Kernel Density Estimates (KDEs) and generative models in Python

Interactive Lecture Smith College

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Big Picture:

Given an observed distribution of stellar ages in the center of our Galaxy, we would like to predict the distribution of stellar ages in other Galaxies

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> In this interactive lecture, we will apply a kernel density estimate to a measured stellar age distribution and use this to make synthetic data sets from a generative model

There are several ways to access and run these exercises

Method 1: Github

- (1) go to https://github.com/mjoyceGR/KDE_exercise
- (2) download and save

 KDE_exercises.ipynb

 KDE_full_solutions.ipynb

 stellar_ages.dat
 in the same folder on your computer
- (3) Load the two ipynb files into your preferred Jupyter Notebook environment. You will want both accessible so you can consult the solutions if you get stuck

Method 2: Google Drive

(1) Scan this QR code, save the link, then open it on the device you will use to code

You should see a Google Drive folder called

Smith_KDE_Exercises

(2) download and save

KDE_exercises.ipynb

KDE_full_solutions.ipynb

stellar_ages.dat



Method 2: Google Drive

(2) Go to

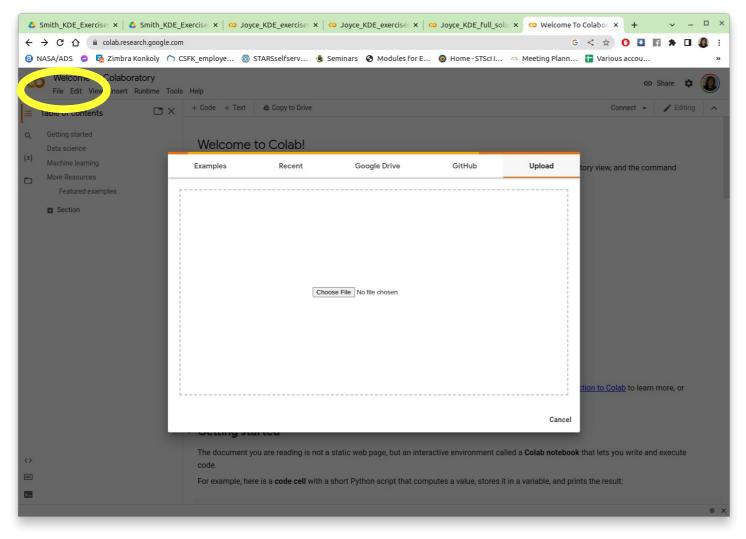
https://colab.research.google.com/

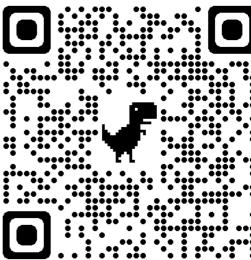


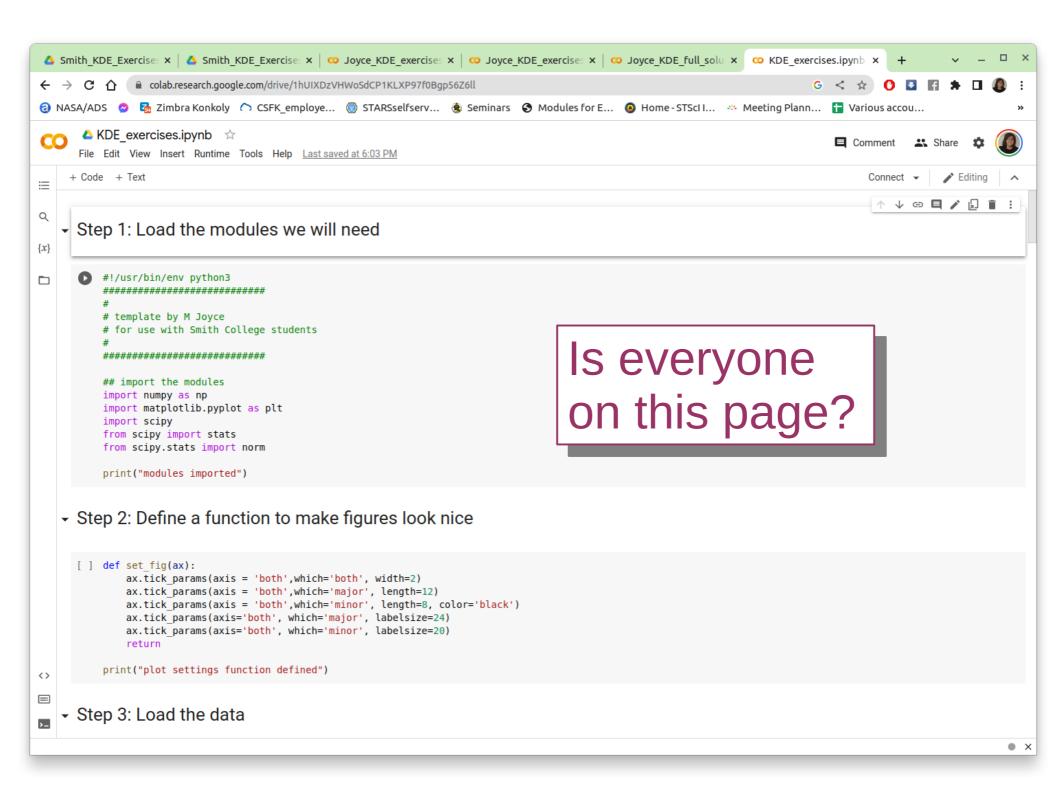
- (i) Under "File" in the top left, click "open notebook"
- (ii) Click "Upload" on the far right of the menu that pops up
- (iii) Upload your downloaded copy of KDE_exercises.ipynb

Do (i- iii) for KDE_full_solutions.ipynb in a different window

https://colab.research.google.com/







Pause

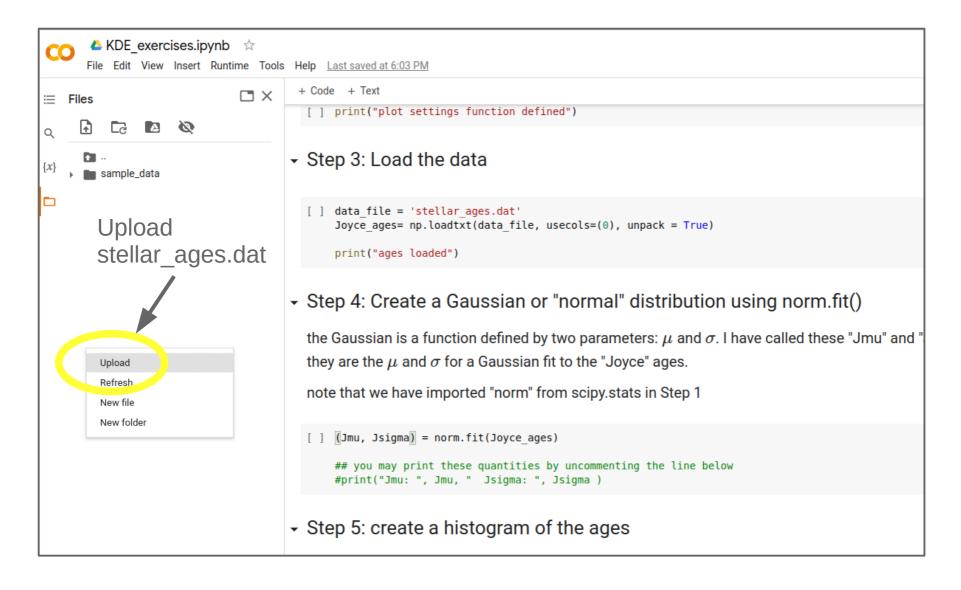
Step 1: Load the modules

Step 2: define a figure function set_fig()

You do not need to understand how this works, just that it makes the figures look nice

Step 3: Load the data

The next cell won't work because we have not uploaded stellar_ages.dat to colab



Step 3: (now) Load the data

The data we are loading is a set of 91 stellar age determinations, measured in Gigayears (1 Gyr = 1 billion years = 10⁹ years)

These are real data from my research, hence "Joyce ages"

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We imported numpy as "np"
We are using a numpy function called "loadtxt" which automatically converts columns into np arrays

Step 3: (now) Load the data

```
▲ KDE exercises.ipynb ☆
          File Edit View Insert Runtime Tools Help Last saved at 6:03 PM
         + Code + Text
    ∷
        Step 3: Load the data
    \{x\}
              data file = 'stellar ages.dat'
              Joyce ages= np.loadtxt(data file, usecols=(0), unpack = True)
    print("ages loaded")
                                                    Python indexes from zero, so the first
                                                    column of stellar_ages.dat is "column 0"
The data we are loading is a
```

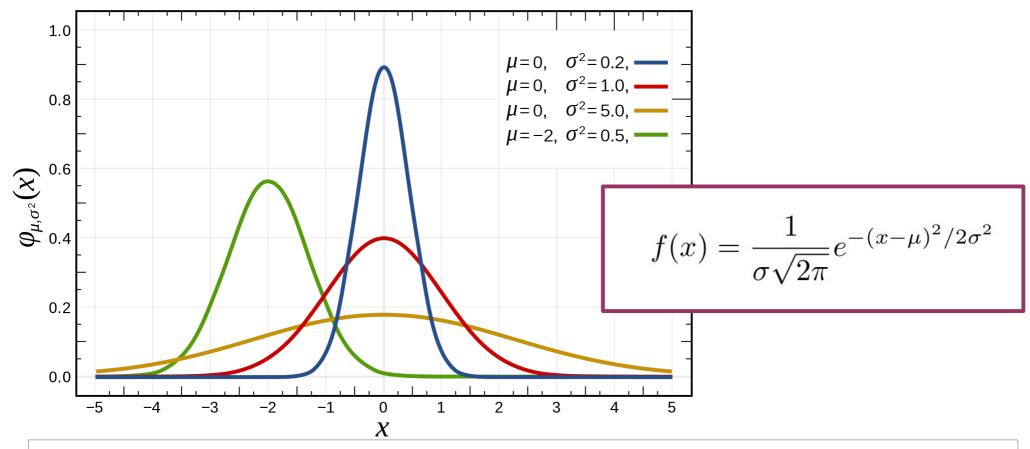
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Step 4: Create a Gaussian



- the shape of the curve is captured by **mu**, the "expected value," or mean, and **sigma**, which is related to the width and represents one standard deviation (sigma^2 is the "variance," as shown in the legend)
- the type of distribution everyone (in astronomy) assumes discrete random variables follow
- also called a "normal distribution"

Step 4: Create a Gaussian

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

Step 4: Create a Gaussian or "normal" distribution using norm.fit()

the Gaussian is a function defined by two parameters: μ and σ . I have called these "Jmu" and "Jsigma" because they are the μ and σ for a Gaussian fit to the "Joyce" ages.

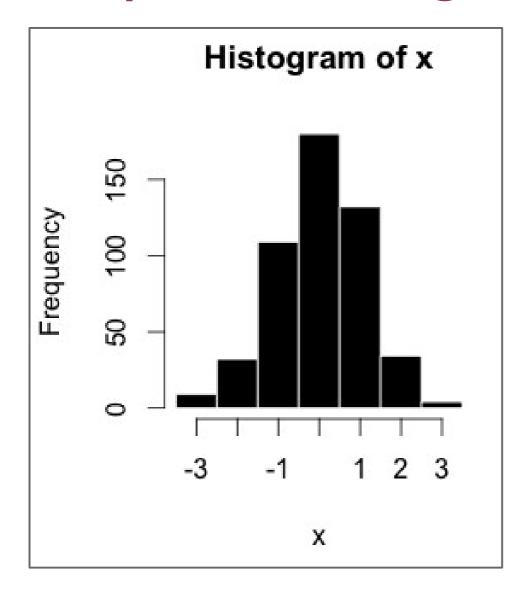
note that we have imported "norm" from scipy.stats in Step 1

```
[ ] [Jmu, Jsigma] = norm.fit(Joyce_ages)

## you may print these quantities by uncommenting the line below
#print("Jmu: ", Jmu, " Jsigma: ", Jsigma )
```

- what this piece of code does is find the "best" values of mu and sigma for a fit of f(x) to the distribution formed by Joyce_ages
- it names these fit parameters *Jmu*, *Jsigma* and we will use them later to make a function

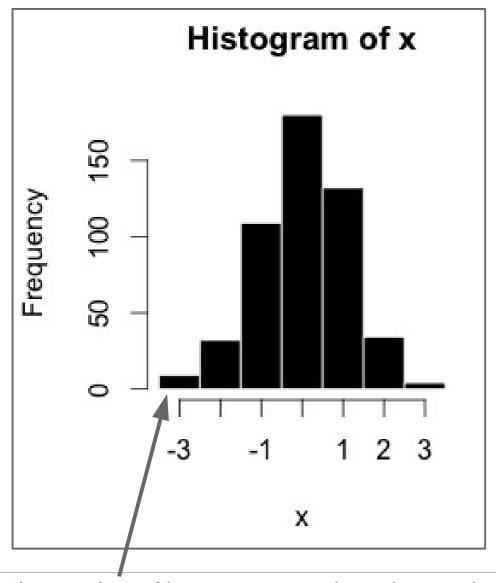
Step 5: Histogram and bins



- on the x-axis, we have observations of some quantity in our case, x = stellar ages
- the y-axis counts the number of occurrences of *x*

So, if out of 91 stars (x), we have 12 stars with an age of 10 Gyr, the y value for x = 10 will be 12.

Step 5: Histogram and bins

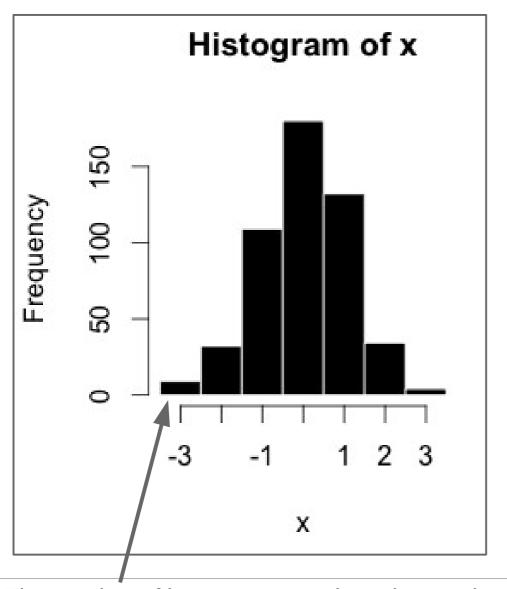


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```
    Step 5: create a histogram of the ages
    [ ] histogram = np.histogram(Joyce_ages)
    Now, grab the bins from the histogram we have created
    [ ] bins = histogram[1]
        ## you may print the bins by uncommenting the line below
        #print("bins: ", bins)
```

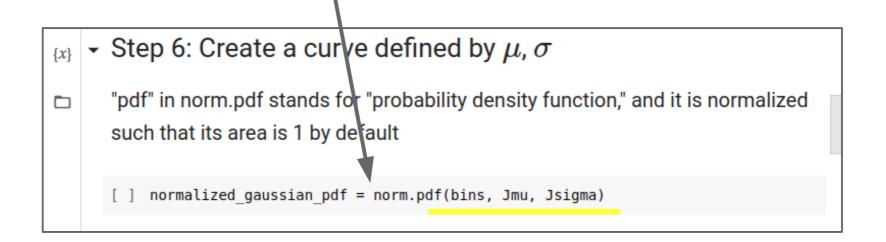
The number of bars corresponds to the number of "bins," in this case, 7. The choice of bin number (or bin size) can have a noticeable effect on the shape of a distribution—this is notorious weakness of histograms.

- we now have bins, mu, and sigma defined for our data (mu = Jmu, sigma = Jsigma)
- we can think of the bins as serving the role of x in the Gaussian function

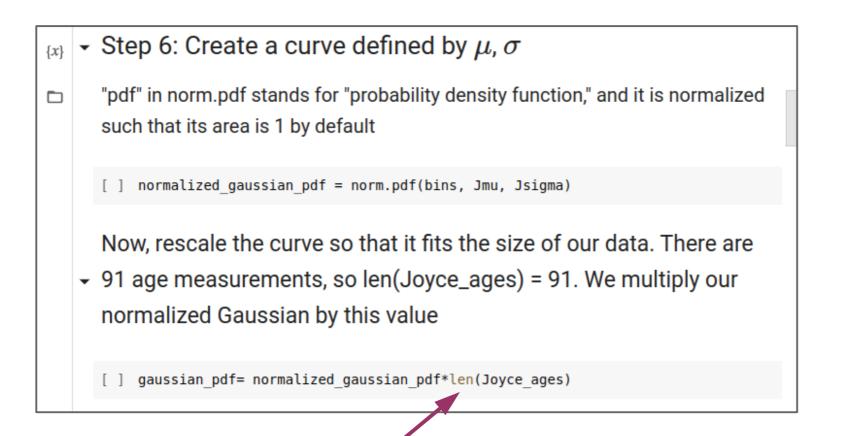
$$f(x) = \frac{1}{\sigma\sqrt{2\pi}}e^{-(x-\mu)^2/2\sigma^2}$$

- we now have bins, mu, and sigma defined for our data (mu = Jmu, sigma = Jsigma)
- we use the scipy.stats function **norm.pdf()** to create our model with this information
 - Step 6: Create a curve defined by μ, σ
 "pdf" in norm.pdf stands for "probability density function," and it is normalized such that its area is 1 by default
 normalized_gaussian_pdf = norm.pdf(bins, Jmu, Jsigma)

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- we use the scipy.stats function **norm.pdf()** to create our model with this information



However (!!) this will generate a Gaussian whose integral is equal to 1, by definition: AKA "normalized"



So, we rescale the normalized Gaussian pdf so that its integral (~ sum over discrete bins) is equal to our data size (91 stellar ages)

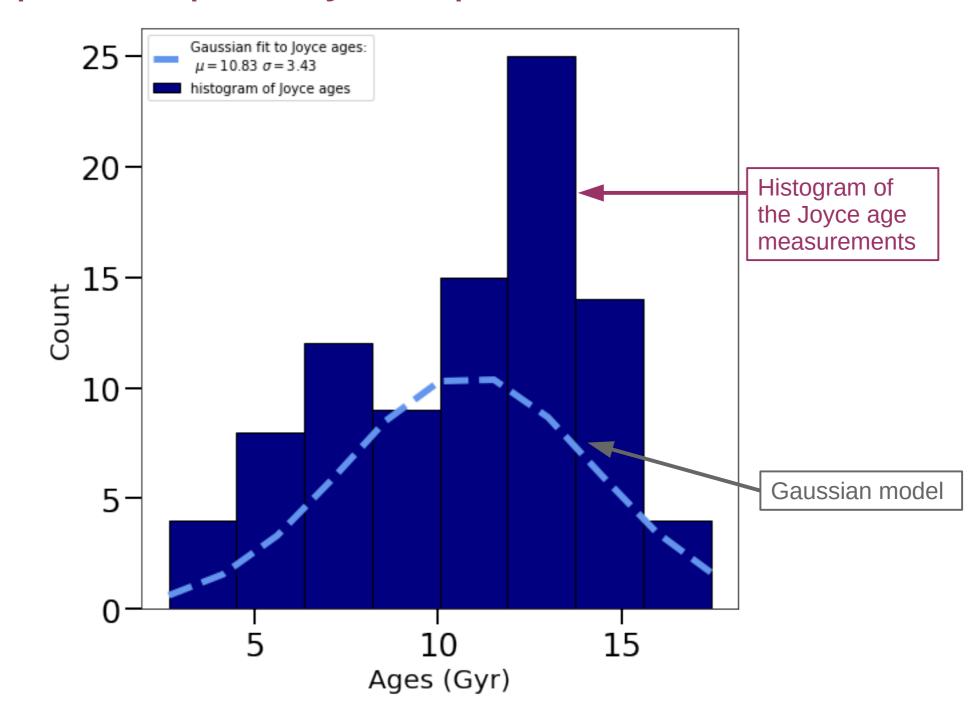
Step 7: Graphically compare data and model

Histogram of the Joyce age measurements

Gaussian model vs bins

```
Step 7: Plot our histogram and the Gaussian curve we have fit to it
```

Step 7: Graphically compare data and model



Pause – how good is this fit?

Pause – how good is this fit?

Not great!

Kernel Density Estimation

Briefly: Math of KDE

Step 8: KDE for Joyce ages

Step 8: Try a Kernel Density Estimate (KDE) instead

Create the kde model for the stellar ages

```
kde_model = stats.gaussian_kde(Joyce_ages)
```

▼ to make the model smoother, we can increase the resolution of the x-axis

the line below subdivides the age range into 1000 equally spaced values. The age range is the minimum age measurement, min(Joyce_ages), to the maximum age measurement, max(Joyce_ages). These correspond to about 2 Gyr (billion years) and 17 Gyr, respectively

```
[ ] age_x_values = np.linspace(min(Joyce_ages), max(Joyce_ages), 1000)
```

the following line evaluates the kde_model function we made at the beginning of Step 8 over the smoother array of x values defined above.

```
[ ] kde = kde_model(age_x_values)
```

once again, the model is normalized to 1, so we must rescale it by the number of age measurements

```
[ ] ## scale the kde by the number of stellar ages in our sample (91)
    scaled_kde = kde*len(Joyce_ages)
```

Step 9: Compare KDE graphically

Python implementation