```
$y_?$, $y$, *.target { color: Crimson      }
$x_*$, *.feat        { color: DodgerBlue   }
$\beta_*$, *.slope   { color: MediumPurple }
```

Consider a dataset $D = \{(x_i, y_i)\}^N$ of N data points, where $x_i = (x_{i1}, x_{i2}, \cdots, x_{iM})$ is a feature vector with M features, and y_i is the target, i.e., the response, variable. Let x_j denote the jth variable in feature space. A typical linear regression model can then be expressed mathematically as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_M x_M$$

This model assumes that the relationships between the target variable y_i and features x_j are linear and can be captured in slope terms $\beta_1, \beta_2, \ldots, \beta_M$.

```
$y_?$, $y$, *.target { color: Crimson      }
$x_*$, *.feat        { color: DodgerBlue   }
$\beta_*$, *.slope   { color: MediumPurple }
$\beta_0$            { color: inherit      }
```

Consider a dataset $D = \{(x_i, y_i)\}^N$ of N data points, where $x_i = (x_{i1}, x_{i2}, \cdots, x_{iM})$ is a feature vector with M features, and y_i is the target, i.e., the response, variable. Let x_j denote the jth variable in feature space. A typical linear regression model can then be expressed mathematically as:

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This model assumes that the relationships between the target variable y_i and features x_j are linear and can be captured in slope terms $\beta_1, \beta_2, \ldots, \beta_M$.

```
$y$ { label: target }
```

$$\underset{\text{target}}{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_M x_M$$

```
$y$              { label: target     }
$\beta_0$        { label: intercept  }
$\beta_?$:nth(1) { label: slope term }
$x_1$ {
  label: feature;
  label-position: below
}
$M$ { label: # of features }
```

$$\underset{\text{target}}{y} = \overset{\text{intercept}}{\beta_0} + \overset{\text{slope term}}{\beta_1} \underset{\text{feature}}{x_1} + \beta_2 x_2 + \cdots + \beta_M x_{\underset{\text{\# of features}}{M}}$$