In an (ontologically) perfect world...
Reality Check

• In our non-ontologically-perfect world, a COVID-19 computable phenotype looks more like this.

• This covers all the concepts, but:
  • Must be translated into a number of different data models and dialects
  • Must be continually manually updated to stay current

• What would it take to be able to write one query script that:
  • Thoroughly covers all the concepts with the fewest possible codes?
  • Can be run at multiple institutions with few (or no) local changes?
  • Results in a consistently, accurately defined cohort?
Reality Check

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  • Thoroughly covers all the concepts with the fewest possible codes?
  • Can be run at multiple institutions with few (or no) local changes?
  • Results in a consistently, accurately defined cohort?
Building Blocks

Literature, Current Practices, Existing Technologies
Computable Phenotyping

- *Computable phenotypes* are algorithms used to query EHR data to identify patient cohorts with conditions or events relevant to some use case.
- Important for research, but difficult to share across institutions in a machine-readable way.
- Rely heavily on standard codesets (ICD-10, LOINC, RxNorm, CPT, etc.)
- The ideal computable phenotype is shareable, data model agnostic, semantically unambiguous, machine-readable, and publicly accessible.
The advantage presented by ontologies

Current state: exact code matches, from all over the hierarchy

Desired state: conceptual matches, powered by ontologies
The Opioid Triplestore

Existing clinical dataset from a prior project*; a triplestore containing EHR, claims, and community-level data for post-surgical patients who were prescribed opioids.

*Collaborative project; see Acknowledgements slide for list of contributors and funding information
Experiments
Comparing Phenotype Performance: Ontology versus ICD-10-CM codeset

• Consider two computable phenotypes: (1) depression, and (2) rheumatoid arthritis.

• Objective is to compare the “coverage” of a computable phenotype defined by a list of ICD-10-CM codes (from PheKB) against a phenotype defined by a single concept (along with its child concepts) from the SNOMED or HPO ontology.

• Measuring the sensitivity and specificity of the phenotype methods is not possible in this study, as there is no way to know who the “true” cases are—we can only know which patients are identified by each phenotyping method.

• What is critical to measure, then, is the degree to which the two phenotyping methods overlap, as well as the degree to which they diverge.
Mapping SNOMED to ICD-10-CM

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>100801000119107</td>
<td>Maternal tobacco use in pregnancy</td>
<td>IFA 1076139100019102</td>
<td>IF TOBACCO USE IN MOTHER COMPLICATING CHILDBIRTH</td>
<td>099.334</td>
<td>Smoking (tobacco) complicating childbirth</td>
</tr>
<tr>
<td>100801000119107</td>
<td>Maternal tobacco use in pregnancy</td>
<td>OTHERWISE TRUE</td>
<td>ALWAYS 099.330</td>
<td>099.330</td>
<td>Smoking (tobacco) complicating pregnancy, unspecified trimester</td>
</tr>
</tbody>
</table>

Context-dependent mapping

Required seventh digit mapping
Mapping SNOMED to ICD-10-CM
Transformation Pipeline
Implementing the Pipeline in KNIME

A. Documentation
B. CSV to RDF/OWL converter
C. FHIR to RDF converter
D. Triplestore loader
E. Data mover (optional)

Pipeline available for download at https://github.com/empfff/clinical-tripleizer
Experimental Steps (Each Phenotype)

1. Execute a SPARQL query in the Opioid Triplestore using the ICD-10-CM codeset from the PheKB phenotype to identify matching patients.

2. Execute a SPARQL query in the Opioid Triplestore using a single ontology concept (SNOMED or HPO*), as well as any child nodes, to identify matching patients.

3. Compare the ICD-10-CM codes in the subgraphs defined by #1 and #2.

4. Compare the patients captured in the subgraphs defined by #1 and #2

*Because HPO maps to SNOMED, though the queries differed, the results were the same.
Results
Depression

• In general, SNOMED/HPO is picks up more patients than the PheKB phenotype, with a broader definition of "depression."

• SNOMED/HPO codeset included all but one of the PheKB codes (F43.21, adjustment disorder), and added more.

• SNOMED/HPO includes several bipolar codes; PheKB phenotype specifically excludes them.

• SNOMED/HPO graph contains two "problem codes": T81.89X (complications from procedure) and B94.9 (sequelae of unspecified disease).
Depression, continued

Table 2. Overlaps and differences between the cohorts defined by the PheKB and SNOMED/HPO depression queries against the Opioid Triplestore

<table>
<thead>
<tr>
<th>Query</th>
<th># patients found</th>
<th># patients found by this query only</th>
<th># patients found by both queries</th>
</tr>
</thead>
<tbody>
<tr>
<td>PheKB</td>
<td>1,739</td>
<td>35</td>
<td>1,704</td>
</tr>
<tr>
<td>SNOMED/HPO</td>
<td>2,029</td>
<td>325</td>
<td>1,704</td>
</tr>
</tbody>
</table>

Of the "problem codes," B94.9 did not match with any actual patients in the Opioid triplestore. T81.89X? would have matched 47 more patients if the ? had been treated as a wildcard.
Rheumatoid Arthritis

• Very different from depression cohort results; SNOMED/HPO was missing several valid codes in the M05*/M06* ranges. (Missing knees, hips, wrists, and ankles!)

• Investigation revealed an issue with a subClassOf relationship in SNOMED, which has since been corrected!
SNOMED Correction (9/20 edition)
Rheumatoid Arthritis, continued

• SNOMED/HPO graph also contains two "problem codes": H20.10 (chronic iridocyclitis) and M25.80 (other specified joint disorders). Only the latter matched patients in the triplestore.

Table 6. Overlaps and differences between the cohorts defined by the PheKB and SNOMED/HPO queries

<table>
<thead>
<tr>
<th>Query</th>
<th># patients found</th>
<th># patients found by this query only</th>
<th># patients found by both queries</th>
</tr>
</thead>
<tbody>
<tr>
<td>PheKB</td>
<td>166</td>
<td>30</td>
<td>136</td>
</tr>
<tr>
<td>SNOMED/HPO</td>
<td>142</td>
<td>6</td>
<td>136</td>
</tr>
</tbody>
</table>
Discussion & Conclusion
Ontologies as a Remedy for Semantic Ambiguity

**Research Question 1:** Can clinical ontologies (specifically SNOMED CT and the Human Phenotype Ontology) offer a less semantically ambiguous mechanism to perform computable phenotyping than reimbursement-focused terminologies (specifically ICD-10-CM)?

- ICD-10-CM serves an important purpose. As it is unlikely for its hierarchy to be modified, SNOMED/HPO provide a valuable augmentation, if not an alternative.
- The superset of "Google-able" or already known ICD-10-CM codes and those in the SNOMED/HPO subgraph may be a good starting point for researchers trying to choose the right codes for their phenotype.
- Using the superset fills in gaps in both SNOMED and ICD-10-CM.
- I would argue that allowing researchers to keep or pitch codes from a longer list is preferrable to not providing the choice.
Semantic Web as a Driver of Interoperability

Research Question 2: Does the use of semantic web technologies and standards (e.g., Resource Description Framework (RDF), triplestores, the Web Ontology Language) in tandem with ontologies improve the interoperability prospects of computable phenotypes and the underlying clinical data?

The infrastructure for this project addressed three interoperability challenges:

- **Challenge**: Inconsistent data models
  - **Addressed By**: FHIR, RDF

- **Challenge**: Differing coding practices
  - **Addressed By**: Ontologies

- **Challenge**: Integration with non-EHR data
  - **Addressed By**: RDF
Limitations

• ICD-10-CM presents a bit of a catch-22—if it is the only diagnosis code type that will ever be attached to a patient, any phenotype method will eventually need to connect to ICD-10-CM. ("You're only as good as your worst ICD-10-CM code.")

• Our two phenotypes performed very differently. If I ran two more, I suspect they would each have their own idiosyncracies. This is a common issue in phenotyping studies.
I want to thank my collaborators and co-authors on the Opioid Triplestore project:

- Robert Bradford
- Marshall Clark
- Dr. Jim Balhoff
- Dr. John Preisser
- Rujin Wang
- Kellie Walters
- Dr. Matt Nielsen

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Thank you!