Cover Sheet

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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.

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William Davis: Conceptualization, Investigation, Data Curation, Software, Validation, Visualization, Writing - Original Draft . **Cassandra R. Hunt:** Supervision, Software, Writing - Review & Editing .

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

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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.

- `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:

S1. **Each** `Station` is managed by **exactly one** `Network`,

S2. **Each** `Channel Group` is in **exactly one** `Station`, and

S3. **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:

S4. **Each** `Network` has a code of **exactly one** network code,

S5. **Each** `Station` has a code of **exactly one** station code,

S6. **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

18 `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.

```
1  def filter_event_CA(event) =
2      filter_latitude(32.6,42.6,event) and
3      filter_longitude(-126.2,-113.7,event)
4
5  def filtered_contributor_event(contributor_name,event) =
6      filter_event_CA(event) and
7      event_kg:contributed(contributor,event) and
8      event_kg:name(contributor,contributor_name)
9      from contributor in event_kg:Contributor
10
11 def count_events(contributor_name,event_total) =
12     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.

```
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 $\sim 35,000$ nodes and $\sim 116,000$ 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.

```
1 def event_in_channel_operational_range(event, channel) =
2     station_kg:operational_from(channel, start_dt) and
3     station_kg:operational_until(channel, end_dt) and
4     event_kg:occurred_at(event, event_dt) and
5     (event_dt > start_dt) and (event_dt < end_dt)
6     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.

```
1  def ridgecrest_event(event) =
2      event_kg:event_id(event,^EventId["C201907060319A"])
3
4  def ridgecrest_query(station) =
5      station_kg:channel_group(station,channelgroup) and
6      station_kg:channel(channelgroup,channel) and
7      is_low_gain_vertical(channel) and
8      event_in_channel_operational_range(ridgecrest_event, channel) and
9      count(station_kg:channel[channelgroup], 3) and
10     event_station_radius_range[0.0,2.0](ridgecrest_event,station)
11     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 $\sim 591,000$ nodes and $\sim 623,000$ edges for the event KG. In particular, we have $\sim 62,000$ `Event Record` and $\sim 49,000$ `Station` entities.

We simulate a highly constrained query to identify scientifically useful event-station paths that sample core phases PKPbc and PKPdf (Tkalčić, 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.

```
1  def filter_epicentral_distance(event,station) =
2      great_circle_distance(
3          event_kg:at_latitude[event],
4          event_kg:at_longitude[event],
5          station_kg:at_latitude[station],
6          station_kg:at_longitude[station],
7          distance
8      ) and
9      (147 < distance) and (distance < 153)
10     from distance
```

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.

```
1  def event_query(event) =
2      depth_below[10](event) and
3      filter_event_magnitude[5.5,7](event) and
4      ( filter_latitude[event_kg,55,90](event) or
5        filter_latitude[event_kg,-90,-55](event) )
6
7  def station_query(station, channel) =
8      station_kg:channel_group(station,channelgroup) and
9      station_kg:channel(channelgroup,channel) and
10     ( station_kg:band_type(channel,^BandType["B"]) or
11       station_kg:band_type(channel,^BandType["H"]) ) and
12     station_kg:instrument_type(channel,^InstrumentType["H"]) and
13     ( filter_latitude[station_kg,55,90](station) or
14       filter_latitude[station_kg,-90,-55](station) )
15     from channelgroup
16
17 def inner_core_query(event,station) =
18     event_query(event) and
19     station_query(station,channel) and
20     event_in_channel_operational_range(event,channel) and
21     filter_epicentral_distance(event,station)
22     from channel
```

We find that 653 `Event Record` and 3145 `Station` entities match the queries `event_query` and `station_query`, respectively. Of the possible ~ 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, 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 properties 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 enable 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 accessibility. 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 at `https://www.fdsn.org/xml/station/`; FDSN Source Identifiers specification is available at `http://docs.fdsn.org/projects/source-identifiers/`.

Data sources used in this article and their corresponding references: station metadata from the Incorporated Research 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 California Earthquake Data Center (NCEDC), acquired using the Northern California Earthquake Catalog Search webservice 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 webservice at `doi.org/10.5066/F7MS3QZH`. Figures 2 and 3 were created with `ormjs`, available at `https://github.`

com/crhunt/ormjs. All websites were last accessed in August 2023.

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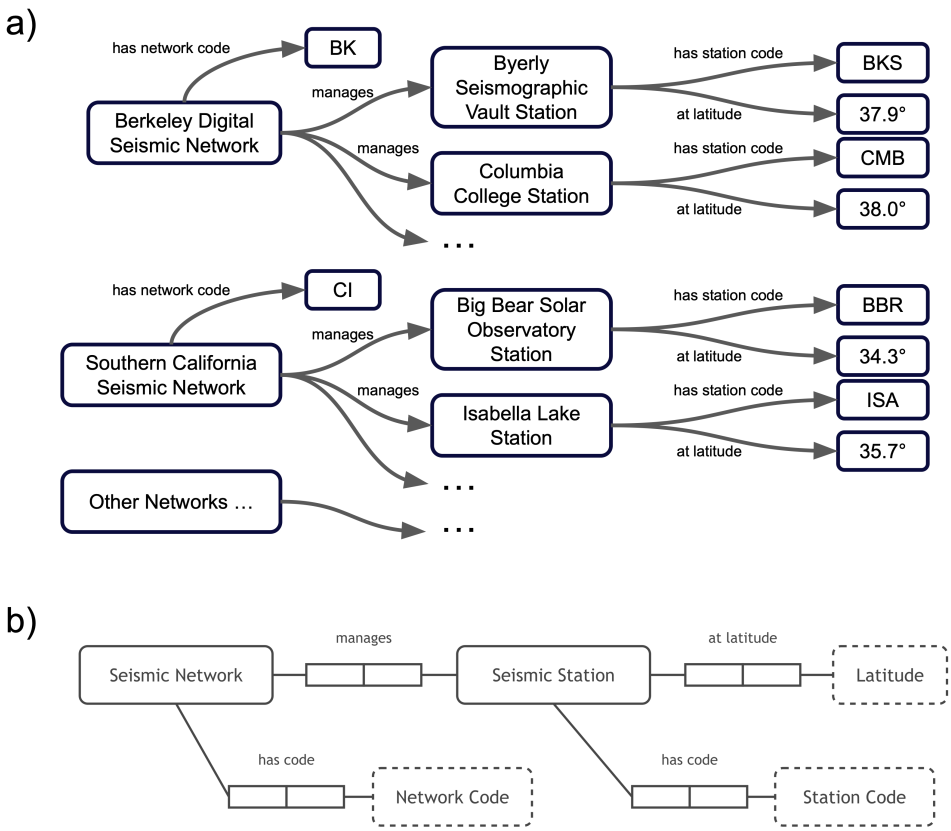

Figure 1: Example knowledge graph (KG) and Object-Role Modelling (ORM) diagram for a model of station metadata. For this illustrative example, details have been substantially simplified. Subplot a): An example knowledge graph for a subset of station metadata. Nodes represent abstract objects (e.g., *the Berkeley Digital Seismic Network* or *the Columbia College Station*) and also atomic values with their data type (e.g., the latitude *37.9°*) and are diagrammed here using rounded boxes. Edges describe relations between objects (e.g., the Berkeley Digital Seismic Network *manages* the Columbia College Station) and are diagrammed using arrows. Subplot b): An ORM diagram for the above KG for station knowledge. Nodes that represent abstract objects are labelled as an "entity type" (e.g., the Columbia College Station is a *Seismic Station*) and are diagrammed using solid-edged rounded boxes. Nodes that are self-identified by their atomic data value are labelled as a "value type" (e.g. 37.9° is a *Latitude*) and are diagrammed using dashed-edged rounded boxes. Edge labels are represented with binary "roleboxes", one connected with a line to each entity type, or to an entity type and value type. A set of roleboxes, and the entity types and value types connected to them, are referred to as a "fact type" in the ontology. For more details on ORM diagrams, see (Halpin, 2015).

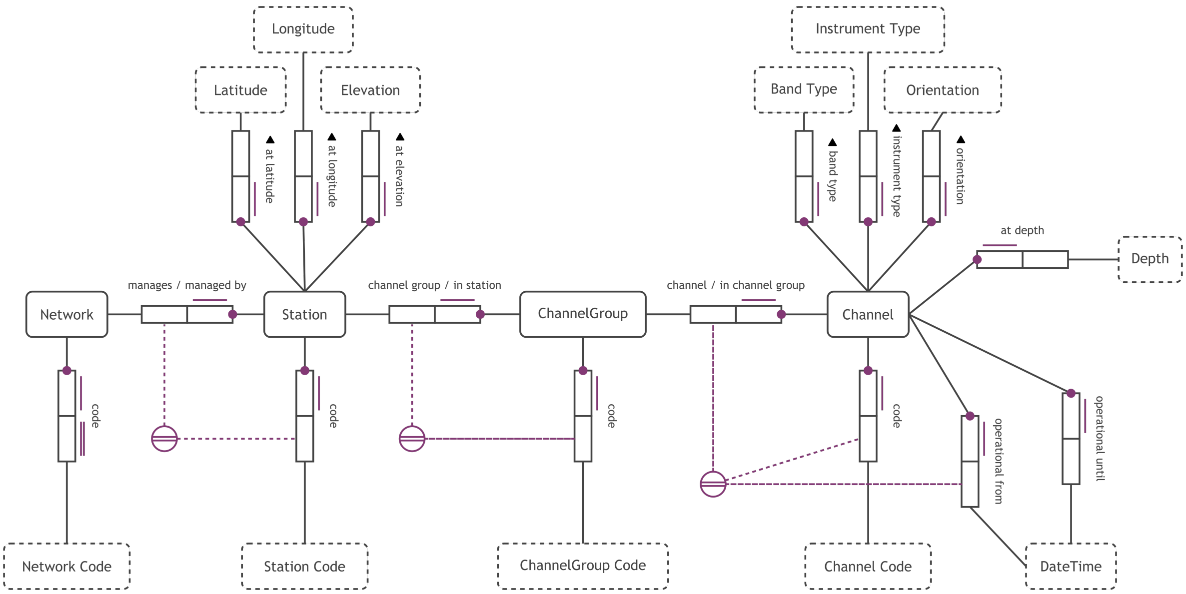

Figure 2: Our ORM diagram for the station knowledge ontology. Entity types (e.g., `Station`) are represented by solid-edged rectangles. Value types (e.g., Elevation) are represented by dashed-edged rectangles. Binary fact types—for example, S1: "**Each** `Station` is managed by **exactly one** `Network`"—are 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.

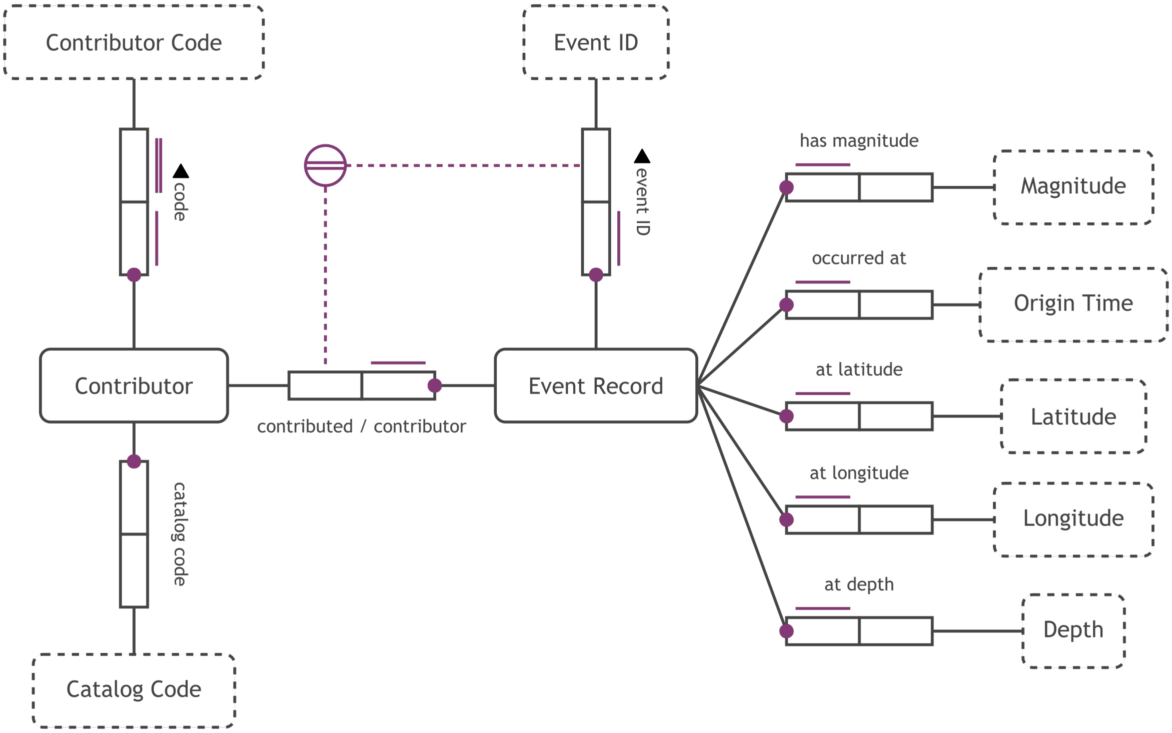

Figure 3: Our ORM diagram for the event knowledge ontology. `Contributor` and `Event Record` entity types are represented by solid-edged rectangles. Each type of property value (e.g., Depth) is represented by a dashed-edged rectangle. Binary fact types—for example, E9: "**Each** `Event Record` has a depth of **exactly one** depth."—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 role boxes indicate uniqueness constraints, whereas violet dots indicate mandatory roles. The double violet lines for contributor name signifies it as a preferred identification scheme. The violet dashed lines leading to the violet ⊜ symbol corresponds to the external preferred identification scheme in constraint E10.

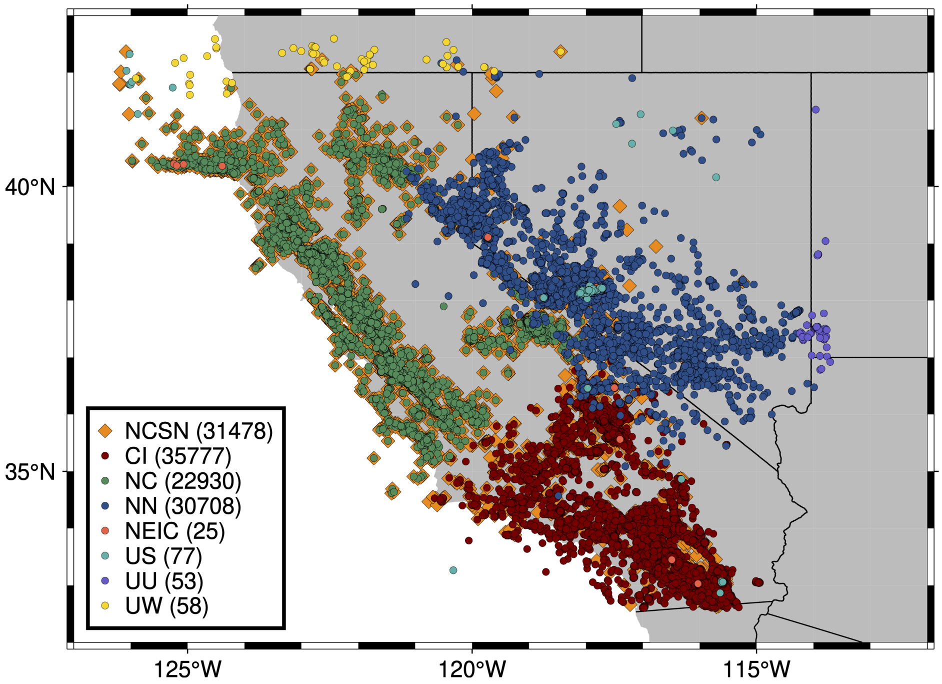

Figure 4: A map of earthquake event locations found in Example 1. The epicenters of the events associated with different contributors are represented by colored symbols, as specified in the legend. The number of events from each contributor is indicated in parentheses. The original source of data for each contributor are as follows: NCSN (NCEDC), CI (USGS), NC (USGS), NN (USGS), NEIC (GCMT), US (USGS), UU (USGS), UW (USGS).

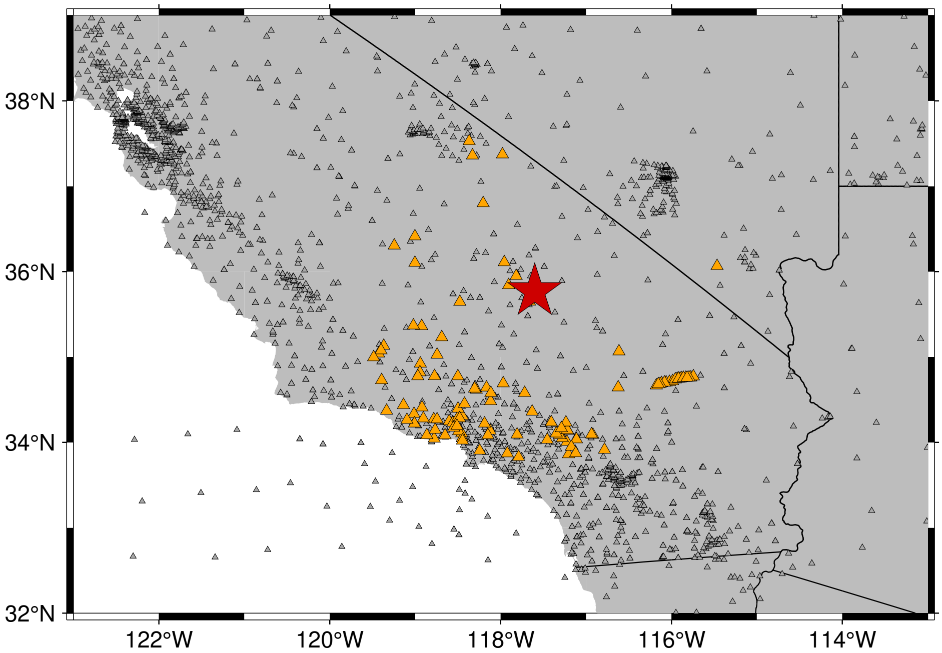

Figure 5: A map of stations around the 2019 Ridgecrest earthquake found in Example 2. The estimated epicenter of the earthquake is indicated with a red star (`doi:10.17611/DP/18001775`) (Trabant et al., 2012). The locations of all 2316 stations present in the dataset area are indicated with triangles. Stations that match the query described in Example 2 are indicated with yellow triangles. Stations that do not match the query are indicated with smaller grey triangles.

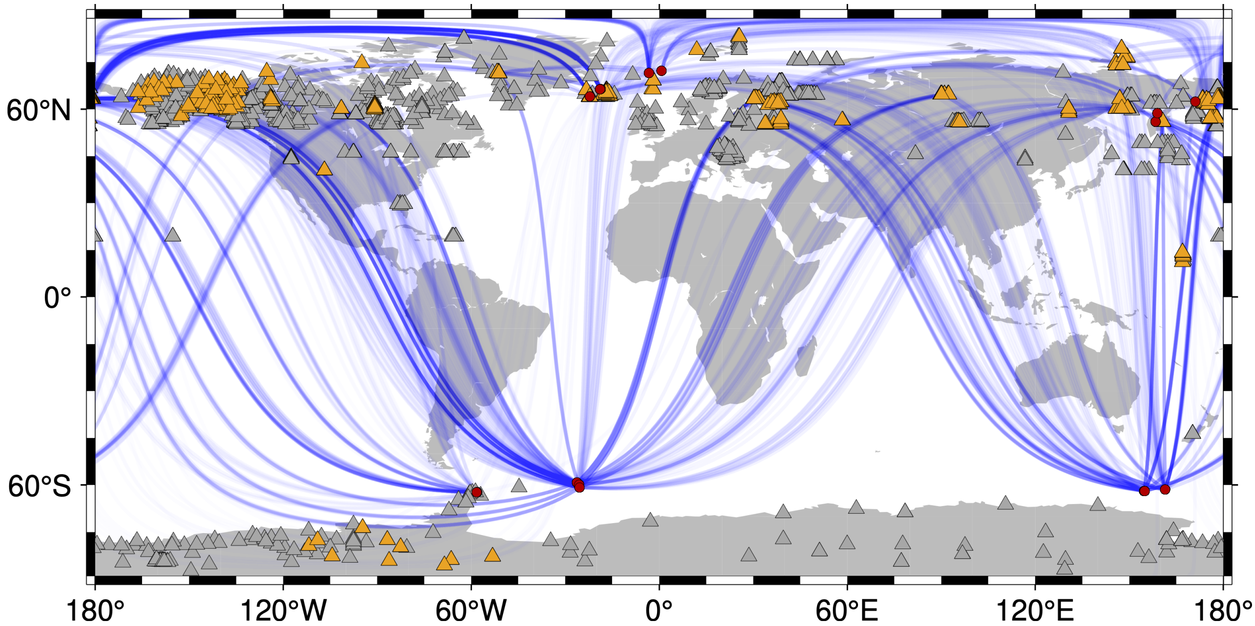

Figure 6: A map of events and stations found in Example 3. For visual clarity, we restrict this plot to only show events occurring in 2020: 16 of the total 653, corresponding to $3,840$ event-station pairs. The locations of earthquakes and nuclear explosions satisfying `event_query` are indicated with circles. The locations of stations satisfying `station_query` are indicated with triangles. Grey symbols indicate events or stations which match `event_query` or `station_query` but do not appear in any of the valid event-station pairs defined by `inner_core_query`. Colored symbols indicate events and stations which satisfy `inner_core_query`, forming valid event-station pairs. Great-circle paths between the valid event-station pairs are shown as transparent blue lines.