1 April 23

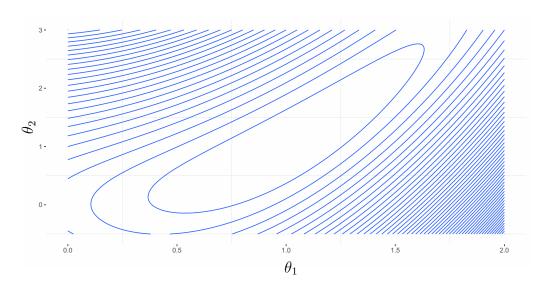
1.1 How to adjust Learning Rate

Assume the objective function,

minimize
$$f(\theta) = 0.5(\theta_1^2 - \theta_2)^2 + 0.5(\theta_1 - 1)^2$$
 (1.1)

where θ includes θ_1 and θ_2 .

The figure for the 2D model looks like,



Next, in order to update θ , we should find the gradients for both θ_1, θ_2 ,

$$\frac{\partial}{\partial \theta_1} f(\theta) = 2\theta_1^3 - 2\theta_1 \theta_2 + \theta_1 - 1$$
$$\frac{\partial}{\partial \theta_2} f(\theta) = -\theta_1^2 + \theta_2$$

Therefore, the update of θ takes the form,

$$\theta_1^{(n+1)} = \theta_1^{(n)} - \alpha_1 \frac{\partial}{\partial \theta_1^{(n)}} f(\theta) = \theta_1^{(n)} - \alpha_1 \left(2(\theta_1^{(n)})^3 - 2\theta_1^{(n)} \theta_2^{(n)} + \theta_1^{(n)} - 1 \right)$$

$$\theta_2^{(n+1)} = \theta_2^{(n)} - \alpha_2 \frac{\partial}{\partial \theta_2^{(n)}} f(\theta) = \theta_2^{(n)} - \alpha_2 \left(-(\theta_1^{(n)})^2 + \theta_2^{(n)} \right)$$

From the definition of fixed point theory, which given a function f defined on the real numbers with real values and given a point x_0 in the domain of f, the fixed point iteration is

$$x_{n+1} = f(x_n), n = 0, 1, \dots$$
 (1.2)

which gives rise to the sequence x_0, x_1, \ldots , which is hoped to converge to a point x.

By implementing fixed point iteration in our update model, we hope $\theta^{(0)}, \theta^{(1)}, \ldots$ at any iteration (Superscript indicates iteration) will converge to a point θ

$$\theta_1^{(n+1)} = f(\theta_1^{(n)}) \to \theta_1^* = f(\theta_1^*)$$

$$\theta_2^{(n+1)} = f(\theta_2^{(n)}) \to \theta_2^* = f(\theta_2^*)$$

By applying Taylor series, we can approximate $f(\theta^*)$

$$f(\theta^*) = f'(\theta^*)|\theta^{(n)} - \theta^*|$$

We hope $0 < |f'(\theta^*)| < 1$, so $f(\theta^*)$ will converge. Following the definitions defined above, we derived the range for the learning rate α_1 ,

$$\frac{\partial}{\partial \theta_1^*} f(\theta_1^*) = 1 - \alpha_1 (6(\theta_1^*)^2 - 2\theta_2^* + 1)$$

Lower Bound : $0 < |f'(\theta_1^*)|$,

$$0 < 1 - \alpha_1 \left(6(\theta_1^*)^2 - 2\theta_2^* + 1 \right)$$
$$\alpha_1 < \frac{1}{6(\theta_1^*)^2 - 2\theta_2^* + 1}$$

Upper Bound : $|f'(\theta_1^*)| < 1$,

$$-1 < 1 - \alpha_1 \left(6(\theta_1^*)^2 - 2\theta_2^* + 1 \right) < 1$$
$$0 < \alpha_1 < \frac{2}{6(\theta_1^*)^2 - 2\theta_2^* + 1}$$

 α_1 boundary,

$$0 < \alpha_1 < \frac{1}{6(\theta_1^*)^2 - 2\theta_2^* + 1}$$

Following the same logic, we derive the bellow formula to extract the range for the learning rate α_2 ,

$$\frac{\partial}{\partial \theta_2^*} f(\theta_2^*) = 1 - \alpha_2$$

Lower Bound : $0 < |f'(\theta_2^*)|$,

$$0 < 1 - \alpha_2$$

$$\alpha_2 < 1$$

Upper Bound : $|f'(\theta_2^*)| < 1$,

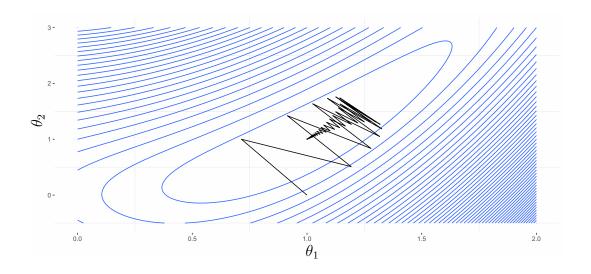
$$-1 < 1 - \alpha_2 < 1$$

$$0 < \alpha_2 < 2$$

 α_2 boundary,

$$0 < \alpha_1 < 1$$

Applying the learning rate $\alpha_1 = \frac{1}{6(\theta_1^*)^2 - 2\theta_2^* + 1}$ and $\alpha_2 = 1$. The searching path,



R code:

```
library (ggplot2)
mytheme = theme\_bw() + theme(panel.border = element\_blank(), panel.grid.major = element\_blank())
\mathtt{theta1\_seq} \; \longleftarrow \; \mathtt{seq} \left( 0 \;, \; \; 2 \,, \mathtt{length} \;. \; \mathtt{out} \; = \; \; 1000 \right)
theta2\_seq < - seq(-0.5,3,length.out = 1000)
data = expand.grid(x = theta1_seq,y = theta2_seq,KEEP.OUT.ATTRS = FALSE)
response = function(theta1, theta2){
       return (0.5*(theta1^2-theta2)^2+0.5*(theta1-1)^2)
\mathbf{data} \, = \, \mathbf{cbind} \, (\, \mathbf{data} \, , \  \, \mathbf{response} \, = \, \mathbf{response} \, (\, \mathbf{data\$x} \, , \mathbf{data\$y} \, ) \, )
\mathbf{plot} \ = \ \mathtt{ggplot} \ (\mathbf{data}, \ \mathtt{aes} \ (\mathtt{x} = \mathtt{x}, \ \mathtt{y} = \mathtt{y}, \ \mathtt{z=response})) \ + \ \mathbf{stat\_contour} \ (\mathtt{binwidth} \ = \ 0.2) + \mathtt{mytheme}
\texttt{searching} = \textbf{data.frame}(\texttt{theta1} = \textbf{rep}(\texttt{0}, \texttt{100}), \texttt{theta2} = \textbf{rep}(\texttt{0}, \texttt{100}), \textbf{response} = \textbf{rep}(\texttt{0}, \texttt{100}))
theta1 = 0
theta2 = 0
for(i in 1:100){
       theta1\_new = theta1 - ((1/((6*(theta1^{2}))) - (2*theta2) + 1)))*(2*theta1^{3} - 2*theta1*theta2 + theta1 - 1)) + (2*theta1^{3} - 2*theta1*theta2 + theta1 - 1)) + (2*theta1^{3} - 2*theta1*theta2 + theta1 - 1)) + (2*theta1^{3} - 2*theta1*theta2 + theta1^{3} - 2*theta1*theta2 + theta1^{3} - 2*theta1*theta2 + theta1^{3} - 2*theta1*theta2 + theta1^{3} - 2*theta1^{3} - 2*theta1^{3}
       theta2_new = theta2 - (1)*(-(theta1^2)+theta2)
       {\tt response\_value} \ = \ {\tt response} \, (\, {\tt theta1\_new}, \, {\tt theta2\_new})
       theta1 = theta1_new
       theta2 = theta2\_new
       \mathbf{cat} ("Iteration:", i, "\n")
       {f cat} ("theta1:", theta1, "\n")
       \mathbf{cat} ("theta2:", theta2, "\n")
       \mathbf{cat} \, (\, "\, \, \mathrm{Response} \, ... \, " \, \, , \, \, \, \mathbf{response} \, ... \, v \, \mathrm{alue} \, \, , \, " \, \setminus n \, " \, )
        searching[i,1] = theta1
```

```
searching[i,2] = theta2
searching[i,3] = response_value
}
plot + geom_path(data=searching, aes(x=theta1,y=theta2))
```