Regression

Profile

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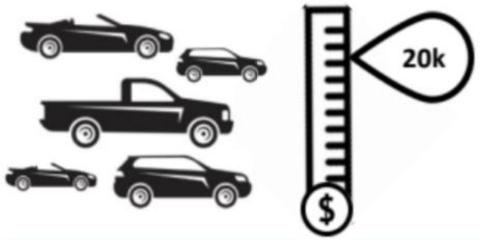
REGRESSION

PREDICT VALUE



CLASSIFICATION

PREDICT CLASS

CLUSTERING

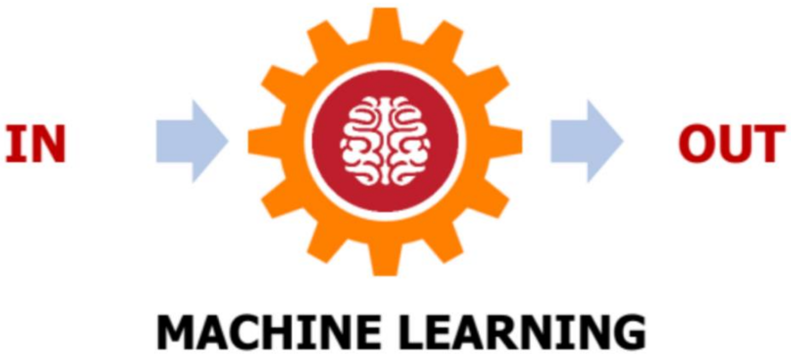
GROUP OBJECT

What is Regression?

Regression Model

Model the relationship between a dependent (target) and independent (predictor) variables with one or more independent variables

Value
Value
Value
.....



Value

Examples of Regression Projects

$82000

$55500

???

Advertisement	Sales
$90	$1000
$120	$1300
$150	$1800
$100	$1200
$130	$1380
$200	??

Regression : Linear Regression

Linear Regression

- Simple Linear Regression

  1 independent variable

  1 dependent variable

  $Y = \alpha + \beta x + \varepsilon$

- Multiple Linear Regression

  n independent variables

  1 dependent variable

  $Y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_n x_n + \varepsilon$

$\mathrm{Y} = \textit{predict value (variable independent)}$

$x = \textit{feature value (variable dependent)}$

$\alpha = \textit{intercept paramenter}$

$\beta = \textit{slope parameter}$

$\varepsilon = \textit{error (residual)}$

Simple Illustration

Dataset of Years of Experience

and Salary (in 1000$)

Independent Variables

Dependent Variables

Years of Experience	Salary in 1000$
2	15
3	28
5	42
13	64
8	50
16	90
11	58
1	8
9	54

Simple Illustration

Years of Experience x_i	Salary (in 1000$) y_i	$(x_i - \bar{x})$	$(y_i - \bar{y})$	$(x_i - \bar{x})(y_i - \bar{y})$	$(x_i - \bar{x})^2$
2	15	-5.56	-30.44	169.24	30.91
3	28	-4.56	-17.44	79.53	20.79
5	42	-2.56	-3.44	8.81	6.55
13	64	5.44	18.56	100.97	29.59
8	50	0.44	4.56	2.01	0.19
16	90	8.44	44.56	376.09	71.23
11	58	3.44	12.56	43.21	11.83
1	8	-6.56	-37.44	245.61	43.03
9	54	1.44	8.56	12.33	2.07
$\bar{x}$=7.56	$\bar{y}$= 45.44			∑ = 1037.8	∑ = 216.19

$$m = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2}$$

$$b = \bar{y} - m * \bar{x}$$

m = 1037.8 / 216.19

m = 4.80

b = 45.44 - 4.80 * 7.56 = 9.15

Hence, **y = mx + *b*** → ***4.80x + 9.15***

y = 4.80x + 9.15

Linear Regression in Python

```python
from sklearn.linear_model import LinearRegression

# Using Multiple Linear Regression
ols_model = LinearRegression().fit(X_train, y_train)

y_train_pred = ols_model.predict(X_train)
y_test_pred = ols_model.predict(X_test)
```

Linear Regression - Regularized

- Lasso Regression

```
# Using Lasso Regression
from sklearn.linear_model import Lasso

lasso_model = Lasso(alpha = 0.8, normalize = True).fit(X_train, y_train)

y_train_pred = lasso_model.predict(X_train)
y_test_pred = lasso_model.predict(X_test)
```

- Ridge Regression

```
# Using Ridge Regression
from sklearn.linear_model import Ridge

ridge_model = Ridge(alpha = 0.1, normalize = True).fit(X_train, y_train)

y_train_pred = ridge_model.predict(X_train)
y_test_pred = ridge_model.predict(X_test)
```

- Elastic-Net Regression

```
# Using Elastic Net Regression
from sklearn.linear_model import ElasticNet

elastic_net_model = ElasticNet(alpha=1, l1_ratio=0.5, normalize=False).fit(X_train, y_train)

y_train_pred = elastic_net_model.predict(X_train)
y_test_pred = elastic_net_model.predict(X_test)
```

Regression : Decision Tree

Tree-based Regressor

```
# Using Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor

dt_regressor = DecisionTreeRegressor().fit(X_train, y_train)

y_train_pred = dt_regressor.predict(X_train)
y_test_pred = dt_regressor.predict(X_test)
```

```
# Using Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor

rf_regressor = RandomForestRegressor().fit(X_train, y_train)

y_train_pred = rf_regressor.predict(X_train)
y_test_pred = rf_regressor.predict(X_test)
```

Evaluation Metrics

Mean Absolute Error

- Regression metric which measures the **average magnitude of errors** in a group of predictions, without considering their directions.

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} |e_t|$$

Mean Squared Error

- **Average squared difference between the predictions and expected results**. In other words, an alteration of MAE where instead of taking the absolute value of differences, they are squared.

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2$$

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