

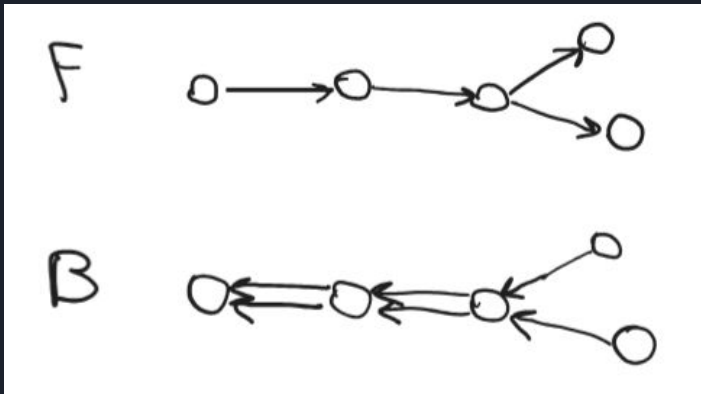


# Fast Backprop for RNNs

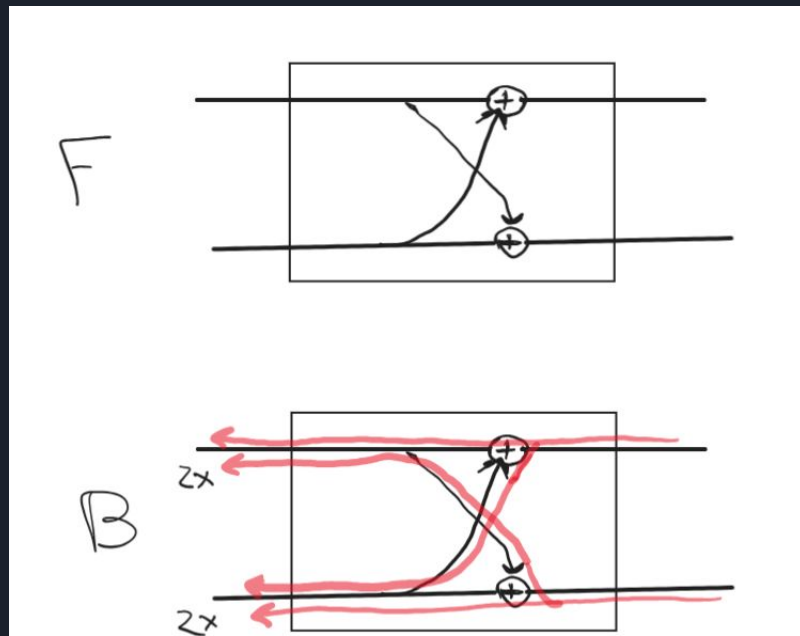
Amir Akhundzianov

# Problem statement

Current Backprop algorithm – triggers all ancestors -> All possible paths are used



In RNNs – exponential complexity





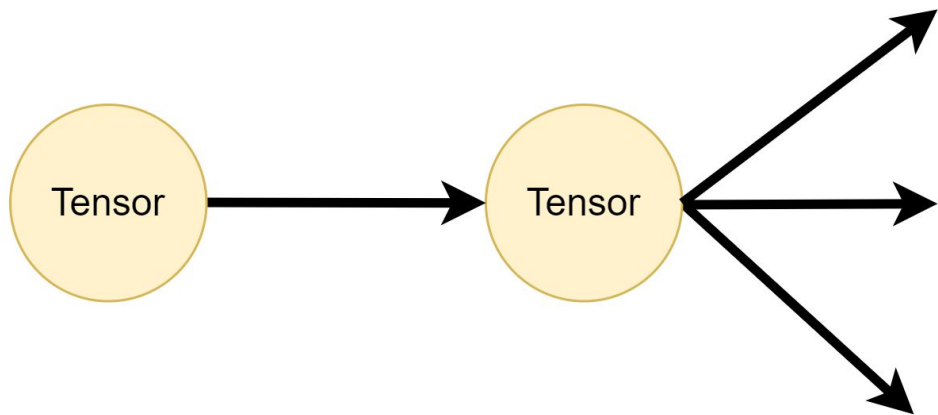
# Solution targets

- minimal code changes on user side
- fair gradient computing
- optimality of asymptotics

# Solution Algorithm

2 backward passes: trial and real

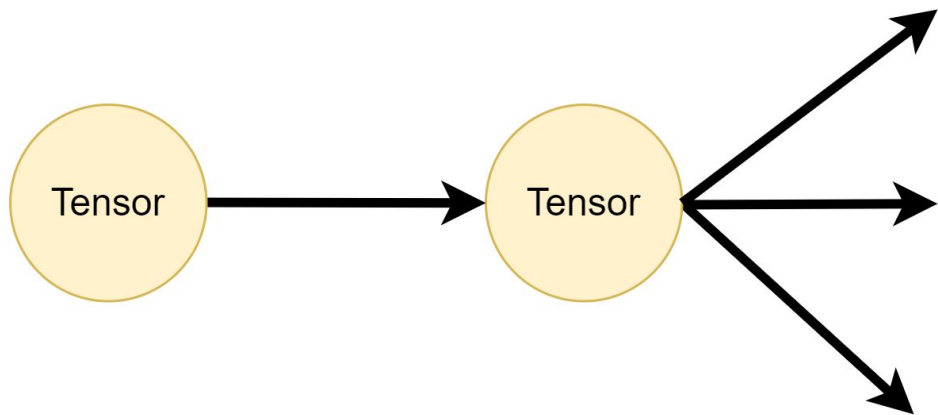
Example of Computational Graph



# Solution Algorithm

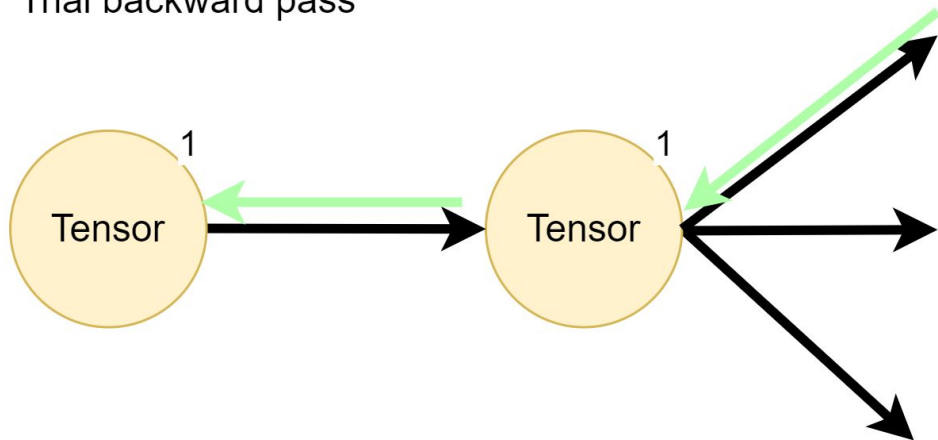
On trial, only forward connections are counted. No gradients passing

Trial backward pass



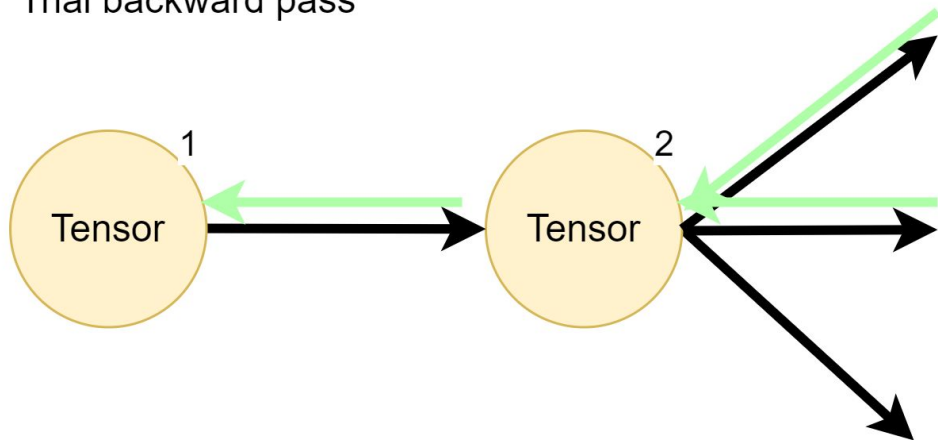
# Solution Algorithm

Trial backward pass



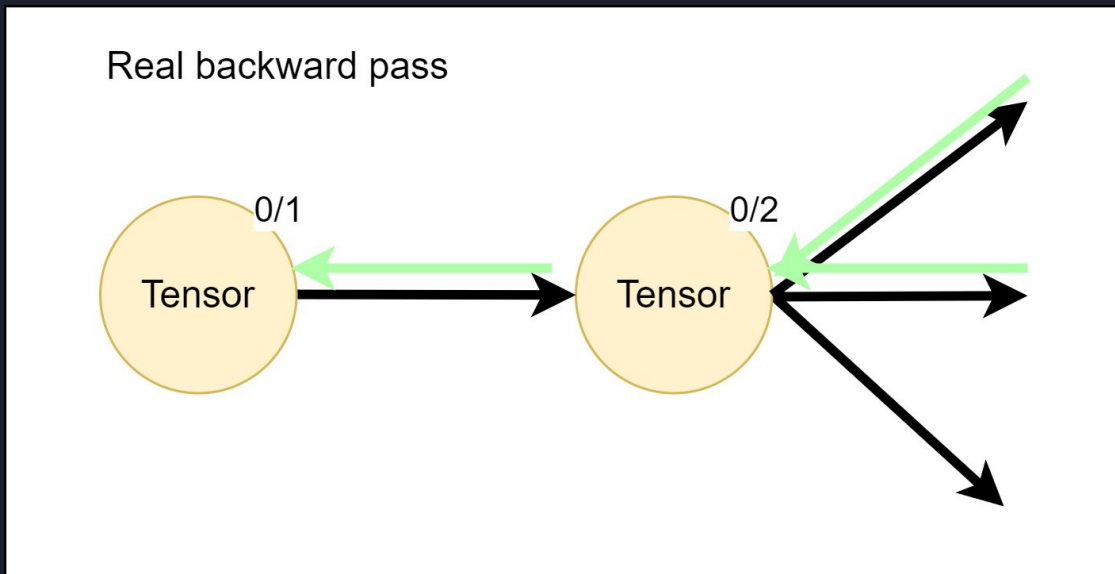
# Solution Algorithm

Trial backward pass



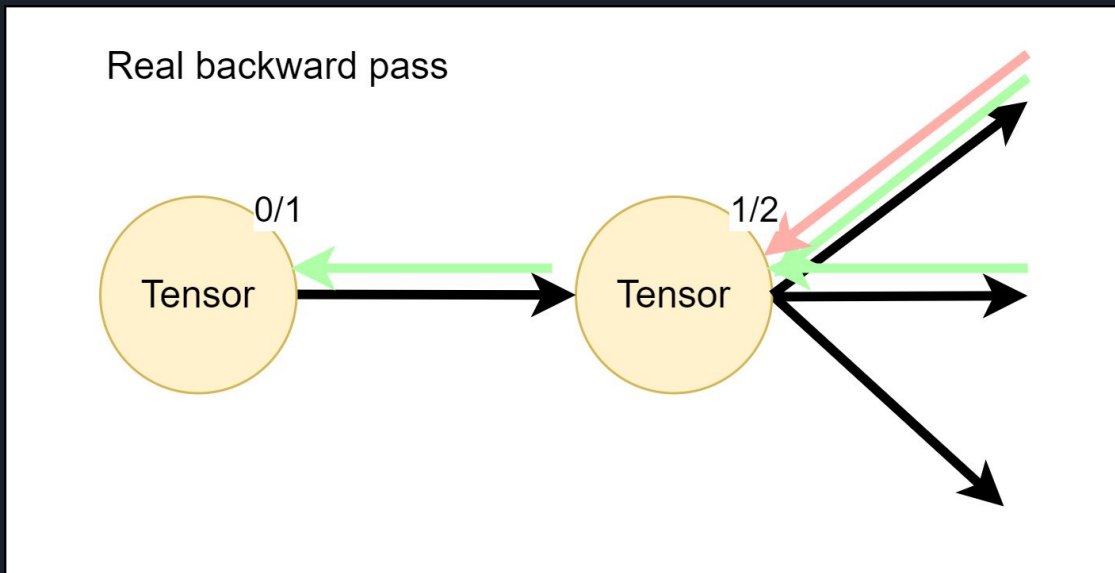
# Solution Algorithm

On real pass, gradients are summed until saturation.

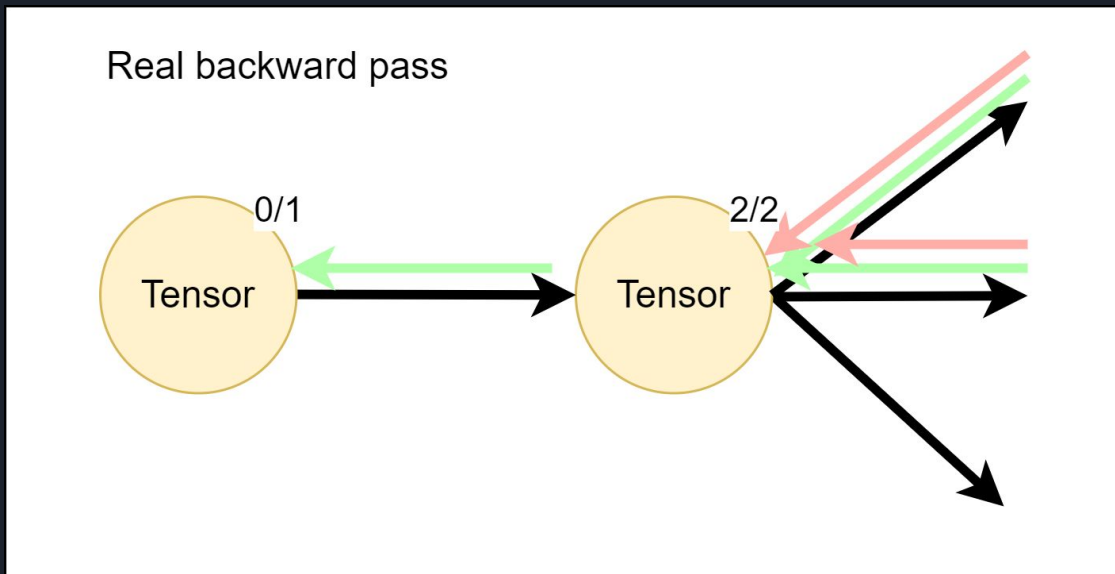




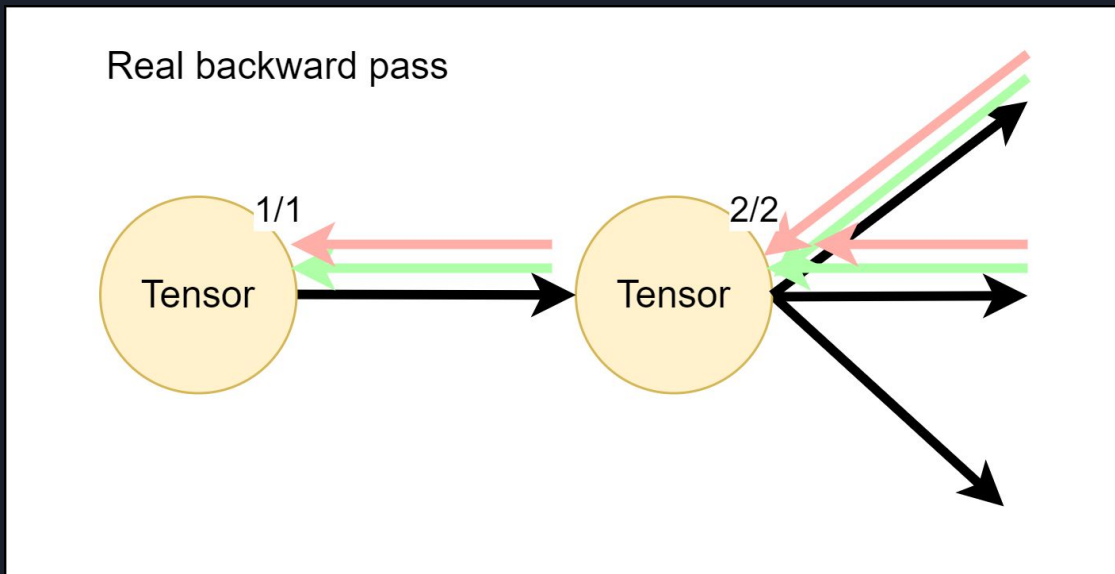
# Solution Algorithm



# Solution Algorithm



# Solution Algorithm

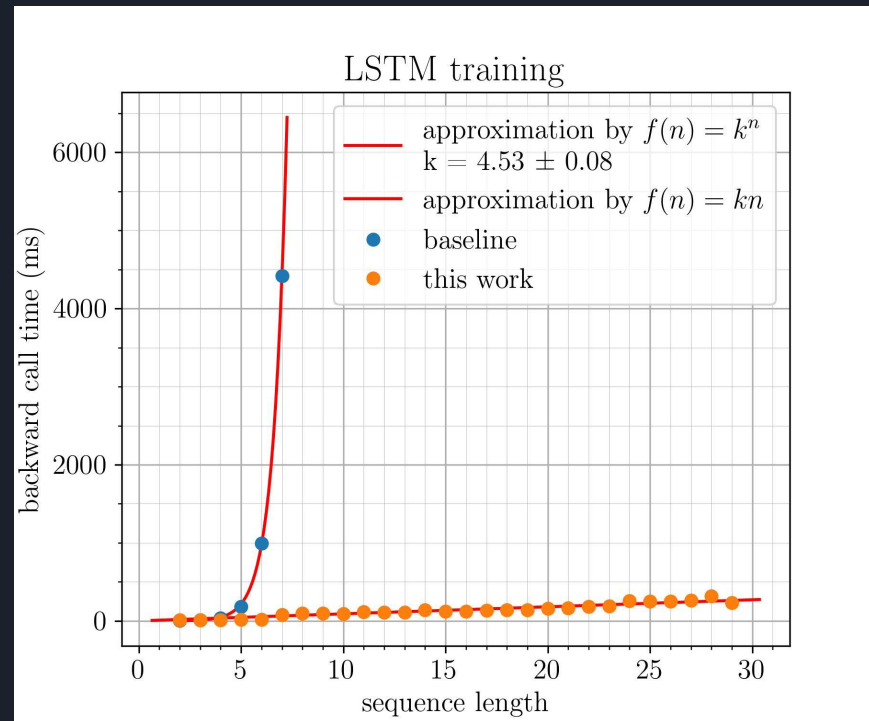
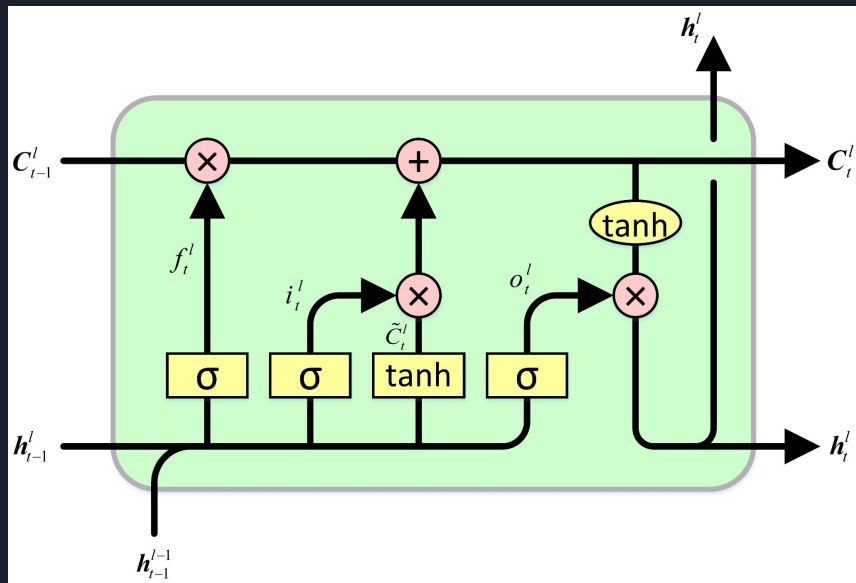




# Code modification

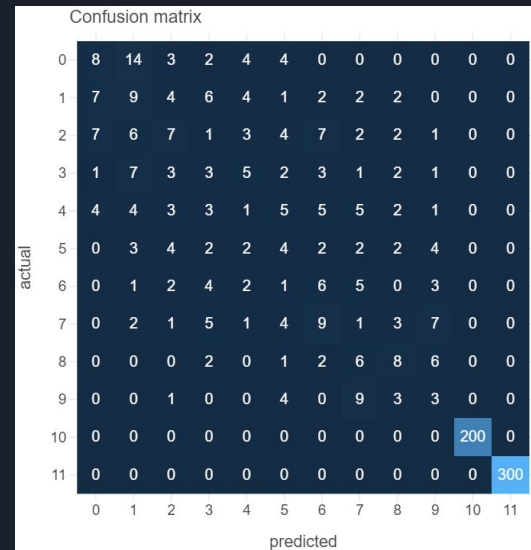
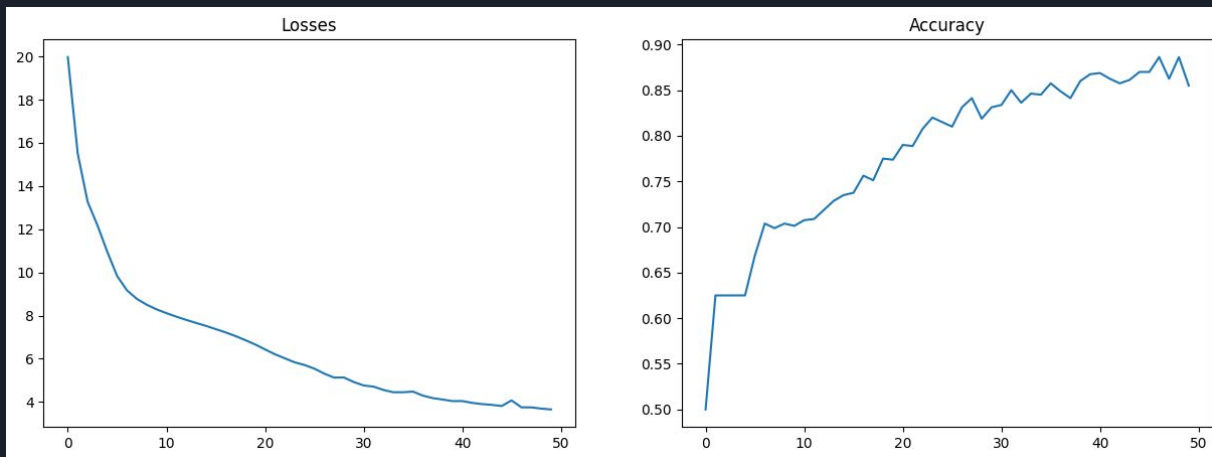
```
class Linear(Function):  
+   def backward(self, grad: np.ndarray, trial_pass):  
        dW = np.dot(self.x.data.T, grad)  
        db = grad.sum(axis=0)  
        grad = np.dot(grad, self.W.data.T)  
+   self.W.backward(dW.reshape(self.W.shape), trial_pass)  
+   self.b.backward(db.reshape(self.b.shape), trial_pass)  
+   self.x.backward(grad.reshape(self.x.shape), trial_pass)
```

# Experimental Performance



# Correctness Check

1. Gradients checks pass
2. LSTM trains on list sorting task





# Conclusion

New fast Deep Learning Framework is available in PyPI (yet another)

```
pip install fast-deep-rnn==0.0.2
```