Cover Sheet

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We welcome feedback and invite you to contact the lead author directly to comment on the manuscript (w1davis@ucsd.edu).

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Knowledge Graphs for Seismic Data and Metadata

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ABSTRACT

The increasing scale and diversity of seismic data, and the growing role of big data in seismology, has raised interest in methods to make data exploration more accessible. This paper presents the use of knowledge graphs (KGs) for representing seismic data and metadata to improve data exploration and analysis, focusing on usability, flexibility, and extensibility. Using constraints derived from domain knowledge in seismology, we define semantic models of seismic station and event information used to construct the KGs. Our approach utilizes the capability of KGs to integrate data across many sources and diverse schema formats. We use schema-diverse, real-world seismic data to construct KGs with millions of nodes, and illustrate potential applications with three big-data examples. Our findings demonstrate the potential of KGs to enhance the efficiency and efficacy of seismological workflows in research and beyond, indicating a promising interdisciplinary future for this technology.

CRediT authorship contribution statement


1. Introduction

Navigating big data is becoming increasingly crucial for seismic studies of the Earth’s structure, tectonic processes, and related geohazards (Arrowsmith et al., 2022). Collectively the field of seismology generates vast amounts of diverse data in many formats, including time-series waveforms, metadata pertinent to the instruments and stations which record them, and catalogues of estimated event source parameters. For instance, the Incorporated Research Institutions for Seismology (IRIS) Data Management Center (DMC) provides access to over 850 TB of archive data, including waveform, station, and event metadata across more than 27 data formats, as well as other higher-level data products (Trabant et al., 2012; Hutko et al., 2017). The scale and diversity of data sources and schema complicate data exploration (Dost et al., 2009; Krischer et al., 2016; Ringler et al., 2022; Arrais et al., 2022). Effective data utilization is further challenged by the rapid acceleration of data generation, primarily driven by the development of new data-dense, distributed sensor systems (Zhan, 2020; Trugman et al., 2022; Spica et al., 2023). Traditional methods of utilizing these data rely on specialized software tools and database systems, requiring researchers to navigate complicated schema outlines or data format specifications. There is increasing recognition that seismic data must be made more accessible, both to improve the research pipelines of the research seismological community (Gil et al., 2018; Arrowsmith et al., 2022), but also to facilitate broader applications to geohazard assessment, oil and gas exploration, data science, and...
machine learning domains (Mohammadpoor and Torabi, 2020; USGS, 2021; Ringler et al., 2022). To serve diverse end goals, seismic data exploration must be flexible and accessible. As new data sources become available, exploration methods must be extensible to accommodate them.

One route to improve data accessibility utilizes graphical user interface-based web services—Weertman (e.g., 2010); Newman et al. (e.g., 2013); Falco et al. (e.g., 2017). These tools enable access to homogeneous data through a single interface, allowing users to query seismic data, for example, based on event parameters—such as location, time, and magnitude. However, these tools are in practice restricted to specific data sources and data search is simplified in a way that restricts query complexity. Recently, (Yu et al., 2021) used cloud-based services to offer a route to scalable storage and computation for seismic data access and analysis. The catalog, hosted in the Amazon Web Services (AWS) Open Dataset Program initiative, brings multiple data sources from the Southern California Seismic Network (SCSN) together in a single “data lake.” The records are searchable via metadata in the names of files or filtering on certain data values recorded in index files.

An alternate and potentially complementary approach is to map heterogeneous data schemas to a common, extensible, and queryable semantic model. Data integration using a common ontology may be realized virtually, with mediated approaches (Halevy et al., 2006; Xiao et al., 2019), or physically in a single database. Recently, knowledge graphs (KGs) have emerged as a promising approach to organize complex and interconnected data in ontologies (Hogan et al., 2021; Gutiérrez and Sequeda, 2021), which can be tailored to meet specific requirements and domains (Abu-Salih, 2021). KGs are being increasingly utilized in geosciences (see Ma, 2022, for a comprehensive review). The use of KGs offers a versatile and extensible solution for many aspects of the data life-cycle, from data representation and curation, integration, and data analysis and result communication (Ma et al., 2014; Wing, 2019).

This paper introduces the idea of using relational KGs for seismic data, delivering a queryable semantic model and addressing the challenges in data exploration with large and schema-diverse seismic data. In this way, KGs complement web service and data lake offerings. We first outline a semantic model consisting of two KG ontologies, one for seismic station metadata and one for earthquake event data. We then present an implementation of these KGs demonstrating the integration of 4 data sources into a common, searchable graph structure, and provide three example applications. Our KGs are constructed from declarative definitions, enabling the abstraction of implementation details and a focus on knowledge modeling (Humphries, 2021). The KG definitions utilize a physical data integration approach, with definitions materialized on-demand, taking advantage of a recently developed scalable, cloud native relational knowledge graph management system (RKGS). We emphasize that we are not introducing a new data format; we are introducing KGs as a “semantic layer” for seismic knowledge (Stirewalt and Búr, 2023), to augment and connect heterogeneous data from existing sources.
2. Knowledge Graphs for Seismic Knowledge

In this study, we model two types of seismic knowledge: station metadata and seismic event data. In seismology, station metadata denotes known information about seismic stations and seismometers, such as geographic location, orientation, local site effects, and instrument type. Conversely, event data, gathered in earthquake catalogs such as the Global Centroid-Moment-Tensor (GCMT) project (Dziewonski et al., 1981; Ekström et al., 2012), describes earthquakes and other anthropogenic activities by their estimated properties, such as location, moment magnitude, and depth. This data differs from station metadata as it is based on inferences of natural events, involving uncertain, idealized representations of physical phenomena. Another type of seismic data is waveform data generated by seismic instruments, however, for simplicity, we choose not to include this in our current study.

We represent seismic knowledge in a graph structure. Nodes represent abstract objects (e.g., the Berkeley Digital Seismic Network or the Columbia College Station). Nodes can also represent atomic property values, like a specific latitude (e.g., 37.9°). Edges describe relations between objects (e.g., the Berkeley Digital Seismic Network manages the Columbia College Station). An example KG is shown in Fig. 1.a).

The nodes and edges in a KG organize data according to an ontology: a formal description of the concepts and relationships within a domain. We diagram the ontologies of seismic knowledge with Object-Role Modelling (ORM) (Halpin, 2015). We choose ORM to represent each ontology as it captures the relationship between nodes and edges as well as data constraints important to populating the KG, as we will show later. Importantly, ORM is attribute-free, modeling all relationships as explicit facts and disentangling ontology semantics from a specific knowledge graph implementation. The ontology is applied here to build a relational knowledge graph, but may be equally applied to a labelled property graph (LPG) or Resource Description Framework (RDF) graph, for example. An example ORM diagram, without data constraints, is shown in Fig. 1.b).

To model seismic knowledge as relational knowledge graphs, we define KG ontologies through the recognition of data integrity constraints, declared in natural language. These directly correspond to fact types in the ontology diagram and determine the relevant entity, value, and edge relations, including the criteria for uniquely identifying each entity. In the following section, we propose ontologies for station metadata and seismic event data.

2.1. Modelling Station Knowledge

The first type of knowledge we consider describes seismic instruments, and their hierarchical groupings and associations. We begin by identifying and verbalizing facts and constraints (S1–19) in the ontology, diagrammed in Fig. 2.

First, we identify four entities:

• Channel: An individual seismic instrument or sensor.
Knowledge Graphs for Seismic Data and Metadata

- **Channel Group**: A group of multiple channels. For practical purposes, channels are often grouped together into orthogonal triples.

- **Station**: A location—for example, a building—housing seismic instrument(s).

- **Network**: A collection of seismic stations, which are either managed and maintained by a specific agency or are linked to a specific scientific campaign.

Often, “(seismic) station” is used as a signifier for this entire hierarchy. The semantic model draws inspiration from the International Federation of Digital Seismograph Networks (FDSN) Source Identifiers specification (Trabant et al., 2019; Benson et al., 2019), and the FDSN Station Extended Markup Language (StationXML) format (see Data and Code Availability). However, we introduce augmentations to give added utility to the model. In particular, Channel Group is not represented as an element in the StationXML format. We emphasize that the semantic concepts here are general, and may be mapped to station metadata represented with other schemas (e.g., Ahern et al., 2009; Schorlemmer et al., 2011).

Identifiers for each entity type node must be graph-unique. This requirement distinguishes a relational knowledge graph representation from highly-normalized data: while the set of edge and node relations are in 6th normal form (6NF), the primary and foreign keys (node identifiers) must represent unique nodes across the entire set of relations in the graph to perform path traversal (Date, 2006). The combined requirement of 6NF representation and graph-unique node identifiers is known as "Graph Normal Form" (Stirewalt and Búr, 2023). To define the combination of data that constitutes a graph-unique identifier for each entity type, we recognize certain edge relations and integrity constrains on those relations:

1. **Each Station** is managed by **exactly one** Network,

2. **Each Channel Group** is in **exactly one** Station, and

3. **Each Channel** is in **exactly one** Channel Group.

Organizational bodies regularly define identification codes for networks, stations, channel groups, and channels (e.g., Buland, 2012; ISC, 2020). Expressed as a modelling decision, this corresponds to each entity having exactly one identification code as part of its reference scheme. We recognize that:

4. **Each Network** has a code of **exactly one** network code,

5. **Each Station** has a code of **exactly one** station code,

6. **Each Channel Group** has a code of **exactly one** channel group code, and
S7. Each Channel has a code of **exactly one** channel code.

A "channel group code" is sometimes referred to as a "location code."

In addition to identification codes, the entities have other associated properties. Some of these properties are explicitly represented in the FDSN StationXML format. For example, we incorporate information on geographic location in our ontology, which are modeled as mandatory and single-value relations:

S8. Each Station is at **exactly one** latitude,

S9. Each Station is at **exactly one** longitude, and

S10. Each Station is at **exactly one** elevation.

Other properties define aspects of channel instrumentation and digitization. The “band type” defines the general sampling rate and response band of the data source. The “instrument type” (or “source”) defines the type of sensor or data source (e.g., seismometer, accelerometer, geophone). The “orientation” (or “subsource”) indicates the orientation of the measurement. The traditionally used orientations are North (N), East (E), and Up (Z). These properties are modeled as mandatory and single-valued:

S11. Each Channel has **exactly one** band type,

S12. Each Channel has **exactly one** instrument type, and

S13. Each Channel has **exactly one** orientation.

Additional properties define depth and operational extent:

S14. Each Channel is at a depth of **exactly one** depth,

S15. Each Channel was operational from **exactly one** date-time, and

S16. Each Channel is operational until **exactly one** date-time.

Finally, we define the minimum combination of data that constitutes a graph-unique preferred identifier for each entity type. We choose to encode the rules of the FDSN Source Identifiers as uniqueness constraints. Networks are uniquely defined by their Network codes (S4) (Buland, 2012; ISC, 2020). For the remaining entity types, uniqueness is defined by the hierarchical constraints S1–3 combined with the entity’s own identification code (S5–7):

S17. **For each** Network and station code,

- at most one Station is managed by that Network and has that station code.
S18. **For each Station and channel group code,**

- **at most one** Channel Group is in **that** Station and has that channel group code.

As the FDSN Source Identifier specifications do not prescribe uniqueness conditions for channels—codes instead indicate instrumentation details—we choose to define the following criterion:

S19. **For each Channel Group and channel code operational from that date-time,**

- **at most one** Channel is in **that** Channel Group and has that channel code and was operational from that date-time.

The start date-time requirement naturally allows enforcement of constraints S15 and S16: a Channel that has multiple operational periods will be represented by multiple Channel nodes, one for each period.

### 2.2. Modelling Seismic Event Knowledge

We now model knowledge associated with records of seismic events in catalogs. As this knowledge reflects idealizations of natural events, records of the same natural event may vary in both schema and data, which the structure of an ontological model should handle. We identify facts and constraints (E1–10) that promote an event knowledge model flexible enough to encompass data from many sources, diagrammed in Fig. 3.

We define two entities associated with event knowledge:

- **Contributor**: An agency or group that manages, maintains, and contributes data to a seismic event catalog.

- **Event Record**: A record or entry of a seismic event.

We use the term “(seismic) event” as a signifier of this ontology. We define a mandatory and single-valued binary relation between these entities:

**E1. Each Event Record is contributed by exactly one Contributor.**

Note that we model the concept of an Event Record in a catalog rather than attempting to model the physical event itself. If one earthquake appears in two catalogs, our model will regard them as two independent event records. Subsequent entity resolution—or deduplication—may be used to associate event records with a unique seismic event (Sun et al., 2020; Obraczka et al., 2021). Each entity has a mandatory and single-valued reference scheme, which we verbalize as:

**E2. Each Contributor has a code of exactly one contributor code, and**

**E3. Each Event Record has exactly one event ID.**
We also model properties of the Contributor and Event Record entities. For each Contributor, we include a mandatory (but not necessarily single-valued) catalog code:

E4. Each Contributor has a catalog code that is some catalog code.

In the GCMT catalog, for example, this refers to the “hypocenter reference catalog” code. Each Event Record has associated property values corresponding to estimated physical parameters of the event. We choose to incorporate a small but fundamental set of (mandatory and single-valued) properties in our ontology:

E5. Each Event Record has a magnitude of exactly one magnitude,

E6. Each Event Record occurred at exactly one origin date-time,

E7. Each Event Record was at a latitude of exactly one latitude,

E8. Each Event Record was at a longitude of exactly one longitude, and

E9. Each Event Record was at a depth of exactly one depth.

Finally, we define the graph-unique preferred identifiers for each entity type. By constraint E2, a Contributor is uniquely defined by their contributor name. For an Event Record, we require that event IDs are unique within catalogs. This is modeled as an external uniqueness constraint over relations E1 and E3:

E10. For each Contributor and event ID,

- At most one Event Record was contributed by that Contributor and has that event ID.

3. Implementation of Station and Event Knowledge Graphs

To study the functionality of the two proposed knowledge graphs, we develop an implementation of the station and event ontologies in a database. This is accomplished using the RelationalAI RKGMS (RAI, 2021a), and modeled using the declarative, relational language Rel (RAI, 2021b; Stirewalt, 2022). We de-emphasize language-specific details in favor of providing an outline of the process of mapping seismic data into KGs (all code is available in the supplementary material). With the ontology of our two KGs outlined in the previous section, we now focus on populating the graphs with real-world seismic data (Hofer et al., 2023).

3.1. Data Selection and Extraction

We identify a range of relevant sources of seismic data to integrate into our KGs. These sources highlight the data-schema diversity present in file formats commonly used by seismologists. We consider:
• Station metadata, in StationXML format, acquired from IRIS DMC using the fdsnws-station webservice (see Data and Code Availability),

• Earthquake event data, in NDK format, acquired from the Global Centroid-Moment Tensor (GCMT) catalog webservice (Dziewonski et al., 1981; Ekström et al., 2012),

• Earthquake event data, in CSV format, acquired from the Northern California Seismic Network (NCSN) catalog using the NCEDC’s Northern California Earthquake Catalog Search webservice (NCEDC, 2014), and

• Earthquake event data, in CSV format, acquired from the United States Geological Survey (USGS) earthquake catalog webservice (USGS, 2017).

The precise search parameters for extracting data from these sources vary depending on the intended application of the KG and are specified in Section 4.

3.2. Data Loading and Transformation

We employ rule-based, declarative relation definitions, written in the Rel language, to transform both structured and semi-structured data sources to a relational KG. With this approach, the transformation logic, source data, and knowledge graph may coexist in the same database, preserving data provenance and allowing queries across graph and source data. The transformation logic takes advantage of Rel’s support for entity generation, querying over schema, higher order logic, and data integrity constraint declarations. However we note that the extract-load-transform process need not be constrained to one approach for all data sources. For example, data transformation between structured formats using domain specific languages has been widely studied (García-González et al., 2020; Hofer et al., 2023).

Mapping input data to KG values requires knowledge of the schema for each data format. For example, in NDK format a magnitude estimate is located in the character range 49–55, whereas NCEDC CSV data stores equivalent information in the “Magnitude” column. In another example, the band type, instrument type, and orientation of a Channel can be inferred from the channel code using the FDSN Source Identifiers. Our implementation populates the station KG with Network, Station, and Channel property labels and values from StationXML data by querying over the source data schema.

Population of edge relations between entity types also differs for each data format. The hierarchical structure of StationXML enables the relations S1–3 to be inferred directly from attributes and sub-elements outlined in the StationXML specification. For the event data, the tabular structure of the source data allows relation E2 to be realized by identifying data appearing in a common row, (or, for NDK files, sets of rows).
### 3.3. Entity Creation

Entity identifiers are represented as hashes of their node label plus the preferred identification data which uniquely identify each node, as declared in Section 2. In the station KG, uniqueness is identified for a Network from the extracted network code (S4). For the remaining station graph entities, we invoke the external uniqueness constraints S17–19, defining:

- Each Station node identifier as a hash of Network node identifier and the station code,
- Each Channel Group node identifier as a hash of the Station node identifier and the channel group code, and
- Each Channel node identifier as a hash of the Channel Group node identifier, channel code, and start date-time.

For the event KG, uniqueness for Contributor entities is identified through the extracted name (E2). With Contributor entities resolved, external uniqueness constraint E10 is invoked, such that:

- Each Event Record node identifier is a hash of its Event ID and Contributor node identifier.

### 3.4. Quality Assurance

For the KGs to be trustworthy and useful for analysis applications, the correctness of the mapped knowledge must be verified (Wang and Strong, 1996). We codify data constraints S1–19 and E1–10 into logical rules—or programmatic integrity constraints—to identify aberrations or logical errors in the KG that may have arisen during construction. If any integrity constraint is violated, the construction of the KG will halt, and the data can be interrogated for aberrations. We note that the data collected across all sources in this study were typically of high quality. Only one case required data cleansing: a StationXML file contained a duplicate channel which was manually removed.

### 4. Querying Examples

To empirically demonstrate the effectiveness of seismic KGs, we show three examples using data described in Section 3.1. These examples range from very simple queries that are readily achievable using existing tools (e.g., Weertman, 2010; Beyreuther et al., 2010; Newman et al., 2013), to more complex queries that take advantage of the KG structure and logical rules.

#### 4.1. Example 1: Filtering Events by Location

We first investigate executing simple queries and determining aggregate measures using a single KG. The objective is to filter a large set of event data—from multiple sources—by geographic position.

We collect all available event data for the year 2020 from the three event sources listed in 3.1 and construct an event KG, event_kg. The resulting KG comprises over 1.6 million nodes and 2.3 million edges in the ontology, including
Contributor entities and approximately 230,000 Event Record entities. We filter the events by geographic position around California and calculate the number of contributions from each contributor. Code for this query is given in Listing 1, and the resulting aggregated counts are shown in the legend of Fig. 4. We take advantage of Rel’s support for ungrounded relations to define reusable logic filter_latitude and filter_longitude, which are evaluated on demand in the query.

Listing 1: Querying the event KG (event_kg) through the constraints outlined in Example 1. Lines 1–3 filter the event KG by latitude and longitude (definitions of filter_latitude and filter_longitude are given in the supplemental material). Lines 5–9 define a binary relation of contributor names and filtered event nodes by performing an inner join over contributed and name. Lines 11-12 define a binary relation of contributor names and the total number of events contributed.

```python
def filter_event_CA(event) =
    filter_latitude(32.6,42.6,event) and
    filter_longitude(-126.2,-113.7,event)

def filtered_contributor_event(contributor_name,event) =
    filter_event_CA(event) and
    event_kg:contributed(contributor,event) and
    event_kg:name(contributor,contributor_name)
    from contributor in event_kg:Contributor

def count_events(contributor_name,event_total) =
    count(filtered_contributor_event[contributor_name],event_total)
```

To further interrogate the event data, we query the KG to determine the spatial distribution of event epicenters for each contributor. Code for this statement is given in Listing 2, and the resulting distributions are shown in Fig. 4.
Listing 2: Querying the event KG (event_kg) through the constraints outlined in Example 1. The code defines a tabular view of contributor names and filtered latitudes and longitudes by performing an inner join over filtered_contributor_event, at_latitude, and at_longitude. The format is column, row, value, with the event node serving as a unique row identifier.

```python
def list_positions =
    :Name, event, contributor_name;
    :Latitude, event, latitude;
    :Longitude, event, longitude
from event in event_kg:EventRecord, contributor_name, latitude, longitude
where
    filtered_contributor_event(contributor_name, event) and
    ~Latitude(latitude, event_kg:at_latitude[event]) and
    ~Longitude(longitude, event_kg:at_longitude[event])

def output = list_positions
```

The overlapping points in Fig. 4 indicate that many Event Record entities from different contributors may correspond to the same physical events. This could arise from catalogs sharing a common data origin, as exemplified between contributors NCSN (acquired from the NCEDC) and NC (acquired from the USGS). Identifying these matches would require entity resolution (Sun et al., 2020; Obraczka et al., 2021).

**4.2. Example 2: An Event Focused Study**

Next, we use both event and station KGs to study a single earthquake in detail. As a case study, we examine the 2019 Ridgecrest earthquake sequence, which caused widespread shaking throughout southern California (Brandenberg et al., 2019). We aim to determine a set of strong-motion instruments that were spatially and temporally coincidental with the earthquake, with the motive that this information can be used to select useful stations when procuring waveform data.

We use the IRIS DMC fdsnws-station webservice to collect station metadata around Southern California for all stations that were operational on or after the day of the earthquake. Next we obtain event data for the year 2019 from the GCMT catalog, and use both datasets to construct event and station KGs. The resulting station KG comprises ~ 35,000 nodes and ~ 116,000 edges in the ontology, including 2316 Station entities. We identify the Event Record entity corresponding to the Mw 7.1 July 6th earthquake through its event ID, C201907060319A, obtained
from the IRIS Moment Tensor page (doi:10.17611/DP/18001775) (Trabant et al., 2012).

Next, we simulate a typical query to identify scientifically useful strong-motion data relating to the 2019 event:

1. The Station must be within 2 degrees (222 km) of the earthquake epicenter,

2. The Station must contain a Channel Group where:
   
   (a) The Channel Group has 3 Channel entities,

3. The Channel Group must have a Channel where:
   
   (a) The Channel band type is either broadband or high broadband,

   (b) The Channel instrument type is an accelerometer,

   (c) The Channel is in the vertical orientation, and

   (d) The Channel was operational at the time of the earthquake,

Requirement (1) compares the latitude and longitude properties of the event KG (E7–8) and the stations KG (S8–9). Similarly, (3.d) compares the event KG date-time property (E6) with the station KG start and end date-time properties (S15–16), as shown in Listing 3. Finally, requirements (3.a–c) are accomplished by filtering the KG by Channel relations S11–13. We use these conditions to query for useful strong-motion stations in Listing 4.

Listing 3: Querying the station KG (station_kg) and event KG (event_kg) through the constraints outlined in Example 2. This statement defines a binary relation of Event Record and Channel pairs, where the channel was operational during the event. This is accomplished through the edge relations for channel nodes operational_from and operational_until and the edge relation for event record nodes occurred_at. The target datetime nodes are then constrained with relational operators on Line 5.

```
def event_in_channel_operational_range(event, channel) =
    station_kg:operational_from(channel, start_dt) and
    station_kg:operational_until(channel, end_dt) and
    event_kg:occurred_at(event, event_dt) and
    (event_dt > start_dt) and (event_dt < end_dt)
    from start_dt, end_dt, event_dt
```
Listing 4: Querying the station KG (station_kg) through the requirements outlined in Example 2. Lines 1–2 identify the Event Record entity of the Ridgecrest earthquake through its event ID. Lines 5–6 traverse the graph from station to channel group to channel nodes. Line 7 filters the channels by low gain and vertically oriented instruments. Line 8 uses the relation in Listing 3 to select stations operational during the Ridgecrest earthquake. Line 9 uses relational composition to select channel groups that contain three channels, with at least one channel in the channel group satisfying Line 7. Line 10 filters event-station pairs by their epicentral distance in degrees. Relations is_low_gain_vertical and event_station_radius_range are defined in the supplementary material. From this query, latitudes and longitudes are realized similarly to Listing 2 and the query is defined in the supplementary material.

```python
1 def ridgecrest_event(event) =
2     event_kg:event_id(event, "EventId["C201907060319A"]")

3 def ridgecrest_query(station) =
4     station_kg:channel_group(station, channelgroup) and
5     station_kg:channel(channelgroup, channel) and
6     is_low_gain_vertical(channel) and
7     event_in_channel_operational_range(ridgecrest_event, channel) and
8     count(station_kg:channel[channelgroup], 3) and
9     event_station_radius_range[0.0, 2.0](ridgecrest_event, station)
10 from channelgroup, channel
```

We find that 107 stations match the query in Listing 4; their spatial distribution is shown in Fig. 5.

4.3. Example 3: A Constrained Global Seismology Study

To illustrate the flexibility and utility of the KG approach, we investigate a case study with highly specific constraints on station and event data: the study of the inner core through deep seismic phases (e.g., Tkalčić et al., 2013; Yu et al., 2017). Such studies commonly require high-gain, low-noise instruments with favorable orientations and often utilize earthquakes of particular magnitudes, depths, and sometimes earthquakes with high latitudes (Frost et al., 2021) or temporally repeating patterns (Yang and Song, 2023). The strictest constraint is placed upon event-station pairs, as very precise event-station epicentral distances are required to observe the necessary core-sampling seismic phases (Young et al., 2013; Tkalčić, 2015). In this example, we use KGs to efficiently determine valid event-station pairs, which informs the acquisition of waveform data for inner core studies.

We collect station metadata from the IRIS DMC, without restrictions on geographic position. To limit the size of
the dataset in this example, we only collect data for stations with operational channels starting on or after 2010. We use earthquake event data from the entire GCMT catalog combined with records of nuclear explosions gathered from the USGS earthquake catalog webservice. The KGs contain ~1.4 million nodes and ~19 million edges for the station KG, and ~591,000 nodes and ~623,000 edges for the event KG. In particular, we have ~62,000 Event Record and ~49,000 Station entities.

We simulate a highly constrained query to identify scientifically useful event-station paths that sample core phases PKPbc and PKPdf (Tkalčič, 2015). Events are defined to have the following requirements:

1. The Event Record magnitude is between 5.5 and 7,
2. The Event Record depth is greater than 10 km, and
3. The Event Record latitude is either greater than 45°N or less than 45°S.

Similarly, stations have the following constraints:

4. The Station latitude is either greater than 45°N or less than 45°S,
5. The Channel band type must be either broadband or high broadband, and
6. The Channel instrument type must be a high-gain seismometer.

Finally, there are constraints on the event-station pairs:

7. The Channel must be operational at the time of the earthquake, and
8. The epicentral distance between the Event Record epicenter and Station is in the range 147°–153°.

Requirements (1–3) can be accomplished by filtering the event KG on relations derived from E5, E7, and E9. Similarly, (4–6) involve filtering the station KG on relations from S9, S11, and S12. Requirement (7) is satisfied by the date-time comparison relation in Listing 3. Finally, (8) requires a join over at_latitude and at_longitude for both the station and event KGs, as well as calculation of the distance, and comparison with the distance range. This constraint is implemented in Listing 5.
Listing 5: Definition of a binary relation of Event Record and Station pairs filtered by epicentral distance, as outlined in Example 3. The relation on Line 2 calculates an epicentral distance and is defined in the supplementary material. Lines 3-7 resolve the Event Record and Station latitudes and longitudes. Line 8 compares this distance with a prescribed epicentral distance range (defined in the supplementary material). From this query, latitudes and longitudes for event-station pairs are realized similarly to Listing 2.

```python
def filter_epicentral_distance(event, station):
    great_circle_distance(
        event_kg:at_latitude[event],
        event_kg:at_longitude[event],
        station_kg:at_latitude[station],
        station_kg:at_longitude[station],
        distance
    ) and
    (147 < distance) and (distance < 153)
```

Using requirements (1–6), along with previously defined relations event_in_operational_range and filter_epicentral_distance, we query the event and station KGs for useful, core-sampling event-station pairs.
Listing 6: Querying the event and station KGs through the constraints outlined in Example 3. The relation `event_query` defines a unary relation of Event Record entities that match the given constraints: Line 2 matches with events below a specified depth; Line 3 matches with events in a range of magnitudes; and Lines 4–5 similarly match with events in two disjoint ranges of latitudes. The relation `station_query` defines a similar unary relation of Station entities that match the given constraints: Lines 8–9 traverses the graph from Station to Channel; Lines 10–12 filter the Channel for (high-)broadband and high-gain seismometers; and Lines 13–14 match with stations in two disjoint ranges of latitudes. The relation `inner_core_query` combines the two previous relations in Lines 18–19, and further constrains with `event_in_channel_operational_range` (Line 20) and `filter_epicentral_distance` (Line 21), (previously defined in Listings 3) and 5, respectively. resolve the event and Station latitudes and longitudes. Auxiliary relations used here are defined in the supplementary material.

```python
def event_query(event) =
    depth_below[10](event) and
    filter_event_magnitude[5.5,7](event) and
    ( filter_latitude[event,55,90](event) or
      filter_latitude[event,-90,-55](event) )

def station_query(station, channel) =
    station_kg:channel_group(station,channelgroup) and
    station_kg:channel(channelgroup,channel) and
    ( station_kg:band_type(channel,^BandType["B"] ) or
      station_kg:band_type(channel,^BandType["H"] ) ) and
    station_kg:instrument_type(channel,^InstrumentType["H"] ) and
    ( filter_latitude[station,55,90](station) or
      filter_latitude[station,-90,-55](station) )
    from channelgroup

def inner_core_query(event,station) =
    event_query(event) and
    station_query(station,channel) and
    event_in_channel_operational_range(event,channel) and
    filter_epicentral_distance(event,station)
    from channel
```
We find that 653 Event Record and 3145 Station entities match the queries `event_query` and `station_query`, respectively. Of the possible $\sim 2$ million event-station pairs, only $\sim 127,000$ match with `inner_core_query`. The spatial distributions of a sample of events, stations, and paths are shown in Fig. 6, revealing areas for potential inner core studies.

5. Discussion and Conclusions

In this paper, we introduce knowledge graphs (KGs) for semantic modeling of seismic station and event data. We define ontologies reflecting domain knowledge in seismology and present three examples of how knowledge from schema-diverse, real-world data can be used to construct KGs. Our examples illustrate how KGs de-emphasize schema-related details of the data, allowing a focus on composition of intelligible queries for data exploration and analysis.

We see several promising avenues for future applications of KGs in seismology. A natural progression would investigate the representation of seismic waveform data, which could be represented in a relational KG using hypergraphs. KGs could be particularly applicable to dense, highly relational, temporary deployments, such as digital acoustic seismometry (Lindsey and Martin, 2021), ocean-bottom seismometry (Suetsugu and Shiobara, 2014), or controlled source seismometry (Mondol, 2010). Another natural step would test the construction of KGs from other seismic data-formats,
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such as (dataless) seed (Ahern et al., 2009), or QuakeML (Schorlemmer et al., 2011). The KGs presented here can
be expanded to incorporate knowledge that seismologists may wish to model. Potential extensions could add proper-
ties for event focal mechanisms, centroid parameters, or include entities for instrument response (Ringler and Bastien,
2020) or virtual networks (Ahern, 2004).

Alongside technical developments, we see potential for integrating seismic KGs with other geoscience products.
Combination with ontology-driven knowledge models of geological maps—Mantovani et al. (e.g., 2020)—could en-
able reasoning concerning the local geology around a station. A KG approach may be amenable for high-level, data-rich
seismic products, including ShakeMaps (Worden et al., 2010), “Did You Feel It?” maps (Wald et al., 2011), seismic
velocity models (Ritsema and Lekić, 2020), or even Green’s function databases (van Driel et al., 2015). Finally, there
is potential for integrating KGs into modern seismic machine learning methodologies (e.g., Zhu and Beroza, 2019;
Yeck et al., 2021). In addition to providing a semantic layer to aid explainability (Lecue, 2020), KGs could enhance
the training of seismic machine learning models by embedding prior logic and structure into training data (Hogan et al.,
2021).

In conclusion, we believe that knowledge graphs have a promising interconnected and interdisciplinary future in
seismology. Used as complementary tools to augment traditional seismic databases, KGs offer flexibility and accessi-
bility. We look forward to further exploring the potential of KGs in seismology and beyond.

Data, Resources, and Code Availability

The data underlying this paper are available in the Dryad Digital Repository, at doi.org/10.6078/D1P430. All
code used in this paper is available in the Zenodo open data repository, at doi.org/10.5281/zenodo.8304009.

The resources mentioned in the article and their corresponding references: International Federation of Digital
Seismograph Networks (FDSN) Station Extended Markup Language format/specification (StationXML) is available

Data sources used in this article and their corresponding references: station metadata from the Incorporated Re-
search Institutions for Seismology (IRIS), acquired using the fdsnws-station webservice at https://service.iris.edu/fdsnws/station/1; earthquake event data from the Global Centroid-Moment Tensor (GCMT) catalog,
acquired using the webservice at https://www.globalcmt.org; earthquake event data from the Northern Cali-
ifornia Earthquake Data Center (NCEDC), acquired using the Northern California Earthquake Catalog Search web-
service at doi.org/10.7932/NCEDC; and earthquake event data from the United States Geological Survey (USGS)
Advanced National Seismic System (ANSS) Comprehensive Earthquake Catalog (ComCat), acquired using the web-
service at doi.org/10.5066/F7MS3QZH. Figures 2 and 3 were created with ormjs, available at https://github.
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All websites were last accessed in August 2023.

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2 Our ORM diagram for the station knowledge ontology. Entity types (e.g., Station) are represented by solid-edged rectangles. Value types (e.g., Elevation) are represented by dashed-edged rectangles. Binary fact types—for example, S1: "Each Station is managed by exactly one Network"—are represented by entity and value types connected to a pair of roleboxes, along with a set of constraints (in violet). Edge names are indicated with text next to the roleboxes. Violet lines next to the roleboxes indicate uniqueness constraints, whereas violet dots indicate mandatory roles. A double violet line indicates a preferred identification scheme, for example, constraint S4. Violet dashed lines leading to violet symbols correspond to an external preferred identification scheme, for example, constraints S17–19.

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