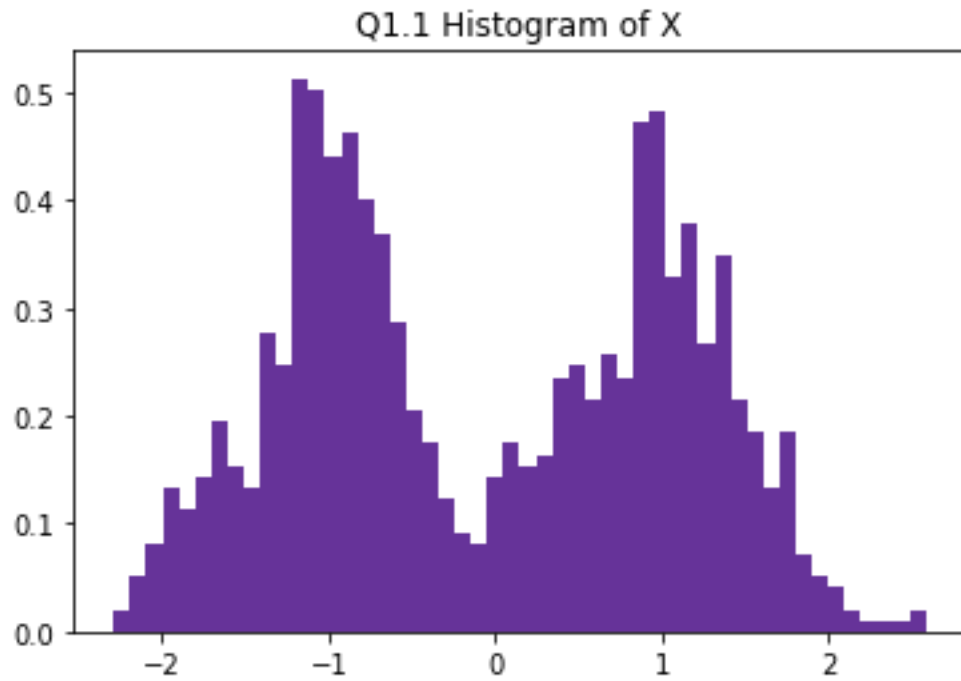


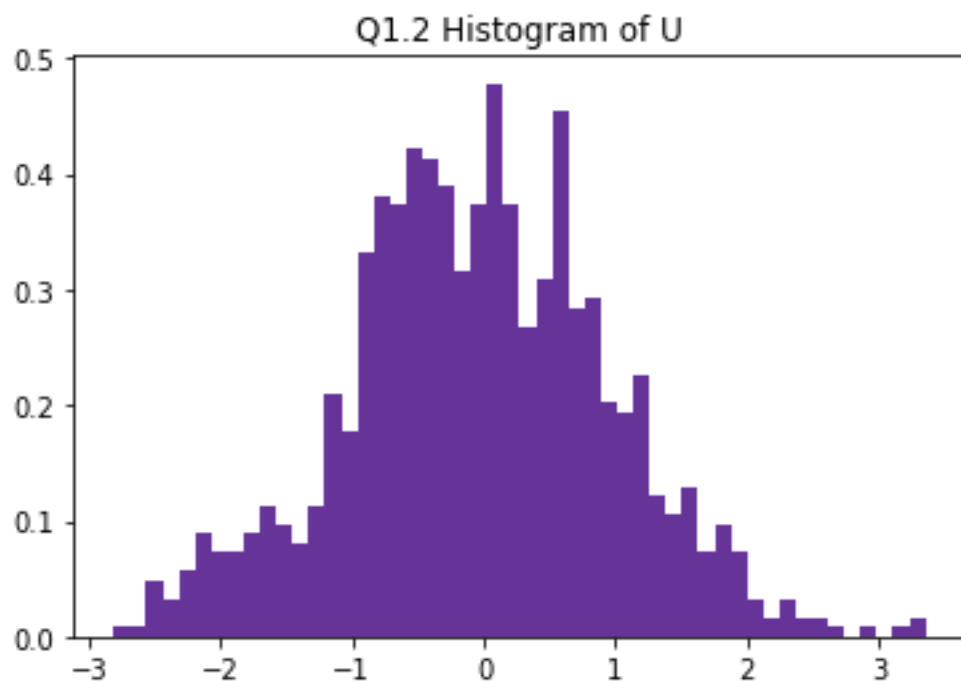
CS680 – Assignment 4

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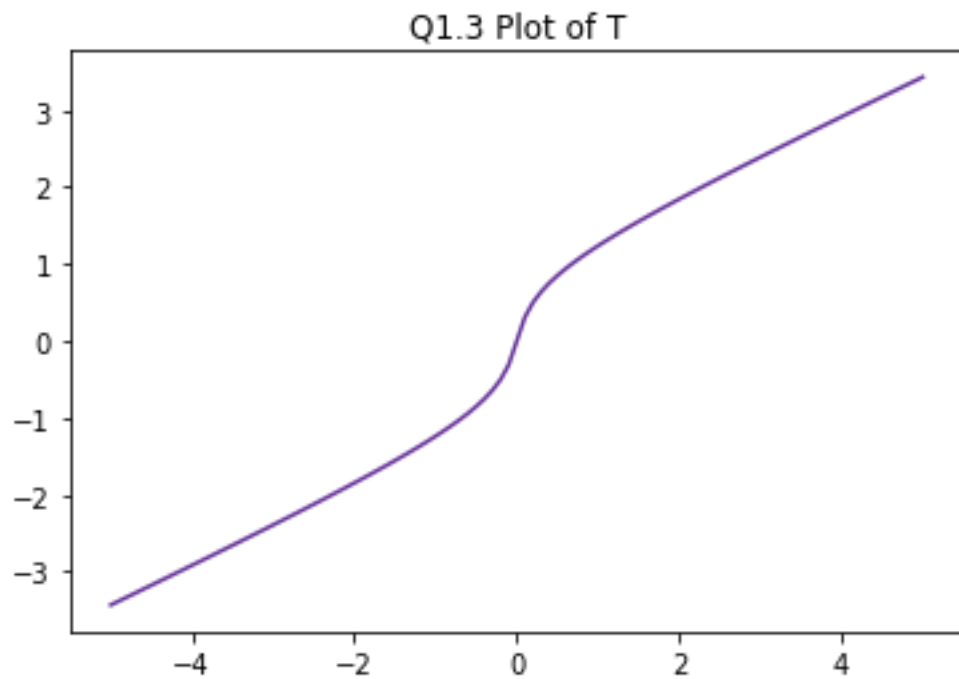
Q1.1:



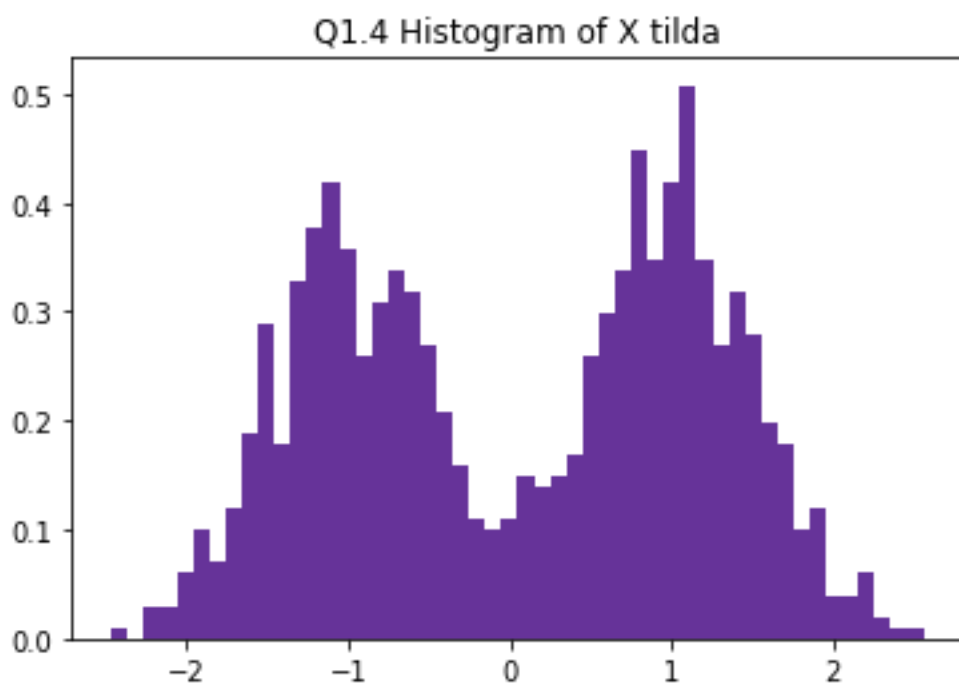
Q1.2: U_i should follow a standard Gaussian distribution approximately.



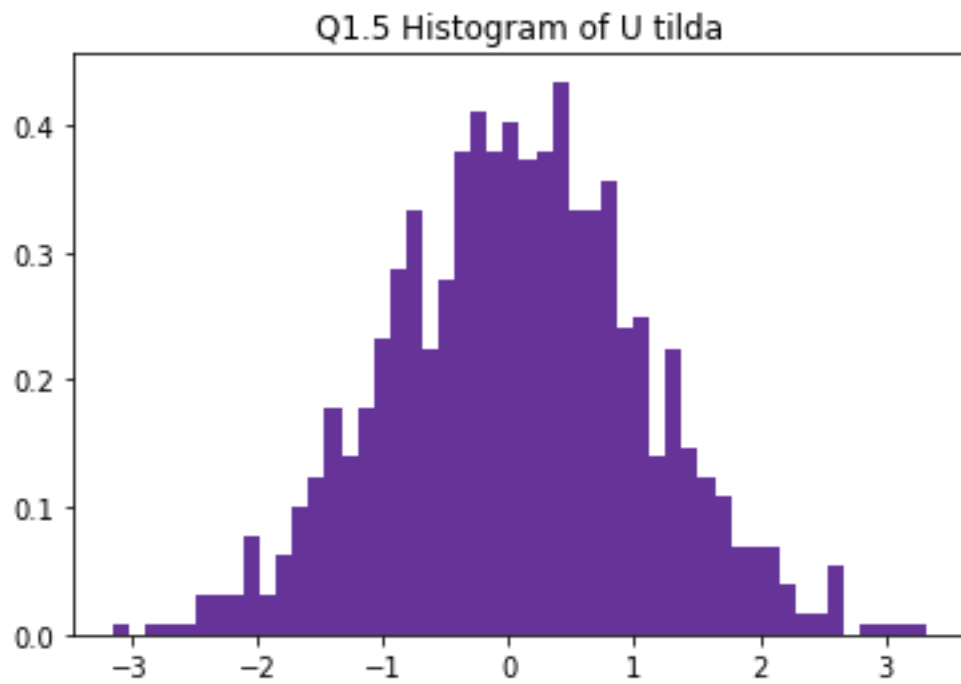
Q1.3: (Note: I ran with the tolerance = $1e-10$ instead of $1e-5$ to get a smooth graph throughout the whole range)



Q1.4: Yes, the histogram is very similar to Q1.1.



Q1.5: U_i should follow a standard Gaussian distribution approximately.



Q2.1

Q2.1: Let $q_i = \exp(x^T x_i / \lambda) / \sum_{j=1}^n \exp(x^T x_j / \lambda)$

So, $\log q_i = x^T x_i / \lambda - \log \left(\sum_{j=1}^n \exp(x^T x_j / \lambda) \right)$

• adding & subtracting $\log q_i$ in the second term

we get

$$\begin{aligned} \underset{P \in \mathbb{R}_+^n, \sum p_i = 1}{\text{argmin}} \quad & \sum_{i=1}^n p_i \cdot \underbrace{-x^T x_i + \lambda p_i (\log p_i - \log q_i + \log q_i)}_{\downarrow} \\ &= \sum_i p_i \cdot -x^T x_i + \lambda p_i \log \frac{p_i}{q_i} + \lambda p_i \log q_i \\ &= \sum_i p_i \left(-x^T x_i + \lambda \log q_i \right) + \lambda p_i \log \frac{p_i}{q_i} \\ &= \sum_i p_i \left(-x^T x_i + x^T x_i - \lambda \log \left(\sum_{j=1}^n \exp(x^T x_j / \lambda) \right) \right) + \lambda p_i \log \frac{p_i}{q_i} \\ &= \sum_i p_i \left(-\lambda \log \sum_{j=1}^n \exp(x^T x_j / \lambda) \right) + \lambda p_i \log \frac{p_i}{q_i} \end{aligned}$$

Let $-\lambda \log \sum_{j=1}^n \exp(x^T x_j / \lambda) = C$ which is independent of i

So the summation becomes

$$C \sum_{i=1}^n p_i + \lambda \sum_{i=1}^n p_i \log \frac{p_i}{q_i}$$

• $\sum_{i=1}^n p_i = 1$ by the constraint & $\sum_{i=1}^n p_i \log \frac{p_i}{q_i} = KL(p \parallel q)$

So the problem becomes

$$\underset{P \in \mathbb{R}_+^n, \sum p_i = 1}{\text{argmin}} \quad C + \lambda KL(p \parallel q)$$

which is minimized when $P = q$

Since $KL(p \parallel q) \geq 0$ & achieves equality iff $P = q$

$$\therefore p_i = q_i = \frac{\exp(x^T x_i / \lambda)}{\sum_{j=1}^n \exp(x^T x_j / \lambda)}$$

Q2.2:

Q 2.2

$$\operatorname{argmin}_{z \in \mathbb{R}^d} \sum_{i=1}^n p_i \|z - x_i\|_2^2$$

↳ differentiating w.r.t. z we get

$$\frac{\partial}{\partial z} = \sum_{i=1}^n 2p_i \cdot (z - x_i) = \vec{0}$$

$$\begin{aligned} &\text{Since} \\ &\|z - x_i\|_2^2 = \langle z - x_i, z - x_i \rangle \\ &= \langle z, z \rangle - 2\langle z, x_i \rangle + \langle x_i, x_i \rangle \end{aligned}$$

$$\rightarrow \sum_{i=1}^n 2p_i z = \sum_{i=1}^n 2p_i x_i$$

$$\rightarrow z \sum_{i=1}^n p_i = \sum_{i=1}^n p_i x_i$$

$$\rightarrow z = \sum_{i=1}^n p_i x_i \quad \text{since } \sum_{i=1}^n p_i = 1$$

Q2.3: They do all converge to one point. It seems like the point of convergence is some kind of mean but I'm not sure which.

