Differentiation

1. Basic idea of differentiation

What is the definition of a derivative?

The "slope of a line" is how much a function changes when its argument changes a little bit. Formally this can be written:

$$\frac{\mathrm{d}f}{\mathrm{d}x} = \lim_{\mathrm{d}x \to 0} \frac{f(x + \mathrm{d}x) - f(x)}{\mathrm{d}x} \tag{1}$$

Can you suggest a way to estimate a derivative numerically?

Just pick a small $\mathrm{d}x$, and evaluate the above expression! To get a very precise derivative, you want $\mathrm{d}x$ to be small. However, round-off error implies that you can't make it *too* small! This method is called the "forward difference" approximation.

How can you estimate the level of approximation error for a given choice of $\mathrm{d}x$?

You can use the Taylor Series expansion:

$$f(x + \mathrm{d}x) = f(x) + \mathrm{d}x \left.\frac{\mathrm{d}f}{\mathrm{d}x}\right|_x + \frac{1}{2!}\mathrm{d}x^2 \left.\frac{\mathrm{d}^2 f}{\mathrm{d}x^2}\right|_x + \frac{1}{3!}\mathrm{d}x^3 \left.\frac{\mathrm{d}^3 f}{\mathrm{d}x^3}\right|_x + \ldots \tag{2}$$

The definition of the derivative is just a rearrangement of this:

$$\begin{aligned}
\left.\frac{\mathrm{d}f}{\mathrm{d}x}\right|_x &= \frac{f(x + \mathrm{d}x) - f(x)}{\mathrm{d}x} - \frac{1}{2!}\mathrm{d}x \left.\frac{\mathrm{d}^2 f}{\mathrm{d}x^2}\right|_x - \frac{1}{3!}\mathrm{d}x^2 \left.\frac{\mathrm{d}^3 f}{\mathrm{d}x^3}\right|_x - \ldots \\
&= \left.\frac{\mathrm{d}f}{\mathrm{d}x}\right|_{\mathrm{fd}} - \frac{1}{2!}\mathrm{d}x \left.\frac{\mathrm{d}^2 f}{\mathrm{d}x^2}\right|_x - \frac{1}{3!}\mathrm{d}x^2 \left.\frac{\mathrm{d}^3 f}{\mathrm{d}x^3}\right|_x - \ldots
\end{aligned} \tag{3}$$

Clearly as $\mathrm{d}x \to 0$, the second and subsequent terms drop to zero, which is the nature of the definition of the derivative. But for finite $\mathrm{d}x$, there is a contribution from these terms, so the first term is just an approximation.

The second term scales as $\mathrm{d}x$ and is related to the second derivative of the function. That is, this approximation does not account for the *change* of the slope across the range $\mathrm{d}x$.

An obvious issue with forward differencing is that there is no reason to choose "forward" over "backward" differencing, yet in general they will yield different answers. This asymmetry is an undesirable feature, since there are many cases where you would like to be able to do the same operation forwards or backwards and get the same answer.

2. Practical differentiation estimates

A better method of approximating the derivative with the same number of function evaluations is the "central difference" algorithm. This approximation is:

$$\left.\frac{\mathrm{d}f}{\mathrm{d}x}\right|_{\mathrm{cd}} = \frac{f(x+\mathrm{d}x/2) - f(x-\mathrm{d}x/2)}{\mathrm{d}x} \tag{4}$$

This is obviously symmetric, and you are performing still only two function evaluations.

Beyond that, it has a nice advantage that is revealed when you estimate the approximation error associated with it.

How can you estimate the approximation error?

You can *again* use the Taylor Series. First on the first term:

$$f(x+\mathrm{d}x/2) = f(x) + \frac{\mathrm{d}x}{2}\left.\frac{\mathrm{d}f}{\mathrm{d}x}\right|_x + \frac{1}{2!}\frac{\mathrm{d}x^2}{4}\left.\frac{\mathrm{d}^2 f}{\mathrm{d}x^2}\right|_x + \frac{1}{3!}\frac{\mathrm{d}x^3}{8}\left.\frac{\mathrm{d}^3 f}{\mathrm{d}x^3}\right|_x + \mathcal{O}(\mathrm{d}x^4) \tag{5}$$

and then on the second term:

$$f(x-\mathrm{d}x/2) = f(x) - \frac{\mathrm{d}x}{2}\left.\frac{\mathrm{d}f}{\mathrm{d}x}\right|_x + \frac{1}{2!}\frac{\mathrm{d}x^2}{4}\left.\frac{\mathrm{d}^2 f}{\mathrm{d}x^2}\right|_x - \frac{1}{3!}\frac{\mathrm{d}x^3}{8}\left.\frac{\mathrm{d}^3 f}{\mathrm{d}x^3}\right|_x + \mathcal{O}(\mathrm{d}x^4) \tag{6}$$

When you subtract these two expressions, *only* the terms with opposite signs remain:

$$f(x+\mathrm{d}x/2) - f(x-\mathrm{d}x/2) = \mathrm{d}x\left.\frac{\mathrm{d}f}{\mathrm{d}x}\right|_x + \frac{1}{3!}\frac{\mathrm{d}x^3}{4}\left.\frac{\mathrm{d}^3 f}{\mathrm{d}x^3}\right|_x + \mathcal{O}(\mathrm{d}x^5) \tag{7}$$

So this can be rearranged:

$$\left.\frac{\mathrm{d}f}{\mathrm{d}x}\right|_x = \frac{f(x+\mathrm{d}x/2) - f(x-\mathrm{d}x/2)}{\mathrm{d}x} + \frac{1}{3!}\frac{\mathrm{d}x^2}{4}\left.\frac{\mathrm{d}^3 f}{\mathrm{d}x^3}\right|_x + \mathcal{O}(\mathrm{d}x^4) \tag{8}$$

The key result is that the approximation error scales as $\mathrm{d}x^2$ instead of $\mathrm{d}x$. This means that for small $\mathrm{d}x$ the approximation is much better. For example, if you happen to be estimating the derivative of a parabola, for which all third and higher derivatives are zero, the estimate of the derivative will have no approximation error.

There is a yet more clever option. Consider the estimate:

$$D_1 = \frac{f(x+\mathrm{d}x/2) - f(x-\mathrm{d}x/2)}{\mathrm{d}x} = \left.\frac{\mathrm{d}f}{\mathrm{d}x}\right|_x = -\frac{1}{3!}\frac{\mathrm{d}x^2}{4}\left.\frac{\mathrm{d}^3 f}{\mathrm{d}x^3}\right|_x + \mathcal{O}(\mathrm{d}x^4) \tag{9}$$

If I reduce $\mathrm{d}x$ by a factor of two I get:

$$D_2 = \frac{f(x+\mathrm{d}x/4) - f(x-\mathrm{d}x/4)}{\mathrm{d}x} = \left.\frac{\mathrm{d}f}{\mathrm{d}x}\right|_x - \frac{1}{4}\frac{1}{3!}\frac{\mathrm{d}x^2}{4}\left.\frac{\mathrm{d}^3 f}{\mathrm{d}x^3}\right|_x + \mathcal{O}(\mathrm{d}x^4) \tag{10}$$

Now if I take a new estimate:

$$D = \frac{4D_2 - D_1}{3} \tag{11}$$

You see that the first terms leave exactly the derivative, and the second order terms cancel leaving:

$$D = \frac{\mathrm{d}f}{\mathrm{d}x}\bigg|_x + \mathcal{O}(\mathrm{d}x^4) \tag{12}$$

This very good approximation of course comes at the expense of more function evaluations!

3. Error assessment

The question arises as to what to choose for $\mathrm{d}x$. The optimal choice will be about when the round-off error is similar to the approximation error.

For the central difference approximation, this yields:

$$\epsilon_{\mathrm{approx}} = \frac{f'''\mathrm{d}x^2}{24} \tag{13}$$

Assuming the function is of order unity, or at least far enough from overflow or underflow, the round-off error in the numerator is the machine precision ϵ_{m}, and so the final round-off is:

$$\epsilon_{\mathrm{ro}} = \frac{\epsilon_{\mathrm{m}}}{\mathrm{d}x} \tag{14}$$

Setting these two equal to each other yields:

$$\mathrm{d}x = \left(\frac{24\epsilon_{\mathrm{m}}}{f'''}\right)^{1/3} \tag{15}$$

Note a few things. The $\mathrm{d}x$ value goes as the cube root of the machine precision, and the approximation error goes as the square of $\mathrm{d}x$. This means that as you increase machine precision the best approximation error improves as the 2/3 power.

The choice of $\mathrm{d}x$ for double precision ($\epsilon_{\mathrm{m}} \sim 3 \times 10^{-15}$ is about $\mathrm{d}x \sim 10^{-5}$.

Finally, it is important to realize that under most circumstances you do not know beforehand exactly what f''' is. After all, if you did, you would not be doing this derivative calculation!

4. Numpy implementation

In NumPy, the function that implements a derivative is `gradient`, which only works on a function tabulated as an array — i.e. it uses central difference on a set of precomputed points. This is in fact an extremely common use case for derivative calculation.

5. Scaling a problem

Note that in a lot of analyses like that above we assume the quantities we are dealing with are far away from overflow or underflow. Indeed, it is good practice to maximize one's dynamic range by dealing in units that are transformed.

For example, in a gravitational context we might calculate a force from the gradient of the potential.

What is the force equation for gravity in spherical symmetry?

In spherical symmetry, this is just the radial gradient:

$$F = \frac{\mathrm{d}^2 r}{\mathrm{d}t^2} = -\frac{\mathrm{d}\phi}{\mathrm{d}r} = \frac{\mathrm{d}}{\mathrm{d}r}\frac{GM}{r} \tag{16}$$

Imagine we are calculating the acceleration on an object near the surface of the Sun. Near the surface of the Sun we have $G - 6.67 \times 10^{-11}$ m^3 kg^{-1} s^{-2}, $M = 2 \times 10^{30}$ kg, $r \sim 10^9$ m. So $\phi \sim 10^{28}$, and $F \sim 10^{19}$.

Two things to note: first, it would be "nicer" if these numbers were closer to unity. In the course of a full calculation of, say, an orbit, these numbers will vary. Also, we will be calculating other numbers (like the position and velocity of the object). We want to minimize the chance that any of these numbers will overflow or underflow. So we should make the natural units of the problem that the *computer* sees as close to unity as we can.

This is especially true if we are working in single rather than double precision. It is not *usually* a good reason to work in double precision just to prevent overflow and underflow. Usually single precision is sufficient from that point of view with a wise choice of units.

Second, there are scaling relations that this set of equations has to obey, as we will see in a second. We can solve one problem and for a large set of situations can scale our results to that new situation.

Specifically we can redefine:

$$\begin{aligned} r' &= \frac{r}{R_\odot} \\ t' &= \sqrt{\frac{GM_\odot}{R_\odot}} \end{aligned} \tag{17}$$

and we find:

$$\frac{\mathrm{d}^2 r'}{\mathrm{d}t'^2} = \frac{\mathrm{d}}{\mathrm{d}r'}\frac{1}{r'} \tag{18}$$

with $r' \sim 1$ (given that we are working near the surface of the Sun). Now there are no stray units. If the derivative on the right hand side yields something far from unity, then this is an unavoidable aspect of the problem, but we have done our best to keep things in range.

Also, if we tabulate results in terms of r' and t', we can adjust to a different length scale R_{new} and mass M_{new} through the above equations, instead of recalculating the whole problem.

Pulling the dimensions out of a problem like this is a generic strategy in numerical physics.