L0.5 for Section 3.5 1

For the penalty term in the optimization problem, we choose q = 0.5 i.e., 0 < q < 1

$$\hat{\theta}_j = \operatorname{argmin}_{\theta}(\frac{1}{2} \sum_{i=1}^{N} [Y_i - \sum_{k=1}^{p} X_{i_k} \theta_k]^2 + \lambda \sum_{k=1}^{p} \sqrt{|\theta_k|}])$$

The math is very similar to the one for LASSO as shown above (Section 3.2). So, we have left the details to the appendix.

$$\theta_j = \frac{sign(T).(|T| - \frac{\lambda}{2\sqrt{\theta_j}})}{N-1}$$

Where, A = N-1 ; B =
$$\frac{\lambda}{2\sqrt{\theta_j}}$$

As seen here, when 0 < q < 1, the solution is in terms of itself. The solution here is non-trivial or non-convex. This solution is in our desired form of Pathwise Coordinate Descent. We have left the implementation as a future scope of the project.

2 L0.5 for Appendix

For the penalty term in the optimization problem, we choose q = 0.5 i.e., 0 < q < 1

$$\hat{\theta}_j = \operatorname{argmin}_{\theta}(\frac{1}{2} \sum_{i=1}^{N} [Y_i - \sum_{k=1}^{p} X_{i_k} \theta_k]^2 + \lambda \sum_{k=1}^{p} \sqrt{|\theta_k|}])$$

We consider the tuning parameter $\lambda \geq 0$. Now, we consider the above optimization problem as 'O' and take its derivative with respect to θ_i to find the stationary points.

$$\frac{\partial O}{\partial \theta_j} = -\sum_{i=1}^{N} x_{ij} (Y_i - x_{ij}\theta_j - \sum_{k \neq j}^{p} x_{ij}\theta_j) + \frac{\lambda sign(\theta_j)}{2\sqrt{|\theta_j|}}$$

$$\frac{\partial O}{\partial \theta_j} = \sum_{i=1}^N x_{ij} (Y_i - \sum_{k \neq j}^p x_{ij} \theta_j) - \sum_{i=1}^N x_{ij}^2 \theta_j + \frac{\lambda sign(\theta_j)}{2\sqrt{|\theta_i|}}$$

Now, since our data is standardised.

$$\sum_{i+1}^{N} x_{ij}^2 = N - 1$$

Setting the derivative to 0.
$$\sum_{i=1}^{N} x_{ij} (Y_i - x_{ij}\theta_j) = (N-1)\theta_j + \frac{\lambda sign(\theta_j)}{2\sqrt{|\theta_j|}} T = \sum_{i=1}^{N} x_{ij} (Y_i - x_{ij}\theta_j)$$

As described before for LASSO, we can divide this into a 2-case argument and parameterize it in terms of A and B for implementing PCD. The 2-case argument is:

1.
$$T \geq \frac{\lambda}{2\sqrt{|\theta_i|}}$$

2. $\theta_j \ge 0$ if $T \ge 0$ else $\theta_j < 0$ if T < 0

Finally, we can write our solution as:

$$\theta_j = \frac{sign(T)(|T| - \frac{\lambda}{2\sqrt{|\theta_j|}})}{N - 1}$$

Where,

A = N-1 ; B =
$$\frac{\lambda}{2\sqrt{\theta_j}}$$