```
import numpy as np
import pandas as pd
from astropy.timeseries import LombScargle
import matplotlib.pyplot as plt
from matplotlib import rc
```

Q₁

Solving Kepler's equation using Newton's Method:

```
In [2]:

def solve_kepler(e, M):
    """

    Solve Kepler's Equation M = E - e sinE
    """

    dEs = []
    E = M + 0.85 * e * np.sign(np.sin(M))
    dE = 1e3
    while abs(E - e * np.sin(E) - M) > 1e-10:
        dE = ((E - e * np.sin(E) - M)) / (1 - e * np.cos(E))
        E -= dE
    return E
```

Verify over 0 < e < 1 and $0 < M < 2\pi$ that Kepler's equation holds down to an error of 10^{-10}

```
In [3]:
    e = np.random.random(size=10000)
    M = 2 * np.pi * np.random.random(size=10000)

for e, M in zip(e, M):
    E = solve_kepler(e, M)
    assert(M - (E - e * np.sin(E)) < 1e-10)</pre>
```

None of the assertions failed, so our solver seems to do the job!

Q2

Calculate radial velocity given six parameters: $(K_{star}, P, t_p, e, \omega, \gamma)$

f = true anomaly(e, M)

return RVs
if t is a float

M = 2 * np.pi / P * (t - tp)

```
f = true_anomaly(e, M)
return K_star * (np.cos(omega) * np.cos(f) - np.sin(omega) * np.sin(f) + e * np.cos(on
```

Q3

To find the period of the mystery planet we will use a Lomb Scargle Periodogram. First, loading in the data:

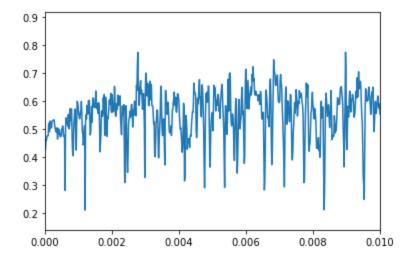
```
In [6]: # Read in data
df = pd.read_csv('mystery_planet01.txt', delim_whitespace=True, header=None, names=['t',
df['t'] = df['t'] - df['t'].min() # begin time at first obs
df.head()
```

```
Out[6]:
                    t
                          rv rv_err
          0
                      -0.125
                               0.014
               0.000
          1
              24.952
                       0.143
                               0.015
             214.831 -0.110
                               0.012
          3 215.842 -0.123
                               0.012
             216.847 -0.129
                               0.012
```

Then some combination of arguments passed into astropy's LombScargle model seems to do the trick...

```
In [7]: freq, power = LombScargle(df['t'], df['rv'], df['rv_err'], nterms=10).autopower(nyquist_fa
# plot frequency vs power
plt.plot(freq, power)
plt.xlim([0,.01])
```

```
Out[7]: (0.0, 0.01)
```



Getting the frequency (in \$days^{-1}) with maximum power:

```
In [8]: f = freq[np.argmax(power)]
f
```

Out[8]: 0.01794830591244739

We plot the folded timeseries to verify if this is the correct frequency

```
In [9]:
```

```
<matplotlib.collections.PathCollection at 0x7fcd50699610>
 Out[9]:
            0.6
            0.4
            0.2
            0.0
           -0.2
                 0.0
                          0.2
                                    0.4
                                             0.6
                                                      0.8
                                                               1.0
          Hmmm close, but not good enough. Try the next harmonic
In [10]:
            P = 2/(f)
In [11]:
            plt.scatter((df['t']%P)/P, df['rv'])
           <matplotlib.collections.PathCollection at 0x7fcd646eacd0>
Out[11]:
            0.6
            0.4
            0.2
            0.0
           -0.2
                          0.2
                                    0.4
                                              0.6
                 0.0
                                                       0.8
                                                                 1.0
In [12]:
           111.4311294757336
Out[12]:
          Much better:) the period is approximately 111.43 days
          Q4
          Using an MCMC to fit the parameters: (K_{star}, P, t_p, e, \omega, \gamma):
```

P = 1/(f)

In [13]:

import emcee

plt.scatter((df['t']%P)/P, df['rv'])

```
def log_likelihood(theta, t, rv, rv_err):
In [14]:
              # return gaussian log likelihood of data given model params theta
              K star, P, tp, e, omega, gamma = theta
              model = RV model(t, K star, P, tp, e, omega, gamma)
              sigma2 = rv err ** 2
              return -0.5 * np.sum((rv - model) ** 2 / sigma2 + np.log(sigma2))
          def log prior(theta):
              # return -inf if params outside of priors, else return 0
              K star, P, tp, e, omega, gamma = theta
              if .2 < K star < .7 and 110 < P < 113 and 0 < tp < 113 and 0 < e < 1 and 0 < omega < 6
                  return 0.0
              return -np.inf
          def log probability(theta, t, rv, rv err):
              # sum of logL and log Priors
              lp = log prior(theta)
              if not np.isfinite(lp):
                  return -np.inf
              return lp + log likelihood(theta, t, rv, rv err)
```

Using chi-by-eye, I determined an initial guess of parameters

```
In [15]: # K_star, P, tp, e, omega, gamma
init = [ 0.5, 111.5, 9.95, .97, 5.2, 0]
```

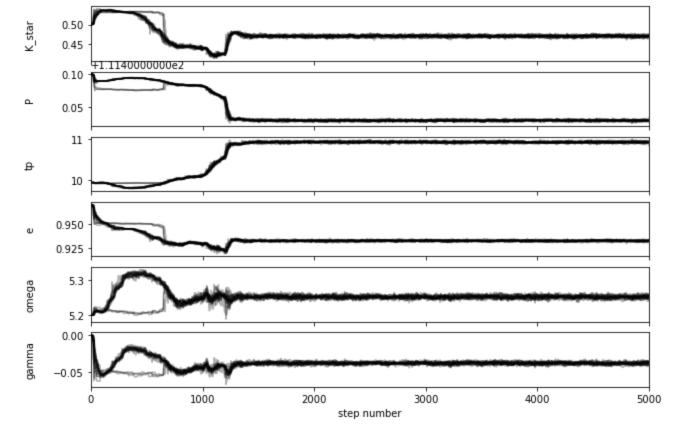
Run the MCMC

```
100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%|
```

Visualize traces to make sure nothing weird is happening

```
In [17]:
    fig, axes = plt.subplots(6, figsize=(10, 7), sharex=True)
    samples = sampler.get_chain()
    labels = ['K_star', 'P', 'tp', 'e', 'omega', 'gamma']
    for i in range(6):
        ax = axes[i]
        ax.plot(samples[:, :, i], "k", alpha=0.3)
        ax.set_xlim(0, len(samples))
        ax.set_ylabel(labels[i])
        ax.yaxis.set_label_coords(-0.1, 0.5)

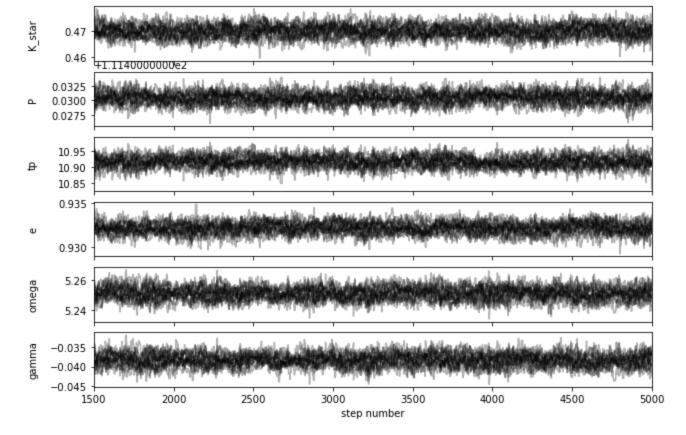
axes[-1].set_xlabel("step number");
```



Looks like it took the MCMC about 1500 steps to converge to the global minimum.

```
In [18]:
    burnin = 1500
    fig, axes = plt.subplots(6, figsize=(10, 7), sharex=True)
    samples = sampler.get_chain(discard=burnin)
    for i in range(6):
        ax = axes[i]
        ax.plot(range(burnin, burnin + len(samples)), samples[:, :, i], "k", alpha=0.3)
        ax.set_xlim(burnin, burnin + len(samples))
        ax.set_ylabel(labels[i])
        ax.yaxis.set_label_coords(-0.1, 0.5)

axes[-1].set_xlabel("step number");
```

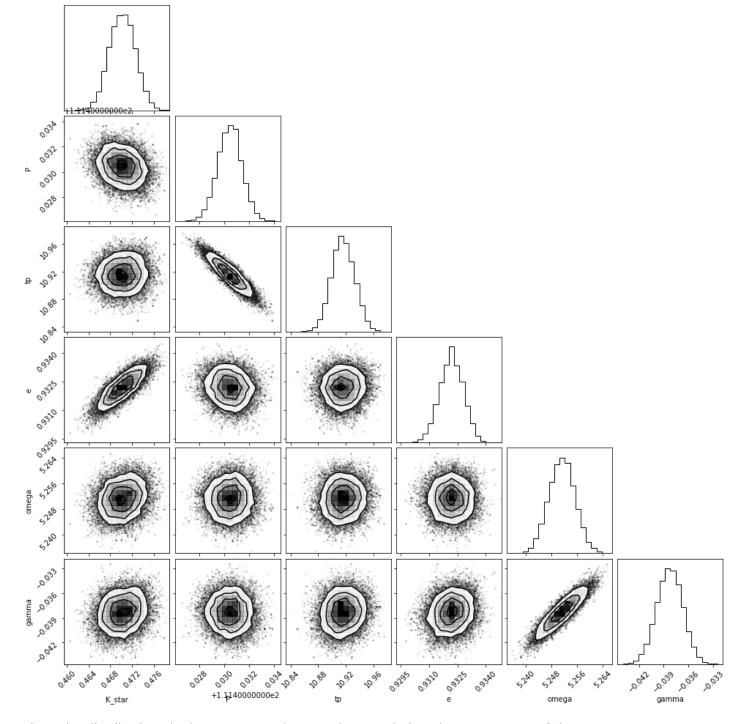


The autocorrelations seem a little high and if I were doing research I'd want to modify the step size and thin out the chain before plotting the posterior distributions. However, since this is just for class I'm going to forge ahead.

Make a corner plot:

```
In [19]: import corner

flat_samples = sampler.get_chain(discard=burnin, flat=True)
fig = corner.corner(
    flat_samples, labels=labels
);
```



Nice! The distributions look pretty smooth. Note the correlations between some of the parameters!

The fitted values of $(K_{star}, P, t_p, e, \omega, \gamma)$ are:

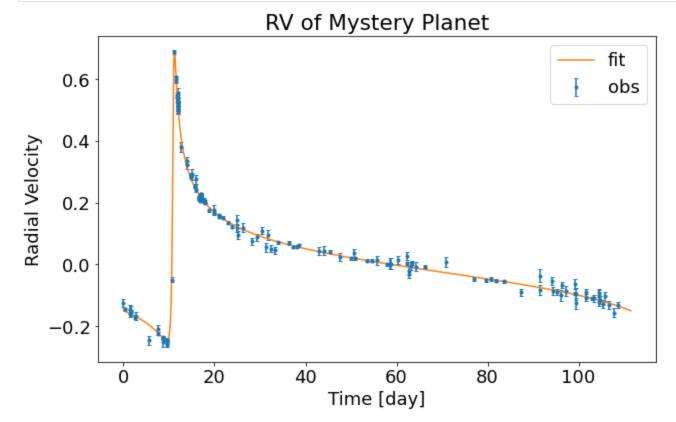
```
In [20]:
          fit = flat_samples.mean(axis=0)
          fit = np.median(flat samples, axis=0)
          for ii, param in enumerate(fit):
              print(labels[ii].ljust(10), round(param, 3))
                     0.47
         K star
         Р
                     111.43
                     10.915
         tp
                     0.932
                     5.251
         omega
         gamma
                     -0.038
```

Plotting the model against the data, we see that the model does really well!

```
In [21]: P = fit[1]
```

```
font = {'size' : 18}
rc('font', **font)

# plot fit
ts = np.linspace(0, P, 1000)
plt.figure(figsize=(10,6))
plt.title('RV of Mystery Planet')
plt.errorbar(df['t'] % P, df['rv'], df['rv_err'], label='obs', fmt='.', capsize=2)
plt.plot(ts, RV_model(ts, *fit), label='fit')
plt.xlabel('Time [day]')
plt.ylabel('Radial Velocity')
plt.legend()
plt.show()
```



ThWhat an eccentric planetary system;)

Q6

Note, in the write up, $\mathbf{r}=\mathbf{x}$ and $\dot{\mathbf{r}}=\mathbf{v}$

a.

Conservation of angular momentum means that cross product of the position and velocity of an object $\mathbf{r} \times \dot{\mathbf{r}}$ in orbit is conserved and equal to $|h|\hat{z}$ where $\hat{z} = \hat{r} \times \dot{\hat{r}}$ is perpendicular to the plane of orbit. Thus $\mathbf{r}(\mathbf{t}) \times \mathbf{r}(\dot{\mathbf{t}}) = \mathbf{r}_0 \times \dot{\mathbf{r}}_0$ for all t as long as there is no change to the orbit.

Now to prove the relation:

$$f\dot{g}-g\dot{f}=1$$

We know that by applying the f and g equations, we can find $\mathbf{r}(\mathbf{t})$ and $\dot{\mathbf{r}}(\dot{\mathbf{t}})$ as a function of $\dot{\mathbf{r}}_0$ and $\dot{\mathbf{r}}_0$:

$$\mathbf{r} = f\mathbf{r}_0 + g\dot{\mathbf{r}}_0 \ \dot{\mathbf{r}} = \dot{f}\,\mathbf{r}_0 + \dot{g}\dot{\mathbf{r}}_0$$

Taking the cross products of each side:

$$\mathbf{r} imes \dot{\mathbf{r}} = (f\mathbf{r}_0 + g\dot{\mathbf{r}_0}) imes (\dot{f}\,\mathbf{r}_0 + \dot{g}\dot{\mathbf{r}_0})$$

Using the following two identities for the crossproduct:

$$\mathbf{x} \times \mathbf{x} = 0$$
$$\mathbf{x} \times \mathbf{y} = -\mathbf{y} \times \mathbf{x}$$

We can reduce the RHS to:

$$\mathbf{r} imes \dot{\mathbf{r}} = (f\mathbf{r}_0 + g\dot{\mathbf{r}}_0) imes (\dot{f}\,\mathbf{r}_0 + \dot{g}\dot{\mathbf{r}}_0)$$
 $\mathbf{r} imes \dot{\mathbf{r}} = (f\mathbf{r}_0 imes \dot{g}\dot{\mathbf{r}}_0) + (g\dot{\mathbf{r}}_0 imes \dot{f}\,\mathbf{r}_0)$
 $\mathbf{r} imes \dot{\mathbf{r}} = (f\dot{g} + -g\dot{f})(\mathbf{r}_0 imes \dot{\mathbf{r}}_0)$

However, because of conservation of momentum, ${f r} imes \dot{{f r}} = {f r}_0 imes \dot{{f r}}_0$, so we are left with:

$$f\dot{g}-g\dot{f}=1$$

b.

The f and g functions are:

$$egin{aligned} f &= rac{a}{r_0}(\cos(E-E_0)-1)+1 \ g &= (t-t_0) + rac{1}{n}(\sin(E-E_0)-(E-E_0)) \ \dot{f} &= -rac{a^2}{rr_0}n\sin(E-E_0) \ \dot{g} &= rac{a}{r}(\cos(E-E_0)-1)+1 \end{aligned}$$

We will set our reference frame so that $E_0=M_0=0$ and that $M=n(t-t_0)$ and also pull out factors of $\frac{a}{r_0}$ and $\frac{a}{r}$ out of f and \dot{g} We can rewrite these equations:

$$egin{aligned} f &= rac{a}{r_0}(\cos E - 1 + rac{r_0}{a}) \ g &= rac{1}{n}(M + \sin E - E) \ \dot{f} &= -rac{a^2}{rr_0}n\sin E \ \dot{g} &= rac{a}{r}(\cos E - 1) + rac{r}{a} \end{aligned}$$

Now solving for $f\dot{g} - g\dot{f}$:

$$egin{aligned} f\dot{g} - g\dot{f} \ &= [rac{a}{r_0}(\cos E - 1 + rac{r_0}{a})][rac{a}{r}(\cos E - 1) + rac{r}{a})] - [rac{1}{n}(M + \sin E - E)][-rac{a^2}{rr_0}n\sin E] \ &= rac{a^2}{rr_0}\Big[(\cos E - 1 + rac{r_0}{a})(\cos E - 1) + rac{r}{a}) + (M + \sin E - E)\sin E\Big] \end{aligned}$$

Making the following substitutions:

$$M=E-e\sin E \ r=a(1-e\cos E) \ r_0=a(1-e\cos E_0)=a(1-e)$$

$$\begin{split} &f\dot{g}-g\dot{f}\\ &=\frac{a^2}{rr_0}\Big[[(\cos E-1+1-e)(\cos E-1+1-e\cos E)]+[(E-e\sin E+\sin E-E)\sin E]\Big]\\ &=\frac{a^2}{rr_0}\Big[[(\cos E-e)(\cos E-e\cos E)]+[\sin E(1-e)\sin E]\Big]\\ &=\frac{a^2}{rr_0}\Big[\cos^2 E-e\cos^2 E-e\cos E+e^2\cos E+\sin^2 E-e\sin^2 E\Big]\\ &=\frac{a^2}{rr_0}\Big[\cos^2 E+\sin^2 E-e(\cos^2 E+\sin^2 E)-e\cos E+e^2\cos E\Big]\\ &=\frac{a^2}{rr_0}\Big[1-e-e\cos E+e^2\cos E\Big]\\ &=\frac{a^2}{rr_0}\Big[(1-e)(1-e\cos E)\Big]\\ &=\frac{a^2}{rr_0}\frac{rr_0}{a^2}\\ &=1 \end{split}$$

Thus if Kepler's equation is satisfied, $f\dot{g}-g\dot{f}=1$ and therefore angular momentum is conserved