**SIMPLE LINEAR REGRESSION:**

**1. Calories\_consumed-> predict weight gained using calories consumed**

**CALORIES CONSUMED**

**model<-lm(Weight.gained..grams.~Calories.Consumed, data =calories\_consumed )**

**summary(model)**

Call:

lm(formula = Weight.gained..grams. ~ Calories.Consumed, data = calories\_consumed)

Residuals:

Min 1Q Median 3Q Max

-158.67 -107.56 36.70 81.68 165.53

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) -625.75236 100.82293 -6.206 4.54e-05 \*\*\*

Calories.Consumed 0.42016 0.04115 10.211 2.86e-07 \*\*\*

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Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 111.6 on 12 degrees of freedom

Multiple R-squared: 0.8968, Adjusted R-squared: 0.8882

F-statistic: 104.3 on 1 and 12 DF, p-value: 2.856e-07

**Equation:**

**Weight gained = -625.75+0.42(Calories)**

**Example, consider calories consumed = 1500**

**Weight gained = -0.625+0.42(1500)**

**= 4.25**

**For consumption of 1500 calories 4.25 grams will increase.**

**2. Delivery\_time -> Predict delivery time using sorting time**

**model<-lm(Delivery.Time~Sorting.Time,data=delivery\_time)**

**summary(model)**

Call:

lm(formula = Delivery.Time ~ Sorting.Time, data = delivery\_time)

Residuals:

Min 1Q Median 3Q Max

-5.1729 -2.0298 -0.0298 0.8741 6.6722

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 6.5827 1.7217 3.823 0.00115 \*\*

Sorting.Time 1.6490 0.2582 6.387 3.98e-06 \*\*\*

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Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.935 on 19 degrees of freedom

Multiple R-squared: 0.6823, Adjusted R-squared: 0.6655

F-statistic: 40.8 on 1 and 19 DF, p-value: 3.983e-06

**Conclusion: Since R-square value is 0.68,though sorting time is highly significant but it is not sufficient to predict correct delivery time. We need some more variables to get exact insights.**

**Equation**

**Delivery time = 6.58 + (1.65\*Sorting time)**

**Example sorting time = 7**

**Delivery time = 6.58+ (1.65\*7)**

**= 18.13**

**3 Empirical Data**

**model<-lm(Churn\_out\_rate~Salary\_hike,data=emp\_data)**

**summary(model)**

lm(formula = Churn\_out\_rate ~ Salary\_hike, data = emp\_data)

Residuals:

Min 1Q Median 3Q Max

-3.804 -3.059 -1.819 2.430 8.072

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 244.36491 27.35194 8.934 1.96e-05 \*\*\*

Salary\_hike -0.10154 0.01618 -6.277 0.000239 \*\*\*

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Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4.469 on 8 degrees of freedom

Multiple R-squared: 0.8312, Adjusted R-squared: 0.8101

F-statistic: 39.4 on 1 and 8 DF, p-value: 0.0002386

**Equation:**

**Churn out rate = 244.36 + (-0.10 \* Salary Hike)**

1. **Salary\_hike -> Build a prediction model for Salary\_hike**

**model<-lm(Salary~YearsExperience,data=Salary\_Data)**

**summary(model)**

Call:

lm(formula = Salary ~ YearsExperience, data = Salary\_Data)

Residuals:

Min 1Q Median 3Q Max

-7958.0 -4088.5 -459.9 3372.6 11448.0

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 25792.2 2273.1 11.35 5.51e-12 \*\*\*

YearsExperience 9450.0 378.8 24.95 < 2e-16 \*\*\*

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Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5788 on 28 degrees of freedom

Multiple R-squared: 0.957, Adjusted R-squared: 0.9554

F-statistic: 622.5 on 1 and 28 DF, p-value: < 2.2e-16

**More Experience More the Salary**

**Salary = 25792+(9450 \*Experience)**