# Geographical Origin Prediction of Folk Music Recordings from the United Kingdom

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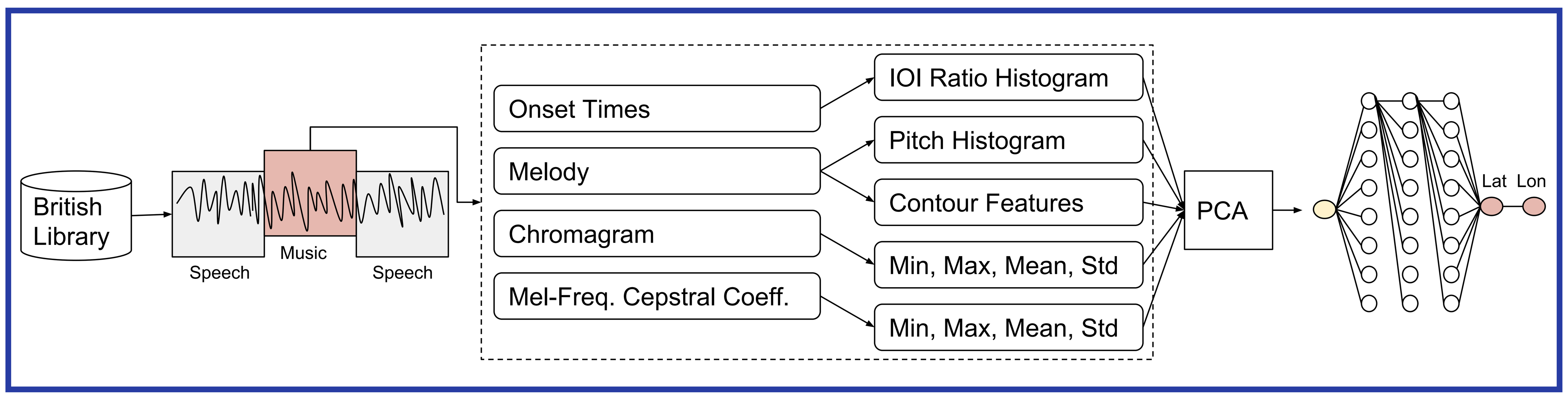
## Motivation

Field recordings from ethnomusicological research since the 1900s are available today in large digitised music archives [1]. We investigate whether there are characteristics of local style which distinguish different UK folk music recordings, and if so, whether MIR tools are able to discern such aspects [2].




## 1. Dataset

- World & Traditional Music collections
- 10055 recordings from UK
- Recording dates: 1904-2002
- Geographical range N-S: 1222 km

## 2. Audio Features

From VAMP plugins:

- Melody Extraction —> pitch contour features [3]
- Note Onset Detector —> IOI ratio histogram [4]
- Chromagram —> min, max, mean, std
- Mel-Freq. Cepstral Coeff. —> min, max, mean, std

## 3. Regression Model

Neural network to predict latitude and longitude

- ADAM optimiser, RELU activations, 0.5 drop out
- Optimisation: 3 hidden layers, L2 regularisation
- Haversine formula as cost function:

$$d = 2r \arcsin([\sin^2(\frac{\phi_2 - \phi_1}{2}) + \cos(\phi_1)\cos(\phi_2)\sin^2(\frac{\lambda_2 - \lambda_1}{2})]^{\frac{1}{2}})$$

where ϕ=latitude, λ=longitude, r=earth's radius.

## 4. Results

| Model No. | Feature Set Name | Error (km) |
|---|---|---|
| 1 | All features | 149.8 |
| 2 | Rhythm: IOIR histogram | 160.0 |
| 3 | Harmony: Chromagram statistics | 152.5 |
| 4 | Timbre: MFCC statistics | 129.0 |
| 5 | Pitch histogram | 160.1 |
| 6 | Contour features mean | 159.8 |
| 7 | Contour features standard deviation | 162.3 |
| 8 | Melody: Pitch hist., contour features | 152.6 |
| 9 | Rhythm and Harmony | 149.1 |
| 10 | Rhythm and Timbre | 120.1 |
| 11 | Rhythm and Melody | 150.5 |
| 12 | Melody and Harmony | 139.4 |
| 13 | Melody and Timbre | 117.1 |
| 14 | Timbre and Harmony | **114.0** |
| 15 | Rhythm, Harmony, and Timbre | 118.3 |
| 16 | Rhythm, Harmony, and Melody | 142.8 |
| 17 | Rhythm, Timbre, and Melody | 119.8 |
| 18 | Harmony, Timbre, and Melody | 140.3 |
| – | Baseline | 167.4 |

**Table**: The mean distance error (in km) of the test set for 18 models trained on different sets of features. The baseline is the mean distance of recordings to the centroid.

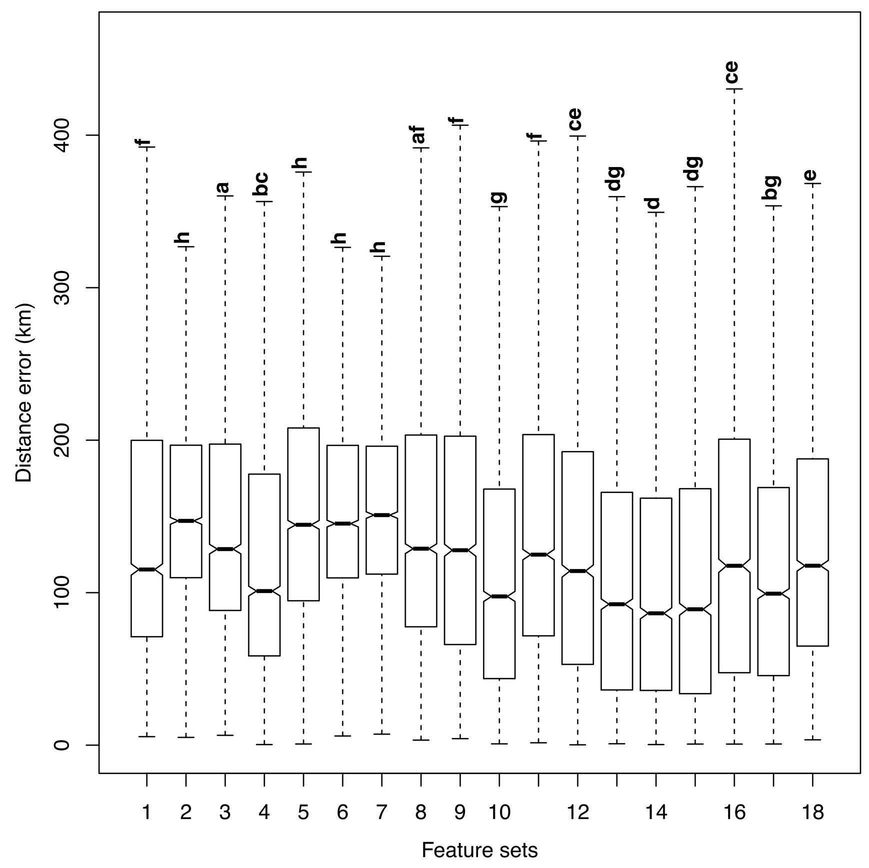



**Figure**: Distance error of predictions for different sets of features. Labels a–l indicate feature sets that have non-significantly different results (Mann-Whitney U, p > 0.05) where they share the same letter. For example, feature set 3 shares the label a with set 8 but shares no label with any other feature set, indicating that results from model 3 are significantly different from all other models except for model 8.

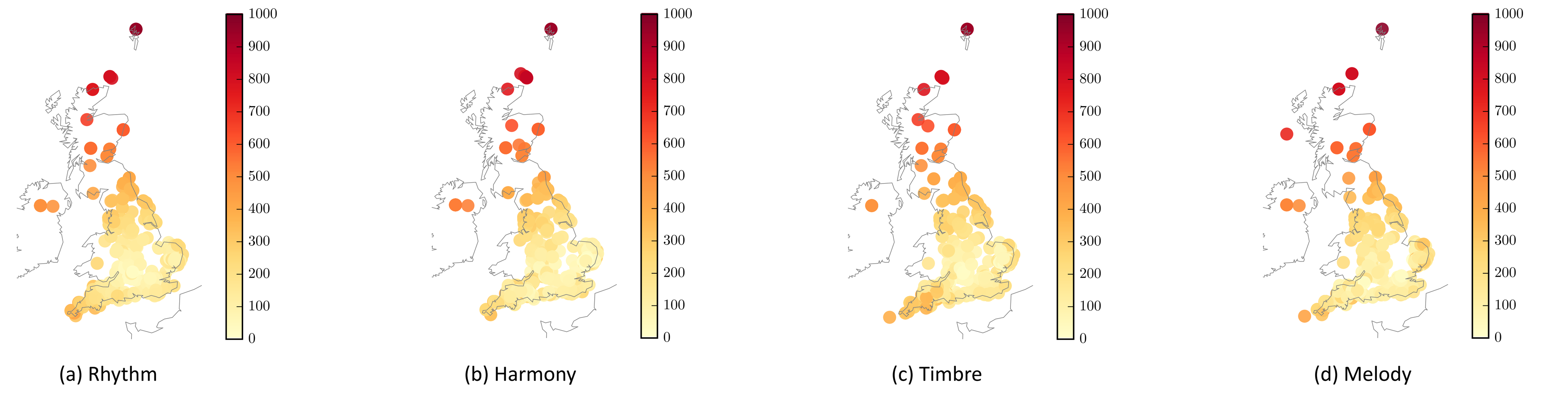



**Figure**: Music recording origins coloured by distance error (in km) for models trained on (a) rhythmic, (b) harmonic, (c) timbral, and (d) melodic features (no. 2, 3, 4, 8 respectively). For all these models the northern areas of the UK are predicted with large distance errors. For the model trained on timbral features (c) the south west of England is predicted with lower accuracy than the harmonic and melodic models (b and d).

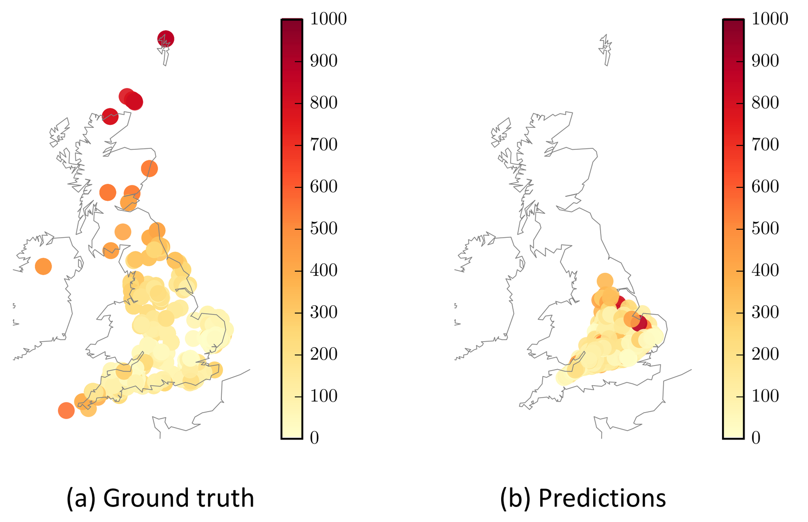



**Figure**: (a) Ground truth and (b) predicted music recording origins, coloured by distance error (in km) for the best model (no. 14).

## 5. Conclusion

- Best model: timbral and harmonic features
- Southern regions of the UK predicted with higher accuracy than northern regions (data bias)
- Combining feature sets gave higher accuracies

Future work:

- Balanced and larger corpus to avoid overfitting

### References

[1] S. Abdallah, E. Benetos, N. Gold, S. Hargreaves, T. Weyde, and D. Wolff. The Digital Music Lab: A Big Data Infrastructure for Digital Musicology. *ACM Journal on Computing and Cultural Heritage*, 10(1), 2017.

[2] F. Zhou, Q. Claire, and R.D. King. Predicting the Geographical Origin of Music. In *IEEE International Conference on Data Mining*, pages 1115–1120, 2014.

[3] M. Panteli, R. Bittner, J. P. Bello, and S. Dixon. Towards the characterization of singing styles in world music. In *IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 636–640, 2017.

[4] F. Gouyon, S. Dixon, E. Pampalk, and G. Widmer. Evaluating rhythmic descriptors for musical genre classification. In Proceedings of the AES 25th International Conference, pages 196–204, 2004.