

Gradient Descent: Time Complexity

- Recall: Time complexity for matrix multiplication
 - $[A \times B] * [B \times C]$ is $O(ABC)$. If $A=B=C$, then is $O(A^3)$
- Assume we do **k** iterations
- Our code is:
 - `pred = x @ cur_weights`
 - `error = pred - t`
 - `gradient = x.T @ error / examples`
- Pred: $[n \times d] * [d \times 1] \Rightarrow O(nd)$ and output is $[n \times 1]$
- Error: $O(n)$, just subtracting two 1D arrays
- Gradient: $[d \times n] * [n \times 1] \Rightarrow O(nd)$
- As we do our algorithm max k iterations, then complexity is **$O(knd)$**

Normal Equations: Time Complexity

- X is $n \times d$ matrix (n examples, each is d features)
- $\Theta = (X^T X)^{-1} X^T y$
- $X^T X$: is $[d \times n] * [n \times d] = O(d^2 n)$ and output is $H = d \times d$ matrix
- H^{-1} is $O(d^3)$ for inverting
- $X^T y$: $[d \times n] * [n \times 1] = O(dn)$ and output is $R = d \times 1$ matrix
- $H^{-1} \times R = [d \times d] * [d \times 1] = O(d^2)$
 - Observe, it is less operations to divide the operations (H/R) than doing sequential multiplications
 - As otherwise we do $H^{-1} \times X^T$ which is $[d \times d] * [d \times n] \Rightarrow O(d^2 n)$
 - In other words: ABC matrices can be grouped: $((A \times B) \times C)$ or $(A(B \times C))$
- In total: $O(d^2 n) + O(dn) + O(d^2) = \mathbf{O(d^2 n)}$

Comparison

- $O(k \times nd)$ vs $O(d \times nd)$
- ~3000 iterations (k) is usually sufficient (if not too much) for many datasets
- If d is huge (e.g. 50k), gradient descent will be way faster

Side note for Matrix Form for derivatives

$$\begin{aligned}\text{MSE, } J(\underline{\theta}) &= \frac{1}{m} \sum_j (y^{(j)} - \hat{y}(x^{(j)}))^2 \\ &= \frac{1}{m} \sum_j (y^{(j)} - \underline{\theta} \cdot \underline{x}^{(j)T})^2\end{aligned}$$

$$\begin{aligned}\underline{\theta} &= [\theta_0, \dots, \theta_n] \\ \underline{y} &= [y^{(1)} \dots, y^{(m)}]^T \\ \underline{X} &= \begin{bmatrix} x_0^{(1)} & \dots & x_n^{(1)} \\ \vdots & \ddots & \vdots \\ x_0^{(m)} & \dots & x_n^{(m)} \end{bmatrix}\end{aligned}$$

$$J(\underline{\theta}) = \frac{1}{m} (\underline{y}^T - \underline{\theta} \underline{X}^T) \cdot (\underline{y}^T - \underline{\theta} \underline{X}^T)^T$$

Python / NumPy:

```
e = Y - X.dot( theta.T );
```

```
J = e.T.dot( e ) / m # = np.mean( e ** 2 )
```