Doctor Consortium for WACV 2019
69-425 Waikoloa Village, HI 96738
January 8-10, 2019

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Doctoral Thesis Title: *Global Semantic Description of objects based on Prototype Theory*[1]

Problem Statement. How to describe and stand for objects, semantically? Can a model of perception system be developed in which objects are described using the same semantic features learned to identify and classify them?

Proposed Solution. This research aims to build a model for the global semantic description of objects based on image features learned to classify them. We introduce a novel semantic description approach based on the foundation of Prototype Theory [2, 3, 15, 16, 19]. Inspired by the human approach used for category semantic representation [14, 17, 18], we propose a novel model that *encodes*, *stores* and *retrieves* the *central semantic meaning* of the objects category: *the prototype*. Our *prototype-based description model* encodes and stores the semantic meaning of an object, while describing its features using semantic prototypes computed with Convolutional Neural Networks (CNNs).

Main Contributions. To achieve this goal, we rely on cognitive semantics studies related to Prototype Theory to introduce:

i) *Semantic prototype*: a mathematical model to code and stand for *semantic prototypes* of objects images categories. Furthermore, we proposed a straightforward algorithm to compute those semantic prototypes using pre-trained CNN-classification models.

ii) *Semantic distance*: a *semantic distance metric*[2] as similarity measure between objects feature extracted from images with CNN-classification models. We proof that our semantic distance function (δ) is a *metric*[3] in CNN-features set. Also, we show that proposed semantic distance metric (prototipical distance) can be understood as a object typicality score within a category ($\textit{typicality score}\ (o) = 1/\delta(o)$).

iii) *CNN-Prototype Model*: We proposed a CNN-Prototype Model (*semantic prototypes + semantic distance*) that is able to describe the internal semantic structure of objects categories using CNN-models. We show that our CNN-prototype model can correctly interpret the object CNN-features and can position it semantically within the category, keeping a *prototypical organization* [14, 17, 18].

iv) *Prototype-based description model*: The proposed prototype-based description model uses semantic prototypes to create discriminative signatures that semantically describe an object, highlighting its most distinctive features within the category. Our Global Semantic Descriptor (GSDP) builds low-dimensional and semantically interpretable signatures encoding that significantly outperforms state-of-the-art global descriptors [1, 5, 6, 9, 10, 20, 21] in terms of cluster metrics (See WACV2019 Accepted paper [11]).

v) *Semantic classification of object images*: (**Ongoing research**) Using our CNN-Prototype Model, we looking forward to introduce the *prototype-based concept of categorization* [4, 12, 13, 15, 18, 22] on CNN-classification models.

[1] See the project page: https://www.verlab.dcc.ufmg.br/global-semantic-description
[2] Based on *the psychological distances between two stimuli* [7] and the *semantic distance* of MPM Model [8, 22].
[3] δ function satisfies the axioms of *non-negativity*, *identity of indiscernible*, *symmetry* and *triangle inequality.*

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