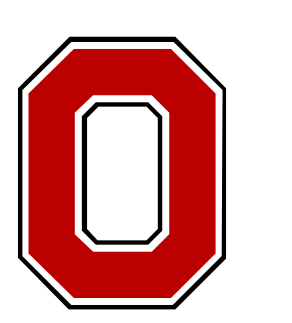


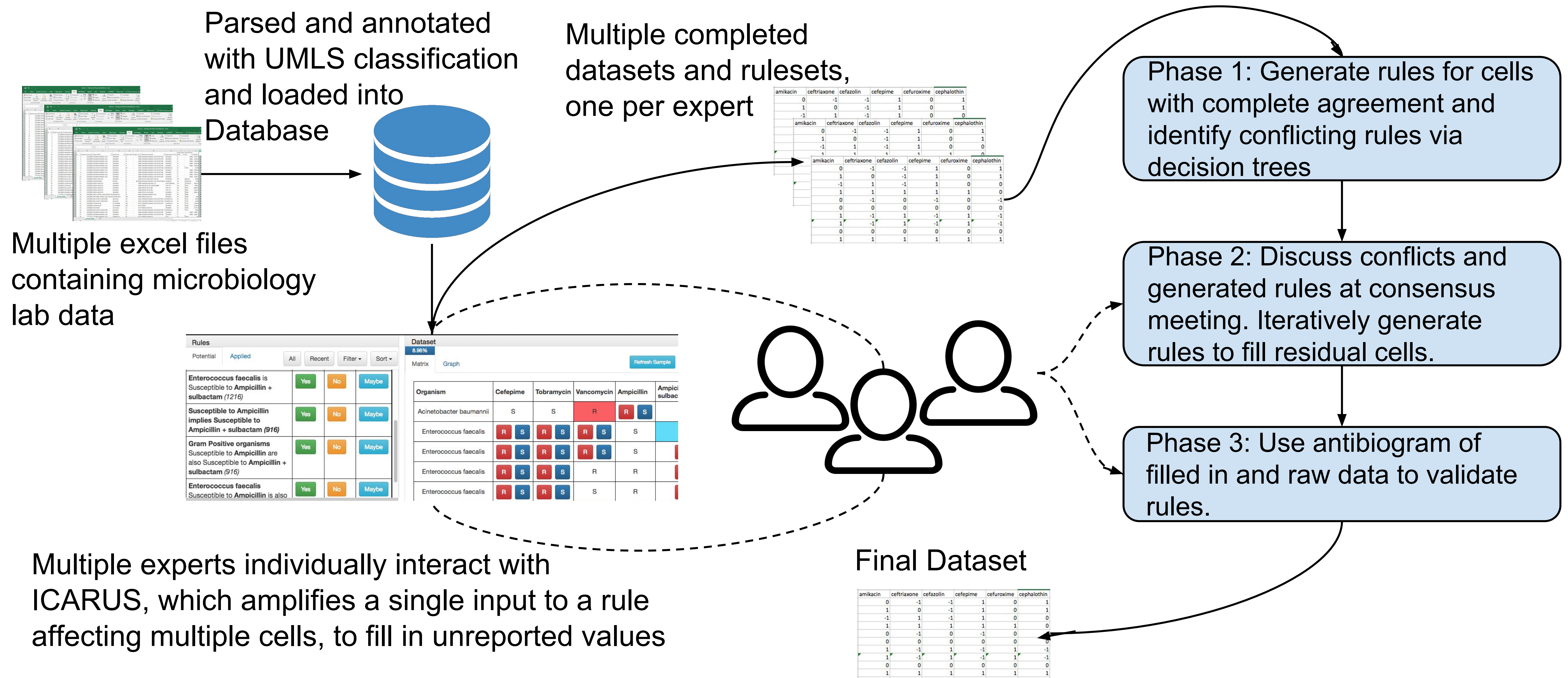
# Derivation of Expert Consensus Rules for Missing Antimicrobial Susceptibility Data



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Multiple experts individually interact with ICARUS, which amplifies a single input to a rule affecting multiple cells, to fill in unreported values

## Motivation

- Preprocessing and cleaning data prior to analysis is iterative and time-consuming.
- Engaging domain experts at this stage can be challenging, due to difficulties in data interaction and expression.
- We discuss our methods for getting expert consensus in filling in 75,000 cells in an antibiotic susceptibility dataset.

## Background

- Antibiotic susceptibility data from microbiology labs are parsed and annotated with Unified Medical Language System (UMLS)<sup>1</sup> classification.
- The parsed data are loaded into ICARUS<sup>2</sup> (our data completion tool built for amplifying domain expertise).
- Experts individually complete datasets which need to be consolidated.

Table 1: Description of Data Challenges and Proposed Solutions

| Theme                            | Challenge   | Solution   |
|----------------------------------|---|--|
| Size of dataset                  | Laborious to annotate manually  | ICARUS provides small snapshots of data to the expert and suggests rule generalizations to amplify input.  |
|                                  | Difficult to make more generalized ontology classifications underlying the dataset allow and less organism-specific rules | Ontology for rules that generalize   |
| Reproducibility and Transparency | Difficult to apply new dataset manually   | Because of the ontologies behind the dataset, once a new annotated dataset has been added with needed information, rules can be automatically used to fill in unreported data. |
|                                  | Difficult to easily document decisions transparently  | All accepted rules are encoded and stored.   |
| Consensus                        | Experts differ in their interpretation and expertise provided by only one expert may introduce bias                       | Allow multiple experts to use their expertise and then synthesize their input in the form of rules.  |

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## Methods

### Rule Generation Via Decision Tree

- Given multiple datasets which were filled in by experts, we use custom decision trees to extract rules that fill in consensus cells (cells that did not have conflicts between experts).
- Features include other antibiotic susceptibilities of the culture, and UMLS annotations.
- The decision tree splits were made along semantic features (antibiotics in the same class and organism hierarchy).

### Consensus Meeting and Validation

- Conflicting rules were extracted and resolved at a consensus meeting with 4 experts.
- Rules were again generated to fill in residual unfilled cells.
- Final set of rules were validated through manual inspection of an antibiogram (a table that summarizes resistances by organism and antibiotics).

## Results

### Validation results (Table 2)

- 171 rules were automatically generated, 105 of which were accepted and 22 were modified.
- 68 conflicting rules were discussed at the consensus meeting
- After final rule generation, 94% of the database was filled.
- Experts reviewed the antibiogram and select visualization (Figure 1) for final validation.

Figure 1: Antibiogram Trends for Validation

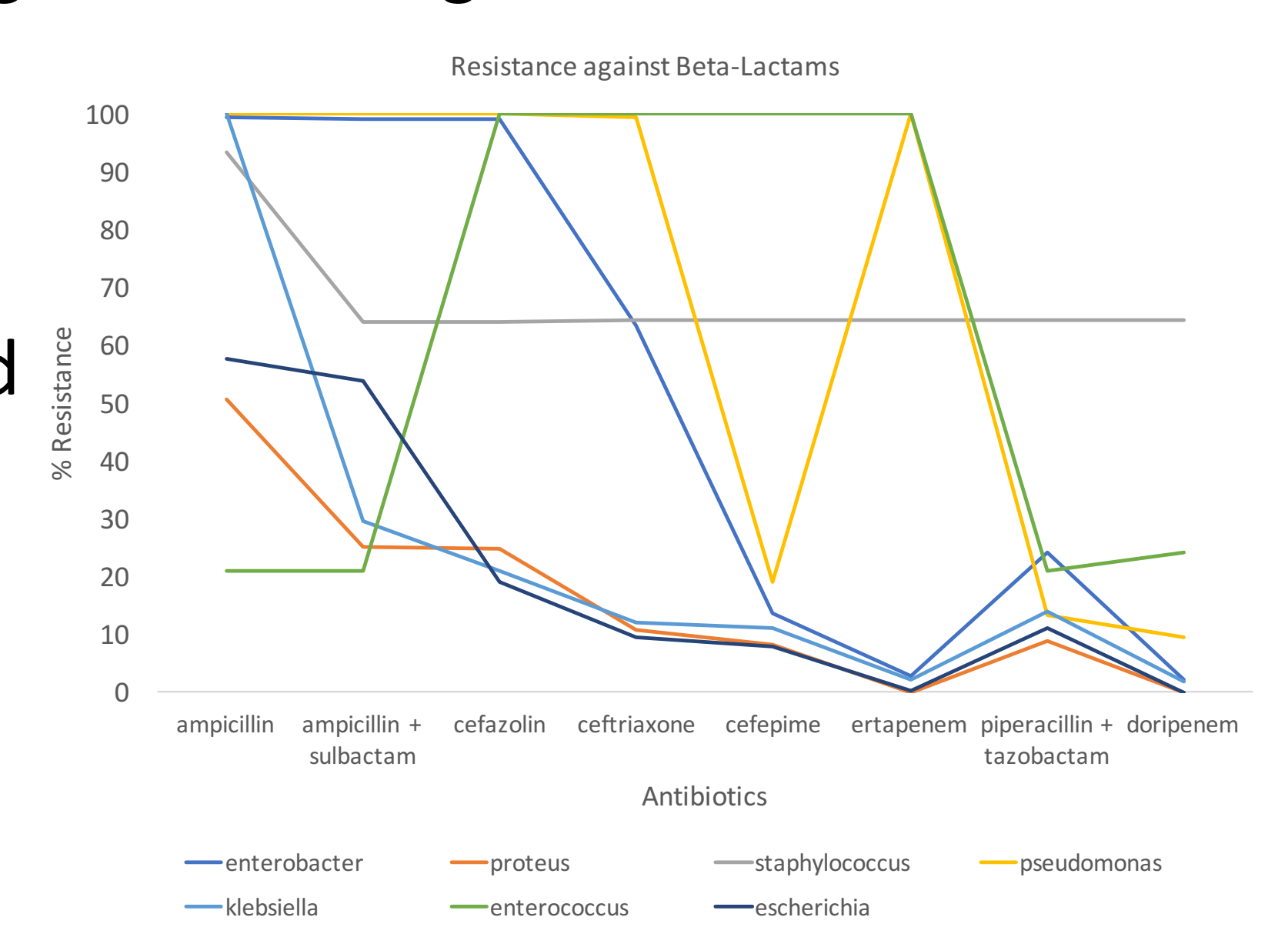


Table 2: Results of Rule Validation

|                   | Total Rules | Accepted | Split | Removed Constraint | Precision* | Added Constraint | Rejected | Cell Impact (% of total missing) |
|-------------------|-------------|----------|-------|--------------------|------------|------------------|----------|----------------------------------|
| Initial Rule Gen. | 171         | 105      | 0     | 22                 | 74%        | 0                | 44       | 52,569 (70%)                     |
| Consensus Meeting | 68          | 40       | 0     | 0                  | n/a        | 1                | 27       | 16,647 (22%)                     |
| Final Rule Gen.   | 55          | 16       | 3     | 5                  | 43%        | 36               | 0        | 4,519 (6%)                       |

\*Precision = (accepted + split + removed constraint)/total

## Future Directions

- Create effective interactive visualization of rules to accelerate consensus meeting [3].
- Validate our methods at a different institution.

## References

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3. Rahman P, Chen J, Hebert C, Pancholi P, Lustberg M, Stevenson K, Nandi A. Exploratory Visualizations of Rules for Validation of Expert Decisions. In DSIA Workshop, IEEE VIS 2018.



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