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# URMC Ger Oncology FINAL PRESENTATION

April 20, 2022

## **Team Members**

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- I. Overview
  - **II.** Data Description & Visualization
  - **III.** Predictive model
    - **IV.** Results
      - V. Key Insights
    - VI. Next Steps

# **01 PROJECT VISION**



Wilmot Cancer Institute aims to increase the effectiveness of chemotherapy in treating older persons with advanced cancer.

## **PROJECT GOALS**



Feature selection based on understanding and rigid thresholds



Predictive models to assess the efficiency of medication features in chemotherapy results



**Refine Data Preprocessing Pipeline** 

## **MILESTONES**

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|    | Task                         | Target<br>Date                      | Actual<br>Date | Status      |
|----|------------------------------|-------------------------------------|----------------|-------------|
| 1  | Project Charter Draft        | 2/23                                | 2/22           | Completed   |
| 2  | Merge Data and Visualization | 2/28                                | 2/26           | Completed   |
| 3  | Project Charter              | 3/1                                 | 2/24           | Completed   |
| 4  | Model 1                      | 3/14                                | 3/14           | Completed   |
| 5  | Midterm Presentation         | 3/20                                | 3/20           | Completed   |
| 6  | Model 2 3/28                 |                                     | 3/30           | Completed   |
| 7  | Model Tuning                 | lel Tuning 4/4 4/6 Co               |                | Completed   |
| 8  | Data Preprocessing Pipeline  | Data Preprocessing Pipeline4/114/11 |                | Completed   |
| 9  | Final Presentation           | 4/20                                | 4/19           | Completed   |
| 10 | Final Report, Code, README   | 5/1                                 |                | In Progress |

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# **02 DATA DESCRIPTION**

- Geriatric Assessment for Patients 70 years and older (GAP-70) Dataset (.csv)
  - **718** observations, **145** features, **77** missing target variables
  - Target Variable
    - RDI: Relative dose intensity (RDI) is the ratio of the delivered dose intensity to the standard dose intensity, reflecting the implementation of the expected dose intensity.



# **02 DATA DESCRIPTION**

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- Demographic
  - ➤ Age, etc.
- Symptoms
  - ➤ Hair loss, etc.
- Medical Records
  Cancer type, etc.

- Psychological Status
  - Anxiety and depression tests
- Cognition Status
  - ≻ Dementia tests
- Physical Status
  - > Weight, body status tests, KPS

- Pre-chemo features: cancer type, number of medicine
  Post-chemo features: dose level (stdofcare), treatment type
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**03 DATA VISUALIZATION** 

### **KPS (Karnofsky Performance Status)**

| KPS      | Explanation  |
|----------|--|
| 0 - 49   | Unable to care for self  |
| 50 - 79  | Unable to work; able<br>to live at home and<br>care for most personal<br>needs |
| 80 - 100 | Able to carry on<br>normal activity and to<br>work                             |



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## **KPS v.s RDI**



• **80%** patients in lowest KPS group have RDI **below** 0.65

 Groups with higher KPS tend to have more patients with higher RDI values

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## treatment\_type v.s RDI



• RDI is **below** the average for the pure chemotherapy group

• Other treatments could largely **increase** the effectiveness of the treatment

## **04 DESCRIPTIVE ANALYSIS**



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#### **04 CORRELATION** . . . Weight6MonthsAgo CurrentWeight 0.952285 HandFootYN HandFootSev 0.900070 SkinYN SkinSev 0.883104 DizzinessSev DizzinessYN 0.876111 ConcentrationYN ConcentrationSev 0.874495 0.870621 SwallowingSev SwallowingYN Symptoms 0.869304 SOBIntrf SOBSev 0.865022 TasteYN TasteSev MouthSoresYN MouthSoresSev 0.863359 RingEarsSev RingEarsYN 0.859921

#### • • Delete Y/N columns ⇒ Keep Severity/Interference columns

• weight\_change = CurrentWeight - Weight6MonthsAgo

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# Predictive Modeling: Classification

Response Variable: RDI Explanatory Variables: Selective features



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## Why Recall?

**Predict Class** 

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|                  |          | Negative, >0.65 | Positive, <=0.65 |
|------------------|----------|-----------------|------------------|
| Negativ<br>>0.65 | ve,<br>5 | True Negative   | False Negative   |
| Positiv<br><=0.6 | re,<br>5 | False Positive  | True Positive    |

In reality, patients won't have the **Rdi** value at first. We use models to predict their **Rdi** and decide whether they are able to accept the chemo treatment or not.

Recall = True Positive True Positive + False Negative

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## Why ROC Curve AUC?



In clinical epidemiology, ROC analysis is widely used to measure how accurately medical diagnostic tests (or systems) can distinguish between two patient states. • • •

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#### **05 RANDOM FOREST** Random Forest Confusion Matrix with labels ROC curve for Random Forest 1.0 True Positive Rate (Positive label: 1) 70 0.8 79 29 + 0.65 Actual Values 60 0.6 - 50 0.4 41 30 0.65 - 40 0.2 1 0 RandomForestClassifier (AUC = 0.62) 30 0.0 0.65 + 0 - 0.65 0.0 0.2 0.4 06 1.0 0.8 False Positive Rate (Positive label: 1) Predicted Values

#### • Grid Search

- Best parameter: {'n\_estimators': 1000, 'min\_samples\_split': 2, 'min\_samples\_leaf': 1, 'max\_features': 'auto', 'max\_depth': 50, 'bootstrap': False}
- Accuracy: 0.609; Recall: 0.423; F1: 0.601; AUC: 0.618



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## 06 PERFORMANCE SUMMARY



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## **SABI Column**

- Integrated numerical column for cancer symptoms
  - Combined all binary results, pain level and interference for a symptom
  - Assigned different weights for different symptoms
- Still under development

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## 06 SUMMARY WITH SABI



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- Can we use the features to predict RDI value?
- Among all 145 features, which ones are important?

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## **07 FEATURE SELECTION**



Random Forest Feature Importance

Top 10 important features

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## **07 FEATURE SELECTION**

- Elastic Net (30 features with lowest MSE 0.063)
- Forward/ Backward Feature Selection (top 50 features)
  - LogisticRegression; scoring: AUC;
- Random Forest Feature Importance (top 50 features)

### **Overlapping features (8 features):**

- Physical Status: CalcTUG, KPS
- Symptoms: DizzinessIntrf, FatigueSev, PainIntrf,
- Medical Record: cancertype, stdofcare, treatment\_type

# **08 PIPELINE REFINEMENT**

Aim to process raw data for physicians, could choose various models

- Dimension reduction: PCA, NMF, ICA
- K-fold
- Encoder: Label, OneHot
- Imputer: KNN, DropNA, Mean, Median
- Feature selection: Ridge, Lasso, Elastic Net



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Complex Dataset



Feature Selection



Model Improvement

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# **10 KEY INSIGHTS**

### Can we use the features to predict RDI value?

- **Logistic regression** works the best to predict the **RDI** value.
- Not ideal metric performance

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### Among all 145 features, which ones are important?

- Features related to **physical status** are insightful for prediction.
- Information such as **demographic**, **psychological status**, and **cognition status** is not critical.







- Continue on insightful suggestions
- Organize charts, graphs, and codes
- Finish report paper

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# **12 ACKNOWLEDGEMENT**

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We appreciate the help from **Dr. Ramsdale** as our sponsor, providing detailed guidance on the phrases explanations and feature selection process.

We appreciate the help from **Professor Anand** as our advisor, providing constructive suggestions towards our model building process.

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# ANY QUESTIONS?

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THANKS! -

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