

**TTIC 31230 Fundamentals of Deep Learning, winter 2019**  
**Framework Problems**

**Problem 1:** Consider the following softmax.

$$\begin{aligned}Z[b] &= \sum_j \exp(s[b, j]) \\p[b, j] &= \exp(s[b, j]) / Z[b]\end{aligned}$$

Give a back-propagation += update based on the second equation for adding to  $s.\text{grad}$  using  $p.\text{grad}$  (and using the forward-computed tensors  $Z$  and  $s$ ).

Give a back-propagation += update based on the second equation for adding to  $Z.\text{grad}$  using  $p.\text{grad}$  (and using the forward-computed tensors  $s$  and  $Z$ ).

Give a back-propagation += update based on the first equation for adding to  $s.\text{grad}$  using  $Z.\text{grad}$  (and using the forward-computed tensor  $s$ ).

**Problem 2:** For the softmax in problem 1 show that we can instead use

$$\begin{aligned}e[b] &= \sum_j p[b, j] p.\text{grad}[b, j] \\s.\text{grad}[b, j] &= p[b, j] (p.\text{grad}[b, j] - e[b])\end{aligned}$$

This formula shows how hand-written back-propagation methods for “layers” such as softmax can be more efficient than compiler-generated back-propagation code. While optimizing compilers can of course be written, one must keep in mind the trade-off between the abstraction level of the programming language and the efficiency of the generated code.