

What is the Ground? Continuous Maps for Grounding Perceptual Primitives

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Abstract

Analysis of the Symbol Grounding Problem has typically focused on the nature of symbols and how they tie to perception without focusing on the actual qualities of what the symbols are to be grounded in. We formalize the requirements of the ground and propose a basic model of grounding perceptual primitives to regions in perceptual space that demonstrates the significance of continuous mapping and how it influences categorization and conceptualization of perception. We also outline methods to incorporate continuous grounding into computational systems and the benefits of applying such constraints.

Keywords: Symbol Grounding; Perception; Language; Machine Learning; Topology

Introduction

The symbol grounding problem underlies a wide range of areas in cognitive science, including perception, philosophy of meaning, child language learning, and artificial agents – “How can the semantic interpretation of a formal symbol system be made intrinsic to the system, rather than just parasitic on the meanings in our heads?” (Harnad, 1990). The answer to this question – how do our words have meaning beyond definitions composed of other words – can guide our models of cognition and our algorithms of artificial agents, providing constraints on the grounding process and enabling capabilities not present in ungrounded systems.

While Harnad clearly states what a symbol system is – a system of explicit representation, syntactic manipulability, semantic interpretability, and systematicity – he does not go into great detail as to what the symbols are grounded in. Attempts to formalize the Symbol Grounding Problem focus on the symbolic aspect, but neglect to incorporate a theoretical categorization of acceptable grounds. This gap in specificity is a detriment to research in the area of symbol grounding – how do we design perceptually grounded systems without knowing what capabilities we are pursuing nor what kinds of systems have these capabilities?

Advantages of a Perceptually Grounded System

To say that an ungrounded system is lacking because its knowledge is circularly-defined is not entirely satisfying if there is no appreciable performance difference between a grounded and ungrounded system. The primary advantage is that a perceptually grounded system is uniquely capable of interfacing its knowledge with perceptual systems, even beyond current computer vision and robotics systems. A perceptually grounded ontology, for example, could be used to recognize objects that had never been seen before based on symbolic knowledge such as in work by Russakovsky and Fei-fei (2012). A computer vision system could not only recognize

physical attributes and their combinations to learn about objects it sees (Farhadi, Endres, Hoiem, & Forsyth, 2009), but would also be built around a framework allowing evaluation of claims that it has actually grounded such attributes in a perceptual model.

Various types of reasoning are also supported only by a perceptually grounded system. Reasoning by mental simulation requires a grounding in physical form to process questions such as “Can an open umbrella fit in the trunk of a car?”¹, which is trivial for a person to answer even though the answer is not explicitly stated in a knowledge base. Qualitative reasoning also draws upon non-symbolic knowledge in reasoning over continuous spatial, temporal, or feature spaces. Rather than explicitly stating the properties and relations between objects for every possible pair of objects, a grounded system can draw upon its perceptual representations to answer questions about relations between objects on the fly.

Previous Work

There have been a number of efforts attempting to provide a theoretical representation that crosses the divide between symbolic knowledge and perceptual representations. Barsalou (1999) proposed a perceptual theory of knowledge to explain the connection between symbolic knowledge and perception. At the center of the theory is the *perceptual symbol*, a neural representation that is tied to the underlying sense modality related to its symbol. A visual symbol, for example, is a record of the neural state in the visual cortex. Perceptual symbols are composed of *perceptual components*, which are the primitives corresponding to sensory features. In this work we consider grounding at the feature level and therefore are concerned with the perceptual components – to convey this level of grounding, we will refer to such components as **perceptual primitives**.

Gärdenfors (2004) proposed his theory of *conceptual spaces* as a non-symbolic framework for information processing, representing concepts as regions in spaces defined according to quality dimensions of the stimulus. His use of the term *conceptual space* indicates that in his model, concepts are identical to the regions in what we define as perceptual space: the space where stimuli are arranged according to a particular set of qualities. We use the term **perceptual space** to make a distinction between the range of possible stimuli and the symbols that are associated with them – symbols which might be distributed according to conceptual similarity in a different space.

In attempting to describe the geometrical constraints on regions in conceptual space, Gärdenfors claims that in such a

¹This example originated with Lenhart Schubert.

framework, natural predicates (corresponding to perceptual primitives) are represented by convex regions with a definition of convexity extended to non-Euclidean spaces. Support for this claim comes from shapes of regions corresponding to colors and phonemes in perceptual space. Mormann (1993) shows that Gärdenfors’s definition of convexity is flawed and not applicable to arbitrary conceptual spaces, and instead proposed path-connectedness as a topological constraint on such regions. Our characterization of such regions as contractible spaces is stronger than Mormann’s restriction while avoiding the problems with the convexity assumption, and therefore allows us to explain some aspects of the shape of regions corresponding to natural predicates in perceptual space without making the geometric assumptions Gärdenfors does about the underlying space.

Other characterizations of the shape of category regions have been more vague, such as Roberson, Davies, and Davidoff’s (2000) claim that similar colors are grouped together. Our model provides a more concrete characterization that makes a distinction between similarity and categorization and avoids the circular definition of categories using similarity.

Criteria for Perceptual Groundings

To formalize perceptual grounding, we must first consider what exactly is being grounded. One has an intuitive notion of what a percept is (often defined as some element of a sensory system such as vision or hearing), and so far previous work has relied on this loose definition serving as an acceptable criterion for distinguishing “grounded” systems from those that are not. We do not ground to percepts directly, but rather to ranges of possible percepts in a perceptual space. For example, “red” refers to a range of values that we consider red, but not one particular experience of red nor the symbolic interpretation of all red objects in the domain.

We believe that a more complete categorization of the advantages of a perceptually grounded system requires more formal criteria for what constitutes a valid grounding for a symbol. We set forth three criteria to characterize the domain of the function from the perceptual space to perceptual primitives: primitiveness, semantic vacuity, and semantic disconnectedness. These are not intended to be exhaustive, but rather are meant to provide a context and justification for pursuing continuous maps as a means for perceptual grounding given the additional advantages we show for such a system.

Primitiveness

Primitiveness refers to an agent’s lack of awareness of the components that make up the percepts, not the physical reality of the stimulus. For example, while our eyes process light according to three receptors, an individual is not cognizant of those components before they are assembled into our perception of color. At some point, in any cognitive system, there will be some level at which the primitive perception must be taken as a given – for us, it is what we refer to as “qualia”, whereas for a computer, it may be the readings of its sensors.

This level, where the nature of the perceptual space is not explained by the agent’s model, is where grounding must occur to avoid grounding in symbols – primitiveness from a perceptual perspective establishes the perceptual primitive as atomic from the symbolic perspective.

Semantic Vacuity

While a concept has a semantic interpretation, a percept must not contain any semantic interpretation inherently. That is, there should be no decoding for the percept’s representation.

For example, if we claimed our agent perceived English characters and was able to name the appropriate letter it perceived, it would be disingenuous if our percept was simply an 8-bit number corresponding to an ASCII code. The notion of a character would not be grounded in a visual representation, as it is simply an encoded symbol.

This constraint is especially important for systems grounded in virtual worlds, as it is easy to learn representations that will not generalize if the agent’s knowledge is applied to sensory data. If we do not ensure that “percepts” are semantically vacuous, we will end up where we started with a concept that needs further decomposition to reach a ground.

Semantic Disconnectedness

We also want to avoid percepts in our perceptual space being tied to an extrinsic semantic interpretation. For example, if we were to define “the color of an apple” as a region in color space, then we would face the issue where the nature of color percepts would be dependent on the agent’s knowledge of the surrounding world. An agent that sees a red object and claims, “That is the color of an apple” would modify the original experience simply by coming across a green apple. Because the agent misattributed a semantic concept (“the color of an apple”) to a percept (an instance of “red”), its perception is dependent on its past and future experiences of apples instead of solely being dependent on the current stimulus.

A Topological Model for Symbol Grounding Through Continuous Maps

Topology is a natural choice for representing the mechanics of symbol grounding, as it is general enough to apply regardless of choice of metrics or dimensions, and can therefore characterize the behavior of neurons and computational systems alike.

In Topology, equivalences are defined according to continuous transformations between topological spaces. A topological space is a pair consisting of a set and a topology, which describes the *open* subsets within that set. An open subset is analogous to an open interval on the number line, whereas a *closed* subset is analogous to a closed interval. This notion of open and closed sets is fundamental to Topology, as it allows us to define higher level properties such as boundaries, continuity, and connectedness, which are not defined over ordinary sets. These properties are known as topological invariants, as they are not affected by certain continuous transformations such as bending, stretching, or contracting the space.

Semantic Space

The **semantic space** contains the symbolic representation of perceptual primitives such that they can be used in a symbolic reasoning process. The space representation removes the requirement for symbolic reasoning in the grounding process while also providing a framework through which semantic distances can be defined. We define the semantic space using the discrete topology, meaning that every point is distinct from the others and has some neighborhood in the space consisting only of itself. Singletons (points) in this space correspond to perceptual primitives, each of which has a corresponding region in a perceptual space.

The abstraction of perceptual primitives as singletons enforces that the semantic space does not encode small differences in perceptual input because symbols are discrete entities – the map from the perceptual space to the symbol is constant. In addition, a perceptual primitive has no subparts and therefore maps intuitively to a singleton.

Assigning the discrete topology to the space does not constrain the representation of the semantic space to a discontinuous space - the discrete topology requires the fewest assumptions about the topology of the space, and the model does not change if we assume a continuous space. For example, perceptual primitives could be distributed along a continuous semantic space as in the representation determined by Huth, Nishimoto, Vu, and Gallant (2012).

Perceptual Space

The **perceptual space** in this model is a map of the stimuli associated with a particular sense such that different points represent distinguishable stimuli, and is divided into regions corresponding to the perceptual primitives in the semantic space. For example, in color vision, the perceptual space would be placed at a higher level than the tristimulus values of colors, where metamers exist (colors that are perceived to be the same even though they are composed of different levels of activation from the different types of cone cells). Similarity between stimuli is judged according to a distance metric in the perceptual space.

We call the function mapping a region in perceptual space to the perceptual primitive in the semantic space a **conceptualization function**, and the function in the opposite direction a **grounding function**.

The Grounding and Conceptualization Functions

Continuity We plan to explain characteristics of symbol grounding over continuous mappings. Continuity in Topology is not as rigidly defined as it is in other fields and can be described roughly as *small changes in input yield small changes in output*. Continuous functions are crucial to this model because they preserve certain properties of the spaces. Therefore, if we know that a function is continuous, then we can make assumptions about its output given the input, allowing even a simple model to make predictions about the shape of regions corresponding to perceptual primitives.

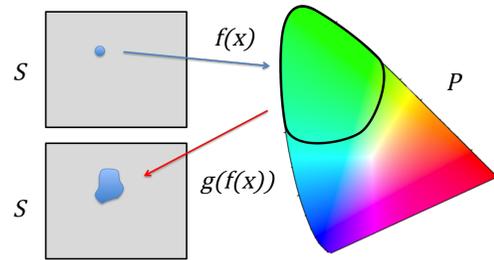


Figure 1: To illustrate the notion of homotopy inverse, here the semantic space S is represented as a continuous space and the singleton representation is relaxed. The grounding function $f(x)$ yields a region in the perceptual space P . The conceptualization function applied to that region ($g(f(x))$) yields a region in semantic space that can be continuously deformed to and from the original input (a perceptual primitive representing “green”) - fitting the definition of f and g as homotopy inverses.

Continuity of Semantically Vacuous Functions The first assumption and the core concept of our model is that the conceptualization and grounding functions are continuous. This is consistent with our constraints – primitiveness and semantic vacuity enforce an absence of subparts or discontinuities in the mapping function arising from higher-level conceptualizations applied to perceptual space.

Grounding and Conceptualization Functions as Homotopy Inverses The second assumption we make is that the grounding and conceptualization functions are homotopy inverses. This requires that their composition can be deformed continuously to the input (Figure 1). Even the stronger claim that the grounding and conceptualization functions are inverses seems to admit most conceptions of a perceptually grounded system – if the system produces an example of a stimulus belonging to a particular category, we would expect that system to categorize it identically if presented with the same stimulus. However, the homotopy inverse assumption gives us more flexibility – it could, for example, allow for contextual effects influencing the mapping in one direction.

Grounded Primitives as Contractible Regions By establishing that the grounding and conceptualization functions are continuous and homotopy inverses of each other, we establish that these functions preserve the neighborhoods of the points in perceptual space, and therefore each point in semantic space is homotopy equivalent to the corresponding region in perceptual space – *i.e.* the number of holes and the limits are preserved over those functions. With perceptual primitives being represented by points in semantic space, we restrict the corresponding shapes of regions in perceptual space to *contractible* spaces, or those which can be continuously deformed into a point with a corresponding continuous inverse mapping. A contractible space cannot have any holes of any dimension, nor can it be composed of separated spaces.

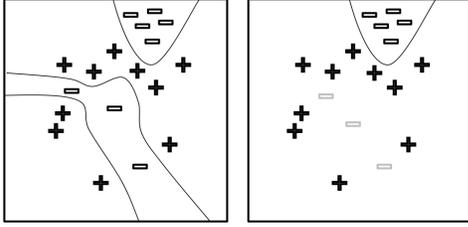


Figure 2: Without the contractible space assumption (left), the noise points from the minus class interfere with the decision boundary of the plus class. With the contractible space assumption applied to the choice of model (right), the noisy data is ignored in favor of preserving contractible decision boundaries.

This contractible property also extends to some higher-order concepts. If we have a concept that is the Cartesian product of any number of contractible spaces, then that new space is also contractible. For example, to model the interaction of vision and hearing in speech perception such as in the McGurk effect (McGurk & MacDonald, 1976), we can take the product of the visual and auditory components of the recognition of the phoneme, and the corresponding region will be contractible. However, other set-theoretic operations which could construct higher-level concepts (such as intersection, union, and complementation) do not preserve contractibility.

Functional Benefits of Continuous Maps

We propose a number of functional benefits of continuous maps from an information processing and concept formation perspective, assuming that learning takes place at the level of perceptual primitives.

Learning from Limited Experiences

The contractible space assumption makes categorization possible given only a few labeled input points by reducing the search space of perceptual models that explain the feature data. Identifying points in perceptual space without any distributional assumptions corresponds to the *nearest neighbor* classifier - a new point is assigned the class of the nearest labeled point. Such a classifier is extremely susceptible to noise, because there is no underlying assumption of the shape of the distribution of the stimuli. With the contractible space assumption, boundary points allow for noise reduction provided that limitations on the complexity of the model prevent pathological cases such as infinitesimal bridges connecting otherwise disconnected components (Figure 2).

Quality Dimensions

A perceptually grounded system will not only be able to identify stimuli (categorization), but it should also be able to identify what quality dimensions lead to that categorization through dimensionality reduction. However, if the stimulus is perceived only by its membership in discrete, discontinuous categories, it is impossible to reconstruct the underlying quality dimensions to understand the relations between different

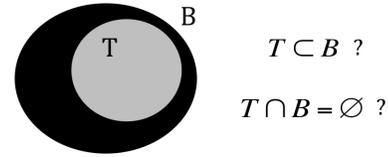


Figure 3: A system without the contractible region assumption cannot distinguish between the possibility of the interior region being a subset of the exterior region or disjoint from it, thus prohibiting hierarchical inference of the data.

perceptual primitives. In line with this limitation, Emberson, Liu, and Zevin (2013) showed that intraclass statistics of stimuli aided in higher level learning of categories.

Knowledge of quality dimensions and their continuous distribution is crucial for metaphorical reasoning, as metaphor relies on adapting quality dimensions from one context to another. For example, when applying the temperature scale to colors, simply specifying the endpoints of “cool” and “warm” corresponding with “blue” and “red” does not accurately provide a link between the two modalities if there is no continuous space over which the values can be correlated.

Hierarchical Categorization

Without the contractible assumption, it is impossible to distinguish between regions that are disjoint yet contained within a larger region, and those that are a conceptual subset of the larger region. For example, is teal a subset of blue, or is it a disjoint concept? With the contractible assumption, we know that if a concept maps to a region in perceptual space contained entirely within another region, then it must be a subset of that region (Figure 3).

Designing Computational Systems with Continuous Grounding

A number of special considerations must be made when developing a computational system for learning grounded language that takes advantage of these constraints.

First, the features used to ground perceptual primitives must be defined over a continuous vector space. This excludes some applications of local features such as SIFT (Lowe, 1999) that provide very good performance for identifying objects corresponding to higher-level concepts. While these features themselves may be defined over a continuous space, considering the contributions of multiple key features (each arising from a salient part of the object) will lead to a discontinuous space because of the inherent higher-level conceptual model.

Second, the system must be trained on attributes rather than solely with object names. Many previous systems have attempted to learn categories of objects, such as *car* or *building*, which do not necessarily correspond to continuous regions due to their indirect tie to perception through semantic interpretation. These categories require more complicated models and thus do not correspond to singletons in the semantic space. However, to achieve grounded language, the

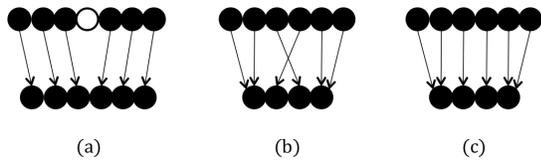


Figure 4: (a) A map that is discontinuous (yet topographical according to certain definitions) because of the discontinuity in white which is not mapped to the output space. (b) A discontinuous, non-topographical map where spatial ordering is not preserved. (c) A continuous, topographic map.

perceptual primitives must be trained with some supervision regarding attributes.

Finally, the classification model for perceptual primitives must be constrained to contractible decision boundaries. This can be enforced with constraints on choice of kernels, the arrangement of mixture models, or neural network topology.

Continuity and Topographical Maps

While continuity is an abstract mathematical concept, it has a close relation to the notion of topographical maps within the brain. Topographical maps typically appear in relation to inputs of sensory maps, and map inputs to outputs in a spatially ordered way. In some cases, such as in low-level vision, the arrangement of the output corresponds to the spatial arrangement of the input. In others, such as in the gustatory system, the arrangement corresponds to the qualities of the stimuli, such that similar stimuli are represented on nearby positions of the perceptual space.

Not every topographic map is a continuous function according to modern usage of the term, although a continuous function satisfies the properties of a topographic map and historically they have been used synonymously (Luo & Flanagan, 2007). However, the same principles that guide the arrangement of neurons composing a topographic map also tend towards continuous functions. Length minimization of neurons (Koulakov & Chklovskii, 2001) and constraints on axonal and dendritic overlap (Pinchas & Baranes, 2013) will preserve neighborhoods of the input space assuming that the two spaces are topologically equivalent. However, if there is a discontinuity in one space that is not shared by the other space, a topographical map will be discontinuous (Figure 4).

Semantic Space

Does the representation of perceptual primitives as singletons (points) have an analogue in the human brain? While the computational approach does not presume any particular processing architecture and should be sufficient for characterizing the relationship between such primitives and their related perceptual regions, it is interesting to note how various models of processing in sensory cortices still permit such an abstraction. Cortical maps share many qualities with the mapping functions in our model, responding both to bottom-up information from the organization of the perceptual map and to top-down information through learning experiences (Polley,

Steinberg, & Merzenich, 2006). They also maintain plasticity through the periods of growth we associate with concept formation (Buonomano & Merzenich, 1998). Finally, cortical maps are often locally continuous, providing further evidence for continuous mappings from the perceptual space to the cortical space (Wandell, Brewer, & Dougherty, 2005).

In searching for a corresponding analogue to singletons in the cortex, there are no significant changes to the model if the points in the semantic space are instead represented as contractible regions to allow for shape of the cortical structures or activation patterns responsible for representing a perceptual primitive. Rather than saying that the regions in perceptual space are homotopy equivalent to a point, we can say that they are homotopy equivalent to the corresponding region in semantic space. This allows more possibilities for how perceptual primitives might be represented in the brain.

A number of neural processing models allow for a singleton representation of symbols. In localist models, a perceptual primitive would be represented by a single neuron which either receives the most activation from another cortical layer in the pooling model, or the neuron which is most sensitive to a particular activation in the lower-envelope model (Parker & Newsome, 1998). Neural codings as described in (Borst & Theunissen, 1999) provide a computational representation, with a specific code corresponding to a concept. Perceptual primitives could also be represented as fixed-point attractors in attractor networks (Plaut, 1995).

Linguistic Significance of Continuous Mappings

While these benefits of continuous mapping have clear applications to artificial intelligence systems, it is less obvious how continuity influences language. Language related to olfactory perception provides an example of the limitations of language grounded in discontinuous maps. The olfactory system, unlike the visual system, maps receptors of the same type to clusters in the olfactory bulb without any regard to the spatial arrangement in the olfactory epithelium. The olfactory bulb mapping begins as a continuous map, but is refined into a discrete map according to the post-natal stimuli (Sakano, 2010). The perceptual space for odors, while defined according to continuously varying feature dimensions, is populated discretely (Castro, Ramanathan, & Chennubhotla, 2013).

The discontinuities in the olfactory map could explain why we have trouble giving names to odors and even further difficulty describing their underlying perceptual qualities beyond pleasantness (Yeshurun & Sobel, 2010). When we do try to identify smells, we identify them according to their source, thereby “grounding” those terms in an experience rather than a mental state. What quality descriptions of smells that do exist in Western language often co-opt descriptive terms of other senses, such as warmth and sourness. In some cultures, this inability is not expressed - the Jahai of the Malay Peninsula can name odors consistently and also have language to describe various feature dimensions of smell (Majid & Burenhult, 2014). If continuity is as significant to grounding as

our model shows, then we would expect to see a more continuously populated perceptual space in those who speak languages with a rich olfactory vocabulary.

Future Work

We plan to continue work on our grounded language learning system (Perera & Allen, 2013) according to the constraints we have outlined. Our previous work demonstrated that learning primitive concepts from only the examples the agent was confident in allowed for faster learning in a context inspired from child language learning. We plan to replace our nearest neighbor classifier with a combination of topology-preserving dimensionality reduction and contractible classifiers to reduce the effect of noise and allow hierarchical inference based on overlapping perceptual regions. With such a system, we can generate a perceptually-grounded ontology based on concepts learned from natural speech and video demonstrations. Implementing a system based on the notion of continuous maps for symbol grounding will allow us to empirically determine whether such constraints improve the performance of language learning systems.

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