Московский государственный технический университет им. Н.Э. Баумана Кафедра «Системы обработки информации и управления»

Лабораторная работа №1 по дисциплине «Методы машинного обучения» на тему «Разведочный анализ данных. Исследование и визуализация данных»

Выполнил: студент группы ИУ5-24М Лясковский М. А.

1. Цель лабораторной работы

Изучение различных методов визуализация данных.

2. Задание

Выбрать набор данных (датасет). Для лабораторных работ не рекомендуется выбирать датасеты большого размера. Создать ноутбук, который содержит следующие разделы:

• Текстовое описание выбранного Вами набора данных.

In [3]: dt = pd.read_csv('data/top_spotify_tracks.csv', header=0)

- Основные характеристики датасета.
- Визуальное исследование датасета.

import seaborn as sn

• Информация о корреляции признаков.

3. Ход работы

20

21

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23

24

5CLGzJsGqhCEECcpnFQA8

3V8UKqhEK5zBkBb6d6ub8

7uzmGiiJyRfuViKKK31Vm
2iUXsY0EPhVqEBwsqP70r

2xJCMIJfcNYDc5iROsAm2

In [4]: dt

In [1]: import pandas as pd

```
Out [4]:
                                id
                                                                             God's P
        0
            6DCZcSspjsKoFjzjrWoCd
        1
            3ee8Jmje8o58CHK66QrVC
        2
            0e7ipj03S05BNilyu5bRz
                                                            rockstar (feat. 21 Sava
        3
            3swc6WTsr7rl9DqQKQA55
                                                          Psycho (feat. Ty Dolla $i
        4
            2G7V7zsVDxg1yRsu7Ew9R
                                                                         In My Feeli
        5
            7dt6x5M1jzdTEt8oCbisT
                                                                             Better 1
        6
            58q2HKrzhC3ozto2nDdN4
                                                                              I Like
        7
            7ef4DlsgrMEH11cDZd32M
                                                              One Kiss (with Dua Li
        8
            76cy1WJvNGJTj78UqeA5z
                                                                                  ID
        9
                                                                                FRIE
            08bNPGLD8AhKpnnERrAc6
        10
            1rfofaqEpACxVEHIZBJe6
                                                                                 Hav
        11
            Os3nnoMeVWz3989MkNQiR
                                                                          Lucid Dre
        12
                                                                         Nice For W
            3CA9pLiwRIGtUBiMjbZmR
        13
            7fa9MBXhVfQ8P8Df90EbD
                                                        Girls Like You (feat. Cardi
        14
            09IStsImFySgyp0pIQdqA
                                                                             The Mid
        15
            3GCdLUSnKSMJhs4Tj6CV3
                                                              All The Stars (with S
        16
            2qT1uLXPVPzGgF0x4jtEu
                                                                  no tears left to
        17
            39N9RPD9MRb5WmoLzNzPe
        18
            0JP9xo3adEtGSdUEISisz
                                                                              Moonli
        19
            4qKcDkK6siZ7Jp1Jb4m0a
                                                              Look Alive (feat. Drai
```

These Days (feat. Jess Glynne, Macklemore & Da.

Te Bot? - Ren

Youngbl

New Ru

25	7qiZfU4dY11W11zX7mPBI	Shape of '
26	45Egmo7icyopuzJN0oMEd	Love Lies (with Norman
27	4e4fqjx0Izh4svvTef1z7	Meant to Be (feat. Florida Georgia Lii
28	7m9OqQk4RVRkw9JJdeAw9	Jocelyn Flo:
29	OtgVpDiO6FyKpA1z0VMD4	Perf
	•••	
70	5Gu0PDLN4YJeW75PpBSg9	Let Me Go (with Alesso, Florida Georgia Line &.
71	6QgjcU0zLnzq50rUoSZ30	Feel It St:
72	77UjLW8j5UAGAGVGhR5oU	Pray For Me (with Kendrick Lama
73	6n4U3TlzUGhdSFbUUhTvL	Walk It Talk
74	5k38wzpLb15YgncyWdTZE	Him & I (with Halse
75	321ItqlMi4LBhb4k0BaSa	Candy Pa:
76	3a11NhkSLSkpJE4MSHpDu	Congratulation
77	4QtiVmuA88tPQiCOHZuQ5	1, 2, 3 (feat. Jason Derulo & De La Ghet
78	6Za3190Sbw39BBC77WSS1	Crimin
79	1ZAyjvIk9YiD76yYyOTEG	Plug Wa
80	Ou2P5u6lvoDfwTYjAADbn	lovely (with Khal:
81	2UVbBKQOdFAekPTRsnkzc	Stir l
82	7KXjTSCq5nL1LoYtL7XAw	HUMBI
83	_	Vaina Lo
	48zFZh27QU5qsrBjn4C2F	
84	1bhUWBOzJMIKr9yVPrkEu	Perfect Duet (Ed Sheeran & Beyon
85	5cepAtqnEQ6yVG6088zMM	Coraz?n (feat. Nego do Bore
86	5Z3GHaZ6ec9bsiI5Benrb	Young Dumb & Bro
87	5Y9fnynLlIvqtM710MHzf	S?guelo Baila
88	3Ga6eKrUFf12ouh9Yw3v2	Downto
89	3xcCix7Jv1Rp90YVmgo35	Bel.
90	5N5k9nd479b1xpDZ4usjr	Promises (with Sam Smi
91	6vN771E9LK6HP2DewaN6H	Yes Inde
92	2P91MQbaiQOfbiz9VqhqK	I Like Me Bet
93	2xGjteMU3E1tkEPVFB008	This Is
94	3GVkPk8mqxz0itaAriG1L	Everybody Dies In Their Nightma:
95	630sXRhIcfwr2e4RdNtjK	Rewrite The Sta
96	2xmrfQpmS2iJExTlklLoA	I Miss You (feat. Julia Michael
97	5WvAo7DNuPRmk4APhdPzi	No Brain
98	1j4kHkkpqZRBwE0A4CN4Y	Dusk Till Dawn - Radio Eo
99	3EPXxR3ImUwfayaurPi3c	Be Alrig
	artists	$ ext{lanceability}$ energy key loudness mode $ackslash$
0	Drake	0.754 0.449 7.0 -9.211 1.0
1	XXXTENTACION	0.740 0.613 8.0 -4.880 1.0
2	Post Malone	0.587 0.535 5.0 -6.090 0.0
3	Post Malone	0.739 0.559 8.0 -8.011 1.0
4	Drake	0.835 0.626 1.0 -5.833 1.0
5	Post Malone	0.680 0.563 10.0 -5.843 1.0
6	Cardi B	0.816 0.726 5.0 -3.998 0.0
7	Calvin Harris	0.791 0.862 9.0 -3.240 0.0
8	Dua Lipa	0.836 0.544 7.0 -5.975 1.0
9	Marshmello	0.626 0.880 9.0 -2.384 0.0
10	Camila Cabello	0.765 0.523 2.0 -4.333 1.0
11	Juice WRLD	0.511 0.566 6.0 -7.230 0.0
_		

12	Drake	0.586	0.909	8.0	-6.474	1.0
13	Maroon 5	0.851	0.541	0.0	-6.825	1.0
14	Zedd	0.753	0.657	7.0	-3.061	1.0
15	Kendrick Lamar	0.698	0.633	8.0	-4.946	1.0
16	Ariana Grande	0.699	0.713	9.0	-5.507	0.0
17	Nicky Jam	0.595	0.773	9.0	-4.736	0.0
18	XXXTENTACION	0.921	0.537	9.0	-5.723	0.0
19	BlocBoy JB	0.922	0.581	10.0	-7.495	1.0
20	Rudimental	0.653	0.809	0.0	-4.057	1.0
21	Nio Garcia	0.903	0.675	11.0	-3.445	0.0
22	Bazzi	0.710	0.789	4.0	-3.874	1.0
23	5 Seconds of Summer	0.596	0.854	7.0	-5.114	0.0
24	Dua Lipa	0.762	0.700	9.0	-6.021	0.0
25	Ed Sheeran	0.825	0.652	1.0	-3.183	0.0
26	Khalid	0.708	0.648	6.0	-5.626	1.0
27	Bebe Rexha	0.642	0.772	10.0	-6.610	1.0
28	XXXTENTACION	0.872	0.391	0.0	-9.144	0.0
29	Ed Sheeran	0.599	0.448	8.0	-6.312	1.0
	•••	•••		•••	•••	
70	Hailee Steinfeld	0.663	0.708	8.0	-4.154	1.0
71	Portugal. The Man	0.801	0.795	1.0	-5.115	0.0
72	The Weeknd	0.735	0.677	2.0	-4.979	1.0
73	Migos	0.909	0.628	2.0	-5.456	1.0
74	G-Eazy	0.589	0.731	2.0	-6.343	1.0
75	Post Malone	0.670	0.654	4.0	-5.944	1.0
76	Post Malone	0.630	0.804	6.0	-4.183	1.0
77	Sofia Reyes	0.792	0.895	1.0	-3.112	0.0
78	Natti Natasha	0.814	0.813	2.0	-3.023	0.0
79	Rich The Kid	0.876	0.519	11.0	-6.531	1.0
80	Billie Eilish	0.351	0.296	4.0	-10.109	0.0
81	Migos	0.815	0.816	2.0	-5.474	1.0
82	Kendrick Lamar	0.908	0.621	1.0	-6.638	0.0
83	Ozuna	0.754	0.805	6.0	-4.249	1.0
84	Ed Sheeran	0.587	0.299	8.0	-7.365	1.0
85	Maluma	0.722	0.738		-6.073	0.0
86	Khalid	0.798	0.539	1.0	-6.351	1.0
87	Ozuna	0.855	0.664	9.0	-7.110	0.0
88	Anitta	0.775	0.679	4.0	-4.985	0.0
89	Wolfine	0.909	0.493	3.0	-6.688	1.0
90	Calvin Harris	0.781	0.768	11.0	-5.991	1.0
91	Lil Baby	0.964	0.346	5.0	-9.309	0.0
92	Lauv	0.752	0.505	9.0	-7.621	1.0
93	Keala Settle	0.284	0.704	2.0	-7.276	1.0
94	XXXTENTACION	0.734	0.570	7.0	-7.066	0.0
95	Zac Efron	0.684	0.619	10.0	-7.005	1.0
96	Clean Bandit	0.638	0.658	3.0	-6.318	1.0
97	DJ Khaled	0.552	0.760	0.0	-4.706	1.0
98	ZAYN	0.258	0.437	11.0	-6.593	0.0
99	Dean Lewis	0.553	0.586	11.0	-6.319	1.0

	speechiness	acousticness	instrumentalness	liveness	valence	temj
0	0.1090	0.033200	0.000083	0.5520	0.3570	77.1
1	0.1450	0.258000	0.003720	0.1230	0.4730	75.03
2	0.0898	0.117000	0.000066	0.1310	0.1400	159.84
3	0.1170	0.580000	0.000000	0.1120	0.4390	140.1
4	0.1250	0.058900	0.000060	0.3960	0.3500	91.0
5	0.0454	0.354000	0.000000	0.1360	0.3740	145.01
6	0.1290	0.099000	0.000000	0.3720	0.6500	136.04
7	0.1100	0.037000	0.000022	0.0814	0.5920	123.99
8	0.0943	0.040300	0.000000	0.0824	0.5100	97.01
9	0.0504	0.205000	0.000000	0.1280	0.5340	95.0
10	0.0300	0.184000	0.000036	0.1320	0.3940	104.98
11	0.2000	0.349000	0.000000	0.3400	0.2180	83.90
12	0.0705	0.089100	0.000109	0.1190	0.7570	93.39
13	0.0505	0.568000	0.000000	0.1300	0.4480	124.9
14	0.0449	0.171000	0.000000	0.1120	0.4370	107.0
15	0.0597	0.060500	0.000194	0.0926	0.5520	96.91
16	0.0594	0.040000	0.000003	0.2940	0.3540	121.99
17	0.0549	0.036400	0.001080	0.3340	0.7110	180.0
18	0.0804	0.556000	0.004040	0.1020	0.7110	128.00
19	0.2700	0.001040	0.000059	0.1050	0.5950	140.0
20	0.0474	0.194000	0.000000	0.1650	0.5500	92.2
21	0.2140	0.542000	0.000013	0.0595	0.4420	96.50
22	0.0722	0.016100	0.000003	0.4510	0.7170	142.93
23	0.4630	0.016900	0.000000	0.1240	0.1520	120.2
24	0.0694	0.002610	0.000016	0.1530	0.6080	116.0
25	0.0802	0.581000	0.000000	0.0931	0.9310	95.9
26	0.0449	0.095600	0.000000	0.1340	0.3380	143.9
27	0.0848	0.047600	0.000000	0.0646	0.5890	153.99
28	0.2420	0.469000	0.000004	0.2970	0.4370	134.01
29	0.0232	0.163000	0.000000	0.1060	0.1680	95.0
	•••	•••	***	•••	•••	
70	0.0473	0.033700	0.000000	0.0841	0.7420	103.0
71	0.0504	0.041700	0.000113	0.0717	0.7540	79.03
72	0.0930	0.076200	0.000022	0.1110	0.1880	100.58
73	0.2010	0.073900	0.000000	0.1080	0.4060	145.90
74	0.0868	0.053400	0.000000	0.3080	0.1910	87.90
75	0.1530	0.627000	0.000001	0.0710	0.4380	180.03
76	0.0363	0.215000	0.000000	0.2530	0.4920	123.14
77	0.0589	0.165000	0.000000	0.0501	0.7940	94.96
78	0.0561	0.030000	0.000093	0.2550	0.8390	79.99
79	0.1430	0.202000	0.000000	0.1080	0.1580	94.98
80	0.0333	0.934000	0.000000	0.0950	0.1200	115.28
81	0.2690	0.002990	0.000000	0.1590	0.4980	181.96
82	0.1020	0.000282	0.000054	0.0958	0.4210	150.0
83	0.0752	0.315000	0.000000	0.2030	0.5550	93.98
84	0.0263	0.779000	0.000000	0.1230	0.3560	94.99
85	0.2470	0.328000	0.000015	0.1980	0.7480	198.0
86	0.0421	0.199000	0.000017	0.1650	0.3940	136.94
87	0.0607	0.165000	0.000040	0.0937	0.6260	98.0
01	0.0001	0.10000	0.000010	3.0001	0.0200	55.5.

88	0.1350	0.180000	0.000073	0.0680	0.6190	166.00
89	0.0735	0.128000	0.000147	0.1270	0.8440	94.0
90	0.0394	0.011900	0.000005	0.3250	0.4860	123.0
91	0.5300	0.035000	0.000000	0.1080	0.5620	119.9
92	0.2530	0.535000	0.000003	0.1040	0.4190	91.9
93	0.1860	0.005830	0.000115	0.0424	0.1000	191.70
94	0.1330	0.847000	0.000021	0.1120	0.6890	129.9
95	0.0386	0.071600	0.000000	0.1220	0.2840	125.04
96	0.0456	0.245000	0.000004	0.0919	0.3300	105.0
97	0.3420	0.073300	0.000000	0.0865	0.6390	135.70
98	0.0390	0.101000	0.00001	0.1060	0.0967	180.04
99	0.0362	0.697000	0.000000	0.0813	0.4430	126.68
	duration_ms	time_signature				
0	198973.0	4.0				
1	166606.0	4.0				
2	218147.0	4.0				
3	221440.0	4.0				
4	217925.0	4.0				
5	231267.0	4.0				
6	253390.0	4.0				
7	214847.0	4.0				
8	217947.0	4.0				
9	202621.0	4.0				
10	217307.0	4.0				
11	239836.0	4.0				
12	210747.0	4.0				
13	235545.0	4.0				
14	184732.0	4.0				
15	232187.0	4.0				
16	205920.0	4.0				
17	173628.0	4.0				
18	135090.0	4.0				
19	181263.0	4.0				
20	210773.0	4.0				
21	417920.0	4.0				
22	131064.0	4.0				
23	203418.0	4.0				
24	209320.0	4.0				
25	233713.0	4.0				
26	201707.0	4.0				
27	164205.0	4.0				
28	119133.0	4.0				
29	263400.0	3.0				

4.0

4.0

4.0

4.0

4.0

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70

71

72

73

74

174800.0

163253.0

211440.0

276147.0

268867.0

75	227533.0	4.0
76	220293.0	4.0
77	201526.0	4.0
78	232550.0	4.0
79	175230.0	4.0
80	200186.0	4.0
81	190288.0	4.0
82	177000.0	4.0
83	176133.0	4.0
84	259550.0	3.0
85	184720.0	4.0
86	202547.0	4.0
87	226800.0	4.0
88	193456.0	4.0
89	197120.0	4.0
90	213309.0	4.0
91	142273.0	4.0
92	197437.0	4.0
93	234707.0	4.0
94	95467.0	4.0
95	217440.0	4.0
96	205748.0	4.0
97	260000.0	5.0
98	239000.0	4.0
99	196373.0	4.0

[100 rows x 16 columns]

In [5]: dt.shape

Out[5]: (100, 16)

In [7]: dt.dtypes

Out[7]: id object nameobject object artists danceability float64 float64 energy key float64 loudness float64 float64 modespeechiness float64 float64 acousticness instrumentalness float64 liveness float64 valence float64 float64 tempo float64 duration_ms time_signature float64

In [8]: dt.describe() Out[8]: danceability loudness mode energy key 100.00000 100.000000 100.000000 100.000000 100.000000 count 0.71646 0.659060 5.330000 -5.677640 0.590000 mean 3.676447 0.13107 0.145067 1.777577 0.494311 std 0.25800 0.296000 -10.109000 0.00000 min 0.000000 25% 0.63550 0.562000 1.750000 -6.650500 0.000000 50% 0.73300 0.678000 5.000000 -5.566500 1.000000 75% 0.79825 0.772250 8.250000 -4.363750 1.000000 0.909000 -2.384000 0.96400 11.000000 1.000000 maxinstrumentalness liveness speechiness acousticness valence 100.000000 100.000000 100.000000 100.000000 100.00000 count 0.48444 mean 0.115569 0.195701 0.001584 0.158302 std 0.104527 0.220946 0.013449 0.111662 0.20614 0.000000 0.07960 min 0.023200 0.000282 0.021500 25% 0.045350 0.040225 0.000000 0.094675 0.34100 0.47050 50% 0.000000 0.074950 0.109000 0.118500 75% 0.137000 0.247750 0.000031 0.170750 0.64150 0.93100 0.530000 0.934000 0.134000 0.636000 max tempo duration_ms time_signature 100.00 count 100.000000 100.000000 119.904180 205206.780000 3.98 mean 0.20 std 28.795984 40007.893404 95467.000000 3.00 min 64.934000 25% 95.730750 184680.000000 4.00 50% 120.116000 205047.500000 4.00 75% 140.022750 221493.250000 4.00 198.075000 417920.000000 5.00 maxIn [9]: dt['id'] = dt['id'].astype('category') dt['name'] = dt['name'].astype('category') dt['artists'] = dt['artists'].astype('category') In [10]: dt['id'] = dt['id'].cat.codes dt['name'] = dt['name'].cat.codes dt['artists'] = dt['artists'].cat.codes In [14]: dt.describe() Out [14]: id name artists danceability energy count 100.000000 100.000000 100.000000 100.00000 100.000000 mean 49.500000 49.500000 36.010000 0.71646 0.659060 std 29.011492 29.011492 19.977004 0.13107 0.145067 min 0.000000 0.000000 0.000000 0.25800 0.296000 25% 24.750000 24.750000 20.750000 0.63550 0.562000 50% 49.500000 49.500000 36.500000 0.73300 0.678000

69.000000

0.79825

0.96400

0.772250

0.909000

74.250000

99.000000

75%

max

74.250000

99.000000

			400 00	key		udness	400	mode	-	hiness		ısticne	
	cou		100.00			000000		000000		000000	1(00.0000	
	mean			0000		677640		590000		115569		0.1957	
	std			6447		777577		194311		104527		0.2209	
	min			0000		109000		000000		023200		0.0002	
	25%			0000		650500		000000		045350		0.0402	
	50%			0000		566500		000000		074950		0.1090	
	75%			0000		363750		000000		137000		0.2477	
	max		11.00	0000	-2.	384000	1.(000000	0.	530000		0.9340	00
			instru	menta]	lness	liv	eness	va	alence	+	tempo	dur	ation_r
	cou	nt		100.00	0000	100.0	00000	100.0	00000	100.00	_	10	0.0000
	meai	n		0.00)1584	0.1	58302	0.4	184443	119.90	04180	20520	6.7800
	std			0.01	13449	0.1	11662	0.2	206145	28.79	95984	4000	7.8934
	min			0.00	0000	0.0	21500	0.0	79600	64.93	34000	9546	7.0000
	25%				0000		94675		341000		30750		0.0000
	50%				0000		18500		170500	120.1	16000		7.5000
	75%			0.00	00031		70750		341500	140.02			3.25000
	max			0.13	34000	0.6	36000	0.9	931000	198.0	75000	41792	0.0000
			time_s	ignatı	ıre								
	coui	nt		100									
	meai				. 98								
	std				. 20								
	min				.00								
	25%				.00								
	50%				.00								
	75%				.00								
	max				.00								
In [15]:	dt												
Out[15]:		id	name	artis	sts	danceab	ilitv	energ	rv ke	ey loud	dness	mode	\
040[10].	0	76	30	ar ork	21		0.754	0.44		•	9.211	1.0	`
	1	49	72		65		0.740	0.61			4.880	1.0	
	2	7	99		52		0.587	0.53			5.090	0.0	
	3	50	66		52		0.739	0.5			3.011	1.0	
	4	25	41		21		0.835	0.62			5.833	1.0	
	5	92	8		52		0.680	0.56			5.843	1.0	
	6	62	36		13		0.816	0.72			3.998	0.0	
	7	93	60		11		0.791	0.86			3.240	0.0	
	8	85	39		22		0.836	0.54			5.975	1.0	
	9	0	22		42		0.626	0.88			2.384	0.0	
	10	21	33		12		0.765	0.52			4.333	1.0	
	11	9	49		30		0.511	0.56			7.230	0.0	
	12	40	57		21		0.586	0.90			6.474	1.0	
	13	94	28		41		0.851	0.54			5.825	1.0	
	14	1	82		68		0.753	0.65			3.061	1.0	
	15	42	3		32		0.755	0.63			4.946	1.0	
	16	33	98		4		0.699	0.71			5.507	0.0	
						-							

17	39	91	46	0.595	0.773	9.0	-4.736	0.0	
18	3	53	65	0.921	0.537	9.0	-5.723	0.0	
19	59	47	9	0.922	0.581	10.0	-7.495	1.0	
20	63	83	55	0.653	0.809	0.0	-4.057	1.0	
21	46	81	47	0.903	0.675	11.0	-3.445	0.0	
22	98	52	5	0.710	0.789	4.0	-3.874	1.0	
23	31	95	0	0.596	0.854	7.0	-5.114	0.0	
24	35	56	22	0.762	0.700	9.0	-6.021	0.0	
25	96	74	24	0.825	0.652	1.0	-3.183	0.0	
26	52	48	33	0.708	0.648	6.0	-5.626	1.0	
27	55	51	6	0.642	0.772	10.0	-6.610	1.0	
28	95	44	65	0.872	0.391	0.0	-9.144	0.0	
29	11	61	24	0.599	0.448	8.0	-6.312	1.0	
		•••		•••	•••	•••			
70	64	45	27	0.663	0.708	8.0	-4.154	1.0	
71	78	23	51	0.801	0.795	1.0	-5.115	0.0	
72	86	64	60	0.735	0.677	2.0	-4.979	1.0	
73	82	88	43	0.909	0.628		-5.456	1.0	
74	72	34	26	0.589	0.731	2.0	-6.343	1.0	
75	38	11	52	0.670	0.654	4.0	-5.944	1.0	
76	48	12	52	0.630	0.804	6.0	-4.183	1.0	
77	54	0	59	0.792	0.895	1.0	-3.112	0.0	
78	79	14	45	0.814	0.813	2.0	-3.023	0.0	
79	14	63	54	0.876	0.519	11.0	-6.531	1.0	
80	12	97	8	0.351	0.296	4.0	-10.109	0.0	
81	28	78	43	0.815	0.816	2.0	-5.474	1.0	
82	91	31	32	0.908	0.621	1.0	-6.638	0.0	
83	53	87	49	0.754	0.805	6.0	-4.249	1.0	
84	15	62	24	0.587	0.299	8.0	-7.365	1.0	
85	71	13	40	0.722	0.738	9.0	-6.073	0.0	
86	70	94	33	0.798	0.539	1.0	-6.351	1.0	
87	69	71	49	0.855	0.664	9.0	-7.110	0.0	
88	44	16	2	0.775	0.679	4.0	-4.985	0.0	
89	51	7	64	0.909	0.493	3.0	-6.688	1.0	
90	66	65	11	0.781	0.768	11.0	-5.991	1.0	
91	83	93	35	0.964	0.346	5.0	-9.309	0.0	
92	26	37	34	0.752	0.505	9.0	-7.621	1.0	
93	34	84	31	0.284	0.704	2.0	-7.276	1.0	
94	43	20	65	0.734	0.570	7.0	-7.066	0.0	
95	73	67	67	0.684	0.619	10.0	-7.005	1.0	
96	37	38	14	0.638	0.658	3.0	-6.318	1.0	
97	68	58	15	0.552	0.760	0.0	-4.706	1.0	
98	18	18	66	0.258	0.437	11.0	-6.593	0.0	
99	41	5	19	0.553	0.586	11.0	-6.319	1.0	
	spee	echiness			rumentaln			valence	ter
0		0.1090	0.033200		0.000		0.5520	0.3570	77.:
1		0.1450	0.258000		0.003		0.1230	0.4730	75.0
2		0.0898	0.117000		0.000	066	0.1310	0.1400	159.8
_		A 447A	A FAAAA		^ ^^	$\sim \sim \sim$	A 440A	A 4000	410

0.1120

0.4390

140.

0.580000

0.1170

3

4	0.1250	0.058900	0.000060	0.3960	0.3500	91.0
5	0.0454	0.354000	0.000000	0.1360	0.3740	145.0
6	0.1290	0.099000	0.000000	0.3720	0.6500	136.0
7	0.1100	0.037000	0.000022	0.0814	0.5920	123.9
8	0.0943	0.040300	0.000000	0.0824	0.5100	97.0
9	0.0504	0.205000	0.000000	0.1280	0.5340	95.0
10	0.0300	0.184000	0.000036	0.1320	0.3940	104.9
11	0.2000	0.349000	0.000000	0.3400	0.2180	83.9
12	0.0705	0.089100	0.000109	0.1190	0.7570	93.3
13	0.0505	0.568000	0.000000	0.1300	0.4480	124.9
14	0.0449	0.171000	0.000000	0.1120	0.4370	107.0
15	0.0597	0.060500	0.000194	0.0926	0.5520	96.9
16	0.0594	0.040000	0.000003	0.2940	0.3540	121.9
17	0.0549	0.036400	0.001080	0.3340	0.7110	180.0
18	0.0804	0.556000	0.004040	0.1020	0.7110	128.0
19	0.2700	0.001040	0.000059	0.1020	0.7110	140.0
20	0.2700	0.194000	0.000009	0.1650	0.5500	92.1
21	0.2140	0.194000	0.000013	0.1030	0.3300	96.
22	0.0722	0.016100	0.000013	0.4510	0.4420	142.9
23			0.000003		0.7170	
	0.4630	0.016900		0.1240		120.1
24	0.0694	0.002610	0.000016	0.1530	0.6080	116.0
25	0.0802	0.581000	0.000000	0.0931	0.9310	95.9
26	0.0449	0.095600	0.000000	0.1340	0.3380	143.9
27	0.0848	0.047600	0.000000	0.0646	0.5890	153.9
28	0.2420	0.469000	0.000004	0.2970	0.4370	134.0
29	0.0232	0.163000	0.000000	0.1060	0.1680	95.0
• •						
70	0.0473	0.033700	0.000000	0.0841	0.7420	103.0
71	0.0504	0.041700	0.000113	0.0717	0.7540	79.0
72	0.0930	0.076200	0.000022	0.1110	0.1880	100.
73	0.2010	0.073900	0.000000	0.1080	0.4060	145.9
74	0.0868	0.053400	0.000000	0.3080	0.1910	87.9
75	0.1530	0.627000	0.000001	0.0710	0.4380	180.0
76	0.0363	0.215000	0.000000	0.2530	0.4920	123.
77	0.0589	0.165000	0.000000	0.0501	0.7940	94.9
78	0.0561	0.030000	0.000093	0.2550	0.8390	79.9
79	0.1430	0.202000	0.000000	0.1080	0.1580	94.9
80	0.0333	0.934000	0.000000	0.0950	0.1200	115.1
81	0.2690	0.002990	0.000000	0.1590	0.4980	181.9
82	0.1020	0.000282	0.000054	0.0958	0.4210	150.0
83	0.0752	0.315000	0.000000	0.2030	0.5550	93.9
84	0.0263	0.779000	0.000000	0.1230	0.3560	94.9
85	0.2470	0.328000	0.000015	0.1980	0.7480	198.0
86	0.0421	0.199000	0.000017	0.1650	0.3940	136.9
87		0 105000	0.000040	0.0937	0.6260	98.0
88	0.0607	0.165000	0.000040			
	0.0607 0.1350	0.180000	0.000040	0.0680	0.6190	166.0
89					0.6190 0.8440	
89 90	0.1350	0.180000	0.000073	0.0680		166.0
	0.1350 0.0735	0.180000 0.128000	0.000073 0.000147	0.0680 0.1270	0.8440	166.0 94.0
90	0.1350 0.0735 0.0394	0.180000 0.128000 0.011900	0.000073 0.000147 0.000005	0.0680 0.1270 0.3250	0.8440 0.4860	166.0 94.0 123.0

93 94 95 96 97 98	0.1860 0.1330 0.0386 0.0456 0.3420 0.0390 0.0362	0.005830 0.847000 0.071600 0.245000 0.073300 0.101000 0.697000
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 29 29 20 20 20 20 20 20 20 20 20 20 20 20 20	duration_ms 198973.0 166606.0 218147.0 221440.0 217925.0 231267.0 253390.0 214847.0 217947.0 202621.0 217307.0 239836.0 210747.0 235545.0 184732.0 232187.0 205920.0 173628.0 135090.0 181263.0 210773.0 417920.0 131064.0 203418.0 209320.0 233713.0 201707.0 164205.0 119133.0 263400.0	time_signature 4.0 4.0 4.0 4.0 4.0 4.0 4.0 4.0 4.0 4.0
70 71 72 73 74 75 76 77 78 79	174800.0 163253.0 211440.0 276147.0 268867.0 227533.0 220293.0 201526.0 232550.0 175230.0	4.0 4.0 4.0 4.0 4.0 4.0 4.0 4.0 4.0

129.

125. 105.

135.

180.

126.

0.1000

0.6890

0.2840

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0.6390

0.0967

0.4430

0.000115

0.000021

0.000000

0.000004

0.000000

0.00001

0.000000

0.0424

0.1120

0.1220

0.0919

0.0865

0.1060

0.0813

80	200186.0	4.0
81	190288.0	4.0
82	177000.0	4.0
83	176133.0	4.0
84	259550.0	3.0
85	184720.0	4.0
86	202547.0	4.0
87	226800.0	4.0
88	193456.0	4.0
89	197120.0	4.0
90	213309.0	4.0
91	142273.0	4.0
92	197437.0	4.0
93	234707.0	4.0
94	95467.0	4.0
95	217440.0	4.0
96	205748.0	4.0
97	260000.0	5.0
98	239000.0	4.0
99	196373.0	4.0

[100 rows x 16 columns]

In [16]: dt.corr()

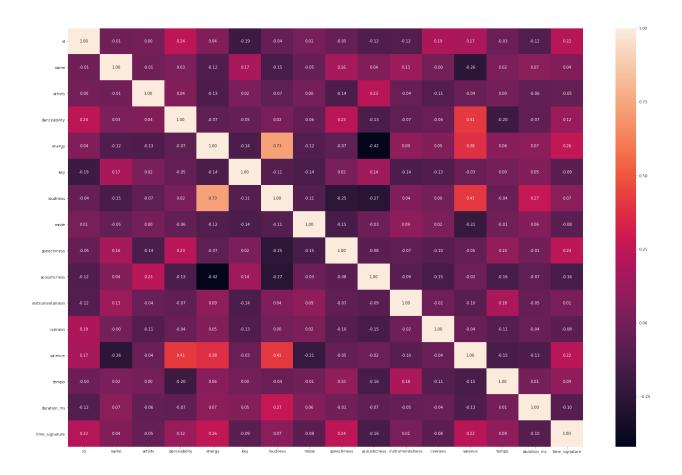
Out[16]:		id	name	artists	danceability	energy
	id	1.000000	-0.010441	0.002588	0.241274	0.044253
	name	-0.010441	1.000000	-0.014997	0.032230	-0.123184
	artists	0.002588	-0.014997	1.000000	0.040227	-0.128267
	danceability	0.241274	0.032230	0.040227	1.000000	-0.072582
	energy	0.044253	-0.123184	-0.128267	-0.072582	1.000000
	key	-0.194095	0.171177	0.021410	-0.051759	-0.136345
	loudness	-0.044764	-0.147399	-0.067940	0.015517	0.732719
	mode	0.010918	-0.051770	0.003488	-0.058019	-0.117555
	speechiness	-0.047514	0.162297	-0.140299	0.227075	-0.073591
	acousticness	-0.122739	0.044537	0.227147	-0.134374	-0.421209
	${\tt instrumentalness}$	-0.115325	0.129523	-0.039444	-0.066592	0.093684
	liveness	0.189145	-0.002064	-0.113832	-0.038761	0.050542
	valence	0.168740	-0.256872	-0.035551	0.413855	0.382434
	tempo	-0.032354	0.017379	0.002093	-0.195012	0.062272
	duration_ms	-0.119480	0.067608	-0.063217	-0.068368	0.073017
	time_signature	0.215867	0.041781	-0.053041	0.119421	0.255235
		kov	loudness	mode	sneechiness	acoustiones

```
-0.141568 -0.110178 1.000000
                                                                 -0.03002
mode
                                                   -0.150076
                  0.019583 -0.252037 -0.150076
                                                    1.000000
                                                                 -0.08153
speechiness
acousticness
                  0.141590 -0.269742 -0.030028
                                                   -0.081536
                                                                  1.00000
instrumentalness -0.136607
                            0.036248 0.089667
                                                   -0.069543
                                                                 -0.08958
liveness
                 -0.125443
                            0.000006
                                      0.024428
                                                   -0.099379
                                                                 -0.15017
valence
                 -0.032622
                            0.407760 -0.210599
                                                   -0.051054
                                                                 -0.02080
tempo
                  0.003737 -0.035156 -0.011911
                                                    0.102999
                                                                 -0.158013
duration_ms
                  0.046144 0.265310 0.055411
                                                   -0.009856
                                                                 -0.06962
                 -0.087096
                            0.072301 -0.083782
                                                    0.235615
                                                                 -0.15893
time_signature
                  instrumentalness
                                                                   durati
                                    liveness
                                                valence
                                                            tempo
id
                         -0.115325
                                    0.189145
                                               0.168740 -0.032354
                                                                     -0.1
name
                          0.129523 -0.002064 -0.256872 0.017379
                                                                      0.0
                         -0.039444 -0.113832 -0.035551
                                                                     -0.0
artists
                                                         0.002093
                         -0.066592 -0.038761 0.413855 -0.195012
                                                                     -0.0
danceability
                          0.093684
                                    0.050542
                                               0.382434
                                                         0.062272
                                                                      0.0
energy
                         -0.136607 -0.125443 -0.032622
                                                                      0.0
                                                         0.003737
key
loudness
                          0.036248 0.000006 0.407760 -0.035156
                                                                      0.2
                                    0.024428 -0.210599 -0.011911
                                                                      0.0
mode
                          0.089667
speechiness
                         -0.069543 -0.099379 -0.051054 0.102999
                                                                     -0.0
acousticness
                         -0.089583 -0.150177 -0.020800 -0.158013
                                                                     -0.0
instrumentalness
                          1.000000 -0.016249 -0.095123 0.178142
                                                                     -0.0
                         -0.016249 1.000000 -0.042612 -0.107652
                                                                     -0.0
liveness
                         -0.095123 -0.042612
                                              1.000000 -0.148423
                                                                     -0.13
valence
tempo
                          0.178142 -0.107652 -0.148423
                                                         1.000000
                                                                      0.0
                         -0.045873 -0.042942 -0.131901
duration_ms
                                                         0.005493
                                                                      1.0
                          0.011894 -0.079558 0.223410
time_signature
                                                         0.090191
                                                                     -0.1
                  time_signature
```

id 0.215867 name 0.041781 artists -0.053041 danceability 0.119421 energy 0.255235 key -0.087096 loudness 0.072301 -0.083782 mode 0.235615 speechiness acousticness -0.158935 instrumentalness 0.011894 liveness -0.079558 valence 0.223410 0.090191 tempo -0.102138 duration_ms 1.000000 time_signature

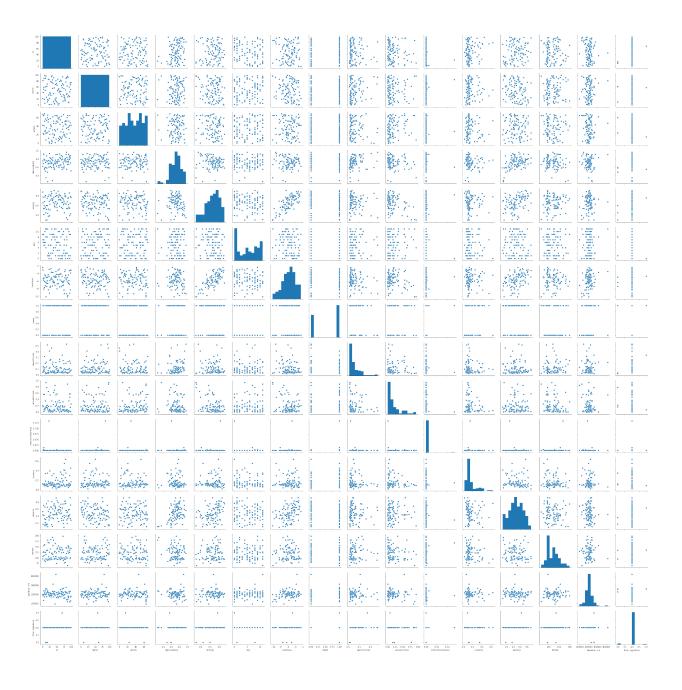
Populating the interactive namespace from numpy and matplotlib

In [19]: sn.heatmap(data=dt.corr(), annot=True, fmt='.2f');



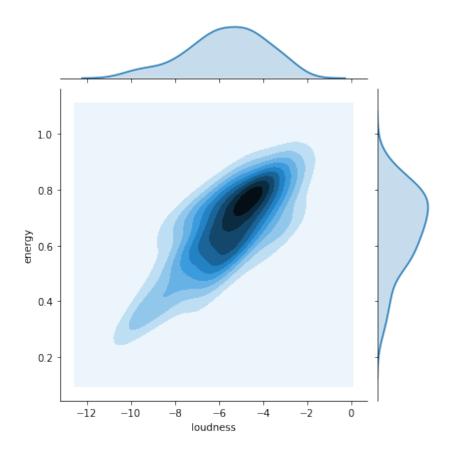
In [20]: sn.pairplot(dt)

Out[20]: <seaborn.axisgrid.PairGrid at 0x7f8c9819b550>



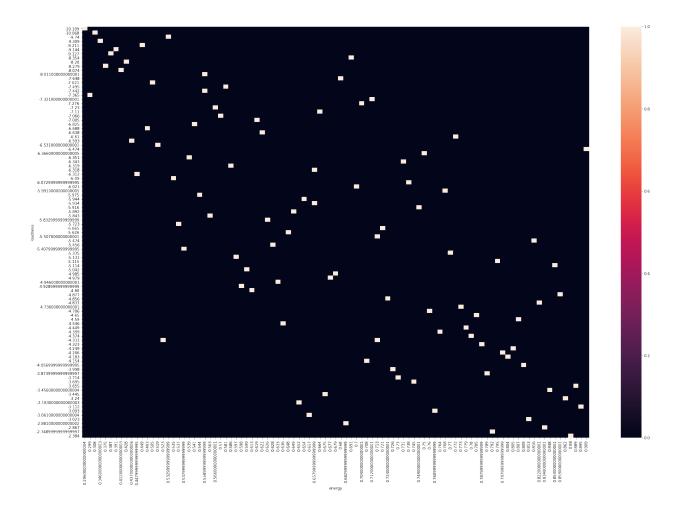
In [21]: sn.jointplot(data=dt, x='loudness', y='energy', kind='kde')

Out[21]: <seaborn.axisgrid.JointGrid at 0x7f8c8dfcbfd0>



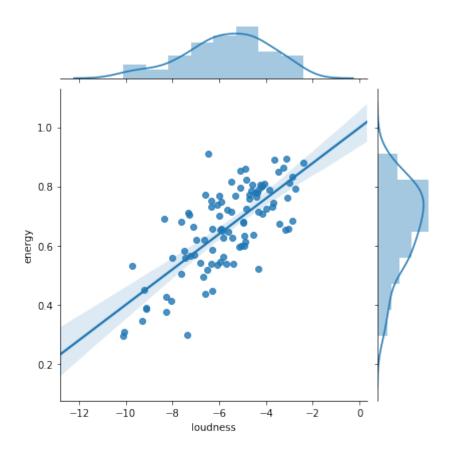
In [22]: sn.heatmap(pd.crosstab(dt['loudness'], dt['energy']))

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8c880a3f98>

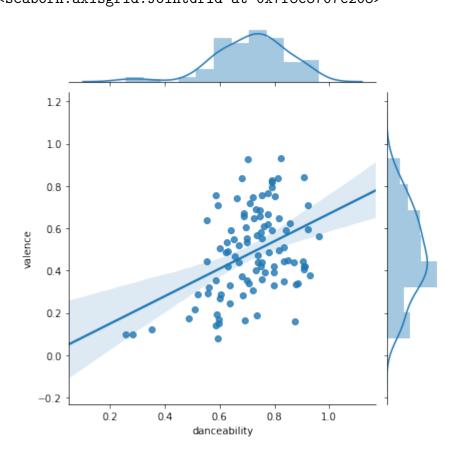


In [30]: sn.jointplot(data=dt, x='loudness', y='energy', kind='reg')

Out[30]: <seaborn.axisgrid.JointGrid at 0x7f8c871902e8>



In [31]: sn.jointplot(data=dt, x='danceability', y='valence', kind='reg')
Out[31]: <seaborn.axisgrid.JointGrid at 0x7f8c8707c208>



In []: