The Prague Relational Learning Repository

Jan Motl
Faculty of Information Technology
Czech Technical University in Prague
Prague, Czech Republic
jan.motl@fit.cvut.cz

Oliver Schulte
School of Computing Science
Simon Fraser University
Vancouver-Burnaby, Canada
oschulte@cs.sfu.ca

March 12, 2024

Abstract

The aim of the Prague Relational Learning Repository is to support machine learning research with multi-relational data. The repository currently contains 148 SQL databases hosted on a public MySQL server located at https://relational-data.org. The server is provided by getML to support the relational machine learning community (www.getml.com). A searchable meta-database provides metadata (e.g., the number of tables in the database, the number of rows and columns in the tables, the number of self-relationships).

1 Goals

Many organizations maintain their data in relational databases, which support complex structured data. Extending machine learning from traditional single-table methods to multi-relational data is an important direction for practical applications. The statistical and algorithmic challenges that arise from multi-relational data have been addressed in a number of research communities, such as Statistical-Relational Learning, Multi-Relational Data Mining, and Inductive Logic Programming. Experience with the UCI Machine Learning Repository[^1] has shown that a shared repository of benchmark datasets facilitates research.

[^1]: http://archive.ics.uci.edu/ml/
progress [1]. The UCI Machine Learning Repository contains mainly datasets stored in a single data table. Our goal is to provide a similar service for the relational learning community for relational datasets that contain multiple interrelated tables.

2 Design

The repository is maintained in a public MySQL server hosted by Czech Technical University in Prague. Each dataset is stored as a MySQL database on the server. Different formats have been introduced for storing multi-relational data. The advantages of using the SQL (SQL stands for “Structured Query Language”) format include the following.

- The SQL format is based on a standard widely used in industry. Using SQL databases in machine learning facilitates cross-community knowledge transfer and collaborations between machine learning and database researchers.

- Because SQL is a common standard, many programming environments support accessing and processing SQL data. This includes machine learning and statistical platforms such as Clowdflows [13], RapidMiner, and Weka. All general application languages provide SQL database connectivity, including R, Python, Java, and C++.

- The data description facilities of SQL provide a standard for defining metadata about the structure of the dataset. For example, information about the entities linked by a relationship is specified using primary and foreign keys. This metadata is recorded in the system catalog, and can be queried by machine learning applications.

To facilitate using tools developed for other relational data formats, we have provided scripts for converting MySQL data to other common data formats used in relational learning.\(^2\) This includes the Wisconsin Logic Learning format (WILL) and the .db format used in the Alchemy system. The ClowdFlows system also provides data format conversion, for example from MySQL to the Aleph Inductive Logic Programming Format.\(^3\)

3 Content

The repository currently contains 148 databases. This includes common benchmark datasets used in relational learning, like eastbound/westbound train dataset \(^15\) or biodegradability dataset \(^3\). Some of the databases are derived from the same base data in different ways (e.g. the repository contains different version

\(^2\)https://www2.cs.sfu.ca/~oschulte/jbm/DataConversion/MLN.html
\(^3\)http://www.cs.ox.ac.uk/activities/machlearn/aleph/aleph.html
of the IMDb dataset). We have aimed at providing a diversity of databases, for instance in terms of the number of records and in terms of the complexity of the relational schema. Hence, also synthetic datasets from different database vendors are included, as they are designed to show off capabilities of their database software. An example of such a synthetic dataset is Adventure Works, which is interesting not only because of its complexity, but also because of:

- it uses both, simple and composite keys;
- it contains a diverse set of data types, including datetime, blob (images) and geometry;
- it contains missing values.

4 Access and Contributions

Read-only access can be obtained via a database connection with the following parameters.

Hostname db.relational-data.org
Port 3306
Username guest
Password relational

To contribute a database, please contact the repository administrators; a web contact form is available [https://relational-data.org/contact](https://relational-data.org/contact). One possibility is to provide us with a MySQL dump of your database. Another option is to provide us with read access to your database on your server, so we can migrate the database to the public server. A web form for contributing is available [https://relational-data.org/contribute](https://relational-data.org/contribute).

5 The Meta-Database

Table 1 shows selected metadata from the meta-database. The meaning of the columns is as follows.

#Relations The number of tables in the database.

#Instances Count of rows in the target table.

Size Size in MB including indexes.

Type The dataset is either a measurement or synthetically generated.

Domain The original domain.
| Database            | #Relations | #Instances | Size  | Type  | Domain         | Task  |
|---------------------|------------|------------|-------|-------|----------------|-------|
| Accidents           | 18         | 495760     | 210.0 | Real  | Goverment      | Class  |
| AdventureWorks      | 71         | 30069      | 234.6 | Synth | Retail         | Regr   |
| AustralianFootball  | 4          | 3036       | 38.0  | Real  | Sport          | Class  |
| Biodegradability    | 5          | 328        | 3.2   | Real  | Medicine       | Regr   |
| Carcinogenesis      | 24         | 329        | 26.3  | Real  | Medicine       | Class  |
| CCS                 | 6          | 1000       | 658.4 | Real  | Finance        | Regr   |
| ClassicModels       | 8          | 273        | 0.5   | Synth | Retail         | Regr   |
| Countries           | 4          | 247        | 8.6   | Real  | Geography      | Regr   |
| Credit              | 9          | 10084      | 443.6 | Synth | Retail         | Class  |
| CS                  | 8          | 100        | 0.3   | Synth | Finance        | Class  |
| Dumur               | 11         | 276        | 0.8   | Real  | Kinship        | Class  |
| Elti                | 11         | 1081       | 0.7   | Real  | Kinship        | Class  |
| Employee            | 7          | 2838426    | 344.6 | Synth | Retail         | Regr   |
| Financial           | 8          | 682        | 94.1  | Real  | Finance        | Class  |
| FTP                 | 2          | 29555      | 7.5   | Synth | Retail         | Class  |
| Genes               | 5          | 862        | 1.9   | Real  | Medicine       | Class  |
| Hepatitis           | 7          | 500        | 2.2   | Real  | Medicine       | Class  |
| Hockey              | 23         | 7759       | 15.5  | Real  | Sport          | Class  |
| IMDb                | 23         | 794625     | 614.6 | Real  | Entertainment  | Class  |
| MovieLens           | 22         | 6039       | 151.9 | Real  | Entertainment  | Class  |
| Lahman              | 25         | 23111      | 84.0  | Real  | Sport          | Regr   |
| LegalActs           | 5          | 564268     | 238.2 | Real  | Goverment      | Class  |
| Mesh                | 9          | 223        | 1.1   | Real  | Industry       | Regr   |
| Mondial             | 13         | 454        | 3.3   | Real  | Geography      | Class  |
| MooneyFamily        | 20         | 92         | 3.3   | Synth | Kinship        | Class  |
| Mutagenesis         | 8          | 188        | 0.9   | Real  | Medicine       | Class  |
| Nations             | 3          | 14         | 2.1   | Real  | Geography      | Class  |
| NBA                 | 23         | 30         | 0.3   | Real  | Sport          | Class  |
| NCAA                | 10         | 268        | 40.6  | Real  | Sport          | Class  |
| Northwind           | 29         | 830        | 1.1   | Synth | Retail         | Regr   |
| Pima                | 14         | 768        | 0.8   | Real  | Medicine       | Class  |
| PremiereLeague      | 19         | 363        | 11.3  | Real  | Sport          | Class  |
| PTE                 | 25         | 299        | 7.3   | Real  | Medicine       | Class  |
| Pubs                | 11         | 18         | 0.4   | Synth | Retail         | Regr   |
| Sakila              | 16         | 15991      | 6.6   | Synth | Retail         | Regr   |
| SalesDB             | 4          | 6148886    | 539.3 | Synth | Retail         | Regr   |
| SameGen             | 7          | 1081       | 0.3   | Real  | Kinship        | Class  |
| Stats               | 8          | 38357      | 621.4 | Real  | Education      | Regr   |
| StudentLoan         | 17         | 1000       | 0.9   | Real  | Education      | Class  |
| PTC                 | 10         | 343        | 7.8   | Real  | Medicine       | Class  |
| Thrombosis          | 7          | 806        | 1.9   | Real  | Medicine       | Class  |
| TPCC                | 12         | 28433      | 174.1 | Synth | Retail         | Class  |
| TPCDS               | 15         | 99550      | 4587.5| Synth | Retail         | Class  |
| TPCH                | 14         | 148255     | 1925.1| Synth | Retail         | Regr   |
| Trains              | 15         | 20         | 0.1   | Synth | Logistic       | Class  |
| University          | 5          | 38         | 0.3   | Synth | Education      | Class  |
| UW-CSE              | 21         | 278        | 0.2   | Real  | Education      | Class  |
| VOC                 | 8          | 8215       | 2.7   | Real  | Logistic       | Class  |
| World               | 3          | 239        | 0.8   | Real  | Geography      | Class  |

Table 1: List of databases in the repository
Task Classification or regression.

The name of the meta-database schema is meta. This schema contains a number of tables with information about the databases, as well as the performance of different learning algorithms on the databases. The name of the table that contains information about the databases is meta.information. Some of this metadata is automatically exported in HTML format for display on the webpage relational-data.org. In the following, we list the names of the main column and their meaning. When we refer to “all columns” or “all rows”, we mean all columns/rows of all tables in a database. The metadata contain the following main groups of information: basic database statistics, information about columns or fields, foreign key structure, classification information.

5.1 Basic Database Statistics
Various basic properties, such as record count and missing values.

row_count The total number of rows, or records.

row_max The maximum number of rows, or records, in a single table.

column_count The total number of columns, or fields.

download_url A URL containing further information about the dataset, such as provenance.

null_count The number of table entries with null values; typically this is the number of table entries with missing values.

5.2 Column Information
These columns contain metainformation about the types of columns/fields/attributes in the database tables. The list is mutually exclusive and collectively exhaustive as it holds: column_count = geo_count + date_count + lob_count + string_count + numeric_count.

geo_count The number of columns that represent spatial attributes. (These are called “geographic” features in MySQL.)

date_count The number of columns that represent temporal attributes (date, time, or year).

lob_count The number of columns that store large objects (e.g., images).

string_count The number of columns that store string values. This typically includes discrete attributes.

numeric_count The number of numeric columns.
5.3 Foreign Key Structure

A foreign key points from one table to another. Chen et al. propose visualizing the foreign key relationships in a semantic relationship graph [5]: The graph contains a directed edge from table $T$ to table $T'$ if table $T$ references $T'$ in a foreign key constraint. These columns represent information about the structure of the semantic relationship graph.

- **primary_key_count** The number of primary keys.
- **composite_key_count** The number of primary keys that comprise more than one column.
- **foreign_key_count** The number of foreign keys.
- **self_referencing_table_count** The number of tables such that the table contains a foreign key pointer to one of its own columns. This occurs for example when a relational schema represents a class hierarchy or taxonomy.
- **has_loop** Whether there exists a loop of foreign key pointers over several tables. An example of a loop is when between a person table and a university table exists two foreign keys - the first foreign key signifies that a person is studying at a university, while the second foreign key signifies that the person is teaching at the university.

5.4 Classification

Many of the databases in the repository have been used to study classification in relational data. There is often a standard class label for such studies; we refer to this as the target attribute. These columns contain information relevant to the target attribute where it exists.

- **target_column** The target attribute most often used in relational classification studies.
- **target_table** The table that contains the target column.
- **target_id** The primary key field of the target table.
- **instance_count** The number of rows in the target table.
- **class_count** The number of class labels.
- **majority_class_ratio** The proportion of the majority class label on instance count.
6 Conclusions

In this paper, we presented the Prague Relational Learning Repository (PRLR), an easily accessible collection of datasets for relational learning. The PRLR was designed with supervised learning in mind. To this end, the PRLR contains 148 ready to download datasets. One of the important features of the PRLR is that it provides meta-data about the datasets. The PRLR meta-data can be accessed at [https://relational-data.org/](https://relational-data.org/).

Acknowledgment

We are grateful to getML for sponsoring and maintaining the database server [www.getml.com](http://www.getml.com). We would like to thank all of the donors who contributed data to the repository, and the author of the web page, Václav Ostrožlík. This work was supported by the Grant Agency of the Czech Technical University in Prague, grant No. SGS15/117/OHK3/1T/18.

References

[1] Stephen D. Bay, Dennis Kibler, Michael J. Pazzani, and Padhraic Smyth. The UCI KDD archive of large data sets for data mining research and experimentation. ACM SIGKDD Explorations Newsletter, 2(2):81–85, dec 2000.

[2] Petr Berka. Workshop notes on Discovery Challenge PKDD’99. 1999.

[3] Hendrik Blockeel, Sašo Džeroski, Boris Kompare, Stefan Kramer, Bernhard Pfahringer, and Wim Van Laer. Experiments in Predicting Biodegradability. Applied Artificial Intelligence, 18(2):157–181, feb 2004.

[4] Peter Boncz, Thomas Neumann, and Orri Erling. TPC-H Analyzed: Hidden Messages and Lessons Learned from an Influential Benchmark. In Performance Characterization and Benchmarking, pages 61–76. Springer International Publishing, 2014.

[5] Hailiang Chen, Hongyan Liu, Jiawei Han, and Xiaoxin Yin. Exploring Optimization of Semantic Relationship Graph for Multi-relational Bayesian Classification. Decision Support Systems, 48(1):112–121, 2009.

[6] Jie Cheng, Christos Hatzip, Hisashi Hayashi, Mark-André Krogel, Shinichi Morishita, David Page, and Jun Sese. KDD Cup 2001 report. ACM SIGKDD Explorations Newsletter, 3(2):47, jan 2002.

[7] Ivan Coursac and Nicolas Duteil. PKDD 2001 Discovery Challenge - Medical Domain. PKDD 2001 Discovery Challenge 2001, 3(2), 2002.
[8] Asim Kumar Debnath, Rosa L. Lopez de Compadre, Gargi Debnath, Alan J. Shusterman, and Corwin Hansch. Structure-activity relationship of mutagenic aromatic and heteroaromatic nitro compounds. Correlation with molecular orbital energies and hydrophobicity. *Journal of Medicinal Chemistry*, 34(2):786–797, Feb 1991.

[9] Bojan Dolšak and Stephen Muggleton. The Application of Inductive Logic Programming to Finite Element Mesh Design. In Stephen Muggleton, editor, *Inductive Logic Programming*, pages 453–472, London, 1992. Academic Press.

[10] Christoph Helma, Ross Donald King, Stefan Kramer, and Ashwin Srinivasan. The Predictive Toxicology Challenge 2000-2001. *Bioinformatics*, 17(1):107–108, Jan 2001.

[11] Yusuf Kavurucu, Pınar Senkul, and Ismail Hakki Toroslu. Concept discovery on relational databases: New techniques for search space pruning and rule quality improvement. *Knowledge-Based Systems*, 23(8):743–756, Dec 2010.

[12] Total Priced KB. 3. tpc-c—the standard benchmark for online transaction processing (oltp). *HISTORY*, 1(253):45–540, 1992.

[13] Janez Kranjc, Vid Podpečan, and Nada Lavrač. CloudFlows: A Cloud Based Scientific Workflow Platform. In *ECML PKDD*, pages 816–819, Bristol, 2012.

[14] Wolfgang May. Information extraction and integration: The Mondial case study. Technical report, UniversitätsInformationszenrum Freiburg, Institut für Informatik, 1999.

[15] Donald Michie, Stephen Muggleton, David Page, and Ashwin Srinivasan. To the international computing community: A new east-west challenge. Technical report, Oxford University Computing laboratory, Oxford, 1994.

[16] Raghunath Othayoth Nambiar and Meikel Poess. The making of TPC-DS. In *Proceedings of the 32nd international conference on Very large data bases*, pages 1049–1058, Seoul, 2006. VLDB Endowment.

[17] Michael Pazzani and Clifford Brunk. Finding accurate frontiers: A knowledge-intensive approach to relational learning. In *Proceedings of the Eleventh National Conference on Artificial Intelligence*, pages 328–334. Morgan Kaufmann, 1993.

[18] Matic Perovšek, Anže Vavpetič, Janez Kranjc, Bojan Cestnik, and Nada Lavrač. Wordification: Propositionalization by unfolding relational data into bags of words. *Expert Systems with Applications*, 42(17-18):6442–6456, 2015.
[19] Fatemeh Riahi, Oliver Schulte, and Qing Li. Identifying Important Nodes in Relational Data. In *AAAI Late Breaking Paper Track*, 2013.

[20] Bradley L. Richards and Raymond J. Mooney. Automated refinement of first-order horn-clause domain theories. *Machine Learning*, 19(2):95–131, May 1995.

[21] Matthew Richardson and Pedro Domingos. Markov logic networks. *Machine Learning*, 62(1-2 SPEC. ISS.):107–136, Feb 2006.

[22] Oliver Schulte, Zhensong Qian, Arthur E. Kirkpatrick, Xiaoqian Yin, and Yan Sun. Fast Learning of Relational Dependency Networks. *Inductive Logic Programming*, 2014.

[23] Oliver Schulte and Kurt Routley. Aggregating predictions vs. aggregating features for relational classification. In *2014 IEEE Symposium on Computational Intelligence and Data Mining (CIDM)*, pages 121–128. IEEE, Dec 2014.

[24] Ashwin Srinivasan, Ross Donald King, Stephen Muggleton, and Michael Joseph Ezra Sternberg. Carcinogenesis predictions using ILP. *Inductive Logic Programming*, 1297:273–287, 1997.

[25] Ashwin Srinivasan, Stephen Muggleton, Ross Donald King, and Michael Joseph Ezra Sternberg. The predictive toxicology evaluation challenge. *Proceedings of the Fifteenth International Joint Conference Artificial Intelligence (IJCAI-97)*, pages 1–6, 1997.