How Long Do Exhibitions at the Minneapolis Institute of Art Last?

Andy Hayes & Zachary Skluzacek

November 2018

1 Introduction

The Minneapolis Institute of Art is a widely influential art museum in Minneapolis, Minnesota with a collection that contains a variety of works from ancient Greek ceramics, to contemporary Native American stilettos, to an eighteenth century Japanese tea room. As most museums do, the Minneapolis Institute of Art (MIA) cycles its pieces in and out of its galleries to ensure that its entire collection can be viewed by the public with the constraint of limited floor and wall space. This process of determining which pieces are to be displayed or stored can open up museums that may even have remarkably diverse collections to be influenced by the biases and worldviews of their curators. In this paper, we will be examining the decisions that MIA has made about how long the pieces in its collection should each be displayed for per cycle, and hope to uncover whether or not the museum is treating pieces from authors with various backgrounds equally.

The commonplace display of art by artists of color in American art museums is a distressingly recent phenomenon. Bridget R. Cooks, an art historian and associate professor of African American studies at the University of California-Irvine, writes that,

> At the end of the 1930s, two exhibitions of art by Negroes were organized by major American art museums, Exhibition of Sculpture by William Edmundson (1937) at the Museum of Modern Art and Contemporary Negro Art (1939) at the the Baltimore Museum of Art. Both exhibitions were the first exhibitions of Negro art in their respective institutions. Both featured the most recent work by living artists on view (2011).

In consensus with Cooks' writing, we fully expect to uncover that prior to the art world's initial twentieth-century demand for diversity, MIA was unlikely to have many pieces, if any at all, by minority American artists that received a significant amount of time on the gallery floor. Additionally, we hope to explore how MIA's practices treat artists of all sorts of varying backgrounds differently than one another.

One model for evaluating the use of public space is Lian, Zhang, Xie, and Sun's work in *Restaurant Survival Analysis with Heterogeneous Information*, in which the authors analyze the potential viability of restaurants based on a number of geographic and user satisfaction data. In their research, Lian et al. look to predict the survival of restaurants based primarily on user reviews and data regarding traffic to and from the area around the restaurant and user satisfaction with the restaurant's service. Although these predictors proved to be overwhelmingly significant and effective at determining a restaurant's potential, our study has neither the data, nor the reason to use this style of analysis. What these authors did produced to the same result of predicting the length of a public attraction that we are hoping for, but an interpretation of their model offers little insight as to what makes something like an art piece survive for longer than other art pieces. In addition, MIA provides little to no public archives regarding the location of their collection throughout the galleries, and we have little interest in museum-goers' reviews of exhibitions. Therefore we chose not to use much of this approach.

We then turned to two papers that discuss the survival of media rather than businesses to hopefully uncover useful techniques for studying the survival of art exhibitions. The first study, *The Effect of Digital Sharing Technologies on Music Markets* by Bhattacharjee et al., attempted to predict the length of time an album spent on sales charts based on the predictors the authors found to be significant: the rank at debut, whether an artist had previously been ranked in the charts, whether the album was produced by a minor label, whether the artist was a solo male or a group, month of release, and which era the album was released in. The only significant predictor coefficients that could be interpreted to inform our study is whether the artist is a male or group. We hope to uncover the biases of MIA's curators, so financial and popularity data are less important in our work.

The other study we borrow strategies from is Scorcu and Zanola's paper, *Survival in the Cultural Market: The Case of Temporary Exhibitions*, which attempts to model the survival of temporary art exhibitions, and permanent exhibitions which were originally intended to be temporary, from around Italy by using data about the exhibitions' region, attendance, physical size and density, genre of art displayed, and local census statistics. This work motivated our study the more than the two previously mentioned, statistically-oriented papers, as Scorcu and Zanola found compelling significance in their predictors that suggests the popular success of an artistic institution largely depends on the genre of art shown and not necessarily the quality of that art. We will attempt to verify this claim and expand upon it as we look to link the biographical information surrounding an artist to the duration of its individual exhibitions.

To prepare for a study such as this, our most involved task was cleaning the MIA archive dataset to properly serve a model of categorical and numeric variables. In this paper, we'll first describe the dataset, and then discuss how we obtained and cleaned the data. We will then describe our methodology for analyzing the data to uncover tendencies of the museum's curators to treat art differently because of its artists biographical information.

2 Data & Methods

2.1 Dataset Overview

For this project we are using data on artwork and exhibits in the Minneapolis Institute of Art (MIA). The data are contained in two datasets, one set on exhibits and another set on individual object data. The exhibit dataset contains information on 754 exhibits that have been on display in MIA over the last 20 years. Some key variables we are utilizing from this dataset are the display dates and the list of object identifiers that were displayed in the exhibit. Our object dataset contains data from 127,000 pieces of art that have been displayed in MIA since its inception in 1889. The dataset includes data on the object identifier, classification, country and continent of origin, approximate date of creation, museum department, object description, and the nationality of the artist.

2.2 Acquiring and Cleaning Data

We found our datasets in a Github repository hosted by the Minneapolis Institute of Art. All of the exhibit and object data were stored in individual JSON files. The exhibit files were contained in three folders while the object data were contained in 127 folders, most of which contained at least 1000 files. To assemble a workable data frame, we developed an R script to iterate over each file, extract its data, and then append that data to the bottom of a continuously growing data frame. In theory, this should not have been a daunting task, but there were a number of inconsistencies within the files. At some point, the creators of this dataset changed conventions and began to label certain variables differently, as well as altering the structure of the data. One example of this was with the list of object identifiers contained in the exhibit data. The beginning of the data stored these object identifiers as a string object, but later the files contained nested lists of object identifiers. Other problems we encountered were changed variable names and how the archivists represented incomplete observations. In come cases, values that were unknown were represented as empty strings, (“ ”), other cases were represented as “NA”, and many others were simply left blank. While iterating over our set of JSON files, we had to wait for our program to encounter an error, find the exact file that caused the error, and then restructure our script to account for the issue at hand. A plethora of small inconsistencies made iterating over the approximately 128,000 files more time consuming that we had anticipated.

After loading all of our data, we encountered more inconsistencies with the format of certain variables. Consider the case where an arbitrary observation represents a display date as “01 01 2001 - 05 10 2001” and another observation represents a date as “September 27, 1999 to February 1, 2000”. Both cases are represented as strings, but we cannot compare these dates in their current format. We needed to be meticulous to transform our data into a consistent, workable, format that when analyzed would not produce any errors. We used regular expression matching to account for all unique representations of dates and to get the desired month, day and year data from each. We then converted each of the dates into *ISOdate* objects. In this way we could do arithmetic on the ISOdate objects to compute the duration that a piece of art was displayed for, in days. The *Days* variable that we created is our response variable in all of the analysis for this project. There were some observations within the exhibit data that did not contain any beginning or end data so we omitted these from our analysis at the risk of systematic bias. Our final exhibit data contained only exact data points, meaning there are no censored data points in our set at this time.

Our object dataset does not contain information regarding the duration of each piece's exhibitions, but we do have this information on the exhibit dataset. Of the 128,000 objects in our object dataset, only 14,252 are listed as appearing in an exhibit at MIA. This means that we can only do our analysis on the 14,252 objects for which we have exhibit duration data. We filtered our object data to only contain objects with identifiers that were found in an exhibit. After fully assembling the dataset, we created a list of all identifiers that occurred in any exhibit, and filtered the 127,000 objects down to only the objects we actually need.

The *Classification* variable in the object dataset has information on the physical nature of the object. There were 70 unique classifications, but many of these were extremely closely related and we decided to group the objects into 11 unique, broader classifications. These categories are *Adornment*, *Basketry*, *Ceramics*, *Drawing*, *Furniture*, *Metalwork*, *Painting*, *Photographs*, *Sculpture*, *Clothing/Textile*, and *Other*. It is important to include the Other category because exhibits that do not showcase traditionally classified objects might have a different survival rate over time than exhibits that display one or more of the commonplace categories listed above. Due to inconsistencies within the data, we needed to redefine categories for the *Country* variable as well. We altered the Country variable so that each country had only one representation for objects. For example, some objects had "Belgium" listed under Country, however some other objects had "Belgium (Flanders)" listed. Another reason we had to alter the variable was that some observations had two countries listed as one category, such as "Cambodia or Thailand". In most cases the object in question was constructed more than 500 years ago. We deduced that the creator(s) of the dataset could not definitively say if the object was from one country or the other. As a result we decided to simply count each of those observations as two separate observations, one for each country.

2.3 Methods

In our analysis we observe the effect of object classification, country, continent, department, date created, and nationality on the duration for which MIA chose to exhibit an object. All of these explanatory variables are categorical except for *Date Created*. An implication of using primarily categorical variables is that it greatly complicates the functions of our models, as each possible value for the categorical variables becomes its own indicator variable with its own coefficient. To combat this overly complex nature of modeling with categorical predictors, we have chosen to limit the number of values that predictor variables can take on. For example, we chose to only look at the ten most common countries of origin for artists as a function with an indicator variable for nearly every country to ever exist would be tediously long.

We have data on the nationalities of the artists in our object dataset, however many of these are unknown (represented as *N/A*) because the object displayed was from a long-past era, and we cannot determine the exact nationality of the artist. It is important to examine the nationality data, however for our analysis it is more important to study the effects of what region in the world the objects came from because our information in the *Country* and *Continent* variables are complete whereas we do not have complete information about the *Nationality* variable.

In order to study the survival times of objects as explained by other predictors, it is necessary to join the object dataset with the exhibit dataset to examine all possible variables associated with an object. The list of pieces in each exhibit dataset row is expanded so that each line in the exhibit dataset has a single object associated with it. To effectively study the duration for which objects were displayed by a variety of predictors, the two datasets were joined to link the exhibition information to the data of each piece.

Prior to making any assumptions about the distribution of the exhibition survival data, it was decided to examine the adequacy of each distribution in modeling the data with no predictors. The two methods used were to overlay the Kaplan-Meier curve associated with the data with an exploratory model of the data with varying distributions, and then to plot the Cox-Snell residuals of the distributions and compare their distribution to the line $y = x$. In addition to ensure that the log-normal distribution was the most adequate, a histogram of the log of the number of days is shown in the figure below. This makes it clear that the logs of the data are normally distributed, which confirms one of the assumptions one makes when choosing the log-normal. After we determined which distribution was most adequate for modeling the data, we added predictors to the models, and carefully vetted their significance using likelihood ratio tests that all but guaranteed the findings.

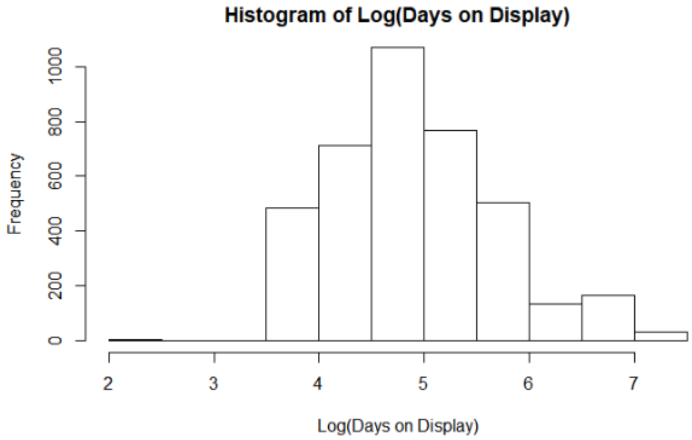

Figure 1: Distribution of Log(Days on Display

3 Results

Plotting a single Kaplan-Meier curve for all of the exhibit data together shoes that the distribution of failure times appeared to be exponential in nature. This can be seen below in Figure 2. One might notice several drop-offs of the curve at the approximate one year, two year, and three year points. This was expected to occur in the dataset as exhibits are not arbitrarily set up and taken down, but rather are likely allotted intentional durations of exhibitions on the gallery floors.

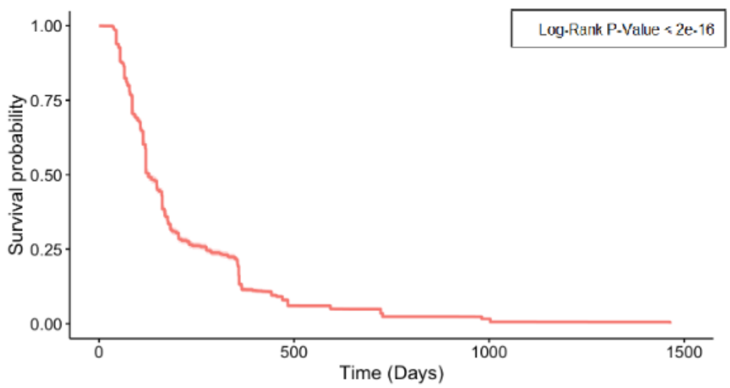

Figure 2: Kaplan-Meier Curve of Piece Exhibitions

After cleaning the Continent variable in the dataset, we looked at failure times while using the *Continent* of the origin of the piece variable. We limited this to the top 4 represented continents because the number of data points in other continents was too few to effectively compare with the more represented continents. These continents in order of representation were North America, Europe, Asia, and Africa. We can see the same Kaplan-Meier curve again in Figure 3, but this time stratified by the Continent variable to highlight the potential for investigation.

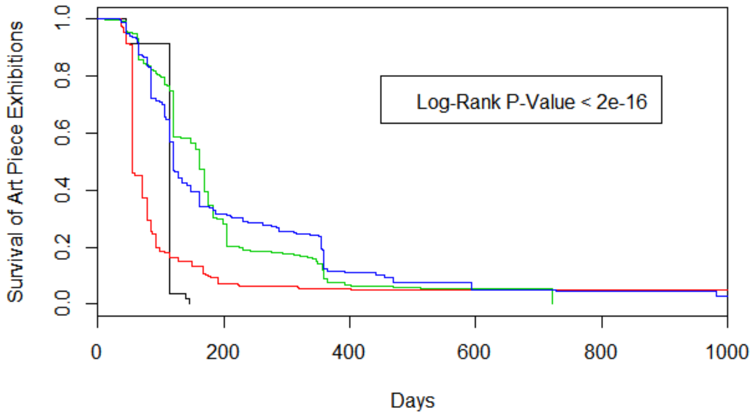

Figure 3: Kaplan-Meier Curve by Continent

First we tried using a Weibull distribution to model the survival times of the exhibits. The Kaplan-Meier curves looked like they could be exponentially distributed, so if this was true we would see a shape parameter that was insignificantly different from 1 in the Weibull model. The resulting plots of the Weibull functions were not as we expected. A significant proportion of the data from the Asian artwork came from one exhibit that happened to be the longest running exhibit in this dataset. As seen in Figure 4. This resulted in the Weibull estimate for the duration of Asian exhibits to be significantly above the actual survival times shown in the Kaplan Meier, while the other 3 curves seemed to fit their respective survival times.

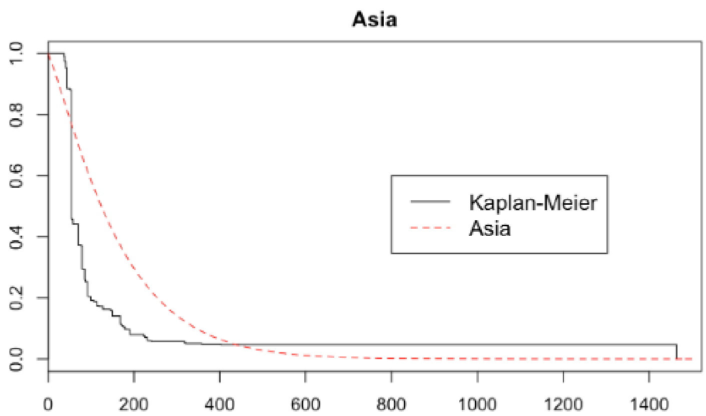

Figure 4: Weibull Model of Survival by Continent (Asia)

The next distribution that was considered was the log-normal distribution. After fitting a model we performed an AIC test with the model log-likelihoods. Based on this test we concluded that the log-normal model is a better fit than the Weibull with no predictors as well as when we included *Country* and *Continent* as covariates in our model (AIC values of 48706 versus 47371.4 and 46863 respectively). We also plotted the Cox-Snell residuals for both distributions and saw that the residuals for the log-normal distribution were much flatter and closer to fitting the line $y = x$ than the Weibull distribution. Both of these tests, shown below in Figure 5, indicate that the log-normal model is more adequate than the Weibull.

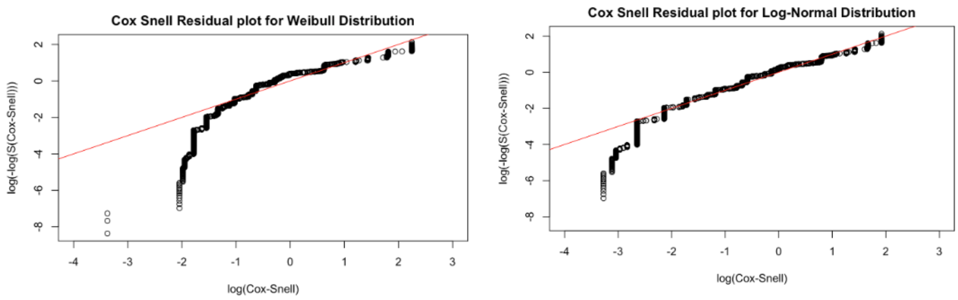

Figure 5: Cox-Snell Residuals

We then assessed whether a Cox proportional hazards model would be appropriate for this data. However, the proportional hazard assumption was clearly not met by any of the proposed predictors, so we chose not to fully asses the Cox proportional hazards model as an option.

4 Discussion

Of the models and distributions we tested during our analysis, we found that the log-normal distribution best models this data. The plot of the Cox-Snell residuals was not perfect, but it proved that the log-normal distribution was relatively much more adequate than the Weibull distribution. It was not surprising to see a violation of the proportional hazards model, the sample size of this data was substantially large, and the Kaplan-Meier curves in figure 3 do not overwhelmingly appear to have proportional hazards.

Similarly, the number of observations played a role in the adequacy of some of the models. Asia and Africa were the least represented continents of the four, and the accuracy of the model estimates for these two groups was consistently worse than the accuracy of the estimates for North America and Europe. The Asia estimates were also affected by a large outlier in our data. The longest running exhibit by far was of art from Asian countries and it accounted for a significant proportion of the artwork observations listed as from Asia.

The predictors in this dataset were primarily categorical, and this limited the number of predictors on which we could train our model while maintaining a high level of interpretability. This limits the scope of this research, but enhances the depth, as many of the exact effects of each level of the categorical variables can inform the discussion around the specifics of the biases of the curators.

In the interpretation of the coefficients of the predictor variables of our log-normal model by *Country* and *Department* is where we find most of the value of this study. Since the log-normal distribution is an Accelerated Failure Time model, the function, $e^{coefficient}$ represents the multiplicative effect on expected survival time of a 1-unit increase in that variable. All accounted for variables, shown in the table below, are indicator variables in which only one variable of each group of predictors' coefficients can have a value of one, while all others in that group have a value of zero. This creates the small constraint of allowing only one country of origin and department in control of the piece, which greatly reduced the number of our viable data.

To further explore these coefficients, one should keep in mind that the shown incredible significance of each coefficient can be partially attributed to the large size of our dataset, and likely reflects an exaggeration of the actual confidence. Also the base level values for each categorical variable are "China" and "Art of Africa and the Americas" respectively. This means that the value of $e^{coefficient}$ must be interpreted in as representing the multiplicative effect in relation to the a case in which the variable was either from China or controlled by the Department of Art of Africa and the Americas. For example the value of $e^{0.625}$ is 1.8691128 and means that a piece of Moroccan Art is likely to be displayed for 1.869 times as long as a piece of Chinese Art. As an additional example, a piece in the Paintings department will likely be shown 0.4436 times as long as a piece in the Art of Africa and the Americas department. The significance of these coefficients shows that we can conclude with the utmost confidence that the country of origin and department of a piece of art significantly contribute to the length of time for which it is exhibited.

Without further study into the causes of our findings, it is difficult to say what caused the significant difference in survival time between art pieces with different nations of origin or that belong to different departments, shown in Figure 6 on the next page. However we chose not to infer in this paper whether the cause of the differences is curator bias or another contributing factor like the museums connections to quality sources of art in these regions. It is also interesting how the interpretations of some coefficients seem counter-intuitive. For example, one would think that because Chinese art has the lowest expected survival of the top 10 nations that the Chinese, South, and Southeast Asian art department would have lower than average exhibition durations, but the opposite is true. This would suggest a difference in how one department may treat a given work of art differently than another department, and could lead one to believe that the difference is likely from the bias of curators in this case.

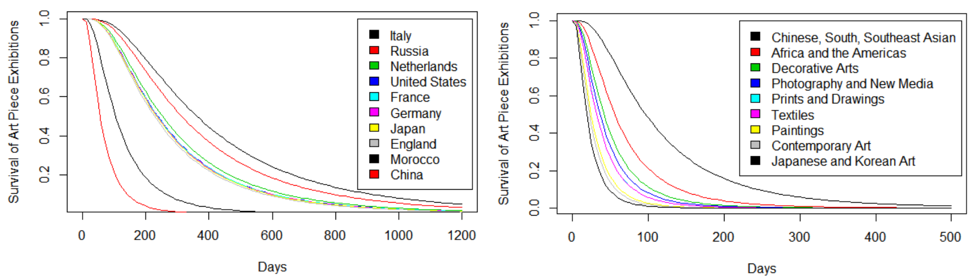

Figure 6: Log-Normal Model by Country and Continent

Table 1:

	Dependent variable:
	days
factor(country)England	1.404*** (0.177)
factor(country)France	1.444*** (0.172)
factor(country)Germany	1.436*** (0.173)
factor(country)Italy	1.864*** (0.175)
factor(country)Japan	1.430*** (0.340)
factor(country)Morocco	0.625*** (0.216)
factor(country)Netherlands	1.507*** (0.179)
factor(country)Russia	1.722*** (0.192)
factor(country)United States	1.447*** (0.169)
factor(department)Chinese, South and Southeast Asian Art	0.546*** (0.211)
factor(department)Contemporary Art	−0.925*** (0.247)
factor(department)Decorative Arts, Textiles and Sculpture	−0.296*** (0.099)
factor(department)Japanese and Korean Art	−1.077*** (0.312)
factor(department)Paintings	−0.813*** (0.118)
factor(department)Photography and New Media	−0.431*** (0.097)
factor(department)Prints and Drawings	−0.556*** (0.098)
factor(department)Textiles	−0.558*** (0.152)
Constant	4.026*** (0.193)
Observations	3,876
Log Likelihood	−23,413.480
χ^2	540.350*** (df = 17)
Note:	*p<0.1; **p<0.05; ***p<0.01

After finding such significant trends using the country of origin and department as predictors, it was decided to explore how significant of a predictor a piece's *Classification* is. The resulting coefficients can be seen in Table 2, and are notably less significant than the coefficients in the previous model. However, this does have two exception in Woodwork and Drawing pieces, which both appear to be significant and opposite predictors of survival with Drawings lasting much longer than average and Woodwork surviving for much shorter periods of time.

Table 2:

	Dependent variable:
	days
classification Books	−0.262 (0.205)
classification Ceramics	−0.174 (0.175)
classification Drawings	0.549*** (0.176)
classification Furniture	0.139 (0.186)
classification Glass	0.098 (0.214)
classification Industrial Design	0.363 (0.235)
classification Metalwork	0.286* (0.174)
classification Paintings	−0.167 (0.175)
classification Photographs	−0.017 (0.170)
classification Prints	−0.384** (0.169)
classification Sculpture	0.085 (0.235)
classification Textiles	−0.271 (0.186)
classification Woodwork	−0.907*** (0.215)
Constant	5.070*** (0.168)
Observations	3,703
Log Likelihood	−22,385.260
χ^2	478.714*** (df = 13)
Note:	*p<0.1; **p<0.05; ***p<0.01

5 Conclusion

The Minneapolis Institute of Art holds a diverse collection of art pieces, and for a number of decades has kept archives, with varying levels of comprehensiveness, of all of its pieces and the exhibitions in which they were featured. Among these data are classifications of artists' nationalities, countries and continents of origin, chosen mediums, and many more less easy-to-analyze data points. This is one of the major limitations of our study is the lack of organization of this massive dataset. Dating back to long before the founding of the field of computer science, the earlier art piece data differed significantly in organizational structure than the later data. The other major limitation of this study was the circumstance that many of the classifications were categorical, which greatly increased the complexity of cleaning and analyzing the dataset, as the levels of the categorical variables were often inconsistently defined. One of the original mishaps of this study was not contacting any of MIA's archivists to discern exactly how to handle some uncertainty in the data, such as inferring what is meant when multiple countries of origin are listed, or to discuss any known trends in the length of exhibitions across the different region-tied departments in the museum to account for differences in departmental structure that may not necessarily represent the biases of its curators. Related to this, it would have been convenient to learn exactly what the limits of the domains of MIA's curators are to more adequately compare the tendencies of various individuals instead of blindly comparing pieces based solely on information about them and their creating artists.

References

[1] Sudip Bhattacharjee, Kaveepan Lertwachara, James R. Marsden, and Rahul Telang. The effect of digital sharing technologies on music markets: A survival analysis of albums on ranking charts. *Management Science*, 53(9):1359–1374, 2017.

[2] Bridget R. Cooks. *Exhibiting Blackness: African Americans and the American Art Museum.* University of Massachussets Press, 2011.

[3] Jianxun Lian, Fuzheng Zhang, Xing Xie, and Guangzhong Sun. Restaurant survival analysis with heterogeneous information. In *Proceedings of the 26th International Conference on World Wide Web Companion*, pages 993–1002, Perth, Australia, 2017.

[4] A.E. Scorcu and R. Zanola. Survival in the cultural market: The case of temporary exhibitions. *Working Paper Series*, 2011.