

Estimating Public Speaking Anxiety from bio-behavioral data

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PROBLEM STATEMENT

Develop a Machine Learning model to estimate the PSA levels based on the *VerBIO* dataset. The aim is to understand the effect of bio-behavioral features on the individuals' affective responses while performing public speaking tasks

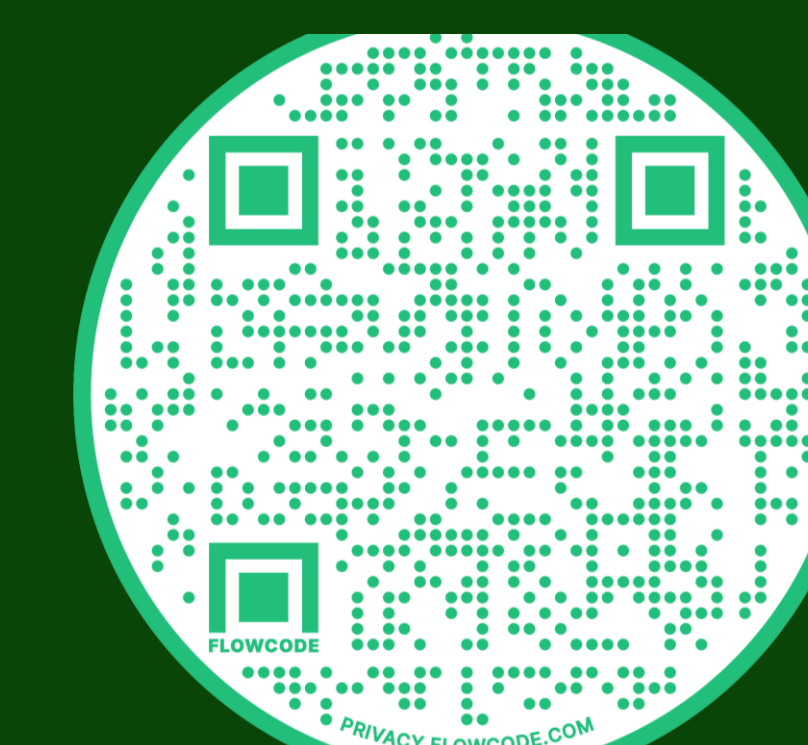
METHODS

- Correlation between various bio-behavioral features with State Anxiety levels were analyzed
- *SelectKBest* filter method with *f_regression* as score function and Recursive Feature Elimination (RFE) wrapper method with Gradient Boosting regressor as optimizer were used to obtain the features that yielded the most information
- FNN model with ReLU activation and Adam optimizer was built. Further, the model was trained on the data obtained from below methods:
 - PCA was used to reduce the dimensionality of the features
 - For the HR and EDA data of each participant, coefficients were computed using linear/polynomial regression
- LSTM, RNN and GRU models were used to estimate the anxiety labels based on the temporal data
- Segregated the data based on native and non-native speakers to build group-specific models
- Visualized the significance of individual features in determining the State Anxiety of the participant through FNN & LSTM

OBSERVATIONS

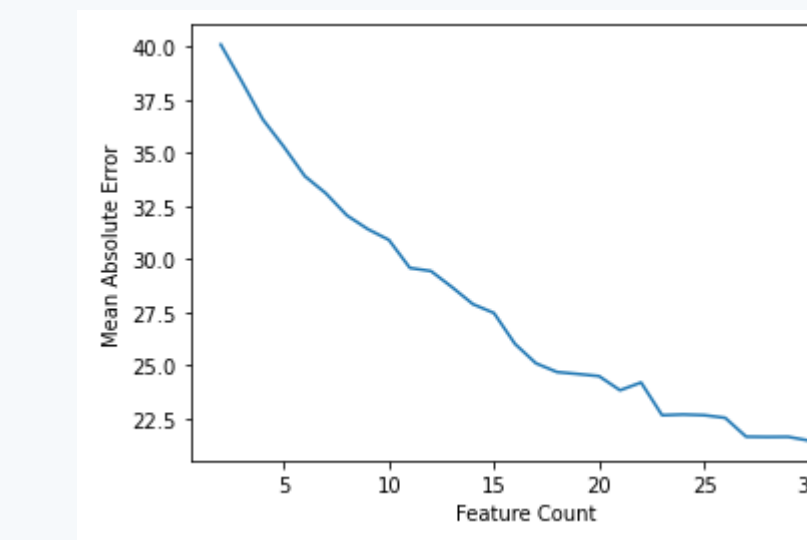
- RMSEnergy & BVP are the most and least correlated features with respect to State Anxiety label, based on Pearson Correlation Coefficient.
- *SelectKBest* filter method yielded the least error with 21 features.
- FNN coupled with PCA, dimensionality reduced to 2, resulted in improved mean absolute errors.
- GRU & RNN models achieved the lowest mean absolute errors using EDA & HR temporal data.
- Speech Voicing Probability, Fundamental Frequency and Pause Frequency are the most correlated features with respect to Anxiety label for non-native speakers as opposed to the Heart Rate and RMSEnergy for native speakers.

- **LSTM & GRU**
performs best with
the temporal data
- **Language based**
segregation of
data, helps in
devising higher
accuracy models
and gaining
insights on
correlations

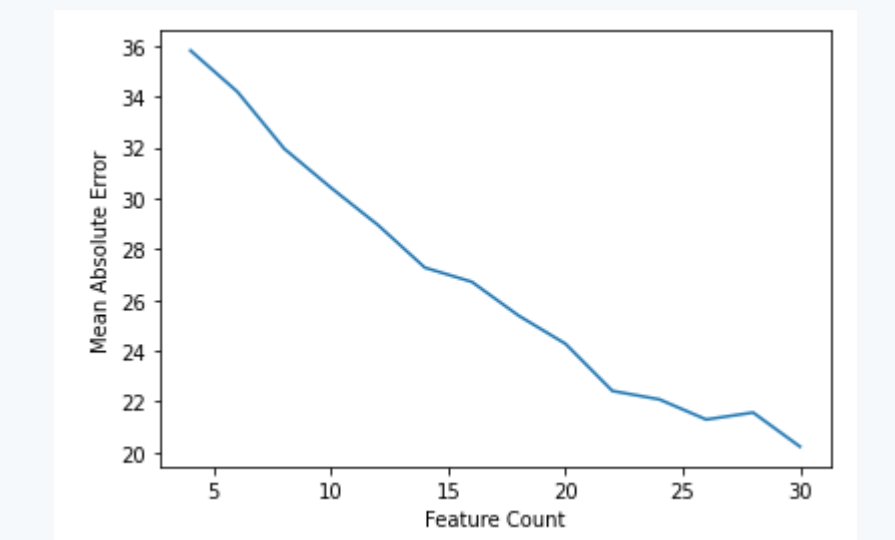


RESULTS

Filter based feature selection



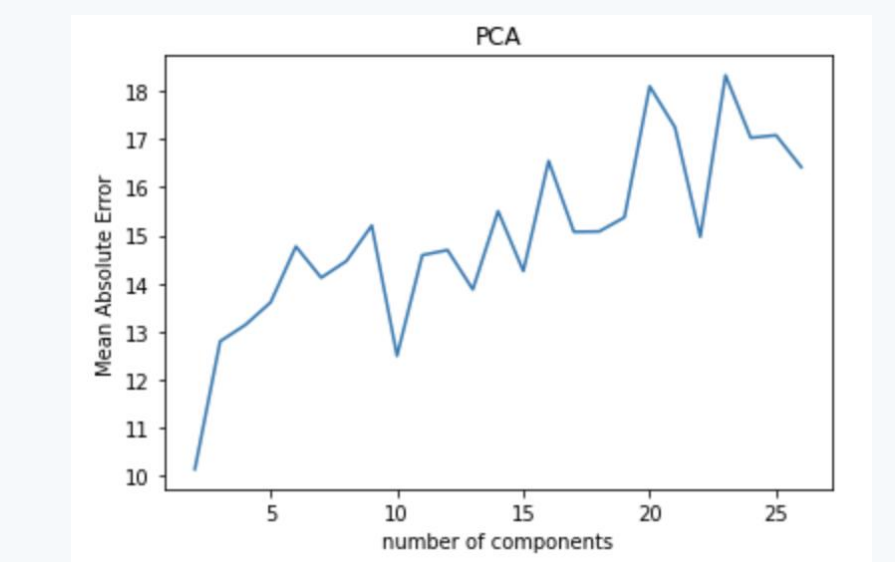
Wrapper based feature selection



Top 10 correlating features

	Feature	Label	Corr	Ab
	RM Senergy	StateAnxiety	-0.236090	0.236090
	mean HR	StateAnxiety	-0.217042	0.217042
	HR	StateAnxiety	-0.217042	0.217042
	ACC	StateAnxiety	-0.216606	0.216606
	IBI	StateAnxiety	0.183156	0.183156
	mfcc[9]	StateAnxiety	-0.167732	0.167732
	var HR	StateAnxiety	-0.165264	0.165264
	mfcc[1]	StateAnxiety	-0.125903	0.125903
	mtfcc[10]	StateAnxiety	0.125598	0.125598
	TEMP	StateAnxiety	-0.120541	0.120541

**PCA based
dimensionality
reduction**



Experimentation Results

Model	Feature Selection	Feature Count	MAE	Datatype
FNN	-	32	23.778	All
FNN	Filter Methods	30	21.471	All
FNN	Wrapper Methods	30	19.414	All
FNN	PCA	26	15.685	Non-Temporal
SimpleRNN	-	2	9.456	Temporal
GRU	-	2	9.483	Temporal
LSTM	-	2	8.454	Temporal
FNN	Native speakers	26	12.737	Non-Temporal
FNN	Non-Native speakers	26	14.307	Non-Temporal

LIME – Interpretable ML

