Supplementary Information

Methods

Participants

Two additional control groups of participants on suburban US college campuses participated in the same experiment, except that instead of reporting stories they imagined when listening to the 60-s music excerpts, they reported imagined stories during 60-s periods of silence. Twenty participants (n = 12, female) were from Princeton University, ages 18 – 23 years (M = 19.5, SD = 1.5); 40% reported no formal music training, while the remaining 60% reported between 1 and 13 years of music training (M = 9.0, SD = 3.6). Fifty-six participants (n = 44, female) were from Michigan State University, ages 18 – 26 years (M = 19, SD = 1.41); 36% reported no formal music training, while the remaining 64% of participants reported between 1 and 13 years of music training (M = 5.9, SD = 3.4). Due to circumstances surrounding the pandemic, we were not able to obtain data from a control group for the Dimen participants; however, we were able to address this lack by testing our hypotheses against other types of nulls that are standard in machine learning research, as described in the main methods.

Materials

To consider the possibility that listeners had any a priori explicit associations between the selected excerpts and specific films and/or TV shows, we conducted a media search. The results of the search revealed that none of the selected excerpts had been used in any recent mainstream film or TV show. Two excerpts were found to have been used in videos that participants were unlikely to have seen. One Glass excerpt is from a score commissioned by Universal for the 1999 DVD release of the 1931 film Dracula. The music was available on DVD (the viewer could choose to watch it with or without the new score) and on special performances at concert halls where a quartet accompanied the screening, but not in national distribution to movie theaters. The Grofé excerpt is from a score for a 1958 Disney short featuring footage of the Grand Canyon with no story or dialogue. Stories for the Glass excerpt in Arkansas and Michigan centered on a chase to catch someone who had committed a crime. Stories for the Grofé excerpt featured a sunrise over a forest or meadow with animals beginning to stir and birds beginning to chirp, hardly the stark, animal-less footage accompanying the clip in the Grand Canyon film. No participants mentioned Dracula, vampires, or the Grand Canyon in response to either excerpt, and a small survey of students on a US college campus found that no respondents (0 out of 8) had seen either movie.

Data Analysis

We used the Scikit-learn implementation of TF-IDF with default parameters (e.g., norm = l2; smooth_idf = True; Sublinear_tf = False; Use_idf = True; package version 0.21.3). Term frequency, $tf(t,d)$, was defined as the number of times that term *t* occurs in nardoc d. Inverse document frequency, $idf(t,D)$, was defined as

$$\mathrm{idf}(t,D) = \log\left(\frac{N+1}{|\{d \in D : t \in d\}| + 1}\right) + 1$$

were N is the total number of nardocs $N = |D|$ and $|\{d \in D : t \in d\}|$ is the number of nardocs where the term *t* appears. TF-IDF was calculated as

$$tfidf(t,d,D) = tf(t,d) \cdot idf(t,D)$$

Overall, our corpus of nardocs roughly complied with Zipf's law: the frequency that a word appeared was inversely proportional to its rank (see Figure S1a). However, the frequency distribution of low rank words demonstrated greater deviation from Zipf's law (i.e., we found fewer high frequency words than predicted). The root mean squared error (RMSE) for the 100 most frequent words was 2.75 times greater than the RMSE for the rest of the distribution (RMSE

= 0.516 and 0.189, respectively). After removal of common stop words as well as task and stimulus related words (see Table S6) the frequency distribution of low rank words further deviated from Zipf's law (see Figure S1b). The root mean squared error (RMSE) for 100 most frequent words was 5.45 times greater than the RMSE for the rest of the distribution (RMSE = 0.848 and 0.156, respectively).

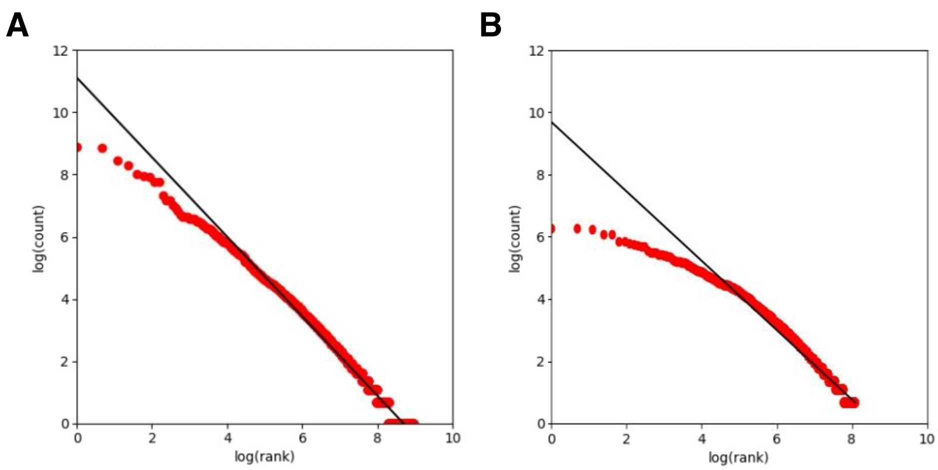

Figure S1: Term frequency-rank distributions for nardocs (A) prior to removal of stop, task, and stimulus words and (B) after text preprocessing. Solid black lines correspond to the predicted values generated by a linear model using log(rank) to predict log(frequency).

While the logarithmic variant is useful in that it helps to dampen the importance of high frequency words, our corpus of nardocs contains only a fraction of the number of words used in typical text categorization and information retrieval applications of TF-IDF (e.g., 3,208 unique words and 47,636 total words after preprocessing compared to hundreds of thousands or millions (1, 2, 3). Indeed, the most frequent words across nardocs occur 528 ("make"), 526 ("man"), and 517 ("dance") times. Because we only retain words related to the content of imagined stories, the low rank (high frequency) words are of direct interest and we did not want to dampen their influence on nardoc similarities. As a result, we chose not to use the logarithmic variant when calculating term frequency.

Results

Sample Size Considerations

One question that emerges is whether the larger sample size (and thus greater nardoc length) for the Arkansas group compared to Dimen group could have impacted the results. Although the Arkansas nardocs are longer than the Dimen nardocs due to the difference in sample size, the Michigan and Dimen samples are very close to the same size (resulting in similar length nardocs); see Table S1. Given that the pattern of results comparing the Michigan vs. Dimen nardocs is the same as the Arkansas vs. Dimen comparison, combined with the observation that we do not observe differences for the Arkansas vs. Michigan comparison, it seems unlikely that differences in nardoc length is contributing to the results in any meaningful way. However, to more directly determine whether the larger number of participants in Arkansas (greater nardocs length) may still have been a significant contributing factor to our results, we re-ran the analysis using a randomly selected subset of Arkansas subjects such that the sample size was matched between the Arkansas and Dimen groups (147 subjects in each). To do this, the subject IDs of the Arkansas group were shuffled into a random order and only the data from the first 147 subjects on this list were included in the analysis. This random sample yielded median cosine similarity values that were similar to those for the full sample for the Arkansas-Michigan comparison (Reduced sample, Mdn = 0.305; Full sample, Mdn = 0.359) and for the Arkansas-Dimen comparison (Reduced sample, Mdn = 0.129; Full sample, Mdn = 0.169). Additional random samples (n = 4) that matched the number of listeners in the Arkansas and Dimen all produce similar median cosine similarity values to those for the full sample (Arkansas-Michigan, $M = 0.30$, $SD = 0.01$; Arkansas-Dimen, $M = 0.13$, $SD = 0.01$).

Effects of Age

Dimen participants were older, on average, than the Arkansas and Michigan participants. To consider whether this might explain the cross-cultural dissimilarity in the imagined stories, we conducted several additional analyses (see Table S4). First, we performed a median split on age for the Dimen group and reran the analyses comparing narrative similarity of the same excerpts across locations using only the participants from the younger half to better match the two US samples. Cosine similarity values were not significantly different for just the younger half of Dimen participants compared to the full (original) sample for either the Arkansas-Dimen comparison, $t(31) = -1.03$, $p = 0.31$, or the Michigan-Dimen, $t(31) = -0.99$, $p = 0.33$. Moreover, estimated cosine similarity values were slightly lower, not higher, when considering just the younger half of Dimen participants. We further examined potential age effects using two additional thresholds, considering only Dimen participants younger than 40 and participants younger than 30, similarly left the results unchanged (see Table S4 for median cosine similarity values with inter-quartile range for the different age groupings). Finally, we considered whether there may have been a relationship between age and quantitative measures of narrative listening. The age of Dimen participants was not correlated with the likelihood that they imagined stories in response to the musical excerpts (Western, $r = -0.10$, $p = 0.22$; Chinese, $r = -0.06$, $p = 0.47$), their overall narrative engagement (Western, $r = -0.10$, $p = 0.21$; Chinese, $r = -0.10$, $p = 0.24$), or their familiarity with the excerpts (Western, $r = -0.01$, $p = 0.94$; Chinese, $r = 0.05$, $p = 0.55$). The lack of difference in cosine similarity of the nardocs for the same-excepts comparisons when considering only the younger Dimen participants in comparison to the two US samples, combined with the lack of correlation between age and narrativity, narrative engagement and familiarity for the Dimen participants, suggests that it is very unlikely that the cross-cultural differences reported in the paper are driven by age differences in the samples.

Effects of Media Exposure

In general, Dimen participants had very little exposure to Western media. 63% of participants reported no exposure to Western media, while the remaining 37% of participants reported some exposure. To order to consider the possibility that some Western media exposure could have impacted the similarity of Dimen generated stories in the cross-cultural comparison to the Arkansas and Michigan generated stories, we separately calculated the cosine similarity values for the Arkansas-Dimen and Michigan-Dimen comparisons for Dimen listeners who reported no Western media exposure and those that reported some Western media exposure. A Media Exposure (No Western Media vs. Some Western Media) x Type of Comparison (Arkansas-Dimen vs. Michigan-Dimen) x Type of Excerpt (Western vs. Chinese) ANOVA on similarity values revealed no effect of Media Exposure, $F(1,120) = 1.86$, $p = 0.18$, no effect of Type of Comparison, $F(1,120) = 2.45$, $p = 0.12$, no effect of Type of Excerpt, $F(1,120) = 2.29$, $p = 0.13$, and no interactions (all p's > 0.80). Thus, the minimal amounts of Western media exposure that some of the Dimen participants reported did not increase the similarity of the Dimen listener stories to either the Arkansas or Michigan listeners stories generated in response to either the Western or Chinese musical excerpts.

Sentiment Analysis

Despite the lack of shared semantic content across cultures there may still have been some more general commonality across cultures in the generated stories. To begin to address this, we considered whether there might be shared sentiment despite divergent semantic content. To consider this possibility, we had a set of three independent judges rate the sentiment of each of the produced narratives by each participant in all three locations, with the raters blind (1) to the excerpt and (2) to the geographical location of the participant who generated the narrative. Sentiment ratings were on a 7-point scale (1 – very negative, 2 – negative, 3 – somewhat negative, 4 – neutral/mixed, 5 – somewhat positive, 6 – positive, 7 – very positive). The intra-class-correlation (ICC) coefficient for three independent judges' ratings of narrative sentiment was very high (Cronbach's alpha = 0.87). We then correlated the average by-excerpt ratings across pairs of locations, calculated separately for Western and Chinese music excerpts in order to consider the possibility that sentiment might be shared for one Music Tradition, but not the other depending on the pairs of locations being compared. As expected, the within-culture Arkansas-Michigan sentiment ratings were highly correlated for both Western excerpts ($r = 0.85$, $p < 0.001$) and Chinese excerpts ($r = 0.84$, $p < 0.001$). In contrast, the two across-culture comparisons were not correlated for the Western excerpts (Arkansas-Dimen, $r = 0.19$, $p = 0.47$; Michigan-Dimen, r = 0.21, $p = 0.43$). They were correlated, however, for the Chinese excerpts for both cross-culture comparisons (Arkansas-Dimen, $r = 0.77$, $p < 0.001$; Michigan-Dimen, $r = 0.81$, $p < 0.001$). Taken together with the semantic similarity results, we find there is neither shared semantic content nor shared generalized sentiment across cultures for the Western excerpts, but both are shared within cultures. Similarly, there is no shared semantic content across cultures for the Chinese excerpts, but some evidence for shared sentiment evoked by the Chinese excerpts in listeners across cultures.

References

1. D. McHugh, S. Shaw, T.R. Moore, L.Z. Ye, P. Romero-Masters, R. Halverson, Uncovering themes in personalized learning: Using natural language processing to analyze school interviews. *J. Res. Technol. Educ.* **52** ,391-402 (2020).
2. B. Trstenjak, S. Mikac, D. Donko, KNN with TF-IDF based framework for text categorization. *Procedia Eng.* **69**, 1356-1364 (2014).
3. Y. Wang, A.J. Bowers, D.J. Fikis, Automated text data mining analysis of five decades of educational leadership research literature: Probabilistic topic modeling of EAQ articles from 1965 to 2014. *Educ. Admin. Q.* **53**, 289-323 (2017).

Tables

Table S1: Sample size and descriptive summary statistics on nardoc composition and length for the three tested geographic locations and for the two control samples where narratives were generated in the absence of a music cue.

Geographic Location	**Sample Size**	**Avg. # Words /Excerpt (SD)**	**Avg. # Excerpts /Subject (SD)**	**Avg. # Subjects/ Nardoc (SD)**
Arkansas	318	29.0 (18.9)	5.6 (1.7)	53.8 (7.0)
Dimen	147	19.7 (10.2)	6.3 (1.7)	29.6 (4.1)
Michigan	157	31.5 (15.0)	6.6 (1.2)	30.4 (3.4)
Michigan (control)	56	49.2 (20.6)	6.0 (1.6)	42.0 (0.8)
Princeton (control)	21	64.7 (35.3)	6.0 (1.4)	15.6 (0.7)

Table S2: Median values with interquartile range (IQR) for cosine similarity distributions shown in Figure 2.

Music Tradition	**Geographic Location**		
	Arkansas	Michigan	Dimen
Chinese/Chinese	0.257 (0.213-0.295)	0.196 (0.163-0.226)	0.361 (0.308-0.402)
Western/Western	0.263 (0.200-0.329)	0.217 (0.189-0.258)	0.329 (0.270-0.374)
Chinese/Western	0.189 (0.157-0.224)	0.147 (0.128-0.172)	0.297 (0.255-0.347)

Table S3: Median values and interquartile range (IQR) for cosine similarity distributions shown in Figure 3.

Music Tradition	**Geographic Location Comparisons**		
	Arkansas-Michigan	Arkansas-Dimen	Michigan-Dimen
Chinese/Chinese	0.211 (0.179-0.249)	0.134 (0.114-0.160)	0.122 (0.103-0.142)
Western/Western	0.231 (0.192-0.268)	0.153 (0.117-0.177)	0.135 (0.111-0.158)
C/W & W/C	0.159 (0.136-0.187)	0.129 (0.107-0.156)	0.118 (0.094-0.143)

Table S4: Same-excerpt similarity between the two US locations and four age-based subsets of Dimen participants shown in comparison to the same-excerpt similarity values for the original (full sample) of Dimen participants.

Age Range	# of Dimen participants	**Geographic Location Comparisons** Median	IQR	# nardocs > same sample threshold	# nardocs > control sample threshold
		Arkansas-Dimen			
Original	147	0.169	0.149 – 0.191	1/32	1/32
> Median Age	74	0.122	0.098 – 0.138	1/32	0/32
< Median Age	73	0.151	0.124 – 0.176	1/32	1/32
< 38 Years	46	0.126	0.104 – 0.166	2/32	1/32
< 30 Years	34	0.102	0.074 – 0.133	2/32	0/32
		Michigan-Dimen			
Original	147	0.153	0.130 – 0.169	2/32	1/32
> Median Age	74	0.111	0.085 – 0.133	0/32	0/32
< Median Age	73	0.138	0.111 – 0.152	3/32	1/32
< 38 Years	46	0.123	0.095 – 0.150	3/32	0/32
< 30 Years	34	0.096	0.076 – 0.123	2/32	0/32

Table S5: Stimuli for the experiment were 32 one-minute excerpts of instrumental art music (Western, n = 16; Chinese, n = 16), which had previously been normed for enjoyment and familiarity. Listed are the composer/artist, title, and timestamp of the track where one-minute excerpt was extracted are listed.

Composer/Arranger/Performer	Title	Timestamp
Phillip Glass, Carducci Quartet	Suite from Dracula: Titles	0
Jean Sibelius, Leif Ove Andsnes	6 Impromptus Op 5, No. 5 in B Minor	0
Gustav Mahler, Michael Tilson Thomas + San Francisco Symphony	Das Lied Von Der Erde II. Der Einsame Im Herbst	0:20
Silvestre Revueltas, Arthur Wesiberg + Ensemble 21	Homenaje a Garcia Lorca: 1. Baiile	0
Igor Stravinsky, Pierre Boulez + Chicago Symphony Orchestra	Four Etudes for Orchestra, No. 4: Madrid. Allegro con moto	0
Ludwig van Beethoven, Hans Preim-Bergrath + Berlin Philharmonic Wind Ensemble	March for Military Music in F Major "Yorck March" WoO 18	0
Camille Saint Saëns, Lorin Maazel + Pittsburgh Symphony Orchestra	Phaéton, Op. 39	2:54
Gioachino Rossini, Gustavo Dudamel + Los Angeles Philharmonic	La Gazza Ladra: Overture	0
Phillip Glass, The Smith Quartet	String Quartet No.5 - Part 3	0
Ferde Grofé, Antal Doráti + Detroit Symphony Orchestra	Grand Canyon Suite I. Sunrise	0
Maurice Ravel, Claudio Abbado + Berlin Philharmonic	Pour le Piano L. 95 No. 3 Toccata	0
Aaron Copland, Leonard Bernstein + New York Philharmonic	Billy the Kid Suite, II. Street in a Frontier Town	0
Gustav Mahler, David Zinman + Tonhalle Zürich	Symphony No. 2 "Resurrection", I. Allegro maestoso. Mit durchaus ernstem und feierlichem Ausdruck	1:25
Ludwig van Beethoven, Stephen Kovacevich + Colin Davis + London Symphony Orchestra	Piano Concerto No. 4 in G Major Op. 58, III. Rondo (Vivace)	0
Albert William Ketèlbey, Robert Sharples + New Symphony Orchestra	In the Mystic Land of Egypt	0
Sergei Prokofiev, Boris Berman	3 Pieces Op. 59 No. 3 Sonatina Pastorale	0
张维良 Zhang Weiliang	Level Sands, Lowering Geese	0
杨瑾 Yang Jin	Timid Song	0
管平湖 Guan Pinghu	Strains of Spring Morning	0
赵良山 Zhao Liangshan	Walking on an Ancient Road	0

杨瑾 Yang Jin	Ambush from Ten Sides	0
周维 Zhou Wei	Racing Horses	0
群星 Various Artists	Liuqin Opera Piece	0
杨瑾 Yang Jin	Spring Sun, White Snow	0
张雪 Zhang Xue	Ballad Tune, Three-Six	0
张雪 Zhang Xue	Zhao Jun's Complaint	0
周维 Zhou Wei	Empty Mountain, Birdsong	0
周维 Zhou Wei	Groans of the Sick	0
谭宝硕 Tan Baoshuo	The Great River Flows East	0
赵良山 Zhao Liangshan	Farewell Pavilion, Slow Melancholy	0
群星 Various Artists	Bamboo Branch Lyric	0
杨瑾 Yang Jin	Great Wave Washes the Sand	0

Table S6: Analysis on narrative content provided by participants removed words that referenced task instructions and/or acoustic features of music excerpts, including possible instrument names and music traditions. There were two types of lists of words used to filter and remove text from nardocs. The first list (task-related) included words that referenced the task instructions. The second list (music-related words), included references to the acoustic features of music or instruments.

Task-related words
music, imagine, imagined, song, think, picture, pictured, scene, story, reminded, movie, setting, excerpt, like, around, also.

Music-related words
piece, play, playing, plays, instrument, instruments, china, chinese, asian, asia, japanese, west, western, american, america, acchan, accordina, accordion, accordola, adungu, afoxe, agida, agogo, agung, ajaeng, akkordolia, alboka, alfaia, algaita, alphorn, angelique, angklung, apinti, archlute, arghul, arobapa, arpeggione, asadullah, ashiko, atabaque, atenteben, aulos, autoharp, ayacucho, babendil, baboula, baglama, bagpipe, bajiao, bak, balaban, balafon, balalaika, balsie, bamboula, bandola, bandolin, bandolon, bandoneon, bandora, bandura, bandurria, bangdi, bangu, bangzi, banhu, banjo, bansuri, baosheng, bara, barbat, barriles, baryton, bass, bassoon, bawu, bayan, bazooka, beatboxing, bedug, bell, berimbau, biangu, bianqing, bianzhong, bifora, bipa, biqigu, birbynė, biwa, blul, bo, bodhran, bofu, bombarde, bongo, boobam, bordonua, bouzouki, buccina, bugle, buleador, bullroarer, buzuq, cabasa, cajon, calliope, candombe, carillon, carimba, castanets, castrato, cavaquinho, caxirola, caxixi, celesta, cello, chacaras, chalumeau, chande, chango, charango, charangon, charangos, chenda, chi, chiban, chico, chillador, choghur, chordophone, chun, cimbalom, cimbasso, cimboa, citole, cittern, cizhonghu, clapstick, clarinet, clarinette, clarytone, claves, clavichord, clavinet, concertina, conga, contrabassoon, contraguitar, cornamuse, cornet, cornett, cornu, corrugaphone, countertenor, cowbell, cromorne, crotales, crumhorn, crystallophone, cuatro, cuica, culoepuya, cymbal, dabakan, dabo, dadihu, daf, dagu, daguangxian, dahu, daluo, damaru, dangzi, danso, dapaqin, daqing, daruan, datong, davul, dayereh, den-den, descant, dhak, dhimay, dhol, dholak, diangu, didgeridoo, dihu, dimdi, diple, diyingehu, diyinruan, dizi, djembe, dobro, dohol, dollu, dombra, domra, dongdi, doshpuluur, dotara, doulophone, drum, duduk, dulcian, dulcimer, dulzaina, dung-dkar, dunun, dutar, duxianqin, dzhamara, ektara, erhu, erxian, esraj, euphonium, faglong, falsetto, fangsheng, fangxiang, fegereng, fengluo, ferrinho, fiddle, fife, fiscorn, flabiol, flageolet, flexatone, flugelhorn, flumpet, flute, flutes, flutina, folgerphone, fortepiano, fou, fuglung, fujara, fusetar, gaida, gandingan, gaogu, gaohu, gaoyinruan, garklein, garmon, gastorena, gayageum, gehu, gemshorn, geomungo, ghatam, ghaychak, gittern, glass harmonica, glasschord, glockenspiel, gong, gottuvadhyam, gralla, guan, guanzi, gudi, guiro, guitar, guitarro, guqin, gusli, guzheng, haegeum, haidi, hailuo, handpan, hang, hano, harmoneon, harmonica, harmonico, harmonika, harmonium, harp, harpsichord, hebei, hegelong, helicon, hexian, hira-daiko, horagai, horn, hosaphone, hotchiku, houguan, huagu, hualaycho, huapanguera, huapengu, huluhu, huluqin, hulusheng, hulusi, hun, huobosi, huqin, hurdy-gurdy, huzuo, hydraulophone, idakka, igihumurizo, igil, ilimba, inci, ingoma, instrument, inyahura, ishakwe, janggu, janzi, jiangu, jiaohu, jiegu, jing, jingbo, jinghu, jingluo, jug, junjung, kabosy, kadlong, kagurabue, kailuluo, kakko, kalaleng, kamancha, kanjira, kantele, kaval, kayamb, kazoo, kebero, kemanak, kemenche, kendang,

kettledrum, kezaixian, khartal, khene, khim, khloy, khlui, khol, khonkhota, khushtar, kobza, kokle, kokyu, komabue, komuz, koncovka, konghou, kora, kortholt, koto, koudi, kouxian, krakebs, kubing, kudyapi, kuhlohorn, kulintang, kwitra, laba, langeleik, laouto, laruan, laud, launeddas, lavta, leiqin, leona, lilie, liliu, lirone, lituus, liujiaoxian, liuqin, livenka, lokanga, lonqin, luo, lur, lusheng, lute, lyre, mabu, madal, maddale, madhalam, maguhu, maktou, mandobass, mandocello, mandola, mandole, mandolin, mandolin-banjo, mandolute, mandora, mandore, mangtong, maraca, maram, marimba, marovany, matouqin, mbira, mejoranera, mellophone, melodeon, melodica, mezzo-soprano, mijwiz, mirwas, mizmar, mizwad, moquegua, moraharpa, mridangam, muye, muyu, nadaswaram, nagak, nagara, nao, naqareh, ney, nguru, niujinqin, niutuiqin, nohkan, nplooj, nulophone, nyckelharpa, o-daiko, oboe, ocarina, octaban, octavin, octobass, okedo-daiko, ophicleide, organ, oud, paiban, paigu, paixiao, pakhavaj, palendag, pampeno, pandero, paqin, parai, pasiyak , pate, pavari, pengling, piano, pibgorn, piccolo, piccolo , pingluo, pipa, piwancha, plasmaphone, pochette, primo, psaltery, pu, pulalu, pyrophone, qanun, qeej, qiben, qilaut, qin, qing, qinqin, quena, quintephone, quinticlave, quinto, rabeca, rackett, raj, rajao, rale-pousse, rapping, rauschpfeife, ravanahatha, rawap, rebab, rebana, rebec, recorder, repicador, repique, requinto, rhaita, ricardo, robero, ronroco, ruan, rubab, ryuteki, sabar, sackbut, saenghwang, sallameh, sambal, samphor, samponia, sanhu, sanshin, santoor, sanxian, sarangi, sargija, sarod, sarrusophone, sataer, saung, saxhorn, saxophone, saxotromba, saxtuba, schwyzerorgeli, se, sea organ, serpent, setar, seul, shakuhachi, shamisen, shangnao, shankha, shaoqin, shawm, shehnai, shekere, shenbo, sheng, shime-daiko, shimianluo, shinobue, sho, shofar, shreiker, shuibo, shuijingdi, shvi, sihu, siku, sintir, sitar, sitarla, sneng, sodina, sonko, sopila, sopranino, soprano, sorna, sousaphone, spoon, sralai, steelpan, subidor, sudrophone, suikinkutsu, suling, suona, superbone, supertumba, surbahar, surdo, surnay, swarmandal, swordblade, synthesizer, tabl, tabla, taepyeongso, taiko, taipinggu, tambori, tamborim, tambourine, tamburica, tan-tan, tanbur, tanggu, tanpura, tao, taodi, tapan, taphon, tar, tarogato, tbilat, tembor, tembur, tenor, tenora, tenoroon, teponaztli, tezhong, thavil, theorbo, tianqin, tible, tiexianqin, tiexianzai, timbales, timpani, timple, tiple, tiqin, toba,, tof, tom-tom, tombak, tonette, tovshuur, tres, triangle, tricordia, trikiti, tro, trombone, tromboon, trumpet, tsukeshime-daiko, tsuri-daiko, tsuzumi, tsymbaly, tuba, tubax, tuhu, tumba, tumpong, tungso, tutek, txalaparta, txistu, tzouras, uchiwa-daiko, ukulele, valiha, vallegrandino, veekku, veena, venova, venu, vibrandoneon, vibraphone, vibraslap, vielle, vihuela, viol, viola, violin, violone, violotta, vuvuzela, walaycho, waldzither, washboard, washint, weichun, wenqin, wenzhenqin, whamola, wheelharp, xaphoon, xeremia, xiao, xiaobo, xiaodihu, xiaoluo, xiaoruan, xindi, xiqin, xun, xylophone, yanggegu, yangqin, yaogu, yazheng, yehu, yinqing, yodel, yotar, yu, yue, yueluo, yueqin, yunluo, yunzheng, zhaleika, zhangu, zheng, zhengni, zhongbo, zhongdihu, zhonghu, zhongruan, zhu, zhuban, zhui, zhuihu, zhuiqin, zhuxun, zill, zither, zufolo, zugtrompette, zurna