided into the following three groups based on the potential needs of users.

<table>
<thead>
<tr>
<th>No.</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group1</td>
<td>Scholars or practitioners in the field of meta-learning.</td>
</tr>
<tr>
<td>Group2</td>
<td>Beginners interested in the field of meta-learning.</td>
</tr>
<tr>
<td>Group3</td>
<td>Scholars and industry practitioners in various fields who hope to use the meta-learning paradigm to improve framework performance or apply it to landing products.</td>
</tr>
</tbody>
</table>

TABLE I: Audience groups

B. Application Scenarios

Awesome-META+ is set up with four different scenarios, each of which targets different user groups and needs. The following table describes the users and their needs for each scenario.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Target Audience</th>
<th>Requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>Group 1/2/3</td>
<td>Users need to configure specific frameworks on their local machines and understand the core technologies and ideas behind the framework’s code.</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>Group 1</td>
<td>Academic researchers need to conduct comparative experiments on multiple meta-learning frameworks to obtain baseline data or improve the performance of specific tasks.</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>Group 2</td>
<td>Individuals who want to understand the current development status of meta-learning, engage in systematic learning, and obtain relevant materials.</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>Group 3</td>
<td>Users hope to use meta-learning to complete multiple specific tasks in fields such as reinforcement learning and achieve industrial application.</td>
</tr>
</tbody>
</table>

TABLE II: Application Scenarios

C. Intended function

Awesome-META+ has several key features that make it highly useful for users interested in meta-learning. Users can search for information, deploy frameworks, access learning resources, and transfer tasks across different domains. The platform is designed to be user-friendly and easy to navigate. It provides a range of resources and tutorials to help users learn more about meta-learning and related topics. The specific features of the platform are listed in the table below.

<table>
<thead>
<tr>
<th>Functional point ID</th>
<th>Function Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Function 1</td>
<td>Search Functionality</td>
<td>Users can locate the desired meta-learning framework, paper, and other related information by using the search bar or navigating through the menu bar, including &quot;Home&quot;, &quot;Tutorials&quot;, &quot;Documentation&quot;, &quot;Examples&quot;, &quot;Papers&quot;, &quot;Datasets&quot;, &quot;Community&quot;, &quot;Changelog&quot;, and &quot;GitHub&quot;. Each module contains multiple sub-search options (e.g., &quot;Changelog&quot; shows version history).</td>
</tr>
<tr>
<td>Function 2</td>
<td>Framework Deployment</td>
<td>Users can browse the frameworks, models, and datasets provided by the platform on the &quot;Home&quot; page and then locate them according to their needs using two methods: directly entering keywords in the search bar or clicking to the corresponding framework deployment method on the &quot;Home&quot; page and obtaining specific details from modules such as &quot;Tutorials&quot;. Users can also pull the source code of meta-learning frameworks and deployment details with one click for quick and easy use.</td>
</tr>
<tr>
<td>Function 3</td>
<td>Learning Platform</td>
<td>Users can locate the &quot;Papers&quot;, &quot;Datasets&quot;, &quot;Community&quot; modules according to their needs, and obtain resources such as the learning curve of the platform, as well as links to download relevant blogs, monographs, and papers.</td>
</tr>
<tr>
<td>Function 4</td>
<td>Multi-Domain Task Transfer</td>
<td>Users can use the &quot;Tutorials&quot;, &quot;Documentation&quot;, &quot;Examples&quot; modules to learn about the platform’s usage instructions and framework information, different domain tasks corresponding to framework details and optimization ideas, and actual cases (such as performance comparison of various frameworks in small-sample image classification using metrics such as ACC, AP, etc.) to locate their desired goals and complete configuration.</td>
</tr>
<tr>
<td>Function 5</td>
<td>Feedback</td>
<td>Users can write feedback or suggestions in the feedback section on the platform’s main page &quot;Home&quot; (which actually redirects to GitHub’s issues) for future maintenance or adding new learning materials.</td>
</tr>
</tbody>
</table>

TABLE III: Functional Points

D. Acceptance criteria

In order to better meet the needs of users, Awesome-META+ needs to achieve four goals, namely reliability, ease of use, maintainability, and iterative updates. The following table provides brief descriptions for these goals.

<table>
<thead>
<tr>
<th>Goal</th>
<th>Specifics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reliability</td>
<td>The platform’s framework has been extensively tested and validated through experiments with ample data. All modules have been tested to ensure their reliability.</td>
</tr>
<tr>
<td>Ease of Use</td>
<td>The user interface is simplified to enable users to quickly and accurately find the required information and deploy the framework quickly.</td>
</tr>
<tr>
<td>Maintainability</td>
<td>User feedback is promptly addressed, and the platform is maintained within one week.</td>
</tr>
<tr>
<td>Updates and Iterations</td>
<td>The platform is designed to allow developers to quickly iterate and add necessary modules based on the current software ecosystem. A &quot;Changelog&quot; is specifically set up within the platform to view product update and iteration information.</td>
</tr>
</tbody>
</table>

TABLE IV: Acceptance criteria
III. SYSTEM DEVELOPMENT

Awesome-META+ is a meta-learning research and learning platform that will be made available to a wide range of internet users in the form of a website. The platform comprises nine modules, including "Home", "Tutorials", "Documentation", "Examples", "Papers", "Datasets", "Community", "Changelog", and "GitHub", covering everything that is required for the application of typical meta-learning frameworks. Figure 1 shows the homepage of our Awesome-META+.

These modules include deployment, usage tutorials, source code, practical examples, as well as academic materials related to meta-learning, such as papers, datasets, blogs, and video tutorials. Additionally, the platform features multiple modules for updating logs and community building.

The platform’s website and code are hosted on GitHub+Vercel, and although the relevant repositories are currently private, they will be made public once the domain formalities are completed.

Users can click on different modules in the menu bar based on their needs, navigate to the corresponding webpages, and complete the relevant operations. Users can also search for models, methods, and practical examples of their interest to enrich the meta-learning research community.

The development and functions of this system consisting of four modules:

- **Front-end system** (Sec.III-A): built with Python + Django + Material for MkDocs to create a responsive website that is bound to the meta-learning framework, deployment, and academic information retrieval functions. The main interface, "Home," provides content and usage instructions for each function page, with the design aimed at giving users a clear understanding of meta-learning and making it easy to use the Awesome-META+ platform.

- **Algorithms and deployment** (Sec.III-B): code is written and reproduced using Python + Anaconda to build twelve typical frameworks, including those based on machine learning frameworks such as Pytorch/TensorFlow [17], [18], seven benchmarks including CIFAR, and two training methods, distributed and single card. A modular design is used for easy developer rewriting, and online running examples are provided.

- **Information integration** (Sec.III-C): includes information crawling and push based on Python. High citation and click-through papers, "meta-learning" keyword papers from large conferences such as ICLR and ICML, and blogs from platforms such as Zhihu are crawled, scored and sorted, and then uploaded to the platform.

- **Testing and deployment** (Sec.IV): includes both automated and manual testing. Automated testing includes website function testing, access and API response testing, and automated testing of frameworks and algorithms. Deployment is done via GitHub + Vercel for web platform demo deployment.

A. Front-end system

The front-end of Awesome-META+ mainly consists of a user interaction interface, which is developed using Python and Django frameworks [19], as well as Material for MkDocs. We have also introduced responsive web design and multiple ports required for model deployment to support local deployment and learning of the meta-learning framework. In addition, we provide practical examples for users to perform online training on platforms such as Colab [20]. Figure 2 shows the process of web page interaction.

Django is an open-source web application framework written in Python. With Django, developers can implement a complete website with simple code and further develop a full-featured web service. Django is based on the MVC (Model-View-Controller) design pattern, consisting of three components: Model, View, and Controller. In addition, a URL
dispatcher is required to distribute page requests to different Views, which then call the corresponding Model and Template. Python+Django web development has advantages such as low coupling, fast development, high reusability, and low maintenance costs, making it possible to quickly deploy a website.

To maintain code compatibility and maintainability, while considering the characteristics of the Awesome-META+ platform and the time required for the deployment of the meta-learning framework, we chose to use Python for responsive interface development. This enables users to use the platform on any mobile or PC interface, improving the platform’s applicability and ease of use.

B. Algorithms and deployment

In order to meet the needs of users as much as possible and at the same time achieve the purpose of meta-learning research, we conducted research from the perspectives of framework expansion, standardization, universality and rapid deployment

Framework expansion. Before development, we need to understand the meta-learning process from the perspective of software development and coding. Meta-learning is the process of learning how to learn, which refers to training machine learning algorithms that can automatically adapt to new tasks and environments. The general meta-learning process is as follows: as follow:

1) Select meta-learning algorithm and model: Choose the appropriate meta-learning algorithm and model, such as gradient-based meta-learning, Bayesian meta-learning, meta reinforcement learning, etc.
2) Select task distribution: Select several tasks from the given task distribution. For example, in image classification tasks, different classification tasks can be selected from different datasets.
3) Divide the dataset: For each task, divide its dataset into training, validation, and test sets.
4) Train the model: For each task’s training set, use the meta-learning algorithm and model to train and obtain the model parameters for that task.
5) Evaluate the model: Use the validation set to evaluate the trained model and obtain the performance metrics for that task.
6) Update the meta-learning model: Use the performance metrics of the task as the input to update the parameters of the meta-learning model, so that it can better adapt to the learning process of different tasks.
7) Select the optimal model: For each task, select the optimal model parameters based on its performance metrics on the validation set.
8) Test the model: Use the test set to test the optimal model for each task and obtain the final performance metrics.
9) Apply the meta-learning model: For new tasks, use the trained meta-learning model to select the most suitable model and parameters based on the nature and characteristics of the task, and perform learning and prediction accordingly.

The above is the general meta-learning process, and the specific implementation can be adjusted and optimized based on specific algorithms and models. We have replicated and extended 12 meta-learning frameworks. Figure 3 lists the framework resources provided by the Awesome-META+ platform. Taking MAML as an example, this model is a classic work in the field of meta-learning, which uses optimization-based model training rules. After defining the initial parameters, the inner loop trains based on the initial parameters, and the loss on the task is accumulated and back-propagated to the outer loop. The outer loop uses SGD to compute the second-order derivative, which updates the initialization parameters. This framework is compatible with any model trained by gradient descent and is suitable for various learning problems. In the development of our platform, we use MAML as a typical example for multi-dataset scenarios and provide standardized instructions. Additionally, we configure multiple datasets, provide both PyTorch and TensorFlow code formats, support distributed and single-card training, and apply it to multiple scenarios such as reinforcement learning [21], [22], [23], gesture recognition [24], [25], and animal detection [26].

Standardization. We have standardized the reproduced meta-
learning framework, including task settings and SGD second-
order derivatives, in order to complete deployment with unified
settings. We have also added these explanations and specific stan-
dardization content to the "Documentation" module on the
Awesome-META+ platform.

1) Dataset standardization: Given any input dataset, custom
tasks can be easily generated based on user scenarios. A
set of tasks are created from the given dataset, which
accepts a list of task transforms that define the types
of tasks to be sampled from the dataset. These tasks
are lazily sampled when indexed (or called using the
.sample() method), and their descriptions are cached for
later use. If the num of tasks is set to -1, TaskDataset will
not cache task descriptions and will continuously sample
new descriptions. In this case, the length of TaskDataset
is set to 1.

2) Model standardization (using MAML as an example):
Taking the optimization-based model of the MAML class
as an example, this class wraps any nn.Module and
expands it using the clone() and adapt() methods. For
the first-order version of MAML (i.e., FOMAML), the
first-order flag is set to True during initialization. In
addition to reproducing the models based on standardization
rules, we have also reproduced the performance testing
experiments in the paper to ensure the correctness of the
reproduction of the twelve frameworks.

**Code for Dataset standardization**

```python
dataset (Dataset) - Dataset of data to compute tasks
task_transforms (list, optional, default=None) -
List of task transformations.
num_tasks (int, optional, default=-1) - Number of
tasks to generate.
dataset = [121].data.MetaDataset(MyDataset())
transforms = [121].data.transforms.NWayS(dataset, n=5),
121.data.transforms.KShots(dataset, k=1),
121.data.transforms.LoadData(dataset),]
taskset = TaskDataset(dataset, transforms, num_tasks
=200000)
for task in taskset:
    X, y = task
```

**Code for Model standardization**

```python
model (Module) - Module to be wrapped
lr (float) - Fast adaptation learning rate
first_order (bool, optional, default=False) -
Whether to use the first-order approximation
of MAML (FOMAML)
allow_unused (bool, optional, default=None) -
Whether to allow differentiation of unused
parameters. Defaults to allow _nograd
allow_nograd (bool, optional, default=False) -
Whether to allow adaptation with parameters that
have requires_grad = False
linear = [121].algorithms.MAML(nn.Linear(20, 10), lr
=0.01)
clone = linear.clone()
error = loss(clone(X), y)
clone.adapt(error)
error = loss(clone(X), y)
error.backward()
```

**Universality.** To better meet the needs of users in deploying
frameworks, we have rewritten the framework to match multi-
datasets, training methods, and multi-tasking capabilities.
Additionally, we have made modifications to the training
methods and environment versions with consideration for the
hardware configurations of future servers and local hardware
resources available to users.

1) Regarding training methods, the framework includes dis-
tributed options (supporting multi-GPU training for hard-
ware configurations such as servers and host machines
with multiple graphics cards) as well as single-GPU
training (supporting GPU-based hardware platforms).

2) Regarding environment versions, some frameworks (such
as MAML and Prototypical Network) are offered both
PyTorch and TensorFlow versions, supporting multiple
training formats.

**Code for multi-GPU training**

```python
args.gpus = gpu
torch.cuda.set_device(gpu)
args.rank = args.node_rank * ngpus + gpu
device = torch.device('cuda:%d' % args.gpus)
if args.dist == 'ddp':
    dist.init_process_group(
        backend='nccl',
        init_method='tcp://%s' % args,
        dist_address,
        world_size=args.world_size,
        rank=args.rank,
    )

n_gpus_total = dist.get_world_size()
assert args.batch_size % n_gpus_total == 0
args.batch_size /= n_gpus_total
if args.rank == 0:
    print(f"{n_gpus_total} GPUs total;
batch_size={args.batch_size} per
GPU")

print(f'--> Proc {dist.get_rank()}/{dist.
get_world_size()}@{socket.gethostname()}'
    , flush=True)
```

**Rapid deployment.** In order to allow users to quickly deploy
locally (online) and meet their needs as much as possible, we
have taken the following (attempted) actions:

1) Code encapsulation for on-demand running with only
two lines of code: Configuration parameters such as
dataset and training method are directly written into the
framework, while functional modules are encapsulated by
class. Users can directly select on the "Tutorials" module of
the Awesome-META+ platform, or follow the deploy-
mint instructions downloaded locally for training and
running. The whole process only involves two statements:
environment configuration and the command for using the
meta-learning framework.

2) Multi-scenario transfer: Experiment examples for multi-
ple scenarios are provided on the "Examples" module of
the Awesome-META+ platform, demonstrating the
effectiveness and practicality of the main framework.

3) Online demo: To facilitate online training, we have at-
ttempted to set up a port linked to Colab on the web page.
A MAML notebook is provided in Colab, which is a free
C. Information integration

Another core feature of the Awesome-META+ platform is to collect academic information, allowing users to access cutting-edge work in the field of meta-learning, including resources such as journals, conferences, and major reports. The information integration process is shown in the Figure 4. This includes:

1) High-quality papers published in recent years: This metric is evaluated based on the impact factor of the journal, the rating of the conference, and the citation count of the paper itself, such as SCI Q1, top conferences in CCF, such as ICML and ICLR.

2) Works in the field of meta-learning: including introductory books for beginners and advanced books for practitioners, works are ranked based on their influence and recommendations from multiple blogs.

3) Discussion videos and conference links related to meta-learning: workshops at important conferences, etc.

4) Meta-learning-related blogs and videos: Blog resources include domestic websites such as Zhihu and CSDN, and foreign websites such as Stackflow and DZone. Video resources are mainly from websites such as Bilibili and YouTube.

To achieve more comprehensive information collection and summary, and push it on the platform, we mainly did the following work:

1) Information was crawled based on keywords for resource web pages and addresses, looking for information related to "meta-learning" and "learn-to-learn"; for works and reports, manual search was conducted (based on discussions in forums).

2) The crawled information was sorted and filtered. The reference and filtering information included: selecting the top 10 papers for each website based on paper citation counts (specifically, the citation count at conferences such as ICLR, oral presentations, and the number of collections on websites such as ResearchGate, based on the influence evaluation indicators provided by these websites) and finally retaining 30 papers; selecting 20 blog and video information based on the number of likes and views, respectively.

3) The filtered information was summarized and manually uploaded to the platform.

Finally, users can access paper information and related materials on the "Home" and "Papers" pages, and download or jump to the content they want to learn.

IV. VERIFICATION AND APPLICATION

A. Testing and verification

The platform testing includes automation testing and manual testing. The automation testing includes function testing based on Playwright + Python for webpages, access and API response testing based on OctaGate SiteTimer, and automation testing based on Python for frameworks and algorithms. The deployment is based on GitHub + Vercel to deploy the webpage platform demo (V1.0).

Automation testing. The testing of the Awesome-META+ platform mainly involves two parts: web testing and integrated framework testing. The web testing includes two components: testing the navigation and interaction of each interface and function, as well as performance testing for the corresponding speed. The platform provides nine interfaces, including "Home", "Tutorials", "Documentation", "Examples", "Papers", "Datasets", "Community", "Changelog", and "GitHub". Among them, "Tutorials", "Papers", "Datasets", and "Examples" can be linked to the "download" operation. "Tutorials" also involves online deployment, and the most important aspect is the navigation relationship between different interfaces. Therefore, we conducted testing from three core functional perspectives: "System Front-end Web Interaction", "System Framework Integration Testing and Deployment", and "Meta-Learning Information Acquisition". The test results are shown in Table V.

For system front-end web interaction, we chose to use the Python community’s Playwright library for web automation testing. Playwright is a pure automation tool designed specifically for the Python language by Microsoft. It can automatically execute Chromium, Firefox, and WebKit browsers through a single API and can achieve automation functions while supporting headless and headed modes. Moreover, Playwright supports Linux, Mac, and Windows operating systems, making it a very suitable web testing tool for the Awesome-META+ platform we want to build.

For integrated framework testing: we designed each framework modularly, which can be activated or deactivated according to the needs. Table X shows the corresponding results of each framework from unit testing to functional testing. The unit testing involves each framework’s corresponding main function and standardized function, and the functional testing covers all algorithms provided by the platform. Each framework includes multiple datasets and tasks, and some frameworks contain multiple training modes (some have distributed and single-card training modes), and the core algorithms are encapsulated in the form of classes and functions.

For meta-learning information acquisition: we randomly extracted 600 data items related to meta-learning to construct the test set. The related entries include paper keywords, title entity words, author, and conference information. 60%...
<table>
<thead>
<tr>
<th>Test (%)</th>
<th>Front-end web interaction</th>
<th>Framework integration testing and deployment</th>
<th>Information acquisition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test 1</td>
<td>99.237</td>
<td>Unit Tests (99.372) Functional Tests (97.832)</td>
<td>100.000</td>
</tr>
<tr>
<td>Test 2</td>
<td>99.372</td>
<td>Unit Tests (100.00) Functional Tests (99.382)</td>
<td>99.827</td>
</tr>
<tr>
<td>Test 3</td>
<td>99.178</td>
<td>Unit Tests (98.893) Functional Tests (99.478)</td>
<td>98.728</td>
</tr>
<tr>
<td>Test 4</td>
<td>99.732</td>
<td>Unit Tests (100.00) Functional Tests (100.00)</td>
<td>99.387</td>
</tr>
<tr>
<td>Test 5</td>
<td>100.000</td>
<td>Unit Tests (100.00) Functional Tests (99.974)</td>
<td>100.000</td>
</tr>
<tr>
<td>Test 6</td>
<td>98.947</td>
<td>Unit Tests (99.287) Functional Tests (98.237)</td>
<td>98.728</td>
</tr>
<tr>
<td>Test 7</td>
<td>99.238</td>
<td>Unit Tests (100.00) Functional Tests (97.473)</td>
<td>100.000</td>
</tr>
<tr>
<td>Test 8</td>
<td>100.000</td>
<td>Unit Tests (100.00) Functional Tests (100.00)</td>
<td>100.000</td>
</tr>
<tr>
<td>Test 9</td>
<td>100.000</td>
<td>Unit Tests (99.783) Functional Tests (98.478)</td>
<td>100.000</td>
</tr>
<tr>
<td>Test 10</td>
<td>99.389</td>
<td>Unit Tests (100.00) Functional Tests (97.873)</td>
<td>99.738</td>
</tr>
</tbody>
</table>

TABLE V: The testing and verification of Awesome-META+. It shows the results of both automated testing and manual testing, with automated testing further divided into three aspects: front-end web interaction, framework integration testing, and deployment, and information acquisition.

Fig. 5: The performance of Awesome-META+.
The platform takes into integrated into The specific deployment schemes and provided platform and server+nginx for the system usage deployed on both the server and local machines for mentoring instructions, and the models were able to run (Astronomical Techniques and Methods) follow the operations, I had a friend from the Astronomy module without any functional errors. For model and the search function can quickly locate the empty form submissions, from affecting the user experience. Error handling and guided prompts were set up for potential issues such as empty form submissions, search failures, and ineffective model download controls to facilitate user use. Table VI shows the results of manual testing. Multiple tests have shown that for front-end interaction, users can obtain resource download responses within 50ms without being affected by internet speed. Empty form submissions and empty package downloads are not expected to occur, and the search function can quickly locate the corresponding module without any functional errors. For model deployment operations, I had a friend from the Astronomy Department (Astronomical Techniques and Methods) follow the deployment instructions, and the models were able to run smoothly on both the server and local machines for training.

B. Deployment and maintenance

Awesome-META+ is presented as a web page, and is deployed using two methods: GitHub Pages for the display platform and server+nginx for the system usage platform. The specific deployment schemes and provided computing resources are presented in Table VII.

To ensure the long-term performance of Awesome-META+ and support the research functionalities, we have designed the system sustainably and reserved interfaces for future updates and iterations. The main work includes:

Modularization of functionalities: All frameworks and specific functionalities are designed with modularity, and ports for activation or deactivation are integrated into deployment instructions, making it easy to locate the functional blocks for future modifications and supplements.

Developer-oriented comments are included in the code, and standardized documents and system design schemes are provided for other standardized engineering in different fields. The integrated frameworks, datasets, optimization packages, and academic materials are all packaged for upload, like building blocks that can be continuously supplemented on the basis of existing resources. With sufficient computing resources, there is no upper limit. The "Changelog" page of Awesome-META+ will provide explanations for version iterations and updates.

C. Performance optimization

The Awesome-META+ platform consists of nine major modules, including "Home", "Tutorials", "Documentation", "Examples", "Papers", "Datasets", "Community", "Changelog", and "GitHub". These modules cover all the necessary aspects for applying typical meta-learning frameworks, such as deployment, usage tutorials, source code, and practical cases, as well as providing information on meta-learning academic resources, including papers, datasets, blogs, and video tutorials. Additionally, the platform includes multiple modules related to platform updates and community building. Figure illustrates the effects of the Awesome-META+ platform.

V. CONCLUSION

The Awesome-META+ platform is a learning and research platform that focuses on the rapid deployment and integration of meta-learning frameworks, based on the background of the general artificial intelligence demand and the research of meta-learning frameworks. The platform takes into account the framework deployment mechanism and platform software ecosystem to build a meta-learning research and learning platform. In the process of system design and development, we also hope to provide a set of examples to provide ideas for the integration and standardization of frameworks in other fields.

The platform provides complete and reliable meta-learning framework code, convenient and simple model deployment solutions, comprehensive information integration and learning functions, and objective and trustworthy performance analysis. These features enable users to easily learn meta-learning in a convenient way, even if they do not have much related academic foundation, and apply it to various fields such as reinforcement learning, gesture recognition, and few-shot image classification.

The two core functions of the Awesome-META+ platform - rapid deployment of meta-learning frameworks and information aggregation and retrieval - provide a learning channel.
for novices and reduce the entry barrier to meta-learning. At the same time, the platform provides rich academic resources such as baselines and benchmarks for meta-learning scholars, saving their time and improving their research efficiency. In addition, the platform also provides a method for industrial personnel to use meta-learning for product development.

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REFERENCES


