RESEARCH

Integration of Structured Biological Data Sources using Biological Expression Language

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Abstract

Background: The integration of heterogeneous, multi-scale, and multi-modal knowledge and data has become a common prerequisite for joint analysis to unravel the mechanisms and aetiologies of complex diseases. Because of its unique ability to capture this variety, Biological Expression Language (BEL) is well suited to be further used as a platform for semantic integration and harmonization in networks and systems biology.

Results: We have developed numerous independent packages capable of downloading, structuring, and serializing various biological data sources to BEL. Each Bio2BEL package is implemented in the Python programming language and distributed through GitHub (https://github.com/bio2bel) and PyPI.

Conclusions: The philosophy of Bio2BEL encourages reproducibility, accessibility, and democratization of biological databases. We present several applications of Bio2BEL packages including their ability to support the curation of pathway mappings, integration of pathway databases, and machine learning applications.

Keywords: Data Integration; Semantic Web; Biological Expression Language; Knowledge graphs

Background

The integration of heterogeneous, multi-scale, and multi-modal biomedical data has become a cornerstone of modern computational investigation of the mechanisms and aetiologies underlying complex diseases (Iyappan et al., 2014; van Dam et al. 2014; Wanichthanarak et al., 2015; Himmelstein et al., 2017; Fan et al., 2019). An overarching strategy was proposed by Davidson et al. more than two decades ago that outlined the transformation of data into a common model, semantic alignment of related objects, integration of schemata, and federation of data (Davidson et al., 1995). However, integration remains a challenging task that requires the identification and deep understanding of biological data sources and their respective formats, conversion, harmonization, and unification.

Initial interest in the semantic web and linked open data along with the adoption of RDF (Resource Description Framework) in the biomedical community led to the Bio2RDF project, in which pipelines for converting and serializing several biological data sources to RDF were developed (Belleau et al., 2008). Several updates have been issued since its deployment such as the inclusion of chemical information systems (Chen et al., 2010). Further, it has also influenced in and has been

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adopted by subsequent projects such as Open PHACTS (Williams et al., 2012). While RDF is highly expressive and each of these projects have developed and enforced well-defined schemata, the format is often not well-suited for downstream analyses and must first be queried with languages like SPARQL (SPARQL Query Language for RDF) and subsequently be transformed into appropriate formats with general-purpose programming languages. Alternatives to RDF/SPARQL such as property graphs (e.g., Neo4j, OrientDB) are comparable (Alocci et al., 2015) but also necessitate similar post-processing.

Conversely, there have been several biologically meaningful integration efforts (e.g., STRING; Warde-Farley, et al. 2010, GeneMANIA; Szklarczyk et al., 2015, GeneCards: Stelzer et al., 2016). However, most suffer from a lack of defined schemata or standardized data format that impede biological database interoperability. As interoperability itself is a multifaceted concept, we would like to highlight three of its facets: first, data sources should refer to named entities using high-quality, publicly accessible terminologies as prescribed by the Minimal Information Requested in the Annotation of Biochemical Models standard (Laibe and Le Novère, 2007). Second, data sources should additionally denote the ontological classes of named entities (e.g., gene, transcript, protein, pathway, disease) along with their reference using controlled vocabularies such as the Systems Biology Ontology (Courtot et al., 2011). Some identifiers, such as those for genes, are often used to refer not only to the physical region of DNA within the genome, but also the corresponding RNA transcript(s) or protein product(s). Unfortunately, many biological databases do not explicitly distinguish between these entity classes. For example, the STRING database lists gene-centric homology relationships, transcript-centric co-expression relationships, and protein-centric protein-protein interactions using gene-centric nomenclature. While it may be possible to identify the classes of entities based on their incident relationships, doing so requires specific knowledge of the database including the semantics of its relationships. Third, resources should, at a minimum, map their relationships to controlled vocabularies such as the Relation Ontology, or further use standardized data formats with defined semantics (e.g., PSI MI-TAB) to minimize both the interpretation and implementation effort when combining them with other resources.

OmniPath (Türei et al., 2016) began to address these facets when it combined several signaling pathway and transcriptional regulation databases. It achieved interoperability between several databases by normalizing the identifiers and relationships between entities from several databases describing the same phenomena (e.g., microRNA-target interactions, protein-protein interactions, etc.) and creating a unified network. However, because it did not use a standard format or schema as mentioned in the third facet for interoperability, OmniPath itself cannot readily be directly integrated with other biological data sources. Pathway Commons (Cerami et al., 2011) addressed this concern when combining several molecular pathway and interaction databases by translating the source databases into the BioPAX standard (Demir et al., 2010) using automated pipelines. However, it suffers from low granularity and low recovery of information from some of its primary biological data sources which may be due to prioritization of software development time, data usage restrictions, or shortcomings in the BioPAX standard. While BioPAX is well-suited

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for representing biological reactions and transformations, it is limited in its ability to represent correlative and associative relationships across multi-scale biology (e.g., at the levels of processes, phenotypes, and clinical observations).

As an alternative, we propose the use of Biological Expression Language (BEL; Slater, 2014) as an integration schema in order to overcome the limits faced by previous efforts and to simultaneously address all three facets of interoperability. BEL has begun to prove itself as a robust format in the curation and integration of previously isolated biological data sources of high granular information on genetic variation (Naz et al., 2016), epigenetics (Irin et al., 2015), chemogenomics (Emon et al., 2017), and clinical biomarkers (Iyappan et al., 2017). Its syntax and semantics are also appropriate for representing, for example, disease-disease similarities, disease-protein associations, chemical space networks, genome-wide association studies, and phenome-wide association studies.

With the same focus on reproducibility as Bio2RDF, OmniPath, and Pathway Commons as well as deference to software maintainability and the ease of development and inclusion of new biological data sources, we have developed a growing list of Bio2BEL packages, each capable of downloading, structuring, and serializing various biological data sources to BEL (Table 2). Each can be found in the Bio2BEL GitHub organization (https://github.com/bio2bel) as an independent opensource Python package that can readily be installed with pip. We have also developed and freely provided a framework (https://github.com/bio2bel/bio2bel) in the Python programming language to enable code reuse and the fast generation of additional Bio2BEL packages. Notably, the list of Bio2BEL packages includes one for OmniPath as a proof of concept that authors of other resources can implement their own Bio2BEL packages. In this article, we present the philosophy and implementation of Bio2BEL packages, a summary of past and future Bio2BEL packages, and finally, several case studies including the utility of Bio2BEL packages during curation of pathway mappings, in the analysis of cancer genome data, and for machine learning applications.

Implementation

Bio2BEL comprises numerous independent open-source Python packages that each enable reproducible access to a given biological data source (Figure 1). Each Bio2BEL package contains five components: 1) a definition of the source database or knowledge base, 2) an automated downloader for the data, 3) a parser for the data, 4) a storage and querying system for the data, and 5) a protocol for serializing the data to BEL (Figure 2). In this section, we outline the components of a Bio2BEL package and their implementation details.

Components of a Bio2BEL package

As this section outlines the core components and philosophy of a Bio2BEL package, it illustrates the tasks and thought process of a scientific software developer as they implement a new Bio2BEL package.

Definition of data

The first step in generating a Bio2BEL package is to understand the source data. This requires determining if the data are publicly accessible, if they are versioned

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(and how the location changes with versions), and if they are available under a permissive license. Bio2BEL packages do not contain data themselves and only refer to the locations of the original data sources. For those that are versioned, providers commonly generate symlinks to the most recent version (e.g., Inter-Pro; ftp://ftp.ebi.ac.uk/pub/databases/interpro). These characteristics help minimize licensing issues while enabling the resulting packages to update their content without changing code. Then, the developer implements custom code that makes the appropriate interpretations to convert the source data to BEL. Below, three types of data that can be readily integrated in BEL are described along with accompanying Table 1.

Taxonomies, Hierarchies, and Ontologies The Medical Subject Headings (MeSH; Rogers, 1963) multi-hierarchy can be converted to BEL by generating an isA relationship between each MeSH descriptor and all of its corresponding parents in the associated MeSH tree. Nomenclatures like the Complex Portal (Meldal et al., (2015) also define partOf relations between protein complexes and their substituents. The multi-hierarchy in Gene Ontology (GO; Carbon et al., 2017) can be converted similarly, which contains both is A relations and part Of relations. Tabular and Relational Data Enzyme inhibitors from ChEMBL and PubChem can be encoded like a(X) directly Decreases act(p(Y), ma(kin)), and disease-specific differential gene expression can be encoded like path(X) positiveCorrelation r(Y) or path(X) negativeCorrelation r(Y), or path(X) causeNoChange r(Y) depending on whether the gene's expression is up-regulated, down-regulated, or not regulated, respectively. Further, BEL relationships can be extended include metadata (i.e., annotations) describing their quantitative aspects. For example, IC50, EC50, or other kinetic assay measurements as well as provenance and biological contextual information (e.g., original publication, cell line, assay type) can be included with the enzyme inhibition relationships from ChEMBL. Similarly, the log2 fold change and p-values can be included with relationships about differential gene expression. Graphs Wetlaboratory experimentation can be used to generate networks of directly observed phenomena (e.g., protein-protein interaction networks) and indirectly observed phenomena (e.g., gene co-expression networks). Graphs are often distributed as tabular data to include additional information about their constituent nodes and edges and there is often overlap with the previous data type describing tabular and relational data. In silico experimentation can also be used to derive edges from experimental data sets or even other graphs. For instance, bipartite graphs can be projected to homogeneous graphs consisting of a single entity and edge type as suggested by Sun et al. (2014). Menche et al. (2015) used this strategy and computed a homogenous graph of disease-disease associations from a bipartite graph of diseases and their associated genes.

Ethics approval and consent to participateNot applicable

Consent for publication Not applicable

Availability of data and materials

Each Bio2BEL package is listed on https://github.com/bio2bel and automatically acquires relevant data from their respective original biological data sources.

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Competing interests

The authors declare that they have no competing interests.

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Author's contributions

CTH conceived and designed the study. CTH, DDF, and SM drafted the manuscript. MHA acquired funding and reviewed the manuscript. All authors performed data curation and developed computational pipelines for extraction, transformation, and loading of various biological data sources. All authors have read and approved the final manuscript.

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References

Figures

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Figure 2 Sample figure title. Figure legend text.

Tables

Table 1 Sample table title. This is where the description of the table should go.

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