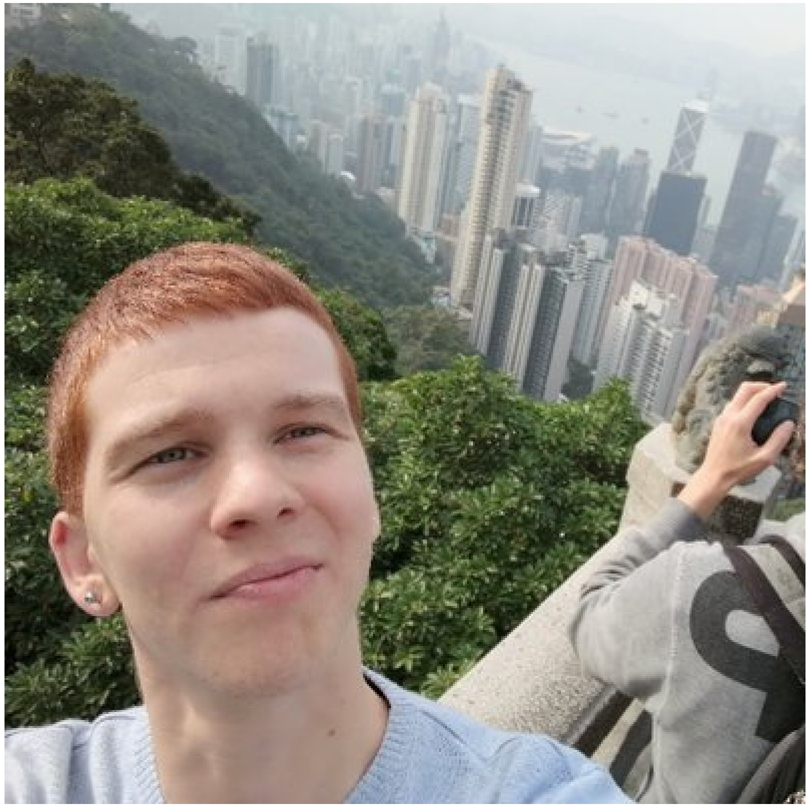
Dissecting tf.function to discover AutoGraph strengths and subtleties

How to correctly write graph-convertible functions in TensorFlow 2.0.

About me



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TensorFlow 2.0 & DataFlow Graphs

- Execution Speed
- Language Agnostic Representation
- Easy to replicate and distribute
- Automatic Differentiation

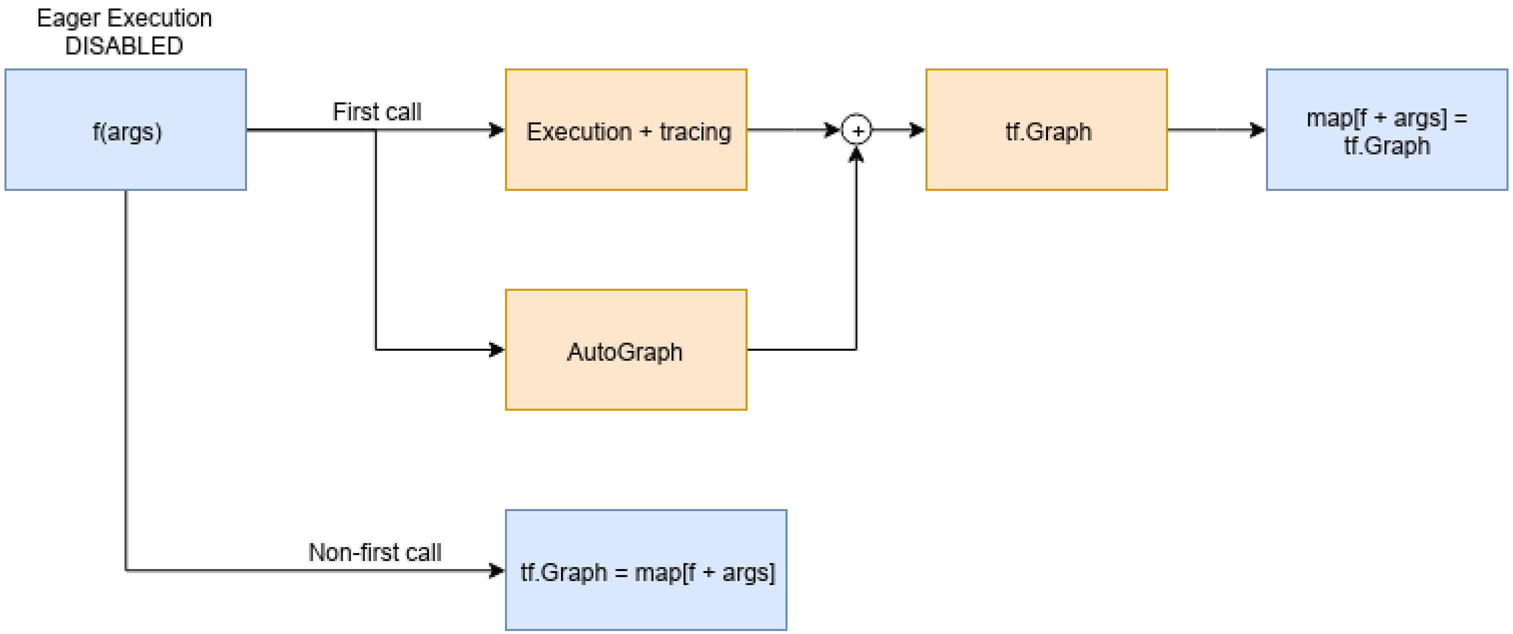
tf.function and AutoGraph

```
# tf.function signature: it is a decorator.
def function(func=None,
             input_signature=None,
             autograph=True,
             experimental_autograph_options=None)
```

tf.function uses AutoGraph

AutoGraph converts Python control flow statements into appropriate TensorFlow graph ops.

tf.function and AutoGraph



The problem

Given the **constant** matrices

$$A = \begin{pmatrix} 10 & 10 \\ 11 & 1 \end{pmatrix}, \quad x = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

And the scalar **variable** $b \in \mathbb{R}$

Compute $Ax + b$

TensorFlow 1.x solution

```
g = tf.Graph()
with g.as_default():
    a = tf.constant([[10,10],[11.,1.]])
    x = tf.constant([[1.,0.],[0.,1.]])
    b = tf.Variable(12.)
    y = tf.matmul(a, x) + b
    init_op = tf.global_variables_initializer()

with tf.Session() as sess:
    sess.run(init_op)
    print(sess.run(y))
```

TensorFlow 2.0 solution: eager execution

```
def f():
    a = tf.constant([[10,10],[11.,1.]])
    x = tf.constant([[1.,0.],[0.,1.]])
    b = tf.Variable(12.)
    y = tf.matmul(a, x) + b
    return y
print([f().numpy() for _ in range(10)])
```

Every tf.* op, produces a `tf.Tensor` object

From eager function to tf.function

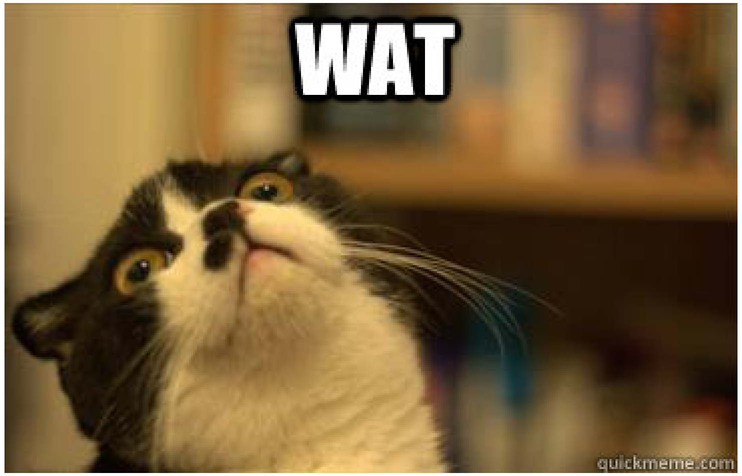
```
@tf.function
def f():
    a = tf.constant([[10,10],[11.,1.]])
    x = tf.constant([[1.,0.],[0.,1.]])
    b = tf.Variable(12.)
    y = tf.matmul(a, x) + b
    print("PRINT: ", y)
    tf.print("TF-PRINT: ", y)
    return y

f()
```

From eager function to tf.function

```
PRINT:  Tensor("add:0", shape=(2, 2), dtype=float32)
```

From eager function to tf.function

```
ValueError: tf.function-decorated function tried to create variables on non-first call.
```



Lesson #1: functions that create a state

A `tf.Variable` object in eager mode is just a Python object that gets destroyed as soon as it goes out of scope.

A `tf.Variable` object in a tf.function-decorated function is the definition of a node in a persistent graph (eager execution disabled).

The solution

```
class F():
    def __init__(self):
        self._b = None

    @tf.function
    def __call__(self):
        a = tf.constant([[10, 10], [11., 1.]])
        x = tf.constant([[1., 0.], [0., 1.]])
        if self._b is None:
            self._b = tf.Variable(12.)
        y = tf.matmul(a, x) + self._b
        print("PRINT: ", y)
        tf.print("TF-PRINT: ", y)
        return y

f = F()
f()
```

Lesson #2: eager function is not graph-convertible as is

There is no 1:1 match between eager execution and the graph built by `@tf.function`.

Define the function thinking about the graph that is being built.

Change the input type

- **Python** is a dynamically-typed language
- **TensorFlow** is a strictly statically typed framework

The function

```
@tf.function
def f(x):
    print("Python execution: ", x)
    tf.print("Graph execution: ", x)
    return x
```

The function parameters type is used to create a graph, that is a statically typed object, and to assign it an ID

tf.Tensor as input

```
print("##### float32 test #####")
a = tf.constant(1, dtype=tf.float32)
print("first call")
f(a)
a = tf.constant(1.1, dtype=tf.float32)
print("second call")
f(a)

print("##### uint8 test #####")

b = tf.constant(2, dtype=tf.uint8)
print("first call")
f(b)
b = tf.constant(3, dtype=tf.uint8)
print("second call")
f(b)
```

tf.Tensor as input

```
##### float32 test #####
first call
Python execution:  Tensor("x:0", shape=(), dtype=float32)
Graph execution:  1
second call
Graph execution:  1.1

##### uint8 test #####
first call
Python execution:  Tensor("x:0", shape=(), dtype=uint8)
Graph execution:  2
second call
Graph execution:  3
```

Everything goes as we expect

Inspecting the function

```
tf.autograph.to_code(f.python_function)
```

```
def tf__f(x):
  try:
    with ag__.function_scope('f'):
      do_return = False
      retval_ = None
      with ag__.utils.control_dependency_on_returns(ag__.converted_call(print, None, ag__.ConversionOptions(re
        tf_1, x_1 = ag__.utils.alias_tensors(tf, x)
        with ag__.utils.control_dependency_on_returns(ag__.converted_call('print', tf_1, ag__.ConversionOption
          x_2 = ag__.utils.alias_tensors(x_1)
          do_return = True
          retval_ = x_1
          return retval_
  except:
    ag__.rewrite_graph_construction_error(ag_source_map__)
```

Inspecting the function

```
with ag__.utils.control_dependency_on_returns(
        ag__.converted_call(
            print, None, ag__.ConversionOptions(
                recursive=True,
                force_conversion=False,
                optional_features=ag__.Feature.ALL,
                internal_convert_user_code=True),
            ('Python execution: ', x), {})
        ):
```

`converted_call` owner parameter is `None`: this line becomes a `tf.no_op()`

Python native type as input

```
def printinfo(x):
  print("Type: ", type(x), " value: ", x)

print("##### int test #####")
print("first call")
a = 1
printinfo(a)
f(a)
print("second call")
b = 2
printinfo(b)
f(b)

print("##### float test #####")
print("first call")
a = 1.0
printinfo(a)
f(a)
print("second call")
b = 2.0
printinfo(b)
f(b)
```

Python native type as input

Call with Python int

```
##### int test #####
first call
Type:  <class 'int'>  value:  1
Python execution:  1
Graph execution:  1

second call
Type:  <class 'int'>  value:  2
Python execution:  2
Graph execution:  2
```

The graph is being recreated at every function invocation

Python native type as input

Call with Python float

```
##### float test #####
first call
Type:  <class 'float'>  value:  1.0
Graph execution:  1
second call
Type:  <class 'float'>  value:  2.0
Graph execution:  2
```

- **The return type is WRONG.**
- **The graphs built for the integers 1 and 2 is reused for the float 1.0 and 2.0**


WAT
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Lesson #3: no autoboxing

`tf.function` does not automatically convert a Python integer to a `tf.Tensor` with dtype `tf.int64`, and so on.
The graph ID, when the input is not a `tf.Tensor` object, is built using the variable **value**.

That's why we used the same graph built for `f(1)` for `f(1.0)`, because `1 == 1.0`.

No autoboxing: performance measurement

```
@tf.function
def g(x):
  return x

start = time.time()
for i in tf.range(1000):
  g(i)
print("tf.Tensor time elapsed: ", (time.time()-start))

start = time.time()
for i in range(1000):
  g(i)
print("Native type time elapsed: ", (time.time()-start))
```

```
tf.Tensor time elapsed:  0.41594886779785156
Native type time elapsed:  5.189513444900513
```

Lesson #4: tf.Tensor everywhere

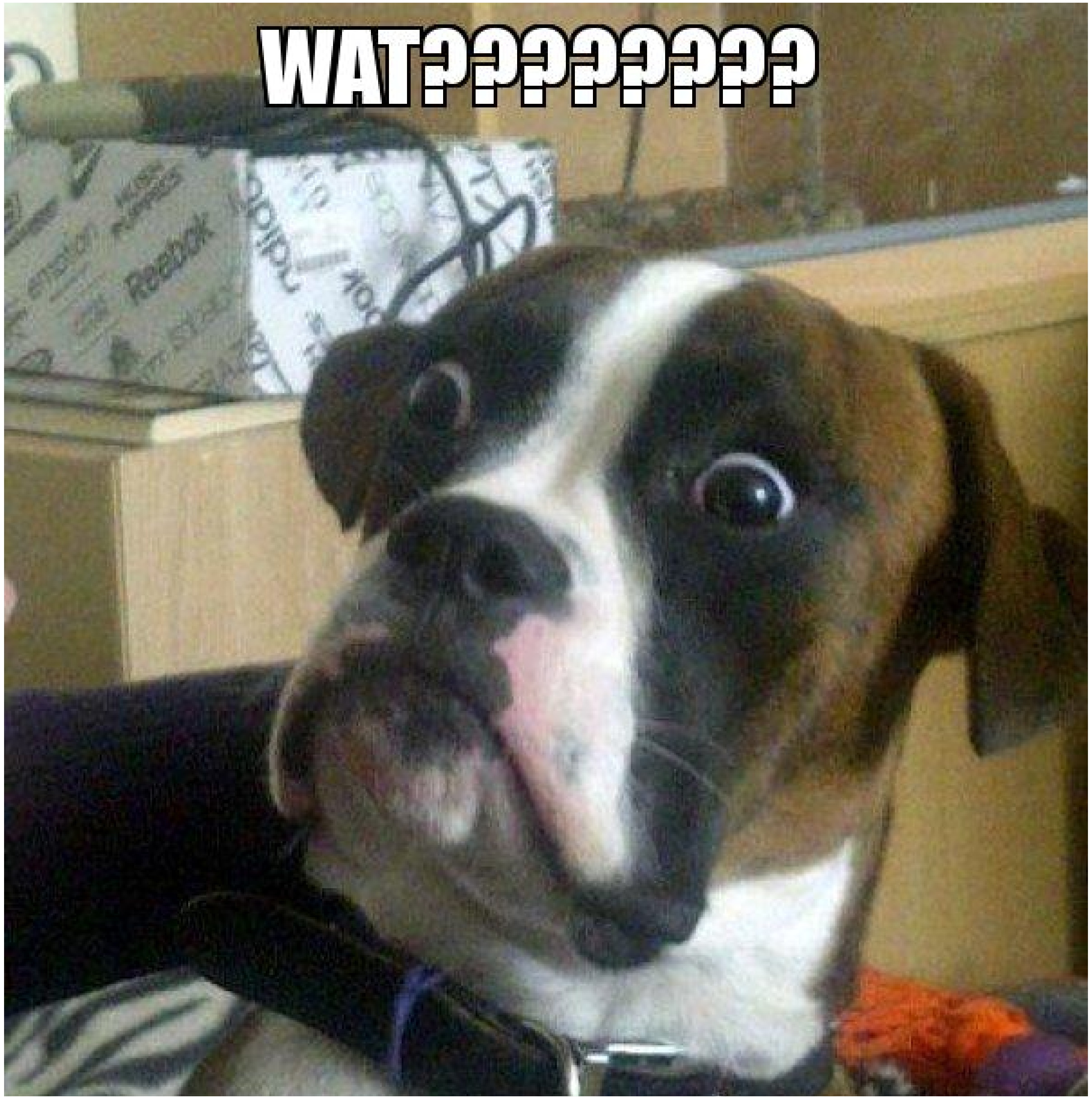
Use `tf.Tensor` everywhere.

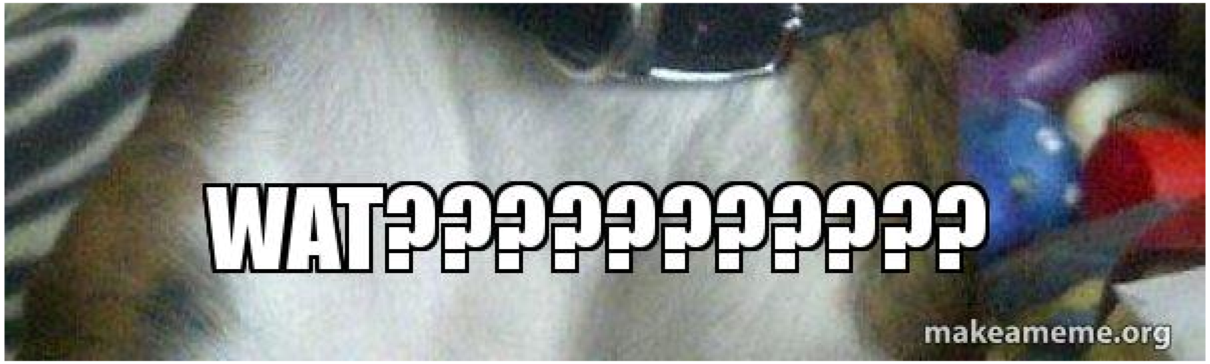
Python Operators

```
@tf.function
def if_elif(a, b):
  if a > b:
    tf.print("a > b", a, b)
  elif a == b:
    tf.print("a == b", a, b)
  elif a < b:
    tf.print("a < b", a, b)
  else:
    tf.print("wat")
x = tf.constant(1)
if_elif(x,x)
```

Python operators

wat

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Problems

- Python `__eq__` is not converted to `tf.equal` (even in eager mode!) but checks for the Python variable identity.
- AutoGraph converts the `if`, `elif`, `else` statements but
- AutoGraph does not converts the Python built-in operators (`__eq__`, `__lt__`, `__gt__`)

Python operators

```
@tf.function
def if_elif(a, b):
  if tf.math.greater(a, b):
    tf.print("a > b", a, b)
  elif tf.math.equal(a, b):
    tf.print("a == b", a, b)
  elif tf.math.less(a, b):
    tf.print("a < b", a, b)
  else:
    tf.print("wat")
```

Lesson 5: operators

Use the TensorFlow operators explicitly everywhere.

Recap

1. `tf.Variable` need a special treatment.
2. Think about the graph while designing the function: eager to graph is not straightforward.
3. There is no autoboxing of Python native types, therefore
4. Use `tf.Tensor` everywhere.
5. Use the TensorFlow operators explicitly everywhere.

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The End

Thank you 😄

- Blog: https://pgaleone.eu/
- Twitter: https://twitter.com/paolo_galeone
- GitHub: https://github.com/galeone (the slides of this talk are here!)