

# Outline

- A. Data and plan
- B. Model Explanation
- C. Result
- D. Discuss
- E. Reference
- F. Code

## A. Data and plan

The training data has 40,000 set of X, Y and height, and Fig. 2 is the contour from x-y plane. We can find that:

1. Data are evenly distributed in region from 1 ~ 1081
2. The contour is quite obvious using training data

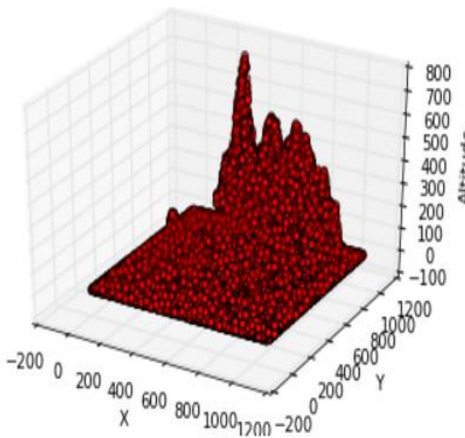


Fig. 1 plot in Python

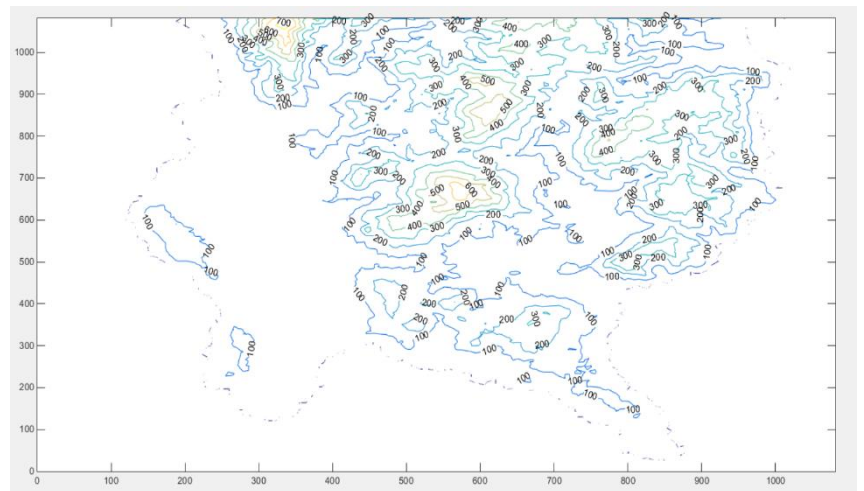


Fig. 2 plot in Matlab

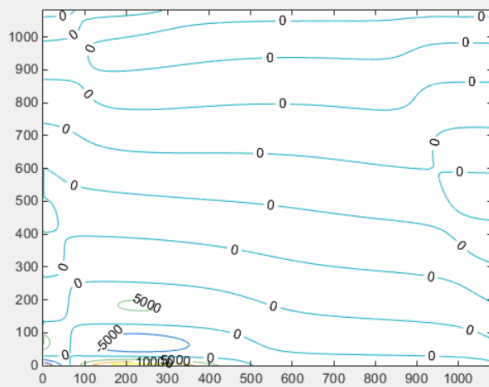
Just before training the model of ML, MAP and Bayesian, I will divide training data into four sets, each with 10,000 data. The cross-validation we are using is 4-folder.

## B. Model Explanation

1. From the rough model using x and y partition in different (spacing).

**Error for fixed variance:**

76974212983.67911



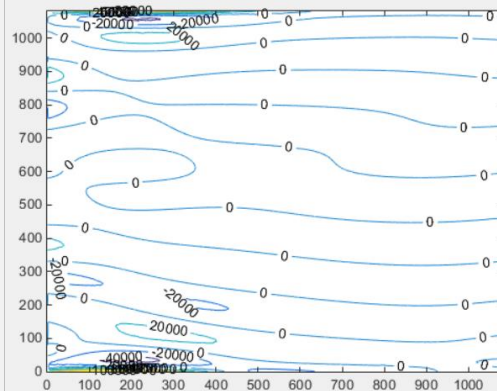
**Tile size(x\*y): 10\* 10**

**Mean:**

**X) 1~1081, space 108**

**Y) 1~1081 space 108**

**Variance : fixed to  $10^5$ .**



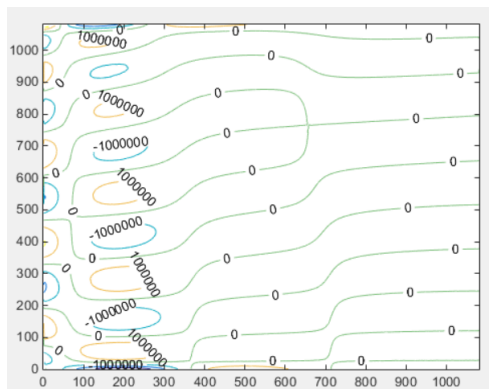
**Tile size(x\*y): 10\* 20**

**Mean:**

**X) 1~1081, space 108**

**Y) 1~1081 space 54**

**Variance : fixed to  $10^5$ .**



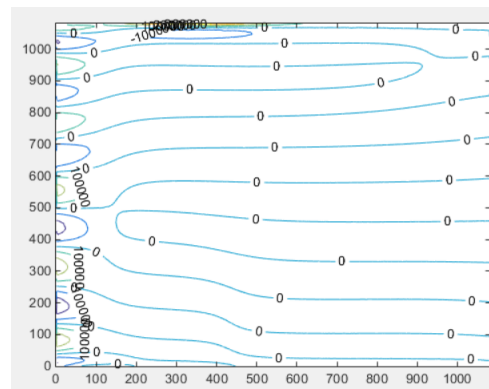
**Tile size(x\*y): 20\* 10**

**Mean:**

**X) 1~1081, space 108**

**Y) 1~1081 space 108**

**Variance : fixed to  $10^5$ .**



**Tile size(x\*y): 20\* 20**

**Mean:**

**X) 1~1081, space 54**

**Y) 1~1081 space 54**

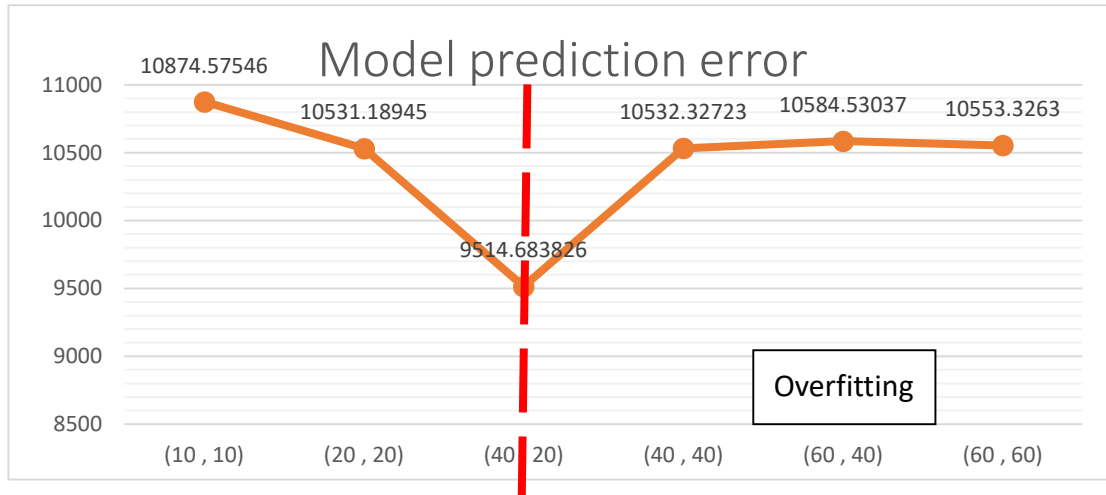
**Variance : fixed to  $10^5$ .**

I have found that the definition in x will have more impact than definition in y.

## 2. Feature Matrix $\Phi$ : Gaussian Mixture Model

$$\Phi_n(x_i, y_i) = \exp\left(-\frac{(x_i - \mu_{n_x})^2}{2s_{n_x}^2} - \frac{(y_i - \mu_{n_y})^2}{2s_{n_y}^2}\right)$$

## 3. The spacing interval for model prediction relationship is shown below:



In general, **the smaller the spacing is the less error will produce**. However, this kind of good property all comes a price. The computing time for 40\*40 titles is roughly 3 minutes, 100 \* 100 titles, in contrary, will take 15 minutes or even more! I will use **40\*20** titles for 40,000 data training (the best in the graph) and higher definition for cross- validation.

## ≡ Maximum likelihood approach (ML) feature vector

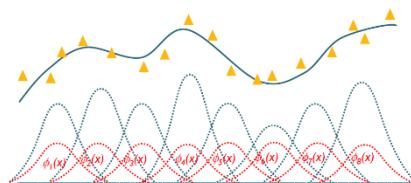
### Data setting

40,000 data to train model

### Likelihood

$$\mu_{n_{x,y}} = \frac{\sum_{i=1}^M f(x_i, y_i) x_i, y_i}{\sum_{i=1}^M f(x_i, y_i)}, M \text{ is number of data}$$

$$y = w_0 + w_1 \phi_1(\mathbf{x}) + w_2 \phi_2(\mathbf{x}) + \dots + w_{M-1} \phi_{M-1}(\mathbf{x})$$



$$Var_{n_{x,y}} = \frac{\sum_{i=1}^M (f(x_i, y_i) - \mu_{n_{x,y}})^2}{M}, M \text{ is number of data}$$

## Solve Weight

$$\vec{w} = (\Phi^T \Phi)^{-1} \Phi^T \vec{t}$$

## Error Estimation

$$E(\mathbf{w}) = \frac{1}{2K} \sum_k^K \|y(\mathbf{x}(k), \mathbf{w}) - t(k)\|^2$$


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## ≡ Maximum a posteriori approach (MAP)

### Data setting

40,000 data to train model

### Likelihood

$$\mu_{n_{x,y}} = \frac{\sum_{i=1}^M f(x_i, y_i) x_i y_i}{\sum_{i=1}^M f(x_i, y_i)}, M \text{ is number of data}$$

$$\text{Var}_{n_{x,y}} = \frac{\sum_{i=1}^M (f(x_i, y_i) - \mu_{n_{x,y}})^2}{M}, M \text{ is number of data}$$

## Solve Weight

$$\vec{w} = \lambda I + (\Phi^T \Phi)^{-1} \Phi^T \vec{t}$$

## Error Estimation

Root Mean Square error ( $E_{\text{QRS}}$ )

$$E_{\text{RMS}} = \sqrt{\frac{\sum_{j=1}^{NM} (y_j - t_i)^2}{NM}}$$

## ≡ Bayesian Estimation

When we use the Bayesian, we have assumed  $w$  is zero-mean isotropic Gaussian  $N(0, \beta)$ . According to the class note :

$$p(t|\mathbf{t}, \alpha, \beta) = \int p(t|\mathbf{w}, \beta) p(\mathbf{w}|\mathbf{t}, \alpha, \beta) d\mathbf{w}$$

$$\text{with } p(t|\mathbf{x}, \mathbf{w}, \beta) = \mathcal{N}(t|y(\mathbf{x}, \mathbf{w}), \beta^{-1})$$

$$p(\mathbf{w}|\mathbf{t}) = \mathcal{N}(\mathbf{w}|\mathbf{m}_N, \mathbf{S}_N) \quad \begin{aligned} \mathbf{m}_N &= \mathbf{S}_N (\mathbf{S}_0^{-1} \mathbf{m}_0 + \beta \Phi^T \mathbf{t}) \\ \mathbf{S}_N^{-1} &= \mathbf{S}_0^{-1} + \beta \Phi^T \Phi. \end{aligned}$$

$$\Rightarrow p(t|\mathbf{x}, \mathbf{t}, \alpha, \beta) = \mathcal{N}(t|\mathbf{m}_N^T \phi(\mathbf{x}), \sigma_N^2(\mathbf{x}))$$

Because of the result,

$$p(t|\mathbf{x}, \mathbf{t}, \alpha, \beta) = \mathcal{N}(t|\mathbf{m}_N^T \phi(\mathbf{x}), \sigma_N^2(\mathbf{x}))$$

therefore the maximum probability or average probability will be  $m_N^T \phi(x)$ , and because the Gaussian prior  $w_{\text{map}}=m_n$ , the target  $t$  will be the same as

$$y = m_N^T \phi(x). \text{ (as MAP result)}$$

### C. Result

for the original training dataset, 40,000 data set, and model with  $11 * 11 = 121$  feature vector and **fixed variance** (around 10 in power of 5), I have weight that is quite strange as below, the weight of each feature, it goes either too high or too low.

gcm.weight	Fixed variable with 10 in power of 5	gcm.weight	Trained variable
array([[	5.98087111e+15],	array([[	-2.01085158e+09],
[	-3.87502210e+16],	[	5.32645203e+09],
[	1.07652739e+17],	[	1.92352807e+09],
[	-1.53769290e+17],	[	7.47213581e+08],
[	7.56609324e+16],	[	-1.53954901e+09],
[	1.41772909e+17],	[	-2.07358632e+09],
[	-4.01986607e+17],	[	-4.97074378e+08],
[	6.48469434e+17],	[	4.44412783e+09],
[	-9.04661756e+17],	[	3.02208938e+09],
[	1.08001184e+18],	[	-4.11129116e+09],
[	-9.37418732e+17],	[	-5.48299224e+09],
[	4.39443597e+17],	[	-4.71032489e+09],
[	3.82767828e+16],	[	-3.23071602e+09],
[	-7.97617321e+16],	[	-9.19358963e+08],
[	-2.70032953e+17],	[	3.19001355e+09],
[	5.86024694e+17],	[	5.75593517e+08],
[	-5.82216592e+17],	[	5.08241576e+09],
[	3.52606255e+17],	[	-4.42547017e+09],
[	-1.33618275e+17],	[	4.04730314e+09],
[	2.89809577e+16],	[	-3.45737258e+09],

### D. Discuss

1. I cannot produce the optimal (or at least acceptable) solution in time mostly due to how I pick **mean** and **variance**. Apparently, I cannot set the mean section too small due to time and memory issue I've mention before[B.3], and again, the solution will as well-optimizer as better computing ability I have.
2. Instead of using ML, MAP, maybe the pre-data will do more efficient work. The question this homework ask is intuitively solved with numerical skill (linear regression) and might have predicted less error result.
3. I neither had time nor computing for finding relationship between minimize the interval and error function. That will be the interesting task after all.

## E. Reference

Mostly class note and Python document

## F. Code

```
class GaussianRegressionModel:

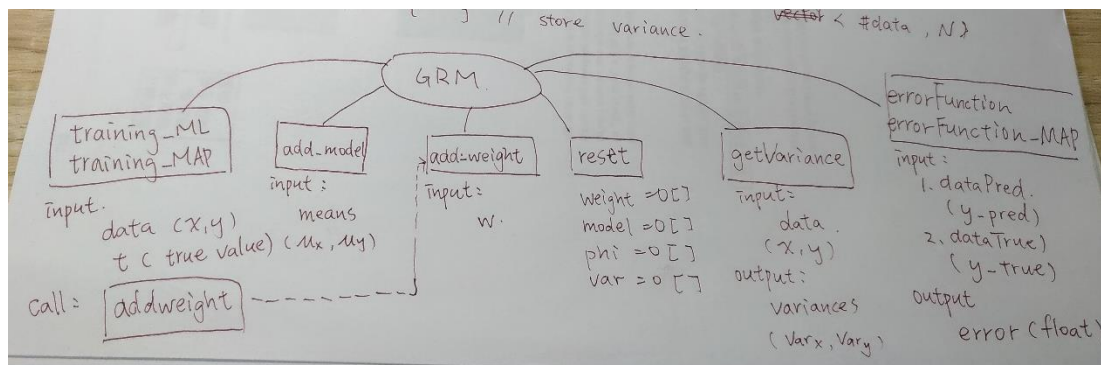
    def add_model(self, means):
    def add_weight(self, w):
    def reset(self):
    def getVariance(self, data):

    def training(self, data, t):
    def training_MAP(self, data, t, Lamb):

    def errorFunction(self, dataPred, dataTrue):
    def errorFunction_MAP(self, dataPred, dataTrue):

    def prediction(self, data):
```

As I've mentioned above, I created a class of Gaussian Regression Model so that it will save my time debugging the code (as well as code maintains).



## Appendix I

≡ Memory issue

I had some hard time programming in python and understanding the model constrain. This is quite exciting for me to actually train a model and learning by doing. Special thanks to my friends for advice and help me with the model.

```
phi : 40000 times 121
phi_trans : 121 times 40000
phi_inv : 121 times 121
t : 40000 times 1

-----
MemoryError                                Traceback (most recent call last)
<ipython-input-5-a768fb2529b6> in <module>()
      8 height = np.asarray(height).reshape(40000,1)
      9 #modeling
----> 10 gcm.modeling(position,height)

<ipython-input-2-3b65701686cf> in modeling(self, data, t)
     41     a = np.dot(self.phi,phi_inv)
     42     b = np.dot(a,phi_trans)
----> 43     weight = np.dot(b,t)
     44     print weight
     45     self.weight = weight

MemoryError:
```

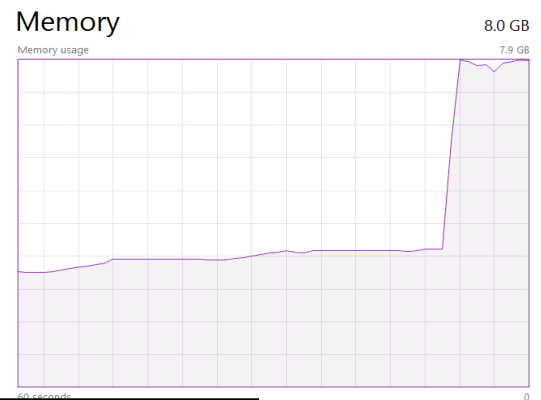


Fig. 3 memory error for using class multiple times

I have faced many problem than expected, it took me more time for debugging than coding or training; however, after understanding the problem and think it through before I mess up with everything really help me save lots of time.

⇒ Python class

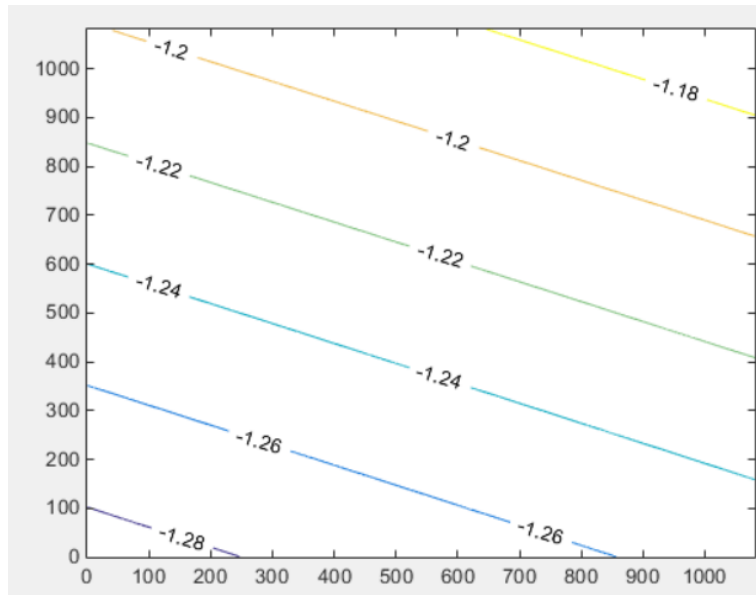
It is much easier to debug or training with different dataset. For example, it only takes me 10% of my time to train the result I want, but it takes 80% for building a model for ML, MAP and Bayesian model prediction. In general, using OOP programming skill will help for the next couple times homework and final projects.

≡ Post handout work (before demo)

This predict model is

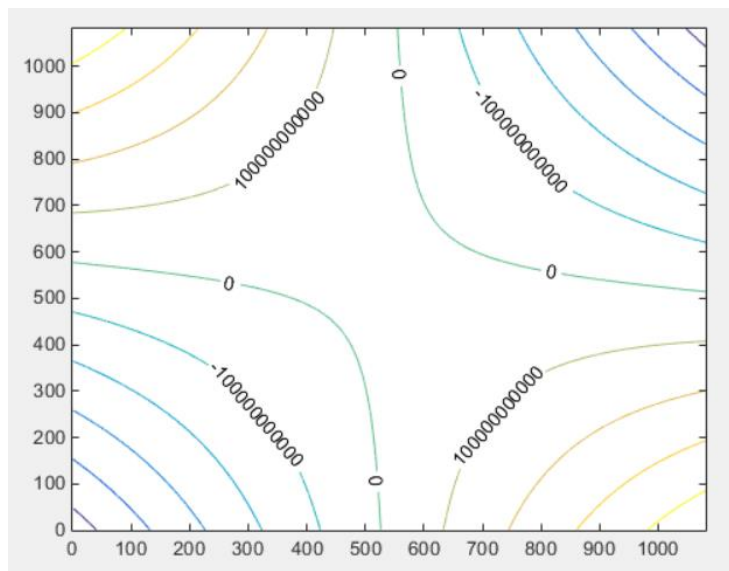
$$\hat{y} = \Phi w$$

Which is not so correct but the concept is quite the same for only discussing how to cut the data.



I have award that I might use the wrong mode for predicting  $\hat{y}$ , and it should be as the class not write:

$$\hat{y} = \Phi(\Phi\Phi^T)^{-1}w$$



In the end, I can't get my final result due to wrong choosing variance and means...