Overview:

Linear Regression

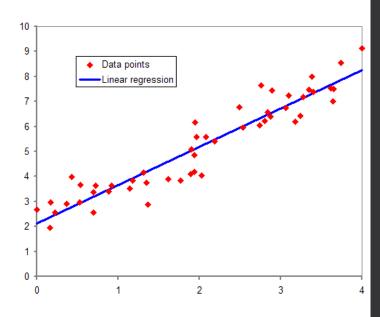
Types of Linear Regression

How Linear Regression Works

Evaluation Metrics

Linear Regression

- Linear regression allows us to make predictions about the dependent variable based on the values of the independent variables
- Predict continuous numerical value
- The linear regression equation is typically represented y=mx+b
- y is the predicted value (dependent variable) m is the slope of the line
- x is the input features(independent variable) b is the y-intercept



Type of Linear Regression:

Simple Linear Regression:

 Simple Linear Regression helps to find the linear relationship between One independent and one dependent feature.

Multi Linear Regression:

 In multi linear regression we have two or more than two input variable

$$y=m1x1+m2x2+m3x3+\cdots+mnxn+b$$

		Contract Con
YearsExperien	ce	Salary
1.1		35342
1.3		46200
1.5		38731
2		44526
2.2		39895
2.9		55645
3		60180
3.2		54445
3.2		64446
3.7		57175
3.9		63218
4		55794
4		57967
4.1		58080

4,1		J0000
у	X_1	X ₂
140	60	22
155	62	25
159	67	24
179	70	20
192	71	15
200	72	14
212	75	14
215	78	11

How Linear Regression Works:

- Linear regression is a supervised machine learning method.
- That is used to finds a linear equation that best describes the correlation of the independent variables with the dependent variable.
- This is achieved by fitting a line to the data using least squares.
- The line tries to minimize the sum of the squares of the residuals.
- The residual is the distance between the line and the actual value of the independent variable.
- Finding the line of best fit is an iterative process
- we use mostly Mean Squared Error which is the average of the squared difference between actual value and predicted value

$$MSE = \frac{1}{N} \sum_{i=1}^{n} (y_i - (mx_i + b))^2$$

Gradient Descent:

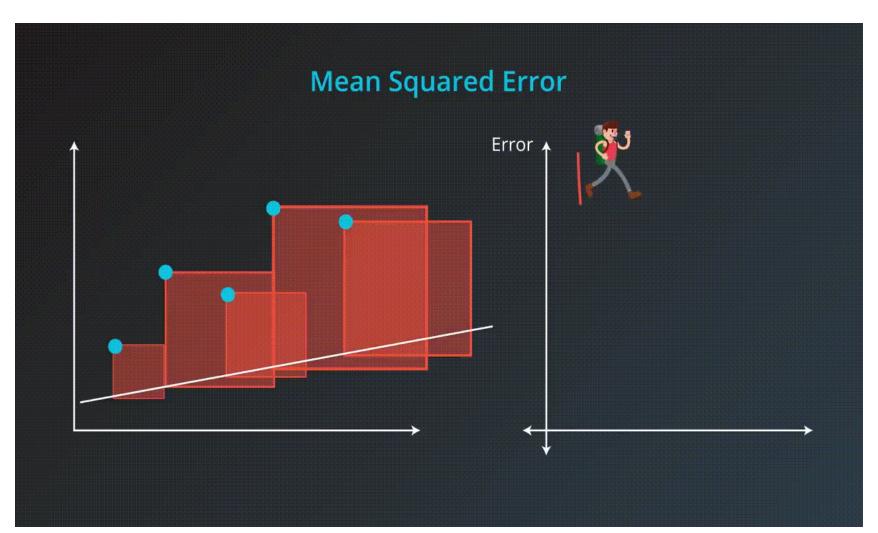
 Gradient Descent is an optimization algorithm used to minimize the cost function (like MSE) by updating model parameters iteratively.

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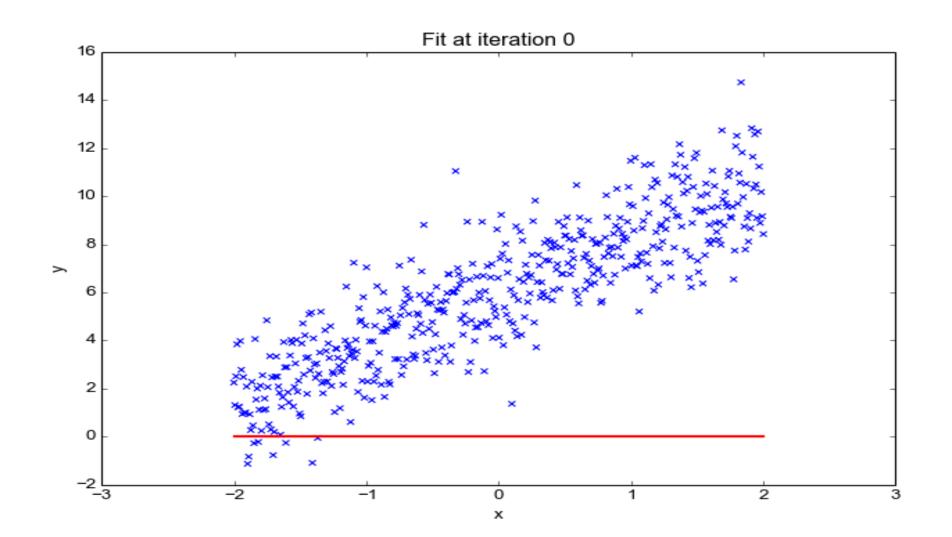
Gradient descent

One feature
$$\begin{array}{c} n \text{ features } (n \geq 2) \\ w = w - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}}_{\partial \overline{w}} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_1}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{x}^{(i)}_n}_{i=1} \\ \downarrow \\ b = b - \alpha \underbrace{\frac{1}{m} \sum_{i=1}^m (f_{w,b}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf$$









Evaluation Metrics:

- MAE: measures the average absolute differences between predicted and actual values.
- MSE: measures the average of the squares of the errors, which gives more weight to larger errors.
- **RMSE:** is the square root of MSE, providing error in the same units as the target variable.

