NAM Digital Learning Collaborative:

Practical Challenges for AI/ML Development, Spread, and Scale

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CENTER FOR POPULATION HEALTH INFORMATICS

Model Explainability

- Machine learning methods
  - Lauded for achieving higher accuracy than traditional statistical methods
  - Criticized for being ‘black boxes’ that are not explainable or interpretable

- One of the key limitations in scale and spread of ML methods has been in areas where transparency and explainability are needed

Rise of Demand for Explainability

- Pivotal Moment: European Union passing General Data Protection Regulations that specifically cover requirements for transparency in automated modeling set to be law in 2018

- DARPA Explainable Artificial Intelligence (2016) RFA/Announcement

Goodman, et al. arXiv:1606.08813
https://www.darpa.mil/program/explainable-artificial-intelligence

Explainable to Whom? How? For What?

- What is explainability, <u>really</u>?
- Whole notion of allowing data science to determine interactions and relationships in the data that are not discernable to humans is core to the discipline
- Not all models have to be interpretable to achieve the desired effect
- Complex ‘traditional statistical’ models are not necessarily easily explainable

Explainability

- Who needs the explanation, and for what:
  - Medical Professional
    - needs to know what is modifiable in the clinical context
    - Needs to know likely impact of using the data - change in outcome(s)
  - Patient
    - needs to trust that the model is not discriminatory (race, SES, gender, sexual orientation, sensitive clinical conditions, etc)
    - Needs to be able to which of their characteristics were important in the modeling and resulting care decisions
  - Medical Societies
    - Needs to know that care supported by modeling is consistent with best practice guidelines and care recommendations

Active Areas of Research

- Methods for visualizing model outputs in a way that are clinically interpretable
- Use of simpler models on top of ML to provide interpretation
- explaining individual prediction versus overall model (parameters, etc)

Overall Model Performance

- How much accuracy is needed for clinical implementation?

- Application & Context Dependent
  - Population Health Care Management
  - Point of Care Management

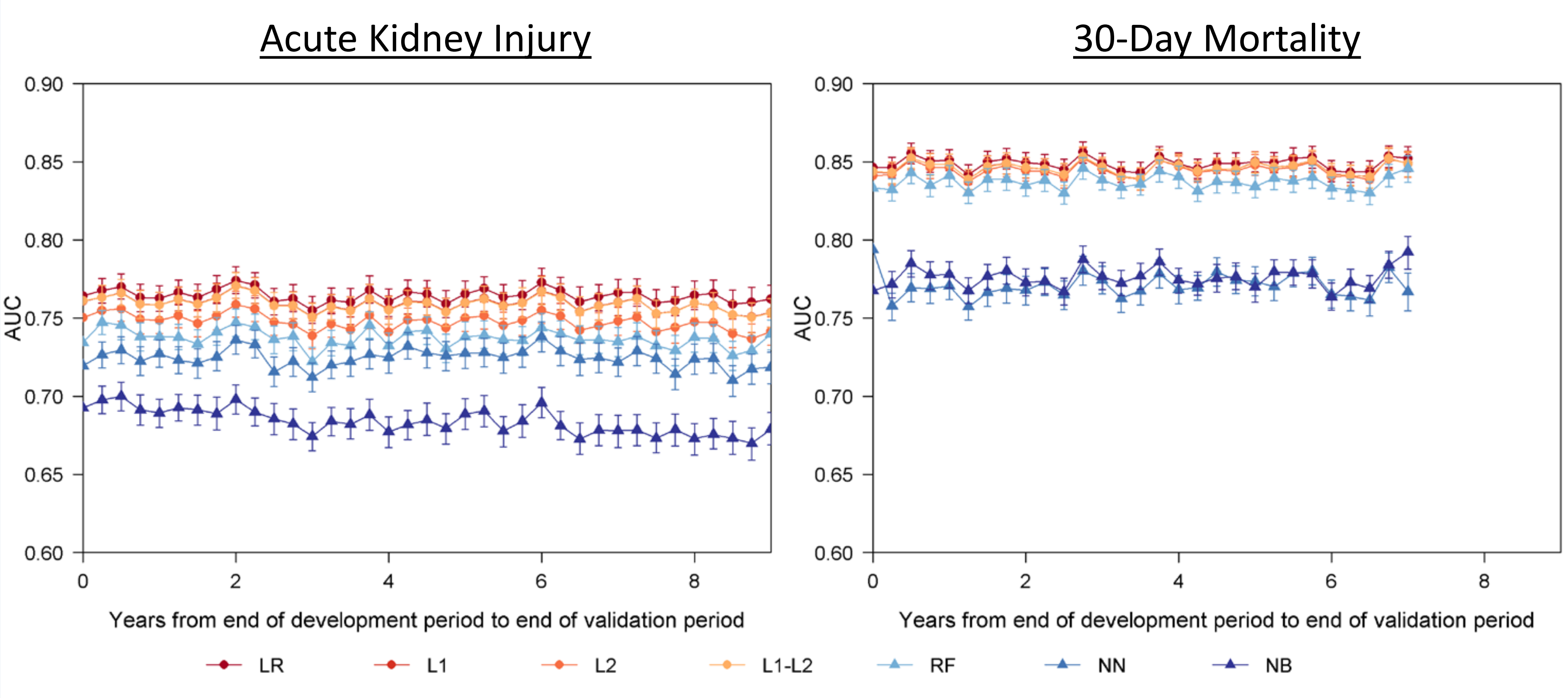
- Knowing when it is sufficient to use a model to separate a ‘yes’ from a ‘no’ (discrimination) and when do you need a range of probabilistic predictions (calibration)

Challenges in Re-Use (Spread) of Models

- Immediately, external application of models face:
  - Variation in underlying data collection
  - Variation in implementation of features
  - EHR Implementation: Real-Time Data changes ('dirty production data')

- Performance Over Time:
  - Changes in clinical practice
  - Changes patient case mix and outcome rates
  - Changes in data collection practices

Discrimination Over Time



Davis SE, et al, Matheny ME. J. Am. Med. Inform. Assoc. 2017 Nov;24:1052-1061.

Davis SE, et al, Matheny ME. AMIA Annu Symp 2017

Calibration Over Time: Estimated Calibration Index