CONCEPTUAL QUESTIONS
For
PREDICTIVE MODELING

ANALYTIXLABS

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ANALYTICS TOOLS FOR DATA SCIENCE

Q: What are some of the tools used for statistical analysis?
Ans: Some popular tools for statistical analysis include

- **SAS:** A suite of analytics software developed by SAS
- **R:** An open source language and environment for statistical computing
- **Python:** An open source language and environment for statistical computing
- **Julia:** An open source language and environment for statistical computing
- **Spark:** An open source language and environment for statistical computing
- **WEKA:** A suite of machine-learning free software written in Java
- **SPSS:** A software for statistical analysis, currently owned by IBM
- **EViews:** Mostly used for econometric analysis, a software developed by Quantitative Micro Software
- **Minitab**: A statistical tool developed at Pennsylvania State University

Q: What are some of the visualization tools available in the market today?
Ans: Visualization tools can be divided into three broad categories:
Graphical tools:

MS Excel: Microsoft Excel is the standard offering in the Microsoft Office bundle. It is used mostly by analysts for all lightweight analysis, as well as a visualization tool.
D3.js: A JavaScript library to create graphs in HTML and related web technologies
FusionCharts: A JavaScript library for graphs on the Web
Google Charts: Interactive charts for web and mobile devices
Power BI: Microsoft product

Dashboard tools:

Tableau: A US-based software company with a flagship product that helps create dashboards on raw data
Qlikview: A dashboard software product by the US-based company Qlik
Spotfire: Dash boarding software by TIBCO
OBIEE: By Oracle
Business Objects: By SAP
Cognos: By IBM
MSBI: By Microsoft
Pantaho:
JasperSoft:
Palantir:
Rshiny: As part of R
Bokeh/Dash: As part of Python

Infographic tools:

Infogram
plotly
Picktochart

Data Audit & Data Sanitization

Data validation

- Total number of observations.
- Total number of fields.
- Each field name, Field type, Length of field.
- Format of field, Label.

BasicChecks

- Are all variables as expected (variables names& variable types).
- Are there some variables which are unexpected?
- Are the data types and length a cross variables correct?
- For known variables, is the data type as expected (For example if age is in date format something is suspicious)
- Have labels been provided and are sensible?
- If anything suspicious we can further investigate it and correct accordingly

DataValidation – snapshot of data

Printing the first few observations all fields in the dataset. It helps in better understanding of the Variable by looking at its assigned values.

Check points for data snapshot output:

1. Do we have any unique identifier? Is the unique identifier getting repeated in different records?
2. Do the text variables have meaningful data? (If text variables have absurd data as '&^%*HF' then either the variable is meaningless or the variable has become corrupt or wasn't properly created.)
3. Are there some coded values in the data? (if for a known variable say State we have category codes like 1-52 then we need definition of how they are coded.)
4. Do all the variables appear to have data? (Incase variables are not populated with non missing meaningful value it would show in print. We can further investigate using means statistics.)

Categorical fields and Frequencies

- Calculate frequency counts cross-tabulation frequencies. Especially for categorical, discrete &class fields.
- Frequencies
    - Help us understanding the variable by looking at the values it's taking and data count a teach value.
    - They also help us in analyzing the relationships between variables by looking at the cross tab frequencies or by looking at association.

Check points for looking frequency table

1. Are values as expected?
2. **Variable understanding:**
    a. Distinct values of a particular variable, missing percentages.
    b. Are there any extreme values or outliers?
    c. Any possibility of creating a new variable having small number of distinct category by clubbing certain categories with others.

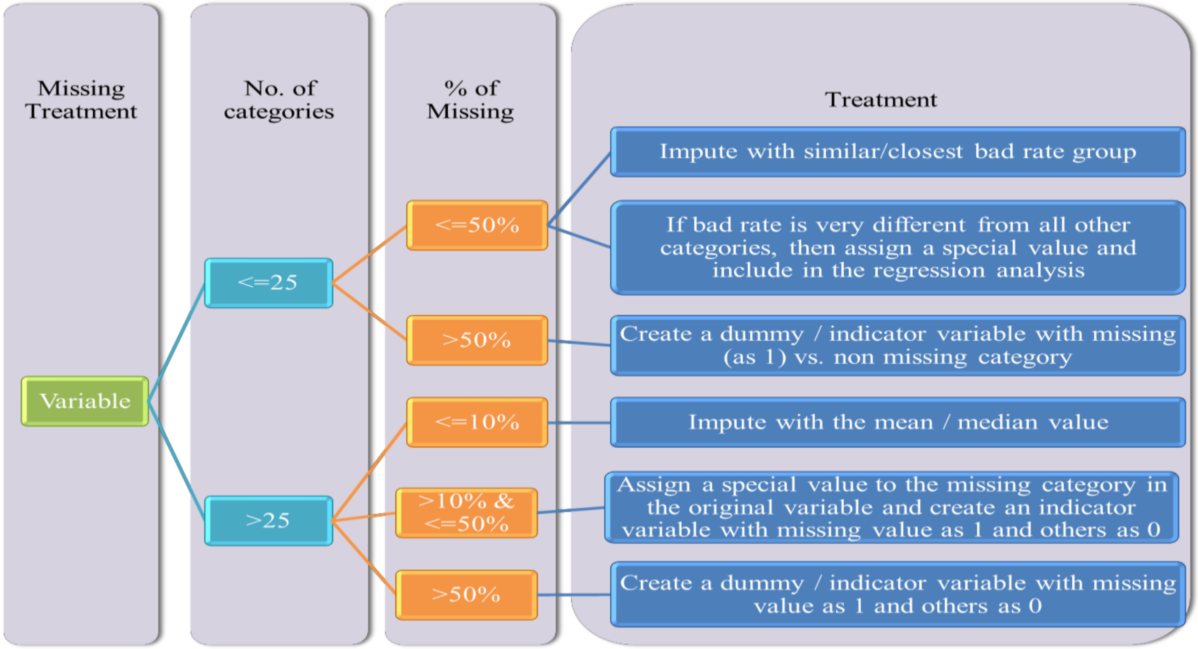
Descriptive statistics for continuous fields

- Distribution of numeric variables by calculating.
    - N–Count of non-missing observations.

- N miss–Count of Missing observations.
- Min, Max, Median, Mean.
- Quartile numbers &percentiles–P1,p5,p10,q1(p25),q3(p75),p90,p99
- Stddev
- Var
- Skewness
- Kurtosis

- **CheckList**
  - Are variable distributions as expected?
  - What is the central tendency of the variable? Mean, Median and Mode across each variable
  - Is the concentration of variables as expected? What are quartiles?
  - Indicates variables which are variables are with stddev=0; the variables which are useless for the current objective.
  - Are there any outliers/extreme values for the variable?
  - Are outlier values as expected or they have abnormally high values-for ex for Age if max and p99 values are 10000. Then should investigate if it's the default or there is some error in data
  - What is the % of missing value associated with the variable?

Missing values and outlier treatment


Missing Treatment
No. of categories
% of Missing
Treatment
Variable
<=25
>25
<=50%
>50%
<=10%
>10% & <=50%
>50%
Impute with similar/closest bad rate group
If bad rate is very different from all other categories, then assign a special value and include in the regression analysis
Create a dummy / indicator variable with missing (as 1) vs. non missing category
Impute with the mean / median value
Assign a special value to the missing category in the original variable and create an indicator variable with missing value as 1 and others as 0
Create a dummy / indicator variable with missing value as 1 and others as 0

REGRESSION PROBLEMS: LINEAR REGRESSION

In this topic, we cover different types of regression models, assumptions and questions related to them, and the estimation method used commonly with regression models.

Q. What is regression analysis?

Ans: Regression analysis is a statistical technique for estimating the relationships among variables. It basically try to measure and identify the cause and effect relationship among the variables. Regression analysis comes indifferent flavors: Logistic, Multiple choice logistic, multinomial, multiple etc.

Q: What is meant by the term "linear regression"?

Ans: Linear regression is a statistical modeling technique that attempts to model the relationship between an explanatory variable and a dependent variable, by fitting the observed data points on a linear equation, e.g., modeling the body mass index (BMI) of individuals by weight.

A linear regression is used if there is a relationship or significant association between the variables. This can be checked by scatter plots. If no association appears between the variables, fitting a linear regression model to the data will not provide a useful model.

A linear regression line takes equations in the following form: **Y = a + bX,**

Where, X = explanatory variable and
Y = dependent variable.
b = slope of the line
a = intercept (the value of y when x = 0).

Q: What are the various assumptions that an analyst takes into account while running a regression analysis?

Ans: Regression analysis depends on the following assumptions:

- The relationship between the variables should be linear (or approximately linear) over the range of population being studied.
- Y variable in the regression analysis should be normal, i.e., should follow the normal curve (exactly or approximately).
- There should be no multicollinearity, i.e., the independent variables should not show correlation among themselves.
- There should be no autocorrelation in the data, i.e., the residuals should be independent of each other.
- The condition of homoscedasticity, i.e., the error terms or residuals along the regression, should be equal.
- Errors normal, Errors iid.

Q: How would you execute regression on Excel?

Ans: Regression on Excel can be performed by using three built-in functions to calculate slope, intercept, and R^2 values or by using the Regression function provided in the Data Analysis toolbar (after installing Analysis ToolPak add-ins). The built-in functions are SLOPE() , INTERCEPT() , and RSQ() .

Q: What is the multiple coefficient of determination or R-squared?

Ans: The multiple coefficient of determination, R^2, is a method by which to calculate the overall effectiveness (in terms of percentage similar to linear regression) of all the independent variables in explaining the dependent variable.
For example, if R^2 = 0.8, this means that the independent variables have 80% of the variation in the value of dependent variables.

Unfortunately, R^2 alone may not be a reliable measure of the accuracy of the multiple regression model, as R^2 increases every time a new variable is added in the model, even though the variable might not be statistically significant. If there is a large number of independent variables, the value of R^2 may be high, even though the variables do not explain the dependent variable that well. This problem is called overestimating the regression.

By adjusting the R^2 value for the number of independent variables, the problem of overestimating the regression can be overcome.

Q. What is the difference between R^2and AdjustedR^2?
Ans:

a) R2 is a statistic that will give some information about the goodness of fit of a model. In regression, the R2 coefficient of determination is a statistical measure of how well the regression line approximates all datapoints. An R2 of 1.0 indicates that the regression line perfectly fits the data.
b) R2 increases whenever we add a new independent variable, Adjusted R2 might increase or decrease based on the variable explanatory power. Too many independent variables can decrease the value of Adj R2
c) Adjusted R2 is a modification of R2 that adjusts for the number of explanatory terms in a model. Unlike R2, the adjusted R2 increases only if the new term improves the model more than would be expected by chance. The adjusted R2 can be negative, and will always be less than or equal to R2. Adjusted R2 is not always better than R2 : adjusted R2 will be more useful only if the R2 Is calculated based on a sample, not the entire population. For example, if our unit of analysis is a state, and we have data for all counties, then adjusted R2 will not yield any more useful information than R2

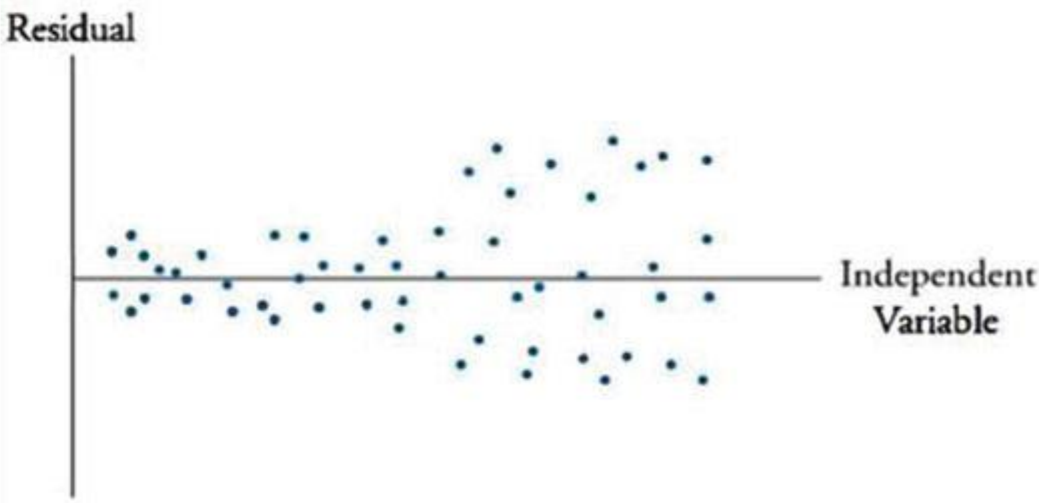
Q. Why do we minimize squares of deviations (OLSE – Ordinary lease square estimator) why cannot we use absolute differences?
Ans: It is hard to deal with absolute differences when you are differentiating and integrating.

Q: What is meant by "heteroscedasticity"?
Ans: When the variance of the residuals differs across observations in the sample, this is called heteroscedasticity. It is one of the errors in regression analysis that analysts have to test before running the regression analysis. One of the assumptions of multiple regression is that the variance of the residuals is constant across observations.

Q: How do you differentiate between conditional and unconditional heteroscedasticity?
Ans: Unconditional heteroscedasticity occurs in cases in which the level of independent variables does not affect heteroscedasticity, i.e., it doesn't change systematically with changes in the value of independent variables. Although this is a defilement of the equal variance assumption, it frequently causes no serious problems with the regression.
Conditional heteroscedasticity is heteroscedasticity that is related to the level of (i.e., conditional upon) the independent variables.

Q: What are the different methods of detecting heteroscedasticity?

Ans: There are two methods of detecting heteroscedasticity: examining scatter plots of the residuals, and using the Breusch-Pagan chi-square test. Plotting the residuals against one or more of the independent variables can help us spot trends among the observations.



The residual plot in the figure indicates the presence of conditional heteroscedasticity. Notice how the variation in the regression residuals increases as the independent variable increases. This indicates that the variance of the dependent variable about the mean is related to the level of the independent variable.

The more common way to detect conditional heteroscedasticity is the Breusch-Pagan test, which calls for the regression of the squared residuals on the independent variables. Independent variables contribute significantly in explaining squared residuals in case of conditional heteroscedasticity.

Q: What are the different methods to correct heteroscedasticity?

Ans: The most common remedy is to calculate robust standard errors. The t-statistics is recalculated using the original regression coefficients and the robust standard errors. A second method to correct for heteroscedasticity is to use generalized least squares, by modifying the original equation.

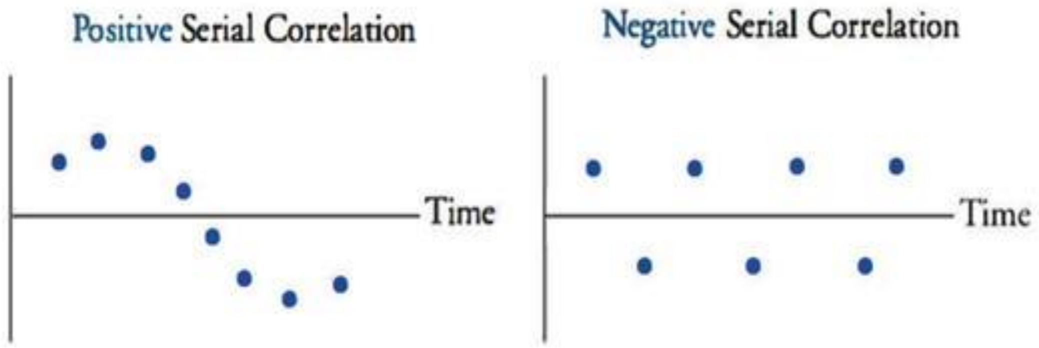
Q: What is meant by the term "serial correlation"?

Ans: Serial correlation, or autocorrelation, is the phenomenon commonly observed in time series data, in which there is a correlation between the residual terms. It is of two types: positive and negative.
When a positive regression error in one time period increases the probability of observing a positive regression for the next time period, this is a positive serial correlation. In a negative serial correlation, the positive regression error causes the probability of observing a negative error to increase.

Q: What are the different methods to detect serial correlation?

Ans: There are two methods that are commonly used to detect the presence of serial correlation: residual plots and the Durbin-Watson statistic.

A scatter plot of residuals vs. time, can reveal the presence of serial correlation.



Scatter plot of residuals vs. time indicating positive and negative serial correlations
The more common method is to use the Durbin-Watson statistic (DW) to detect the presence of serial correlation.

Q: What are the different methods to correct multicollinearity?

Ans: The most common method to remove multicollinearity is to omit independent variables having a high correlation with the variable set. Unfortunately, it is not always an easy task to identify the variable(s) that are the source of the multicollinearity. There are statistical procedures that may help in this effort, such as stepwise regression, which systematically removes variables until multicollinearity is reduced.

A summary of violations of the assumptions of multiple regression is offered in Table.

	Conditional Heteroscedasticity	**Serial Correlation**	**Multicollinearity**
What is it?	Residual variance related to level of independent variables	Residuals are correlated	High correlation among two or more independent variables
Effect?	Coefficients are consistent. Standard errors are underestimated. Too many Type I errors	Coefficients are consistent. Standard errors are underestimated. Too many Type I errors (positive correlation)	Coefficients are consistent (but unreliable). Standard errors are overestimated. Too many Type II errors
Detection?	Breusch-Pagan chi-square test	Durbin-Watson test	Conflicting t and F statistics; correlations among independent variables if k = 2
Correction?	Use White-corrected standard errors	Use the Hansen method to adjust standard errors.	Drop one of the correlated variables.

Q. What is MLE (maximum likelihood estimator?)

Ans: Used in estimating statistical parameters, It assumes a(NO) distribution of the parameter and maximize sits joint probability distribution, estimate is obtained at the point where probability distribution of parameter is maximum.

Starts with arbitrary values of the regression coefficients and constructs an initial model for predicting the observed data. Then evaluates errors in such prediction and changes the regression coefficients so as make the likelihood of the observed data greater under the new model. Repeats until the model converges, meaning the differences between the newest model and the previous model are trivial.

It assumes the distribution of the variable under consideration and finds out the parameters of that distribution by maximizing the likelihood function (JDF).

Q. When do you go for generalize d linear models (GLM)?

Ans: When above assumptions fail……. eg: errors are not normal; OR When you have discrete independent variable eg: yes/no; 1or0

Q. How do you find parameters of GLM (OLSE or MLE)?

Ans: MLE

Q. What is Multicollinearity?

Ans:

1) Multicollinearity refers to a situation in which two or more explanatory variables in a multiple regression model are highly correlated. We have perfect multicollinearity if the correlation between two independent variables is equal to 1 or-1. In practice, we rarely face perfect multicollinearity in a dataset. More commonly, the issue of multicollinearity arises when there is a high degree of correlation (either positive or negative) between two or more in depend invariables.
2) Multicollinearity is a statistical phenomenon in which two or more predictor variables in a multiple regression model are highly correlated. In this situation the coefficient estimates may change erratically in response to small changes in the model or the data. Multicollinearity does not reduce the predictive power or reliability of the model as a whole; it only affects calculations regarding individual predictors. That is, a multiple regression model with correlated predictors can indicate how well the entire bundle of predictors predicts the outcome variable, but it may not give valid results about any individual predictor, or about which predictors are redundant with others.

Q. How do you detect Multicollinearity and how will you remove it?

Ans: Multicollinearity is Interdependency of independent (predictor variables).

a) High Variance inflation factor (VIF)
b) High F but low t values
c) Conditional index (CI)

Use PCA or FA, Drop problematic variables, Ridge regression

Q. What is variance inflation factor (VIF)?

Ans: Each of the predictor variables is regressed upon other predict or vars. If that R-squared is high then this variable has co linearity with others.

Q. Why do we check for multi co-linearity in nonlinear regression models?
Ans: Model is nonlinear i.e: the regression coefficients are nonlinear not predictor variables, so there is a chance of co linearity relation between the predictor vars.

Q. What procedure do you use to fit regression model in SAS?
Ans: Procreg, proc glm

Q. What is the procedure for non-linear regression in SAS?
Ans: Proc logistic, Proc genmod.

Q. What is log-linear model?
Ans: Use log as link function instead of logit, which is used for Poisson response variable (y=0,1,2,3,…)

Q. How do you find good ness fit of your model in GLM?
Ans:

a) It's not R-square, here it is Chi-square.
b) Percent Correct Predictions
c) Hosmer and Lemeshow Goodness-of-Fit Test
d) ROC curves
e) Somers'D
f) Gamma
g) Tau-a
h) C
i) More than a dozen “R2”-type summaries.

Q. Why linear regression is called linear?
Ans: Because the output variable is modeled as a **linear** function of the input variables. The case of one explanatory variable is **called** simple **linear regression**. For more than one explanatory variable, the process is **called** multiple **linear regression**.

Q. What is Ks test?
Ans: In statistics, the Kolmogorov–Smirnov **test** (**KS test**) is a nonparametric **test** of the equality of continuous, one-dimensional probability distributions that can be used to compare a sample with a reference probability distribution (one-sample KS **test**), or to compare two samples (two-sample KS **test**).

Certainly! Here are the Ans. s to your questions:

Q. Can you define regression in layman terms?
Regression is a statistical technique that helps us understand the relationship between two or more variables. It allows us to predict or estimate the value of one variable based on the values of other variables.

Q. Why do you require regression?
Regression is used to analyze and understand the relationship between variables, make predictions or forecasts, identify significant factors, and determine the strength and direction of the relationship.

Q. Can you explain in what different situations you have used linear regression?

Linear regression has been used in various situations, such as predicting house prices based on features like size, location, and number of rooms, estimating sales based on advertising expenditure, analyzing the impact of education level on income, and determining the relationship between variables in scientific research.

Q. Explain the major steps in linear regression model building.

The major steps in linear regression model building include:

a. Defining the problem and selecting the relevant variables.
b. Collecting and preparing the data.
c. Exploratory data analysis to understand the relationship between variables.
d. Splitting the data into training and testing sets.
e. Selecting a suitable regression model.
f. Estimating the model parameters.
g. Evaluating the model's performance and making necessary adjustments.

Q. What are the basic assumptions of linear regression?

The basic assumptions of linear regression are:

a. Linearity: The relationship between variables is linear.
b. Independence: Observations are independent of each other.
c. Homoscedasticity: The variability of residuals is constant across all levels of predictors.
d. Normality: Residuals follow a normal distribution.
e. No multicollinearity: The predictors are not highly correlated with each other.

Q. What are the consequences when assumptions fail?

When assumptions fail, the estimated coefficients may be biased or inefficient, leading to incorrect conclusions or predictions. The model may not accurately represent the underlying data, and the statistical tests and inferences may be invalid.

Q. How do you test assumptions?

Assumptions can be tested using various methods:

a. Linearity: Scatter plots, residual plots, or partial regression plots.
b. Independence: Durbin-Watson test or visual inspection of residuals.
c. Homoscedasticity: Residual plots, the Breusch-Pagan test, or the White test.
d. Normality: Normal probability plots or Shapiro-Wilk test.
e. No multicollinearity: Correlation matrices or variance inflation factor (VIF) analysis.

Q. How do you define dependent variables & independent variables?

The dependent variable (also called the response variable) is the variable we want to predict or explain. Independent variables (also called predictors or explanatory variables) are the variables used to predict or explain the value of the dependent variable.

Q. How do you sample the data for validation?

Data can be sampled for validation by randomly splitting the dataset into training and testing sets. Another approach is using cross-validation techniques like k-fold cross-validation or holdout validation, where the data is divided into multiple subsets for training and testing.

Q. What is the global hypothesis in linear regression? How do you interpret it from the output?

The global hypothesis in linear regression tests the overall significance of the model by examining whether all the regression coefficients are simultaneously equal to zero. It assesses if there is a significant relationship between the independent variables and the dependent variable. The hypothesis is typically tested using the F-test, and if the p-value is below a certain significance level (e.g., 0.05), we can reject the null hypothesis and conclude that the model is significant.

Q. How do you interpret your linear regression SAS output? What are the different tables you look into the output to finalize the model?

In SAS output for linear regression, key tables to look into include the ANOVA table (for global hypothesis testing), coefficient table (for individual predictor significance and effect size), standard error table (for precision of estimates), and diagnostics table (for assessing assumptions and model fit). Interpretation involves examining the p-values, coefficients, standard errors, R-squared, and other statistics to assess the significance, direction, and strength of relationships.

Q. What is the importance of the constant in the equation?

The constant (intercept) in the equation allows for a baseline value of the dependent variable when all independent variables are zero. It accounts for the average value of the dependent variable when the predictors have no effect.

Q. What is VIF? And Condition Index? How do you calculate VIF/Condition Index?

VIF (Variance Inflation Factor) measures the extent of multicollinearity between predictor variables. It quantifies how much the variance of the estimated regression coefficients is inflated due to multicollinearity. VIF values greater than 1 indicate the presence of multicollinearity, with higher values indicating stronger collinearity. Condition Index is a measure of the severity of multicollinearity. VIF can be calculated by regressing each predictor against all other predictors and calculating the reciprocal of the tolerance. Condition Index is calculated using the eigen values of the correlation matrix.

Q. What are standardized Betas? How are they different from normal Betas?

Standardized Betas, also known as standardized regression coefficients, represent the standardized effect size of each predictor variable on the dependent variable. They indicate the change in the dependent variable (in standard deviation units) associated with a one standard deviation change in the predictor variable. Standardized Betas allow for direct comparison of the relative importance of predictors, regardless of the scale of the variables. Normal Betas, on the other hand, represent the change in the dependent variable associated with a one-unit change in the predictor variable.

Q. How do you test goodness of fit?

Goodness of fit in linear regression can be tested using various measures:

a. R-squared: It measures the proportion of variance explained by the model.
b. Adjusted R-squared: It adjusts R-squared for the number of predictors and sample size.
c. Residual analysis: Examining residual plots, such as scatter plots or histograms, to assess the distribution and patterns of residuals.
d. F-test: Testing the overall significance of the model.

Q. What is R-square/Adjusted R-square? How do you calculate R-Square & Adjusted R-Square?

R-squared (coefficient of determination) represents the proportion of the variance in the dependent variable that is explained by the regression model. It ranges from 0 to 1, where higher values indicate a better fit. Adjusted R-squared adjusts R-squared for the number of predictors and sample size, penalizing the addition of unnecessary predictors. Both R-squared and adjusted R-squared can be calculated from the sum of squares of the model and the sum of squares of residuals.

Q. What is t-value and p-value and their significance with respect to linear regression?
In linear regression, the t-value represents the ratio of the estimated coefficient to its standard error. It measures the significance of the relationship between each predictor variable and the dependent variable. The p-value associated with the t-value indicates the probability of observing the coefficient's value if the null hypothesis (no relationship) is true. Lower p-values indicate a higher level of significance, suggesting that the predictor variable is significantly related to the dependent variable.

Q. How do you validate linear models? What are the statistics you look for validation of models?
Linear models can be validated by assessing various statistics and diagnostics:

a. Residual analysis: Checking for patterns or trends in residual plots.
b. Normality of residuals: Examining the distribution of residuals.
c. Homoscedasticity: Assessing if residuals have a constant spread across different values of predictors.
d. Influential observations: Detecting outliers or influential data points.
e. Goodness of fit measures: Evaluating R-squared, adjusted R-squared, and F-test results.
f. Cross-validation: Assessing the model's performance on independent data.

Q. What is decile analysis? What is the importance of decile analysis in linear regression models?
Decile analysis involves dividing the data into ten equal groups based on the predicted values from a linear regression model. It allows for examining how well the model predicts the actual values across different segments of the data. Decile analysis helps assess model performance, identify potential biases or differences across subgroups, and gain insights into the predictive power of the model.

CLASSIFICATION TECHNIQUES

A classification technique plays an important role in the whole of analytics-based decision making. This is probably the most important group of techniques to be learned by an analytics professional. Also, given the breadth and depth of these techniques and their vast usage, you are bound to get many questions on this subject in a job interview. So, arm yourself with some basic concepts.

Further, I will delve into some analytics tools, such as R, SAS, and Tableau, which will surely come up in an interview. Besides, having some basic knowledge of databases, SQL, and big data will help you showcase an all-around knowledge of this subject.

I will also briefly touch upon big data, although it is not within the scope of this book.

Q: What is understood by “classification”?
Ans: Classification is the grouping of a data set, based on some predefined criteria. The criteria are usually based on some historic information, and classification tries to classify the data set, based on information received from that historic criteria.

An example: A company wants to have a database of 1 million customers in the United States, including their demographic information. It wants to identify the top 50,000 customers who have highest propensity to respond to an offer campaign.

The company’s analyst retrieves past data on response rates for a similar campaign on 200,000 customers. Their response rate is trained on a classification technique that tries to separate respondents with non respondents and also create a scorecard for the customers. The model is then executed on a 1-million-customer base, to classify respondents from non respondents and pick the top 50,000 respondents who should be sent the new campaign.

Other examples include

- Google identifying whether a mail is spam, based on its content and other information
- Assessing whether an employee would attrite, based on his/her past information

Q: Can you name some popular classification methodologies?

Ans: There are numerous classification techniques today. This is probably the most widely studied area and encompasses techniques that are so vast and differentiated from one another that the topic itself is mammoth in proportion.

Some of the more widely known techniques are

- Logistic regression
- Neural network
- Decision tree
- Random forest
- Discriminant analysis

Q: Briefly, what is understood by "logistic regression"?

Ans: Logistic regression is the technique of finding relationships between a set of input variables and an output variable (just like any regression), but the output variable, in this case, would be a binary outcome (think of 0/1 or yes/no).

For example: Will there be a traffic jam in a certain location in Bangalore? is a binary variable. The output is a categorical yes or no.

The probability of occurrence of a traffic jam can be dependent on such attributes as weather conditions, day of the week and month, time of day, number of vehicles, etc. Using logistic regression, we can find the best-fitting model that explains the relationship between independent attributes and traffic jam occurrence rates and predict the probability of jam occurrence.

Q: What is an odds ratio?

Ans: Odds is the relative occurrence of different outcomes, expressed as a ratio of the form a:b. For example, if the odds of an event are said to be 5:2 in favor of the first outcome, this means that the first outcome occurs five times for the second outcome to occur twice. Odds are related to probability and can be shown mathematically as follows:

Odds = a:b

Probability = a/(a+b)

Probability = Odds/(1 + Odds)

Odds = Probability/(1 - Probability)

Q: How is linear regression different from logistic regression?

Ans: Linear regression is applicable on numerical or continuous variables, but logistic regression is applicable when the dependent variable is categorical (a commonly dichotomous variable). The output of logistic regression is between 0 and 1, where 1 denotes "success" and 0 denotes "failure." But in linear regression, the output is continuous, which can assume any range of value.

Linear regression predicts numerical outputs, such as sales or profit, whereas logistic regression predicts dichotomous output, such as yes and no or living and dead.

Q. What is logistic regression, when do u use it?

Ans:

a) When basic assumption of regression fail,

b) When there is binary (categorical) response.

Q. Give an example where you can use logistic regression?

Ans:

a). Response/Non response

b). Good customer, Bad customer……all binary cases

Q: Can you give a brief overview of decision trees?

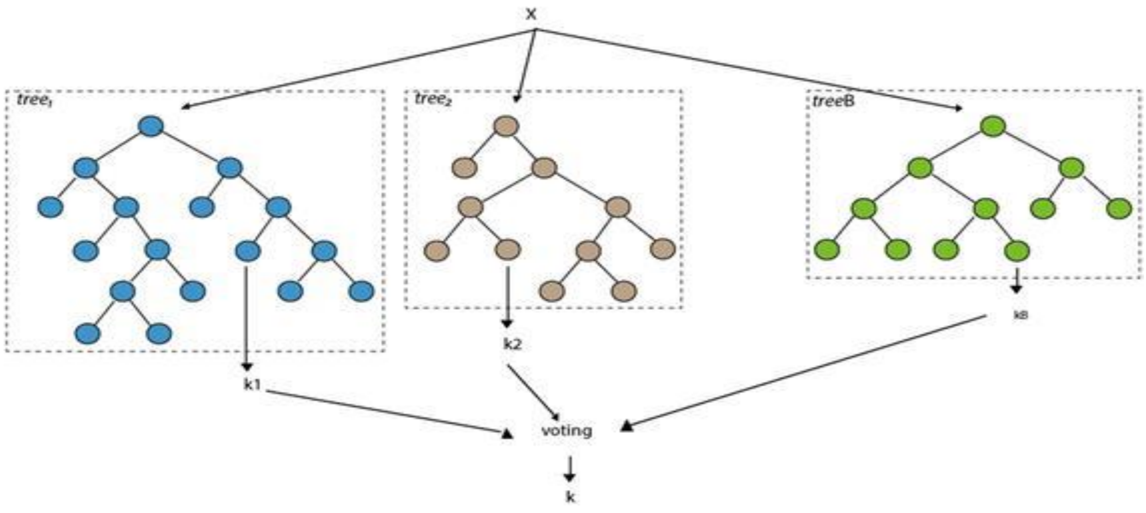
Ans: Decision trees, as the name suggests, are tree-shaped visual representations by which one can reach a particular decision, by laying down all options and their probability of occurrence. Decision trees are extremely easy to understand and interpret. At each node of the tree, one can interpret what the consequence of selecting that node or option will be.

Q: Can you explain briefly the random forest method of classification?

Ans: Random forest is currently the most accurate of all classification techniques available. Random forest is an ensemble method that works on the principle that many weak learners can come together to make a strong prediction. In this case, the weak learner is a simple decision tree, and random forest is strong learner.

Random forest optimizes the output from many decision trees formed from samples of the same data set. In general, the higher the number of trees, the better the accuracy of the resulting random forest ensemble will be. Yet, at higher numbers, the gain in accuracy decreases. So, the analyst has to decide on the number of trees, based on the cost of implementation that he/she will face with higher numbers of trees.

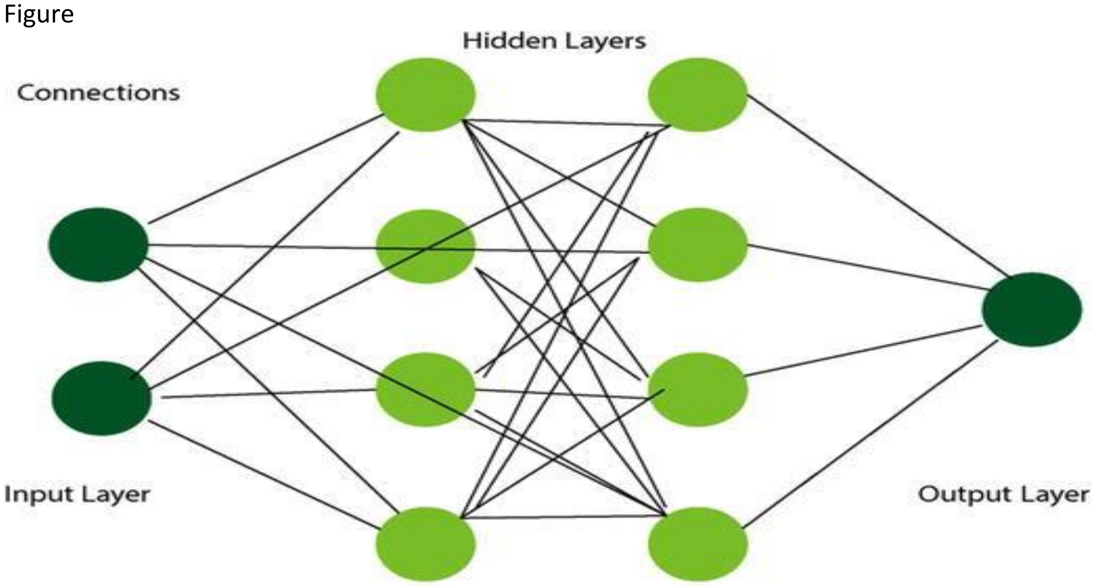
The trees are combined according to a voting mechanism. The voting is based on the success criteria of each tree. The best results are gained using a weighted approach, wherein the votes are weighted, based on the accuracy of individual trees.



Q: What is understood by “neural network”?

Ans: Neural network (also known as artificial neural network) is inspired by the human nervous system: how complex information is absorbed and processed by the system. Just as with humans, neural networks learn by example and are configured to a specific application.

Neural networks are used to find patterns in complex data, and thus can forecast and classify data points. Neural networks are normally organized in layers. Layers are made up of a number of interconnected nodes. Patterns are presented to the network via the input layer, which communicates to one or more hidden layers, in which the actual processing is done. The hidden layers then link to an output layer, where the Ans. is output, as shown in Figure



Q: How is neural network different from conventional computing?
Ans: Conventional computing comprises predefined instructions that form the building blocks of its processing system. Neural networks, on the other hand, do not have predefined steps to processing a system. Rather, they learn from past experiences to chart their own steps in processing.

Q: Can you explain discriminant analysis, in brief?
Ans: Discriminant analysis –based classification works according to the concept of analysis of variance (ANOVA), which is to test whether there is a significant difference between the mean of two or more groups with respect to a particular variable. If the mean of a variable is significantly different in different groups, it can safely be said that this variable classifies the data set into groups.
To extend this concept, MANOVA, or multivariate analysis of variance, can be executed to classify a data set based on multiple variables.

Q. What is purpose of discriminant analysis?
Ans: The main purpose of a discriminate function analysis is to predict group membership based on a linear combination of the interval variables. The procedure begins with a set of observations where both group membership and the values of the interval variables are known. The end result of the procedure is a model that allows prediction of group membership when only the interval variables are known. A second purpose of discriminate function analysis is an understanding of the dataset, as a careful examination of the prediction model that results from the procedure can give insight into the relationship between group membership and the variables used to predict group membership.

Q: How would you assess the performance of a classification model?

Ans: The performance of a classification model is assessed by a table called a confusion matrix. It is based on the count of records that are accurately predicted vs. counts of records incorrectly predicted.
Following table is a confusion matrix for a two-class problem.

		Predicted values	
		Class 1	**Class 2**
Actual Values	Class 1	A	B
	Class 2	C	D

Here, A is the number of records of Class 1 that are correctly predicted to be Class 1.B is the count of records of Class 1 that are incorrectly predicted to be Class 2. So, total correct predictions are A+D. Total incorrect predictions are B+C.
Accuracy of a model = Total correct predictions/Total records = A+D/A+B+C+D.
Error Rate of a model = Total incorrect predictions/Total records = B+C/A+B+C+D.
A robust classification model aims to increase the accuracy rate or decrease the error rate of a prediction.

Q. What is: lift, KPI, robustness, model fitting, design of experiments, 80/20 rule?
Ans:
Lift:
It's measure of performance of a targeting model (or a rule) at predicting or classifying cases as having an enhanced response (with respect to the population as a whole), measured against a random choice targeting model. Lift is simply: target response/average response.
Suppose a population has an average response rate of 5% (mailing for instance). A certain model (or rule) has identified a segment with a response rate of 20%, then lift=20/5=4
Typically, the modeler seeks to divide the population into quantiles, and rank the quantiles by lift. He can then consider each quantile, and by weighing the predicted response rate against the cost, he can decide to market that quantile or not.
"if we use the probability scores on customers, we can get 60% of the total responders we'd get mailing randomly by only mailing the top 30% of the scored customers".

KPI:
- Key performance indicator
- A type of performance measurement
- Examples: 0 defects, 10/10 customer satisfaction
- Relies upon a good understanding of what is important to the organization

More examples:
Marketing & Sales:
- New customers acquisition
- Customer attrition
- Revenue (turnover) generated by segments of the customer population
- Often done with a data management platform

IT operations:
- Mean time between failure
- Mean time to repair

Robustness:
- Statistics with good performance even if the underlying distribution is not normal
- Statistics that are not affected by outliers
- A learning algorithm that can reduce the chance of fitting noise is called robust
- Median is a robust measure of central tendency, while mean is not
- Median absolute deviation is also more robust than the standard deviation

Model fitting:
- How well a statistical model fits a set of observations
- Examples: AIC, R^2, Kolmogorov-Smirnov test, Chi^2, deviance (glm)

Design of experiments:
The design of any task that aims to describe or explain the variation of information under conditions that are hypothesized to reflect the variation.
In its simplest form, an experiment aims at predicting the outcome by changing the preconditions, the predictors.
- Selection of the suitable predictors and outcomes
- Delivery of the experiment under statistically optimal conditions
- Randomization
- **Blocking:** an experiment may be conducted with the same equipment to avoid any unwanted variations in the input
- **Replication:** performing the same combination run more than once, in order to get an estimate for the amount of random error that could be part of the process
- **Interaction:** when an experiment has 3 or more variables, the situation in which the interaction of two variables on a third is not additive

80/20 rule:
- Pareto principle
- 80% of the effects come from 20% of the causes
- 80% of your sales come from 20% of your clients
- 80% of a company complaints come from 20% of its customers

Q. What was the problem statement? Why were you creating the attrition model? What technique has been used? Initial questions were to judge knowledge about requirements understanding.

Ans. The problem statement was to develop an attrition model to predict the likelihood of employees leaving the organization. The primary goal was to proactively identify employees at risk of attrition and take necessary actions to retain them, thus reducing turnover and associated costs. The technique used for this task was logistic regression, a popular statistical method for binary classification problems.

Q. At what level did you build the model? (like customer level, branch level, etc.)

Ans. The model was built at the employee level, where each individual employee was considered as a separate observation, and the model predicted the likelihood of that specific employee's attrition.

Q. What was the hypothesis, and how did you check whether you can accept the hypothesis?

Ans: The hypothesis was that certain factors or variables could be indicative of an employee's likelihood of attrition. These variables might include factors like salary, job satisfaction, work-life balance, career growth opportunities, etc. To check the hypothesis, we conducted exploratory data analysis to identify patterns and correlations between these variables and the target variable (attrition). We then used statistical tests and feature importance techniques to determine whether these variables significantly contributed to the model's predictive power.

Q. Explain the steps used in modeling?

Ans: The steps used in modeling were as follows:

a. Data Collection: Gathered relevant data, including employee attributes and historical attrition records.

b. Data Preprocessing: Cleaned the data, handled missing values, and encoded categorical variables.

c. Feature Engineering: Created derived variables and performed variable transformations if required.

d. Model Building: Employed logistic regression to build the predictive model.

e. Model Validation: Split the data into training and validation sets, assessed the model's performance, and fine-tuned hyperparameters if needed.

f. Out-of-Time Validation: Validated the model's performance on a separate time period to check generalization.

g. Model Interpretation: Examined feature importance and model coefficients to understand the impact of variables on attrition prediction.

Q. How did you define the model target variable? Explain the steps, like for problem definition, how did you arrive at the attrition definition? What was the strategy you used, etc.? How much time did each step take?

Ans: The model target variable, in this case, was "attrition," which was binary (Yes/No). To define the target variable, we used historical employee records and identified those who had left the organization as "attrited" (1) and those who were still employed as "non-attrited" (0). The time spent on this step would depend on the data collection and the accuracy of attrition records available.

Q. What do you mean by the observation period, performance period, and lag period? Why is a lag period needed?

Ans: The observation period refers to the timeframe during which employee data was collected to build the model. The performance period is the subsequent timeframe during which the model's predictions are observed in the real-world scenario. The lag period is the time gap between the end of the observation period and the beginning of the performance period.

The lag period is needed to assess how well the model performs in a real-world scenario where predictions are made for new employees who were not part of the original dataset used to build the model. This allows us to measure the model's ability to generalize to unseen data.

Q. How many variables did you use?

Ans: The number of variables used in the model would depend on the data available and the feature selection process. Typically, we used a subset of relevant variables that showed significant correlations with the target variable and had a reasonable impact on the model's predictive power.

Q. Have you created any derived variables? What are they?

Ans: Yes, derived variables were created based on the available data. Examples of derived variables could include variables like "years of service" calculated from the employee's hire date and the current date, or "employee performance index" calculated based on performance ratings and tenure.

Q. Have you transformed the variables? In what situations have you used transformations? Why do you require variable transformation?

Ans: Variable transformations were performed in certain situations to improve the model's performance or address issues such as non-linearity or skewed distributions. Common transformations include logarithmic, square root, or inverse transformations. Transformations were applied when variables had skewed distributions, or when relationships between variables and the target variable were not linear.

Q. Explain the steps in data preparation?

Ans: The steps in data preparation typically include:
a. Data Cleaning: Handling missing values, correcting data inconsistencies, and removing duplicates.
b. Encoding Categorical Variables: Converting categorical variables into numerical representations suitable for modeling, such as one-hot encoding or label encoding.
c. Scaling and Normalization: Ensuring that variables are on a similar scale to prevent any dominance by variables with larger values.
d. Handling Outliers: Identifying and treating outliers if they exist, either by removing them or applying appropriate transformations.
e. Splitting into Training and Validation Sets: Dividing the dataset into two subsets for model training and performance evaluation.

Q. Explain the steps in variable reduction?

Ans: Variable reduction is the process of selecting a subset of relevant variables from the available pool. The steps involved in variable reduction may include:

a. Univariate Analysis: Assessing the individual relationship between each variable and the target variable.

b. Feature Importance: Utilizing techniques like statistical tests, information gain, or ensemble methods to determine the importance of variables in predicting the target.

c. Correlation Analysis: Identifying and removing highly correlated variables to avoid multicollinearity issues.

d. Stepwise Selection: Iteratively adding or removing variables based on their impact on the model's performance.

Q. Explain the model building and validation?

Ans: Model building involves training a predictive model using the selected variables and a suitable algorithm, such as logistic regression. The model is then validated to assess its performance. The validation process typically includes:

a. Splitting the Data: Dividing the data into training and validation sets, with a majority portion allocated for training and a smaller portion for validation.

b. Training the Model: Fitting the model on the training set using the chosen algorithm and hyperparameters.

c. Model Evaluation: Assessing the model's performance on the validation set using appropriate evaluation metrics, such as accuracy, precision, recall, or ROC-AUC.

d. Fine-tuning: Adjusting the model's hyperparameters, such as regularization strength or learning rate, to optimize its performance.

Q. How do you sample the data for training, validation, and out-of-time validation? How did you check correlation between your variables? What is multiple regression?

Ans: Data sampling for training and validation involves randomly splitting the available dataset into two sets, with a certain proportion allocated for training and the remaining portion for validation. Out-of-time validation involves using a separate dataset that represents a different time period to evaluate the model's performance on unseen data.

To check correlation between variables, we can calculate correlation coefficients, such as Pearson's correlation coefficient or Spearman's rank correlation coefficient. These coefficients measure the strength and direction of the linear relationship between variables.

Multiple regression is a statistical technique used to analyze the relationship between a dependent variable and multiple independent variables. It extends the concept of simple linear regression to account for multiple predictors simultaneously

Q. What are p-values, and why are they important in determining whether a variable is important for the model or not? Explain the concept of p-value in a non-technical way?

Ans: P-values are statistical measures that indicate the strength of evidence against a null hypothesis. In the context of modeling, p-values help determine the significance of a variable's contribution to the model. A lower p-value suggests stronger evidence that the variable has a significant impact on the model's predictions.

Think of the p-value as a measure of how likely it is that a variable's effect on the model's predictions is just due to random chance. A low p-value indicates that the observed relationship between the variable and the target variable is unlikely to occur by chance alone. Therefore, variables with low p-values are considered important for the model as they provide meaningful information and contribute significantly to its predictive power.

Q. What are the parameters that determine whether a logistic model is good or not?

Ans: Several parameters are considered to determine whether a logistic model is good or not:

a. Accuracy: The proportion of correctly classified instances by the model.

b. Precision: The ability of the model to correctly identify positive instances among the predicted positives.

c. Recall (Sensitivity): The ability of the model to correctly identify positive instances among the actual positives.

d. Specificity: The ability of the model to correctly identify negative instances among the actual negatives.

e. ROC-AUC: The area under the Receiver Operating Characteristic curve, which measures the overall performance of the model in distinguishing between positive and negative instances.

Q. If the model is not validating in out-of-time validation, what are the possible reasons for that?

Ans: If the model does not perform well in out-of-time validation, possible reasons could include:

a. Changes in the data distribution: The patterns and relationships present in the validation data might differ significantly from the training data due to changes in underlying factors or external influences.

b. Lack of generalization: The model might be overfitting to the training data, meaning it is too specific to the training examples and fails to capture the broader patterns necessary for generalization.

c. Non-stationarity: The relationship between variables and the target variable might change over time, making the model less effective when applied to a new time period.

d. Insufficient training data: The model might not have been trained on a representative and diverse enough dataset, leading to poor performance when faced with new examples.

Q. What is a misclassification matrix?

Ans: A misclassification matrix, also known as a confusion matrix, is a table that summarizes the performance of a classification model by counting the number of correct and incorrect predictions made by the model. It presents the predicted classes (e.g., attrited vs. non-attrited) against the actual classes, allowing us to assess the model's accuracy, precision, recall, and other evaluation metrics.

Q. What is concordance/discordance? How do you calculate them?

Ans: Concordance and discordance are terms used in survival analysis or time-to-event modeling. In the context of an attrition model, concordance refers to instances where the predicted attrition probabilities are correctly ordered relative to the actual attrition outcomes. Discordance occurs when the predicted probabilities are incorrectly ordered.

The concordance index (C-index), also known as the concordance statistic or area under the ROC curve for survival models, quantifies the proportion of concordant pairs among all possible pairs of observations. It ranges from 0.5 (no concordance, equivalent to random predictions) to 1 (perfect concordance).

Q. What is Somers's D, and how is it different from Gini?

Ans: Somers's D is a measure of rank correlation often used in logistic regression to assess the predictive power of a model. It evaluates the agreement between the predicted probabilities and the actual outcomes, ranging from -1 to +1. A value of 0 indicates no association, while values closer to +1 indicate strong positive correlation.

Gini, on the other hand, is a measure used to evaluate the performance of models, typically in binary classification problems. It represents the area between the Receiver Operating Characteristic (ROC) curve and the diagonal line (indicating random guessing). The Gini coefficient ranges from 0 to 1, with a higher value indicating better discrimination power of the model.

Q. What is the p-value, and what are Type I and Type II errors in logistic regression modeling?

Ans: The p-value is a statistical measure that indicates the strength of evidence against a null hypothesis. In logistic regression modeling, the p-value associated with each variable assesses whether the variable has a significant impact on the model's predictions.

Type I error refers to incorrectly rejecting the null hypothesis when it is actually true. In logistic regression, this would mean considering a variable as significant when it does not truly have an impact on the target variable.

Type II error, on the other hand, refers to failing to reject the null hypothesis when it is actually false. In logistic regression, this would mean considering a variable as insignificant when it does have a significant impact on the target variable.

Q. What is AIC/BIC? How are they helpful in model building?

Ans: AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) are statistical measures used to compare different models and select the best-fitting model.

AIC and BIC take into account both the goodness-of-fit of the model and the complexity of the model (number of variables or parameters). Lower values of AIC and BIC indicate a better balance between model fit and complexity. These criteria help in selecting the most appropriate model that maximizes predictive power while minimizing the risk of overfitting.

Q. What is bootstrapping, and how is it used?

Ans: Bootstrapping is a statistical technique used to estimate the uncertainty or variability of a model's performance metrics. It involves repeatedly sampling observations from the dataset with replacement to create multiple bootstrap samples. These samples are used to calculate performance metrics such as accuracy, precision, or ROC-AUC, and their distribution provides an estimate of the variability in the model's performance.

Bootstrapping is useful when the available dataset is limited, as it allows us to generate additional pseudo-samples and obtain more robust estimates of performance metrics.

Q. What is the Hosmer-Lemeshow test, and what is its use?

Ans: The Hosmer-Lemeshow test is a statistical test used to assess the goodness-of-fit of a logistic regression model. It evaluates whether the observed outcomes match the predicted probabilities of the model. The test divides the predicted probabilities into groups (usually deciles) and compares the observed and expected frequencies within each group.

The Hosmer-Lemeshow test helps determine whether the model's predictions align well with the actual outcomes. A significant p-value from the test suggests poor model fit, indicating the need for model improvement or reassessment of the chosen variables.

Q. What is multicollinearity? What are the consequences of multicollinearity in logistic regression?

Ans: Multicollinearity refers to a high degree of correlation between two or more independent variables in a logistic regression model. It indicates that these variables are measuring similar or redundant information, making it difficult for the model to estimate their individual effects accurately.

Consequences of multicollinearity in logistic regression include:

a. Unreliable coefficients: Multicollinearity makes it challenging

to interpret the coefficients of the correlated variables accurately. The coefficients can become unstable and have counterintuitive signs or magnitudes.

b. Reduced statistical significance: Multicollinearity inflates the standard errors of the coefficients, leading to wider confidence intervals and reduced statistical significance. It becomes harder to determine the variables that are truly important for the model.

c. Overfitting: Multicollinearity can lead to overfitting, as the model may fit the noise or redundancy in the data rather than the true underlying relationships. This reduces the model's ability to generalize to new data.

Q. What is ROC, and what is its use?

Ans: ROC stands for Receiver Operating Characteristic. It is a graphical plot that illustrates the performance of a binary classification model across different classification thresholds. The ROC curve plots the True Positive Rate (sensitivity) against the False Positive Rate (1 - specificity) at various threshold settings.

The ROC curve is useful for assessing the trade-off between the true positive rate and the false positive rate, allowing the model's performance to be evaluated at different decision thresholds. The area under the ROC curve (ROC-AUC) provides a single metric to compare the overall performance of different models. A higher ROC-AUC indicates better discrimination power of the model in distinguishing between positive and negative instances.

Q. What is sensitivity and specificity? What is their use?

Ans: Sensitivity and specificity are performance measures used to evaluate the accuracy of a binary classification model.

Sensitivity, also known as the True Positive Rate, measures the proportion of actual positive instances correctly identified by the model. It indicates the model's ability to detect positive instances.

Specificity, on the other hand, measures the proportion of actual negative instances correctly identified by the model. It indicates the model's ability to correctly classify negative instances.

Both sensitivity and specificity are important in assessing the overall performance of a model. They provide insights into how well the model is able to identify both positive and negative instances correctly.

Q. What is the difference between in-time validation and out-of-time validation?

Ans: In-time validation refers to evaluating the model's performance on a portion of the available data that was not used for model training, but it belongs to the same time period or data distribution. It helps assess how well the model performs on unseen instances within the same time period.

Out-of-time validation, on the other hand, involves evaluating the model's performance on a separate dataset that represents a different time period. It tests the model's ability to generalize to new instances or future data, providing an indication of its predictive power beyond the training period.

Q. What is overfitting, and what are the consequences of it?

Ans: Overfitting occurs when a model performs extremely well on the training data but fails to generalize well to new, unseen data. It happens when the model captures noise or random fluctuations in the training data rather than the true underlying patterns.

Consequences of overfitting include:
a. Poor generalization: An overfitted model may perform poorly on new, unseen data as it has learned noise or irrelevant patterns specific to the training set.
b. Reduced interpretability: Overfitting can lead to complex models that are difficult to interpret, as they try to fit every data point rather than capturing the true underlying relationships.
c. Sensitivity to noise: Overfitting makes the model sensitive to small changes in the training data, resulting in unstable predictions.
d. Increased complexity: Overfitted models often have an excessive number of variables or complex relationships, making them harder to interpret and potentially increasing the risk of multicollinearity.

Q. How do you implement the model or score the population or database?

Ans. To implement the model and score a population or database, you typically follow these steps:
a. Preprocess the data: Apply the same preprocessing steps used during model training, such as handling missing values, encoding categorical variables, and scaling numerical variables.
b. Extract relevant variables: Select the variables required by the model for prediction. Exclude any variables not used in the final model.
c. Apply any necessary transformations: Apply the same transformations (e.g., logarithmic, square root) to the variables as used during model training.

d. Calculate predicted probabilities: Use the logistic regression model to calculate the predicted probabilities of the target variable (e.g., attrition) for each individual or record in the population or database.

e. Classify individuals: Apply a decision threshold (e.g., 0.5) to convert the predicted probabilities into binary predictions (e.g., attrited or non-attrited) based on the model's objective.

f. Generate output: Provide the scored population or database with the predicted classes or probabilities, allowing further analysis or decision-making based on the model's predictions.

MODEL BUILDING

1. Checking Avaibility of observations
2. Descriptive Statistics
3. Outlier Treatment
4. Missing value Treatment
5. Create New variable
6. Variable Analysis and Reduction
7. Splitting the data set into development and validation
8. Model building
9. Analysis

Checking Avaibility of observations:

- Total number of observations
- Number of available observations
- Percentage of Available observation
- Number of missing observations
- Percentage of missing observations
- Number of positive values
- Number of negative Values
- Number of observations with zero value

Descriptive Statistics

- Minimum value
- Maximum value
- Mean
- Median
- Standard deviation
- Skewness
- Kurtosis

Outlier Treatment

How to Detect Outliers

- Dot plot or Scatter plot
- Box plot

What Should We Do About Them?

- Transformation
- Deletion
- Winsorised Mean
- Trim med Mean

Missing value Treatment

- Dropping variables (when more than70 % of the data are missing, if the variable is very important we will go up to 60%)
- List wise/Case wise deletion
- Business Ratios and using ranges to cap/delete observation
- Nominal variables: Treat missing data as just another category
- Substituted (plugged in) values, i.e. (Single)Imputation
  1. Mean
  2. Subgroup Mean
  3. Median
  4. Subgroup Median
  5. A regression estimate
- Maximum Likelihood Estimation and Multiple Imputation

Variable Analysis and Reduction

- Chi-squared statistic
- Information value
- Spearman rank order correlation co efficient
- Clustering techniques
- Multicollinearity check
  1. Correlation Matrix(Rvaluemustlie between-0.4and 0.4,ideally)
  2. Tolerance(shouldbemorethan0.4,ideally)
  3. Variance Inflation Factor(should belessthan2.5,ideally)

Splitting the Data set into Development and Validation Sample

Development Sample(80%ofthe full file)Validation
sample(20%ofthefull file)
*Situation may change if the number of observation in the full dataset is small

FACTOR ANALYSIS

Q. Why do we do Factor analysis?

Ans: To reduce the number of variables for a better presentation of the key factors.

Q: What is understood by dimension reduction techniques?

Ans: Dimension (variable) reduction techniques aim to reduce the data set with higher dimension to one of lower dimension, without the loss of feature of information that is conveyed by the data set. The dimension here can be conceived as the number of variables that a data set contains.

With the advent of big data and the ability to process and store large amounts of data, organizations today try to store as much data as possible. This leads to an increase in the attributes that are stored. Think of it as a database table that increases not just in rows but also in terms of columns (variables).

For data scientists creating appropriate models, not all variables are relevant. In addition, large multicollinearity, which diminishes model performance, may be encountered. Variable reduction techniques help weed out this issue. Also, the model is much more crisp in terms of being able to be understood and explained and is less costly (uses less computational resources).

Dimension reduction techniques are almost always executed as a precursor to another technique, such as regression. It is a way to speed up model-building without compromising on the potential of a model.

Q: What are some commonly used variable reduction techniques?

Ans: Two commonly used variable reduction techniques are:

- Principal component analysis (PCA)
- Factor analysis

Q: Can you provide a brief overview of principal component analysis?

Ans: The crux of PCA lies in measuring the data from the perspective of a principal component. A principal component of a data set is the direction with largest variance. A PCA analysis involves rotating the axis of each variable to the highest eigenvector/eigenvalue pair and defining the principal components, i.e., the highest variance axis or, in other words, the direction that most defines the data. Principal components are uncorrelated and orthogonal.

Q: Can you provide a brief overview of factor analysis?

Ans: The key concept behind factor analysis is the presence of a latent variable that stores much of the information of a set of variables in a data set. For example, a group of respondents can Ans. questions relating to income, education, and spending similarly, because they are in the same socioeconomic category.
In factor analysis, we define factors that are the same in number as the number of variables in a data set. Each factor captures a certain amount of variance in each variable. The eigen value is the measure of how much variance of observed variables is captured by a factor.

All factors are sorted in their descending order of value. The factors with low value are discarded, and top factors are retained as factors that explain most variance in the observed variance. It is helpful to know the number of factors in advance.

Q. What is use of factor analysis?

Ans: Factor analysis is used to uncover the latent structure (dimensions) of a set of variables. It reduces attribute space from large number of variables to smaller number of factors and as such is a "non-dependent" procedure (that is, it does not assume a dependent variable is specified). Factor analysis could be used for any of the following purposes:

- To reduce a large number of variables to a smaller number of factors for modeling purposes, where the large number of variables precludes modeling all the measures individually. As such, factor analysis is integrated in structural equation modeling(SEM), helping confirm the latent variables modeled by SEM. However, factor analysis can be and is often used on a stand-alone basis for similar purposes.
- To establish that multiple tests measure the same factor, thereby giving justification for administering fewer tests. Factor analysis originated a century ago with Charles Spearman's attempts to show that a wide variety of mental tests could be explained by a single underlying intelligence factor (a notion now rejected, by the way)
- To validate a scale or index by demonstrating that its constituent items load on the same factor, and to drop proposed scale items which cross-load on more than one factor.
- To select a subset of variables from alargerset, based on which original variables have the highest correlations with the principal component factors.
- To create a set of factors to be treated as uncorrelated variables as one approach to handling multicollinearity in such procedures as multiple regression
- To identify clusters of cases and/or outliers.
- To determine network groups by determining which sets of people cluster together (using Q-mode factor analysis, discussed below)

Q. What are the different types of rotation in Factor loading?

Ans:

a. Varimax rotation is an orthogonal rotation of the factor axes to maximize the variance of the squared loadings of a factor (column) on all the variables (rows) in a factor matrix, which has the effect of differentiating the original variables by extracted factor. Each factor will tend to have either large or small loadings of any particular variable. A varimax solution yields results which make it as easy as possible to identify each variable with a single factor. This is the most common rotation option.

b. Quartimax rotation is an orthogonal alternative which minimizes the number of factors needed to explain each variable. This type of rotation often generates a general factor on which most variables are loaded to a high or medium degree. Such a factor structure is usually not helpful to the research purpose.

c. Equimax rotation is a compromise between Varimax and Quartimax criteria.

d. Direct oblimin rotation is the standard method when one wishes a non-orthogonal (oblique) solution–that is, one in which the factors are allowed to be co-related. This will result in higher eigen values but diminished interpretability of the factors. See below.

e. Promax rotation is an alternative non-orthogonal (oblique) rotation method which is computationally faster than the direct oblimin method and therefore is sometimes used for very large datasets.

Q: What is factor loading?

Ans: Each factor in a data set defines the latent variable, in other words, the underlying variable that defines a set of variables in a data set. Factor loading describes the relationship or association between each variable and each factor. Higher association indicates that the factor can be used to describe that variable.

An example: While analyzing 70 variables that affect customer churn, a factor analysis was run, and because 70 variables were used for this analysis, the algorithm gave 100 factors. On observing the factor loading, it is found that demographic variables have high loading for one specific factor. So, these variables are combined into one factor, and so on, for other variables.

Factor loading is an important parameter to assess factor-variable dependence.

SEGMENTATION

Q: What is Segmentation?
Ans: Segmentation is the process of dividing a data set into clearly differentiated groups, relevant to a particular business. Companies segment their customers into different clusters to decide how to create differentiated strategies for each cluster and to maximize the value of the business.

But segmentation is not just used for customer analytics; it can be used for myriad other solutions. We might want to segment geographical areas based on their population density, or employees on their propensity to attrite.

Segmentation algorithms (also known as clustering algorithms) are very common, and the chances are extremely high that you will be tested on these concepts in an interview. In this chapter, I will go through some common interview questions related to segmentation and clustering.

Q: What are supervised and unsupervised learning algorithms? How are they different from each other?
Ans: Supervised and unsupervised learning algorithms are the two broad classifications for all statistical algorithms. The major difference between the two is how outputs to a model are defined. Keeping this segregation in mind helps an analyst to better choose which kind of problem-solving is best suited to a situation.

In supervised learning, model defines the cause and effect of inputs on given outputs. In other words, the inputs define what we are looking for in a model. So, in supervised learning models, we focus the model on existing relationships between inputs and outputs, to define and predict the unknown.
For example, in all classification techniques, we know from historic data what the different categories in dependent variables are. The goal of these techniques is not to come up with categories but to define them and how they are dependent on independent variables.

In unsupervised learning, the output of the model is not defined. The unsupervised learning models are used to define what our output looks like. Clustering techniques are a classic example of unsupervised learning. Here, we do not have the clusters (output) beforehand; rather, the model comes out with the clusters based on the input and criteria.

Q: Can you give an example to differentiate between supervised and unsupervised learning algorithms?
Ans: The example I'll use here is face recognition.

- Supervised learning: Learning, from examples, what a face is, in terms of structure, color, etc., so that after several iterations, the algorithm can define a face.
- Unsupervised learning: Because the example provided does not yield a desired output, categorization is undertaken, so that the algorithm differentiates correctly between the face of a horse, cat, or human (clustering of data).

Q: What are some of the supervised and unsupervised algorithms?
Ans: All classification algorithms fall under the supervised category. Following is a list of a few classification techniques:

- Naïve Bayes
- Support vector machine
- Ensemble Learning (Random forest, Bagging, Boosting)
- Decision tree
- Logistic regression
- K-Nearest Neighbors

Etc.

All Regression algorithms fall under the supervised category. Following is a list of a few regression techniques:

- Linear regression
- Decision trees (Regression)
- Ensemble learning (Random Forest, Bagging, Boosting)
- K-Nearest Neighbors

Etc.

All segmentation algorithms and variable reduction algorithms (such as those in the following list) fall under the unsupervised category.

- K-means
- Fuzzy clustering
- Hierarchical clustering
- DBSCAN
- Spectral Clustering
- Factor analysis
- Association Analysis (Market Basket Analysis)

Q. Tell us something about cluster analysis?

Ans: Cluster analysis or clustering is the assignment of a set of observations into subsets (called clusters) so that observations in the same cluster are similar in some sense. Clustering is a method.

- To validate a scale or index by demonstrating that its constituent items load on the same factor, and to drop proposed scale items which cross-load on more than one factor.
- To select a subset of variables from a larger set, based on which original variables have the highest correlations with the principal component factors.
- `To create a set of factors to be treated as un correlated variables as one approach to handling multi collinearity in such procedures as multiple regression
- To identify clusters of cases and/or outliers.
- To determine network groups by determining which sets of people cluster together (using Q-mode factor analysis, discussed below)

Q: How is clustering defined?

Ans: Clustering (or segmentation) is a kind of unsupervised learning algorithm in which a data set is grouped into unique, differentiated clusters.

Let's say we have customer data spanning 1,000 rows. Using clustering, we can group the customers into differentiated clusters or segments, based on the variables. In the case of customers' data, the variables can be demographic information or purchasing behavior.

Clustering is an unsupervised learning algorithm, because the output is unknown to the analyst. We do not train the algorithm on any past input-output information, but let the algorithm define the output for us. Therefore (just like any other modeling exercise), there is no right solution to a clustering algorithm; rather, the best solution is based on business usability.

Q: What are the two basic types of clustering methods?

Ans: There are two basic types of clustering techniques:

- Hierarchical clustering
- Partitional clustering

Q: How is hierarchical clustering defined?

Ans: Hierarchical clustering attempts to either merge smaller clusters into larger ones or break larger clusters into smaller ones. The basic rule at the core of this technique is deciding how two small clusters are merged or which large cluster is split. The final outcome of the algorithm is a tree of clusters called a dendrogram, which displays how the clusters are related. By splitting the dendrogram at a chosen level, a clustering of the data set into separate groups is achieved.

As shown in Figure, the dendrogram is split at various levels to come up with the required number of clusters.

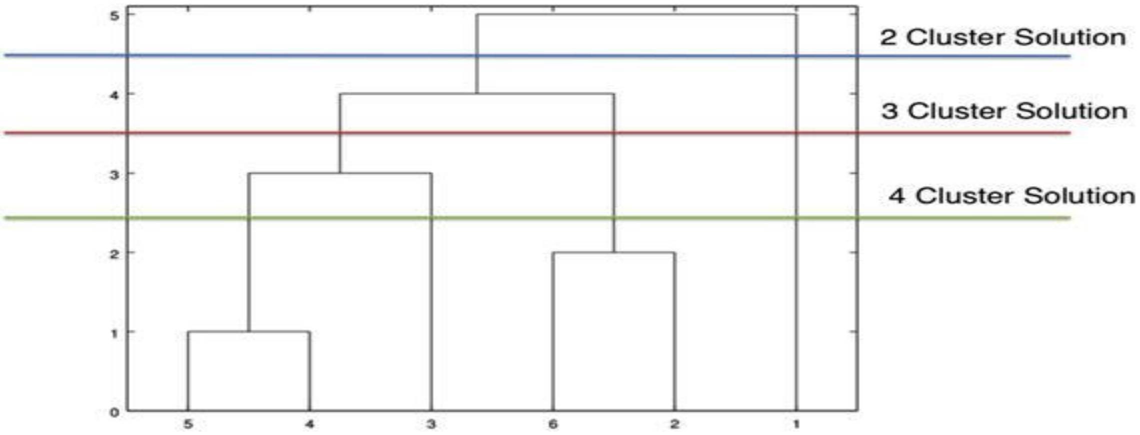


Figure: Dendrogram and cluster solutions

Q: How is partitional clustering defined?

Ans: Partitional clustering works to directly decompose the data set into a set of differentiated clusters. The core rule here is to minimize some measure of dissimilarity in the samples within each cluster, while maximizing the dissimilarity of different clusters.

For example: At most times, researchers try to reduce the within-cluster variance and increase variance between the cluster. A good measure is to take the ratio of the 2 measure and maximize it to ascertain the right number of clusters.

Q: What is meant by “exclusive clustering”?

Ans: This is the most common type of clustering, in which each object or data point belongs exclusively to only one cluster. This is also the most desired form of clustering, in most cases. For example, it would be necessary for a customer to be part of only one segmentation group, so that a unique, dedicated, and exclusive marketing effort could be formulated as part of a campaign.

Q: What is non-exclusive or overlapping clustering?

Ans: Often, if not always, an object can be part of more than one cluster. These are mostly borderline objects, in which we define the boundaries of clusters to overlap each other.

An example is demographic clustering, in which students can be part of both a student cluster and a high-spender cluster, which would be rare.

Q: What is the concept behind fuzzy clustering?

Ans: Rather than an object being part of clusters only (one-to-one mapping), an object can be part of all clusters, with varying degrees of membership. We call this type of clustering fuzzy clustering.

Each object is given a score (between 0 and 1) that depicts the degree to which an object is part of a specific cluster. An example is the cluster of employees on the basis of their skill sets. An employee can possess all skill sets but exhibit varying degrees of competency in each.

Q: Can you differentiate between a complete vs. a partial clustering?

Ans: In a complete clustering, all objects in the data sets are forced to be part of a cluster. Even when there are outliers in the data sets, they are definitely attached to a cluster or are clusters in themselves.

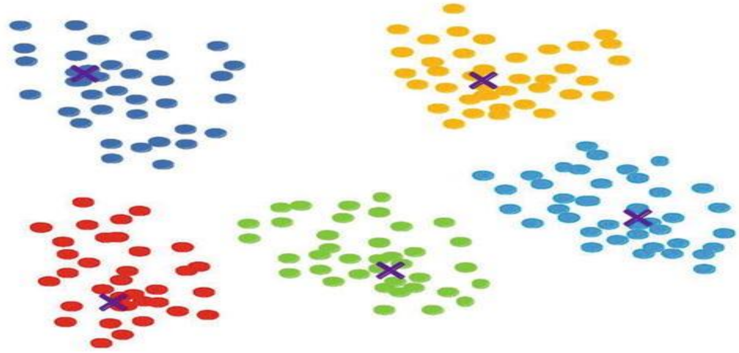
On the other hand, in a partial cluster, all data points are not necessarily part of a cluster. An example of this can be employees with different skill sets. An employee can be part of more than one cluster of skills.

Q: What is meant by "k-means clustering"?

Ans: K-means is the most widely used clustering algorithm in industry. The reason for its popularity is based on the fact that it's both easy to execute and understand.

At the crux of it, k-means clustering identifies random means centers in data sets and attributes cluster membership around those means.

As shown in Figure, random points are determined which later form the cluster centers.



Q: What is the basic algorithm of k-means clustering, in layperson's terms?

Ans: We first choose the k random means from our data sets. K is the number of clusters that we would like to finally extract from our data set.

Now, each data point is attached to each mean that we have chosen, based on the proximity of that data point to the mean. The group of all these data points with their respective mean will form a cluster.

We then recompute the mean for each computed cluster. The preceding steps are rerun until the recomputed means of all clusters are correctly determined.

Q: What is the proximity measure that you take in k-means clustering?

Ans: There are various proximity measures that can be employed. Euclidean distance is one such measure that is heavily used. It is simply the ordinary distance between two points. Other measures include Taxicab metric, Manhattan distance, and Jaccard measure.

Q: What differentiates a k-means from a k-median? When would you use k-median as opposed to k-means?

Ans: A k-median employs median as the centroid metric, as opposed to the means used in a k-means technique. The basic reason someone would use a k-median rather than a k-means is generally the same as that for using a median. To a large extent, the presence of outliers tends to skew the centroid of a data set. An analyst should be able to judge whether outliers are true representatives of a data set. If they are, then using k-means would be preferred; otherwise, a k-median is used.

Q: What are some of the limitations of the k-means clustering technique?
Ans: The biggest limitation with the k-means technique is inherent in the way it is calculated. The user is required to know beforehand the number of clusters that he or she intends to extract from the data set. This can be both a positive and a negative. It can be positive, because the algorithm is forced to give out the number of clusters that the user requires for business execution, irrespective of whether there is a better cluster solution.

On the other hand, it is a limitation, because the user is not informed whether there is a better cluster solution for the data set. A seven-cluster solution might be better than a four-cluster solution. Analysts usually run all cluster solutions and then pick the one that is most efficient or makes most business sense.

The other biggest issue with the k-means technique is the fact that the algorithm can give different results in different iterations. This is because of the way this technique is designed. Because the first step involves identifying random centroid values, each iteration would have different values and thus can give different results.

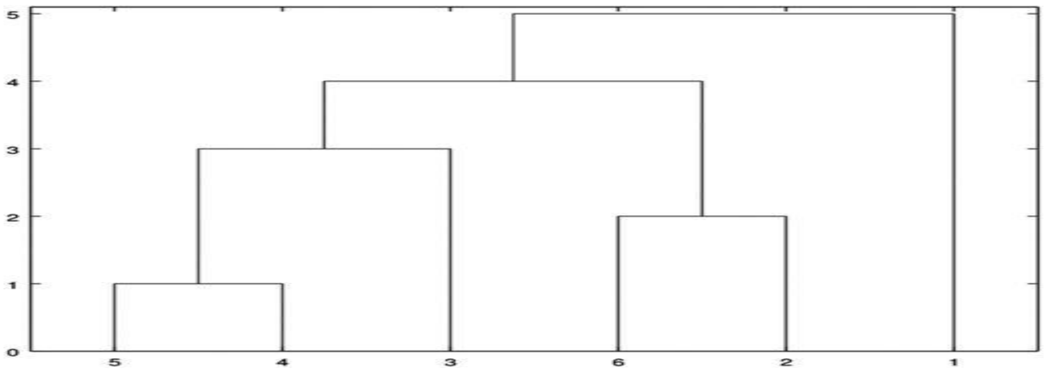
Q: Given that each iteration of k-means gives us different results, how would you ensure picking the best results?
Ans: This is done by calculating the SSE for each iteration. SSE stands for sum of squared error. SSE is calculated by first determining the distance between each data point and closest computed centroid and then summing all these distances. A smaller SSE represents a better solution.

Q: What are the two types of hierarchical clustering?
Ans: The two types are

- Agglomerative clustering
- Divisive clustering

Q: What is the difference between agglomerative vs. divisive clustering?
Ans: The main difference lies in how the initial group is defined. In agglomerative clustering, each data point is considered a cluster of its own. In each iteration, the data points are merged to form clusters that eventually form one big cluster containing all data points. Consider this a bottom-up approach.
On the other hand, divisive clustering is a top-down approach, in which all data points are initially considered part of one big cluster and then eventually broken into sub-clusters. Finally, the optimal number of clusters is derived.

Q: What is a dendrogram?
Ans: A dendrogram is a graphical representation of data sets and their cluster membership, using a tree-like diagram. Each vertical line represents either a data point or a cluster. The bottom-most vertical lines represent a data point. As we subsequently move up the diagram, the vertical lines merge (finally, into one), to reveal the cluster formation.



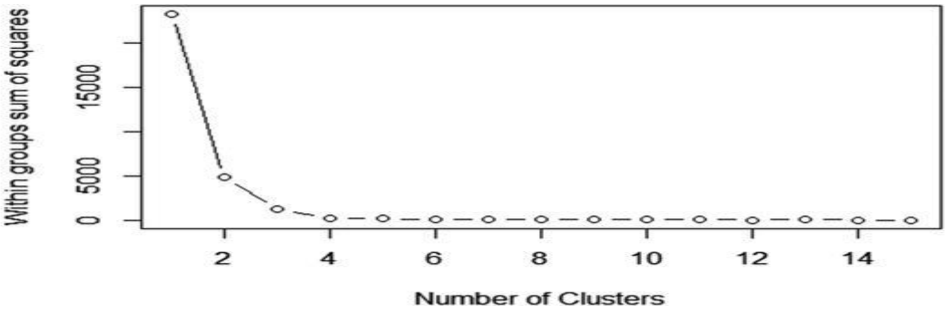
Q: What is the basic algorithm behind the agglomerative clustering technique?
Ans: First, consider all data points as a separate cluster. Then, using a proximity measure, define the proximity between all clusters. Combine clusters that are closest. Repeat this until only one cluster is left.

Q: Can you briefly explain some of the proximity measures that are used in hierarchical clustering techniques?
Ans: There are numerous proximity measures used in the clustering techniques. Min defines cluster proximity as the minimum distance between the closest two points in the clusters, whereas max defines cluster proximity as the maximum distance between any two points.
Group average refers to the average of all pair-wise distance between the points in the clusters.
An alternative technique, Ward's method, is more widely used.

Q: What is Ward's method of defining cluster proximity?
Ans: Ward's method is very similar to the k-means method of finding optimal cluster numbers. It measures the proximity by the increase in SSE when two clusters are merged. In other words, it reduces the sum of squared errors while clusters are joined together.

Q: How do you determine the optimal number of clusters for a data set?
Ans: A clustering technique is both an art and a science. Determining the optimal number of clusters is a crucial part of a clustering technique, and it is different from the actual clustering itself.
Determining optimal clusters requires consideration of both the technical aspects as well as the business aspects.
Technical Methods: Dendogram, Elbow method
Statistical Metrics: Silhouette coefficient (SC value), Pseudo F-value, Cubic Clustering Criteria etc
Business Aspects: Using Profiling, you can check which solution is differentiating
Best Practices: Looking at cluster size (should not have very big or very small clusters)

Q: Can you briefly explain the elbow method to determine the optimal cluster solution?
Ans: An elbow plot is a graph drawn from a number of clusters on an x axis and the SSE of each cluster solution on a y axis. We also call this a hockey stick graph, because the curve bends sharply, like an elbow point. We consider the point on the bend of the x axis as the optimal cluster solution.



In the above figure, we notice that the curve bends sharply at cluster number 4.The incremental reduction in error terms, while increasing the number of cluster solutions after 4, is very low. Thus, we consider 4 as the optimal cluster solution.

Q: What is the business aspect of determining the optimal cluster solution?
Ans: A clustering algorithm only segments a data set into various clusters, in which data sets are closer together, based on various attributes. Defining these clusters into meaningful definitions and identifying usage and business strategy around them is something that an analytical person or data scientist brings to the mix.

Each cluster identified by an algorithm should have a business meaning. For example, demographic segmentations can yield clusters that are meaningless for business usage. Also, clustering solutions cannot identify segments that actually have some meaning. For example, attributes with absolute zero values cannot be identified by the algorithm, as they almost always cluster data sets in a vicinity.

This is where the business aspect of the solution comes into the picture. Most of time, analysts come out with a high number of optimal cluster solutions, using technical aspects. Then they merge various clusters, using business rules. As stated previously, this is as much an art as a science.

Q: Can you explain, using a case study, the use of clustering techniques in the retail industry?
Ans: A mobile phone manufacturer would like to launch in a new geographical area. Traditionally, the phone manufacturer competes at all price levels and custom-creates phones to suit different buyers in a particular area. For the new geographical area, the manufacturer starts out by clustering the large sample data set of citizen demographics. This data set is then enriched using a primary survey of needs of various mobile phone users. Using this clustering methodology, the manufacturer is able to distinctly identify five clusters that behave in different ways and have unique needs. Thus, the manufacturer custom-creates a mobile phone for these five segments. Subsequently, marketing campaigns are also designed by keeping the behavior of these five segments in mind.

Q. I want to know for my product what my target population is. How do I do that using which statistical technique?
Ans: Need to do market segmentation using Cluster analysis. First do hierarchical clustering to identify no of segment of the market for similar product and then do K-means cluster to identify the levels of the parameters of the cluster to target.

Q. Usually how the analysis happens in a customer engagement analysis etc whether we do factor analysis first or cluster analysis or regression?
Ans: First we do factor analysis to reduce variables then with the factors we do regression to identify important factors then we do Cluster analysis based on the important factors.

Q. What is the data considered for this analysis?

Ans: The data considered for this analysis depends on the specific project or context. It could include various types of data such as customer data, transactional data, demographic data, survey data, or any other relevant data sources. The data should be representative of the target population or market under study.

Q. What level are you doing the analysis (customer level/product level/category level/region level)?

Ans: The level of analysis depends on the objectives of the project. It could be performed at various levels such as customer level, product level, category level, region level, or a combination of these levels. The choice of the level of analysis is determined by the specific research questions or business objectives and the available data.

Q. What variables did you select for this analysis?

Ans: The selection of variables for analysis depends on the research questions or business objectives. Typically, a combination of demographic, behavioral, attitudinal, or transactional variables are considered. These variables should have relevance and influence on the outcomes or patterns being studied, such as customer behavior, preferences, or segmentation.

Q. What is multicollinearity? What are the consequences of multicollinearity in segmentation?

Ans: Multicollinearity refers to a high degree of correlation between independent variables in a regression or segmentation analysis. It indicates that the variables are measuring similar or redundant information, making it difficult to determine their individual effects accurately.

Consequences of multicollinearity in segmentation include:

a. Unreliable variable importance: Multicollinearity can distort the importance or contribution of variables in the segmentation analysis. It becomes challenging to identify the key drivers of segment differences.

b. Inconsistent or unstable segment solutions: Multicollinearity can lead to unstable or inconsistent segment solutions, as small changes in the data or variables can significantly impact the segments.

c. Difficulty in interpretation: Multicollinearity makes it difficult to interpret the relationship between variables and segments, as the effects of correlated variables get mixed up.

Q. How will you remove multicollinearity?

Ans: There are several techniques to mitigate multicollinearity in segmentation analysis:

a. Variable selection: Identify and exclude highly correlated variables from the analysis, keeping only the most relevant or independent ones.

b. Data transformation: Apply data transformations, such as standardization, normalization, or centering, to reduce the correlation between variables.

c. Principal Component Analysis (PCA): Use PCA to create orthogonal or uncorrelated variables (principal components) that capture most of the variance in the data while removing multicollinearity.

d. Ridge regression: Utilize ridge regression, a regularization technique, to shrink the coefficients of correlated variables and reduce multicollinearity.

e. Collect additional data: Collecting more diverse or independent data can help alleviate multicollinearity issues.

Q. Do you know about factor analysis?

Ans: Factor analysis is a statistical technique used to uncover underlying latent factors or dimensions from a set of observed variables. It aims to explain the relationships and patterns among variables by identifying groups of variables that tend to co-vary together.

Q. What is the importance of factor analysis?

Ans: Factor analysis is important for several reasons:

a. Dimension reduction: It helps in reducing a large number of observed variables to a smaller number of underlying factors or dimensions, simplifying the analysis and interpretation.

b. Data exploration: Factor analysis allows for the exploration of relationships among variables, identifying hidden patterns or commonalities that are not apparent from individual variables.

c. Variable selection: Factor analysis assists in selecting a subset of variables that are most representative of the underlying factors, thereby reducing multicollinearity and improving model performance.

d. Construct validity

: It helps assess the validity of measurement scales or questionnaires by examining the extent to which observed variables are related to the hypothesized underlying factors.

e. Variable transformation: Factor analysis can be used to transform the observed variables into factor scores, which can be used in subsequent analyses or models.

Q. What is the difference between factor analysis and principal component analysis?

Ans: Factor analysis and principal component analysis (PCA) are both dimension reduction techniques, but they differ in their underlying assumptions and objectives.

In factor analysis, the goal is to uncover the latent factors or dimensions that explain the correlation patterns among observed variables. It assumes that the observed variables are influenced by both the common factors and unique factors (error or specific variance). The focus is on interpreting the factors in terms of meaningful constructs.

On the other hand, PCA aims to extract linear combinations of the observed variables (principal components) that explain the maximum amount of variance in the data. It does not differentiate between common and unique factors and treats all the variance as important. PCA is primarily used for data reduction and identifying the most informative components.

Q. Do you require standardizing variables for factor analysis?

Ans: Standardizing variables in factor analysis is generally recommended to ensure that variables with different scales or measurement units are on a comparable basis. Standardization helps give equal weight to each variable and prevents variables with larger variances from dominating the analysis. It also makes the interpretation of factor loadings easier, as they represent the correlations between variables and factors.

Q. How many factors did you get in your analysis? How did you finalize?

Ans: The determination of the number of factors in factor analysis can be based on various methods, including:

a. Kaiser's criterion: Retain factors with eigen values greater than 1 (Kaiser's rule).

b. Scree plot: Examine the scree plot of eigen values and retain factors before the steep drop-off occurs.

c. Proportion of variance: Retain factors that cumulatively explain a significant proportion of the total variance

(e.g., 70-80%).
d. Theoretical or interpretability considerations: Consider the theoretical meaning or interpretability of the factors to decide on the final number.

Q. What are Eigen values/latent roots, and their importance?

Ans: Eigen values or latent roots in factor analysis represent the amount of variance explained by each factor. They indicate the importance or contribution of each factor in explaining the correlation patterns among observed variables. Larger eigen values indicate more influential factors that capture a greater amount of variance in the data.

Eigen values are important in determining the number of factors to retain. Factors with eigen values above a certain threshold (e.g., Kaiser's criterion of 1) are considered significant and retained in the analysis. Eigen values also help assess the relative importance of each factor in explaining the variability in the data.

Q. What is the importance of standardization? What are the different ways to standardize the data?

Ans: Standardization is important in factor analysis for the following reasons:
a. Comparability: Standardization ensures that variables with different scales or measurement units are on a comparable basis, allowing for meaningful comparisons.
b. Equal weighting: Standardization gives equal weight to each variable, preventing variables with larger variances from dominating the analysis.
c. Interpretation: Standardization makes it easier to interpret factor loadings, as they represent correlations between variables and factors.

Different ways to standardize the data include:
a. Z-score standardization: Subtracting the mean and dividing by the standard deviation of each variable.
b. Min-max scaling: Scaling each variable to a specified range, such as [0, 1].
c. Decimal scaling: Dividing each variable by an appropriate power of 10 to bring it within a desired range.

Q. How do you standardize in Python?

Ans:
c. Python: In Python, you can use libraries such as scikit-learn or pandas to standardize variables. The `StandardScaler` class in scikit-learn or the `StandardScaler()` function in pandas can be used for standardization.

Q. What segmentation technique did you use in your project (K-Means/K-Medians/Hierarchical/DBSCAN)?

Ans: The choice of segmentation technique depends on the specific project requirements and the characteristics of the data. Different techniques have different strengths and limitations. It is important to select a technique that aligns with the objectives of the analysis and the nature of the data.

Q. Is standardization required for Hierarchical segmentation?

Ans: Standardization is not required for Hierarchical segmentation since it uses dissimilarity or distance measures to form clusters. Hierarchical segmentation focuses on the relative distances between observations and does not depend on the scales or units of the variables.

Q. What is the difference between K-means and Hierarchical segmentation? Which one do you prefer?

Ans: The main differences between K-means and Hierarchical segmentation are:

a. Approach: K-means is a partitioning algorithm that assigns each observation to one of the predefined K clusters. Hierarchical segmentation creates a hierarchy of clusters by iteratively merging or splitting clusters based on distance measures.

b. Number of clusters: K-means requires the specification of the number of clusters (K) in advance, while Hierarchical segmentation does not require this information.

c. Cluster structure: K-means generates non-overlapping clusters, while Hierarchical segmentation can produce overlapping or nested clusters.

d. Interpretation: K-means clusters are independent of each other, whereas Hierarchical segmentation allows for a more hierarchical and interpretable cluster structure.

The choice between K-means and Hierarchical segmentation depends on the specific requirements of the project. K-means is computationally efficient and suitable for large datasets, while Hierarchical segmentation provides a more flexible and visualizable cluster structure.

Q. How do you finalize the segment solution? And optimize the solutions?

Ans: Finalizing the segment solution involves evaluating the quality and meaningfulness of the clusters generated. This can be done through several steps:

a. Assessing cluster cohesion: Analyze the within-cluster homogeneity or compactness to ensure that observations within each cluster are similar to each other.

b. Evaluating cluster separation: Examine the between-cluster separation to ensure distinctiveness and differences between clusters.

c. Interpretation and validation: Interpret the characteristics and profiles of each cluster to ensure meaningful and actionable segments. Validate the segments through external criteria or expert judgment.

d. Optimizing solutions: Fine-tune the segment solution by adjusting parameters (e.g., the number of clusters, distance metrics) or exploring alternative techniques to improve the segmentation quality and alignment with the business objectives.

Q. How many segments did you get in your analysis? What is their importance?

Ans: The number of segments obtained in the analysis depends on the data and the segmentation technique used. The importance of segments lies in their ability to capture meaningful differences or patterns in the data. Segments allow for targeted marketing strategies, personalized messaging, tailored product offerings, and improved customer understanding. Each segment represents a distinct group with specific characteristics, preferences, or behaviors, enabling more effective decision-making and resource allocation.

Q. How will you implement the solution?

Ans: Implementing the segmentation solution involves operationalizing the segments in a practical and actionable manner. This may include:

a. Developing segment profiles: Creating detailed descriptions of each segment, including demographic, behavioral, or attitudinal characteristics.

b. Assigning customers to segments: Applying the segmentation algorithm or rules to assign new or existing customers to the appropriate segments based on their attributes or behaviors.

c. Developing segment-specific strategies: Designing marketing campaigns, product offerings, or customer experiences tailored to each segment's needs and preferences.

d. Monitoring and evaluating: Continuously tracking segment performance, analyzing segment-specific metrics, and refining strategies based on feedback and results.

Q. How do you score your entire population?

Ans: Scoring the entire population involves applying the segmentation model or rules to assign segment labels to all individuals or entities in the target population. This is typically done by using the variables or attributes used in the segmentation analysis as input and applying the segmentation algorithm or rules to determine the segment membership. The scoring process can be automated using programming or analytical tools, allowing for efficient and scalable application of the segmentation solution.

Q. What is the importance of segmentation?

Ans: Segmentation plays a crucial role in various areas of business and marketing. Some key importance of segmentation includes:

a. Targeted marketing: Segmentation enables businesses to identify and understand distinct groups of customers with specific needs, preferences, and behaviors. This allows for more targeted and personalized marketing strategies, leading to higher customer engagement and conversion rates.

b. Product customization: By segmenting the market, businesses can tailor their products or services to meet the unique requirements of different customer segments. This increases customer satisfaction and loyalty.

c. Resource allocation: Segmentation helps allocate marketing resources, such as budget, time, and effort, more effectively. By focusing resources on the most promising segments, businesses can optimize their return on investment and improve overall business performance.

d. Competitive advantage: Effective segmentation helps businesses differentiate themselves from competitors by understanding and catering to niche markets or underserved segments. This can lead to increased market share and a stronger market position.

e. Customer retention: By understanding the specific needs and preferences of different segments, businesses can develop targeted retention strategies to improve customer satisfaction, loyalty, and reduce churn.

Q. Can you explain a few situations where you have used segmentation?

Ans: Sure, here are a few examples of situations where segmentation can be applied:

a. Customer segmentation: Identifying different segments of customers based on their demographics, purchasing behavior, or preferences to develop targeted marketing campaigns, personalized offers, or loyalty programs.

b. Product segmentation: Segmenting products or services based on customer needs, usage patterns, or price sensitivity to optimize pricing strategies, product positioning, or new product development.

c. Market segmentation: Segmenting the overall market based on geographic, demographic, or psychographic factors to identify target markets, tailor messaging, and optimize distribution strategies.

d. Behavior-based segmentation: Grouping customers based on their behavioral patterns, such as usage frequency, purchase recency, or engagement level, to develop customer lifecycle strategies, churn prevention programs, or personalized recommendations.

e. Channel segmentation: Segmenting customers based on their preferred communication channels or touch points to optimize marketing channel selection, customer service strategies, or user experience design.

PROCESS & MISCELLANEOUS

Q. How to optimize algorithms? (Parallel processing and/or faster algorithms). Provide examples for both?
Ans:"Premature optimization is the root of all evil"; Donald Knuth

Parallel processing: for instance in R with a single machine.
- doParallel and for each package
- doParallel: parallel backend, will select n-cores of the machine
- for each: assign tasks for each core
- using Hadoop on a single node
- using Hadoop on multi-node

Faster algorithm:
- In computer science: Pareto principle; 90% of the execution time is spent executing 10% of the code
- Data structure: affect performance
- Caching: avoid unnecessary work
- Improve source code level

For instance: on early C compilers, WHILE(something) was slower than FOR, because WHILE evaluated "something" and then had a conditional jump which tested if it was true while FOR had unconditional jump.

Q. Examples of NoSQL architecture
Ans:

- Key-value: in a key-value NoSQL database, all of the data within consists of an indexed key and a value. Cassandra, DynamoDB
- Column-based: designed for storing data tables as sections of columns of data rather than as rows of data. HBase, SAP HANA
- Document Database: map a key to some document that contains structured information. The key is used to retrieve the document. MongoDB, CouchDB
- Graph Database: designed for data whose relations are well-represented as a graph and has elements which are interconnected, with an undetermined number of relations between them. Polyglot Neo4J

Q. Provide examples of machine-to-machine communications
Ans:
Telemedicine
- Heart patients wear specialized monitor which gather information regarding heart state
- The collected data is sent to an electronic implanted device which sends back electric shocks to the patient for correcting incorrect rhythms

Product restocking
- Vending machines are capable of messaging the distributor whenever an item is running out of stock

Q. Is it better to have 100 small hash tables or one big hash table, in memory, in terms of access speed (assuming both fit within RAM)? What do you think about in-database analytics?
Ans:
Hash tables:
- Average case O(1) lookup time
- Lookup time doesn't depend on size

Even in terms of memory:
- O(n) memory
- Space scales linearly with number of elements
- Lots of dictionaries won't take up significantly less space than a larger one

In-database analytics:
- Integration of data analytics in data warehousing functionality
- Much faster and corporate information is more secure, it doesn't leave the enterprise data warehouse
Good for real-time analytics: fraud detection, credit scoring, transaction processing, pricing and margin analysis, behavioural ad targeting and recommendation engines

Q. What is star schema? Lookup tables?

Ans: The star schema is a traditional database schema with a central (fact) table (the "observations", with database "keys" for joining with satellite tables, and with several fields encoded as ID's). Satellite tables map ID's to physical name or description and can be "joined" to the central fact table using the ID fields; these tables are known as lookup tables, and are particularly useful in real-time applications, as they save a lot of memory. Sometimes star schemas involve multiple layers of summarization (summary tables, from granular to less granular) to retrieve information faster.

Lookup tables: Array that replace runtime computations with a simpler array indexing operation

Q. What is the life cycle of a data science project?

Ans:

1. **Data acquisition:** acquiring data from both internal and external sources, including social media or web scraping. In a steady state, data extraction and routines should be in place, and new sources, once identified would be acquired following the established processes
2. **Data preparation**: Also called data wrangling: cleaning the data and shaping it into a suitable form for later analyses. Involves exploratory data analysis and feature extraction.
3. **Hypothesis & modelling**: Like in data mining but not with samples, with all the data instead. Applying machine learning techniques to all the data. A key sub-step: model selection. This involves preparing a training set for model candidates, and validation and test sets for comparing model performances, selecting the best performing model, gauging model accuracy and preventing overfitting
4. **Evaluation & interpretation:**
   Steps 2 to 4 are repeated a number of times as needed; as the understanding of data and business becomes clearer and results from initial models and hypotheses are evaluated, further tweaks are performed. These may sometimes include step5 and be performed in a pre-production.
5. **Deployment**
6. **Operations:** Regular maintenance and operations. Includes performance tests to measure model performance, and can alert when performance goes beyond a certain acceptable threshold
7. **Optimization:** Can be triggered by failing performance, or due to the need to add new data sources and retraining the model or even to deploy new versions of an improved model

Note: with increasing maturity and well-defined project goals, pre-defined performance can help evaluate feasibility of the data science project early enough in the data-science life cycle. This early comparison helps the team refine hypothesis, discard the project if non-viable, change approaches.

8. How to efficiently scrape web data, or collect tons of tweets?

Ans: Python example

- Requesting and fetching the webpage into the code: httplib2 module
- Parsing the content and getting the necessary info: BeautifulSoup from bs4 package
- Twitter API: the Python wrapper for performing API requests. It handles all the OAuth and API queries in a single Python interface
- MongoDB as the database
- PyMongo: the Python wrapper for interacting with the MongoDB database
- Cronjobs: a time based scheduler in order to run scripts at specific intervals; allows to bypass the "rate limit exceed" error

Q. How to clean data?

Ans: 1. First: detect anomalies and contradictions

Common issues:

- Tidy data: column names are values, not names, e.g.<15-25, >26-45…
  multiple variables are stored in one column, e.g. m1534 (male of 15-34 years' old age)
  variables are stored in both rows and columns, e.g. tmax, tmin in the same column
  multiple types of observational units are stored in the same table. e.g, song dataset and rank dataset in the same table
  *a single observational unit is stored in multiple tables (can be combined)
- Data-Type constraints: values in a particular column must be of a particular type: integer, numeric, factor, boolean
- Range constraints: number or dates fall within a certain range. They have minimum/maximum permissible values
- Mandatory constraints: certain columns can't be empty
- Unique constraints: a field must be unique across a dataset: a same person must have a unique SS number
- Set-membership constraints: the values for a columns must come from a set of discrete values or codes: a gender must be female, male
- Regular expression patterns: for example, phone number may be required to have the pattern: (999)999-9999
- Misspellings
- Missing values
- Outliers
- Cross-field validation: certain conditions that utilize multiple fields must hold. For instance, in laboratory medicine: the sum of the different white blood cell must equal to zero (they are all percentages). In hospital database, a patient's date or discharge can't be earlier than the admission date

2. **Clean the data using:**
   - Regular expressions: misspellings, regular expression patterns
   - KNN-impute and other missing values imputing methods
   - Coercing: data-type constraints
   - Melting: tidy data issues
   - Date/time parsing
   - Removing observations

Q. How frequently an algorithm must be updated?

Ans: You want to update an algorithm when:
- You want the model to evolve as data streams through infrastructure
- The underlying data source is changing
Example: a retail store model that remains accurate as the business grows
- Dealing with non-stationarity

Some options:
- Incremental algorithms: the model is updated every time it sees a new training example
Note: simple, you always have an up-to-date model but you can't incorporate data to different degrees.
Sometimes mandatory: when data must be discarded once seen (privacy)
- Periodic re-training in "batch" mode: simply buffer the relevant data and update the model every-so-often
Note: more decisions and more complex implementations

How frequently?
- Is the sacrifice worth it?
- Data horizon: how quickly do you need the most recent training example to be part of your model?

- **Data obsolescence:** how long does it take before data is irrelevant to the model? Are some older instances more relevant than the newer ones?
Economics: generally, newer instances are more relevant than older ones. However, data from the same month, quarter or year of the last year can be more relevant than the same periods of the current year. In a recession period: data from previous recessions can be more relevant than newer data from different economic cycles.

Q. What is POC (proof of concept)?
Ans:

- A realization of a certain method to demonstrate its feasibility
- In engineering: a rough prototype of a new idea is often constructed as a proof of concept

Q. Explain Tufte's concept of "chart junk"
Ans: All visuals elements in charts and graphs that are not necessary to comprehend the information represented, or that distract the viewer from this information

Examples of unnecessary elements include:
- Unnecessary text
- Heavy or dark grid lines
- Ornamented chart axes
- Pictures
- Background
- Unnecessary dimensions
- Elements depicted out of scale to one another
- 3-D simulations in line or bar charts

Q. How would you come up with a solution to identify plagiarism?
Ans: Vector space model approach

- Represent documents (the suspect and original ones) as vectors of terms
- Terms: n-grams; n=1 to as much we can (detect passage plagiarism)
- Measure the similarity between both documents
- Similarity measure: cosine distance, Jaro-Winkler, Jaccard
- Declare plagiarism at a certain threshold

Q. How to detect individual paid accounts shared by multiple users?
Ans:

- Check geographical region: Friday morning a log in from Paris and Friday evening a log in from Tokyo
- Bandwidth consumption: if a user goes over some high limit
- Counter of live sessions: if they have 100 sessions per day (4 times per hour) that seems more than one person can do

Q. Is it better to spend 5 days developing a 90% accurate solution, or 10 days for 100% accuracy? Depends on the context?
Ans:

- At the beginning: quick-and-dirty model is better
- Optimization later

Other Ans
- Depends on the context
- Is error acceptable? Fraud detection, quality assurance

Q. What is your definition of big data?

Ans: Big data is high volume, high velocity and/or high variety information assets that require new forms of processing.

- Volume: big data doesn't sample, just observes and tracks what happens
- Velocity: big data is often available in real-time
- Variety: big data comes from texts, images, audio, video…

Difference big data/business intelligence:

- Business intelligence uses descriptive statistics with data with high density information to measure things, detect trends etc.
- Big data uses inductive statistics (statistical inference) and concepts from non-linear system identification to infer laws (regression, classification, clustering) from large data sets with low density information to reveal relationships and dependencies or to perform prediction of outcomes or behaviours

Q. Explain the difference between "long" and "wide" format data. Why would you use one or the other?

Ans:

- Long: one column containing the values and another column listing the context of the value Fam_id year fam_inc
- Wide: each different variable in a separate column
  Fam_id fam_inc96 fam_inc97 fam_inc98

Long Vs Wide:

- Data manipulations are much easier when data is in the wide format: summarize, filter
- Program requirements

Q. Do you know a few "rules of thumb" used in statistical or computer science? Or in business analytics?

Ans:

Pareto rule:

- 80% of the effects come from 20% of the causes
- 80% of the sales come from 20% of the customers

Computer science: "simple and inexpensive beats complicated and expensive" - Rod Elder

Finance, rule of 72:

- Estimate the time needed for a money investment to double
- 100$ at a rate of 9%: 72/9=8 years

Rule of three (Economics):

- There are always three major competitors in a free market within one industry

Q. Name a few famous API's (for instance Google Search)

Ans: Google API (Google Analytics, Picasa), Twitter API (interact with Twitter functions), GitHub API, LinkedIn API (users data)