Orchestral Concert Programming Analysis - STA 723 Final Project

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Executive Summary

Orchestral programming is a challenging, yet critical, task for expanding audience engagement. This project analyzes which factors are important in determining composers that are performed together by the Boston Symphony Orchestra. Network models with additive and multiplicative random effects are used to model concert programming over the past 20 years. We find that the type of composition is the most important covariate in determining which composers are performed together. Additionally, the results for the additive and multiplicative effects are logical from an orchestral programming perspective.

1 Introduction

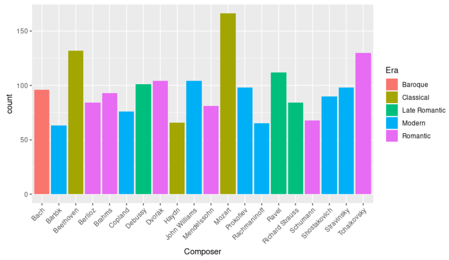
Orchestral concert programming involves selecting pieces to be performed, both for specific concerts and across an entire season. Programming is the most important task for an orchestra's music or artistic director and involves balancing numerous factors. The artistic director must take into account the length of different concerts, the musical tone of each piece, the balance of new works and classics, hiring soloists and audience demand. Especially as audience attendance at classical music concerts decreases, the importance of orchestral programming increases.

The goal of this project is to explore which factors determine if specific composers are programmed together in the same concert. The analysis focuses on composer traits and covariates, rather than on individual pieces. The data consists of **2464** unique concerts performed by the Boston Symphony Orchestra (BSO) from the 1999-2000 season through the 2017-2018 season [1]. Over **323** unique composers are represented and covariates include the era, nationality by region, year of birth and type of piece performed by each composer.

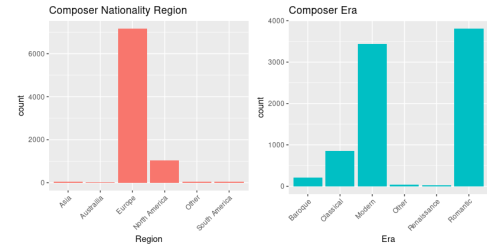
2 Exploratory Data Analysis

An exploration of the data confirms several conventional wisdoms about the types of composers programmed. Overall, the composers performed most often include the most popular Western composers, such as Mozart, Bach and Beethoven (Figure 1a). Interestingly, John Williams is also one of the most frequently performed conductors, likely due to his popularity in pops style concerts and the fact that he is the conductor emeritus of the sister Boston Pops. Shostakovich is also performed more frequently than may be expected for a "typical" orchestra. The BSO is currently recording all Shostakovich symphonies and thus the composer has been performed frequently, especially recently.

The majority of composers performed are from Europe, though there are also many American composers performed (Figure 1b). Romantic era and modern works are the most commonly performed (Figure 1b). The category "Other" corresponds to traditional or anonymous pieces, such



(a) Top 20 composers.



(b) Composer era and region nationality.

Figure 1: (a) Top 20 most frequently performed composers by the BSO and Boston Pops. (b) Eras and nationality regions of composers.

as *Shenandoah*, that do not have a specific composer. Finally, the overall network structure of the data is quite dense among the composers that are performed frequently, while new works by contemporary composers are performed infrequently.

3 Methods

Several different network models are considered to explore the relationship between composers that are programmed together. For all models considered, the binary outcome variable of interest is $\boldsymbol{Y_{ij}}$, where $Y_{ij} = 1$ indicates that composer i and composer j are programmed together. The nodal covariates $X_r = X_c$ are the nationality Region, Year of Birth, Era and type of composition by each composer. Region and Era are categorical variables, year of birth is numeric, and Symphony, Concerto, Overture and Other are binary variables indicating if that type of work by a composer has been performed. "Other" includes works that are not titled as Symphonies, Concertos or Overtures.

The full network model is given in Equation 1. This is a probit social relations regression model with additive and multiplicative effects (AME model) [2, 3]. β_r and β_c represent the row and column regression coefficients, respectively, $\{a_i\}_{i=1}^n$ are the row additive effects, $\{b_j\}_{j=1}^n$ are the column additive effects and $\{u_i\}_{i=1}^n$ and $\{v_j\}_{j=1}^n$ are the row and column multiplicative effects, respectively. The multiplicative effects can be viewed as latent factors that allow the model to capture higher order network dependencies; the dimension of the latent space considered here is $R = 3$.

The variance structure includes σ_a^2 and σ_b^2, which represent across row and across-column heterogeneity, respectively, σ_{ab}, which represents the linear association between row and column means, σ_ϵ^2, which represents additional variability across dyads, and ρ, which is the within dyad correlation that is not explained by σ_{ab} [2]. Standard g-priors are placed on the regression coefficients, β_r and β_c, a Uniform prior is placed on ρ and an Inverse Gamma prior on σ_ϵ^2. Empirical Bayes estimates from the data are used to specify the Inverse-Wishart priors on Σ_{ab} and Ψ [3, 4].

$$
\begin{aligned}
z_{ij} &= \beta_r^T X_{ri} + \beta_c^T X_{ci} + a_i + b_j + u_i^T v_j + \epsilon_{ij} \\
Y_{ij} &= \mathbf{1}(z_{ij} > 0) \\
(a_i, b_i) &\overset{iid}{\sim} N(0, \Sigma_{ab}),\ i = 1, \ldots, n \\
\{(\epsilon_{ij}, \epsilon_{ji}) : i \neq j\} &\overset{iid}{\sim} N(0, \Sigma_\epsilon)
\end{aligned}
\qquad
\begin{aligned}
\Sigma_{ab} &= \begin{bmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{bmatrix} \\
\Sigma_\epsilon &= \sigma_\epsilon^2 \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \\
(u_1, v_1), \ldots, (u_n, v_n) &\overset{iid}{\sim} N_R(0, \Psi)
\end{aligned}
\tag{1}
$$

Two forms of network structure are considered. The first is a symmetric graph structure, where the order in which composers are performed in the same concert does not matter. The second is an asymmetric graph structure where the order of performance does matter. That is, $Y_{ij} = 1$ if composer i is performed before composer j in the same concert. Additionally, several variations of the full model described above are considered: the Simple Random Graph (SRG) model, $z_{ij} = \mu + \epsilon_{ij}$, which only contains an intercept term, the Social Relations Model (SRM), $z_{ij} = \mu + a_i + b_j + \epsilon_{ij}$, which only contains additive random effects and no covariates, the Social Relations Regression Model (SRRM), $z_{ij} = \beta_r^T x_{ri} + \beta_c^T x_{ci} + a_i + b_j + \epsilon_{ij}$, with additive effects and covariates, a logistic regression model, $z_{ij} = \beta_r^T x_{ri} + \beta_c^T x_{ci} + a_i + b_j + \epsilon_{ij}$, which assumes the error terms are iid and thus does not take into account the network structure of the data, and finally the full Additive and Multiplicative Effects (AME) model, Equation 1. The dimension of the multiplicative effect vectors is $R = 3$. All models are fit using the AMEN package in R [5].

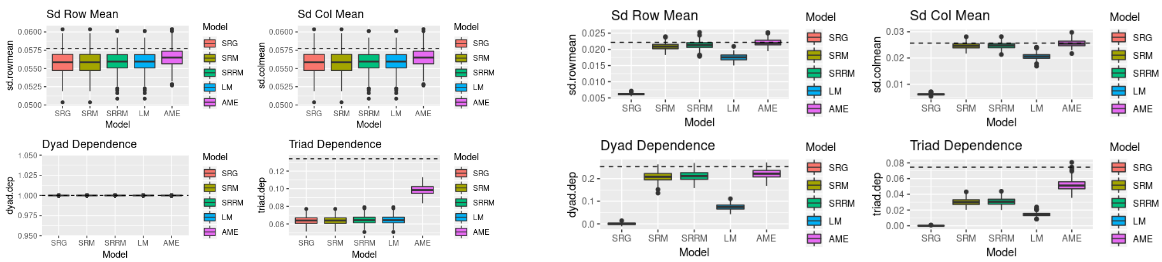
4 Results

The model fit of each of the modeling variations described in section 3 is assessed and the full AME model for the asymmetric graph structure is found to give the best fit, especially for higher order network effects. The various parameters in this full AME model are explored in the context of orchestral programming.

Model Fit Observed values and posterior predictive draws for four goodness of fit statistics are given in Figure 2a for the symmetric graph and Figure 2b for the asymmetric graph. The goodness of fit statistics are the standard deviations of the row and column means of the network, the dyad dependence and the triad dependence. The dyad dependence is the correlation between the rows and columns of the adjacency matrix for the network, and so is identically 1 for the symmetric network. The AME model achieves the best fit for all four statistics for the asymmetric network model. The triad dependence is still not extremely well captured by this model, but the posterior predictive draws are closest to the observed value.

As expected, the baseline SRG and logistic regression models do not model either the symmetric or asymmetric networks very well and are not able to capture dyad or triad dependencies in either network, as the model structure does not consider this more complex structure. The AME model achieves the best model fit in terms of these statistics on the asymmetric network. Thus, it is important to include composer nodal covariates and additive and multiplicative random effects. The order in which composers are performed is also important, as this asymmetric structure is better captured by the AME models considered than the symmetric network structure. All remaining results will be presented in the context of the AME model on the asymmetric network.

Regression Coefficients and Variance The posterior distributions for the regression coefficients for the AME model for the asymmetric network are given in Figure 3. The most important covariates are the type of piece performed by each composer (Symphony, Concerto, Overture and Other), both for the row and column covariates. The region and era coefficients either contain 0 in their 95% credible intervals or tend to be negative. This indicates that in determining which composers will be performed together, the type of piece by a given composer is the most important factor. This makes sense from a programming perspective, as regardless of the composer chosen, it would be unusual to have a concert of only overtures or only concertos. There are few pieces performed from the Renaissance era or “Other” (i.e. traditional or anonymous pieces), leading to



(a) Symmetric graph.

(b) Asymmetric graph.

Figure 2: Goodness of fit checks for the (a) symmetric and (b) asymmetric graph models. The horizontal black lines represent the observed value of each statistic, while the boxplots for each model are posterior predictive samples. The asymmetric graph models better capture higher order dependencies in the network structure.

the larger variances in the posterior samples.

Posterior summaries for the variance parameters in the AME model indicate that there is significant correlation between dyads that is not explained by σ_{ab}. The posterior mean for ρ is 0.22, again indicating that it is critical for this data to take the network structure into account when modeling relationships between composers.

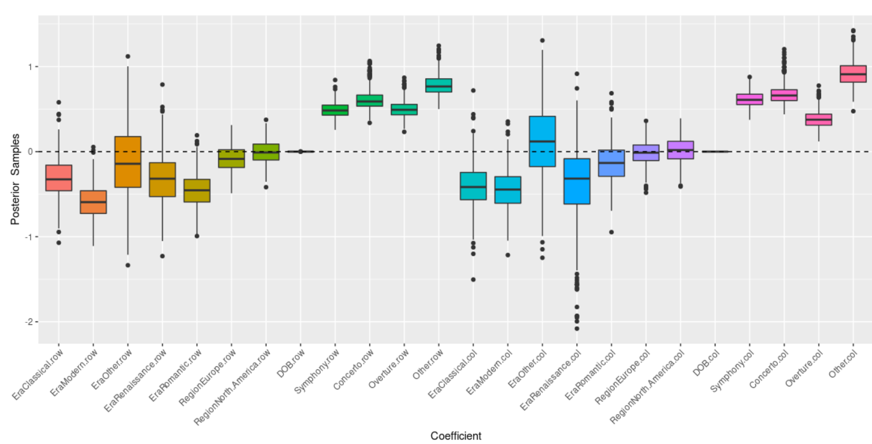
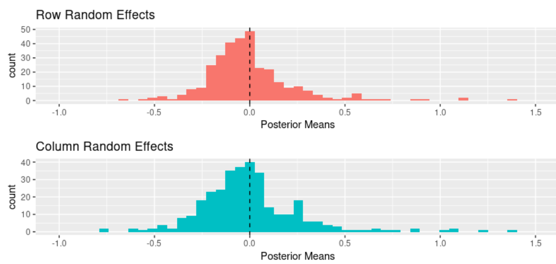
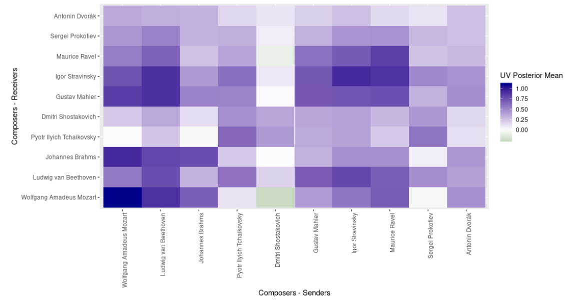


Figure 3: Posterior samples for the regression coefficients for the AME model. The type of composition is significant, and the row (β_r) and column (β_c) regression coefficients are not the same.

Additive Random Effects Most of the additive row and column random effects are relatively small and centered around 0 (Figure 4a). However, there are some composers which do have large additive random effects, such as Debussy (1.36), Ravel (1.14) and Bach (1.11), indicating that these composers are more likely to be performed with any other composer. Indeed, these three composers can be and are programmed with a wide variety of other composers. On the other hand, contemporary composers Glazunov (-0.68), Knussen (-0.54) and Wuorinen (-0.53) have the largest negative additive random effects. Most new works are not performed again after their premiere, so it makes sense that many contemporary composers are not likely to be performed with any other composers and hence the large, negative additive random effects.



(a) Additive random effects, a_i and b_j.



(b) Multiplicative random effects, UV^T.

Figure 4: Posterior means of the (a) additive and (b) multiplicative random effects for the asymmetric AME model. The posterior mean for the matrix UV^T is shown in (b), subset to highlight the top 10 most frequently performed composers. Rows indicate that that composer was performed before a composer in a specific column.

Multiplicative Effects The multiplicative effects can be examined by looking at the posterior mean of the UV^T multiplicative random effects matrix, given for the 10 most frequently performed composers in Figure 4b. The column for Shostakovich has low or negative values relative to the other composers considered here. Works by Shostakovich, especially his symphonies, tend to be longer and rather "heavy" or "dark" in tone, and are thus less likely to be programmed after a lighter work by Mozart, for example. On the other hand, a composer like Brahms has many shorter works, including frequently performed overtures, that can be programmed before many of the top 10 composers considered here, which can be seen in the higher values for the Brahms row in the UV^T matrix.

5 Conclusions and Future Work

Overall, orchestral programming networks have higher level network structure, such as dyad and triad dependence, that full AME models are able to capture relatively well. When exploring which composers are likely to be programmed together, the type of composition is the most important factor to take into account, while the era is much less important. Additionally, the results of the AME model emphasize that many new works are never performed again after their premiere, for example in the additive random effects, which tend to be large and negative for many contemporary composers.

In the future, it would be interesting to add more covariates to the analysis. From a musical perspective, covariates such as the length of each piece, instrumentation, whether there is a soloist or not and more subjective descriptions of each composer, such as musical tone, would be helpful to further explore which factors are most important in concert programming. Additionally, including orchestra revenue would be interesting for exploring how programming influences attendance and revenue. Finally, considering dynamic network models would allow for exploring how programming practices have changed over time and with music directors.

References

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[5] Peter Hoff and Bailey Fosdick and Alex Volfovsky and Yanjun He. Package 'amen': Additive and Multiplicative Effects Models for Networks and Relational Data. https://cran.r-project.org/web/packages/amen/amen.pdf, 2017.