voice

easier audio analysis for digital phenotyping

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Summary

1.Mental health

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- Emotional valence
  - The positive or negative quality of an emotion

2. Why another package

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Package	Rec/play	Conversion	Photo/Video	Visualization	Features	Sheet music	Remove vocals	Chords/scales	Diarization
audio	✓								
av	✓	✓	✓	✓					
EMU-SDMS	✓	✓		✓	✓				
gm	✓			✓		✓		✓	
karaoke							✓		
music	✓			✓				✓	
seewave	✓	✓		✓	✓				
signal		✓		✓	✓				
sound	✓								
tabr	✓			✓		✓			
tuneR				✓	✓				
voice		✓		✓	✓	✓		✓	✓
voiceR								✓	
wrassp					✓				
BirdNET-Analyzer	✓	✓		✓	✓				
Librosa				✓	✓			✓	
Parselmouth	✓	✓		✓	✓				
pyannote-audio	✓	✓		✓	✓				✓
SpeechBrain	✓	✓		✓	✓				✓

Some R and Python packages for handling audio

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seewave	✓	✓		✓	✓				
signal		✓		✓	✓				
sound	✓								
tabr	✓			✓		✓			
tuneR				✓	✓				
voice		✓		✓	✓	✓		✓	✓
voiceR								✓	
wrassp					✓				
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- Allows the use of music notation and theory (ongoing work)

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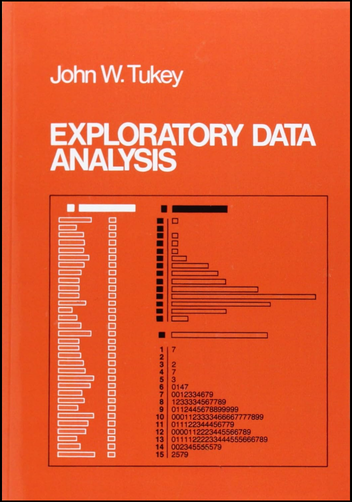

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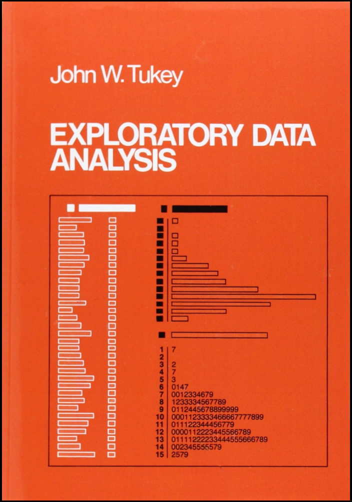

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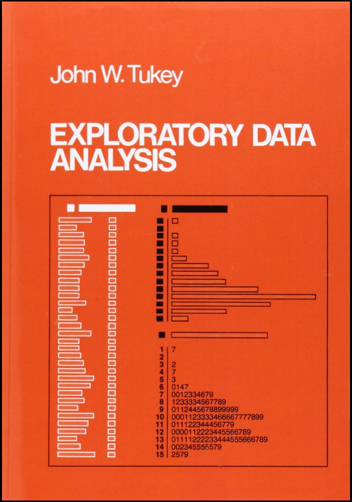

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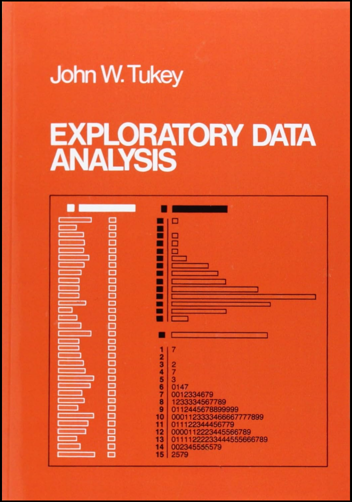

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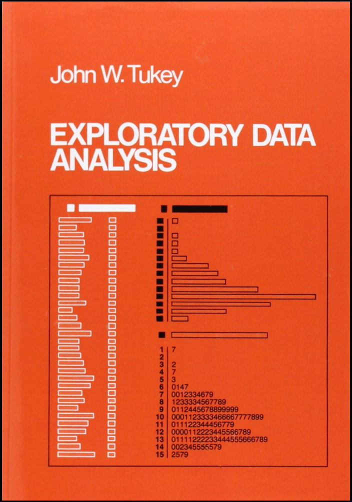

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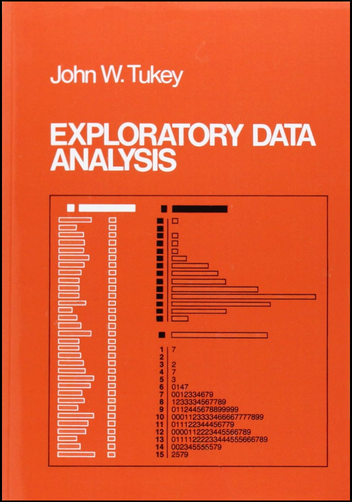

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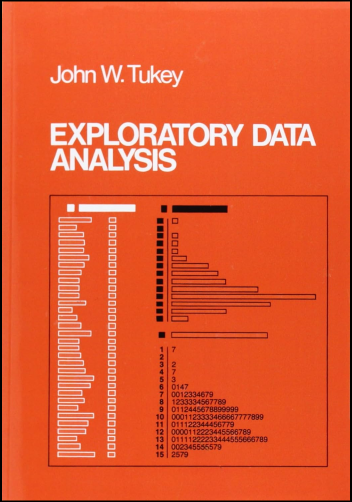

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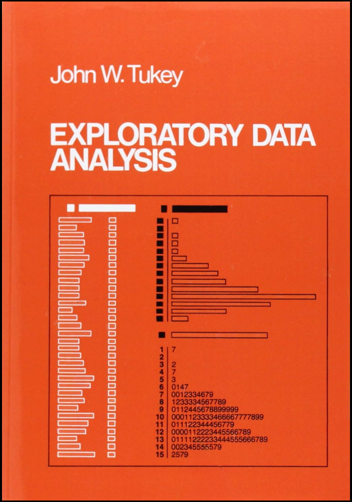

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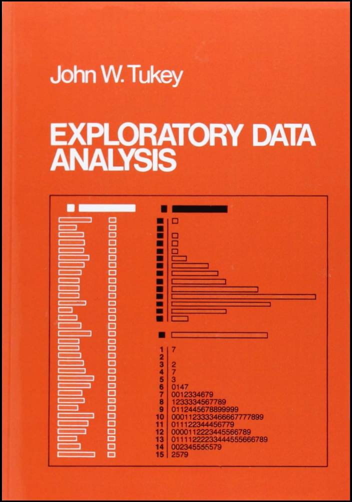

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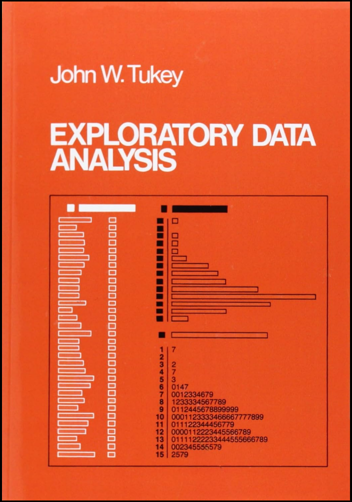

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  1. Mean

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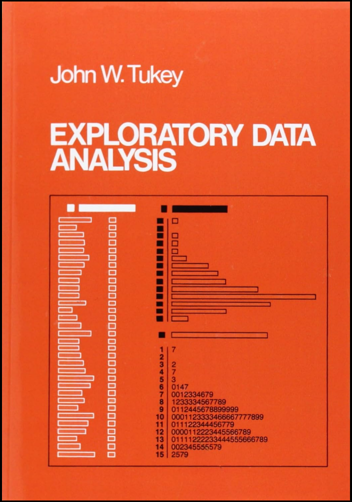

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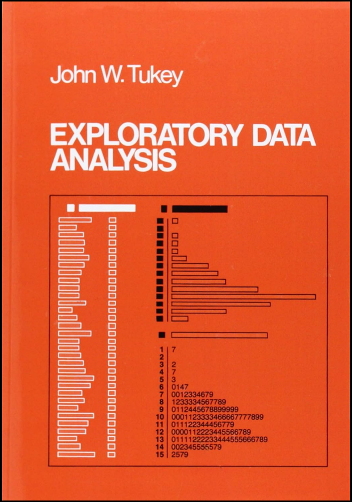

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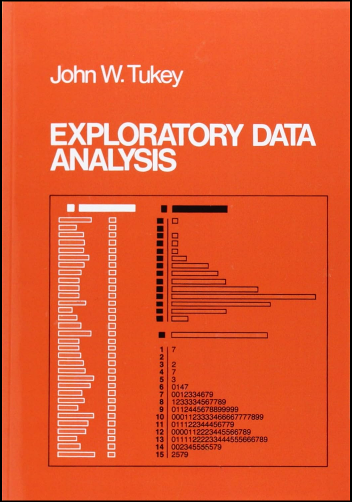

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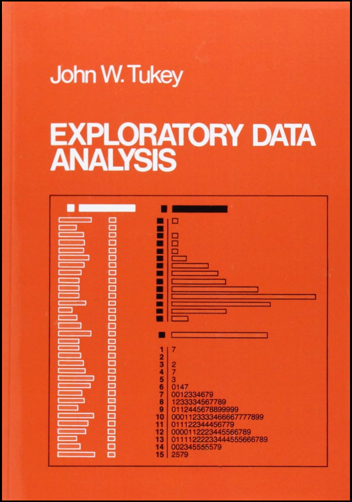

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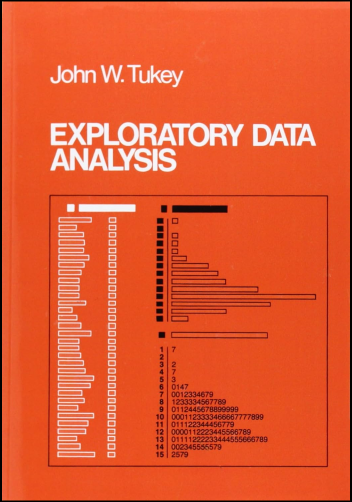
  5. Interquartile range



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5. Article 1

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  - Highlights the package's performance and availability

1. Extract features

1.1 Load packages and audio files

```
# packs
library(voice)
library(tidyverse)

# get path to audio file
wavDir <- list.files(system.file('extdata', package = 'wrassp'),
                     pattern = glob2rx('*.wav'), full.names = TRUE)
```

1.2 Extract features

```
# minimal usage
M <- voice::extract_features(wavDir)
glimpse(M)
#> Rows: 1,196
#> Columns: 13
#> $ section_seq      <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16…
#> $ section_seq_file <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16…
#> $ wav_path         <chr> "/Library/Frameworks/R.framework/Versions/4.5-arm64/R…
#> $ f0               <dbl> NA, NA, NA, NA, NA, NA, NA, 115.8593, 108.9439, 107.4…
#> $ f1               <int> NA, NA, NA, NA, 185, 260, 254, 277, 261, 231, 177, 19…
#> $ f2               <int> 1854, 1886, 1749, 1888, 1962, 1973, 2026, 2037, 2130,…
#> $ f3               <int> NA, 2893, 2676, 2659, 2639, 2676, 2993, 2932, 3016, 2…
#> $ f4               <int> 3113, 3708, 3509, 3658, 3248, 3239, 3830, 3479, 3561,…
#> $ f5               <int> 4191, 4678, 4502, 4331, 3653, 3836, 4602, 4585, 4720,…
#> $ f6               <int> 5226, 5659, 5035, 5177, 5208, 5146, 5233, 5390, 5366,…
#> $ f7               <int> 6077, 6725, 6526, 6518, 6493, 6567, 6603, 6532, 6510,…
#> $ f8               <int> 6675, NA, NA, NA, 7681, 7751, 7803, NA, 7835, 7614, 7…
#> $ gain             <dbl> 21.63347, 22.76034, 28.52825, 29.67069, 36.25124, 43.…
```

2. Tag

```
# creating Extended synthetic data
E <- dplyr::tibble(subject_id = c(1,1,1,2,2,2,3,3,3), wav_path = wavDir)
E
#> # A tibble: 9 × 2
#>   subject_id wav_path
#>        <dbl> <chr>
#> 1          1 /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/libra…
#> 2          1 /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/libra…
#> 3          1 /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/libra…
#> 4          2 /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/libra…
#> 5          2 /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/libra…
#> 6          2 /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/libra…
#> 7          3 /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/libra…
#> 8          3 /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/libra…
#> 9          3 /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/libra…
```

```r
# minimal usage
voice::tag(E)
#> # A tibble: 9 × 7
#>   wav_path    f0_tag_mean f0_tag_sd f0_tag_vc f0_tag_median f0_tag_iqr f0_tag_mad
#>   <chr>             <dbl>     <dbl>     <dbl>         <dbl>      <dbl>      <dbl>
#> 1 /Library/…         85.4      17.6     0.206          76.1       29.4       7.53
#> 2 /Library/…         85.4      15.6     0.183          80.1       27.8      14.4
#> 3 /Library/…         84.6      13.0     0.154          78.8       23.9      14.0
#> 4 /Library/…         84.8      14.5     0.171          79.1       28.1      11.9
#> 5 /Library/…         86.0      14.7     0.170          78.7       30.0      11.0
#> 6 /Library/…         82.9      15.6     0.188          74.8       23.8       4.78
#> 7 /Library/…         78.2      16.2     0.207          73.5       13.4       6.82
#> 8 /Library/…         84.5      14.5     0.172          78.1       17.8       8.95
#> 9 /Library/…         81.0      12.2     0.151          75.9       23.1       9.14

# canonical data
voice::tag(E, groupBy = 'subject_id')
#> # A tibble: 3 × 7
#>   subject_id f0_tag_mean f0_tag_sd f0_tag_vc f0_tag_median f0_tag_iqr f0_tag_mad
#>        <dbl>       <dbl>     <dbl>     <dbl>         <dbl>      <dbl>      <dbl>
#> 1          1        85.1      15.3     0.180          78.3       26.8      11.9
#> 2          2        84.6      14.9     0.176          76.4       28.3       7.97
#> 3          3        81.0      14.6     0.180          75.6       21.6       8.68
```

5. Diarize

```r
# download
url0 <- 'https://github.com/filipezabala/voiceAudios/raw/main/wav/sherlock0.wav'
wavDir <- normalizePath(tempdir())
download.file(url0, paste0(wavDir, '/sherlock0.wav'), mode = 'wb')
```

Diarization can be performed to detect speaker segments (i.e., 'who spoke when').

```r
# diarize
voice::diarize(fromWav = wavDir, toRttm = wavDir, token = 'YOUR_TOKEN')
#> Time difference of 27.49933 secs
```

The `voice::diarize()` function creates Rich Transcription Time Marked (RTTM)[1] files, space-delimited text files containing one turn per line defined by NIST - National Institute of Standards and Technology. The RTTM files can be read using `voice::read_rttm()`.

```
# read_rttm
(rttm <- voice::read_rttm(wavDir))
#> $doremi.rttm
#>      type   file chnl  tbeg  tdur ortho stype       name conf slat
#> 1 SPEAKER doremi    1 0.031 5.805  <NA>  <NA> SPEAKER_00 <NA> <NA>
#>
#> $sherlock0.rttm
#>      type      file chnl   tbeg  tdur ortho stype       name conf slat
#> 1 SPEAKER sherlock0    1  0.908 5.231  <NA>  <NA> SPEAKER_00 <NA> <NA>
#> 2 SPEAKER sherlock0    1  6.933 6.463  <NA>  <NA> SPEAKER_00 <NA> <NA>
#> 3 SPEAKER sherlock0    1 13.565 8.674  <NA>  <NA> SPEAKER_00 <NA> <NA>
```

Finally, the audio waves can be automatically segmented.

```
# split audio wave
voice::splitw(fromWav = wavDir, fromRttm = wavDir, to = wavDir)
#> TOTAL TIME 0.262 SECONDS
dir(wavDir, pattern = '.[Ww][Aa][Vv]$')
#> [1] "doremi_split_1.wav"    "doremi.wav"            "sherlock0_split_1.wav"
#> [4] "sherlock0_split_2.wav" "sherlock0_split_3.wav" "sherlock0.wav"
```

6. Article 2

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- Predicting sex and emotional valence automatically from voice

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  - Submitted to Journal of Biomedical Informatics (JBI-Elsevier)

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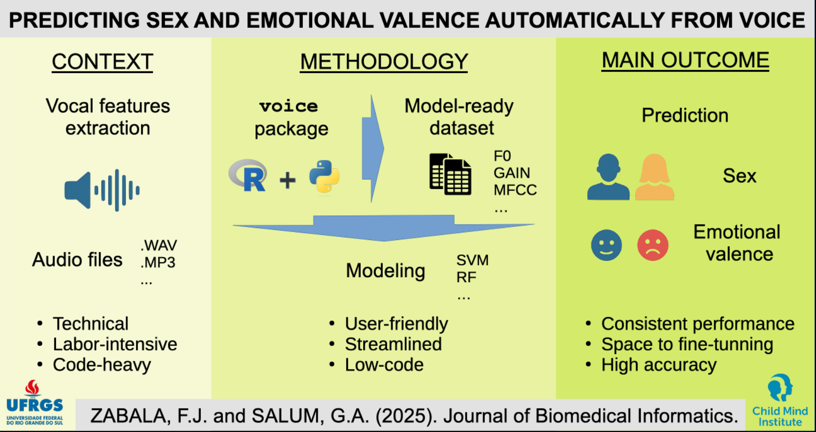
  - Models achieve accuracy statistically superior to the No Information Rate, the largest proportion of the observed classes
  - RF and SVM consistently demonstrate strong performance across all evaluated variables and quality measures
  - Emotional valence classification is feasible but may require hyperparameter optimization



Graphical abstract

	RAVDESS	CREMA-D
Rows/audios	1440	7442
Speakers	24	91
Language	English	English
Sex (M/F)		
#	720/720	3930/3512
%	50/50	52.8/47.2
Emotional Valence (−/+)		
#	672/768	5084/2358
%	53.3/46.7	68.3/31.7

Datasets summary

- Models

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    - BL - Binary Logistic

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- 1,000 runs
- 9 quality measures evaluated
- Results presented with Tukey's 5-number summary

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Under H_0 : Accuracy $\leq$ NIR *vs* H_1 : Accuracy $>$ NIR,

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Under H_0 : Accuracy $\leq$ NIR *vs* H_1 : Accuracy $>$ NIR,

$$\begin{aligned} \text{AccuracyPValue} &= P(X \geq TP + TN | \text{Accuracy} = \text{NIR}) \\ &= \sum_{i=TP+TN}^{n} \binom{n}{i} \text{NIR}^{i} (1 - \text{NIR})^{n-i} \end{aligned}$$

	Accuracy					Sensitivity					Specificity				
	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%
RAVDESS															
BART	0.127	0.776	0.842	0.927	0.998	0.002	0.757	0.971	1.000	1.000	0.007	0.738	0.946	1.000	1.000
RF	0.100	0.806	0.885	0.933	0.998	0.125	0.883	0.967	0.992	1.000	0.100	0.760	0.908	0.983	1.000
SVM	0.056	0.841	0.912	0.950	1.000	0.056	0.897	0.983	1.000	1.000	0.106	0.820	0.938	0.994	1.000
BL	0.360	0.729	0.792	0.842	0.965	0.274	0.751	0.871	0.953	1.000	0.319	0.690	0.812	0.906	1.000
CREMA-D															
BART	0.284	0.857	0.907	0.929	0.978	0.129	0.859	0.940	0.978	1.000	0.179	0.859	0.931	0.974	1.000
RF	0.609	0.888	0.910	0.928	0.969	0.554	0.909	0.947	0.972	1.000	0.479	0.844	0.903	0.944	0.998
SVM	0.654	0.913	0.934	0.948	0.986	0.578	0.920	0.955	0.980	1.000	0.548	0.897	0.940	0.972	1.000
BL	0.630	0.881	0.905	0.922	0.974	0.549	0.882	0.926	0.957	0.999	0.555	0.864	0.913	0.948	1.000

	Pos Pred Value					Neg Pred Value					F1				
	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%
RAVDESS															
BART	0.126	0.698	0.947	1.000	1.000	0.125	0.710	0.972	1.000	1.000	0.005	0.771	0.842	0.930	0.998
RF	0.155	0.729	0.915	0.988	1.000	0.168	0.835	0.965	0.992	1.000	0.222	0.804	0.887	0.940	0.998
SVM	0.169	0.779	0.938	0.996	1.000	0.157	0.853	0.982	1.000	1.000	0.107	0.832	0.916	0.953	1.000
BL	0.173	0.653	0.822	0.922	1.000	0.160	0.699	0.868	0.958	1.000	0.296	0.735	0.795	0.848	0.965
CREMA-D															
BART	0.288	0.861	0.937	0.978	1.000	0.200	0.837	0.934	0.978	1.000	0.229	0.864	0.910	0.932	0.979
RF	0.389	0.851	0.915	0.957	0.999	0.327	0.883	0.941	0.971	1.000	0.560	0.894	0.917	0.933	0.971
SVM	0.423	0.894	0.947	0.978	1.000	0.340	0.898	0.952	0.979	1.000	0.595	0.918	0.937	0.951	0.987
BL	0.439	0.865	0.922	0.959	1.000	0.325	0.855	0.919	0.957	0.999	0.609	0.887	0.910	0.926	0.976

	Detection Rate					Kappa					AccuracyPValue				
	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%
RAVDESS															
BART	0.002	0.375	0.431	0.481	0.554	0.001	0.572	0.689	0.854	0.996	0.000	0.000	0.000	0.000	1.000
RF	0.000	0.373	0.475	0.498	0.604	0.000	0.620	0.760	0.863	0.996	0.000	0.000	0.000	0.000	1.000
SVM	0.000	0.375	0.481	0.498	0.604	0.000	0.685	0.821	0.897	1.000	0.000	0.000	0.000	0.000	1.000
BL	0.123	0.360	0.410	0.448	0.565	0.076	0.473	0.591	0.684	0.929	0.000	0.000	0.000	0.000	1.000
CREMA-D															
BART	0.106	0.450	0.476	0.492	0.528	0.050	0.719	0.813	0.857	0.956	0.000	0.000	0.000	0.000	1.000
RF	0.249	0.454	0.495	0.526	0.590	0.306	0.775	0.818	0.854	0.937	0.000	0.000	0.000	0.000	1.000
SVM	0.249	0.458	0.498	0.529	0.603	0.329	0.823	0.868	0.894	0.971	0.000	0.000	0.000	0.000	1.000
BL	0.248	0.448	0.482	0.511	0.567	0.303	0.761	0.810	0.843	0.949	0.000	0.000	0.000	0.000	1.000

Summary of SEX classification performance over 1,000 simulations

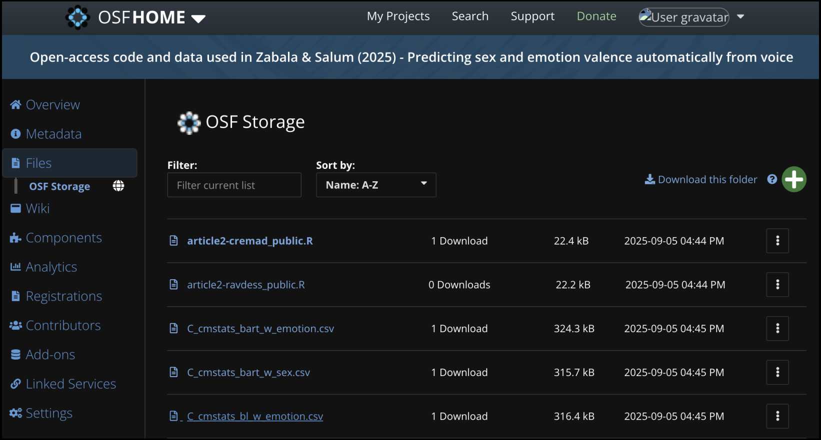
	Accuracy					Sensitivity					Specificity				
	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%
RAVDESS															
BART	0.606	0.698	0.717	0.735	0.804	0.625	0.707	0.727	0.746	0.828	0.536	0.674	0.705	0.737	0.826
RF	0.613	0.698	0.719	0.738	0.796	0.684	0.766	0.789	0.812	0.895	0.442	0.603	0.638	0.674	0.795
SVM	0.635	0.710	0.731	0.748	0.802	0.711	0.789	0.812	0.832	0.898	0.469	0.598	0.638	0.674	0.795
BL	0.487	0.575	0.600	0.621	0.704	0.449	0.574	0.602	0.625	0.703	0.455	0.562	0.598	0.625	0.728
CREMA-D															
BART	0.633	0.669	0.677	0.685	0.716	0.573	0.625	0.636	0.646	0.684	0.645	0.751	0.766	0.781	0.835
RF	0.704	0.725	0.731	0.736	0.764	0.902	0.935	0.944	0.952	0.970	0.181	0.255	0.275	0.294	0.373
SVM	0.718	0.740	0.746	0.753	0.775	0.863	0.900	0.912	0.920	0.952	0.309	0.376	0.393	0.409	0.492
BL	0.535	0.584	0.601	0.645	0.716	0.495	0.581	0.607	0.661	0.790	0.461	0.577	0.604	0.627	0.692

	Pos Pred Value					Neg Pred Value					F1				
	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%
RAVDESS															
BART	0.622	0.717	0.739	0.760	0.834	0.583	0.673	0.693	0.712	0.798	0.635	0.714	0.732	0.749	0.819
RF	0.623	0.693	0.714	0.733	0.815	0.596	0.701	0.724	0.747	0.846	0.654	0.732	0.749	0.765	0.818
SVM	0.635	0.698	0.720	0.740	0.817	0.635	0.724	0.747	0.768	0.853	0.685	0.746	0.762	0.776	0.825
BL	0.520	0.605	0.629	0.653	0.742	0.452	0.542	0.567	0.590	0.668	0.484	0.592	0.615	0.637	0.711
CREMA-D															
BART	0.792	0.846	0.854	0.862	0.891	0.446	0.486	0.494	0.503	0.539	0.682	0.721	0.729	0.736	0.766
RF	0.715	0.732	0.736	0.741	0.765	0.585	0.670	0.696	0.721	0.789	0.810	0.824	0.827	0.830	0.846
SVM	0.742	0.759	0.763	0.768	0.792	0.593	0.654	0.673	0.695	0.761	0.811	0.826	0.831	0.835	0.850
BL	0.709	0.751	0.766	0.786	0.834	0.353	0.394	0.413	0.456	0.544	0.592	0.657	0.675	0.718	0.777

	Detection Rate					Kappa					AccuracyPValue				
	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%
RAVDESS															
BART	0.333	0.377	0.388	0.398	0.442	0.205	0.394	0.432	0.468	0.606	0.000	0.000	0.000	0.000	0.001
RF	0.365	0.408	0.421	0.433	0.477	0.216	0.389	0.430	0.469	0.587	0.000	0.000	0.000	0.000	0.000
SVM	0.379	0.421	0.433	0.444	0.479	0.259	0.412	0.454	0.490	0.602	0.000	0.000	0.000	0.000	0.000
BL	0.240	0.306	0.321	0.333	0.375	-0.028	0.147	0.198	0.239	0.409	1.000	1.000	1.000	1.000	1.000
CREMA-D															
BART	0.392	0.426	0.434	0.441	0.465	0.244	0.336	0.350	0.364	0.419	0.000	0.403	0.714	0.922	1.000
RF	0.616	0.638	0.644	0.650	0.662	0.260	0.277	0.362	0.377	0.369	0.000	0.000	0.000	0.000	0.013
SVM	0.591	0.615	0.622	0.628	0.648	0.263	0.325	0.341	0.358	0.419	0.000	0.000	0.000	0.000	0.000
BL	0.338	0.397	0.414	0.452	0.541	0.064	0.148	0.181	0.249	0.391	1.000	1.000	1.000	1.000	1.000

Summary of EMOTIONAL VALENCE classif. performance over 1,000 simulations

6. Article 2



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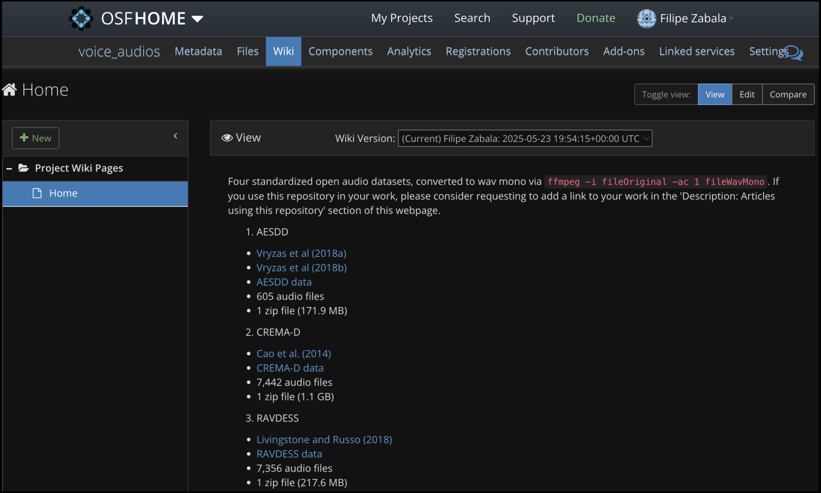
6. Article 2



https://osf.io/9g73a/wiki/home/

Thank you!

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