ABSTRACT

Many musicians, from up-and-comers to established artists, rely heavily on performing live to promote and disseminate their music. To advertise live shows, artists often use concert discovery platforms that make it easier for their fans to track tour dates. In this paper, we ask whether digital traces of live performances generated on those platforms can be used to understand career trajectories of artists. First, we present a new dataset we constructed by cross-referencing data from such platforms. We then demonstrate how this dataset can be used to mine and predict important career milestones for the musicians, such as signing by a major music label, or performing at a certain venue. Finally, we perform a temporal analysis of the bipartite artist-venue graph, and demonstrate that high centrality on this graph is correlated with success.

 CCS CONCEPTS

• Information systems → Data mining; Web mining; • Networks → Online social networks; • Human-centered computing → Collaborative and social computing; • Computing methodologies → Machine learning approaches; Network science;

KEYWORDS

networks, art and music, multidisciplinary topics and applications

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1 Introduction

Live performances are a crucial part of the life of a music artist. According to a recent industry report,¹ the revenues from live performances in the US have grown from $8.72B in 2012 to $9.94B in 2016, and are projected to reach almost $12B by 2022. A recent study discovered a connection between live events and increased digital listenership [37] (which is the second highest source of income for a band after live performances). In light of this, it becomes increasingly more important for artists to be able to understand what milestones matter to accomplish the dream of a professional career: playing at top venues goes hand-in-hand with getting more digital listeners, which in turn may increase their likelihood of being signed with major music labels.

In this work, we aim to determine whether it is possible to model and predict these career trajectories under the emerging framework of Science of Success [9, 14]: recent work studying how careers in different fields, as well as individual and team success, can be predicted early by leveraging records of performance from digital traces. This data-driven framework has been applied to domains as diverse as education and academia [17, 21, 35], (e)sports [7, 8, 34, 39, 42], social media [3, 13, 24, 36], culture [2, 46], and even the entertainment industry [29, 33].

In light of these promising results, we pose the question: is it possible to find open data to understand and forecast careers and success in the music industry? To accommodate the increasing demand of music artists to get their message out to their fans, specialized sites like Songkick and Discogs have sprung up to create centralized repositories of music events and music artists. These sites contain rich metadata about the artists themselves as well as the concerts they perform. They allow the artists to attract interests in their concerts. Indirectly, this goldmine also allows researchers to model the music industry dynamics.

Research Problem

In this paper, we are interested in the problem of characterizing and understanding the career trajectories of the artists across different genres. Toward this goal, we analyze a large-scale longitudinal data of musical events occurring at various venues worldwide.

Specifically, we address the following research questions:

(1) Is the choice of venues where an artist performs correlated with the eventual success of that artist (for a given definition of success)? If so, can we leverage those correlations to forecast success?

(2) Can we predict which venues an artist/band will perform based on the history of his/her/their past performances?

(3) How do we measure the relative importance of performances in specific venues and their impact on career trajectories, and how do we jointly characterize influential artists and venues?
Contributions of this Work

Our main contributions are summarized as follows:

- We construct and present a new dataset by collecting all of the artists and concerts from the Songkick platform, and supplement this dataset with information from Discogs, which contains more granular details about the artists—such as their discographies.\(^2\)
- We define a measure of success based on whether an artist has signed a contract with one of the major music record labels, and propose a forecasting task to differentiate between career trajectories of artist based on this measure of success.
- We demonstrate the viability of forecasting future performances of artists, and therefore their success, based on the history of past performances.
- We propose a centrality measure suited for the bipartite artist-venue network and demonstrate that it correlates strongly with the venue reputation.

The rest of the paper is organized as follows. After describing related work in Section 2, we describe the dataset in Section 3 and provide its basic statistics in Section 4. In Section 5 we define three related tasks - forecasting artist success, predicting future events by artist at specific venues, and identifying influential artists and venues - describe our approach for addressing those tasks, and present results. We conclude the paper by summarizing our main findings in Section 6.

2 RELATED WORK

Quantifying and forecasting success refers to the broader body of work that attempts to discover the patterns and performance trajectories that correlate with certain desirable outcomes: from forecasting highly-cited academic authors and papers [20, 38] to predicting future Nobel Prize winners [25], from uncovering successful fund-raising campaigns [27], to early identifying the next top model [29], or movie box office hit [11]. The new field of Science of Success brings a strong data-driven perspective on applying forecasting problems set in the real world.

Judge et al. [18] postulated that career success has intrinsic cues, like the person’s own perception of success and self-satisfaction, and extrinsic ones, like awards, recognition or achievements. Since judgments about success in a creative profession like music are unavoidably subjective, we don’t consider intrinsic factors and focus on objectively observable career accomplishments only.

Music industry criteria called “traditional markers of artist success” [12], like performance opportunities, labels, charts, awards, sales of recorded music or airplay, provide us with a number of possible directions for defining success of music artists. However, digitization has shaken these traditional markers—digital music has been linked to fall in record sales, airplay and charts no longer adequately measure popularity, given numerous streaming services and listenershio outside of them—views on YouTube and/or illegal file-sharing. Given this, some researchers look at the popularity of music artists on digital delivery platforms like Last.fm, and formulate a forecasting problem to predict new song hits from the early adoption patterns of music listeners [33].

Success in post-digital music world can still be adequately represented by contracts with major labels. Music record labels are still important players in the industry—even though theoretically digital technologies allow artists to perform production, promotion and sales on their own, practically this doesn’t happen very often [26]. Hence, in this work, forecasting success is operationalized as predicting the artists that are going to be signed by a major music recording label. To the best of our knowledge, this is a novel formulation that has not been presented in the literature before.

From a methodological perspective, our work is rooted on a blend of machine learning and network science techniques. We focus in particular on a broad class of problems often referred to as link mining (a.k.a. link prediction). Link mining is the problem of discovering new (unforeseen) edges in a graph. Typical possible applications are either network reconstruction [10, 15], or modeling the evolution of a network [5, 19, 41]. One common operationalization of link prediction is finding pairs of nodes that have high probability of being connected. This often translates into measuring node similarities, as mentioned by Liben-Nowell and Kleinberg [23]. However, other authors [22] noted that using traditional link prediction on bipartite graphs is not straightforward and often produces counterintuitive results. In order to address this shortcoming, some authors proposed modified similarity metrics [22, 23], or used techniques from recommender systems, such as low-rank matrix factorization and collaborative filtering [1, 6], and supervised learning approaches [4, 30]. We follow the example of those authors and use collaborative filtering and recommender systems inspired methods to perform link prediction for our task. In the results section, we will show how to leverage BiRank [16]—a modification to the PageRank [28] algorithm that tunes it towards bipartite graphs—to measure and predict the popularity of the artists and venues.

3 DATASET

Songkick\(^3\) is a concert-discovery platform that aims to link fans to artists’ events. It contains information about over 6 million concerts (and other music events like festivals), the artist(s) that perform at each event, and the venue where each event takes place. The “gigography” of an artist is the term that Songkick uses to refer to all of that artist’s events.

Songkick data can be accessed through their website or via their API, which allows querying any artist’s gigography. Songkick is our main repository of information for music events.

Discogs\(^4\) is a music database that contains cross-referenced discographies of artists and labels. Each recording, artist, or label in Discogs can be uniquely identified by their IDs. Discogs provides separate data dumps\(^5\) for artists, labels, and recordings. We used recordings data dump from May 1, 2017 to obtain artist and label IDs associated with each release. This data dump contains more than 8 million recordings. Most of the recordings have information about their release dates, and thus allow tracking the history of releases with different labels for each artist.

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\(^2\)The dataset is available at https://github.com/shushanarakelyan/forecasting_success

\(^3\)https://www.songkick.com/

\(^4\)https://www.discogs.com/

\(^5\)https://data.discogs.com/
3.1 Data Collection

Songkick does not provide a lookup directory of artists, nor there is a direct mechanism to get all gigographies. For getting Songkick artist IDs we queried artist names present in Discogs’ recordings data dump. As a result, all of the artists in our dataset have at least one recording on Discogs. This can be either self-recorded or recorded under a contract with a music label. This strategy avoids introduction of bias towards artists that did not publish any recordings, which are therefore excluded from our analysis.

The Songkick API call returns a list of possibly relevant artists, allowing for some inexact name matching. We processed the API output to retain data on artists that exactly matched the Discogs artist name.

From this name match we obtained artist IDs, and used them for another round of API calls, to get the gigographies of each artist. For each concert in the gigography, we extracted the following information: ID, date, city, country, state (if applicable), latitude and longitude of the venue, venue ID and venue name, name of the event and its popularity score as calculated by Songkick.

For every event there is information about billing for each artist, i.e., whether that artist was a headliner or a support artist at the concert. However, we did not consider headliners and support artists separately in the analysis presented further.

Collected data was organized into separate artist, event, and venue data frames. Each artist is indexed by its Songkick and Discogs IDs. Venues and events are indexed by their Songkick IDs. There are also several lists of cross-references: mapping venues to the events that happened there, and events to the venues where they took place. A similar mapping is available for events and artists, and releases and artists.

3.2 Data Preprocessing

Due to the fact that the goal of Songkick is connecting fans to their favorite artists through concerts, the platform puts less relevance on events that occurred prior to their inception. Songkick was founded in 2007 and there is a noticeable increase in the number of artists that have their earliest concerts recorded on Songkick in 2007 or later. From Figure 2 it can be seen that the total number of concerts per year peaked in 2010.

In Figure 2 we show the dynamics of the number of events and number of artists from 1987 to 2017. As already mentioned, there is a significant increase in the number of artists that have their earliest concerts recorded on Songkick in 2007 or later. From Figure 2 it can be seen that the total number of concerts per year peaked in 2010.

Next, we look at the geographic distribution of venues in the dataset. There are 63 different countries with at least one event, and a very large set of artists and venues associated with very few events.

In the following we provide some statistical analysis of our dataset. The dataset contains 645,507 concerts, 13,912 artists, and 11,428 venues, collected for the time frame between 2007 and 2017. Artists in the dataset are associated with 39,641 distinct record labels, 286 of which are major labels, or their subsidiaries. One condition to be labeled as a “successful” artist in our study is to have recorded at least one album under any of these 286 recording labels.

4 STATISTICS

In Table 1, n-grams of length 4 and 5 show some frequent routes of artists’ performances. Double-sided arrows indicate that these routes are frequently found in the data in both directions.

| Frequent routes that artists follow |
|-----------------------------------|
| San Diego ↔ Los Angeles ↔ SF Bay Area ↔ Portland ↔ Seattle |
| Portland ↔ Seattle ↔ Boise ↔ Salt Lake City ↔ Denver |
| Chicago ↔ Toronto ↔ Montreal ↔ Boston/Cambridge ↔ New York |
| Washington ↔ Philadelphia ↔ New York ↔ Boston/Cambridge |
| London ↔ Birmingham ↔ Manchester ↔ Glasgow |
| Brisbane ↔ Sydney ↔ Melbourne ↔ Adelaide |
| Austin ↔ Houston ↔ New Orleans ↔ Atlanta |

has less than 10 concerts associated with them before the change point. This also takes care of venues that may have been used for occasional events, or artists with short-lived careers.

https://en.wikipedia.org/wiki/Record_label#Major_labels
cities that artists take while touring. Following the distribution of the venues and concerts in the dataset, most frequent routes mostly include US cities. As demonstrated in Table 1, frequent routes contain clear patterns of artists performing in big cities on their way, while travelling from North to South or from East to West, etc.

5 ANALYSIS AND RESULTS

To better illustrate the idea that the music artist career trajectory can be predicted from artist-venue interactions we formulated the following 3 tasks, discussed next:

- Task 1: Forecasting artist success;
- Task 2: Event prediction;
- Task 3: Joint discovery of influential artists and venues.

In the next subsections, we describe each of those tasks in more details, elaborate on our approach for addressing them, and present our results.

5.1 Task 1: Forecasting Artist Success

Due to the nature of the partnership between artists and record companies, the bigger the recording label the more resources and opportunities it has to offer for its artists. Artists, nurtured by labels, have the chance to develop their sound, their craft, and their careers. Besides, record companies facilitate introductions to world-class producers, writers, and other performers, which can determine careers and bring huge rewards.

The recording industry has been marked by concentration and centralization for a while now. During the phase of consolidation in 1970s, most of the major labels were acquired by very few umbrella corporations or music groups. The Beatles, Frank Sinatra, Pink Floyd and even Maria Callas found prominence through those major record labels. From 1988 till 2012 the number of major record companies has decreased from six to three, as some of them got absorbed by the others. The remaining three major music groups, or the Big Three (Sony BMG, Universal Music Group, and Warner Music Group), have held a large share of the world music production since 2012.

Because of the influence and patronizing that the major labels provide, we consider artists that have a recording with either the parent major label, or one of its subsidiaries, as successful. We set to see if the rise to success can be predicted from a sequence of performances. Our goal in this task is, therefore, to identify successful artists from their career trajectories.

Ideally, we want to be able to identify such artists in a post-hoc manner. In other words, we want to detect the change that will lead
We used those vectors as features for the prediction and forecasting Australia cumulatively accounting for nearly 70% of the to-
we assume that the artist was successful and label it as a positive 
with (this information was obtained from Discogs). If among these 
with a major music label. However, for the prediction task we 
is in line with the commonsense notion of popularity in the music 
the positive instances (successful artists) are very infrequent: this 
instance—negative otherwise.

music labels there are either major ones or one of their subsidiaries, 
tal events, and over 60% of the total venues.

iterating over all the music labels that each artist has ever recorded 
the Songkick data, with United States, United Kingdom, and 
ence toward English-speaking countries can be observed in 
affiliation matrix an artist is represented as a bag-of-words vector 
tasks we used the 
affiliation matrix 

Figure 3: Log-scale distribution of concert frequencies in (i) 
the top 10 most active countries, and (ii) the number of dis-
ton to a release with a major label before the release itself happens. In 
the following discussion we refer to this task as forecasting.

We also consider the simpler task of discriminating artists that 
are already successful in our setup from the ones that are not. We 
refer to this task as prediction.

5.1.1 Experimental Setting. For both forecasting and prediction 
tasks we used the affiliation matrix of artists and venues. In such an 
affiliation matrix an artist is represented as a bag-of-words vector 
over the venues where the artist has performed. The entries in the 
matrix are the numbers of times the artists performed at the venue. 
We used those vectors as features for the prediction and forecasting 
tasks.

In the forecasting task for any artist we did not include any 
concert that happened after the artist released their first recording 
with a major music label. However, for the prediction task we 
cluded those performances too.

The classification labels (successful or not) were obtained by 
iterating over all the music labels that each artist has ever recorded 
with (this information was obtained from Discogs). If among these 
music labels there are either major ones or one of their subsidiaries, 
we assume that the artist was successful and label it as a positive 
instance—negative otherwise.

As a result of the procedure above, we labeled about 500 artists as 
successful, which is 3.6% of the total number. It is worth noting that 
our labeling procedure yields a highly unbalanced dataset where 
the positive instances (successful artists) are very infrequent: this 
is in line with the commonsense notion of popularity in the music 
industry, where musicians that thrive with a professional career 
are exceptionally rare.

5.1.2 Metrics. A natural choice for evaluating a success forecast-
ing or prediction task is classification accuracy. However, due 
to high imbalance in the data, we need metrics that are more sensi-
tive and account for under-represented classes. Such metrics are 
Precision, Recall and F1 score, as well as ROC AUC score, which 
we used for evaluation.

5.1.3 Learning Models and Configuration. For Task 1, we defined 
three simple models described next, and used them to carry out the 
forecasting and predictions exercises.

Baseline: We can intuitively connect success of the artist to the 
number of their performances. We picked a baseline that would 
prove or disprove this scenario by using the number of concerts, 
scaled by the maximum number of concerts by an artist, as a proxy 
for probability for becoming successful.

Logistic Regression: As a base classifier in both prediction 
and forecasting experiments we used Logistic Regression from the 
scikit-learn library [31]. We used $L_2$ norm for regularization, and 
tuned one parameter, i.e., the inverse of regularization strength $C$.

SVD: Since the affiliation matrix we use has over 99% sparsity 
(percentage of zero entries), dimensionality reduction techniques 
could yield prediction performance improvements by transforming 
 sparse data into dense. We performed dimensionality reduction 
using Singular Value Decomposition (SVD). Via cross-validation 
we discovered that best results are achieved when we use 750 com-
ponents in prediction task and 1000 components in forecasting 
task.

For each model, we performed hyperparameter tuning via grid 
search with 3-fold cross validation on the training set. The results 
reported are obtained by using cross-validated average over 3 dif-
ferent train-test splits in 80-20 ratio.

5.1.4 Task Summary. The results for this task are presented in 
Table 2. Suggested baseline shows existing correlation between the 
number of concerts and prediction label, and this correlation is 
stronger in prediction task than in forecasting task. Next, simple 
logistic regression achieves 0.22 F1 score on the forecasting task 
and 0.4 on the prediction task. We can see that while reducing 
dimensions increase ROC AUC and F1 scores by several points in 
forecasting task, its improvement for prediction task is marginal.

The improvement in performance on the prediction task indi-
cates there is a difference in distributions of artist performances 
before and after they record their first album with a major music 
label. This suggests the existence of change points in careers that 
are caused by recording with major labels, which corroborates our 
notion of artist’s success. We expect that employing more sophis-
ticated models for discovering change points would give better 
forecasting results.

5.2 Task 2: Event Prediction

Besides artist career trajectories, we are also interested in the overall 
dynamics of the network, where both venues and artists evolve and 
their influence changes as a result of constant interactions between 
venues and artists.
Table 2: Precision (P), Recall (R), F1-score and AUC for artist success forecasting (FCST) and prediction (PRED) tasks. We show results of logistic regression on full data (FCST/PRED LR) and with reduced dimensions (FCST/PRED LR+SVD).

| Task  | Model     | P   | R   | F1  | AUC  |
|-------|-----------|-----|-----|-----|------|
| FCST  | Baseline  | 0.07| 0.26| 0.11| 0.60 |
| FCST  | LR        | 0.18| 0.29| 0.22| 0.74 |
| FCST  | LR+SVD    | 0.18| 0.35| 0.23| 0.78 |
| PRED  | Baseline  | 0.25| 0.35| 0.29| 0.82 |
| PRED  | LR        | 0.36| 0.45| 0.40| 0.86 |
| PRED  | LR+SVD    | 0.39| 0.40| 0.40| 0.87 |

To see if we can explain part of those interactions, we formulate the artist-venue link prediction task. As in the forecasting artist success task, we consider here two configurations—forecasting and prediction. For this task we used the same affiliation network as in the previous task, but since we are interested in predicting new or hidden edges, we only use a binary affiliation matrix here.

In the previous task prediction experiments were performed to test whether or not our suggested definition of success is viable. For (artist – venue) link mining task, however, we exercise prediction alongside to the forecasting to test for possible major temporal shifts in artists’ behavior.

5.2.1 Experimental Setting. In the forecasting task, we looked for new (artist, venue) links, or edges, based on the history of old ones. In particular, we used all performances from 2007 to 2015 as “history” (i.e., training data), and the performances in 2016 and 2017 as “future” (i.e., test set). We then went on and recursively removed all artists and venues that have less than 5 concerts associated with them in the training set. As a result we had 12,871 artists, 10,269 venues, 385,845 events in the training set and 43,122 events in the test set.

In the prediction task we kept the same set of artists and venues as described above for the forecasting task. We then randomly picked 20% of all links and hid them in the test data, using the remaining 80% for training purposes, similarly to a link prediction problem. Results reported are averaged over three random splits. We binarized all the links as we are only interested in predicting new links, i.e. new venues, where artist performs.

5.2.2 Metrics. We measured the performance on this task using Area Under the Receiver Operating Characteristic curve (ROC AUC). One of the main advantages of this metric is the fact that it operates on rankings and is calculated for a range of thresholds, rather than prediction classes. This allows us to interchangeably use simple recommender system objectives for venue prediction.

5.2.3 Learning Models and Configuration. For Task 2, we decided to adopt some popular heuristic scores for link prediction, a simple matrix factorization technique and node similarity based model, all described in the following.

Heuristic scores: Likelihood of a link existing between a pair of nodes is often approximated in terms of the number of common direct neighbors of that pair. However, a score calculated in this way will always be zero in a bipartite graph. Hence, we extended popular methods—Common Neighbors and Jaccard’s coefficient—to use 2-hop neighbor sets of the pair instead of direct neighbors, as shown in Table 3, where $N(u)$ is defined as the set of direct neighbors of node $u$, and $\hat{N}(u) = \cup_{v \in N(u)} N(v)$ is the set of neighbors of neighbors of node $u$. Another popular link prediction heuristic is Preferential attachment, which can be applied to a bipartite graph without any modifications.

Matrix factorization: Link mining in a bipartite graph can be naturally presented as a recommendation task. For each artist we have a list of “relevant” venues—the ones where the artist performed. Using methods for collaborative filtering we can find latent features or representations of venues that make them relevant for certain artists. Based on these hidden representations, we can then predict which venues are most relevant for the artist.

In this task, we used a simple yet popular collaborative filtering method based on matrix factorization—Singular Value Decomposition (SVD). To find the number of components for SVD, we used grid search—from 10 to 2000—and reported the result for 25.

Node similarity: Building and using graph representations is another approach that is often employed for link prediction. In our experiments we leveraged Deepwalk [32] for obtaining node representations and then used cosine similarity of a pair of nodes as an estimate for the probability of a link existing between them. Deepwalk is similar to training a Word2Vec model on a random walk sampled starting from every node in the graph. In our graph we gave preference to a larger number of short walks so we searched for the optimal number of walks of length 10. We report results for using 40 random walks. We then used cosine similarity of node representations as a proxy for probability of creating a new edge between those nodes.

Hyperparameters like number of hidden components in SVD and Deepwalk parameters in this task were only tuned for prediction task. We then used the same values for forecasting task. All parameters were estimated via grid search with 5-fold cross-validation, with 20% of all edges in each fold.

5.2.4 Task Summary. The results for the venue prediction task are presented in Table 4. As it can be seen, every method performs better on the prediction task than on forecasting, though for heuristic methods the improvement in performance is marginal. This hints that there might be a shift in artists’ preferences for choosing a venue over time. It also indicates that while coarse statistics like Common Neighbors or Jaccard’s coefficient are not affected much

| Common Neighbors (CN($u$, $v$)) | Jaccard’s Coefficient | Preferential Attachment |
|---------------------------------|----------------------|------------------------|
| $|N(u)\cap N(v)|\cup |\hat{N}(u)\cap \hat{N}(v)|$ | $|\hat{N}(u)\cup N(v)|\cap |\hat{N}(u)||\hat{N}(v)|$ | $|N(u)|\cdot |N(v)|$ |
Table 4: Results for \((\text{artist, venue})\) link prediction task, measured in Area Under Receiver Operating Characteristics curve (AUC).

| Task | Model                   | AUC  |
|------|-------------------------|------|
| FCST | Common Neighbors        | 0.87 |
| FCST | Jaccard’s coef          | 0.89 |
| FCST | Preferential Attachment | 0.79 |
| FCST | SVD                     | 0.81 |
| FCST | Node similarity         | 0.84 |
| PRED | Common Neighbors        | 0.91 |
| PRED | Jaccard’s coef          | 0.90 |
| PRED | Preferential Attachment | 0.84 |
| PRED | SVD                     | 0.91 |
| PRED | Node similarity         | 0.90 |

by those shifts, slightly more sensitive methods like SVD and node similarity, that rely on the inner structure of the graph, are affected more. Yet, either that structure is not expressive, or the methods are not powerful enough, neither of those methods performs better than heuristic scores. Interestingly, four models out of five give performance of around 0.9 ROC AUC on prediction task. Out of all the methods we tried, Preferential Attachment has the lowest performance for both tasks.

5.3 Task 3: Joint Discovery of Influential Artists and Venues

In the previous tasks, we have attempted to classify an artist as about to be signed or not about to be signed. In this task we will investigate whether we can identify top artists and venues automatically by mining their performances.

To measure the popularity of the artists and venues, we leverage BiRank \[16\]. This algorithm is a modification to the PageRank \[28\] algorithm that tunes it towards bipartite graphs. The algorithm iteratively identifies influential venues by observing which influential artists play at them. Simultaneously, it measures influential artists by measuring their frequency of playing at influential venues.

Before running this algorithm, we set the initial ranking based upon the following measure:

\[
g_i = \frac{\log(N_i + 1)}{\sum_{a \in \mathcal{A}} \log(N_a + 1)},
\]

where \(N_i\) measures the number of links to the node \(i\), \(\mathcal{A}\) is the set of artists in the dataset, and \(i \in \mathcal{A}\). This constitutes the artist’s initial score. Similarly, we compute:

\[
g_j = \frac{\log(N_j + 1)}{\sum_{v \in \mathcal{V}} \log(N_v + 1)},
\]

where \(\mathcal{V}\) is the set of venues and \(j \in \mathcal{V}\). With this initial seed score, we proceed to run the BiRank algorithm to identify the most influential nodes in each set. Finally, it is important to note that there is a temporal weighting in the links. Each link in the adjacency matrix has a weight of \(\delta^{2017-y_0}\), where delta is the decay parameter (set to 0.85 in the experiments), and \(y_0\) is the year of the first link.

We subtract this number from 2017 as this is the most recent year in the dataset. This experimental setup closely resembles that of \[16\].

The results of this experiment can be seen in Table 5. These results seem to indicate promise for this method on our dataset. In the case of the venues, they correspond to some of the most popular venues in the world. As for the artists, the story is different. While they do not correspond to the most popular in terms of followers, these are the artists that have more performances in the dataset.
Table 5: The most influential nodes of each class identified by BiRank.

| Rank | Artists         | Venues                                      |
|------|-----------------|---------------------------------------------|
| 1    | Frank Turner    | The Observatory, Los Angeles, CA            |
| 2    | Every Time I Die| The Masquerade, Atlanta, GA                 |
| 3    | Against Me!     | The Bowery Ballroom, New York, NY           |
| 4    | Reel Big Fish   | Webster Hall, New York, NY                  |
| 5    | All Time Low    | 9:30 Club, Washington, DC                   |
| 6    | The Black Dahlia Murder | House of Blues, Boston / Cambridge, MA |
| 7    | Hatebreed       | Theater of the Living Arts, Philadelphia, PA |
| 8    | Future Islands  | The Middle East Downstairs, Boston / Cambridge, MA |
| 9    | Halestorm       | Vienna Arena (Arena Wien), Vienna           |
| 10   | Hawthorne Heights| Brudenell Social Club, Leeds                |

However, a natural question regarding the dynamics of BiRank is how indicative it is of artist success. To measure this phenomenon, we plot the histogram of BiRank scores for both signed and unsigned artists. This can be seen in Figure 4, where we see that the signed artists tend to have a higher BiRank score than unsigned artists.

The BiRank scores can also be useful for measuring the trajectory of an artist. By calculating the BiRank scores as previously indicated every year, with a three year moving window, we can observe the ranking of artists at different points in time. An example of this phenomenon can be seen in Figure 5. This figure shows the BiRank ranking of the artist “Future Island” over time. We can see that their ranking begins around the 2,300 mark. Over the course of the next years, their ranking dramatically improves, peaking with them being the top artist according to BiRank in 2014. This is corroborated by The Telegraph naming them the “breakthrough band of the year.”

6 CONCLUSION

In this paper we presented a novel dataset of artists and their live performances from Songkick. We complemented that data by information collected from Discogs, which contains full history of their recordings and releases. The dataset can be used for a variety of tasks which we exemplified by performing success forecasting and event prediction.

We proposed an operational definition of success - signing with a major label and/or their subsidiaries - and demonstrated that the event data contains useful information that can be leveraged to forecast artists’ success with better than baseline accuracy. Similarly, we observed that by utilizing the underlying structure of this data, one can also predict whether an artist will have a concert in a particular venue. The performance of simple baseline models that we carried out in all three tasks indicates that much better results can be achieved with more carefully designed methods.

Finally, we illustrated how artist or venue influence can be measured based on analyzing a time-varying bipartite artist-venue graph. Specifically, we analyzed the evolution of the bipartite generalization of the Pagerank score, and demonstrated both qualitatively and quantitatively that its dynamics can be used to identify successful artists.

As future work, it will be interesting to perform more fine-grained analysis of all three tasks examined here. For instance, the results presented here were averaged across different genres. It is plausible, however, that analysis will yield (subtle) differences when conditioned on the genre. Similarly, our preliminary analysis of event sequence (as opposed to bag of word representation of events) yielded some interesting geographic patterns, which warrant further and more detailed studies.

Finally, we would like to point out two potentially important limitations of the present work. First, the definition of success used here, while operationally useful, is by no means comprehensive. Indeed, many artists who work with independent labels, or specialize in commercially less-viable genres, can still have very successful and celebrated careers. And second, we note that despite its demonstrated usefulness, the dataset presented here is not perfect and is likely to have some intrinsic biases, e.g., musicians might have varying incentives for joining platforms such as Songkick depending on the stage of their career. Identifying and potentially correcting for such biases is another important future task.

ACKNOWLEDGEMENTS

This research was supported in part by ARO (contract no. W911NF-12-R-0012) and DARPA (grant no. D16AP00115). This project does not necessarily reflect the position/policy of the Government; no official endorsement should be inferred. Approved for public release; unlimited distribution.
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