Fundamentals

This introductory module is focused on introducing several core software engineering methods for testing and debugging, and also includes some basic mathematical foundations.

Before starting this assignment, make sure to set up your workspace following the setup guide, to understand how the code should be organized.

Guides

Each module has a set of guides to help with the background material. We recommend working through the assignment and utilizing the guides suggested for each task.

- Contributing
- Functional Python
- Property Testing
- Modules
- Visualization

Task 0.1: Operators

This task is designed to help you get comfortable with style checking and testing. We ask you to implement a series of basic mathematical functions. These functions are simple, but they form the basis of MiniTorch. Make sure that you understand each of them as some terminologies might be new.

> **Todo**
>
> Complete the following functions in `minitorch/operators.py` and pass tests marked as `task0_1`.

`minitorch.operators.mul(x: float, y: float) -> float`

$$f(x, y) = x * y$$

`minitorch.operators.id(x: float) -> float`

$$f(x) = x$$

`minitorch.operators.eq(x: float, y: float) -> float`

$f(x) =$ 1.0 if x is equal to y else 0.0

`minitorch.operators.neg(x: float) -> float`

$f(x) = -x$

`minitorch.operators.add(x: float, y: float) -> float`

$f(x, y) = x + y$

`minitorch.operators.max(x: float, y: float) -> float`

$f(x) =$ x if x is greater than y else y

`minitorch.operators.lt(x: float, y: float) -> float`

$f(x) =$ 1.0 if x is less than y else 0.0

`minitorch.operators.sigmoid(x: float) -> float`

$f(x) = \frac{1.0}{(1.0+e^{-x})}$

(See https://en.wikipedia.org/wiki/Sigmoid_function)

Calculate as

$f(x) = \frac{1.0}{(1.0+e^{-x})}$ if x >=0 else $\frac{e^x}{(1.0+e^x)}$

for stability.

`minitorch.operators.relu(x: float) -> float`

$f(x) =$ x if x is greater than 0, else 0

(See https://en.wikipedia.org/wiki/Rectifier_(neural_networks) .)

`minitorch.operators.inv(x: float) -> float`

$f(x) = 1/x$

`minitorch.operators.inv_back(x: float, d: float) -> float`

If $f(x) = 1/x$ compute $d \times f'(x)$

`minitorch.operators.relu_back(x: float, d: float) -> float`

If $f = relu$ compute $d \times f'(x)$

`minitorch.operators.log_back(x: float, d: float) -> float`

If $f = log$ as above, compute $d \times f'(x)$

`minitorch.operators.is_close(x: float, y: float) -> float`

$$f(x) = |x - y| < 1e - 2$$

Task 0.2: Testing and Debugging

We ask you to implement property tests for your operators from Task 0.1. These tests should ensure that your functions not only work but also obey high-level mathematical properties for any input. Note that you need to change arguments for those test functions.

> **Todo**
>
> Complete the test functions in `tests/test_operators.py` marked as `task0_2`.

Task 0.3: Functional Python

To practice the use of higher-order functions in Python, implement three basic functional concepts. Use them in combination with operators described in Task 0.1 to build up more complex mathematical operations that work on lists instead of single values.

> **Todo**
>
> Complete the following functions in `minitorch/operators.py` and pass tests marked as `tasks0_3`.

`minitorch.operators.map(fn: Callable[[float], float]) -> Callable[[Iterable[float]], Iterable[float]]`

Higher-order map.

See https://en.wikipedia.org/wiki/Map_(higher-order_function)

Parameters:

- **fn** (`Callable[[float], float]`) – Function from one value to one value.

Returns:

- `Callable[[Iterable[float]], Iterable[float]]` – A function that takes a list, applies `fn` to each element, and returns a

- `Callable[[Iterable[float]], Iterable[float]]` – new list

minitorch.operators.negList(ls: Iterable[float]) -> Iterable[float]

Use `map` and `neg` to negate each element in `ls`

minitorch.operators.zipWith(fn: Callable[[float, float], float]) -> Callable[[Iterable[float], Iterable[float]], Iterable[float]]

Higher-order zipwith (or map2).

See https://en.wikipedia.org/wiki/Map_(higher-order_function)

Parameters:

- **fn** (`Callable[[float, float], float]`) – combine two values

Returns:

- `Callable[[Iterable[float], Iterable[float]], Iterable[float]]` – Function that takes two equally sized lists `ls1` and `ls2`, produce a new list by
- `Callable[[Iterable[float], Iterable[float]], Iterable[float]]` – applying fn(x, y) on each pair of elements.

minitorch.operators.addLists(ls1: Iterable[float], ls2: Iterable[float]) -> Iterable[float]

Add the elements of `ls1` and `ls2` using `zipWith` and `add`

minitorch.operators.reduce(fn: Callable[[float, float], float], start: float) -> Callable[[Iterable[float]], float]

Higher-order reduce.

Parameters:

- **fn** (`Callable[[float, float], float]`) – combine two values
- **start** (`float`) – start value x_0

Returns:

- `Callable[[Iterable[float]], float]` – Function that takes a list `ls` of elements
- `Callable[[Iterable[float]], float]` – $x_1 \ldots x_n$ and computes the reduction :math:`fn(x_3, fn(x_2,
- `Callable[[Iterable[float]], float]` – fn(x_1, x_0)))`

minitorch.operators.sum(ls: Iterable[float]) -> float

Sum up a list using `reduce` and `add`.

`minitorch.operators.prod(ls: Iterable[float]) -> float`

Product of a list using `reduce` and `mul`.

Task 0.4: Modules

This task is to implement the core structure of the :class:`minitorch.Module` class. We ask you to implement a tree data structure that stores named :class:`minitorch.Parameter` on each node. Such a data structure makes it easy for users to create trees that can be `walked` to find all of the parameters of interest.

To experiment with the system use the `Module Sandbox`:

```
>>> streamlit run app.py -- 0
```

Todo

Complete the functions in `minitorch/module.py` and pass tests marked as `tasks0_4`.

`minitorch.module.Module.train() -> None`

Set the mode of this module and all descendent modules to `train`.

`minitorch.module.Module.eval() -> None`

Set the mode of this module and all descendent modules to `eval`.

`minitorch.module.Module.named_parameters() -> Sequence[Tuple[str, Parameter]]`

Collect all the parameters of this module and its descendents.

Returns:

- `Sequence[Tuple[str, Parameter]]` – The name and `Parameter` of each ancestor parameter.

`minitorch.module.Module.parameters() -> Sequence[Parameter]`

Enumerate over all the parameters of this module and its descendents.

Task 0.5: Visualization

For the first few assignments, we use a set of datasets implemented in `minitorch/datasets.py`, which are 2D point classification datasets. (See TensorFlow Playground for similar examples.) Each of these dataset can be added to the visualization.

To experiment with the system use:

```
streamlit run app.py -- 0
```

Read through the code in `project/run_torch.py` to get a sneak peek of an implementation of a model for these datasets using Torch.

You can also provide a model that attempts to perform the classification by manipulating the parameters.

Parameters

Parameter: linear.weight_0_0

-10.00 10.00

Parameter: linear.weight_1_0

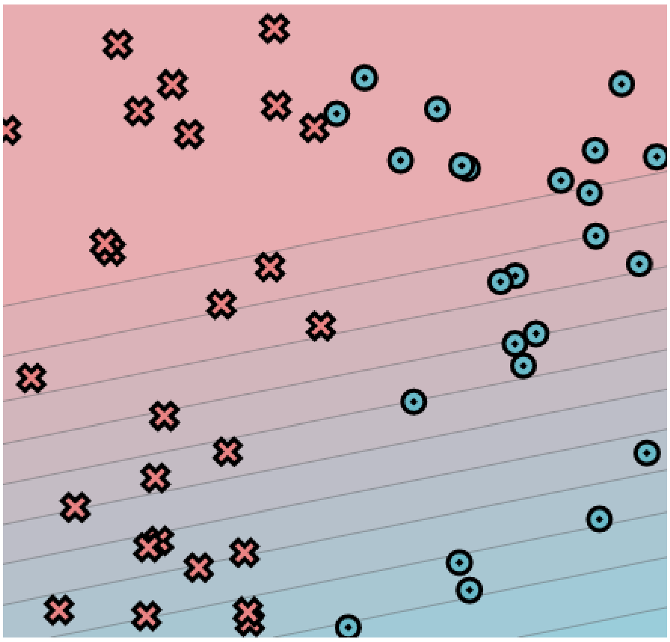
-10.00 10.00

Parameter: linear.bias_0

-10.00 10.00

☐ Show X-Axis Only (For Simple)

Initial setting



Todo

Start a streamlit server and print an image of the dataset. Hand-create classifiers that split the linear dataset into the correct colors.

Add the image in the README file in your repo along with the parameters that your used.