Gradient Descent

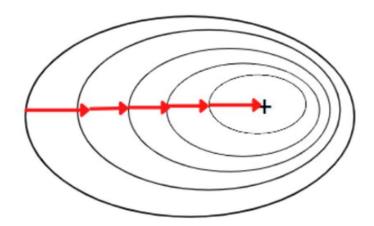
- Gradient Descent is an optimization algorithm that helps machine learning models converge at a minimum value through repeated steps.
 Essentially, gradient descent is used to minimize a function by finding the value that gives the lowest output of that function
- Often times, this function is usually a loss function. Loss functions
 measure how bad our model performs compared to actual occurrences.
 Hence, it only makes sense that we should reduce this loss. One way to
 do this is via Gradient Descent.
- There is a concept of learning schedule to smooth the fluctuation of stochastic GD to reach the solution.

A simple gradient Descent Algorithm is as follows:

- Obtain a function to minimize F(x)
- Initialize a value x from which to start the descent or optimization from
- Specify a learning rate that will determine how much of a step to descend by or how quickly you converge to the minimum value
- Obtain the derivative of that value x (the descent)
- Proceed to descend by the derivative of that value multiplied by the learning rate
- Update the value of x with the new value descended to
- Check your stop condition to see whether to stop
- If condition satisfied, stop. If not, proceed to step 4 with the new x value and keep repeating algorithm

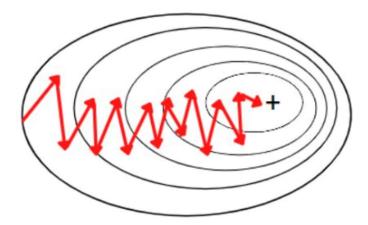
Types of Gradient Descent

1. Batch Gradient Descent:



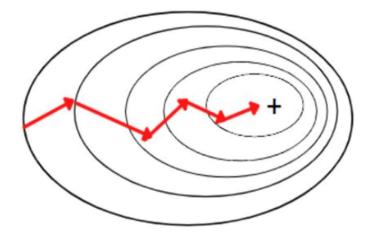
- **Description:** Uses the entire dataset to compute the gradient of the loss function for each iteration.
- **Pros:** Can converge smoothly to the minimum.
- **Cons:** Can be computationally expensive and slow for large datasets.

2. Stochastic Gradient Descent (SGD):



- **Description:** Uses a single data point (or a single example) to compute the gradient and update the parameters.
- **Pros:** Faster and more suitable for large datasets. Introduces more noise, which can help escape local minima.
- **Cons:** Convergence can be noisy and less stable. Requires careful tuning of the learning rate.

3. Mini-Batch Gradient Descent:



- **Description:** Uses a subset (mini-batch) of the data to compute the gradient. It combines the advantages of both batch and stochastic gradient descent.
- **Pros:** Balances the trade-offs between the stability of batch gradient descent and the efficiency of stochastic gradient descent.
- **Cons:** Requires choosing the size of the mini-batch, which can affect performance.

(1) Linear model

```
X,y = load_diabetes(return_X_y=True)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2)
reg = LinearRegression()
reg.fit(X_train, y_train)

print('intercepts :', reg.intercept_)
print('coef :', reg.coef_)

intercepts : 151.88331005254167
coef : [ -9.15865318 -205.45432163 516.69374454 340.61999905 -895.5520019
561.22067904 153.89310954 126.73139688 861.12700152 52.42112238]
```

Compare all GD with linear model

(1) Batch GD

```
#Batch Gradient Descent
class MyGDRegressor:
    def __init__(self,learning_rate=0.1,epochs=100):
        self.coef=None
        self.intercept=None
        self.lr=learning_rate
        self.e=epochs
    def fit(self, X, y):
        self.intercept=0
        self.coef=np.ones(X.shape[1])
        for i in range(self.e):
            y_hat=np.dot(X,self.coef)+self.intercept
            intercept_der=-2* np.mean(y-y_hat)
            self.intercept=self.intercept-(self.lr*intercept_der)
            coef_der=(-2*np.dot((y-y_hat),X))/(X.shape[0])
            self.coef=self.coef-(self.lr*coef_der)
        print('intercepts :',self.intercept,'\n','coef :',self.coef)
gdr = MyGDRegressor(learning_rate=0.5,epochs=1000)
gdr.fit(X_train,y_train)
```

(2) Mini - batch

```
# Mini-batch
import random
class MBGDRegressor:
    def __init__(self, batch_size, learning_rate=0.01, epochs=100):
        self.coef_ = None
        self.intercept_ = None
        self.lr = learning_rate
        self.epochs = epochs
        self.batch_size = batch_size
    def fit(self, X, y):
        self.intercept_ = 0
        self.coef_ = np.ones(X.shape[1])
        for i in range(self.epochs):
            for j in range(int(X.shape[0]/self.batch_size)):
                 idx = random.sample(range(X.shape[0]), self.batch_size)
                 y_hat = np.dot(X[idx],self.coef_) + self.intercept_
                 #print("Shape of y_hat",y_hat.shape)
                 intercept_der = -2 * np.mean(y[idx] - y_hat)
                 self.intercept_ = self.intercept_ - (self.lr * intercept_der)
                 coef_der = -2 * np.dot((y[idx] - y_hat), X[idx])
                 self.coef_ = self.coef_ - (self.lr * coef_der)
        print('intercepts :',self.intercept_,'\n','coef :',self.coef_)
 mbr = MBGDRegressor(batch_size=int(X_train.shape[0]/50),learning_rate=0.01,epochs=100)
 mbr.fit(X_train,y_train)
intercepts: 152.89814913923837
coef: [ 28.42076017 -140.80852187 454.82844668 302.86621213 -24.62868749
 -91.36997095 -188.58317896 111.25902101 405.96116794 110.11405951]
```

(3) Stochastic

```
# Stochastic gradient
class SGDRegressor:
    def __init__(self,learning_rate=0.01,epochs=100):
        self.coef_ = None
        self.intercept_ = None
        self.lr = learning_rate
        self.epochs = epochs
    def fit(self, X_train, y_train):
        # init your coefs
        self.intercept_ = 0
        self.coef_ = np.ones(X_train.shape[1])
        for i in range(self.epochs):
            for j in range(X_train.shape[0]):
                idx = np.random.randint(0, X_train.shape[0])
                y_hat = np.dot(X_train[idx], self.coef_) + self.intercept_
                intercept_der = -2 * (y_train[idx] - y_hat)
                self.intercept_ = self.intercept_ - (self.lr * intercept_der)
                coef_der = -2 * np.dot((y_train[idx] - y_hat), X_train[idx])
                self.coef_ = self.coef_ - (self.lr * coef_der)
        print('intercepts :',self.intercept_,'\n','coef :',self.coef_)
  sgd = SGDRegressor(learning_rate=0.01,epochs=40)
  sgd.fit(X_train,y_train)
intercepts: 151.38774327686912
coef: [ 69.87732552 -49.6438614 314.97645107 235.75450369
                                                                 17.77718278
 -22.89424533 -162.76510881 125.67350101 290.26070524 137.4998188
```