Linear Regression For Accidents Using R

road_accident_data <- data.frame(DATASET_2)

Create the linear regression model

model <- lm(X ~ Y, data = road_accident_data)

Summary of the model

summary(model)

	A	B
1	Road Quality (Independent Variable, X)	Severity Level (Dependent Variable, Y)
2	18	1

Dependent and Independent Variables

```
Untitled1 ×   Untitled2* ×   DATASET_2 ×
Source on Save                         Run     Source
1  road_accident_data <- data.frame(DATASET_2)
2  # Create the linear regression model
3  model <- lm(X ~ Y, data = road_accident_data)
4
5  # Summary of the model
6  summary(model)
7
6:15   (Top Level) ÷                                              R Script ÷

Console   Terminal ×   Background Jobs ×
R 4.2.3 · ~/
> road_accident_data <- data.frame(DATASET_2)
> # Create the linear regression model
> model <- lm(X ~ Y, data = road_accident_data)
>
> # Summary of the model
> summary(model)

Call:
lm(formula = X ~ Y, data = road_accident_data)

Residuals:
     Min       1Q   Median       3Q      Max
-1.62857 -1.06786  0.07857  0.68214  1.68214

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  22.1107     0.7335   30.15 1.59e-15 ***
Y            -3.8964     0.2108  -18.49 3.20e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.176 on 16 degrees of freedom
Multiple R-squared:  0.9553,	Adjusted R-squared:  0.9525
F-statistic: 341.8 on 1 and 16 DF,  p-value: 3.205e-12

>
```

Benefits Of Linear Regression For Accidents Prevention

1. Identify high-risk conditions: The model can identify factors that have the strongest correlation with severe accidents, like speeding, weather conditions, road design, etc. This allows transportation authorities to focus on the most dangerous areas.

2. Guide policy interventions: By quantifying the impact of different factors on accident severity, data-driven models can guide interventions like setting appropriate speed limits, enforcing drunk driving laws, improving road lighting and signage, etc. in a targeted manner.

3. Prioritize infrastructure improvements: The model can identify infrastructure deficiencies that contribute to accidents, like poor road conditions, absence of separators, lack of signals at intersections, etc. This can help prioritize infrastructure investments.

4. Compare interventions: As interventions are implemented over time, the model can continue to be applied to the latest data. By comparing coefficients over time, the impact of specific interventions can be evaluated.

5. Cost-benefit analysis: Monetary costs of injuries and fatalities can be compared to the costs of implementing preventive measures. This allows quantitative cost-benefit analysis of different policies.

6. Resources optimization: With limited resources, data-driven models allow scientifically determining the most impactful interventions for a given budget. This is especially useful in underdeveloped regions.