Predicting Empiric Antibiotic Coverage Based on Patient Factors

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Motivation

- Providers prescribe empiric antibiotics based on patient risk factors and guideline recommendations.
- Prior work has looked at modeling probability of coverage of individual antibiotics based on patient factors[1].
- However, combining results from multiple models to find the ideal antibiotic is challenging.

Empiric Prescription

- Antibiotics fall on a spectrum based on their coverage[2]:
  - Prescribing a *narrow–spectrum antibiotic* risks the patient's infection not being treated appropriately.
  - Prescribing a *broad-spectrum antibiotic* can increase antibiotic resistance in the community.

- For any treatment option, we are interested in two metrics:
  - Percentage of infections covered in the entire dataset:

$$\frac{\sum Infection\ Covered}{Total\ No.of\ Patients}$$

  - Average breadth score (determined by expert survey[2]) for correctly treated patients:

$$\frac{\sum(Infection\ Covered \times Antibiotic\ Breadth)}{\sum Infection\ Covered}$$

- For each infection:
  - We defined an **ideal antibiotic** as the antibiotic with the lowest breath score that covered the infection.
  - We defined the **actual empiric antibiotic regimen** as all antibiotics prescribed within 24hrs of admission.

- **How does the ideal antibiotic compare with the actual empiric antibiotic regimen for these metrics?**

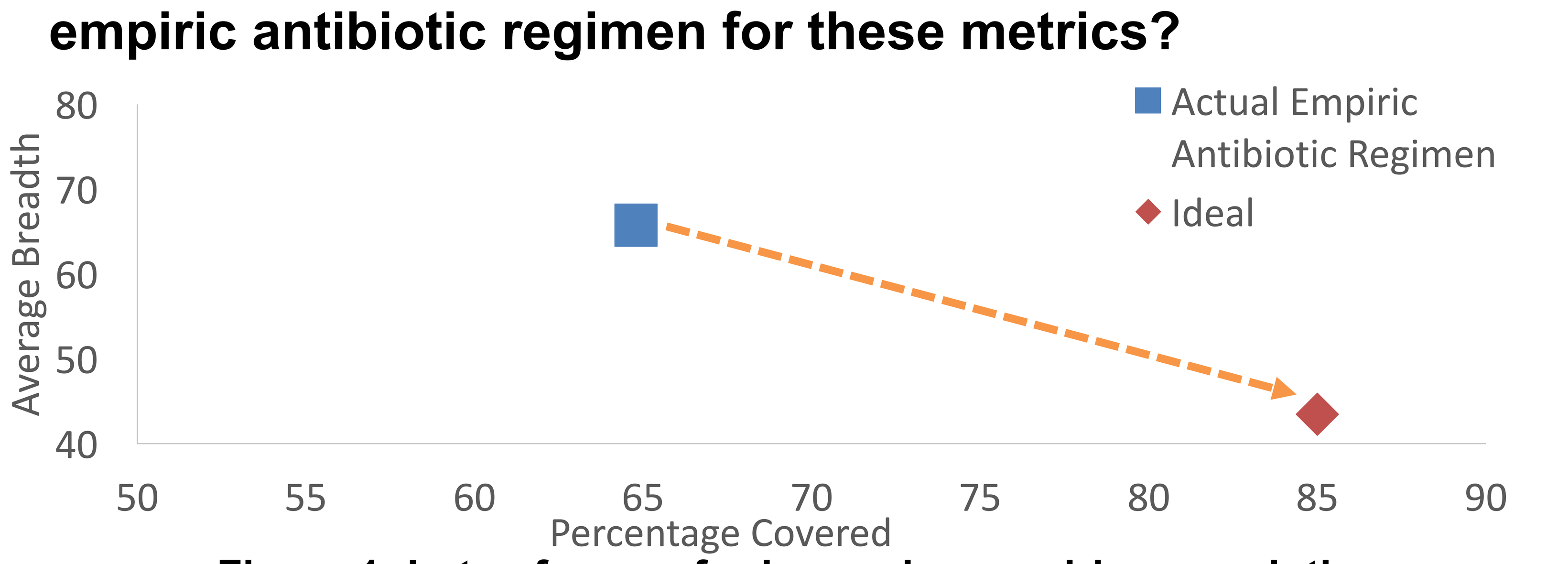

Figure 1: Lots of scope for improving empiric prescription

Modeling Antibiotic Resistance

- *Dataset*: Hospitalized adult patients with a positive urine culture within 48hrs of admission.
  - N=6,366, train = 5,093, test = 1,273
- Each row in our data corresponds to a patient's infection. We determined the outcome for each antibiotic based on whether this antibiotic would cover the patient's infection[3].
- We model individual antibiotic coverage with penalized logistic regressions[1].

Antibiotic	Patient 1	Patient 2
Piptazo	95%	90%
Cefepime	86%	65%
Ciprofloxacin	72%	44%
Ceftriaxone	87%	60%
Cefazolin	81%	50%

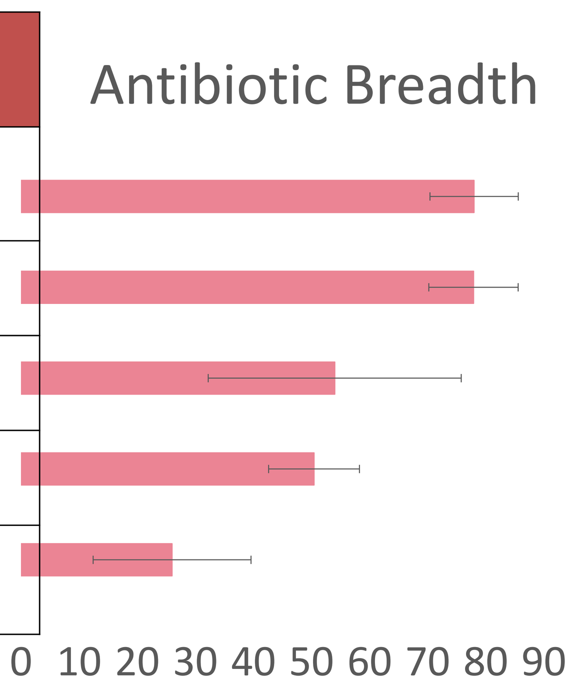

Figure 2: Model outcomes for 2 example patients.

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Recommending an Antibiotic

- **How do we recommend one antibiotic from Figure 2?**
  1. Pick the antibiotic with highest probability of coverage (gray circle)
  2. Recommending one antibiotic for all patients: For example ceftriaxone (yellow circle) – this is followed by many providers
  3. Choose a threshold: For example, recommend the narrowest antibiotic with at least 0.65 probability of coverage (green circle)

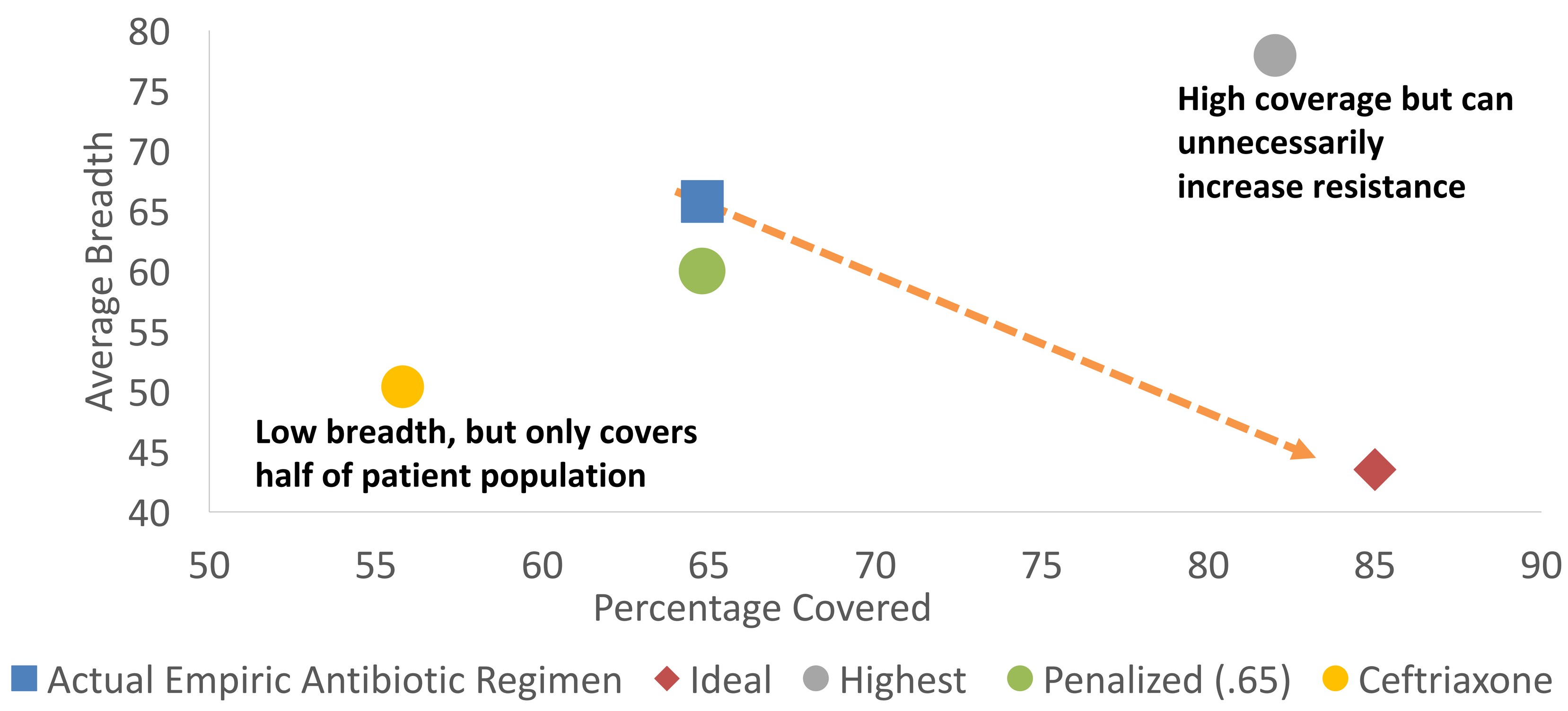

Figure 3

- **Can we do better?**
  - Picking different thresholds for each antibiotic varies the two metrics (green circles in Figure 4).
  - Increasing coverage requires increasing breadth, as expected.
- Neural Network: As a first step in directly modelling the ideal antibiotic, we used a hierarchical feedforward network:
  - Three fully connected layers
  - Dropout rate of 0.2 after each layer
  - Binary crossentropy loss function
  - Sigmoid activation
- The results from the neural network (purple crosses) are comparable to the penalized models.

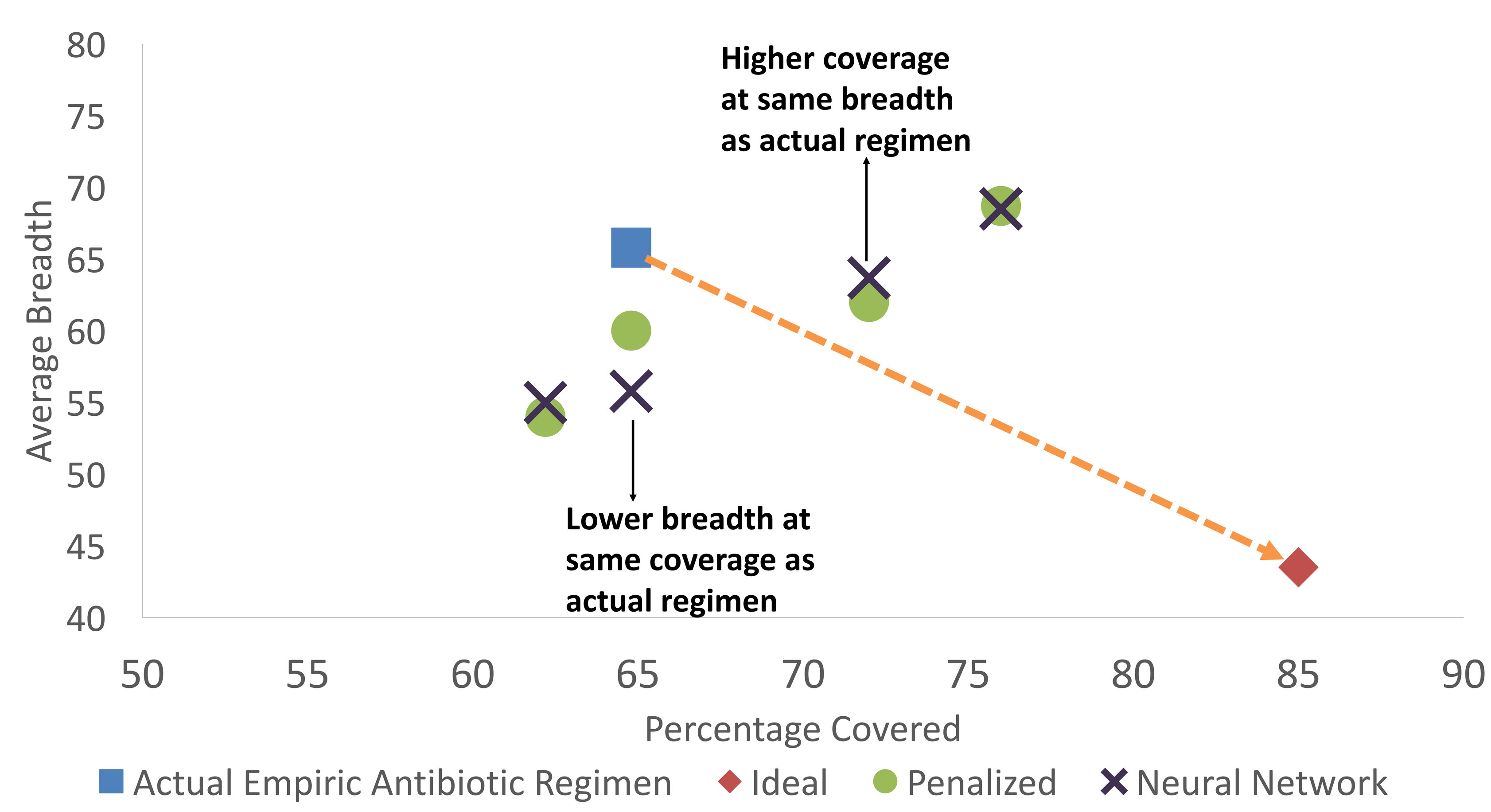

Figure 4

Limitations and Future Directions

- Actual empiric treatment is based on other factors that may not have been taken into account in this analysis: allergies, drug-drug interactions, severity of infection (sepsis), concurrent infections.
- Data-driven models have the potential to cover the same number of infections with narrower-spectrum antibiotics.
- Deploying these models to decision-makers requires additional studies on when, what and how to present this information.

References

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