Podcast Topic Segmentation

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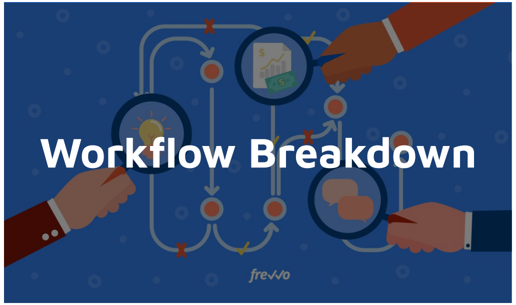
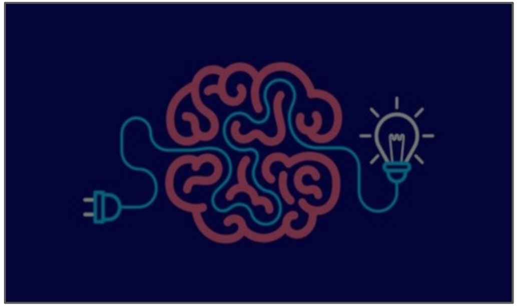
Agenda


Introduction


Literature Review


Workflow Breakdown




Conclusion

Introduction

Problem: Long-form audio/podcast discovery is rudimentary and specific content hard to find

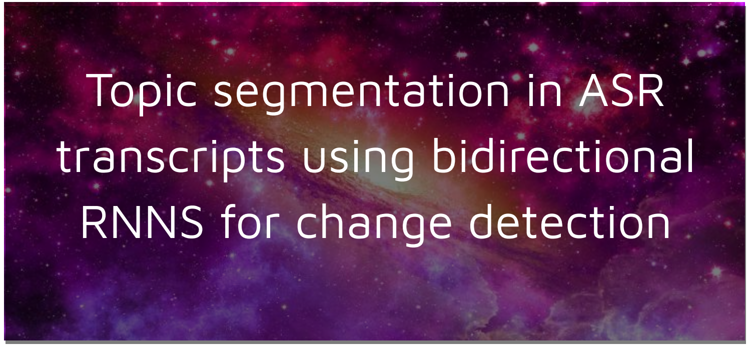
Solution: NLP-driven podcast analysis to facilitate search and discovery of relevant discussions

Topic: 2022 Oscars recap podcasts analyzing

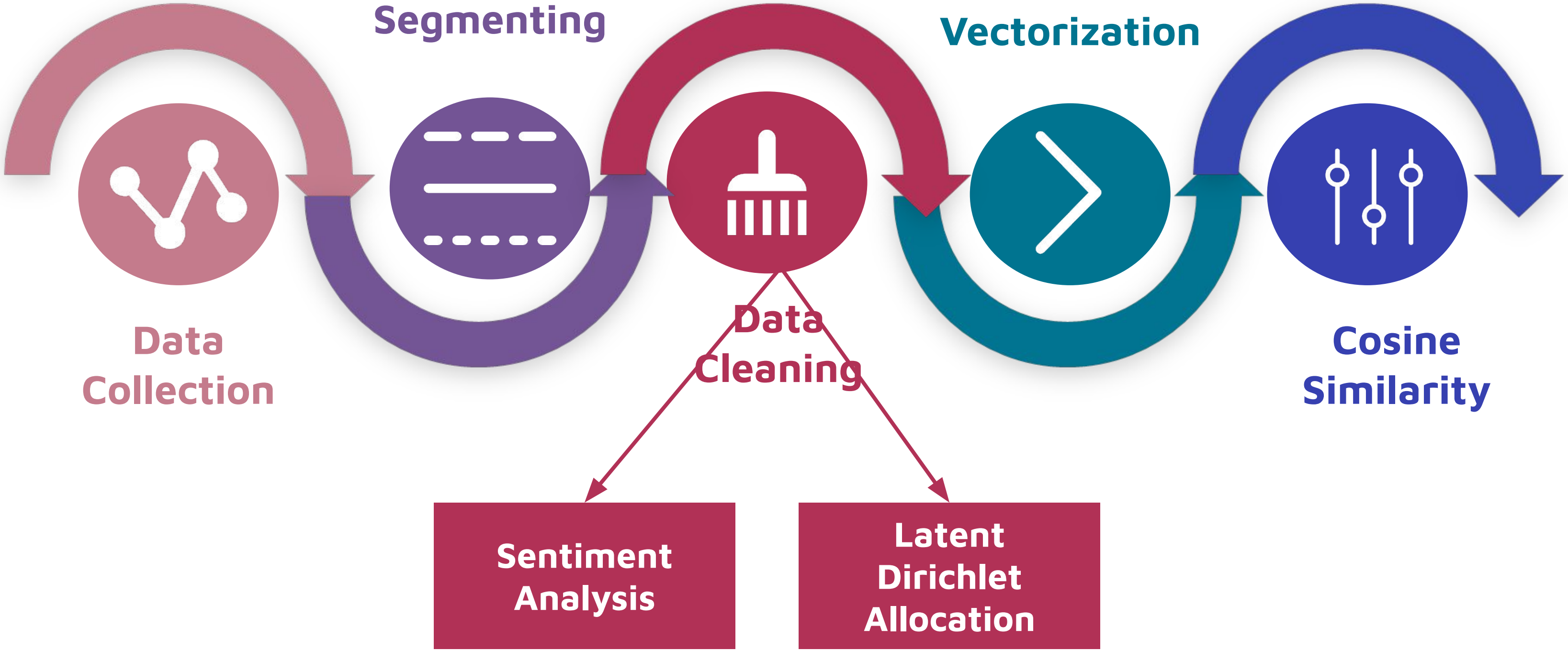
Objective: Find podcast segments from within larger corpus that relate to specific topic and compare segments between podcasts

Approaches: Methods including Cosine Similarity, LDA and Sentiment Scoring

Literature Review



Workflow Breakdown



Data Collection

iTunes Search	Mp3	Download	API	Corpus
iTunes Search for full podcasts	**Podcast episodes downloaded into .mp3 format**	**20 podcasts downloaded in total** -15 Oscars-related podcasts -5 non-Oscars podcasts (subjects: Grammys, AirBnB, Bitcoin)	**Use IBM Watson Speech-to-Text API with customization, producing:** -Basic speech conversion for each podcast, list of words with confidence scores -Speaker labels -Timestamps	**Speech-to-Text API run for each podcast** -Each transcript becomes corpus -Collection of 20 corpuses (small but sufficient for our project)

Methodology and Validation Performance Measure

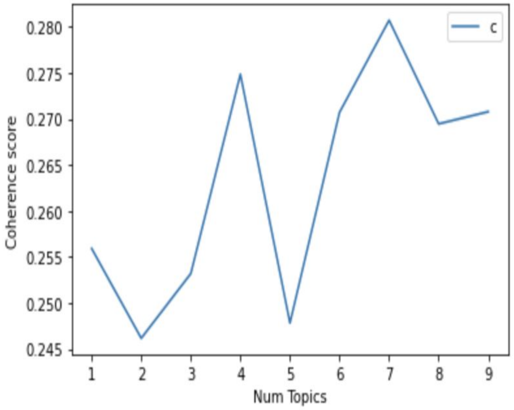
Segmentation

Segmentation performed via a custom function	Function takes keyword(s) as argument	Checks whether word(s) appear in full corpus	If yes, returns a sorted list object of timestamps for each occurrence of keyword	Multiple searches help define a segment e.g. “Chris Rock”, “Will Smith”, and “slap”
Segmented text is exported via a second custom function	Text boundaries for segment = first occurrence of keyword -15 words and last occurrence of keyword + 15 words		Function outputs txt file for each segment for analysis stage	Produces very good rough approximation of segments, could be refined later

LDA(Latent Dirichlet Allocation)

Why LDA?

LDA



Topic Extraction

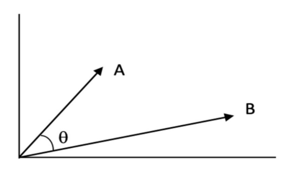
```
(0, '0.013*"know" + 0.013*"go" + 0.013*"get" + 0.013*"chri"')
(1, '0.001*"know" + 0.001*"like" + 0.001*"chri" + 0.001*"got"')
(2, '0.024*"know" + 0.020*"like" + 0.015*"think" + 0.014*"go"')
(3, '0.063*"n" + 0.011*"energi" + 0.011*"twenti" + 0.011*"climat"')
(4, '0.074*"like" + 0.028*"know" + 0.023*"yeah" + 0.021*"think"')
(5, '0.019*"like" + 0.016*"right" + 0.014*"know" + 0.013*"rock"')
(6, '0.014*"know" + 0.013*"yeah" + 0.013*"got" + 0.011*"go"')
(7, '0.001*"n" + 0.001*"know" + 0.001*"like" + 0.001*"get"')
(8, '0.001*"n" + 0.001*"like" + 0.001*"know" + 0.001*"go"')
(9, '0.142*"n" + 0.015*"like" + 0.010*"one" + 0.008*"talk"')
```

Word Cloud


```
Coherence Score:  0.28181650732521046
```

Cosine Similarity

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$



Vectorize using word embedding

- Word2Vec:

Two layer neural network that takes a corpus as input and outputs a vector representation of the corpus

Cosine similarity result for the segmented podcasts

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	1	0.999742	0.999928	0.999871	0.999881	0.999927	0.999855	0.999887	0.99992	0.999789	0.999797	0.999779	0.999924	0.999931	0.999917	0.9999	0.999949	0.999911	0.9998	0.999622
1	0.99974	1	0.999744	0.999607	0.999679	0.999713	0.999625	0.999714	0.9997	0.999917	0.999876	0.999918	0.999717	0.99973	0.999758	0.99975	0.999695	0.999754	0.9997	0.999802
2	0.99992	0.999744	1	0.999903	0.999872	0.99994	0.999916	0.999921	0.99992	0.999793	0.999828	0.999818	0.999961	0.999942	0.999951	0.9999	0.999926	0.999933	0.99988	0.999629
3	0.99987	0.999607	0.999903	1	0.999845	0.999888	0.999886	0.999893	0.99988	0.999637	0.999721	0.999659	0.999937	0.999905	0.999912	0.999873	0.999912	0.999911	0.9998	0.999465
4	0.99988	0.999679	0.999872	0.999845	1	0.999869	0.999808	0.999825	0.99982	0.99976	0.99969	0.999736	0.999855	0.999871	0.999864	0.999875	0.999874	0.999877	0.99984	0.999545
5	0.99992	0.999713	0.99994	0.999888	0.999869	1	0.999882	0.999931	0.99989	0.999733	0.999789	0.999749	0.999963	0.999952	0.999968	0.999937	0.999961	0.999936	0.99993	0.999563
6	0.99985	0.999625	0.999916	0.999886	0.999808	0.999882	1	0.999891	0.9998	0.999689	0.999773	0.999752	0.999922	0.999882	0.999909	0.999836	0.999898	0.999874	0.99982	0.999564
7	0.99988	0.999714	0.999921	0.999893	0.999825	0.999931	0.999891	1	0.99991	0.999752	0.999804	0.999766	0.999952	0.999923	0.999928	0.999844	0.99992	0.999875	0.99984	0.999586
8	0.99992	0.9997	0.999929	0.999883	0.999825	0.999895	0.99985	0.999913	1	0.999748	0.999777	0.999748	0.999939	0.999926	0.999911	0.99986	0.999927	0.99988	0.9998	0.99958
9	0.99978	0.999917	0.999793	0.999637	0.99976	0.999734	0.999689	0.999752	0.99974	1	0.999894	0.999931	0.999748	0.999732	0.999764	0.99974	0.999733	0.999723	0.99960	0.999797
10	0.99979	0.999876	0.999828	0.99972	0.99969	0.999789	0.999773	0.999804	0.99977	0.999894	1	0.999891	0.99981	0.99978	0.99983	0.99977	0.999788	0.999781	0.99970	0.999771
11	0.99977	0.999918	0.999818	0.999659	0.999736	0.999749	0.999752	0.999766	0.99974	0.999931	0.999891	1	0.99977	0.999757	0.999784	0.999743	0.999747	0.999781	0.99968	0.999835
12	0.99992	0.999717	0.999961	0.999937	0.999855	0.999963	0.999922	0.999952	0.99993	0.999748	0.99981	0.99977	1	0.999959	0.999968	0.999908	0.999963	0.999938	0.99992	0.999606
13	0.99993	0.99973	0.999942	0.999905	0.999871	0.999952	0.999882	0.999923	0.99992	0.999732	0.99978	0.999757	0.999959	1	0.999957	0.99994	0.999944	0.999957	0.99994	0.999588
14	0.99991	0.999758	0.999951	0.999912	0.999864	0.999968	0.999909	0.999928	0.9999	0.999764	0.99983	0.999784	0.999968	0.999957	1	0.999935	0.999957	0.999968	0.99994	0.999599
15	0.9999	0.99975	0.9999	0.999873	0.999875	0.999937	0.999836	0.999844	0.9998	0.99974	0.99977	0.999743	0.999908	0.99994	0.999935	1	0.999916	0.999935	0.99994	0.999548
16	0.99994	0.999695	0.999926	0.999912	0.999874	0.999961	0.999898	0.99992	0.99992	0.999733	0.999788	0.999747	0.999964	0.999943	0.999957	0.999916	1	0.999931	0.99991	0.999603
17	0.99991	0.999754	0.999933	0.999911	0.999876	0.999936	0.999874	0.999875	0.9998	0.999723	0.999781	0.999781	0.999938	0.999957	0.999968	0.999935	0.999931	1	0.99994	0.999596
18	0.9998	0.9997	0.999884	0.999871	0.999843	0.999938	0.999821	0.999844	0.9998	0.999663	0.999703	0.999686	0.999927	0.999943	0.999945	0.999949	0.999916	0.999949	1	0.999519
19	0.99962	0.999802	0.999629	0.999465	0.999545	0.999562	0.999564	0.999586	0.9995	0.999797	0.999771	0.999835	0.999606	0.999588	0.999599	0.999548	0.999603	0.999596	0.99951	1

- Visually observed 5 podcasts (highlighted) have lower similarity score compared to all other podcasts
  - [1, 9, 10, 11, 19]
- Limitation: All of the scores are high 0.99xxxx

Cosine Similarity

Grouping similar and dissimilar podcasts with a selected threshold

By comparing each podcast with the rest of podcast, we get the lists of comparably dissimilar podcasts (similarity score <0.99975)

By comparing each podcast with the rest of podcast, we get the lists of similar podcasts (similarity score >0.99995)

Ind▲	Type	Size	
0	list	2	[1, 19]
1	list	15	[0, 2, 3, 4, 5, 6, 7, 8, 12, 13, ...]
2	list	2	[1, 19]
3	list	5	[1, 9, 10, 11, 19]
4	list	5	[1, 9, 10, 11, 19]
5	list	4	[1, 9, 11, 19]
6	list	5	[1, 9, 10, 11, 19]
7	list	3	[1, 9, 19]
8	list	4	[1, 9, 11, 19]
9	list	13	[3, 4, 5, 6, 7, 8, 12, 13, 14, 15, ...]
10	list	7	[3, 4, 6, 13, 15, 17, 18]
11	list	9	[3, 4, 5, 6, 8, 13, 15, 16, 18]
12	list	3	[1, 9, 19]
13	list	5	[1, 9, 10, 11, 19]
14	list	3	[1, 9, 19]
15	list	5	[1, 9, 10, 11, 19]
16	list	4	[1, 9, 11, 19]
17	list	4	[1, 9, 10, 19]
18	list	5	[1, 9, 10, 11, 19]
19	list	15	[0, 2, 3, 4, 5, 6, 7, 8, 12, 13, ...]

Dissimilar Podcasts:
[1, 9, 10, 11, 19]

Ind▲	Type	Size	
0	list	1	[0]
1	list	1	[1]
2	list	2	[2, 12]
3	list	1	[3]
4	list	1	[4]
5	list	4	[5, 12, 14, 16]
6	list	1	[6]
7	list	1	[7]
8	list	1	[8]
9	list	1	[9]
10	list	1	[10]
11	list	1	[11]
12	list	6	[2, 5, 12, 13, 14, 16]
13	list	4	[12, 13, 14, 17]
14	list	6	[5, 12, 13, 14, 16, 17]
15	list	1	[15]
16	list	4	[5, 12, 14, 16]
17	list	3	[13, 14, 17]
18	list	1	[18]
19	list	1	[19]

Similar Podcasts:
[2, 5, 12, 13, 14, 16]
[5, 12, 13, 14, 16, 17]...

Similar podcasts

- Oscar related words
  - “Peopl”, “realli”, “right”, “joke”, “smith”, “chri” “rock”, “slap”, “oscar”

Dissimilar podcasts

- Grammy, bitcoin, airbnb related words:
  - “One”, “twenti”, “grammi”, “bit”, “coin”, “place”, “climat”, “stay”

CountVectorizer

Transformed text into vectors on the basis of frequency of each word that occurs in the entire text

ngram_range = (1,2)

Applied cos similarity to CountVectorizer result

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	1	0.2227	0.3584	0.2772	0.2855	0.3823	0.2745	0.3149	0.3245	0.164	0.1604	0.1502	0.3552	0.4144	0.4175	0.3902	0.3013	0.4443	0.4117	0.07297
1	0.2227	1	0.2378	0.224	0.1377	0.3698	0.2251	0.179	0.2335	0.1615	0.1695	0.2108	0.3272	0.3225	0.3994	0.3814	0.2373	0.4027	0.4382	0.1134
2	0.3584	0.2378	1	0.344	0.3865	0.4772	0.3736	0.3432	0.4624	0.1922	0.2008	0.2305	0.5071	0.4638	0.555	0.4029	0.4874	0.4551	0.3813	0.09721
3	0.2772	0.224	0.344	1	0.2904	0.3937	0.3302	0.3241	0.3563	0.1513	0.2073	0.189	0.4205	0.4106	0.3804	0.3362	0.3571	0.3363	0.3044	0.1035
4	0.2855	0.1377	0.3865	0.2904	1	0.3484	0.2428	0.2727	0.382	0.1504	0.1313	0.1465	0.3922	0.3958	0.3733	0.28	0.324	0.318	0.2882	0.05665
5	0.3823	0.3698	0.4772	0.3937	0.3484	1	0.4228	0.429	0.4985	0.2873	0.2982	0.3017	0.6365	0.6048	0.6539	0.6259	0.5242	0.5926	0.6453	0.143
6	0.2745	0.2251	0.3736	0.3302	0.2428	0.4228	1	0.3813	0.3588	0.2077	0.2526	0.2844	0.4973	0.4572	0.4376	0.3097	0.4064	0.3565	0.3336	0.1198
7	0.3149	0.179	0.3432	0.3241	0.2727	0.429	0.3813	1	0.417	0.253	0.269	0.24	0.4568	0.4272	0.4181	0.3211	0.3935	0.3072	0.2852	0.1313
8	0.3245	0.2335	0.4624	0.3563	0.382	0.4985	0.3588	0.417	1	0.2624	0.2668	0.2333	0.5719	0.5253	0.5574	0.4777	0.4587	0.4765	0.4569	0.09893
9	0.164	0.1615	0.1922	0.1513	0.1504	0.2873	0.2077	0.253	0.2624	1	0.1898	0.1841	0.3149	0.2315	0.2806	0.1902	0.2409	0.2019	0.1941	0.1035
10	0.1604	0.1695	0.2008	0.2073	0.1313	0.2982	0.2526	0.269	0.2668	0.1898	1	0.2162	0.3301	0.3064	0.2944	0.2432	0.2388	0.2223	0.2214	0.1357
11	0.1502	0.2108	0.2305	0.189	0.1465	0.3017	0.2844	0.24	0.2333	0.1841	0.2162	1	0.3393	0.2658	0.3031	0.2002	0.2399	0.2584	0.2663	0.1185
12	0.3552	0.3272	0.5071	0.4205	0.3922	0.6365	0.4973	0.4568	0.5719	0.3149	0.3301	0.3393	1	0.6147	0.6416	0.4874	0.5384	0.5253	0.5651	0.1596
13	0.4144	0.3225	0.4638	0.4106	0.3958	0.6048	0.4572	0.4272	0.5253	0.2315	0.3064	0.2658	0.6147	1	0.63	0.6159	0.4791	0.5983	0.6579	0.1015
14	0.4175	0.3994	0.555	0.3804	0.3733	0.6539	0.4376	0.4181	0.5574	0.2806	0.2944	0.3031	0.6416	0.63	1	0.6293	0.543	0.6505	0.6627	0.1421
15	0.3902	0.3814	0.4029	0.3362	0.28	0.6259	0.3097	0.3211	0.4777	0.1902	0.2432	0.2002	0.4874	0.6159	0.6293	1	0.4847	0.7035	0.7703	0.05028
16	0.3013	0.2373	0.4874	0.3571	0.324	0.5242	0.4064	0.3935	0.4587	0.2409	0.2388	0.2399	0.5384	0.4791	0.543	0.4847	1	0.4209	0.3962	0.1056
17	0.4443	0.4027	0.4551	0.3363	0.318	0.5926	0.3565	0.3072	0.4765	0.2019	0.2223	0.2584	0.5253	0.5983	0.6505	0.7035	0.4209	1	0.7542	0.08399
18	0.4117	0.4382	0.3813	0.3044	0.2882	0.6453	0.3336	0.2852	0.4569	0.1941	0.2214	0.2663	0.5651	0.6579	0.6627	0.7703	0.3962	0.7542	1	0.07842
19	0.07297	0.1134	0.09721	0.1035	0.05665	0.143	0.1198	0.1313	0.09893	0.1035	0.1357	0.1185	0.1596	0.1015	0.1421	0.05028	0.1056	0.08399	0.07842	1

CountVectorizer ----> Cos Similarity

CountVectorizer

Sort 5 most dissimilar and most similar podcasts for each of them

1 — Airbnb;
19 — Bitcoin;
9,10,11 — Grammy;
Rest of podcasts — Oscars related

Ke	Type	Size	
0	Array of int64	(5,)	[19 11 10 9 1]
1	Array of int64	(5,)	[19 4 9 10 7]
2	Array of int64	(5,)	[19 9 10 11 1]
3	Array of int64	(5,)	[19 9 11 10 1]
4	Array of int64	(5,)	[19 10 1 11 9]
5	Array of int64	(5,)	[19 9 10 11 4]
6	Array of int64	(5,)	[19 9 1 4 10]
7	Array of int64	(5,)	[19 1 11 9 10]
8	Array of int64	(5,)	[19 11 1 9 10]
9	Array of int64	(5,)	[19 4 3 1 0]
10	Array of int64	(5,)	[4 19 0 1 9]
11	Array of int64	(5,)	[19 4 0 9 3]
12	Array of int64	(5,)	[19 9 1 10 11]
13	Array of int64	(5,)	[19 9 11 10 1]
14	Array of int64	(5,)	[19 9 10 11 4]
15	Array of int64	(5,)	[19 9 11 10 4]
16	Array of int64	(5,)	[19 1 10 11 9]
17	Array of int64	(5,)	[19 9 10 11 7]
18	Array of int64	(5,)	[19 9 10 11 7]
19	Array of int64	(5,)	[15 4 0 18 17]

Most dissimilar podcasts
1,9,10,11,19

Ke	Type	Size	
0	Array of int64	(5,)	[0 17 14 13 18]
1	Array of int64	(5,)	[1 18 17 14 15]
2	Array of int64	(5,)	[2 14 12 16 5]
3	Array of int64	(5,)	[3 12 13 5 14]
4	Array of int64	(5,)	[4 13 12 2 8]
5	Array of int64	(5,)	[5 14 18 12 15]
6	Array of int64	(5,)	[6 12 13 14 5]
7	Array of int64	(5,)	[7 12 5 13 14]
8	Array of int64	(5,)	[8 12 14 13 5]
9	Array of int64	(5,)	[9 12 5 14 8]
10	Array of int64	(5,)	[10 12 13 5 14]
11	Array of int64	(5,)	[11 12 14 5 6]
12	Array of int64	(5,)	[12 14 5 13 8]
13	Array of int64	(5,)	[13 18 14 15 12]
14	Array of int64	(5,)	[14 18 5 17 12]
15	Array of int64	(5,)	[15 18 17 14 5]
16	Array of int64	(5,)	[16 14 12 5 2]
17	Array of int64	(5,)	[17 18 15 14 13]
18	Array of int64	(5,)	[18 15 17 14 13]
19	Array of int64	(5,)	[19 12 5 14 10]

Most similar podcasts

Tf-idf

A numerical statistic that is intended to reflect how important a word is to a document

- The term frequency of a word in a document
- The inverse document frequency of the word across a set of documents
- ngram_range = (1,2)

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	1	0.05775	0.136	0.07999	0.1049	0.1341	0.09109	0.1175	0.1062	0.05306	0.05528	0.04072	0.1327	0.1625	0.1631	0.1547	0.1084	0.1669	0.1691	0.02744
1	0.05775	1	0.07013	0.06577	0.03748	0.1153	0.06688	0.05493	0.06725	0.04354	0.04865	0.05704	0.1038	0.1086	0.1368	0.132	0.07251	0.1199	0.1561	0.0416
2	0.136	0.07013	1	0.1101	0.1362	0.1903	0.1355	0.1073	0.1826	0.05512	0.06168	0.06807	0.2093	0.2079	0.2393	0.206	0.1951	0.1992	0.1921	0.02818
3	0.07999	0.06577	0.1101	1	0.08333	0.1493	0.1071	0.09752	0.1124	0.03918	0.0578	0.047	0.1587	0.1619	0.1409	0.1412	0.1223	0.1201	0.1342	0.03327
4	0.1049	0.03748	0.1362	0.08333	1	0.1217	0.08403	0.07442	0.1218	0.03276	0.03089	0.03414	0.1353	0.1537	0.1375	0.1289	0.1147	0.1167	0.1245	0.01587
5	0.1341	0.1153	0.1903	0.1493	0.1217	1	0.163	0.1547	0.1923	0.09114	0.1081	0.09923	0.2758	0.28	0.2905	0.3117	0.209	0.2471	0.3303	0.05774
6	0.09109	0.06688	0.1355	0.1071	0.08403	0.163	1	0.1293	0.1314	0.06518	0.07725	0.08101	0.2012	0.2129	0.1812	0.1523	0.1439	0.1475	0.1652	0.04498
7	0.1175	0.05493	0.1073	0.09752	0.07442	0.1547	0.1293	1	0.1428	0.07624	0.08348	0.06062	0.169	0.1701	0.1625	0.1393	0.1314	0.1083	0.1245	0.04456
8	0.1062	0.06725	0.1826	0.1124	0.1218	0.1923	0.1314	0.1428	1	0.07829	0.08294	0.06528	0.2431	0.2335	0.2375	0.2305	0.1618	0.1884	0.2306	0.03775
9	0.05306	0.04354	0.05512	0.03918	0.03276	0.09114	0.06518	0.07624	0.07829	1	0.05129	0.05247	0.09822	0.08023	0.09265	0.07118	0.07112	0.06745	0.07429	0.03245
10	0.05528	0.04865	0.06168	0.0578	0.03089	0.1081	0.07725	0.08348	0.08294	0.05129	1	0.05824	0.1301	0.1234	0.1059	0.09727	0.0725	0.07666	0.09586	0.04856
11	0.04072	0.05704	0.06807	0.047	0.03414	0.09923	0.08101	0.06062	0.06528	0.05247	0.05824	1	0.1034	0.08566	0.09317	0.0693	0.06863	0.08025	0.1014	0.04262
12	0.1327	0.1038	0.2093	0.1587	0.1353	0.2758	0.2012	0.169	0.2431	0.09822	0.1301	0.1034	1	0.3088	0.295	0.2568	0.2228	0.226	0.3135	0.06494
13	0.1625	0.1086	0.2079	0.1619	0.1537	0.28	0.2129	0.1701	0.2335	0.08023	0.1234	0.08566	0.3088	1	0.3051	0.3472	0.2261	0.269	0.375	0.04393
14	0.1631	0.1368	0.2393	0.1409	0.1375	0.2905	0.1812	0.1625	0.2375	0.09265	0.1059	0.09317	0.295	0.3051	1	0.3413	0.2418	0.2874	0.357	0.05677
15	0.1547	0.132	0.206	0.1412	0.1289	0.3117	0.1523	0.1393	0.2305	0.07118	0.09727	0.0693	0.2568	0.3472	0.3413	1	0.2363	0.3487	0.475	0.02623
16	0.1084	0.07251	0.1951	0.1223	0.1147	0.209	0.1439	0.1314	0.1618	0.07112	0.0725	0.06863	0.2228	0.2261	0.2418	0.2363	1	0.1796	0.1956	0.04158
17	0.1669	0.1199	0.1992	0.1201	0.1167	0.2471	0.1475	0.1083	0.1884	0.06745	0.07666	0.08025	0.226	0.269	0.2874	0.3487	0.1796	1	0.3781	0.03451
18	0.1691	0.1561	0.1921	0.1342	0.1245	0.3303	0.1652	0.1245	0.2306	0.07429	0.09586	0.1014	0.3135	0.375	0.357	0.475	0.1956	0.3781	1	0.0389
19	0.02744	0.0416	0.02818	0.03327	0.01587	0.05774	0.04498	0.04456	0.03775	0.03245	0.04856	0.04262	0.06494	0.04393	0.05677	0.02623	0.04158	0.03451	0.0389	1

Tf-idf ----> Cos Similarity

Tf-idf

Sort 5 most dissimilar and most similar podcasts for each of them

1 — Airbnb;
19 — Bitcoin;
9,10,11 — Grammy;
Rest of podcasts — Oscars related

Ke	Type	Size	
0	Array of int64	(5,)	[19 11 9 10 1]
1	Array of int64	(5,)	[4 19 9 10 7]
2	Array of int64	(5,)	[19 9 10 11 1]
3	Array of int64	(5,)	[19 9 11 10 1]
4	Array of int64	(5,)	[19 10 9 11 1]
5	Array of int64	(5,)	[19 9 11 10 1]
6	Array of int64	(5,)	[19 9 1 10 11]
7	Array of int64	(5,)	[19 1 11 4 9]
8	Array of int64	(5,)	[19 11 1 9 10]
9	Array of int64	(5,)	[19 4 3 1 10]
10	Array of int64	(5,)	[4 19 1 9 0]
11	Array of int64	(5,)	[4 0 19 3 9]
12	Array of int64	(5,)	[19 9 11 1 10]
13	Array of int64	(5,)	[19 9 11 1 10]
14	Array of int64	(5,)	[19 9 11 10 1]
15	Array of int64	(5,)	[19 11 9 10 4]
16	Array of int64	(5,)	[19 11 9 10 1]
17	Array of int64	(5,)	[19 9 10 11 7]
18	Array of int64	(5,)	[19 9 10 11 4]
19	Array of int64	(5,)	[4 15 0 2 9]

Most dissimilar podcasts
1,9,10,11,19

Ke	Type	Size	
0	Array of int64	(5,)	[0 18 17 14 13]
1	Array of int64	(5,)	[1 18 14 15 17]
2	Array of int64	(5,)	[2 14 12 13 15]
3	Array of int64	(5,)	[3 13 12 5 15]
4	Array of int64	(5,)	[4 13 14 2 12]
5	Array of int64	(5,)	[5 18 15 14 13]
6	Array of int64	(5,)	[6 13 12 14 18]
7	Array of int64	(5,)	[7 13 12 14 5]
8	Array of int64	(5,)	[8 12 14 13 18]
9	Array of int64	(5,)	[9 12 14 5 13]
10	Array of int64	(5,)	[10 12 13 5 14]
11	Array of int64	(5,)	[11 12 18 5 14]
12	Array of int64	(5,)	[12 18 13 14 5]
13	Array of int64	(5,)	[13 18 15 12 14]
14	Array of int64	(5,)	[14 18 15 13 12]
15	Array of int64	(5,)	[15 18 17 13 14]
16	Array of int64	(5,)	[16 14 15 13 12]
17	Array of int64	(5,)	[17 18 15 14 13]
18	Array of int64	(5,)	[18 15 17 13 14]
19	Array of int64	(5,)	[19 12 5 14 10]

Most dissimilar podcasts

Sentiment Scoring

Highest	Oscars (2022) 0.639
Lowest	Bitcoin Podcast -0.538
Mean	0.242

titles	simple_sentiment
2022 Oscars Recap Excerpt	0.322034
AirBnB Podcast Excerpt	0.5
Between (Chris) Rock And A Hard Place Excerpt	-0.258065
Chris Rock Allowed Will Smith to Stay at Oscars Excerpt	0.153846
Chris Rock vs Will Smith Excerpt	-0.0909091
Chris Rock_s Response, Comics React and Josh Wolf Excerpt	0.521739
Ebro In The Morning - Talking Smack_ Conspiracy Theories Excerpt	0.322034
Ebro In The Morning - The Smack Heard Around The World Excerpt	0.47619
Episode 156_ The Will Smith and Chris Rock Fight Excerpt	0.142857
Grammys1 Excerpt	0.586207
Grammys2 Excerpt	0.0967742
Grammys3 Excerpt	-0.12
I AM ATHLETE _ Will Smith Slaps Chris Rock_ Was He Right or Wrong_ Excerpt	0.0172414
Jocko Evaluates Celebrities Slapping Each Other. Will Smith _ Chris Rock. Oscars. 1 Excerpt	0.261538
Live From Inside the Oscars_ The Will Smith-Chris Rock Slap Excerpt	0.464286
Oscars (2022) Excerpt	0.639098
Oscars Reactions, Apple Subscriptions, and The Team Behind Super Pumped_ The Battle for Uber Excerpt	0.285714
Podcast5 Excerpt	0.446809
Will Smith vs. Chris Rock NFL OT changes Excerpt	0.606557
Bitcoin Podcast Excerpt	-0.538462

Conclusion


THANK YOU!