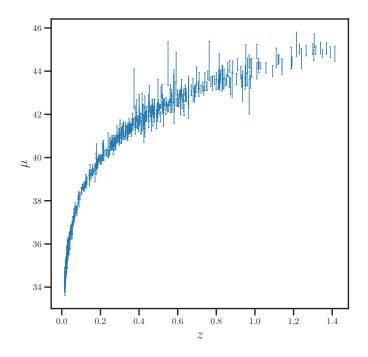
# Data Science Lab Astrophysics 2022: Lab Worksheet 4: Linear Regression

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In this week's lab, we will be looking at **supernova** measurements from the Supernova Cosmology Project (https://supernova.lbl.gov/Union/), specifically the "Union2.1" dataset (see https://supernova.lbl.gov/Union/figures/SCP\_Union\_Astroph\_25\_04.pdf for the accompanying paper). Type Ia supernovae are so-called **standard candles** in cosmology: since the peak luminosity of every supernova is (roughly) the same, their visual magnitude as seen from Earth can be used to determine the distance to their host galaxy.

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Using this data, you will estimate the Hubble constant and the age of our Universe. Notice that in practice, there are some further intricacies involved (such as K-corrections, Malmquist bias, Galactic extinction, etc.), which we will ignore in this lab.

## Getting the data

Download the dataset containing 580 supernovae measurements from the Moodle page of the course (mu\_vs\_z.txt). You can load the file in Python using Pandas with

```
import pandas as pd
filename = "mu_vs_z.txt"
data_full = pd.read_csv(filename, delim_whitespace=True)
```

The data contains 5 columns:

- Supernova: Supernova name
- Redshift: Redshift of the supernova's host galaxy
- Modulus: Distance modulus  $\mu$ , related to distance d [pc] via  $d = 10^{\mu/5+1}$
- Error: Uncertainty of distance modulus measurement  $(1\sigma_{\mu})$
- LMGProb: Probability that the supernova was hosted by a low-mass galaxy

Note: In this lab, we will always treat the redshift z (and quantities that are analytically derived from the redshift such as the recessional velocity) as the *independent* variable (on the "x"-axis) that we assume to know perfectly without any uncertainties, and the distance (modulus) as the *dependent* variable (on the "y"-axis) with associated uncertainties.

### Exploring and manipulating the data

1. Open the supernova data, inspect the columns of the PANDAS dataframe, and plot the distance modulus  $\mu$  as a function of redshift z. Also plot the uncertainties of the distance moduli  $\sigma_{\mu}$ .

For now, we will work only with nearby supernovae at redshifts  $z \leq 0.1$ .

2. Apply a redshift cut to the supernova dataset and select those with  $z \leq 0.1$ . Convert the distance modulus  $\mu$  to a distance d in Megaparsec (Mpc) and make a plot of distance d vs. redshift z.

For small distances d, the redshift z is directly proportional to the recessional velocity v, related via the formula

$$z = \frac{v}{c},\tag{1}$$

where c is the speed of light.

3. Use this formula to convert the redshifts to recessional velocities, and plot the distance d as a function of recessional velocity v.

#### Determining the Hubble constant from nearby supernovae

Hubble's famous law (also known as the Hubble-Lemaître law) states that the recessional velocity v with which far-away objects like other galaxies move away from us due to the expansion of the Universe is proportional to the distance of the object d, i.e.

$$v = H_0 d, (2)$$

where  $H_0$  [km/s/Mpc] is the **Hubble constant** that describes the (current) speed of the expansion of the Universe. The reciprocal of the Hubble constant, which has units of time, is known as the **Hubble time**  $t_H = 1/H_0$ . The Hubble time would be the current age of the Universe if its expansion had been linear throughout cosmic history (which is in fact not quite the case).

1. Least-square estimate Given the distances d to the supernovae and the recessional velocities v of their host galaxies (as determined from their redshifts), find the least-square estimate for the Hubble time  $t_H$  (for now ignoring the uncertainties in d). Recall that we are treating the recessional velocities v as the "x"-variable and the (uncertain) distances as the "y"-variable. Then, convert this estimate for  $t_H$  to an estimate for  $H_0$ .

Now, let us include our knowledge about different uncertainties for different supernovae into the fit. Since we only have uncertainties for the distance moduli  $\mu$ , we first need to convert the uncertainties in  $\mu$  into uncertainties in d. In order to do so, recall the uncertainty propagation formula

$$\sigma[d(\mu)] = |d'(\mu)| \, \sigma_{\mu},\tag{3}$$

where  $d'(\mu)$  denotes the derivative of  $d(\mu)$  and  $\sigma_{\mu}$  is the uncertainty of the distance modulus (different for each data point).

- 2. Use the above formula to obtain uncertainties  $\sigma_d := \sigma[d(\mu)]$  for the distances  $d = d(\mu)$ .
- 3. Maximum likelihood estimate Now, assuming Gaussianity of the errors  $\sigma_d$ , determine the maximum likelihood estimate for  $t_H$ . Again, convert this estimate to an estimate for  $H_0$ .
- 4. Plot again the distances d as a function of the recessional velocity v and add the least-square estimate and the maximum likelihood estimate to the plot. How do they compare?

#### Considering all supernovae and determining the age of the Universe

Now, we will look again at *all* the supernovae in the data (not only those with  $z \leq 0.1$ ). For the remainder of this lab, we will take the redshift z to be the independent variable (on the "x"-axis), rather than the recessional velocity.

- 1. Polynomial regression As a first "cosmology-agnostic" approach, fit a polynomial of degree r=4 (so there are K=5 model parameters including the constant intercept) to the  $\mu=\mu(z)$  distance moduli by computing the maximum likelihood estimate for  $\boldsymbol{\theta}=(\theta_0,\ldots,\theta_4)^T\in\mathbb{R}^5$ , taking into account the uncertainties  $\sigma_{\mu}$  for  $\mu$ . Plot the polynomial with the maximum likelihood parameters over the data. Is this polynomial a good model for the data? Do you expect this model to generalize to new supernova data at higher redshifts z>1.5?
- 2. "Cosmological" regression Now, let us consider a regression model that is motivated by cosmology. From theory, we know that the relationship between the (luminosity) distance d and the redshift z should be given by

$$d(z;t_H) = (1+z) c t_H \int_0^z \frac{dz}{E(z)},$$
(4)

where

$$E(z) = \sqrt{\Omega_{\Lambda} + \Omega_{m}(1+z)^{3}}.$$
 (5)

For the current dark energy and matter density parameters  $\Omega_{\Lambda}$  and  $\Omega_{m}$ , respectively, we take the parameters determined by the Planck Collaboration  $\Omega_{\Lambda} = 0.685$  and  $\Omega_{m} = 0.315$ .

Note that while  $d(z;t_H)$  is nonlinear in z, it is *linear* in our free parameter  $t_H$ , so we can determine the maximum likelihood estimate for  $t_H$  using what we have learned in the lecture. The steps to do this are:

- (a) Convert the uncertainties for  $\mu$  into uncertainties for d again, now for all the supernovae (using Eq. (3)).
- (b) Build the feature matrix  $\boldsymbol{\Phi} \in \mathbb{R}^{N \times 1}$  using Eq. (4). Recall the definition of the feature matrix (which only has a single column now because we only have a single parameter  $t_H$ ): the feature matrix should be such that  $\mathbf{d} = \boldsymbol{\Phi} t_H + \boldsymbol{\varepsilon}$ , where  $\mathbf{d} \in \mathbb{R}^N$  contains the N distance measurements and  $\boldsymbol{\varepsilon} \in \mathbb{R}^N$  is a noise vector.
- (c) Build the precision matrix  $C^{-1}$  containing the inverse of the uncertainty variances for d on the diagonal.
- (d) Find the maximum likelihood estimate for  $t_H$ .

Overplot the maximum likelihood fit onto the data. Is this a good model for the data? What is the value of  $t_H$  (and consequently of  $H_0$ ) that you obtained?

Hint: for the integral in Eq. (4), you can use the function scipy.integrate.quad.

From the Hubble time  $t_H$  (together with the cosmological parameters  $\Omega_{\Lambda}$  and  $\Omega_m$ ), we can compute the age of the Universe t=t(z) at redshift z via the formula

$$t(z) = t_H \int_z^\infty \frac{dz}{(1+z)E(z)},\tag{6}$$

where E(z) is defined as above.

- 3. Age of the Universe Using the maximum likelihood estimate for  $t_H$  obtained in the previous part, compute the current age of our Universe (at redshift z = 0).
  - *Hint 1*: The function scipy.integrate.quad also accepts numpy.infty as an integration boundary.
  - Hint 2: make sure to be careful with the units, especially for the Hubble time.