

To show that  $f'(x) \approx \frac{f(x+h)-f(x)}{h}$ , we will approximate using the Taylor series expansion of  $f(x+h)$  around  $x$ :

Def:

$$f(x) = \sum_{n=0}^{\infty} \frac{f^{(n)}(x_0)}{n!} (x - x_0)^n$$

then:

$$f(x+h) = \sum_{n=0}^{\infty} \frac{f^{(n)}(x)}{n!} h^n$$

and for a first order approximation, we will only go until the linear term:

$$f(x+h) \approx f(x) + hf'(x)$$

The remainder term  $R_n(x)$  in Taylor's theorem, which provides the error of this approximation, is:

$$R_n(x) = \frac{f^{(n+1)}(c)}{(n+1)!} (x - x_0)^{(n+1)}$$

For the first-order approximation, the remainder term is  $R_1(x+h) = \frac{f''(c)}{2!} h^2$ , where  $x < c < x+h$ .

And the remainder term  $R_1(x+h)$  for the first-order approximation is given by:

$$R_1(x+h) = f(x+h) - T_1(x+h) = \frac{f''(c)}{2!} h^2$$

Since  $f(x+h) \approx f(x) + hf'(x)$

Then we have

$$\frac{f(x+h) - f(x)}{h} = f'(x) + \frac{f''(c)}{2} h$$

Which results that:

$$f'(x) = \frac{f(x+h) - f(x)}{h} + O(h)$$

For the second-order approximation, we will use the Taylor series expansions of  $f(x+h)$  and  $f(x-h)$  around  $x$ :

$$\begin{aligned} f(x+h) &= f(x) + hf'(x) + \frac{h^2}{2!} f''(x) + \frac{h^3}{3!} f'''(c_1) + \dots \\ f(x-h) &= f(x) - hf'(x) + \frac{h^2}{2!} f''(x) - \frac{h^3}{3!} f'''(c_2) + \dots \end{aligned}$$

where  $c_1 \in (x, x+h)$  and  $c_2 \in (x-h, x)$ .

When we subtract the second expansion from the first, the odd-powered terms (like  $hf'(x)$  and the cubic term) cancel out =>

$$f(x+h) - f(x-h) = 2hf'(x) + \frac{h^3}{3!}(f'''(c_1) - f'''(c_2))$$

Divide both sides with  $2h$ :

$$\frac{f(x+h) - f(x-h)}{2h} = f'(x) + \frac{h^2}{6}(f'''(c_1) - f'''(c_2))$$

The term  $\frac{h^2}{6}(f'''(c_1) - f'''(c_2))$  is the error term, which is of order  $h^2$  (second order approx.)

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[4]: import math
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline
```

We will take  $f(x) = e^x$ , its derivative is  $f'(x) = e^x$

```
[34]: f = lambda x: np.exp(x)
df = lambda x: np.exp(x)

def first_order(x, h):
    return (f(x + h) - f(x)) / h

def second_order(x, h):
    return (f(x + h) - f(x - h)) / (2 * h)
```

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[12]: # h values close to 0
h_values = np.logspace(-10, 0, 400)
```

```
[35]: # Take our point at x0 = 0
x0 = 0

actual_result = df(x0)
actual_result
```

```
[35]: 1.0
```

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[46]: first_order_errors = []
second_order_errors = []

for h in h_values:
    first_error = first_order(x0, h) - actual_result
    second_error = second_order(x0, h) - actual_result

    first_order_errors.append(first_error)
    second_order_errors.append(second_error)

max(first_order_errors)
```

[46]: 0.7182818284590451

```
[47]: plt.figure(figsize=(12, 8))
plt.loglog(h_values, first_order_errors, label='First order errors', marker='o',
           linestyle='-', markersize=4)
plt.loglog(h_values, h_values, label='Proportional to h', linestyle='--',
           color='gray')
plt.loglog(h_values, second_order_errors, label='Second order errors',
           marker='s', linestyle='-', markersize=4)
plt.loglog(h_values, h_values**2, label='Proportional to h^2', linestyle='--',
           color='black')

# annotations
plt.xlabel('h')
plt.ylabel('Error')
plt.title('First and second orders errors for e^x')
plt.legend()
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.show()
```

