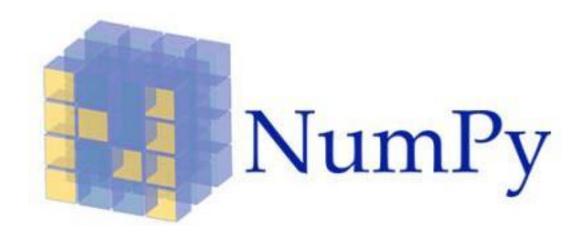
#### Multi-dimensional data

- NumPy
- matrix multiplication, @
- numpy.linalg.solve, numpy.polyfit

Array programming with NumPy
Harris et al.
Nature, volume 585, pages 357–362, 2020
DOI 10.1038/s41586-020-2649-2



NumPy is a Python package for dealing with multi-dimensional data

### pylab?

Guttag [2<sup>nd</sup> edition] uses pylab in the examples, but...

"pylab is a convenience module that bulk imports matplotlib.pyplot (for plotting) and numpy (for mathematics and working with arrays) in a single name space. Although many examples use pylab, it is no longer recommended."

# NumPy arrays (example)

```
Python shell
> range(0, 1, .3)
| TypeError: 'float' object cannot be
  interpreted as an integer
> [1 + i / 4 for i in range(5)]
| [1.0, 1.25, 1.5, 1.75, 2.0]
```

python only supports ranges of int generate 5 uniform values in range [1,2]

#### Python shell

```
> import numpy as np
> np.arange(0, 1, 0.3)
| array([0. , 0.3, 0.6, 0.9])
> type(np.arange(0, 1, 0.3))
| <class 'numpy.ndarray'>
> help(numpy.ndarray)
| +2000 lines of text
> np.linspace(1, 2, 5)
| array([1. , 1.25, 1.5 , 1.75, 2. ])
```

numpy can generate ranges with float

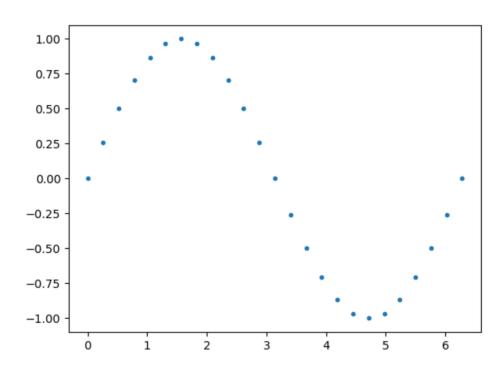
returns a "NumPy array" (not a list)
"arange" = "array range" and generates the array explicitly

generate n uniformly spaced values

# Plotting a function (example)

```
import matplotlib.pyplot as plt
import math
n = 25
x = [2 * math.pi * i / (n - 1) for i in range(n)]
y = [math.sin(v) for v in x]
plt.plot(x, y, '.')
plt.show()
```

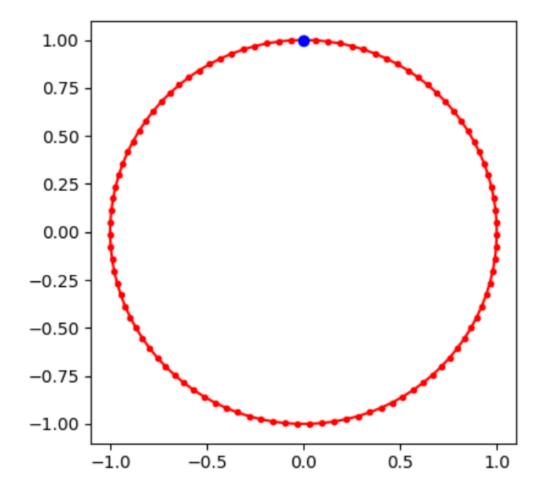
```
import matplotlib.pyplot as plt
import numpy as np
x = np.linspace(0, 2 * np.pi, 25)
y = np.sin(x)
plt.plot(x, y, '.')
plt.show()
```



- np.sin applies the sin function to each element of x
- pyplot accepts NumPy arrays
- math.pi == np.pi  $\approx \frac{22}{7}$

#### A circle

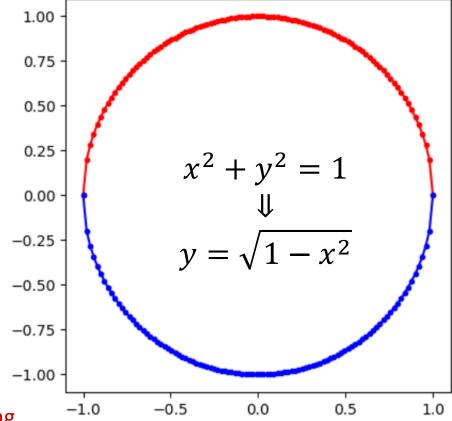
```
circle.py
import matplotlib.pyplot as plt
import numpy as np
a = np.linspace(0, 2 * np.pi, 100)
x = np.sin(a)
y = np.cos(a)
plt.plot(x, y, 'r.-')
plt.plot(x[0], y[0], 'bo')
plt.show()
```



#### Two half circles

```
half_circles.py
import matplotlib.pyplot as plt
import numpy as np

x = np.linspace(-1, 1, 100)
plt.plot(x, np.sqrt(1 - x ** 2), 'r.-')
plt.plot(x, -np.sqrt(1 - x ** 2), 'b.-')
plt.show()
```



compact expression computing something quite comlicated

- x is a NumPy array
- \*\* NumPy method pow squaring each element in x
- binary NumPy method \_\_rsub\_\_ that for each element e in x computes 1 e
- np.sqrt NumPy method computing the square root of each element in x
- unary NumPy method neg that negates each element in x

#### Creating one-dimensional NumPy arrays

```
Python shell
```

```
> np.array([1, 2, 3])
 array([1, 2, 3])
> np.array((1, 2, 3))
 array([1, 2, 3])
> np.array(range(1, 4))
 array([1, 2, 3])
> np.arange(1., 4., 1.)
 array([1., 2., 3.])
> np.linspace(1, 3, 3)
 array([1., 2., 3.])
> np.zeros(3)
 array([0., 0., 0.])
> np.ones(3)
 array([1., 1., 1.])
> np.full(3, 7)
 array([7, 7, 7])
> np.random.random(3)
 array([0.73761651,
  0.60607355, 0.3614118 ])
```

```
> np.array([1, 2, 3]).dtype # type of all values
dtype('int32')
> np.arange(3, dtype='float')
array([0., 1., 2.])
> np.arange(3, dtype='int16') # 16 bit integers
 array([0, 1, 2], dtype=int16)
> np.arange(3, dtype='int32') # 32 bit integers
array([0, 1, 2])
> 1000 ** np.arange(5)
 array([1, 1000, 1000000, 1000000000,
  -727379968], dtype=int32) # OOPS.. overflow A
> 1000 ** np.arange(5, dtype='0')
  array([1, 1000, 1000000, 1000000000,
  10000000000], dtype=object) # Python integer
> np.arange(3, dtype='complex')
 array([0.+0.j, 1.+0.j, 2.+0.j])
     Elements of a NumPy array are not arbitrary precision integers by
    default – you can select between +25 number representations
```

### Mantissa size in various numpy floats

```
Python shell
> for data type in ['half', 'float', 'single', 'double', 'longdouble', 'float32', 'float64']:
    x = np.array([1], dtype=data_type)
    for i in range (100):
      if x == x + (x / 2) ** i: \leftarrow
                                                                     mantissa
        break
    print(data type, i - 1, 'bits mantissa')
                                                                 1.0000100000
  half 10 bits mantissa
  float 52 bits mantissa
  single 23 bits mantissa
  double 52 bits mantissa
  longdouble 52 bits mantissa
  float32 23 bits mantissa
                                      # platform independent
                                       # platform independent
  float64 52 bits mantissa
```

### Creating multi-dimensional NumPy arrays

```
Python shell
> np.array([[1, 2, 3], [4, 5, 6]])
                                      > x.size
 array([[1, 2, 3],
                                       12
         [4, 5, 6]])
                                      > x.ndim
                                       3
> np.arange(1, 7).reshape(2, 3)
array([[1, 2, 3],
                                      > x.shape
         [4, 5, 6]])
                                      (2, 2, 3)
> x = np.arange(12).reshape(2, 2, 3)
                                     > x.dtype
                                      dtype('int32')
> x
 array([[[ 0, 1, 2],
                                      > x.flatten()
         [3, 4, 5]],
                                      array([0,1,2,3,4,5,6,7,8,9,10,11])
                                      > list(x.flat) # flat is an iterator
         [[6, 7, 8],
                                      [0,1,2,3,4,5,6,7,8,9,10,11]
         [ 9, 10, 11]])
                                      > np.eye(3) # diagonal 2D array
> numpy.zeros((2, 5), dtype='int32')
                                      array([[1., 0., 0.],
 array([[0, 0, 0, 0, 0],
                                               [0., 1., 0.],
         [0, 0, 0, 0, 0]
                                               [0., 0., 1.]])
```

### View vs Copy

- Numpy is optimized to handle big multi-dimensional arrays
- To avoid copying data, views allows one to look at the underlying data in different ways (data can be shared by multiple views)
- reshape, ravel and slicing are examples creating views
- flatten and ravel both turn multiple dimensional arrays into one dimensional arrays but flatten creates an explicit copy whereas ravel creates a space efficient view

#### Python shell

```
> x = np.arange(6)
> y = x.reshape(2, 3) # view
> y[0][0] = 42 # updates x
> x
array([42, 1, 2, 3, 4, 5])
> y
| array([[42, 1, 2],
        [ 3, 4, 5]])
> z = y.flatten() # copy
> z[5] = 0
array([42, 1, 2, 3, 4, 0])
> x
array([42, 1, 2, 3, 4, <mark>5</mark>])
> w = y.ravel() # view
> w[5] = -1
 array([42, 1, 2, 3, 4, -1])
> x
 array([42, 1, 2, 3, 4, -1])
```

# NumPy operations

```
Python shell
> x = numpy.arange(3)
                                                  > a = np.arange(6).reshape(2,3)
> x
                                                  > a
| array([0, 1, 2])
                                                   array([[0, 1, 2],
> x + x # elementwise addition
                                                           [3, 4, 5]])
                                                  > a.T # matrix transposition, view
array([0, 2, 4])
> 1 + x # add integer to each element
                                                   array([[0, 3],
| array([1, 2, 3])
                                                           [1, 4],
> x * x # elementwise multiplication
                                                           [2, 5]])
                                                  > a @ a.T # matrix multiplication
| array([0, 1, 4])
> np.dot(x, x) # dot product
                                                   array([[ 5, 14],
                                                           [14, 50]])
> np.cross([1, 2, 3], [3, 2, 1]) # cross product
                                                  > a += 1
 array([-4, 8, -4])
                                                   array([[1, 2, 3],
                                                           [4, 5, 6]])
```

# Universal functions (apply to each entry)

#### **Axis**

```
Python shell
> x = np.arange(1, 7).reshape(2, 3)
> x
 array([[1, 2, 3],
         [4, 5, 6]])
> x.sum() # = x.sum(axis=(0, 1))
 21
> x.sum(axis=0)
 array([5, 7, 9])
> x.sum(axis=1)
 array([6, 15])
> x.min() # = x.min(axis=(0, 1))
 1
```

```
Python shell
> x.min(axis=0)
 array([1, 2, 3])
> x.min(axis=1)
 array([1, 4])
> x.cumsum()
 array([ 1, 3, 6, 10, 15, 21], dtype=int32)
> x.cumsum(axis=0)
 array([[1, 2, 3],
         [5, 7, 9]], dtype=int32)
> x.cumsum(axis=1)
 array([[ 1, 3, 6],
         [ 4, 9, 15]], dtype=int32)
```

### Slicing

#### Python shell > x = numpy.arange(20).reshape(4,5)> x array([[ 0, 1, 2, 3, 4], [ 5, 6, <mark>7</mark>, **8**, 9], [10, 11, 12, 13, 14], [15, 16, **17**, **18**, 19]]) > x[2, 3] # = x[(2, 3)]13 > x[1:4:2, 2:4:1] # rows 1 and 3, and columns 2 and 3, view | array([[ 7, 8], [17, 18]]) > x[:, 3]array([ 3, 8, 13, 18]) > x[..., 3] # ... is placeholder for ':' for all missing dimensions array([ 3, 8, 13, 18]) > type(...) <class 'ellipsis'>

# Broadcasting (stretching arrays to get same size)

Numpy tries to apply broadcasting, if array shapes do not match, i.e. adds missing leading dimensions and repeats a dimension with only one element:

```
[[1],[2]] + [10,20] column + row vector

\equiv [[1],[2]] + [[10,20]] both ndim = 2

\equiv [[1,1],[2,2]] + [[10,20]]

\equiv [[1,1],[2,2]] + [[10,20],[10,20]]

\equiv [[11,21],[12,22]]
```

To prevent unexpected broadcasting, add an assertion to your program:

```
assert x.shape == y.shape
```

```
Python shell
> x = np.array([[1, 2, 3], [4, 5, 6]])
> y = np.array([1, 2, 3]) # one row
> z = np.array([[1], [2]]) # one column
> x + 3 \# add 3 to each entry
 array([[4, 5, 6],
         [7, 8, 9]])
> x + y # add y to each row
 array([[2, 4, 6],
    [5, 7, 9]])
> x + z # add z to each column
 array([[2, 3, 4],
     [6, 7, 8]])
> y + z # 2 rows with y + 3 columns with z
 array([[2, 3, 4],
         [3, 4, 5]])
> z == z.T \# [[1,1],[2,2]] == [[1,2],[1,2]]
 array([[ True, False],
         [False, True]])
```

### Masking

```
Python shell
> x = np.arange(1, 11).reshape(2, 5)
> x
array([[ 1, 2, 3, 4, 5],
        [6, 7, 8, 9, 10]])
> x % 3
array([[1, 2, 0, 1, 2],
        [0, 1, 2, 0, 1]], dtype=int32)
> x % 3 == 0
 array([[False, False, True, False, False],
         [ True, False, False, True, False]])
> x[x % 3 == 0] # use Boolean matrix to select entries
array([3, 6, 9])
> x[:, x.sum(axis=0) % 3 == 0] # columns with sum divisible by 3
 array([[ 2, 5],
        [ 7, 10]])
```

### Numpy is fast... but be aware of dtype $\triangle$



#### Python shell > sum([x\*\*2 for x in range(1000000)]) 333332833333500000 > (np.arange(1000000)\*\*2).sum() 584144992 # wrong since overflow when default dtype='int32' > (np.arange(1000000, dtype="int64")\*\*2).sum() 33333283333500000 # 64 bit integers do not overflow > import timeit from timeit > timeit('sum([x\*\*2 for x in range(1000000)])', number=1) 0.5614346340007614 > timeit('(np.arange(1000000)\*\*2).sum()', setup='import numpy as np', number=1) 0.014362967000124627 # ridiculous fast but also wrong result... > timeit('(np.arange(1000000, dtype="int64")\*\*2).sum()', setup='import numpy as np', number=1) 0.048017077999247704 # fast and correct > np.iinfo(np.int32).min -2147483648 > np.iinfo(np.int32).max





2147483647

#### numpy.int32 – 32 bit signed two's-complement integers

32 bits  $b_{31}b_{30}b_{29}b_{28}\cdots b_2b_1b_0$  represent the value

$$-b_{31} \cdot 2^{31} + \sum_{i=0}^{30} b_i \cdot 2^i$$

	100000000000000000000000000000000000000	-2147483648
	100000000000000000000000000000000000000	-2147483647
	<b>1</b> 11111111111111111111111111111111111	-2
	<b>1</b> 11111111111111111111111111111111111	-1
	000000000000000000000000000000000000000	0
	000000000000000000000000000000000000000	1
	<b>:</b>	
	0111111111111111111111111111111111111	2147483646
	011111111111111111111111111111111111111	2147483647
1		

Note: There is one more negative number than positive



- > np.int32(- 2 \*\* 31)
- -2147483648
- > np.int32(- 2 \*\* 31) + 1
  - -2147483647
- > np.int32(- 2 \*\* 31) 1
- 2147483647
- > np.int32(2 \*\* 31)
- OverflowError: Python int too large to convert to C long
- > np.int32(2 \*\* 31 1)
  - 2147483647
- > np.int32(2 \*\* 31 1) + 1
- -2147483648
- > abs(np.int32(-2147483647))
  - 2147483647
- > abs(np.int32(-2147483648))
  - -2147483648





# Linear algebra

#### Python shell

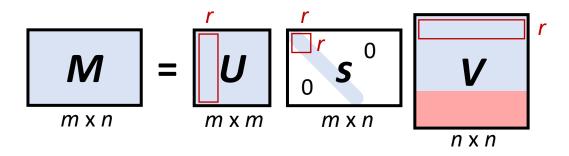
```
> x = np.arange(1, 5, dtype=float).reshape(2, 2)
> x
 array([[1., 2.],
     [3., 4.]])
> x.T # matrix transpose
 array([[1., 3.],
        [2., 4.]])
> np.linalg.det(x) # matrix determinant
 -2.0000000000000004
> np.linalg.inv(x) # matrix inverse
 array([[-2. , 1.],
         [1.5, -0.5]
> np.linalg.eig(x) # eigenvalues and eigenvectors
 (array([-0.37228132, 5.37228132]),
  array([[-0.82456484, -0.41597356], [0.56576746, -0.90937671]]))
> y = np.array([[5.], [7.]])
> np.linalg.solve(x, y) # solve linear matrix equations
 array([[-3.], # z1
         [ 4.]]) # z2
```

#### numpy.matrix

"It is no longer recommended to use this class, even for linear algebra. Instead use regular arrays. The class may be removed in the future."

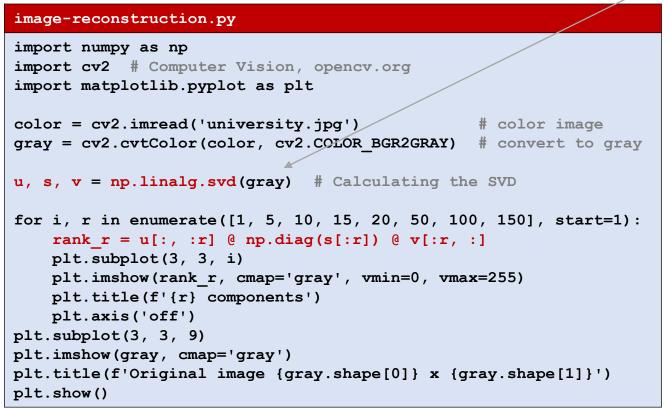
$$\begin{pmatrix} 1 & 2 \\ 3 & 4 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} = \begin{pmatrix} 5 \\ 7 \end{pmatrix}$$

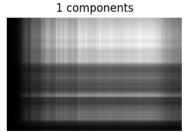
# Singular value decomposition, np.linalg.svd



- U and V unitary matrix  $(UU^T = I)$
- S diagonal matrix, decreasing singular values

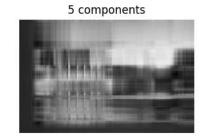
np.ndarray shape=(520, 800) dtype=uint8 min=0 max=252

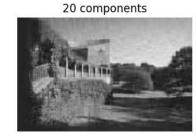




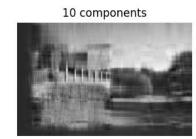




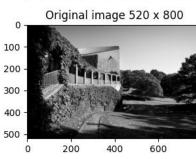












150 components

#### ... and in color

```
image-reconstruction-color.py
import numpy as np
import matplotlib.pyplot as plt
                                               shape=(520, 800, 3)
from matplotlib.image import imread
                                               3 = (red, blue, green)
color = imread('university.jpg') 
color = color / 255 # convert integers 0..255 to floats 0..1
plt.subplot(4, 2, 8)
plt.imshow(color)
plt.axis('off')
plt.title(f'Original')
                                               shape=(520, 2400)
height, width, colors = color.shape
u, s, v = np.linalg.svd(color.reshape((height, width * colors)),
                         full matrices=False)
for i, r in enumerate([1, 2, 5, 10, 25, 50, 125], start=1):
    rank r = u[:, :r] @ np.diag(s[:r]) @ v[:r, :]
    plt.subplot(4, 2, i)
    plt.imshow(rank r.reshape((height, width, colors)))
    plt.title(f'{r} components')
                                                 v shape=(520, 2400)
    plt.axis('off')
                               shape=(520, 800, 3) instead of (2400, 2400)
plt.show()
```

#### 1 components



5 components



25 components



125 components



2 components



10 components



50 components



Original



# ... and in color (stacked)

```
image-reconstruction-color-stacked.py
import numpy as np
import matplotlib.pyplot as plt
                                               shape = (520, 800, 3)
from matplotlib.image import imread
color = imread('university.jpg')
color = color / 255 # convert integers 0..255 to floats 0..1
plt.subplot(4, 2, 8)
plt.imshow(color)
                                               shape = (3, 520, 800)
plt.axis('off')
plt.title(f'Original')
u, s, v = np.linalg.svd(color.transpose(2, 0, 1), full matrices=False)
print(f'{u.shape=} {s.shape=} ')
for i, r in enumerate([1, 2, 5, 10, 25, 50, 125], start=1):
    rank r = (u[:, :, :r] * s[:, None, :r]) @ v[:, :r, :] +
    plt.subplot(4, 2, i)
                                                          element-wise
    plt.imshow(rank r.transpose(1, 2, 0))
                                                        multiplication (*),
    plt.title(f'{r} components')
                                                       broadcasting (None),
    plt.axis('off')
                            shape = (520, 800, 3)
                                                      stacked for each color (:)
plt.show()
Python shell
   u.shape=(3, 520, 520) s.shape=(3, 520) v.shape=(3, 520, 800)
```

#### 1 components



5 components



25 components



125 components



2 components



10 components



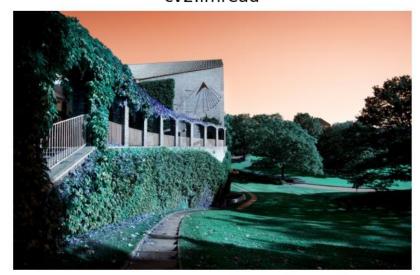
50 components



Original









#### color-image.py

```
import matplotlib.pyplot as plt
import matplotlib.image
import cv2
img1 = matplotlib.image.imread('university.jpg')
img2 = cv2.imread('university.jpg')  # cv2 uses BGR instead of RGB
img3 = img2[:, :, ::-1]  # change color order BGR to RGB

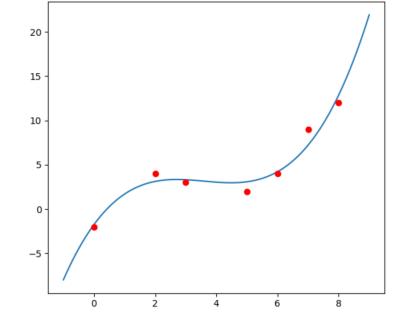
Images = [(img1, 'matplotlib.image.imread'), (img2, 'cv2.imread'), (img3, 'cv2.imread corrected')]
for i, (img, title) in enumerate(images, start=1):
    plt.subplot(1, 3, i)
    plt.imshow(img)
    plt.axis('off')
    plt.title(title)

plt.show()
```

# numpy.polyfit

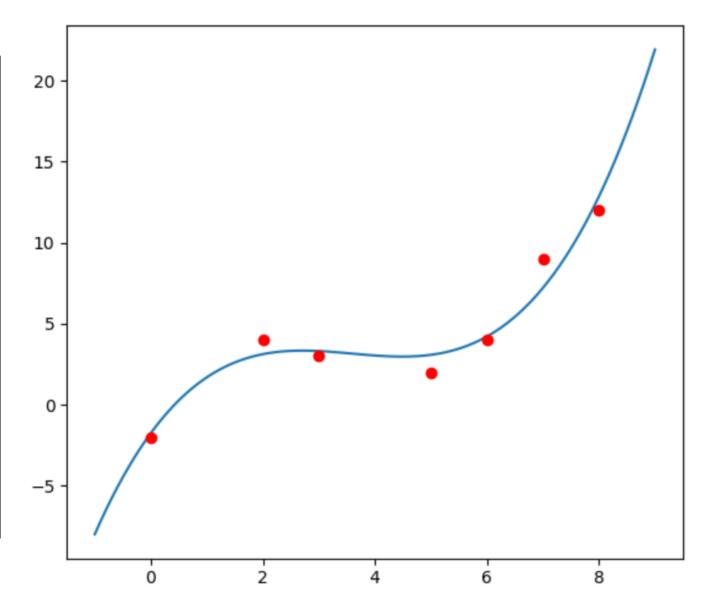
- Given n points with  $(x_0, y_0), ..., (x_{n-1}, y_{n-1})$
- Find polynomial p of degree d that minimizes

$$\sum_{i=0}^{n-1} (y_i - p(x_i))^2$$

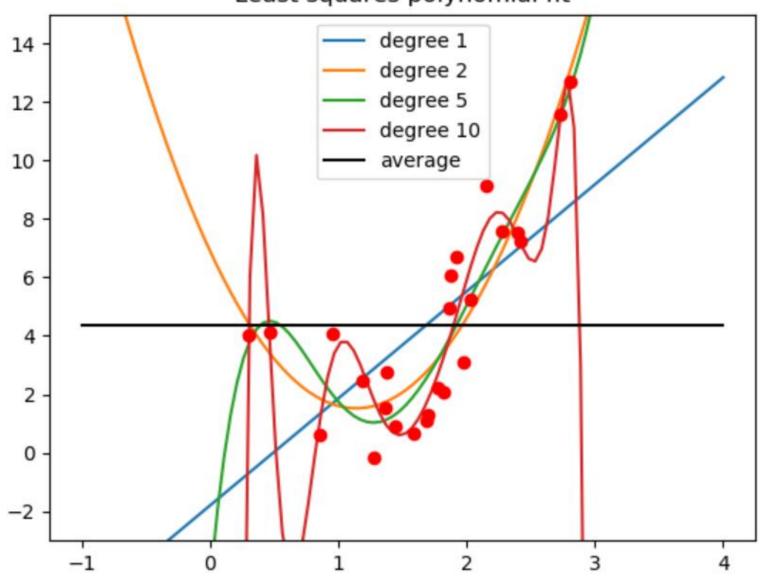


know as least squares fit / linear regression / polynomial regression

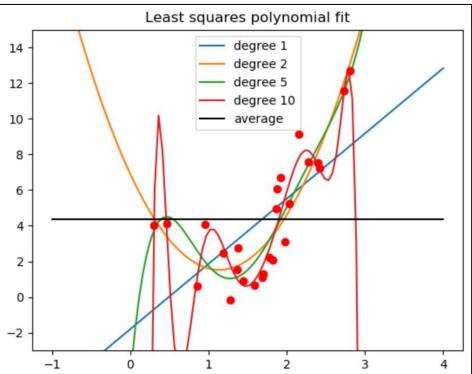
#### fit.py import matplotlib.pyplot as plt import numpy as np x = [0, 2, 3, 5, 6, 7, 8]degree y = [-2, 4, 3, 2, 4, 9, 12]coefficients = np.polyfit(x, y, 3)fx = np.linspace(-1, 9, 100)fy = np.polyval(coefficients, fx) plt.plot(fx, fy, '-') plt.plot(x, y, 'ro') plt.show()



#### Least squares polynomial fit



```
12
polyfit.py
                                                     10
import matplotlib.pyplot as plt
import numpy as np
x = 3 * np.random.random(25)
noise = np.random.random(x.size) ** 2
y = 5 * x ** 2 - 12 * x + 7 + 5 * noise
for degree in [1, 2, 5, 10]:
                                                    -2 -
    coefficients = np.polyfit(x, y, degree)
    fx = np.linspace(-1, 4, 100)
    fy = np.polyval(coefficients, fx)
    plt.plot(fx, fy, '-', label="degree %s" % degree)
avg = np.average(y)
plt.plot(x, y, 'ro')
plt.plot([-1, 4], [avg, avg], 'k-', label="average")
plt.ylim(-3, 15)
plt.title('Least squares polynomial fit')
plt.legend()
plt.show()
```

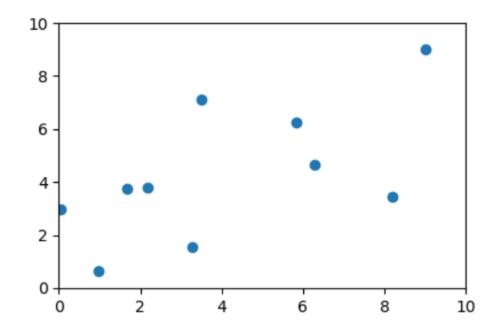


### Animating bouncing balls

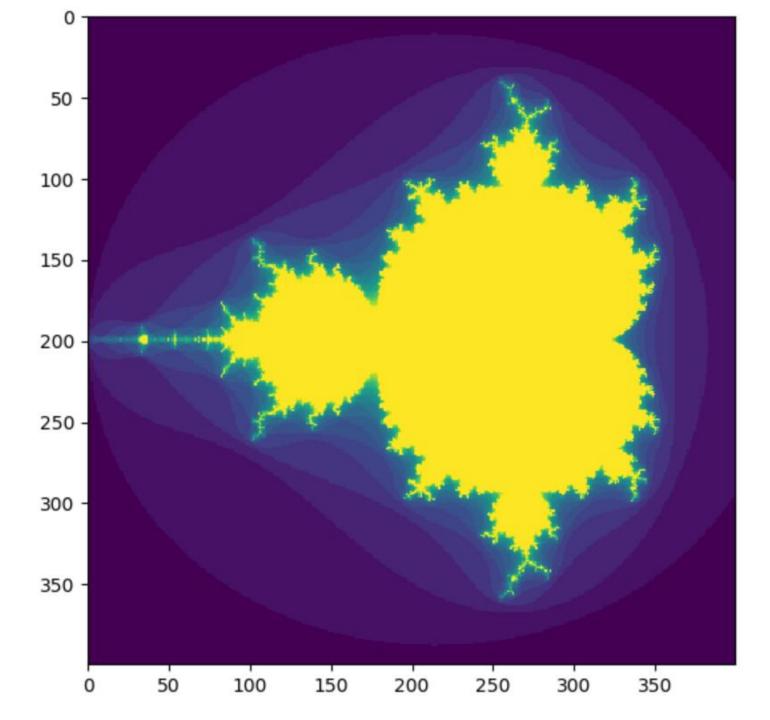
matplotlib figures can be animated using

```
matplotlib.animation.FuncAnimation
```

that as arguments takes the figure to be updated/ redrawn, a function to call for each update, and an interval in milliseconds between updates



```
balls.py
import matplotlib.pyplot as plt
from matplotlib.animation import FuncAnimation
from numpy import zeros, maximum, minimum
from numpy.random import random
q = 0.01
N = 10
x, y = 10.0 * random(N), 1.0 + 9.0 * random(N)
dx, dy = random(N) / 5, zeros(N)
fig = plt.figure()
plt.xlim(0, 10)
plt.ylim(0, 10)
balls, = plt.plot(x, y, 'o') # returns Line2D obj
def move(frame):
    global x, y, dx, dy
    x += dx
    bounce = (x > 10.0) | (x < 0.0) # numpy mask
    dx[bounce] = -dx[bounce]
    x = minimum(10.0, maximum(0.0, x))
    y += dy
    bounce = y < 0.0 # numpy mask
    y[bounce] -= dy[bounce]
    dy[bounce] = -dy[bounce]
    dy -= q
    balls.set data(x, y) # update positions
# removing 'ani =' causes program to fail...
ani = FuncAnimation(fig, move, interval=25)
plt.show()
```



```
mandelbrot.py
import numpy as np
import matplotlib.pyplot as plt
def mandelbrot(h, w, maxit=20):
    '''Returns an image of the Mandelbrot fractal of size (h, w).'''
    x = np.linspace(-2.0, 0.8, w).reshape(1, w) # row vector
    y = np.linspace(-1.4, 1.4, h).reshape(h, 1) # column vector
    c = x + v * 1i
                                                 # broadcast & complex
    z = c
    divtime = np.full(z.shape, maxit, dtype=int) # all values = maxit
    for i in range (maxit):
        z = z * z + c
                                                 # elementwise
        diverge = z * np.conj(z) > 4
                                      # who is diverging
        div now = diverge & (divtime == maxit) # who is diverging now
        divtime[div now] = i
                                                 # note when
        z[diverge] = 0
                                                 # limit divergence
    return divtime
                                                 # (avoids overflows)
plt.imshow(mandelbrot(400, 400))
plt.show()
```