FML PROJECT

eICU Conceptual Fragmentation

Here is a recommended *conceptual* split of the eICU database into nine separate databases, by clinical department. Below each department are 1-2 tables that form the database associated with that department.

Admissions or Central Administration
1. `patient`: This table includes general information about the patient admissions, such as admission and discharge times, hospital and ICU unit types, and overall patient tracking.

Pharmacy
1. `admissionDrug`: Contains details about medications ordered and administered during hospital admission.

2. `medication`: Details medications administered to patients

Medical Records or Admissions
1. `admissionDx`: This table provides diagnostic information for the patient at the time of admission.

Laboratory
1. `lab`: Includes results from laboratory tests performed on patients.

Nursing
1. `nurseCharting`: Consists of routine and non-routine charting information entered by nurses, such as patient assessments and care details, which is typically managed by nursing staff.

Physical Therapy or Rehabilitation
1. `physio`: Contains data related to physiotherapy and rehabilitation services provided to patients.

Respiratory Therapy
1. `respiratoryCare`: Includes detailed records of respiratory therapy provided to patients, such as ventilator settings and support.

Specialized Department (depending on therapy)
1. `treatment`: Details treatments administered from specific departments (surgery, oncology etc.)

Intensive Care Unit

1. `vitalPeriodic and vitalAperiodic`: These tables record periodic and aperiodic vital signs, which are typically monitored and recorded by nursing staff or in more critical cases, directly within the ICU.

Analytics Problems on Machine Learning Federation (over the above nine data collections)

1. Predictive Analytics for Patient Readmission

Task Description: Develop a federated learning model to predict the likelihood of patient readmission within 30 days of discharge. This prediction can help in planning post-discharge care and interventions to reduce readmission rates.

Relevant Tables and Columns:
`patient`: age, gender, ethnicity (general demographics)
`admissionDx`: admitDxName (diagnosis at admission)
`hospital`: hospitalID, hospitalDischargeStatus (discharge outcomes)

Privacy Aspect: Use differential privacy to perturb the model updates, ensuring that sensitive demographic and health status information remains confidential.

Evaluation: Utility vs. Privacy Trade-off

Evaluate how changes in the privacy budget impact the model's performance and the level of privacy protection. This involves measuring the model's accuracy with various privacy budgets and assessing the impact of these changes on patient data confidentiality.

2. Treatment Effectiveness Across Diverse Populations

Task Description: Analyze the effectiveness of different treatments across various demographics to understand how factors like age, gender, and ethnicity affect treatment outcomes. This can guide personalized medicine approaches.

Relevant Tables and Columns:
`patient`: age, gender, ethnicity
`treatment`: treatmentType, drugName (specific treatments received)
`admissionDx`: admitDxName (related to the reason for the treatment)
`hospital`: hospitalID (to anonymize specific hospital data)

Privacy Technology: Implement federated learning with a differential privacy mechanism to add noise to model parameters, ensuring that insights about treatment effectiveness do not compromise patient privacy.

Evaluation: Utility vs. Privacy Trade-off

Explore how different levels of the privacy budget affect the statistical analysis of treatment effectiveness: adjust the privacy budget and observe changes in the accuracy and reliability of the results.

How can you then find an optimal privacy budget that maintains meaningful insights into treatment effectiveness, yet ensures robust privacy protection ?