

# Problematic Internet Use Classification

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<https://github.com/mdlu02/InternetUseClassification>

# Background and Review

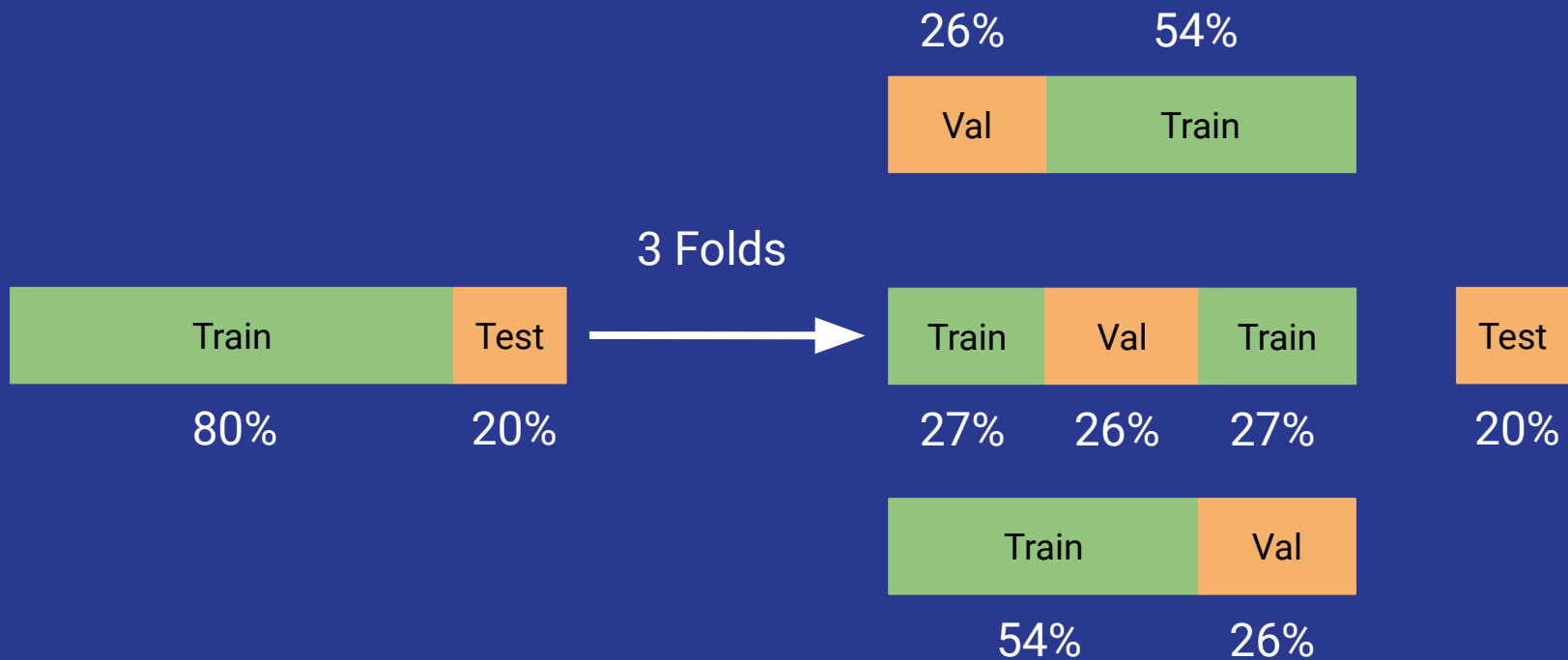
## Problem & Goal

- Increased internet use associated with mental health problems.
- Predict severity of negative internet use.
- Tabular and time series data for ~5000 5-22 year-olds.
- Classification vs. Regression

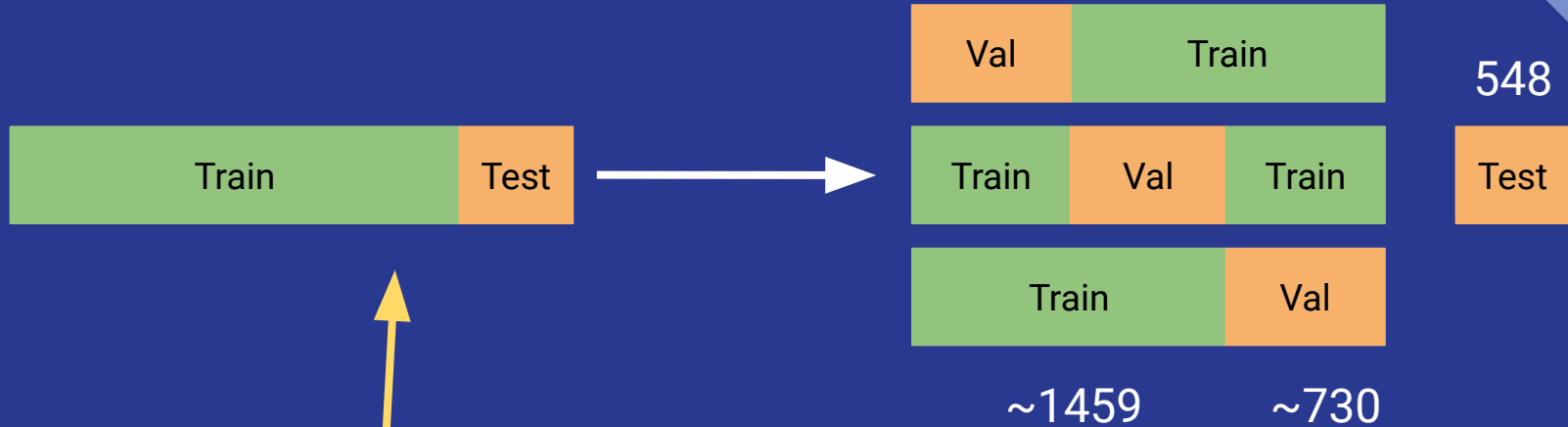
## Challenges

- Significant amount of missing data.
- Highly imbalanced dataset.
- Time series and tabular data.

# Split + Crossfold Validation



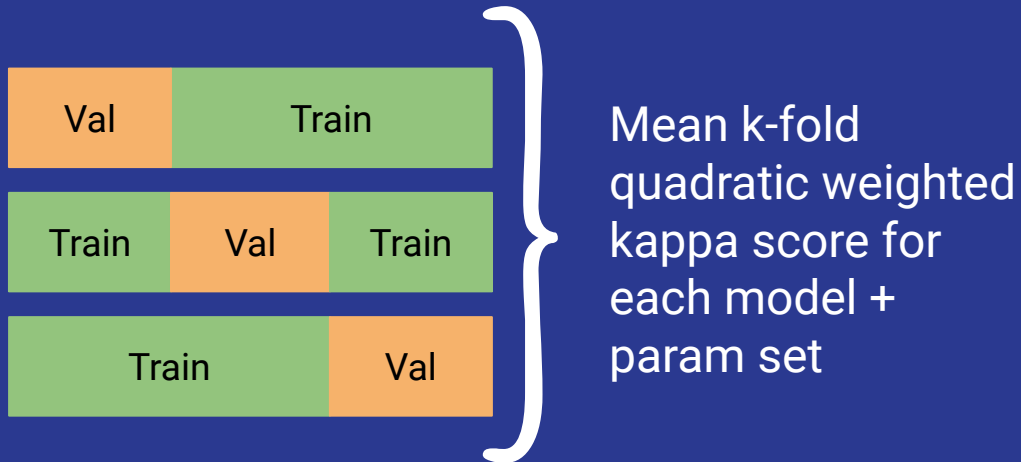
# Split + Crossfold Validation



Stratified by **SII**, age group, **sex**, and the existence of time series data.

# Cross Validation

For each ML model and  
associated parameter set:



# Cross Validation - QWK

## Quadratic Weighted Kappa:

- Ranges from -1 to 1
- Measures agreement between two outcomes
  - <0 is worse than random
  - 0 is random/baseline agreement
  - 1 is perfect agreement
  - Current 1st place achieves 0.5 QWK
- Baseline score is always 0 even if the data is unbalanced!

To compute the quadratic weighted kappa, we construct three matrices,  $O$ ,  $W$ , and  $E$ , with  $N$  the number of distinct labels.

The matrix  $O$  is an  $N \times N$  histogram matrix such that  $O_{i,j}$  corresponds to the number of instances that have an actual value  $i$  and a predicted value  $j$ .

The matrix  $W$  is an  $N \times N$  matrix of weights, calculated based on the squared difference between actual and predicted values:

$$W_{i,j} = \frac{(i-j)^2}{(N-1)^2}$$

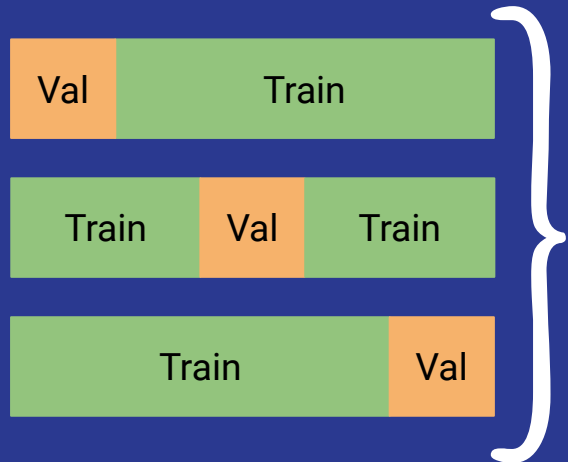
The matrix  $E$  is an  $N \times N$  histogram matrix of expected outcomes, calculated assuming that there is no correlation between values. This is calculated as the outer product between the actual histogram vector of outcomes and the predicted histogram vector, normalized such that  $E$  and  $O$  have the same sum.

From these three matrices, the quadratic weighted kappa is calculated as:

$$\kappa = 1 - \frac{\sum_{i,j} W_{i,j} O_{i,j}}{\sum_{i,j} W_{i,j} E_{i,j}}.$$

# Cross Validation

For each ML model and associated parameter set:



Select best params  
for each model by  
val QWK.



Train on full CV data  
and test on hold out  
test set. Track:

- RMSE, QWK, Weighted F1
- Confusion matrix, AUC-ROC, and Precision-Recall Curves

548

Test

# ML Models + Hyperparameters

Linear Regression

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Elastic Net

alpha	l1_ratio
0.1	0.1
0.5	0.5
1	0.9

KNN Regressor

n_neighbors	weights
3	uniform
5	distance
10	

XGBoost Regressor

n_estimators	max_depth	learning_rate	subsample
50	3	0.1	0.8
100	5	0.01	1
	7		

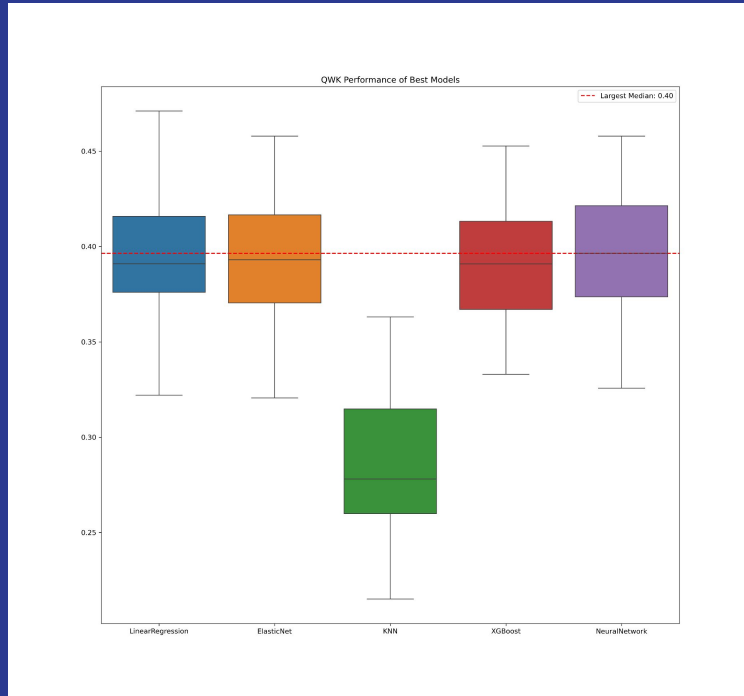
Neural Network

layers	layer_sizes	learning_rate	epochs	batch_size	activation
1	4	0.001	5	8	relu
2	8	0.01	10	16	
4				32	

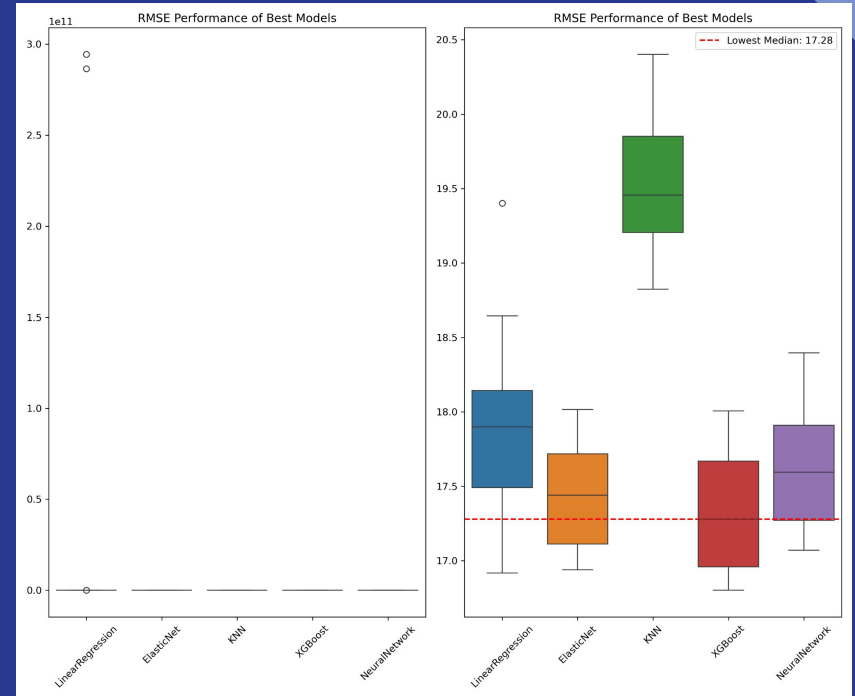


# Results - Best Models

QWK Performance (larger is better)

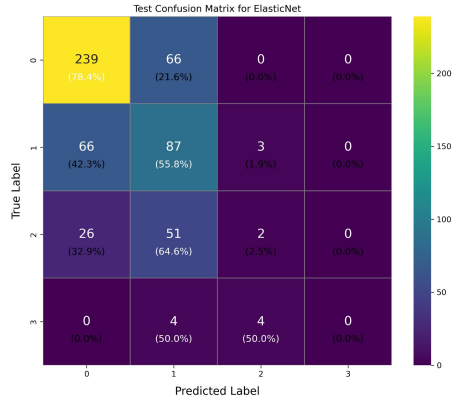


RMSE Performance (smaller is better)

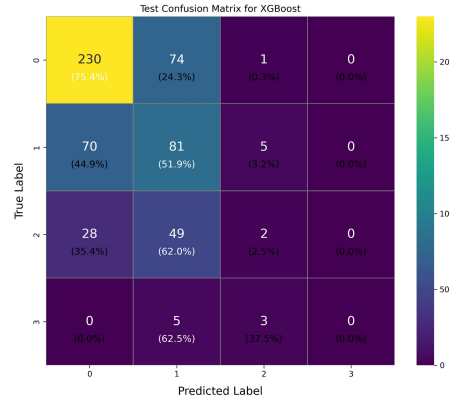


# Results - Confusion Matrices

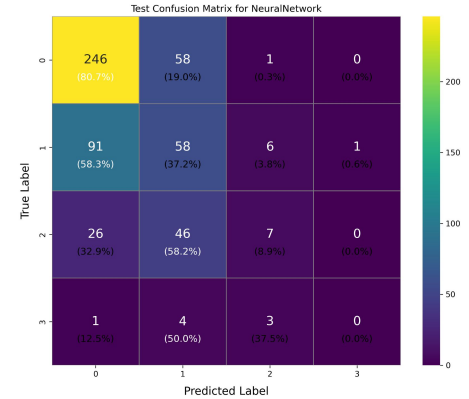
## Elastic Net



## XGBoost

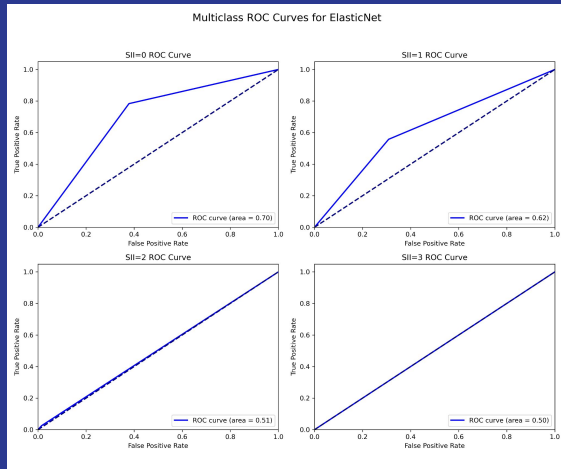


## Neural Network

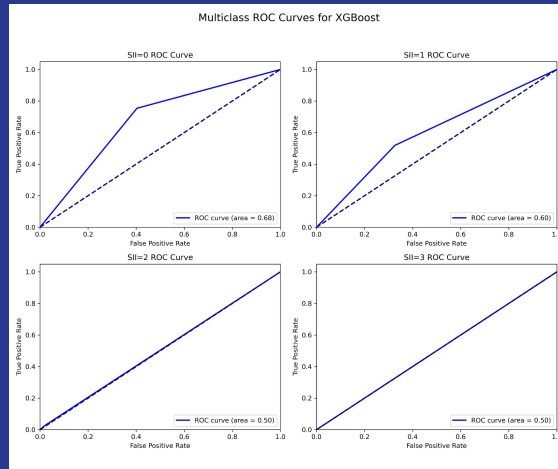


# Results - AUC-ROC Curves

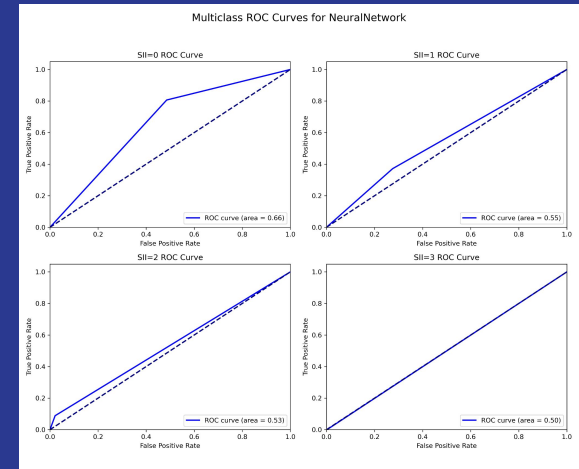
## Elastic Net



## XGBoost

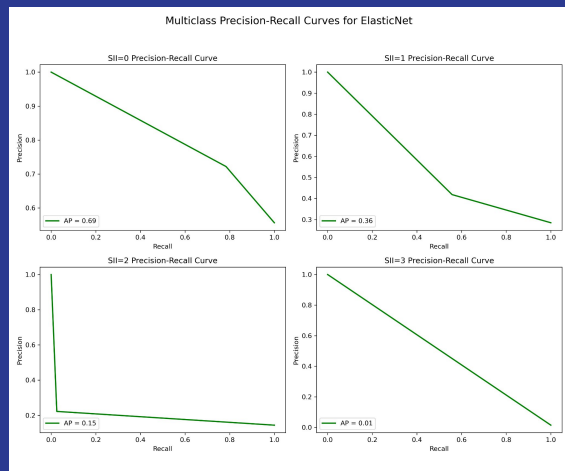


## Neural Network

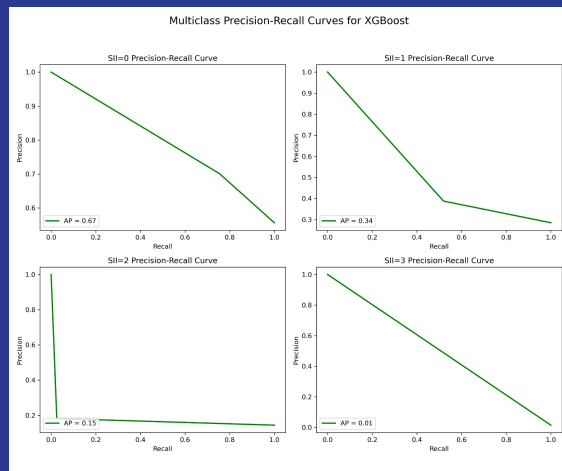


# Results - Precision-Recall Curves

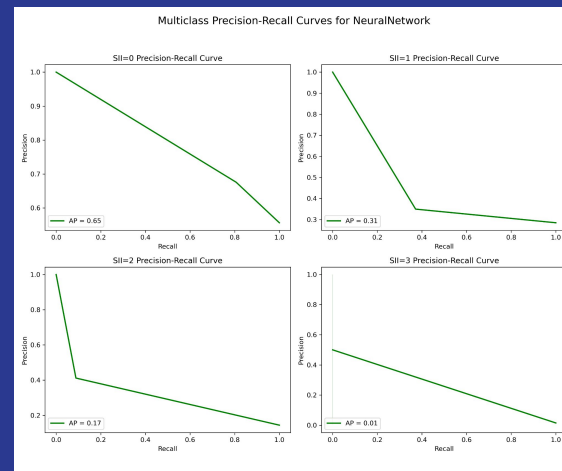
## Elastic Net



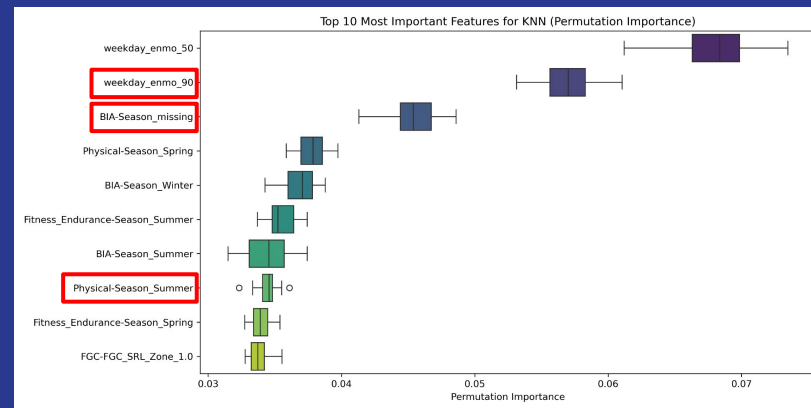
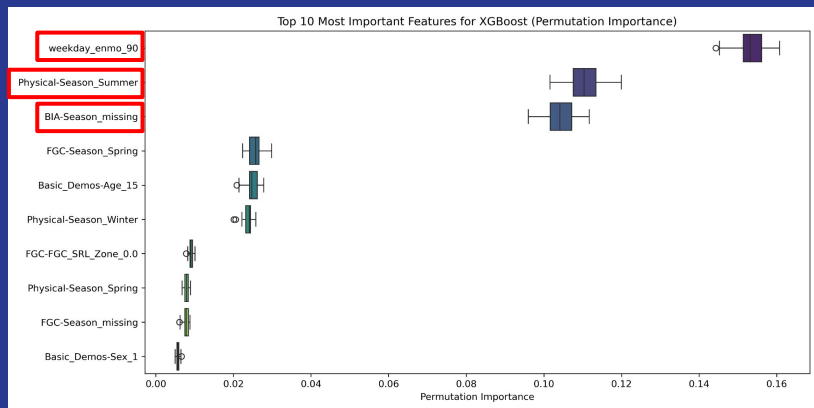
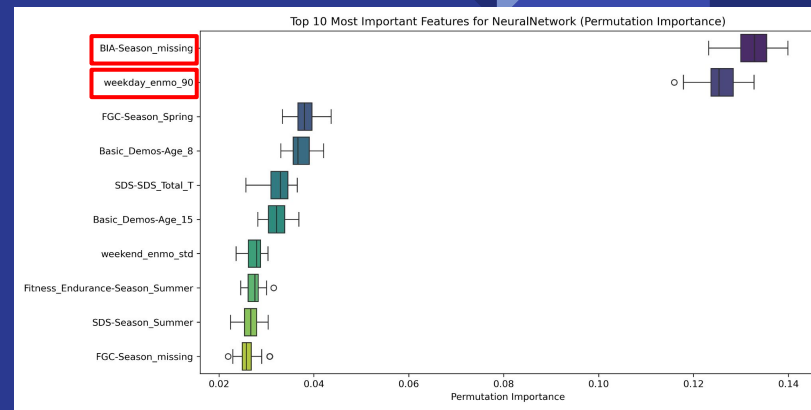
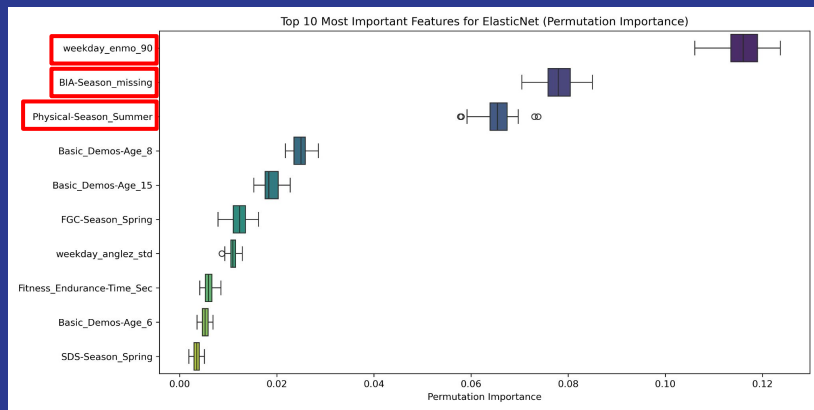
## XGBoost



## Neural Network



# Interpretation - Permutation Importance



# Outlook

- Expand parameter grid to maximize performance of each model.
- Try classification approach to allow class weighting to help with imbalance.
- Use SHAP to investigate local performance.

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