As a recommendation to Ticketmaster, we suggest the company use its data to implement a recommendation system for its users. M.A.H.A has created two recommendation systems to implement, both of which have merits and faults; however, when used in weighted combination and to corroborate one another, the accuracy of recommendation to users based on previous purchase data should present a highly lucrative way to expand Ticketmaster's current business.

Our primary recommendation mechanism relies on a Markov chain, in which we aggregate previous genre and location data on repeat customers to assign probabilities to customers to the type of show they are most likely to see next. To do so, we sampled 100,000 transactions from the original data set and determined the number of performances each person attended in each "genre-location" in the data set; for example, person 1 attended 2 "Alternative Rock-West Shows," and person 2 attended 1 "Rock/Pop-North East Shows" and 3 "Rock/Pop-Canada Shows." (Note we divided the regions into Northeast, South, Midwest, West, and Canada). In order to generate the stochastic matrix forming the base of our Markov chain, we first needed to find the probabilities a person who attended a West Alternative Rock concert will attend West Alternative Rock again in addition to each of the other genre-location pairs. To accomplish this, we made use of a frequentist proxy approach, whereby we used proportions in the data to approximate conditional probabilities. Afterward, we standardized the proportions to ensure rows equal to 1 and thus obtained the stochastic matrix.

	Canada ADULT CONTEMPORARY	Canada ALTERNATIVE ROCK
Canada ADULT CONTEMPORARY	1	0.0000000000
Canada ALTERNATIVE ROCK	0	0.7101449275

Our process works as follows. When a person buys a ticket on Ticketmaster, he generates a proportion vector based on the number and kind of shows he attended. We multiply this vector by our stochastic matrix to generate an initial distribution of the probabilities of where he is most likely to go next, and based on the set of probabilities, we can recommend a varying number of shows. In order to predict where this person is likely to go for the second, third, and fourth show, we multiply the result by the matrix a second, third, and fourth time in a classic Markov chain; we can therefore provide richer recommendation right off the bat based on the series of results we can obtain and predict the customer's "probabilistic show trajectory". As the machine learning aspect of this, as we obtain more data from customers, this would feed into our base stochastic matrix and increasingly improves our understanding of the population as a whole. As one drawback to this method, since the customer's matrix is based on proportions, we do not discern between a person who has attended one West Alternative Rock concert and three West Alternative Rock concerts. However, we hope to implement increasingly higher dimensional analysis to further segment the customers, and for now, we may use our second recommendation mechanism to corroborate and improve results.

The second recommender system is a form of Affinity Analysis, which is making recommendations based on people who exhibit similar consumer behaviors with the given customer. This approach first calculates the propensities for a set of n customers to go to a list of k artists. We end up with a $n \times k$ matrix where each column is an artist j, and each row is a vector of propensity probabilities for customer i. Each row should sum to 1. Each cell is calculated by calculated by (the number of times customer i goes to artist j's concert) / (the total number of concerts customer k has gone to). Then, for each pair of customers, calculate the affinity score between them. We end up with a $n \times n$ matrix of affinity scores for all pairs of customers. Affinity score is the sum of the squared differences between two customers' vectors of propensity probabilities. For example, A has 1/4 probability of going to a Justin Bieber concert and 3/4 probability of going to a Taylor Swift concert.. B has 1/2 probability of going to a Justin Bieber concert and 1/2 probability of going to a Taylor Swift concert. The affinity score for A & B is (1/4-1/2)^2 + (3/4-1/2)^2. Finally, for each customer, we make recommendations for her/him based on people who are the most similar to them. For example, For A, the affinity score for B is the lowest, which means A and B are the most similar. We then recommend concerts that B has been to to A within a certain time frame and region.

In our analysis, we selected 500 customers who have the most records (who have gone to the highest number of concerts.) For customer "00e968539df49b82ef5b", his/her vector of affinity scores is [0.000, 0.047, 0.154, 0.080, 0.128, 0.223...] (a total of 500 scores). We select the 10 smallest scores, find the corresponding 10 customers and recommend the concerts they have been to to customer "00e968539df49b82ef5b". In this case, the person that is the most similar to him/her is customer "00fbb971ac6aebf74133". (They have the lowest score of 0.0225). One drawback is that this system is not applicable to those who do not have a lot of historical records.