3. Choose the *dimensions* of the business process: typical dimensions are time, product, customer and promotion. With the choice of each dimension, describe all discrete, text-like dimensional attributes that fill out each dimension.

4. Choose the measures of the business process: typical measures are numeric additive quantities like quantity sold and dollars sold.

2.1.3 Interaction between OLAP and DM

The multidimensional model supports OLAP and DM tools separately. Besides that, great benefits could reside in the interaction between these tools. KDD process can have improved user interaction when learning and hypothesis verification tools are provided.

Interactive data mining should be encouraged to allow users to interactively refine a data mining request, dynamically change focusing, progressively deepen a data mining process, and flexibly view data and data mining results at multiple levels of abstraction and from different angles. With integrated with OLAP tools, a data miner could drill down along any dimension in a data warehouse to find interesting patterns at multiple levels of abstraction, which will increase the usefulness of both data mining and data warehousing systems.

OLAP tools can also be powerful tools in the post-processing steps of KDD. In most cases, the examination of discovered knowledge generates new hypothesis. When the user finds a rule that describes an unusual situation, for example, OLAP tools may support further investigation, as the user tries to figure out the causes of that particular situation.

2.2 Visualization in post-processing steps

Data mining can be successful only if the user can easily find out the useful pieces of knowledge that are discovered, among the obvious and useless ones. Users must also be able to make proper interpretation to figure out how this information can be used to provide strategic advantage. As such interpretation of data mining results can only be performed by domain users, who cannot be expected to be data mining experts, post-processing steps become critical. Comfortable interaction with data mining tools must be provided, presenting knowledge in a notationally convenient way to the target user.
There are different kinds of users, who can feel more comfortable with different ways to represent information. Even the same user may need different perspectives of system’s outcome. Some representation formalisms can be very expressive, representing details, while they may lack in structuring or in a more “global” perspective. This happens in many different applications, not only in data mining.

Some knowledge representation formalisms can be easily mapped into other representations. Rule discovery, which is the focus of this work, can be represented through knowledge graphs [LEA90] and rule hierarchies, which have proved in our applications to be very efficient as complementary views of discovered knowledge.

2.2.1 Rule list

Most data mining software that discover rules display a list of “IF… THEN…” rules, along with some information about each rule’s strength, such as confidence and support, for example. These measures can be used to filter and sort rules to be shown, which can also be grouped by the class they represent. Rules can also be filtered by the occurrence of some attribute or attribute value. Figure 3 shows a rule list from movie database, mined with AIRA Data Mining Tool [HIC98], where the exceptions to the rules are also displayed; exceptions can sometimes represent anomalies, database errors or even frauds, depending on the application.

![Rule list report](image)

Figure 3 – Rule list

Although rules are considered powerful as representation formalism for knowledge engineering, and allow a high detail level, in data mining, when the number of discovered rules is large, it can be difficult for the user to keep the context. Each rule represents a separate