# Context-Aware Framework for Machine Learning Model Interpretation: A Case Study in Asthma Attack Prediction

Asthma UK Centre for Applied Research

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**CONTEXT:** Most machine learning (ML) models for predicting asthma attacks, as well as in healthcare more broadly, are evaluated using metrics such as the area under the curve (AUC), which rely on discriminant factors only. Decision Curve Analysis (DCA) is a complementary technique that estimates clinical net benefit.

**PROBLEM: Lack of contextualisation** in AUC and DCA. How can we assess (and adjust) a model's behaviour in different settings and scenarios, given practical constraints (e.g. resource limitations)?

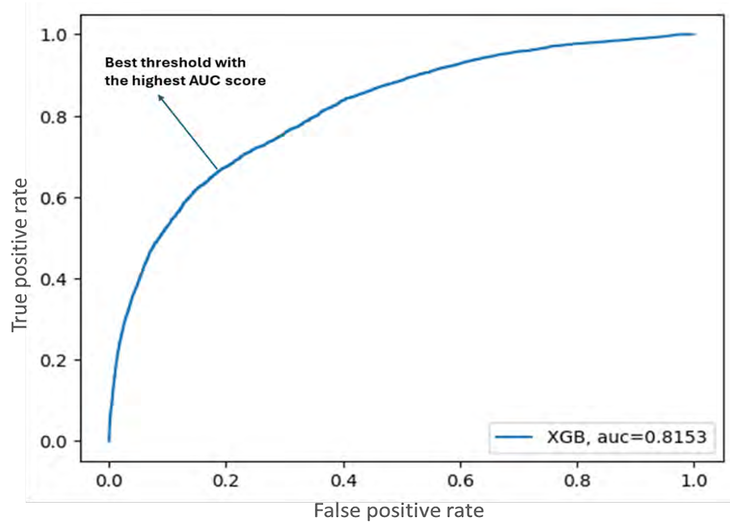



Fig 1. AUC Plot

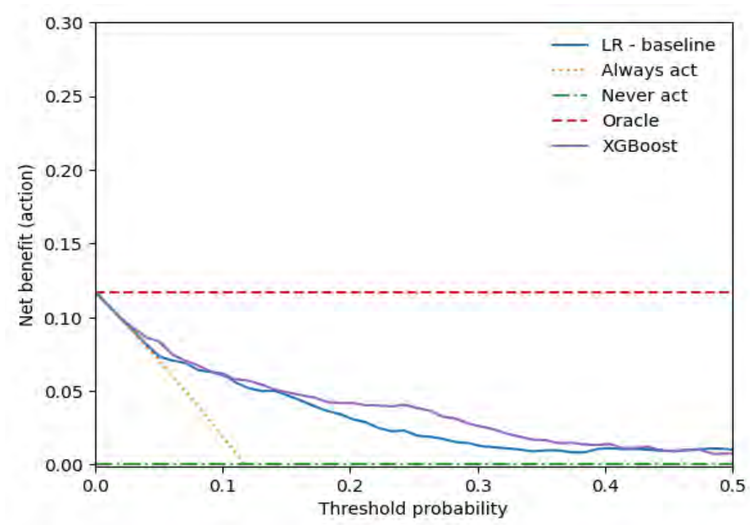
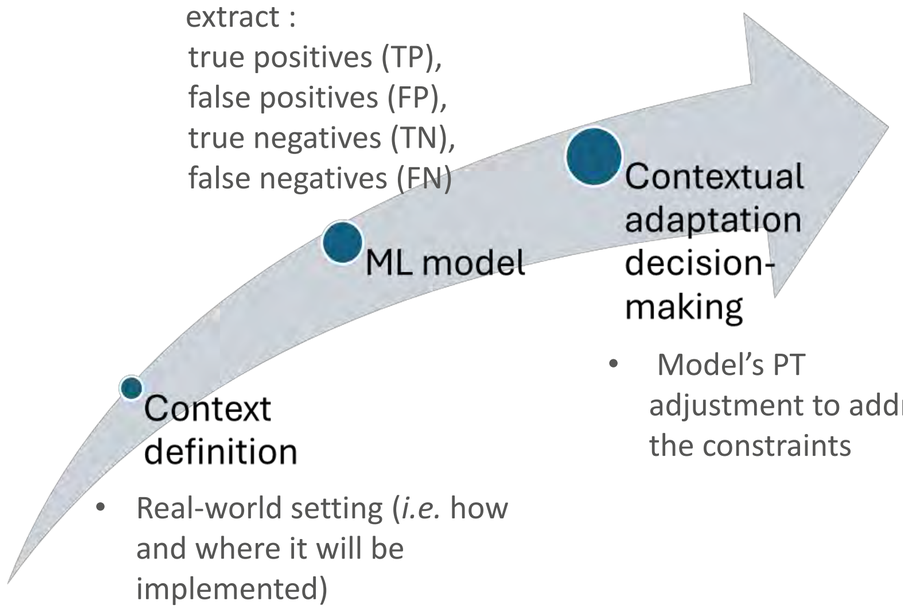



Fig 2. DCA Plot

**OUR IDEA:**

Context-Aware Model Interpretation (CMI) Framework

- For every model's probability threshold (PT), extract : true positives (TP), false positives (FP), true negatives (TN), false negatives (FN)




- Real-world setting (*i.e.* how and where it will be implemented)
- Practical constraints

- Model's PT adjustment to address the constraints

**OUR EXPERIMENT:**

Model:
- XGBoost model trained on Optimum Patient Care Research Database (OPCRD) data

Setting:
- Follow-up appointment allocation in the clinic after the asthma annual review for high-risk patients

Constraints:
- Limited appointments can be offered in a clinic

Challenge:
- How to identify and use only those model thresholds that align with real-world capacity limits for a specific clinic

| Parameters | Clinic 1 (low prevalence) | Clinic 2 (high prevalence) |
|---|---|---|
| Number of registered asthma patients | 828 | 503 |
| Number of patients at high risk of asthma attack (% prevalence) | 30 (3.6%) | 193 (38.4%) |
| Capacity (assumed as 50% of total asthma patients) | 414 | 252 |

**RESULTS:** For each clinic, we plotted the capacity fulfilment by leveraging the ML model to identify patients with a high risk of asthma attacks.

**TAKEAWAYS:** This framework links model performance to clinical context, enabling threshold adjustments tailored to operational needs. Capacity increases led to varying threshold changes, showing how model behaviour differs across settings.

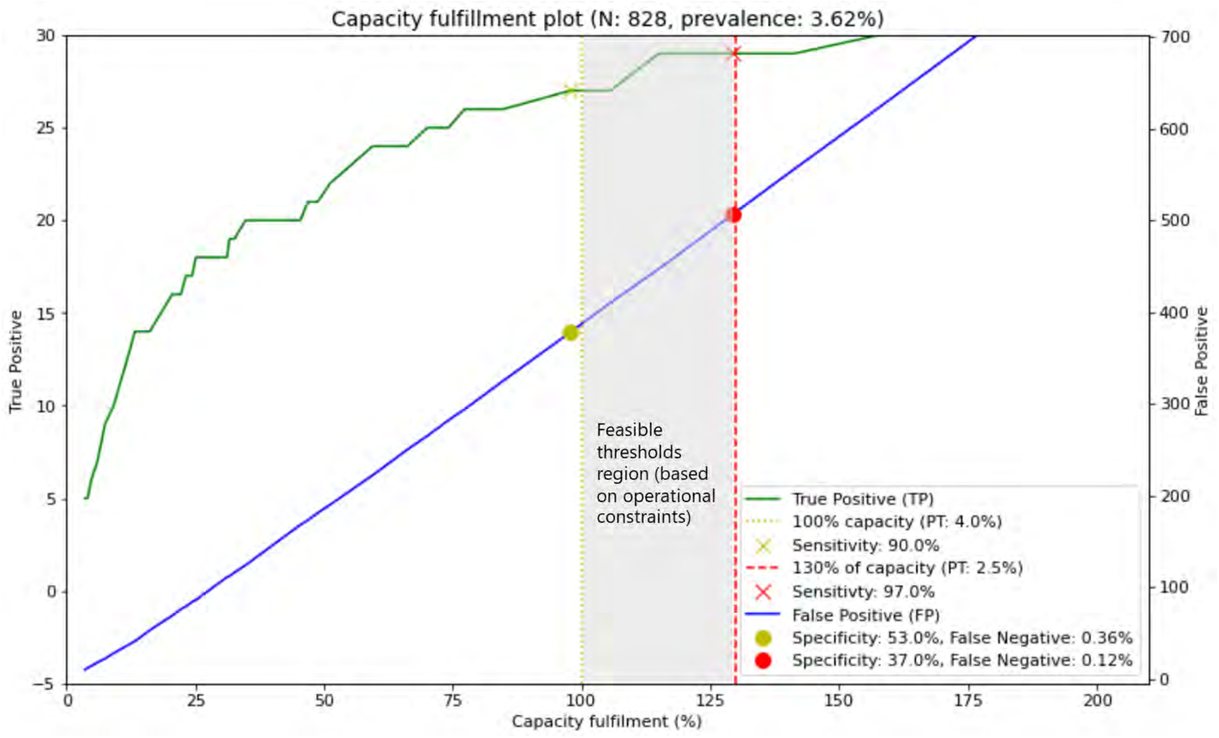



Fig 3. Model interpretation for Clinic 1

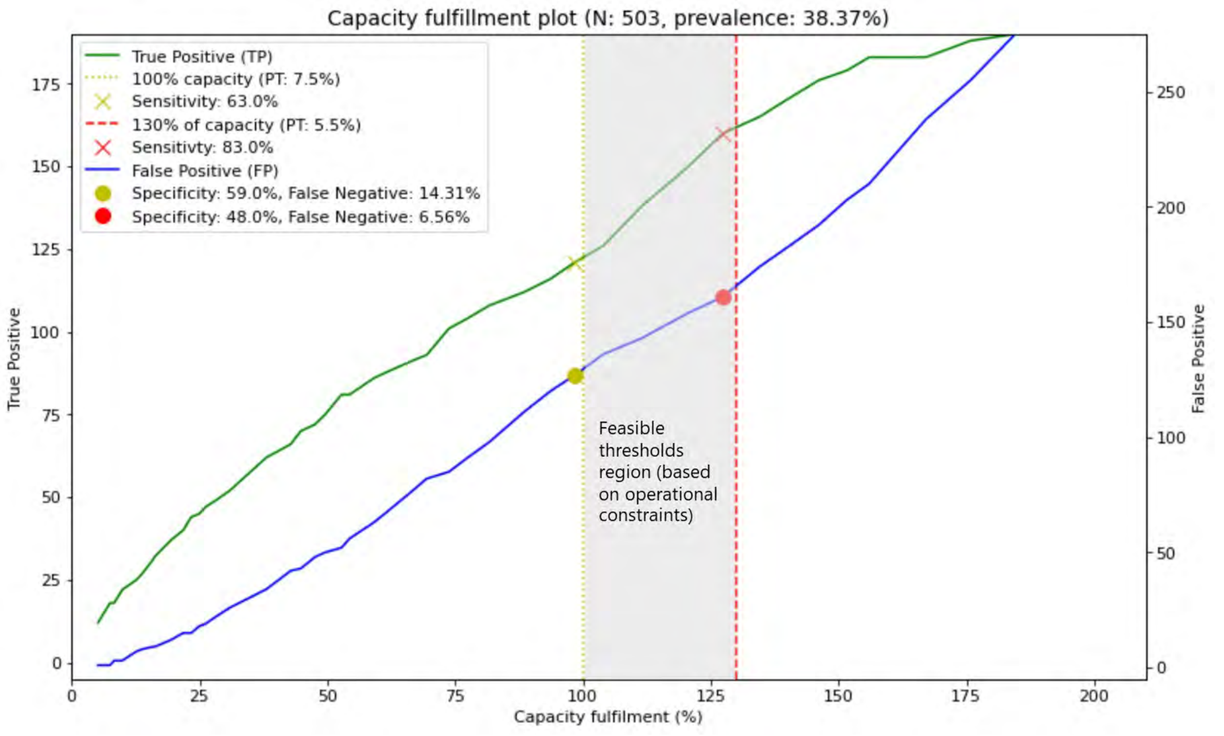



Fig 4. Model interpretation for Clinic 2

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