Systems generate massive amounts of data. Accordingly, thousands of decisions are taken daily. With such a volume, the manual analysis is inefficient and even impossible, especially if the velocity, the variety, and the veracity of data are at stake.

Business Analytics is all about deriving knowledge from possibly large volumes of data or generally “difficult” data. This process combines several disciplines such as statistics, machine learning, information science, database management, and data visualization – areas that have only become recognized and accessible due to the technological developments in our times.

There are three main motivations behind developing an analytics engine to cater to your business:
- On a daily basis, systems generate and store massive amounts of data. Accordingly, thousands of decisions are taken. With such a volume, the manual analysis of data is inefficient if not impossible, especially if the velocity, the variety, and the veracity of data are taken into account.
- The conventional process is limited to incident identification, avoidance detection, and surveillance. But the analytics engine can unveil implicit relationships, trend patterns, exceptions, and anomalies that are hidden to human analysts and expert rules.
- The analytics engine is tailored to the enterprise’s experience: In fact, its algorithms are trained on the historical databases, and not on generic data. Thus, it allows the enterprise to learn about its clients and their behavior from its own experience with them, instead of relying solely on generic rules and expert judgment.

Applications of Analytics
The journey from hindsight to insight to foresight consists four main stages
- Descriptive Analytics which presents what happened and identifies past successes and failures.
- Diagnostic Analytics which allows the drill-down to the root cause(s) of problems.
- Predictive Analytics which calculates the likelihood of future events, and is usually based on the analysis of past trends.
- Prescriptive Analytics which advises on the best course of action, upon simulating multiple futures and assessing the outcomes.

Analytics Life Cycle
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**Key Features:**

- **Comprehensive and extensible risk scoring function**
- **Continuous customer monitoring for risk throughout the life of the customer relationship**
- **Real-time and batch interfaces to integrate with other systems**
- **An advanced, enhanced due diligence process to enable quality investigations without increasing costs**
- **Reduce customer risk exposure on the front lines and enhance customer relationships**
- **Achieve end to end compliance by leveraging core with Valoores applications**
- **Utilize standard interfaces to exchange information with third party systems.**

- **Business Understanding:** At this stage, the business requirements are analyzed and reframed as data analytics problems. The business question is refined to be Specific, Measurable, Achievable, Relevant, and Time-bound. Moreover, a preliminary plan to achieve the business objectives is designed.
- **Data Understanding:** At this stage, initial collections of data are performed, and data limitations are identified. A plan is developed to treat outliers and missing values, and to discover first insights into the data or to detect hidden information. Moreover, the business rules are validated to audit the data and improve its quality, if possible. To illustrate the critical importance of this stage, suppose for example that an enterprise is developing a model around the customers’ behavior. The forward-looking nature of this task can be established using predictive analytics: A selected historical client data set will be fed to an algorithm, to train it on predicting behaviors. Roughly speaking, for the algorithm to be “well-trained”, the “quality” of the historical client data set should meet certain standards. The lack of sufficient quality data is a major obstacle to the development of effective and accurate models, which demand faithful preservation and treatment of history.
- **Data Preparation:** At this stage, different activities are performed to construct the final data set from the initial raw data, via transformations, modifications, mutations, substitutions, and selections...
- **Modeling:** At this stage, the mathematical and statistical models which can answer the business question using the available data are identified. Herein, mathematical and statistical models are fed the dataset(s) prepared in the previous stage, and are trained on them, to gain predictive capabilities. Different models might be used to analyze different aspects of the business problem.
- **Evaluation & Interpretation:** At this stage, the models developed in Stage 4 are thoroughly evaluated and their accuracy, reliability, interpretability, and bias are rigorously assessed. The fulfillment of the business objectives is also evaluated and revised. We train different algorithms in the same set on the same data set. Each data set has its own story, and Algorithm A might be able to tell it much better than algorithm B. Deployment and testing requires a continuous monitoring of the models’ accuracy.