Extensive Patient Data Facilitates the Development of Personalized Cancer Treatment Plans

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INTRODUCTION

Cancer is responsible for approximately 14.6% of all human deaths, and survivability is dependent on multiple factors which include age, genetics, disease progression, and health status at diagnosis. The interaction of these variables drives the uniqueness of each patient's cancer, complicating the choice of treatment.

Electronic health records (EHR) provide large amounts of medical data, which increase exponentially with modern automation.² EHR are designed for specific medical uses, and their format makes it difficult to ask meaningful research questions about the data. The creation of a database which relates all of this information together in a cleaned and standardized format will allow for exploration across multiple patients and types of data.

Extensive diagnostic, treatment, and demographic information for thousands of cancer patients organized in an intuitive, relational database can be used to research effective personalized cancer treatment plans.

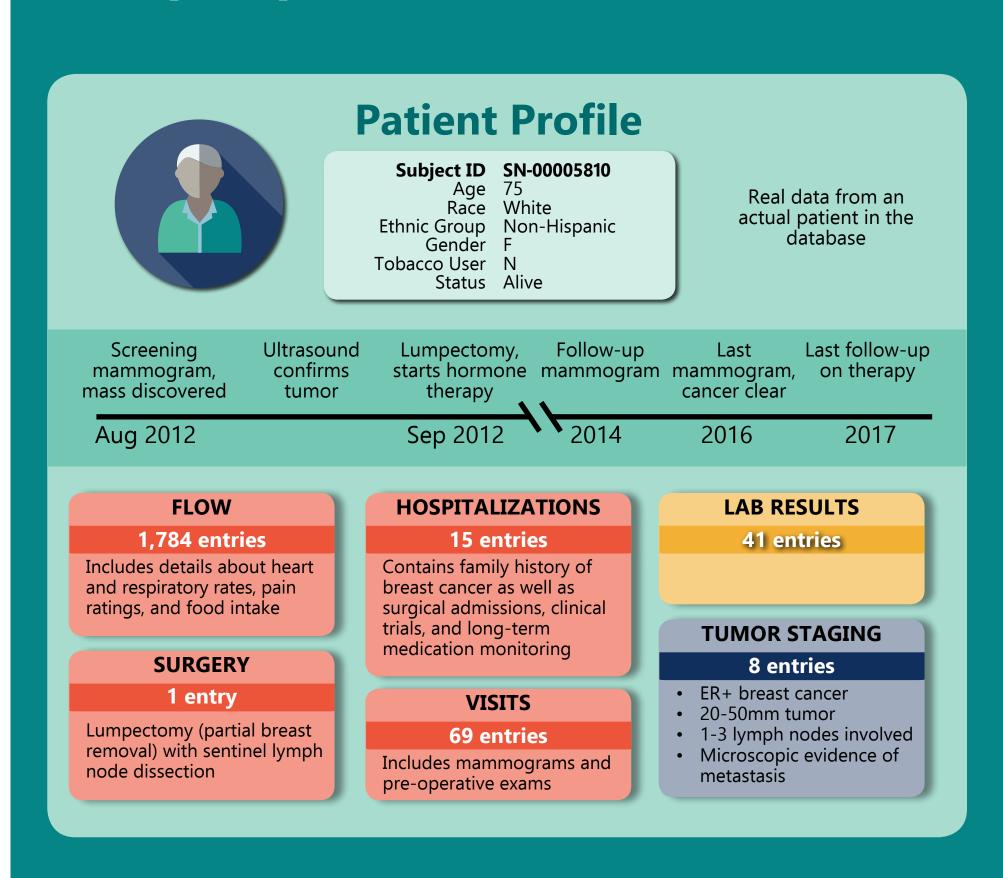
WHY USE A RELATIONAL **DATABASE?**

Due to the export process, the data arrived in a disconnected and poorly-organized form. This dataset is particularly valuable because of the depth of information available for each patient. A relational database allows us to store the data in a modular format which still preserves interrelatedness.

The database structure enforces strict data types that allow users to ask complex questions based on the type of information involved. For example, a researcher could ask for the projected survival time based on patients' biological sex, BMI, number of surgeries, and white blood cell count. This kind of data exploration could also lead to the discovery of previously unknown risk factors.

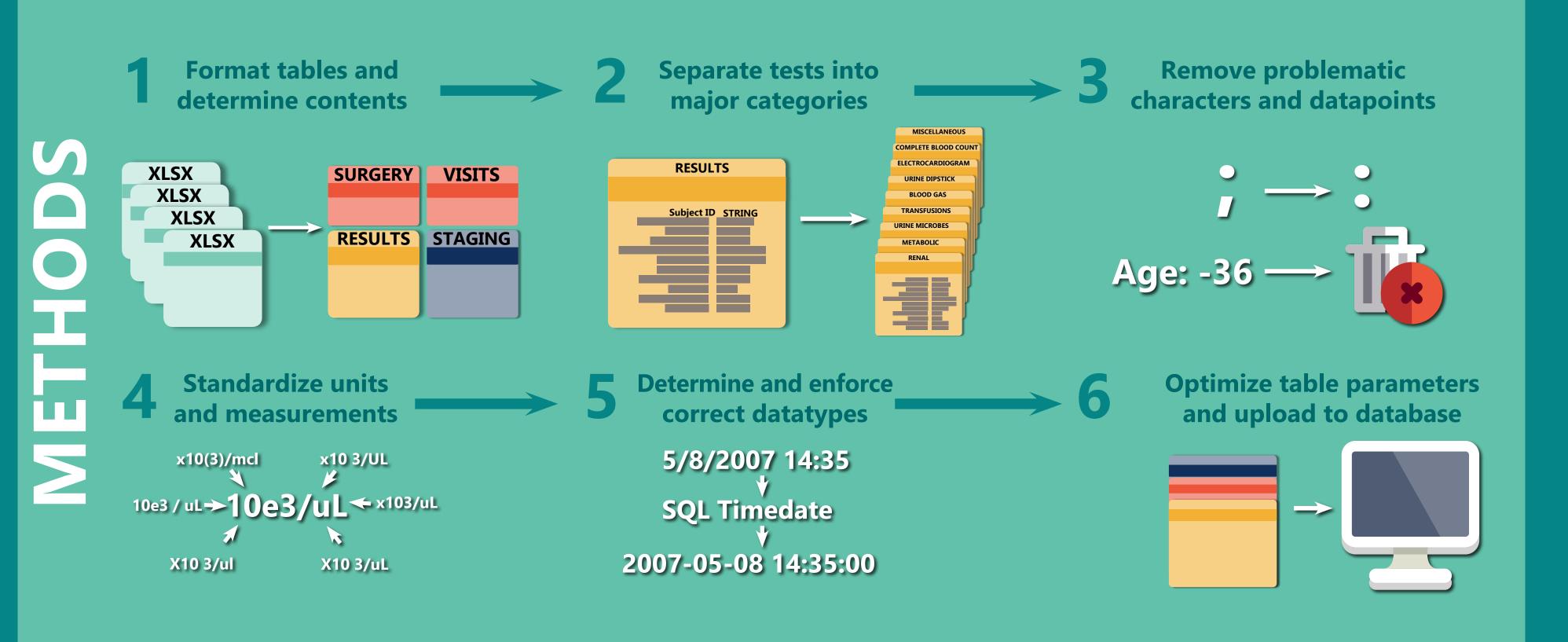
GOALS

- Compile patient data into an intuitive relational database
 - Standardize data formats
- Remove illogical typos • Explore data to find trends
- Integrate with tissue images for more comprehensive and specific prediction





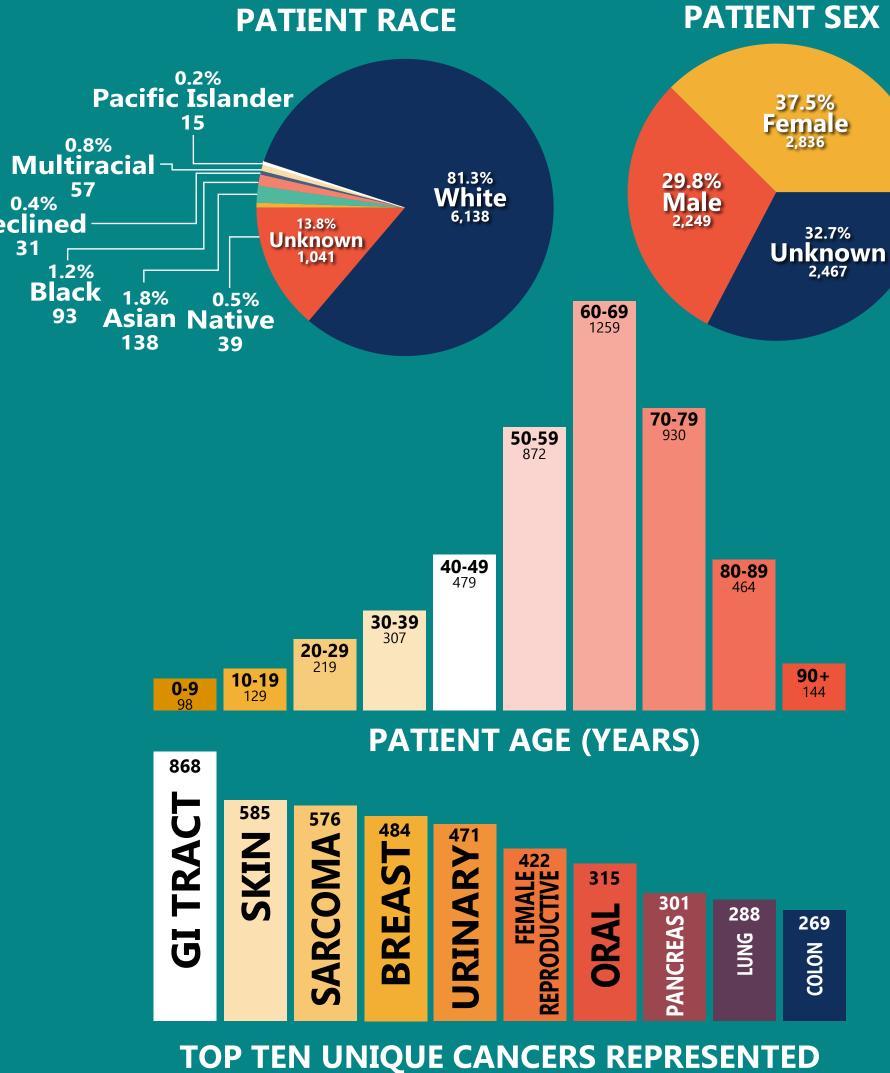
7,552 cancer patients Spanning 2 decades Over 1.5 million rows of data Available data varies based on patient consent



DEMOGRAPHICS LAB TEST LEGEND **RESULT TABLES TABLE NAME** 7,552 sets of demographic information on patients in the database **Description of contents MISCELLANEOUS** 139,173 uncategorized test results Primary Key TYPE **Subject ID STRING COMPLETE BLOOD COUNT** REAL 127,362 blood counts by cell type **VITAL SIGN TABLES STRING ELECTROCARDIOGRAM** Ethnic Group 13,827 ECG results **HOSPITALIZATIONS** CHARACTER (M/F) Gender **URINE DIPSTICK** CHARACTER (Y/N) 16,038 urine dipstick tests STRING (ALIVE/DECEASED) **Subject ID STRING BLOOD GAS** Hospital Admission DATE/TIME Admission Diagnosis STRING 1,625 blood gas concentration data point Admission Procedures STRING 5 **TRANSFUSIONS** 9,147 IV transfusions **VISITS URINE MICROBES** 483,995 doctor visits with vital signs **TUMOR STAGING SURGERY** 18,172 urine cultures Subject ID STRING 38,750 evaluations of cancer progression 6,480 data points collected during surgery Visit Date Time DATE/TIME **METABOLIC Subject ID** Tissue Type STRING **Subject ID STRING** 113,326 records from metabolic panels REAL Surgery Date DATE/TIME **RENAL** Diagnosis STRING Blood Pressure INTEGER Metastasis STRING Height REAL Visit Diagnosis STRING RBC Size Distribution STRING 25,482 kidney function lab tests Weight REAL Surgery Diganosis STRING Tumor Path STRING Lymph Node Path STRING Surgery Procedures **FLOW** Surgery Description Metastasis Path STRING **Subject ID STRING** 483,963 records of longitudinal test data (e.g. breathing, oxygenation, heart rate) Lab Status STRING Anesthesia Type Estrogen Level REAL Result Status STRING Specimen Taken Time DATE/TIME Hemoglobin A1C REAL Progesterone Level REAL Metastasis Site STRING Pre-Ŏp Glucose INTEGER Subject ID STRING Post-Op Glucose INTEGER Tumor Grade STRING Result Time DATE/TIME FSD ID INTEGER Description STRING Pre-Op CBG INTEGER Percent Tumor INTEGER Recorded Date DATE/TIME Test Name STRING Diabetes STRING Percent Necrosis INTEGER Entry Date DATE/TIME Test ID REAL ASA Score STRING Gene Marker Test STRING Description Name STRING HPRO Type STRING Reference Range STRING Chromosome Location STRING Measured Name STRING Surgery Duration INTEGER Result Flag STRING Gene Marker Result STRING Measured Value REAL Wound Class STRING Tissue Image ID STRING Unit STRING

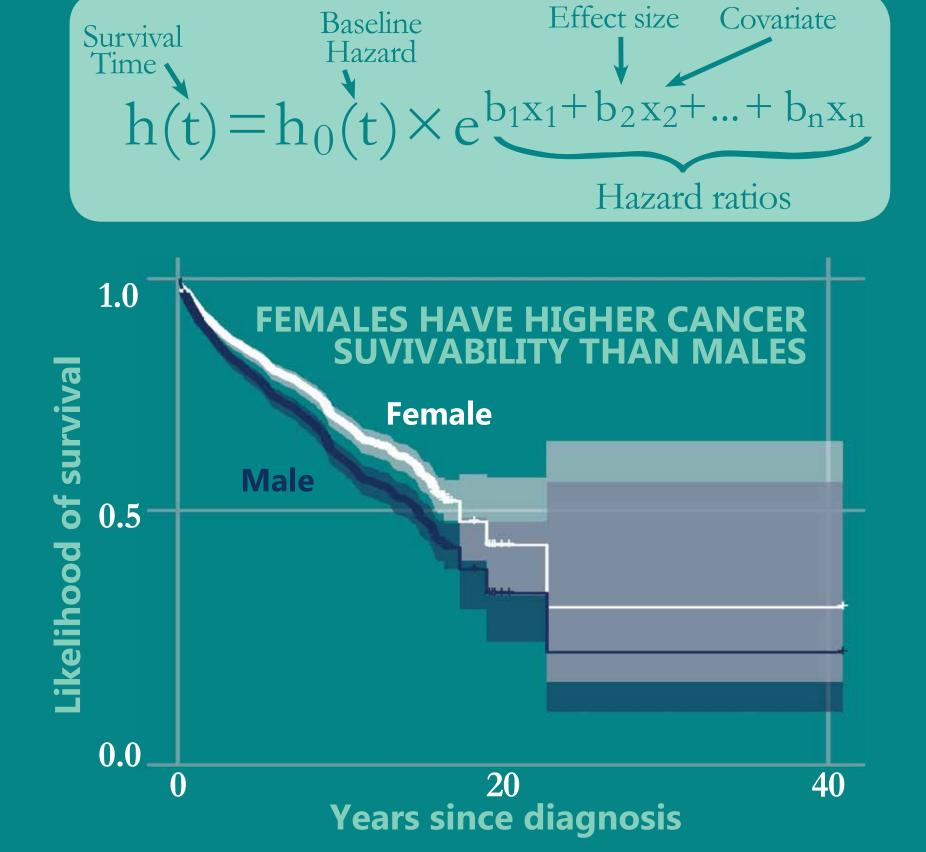
The PostgreSQL (version 10.5) database is hosted on a Red Hat Linux virtual machine at the University of Oregon. Tables are connected by subject ID.

THE DATABASE PATIENTS



PROPORTIONAL HAZARDS

- The Cox Proportional-Hazards model, a widely used regression analysis of survival data, estimates survivability based on predictors (called covariates).4
- This model assumes that hazard ratios do not change over time.
- This approach uses the date of a deceased patient's final datapoint as a proxy for time of death.



FUTURE DIRECTIONS

- Expand database with additional patient data sets
- Integrate with machine learning tissue-imaging diagnostics
- Identify predictors of treatment response to facilitate "all in a day" development of personalized treatment plans



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