SUBJECT-SPECIFIC PREDICTIVE MODELLING FOR URBAN AFFECT ANALYSIS

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Abstract. Recent developments in crowd-sourced data collection and machine intelligence have facilitated data-driven analyses of the affective qualities of urban environments. While past studies have focused on the commonalities of affective experience across multiple subjects, this paper demonstrates an integrated framework for subject-specific affective data collection and predictive modelling. For demonstration, 10 field observers recorded their affective appraisals of various urban environments along the scales of Liveliness, Beauty, Comfort, Safety, Interestingness, Affluence, Stress and Familiarity. Data was collected through a mobile application that also recorded geo-location, date, time of day, a high resolution image of the user's field of view, and a short audio clip of ambient sound. Computer vision algorithms were employed for extraction of six key urban features from the images - built score, paved score, auto score, sky score, nature score, and human score. For predictive modelling, K-Nearest Neighbour and Random Forest regression algorithms were trained on the subject-specific datasets of urban features and affective ratings. The algorithms were able to accurately assess the predicted affective qualities of new environments based on the specific individual's affective patterns.

Keywords. Urban Affect; Subjective Experience; Predictive Modelling; Affect Analysis.

1. Introduction and Background

The affective qualities of urban environments play a major role in shaping the lived experiences of citizens. Different urban areas 'feel' different due to their different perceptual and experiential qualities, and, as a result, give rise to very different emotional responses among urban dwellers. These varied experiential qualities are often homogenized, and described simply as urban 'character'. Moreover, the parameters of urban experience are usually referred to as the 'intangible' and 'subjective' qualities of the urban realm.

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For long, this so called 'intangible' nature of such qualities had resulted in them being situated outside the purview of quantitative inquiry and data driven analysis. Recent developments in the fields of computer science, environmental psychology and geo-informatics have, however, begun to open up new methodological frameworks for the collection, visualization and analysis of big-data pertaining to urban affect. Crowd-sourced platforms have become powerful tools for collecting large datasets of environmental and affective parameters. Developments in machine-learning, notably computer vision, have made it possible to extract urban features from sources such as panoramic street-view images, crowd sourced photographs or social media data. These have been correlated with user-reported affective appraisals to build predictive models capable of evaluating the experiential qualities of urban areas.

Of greater interest, however, is the 'subjective' nature of the experiential realm. Much of the data driven analyses carried out so far have relied on the commonalities of experience across multiple subjects that constitute a dataset, rather than the subject-specific affective nuances that often make urban experience so unpredictable. A single urban environment can give rise to varied subjective experiences across individuals. A number of subject-specific factors such as cultural background, personality traits, prior experiences and the like become important in this regard. As a result, no two citizens ever experience a city or an urban environment in the exact same way. The broad domain of subjective experience has long been the central focus of studies in the phenomenology of architecture and the urban, and has given rise to multiple theoretical positions and points of view. There have, however, been very few data driven frameworks which attempt to engage with subject-specific experiential qualities within a quantitative framework.

This research attempts to provide a step in that direction. There is immense potential for the adoption of existing data collection and analysis methodologies for the synthesis of a data driven framework for subject-specific predictive affect-modelling. Such a framework will rely on the analysis of subject-specific affective data to train predictive models and thus automate the evaluation of new urban environments based on the affective nuances of the concerned subject.

2. Data driven urban affect analysis

Recent quantitative studies in urban affect have focused on specific experiential parameters such as liveliness, pleasantness, diversity, stress, safety, attractiveness and the like. Huang and Gartner (2016) employed mobile applications allowing users to report affective responses to urban environments on scales such as calm-hectic, diverse-monotonous, safe-unsafe, and appealing-unattractive, thus generating 'affect maps' of the city. Similar studies have used geo-tagged Twitter, Flikr and Instagram data to produce 'smell maps' (Quercia, et al., 2015) and 'sound maps' (Aiello, et al., 2016) of urban areas. The 'Urban Emotions' project (Zeile, et al., 2015) combined the use of social media data, app based affective appraisals and objective measurements from wearable sensors to extract, visualize and analyze the affective qualities of cities.

Allied lines of inquiry have focused on employing machine learning algorithms for urban feature extraction from big data sources, and the subsequent visualization of specific perceptual parameters of urban areas. Li (2015) applied pixel classification techniques to Google Street View (GSV) images to calculate Green View Indices and analyze perceived greenery across lower Manhattan. Shen et al. (2017) sampled thousands of GSV images and applied the SegNet (Badrinarayanan, et al., 2017) semantic labeling tool to identify greenery, sky, buildings, roads and vehicles, which could then be represented and analyzed through an interactive visual analytics system. Verma (2018) employed mobile app based image collection platforms coupled with object detection and semantic segmentation models in order to compute and map the perceptual parameters of naturalness, diversity and sky view of a localized urban area.

Further research directions have correlated urban features and affective parameters based on such large training datasets. Naik et al. (2014) relied on a crowd-sourced web based scoring system of perceived safety for over 1 million urban scenes collected through Google Street View images. Urban feature values extracted from the scenes were correlated with safety scores using support vector regression to generate predictive safety maps for 21 US cities. Along similar lines, Dubey et al. (2016) applied Convolutional Neural Networks (CNNs) to predict affective qualities along the parameters of safe, lively, boring, wealthy, depressing, and beautiful.

There is, thus, immense potential for the development of an affect analysis framework that builds upon the methodologies tested out in allied disciplines in order to engage with the subject-specific perceptual and affective qualities of urban environments. While there have been initial advances in the development of similar predictive frameworks for the analysis of architectural enclosures (Sanatani 2020), extending such research directions to tackle subjective experience in the urban realm can lead to promising results.

3. Framework for subject-specific urban affect modelling

The very first step towards an analysis of the 'subjective' affective qualities of the urban realm is the collection of subject-specific data. The framework would need to rely upon datasets that reflect the unique lived experiences of particular individuals at various points in space and time. For predictive modeling, data pertaining to both the form-space-activity parameters of an area, as well the reported experiential qualities of that area need to be collected. The urban parameters (or features) can then be correlated with the experiential qualities for the predictive evaluation of new areas.

3.1. PARAMETER SYNTHESIS

As seen in prior studies, the realm of urban affect can be broken down into specific parameters which focus on specific aspects of the urban experience. Some parameters, such as beauty or attractiveness may tend to primarily capture the visual qualities of the urban realm. Parameters such as perceived safety on the other hand may capture the sensorial as well as the social dimensions of

experience. Urban comfort and stress may be influenced greatly by ambient environmental parameters, while perceived familiarity may be strongly driven by prior experience.

While many studies have examined perceptual parameters such as perceived enclosure, greenery, sky view etc, these may not be considered to be affective parameters per say. In fact, these may be considered to be independent parameters which influence the dependent parameters of urban affect. For example, perceived greenery may play a role in determining the rated beauty of an area, depending on the subjective preferences of the individual. Since the focus of this paper is the realm of affect, only a set of dependent affective parameters were shortlisted for the framework.

Based on a critical review of past studies (Huang and Gartner, 2016, Dubey et al., 2016), the following affective parameters were synthesized: **Liveliness, Beauty, Comfort, Safety, Interestingness, Affluence, Stress** and **Familiarity**. The parameter of Familiarity had been included initially as a dependent parameter, as the field observers had been asked to rate how familiar they perceive that area to be. However, in all cases, the post-survey discussions indicated that their ratings reflected how often they have visited that particular area in the past. As a result, this parameter was considered as an independent parameter for the study.

3.2. DATA COLLECTION FRAMEWORK AND TOOLS

10 field observers from diverse linguistic, professional and geographical backgrounds participated in the project **(Table 1)**. For collection of the data points regarding urban features and affective appraisals, an open source mobile application (ODK Collect) was used. Mobile app based data collection has a high degree of scalability, and a framework relying on such tools can be deployed for much larger studies involving larger sample sizes. Affective appraisals of different urban environments within a ˜5 sq.km area in and around Saidulajab in South Delhi were collected. The area was chosen keeping in mind accessibility within the restrictions imposed due to the COVID-19 pandemic. The area also presented a significant diversity of urban character, and thus elicited a wide range of affective responses for further study and analysis. Data collection took place over multiple days, and covered responses between 8 AM in the morning and 7 PM in the evening.

Table 1. Physical and socio-cultural attributes for all observers.

	Observer									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Gender	male	female	male	male	female	male	male	female	male	male
Age	27	29	22	26	26	23	30	23	31	32
Knowledge Domain	Urban Designer	Landscape Architect	Engineer	Architect	Interior Designer	Architect	Project Manager	Economist	Project Manager	VFX Artist
Native Region	West Bengal	Rajasthan	Rajasthan	Haryana	New Delhi	Andhra Pradesh	West Bengal	West Bengal	Tripura	Bihar

Data points were recorded by the observers through a custom form generated for the ODK platform. The form collected the rated values of the 8 affective

parameters, along with the geo-location of the observer and the current date and time. In addition, for each data point, the form allowed the observer to take a single photograph along his/her field of view, and record a ˜5 second audio clip of the ambient environment. These were then used for the extraction of urban features as described in the following section. On an average, each observer rated ˜50 scenes, the data for which were synced to a common cloud server for further processing.

3.3. FEATURE EXTRACTION FRAMEWORK AND TOOLS

The collected datasets thus comprised of affective appraisals across subjects for diverse urban environments at different times of day. For analysis and predictive modeling, the key urban features for analysis needed be decided upon, and these features for each of the environments needed to be extracted from the photographs. Based on a review of past methodological approaches, a semantic segmentation approach was taken forward. This allowed for an effective analysis of the key elements within the observer's visual field at the time of rating. A pixel segmentation model, DeepLab (Chen et al., 2017) trained on the CityScapes dataset (Cordts et al., 2016) was adopted for this purpose. The model classified each pixel of the dataset into one of 20 categories (such as road, building, car, person etc.) commonly occurring in urban scenes **(Fig. 1)**. Similar categories such as roads and sidewalks, buildings and walls, etc were then clubbed together, and the total assigned pixels for each category were expressed as a percentage of total pixels in the image. This resulted in the following values (on 100) for each scene: **built score, paved score, auto score, sky score, nature score**, and **human score**.

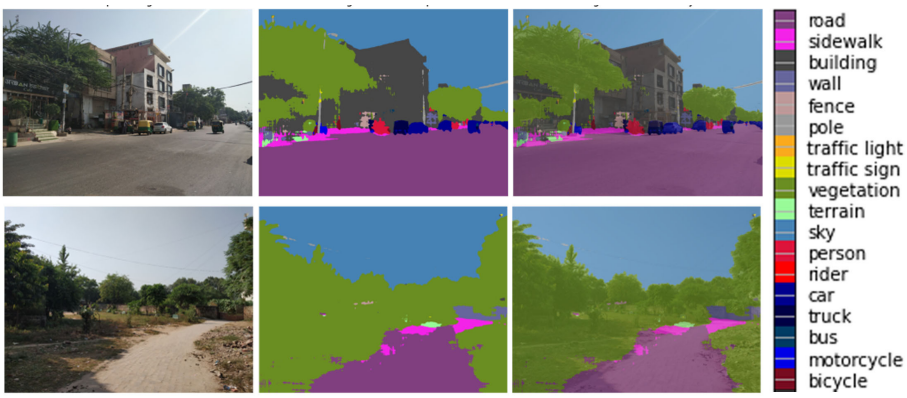

Figure 1. Semantic segmentation of urban scenes.

While a feature extraction model trained on the 'Urban Sounds' dataset (Salamon et al., 2014) was tested out for the semantic labeling of audio clips, the training classes were not found to cover the common ambient sounds occurring in the recordings captured in this study. Manual semantic labeling was thus carried out for preliminary analysis. With the extraction of the key visual parameters, the dataset now comprised of both the dependent affective ratings as well as the

independent urban features **(Table 2)**. This data could now be used as training data for predictive modelling using appropriate machine learning algorithms.

Table 2. Key dataset parameters (Observer 1).

	liveliness	beauty	comfort	safety	intrstngnss	affluence	stress	built_score	paved_score	auto_score	sky_score	nature_score	human_score
count	85.000000	85.000000	85.000000	85.000000	85.000000	85.000000	85.000000	85.000000	85.000000	85.000000	85.000000	85.000000	85.000000
mean	4.929412	5.105882	6.011765	7.141176	5.376471	5.176471	4.600000	32.302438	25.200189	3.041879	10.604261	25.292933	2.173679
std	1.956602	1.739072	1.499953	1.114332	1.765924	1.589972	1.226687	26.689994	7.743308	3.679877	12.375720	22.311774	2.760550
min	1.000000	1.000000	3.000000	4.000000	1.000000	2.000000	2.000000	0.000000	9.164469	0.000000	0.000000	0.230225	0.000000
25%	4.000000	4.000000	5.000000	7.000000	4.000000	4.000000	4.000000	4.519368	19.205404	0.389160	0.892578	5.516927	0.376302
50%	5.000000	5.000000	6.000000	7.000000	5.000000	5.000000	5.000000	28.963542	24.530192	1.429443	5.360840	19.770833	1.241618
75%	6.000000	6.000000	7.000000	8.000000	7.000000	6.000000	5.000000	57.562337	31.091309	3.956624	18.760742	38.232259	2.702393
max	9.000000	9.000000	9.000000	9.000000	9.000000	8.000000	8.000000	84.028890	41.054036	12.966471	43.085531	77.514242	14.260661

3.4. PRELIMINARY DATA ANALYSIS

Correlation matrices **(Fig. 2)** were generated for each observer to understand the relationships between the independent variables extracted from the images and the dependent variables rated by the observers. These allow the framework to form user-specific baselines on the basis of the ratings recorded by specific individuals. Given the aim of the framework, a baseline generalized on a sample population data would be inapplicable and inaccurate.

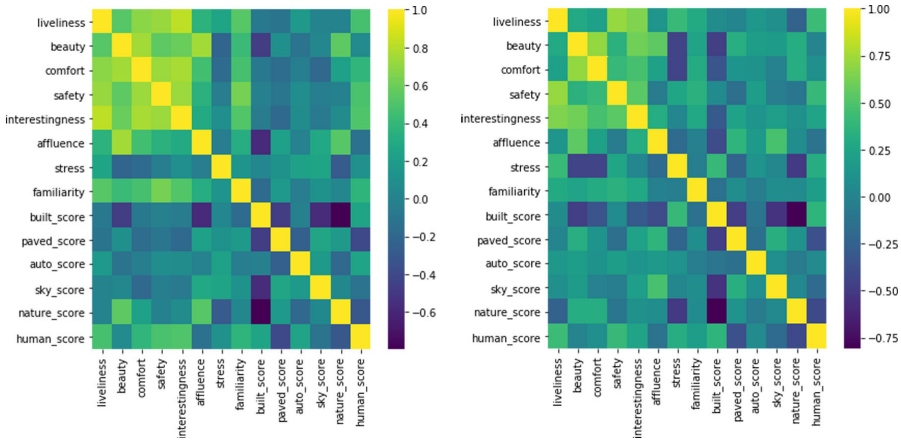

Figure 2. Correlation matrices for Observer 1 (left) and Observer 2 (right).

3.4.1. Subject specificities and affective nuances

On a preliminary analysis of the training data, certain subject-specific nuances were observed. Observers 2, 5, 3 & 10 were found to have high inverse correlations between nature_score and rated stress (r = -0.51, -0.57, -0.72, -0.61), unlike the other observers where there was negligible correlation. Moreover, notable direct correlations between built_score and rated stress appeared for Observers 2, 3, 5 and 8. Similarly, a significant correlation between nature_score and rated beauty (r = 0.56, 0.54, 0.6, 0.69, 0.54) was seen in observers 1, 4, 5, 6 and 10 while

the correlation was lower or negligible for the others. Observer 1 also showed a significant correlation (r = 0.51) between people_score and rated 'interestingness', which was not seen among the other observers of the dataset. This would appear to indicate a possibly unique relationship for this observer wherein they appear to identify areas with more people as more interesting. However, all subjects showed an inverse correlation between built_score and rated beauty, indicating that certain general trends might emerge in larger datasets.

While most observers had a high correlation between 'safety' & 'liveliness', observers 5,6 and 8 showed low correlations between these 2 variables. It is interesting to note that there was significant diversity across female observers (r = 0.19, 0.33 and 0.72) showcasing the subject specificities within gendered safety perceptions in the public realm. Reviewing human_score and rated liveliness, observers 1, 2 & 10 showed a significant positive correlation (r = 0.47, 0.42, 0.44) which was much lower for the other observers. Analyzing built_score and affluence, it was seen that Observers 1,2 and 4 to 8 had a high negative correlation (r = -0.33 to -0.75) in contrast to the remaining observers. However, all observers reported a high positive correlation (r = 0.4-0.82) between rated 'affluence' and rated 'beauty'.

Figure 3. Correlations between rated 'liveliness', human_score, and ambient sound for Observers 1(left) and 2(right).

On analyzing specific data points, certain notable patterns emerged. In large, public open spaces (parks, playgrounds etc.), it was seen that, despite a low human_score, some subjects had rated the area high on the liveliness scale **(Fig 3)**. However, the audio recordings for these areas were labeled 'human', indicating the presence of human activity in the ambient surroundings. Thus, it can be seen that, due to the auditory inputs received by the observer, there was an awareness of groups of people located nearby, which led to the observer's "perceived liveliness" of the area. Similarly, a higher liveliness score was recorded on major roads which had a higher auto score even though these areas had a lower human score. Both these parameters thus influenced liveliness perceptions for some subjects.

Such nuances, revealed through the preliminary analysis, showcases the widely differing emotional impacts of urban environments, and the complex relationship between the physical and the emotional realms in cities. Though further research is required, the initial findings show the complexity of integrating positive emotional responses when designing urban environments for specific user-groups or communities. It also justifies the need for adopting a subject-specific approach, so as to ensure that singular affective nuances of people can be catered to.

3.5. PREDICTIVE AFFECT MODELLING

Having established the subjective nature of the affective ratings, the individual data sets were taken up for predictive modelling. Each scene rated by the subjects had thus the 6 extracted features that were considered to be independent parameters (predictor variables), and 7 rated affective qualities (dependent variables). For initial demonstration of the framework, possible correlations between dependent variables were not taken into account, and the affective ratings were considered to be independent of each other. Separate machine learning models were thus trained for each of the affective qualities.

3.5.1. Algorithm Selection and Error Metrics

Since the affective ratings were collected as numeric data on a 1-9 scale, the models would be predicting the values of single a continuous variable for each affective quality. It was thus necessary to choose an appropriate regression algorithm for this purpose. While non-linear and support vector regression models were tested out, K-Nearest Neighbor (KNN) and Random Forest (RF) Regression algorithms were decided to be most appropriate for initial demonstration. The relatively small training data size for each subject, along with the presence of possible confounding variables supported this choice.

Table 3. Key error metrics for the predictive framework.

	Root mean squared (RMS) error													
	Liveliness		**Beauty**		**Comfort**		**Safety**		**Interestingness**		**Affluence**		**Stress**	
	KNN	RF	KNN	RF	KNN	RF	KNN	RF	KNN	RF	KNN	RF	KNN	RF
Observer 1	1.67	1.77	0.98	0.95	1.23	1.43	0.96	1.22	1.56	1.69	1.19	1.27	0.85	0.86
Observer 2	1.45	1.87	1.45	1.22	1.12	1.39	0.71	1.1	1.72	1.62	1.29	1.68	2.34	2.41
Observer 3	0.43	0.64	0.94	0.5	0.88	1.13	0.92	1.32	1	1.08	1.29	1.53	0.58	0.92
Observer 4	2.54	2.18	2.43	2.48	1.85	1.85	1.98	2.42	2.32	2.29	2.12	1.78	1.84	2.01
Observer 5	2.1	1.97	1.67	1.42	1.94	2.32	2.12	2.28	2.07	1.81	1.18	1.67	1.52	1.57
Observer 6	1	2.43	0.74	1.49	1.41	1.84	1.26	1.33	1.3	1.92	1.19	1.84	1.84	2.02
Observer 7	1.73	2.95	1.96	2.73	1.29	2.11	1.41	1.88	2.19	2.88	1.72	2.08	1.94	2.31
Observer 8	1.25	1.19	1.49	1.73	1.47	2.25	0.54	0.7	0.85	1.2	1.07	1.16	0.71	1.28
Observer 9	1.7	1.69	2.45	2.47	1.29	1.46	1.38	1.34	1.29	1.42	1	1.87	1.29	1.85
Observer 10	0.29	0.46	1.02	1.16	1.3	1.3	0.33	0.25	0.95	1.31	0.27	0.47	0.54	0.96
Mean	**1.416**	**1.715**	**1.513**	**1.615**	**1.378**	**1.708**	**1.161**	**1.384**	**1.525**	**1.722**	**1.232**	**1.535**	**1.345**	**1.619**

The regression algorithms were built in Python using the using the scikit-learn library (Buitinck et al. 2013). In the current version of the framework, the algorithms were able to predict the values of the 7 affective parameters with an average root mean squared (rms) errors of **1.37** (KNN) and **1.61** (RF), on 9-point scales between 1 to 9. **Table 2** describes the key error metrics of the predictive model.

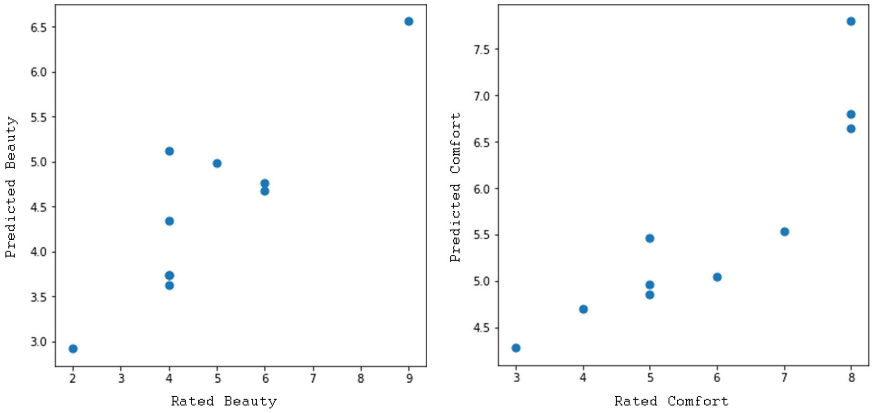

Figure 4. Predicted vs Rated Values of Beauty (left) and Comfort (right) for Observer 1.

4. Opportunities, Challenges and Future Directions

Though in an initial stage of development, this paper attempts to engage with subject-specific experiential qualities within a quantitative data driven framework. Data-driven design and planning strategies within the realm of urban experience often run the risk of homogenizing diverse lived experiences across citizens and communities. This framework adopts the very same methods to address this very issue.

Given the relative ease of collecting user-specific data through personal mobile devices, such a predictive framework may be taken forward for multiple use cases. While route optimization systems in urban areas often provide quickest or shortest routes based on real time data along multiple parameters such as traffic conditions, restrictions etc., affect-based route suggestion based on individual preferences also has great potential. Along similar lines, recommender systems for urban leisure as well as tourism can rely upon such predictive models. Moreover such a framework may be utilized to gain valuable insights into the nuances of affective response for specific demographic groups/communities.

Such directions however do pose multiple challenges. Prediction accuracy becomes critical for the success of such a framework, and the accuracy of the models depends greatly on the consistency of user responses. The choice of affective variables, the data collection methodology, and the user interface become extremely important in this regard. The methodology demonstrated in this framework has scope for refinement keeping such factors in mind. Moreover, any kind of user-specific predictive modeling gives rise to concerns regarding data privacy. Building trust amongst target users of tools which cater to the previously discussed use-cases thus also becomes a major factor. It is hoped that appropriate steps to engage with such challenges are synthesized in the near future, and that this line of inquiry serves as a step towards data-driven analyses of subjective experience in cities.

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