What are They Even Saying???

An exploration of the linguistic styles of podcasts

Plan and Hypothesis

I started with an ambitious but admittedly not revolutionary idea - train a model that could “read” podcast transcripts and learn genre, rating, topics, format, and year from various textual and non-textual features. Initially, I also thought that I would be able to clean the transcript text enough to parse out each host’s speech, then use that data to train a model to assign a host-name label to a random string of text.

This is basically the story of how those plans collapsed . . . while providing some interesting data along the way.

Where did the data come from?

I collected transcripts from 24 podcasts, 5 of which fell victim to the re-reading of the website's copyright rules, so my total number of podcasts was 19.

I used transcripts from the podcast's official page, with one exception (NeoScum, whose transcripts were fan-made and in a Google drive with guest access).

Data overview:

- 1584 episodes
- 16,650,103 transcript tokens (as opposed to title tokens)

Target features

```
pod_feats = [['Welcome to Nightvale', 1, ['comedy', 'sci-fi'], 'scripted', 'fiction', 'news', 4.8],
             ['Move Your DNA', 2, ['health', 'fitness'], 'unscripted', 'nonfiction', 'chat', 4.8],
             ['You\'re Wrong About', 2, ['history', 'education'], 'unscripted', 'nonfiction', 'chat', 4.6],
             ['Unlocking Us', 1.5, ['health', 'lifestyle'], 'unscripted', 'nonfiction', 'interview', 4.6],
             ['Radiolab', 2, ['society', 'education'], 'unscripted', 'nonfiction', 'storytelling', 4.7],
             ['This American Life', 1.5, ['society','history'], 'unscripted', 'nonfiction', 'storytelling', 4.6],
             ['Bullseye with Jesse Thorn' , 1.5, ['comedy', 'society'], 'unscripted', 'nonfiction', 'interview', 4.7],
             ['One Bad Mother', 2.5, ['comedy', 'parenting'], 'unscripted', 'nonfiction', 'chat', 4.7],
             ['Judge John Hodgman', 1.5, ['comedy, advice'], 'unscripted', 'nonfiction', 'chat', 4.8],
             ['The Flophouse' , 3, ['comedy', 'movies'], 'unscripted', 'nonfiction', 'recap', 4.8],
             ['Switchblade Sisters', 1.5, ['comedy', 'movies'], 'unscripted', 'nonfiction', 'chat', 4.9],
             ['MBMBaM', 3, ['comedy','advice'], 'unscripted', 'nonfiction', 'chat', 4.9],
             ['Sawbones', 2, ['history', 'medicine'], 'unscripted', 'nonfiction', 'storytelling', 4.8],
             ['Wonderful', 2, ['comedy', 'society'], 'unscripted', 'nonfiction', 'chat', 4.9],
             ['The Greatest Generation', 2, ['comedy', 'TV'], 'unscripted', 'nonfiction', 'recap', 4.9],
             ['Friendly Fire', 3, ['history', 'movies'], 'unscripted', 'nonfiction', 'recap', 4.6],
             ['Shmanners', 2, ['society', 'advice'], 'unscripted', 'nonfiction', 'chat', 4.8],
             ['The Adventure Zone', 4, ['games', 'RP'], 'unscripted', 'fiction', 'LARP', 4.9],
             ['NeoScum', 5, ['games', 'RP'], 'unscripted', 'fiction', 'LARP', 4.9]]

# In case you're a cool person reading this and don't know, LARP is live action role playing.
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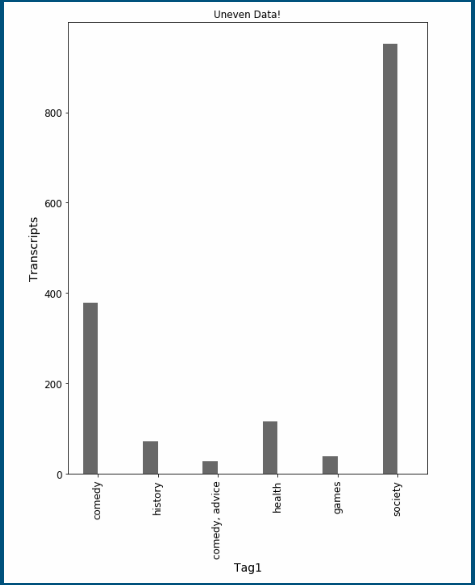
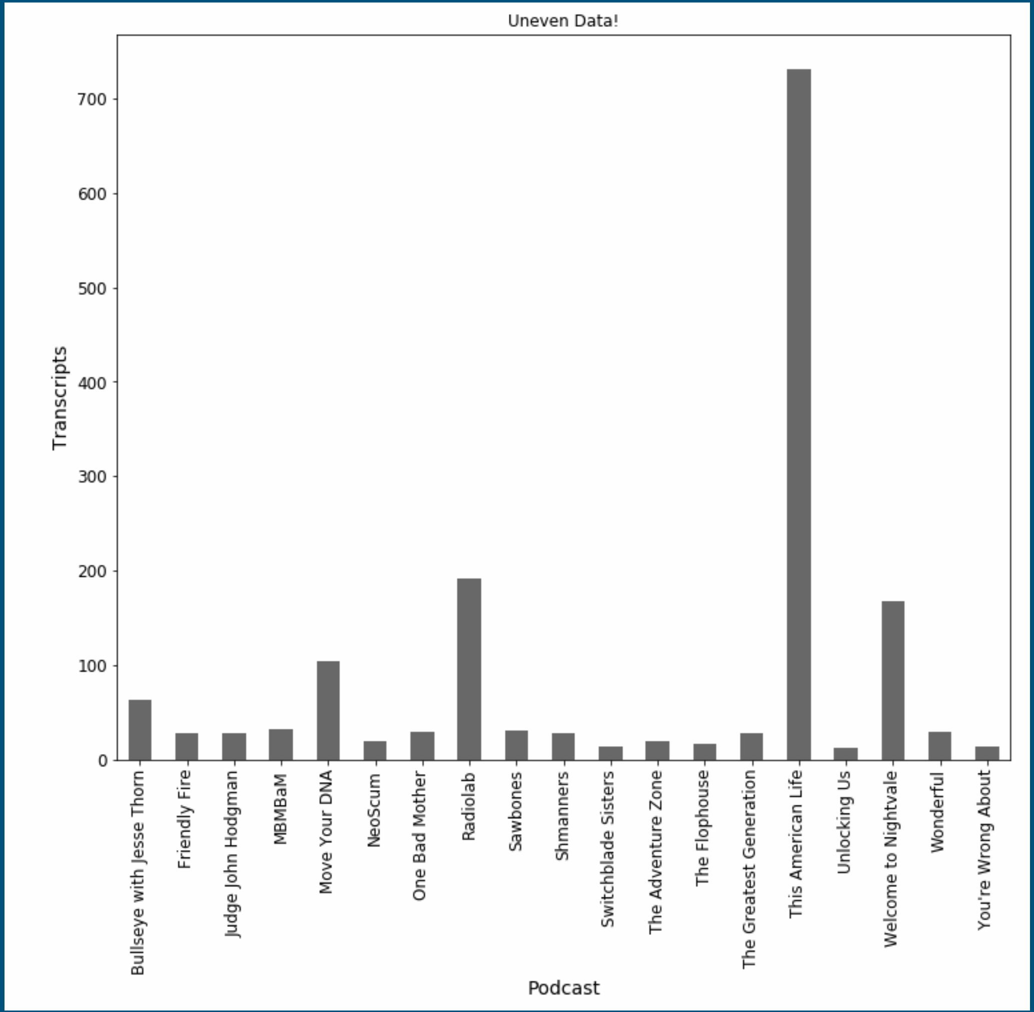
A disclaimer - unbalanced data

Data isn't evenly distributed, so all findings come with a gigantic grain of salt. This American life had by far the most episodes available. Only 520 episodes had a year listed on the transcript page and 53 episodes did not list a title - they were all called "Final Draft" for some reason.





Scraping and cleaning

```
['\n    Smile My Ass\n  ',
 '\n    January 29, 2021\n  ',
 "\n            Jad: \r\n Wait, you're listening... \r\n \xa0 \r\n Speaker 2: \r\n Okay. \r\n \xa0 \r\n Jad: \r\n All right.
\r\n \xa0 \r\n Speaker 2: \r\n Okay. \r\n \xa0 \r\n Jad: \r\n All right. You are listening to radio lab radio lab. W. N Y. C.
all right. Latif, if you can rewind your mind back to a time when your life wasn't dominated by Allen Funt in Candid Camera.
How did this start? \r\n \xa0 \r\n Latif: \r\n So I first, unlike a lot of people, I did not grow up watching candid camera.
I had never heard of candid camera when I was a kid. \r\n \xa0 \r\n Jad: \r\n You never heard of candid camera? \r\n \xa0 \r
\n Robert: \r\n You've never heard of candid camera? \r\n \xa0 \r\n Latif: \r\n No. \r\n \xa0 \r\n Jad: \r\n Wait. How... \r
\n \xa0 \r\n Robert: \r\n Have you heard of the Declaration of Independence, that ringing the bell? \r\n \xa0 \r\n Latif: \r
```

```
Smile My Ass
Jad: Wait, you're listening... Speaker 2: Okay. Jad: All right. Speaker 2: Okay. Jad: All right. You are listening to radio lab radio lab. W. N Y.
r life wasn't dominated by Allen Funt in Candid Camera. How did this start? Latif: So I first, unlike a lot of people, I did not grow up watching
You never heard of candid camera? Robert: You've never heard of candid camera? Latif: No. Jad: Wait. How... Robert: Have you heard of the Declarat
hat? Robert: No, but it's sort of, he's up there with it. It's very noticeable. Latif: Okay, cool. Jad: He is actually, no BS, a founding father i
I'm Robert Krulwich. Jad: This is radio lab... Robert: When you least expect it, you're addicted, you're the one today. Jad: Okay, just to set tha
between show and life was really clear. Jad: Then along came a guy named Allen Funt who muddied that line in a way that was fascinating and would
arks are on all of our butts. So check your tush and listen to this story from our producer Latif Nasser. Latif: So I first heard about candid cam
```

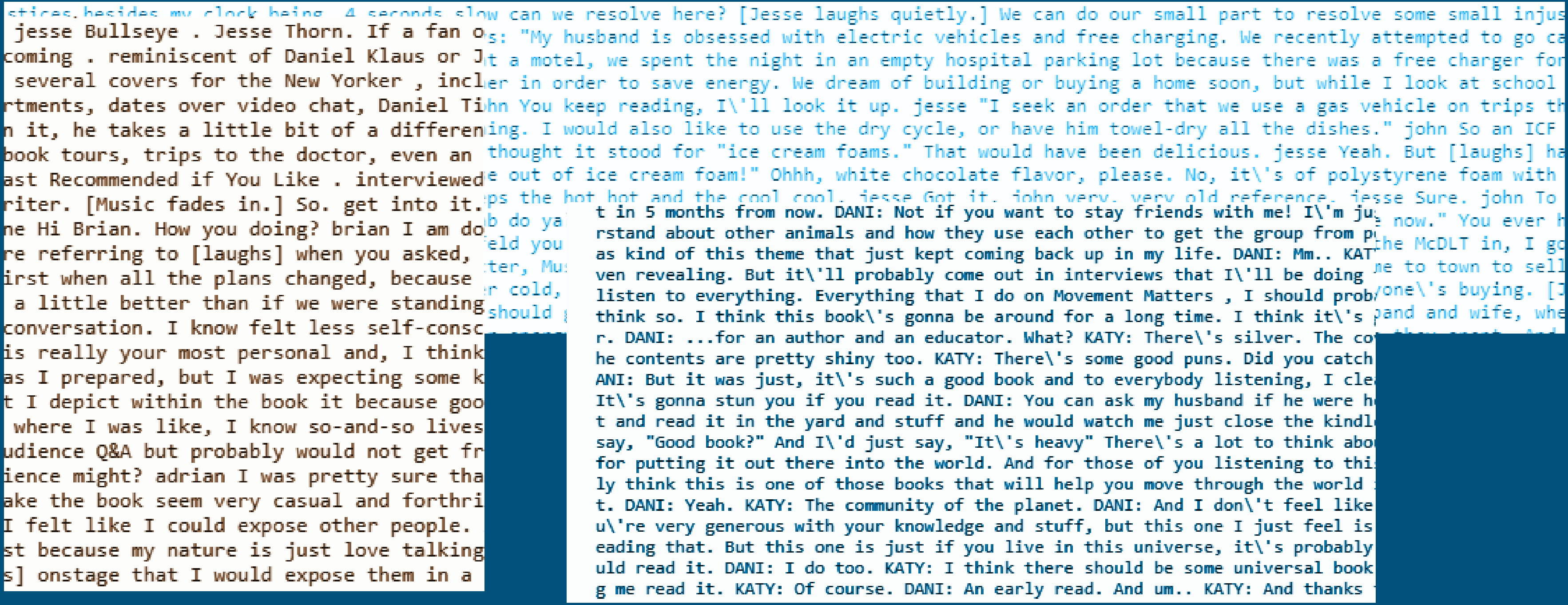
The unpredictable variation in website setup meant that I needed an individual scraper for each podcast or each podcast network. I would have liked to parse out host names and separate their speech, then analyze each host's style, but that was only possible for a select few podcasts. Radiolab, for instance, had four different formatting styles for speaker tags, and NeoScum's tags varied within each transcript.

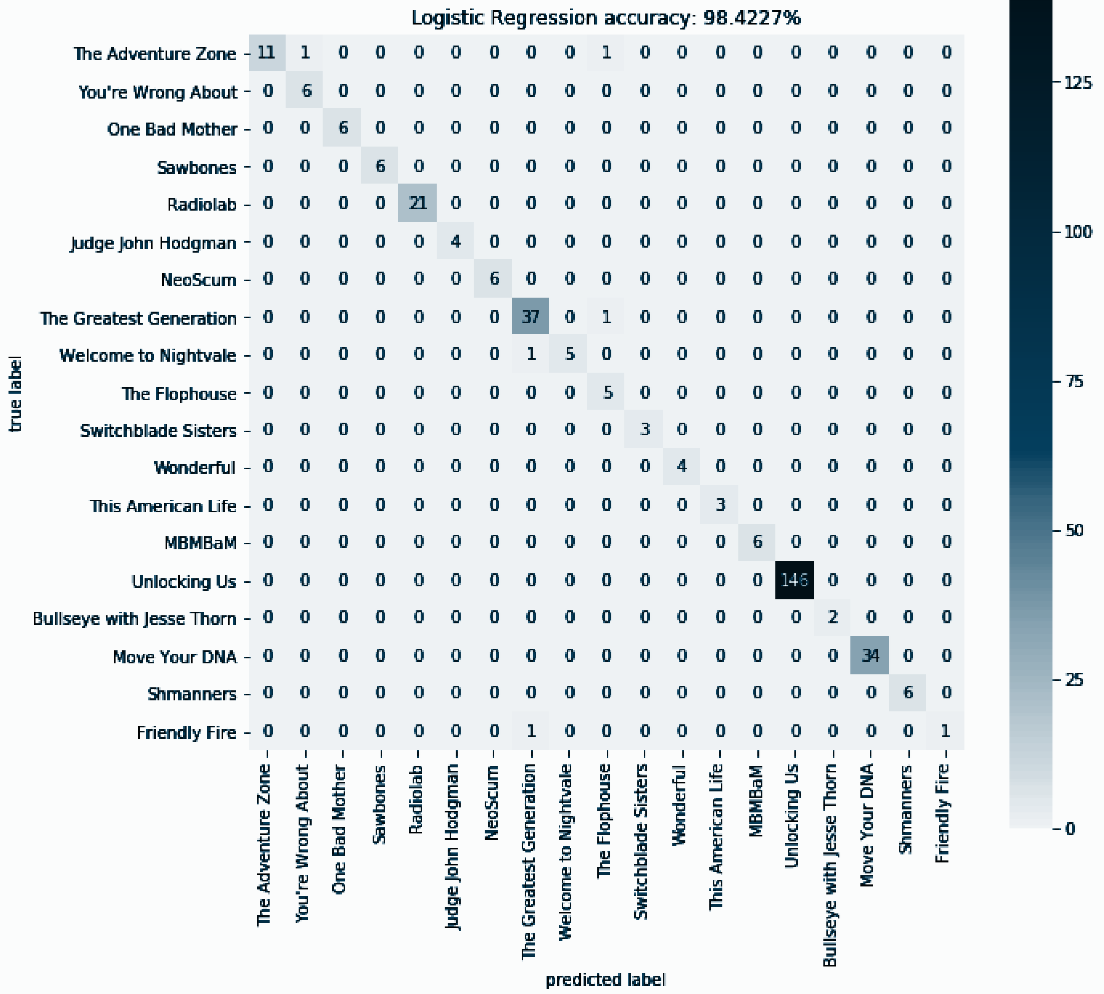
Machine Learning Part A: Regression

I went a little bit wild with extracting non-textual features. I'll briefly describe all of them now (briefly because there are 50 of them):

- Token count (int, transcript length)
- Token lengths (list of tuples: (token, length))
- Avgerage token length (float, mean of all alphabetic token lengths)
- TTR (float, type/token ratio measured against 300 characters)
- Avgerage kband (float, mean kband)
- Part of speech frequency (dictionary as {POS: % of entire document})
    - Noun
    - Verb
    - Adjective
    - Adverb
    - Interjection
    - Preposition
    - Conjunction
- Average sentence length (float, average sentence length over entire transcript)
- Part of speech length (dictionary as {POS: average POS length})
    - Noun
    - Verb
    - Adjective
    - Adverb
- Pronoun counts (dictionary as {pronoun: % of all pronoun occurrence that this pronoun makes up})
    - I
    - You
    - She
    - He
    - It
    - They
    - We
- Verb lemmas (dictionary of 20 most common verb lemmas as {lemma: % of all verbs that a verb comprises}) and their frequencies
    - Know
    - Be
    - Do
    - Mean
    - Make
    - Go
- Entities (dictionary as {spacy's ent tag of token: % of ent occurrence over document length})
    - Organization
    - Art
    - Date
    - Geopolitical (countries, cities, etc)
    - Cash
    - time\
    - product
- Opinioncount (float, occurrence of pronoun followed by optional auxiliary followed by lemma think or feel weighed against total verb occurrence)
- Prepositions per sent (float, average occurrence of prepositions per sentence)
- Donation appeal (int, count of "donate" occurring as a phrase root)
- Social count (int, count of how many times a social media platform is mentioned)
- And several more . . .

Machine Learning Part B: Tfidf Vectorizer and Multinomial NB



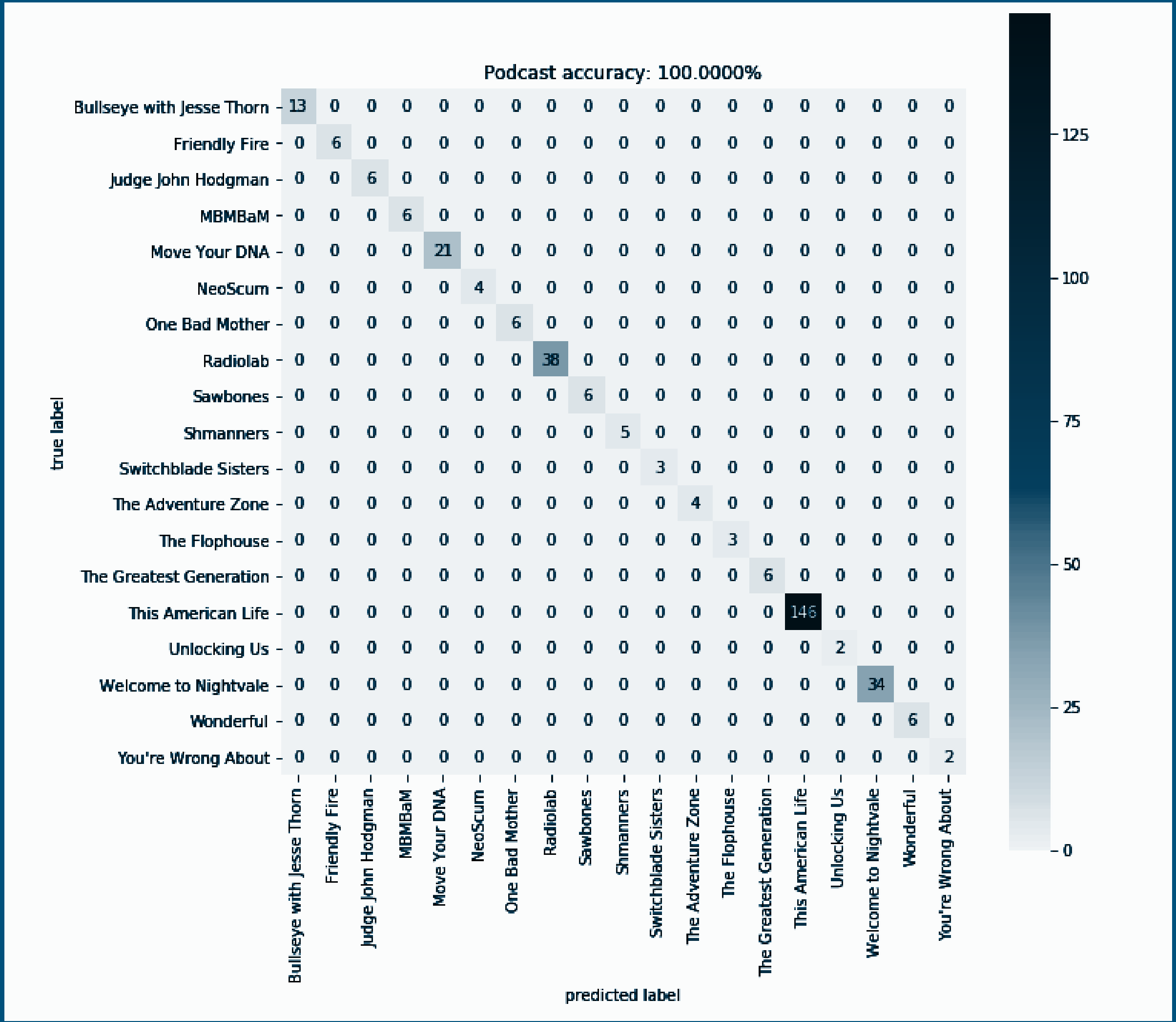


Test #1A: Predicting Podcast

Logistic regression

Test #1B: Predicting Podcast

Tfidf and NB only 1,000 features!



Understanding the most informative features . . .

Bullseye with Jesse Thorn: did, promo, time, wanna, mean, gonna, people, chuckles, yeah, laughs, jordan, really, kind, think, fades, just, music, like, know, jesse

Friendly Fire: guy, laugh, music, really, know, right, clip, gonna, think, just, war, yeah, film, laughs, movie, like, john, ben, adam, host

Judge John Hodgman: wanna, joel, think, mm, quietly, right, laughter, gonna, hm, don, uh, just, judge, know, laugh, yeah, like, laughs, jesse, john

MBMBaM: good, got, wanna, laughing, right, think, oh, um, know, fucking, gonna, just, okay, uh, yeah, laughs, like, justin, griffin, travis

Move Your DNA: don, lot, kind, way, things, stephanie, time, body, going, yeah, people, really, right, think, know, movement, just, like, dani, katy

NeoScum: gonna, right, laughs, got, going, oh, guys, like, okay, just, tech, yeah, mm, dak, dr, es, tw, ct, bb, gr

One Bad Mother: wanna, time, music, okay, job, good, host, think, doing, right, know, really, yeah, crosstalk, gonna, just, like, laughs, theresa, biz

Radiolab: pat, annie, radiolab, right, matt, okay, people, speaker, clip, yeah, simon, know, krulwich, latif, just, molly, like, abumrad, robert, jad

Sawbones: say, things, mean, really, medical, lot, gonna, right, yeah, think, okay, uh, people, just, um, know, laughs, like, justin, sydnee

Shmanners: lot, hmm, thing, oh, say, people, yes, gonna, think, just, yeah, know, uh, laughs, right, um, okay, like, travis, teresa

Switchblade Sisters: kelly, way, people, laughs, speaker, music, gonna, quote, really, yeah, movie, kind, think, uh, just, film, know, like, um, april

The Adventure Zone: mean, ve, right, kind, oh, think, um, gonna, just, laughs, know, yeah, like, okay, uh, justin, clint, griffin, travis, fitzroy

The Flophouse: justin, think, know, okay, people, laughter, uh, gonna, multiple, audience, just, laugh, yeah, movie, crosstalk, laughs, like, dan, stuart, elliott

The Greatest Generation: scene, really, mm, make, just, gonna, think, know, right, episode, promo, music, uh, laughs, yeah, clip, like, ben, adam, host

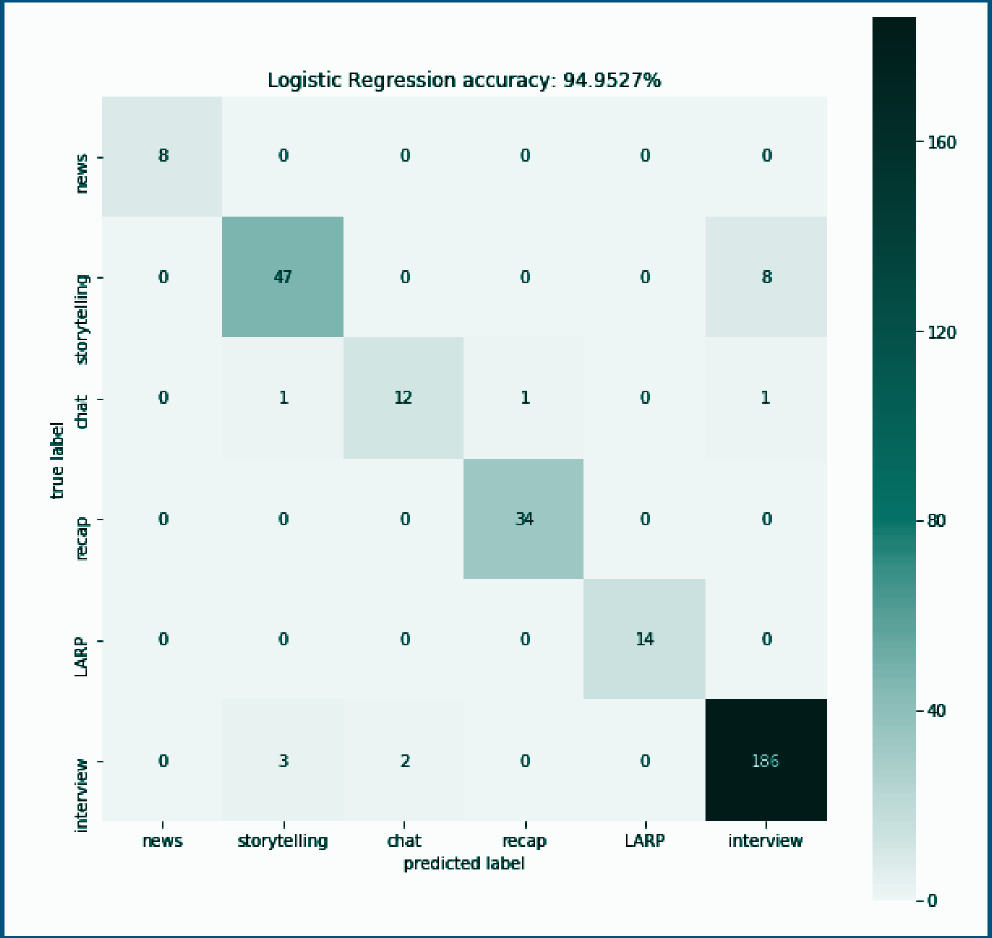
This American Life: act, way, did, say, right, got, ve, really, time, didn, think, said, going, don, know, people, just, glass, like, ira

Unlocking Us: julie, way, book, right, time, black, love, said, want, yeah, white, really, say, going, know, think, just, people, like, bb

Welcome to Nightvale: new, station, police, dana, old, secret, did, city, good, mayor, town, time, listeners, know, said, just, like, cecil, night, vale

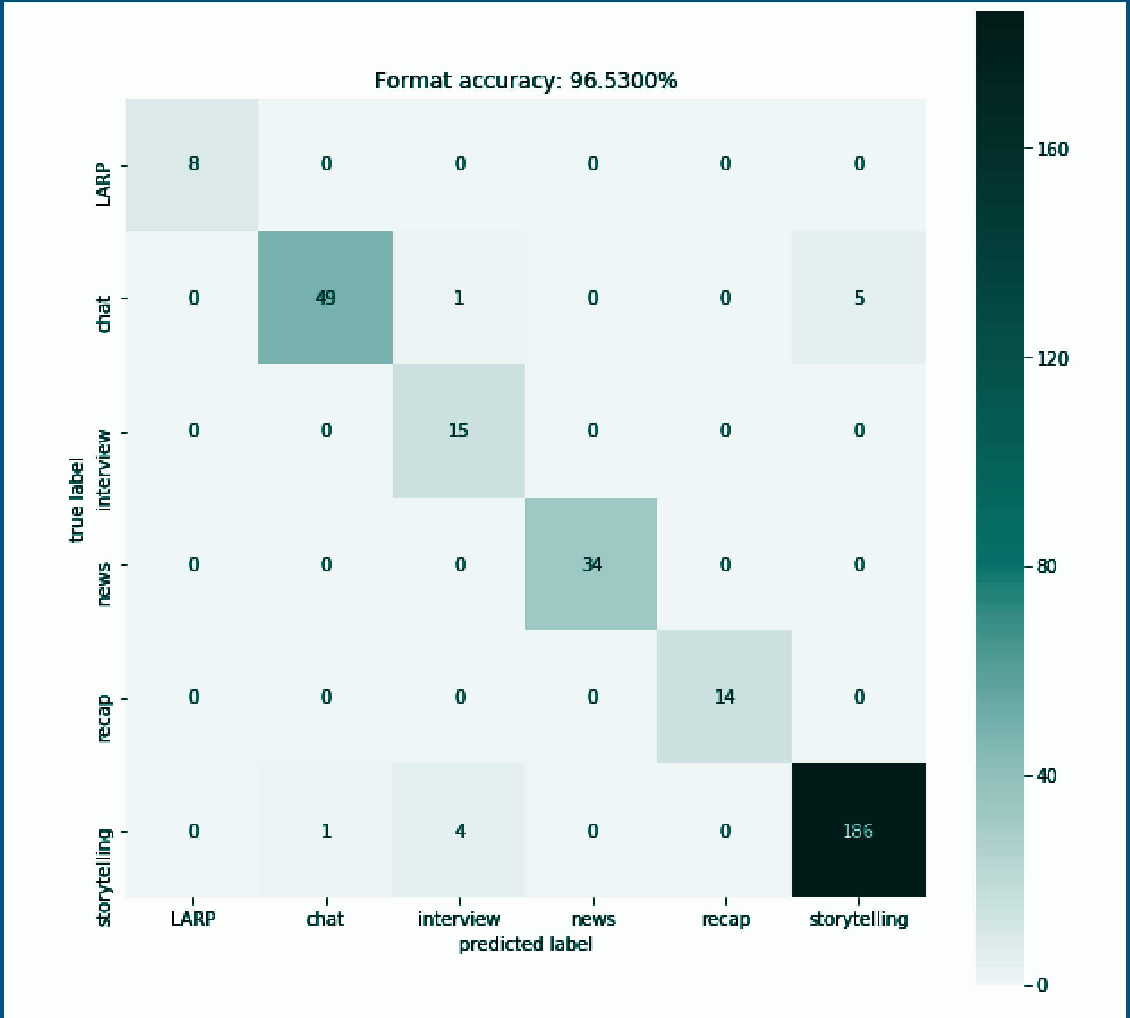
Wonderful: right, good, sort, thing, oh, gonna, kind, okay, lot, really, um, think, know, just, yeah, laughs, uh, like, rachel, griffin

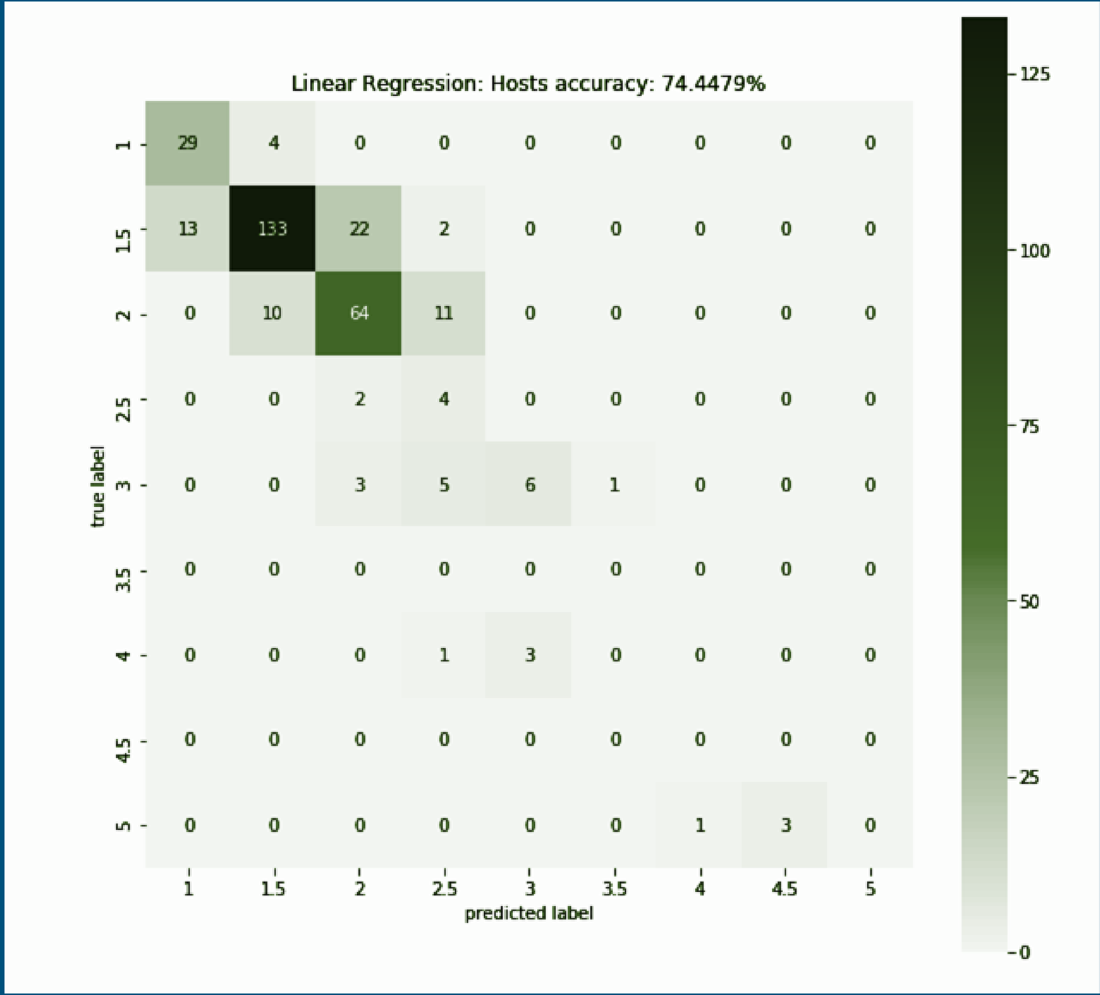
You're Wrong About: movie, okay, right, thing, time, kind, sort, really, going, don, think, yeah, know, people, just, michael, marshall, mike, sarah, like



Test #2A: Predicting format

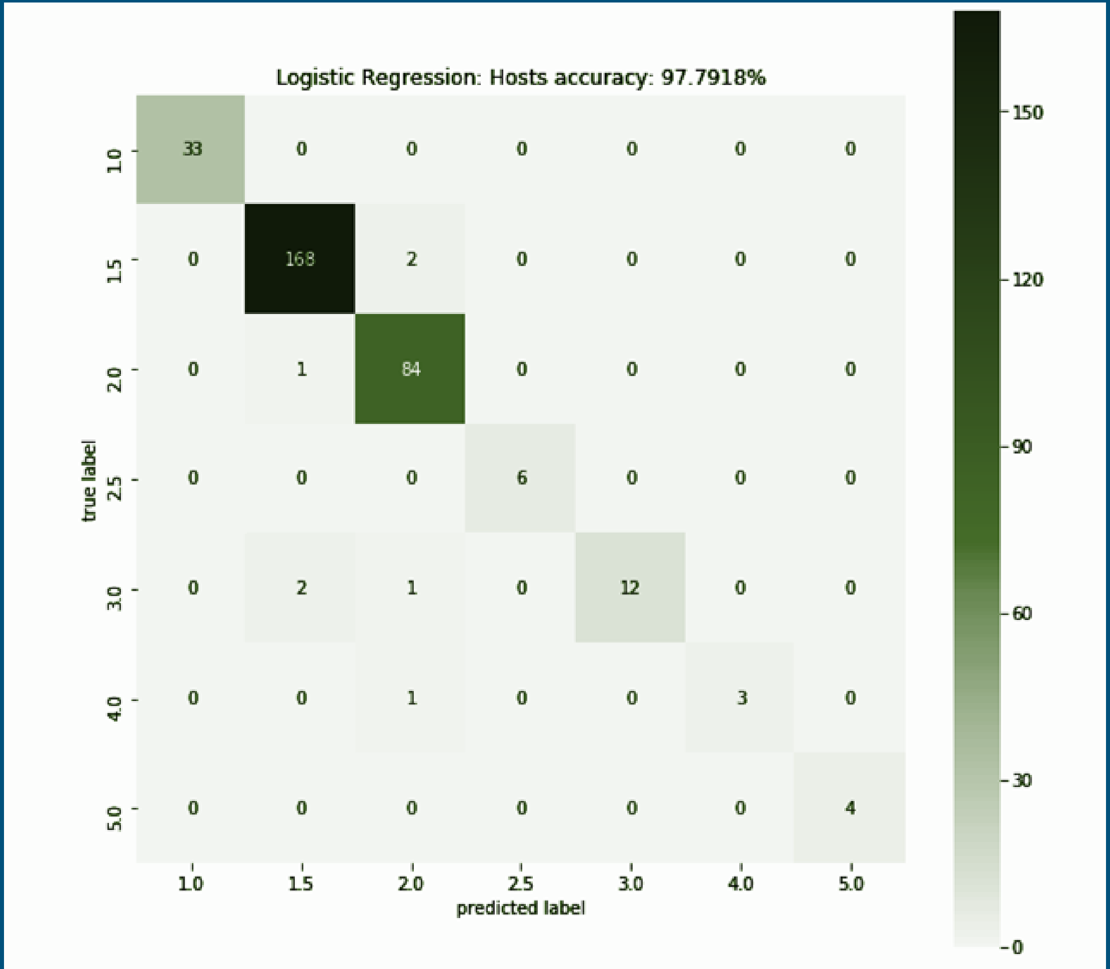
Test #2B: Predicting format





Test #3A: Predicting hosts

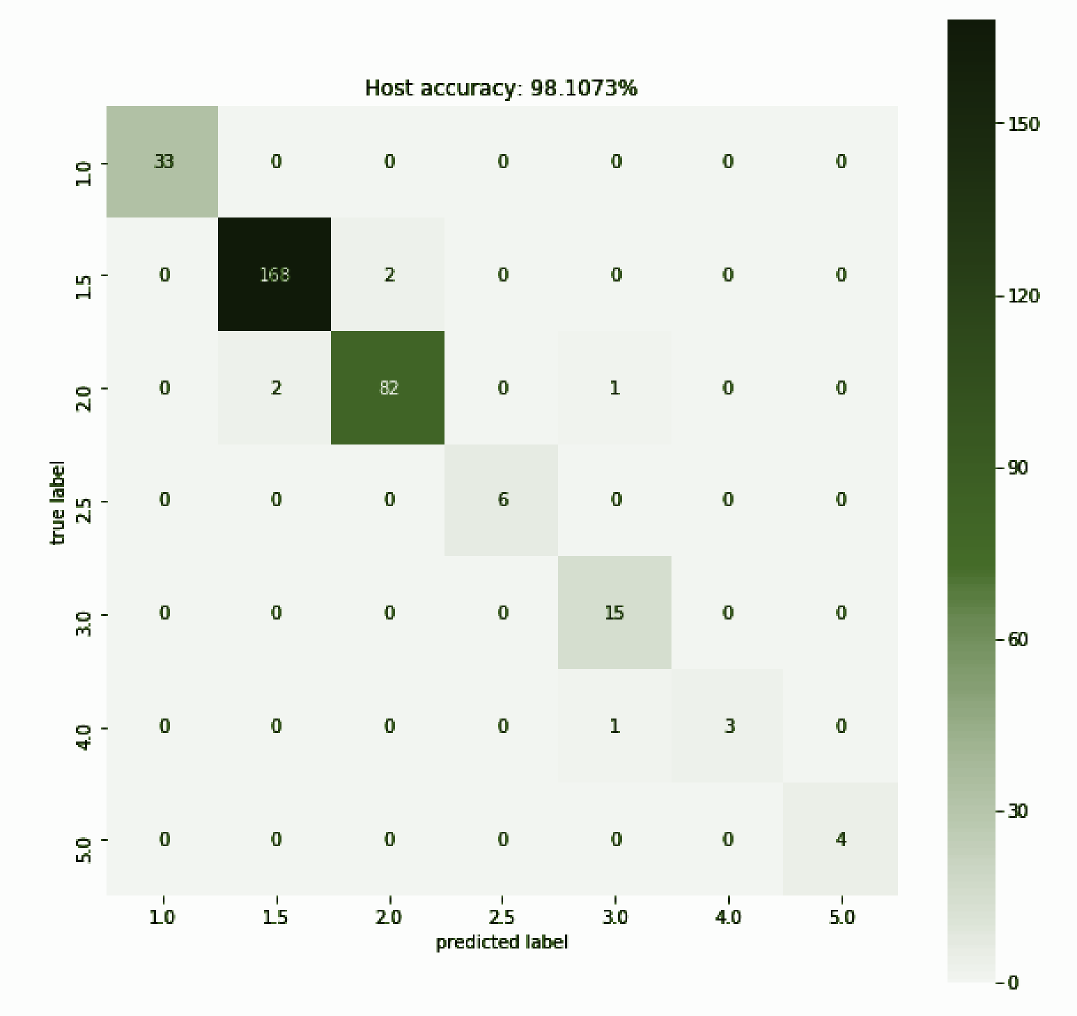
This one was a bit tricky, since the host numbers aren't actual values, but numerical representations, so they function as labels. Had to do some rounding of the predictions.

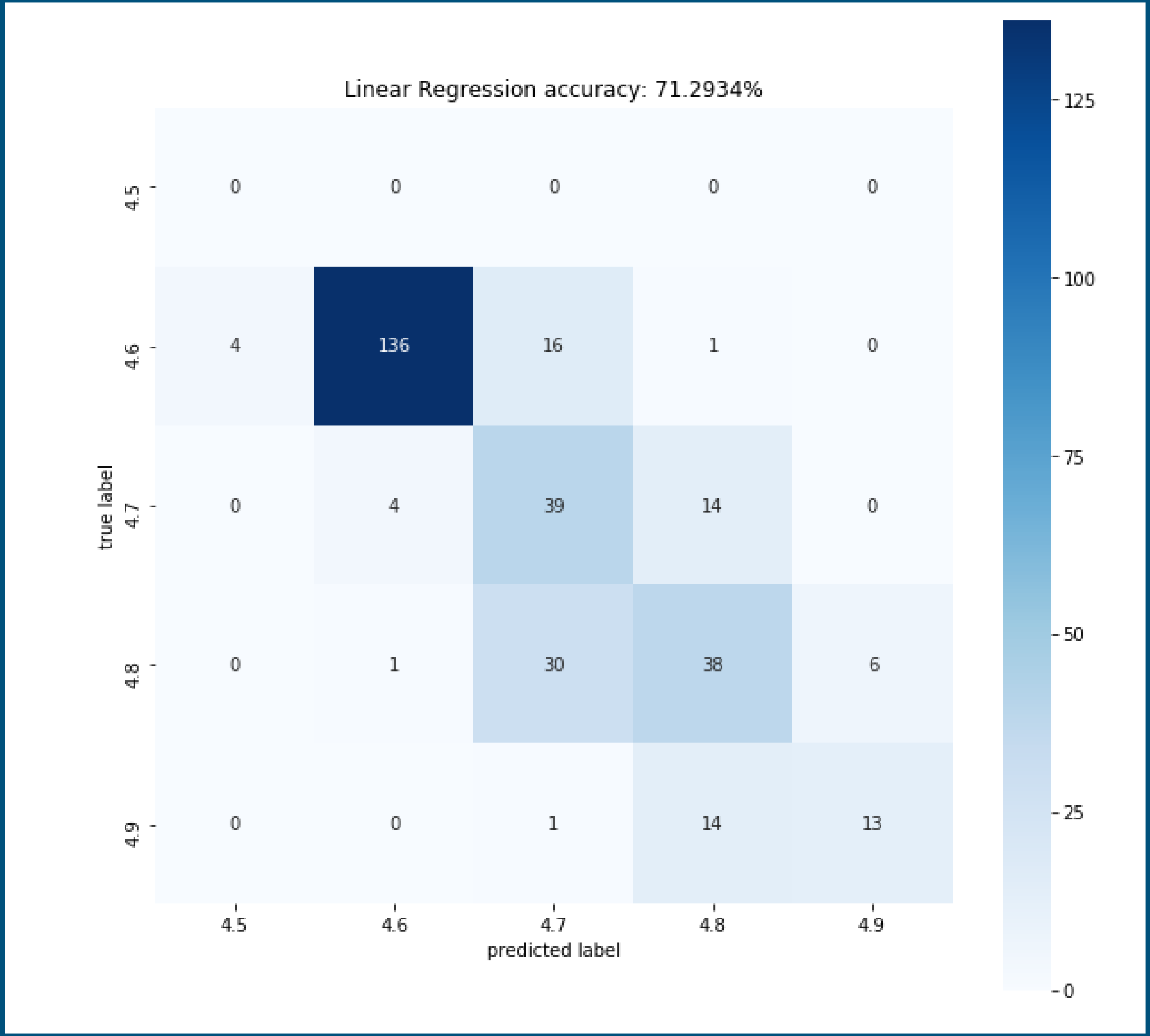


Test #3A: Predicting hosts

Turns out logistic regression worked best on this, since the target values are technically labels.

Test #3B: Predicting hosts



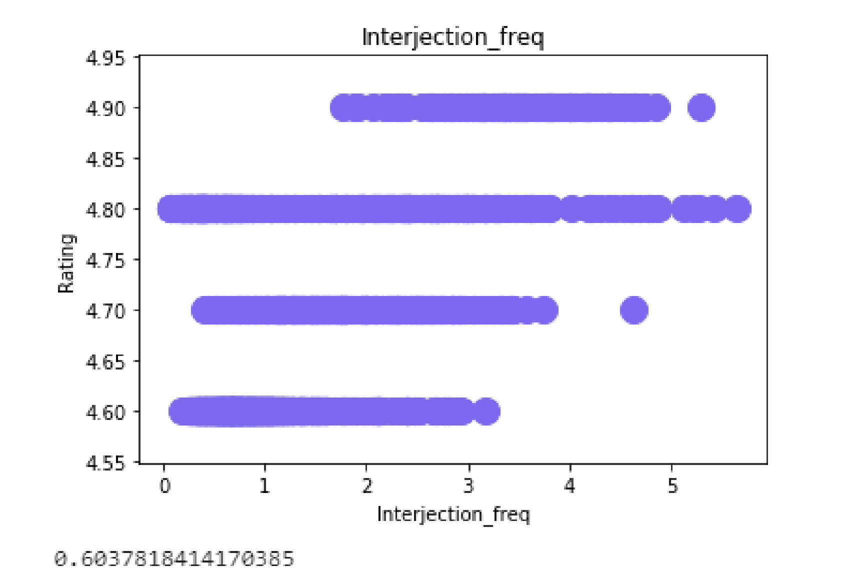


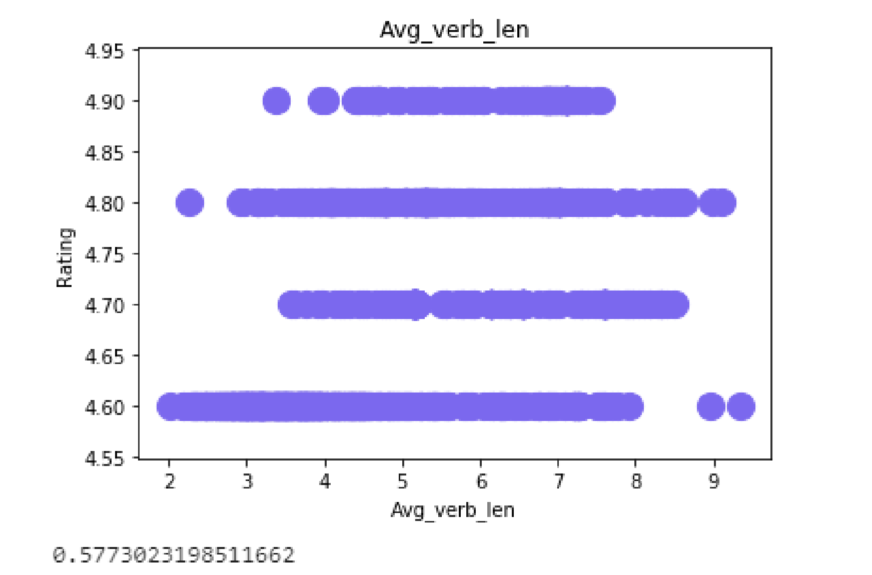
Test #4A: Predicting rating

Ratings ranged from 4.6 to 4.9. This makes sense, since poorly-rated podcasts don’t have transcripts. This tiny margin isn’t ideal for training a model.

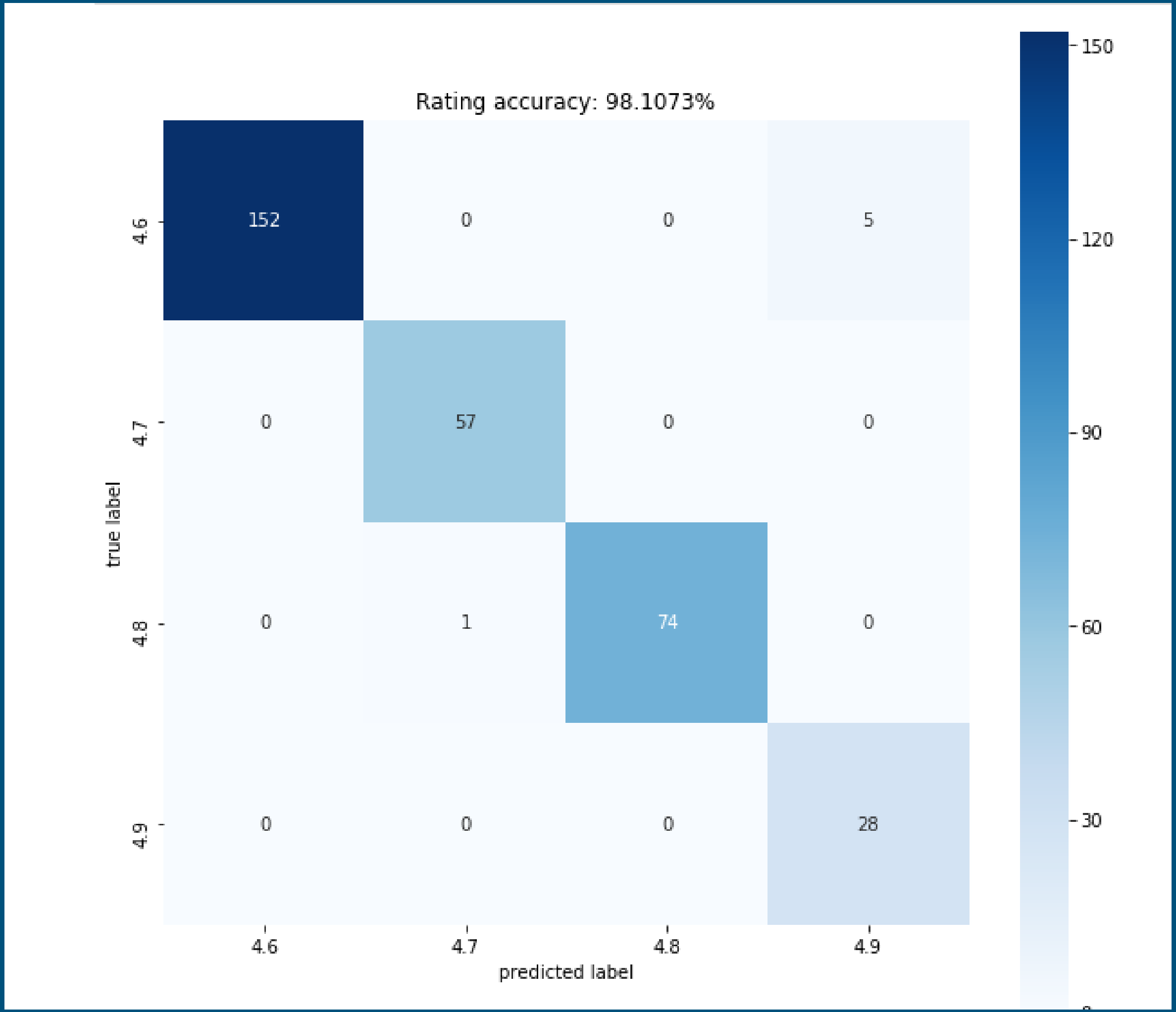
An aside . . . do any non-textual values correlate to rating?

Possibly? Here are the highest correlation values:



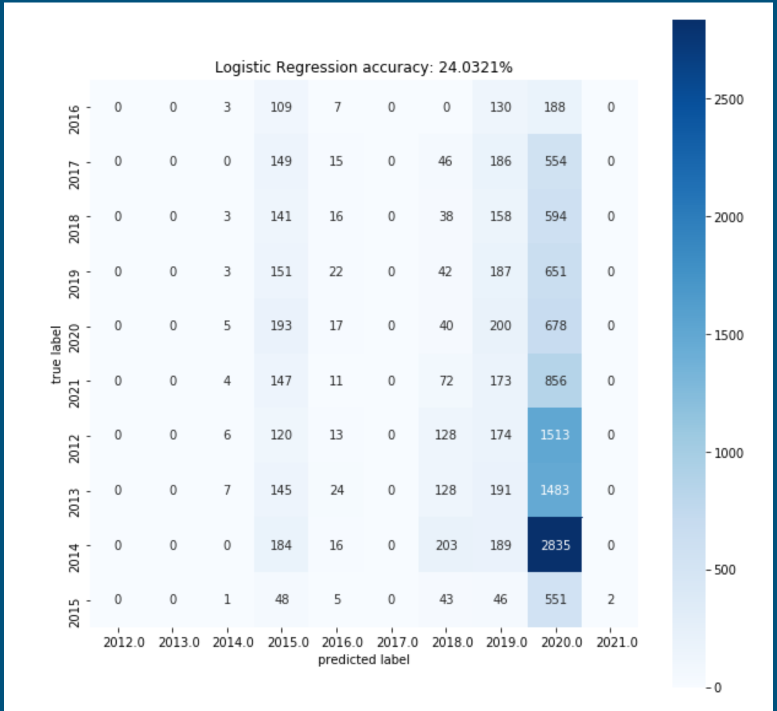


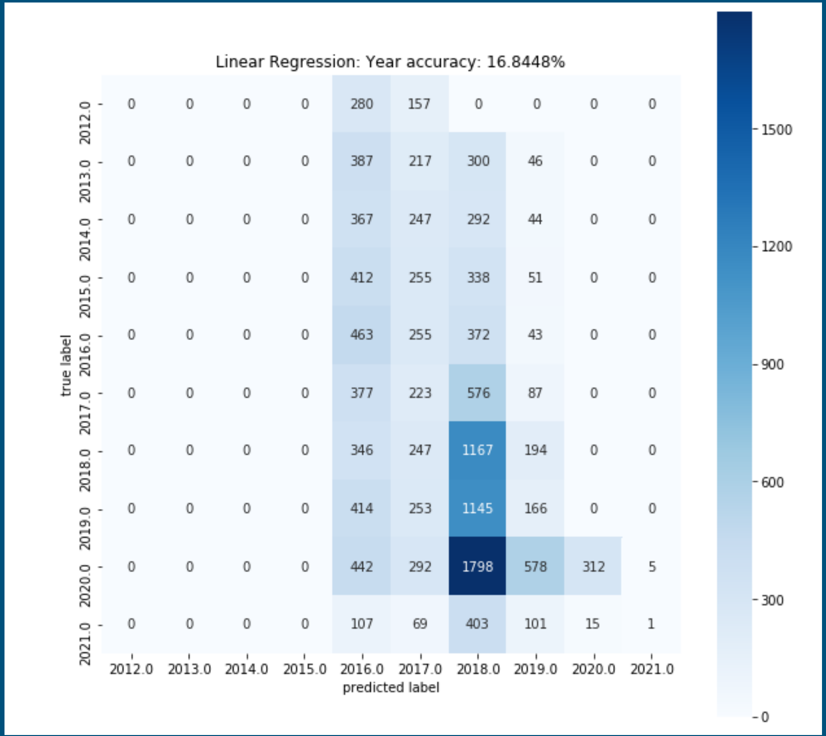
Test #4B: Predicting rating



Test #5A: Predicting year

Logistic





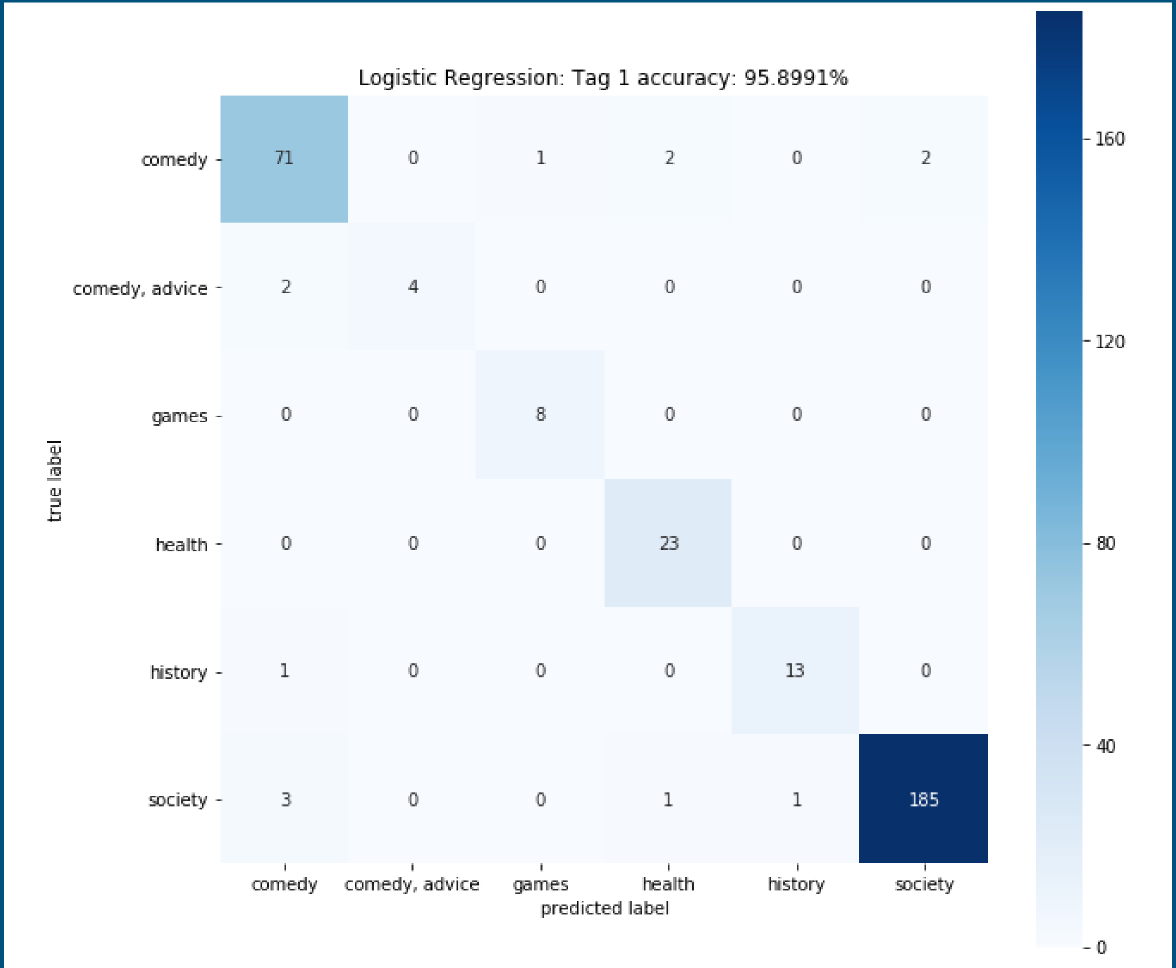
Linear

*only 520 of the transcript pages had scrapable year metadata. Extremely limited sample size! 205 of the 520 year-labeled transcripts were from 2020, so both models performed worse than if they would have guessed “2020” for all labels.

Test #5B: Another failed attempt at predicting year

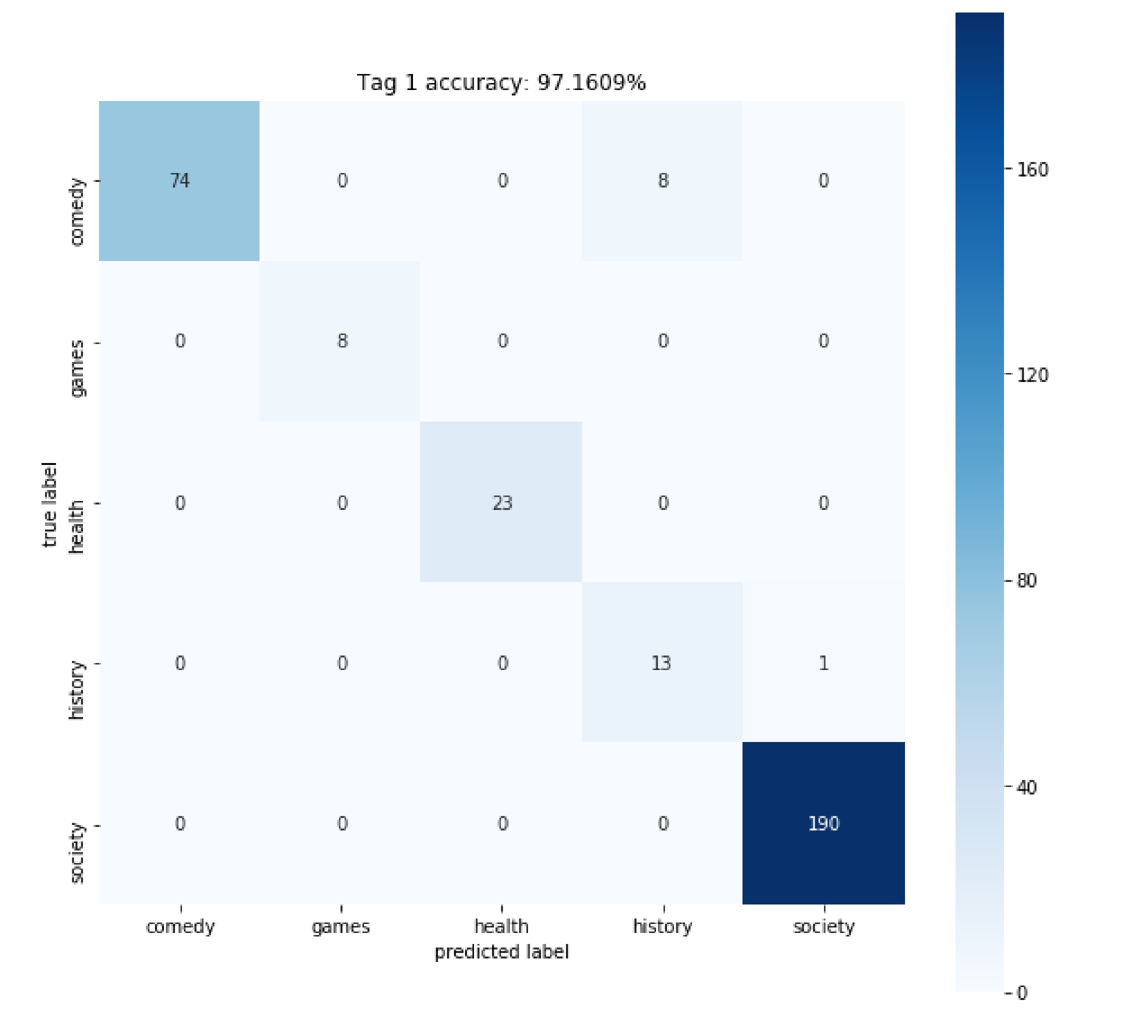
After running a gridsearch using a vectorizer, the best accuracy was still pretty abysmal at 0.39423. I will definitely say that, at least with this small of a data set, there is no way of predicting year from podcast.

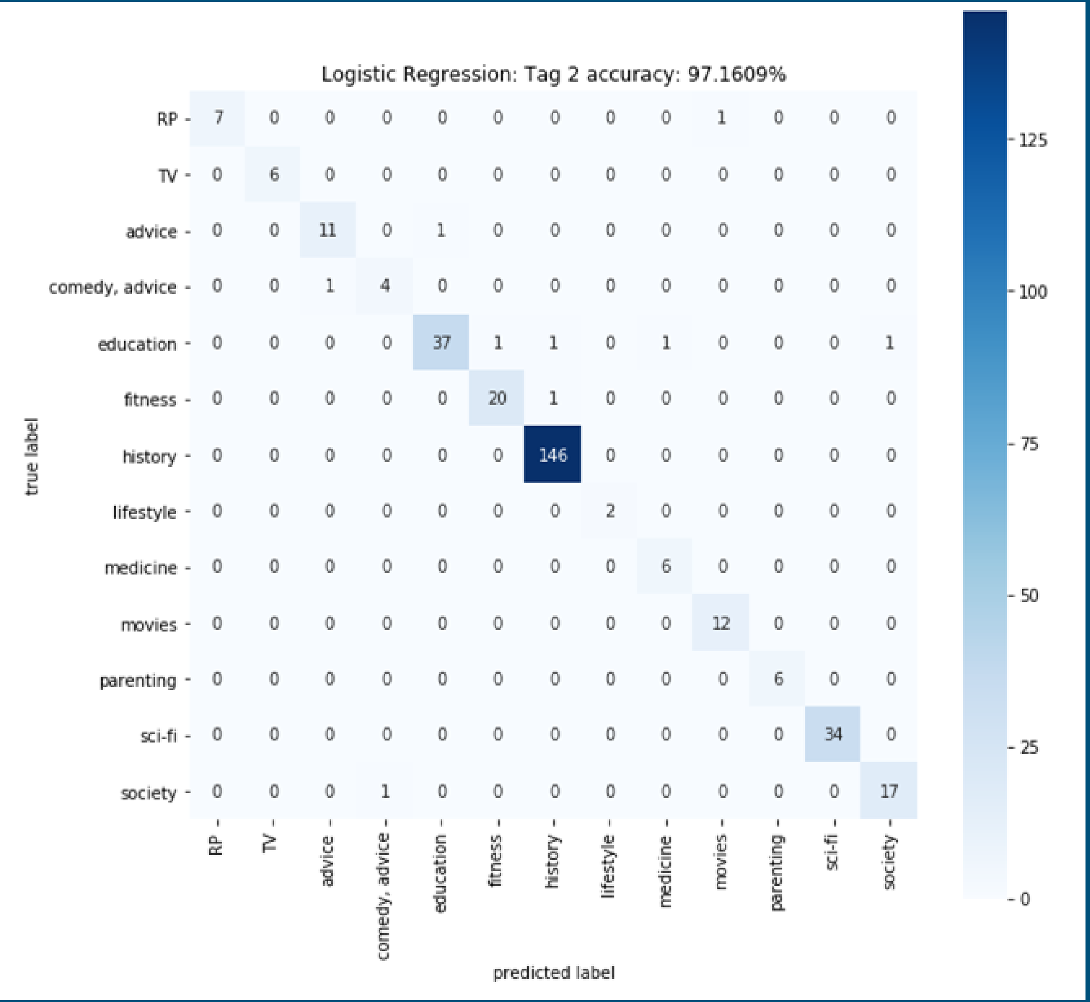
Maybe when more transcripts become available, a vectorizer model will be able to do this task with higher accuracy. It would be interesting to see the most informative features from year to year.



Test #6A: Predicting Main Tag

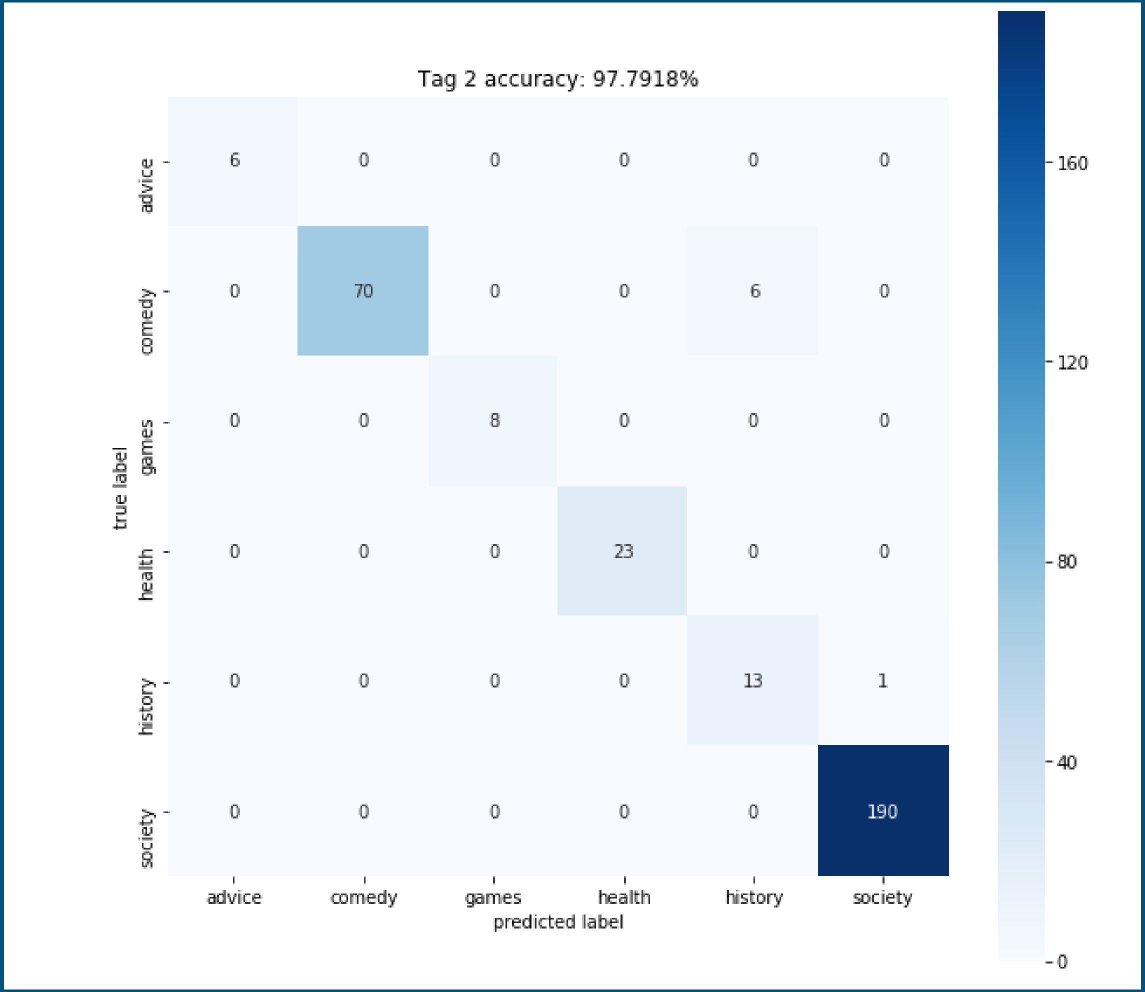
Test #6B: Predicting Main Tag



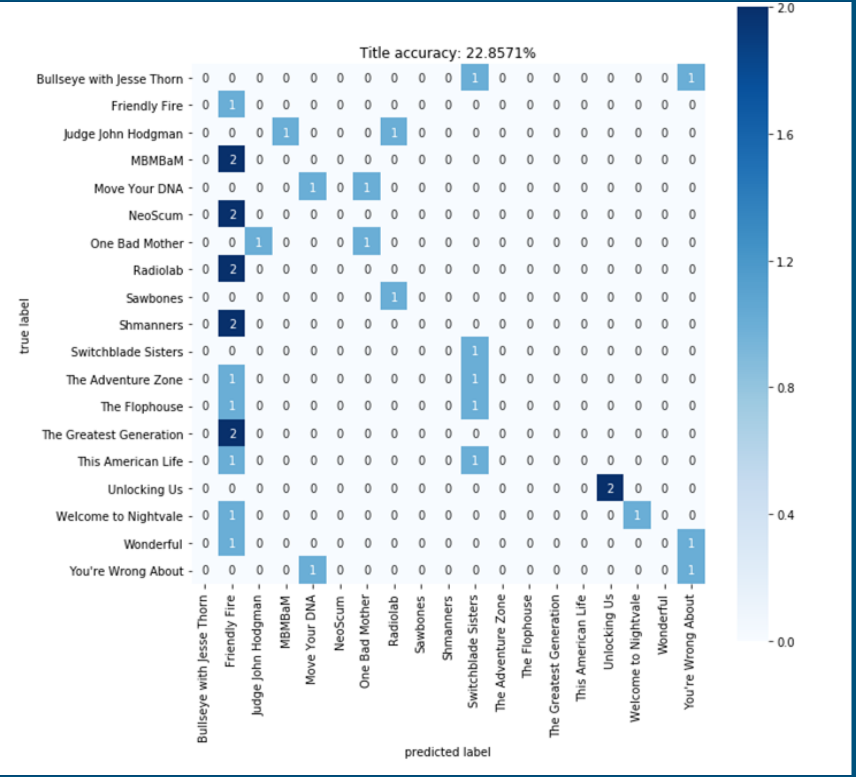


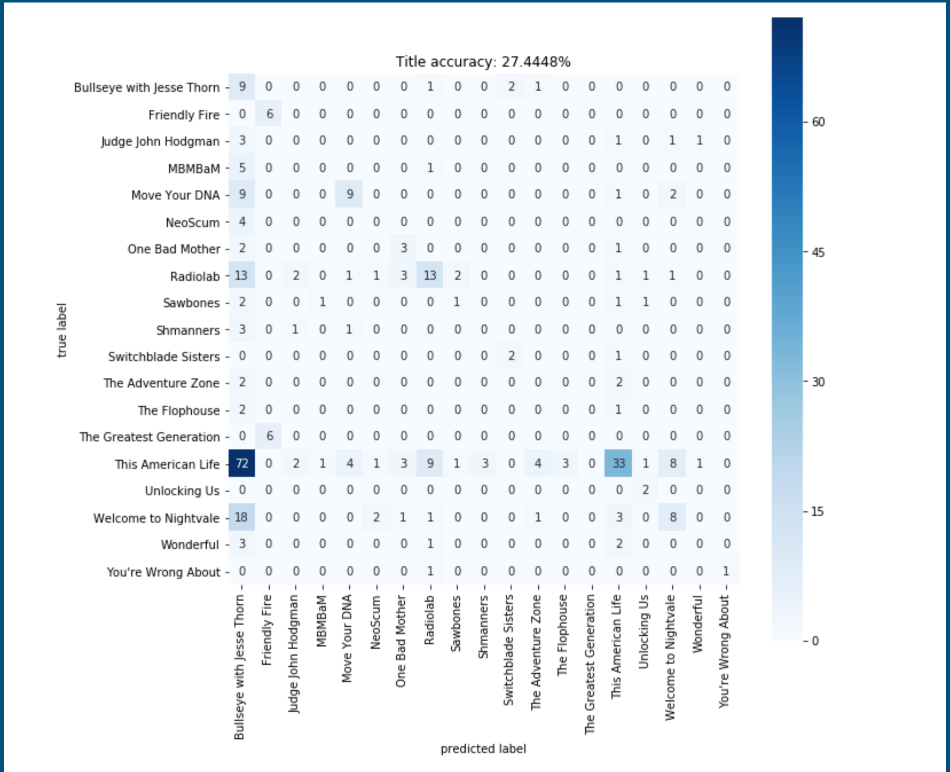
Test #7A: Predicting Secondary Tag

Test #7B: Predicting Main Tag



Predicting podcast from vectorized title





<< even representation among podcasts (228 total)

This American Life	731
Radiolab	192
Welcome to Nightvale	168
Move Your DNA	104
Bullseye with Jesse Thorn	63

Using the classifier

Emma chapter 1 = This American Life

This makes sense, even though the classifier was probably just highly-weighted in favor of TAL. This American Life is about peoples' very personal stories, usually with a lot of emotional speech involved.

Leviathan Wakes (from The Expanse) = Welcome to Nightvale

This also tracks. Leviathan Wakes is a science fiction book, with lots of talk about space, spaceships, and the like. Welcome to Nightvale is also science-fictiony.

My AI Essay from Comp Ling = Move Your DNA

I don't quite get this one . . .

Real-world uses of this data

I personally think that podcasts are a very accurate representation of casual conversation. When I have to do another data science project, I'll find out how true that instinct is by comparing it to some real-world conversation in the form of corpora that we talked about in class.

If podcast data *does* reflect casual speech, transcripts would be very useful in training predictive text language models, speech synthesis, and second language acquisition.

Thanks for listening!

Credits roll. [ending sax music plays]

Make it so! Make make make-make-make-make make it so!

Kiss your dad square on the lips.

All right. Bye-bye.

But I will enjoy talking to you next time.

Thank you for listening. Please stay safe everybody.

And gonna do it for us, so join us again next week! No RSVP required.

Good night, listeners. Good night.

And we always appreciate you listening. Thank you for being with us. You especially. You, now, hearing this? You’re our favorite. And if there’s more than one person in the room? Both of you are our favorites.

I mean, not like I'm your dad! be safe out there! And wash your hands!

And as always, don’t drill a hole in your head!

Just remember: all great radio hosts have a signature sign off.