Astropy (PHYS265)

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Date: 05/09/2025

Below is the description of the Astropy Module focusing on its fitting and modelling codes. This was written as the final project for the class PHYS265 in the Spring 2025 semester

Model and Fitting is Astropy

In the following notebook, I will take the data from Free-Fall of mass experiment done by me in the Lab course of PHYS275

For this data we will use the data collected by me in the experiment done to compare the data collected during slanted falling of object on air track with the formula below using Astropy LevMarLSQFitter and compare the fit with scipy curve_fit

$$s = s_0 + v_0 t + \frac{1}{2} a_0 t^2$$

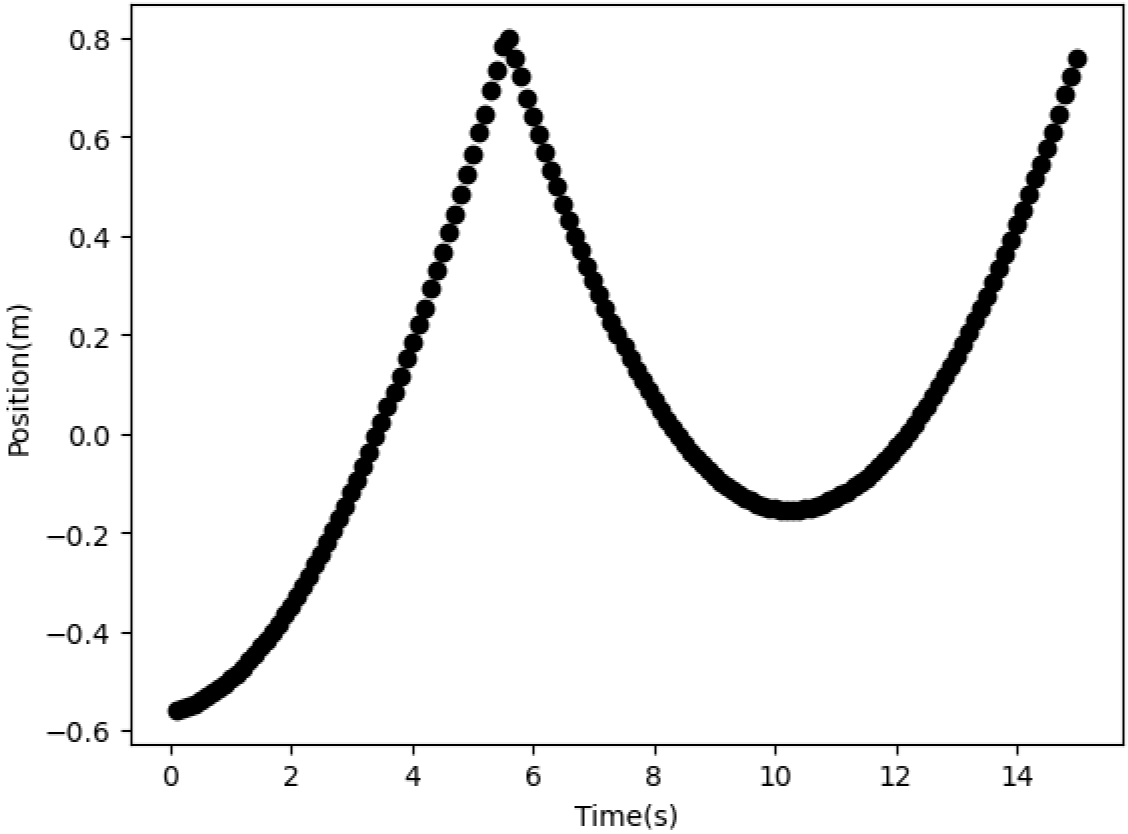
For this I will use the fns:

1. numpy.random.poisson
2. astropy.modeling.fitting.LevMarLSQFitter
3. astropy.modeling.fitting.custom_model
4. scipy.optimize.curve_fit

Before we start lets visualize the data...

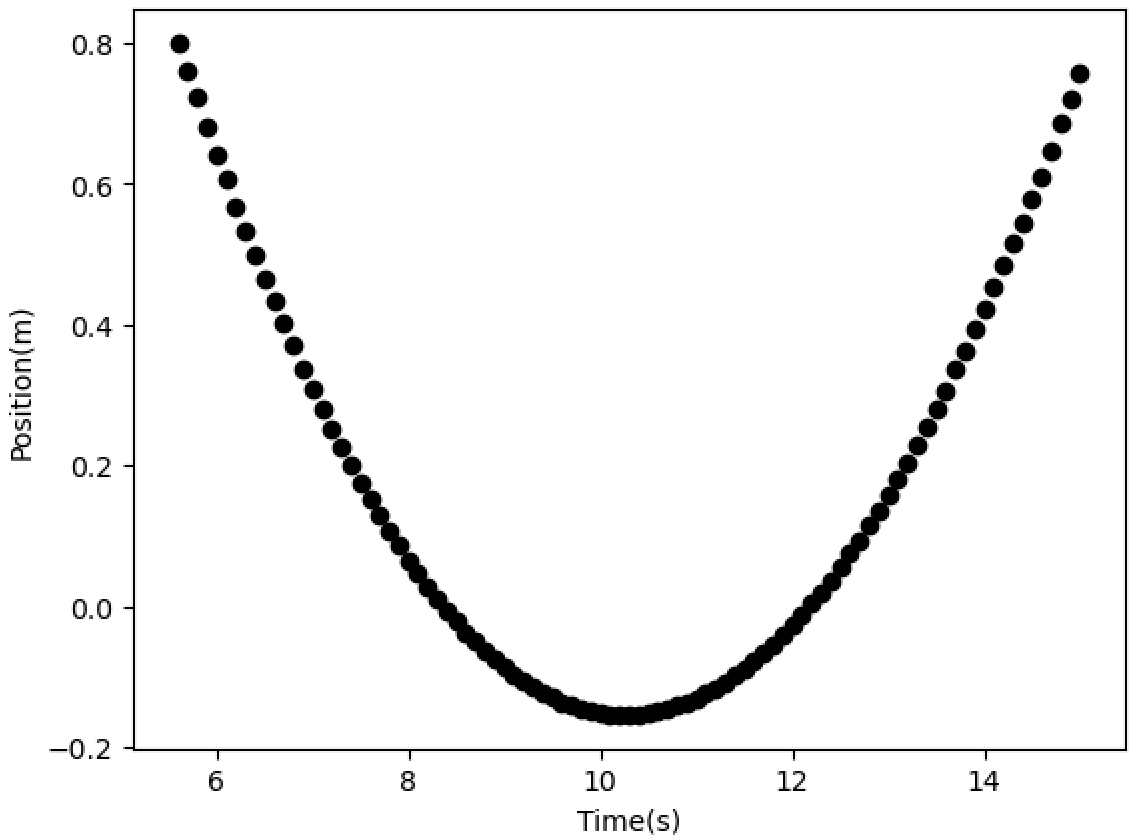
In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit
from astropy.modeling import fitting,custom_model
import scipy.stats as st
```

In [2]:
```
data = np.loadtxt("PHYS265 Data.csv",skiprows=1,delimiter=',')
Time = data[:,0]
s_data = data[:,1]
stdev = data[:,2]
fig,ax = plt.subplots()
ax.plot(Time,s_data,'ok',label='data');
ax.set_xlabel("Time(s)");
ax.set_ylabel("Position(m)");
```



From this data we will mask the data before the parabola to get proper results from the formula

In [3]:
```
posdif = s_data[1:]-s_data[:-1]
dec_index = np.argmax(posdif < 0)
s_masked = s_data[dec_index:]
t_masked = Time[dec_index:]
stdev_masked = stdev[dec_index:]
fig,ax = plt.subplots()
ax.plot(t_masked,s_masked,'ok',label='data');
ax.set_xlabel("Time(s)");
ax.set_ylabel("Position(m)");
```



Here x_masked is the position of the masked values and t_masked is the same for time

Fitting the data using Astropy

We will fit the data using the custom model created below:

In [4]:
```
@custom_model
def s_astropy(t,s0=0.0,v0=0.0,a0=0.0):
    return s0+v0*t+(1/2)*a0*(t**2)
```

In [5]:
```
model = s_astropy(s0=1,v0=1,a0=1)
fitter = fitting.LevMarLSQFitter()
weights = 1/(stdev_masked**2)
s_fitmodel = fitter(model,t_masked,s_masked,weights=weights)
s_fit_astropy = s_fitmodel(t_masked)
print(f"The value of fitted parameters was found as: s0={s_fitmodel.s0.value:.1f},
```

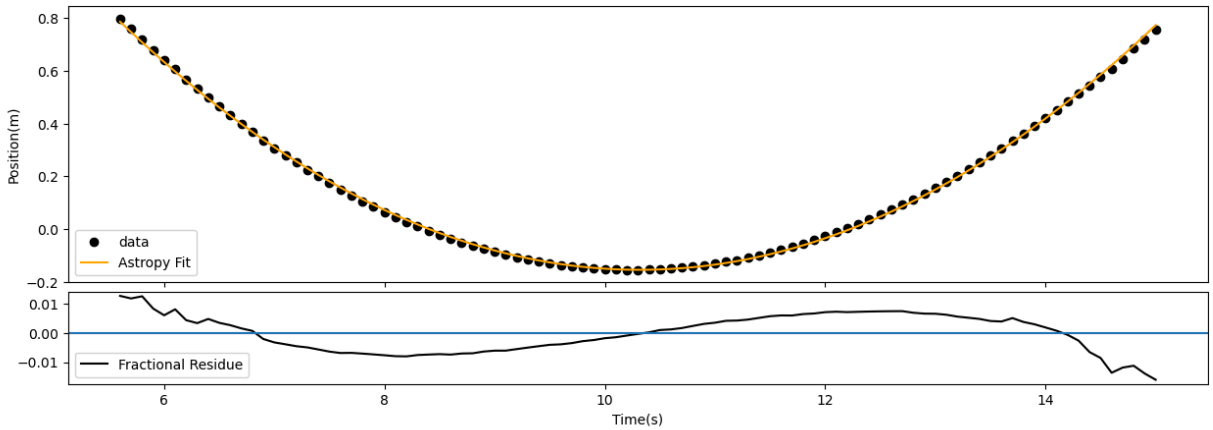
```
The value of fitted parameters was found as: s0=4.3, v0=-0.9 and a0=0.1
```

Visualizing our data:

In [6]:
```
fig,(ax_top,ax_bot) = plt.subplots(
    2,1,sharex=True,figsize=(15,5),gridspec_kw={'height_ratios':[3,1],'hspace':0.05
)
ax_top.plot(t_masked,s_masked,'ok',label='data');
ax_top.plot(t_masked,s_fit_astropy,label='Astropy Fit',color='orange');

ax_top.set_ylabel("Position(m)");
```

```
ax_top.legend();
fracres = (s_masked-s_fit_astropy)
ax_bot.plot(t_masked,fracres,color='k',label='Fractional Residue')
ax_bot.axhline(0)
ax_bot.set_xlabel("Time(s)");
ax_bot.legend()
fig.savefig('Figure 1',bbox_inches='tight')
```



Fitting data using Scipy Curve_Fit

We will fit the data using the fn defined below:

In [7]:
```
def s_scipy(t,s0=0.0,v0=0.0,a0=0.0):
    return s0+v0*t+(1/2)*a0*(t**2)
```

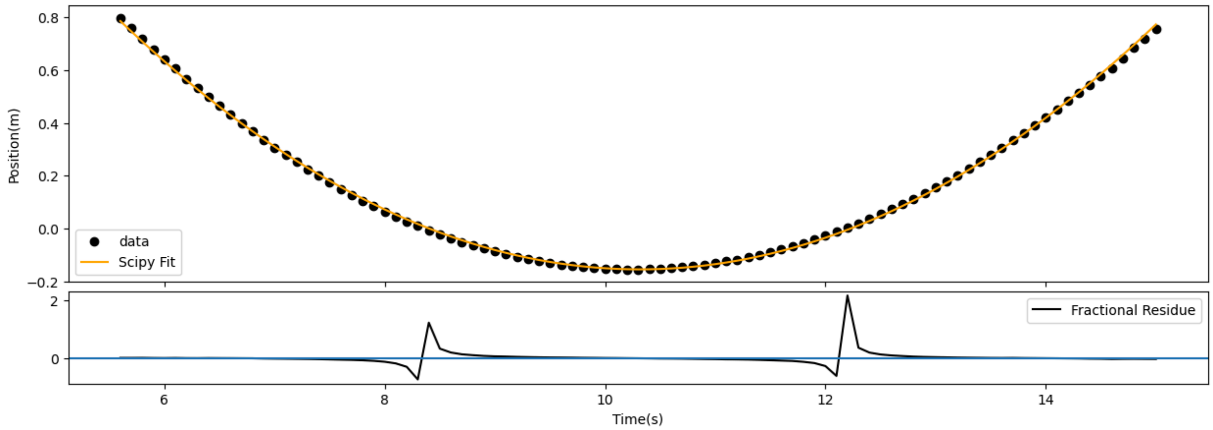
In [8]:
```
params,pcov = curve_fit(s_scipy,t_masked,s_masked,sigma=stdev_masked)
s_fit_scipy = s_scipy(t_masked,*params)
print(f"The value of fitted parameters was found as:s0={params[0]:.1f},v0={params[1
```

```
The value of fitted parameters was found as:s0=4.3,v0=-0.9 and a0=0.1
```

Visualizing our data:

In [9]:
```
fig,(ax_top,ax_bot) = plt.subplots(
    2,1,sharex=True,figsize=(15,5),gridspec_kw={'height_ratios':[3,1],'hspace':0.05
)
ax_top.plot(t_masked,s_masked,'ok',label='data');
ax_top.plot(t_masked,s_fit_scipy,label='Scipy Fit',color='orange');

ax_top.set_ylabel("Position(m)");
ax_top.legend();
fracres = (s_masked-s_fit_scipy)/s_masked
ax_bot.plot(t_masked,fracres,color='k',label='Fractional Residue')
ax_bot.axhline(0)
ax_bot.set_xlabel("Time(s)");
ax_bot.legend()
fig.savefig('Figure 2',bbox_inches='tight')
```



Now to properly compare the fits, we will find out the chi-square values of each and compare them:

In [10]:
```
chisq_astropy = np.sum(((s_masked-s_fit_astropy)/stdev_masked)**2)
chisq_scipy = np.sum(((s_masked-s_fit_scipy)/stdev_masked)**2)
ndof = len(s_masked) - 3 #Since there were 3 parameters to fit
reducedchisq_astropy = chisq_astropy/ndof
pvalue_astropy = st.chi2.sf(chisq_astropy,ndof)
reducedchisq_scipy = chisq_scipy/ndof
pvalue_scipy = st.chi2.sf(chisq_scipy,ndof)
```

In [11]:
```
print(f"From this we get that the chisq value of fit by astropy is {chisq_astropy:.
print(f"From this we get the value of reduced chisq done by astropy and scipy respe
print(f"And thus we get the p-value of astropy as {pvalue_astropy} and for scipy as
print(f"Since both values are 0 which is due to high precision of sonic ranger,we c
```

```
From this we get that the chisq value of fit by astropy is 127551.67 and by scipy is
127551.67
From this we get the value of reduced chisq done by astropy and scipy respectively a
s: 1386.43,1386.43
And thus we get the p-value of astropy as 0.0 and for scipy as 0.0
Since both values are 0 which is due to high precision of sonic ranger,we can't depe
nd on p-value for comparision and would have to rely on chisq only
```

In [12]:
```
if chisq_astropy>chisq_scipy:
    print(f"By comparing the chi-sq values we can see that scipy does better fit as
elif chisq_astropy<chisq_scipy:
    print(f"By comparing the chi-sq values we can see that astropy does better fit
else:
    print(f"Both have equally good capabilities of fitting")
```

```
By comparing the chi-sq values we can see that astropy does better fit as it has low
er chi-sq value
```

Thus we can see that Astropy's LevMarLSQFitter has better fitting capabilities than Scipy and thus could be used instead of the scipy curve_fit although the difference isn't huge and thus could be be given to rounding errors done from Scipy since the values of the parameteres and the graphs are hugely similar

It is also noticable that for such a simple fit Astropy used 5 lines of code other than model defination whereas scipy used only 2 lines of code and thus is more reliable for faster computing