Assume we have a pulsar (J0030 from the first IPTA Mock Data Challenge, open1, here), and read it in an HDF5 file

```
In [3]: # Creating hdf5 files goes through the DataFile class
        t2df = pic.DataFile('J0030.h5')
        t2df.addpulsar('mdc1-open1/J0030+0451.par', 'mdc1-open1/J0030+0451.tim')
In [2]: # With a datafile, we can construct a 'likelihood' object, which is the central class of the package
        likob = pic.ptaLikelihood('J0030.h5')
In [3]: # A model for the data (all data in the hdf5, so can be multi-pulsar) can be made with the initModel member func
        # Likelihood function 'mark3' is the standard for red noise analysis, and will default to that if not given
        likob.initModel(nfregmodes=30, varyEfac=True, incRedNoise=True, noiseModel='powerlaw', likfunc='mark3')
In [4]: # The model has the following variable dimensions.
        print "Number of dimensions: ", likob.dimensions
        # A total dictionary of all parameters is kept in likob.pardes (I'll make the names more descriptive). Do
        # not edit the pardes dictionary yourself. The 'real' model is saved in sub-classes and must be edited through
        # the initModel function
        for i in range(len(likob.pardes)): print likob.pardes[i]
        Number of dimensions: 3
        {'index': 0, 'name': 'pulsarname', 'sigtype': 'efac', 'sigindex': 0, 'correlation': 'single', 'pulsar': 0,
         'id': u'efacJ0030+0451'}
        {'index': 1, 'name': 'powerlaw', 'sigtype': 'powerlaw', 'sigindex': 1, 'correlation': 'single', 'pulsar': 0,
         'id': 'RN-Amplitude'}
        {'index': 2, 'name': 'powerlaw', 'sigtype': 'powerlaw', 'sigindex': 1, 'correlation': 'single', 'pulsar': 0,
         'id': 'RN-spectral-index'}
        {'index': -1, 'name': 'powerlaw', 'sigtype': 'powerlaw', 'sigindex': 1, 'correlation': 'single', 'pulsar':
        0, 'id': 'low-frequency-cutoff'}
```

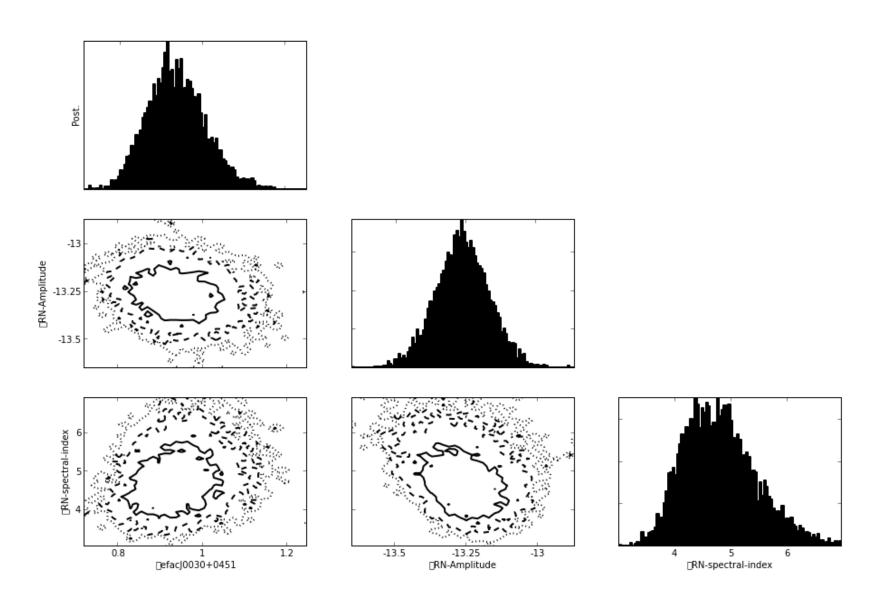
```
In [5]: # The default start parameters, minimum value, maximum value, and stepsize
         # Parameter indices belong to the 'index' key of the likob.pardes dictionary.
         # A '-1' in the pardes dictionary means that the parameter is kept fixed in a
          # subsequent analysis.
         print likob.pstart, likob.pmin, likob.pmax, likob.pwidth
          ſ 1.
                  -14.
                           2.01] [ 0.001 -16.
                                                                          -5.
                                                      1.02 ] [ 1000.
                                                                                     [6.98] [0.1 0.1 0.1]
 In [6]: # Calculate the value of the posterior, likelihood, or prior:
         print likob.logprior(likob.pstart), likob.loglikelihood(likob.pstart), likob.logposterior(likob.pstart)
          -11.0907200329 1132.24124175 1121.15052171
In [22]: # Run a t-walk algorithm on the posterior for 20000 steps (analyse=True prints the figure)
         pic.Runtwalk(likob, 20000, 'J0030-twalk-burnin.txt', thin=5, analyse=True)
          pytwalk: Running the twalk with 20000 iterations. Wed, 07 Aug 2013, 12:39.
                 Finish in approx. 17 seconds.
          pytwalk: finished, Wed, 07 Aug 2013, 12:39:30.
          Acceptance rates for the Walk, Traverse, Blow and Hop kernels: [ 0.45564063 0.16266099 0.20359281
          0.01129944]
          Global acceptance rate: 0.30515
          AutoMaxlag: maxlag= 57.
          Integrated Autocorrelation Time:
                                               12.2, IAT/n:
                                                                 4.1
             1900
             1800
            1700
          1600 logoctive
1500
1400
            1300
            1200
            1100
                         5000
                                  10000
                                            15000
                                                       20000
                                  Iteration
```

```
In [24]: # Removing the burn-in of the MCMC chains is easy on the command line
         !sed '1,300d' J0030-twalk-burnin.txt > J0030-twalk.txt
In [28]: # We can run a more optimal Metropolis algorithm by using the t-walk as a tuning chain
         pic.RunMetropolis(likob, 20000, 'J0030-metro.txt', initfile='J0030-twalk.txt', resize=1.0)
         Obtaining initial positions from 'J0030-twalk.txt'
          Running Metropolis-Hastings sampler
          Sample: 19900 = 99.5% acc. fr. = 0.432028 pos = -1.322027e+01 4.794301e+00 lnprob = 1.871749e+03
          ('Mean acceptance fraction:', 0.43202839858007097)
          ('Autocorrelation time:', 23.371900797369577)
In [29]: # The parameters in the chain are stored in 'J0030-metro.txt.parameters.txt'.
         # All sampler routines use this convention
         !cat J0030-metro.txt.parameters.txt
                                  single pulsarname
         0
                          efac
                                                          efacJ0030+0451
         1
                          powerlaw
                                         single powerlaw
                                                                 RN-Amplitude
          2
                          powerlaw
                                         single powerlaw
                                                                 RN-spectral-index
          - 1
                  0
                          powerlaw
                                          single powerlaw
                                                                 low-frequency-cutoff
```

In [31]: # Plot the results of the MCMC (which uses the .parameters.txt file)
pic.triplot('J0030-metro.txt')

parametersfilename = J0030-metro.txt.parameters.txt figurefilename = J0030-metro.txt.fig.eps chainfilename = J0030-metro.txt

J0030-metro.txt



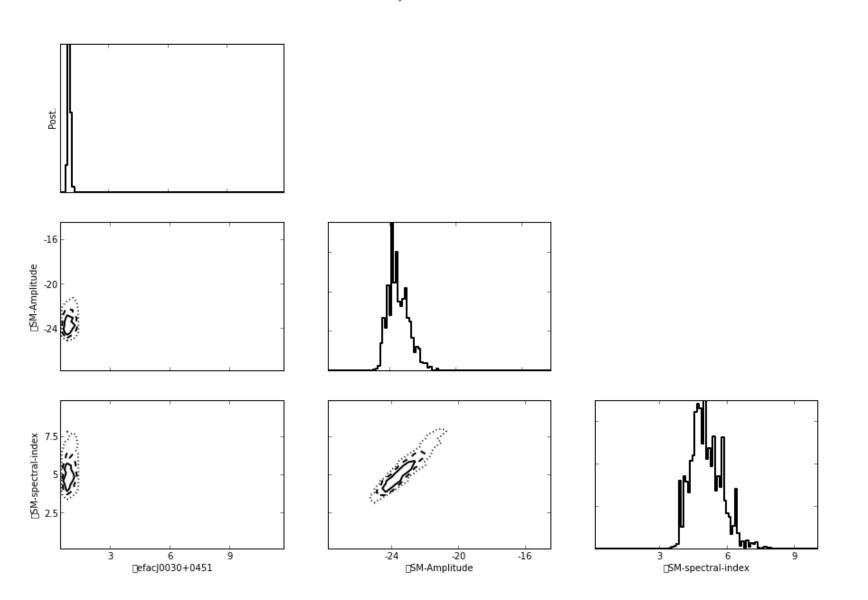
4 of 7

```
In [18]: # Note: evidence = 1857
         # pic.RunMultiNest(likob, 'J0030-mn')
 In [8]:
In [15]:
 In [9]:
In [43]: # We are now going to do the same thing as above, but with different noise models. We make two extra likelihood
         likobsm = pic.ptaLikelihood('J0030.h5') # Same model as in the Tempo2 'spectralModel' plugin
         likobsp = pic.ptaLikelihood('J0030.h5')
                                                    # Frequencies individually parameterised
In [44]: # Prepare the likelihood objects
         likobsm.initModel(nfreqmodes=30, varyEfac=True, incRedNoise=True, noiseModel='spectralModel')
         likobsp.initModel(nfreqmodes=30, varyEfac=True, incRedNoise=True, noiseModel='spectrum')
In [45]: # Instead of using Metropolis, we'll now use MultiNest to sample. This time on the 'spectralModel' object
         # TODO: MultiNest parameters in 'piccard.py' need to be tweaked a bit
         # Note: evidence = 1858
         pic.RunMultiNest(likobsm, 'J0030-sm')
```

In [46]: # Plotting is done with the same triplot routine
pic.triplot('J0030-sm.txt')

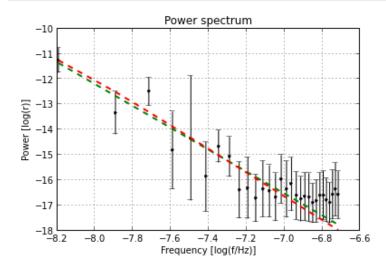
parametersfilename = J0030-sm.txt.parameters.txt figurefilename = J0030-sm.txt.fig.eps chainfilename = J0030-sm.txt

J0030-sm.txt



```
In [20]: # For the spectrum, we'll do a t-walk/Metropolis combo again
pic.Runtwalk(likobsp, 50000, 'J0030-sp-twalk-burnin.txt', thin=5)
!sed '1,300d' J0030-sp-twalk-burnin.txt > J0030-sp-twalk.txt
pic.RunMetropolis(likobsp, 50000, 'J0030-sp-metro.txt', initfile='J0030-sp-twalk.txt', resize=0.2)

Obtaining initial positions from 'J0030-sp-twalk.txt'
Running Metropolis-Hastings sampler
Sample: 49900 = 99.8% acc. fr. = 0.313254 pos = -1.609344e+01 -1.700385e+01 lnprob = 1.800602e+03
('Mean acceptance fraction:', 0.31325373492530151)
('Autocorrelation time:', 253.51048048387293)
```



In [46]:

In []: