What is the Log-Sum-Exp Function?

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The log-sum-exp function takes as input a real n-vector x and returns the scalar

$$lse(x) = log \sum_{i=1}^{n} e^{x_i},$$

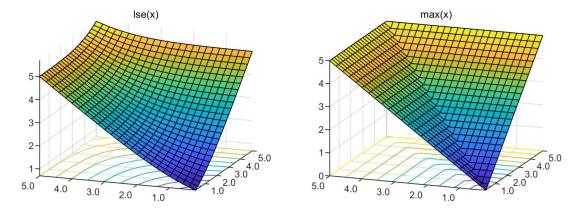
where log is the natural logarithm. It provides an approximation to the largest element of x, which is given by the max function, $\max(x) = \max_i x_i$. Indeed,

$$e^{\max(x)} \le \sum_{i=1}^{n} e^{x_i} \le n e^{\max(x)},$$

and on taking logs we obtain

$$\max(x) \le \operatorname{lse}(x) \le \max(x) + \log n.$$
 (*)

The log-sum-exp function can be thought of as a smoothed version of the max function, because whereas the max function is not differentiable at points where the maximum is achieved in two different components, the log-sum-exp function is infinitely differentiable everywhere. The following plots of lse(x) and max(x) for n = 2 show this connection.



The log-sum-exp function appears in a variety of settings, including statistics, optimization, and machine learning.

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For the special case where $x = [0 \ t]^T$, we obtain the function $f(t) = \log(1 + e^t)$, which is known as the softplus function in machine learning. The softplus function approximates the ReLU (rectified linear unit) activation function $\max(t,0)$ and satisfies, by (*),

$$\max(t,0) \le f(t) \le \max(t,0) + \log 2.$$

Two points are worth noting.

- While $\log(x_1 + x_2) \neq \log x_1 + \log x_2$, in general, we do (trivially) have $\log(x_1 + x_2) = \log(\log x_1, \log x_2)$, and more generally $\log(x_1 + x_2 + \cdots + x_n) = \log(\log x_1, \log x_2, \ldots, \log x_n)$.
- The log-sum-exp function is not to be confused with the exp-sum-log function: $\exp \sum_{i=1}^n \log x_i = x_1 x_2 \dots x_n$.

Here are some examples:

The MATLAB function logsumexp used here is available at https://github.com/higham/logsumexp-softmax.

Straightforward evaluation of log-sum-exp from its definition is not recommended, because of the possibility of overflow. Indeed, $\exp(x)$ overflows for x=12, x=89, and x=710 in IEEE half, single, and double precision arithmetic, respectively. Overflow can be avoided by writing

$$lse(x) = \log \sum_{i=1}^{n} e^{x_i} = \log \sum_{i=1}^{n} e^a e^{x_i - a} = \log \left(e^a \sum_{i=1}^{n} e^{x_i - a} \right),$$

which gives

$$lse(x) = a + log \sum_{i=1}^{n} e^{x_i - a}.$$

We take $a = \max(x)$, so that all exponentiations are of nonpositive numbers and therefore overflow is avoided. Any underflows are harmless. A refinement is to write

$$lse(x) = \max(x) + log1p\left(\sum_{\substack{i=1\\i\neq k}}^{n} e^{x_i - \max(x)}\right), \qquad (\#)$$

where $x_k = \max(x)$ (if there is more than one such k, we can take any of them). Here, $\log 1p(x) = \log(1+x)$ is a function provided in MATLAB and various other languages

that accurately evaluates $\log(1+x)$ even when x is small, in which case 1+x would suffer a loss of precision if it was explicitly computed.

Whereas the original formula involves the logarithm of a sum of nonnegative quantities, when $\max(x) < 0$ the shifted formula (#) computes $\mathrm{lse}(x)$ as the sum of two terms of opposite sign, so could potentially suffer from numerical cancellation. It can be shown by rounding error analysis, however, that computing log-sum-exp via (#) is numerically reliable.

References

This is a minimal set of references, which contain further useful references within.

- Pierre Blanchard, Desmond J. Higham, and Nicholas J. Higham, Accurately Computing the Log-Sum-Exp and Softmax Functions, IMA J. Numer. Anal., Advance access, 2020.
- Ian Goodfellow, Yoshua Bengio, and Aaron Courville, Deep Learning, MIT Press, 2016.

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