



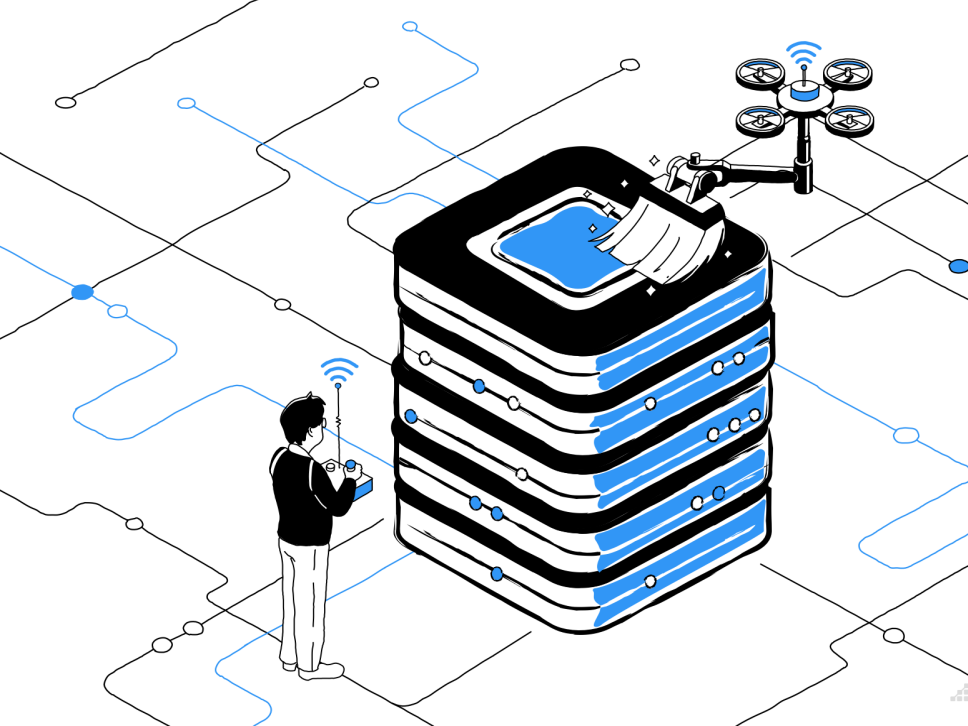
Data Science in Paleontology

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Welcome!

*The legendary engineer W. Edwards Deming put it “Without data, you’re just another person with an opinion.” Without insight into **data**, people make decisions based on **instinct**, **speculation**, or prevalent **theory**.*



Context



Motivation: Difficulty in **integrating** paleontological data from **different** sources (PBDB, museum collections, literature).



Premise: **Unify and clean** fossil occurrence data using *open-source* tools.



Target audience: Paleontology students and researchers working with large datasets.

Why Python for Paleobiological Data?

Available options:

- GUI tools (Tableau, Power BI, OpenRefine)
- Programming (Python, R)
- Enterprise solutions (Alteryx, IBM)



Our choice: Python

- Reproducible research
- Free and open-source
- Flexible for any workflow
- Transparent processing



OpenRefine





Python Ecosystem:

- pandas: Data manipulation and cleaning
- requests: API access to PBDB
- numpy: Numerical operations
- matplotlib/seaborn: Visualization



Additional Tools:

- geopandas: Spatial data handling
- scipy: Statistical analysis
- jupyter: Interactive notebooks

The Paleobiology Database (PBDB)



What: Global repository of **fossil occurrence data**

- >1.4 million fossil occurrences
- >400,000 taxonomic names
- Community-driven, peer-reviewed contributions



Access: <https://paleobiodb.org>

- Web interface (Navigator)
- [API](#) for programmatic access
- Download formats: CSV, JSON, TSV

Common Data Quality Issues in PBDB



Taxonomic Issues:

- **Synonyms** and homonyms
- **Outdated** classifications
- Misspellings

Temporal Issues:

- Mixed time scales
- **Uncertain** age ranges
- **Missing** epochs/stages

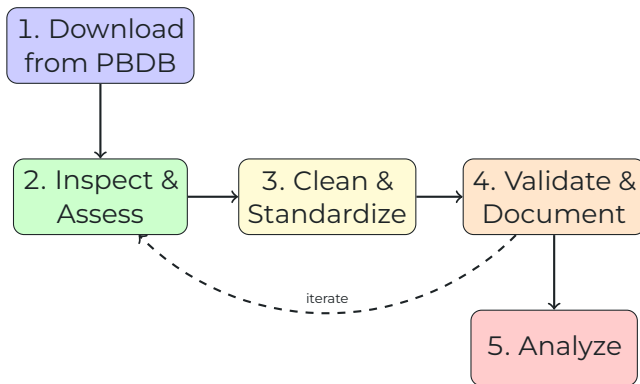
Geographic Issues:

- Missing coordinates
- Coordinate **precision**
- **Incorrect** datum/projection

Completeness Issues:

- Missing identifiers
- **Incomplete** references
- Environmental data gaps

Data Preparation Workflow



Today's Practical Exercise

1. **Download** fossil occurrence data for a specific class
2. **Inspect** data quality using summary statistics
3. **Identify** and handle missing/problematic records
4. **Standardize** taxonomic names and temporal assignments
5. **Visualize** cleaned data (geographic and temporal distribution)

Example: Trilobite occurrences from the Paleozoic



Best Practices: Documentation



Always document:

- Data **source** (PDB) and download **timestamp**
- Query parameters used (taxon, interval, geographic bounds)
- **Cleaning** decisions and rationale
- Number of records **removed** at each step
- Software **versions** (Python, pandas, etc.)

PBDB API: Key Parameters



Common query parameters:

- `base_name`: Taxonomic name (e.g., 'Trilobita')
- `interval`: Time interval (e.g., 'Cambrian', 'Jurassic,Cretaceous')
- `min_ma`, `max_ma`: Age range in millions of years
- `lngmin`, `lngmax`, `latmin`, `latmax`: Geographic bounding box
- `show`: Additional fields to include



Useful 'show' options: `coords`, `phylo`, `ident`, `loc`, `strat`, `time`, `ref`

Step 1: Downloading Data from PBDB



Using Python with requests and pandas:

```
1 import pandas as pd
2 import requests
3
4 # PBDB API endpoint
5 base_url = "https://paleobiodb.org/data1.2/occs/list.csv"
6
7 # Query parameters
8 params = {
9     'base_name': 'Trilobita',
10    'interval': 'Cambrian,Permian',
11    'show': 'coords,phylo,ident'
12 }
13
14 # Download data
15 response = requests.get(base_url, params=params)
16 trilobites = pd.read_csv(pd.io.common.StringIO(response.text))
17
18 print(f"Downloaded {len(trilobites)} occurrences")
```

Documenting Your Download



```
1 from datetime import datetime
2
3 # Record download metadata
4 metadata = {
5     'source': 'Paleobiology Database',
6     'url': base_url,
7     'download_datetime': datetime.now().isoformat(),
8     'query_params': params,
9     'n_records': len(trilobites)
10 }
11
12 # Save metadata with your data
13 import json
14 with open('download_metadata.json', 'w') as f:
15     json.dump(metadata, f, indent=2)
16
17 # Or add to your dataframe
18 print(f>Data downloaded: {metadata['download_datetime']}")
19 print(f"Query: {metadata['query_params']}")
```

Why timestamp matters:

- PBDB is **continuously updated** (new data, corrections, taxonomic revisions)
- Results from the same query can differ over time
- Essential for **reproducibility** and **citation**

Step 2: Inspect the Data



Check data completeness and structure:

```
1 # Basic information
2 print(trilobites.shape) # Rows and columns
3 print(trilobites.columns) # Column names
4
5 # Missing values per column
6 print(trilobites.isnull().sum())
7
8 # Summary statistics for key variables
9 print(trilobites[['max_ma', 'min_ma', 'lng', 'lat']].describe())
10
11 # Unique taxonomic levels
12 print(f"Unique genera: {trilobites['genus'].nunique()}")
13 print(f"Unique families: {trilobites['family'].nunique()}")
```

Step 3: Assess Data Quality



Identify problematic records:

```
1 # Records without coordinates
2 no_coords = trilobites[trilobites['lng'].isnull() |
3                       trilobites['lat'].isnull()]
4 print(f"Missing coordinates: {len(no_coords)} records")
5
6 # Records with suspicious ages (max_ma < min_ma)
7 bad_ages = trilobites[trilobites['max_ma'] < trilobites['min_ma']]
8 print(f"Invalid age ranges: {len(bad_ages)} records")
9
10 # Records without genus identification
11 no_genus = trilobites[trilobites['genus'].isnull()]
12 print(f"Missing genus: {len(no_genus)} records")
13
14 # Age uncertainty (large ranges)
15 trilobites['age_range'] = trilobites['max_ma'] - trilobites['min_ma']
16 print(trilobites['age_range'].describe())
```


Step 4: Data Cleaning Strategies



Decision points: Remove or impute?

```
1 # Strategy 1: Remove records without coordinates
2 # (if spatial analysis is critical)
3 clean_data = trilobites.dropna(subset=['lng', 'lat'])
4
5 # Strategy 2: Keep all, flag problematic records
6 trilobites['has_coords'] = ~(trilobites['lng'].isnull())
7 trilobites['valid_age'] = trilobites['max_ma'] >= trilobites['min_ma']
8
9 # Strategy 3: Calculate midpoint ages
10 trilobites['mid_ma'] = (trilobites['max_ma'] +
11                        trilobites['min_ma']) / 2
12
13 # Document your decisions!
14 print(f"Original: {len(trilobites)} records")
15 print(f"After cleaning: {len(clean_data)} records")
16 print(f"Removed: {len(trilobites) - len(clean_data)} records")
```

Step 5: Handle Taxonomic Issues

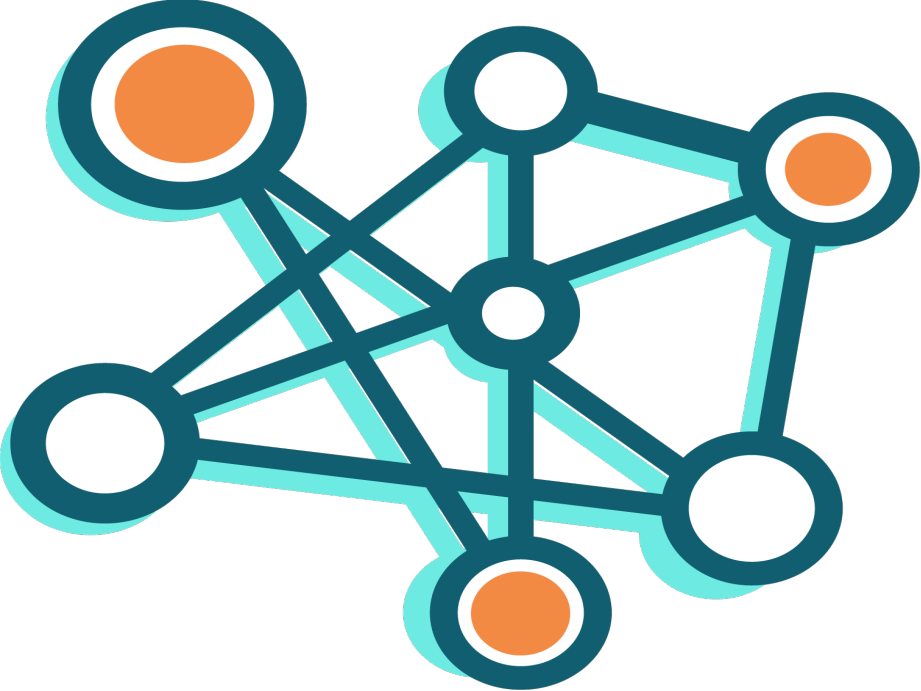


```
1 # Check for taxonomic inconsistencies
2 print(trilobites['accepted_name'].value_counts().head(10))
3
4 # Identify records with different accepted vs. identified names
5 changed = trilobites[trilobites['accepted_name'] !=
6                     trilobites['identified_name']]
7 print(f"Taxonomic revisions: {len(changed)} records")
8
9 # Standardize to accepted names
10 trilobites['taxon_clean'] = trilobites['accepted_name'].fillna(
11                             trilobites['identified_name'])
12
13 # Remove tentative identifications (e.g., "cf.", "?")
14 trilobites['uncertain'] = trilobites['taxon_clean'].str.contains(
15                             'cf\.|aff\.|\\?', na=False)
16 print(f"Uncertain identifications: {trilobites['uncertain'].sum()}")
```

Step 6: Visualize Cleaned Data



```
1 import matplotlib.pyplot as plt
2 import seaborn as sns
3
4 # Temporal distribution
5 fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
6
7 # Histogram of ages
8 clean_data['mid_ma'].hist(bins=50, ax=ax1)
9 ax1.set_xlabel('Age (Ma)')
10 ax1.set_ylabel('Number of occurrences')
11 ax1.set_title('Temporal Distribution')
12
13 # Geographic distribution
14 ax2.scatter(clean_data['lng'], clean_data['lat'],
15             alpha=0.5, s=10)
16 ax2.set_xlabel('Longitude')
17 ax2.set_ylabel('Latitude')
18 ax2.set_title('Geographic Distribution')
19
20 plt.tight_layout()
21 plt.show()
```



Beyond Tabular Data: Knowledge Representation



Challenge: Tabular data (CSV, spreadsheets) stores information in rows and columns, but struggles to represent **complex relationships**.

Tabular format:

- Good for: Simple queries, statistics
- Limited: Relationships are implicit
- Example: “Family” is just a column

Knowledge graph:

- Good for: Complex relationships
- Explicit: Connections are first-class
- Example: “belongs_to” is a relation



Next: We'll transform our cleaned PBDB data into a knowledge graph to unlock deeper insights.

What is a Knowledge Graph?



Formally, a KG is defined as a collection of **triples** of the form $\langle h, r, t \rangle$, where:

- h = **head entity** (source node)
- r = **relation** (edge)
- t = **tail entity** (target node)

Each triple represents a **true known fact**.

Paleontological example:

$\langle \textit{Elrathia kingii}, \textit{belongs_to}, \textit{Ptychopariidae} \rangle$

This triple states the fact that *Elrathia kingii* belongs to the family Ptychopariidae.

KG: Paleontological Entities & Relations

Entities (Nodes):

- **Taxonomic:** Species, Genus, Family, Order, Class, Phylum
- **Temporal:** Geological periods, epochs, stages
- **Spatial:** Localities, formations, collections
- **Occurrences:** Individual fossil finds

Relations (Edges):

- **belongs_to:** Taxonomic hierarchy
- **found_in:** Geographic occurrence
- **lived_during:** Temporal range
- **collected_from:** Collection information
- **identified_as:** Taxonomic identification

From our cleaned PBDB data, we can extract these entities and relations to build a knowledge graph.



Example Triples from PBDB Data



Taxonomic relations:

⟨Elrathia kingii, belongs_to, Elrathia⟩

⟨Elrathia, belongs_to, Ptychopariidae⟩

⟨Ptychopariidae, belongs_to, Ptychopariida⟩

Temporal relations:

⟨Occurrence_12345, lived_during, Middle Cambrian⟩

Spatial relations:

⟨Occurrence_12345, found_in, Wheeler Formation⟩

Identification relations:

⟨Occurrence_12345, identified_as, Elrathia kingii⟩

Why Use Knowledge Graphs in Paleontology?

Advantages over tabular data:

- **Integration**: Combine data from PBDB, museum collections, literature
- **Querying**: Ask complex relationship-based questions
 - ▶ “Find all genera in family X that lived during period Y”
 - ▶ “What localities contain fossils from the same family?”
- **Reasoning**: Infer new knowledge via transitivity
 - ▶ If $\langle A, \text{belongs_to}, B \rangle$ and $\langle B, \text{belongs_to}, C \rangle$
 - ▶ Then A is related to C through B
- **Flexibility**: Easy to add new entity types and relations
- **Visualization**: See connections and patterns clearly

When & Who Uses KGs?

When to use:

- Highly interconnected data
- Multiple data sources
- Complex relationship queries
- Need for inference/reasoning
- Evolving schemas

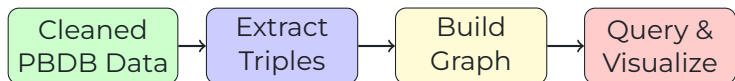
Who uses KGs:

- Google KG
- Biomedical ontologies
- Wikidata
- DBpedia
- Scientific domains

Paleontology use cases: Link fossil occurrences with taxonomy, stratigraphy, phylogeny, and paleoenvironments across multiple databases.



Our Workflow: Clean Data → Knowledge Graph



Steps:

1. Start with our cleaned trilobite data
2. Extract entities and relations (create triples)
3. Build graph structure using NetworkX
4. Query and visualize the knowledge graph



Extract Triples from Clean Data (1/4)



Starting with our cleaned data:

```
1 import pandas as pd
2 import networkx as nx
3 import matplotlib.pyplot as plt
4
5 # Assume we have our cleaned trilobite data
6 # (from previous data cleaning steps)
7 print(f"Clean data: {len(clean_data)} occurrences")
8 print(f"Columns: {clean_data.columns.tolist()}")
9
10 # Initialize triple store
11 triples = []
12
13 # We'll extract triples following the <h, r, t> pattern
14 # where h = head entity, r = relation, t = tail entity
```

We transform each row of tabular data into multiple knowledge triples.



Extract Triples from Clean Data (2/4)



Create triples for each occurrence:

```
1  # Extract triples from each occurrence
2  for idx, row in clean_data.iterrows():
3      # Create unique occurrence identifier
4      occ_id = f"Occurrence_{row['occurrence_no']}"
5
6      # Extract entities
7      taxon = row['accepted_name']
8      genus = row['genus'] if pd.notna(row['genus']) else None
9      family = row['family'] if pd.notna(row['family']) else None
10     order = row['order'] if pd.notna(row['order']) else None
11     time_period = row['early_interval']
12     locality = row['collection_name'] if pd.notna(row['collection_name']) \
13                else f"Locality_{idx}"
14
15     # Create identification and spatiotemporal triples
16     triples.append((occ_id, 'identified_as', taxon))
17     triples.append((occ_id, 'lived_during', time_period))
18     triples.append((occ_id, 'found_in', locality))
19
20     # (continued on next slide...)
```



Create taxonomic hierarchy triples:

```
1      # (continued from previous slide...)
2
3      # Create taxonomic hierarchy triples
4      if genus:
5          triples.append((taxon, 'belongs_to', genus))
6      if family:
7          parent = genus if genus else taxon
8          triples.append((parent, 'belongs_to', family))
9      if order:
10         parent = family if family else (genus if genus else taxon)
11         triples.append((parent, 'belongs_to', order))
12
13     print(f"Extracted {len(triples)} triples from {len(clean_data)} occurrences")
14
15     # Display example triples
16     print("\nExample triples:")
17     for i, (h, r, t) in enumerate(triples[:10]):
18         print(f"{i+1}. <{h}, {r}, {t}>")
```

Build Graph from Triples (4/4)



Create directed graph structure:

```
1 # Build directed graph from triples
2 G = nx.DiGraph()
3
4 for head, relation, tail in triples:
5     G.add_edge(head, tail, relation=relation)
6
7 print("\nKnowledge Graph Statistics:")
8 print(f"  Nodes: {G.number_of_nodes()}")
9 print(f"  Edges: {G.number_of_edges()}")
10
11 # Classify node types for visualization
12 node_types = {}
13 for node in G.nodes():
14     if 'Occurrence' in str(node):
15         node_types[node] = 'occurrence'
16     elif any(p in str(node) for p in ['Cambrian', 'Ordovician', 'Silurian']):
17         node_types[node] = 'time'
18     elif 'Locality' in str(node) or 'Formation' in str(node):
19         node_types[node] = 'locality'
20     else:
21         node_types[node] = 'taxon'
22
23 print(f"\nNode type distribution:")
24 for ntype, count in pd.Series(node_types).value_counts().items():
25     print(f"  {ntype}: {count}")
```

Visualize the Knowledge Graph (1/2)



Setup visualization with colors by node type:

```
1  # Color mapping for different entity types
2  color_map = {
3      'occurrence': 'lightblue',
4      'taxon': 'lightgreen',
5      'time': 'yellow',
6      'locality': 'pink'
7  }
8
9  node_colors = [color_map.get(node_types.get(n, 'taxon'), 'gray')
10                 for n in G.nodes()]
11
12 # Create layout
13 plt.figure(figsize=(16, 12))
14 pos = nx.spring_layout(G, k=0.8, iterations=50, seed=42)
15
16 # Draw nodes
17 nx.draw_networkx_nodes(G, pos, node_color=node_colors,
18                        node_size=500, alpha=0.8)
19
20 # Draw edges
21 nx.draw_networkx_edges(G, pos, edge_color='gray',
22                        arrows=True, arrowsize=10,
23                        alpha=0.5, width=1.5)
```


Visualize the Knowledge Graph (2/2)



Add labels and save:

```
1  # Draw node labels
2  labels = {n: n.split('_')[-1] if 'Occurrence' in str(n) else n
3            for n in G.nodes()}
4  nx.draw_networkx_labels(G, pos, labels, font_size=6, font_weight='bold')
5
6  # Draw edge labels (relations)
7  edge_labels = nx.get_edge_attributes(G, 'relation')
8  nx.draw_networkx_edge_labels(G, pos, edge_labels, font_size=5)
9
10 # Add legend
11 from matplotlib.patches import Patch
12 legend_elements = [
13     Patch(facecolor='lightblue', label='Occurrence'),
14     Patch(facecolor='lightgreen', label='Taxon'),
15     Patch(facecolor='yellow', label='Time Period'),
16     Patch(facecolor='pink', label='Locality')
17 ]
18 plt.legend(handles=legend_elements, loc='upper right')
19
20 plt.title("Knowledge Graph: Trilobite Occurrences from PBDB", fontsize=16)
21 plt.axis('off')
22 plt.tight_layout()
23 plt.savefig('trilobite_kg.png', dpi=300, bbox_inches='tight')
24 plt.show()
```



Find triples matching specific patterns:

```
1 def find_triples(triples, head=None, relation=None, tail=None):
2     """
3     Find triples matching the pattern <head, relation, tail>
4     Use None as wildcard for any component
5     """
6     results = []
7     for h, r, t in triples:
8         if ((head is None or h == head) and
9             (relation is None or r == relation) and
10             (tail is None or t == tail)):
11             results.append((h, r, t))
12     return results
13
14 # Query 1: Find all entities belonging to 'Ptychopariidae'
15 q1 = find_triples(triples, head=None, relation='belongs_to',
16                  tail='Ptychopariidae')
17 print(f"Found {len(q1)} entities in Ptychopariidae:")
18 for h, r, t in q1[:3]:
19     print(f"  <{h}, {r}, {t}>")
20
21 # Query 2: Find all occurrences from 'Middle Cambrian'
22 q2 = find_triples(triples, head=None, relation='lived_during',
23                  tail='Middle Cambrian')
24 print(f"\nFound {len(q2)} occurrences in Middle Cambrian")
```

Beyond Basic Knowledge Graphs

Advanced topics (beyond this lecture):

- **Graph databases:** Neo4j, Amazon Neptune for large-scale KGs
- **Ontologies:** Formal schemas (OWL, RDF) for knowledge representation
- **SPARQL:** Query language specifically for KGs
- **KG embeddings:** ML on graph structure
- **Link prediction:** Infer missing relationships
- **Integration:** Combine multiple data sources (PBDB + museum data + literature)

Resources:

- NetworkX documentation: <https://networkx.org>
- Neo4j (graph database): <https://neo4j.com>
- RDF and SPARQL: <https://www.w3.org/RDF/>

Summary

Step	Action	Key Outputs
1. Download	Retrieved PBDB data via API	Raw occurrence dataset
2. Inspect	Assessed quality dimensions	Identified missing coords, invalid ages
3. Clean	Removed/flagged bad records	Clean dataset, quality metrics
4. Standardize	Unified taxonomy, calculated ages	Consistent, analysis-ready data
5. Validate	Documented decisions	Metadata, removal statistics
6. Visualize	Created distribution plots	Temporal/spatial patterns
7. Extract	Converted tables to triples	$\langle h, r, t \rangle$ collection
8. Build KG	Constructed graph structure	NetworkX graph object
9. Visualize KG	Plotted entities & relations	Network diagram
10. Query	Pattern matching, reasoning	Complex relationship queries

Complete pipeline: Raw data → Quality assessment → Cleaning → Validation → Visualization → Knowledge representation → Advanced querying



QR-Code



https://github.com/matpato/Paleo_DataScience.git

Thanks!

High-quality data enables powerful knowledge representation and discovery.