Explainability pipeline for urban images

ABSTRACT

Recent advances in deep neural networks and generative adversarial networks allow us to both create discriminative models and invert the processes to enable generative models, capable of generating image samples very close to real world natural images. This has proven a useful tool in visualizing what a network learns when it learns to classify cats, dogs and objects. The challenge is to understand whether the same approaches can be useful in understanding much more abstract and meta properties like Beauty, Liveliness, depression etc. This paper proposes a pipeline and the necessary framework to infer affective components in urban images.

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1 INTRODUCTION

Deep neural nets are progressing at an amazing pace over the past decade. The community as a whole has been breaking new ceilings when it comes to classification and inference records for specific tasks like object detection, scene detection, language modeling etc. But the internal workings and the internal process of neural nets before coming to a particular decision, more or less still remains a mystery. Neural nets have more or less remained a black box for its users. Explain-ability and understanding the deep reasoning behind decisions is one of the most researched problems in the machine learning community.

The problem of explain-ability becomes even more abstract and obscured, when we are dealing with tasks that handle meta, and abstract quantities like sentiment, affects and aesthetics. Despite the black box like nature, deep neural networks have done remarkable strides in understanding creativity [10], memorability [6] or beauty [12]. These works explore perceptual qualities of media objects using deep learning, and treat the explainability of the models using round about methods like perturbation of input and understanding correlation of several governing variables with decisions of the network etc. These methods are perfectly valid and do give some interesting insights into the decision influencing factors for the models, however still fail to explain the decision making process of the model itself.

This paper builds on top of several works done before, in the areas of explainability of neural nets and understanding affective dimensions as listed before takes a step towards extending these to the realm of urban emotions and aesthetics. More so we strive to propose a generalizable pipeline for analyzing geo-referenced images.

symbol	**stands for**
X	Georeferenced image set
I_i	Georeferenced image
Y	Annotations classes for X
y_i	Annotation class in Y
$\hat{I}_j$	Template image
I'	Target Image
term	**stands for**
Template Image $\hat{I}_j$	A synthetic transformation of input image I towards the class y_j
Target Image I'	The natural image which is most visually similar to the template image
Data Clustering	A process which groups images in X according to visual similarity (e.g urban vs rural)
Data Augmentation	A process which looks for images taken in the surrounding areas of the georeferenced images in X
Classifier	A deep-learning framework that is able to classify images into one of the classes in Y
Generator (*GAN*)	A deep-learning based generative framework to produce images similar to the ones in X
DGN − AM	A framework that, given the GAN and the Classifier, transforms an input image into the template image.

Table 1: Notations and Terms.

2 PIPELINE

With the motivation of creating a streamlined framework, we propose an end-to-end pipeline for explaining urban image categories, which is illustrated in Figure 1.The system allows anyone with an arbitrarily set of image data $X = I_1, I_2....I_n$ annotated in classes $Y = y_1, y_2, ..., y_k$, to transform natural images between classes: the pipeline can transform an arbitrary image I_i belonging to class $y_i \in Y$, to image I_j from class $y_j \in Y$. This allows to visually reason about the discriminative properties between classes $y_i, y_j \in Y$, and visually understand what are the salient characteristics that drive a classifier to distinguish between classes y_i, y_j. These questions might be trivial for tangible classes of objects, but still remain largely unexplored for intangible classes representing concepts like affects and aesthetics.

This pipeline approaches the transformation problem in two phases. Assuming the previous example where we transform images from class y_i to class y_j, the first step is to produce a prototype image or a template image $\hat{I}_j$, that represents the basic traits of the the destination class $y_j \in Y$. The second step is to match this template image $\hat{I}_j$, with the closest natural image in X. In mathematical terms, we want to choose a target image I' from X so as to minimize $E(I', \hat{I}_j)$, where $E(I_1, I_2)$ is some error measure that quantifies visual error between two images. This image I' is effectively a natural transformed image.

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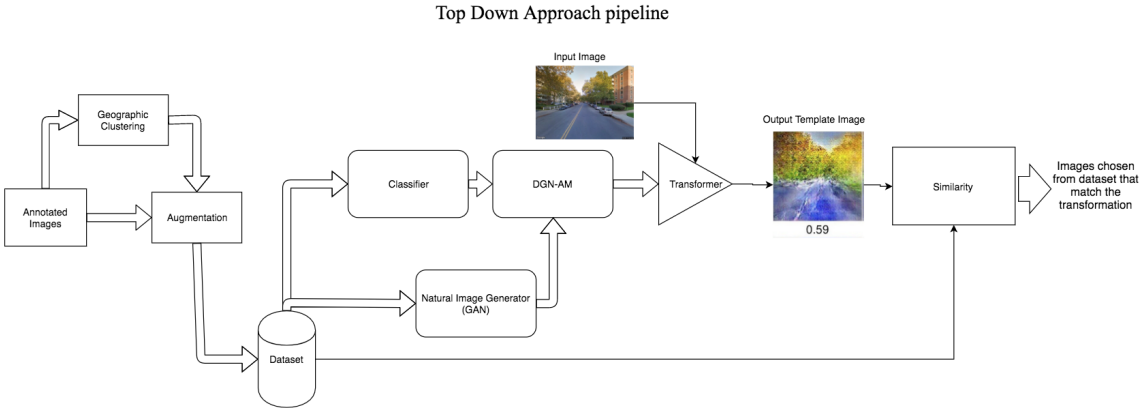

Figure 1: Process pipeline for the "Top Down" approach for explainability

2.1 Pre-Processing: Data Clustering and Augmentation

We assume that the input to the framework is simply a crawl of geo-referenced images, annotated for an arbitrary use case. The data needs to be preprocessed in two separate ways: Data clustering and Data Augmentation.

2.1.1 Data Clustering. In urban images, the variance in structure and composition can be extremely high. The main aim of data clustering is to reduce the diversity and variance in the image set. This is needed when working with state of the art deep-learning classifiers, which generally work on highly specific classes of objects with low variance in the image semantics. Two clustering methods are listed below.

- The most simple yet effective way to cluster data is based on geographical context. This can be done simply by using geographical boundaries of areas of interest and clustering images based on attributes like rural, urban, suburban, city etc. This seems like an intuitive pre-processing step, as images from countryside look widely different compared to the images from the urban environment, and might be look visually diverse despite having similar annotations.
- The other solution is to cluster images based on some visual/latent similarity measure. One possible way to do this is by extracting higher dimensional features, and clustering images based on these features.

2.1.2 Data Augmentation. In the due process of clustering, it is expected that the total size of data available to train would reduce. Smaller data size implies that a machine learning model has a risk of over-fitting and in the worst case not learning anything at all. Hence there is a need to augment this clustered data with some additional real and transformed data. Some of the techniques that may be used are listed below.

- The most common augmentation technique in deep learning literature is to do transformations on the image. Transformations like flipping images, cropping, adding noise , shifting color histograms can increase the data points for training and at the same time reduce the risks of over fitting.
- Because the images are geo tagged, one can augment the data by acquiring additional images which fall very close geographically to the original image. In this approach, care must be taken to maintain visual similarity of additional images. This can be achieved by several ways including, but not limited to, using higher dimensional features extracted using some pre-trained image models, to measure visual similarity (as described in the clustering section).

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2.2 Template Generator

We now want to design a framework to transform any image I into a template image $\hat{I}_j$ (as shown in Figure 1) $\hat{I}_j$ is a synthetic version of the original image, with added features and motifs that maximize class y_j. To produce the template image $\hat{I}_j$, we need the following components in place, 1) A classifier which learns how to distinguish between different image categories y_i 2) A generative model (GAN), that can generate samples from the distribution of the dataset images. 3) An activation maximization framework, that, based on the GAN generator, generates images that maximizes activation for a given annotation class [2] (our template images).

- *Classifier*. To create synthetic representations of annotation classes, we first train a deep learning based classifier, that, given an image I, can correctly classify it in one of the k classes. The aim of the rest of this pipeline is to explain *what* the classifier is learning about the annotations. The assumption here is, once the classifier learns to discriminate amongst the classes, it also learns discriminative properties about the images that fall in those annotation categories.
- *Generator*. We train a generative adversarial network (GAN) which can generate an approximate natural looking image drawn from distribution of a particular class of images, similar to the one in [2]. This GAN generator would learn to generate a natural-like image that represents the overall structure and knowledge about the Dataset.
- *Activation Maximization*. We plug in the GAN and the classifier network into an Activation Maximisation (AM) framework. Given these components, an input image I, and

a target class y_i, the AM transforms I in an ideal image $\hat{I_j}$ (that maximizes the activation for class y_i). Essentially $\hat{I_j}$ is a representation of the overall knowledge about a particular annotation class, that the classifier network has learned through training.

2.3 Similarity and inference

In this final step we find a target image I' from the dataset that is closely aligned, in terms of some visual similarity metric $E(I_1, I_2)$, with the generated template image $\hat{I_j}$. The result of this exercise is to find the most similar looking image to an input image I that maximizes a particular annotation class y_j.The visual differences in these two natural images, can act as the subject of reasoning for the explainability.

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