How can we use the lm() function in R to fit linear models?

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The lm() function in R is a powerful tool for fitting linear models to data. It allows users to create and manipulate linear models through various statistical methods and techniques. By inputting a formula and dataset, the function automatically calculates the best-fitting line for the data, providing important information such as the coefficients, residuals, and summary statistics. Additionally, the lm() function allows for further analysis and modification of the linear model, making it a versatile tool for statistical analysis in R. Overall, the lm() function is a valuable resource for accurately fitting linear models and gaining valuable insights from data.

Use lm() Function in R to Fit Linear Models

The lm() function in R is used to fit linear regression models.

This function uses the following basic syntax:

lm(formula, data, ...)

where:

formula: The formula for the linear model (e.g. y ~ x1 + x2)data: The name of the data frame that contains the data

The following example shows how to use this function in R to do the following:

Fit a regression modelView the summary of the regression model fitView the diagnostic plots for the modelPlot the fitted regression modelMake predictions

using the regression model

Fit Regression Model

The following code shows how to use the lm() function to fit a linear regression model in R:

```
#define data
df = data.frame(x=c(1, 3, 3, 4, 5, 5, 6, 8, 9, 12),
y=c(12, 14, 14, 13, 17, 19, 22, 26, 24, 22))

#fit linear regression model using 'x' as predictor and 'y' as response variable
model <- lm(y ~ x, data=df)
```

View Summary of Regression Model

We can then use the summary() function to view the summary of the regression model fit:

```
#view summary of regression model
summary(model)
```

```
Call:
lm(formula = y ~ x, data = df)

Residuals:
```

Min 1Q Median 3Q Max
-4.4793 -0.9772 -0.4772 1.4388 4.6328

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 11.1432 1.9104 5.833 0.00039 *
x 1.2780 0.2984 4.284 0.00267 ****

Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Residual standard error: 2.929 on 8 degrees of freedom
Multiple R-squared: 0.6964, Adjusted R-squared: 0.6584
F-statistic: 18.35 on 1 and 8 DF, p-value: 0.002675

Here's how to interpret the most important values in the model:

F-statistic = 18.35, corresponding p-value = .002675. Since this p-value is less than .05, the model as a whole is statistically significant.Multiple R-squared = .6964. This tells us that 69.64% of the variation in the response variable, y, can be explained by the predictor variable, x.Coefficient estimate of x: 1.2780. This tells us that each additional one unit increase in x is associated with an average increase of 1.2780 in y.

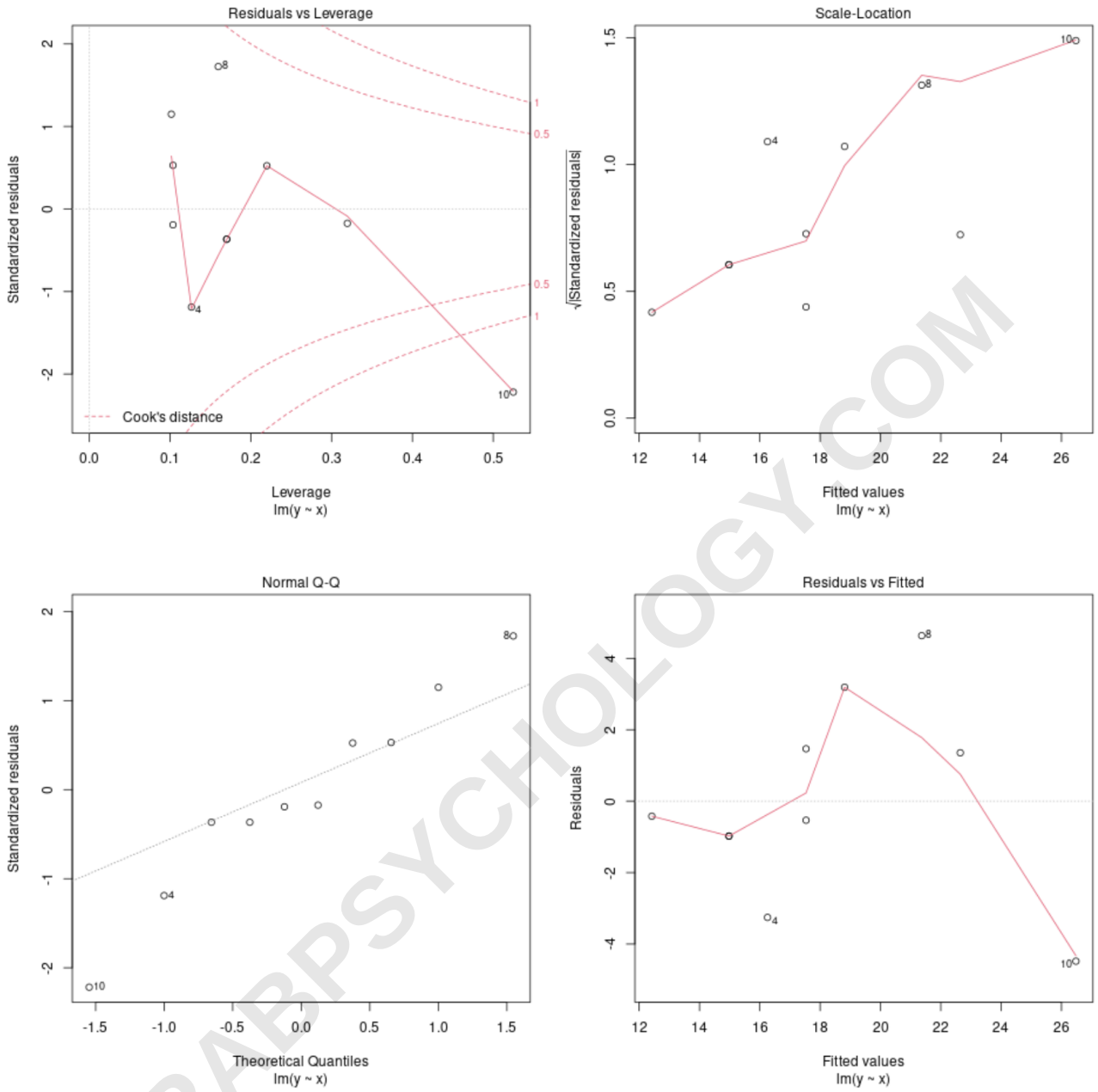
We can then use the coefficient estimates from the output to write the estimated regression equation:

y = 11.1432 + 1.2780*(x)

View Diagnostic Plots of Model

We can then use the plot() function to plot the diagnostic plots for the regression model:

```
#create diagnostic plots
plot(model)
```



These plots allow us to analyze the of the regression model to determine if the model is appropriate to use for the data.

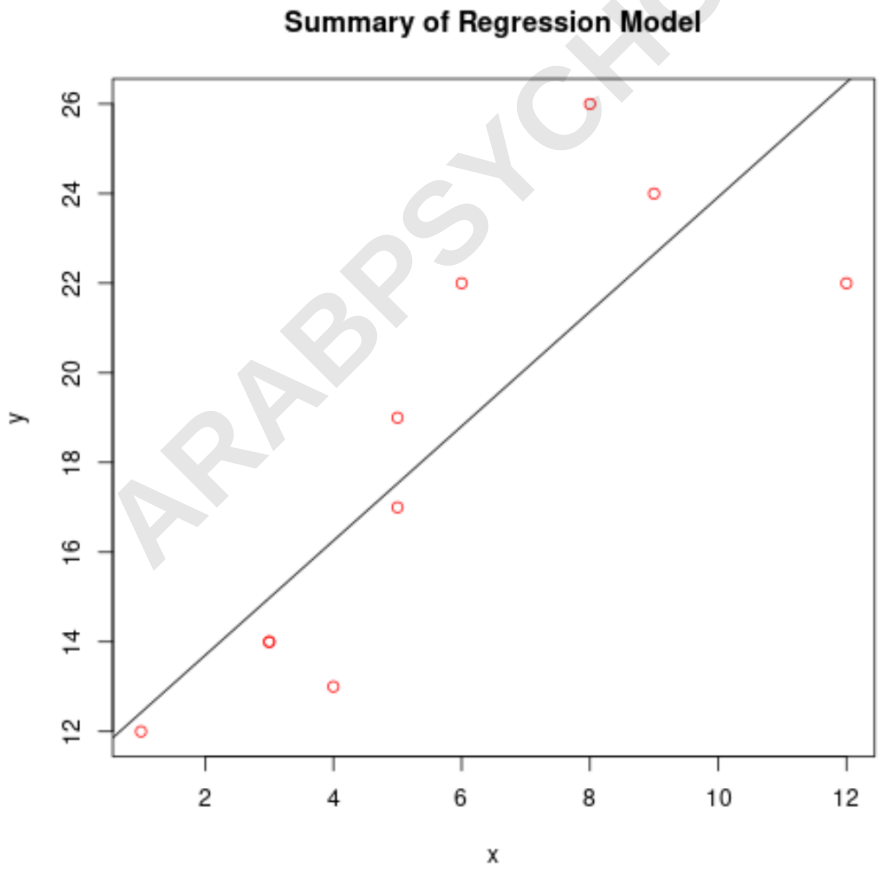
Refer to for a complete explanation of how to interpret the diagnostic plots for a model in R.

Plot the Fitted Regression Model

We can use the abline() function to plot the fitted regression model:

```
#create scatterplot of raw data
plot(df$x, df$y, col='red', main='Summary of Regression Model', xlab='x', ylab='y')

#add fitted regression line
abline(model)
```



Use the Regression Model to Make Predictions

We can use the predict() function to predict the response value for a new observation:

```
#define new observation
new <- data.frame(x=c(5))

#use the fitted model to predict the value for the new observation
predict(model, newdata = new)

1
17.5332
```

The model predicts that this new observation will have a response value of 17.5332.