Data Mining in Astronomical Databases

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Abstract. A Virtual Observatory (VO) will enable transparent and efficient access, search, retrieval, and visualization of data across multiple data repositories, which are generally heterogeneous and distributed. Aspects of data mining that apply to a variety of science user scenarios with a VO are reviewed.

1 Science Requirements for Data Mining

What is data mining and why is applicable to scientific research? Data mining is defined as an information extraction activity whose goal is to discover hidden facts contained in databases. Data mining has taken the business community by storm and there is consequently now a vast array of resources and research techniques available for exploitation by the scientific communities. It is useful therefore to examine a categorization of data mining thrusts and their sub-components, since these are likewise applicable to the scientific exploration of large astronomical databases. Data mining is used to find patterns and relationships in data by using sophisticated techniques to build models – abstract representations of reality. A good model is a useful guide to understanding that reality and to making decisions. There are two main types of data mining models: descriptive and predictive. Descriptive models describe patterns in data and are generally used to create meaningful subgroups or clusters. Predictive models are used to forecast explicit values, based upon patterns determined from known results.

There is another differentiation of data mining into two categories that we find particularly appropriate to knowledge discovery in large astronomical databases: event-based mining and relationship-based mining. At the risk of trivializing some fairly sophisticated techniques, we classify event-based mining scenarios into four orthogonal categories:

- **Known events / known algorithms** – use existing physical models (descriptive models) to locate known phenomena of interest either spatially or temporally within a large database.
- **Known events / unknown algorithms** – use pattern recognition and clustering properties of data to discover new observational (in our case, astrophysical) relationships among known phenomena.
- **Unknown events / known algorithms** – use expected physical relationships (predictive models) among observational parameters of astrophysical phenomena to predict the presence of previously unseen events within a large complex database.
• Unknown events / unknown algorithms – use thresholds to identify transient or otherwise unique (“one-of-a-kind”) events and therefore to discover new phenomena.

For relationship-based mining, we identify three classes of association-driven scenarios that would find application in astronomical research:

• Spatial associations – identify events (astronomical objects) at the same location in the sky.
• Temporal associations – identify events occurring during the same or related periods of time.
• Coincidence associations – use clustering techniques to identify events that are co-located within a multi-dimensional parameter space.

From this discussion, we thus derive a reduced set of science requirements for data mining that correspond to the following exploratory approaches to mining large databases: Object Cross-Identification, Object Cross-Correlation, Nearest-Neighbor Identification, and Systematic Data Exploration. (a) “Object cross-identification” refers to the classical problem of connecting the source list in one catalog (or observation database) to the source list in another, in order to derive new astrophysical understanding of the cross-identified objects (e.g., gamma-ray burst counterparts). (b) “Object cross-correlation” refers to the application of “what if” scenarios to the full suite of parameters in a database (e.g., identify distant galaxies as U-band dropouts in a color-color scatter plot from the HDF survey). (c)”Nearest-neighbor identification” refers to the general application of clustering algorithms in multi-dimensional parameter space (e.g., finding the closest known population of young stars – in the TW Hydrae association – through their similar kinematics, X-ray emission, $H\alpha$, and Li abundance). (d) “Systematic data exploration” refers to the application of the broad range of event-based and relationship-based queries to a database in the hope of making a serendipitous discovery of new objects or a new class of objects (e.g., finding new types of variable stars, such as “bumpers”, in the MACHO database).

2 User Scenarios for Mining Astronomical Databases

It is well established that a significant fraction of all galaxies have been involved in galaxy-galaxy interactions at some time(s) in their past. The rate of these interactions is not yet well determined empirically. In our first astronomical data mining user scenario, we attempted an initial exploration of several on-line databases in order to estimate the galaxy interaction rate. We began by exploring an on-line catalog of galaxies (available through NASA’s ADC = Astronomical Data Center): the Updated Zwicky Catalog. This catalog identifies multiple-galaxy groupings, which we used to reduce the full list of 19,000 galaxies to the set of 1800 multiples. We then selected a very
small sub-sample from this list to conduct a proof-of-concept investigation. We used existing catalog visualization tools and archive linkage tools at the ADC to find all possible NASA mission data and most of the all-sky survey data for these selected objects [4]. We then identified characteristics in the optical images or in the IRAS fluxes or in the X-ray emissions to verify that the associated multiple galaxy systems are in fact (to high probability) bound groups (pairs, triples, quartets, etc.). The expectation that these small galaxy-galaxy separations and other evidences for physical association do in fact imply an on-going interaction was often confirmed through inspection of the DSS (Digital Sky Survey) imagery, which showed signs of interaction in many cases (e.g., distorted morphologies). Thus, by applying knowledge of astrophysical signatures of interactions, we were able to explore multiple distributed databases in a coherent organized manner. We estimate that the galaxy interaction rate in the local Universe is \( \sim 8\% \).

Among the exciting results of the COBE mission was the discovery of an extragalactic CIB (Cosmic Infrared Background; [3]). There has been a storm of activity to identify the sources of the CIB and to understand what powers the strong IR emissions. In our second data mining scenario, we initiated a proof-of-concept search scenario for identifying potential candidate contributors to the CIB. Our approach is similar to that of [2], except that we are applying the full power of on-line databases and linkages between these databases, archives, and published literature. Our search scenario involved finding object cross-identifications among the IRAS Faint Source Catalog and FIRST survey catalog, and then attempting to find those commonly identified objects also within other databases, such as the HST observation log. In a very limited test sample of targets, we did find one object in common among the HST-IRAS-FIRST databases: a known hyperluminous infrared galaxy (HyLIRG) at \( z=0.780 \) harboring an AGN, which was specifically imaged by HST because of its known HyLIRG characteristics. In this limited test scenario, we did in fact find what we were searching for: a distant IR-luminous galaxy that is a likely contributor to the CIB, or else a local analog of the more distant objects that likely comprise the CIB.

Our two user scenarios (including Web screen shots) are presented at the following web site (under the category “How to use the ADC for scientific research projects”): [http://adc.gsfc.nasa.gov/adc/how_to.html](http://adc.gsfc.nasa.gov/adc/how_to.html).

**References**

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