Learn As You Go

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Python implementation of the Learn As You Go algorithm described in arxiv:1506:01079 and arxiv:2004.11929.

The package defines a decorator that can be applied to functions to convert them to functions which learn outputs as they go and emulate the true function when expected errors are low. Two emulators are included: the *k*-nearest neighbors Monte Carlo accelerator described there, and a simple neural network.

The basic usage of the emulator code is something like this:

```
@emulate(CholeskyNnEmulator)
def loglike(x):
    """
    Your complex and expensive function here
    """
    return -np.dot(x,x)
```

This decorates the function loglike so that it is an instance of the Learner class. It can be used in the same way as the original function: just call it as loglike (x).

The __call__(x) method now hides some extra complexity: it uses the Learn As You Go emulation scheme. It learns both the output of loglike(x) and the difference between the emulated and the true values of loglike(x) so that it can make a prediction of future the error residuals. We then put a cutoff on the amount of error that one will allow for any local evaluation of the target function. Any call to the emulator that has a too-large error will be discarded and the actual function loglike(x) defined above will be evaluated instead.

The logic for generating training sets and returning a value from either the true function or the emulated function are contained in the Learner class. The Learner class relies on an emulator class to do the actual emulation.

You can define you own emulator. Define a class that inherits from BaseEmulator and define two methods on it: set_emul_func(self, x_train: np.ndarray, y_train: np.ndarray) and set_emul_error_func(self, x_train: np.ndarray, y_train: np.ndarray) that set functions for, respectively, self.emul_func and self.emul_error_func. An example of this definition is provided in *examples/example_custom_emulator.py*.

See readthedocs.org for more documentation.

CHAPTER 1

Installation

pip

The package is available on pypi.org. Install it with

pip install layg

anaconda

If you use anaconda you can create an appropriate environment and install to your python path by running

```
conda env create --file environment.yml
pip install -e .
```

from this directory.

1.1 Examples

1.1.1 Basic Usage

An example of basic use of *layg*.

```
"""
An example use of the `layg` package
"""
import matplotlib.pyplot as plt # type: ignore
import numpy as np # type: ignore
# TODO: remove NOQA when isort is fixed
from layg import CholeskyNnEmulator as Emulator # NOQA
from layg import emulate # NOQA
```

```
def main():
   ndim = 2
   # Toy likelihood
   @emulate (Emulator)
   def loglike(x):
       if x.ndim != 1:
           loglist = []
           for x0 in x:
               loglist.append(-np.dot(x0, x0))
           return np.array(loglist)
       else:
           return np.array([-np.dot(x, x)])
    # Make fake data
   def get_x(ndim):
       .....
       Sample from a Gaussian with mean \ensuremath{0} and std \ensuremath{1}
       .....
       return np.random.normal(0.0, 1.0, size=ndim)
   if ndim == 1:
       Xtrain = np.array([get_x(ndim) for _ in range(1000)])
       xlist = np.array([np.linspace(-3.0, 3.0, 11)]).T
   elif ndim == 2:
       Xtrain = np.array([get_x(ndim) for _ in range(10000)])
       xlist = np.array([get_x(ndim) for _ in range(10)])
   else:
       raise RuntimeError(
           "This number of dimensions has not been implemented for testing yet."
       )
   Ytrain = np.array([loglike(X) for X in Xtrain])
   loglike.train(Xtrain, Ytrain)
   loglike.output_err = True
   for x in xlist:
       print("x", x)
       print("val, err", loglike(np.array(x)))
   loglike.output_err = False
   # Plot an example
   assert loglike.trained
   fig = plt.figure()
   ax = fig.add_subplot(111)
```

```
x_{len} = 100
   x_data_plot = np.zeros((x_len, ndim))
    for i in range(ndim):
        x_data_plot[:, i] = np.linspace(0, 1, x_len)
   y_true = np.array([loglike.true_func(x) for x in x_data_plot])
   y_emul = np.array([loglike(x) for x in x_data_plot])
   y_emul_raw = np.array([loglike.emulator.emul_func(x) for x in x_data_plot])
   ax.plot(x_data_plot[..., 0], y_true, label="true", color="black")
   ax.scatter(x_data_plot[..., 0], y_emul, label="emulated", marker="+")
   ax.scatter(
        x_data_plot[..., 0],
        y_emul_raw,
        label="emulated\n no error estimation",
        marker="+",
    )
   ax.legend()
   ax.set_xlabel("Input")
   ax.set_ylabel("Output")
    fig.savefig("check.png")
def test_main():
   main()
if ___name_
          _ == "__main__":
   main()
```

1.1.2 Use with emcee

An example using layg with the common Markov chain Monte Carlo sampler emcee.

```
"""
An example use of the `learn_as_you_go` package with emcee
"""
import emcee # type: ignore
import gif # type: ignore
import matplotlib.pyplot as plt # type: ignore
import numpy as np # type: ignore
# TODO: remove NOQA when isort is fixed
from layg import CholeskyNnEmulator # NOQA
from layg import emulate # NOQA
def main():
```



```
ndim = 2
   nwalkers = 20
   niterations = 1000
   nthreads = 1
   np.random.seed(1234)
    # Toy likelihood
   @emulate(CholeskyNnEmulator)
   def loglike(x):
        return np.array([-np.dot(x, x) ** 1])
    loglike.output_err = True
   loglike.abs_err_local = 2
    # Starting points for walkers
   p0 = np.random.normal(-1.0, 1.0, size=(nwalkers, ndim))
    sampler = emcee.EnsembleSampler(nwalkers, ndim, loglike, threads=nthreads)
    # Sample with emcee
   with open("test.txt", "w") as f:
        for result in sampler.sample(p0, iterations=niterations, storechain=True):
            for pos, lnprob, err in zip(result[0], result[1], result[3]):
                for k in list(pos):
                    f.write("%s " % str(k))
                f.write("%s " % str(lnprob))
                f.write("%s " % str(err))
                f.write("\n")
   print("n exact evals:", loglike._nexact)
   print("n emul evals:", loglike._nemul)
    # Plot points sampled
   nframes = 50
   duration = 10
   frames = []
   lim = (-3, 3)
   for i in range(0, niterations * nwalkers, niterations * nwalkers // nframes):
       x = sampler.chain.reshape(niterations * nwalkers, ndim)[:i]
        y = np.array(sampler.blobs).reshape(niterations * nwalkers)[:i]
        frame = plot(x, y, lim)
        frames.append(frame)
   gif.save(frames, "mc.gif", duration=duration)
@gif.frame
def plot(x, err, lim):
   true = x[err == 0.0]
   emul = x[err != 0.0]
   plt.figure(figsize=(5, 5), dpi=100)
```

1.1.3 Custom Emulators

This example shows how to build a custom emulator by defining a subclass of layg.emulator.BaseEmulator.

The emulator simply learns the mean and standard deviation of the supplied training data.

In this example the emulated function is very simple: it returns real numbers drawn from a Gaussian distribution with some mean.

```
from typing import Callable
import matplotlib.pyplot as plt # type: ignore
import numpy as np # type: ignore
from layg import BaseEmulator, emulate # NOQA
class MeanEmulator(BaseEmulator):
    An emulator that returns the mean of the training values
   The error estimate is the standard deviation of the error in the cross validation.
\rightarrow data.
   This emulator is not very useful other than as an example of how to write one.
    .....
   def set_emul_func(self, x_train: np.ndarray, y_train: np.ndarray) -> None:
        self.emul_func: Callable[[np.ndarray], np.ndarray] = lambda x: np.mean(y_
→train)
   def set_emul_error_func(self, x_cv: np.ndarray, y_cv_err: np.ndarray) -> None:
        self.emul_error: Callable[[np.ndarray], np.ndarray] = lambda x: y_cv_err.std()
MEAN = 2 + np.random.uniform(size=1)
```

```
@emulate (MeanEmulator)
def noise(x: np.ndarray) -> np.ndarray:
    ......
    Sample from a Gaussian distribution
    The scatter is small enough that the emulated value is always used.
    .....
   return np.random.normal(loc=MEAN, scale=1e-2, size=1)
def main():
    ......
   Plot some output from this emulator
    ......
   NUM_TRAIN = noise.init_train_thresh
   NUM\_TEST = 20
   XDIM = 1
    # Train the emulator
   x_train = np.random.uniform(size=(NUM_TRAIN, XDIM))
   y_train = np.array([noise(x) for x in x_train])
    # Output error estimates
   noise.output_err = True
    # Get values from the trained emulator
   x_emu = np.random.uniform(size=(NUM_TEST, XDIM))
   y_emu = np.zeros_like(x_emu)
   y_err = np.zeros_like(x_emu)
   for i, x in enumerate(x_emu):
       val, err = noise(x)
       y_emu[i] = val
       y_err[i] = err
    # Plot the results
   fig = plt.figure()
   ax = fig.add_subplot(111)
   ax.scatter(x_train[:, 0], y_train, marker="+", label="training values")
    ax.errorbar(
        x_emu,
       y_emu,
        yerr=y_err.flatten(),
        linestyle="None",
        marker="o",
        capsize=3,
        label="emulator",
        color="red",
   )
    ax.legend()
```

```
# `__file__` is undefined when running in sphinx
try:
    fig.savefig(__file__ + ".png")
except NameError:
    pass

def test_main():
    """
    Runs in pytest
    """
    main()

if __name__ == "__main__":
    main()
```



1.2 API

layg.learner.Learner(true_func,)	A class that contains logic for learning as you go
layg.emulator.BaseEmulator()	Base class from which emulators should inherit
layg.emulator.cholesky_nn_emulator.	An emulator based on Cholesky decomposition and
CholeskyNnEmulator()	nearest neighbours
layg.emulator.torch_emulator.	Class that uses pytorch to do emulation
TorchEmulator()	

1.2.1 layg.learner.Learner

class layg.learner.Learner(true_func: Callable[[numpy.ndarray], numpy.ndarray], emulator_class) A class that contains logic for learning as you go

This class does not contain any emulation but should be constructed with an emulator containing emulation logic. The emulator must be a subclass of BaseEmulator, implementing two methods, *set_emul_func* and *set_emul_error_func*, that set the respective functions.

Attributes

emulator_class [BaseEmulator] The type of emulator used.

- **emulator** [BaseEmulator] An instance of the class *emulator_class*. This is where the heavy lifting goes on.
- true_func [Callable] The function which is emulated
- frac_err_local [float] Maximum fractional error in emulated function. Calls to emulation function that exceed this error level are evaluated exactly instead. Default: 1.0
- **abs_err_local** [float] Maximum absolute error allowed in emulated function. Calls to emulation function that exceed frac_err_local but are lower than abs_err_local are emulated, rather than exactly evaluated. FIXME: this doesn't happen Default: 0.05
- **output_err** [bool] Whether to output an error estimate. Set to False if you do not want the error to be an output of the emulated function. Set to True if you do. Default: False
- trained [bool] Whether the emulator has been trained
- used_train_x [List[np.ndarray]]
- **used_train_y** [List[np.ndarray]] Values from the true function that were used last time the emulator was trained
- batch_train_x [List[np.ndarray]]
- **batch_train_y** [List[np.ndarray]] Values from the true function that have not yet been used to train the emulator
- init_train_thresh [int] Number of points to accumulate before training the emulator
- **frac_cv** [float] Fraction of training set to use for error modelling The default value of 0.5 means that the prediction and the error are estimated off the same amount of data.

Methods

call(self, x)	The method that is executed when the wrapped func-
	tion is called

Continued on next page

Table 2 – continued from previous page		
emulation_is_valid(self, val, err)	Check if an emulated value is valid and likely accu-	
	rate	
eval_true_func(self, x)	Wrapper for evaluating true function	
split_CV(self, xdata, ydata, frac_cv)	Splits a dataset into a cross-validation and training	
	set.	
<pre>train(self, x_train, y_train)</pre>	Train a ML algorithm to replace true_func: $X \rightarrow Y$.	

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___init___(self, true_func: Callable[[numpy.ndarray], numpy.ndarray], emulator_class) Constructor for Learner class

Parameters

true_func [Callable] Function to be emulated

emulator_class [BaseEmulator] The emulator class to be used

Methods

	Constructor for Learner class
emulation_is_valid(self, val, err)	Check if an emulated value is valid and likely accu-
	rate
eval_true_func(self, x)	Wrapper for evaluating true function
<pre>split_CV(self, xdata, ydata, frac_cv)</pre>	Splits a dataset into a cross-validation and training
	set.
<pre>train(self, x_train, y_train)</pre>	Train a ML algorithm to replace true_func: $X \rightarrow Y$.

1.2.2 layg.emulator.BaseEmulator

class layg.emulator.BaseEmulator

Base class from which emulators should inherit

This class is abstract. The child class must implement the marked methods.

Methods

add_data(self, x_train, y_train)

Add data to the training set on the fly

<pre>set_emul_error_func</pre>	
set_emul_func	

___init___(self)

Initialize self. See help(type(self)) for accurate signature.

Methods

	Initialize self.
add_data(self, x_train, y_train)	Add data to the training set on the fly

Continued on next page

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set_emul_error_func(self, x_cv, y_cv_err)
set_emul_func(self, x_train, y_train)

1.2.3 layg.emulator.cholesky_nn_emulator.CholeskyNnEmulator

class layg.emulator.cholesky_nn_emulator.**CholeskyNnEmulator** An emulator based on Cholesky decomposition and nearest neighbours

This emulator described in detail in arXiv:1506.01079.

Methods

add_data(self, x_train, y_train)

Add data to the training set on the fly

<pre>set_emul_error_func</pre>	
set_emul_func	

__init__(self)

Initialize self. See help(type(self)) for accurate signature.

Methods

init(self)	Initialize self.
add_data(self, x_train, y_train)	Add data to the training set on the fly
<pre>set_emul_error_func(self, x_cv, y_cv_err)</pre>	
<pre>set_emul_func(self, x_train, y_train)</pre>	

1.2.4 layg.emulator.torch_emulator.TorchEmulator

class layg.emulator.torch_emulator.TorchEmulator

Class that uses pytorch to do emulation

The Universal Approximation Theorem says that any Lebesgue integrable function can be approximated by a feed-forward network with sufficient layers of sufficient width. It doesn't guarantee that we can train the network though.

Methods

add_data(self, x_train, y_train)	Add data to the training set on the fly
<pre>set_emul_error_func(self, x_cv, y_cv_err)</pre>	Fit a quadratic to the residuals and mean distance to
	nearby points

set_emul_func

__init__(self)

Initialize self. See help(type(self)) for accurate signature.

Methods

init(self)	Initialize self.
add_data(self, x_train, y_train)	Add data to the training set on the fly
<pre>set_emul_error_func(self, x_cv, y_cv_err)</pre>	Fit a quadratic to the residuals and mean distance to
	nearby points
<pre>set_emul_func(self, x_train, y_train)</pre>	

CHAPTER 2

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