

Twitter Killed the Radio Star

Thoughtful Supervised Learning Capstone
Conner Brown
23 May 2018



Motivation

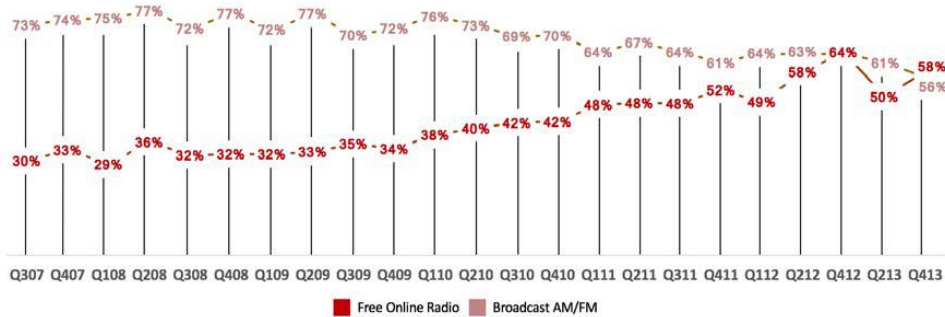
How do radio stations react to streaming services?

Common suggestion: get on social media!

Does this have an impact on radio station popularity?

What other factors affect radio station popularity?

**% LISTENING TO MUSIC BY SERVICE TYPE: PAST 3 MONTHS
TEENS (13-17)**



Source: MusicWatch MusicAcquisitionMonitor Q3 2007-Q4 2013. Based on online survey to ~5000 respondents per wave and projected to internet using population 13 and older. Study was quarterly between 2007 and 2011; semi-annual from 2012 forward.

Data Scraping

AllAccess.com Data (Selenium)

Nielsen Markets Table	Market Name, Demographics, State, Market Stations Link
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Market Stations Table	Format, Listeners per season, Owner, Station Link
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Twitter Data (tweepy)

Twitter API	Tweets, Followers, Statuses, Favourites, Created At
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Data

Rows 2110
Columns 17

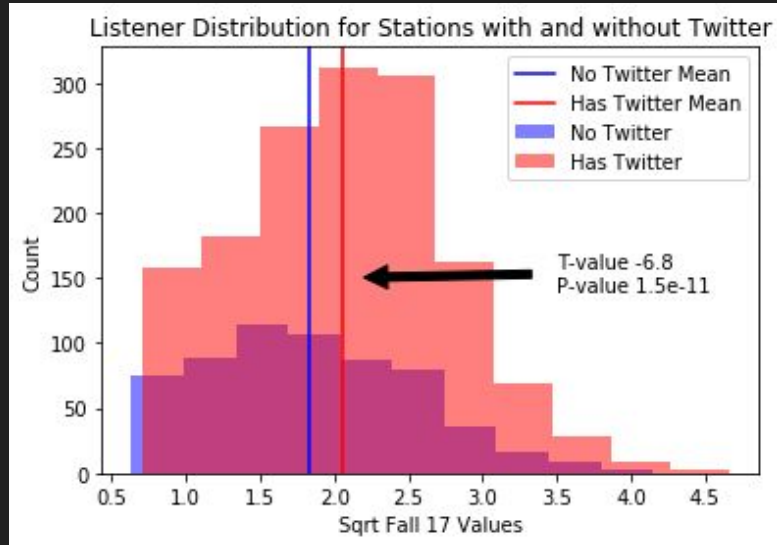
AllAccess.com Data

Twitter Data

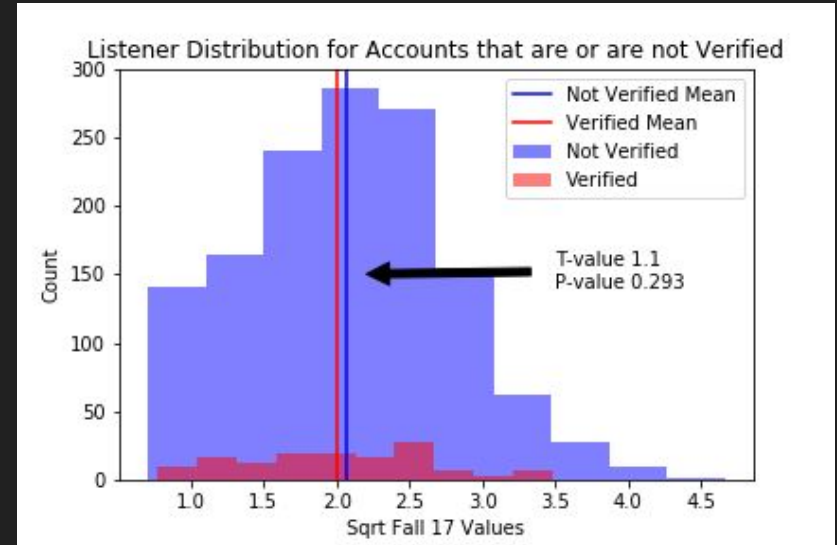
	Format	Population	Spr 17	Spr 16	Black	State	Fall 16	Hispanic	Owner	Fall 17	Followers Count	Friends Count	Listed Count	Created At	Favourites Count	Verified	Statuses Count
0	Country	144700.0	7.5	8.7	11500.0	TX	6.3	31500.0	Townsquare	9.3	2030.0	1754.0	25.0	2010-11-08 20:22:46	191.0	False	10156.0
1	Classic Hits	144700.0	7.5	7.2	11500.0	TX	6.3	31500.0	Townsquare	7.9	578.0	475.0	11.0	2010-12-07 17:00:43	25.0	False	21834.0
2	Top 40/M	144700.0	6.8	7.2	11500.0	TX	7.7	31500.0	Cumulus	6.6	235.0	36.0	12.0	2009-12-17 09:53:19	1.0	False	12.0

Data Type	Columns
Categorical	Format, State, Owner
Numeric	Population, Black, Hispanic, Followers Count, Friends Count, Listed Count, Favourites Count, Statuses Count
Datetime	Created At
Boolean	Verified
Time Series	Spr 16, Fall 16, Spr 17, Fall 17

Data Statistics



- P-value $\ll 0.05$
- Difference is most likely NOT due to chance
- Safe to assume stations with twitter accounts have more listeners



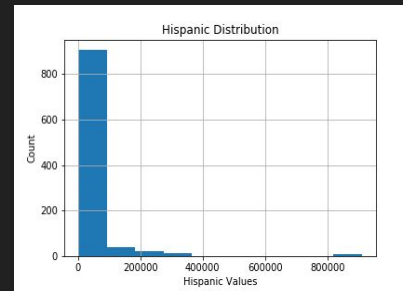
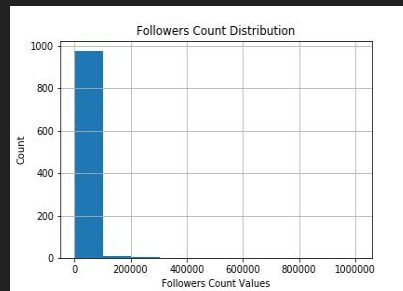
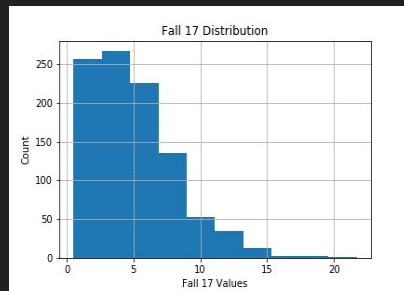
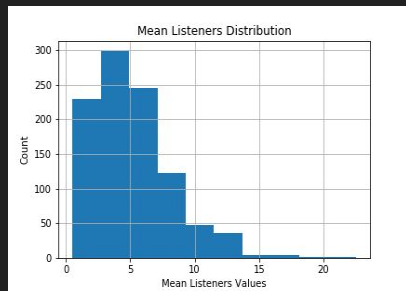
- P-value > 0.05
- Difference may be due to chance
- High variance in 'verified' data (what's going on here?)

Feature Engineering (derived)

```
# grouped columns based on seasonal listeners
df_listeners = df_feat[['Spr 16','Fall 16','Spr 17']]
av_listeners = df_listeners.mean(axis = 1)
df_feat['Low Listeners'] = np.transpose([av_listeners < 3])
df_feat['Mid Listeners'] = np.transpose([(av_listeners < 7) & (av_listeners >= 3)])
df_feat['High Listeners'] = np.transpose([(av_listeners < 12) & (av_listeners >= 7)])
df_feat['Stellar Listeners'] = np.transpose([av_listeners >= 12])
```

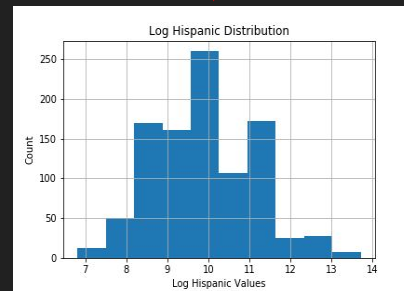
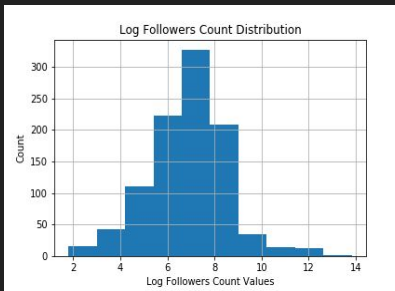
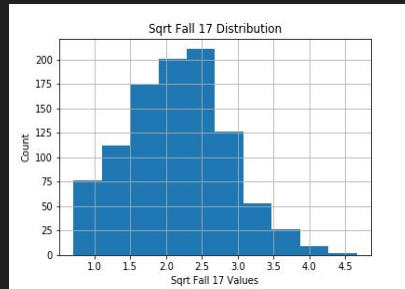
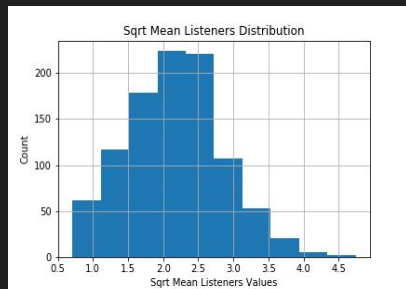
```
# time series stats
df_feat['Mean Listeners'] = av_listeners
df_feat['Std Listeners'] = df_listeners.std(axis = 1)
slopes = []
intercepts = []
for row in df_feat.index:
    slope, intercept, r_value, p_value, std_err = stats.linregress(list(range(1,4,1)),df_listeners.loc[row])
    slopes.append(slope)
    intercepts.append(intercept)
df_feat['Slope Listeners'] = slopes
df_feat['Intercept Listeners'] = intercepts
```

Feature Engineering (continuous)



Square Root(X)

Log(X + 1)



More normal!

No more outliers!

Normal-ish

Feature Engineering (categorical)

59 unique Formats

Country	580
Top 40/M	363
AC	289
Classic Rock	273
Sports	268
Talk	266
N/T	250
Classic Hits	223
Hot AC	205
Top 40/R	120

Name: Format, dtype: int64

52 unique States

CA	393
TX	306
FL	278
NY	263
NC	172
PA	165
IL	120
OH	117
MI	111
IA	105

Name: State, dtype: int64

568 unique Owners

iHeartMedia	890
Cumulus	404
Entercom	302
Townsquare	250
Alpha	119
Cox Radio	67
Midwest	67
Univision	59
Beasley	57
Urban One	50

Name: Owner, dtype: int64

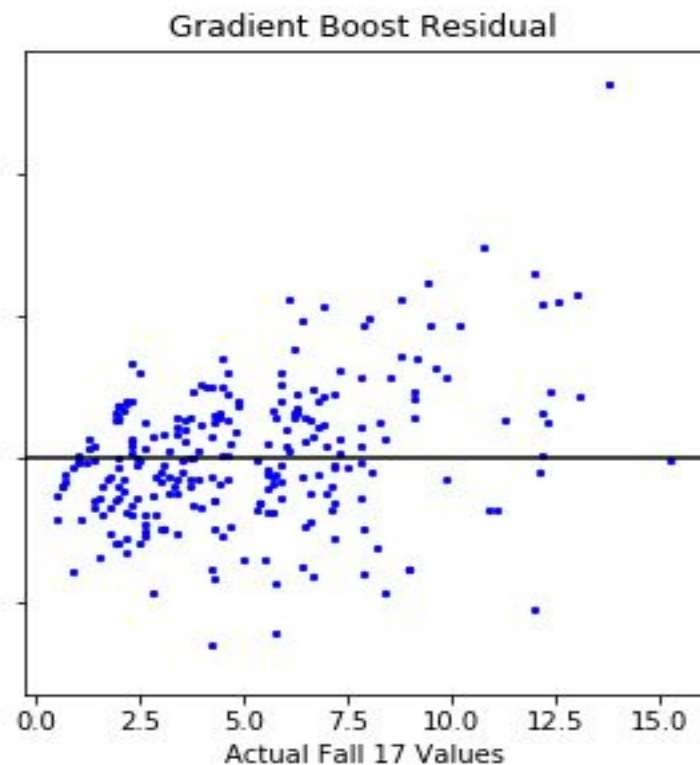
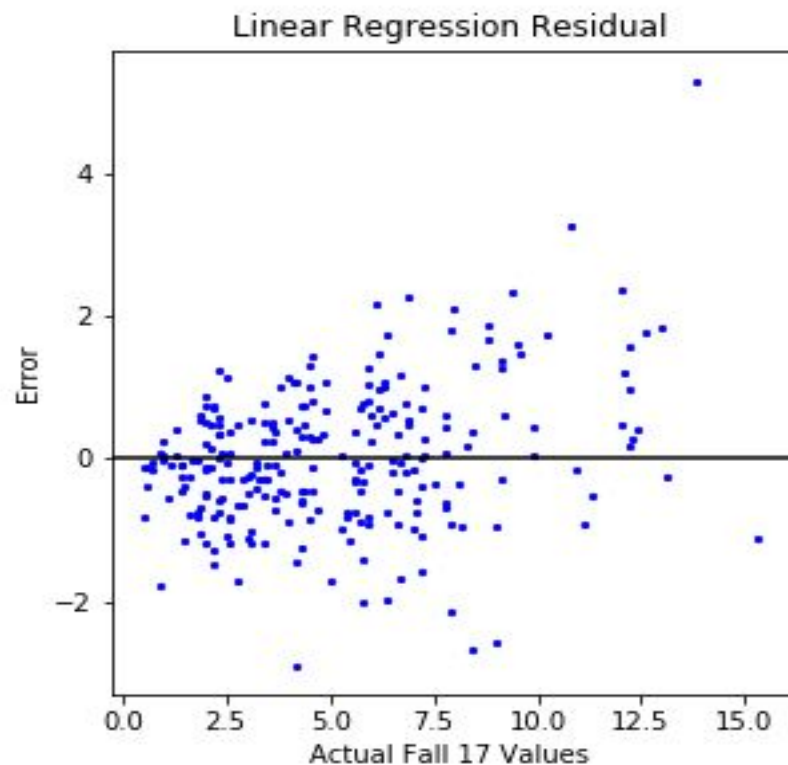
```
# OHE categorical variables: Format, top 20 Owners, State
# get_dummies Format, State
df_feat = pd.get_dummies(df_feat, columns = ['Format', 'State'])
# top 20 Owners
top_owners = list(df_feat['Owner'].value_counts()[:20].index)
for owner in top_owners:
    df_feat["Owner_" + owner] = (df_feat['Owner'] == owner).astype(int)
df_feat.drop('Owner', axis = 1, inplace = True)
```


Model Results

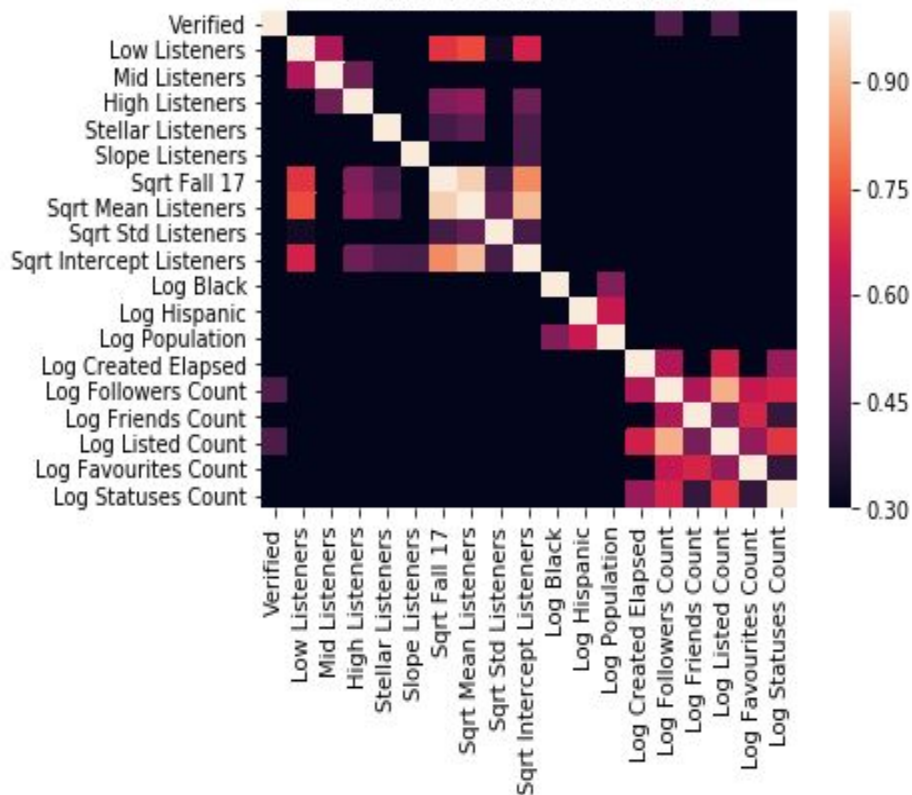
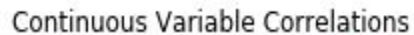
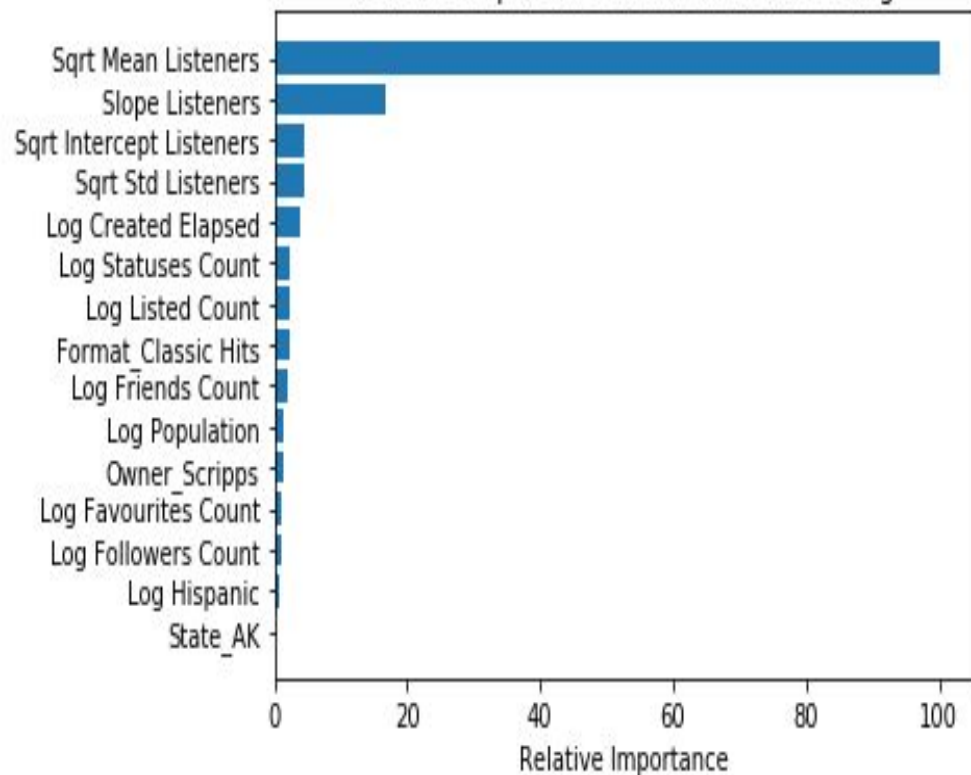
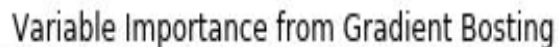
MAE Score = Mean Absolute Error
R-squared = measure of explained variance
Explained Variance = measure of explained variance (if not equal to R-squared then may indicate biased error)

	Baseline	Linear Regression	Random Forest	Gradient Boost
MAE Score	0.782661	0.743576	0.767419	0.749029
R-squared	0.889993	0.898139	0.891722	0.895367
Explained Variance	0.891066	0.898139	0.891722	0.895368

Model Results



Model Results



Further Research

- More Data
- Perform A/B test
 - Step 1: steady state (A/A test)
 - Step 2: make a twitter account
 - Step 3: Profit.
- Analyze using time-series concepts

Acknowledgements

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DJ:	Ultra 2018 Festival Mix
Bed-time Storyteller:	PEP 8
Motivator:	Rent
Tailor:	H&M
Heart Attack Inducer:	Ubuntu 17.10
Main Squeeze:	Ubuntu 16.04 LTS
Lord and Savior:	Grae