Regis met [.q c.q pri	uosures rlang uosures rlang nt.quosures rlang
setwo data attao	p 1- Importing the Dataset d("C:/Users/user/OneDrive/Desktop/Sparks/Task 2") <-read.csv("iris.csv") ch(data) s(data)
3. '\$ 4. 'I 5. 'I	Id' SepalLengthCm' SepalWidthCm' PetalLengthCm' PetalWidthCm' PetalWidthCm' Species'
Ste	p 2- Data Observation (data, 10) spallengthCm SepalWidthCm PetalLengthCm PetalWidthCm Species
1 2 3 4 5	5.1 3.5 1.4 0.2 Iris-setosa 4.9 3.0 1.4 0.2 Iris-setosa 4.7 3.2 1.3 0.2 Iris-setosa 4.6 3.1 1.5 0.2 Iris-setosa 5.0 3.6 1.4 0.2 Iris-setosa
6 7 8 9 10	5.4 3.9 1.7 0.4 Iris-setosa 4.6 3.4 1.4 0.3 Iris-setosa 5.0 3.4 1.5 0.2 Iris-setosa 4.4 2.9 1.4 0.2 Iris-setosa 4.9 3.1 1.5 0.1 Iris-setosa
head str(<pre>c-data[,-1] (data,5) data) lengthCm</pre>
	4.9 3.0 1.4 0.2 Iris-setosa 4.7 3.2 1.3 0.2 Iris-setosa 4.6 3.1 1.5 0.2 Iris-setosa 5.0 3.6 1.4 0.2 Iris-setosa .frame': 150 obs. of 5 variables:
\$ Se \$ Pe \$ Pe \$ Sp	palLengthCm: num 5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 palWidthCm: num 3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 talLengthCm: num 1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 talWidthCm: num 0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ecies : Factor w/ 3 levels "Iris-setosa",: 1 1 1 1 1 1 1 1 1 1
Min. 1st (Media Mean 3rd (Max.	LengthCm SepalWidthCm PetalLengthCm PetalWidthCm :4.300 Min. :2.000 Min. :1.000 Min. :0.100 Min. :5.100 1st Qu.:2.800 1st Qu.:1.600 1st Qu.:0.300 Median :3.000 Median :4.350 Median :1.300 Median :3.054 Mean :3.759 Mean :1.199 Mean :3.054 Mean :3.759 Mean :1.199 Mean :3.300 3rd Qu.:5.100 3rd Qu.:1.800 :7.900 Max. :4.400 Max. :6.900 Max. :2.500 Species Species -setosa :50
Iris	-versicolor:50 -virginica :50 p 3- Data Visualization
ged xla yla	cot(data, aes(x=SepalLengthCm, y=SepalWidthCm, col=Species))+ com_point(size=2)+ ab("Sepal Length (in cm)")+ ab("Sepal Width (in cm)")+ title("Scatterplot of Sepal Length-Sepal Width") Scatterplot of Sepal Length-Sepal Width
4.	
4.0	
Sepal Width (in cm)	Species Iris-setosa Iris-versicolor
Seps	lris-virginica
2.8	
2.0	Sepal Length (in cm)
iris_ head set.s wss	p 4- Choosing Optimum No. of Clusters (Elbow Method) _cl=data[,1:4] (iris_cl) seed(2021) <-array(0) (i in 1:15) { .out <- kmeans(iris_cl, centers = i, nstart = 10, iter.max = 300)
km wss } plot	<pre>cout <- kmeans(iris_cl, centers = i, nstart = 10, iter.max = 300) s[i] <- km.out\$tot.withinss (1:15, wss, type = "b",</pre>
	5.1 3.5 1.4 0.2 4.9 3.0 1.4 0.2 4.7 3.2 1.3 0.2 4.6 3.1 1.5 0.2 5.0 3.6 1.4 0.2
	5.4 3.9 1.7 0.4 8
,S)	009
f Squares(WCSS)	700 200 -
Within Clusters Sum of	
Within	700 - 700
	2 4 6 8 10 12 14
	Number of Clusters see that, as number of clusters increases, WCSS decreases. We can see that, after the number of clusters 3, the decrease in WCSS is minimal. So, we choose the optimum value of k to be 3. p 5- k-means clustering with k=3
kmear iris_	ns.cl=kmeans(iris_cl,centers=3,nstart=10) ns.cl\$cluster _cl\$cluster <- as.character(kmeans.cl\$cluster) (iris_cl)
12. 1 13. 1 14. 1 15. 1 16. 1 17. 1 18. 1 20. 1 21. 1 22. 1 23. 1 24. 1 25. 1 26. 1 27. 1 28. 1 29. 1 30. 1	
31. 1 32. 1 33. 1 34. 1 35. 1 36. 1 37. 1	
38. 1 39. 1 40. 1 41. 1 42. 1 43. 1	
44. 1 45. 1 46. 1 47. 1 48. 1 49. 1 50. 1	
51. 2 52. 2 53. 3 54. 2 55. 2 56. 2	
57. 2 58. 2 59. 2 60. 2 61. 2 62. 2	
64. 2 65. 2 66. 2 67. 2 68. 2	
70. 2 71. 2 72. 2 73. 2 74. 2 75. 2	
76. 2 77. 2 78. 3 79. 2 80. 2 81. 2	
83. 2 84. 2 85. 2 86. 2 87. 2	
88. 2 89. 2 90. 2 91. 2 92. 2 93. 2 94. 2	
95. 2 96. 2 97. 2 98. 2 99. 2	
101. 3 102. 2 103. 3 104. 3 105. 3	
107. 2 108. 3 109. 3 110. 3 111. 3 112. 3 113. 3	
114. 2 115. 2 116. 3 117. 3 118. 3	
120. 2 121. 3 122. 2 123. 3 124. 2 125. 3	
126. 3 127. 2 128. 2 129. 3 130. 3 131. 3	
133. 3 134. 2 135. 3 136. 3 137. 3	
139. 2 140. 3 141. 3 142. 3 143. 2 144. 3	
145. 3 146. 3 147. 2 148. 3 149. 3 150. 2	
µalL	sengthCm SepalWidthCm PetalLengthCm PetalWidthCm cluster 5.1 3.5 1.4 0.2 1 4.9 3.0 1.4 0.2 1 4.7 3.2 1.3 0.2 1 4.6 3.1 1.5 0.2 1 5.0 3.6 1.4 0.2 1
ggplo geo	p 6- Visualizing the Clusters ot(iris_cl, aes(x = SepalLengthCm, y = SepalWidthCm, colour=cluster)) + com_point(size=2)+
ged col ged col (<pre>com_point(size=2)+ com_point(aes(x=kmeans.cl\$center[1,1],y=kmeans.cl\$center[1,2]), lour="purple",size=5,shape=19)+ com_point(aes(x=kmeans.cl\$center[2,1],y=kmeans.cl\$center[2,2]), lour="purple",size=5,shape=19)+ geom_point(aes(x=kmeans.cl\$center[3,1],y=kmeans.cl\$center[3,2]), lour="purple",size=5,shape=19)+ geom_text(label="centroid 1",x=kmeans.cl\$center[1,1],y=kmeans.cl\$center[1,2],color = "black")+ geom_text(label="centroid 2",x=kmeans.cl\$center[2,1],y=kmeans.cl\$center[2,2],color = "black")+</pre>
scal	geom_text(label="centroid 3", x=kmeans.cl\$center[3,1], y=kmeans.cl\$center[3,2], color = "black")+ le_shape_discrete(labels = c("1(iris-setosa)", "2(iris-versicolor)", "3(iris-virginica)"))+ scale_color_discrete(labels = c("1(iris-setosa)", "2(iris-versicolor)", "3(iris-virginica)"))+
4.	Visualization of k-means clustering 5
4.0	
Sepal Width (in cm)	cluster 1(iris-setosa) 2(iris-versicolor)
Sepal \	centroid 2
2.8	
2.0	
Cor	ndicated the centroids and plotted the predicted graph, which is pretty similar to the actual graph. Clusion: Successfully obtained the optimum number of clusters for this 'Iris' dataset and run the k-means algorithm with the chosen number of clusters.
	ank you