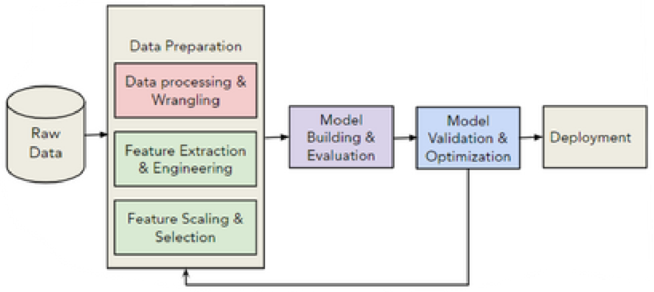
SLR cheat sheet

Steps in ML Model deployment



Raw Data
Data Preparation
Data processing & Wrangling
Feature Extraction & Engineering
Feature Scaling & Selection
Model Building & Evaluation
Model Validation & Optimization
Deployment

Simple Linear Regression formula

$y = \beta_0 + \beta_1 x + \varepsilon$

Where:

- β_0 = y intercept
- β_1 = slope
- x = set of values taken by independent variable X
- y = target/dependent variable
- ε = random error term

Note: Error term also called residual, it represents the distance of the observed value from the value predicted by regression line.

ε = yactual - ypredicted

Multiple linear regression

$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n + \varepsilon$

$\beta_0, \beta_1, \beta_2, \beta_3, \ldots, \beta_n$ are the parameters of the linear regression model with n

independent variables

y = set of values taken by dependent variable Y

xi = set of values taken by independent variable Xi , i ∈ [1,n] β_0 = y intercept

β_i = beta coefficient for the ith independent variable Xi, i ∈ [1,n]

ε = random error component

Ordinary least Squares

$$min \sum_{i=1}^{n} (y_i - \beta_i x_i)^2$$

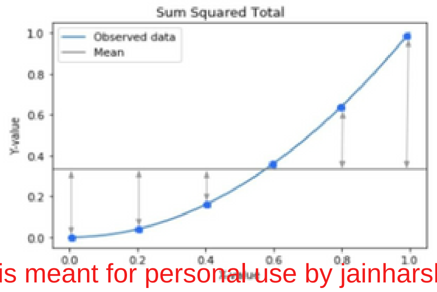
- The ordinary least square method is used to find the best fit line for given data
- This method aims at minimizing the sum of squares of the error terms, that is, it determines those values of **β_0 and β_1 at which the error terms are minimum**

Measures of variation

Sum of squares total (SST)

It can be seen as the total variation of the response variable about its mean value.

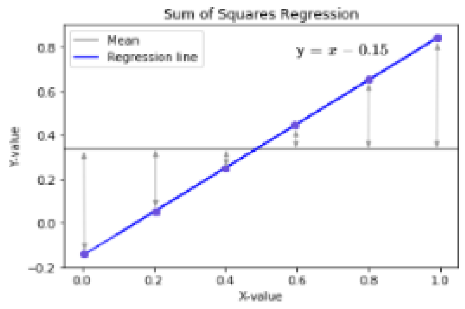
$$SST = \sum_{i=1}^{n} (y_i - \bar{y})^2$$



Sum of Squares Regression (SSR)

SSR is the measure of variability in the response variable considering the effect of predictor variable . It is the explained variation

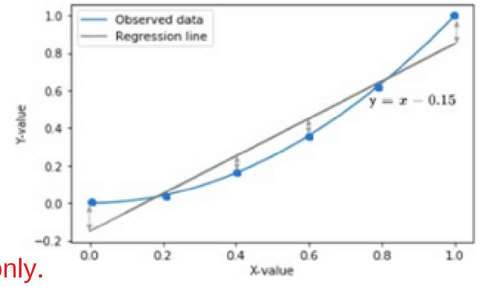
$$SSR = \sum_{i=1}^{n} (\hat{y} - \bar{y})^2$$

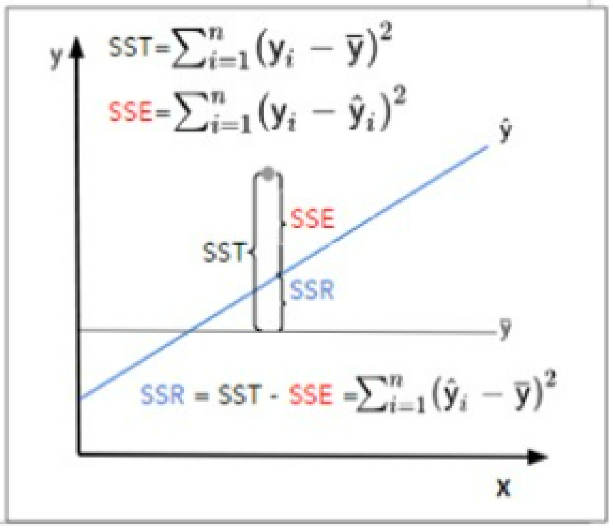


Sum of squares of error (SSE)

The sum of squares of error (SSE) is the sum of squared differences between observed response variable and its predicted value

$$SSE = \sum_{i=1}^{n} (y_i - \hat{y})^2$$





$SST=\sum_{i=1}^{n}(y_i-\bar{y})^2$
$SSE=\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$
y
$\hat{y}$
SSE
SST
SSR
$\bar{y}$
$SSR = SST - SSE = \sum_{i=1}^{n}(\hat{y}_i-\bar{y})^2$
x

Measure of unexplained variation

- Standard error of estimate is a measure of the unexplained variance
- Smaller value of standard error of estimate indicates a better model

$$min \sum_{i=1}^{n}(y_i - \beta_i x_i)^2$$

n = sample size
k = number of parameter estimates (β0,β1)

Measure of explained variation

R2 also called the coefficient of determination gives total percentage of variation in Y that is explained by predictor variable.

$$R^2 = \frac{\text{Explained variation}}{\text{Total variation}} = \frac{SSR}{SST}$$

$$0 \leq R^2 \leq 1$$

$$R^2 = 1 - \frac{SSE}{SST}$$

T-test for significance in SLR

H0: The parameter β is not significant
H1: The parameter β is significant

T-test for slope in SLR

H0: There is no relationship between variables X and Y
H1: There is relationship between variables X and Y

The t test for intercept

H0: The parameter β0 is not significant
H1: The parameter β0 is significant

ANOVA for regression

H0: The regression model is not significant
H1: The regression model is significant

R2 vs. Adjusted R2

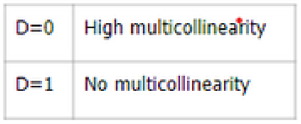
- The value of R Squared never decreases. If we add new independent variables, then the value of R Squared increases. It cannot show the effect of adding a bad or insignificant variable
- As compared to the R-Squared value, Adj. R-Squared has an ability to decrease whenever a bad or an insignificant variables are added to the model. Thus we get an accurate evaluation.

Assumptions of Linear Regression

1. **The dependent variable must be numeric**
   - check the data type of target variable

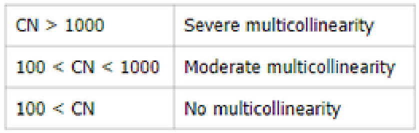
2. Predictors must not show multicollinearity

- Multicollinearity arises when the **independent variables have high correlation** among each other.
- Detection of multicollinearity:
  - Determinant of correlation matrix
    - Let D be the determinant of correlation matrix.
      - 0 < D < 1



D=0	High multicollinearity
D=1	No multicollinearity

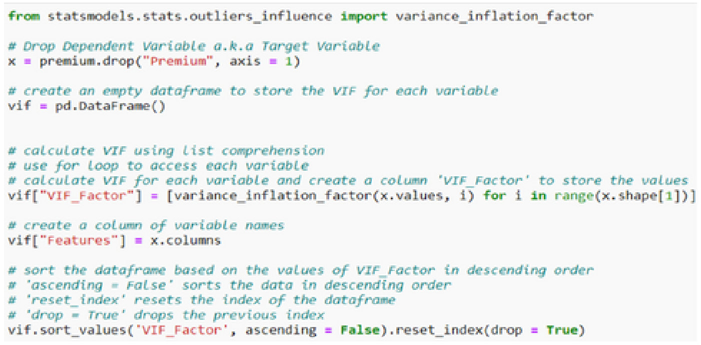
  - Condition Number (CN)
    - present in OLS summary



CN > 1000	Severe multicollinearity
100 < CN < 1000	Moderate multicollinearity
100 < CN	No multicollinearity

  - Correlation matrix
    - .corr()
  - Variance Inflation Number (VIF)

$$VIF = \frac{1}{1-R^2}$$

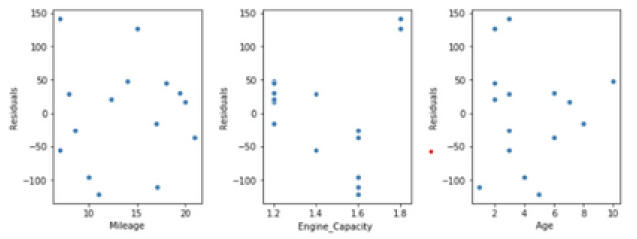


```
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Drop Dependent Variable a.k.a Target Variable
x = premium.drop("Premium", axis = 1)

# create an empty dataframe to store the VIF for each variable
vif = pd.DataFrame()


# calculate VIF using list comprehension
# use for loop to access each variable
# calculate VIF for each variable and create a column 'VIF_Factor' to store the values
vif["VIF_Factor"] = [variance_inflation_factor(x.values, i) for i in range(x.shape[1])]

# create a column of variable names
vif["Features"] = x.columns

# sort the dataframe based on the values of VIF_Factor in descending order
# 'ascending = False' sorts the data in descending order
# 'reset_index' resets the index of the dataframe
# 'drop = True' drops the previous index
vif.sort_values('VIF_Factor', ascending = False).reset_index(drop = True)
```

3.Linear relationship between dependent and independent variables

  - This can be checked by plotting a scatter plot of residuals vs predictors

- A scatter plot depicting no pattern indicates that the variable has a linear relationship with the response variable



4.Independence of observations should exist(ie. Absence of Auto correlation

- Assumption of autocorrelation is violated **when residuals are correlated within themselves**, ie they are serially correlated
- **Durbin - Watson Test (present in OLS summary)**
  - H0: The error terms are not autocorrelated
  - H1: The error terms are autocorrelated

Value	Interpretation
0 < d <2	Positive autocorrelation
d = 2	No autocorrelation
2 < d < 4	Negative autocorrelation

5.The error terms should be homoscedastic

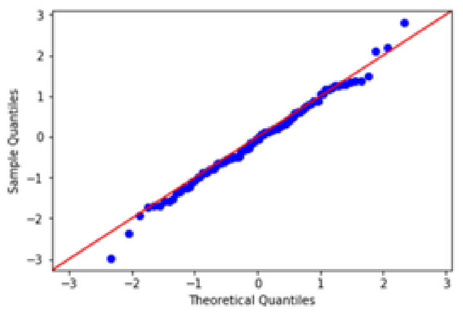
- Variance of the residual is assumed to be independent of the explanatory variables
- Heteroscedasticity: non-constant variance of residuals
- Statistical tests:
  - Goldfeld Quandt test
    - H0: The errors terms are homoskedastic
    - H1: The errors terms are heteroskedastic
  - Breusch Pagan test
    - H0: The errors terms are homoskedastic
    - H1: The errors terms are heteroskedastic

import statsmodels.stats.api as gq
gq.het_goldfeldquandt(model.resid,predictors)

6.The error terms should follow a normal distribution

Normality test:

- Quantile-Quantile Plot



- Jarque-Bera (JB) Test
  - H0: Skewness (S) = 0 and Kurtosis (K) = 0
  - H1: Skewness (S) ≠ 0 and Kurtosis (K) ≠ 0

  scipy.stats.jarque_bera(model.resid)
- Shapiro-Wilk Test
  - H0: The data is normally distributed
  - H1: The data is not normally distributed

  stats.shapiro(model.resid)

Feature Transformation

- Incase of skewed (predictor and/or dependent) variable, we transform it to reduce the skewness.
- If the assumptions of linear regression are not met, transformation of skewed target variable can be used for making the error terms more compatible to the assumptions
- Transformation methods
  - Log-Transform(postivie values only)
    - data_log = np.log(data)
  - Squareroot Transform(positive and zero values)
    - data_log = np.sqrt(data)
  - Yeo-Johnson(positive,zero and negative values)

from scipy import stat
transformed_data = st

  - Reciprocal Transformation(positive and negative values)

    transformed_data = np.reciprocal(data)
  - Exponential Transformation(reverse of log)

    transformed_data = np.exp(data)

Feature Scaling

It is a technique used to transform the data into a common scale

Feature Scaling methods:

- Standardization
  - Standardization rescales the feature such that it has mean 0 and unit variance
  - from sklearn.preprocessing import StandardScaler
  - scaler = StandardScaler()
  - data_scaled=scaler.fit_transform(data)

$$x' = \frac{x-\bar{x}}{\sigma}$$

- Normalization
  - Normalization is the process of rescaling features in the range 0 to 1
  - from sklearn.preprocessing import MinMaxScaler
  - scaler = MinMaxScaler()
  - data_scaled=scaler.fit_transform(data)

$$x' = \frac{x-\min(x)}{\max(x)-\min(x)}$$

Feature Selection

- Feature selection is the process of including the significant features in the model
- This can be achieved by:
    - Forward selection method
    - Backward elimination method
    - Stepwise method

- **Forward Selection**

```
from mlxtend.feature_selection import
SequentialFeatureSelector as sfs

Ridgelinreg_forward = sfs(estimator = model,
k_features, forward = True
```

- **Backward Elimination**

```
from mlxtend.feature_selection import
SequentialFeatureSelector as sfs

linreg_backward = sfs(estimator = model,
k_features, forward = False)
```

- **Recursive Feature Elimination**

```
from sklearn.feature_selection import RFE

rfe_model = RFE(estimator = model,
n_features_to_select)
```

Bias and Variance

- Model which doesn't perform well on Train data itself will have High Bias
- Model which performs well on train data but doesnt perform well on test data will have High Variance

Bias

- If the **model is too simple** it will have a **high bias and low variance**
- Such a model will give not perfectly accurate predictions, but the predictions will be consistent
- The model will not be flexible enough to learn from majority of given data, this is termed as underfitting

Variance

- If the **model is too complex** it will have a **low bias and high variance**
- Such a model will give accurate predictions but inconsistently
- The high variance indicates it will have a much better fit on the train data compared to the test data, this is termed as overfitting

Linear Regression

#Using sklearn

```
from sklearn.linear_model import
LinearRegression
model=LinearRegression().fit(Xtrain,ytrain)
```

Or

#Using statmodels

```
import statsmodels.api as sm
model=sm.OLS(ytrain,sm.add_constant(Xtrain))
model.summary() #to get ols summary
```

Model Prediction

```
ypred=model.predict(Xtest)
```

Model Evaluation

R-Squared

```
from sklearn.metrics import r2_score
r_sq = r2_score(y_test, y_pred)
```

Adjusted R-Squared

```
n = number of observations
k = number of columns (including intercept)
adj_r_squared = 1 - (((1 - r_sq) * (n - 1)) / (n - k -
1))
```

Mean Squared Error

```
from sklearn.metrics import
mean_squared_error
MSE = mean_squared_error(y_test, y_pred)
```

Root Mean Squared Error

```
RMSE = np.sqrt(MSE)
```

Mean Absolute Error

```
from sklearn.metrics import
mean_absolute_error
MAE = mean_absolute_error(y_test, y_pred)
```

Mean Absolute Percentage Error

```
MAPE = np.mean(np.abs((y_test - y_pred) /
y_test)) * 100
```

Model Validation

The model validation methods use test data to validate the model built using train data

Cross_val_score

This method is known as two fold cross validation

Here, each observation is used exactly once for training and once for testing

```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(estimator = LinearRegression(), X = X_train, y = y_train, cv, scoring)
```

K-Fold CV

Here, each observation is used exactly k times for training and exactly once for testing

```
from sklearn.model_selection import KFold
kf = KFold(n_splits)
```

Leave One Out CV

It is a special case of k - fold cross validation method. Instead of subsetting the data, at every run one observation is considered as the test set

```
from sklearn.model_selection import LeaveOneOut
loocv = LeaveOneOut()
```

Grid Search

The estimates of parameters are usually estimated from the data

```
from sklearn.model_selection import GridSearchCV
grid_model = GridSearchCV(estimator, param_grid , cv )
```

Cost Function

- A cost function tells how good the model performs at making predictions for a given set of parameters
- Cost function = Loss function = Error function

$$Error = \sum_{i=1}^{n} (y_{act} - y_{pred})^2$$

Note: where yact is the actual value and ypred is the predicted value.

Gradient Descent

- The gradient descent is an optimization technique which finds the parameters such that the error term is minimum.
- It is an iterative method which converges to the optimum solution.
- It takes large steps when it is away from the solution and takes smaller steps closer to the optimal solution.
- The estimates of the parameter are updated at every iteration.

```
from sklearn.linear_model import SGDRegressor
 sgd = SGDRegressor()
```

Regularization

- Regularization refers to the modifications we make to a learning algorithm, that help in reducing its generalization error but not its training error
- Regularization adds a cost function such tha higher variance receives a larger penalty
- It chooses a model with smaller parameter values (i.e. shrunk coefficients) that has less error

$$\text{Loss function}_{\text{regularization}} = \text{Loss function}_{\text{ols}} + \text{Penalty term}$$

Ridge Regression

- Ridge regression uses squared L-2 norm regularization i.e it adds a squared L-2 penalty
- It diminishes the insignificant predictors but does not completely eliminate them

```
from sklearn.linear_model import Ridge
ridge = Ridge(alpha)
```

Lasso Regression

- Lasso regression uses L-1 norm regularization i.e it adds a L-1 penalty
- It extinguishes the insignificant predictors

```
from sklearn.linear_model import Lasso lasso = Lasso(alpha)
```

Elastic-net regression

- Elastic-net regression uses both L-1 and L-2 norm regularization
- Elastic-net regression is the combination of lasso and ridge regression

```
from sklearn.linear_model import ElasticNet
enet = ElasticNet(alpha, l1_ratio)
```