Do podcast and music compete with one another?
Understanding users’ audio streaming habits

Ang Li  University of Pittsburgh
Alice Y Wang, Zahra Nazari, Praveen Chandar, Benjamin Carterette, Spotify
Interned 2019 summer with Spotify Tech Research
OUTLINE

› Motivation and research questions
› Methodology
› Results
› Conclusion
Podcasts have become one of the fastest growing online audio streaming media

- **Podcast**: portable and on-demand forms of spoken-word audio content

- As of April 2019, there are over 29M episodes of Podcasts

Motivation and Research questions

The popularity of podcasts has created great demand

Market as of 2018:
- > 525K active podcast shows, > 18.5 billion downloads
- Several music-focused platforms started to expand services by adding podcast content alongside music
  - Satisfy user demand by providing diverse content

Incorporating podcasts introduces new challenges for these platforms

- The functional use for podcasts and music listening may largely overlap
- Two types of content may compete for the limited amount of time that users may allocate for daily audio streaming.

**Music**: entertainment, pleasure, passing time, education, facilitate social interactions

**Podcasts**: entertainment, relaxation, education.

One of the most popular topics among podcast consumers is music

- As a result, incorporating podcast listening to music streaming may influence and change the original way users consume music
Necessary for these platforms to understand the influence and users’ listening habits

- It is necessary for platforms to understand:
  - What is the effects of injecting new type of audio content to users’ listening habits
  - How users’ listening habits change before vs. after the arrival of new content

- … provide best support for their users
  - Content consumers: support them with a better recommender system i.e. provide the right content at the right time
  - Content creators: make their shows more tailored based on users listening habits
IN THE CURRENT STUDY . . .

We focus on music listeners who incorporate podcasts to their listening activities for the first time, and ask:

**RQ1.** Would users’ music listening habits change as a result of adopting podcast listening?

**RQ2. a.** For music users who have adopted podcast listening for the first time, what are their listening habits for podcasts vs. music? **b.** What are the content of podcasts they consume, especially before the adoption?

**RQ3.** When a user starts a new listening session, can we predict whether s/he will listen to a podcast based on their listening habits?
USING Spotify AS OUR RESEARCH PLATFORM

- One of the most popular (271M users) online audio streaming platforms
- Traditionally focus on music streaming
- Started to provide Podcast content in recent years

Define 3 levels of podcast engagement [based on internal user study]:

- **Music Only**: Only listened to music
- **Podcast Seekers**: Just started listening to podcasts, still explore, seek Podcasts to listen to
- **Podcast Adopters**: Have passed a threshold level of streaming podcast, a proxy for assuming that they start to incorporate podcast into their listening habits

> 1 hour for a Podcast show
> 3 episodes of that show
Adding podcasts may influence music listening?

**Pairs** of similar users

**Controls & Treatments**
- similar \( P(\text{treated}) \)

---


PAIRS OF SIMILAR USERS: Music Only VS. Podcast Adopters

Pool of active users from May (US)

### Treatment: convert to Adopter

- **Music**
- **Music + Pod Seeker**
- **Music + Podcast Adopter**

---

**Treatment users:**
270K users

**Control users:**
Never listen to Podcast

---

**RQ1:** Would users’ music listening habits change as a result of adopting podcast listening?

---

**Podcast Adopter:**

**RQ2a.** What are their listening habits for podcasts vs. music?
- When do they listen to What type of content (i.e. podcasts vs. music)?
PAIRS OF SIMILAR USERS: Seekers VS. Adopters

Pool of active users from May (US)

Adopters

Treatment users:
270K users

Seekers

Control users:
Never converted to adopters

Examining the seeking period for both groups:
RQ2b. What are the content of podcasts they consume, especially before the adoption? – differences on listened show types for adopters vs. seekers?

RQ3. Predict: when a user launch a new session, whether he/she will listen to Podcast?
PROPENSITY SCORE MATCHING TO FIND SIMILAR PAIRS

Music listening behavior before listen to Podcast

16 Confounds Xi:
- Gender, age
- Registration
- Music streaming behavior:
  - Overall - streams/time
  - Dayparts
  - Weekdays/Weekend
  - # of artists
  - # of tracks

Estimate Propensity score:
\[ \pi_i := \pi(X_i) = Pr(T_i = 1 \mid X_i) \].

Difference-in-difference = changes in outcomes over time between the intervention group and the control group

Methods

PROPENSITY SCORE: Before VS. After MATCHING

- We are able to match each treatment user with a control user based on their propensity scores.
- After matching, the distribution of propensity scores for treatment and control groups overlapped.

Methodology

Matching: 270K treatment 270K control
RQ1: Will users’ Music listening habits change as a result of adding Podcast listening?
Users music listening habits stay almost the same

Music streaming duration:

- After **podcasts** were adopted, users spent just 1% shorter time (than before) listening to music

Had similar findings for **music listening frequency**, please refer to paper for details
Users add additional time in listening podcasts

Total streaming duration:
- After podcasts were adopted, users spent **20% (at most) longer time** streaming in platform than before.
RQ2a: Podcast Vs. Music both play unique role – very different listening habits
Music listening is a daily activity; Vs. Podcast listening is a weekly activity

**Weekly: # of active days listened to music**

Median = 5-6 days

**Weekly: # of days listened to Podcast**

Median = 2 days

Music listening is a daily activity
In average, **5 - 6 Music active days** per week

Podcast listening is a weekly activity
In average, **2 Podcast active days** per week
Podcast Adopters: Listening frequency across a Week

Day of Week - listening frequency

Podcast listening
High during weekdays, peaks on Wednesday

Music listening
High during weekends, peaks on Friday

Results of RQ2a
Podcast Adopters: Listening frequency across a Day

Listening distribution

Morning:
Podcast listening time

Evening/Night:
Music listening time

Results of RQ2a
Podcast Adopters: Different shows Vs. Day of Week

Music listening activities: different from Podcast listening

Podcast listening: No difference for topics across different day of a week
Podcast Adopters: When do they listen to different shows?

Informational shows

Entertainment shows

Compare to Music listening → Informational show streaming peaks on early Morning

Entertainment show streamings’ trend is more similar to Music listening
RQ2b: Consumed Podcast Content:
Compared to **seekers**, what are the podcast show types that **adopters** consumed, especially before the conversion?
Compared to *seekers*, **Adopters** tend to

Listen significantly **more**
- Sports, Stories, Comedy, True Crime

Listen **less**
- Music, Art, Health
- Educational, News, Business

The streamed show types in users’ podcasts during the **seeking period** can be very important – there are certain show types that are more attractive to users who have **adopted** podcast listening.
The streamed show types during seeking period are strong predictors for conversion of Podcast adopters

- Retrieve only the first day activities of podcast listening for users from two groups (seekers, adopters)
- Predict a user’s membership – who will become podcast adopters eventually?

Features: extracted based on users’ first day activities of Podcast listening
- **Show types**: # of Stories, Comedy, True Crime, Music, Education, etc
- → **Referral types**: (the stream is referred from) a browse, search, home, library
- → **Activity**: # streams, # shows, # episodes

Data: ~500K users from two groups (seekers, adopters)
- Excluded users who completed conversion within their first day
- Training data: 70%; Test data: 30%
**Show types are important in all predictions**

- Logistic regression in predicting user’s membership
- Iteratively add features and check the feature prediction power

<table>
<thead>
<tr>
<th>Features</th>
<th>Training model accuracy</th>
<th>Testing model accuracy</th>
<th>Top 3 Predictive Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Show types</td>
<td>69.50%</td>
<td>68.80%</td>
<td>1. # of listened Sports/Recreation shows; 2. # of listened True Crime shows; 3. # of listened Comedy shows</td>
</tr>
<tr>
<td>+ Referral types</td>
<td>70.40%</td>
<td>70.30%</td>
<td>1. # of listened Sports Recreation shows; 2. # of listened True Crime shows; 3. # of referral from library</td>
</tr>
<tr>
<td>+ Activity</td>
<td>71.00%</td>
<td>70.90%</td>
<td>1. # of listened Sports Recreation shows; 2. # of listened True Crime shows; 3. # of referral from library</td>
</tr>
</tbody>
</table>

- Including ONLY Show types features, the model can already achieve the accuracy rate as 68.8%.
- Adding referral types features and users’ activities features, the model improves only 2%
- Across all three models, the show types features have consistently been identified as top predictors
SO FAR WE UNDERSTAND . . .

Although there is a mild competition, Podcast and Music are both important and do not substitute for one another: users open a new time window listen to Podcasts

**Daily** activity: 5-6 active days per week

**Entertainment:**
- More likely to happen during Evening
- On weekends, Peak on Friday

**Weekly** activity: 1-2 active days per week

**Information/Education:**
- More likely to happen during Early morning, for informational types of shows
- On weekdays, Peak on Wednesday

**Consumed Podcast Content during Seeking period is important:**
There are certain show types that have lower entry barriers for Podcast listening – show types are strong predictors of the user conversion
RQ₃: Prediction: When a user starts a new listening session, will she/he listen to a podcast?
SESSION LISTENING PREDICTION

Session Data:

- A session: idle time > 10 mins
- 10% positive sessions (have Podcast listening)

Features (X):

User features:
Gender, Age, Registration

Music and Podcast listening activities:
The last 1 session, So far for today So far for this week

Target (Y):

Current session - Podcast listening?

Unbalanced: 10% Podcast listening session
WILL USER LISTEN TO PODCAST IN THIS SESSION?

5 folds cross validation at the user level:
• Make sure that sessions generated from one user will not appear in different folders
• Avoid potential issues such as predicting past events based on the future

<table>
<thead>
<tr>
<th>Feature</th>
<th>Logistic regression [mean, std]</th>
<th>Random Forest [mean, std]</th>
</tr>
</thead>
<tbody>
<tr>
<td>User features + the last 1 session</td>
<td>Train_f1: [0.363, 0.0135]</td>
<td>Test_f1: [0.361, 0.0191]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>+ current time</td>
<td>Train_f1: [0.404, 0.0134]</td>
<td>Test_f1: [0.402, 0.0206]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>+ so far for today</td>
<td>Train_f1: [0.413, 0.0123]</td>
<td>Test_f1: [0.411, 0.0258]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>+ so far for this week</td>
<td>Train_f1: [0.439, 0.0130]</td>
<td>Test_f1: [0.437, 0.0301]</td>
</tr>
</tbody>
</table>

- Logistic regression with [User features + the last 1 session] as a baseline model
- Iteratively add features and check the model performance, best model has mean F1 = 0.6
LSTM using past 7 sessions demonstrates better performance

Model:
1. LSTM layer with dimension of hidden states = 150
2. A dropout layer (rate = 0.2) to avoid overfitting
3. Dense layer for final output

Output:
current session: Y_t - podcast?

Input of S: t-n
User
Current session
- time
- listening

<table>
<thead>
<tr>
<th></th>
<th>Train [mean, std]</th>
<th>Test [mean, std]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recall</td>
<td>[0.671, 0.021]</td>
<td>[0.666, 0.032]</td>
</tr>
<tr>
<td>Precision</td>
<td>[0.828, 0.013]</td>
<td>[0.825, 0.027]</td>
</tr>
<tr>
<td>F1</td>
<td><strong>[0.741, 0.011]</strong></td>
<td><strong>[0.737, 0.027]</strong></td>
</tr>
<tr>
<td>Accuracy</td>
<td><strong>[0.963, 0.001]</strong></td>
<td><strong>[0.962, 0.002]</strong></td>
</tr>
</tbody>
</table>

* Average time for the past 7 sessions is about 24 hours
Conclusion
WHAT WE STILL DON’T KNOW . . .

1. **Causal inference**: only accounted for observable confounders; Things may happen outside Spotify

2. Our observation window is **only 2 months** after conversion – the observed behavior maybe related to the novelty of the experiences

3. Our definition for “Podcast Adopters” is based on a threshold level of user engagement with Podcast – there can be potential selection bias

4. The listening habits discovered in the current study may be **caused by inherent differences in the two media forms** i.e. users listen to musics repeatedly but listen to podcasts only when new episodes are released.
Podcast and Music are NOT substitutable with one another:
  › Users open another time window (20% longer streaming time per week) to listen to podcasts.

Podcast and Music both play important and unique roles:
  ● Users demonstrate different listening habits
    ○ Music: daily activities, during evening/night, weekends
    ○ Podcast: weekly activities, during morning, weekdays, and for information
    ○ The Podcast Content consumed during Seeking period is important: There are certain show types that have lower entry barriers for Podcast listening.

Finally, using the above results to create input features to a machine learning model, a podcast listening session is predictable with high accuracy rate.
Thanks!
Questions?