Anxiety and Biobehavioral Data

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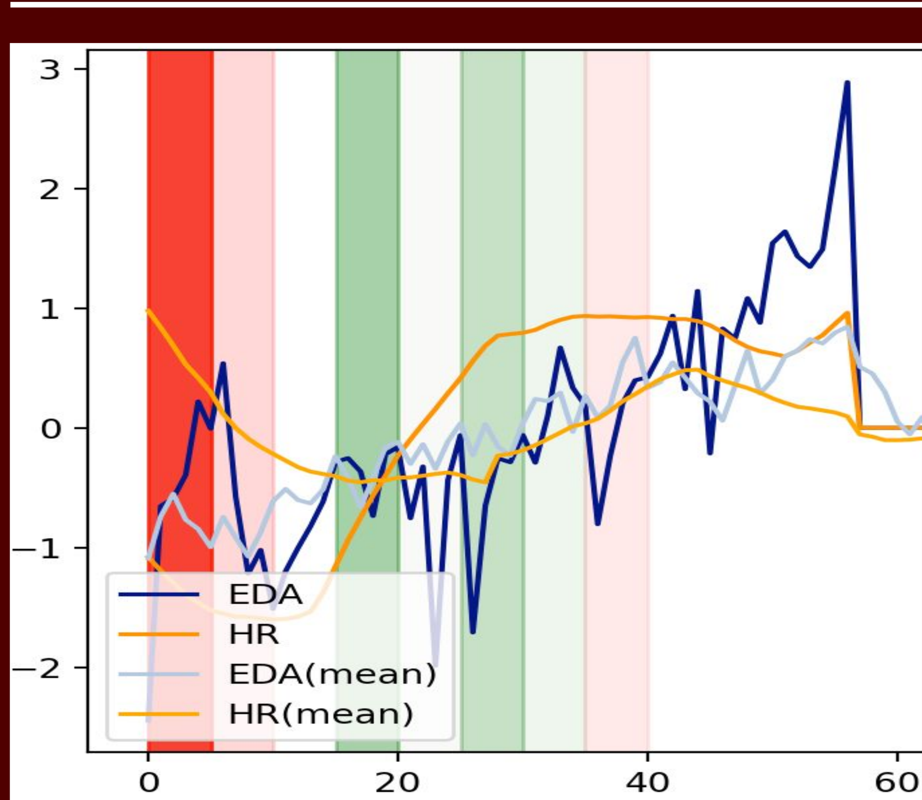
Time-series - RNN

RNNs take hints from time-series data to derive final answer.



Algorithm	Data	Avg Abs Err
Classification	EDA	7.14
	HR	7.48
	EDA+HR	7.45
Regression	EDA	7.08
	HR	7.22
	EDA+HR	7.06

Model	Avg Abs Err
RNN	7.12
LSTM	7.35

Right table shows averaged validation loss from total of 96 training runs using 5-fold cross validation.
Left figure shows how time-series impacts an RNN *classifier*'s final decision. The model is trained with EDA+HR time-series, red means negative impact to the chosen class's probability, and green shows positive impact.

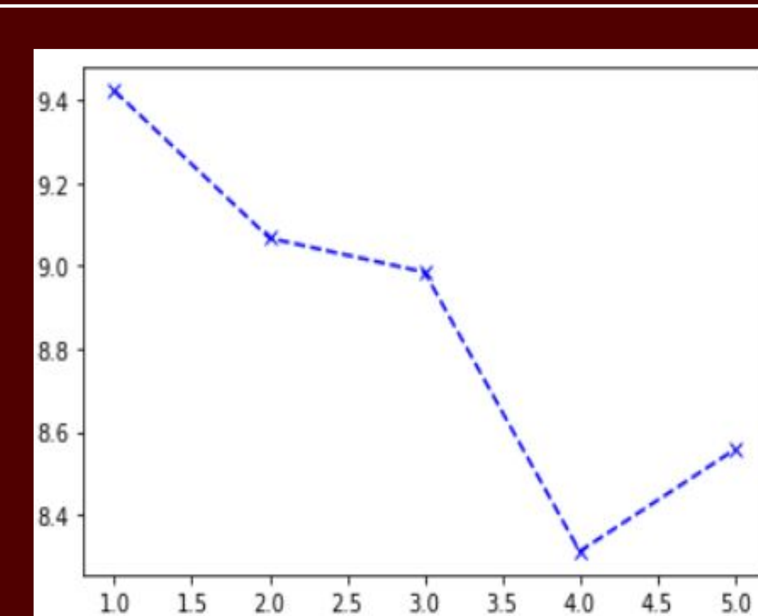
Experiments show RNNs can utilize time-series data to derive good prediction and each segment of the time-series impacts the classifier probability differently. We ran 96 training runs and found regression is generally a better choice of algorithm and utilizing both EDA and HR data show better loss regardless of algorithm choices. Also, RNN shows better prediction than LSTM. We theorize that our N-to-1 task is basic enough for a simple RNN.

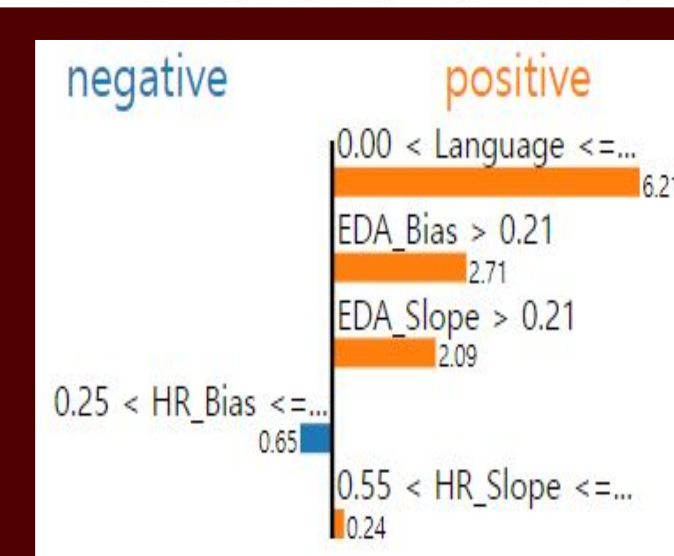
Natives speakers are tougher to predict.

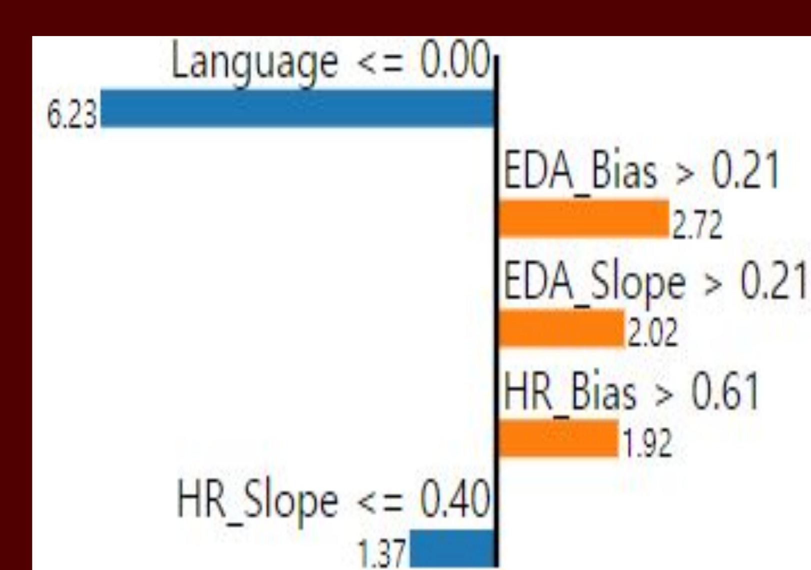
Data	Avg Abs Err
All	9.87
Native	12.08
Non-native	7.34

Left show training results when we divide data into native/non-native groups. Training uses randomized splits (train:valid:test=70%:15%:15%.) and the errors reported are means over 20 training runs. *Note that, error values are incomparable with previous tables' results (5-fold).* While non-native prediction error is positively impacted from division native speakers show higher error.

Time-series - FNN



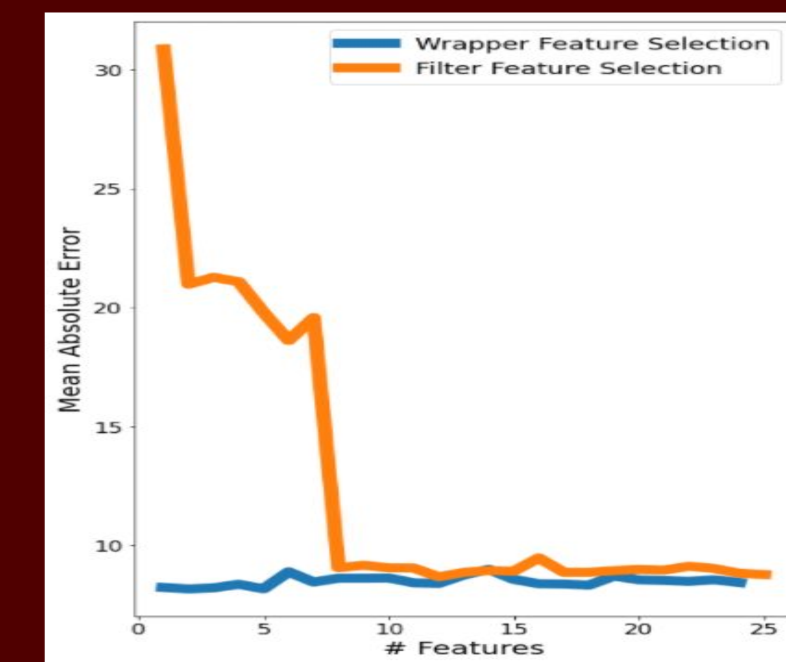


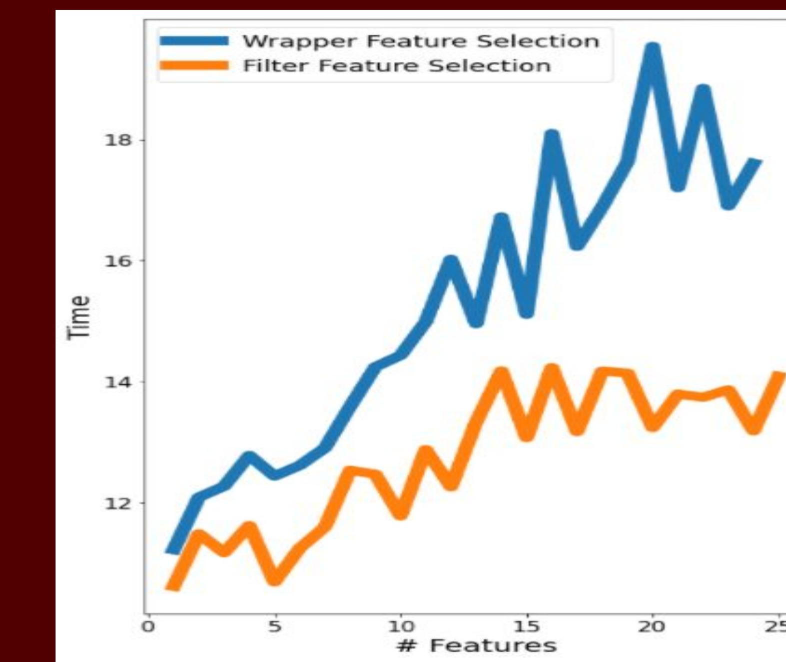


Experiments show an FNN with linear regression features from time series is not a decent model to predict participants' anxiety values. By tuning parameters one can achieve loss as low as 8. However, as we can see from Explainable AI model, Language feature (whether volunteer is native or non-native) affect more on deciding the labels than any bias or slope derived from regression model.

Feature Selection

FNN can achieve similar performance with less features



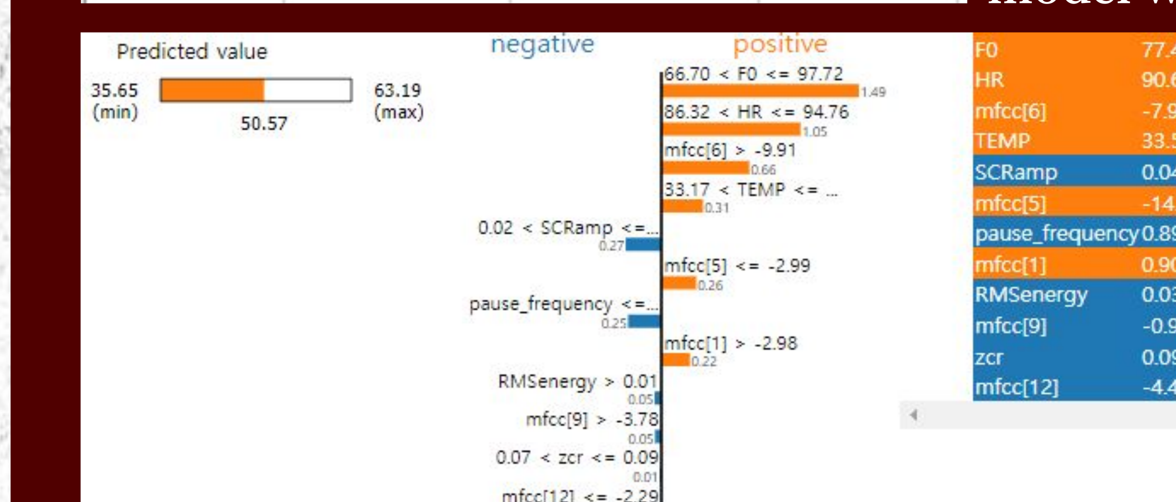


First figure shows average absolute error from FNN models with the feature selection methods with different number of features. **Second figure** shows computation time for the models with different number of features.

The results of experiments show that feature selection can be utilized to reduce computation time without losing the model performance. We applied forward feature selection for wrapper method and fisher criterion feature selection for filter method and trained models with selected features. The performance of the models with the methods were similar to the performance of the model with all features. With LIME, we found speech fundamental frequency impacts the most on the decision of the model.

Method	# Features	Avg Abs Err	Time
Wrapper	2	8.175	12.088
Filter	12	8.684	12.258

Left table shows the best number of features and the performance of FNN model with the feature selection method.



Left figure shows the output of interpretable machine learning algorithm LIME. Features are selected using fisher criterion feature selection method.

Feature Transformation

We can reduce the input to 18 dimensions with 98% variance retained.

- PCA with k=18 performs best with error = 10.49
- We can reduce the input to 18 dimensions to reduce the training parameters and complexity.