

1.7. Scope of Variables

Local scope: Variables inside a function can only be used in the function

💡 You can have functions in functions like

```
def myfunc():  
    x = 300  
    def myinnerfunc():  
        print(x)  
    myinnerfunc()
```

Global scope: Variables from outside of the function

```
x = 300  
def myfunc():  
    print(x);
```

```
x = 200; print(x)
```

↖ myfunc()

```
global x;
```

↑ inserting these two statements will cause an error to avoid it use

1.8. Expanding Python

Proverb: Don't reinvent the wheel

Example: We need π . Leibniz formula:

$$\frac{\pi}{4} = \sum_{k=0}^{\infty} \frac{(-1)^k}{2k+1} \quad \text{or faster}$$

```
import math
```

↖ library, contains also functions like sin, cos, ...

```
print(math.pi)
```

```
Print ( math.sin (math.pi))
```

for more information check `pydoc math`

to spare the `math.` you can use

```
from math import pi, sin, cos
```

```
from math import *
```

10.9. Handy libraries

- numpy i.e. for matrix products (and much more)

```
import numpy as np
```

```
a = np.array([[1,2],[3,4]])
```

```
b = np.array([[5,6],[7,8]])
```

```
Print ( np.matmul (a, b) )
```

- SciPy for algorithms, like numerical integration, solving ODEs, Fourier transformation ...

- matplotlib for visualization

```
import matplotlib.pyplot as plt
```

```
import numpy as np
```

```
t = np.array (0.0, 2.0, 0.01)
```

```
s = 1 + np.sin (2 * np.pi * t)
```

```
fig, ax = plt.subplots ()
```

```
ax.plot (t, s)
```

```
ax.grid ()
```

```
plt.show ()
```

2. Representation of numbers

Problem: continuous real numbers have to be discretized by

2.1. Fixed and floating point

(i) fixed point: integer, multiplied with a fixed scale factor b^E

consisting of a basis b and exponent E

example: $9.99 = 999 \cdot 10^{-2}$

properties:
• rounding errors } on small / large scales
• overflows }
important for physics

(ii) floating point to cope with this problem represent numbers as

$$X = \underbrace{\quad}_{\text{Sign } S} \cdot \underbrace{0.1234567}_{\text{fraction } F} \cdot \underbrace{10^2}_{\text{scale factor } b^E}$$

$$X = S \cdot F \cdot b^E$$

assume we have 32 bits with $b=2$ (IEEE 754)

b_{31}	b_{30}	...	b_{23}	b_{22}	...	b_0
S	E'			F		

$$X = (-1)^{b_{31}} \times 2^{(E' - 127)} \times \left(1 + \sum_{i=1}^{23} b_{23-i} 2^{-i} \right)$$

regular range of exponent $-126 \leq E < 127$

E	F = 1	F ≠ 1
0	± 0	
255	± ∞	NaN = Not a Number

Properties: distance between neighbors increases with exponent

→ absolute rounding error = $|\underbrace{\text{rd}(x)}_{\text{rounding of } x} - x| = 2^{E - \underbrace{l_F}_{\text{length of } F \text{ in bits}}}$

better use relative error:

$$\epsilon = \frac{|\text{rd}(x) - x|}{x} \sim 2^{-l_F}$$

2.2. Errors

two major sources of numerical errors are

a) rounding with $\text{rd}(x) = x(1 + \epsilon)$
 required by discretisation of x

↳ propagate, for example

$$f(x(1 + \epsilon)) \approx f(x) + f'(x)x\epsilon$$

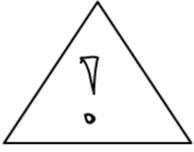
$$\epsilon_f = \left| \frac{f'(x)x}{f(x)} \right| \epsilon_x \quad \text{particularly bad when } f(x) \approx 0$$

b) truncation iterations and recursions

example: $e^x \approx \sum_{n=0}^{N-1} \frac{1}{n!} x^n$

$$\text{error} = \sum_{n=N}^{\infty} \frac{1}{n!} X^n \leq \frac{1}{N!} X^N e^X$$

→ choose N appropriately



Numerical methods have to be stable with respect to these errors, implying that small, unavoidable numerical errors will not be amplified.