

Clarifying matrix algebra exceptions in Python visually with TensorSensor

Examples and implementation details

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See <https://github.com/parrt/tensor-sensor> and <https://explained.ai/>

The problem

```
Whh = torch.eye(nhidden, nhidden)
Uxh = torch.randn(d, nhidden)
bh = torch.zeros(nhidden, 1)
h = torch.randn(nhidden, 1)
r = torch.randn(nhidden, 1)
X = torch.rand(n,d)
```

- It's easy to lose track of matrix/tensor dimensionality in matrix algebra expressions (even in statically-typed languages)
- Upon error, we often get less than helpful exception messages, such as this (PyTorch) message:

```
---> 15 h = torch.tanh(Whh @ (r*h) + Uxh @ X.T + bh)
```

```
RuntimeError: mat1 and mat2 shapes cannot be multiplied (764x256 and 764x200)
```

- The offending operator and operands are not identified, since Python exceptions occur at the line level rather than the operator level

We could rerun using the debugger but...

- The debugger still does not tell us which subexpression caused the exception, due to line-level granularity of Python exceptions
- We must write down shape of all operands then line up and compare dimensions on all subexpressions manually
- Besides
 - Python debuggers seem much slower than normal execution
 - Even regular execution could take hours before faulting
 - Sometimes it's hard to set a breakpoint on the right statement when it's in a loop
 - Conditional breakpoints are challenging when the values are high-dimension matrices



What most people do

- Most data scientists laboriously inject code and rerun to isolate:

Or, they
stop here

```
print(Whh.shape, r.shape, h.shape, Uxh.shape, X.shape, bh.shape)
print((r*h).shape)
print((Whh@(r*h)).shape)
print((Uxh@X.T).shape) # <-- exception!
print((Whh@(r*h)+Uxh@X.T).shape)
print((Whh@(r*h)+Uxh@X.T+bh).shape)
h = torch.tanh(Whh @ (r*h) + Uxh @ X.T + bh)
```

RuntimeError

Traceback (most recent call last)

<ipython-input-2-b5160030ac99> in <module>

```
16 print((r*h).shape)
17 print((Whh@(r*h)).shape)
----> 18 print((Uxh@X.T).shape)
19 print((Whh@(r*h)+Uxh@X.T).shape)
20 print((Whh@(r*h)+Uxh@X.T+bh).shape)
```



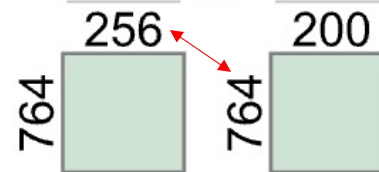
What TensorSensor proposes

- First, augment the exception message to identify the op/opnds:

```
RuntimeError: mat1 and mat2 shapes cannot be multiplied (764x256 and 764x200)  
Cause: @ on tensor operand Uxh w/shape [764, 256] and operand X.T w/shape [764, 200]
```

- But we can help programmers even more...
- The key is to line up dimensions, so let's show that visually!

`h = torch.tanh(Whh @ (r*h) + Uxh @ X.T + bh)`



Believe it or not, this is all **matplotlib**

A nice-to-have feature: viz correct code

`a = torch.relu(x)`

Very helpful when trying to read (even correct) code

`b = W @ b + torch.zeros(2000,1) + (h + 3).dot(h)`

`batch = X[i,:,:]`

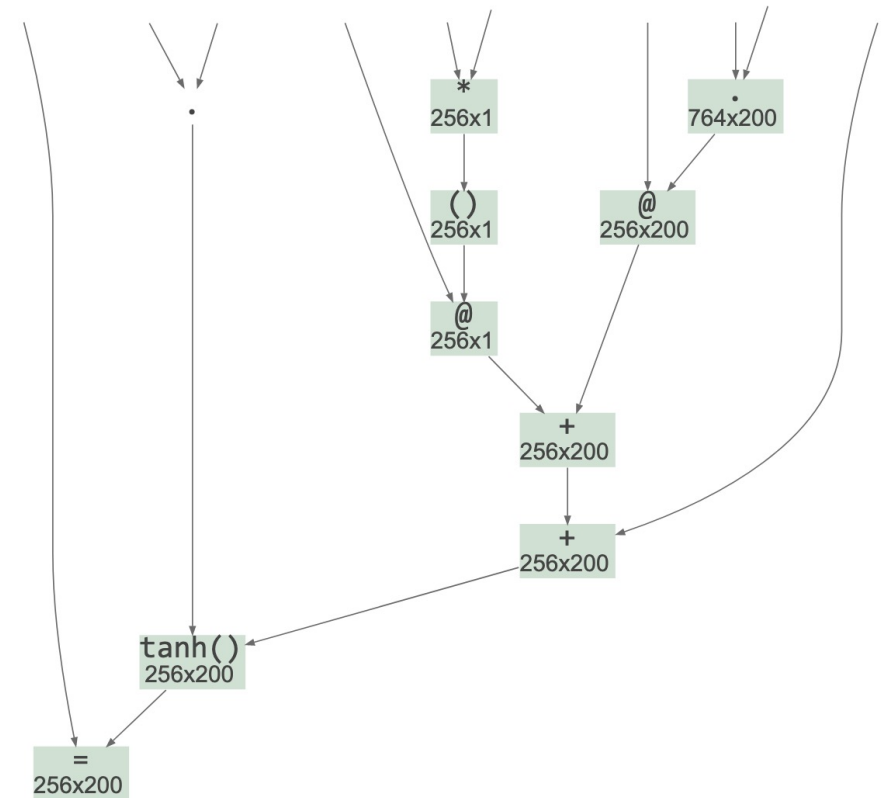
Greater than 2 and 3 dimensions

`y = b @ b.T`

A nice-to-have feature: Abstract syntax trees with dimensions

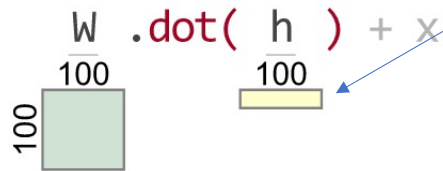
Shows tensor dimensions for all
subexpression partial results
(currently must call explicit function)

```
h_ = torch.tanh(Whh_ @ (r * h) + Uxh_ @ X.T + bh_)
```



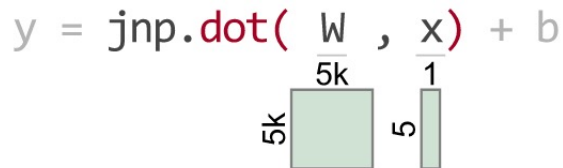
Oh, and support multiple libraries

(1D vectors are yellow)



PyTorch

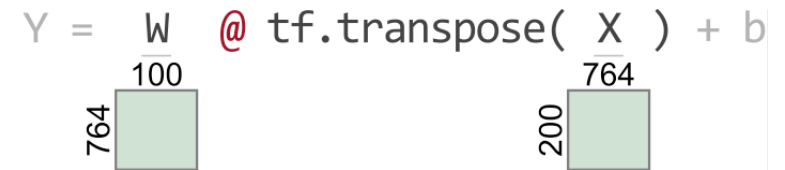
```
RuntimeError: 1D tensors expected, but got  
2D and 1D tensors  
Cause: W.dot(h) tensor arg h w/shape [100]
```



JAX

```
TypeError: Incompatible shapes for dot: got (5000, 5000)  
and (5, 1).  
Cause: jnp.dot(W, x) tensor arg W w/shape (5000, 5000),  
arg x w/shape (5, 1)
```

TensorFlow



```
InvalidArgumentError: In[0] mismatch In[1] shape:  
100 vs. 764: [764,100] [764,200] 0 0 [Op:MatMul]  
Cause: @ on tensor operand W w/shape (764, 100) a  
nd operand tf.transpose(X) w/shape (764, 200)
```


Design goals

(knowing what to build is as important as knowing how to build)

- Should be as unobtrusive as possible with least user effort
- Users shouldn't have to reorganize code
- Trap just matrix-related exceptions
- Avoid need for an external tool or translator
- Avoid spewing output until exception occurs
- Can we avoid CPU cost until an exception?
- Ideally, implementation would be small and straightforward (at least to language engineers)

TensorSensor programmer interface

- The Python **with** statement gives us the hooks we need

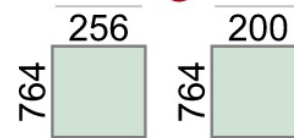
```
import tsensor
```

(From within a Jupyter notebook)

```
with tsensor.clarify():
```

```
    h = torch.tanh(Whh @ (r*h) + Uxh @ X.T + bh)
```

```
h = torch.tanh(Whh @ (r*h) + Uxh @ X.T + bh)
```



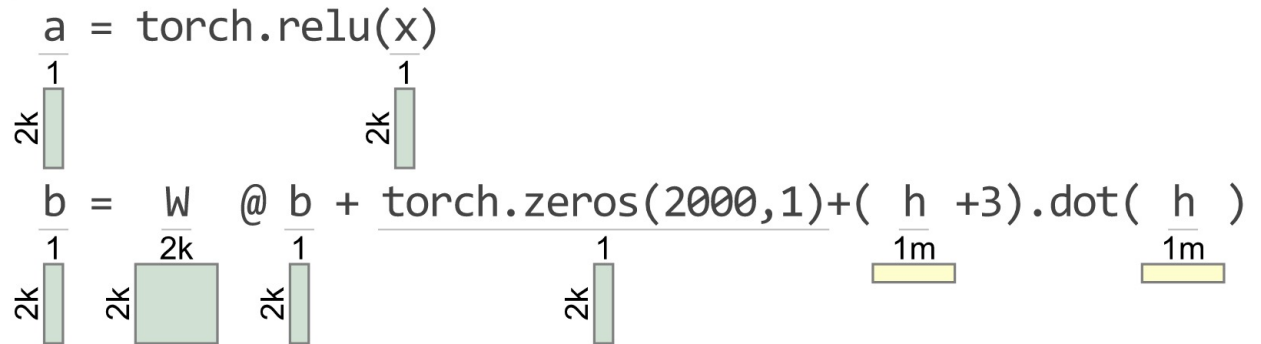
```
RuntimeError                                Traceback (most recent call last)
<ipython-input-13-b9a515efa8ef> in <module>
      2
      3 with tsensor.clarify():
----> 4     h = torch.tanh(Whh @ (r*h) + Uxh @ X.T + bh)

RuntimeError: mat1 and mat2 shapes cannot be multiplied (764x256 and 764x200)
Cause: @ on tensor operand Uxh w/shape [764, 256] and operand X.T w/shape [764, 200]
```

Explaining correct matrix code

- **clarify()** has no effect unless tensor code triggers an exception
- But **explain()** gens a visualization for each statement within the block

```
import torch
import tsensor
W = torch.rand(size=(2000,2000))
b = torch.rand(size=(2000,1))
h = torch.rand(size=(1_000_000,))
x = torch.rand(size=(2000,1))
with tsensor.explain():
    a = torch.relu(x)
    b = W @ b + torch.zeros(2000,1)+(h+3).dot(h)
```



Approaches I rejected

- Python decorators: would require wrapping user code in functions
- Try/except blocks →
- Program rewriting is complex and requires a separate tool
- Bytecode injection:
 - slows down entire program
 - could require huge cache of subexpression partial results
 - function-level granularity

```
try:  
    ... my code ...  
except Exception as e:  
    tsensor.do_everything(e)
```

(might not be able to hide everything here, like reraising `e`)



TensorSensor implementation

Impl. relies on “context manager” objects

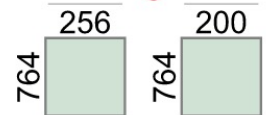
- Python “**with b**” blocks call `__enter__()`, `__exit__()` on object **b** and `__exit__()` receives exception object and execution stack
- **clarify()** needs the exception object to augment messages and the execution stack to obtain subexpression values, identify offending operator
- `__exit__()` can automatically gen visualization in notebook or pop-up a window if run outside a notebook
- There’s no cost unless exception occurs within the **with** block

```
import tsensor
```

```
with tsensor.clarify():
```

```
    h = torch.tanh(Whh @ (r*h) + Uxh @ X.T + bh)
```

```
h = torch.tanh(Whh @ (r*h) + Uxh @ X.T + bh)
```



TensorSensor's `explain()` mechanism

(Visualizing correct Python code on-the-fly)

- **`explain()`** object's **`__enter__()`** method creates a tracer object and registers it with Python via **`sys.settrace()`** [1]
- The tracer is notified upon each source line execution
- Using same mechanism as **`clarify()`** to identify operand shapes
- Even in a loop within **`with`** block, statements visualized just once
- Slows down execution (a lot) but it's still useful
- Watch out for side effects; e.g., this prints "hi" twice:

```
with tsensor.explain():  
    print("hi")
```

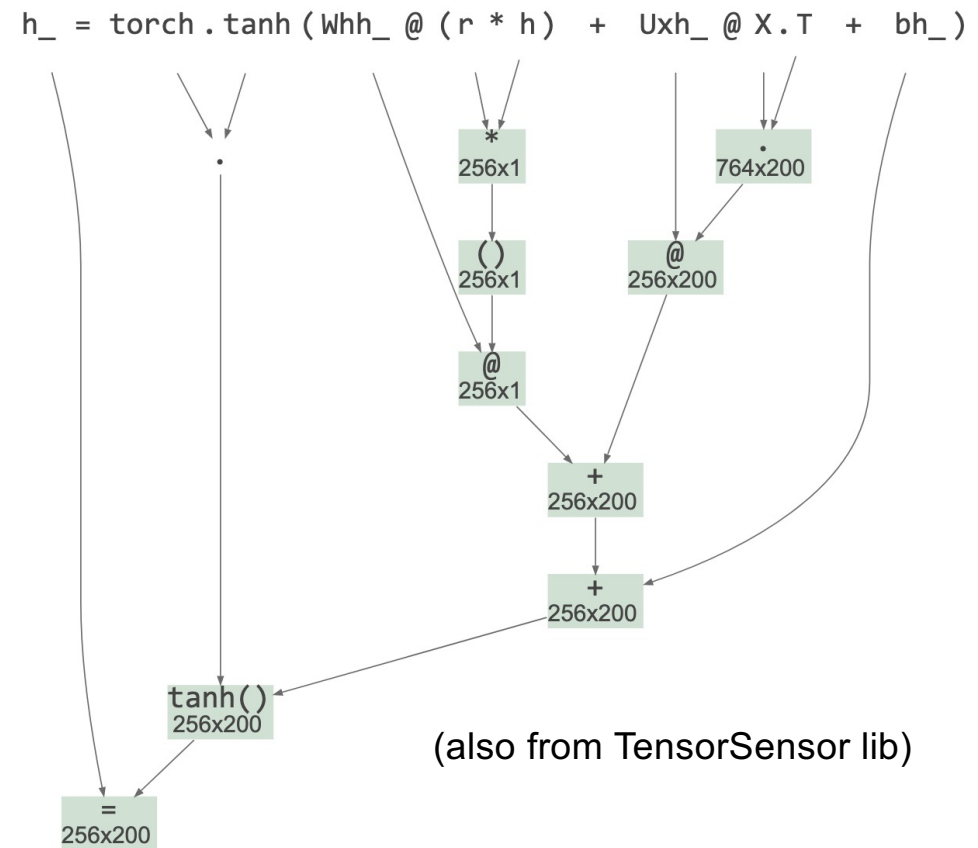
[1] <https://docs.python.org/3/library/sys.html#sys.settrace>

Getting operator-level exceptions w/o bytecode instrumentation requires a total hack

- We have: (1) the full execution stack from which we can get (2) the offending line of source code (**`inspect.getframeinfo()`**)
- To identify the individual operator and operands that triggered an exception, use brute-force:
 - reevaluate each operation in the line, piece-by-piece, in proper order, and in the correct execution context (must pick correct stack frame)
- Wait for an operator to cause an exception, report op/opnds
- Assumes side-effect free operations
- Even if side-effecting, who cares (usually)?
The program is about to terminate

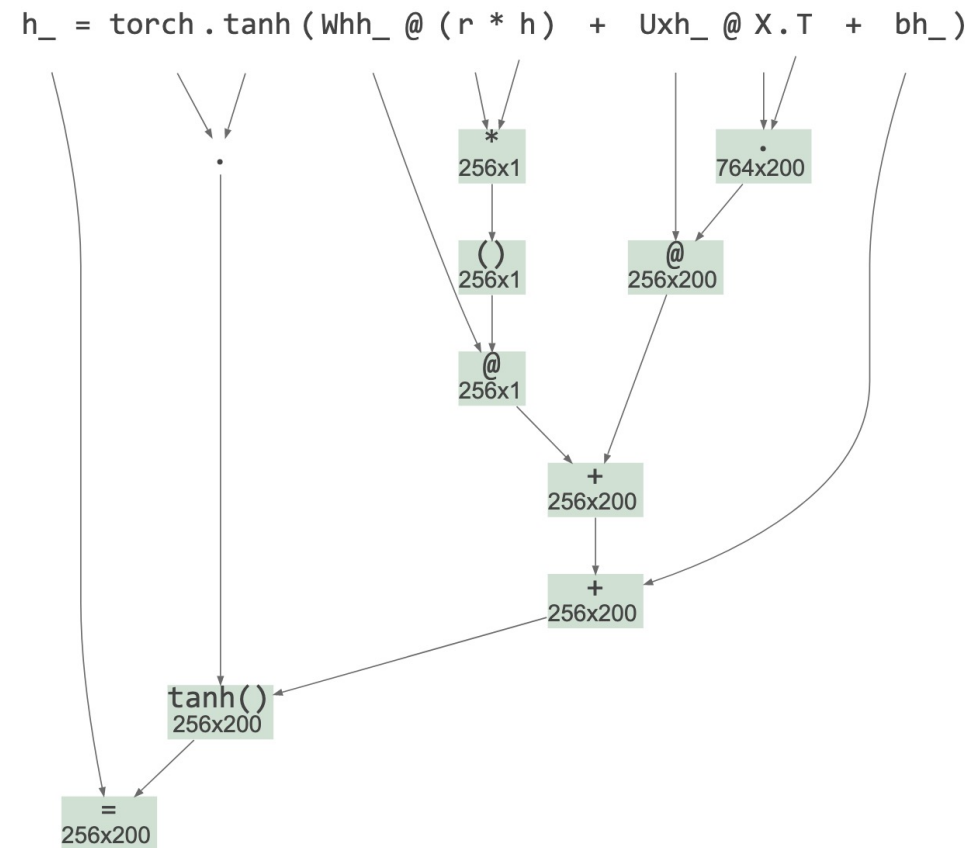
Reevaluation mechanism

- First, check if exception is tensor-related or if exec stack descends into a known tensor lib
- If so, scan stack to find and parse deepest *user-level* offending statement and build an appropriate AST with operators as subtree roots
- Uses built-in Python tokenizer
- Uses handbuilt Python parser for subset of statements / exprs
- Avoided ANTLR to avoid introducing a lib dependency 🤪
- Avoided built-in Python parser since reorg'ing its AST is same work as rolling my own "parrser"



Reevaluation mechanism continued

- Evaluate operators of AST bottom-up in proper exec order
- Call **eval()** on Python source of subexpressions using the appropriate execution contexts, saving results in associated nodes
- Trap and absorb exception from **eval()**, record that exception and offending AST node
- Augment original exception message with info derived this new exception, op, operands



Picking the right execution context

- The goal is to identify user code not library code that (eventually) triggers a tensor-related exception
- TensorSensor **clarify**() descends into any user code function calls, stopping only when it reaches a tensor library function
- Source file prefix indicates user code boundary, such as:
`.../lib/python3.8/site-packages/tensorflow/...`
- Boundary frame is any whose package is in `{numpy, torch, tensorflow, jax}`

Example: Picking the execution frame boundary

$$\text{return } \underbrace{\frac{W}{2}}_{\sim} @ \underbrace{\frac{x}{1}}_{\sim} + b$$

t.py source

```
def f(x):  
    W = tf.constant([[1, 2], [3, 4]])  
    b = tf.reshape(tf.constant([[9, 10]]), (2, 1))  
    → return W @ x + b # line 4  
  
with tsensor.clarify():  
    x = tf.reshape(tf.constant([[8, 5, 7]]), (3, 1))  
    y = f(x) # line 8
```

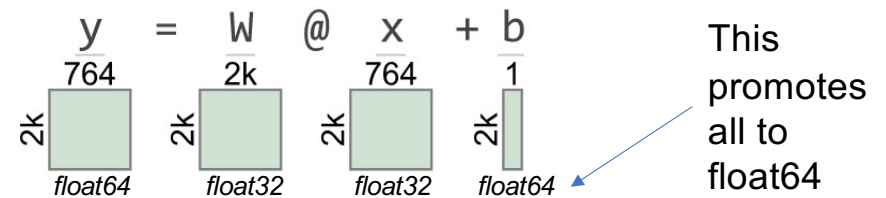
Execution stack

t.py:8 (in main)
t.py:4 (in f)
math_ops.py:1124
dispatch.py:201
math_ops.py:3253
gen_math_ops.py:5624
ops.py:6843

Raises exception

Examples of future work

- Lots of meat still on the bone
- Add tensor element type to messages and visualizations
 - we don't want integers becoming floats if they are used as indexes
 - might need to restrict to 32 bits
- Viz errors in predefined layers; currently highlights **model(X)** not layer in **nn.Sequential**



```
model = nn.Sequential(  
    nn.Linear(784, n_neurons), # 28x28 flattened image  
    nn.ReLU(),  
    nn.Linear(10, n_neurons), # 10 output classes (0-9)  
    nn.Softmax(dim=1)  
)  
X = torch.rand(n, 784) # n instances of feature vectors w  
with tsensor.clarify():  
    Y = model(X)
```

parrrt: run demo!

Summary

- Finding and implementing an unobtrusive mechanism took a lot of experimentation (and had to learn about Python's rich runtime)
- TensorSensor users think that visualization was the hard part, but that was just painful not hard (I abused matplotlib horribly!)
- The tricky bit was getting fine-grained exceptions from Python
 - The key idea is to reevaluate the offending line operator-by-operator and wait for the exception to happen again
 - Involves extracting the source line, parsing into an AST, then calling **eval()**
- Language engineering is useful far beyond building compilers and interpreters
- Article: <https://explained.ai/tensor-sensor/index.html>
- Code: <https://github.com/parrrt/tensor-sensor>