

FasterAnalytics for Healthcare – A Clinical Case Study

Introduction

DecisionQ has developed FasterAnalytics, a unique analytical package that enables researchers, analysts, and managers to use sophisticated predictive analytics from their desktop. FasterAnalytics creates high quality, predictive models from data that enable efficient review of clinical data, real-time hypothesis testing, and rapid decisions.

FasterAnalytics uses a modeling approach called Bayesian Networks to provide a mapping of the complex relationships in data, which can then be used to make high quality predictions. Users can:

- Get an instant global view of their data.
- Understand the driving factors in the data.
- Test hypotheses in real time in our model Explorer.
- Produce reports that can be exported to other applications.
- Make determinations that can help prioritize the use of scarce research resources.

Market Overview

Clinical data analysis is instrumental to both the approval of new therapies and the provision of proper medical care. The need for clinical data analysis is currently served by a combination of services firms that analyze data, decision support products that use proprietary protocols for management of care, and traditional statistical and data analysis tools.

Value to the Customer

FasterAnalytics enables both experts and non-experts in statistics to discover and leverage knowledge from large quantities of data quickly. Examples include:

- Automatically mapping data where targets are unknown to reveal correlations.
- Discovering new relationships between variables and identifying new opportunities to improve care or reduce cost.
- Identifying potential morbidities early.
- Discovering populations that may have substantially different responses from the population at large.
- Predicting the behavior of any factor or combination of factors in the model.
- Allowing analysts to develop new models in minutes, keeping pace with shifting data.

FasterAnalytics is designed for real-time environments. Bayesian models are highly effective at identifying emerging trends that can be used to either to identify potential adverse events or improve quality of outcomes.

Product and Technology

DecisionQ Corporation has produced a range of modules that perform data analysis, modeling, visualization, reporting, and decision optimization. FasterAnalytics modules include:

- *Discretizer.* Automatically configures the data for modeling.

- *Modeler.* Quickly creates a visual model of the data.
- *Explorer.* Allows real-time generation and testing of hypotheses.
- *Reporter.* Extracts insights and key points for inclusion in reports and presentations.

Using the System: A Clinical Example

The following is an example of our software applied to a publicly available set of clinical data. We have used a data set comprised of the initial trial cohort for the Diabetes Control and Complications Trial, consisting of 1,441 participants reporting on 81 attributes. FasterAnalytics built the model in this example, from start to finish, in less than 30 minutes.

To build predictive models, our learning engine requires the data to be in a flat tabular format. The data can be numerical, or variable character strings. Our software can also handle missing values automatically and will either impute a value or treat missing values as a special category, at the user's discretion.

Figure 1: This example uses a data set from an Excel spreadsheet as shown below (Partial).

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | |
|----|----------|-------|---------|------|-----|----------|----------|---------|-------|---------|--------|---------|------|---------|---------|----|
| 1 | GROUP | PHASE | RETBASE | TYPE | AGE | DURATION | F002DATE | OBONSET | PPDUR | MARRIED | OBMARR | PRIORHY | OBC9 | HOLLSCO | OBPATJO | OE |
| 2 | EXPERIME | 2 | SCND | 1 | 17 | 178 | 62383 | 868 | 52 | 0 | 1 | 0 | 0 | 23 | 11 | |
| 3 | STANDAR | 2 | SCND | 2 | 29 | 142 | 71283 | 971 | 142 | 1 | 2 | 0 | 0 | 15 | 12 | |
| 4 | STANDAR | 2 | SCND | 2 | 35 | 175 | 52783 | 1068 | 175 | 1 | 2 | 0 | 0 | 22 | 2 | |
| 5 | EXPERIME | 2 | PRIM | 1 | 14 | 31 | 70183 | 1280 | 24 | 0 | 1 | 0 | 0 | 26 | 11 | |
| 6 | EXPERIME | 2 | SCND | 2 | 32 | 72 | 51983 | 577 | 72 | 1 | 2 | 0 | 0 | 40 | 4 | |
| 7 | STANDAR | 2 | SCND | 2 | 26 | 106 | 72283 | 974 | 106 | 0 | 1 | 0 | 0 | 47 | 3 | |
| 8 | STANDAR | 2 | SCND | 2 | 26 | 168 | 50683 | 569 | 168 | 0 | 1 | 0 | 0 | 19 | 1 | |
| 9 | EXPERIME | 2 | SCND | 2 | 28 | 147 | 61783 | 371 | 147 | 1 | 2 | 0 | 0 | 43 | 7 | |
| 10 | EXPERIME | 2 | SCND | 2 | 37 | 14 | 80383 | 682 | 14 | 1 | 2 | 0 | 0 | | 11 | |
| 11 | STANDAR | 2 | SCND | 2 | 23 | 80 | 62183 | 1076 | 80 | 0 | 1 | 0 | 0 | 37 | 11 | |
| 12 | STANDAR | 2 | SCND | 1 | 13 | 148 | 52083 | 171 | 6 | 0 | 1 | 0 | 0 | 11 | 11 | |
| 13 | STANDAR | 2 | PRIM | 1 | 13 | 30 | 72683 | 181 | 3 | 0 | 1 | 0 | 0 | 30 | 11 | |
| 14 | STANDAR | 2 | SCND | 2 | 21 | 126 | 52483 | 1172 | 105 | 0 | 1 | 0 | 0 | 11 | 11 | |
| 15 | STANDAR | 2 | SCND | 2 | 27 | 116 | 52183 | 973 | 116 | 1 | 2 | 0 | 0 | 11 | 1 | |
| 16 | EXPERIME | 2 | SCND | 2 | 38 | 133 | 62283 | 572 | 133 | 1 | 2 | 0 | 0 | 11 | 1 | |
| 17 | STANDAR | 2 | PRIM | 2 | 37 | 38 | 81183 | 680 | 38 | 1 | 2 | 0 | 0 | 15 | 1 | |
| 18 | EXPERIME | 2 | SCND | 2 | 27 | 40 | 71983 | 380 | 40 | 1 | 2 | 0 | 0 | 22 | 2 | |
| 19 | STANDAR | 2 | SCND | 2 | 23 | 61 | 61783 | 578 | 61 | 0 | 1 | 0 | 0 | 47 | 3 | |
| 20 | EXPERIME | 2 | SCND | 1 | 17 | 77 | 70183 | 277 | 55 | 0 | 1 | 0 | 0 | 11 | 11 | |
| 21 | EXPERIME | 2 | SCND | 2 | 22 | 35 | 72283 | 880 | 35 | 0 | 1 | 0 | 0 | 58 | 11 | |
| 22 | STANDAR | 2 | SCND | 2 | 25 | 168 | 81683 | 869 | 147 | 1 | 2 | 0 | 0 | 11 | 1 | |
| 23 | EXPERIME | 2 | SCND | 1 | 14 | 71 | 62483 | 777 | 24 | 0 | 1 | 1 | 1 | 11 | 11 | |
| 24 | EXPERIME | 2 | PRIM | 2 | 28 | 27 | 50583 | 281 | 27 | 1 | 2 | 0 | 0 | 44 | 4 | |
| 25 | STANDAR | 2 | SCND | 1 | 15 | 107 | 60683 | 774 | 36 | 0 | 1 | 0 | 0 | 55 | 11 | |
| 26 | EXPERIME | 2 | SCND | 2 | 35 | 79 | 71283 | 1276 | 79 | 1 | 2 | 0 | 0 | 26 | 10 | |
| 27 | STANDAR | 2 | SCND | 2 | 28 | 50 | 62783 | 479 | 50 | 1 | 2 | 0 | 0 | 26 | 2 | |
| 28 | STANDAR | 2 | SCND | 2 | 26 | 176 | 70583 | 1168 | 163 | 1 | 2 | 0 | 0 | 19 | 1 | |
| 29 | STANDAR | 2 | SCND | 2 | 24 | 47 | 60183 | 779 | 47 | 1 | 2 | 0 | 0 | 15 | 1 | |
| 30 | EXPERIME | 2 | SCND | 1 | 16 | 135 | 80583 | 572 | 41 | 0 | 1 | 0 | 0 | 77 | 11 | |
| 31 | EXPERIME | 2 | SCND | 2 | 33 | 147 | 72683 | 471 | 147 | 1 | 2 | 0 | 0 | 47 | 7 | |
| 32 | EXPERIME | 2 | SCND | 2 | 22 | 117 | 70583 | 1073 | 117 | 0 | 1 | 0 | 0 | 19 | 1 | |
| 33 | STANDAR | 2 | SCND | 2 | 39 | 99 | 91483 | 675 | 99 | 1 | 2 | 0 | 0 | 58 | 6 | |
| 34 | STANDAR | 2 | PRIM | 1 | 13 | 26 | 70983 | 581 | 7 | 0 | 1 | 0 | 0 | 55 | 11 | |
| 35 | EXPERIME | 2 | SCND | 2 | 39 | 162 | 90683 | 370 | 162 | 1 | 2 | 0 | 0 | 15 | 1 | |

In the example below, we examine how selecting the Type I or Type II diabetic population affects the profile of the trial cohort. We begin by selecting our target variable, Type II. The thick border indicates that this is the target selected, and its color red indicates that we are interested in analyzing how other variables behave when the target is Type II diabetics (instead of Type I). When we toggle the value of the TYPE node between Type I and Type II, we notice the colors of other nodes change to express positive or negative correlations with this node. (See Figure 3 and Figure 4). The tint of color indicates the degree of positive or negative correlation.

Figure 3: TYPE variable set to Type II

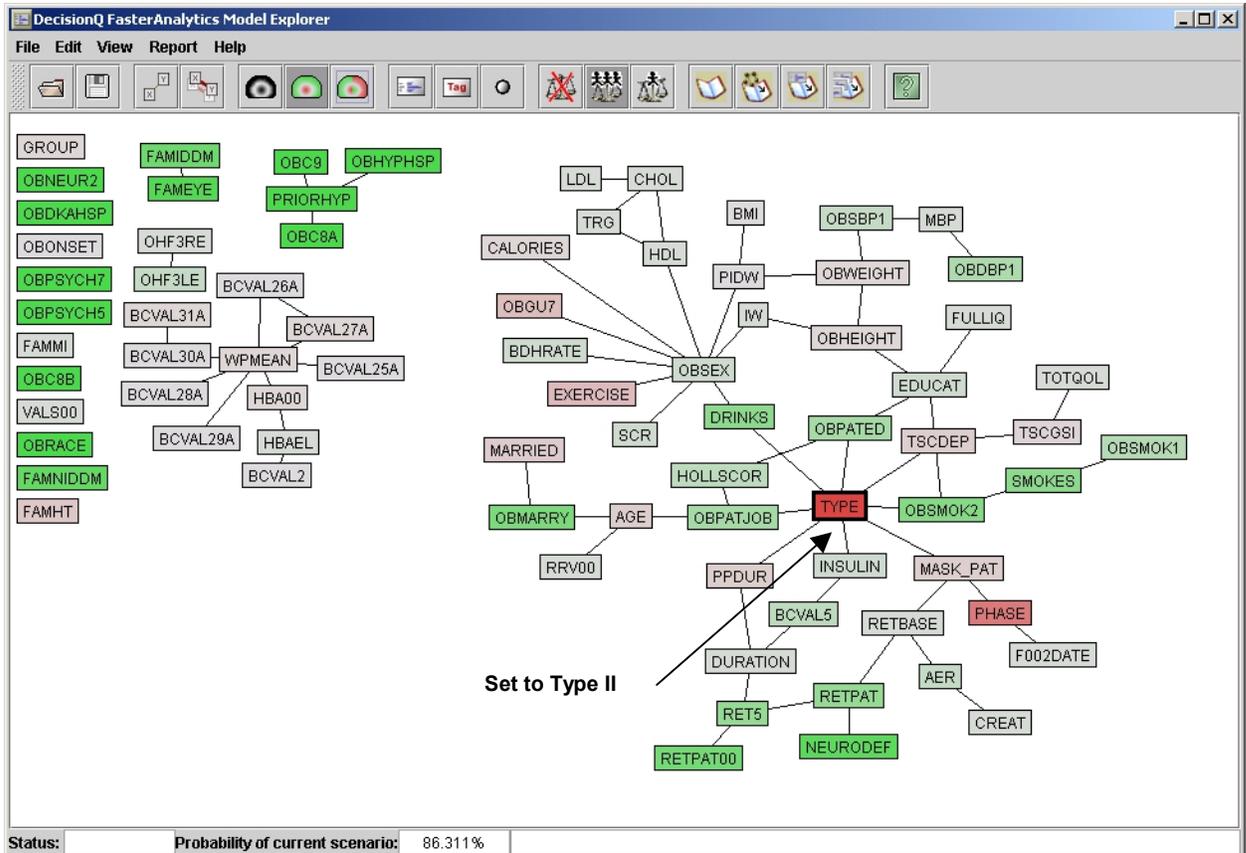
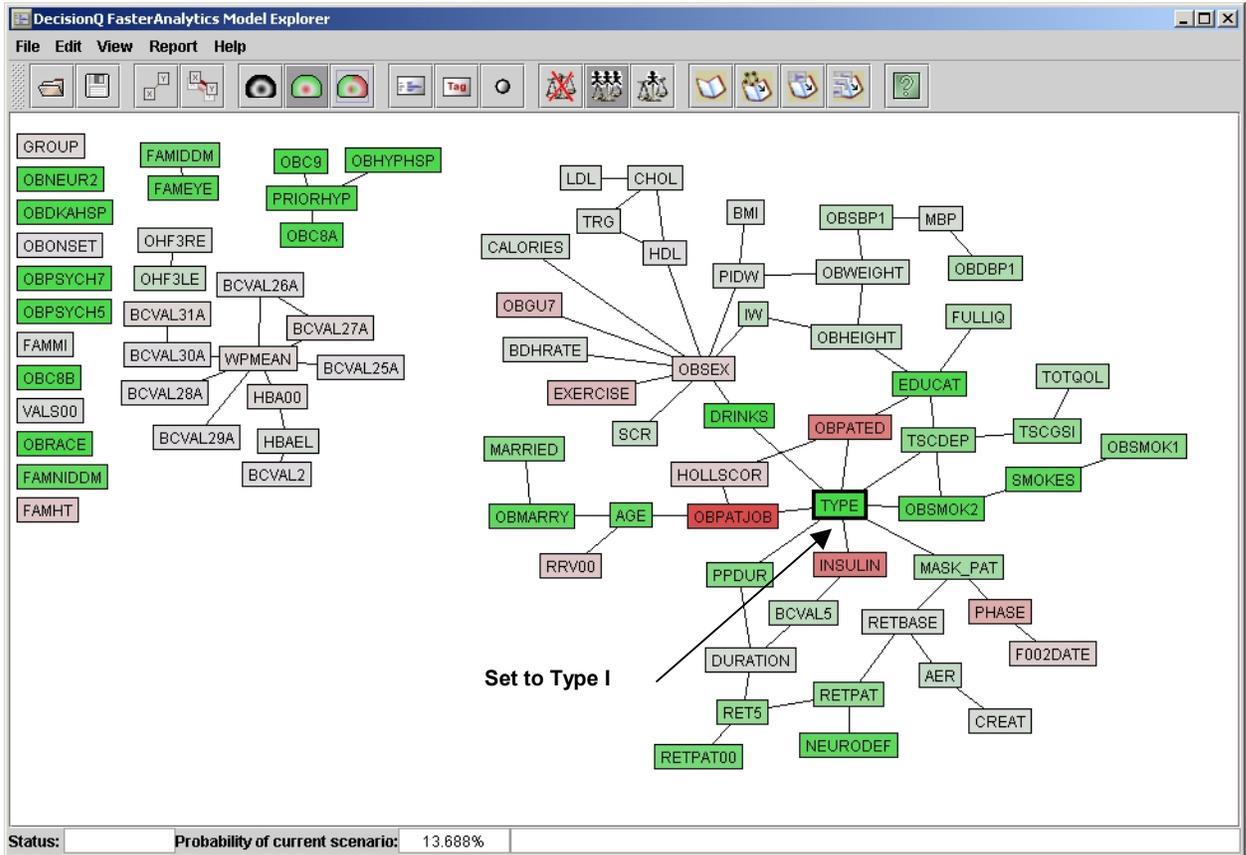


Figure 4: TYPE variable set to Type I



Compare the two models in Figure 3 and 4 above with the base level in Figure 1. While the Type II population is not particularly different from the overall cohort, the Type I population has a dramatically different profile. The coloring in the graphical model shows the change in population profile quickly and effectively.

It is also possible to select two or more variables simultaneously. The extent to which weight also affects the population profile can be studied in conjunction with other factors such as gender.

Figure 6a: Low INSULIN and CREATININE and their effect on diabetic RETINOPATHY

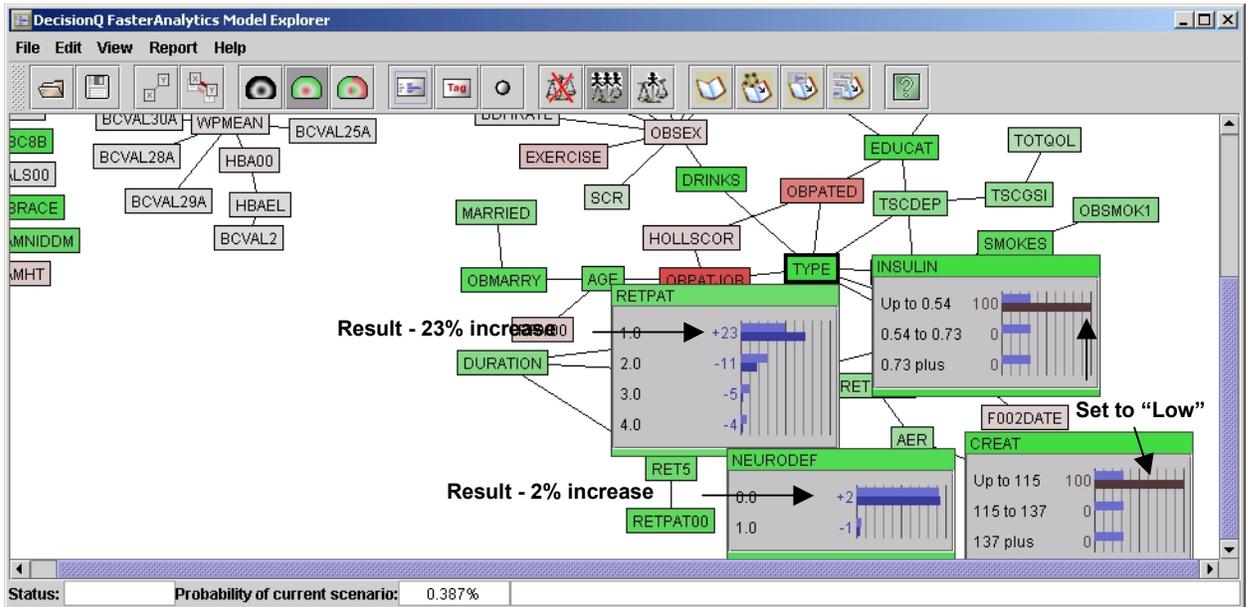
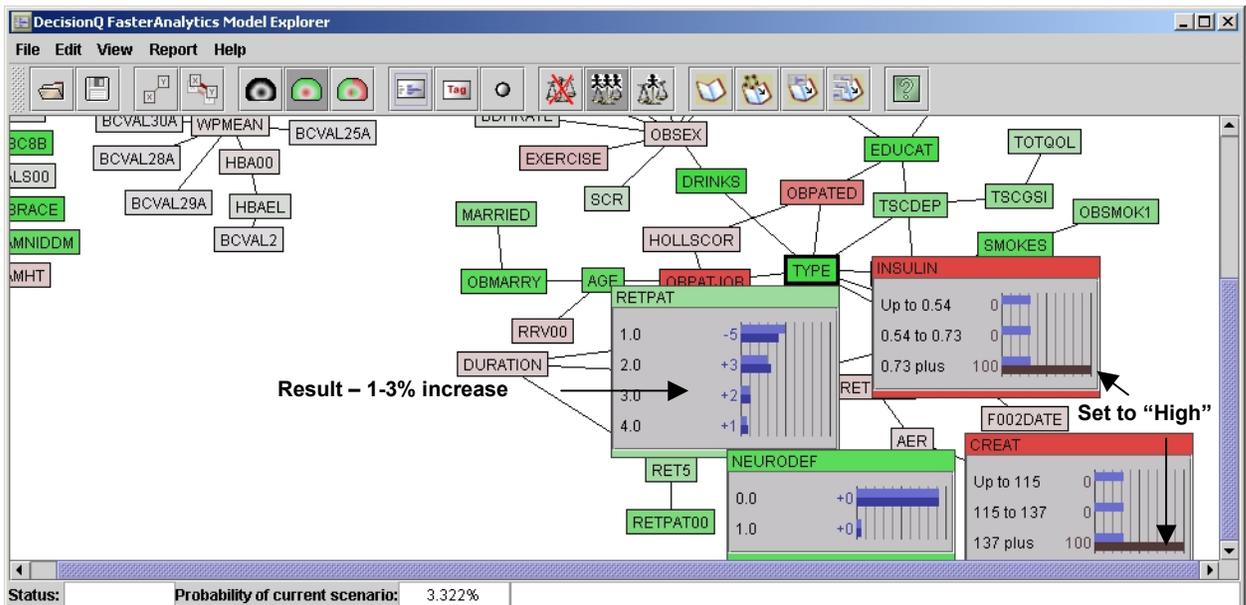


Figure 6b: High INSULIN and CREATININE and their effect on diabetic RETINOPATHY



The Report module can be used to create a report that will show the conditional probabilities (or predicted likelihood) of any target variables, given the expression of any independent variable(s). Any part of the model visualization can be pasted into Reporter and then transferred into other applications. Figure 7 shows a sample report.

Figure 7: A sample report listing the probabilities of retinopathy and neurological deficit given creatinine and insulin levels

| Probability of case | Drivers | | | Targets | |
|---------------------|---------|--------------|-----------|---------------------|---|
| | TYPE | INSULIN | CREAT | NEURODEF | RETPAT |
| 0.387% | 1.0 | Up to 0.54 | Up to 115 | 0.0 95.3 1.0 4.7 | 1.0 73.8 2.0 19.6 3.0 3.8 4.0 2.9 |
| 10.908% | 2.0 | Up to 0.54 | Up to 115 | 0.0 94.3 1.0 5.7 | 1.0 61.4 2.0 25.7 3.0 7.2 4.0 5.7 |
| 0.849% | 1.0 | 0.54 to 0.73 | Up to 115 | 0.0 94.2 1.0 5.8 | 1.0 59.1 2.0 26.8 3.0 7.8 4.0 6.2 |
| 10.568% | 2.0 | 0.54 to 0.73 | Up to 115 | 0.0 93.4 1.0 6.6 | 1.0 48.4 2.0 32.0 3.0 10.8 4.0 8.7 |
| 0.400% | 1.0 | 0.54 to 0.73 | Up to 115 | 0.0 93.3 | 1.0 47.4 2.0 32.5 |

DecisionQ sells predictive modeling software and complementary professional services. Alternatively, components from FasterAnalytics can be integrated into third party applications as part of broad data management and analysis platform.

If you have any further questions or would like to schedule a more detailed demonstration in person or over the web, please contact us.

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