

## UNIT III

### CHAPTER 3

# Big Data Analytics Life Cycle

#### Syllabus Topics

Introduction to Big Data, sources of Big Data, Data Analytic Lifecycle: Introduction, Phase 1: Discovery, Phase 2: Data Preparation, Phase 3: Model Planning, Phase 4: Model Building, Phase 5: Communication results, Phase 6: Operationalize.

**Case study :** Global Innovation Social Network and Analysis (GINA).

3.1	Data Analytic Life Cycle : Overview .....	3-2
UQ.	Explain different phases of data analytics life cycle. (SPPU – Q. 1(b), Aug. 18, 6 Marks).....	3-2
UQ.	Explain Data Analytic Life cycle.(SPPU – Q. 1(a), Dec. 18, Q. 2(b), Oct. 19, 8 Marks).....	3-2
UQ.	Draw Data Analytics Lifecycle & give brief description about all phases.  (SPPU – Q. 1(b), May 19, 5 Marks).....	3-2
3.1.1	Phase 1 - Discovery Phase,.....	3-2
3.1.2	Phase 2 - Data Preparation .....	3-2
3.1.3	Phase 3 - Model Planning.....	3-3
3.1.4	Phase 4 - Model Building .....	3-3
3.1.5	Phase 5 - Communicate Results .....	3-3
3.1.6	Phase 6 - Operationalize.....	3-3
3.2	Case Study - GINA : Global Innovation Network and Analysis .....	3-4
UQ.	Write a case study on Global Innovation Network & Analysis (GINA).  (SPPU – Q. 2(a), May 19, Q. 2(b), Dec. 19, 5 Marks).....	3-4
3.2.1	Phase 1 - Discovery.....	3-4
3.2.2	Phase 2 - Data Preparation .....	3-5
3.2.3	Phase 3 - Model Planning.....	3-5
3.2.4	Phase 4 - Model Building .....	3-6
3.2.5	Phase 5 - Communicate Results .....	3-7
3.2.6	Phase 6 - Operationalize.....	3-7
►	Chapter Ends .....	3-7

## **M 3.1 DATA ANALYTIC LIFE CYCLE : OVERVIEW**

- UQ.** Explain different phases of data analytics life cycle.  
**UQ.** Explain Data Analytic Life cycle.  
**UQ.** Draw Data Analytics Lifecycle & give brief description about all phases.  
**(SPPU - Q. 1(a), Dec. 18, Q. 2(b), Oct. 19, 8 Marks)**  
**(SPPU - Q. 1(b), May 19, 5 Marks)**

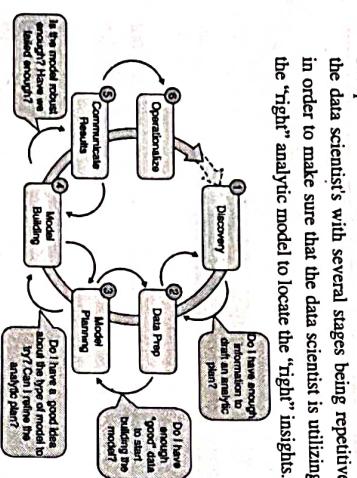


Fig. 3.1.1 : Data Scientist Lifecycle

### **3.1.1 Phase 1 - Discovery Phase**

The following activities of data scientists can be focused by the Discovery :

- Acquisition of a complete understanding of the business process and the business domain. This consists of recognizing the key metrics and KPIs against which the business users will measure success.
- Recognizing the most vital business questions and business decisions that the business users are attempting to answer in support of the targeted business process. This also should contain the occurrence and optimal timeliness of those answers and decisions.

- Evaluating available resources and going through the process of framing the business problem as an analytic hypothesis. At this stage data scientist constructs the initial analytics development plan that will be used to direct and document the resulting analytic models and insights.
- It should be noticed that understanding into which production or operational environments the analytic insights requires to be published is somewhat that should be recognized in the analytics development plan.
- Such information will be essential as the data scientist recognizes in the plan where to "operationalize" the analytic insights and models.
- This is a best opportunity for tight association with the BI analyst who likely has already defined the metrics and processes required to support the business proposal.
- Requirements and the decision making environment of the business users can be well understand by the BI analyst to starts the data scientist's analytics development plan.

### **3.1.2 Phase 2 - Data Preparation**

The following activities of data scientists can be focused by the data preparation :

- Provisioning an analytic workspace, or an analytic sandbox, where the data scientist can work free of the constraints of a production data warehouse environment. Preferably, the analytic environment is set up such that the data scientist can self-provision as much data space and analytic horsepower as required and can fine-tune those requirements throughout the analysis process.

- Obtaining, cleaning, aligning, and examining the data. This contains use of data visualization techniques and tools to get an understanding of the data, recognizing outliers in the data and calculating the gaps in the data to decide the overall data quality, determine if the data is "good enough."
- Transforming and enhancing the data. The data scientist will look to use analytic techniques, such as logarithmic and wavelet transformations, to sort out the potential skewing in the data. The data scientist will

- also look to use data enhancement techniques to create new composite metrics such as frequency, recency, maximum quality, most predictive and actionable and order. The data scientist will make use of standard tools like SQL and Java, as well as both commercial and open source extract, transform, load (ETL) tools to transform the data.
- After this stage is completed, the data scientist wants to feel comfortable enough with the quality and prosperity of the data to move ahead to the next stage of the analytics development process.

### **3.1.3 Phase 3 - Model Planning**

The following activities of data scientists can be focused by the model planning :

- Determining the numerous analytical models, methods, techniques and workflows to discover as part of the analytic model development. The data scientist knows in advance that which of the analytic models and methods are suitable but it is good thing to plan to check at least one to make sure that the opportunity to build a more predictive model is not missed.
- Determine association and co-linearity between variables in order to select key variables to be used in the model development. The data scientist desires to estimate the cause-and-effect variables as early as possible. Keep in mind, association does not provides assurance causation, so care must be taken in choosing variables that can be calculated while going forward.

### **3.1.4 Phase 4 - Model Building**

The following activities of data scientists can be focused by the model building :

- Manipulating the data sets for testing, training, and production. Whatever new transformation techniques are developed can be tested to observe if the quality, reliability, and predictive capabilities of the data can be enhanced or not.
- Calculating the feasibility and reliability of data to use in the predictive models. Decision calls are depends on quality and reliability of the data to check, is the data "good enough" to be used in developing the analytic models.
- At the end, developing, testing, and filtering the analytic models is done. Testing is carrying out 10

- The following activities of data scientists can be focused by the operationalize :
- Providing the final suggestions, reports, meetings, code, and technical documents.
- Optional, running a pilot or analytic lab to validate the business case, and the financial return on investment (ROI) and the analytic lift.
- Carrying out the analytic models in the production and operational environments. This engross working with

- Notice which variables and analytic models deliver the maximum quality, most predictive and actionable analytic insights.
- The model building stage is highly iterative step where manipulation of the data, calculating the reliability of the data, and determining the quality and predictive powers of the analytic model will be modified number of times.
- In this stage the data scientist may be unsuccessful many times in testing different variables and modeling techniques before resolved into the "right" one.

**Data Science and Big Data Analytics (SPPU-Sem 6-Comp)**

- Data Science and Big Data Analytics (SPPU-Sem 6-Comp) best to surface the analytic results and insights.
- Combining the analytic scores into management dashboards and operational reporting systems, like sales systems, procurement systems, and financial systems etc.
- The operationalization stage is another area where association between the data scientist and the BI analysts should be very useful.

- Numerous BI analysts have the experience of combining reports and dashboards into the operational systems, as well as establishing centers of excellence to spread analytic learning and skills across the organization.

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### 3.2 CASE STUDY - GINA : GLOBAL INNOVATION NETWORK AND ANALYSIS

- UQ.** Write a case study on Global Innovation Network & Analysis (GINA). **(SPPU – Q. 2(a), Q. 2(b), Dec. 19, 5 Marks)**
- Q6.** Write a short note on Case of GINA. **(8 Marks)**

- They consults with various experts and decided to outsource the work to the volunteers within EMC.
- The list of roles is as follows on the working team which were fulfilled:

- i) User of Business, Sponsor of Project, Manager of Project :** Vice President from IT Field

- ii) Business Intelligence Analyst :** Representatives from IT Field

- iii) DBA (Data Engineer and Database Administrator) :** Representatives from IT

- iv) Data Scientist :** Distinguished Engineer who are able to develop social graphs.

- The main goal of team is to connect employees all over the world to drive innovation, research as well as university partnerships.

- The basic consideration of GINA team was that its approach would offer an interface to share ideas globally and enhance sharing of knowledge between GINA members who are not at one place geographically.
- A data repository has been created to store both structured and unstructured data to achieve three important goals :

1. Store formal as well as informal data.
2. Keep track of research from technologists all over the world.
3. To enhance the operations and strategy, extract data for patterns and insights.

- The Innovation Roadmap is nothing but an organic innovation process in which ideas are submitted by employees globally which are then judged.
- For further incubation, rest out of these ideas are selected.

- In the GINA project, for large amount of dataset, it looks viable to use social network analysis techniques to observe the networks regarding innovators.
- In other cases, it was hard to provide appropriate methods to test hypotheses because of the lack of data.

- In one case (IH9), a decision is made by the team to begin a longitudinal study to start tracking data points over time about people who are developing new intellectual property.

#### 3.2.1 Phase 1 - Discovery

- In this phase, identification of data sources is started by the team.
- Even though GINA has technologists which are skilled in several different aspects of engineering, it had few data and ideas regarding what it needs to explore but do not have a formal team which could perform these analytics.

- The second category of data consists of encompassed minutes as well as notes which represents innovation and research activity globally.
- Additionally it represents combination of structured and unstructured data. The structured data consists of attributes like dates, names as well as geographic locations.

- In the unstructured documents data is regarding "who, what, when, and where" which represents rich data regarding knowledge growth and transfer inside the company.

- There are 10 important IHs which are developed by GINA team :

- 1. **IH1 :** It is possible to map innovation activity in dissimilar geographic locations to corporate strategic directions.

- 2. **IH2 :** The delivery time of ideas minimizes by the transfer of global knowledge as part of the idea delivery process.

- 3. **IH3 :** Innovators participating in global knowledge are able to deliver ideas fast as compared to those who do not.

- 4. **IH4 :** It is possible to analyze and evaluate an idea submission for the likelihood of receiving funding.

- 5. **IH5 :** Knowledge invention and increase for a specific topic can be measured as well as compared across geographic locations.

- 6. **IH6 :** Research-specific boundary can be identified by the knowledge transfer activity spanners in different regions.

- 7. **IH7 :** It is possible to map strategic corporate themes to geographic locations.

- 8. **IH8 :** Continuous knowledge growth and transfer events minimize the time required to create a corporate asset from an idea.

#### 3.2.2 Phase 2 - Data Preparation

- A new analytics sandbox is set up by the team with its IT department for the purpose of storing and experimenting on the data.
- In the process of data exploration exercise, the data scientists and data engineers come to know that specific data require conditioning and normalization.

- Also they come to know that various missing datasets were difficult to testing some of the analytic hypotheses.

- As data is explored by the team, it promptly realized that without good quality data, it would not be able to carry out the subsequent steps in the lifecycle process.

- Consequently it was essential to conclude for project what level of data quality and cleanliness was necessary.

- In the case of the GINA, the team realizes that several of the names of the researchers and people who are communicating with the universities were misspelled or had spaces at leading and trailing side in the datastore.

- Such little problems must be addressed in this phase to enable better analysis as well as data aggregation in subsequent phases.

#### 3.2.3 Phase 3 - Model Planning

- In the GINA project, for large amount of dataset, it looks viable to use social network analysis techniques to observe the networks regarding innovators.

- In other cases, it was hard to provide appropriate methods to test hypotheses because of the lack of data.

- In one case (IH9), a decision is made by the team to begin a longitudinal study to start tracking data points over time about people who are developing new intellectual property.

