Using Machine Learning to Map Grief Stages and Optimize Support for Military Survivors

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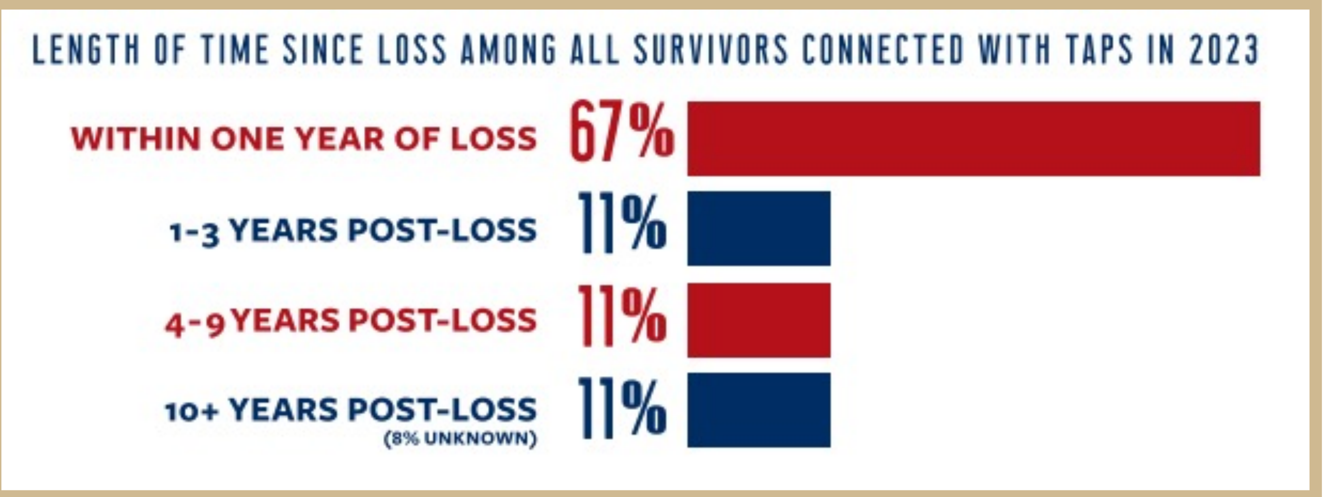
ABSTRACT

We developed a predictive model to map grief stages for individuals impacted by military-related deaths, designed for the Tragedy Assistance Program for Survivors (TAPS). Military loss presents unique grief challenges, often involving trauma, sudden death, and loss of identity, which traditional support systems struggle to address. This model aims to help TAPS allocate resources more effectively and provide tailored support to survivors based on their specific grief stage. Using machine learning techniques, including Random Forest and Neural Networks with ensemble methods, we analyzed complex grief data to uncover patterns across different grief phases. Our findings show high accuracy in predicting grief stages, demonstrating the model's potential to guide TAPS in delivering adaptive, evidence-based support. This approach ensures that survivors receive the right resources at the right time, enhancing TAPS' ability to support individuals throughout their grief journey.

BUSINESS PROBLEM

- Topic Importance: Military-related grief poses distinct challenges, including trauma, sudden loss, and identity disruption—factors that standard support systems often fail to address. This project, designed for the Tragedy Assistance Program for Survivors (TAPS), leverages predictive modeling to map grief stages, enabling TAPS to provide adaptive, evidence-based support that evolves with each individual's needs. TAPS' stakeholders, including mental health professionals and the military survivor community, face the challenge of addressing complex grief patterns with limited resources. This model empowers TAPS to deliver targeted interventions, maximizing impact and resource allocation.

- Motivation: As the American Cancer Society notes, "It's common for the grief process to take a year or longer… but the sense of loss can last for decades." This highlights the need for timely, structured support, especially as 67% of individuals connected with TAPS in 2023 were in their first year of loss, often a period of intense emotions. While early intervention is crucial, the long-term connection of survivors with TAPS (11% at 1-3 years, 4-9 years, and 10+ years) shows that grief is ongoing. This supports the use of predictive models to provide adaptive, evolving support throughout the grief journey. By enabling TAPS to deliver timely, targeted assistance, the model optimizes resource allocation, maximizes impact, and reinforces TAPS' role as a continuous, trusted support system for those experiencing military-related grief.



ANALYTICS PROBLEM FRAMING

- The objective of this project is to automate the classification of TAPS survivors' survey responses into grief stages using NLP and machine learning. This will enable TAPS to deliver more effective, stage-specific support to each survivor.
- The assumptions are that grief can be segmented into distinct stages, data quality is high, and the system can manage the complex, non-linear nature of grief progression. These assumptions are crucial for reliable, accurate predictions.
- The success metrics are classification accuracy to ensure appropriate support, along with timeliness and scalability. These metrics will help TAPS serve a growing user base with personalized care.
- The impact is an improved ability for TAPS to provide personalized, timely care to survivors. This aligns with TAPS's mission to support those grieving military-related losses more effectively and efficiently.

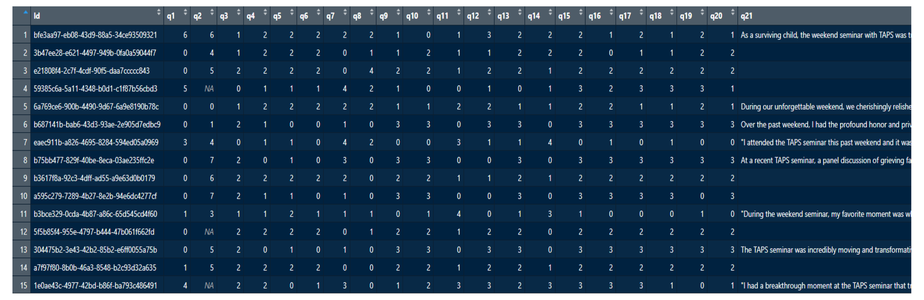
RESEARCH QUESTIONS

Clearly state your research question(s) with bullets:

- **How can we utilize AI models to classify an individual's grief stage based on survey responses?**
- **What model best identifies in a multi-label, non-linear grief process?**

DATA

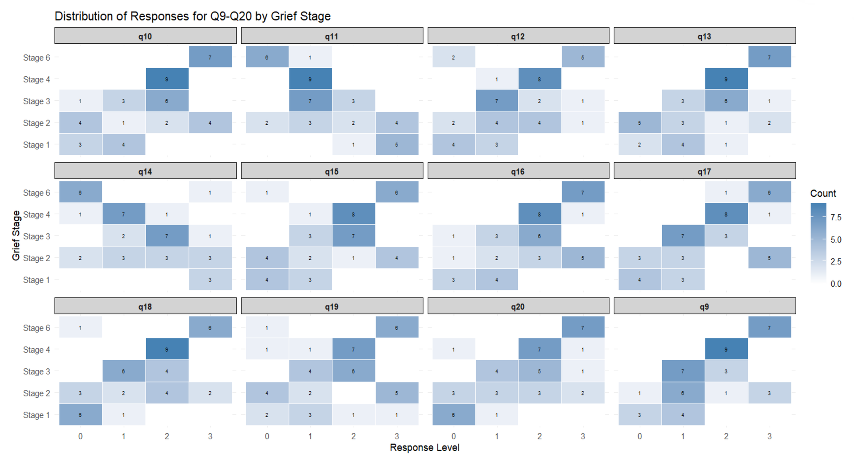
- Base data provided by TAPS in the format seen to right:



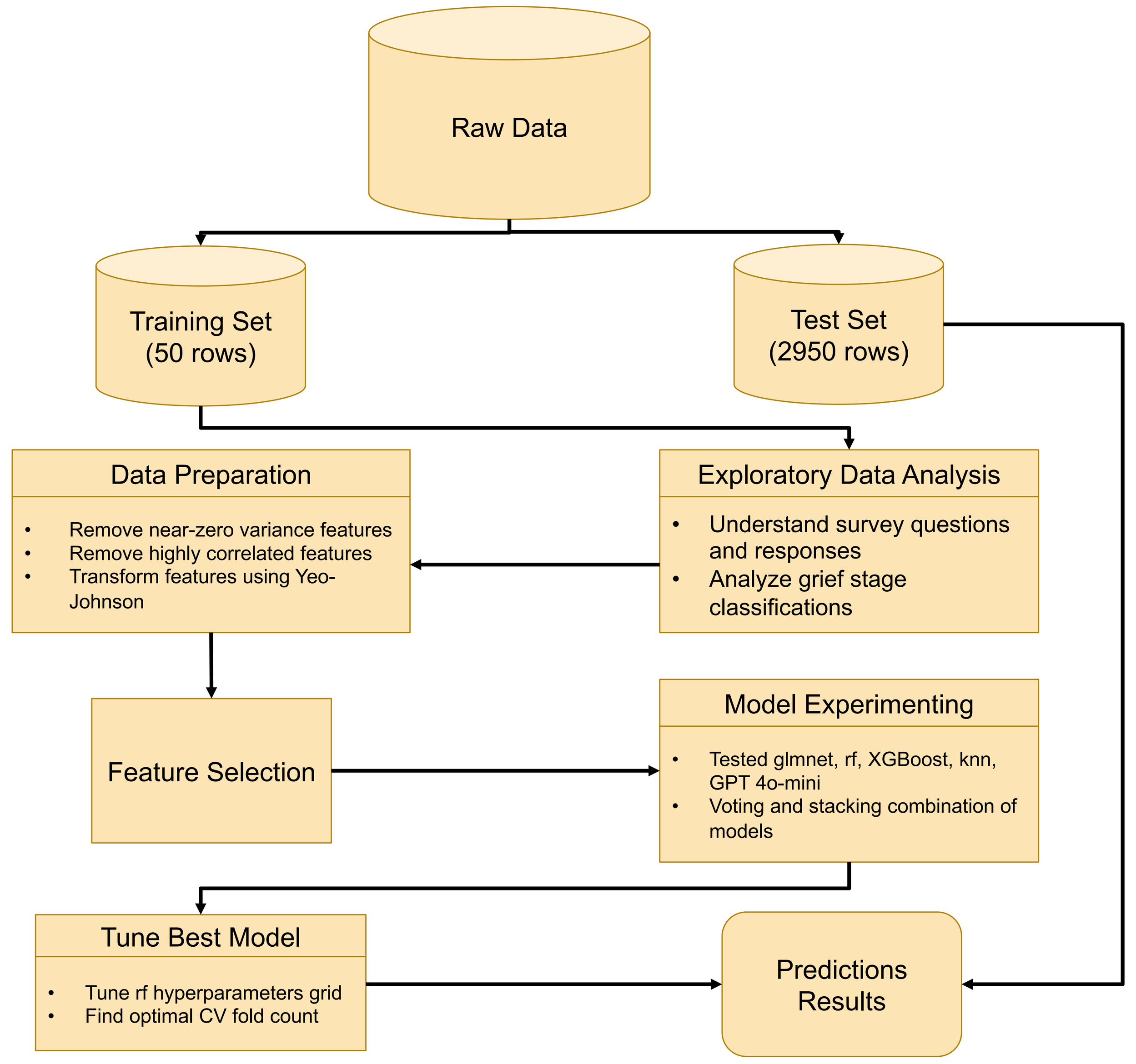
Data Cleaning & Transformation

Text Mining & Word Cloud Visualization

EDA & Data Visualizations



METHODOLOGY



MODEL BUILDING AND EVALUATION – STATISTICAL PERFORMANCE

Highest score of 0.89532 was a Random Forest Model

Reference

Prediction	X1	X2	X3	X4	X5	X6
X1	7	0	0	0	0	0
X2	0	11	0	0	0	0
X3	0	0	9	0	0	0
X4	0	0	0	9	0	0
X5	0	0	0	0	6	0
X6	0	0	0	0	0	7

Random Forest Interpretation:

1. Model Tuning: Random Forest model is being fine-tuned with different hyperparameters using cross-validation
2. Model Training: Final model is trained using best hyperparameters and uses training data to build the forest model
3. Evaluation: After training, the model is evaluated to the training set using confusion matrix
4. Predictions: make predictions based on test set

Areas for Improvement:

- Feature Selection: Eliminate more variables that may not contribute much information for the prediction. Use to identify the most predictive variables. this
- Hyperparameter Tuning: Using other cross validations which can help select the best parameters for Random Forest

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Overall Statistics

               Accuracy : 0.98
                 95% CI : (0.8935, 0.9995)
    No Information Rate : 0.22
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.9758

 Mcnemar's Test P-Value : NA
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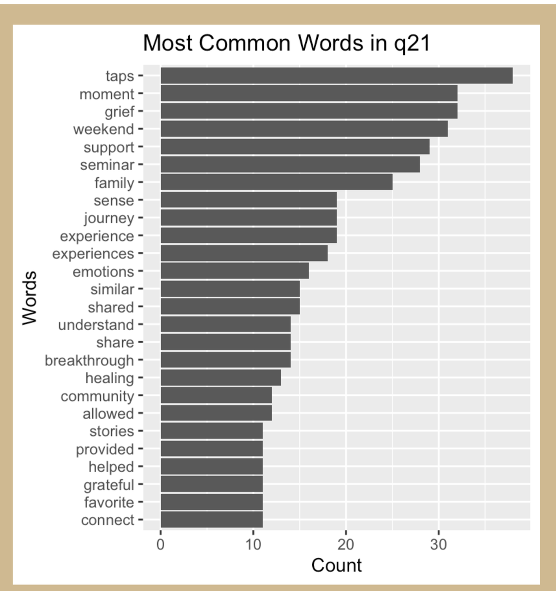
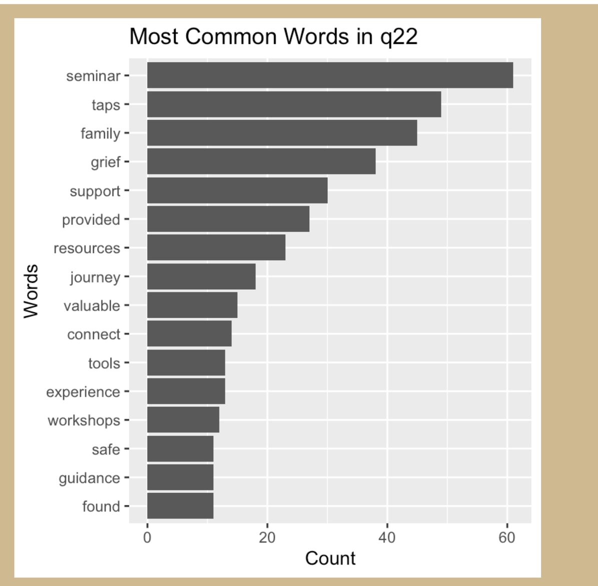
Statistics by Class:

	Class: X1	Class: X2	Class: X3	Class: X4	Class: X5	Class: X6
Sensitivity	1.00	1.00	0.9000	1.0000	1.00	1.00
Specificity	1.00	1.00	1.0000	0.9756	1.00	1.00
Pos Pred Value	1.00	1.00	1.0000	0.9000	1.00	1.00
Neg Pred Value	1.00	1.00	0.9756	1.0000	1.00	1.00
Prevalence	0.14	0.22	0.2000	0.1800	0.12	0.14
Detection Rate	0.14	0.22	0.1800	0.1800	0.12	0.14
Detection Prevalence	0.14	0.22	0.1800	0.2000	0.12	0.14
Balanced Accuracy	1.00	1.00	0.9500	0.9878	1.00	1.00





Text Mining Interpretation:

- Identifies the words that are most commonly in the questions "Please share with TAPS your favorite moment of the weekend? Did you have a breakthrough moment this weekend you would like to share?" and "Please share any additional feedback you have regarding your TAPS Seminar experience."

Areas for Improvement:

- Sentiment Analysis: See what kind of sentiment each of the common words associates with so we can categorize them into different grieving stages easier

MODEL EVALUATION – BUSINESS IMPLICATIONS

Confusion Matrix

- Demonstrates counts of true and predicted classification for X1 to X6
- Each number represents samples predicted in each category compared to their true category
- Diagonal is the cases that are correctly classified and off diagonal is misclassifications

Overall Statistics

- Model correctly classified 98% of the samples
- 95% confidence interval for accuracy
- No Information Rate (NIR) is the accuracy that would be achieved if the model made predictions by always guessing the majority class which is the known as the most frequent class
- P value less than NIR means the model's accuracy is statistically significant compared to random chance
- Kappa is a measure of agreement between predictions and actual classifications

Statistics by Class

- With high sensitivity and specificity across classes this means that model was able to identify what correctly belongs and does not belong in each class

Impact of Using Model

- Better resources for people that are characterized in each grief stage
- Focusing on identifying these trends that are similar in each grief stage

Testimony of Business Impact

- Increases responsiveness to individuals that are grieving

Future Scope

- Models that will allow real-time feedback, so changes can be made from feedback that individuals submit

CONCLUSIONS

Addressing the research questions:

- Our best results included using the Random Forest Model, but there are other types of models that could drive better results
- We thought that the stacking model and voting model would be effective in identifying multilabel, nonlinear grief process
  - Results were not as high as Random Forest Model

Model displayed an accuracy of 0.98, but when put into Kaggle the results was almost ten percent lower. A place that our model could have struggled with was classifying into each grief stage because there often can be individuals that are in between stages and do not have one grief stage they resonate mostly with. Also, since grief is not always linear it is hard to establish a consistent flow throughout all the grieving stages.

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