# Efficient Sampled Softmax Loss in Tensorflow

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#### Abstract

This short paper discusses an efficient implementation of *sampled soft-max loss* for Tensorflow. The speedup is achieved due to simplification of the graph for the forward and backward passes.

### 1 Introduction

The softmax function is used in prediction and classification tasks to map outputs of a network into probabilities. The corresponding formula reads

$$y_c = \frac{\exp(o_c)}{\sum_{c'} \exp(o_{c'})}$$

where c is the output class of interest, o are network outputs and the summation over c' is taken over all possible classes. It is typically trained under cross-entropy loss. Unfortunately computing the loss is computationally expensive because of *explicit normalization*. The factor in the denominator runs over all classes which may be quite large ( $10^5$  and more for NLP problems).

The solution is to approximate the loss function. One strategy, called *sam-pled softmax* [JCMB14], is to compute softmax over a random subsample containing the target (true) class.

In this note we present a more efficient implementation of the coupled  $sam-pled\ softmax+cross\ entropy\ loss\ for\ the\ leading\ machine\ learning\ framework\ TensorFlow\ [AAB+15]$ . The code is available online<sup>1</sup>.

# 2 Implementation

We find that the existing implementation <code>tf.nn.sampled\_softmax\_loss</code> from TensorFlow [Ten20] produces a graph which is overly complicated. Simplifying this graph we obtain a considerable improvement. We also simplify and explicitly calculate the gradients of the composed loss function, instead of relying on auto-differentiation. Tests are provided for correctness of both: forward and backward passes.

 $<sup>^1\</sup>mathrm{See}$  the GitHub repo https://github.com/maciejskorski/ml\_examples/blob/master/efficient\_sampled\_softmax.ipynb

### 2.1 Implementation of Forward Pass

```
with tf.variable_scope('sampled_softmax'):
with tf.variable_scope('target_embeddings'):
  samples_embed = tf.gather(target_embed_kernel, samples) #
       (N\_SAMPLED, N\_EMBED)
  labels_embed = tf.gather(target_embed_kernel, labels, axis
      =0) # (N\_BATCH, N\_EMBED)
with tf.variable_scope('labels_logits'):
  labels_logits = tf.matmul(tf.expand_dims(labels_embed,1)
      , tf.expand_dims(inputs_embed, -1)) # (N_BATCH, 1, 1)
  labels\_logits = tf.squeeze(labels\_logits, -1) # N\_BATCH, 1
  labels_logits = labels_logits-tf.log(labels_prior) # add
       prior-correction
with tf.variable_scope('sampl_logits'):
  samples_logits = tf.matmul(inputs_embed, samples_embed,
      transpose_b=True) # (N_BATCH, N_SAMPLED)
  samples_logits = samples_logits-tf.log(samples_prior) #
      add prior-correction
with tf.variable_scope('sampl_loss'):
  candidate_logits = tf.concat([samples_logits,
      labels\_logits], axis=-1) # (N_BATCH, N_SAMPLED+1)
  Z = tf.reduce_logsumexp(candidate_logits, axis=-1,
      keepdims=True) # (N_BATCH, 1)
  loss = tf.reduce_mean(-labels_logits+Z)
return loss
```

### 2.2 Implementation of Backward Pass

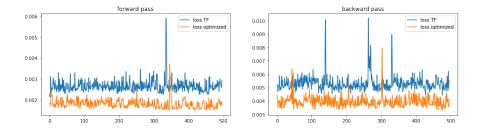
## 3 Performance Benchmarks

We compare performance of the forward and backward pass for our and default tensorflow implementation. To this end we generated random data of size matching a typical SkipGram problem where the sampled loss is often used. The parameters are summarized in Table 1

classes	samples	embeded size	batch
100,000	100	300	256

Table 1: Setup for our benchmark.

The improvement is about 2 times for forward and backward pass, as illustrated on the graph below



The code is included in the repo. The testing has been done in Google Colab.

#### References

[AAB+15] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dandelion Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng, TensorFlow: Largescale machine learning on heterogeneous systems, 2015, Software available from tensorflow.org.

- [JCMB14] Sébastien Jean, Kyunghyun Cho, Roland Memisevic, and Yoshua Bengio, On using very large target vocabulary for neural machine translation, arXiv preprint arXiv:1412.2007 (2014).
- [Ten20] Tensorflow, https://www.tensorflow.org/api\_docs/python/tf/nn/sampled\_softmax\_loss, 2020.