Stack Semantics in Trax: Ungraded Lab

In this ungraded lab, we will explain the stack semantics in Trax. This will help in understanding how to use layers like Select and Residual which operates on elements in the stack. If you've taken a computer science class before, you will recall that a stack is a data structure that follows the Last In, First Out (LIFO) principle. That is, whatever is the latest element that is pushed into the stack will also be the first one to be popped out. If you're not yet familiar with stacks, then you may find this short tutorial useful. In a nutshell, all you really need to remember is it puts elements one on top of the other. You should be aware of what is on top of the stack to know which element you will be popping. You will see this in the discussions below. Let's get started!

Imports

```
In [1]:
```

```
import numpy as np  # regular ol' numpy

from trax import layers as tl  # core building block

from trax import shapes  # data signatures: dimensionality and type

from trax import fastmath  # uses jax, offers numpy on steroids

INFO:tensorflow:tokens length=568 inputs length=512 targets length=114 noise density=0.15
```

 $INFO: tensorflow: tokens_length=568 inputs_length=512 targets_length=114 noise_density=0.15 mean_noise_span_length=3.0$

1. The tl. Serial Combinator is Stack Oriented.

To understand how stack-orientation works in <u>Trax</u>, most times one will be using the <u>Serial</u> layer. We will define two simple <u>Function layers</u>: 1) Addition and 2) Multiplication.

Suppose we want to make the simple calculation (3 + 4) * 15 + 3. Serial will perform the calculations in the following manner 3 4 add 15 mul 3 add. The steps of the calculation are shown in the table below. The first column shows the operations made on the stack and the second column the output of those operations. Moreover, the rightmost element in the second column represents the top of the stack (e.g. in the second row, Push (3) pushes 3 on top of the stack and 4 is now under it).

After processing all the stack contains 108 which is the answer to our simple computation.

From this, the following can be concluded: a stack-based layer has only one way to handle data, by taking one piece of data from atop the stack, termed popping, and putting data back atop the stack, termed pushing. Any expression that can be written conventionally, can be written in this form and thus be amenable to being interpreted by a stack-oriented layer like Serial.

Coding the example in the table:

Defining addition

```
In [2]:
```

```
def Addition():
    layer_name = "Addition"  # don't forget to give your custom layer a name to identify

    # Custom function for the custom layer
    def func(x, y):
        return x + y

    return tl.Fn(layer_name, func)

# Test it
add = Addition()

# Inspect properties
print("-- Properties --")
print("name :", add.name)
print("expected inputs :", add.n_in)
print("promised outputs :", add.n_out, "\n")
```

```
# Inputs
x = np.array([3])
y = np.array([4])
print("-- Inputs --")
print("x :", x, "\n")
print("y :", y, "\n")
# Outputs
z = add((x, y))
print("-- Outputs --")
print("z :", z)
-- Properties --
name : Addition
expected inputs : 2
promised outputs : 1
-- Inputs --
x : [3]
y: [4]
-- Outputs --
z : [7]
Defining multiplication
```

```
In [3]:
def Multiplication():
   layer name = (
        "Multiplication" # don't forget to give your custom layer a name to identify
    # Custom function for the custom layer
    def func(x, y):
       return x * y
    return tl.Fn(layer name, func)
# Test it
mul = Multiplication()
# Inspect properties
print("-- Properties --")
print("name :", mul.name)
print("expected inputs :", mul.n_in)
print("promised outputs :", mul.n_out, "\n")
# Inputs
x = np.array([7])
y = np.array([15])
print("-- Inputs --")
print("x :", x, "\n")
print("y :", y, "\n")
# Outputs
z = mul((x, y))
print("-- Outputs --")
print("z :", z)
-- Properties --
name : Multiplication
expected inputs : 2
promised outputs: 1
-- Inputs --
x : [7]
y: [15]
-- Outputs --
```

z : [105]

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Implementing the computations using Serial combinator.

```
In [4]:
```

```
# Serial combinator
serial = tl.Serial(
   Addition(), Multiplication(), Addition() # add 3 + 4 # multiply result by 15
x = (np.array([3]), np.array([4]), np.array([15]), np.array([3])) # input
serial.init(shapes.signature(x)) # initializing serial instance
print("-- Serial Model --")
print(serial, "\n")
print("-- Properties --")
print("name :", serial.name)
print("sublayers :", serial.sublayers)
print("expected inputs :", serial.n in)
print("promised outputs :", serial.n_out, "\n")
# Inputs
print("-- Inputs --")
print("x :", x, "\n")
# Outputs
y = serial(x)
print("-- Outputs --")
print("y :", y)
-- Serial Model --
Serial in4[
 Addition in2
 Multiplication_in2
 Addition_in2
]
-- Properties --
name : Serial
sublayers : [Addition in2, Multiplication in2, Addition in2]
expected inputs: 4
promised outputs: 1
-- Inputs --
x : (array([3]), array([4]), array([15]), array([3]))
-- Outputs --
y: [108]
```

The example with the two simple adition and multiplication functions that where coded together with the serial combinator show how stack semantics work in Trax .

2. The tl.Select combinator in the context of the Serial combinator

Having understood how stack semantics work in Trax, we will demonstrate how the tl.Select combinator works.

First example of tl.Select

Suppose we want to make the simple calculation (3 + 4) * 3 + 4. We can use Select to perform the calculations in the following manner:

```
    4
    3
    t1.Select([0,1,0,1])
```

```
4. add
```

- 5. mul
- 6. add.

The t1.Select requires a list or tuple of 0-based indices to select elements relative to the top of the stack. For our example, the top of the stack is 3 (which is at index 0) then 4 (index 1) and we Select to add in an ordered manner to the top of the stack which after the command is $3 \ 4 \ 3 \ 4$. The steps of the calculation for our example are shown in the table below. As in the previous table each column shows the contents of the stack and the outputs after the operations are carried out.

After processing all the inputs the stack contains 25 which is the answer we get above.

```
In [5]:
```

```
serial = tl.Serial(tl.Select([0, 1, 0, 1]), Addition(), Multiplication(), Addition())
# Initialization
x = (np.array([3]), np.array([4])) # input
serial.init(shapes.signature(x)) # initializing serial instance
print("-- Serial Model --")
print(serial, "\n")
print("-- Properties --")
print("name :", serial.name)
print("sublayers :", serial.sublayers)
print("expected inputs :", serial.n_in)
print("promised outputs :", serial.n_out, "\n")
# Inputs
print("-- Inputs --")
print("x :", x, "\n")
# Outputs
y = serial(x)
print("-- Outputs --")
print("y :", y)
-- Serial Model --
Serial_in2[
 Select[0,1,0,1] in2 out4
 Addition in2
 Multiplication in2
 Addition in2
]
-- Properties --
name : Serial
sublayers : [Select[0,1,0,1]_in2_out4, Addition_in2, Multiplication in2, Addition in2]
expected inputs : 2
promised outputs: 1
-- Inputs --
x : (array([3]), array([4]))
-- Outputs --
y: [25]
```

Second example of tl.Select

Suppose we want to make the simple calculation (3 + 4) * 4. We can use Select to perform the calculations in the following manner:

```
1. 4
2. 3
3. tl.Select([0,1,0,1])
4. add
5. tl.Select([0], n_in=2)
6. mul
```

The example is a bit contrived but it demonstrates the flexibility of the command. The second t1.Select pops two elements (specified in n_in) from the stack starting from index 0 (i.e. top of the stack). This means that 7 and 3 will be popped out because $n_i = 2$) but only i = 2 but only i = 3 but onl

After processing all the inputs the stack contains 28 which is the answer we get above.

```
In [6]:
```

```
serial = tl.Serial(
    tl.Select([0, 1, 0, 1]), Addition(), tl.Select([0], n in=2), Multiplication()
# Initialization
x = (np.array([3]), np.array([4])) # input
serial.init(shapes.signature(x)) # initializing serial instance
print("-- Serial Model --")
print(serial, "\n")
print("-- Properties --")
print("name :", serial.name)
print("sublayers :", serial.sublayers)
print("expected inputs :", serial.n_in)
print("promised outputs :", serial.n_out, "\n")
# Inputs
print("-- Inputs --")
print("x :", x, "\n")
# Outputs
y = serial(x)
print("-- Outputs --")
print("y :", y)
-- Serial Model --
Serial_in2[
 Select[0,1,0,1] in2 out4
 Addition in2
 Select[0] in2
 Multiplication in2
]
-- Properties --
name : Serial
sublayers : [Select[0,1,0,1] in2 out4, Addition in2, Select[0] in2, Multiplication in2]
expected inputs : 2
promised outputs : 1
-- Inputs --
x : (array([3]), array([4]))
-- Outputs --
y : [28]
```

In summary, what Select does in this example is a copy of the inputs in order to be used further along in the stack of operations.

3. The tl.Residual combinator in the context of the Serial combinator

tl.Residual

Residual networks are frequently used to make deep models easier to train and you will be using it in the assignment as well. Trax already has a built in layer for this. The Residual layer computes the element-wise sum of the stack-top input with the output of the layer series. For example, if we wanted the cumulative sum of the following series of computations (3 + 4) * 3 + 4. The result can be obtained with the use of the Residual combinator in the following manner

```
    4
    3
    t1.Select([0,1,0,1])
    add
    mul
    t1.Residual.
```

For our example the top of the stack is 3 4 and we select to add the same to numbers in an ordered manner to the top of the stack which after the command is 3 4 3 4. The steps of the calculation for our example are shown in the table below together with the cumulative sum which is the result of tl.Residual.

After processing all the inputs the stack contains 50 which is the cumulative sum of all the operations.

The cumulative sum is calculated by adding all elements in the current layer with all elements in the previous layer element-wise

```
In [8]:
```

```
serial = tl.Serial(
   tl.Select([0, 1, 0, 1]), Addition(), Multiplication(), Addition(), tl.Residual()
# Initialization
x = (np.array([3]), np.array([4])) # input
serial.init(shapes.signature(x)) # initializing serial instance
print("-- Serial Model --")
print(serial, "\n")
print("-- Properties --")
print("name :", serial.name)
print("sublayers :", serial.sublayers)
print("expected inputs :", serial.n_in)
print("promised outputs :", serial.n_out, "\n")
# Inputs
print("-- Inputs --")
print("x :", x, "\n")
# Outputs
y = serial(x)
print("-- Outputs --")
print("y :", y)
-- Serial Model --
Serial in2[
 Select[0,1,0,1]_in2_out4
 Addition in2
 Multiplication in2
 Addition in2
  Serial[
   Branch out2[
     Serial
   Add in2
]
-- Properties --
name : Serial
sublayers : [Select[0,1,0,1]_in2_out4, Addition_in2, Multiplication_in2, Addition_in2, Serial[
 Branch_out2[
   None
   Serial
  Add in2
]]
expected inputs : 2
promised outputs: 1
```

```
-- Inputs --
x : (array([3]), array([4]))
-- Outputs --
y : [50]
```

A slightly trickier example:

Normally, the Residual layer will accept a layer as an argument and it will add the output of that layer to the current stack top input. In the example below, you'll notice that in the last step, we specify t1.Residual(Addition()). If you refer to the same figure above, you'll notice that the stack at that point has 21 4 where 21 is the top of the stack. The Residual layer remembers this value (i.e. 21) so the result of the Addition() layer nested into it (i.e. 25) is added to this stack top input to arrive at the result: 46.

```
In [9]:
serial = tl.Serial(
   tl.Select([0, 1, 0, 1]), Addition(), Multiplication(), tl.Residual(Addition())
# Initialization
x = (np.array([3]), np.array([4])) # input
serial.init(shapes.signature(x)) # initializing serial instance
print("-- Serial Model --")
print(serial, "\n")
print("-- Properties --")
print("name :", serial.name)
print("sublayers :", serial.sublayers)
print("expected inputs :", serial.n in)
print("promised outputs :", serial.n out, "\n")
# Inputs
print("-- Inputs --")
print("x :", x, "\n")
# Outputs
y = serial(x)
print("-- Outputs --")
print("y :", y)
-- Serial Model --
Serial_in2[
 Select[0,1,0,1]_in2_out4
 Addition in2
  Multiplication in2
  Serial in2[
   Branch in2 out2[
     None
     Addition in2
   Add in2
 1
]
-- Properties
name : Serial
sublayers : [Select[0,1,0,1]_in2_out4, Addition_in2, Multiplication_in2, Serial_in2[
 Branch_in2_out2[
   None
   Addition in2
 Add in2
11
expected inputs: 2
promised outputs: 1
-- Inputs --
x : (array([3]), array([4]))
-- Outputs --
```

| у : [46] | | | |
|----------|--|--|--|
| In []: | | | |
| | | | |