Liu et al. *EPJ Data Science* (2019) 8:4
https://doi.org/10.1140/epjds/s13688-019-0182-z

EPJ Data Science
a SpringerOpen Journal

REGULAR ARTICLE

Open Access

Inside 50,000 living rooms: an assessment of global residential ornamentation using transfer learning

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Abstract

The global community decorates their homes based on personal decisions and contextual influences of their larger cultural and economic surroundings. The extent to which spatial patterns emerge in residential decoration practices has been traditionally difficult to ascertain due to the private nature of interior home spaces. Yet, measuring these patterns can reveal the presence of geographic culture hearths and/or globalization trends.

In this work, we collected over one million geolocated images of interior living spaces from a popular home rental website, Airbnb (http://airbnb.com), and used transfer learning techniques to automatically detect the presence of key stylistic objects: plants, books, decor, wall art and predominance of vibrant colors. We investigated patterns of home decor practices for 107 cities on six continents, and performed a deep dive into six major U.S. cities.

We found that world regions show statistically significant variation in decorative element prevalence, indicating differences in geographic cultural trends. At the U.S. neighborhood level, elements were only weakly spatially clustered and found to not correlate with socio-economic neighborhood variables such as income, unemployment rates, education attainment, residential property value, and racial diversity. These results may suggest that American residents in different socio-economic environments put similar effort into personalizing and caring for their homes. More broadly, our results represent a new view of worldwide human behavior and a new application of machine learning techniques to the exploration of cultural phenomena.

Keywords: Computer vision; Interior decor; Maps; Indoors; Homes; Spatial analysis

1 Introduction

Interior decoration and ornamentation is a key form of human self-expression and communication of values and ideals [1–3]. This is especially true in the home, where residents and owners have agency to personalize their surroundings and cultivate a space for themselves and visitors [4]. Configuring a domestic space has both internal and contextual (socio-cultural and geographic) components, which together reflect a need for privacy, interpersonal relationships, symbolization of the self, and aesthetic stimulation [5]. Although ornamentation is known as an indicator of social and economic status [6], today, large-scale manufacturing as well as a culture of re-sale and re-use has encouraged people of varying means to customize their living spaces with affordable choices [2] including affordable methods of painting, re-purposed materials, and old or free furnishings. Even wealthier homeowners have strayed from choosing professional decorators, [7] instead embracing a growing trend of do-it-yourself (DIY) culture. While there may be unequal access to interior decor elements and the ability to purchase these goods in all global regions, globalization and the "IKEAficiation" of furniture has penetrated urban and rural regions in the developed and developing world alike [8]. If similar elements are available around the world, there may be an increasing convergence between international cultural decorative behaviors that reveal an underlying similarity in decorative preferences regardless of locality.

Given the increasing accessibility and globalizing influence of material decor, a key question for the modern assessment of residential life is whether interior living spaces exhibit similar decorative properties, or if these properties differ by geographic region. Accordingly, the research question addressed in this work is: To what extent is residential ornamentation behavior localized into spatial clusters and regions? Our research objectives are to successfully detect ornamentation evidence from a large set of global interior living rooms and to discover the extent of statistical geographic variation in interior ornamentation choices across global regions and across inter-city neighborhoods. Our null hypothesis is that each ornamentation element is distributed randomly across geographic space, and alternative hypothesis is that there are distinct geographic trends inherent to the presence of these elements.

Here, we examine a set of global cities using images from a popular home rental site, Airbnb (http://airbnb.com). Airbnb allows members to list their personal homes as an alternative to hotels for visitors, and provides interiors images of the spaces for rent in their postings. Airbnb was chosen for its international penetration, corporate validity and temporal online persistence, as well as its ability to represent thoughtfully-photographed global residential interiors, i.e. everyday homes. This site offers over five million listings in 191 countries and 81,000 locales. The listed rentals are uniquely created and furnished by individuals and families (although exceptions exist). While they can be decorated to entice consumers [9], the interiors also have an added personal dimension of individual decor and style choices. We originally collected over one million listing images and analyzed over 130,000 images representing about 54,000 living rooms from 107 global cities in 65 countries over six continents, and in detail in six U.S. cities (Chicago, Houston, Los Angeles, New York, Philadelphia and Washington, D.C.). We specifically chose listings where renters rented a bedroom in a unit or home, i.e. not a hostel-style room or the whole home/unit, in order to capture homes where the owner may live. While it is not guaranteed that the owner also lives on site, this check increases the likelihood that the owner lives in the house and ostensibly decorated the common spaces [10].

We codify ornamentation behaviors as the presence of indoor plants, books, wall art, general decor, and vibrant paint colors within living rooms, as they met two criteria. First, these "small" (movable, lightweight) choices communicate a personal decision to decorate (unlike a wall-to-wall carpet from a rental unit, built-in lighting, or architectural design). Second, these objects were detected with high success rates in the machine learning process. Third, these elements have been previously listed in former research on interior design theory via qualitative interior photograph analysis [5, 11]. In the following sections, we describe prior research, our dataset, processing, methods and results.

2 Related work

2.1 Conceptually-related work

Our research question is examined through an exploratory data science lens that takes advantage of a new trove of online geolocated images. Today, the quantitative analysis of large datasets of user-generated image content is a burgeoning research task. Image analysis techniques often detect objects and report descriptive statistics, and more recently have advanced toward more 'intelligent' tasks. Regarding interiors, machine learning methods have been used to recognize types of "style" from large collections of photographs of keyword-tagged furniture [12] and art using a set of classified Wikipaintings images [13]. Resulting classes include "vintage", "rustic", "baroque", and "modern", which help characterize the design style of an interior quickly and efficiently.

At the scale of the interior room, both commercial and residential interiors can be analyzed with machine learning methods. Interior images from Zillow.com and Houzz.com have been classified by levels of "luxury" to improve estimates of home valuation and sale price prediction, [14]. A similar study used machine learning methods on photographs of restaurant interiors uploaded by Yelp.com users in order to predict restaurant success [15].

When photographs are geolocated, different image qualities can be mapped to neighborhoods and cities. For example, [16] detected different ambiance from crowdsourced Foursquare images and found that cities like Barcelona had 'artsy' photos, while Paris had more 'romantic' scenes. Objects within the city are also studied. Object detection methods have been used to detect the makes and models of cars from Google Street View images and associate car type with the surrounding neighborhood demographics using GIS analysis [17]. Next, the locations of different types of street art have been detected from geolocated Instagram photos [18] to produce maps that allow visitors and residents to locate and appreciate the different artistic offerings local cities. Lastly, even the presence of environmental features—the locations of flowers and snow—have been mapped using geolocated Flickr photos [19].

At the intersection of interior image analysis and the spatial analysis of processed image features, two recent studies detected color and ambiance from online interior rental photos [20, 21], finding differences in interior decor across continents using two nations, and 10 cities, respectively. Our study's research design is modeled after these examples.

2.2 Background on geographic and cultural variation of interior elements

The study of geographic variation in residential design has overwhelmingly focused on exterior architecture, building materials and cultural use of space in homes [22]. However, there is some indication that decorative emblems and styles differ across geographic spaces, regions and countries. For instance, it was found that traditional French cultures value ornateness in their choice of decor, while Italians prefer objects with functional purposes [5]. In terms of our chosen elements, various scholars have examined the presence of books, plants, the abundance of wall art and ornaments [5], and the presence of predominant colors across global cities through photographs [11].

2.2.1 Elements

The presence of books in the home has historically reflected the pursuit and investment in knowledge [23]. More specifically, the size of the home library is correlated with, and is used to define, a household's "scholarly culture" [23–25] via [26]. The prevalence of books in interiors has been linked to education and literacy rates, as found by a survey conducted in 43 nations [27] wherein the fewest residential books appeared in Macedonia, Brazil, Indonesia and Romania and the most reading material in Hungary, Czech Republic, Austria, and Germany [26].

The practice of keeping indoor plants has been studied as an important expression of organic decoration i.e. "biophilia" [28], which psychologically brings inhabitants closer to nature. Interior plants have been studied for their health and workplace benefits. The presence of indoor plants has been said to create an environment that promotes wellness and holistic health [29], and indoor foliage has been shown to improve health and reduce stress in hospital patients [30]. In another study, after the introduction of office flora, worker participants were more productive and less stressed [31]. It has also been shown that windows overlooking greenery produce the same stress-reducing effects as having indoor plants [32]. However, it is unclear specifically where, geographically, plant-rearing is a common practice

The study of global differences of art and decor within homes has been approached through the study of material culture, which stresses the decorative or functional utility of items [33] or object symbolism and anthropological practices related to objects (such as cooking) [34]. Fewer studies have delineated the geographic presence of a particular decorative element. Exceptions include the study of transferability of residential items through cultural diffusion. For instance, African-American Muslims in Philadelphia neighborhoods decorate their homes with melting-pot-like decor from the overseas Muslim world [35], while Indian immigrants in the United States define their interiors with symbolic elements of the religion and culture of their native nations [36].

2.2.2 Color

Cultural color perception and usage has been typically (and widely) studied alongside psychological and marketing topics of branding and affect (e.g. [37]) ranging from best practices for fast food restaurant walls to space station interior color [38]. In an international study of color preference, 21,060 subjects reported remarkably uniform preferences for, in order: blue, red, green, purple, orange, yellow [39], rendering lack of proof for racial or geographic difference in color preferences. More recently, a cross-cultural study including volunteers from multiple continents, detected similarities in color preferences (such as blue and black) and color meaning associations (such as red for aggression and power) [40]. Different cultures also report affective responses between colors: Afghan and Mysurur respondents reported the least affective differences between colors while Thai and Finnish subjects reported the highest affective differences between colors [41]. Similarly, [42] showed that American, British, Korean, and Japanese subjects described preferences for color elements including hue and chroma. Another color research study revealed that African American subjects preferred colors in a red-purple-black hue spectrum whereas white subjects tended to prefer greens and blue [40].

Color is also a key part of interior design, the topic of this work. Some interior color decisions are motivated by financial reasons. For example, international hotel chains have incorporated local cultural elements and their meanings in different geographic markets to draw more guests [42]. Others are guided by government influence on culture: In the 1970s, the Singaporean Government warned citizens against using heavy colors and suggested more practical lighter colors which represented purported cleanliness ideals brought about by English colonialism, yet this rhetoric is not as common today [43].

There is also geographic variation in home color preferences. In a cross-cultural study of 12 sites, authors found that Greece dons colorful pastels; Scotland uses a deep, rich palette; India exhibits shades of blue; and Guatemala has a preference for teal [44]. Another study of geographic communities' use of color from natural and synthetic elements revealed a proliferation of blue and black in Europe, as well as red in Asia, among other trends [45]. In addition, exterior home colors in a contemporary Chinese city were found to lack a discernible statistical pattern but that color choices mixed throughout the city [46]. With these previous findings in mind, we next discuss the use of a large data corpus to assess urban interiors. Our approach extends the aforementioned research by using a high volume of cases to detect quantifiable, discrete objects and colors.

3 Materials and methods

3.1 Data

3.1.1 Image retrieval

We collected listing information and images from Airbnb's public API (https://www.airbnb.com/partner). Listing information included the home's location (longitude and latitude) and other properties such as price, amenities, and average customer rating out of five stars. Geographical coordinates were jittered and therefore slightly deviate from their exact location.

The data collection process was comprised of two main stages. We first collected the unique ids of listings located within the geographic area of interest. Due to API constraints, we collected listing ids by querying based on geographic identifiers, such as city name and zip code, which retrieved a maximum of 300 listing ids per name. We also queried by geographical bounding box, which returned a maximum of 50 listing ids per box. Once ids were retrieved, we then requested listing information and images through the API based on the retrieved listing ids.

Data and listing information were collected at both global and U.S. city levels in two waves (Oct. 2017 and Feb. 2018), respectively. At the global level, we collected data for 107 highly populated cities on six continents totaling over 38,000 listings (500,000 images). Cities were chosen based on population and availability of rentals. After image classification (described in the following section), and filtering for only living rooms, there remained 21,543 listings (49,000 images) for global analysis.

We also retrieved an oversample of data for six major U.S. cities, chosen by metropolitan area population: Chicago, IL; Houston, TX; Los Angeles, CA; New York, NY; Philadelphia, PA and Washington, DC. We first queried listing ids based on urban zip codes and then queried using $0.01^\circ \times 0.01^\circ$ bounding boxes across the city boundaries in order to improve geographic coverage. For the six cities, we collected over 50,000 listings (600,000 images). After image classification, and filtering for only living rooms, there remained 32,389 listings (81,000 images) for city-level analysis.

3.1.2 Census data

For each U.S. city, we characterized the neighborhoods of geolocated households using socioeconomic factors retrieved from the 2016 American Community Survey (ACS), including median household income, unemployment rate, percent of residents with bachelor's degrees, and median house value. We also computed an entropy-based racial diversity measure defined by the classic information entropy equation: $H(X) = -\sum_{i=1}^{n} p(x_i) \log p(x_i)$, where $p(x_i)$ is the proportion of a certain race/ethnicity (Asian, Black, Hispanic, White, and Other) within a tract.

3.2 Methodology

In this section, we introduce methods for retrieving living room images, analyzing ornamental elements and colors, and the statistical models used in the study. The filtering of living rooms from all images and the analysis of ornamental elements were conducted as image classification and object detection tasks, respectively (Fig. 1). We applied transfer learning techniques to customize the deep learning tools in computer vision to complete these tasks. Transfer learning, a technique commonly used in computer vision applications, refers to retraining a small number of parameters in a pre-trained deep learning model with customized data, in order to leverage the knowledge that the model has learned from massive data for a specific task with only a small number of training data. The image classification and object detection models were implemented with TensorFlow [47].

3.2.1 Labeling training data

To classify room types from the listing images, we manually labeled 36,657 photos. A set of training images was first labeled by workers on Amazon Mechanical Turk and then checked by graduate and undergraduate student volunteers, who also labeled some images directly. We ensured that the training data covered images from different geographical regions. To maintain the highest possible classification performance and create a balance across image categories (instead of using a binary label of "living room" and "non-living room") we used eight categories: living room, bedroom, kitchen, bathroom, dining room, other indoor rooms, object, and not indoor room.

To train object detection models, we labeled the training data by defining a bounding box around each object in the image and labeling the box by object type. Plants and books

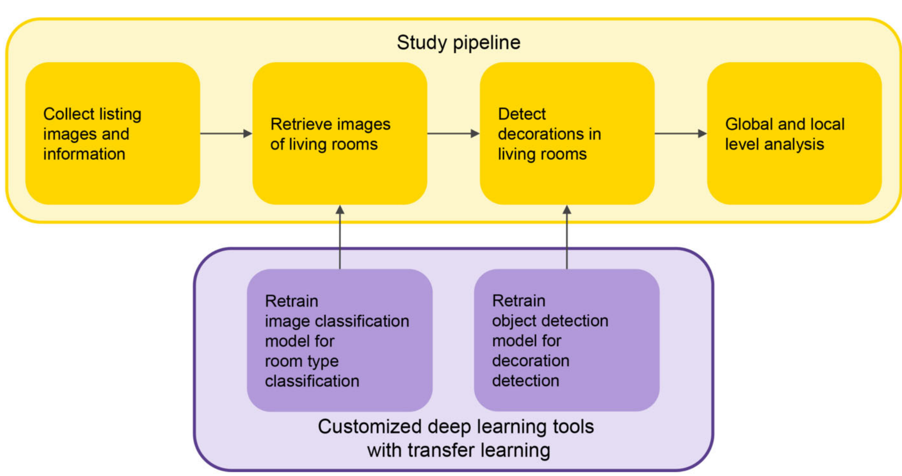

Figure 1 Methodological workflow. A workflow diagram illustrates our methodological steps from preprocessing, training and output

were detected using pre-trained models, so we only labeled images for training models to detect wall art and general decor. Using the LabelImg tool (https://github.com/tzutalin/labelimg), student volunteers labeled 692 living room images as training data. For each image, the bounding box information for each wall art and decor object and their categories were recorded as XML files in PASCAL VOC format. Other potential false-positive objects in the images, such as televisions and windows, were also labeled to ensure that the re-trained model could distinguish between these similar objects (Fig. 2).

3.2.2 Image classification

We retrained the Inception V3 model [48] using the labeled data to classify listing images into the eight room type categories, and retrieved only living room images for the following analyses. The Inception V3 model was pre-trained with the ImageNet dataset [49] with 3.46% top-5 error rate. We retrained the last layer of the model (the fully connected layer) with 80% of the labeled photos, saving 20% for use as test data. The overall accuracy of our retrained model on the test set was 81.1%. The living room category had a precision of 80.2% and recall of 75.3%.

3.2.3 Object detection

The goal of the object detection task was to count the frequency of certain decoration elements in the living room images. For object detection of plants, wall arts, and decor, if a listing contained more than one living room image, we used the maximum number of each decoration element type to represent the number of the listing. For example, if listing A had two living room images, one with three pieces of wall art and the other with four, we would consider listing A to have four pieces of wall art.

We used and retrained the faster_rcnn_nas model in the TensorFlow Object Detection API [50] to detect decor in living room images. The model is based on Faster RCNN [51] and Neural Architecture Search (NAS) [52] methods. The model was pre-trained on the COCO dataset [53] and had the highest mean Average Precision (mAP) among all available models at the time of access. The pre-trained model was used directly to detect books and plants in each living room. We then retrained the model to detect wall art and decor with labeled images.

We hand-selected 100 living room images that contained various decorative elements and were not used in the training process to test the model's ability to detect the four ornamentation elements. We prioritized high precision over recall in our model since we combined the objection-detection results of multiple living room images for a single listing. This means that if an object was not detected in image A of a living room (a false negative), it could still be detected from image B of the same living room (producing a true positive). Moreover, when aggregating the object detection results for city-level or neighborhood-level analysis, a higher precision suggests that although the numbers may be smaller, they correctly reflect the real-world patterns. The precision and recall rates (Table 1) were both above 0.9 for wall art detection, while the remaining three elements had slightly lower recall rates. The elements that most frequently went undetected were books and decor, but the classifier rarely signaled elements that were not present (Table 1).

3.2.4 Color detection

We also detected predominant colors in each living room using HSV (hue, saturation, value) numbers to characterize colors found in the images. Hue represents the value on

Figure 2 Object detection. Object detection examples for living room images. Ivory and orange bounding boxes in (**a**) and (**b**) are the model's results for plant and book identification, respectively. Green and blue bounding boxes in (**c**) and (**d**) are the model results for wall art and decor identification, respectively

the color spectrum, saturation describes a color's "purity" or how far it differs from gray, and value represents brightness along a white to black range [54]. To define "vibrant" colors, we set minimum thresholds of 0.50 saturation (range: 0–1) and 0.75 value (range: 0–1) and set no threshold for hue. These thresholds, while uncalibrated, ensured that no pastels, grays, or dark colors were included in the set of vibrant colors. We used the colorgram python package (https://github.com/obskyr/colorgram.py) to extract the 10 most dominant colors in each living room image (see Additional file 1 for more information). If one living room image contained a vibrant dominant color, we considered this listing to contain vibrant colors.

3.2.5 Descriptive variable representation and statistical analysis
Some living rooms contained many decorative elements, e.g. more than 40 small wall art pieces, which served as outliers in our analysis. Thus, we used the following numerical distinctions: plants, wall art and decor were each capped at 5 instances (so that if a living room has 10 plants, this is represented as 5). Books often appeared as piles or a shelf of books, and the model had difficulty distinguishing the exact number of books in the images. Thus, we considered the presence of books as a binary value, signifying the presence of any books (ranging from a single book to over 100 books), or a 0 for no detected books. Finally, the presence of at least one vibrant color in the top 10 major retrieved colors for an image was also presented as a binary variable. (See Additional file 1 for more information).

In the global analysis, we used Moran's I and ANOVA to detect spatial clustering and regional differences of image element preponderance, respectively. These tests were conducted using the city as the spatial unit of analysis. Moran's I was parameterized with a 4000-kilometer Haversine distance search radius and neighbor importance was weighted

Table 1 Precision and recall for detecting the four decoration elements

Element type	Precision	Recall
Plants	0.984	0.709
Books	0.968	0.638
Wall Art	0.961	0.913
Decor	0.870	0.681

using inverse-distance weighting. More information of the influence of parameters on results is listed in Additional file 1.

For U.S. cities, we used Moran's I to detect clusters of element concentrations in neighborhoods. Next, we examined whether the presence of certain living room elements correlated with the neighborhood's socio-economic indicators. We used linear regression (LR) and geographically weighted regression (GWR) to detect potential correlations: the dependent variables for our regressions were the detected elements (plants, books, etc.). The independent variables were socio-economic factors including median household income, unemployment rate, percent of residents with bachelor's degrees, median house value, and racial diversity retrieved from the U.S. Census.

Listings located in census tracts with incomplete census information (about 1.6% of all the listings) were removed for the regression analysis. For LR, the values of interior elements were averaged by tract, and tracts with fewer than 5 rental listings were removed. For GWR, a regression equation was applied to each individual listing that included the socio-economic data of the listing's corresponding tract. As a result, each tract was given its own regression equation with unique variable parameters and R squared values. The optimal GWR Gaussian kernel bandwidth size (i.e. search radius) was calibrated to minimize cross-validation error using the spgwr package in R (https://cran.r-project.org/web/packages/spgwr), and found to be 85 nearest neighbors.

4 Results

At the global level, an average of 201.34 private room listings with living room photos were detected in each city (min. 12 (Kinshasa, D.R.C.), max. 348 (Bogotá, Columbia)). The small numbers of detected residences in some cities were due to the limited availability of home offerings. (For residence count and resultant statistics for all 107 cities, see Additional file 2.)

4.1 Global cities and regions analysis

Most elements of interior design, including books, plants, wall art and color, were spatially clustered in the global city system. Their presence also differed significantly across regional culture hearths. In support of spatial clustering of cities with similar characteristics, a Moran's I test (Table 2), reported that books and wall art tended to have the most concentrated clustering patterns. The presence of books was most significantly clustered, and centered around Europe and the Americas (Fig. 3(b)). The presence of plants and vibrant colors were clustered less significantly, with plant concentrations in Northern Europe and China (Fig. 3(a)) and color concentrations in Japan, India and other locales (Fig. 3(e)). The presence of general decor in homes was not significantly clustered across global cities; cities exhibited high and low levels of decor with no observable spatial patterning. Across regions, the ANOVA F-test statistic revealed that the presence or absence of each element, except for decor, was more similar within regions than across regions (Table 2) and

Table 2 Patterning of interior elements across global cities (Moran's I) and between regions (ANOVA)

Element	Moran's I	Moran's I Z-score	Moran's I P-value	ANOVA F Statistic	ANOVA P-Value	Pattern
Plants	0.254	5.326	<0.001	5.344	<0.001	Clustered
Books	0.298	6.209	<0.001	5.094	<0.001	Clustered
Wall Art	0.291	6.064	<0.001	8.925	<0.001	Clustered
Decor	0.104	2.288	<0.05	1.463	0.181	Random
Color	0.132	2.877	<0.01	2.797	<0.001	Clustered

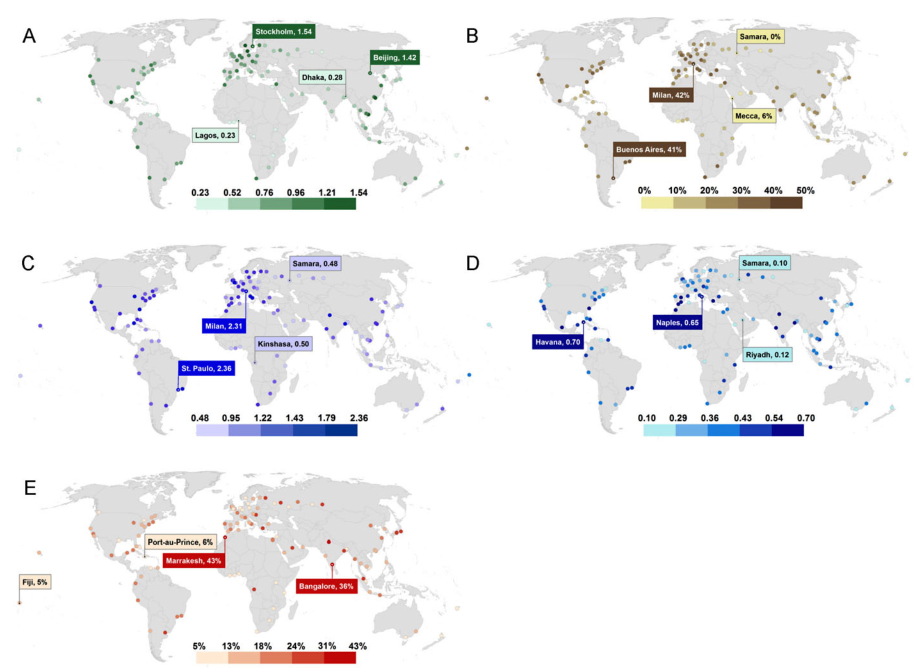

Figure 3 Prevalence of ornamentation elements in global cities. Results of interior elements in 107 global cities indicated regional clustering of prevalence of (**a**) number of plants, (**b**) percentage of homes that include at least one book, (**c**) wall art, (**d**) ornamental decor, (**e**) percentage of homes with vibrant colors

(Fig. 4). Of each element that exhibited significant regional variation, the use of vibrant colors was the least unique to regions, while the presence of wall art was the most unique to regions (Fig. 4). Moran's I results and the ANOVA results aligned to suggest that factors including climate, wealth and culture may statistically influence design in interior spaces. As such, we reject the null hypothesis of randomness of the choice to use plants, books, wall art and vibrant colors to decorate interior spaces across the globe. We do not reject this hypothesis for the use of general decor items, meaning that there is a universal trend of residential ornamentation via artistic objects, but not for more specific elements. We examine these patterns further below.

On the whole, European cities were the most decorated, and cities in Sub-Saharan Africa and Oceania were least decorated (Fig. 4). The top cities for overall ornamentation were found in India, Brazil and Italy (Table 3). In addition, tourist-focused Charleston (U.S.) had high levels of personalization in decor, as did megacities Beijing and Mexico City. Cities with the most austere decorating styles were found in Russia, Saudi Arabia and in Sub-Saharan Africa (Nigeria, Ghana, Cote d'Ivoire, D.R.C. and Uganda) (Fig. 3). Interestingly,

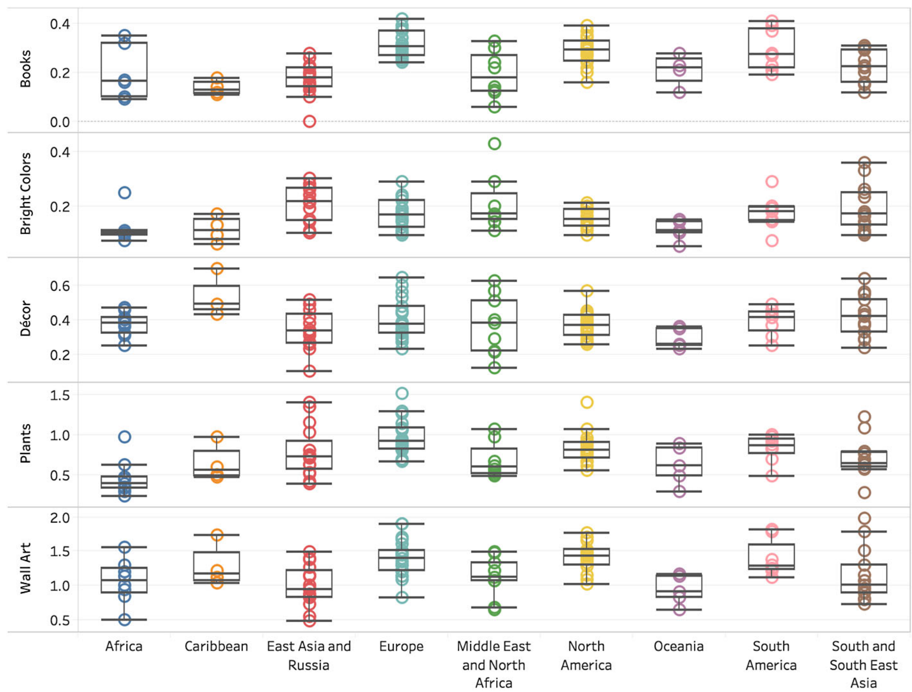

Figure 4 Regional variation in ornamentation and color prevalence. Each city is represented as one circle and classified by region to depict rates of interior various design elements. In summary, Europe and North America led in ornamental objects, followed by South East Asia. The Middle East had the greatest variation

Fiji, a tropical tourist destination, decorated very little, as did Bangladesh, a neighbor to India (Table 3).

4.1.1 Plants and books

On average, 46.3% of listings had plants and 25.5% of listings had books. We found that Scandinavian and Chinese cities often decorated with plants, where the reverse was true in the Middle East, Africa and Central Russia (Fig. 3(a)). This can be grounded in two veins of reasoning: first, that plants can only survive year-round indoors in colder climates, thus they are invited to live indoors. Second, plants in the tropics may be more likely to harbor insects that could have a negative effect on health. Furthermore, in the Middle East, plants may not be strongly reflected in the culture, or the desert atmosphere may not allow for facile plant maintenance. We found a preponderance of books in the United States, Central/Western Europe, South America, and cities Mexico City and Capetown (Fig. 3(b)). This finding cannot be responsibly tied to literacy rates, as books could be found in other parts of the home (such as the bedroom), but not used as living room ornamentation. However, it may suggest that some cultures may be more interested in sharing books as part of a space for guests while others keep books in more private locations, or do not keep books in the home.

4.1.2 Art and color

On average, 62.4% listings had wall art, 30.2% had decor and 16.6% had vibrant colors. Cities in India and Morocco, as well as Madrid, Havana, and Naples had top levels of decor. Qualitative findings support high levels of ornamentation in Morocco, citing the

Table 3 Top and bottom global cities by presence of decorative elements

Plants	Books	Wall Art	Decor	Bright Colors
Top Ten Cities				
Stockholm, Sweden	Milan, Italy	Delhi, India	Havana, Cuba	Marrakesh, Morocco
Beijing, China	Buenos Aires, Argentina	Milan, Italy	Naples, Italy	Bangalore, India
Mexico City, Mexico	Paris, France	Naples, Italy	Delhi, India	Delhi, India
Shenzhen, China	Chicago, U.S.	Sao Paulo, Brazil	Tangier, Morocco	Osaka, Japan
Oslo, Norway	Saint Paulo, Brazil	Rio de Janeiro, Brazil	Madrid, Spain	Riyadh, Saudi Arabia
Copenhagen, Denmark	Athens, Greece	Kolkata, India	Marrakesh, Morocco	Buenos Aires, Argentina
Ho Chi Minh, Vietnam	Charleston, U.S.	Charleston, U.S.	Mexico City, Mexico	Athens, Greece
Guangzhou, China	Oxford, U.K.	Havana, Cuba	Charleston, U.S.	Kyoto, Japan
Berlin, Germany	Rio de Janeiro, Brazil	San Francisco, U.S.	Kolkata, India	St. Petersburg, Russia
Helsinki, Finland	San Francisco, U.S.	Rome, Italy	Granada, Spain	Tokyo, Japan
Bottom Ten Cities				
Lagos, Nigeria	Samara, Russia	Samara, Russia	Samara, Russia	Fiji
Dhaka, Bangladesh	Mecca, Saudi Arabia	Kinshasa, D.R.C.	Riyadh, Saudi Arabia	Port au Prince, Haiti
Apia, Samoa	Riyadh, Saudi Arabia	Novosibirsk, Russia	Algiers, Algeria	Abidjan, Cote d'Ivoire
Kampala, Uganda	Abidjan, Cote d'Ivoire	Apia, Samoa	Mecca, Saudi Arabia	Caracas, Venezuela
Kinshasa, D.R.C.	Omsk, Russia	Riyadh, Saudi Arabia	Novosibirsk, Russia	Bahamas
Dar es Salaam, Tanzania	Accra, Ghana	Mecca, Saudi Arabia	Melbourne, Australia	Copenhagen, Denmark
Omsk, Russia	Trinidad and Tobago	Kyoto, Japan	Stockholm, Sweden	Harare, Zimbabwe
Abidjan, Cote d'Ivoire	Dubai, U.A.E.	Kuala Lumpur, Malaysia	Yangon, Myanmar	Houston, U.S.
Kyoto, Japan	Manila, Philippines	Yangon, Myanmar	Caracas, Venezuela	Kampala, Uganda
Harare, Zimbabwe	Fiji	Dhaka, Bangladesh	Kinshasa, D.R.C.	Oxford, U.K.

"melting pot" of Muslim culture dating back centuries and manifested through vibrant colors [35]. Cities in India, Italy, Brazil and the U.S. had the highest rates of wall art. The distribution of decor was more varied across the globe, but notably present in Southern regions of Africa (Figs. 3(c) and 3(d)).

Conversely, cities in Russia, Saudi Arabia, and Sub-Saharan Africa had very few wall hangings, and were more reserved with their ornamentation decisions. In addition, Kyoto, Kuala Lumpur, Yangon and Dhaka also had low rates of wall art in their homes. These results differentiated Dhaka from neighboring Indian cities such as Delhi and Kolkata, and highlighted Kyoto as a place of potential minimalism, as found with previous results on austerity in Japan [21].

The highest rates of vibrant colors were found in Central Asia, S.E. Asia and North Africa (Fig. 3(e)). The use of calmer colors was found in Sub-Saharan Africa, the Caribbean and Oceania. This distinction seems to have little do to with (warm) climate and light colors' ability to reflect the sun, as S.E. Asia and North Africa have similar temperatures, but prefer to personalize their spaces with saturated walls. Instead, this difference may be attributed to cultural roots. The popularity of bright colors in India, for example, may reflect the decoration styles of the Hindu population, where vibrant oranges are said to be sacred [40]. Ties between Hindu worship and color are key, as every god exhibits a different choice of color; these preferences are manifested in the homes to appease gods like Ganesh, who is said to prefer red and orange [36] (pg. 146). A lack of bright colors may also reflect a legacy of cultural heritage. Another property of interest with the use of white and light colors may stem from persistence from colonial ideals of cleanliness [43], persisting into the 21st century.

4.2 U.S. intra-city level analysis

With regards to the six U.S. cities of interest, we discovered evidence of weak spatial clustering. Thus, we reject the null hypothesis of randomness in decorative proclivities across geographic space within these cities. We also discovered no statistically significant relationship between decorative behavior and socio-economic indicators within U.S. cities.

First, we found that each element was weakly spatially clustered within each city (Table 4), as denoted by low Moran's I scores, which range from –1.0 to 1.0. Although we can reject the null hypothesis of randomness within cities, the resultant statistics do not communicate a strong conviction towards clustering. For example, elements were very weakly clustered in New York, illustrating that key ornamentation practices, especially decor and bright colors, were not constrained or concentrated in neighborhood culture hearths, but were distributed throughout the city. This finding may re-frame ideas that certain NYC neighborhoods such as Greenwich Village are more 'artsy' than other neighborhoods. Yet, New York neighborhoods also exhibited high z-scores, especially in terms of books and plants. That said, low Moran's I scores may be an artifact of the high sample size of the New York case. Elements in other cities, such as Houston, tended to be slightly more clustered, indicating that ornamentation was not widespread but concentrated in smaller pockets. To contextualize these findings, (Table 5) provides summary statistics of the prevalence and sample size of each city.

While each city cannot be compared to one another, i.e. ranked by Moran's I or z value, these findings suggest that certain elements (such as plants) had stronger clustering tenancies, and that these tenancies were not necessarily equivalent in each city. Still, clustering results of the elements can provide a linkage between the global and intra-city analyses. In

Table 4 Combined Moran's I and z-score statistics for element clustering in selected U.S. cities

City/Element	Plants	Books	Wall Art	Decor	Bright Colors
Chicago, IL	0.031 (10.42)	0.028 (9.39)	0.041 (13.64)	0.028 (9.42)	0.026 (8.84)
Houston, TX	0.043 (7.18)	0.05 (8.36)	0.036 (6.06)	0.027 (4.62)	0.044 (7.35)
Los Angeles, CA	0.029 (16.74)	0.029 (16.66)	0.045 (26.4)	0.021 (12.34)	0.016 (9.42)
New York, NY	0.025 (43.99)	0.011 (19.41)	0.007 (11.83)	0.005 (9.06)	0.004 (7.14)
Philadelphia, PA	0.046 (12.12)	0.029 (7.63)	0.022 (5.88)	0.015 (4.13)	0.02 (5.30)
Washington, DC	0.015 (3.35)	0.016 (3.55)	0.021 (4.63)	0.016 (3.57)	0.023 (5.06)

Z-scores are in parentheses. All statistical results are found to be weakly clustered with a p value of < 0.001.

Table 5 Average interior element frequency across selected U.S. cities

City	Number of Listings	Plants	Books	Wall Art	Decor	Bright Colors
Chicago, IL	2772	0.84	0.36	1.54	0.40	0.19
Houston, TX	1746	0.58	0.25	1.41	0.40	0.12
Los Angeles, CA	9368	0.81	0.30	1.47	0.42	0.15
New York, NY	12,537	0.76	0.34	1.41	0.36	0.17
Philadelphia, PA	1820	0.81	0.32	1.47	0.38	0.16
Washington, DC	4146	0.66	0.36	1.67	0.39	0.18
Total/Average	32,389	0.76	0.33	1.48	0.39	0.16

terms of individual element and color types, plants and wall art were the most localized element and decor was the least localized element (Table 4). Plants were least popular in the low-latitude, warm climate of Houston, TX and most popular in colder cities Chicago and Philadelphia. However, plants were also popular in Los Angeles, which also has a warm climate. Yet, bright colors were less prevalent in Los Angeles and even less so in Houston than other, colder cities, which is consistent with global findings (Table 5).

Neither the linear regression (LR) and geographically weighted regression (GWR) models revealed a consistent correlation between any single or combination of socioeconomic factors and interior space ornamentation. LR and GWR modeled most often yielded R^2 values of <0.1 (See Additional file 1 for model parameters and results). Thus, we accepted the null hypothesis, in this case, that decorative tendencies in these U.S. cities does not depend on the socio-economic characteristics of the surrounding neighborhoods, but instead, appear consistently across the socio-economic spectrum. While a different suite of statistical tests, socio-economic indicators and detected objects may indicate, conversely, a significant relationship between neighborhood social fabric and interior decorative element choice, our particular approach did not. Our results demonstrated that decorating one's living space is not an emblem of a specific demographic profile or extraordinary economic means. In other words, the self-expression and fulfillment inherent to space personalization [2] did not seem to be entirely constrained to privileged groups in large U.S. cities. Of course, it is still easy to believe that those with more disposable income may decorate luxuriously [14], but given today's modern DIY culture [7], it is also possible that the average citizen is going to creative lengths can also decorate their home creatively.

We now visualize two examples of localization of ornamentation elements. The data analysis revealed a difference in local neighborhood use of elements of books and wall art in Philadelphia and New York, respectively (Fig. 5). In Philadelphia, up to 63% of homes in the neighborhood of Fishtown, known as a gentrifying area, contained books in their living rooms. However, in areas such as Kensington and Point Breeze, the majority of living rooms contained no books (Fig. 5(a)). Smaller living areas in the downtown, Univer-

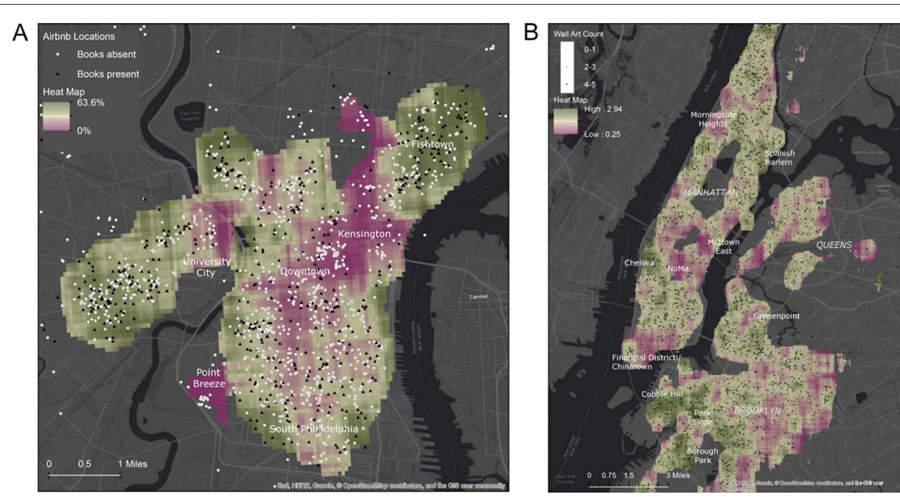

Figure 5 Frequency of ornamental elements by neighborhood. These images illustrate a north-south variation in book presence in Philadelphia, PA where more books are found to the northeast of the downtown area, and wall art frequency in New York City, where key wealthy neighborhoods in Manhattan lack wall art

sity City and Kensington may contribute to a lack of interior decor such as books. South Philadelphia, an area with a concentrated African American population within the segregated city, had mixed proclivities to display books, and did not differ significantly from other Philadelphia neighborhoods. In New York, units of wall art were concentrated in neighborhoods in Brooklyn, Spanish Harlem and Chelsea which have up to nearly three wall hangings on average (Fig. 5(b)). There is a lack of art, averaging at 0.25 wall hangings per home in North of Manhattan (NoMa), Midtown East and the Financial District, although these areas are home to wealthy Manhattanites. A lack of art and books in Philadelphia and New York may be due to high levels of rental properties and tall apartment buildings that host transient populations and those looking for a more utilitarian living style. Poverty may also be a factor, as lower-income areas of eastern Brooklyn also had fewer units of wall art. Still, the tract-based economic analysis did not point to a correlation between income and prevalence of decorative features.

5 Discussion and conclusions

5.1 Discussion

In our study of geolocated images of interior living spaces, we discovered that residents in world regions tend to decorate in statistically-different ways regarding wall art, color, plants, and books—but exhibit similarities in their use of general decor. At the U.S. intra-city level, the wide distribution of ornamentation across different socioeconomic neighborhoods confirmed that carefully personalizing spaces is not reserved for any certain geographic or social group. As such, although home values and income differ widely across cities, we find a commonality in intentions to cultivate a thoughtful interior space. This care and self-expression could be seen as a unifying, not dividing, statistic for even the most segregated cities.

These findings are part of a novel set of studies that take advantage of online datasets that evidence agent-based decisions and personal practices (i.e. decorating one's own home) to help define culture and culture hearths using quantitative analytics (e.g. [20]). These findings can also be situated within a larger family of geospatial urban data on human behavior that augment traditional top-down demographics. More broadly, this analysis illustrates how geographical cultural practices can be found within large online datasets, and assessed using advancements in computer vision.

5.2 Limitations

The conclusions drawn from this research are limited in part by potential biases inherent to the data source. First, it is unclear how well the data hosts represent the larger population. Hosts who list their properties are willing and able to rent extra space in their homes, and thus, may not represent the typical resident who does not have extra space or is not interested in hosting visitors. This may include residents with small children, strict adherence to religious observances, illness, or other reasons. A study of Airbnb rental hosts revealed that hosts are motivated by financial reasons, but also to cultivate social and interpersonal interactions [55, 56]. In addition, the typical host may be different depending on the type of listing. In a study of Airbnb rentals in London, it was shown that room rentals were associated with highly-educated expat renters, while entire homes were found in high-end neighborhoods [10].

Next, due to the competitiveness for bookings, decorating listings in order to appeal to consumers is a strategy that may compromise how an owner would naturally decorate his or her home if it was not posted to the public and furnished to entice visitors. Design factors are key marketing tools in the hospitality industry [57–59], where stylish spaces and comfort are key elements of travelers' choices of where to stay [60–62], and the servicescape is no exception [3]. It is also clear that hosts seek guidance when decorating. An online search retrieves many advice articles, including excerpts from the Washington Post [63] and the Airbnb official blog [64], for decorating one's home as a short-term rental. Informally, these suggest that the owner limits displaying many pictures of family, and perhaps choose local art and photos to add a 'sense of place'. In a typical home that is not for rent, there may be more personalized items, such as family portraits, children's drawings, religious icons or memorials, or even brighter colors. Moreover, hosts may be influenced to emulate design factors from existing successful site listings (and even peruse customer feedback for hints on what visitors might like). While the extent to which this process drives decorative decision-making for hosts is unknown, we acknowledge that it adds potential noise to photos as indicators of individual self-expression.

Finally, our examination of urban areas provided a perspective that may not be found in rural, small city, or even suburban areas, which tend to be more traditional [8]. Urban areas tend to have more modern spaces that can lack traditional symbolic elements that are more prevalent in rural locales [4]. In the future, including geolocatable residential interior images from sites such as Craigslist or U.S.-focused Zillow [14], may help add diversity to the image corpus and analysis.

Future directions for this research include training our model to discover different styles of artwork, perhaps ranging by time period, medium and cultural origin. We can also train our model to discover the proliferation of meaningful elements such as historical emblems, world flags, photos of world leaders, modern technological devices, etc. As such, we can help bridge the gap between big data and human geographical, cultural and urban theory to learn more about widespread practices and patterns around the world. We can also test new hypotheses generated and informed through qualitative cultural research on a larger, more expansive sample of cases.

Additional material

Additional file 1: Supplementary information. (PDF 6.9 MB)
Additional file 2: Multi-page .csv of all 107 cities and element counts. Table of all global cities with average rates of decor prevalence for each indicator. (CSV 7 kB)

Acknowledgements
The authors acknowledge Hanzhou Chen and Luca Maria Aiello for helpful conversations, and the availability of the online Airbnb API for providing the data used in this study. The authors also acknowledge the support of NVIDIA Corporation with a donation of the Titan Xp GPU used for this research.

Funding
The authors declare no funding sources for this work.

Abbreviations
ACS, American Community Survey; ANOVA, Analysis of Variance; API, Application Programming Interface; GIS, Geographic Information Systems; GWR, Geographically-Weighted Regression; HSV, Hue, Saturation, Value; LR, Linear Regression; NAS, Neural Architecture Search; RCNN, Recurrent Convolutional Neural Network.

Availability of data and materials
Anonymized data will be made available through our university-hosted website upon article publication (via http://www.friendlycitieslab.com/). Users will be able to access a public link, provided they use the data for academic and research purposes, as described on the site. These .csv data will include a longitude-latitude (coordinate) value, the elements discovered and presence of vibrant colors, at each location (see Additional file 2).

Competing interests
The authors declare that they have no competing interests.

Authors' contributions
CA conceived of the study. XL, CA and SR designed the study. XL and SR retrieved and cleaned the data. XL, CA, ZH and SR analyzed data. XL, CA and ZH designed visualizations and XL and CA wrote the paper. All authors read and approved the final manuscript.

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Publisher's Note
Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Received: 16 August 2018 Accepted: 24 January 2019 Published online: 08 February 2019

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