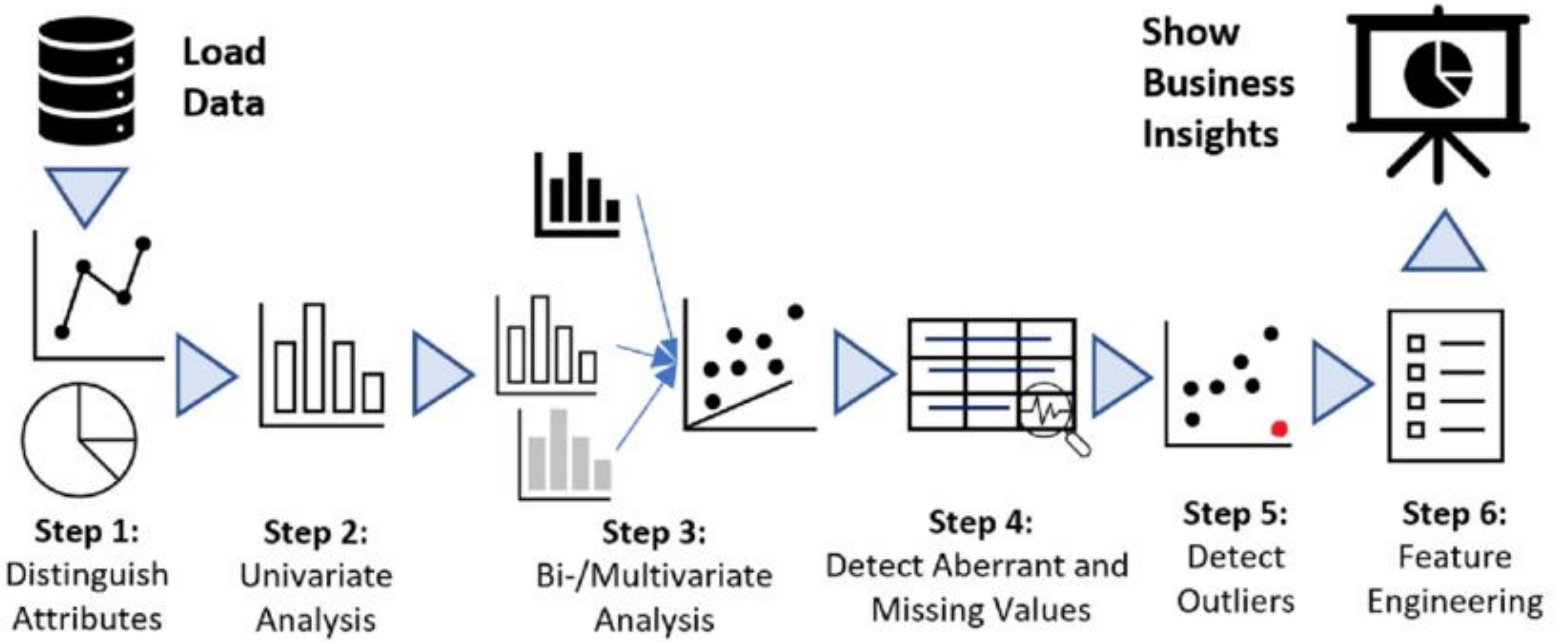
Exploratory Data Analysis

CS 459 Business Intelligence

Summarizing 6-steps of Data Wrangling

EDA



Load Data
Show Business Insights
Step 1: Distinguish Attributes
Step 2: Univariate Analysis
Step 3: Bi-/Multivariate Analysis
Step 4: Detect Aberrant and Missing Values
Step 5: Detect Outliers
Step 6: Feature Engineering

Multi-Variate Analysis

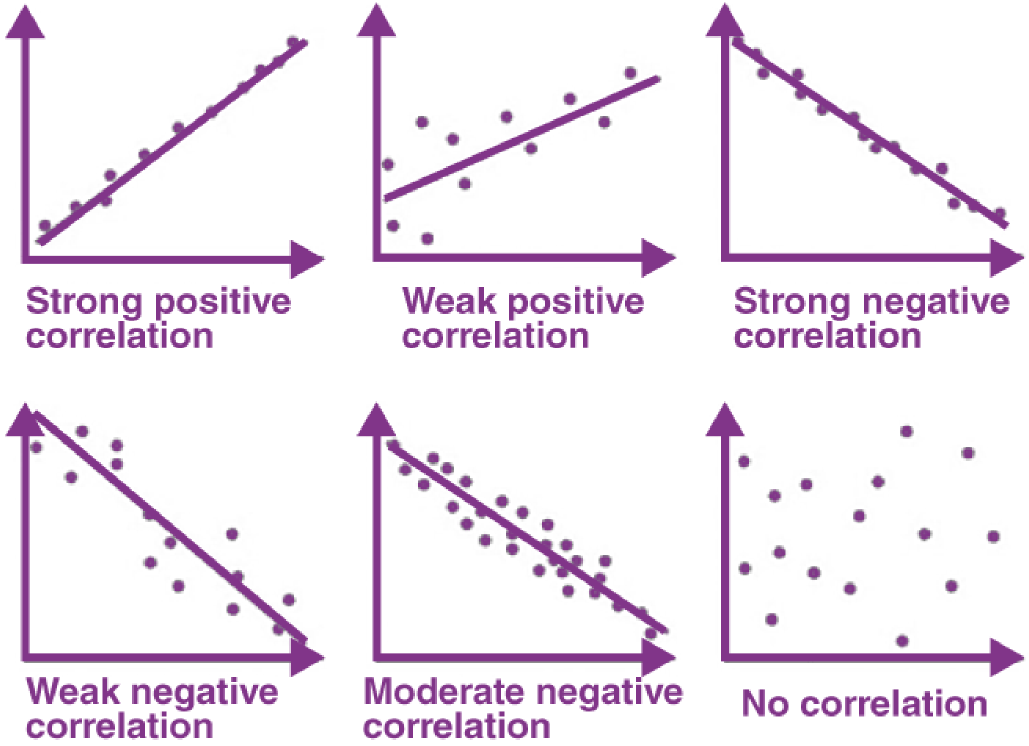
Bi-variate/ Multivariate Statistical Testing

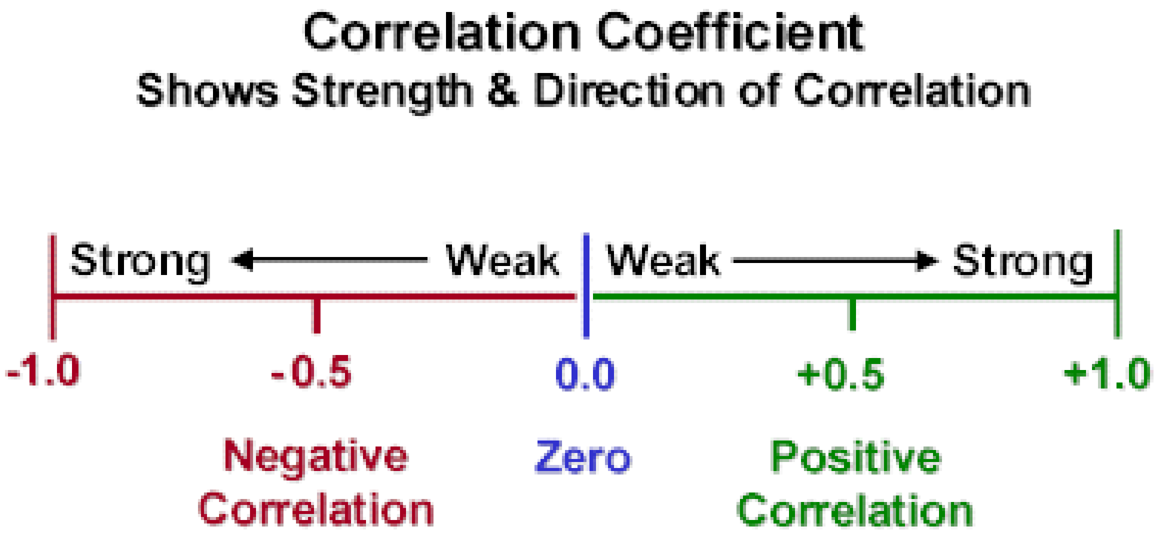
	Categorical	Numerical
Categorical	Chi-Square Test	T-test ANOVA
Numerical Continuous	Regression	Correlation Test

Correlation Testing

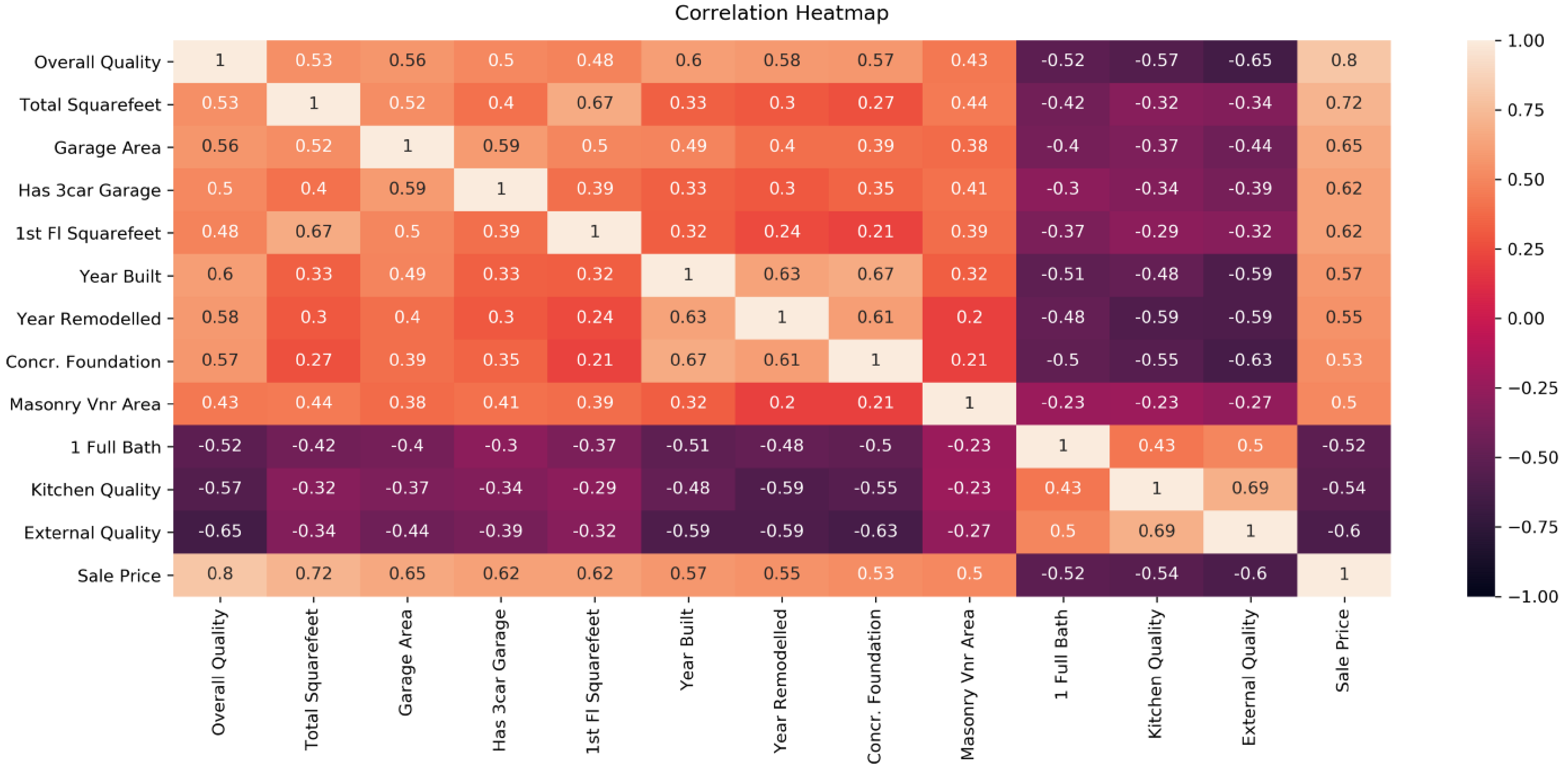
- One way to quantify the relationship between two variables is to use the *Pearson correlation* coefficient, which measures the linear association between two variables.
- *Correlation Coefficient*
  - **-1** indicates a perfectly negative linear correlation
  - **0** indicates no linear correlation
  - **1** indicates a perfectly positive linear correlation

Correlation Analysis





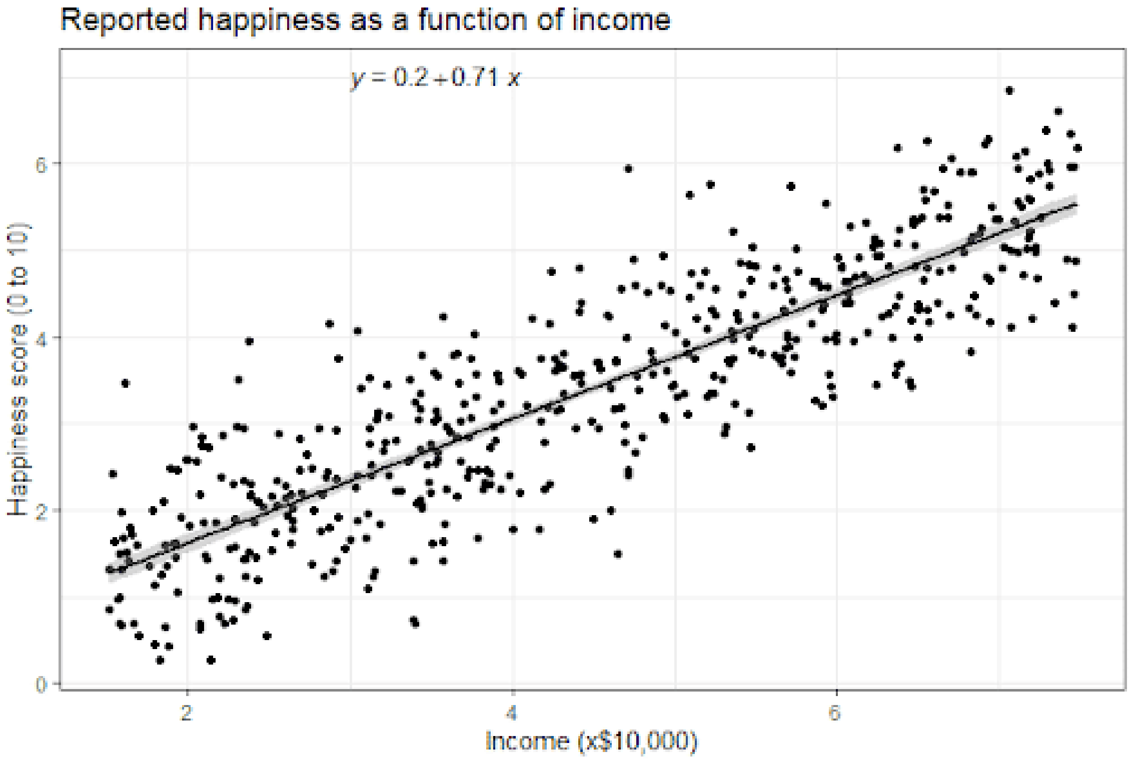
Correlation heat map



P-value in Hypothesis Testing

- The **p-value** indicates the **strength of evidence against a null hypothesis**.
- Smaller p-value → Stronger evidence against the null hypothesis
- The commonly used threshold (**α**) is **0.05 (5%)**.
- **If p-value < 0.05:** Reject the null hypothesis and **accept the alternative hypothesis**.
- **If p-value ≥ 0.05: Fail to reject** the null hypothesis (not enough evidence to accept the alternative hypothesis).

Regression



- In statistical modeling, regression analysis is a set of statistical processes for estimating the relationships between a **dependent variable** and **one or more independent variables**.

Regression

- **Linear Regression:**
  - Used when the dependent variable is numerical.
  - Example: Predicting house prices based on size and location.
- **Logistic Regression:**
  - Used when the dependent variable (target) is categorical.
  - Example:
    - Predicting whether an email is spam (1) or not (0).
    - Determining if a tumor is malignant (1) or benign (0).

Interpreting Results

R-square value:

- This means that **76.67%** of the variation in the response variable can be explained by the two predictor variables in the model.

```
from sklearn.linear_model import LinearRegression

#initiate linear regression model
model = LinearRegression()

#define predictor and response variables
X, y = df[['x1', 'x2']], df.y

#fit regression model
model.fit(X, y)
```

```
#display regression coefficients and R-squared value of model
print(model.intercept_, model.coef_, model.score(X, y))

70.4828205704 [ 5.7945 -1.1576] 0.766742556527
```

$$y = 70.48 + 5.79x_1 - 1.16x_2$$

```python
import statsmodels.api as sm

#define response variable
y = df['y']

#define predictor variables
x = df[['x1', 'x2']]

#add constant to predictor variables
x = sm.add_constant(x)

#fit linear regression model
model = sm.OLS(y, x).fit()

#view model summary
print(model.summary())
```

P-value for each variable can also be computed. This gives the statistical significance of each variable when p value is less than 0.05.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.767
Model:                            OLS   Adj. R-squared:                  0.708
Method:                 Least Squares   F-statistic:                     13.15
Date:                Fri, 01 Apr 2022   Prob (F-statistic):            0.00296
Time:                        11:10:16   Log-Likelihood:                -31.191
No. Observations:                  11   AIC:                             68.38
Df Residuals:                       8   BIC:                             69.57
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         70.4828      3.749     18.803      0.000      61.839      79.127
x1             5.7945      1.132      5.120      0.001       3.185       8.404
x2            -1.1576      1.065     -1.087      0.309      -3.613       1.298
==============================================================================
Omnibus:                        0.198   Durbin-Watson:                   1.240
Prob(Omnibus):                  0.906   Jarque-Bera (JB):                0.296
Skew:                          -0.242   Prob(JB):                        0.862
Kurtosis:                       2.359   Cond. No.                         10.7
==============================================================================
```

ANOVA – Analysis of Variance

- **ANOVA** is a statistical formula used to compare variances across the means (or average) of different groups.
- A range of scenarios use it to determine if there is any difference between the means of different groups

	fertilizer	weight
1	None	55
2	None	45
3	None	46
4	Biological	64
5	Biological	52
6	Biological	42
7	Chemical	65
8	Chemical	51
9	Chemical	66
10	Chemical	55


EMPLOYEE TRAINING IMPACT
ON CUSTOMER SATISFACTION
qualtrics.XM
Customer Satisfaction Ratings
10
9
8
7
6
5
4
3
2
1
Beginner
Intermediate
Advanced
Levels of Employee Training

Interpreting Results

- A one-way ANOVA uses the following null and alternative hypotheses:
- **H_0 (null hypothesis):** $\mu_1 = \mu_2 = \mu_3 = \ldots = \mu_k$
  (all the population means are equal)
- **H_1 (alternate hypothesis):** at least one population mean is different from the rest

ANOVA Results

```
from scipy.stats import f_oneway

#perform one-way ANOVA
f_oneway(group1, group2, group3)

(statistic=2.3575, pvalue=0.1138)
```

The F test statistic is **2.3575** and the corresponding p-value is **0.1138**.

F-Statistic (Fisher Statistic):

A measure used to test the overall significance of a statistical model by comparing model fit against a baseline model.

- The F-statistic is compared with a critical value or evaluated using the p-value.
- If the **p-value < 0.05**, the model is considered statistically significant (**Reject the null hypothesis**).
- If the **p-value ≥ 0.05**, the model is not statistically significant (**Fail to reject the null hypothesis**).
- **Note:** A large F-statistic generally corresponds to a small p-value, indicating statistical significance.

Head over to
Descriptive Statistics Notebook

Create a Summary Table for the ANOVA Test

Column A	Column B	P-Value	Reject / Fail to Reject	Difference exists / No Difference
Sales	Order Priority	0.22		

Complete Table for ANOVA test

Column A	Column B	P-Value	Reject / Fail to Reject	Difference exists / No Difference
Sales	Order Priority	0.22		
Sales	Ship Mode	0.00		
Sales	Region	0.33		
Sales	Customer Segment	0.63		
Sales	Product Category	4.908931e-168		
Sales	Sub Category	0.00		
Sales	Product Container	0.00		

Tukey Test

- Tukey's test determines the individual means which are significantly different from a set of means.
- Tukey's test is a multiple comparison test and is applicable when there are more than two means being compared (for two means, utilize a *t* test).
- Typically, Tukey's test is utilized after ANOVA has shown that significant difference exists and this determines where the difference exists.

Interpret ANOVA

```
#enter data for three groups
a = [85, 86, 88, 75, 78, 94, 98, 79, 71, 80]
b = [91, 92, 93, 90, 97, 94, 82, 88, 95, 96]
c = [79, 78, 88, 94, 92, 85, 83, 85, 82, 81]

#perform one-way ANOVA
f_oneway(a, b, c)

F_onewayResult(statistic=5.167774552944481, pvalue=0.012582197136592609)
```

- H0 : all the population means are equal
- We can see that the overall p-value from the ANOVA table is **0.01258**.

- Since this is less than 0.05, reject null hypothesis which implies that the mean values across each group are not equal.
- Proceed to perform Tukey's Test to determine exactly which group means are different.

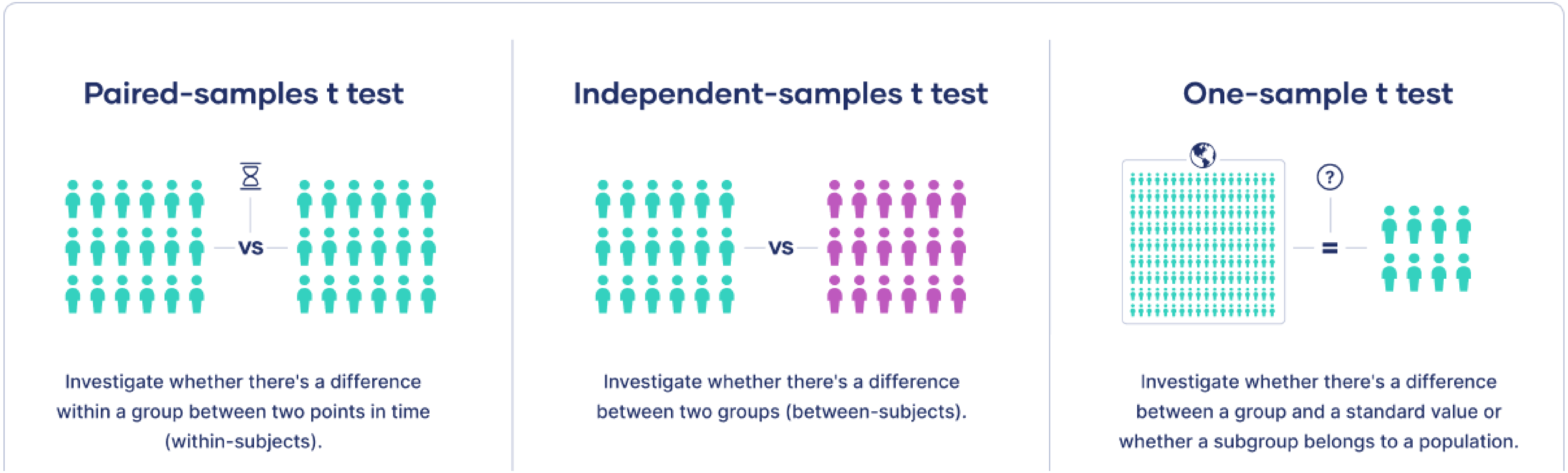
Interpreting Tukey

- There is a statistically significant difference between the means of groups *a* and *b* and groups *b* and *c*, but not a statistically significant difference between the means of groups *a* and *c*.

```
Multiple Comparison of Means - Tukey HSD, FWER=0.05
=====================================================
group1 group2 meandiff p-adj   lower    upper  reject
-----------------------------------------------------
     a      b      8.4 0.0158   1.4272 15.3728   True
     a      c      1.3 0.8864  -5.6728  8.2728  False
     b      c     -7.1 0.0453 -14.0728 -0.1272   True
-----------------------------------------------------
```

T-test

- A t-test is a statistical test that **compares the means of two samples**. Null hypothesis: The difference in group means is zero and an alternate hypothesis that the difference in group means is different from zero.



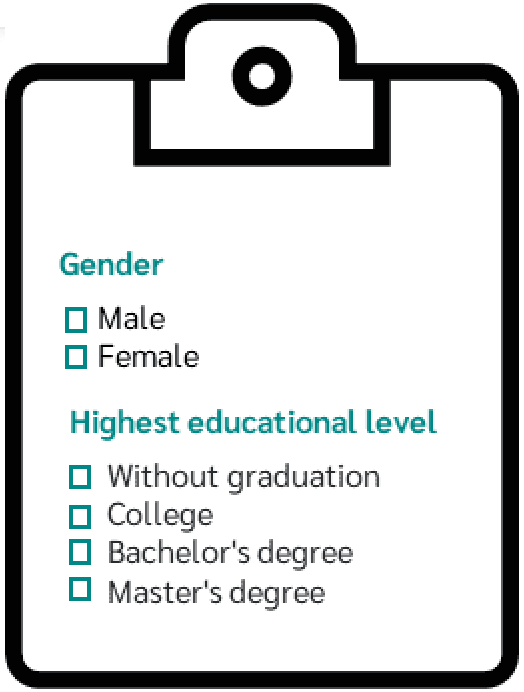
Interpreting Results

Compare **P-value** in the same way.

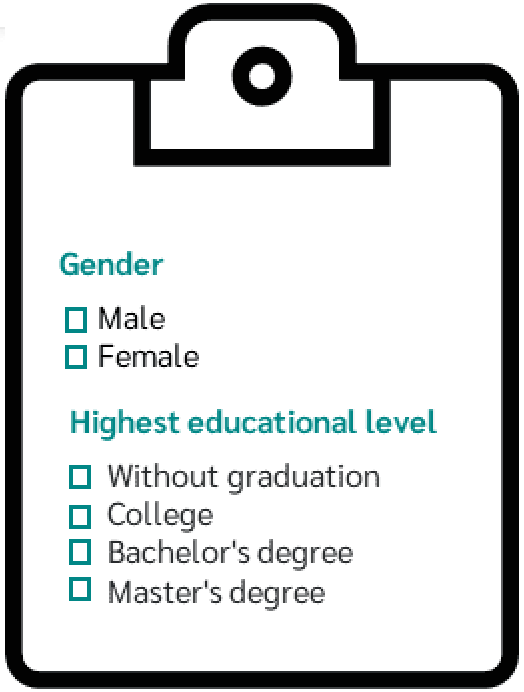
The **t-value** measures the size of the difference relative to the variation in your sample data. Put another way, T is simply the calculated difference represented in units of standard error. **The greater the magnitude of T, the greater the evidence against the null hypothesis**.

Chi-square

- **Chi-square** is a statistical test used to examine the differences between **categorical variables** from a random sample in order to judge goodness of fit between expected and observed results.
- **Chi-square** is most commonly used by researchers who are studying survey response data because it applies to categorical variables. Demography, consumer and marketing research, political science, and economics are all examples of this type of research
- **Example**: Is gender related to political party preference?



Gender
Male
Female
Highest educational level
Without graduation
College
Bachelor's degree
Master's degree



Fall	Gender	Highest educational level
1	Male	College
2	Female	Without graduation
3	Male	Without graduation
4	Male	Bachelor's degree
5	Female	Master's degree
6	Male	Bachelor's degree
7	Female	Master's degree
...	...	...

Gender

- ☐ Male
- ☐ Female

Highest educational level

- ☐ Without graduation
- ☐ College
- ☐ Bachelor's degree
- ☐ Master's degree

Fall	Gender	Highest educational level
1	Male	College
2	Female	Without graduation
3	Male	Without graduation
4	Male	Bachelor's degree
5	Female	Master's degree
6	Male	Bachelor's degree
7	Female	Master's degree
...	...	...

	Female	Male
Without graduation	6	7
College	13	16
Bachelor's degree	16	15
Master's degree	8	11
Total	43	49

Is there a correlation between gender and the highest level of education? → Chi^2 - Test

Interpreting Results

- **Chi-Square Statistic (χ^2):**
  - Compares observed and expected frequencies.
  - If $\chi^2 >$ critical value, reject the null hypothesis.
  - Indicates a significant association between variables.
- **P-value:**
  - Helps determine the statistical significance of the results.
  - A small p-value (typically < 0.05) suggests a significant relationship.
- **Degrees of Freedom (df):**
  - Represents the number of independent categories that can vary.
  - For a Chi-square test with a contingency table:
    df = (R - 1) * (C - 1) Example: For a 4x3 table, **df = (4 - 1) * (3 - 1) = 6**.

Interpreting Results

- For interpretation, we use the **p-value**.
- If less than alpha (set the threshold for analysis), then we reject H0 which would imply the dependency between the 2 variables.

```
stat, p, dof, expected = chi2_contingency(data_crosstab)
print('dof=%d' % dof)
print(expected)

# interpret p-value
alpha = 0.05
print('significance=%.3f, p=%.3f' % (alpha, p))
if p <= alpha:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
dof=6
[[ 338.47791404  905.09465413  405.42743184]
 [ 631.38754614 1688.33908799  756.27336588]
 [ 417.09346351 1115.31372782  499.59280867]
 [ 337.04107632  901.25253006  403.70639362]]
significance=0.050, p=0.349
Independent (fail to reject H0)
```

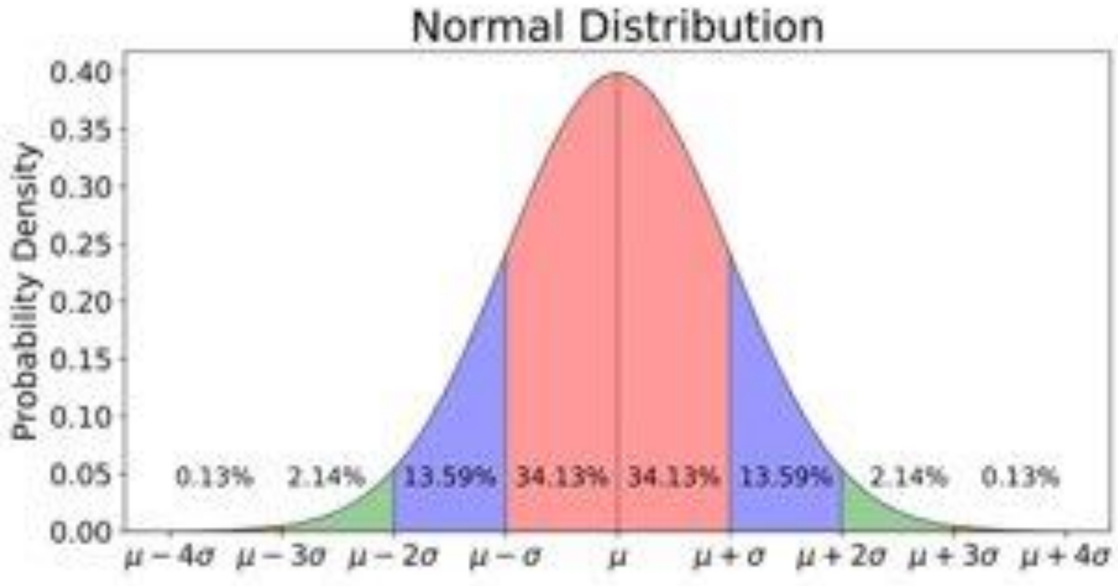
Normality Testing

Normality

Normality means the data should follow a **normal distribution**.

Why do we need to test?

Many statistical techniques and models assume that the data is normally distributed. For instance, parametric statistical tests like t-tests, ANOVA, linear regression, etc., assume normality of the data.



Shapiro-Wilk Test

- **H0: Null hypothesis – the distribution of the data sample is normal**

```
# considered to be reliable for smaller datasets
# Null hypothesis=data is normal
# Alternate hypothesis= data is not normal
W, pvalue = shapiro(data)
print('W=%.4f, p=%.4f' % (W, pvalue))
```

```
W=0.9874, p=0.4667
```

- P-value is <0.05, Reject Null hypothesis
- In this case, P-value is 0.4667 which means that you cannot reject the H0 hence, data is normal.

K^2 or K-squared Test

The D'Agostino's K^2 test calculates summary statistics from the data, namely kurtosis and skewness, to determine if the data distribution departs from the normal distribution, named for Ralph D'Agostino.

K2 test

```
#checks gaussianness based on skewness and kurtosis
# Null hypothesis=data is normal
# Alternate hypothesis= data is not normal
k2stat, pvalue = normaltest(data)
print('K2stat=%.4f, p=%.4f' % (k2stat, pvalue))
```

```
K2stat=0.9570, p=0.6197
```

- **Skewness:** Measures how much a distribution is pushed left or right. Positive skewness means a longer tail on the right, negative skewness means a longer tail on the left.

- **Kurtosis:** Measures how much of the distribution is in the tails. High kurtosis means heavy tails and a peakier center, while low kurtosis means lighter tails and a flatter peak.

Kolmogorov-Smirnov Test --> Anderson-Darling Test

Evaluate whether a data sample comes from one of among many known data samples, named for *Theodore Anderson and Donald Darling.*

A version of Kolmogorov-Smirnov test- With more sophistication

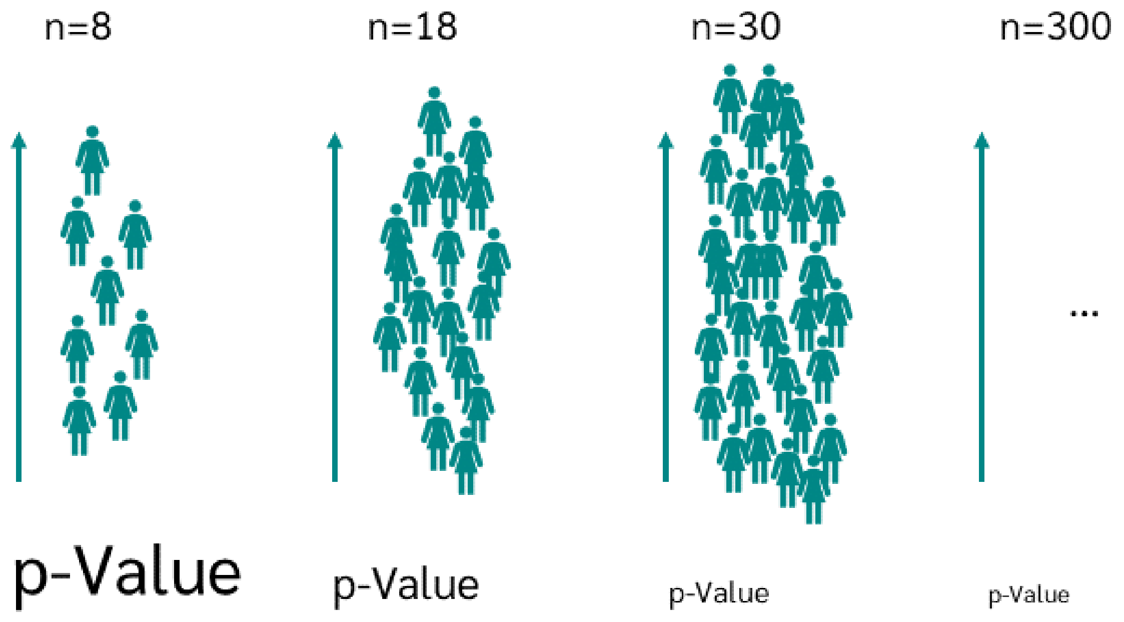
We can interpret the results by failing to reject the null hypothesis that the data is normal if the calculated test statistic is less than the critical value at a chosen significance level.

Which test to use?

- Use tests where appropriate to gauge the normality
- A failure of even one normality test means that your data is not normal.
- *Either investigate why your data is not normal (outliers, skewness, etc) OR use data transformation techniques (e.g. log, square root) to normalize the data.*
- If some tests show normality others don't, you may treat the data as *Gaussian-like* and proceed.

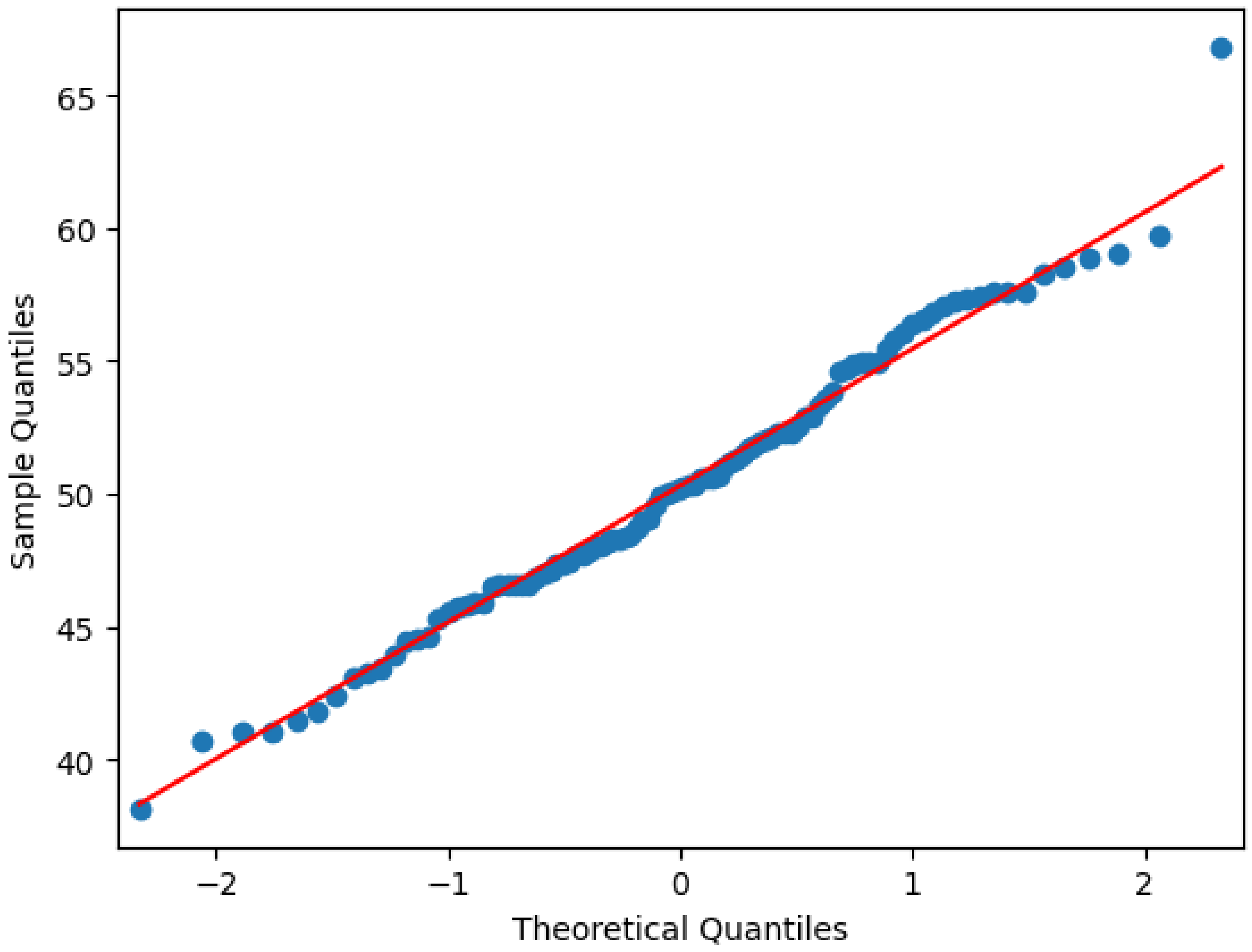
Statistical Testing VS Graphical Approach

- Normality tests allows us to validate for normal distribution.
- *There is a problem :* When the data population increases, the p-value decreases which leads to rejection of the null hypothesis hence implied a non-normal distribution while, it may be un-true.
- Create graphs like histograms, box plots and **qqplots** to visualize the distributions.



QQ Plot

- The QQ plot compares the distribution of the dataset against the theoretical normal distribution.
- Specifically, it plots the quantiles of the dataset against the quantiles of a theoretical normal distribution.
- If the dataset is normally distributed, the points on the QQ plot will lie approximately along a straight line. Any deviation from a straight line suggests deviation from normality.



Python Notebook

Normality Testing

EDA Graded Activity

Recall interpretations on the statistical testing notebook for tests already conducted.

Conduct additional tests:

Generate a Correlation Heat Map

ANOVA/Tukey for Profit

Chi-square for different sets of categorical columns.

Interpret the results and record your findings in your notebook.

LMS submission – end of class

Assignment 02
Data Wrangling and EDA

Deadline:
Sunday, 6th April, 2024 @11.55pm
No extensions possible

Midterm Exam Structure

- All topics studied till today are included in the exam
- 2 sections:
  - Section A: MCQs and Short questions
  - Section B: Long questions

All the Best for Your Exams
and
Happy Spring Break!