Note on Business Analytics

More than ever before, organizations understand that good business decisions are based on data and that data-driven decision-making enables firms to be more customer-focused, more productive, and more profitable. Data analysis can be performed from a number of perspectives and achieved with a wide variety of tools, but managers need to know how to use those tools and perspectives to achieve positive business results.

What *is* Business Analytics?

Business analytics is data analytics for business decision-making; it transforms data into insights that inform business decisions. Data analytics can be defined as the exploration, discovery, interpretation, and communication of meaningful patterns in data. Analytics involves the use of data management, data visualization, predictive modeling, data mining, forecasting, and simulation.

Some sources make a distinction between **business intelligence** and business analytics, defining business intelligence as the process of collecting data from a variety of sources and preparing it for business analytics; others define business intelligence as encompassing the tools that *describe* patterns in data rather than the tools that use data to *predict* outcomes.

At Questrom, we emphasize that all of these are important in the business decision-making process, which comprises identifying a business need and defining the organization's goal in relation to that need, collecting data, analyzing the data, identifying alternative plans of action, making a decision about which alternative to choose, implementing a change in business processes, and evaluating subsequent performance (Figure 1).

Figure 1: The Business Decision-Making Process
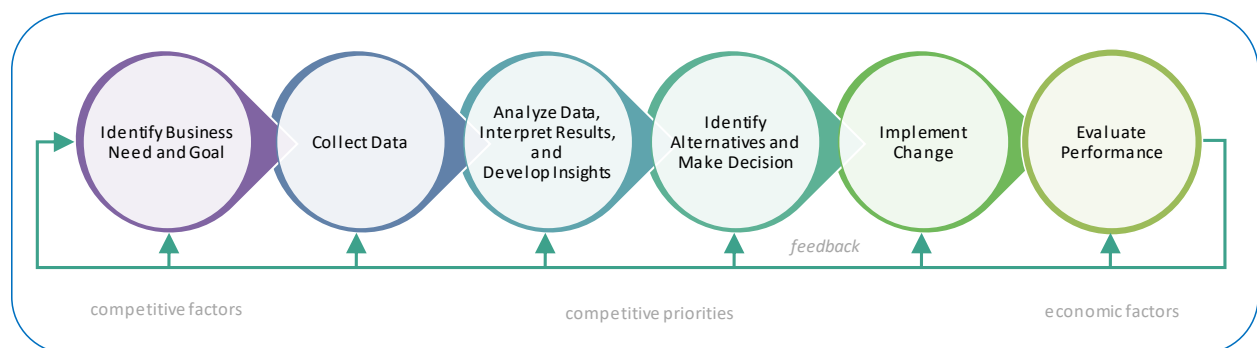
Although this figure shows the business decision-making process as linear, feedback between steps refines the question and the approaches at each step.

Identify the Business Need (and the Goal)
The first step in business decision-making is identifying the business need (or problem). Most organizations will have several strategic business needs in common, including growing the customer base, increasing profits (or increasing services in not-for-profit organizations), improving customer satisfaction, allocating scarce organizational resources effectively, developing organizational capabilities, etc. Organizations also use business analytics to address issues that sometimes may have a more tactical but nonetheless significant effect on business success, including reducing waste and redundancy, improving financial portfolio profitability, detecting fraud, and many others. In addition to solving specific problems or meeting specific challenges, organizations also collect data in order to understand what's going on in the environment. This kind of "business listening" reflects a different kind of organizational need – the need to know what you don't know.

Whatever the business need, it is important to define the business need *specifically* and to be clear on the organization's goal before the data are collected.

Collect Data
The next step in the business decision-making process is to collect the appropriate data. There are two basic sources of data: primary and secondary (Figure 2). *Primary data* are data collected for the analysis of the particular business need. Sources of primary data include:
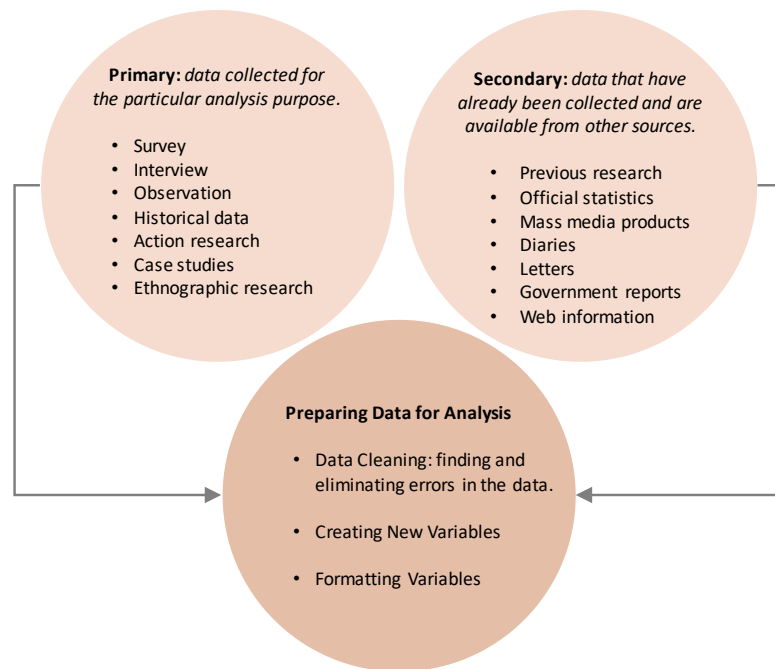- Surveys.
- Interview.
- Direct observations and ethnographic research.
- Action research (iteratively collecting data, making changes, evaluating results) .
- Case studies.
- Field experiments.
- Historical firm data (for example, past inventory, transactions).
- New firm data (for example, systems for collecting ongoing accounting transactions, production logs, customer activity, inventory data, etc.)

Secondary data are data that have already been collected and are available from other sources. Some examples of secondary data include:
- Published research and related data sets).
- Official statistics (for example, census data).
- Mass media products (for example, Yelp reviews).Government reports (for example, Yougov data).
- Web information (for example, earned media, social media).
- Consumer panel data (for example, AC Nielsen/IRI).
- Firm financial reporting (for example, CRSP/Compustat).
- Web tracking data (for example, Comscore, retail online transactions data).

Much of the data businesses collect is quantitative, but they also collect qualitative data that must be analyzed to provide insights into decisions.

Figure 2: Sources of Data and Preparing Data for Analysis

Primary: *data collected for the particular analysis purpose.*

- Survey
- Interview
- Observation
- Historical data
- Action research
- Case studies
- Ethnographic research

Secondary: *data that have already been collected and are available from other sources.*

- Previous research
- Official statistics
- Mass media products
- Diaries
- Letters
- Government reports
- Web information

Preparing Data for Analysis

- Data Cleaning: finding and eliminating errors in the data.
- Creating New Variables
- Formatting Variables

After the data have been collected, the dataset has to be prepared for analysis. This involves detecting and correcting (or removing) corrupt or inaccurate records in the data, such as:

- Impossible or incorrect values for specific variables.
- Duplicates.
- Missing data.
- Outliers (need to be able to explain *why* it is appropriate to exclude them).

It also involves creating new variables: defining new variables from the data you collected in order to answer your business question. This phase can include:

- Recoding variables.
- Creating new variables (for example, interaction variables or dummy variables from categorical data).
- Transforming variables (for example, difference in sales from one year to the next).
  - Indices created from a scale.
  - Rescaling variables (for example, natural logs).
- Accounting for non-linearity (for example, concave vs. convex functions).
- Identifying relevant vs. irrelevant variables.

The data preparation and cleaning phase is painstaking, but analysis results are only as good as the dataset being analyzed.

Analyze Data, Interpret Results, Develop Insights

Once the dataset has been prepared, the data can be analyzed. Organizations typically analyze business data to describe, predict, and improve business performance.
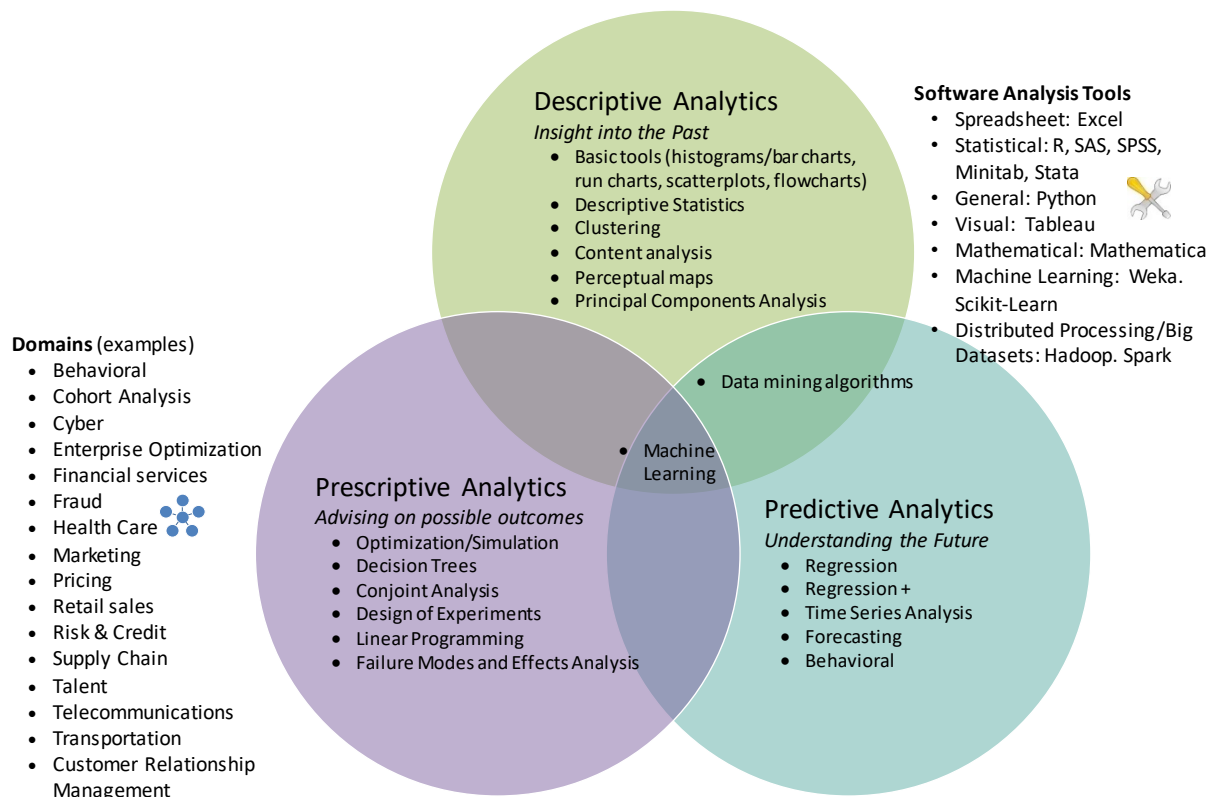
Descriptive analytics employ basic visualizing and statistical techniques that describe what has happened. For example, a department store may use histograms, bar charts, time series plots, scatterplots, and measures of central tendency and variation all to describe sales volume, customer characteristics, and profits for a particular store.

Predictive analytics apply advanced statistical techniques, information analysis, and operations research techniques to build models that identify trends and relationships to determine what could happen in the future. That same department store may use multiple regression to forecast the sales of a product or service when advertising, promotion, price, and store location are changed.

Prescriptive analytics use applied mathematical techniques or experimental approaches to provide insight or "advice" into what should be done. The department store may use prescriptive analytics such as A-B testing to optimize their Internet store and optimization models to determine how to most effectively allocate their marketing budget dollars to ads, promotions, and in-store sales in order to maximize returns on marketing dollars.

Figure 3 shows the relationship between these three types of analytics and lists some of the analysis techniques used for each. It also shows some of the domains in which business analytics can be applied.

Figure 3: Analytics Types, Domains, and Tools

Descriptive Analytics
Insight into the Past
- Basic tools (histograms/bar charts, run charts, scatterplots, flowcharts)
- Descriptive Statistics
- Clustering
- Content analysis
- Perceptual maps
- Principal Components Analysis

Software Analysis Tools
- Spreadsheet: Excel
- Statistical: R, SAS, SPSS, Minitab, Stata
- General: Python
- Visual: Tableau
- Mathematical: Mathematica
- Machine Learning: Weka. Scikit-Learn
- Distributed Processing/Big Datasets: Hadoop. Spark

- Data mining algorithms
- Machine Learning

Domains (examples)
- Behavioral
- Cohort Analysis
- Cyber
- Enterprise Optimization
- Financial services
- Fraud
- Health Care
- Marketing
- Pricing
- Retail sales
- Risk & Credit
- Supply Chain
- Talent
- Telecommunications
- Transportation
- Customer Relationship Management

Prescriptive Analytics
Advising on possible outcomes
- Optimization/Simulation
- Decision Trees
- Conjoint Analysis
- Design of Experiments
- Linear Programming
- Failure Modes and Effects Analysis

Predictive Analytics
Understanding the Future
- Regression
- Regression +
- Time Series Analysis
- Forecasting
- Behavioral

4

Identify Alternatives and Make Decision

After the analysis of the data is complete, alternatives can be identified and possible outcomes of each choice can be evaluated. Data analysis alone typically does not provide *the* answer to business questions, but is a critical input to the decision. Other factors (economic, financial, competitive, market, technological, organizational) must also be considered along with the data.

Implement Change

The analysis continues as the organization implements the decision. While changes are made, additional data may come to light and need to be considered.

Evaluate Performance

Finally, once the implementation is complete, the performance of the system needs to be continuously analyzed, first to evaluate the effectiveness of the change, and then to monitor over time (perhaps with business dashboards) as the business environment changes.

Business Analytics at Questrom

The business decision-making process requires knowledge, skills and perspectives that can be mapped to the steps in the process (Table 1).

Table 1: Mapping Knowledge, Skills, and Perspectives to Business Decision-Making Process

Process step		Knowledge, Skills, and Perspectives
General	1	General knowledge of data-driven business decision making as a management culture; appreciation of its advantages and pitfalls; awareness of a number of relevant case studies across a number of business domains.
	2	Understanding of the overall process of data-driven business decision making and the skills and resources required for each step; ability to effectively staff and manage such projects.
Identify business need and goal	3	Ability to translate a business question into a data analysis question; ability to reason about what data will be needed and where this data can be found or generated.
Collect data	4	Ability to collect/scrape/mine and integrate secondary data from a variety of sources.
	5	Ability to plan and implement a project for obtaining primary data via surveys, MTurk, a live experiment or other means.
	6	Ability to assess the quality of data and make the necessary interventions to prepare them for data analysis.
Analyze data, interpret results, develop insights	7	Ability to apply one or more data analysis techniques.
	8	Ability to translate the results of data analyses into a set of managerial insights and a story that can be relayed to management.
Identify alternatives and make decision	9	Ability to assess the insights and recommendations that are derived from data analysis; ask key questions to determine the soundness of the approach that was followed; be able to identify key pitfalls of data analysis
	10	Ability to combine insights derived from data analysis with knowledge of the business to derive effective managerial action.
Implement change, evaluate performance		Combination of #4-10.

Students gain these capabilities, within Questrom, in courses that prepare them for four career pathways that require different levels of analytics capability:

Level 1: Awareness of Analytics Importance and Mastery of Basic Tools (all managerial roles)
Courses in this level build an awareness of analytics and its modern importance. They provide an understanding of how analytics are used to make business decisions as well as some hands-on experiences with basic analytics tools and concepts. The analysis at this level is primarily conducted within Excel.

Level 2: Application of Data-Driven Decision-Making (all managerial roles)
These courses provide more exposure to analytics concepts within a particular function or discipline. The courses will equip them to do some additional hands-on analytics work and planning around analytics. They will have exposure to the analytics used in particular business domains, such as marketing or operations. The analyses at this level may still be conducted within Excel or using statistical software.

Level 3: Analytics Management
These students want to be in a position to manage data scientists or to act as a "bridge" between data scientists and management/sales/etc. Coursework will include programming, advanced machine learning techniques, data gathering and mining, and databases. Students will be equipped to run basic to intermediate analysis themselves, but they are not skills experts. Rather, they learn these skills so they can be successful managers and explainers. Analyses at this level will be conducted in basic and statistical programming languages such as Python and R.

Level 4: Data Science
These students will likely come to Questrom with strong backgrounds in programming, stats, math, physics etc., and want to be able to apply their analytical skills in business context. They may still have managerial/bridging rolls, using their MBA skills but they also have the ability to perform analyses, both simple and relatively complex, themselves. They will be seen as "equipped" by other data scientists, and able to do both management and analytical work.

Figure 4 shows these four levels of preparation, provides a sense of what students will do and learn at each level.

Figure 4: Levels of Questrom Business Analytics Preparation
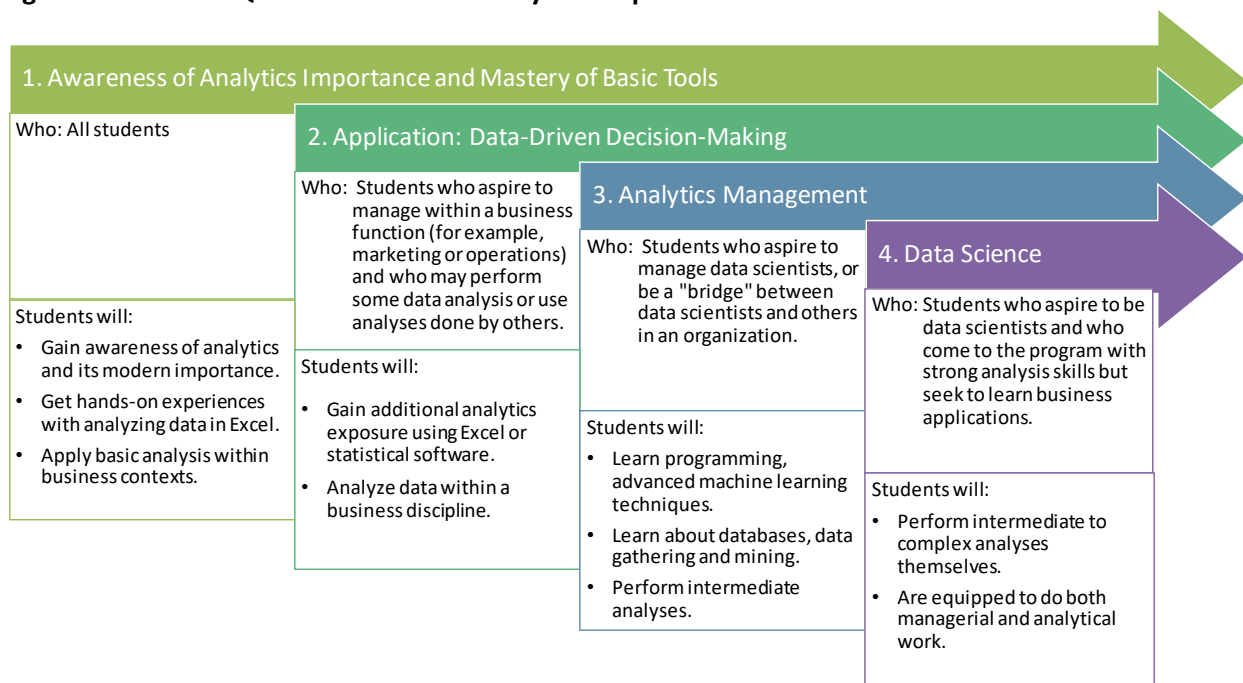
Summary

Fundamentally, *all* courses within Questrom are about data-driven decision-making. The business analytics courses expose students to a set of tools and perspectives that can be used to enhance data-driven decision-making in any managerial role.