Predicting Hospital Readmissions

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BUS 458 (001H)

Team

We unite a team of data scientists with diverse experiences in data analytics, marketing research, supply chain management, and information technology.

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Today's Agenda

Our Objective

Business Challenge

Understanding the Industry

Analytical Data Preparation

Exploratory Data Analysis

Data Mining

Predictive Modeling

Limitations

Recommendations

Next Steps

Desired Outcomes

Our Objective

Create an accurate model to predict hospital readmissions to ultimately lower the number of readmissions, reduce hospital costs, and improve patient experience.

Key Challenges Facing the Hospital

1. **15-25%** of people who are discharged from the hospital will be readmitted within 30 days or less.

2. Preventable readmissions divide into three categories:
    1. Hospital stay complications
    2. Poorly managed transitions
    3. Chronic conditions

3. In 2011, patient readmission costs for readmissions under 30 days after discharge reached **$41.3 billion**.

4. In 2015, The **Hospital Readmission Reduction Program** (HRRP) was implemented to penalize hospitals with higher readmission rates than peers.

Understanding the Industry

Business Value of Readmission Analysis

Understanding and predicting readmissions leads to a stronger ability to address them and lower future readmission rates - both improving the quality of service and reducing penalties imposed by HRRP.

$17M

Cost to Medicare of readmissions within 30 days in 2017

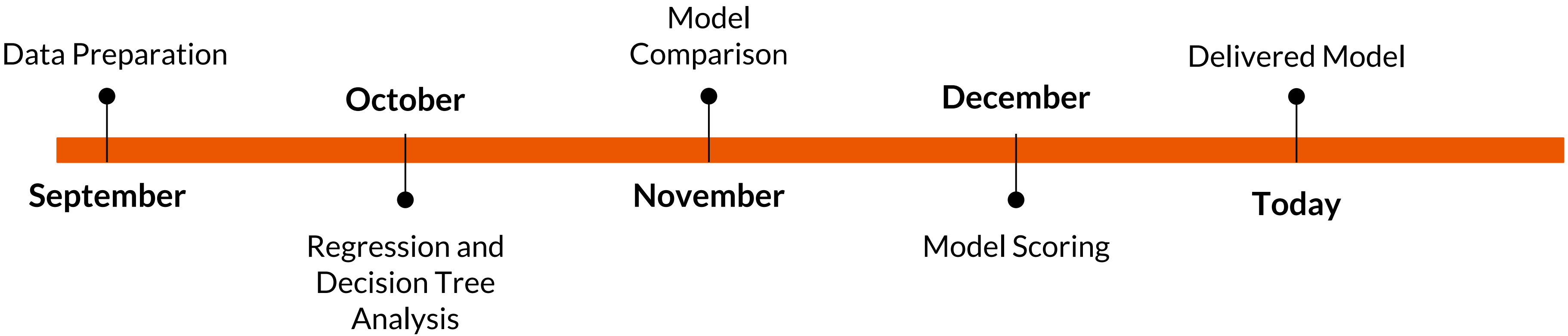
20%

Of all Medicare discharges had a readmission within 30 days

$1B

How much Medicare could save by preventing 10% of readmissions

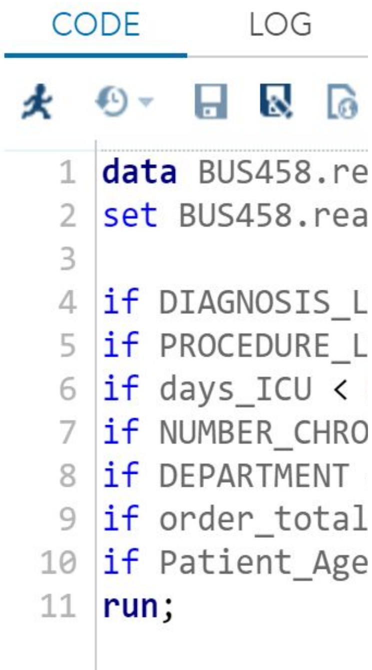
Our Process


Data Preparation
September
October
Regression and Decision Tree Analysis
Model Comparison
November
December
Model Scoring
Delivered Model
Today

Data Preparation

Data Preparation
Uniting the Data

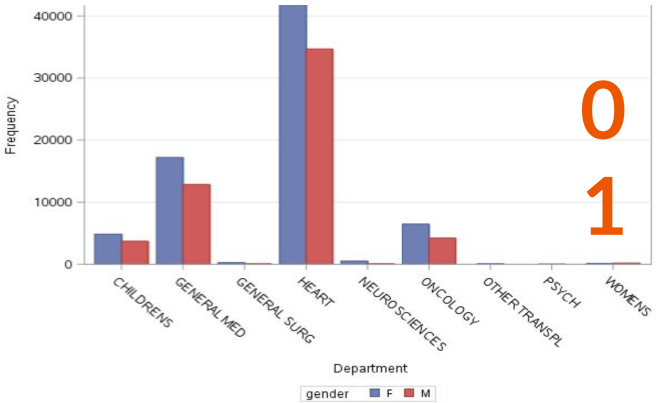
1. Start with **4 Excel spreadsheets**
2. Employ **SAS Studio** to merge files based on encounters
3. Create **SAS code** to correct errors / missing data



Exploratory Analysis

Exploring the Data

The Heart Department Dominates Stays



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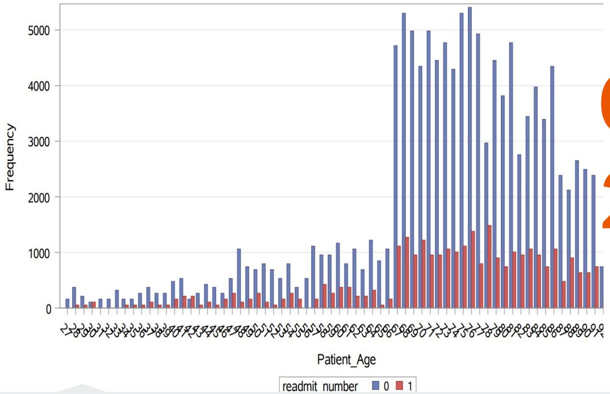

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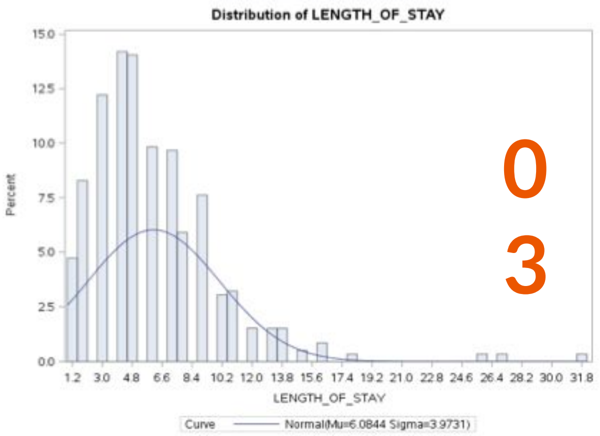
The Elderly Dominate the Sample

Exploring the Data



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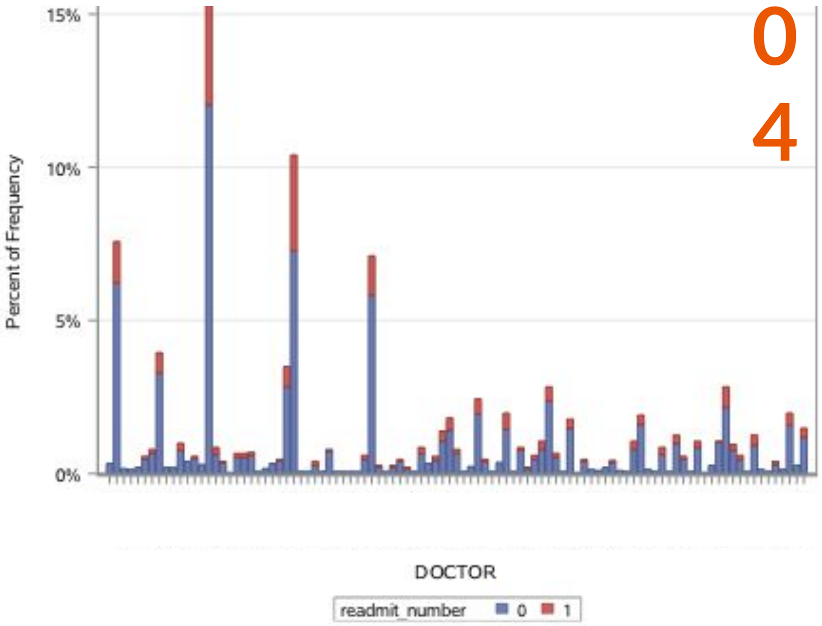
Length of Stay

Doctor Effects



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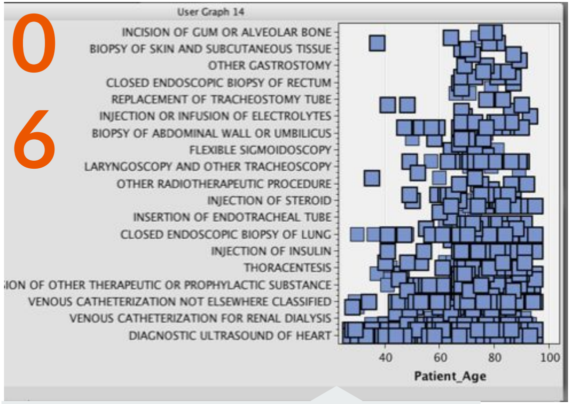
Interactions

Interaction Analysis

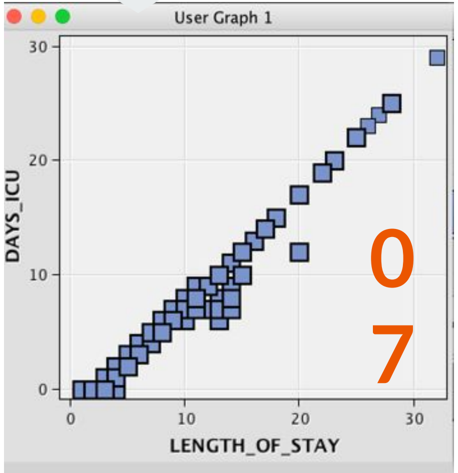
Interactions	Lift	Misclassification Rate
NO INTERACTIONS	2.37	.175
DAYS ICU X LENGTH OF STAY	2.4	.173
DAYS ICU X LENGTH OF STAY OPS VISITS X OP COUNT	2.4	.174
DAYS ICU X LENGTH OF STAY OPS VISITS X LENGTH OF STAY	2.41	.172
DAYS ICU X LENGTH OF STAY DIAGNOSIS GROUP X LENGTH OF STAY	2.38	.173
DAYS ICU X LENGTH OF STAY DAYS ICU X OPS VISITS	2.41	.173
DAYS ICU X LENGTH OF STAY AGE X OPS VISITS	2.41	.173
DAYS ICU X LENGTH OF STAY AGE X LENGTH OF STAY	2.41	.173
DAYS ICU X LENGTH OF STAY LENGTH OF STAY X OPERATION COUNT	2.41	.173
DAYS ICU X LENGTH OF STAY OPERATION COUNT X PATIENT AGE	2.4	.17
DAYS ICU X LENGTH OF STAY DAYS ICU X PATIENT AGE	2.42	.173
BEST: DAYS ICU X LENGTH OF STAY PROCEDURE X PATIENT AGE	2.46	.166
DAYS ICU X LENGTH OF STAY PROCEDURE X PATIENT AGE DAYS ICU X PATIENT AGE	2.46	.166

05



Patient Age x Procedure

Days ICU x Length of Stay



Data Mining & Predictive Modeling

Explored Models

Business Centric

1. Interactive Decision Tree
3. Logistic Regression With Interactions

Statistic Centric

2. Decision Tree
4. Logistic Regression

Comparing The Models

Decision Tree	11.7%	Focus on getting the best predictive power	→ 2.90x more likely to find someone being readmitted
Logistic Regression Interaction	14.5%	Interaction used to enhance model	→ 1.88x more likely to find someone being readmitted → Based on hypothesis testing
Logistic Regression	15%	**Top variables:** Procedure Long Desc, Diagnosis Long Desc, Standard Order Used & Statecode	→ 2.76x more likely to find someone being readmitted
Decision Tree Interactive	19%	**Built on 3 Variables:** (1) Diagnosis Long Desc, (2) Procedure Long Desc & (3) Doctor	→ 1.78x more likely to find someone being readmitted

The Winning Model: Original Decision Tree

1. **Of 11 significant variables, the 5 most predictive variables are:**
   ➔ Doctor, Procedure Long Description, Standard Order Used, Diagnosis Long Description & Discharge Nurse ID

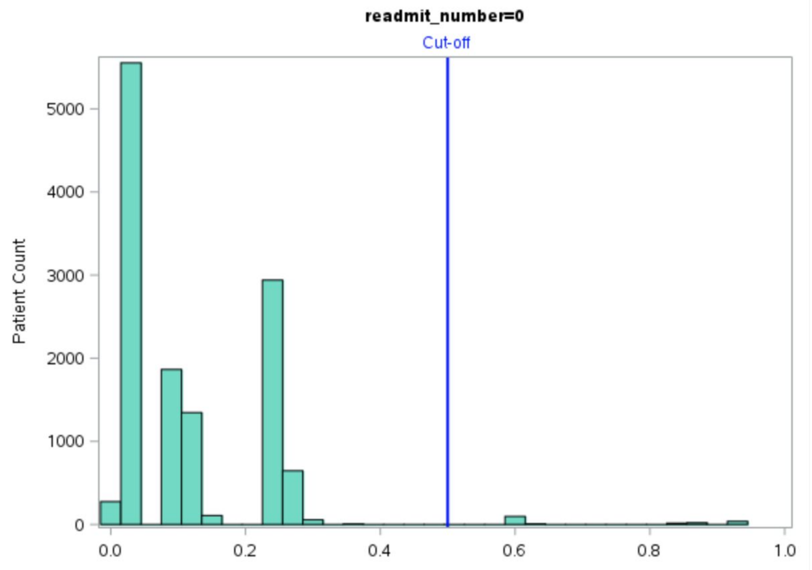
2. **This model had the best predictive power:**
   ➔ Error rate of 11.7%
   ➔ 2.90x more likely to predict than random guessing

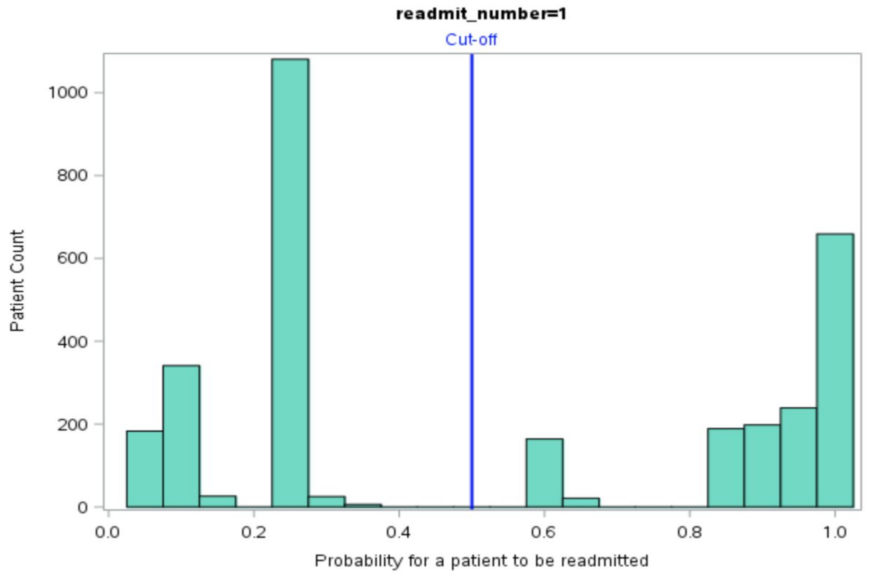
3. **Insights:**
   ➔ When Standard order wasn’t used there was 15% increase in Readmittance
   ➔ Certain doctors and discharge nurses cause higher re-admittance rate.

Model Effectiveness

Business Insight

Our model was very effective at classifying which patients would not be readmitted - thus helping the hospital to better focus on patients who are more likely to be readmitted.





Key Limitations

01 | Sample size

02 | Absence of other important variables

03 | Exogenous factors upon discharge

04 | Overpowering of certain variables

Recommendations

Standard Orders

Proposed Solution:

New

Standard Orders

- ➔ Expand Standard Orders for more cases
- ➔ Revise Standard Orders for High-Readmission Procedures & Diagnoses

Standard Orders are not used 20% of the time, which raises readmission risk from 19% to 34%

Doctor

Proposed Solution:

New System to track Doctor Performance

- ➔ Flag Doctors with Readmission Risk in the top 20th percentile annually
- ➔ Ensure Doctors follow Standard Orders

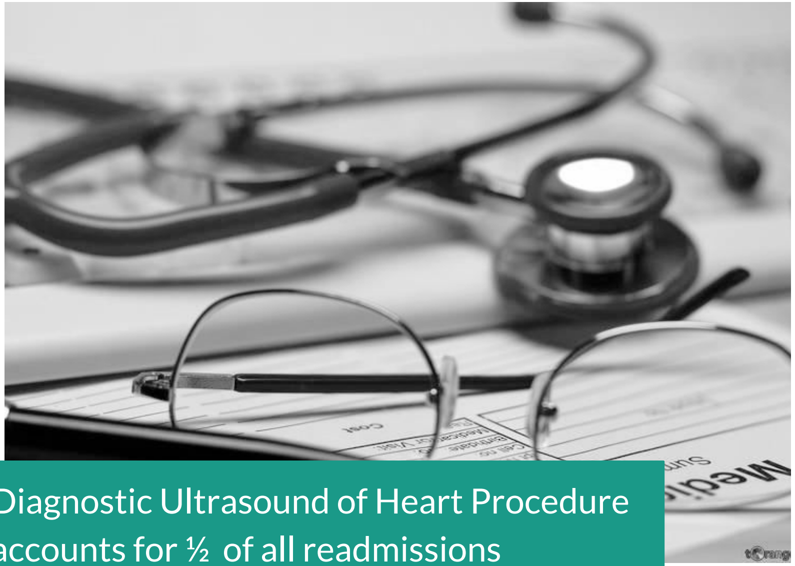
When Standard Orders are not used, Readmission Risk can vary 28% depending on the doctor

Procedure

Proposed Solution:

Specialized Care for At-Risk Procedures

- ➔ Diagnostic Ultrasound of Heart
- ➔ Venous Catheterization
- ➔ Hemodialysis
- ➔ Injection of Therapeutic Substance



Diagnostic Ultrasound of Heart Procedure accounts for ½ of all readmissions

Diagnosis

Proposed Solution:

Specialized Care for At-Risk Diagnoses

- ➔ Congestive Heart Failure
- ➔ Acute on Chronic Systolic Heart Failure
- ➔ Acute on Chronic Diastolic Heart Failure
- ➔ Pneumonia

These Diagnoses represent 70% of readmissions

Reducing Readmissions Initiative

1. **New Standard Orders for More Use Cases and High Risk Patients**
   ➔ Specialists work together to design new Standard Orders

2. **Design and Implement Doctor Tracking System**
   ➔ Flag Doctors not utilizing Standard Orders and with High Readmission Risk

3. **Create Application for Post-Care Communication**
   ➔ App Highlights Medication, Diet, and Discharge instructions for Patient

Conclusions & Next Steps

Next Steps

Encourage Hospital-wide use of model through step-by-step implementation plan

Quarter 1

- Test Run: Employ model to predict readmissions in cases of acute myocardial infarction, heart failure, and pneumonia
- Begin designing *Doctor Tracking System*

Quarter 2

- Employ decision tree in treatment of wider variety of high-readmission diseases
- Incorporate new incoming data into model to improve predictive ability
- Test *Doctor Tracking System*

Quarters 3-4

- Incorporate optimized model into hospital-wide treatment of patients to tailor treatments
- Implement, Improve, and Analyze effects of *Doctor Tracking System*
- Develop *Discharge Application* and begin preliminary testing

Desired Outcomes

1. Provide effective care and treatment for patients during and after stay
2. Monitor required level of care and adjust resources to reduce per-patient costs
3. Open bed space and services for additional patients
4. Decrease burden placed on healthcare payment plans and HRRP penalties

Thank You.