Song offensiveness vs time and popularity

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Abstract

This document contains the instructions for preparing a report for ADA 2017. The document itself conforms to its own specifications, and is therefore an example of what your manuscript should look like. This document is based on the ACL 2014 paper format.

1 Introduction

2 Analysis

2.1 Basic correlations

The first task was to check whether there is a general correlation between the offensiveness (the number of offensive words) and the popularity of a song. Our results are shown on figure 1. We see that the wanted correlations, i.e. the offensiveness-hotness and the offensiveness-counts (play counts) are close to zero so there is no linear dependency if we take all valid songs (those where the play count is greater than 1 and the year is known) into account.

We have also tried many different ways to find correlations in our data:

- we have tried using the logarithm of the play count instead of the original number of times the songs have been played. This was because the songs which were played often could have a huge value as compared to the ones which were played only 1, 2, 3, or a few times. We wanted to smooth those values so that the difference between popular and non popular songs can be better measured. Unfortunately this didn't give us better correlations than before. However we notice that the correlation between song hotness and play counts suddenly jumped from 0.13 to 0.51 so, at least, we got some insights about the way the song hotness was computed in the Million Songs dataset: they probably also used the logarithm of the play counts value as one of the measures of popularity.

- We removed songs where the play count was very low hoping that the data was better for more popular songs. So we took only songs that were played at least 4 times. Unfortunately, we still didn't get any improvement out of this.

- In the same spirit as the previous one we tried to keep only recent songs (we tried both with songs which were released after 1990 and those which were released after 2000). We hoped that the data was better for recent songs and that we could get some meaningful correlations with this strategy, but nothing: the correlations are still close to zero.

2.2 Correlations over time

Since we didn't get meaningful correlations using all songs at once, it might be interesting to include the temporal dimension and try to figure out whether there are correlations for specific years. We show the results on figure 2.

As we see there are no correlations except in the beginning of the time period of the Million Song dataset. Unfortunately, we have very few songs for that time period and we tried to get more insights on them (see the chapter on Ratio experiments). Before giving more details let us take a closer look at figure 3. We have plotted the same correlations as before but this time we did this for some of the swear words categories.

Again, we see the same trend as before. The plot has many colors but it is not so annoying since we clearly see that all curves (for all swear word categories) follow the same trends: they are very high in the first few years and them they tend to 0. We might be tempted to think that, for music

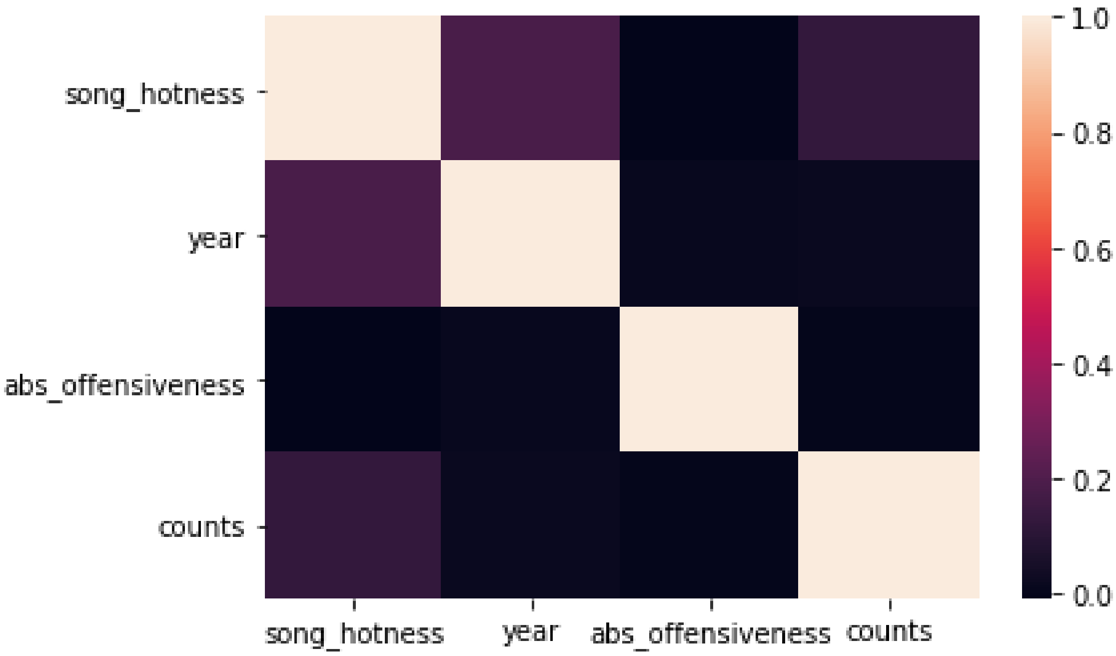


Figure 1: Basic correlations for all songs

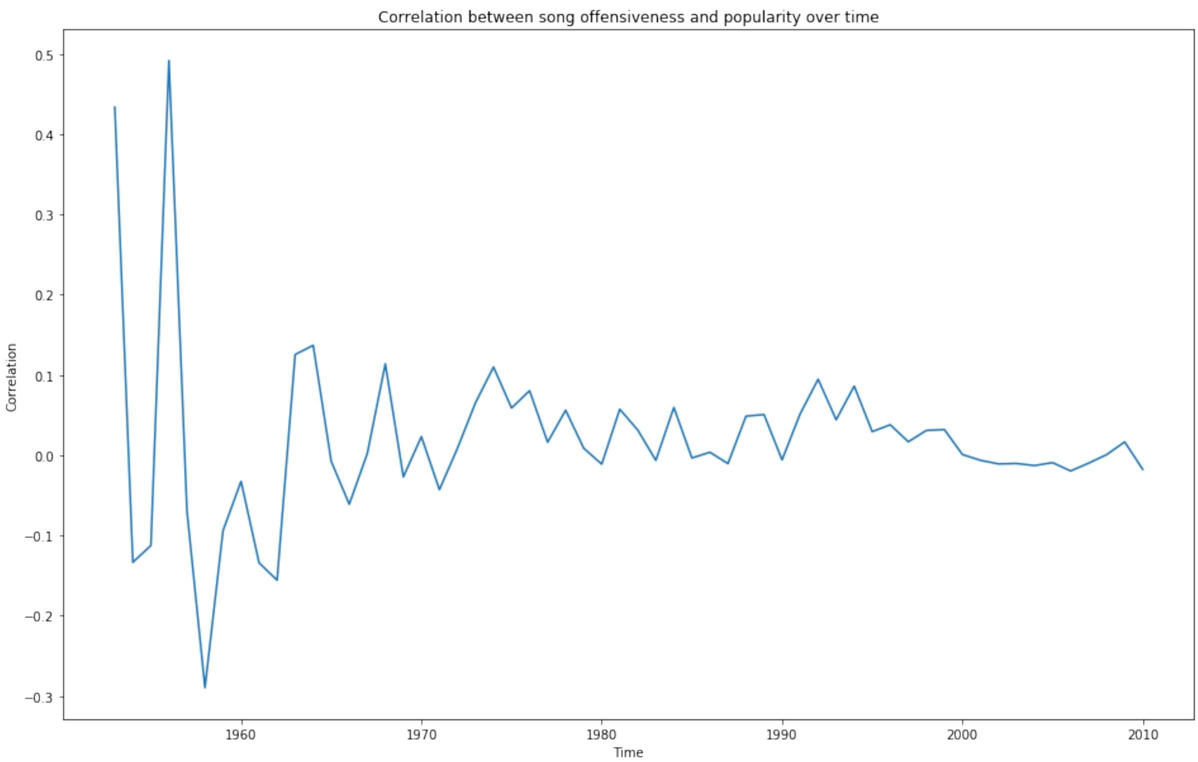


Figure 2: Correlation between song offensiveness and popularity over time

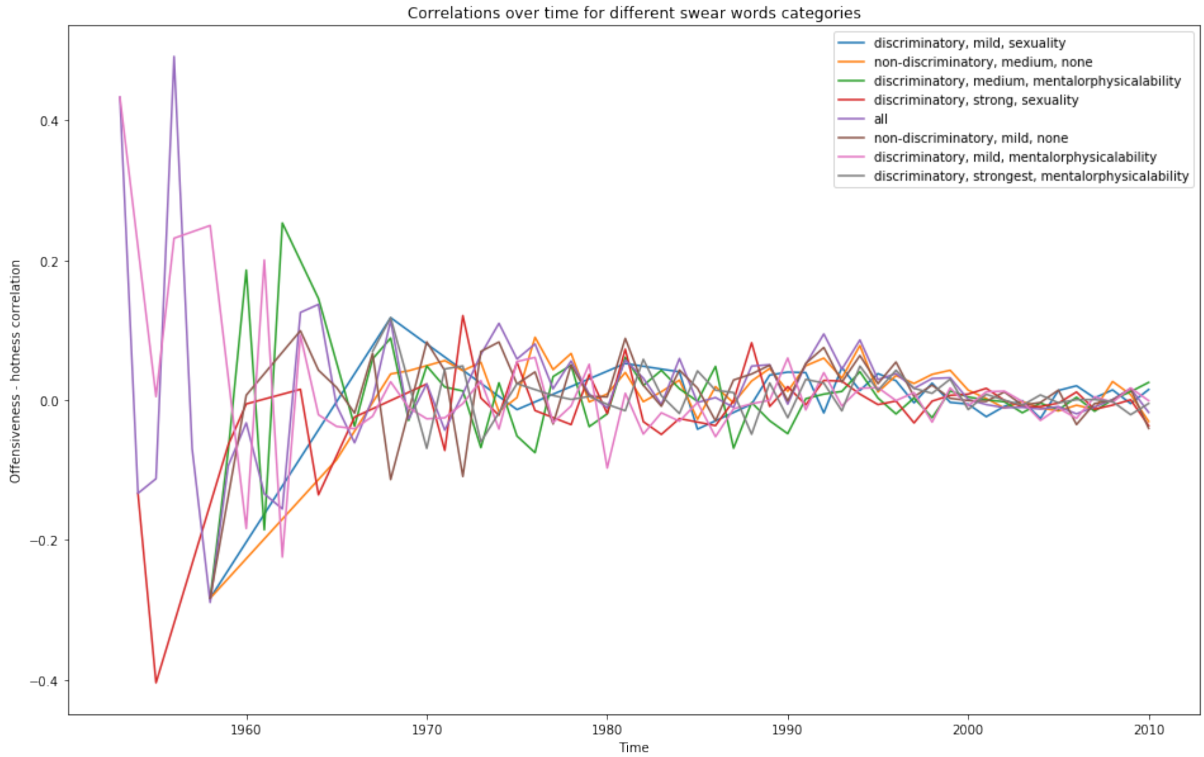


Figure 3: Correlation between song offensiveness and popularity over time for different swear words categories

in the mid-10th century, popularity is more correlated with offensiveness because of the Second World War but this is probably wrong. In the following we will see that we have very little data for those years so it is normal that the correlations are much stronger as soon as one song has one word that is interpreted as a swear word by our algorithms (sometimes it makes mistakes because the lyrics data: we will see an example where the lyrics contain the words Whoo - hoo which doesn't mean anything but MusixMatch put the "hoo" as "ho", which is a swear word in our data).

2.3 Data visualization

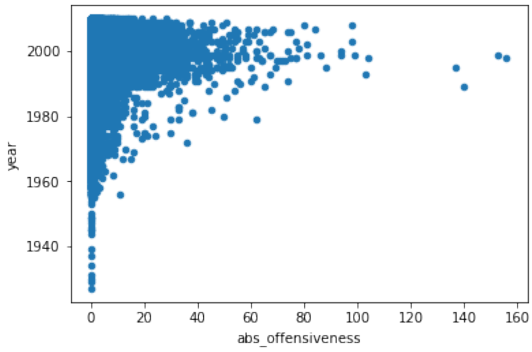
Everything we did until now seems to show that there is no linear dependency for our data. But this does not mean there is no dependency at all. Another very useful method to get better insights about data is to visualize it. Now let us have a deeper look at the scatter plots on figure 4.

We show the offensiveness compared to time (on figure 4a), to play counts(on figure 4b) and to popularity/hotness (on figure 4c). The median of absolute offensiveness is 2 so we decided to also try to plot the same graphs for songs with 2 or more swear words on figure 5.

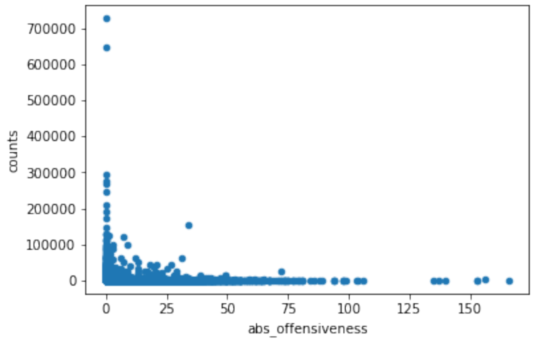
There is not much difference between the 2 scatter plots groups but we can see some structure in the data. First, we see that offensiveness increases over time. The most offensive period in music history is probably located in the last decade of the 20th century but it seems to decrease a little after that. As for the play counts, we can note that the songs which are the most listened to are in general not offensive and that play counts seem to decrease with offensiveness. But the most interesting plot is the hotness one on figures 4c and 5c. It shows that the average hotness songs tend to be more offensive than the others. We see this kind of vertical gaussian shape which seems to culminate somewhere around hotness 0.55. The trends we observe are driven by a small subset of data points but the mass in center is useless.

2.4 Ratio experiment

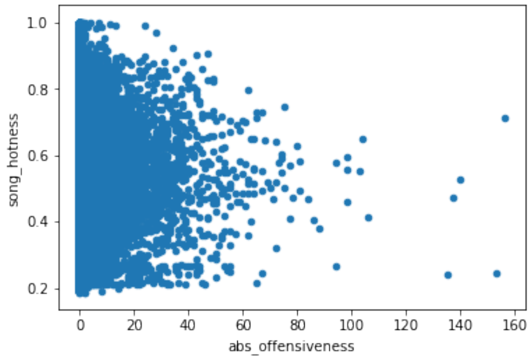
In this section we introduce a new metric for analysing offensiveness over time: the ratio of offensive songs for a given year. We simply count all the offensive songs and divide it by the total number of song for that year. Our results are shown on figure 6. Of course we have to specify what it means for a song to be offensive. In our plots



(a) Offensiveness over time

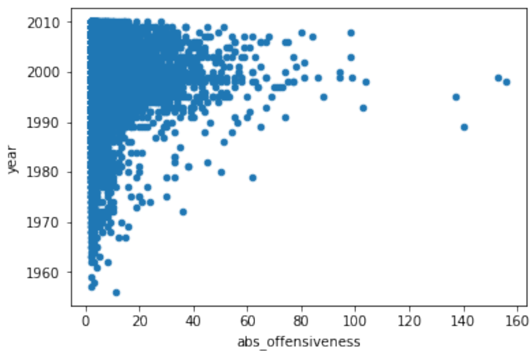


(b) Play counts vs offensiveness

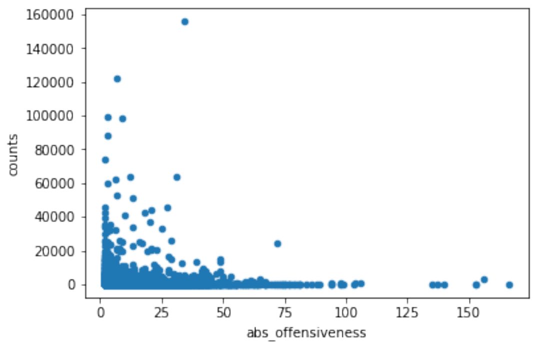


(c) Popularity vs offensiveness

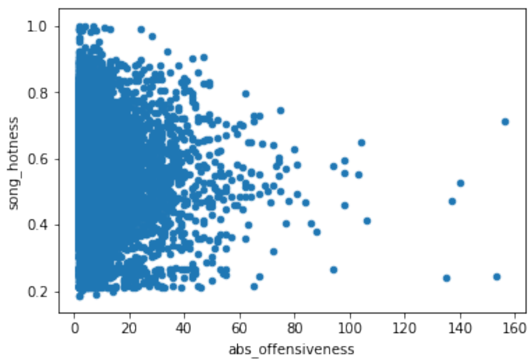
Figure 4: Scatter plots



(a) Offensiveness over time



(b) Play counts vs offensiveness



(c) Popularity vs offensiveness

Figure 5: Scatter plots for songs with 2 or more offensive words

we simply put a threshold on the number of offensive words. On figure 6 the threshold is 1 so any song which contains at least one swear word will be considered as offensive. However, we try to vary that threshold and we show more general results on figure 7.

All the threshold seem to lead to a similar conclusion: the offensiveness trends start to spike in the 1990-2000 decade and then decrease when we enter the 21st century. They are nevertheless ”kept alive” for a few more years after 2000 before starting to fade. This confirms our intuition from the scatter plots about offensiveness over time.

2.5 Number of swear words experiment

Now what if we try to simply plot the number of offensive words without taking the songs themselves into account. We simply take all the lyrics for a given year, count the swear words and keep that result. You can observe what we obtain on figure 8a. Of course this is not the right measure since the number of total songs is varying over time so we show the average number of swear words per song on figure 8b

Again, we are in the same situation as before: the offensiveness spikes in the last decade of the 20th century and then slowly starts to decrease after the year 2000. Do not be confused by the sudden spike in the year 1956. Actually it is due to a ”bug” in the lyrics data. There are 12 songs for that year in our dataset and one of them, ”Smokestack Lightning” by Howlin’Wolf, apparently contains 11 swear words. But if we look at the lyrics we see that there are absolutely no swear words in that song. The problem is that the chorus contains the onomatopeia ”Whoo hooo” which doesn’t mean anything by itself but was recorded by MusixMatch as the word ”ho” which is a swear word !

We show the most offensive songs in our dataset in table 9.

2.6 Machine learning experiment

3 Outview

In this section we will look at what we could have done differently but didnt do simply because it was too complicated or it didnt make a lot of sense.

3.1 The hotness problem

In our dataset we have this hotness (hotttnesss) attribute for each song which is supposed to be a measure of popularity. However, a lot of songs have a hotness equal to 0 or NaN, which makes our final dataset smaller. But another problem is that we dont really know how this parameter was generated. In our analysis we simply trusted it without being sure how it is calculated. so we tried to come up with other ways of calculating the popularity of songs :

3.1.1 Youtube

The main problem is that Youtube was founded in 2005 so we would have no data for music before that year. This would leave us with a lot of songs we cant even talk about. And, since one of the core ideas of our project is to do our analysis based on time (compute the correlations between offensiveness and popularity over time), this would have left us with only a few years between 2005 and 2010 (the data stops at 2011), which is probably not enough to do get interesting data. Another issue tightly related to this one is that the popularity of Youtube itself is variable. For example Despacito is the most viewed video on Youtube today with over 4.5 billion views but, 7 years ago, it was Justin Biebers Baby with only 1.7 billion views. Its probably not that Despacito is 2.6 times more popular than Baby was but just that Youtube was not used as much as it is used today. A lot less people had a connection to the Internet and there were also other means of listening to music (there are also other means today but they are not the same as before). Simply said, there is a variable we might call Youtube usage (or poularity or acces you can call it however you want) which varies over time and we would have to scale the number of views according to this variable, which is quite difficult or maybe even non feasible.

One other problem is the way data is structured on Youtube. The way we would gather our info would be to simply try to match the names of our songs with the name on Youtube since the track id used in the Million Songs dataset simply doesnt exist on Youtube. But, however, we know there can be many videos for one song. We often have the official video and additional videos with lyrics posted by fans (and there can be many of them). So the total number of views is scattered all around and we have no way to find a guarantee that what we are scraping is enough. We might take only official videos but even that is not such a good idea because we would probably lose a lot of info and we would also fall for fake official videos. And the

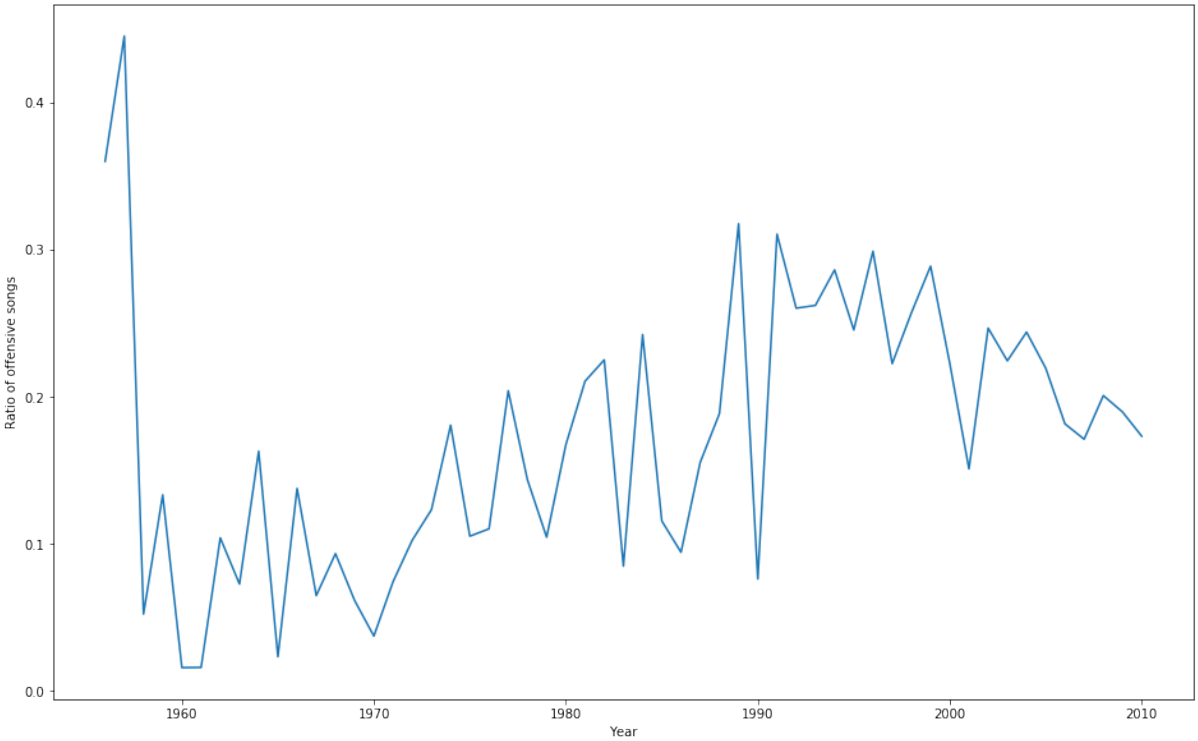


Figure 6: Ratio of offensive songs over time (threshold = 1)

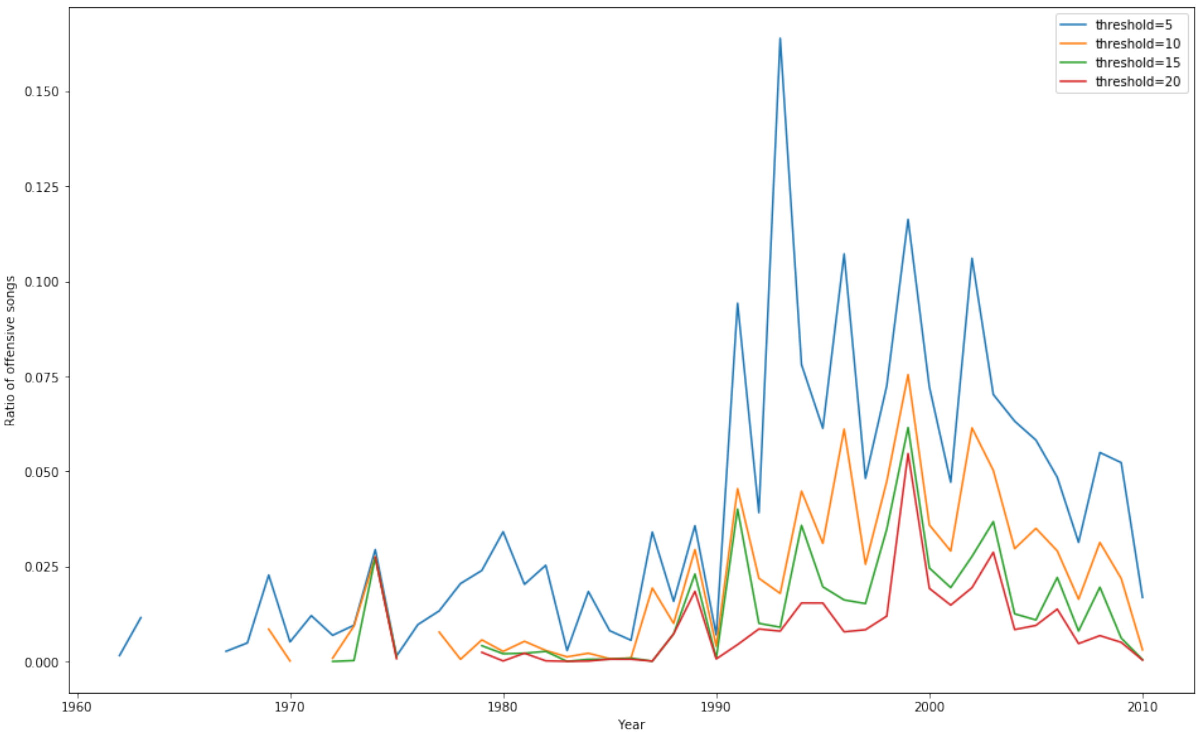
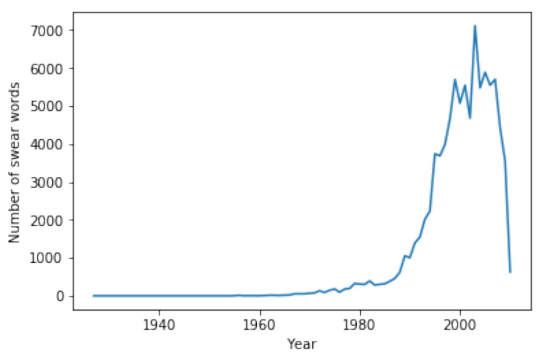
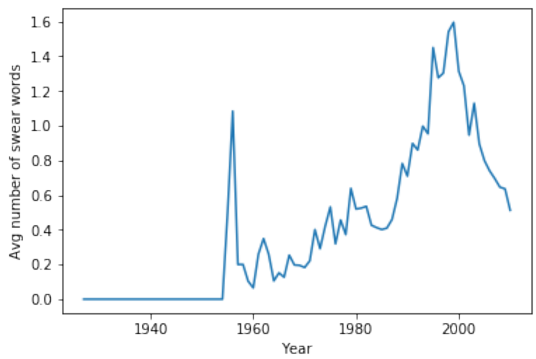


Figure 7: Ratio of offensive songs over time (higher thresholds)



(a) Overall



(b) On average per song

title	year	abs_offensiveness	song_hotness	counts
Don't Gimme No H.A.N./?	0	166.0	NaN	38
Gangster Tripping	1998	156.0	0.711211	3326
Down For My N's	0	153.0	0.246865	65
Bitch Niggas	1999	153.0	NaN	58
Roll Call	1989	140.0	0.528782	138
Can't Tell Me Shit	1995	137.0	0.471971	26
Booty Man (Remix)	0	135.0	0.239629	135
Stop Fuckin Wit Me	0	106.0	0.415050	443
Acid 8000	1998	104.0	0.648113	424
Lose A Hoe_ Gain A Hoe	1993	103.0	0.552007	1
Playa Ass Shit (Explicit)	1999	99.0	NaN	6
Fuck That Shit	2003	98.0	0.554983	509

Figure 9: Most offensive songs

view count is not a good measure because a video can be removed and reuploaded because of artist rights or other things.

3.1.2 Spotify

One other idea we had in mind was to use the Spotify API. Spotify is one of the most popular apps today for listening to music so it can probably be used to gather interesting information. The Spotify API is very complete since it provides us with all the values we would need in our analysis, especially with the track info such as play counts for users or popularity. However, this popularity attribute seems to vary over time because the documentation specifies that a song which has more play counts now will have a better popularity than a song which has the same number of play counts in the past. We might still use the play count or other attributes in our analysis so it would probably give some interesting results. However, the effort to put in is too high because the process for registering an app for being able to use that API seems to be quite long. It is probable that this method would not give better results than the hotness/playcounts analysis we already did. But it might be interesting for some future work.

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