Visual Ground Truth Construction as Faceted Classification

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Abstract
Recent work in Machine Learning and Computer Vision has provided evidence of systematic design flaws in the development of major object recognition benchmark datasets. One such example is ImageNet, wherein, for several categories of images, there are incongruences between the objects they represent and the labels used to annotate them. The consequences of this problem are major, in particular considering the large number of machine learning applications, not least those based on Deep Neural Networks, that have been trained on these datasets. In this paper we posit the problem to be the lack of a knowledge representation (KR) methodology providing the foundations for the construction of these ground truth benchmark datasets. Accordingly, we propose a solution articulated in three main steps: (i) deconstructing the object recognition process in four ordered stages grounded in the philosophical theory of teleosemantics; (ii) based on such stratification, proposing a novel four-phased methodology for organizing objects in classification hierarchies according to their visual properties; and (iii) performing such classification according to the faceted classification paradigm. The key novelty of our approach lies in the fact that we construct the classification hierarchies from visual properties exploiting visual genus-differentiae, and not from linguistically grounded properties. The proposed approach is validated by a set of experiments on the ImageNet hierarchy of musical experiments.

1 Introduction
In Machine Learning (ML), and Computer Vision (CV) as a particular case, the models developed are informed by training them on annotated datasets, which are supposed to be a ground truth, i.e., a high quality objective representation of what is the case in the world. In many cases, e.g., with datasets used to train Deep Neural Networks, the size of these datasets can become very large, some examples being Open Images (Krasin et al. 2016), COCO (Lin et al. 2014), YFCC100M (Thomee et al. 2016), YouTube-8M (Abu-El-Haija et al. 2016), NTU RGB+D (Shahroudy et al. 2016). Within this line of work, maybe the most relevant dataset is ImageNet (Deng et al. 2009), its main strengths being the size (counting millions of photos), the quality, as compared to the others (ImageNet was built by populating WordNet (Miller 1995)), and the fact that, in the last years, it has been used to train some of the most successful Neural Networks, see, e.g., AlexNet (Krizhevsky, Sutskever, and Hinton 2012), VGGnet (Simonyan and Zisserman 2015), GoogleNet (Szegedy et al. 2015), ResNet (He et al. 2016), DenseNet (Huang et al. 2017), becoming a de-facto benchmarking standard. However, lately a major concern has grown about the quality of these ground truth datasets and of the implications on the quality and performance of the resulting ML models, see, e.g., (Sambasivan et al. 2021; Raji et al. 2021; Koch et al. 2021) and also (Cheng et al. 2015) which suggests using WordNet for improving the quality of the labels used to search for and annotate images. Of specific relevance is the work in (Tsipras et al. 2020)\(^1\) which focuses on the mistakes in ImageNet. Our basic tenet is that these mistakes are not and simply the result of carelessness on the side of the annotators, being in fact deeply grounded in the way language and perception interact. As a matter of fact, an early version of this type of problems was crystallized, already in 2000, as the Semantic Gap Problem (SGP) (Smeluders et al. 2000), where the SGP was described as the “lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation”. This problem, still unsolved, has been generalized in (Giunchiglia, Erculiani, and Passerini 2021) as the fact that there is a many-to-many mapping between the information extracted from the visual data and its possible contextual interpretations. As from this work, the SGP is a very general phenomenon which manifests itself anytime an object inside an image is linguistically annotated multiple times, possibly even by the same person. The SGP is in fact a consequence of the fact that linguistic descriptions of images are subjective and context dependent. (Giunchiglia and Fumagalli 2016) provides a detailed analysis, grounded on the Teleosemantics theory of meaning (Macdonald, Papineau, and others 2006; Millikan 2000; Millikan 1989), of the mechanisms by which the SGP arises.

The goal of this paper is to provide a general Knowledge Representation (KR) methodology for generating high-quality ground truth datasets. The intuition is that KR can provide modeling guidelines which will drive the organization of the datasets used to train ML models, thus indirectly inducing in them the semantics awareness that they are miss-

\(^1\)See also the extended arXiv version of the paper at: https://arxiv.org/abs/2005.11295
The visual properties introduced in (Giunchiglia, Erculiani, and Passerini 2021) and depicted in images. To this extent we follow the theory in-\hspace{0.5mm} to a lexico-semantic hierarchy. The issue is to align this hierarchy with the visual semantics encoded in the objects depicted in images. To this extent we follow the theory introduced in (Giunchiglia, Erculiani, and Passerini 2021) and associate objects, as depicted in (multiple) images, with sets of visual properties, e.g., sets of (visual) frames, which describe their appearance. In this way, the annotation process is no longer that of annotating (objects in) images with labels but, rather, of aligning the visual properties of (objects in) images with those lexically described properties which describe the meaning of ImageNet classes, i.e., their definition, or gloss, as it is called in WordNet (Miller 1995). Labels are then (optionally) associated to ImageNet classes when their definition is consolidated from both a language and a vision point of view. We organize the methodology we propose as a stratified four-step annotation process whereby: first (i) the relevant objects in an image are identified, then (ii) these objects are characterized by their visual properties, then (iii) they are linguistically annotated using ImageNet-like labels and, finally, (iv) they are associated a unique identifier. The main contributions of this paper are as follows:

- A reconstruction and extension of the annotation mistakes highlighted in (Tsipras et al. 2020) as specific instances of the SGP.
- The definition of a four-step annotation process dealing with the SGP. Of notable relevance is that annotations are done in terms of Genus-Difference of the visual properties of objects, making sure that these visual properties are aligned with the linguistic properties described in glosses.
- The implementation of the four-step annotation process as faceted classification (Ranganathan 1967; Ranganathan 1989), suitably adapted to deal with visual properties and images (Giunchiglia and Bagchi 2021; Giunchiglia, Dutta, and Maltese 2014), thus providing precise guidelines (so called canons in faceted classification) towards high quality annotation results.
- The exploitation of state of the art multi-lingual lexical resources, this allowing, among other things, the possibility of language-aware annotations, well beyond the current practice of English-only annotations (Giunchiglia, Baturen, and Bella 2017).

The paper is organized as follows. In Section 2 we describe the types of mistakes which arise because of the SGP. In Section 3 we describe the annotation process and how it deals with the mistakes just mentioned. In Section 4 we describe how to implement it as faceted classification. In Section 5 we evaluate the proposed methodology. We do this via an annotation and a machine learning experiment. Section 6 describes the related work, while Section 7 concludes the paper. All along the paper, we use the dataset represented in Fig.1, consisting of nine categories and 3660 images.

## 2 The Semantic Gap Problem

As from (Tsipras et al. 2020), in ImageNet there are three recurring design flaws which are associated to three specific types of images. Following this characterization, we categorize the images in ImageNet into three plus one broad categories, where the fourth one is the category of the images that in (Tsipras et al. 2020) are taken as being properly annotated. We have the following.

1. **Good Images**, for which there is wide inter-annotator agreement.

2. **Multi-Object Images**, where the flaw arises from the occurrence of multiple objects in the same image.

3. **Single-Object Images**, where the flaw arises due to the assignment of mutually exclusive labels to a single object.

4. **Mislabelled Images**, where the flaw arises due to labelling mistakes.

Evidence that the last three categories suffer from the SGP is provided by the fact that the ImageNet creators and the authors of (Tsipras et al. 2020) have contradictory opinions about them. However, also the Good Images category suffers from the SGP. As a matter of fact, all four categories present the SGP problem as it appears in Good Images, the last three showing an additional form of SGP specific to the class. Let us analyze these four categories in detail.

**Good Images**: We can notice at least three characteristics definitive of what we categorize to be a good image. Firstly, these images are almost always those images containing a single object (the ‘main object’ as called in (Tsipras et al. 2020)). Secondly, these images are less noisy, in the sense that they have minimum influence of confounding variables such as occlusion and clutter distorting them. Thirdly, all of these images are captured from an optimal viewpoint leading to clear visibility of their defining visual characteristic; see, e.g., the image-label pairs for (I) Good Images in Fig.2 (‘IL’ stands for ImageNet Label).

Three observations. Firstly, though it is a fact that confounding variables are ubiquitous in open world settings (Bendale and Boult 2015), the training corpora for object recognition models should be majorly, but not only, comprised of good images. This is crucial given the fact that it is only the good images which can allow the model to extract and learn about its distinguishing visual characteristics. Secondly, and again ubiquitous in open world settings, is the issue of parts of an object in an image. Studies
such as (Tsipras et al. 2020) have considered different labels for objects and its parts (e.g., ‘car’ vs ‘car wheel’) treating them as distinct objects. The present work being focused on methodological visual classification postpones the specific issue of detection of parts of an object to a future version of the methodology. Thirdly, the SGP still persists for any of these images, even if agreed upon by multiple annotators. To realize this it is sufficient to think of the many other labels we could subjectively use to describe any of the good images in Figure 2. (As from above, see (Giunchiglia and Fumagalli 2016) for an in depth analysis of this phenomenon.)

**Multi-Object Images:** An image in ImageNet is associated with only one label, this causing the first category of design flaw in case of multi-object images, i.e. images comprising objects from multiple classes. With such images constituting more than one-fifth of ImageNet’s total image populace, the flaw stems from the systematic incongruence between the ImageNet label of (each of) such images and the label of the most likely main object in (each of) them as deemed by humans. A famous example is the image of a ‘stage’ labelled by humans as such, having the ImageNet (IL) label as ‘Electric Guitar’ (see this and more examples in (II) Multi-Object Images of Fig.2).

Multi-object images assume central importance due to two pivotal observations. Firstly, from empirical evidence in cognitive psychology (Rosch et al. 1976), the observation that the main object chosen by humans possesses the highest ‘cue validity’, in other words, carry the most information via perceptual attributes (stimuli) and thus is visually the most salient. Secondly, in violation of the first observation, ImageNet exhibits an established bias for many multi-object images wherein, for such an image, its label correspond to a very distinctive object instead of the main object in that image, thus exploiting features that don’t generalize to object recognition in the wild (Tsipras et al. 2020).

**Single-Object Images:** The second category of design flaw concerns single-object images. It stems from the empirical observation that humans may assign multiple mutually exclusive labels possibly due to the object in the image being visually polysemic\(^2\) or in the case of classes having synonyms labels (such as in confusing class pairs). Images are visually polysemic when their “semantics are described only partially” (Smeulders et al. 2000) and their interpretation is not unique. A concrete example (amongst many others) of visual polysemity in ImageNet is the case of an image (see the image of IL: Guitar in (III) Single-Object Images of Fig.2) for which both the labels ‘guitar’ and ‘bass’ can equally contextually be assigned. (Tsipras et al. 2020) observes that not only do humans assign an alternative label “as often as” the ImageNet label for 40% of ImageNet images, they also assign as many as up to 10 labels for many single-object images.

The second case of confusing class pairs occurs when humans are unable to disambiguate pair of (semantically very similar) classes and assign same (set of) labels for either of them. A prominent example in ImageNet are the two images labelled as ‘IL: Dulcimer’ (see (III) Single-Object Images of Fig.2) which, though considered semantically very similar by humans and assigned the ImageNet label ‘Dulcimer’ out of ambiguity, essentially belong to two different genres of musical instruments. The study in (Tsipras et al. 2020) attributes two design factors of ImageNet behind such confusing class pairs. Firstly, some of the cases could be due to possible overlap or mixup in their image distributions due to ImageNet’s automated image retrieval process. Secondly, and most importantly, choosing disjoint labels grounded in linguistic properties is insufficient for humans to visually disambiguate confusing class pairs in the face of potential overlapping image distributions.

**Mislabelled Images:** The third category of design flaw relates to mislabelled images, for (each of) which there is no match between the ImageNet label and the (correct) label(s) assigned by humans. Such images can be grouped into two categories based on their mode of identification. The first category are those for which the selection frequency of the ImageNet label was zero, or, in other words, no human selected (an object corresponding to) the ImageNet label to be contained in such images. The second category are those for which the ImageNet label was not even considered by humans for annotating any object within such images. A concrete example, for instance, can be seen in Fig.2 (See (IV) Mislabelled Images) wherein the image labelled by ImageNet as ‘acoustic guitar’ is a ‘fake’ guitar shaped on a birthday cake, and easily identifiable as such.

### 3 The Four-Stage Annotation Process

The proposed stratification of the annotation process is founded on a fundamental distinction, and consequent execution order between object detection and visual (image) classification. This is a crucial step which is actually sys-
tematically collapsed and non-delineated in state-of-the-art object recognition approaches (see footnote in page 1 of (Russakovsky et al. 2015)). In this context, by object detection we mean the activity by which all objects in an image are localized (but not identified), for instance via bounding polygons (Russakovsky et al. 2015). On the other hand, by *image classification*, we mean the activity which determines what object classes are present in an image (Russakovsky et al. 2015). This latter task, which is semantics-intensive, is performed post object detection, wherein, given a continuous feed of images, the goal is to organize the objects in them into a classification hierarchy of visual objects based on their visual genus-differentia (Giunchiglia, Erculiani, and Passerini 2021).

We ground the above ordered distinction in the empirically validated theory of teleosemantics (Giunchiglia and Fumagalli 2016; Giunchiglia and Fumagalli 2017; Millikan 2020), as originally postulated by the philosopher Ruth Millikan (Millikan 1989; Millikan 2000; Millikan 2004; Millikan 2005). At the outset, we outline two key postulates. Firstly, we model the (part of the) world as being populated by substances which are "things about which you can learn from one encounter something of what to expect on other encounters, where this is no accident but the result of a real connection" [Quote from (Millikan 2000)]. Notice that the notion of substances we commit to here are constrained to only those which can be visually perceived (i.e. objects). Secondly, we model concepts generated from substances as mental abilities implementing suitable (etiological) functions which must be understood as 'intended for' a specific purpose. Such a modelling paradigm enables us to distinguish between the distinct abilities which drive image classification, e.g., object detection, object recognition and linguistic description. Accordingly, we have substance concepts (SCs) focused on (continual) object detection and visual classification from substances, and (ii) classification concepts (CCs) geared towards (continual) linguistic classification and description of substance concepts (Fumagalli, Bella, and Giunchiglia 2019).

Based on the above assumptions, we stratify the annotation process (and, therefore, as from above, the recognition process) in four stages, as from Table 1. Here, the first column reports the specific annotation stage, while the second maps these stages to the corresponding Teleosemantics activity. Let us consider these stages in detail.

**S1: Object Detection.** Substances are detected over multiple sets of encounters (e.g., sets of images), as visual objects, i.e., sets of similar visual frames. Substance concepts are, in turn, modelled as "sets of visual objects" used to "represent substances as they are perceived", incrementally, at different levels of abstraction. This process involves (continual) extraction of distinguishing visual properties unique to a substance concept, and thereby delineating substance concepts, for instance, via bounding polygons. Subsequently, substance concepts are stored in a "cumulative memory $M$ of all the times they were previously perceived" (Giunchiglia, Erculiani, and Passerini 2021).

There are three key features which characterize substance concepts to be perfectly amenable for incremental object detection. Firstly, differently from conventional KR formalisms, the detection process of substances is independent, *per se*, of the distinction between an individual (such as 'guitar#123') or a real kind (such as 'guitar'). The exact granularity of object detection depends on the purpose of (the user of) the object recognition system. Secondly, the key to continual detection of a substance as different from substance concepts is grounded in its internal causal factor (Giunchiglia and Fumagalli 2016) which is incrementally manifested and extracted as perceivable visual properties. Finally, and most importantly, substance concepts are perdurant representations (Gangemi et al. 2002) of objects as "we never have a full (visual) picture of the object but that its visual representation is built progressively, in time" (Giunchiglia, Erculiani, and Passerini 2021). The perdurant representation is, in fact, grounded in the notions of space and time persistence (Giunchiglia, Erculiani, and Passerini 2021) which ensures that even if an object isn’t fully visually perceivable at once, it does exhibit very slow spatio-temporal variance which allows for its detection and substance concept representation to be built, progressively and cumulatively, in time.

**S2: Visual Classification.** Concurrently with continual object detection, and after new objects are detected, the next step is to build visual subsumption hierarchies exploiting the visual genus-differentia as (continually) extracted from the (incrementally) perceivable visual properties of the new images. The key notion of visual subsumption hierarchy, as introduced in (Giunchiglia, Erculiani, and Passerini 2021), refers to a (dynamic) classification hierarchy of the continually perceived substance concepts learnt, *ab initio*, from visual genus-differentiae. Visual Genus refers to a set of visual properties shared across distinct objects, of which a certain representative object is referred to as the Genus Object. Visual Differentia, on the other hand, refers to a set of novel visual properties different from those of the visual genus, which are exploited to differentiate amongst different objects with the same genus. The key observation is that, for any category, the *differentia one level up, becomes the genus one level down*. In other words, what one level up differentiates a class (of objects) from another, is the common part shared by all objects in the category one level down. This common part then then becomes the new genus, namely the starting point for a new split based on a new and more refined differentia. In other words, differentia is the only

| Annotation Stage | Teleosemantics Grounding | Faceted Classification | Problem | Solution |
|------------------|--------------------------|------------------------|---------|----------|
| S1: Object Detection | Generation and Modelling of SCs | Pre-Idea Stage | Multi-Object Images | Bounding Polygons |
| S2: Visual Classification | Hierarchy Construction of SCs | Idea Plane | All Images SGP | Visual Genus-Differentia |
| S3: Linguistic Classification | Linguistically Labelling SCs as CCs | Verbal Plane | Mislabeled Images | Language Labels |
| S4: Conceptual Classification | Linguistic Rendering of CCs | Notational Plane | Single-Object Images | Alinguistic Identifiers |
key notion that we need when building a visual subsumption hierarchy. For example, given that we take the basic category ‘stringed instrument’ as the representative Genus Object with its Visual Genus as the ‘presence of taut strings’, one pre-eminent way of visually classifying further can be based on the Visual Differentia ‘the number of taut strings’ with its different instantiations, e.g., ‘six taut strings’, ‘thirteen taut strings’ etc.

The crucial and most important observation is that, during this stage, the many-to-many mapping of the SGP, as it occurs in the Good Images category (see Section 2) is caused exactly by the choice of different differentiae for the same genus. And this is also why a classification based on class labels, will generate the SGP many-to-many mapping. It is sufficient that two annotators, or even the same annotator, based on their personal experience, when selecting the class label, implicitly (and without noticing) apply a different differentia to two images of the same object, and the SGP will appear. For instance, the image labelled as Keyboard Instrument in Fig.2 (I) can be labelled differently as synthesizer but also as a keyboard workstation, the underlying (though implicit) visual differentia for the former being just the presence of ‘keyboard’ (e.g., for a common user) and for the latter the visual presence of the ‘control panel’ (e.g., for a musician).

Because of this, in this stage S2, our methodology makes three fundamental assumptions:

1. The visual subsumption hierarchy is built based on the visual genus and differentia of objects and not on their class labels.
2. The visual properties on which the differentia is computed are consistent across all objects in that category.
3. The visual properties used to compute the visual differentia are consistent with the modelling decisions that are taken linguistically, i.e., with the genus and differentia as they are described in the gloss of the corresponding (ImageNet) category.

Notice how our approach is a radical departure from mainstream CV and in particular from how ground truth datasets have been generated so far. Notice also how visual classification, more specifically, the (successive) selection of the visual differentia assumes an egocentric setting (Erculiani, Giunchiglia, and Passerini 2020), in other words, such selection is completely bound to the point-of-view, experience and the purpose of the user. In fact, as evidenced from cognitive psychology (Palmer et al. 1989), the selection of what we define as visual differentia depends on the highly egocentric differentiation of affordances (Gibson 1977) - visual properties which have meaning for function of an object (e.g., the visual property taut strings for a musical instrument denotes the function of playing them to produce sound). From this point of view, Wordnet and ImageNet are just the result of a series of subjective choices, the first on the differentia provided linguistically, the latter on the corresponding visual differentia. No claim of universality can be made, we can only strive for achieving the most widely accepted organization of concepts, see also the discussion in (Giunchiglia, Batsuren, and Freihat 2018).

**S3: Linguistic Classification.** This phase focuses on (continual) linguistic labelling of the represented substance concepts with ground truth labels as soon as the corresponding objects are detected and visually classified. This results in also a continual conversion of substance concepts into classification concepts - the linguistic description of substance concepts - which, differently from substance concepts, acts as vehicles for formal communication and reasoning (Pumagalli, Bella, and Giunchiglia 2019).

Notice, however, that this phase is non-trivial with respect to at least four decisive aspects. Firstly, the fact that linguistic phenomena such as synonymy and polysemy induce a many-to-many mapping between substance concepts and classification concepts, thus, resulting in a combinatorial explosion of ground truth labels to choose from, both within and among different natural languages as well as domain languages. Secondly, the crucial influence of lexical gaps (Giunchiglia, Batsuren, and Bella 2017; Giunchiglia, Batsuren, and Freihat 2018) on (cross-lingual) object recognition, namely the inviolable fact that a substance concept can be recognized if and only if it has at least one corresponding classification concept (e.g., the label ‘koto’ denoting a musical instrument is a lexical gap in Bengali language). Thirdly, as amply exemplified in (de Vries et al. 2019), the fact that even for a single concept (e.g., marriage), the visual stimuli (e.g., images) can be radically diverse depending on the language (and ultimately, culture) via which it is visually conceptualized (e.g., images of marriages as conceptualized in English vs. Hindi (de Vries et al. 2019)). Last but not the least, differently from mainstream CV where visual classification itself is via labels only, we keep visual classification (effectuated via visual genus-differentiae) characteristically distinct (but, functionally linked) from linguistic ground truth labelling.

**S4: Conceptual Classification.** The focus of the last stage of our stratified approach, conceptual classification, is to render linguistically grounded classification concepts alinguistic. The ultimate goal is to represent each (word sense of the) ground truth label linked to a unique classification concept (which, in turn, is linked to several images) as a language independent or alinguistic numerical identifier (as a result of which, linguistic phenomena such as polysemy and synonymy are tackled).

This stage is crucial due to the following three observations. Firstly, our solution approach attempts to seamlessly integrate semantically equivalent ground truth labels across multiple languages (inclusive of both natural languages and domain languages). Thus, in a nutshell, it ventures beyond mainstream object recognition systems exhibiting a unilingual bias, mostly, towards the English language as detailed in (de Vries et al. 2019). Secondly, it transcends multiple cultures, in the sense that, for an object recognition system to be representational and fair (de Vries et al. 2019), it must accommodate conceptual hierarchies composed of different levels of abstraction, primarily, but not only, due to different genres of representation diversity (Giunchiglia and Pumagalli 2020) pervasive across cultures and domains. Finally, as a consequence of the above two observations, it is im-
important to notice that our approach accommodates and links together representations of multiple ground truth hierarchies as experienced via different languages and cultures.

The four stages above allow to deal with the design flaws described in section 2. The fourth column in Table 1 reports the flaw while the fifth describes the specific solution. Firstly, the crucial highlight that the object detection stage especially tackles the problem of multi-object images as it extracts (features of) different substance concepts and uniquely delineates (each of) them via bounding polygons. For instance, in Fig.2 (II), via object detection, the objects in the image labelled as Koto can be delineated via bounding polygons to be not only comprising of koto but also flute, music stand etc. This ensures the rejection of very poor quality ‘confounding’ multi-object images as ground truth. Secondly, the visual classification stage implemented via exploiting visual genus-differentiae of (delineated) objects is equally pivotal for all image categories SGP (including good images). It eliminates those images (e.g. the image labelled electric guitar in Fig.2 (II)) as ground truth where the visual differencia is opaque. The linguistic classification stage, on the other hand, provides a specific solution to the mislabelled images because it offers a repertoire of natural language as well domain vocabularies from which to choose appropriate language labels for annotation. For instance, the guitar shaped cake in Fig.2 (IV) will never be labelled as an acoustic guitar following linguistic classification. The last stage of conceptual classification provides a unified solution for all image categories via the assignment of a unique alinguistic identifier to a visual concept, which mutadis mutandis, replicate the same notion in lexical semantics to absorb polysemy. This stage especially tackles the visually polysemic single-object images such as the two images labelled as dulcimers in Fig.2 (III) as, following conceptual classification, the visual concept of dulcimer will have a unique alinguistic meaning and hence, at most, one of the aforementioned images can be a dulcimer.

Finally, even though the four-stage stratified process above provides a teleosemantically well-founded mechanism for modelling media annotations, the SGP many-to-many problem still persists. For example, let us take the simplest case of the (good) image “stringed instrument” (Fig.2 (I)) as the visual data. The process above doesn’t provide any guiding principle(s) which can enforce a high quality explicit selection, successive application and hierarchical modelling of visual differentiae from visual data. The first consequence of this is the (open) possibility to conceptualize radically diverse substance concepts from the image (such as acoustic guitar but also ochre-colored guitar etc.), each of which can further be visualized as diverse images. The second consequence is the fact that even for a single substance concept, the labelling can be done differently in diverse languages and cultures, the precise semantics of which might be similar but not necessarily the same. E.g., the acoustic guitar can be labelled variously as hawaiian guitar, non-electric guitar etc., each of which can further have diverse imagery. This is exactly the problem dealt via faceted classification, as described in the next section. In this perspective faceted classification can be seen as the general methodology for generating and/or evaluating the correctness and/or modifying or extending ImageNet-like datasets.

4 The Faceted Classification Process

As from Fig.2 (third column) the four stages introduced in the previous section can be enforced following the faceted classification methodology, being in fact mapped one-to-one to its four phases, i.e., Pre-Idea Stage, Idea Plane, Verbal Plane and Notational Plane. In fact, the Pre-Idea Stage is causally concerned with the detection of objects as substance concepts, which are then (visually) classified in the Idea Plane, while the Verbal and the Notational Plane provide a standard mechanism for linguistic labelling and alinguistic rendering of the substance concept hierarchy, respectively. The key property of faceted classification is the fact that the work in all the phases is guided by a dedicated body of canons ensuring classificatory finesse (Satija 2017), namely guidelines and principles which must be followed in the annotation process, thus enabling the generation of high quality annotations with the further added value of increasing explainability (Doran, Schulz, and Besold 2018). Canons constitute the core over which the methodology introduced in this paper is based.

For lack of space we concentrate on the Idea Plane, this being the layer where the core part of SGP many-to-many mapping problem is concentrated, namely the problem of how to create one-to-one mappings between visual and linguistic properties. The reader can consult (Giunchiglia and Bagchi 2021) for an overall view of the canons of the other stages and (Giunchiglia, Batsuren, and Freihat 2018) to see how these canons have been followed (with local mistakes) for the generation of a multi-lingual WordNet-like lexical resource3. We concentrate on three sets of canons of prominent relevance for what concerns building the visual subsumption hierarchy, namely:

1. Canons for the selection and succession of concepts, focusing on how to select visual features in any given point in the hierarchy.

2. Canons for horizontal concept expansion, focusing on how to generate siblings.

3. Canons for vertical concept expansion, focusing on how to expand the hierarchy into progressively higher levels of detail.

Let us consider these three sets of canons in some detail.

Selection and Succession of concepts. This set of canons norm as to how a particular visual characteristic should be selected as the visual differencia and how they should be applied in succession at different levels of abstraction. We mention three such canons. The first is the canon of relevance which norms that the selected differencia should be relevant to the purpose of the classification. E.g., sound producing mechanisms such as taut strings, keyboards etc. are appropriate visual differencia if the purpose is to classify musical instruments as per affordances. Secondly, the canon

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3This resource can be navigated at http://ukc.datascientia.eu/. This site will be extended to allow for the navigation of images.
of ascertainability enforces that a visual differentia “should be definite and ascertainable” (Ranganathan 1967). E.g., a truss rod being visually insignificant can’t be used as a visual differentia differentiating a guitar from other musical instruments. Finally, the canon of relevant succession norms that the succession of visual differentia should be relevant to the purpose of the classification. E.g., we take number of taut strings as the first visual differentia to differentiate, for instance, between guitar and koto, with respect to which the former has six strings whereas the latter has thirteen. Further, the presence or absence of input jack can be used as the second visual differentia to differentiate between, for instance, electric guitar and acoustic guitar.

**Horizontal concept expansion.** This set of canons prescribe as to how the sibling substance concepts at a specific level of abstraction should be modelled. We focus specifically on the canon of exhaustiveness which prescribes that sibling substance concepts in an array “should be totally exhaustive of their respective common immediate universes” (Ranganathan 1967). It further adds that a newly encountered object should either be classified into one of the existing visual categories represented as substance concepts or as a new substance concept altogether. This is crucial for image annotation where, for instance, all the known varieties of stringed instrument (such as guitar, koto etc.) should be made sibling concepts of the parent ‘stringed instrument’ with the possibility that a newly designed variety of string instrument can be assigned to any of the existing concepts or be classified as a new one based on the introduction of a new visual differentia.

**Vertical concept expansion.** The final set of canons provide guidance as to how taxonomically clean paths can be modelled in the visual subsumption hierarchy. One such canon is the canon of modulation, which prescribes that a chain should be modelled such that it should comprise one concept “of each and every order that lies between the orders of the first link and the last link of the chain” (Ranganathan 1967), in other words, ensuring that there shouldn’t be gaps or missing links in visual classification hierarchies. A direct justification of the canon vis-à-vis recognition comes from the established fact (Rosch et al. 1976) that there are basic categories which are probabilistically most optimal to be perceptually recognized and can never be missed out (for example, for musical instruments, the category guitar cannot be superseded to directly jump from string instrument to acoustic guitar).

There are two important observations. Firstly, the fact that though we have a detailed set of canonical principles for ensuring the visual subsumption hierarchy to be ontologically thorough, the task becomes particularly challenging due to the tradeoff between the appropriate vertical and horizontal choice in uniquely classifying an object (see Giunchiglia, Zaihrayeu, and Kharkevich 2007)). Secondly, the canons, in association with the four staged annotation, do provide the guidelines for enforcing a quality control infrastructure which can be exploited to design a high quality ImageNet-like dynamically extensible visual hierarchy. The key point, also factoring in other phases, is that the faceted classification process, while (of course) not eliminating human subjectivity, does provide the guidelines for enforcing a one-to-one mapping between visual and linguistic properties.

### 5 Experiments

The experiments have been performed using the musical instruments ImageNet sub-hierarchy in Fig.1. As a first step, we use the proposed methodology to construct a ground truth dataset. Then, we describe an annotation experiment providing an evaluation of our proposed ground truth construction methodology. Finally, we compare the performance of various state-of-the-art ML algorithms, trained with various ground truths, including ours.

#### 5.1 Ground Truth Construction

Following the categorization in Section 2, and applying the methodology in Section 3, we have organized the images into the four categories Good Images, Multi-Object Images, Single-Object Images, and Mislabelled Images. The final classification results are reported in Table 2 in the sub-column labeled “Original”, each column being associated with the corresponding category we are considering.

Some observations. The number of good images that meet our visual classification criteria, for each category, is quite variable and dependent on the category, always involving less than half of the total number of images, with multi-object images being always the biggest category and the single-object images always the smallest. The ability of our methodology to identify mistakes is also highlighted by the fact that (Tsipras et al. 2020) discovered 270 mislabelled images out of around 10k images while we found a total of 264 out of around 3,66k images. As a case in point, though the image of a guitar-shaped wooden body without frets and taut strings can labelled as Guitar (Fig.2 (III)) following (Tsipras et al. 2020), it is in our consideration a mislabelled image since it doesn’t display any visual differentia such as ‘six taut strings’.

#### 5.2 Annotation Experiment

The goal of this experiment was to evaluate how our methodology would perform when applied by non-expert annotators, as it is usually the case (given the size of the annotation tasks, the involvement of experts is unfeasible). To this extent, we asked two groups of annotators to re-annotate the same subset of four hundred and fifty images from the ImageNet categories in Fig.1 (fifty images per category). To

| Number | Musical Instrument | Stringed Instrument | Keyboard Instrument | Wind Instrument | Guitar | Harp | Koto | Acoustic Guitar | Electric Guitar |
|--------|--------------------|---------------------|---------------------|----------------|--------|------|------|----------------|-----------------|
| Good Images | 113 | 32 | 114 | 32 | 209 | 22 | 244 | 42 | 236 | 23 | 209 | 33 | 166 | 44 | 188 | 19 | 202 | 27 |
| Multi-Object Images | 326 | 32 | 345 | 34 | 209 | 22 | 244 | 42 | 236 | 23 | 209 | 33 | 166 | 44 | 188 | 19 | 202 | 27 |
| Single-Object Images | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Mislabelled Images | 5 | 1 | 18 | 2 | 28 | 3 | 27 | 5 | 64 | 6 | 14 | 2 | 3 | 1 | 54 | 5 | 50 | 7 |
| All Images | 506 | 50 | 497 | 50 | 479 | 50 | 290 | 50 | 504 | 50 | 316 | 50 | 188 | 50 | 505 | 50 | 375 | 50 |
Table 3: Group 1 and 2 Annotation Results.

| Index | GT1 | GT2 | Categories | GT1 (Annotation via Differentia) | GT2 (Annotation via Labels) | S.D. |
|-------|-----|-----|------------|----------------------------------|-----------------------------|------|
| 1     | 17  | 2   | Differentia | V1.1, V1.2, V1.3, V1.4, V1.5, V1.6 | V2.1, V2.2, V2.3, V2.4, V2.5, V2.6 |      |
| 1-1   | 50  | 123 | Differentia | 20  | 20  | 21  | 23  | 14  | 12  | 19  | 21  | 28.5354 |
| 1-3   | 50  | 43  | Differentia | 44  | 46  | 47  | 45  | 28  | 12  | 43  | 26  | 32.6981 |
| 1-4   | 50  | 40  | Differentia | 46  | 66  | 77  | 53  | 54  | 26  | 18  | 68  | 26.3258 |
| 2     | 1   | 2   | Differentia | 1   | 2   | 1   | 2   | 1   | 2   | 1   | 2   | 18.2757 |

Table 4: Group 1 and 2 Annotation Results - single object images.

| Index | GT1 | GT2 | Categories | GT1 (Annotation via Single-Object Images) | GT2 (Annotation via Labels) | S.D. |
|-------|-----|-----|------------|------------------------------------------|-----------------------------|------|
| 1     | 17  | 2   | Categories | V1.1, V1.2, V1.3, V1.4, V1.5, V1.6 | V2.1, V2.2, V2.3, V2.4, V2.5, V2.6 |      |
| 1-1   | 50  | 123 | Categories | 20  | 20  | 21  | 23  | 14  | 12  | 19  | 21  | 28.5354 |
| 1-3   | 50  | 43  | Categories | 44  | 46  | 47  | 45  | 28  | 12  | 43  | 26  | 32.6981 |
| 1-4   | 50  | 40  | Categories | 46  | 66  | 77  | 53  | 54  | 26  | 18  | 68  | 26.3258 |
| 2     | 1   | 2   | Categories | 1   | 2   | 1   | 2   | 1   | 2   | 1   | 2   | 18.2757 |

Table 5: Category Labels suggested by Group 1 annotators.

| User | Acoustic Guitar | Dulcimer | Koto |
|------|-----------------|----------|------|
| 1.1  | Guitar          | Appollonian Dulcimer | Birra |
| 1.2  | Guitar          | IDK (I Don't Know) | IDK |
| 1.3  | Wooden guitar   | IDK       | IDK  |
| 1.4  | Guitar          | 3-4 String Musical Instrument | IDK |
| 1.5  | Hawaiian Guitar | 3-String Slotted Erdguitar | 3-String Koto |
| 1.6  | Slotted string instrument | Rectangular Stringed Instrument | Rectangular Stringed Instrument |
| 1.7  | Classic Dulcimer | Elliptical Stringed Instrument | IDK |
| 1.8  | Non-Powered Guitars | Short-Stringed Music Instruments | Japanese Stringed Instrument |

The first key observation is the high variance with both GT1 and GT2. A rather negative result. However, if one looks closely at the last row, she will notice that in GT1 the average deviation is much lower than in GT2, being reduced by about 39%. This by itself provides some evidence that our approach works. But things turn out definitely if one looks at Table 4 which reports the results only for single object images, thus not considering the noise introduced by multiple objects (which, according to our methodology are handled in Stage S1). Here it can be noticed that the average deviation decreases, with respect to GT2, of a factor of around 4.4, and with respect to GT1 of a factor of around 2.7, with an average value of 3.0080. And this result could be improved even more by eliminating the other two design flaws (see Section 2). The interpretation of these results improves even more if we notice that U1,0.1 is an outlier in that she made a serious mistake in distinguishing the two categories “1-1.1.1” and “1-1.1.2”, annotating a large number of images containing “with Input Jack” as the “with No Input Jack” category. If we fix this mistake, the S.D. of these two categories in GT1 drops significantly to 15.3198 and 17.9523, with the Average S.D. going to 6.8699.

A second observation is that in Group 2, but not in Group 1, some annotators were unable to annotate some images (see, e.g., the “0”s in Table 3). Two such examples are “Dulcimer” and “Koto”. ! This observation is also confirmed in Table 5, which reports some example labels provided during the second part of the Group 1 experiment. The observation here is that, despite properly labeling images via differentia, some annotators did not know the names of some categories, e.g., those of “Dulcimer” and “Koto”, or had in mind wrong or more generic labels, and in one case a more specific label. This provides further evidence that annotations via visual differentia improve the quality of annotations avoiding the problems of missing linguistic knowledge.

All in all, these experiments provide evidence of the pervasiveness of the SGP but also of how our stratified methodology allows to deal with it, one type of mistake at the

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time, following the process described in Section 4. At the same it also shows, as also empirically pointed out in (Rus-sakovskys et al., 2015), that it is crucial to enforce a quality control which minimizes the probability of random mistakes by non-expert annotators. This is the next frontier for the scale up of high quality datasets.

5.3 Machine Learning Experiment

In this experiment we used four datasets DS1, DS2, DS3 and DS4. All four datasets contain the usual nine categories with a total of 1438 images, of which 1295 have been used as training sets and 143 as testing sets. The difference among the datasets was in the annotation process. DS1 was generated by general users according to the proposed methodology (similar to GT1), DS2 was generated by labelling categories (similar to GT2), DS3 consisted of the ImageNet labels (similar to GT3), while DS4 (similar to GT4) was generated by experts based on the proposed methodology.

All the experiments were implemented with PyTorch with identical settings. In the training, we have performed the same data augmentation (random scaling and horizontal flipping) on each dataset and randomly sampled \(224 \times 224\) crops from augmented images. All experiments were optimized using Adaptive Moment Estimation (Kingma and Ba, 2014), with learning rate (Zukifli 2018) initialized to 0.0002, momentum initialized (Sutskever et al. 2013) to 0.9, and weight decay (Loschilov and Hutter 2018) to \(10^{-8}\). We used eight state-of-the-art ML methods to train the dataset collected by the three different annotation processes mentioned above, as listed in the first column of Table 6. All models were trained from scratch with no pre-training.

Table 6: Classification results for the four datasets.

| Method | DS1 | DS2 | DS3 | DS4 |
|-------|-----|-----|-----|-----|
| AlexNet (Krizhevsky, Sutskever, and Hinton 2012) | 0.587 | 0.594 | 0.510 | 0.608 |
| ZFNet (Zeller and Fergus 2014) | 0.657 | 0.608 | 0.678 |
| VGG16 (Simonyan and Zisserman 2015) | 0.748 | 0.734 | 0.699 | 0.755 |
| GoogleNet (Szegedy et al. 2015) | 0.818 | 0.804 | 0.727 | 0.825 |
| ResNet 18 (He et al. 2016) | 0.727 | 0.706 | 0.538 | 0.734 |
| DenseNet (Huang et al. 2017) | 0.769 | 0.741 | 0.692 | 0.783 |
| Residual Attention Networks (Wang et al. 2017) | 0.755 | 0.748 | 0.706 | 0.776 |
| SENets (Hu, Shen, and Sun 2018) | 0.790 | 0.783 | 0.734 | 0.804 |

6 Related Work

As far as we know, this is the first time that a general full-fledged KR methodology is proposed, whose main goal is to produce high quality media datasets to be used for training and benchmarking CV algorithms. Still, in this work, we heavily rely and build on top of the ImageNet work (Deng et al. 2009). With respect to this work the main innovations are as follows. First, the idea of using properties, and not only class names, for labeling images. Second, the idea of defining an annotation methodology, rather than just producing a data set, ready to be used to produce future high quality resources. A relevant issue is that the proposed methodology is fully incremental and can be used to improve, both in size and in quality the existing resources. ImageNet included. Third, the exploitation of the faceted classification approach as a powerful technique for further improving the annotation quality. Finally, the fact that our approach allows for the generation of language aware annotations. A relevant issue here, which is a consequence of the work on the development of multi-lingual lexical resource which this work builds upon, is that the labels across language with the same meaning are all connected, still dealing with the well known untranslatability problems which exist when moving from one language to another, including the presence of lexical gaps (Giunchiglia, Batsuren, and Freihat 2018).

As also hinted in the introduction, the work proposed here constitutes also a solution to the SGP, restricted to how it appears in datasets. As shown in (Giunchiglia, Erculiani, and Passerini 2021) this is the first necessary step for development of algorithms which do not suffer from this problem. The work in (Giunchiglia, Erculiani, and Passerini 2021) is a first step in this direction. Our approach to the solution of the SGP is also quite novel. Earlier work has focused on how to integrate feature-level information with semantic level information. Thus, some have proposed using ontologies (Hare et al. 2006), others have proposed to use high-level features (Ma et al. 2010; Elahi et al. 2017), others have proposed to ask users, also using active learning (Tang et al. 2011). More recently (Pang et al. 2019) has proposed to handle the semantic gap in Deep Neural Networks when aggregating multi-level features. The common denominator in all this work is that it focuses on object labels, linguistically defined, rather than on the alignment between the visual properties of objects, as represented in media, and their linguistic description.

Finally, a fair amount of work has also been done trying to model objects in a way which is compliant to how humans think about objects. Most of this work, motivated by (Cognitive) Robotic applications has concentrated on identifying the function of objects see, e.g., (DiManzo et al. 1989; Stark and Bowyer 1991; Bogoni and Bajcsy 1995; Woods et al. 1995; Pechuk, Soldea, and Rivlin 2005; Levesque and Lakemeyer 2008). The key difference is that this work has concentrated on how to enable a meaningful interaction and collaboration between humans and machines and not, as it is the case in this work, on how to enforce a process where there is coherence between how humans and machines describe and name objects.

7 Conclusion

In this paper we have proposed a general KR methodology for producing high quality ground truth media datasets. The motivation for this work lies in the need of overcoming some of the limitations of current CV systems, partly induced by
the low quality of annotation datasets. This is only a first step. We believe in fact that using KR models as the main mechanism for informing which examples should be fed in ML models is the key for the development of explainable and high performance ML systems (Gini et al. 2019).

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