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Spotify Music Features

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Import Package

```
import pandas as pd  
import numpy as np  
import matplotlib.pyplot as plt  
import seaborn as sns
```

```
import spotipy  
import spotipy.util as util
```

```
pip install spotipy
```

Training

使用csv來訓練情緒的分類

```
df_feature_selected = df.drop(['f_name', 'a_name', 'title', 'lyrics', 'spot_id', 'sr_json', 'tr_json', "mood"], axis=1)
```

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	f_name	a_name	title	lyrics	spot_id	sr_json	tempo	energy	danceability	loudness	valence	acousticness	tr_json	mood
2	angry_all/50	PJ Harvey	50 Ft Queen	Hey I'm one	3fJprjhRxTV	{ "tracks": {	126.366	0.667	0.382	-16.077	0.718	0.000652	{	1
3	angry_all/A	Keane	A Bad Drea	Why do I ha	17ScnUBsr3	{ "tracks": {	145.035	0.76	0.405	-4.852	0.316	0.00824	{	1
4	angry_all/Ag	The Faint	Agenda Suic	You could fc	4Mhj9IjSxT	{ "tracks": {	144.585	0.703	0.574	-7.789	0.275	0.00658	{	1
5	angry_all/Al	Stiff Little F	Alternative U	There's nothi	0MDJjySh4	{ "tracks": {	118.181	0.925	0.6	-9.148	0.382	0.00882	{	1
6	angry_all/Ar	The Cranber	Animal Insti	Suddenly sor	3J58Coc5iTt	{ "tracks": {	132.145	0.823	0.622	-5.381	0.605	0.0946	{	1
7	angry_all/Bl	Living Sacrif	Bloodwork	A simple tes	4wmH0KK	{ "tracks": {	86.383	0.879	0.344	-5.111	0.479	0.000427	{	1
8	angry_all/Bc	Pixies	Bone Machin	(This is a sor	58BsY HaW	{ "tracks": {	115.906	0.678	0.63	-12.757	0.964	0.000677	{	1
9	angry_all/Bc	Ice Cube	Bop Gun	At these up	10oZiK5HCM	{ "tracks": {	103.05	0.837	0.891	-5.402	0.767	0.283	{	1
10	angry_all/Bc	Kaiser Chief	Boxing Chat	We went to	1r7XNA9Cz	{ "tracks": {	119.674	0.553	0.494	-4.848	0.296	0.962	{	1
11	angry_all/Br	Recoil	Breath Cont	Who wouldr	4CSyaZkuA	{ "tracks": {	162.002	0.645	0.58	-9.784	0.546	0.0609	{	1
12	angry_all/Br	Evanescence	Bring Me To	How can you	0COqiPhxz	{ "tracks": {	189.931	0.945	0.316	-3.169	0.32	0.00895	{	1
13	angry_all/Bu	Nine Inch N	Burn	This world r	0n CvBep0q	{ "tracks": {	89.919	0.912	0.592	-6.81	0.647	0.00146	{	1
14	angry_all/Ca	Kelis	Caught Out	Yo, this song	1nZkrUFLq	{ "tracks": {	92.996	0.691	0.848	-6.775	0.922	0.0512	{	1
15	angry_all/Ch	Ice Cube	Check Yo S	So come on	3NGT0Td7E	{ "tracks": {	101.368	0.735	0.934	-6.668	0.768	0.031	{	1

Fit to random forests

```
clf = RandomForestClassifier( min_samples_split=4, criterion="entropy" )
```

```
features_train, features_test, labels_train, labels_test = train_test_split( features, labels, test_size=0.20,  
random_state=91)
```

```
Test Accuracy: 0.848314606741573
```

```
-----  
Precision: 0.8506850837253214
```

```
Recall: 0.848314606741573
```

```
confusion matrix
```

```
[[63 9 3 4]
```

```
 [ 9 83 4 2]
```

```
 [ 4 1 69 4]
```

```
 [ 4 0 10 87]]
```

find the accuracy of the model

try other classifier

kNN 、 SVM 、 Decision Tree

Try other classifier

Random Forest Classifier ★

RandomForest Train Accuracy: 0.9823943661971831
RandomForest Test Accuracy: 0.8202247191011236

RandomForest Precision: 0.8210756861425652
RandomForest Recall: 0.8202247191011236
RandomForest confusion matrix
[[70 9 11 1]
[10 82 2 6]
[3 5 61 8]
[2 0 7 79]]

Decision Tree Classifier

DecisionTree Train Accuracy: 0.9929577464788732
DecisionTree Test Accuracy: 0.797752808988764

DecisionTree Precision: 0.8009008060227272
DecisionTree Recall: 0.797752808988764
DecisionTree confusion matrix
[[69 10 8 4]
[9 72 9 10]
[2 5 61 9]
[3 0 3 82]]

Support Vector Machines, SVM

SVM Train Accuracy: 0.676056338028169
SVM Test Accuracy: 0.5056179775280899

SVM Precision: 0.4998380210144346
SVM Recall: 0.5056179775280899
SVM confusion matrix
[[34 20 20 17]
[22 48 16 14]
[12 17 32 16]
[9 2 11 66]]

K Nearest Neighbor, kNN

kNN Train Accuracy: 0.652112676056338
kNN Test Accuracy: 0.5084269662921348

kNN Precision: 0.5111367785310117
kNN Recall: 0.5084269662921348
kNN confusion matrix
[[43 23 13 12]
[29 48 12 11]
[19 14 32 12]
[15 4 11 58]]



Try other classifier

AdaBoost Classifier

AdaBoost Train Accuracy: 0.5091549295774648

AdaBoost Test Accuracy: 0.46629213483146065

AdaBoost Precision: 0.4817275400870143

AdaBoost Recall: 0.46629213483146065

AdaBoost confusion matrix

[[38 15 18 20]

[17 55 10 18]

[7 7 37 26]

[10 12 30 36]]

Predict New Music

code for spotify get meta

```
username = 'qnwv65t11cplaz4dikhl4mjgi'  
CLIENT_ID = '07f9611e9b234caea4fcee288da82e61'  
CLIENT_SECRET = '087b1a26a1294bc58a0a89d4a29463e4'  
REDIRECT_URI = 'http://localhost/'  
SCOPE = 'user-library-read'
```

My Spotify

An innovative Spotify integration that does creative things.

Client ID 07f9611e9b234caea4fcee288da82e61

Client Secret 087b1a26a1294bc58a0a89d4a29463e4 **RESET**

HIDE CLIENT SECRET

Account overview

Profile

Username

qnwv65t11cplaz4dikhl4mjgi

Email

chiouchingyi@mail.nchu.edu.tw

Date of birth

1/21/96

Country

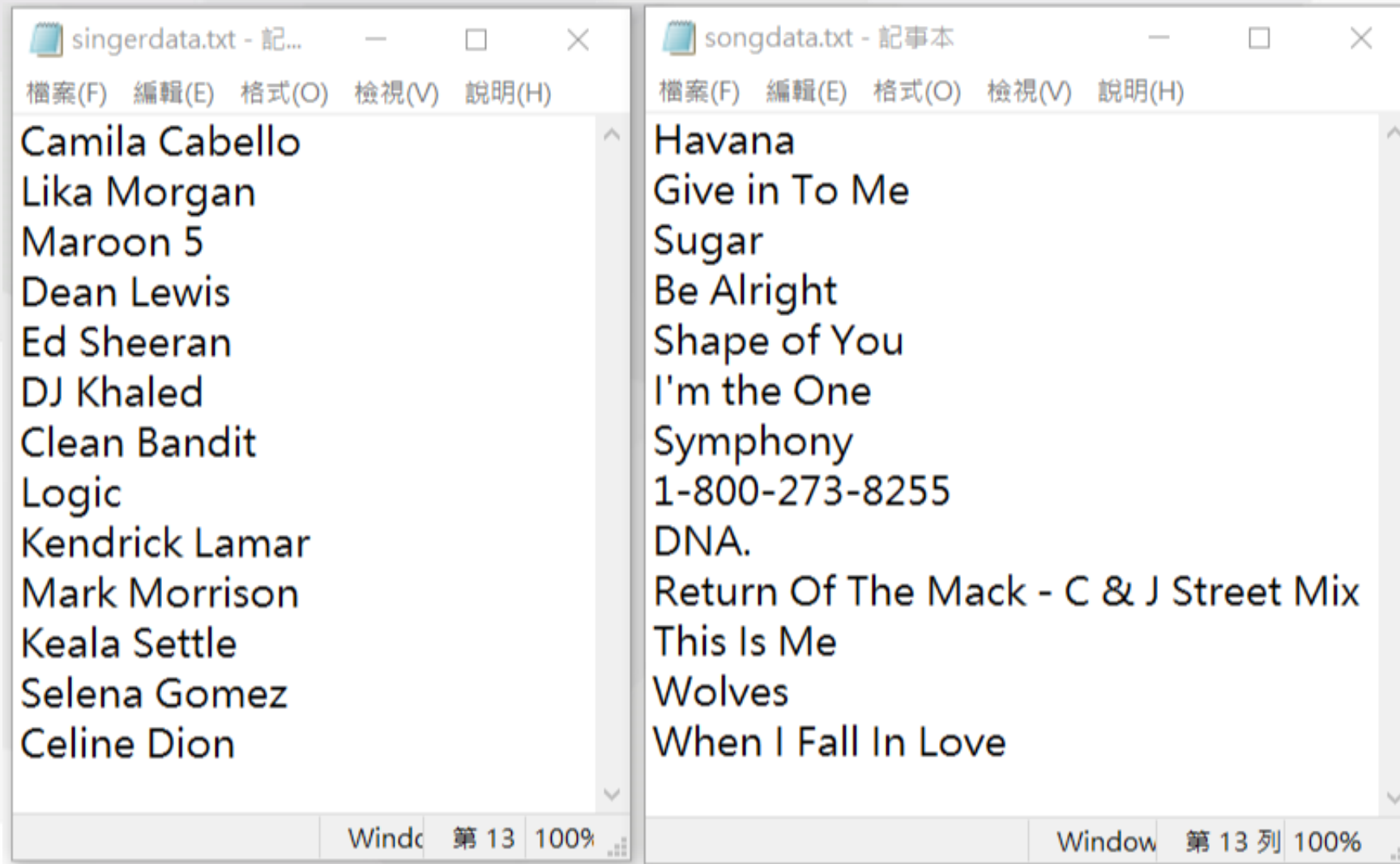
TW

Predict New Music

Spotify Features

[{'danceability': 0.674,	# 跳舞性 (tempo, rhythm stability, beat strength, and overall regularity)
'energy': 0.881,	# 強度
'key': 9,	# 調性 (0 = C 、 1 = C#/D \flat 、 2 = D ... · 沒偵測到=-1)
'loudness': -2.853,	# 音軌的總響度(dB)
'mode': 1,	# 模式 (0=小調minor 、 1=大調major)
'speechiness': 0.147,	# 音軌中存在的口語單詞
'acousticness': 0.296,	# acoustic (0-1之間)
'instrumentalness': 3.01e-06,	# 預測音軌包含人聲的程度
'liveness': 0.0793,	# 檢測錄製中是否有觀眾 (值越高代表是live)
'valence': 0.234,	# 音樂正向性 (值越高情緒越正面)
'tempo': 98.994,	# bpm (每秒幾拍)
'type': 'audio_features',	
'id': '5WHTFyqSii0ImT9R21abT8',	# 音樂ID
'uri': 'spotify:track:5WHTFyqSii0ImT9R21abT8',	# 音樂uri
'track_href': 'https://api.spotify.com/v1/tracks/5WHTFyqSii0ImT9R21abT8',	
'analysis_url': 'https://api.spotify.com/v1/audio-analysis/5WHTFyqSii0ImT9R21abT8',	
'duration_ms': 178480,	# 音軌時間長度(毫秒)
'time_signature': 4}]	# 拍號 (每一小節有多少拍)

Predict New Music



Predict New Music

Table = [['Song Name', ' Singer', 'tempo', 'energy', 'loudness', 'danceability', 'valence', 'acousticness', 'happy', 'angry', 'sad', 'relax', 'Mood Class']]

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Havana	Camila Cabello	104.988	0.523	-4.333	0.765	0.394	0.184	12	51.33333	36.66667	0	1
2	Give in To Me	Lil Nas X	124.071	0.871	-4.069	0.769	0.672	0.0873	45	10	35	10	0
3	Sugar	Maroon 5	120.076	0.788	-7.055	0.748	0.884	0.0591	20	16	34	30	2
4	Be Alright	Dean Lewis	126.684	0.586	-6.319	0.553	0.443	0.697	23.33333	22.66667	22.5	31.5	3
5	Shape of You	Ed Sheeran	95.977	0.652	-3.183	0.825	0.931	0.581	20	40	30	10	1
6	"I'm the One"	DJ Khaled	80.924	0.668	-4.284	0.609	0.811	0.0552	5.714286	26	58.28571	10	2
7	Symphony	Clean Bandit	122.863	0.629	-4.581	0.707	0.457	0.259	5.714286	40	34.28571	20	1
8	1-800-273	Logic	100.021	0.574	-7.788	0.62	0.352	0.57	15	41.66667	20	23.33333	1
9	DNA.	Kendrick Lamar	139.913	0.523	-6.664	0.638	0.422	0.00454	6	14	60	20	2
10	Return Of The 3K	Mark Morano	95.487	0.833	-5.379	0.715	0.612	0.00631	25.71429	6	38.28571	30	2
11	This Is Me	Keala Settle	191.702	0.704	-7.276	0.284	0.1	0.00583	10	6	64	20	2
12	Wolves	Selena Gomez	124.946	0.807	-4.59	0.72	0.305	0.129	15.71429	10	44.28571	30	2
13	When I Fall Asleep	Celine Dion	68.353	0.241	-13.251	0.19	0.107	0.577	56.66667	0	43.33333	0	0

Song Name
Singer

6 features

percent of 4 emotion

emotion
result

Problems

yourOutputTest.csv

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Havana	Camila Ca	104.988	0.523	-4.333	0.765	0.394	0.184	12	51.33333	36.66667	0	1
2	Give in To	Lika Morg	124.071	0.871	-4.069	0.769	0.672	0.0873	45	10	35	10	0
3	Sugar	Maroon 5	120.076	0.788	-7.055	0.748	0.884	0.0591	20	16	34	30	2
4	Be Alright	Dean Lew	126.684	0.586	-6.319	0.553	0.443	0.697	23.33333	22.66667	22.5	31.5	3
5	Shape of M	Ed Sheera	95.977	0.652	-3.183	0.825	0.931	0.581	20	40	30	10	1
6	"Im the O	DJ Khalec	80.924	0.668	-4.284	0.609	0.811	0.0552	5.714286	26	58.28571	10	2
7	Symphony	Clean Ban	122.863	0.629	-4.581	0.707	0.457	0.259	5.714286	40	34.28571	20	1
8	1-800-273	Logic	100.021	0.574	-7.788	0.62	0.352	0.57	15	41.66667	20	23.33333	1
9	DNA.	Kendrick L	139.913	0.523	-6.664	0.638	0.422	0.00454	6	14	60	20	2
10	Return Of	Mark Mor	95.487	0.833	-5.379	0.715	0.612	0.00631	25.71429	6	38.28571	30	2
11	This Is Me	Keala Sett	191.702	0.704	-7.276	0.284	0.1	0.00583	10	6	64	20	2
12	Wolves	Selena Go	124.946	0.807	-4.59	0.72	0.305	0.129	15.71429	10	44.28571	30	2
13	When I Fa	Celine Dic	68.353	0.241	-13.251	0.19	0.107	0.577	56.66667	0	43.33333	0	0

yourOutputTest2.csv

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Havana	Camila Ca	104.988	0.523	-4.333	0.765	0.394	0.184	35	40	2.5	22.5	1
2	Give in To	Lika Morg	124.071	0.871	-4.069	0.769	0.672	0.0873	25	45	12.5	17.5	1
3	Sugar	Maroon 5	120.076	0.788	-7.055	0.748	0.884	0.0591	23.33333	20	26.66667	30	3
4	Be Alright	Dean Lew	126.684	0.586	-6.319	0.553	0.443	0.697	56	4	20	20	0
5	Shape of M	Ed Sheera	95.977	0.652	-3.183	0.825	0.931	0.581	30.83333	26.66667	32.5	10	2
6	"Im the O	DJ Khalec	80.924	0.668	-4.284	0.609	0.811	0.0552	20	68	12	0	1
7	Symphony	Clean Ban	122.863	0.629	-4.581	0.707	0.457	0.259	25	50	25	0	1
8	1-800-273	Logic	100.021	0.574	-7.788	0.62	0.352	0.57	49.33333	14	33.33333	3.333333	0
9	DNA.	Kendrick L	139.913	0.523	-6.664	0.638	0.422	0.00454	15	33	32	20	1
10	Return Of	Mark Mor	95.487	0.833	-5.379	0.715	0.612	0.00631	33.33333	20	36.66667	10	2
11	This Is Me	Keala Sett	191.702	0.704	-7.276	0.284	0.1	0.00583	30	0	50	20	2
12	Wolves	Selena Go	124.946	0.807	-4.59	0.72	0.305	0.129	40	50	10	0	1
13	When I Fa	Celine Dic	68.353	0.241	-13.251	0.19	0.107	0.577	15	0	55	30	2

解決：np.random.seed(1)
每一次跑出來都一樣

Music Dataset

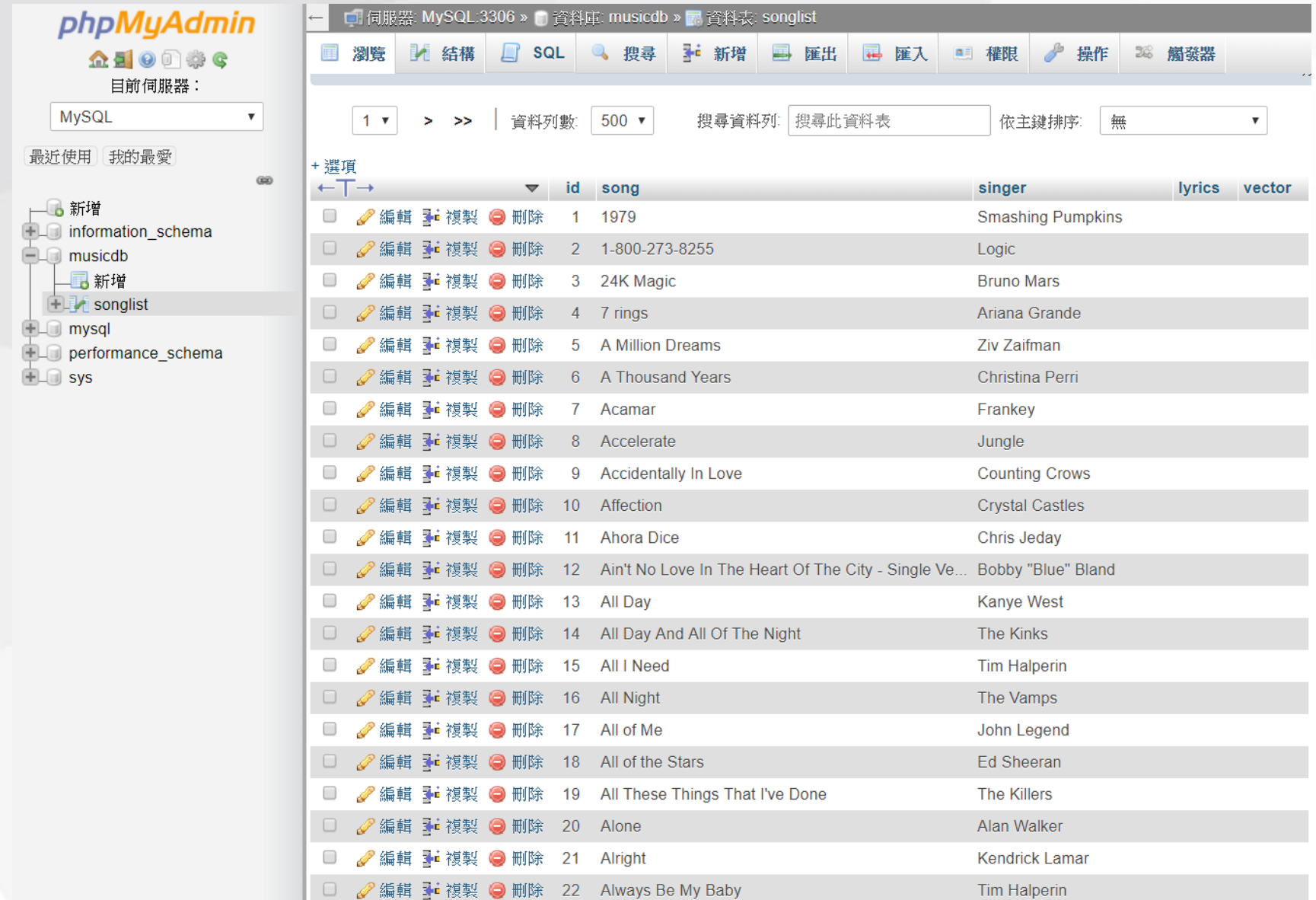
Happy : 117

Angry : 134

Sad : 177

Relax : 122

Total : 550



	id	song	singer	lyrics	vector
<input type="checkbox"/>	1	1979	Smashing Pumpkins		
<input type="checkbox"/>	2	1-800-273-8255	Logic		
<input type="checkbox"/>	3	24K Magic	Bruno Mars		
<input type="checkbox"/>	4	7 rings	Ariana Grande		
<input type="checkbox"/>	5	A Million Dreams	Ziv Zaifman		
<input type="checkbox"/>	6	A Thousand Years	Christina Perri		
<input type="checkbox"/>	7	Acamar	Frankey		
<input type="checkbox"/>	8	Accelerate	Jungle		
<input type="checkbox"/>	9	Accidentally In Love	Counting Crows		
<input type="checkbox"/>	10	Affection	Crystal Castles		
<input type="checkbox"/>	11	Ahora Dice	Chris Jeday		
<input type="checkbox"/>	12	Ain't No Love In The Heart Of The City - Single Ve...	Bobby "Blue" Bland		
<input type="checkbox"/>	13	All Day	Kanye West		
<input type="checkbox"/>	14	All Day And All Of The Night	The Kinks		
<input type="checkbox"/>	15	All I Need	Tim Halperin		
<input type="checkbox"/>	16	All Night	The Vamps		
<input type="checkbox"/>	17	All of Me	John Legend		
<input type="checkbox"/>	18	All of the Stars	Ed Sheeran		
<input type="checkbox"/>	19	All These Things That I've Done	The Killers		
<input type="checkbox"/>	20	Alone	Alan Walker		
<input type="checkbox"/>	21	Alright	Kendrick Lamar		
<input type="checkbox"/>	22	Always Be My Baby	Tim Halperin		

Music Dataset

<input type="checkbox"/>	 編輯	 複製	 刪除	1	1979	Smashing Pumpkins
<input type="checkbox"/>	 編輯	 複製	 刪除	2	1-800-273-8255	Logic
<input type="checkbox"/>	 編輯	 複製	 刪除	3	24K Magic	Bruno Mars
<input type="checkbox"/>	 編輯	 複製	 刪除	4	7 rings	Ariana Grande
<input type="checkbox"/>	 編輯	 複製	 刪除	5	A Million Dreams	Ziv Zaifman
<input type="checkbox"/>	 編輯	 複製	 刪除	6	A Thousand Years	Christina Perri
<input type="checkbox"/>	 編輯	 複製	 刪除	7	Acamar	Frankey
<input type="checkbox"/>	 編輯	 複製	 刪除	8	Accelerate	Jungle
<input type="checkbox"/>	 編輯	 複製	 刪除	9	Accidentally In Love	Counting Crows
<input type="checkbox"/>	 編輯	 複製	 刪除	10	Affection	Crystal Castles
<input type="checkbox"/>	 編輯	 複製	 刪除	11	Ahora Dice	Chris Jeday
<input type="checkbox"/>	 編輯	 複製	 刪除	12	Ain't No Love In The Heart Of The City	Bobby "Blue" Bland
<input type="checkbox"/>	 編輯	 複製	 刪除	13	All Day	Kanye West
<input type="checkbox"/>	 編輯	 複製	 刪除	14	All Day And All Of The Night	The Kinks
<input type="checkbox"/>	 編輯	 複製	 刪除	15	All I Need	Tim Halperin
<input type="checkbox"/>	 編輯	 複製	 刪除	16	All Night	The Vamps
<input type="checkbox"/>	 編輯	 複製	 刪除	17	All of Me	John Legend
<input type="checkbox"/>	 編輯	 複製	 刪除	18	All of the Stars	Ed Sheeran
<input type="checkbox"/>	 編輯	 複製	 刪除	19	All These Things That I've Done	The Killers
<input type="checkbox"/>	 編輯	 複製	 刪除	20	Alone	Alan Walker
<input type="checkbox"/>	 編輯	 複製	 刪除	21	Alright	Kendrick Lamar
<input type="checkbox"/>	 編輯	 複製	 刪除	22	Always Be My Baby	Tim Halperin
<input type="checkbox"/>	 編輯	 複製	 刪除	23	Always Remember Us This Way	Lady Gaga
<input type="checkbox"/>	 編輯	 複製	 刪除	24	Amazing	Westlife
<input type="checkbox"/>	 編輯	 複製	 刪除	25	Amsterdam	Coldplay

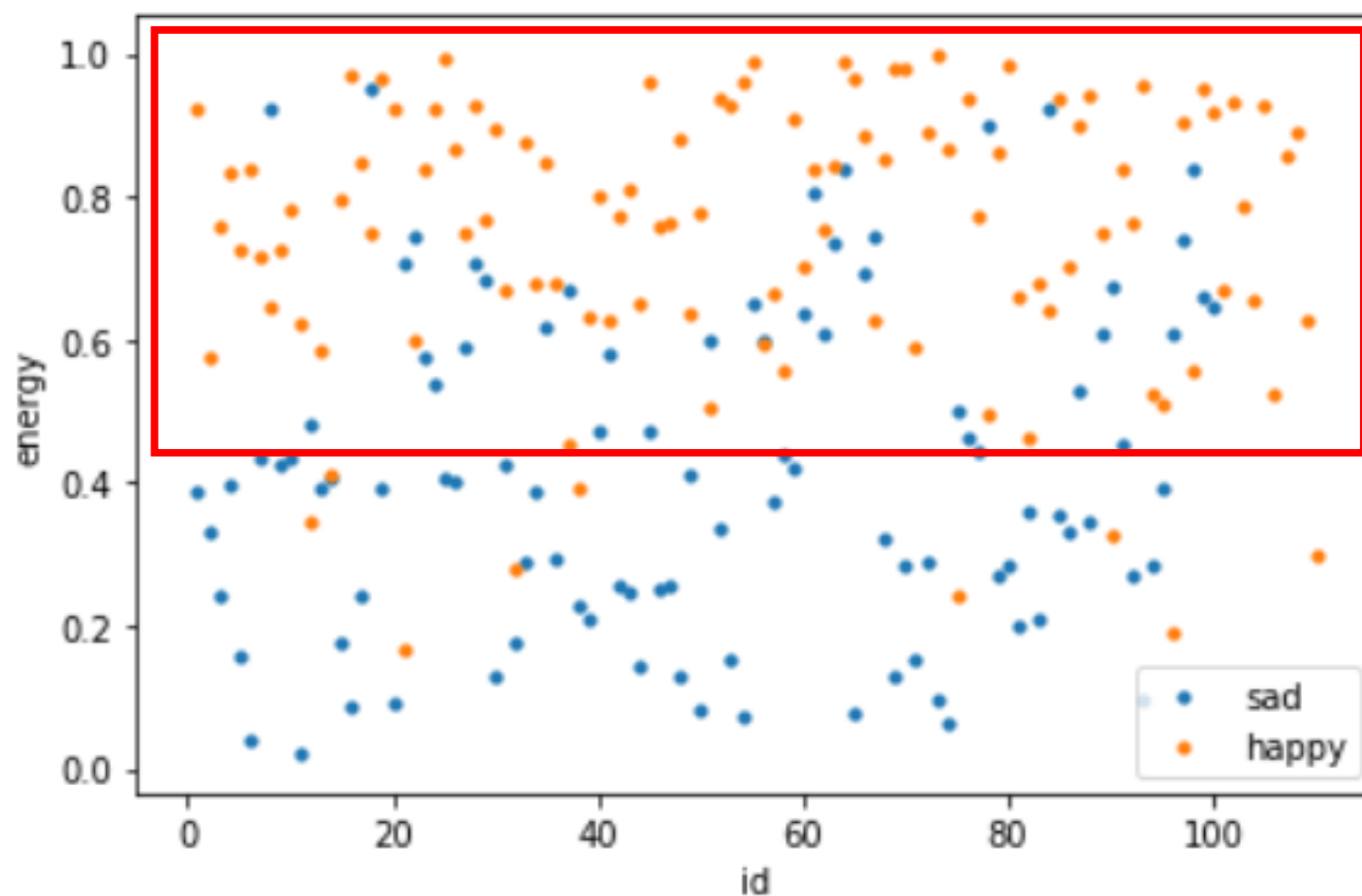
songdata7_0408.txt

singerdata7_0408.txt

移除歌名有feat等等

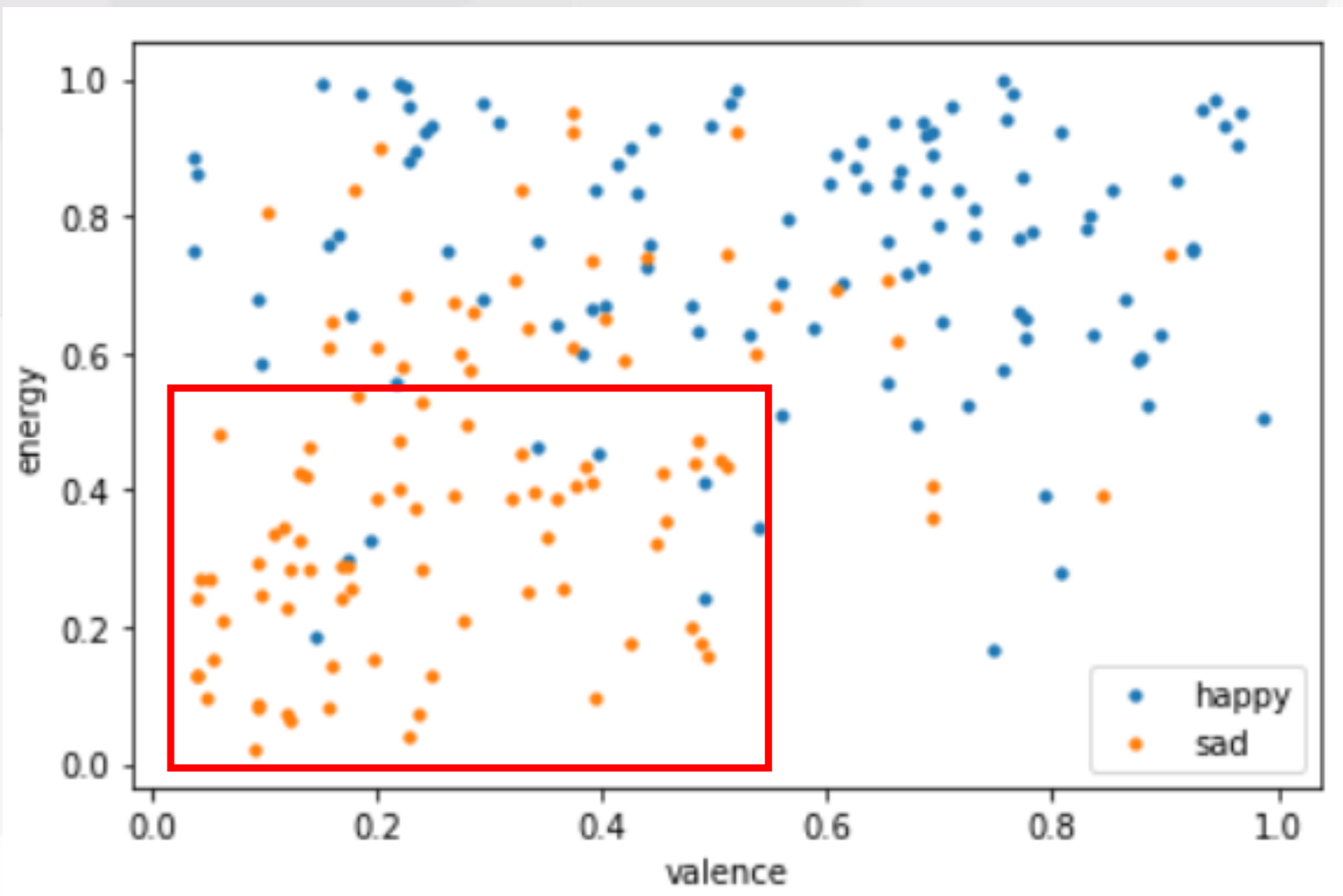
yourOutput_0408.csv

Features Analyze



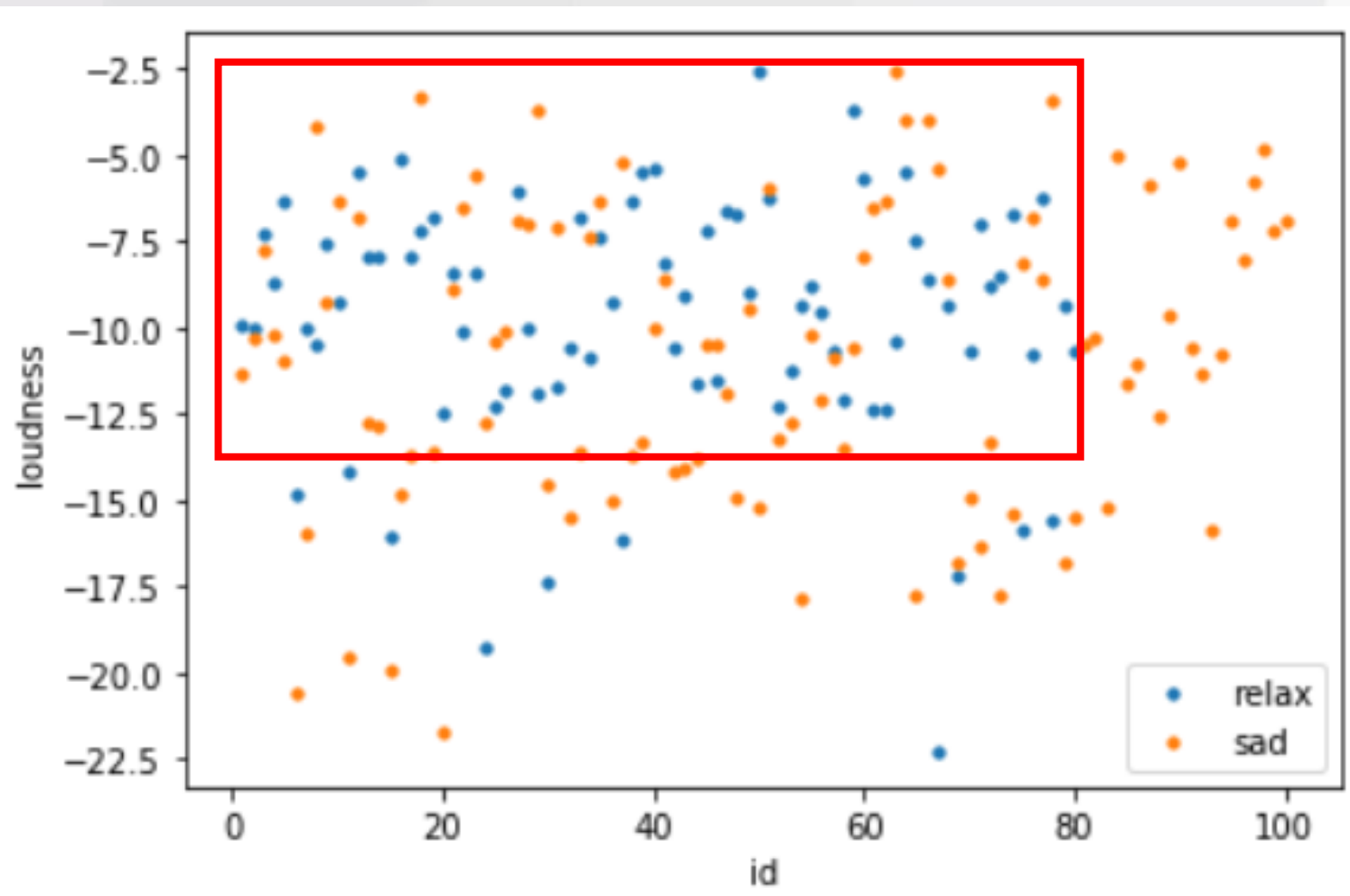
happy → energy高 / sad → energy低

Features Analyze



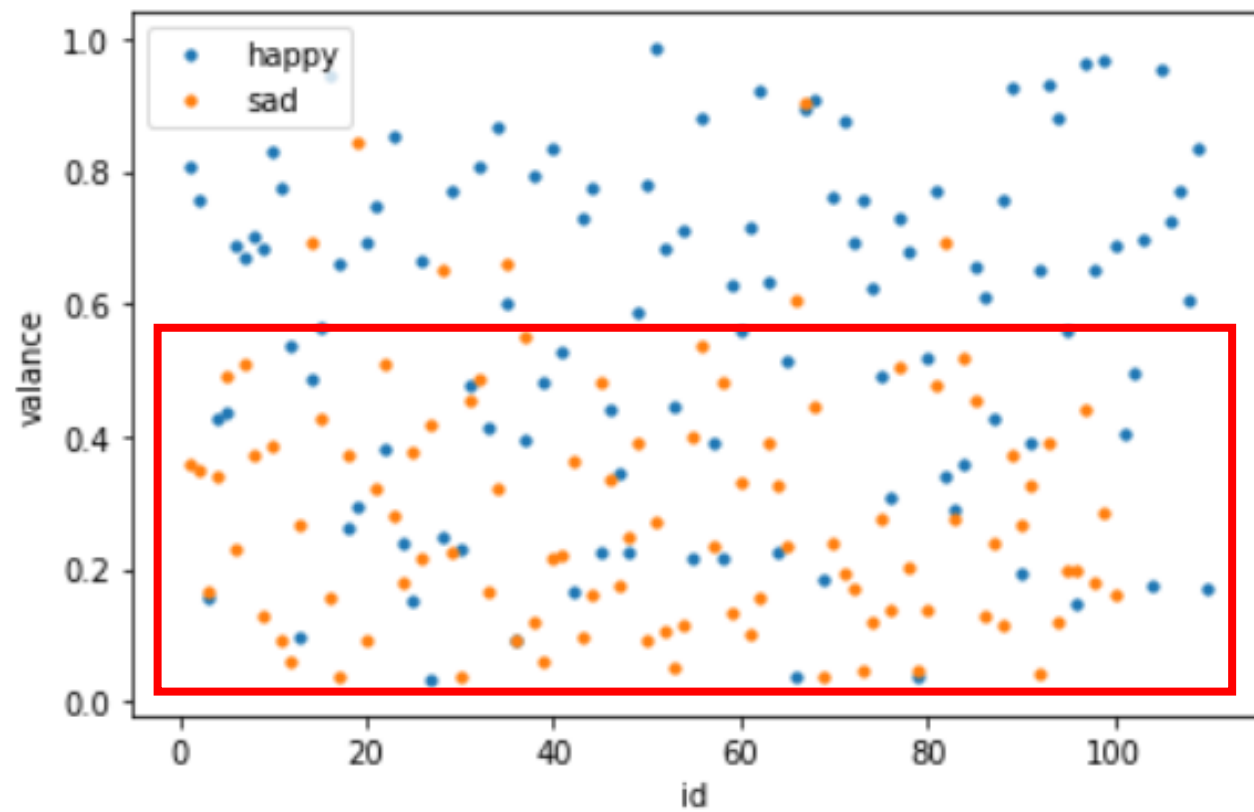
sad → valence低、energy低

Features Analyze

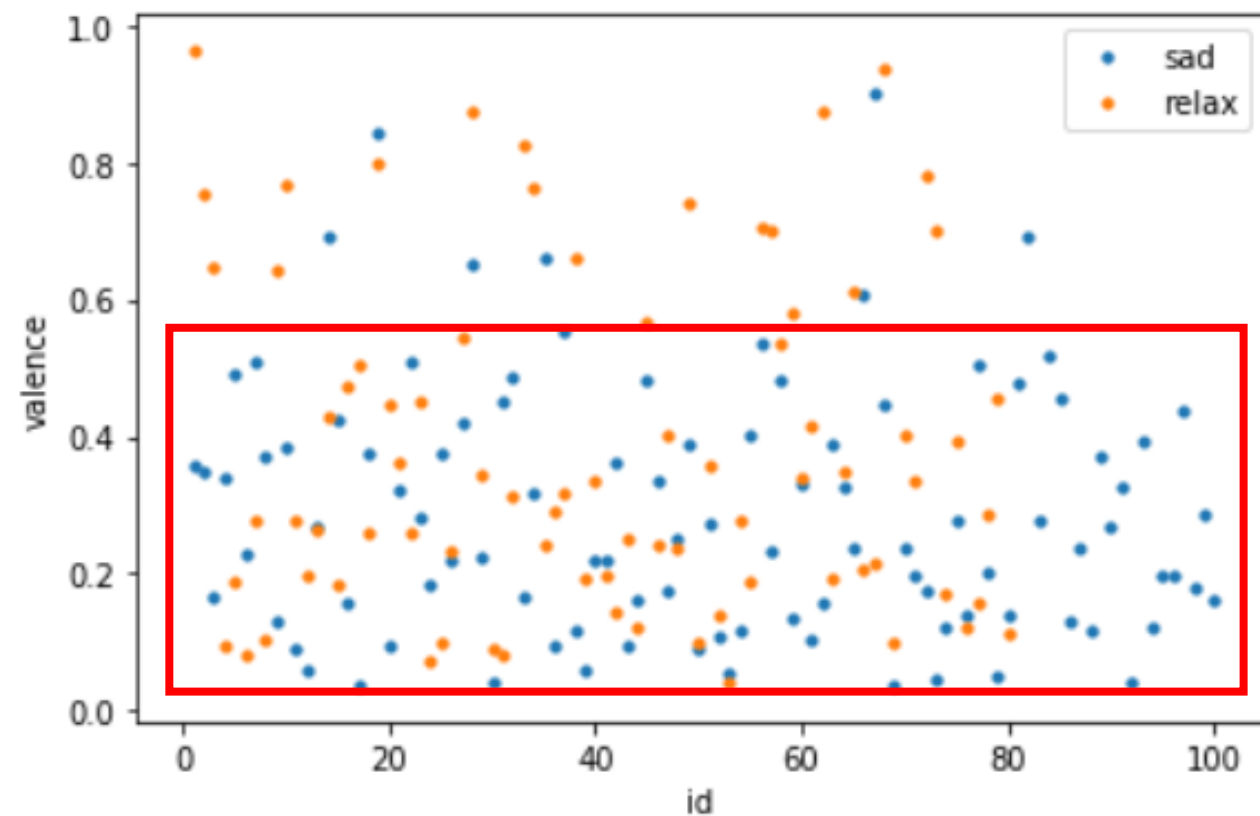


relax → loudness大

Features Analyze

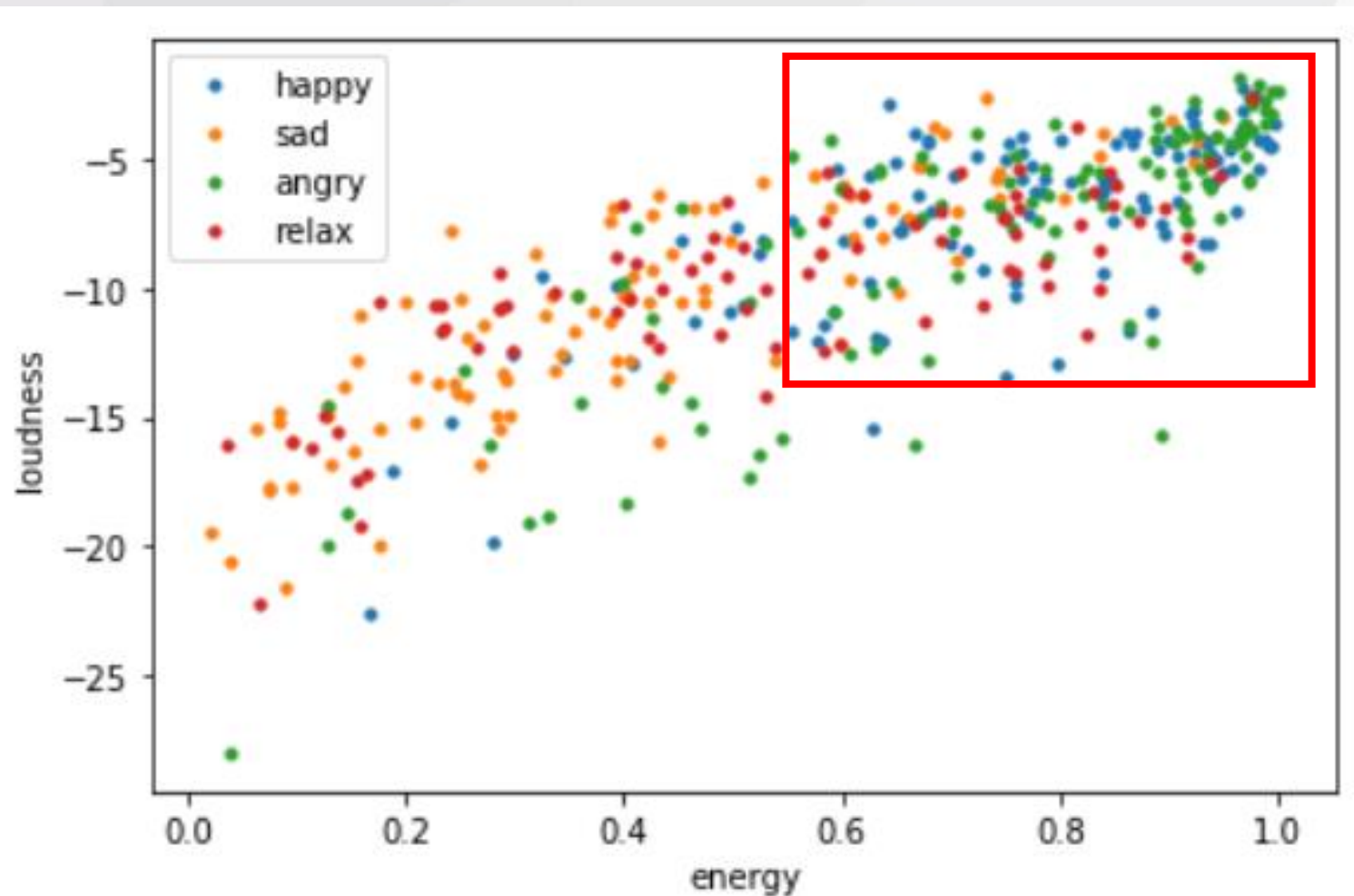


sad \rightarrow valence低



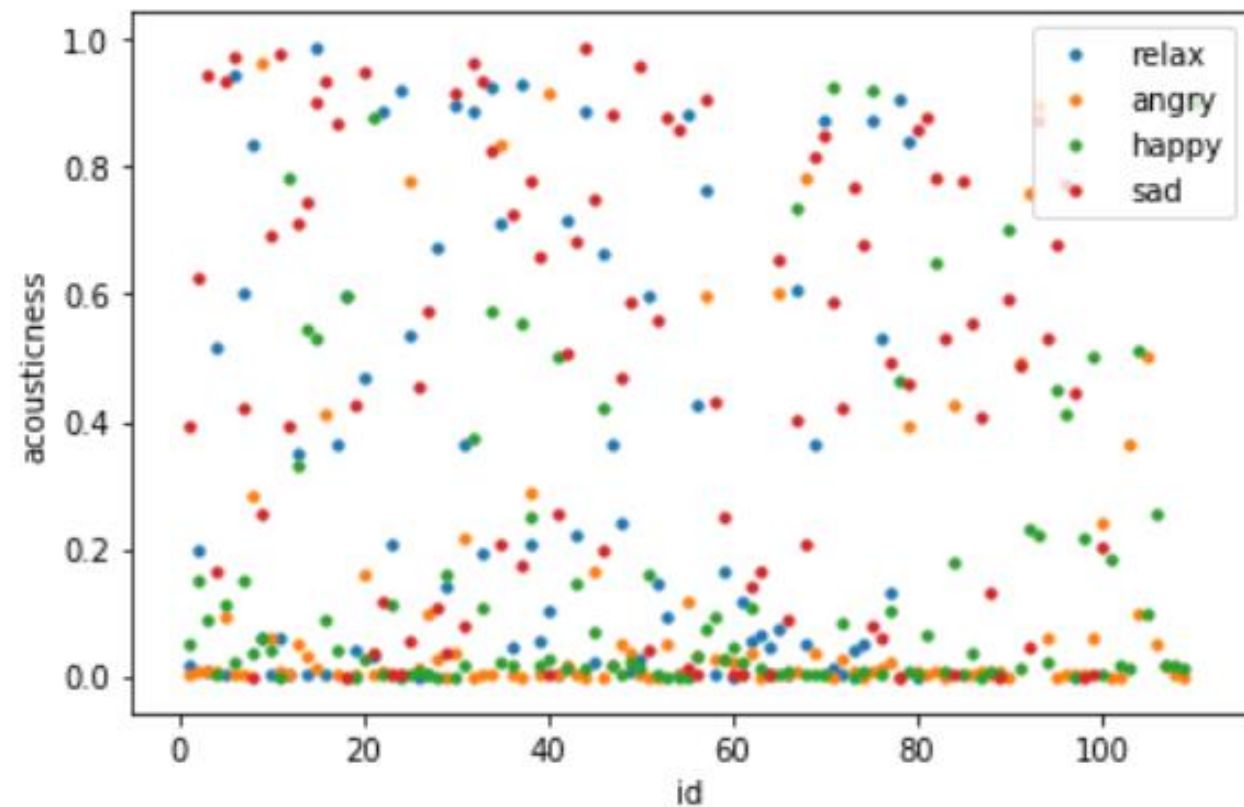
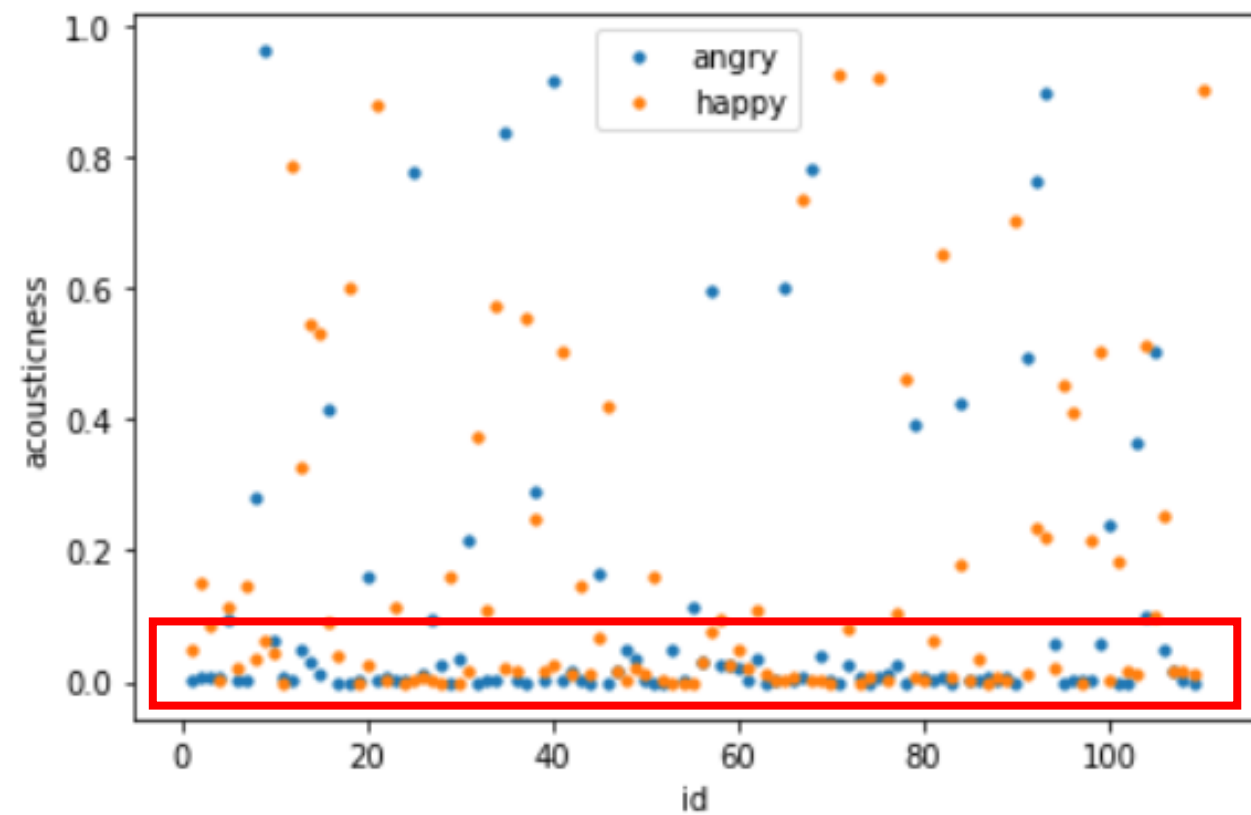
sad 、 relax \rightarrow valence低

Features Analyze



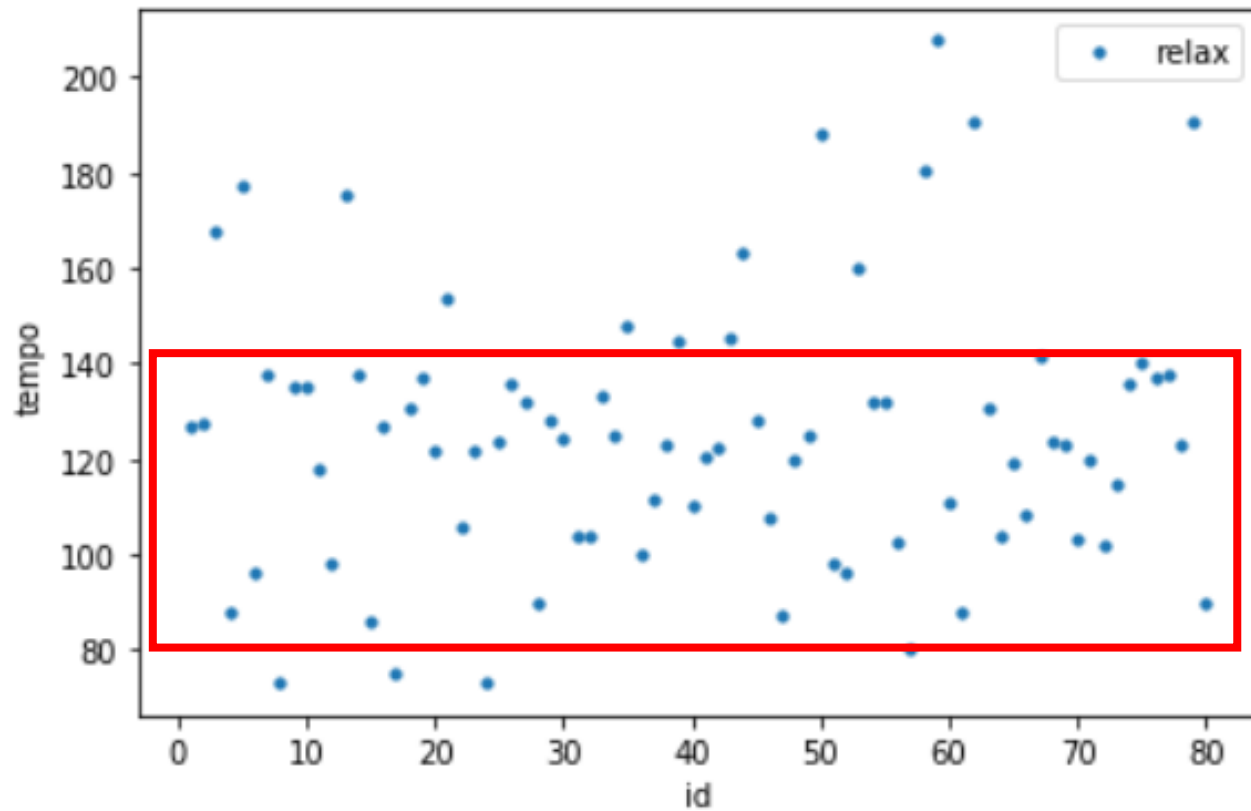
happy、angry → energy高、loudness大

Features Analyze

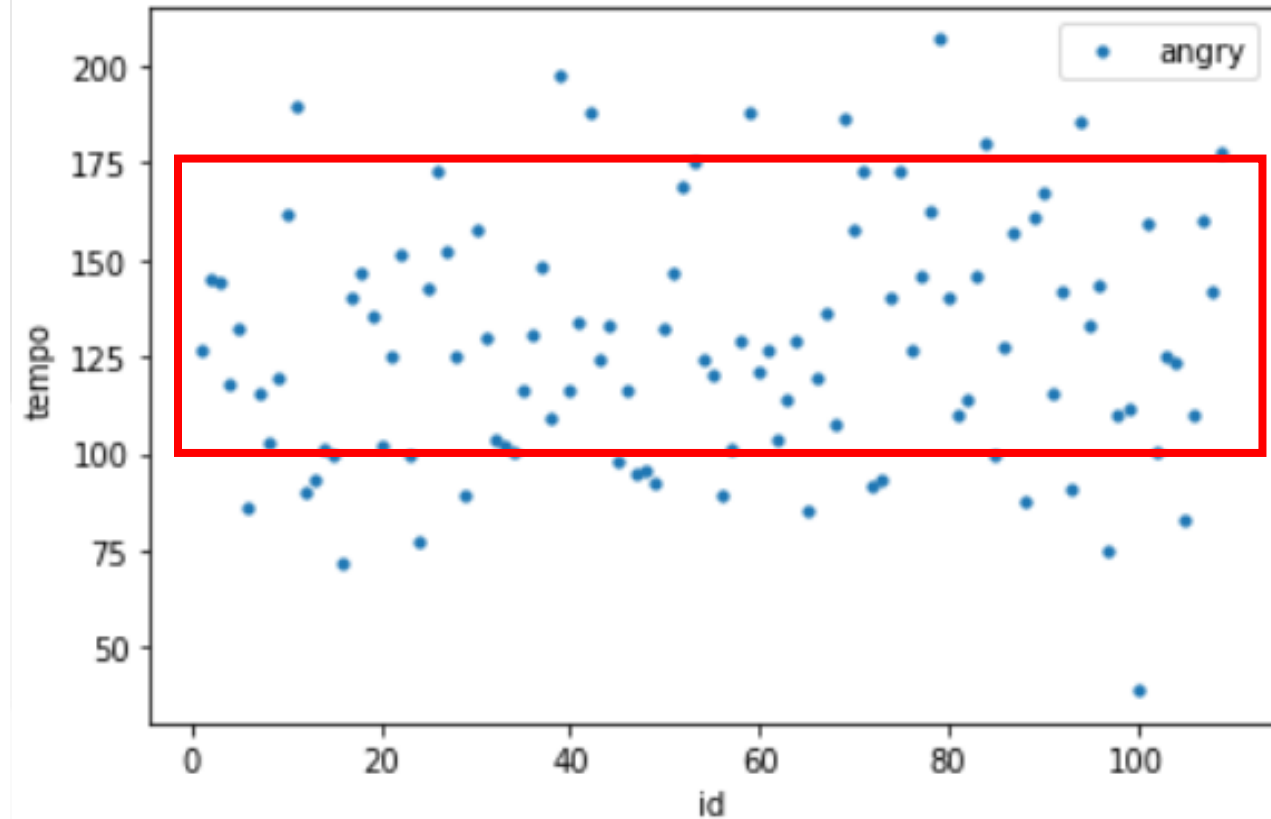


angry 、 happy \rightarrow acousticness低

Features Analyze



relax → tempo(80-140)



angry → tempo(100-175)



Features Analyze

sad → valence低、energy低

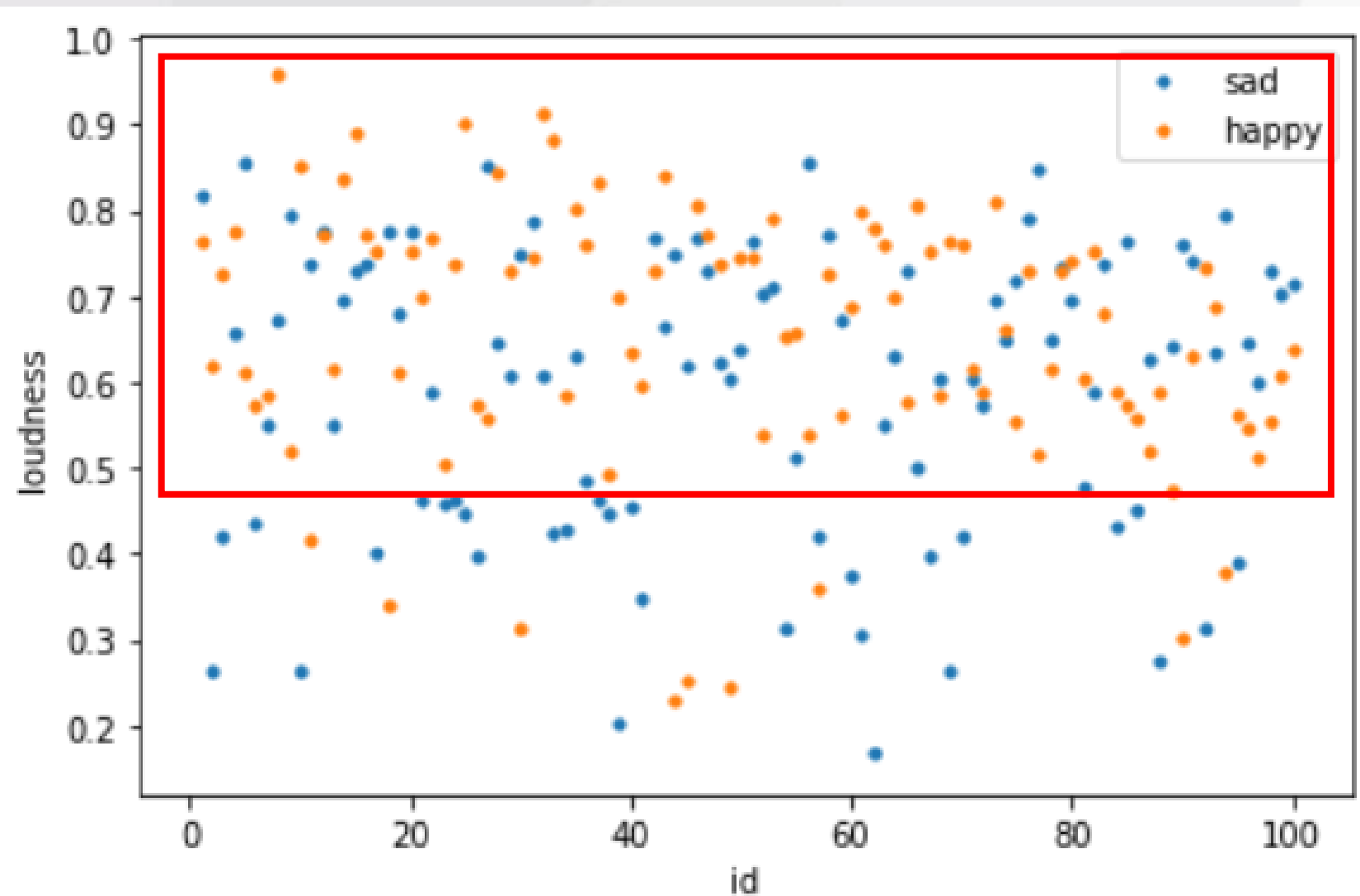
relax → loudness大、tempo(80-140)

happy、angry → energy高、loudness大、acousticness低

angry → tempo(100-175)

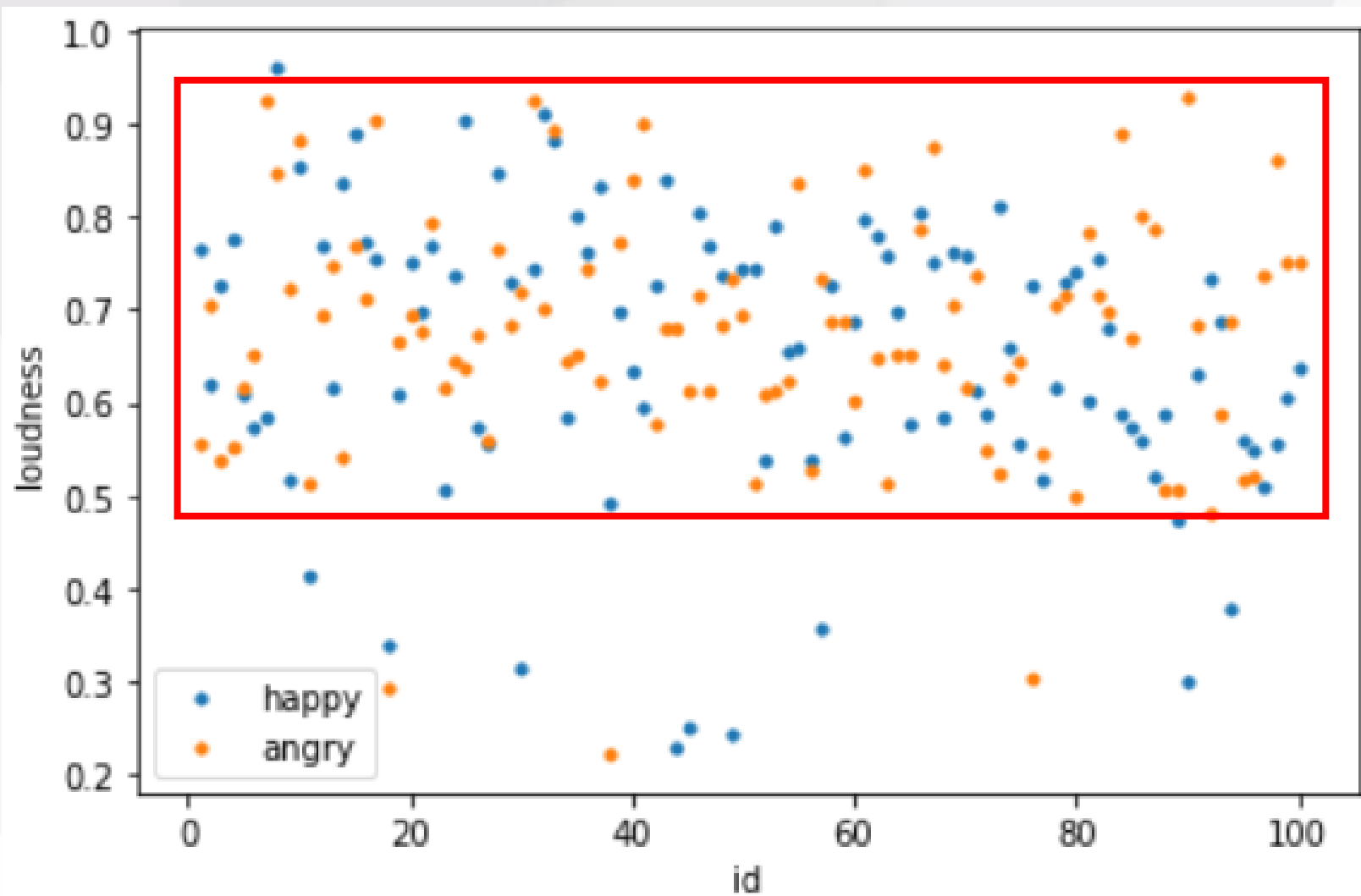
angry、happy 區分？

Features Analyze



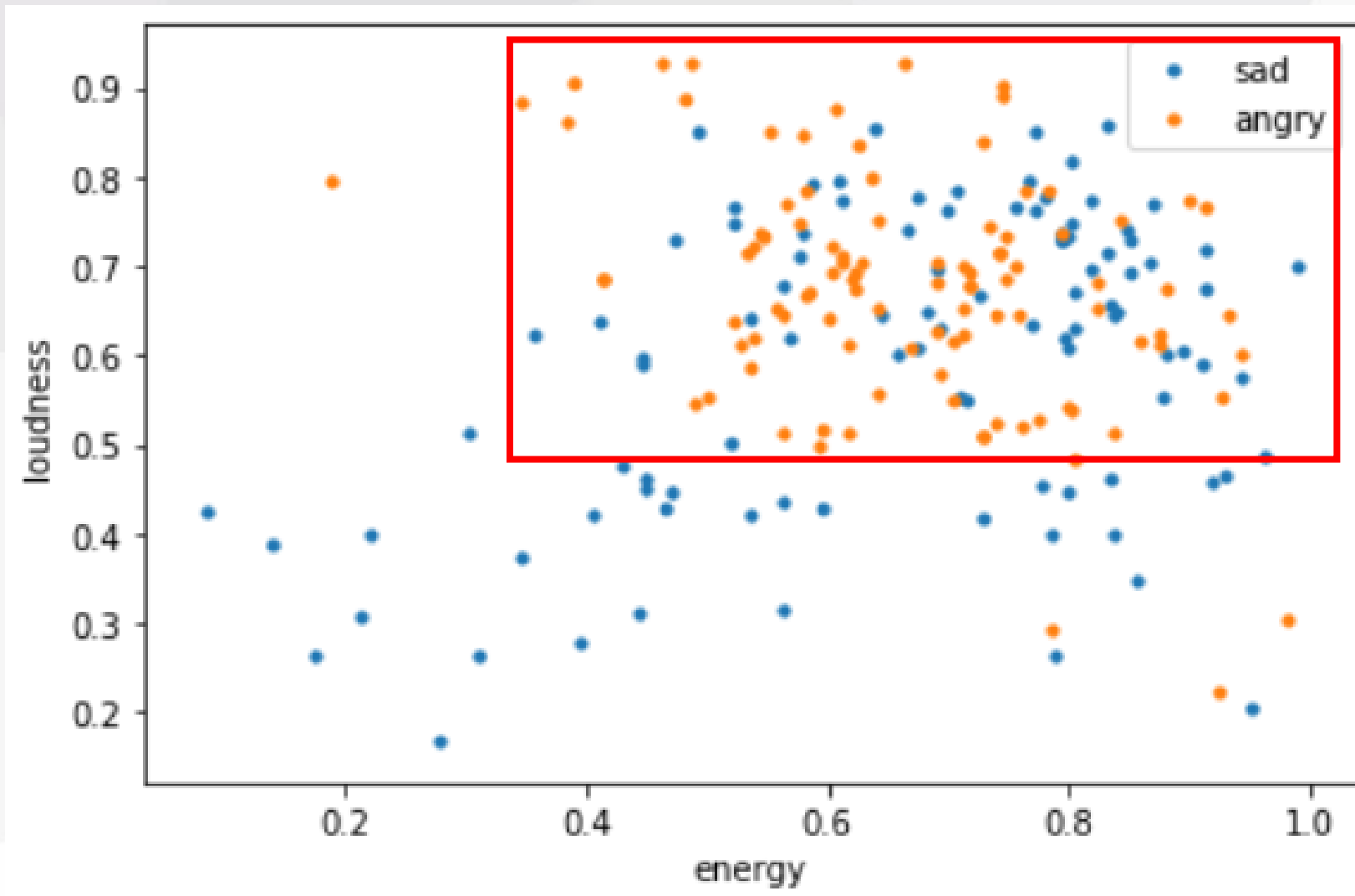
happy → loudness大

Features Analyze



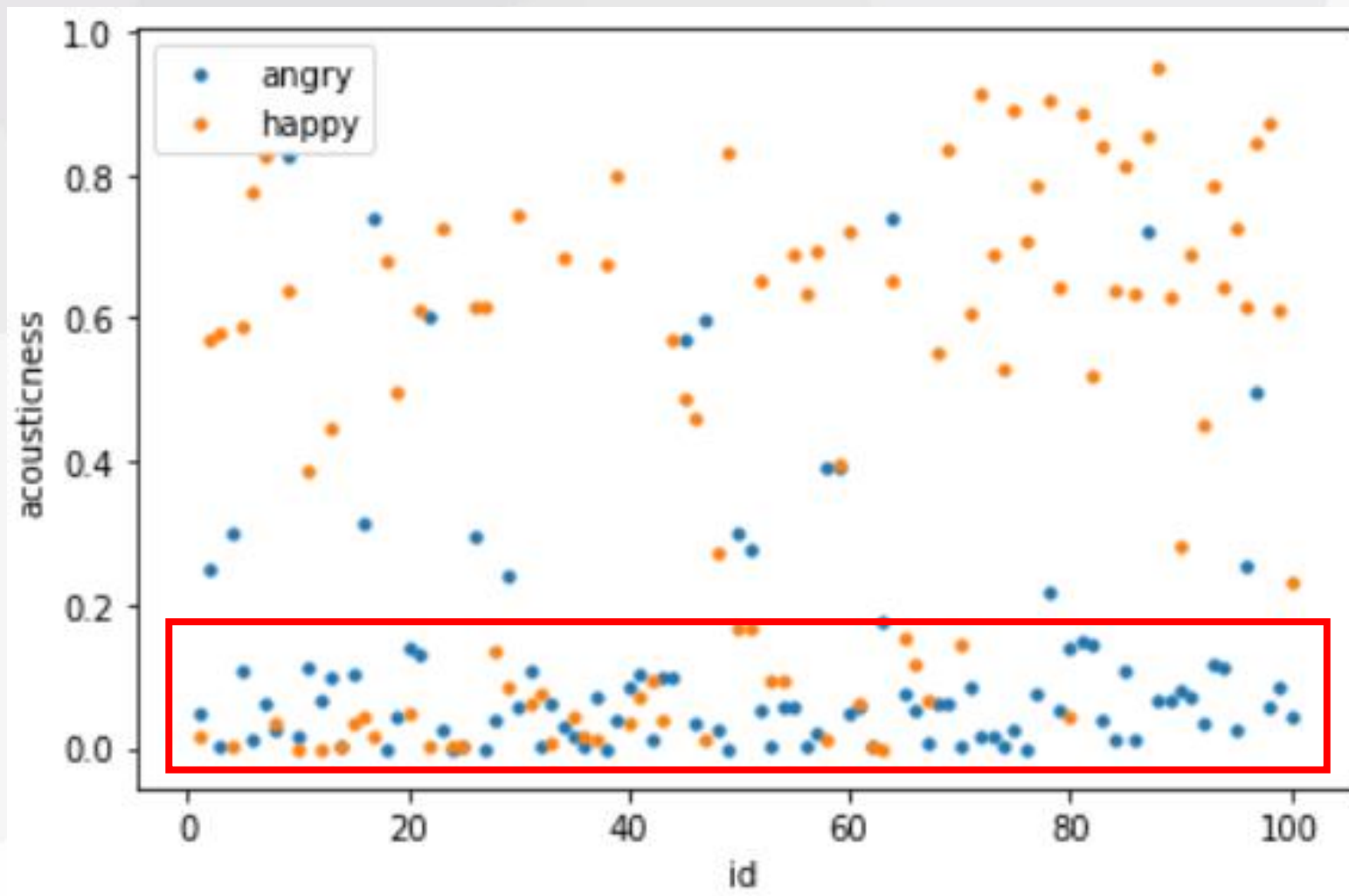
happy 、 angry → loudness大

Features Analyze



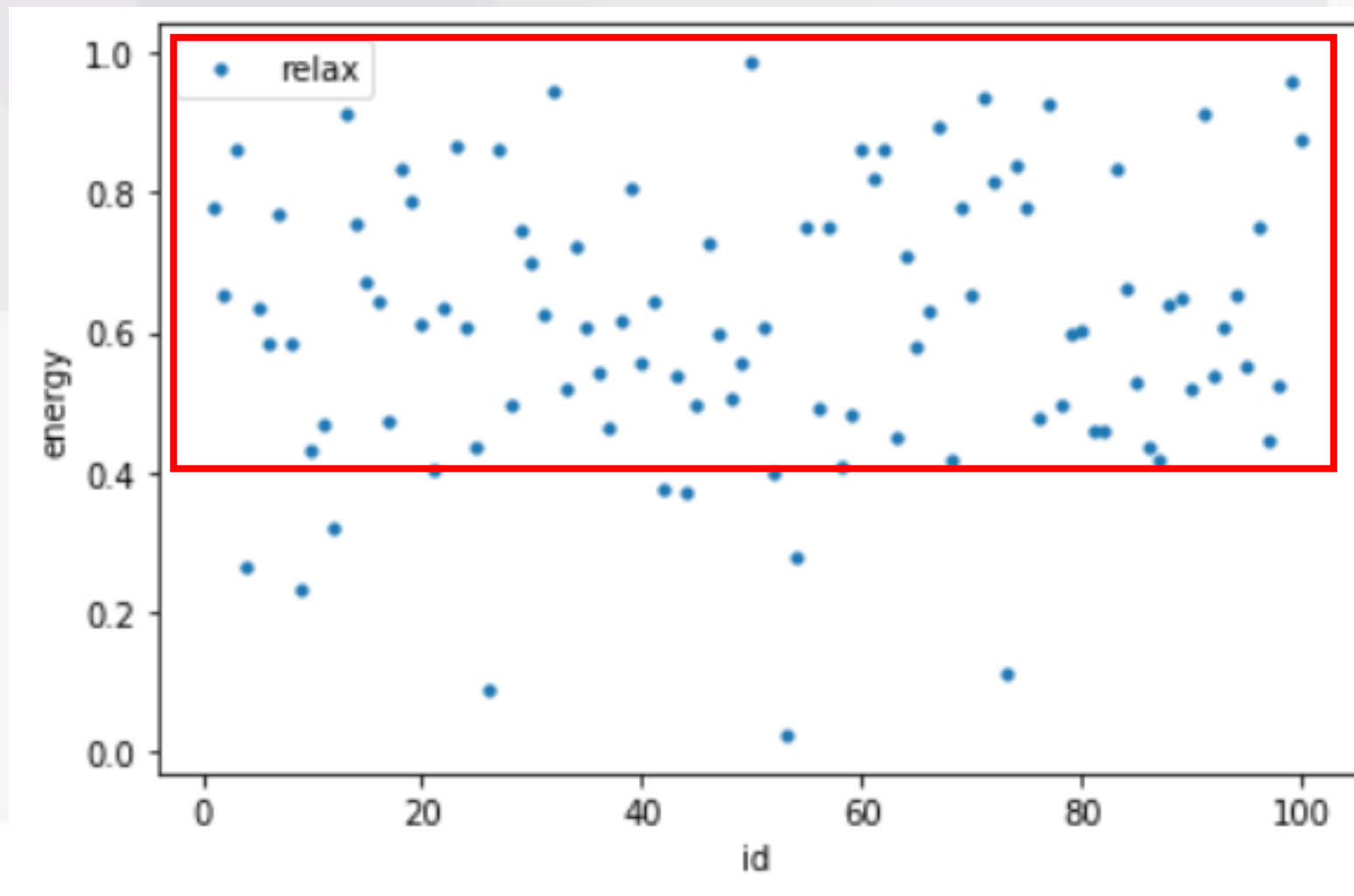
angry → energy高、loudness大

Features Analyze



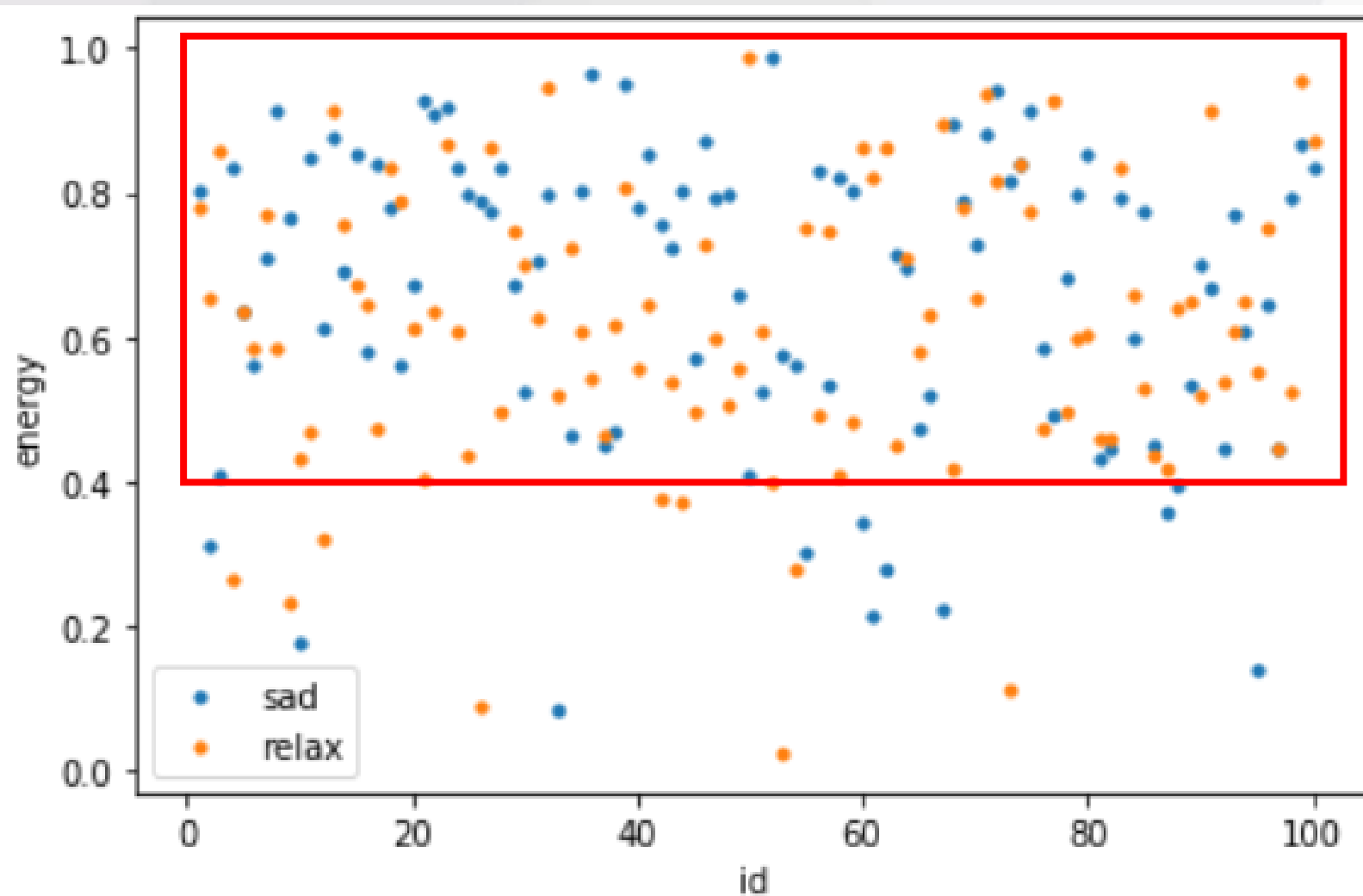
angry → acoustictness低

Features Analyze



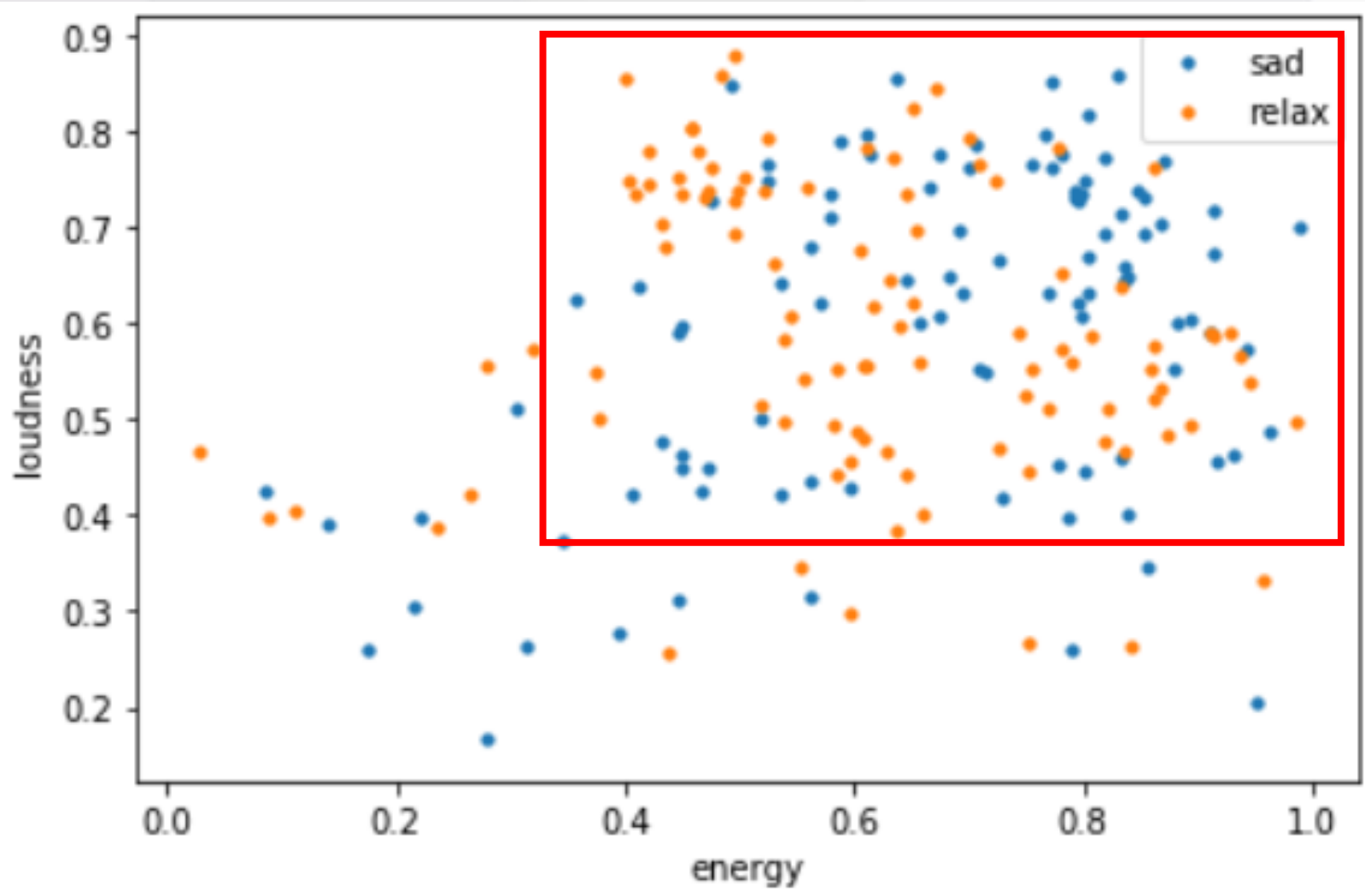
relax → energy高

Features Analyze



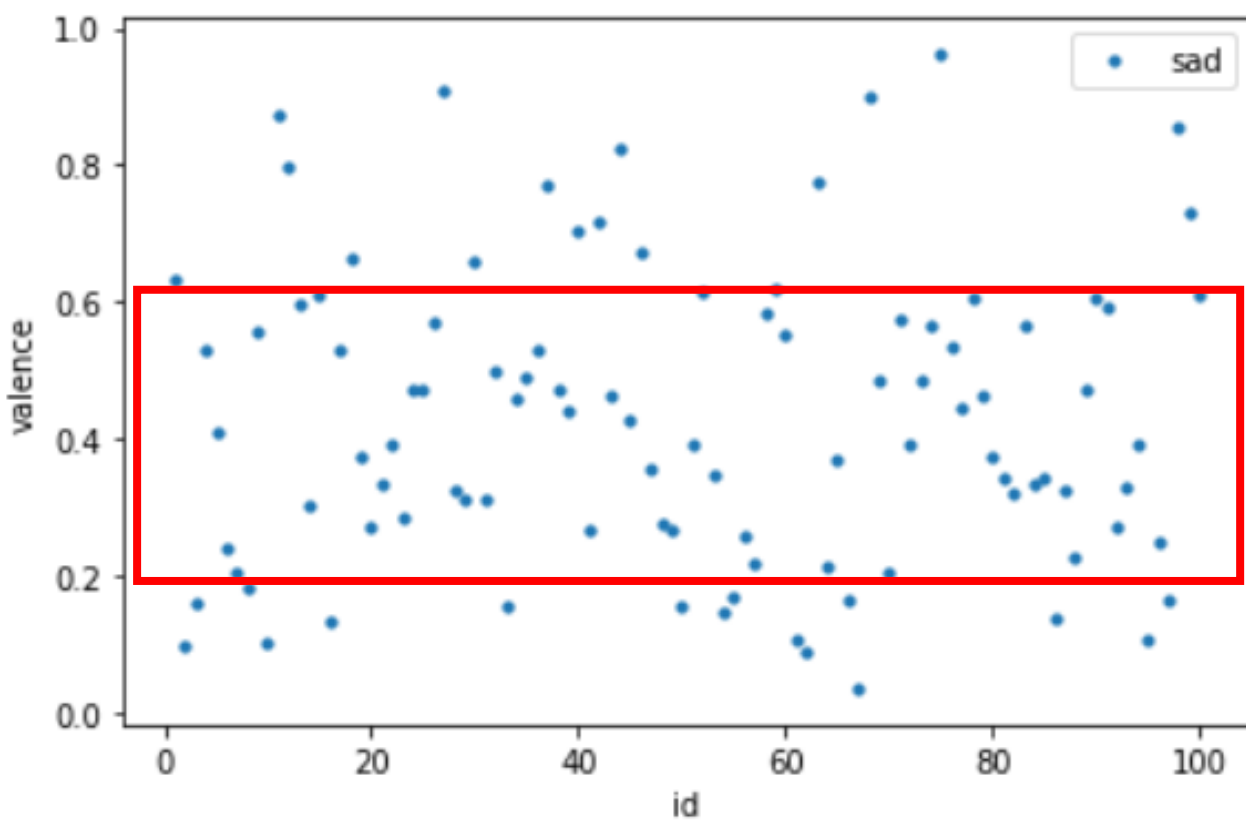
sad 、 relax → energy高

Features Analyze

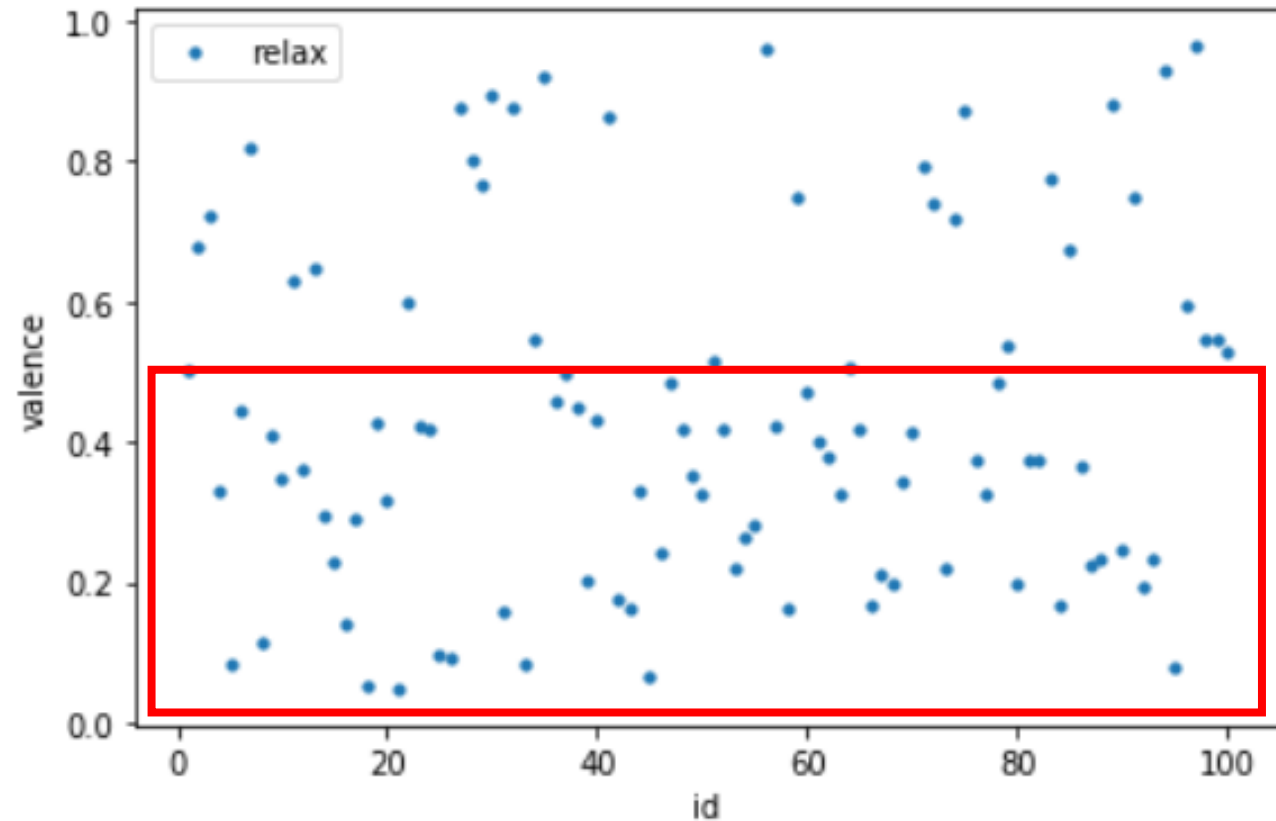


sad、relax → loudness大、energy高

Features Analyze

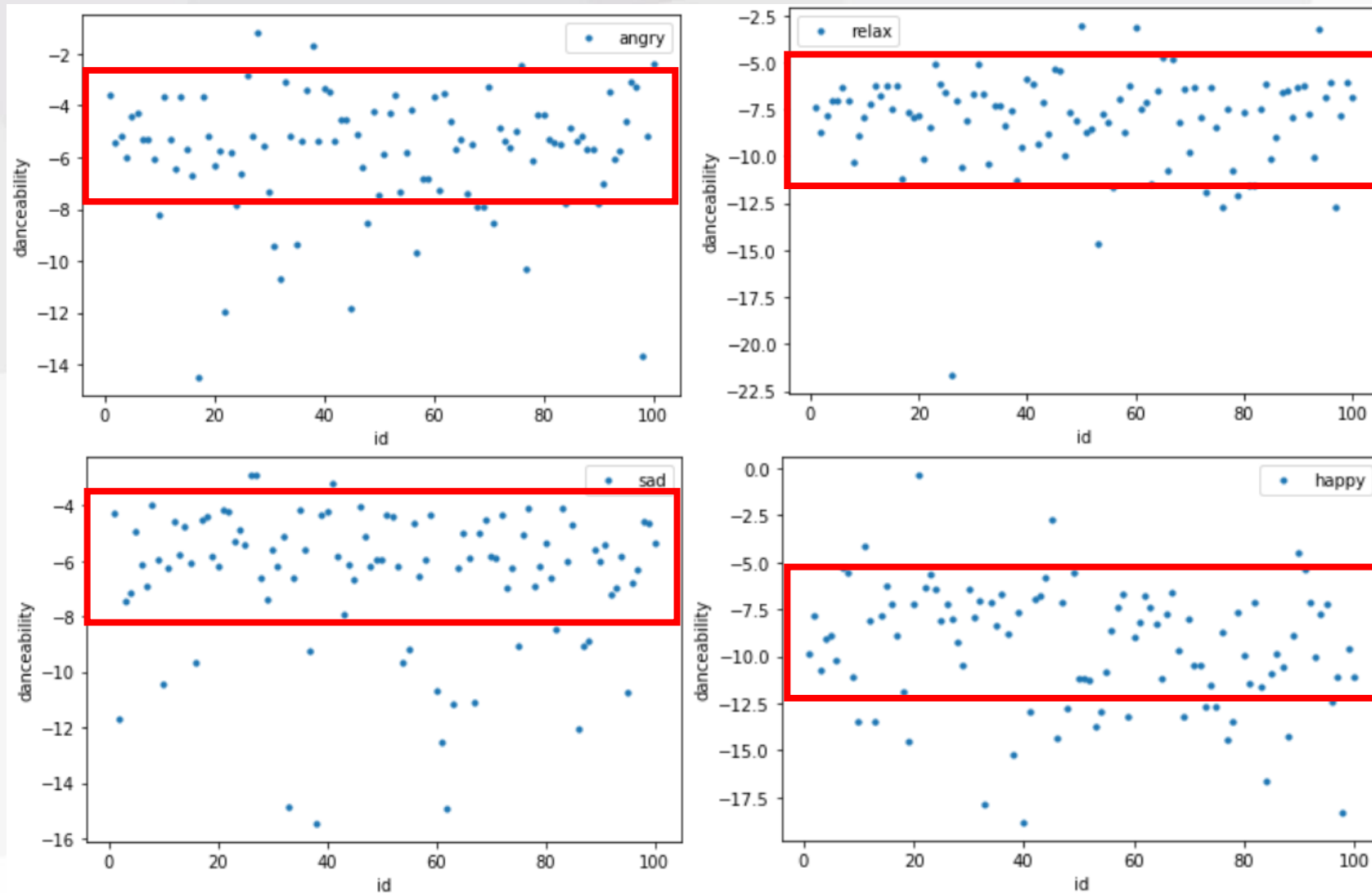


sad \rightarrow valence (0.2~0.6)



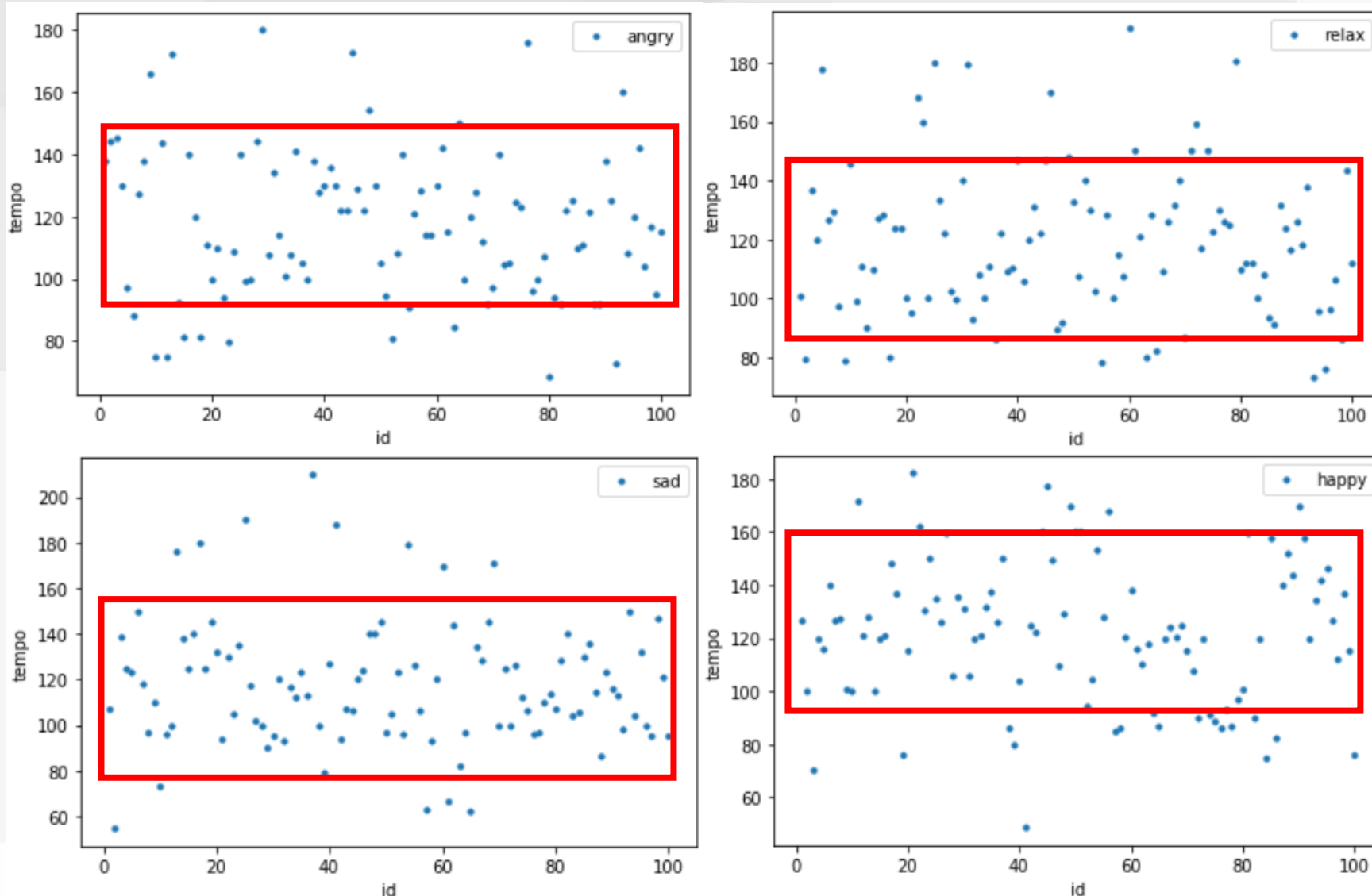
relax \rightarrow valence (0.0~0.5)

Features Analyze



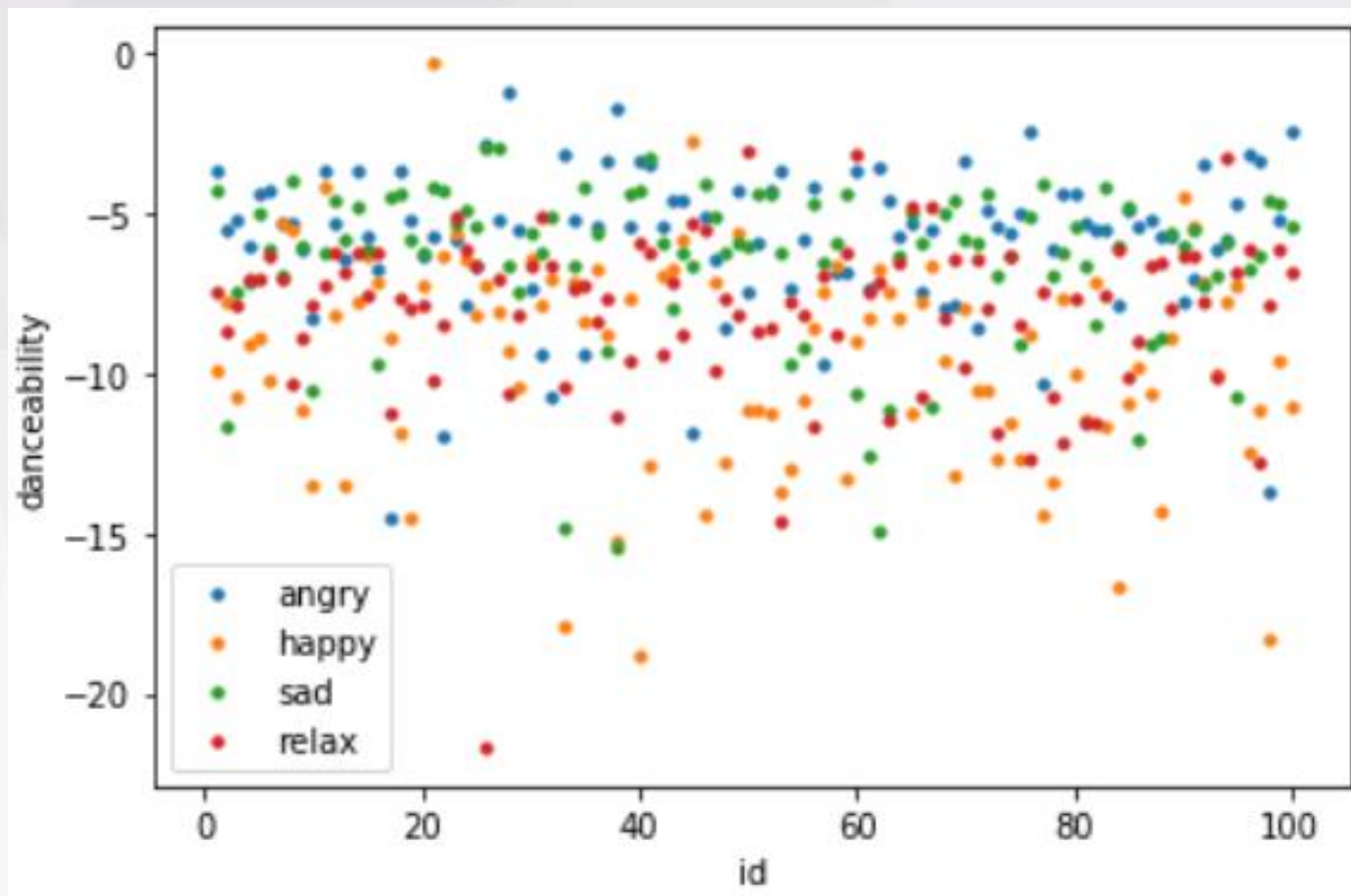
angry \rightarrow danceability(-3.5~-8) / sad \rightarrow danceability(-4~-8)
relax \rightarrow danceability(-5~-11) / happy \rightarrow danceability(-5~-15)

Features Analyze



angry \rightarrow tempo(90-150) / sad \rightarrow tempo(80-150) / relax \rightarrow tempo(90-150) / happy \rightarrow tempo(100-160)

Features Analyze



Features Analyze

happy 、 angry → loudness大 (✓)

angry → energy高 、 loudness大 、 acousticness低 (✓)

sad 、 relax → loudness大 (✓) 、 energy高

sad → valence (0.2~0.6)

relax → valence (0.0~0.5)

sad → valence低

relax → loudness大 、 tempo(80-140)

happy 、 angry → energy高 、 loudness大 、 acousticness低

angry → tempo(100-175)

Spotify Audio Features

Learn more about the audio properties of your favourite tracks, including detailed rhythmic information.

To get these values, we use the Spotify API's [Get Audio Analysis for a Track](#) endpoint.

Let's search for a track:

SUBMIT

- [Now the Day is Done - Frank Howard](#)
- [And Now The Day Is Done - Ron Sexsmith](#)

Sections

Bars

Beats

Segments

Tatums

Spotify Audio Features

Learn more about the audio properties of your favourite tracks, including detailed rhythmic information.

To get these values, we use the Spotify API's [Get Audio Analysis for a Track](#) endpoint.

Let's search for a track:

SUBMIT

- [Almost Lover - A Fine Frenzy](#)
- [Almost Lover - Jasmine Thompson](#)

Sections

Bars

Beats

Segments

Tatums

Spotify切割區段 - Audio Analysis Object

KEY	VALUE TYPE	VALUE DESCRIPTION
bars	an array of time interval objects	The time intervals of the bars throughout the track. A bar (or measure) is a segment of time defined as a given number of beats. Bar offsets also indicate downbeats, the first beat of the measure.
beats	an array of time interval objects	The time intervals of beats throughout the track. A beat is the basic time unit of a piece of music; for example, each tick of a metronome. Beats are typically multiples of tatums.
sections	an array of section objects	Sections are defined by large variations in rhythm or timbre, e.g. chorus, verse, bridge, guitar solo, etc. Each section contains its own descriptions of tempo, key, mode, time_signature, and loudness.
segments	an array of segment objects	Audio segments attempts to subdivide a song into many segments, with each segment containing a roughly consistent sound throughout its duration.
tatums	an array of time interval objects	A tatum represents the lowest regular pulse train that a listener intuitively infers from the timing of perceived musical events (segments). For more information about tatums.

Spotify Accounts Authentication

download node.js

λ npm install

- authorization_code
- client_credentials
- implicit_grant
- node_modules**
- .gitignore
- LICENSE
- package.json
- package-lock.json
- README.md

```
app.js index.html
9
10 var express = require('express'); // Express web server framework
11 var request = require('request'); // "Request" library
12 var cors = require('cors');
13 var querystring = require('querystring');
14 var cookieParser = require('cookie-parser'); Using your own credentials
15
16 var client_id = '07f9611e9b234caea4fcee288da82e61'; // Your client id
17 var client_secret = '087b1a26a1294bc58a0a89d4a29463e4'; // Your secret
18 var redirect_uri = 'http://localhost:8888/callback'; // Your redirect uri
19
20 /**
21  * Generates a random string containing numbers and letters
22  * @param {number} length The length of the string
23  * @return {string} The generated string
24  */
25 var generateRandomString = function(length) {
26   var text = '';
27   var possible = 'ABCDEFGHIJKLMNOPQRSTUVWXYZabcdefghijklmnopqrstuvwxyz0123456789';
28
29   for (var i = 0; i < length; i++) {
30     text += possible.charAt(Math.floor(Math.random() * possible.length));
31   }
32   return text;
33 };
34
35 var stateKey = 'spotify_auth_state';
36
37 var app = express();
38
39 app.use(express.static(__dirname + '/public'))
40   .use(cors())
41   .use(cookieParser());
42
43 app.get('/login', function(req, res) {
44
45   var state = generateRandomString(16);
46   res.cookie(stateKey, state);
47
48   // your application requests authorization
49   var scope = 'user-library-read user-read-private user-read-email';
50   res.redirect('https://accounts.spotify.com/authorize?' +
51     querystring.stringify({
52       response_type: 'code',
53       client_id: client_id,
54       scope: scope,
```

Spotify Accounts Authentication

```
λ cd D:\中興資管所\7 實驗進度\音頻情緒分類\web-api-auth-examples-master\authorization_code
```

```
λ node app.js
```



```
D:\Software\Cmder
λ cd D:\中興資管所\7 實驗進度\音頻情緒分類\web-api-auth-examples-master\authorization_code

D:\中興資管所\7 實驗進度\音頻情緒分類\web-api-auth-examples-master\authorization_code
λ node app.js
Listening on 8888
```

← → ✕ 🏠 ⓘ localhost:8888

current_user_saved_tracks()

print the track that the user saved

```
# 歌單中的歌名以及歌手名稱(最愛的歌曲)
sp = spotipy.Spotify(auth=token)
results = sp.current_user_saved_tracks()
print("最愛的歌曲： ")
for item in results['items']:
    track = item['track']
    print ('| - ' + track['name'] + ' | ' + track['artists'][0]['name'])
```

lyrics emotion

LogisticRegression方法

LogisticRegression方法 Testing accuracy score: 0.7584269662921348

LogisticRegression方法 Traing accuracy score: 0.9316901408450704

LogisticRegression方法 confusion matrix

[[71 17 3 2]

[2 83 2 0]

[11 26 48 6]

[5 9 3 68]]

LinearSVC方法

LinearSVC方法 Testing accuracy score: 0.6769662921348315

LinearSVC方法 Traing accuracy score: 0.9316901408450704

LinearSVC方法 confusion matrix

[[71 17 3 2]

[2 83 2 0]

[11 26 48 6]

[5 9 3 68]]

lyrics emotion

LogisticRegression方法

```
In [11]: 1 pred=model.predict(X_test)
          2 print("Testing accuracy score: " + str(model.score(X_test, y_test)))
```

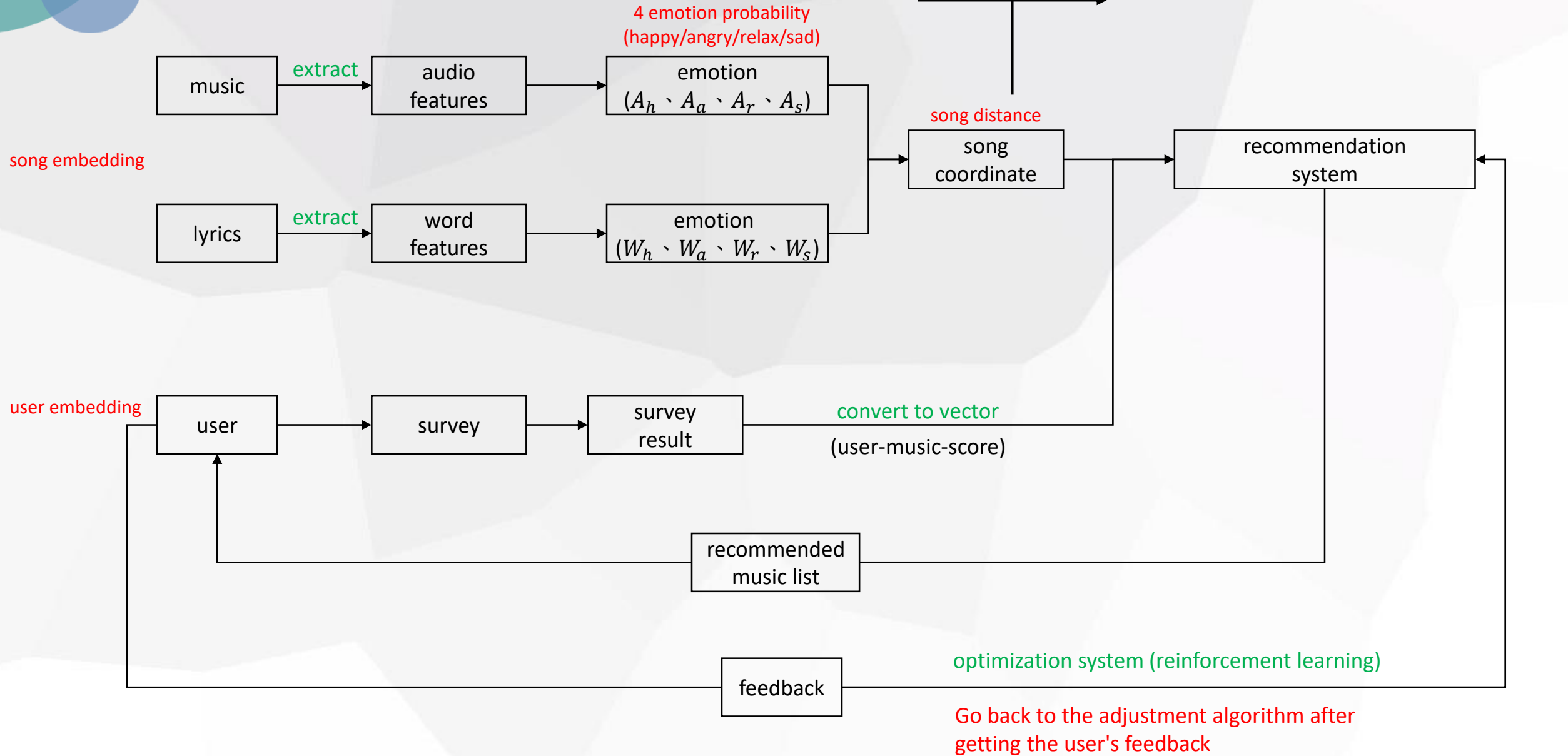
Testing accuracy score: 0.3177570093457944

LinearSVC方法

```
In [13]: 1 #LinearSVC方法
          2 linear_svc = LinearSVC(C=1.0, penalty='l1', max_iter=3000, dual=False)
          3 model2 = linear_svc.fit(X_train,y_train)
          4 pred = model2.predict(X_test)
          5 print("LinearSVC Testing accuracy score: " + str(model2.score(X_test, y_test)))
```

LinearSVC Testing accuracy score: 0.30218068535825543

Framework



Survey Page

Enter your information

Username

Gender

☐

Male

☐

Female

Age



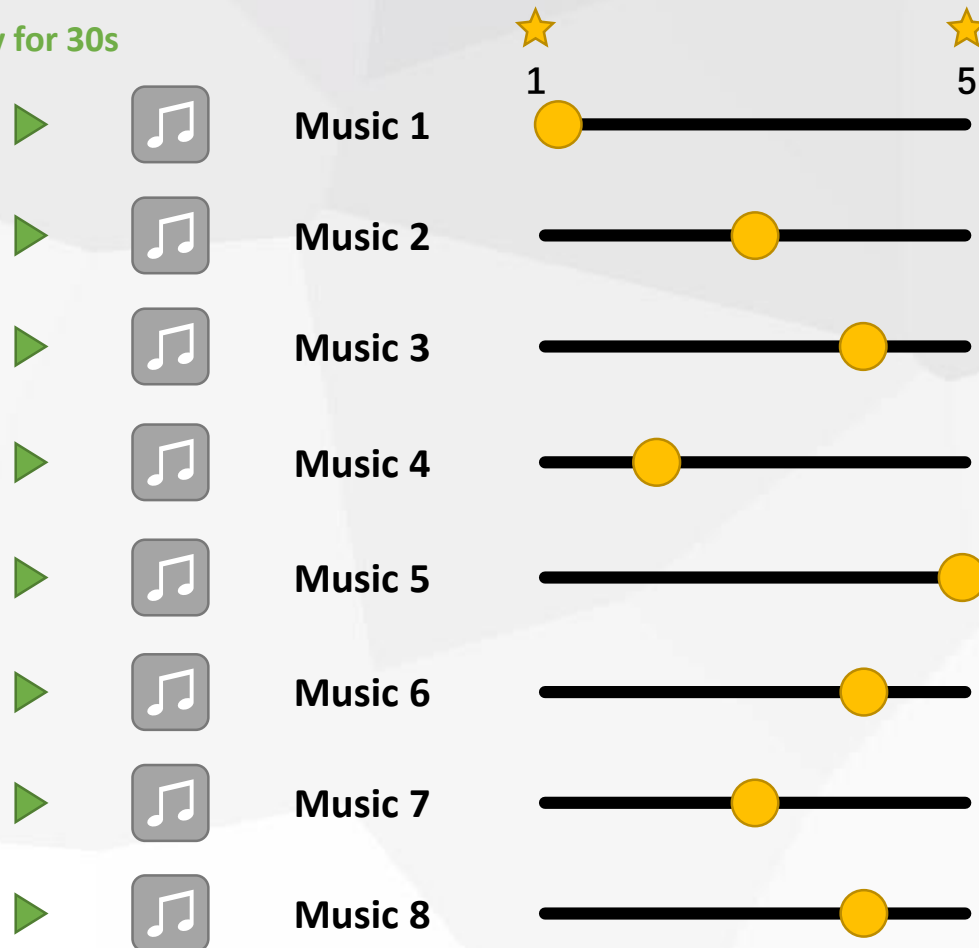
NEXT

Survey Page

How many songs take as a reference ? (give several songs for initial user to rate)

Score the following songs according to your preferences

play for 30s



OK

Preferences List

- ★ 5 Music 5
- ★ 4 Music 3 、 Music 6 、 Music 8
- ★ 3 Music 2 、 Music 7
- ★ 2 Music 4
- ★ 1 Music 1

data : user-music-score



THANKS!

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