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.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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

1.1. Thesis outline.

This work consists of seven chapters, first is this introduction, which shows the importance of both the automatic calculation of urban perception, and explainability in artificial intelligence, and ends with the hypothesis of this research. Chapter 2 is a detailed description of the research objectives. Chapter 3 consists of a summary of the 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 and 7 consist of the results and conclusions of the research.

1.2. Importance of automatic urban perception

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).

The 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, in order for the limited resources of local governments to be applied appropriately (Santani, Ruiz-Correa, &

Gatica-Perez, 2018), but traditional methods for the measuring of urban perception, consist of hand made polls about specific locations making it a extremely costly and hard to escalate process (Clifton & Ewing, 2008).

Considering these facts, automatic estimation of urban perception at great scales becomes a very relevant research problem, because the generated data would be a powerful tool to guide the improvement of public spaces and the design of public policy.

1.3. Importance of explainability in deep learning.

Currently, thanks to the great volumes of data generated by web platforms (Salesses et al., 2013) and to modern deep learning techniques (LeCun, Bengio, & Hinton, 2015), the problem of estimating urban perception has become feasible, and some previous studies have achieved relevant results (Dubey, Naik, Parikh, Raskar, & Hidalgo, 2016; Rossetti et al., 2019).

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 problems 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). Current research in this matter 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 networls, such as the work by Ghorbani, Wexler, Zou, and Kim (2019).

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

1.4. Hypothesis

2. OBJECTIVES

This are the thesis objectives

3. RELATED WORK

This are some related investigations.

4. PROPOSED ARCHITECTURE

4.1. Problem Definition

4.2. Network architecture

4.3. Loss function

5. METHODOLOGY

5.1. Implementation

5.2. Training

6. RESULTS

7. CONCLUSIONS

Nothing to say. Be happy.

REFERENCES

Adadi, A., & Berrada, M. (2018, 09). Peeking inside the black-box: A survey on explainable artificial intelligence (xai). *IEEE Access*, *PP*, 1-1. doi: 10.1109/ACCESS.2018.2870052

Antonakos, C. L. (1995). Environmental and travel preferences of cyclists. *Transportation Research Part A: Policy and Practice*, *29*(1), 85.

Clifton, K., & Ewing, R. (2008, 03). Quantitative analysis of urban form: A multidisciplinary review. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, *1*, 17-45. doi: 10.1080/17549170801903496

Dong, Y., Su, H., Zhu, J., & Zhang, B. (2017). Improving interpretability of deep neural networks with semantic information. *CoRR*, *abs/1703.04096*. Retrieved from `http://arxiv.org/abs/1703.04096`

Dubey, A., Naik, N., Parikh, D., Raskar, R., & Hidalgo, C. A. (2016). Deep learning the city: Quantifying urban perception at a global scale. *ArXiv*, *abs/1608.01769*.

Ghorbani, A., Wexler, J., Zou, J., & Kim, B. (2019). *Towards automatic concept-based explanations.*

Khisty, C. J. (1994). Evaluation of pedestrian facilities: beyond the level-of-service concept. *Transportation Research Record*, *1438*, 45-50.

LeCun, Y., Bengio, Y., & Hinton, G. (2015, 05). Deep learning. *Nature*, *521*, 436-44. doi: 10.1038/nature14539

Ordonez, V., & Berg, T. L. (2014). Learning high-level judgments of urban perception. In D. Fleet, T. Pajdla, B. Schiele, & T. Tuytelaars (Eds.), *Computer vision – eccv 2014* (pp. 494–510). Cham: Springer International Publishing.

Rossetti, T., Lobel, H., Rocco, V., & Hurtubia, R. (2019). Explaining subjective perceptions of public spaces as a function of the built environment: A massive data approach. *Landscape and Urban Planning*, *181*, 169-178.

Salesses, P., Schechtner, K., & Hidalgo, C. A. (2013, 07). The collaborative image of the city: Mapping the inequality of urban perception. *PLOS ONE*, *8*(7), 1-12. Retrieved from https://doi.org/10.1371/journal.pone.0068400 doi: 10.1371/journal.pone.0068400

Santani, D., Ruiz-Correa, S., & Gatica-Perez, D. (2018). Looking south: Learning urban perception in developing cities. *ACM Transactions on Social Computing*.

APPENDIX

A. FIRST APPENDIX