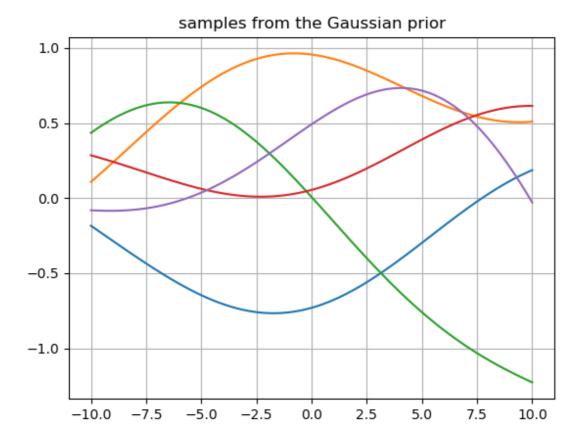
## Gaussian Process Posterior (Python)

Asked 4 years ago Active 4 years ago Viewed 1k times



I have created and sampled a jointly Gaussian prior with mean=0 using the code below:

```
4
        import numpy as np
        import matplotlib.pyplot as plt
       from math import pi
       from scipy.spatial.distance import cdist
        import scipy.stats as sts
       x prior = np.linspace(-10,10,101)
       x_prior = x_prior.reshape(-1,1)
       mu = np.zeros(x_prior.shape)
        #defining the Kernel for the covariance function
        def sec(a,b, length_scale , sigma) :
           K = sigma * np.exp(-1/(2*length_scale) * cdist(a,b)**2)
            return K
        #defining the Gaussian Process prior
        def GP(a , b, mu , kernel , length_scale, sigma , samples ) :
           f = np.random.multivariate_normal(mu.flatten(), kernel(a ,b , length_scale , sigma
        ) , samples)
           return f
        prior = GP(x_prior, x_prior, mu, sec, 100, 1, 5)
        plt.figure()
        plt.grid()
        plt.title('samples from the Gaussian prior')
        plt.plot(x_prior , prior.T)
        plt.show()
```



Then, when adding in some 'observed' data, I wish to compute the posterior over these points but this is where I become stuck.

Here's my code for introducing new data:

```
x_train = np.array([-10,-8,5,-1,2])
x_train = x_train.reshape(-1,1)
def straight_line(m , x , c):
    y = 5*x + c
    return y
ytrain = straight_line(5 , x_train , 0)
```

It's my understanding that you calculate a conditional distribution over the new data given the prior and new x values associated with the observed data.

Do you then wish to update the multivariate prior to become the posterior by performing some sort of change to the mean values to include the new y values?

I have used the following resources to try and attempt this:

http://katbailey.github.io/post/gaussian-processes-for-dummies/ https://www.robots.ox.ac.uk/~mebden/reports/GPtutorial.pdf

but I'm really trying to understand what happens at each stage, and why, so that when I get a posterior (which I can't do) I know exactly how I got there.

Here's some solutions I've been trying to implement but so far no avail:

```
K_train = sec(x_train , x_train , 1,1)
K_prior = sec(x_prior , x_prior , 1,1)
K_pt = sec(x_prior , x_train , 1,1)
K_tp = sec(x_train , x_prior , 1,1) ## = k_tp transpose
prior = sts.multivariate_normal(mu.flatten(), K_prior)
#mean_test = np.dot(K_p , np.linalg.inv(K_prior))
mean_function = np.dot(np.dot(K_tp ,np.linalg.inv(K_prior).T) , prior )
covariance_function = K_train - np.dot(np.dot(K_tp ,np.linalg.inv(K_prior).T) , K_pt)

python process gaussian sampling Edit tags

Share Edit Follow Close Flag

asked Nov 27 '17 at 18:08

user8188120
```

## 2 Answers



- Just for additional follow-up. I have written my code into a Juypiter format here:
  - 1 <a href="https://github.com/SpaceMeerkat/Scariff">https://github.com/SpaceMeerkat/Scariff</a>
- with associated read-through material here:
- https://spacemeerkat.wordpress.com/

Just in case anyone wanted to work through this kind of material and became stuck like I did.

Share Edit Follow Flag



705

1 9 20

- Just an update for anyone who looked at this. I found the solution reading this paper:
  - 0 <u>https://arxiv.org/pdf/1711.10834.pdf</u>
- and the following code:
- mean\_function = np.dot(np.dot(K\_pt ,np.linalg.inv(K\_train)), ytrain)
  covariance\_function = K\_prior np.dot(np.dot(K\_pt ,np.linalg.inv(K\_train)) , K\_tp)
  f = np.random.multivariate\_normal(mean\_function[:,0],covariance\_function , 100)

where f is the posterior joint Gaussian from which you sample from

Share Edit Follow Flag answered Nov 30 '17 at 11:32

