

MCMC Example

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Program

- Data vector
- Bayesian Statistic
- Synthetic Data + REAL world measurement
- MCMC implementation (emcee)

Data vector

How much stressed is a PhD. student as a function of
time and weather?

Model

Parameters:

1. Thesis anxiety
2. What am I doing?
3. Pub attendance
4. Finish the paper!
5. Sport activities

```
11  """
12  variables of the data vector function:
13  time from 0 to 36 months,
14  weather conditions
15  from - 0.3 (rain/cold/pollution --> Mordor ) to + 0.3 (sun --> Shire)
16  """
17
18  """
19  define data vector function,
20  theoretical model
21  """
22  def phd_stress_function(time, weather, theta_ar, doing_sport):
23
24      """ different factors """
25      thesis_anxiety = theta_ar[0] * np.exp(time / 36.0)
26      what_am_i_doing = theta_ar[1] * np.exp(- time / 36.0)
27      pub_attendance = theta_ar[2] * ((time - 18.0) / 36.0) ** 2.0 + weather
28      finish_the_paper = theta_ar[3] * (np.sin((5.0 * 2.0) * np.pi * time / 36.0) + 1.0)
29
30      if doing_sport == True:
31          sport_activities = theta_ar[4] * (- time / 36.0) + 1.0 + weather
32          return thesis_anxiety + what_am_i_doing - pub_attendance \
33              + finish_the_paper - sport_activities
34
35      return thesis_anxiety + what_am_i_doing - pub_attendance + finish_the_paper
```


Unavoidable Bayesian Statistic Slide

- Prior: previous knowledge / degree of belief
- Likelihood: is the probability of the evidence given the parameters (wikipedia)
- Posterior: is the probability of the parameters given the evidence (again wikipedia)

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)}$$

Diagram illustrating the components of the Bayesian formula:

- Likelihood** points to $P(x|c)$
- Class Prior Probability** points to $P(c)$
- Posterior Probability** points to $P(c|x)$
- Predictor Prior Probability** points to $P(x)$

Pythonically speaking:

```
39  """
40  define prior, likelihood, posterior functions
41  """
42  def lnprior(x, ranges):
43
44      par_list = x
45
46      for i in range(len(par_list)):
47          if (par_list[i] < ranges[i,0]) or (par_list[i] > ranges[i,1]):
48              return -np.inf
49
50      return 0.0
51
52  """
53  """
54  def lnlike(x, meas, params, inv_cov):
55
56      par_list = x
57
58      time_ar, weather, theta_ranges, doing_sport = params
59
60      theta_ar = np.array(par_list)
61      model = phd_stress_function(time_ar, weather, theta_ar, doing_sport)
62      diff = model - meas
63
64      return - np.dot(diff, np.dot(inv_cov, diff)) / 2.0
```

N.B. uninformative prior

```
66  """
67  """
68  def lnprob_f( x, meas, params, icov):
69
70      time_ar, weather, theta_ranges, doing_sport = params
71
72      lp = lnprior(x, theta_ranges)
73
74      if not np.isfinite(lp):
75          return - np.inf
76
77      lnprob = lp + lnlike(x, meas, params, icov)
78
79      # Check for lnprob returning NaN.
80      if np.any(np.isnan(lnprob)):
81          # Find indexes of lnprob array with NaN values.
82          indxs_of_bad_p = np.where(np.isnan(lnprob) == True)[0]
83          # Print some debugging stuff.
84          print("NaN value of lnprob for parameters: ")
85          print(x[indxs_of_bad_p])
86          # Finally raise exception.
87          raise ValueError("lnprob returned NaN.")
88
89      return lnprob
90
```


Main Code: synthetic data + REAL Life PhD. student opinion

```
101 """ spoiler alert: true values parameters """
102
103 true_theta_ar = np.array([1.0, 1.8, 2.7, 0.2, 0.6])
104 doing_sport   = False
105
106 """ when we asked the PhD. students their opinions and what was the weather like (coordinates) """
107 time_ar = np.linspace(1.0,36.0,72)
108 weather = np.cos(6.0 * np.pi * time_ar / 36.0 + np.pi/3.0 ) * 0.3
109
110 """ generate N independent / uncorrelated PhD. students opinions (SYNTHETIC DATA !!) """
111 N_phd_students      = 200
112 true_stress         = phd_stress_function(time_ar, weather, true_theta_ar, doing_sport)
113 std_normal_dist     = np.ones(true_stress.size) * 0.1
114 N_survey_measurements = np.random.normal(true_stress, std_normal_dist, (N_phd_students, true_stress.size ))
115
116 """ covariance matrix derived from synthetic data """
117 cov_matrix          = np.cov(N_survey_measurements.T)
118
119 """ special PhD. student (MEASUREMENT ON REAL DATA) """
120 selected_phd_opinion = np.random.normal(true_stress, std_normal_dist * 0.1, (true_stress.size ))
121
```


MCMC set up:

- how many walkers (aka hobbits)
- burn in steps (training for the long hike to Mordor)
- Steps (to Mordor)
- Initial position of the walkers (Hobbiton, Shire, NW13 OLA)
- Sampler: magically tells the walkers where to go in the parameter space (aka Gandalf)

Result: CHAIN (it has kept track of the hobbits wandering around)

Again in python (1):

```
136 """ walkers """
137 n_hobbits      = 200
138
139 """ burn_in """
140 warm_up_steps  = 200
141
142 """ steps tracked in the chain """
143 steps_to_mordor = 1000
144
145 """ run in parallel using MPI """
146 mpi_or_not      = False
147
148 """ initial guess for the maximum likelihood parameters """
149 shire_perimeter = np.array([[0.8,1.2], [1.5,2.5], [2.0,3.5], [0.0,0.6], [0.3,1.0]])
150 if doing_sport == False:
151     shire_perimeter = np.array([[0.8,1.2], [1.5,2.5], [2.0,3.5], [0.0,0.6]])
152
153 """ starting point of walkers based on the initial guess """
154 hobbiton        = np.random.rand(par_num * n_hobbits).reshape((par_num,n_hobbits))
155
156 for i in range(par_num):
157     hobbiton[i] = shire_perimeter[i,0] + (shire_perimeter[i,1] - shire_perimeter[i,0]) * hobbiton[i]
158
159 hobbiton        = hobbiton.T
160
161 """ additional parameters to pass to the model function, including coordinates """
162 params          = time_ar, weather, middle_earth, doing_sport
```


Again in python (2):



```
167 if mpi_or_not == False:
168
169     """ initialise the MAGIC sampler """
170     gandalf = emcee.EnsembleSampler(n_hobbits, par_num, lnprob_f,
171                                   args=[selected_phd_opinion, params, np.linalg.inv(cov_matrix)], threads = 1)
172
173     "burn in"
174     pos, prob, state = gandalf.run_mcmc(hobbiton, warm_up_steps)
175     gandalf.reset()
176
177     "run mcmc"
178     gandalf.run_mcmc(pos, steps_to_mordor)
179
180     "reshape"
181     samples = gandalf.chain[:, :, :].reshape((-1, par_num))
182
183     "intervals"
184     mcmc_list = []
185     mcmc_list = map(lambda v: (v[1], v[2] - v[1], v[1] - v[0]),
186                     zip(*np.percentile(samples, [16, 50, 84],
187                                         axis=0)))
```




UCL

1-2D
marginalised
posterior
distribution plot

References:

- https://github.com/davidegua/mcmc_example

- <http://dfm.io/emcee/current/>

Gualdi et al. in prep.
(2018)

