

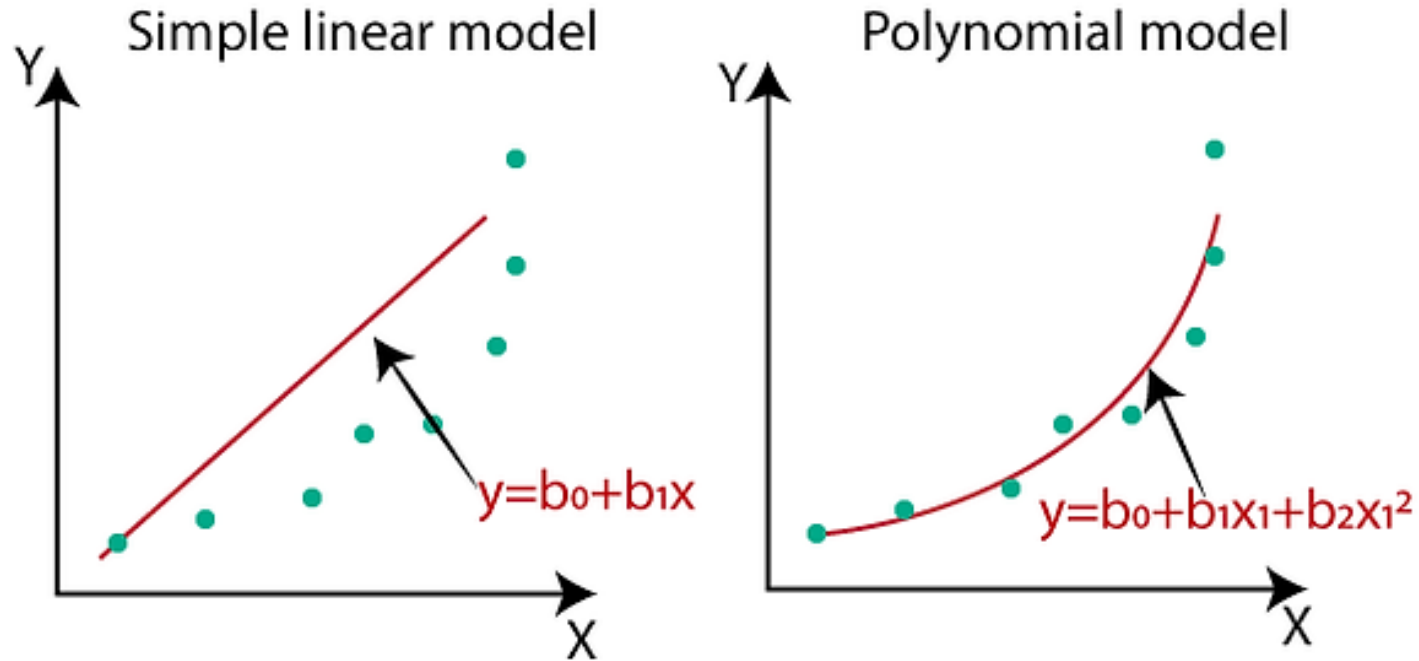
# AI Algorithms – 5: Linear and Polynomial Regressions

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- MSc in Data Science and Analytics (Toronto Metropolitan University/Ryerson)
- MSc in Computer Science (U of Manitoba)
- BSc. Engineering in Computer Science and Engineering (BUET)
- Extensive experience in Software Development and Engineering (primarily in Canada)
- Significant experience in Teaching
- Taught in Universities, Colleges, and Training Institutes



# Linear vs Polynomial Regressions



- <https://www.numpyninja.com/post/why-polynomial-regression-and-not-linear-regression>

# Linear vs Polynomial Regressions

## Regressions

Simple  
Linear  
Regression

$$y = b_0 + b_1x_1$$

Multiple  
Linear  
Regression

$$y = b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n$$

Polynomial  
Linear  
Regression

$$y = b_0 + b_1x_1 + b_2x_1^2 + \dots + b_nx_1^n$$

- <https://www.i2tutorials.com/difference-between-simple-linear-regression-and-multi-linear-regression-and-polynomial-regression/>

# Variations: Polynomials

Polynomials	Form	Degree	Examples
Linear Polynomial	$p(x): ax+b, a \neq 0$	Polynomial with Degree 1	$x + 8$
Quadratic Polynomial	$p(x): ax^2+b+c, a \neq 0$	Polynomial with Degree 2	$3x^2-4x+7$
Cubic Polynomial	$p(x): ax^3+bx^2+cx, a \neq 0$	Polynomial with Degree 3	$2x^3+3x^2+4x+6$

- <https://www.analyticsvidhya.com/blog/2021/10/understanding-polynomial-regression-model/>

# L1, L2 Loss and Regularization

L1 regularization on least squares:

$$\mathbf{w}^* = \arg \min_{\mathbf{w}} \sum_j \left( t(\mathbf{x}_j) - \sum_i w_i h_i(\mathbf{x}_j) \right)^2 + \lambda \sum_{i=1}^k |w_i|$$

$$L(x, y) \equiv \sum_{i=1}^n (y_i - h_{\theta}(x_i))^2 + \lambda \sum_{i=1}^n \theta_i^2$$

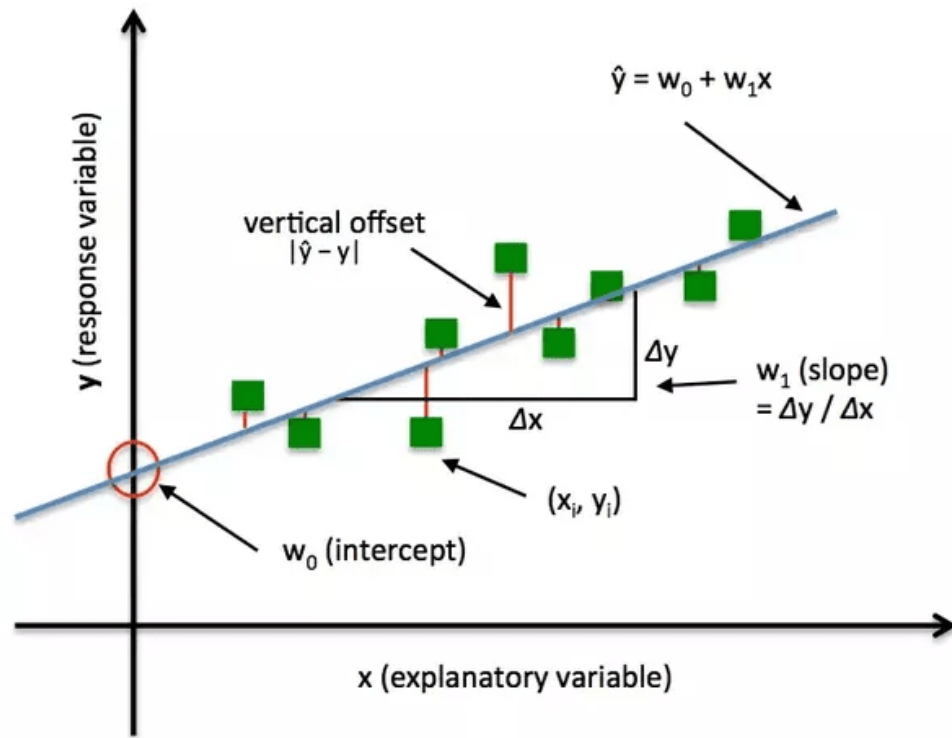
L2 regularization on least squares:

$$\mathbf{w}^* = \arg \min_{\mathbf{w}} \sum_j \left( t(\mathbf{x}_j) - \sum_i w_i h_i(\mathbf{x}_j) \right)^2 + \lambda \sum_{i=1}^k w_i^2$$

<https://medium.datadriveninvestor.com/l1-l2-regularization-7f1b4fe948f2>

- <https://towardsdatascience.com/only-numpy-implementing-different-combination-of-l1-norm-l2-norm-l1-regularization-and-14b01a9773b?gi=698f128eaf25>

# Loss Functions (Regression)



- <https://www.datarobot.com/blog/introduction-to-loss-functions/>

# L1 and L2 Loss

## L1 Loss Function

L1 Loss Function is used to minimize the error which is the sum of the all the **absolute** differences between the true value and the predicted value.

$$L1LossFunction = \sum_{i=1}^n |y_{true} - y_{predicted}|$$

## L2 Loss Function

L2 Loss Function is used to minimize the error which is the sum of the all the **squared** differences between the true value and the predicted value.

$$L2LossFunction = \sum_{i=1}^n (y_{true} - y_{predicted})^2$$

- <https://amitshekhar.me/blog/l1-and-l2-loss-functions>



# L1 vs L2 Loss

What is the difference between regression L1 and L2 loss?

L1, also known as the Absolute Error Loss, is the absolute difference between the prediction and the actual. L2, also known as the Squared Error Loss, is the squared difference between the prediction and the actual. Jun 24, 2022



stephenallwright.com

<https://stephenallwright.com/l1-vs-l2-loss>

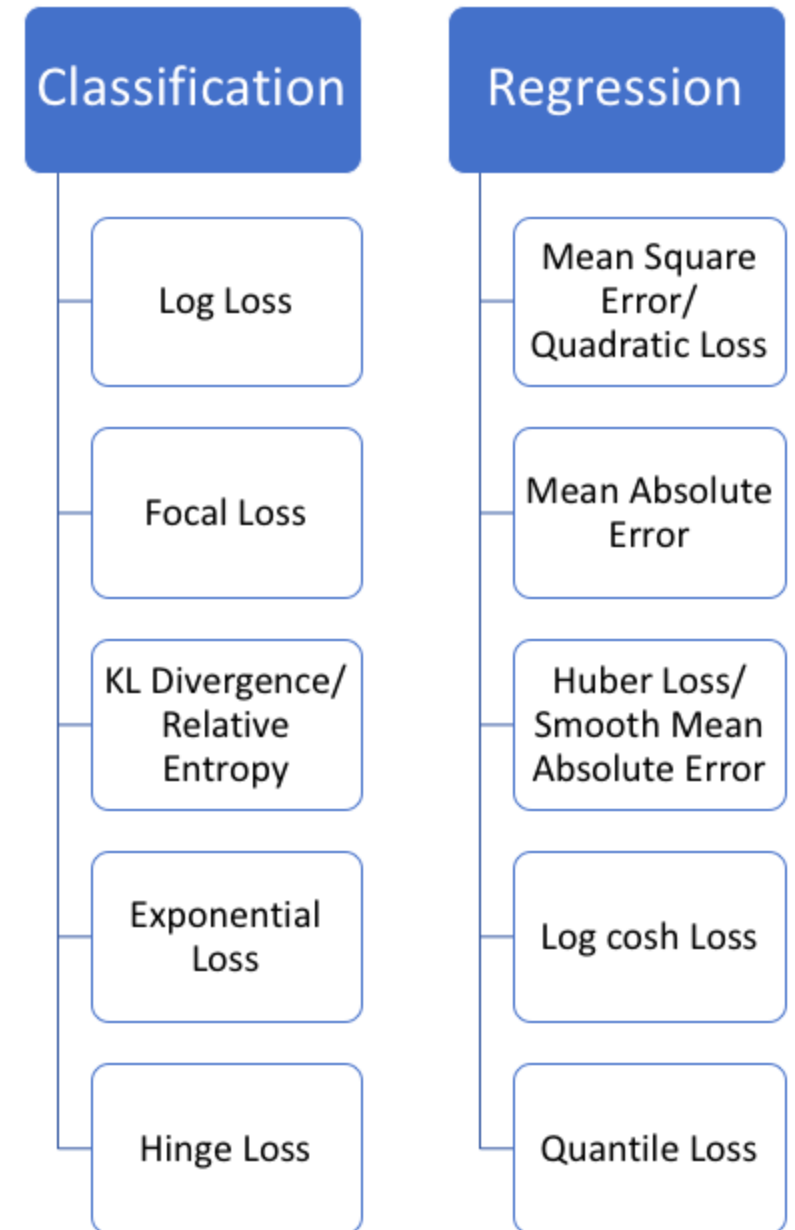
L1 vs L2 loss functions, which is best to use? - Stephen Allwright

Predicted price	Actual price	L1 loss	L2 loss
100,000	105,000	5,000	25,000,000
120,000	118,000	2,000	4,000,000
220,000	170,000	50,000	2,500,000,000

- <https://stephenallwright.com/l1-vs-l2-loss>



# Loss functions for Classification and Regression

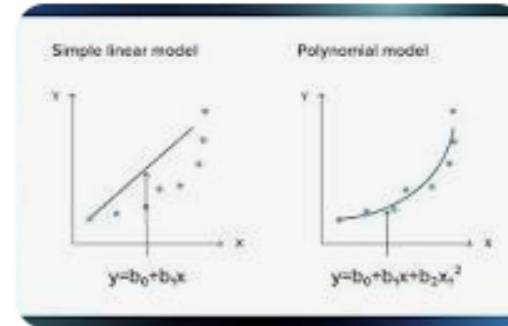


- <https://heartbeat.comet.ml/5-regression-loss-functions-all-machine-learners-should-know-4fb140e9d4b0>

# Why Polynomial Regression?

Why is polynomial regression better?

Polynomial regression is useful in many cases. Since a relationship between the independent and dependent variables isn't required to be linear, you get more freedom in the choice of datasets and situations you can be working with. So this method can be applied when simple linear regression underfits the data. Sep 21, 2021



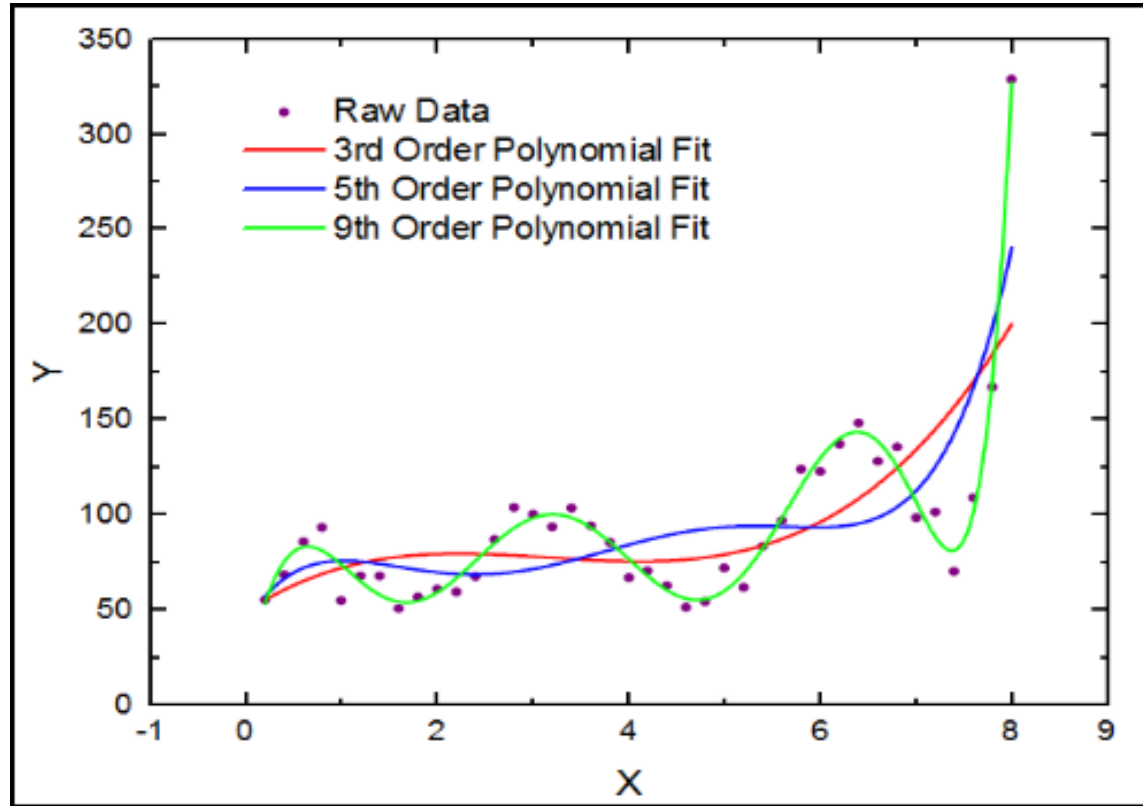
serokell.io

<https://serokell.io> > Blog > Artificial Intelligence ▼

Introduction to Polynomial Regression Analysis - Serokell

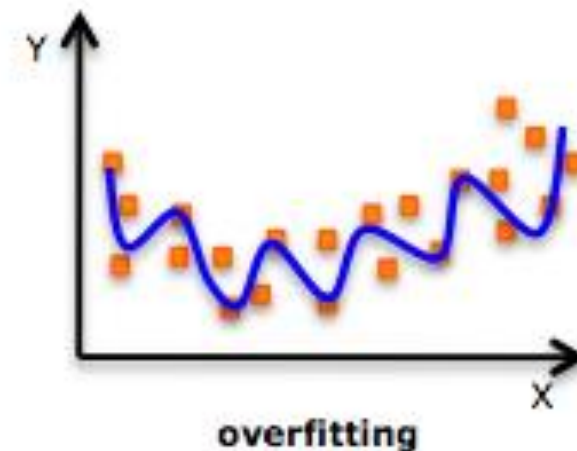
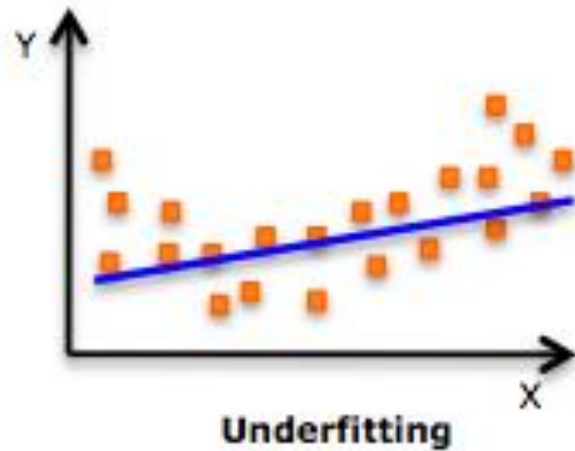
- <https://serokell.io/blog/polynomial-regression-analysis>

# Polynomial Fitting of Data



- <https://towardsdatascience.com/polynomial-regression-an-alternative-for-neural-networks-c4bd30fa6cf6>

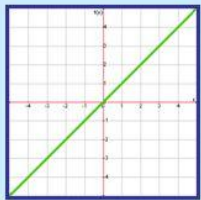
# Underfitting, Overfitting



- <https://mindmajix.com/polynomial-regression>

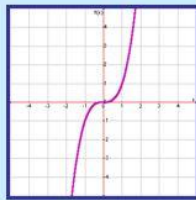
# Linear, Quadratic, Cubic Fitting

Supplement: Curve Fitting  
aka ... Choosing the appropriate  
model to fit the data



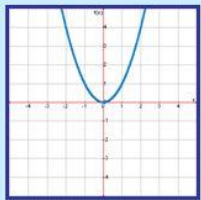
**Linear**

$$y = ax + b$$



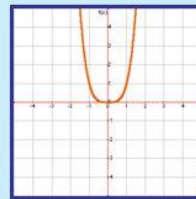
**Cubic**

$$y = ax^3 + bx^2 + cx + d$$



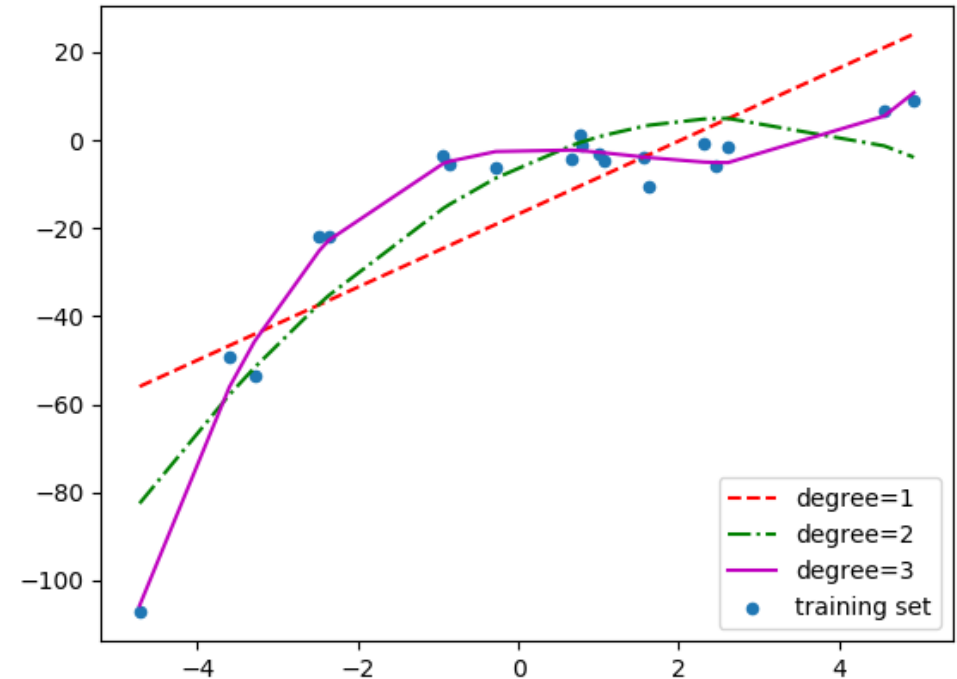
**Quadratic**

$$y = ax^2 + bx + c$$



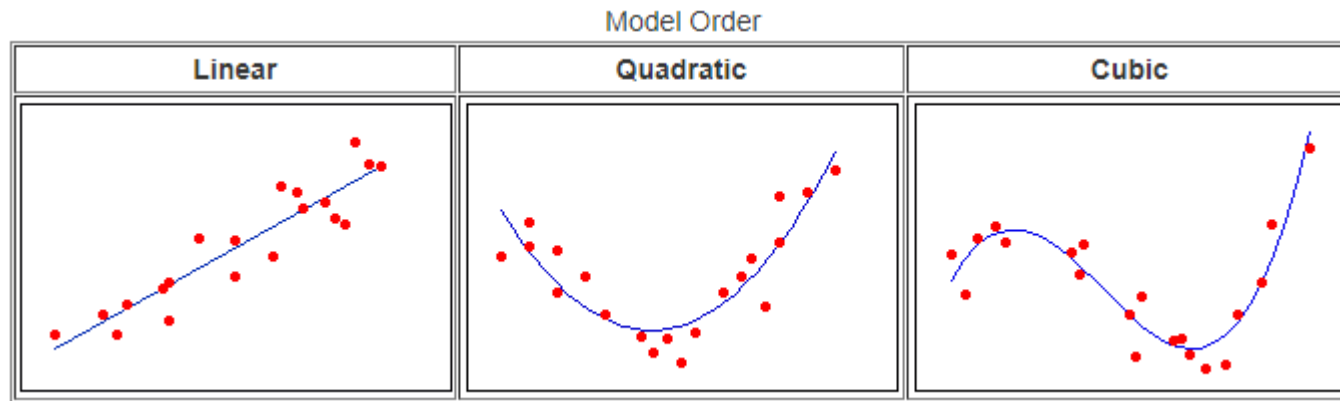
**Quartic**

$$y = ax^4 + bx^3 + cx^2 + dx + e$$



- <https://slideplayer.com/slide/10830946/> <https://towardsdatascience.com/polynomial-regression-bbe8b9d97491>

# Linear, Quadratic, Cubic Fitting



## Linear, Quadratic and Cubic Polynomials



Polynomials	Form	Degree	Examples
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- <https://skill-lync.com/student-projects/Fitness-Characteristics-of-Linear-Cubic-polynomial-Curve-Fitting-for-Cp-data-using-MATLAB-67420> ,  
<https://www.cuemath.com/algebra/linear-quadratic-and-cubic-polynomials/>

# Loss Function for Polynomial Regression

$$\text{Cost function, } J = \frac{1}{n} \sum_{i=1}^n (\text{Predicted value} - \text{Expected value})^2$$

“Loss Function refers to a single training example, whereas the Cost Function refers to the complete training set.”

## Loss and Cost Function – Polynomial Regression

The Cost Function is a function that evaluates a Machine Learning model's performance for a given set of data. The Cost Function is a single real number that calculates the difference between anticipated and expected values. Many people don't know the differences between the Cost Function and the Loss Function. To put it another way, the Cost Function is the average of the n-sample error in the data, whereas the Loss Function is the error for individual data points. To put it another way, the Loss Function refers to a single training example, whereas the Cost Function refers to the complete training set.

- <https://www.analyticsvidhya.com/blog/2021/10/understanding-polynomial-regression-model/>



# References

- Given on the Slides
- Google Images
- Internet