

תרגיל 4 | BML

מגיש: אבי כוגן | ת.ז: 205417710

תיאורטי

שאלה 1

עבור p_2 :

$$k(x_i, x_j) = e^{-\beta \|x_i - x_j\|^2} \stackrel{\beta \rightarrow \infty}{=} \begin{cases} 1 & x_i = x_j \\ 0 & o.w \end{cases}$$

מתקיים $\beta = \alpha \rightarrow \infty$ לכן נקבל

$$p(\mathbf{f}) \sim N(0, I_M)$$

עבור p_1 :

$$k(x_i, x_j) = e^{-\beta \|x_i - x_j\|^2} \stackrel{\beta \rightarrow 0}{=} 1$$

מתקיים $\beta = \frac{1}{\alpha} \rightarrow 0 \Leftarrow \alpha \rightarrow \infty$ לכן נקבל

קיבלנו $K = \mathbf{11}^T$, לכן $p(\mathbf{f}) \sim N(0, \mathbf{11}^T)$

שאלה 2

א.

עבור p_1 :

מסעיף קודם נסיק:

$$p(\mathbf{f}|p_1) = P\left(\begin{pmatrix} \mathbf{f}_1 \\ \cdot \\ \mathbf{f}_M \end{pmatrix} | p_1\right) = \begin{cases} \frac{1}{\sqrt{2\pi}} e^{-\frac{\mathbf{f}_i^2}{2}} & \mathbf{f}_i = \mathbf{f}_1 \ i \in [M] \\ 0 & o.w \end{cases}$$

$$\Rightarrow \begin{cases} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}} & \mathbf{f}_i = \pm 1 \ i \in [M] \\ 0 & o.w \end{cases}$$

ב.

עבור p_2 :

מתקיים ש- $f_i \perp f_j$ מכך ש- $p(\mathbf{f}) \sim N(0, I_M)$ ונקבל:

$$p(\mathbf{f} = v | p_2) = P\left(\begin{pmatrix} v_1 \\ \cdot \\ v_2 \end{pmatrix} | p_2\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{\|v\|^2}{2}}$$

שאלה 3

ב2 המקרים כאשר $\alpha \rightarrow \infty$:
משאלה קודמת:

$$\log(p(v|p_1)) = \begin{cases} -\frac{1}{2}(\log(2\pi)) + v_1^2 & v_1 = v_i \ i \in [M] \\ 0 & o.w \end{cases}$$

$$\log(p(v|p_1)) = -\frac{M}{2} \left(\frac{\|v\|^2}{M} \log(2\pi) \right)$$

עבור $\mathbf{f}_1 = (1, \dots, 1)^T$

$$\log(p(\mathbf{f}_1|p_1)) = -\frac{1}{2}(\log(2\pi) + 1)$$

$$\log(p(\mathbf{f}_1|p_2)) = M \left(-\frac{1}{2}(1 + \log(2\pi)) \right) = M \log(p(\mathbf{f}_1|p_1))$$

מתקיים $\log(p(\mathbf{f}_1|p_1)) < 0$ ו $M > 1$ לכן נבחר ב- p_1 .

עבור $\mathbf{f}_2 = (-1, 1, \dots, -1, 1)^T$

$$\log(p(\mathbf{f}_2|p_1)) \rightarrow -\infty$$

$$\log(p(\mathbf{f}_2|p_2)) \rightarrow M \log(p(\mathbf{f}_1|p_1))$$

לכן נבחר ב- p_2 .

שאלה 4

מתקיים לכל $\{x_i\}_{i=1}^N$ שמטריצת הגראם המתקבלת עבור $k(x, y) = 1$ היא $K = \mathbf{1}\mathbf{1}^T$. לכן לכל v נקבל $v^T \mathbf{1}\mathbf{1}^T v = \|\mathbf{1}^T v\|_2^2 \geq 0$ קיבלנו ש K היא PSD ולכן קרנל חוקי.
מתקיים $K = H \Sigma H^T$ עבור Σ השונות של ה- $prior$ ו- H מטריצת פונק' הבסיס מופעלות על התצפיות.

לכן נוכל להניח במקרה זה ש $\Sigma = \mathbf{1}$ ו- H , כלומר $\theta \sim N(0, 1)$ והבעיה הפרימלית היא:
 $f_\theta(x) = H^T \theta$

שאלה 5

$$\begin{aligned}
 \alpha_i &= [(\mathbf{1}\mathbf{1}^T + \sigma^2 \cdot I)^{-1} y]_i^* \\
 &= [\sigma^{-2} (I - \cancel{\sigma^2} (\frac{\cancel{\sigma^2}}{\sigma^2 + N}) \mathbf{1}\mathbf{1}^T) y]_i \\
 &= [\sigma^{-2} y - \sigma^{-2} (\frac{\cancel{\sigma^2}}{\sigma^2 + N}) \mathbf{1}\mathbf{1}^T y]_i \\
 &= \sigma^{-2} y_i - \frac{\mathbf{1}^T y}{\sigma^2(\sigma^2 + N)}
 \end{aligned}$$

$$\begin{aligned}
 * : (\mathbf{1}\mathbf{1}^T + \sigma^2 \cdot I)^{-1} &\stackrel{Woodbury}{=} \sigma^{-2} I - \sigma^{-2} I \cdot \mathbf{1} (I^{-1} + \mathbf{1}^T \sigma^{-2} I \mathbf{1})^{-1} \mathbf{1}^T \sigma^{-2} I \\
 &= \sigma^{-2} (I - \sigma^{-2} \cdot \mathbf{1} (I + (\sigma^{-2} \cdot N) I)^{-1} \mathbf{1}^T) \\
 &= \sigma^{-2} (I - \sigma^{-2} (1 + \frac{N}{\sigma^2})^{-1} \mathbf{1}\mathbf{1}^T) \\
 &= \sigma^{-2} (I - \cancel{\sigma^2} (\frac{\cancel{\sigma^2}}{\sigma^2 + N}) \mathbf{1}\mathbf{1}^T) \\
 &= \sigma^{-2} (I - (\frac{\mathbf{1}\mathbf{1}^T}{\sigma^2 + N}))
 \end{aligned}$$

שאלה 6

$$\begin{aligned}
 f_\alpha(x) &= \sum_i \alpha_i \overbrace{k(x, x_i)}^1 \\
 &= \sum_i [\sigma^{-2} y_i - \frac{\mathbf{1}^T y}{\sigma^2(\sigma^2 + N)}] \\
 &= \sigma^{-2} \sum_i y_i - N \frac{\mathbf{1}^T y}{\sigma^2(\sigma^2 + N)} \\
 &= (\sigma^{-2} - \frac{N}{\sigma^2(\sigma^2 + N)}) \mathbf{1}^T y \\
 &= (\cancel{\sigma^2} + \cancel{N} \cancel{N} / \cancel{\sigma^2}(\sigma^2 + N)) \mathbf{1}^T y \\
 &= \frac{1}{\sigma^2 + N} \mathbf{1}^T y
 \end{aligned}$$

לכן:

$$f_{\alpha}(x) \xrightarrow{\sigma^2 \rightarrow 0 \wedge N \rightarrow \infty} 0$$

נקבל:

$$\begin{aligned} \text{Train error} &= \frac{1}{N} \sum_i ||\text{sign}(x_i) - f_{\alpha}(x_i)||^2 \\ &\stackrel{\sigma^2 \rightarrow 0 \wedge N \rightarrow \infty}{=} \frac{1}{N} \sum_i ||\text{sign}(x_i) - 0||^2 \\ &= \frac{1}{N} \sum_i 1 = 1 \end{aligned}$$

שאלה 7

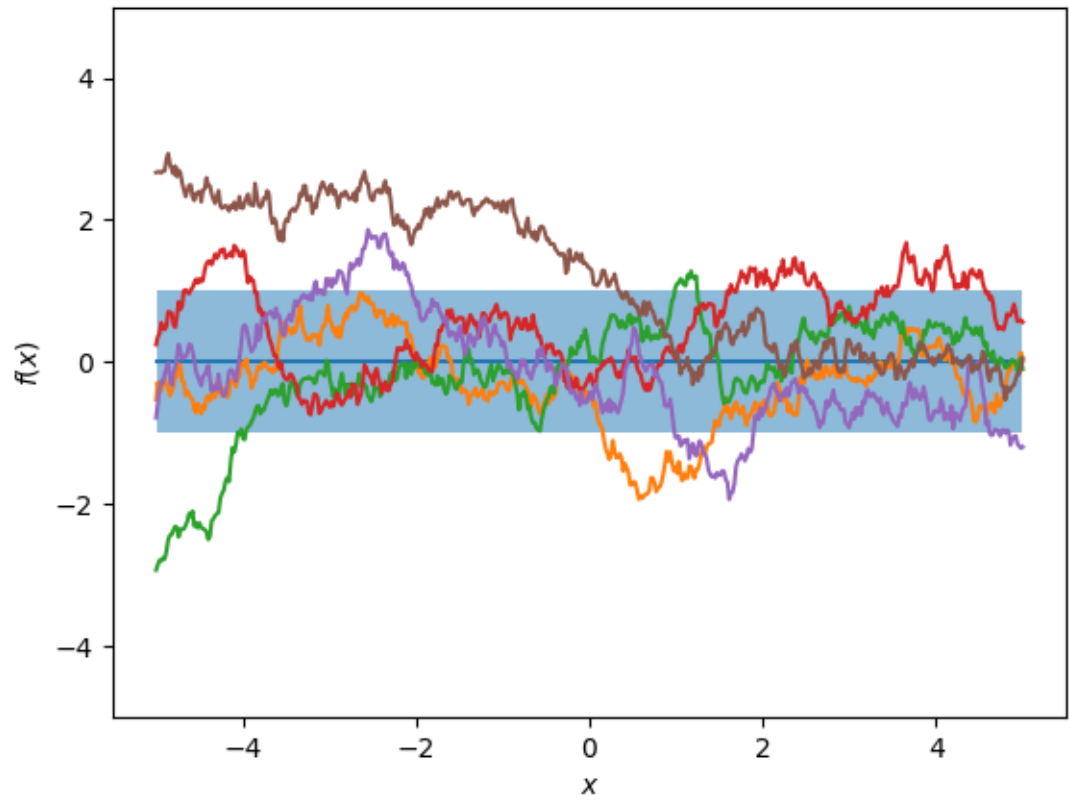
ראינו בתרגול ש-RBF הוא $kernel PD$ לכן כאשר $\sigma^2 \rightarrow 0$ אז שגיאת האימון היא 0.

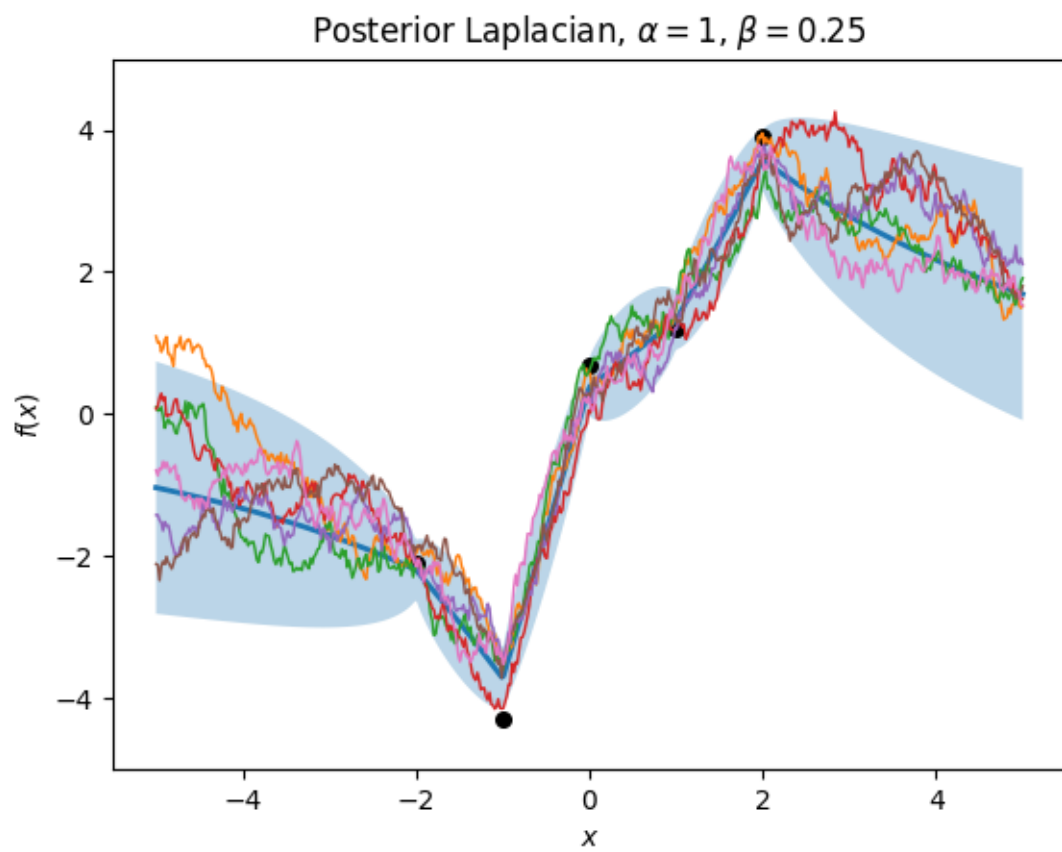
פרקטי

שאלות 2,3

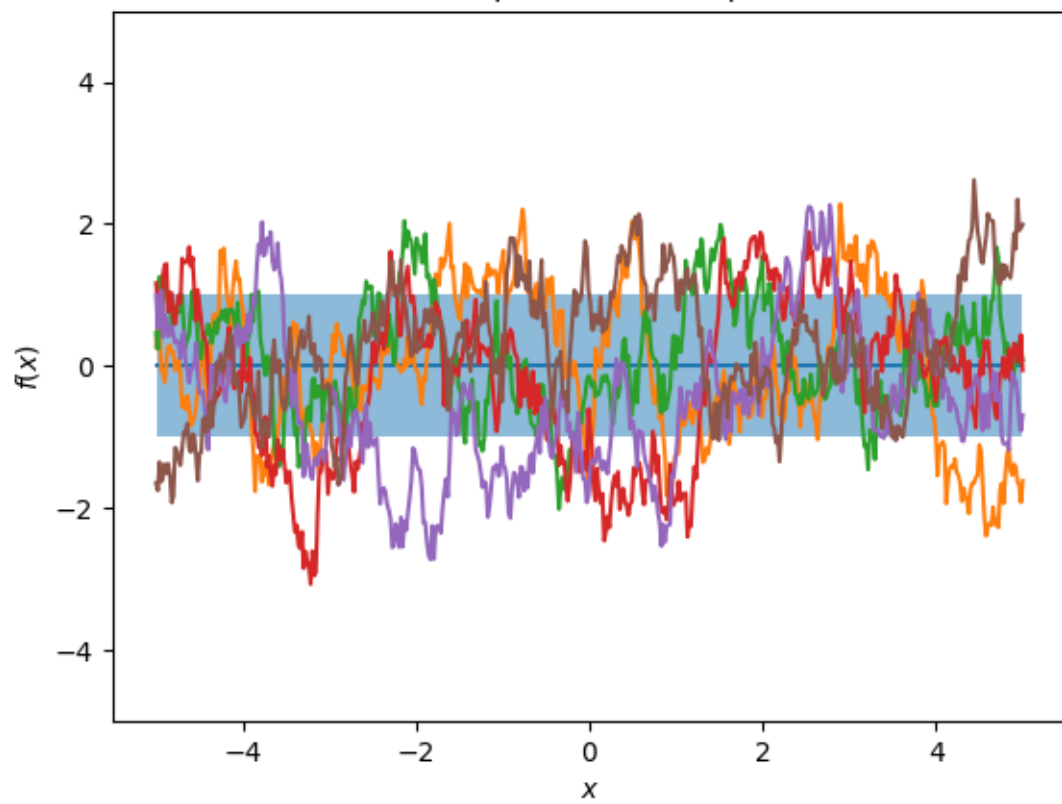
:*Laplacian*

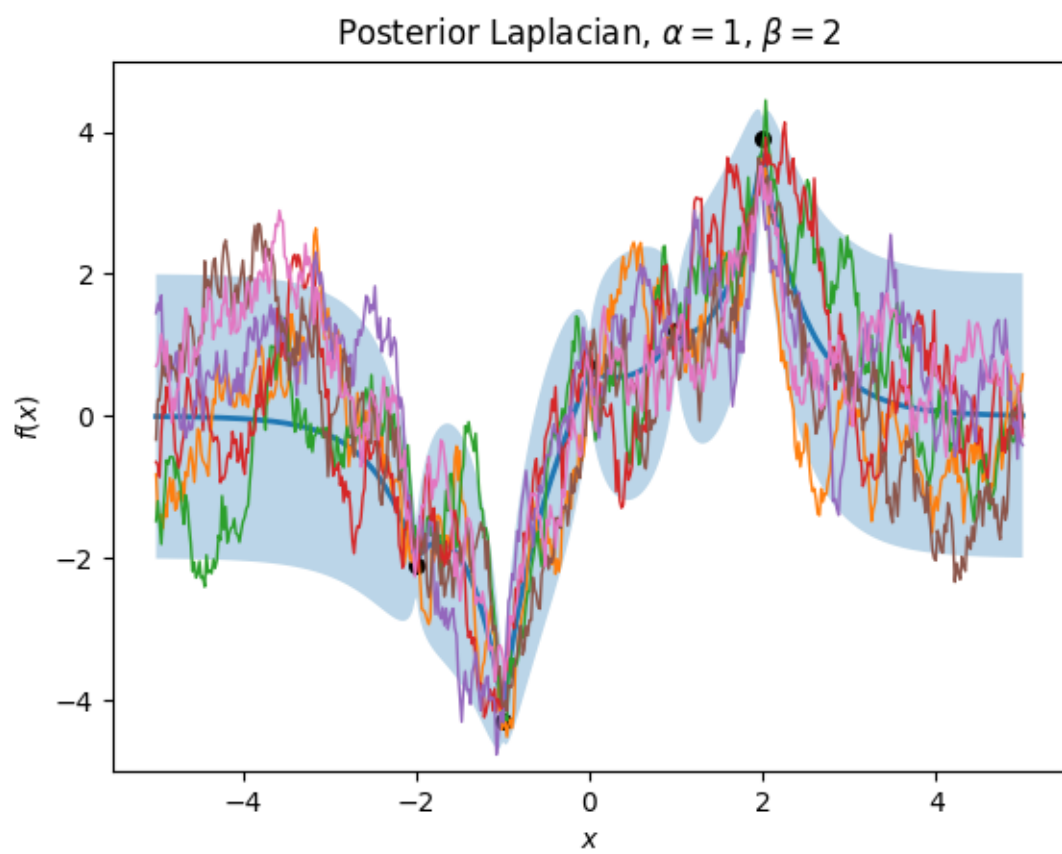
Prior Laplacian, $\alpha = 1$, $\beta = 0.25$

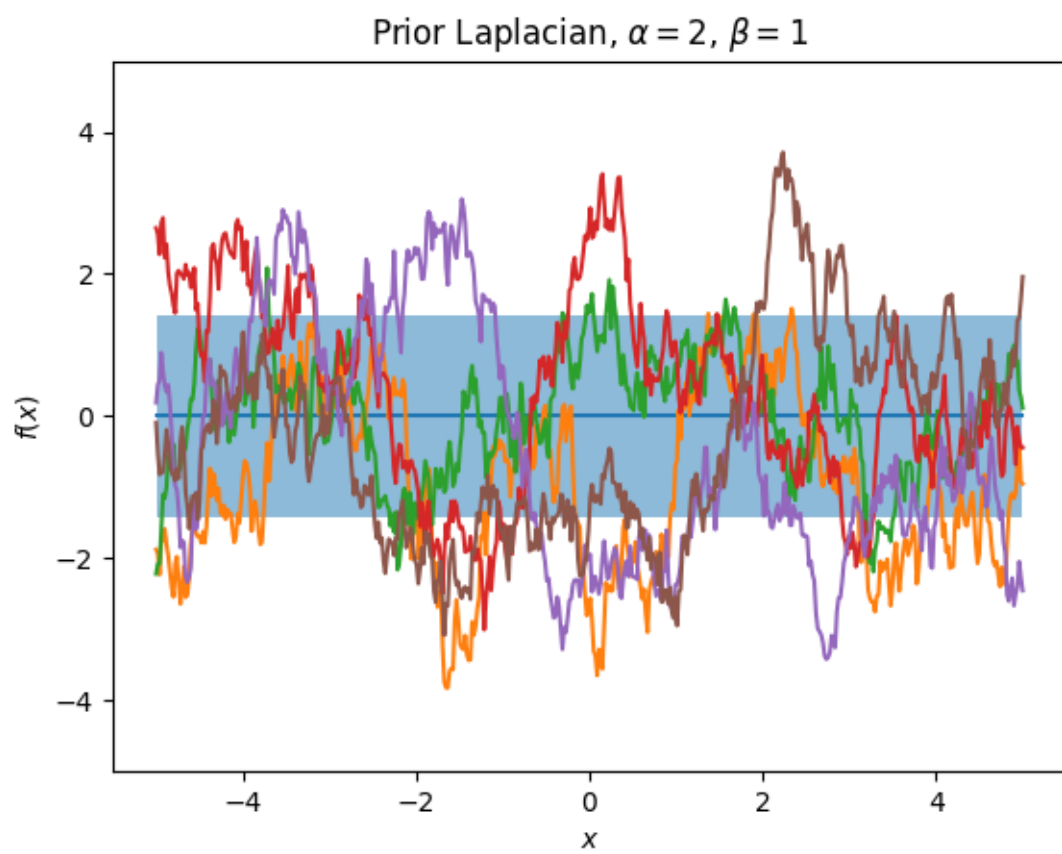




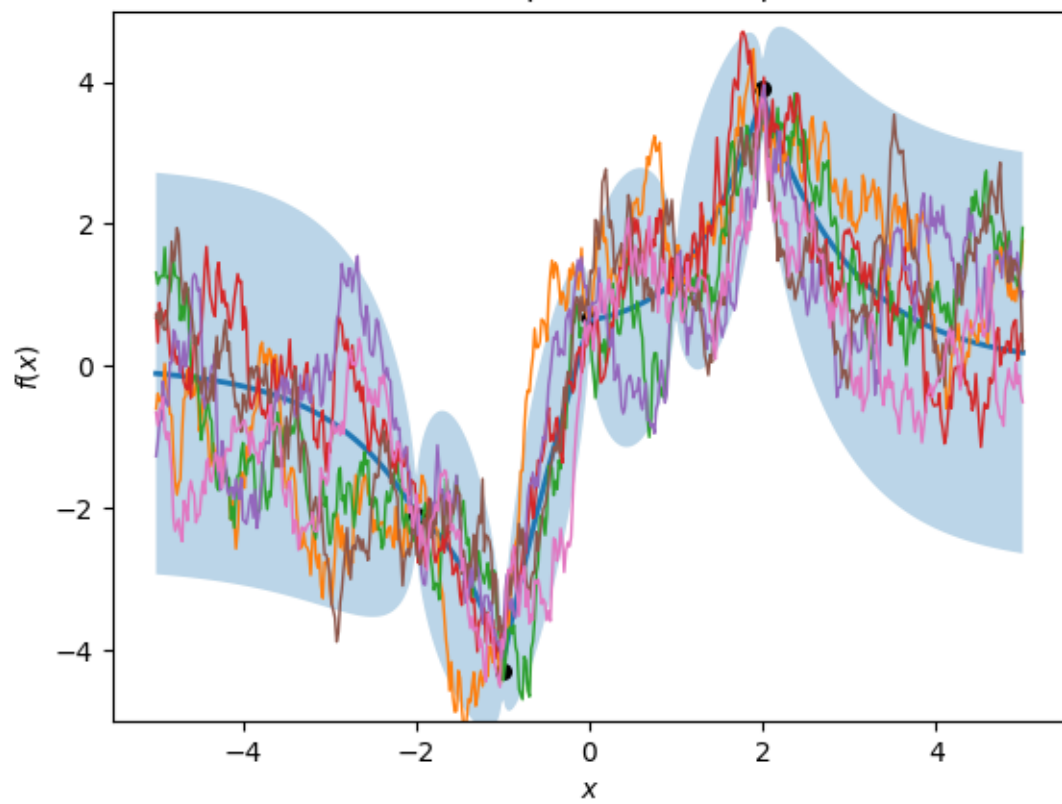
Prior Laplacian, $\alpha = 1, \beta = 2$



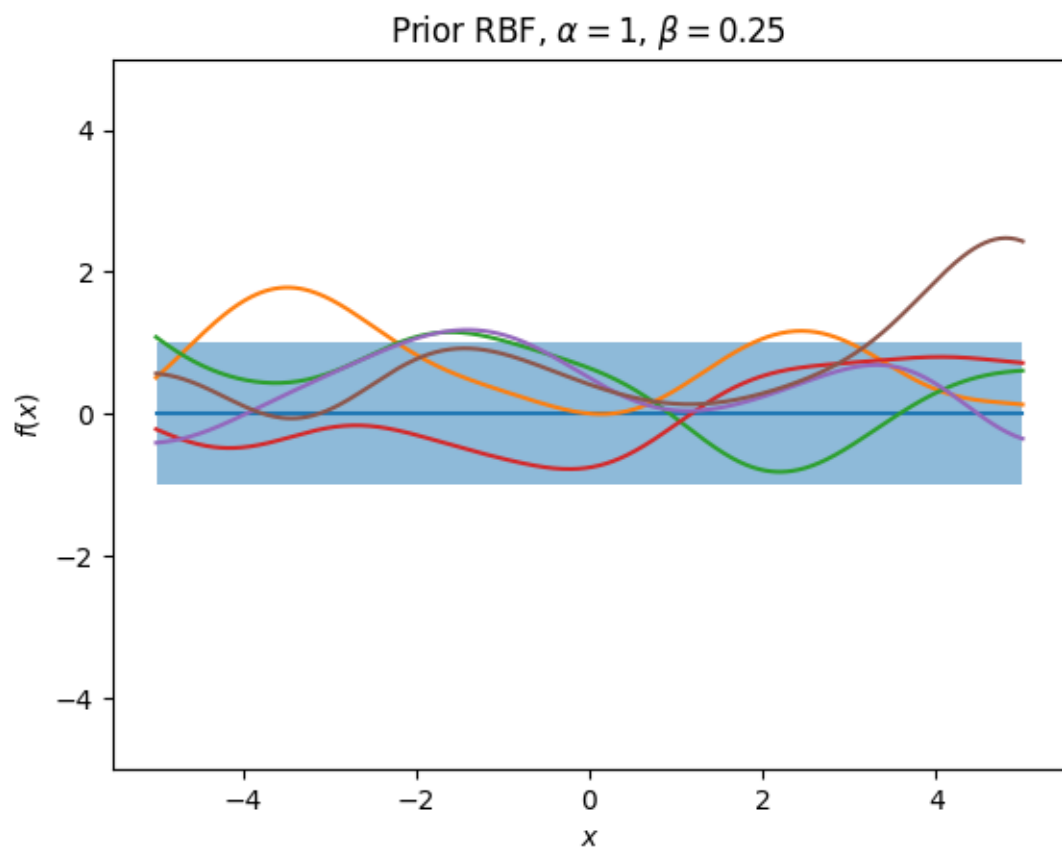


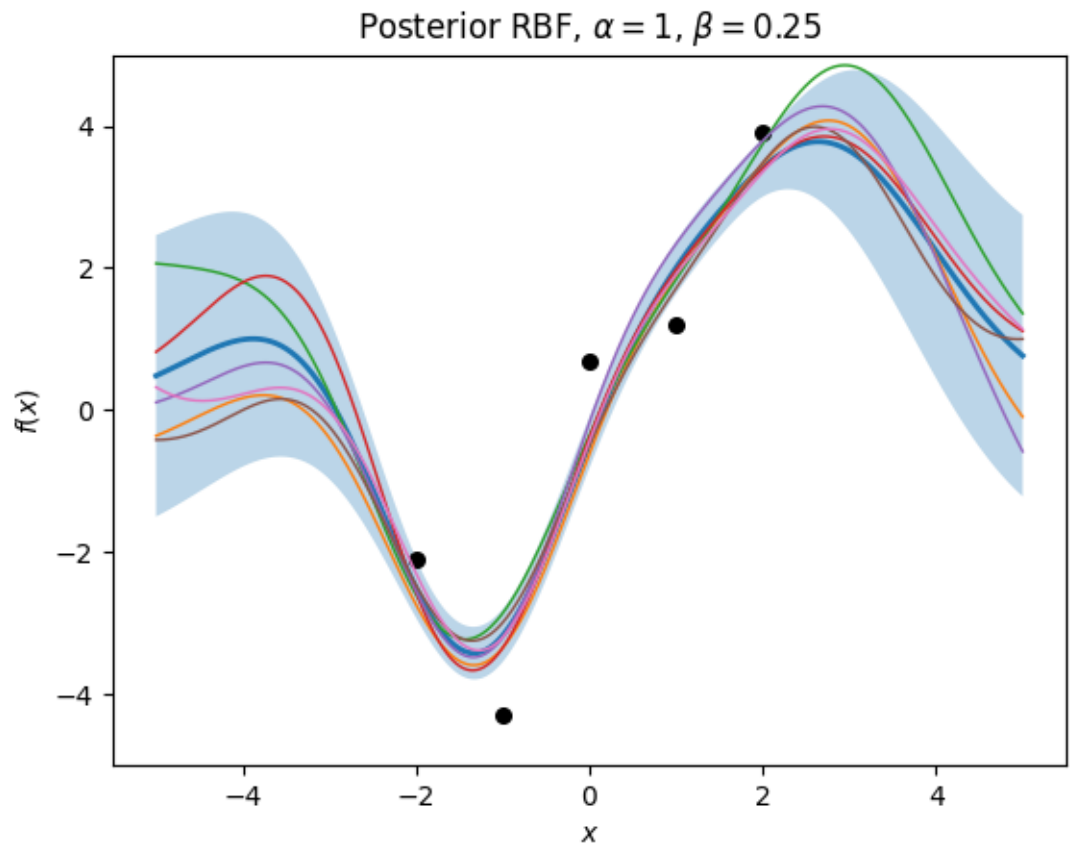


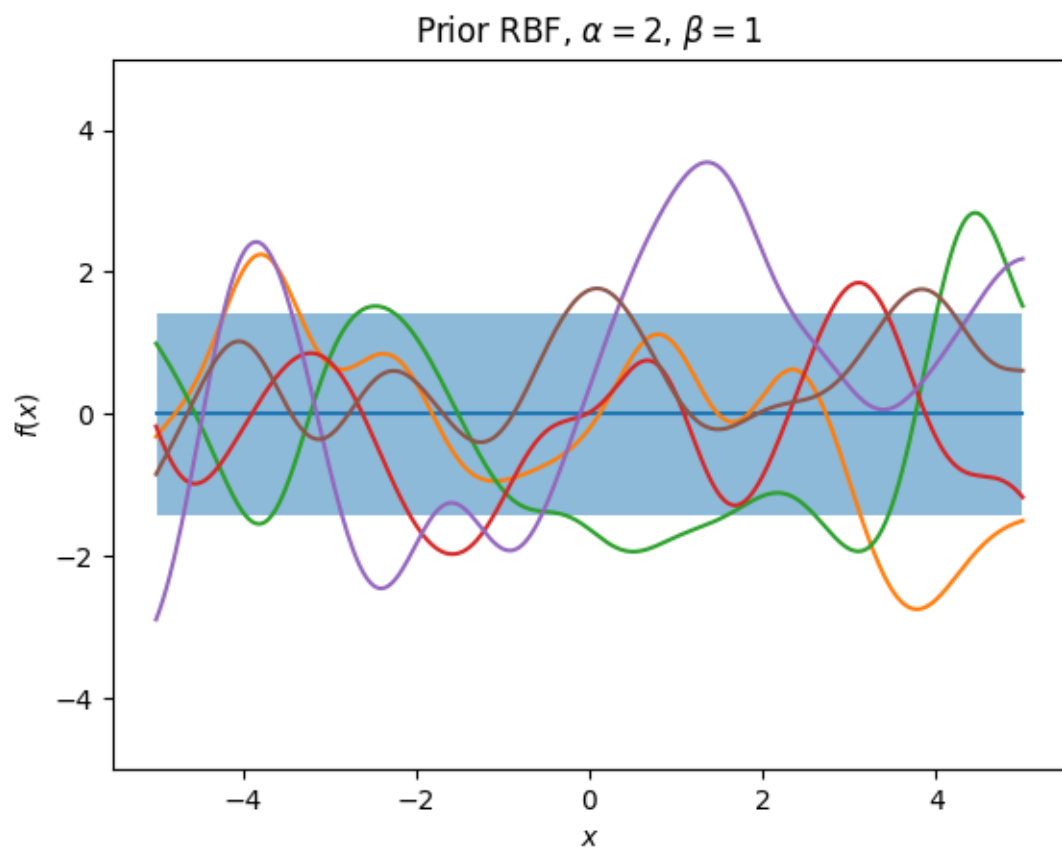
Posterior Laplacian, $\alpha = 2, \beta = 1$

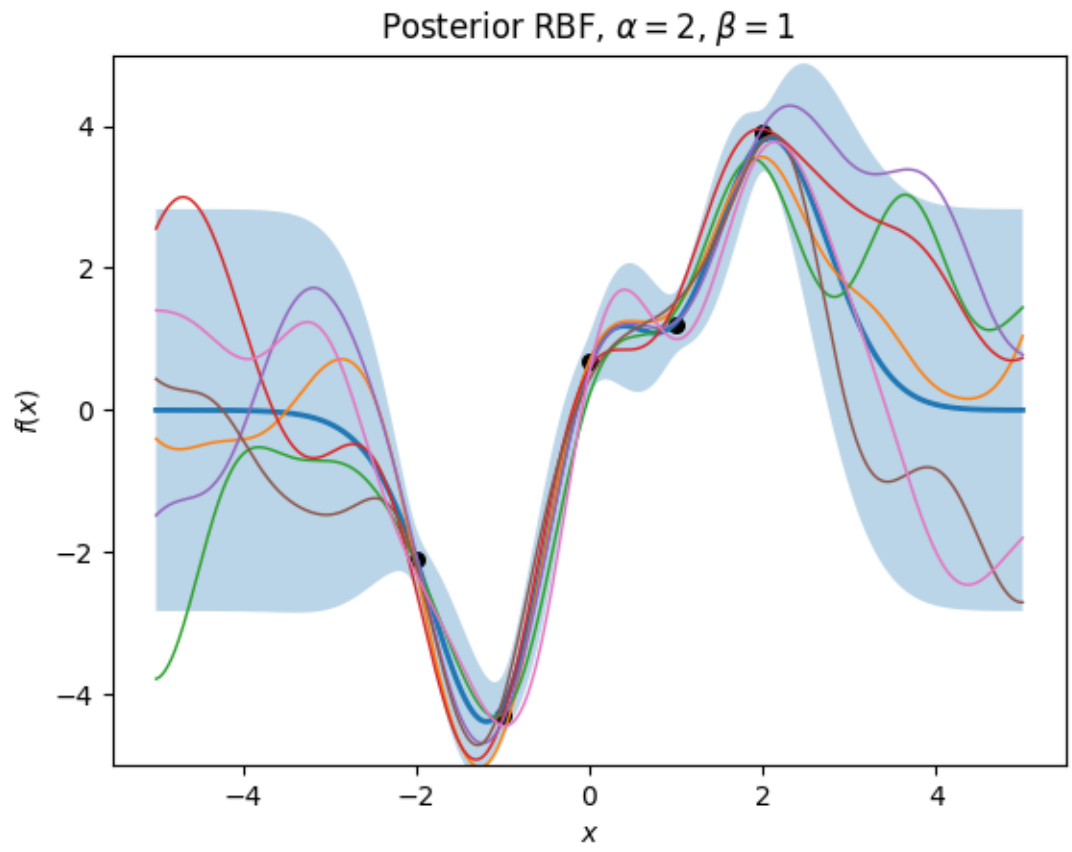


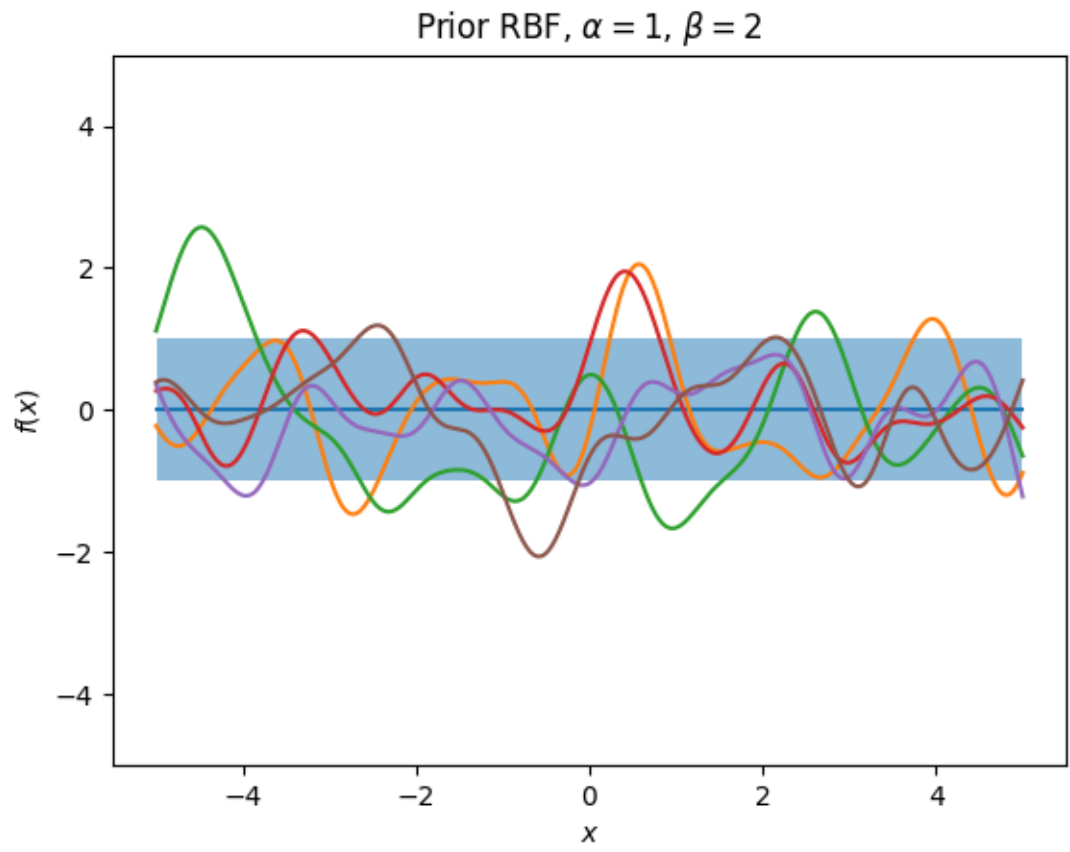
:RBF

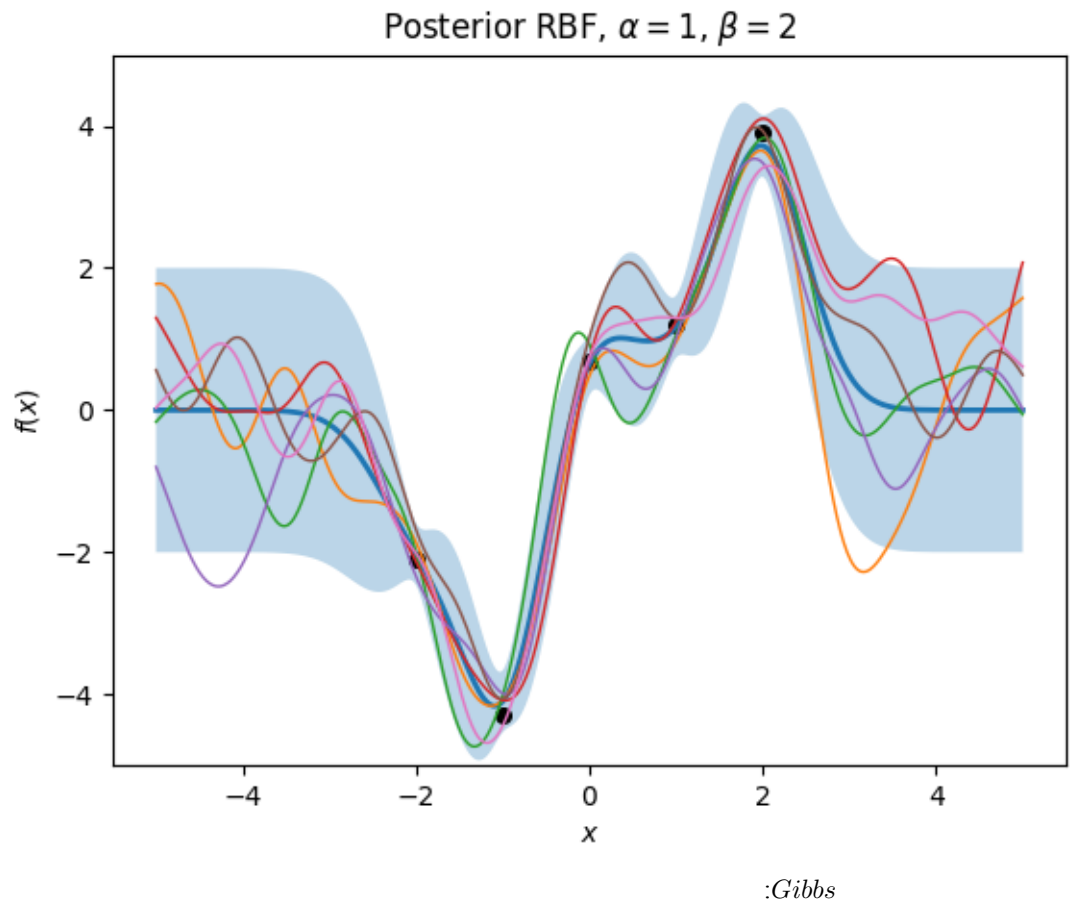


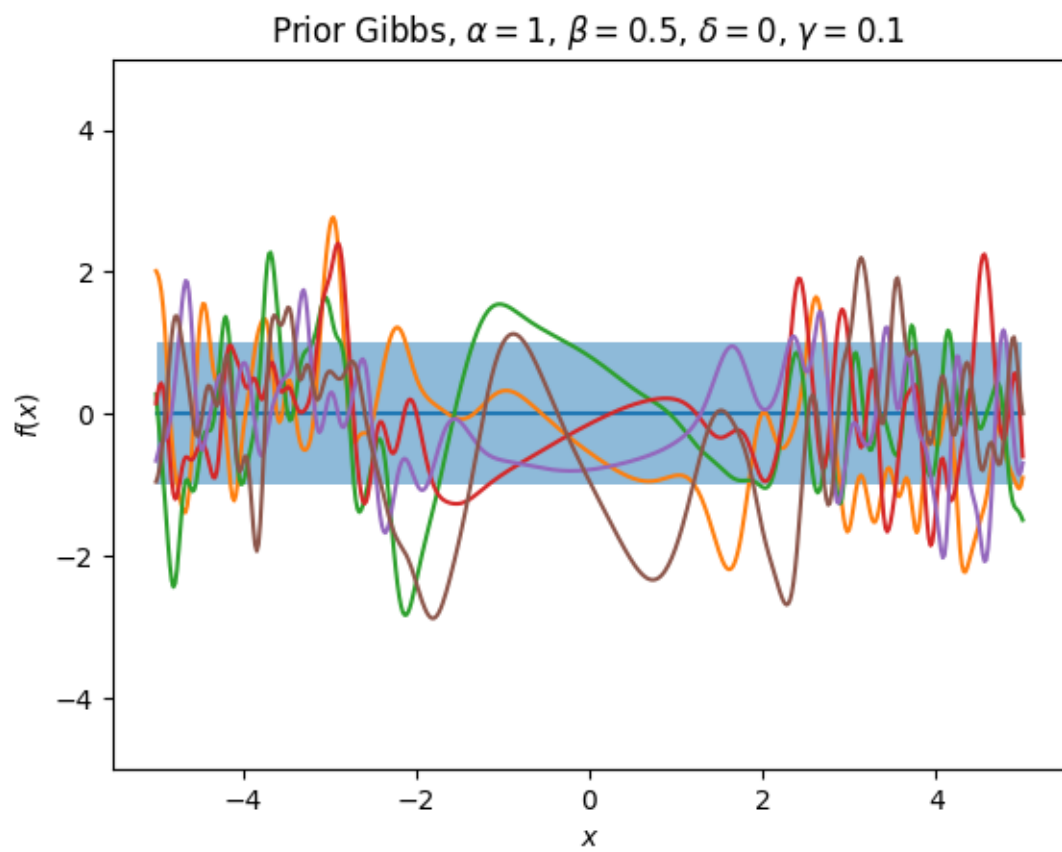




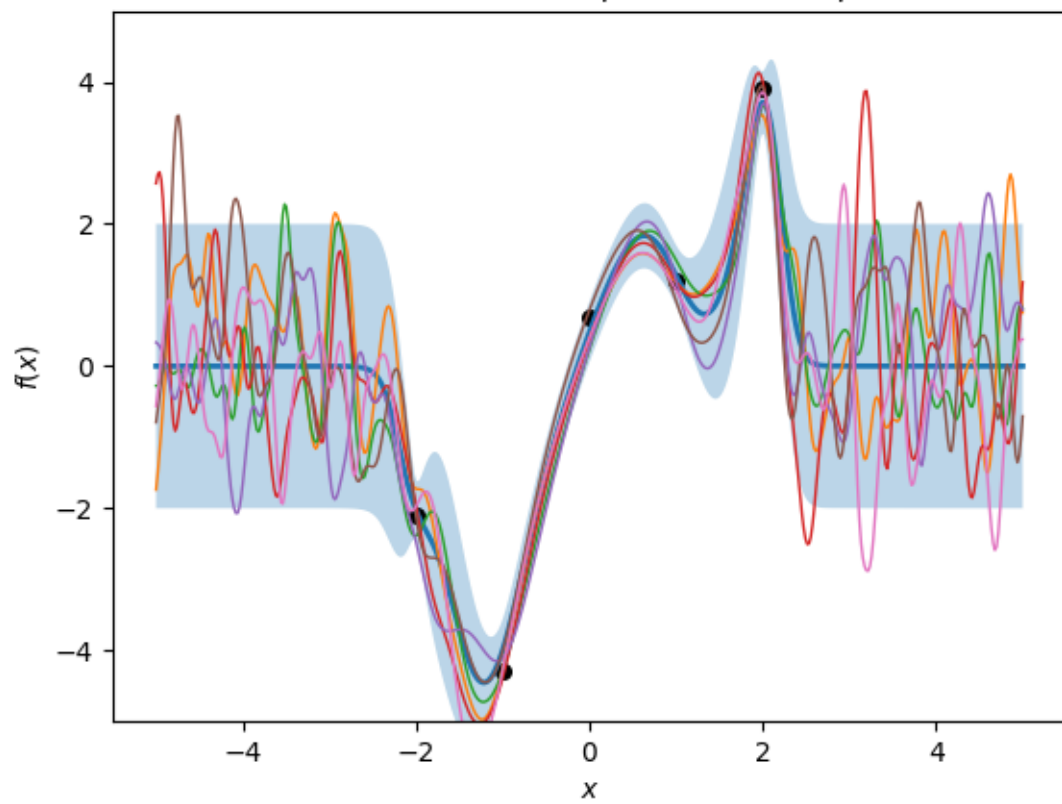


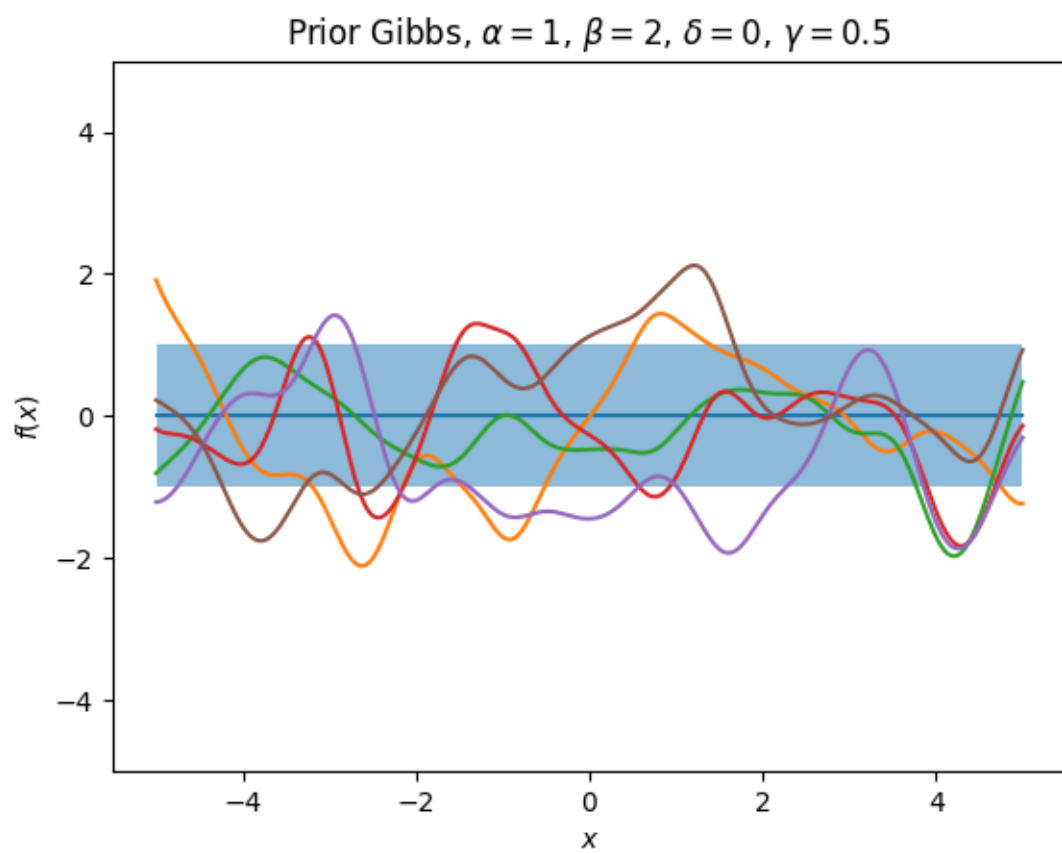


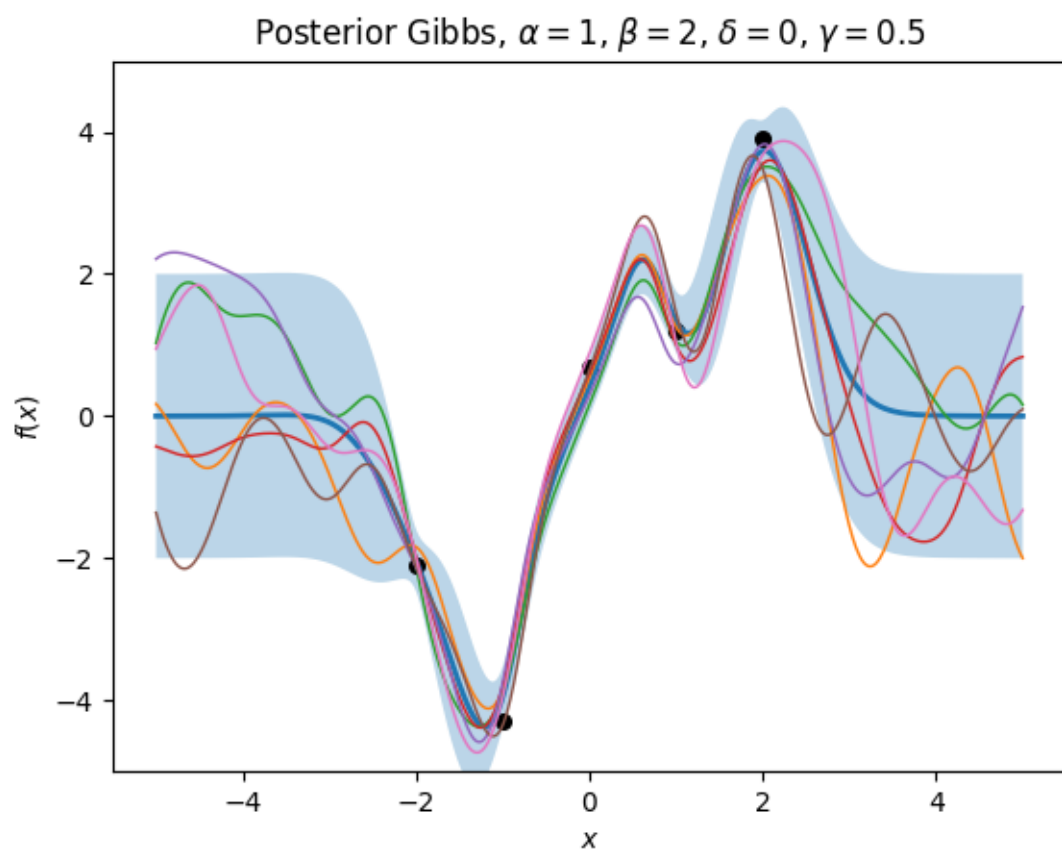




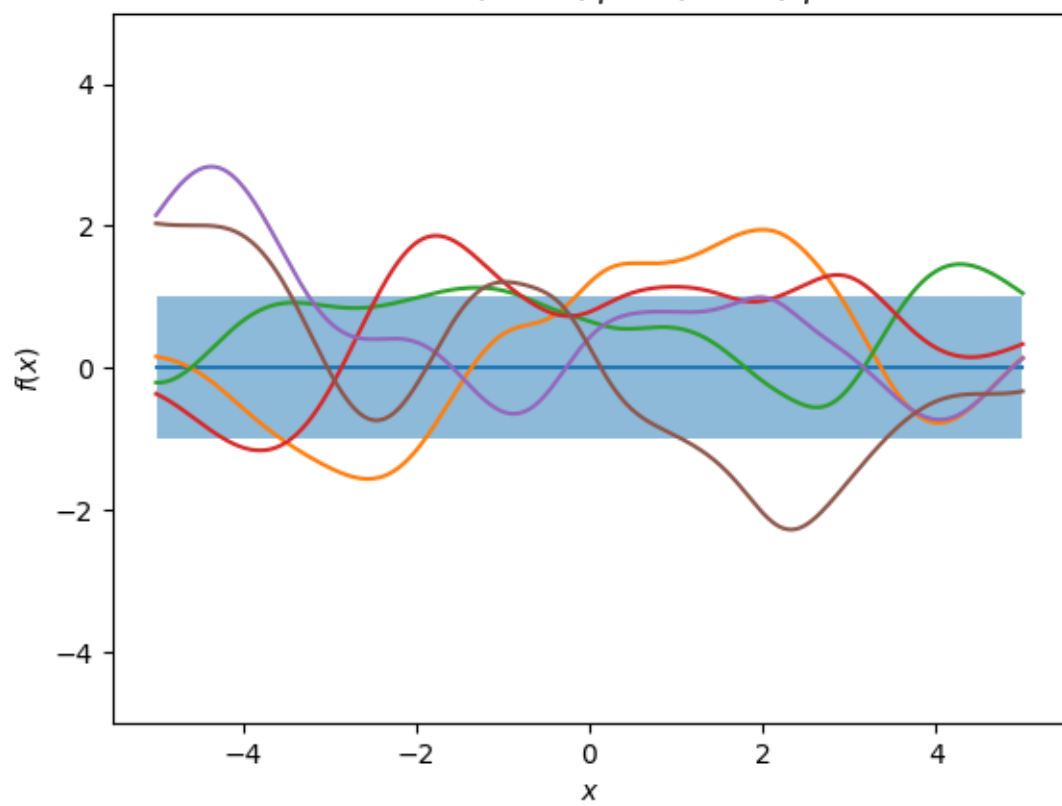
Posterior Gibbs, $\alpha = 1, \beta = 0.5, \delta = 0, \gamma = 0.1$

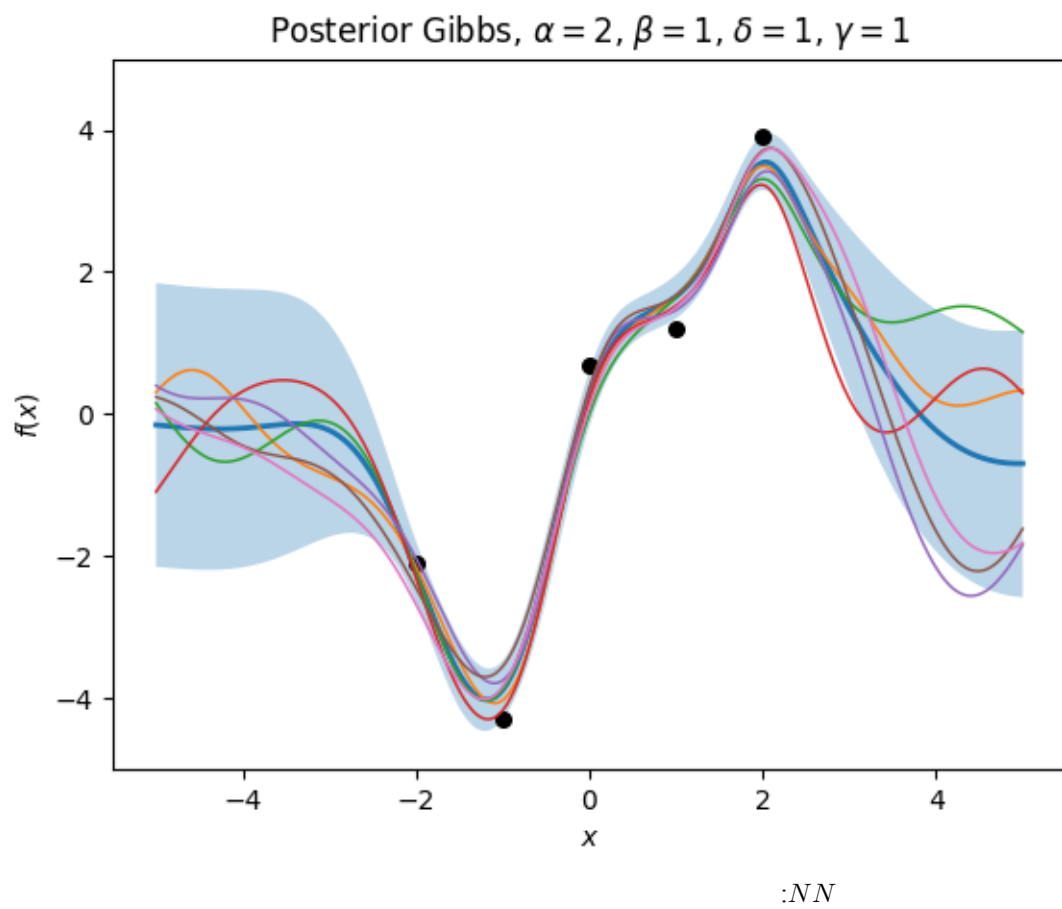


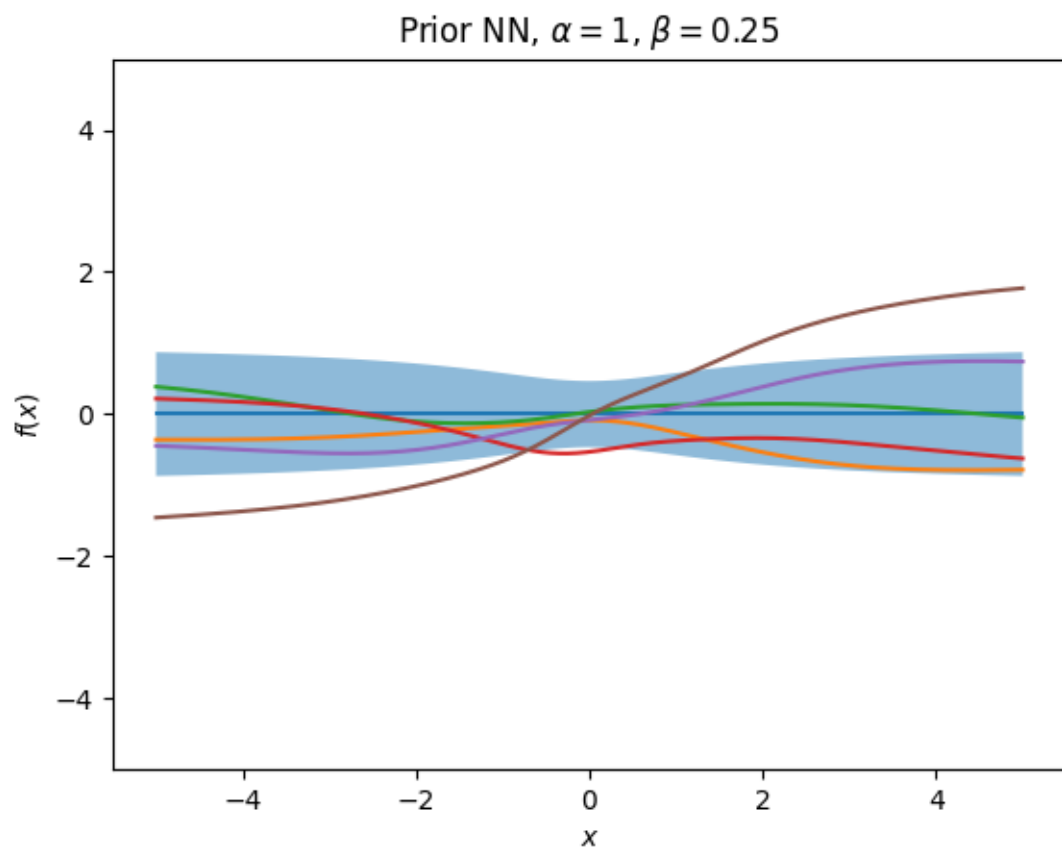


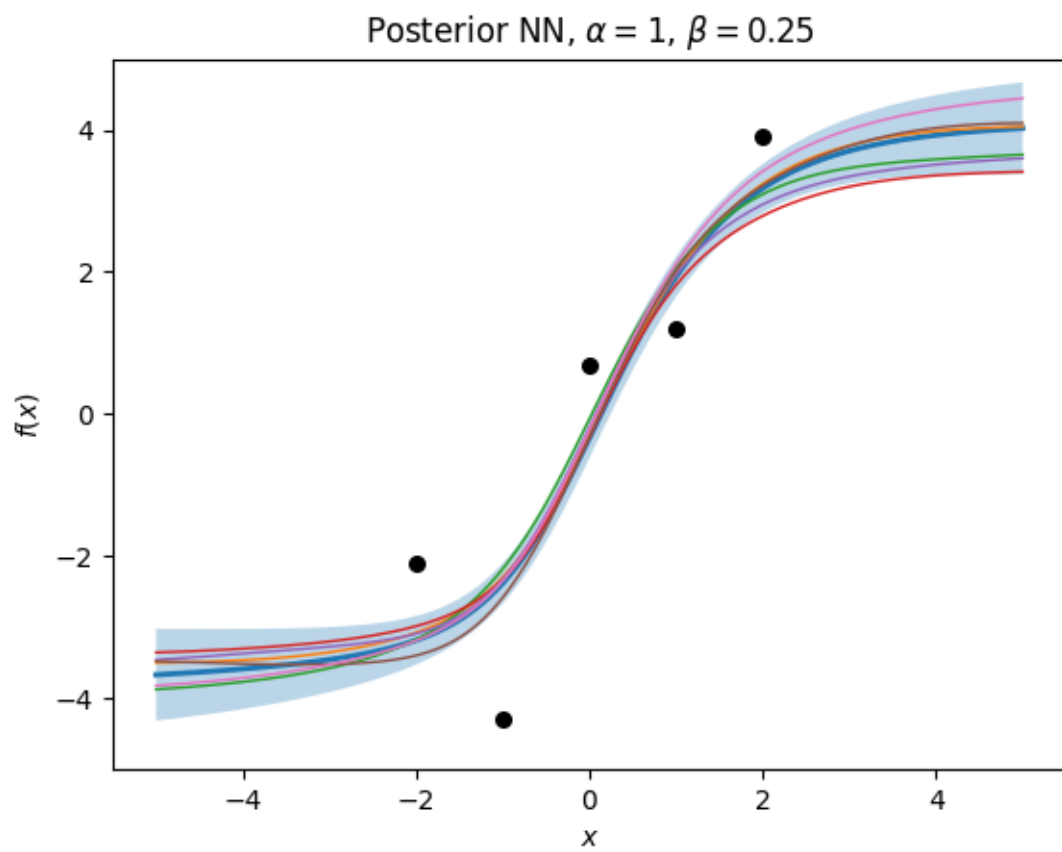


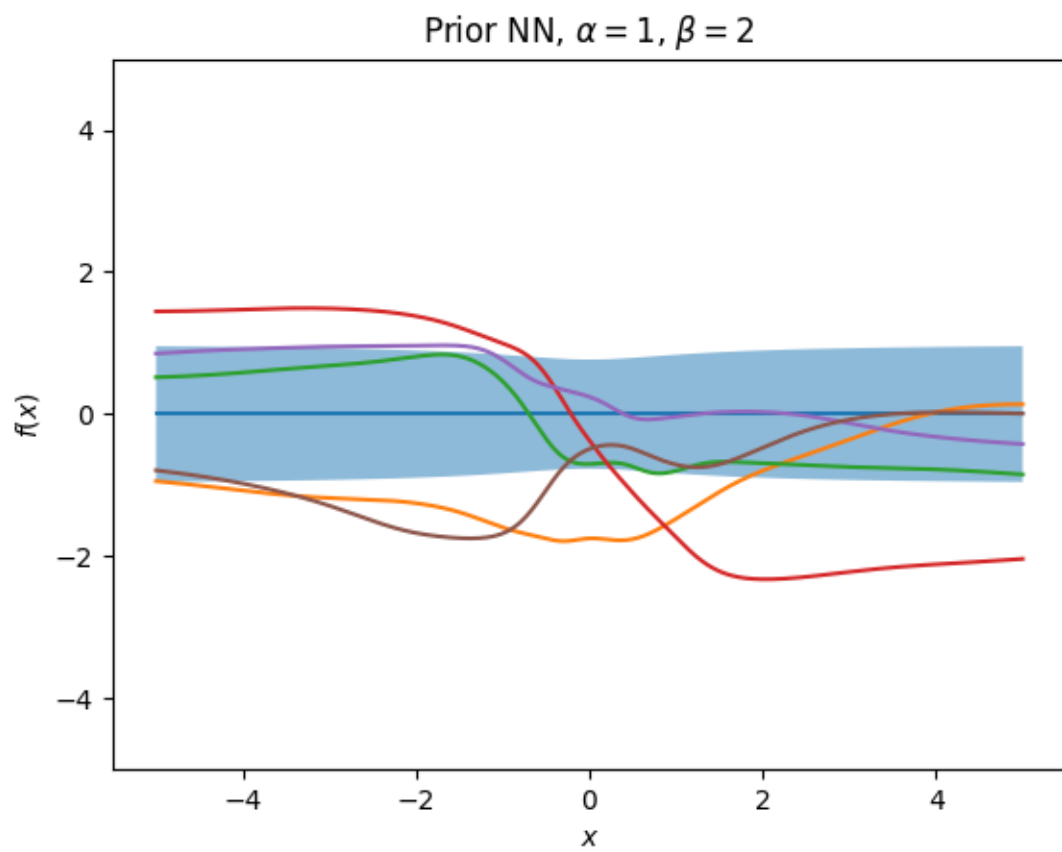
Prior Gibbs, $\alpha = 2, \beta = 1, \delta = 1, \gamma = 1$

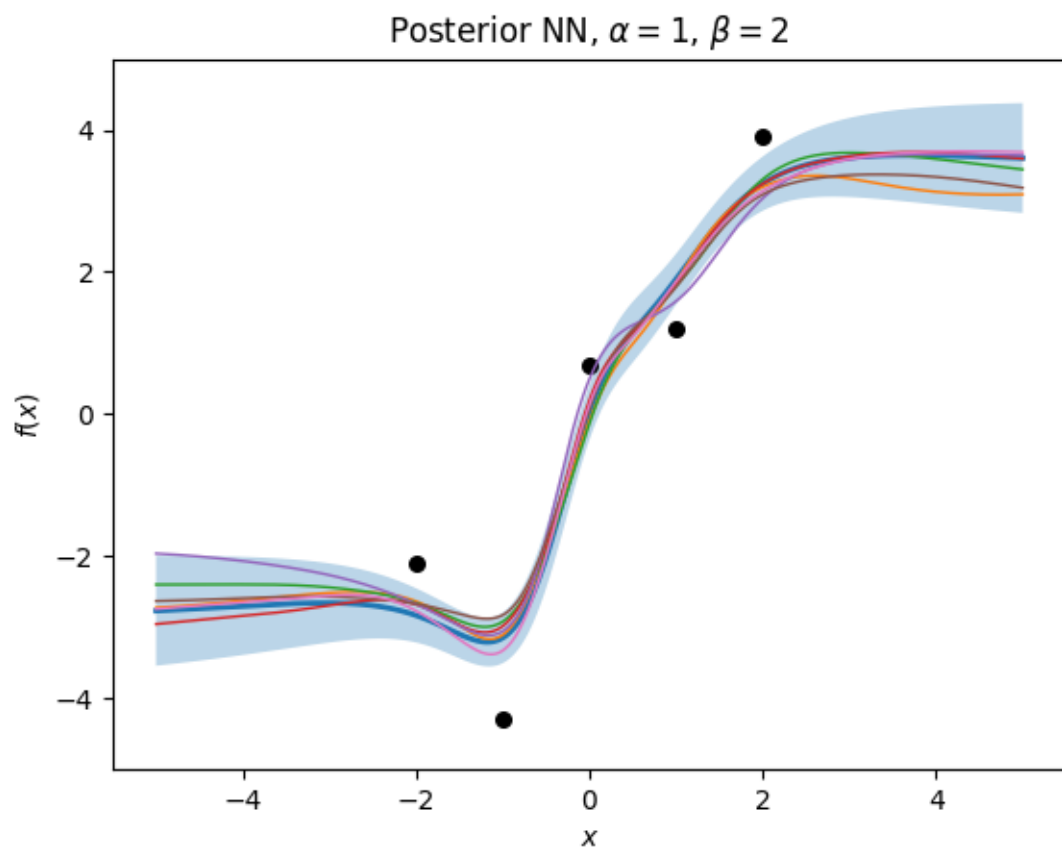


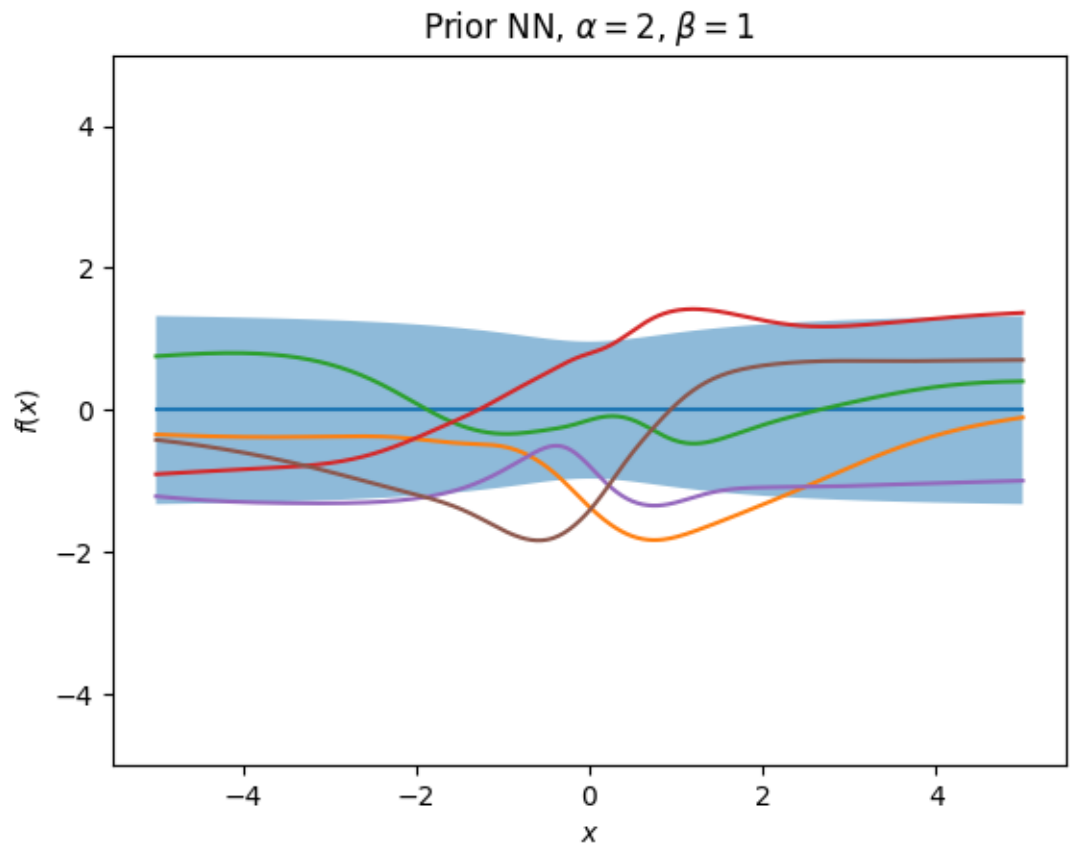


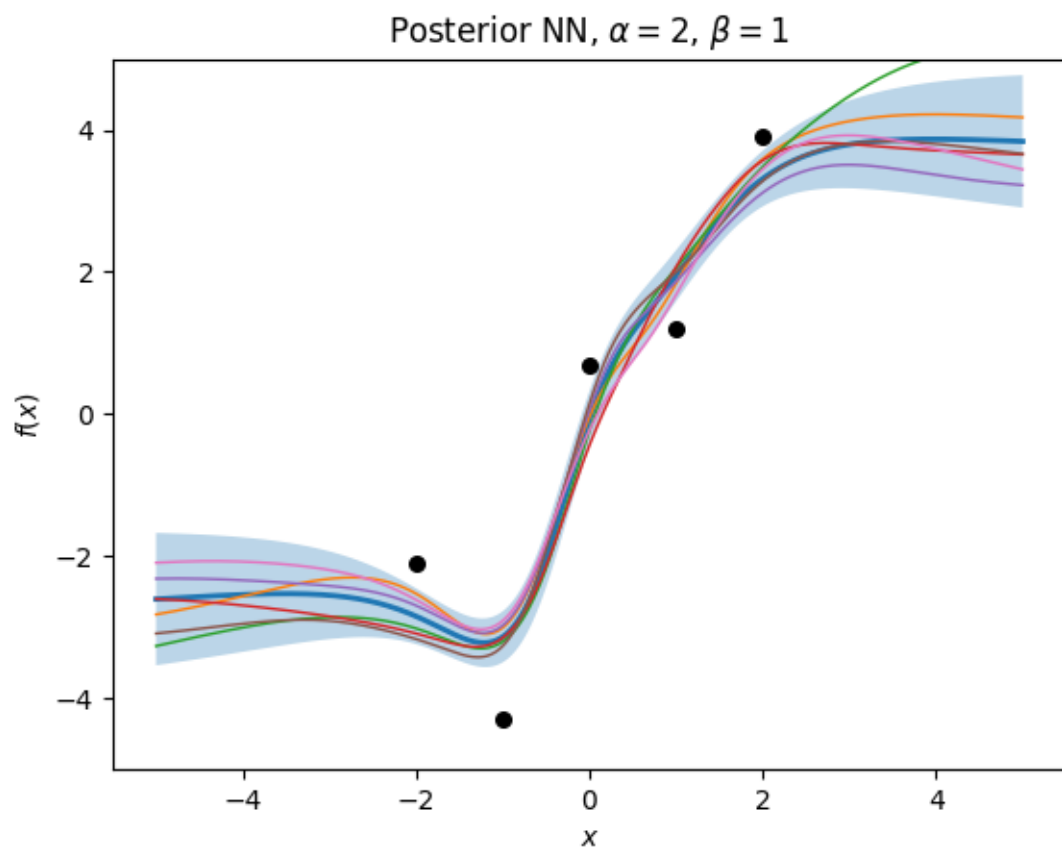




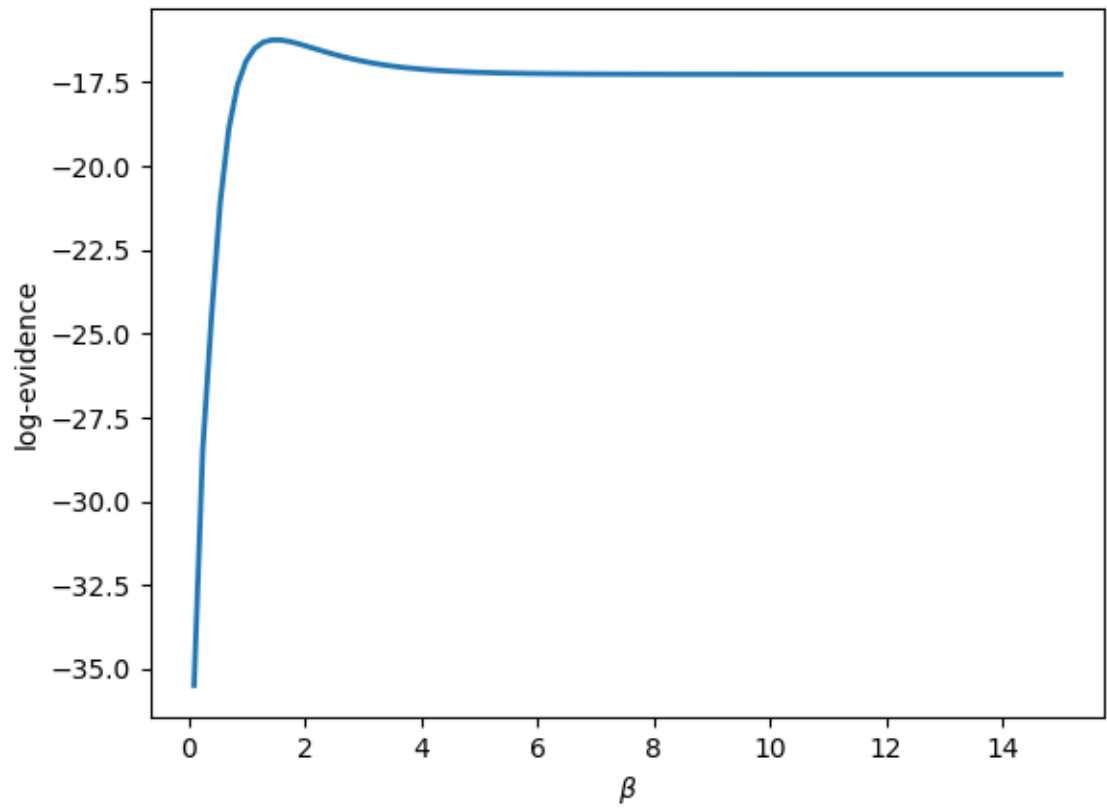




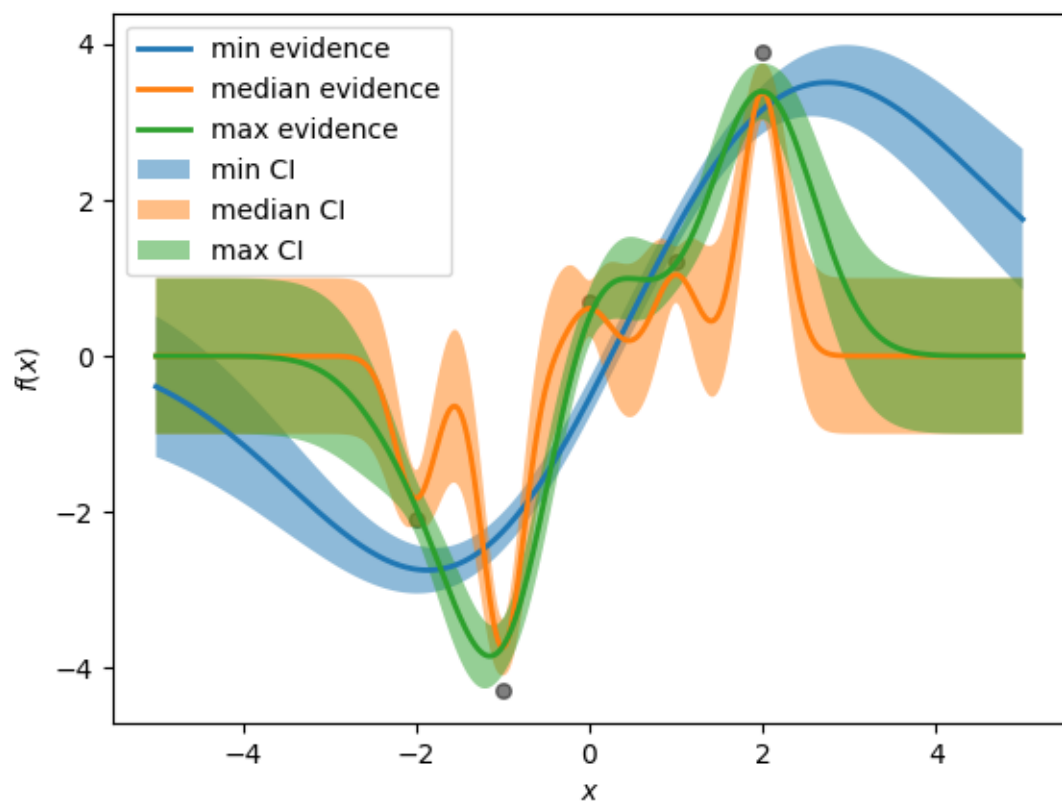




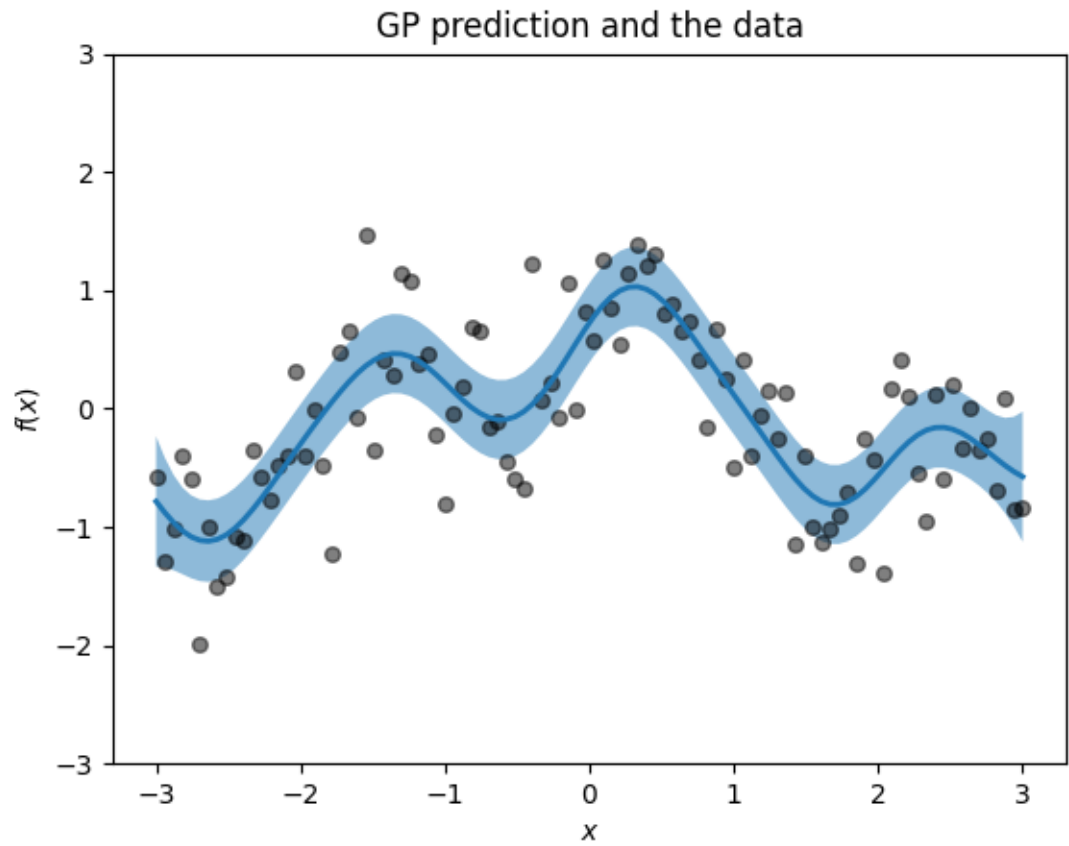
שאלה 4



עבור $\beta = 1.441$ יש את הערך *evidence* הטוב ביותר.

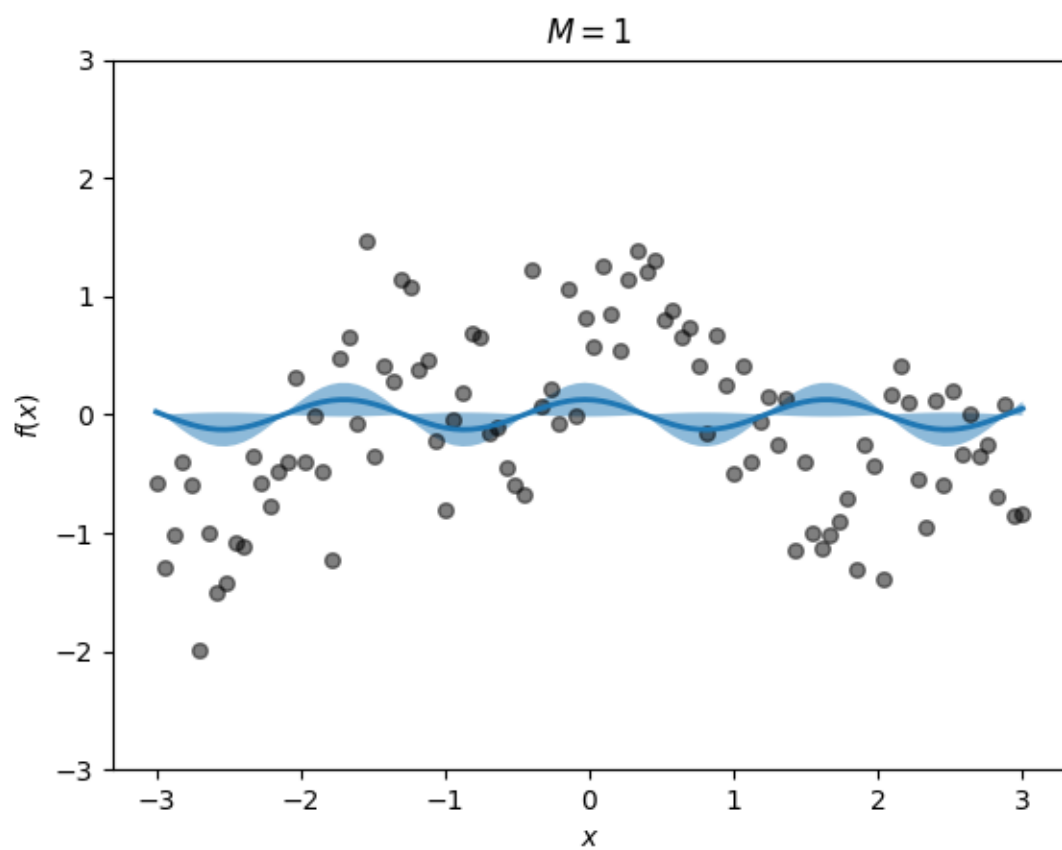


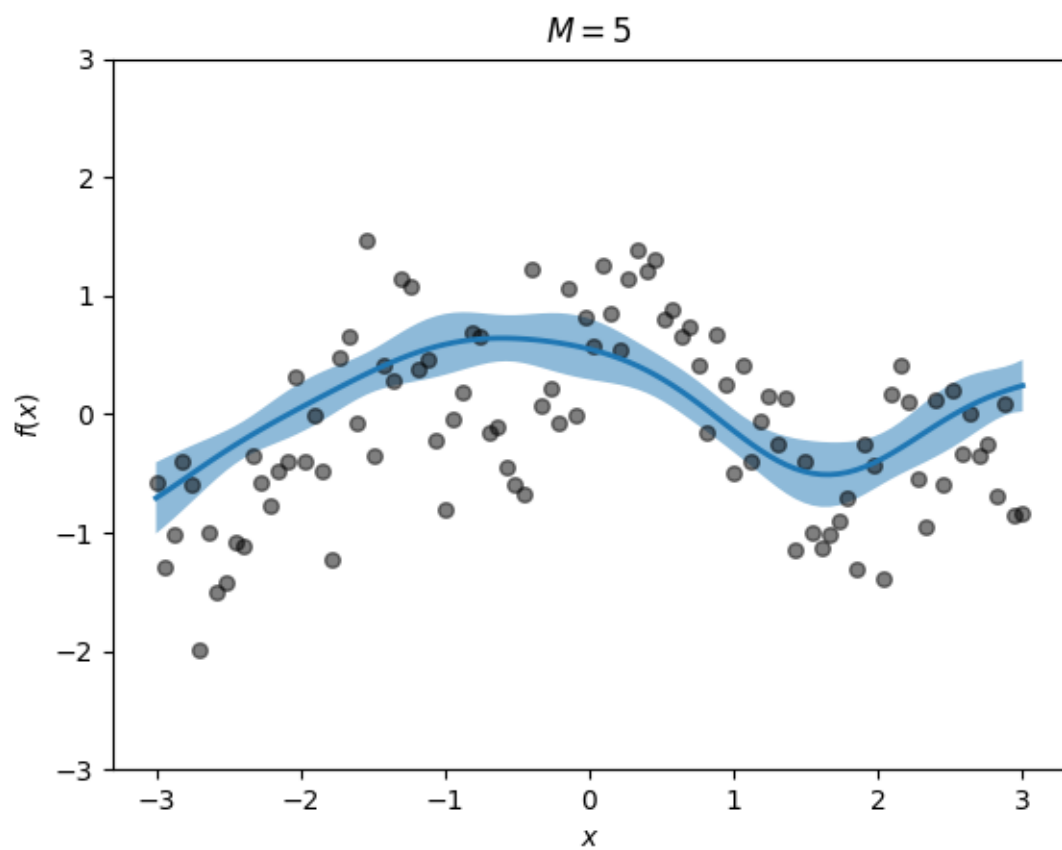
שאלה 5

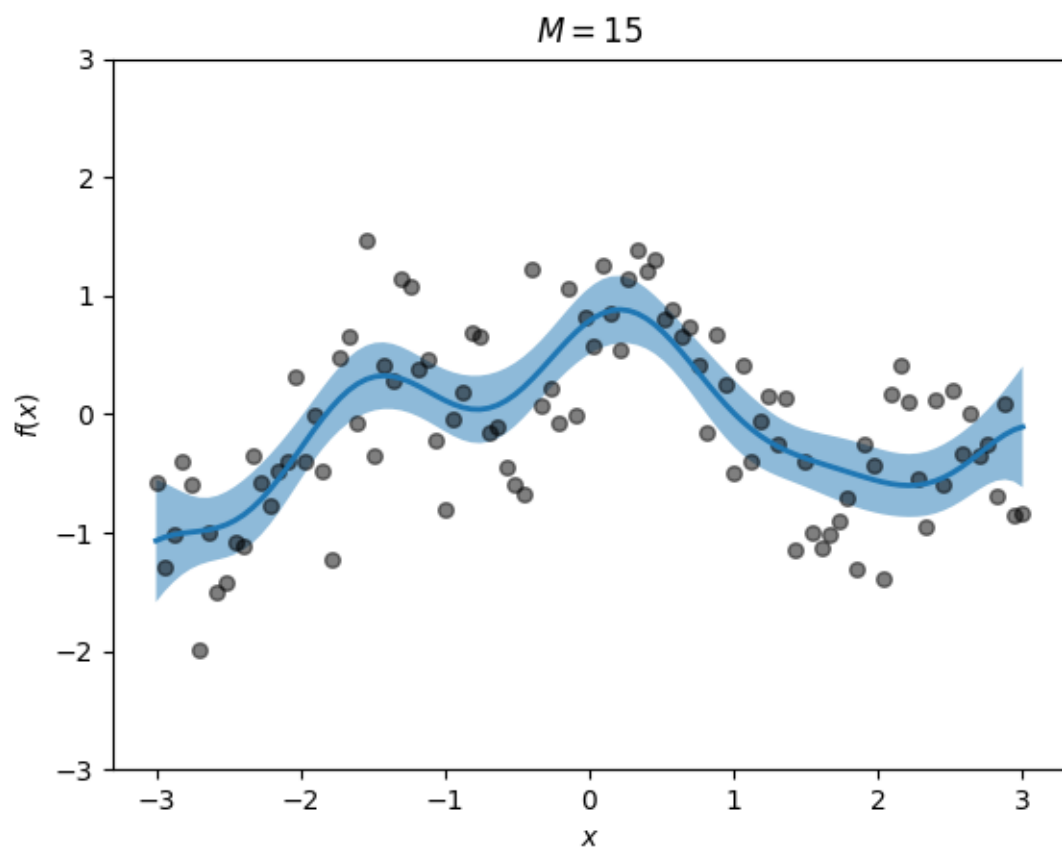


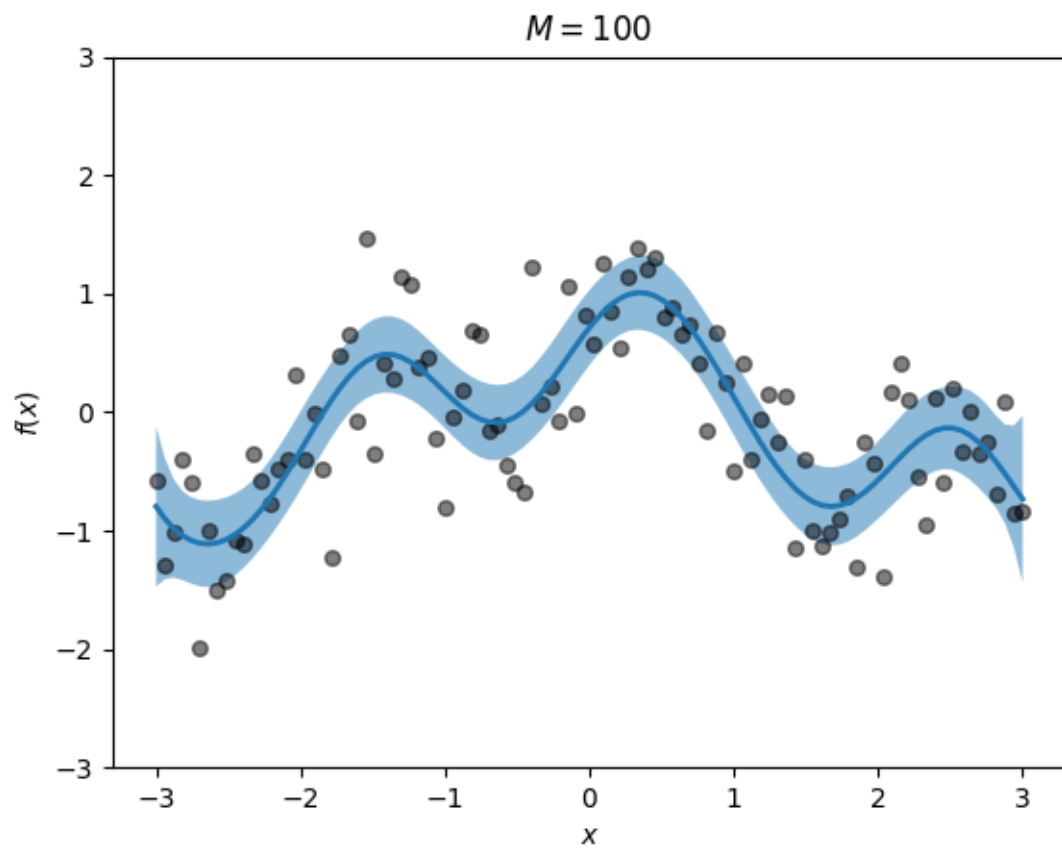
וקיבלנו : 0.20 Average squared error of the GP is :

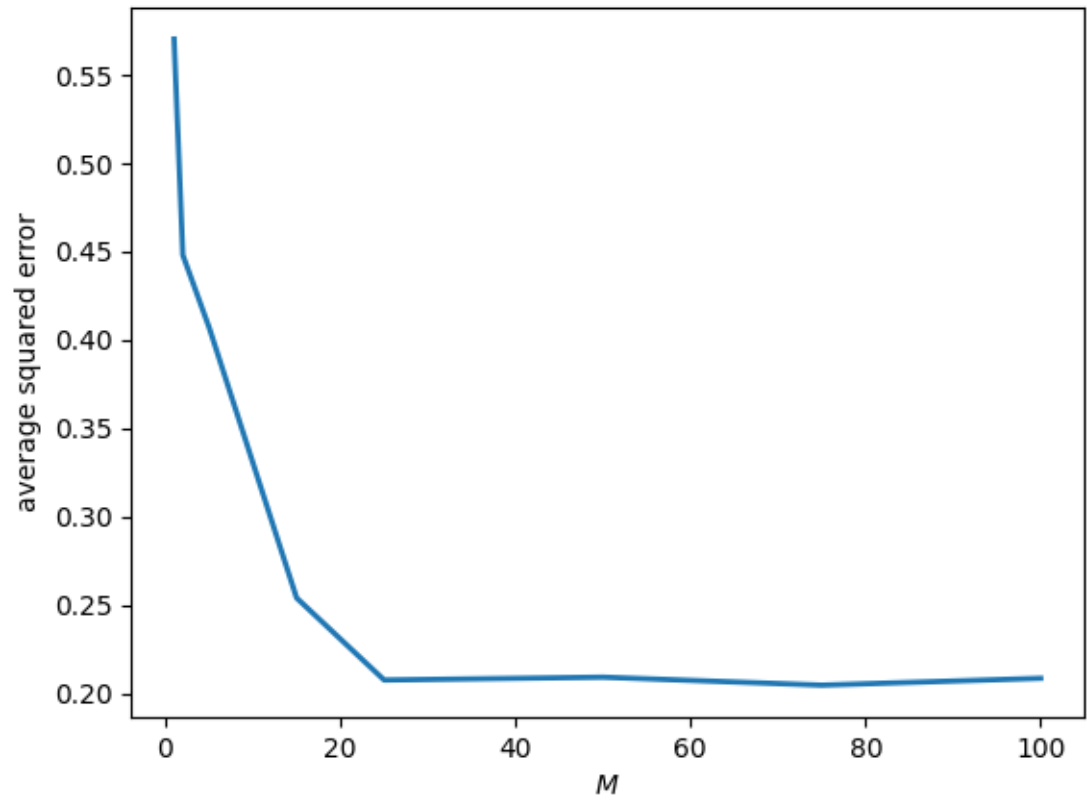
שאלה 7











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Average squared error with M=1 random features: 0.57
Average squared error with M=2 random features: 0.45
Average squared error with M=5 random features: 0.41
Average squared error with M=15 random features: 0.25
Average squared error with M=25 random features: 0.21
Average squared error with M=50 random features: 0.21
Average squared error with M=75 random features: 0.20
Average squared error with M=100 random features: 0.21
```