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11-761 Language and Statistics

Assignment 1

1/23/2015

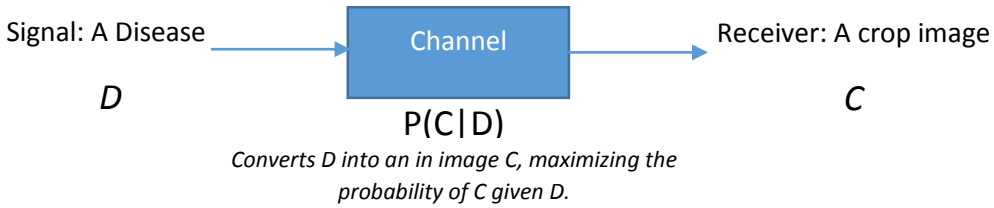
Question 1

For each of the following two problems (A and B), formulate it in the source-channel paradigm:

A. Given satellite images of crops in a field one might hope to determine which, if any, disease is currently affecting the crops.

Input: Image **Output**: Classification, e.g. {'disease', 'locusts', etc.}

The source-channel paradigm assumes we have a *source* signal x, a *receiver* of the signal, and a channel which performs some kind of transform on x to get x', which is read by the receiver. To model this, we are going to flip the above.



The posterior, **D'**, is the argmax of all possible diseases that maximizes the likelihood of the observed image **C.** We can write this as follows:

$$\mathbf{D' = \text{argmax}\ P(D|C) = \ \text{argmax}\ P(D)\ P(C|D)}$$

The prior, **P(D)**, is the likelihood that a crop has a given disease **D** a priori. We then find the disease that maximizes the prior times **P(C|D)** which is the likelihood of a crop image *given* a particular disease. To model **P(D)** there's a variety of things we can do, but it is probably most important to be able to tell how likely it is that the image is not to be confused with 1.) Another disease and 2.) A false alarm. A crop image is akin to, say, an HIV blood-test, or a TB skin test. The test itself is error prone, even if we are 99% sure that we are correct. For instance:

Outcomes	P(Crop has disease D)	P(Does not have disease D)
P(Image C shows disease D)	True Positive	False positive
P(C not shows disease D)	False Negative	True Negative

The prior in this case is the marginal probability of the cases where the crop has disease **D**, regardless of the image, which in this case is the sum of the true positive and false negative. Furthermore, the prior is just a guess. Once we go through a trial, the posterior **D'** becomes our new prior, which accounts for the new evidence presented by practical experience. So the prior will get better with time.

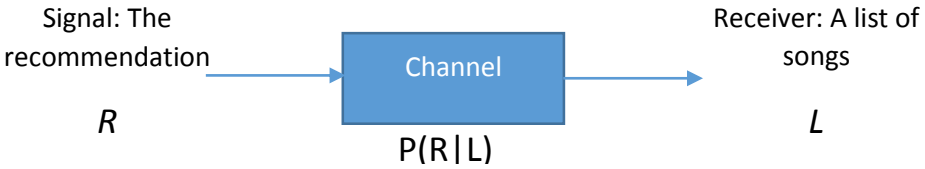
B. Choose a language technology on your own that was not discussed in class.

Problem: Music recommendations based on one's listening history.

Input: List of a person's previously heard songs

Output: A new song that the person is likely to enjoy

The source-channel paradigm assumes we have a *source* signal x, a *receiver* of the signal, and a channel which performs some kind of transform on x to get x', which is read by the receiver. To model this, we are going to flip the above.



Converts R into L, maximizing the probability of L given R.

The posterior, **R'**, is the argmax of all possible songs that maximizes the likelihood of the observed playlist **L.** We can write this as follows:

$$\mathbf{R' = \text{argmax } P(R|L) = \text{argmax } P(R)\,P(L|R)}$$

The prior, **P(R)**, is the likelihood of a person listening to a song **R** a priori. We then find the song that maximizes the prior times **P(L|R)** which is the likelihood of a playlist *given* **R**. The prior in this case is the marginal probability of the cases where a person listens to **R**, regardless of the person's listening history. Once we go through a trial, the posterior **R'** becomes our new prior, which accounts for the new evidence presented by practical experience. So the prior will get better with time. Furthermore, if the person liked the song, that song **R** will become part of **L**, which can help with later recommendations.

Question 2

Motivation – A Most Subjective and Unscientific Commentary

Popular music is one of the most divisive forms of social self-identifcation. I remember, growing up in the stratified and racially tense cultural environment of South Florida's public school system (in the 90s, no doubt), the music you listened to determined most of your social life. People used to self-authenticate with such expedient terms as "baser" (meaning you listened to rap and hip-hop) or "metalhead" (meaning you listened to rock and metal.) You either conformed to a specific genre and were included in the so-concerned social circles, or you were excluded. The more strictly you adhered to a particular sub-genre of music, the more likely you were to be liked and respected by your friends. The lines in the sand were fixed. One often faced severe social pressure for even trying to cross over. If desired, one might even choose to commit social suicide with their current group of friends (and take up with an entirely new set of people) simply by declaring that the type of music they liked had changed, and appropriately switching out the stickers on their backpack. And, if one chose not to follow this process of rigid self-imposed segregation you wound up being implictly forced into a special group known as the nonconformists.

It was stupid. But we were just kids.

Today, now that the people who grew up in that day and age are starting to fill the ranks of so-called established social commentary, I am beginning to see the real effect that this type of childhood environment has had on my generation. Far beyond "getting over it," I notice there's a real dearth of variety in the musical preferences of many people my age. And, as we in the computer science field know all too well, much of technology today is being built specifically to accommodate people in their comfort zones to further isolate themselves both culturally and musically, and to find other people who think and do likewise more efficiently than ever before. People assume there's some choice in the matter, but many social psychologists would argue there's likely a well-hardened childhood bias at work here as well.

In typical fashion, as people grow older they try to intellectualize their inherently irrational preferences, and that's what leads people like Virgil Griffith (a now-famous software developer and social commentator from Caltech) to observe some very trite statistical correlations between the publicly listed musical preferences of people on Facebook, the publicly listed universities they attend, and the average SAT scores of people at those universities. But wait, it gets better! Mr. Griffith "published" his findings on his personal website using a graph generator that laid out a continuum of musical preferences plotted against an axis of average SAT scores. Well, that's fun, right?

Turns out this post of Mr. Griffith's went viral and was reposted many times over by some of the biggest news organizations in the world, including but not limited to the Washington Post, the UK Telegraph, The Wall Street Journal, and pop culture site TMZ. If you Google the words "intelligence and musical taste" the entire first page of results is a series of high-profile reposts of Mr. Griffith's graph. Suggestively baited titles like, "Can the music you listen to determine how clever you are?" quickly earn clicks from lay Internet surfers looking for validation. And boy do they find it! "Smart People Listen to Radiohead and Dumb People Listen to Beyoncé, According To Study" reads a blog post on Metro.co.uk.

All this could be chalked up to a "nuh uh!" and moving on with our lives, but there's another theme at work here. This is not the first "study" to conclude that musical preferences are a good predictor of intelligence. But why is it that they always seem to "discover" that rap and hip-hop are for "dumb" people? Why is it that black musicians are always the first on the chopping blocks of social commentary?

It's not a coincidence. When jazz music first began gaining popularity in the U.S., as Amiri Baraka writes in a 1960 critique, most of the critics were white, and most of the musicians were black. It took a while before white Americans "warmed up" to jazz music, just as it took a while before there were any white hip-hop artists. There is a long historical tradition in America of inventive new trends in music coming from black musicians, and white Americans criticizing them. The type of juvenile commentary offered by Virgil Griffith's "study" is just another edition to this long, racist social commentay built on nothing.

But there's a new devil in the details of Mr. Griffith's commentary: Math. There is a strong social bias towards pseudo-intellectually based arguments in America, and a severe lack of critique in response to social commentary which builds its legitimacy not on the real arguments it intends to make (e.g. "Rap is crap!"), but rather a bluster of words which are related to statistics in some way. On one level it's a smart bait-and-switch. I have no doubt that the correlations Mr. Griffith calculated from the data he was working with are, so to speak, "mathematically" sound. But data is easy to fudge in this way. For example, there is a 0.993 correlation between the divorce rate in Maine and the per-capita consumption of margarine in the U.S. since the year 2000 (source: http://www.tylervigen.com/). Does that mean I can estimate the likelihood of a successful marriage in Maine this year based on the stock price of I-Can't-Believe-It's-Not-Butter?

No. Of course you can't. Neither can you say that someone who listens to Beyoncé is dumb or any more likely to be dumb *as a result* of this musical preference. With enough data I can say pretty much anything I want about Beyoncé's cancer-curing fans, and pass it off with the legitimacy of faux statistics. In this situation, however, I think there's another way. What can we actually say about the critiques of rap and hip hop *using* statistics? One of the most common nonsensical arguments about rap is that it requires no musical, literary, or lyrical talent, that its content is repetitive and vapid, and that all that's going on is a flurry of expletives padded by animal sounds. Can we show that this is not the case? Well, you could, y'know, just listen to some hip-hop with an open mind, but that's too much to ask of the lay (typically white) rap-hater.

It would be fair, I think, to show that music typically listened to by white, affluent Americans (i.e. rock, metal and country) is no more linguistically "interesting" than rap and hip hop – and there are perfectly appropriate empirical things we can calculate in this respect without getting into subjectives. Of course, rock music as a genre is less narrative and concerned with words than hip hop, so what's the point of comparing them on a lexical basis? It's somewhat implied by the assertion that rap makes you less intelligent – as ridiculous as that already is – that its content must also be, in a word, "dumb." Lyrical content is the determining factor here, as musicality itself is a moot point. The notion that listening to mostly non-lyrical classical music like Mozart and Beethoven makes you smarter has been roundly discredited. If one can unequivocally show greater lexical variety and content in rap and hip hop over rock and country, it is difficult to maintain any assertions about correlations between music genres and intelligence as per their content. It doesn't prove anything either way, but it still makes an argument that critics must answer.

But maybe we can even do even better than that. Who is the greatest lyricist – the greatest writer – of all time in the English language? Tupac? No, silly! Shakespeare! With a vocabulary of roughly 27379 word types (after stop word removal), Bill Shakespeare's sonnets and plays are among the most lexically rich writings in the English Language. I wouldn't be so bold in my hypotheses to predict that any single rapper has a greater lexical inventory than Shakespeare, but in this study we will unequivocally run the exact same analyses on the complete works of Shakespeare that we will on the likes of the most popular rap, hip-hop, rock, metal, and country artists of that legendary musical decade – the 1990s. This will ground our numbers with some anchor in the real world. How rich *are* any particular artist's works compared to the greatest of all time? This seems like a useful sanity check. Anyway…

My Hypotheses

I intend to calculate lexical statistics on a representative sample of artists from the 1990s in what have commonly been referred to as polar opposite genres: Rap, hip-hop, rhythm & blues (R&B) – and rock, grunge, heavy metal, country, etc. One might suggest that we're trying to lump white artists and contrast them with black artists, but I will assert no such thing. These are self-evidently considered by society to be "opposite" genres in competition for fans, whose listeners seldom exhibit much cross-over. At least, that's how it seemed in the 90s. But why the 90s? Both of these genres also experienced so-called "golden ages" in the early-to-mid 90s. Almost all of the canonical artists in these genres got their start in the music scene of the 1990s. With 15 years of hindsight on an interesting decade at this point, it is clear that there were some extremely rich developments in hip hop and heavy metal in tandem in the early 1990s. It would therefore

stand to reason that something interesting can be said about both of these genres by examining corpora of their respective lyrics from that time. But what will we find?

My prediction is that we will observe that hip-hop and rap (HHR) music are more lexically diverse than rock, metal, and country (RMC) music, and that HHR music is actually comparable as a whole to the works of Shakespeare in terms of its linguistic features and lexical variety.

By demonstrating this, I intend to show that the very vector in which HHR music *seeks* to excel – language – it both succeeds and also does a lot more with the ever-changing English language than it's often credited. And when history looks back on this period it will appreciate better than it currently does the contributions of HHR music to human expression – just as we do with that wordsmith Shakespeare today. Shakespeare, for all of his celebrated talents, was never one to shy away from pushing the English language in a direction it didn't necessarily want to go. He wrote things – often – as they were actually spoken, commuted consonants and the like – and made people speak differently by writing things in new ways. He did, in a way, what rap music is doing with English today. Fo rizzle.

This will not prove anything about the intelligence of the listeners of any particular genre. It will, however, lay to rest any nonsensically lingering notions of lyrical or lexical impoverishment in HHR music – precisely the domain it as a genre seeks to explore. There's a reason heavy metal lyrics are few and far between – it's about the guitar solos, dude. Likewise, it doesn't make sense to criticize HHR music on the basis of sampling, repetitive "musical" content, or "playing" an instrument of any kind. Playing an instrument is not the point of HHR – it's about wordplay. And play with words they do, in amazing ways.

Notes on Methodology

When I started this project I looked for existing corpora of music lyrics. I found none. Furthermore, I was interested in a dataset for the music that typified popular culture in the 1990s. While websites offering lyrics for songs are mostly free, their content is still proprietary and, as such, *not* free. The site azlyrics.com (which I believe my IP address is now banned from) offers a front end to the Musixmatch database, which contains lyrics for more than a million songs. One can freely access this database via several APIs with limitations on the number of requests you are allowed to make in a day. You can pay if you want to remove this limitation.

So I had to build a corpus myself. The assignment called for a million words or more, so I set about finding crowd-sourced lists of the most popular bands, songs, and albums of the 1990s. I found many such lists on Ranker.com, and various other music blogs. I also culled Billboard.com for historical lists of the biggest hits for each year in the 1990s, and I scraped Wikipedia's lists of musicians to find more names. I made cursory attempts at making sure each artist was popular at some point in the 90s, though with 600-800 artists it was a tad messy. For the most part the artists either got their start in the 90s or were around beforehand and remained popular during the 90s. Some artists have also continued since the 90s and have remained popular until even today, e.g. Jay-Z. I did not try to account for whether the lyrics themselves came from the 90s except in the case of the song-based type rankings (and even then I was lenient). If an artist made a splash in the 90s at all, I downloaded their "entire" corpora, i.e. whatever I could scrape. Granted, this resulted in a lot of songs from the 70s, 80s and 2000s, but, very obviously pre-90s artists like The Beatles, Jimi Hendrix, The Doors, Elvis Presley, Led Zeppelin et al are *not* in my corpus. My intention in doing all this was twofold: 1.) Capture the popular music of the era, and 2.) Get enough words to do some real number-crunching.

When I concatenated the artist lists I assembled it was on the order of 12,000 lines in total. From this I chopped it down to unique names, collapsing obvious dupes (like 2pac / Tupac, NWA and N.W.A., Motorhead / Motörhead, Björk / Bjork, Queenryche / Queensrÿche, Rage, Rage Against the Machine, RATM, etc.) and made ranked lists of artists based on their mentions. I then went in order and began scraping various lyrics websites (mostly azlyrics.com and mldb.org) for as many lyrics as were publicly available. I then cross-compared the lyrics available on several sites and came to the conclusion that lyrics websites are mostly copied from one another and no particular site is preferable, other than the fact that there are unwritten caps on the number of requests any anonymous IP address can make to their databases. Thus, for every 300 song lyrics I downloaded I had to get a new IP address. Open VPN came in very handy.

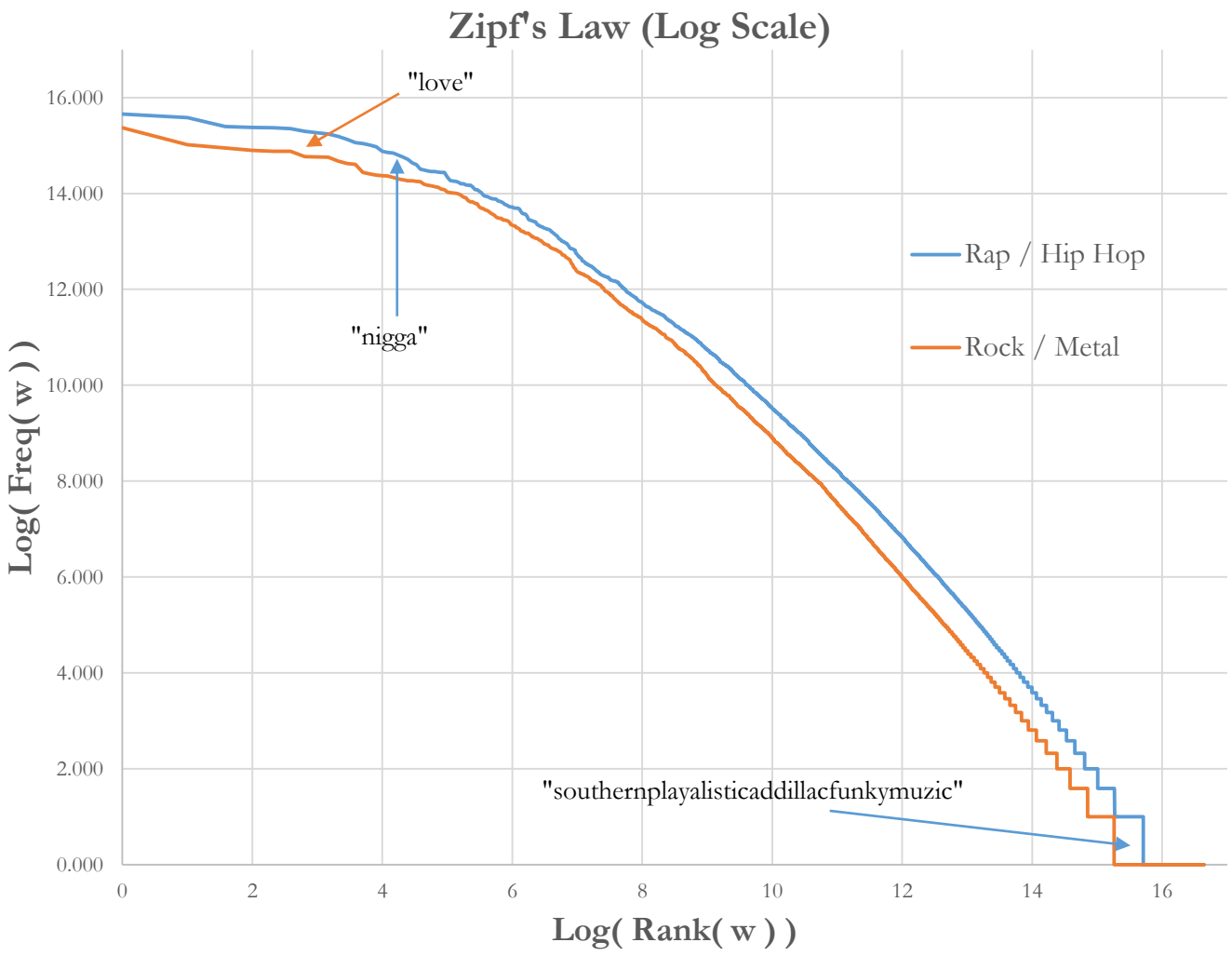
In the end I had a corpus of .txt files which was roughly 71 MB in size. I then ordered the artists whose lyrics were found online by the number of songs they each had. I took the top 300 most prolific artists in each genre, so my parallel corpora was thus a comparison of the available lyrics for 300 artists in two genres, hip-hop/rap (HHR), and rock/metal/country (RMC). In total, stripping for punctuation, removing the top 21 stop words and using simple word/line separation rules, my corpus thus consisted of 9279811 tokens, or roughly 9.3 million words.

The hard part was getting the data. Crunching the numbers was fairly straightforward. I spent more time making these graphs than actually writing the statistics-gathering code. Everything, including the scripts to find popular artists and download their lyrics amounted in all to about 1200 lines of Python.

Results

My hypotheses were confirmed – big time. Shakespeare turned out to be a little better than I expected, but the general result is the same: HHR music blows RMC out of the proveribal water in terms of its lexical richness. I will start with a discussion of the Zipf's law behavior exhibited by the respective HHR and RMC corpora upon examination, and proceed with a more in-depth discussion of the results. Then, I will discuss a new means of representing lexical variety in terms of type/token curves normalized by document length and plotted in logarithmic space. Finally, I will examine in more detail a few high-scoring individual songs from both HHR and RMC artists. But enough talk. Most of the data speaks for itself, if you feel so inclined to just flip through the charts….

Here is the plot of the Zipf's law behavior, plotted for both corpora:



Discussion of Zipf's Law Behavior

With a large corpora of words we expect the graph of the log of the rank of each word versus the log of its frequency to exhibit the behavior above, with a relatively smooth curve in the center of the graph and this "step behavior" on the extreme ends. This demonstrates the constant inverse proportionality between the rank of a word type and its token frequency. The hip-hop/rap corpus has a very long tail of single-digitons formed from a large vocabulary of slang / invented words and various semantic encodings via what appear to be "misspellings." In quite a few cases, the spellings are unique to a particular artist.

Examples:

Rank 26529 (7-ton): Ice Cube's spelling of "AmeriKKKa" – This is quite clearly intended to convey a particular defintion of "America." It cannot be considered the same type as the word "America," regardless of how much the innate spell-checker inside us all dislikes it.

Rank 92787 (singleton): Outkast's "southernplayalisticadillacfunkymuzik" is a variation on the name of the 1994 album "Southernplayalisticadillacmuzik." Again, we see here a wealth of semantic information packed into one word, which can stand on its own, perfectly distinct from the individual sub-words of which it is clearly comprised. It is linguistic inventiveness like this that allows the tail of the blue curve to exhibit such interestingly "smooth" behavior.

Rank 92863 (singleton): "supercalifragilisticexpialidocious" – Mary Poppins's own creation, used by the same artist in the same song.

Rank 93698 (singleton): "hiphopgesetze" – I cannot claim to know what this means exactly, but it is yet another example of the type of wordplay that typifies hip hop.

The curve goes on like this to rank 102502. From rank 18033 down to 102502, the last 84468 word types are mentioned 10 times or less in the entire corpus. At the other end, there are a lot of words that might be considered by some to be stop words but, for example, in positions 3, 2, 1 are the words "all", "get", and "up", respectively. These are not stop words, because they are crucial to the context of hip hop music, which usually involves dancing, (e.g. a chorus for a famous Afrika Bambaataa hit from the 1980's is, "Y'*all* just *get up* and dance!") There is a short vocabulary of words at the top of the word frequency list which are important in hip-hop for things like vamping and rhythmic word filler, but they differ from stop words in that they carry a lot of cultural, contextual, and semantic (i.e. "attitude setting") information. Though it needs no explanation, in position 20, (well within the range of most heuristic stop-word removal windows) is the word "nigga," which is right around the beginning of the step function behavior. These are clearly features of the Hip-Hop/Rap curve and not just stop words.

The Rock/Metal/Country graph has sharp uptick at the top, in contrast to the Hip-Hop/Rap curve, because rock music has relatively low lexical variety for the vast majority of songs, e.g. in position 5 of the ranking is the word "love," which accounts for an entire 0.8% of the words in the entire Rock/Metal/Country corpus.

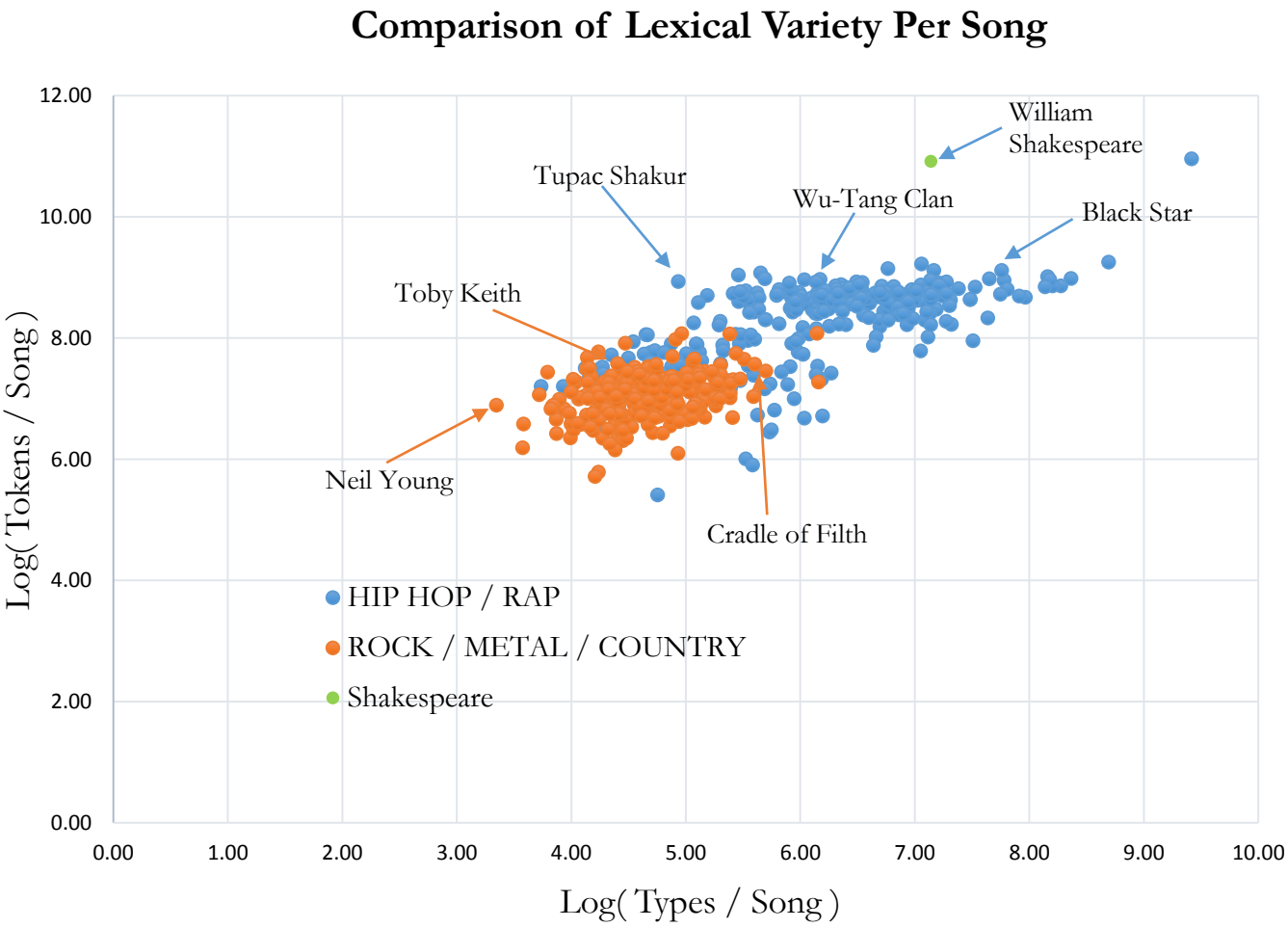
Discussion of Lexical Variety in Corpora

This issue of word variety is important because it provides one of the main sources of distinction between the Hip-Hop/Rap HHR corpus and the Rock/Metal/Country (RMC) corpus. The statistics gathered on the genre level pretty much say it all:

Genre	Artists	Songs	Types	Tokens	MALL	Unigram	Bigram	Trigram
HHR	300	16206	102502	5430793	5.1	up	dont_know	la_la_la
RMC	300	27886	70339	3849018	4.46	all	dont_know	la_la_la
W.S.	1	~194	27379	652812	6.78	not	thou_art	exeunt_all_but

In extremely rough terms, the number of songs in the RMC corpus is on its way to being double the number of songs in the HHR corpus. At first, my suspicion was that the RMC artists were that much more prolific than those in HHR and therefore comparing these corpora would not be interesting. But not only are there 32163 (46%) *more* types in the HHR corpus, with only 16206 songs compared to 27886 in RMC, there are also more than 1.5 *million* more words in HHR! The mean average line length (MALL) per verse in both corpora are about the same, and interestingly the top bigram and trigram words in HHR and RMC are identical. Furthermore, it is interesting that the mean average line length hovers around 5. This may be related to the historically common convention of using iambic pentameter in poetry, though without further investigation it would be impossible to say this for sure. It is an interesting idea, however.

Clearly there is something going on in HHR to account for this discrepancy. With so few songs by comparison (and mind you these are only the songs I could scrape from the web), the diversity of words per song in HHR must be far greater than that of RMC. Lexically, hip hop and rap are much more interesting than rock, metal, or country. To visualize this I have created following graph:



This graph shows a comparison of the type/token ratio between HHR and RMC normalized per song on a log scale. Comparing these in normal space is a bit unwieldy due to the outliers, i.e. artists for which lyrics for only one or two songs were found online but which had an extremely high type/token ratio. Furthermore this better demonstrates the separation of the data. On the horizontal axis we see the log of the type/song ratio. Vertically we have the log of the token/song ratio. Data points lying to the upper right of the graph exhibit greater lexical variety on a per song basis. As you can see, almost *all* HHR artists appear to exhibit greater lexical variety than their counterparts in RMC. This makes somewhat intuitive sense given the fact that hip hop and rap are heavily driven by lyrical content as opposed to musicality. (Of course, this is the 90s and we're talking about bands like Nirvana and Pantera here. "Musicality" is a loose term.)

If we were to simply compare type/token ratios between HHR and RMC we would see a lot of numbers in the 10%-20% range, with a few crucially misleading values. Neil Young, the most prolific rock artist in the RMC list (who oddly showed up in a bunch of 90s rock band lists, for some reason), has a type/token ratio (TTR) of around 9%, which is lower than most. This turns out to be a reasonable number, though it is seemingly contradicted by the fact that William Shakespeare – the most lexically prolific single artist of all time – has a type/token ratio of 4%. (By comparison, Britney Spears' TTR is actually 9% as well.) If greater TTR is an indication of greater linguistic variety, then this doesn't seem to make sense. Normalizing for the lexical variety on a per-document basis and putting things on a log scale better clarifies the separation of the data and shows us, as we'd expect, Neil Young in the lower lexical ranks (which doesn't necessarily mean he's lexically impoverished, just that he writes a lot of songs with similar words), and William Shakespeare flying high above the rest (Bill is marked as the isolated green dot in the upper right-hand corner).

My argument is that this type of comparison makes a lot of sense in terms of demonstrating the lexical diversity of comparable corpora, and in this case specifically HHR music. Excluding the odd outliers, (which are flukes because we only have one or two songs by each of the floating blue dots high on the right) the data here lays out as expected. Tupac Shakur is easily distinguished by his barrage of lyrical fury, but for all of his lexical variety he also has an extremely large number of common so-called 'filler' words. The top 1, 2, and 3 bigrams for Tupac are "2pac ya'll", "that's right", and "ain't nothin," and one of his most common trigrams is "fuck all ya'll." So, on a per song basis, Tupac's token counts are high though his type count is comparatively low. Of course, examining individual songs for their statistically interesting features is also worth a look. The table below is a comparison of the top ten songs in HHR and RMC ordered by type counts.

Hip Hop / Rap *…Give Ras-Kass a listen, if you get the chance!*

ARTIST	SONG	TYPES	TOKENS	ALL	UNIGRAM	BIGRAM	TRIGRAM	TTR
The-Roots	The-Session-Longest-Posse-Cut-In-History	902	1891	5.68	('have', 73)	('have_fun', 50)	('have_fun_have', 40)	48%
Ras-Kass	Nature-Of-The-Threat	688	1052	5.88	('was', 14)	('his_name', 3)	('around_2000_bc', 2)	65%
The-Sugarhill-Gang	Rappers-Delight	684	1987	5.78	('ya', 50)	('n_n', 23)	('n_n_n', 15)	34%
Kanye-West	Last-Call	681	1812	7.37	('was', 59)	('jay_z', 9)	('was_gonna_do', 4)	38%
Busta-Rhymes	Flipmode-Squad-Meets-Def-Squad	673	1023	5.98	('up', 20)	('def_squad', 6)	('lord_have_mercy', 3)	66%
Beastie-Boys	B-Boy-Bouillabaisse	641	1047	5.98	('as', 12)	('new_york', 4)	('his_fists_against', 3)	61%
Blackalicious	Release-Part-1-2-3	612	941	4.61	('all', 14)	('get_focus', 4)	('accelerate_never_wait', 4)	65%
Lootpack	Episodes	603	1093	6.21	('ya', 26)	('hip_hop', 7)	('la_la_la', 4)	55%
Wu-Tang-Clan	Triumph	595	775	5.46	('from', 12)	('wu_tang', 5)	('ol_dirty_bastard', 2)	77%
Company-Flow	Collude	572	804	6.76	('they', 12)	('will_fall', 4)	('timewarner_will_fall', 2)	71%

Rock / Metal / Country *This is why 'Cradle of Filth' was marked on the previous graph!*

ARTIST	SONG	TYPES	TOKENS	ALL	UNIGRAM	BIGRAM	TRIGRAM	TTR
Dream-Theater	Six-Degrees-Of-Inner-Turbulence	481	915	4.12	('she', 29)	('he_was', 7)	('his_solitary_shell', 5)	53%
Cradle-Of-Filth	Beneath-The-Howling-Stars	413	560	3.94	('her', 22)	('beneath_howling', 3)	('beneath_howling_stars', 3)	74%
Neil-Young	Sixty-To-Zero	403	763	3.93	('he', 31)	('he_was', 5)	('put_hose_down', 2)	53%
Bob-Dylan	Brownsville-Girl	383	775	8.07	('was', 22)	('brownsville_girl', 12)	('world_brownsville_girl', 4)	49%
Nirvana	The-Priest-They-Called-Him	382	700	8.33	('he', 23)	('get_out', 3)	('back_his_room', 2)	55%
Savatage	Turns-To-Me	373	706	3.92	('time', 14)	('all_those', 5)	('all_those_moments', 4)	53%
Cradle-Of-Filth	Thirteen-Autumns-And-A-Widow	358	466	4.31	('her', 22)	('when_she', 3)	('light_so_when', 2)	77%

Cradle-Of-Filth	A-Gothic-Romance-Red-Roses-For-The-Devils-Whore	350	431	4.63	('her', 12)	('velvet_enrobed', 2)	('must_know_art', 1)	81%
Mekong-Delta	Dances-Of-Death	334	605	3.46	('all', 12)	('days_betrayal', 7)	('days_betrayal_days', 5)	55%
Lou-Reed	A-Dream	331	651	5.05	('was', 26)	('was_so', 4)	('was_very_cold', 2)	51%

NOTE: I had to "massage" the data in the RMC table because many artists which may have had hits in the 90s have been around for quite some time, e.g. Bruce Springsteen, Bob Dylan, Rush, etc. Some of the songs in this table are "near" the 90s, admittedly, e.g. Sixty-to-Zero was popular in the 90s even though it came out in 1989. But it is quite interesting to give the songs themselves a listen to see their lexical variety for yourself. Many of the rock songs are extremely long, which likely accounts for their Type/Token counts. I also had to clean up some songs which were too far out of the 90s to be a part of this study, and there were some hip-hop artists in there which I was unable to automatically clean out – after all there are 600 artists in this study and I do not know them all by name!

In the previous chart I marked Cradle of Filth as being an interesting outlier. I suspected a priori that they would be somewhere near the top. Their TTR for 117 songs is 26%, which is a high ratio for an artist with 100+ songs. The metal band 'Sodom' appears high in this category as well with a TTR of 29% but they have a much lower type count than Cradle of Filth. Unsurprisingly, Cradle of Filth have *3 songs* in the top ten most lexically rich RMC songs from the 1990s era.

The reader is recommended to give the links in this list a listen. They are all, interestingly, songs which I was not even aware of for the most part prior to doing this study. The most interesting part, at the end of the day, is the fact that these findings more or less confirm what has often written subjectively about these artists by music critics and other pop culture observers.

Conclusions

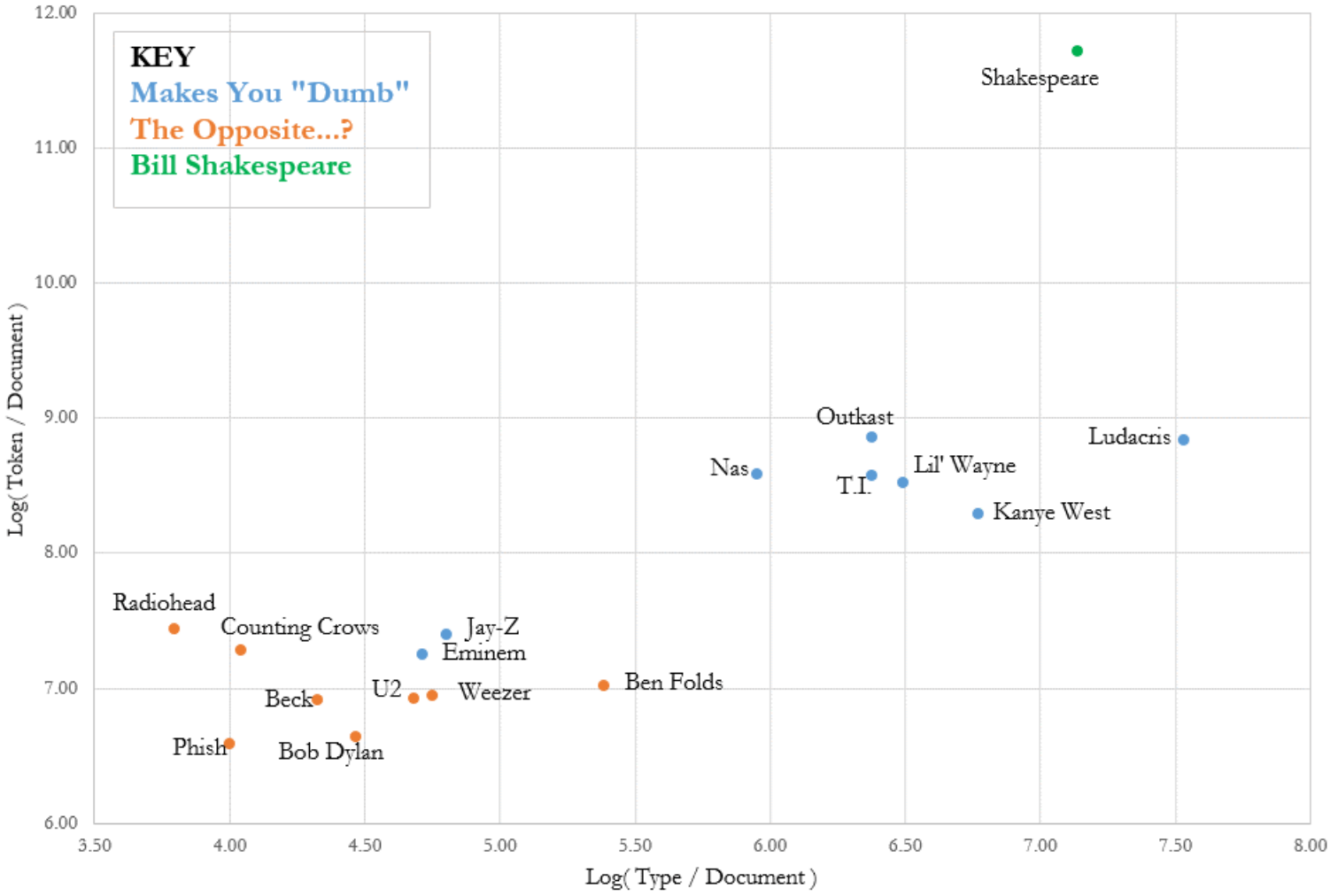
I don't intend to rehash the discussion above, but in the final analysis, the results of this study fly somewhat in the face of the supposed "findings" by Virgil Griffith and his notions of "music that *makes* you dumb." Given the fact that, again, his chart was picked up and published by such notable publications as The (Pulitzer-prize winning) Guardian, the Wall Street Journal, Yahoo! News, The Washington Post, The Times of India, the New Yorker, The Canberra Times, and the UK Telegraph, it is not quite "just fun" to make such claims. The tagline on the website itself says the following:

"Yes, I'm aware correlation ≠ causation. The results are hilarity incarnate regardless of causality. You can stop sending me email about this distinction. Thanks."

Hilarity incarnate? Hardly. Mr. Griffith is promoting racist stereotypes in musical preferences using the aura of statistical inference to gain legitimacy in the minds of uncritical audiences. Such actions can be extremely derisive, offensive, misleading and destructive. Millions of people have likely seen this graph. It's arguably no coincidence (whether the author acknowledges his implicit bias or not) that the artists with the "dumbest" listeners are all black, and likewise no coincidence that the artists on the opposite end of the spectrum are all white. Empirically, the data may be a manifestation of some underlying sociological phenomenon, but to brazenly make assertions about human intelligence in this format is quite frankly unworthy of someone bearing a @caltech.edu email address.

So, let's examine some of the artists on opposite sides of Mr. Griffith's chart. In the Rap / Hip Hop section (the section with the supposed lowest SAT-scoring listeners by far), Mr. Griffith lists Outkast, Eminem, Kanye West, "Rap", Nas, Akon, Ludacris, Jay-Z, "Hip Hop", T.I. and Lil Wayne. In the section listing artists whose listeners have apparently higher than 1156 scores on the SAT, we see Norah Jones, U2, Counting Crows, Bob Dylan, Beck, Weezer, The Shins, Radiohead, Ben Folds, Sufjan Stevens, Guster, and Beethoven. Some of these artists have been excluded in my study because they got their start after the year 2000, so I have no data on them. Without further discussion, I conclude with this comparative graph sorted by the logs of the word type / document ratio.

Comparison of Lexical Variety Based on Whether or Not Listenting to the Artist "Makes You Dumb"



Appendices

Top-20 Artists in HHR sorted by Type Counts

ARTIST	SONGS	TYPES	TOKENS	MALL	UNIGRAM	BIGRAM	TRIGRAM
Tupac-Shakur	338	10338	165195	5.34	('they', 1639)	('rock_body', 173)	('body_rock_body', 142)
Ll-Cool-J	208	10259	89313	5.11	('up', 873)	('cool_j', 642)	('ll_cool_j', 538)
Nas	155	9773	66155	5.72	('they', 647)	('chorus_nas', 72)	('bap_bap_bap', 48)
Wu-Tang-Clan	117	9744	54076	5.53	('up', 443)	('wu_tang', 203)	('ol_dirty_bastard', 38)
Jay-Z	210	9674	92315	5.53	('this', 805)	('jay_z', 616)	('uh_huh_uh', 99)
Method-Man	134	9505	57547	5.37	('up', 616)	('method_man', 295)	('yo_yo_yo', 47)
Eminem	158	9418	72362	5.8	('up', 788)	('slim_shady', 96)	('ha_ha_ha', 38)
Snoop-Dogg	250	9121	104350	5.48	('up', 1433)	('snoop_dogg', 494)	('d_o_double', 93)
Ghostface-Killah	120	8646	47355	5.87	('up', 520)	('ghostface_killah', 234)	('ghostface_killah_yo', 34)
Cypress-Hill	176	8506	60747	5.33	('up', 745)	('b_real', 397)	('la_la_la', 84)
Lil-Wayne	190	8383	73905	5.52	('got', 774)	('lil_wayne', 350)	('wee_ooh_wee', 72)
The-Roots	100	8354	40537	5.42	('get', 403)	('black_thought', 204)	('zen_zen_zen', 74)
Busta-Rhymes	142	8086	61255	5.45	('shit', 801)	('busta_rhymes', 383)	('yo_yo_yo', 78)
Ice-Cube	170	7967	65056	5.17	('get', 747)	('ice_cube', 557)	('chorus_ice_cube', 49)
Bone-Thugs-N-Harmony	179	7878	94286	6.6	('up', 1436)	('krayzie_bone', 207)	('bone_bone_bone', 101)
Public-Enemy	198	7813	61380	4.27	('they', 715)	('chuck_d', 126)	('give_up_give', 47)
Twista	111	7281	55350	5.77	('up', 817)	('w_w', 96)	('w_w_w', 80)
Gang-Starr	119	7174	42777	5.83	('so', 482)	('dj_premier', 71)	('dj_premier_cuts', 35)
South-Park-Mexican	102	7094	37841	5.09	('got', 364)	('wiggy_wiggy', 136)	('wiggy_wiggy_wiggy', 108)
Dmx	165	7040	70203	5.64	('what', 1020)	('dont_know', 111)	('uh_uh_uh', 47)

Top-20 Artists in RMC sorted by Type Counts

ARTIST	SONGS	TYPES	TOKENS	MALL	UNIGRAM	BIGRAM	TRIGRAM
Celine-Dion	325	7217	78332	4.39	('love', 1017)	('la_la', 179)	('la_la_la', 133)
Bob-Dylan	340	7208	65049	5.36	('he', 651)	('no_more', 74)	('when_gonna_wake', 27)
Bruce-Springsteen	378	6633	68148	5.64	('just', 619)	('la_la', 120)	('la_la_la', 102)
Elvis-Costello	330	6203	45155	4.9	('but', 513)	('dont_know', 84)	('la_la_la', 28)

Rush	187	6008	29707	4.1	('all', 277)	('brollic_brollic', 32)	('what_what_what', 20)
Cradle-Of-Filth	117	5683	22207	3.85	('her', 476)	('nymphetamine_nymphetamine', 26)	('no_no_no', 16)
Bad-Religion	212	5224	24893	5.19	('all', 301)	('no_one', 40)	('come_join_us', 24)
Jethro-Tull	212	5098	24894	4.99	('no', 206)	('watching_watching', 27)	('step_no_step', 17)
Rem	241	5004	32165	4.65	("it's", 348)	('la_la', 96)	('la_la_la', 86)
311	113	4903	24264	4.83	('but', 250)	('throw_down', 49)	('time_throw_down', 43)
Live	162	4781	33569	4.65	('all', 419)	('brother_marquis', 129)	('fresh_kid_ice', 97)
Rage Against The Machine	208	4709	30580	4.46	('they', 300)	('p_wagner', 132)	('by_p_wagner', 112)
Neil-Young	458	4659	54417	3.26	('love', 652)	('he_was', 76)	('wanna_wanna_wanna', 44)
Lou-Reed	196	4606	35946	4.63	('no', 419)	('na_na', 354)	('na_na_na', 338)
Tori-Amos	231	4514	30048	3.59	('this', 292)	('dont_know', 39)	('just_two_us', 21)
Rod-Stewart	274	4470	41590	4.54	('love', 610)	('long_time', 57)	('when_mans_love', 36)
Marillion	129	4462	21893	4.53	('all', 210)	('marillion_lyrics', 52)	('music_marillion_lyrics', 52)
Red-Hot-Chili-Peppers	165	4339	24936	3.79	('all', 256)	("i've_got", 48)	('magik_sex_magik', 32)
Sting	170	4269	27006	4.75	('all', 285)	('one_day', 40)	('only_only_only', 27)
Barenaked-Ladies	164	4135	26156	4.61	("it's", 301)	('la_la', 88)	('la_la_la', 80)

Top-20 Artists in HHR found from web scraping

ARTIST	FREQUENCY
Dr. Dre	22
Arrested Development	19
Naughty By Nature	18
A Tribe Called Quest	16
Ice Cube	16
Bone Thugs-N-Harmony	15
Public Enemy	15
The Notorious B.I.G.	15
Gang Starr	14
Cypress Hill	14
Ll Cool J	14
Digital Underground	13
Tupac Shakur	13
Ice Cube Feat. Das Efx	13
Snoop Dogg	13
Redman	13

Salt-N-Pepa	12
Nas	12
Epmd	12
Geto Boys	12

Top-20 Artists in RMC found by web scraping

ARTIST	FREQUENCY
Aerosmith	62
Nirvana	61
Depeche Mode	61
The Cure	60
Rush	59
The Black Crowes	59
Red Hot Chili Peppers	57
U2	57
Concrete Blonde	57
R.E.M.	56
Eric Clapton	56
Faith No More	56
Damn Yankees	56
Garth Brooks	55
The Jesus & Mary Chain	55
World Party	55
Van Halen	55
The Church	55
The Psychedelic Furs	55
Peter Murphy	55

Top 20 Unigrams, Bigrams, and Trigrams in HHR

UNIGRAM	FREQUENCY	BIGRAM	FREQUENCY2	TRIGRAM	FREQUENCY3
up	51659	dont_know	4413	la_la_la	1666
get	48993	aint_no	3810	oh_oh_oh	1514
all	43110	know_what	3802	yeah_yeah_yeah	1493
so	42625	yeah_yeah	3472	no_no_no	1267
dont	42311	oh_oh	2539	na_na_na	1241
got	41767	no_more	2417	dont_give_fuck	995
this	40278	no_no	2257	ha_ha_ha	974
but	39418	uh_huh	2253	yo_yo_yo	866
know	38622	la_la	2250	da_da_da	762
what	37361	dont_wanna	2204	uh_uh_uh	740
no	35805	verse_2	2034	do_do_do	721
it's	34184	dont_want	2031	dont_know_what	706
they	33748	yo_yo	2026	ll_cool_j	599
when	32995	verse_1	2008	aint_got_no	550

out	32211	ha_ha	1977	as_long_as	541
now	30182	it's_all	1924	hey_hey_hey	472
do	29661	know_how	1859	what_what_what	458
just	29335	what_do	1826	it's_all_about	456
nigga	28500	this_shit	1818	know_what_sayin	434
if	27644	dont_stop	1795	bang_bang_bang	422

Top 20 Unigrams, Bigrams, and Trigrams in RMC

UNIGRAM2	FREQUENCY3	BIGRAM	FREQUENCY2	TRIGRAM	FREQUENCY32
all	42289	dont_know	4605	la_la_la	1878
dont	33118	no_one	2921	na_na_na	1839
but	31537	i've_been	2902	oh_oh_oh	1221
so	30592	i've_got	2542	yeah_yeah_yeah	1192
love	30160	oh_oh	2420	no_no_no	926
it's	30152	la_la	2379	dont_know_what	842
know	27837	know_what	2364	do_do_do	561
just	27787	dont_want	2264	dont_know_why	521
no	27669	yeah_yeah	2250	there_aint_no	500
this	26147	there's_no	2130	as_long_as	498
when	25291	na_na	2122	hey_hey_hey	485
what	24971	let_go	1861	dont_know_how	432
up	22233	it's_all	1844	doo_doo_doo	376
can	21729	no_more	1786	love_love_love	373
out	21347	you've_got	1762	ah_ah_ah	357
now	21185	no_no	1734	ha_ha_ha	350
down	21124	can_see	1716	come_come_come	333
do	20656	what_do	1667	all_night_long	329
got	20196	it's_not	1655	it's_too_late	322
if	19942	dont_wanna	1588	dont_know_where	317

Top 20 Unigrams, Bigrams, and Trigrams in Shakespeare

UNIGRAM	FREQUENCY	BIGRAM	FREQUENCY	TRIGRAM	FREQUENCY
not	8501	thou_art	538	exeunt_all_but	91
his	6853	will_not	532	exeunt_scene_ii	83
this	6585	do_not	526	exeunt_scene_iii	69
but	6266	no_more	510	know_not_what	54
he	6250	king_henry	386	act_v_scene	50
have	5881	thou_hast	369	as_well_as	49
as	5733	he_hath	349	exeunt_scene_iv	47
thou	5478	exeunt_scene	346	do_not_know	47
him	5194	they_are	339	as_much_as	46
so	5035	if_thou	334	would_not_have	44

will	4968	more_than	324	act_iv_scene	44
what	4456	not_so	313	act_iii_scene	43
thy	4032	how_now	294	act_ii_scene	42
all	3912	would_not	285	what_art_thou	41
her	3847	king_richard	272	no_more_than	40
no	3771	i'_th'	269	as_thou_art	39
by	3757	would_have	261	fare_thee_well	39
do	3747	if_he	258	thou_canst_not	39
shall	3583	let_us	256	why_dost_thou	39
if	3488	re_enter	251	exeunt_act_v	38

"