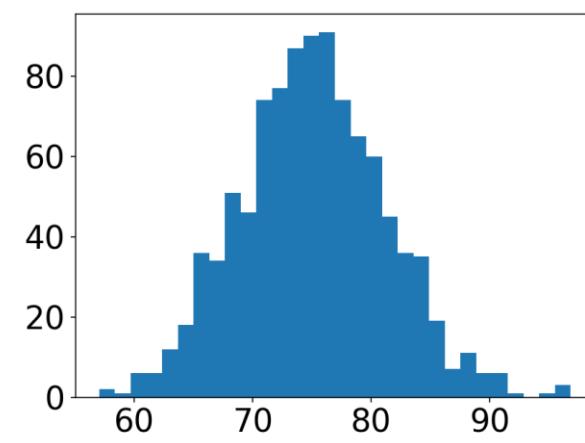
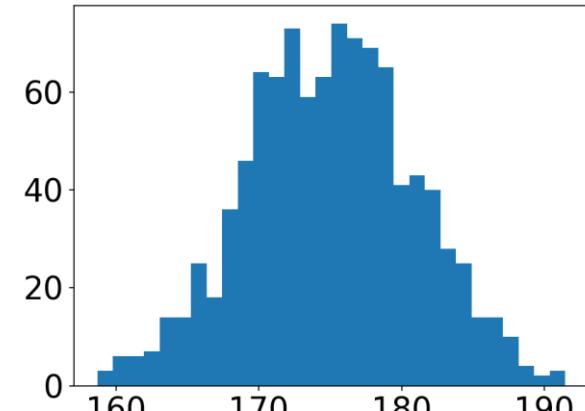
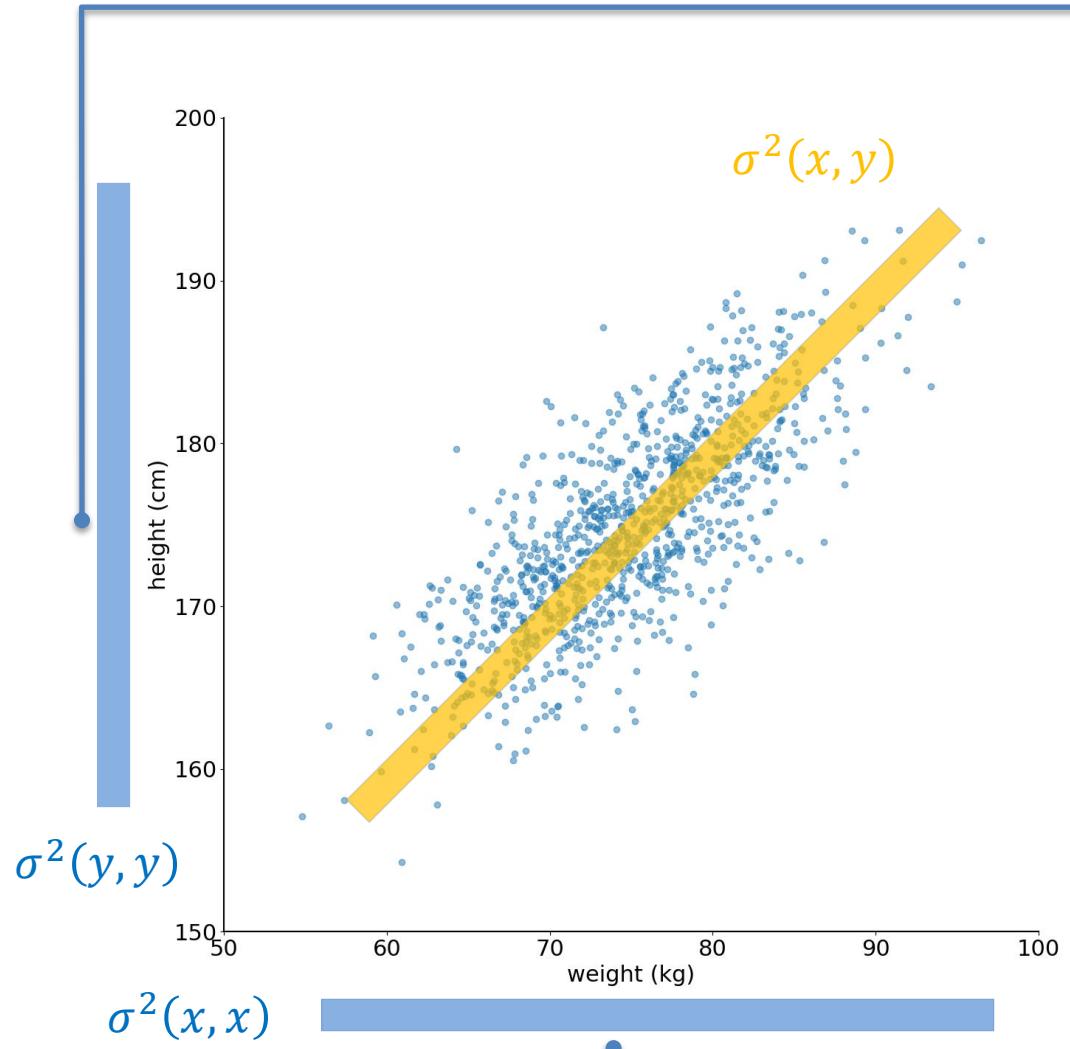


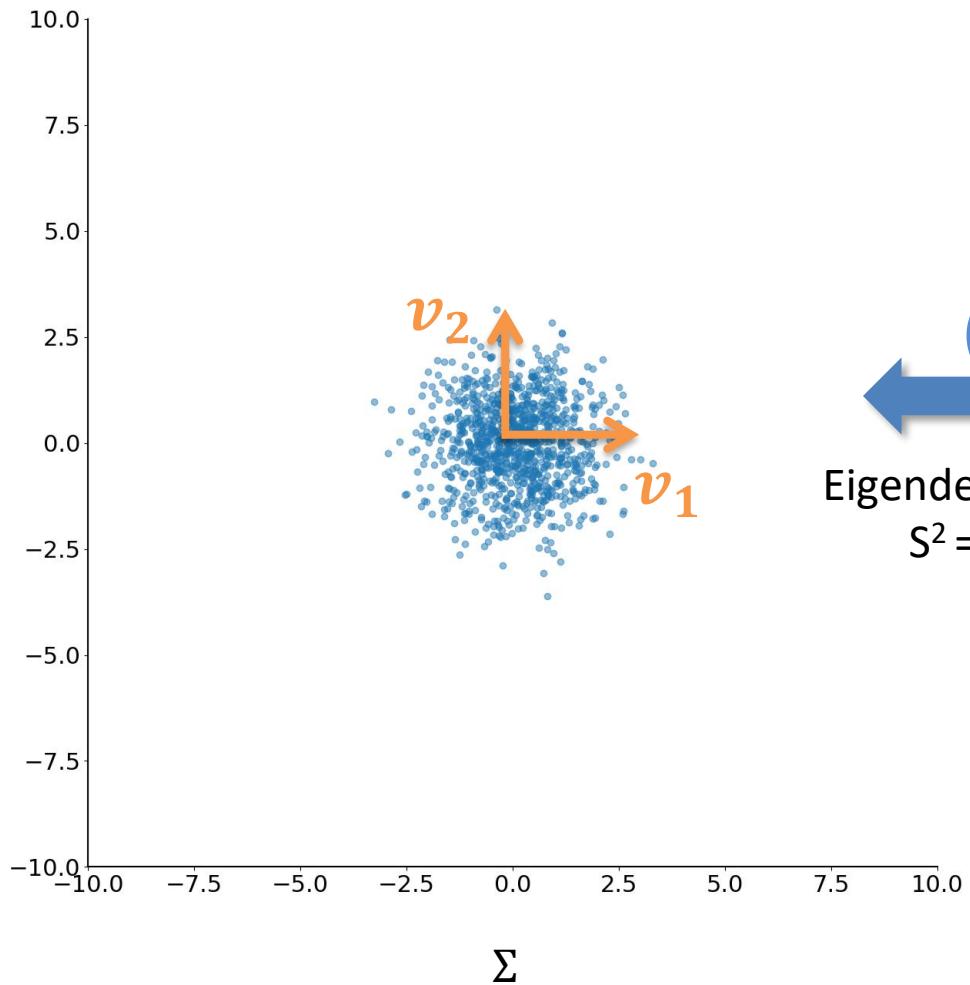
PFE 6

Dr W Palubicki

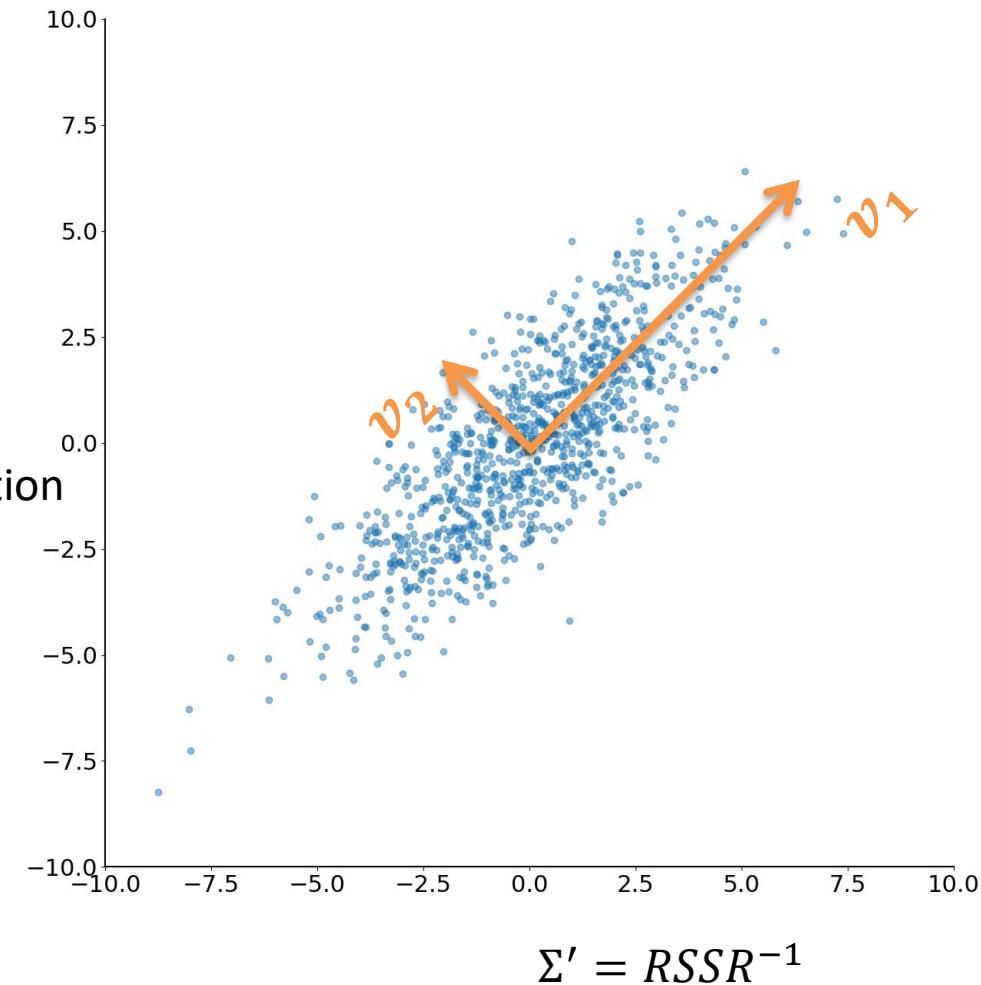
Covariance



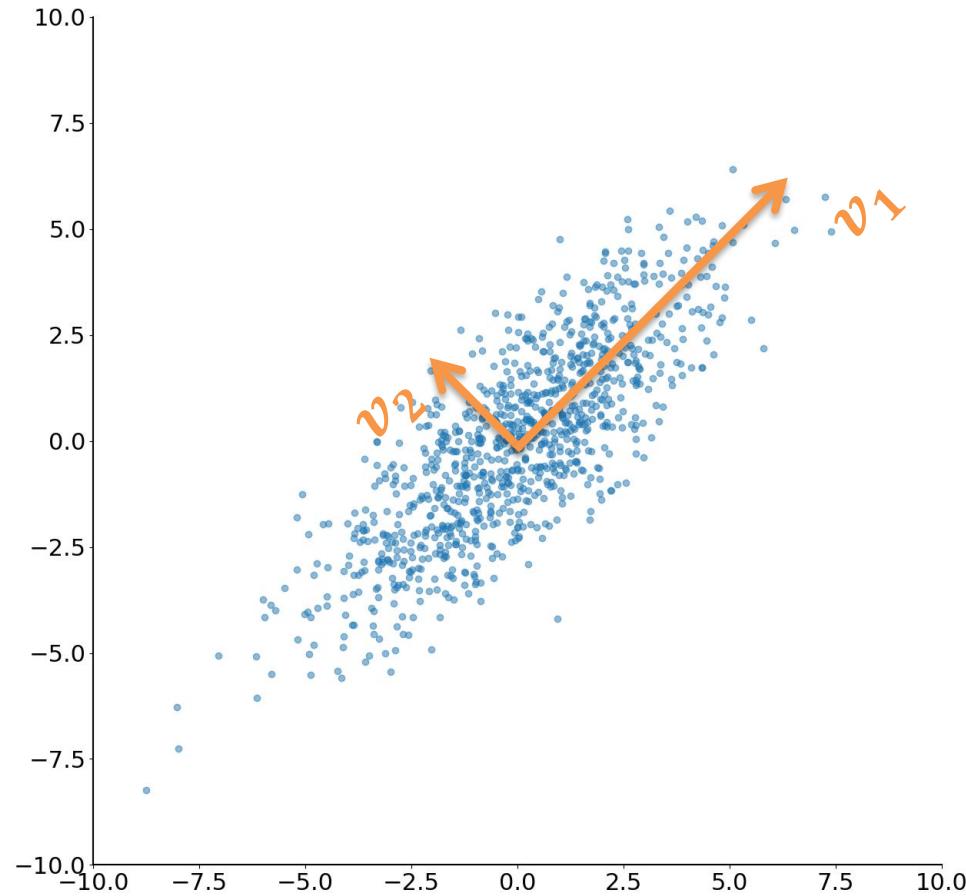
Covariance as Linear Transformations



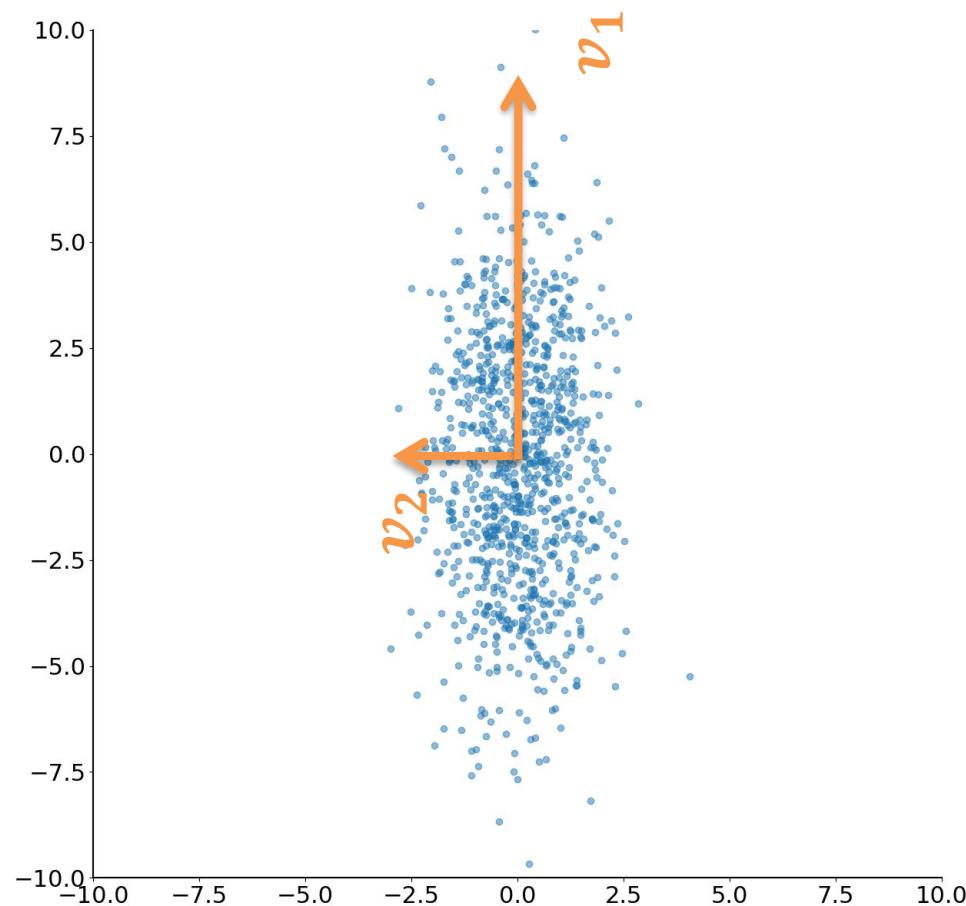
Eigendecomposition
 $S^2 = L, R = V$



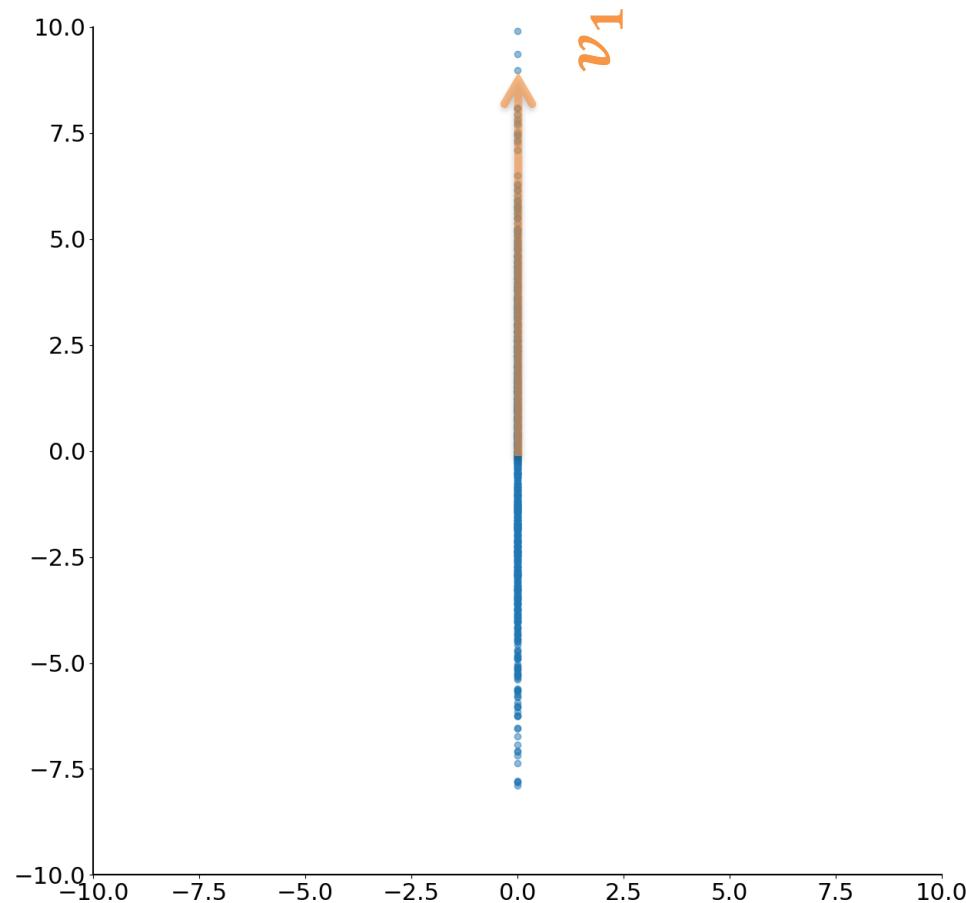
Dimensionality Reduction



Dimensionality Reduction

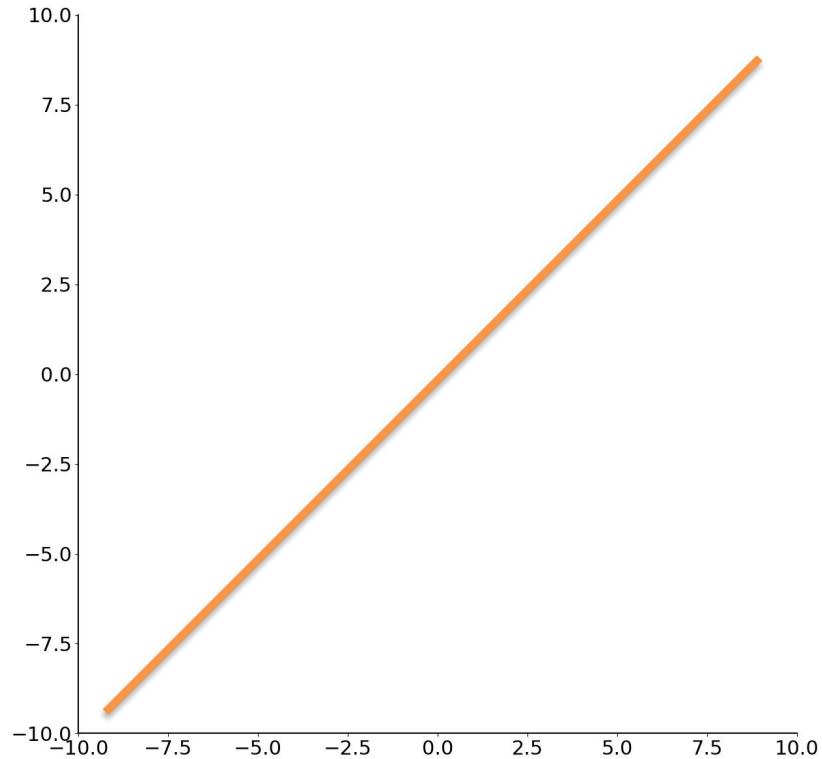


Dimensionality Reduction



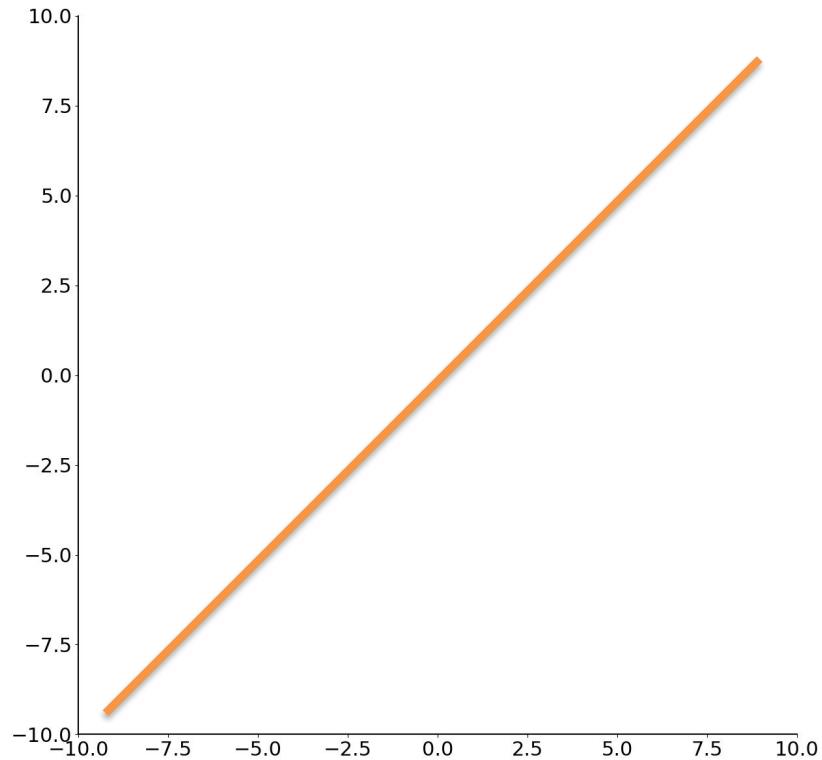
Projection of data on largest eigenvector

Data Model

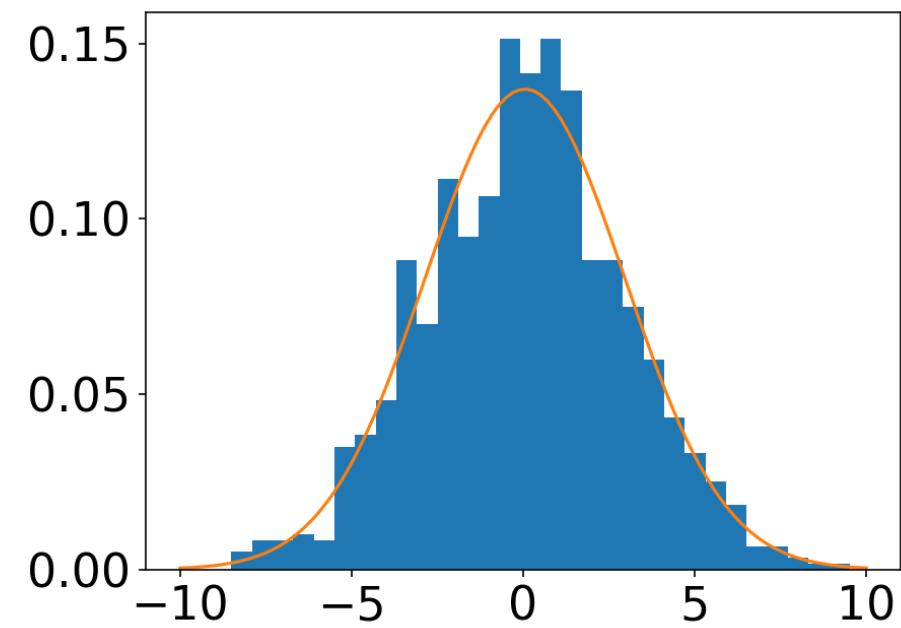


gradient = 1, offset = 0

Data Model

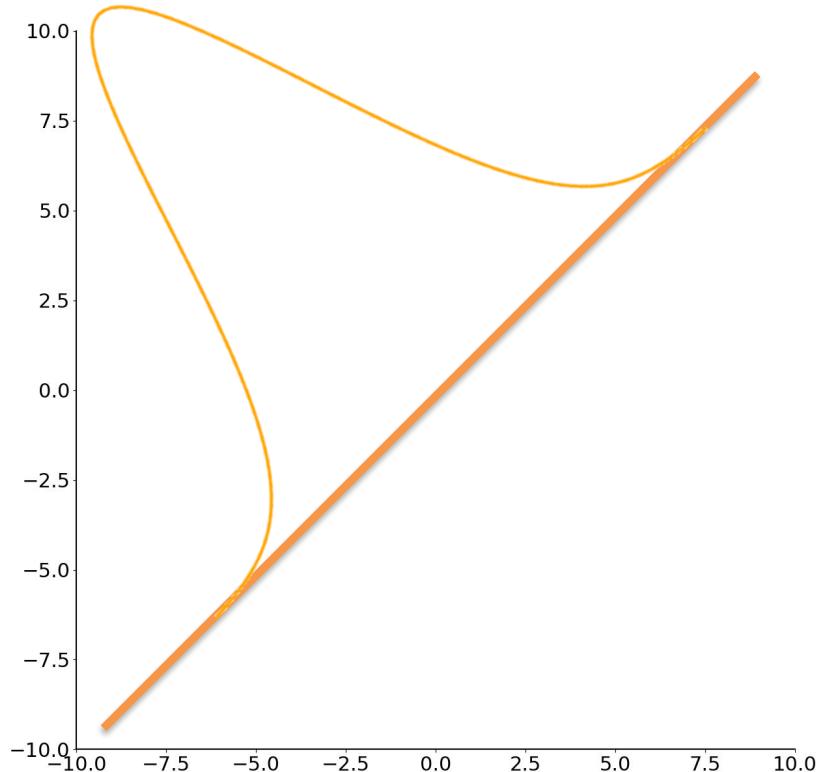


gradient = 1, offset = 0

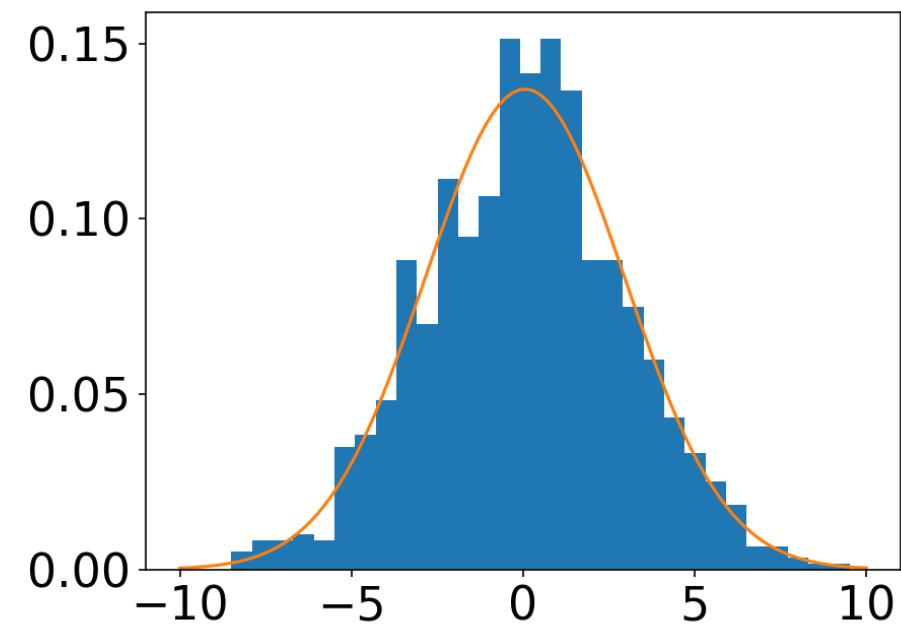


mu = 0.05, sigma = 2.91

Data Model



gradient = 1, offset = 0

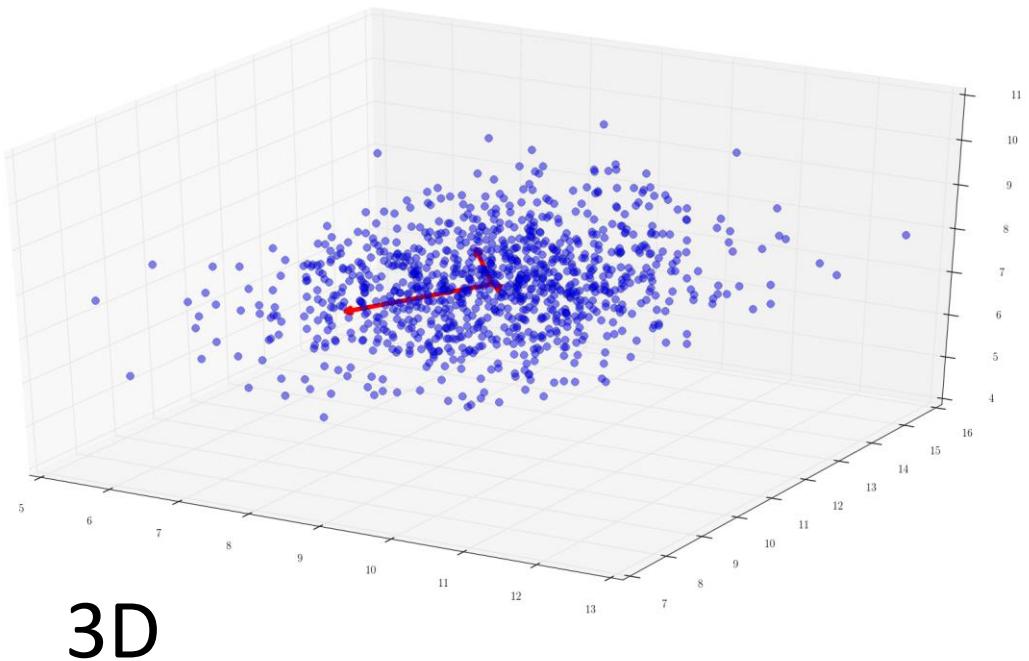


mu = 0.05, sigma = 2.91

Describe data set of 2000 points with just 4 numbers!

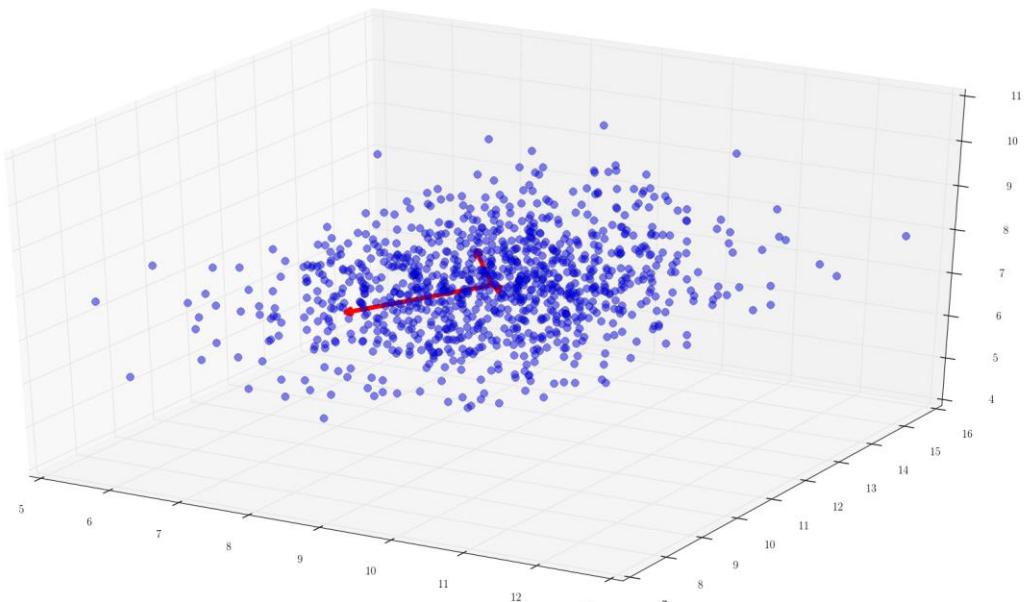
Principal component analysis (PCA)

- Reduce dimensions of data sample by projecting onto a lower dimension (while preserving the high variance information)

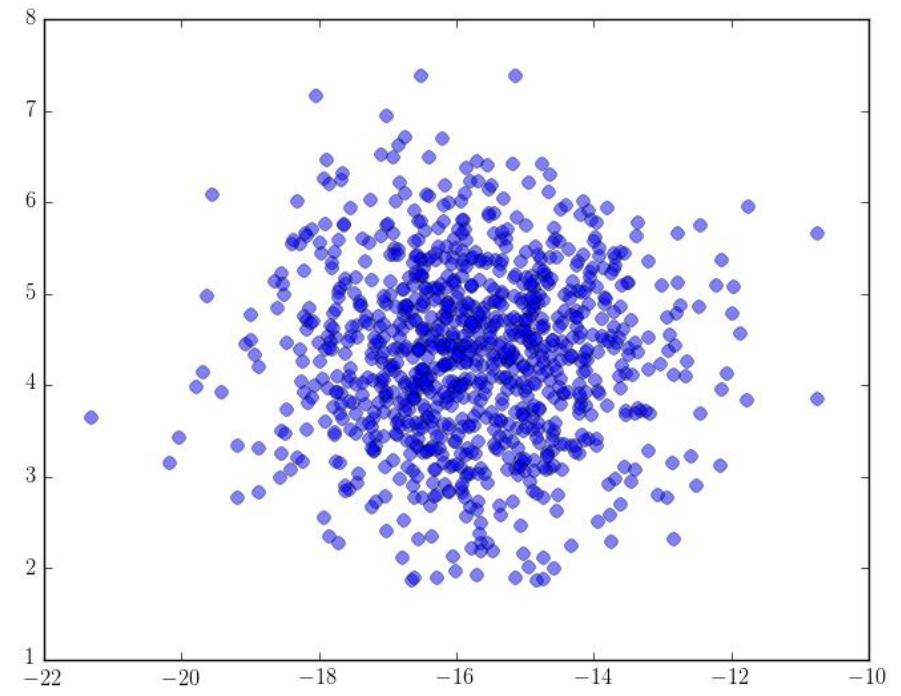


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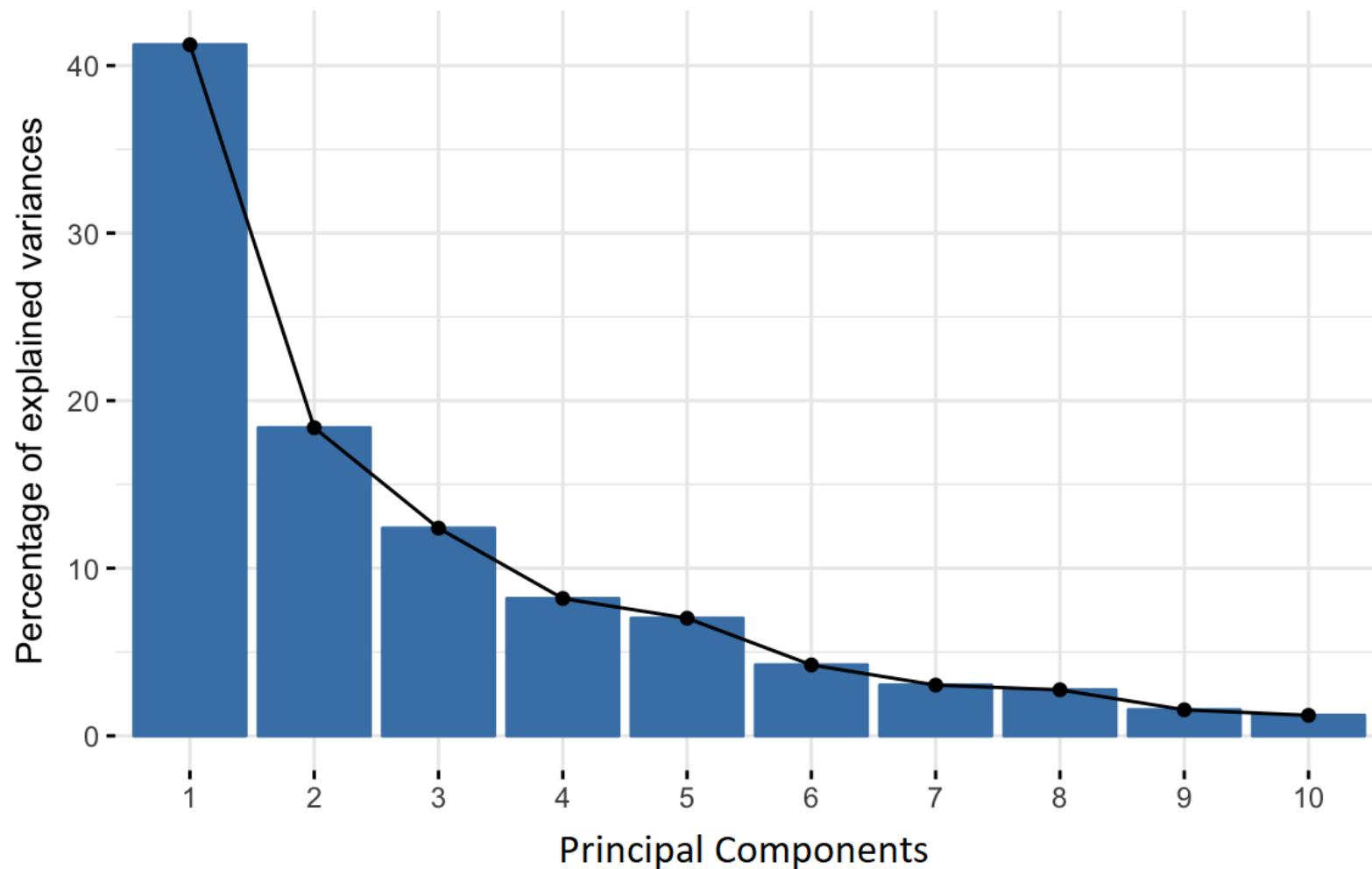


3D



2D

10-Dimensional case



PCA Algorithm

- **Input:** Data X of sample size N
- **Output:** k principal components
- **Centering:** Subtract mean from data
- **Scaling:** Scale each dimension by its variance
- Compute **covariance matrix** C
- Compute k largest **eigenvectors** of C (alternatively calculate **SVD**)

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- Compute **covariance matrix** C
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Describes only linear relations in data set!

sklearn.decomposition.PCA

```
class sklearn.decomposition.PCA(n_components=None, copy=True, whiten=False, svd_solver='auto', tol=0.0,  
                                 iterated_power='auto', random_state=None)
```

[\[source\]](#)

Principal component analysis (PCA)

Linear dimensionality reduction using Singular Value Decomposition of the data to project it to a lower dimensional space.

It uses the LAPACK implementation of the full SVD or a randomized truncated SVD by the method of Halko et al. 2009, depending on the shape of the input data and the number of components to extract.

It can also use the `scipy.sparse.linalg` ARPACK implementation of the truncated SVD.

Notice that this class does not support sparse input. See [TruncatedSVD](#) for an alternative with sparse data.

Read more in the [User Guide](#).

Parameters:

`n_components : int, float, None or string`

Number of components to keep. if `n_components` is not set all components are kept:

```
n_components == min(n_samples, n_features)
```

If `n_components == 'mle'` and `svd_solver == 'full'`, Minka's MLE is used to guess the dimension. Use of `n_components == 'mle'` will interpret `svd_solver == 'auto'` as `svd_solver == 'full'`.

If `0 < n_components < 1` and `svd_solver == 'full'`, select the number of components such that the amount of variance that needs to be explained is greater than the percentage specified by `n_components`.

If `svd_solver == 'arpack'`, the number of components must be strictly less than the minimum

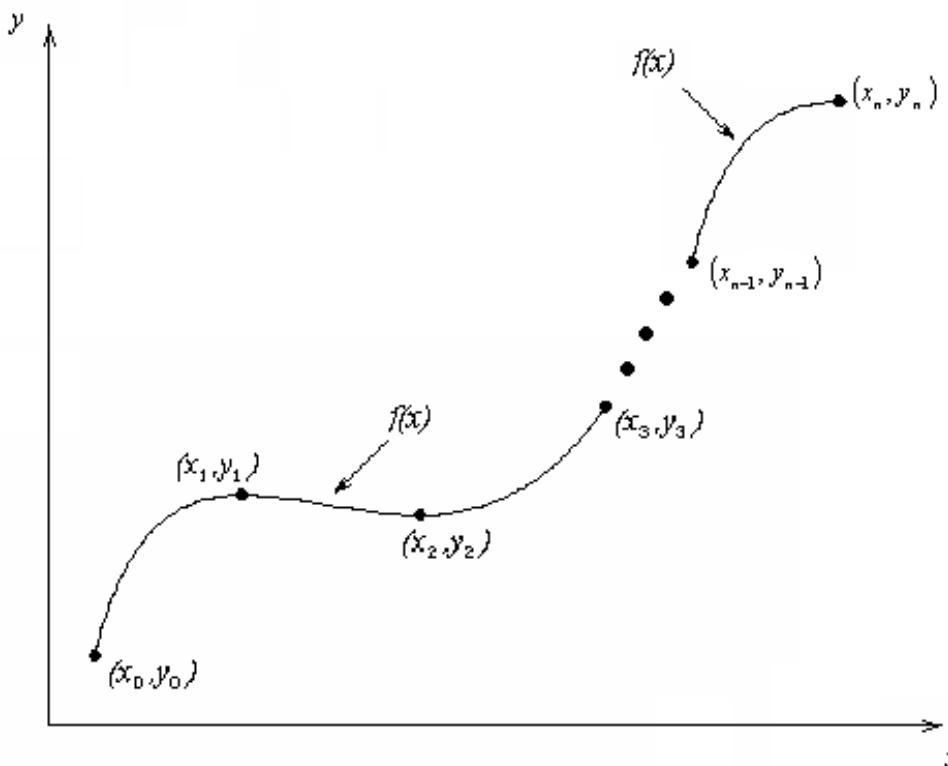
Overview – Next Topics

- **Interpolation**
- **Statistics**
- **Differential equations**
- **Modeling of real world patterns (in 3D)**

What is interpolation?

What is interpolation?

- For given points $(x_0, y_0), (x_1, y_1), \dots (x_n, y_n)$ find new points within the range of the given points, e.g. via a function f



Interpolation of images



low-resolution
image (100×100)



high-resolution
image (400×400)

Color interpolation

Original pixel locations

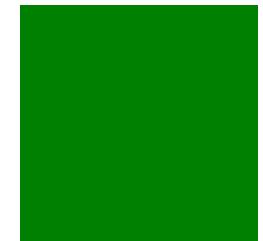


scale →

Scaled pixel locations



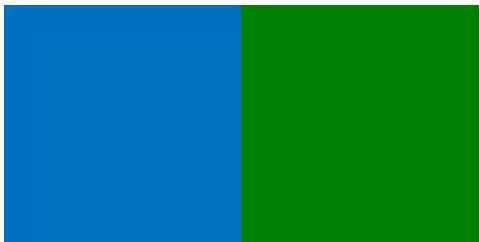
(R_1, G_1, B_1)



(R_4, G_4, B_4)

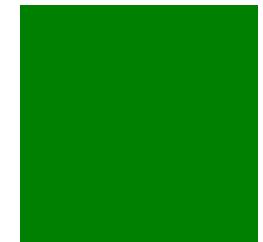
Color interpolation

Original pixel locations



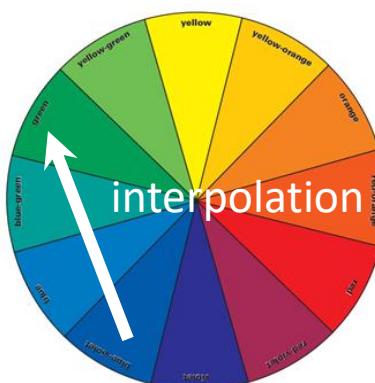
scale →

Scaled pixel locations



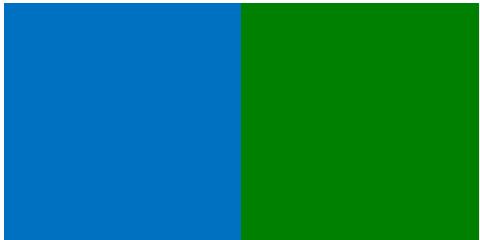
(R₁, G₁, B₁)

(R₄, G₄, B₄)



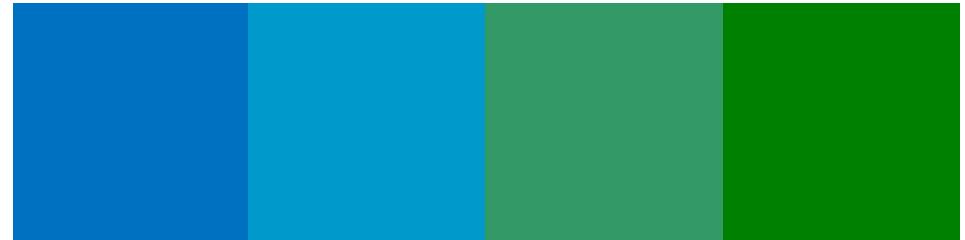
Color interpolation

Original pixel locations

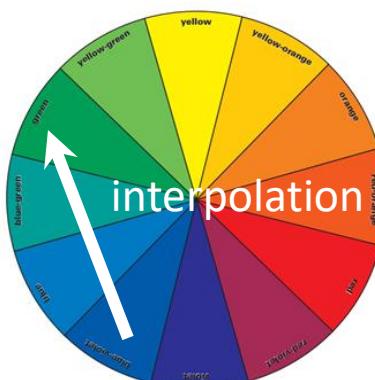


scale →

Scaled pixel locations



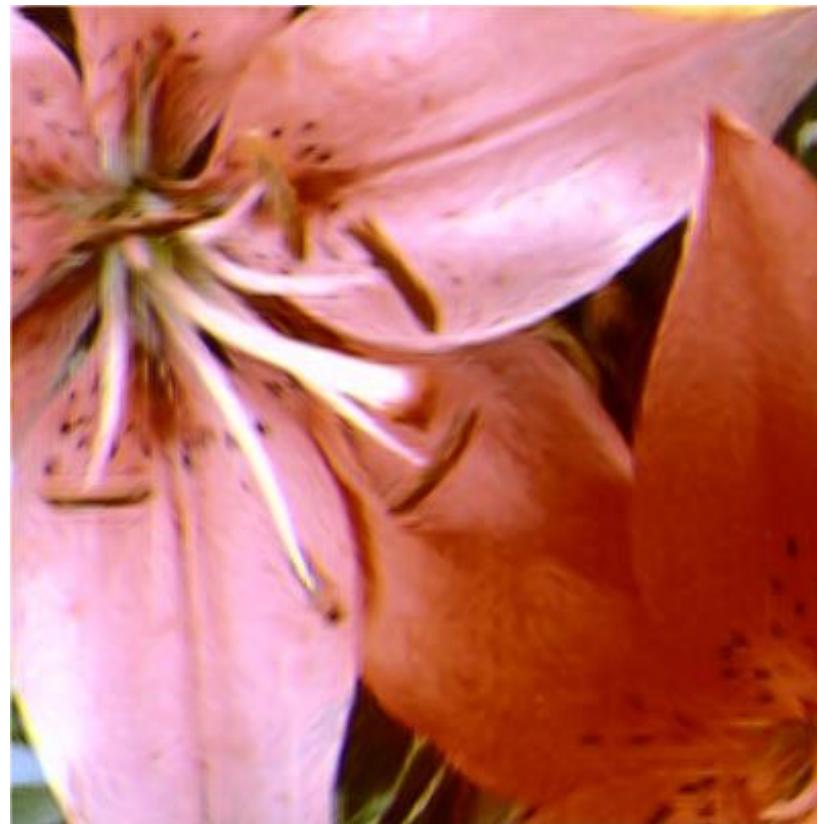
(R_1, G_1, B_1) (R_2, G_2, B_2) (R_3, G_3, B_3) (R_4, G_4, B_4)



Edge-directed interpolation (Li&Orchard'2000)



low-resolution
image (100×100)



high-resolution
image (400×400)

Coloring of images



<http://www.cs.huji.ac.il/~yweiss/Colorization/>

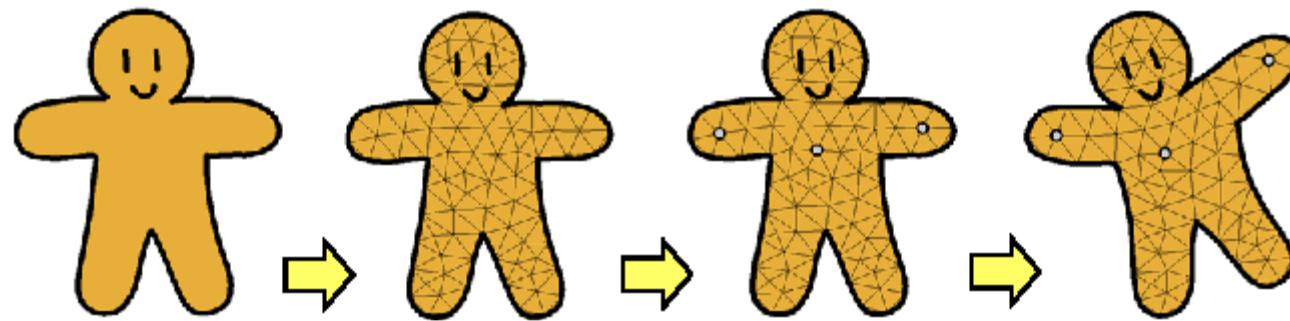
Shape interpolation



http://www.cs.tau.ac.il/~dcor/online_papers/papers/arap.pdf

<https://en.wikipedia.org/wiki/Morphing>

Shape interpolation

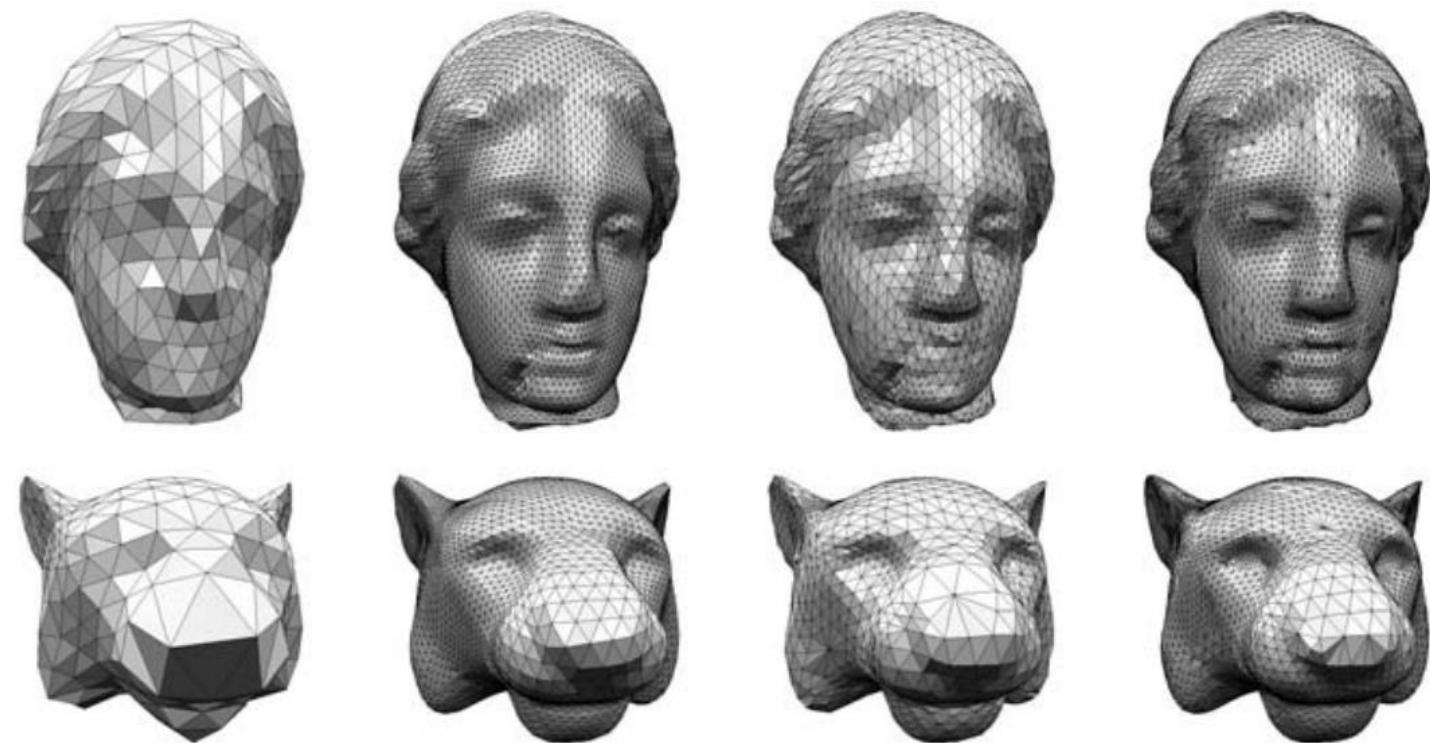
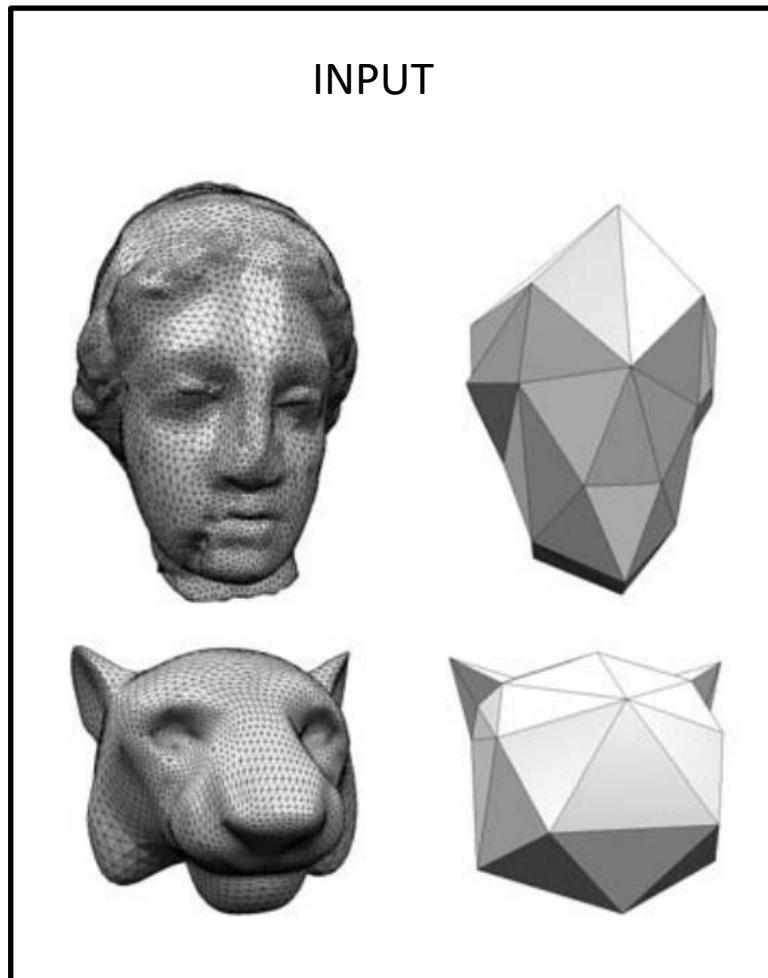


Find outline

Create vertex mesh

Interpolate on meshes

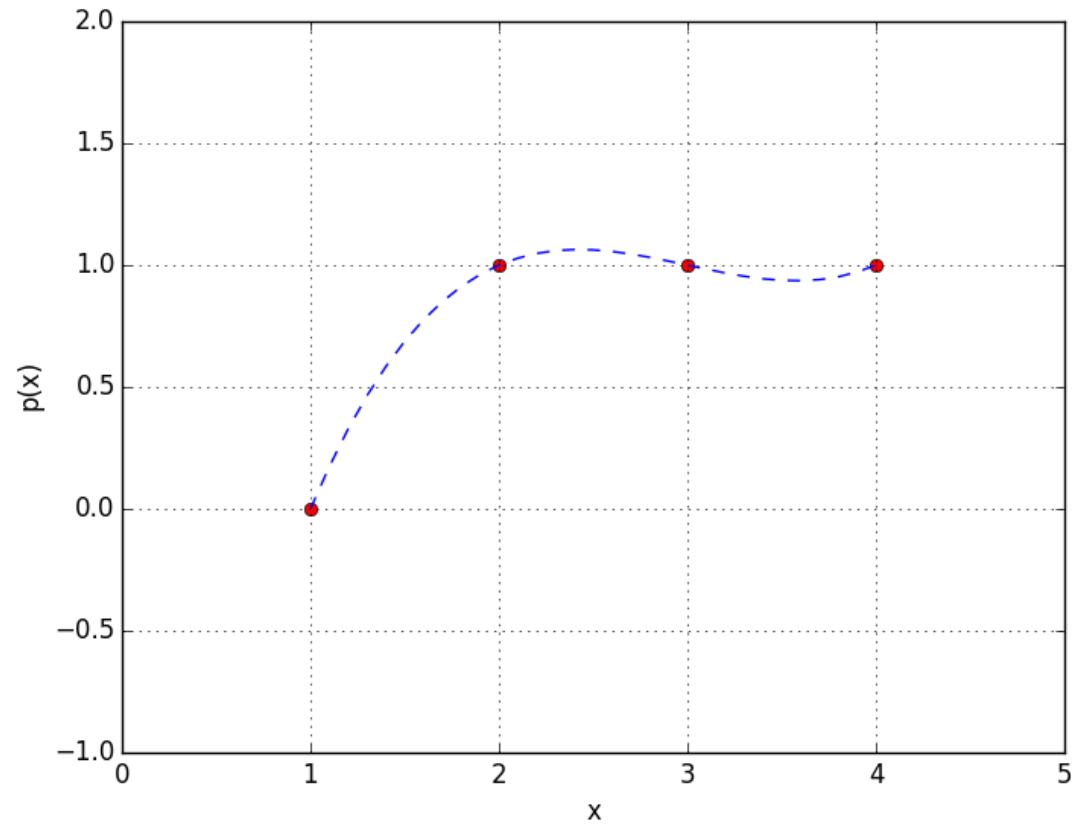
Multi-scale resolution



Lagrange Interpolation

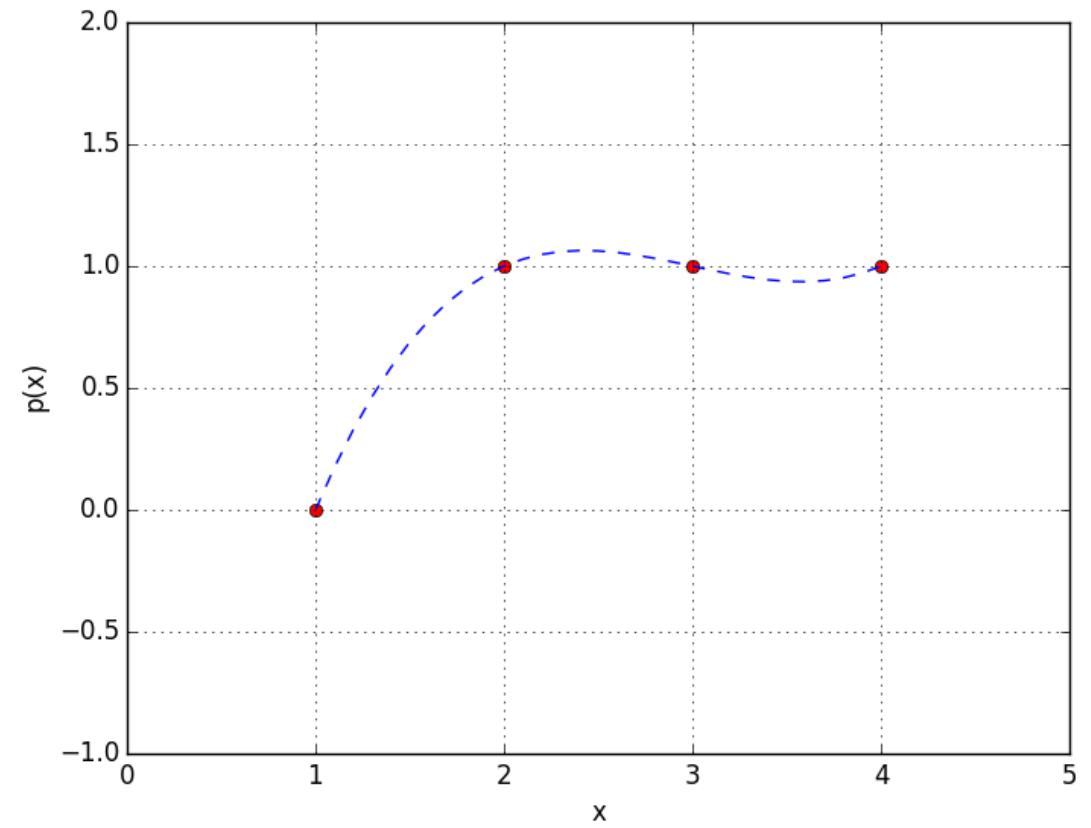
Idea: Create a polynomial basis function for each point that is 1 at that position along the x-axis and 0 at the x-positions of all other points. Then add and scale them together to obtain a polynomial that exactly goes through the specified points.

Example points: (1,0), (2,1), (3,1), (4,1)



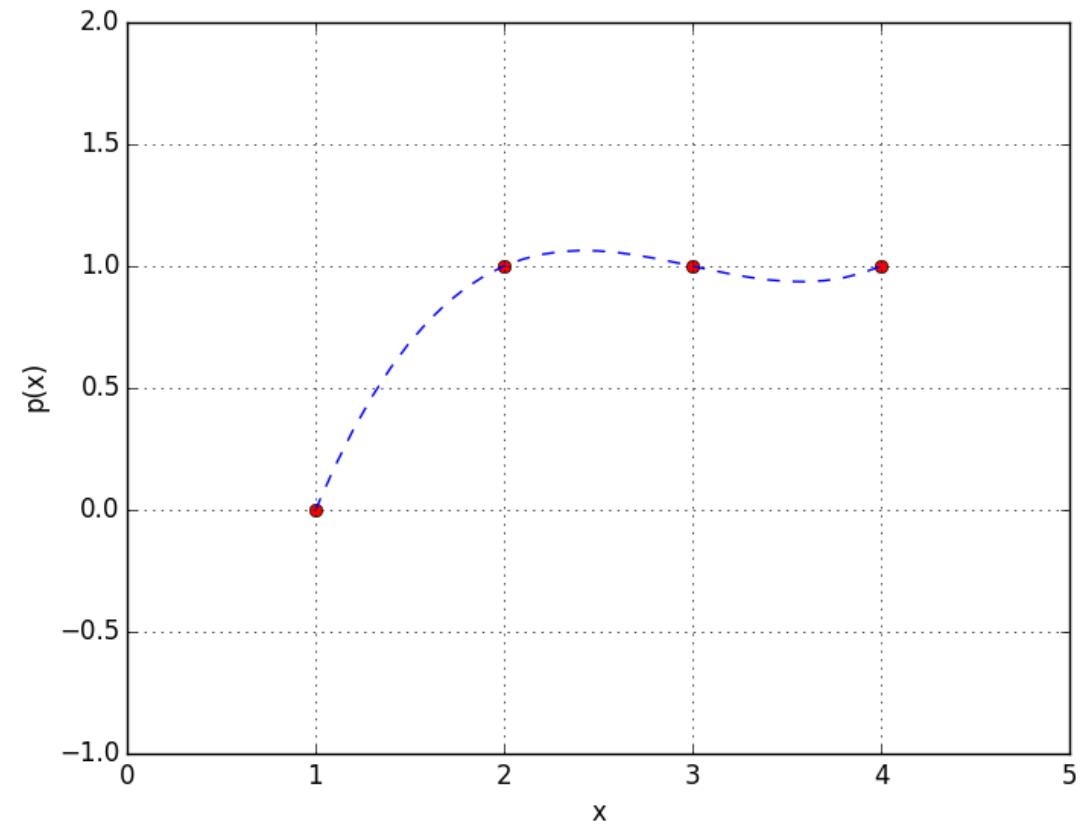
Lagrange Interpolation

$$(x - 2)(x - 3)(x - 4)$$



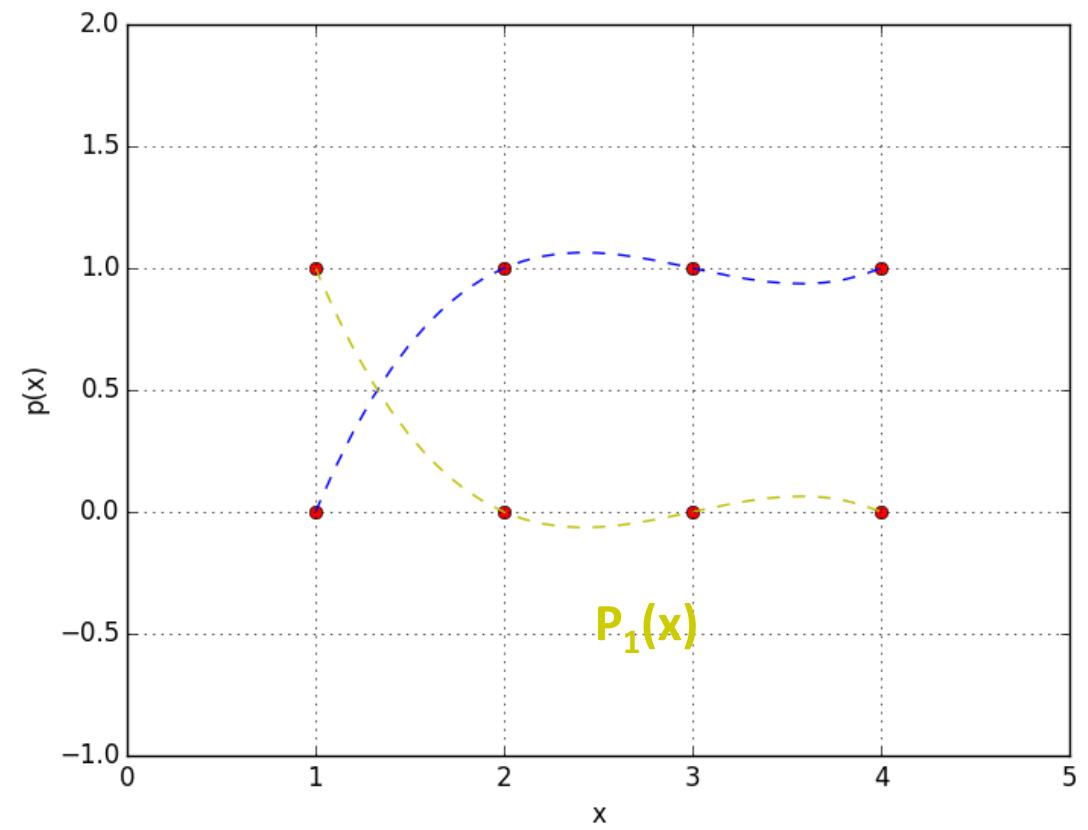
Lagrange Interpolation

$$\frac{(x - 2)(x - 3)(x - 4)}{(1 - 2)(1 - 3)(1 - 4)}$$



Lagrange Interpolation

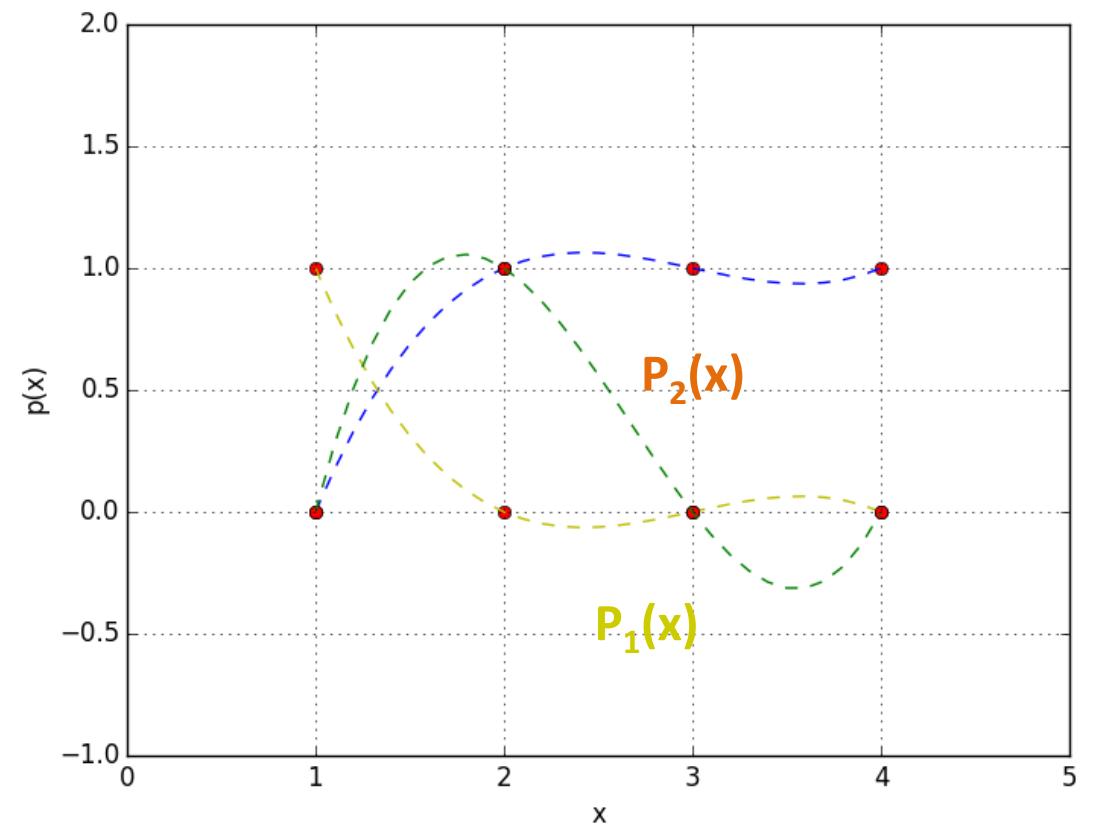
$$P_1(x) = \frac{(x - 2)(x - 3)(x - 4)}{(1 - 2)(1 - 3)(1 - 4)}$$



Lagrange Interpolation

$$P_1(x) = \frac{(x - 2)(x - 3)(x - 4)}{(1 - 2)(1 - 3)(1 - 4)}$$

$$P_2(x) = \frac{(x - 1)(x - 3)(x - 4)}{(2 - 1)(2 - 3)(2 - 4)}$$

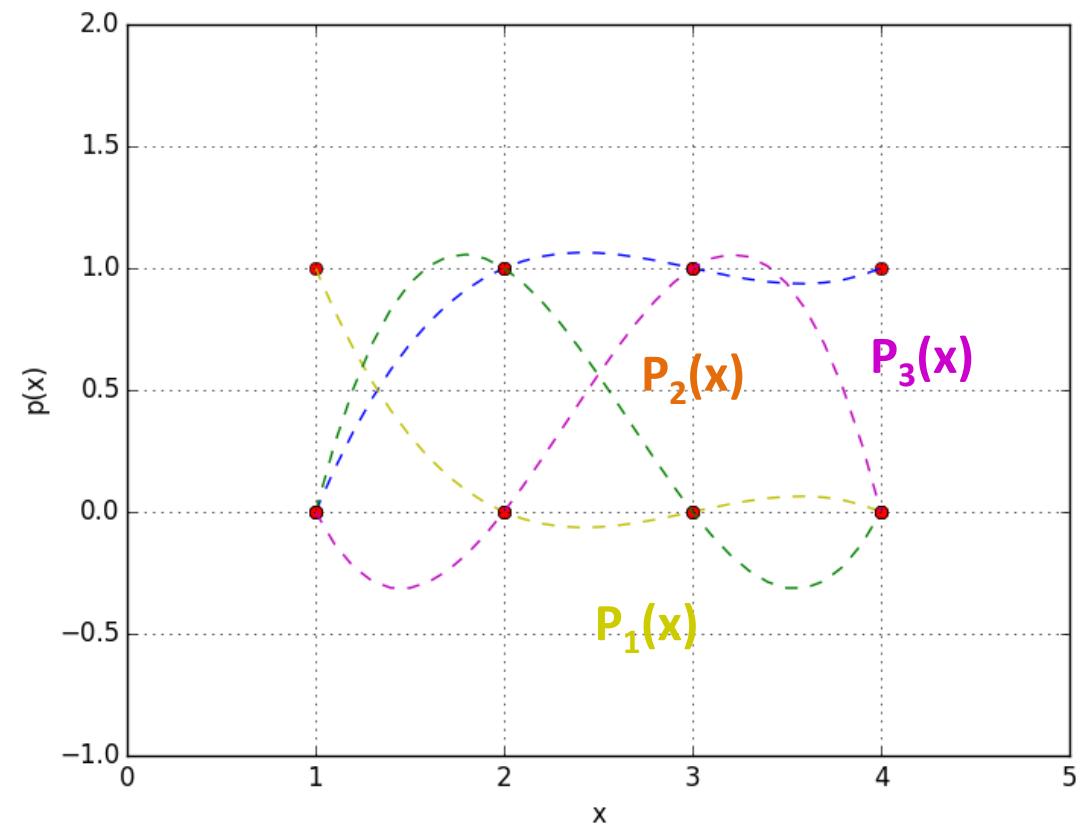


Lagrange Interpolation

$$P_1(x) = \frac{(x - 2)(x - 3)(x - 4)}{(1 - 2)(1 - 3)(1 - 4)}$$

$$P_2(x) = \frac{(x - 1)(x - 3)(x - 4)}{(2 - 1)(2 - 3)(2 - 4)}$$

$$P_3(x) = \frac{(x - 1)(x - 2)(x - 4)}{(3 - 1)(3 - 2)(3 - 4)}$$



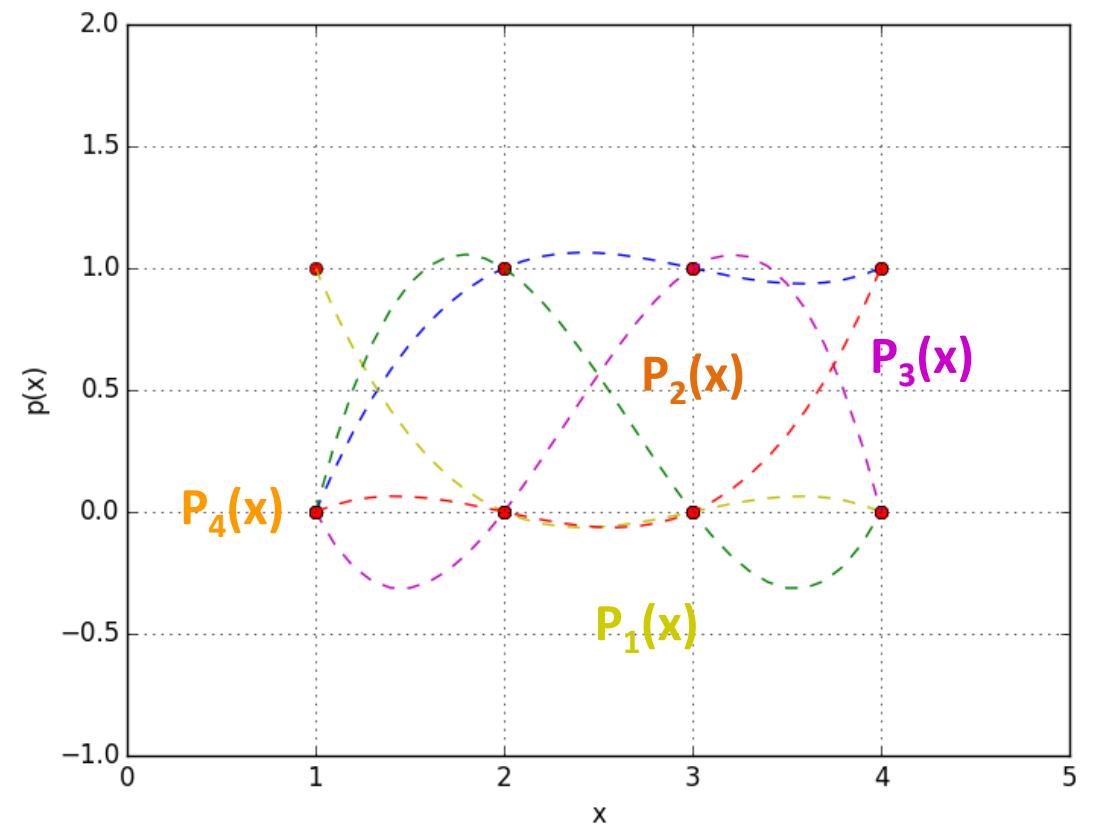
Lagrange Interpolation

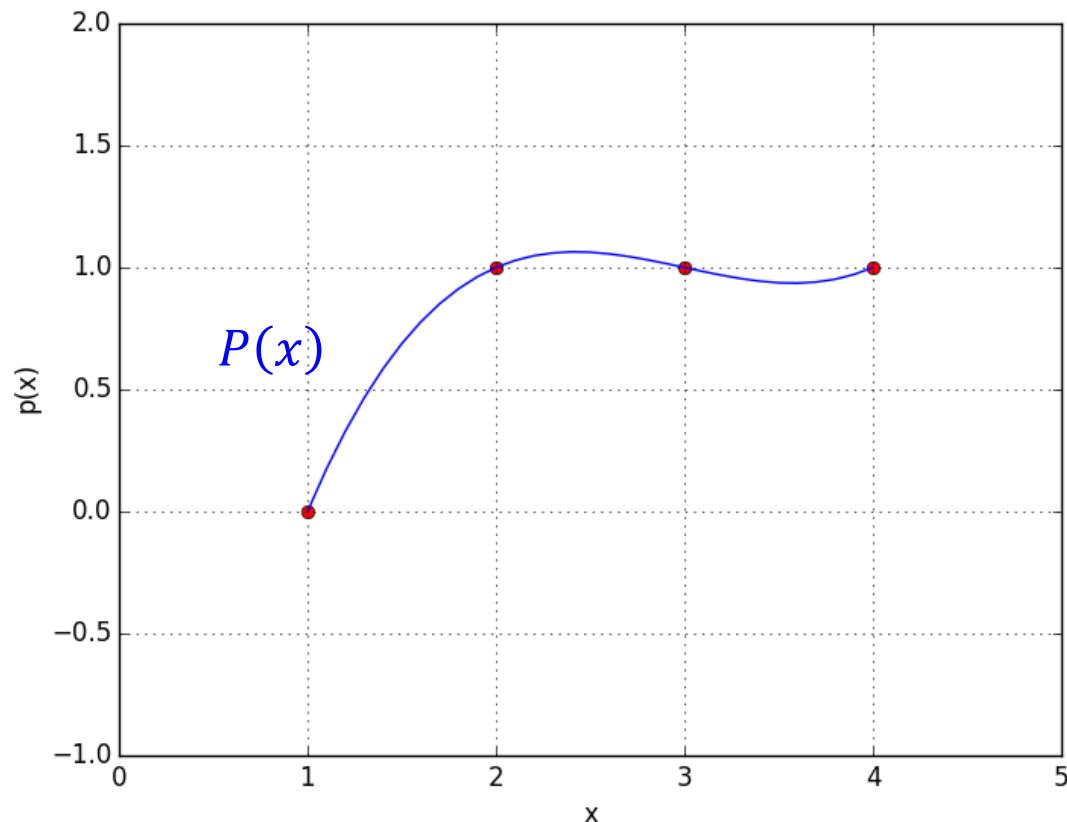
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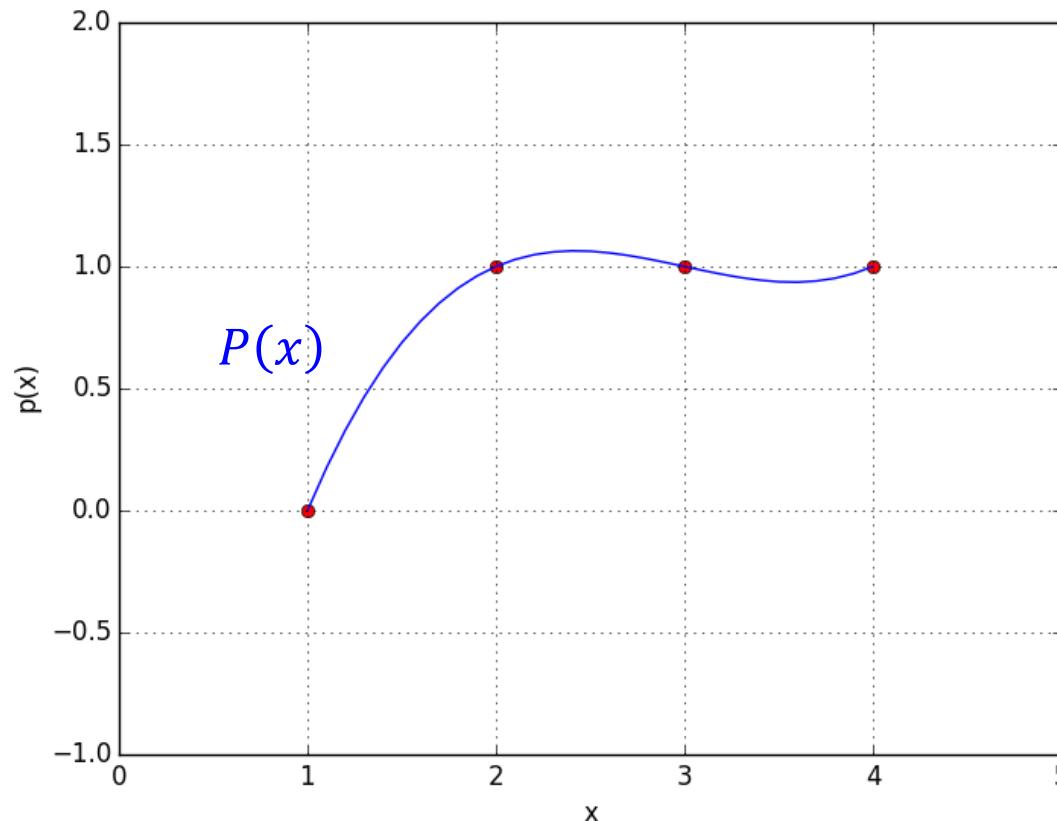
$$P_3(x) = \frac{(x - 1)(x - 2)(x - 4)}{(3 - 1)(3 - 2)(3 - 4)}$$

$$P_4(x) = \frac{(x - 1)(x - 2)(x - 3)}{(4 - 1)(4 - 2)(4 - 3)}$$

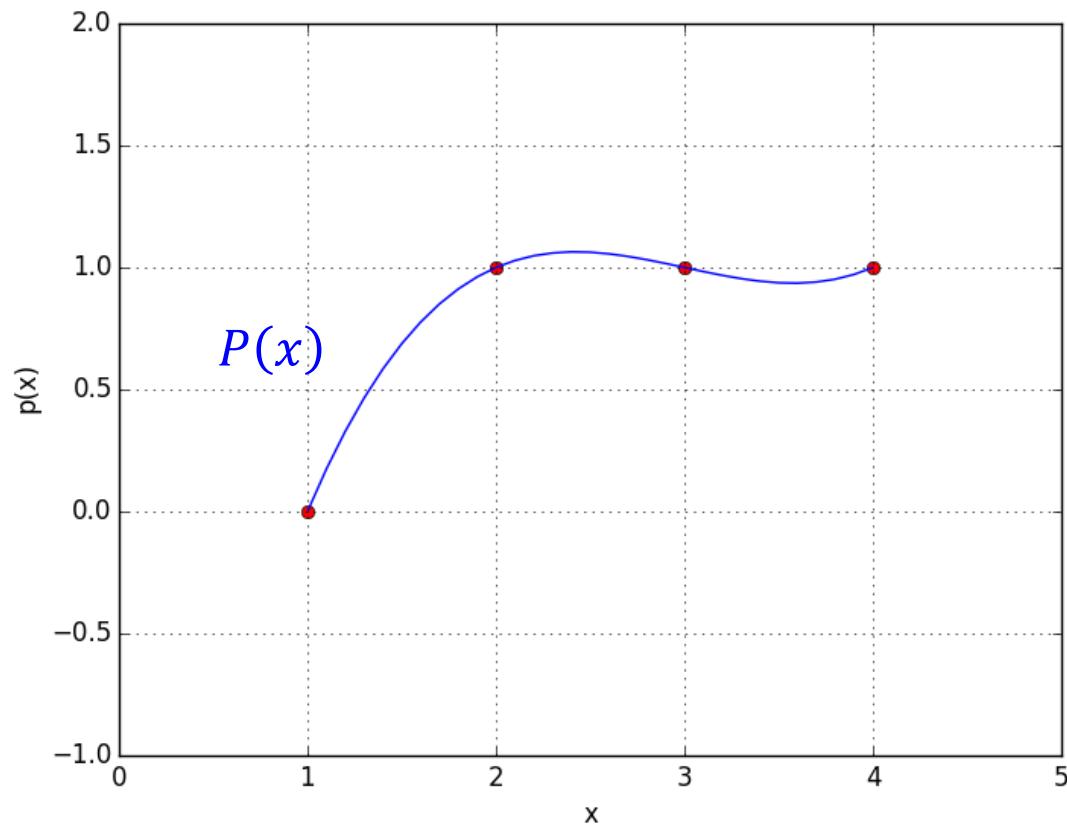




$$P(x) = 0 \cdot P_1(x) + 1 \cdot P_2(x) + 1 \cdot P_3(x) + 1 \cdot P_4(x)$$



$$\begin{aligned}P(x) &= 0 \cdot P_1(x) + 1 \cdot P_2(x) + 1 \cdot P_3(x) + 1 \cdot P_4(x) = \\&= -3 + \frac{13}{3}x - \frac{3}{2}x^2 + \frac{1}{6}x^3\end{aligned}$$



$$P(x) = -3 + \frac{13}{3}x - \frac{3}{2}x^2 + \frac{1}{6}x^3$$

Polynomial Interpolation

$$y = a_0 + a_1x^1 + a_2x^2 + \cdots + a_{n-1}x^{n-1}$$

Polynomial Interpolation

$$a_0 + a_1x_0 + a_2x_0^2 + \cdots + a_{n-1}x_0^{n-1} + a_nx_0^n = y_0$$

$$a_0 + a_1x_1 + a_2x_1^2 + \cdots + a_{n-1}x_1^{n-1} + a_nx_1^n = y_1$$

⋮

$$a_0 + a_1x_n + a_2x_n^2 + \cdots + a_{n-1}x_n^{n-1} + a_nx_n^n = y_n$$

Vandermonde Matrix

$$\begin{bmatrix} x_0^n & x_0^{n-1} & x_0^{n-2} & \dots & x_0 & 1 \\ x_1^n & x_1^{n-1} & x_1^{n-2} & \dots & x_1 & 1 \\ \vdots & \vdots & \vdots & & \vdots & \vdots \\ x_n^n & x_n^{n-1} & x_n^{n-2} & \dots & x_n & 1 \end{bmatrix} \begin{bmatrix} a_n \\ a_{n-1} \\ \vdots \\ a_0 \end{bmatrix} = \begin{bmatrix} y_0 \\ y_1 \\ \vdots \\ y_n \end{bmatrix}$$

Polynomial interpolation

numpy.polynomial.polynomial.polyvander

`numpy.polynomial.polynomial. polyvander(x, deg)`

[source]

Vandermonde matrix of given degree.

Returns the Vandermonde matrix of degree *deg* and sample points *x*. The Vandermonde matrix is defined by

$$V[..., i] = x^i,$$

where $0 \leq i \leq \text{deg}$. The leading indices of *V* index the elements of *x* and the last index is the power of *x*.

If *c* is a 1-D array of coefficients of length *n* + 1 and *V* is the matrix `v = polyvander(x, n)`, then `np.dot(v, c)` and `polyval(x, c)` are the same up to roundoff. This equivalence is useful both for least squares fitting and for the evaluation of a large number of polynomials of the same degree and sample points.

Parameters: `x : array_like`

Array of points. The dtype is converted to float64 or complex128 depending on whether any of the elements are complex. If *x* is scalar it is converted to a 1-D array.

`deg : int`

Degree of the resulting matrix.

Returns: `vander : ndarray`

The Vandermonde matrix. The shape of the returned matrix is `x.shape + (deg + 1,)`, where the last index is the power of *x*. The dtype will be the same as the converted *x*.

See also:

`polyvander2d`, `polyvander3d`

numpy.poly1d¶

class numpy.poly1d(c_or_r, r=0, variable=None)

[\[source\]](#)

A one-dimensional polynomial class.

A convenience class, used to encapsulate “natural” operations on polynomials so that said operations may take on their customary form in code (see Examples).

```
In [5]: p = np.poly1d([1,2,3])
```

```
In [6]: print np.poly1d(p)
      2
1 x + 2 x + 3
```

- Arithmetic operations (+,-,/,*) work on polynomials

numpy.poly1d¶

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```
In [7]: p(1)
Out[7]: 6
```

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```
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```

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```
In [9]: p(1.5)
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```
In [10]: print p.deriv(m=1)
      2
2 x + 2
```

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`class numpy.poly1d(c_or_r, r=0, variable=None)`

[\[source\]](#)

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```
In [10]: print p.deriv(m=1)
      2
2 x + 2
```

```
In [11]: print p.integ(m=2)
      4      3      2
0.08333 x + 0.3333 x + 1.5 x
```

numpy.poly1d¶

`class numpy.poly1d(c_or_r, r=0, variable=None)`

[\[source\]](#)

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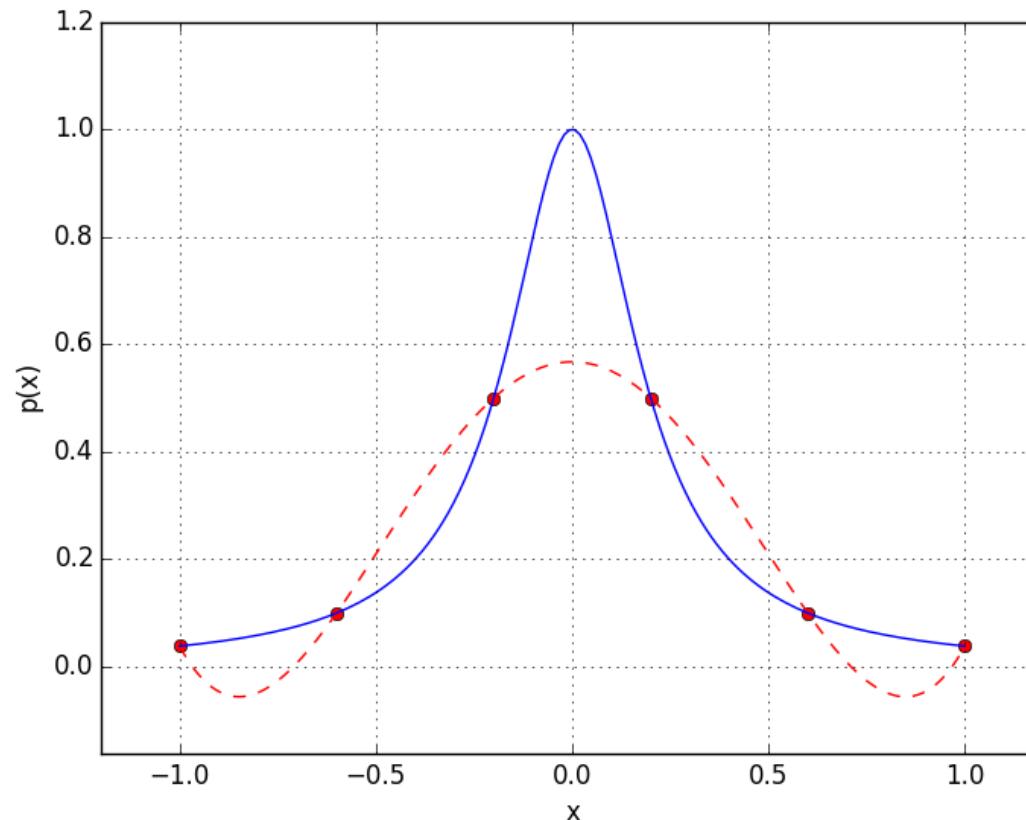
```
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2 x + 2
```

```
In [11]: print p.integ(m=2)
      4      3      2
0.08333 x + 0.3333 x + 1.5 x
```

```
In [12]: print p.roots
[-1.+1.41421356j -1.-1.41421356j]
```

Example Lagrange

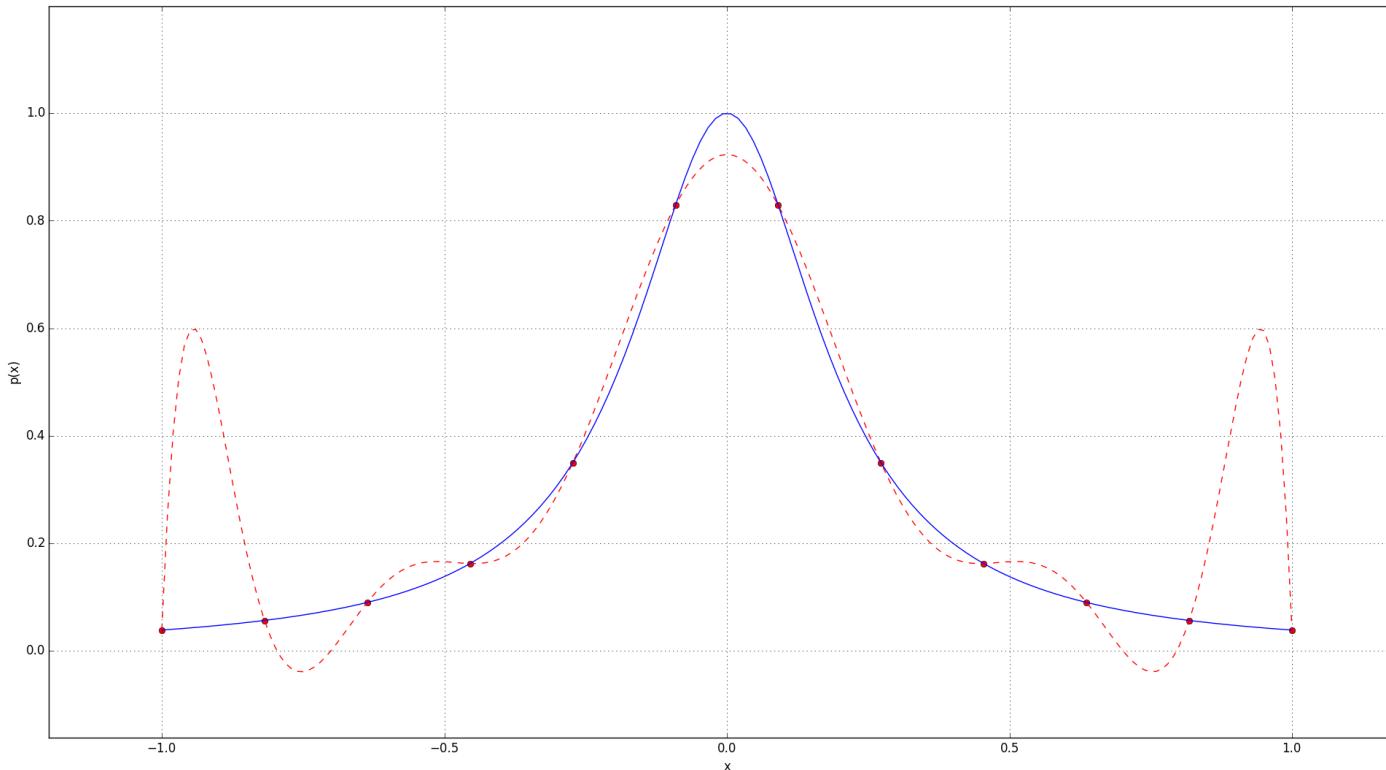
$$f(x) = \frac{1}{1 + 25x^2}$$



6 points

Overfitting

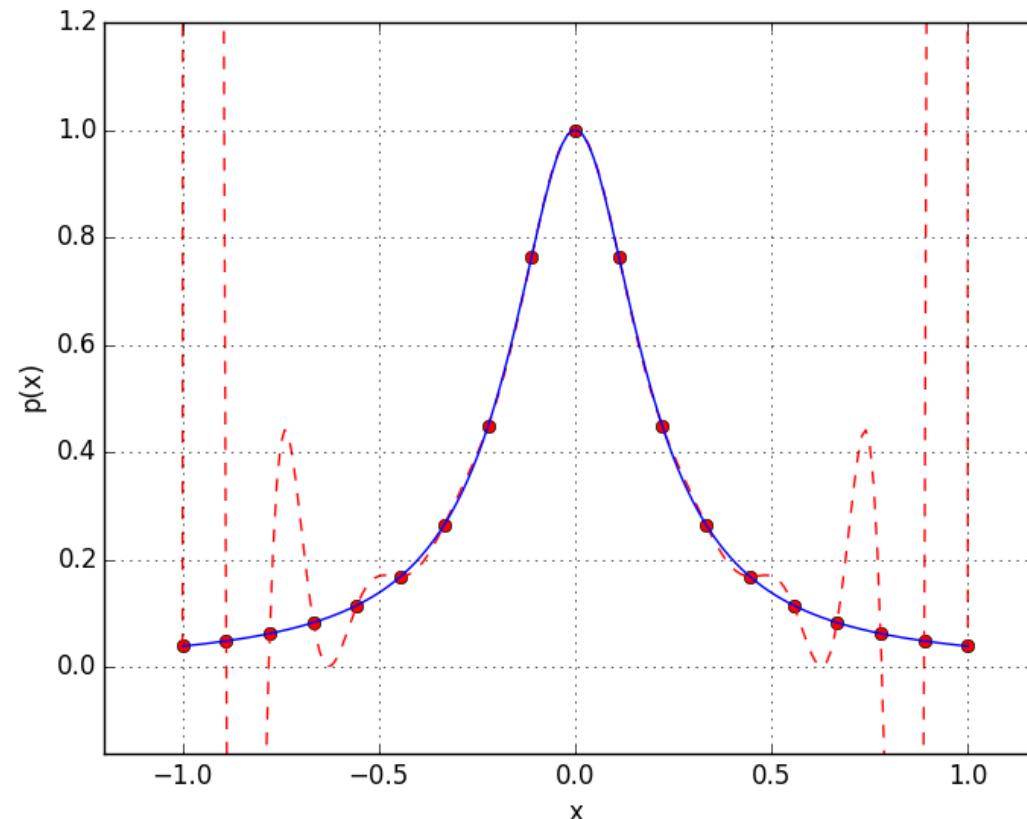
$$f(x) = \frac{1}{1 + 25x^2}$$



12 points

Overfitting

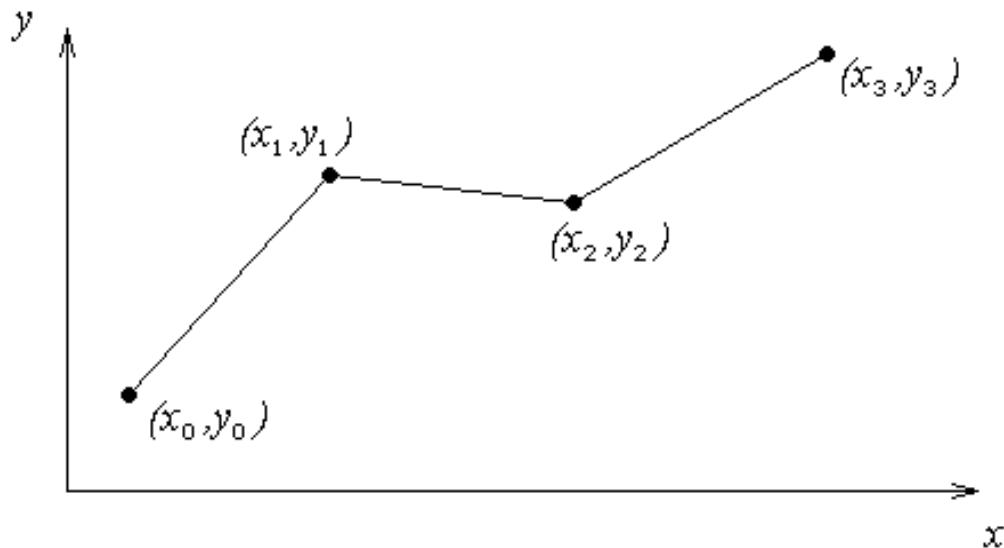
$$f(x) = \frac{1}{1 + 25x^2}$$



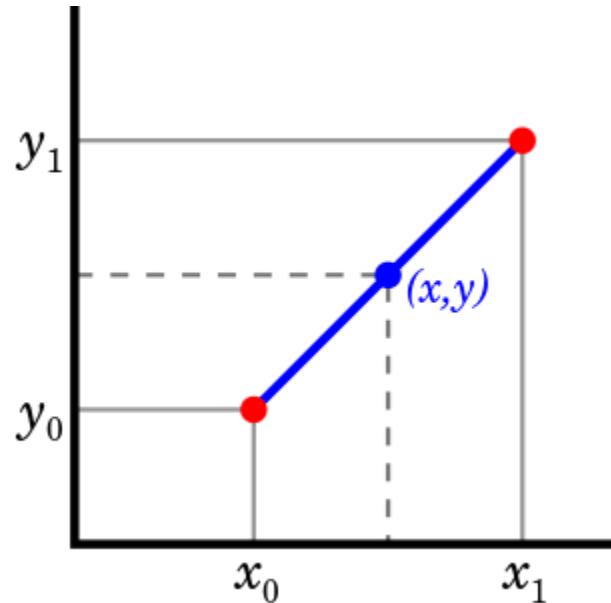
20 points

Linear Spline Interpolation

- For given points $(x_0, y_0), (x_1, y_1), \dots (x_n, y_n)$ fit spline functions. We create lines that connect consecutive points. Linear splines are defined by $y_i = f(x_i)$



Linear Interpolation

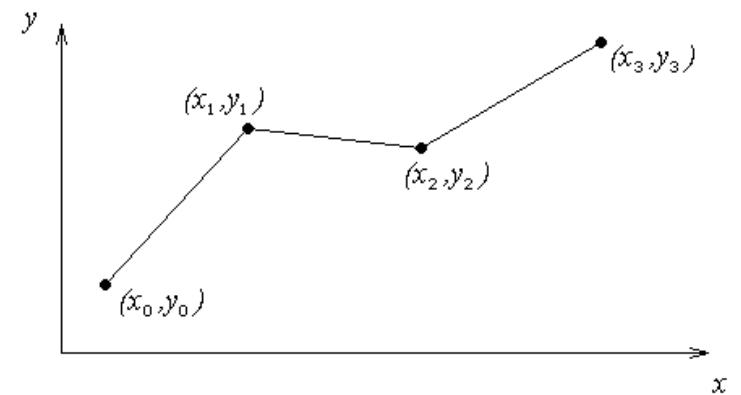


$$\frac{y - y_0}{x - x_0} = \frac{y_1 - y_0}{x_1 - x_0}$$

$$y = y_0 + (y_1 - y_0) \frac{x - x_0}{x_1 - x_0}$$

Linear Interpolation

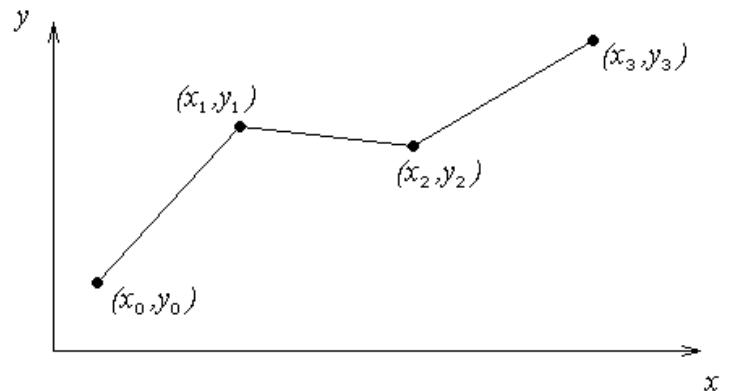
$$f(x) = f(x_0) + \frac{f(x_1) - f(x_0)}{x_1 - x_0}(x - x_0), \quad x_0 \leq x \leq x_1$$



Linear Interpolation

$$f(x) = f(x_0) + \frac{f(x_1) - f(x_0)}{x_1 - x_0}(x - x_0), \quad x_0 \leq x \leq x_1$$

$$= f(x_1) + \frac{f(x_2) - f(x_1)}{x_2 - x_1}(x - x_1), \quad x_1 \leq x \leq x_2$$



Linear Interpolation – Spline Interpolation

$$f(x) = f(x_0) + \frac{f(x_1) - f(x_0)}{x_1 - x_0}(x - x_0), \quad x_0 \leq x \leq x_1$$

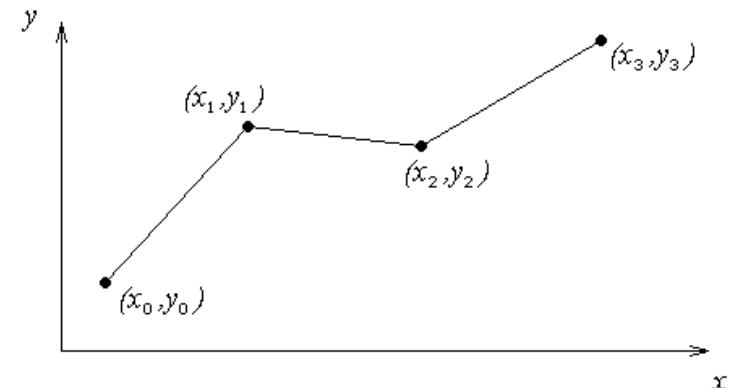
$$= f(x_1) + \frac{f(x_2) - f(x_1)}{x_2 - x_1}(x - x_1), \quad x_1 \leq x \leq x_2$$

.

.

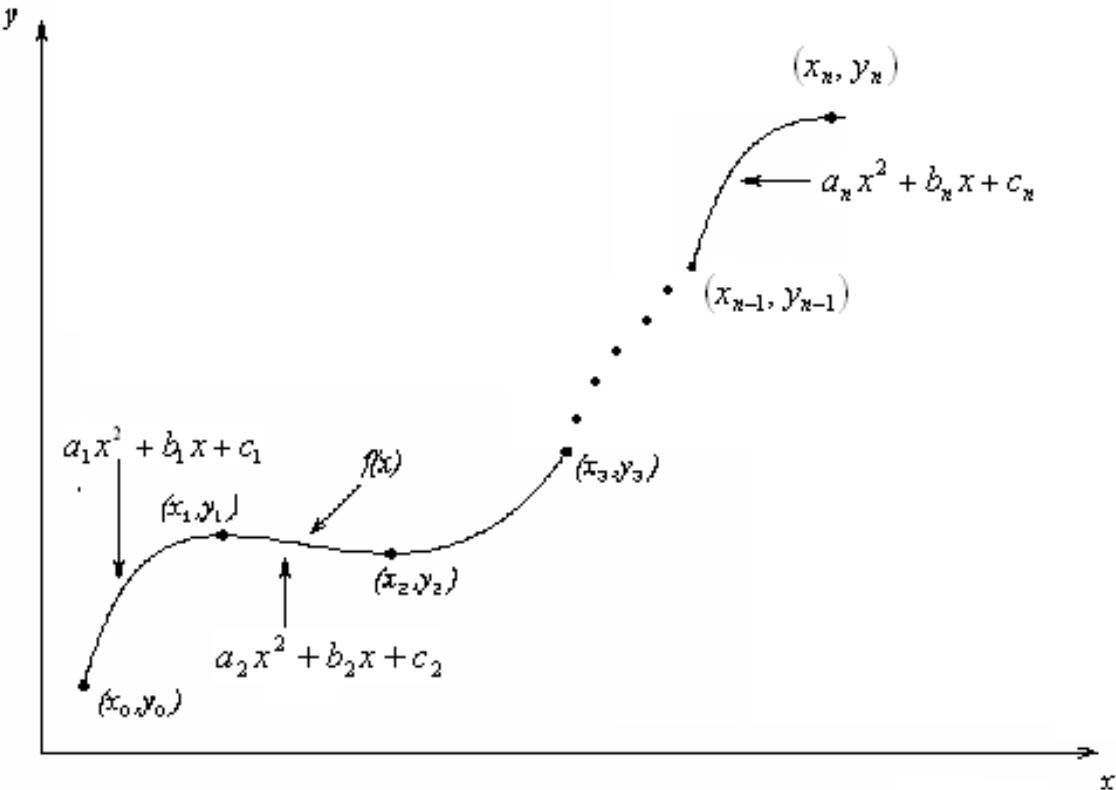
.

$$= f(x_{n-1}) + \frac{f(x_n) - f(x_{n-1})}{x_n - x_{n-1}}(x - x_{n-1}), \quad x_{n-1} \leq x \leq x_n$$



Quadratic spline interpolation

$$\begin{aligned} f(x) &= a_1 x^2 + b_1 x + c_1, & x_0 \leq x \leq x_1 \\ &= a_2 x^2 + b_2 x + c_2, & x_1 \leq x \leq x_2 \\ &\vdots \\ &= a_n x^2 + b_n x + c_n, & x_{n-1} \leq x \leq x_n \end{aligned}$$



Python Interpolation

scipy.interpolate

- **1D and 2D interpolation**
 - Creates an interpolating **function** from a set of points
 - The created function returns a scalar value for an array of data.

scipy.interpolate.interp1d

```
class scipy.interpolate.interp1d(x, y, kind='linear', axis=-1, copy=True, bounds_error=True, fill_value=np.nan,  
assume_sorted=False)
```

[\[source\]](#)

Interpolate a 1-D function.

x and *y* are arrays of values used to approximate some function $f: y = f(x)$. This class returns a function whose call method uses interpolation to find the value of new points.

Parameters: *x* : ($N,$) *array_like*

A 1-D array of real values.

y : (\dots, N, \dots) *array_like*

A N-D array of real values. The length of *y* along the interpolation axis must be equal to the length of *x*.

kind : *str or int, optional*

Specifies the kind of interpolation as a string ('linear', 'nearest', 'zero', 'slinear', 'quadratic', 'cubic' where 'slinear', 'quadratic' and 'cubic' refer to a spline interpolation of first, second or third order) or as an integer specifying the order of the spline interpolator to use. Default is 'linear'.

axis : *int, optional*

Specifies the axis of *y* along which to interpolate. Interpolation defaults to the last axis of *y*.

copy : *bool, optional*

If True, the class makes internal copies of *x* and *y*. If False, references to *x* and *y* are used. The default is to copy.

bounds_error : *bool, optional*

If True, a ValueError is raised any time interpolation is attempted on a value outside of the range of *x* (where extrapolation is necessary). If False, out of bounds values are assigned *fill_value*. By default, an error is raised.

fill_value : *float, optional*

If provided, then this value will be used to fill in for requested points outside of the data range. If not provided, then the default is NaN.

assume_sorted : *bool, optional*

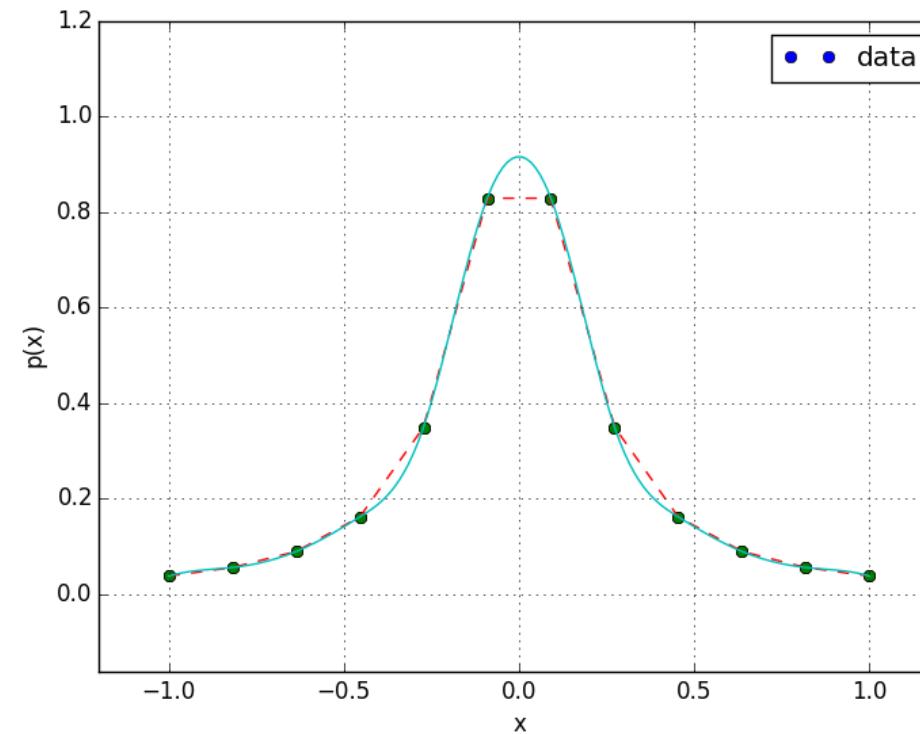
If False, values of *x* can be in any order and they are sorted first. If True, *x* has to be an array of monotonically increasing values.

Examples

```
>>> from scipy import interpolate >>>
>>> x = np.arange(0, 10)
>>> y = np.exp(-x/3.0)
>>> f = interpolate.interp1d(x, y)

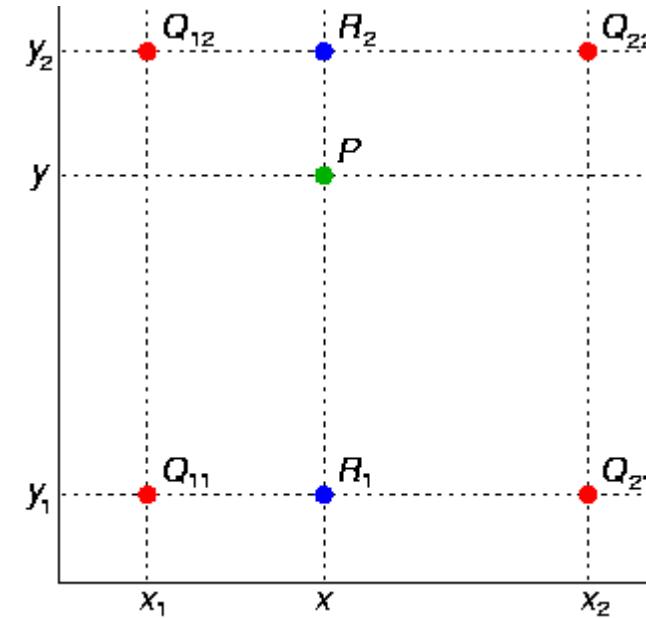
>>> xnew = np.arange(0, 9, 0.1) >>>
>>> ynew = f(xnew)    # use interpolation function returned by `interp1d`
>>> plt.plot(x, y, 'o', xnew, ynew, '-')
>>> plt.show()
```

Example linear/cubic spline interpolation



Bilinear interpolation

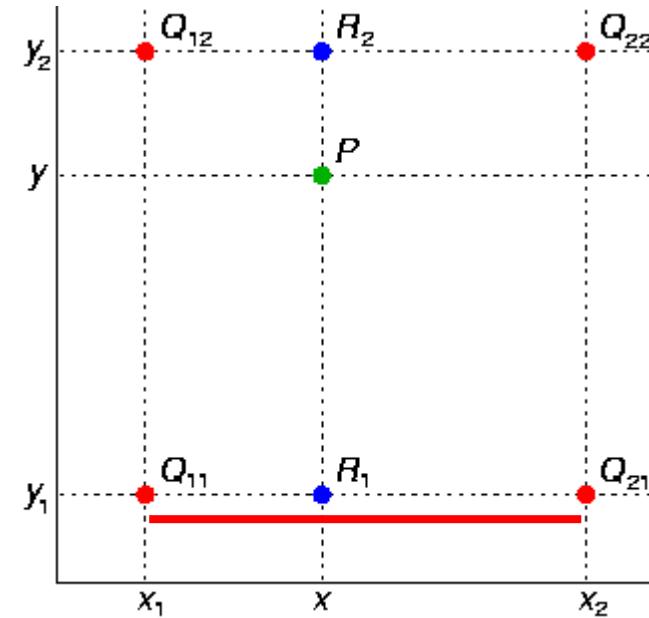
- Interpolating in 2D?
 - First interpolate in respect to x , then in respect to y



[http://en.wikipedia.org/wiki/
Bilinear_interpolation](http://en.wikipedia.org/wiki/Bilinear_interpolation)

Bilinear interpolation

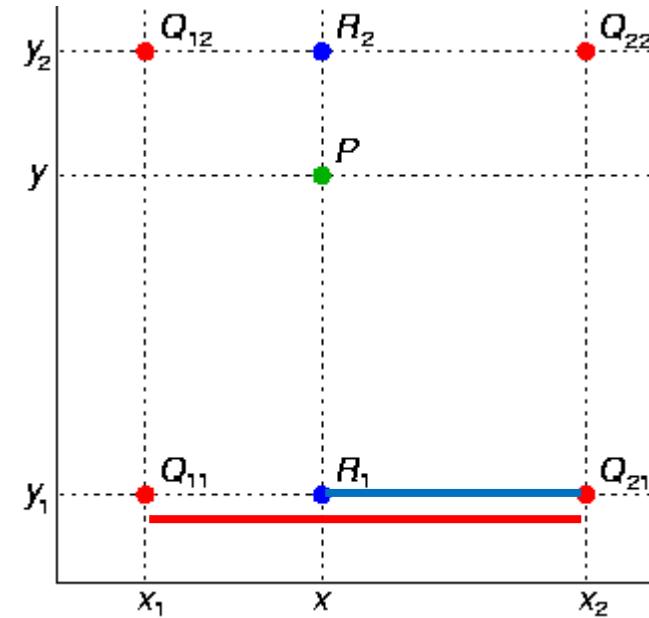
$$f(x, y) \approx \frac{f(Q_{11})}{(x_2 - x_1)(y_2 - y_1)}(x_2 - x)(y_2 - y)$$



[http://en.wikipedia.org/wiki/
Bilinear_interpolation](http://en.wikipedia.org/wiki/Bilinear_interpolation)

Bilinear interpolation

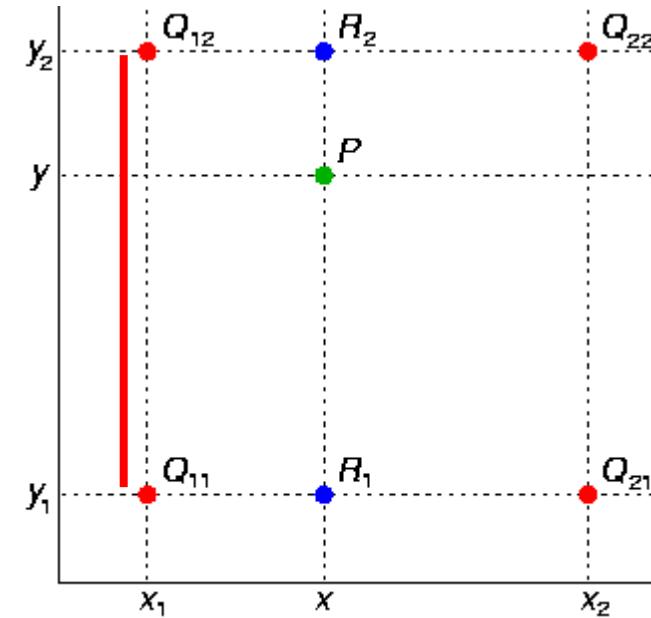
$$f(x, y) \approx \frac{f(Q_{11})}{(x_2 - x_1)(y_2 - y_1)} (x_2 - x)(y_2 - y)$$



[http://en.wikipedia.org/wiki/
Bilinear_interpolation](http://en.wikipedia.org/wiki/Bilinear_interpolation)

Bilinear interpolation

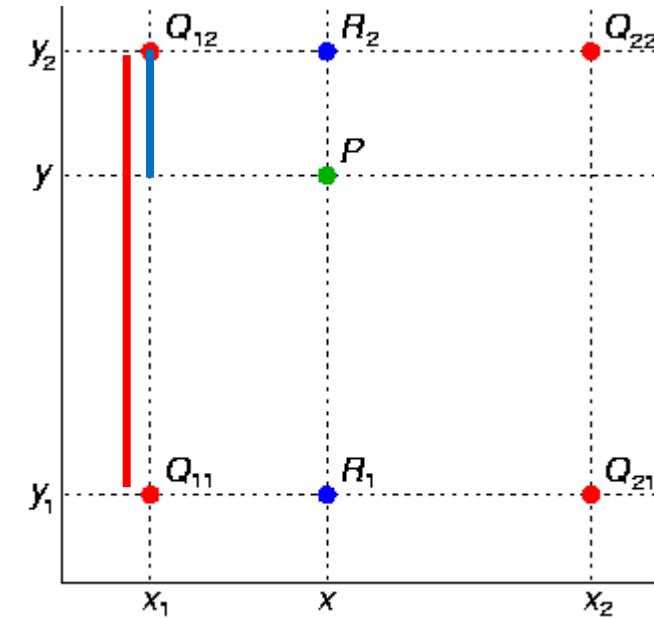
$$f(x, y) \approx \frac{f(Q_{11})}{(x_2 - x_1)(y_2 - y_1)}(x_2 - x)(y_2 - y)$$



[http://en.wikipedia.org/wiki/
Bilinear_interpolation](http://en.wikipedia.org/wiki/Bilinear_interpolation)

Bilinear interpolation

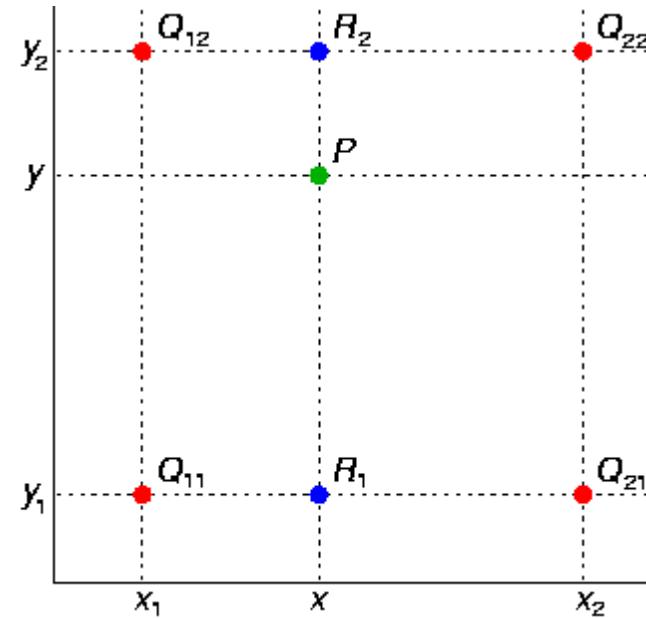
$$f(x, y) \approx \frac{f(Q_{11})}{(x_2 - x_1)(y_2 - y_1)}(x_2 - x)(y_2 - y)$$



[http://en.wikipedia.org/wiki/
Bilinear_interpolation](http://en.wikipedia.org/wiki/Bilinear_interpolation)

Bilinear interpolation

$$\begin{aligned}f(x, y) \approx & \frac{f(Q_{11})}{(x_2 - x_1)(y_2 - y_1)}(x_2 - x)(y_2 - y) \\& + \frac{f(Q_{21})}{(x_2 - x_1)(y_2 - y_1)}(x - x_1)(y_2 - y) \\& + \frac{f(Q_{12})}{(x_2 - x_1)(y_2 - y_1)}(x_2 - x)(y - y_1) \\& + \frac{f(Q_{22})}{(x_2 - x_1)(y_2 - y_1)}(x - x_1)(y - y_1).\end{aligned}$$



[http://en.wikipedia.org/wiki/
Bilinear_interpolation](http://en.wikipedia.org/wiki/Bilinear_interpolation)

scipy.interpolate.interp2d

```
class scipy.interpolate.interp2d(x, y, z, kind='linear', copy=True, bounds_error=False, fill_value=nan)
```

Interpolate over a 2-D grid.

[\[source\]](#)

x, y and z are arrays of values used to approximate some function f: $z = f(x, y)$. This class returns a function whose call method uses spline interpolation to find the value of new points.

If x and y represent a regular grid, consider using RectBivariateSpline.

Parameters:

x, y : array_like

Arrays defining the data point coordinates.

If the points lie on a regular grid, x can specify the column coordinates and y the row coordinates, for example:

```
>>> x = [0,1,2]; y = [0,3]; z = [[1,2,3], [4,5,6]]
```

>>>

Otherwise, x and y must specify the full coordinates for each point, for example:

```
>>> x = [0,1,2,0,1,2]; y = [0,0,0,3,3,3]; z = [1,2,3,4,5,6]
```

>>>

If x and y are multi-dimensional, they are flattened before use.

z : array_like

The values of the function to interpolate at the data points. If z is a multi-dimensional array, it is flattened before use. The length of a flattened z array is either len(x)*len(y) if x and y specify the column and row coordinates or len(z) == len(x) == len(y) if x and y specify coordinates for each point.

kind : {'linear', 'cubic', 'quintic'}, optional

The kind of spline interpolation to use. Default is 'linear'.

copy : bool, optional

If True, the class makes internal copies of x, y and z. If False, references may be used. The default is to copy.

bounds_error : bool, optional

If True, when interpolated values are requested outside of the domain of the input data (x,y), a ValueError is raised. If False, then fill_value is used.

fill_value : number, optional

If provided, the value to use for points outside of the interpolation domain. If omitted (None), values outside the domain are extrapolated.

Returns:

values_x : ndarray, shape xi.shape[:-1] + values.shape[ndim:]

Interpolated values at input coordinates.

Examples

Construct a 2-D grid and interpolate on it:

```
>>> from scipy import interpolate
>>> x = np.arange(-5.01, 5.01, 0.25)
>>> y = np.arange(-5.01, 5.01, 0.25)
>>> xx, yy = np.meshgrid(x, y)
>>> z = np.sin(xx**2+yy**2)
>>> f = interpolate.interp2d(x, y, z, kind='cubic')
```

Now use the obtained interpolation function and plot the result:

```
>>> xnew = np.arange(-5.01, 5.01, 1e-2)
>>> ynew = np.arange(-5.01, 5.01, 1e-2)
>>> znew = f(xnew, ynew)
>>> plt.plot(x, z[0, :], 'ro-', xnew, znew[0, :], 'b-')
>>> plt.show()
```

numpy.meshgrid

`numpy.meshgrid(*xi, **kwargs)`

[\[source\]](#)

Return coordinate matrices from coordinate vectors.

Make N-D coordinate arrays for vectorized evaluations of N-D scalar/vector fields over N-D grids, given one-dimensional coordinate arrays x_1, x_2, \dots, x_n .

Changed in version 1.9: 1-D and 0-D cases are allowed.

Parameters: `x1, x2, ..., xn : array_like`

1-D arrays representing the coordinates of a grid.

`indexing : {‘xy’, ‘ij’}, optional`

Cartesian (‘xy’, default) or matrix (‘ij’) indexing of output. See Notes for more details.

New in version 1.7.0.

`sparse : bool, optional`

If True a sparse grid is returned in order to conserve memory. Default is False.

New in version 1.7.0.

`copy : bool, optional`

If False, a view into the original arrays are returned in order to conserve memory.

Default is True. Please note that `sparse=False, copy=False` will likely return non-contiguous arrays. Furthermore, more than one element of a broadcast array may refer to a single memory location. If you need to write to the arrays, make copies first.

New in version 1.7.0.

Returns: `X1, X2, ..., XN : ndarray`

For vectors x_1, x_2, \dots, x_n with lengths $N_i = \text{len}(x_i)$, return $(N_1, N_2, N_3, \dots, N_n)$ shaped arrays if `indexing='ij'` or $(N_2, N_1, N_3, \dots, N_n)$ shaped arrays if `indexing='xy'` with the elements of x_i repeated to fill the matrix along the first dimension for x_1 , the second for x_2 and so on.

```
In [53]: x = np.arange(3)
```

```
In [54]: y = np.arange(3)
```

```
In [55]: xx, yy = np.meshgrid(x, y)
```

```
In [56]: xx
```

```
Out[56]:
```

```
array([[0, 1, 2],  
       [0, 1, 2],  
       [0, 1, 2]])
```

```
In [57]: yy
```

```
Out[57]:
```

```
array([[0, 0, 0],  
       [1, 1, 1],  
       [2, 2, 2]])
```

numpy.meshgrid

`numpy.meshgrid(*xi, **kwargs)`

[\[source\]](#)

Return coordinate matrices from coordinate vectors.

Make N-D coordinate arrays for vectorized evaluations of N-D scalar/vector fields over N-D grids, given one-dimensional coordinate arrays x_1, x_2, \dots, x_n .

Changed in version 1.9: 1-D and 0-D cases are allowed.

Parameters: `x1, x2, ..., xn : array_like`

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`indexing : {'xy', 'ij'}, optional`

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```
In [60]: z = sqrt(xx**2 + yy**2)
```

```
In [61]: z
```

```
Out[61]:
```

```
array([[ 0.          ,  1.          ,  2.          ],
       [ 1.          ,  1.41421356,  2.23606798],
       [ 2.          ,  2.23606798,  2.82842712]])
```

numpy.meshgrid

`numpy.meshgrid(*xi, **kwargs)`

[\[source\]](#)

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Parameters: `x1, x2, ..., xn : array_like`

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In [61]: `z`

Out[61]:

```
array([[ 0.          ,  1.          ,  2.          ],
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       [ 2.          ,  2.23606798,  2.82842712]])
```

$\sqrt{0^{**2} + 0^{**2}}$

numpy.meshgrid

`numpy.meshgrid(*xi, **kwargs)`

[\[source\]](#)

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Out[61]:

```
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       [ 2.          ,  2.23606798,  2.82842712]])
```

$\sqrt{0^{**2} + 0^{**2}}$

$\sqrt{1^{**2} + 0^{**2}}$

numpy.meshgrid

`numpy.meshgrid(*xi, **kwargs)`

[\[source\]](#)

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In [61]: `z`

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array([[ 0.          ,  1.          ,  2.          ],
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       [ 2.          ,  2.23606798,  2.82842712]])
```

$\sqrt{0^{*2} + 0^{*2}}$

$\sqrt{1^{*2} + 0^{*2}}$

$\sqrt{2^{*2} + 0^{*2}}$

array([[0. , 1. , 2.],
 [1. , 1.41421356, 2.23606798],
 [2. , 2.23606798, 2.82842712]])

array([0. , 1. , 2.],
 [1. , 1.41421356, 2.23606798],
 [2. , 2.23606798, 2.82842712]])

array([0. , 1. , 2.],
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numpy.meshgrid

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[\[source\]](#)

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Changed in version 1.9: 1-D and 0-D cases are allowed.

Parameters: `x1, x2, ..., xn : array_like`

1-D arrays representing the coordinates of a grid.

`indexing : {'xy', 'ij'}`, optional

Cartesian ('xy', default) or matrix ('ij') indexing of output. See Notes for more details.

New in version 1.7.0.

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New in version 1.7.0.

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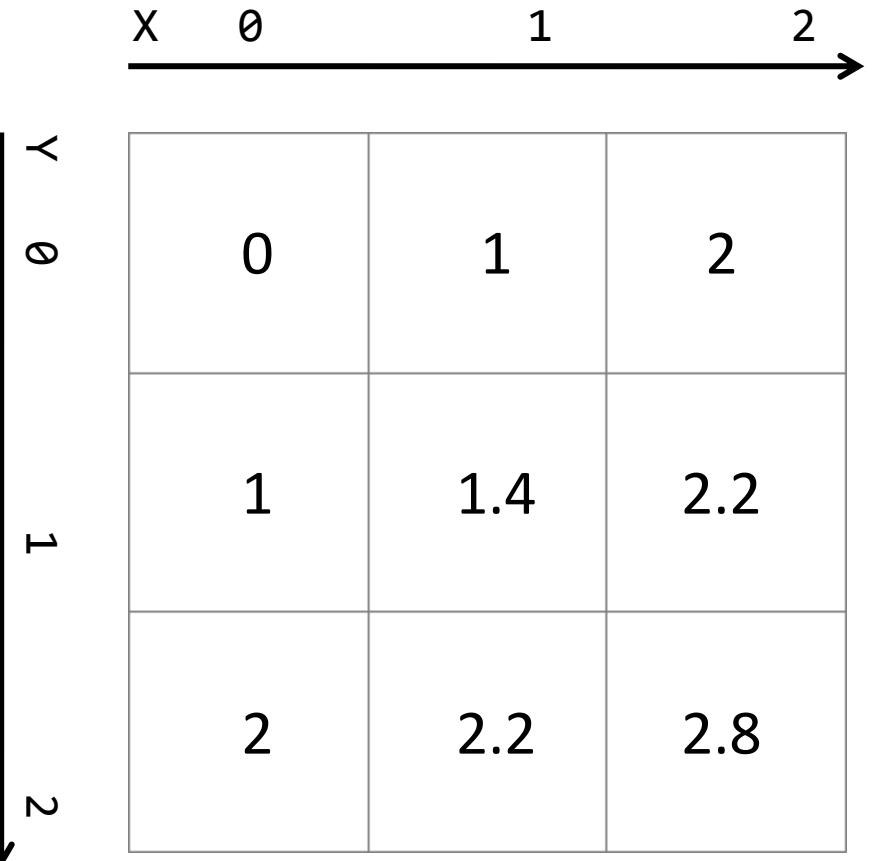
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New in version 1.7.0.

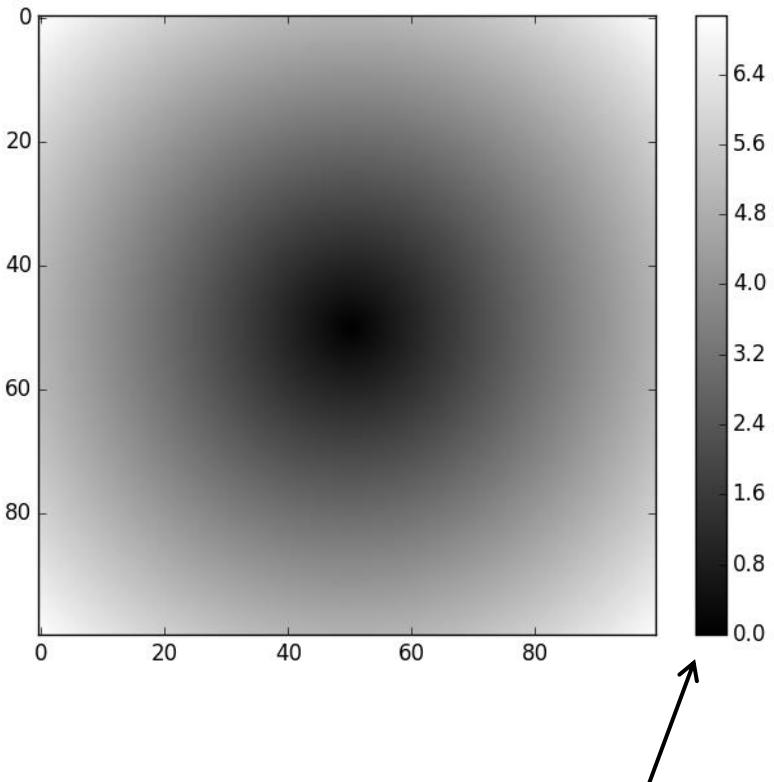
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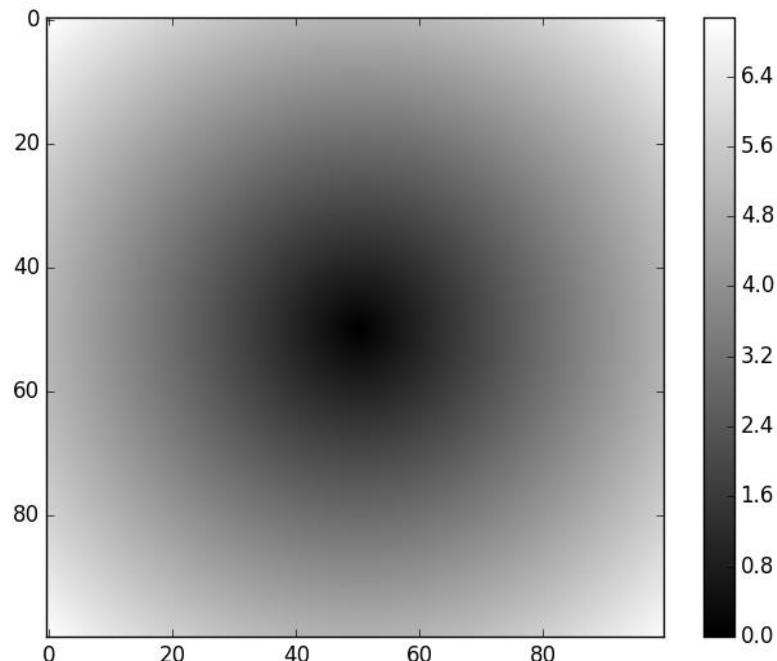
Visualizing 2D functions as color images

$$f(x, y) = \sqrt{x^2 + y^2}$$



*`plt.colorbar()` creates a color bar

$$f(x, y) = \sqrt{x^2 + y^2}$$



*plt.colorbar() creates a color bar

```
matplotlib.pyplot.imshow(X, cmap=None, norm=None, aspect=None, interpolation=None, alpha=None, vmin=None,
vmax=None, origin=None, extent=None, shape=None, filternorm=1, filterrad=4.0, imlim=None, resample=None,
url=None, hold=None, data=None, **kwargs)
```

Display an image on the axes.

Parameters:

X: array_like, shape (n, m) or (n, m, 3) or (n, m, 4)

Display the image in x to current axes. x may be a float array, a uint8 array or a PIL image. If x is an array, it can have the following shapes:

- MxN – luminance (grayscale, float array only)
- MxNx3 – RGB (float or uint8 array)
- MxNx4 – RGBA (float or uint8 array)

The value for each component of MxNx3 and MxNx4 float arrays should be in the range 0.0 to 1.0; MxN float arrays may be normalised.

cmap : Colormap, optional, default: None

IfNone, default to rc image.cmap value. cmap is ignored when x has RGB(A) information

aspect : [‘auto’ | ‘equal’ | scalar], optional, default: None

If‘auto’, changes the image aspect ratio to match that of the axes.

If‘equal’, and extent is None, changes the axes aspect ratio to match that of the image. Ifextent is notNone, the axes aspectratio is changed to match that of the extent.

IfNone, default to rc image.aspect value.

interpolation : string, optional, default: None

Acceptable values are ‘none’, ‘nearest’, ‘bilinear’, ‘bicubic’, ‘spline16’, ‘spline36’, ‘hanning’, ‘hamming’, ‘hermite’, ‘kaiser’, ‘quadric’, ‘catrom’, ‘gaussian’, ‘bessel’, ‘mitchell’, ‘sinc’, ‘lanczos’

Ifinterpolation is None, default to rc image.interpolation. See also the filternorm and filterrad parameters. If interpolation is ‘none’, then no interpolation is performed on the Agg, ps and pdfbackends. Otherbackends will fall back to ‘nearest’.

norm : Normalize, optional, default: None

A Normalize instance is used to scale luminance data to 0, 1. IfNone, use the default funcnormalize. norm is only used ifx is an array of floats.

```
z = sqrt(xx**2 + yy**2)
plt.imshow(z)
```

```
matplotlib.pyplot.imshow(X, cmap=None, norm=None, aspect=None, interpolation=None, alpha=None, vmin=None,
vmax=None, origin=None, extent=None, shape=None, filternorm=1, filterrad=4.0, imlim=None, resample=None,
url=None, hold=None, data=None, **kwargs)
```

Display an image on the axes.

Parameters:

X: array_like, shape (n, m) or (n, m, 3) or (n, m, 4)

Display the image in x to current axes. x may be a float array, a uint8 array or a PIL image. If x is an array, it can have the following shapes:

- MxN – luminance (grayscale, float array only)
- MxNx3 – RGB (float or uint8 array)
- MxNx4 – RGBA (float or uint8 array)

The value for each component of MxNx3 and MxNx4 float arrays should be in the range 0.0 to 1.0; MxN float arrays may be normalised.

cmap : Colormap, optional, default: None

IfNone, default to rc image.cmap value. cmap is ignored when x has RGB(A) information

aspect : ['auto' | 'equal' | scalar], optional, default: None

If'auto', changes the image aspect ratio to match that of the axes.

If'equal', and extent is None, changes the axes aspect ratio to match that of the image. Ifextent is notNone, the axes aspectratio is changed to match that of the extent.

IfNone, default to rc image.aspect value.

interpolation : string, optional, default: None

Acceptable values are 'none', 'nearest', 'bilinear', 'bicubic', 'spline16', 'spline36', 'hanning', 'hamming', 'hemitte', 'kaiser', 'quadric', 'catrom', 'gaussian', 'bessel', 'mitchell', 'sinc', 'lanczos'

Ifinterpolation is None, default to rc image.interpolation. See also the filternorm and filterrad parameters. If interpolation is 'none', then no interpolation is performed on the Agg, ps and pdfbackends. Otherbackends will fall back to 'nearest'.

norm : Normalize, optional, default: None

A Normalize instance is used to scale luminance data to 0, 1. IfNone, use the default funcnormalize. norm is only used ifx is an array of floats.

`matplotlib.pyplot.pcolormesh(*args, **kwargs)`

Plot a quadrilateral mesh.

Call signatures:

```
pcolormesh(C)
pcolormesh(X, Y, C)
pcolormesh(C, **kwargs)
```

Create a pseudocolor plot of a 2-D array.

`pcolormesh` is similar to `pcolor()`, but uses a different mechanism and returns a different object; `pcolor` returns a `PolyCollection` but `pcolormesh` returns a `QuadMesh`. It is much faster, so it is almost always preferred for large arrays.

`C` may be a masked array, but `X` and `Y` may not. Masked array support is implemented via `cmap` and `norm`; in contrast, `pcolor()` simply does not draw quadrilaterals with masked colors or vertices.

Keyword arguments:

`cmap`: [`None` | Colormap]

A `matplotlib.colors.Colormap` instance. If `None`, use rc settings.

`norm`: [`None` | Normalize]

A `matplotlib.colors.Normalize` instance is used to scale luminance data to 0,1. If `None`, defaults to `normalize()`.

`vmin/vmax`: [`None` | scalar]

`vmin` and `vmax` are used in conjunction with `norm` to normalize luminance data. If either is `None`, it is autoscaled to the respective min or max of the color array `C`. If not `None`, `vmin` or `vmax` passed in here override any pre-existing values supplied in the `norm` instance.

plt.pcolormesh(x, y, z)

```
matplotlib.pyplot.pcolormesh(*args, **kwargs)
```

Plot a quadrilateral mesh.

Call signatures:

```
pcolormesh(C)
pcolormesh(X, Y, C)
pcolormesh(C, **kwargs)
```

Create a pseudocolor plot of a 2-D array.

`pcolormesh` is similar to `pcolor()`, but uses a different mechanism and returns a different object; `pcolor` returns a `PolyCollection` but `pcolormesh` returns a `QuadMesh`. It is much faster, so it is almost always preferred for large arrays.

`C` may be a masked array, but `X` and `Y` may not. Masked array support is implemented via `cmap` and `norm`; in contrast, `pcolor()` simply does not draw quadrilaterals with masked colors or vertices.

Keyword arguments:

`cmap`: [`None` | Colormap]

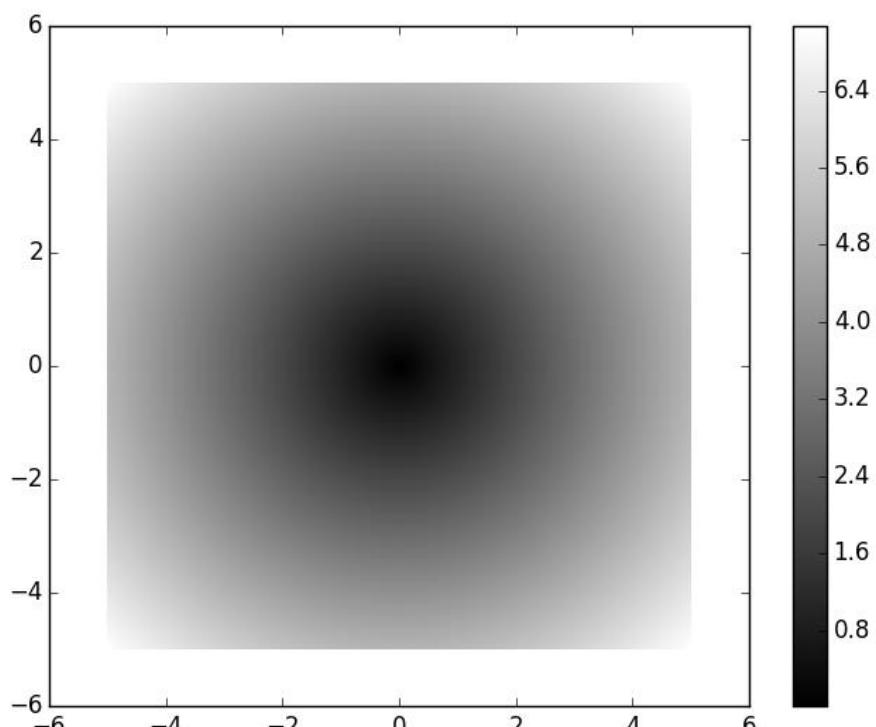
A `matplotlib.colors.Colormap` instance. If `None`, use rc settings.

`norm`: [`None` | Normalize]

A `matplotlib.colors.Normalize` instance is used to scale luminance data to 0,1. If `None`, defaults to `normalize()`.

`vmin/vmax`: [`None` | scalar]

`vmin` and `vmax` are used in conjunction with `norm` to normalize luminance data. If either is `None`, it is autoscaled to the respective min or max of the color array. `C`. If not `None`, `vmin` or `vmax` passed in here override any pre-existing values supplied in the `norm` instance.



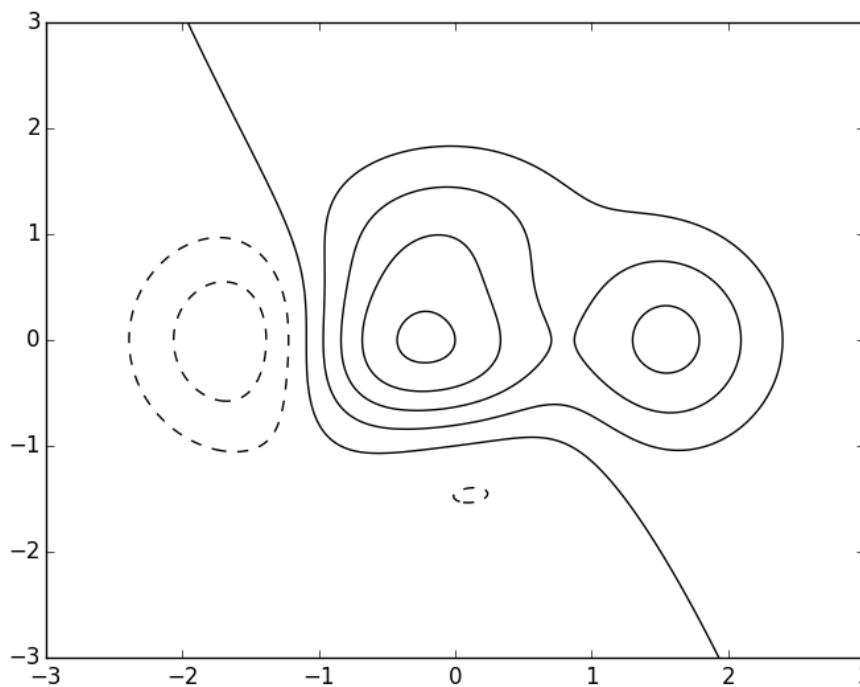
```
plt.pcolormesh(x, y, z)
```

```
matplotlib.pyplot.contour(*args, **kwargs)
```

Plot contours.

`contour()` and `contourf()` draw contour lines and filled contours, respectively. Except as noted, function signatures and return values are the same for both versions.

`contourf()` differs from the MATLAB version in that it does not draw the polygon edges. To draw edges, add line contours with calls to `contour()`.

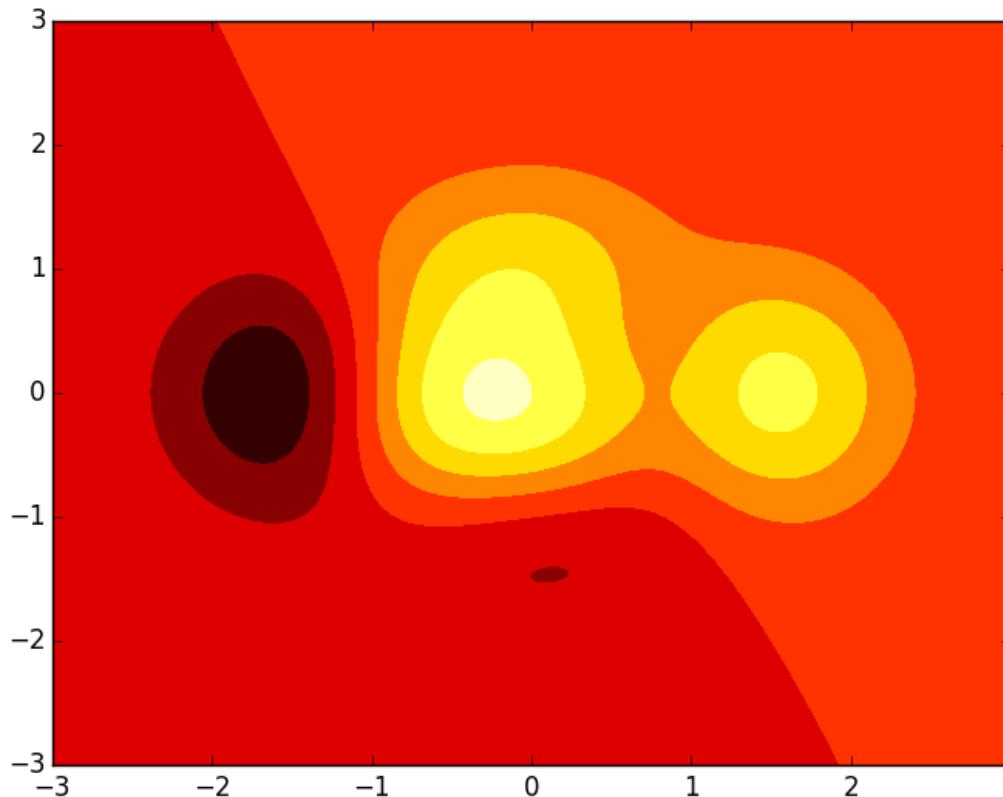


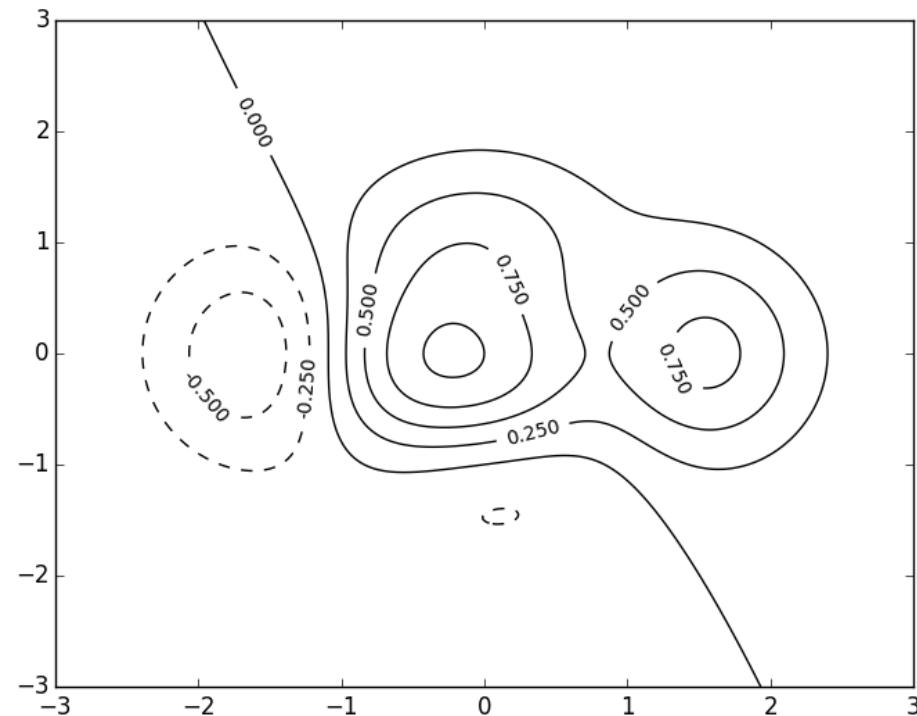
```
matplotlib.pyplot.contourf(*args, **kwargs)
```

Plot contours.

`contour()` and `contourf()` draw contour lines and filled contours, respectively. Except as noted, function signatures and return values are the same for both versions.

`contourf()` differs from the MATLAB version in that it does not draw the polygon edges. To draw edges, add line contours with calls to `contour()`.





`matplotlib.pyplot.clabel(cs, *args, **kwargs)`

Label a contour plot.

Call signature:

```
clabel(cs, **kwargs)
```

Adds labels to line contours in `cs`, where `cs` is a `ContourSet` object returned by `contour`.

```
clabel(cs, v, **kwargs)
```

only labels contours listed in `v`.

Optional keyword arguments:

`fontsize`:

size in points or relative size e.g., 'smaller', 'x-large'

`colors`:

- if `None`, the color of each label matches the color of the corresponding contour
- if one string color, e.g., `colors = 'r'` or `colors = 'red'`, all labels will be plotted in this color
- if a tuple of matplotlib color args (string, float, rgb, etc), different labels will be plotted in different colors in the order specified

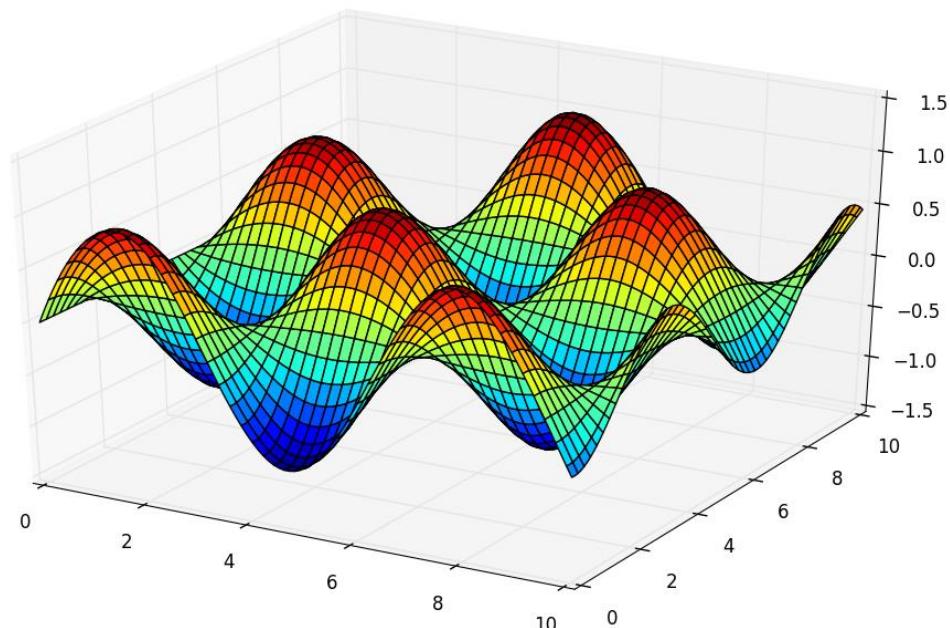
`inline`:

controls whether the underlying contour is removed or not. Default is `True`.

`inline_spacing`:

space in pixels to leave on each side of label when placing `inline`. Defaults to 5. This spacing will be exact for labels at locations where the contour is straight, less so for labels on curved contours.

- **Axes3D(plt.gcf())** creates a 3D graph.



```
from mpl_toolkits.mplot3d import Axes3D
```

`plot_surface(X, Y, Z, *args, **kwargs)`

Create a surface plot.

By default it will be colored in shades of a solid color, but it also supports color mapping by supplying the `cmap` argument.

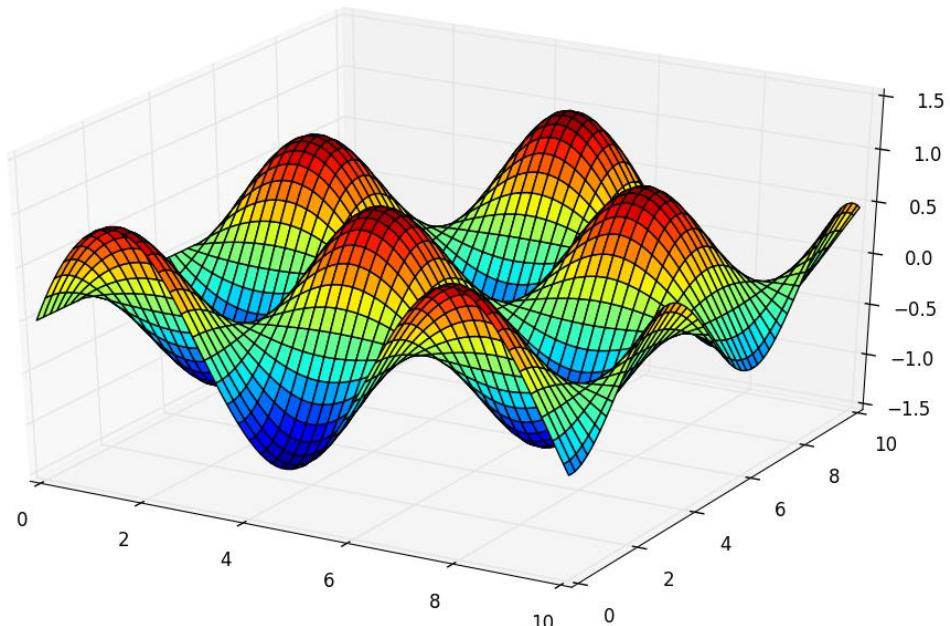
The `rstride` and `cstride` kwargs set the stride used to sample the input data to generate the graph. If 1k by 1k arrays are passed in the default values for the strides will result in a 100x100 grid being plotted.

Argument	Description
<code>X, Y, Z</code>	Data values as 2D arrays
<code>rstride</code>	Array row stride (step size), defaults to 10
<code>cstride</code>	Array column stride (step size), defaults to 10
<code>color</code>	Color of the surface patches
<code>cmap</code>	A colormap for the surface patches.
<code>facecolors</code>	Face colors for the individual patches
<code>norm</code>	An instance of <code>Normalize</code> to map values to colors
<code>vmin</code>	Minimum value to map
<code>vmax</code>	Maximum value to map
<code>shade</code>	Whether to shade the facecolors

Other arguments are passed on to `Poly3DCollection`

3D Plots

- `ax = plt.figure().add_subplot(projection='3d')`



`plot_surface(X, Y, Z, *args, **kwargs)`

Create a surface plot.

By default it will be colored in shades of a solid color, but it also supports color mapping by supplying the `cmap` argument.

The `rstride` and `cstride` kwargs set the stride used to sample the input data to generate the graph. If 1k by 1k arrays are passed in the default values for the strides will result in a 100x100 grid being plotted.

Argument	Description
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<code>facecolors</code>	Face colors for the individual patches
<code>norm</code>	An instance of <code>Normalize</code> to map values to colors
<code>vmin</code>	Minimum value to map
<code>vmax</code>	Maximum value to map
<code>shade</code>	Whether to shade the facecolors

Other arguments are passed on to `Poly3DCollection`

3D Plots

- Create mesh grids: `meshgrid(x, y)`
- Calculate z
- `ax.plot_surface(x, y, z)`

`plot_surface(X, Y, Z, *args, **kwargs)`

Create a surface plot.

By default it will be colored in shades of a solid color, but it also supports color mapping by supplying the `cmap` argument.

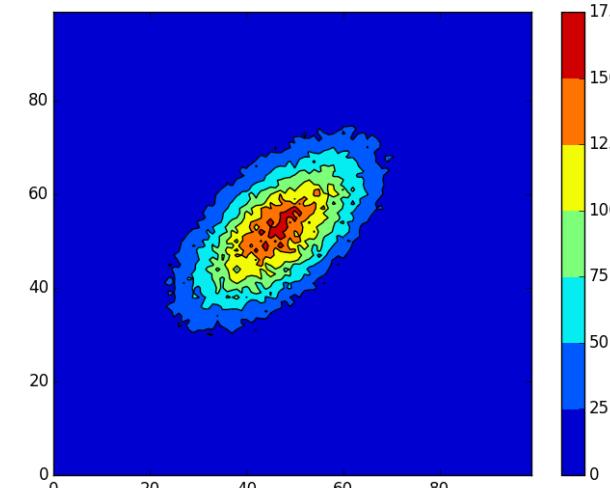
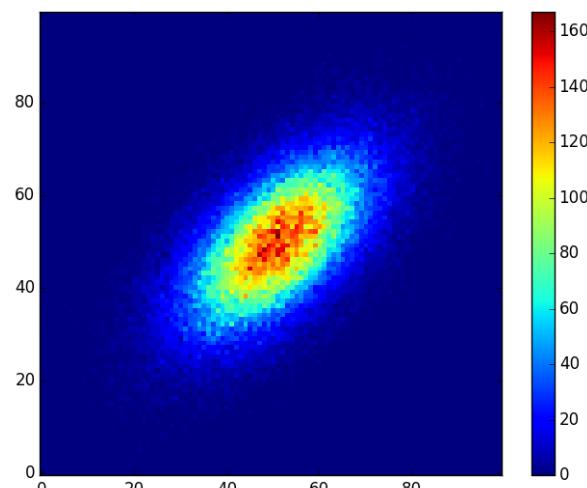
The `rstride` and `cstride` kwargs set the stride used to sample the input data to generate the graph. If 1k by 1k arrays are passed in the default values for the strides will result in a 100x100 grid being plotted.

Argument	Description
<code>X, Y, Z</code>	Data values as 2D arrays
<code>rstride</code>	Array row stride (step size), defaults to 10
<code>cstride</code>	Array column stride (step size), defaults to 10
<code>color</code>	Color of the surface patches
<code>cmap</code>	A colormap for the surface patches.
<code>facecolors</code>	Face colors for the individual patches
<code>norm</code>	An instance of <code>Normalize</code> to map values to colors
<code>vmin</code>	Minimum value to map
<code>vmax</code>	Maximum value to map
<code>shade</code>	Whether to shade the facecolors

Other arguments are passed on to `Poly3DCollection`

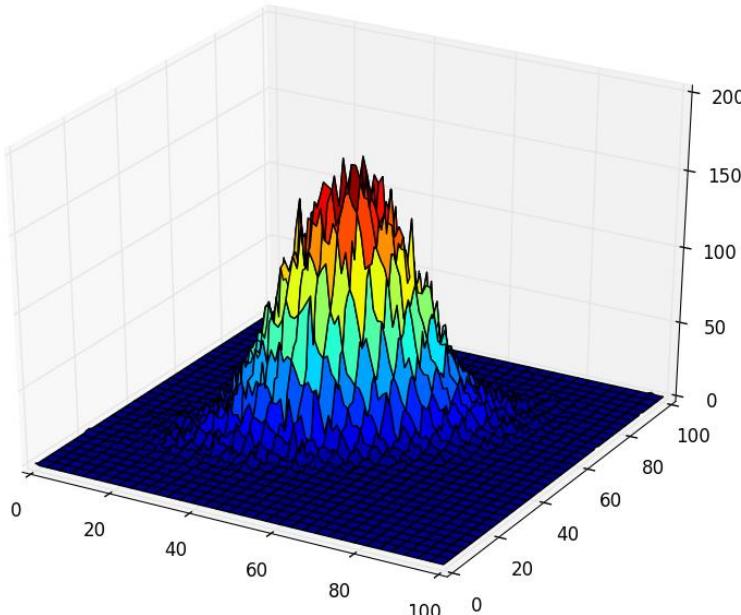
Exercise

- Download the files [X](#) and [Y](#) containing two parameters representing some real world data. Create a 2D histogram of these two data samples – visualize them as an image and as a contour plot. Use the function [histogram2D](#) to create a 2D histogram. Draw a color bar.



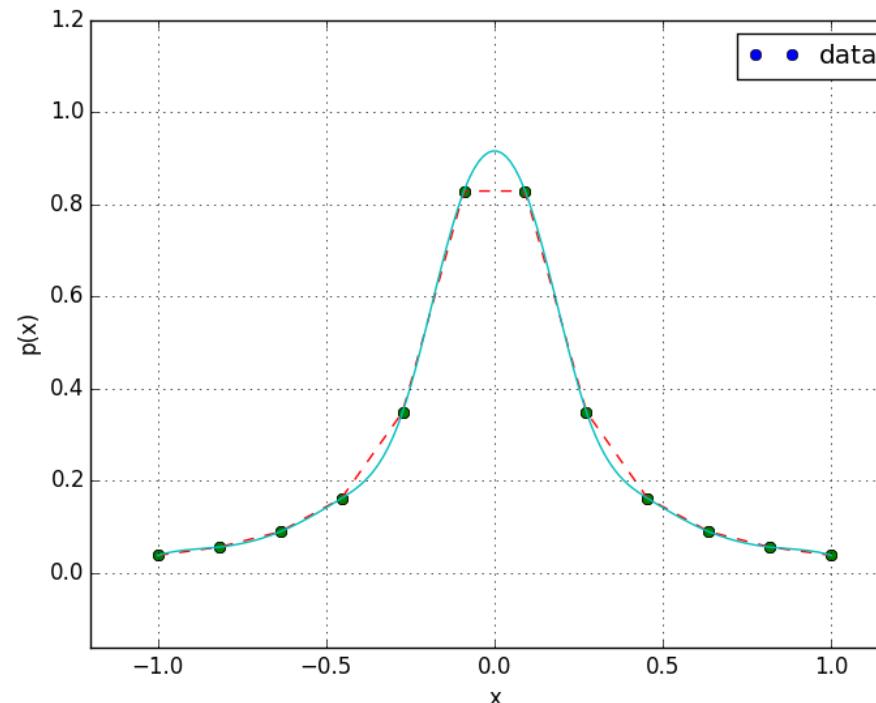
Exercise

- Create a 3D plot of the 2D histogram from the previous exercise. Generate a mesh grid for x and y from 0 to 100 with the linspace and meshgrid functions. Use the `plot_surface` function with the color map “jet” to visualize the 3D plot.



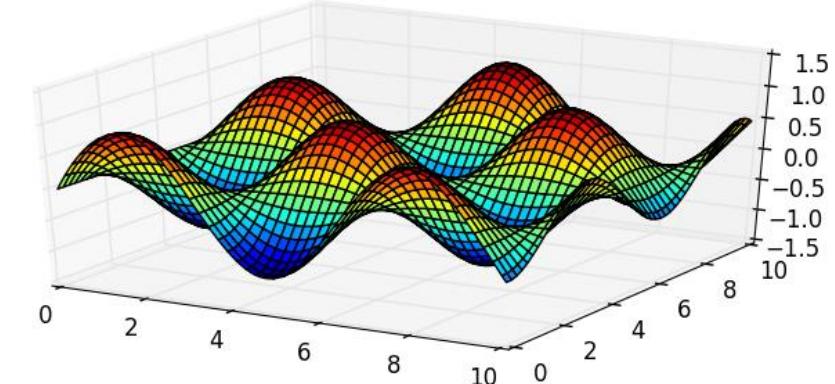
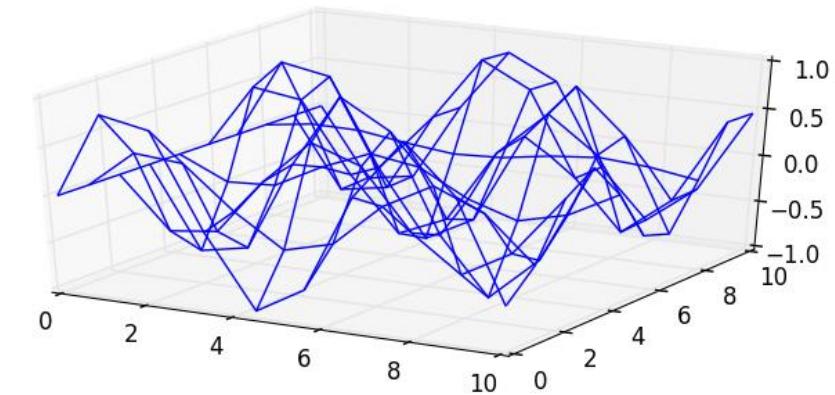
Exercise

- Find a cubic spline interpolation of the points (x and y coordinates) contained in the file [inter1D.npz](#) in the range $x \in [-1.0, 1.0]$. Draw the points and the interpolating function.



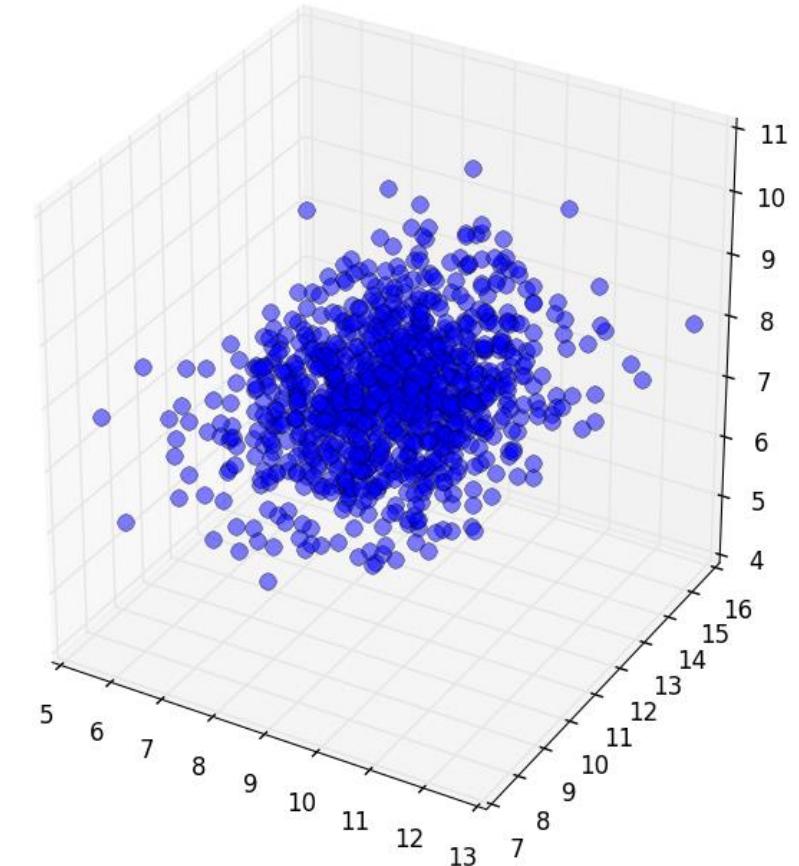
Exercise

- Open the file [inter2D.npz](#) and visualize the data as a 3D wireframe plot ([plot wireframe](#))
- Find a smoother (increase stride) cubic 2D spline interpolation for these data points (x , y and z coordinates) in the range $x, y \in [0, 10]$ and visualize the result as a 3D plot.



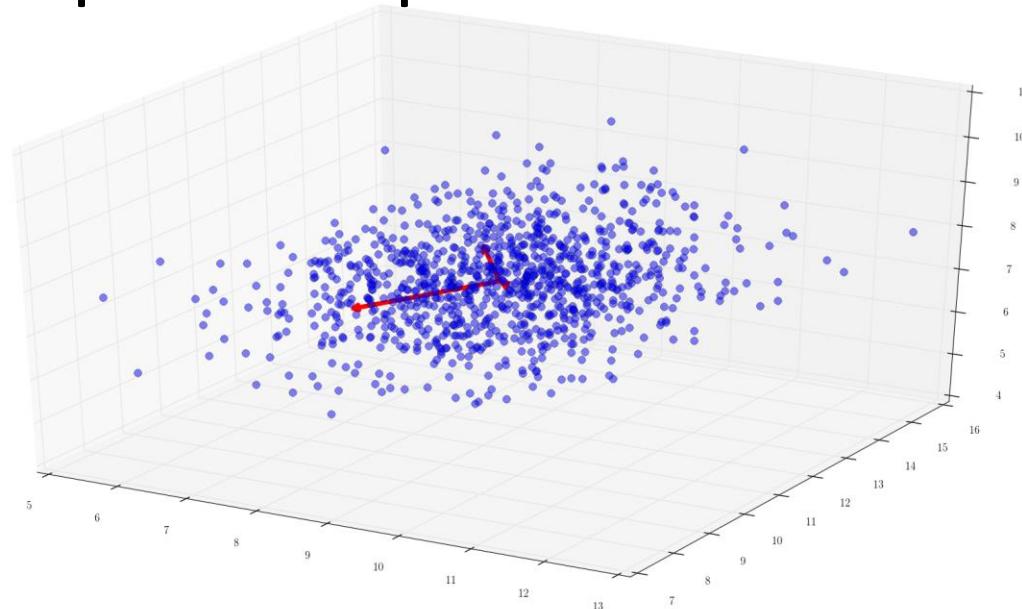
Exercise

- Visualize measurements of the flowers of *ludwiga octovalvis* on a 3D plot. Compute the means and the covariance matrix as well as the correlation matrix – what can you say about the relations of the 3 parameters: sepal length, petal length and sepal width?



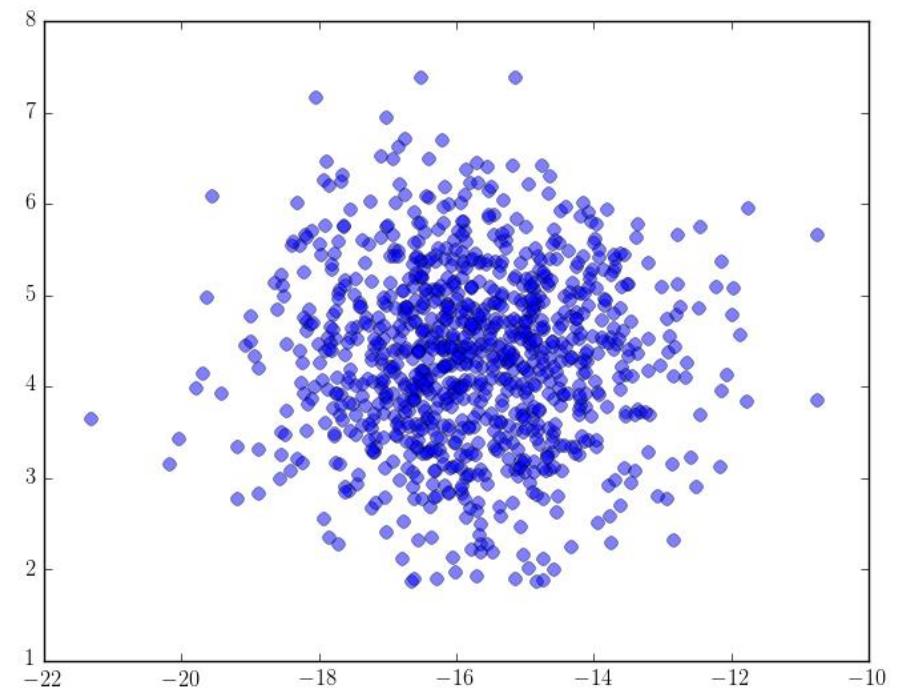
Exercise

- Calculate eigenvectors and eigenvalues of the covariance matrix. Visualize the vectors originating at the data mean ([code](#)). To reduce the dimensionality of the data from three to two dimensions what subspace will preserve most information?



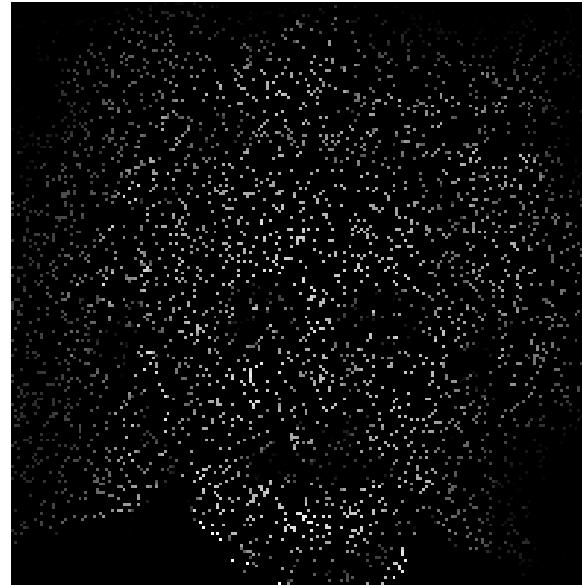
Exercise

- Project the data from 3D to 2D and visualize the result on another plot (multiply the data with a 3×2 matrix constructed from the two largest eigenvectors – alternatively use SVD). Compare your results to the PCA method from the module `matplotlib.mlab` or `sklearn`.



Exercise

- Reconstruct the [image](#) using an interpolation method of your choice. Which person is depicted in the image?



[scipy.interpolate.griddata\(points, values, xi, method='linear', fill_value=nan, rescale=False\)](#)