Making better business decisions with analytics and business rules

An overview of the IBM Decision Management product stack

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This article provides an overview of how predictive analytics and business rules can be used together for better business outcomes. A banking example illustrates how IBM decision management products might be used for smarter business processes.

Introduction

Business rules play an important role in applying the outcomes of data analysis to improve processes. Rules work with data, as do analytics. Predictive analytics uses historical data to find patterns, and the outcome of such analysis is often mathematical scores that are best applied when combined with experience-based human validation provided by rules.

Business rules are everywhere, but in decision management, the focus changes from automation and management of business rules to business decisions. This article provides an overview of decision management and the IBM® product stack and integration techniques that can be used to improve business decisions.

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This article also presents a scenario about a fictitious bank's use of predictive analytics combined with business rules to perform better risk analysis. The article examines integration techniques and the interplay of complementary technologies using IBM software, but not the development of predictive models or business rule applications.

The following products are discussed in this article:

- IBM SPSS® Modeler
- IBM SPSS Collaboration and Deployment Services
- IBM Analytical Decision Management
Business case
Saba Bank, a fictitious bank, has just completed an enterprise information management program to ensure data quality, consistency, and integrity and is embarking on modernizing its Know your Customer (KYC or customer identification procedure) and Anti-money Laundering operations.

Saba Bank defined the objectives of the KYC modernization effort as follows:

- Achieve 100% compliance with the more stringent guidelines for KYC released by regulatory authorities and avoid hefty fines.
- Prevent potentially profitable customers from being filtered out based on blanket risk scoring. Achieve better accuracy in identifying risk as the manual process is found to be error prone with an accuracy of 60% and large variation in risk score during re-assessment.
- Manage customer information more efficiently so that time and effort are spent on investigating the more risky customers and thus achieve significant reduction in KYC processing time.
- Help provide a 360-degree view of the customer for improved customer relationship management and profitability with more targeted offers and improve offer response rate by 10%.

Solution architecture
The bank adopts a decision management solution using a combination of predictive analytics and business rules to achieve their objectives and implement a smarter process. Figure 1 shows the Saba Bank KYC architecture overview.

Figure 1. Solution architecture overview

The following sections describe the solution components, integration techniques, and the product stack, including a sample use case for identifying customer risk.

What is predictive analytics?
Predictive analytics is an area of data mining that deals with extracting information from data and using it to predict trends and behavior patterns. Predictive models capture relationships among many factors to assess the risk potential associated with a particular set of conditions, thus guiding decision making for candidate transactions.

Cross Industry Standard Process for Data Mining (CRISP-DM) is a data mining process model that describes commonly used approaches that expert data miners use to tackle problems. First published in 1999, CRISP-DM 1.0 was produced by a consortium of companies under the European Union's Framework IV R&D initiative. While many non-IBM data mining practitioners use
CRISP-DM, IBM is the primary corporation that currently embraces the CRISP-DM process model. This process is illustrated in Figure 2.

**Figure 2. CRISP-DM process**

![CRISP-DM process diagram]


The key steps in the CRISP-DM process are as follows:

- **Business Understanding** involves determining and defining business objectives in business terms, translating these to data mining goals and making a project assessment and plan.
- **Data Understanding** involves collecting initial data, describing the data in terms of amount, type and quality of data, exploring data using available tools and verifying data quality.
- **Data Preparation** is an important and time-consuming part of data mining which can take up 50–70% of the project’s time and effort. It involves selecting data to include, cleaning data to improve data quality, constructing new data that may be required, integrating multiple data sets, and formatting data.
- **Modeling** involves selecting suitable modeling techniques, generating test designs to validate the model, building predictive models and assessing these models. A predictive model is a mathematical function that predicts the value of some output variables based on the mapping between input variables. Historical data is used to train the model to arrive at the most suitable modeling technique. For example, a predictive model might predict the risk of developing a certain disease based on patient details. Some commonly used modeling techniques are as follows:
  - Regression analysis that analyzes the relationship between the response or dependent variable and a set of independent or predictor variables.
  - Decision trees that help explore possible outcomes for various options.
  - Cluster analysis that groups objects into clusters to look for patterns.
  - Association techniques that discover relationships between variables in large databases.
- **Evaluation** involves evaluating the results against the business success criteria defined at the beginning of the project.
- **Deployment** involves consolidating the findings, determining what might be deployed and planning the monitoring and maintenance required to keep the model relevant.

**SPSS software overview**

The IBM SPSS products are predictive analytics software applications that help businesses make smarter decisions and improve business outcomes. Figure 3 describes the SPSS product family.
The products in the SPSS Modeling family and Deployment family, which are the primary tools for predictive model development and deployment, are of particular interest for the Saba Bank use case.

- The SPSS Modeler is the primary tool for predictive model development and supports the CRISP-DM methodology with tooling to organize projects for effective data mining with CRISP-DM guidance.
- The SPSS Collaboration and Deployment Services product helps share and deploy predictive models with the ability to make predictive models available as scoring services.
- The SPSS Analytical Decision Management product helps build applications that combine predictive models and business rules.

What are business rules?

A business rule is a statement that describes a business policy or procedure. Business rules describe, constrain, or control some aspect of your business.

For example, a business rule could be that a customer with less than $25000 income is not eligible for a loan, or if a total purchase is more than $4000, the customer is granted a 4% discount.

What is a business rule management system?

A business rule management system (BRMS) enables business rules to be defined, deployed, monitored and maintained separately from application code, thus improving the agility of business processes with automation of repeatable decisions.

Agile Business Rule Development (ABRD) is a practice that helps implement business applications using BRMS and rule engine technology. The ABRD activities are described in the process diagram in Figure 4. Rules are developed incrementally in multiple iterations of short time frames, but the entire process lifecycle might not be followed each iteration.
An ABRD project usually has the following phases. Each of these phases consists of some of the activities in Figure 4.

- **Harvesting** is the activity of gathering business rules, which includes rule discovery and analysis.
- **Prototyping** is the activity of entering business rules into the BRMS; this includes rule discovery, analysis, design and authoring.
- **Building** is the activity of building a system that represents the organization's business rules. This includes all the rule activities except deployment: rule discovery, analysis, design, authoring and validation.
- **Integrating** is the activity of deploying the rules to an environment for end-to-end testing, which includes rule validation and deployment.
- **Governance** is the activity of monitoring, maintaining and enhancing the business rules, which includes all rule activities.

**Operational Decision Manager overview**

Operational Decision Manager (formerly ILOG JRules) is a leading BRMS that also provides business event processing capabilities. The components of Operational Decision Management are described in Figure 5. The designers are used for rule application development. **Decision Center** is the web interface for rule management and authoring. **Decision Server** is the rule execution server.

**Figure 5. Operational Decision Management architecture**

Source: Operational Decision Manager Knowledge Center.

**Analytical Decision Management overview**

Analytical Decision Management is software that provides the ability to create custom applications combining predictive models, business rules and optimization. It also provides scenario analysis and simulation capabilities. The basic architecture is shown in Figure 6.
The key components in the Analytical Decision Management architecture are the following:

- **Modeler Client** is used to create predictive models easily without much programming.
- **Modeler Server** is used to distribute requests for resource-intensive operations to powerful server software, resulting in faster performance on larger data sets.
- **Platform Services**, which is part of the J2EE server, has the Collaboration and Deployment Services (C&DS) that allow sharing predictive models in a team environment and deploying the predictive model as a scoring service.
- **Decision Management Framework** allows the creation of applications combining business rules and predictive models that might be deployed using the Collaboration and Deployment Services.
- **Deployment Manager Client** allows you to connect to a Collaboration and Deployment Services server to share predictive model streams and configure scoring for these streams.

**Selecting the product mix**

In the previous sections, the Saba Bank defined their business objectives and adopted decision management solution architecture. The next step is selecting the product mix to achieve the desired business outcomes. The key questions to ask are as follows:

- Do you have an existing investment in predictive analytics or business rules products that you can leverage?
- Are you starting with an analytics focus or a business rules focus? Do you need considerable predictive analytics with a few simple business rules? The business rules capability in SPSS Analytical Decision Management is suitable in this case. Or, do you need a considerable amount of medium to complex business rules augmented with predictive analytics? A more full-fledged BRMS like Operational Decision Management is suitable in this case.
- Are business events involved? Operational Decision Management also supports business event processing. Business event processing (BEP) software helps businesses detect, evaluate, and react to event patterns in time to meet the business objectives.

It is usually not necessary to have both Analytical Decision Management and Operational Decision Management. Analytical Decision Management does have some support for using business rules
in Operational Decision Management, and Operational Decision Management has a predictive analytics Support Pac (LB02) that provides integration with SPSS. Select the right mix based on your business needs.

**Customizing the methodology**

The Saba Bank chooses a methodology that combines the CRISP-DM process and the Agile Business Rule Development (ABRD) process. This is described in Figure 7.

**Figure 7. Decision Management Application development methodology**

The following sections cover the methodology for the Saba Bank example scenario.

**Understanding business requirements**

The process starts with understanding the business requirements and objectives, which involves the following:

- Identifying the decision points
- Harvesting business rules
- Identifying analytical outcomes and data mining goals

The first step is identifying the decision points. The decision in this case is the customer risk category that determines the level of further investigation required. A customer's risk category is defined as:

\[
\text{Risk category} = \text{Higher of predicted risk category from profile analysis and risk category from business rules.}
\]

For more information about decision modeling approaches that help to discover decisions in business processes see the IBM Redbooks publication, *Discovering the Decisions within Your Business Processes using IBM Blueworks Live*.

You review and analyze the decision points to harvest the business rules. The decision point Determine Risk Category is used to identify the business rules and analytical outcomes that
determine risk category. For the purpose of demonstration, 10 of the simpler rules were selected and classified as:

- Business Rule Only (R)
- Analytical Outcome + Business Rule (RA)

You then assign risk points to the rules, which are totaled to calculate the risk score. The risk score is then translated to a risk category of high, medium or low. The historical data analysis also provides a risk category. The combined risk category assigned is the higher of rule risk category and customer profile risk category. The risk terminology is defined as follows:

- Risk point is the risk associated with a single rule.
- Risk score is the total risk points calculated for a customer.
- Risk category is the risk classification of high, medium or low, based on the risk score.

The rule table looks as follows after this analysis.

**Table 1. Rule analysis**

<table>
<thead>
<tr>
<th>Rule</th>
<th>Classification</th>
<th>Analytical Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>If source of funds is not &quot;Salary&quot; or &quot;Government&quot; Add 20 risk points</td>
<td>R</td>
<td></td>
</tr>
<tr>
<td>If Identity verification status or Address Verification status is not &quot;Verified&quot; Add 70 risk points</td>
<td>R</td>
<td></td>
</tr>
<tr>
<td>If nationality is &quot;Non Resident&quot;, add 80 risk points</td>
<td>R</td>
<td></td>
</tr>
<tr>
<td>If gross total income &gt; 100000$ Add 30 risk points</td>
<td>R</td>
<td></td>
</tr>
<tr>
<td>If Political Exposure for &quot;Self&quot; Add 100 risk points</td>
<td>R</td>
<td></td>
</tr>
<tr>
<td>If Political Exposure for &quot;Close Relative&quot; Add 50 risk points</td>
<td>R</td>
<td></td>
</tr>
<tr>
<td>If total risk score &lt; 50, set rule risk category as &quot;low&quot;</td>
<td>R</td>
<td></td>
</tr>
<tr>
<td>If total risk score &gt; =50 and &lt; 70, set rule risk category as &quot;medium&quot;</td>
<td>R</td>
<td></td>
</tr>
<tr>
<td>If total risk score &gt; 70, set rule risk category as &quot;high&quot;</td>
<td>R</td>
<td></td>
</tr>
<tr>
<td>If customer profile risk category is greater than rule risk category, set combined risk category to customer profile risk category, else set combined risk category to rule risk category</td>
<td>RA</td>
<td>Customer profile risk category</td>
</tr>
</tbody>
</table>

There is only one business rule using an analytical outcome in this case, but there could be more for other use cases. For example, the bank might decide to roll out specific offers based on a niche segment identified from customer profiling. One has to consciously look for and discover analytical outcomes that augment the business rules and provide benefit to business.
Selecting a suitable approach

The next step is to identify the most suitable approach for Saba Bank in integrating these two complementary approaches to risk scoring. The following sections discuss the possible approaches.

Approach 1 – Without integration

The first approach uses a business rule application and customer information to derive the analytical risk scores and risk category, which are used to calculate the combined risk category. The analytical scoring does not happen in real time. This approach is suitable for batch mode operations where the predictive model is run on a batch of customer information periodically so that business rules in turn might use this outcome to arrive at the combined risk category. This approach is described in Figure 8.

Figure 8. Non-real-time approach (SPSS Modeler and Operational Decision Manager)

Approach 2 – Integration with Operational Decision Manager

The second approach makes use of an analytical scoring service to get the risk category in real time. A decision service is exposed that is a combination of the analytical scoring service and the business rules service as described in Figure 9.

Figure 9. Real time integration (SPSS Modeler, SPSS Collaboration and Deployment Services, Operational Decision Manager, Wrapper web service)
Approach 3 – Integration with Operational Decision Manager using LB02 SupportPac

A third approach involves integrating the scoring service into the business rule using the LB02 Support Pac, which has the functionality to define business rules that reference predictive scores obtained at runtime by invoking the SPSS scoring service.

This approach is described in detail in the developerWorks series Integrating SPSS predictive analytics into Business Intelligent applications, Part 2: Integrating the scoring service into an ILOG JRule.

This approach is made possible with support for Predictive Model Markup Language (PMML) in Operational Decision Manager. The PMML is an XML-based file format developed by the Data Mining Group to provide a way for applications to describe and exchange models produced by data mining and machine learning algorithms.

Because PMML enables the scoring configuration to be imported into Operational Decision Manager, it is possible to create better business rules using analytical outcomes at design time. The scoring service is invoked during the rule execution.

Figure 10. Real time integration (SPSS Modeler, SPSS Collaboration and Deployment Services, Operational Decision Manager with LB02 Support Pac)

Approach 4 – Using Analytical Decision Management

If using Analytical Decision Management, no additional integration is needed because Analytical Decision Management already has SPSS Modeler as part of its core analytic infrastructure, and predictive models may be imported into the solution. An Analytical Decision Management application is a combination of business rules and predictive models. For example, an Analytical Decision Management application can combine predictive data for customer churn, lifetime value, and customer satisfaction with business rules from the marketing team to suggest the right offers for a telecom customer.

Building an Analytical Decision Management application typically involves seven steps as shown in Figure 11. Simple applications might include only a few steps while advanced applications might include all seven steps. The application is defined by an XML template and there are prebuilt applications available that might be used to create a new application rather than build from scratch.
Figure 11. Analytical Decision Management application development

The following screenshots show the settings for a sample application for Customer Interactions that comes with Analytical Decision Management software:

1. Use the **Data** tab to select data sources, connect to data and decide what input data to use.

   **Figure 12. Application development – Select Data**

2. Use the **Global Selections** tab to define the decision scope and whether to include or exclude records from processing.

   **Figure 13. Application development – Global Selections**

3. Use the **Define** tab to define desired outcomes that could be a range of possible decisions or recommendations and the rules and predictive models that determine it.

   **Figure 14. Application development – Define**

4. Use the **Combine**, **Prioritize** or **Optimize** tabs to specify how the final decision is made. This may use a prioritization or optimization equation or combine the output from multiple rules and models using a matrix.
5. Use the **Deploy** tab to configure for batch or real-time scoring and integrate as required with existing IT systems. Select the type of deployment.

**Figure 16. Application development – Deploy**

6. From the **Reports** tab, you can add and view reports. Analytical Decision Management supports the reporting functionality enabled by Business Intelligence and Reporting Tools (BIRT).

**Figure 17. Application development – Reports**

**Approach 5 – Using Analytical Decision Management and Operational Decision Manager**

Approach 5 uses Analytical Decision Management and references external business rules already created in Operational Decision Manager. Specific instructions to implement this approach are described in the IBM Analytical Decision Management Application Designer’s Guide.

The following summary table lists all the approaches and the products used for each.

**Table 2. Summary of approaches**

<table>
<thead>
<tr>
<th>Approach</th>
<th>ODM</th>
<th>SPSS Modeler</th>
<th>SPSS C&amp;DS</th>
<th>SPSS ADM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approach 1 – without full integration</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Saba Bank makes an architectural decision to use Approach 2 for the following reasons:

- There are a large number of business rules and a full-fledged BRMS is necessary. Therefore, Operational Decision Manager is the platform of choice for business rules.
- SPSS Modeler is the platform of choice for predictive model development.
- It is expected that the new KYC system will achieve significant reduction in processing time, so that more time can be spent on investigating the risky customers. The next phase of the project involves rolling out more personalized offers through multiple channels based on customer profiles and their interactions. This requires an approach where real-time integration is possible. SPSS Collaboration and Deployment Services provides the required scoring service support.
- This leaves Approach 2 and 3 in the table above as options. As Approach 2 decouples rule execution from predictive scoring more effectively, this is chosen for architectural flexibility.

Predictive model development and rule development may happen in parallel, but could feed into each other. For example, data understanding might help harvest new business rules or a business rule might be identified as considerably enhanced if combined with an analytical outcome.

Developing a predictive model

The following sections describe a simple predictive model using fictitious customer data to train the model. The scenario uses a classification model known as Chi Square Automatic Interaction Detection (CHAID) to derive a risk category based on the input values selected as applicable for risk category. The CHAID analysis is a form of analysis that determines how variables best combine to explain the outcome in a given dependent variable.

For a detailed explanation of deploying a predictive model as a scoring service, see Integrating SPSS predictive analytics into Business Intelligent applications, Part 1: Integrating SPSS Modeler and Collaboration and Deployment Services.

Training the predictive model involves using historical customer data with risk category as input. Figure 18 shows a snapshot of the sample customer data.

Figure 18. Sample historical customer information
Figure 19 shows how the input variables and the target variable (for prediction) are defined.

**Figure 19. Sample historical data preparation**

Figure 20 shows a predictive modeling stream that is created to predict the risk category. The SPSS Modeler graphical interface represents data operations as nodes and streams. Nodes, which represent individual operations on data, are linked together in a stream to represent the flow of data. Algorithms are represented by a modeling node, which is a five-sided shape. When a stream contains a modeling node, the resulting model is represented as a model “nugget,” and is shaped like a gold nugget.

**Figure 20. Predictive modeling stream**

Figure 21 displays the final output. The $R$-Risk Category column shows the predicted risk category. Comparing the predicted value with the available value helps assess model accuracy. If the predictive model is not found to be reasonably accurate, other modeling techniques are evaluated to decide the most suitable technique.

**Figure 21. Predictive model training data output**

When the modeling node is run, a reusable golden model nugget (CHAID risk category) is generated as shown in Figure 20. After training models using a dataset where the risk category value is known, you can score records where the risk category value is not known by using the
nugget that is generated during the training process. A scoring data file contains the same fields as a training data file, except that the risk category is not set as the target field. The highlighted path in Figure 20 shows a scoring stream that populates the scoring outcome to a database.

The sample predictive model (kyc.str) and input data (kyc_generated_data.xls) are available in the samples provided with this article.

Developing business rules

The business rule development might happen in parallel. Saba Bank opted for the Operational Decision Manager business rule development approach (Approach 2) described in the section Selecting a suitable approach.

The Operational Decision Manager business rule development approach is summarized in Figure 22.

Figure 22. Operational Decision Manager application development

The initial phase of rule discovery and analysis is now complete, as described in the section Understanding business requirements. The next phase is rule development. The rule development details are not in scope of this article. Refer to the article Develop decision services, Part 1: A smarter city case study for more details on rule development.

Two sample business rule applications are provided in the Samples section.

- The business rule application kyc-calculated-risk calculates risk category based on business rules.
- The business rule application kyc-combined-risk calculates risk category based on the predicted risk category and the business rule calculated risk category.

Integrating and deploying the models

Once the predictive models and business rules are developed and tested, the model is integrated and deployed as described in the section Approach 2 – Integration with Operational Decision Manager.

The technical steps to achieve this for Approach 2 are as follows:
1. Deploy `kyc-calculated-risk` ruleset that calculates risk category based on business rules on the Rule Execution server.
2. Generate web service client code for the ruleset `kyc-calculated-risk` available as a hosted transparent decision service.
3. Configure the predictive model as a scoring service. Deploy predictive modeling stream (`kyc.str`) on SPSS Collaboration and Deployment Services using the SPSS Deployment Manager thick client. The scoring can be tested using the deployment manager thin client at URL like `http://hostName:port/peb`.
4. Generate web service client code for scoring service. The scoring service requires authentication, so modify web service client code to add the security headers. This is demonstrated in the sample code.
5. Deploy `kyc-combined-risk` ruleset that calculates risk category based on business rules on the Rule Execution server.
6. Generate web service client code for the ruleset `kyc-combined-risk` available as a hosted transparent decision service.
7. Create a customer risk service that invokes web services `kyc-calculated-risk`, predictive scoring service and `kyc-combined-risk` to return the customer risk category.

The key steps are deploying the predictive model and creating and deploying a decision service as described in the following sections. The sample code provided demonstrates how this is done.

**Predictive model deployment**

The predictive model is created using SPSS Modeler and is deployed on SPSS Collaboration and Deployment Services server as a scoring service. This scoring service returns the risk category for customer information provided. The predictive model (`kyc.str`) is deployed as a scoring service using SPSS Deployment Manager as shown in Figure 23.

**Figure 23. Scoring service**

For more information on deploying a predictive model, see [Integrating SPSS predictive analytics into Business Intelligent applications, Part 1: Integrating SPSS Modeler and Collaboration and Deployment Services](#).

**Creating the decision service**

After deploying the predictive model and business rule applications, the next step is to create a wrapper decision service that returns the combined risk category as shown in Figure 10.

The business rule application is a simple example using an XML execution object model (XOM) and is enabled as a hosted transparent decision service following deployment on the Rule Execution server.
As the combined risk category calculation is also a business rule in this case, another business rule application is created that returns the combined risk category based on the predicted risk category and business rule risk category.

The new decision service does the following:

- Gets the predicted risk category for customer.
- Gets the business rule risk category for customer.
- Gets the combined risk category for customer.
- Returns the customer risk category.

The details of decision service development are beyond the scope of this article, but a sample decision service (CustomerRiskService) is provided to demonstrate the Saba solution.

**Decision validation and governance**

This section describes how the IBM decision management products help support predictive model validation and governance.

The SPSS Collaboration and Deployment Services platform supports predictive model governance in the following ways:

- Suitable roles and permissions can be configured to deploy and manage the model, such as an IT admin to schedule jobs or real-time scoring for the models.
- Model performance is automatically monitored and can be configured to provide an alert when a model's accuracy degrades to a predetermined level. This level may be based on business rules, target variables or both.
- While an instance of a model is deployed into production, the model itself can be configured to automatically challenge the production model against other algorithms to ensure that the best performing, most accurate model is in production based on new data. If a more effective model is found, an alert can be sent to notify users, or it can be automatically deployed into production to replace the existing instance.
- Models and the related performance metrics are version controlled within the decision management platform. This gives users insight into model characteristics and performance.
- The predictive model is periodically trained on new data, and this is done using a model refresh. A model refresh is the process of rebuilding an existing model in a stream using newer data. The stream itself does not change in the repository. For example, the algorithm type and stream-specific settings remain the same, but the model is retrained on new data, and updated if the new version of the model works better than the old one.

The sample application provides a basic user interface to test the risk service as shown in the following screenshots.
Operational Decision Manager supports Decision Validation Services in both the developer and business user environments to do the following:

- Create and run tests to validate rule changes.
- Simulate the potential business impact of rule changes and interpret the results based on key performance indicators (KPIs).

Decision Warehouse is a tool within Operational Decision Manager that monitors rule execution and stores execution traces in a database. After deployment, Operational Decision Manager stores the decisions in the Decision Warehouse. The risk management team at Saba Bank can then generate reports and make an assessment of the following:

- The number of customers classified as high, medium, or low risk.
- The major deciding criteria for high, medium, or low risk classification.
- The impact of business rule changes on risk classification.

Governance is also set in place for business rules. Operational Decision Manager supports business rule governance with Decision Validation Services and Decision Warehouse, and also with version management, access control and reporting.

Conclusion

This article provided a comprehensive overview of the business rules and predictive analytics product stack from IBM for decision management. We have covered the application development methodology using a case study.
Acknowledgements

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Sample applications

The prerequisites for the customer risk application are SPSS Modeler and Operational Decision Manager 8.0.1 installed locally, and SPSS Collaboration and Deployment Services and SPSS ADM installed on a remote server. The customer risk application consists of the following:

- SPSS stream (kyc.str) and sample data (kyc_generated_data.xls). SPSS Modeler V 15.0 is required to open the modeling stream. Refer to the article Integrating SPSS predictive analytics into Business Intelligent applications, Part 1: Integrating SPSS Modeler and Collaboration and Deployment Services for instructions on configuring scoring on SPSS Collaboration and Deployment Services server.
- Operational Decision Manager business rules application (kyc-calculated-risk and kyc-combined-risk). Operational Decision Management 8.0.1 or above is required to import and deploy these rulesets. Import the rule projects in Rule Designer and refer to the section Deploying rulesets in the Operational Decision Manager Knowledge Center to create the ruleapps (kyc-calculated-risk-ruleapp and kyc-combined-risk-ruleapp). Deploy these rulesets to the Decision Server.
- The Decision Service (CustomerRiskService) can be deployed on IBM WebSphere® Application Server 8.0. Testing this service requires the predictive scoring service to be deployed on SPSS Collaboration & Deployment Services.
- Modify the host name and port for the Operational Decision Manager server if this is not a local host and port 9080. Modify the following line in com.saba.riskservice.RiskServiceSOAPImpl Java Class in CustomerRiskService Java project to point to the host name and port for the SPSS Collaboration and Deployment Services server, as follows:

  ```java
  ```

Resources

Related articles

Integrating SPSS predictive analytics into Business Intelligent applications, Part 1: Integrating SPSS Modeler and Collaboration and Deployment Services

Integrating SPSS predictive analytics into Business Intelligent applications, Part 2: Integrating the scoring service into an ILOG JRule

WebSphere ILOG BRMS Blog, Rules and Predictive Analytics

Predicting the future, Part 1: What is predictive analytics?
Making your enterprise ready for optimized decision making (PDF)

Popular Decision Tree: CHAID Analysis

Everything Decision Management blog

Methodology

CRISP Data Mining Guide (PDF)

Agile Business Rule Development Practice wiki

Business Rule Design and Development

Develop decision services, Part 1: A smarter city case study

Operational Decision Manager Knowledge Center

IBM Operational Decision Manager Version 8.0.1 Information Center

SPSS documentation

SPSS documentation PDFs

SPSS Modeler Knowledge Center

Analytical Decision Management documentation

Analytical Decision Management Knowledge Center

Application Designer's Guide (PDF)

IBM Blueworks Live

BlueworksLive – cloud based tool for process and decision modeling

Discovering the decisions in business processes using IBM Blueworks Live (Redbook)
## Downloadable resources

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<tr>
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<td><code>customer_risk_sample_application.zip</code></td>
<td>3187 KB</td>
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