Week 5

Part 2: Case Study Application

Problem Scope

- **Problem:** Binary classification predicting patient readmission within 30 days of discharge.
- **Objective:** Identify high-risk patients for targeted interventions to reduce readmissions.
- **Stakeholders:** Patients, clinicians, hospital administrators, insurance providers.

Data Strategy

- **Data Sources:** EHRs (lab results, diagnoses, medications), patient demographics, discharge records.
- **Ethical Concerns:**
    1. **Patient Privacy:** Protecting PHI under HIPAA regulations.
    2. **Bias/Fairness:** Model may perform poorly on underrepresented demographic groups.
- **Preprocessing Pipeline:**
    1. Handle missing values (imputation/removal).
    2. Encode categorical variables (One-Hot Encoding).
    3. Feature Engineering: Create features like Number_of_prior_admissions, Length_of_stay, Comorbidity_count.

Model Development

- **Model: Gradient Boosting (XGBoost)**. Handles mixed data types, captures complex patterns, provides feature importance.
- **Confusion Matrix & Metrics (Hypothetical):**
    - TN=800, FP=100, FN=150, TP=450
    - **Precision** = 450 / (450 + 100) = **0.82**
    - **Recall** = 450 / (450 + 150) = **0.75**

Deployment

- **Integration Steps:**
    1. Package model as REST API (Flask/FastAPI).
    2. Integrate API with Hospital EMR system.
    3. Run batch predictions on discharged patients.
    4. Display risk scores in the clinician dashboard.
- **Compliance (HIPAA):**
    - Data de-identification/anonymization.
    - Secure API endpoints (HTTPS, authentication).
    - Access controls and audit trails.

Optimization

- **Method: Regularization via Early Stopping** in XGBoost. Stops training when validation performance plateaus to prevent overfitting.

Part 3:Ethics & Bias

- **Impact of Biased Data:**
  Biased training data can lead to systematically worse predictions for specific patient groups (e.g., based on race, socioeconomic status, or insurance type). This could:
    1. **Under-predict risk** for disadvantaged groups, denying them necessary follow-up care and increasing their likelihood of complications.
    2. **Over-predict risk** for others, leading to unnecessary and costly interventions, straining hospital resources and patient trust.
- **Bias Mitigation Strategy:**
  Pre-process the training data using techniques like reweighting or resampling to ensure the dataset is representative across sensitive attributes (e.g., race, age, gender). This helps the model learn patterns that are fair across all subgroups.

Trade-offs

- **Interpretability vs. Accuracy:**
  In healthcare, interpretability is often prioritized. A slightly less accurate but interpretable model (like Logistic Regression or a shallow Decision Tree)

allows clinicians to understand *why* a prediction was made, fostering trust and enabling clinical validation. A "black box" model like a complex ensemble may

- be more accurate but is dangerous if its reasoning cannot be scrutinized, potentially leading to uncaught errors or ethical issues.
- **Impact of Limited Computational Resources:**
  Limited resources would shift the model choice away from computationally intensive algorithms like deep neural networks or large ensembles. The focus would be on **simpler, more efficient models** like Logistic Regression, shallow Decision Trees, or Naive Bayes, which require less power for both training and inference and can run on standard hardware.

PART 4: Critical thinking

Reflection

Most Challenging Part: Data Quality and Feature Engineering. The UCI diabetes dataset contained significant data quality issues, including missing values, inconsistent coding (like '?' for missing data), and complex medical variables that required domain expertise to properly interpret. Creating meaningful features that accurately predict readmission risk without medical domain knowledge was particularly difficult.

Improvements with More Time/Resources:

1. **Clinical Collaboration:** Work with healthcare professionals to better understand medical codes, treatment patterns, and clinically relevant feature engineering.
2. **Advanced Data Pipeline:** Implement automated data validation, comprehensive feature stores, and systematic handling of temporal patient data across multiple visits.
3. **Robust Model Validation:** Conduct extensive fairness audits across demographic subgroups and implement continuous monitoring for model drift and performance degradation in production.