Apply NN to recover the theory of diffraction

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My idea is that morden science is closely related to technical innovation. But back in the 80s and 90s, mechanical engineering and manufactory is still in the infancy, as well as data sampling and analytic methods. Even though the foundation of morden science is considered solid and proven, there is still chance that the perspective we have is not the only solution. Just like Newtonian gravity theory is an approximation of general relativity.

To explore and test it out, I first decide to do a simulation based on established theory to get example data. Diffraction is one of the most classic phenomenon that is well explained but also is explosured to the dawn of Quantum mechanics. To make it more realistic, I add white noise as systemactical error due to measurement and try to use ML, (a straightforward neural network in this case) to reveal the nature of the problem. But due to the high percision it required to realize the numerical experiment, I run into some data format issue that couldn't be solved in short timeframe.

So I decide to use gaussian process regression with the morden statistical method, Bayesian inference to catch the hidden nature from a small uniform random sampling data set. I put flat prior to avoid any prejustical knowledge about model and GP returned a reasonable good result, without excluding the possibility of alternative diffraction theory. See Cell 43 and Cell 45. The red dots are sampled based on theory, black dots with flat error bar are the data used to explore the model space. The *color density* indicates the probability and Cell 26 shows the fructuation from measurement.

My next step is to establish a mechanical system based on raspberrypi and step motor to stimulate in real case. Use the data measured in a large scale to revisit my temperate conclusion.

RFF

- paper about Optics simulations with python
 (https://www.osapublishing.org/DirectPDFAccess/47E6CA42-FADB-6891 CA9B67A17E5174B4 354793/ETOP-2015-DTE14.pdf?da=1&id=354793&uri=ETOP-2015-DTE14&seq=0&mobile=no)
- <u>aithub for python code (https://github.com/kalekundert/DoubleSlit)</u>
- wiki about diffraction (https://en.wikipedia.org/wiki/Diffraction)

```
In [1]: %pylab inline
    from decimal import Decimal
    import math
```

Populating the interactive namespace from numpy and matplotlib

1-D diffraction

$$\frac{I(x)}{I(0)} = \left[\frac{\sin(\frac{\pi b}{\lambda} \frac{x}{D})}{(\frac{\pi b}{\lambda} \frac{x}{D})}\right]^2$$

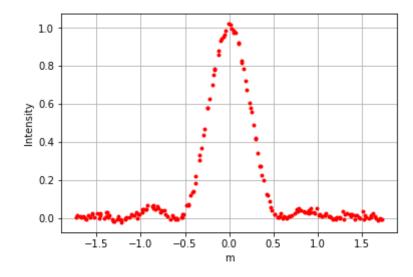
- *b*: slit width
- λ: wavelength
- D: distance to screen

```
In [2]: d_b = Decimal(1.E-6) # 1 micron
d_lambda = Decimal(float(600)*1.E-9) # 600 nm
d_D = Decimal(float(100)*1.E-2) # 1 m
```

```
In [4]: def Fraunhofe(x, params):
    b, lamda, D = params
    if size(x) == 1:
        return (Decimal(math.sin(Decimal(pi)*b/lamda*x/D))/(Decimal(pi)*b/lamda*x/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D))/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lamda*i/D)/(Decimal(pi)*b/lam
```

```
In [5]: d_I = Fraunhofe(d_x, [d_b, d_lambda, d_D])
```

```
In [6]: fig = figure()
    ax1=fig.add_subplot(1,1,1)
    ax1.plot(d_x, d_I,'r.')
    ax1.set_xlabel('m')
    ax1.set_ylabel('Intensity')
    ax1.grid(True)
```



```
In [7]: assert size(d_I) == measurement*2
```

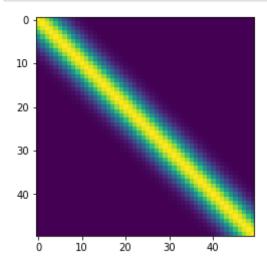
In []:

```
In [8]: import tensorflow as tf
In [57]: dm_input = measurement * 2 + 3
         dm output = measurement * 2
         x = tf.placeholder(tf.float32, [None, dm_input])
         W = tf.Variable(tf.zeros([dm_input, dm_output]))
         b = tf.Variable(tf.zeros([dm output]))
In [10]: y = tf.nn.softmax(tf.matmul(x, W) + b)
In [11]: y = tf.placeholder(tf.float32, [None, dm_output])
         cross_entropy = tf.reduce_mean(-tf.reduce_sum(y_ * tf.log(y), reduction_ind)
In [12]:
In [13]: train step = tf.train.GradientDescentOptimizer(0.5).minimize(cross entropy)
In [14]: sess = tf.InteractiveSession()
In [15]: tf.global_variables_initializer().run()
In [16]: for _ in range(1000):
             d x = np.array([Decimal(np.random.uniform(-1, 1)) * Decimal(math.tan(ome
                                  for i in range(measurement*2)])
             d b = Decimal(1.E-6 * np.random.uniform(1,10)) # 1 micron
             d_lambda = Decimal(float(600) * np.random.uniform(1,10) * 1.E-9) # 600
             dD = Decimal(float(100) * np.random.uniform(1,10) * 1.E-2) # 1 m
             batch xs = np.append(d x,[d b, d lambda, d D]).reshape(-1, dm input)
             batch ys = Fraunhofe(d x, [d b, d lambda, d D]).reshape(-1, dm output)
             sess.run(train step, feed dict={x: batch xs, y : batch ys})
In [17]: correct prediction = tf.equal(tf.argmax(y,1), tf.argmax(y,1))
         accuracy = tf.reduce mean(tf.cast(correct prediction, tf.float32))
In [64]: d x = np.array([Decimal(np.random.uniform(-1, 1)) * Decimal(math.tan(omega))
                              for i in range(measurement*2)])
         d b = Decimal(1.E-6 * np.random.uniform(1,10)) \# 1 \text{ micron}
         d lambda = Decimal(float(600) * np.random.uniform(1,10) * 1.E-9) # 600 nm
         dD = Decimal(float(100) * np.random.uniform(1,10) * 1.E-2) # 1 m
         batch xs = np.append(d x,[d b, d lambda, d D]).reshape(-1, dm input)
In [65]: x.shape
Out[65]: TensorShape([Dimension(None), Dimension(201)])
In [66]: batch_xs.shape
Out[66]: (1, 201)
```

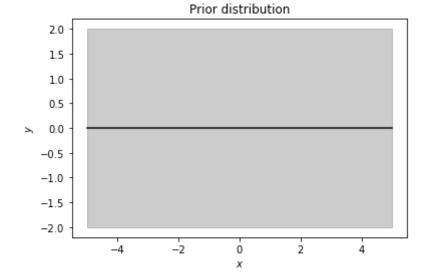
```
predictions = sess.run(accuracy, feed_dict={x: batch_xs})
         InvalidArgumentError
                                                    Traceback (most recent call las
         /Users/domi/anaconda3/envs/py35/lib/python3.5/site-packages/tensorflow/py
         thon/client/session.py in _do_call(self, fn, *args)
            1326
                     try:
         -> 1327
                       return fn(*args)
            1328
                     except errors.OpError as e:
         /Users/domi/anaconda3/envs/py35/lib/python3.5/site-packages/tensorflow/py
         thon/client/session.py in run fn(session, feed dict, fetch list, target
         list, options, run_metadata)
            1305
                                                     feed dict, fetch list, target
         list,
         -> 1306
                                                     status, run_metadata)
            1307
         /Users/domi/anaconda3/envs/py35/lib/python3.5/contextlib.py in __exit__(s
In [ ]:
In [ ]:
         import matplotlib.pyplot as plt
In [22]:
         from scipy.spatial.distance import cdist
         from numpy.random import multivariate normal
         from numpy.linalg import inv
         from numpy.linalg import slogdet
         from scipy.optimize import fmin
In [23]: def SEKernel(par, x1, x2):
             A, Gamma = par
             D2 = cdist(x1.reshape(len(x1),1), x2.reshape(len(x2),1),
                        metric = 'sqeuclidean')
             return A * np.exp(-Gamma*D2)
```

```
In [24]: x = np.linspace(-5,5,50)
K = SEKernel([1.0,1.0],x,x)

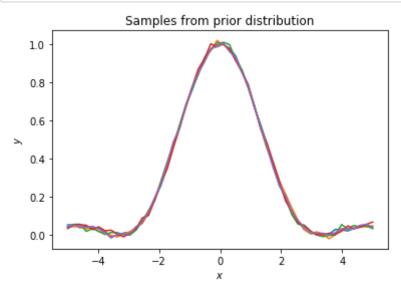
plt.imshow(K,interpolation='none');
```



```
In [25]: m = np.zeros(len(x))
    sig = np.sqrt(np.diag(K))
    plt.plot(x,m,'k-')
    plt.fill_between(x,m+2*sig,m-2*sig,color='k',alpha=0.2)
    plt.xlabel(r'$x$')
    plt.ylabel(r'$y$')
    plt.title('Prior distribution');
```



```
In [26]: x = np.array([ Decimal(i) for i in x])
y = np.array( [Fraunhofe(x, [d_b, d_lambda, d_D]) for i in range(5)] )
plt.plot(x, y.T)
plt.xlabel(r'$x$')
plt.ylabel(r'$y$')
plt.title('Samples from prior distribution');
```

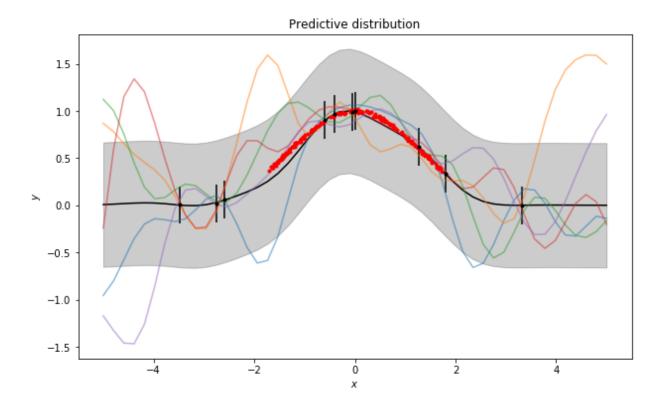


```
In [27]:
         def Pred_GP(CovFunc, CovPar, xobs, yobs, eobs, xtest):
             # evaluate the covariance matrix for pairs of observed inputs
             K = CovFunc(CovPar, xobs, xobs)
             # add white noise
             K += np.identity(xobs.shape[0]) * eobs**2
             # evaluate the covariance matrix for pairs of test inputs
             Kss = CovFunc(CovPar, xtest, xtest)
             # evaluate the cross-term
             Ks = CovFunc(CovPar, xtest, xobs)
             # invert K
             Ki = inv(K)
             # evaluate the predictive mean
             m = np.dot(Ks, np.dot(Ki, yobs))
             # evaluate the covariance
             cov = Kss - np.dot(Ks, np.dot(Ki, Ks.T))
             return m, cov
```

```
In [42]: xobs = np.array([ Decimal(np.random.uniform(-4,4)) for i in range(10)])
yobs = Fraunhofe(xobs, [d_b, d_lambda, d_D])
```

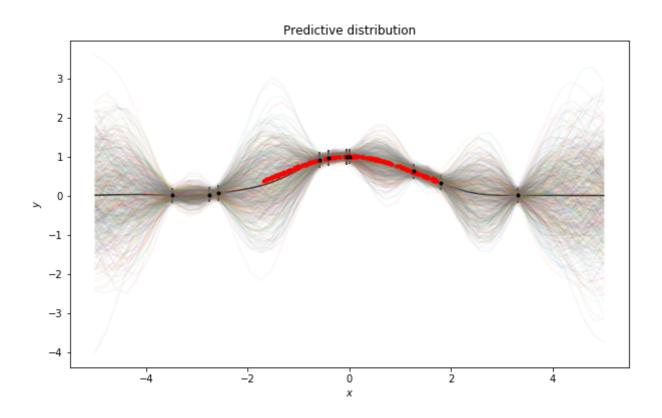
```
In [43]:
         eobs = 0.1
         xobs = xobs.astype(float)
         yobs = yobs.astype(float)
         plt.figure(figsize=(10,6))
         m,C= Pred_GP(SEKernel,[1.0,1.0],xobs,yobs,eobs,x)
         sig = np.std(np.diag(C))
         samples = multivariate normal(m,C,5)
         plt.errorbar(xobs,yobs,yerr=2*eobs,capsize=0,fmt='k.')
         plt.plot(x,m,'k-')
         x = x.astype(float)
         plt.fill_between(x,m+2*sig,m-2*sig,color='k',alpha=0.2)
         plt.plot(x,samples.T,alpha=0.5)
         d_I = Fraunhofe(d_x, [d_b, d_lambda, d_D])
         plt.plot(d_x, d_I,'r.')
         plt.xlabel(r'$x$')
         plt.ylabel(r'$y$')
         plt.title('Predictive distribution');
```

/Users/domi/anaconda3/envs/py35/lib/python3.5/site-packages/ipykernel_lau ncher.py:8: RuntimeWarning: covariance is not positive-semidefinite.



```
In [45]:
         eobs = 0.1
         xobs = xobs.astype(float)
         yobs = yobs.astype(float)
         plt.figure(figsize=(10,6))
         m,C= Pred_GP(SEKernel,[1.0,1.0],xobs,yobs,eobs,x)
         sig = np.std(np.diag(C))
         samples = multivariate normal(m,C,500)
         plt.errorbar(xobs,yobs,yerr=2*eobs,capsize=0,fmt='k.')
         plt.plot(x,m,'k-')
         x = x.astype(float)
         # plt.fill between(x,m+2*sig,m-2*sig,color='k',alpha=0.01)
         plt.plot(x,samples.T,alpha=0.05)
         d_I = Fraunhofe(d_x, [d_b, d_lambda, d_D])
         plt.plot(d_x, d_I,'r.')
         plt.xlabel(r'$x$')
         plt.ylabel(r'$y$')
         plt.title('Predictive distribution');
```

/Users/domi/anaconda3/envs/py35/lib/python3.5/site-packages/ipykernel_lau ncher.py:8: RuntimeWarning: covariance is not positive-semidefinite.



Interpretion

- There is room for alternative form of diffraction equation, but sampling is very biased and uneven
- Flat prior, is too big.
- Gaussian process regression can incooperate with biased sampling, which is more realistic

• I am not good at TensorFlow

In [1:	
[J -	