COMBINING MUSICAL FEATURES FOR COVER DETECTION

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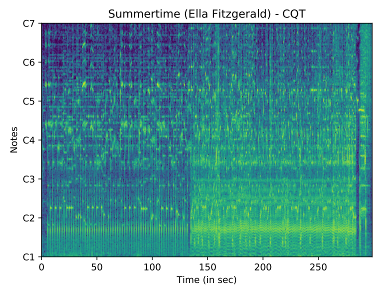
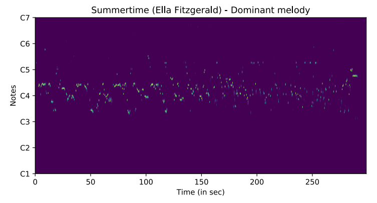
Recent studies addressed the automatic cover detection problem with the metric learning paradigm, using various input features:

full spectrum features

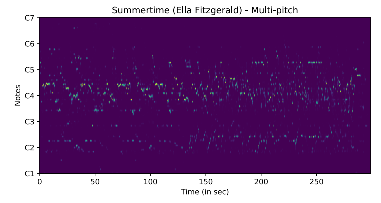


CQT [1]

melodic features

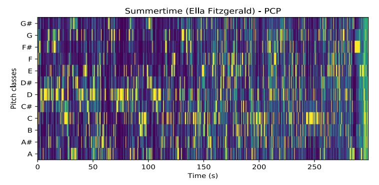


dominant melody [2]

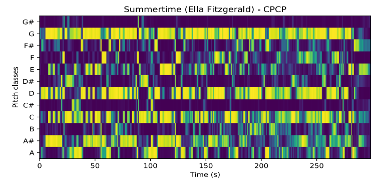


multi-pitch [3]

harmonic features

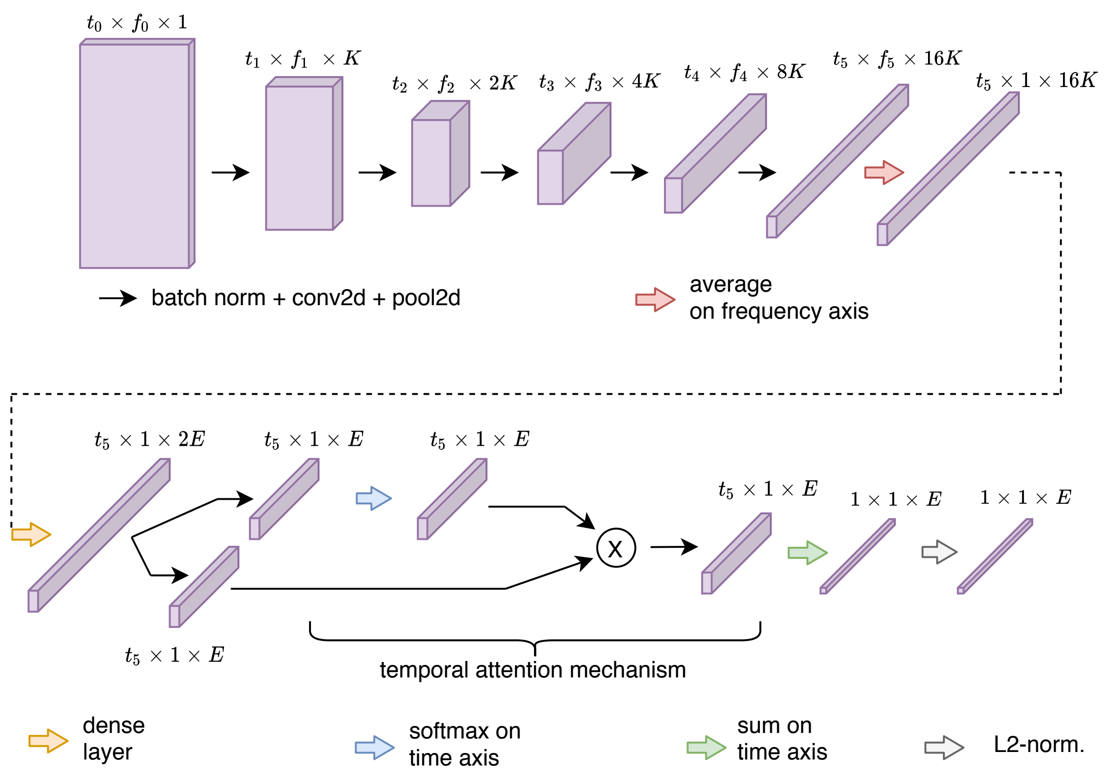


chroma [4]



Crema-PCP [5,6]

We compare these features with the same model using a time attention mechanism:

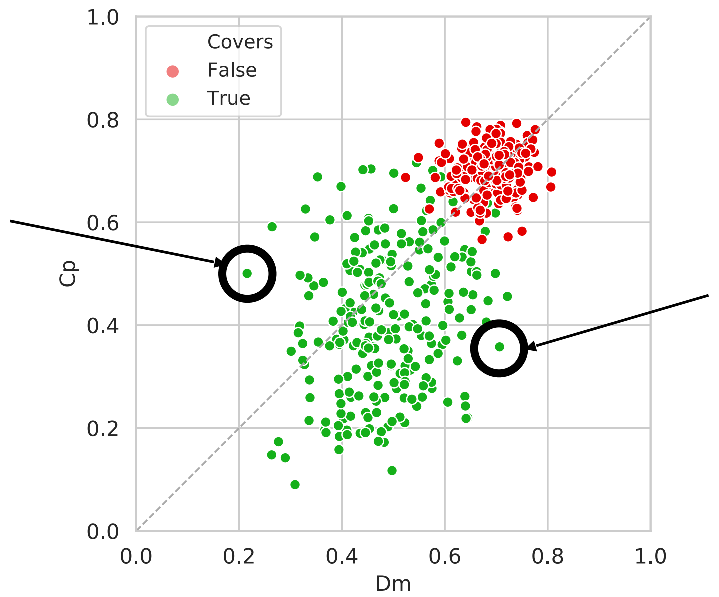

$t_0 \times f_0 \times 1$
$t_1 \times f_1 \times K$
$t_2 \times f_2 \times 2K$
$t_3 \times f_3 \times 4K$
$t_4 \times f_4 \times 8K$
$t_5 \times f_5 \times 16K$
$t_5 \times 1 \times 16K$
batch norm + conv2d + pool2d
average on frequency axis
$t_5 \times 1 \times 2E$
$t_5 \times 1 \times E$
$t_5 \times 1 \times E$
$t_5 \times 1 \times E$
$1 \times 1 \times E$
$1 \times 1 \times E$
$t_5 \times 1 \times E$
temporal attention mechanism
dense layer
softmax on time axis
sum on time axis
L2-norm.

➡ On two publicly available cover datasets, Crema-PCP — a harmonic feature — consistently yield the best results, followed by melodic features.

	Da-TACOS			SHS$_{4\text{-}}$		
Input	MAP	MT@10	MR1	MAP	MT@10	MR1
Cq	0.215	2.468	94	0.397	0.718	886
Dm	0.311	3.521	111	0.412	0.722	1431
Mp	0.293	3.290	**71**	0.422	0.760	**862**
Ch	0.121	1.476	117	0.174	0.371	1465
Cp	**0.375**	**4.084**	86	**0.499**	**0.842**	1169

(Cq = CQT, Dm = dominant melody, Mp = multi-pitch, Ch = chroma, Cp = CPCP)

These features do not encode the same information:



This cover pair obtains a high distance with the Crema-PCP (Cp), but not with the dominant melody (Dm).

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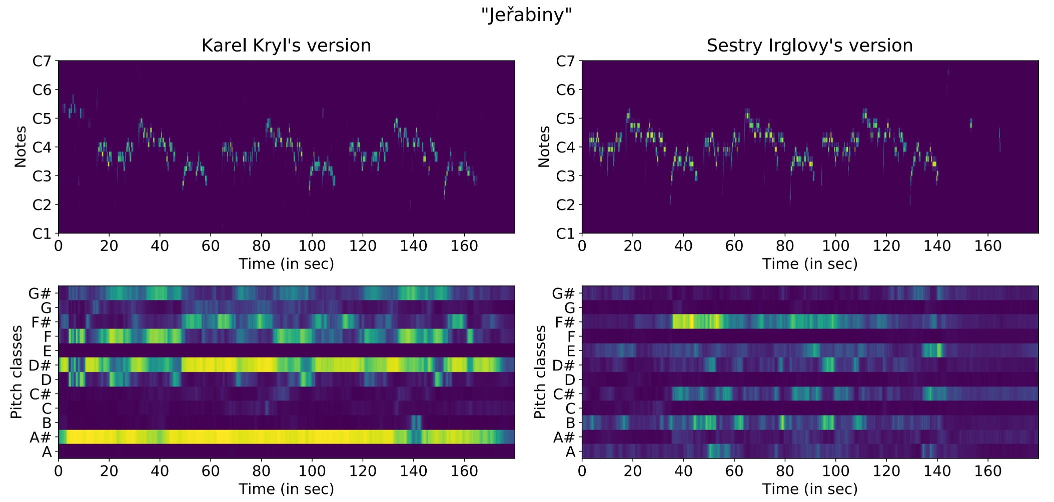
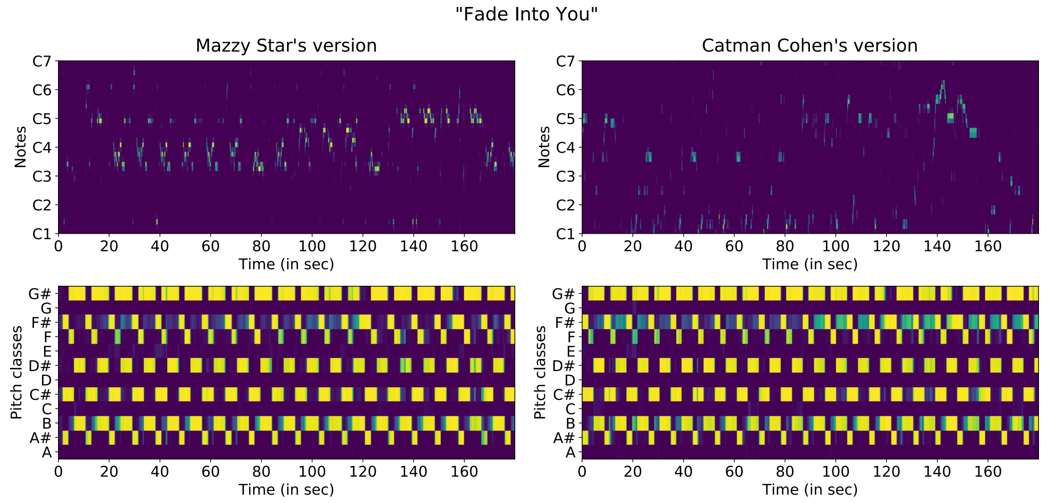
For instance, these two covers have a similar melody, but a different harmonic structure…



… while these two covers have a different melody, but a similar harmonic structure:



(see and listen to more examples on the Slack channel).

➡ This suggest that different features are complementary, and that merging them could benefit of this complementarity

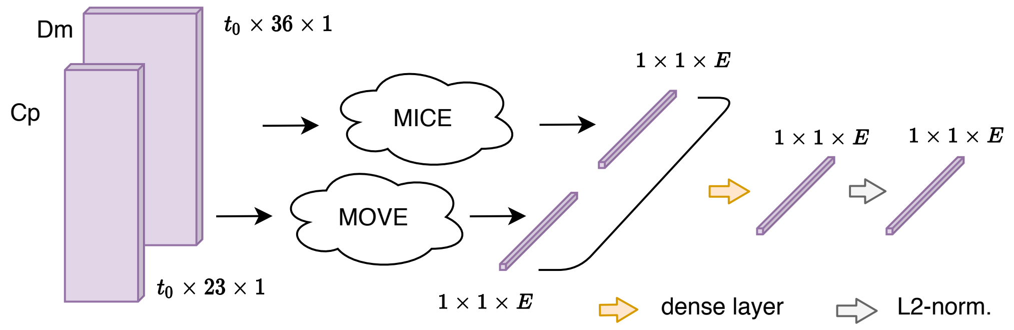
We combine these features with a simple averaging scheme — define each pair of songs (x, y) new distance as the average of their distances obtained for different features, e.g:

$$d(x,y) = \frac{d_{Dm}(x,y) + d_{Cp}(x,y)}{2}$$

➡ Combining dominant melody — a melodic feature and Crema-PCP — a harmonic feature — yields the best results.

Test set	Da-TACOS			SHS$_{4\text{-}}$		
Input	MAP	MT@10	MR1	MAP	MT@10	MR1
Cq+Dm	0.359	4.002	62	0.590	0.982	567
Cq+Mp	0.324	3.603	62	0.530	0.909	623
Cq+Cp	0.427	4.636	46	0.621	1.024	581
Dm+Mp	0.394	4.347	61	0.571	0.956	614
Dm+Cp	**0.547**	**5.861**	**37**	**0.679**	**1.098**	**529**
Mp+Cp	0.496	5.330	40	0.627	1.034	593

We also trained a new model to learn to combine these features:



➡ Combining musical features yields new SoA results:

	Da-TACOS			SHS$_{4-}$		
Input	MAP	MT@10	MR1	MAP	MT@10	MR1
Dm (MICE)	0.360	4.032	94	0.412	0.722	1431
Cp (MOVE)	0.484	5.214	59	0.533	0.890	1188
Dm+Cp (A)	0.621	6.613	32	**0.697**	**1.120**	**517**
Dm+Cp (LF-a)	0.570	6.101	**29**	0.617	1.017	686
Dm+Cp (LF-b)	0.592	6.318	32	0.655	1.059	655
Dm+Cp (LF-c)	**0.635**	**6.744**	30	0.660	1.080	657
Doras et al. [3]	n/a	n/a	n/a	0.323	0.615	1476
Yesiler et al. [6]	0.507	-	40	n/a	n/a	n/a

[1] Yu et al., "Learning a representation for cover song identification using convolutional neural network", ICASSP 2020
[2] Doras and Peeters, "Cover detection using dominant melody embeddings", ISMIR 2019
[3] Doras and Peeters, "A prototypical triplet loss for cover detection", ICASSP 2020
[4] Xu et al., "Key-invariant convolutional neural network toward efficient cover song identification", ICME 2019
[5] McFee and Bello, "Structured training for large-vocabulary chord recognition", ISMIR 2017
[6] Yesiler et al., "Accurate and scalable version identification using musically-motivated embeddings", ICASSP 2020