PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE
ESCUELA DE INGENIERÍA

DEEP NEURAL NETWORK MODELS WITH EXPLAINABLE COMPONENTS FOR URBAN SPACE PERCEPTION.

ANDRÉS CÁDIZ VIDAL

Thesis submitted to the Office of Research and Graduate Studies
in partial fulfillment of the requirements for the degree of
Master of Science in Engineering

Advisor:
HANS LÖBEL

Santiago de Chile, July 2020

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Gratefully to my parents and siblings

ACKNOWLEDGEMENTS

Write in a sober style your acknowledgements to those persons that contributed to the development and preparation of your thesis.

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ABSTRACT

The abstract must contain between 100 and 300 words. The abstract must be written in English and Spanish. In the case of doctoral theses, the layout of the abstract page is different, so please check the template provided by the OGRS.

Keywords: thesis template, document writing, **(Write here the keywords relevant and strictly related to the topic of the thesis)**.

RESUMEN

El resumen debe contener entre 100 y 300 palabras. El resumen debe ser escrito en inglés y español. En el caso de tesis de doctorado, el formato de la página del resumen es distinta, por favor verifique la plantilla entregada por la Dirección de Postrgrado.

Palabras Claves: plantilla de tesis, escritura de documentos, **(Colocar aquí las palabras claves relevantes y estríctamente relacionadas al tema de la tesis)**.

1. INTRODUCTION

Urban perception is a feeling held by people about a location. These feelings can be and are often related to a particular characteristic, like happiness or beauty, or also inherently negative ones, like insecurity or fear (Ordonez & Berg, 2014). Understanding the cause of these feelings is a complex task, since unique social and psychological aspects of each individual affect how they perceive and the spaces they observe (Nasar, 1990).

Visual urban perception is responsible for a large parte of the experience that people go through while being at or using an urban space, this not only affects how much the spaces themselves are used (Khisty, 1994) but also the use of related means of transport (Antonakos, 1995). Other studies have also found correlations between urban perception, crime statistics (Ordonez & Berg, 2014) and wealth, and therefore used it as a proxy measure of inequality (Ordonez & Berg, 2014; Salesses, Schechtner, & Hidalgo, 2013; Rossetti, Lobel, Rocco, & Hurtubia, 2019).

On the other hand, being able to understand a community's need and perception of a city at scale is something of key importance on developing cities, so that the limited resources of local governments can be applied more efficiently (Santani, Ruiz-Correa, & Gatica-Perez, 2018).

Traditional methods for obtaining this type of data, consist of hand made polls about specific locations making systematic evaluation of perception an extremely costly and hard to escalate task (Nasar, 1990; Clifton & Ewing, 2008). Other approach consist of surveys based on computer generated images of simulated spaces, this is more scalable, but is limited to experimental design and it doesn't apply to a real space (Laing et al., 2009; Iglesias, Greene, & de Dios Ortúzar, 2013).

Currently, thanks to the great volumes of data generated by web platforms (Salesses et al., 2013) and to modern deep learning (DL) and computer vision techniques (LeCun, Bengio, & Hinton, 2015), new solutions for estimating urban perception have become

feasible, and some previous studies have achieved significant results, either by applying traditional deep learning (Dubey, Naik, Parikh, Raskar, & Hidalgo, 2016) or by combining it with other approaches (Rossetti et al., 2019; Zhang et al., 2018). The solutions consist mainly of training convolutional neural network models (LeCun et al., 1989) with datasets of urban images that have some sort of label that is used as an estimator for the perception of that urban space. Most of the research is based on the place pulse dataset (Dubey et al., 2016), which consists of pairs of images along with labels that indicate which of the images is more representative of a particular attribute.

However, current deep learning methodologies, have the disadvantage of being ”black boxes”, in other words, they lack a direct or systematic way to explain or interpret the obtained results. This problem comes from the end to end nature of the neural network models and from the millions of learnable parameters they contain. Many of the problems in which these models are used would greatly benefit of more human understandable explanations of the results, making this a very important area of research for the deep learning field (Adadi & Berrada, 2018).

For the particular case of urban perception, explainability of the results is highly relevant, since the added information is valuable for the design of public policy, for example, it could be use to better discriminate which locations would be better recipients of an intervention, and which elements to modify so it convenes an effective improvement of perception.

Current research in explainability is primarily moving in two directions: one is to design novel neural network architectures and training methods so the models are more interpretable, such as the work by Dong, Su, Zhu, and Zhang (2017), the other direction is to create post-hoc algorithms (Adadi & Berrada, 2018) that analyze the results given by the neural network, these algorithms sometimes use other machine learning models, including neural networks, such as the work by Ghorbani, Wexler, Zou, and Kim (2019).

The work by Rossetti et al. (2019), presents an approach to this problem for the urban perception case by using semantic segmentation of the images (Badrinarayanan, Kendall, & Cipolla, 2015) as input for a discrete choice model that estimates the perception. The approach allows for a post-hoc aggregated analysis of the results, since the weights of the model are measure of the importance of each class of the semantic segmentation in the calculation of the perception.

The objective of this work is to design and train a model for the urban perception problem, that can give explainable insights on an instance level. For that it proposes a novel solution, consisting of a neural network architecture, that is end-to-end trainable and by using semantic segmentation (Zhao, Shi, Qi, Wang, & Jia, 2016) and self attention mechanisms (Vaswani et al., 2017) can show explainable insights for each of the input images.

ESTO HAY QUE ARREGLARLO AL FINAL

The remainder of this manuscript is organized as follows, Chapter 3 summarizes relevant previous research. In chapter 4 the problem is formally defined and the proposed model is described. Chapter 5 gives details on model implementation and training. Finally, in chapter 6 presents the research results and 7 the final conclusion.

2. RELATED WORK

This chapter consists of two sections, the first one shows an overview some of the different methods that have been previously used in the literature for understanding or estimating urban perception, these methods are separated into 3 types: the classic approaches (all the methods not relying on massive amounts of data are grouped here), approaches based on machine learning and approaches consisting of machine learning models combined with other techniques. The different methods are explained and a brief analysis of advantages and disadvantages is provided for each of them. Section two summarizes the main aspects of the research on explainability on deep learning, and describes some techniques that have been applied in urban perception or other domains that are relevant for this work.

2.1. Solutions for estimating urban perception.

2.1.1. Classic approaches.

Methods for measuring perception of urban spaces have appeared in the literature of several disciplines for many years, with some of the most influential studies dating back to 1960 (Lynch, 1960). Due to technological limits the literature consisted mainly of several types of qualitative surveys for a long time. This surveys consisted in having subjects, complete different tasks such as drawing maps of a certain place (Lynch, 1960), evaluating fundamental aspects of a neighborhood (Nasar, 1990), or in more recent approaches evaluating the impact of transformations generated with edited images (Jiang, Mak, Larsen, & Zhong, 2017). Most of these surveys were conducted in person or by phone, and then the results were analyzed manually, making it very difficult and costly to scale to multiple locations, or larger amounts of samples. The main benefit of this approach, is that it permits a very refined control of the observation process since both the subjects being interviewed and the spaces in question are chosen by the researcher. Added to that, the experiments

conducted in person allow for the observer to use senses different than vision to analyze the subject space, resulting in a richer appreciation.

Other methodology, more common in economics and engineering, consists of using discrete choice models and stated choice surveys to model the effect of different variables in perception or other urban related variables (Rose & Bliemer, 2009; Iglesias et al., 2013; Torres, Greene, & Ortúzar, 2013). The amount and complexity of the variables measured depends on the model design. To have and exact control of the variables that have an effect on the survey, computer generated images of urban spaces can be used (Iglesias et al., 2013; Torres et al., 2013).

The advantage of this method is that through the estimated parameters of the model, the effect of each of the studied variables on the perception estimation can be measured, allowing for quantitative results and an understanding of the impact different elements have on the perception of the urban landscape. The main disadvantage of this approach comes from the difficulty of the survey design, variables need to be chosen carefully and the process its vulnerable to biases from the model designer.

2.1.2. Pure machine learning approaches.

2.1.3. Mixed approaches.

2.2. Explainability in deep learning.

3. PROPOSED ARCHITECTURE

3.1. Problem Definition

3.2. Network architecture

3.3. Loss function

4. METHODOLOGY

4.1. Implementation

4.2. Training

5. RESULTS

6. CONCLUSIONS

Nothing to say. Be happy.

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APPENDIX

A. FIRST APPENDIX