Music Mood Categorization

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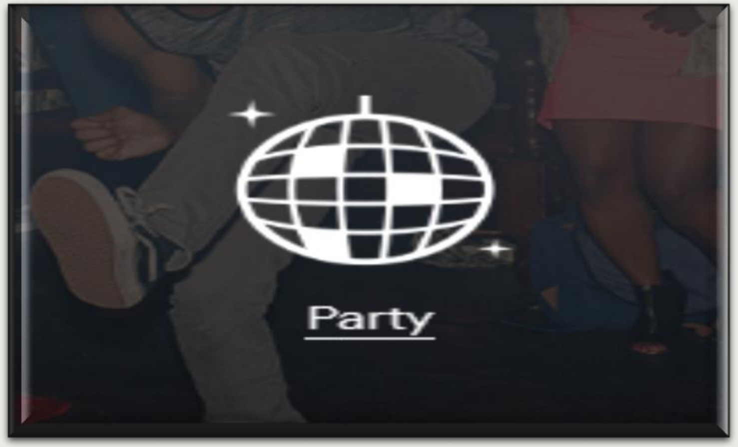
Why Mood Classification?



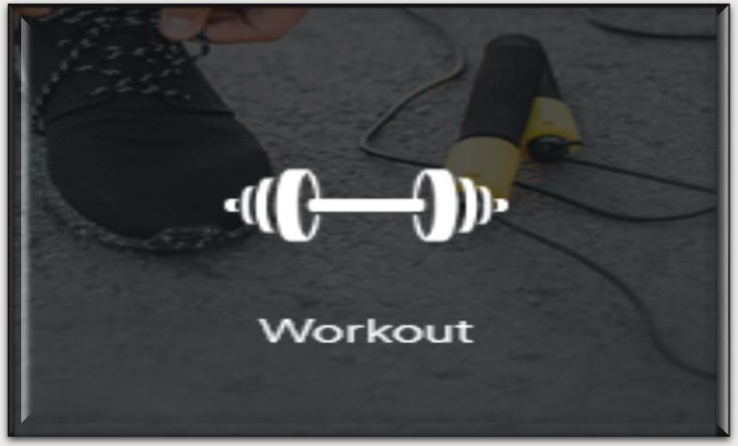


Image source: Spotify

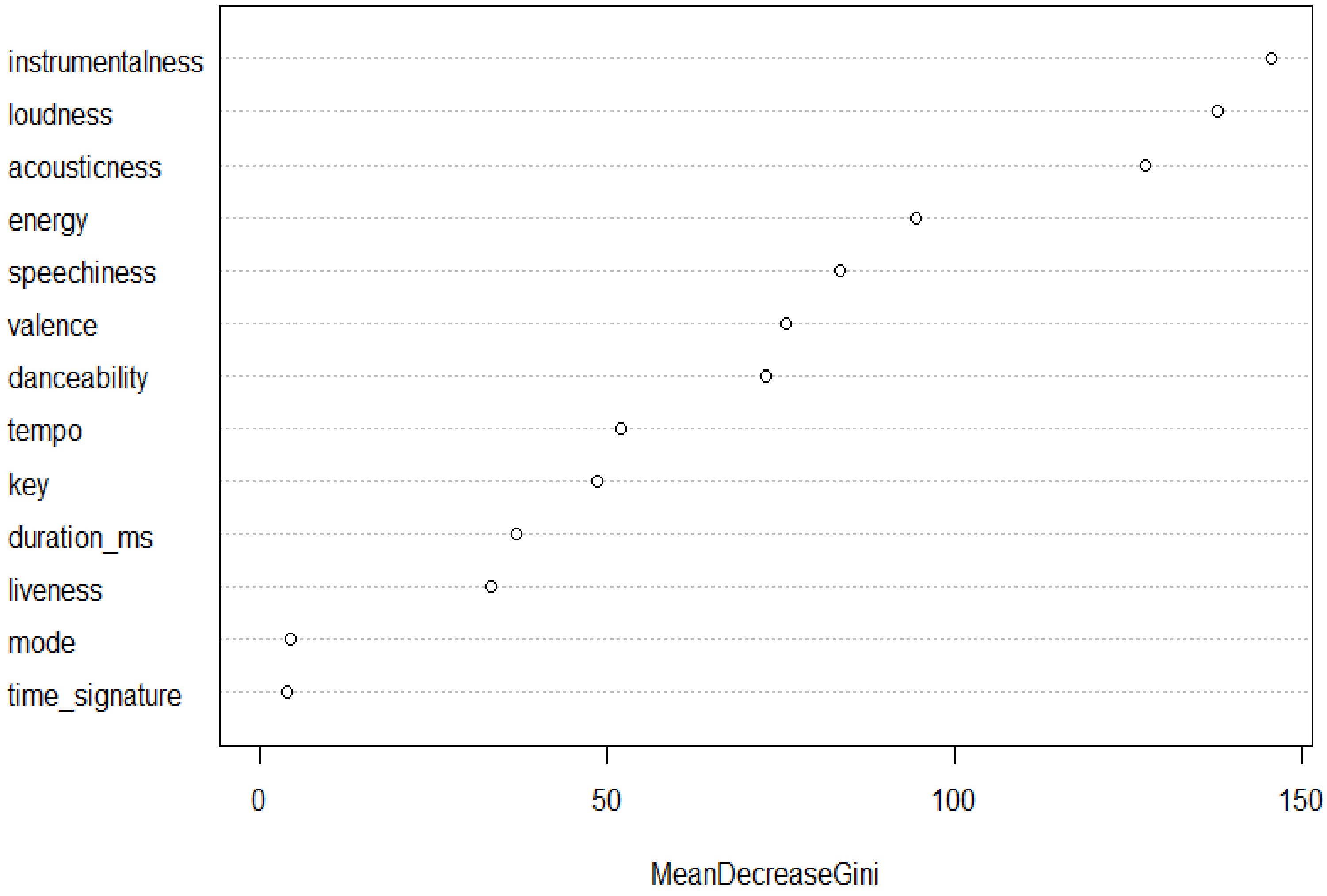
Spotify API

- Audio-features for songs

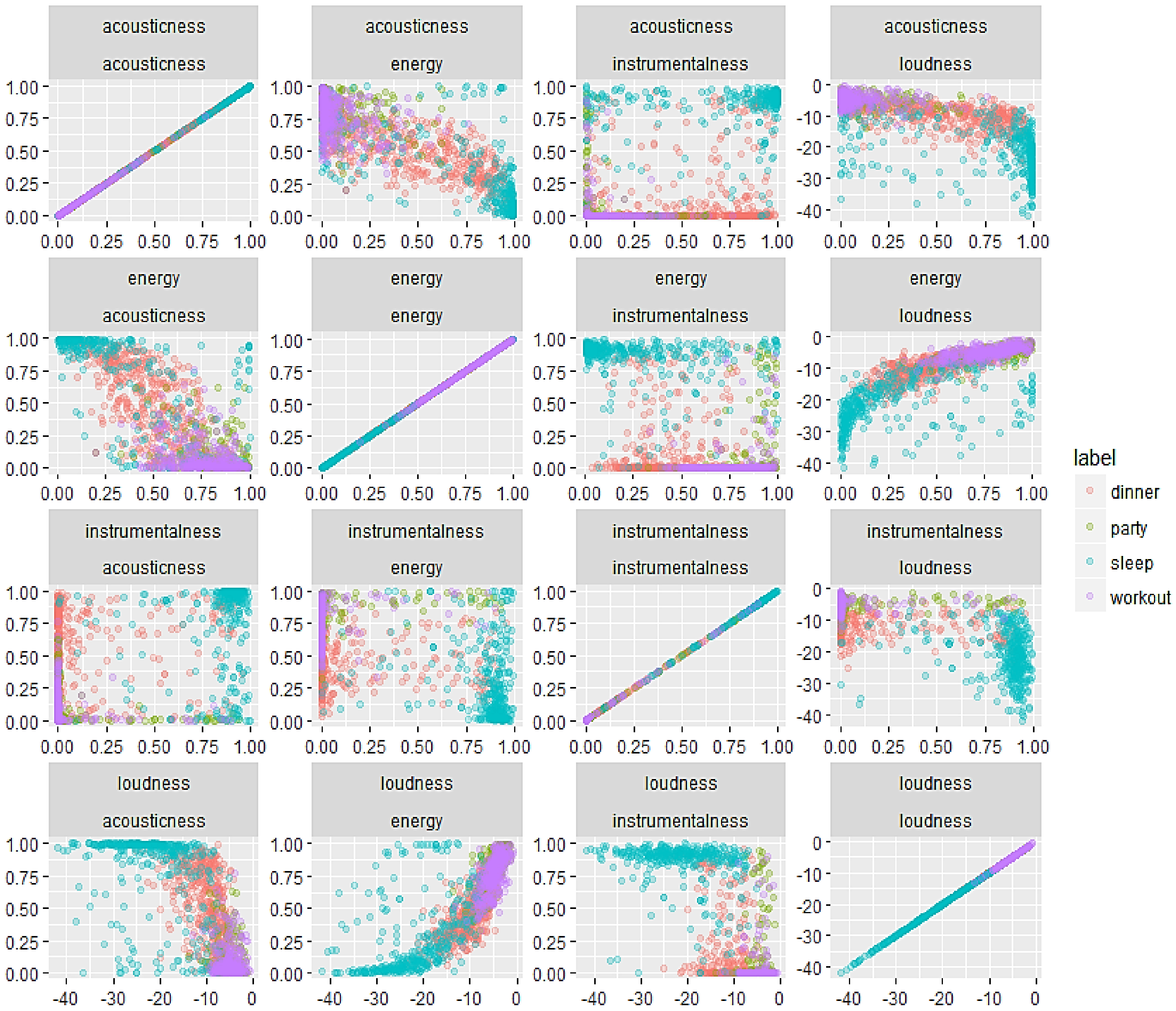
~~Inquiry~~	~~Id~~	~~Uri~~
~~Analysis_url~~	Key [0, 11]	Loudness [dB]
Mode [0,1]	Speechiness	Acousticness
Instrumentalness	Liveness	Valence
Tempo (0, 214)	Duration [ms]	Time_signature [1,5]
Danceability (0,1)	Energy	**Label [1,4]**

Conditioning

- Converted to factor
  - label, key, and mode
- Took logarithm
  - duration_ms, liveness, speechiness
- Normalized on [0,1]
  - duration_ms, liveness, speechiness
- Removed
  - The NA row
  - mode, time_signature
    - Little affect



Random Forest Variable Importance



Top Feature Interactions

General Boosted Model

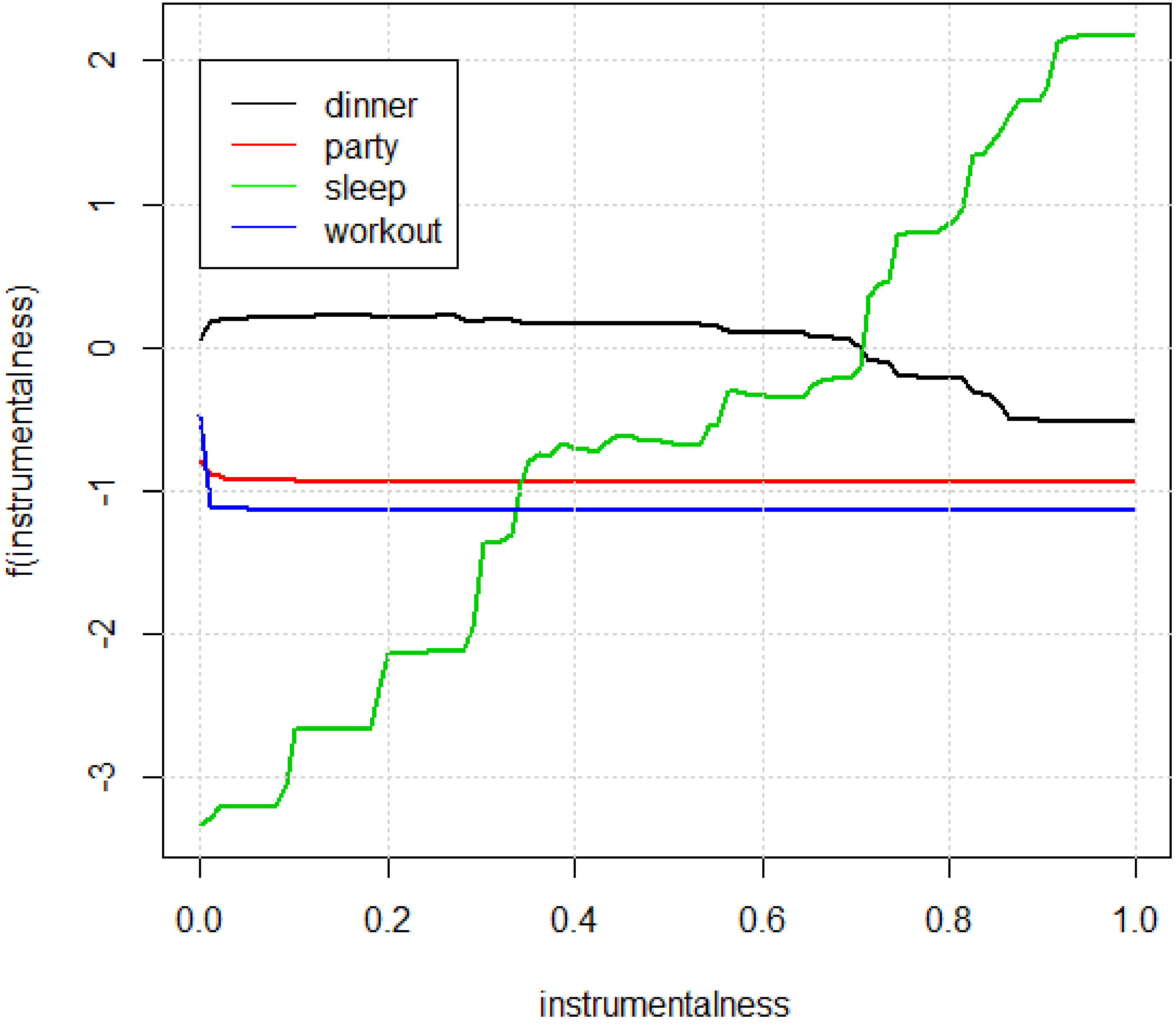
• Learning rate	0.0007
• Number of trees	13000
• Interaction depth	2
• CV folds	5
• Distribution	multinomial

- Separate testing and training datasets were used.

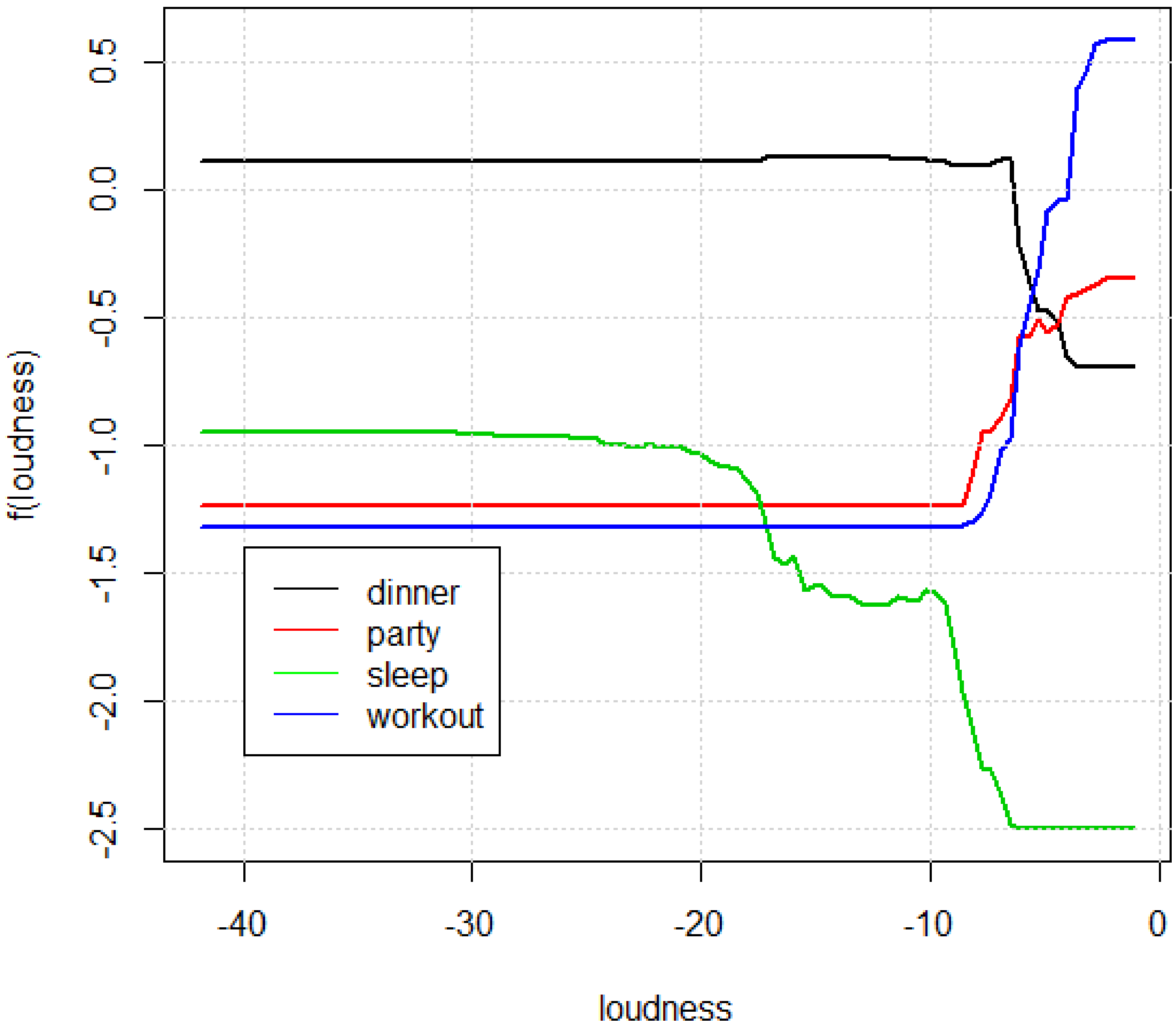
Confusion matrix

	Reference				
Prediction	**Dinner**	**Party**	**Sleep**	**workout**	**Sensitivity**
Dinner	105	4	4	4	89%
Party	3	27	1	12	52%
Sleep	3	0	63	0	93%
Workout	7	21	0	64	80%
Prevalence	37%	16%	21%	25%	

Overall accuracy: 81%

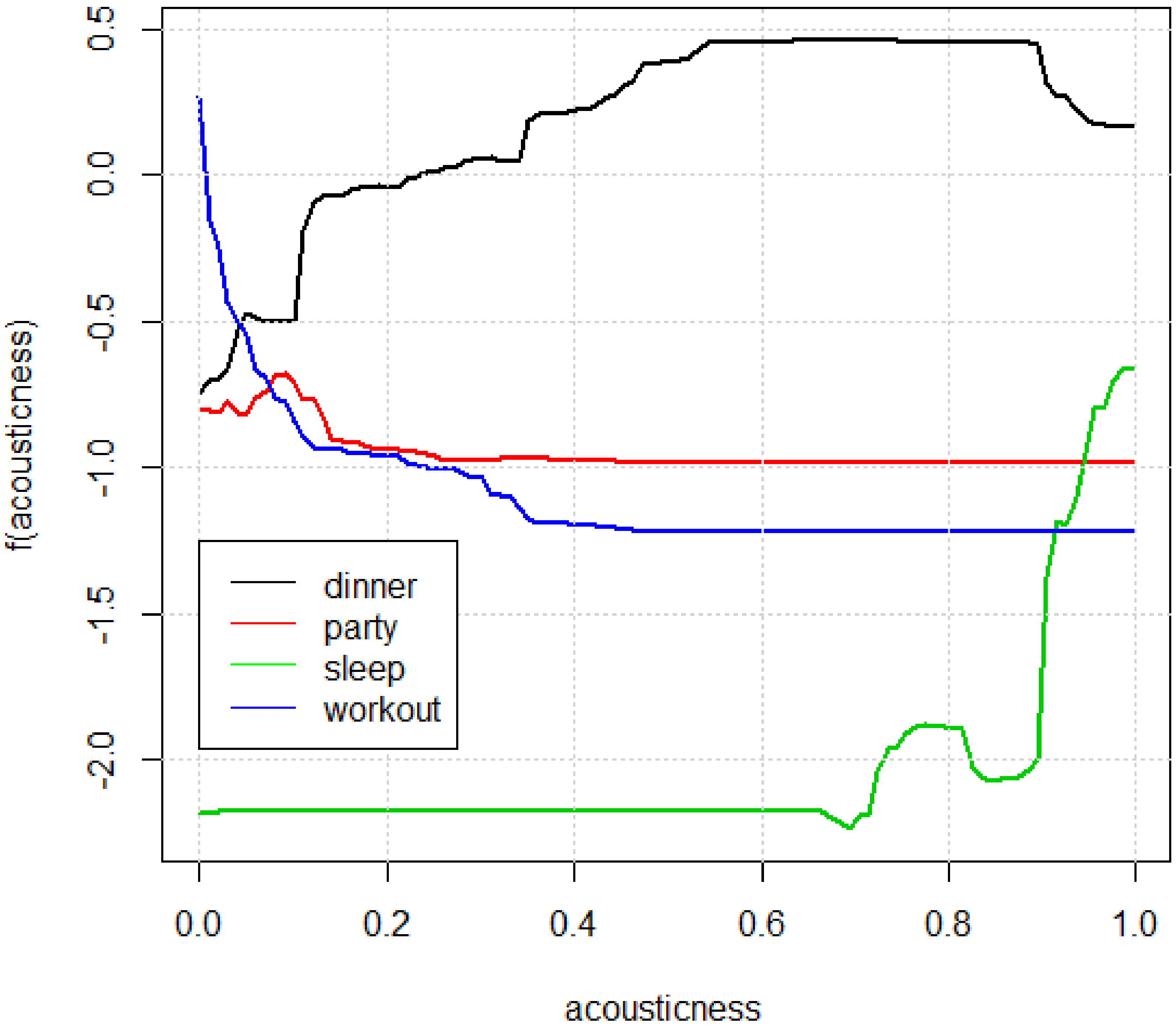


Instrumental-ness

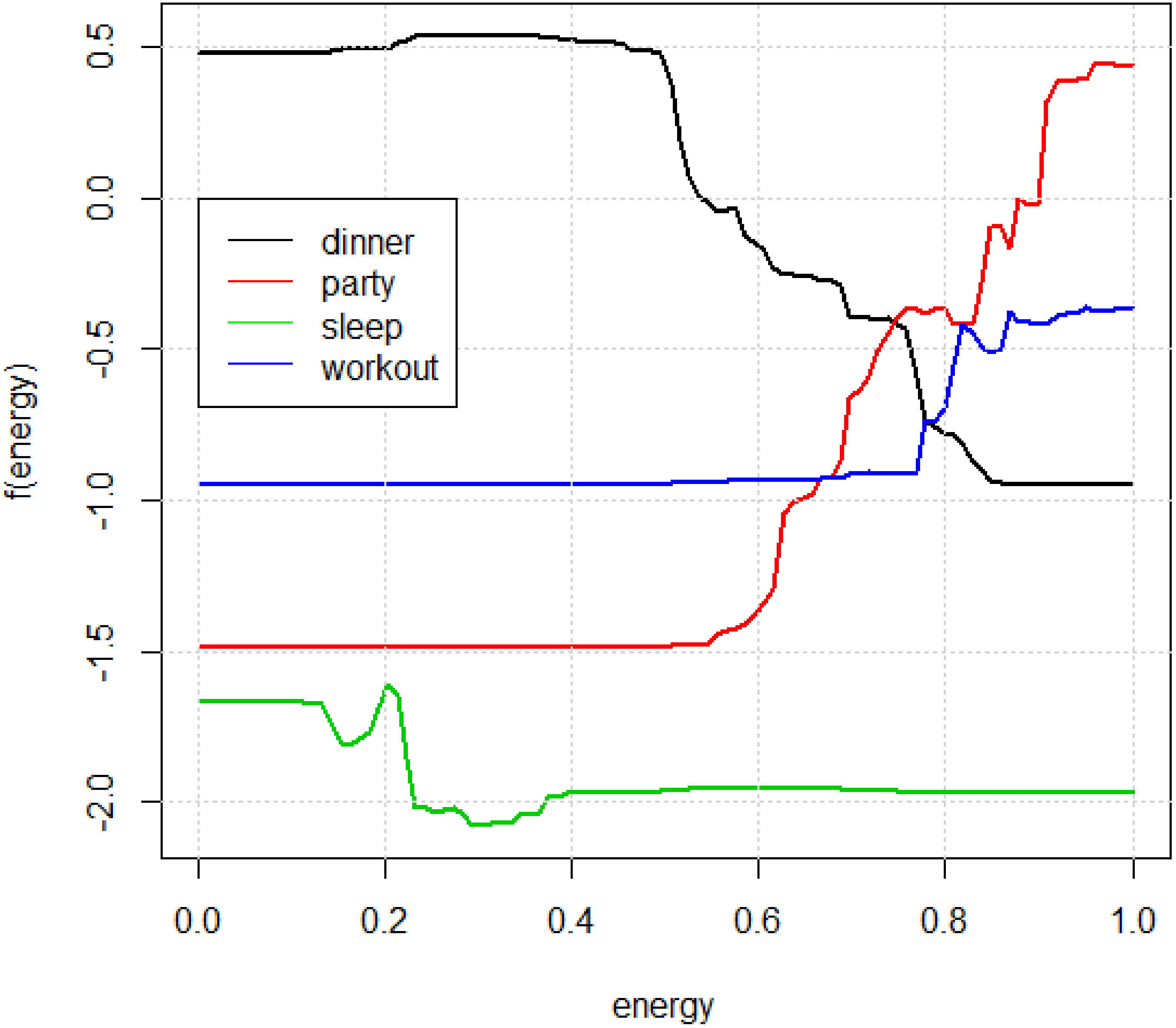


dinner
party
sleep
workout
f(loudness)
loudness
0.5
0.0
-0.5
-1.0
-1.5
-2.0
-2.5
-40
-30
-20
-10
0

loudness

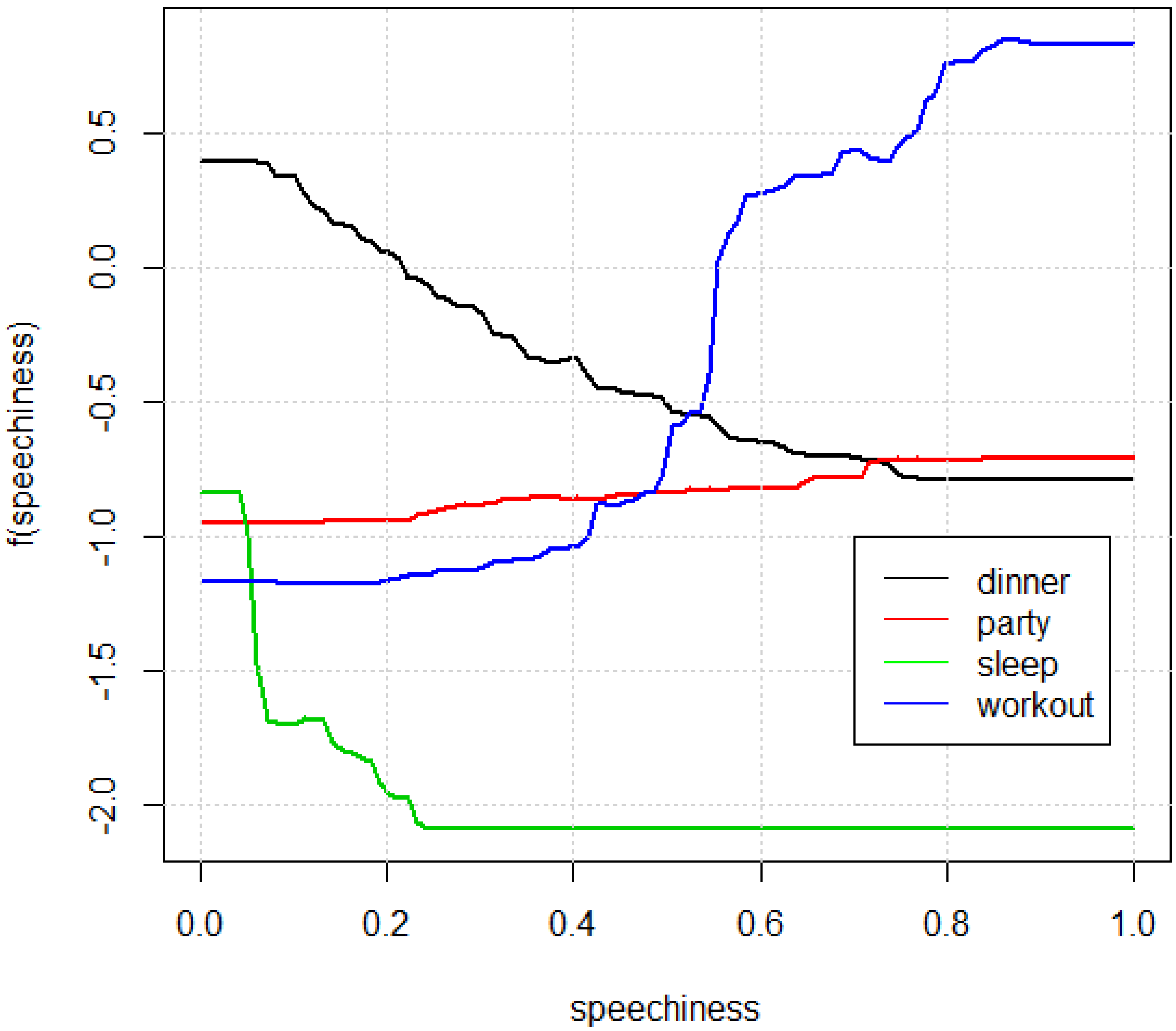


Acousticness



dinner
party
sleep
workout
f(energy)
energy
0.5
0.0
-0.5
-1.0
-1.5
-2.0
0.0
0.2
0.4
0.6
0.8
1.0

Energy



Speechiness

Conclusion

- Dinner
  - Baseline class
- Sleep
  - High instrumentalness and acousticness
  - Low loudness and speechiness
- Workout
  - High Loudness and speechiness
- Party
  - High Energy