

# ENGG1003 - Monday Week 10

Normal distribution: extensions and applications  
Fitting straight line to data

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# Lecture overview

## 1 Normal distribution

- ▶ extension of *standard* normal distribution (previous lecture)
- ▶ application

## 2 Fitting straight line to data

- ▶ using Python to fit a straight line to data
- ▶ application

# 1) Normal distributions

- **quick recap** of standard normal PDF: equation, interpretation, how to generate & plot histogram
- reiterate importance of normal distribution in applications
- but standard normal is inflexible

# Recap: standard normal distribution

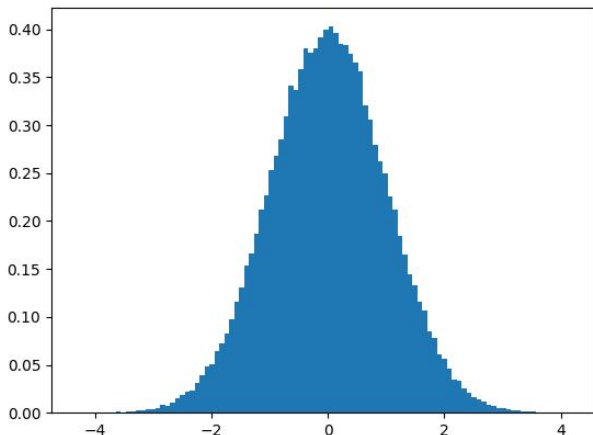
Standard normal probability density function:

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2}$$

- *standard* normal distribution is a special case of normal (Gaussian) distribution
- corresponds to parameters **0.0** and **1.0** in:

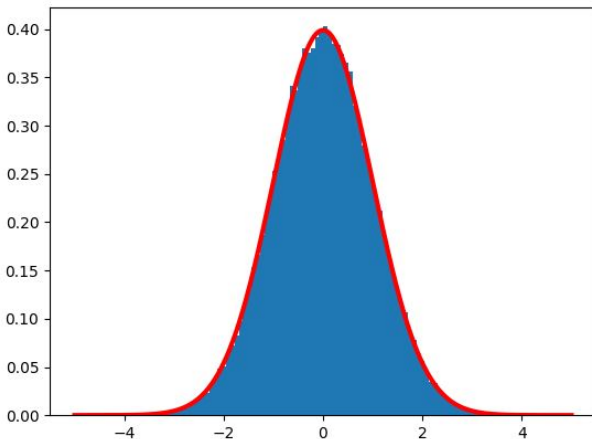
```
x = np.random.normal(0.0, 1.0, size=100000)
```

# Normalized histogram (area 1), 100 bins



- same histogram, except total area of rectangles is normalized to be 1

# Normalized histogram with PDF

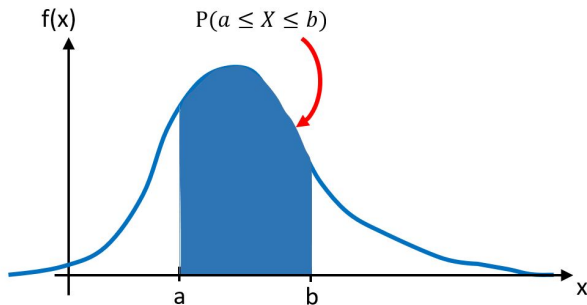


red curve is *probability density function (PDF)*

# Probability density functions

If  $X$  is a random number drawn from a distribution with PDF  $f(x)$ , probability  $X$  takes a value in interval  $[a, b]$  is

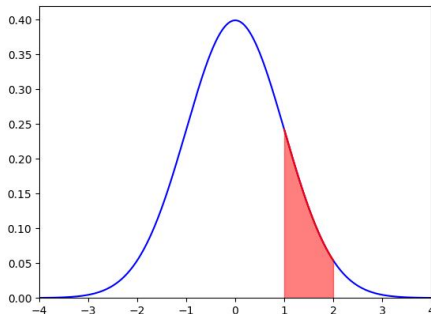
$$P(a \leq X \leq b) = \int_a^b f(x)dx$$



# Example

Use trapezoidal method to approximate  $P(1 \leq X \leq 2)$  when  $X$  is drawn from standard normal distribution

$$P(1 \leq X \leq 2) = \frac{1}{\sqrt{2\pi}} \int_1^2 e^{-x^2/2} dx \approx \mathbf{0.1359}$$



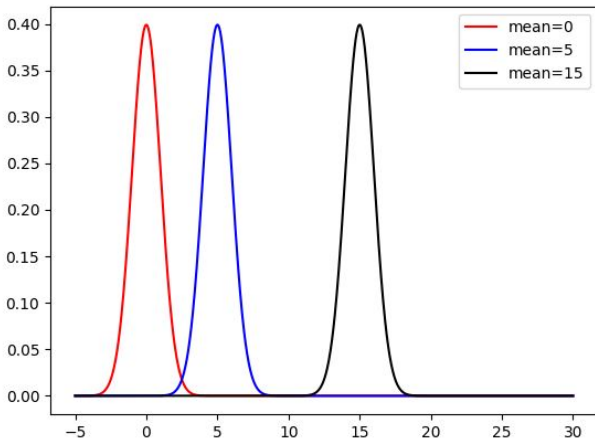


- reiterate importance of normal/Gaussian in applications
- but standard normal is inflexible
- now **experimentally observe** impact of first two parameters in `normal()` function call

# Impact of mean

- shifts average (mean) value
- left-right shift of PDF
- image here: overlay PDFs for  $\mu = 0, 5, 20$

# Mean demo



• blah

# Python code

meandemo.py

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 def f(x, mu, sigma):
5     return 1/(sigma * np.sqrt(2 * np.pi)) * np.exp(-(x - mu)**2 /
6         (2 * sigma**2 ))
7
8 x = np.linspace(-5, 30, 1000)
9
10 plt.plot(x, f(x, 0, 1), color='r', label='mean=0')
11 plt.plot(x, f(x, 5, 1), 'b', label='mean=5')
12 plt.plot(x, f(x, 15, 1), 'k', label='mean=15')
13 plt.legend()
14 plt.show()
```

- blah

# Impact of standard deviation $\sigma$

- shifts spread of PDF
- interpretation of “standard deviation”
- image here
- “most” of PDF within plus/minus 3 sigma of mean

“In statistics, the standard deviation is a measure of the amount of variation or dispersion of a set of values. A low standard deviation indicates that the values tend to be close to the mean (also called the expected value) of the set, while a high standard deviation indicates that the values are spread out over a wider range.

Standard deviation may be abbreviated SD, and is most commonly represented in mathematical texts and

# Impact of stedev

- XXX

# Stddev demo

- blah

# Normal PDF

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

- mean  $\mu$
- standard deviation  $\sigma$
- what are you expected to do with this PDF?
  - 1 call `np.random.standard()` to generate random numbers for specified  $\mu$  and  $\sigma$
  - 2 compute prob X in range  $[a, b]$  using numerical integration (trapezoidal)



# Standard normal as special case

Important special case:  $\mu = 0$  and  $\sigma = 1$

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2}$$

**Key point:** standard normal distribution has a mean of 0 and a standard deviation of 1

# Application

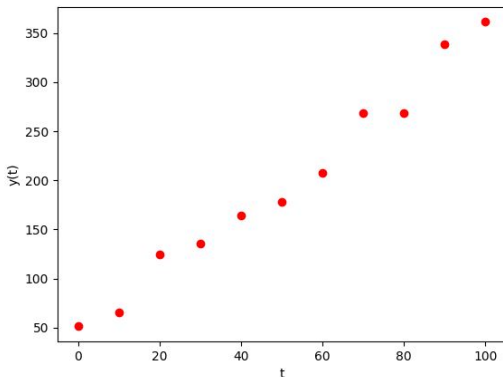
● XXX

## 2) Fitting straight line to data

- **Aim:** construct a function that best fits a series of data points
  - ▶ simplest function is a *straight line*
- two common forms of *curve-fitting* in Engineering applications:
  - 1 *interpolation*
    - week 6, Monday lecture
  - 2 *regression*
    - today's lecture
- we now demonstrate both curve-fitting methods applied to the same dataset

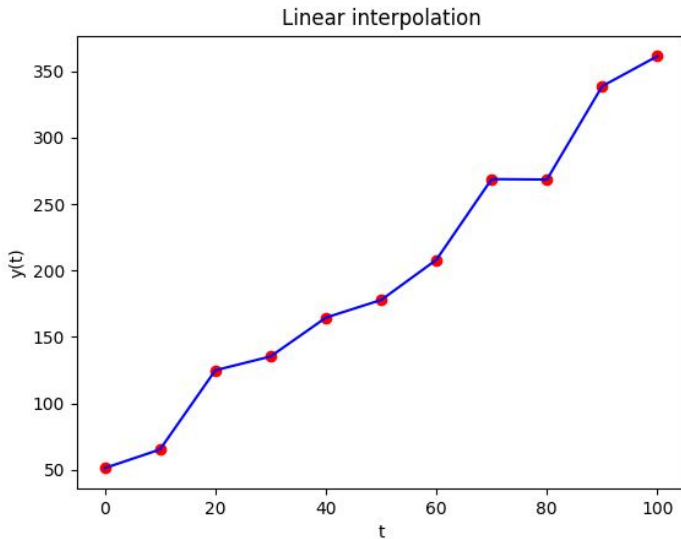
# Curve-fitting dataset

Week6Monday.py

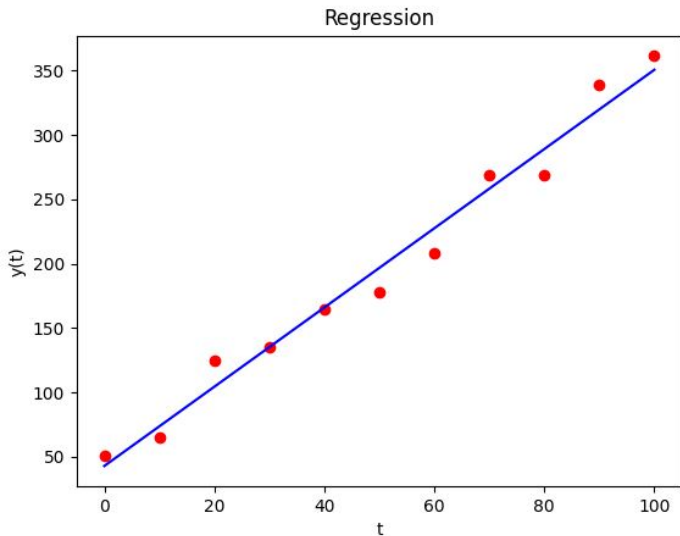


- 11 pairs of data points  $(t_i, y_i), i = 0, 1, 2, \dots, 10$   
 $(0, 51.29), (10, 65.24), (20, 124.89), \dots, (100, 361.32)$

# Interpolation



# Regression: straight-line fit



# Interpolation vs. regression

- **interpolation:** joining the dots
  - ▶ obtain value of  $y$  at some intermediate point
  - ▶ week 6, Monday lecture
  - ▶ linear interpolation, cubic spline interpolation
- **regression:** fitting a straight line
  - ▶ when there's "too much data", simplify
  - ▶ here, simplifying to a straight line
  - ▶ today's lecture
- both interpolation & regression involve creating a function (blue line) from data (red dots)

# Line-fitting in Python

- input data consists of  $(x, y)$  data pairs
- goal is to calculate gradient  $m$  and  $y$ -intercept  $b$  of line-of-best-fit

$$y = mx + b$$

- in Python, we use `curve_fit()` function in `scipy.optimize` library to find  $m$  and  $b$ 
  - ▶ may need `pip install scipy` in terminal

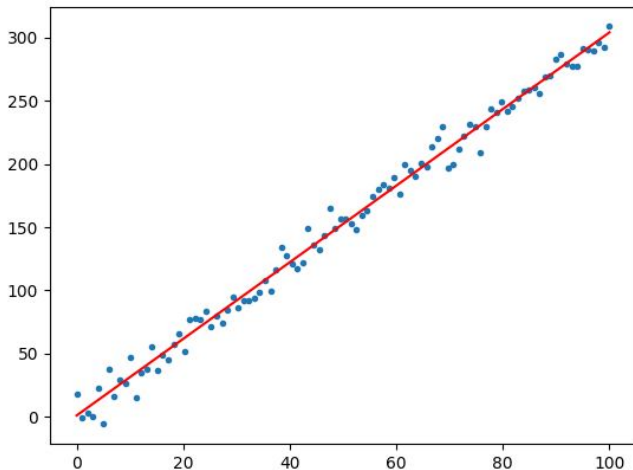
```
1 popt, pcov = curve_fit(line, x, y)
2 m = popt[0]
3 b = popt[1]
```

- ignore `pcov` returned by `curve_fit`



# Line-fitting example

Output generated by `linefitdemo.py`



# Python code: line-fitting

linefitdemo.py

```
1 # linefitdemo
2 import numpy as np
3 from scipy.optimize import curve_fit
4 import matplotlib.pyplot as plt
5
6 def line(x, m, b):
7     return m * x + b
8
9 np.random.seed(1) # replicate results by fixing seed
10 x = np.linspace(0, 100, 100)
11 y = 3. * x + 2. + np.random.normal(0., 10., 100)
12 plt.plot(x, y, '.')
13
14 popt, pcov = curve_fit(line, x, y)
15 m = popt[0]
16 b = popt[1]
17 print('Straight-line gradient m = {:.2f}'.format(m))
18 print('Straight-line intercept b = {:.2f}'.format(b))
19
20 xfine = np.linspace(0., 100., 100)
21 plt.plot(xfine, line(xfine, m, b), 'r')
22 plt.show()
```

# Python code: commentary

- lines 6–7: prepare to fit a straight line to  $(x, y)$  data
  - ▶ line equation  $y = mx + b$
- lines 9–12: create and plot  $(x, y)$  data pairs
  - ▶ straight line (gradient 3 and  $y$ -intercept  $b$ )  
+ Gaussian noise ( $\mu = 0, \sigma = 10$ )
- lines 14–16: where the action happens!
  - ▶ `curve_fit()` function calculates  $m$  and  $b$  which provide best fit to  $(x, y)$  data
- lines 20–21: plot best-fit straight line

# How does line-fitting work?

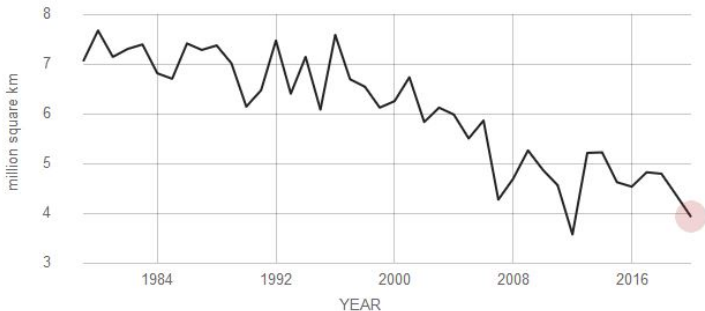
- least-squares
- maybe an image?
- extension to higher-order polynomials fitting

# Application of line-fitting: sea-ice extent

## AVERAGE SEPTEMBER MINIMUM EXTENT

Data source: Satellite observations. Credit: NSIDC/NASA

RATE OF CHANGE  
↓ **13.1**  
percent per decade



<https://climate.nasa.gov/vital-signs/arctic-sea-ice/>

# Fitting a straight line to sea-ice data

- graph shows average monthly Arctic sea ice extent each September since 1979, derived from satellite observations

**Aim:** use straight-line fit to data to estimate when Arctic will be free of sea-ice

▶ ie: when sea-ice extent is zero

- Key steps in solution
  - 1 fit straight line to data, using `scipy.optimize.curve_fit`
  - 2 line  $y = mx + b$  intersects  $x$ -axis ( $y = 0$ ) when  $x = -b/m$

# Python code: sea-ice extent

seaice.py

```
1 # seaiceextent
2 import numpy as np
3 import matplotlib.pyplot as plt
4 from scipy.optimize import curve_fit
5
6 def line(x, m, b):
7     return m * x + b
8
9 # dataset: September sea-ice extent 1979–2020
10 # https://climate.nasa.gov/vital-signs/arctic-sea-ice/
11 year = np.arange(1979, 2021)
12 extent = np.array([7.05, 7.67, 7.14, 7.3, 7.39, 6.81, 6.7, 7.41,
13                   7.28, 7.37, 7.01, 6.14, 6.47, 7.47, 6.4, 7.14, 6.08,
14                   7.58, 6.69, 6.54, 6.12, 6.25, 6.73, 5.83, 6.12,
15                   5.98, 5.5, 5.86, 4.27, 4.69, 5.26, 4.87, 4.56,
16                   3.57, 5.21, 5.22, 4.62, 4.53, 4.82, 4.79, 4.36, 3.92])
```

- lines 6–7: prepare to fit a straight line to data
- lines 11–12: sea-ice extent dataset, 1979–2020

# Python code: sea-ice extent

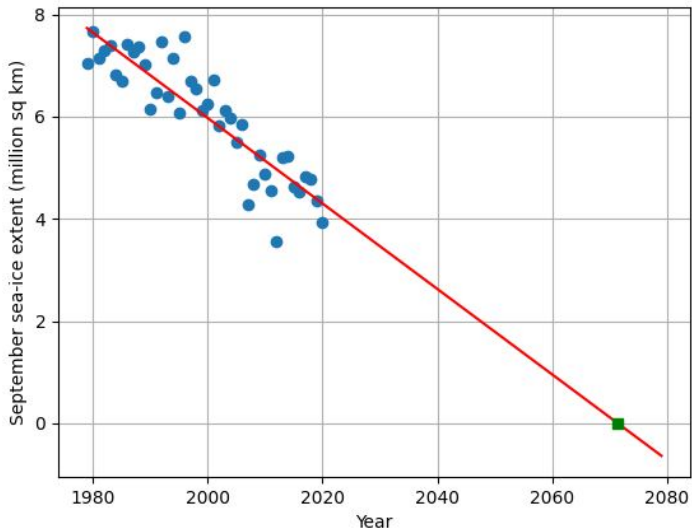
## seaice.py—continued

```
1 popt, pcov = curve_fit(line, year, extent)
2 m = popt[0]          # gradient of best straight-line fit
3 b = popt[1]          # intercept
4
5 yearto2080 = np.arange(1979,2080)
6
7 print('extent(yr) = {:.3f}*year + {:.3f}'.format(m, b))
8 print('Estimate September sea-ice extent is 0 in year = {}'.
9       format(int(-b/m)))
9 plt.plot(year, extent, 'o')
10 plt.plot(yearto2080, line(yearto2080, m, b), 'r')
11 plt.plot(-b/m,0,'gs')  # green square when ice extent is zero
12 plt.xlabel('Year')
13 plt.ylabel('September sea-ice extent (million sq km)')
14 plt.grid()
15 plt.show()
```

- lines 1–3: fit line to data:  $x = \text{year}$ ,  $y = \text{extent}$
- line 5: straight line fit over years 1979–2080
- line 8: line intersects horizontal axis at  $-b/m$



# Estimate Arctic sea-ice free in year 2071



# Lecture summary

- Normal distribution
- Fitting straight line to data