Module 0.2 - Models and Modules

Module 0.2

Models and Modules

Class Note

- You need to link your GitHub account
- Still several students with unlinked accounts

Review

Function Type

```python
def add(a: float, b: float) -> float:
    return a + b


def mul(a: float, b: float) -> float:
    return a * b


v: Callable[[float, float], float] = add
```

Functions as Arguments

```python
from typing import Callable


def combine3(
    fn: Callable[[float, float], float], a: float, b: float, c: float
) -> float:
    return fn(fn(a, b), c)


print(combine3(add, 1, 3, 5))
print(combine3(mul, 1, 3, 5))
```

```
9
15
```

Functional Python

Functions as Returns

```python
def combine3(
    fn: Callable[[float, float], float]
) -> Callable[[float, float, float], float]:
    def new_fn(a: float, b: float, c: float) -> float:
        return fn(fn(a, b), c)

    return new_fn
```

```python
add3: Callable[[float, float, float], float] = combine3(add)
mul3: Callable[[float, float, float], float] = combine3(mul)

print(add3(1, 3, 5))
```

```
9
```

Quiz

Outline

- Modules
- Visualization
- Datasets

Modules

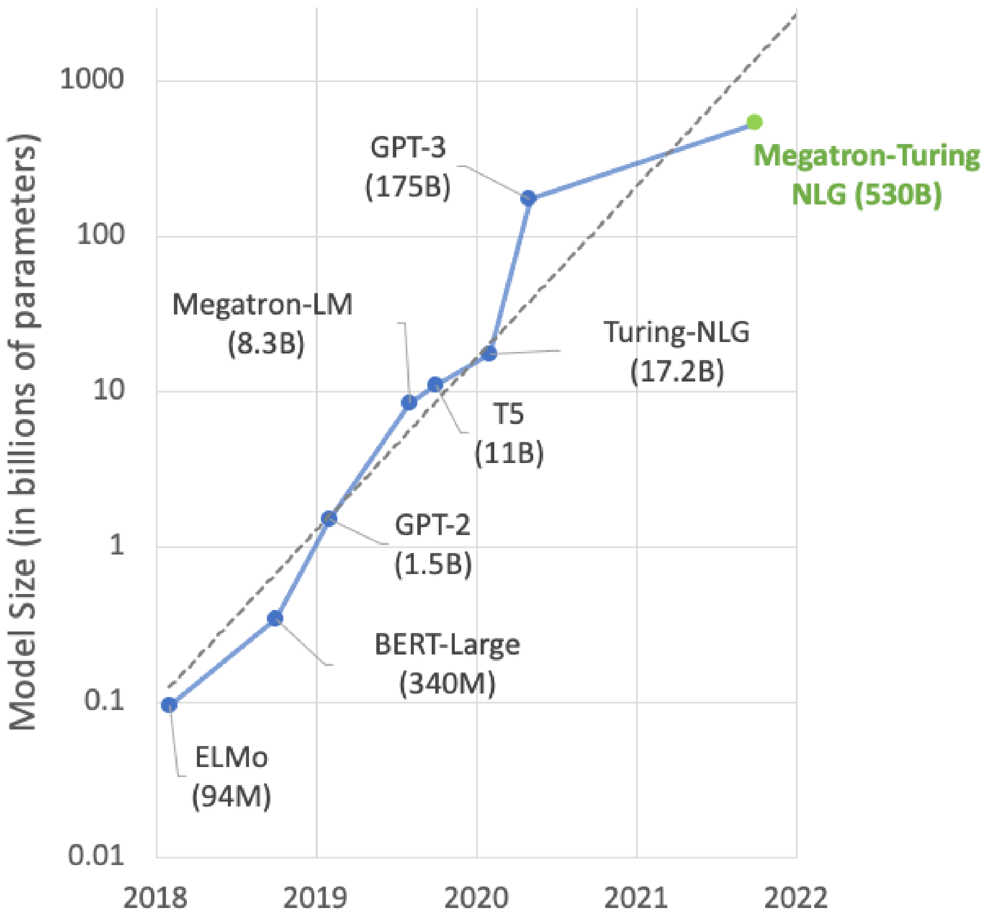
Model

- Models: parameterized functions.
    - $m(x;\theta)$
    - x - input
    - m - model
- Initial Focus:
    - θ - parameters

Parameters

- Anything learned is in the parameters.
- Modern parameters sets are both:
    - Large
    - Complex

Growth in Parameter Size



Complexity

Inception - Table of precise sizes

type	patch size/stride or remarks	input size
conv	$3\times3/2$	$299\times299\times3$
conv	$3\times3/1$	$149\times149\times32$
conv padded	$3\times3/1$	$147\times147\times32$
pool	$3\times3/2$	$147\times147\times64$
conv	$3\times3/1$	$73\times73\times64$
conv	$3\times3/2$	$71\times71\times80$
conv	$3\times3/1$	$35\times35\times192$
$3\times$Inception	As in figure 5	$35\times35\times288$
$5\times$Inception	As in figure 6	$17\times17\times768$
$2\times$Inception	As in figure 7	$8\times8\times1280$
pool	8×8	$8\times8\times2048$
linear	logits	$1\times1\times2048$
softmax	classifier	$1\times1\times1000$

Specifying Parameters

- Datastructures to specify parameters
- Requirements
    - Independent of implementation
    - Compositional

Module Trees

- Each Module owns a set of parameters
- Each Module owns a set of submodules

Module Trees

Benefits

- Can extract all parameters without knowing about Modules
- Can use mix and match Modules for different tasks

Downsides

- Verbose, repeats some functionality of declaration and use.

Module Storage

Stores three things:

- Parameters
- Submodules
- Generic Python attributes

Module Example

```
from minitorch import Module, Parameter

class OtherModule(Module):
    def __init__(self):
        # Must initialize the super class!
        super().__init__()
        self.uncool_parameter = Parameter(60)

class MyModule(Module):
    def __init__(self):
        # Must initialize the super class!
        super().__init__()

        # Type 1, a parameter.
        self.parameter1 = Parameter(15)
        self.cool_parameter = Parameter(50)

        # Type 2, user data
        self.data = 25

        # Type 3. another Module
        self.sub_module_a = OtherModule()
        self.sub_module_b = OtherModule()
```

Parameters

- Everything that is learned in the model
- Controlled and changed outside the class

Submodules

- Other modules that are called
- Store their own parameters and submodules
- Together forms a tree

Everything Else

- Modules act mostly like standard python objects
- You can have additional information stored

Module Example

```python
MyModule().named_parameters()
```

```
[('parameter1', 15),
 ('cool_parameter', 50),
 ('sub_module_a.uncool_parameter', 60),
 ('sub_module_b.uncool_parameter', 60)]
```

Extended Example

```python
class Module2(Module):
    def __init__(self):
        super().__init__()
        self.p2 = Parameter(10)

class Module3(Module):
    def __init__(self):
        super().__init__()
        self.c = Module4()

class Module4(Module):
    def __init__(self):
        super().__init__()
        self.p3 = Parameter(15)
```

Extended Example

```
class Module1(Module):
    def __init__(self):
        super().__init__()
        self.p1 = Parameter(5)
        self.a = Module2()
        self.b = Module3()

Module1().named_parameters()
```

```
[('p1', 5), ('a.p2', 10), ('b.c.p3', 15)]
```

How does this work?

- Internally `Module` spies to find `Parameter` and `Module` objects
- A list is stored internally.
- Implemented through Python magic methods

Detail: Magic Methods

- Any method that starts and ends with `__`
- Used to override default behavior of the language.
- We will use for many things, including operator overloading

Interception Code

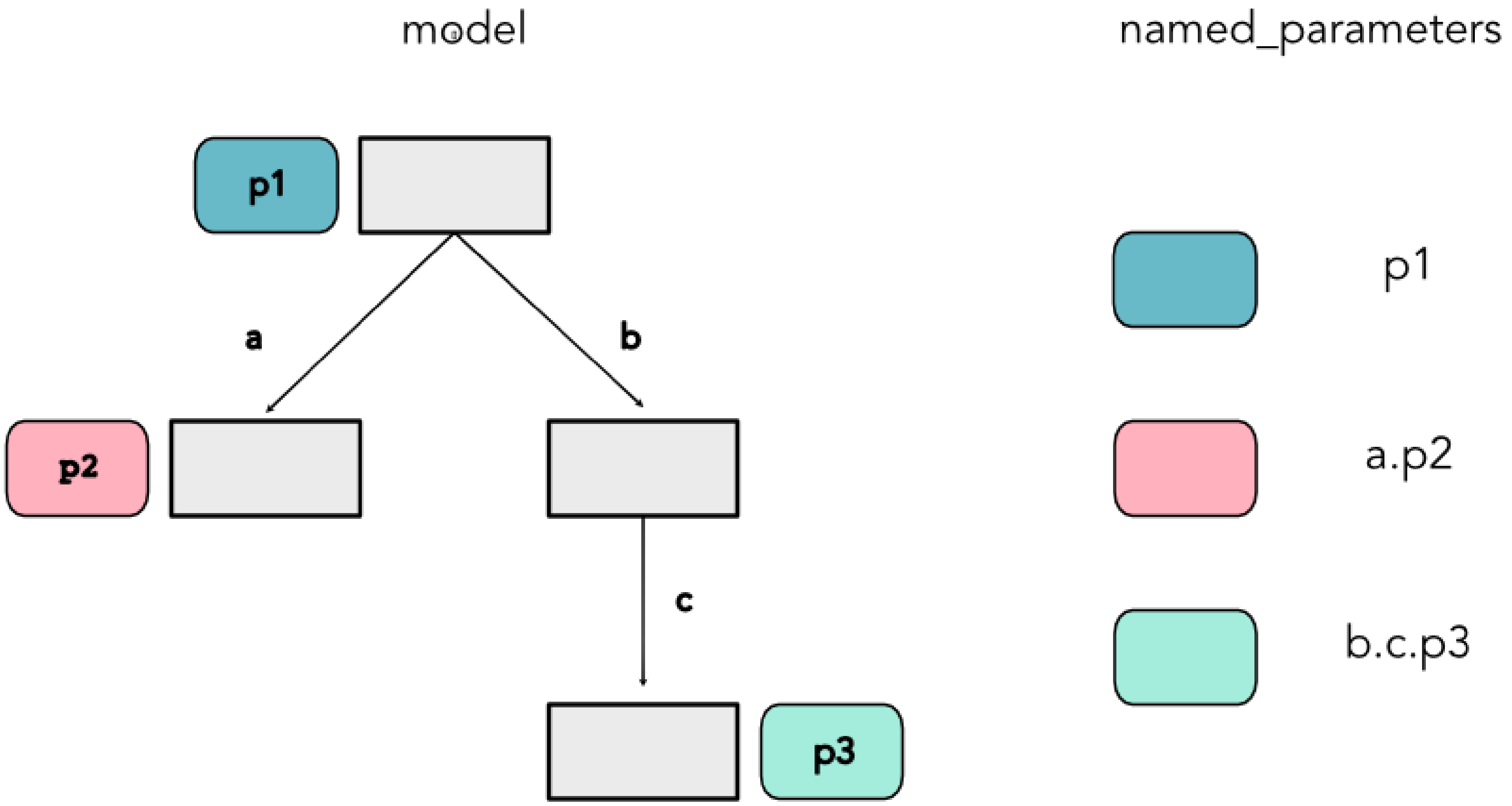
Module construction

```
class MyModule(Module):
    def __setattr__(self, key, val):
        if isinstance(val, Parameter):
            self.__dict__["_parameters"][key] = val
        elif isinstance(val, Module):
            self.__dict__["_modules"][key] = val
        else:
            super().__setattr__(key, val)
```

Parameter Naming

- Every parameter in a model has a unique name.
- Naming is determined by walking the tree.
- Names are prefixed by the path from the root.

Module Naming



Other Module Metadata

- Other information can be communicated through the tree.
- Common example: Is the model in train or test mode?

Homework Note

- Must be recursive implementation
- Have to walk the full tree
- (Companies love this as an interview question!)

Real World Examples

Code for language modeling

```
from torch import nn

class Block(nn.Module):
    def __init__(self, n_ctx, config, scale=False):
        super().__init__()
        hidden_size = config.n_embd
        inner_dim = config.n_inner if config.n_inner is not None else 4 * hidden_s
        self.ln_1 = nn.LayerNorm(hidden_size, eps=config.layer_norm_epsilon)
        self.attn = Attention(hidden_size, n_ctx, config, scale)
        self.ln_2 = nn.LayerNorm(hidden_size, eps=config.layer_norm_epsilon)
        if config.add_cross_attention:
            self.crossattention = Attention(
                hidden_size, n_ctx, config, scale, is_cross_attention=True
            )
            self.ln_cross_attn = nn.LayerNorm(
                hidden_size, eps=config.layer_norm_epsilon
            )
        self.mlp = MLP(inner_dim, config)
```

Real World Examples

Block from image classification

```
class Inception3(nn.Module):
    def __init__(
        self,
        num_classes=1000,
        aux_logits=True,
        transform_input=False,
        inception_blocks=None,
        init_weights=None,
    ):
        super(Inception3, self).__init__()
        ...
        self.aux_logits = aux_logits
        self.transform_input = transform_input
        self.Conv2d_1a_3x3 = conv_block(3, 32, kernel_size=3, stride=2)
        self.Conv2d_2a_3x3 = conv_block(32, 32, kernel_size=3)
        self.Conv2d_2b_3x3 = conv_block(32, 64, kernel_size=3, padding=1)
        self.maxpool1 = nn.MaxPool2d(kernel_size=3, stride=2)
        self.Conv2d_3b_1x1 = conv_block(64, 80, kernel_size=1)
        self.Conv2d_4a_3x3 = conv_block(80, 192, kernel_size=3)
        self.maxpool2 = nn.MaxPool2d(kernel_size=3, stride=2)
```

Visualization

Main Idea

- Show properties of your model as you code
- See real time graphs as you train models
- Make convincing figures of your full system

Library: Streamlit

Easy to use Python GUI

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

Code Snippet

Streamlit windows

```
import streamlit as st
st.write("## Sandbox for Model Training")
    ...
st.plotly_chart(fig)
```

Gotchas

- Changes to the visualization code will autoupdate
- Changes to the library will not autoupdate

Other Options

Many other ML tailored options

- Tensorboard
- Hosted services: Weights and Biases, Comet

Datasets

Sneak Preview

- Task 0.5: Intro to our first ML problem
- Basic separation of points on a graph
- Manual classifier

Datasets

- Simple
- Diag
- Split
- Xor

Parameter Knobs

- W1
- W2
- Bias

Sneak Preview

Playground

Q&A