Learning from Discovering: An unsupervised approach to Geographical Knowledge Discovery using street level and street network images

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ABSTRACT
Recent researches have shown the increasing use of machine learning methods in geography and urban analytics, primarily to extract features and patterns from spatial and temporal data. Research, integrating geographical processes in machine learning models and, leveraging on geographical information to better interpret these methods had been sparse. This research contributes to the ladder, where we show how latent variables learned from unsupervised learning methods can be used for geographic knowledge discovery. In particular, we propose a simple and novel approach called Convolutional-PCA (ConvPCA) which are applied on both street level and street network images in finding a set of uncorrelated visual latent responses. The approach allows for meaningful explanations using a combination of, geographical and generative visualizations to explore the latent space, and to show how the learned embeddings can be used to predict urban characteristics such as street-level enclosures and street network density.

KEYWORDS
urban analytics, unsupervised learning, convolutional neural networks, knowledge discovery, computer vision

1 INTRODUCTION
According to [21], Geographic knowledge discovery (GKD) is the process of using computational methods and visualization to explore spatial databases to discover useful geographic knowledge. Despite the increasing availability of spatio-temporal data and the subsequent use of machine learning to retrieve geographical knowledge, the majority of the research have mostly focused on learning a specific objective. For example, on the use of convolutional neural networks to make inferences for an output such as perceived safety [23], house price [18] and scenicness [27]. These researches require effort on both collecting the data and on learning a specific objective.

This study contributes to these research questions and proposes a model called Convolutional-PCA (ConvPCA) that summarises urban imagery into a set of lower dimensional latent responses. We apply this method to Google StreetView images [10] and Open Streets Maps (OSM) street network images [24]. In the experiments, we first map and visualise the extremes of the responses to explore spatial patterns and interpret the data geographically and visually. We then study the latent responses by associating it to different geographical datasets such as street enclosure for the StreetView data and network density for the street network data. The research finds that the visual response from the ConvPCA model has interpretable meaning with associations to geographical labelled data. From a machine learning perspective, we gain new knowledge about these latent responses which contributes to the recent efforts in linking the two disciplines [17] [25].

2 RELATED WORKS
2.1 StreetViews
Street-level images have been used extensively in smart transportation. Specifically on the deployment of autonomous vehicles where convolutional neural networks (CNN) had been applied for urban scene understanding [26]. More recently, we have also seen the use of Generative Adversarial Networks (GAN) to synthetically create street scenes that could be used to train self-driving vehicles [31]. Despite its popularity in transportation research, there had been limited effort on using street-level imagery to recover geographical knowledge. One such example is StreetScore where [23] collected human perception data from street images through a crowd-sourced survey (Place Pulse 2.0) which are then used to predict the perceived safety of a place [8]. Another example is the work of Gebru et al. [9] whom extracted features such as car types from Google StreetView images to predict the income, race, education, and voting patterns for cities in the States. We have also seen the use of urban images [27] to predict scenicness ratings which were found to affect urban wellbeing. These recent works rely on extracting an interpretable medium level feature from street-level images. In contrast to these works, Law et al [18] extracted visual responses of StreetView images directly from house price. A distinguishing difference here is that the method did not extract an interpretable medium-level variable from an image but rather a general visual response that corresponds directly to house price. Our research extends from this work but rather than learning a visual response that estimates house price, we propose a method to learn a set of generic visual summaries using an unsupervised learning approach. These summaries can be interrogated, perturbed and studied for knowledge discovery.

2.2 Street Networks
In the case of street networks, there has been a long-standing effort to analyse and to understand them from a quantitative perspective and to generate models that are able to reproduce their empirical features. Previous works have largely been based on complexity theory and network science perspective [5, 19, 29]. This includes analyzing the spatial configuration of urban street networks [13] and
We propose here the Convolutional-PCA (where the encoding layer reduces the dimension to a latent variable while the decoding layer increases the dimension back to image space. The sequential architecture can be seen in figure 1. Generative models have also been used to generate synthetic street networks. Variational Autoencoders trained on street network images have been used by sampling from the latent space $z$, however the resolution of these are low, and fail to capture fine grain detail of local streets. Generative Adversarial Networks such as StreetGAN [12] has also been proposed to generate a multitude of arbitrary sized street networks that faithfully reproduce the style of the original datasets. Current limitations in the use of VAE, CAE, and GANs on street networks lie in the interpretability of the latent space and its relationship to geometrical and topological properties used in established network measures. Our research contributes to these by developing a methodology to interpret the low-dimensional embedding learnt by a convolution auto-encoder. This allows for greater control on the generative model, as well as providing some initial results as to the relationship between the embedding and established network measures.

3 METHODS AND MATERIALS

3.1 Convolutional-PCA

We propose here the Convolutional-PCA (ConvPCA), which combines a type of Convolutional Neural Network called the Convolutional Auto Encoder (CAE) with a linear PCA ($\text{PCA}_{\text{lin}}$) to retrieve a set of visual responses that summarises a StreetView image or a street networks image. We first describe the CAE followed by the $\text{PCA}_{\text{lin}}$. Deep Convolutional Autoencoder CAE are unsupervised methods that uses convolutional neural network (CNN) to extract image features [3, 11, 20]. Deep CAE consists of two set of layers, an encoder $f_w(\cdot)$ and a decoder $g_u(\cdot)$

\[
  f_w(x) = \sigma(x \ast W) \equiv z
\]

\[
  g_u(z) = \sigma(z \ast U)
\]

where $x$ is the input vector, $z$ is the latent features, $\ast$ is the convolution operator that extract image features and $\sigma$ is a typical activation function such as ReLU to model nonlinearity in the neural network. These convolutional layers can be stacked sequentially where the encoding layer reduces the dimension to a latent variable $z$ while the decoding layer increases the dimension back to image space. The sequential architecture can be seen in figure 1.

Following [20], the parameters of the encoder $z = F_w(x)$ and the decoder $x' = G_u$ are updated by minimising the reconstruction errors between $x$ and $x'$.

\[
  L_r(x, x') = \frac{1}{n} \sum |x_i - G_u(F_w(x_i))|^2
\]

In our research, we further compress the latent visual features by applying a linear principal component analysis $\text{PCA}_{\text{lin}}$ which summarises the visual feature $z$ into a set of linearly uncorrelated variables $u$. To compute PCA, we first standardise $x$ and compute the Eigenvectors and Eigenvalues of the feature covariance matrix $P$. We then take the Eigenvectors to calculate the full principal component decomposition of $z$, given by $V = WX$, where $W$ is the eigenvector matrix. $V$ can be re-projected back on to the original latent space produced by the encoder before passing in to the decoder to reconstruct the images. This process allows us to:

- Retrieve a set of uncorrelated visual features that can be mapped and interpreted geographically.
- Make changes to individual features to test their response in the generator.
- Relate learnt visual features to geographical labelled data.

3.2 Materials

We collected two datasets. The first dataset is street images taken from the Google StreetView API [10]. Differ from [18], two building-facing images were collected for each street in the Greater London Area. To collect the dataset, we constructed a line-graph from the street network of London (OS Meridian line2 dataset [30]). We then take the geographic median and the azimuth of the street edge to give both the location and the bearing when collecting each image. We collected a total of 110, 493 street images in London. For more details in the data collection method please see [18]. Figure 3 illustrates typical images from the dataset.

The second dataset is the street network dataset taken from Open Streets Maps [24], we query all the cities and towns for a total of 107, 973. For each city and town we download the street network within a 1.5km x 1.5km box at the centroid of each place using osmnx [4]. Figure 4. For each 1.5km x 1.5km grid we retrieve a graph $G = (V,E)$ where each vertex $v$ corresponds to a street intersection and $e$ edge corresponds to a street segment. For each $G$ we rasterise into a 256 x 256 pixel image Figure 5, we also calculate basic network features [6] that are latter used to test the learnt features of the images.
4 EXPERIMENTAL RESULTS

In order to discover new knowledge and interpretations from these visual responses, we will visualise these latent response followed by a prediction model for both types of data.

4.1 streetview images

4.1.1 Visualisation experiments. The ConvPCA first learns a mapping from a three channel street level images (224 x 224 x 3) down to a lower dimensional embedding (4,096 dimensions) using an autoencoder. The lower dimension embedding was then further summarised into a set of uncorrelated responses using PCA_{lin}. For the autoencoder, we adopted a VGG16 [28] as the basis of the architecture where we keep the kernel size and filter numbers constant across both the encoder and decoder.

To show the results, we visualise the first two components in figure 7. The images plotted above the map show the two extremes of the visual response. We interpret the first visual response $v_1$ as a proxy for urban richness while we interpret the second visual response $v_2$ as a measure for urban density.

We then visualise the extreme values of four other components for further interpretation. In this case, component $7^{th}$ has blank facade in one of the extremes and natural scenarios in the other. The $10^{th}$ and the $30^{th}$ component shows a tunnel space in one extreme and a mixture of urban scenarios in the other. While the $14^{th}$ component has buildings in one extreme and blank facades in the other extremes. Later components shows less patterns. Further work in visual explanation is needed to better understand these visual summaries.
when we perturbed the images to the other axis, the trees start filling the view. These results show geographical and generative visualisations are useful approaches to interrogate and to discover the meaning of these visual latent responses.

Furthermore, we visualised one of the StreetView images and perturbed its first principal component while holding all the other component values constant. The plot shows when we perturbed the images towards one of the axis, building details increase, and when we perturbed the images to the other axis, the trees start filling the view. These results show geographical and generative visualisations are useful approaches to interrogate and to discover the meaning of these visual latent responses.

Figure 7: London StreetView Urban Richness. We interpret this component as a measure of urban richness, where red denotes higher urban richness and blue denotes lower urban richness.

Figure 8: London StreetView Urban Density. We interpret this component as a measure of urban density or building intensity where red denotes higher density and blue denotes lower density.

Figure 9: Visual response perturbations of a London StreetView image. By perturbing the first principal component of a typical StreetView, we show greater building details in one of the extremes and greater urban greenery in the other extreme.

4.1.2 Prediction experiment. In order to interpret these visual response and demonstrate its usefulness, we regress a set of visual responses to predict a generic urban characteristic such as street enclosure. Street enclosure here is defined as the average height of the building of a street divided by the average width between the buildings of the same street illustrated in fig 10. This measures had been computed using GIS with Ordnance Survey data [30]. For each street in London, we split the dataset randomly into a train (70%), validation (15%) and test set (15%). We then train a multi-layer perceptron $F(\cdot)$ to predict normalised street enclosure from the visual response $V$ as inputs, parameterized by a set of weights $W_v$. The multi-layer perceptron here is defined as a fully connected neural network with two hidden layers. The first fully connected layer has 64 hidden nodes, while the second layer has 32 hidden nodes. A dropout layer was included for better generalisation. To test the importance of the visual response with respect to the model accuracy, we constructed four different models based on the number of components [4,8,16,32] using the same architecture for all models. We train the model to minimize the mean squared error on a training set, using the ADAM [16] optimizer with the initial learning rate set at 0.001. We then report the mean squared error (MSE) and the coefficient of determination $R^2$ between the model prediction and the street enclosure for the test-set. All the experiments are conducted with the Keras library [7] using a Tensorflow [1] back-end.
Figure 10: Street Enclosure Diagram. We define street enclosure as the ratio between $\frac{\text{avg.height}}{\text{avg.width}}$.

The results in Table 1 shows the mean squared error and $R^2$ for all four models when applied to a spatially random test-set. The model with 32 components achieves 60% accuracy, while the model with 4 components achieve 50% accuracy. The results show that we can achieve a good accuracy with minimal number of components in the model. However further prediction experiments are needed to confirm its usefulness for other geographical tasks.

Table 1: Street Enclosure Results

|                  | $R^2$  | MSE  |
|------------------|--------|------|
| 4 components (Vis) | 49.51% | 0.53 |
| 8 components (Vis) | 55.76% | 0.47 |
| 16 components (Vis) | 57.31% | 0.45 |
| 32 components (Vis) | 59.7%  | 0.43 |

4.2 street network

4.2.1 Visualisation experiments. For the street network, the trained autoencoder learned a mapping from the space of street network images (256 x 256 x 1 or 65,536 dimensions) to a lower dimensional latent space (640 dimensions) which are then further summarised into a set of linearly uncorrelated variables by applying $(\text{PCA})_{lin}$. By plotting out the street network images with the lowest to highest values of each component we can start to interpret the learn latent space. In figure 11, we show the first five. These plots all relate to density of streets in different spatialised regions. The first $\text{pca}$ encodes general density, while $\text{pca}$ 2-5 encode spatialised densities (left-right, top-bottom, center-periphery, diagonals) respectively.

To make it easier to interpret each $\text{pca}$ we create a mean vector ̂$\mathbf{v}$, where we keep all values in ̂$\mathbf{v}$ constant and vary only the $\text{pca}$ before passing it to the generator to create a synthetic image. In figure 12, we show a subset of the different visual response encoded by the $\text{pca}$ values. We show that the first 10 $\text{pca}$ encode regions of spatialised density, $\text{pca}$ 11-50 encode global structure of the network (coarse grain detail), and $\text{pca}$ 50-640 encode local structure of the network (finer grain detail).

4.2.2 Prediction experiment. Lastly we test the ability of these encoding to capture network features by using them to predict network statistics such as: average circuity, intersection density...
We have presented a simple but novel unsupervised approach to extract and interrogate visual latent responses from urban images. This research sits in contrast to previous works which focused on supervised learning [9, 18, 23, 27] and unsupervised learning for reconstruction [14, 31]. Through visualisation, both geographically and generative, and prediction experiments we were able to retrieve meaning from these latent responses.

In the case of the street level images, by visualising the extremes of the latent variable and perturbing it, we were able to discover meaning from the data such as the visual richness and urban density of a street. We also find that the latent variables are able to predict a generic urban characteristic such as street enclosure. However to validate the method, future works is needed on a) creating higher quality reconstructions using more advance generative methods such as VAE or GAN b) developing quantitative methods to systematically explain these visual latent responses and c) conducting research on multi-task and multi-modal learning for different geographical tasks.

In the case of the street networks, although the model is able to predict road network density, it fails to capture more complex street network features, we believe this is because the self-organized pattern of street networks is the result of both geometrical order/disorder as well as local rules of optimality. Through rasterising the street networks, the explicit topological data of the graph is lost, and the model is not able to recover this from the image alone. Future work can explore ways to incorporate topological properties of the networks in the model. Recent advances in graph neural networks provide promising directions that would allow both topological and geometric properties to be incorporated into the model, this would allow a richer representation of the street network as both local connectivity structure and their spatial embedding would be preserved.

An immediate implication of the study, is that by discovering general knowledge from these urban images, we can use this information for other downstream geographical tasks. For example in using street-level images to predict land classification. Conversely, this can reduce compute time and data collection costs significantly. More importantly though, the knowledge discovery process of using a combination of visualisation and inference, can represent an exploratory approach for learning more about these complex non-linear methods such as neural networks and higher dimensional datasets such as images.

To conclude, this research contributes to recent efforts in linking the disciplines of geography and machine learning. On the one hand, we find the visual latent responses as learnt from street level images to predict road network density, it fails to capture more complex street network features, we believe this is because the self-organized pattern of street networks is the result of both geometrical order/disorder as well as local rules of optimality. Through rasterising the street networks, the explicit topological data of the graph is lost, and the model is not able to recover this from the image alone. Future work can explore ways to incorporate topological properties of the networks in the model. Recent advances in graph neural networks provide promising directions that would allow both topological and geometric properties to be incorporated into the model, this would allow a richer representation of the street network as both local connectivity structure and their spatial embedding would be preserved.

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To conclude, this research contributes to recent efforts in linking the disciplines of geography and machine learning. On the one hand, we find the visual latent responses as learnt from street level and street network images have interpretable meanings. On the other hand, we also demonstrate how geographical datasets and visualisation techniques can be used to enrich our understanding of machine learning methods.

5 DISCUSSION AND CONCLUSION

We have presented a simple but novel unsupervised approach to extract and interrogate visual latent responses from urban images. This research sits in contrast to previous works which focused on supervised learning [9, 18, 23, 27] and unsupervised learning for reconstruction [14, 31]. Through visualisation, both geographically and generative, and prediction experiments we were able to retrieve meaning from these latent responses.

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