deepforge Documentation

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Getting Started

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CHAPTER 1

Getting Started

1.1 What is DeepForge?

Deep learning is a promising, yet complex, area of machine learning. This complexity can both create a barrier to entry for those wanting to get involved in deep learning as well as slow the development of those already comfortable in deep learning.

DeepForge is a development environment for deep learning focused on alleviating these problems. Leveraging principles from Model-Driven Engineering, DeepForge is able to reduce the complexity of using deep learning while providing an opportunity for integrating with other domain specific modeling environments created with WebGME.

1.2 Design Goals

As mentioned above, DeepForge focuses on two main goals:

1. **Improving the efficiency** of experienced data scientists/researchers in deep learning
2. **Lowering the barrier to entry** for newcomers to deep learning

It is important to highlight that although one of the goals is focused on lowering the barrier to entry, DeepForge is intended to be more than simply an educational tool; that is, it is important not to compromise on flexibility and effectiveness as a research/industry tool in order to provide an easier experience for beginners (that's what forks are for!).

1.3 Overview and Features

DeepForge provides a collaborative, distributed development environment for deep learning. The development environment is a hybrid visual and textual programming environment. Higher levels of abstraction, such as creating architectures, use visual environments to capture the overall structure of the task while lower levels of abstraction, such as defining custom training functions, utilize text environments. DeepForge contains both a pipelining language

and editor for defining the high level operations to perform while training or evaluating your models as well as a language for defining neural networks (through installing a DeepForge extension such as DeepForge-Keras).

1.3.1 Concepts and Terminology

- *Operation* - essentially a function written in Python (such as training a model, visualizing results, etc)
- *Pipeline* - directed acyclic graph composed of operations - e.g., a training pipeline may retrieve and normalize data, train an architecture and return the trained model
- *Execution* - when a pipeline is run, an "execution" is created and reports the status of each operation as it is run (distributed over a number of worker machines)
- *Artifact* - an artifact represents some data (either user uploaded or created during an execution)
- *Resource* - a domain specific model (provided by a DeepForge extension) to be used by a pipeline such as a neural network architecture

CHAPTER 2

Quick Start

There are two ways to give DeepForge a try: visit the public deployment at https://editor.deepforge.org, or spin up your own deployment locally.

2.1 Connecting to the Public Deployment

As of this writing, registration is not yet open to the public and is only available upon request.

After getting an account for https://editor.deepforge.org, the only thing required to get up and running with DeepForge is to determine the compute and storage adapters to use. If you already have an account with one of the existing integrations, then you should be able to use those without any further setup!

If not, the easiest way to get started is to connect your own desktop to use for compute and to use the S3 adapter to storage data and trained model weights. Connect your own desktop for computation using the following command (using docker):

```
docker run -it deepforge/worker:latest --host https://dev.deepforge.org -t <access␣
↪token>
```

where <*access token*> is an access token for your user (created from the profile page of https://editor.deepforge.org).

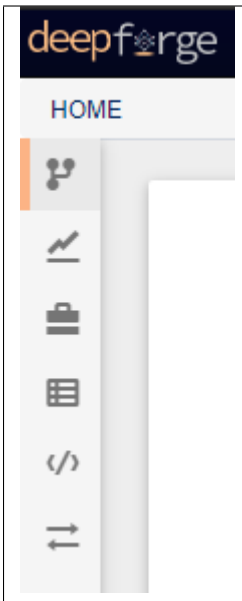
After connecting a machine to use for computation, you can start creating and running pipelines w/o input or output operations! To save artifacts in DeepForge, you will need to connect a storage adapter such as the S3 adapter.

To easily create a custom storage location, minio is recommended. Simply spin up an instance of minio on a machine publicly accessible from the internet. Providing the public IP address of the machine (along with any configured credentials) to DeepForge when executing a pipeline will enable you to save any generated artifacts, such as trained model weights, to the minio instance and register it within DeepForge.

CHAPTER 3

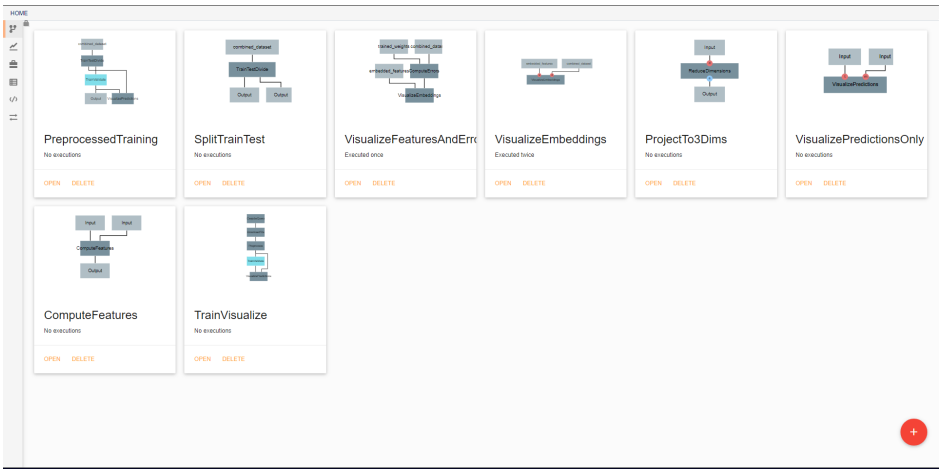
Interface Overview

The DeepForge editor interface is separated into six views for defining all of the necessary features of your desired project. The details of each interface tab are detailed below. You can switch to any of the views at any time by clicking the appropriate icon on the left side of the screen. In order, the tabs are:



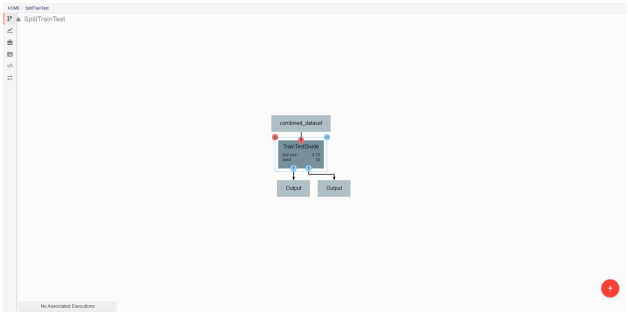
- *Pipelines*
- *Executions*
- *Resources*
- *Artifacts*
- *Custom Utils*
- *Custom Serialization*

3.1 Pipelines



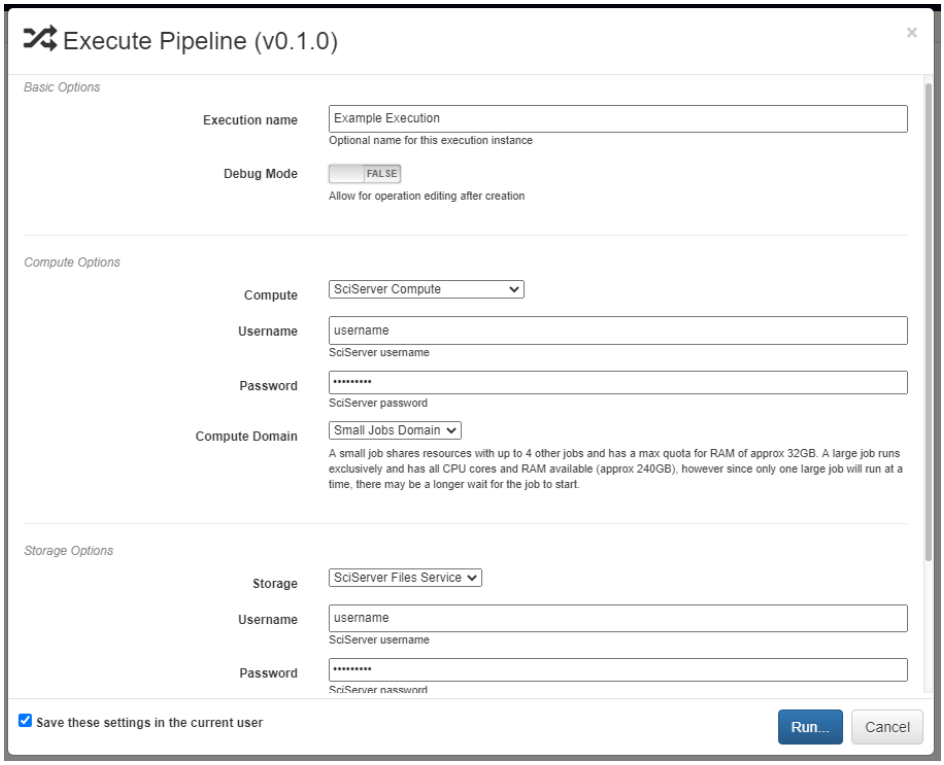
In the initial view, all pipelines that currently exist in the project are displayed. New pipelines can be created using the floating red button in the bottom right. From this screen, existing pipelines can also be opened for editing, deleted, or renamed.

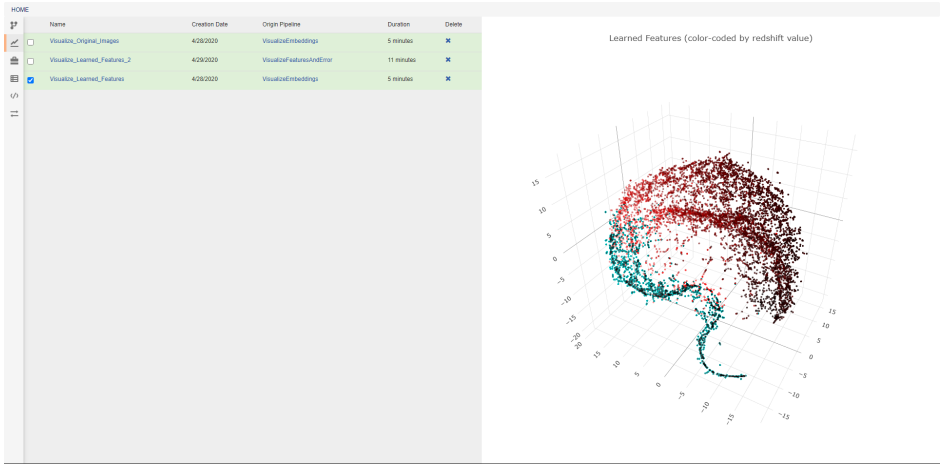
3.1.1 Pipeline editing



DeepForge pipelines are directed acyclic graphs of operations, where each operation is an isolated python module. Operations are added to a pipeline using the red plus button in the bottom right of the workspace. Any operations that have previously been defined in the project can be added to the pipeline, or new operations can be created when needed. Arrows in the workspace indicate the passing of data between operations. These arrows can be created by clicking on the desired output (bottom circles) of the first operation before clicking on the desired input (top circles) of the second operation. Clicking on a operation also gives the options to delete (red X), edit (blue </>), or change attributes. Information on the editing of operations can be found in Custom Operations

Pipelines are executed by clicking the yellow play button in the bottom right of the workspace. In the window that appears, you can name the execution, select a computation platform, and select a storage platform. Computation platforms specify what the compute resources used for execution of the operations, such as SciServer Compute, will be. Supported storage platforms, such as endpoints with an S3-compatible API, are used to store intermediate and output data. The provided storage option will be used for storing both the output objects defined in the pipeline, as well as all files used in execution of the pipeline.

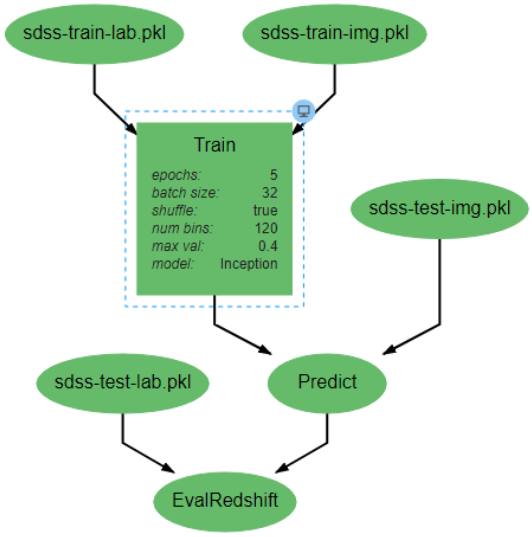

Execute Pipeline (v0.1.0)
Basic Options
Execution name
Example Execution
Optional name for this execution instance
Debug Mode
FALSE
Allow for operation editing after creation
Compute Options
Compute
SciServer Compute
Username
username
SciServer username
Password
SciServer password
Compute Domain
Small Jobs Domain
A small job shares resources with up to 4 other jobs and has a max quota for RAM of approx 32GB. A large job runs exclusively and has all CPU cores and RAM available (approx 240GB), however since only one large job will run at a time, there may be a longer wait for the job to start.
Storage Options
Storage
SciServer Files Service
Username
username
SciServer username
Password
SciServer password
Save these settings in the current user
Run...
Cancel


HOME
Name
Creation Date
Origin Pipeline
Duration
Delete
Visualize_Original_Images
4/28/2020
VisualizeEmbeddings
5 minutes
Visualize_Learned_Features_2
4/29/2020
VisualizeFeaturesAndError
11 minutes
Visualize_Learned_Features
4/28/2020
VisualizeEmbeddings
5 minutes
Learned Features (color-coded by redshift value)

3.2 Executions

This view allows the review of previous pipeline executions. Clicking on any execution will display any plotted data generated by the pipeline, and selecting multiple executions will display all of the selected plots together. Clicking the provided links will open either the associated pipeline or a trace of the execution (shown below). The blue icon in the top right of every operation allows viewing the text output of that operation. The execution trace can be viewed during execution to check the status of a running job. During execution, the color of a operation indicates its current status. The possible statuses are:

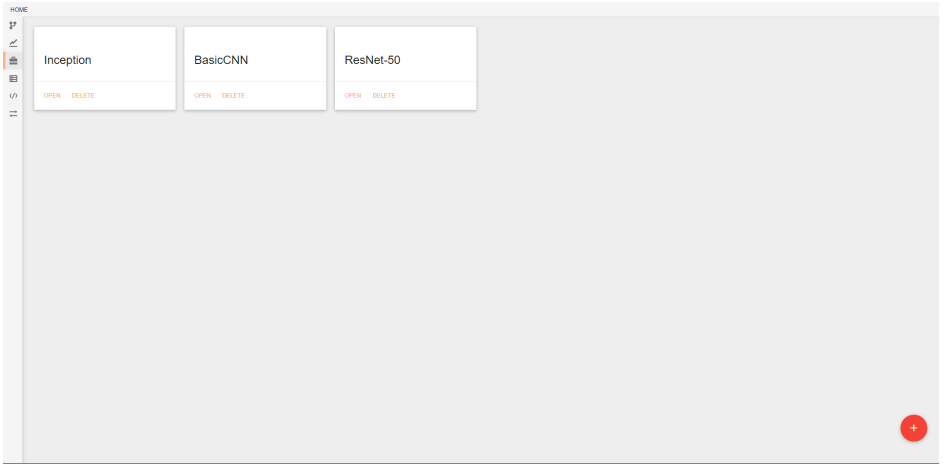
- **Dark gray**: Pending Execution
- **Light gray**: Execution Queued
- **Yellow**: Execution in Progress
- **Orange**: Execution Cancelled
- **Green**: Successfully Finished Execution
- **Red**: Execution Failed

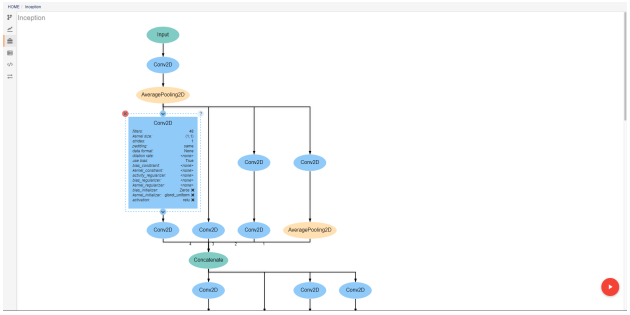


3.3 Resources

This view shows the resources available for use in pipelines. Different types of resources are made available through DeepForge extensions and enable the introduction of new concepts into the project. One such example is deepforge-keras which enables users to make neural networks architectures with a custom visual editor. The created architectures can then be referenced and used by operations for tasks such as training. From this view, resources can be created, deleted, and renamed.

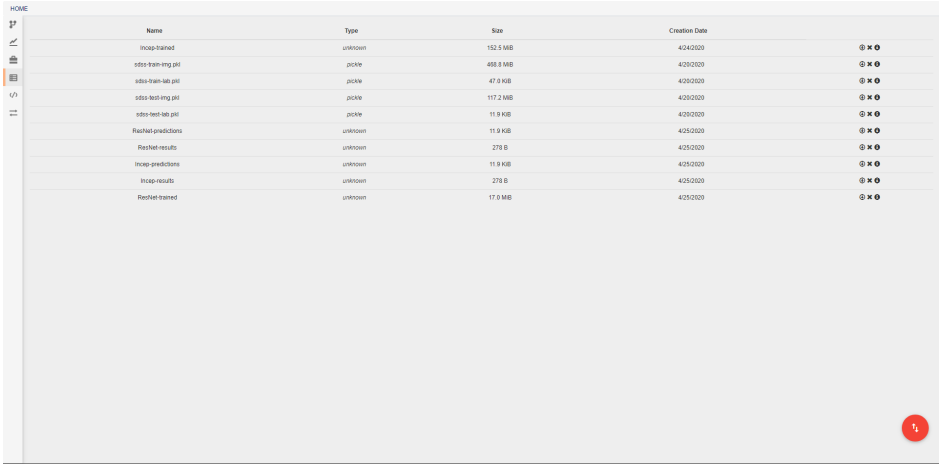
As with pipelines, the neural networks are depicted as directed graphs. Each node in the graph corresponds to a single layer or operation in the network (information on operations can be found on the keras website). Clicking on a layer provides the ability to change the attributes of that layer, delete the layer, or add new layers before or after the current layer. Many operations require that certain attributes be defined before use. The Conv2D operation pictured above, for example, requires that the *filters* and *kernel_size* attributes be defined. If these are left as <*none*>, a visual indicator





will show that there is an error to help prevent mistakes. In order to ease analysis and development, hovering over any connecting line will display the shape of the data as it moves between the given layers.

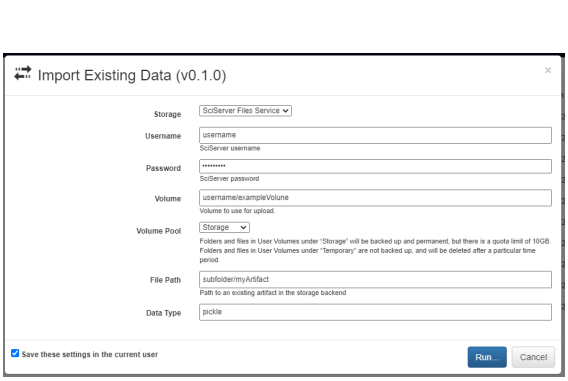
3.4 Artifacts

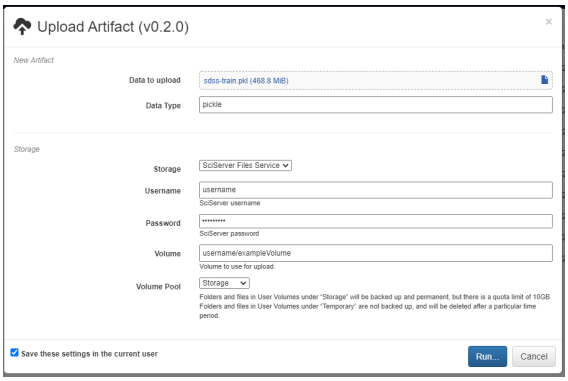


In this view, you can see all artifacts that are available to your pipelines. These artifacts can be used in any pipeline through the inclusion of the built in **Input** operation. Artifacts are pieces of saved data that may be associated with some Python data type. Any arbitrary type of data may be used for creating an artifact, but if a data type is not specified, or if a data type is not provided with a *custom serialization*, the artifact will be treated as a pickle object. If you have data that cannot be opened with Python's pickle module, you will need to create a custom serialization as described

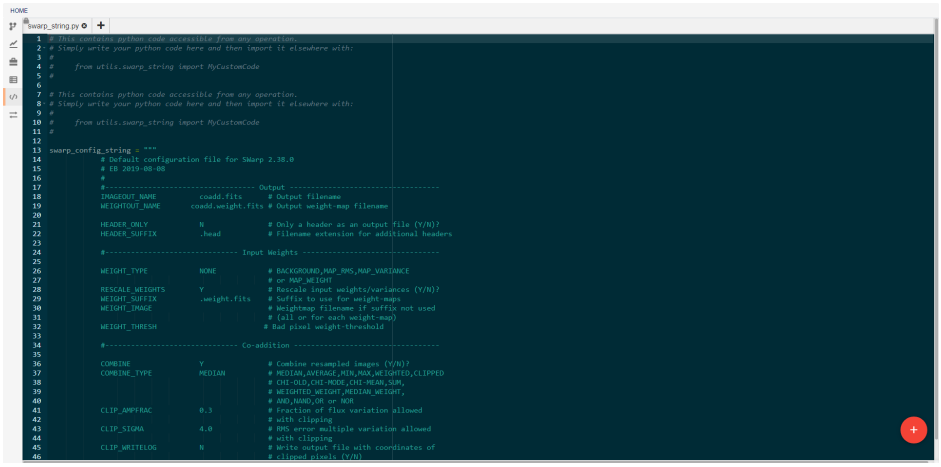
below. Some deepforge extenstions may also support additional data types by default. DeepForge-Keras, for example, supports saved keras models, in addition to the standard pickle objects, without the need for custom serialization.

A new artifact can be created in one of three ways. First, artifacts are automatically created during the execution of any pipeline that includes the built-in **Output** operation. Second, artifacts can be directly uploaded in this view using the red upload button in the bottom right of the workspace. Using this option will also upload the artifact to the storage platform specified in the popup window. Finally, artifacts that already exist in one of the storage platforms can be imported using the blue import button in the bottom right of the workspace.





3.5 Custom Utils

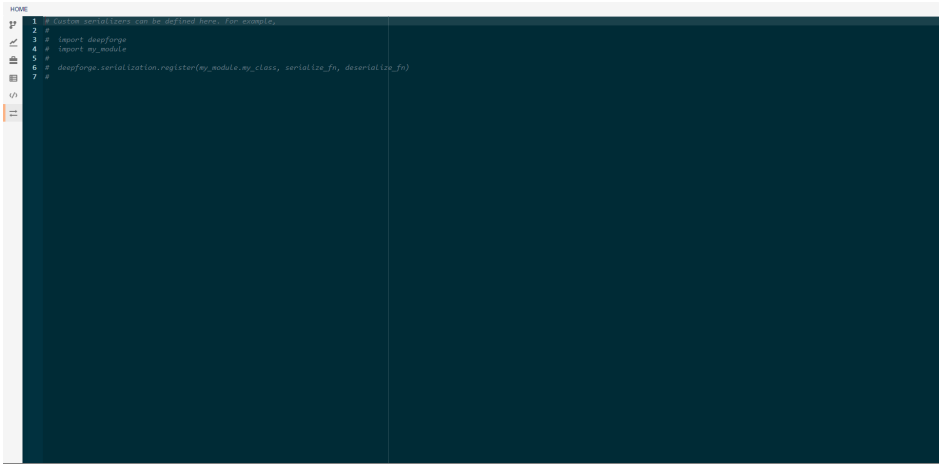


This view allows the creation and editing of custom utility modules. Utilities created here can be imported into any pipeline operation. For example, the *swarp_config_string* shown above can be printed out in a operation using the following code:

```
import utils.swarp_string as ss
print(ss.swarp_config_string)
```

3.6 Custom Serialization

In this view, you can create custom serialization protocols for the creation and use of artifacts that are neither python pickle objects nor keras models. To create a serialization, you will need to define two functions, one for serialization and one for deserialization. These functions must then be passed as arguments to the *deepforge.serialization.register*



function as shown in the commented code above. The serializer and deserializer should have the same signatures as the dump and load functions respectively from python's pickle module.

CHAPTER 4

Custom Operations

In this document we will outline the basics of custom operations including the operation editor and operation feedback utilities.

4.1 The Basics

Operations are used in pipelines and have named inputs and outputs. When creating a pipeline, if you don't currently find an operation for the given task, you can easily create your own by selecting the *New Operation...* operation from the add operation dialog. This will create a new operation definition and open it in the operation editor. The operation editor has two main parts, the interface editor and the implementation editor.

The interface editor is provided on the right and presents the interface as a diagram showing the input data and output data as objects flowing into or out of the given operation. Selecting the operation node in the operation interface editor will expand the node and allow the user to add or edit attributes for the given operation. These attributes are exposed when using this operation in a pipeline and can be set at design time - that is, these are set when creating the given pipeline. The interface diagram may also contain light blue nodes flowing into the operation. These nodes represent "references" that the operation accepts as input before running. When using the operation, references will appear alongside the attributes but will allow the user to select from a list of all possible targets when clicked.

The operation editor also provides an interface to specify operation python dependencies. DeepForge uses `conda` to manage python dependencies for an operation. This pairs well with the integration of various compute platforms that available to the user and the only requirement for a user is to have Conda installed in their computing platform. You can specify operation dependencies using a conda environment file as shown in the diagram below:

To the left of the operation editor is the implementation editor. The implementation editor is a code editor specially tailored for programming the implementations of operations in DeepForge. It also is synchronized with the interface editor. A section of the implementation is shown below:

```
import numpy as np
from sklearn.model_selection import train_test_split
import keras
import time
from matplotlib import pyplot as plt
```

(continues on next page)

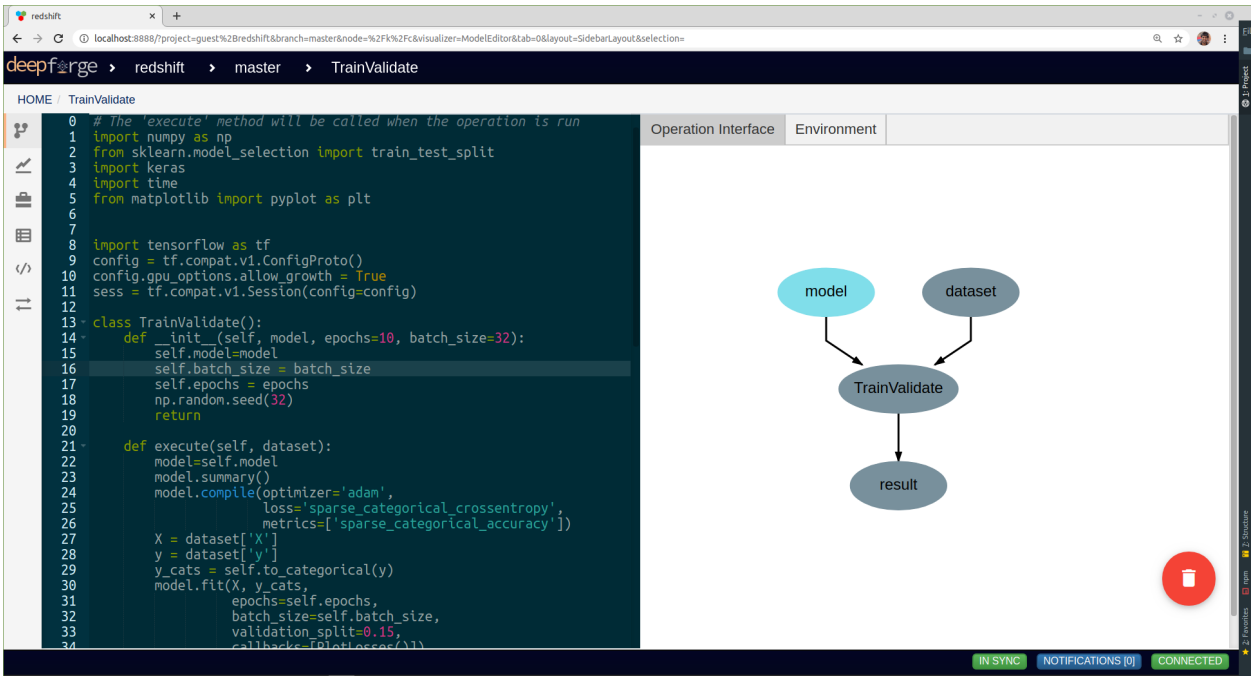


Fig. 1: Editing the "TrainValidate" operation from the "redshift" example

(continued from previous page)

```
import tensorflow as tf

import tensorflow as tf
config = tf.compat.v1.ConfigProto()
config.gpu_options.allow_growth = True
sess = tf.compat.v1.Session(config=config)

class TrainValidate():
    def __init__(self, model, epochs=10, batch_size=32):
        self.model=model
        self.batch_size = batch_size
        self.epochs = epochs
        np.random.seed(32)
        return

    def execute(self, dataset):
        model=self.model
        model.summary()
        model.compile(optimizer='adam',
                      loss='sparse_categorical_crossentropy',
                      metrics=['sparse_categorical_accuracy'])
        X = dataset['X']
        y = dataset['y']
        y_cats = self.to_categorical(y)
        model.fit(X, y_cats,
                  epochs=self.epochs,
                  batch_size=self.batch_size,
                  validation_split=0.15,
                  callbacks=[PlotLosses()])
```

(continues on next page)

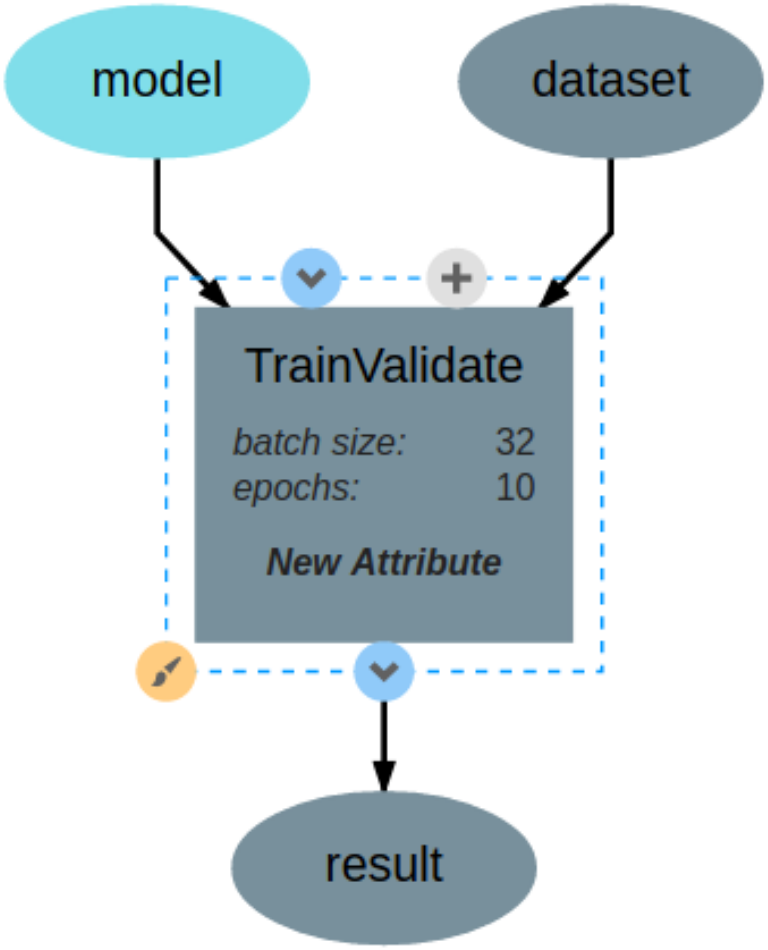


Fig. 2: The TrainValidate operation accepts training data, a model and attributes for setting the batch size, and the number of epochs.

Operation Interface | Environment

```
1  # Conda environment to use when executing the given operation.
2  # For more information, check out https://docs.conda.io/projects/cond
3  dependencies:
4    - python=3.7
5    - pip:
6      - tensorflow==1.14
7      - keras=2.2.5
8      - matplotlib
9      - numpy
10     - scikit-learn
11
```

Fig. 3: The operation environment contains python dependencies for the given operation.

(continued from previous page)

```
        return model.get_weights()

    def to_categorical(self, y, max_y=0.4, num_possible_classes=32):
        one_step = max_y / num_possible_classes
        y_cats = []
        for values in y:
            y_cats.append(int(values[0] / one_step))
        return y_cats

    def datagen(self, X, y):
        # Generates a batch of data
        X1, y1 = list(), list()
        n = 0
        while 1:stash@{1}
            for sample, label in zip(X, y):
                n += 1
                X1.append(sample)
                y1.append(label)
                if n == self.batch_size:
                    yield [[np.array(X1)], y1]
                    n = 0
                    X1, y1 = list(), list()


class PlotLosses(keras.callbacks.Callback):
    def on_train_begin(self, logs={}):
        self.i = 0
        self.x = []
        self.losses = []

    def on_epoch_end(self, epoch, logs={}):
        self.x.append(self.i)
        self.losses.append(logs.get('loss'))
        self.i += 1

        self.update()

    def update(self):
        plt.clf()
        plt.title("Training Loss")
        plt.ylabel("CrossEntropy Loss")
        plt.xlabel("Epochs")
        plt.plot(self.x, self.losses, label="loss")
        plt.legend()
        plt.show()
```

The "TrainValidate" operation uses capabilities from the `keras` package to train the neural network. This operation sets all the parameters using values provided to the operation as either attributes or references. In the implementation, attributes are provided as arguments to the constructor making the user defined attributes accessible from within the implementation. References are treated similarly to operation inputs and are also arguments to the constructor. This can be seen with the `model` constructor argument. Finally, operations return their outputs in the `execute` method; in this example, it returns a single output named `model`, that is, the trained neural network.

After defining the interface and implementation, we can now use the "TrainValidate" operation in our pipelines! An example is shown below.

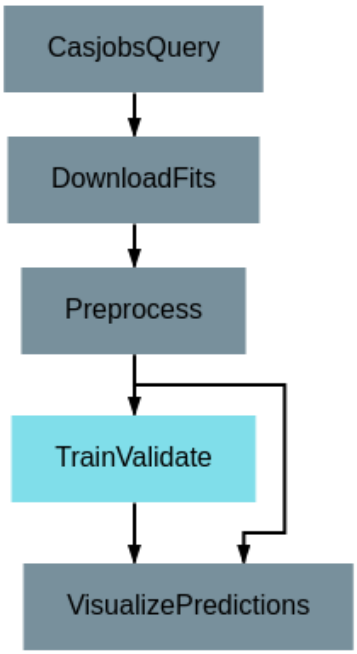


Fig. 4: Using the "TrainValidate" operation in a pipeline

4.2 Operation Feedback

Operations in DeepForge can generate metadata about its execution. This metadata is generated during the execution and provided back to the user in real-time. An example of this includes providing real-time plotting feedback. When implementing an operation in DeepForge, this metadata can be created using the `matplotlib` plotting capabilities.

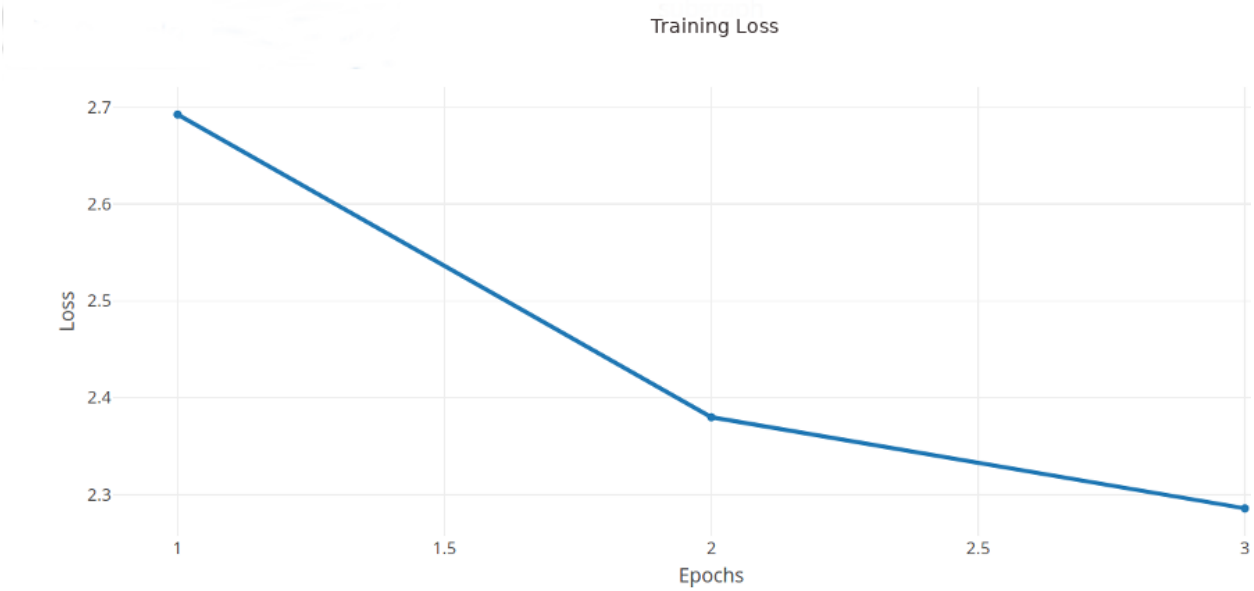


Fig. 5: An example graph of the loss function while training a neural network.

CHAPTER 5

Storage and Compute Adapters

DeepForge is designed to integrate with existing computational and storage resources and is not intended to be a competitor to existing HPC or object storage frameworks. This integration is made possible through the use of compute and storage adapters. This section provides a brief description of these adapters as well as currently supported integrations.

5.1 Storage Adapters

Projects in DeepForge may contain artifacts which reference datasets, trained model weights, or other associated binary data. Although the project code, pipelines, and models are stored in MongoDB, this associated data is stored using a storage adapter. Storage adapters enable DeepForge to store this associated data using an appropriate storage resource, such as a object store w/ an S3-compatible API. This also enables users to "bring their own storage" as they can connect their existing cyberinfrastructure to a public deployment of DeepForge. Currently, DeepForge supports 3 different storage adapters:

1. S3 Storage: Object storage with an S3-compatible API such as minio or AWS S3
2. SciServer Files Service : Files service from SciServer
3. WebGME Blob Server : Blob storage provided by WebGME

5.2 Compute Adapters

Similar to storage adapters, compute adapters enable DeepForge to integrate with existing cyberinfrastructure used for executing some computation or workflow. This is designed to allow users to leverage their existing HPC or other computational resources with DeepForge. Compute adapters provide an interface through which DeepForge is able to execute workflows (e.g., training a neural network) on external machines.

Currently, the following compute adapters are available:

1. WebGME Worker: A worker machine which polls for jobs via the WebGME Executor Framework. Registered users can connect their own compute machines enabling them to use their personal desktops with DeepForge.
2. SciServer-Compute: Compute service offered by SciServer

3. Server Compute: Execute the job on the server machine. This is similar to the execution model used by Jupyter notebook servers.

CHAPTER 6

Quick Start

The recommended (and easiest) way to get started with DeepForge is using docker-compose. First, install docker and docker-compose.

Next, download the docker-compose file for DeepForge:

```
wget https://raw.githubusercontent.com/deepforge-dev/deepforge/master/docker/docker-
↪compose.yml
```

Next, you must decide if you would like authentication to be enabled. For production deployments, this is certainly recommended. However, if you just want to spin up DeepForge to "kick the tires", this is certainly not necessary.

6.1 Without User Accounts

Start the docker containers with `docker-compose run`:

```
docker-compose --file docker-compose.yml run -p 8888:8888 -p 8889:8889 -e "NODE_
↪ENV=default" server
```

6.2 User Authentication Enabled

First, generate a public and private key pair

```
mkdir -p deepforge_keys
openssl genrsa -out deepforge_keys/private_key
openssl rsa -in deepforge_keys/private_key -pubout > deepforge_keys/public_key
export TOKEN_KEYS_DIR="$(pwd)/deepforge_keys"
```

Then start DeepForge using `docker-compose run`:

```
docker-compose --file docker-compose.yml run -v "${TOKEN_KEYS_DIR}:/token_keys" -p
↪8888:8888 -p 8889:8889 server
```

Finally, create the admin user by connecting to the server's docker container. First, get the ID of the container using:

```
docker ps
```

Then, connect to the running container:

```
docker exec -it <container ID> /bin/bash
```

and create the admin account

```
./bin/deepforge users useradd admin <admin email> <password> -c -s
```

After setting up DeepForge (with or without user accounts), it can be used by opening a browser to http://localhost:8888!

For detailed instructions about deployment installations, check out our deployment installation instructions An example of customizing a deployment using docker-compose can be found here.

CHAPTER 7

Overview

7.1 DeepForge Component Overview

DeepForge is composed of four main elements:

- *Client*: The connected browsers working on DeepForge projects.
- *Server*: Main component hosting all the project information and is connected to by the clients.
- *Compute*: Connected computational resources used for executing pipelines.
- *Storage*: Connected storage resources used for storing project data artifacts such as datasets or trained model weights.

7.2 Component Dependencies

The following dependencies are required for each component:

- *Server* (NodeJS LTS)
- *Database* (MongoDB v3.0.7)
- *Client*: We recommend using Google Chrome and are not supporting other browsers (for now). In other words, other browsers can be used at your own risk.

7.3 Configuration

After installing DeepForge, it can be helpful to check out configuring DeepForge

CHAPTER 8

Native Installation

8.1 Dependencies

First, install NodeJS (LTS) and MongoDB. You may also need to install git if you haven't already.

Next, you can install DeepForge using npm:

```
npm install -g deepforge
```

Now, you can check that it installed correctly:

```
deepforge --version
```

After installing DeepForge, it is recommended to install the deepforge-keras extension which provides capabilities for modeling neural network architectures:

```
deepforge extensions add deepforge-dev/deepforge-keras
```

DeepForge can now be started with:

```
deepforge start
```

8.1.1 Database

Download and install MongoDB from the website. If you are planning on running MongoDB locally on the same machine as DeepForge, simply start *mongod* and continue to setting up DeepForge.

If you are planning on running MongoDB remotely, set the environment variable "MONGO_URI" to the URI of the Mongo instance that DeepForge will be using:

```
MONGO_URI="mongodb://pathToMyMongo.com:27017/myCollection" deepforge start
```

8.1.2 Server

The DeepForge server is included with the deepforge cli and can be started simply with

```
deepforge start --server
```

By default, DeepForge will start on *http://localhost:8888*. However, the port can be specified with the *–port* option. For example:

```
deepforge start --server --port 3000
```

8.1.3 Worker

The DeepForge worker (used with WebGME compute) can be used to enable users to connect their own machines to use for any required computation. This can be installed from *https://github.com/deepforge-dev/worker*. It is recommended to install Conda on the worker machine so any dependencies can be automatically installed.

8.1.4 Updating

DeepForge can be updated with the command line interface rather simply:

```
deepforge update
```

```
deepforge update --server
```

For more update options, check out *deepforge update –help*!

8.2 Manual Installation (Development)

Installing DeepForge for development is essentially cloning the repository and then using *npm* (node package manager) to run the various start, test, etc, commands (including starting the individual components). The deepforge cli can still be used but must be referenced from *./bin/deepforge*. That is, *deepforge start* becomes *./bin/deepforge start* (from the project root).

8.2.1 DeepForge Server

First, clone the repository:

```
git clone https://github.com/dfst/deepforge.git
```

Then install the project dependencies:

```
npm install
```

To run all components locally start with

```
./bin/deepforge start
```

and navigate to *http://localhost:8888* to start using DeepForge!

Alternatively, if jobs are going to be executed on an external worker, run *./bin/deepforge start -s* locally and navigate to *http://localhost:8888*.

8.2.2 Updating

Updating can be done the same as any other git project; that is, by running *git pull* from the project root. Sometimes, the dependencies need to be updated so it is recommended to run *npm install* following *git pull*.

8.3 Manual Installation (Production)

To deploy a deepforge server in a production environment, follow the following steps. These steps are for using a Linux server and if you are using a platform other than Linux, we recommend using a dockerized deployment.

1. Make sure you have a working installation of Conda in your server.
2. Clone this repository to your production server.

```
git clone https://github.com/deepforge-dev/deepforge.git
```

3. Install dependencies and add extensions:

```
cd deepforge && npm install
./bin/deepforge extensions add deepforge-dev/deepforge-keras
```

2. Generate token keys for user-management (required for user management).

```
chmod +x utils/generate_token_keys.sh
./utils/generate_token_keys.sh
```

Warning: The token keys are generated in the root of the project by default. If the token keys are stored in the project root, they are accessible via */extlib*, which is a security risk. So, please make sure you move the created token keys out of the project root.

3. Configure your environment variables:

```
export MONGO_URI=mongodb://mongo:port/deepforge_database_name
export DEEPFORGE_HOST=https://url.of.server
export DEEPFORGE_PUBLIC_KEY=/path/to/public_key
export DEEPFORGE_PRIVATE_KEY=/path/to/private_key
```

4. Add a site-admin account by using `deepforge-users` command:

```
./bin/deepforge-users useradd -c -s admin_username admin_email admin_password
```

5. Now you should be ready to deploy a production server which can be done using `deepforge` command.

```
NODE_ENV=production ./bin/deepforge start --server
```

Note: The default port for a deepforge server is 8888. It can be changed using the option *-p* in the command above.

CHAPTER 9

Tutorial Project - Redshift

The project described on this page can be found in the examples repo on GitHub under the name **Redshift-Tutorial.webgmex**

9.1 Pipeline Overview

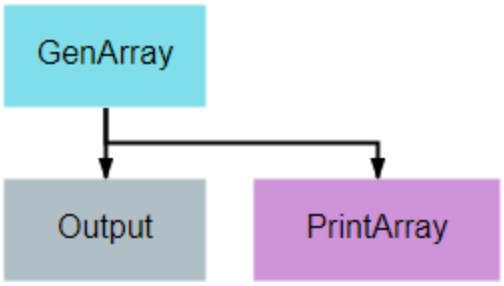
1. *Basic Input/Output*
2. *Display Random Image*
3. *Display Random CIFAR-10*
4. *Train CIFAR-10*
5. *Train-Test*
6. *Train-Test-Compare*
7. *Train-PredVis*
8. *Download-Train-Evaluate*

9.2 Pipelines

9.2.1 Basic Input/Output

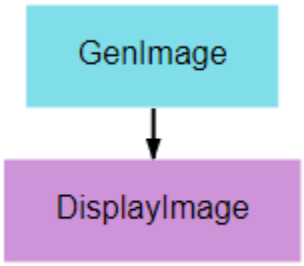
This pipeline provides one of the simplest examples of a pipeline possible in DeepForge. Its sole purpose is to create an array of numbers, pass the array from the first node to the second node, and print the array to the output console.

The **Output** operation shown is a special built-in operation that will save the data that is provided to it to the selected storage backend. This data will then be available within the same project as an artifact and can be accessed by other pipelines using the special built-in **Input** operation.



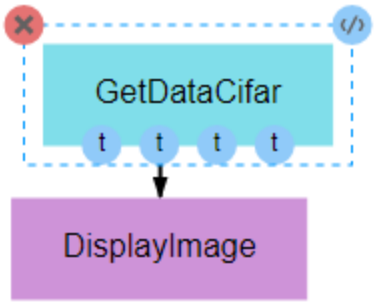

```
import numpy

class GenArray():
    def __init__(self, length=10):
        self.length = length
        return

    def execute(self):
        arr = list(numpy.random.rand(self.length))
        return arr
```

9.2.2 Display Random Image



This pipeline's primary purpose is to show how graphics can be output and viewed. A random noise image is generated and displayed using matplotlib's pyplot library. Any graphic displayed using the **plt.show()** function can be viewed in the executions tab.

```
from matplotlib import pyplot as plt
from random import randint

class DisplayImage():
    def execute(self, image):
        if len(image.shape) == 4:
            image = image[randint(0, image.shape[0] - 1)]
        plt.imshow(image)
        plt.show()
```



9.2.3 Display Random CIFAR-10

As with the previous pipeline, this pipeline simply displays a single image. The image from this pipeline, however, is more meaningful, as it is drawn from the commonly used CIFAR-10 dataset. This pipeline seeks to provide an example of the input being used in the next pipeline while providing an example of how the data can be obtained. This is important for users who seek to develop their own pipelines, as CIFAR-10 data generally serves as an effective baseline for testing and development of new CNN architectures or training processes.

Also note, as shown in the figure above, that it is not necessary to utilize all of the outputs of a given node. Unless specifically handled, however, it is generally inappropriate for an input to be left undefined.

```
from keras.datasets import cifar10

class GetDataCifar():
    def execute(self):
        ((train_imgs, train_labels),
        (test_imgs, test_labels)) = cifar10.load_data()
        return train_imgs, train_labels, test_imgs, test_labels
```

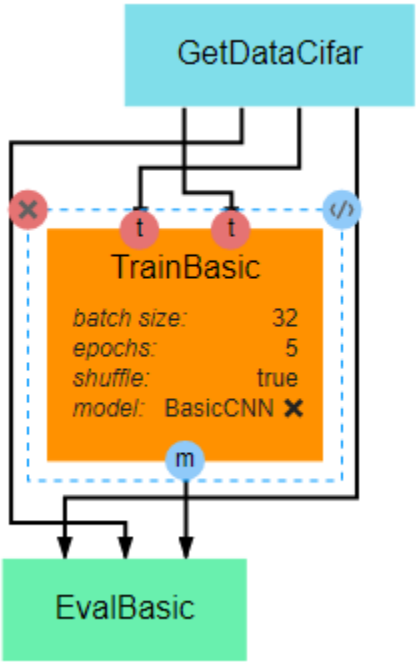
9.2.4 Train CIFAR-10

This pipeline gives a very basic example of how to create, train, and evaluate a simple CNN. The primary takeaway from this pipeline should be the overall structure of a training pipeline, which should follow the following steps in most cases:

1. Load data
2. Define the loss, optimizer, and other metrics
3. Compile model, with loss, metrics, and optimizer, using the **compile()** method
4. Train model using the **fit()** method, which requires the training inputs and outputs
5. Output the trained model for serialization and/or utilization in subsequent nodes

```
import numpy as np
import keras

class TrainBasic():
    def __init__(self, model, epochs=20, batch_size=32, shuffle=True):
        self.model = model
        self.epochs = epochs
        self.batch_size = batch_size
        self.shuffle = shuffle
```

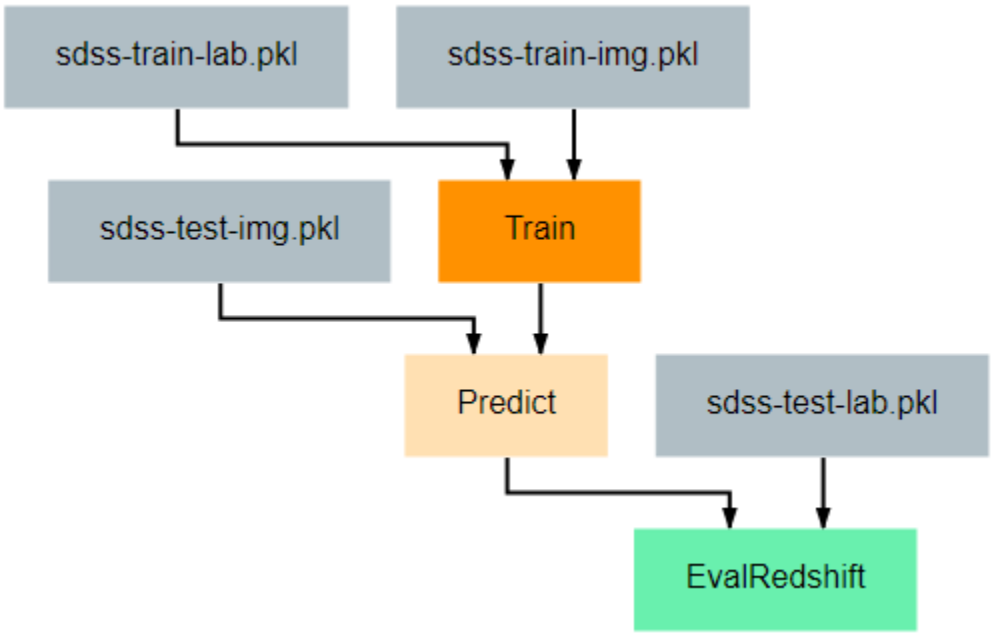
(continues on next page)



(continued from previous page)

```
        return

    def execute(self, train_imgs, train_labels):
        opt = keras.optimizers.rmsprop(lr=0.001)
        self.model.compile(loss='sparse_categorical_crossentropy',
                           optimizer=opt,
                           metrics=['sparse_categorical_accuracy'])
        self.model.fit(train_imgs,
                       train_labels,
                       batch_size=self.batch_size,
                       epochs=self.epochs,
                       shuffle=self.shuffle,
                       verbose=2)
        model = self.model
        return model
```

```
class EvalBasic():
    def __init__(self):
        return

    def execute(self, model, test_imgs, test_labels):
        results = model.evaluate(test_imgs, test_labels, verbose=0)
        for i, metric in enumerate(model.metrics_names):
            print(metric,'-',results[i])
        return results
```



9.2.5 Train-Test

This pipeline provides an example of how one might train and evaluate a redshift estimation model. In particular, the procedure implemented here is a simplified version of work by Pasquet et. al. (2018). For readers unfamiliar with cosmological redshift, this article provides a simple and brief introduction to the topic. For the training process, there are two primary additions that should be noted.

First, the **Train** class has been given a function named **to_categorical**. In line with the Paquet et. al. method linked above, this tutorial uses a classification model rather than a regression model for estimation. Because we are using classification models, the keras model expects the output labels to be either one-hot vectors or a single integer where the position/value indicates the range in which the true redshift value falls. This function converts the continuous redshift values into the necessary discrete, categorical format.

Second, a class has been provided to give examples of how researchers may define their own keras Sequence for training. Sequences are helpful in that they allow alterations to be made to the data during training. In the example given here, the **SdssSequence** class provides the ability to rotate or flip images before every epoch, which will hopefully improve the robustness of the final model.

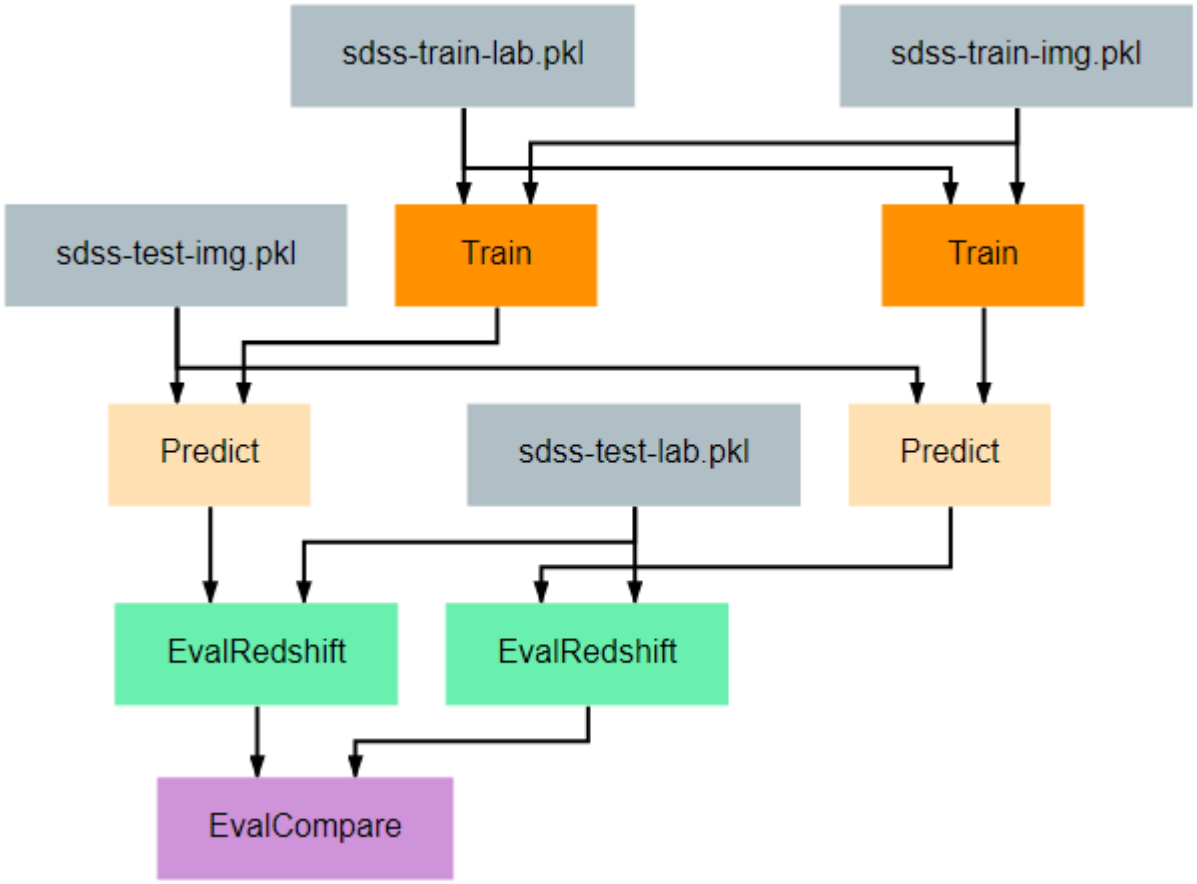
The evaluation node has also been updated to provide metrics more in line with redshift estimation. Specifically, it calculates the fraction of outlier predictions, the model's prediction bias, the deviation in the MAD scores of the model output, and the average Continuous Ranked Probability Score (CRPS) of the output.

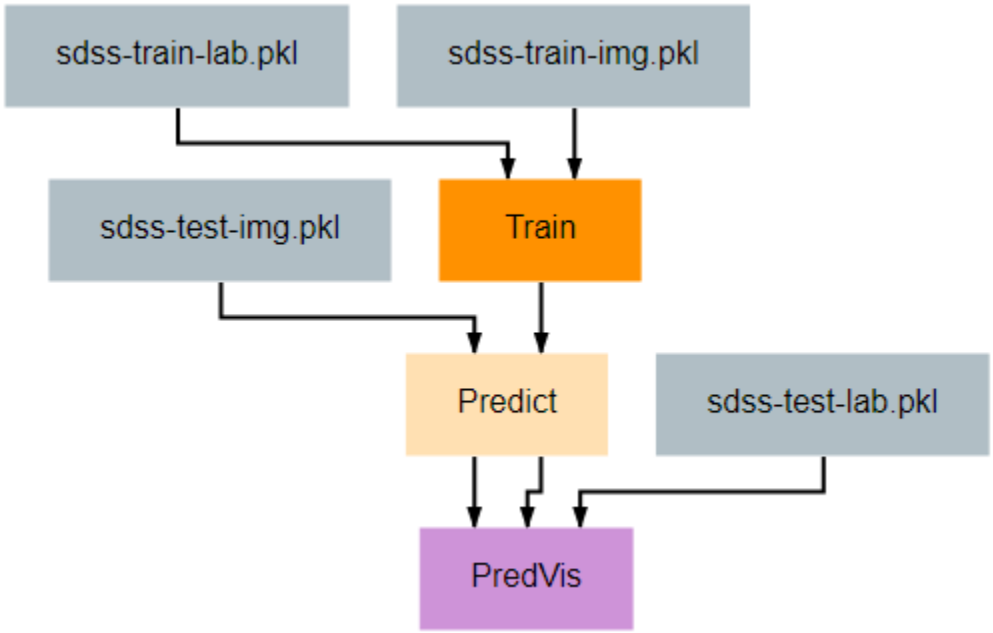
9.2.6 Train-Test-Compare

This pipeline gives a more complicated example of how to create visualizations that may be helpful for understanding the effectiveness of a model. The **EvalCompare** node provides a simple comparison visualization of two models.

9.2.7 Train-PredVis

This pipeline shows another more complex and useful visualization example that can be helpful for understanding the effectiveness of your redshift estimation model. It generates a set of graphs like the one below that show the output

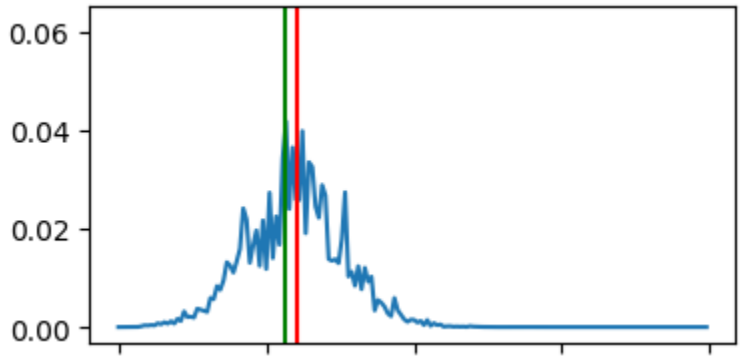

sdss-train-lab.pkl
sdss-train-img.pkl
sdss-test-img.pkl
Train
Train
Predict
sdss-test-lab.pkl
Predict
EvalRedshift
EvalRedshift
EvalCompare


sdss-train-lab.pkl
sdss-train-img.pkl
sdss-test-img.pkl
Train
Predict
sdss-test-lab.pkl
PredVis

probability distribution function (pdf) for the redshift values of a set of random galaxies' images. A pair of vertical lines in each subplot indicate the actual redshift value (green) and the predicted redshift value (red) for that galaxy.

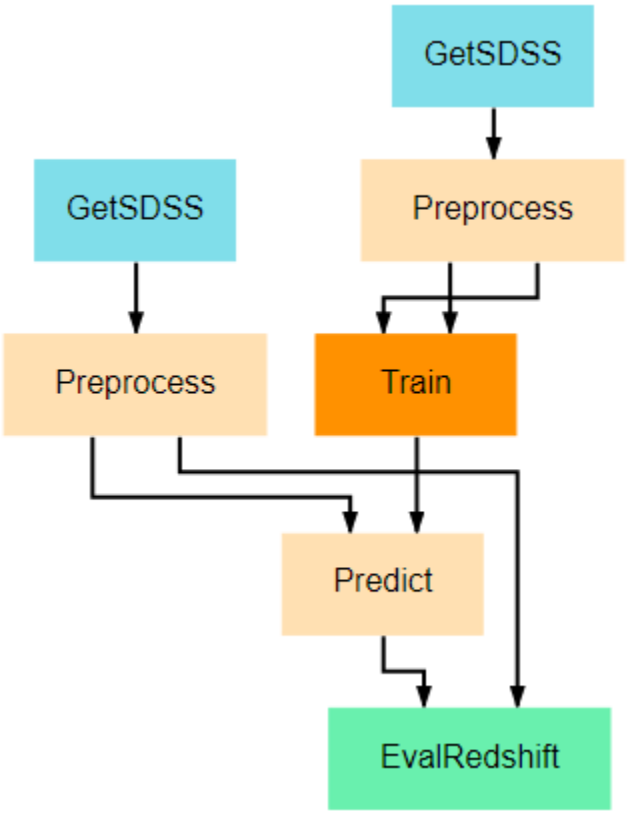
As shown in this example, any visualization that can be created using the matplotlib.pyplot python library can be created and displayed by a pipeline. Displaying these visualizations can be accomplished by calling the **pyplot.show()** function after building the visualization. They can then be viewed from the Executions view.

```
import numpy as np
from matplotlib import pyplot as plt

class PredVis():
    def __init__(self, num_bins=180, num_rows=1, num_cols=1, max_val=0.4):
        self.num_rows = num_rows
        self.num_cols = num_cols
        self.xrange = np.arange(0, max_val, max_val / num_bins)
        return

    def execute(self, pt, gt, pdfs):
        fig, splts = plt.subplots(self.num_rows, self.num_cols, sharex=True,␣
↪sharey=True)

        num_samples = self.num_rows * self.num_cols

        random_indices = np.random.choice(list(range(len(gt))), num_samples,␣
↪replace=False)

        s_pdfs = np.take(pdfs, random_indices, axis=0)
        s_pt = np.take(pt, random_indices, axis=0)
        s_gt = np.take(gt, random_indices, axis=0)

        for i in range(num_samples):
            col = i % self.num_cols
            row = i // self.num_cols
            splts[row,col].plot(self.xrange, s_pdfs[i],'-')
            splts[row,col].axvline(s_pt[i], color='red')
            splts[row,col].axvline(s_gt[i], color='green')
        plt.show()
```



9.2.8 Download-Train-Evaluate

This pipeline provides an example of how data can be retrieved and utilized in the same pipeline. The previous pipelines use manually uploaded artifacts. In many real cases, users may desire to retrieve novel data or more specific data using SciServer's CasJobs API. In such cases, the **DownloadSDSS** node here makes downloading data relatively



simple for users. It should be noted that the data downloaded is not in a form easily usable by our models and first requires moderate preprocessing, which is performed in the **Preprocessing** node. This general structure of download-process-train is a common pattern, as data is rarely supplied in a clean, immediately usable format.

CHAPTER 10

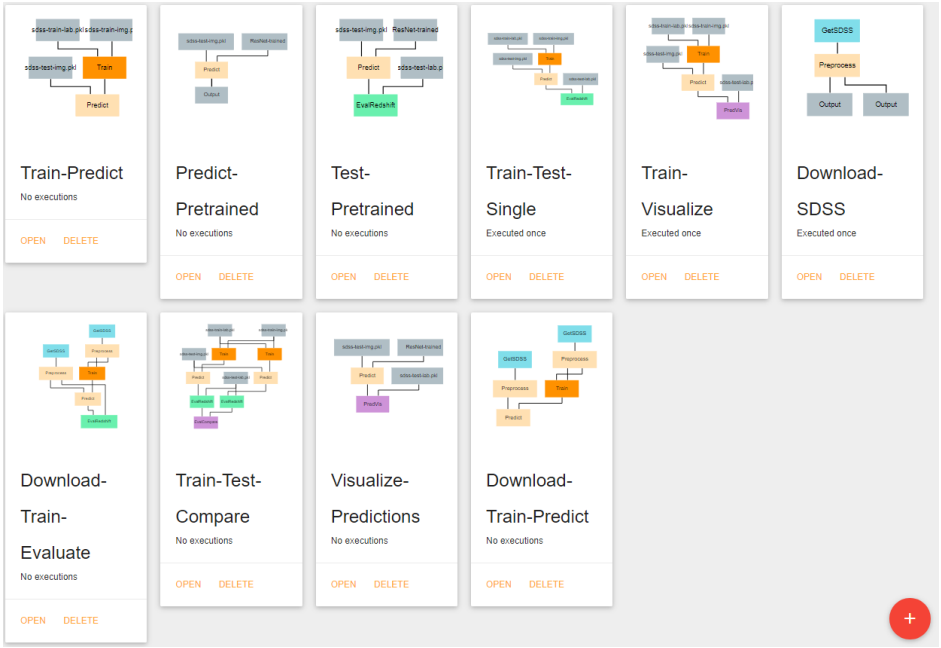
Redshift Estimation

The project described on this page can be found in the examples repo on GitHub under the name **Redshift-Application.webgmex**

This project provides a small collection of generalized pipelines for the training and utilization of redshift estimation models. This project is designed to allow simple use by only requiring that the configuration parameters of individual nodes be defined where necessary. The most involved alterations that should be necessary for most users is the definition of additional architectures in the **Resources** tab. It should be noted that any newly defined architecture should have an output length and input shape that match the *num_bins* and *input_shape* configuration parameters being used in the various pipelines.

10.1 Pipeline Overview

- *Train Test Single*
- *Train Test Compare*
- *Download Train Evaluate*
- *Train Predict*
- *Predict Pretrained*
- *Test Pretrained*
- *Download SDSS*
- *Download Train Predict*
- *Visualize Predictions*



10.2 Pipelines

10.2.1 Train Test Single

Trains and evaluates a single CNN model. Uses predefined artifacts that contain the training and testing data. For this and all training pipelines, the artifacts should each contain a single numpy array. Input arrays should be a 4D array of shape **(n, y, x, c)** where n=number of images, y=image height, x=image width, and c=number of color channels. Output (label) arrays should be of shape **(n,)** .

10.2.2 Train Test Compare

Trains and evaluates two CNN models and compares effectiveness of the models.

10.2.3 Download Train Evaluate

Downloads SDSS images, trains a model on the images, and evaluates the model on a separate set of downloaded images. Care should be taken when defining your own CasJobs query to ensure that all queried galaxies for training have a redshift value below the **Train** node's *max_val* configuration parameter's value.

10.2.4 Train Predict

Trains a single CNN model and uses the newly trained model to predict the redshift value of another set of galaxies.

10.2.5 Predict Pretrained

Predicts the redshift value of a set of galaxies using a pre-existing model that is saved as an artifact.

10.2.6 Test Pretrained

Evaluates the performance of a pre-existing model that is saved as an artifact.

10.2.7 Download SDSS

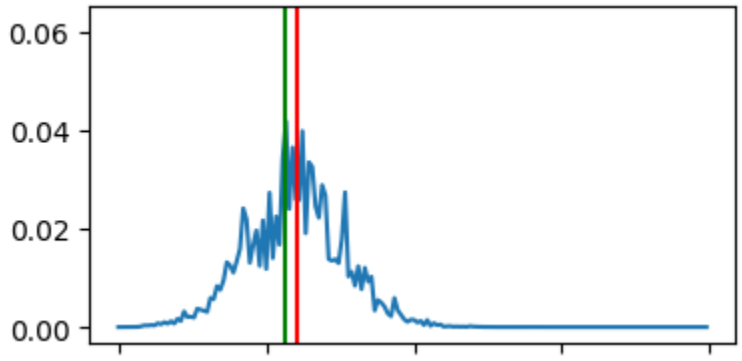
Download SDSS images and save them as artifacts. Can be used in conjunction with the other pipelines that rely on artifacts rather than images retrieved at execution time.

10.2.8 Download Train Predict

Download SDSS images and use some images to train a model before using the model to predict the redshift value of the remaining galaxies.

10.2.9 Visualize Predictions

This pipeline produces a visualization that can be helpful for understanding the effectiveness of your redshift estimation model. It generates a set of graphs like the one below that show the output probability distribution function (pdf) for the redshift values of a set of random galaxies' images. A pair of vertical lines in each subplot indicate the actual redshift value (green) and the predicted redshift value (red) for that galaxy. This allows users to see how far the model's predictions are from the correct answers and can help with identifying biases or weak-points the model may have (for example, consistently underestimation or inaccuracy with galaxies in a specific redshift range).



CHAPTER 11

Command Line Interface

This document outlines the functionality of the deepforge command line interface (provided after installing deepforge with `npm install -g deepforge`).

- Installation Configuration
- Starting DeepForge or Components
- Update or Uninstall DeepForge
- Managing Extensions

11.1 Installation Configuration

Installation configuration can be edited using the `deepforge config` command as shown in the following examples:

Printing all the configuration settings:

```
deepforge config
```

Printing the value of a configuration setting:

```
deepforge config blob.dir
```

Setting a configuration option, such as `blob.dir` can be done with:

```
deepforge config blob.dir /some/new/directory
```

For more information about the configuration settings, check out the configuration page.

11.2 Starting DeepForge Components

The DeepForge server can be started with the `deepforge start` command. By default, this command will start both the server and a mongo database (if applicable).

The server can be started by itself using

```
deepforge start --server
```

11.3 Update/Uninstall DeepForge

DeepForge can be updated or uninstalled using

```
deepforge update
```

DeepForge can be uninstalled using `deepforge uninstall`

11.4 Managing Extensions

DeepForge extensions can be installed and removed using the `deepforge extensions` subcommand. Extensions can be added, removed and listed as shown below

```
deepforge extensions add https://github.com/example/some-extension
deepforge extensions remove some-extension
deepforge extensions list
```

CHAPTER 12

Configuration

Configuration of deepforge is done through the *deepforge config* command from the command line interface. To see all config options, simply run *deepforge config* with no additional arguments. This will print a JSON representation of the configuration settings similar to:

```
Current config:
{
  "blob": {
    "dir": "/home/irishninja/.deepforge/blob"
  },
  "mongo": {
    "dir": "~/.deepforge/data"
  }
}
```

Setting an attribute, say *blob.dir*, is done as follows

```
deepforge config blob.dir /tmp
```

12.1 Environment Variables

Most settings have a corresponding environment variable which can be used to override the value set in the cli's configuration. This allows the values to be temporarily set for a single run. For example, starting the server with a different blob location can be accomplished by setting *blob.dir* can be done with:

```
DEEPFORGE_BLOB_DIR=/tmp deepforge start -s
```

The complete list of the environment variable overrides for the configuration options can be found here.

12.2 Settings

12.2.1 blob.dir

The path to the blob (large file storage containing models, datasets, etc) to be used by the deepforge server.

This can be overridden with the *DEEPFORGE_BLOB_DIR* environment variable.

12.2.2 mongo.dir

The path to use for the *–dbpath* option of mongo if starting mongo using the command line interface. That is, if the MONGO_URI is set to a local uri and the cli is starting the deepforge server, the cli will check to verify that an instance of mongo is running locally. If not, it will start it on the given port and use this setting for the *–dbpath* setting of mongod.

CHAPTER 13

Operation Feedback

Operations can provide a variety of forms of real-time feedback including subplots, 2D and 3D plots and images using `matplotlib`.

13.1 Graphs

The following example shows a sample 3D scatter plot and its rendering in DeepForge.

```
import matplotlib.pyplot as plt
import numpy as np
from mpl_toolkits.mplot3d import Axes3D

class Scatter3DPlots():

    def execute(self):
        # Set random seed for reproducibility
        np.random.seed(19680801)


        def randrange(n, vmin, vmax):
            '''
            Helper function to make an array of random numbers having shape (n, )
            with each number distributed Uniform(vmin, vmax).
            '''
            return (vmax - vmin)*np.random.rand(n) + vmin

        fig = plt.figure()
        ax = fig.add_subplot(111, projection='3d')

        n = 100

        # For each set of style and range settings, plot n random points in the box
        # defined by x in [23, 32], y in [0, 100], z in [zlow, zhigh].
```

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```
        for m, zlow, zhigh in [('o', -50, -25), ('^', -30, -5)]:
            xs = randrange(n, 23, 32)
            ys = randrange(n, 0, 100)
            zs = randrange(n, zlow, zhigh)
            ax.scatter(xs, ys, zs, marker=m)

        ax.set_xlabel('X Label')
        ax.set_ylabel('Y Label')
        ax.set_zlabel('Z Label')
        plt.show()
```

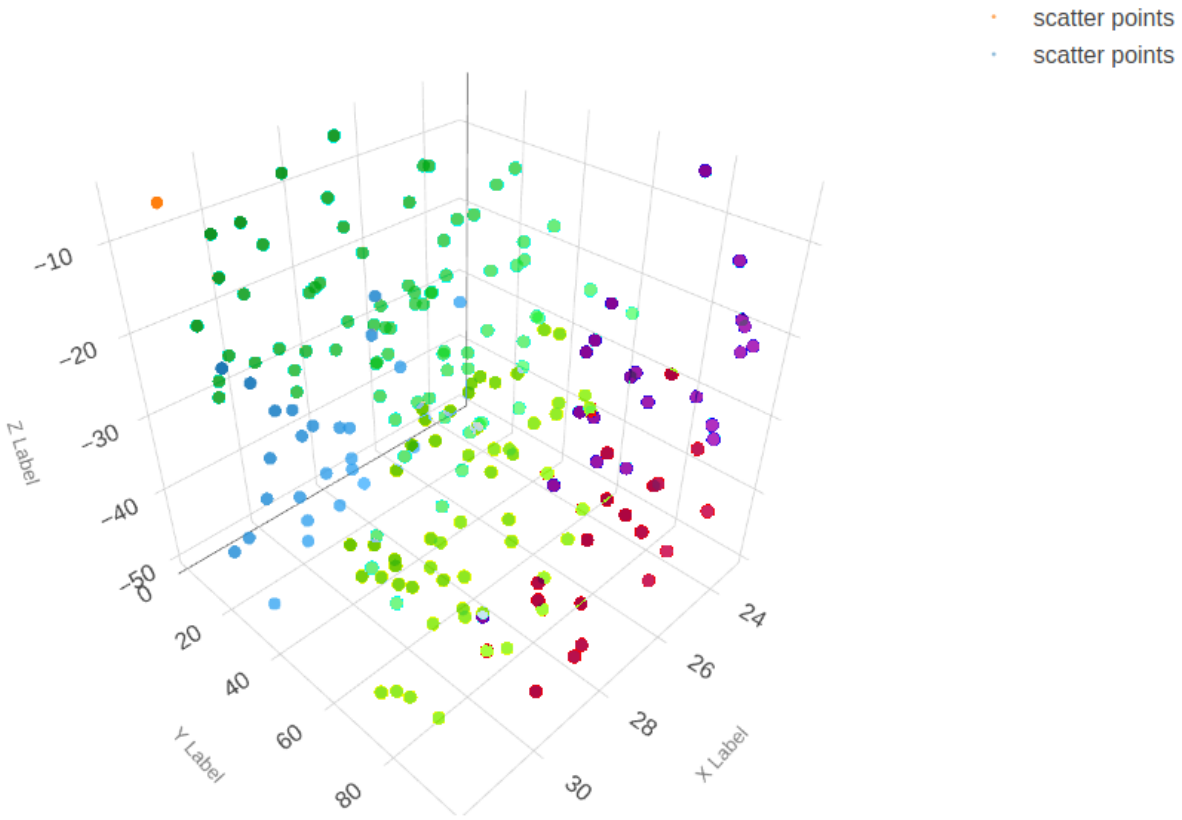

Fig. 1: Example of a 3D scatter plot using matplotlib in DeepForge

13.2 Images

Visualizing images using *matplotlib* is also supported. The following example shows images from the *MNIST fashion dataset*.

```
from matplotlib import pyplot
from keras.datasets import fashion_mnist

class MnistFashion():

    def execute(self):

        (trainX, trainy), (testX, testy) = fashion_mnist.load_data()
        # summarize loaded dataset
        print('Train: X=%s, y=%s' % (trainX.shape, trainy.shape))
        print('Test: X=%s, y=%s' % (testX.shape, testy.shape))
        for i in range(9):
            pyplot.subplot(330 + 1 + i)  # define subplot
            pyplot.imshow(trainX[i], cmap=pyplot.get_cmap('gray'))  # plot raw pixel
↪data
        pyplot.show()
```