From Studio to Symphony:
An Empirical Study of Conservatory Representation in American Orchestras

Jeffrey Ryan

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Abstract

Which music schools produce students who win orchestra jobs? Music colleges and conservatories are often marketed as pipelines to professional performance, but empirical evidence suggests that these pipelines are heavily skewed toward just a few schools. Using data scraped from official orchestra websites, this study analyzes the educational backgrounds of 2,288 musicians across 32 major US orchestras to evaluate the relationship between music schools and employment outcomes in top ensembles. The results reveal an extraordinary concentration of school representation; 47% of the musicians in the study attended one of just four schools. Normalizing each school's presence in orchestras by student population shifts several rankings but does not change the pattern of dominance by a small, elite group of schools. Additional analysis segmenting by instrument and orchestra uncovered patterns of studio specialization and regional clustering. These findings provide quantitative evidence for long-held assumptions in music education, giving prospective students and institutions a clearer picture of the past and present state of orchestral careers.

Introduction

When someone decides where to pursue higher education, a key question is: "Will I be employed when I graduate?" As tuition prices and cost of living skyrocket, young people are increasingly anxious about if their college studies will lead to a good career. This question is especially important to musicians, whose field is notorious for financial challenges.

One tried-and-true method for finding stable income as a musician is to win a job in a symphony orchestra. Once someone secures one of these positions, it's a lot like being a Supreme Court justice–consistent work and income until you choose to retire or die[1]. Unfortunately, auditioning for these positions is extraordinarily difficult and stressful. Since tenure is held so strongly, every time one opens up, a professional battle royale ensues. Every qualified musician in the country–if not the world–trains for months to compete against each other in a one-shot winner-takes-all audition.

Imagine yourself as an anxious prospective music student. You need to justify to your parents that studying classical music gives you solid paths to a safe and stable career. On the other side, imagine a conservatory or university that wants to attract students. These institutions ask a lot

[1] In fact, it is likely more severe than the Supreme Court. From supremecourt.gov/about/faq_justices, the average Supreme Court justice tenure is 16 years. By comparison, 49.6% of current orchestra musicians have held their position for over 16 years. (This percent is artificially lowered since it only accounts for current members, not the total tenure at the time of retirement). As a general statistic, the data in this study found that 40% of orchestra musicians have held their current position for over 20 years. These metrics paint a clear picture that orchestra jobs are some of the most enduring institutional positions in the United States.

of these young adults–audition for the school, pay high tuition, and spend years studying with their staff. What can schools tell them about how a degree impacts their future prospects? Both sides would greatly benefit from a clear understanding of the route from schools to professional orchestras.

Often, music conservatories and universities are seen as the pipelines that feed into these orchestra jobs. The thinking goes: "If I study at a prestigious school, the combination of high-level musical training and relationships built with important people will launch me towards a successful career." However, do the data support this narrative? Surprisingly, there is a wealth of untapped, accessible data on current orchestra members and where they studied. By gathering, cleaning, and analyzing these data, this paper will uncover invaluable information for both students and music schools.

Data Collection

Data sourcing

The study in this paper will use a collection of three facts from a sample of 2288 actively performing orchestra musicians:

1. The orchestra that each musician performs with
2. The instrument(s) each musician plays
3. The college/conservatory-level schools each musician attended

These data were collected from 32 prominent orchestras in the US: [Alabama Symphony Orchestra, Arkansas Symphony, Atlanta Symphony Orchestra, Austin Symphony Orchestra, Baltimore Symphony Orchestra, Buffalo Philharmonic Orchestra, Boston Symphony Orchestra, Cincinnati Symphony Orchestra, The Cleveland Orchestra, Colorado Symphony, Chicago Symphony Orchestra, Detroit Symphony Orchestra, Dallas Symphony Orchestra, Houston Symphony, Indianapolis Symphony Orchestra, Kansas City Symphony, Los Angeles Philharmonic, Louisville Orchestra, Minnesota Orchestra, Milwaukee Symphony, Nashville Symphony, New Jersey Symphony, National Symphony Orchestra, New York Philharmonic, Oregon Symphony, The Philadelphia Orchestra, Pittsburgh Symphony, Rochester Philharmonic Orchestra, Seattle Symphony, San Francisco Symphony, St. Louis Symphony Orchestra, and Utah Symphony]. These ensembles were selected by a rough combination of prestige and budget, but are not based on any strict criterion. All data were sourced directly from official orchestra websites in April of 2025.

The collection method relied on one crucial pattern in orchestra website design: orchestras tend to list a short biography for each musician in their ensemble. These bios always include the musicians' names and what they play. Additionally, these biographies nearly always mention where the musician studied–which is the primary focus of this analysis. Musicians that had empty bios or otherwise significantly missing data were not included in the analysis. This left 2288 musicians in the dataset.

Data cleaning

Unfortunately, the musician biographies are natural language–not in a structured, consistent format. Because the data are natural language, many techniques need to be applied before the data is clean enough for analysis. In particular, the canonization of schools is a difficult problem in data science. Here, canonization refers to the problem where every variant of a school's name needs to be connected to a single entity. For example, Northwestern University = Bienen School of Music = Northwestern Bienen School of Music = Northwetsern's Bienen School. In this study, this problem was solved using the *layered canonization* approach. To read about the specifics of this implementation, see Appendix A.

The data on musicians' names was assumed to be a canon from the outset, since it is very rare for a single performer to be a full-time member of multiple orchestras. The instrument data also required some canonization, but the number of name variants was small enough to manually verify the solution.

Results

Schools' share of jobs

The simplest way to investigate each school's presence in orchestras is to find the percentage of active performers who studied at that school. This reveals a shocking distribution:

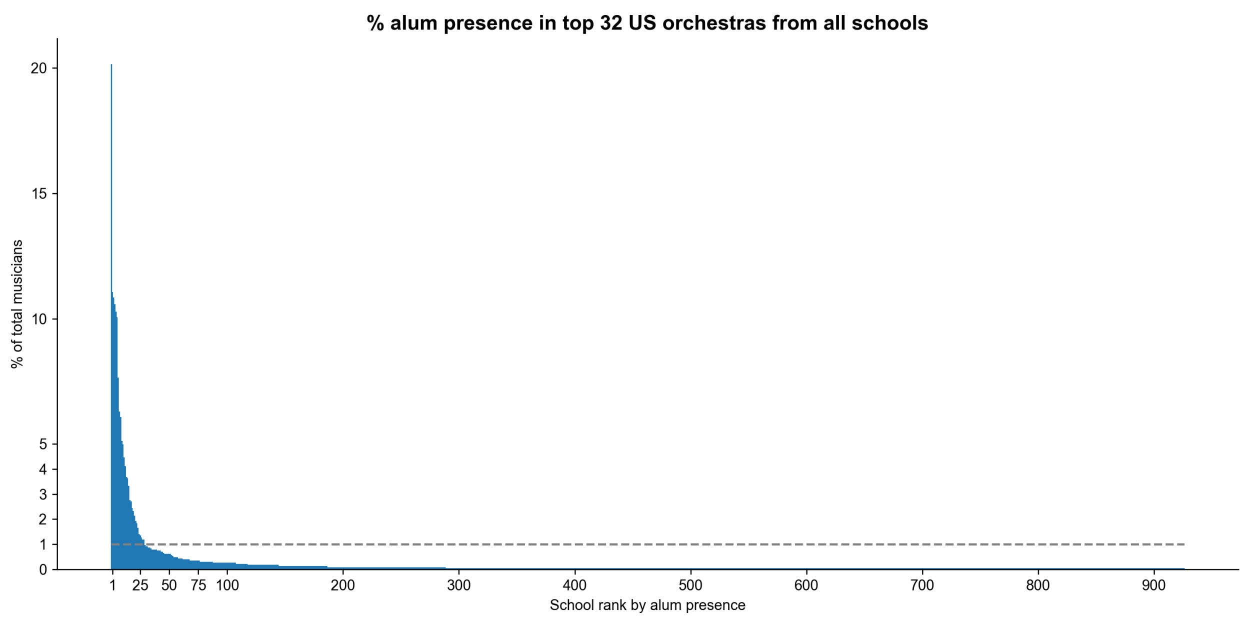

Figure 1: All schools alumni percentages

While the top schools' alumni make up 10-20% of orchestra jobs, by school 25, that number crashes to just 1% of jobs in the dataset. Beyond the 50th school, representation drops to nearly zero. Zooming in on the top 30 schools gives a clearer picture of these big players:

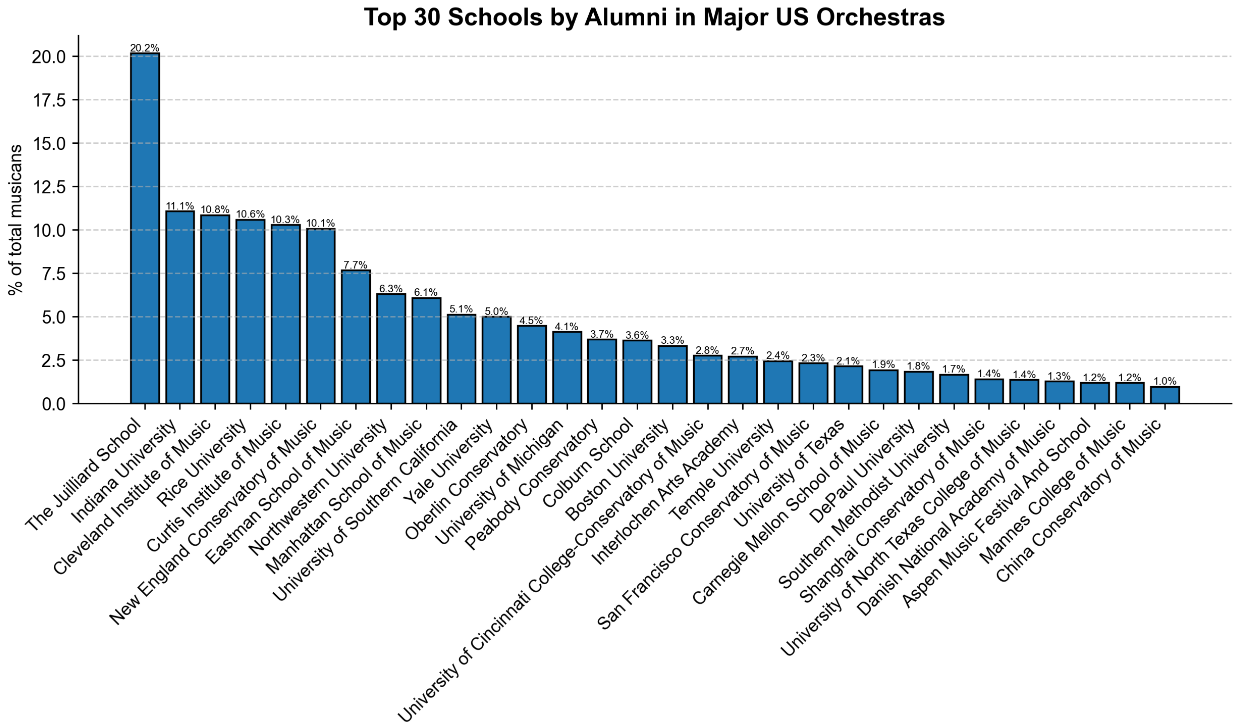

Figure 2: Top 30 schools alumni percentages

Similarly, the same plot can be made in terms of counts instead of percents:

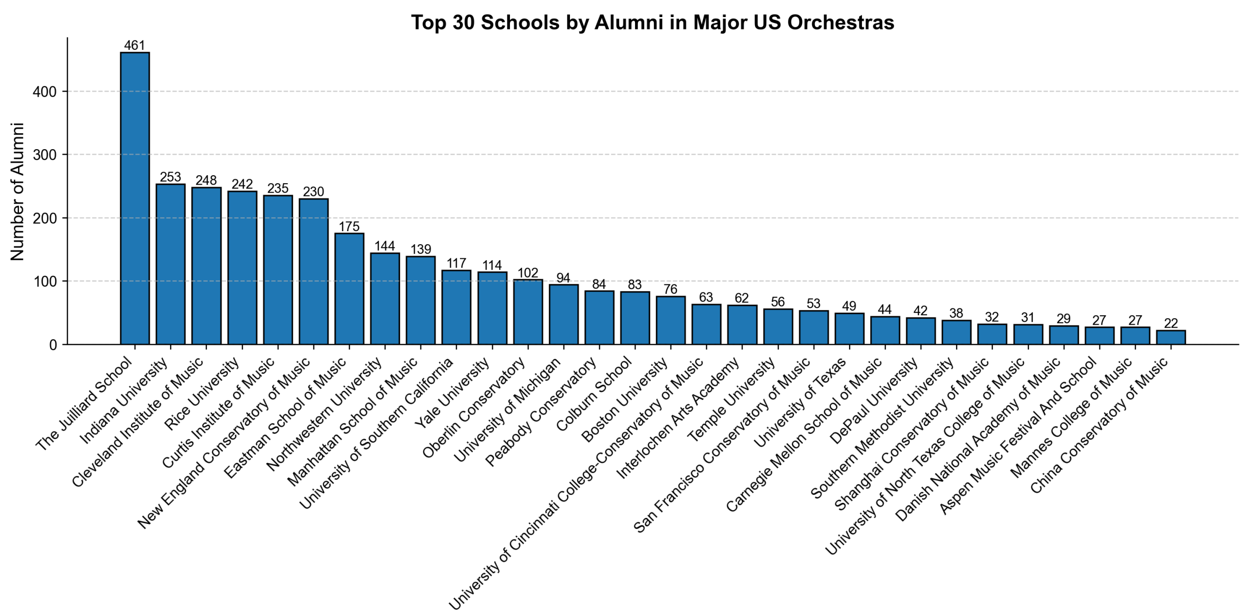

Figure 3: Top 30 schools alumni counts

These plots reveal extreme differences between the few top music schools and the hundreds of schools below. Even in the top 30 alone, alumni percentage dips by a factor of four from the 1st to the 10th school and a factor of 21 from the 1st to the 30th[2].

Perhaps the most illuminating way to understand these data is a cumulative distribution of the top 30 schools. In this context, the cumulative distribution a the running total of musicians who studied at least one of the top n schools. For example, 47% of the musicians in the data studied at either The Juilliard School, Indiana University, The Cleveland Institute of Music, or The Curtis Institute of Music:

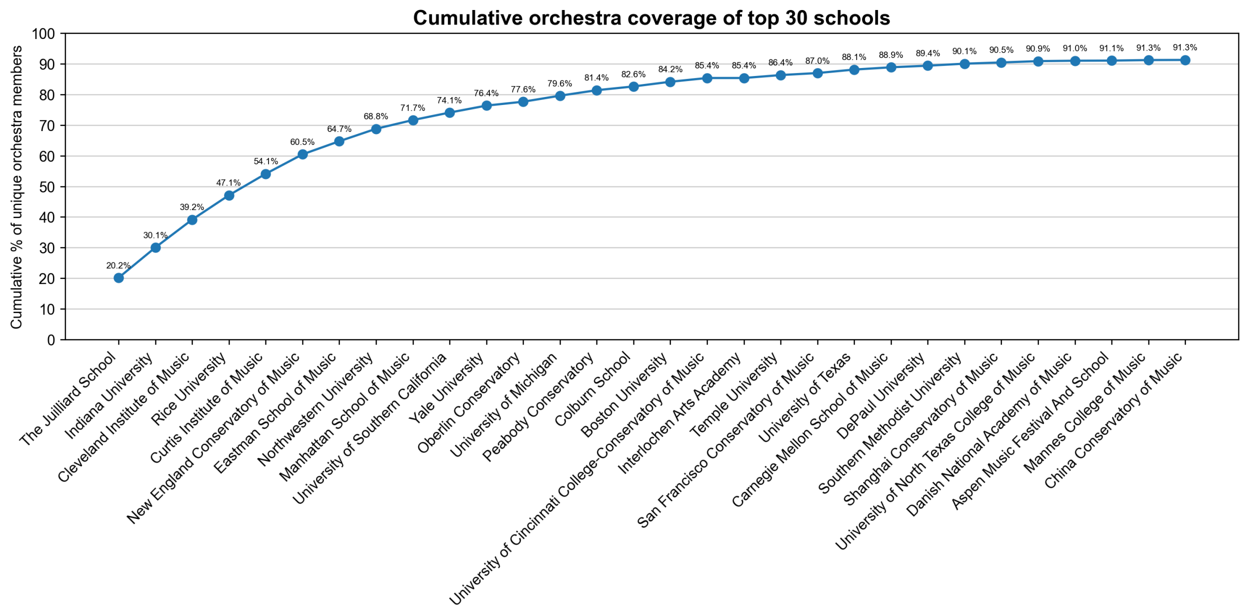

Figure 4: Cumulative distribution of school shares

These results show that pipelines to major orchestras are highly concentrated in just a few schools. The top 5 schools account for over 50% of total jobs, the top 11 for 75%, and just 26 schools account for 90% of orchestra jobs in the data.

Schools' weighted presence

Before the results above are fully accepted, a clear confounding variable must be accounted for: schools are not the same size. A school that graduates 10 students a year with 5% orchestra presence deserves more credit than another with 1,000 yearly graduates. However, finding data to correct for this fact is difficult.

Schools rarely publish exact figures for graduating class size–and it is even rarer to see those numbers for music majors alone. Even if these figures were known, the quality of education and size of music programs change over time. These fluctuations are significant in a field where people often keep their positions for decades (the data show 40% of orchestra members have held their job for over 20 years). If, somehow, all of those factors could be accounted for, these data would still not enable full corrective scaling. In reality, each school's proportion of students who end up auditioning for an orchestra would be needed to make direct comparisons. Though it may be

[2] In statistical terms, this distribution would be classified as highly heavy-tailed–meaning the data frequently sees large deviations from the average. From under 1000 observations, these data have 9 instances that exceed the average by 4 standard deviations above the average, and 5 instances that exceed the average by 7 standard deviations. (These values were calculated after throwing out the bottom 300 schools to help correct for canonization errors–which overrepresent small instances.)

possible to source these data for case studies or internal reviews by institutions, it seems nearly impossible to source at scale.

Given these challenges, the population of music students at each school–or the entire student population of conservatories–will be used as a proxy. Even these data were difficult to find and had to be roughly estimated in many cases. However, this confounding variable is too important to not attempt an approximation.

Focusing on just the top 30 schools–which account for over 90% of orchestra jobs–school websites were checked for music student population figures. For most schools, a precise value could not be found, so a rough estimate had to be used. The methods for each school can be seen in Appendix B.

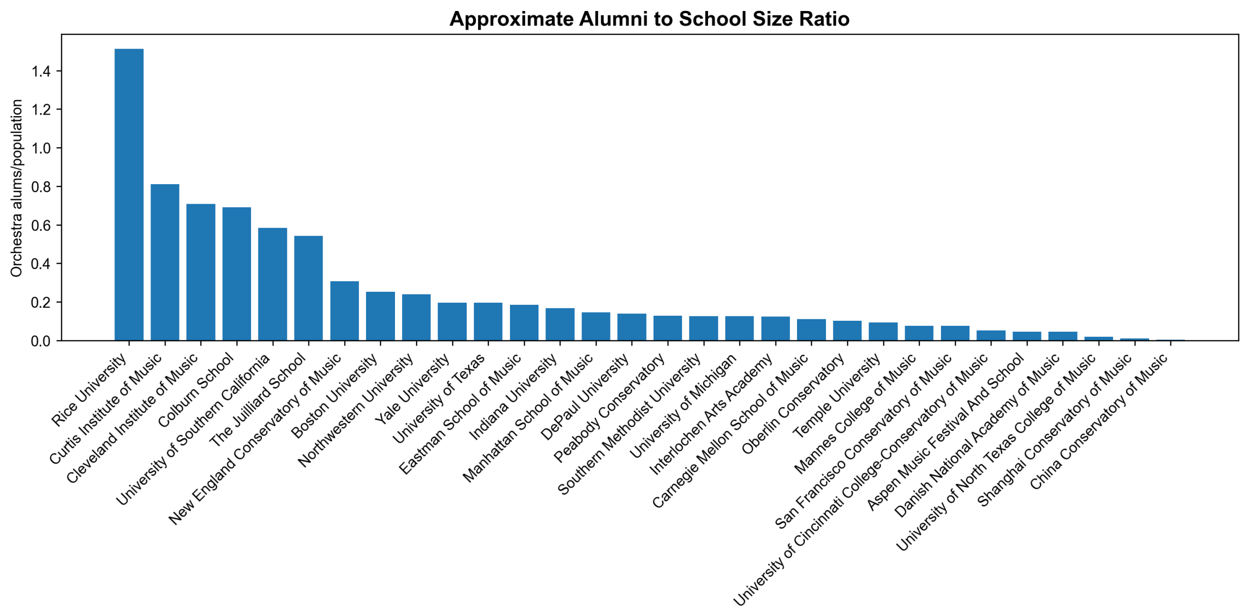

Figure 5: Approximate top 30 schools' normalized orchestra presence

The units of this chart are not immediately clear. This is not the proportion of alumni who hold an orchestra job or the number of jobs expected to be won by the current student population. Very precisely, for each school, this is the ratio of alumni holding orchestra jobs to the number of students currently studying music. Intuitively, this metric is a sort of jobs-per-capita for each school's student body. For example, these results support the claim "for every student studying music at Rice University, there are around 1.4 alumni currently making a living playing in an orchestra."

The order of the data changed noticeably after applying this normalization. Specifically, the following moves occurred:

School	**Pre**	**Post**	**Change**
The Juilliard School	1	6	↓ 5
Indiana University	2	13	↓ 11
Cleveland Institute of Music	3	3	–
Rice University	4	1	↑ 3
Curtis Institute of Music	5	2	↑ 3
New England Conservatory of Music	6	7	↓ 1
Eastman School of Music	7	12	↓ 5
Northwestern University	8	9	↓ 1
Manhattan School of Music	9	14	↓ 5
University of Southern California	10	5	↑ 5
Yale University	11	10	↑ 1
Oberlin Conservatory	12	21	↓ 9
University of Michigan	13	18	↓ 5
Peabody Conservatory	14	16	↓ 2
Colburn School	15	4	↑ 11
Boston University	16	8	↑ 8
University of Cincinnati College-Conservatory of Music	17	25	↓ 8
Interlochen Arts Academy	18	19	↓ 1
Temple University	19	22	↓ 3
San Francisco Conservatory of Music	20	24	↓ 4
University of Texas	21	11	↑ 10
Carnegie Mellon School of Music	22	20	↑ 2
DePaul University	23	15	↑ 8
Southern Methodist University	24	17	↑ 7
Shanghai Conservatory of Music	25	29	↓ 4
University of North Texas College of Music	26	28	↓ 2
Danish National Academy of Music	27	27	–
Aspen Music Festival And School	28	26	↑ 2
Mannes College of Music	29	23	↑ 6
China Conservatory of Music	30	30	–

Table 1: Change in approximate rank before and after size normalization

From the table, there are some significant moves once school size is taken into account–including both an upward and downward move by 11 places.

By statistical construction, the average move is 0 places. However, it is worth asking if some slices of the ranking move in particular ways. For example, do the top schools tend to move one way after accounting for school size while the bottom schools move another? A Mann-Whitney U test of comparing the change in medians of the top and bottom 15 schools yielded a p-value of 0.177. Since the p-value is greater than 0.05 by a firm margin, it suggests there is not a significant difference in rank change direction between the top and bottom 15 schools. In other words, rank change is likely unrelated to initial ranking.

We can also ask if the size of the school correlates with the change in rank–i.e. does quality of education change predictability based on school size. A linear regression between school position and change in position had a p value of 0.124, indicating that the result is not statically significant. This test shows school size is not a good predictor of rank change. Other factors–like faculty and resources per student–are more plausible drivers.

Due to the difficulty of finding high-fidelity data to normalize by school size, the rest of the analysis will use simple counts and percentages. However, if these data can be sourced in the future–in particular, data on audition participation by school–significantly stronger comparisons can be made.

Slicing by instrument

In general, music schools at the college level function not as a single body but as a collection of loosely connected studios. Because of this structure, the prestige of faculty, resource allocation, and emphasis on audition prep can vary significantly by instrument within the same school. Given these factors, an analysis of orchestra presence by instrument may be even more important than the global analysis above–especially to future students.

Positions in the orchestra can be divided into five instrument families: strings, woodwinds, brass, percussion, and other (where other is generally keyboardists, harpists, or specialty instrumentalists).[3]

As before, the count of orchestra alumni per school was calculated, now with the added dimension of instrument family:

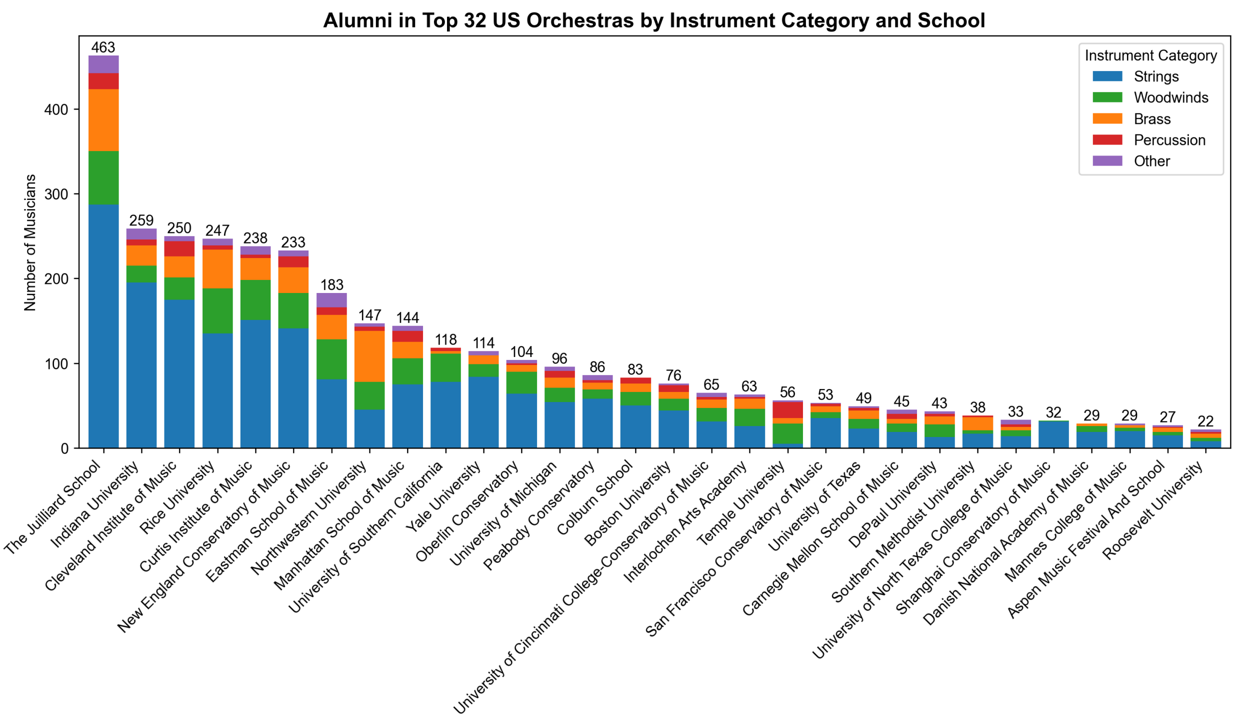

Figure 6: School presence split by instrument family

For a more precise view, it is helpful to calculate the percent distribution for each family separately:

[3]Though harp is a string instrument, its institutional role is much closer to the instruments in the "other" category than violin, viola, cello, and double bass, which make up the strings category.

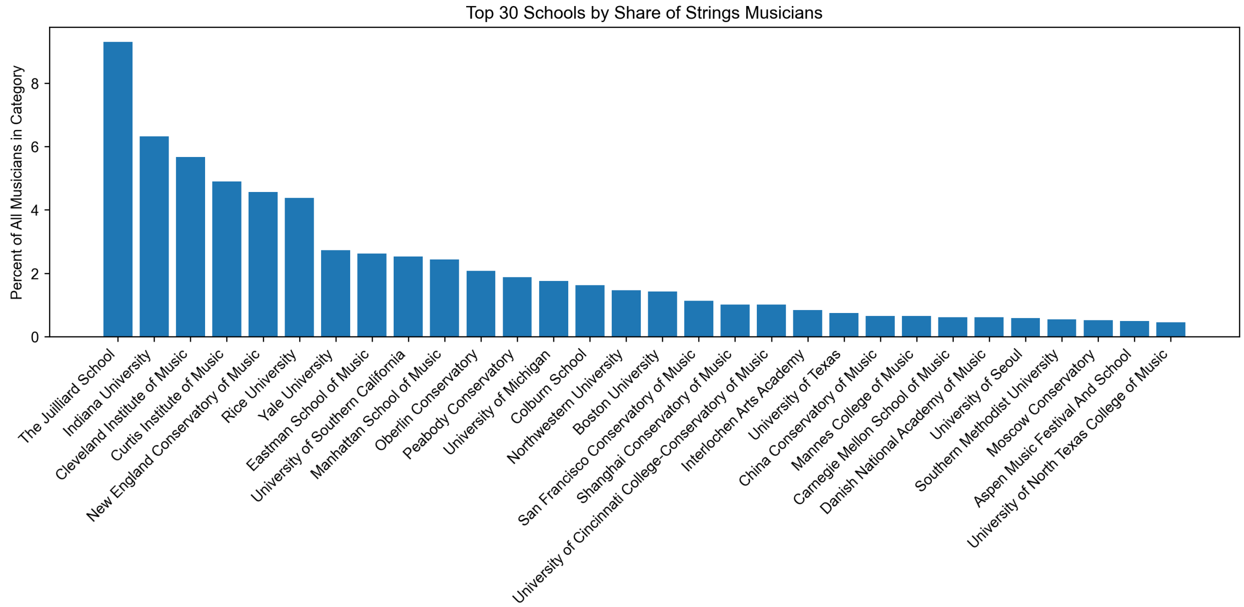

Figure 7: School presence for strings

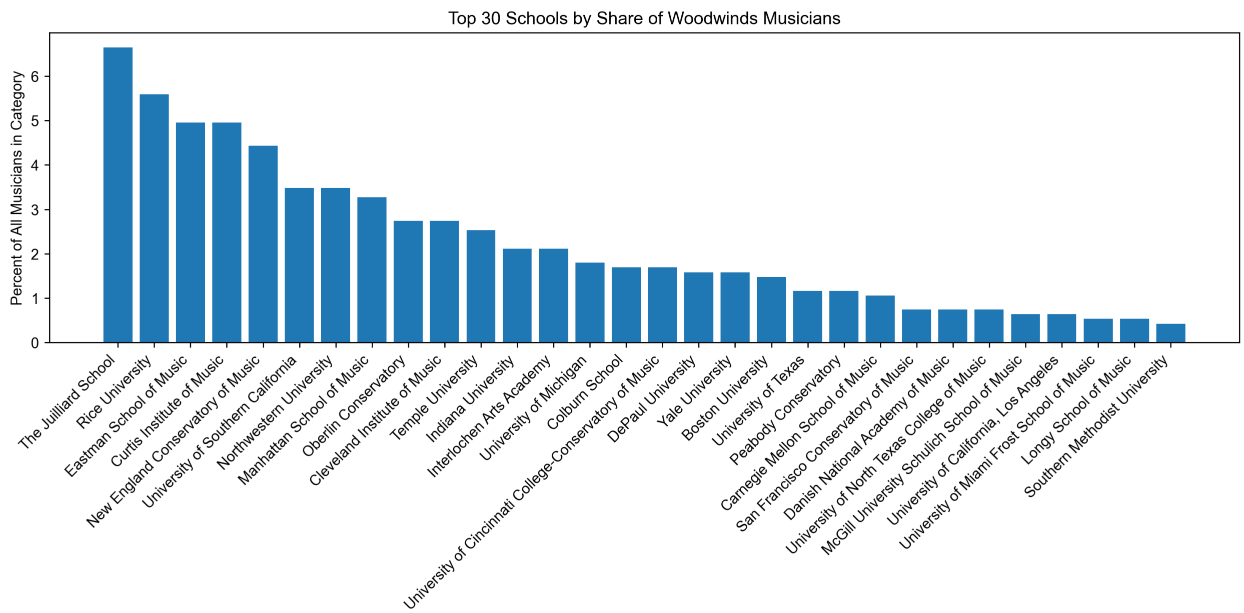

Figure 8: School presence for woodwinds

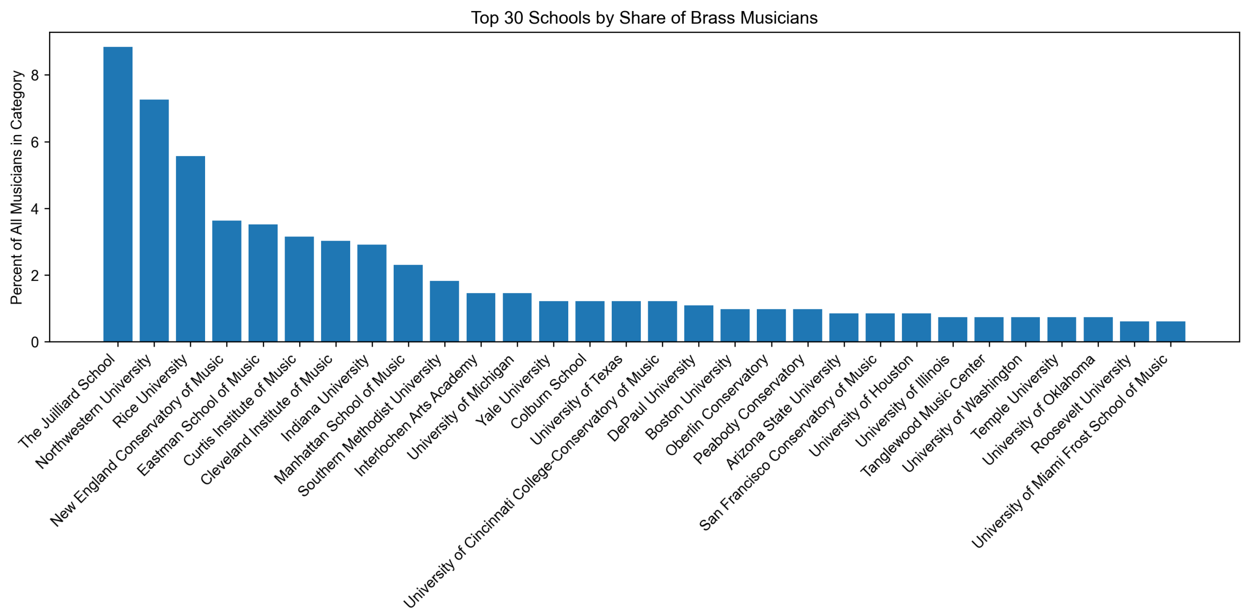

Figure 9: School presence for brass

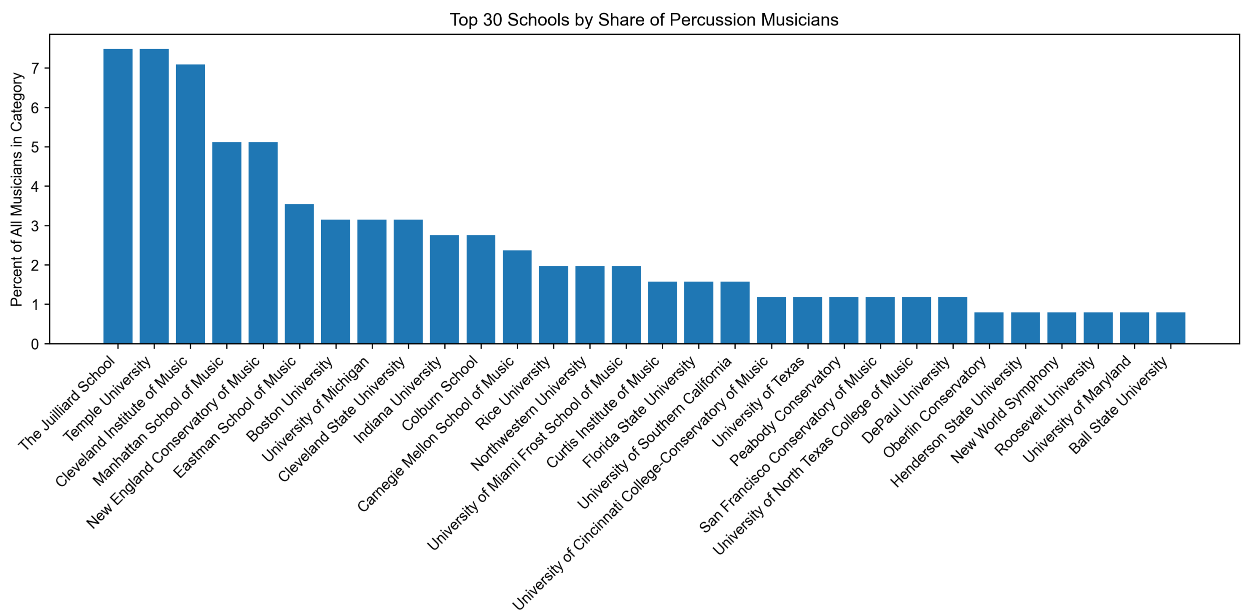

Figure 10: School presence for percussion

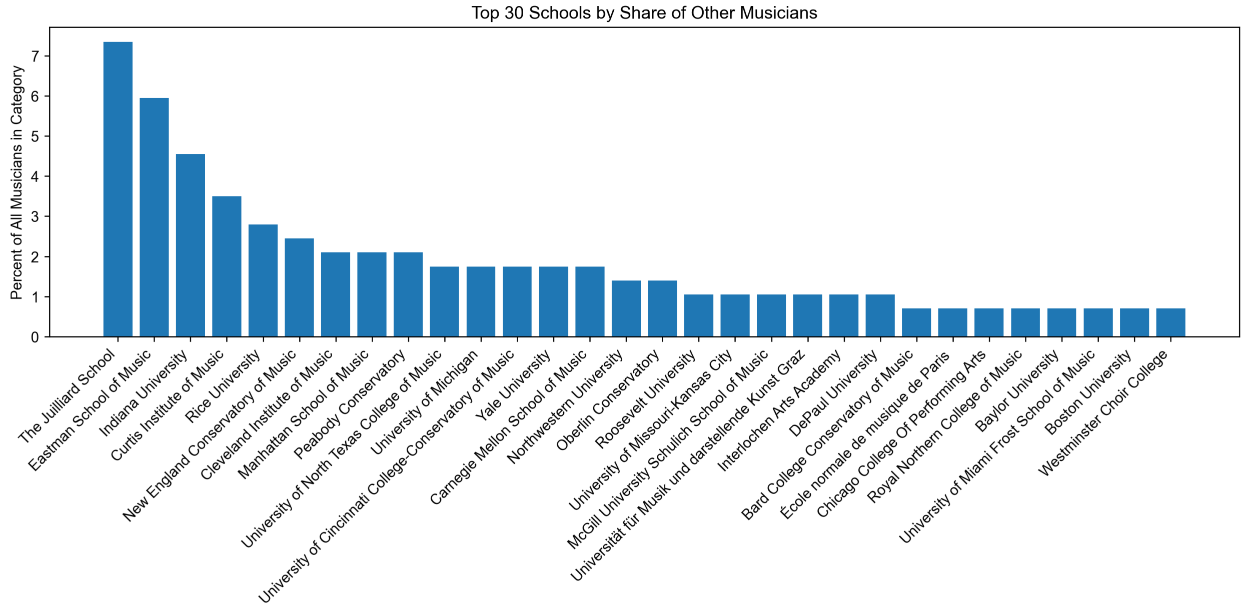

Figure 11: School presence for other instruments

At first, these results may seem paradoxical. For example, how can Juilliard have 20% presence overall, but never over 10% in each category? To resolve this, note that Juilliard is the only school to have the largest share of musicians in *every* category, causing its total share to exceed the average of its per-category share. Similarly, schools that place high in only one or two categories can place much lower overall, while others that place solidly–but not extraordinarily–in every category have a higher overall presence.

The above plots show evidence that some schools do specialize significantly. Some shares that are particularly notable–contrasting the overall rankings: Temple Univerity and The Manhattan School of Music are strong in percussion, Northwestern University has a strong brass program, and The Eastman School of Music is strong in woodwinds and miscellaneous instruments.

Given the studio structure of most music schools, the analysis should go to the instrument level. For this analysis, the top 5 feeder schools for each instrument were queried, along with the percentage of current performers for that instrument from that school:

		1st Place		2nd Place		3rd Place		4th Place		5th Place	
Instrument	Number	School	%	School	%	School	%	School	%	School	%
Bass Clarinet	18	NU	22.2	USC	22.2	DePaul	16.7	UM	11.1	IU	11.1
Bass Trombone	22	Juilliard	40.9	NEC	22.7	TMC	9.1	Rice	9.1	SMU	9.1
Bassoon	95	Rice	22.1	Juilliard	17.9	ESM	13.7	Curtis	12.6	USC	11.6
Cello	241	Juilliard	22.8	NEC	14.9	CIM	13.7	Curtis	13.3	IU	11.2
Clarinet	92	USC	16.3	NU	14.1	ESM	13.0	NEC	9.8	Yale	8.7
Double Bass	183	Rice	20.2	IU	16.9	Juilliard	15.8	Curtis	15.3	BU	8.7
Flute	91	MSM	14.3	Rice	14.3	ESM	13.2	Curtis	13.2	Juilliard	12.1
French Horn	140	Juilliard	19.3	Rice	17.9	NU	17.1	ESM	8.6	NEC	6.4
Oboe	103	Juilliard	27.2	NEC	15.5	Curtis	15.5	Oberlin	13.6	Rice	11.7
Percussion	93	Temple	18.3	Juilliard	18.3	CIM	17.2	MSM	12.9	NEC	12.9
Timpani	39	Juilliard	23.1	CIM	17.9	Temple	17.9	CSU	12.8	MSM	12.8
Trombone	68	Juilliard	25.0	NU	20.6	MSM	11.8	Curtis	10.3	NEC	10.3
Trumpet	92	NU	22.8	Juilliard	15.2	CIM	14.1	Rice	13.0	ESM	13.0
Tuba	30	Juilliard	23.3	U Houston	10.0	Rice	10.0	IU	10.0	Curtis	10.0
Viola	248	Juilliard	22.6	CIM	17.3	IU	12.9	Curtis	12.1	NEC	9.7
Violin	697	Juilliard	21.4	IU	14.9	CIM	12.9	Rice	9.9	NEC	9.8

Abbreviation key: BU: Boston University, CIM: Cleveland Institute of Music, CSU: Cleveland State University, Curtis: Curtis Institute of Music, DePaul: DePaul University, ESM: Eastman School of Music, IU: Indiana University, Juilliard: The Juilliard School, MSM: Manhattan School of Music, NEC: New England Conservatory of Music, NU: Northwestern University, Oberlin: Oberlin Conservatory, Rice: Rice University, SMU: Southern Methodist University, Temple: Temple University, TMC: Tanglewood Music Center, U Houston: University of Houston, UM: University of Michigan, USC: University of Southern California, Yale: Yale University

Table 2: Top school coverage by instrument among top orchestras

Here it is revealed that the rankings by instrument can vary significantly from the overall rankings of schools. Using a rough metric[4] where values close to 0 indicates significant rankings shifts and 1 indicates indicate few rankings shifts:

[4]These values are calculated using inverse Normalized Discounted Cumulative Gain (NDCG) for the top 5 rankings. The specifics of their mechanics are not important, since these values are not meant to have precise interpretations, but the method of calculation is borrowed from well-established techniques in recommendation algorithms.

Instrument	Ranking change
clarinet	0.36
flute	0.45
bass clarinet	0.47
percussion	0.56
trumpet	0.64
bassoon	0.65
double bass	0.66
bass trombone	0.85
trombone	0.86
tuba	0.87
oboe	0.88
timpani	0.88
french horn	0.90
cello	0.93
viola	0.97
violin	0.99

Table 3: School presence ranking change from overall rank to instrument rank

These results reveal that certain instruments–in particular clarinets and flutes–have pipelines that contrast with overall trends in school presence.

Slicing by orchestra

Finally, similar methods can be used to see how schools compose particular orchestras. The table below shows the cumulative percent of musicians in each orchestra who studied at the top five schools—Juilliard, Indiana University, Cleveland Institute of Music (CIM), Rice University, and The Curtis Institute of Music. Each row represents an orchestra, and the values indicate the running total percent of musicians educated at these schools:

Orchestra/Cumulative coverage	Juilliard	Indiana	CIM	Curtis	Rice
Alabama Symphony Orchestra	10	27	43	43	50
Arkansas Symphony	5	20	20	20	24
Atlanta Symphony Orchestra	13	31	45	50	55
Austin Symphony Orchestra	4	15	17	17	26
Baltimore Symphony Orchestra	24	32	39	47	55
Boston Symphony Orchestra	20	26	31	45	52
Buffalo Philharmonic Orchestra	25	36	52	57	59
Chicago Symphony Orchestra	23	29	35	43	46
Cincinnati Symphony Orchestra	19	28	41	42	47
Colorado Symphony	12	30	38	42	52
Dallas Symphony Orchestra	24	38	46	49	52
Detroit Symphony Orchestra	16	23	36	37	45
Houston Symphony	12	14	18	23	61
Indianapolis Symphony Orchestra	8	43	53	58	65
Kansas City Symphony	11	21	29	34	49
Los Angeles Philharmonic	23	29	35	41	48
Louisville Orchestra	8	29	46	50	50
Milwaukee Symphony	16	25	38	41	54
Minnesota Orchestra	22	34	44	53	66
Nashville Symphony	8	42	42	42	50
National Symphony Orchestra	19	30	40	50	60
New Jersey Symphony	49	51	53	60	60
New York Philharmonic	51	52	54	66	66
Oregon Symphony	9	17	29	32	39
Pittsburgh Symphony	24	30	41	52	53
Rochester Philharmonic Orchestra	21	26	38	39	42
San Francisco Symphony	31	36	40	44	49
Seattle Symphony	19	26	32	45	61
St. Louis Symphony Orchestra	20	37	45	53	64
The Cleveland Orchestra	21	26	58	67	71
The Philadelphia Orchestra	24	29	33	69	72
Utah Symphony	13	27	35	38	42
Average %	**18.9**	**29.9**	**38.9**	**46.7**	**52.7**

Table 4: Cumulative coverage of top 5 schools in each orchestra

From the top 5 column of this table, an average orchestra sees 52.7% of its members come from a top 5 school[5]. Interestingly, this proportion varies significantly from orchestra to orchestra, with the minimum top 5 coverage being 24% and the maximum being 72%.

It is also helpful to explore school diversity within each orchestra. Intuitively, we can find the probability that two randomly chosen members of an orchestra share at least one Alma matter. This will be called "school similarity." Ordering by this metric, it is illustrative to see the top 3 prevalent schools for each orchestra–in contrast to the top overall schools shown above:

[5] These averages differ from the percentages given for these same schools earlier due to a subtle difference in calculation. Previously, percent coverage was calculated per musician, while this new table is calculated per orchestra. As a result, the weight of school presence in small orchestras is inflated and the weight of school presence in deflated–since each orchestra has the same contribution to this average regardless of size.

Orchestra	**Sim**	**Sch 1**	**%**	**Sch 2**	**%**	**Sch 3**	**%**
New York Philharmonic	0.355	Juilliard	51	MSM	23	Curtis	20
Rochester Philharmonic Orchestra	0.344	ESM	53	Juilliard	21	CIM	14
The Philadelphia Orchestra	0.320	Curtis	49	Juilliard	24	Temple	17
New Jersey Symphony	0.290	Juilliard	49	MSM	19	Curtis	11
Houston Symphony	0.279	Rice	48	NU	13	Juilliard	12
The Cleveland Orchestra	0.269	CIM	43	Juilliard	21	Curtis	12
Boston Symphony Orchestra	0.243	NEC	34	BU	23	Juilliard	20
Los Angeles Philharmonic	0.202	USC	33	Juilliard	23	NEC	12
Austin Symphony Orchestra	0.189	U Texas	39	IU	11	U Houston	9
San Francisco Symphony	0.184	Juilliard	30	SFC	17	NEC	17
Indianapolis Symphony Orchestra	0.180	IU	35	NU	11	Rice	10
St. Louis Symphony Orchestra	0.174	Rice	20	Juilliard	20	IU	18
Minnesota Orchestra	0.158	Juilliard	22	Rice	18	Curtis	14
Pittsburgh Symphony	0.150	Juilliard	24	Curtis	17	CIM	11
Seattle Symphony	0.146	Rice	20	Juilliard	19	Curtis	14
Dallas Symphony Orchestra	0.145	Juilliard	24	IU	18	SMU	12
Louisville Orchestra	0.145	U Louisville	25	IU	25	CIM	17
Buffalo Philharmonic Orchestra	0.145	Juilliard	25	CIM	16	NEC	14
Baltimore Symphony Orchestra	0.144	Juilliard	24	NEC	13	Peabody	13
Detroit Symphony Orchestra	0.146	Rice	19	Juilliard	16	UM	15
National Symphony Orchestra	0.139	Juilliard	19	Rice	13	CIM	13
Nashville Symphony	0.136	IU	33	UM	17	Rice	17
Cincinnati Symphony Orchestra	0.134	CCM	22	Juilliard	19	CIM	14
Chicago Symphony Orchestra	0.128	Juilliard	23	Roosevelt	11	DePaul	11
Milwaukee Symphony	0.124	Juilliard	16	Rice	14	CIM	14
Colorado Symphony	0.122	IU	20	Rice	12	Juilliard	12
Utah Symphony	0.122	NEC	17	ESM	14	IU	14
Atlanta Symphony Orchestra	0.119	IU	19	CIM	18	Juilliard	13
Kansas City Symphony	0.101	Rice	18	Juilliard	11	IU	10
Oregon Symphony	0.093	NEC	15	CIM	12	ESM	11
Alabama Symphony Orchestra	0.092	CIM	17	IU	17	USC	10
Arkansas Symphony	0.055	IU	15	UM	10	CCM	7
Average	**0.174**		**28.1**		**16.8**		**13.4**

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Table 5: Top 3 most represented schools in each orchestra and their relative shares

The school similarity metric shows a wide range over all the orchestras. For the question, "what's the probability two randomly selected members share an Alma matter," the odds are three times higher in the first four orchestras than the last four. At the extremes, the highest probability is a 35.5% chance, which is over six times higher than the lowest probability at 5.5%. On average, this probability settles at 17.4% odds. This probability is 11% lower than the average coverage of an orchestra's most prevalent school. This is likely because– even though a few schools' alumni tend to hold most positions in an orchestra–the rest of the orchestra typically comes from a much wider mix of schools. This variety lowers the overall chance that any two members went to the same school, even if some schools are especially well represented.

Looking to the averages for each orchestra's top three schools, all three averages are higher than the top three school coverages overall. For example, the average coverage for an orchestra's most prevalent school is 8.6% higher than the overall top school's coverage (Juilliard). These increases are 5.7% and 2.5% for the second and third top schools. These increases demonstrate that each orchestra has its own, somewhat unique feeder schools. This conclusion is supported further by the average cumulative coverage for each orchestra's top three feeder schools: 51.8%. Recall that the cumulative coverage of the top three overall schools was only 39.7%, so this 18.4% change represents a significant increase. This result is strong evidence that orchestras have notably unique feeder schools and that these unique preferences are a much stronger force than overall rankings.

Slicing by orchestra, inverted

If orchestras seem to have preferences for schools, a natural final question is whether schools have preferences for orchestras. Below, the same analysis from the previous table is flipped:

School	Sim	Orch 1	%	Orch 2	%	Orch 3	%
University of Texas	0.152	AUS	37.5	DAL	8.3	KC	8.3
Southern Methodist University	0.127	DAL	34.2	AUS	7.9	MIL	7.9
University of North Texas College of Music	0.108	DAL	29.0	KC	16.1	AUS	9.7
Boston University	0.098	BOS	28.9	PHI	7.9	DAL	5.3
Temple University	0.095	PHI	28.6	PIT	8.9	HOU	7.1
Danish National Academy of Music	0.094	NYP	27.6	KC	13.8	CLE	6.9
University of Cincinnati College	0.089	CIN	27.0	BUF	6.3	DAL	6.3
University of Southern California	0.088	LAP	25.6	CIN	6.8	DET	6.0
San Francisco Conservatory of Music	0.078	SFS	24.5	UTA	11.3	ORE	5.7
Curtis Institute of Music	0.069	PHI	20.0	NYP	8.1	BOS	6.4
Aspen Music Festival And School	0.066	NYP	18.5	PHI	14.8	ATL	7.4
Mannes College of Music	0.063	NYP	14.8	PHI	14.8	CHI	11.1
Eastman School of Music	0.063	ROC	20.0	UTA	5.7	CLE	4.6
Carnegie Mellon School of Music	0.059	PIT	20.5	ORE	9.1	BAL	6.8
DePaul University	0.055	CHI	21.4	ALB	4.8	ARK	4.8
Rice University	0.054	HOU	15.4	MIN	6.6	SEA	6.2
Cleveland Institute of Music	0.050	CLE	15.8	ATL	6.1	CIN	4.5
New England Conservatory of Music	0.049	BOS	14.3	SFS	5.7	STL	5.7
Manhattan School of Music	0.049	NYP	15.8	NJS	7.2	UTA	5.8
Peabody Conservatory	0.045	NSO	13.3	BAL	12.0	ORE	6.0
Colburn School	0.043	LAP	12.0	SEA	9.6	BAL	6.0
The Juilliard School	0.043	NYP	10.6	NJS	5.6	DAL	5.4
University of Michigan	0.040	DET	12.0	MIL	7.6	COL	6.5
Indiana University	0.040	IND	10.0	DAL	7.6	ATL	6.4
Shanghai Conservatory of Music	0.038	CHI	12.5	DET	12.5	LAP	9.4
Oberlin Conservatory	0.037	CLE	9.0	KC	7.0	MIN	7.0
Northwestern University	0.037	HOU	6.9	MIN	6.9	SFS	6.2
Yale University	0.036	SEA	8.3	MIN	7.4	DAL	6.5
Interlochen Arts Academy	0.031	DET	8.1	NYP	8.1	CLE	6.5
China Conservatory of Music	0.030	NYP	13.6	BAL	9.1	HOU	9.1
Average	**0.064**		**18.5**		**8.8**		**6.7**

Orchestra Abbreviations: ALB: Alabama Symphony, AUS: Austin Symphony, ATL: Atlanta Symphony, BAL: Baltimore Symphony, BOS: Boston Symphony, BUF: Buffalo Philharmonic, CHI: Chicago Symphony, CIN: Cincinnati Symphony, CLE: Cleveland Orchestra, COL: Colorado Symphony, DAL: Dallas Symphony, DET: Detroit Symphony, HOU: Houston Symphony, IND: Indianapolis Symphony, KC: Kansas City Symphony, LAP: Los Angeles Philharmonic, MIL: Milwaukee Symphony, MIN: Minnesota Orchestra, NJS: New Jersey Symphony, NSO: National Symphony Orchestra, NYP: New York Philharmonic, ORE: Oregon Symphony, PHI: Philadelphia Orchestra, PIT: Pittsburgh Symphony, ROC: Rochester Philharmonic, SEA: Seattle Symphony, SFS: San Francisco Symphony, STL: St. Louis Symphony, UTA: Utah Symphony

Table 6: Top 3 most represented orchestras per school and their working alumni shares

When interpreting these results, it is crucial to remember that this study's data only represents musicians who currently hold orchestra jobs. For example, it is incorrect to say "38% of University of Texas alumni play in the Austin Symphony," but we can say "38% of US orchestra musicians who studied at the University of Texas play in the Austin Symphony."

Immediately, these values are all much lower than the by-orchestra version of this table. Indeed, the average similarity by orchestras is almost three times higher than the average similarity by school. Similar decreases are seen for the average share across all three top slots.

Interestingly–though the scale of the values is different–the underlying distribution of similarities is actually quite similar. If the results from the per school table are scaled up by a factor of 2.89

(the average factor difference of the two similarity columns), we find:

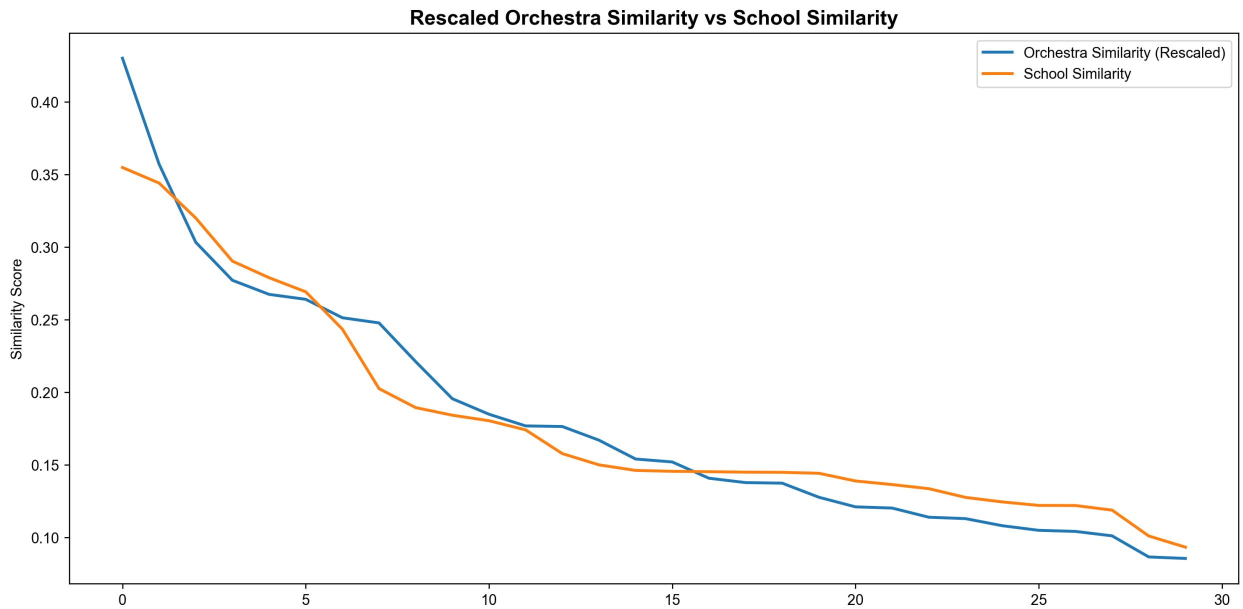

Figure 12: Similarity distribution comparison

These curves have very similar shapes, implying that the forces that cause the distributions to emerge are likely similar–though the magnitude of the effect is different.

Overall, this table demonstrates that the proportions of a school's alumni who work in the same orchestra tend to be smaller than the proportion of orchestra members who attended the same school (though there are a few notable exceptions in Texas).

Discussion

This study offers the first large-scale empirical confirmation of a long-assumed but rarely quantified dynamic: a small number of elite conservatories dominate the pipelines to professional orchestras in the United States. The analysis of over 2,288 musicians from 32 top orchestras revealed several key patterns.

Hyper-Concentration of Opportunity

One of the most striking findings is that nearly half (47%) of the musicians in the data studied at one of just four schools: Juilliard, Indiana University, Cleveland Institute of Music, and Curtis Institute of Music. This concentration is so intense that by the 30th most common school, alumni presence drops by a factor of 20 relative to Juilliard. The same trend causes more than 90% of orchestra jobs to be claimed by graduates of the top 26 schools. This level of skew would be considered extraordinary in nearly any professional field. Whether it is a result of talent selection, superior training, network access, or prestige, this pronounced skew demands careful consideration regarding equity and access in music education.

Normalization Complicates the Story

When adjusting for estimated music student populations, the ranking of alumni per school changes significantly. Conversely, smaller institutions like Curtis, with fewer than 200 students, emerge as exceptionally efficient pipelines, boasting more than one working alum for every current student. However, even after size normalization, the top schools largely retain their positions—a signal that volume alone does not account for dominance.

Notably, statistical testing showed no significant difference in rank shifts between the top and bottom halfs of the top 30 schools. This suggests that the schools with the best raw rankings are not, as a group, overstated in their positions. Similarly, the lower half of the top-tier schools is not, as a group, understated in their positions.

A test was run to see if changes in rank before and after normalization was driven by school size–potentially indicating bigger is better or David beats Goliath in music school–, but no statistically significant results were found. This lack of relationship is evidence that other factors, like the quality of faculty and emphasis on audition prep, drive outcomes more than school size alone.

Studio Specialization Matters

At a finer scale, this study confirms what many in music education anecdotally believe: Sometimes the studio matters more than school. When slicing by instrument family, schools often rise or fall significantly in the rankings. At the instrument level, some instruments have an individual top five that is far different from the overall rankings. This implies that prospective students should consider each school's track record for their instrument family and even their specific instrument.

Tailored Pipelines

Finally, the slicing by orchestra reveals unique hiring preferences for each ensemble. Despite the dominance of a few elite institutions overall, many orchestras favor particular schools more heavily than national trends suggest. However, these trend varies massively. While some orchestras have over 70% of their members come from the top five ranked schools, in others that share is below 30%. Interestingly, this preference is asymmetric, causing orchestras have stronger affinities for specific schools than schools do for specific orchestras.

Limitations

Though the results of this analysis likely capture broad trends in school-to-orchestra pipelines accurately, a few limitations should be considered. First and foremost, all of the raw data used in this study was originally presented as natural language. Even with state-of-the-art data cleaning techniques, it is difficult to achieve 100% accuracy when extracting facts from natural language. In particular, this introduces two sources of error into the statistical analysis.

The first source of error is under and overpulling of keywords. For example, a biography is under-pulled if the web scraper and data processing did not capture every time the biography mentioned a performer's Alma mater. Underpulls most frequently result in a school or missing from a performer's profile in the dataset. Overpulling is the opposite, and usually occurs when a school or instrument is mentioned in a bio, but the performer did not attend that school or does not play that instrument in their current position.

Though it may be impossible to check and correct all underpulls and overpulls at this scale, anecdotal checks of the data show that they are not common in the dataset. A specific error rate is impossible to calculate, but it seems reasonable that the number of errors is small enough that the overall statistical patterns are accurate.

The second source of error for this analysis is errors in canonization. Some variations of the names of schools likely exist that were not correctly merged into a single entity. However, unlike the data pulling errors, we can make specific claims about how these errors impact the analysis. The layered canonization technique tends to underfit–not merge name variants when it should have–than overfit–merge separate institutions with similar names. This property can be leveraged to claim that if errors from canonization exist, they almost certainly cause percentage values to be slightly too small throughout the analysis.

Since these challenges are known and the Dynamic Ties community has been asked to help remedy them when they are noticed, the dataset will become more accurate with time. For reference purposes, a snapshot of the data as of 2025/05/28 has been preserved and is available upon request.

Future Work

Along with the insights these techniques revealed, the analysis has sparked even more avenues for further investigation. Without any additional data, a geographic perspective could also be formed. By noting the locations of each school and orchestra, patterns of migration can be charted. Geographic proximity may explain why some orchestras seem to prefer certain schools, but other pipelines are more mysterious–like Rice University to The Seattle Symphony and Indiana University to The Atlanta Symphony Orchestra. Related factors like city size and cost of living could also provide insight into why people move where.

In addition to the data used in this study, two more data points are ripe for their own exploration. First is the data on what year each musician joined their current orchestra. Though survivorship bias will have to be carefully considered, applying the techniques from this analysis with a longitudinal perspective can reveal fascinating trends. Second, in addition to where they studied the data for who each musician studied with was also recorded. Though this canonization challenge will be extremely difficult with current tools, analysis with teachers included would allow for rich and informative results.

Overall, the results of this analysis show that the information in the Dynamic Ties dataset can illuminate nuanced and pertinent patterns in the world of classical orchestras.

Appendix A: School Canonization Approach

The overall approach to creating a layered canonization was as follows:

1. Pull all music schools from Wikipedia's "List of university and college schools of music"

2. Set Wikipedia list as the base canon, i.e. the initial set of ground truth schools

3. For each school in the base canon, generate a list of other names that the school is known by

4. Iterate over all schools in the musician's bios, try to match them with either a name in the base cannon or the layer of nicknames. If a nickname matches, map it to the matching name in the base cannon. If a name in a bio is sufficiently different than all names in the base cannon and nickname layer, add it to the cannon as a new name.

Step 1 was achieved using simple web scraping techniques via Python's Beautiful Soup library. For Step 2, the list from the Wikipedia page was pared down to only schools which actually appeared in some form in the data to reduce computational load. This reduction was achieved by requiring each school in the base cannon to share at least one word with any musician's list of raw school names from the biographies–minus filler words like "the" and "of".

Step 3 was accomplished by sending API LLM calls to Google Gemini with the following instruction: {"List up to 4 variants that people use to refer to 'name'. Prioritize an instance of the school name with department, e.g. BOTH 'Northwestern Bienen school of music' and 'Bienen School of Music' from the initial name Northwestern University. Don't repeat the original name exactly. Return only a plain list of strings. Do not include contexts or asides, just purely the list of names. No elements should be parenthetical. Do not include variations which are clearly not unique to the school in question, e.g. 'the college'"}. The list of alternate names were then mapped to their matching names in the base canon.

Step 4 involved iterating over each school name mentioned in each musician's biography. For each of these raw name texts, the maximum similarity among all words in the base cannon and nickname layer was calculated using Term Frequency-Inverse Document Frequency (TF-IDF) and cosine similarity. If the maximum similarity exceeded a threshold, the natural text was matched to that entry in the canon (or the corresponding base canon word if the best match was to a nickname). If no match exceeded the similarity threshold, the original raw text was stored as the final result.

The result is not 100% accurate, and even a perfect canon will have ambiguous or arguable cases. For example, is The Juilliard School the same entity as Juilliard Pre-College? Despite the imperfect nature of canonization for large data, these methods have created a significantly realistic taxonomy of music schools–certainly accurate enough to observe and discuss the large-scale patterns discussed in the analysis.

Appendix B: School Size Approximations

School Name	Population	Method Used	URL(s)
Aspen Music Festival And School	600	Estimate based on available data	`https://www.aspenmusicfestival.com/about/fast-facts`
Boston University	300	Estimate based on available data	`https://www.bu.edu/cfa/music/`
Carnegie Mellon School of Music	250	Estimate based on available data	`https://www.cmu.edu/cfa/music/`
China Conservatory of Music	5000	Estimate based on available data	N/A
Cleveland Institute of Music	350	Official reported value	`https://www.cim.edu/aboutcim`
Colburn School	120	Official reported value	`https://www.colburnschool.edu/`
Curtis Institute of Music	160	Official reported value	`https://www.curtis.edu/about/`
Danish National Academy of Music	650	Estimate based on available data	N/A
DePaul University	300	Estimate based on available data	`https://music.depaul.edu/`

Eastman School of Music	950	Estimate based on available data	https://www.esm.rochester.edu/admissions/
Indiana University	1500	Estimate based on available data	https://music.indiana.edu/index.html
Interlochen Arts Academy	500	Estimate based on available data	https://www.interlochen.org/academy
Manhattan School of Music	950	Estimate based on available data	https://www.msmnyc.edu/admissions/
Mannes College of Music	350	Estimate based on available data	https://www.newschool.edu/mannes/admission/mannes-school-music-admission/
New England Conservatory of Music	750	Estimate based on available data	https://necmusic.edu/admissions
Northwestern University	600	Estimate based on available data	https://music.northwestern.edu/
Oberlin Conservatory	580	Estimate based on available data	https://www.oberlin.edu/conservatory
Peabody Conservatory	650	Estimate based on available data	https://peabody.jhu.edu/admissions/
Rice University	290	Estimate based on available data	https://music.rice.edu/
San Francisco Conservatory of Music	400	Estimate based on available data	https://sfcm.edu/admissions
Shanghai Conservatory of Music	3000	Estimate based on available data	N/A
Southern Methodist University	300	Estimate based on available data	https://www.smu.edu/Meadows
Temple University	600	Estimate based on available data	https://boyer.temple.edu/
The Juilliard School	850	Estimate based on available data	https://www.juilliard.edu/admissions
University of Cincinnati College-Conservatory of Music	1200	Estimate based on available data	https://ccm.uc.edu/admissions.html
University of Michigan	750	Estimate based on available data	https://smtd.umich.edu/admissions/
University of North Texas College of Music	1600	Estimate based on available data	https://music.unt.edu/
University of Southern California	1000	Estimate based on available data	https://music.usc.edu/
University of Texas	700	Estimate based on available data	https://music.utexas.edu/
Yale University	200	Estimate based on available data	https://music.yale.edu/