

Decoding drums, instrumentals, vocals, and mixed sources in music using human brain activity with fMRI

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Motivation

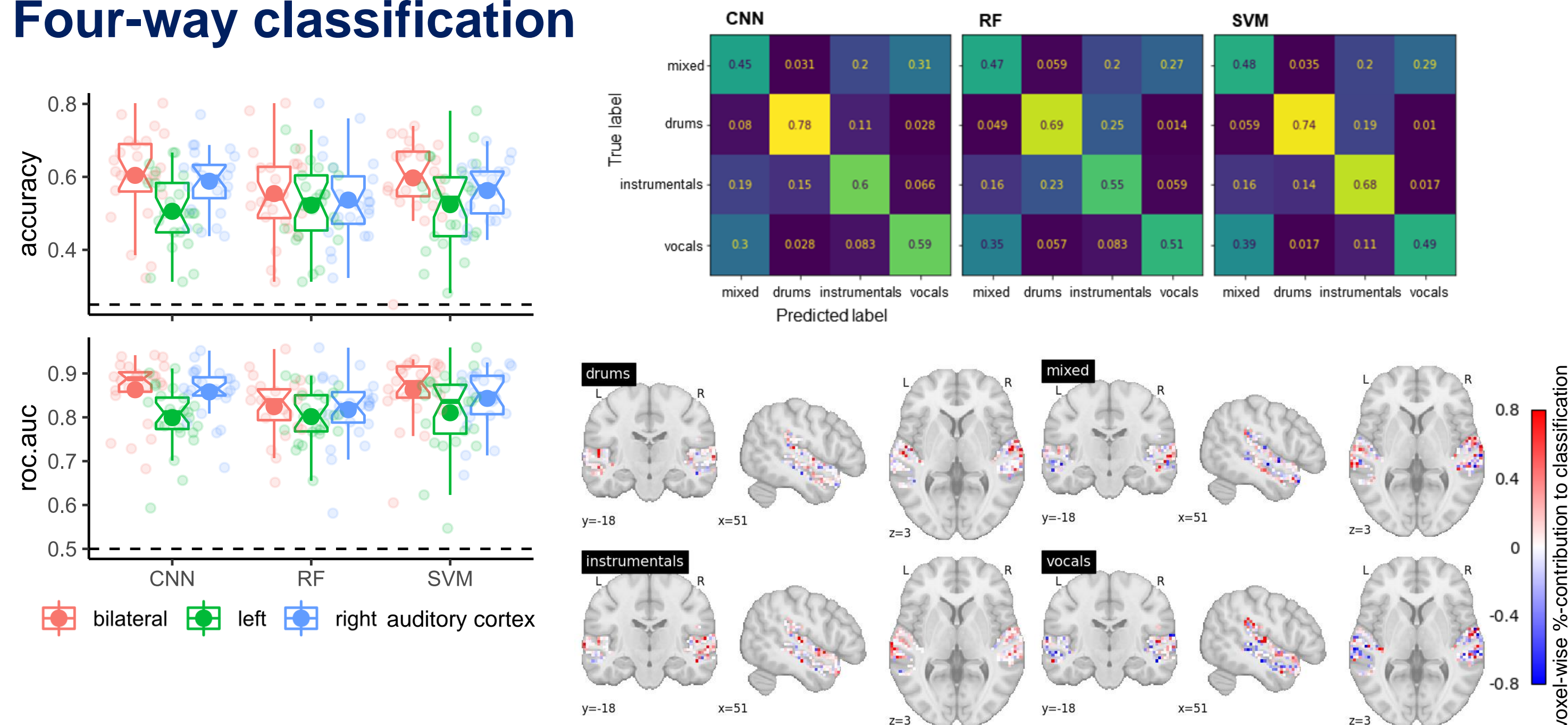
- Decomposing a sound mixture into a linear combination of instrumental sources is a well-established MIR task
- However, current brain decoding models only classify musical instruments from single- or a few notes [1,2], or via attention deployment to a given source [3,4]
- We show that instrument sources in natural music can be decoded from human auditory cortex activity using functional magnetic resonance imaging (fMRI)

Experiment

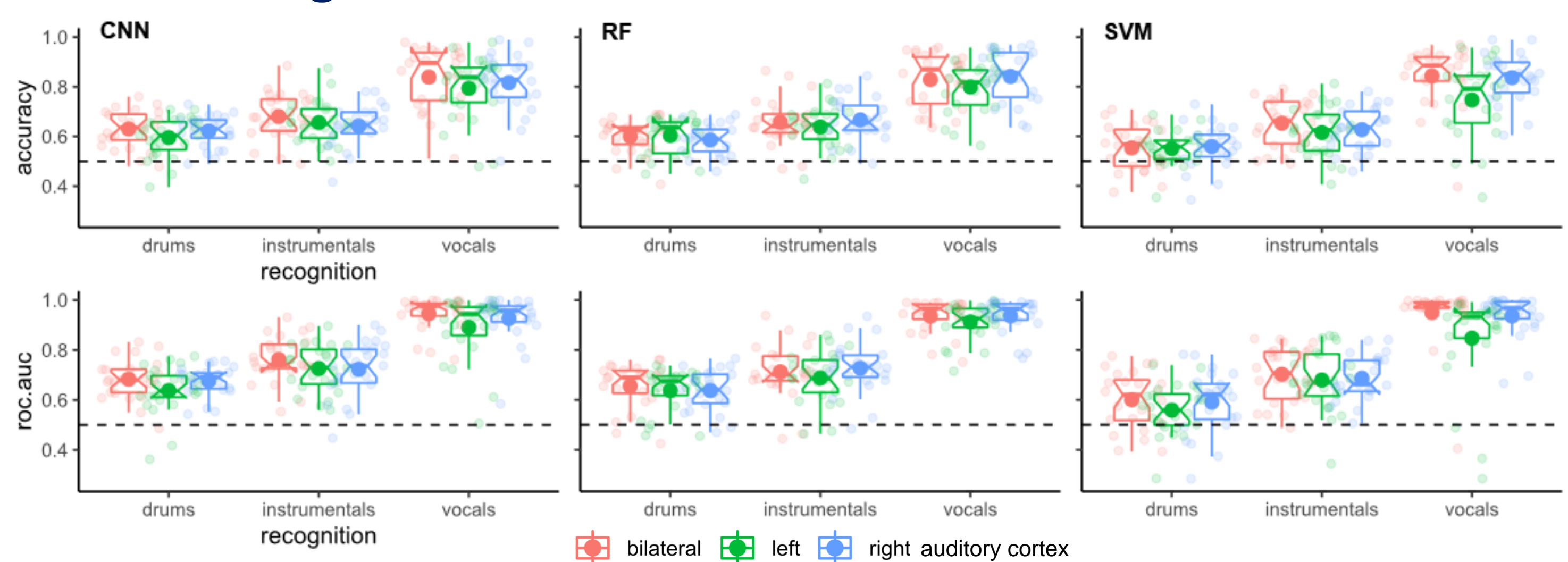
- 96 loudness-normalised stimuli were derived from the first 15s of the chorus in 24 unreleased pop/rock songs separated into four sources using Demucs v4 [5]:
 - Drums
 - Vocals
 - Instrumentals (= bass + others)
 - Mixed (= drums + vocals + instrumentals)
- Brain activity from 24 healthy adults was recorded using 3T MRI scanner during stimulus presentation

Results (using leave-one-subject-out cross-validation)

Four-way classification

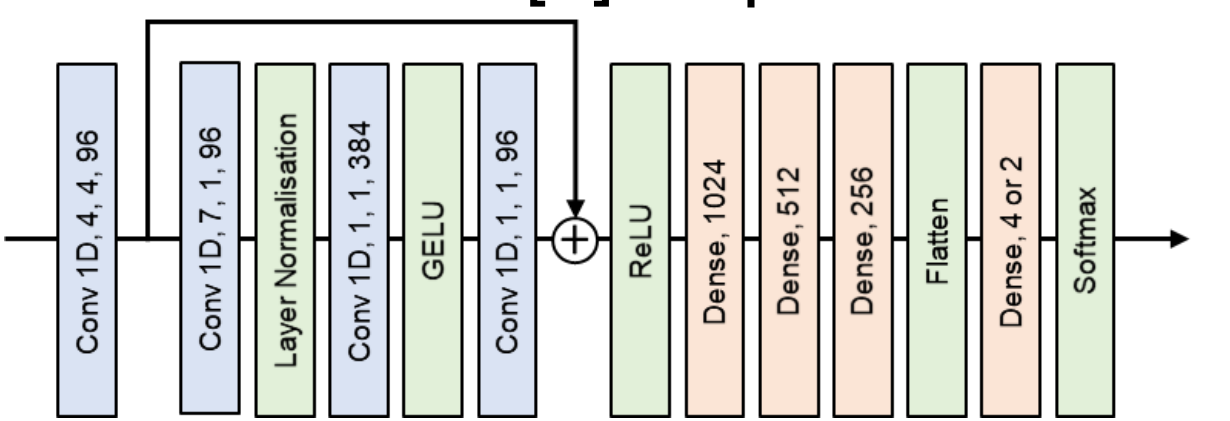


Source recognition



Brain decoders

- ConvNeXt [6]-inspired CNN



- Random forest (RF)
- Support vector machine (SVM)

	CNN		RF		SVM	
	acc	auc	acc	auc	acc	auc
<i>Four-way classification</i>						
<i>l AC</i>	.506	.799	.523	.802	.524	.810
<i>r AC</i>	.588	.858	.536	.817	.563	.843
<i>l+r AC</i>	.604	.863	.554	.824	.597	.863
<i>l+r PV</i>	.301	.560	.319	.554	.253	.510
<i>l+r SM</i>	.304	.547	.332	.550	.276	.554
<i>Drums recognition</i>						
<i>l AC</i>	.595	.638	.603	.637	.550	.559
<i>r AC</i>	.622	.677	.586	.638	.559	.591
<i>l+r AC</i>	.630	.683	.599	.655	.553	.601
<i>l+r PV</i>	.507	.505	.528	.533	.526	.531
<i>l+r SM</i>	.517	.544	.530	.545	.490	.500
<i>Instrumentals recognition</i>						
<i>l AC</i>	.656	.726	.638	.688	.615	.679
<i>r AC</i>	.642	.723	.666	.727	.627	.687
<i>l+r AC</i>	.680	.762	.657	.712	.652	.703
<i>l+r PV</i>	.577	.593	.585	.611	.495	.509
<i>l+r SM</i>	.558	.576	.580	.600	.517	.553
<i>Vocals recognition</i>						
<i>l AC</i>	.794	.891	.799	.913	.746	.847
<i>r AC</i>	.816	.926	.841	.937	.836	.936
<i>l+r AC</i>	.839	.946	.829	.936	.843	.950
<i>l+r PV</i>	.527	.527	.525	.541	.495	.502
<i>l+r SM</i>	.516	.544	.563	.581	.516	.552

acc = accuracy, auc = ROC AUC; l/r/l+r = left/right/bilateral; AC = auditory, PV = primary visual, SM = somatosensory-motor cortices

Conclusions

- Spatial representations in the human auditory cortex activity provide useful information across classifiers towards decoding different instrument sources
- High performance in recognising vocals suggests enhanced perceptual sensitivity towards vocal information during music listening
- Future work could exploit neural representations as an alternative to subjective tests such as MUSHRA or MOS

References

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