# Baby steps towards few-shot learning with multiple semantics

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#### Abstract

Learning from one or few visual examples is one of the key capabilities of humans since early infancy, but is still a significant challenge for modern AI systems. While considerable progress has been achieved in few-shot learning from a few image examples, much less attention has been given to the verbal descriptions that are usually provided to infants when they are presented with a new object. In this paper, we focus on the role of additional semantics that can significantly facilitate few-shot visual learning. Building upon recent advances in few-shot learning with additional semantic information, we demonstrate that further improvements are possible using richer semantics and multiple semantic sources. Using these ideas, we offer the community a new result on the one-shot test of the popular *mini*ImageNet benchmark, comparing favorably to the previous state-of-the-art results for both visual only and visual plus semantics-based approaches. We also performed an ablation study investigating the components and design choices of our approach.



Figure 1: Pointing out to a new kind of object for a child is often accompanied by additional associated (multiple) semantic information.

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## 1 Introduction

Modern day computer vision has experienced a tremendous leap due to the advent of deep learning (DL) techniques. The DL-based approaches reach higher levels of performance even compared to humans in tasks requiring expertise, such as recognizing dog breeds, or faces of thousands of celebrities. Yet, despite all the advances, some innate human abilities available to us at a very young age, still elude modern AI systems. One of these abilities is to be able to learn and later successfully recognize new, previously unseen, visual categories when presented to us with one or very few examples. This 'few-shot learning' task has been thoroughly explored in the computer vision literature and numerous approaches have been proposed (please see [4] for a recent review). Yet so far, the performance of even the best few-shot learning methods fall short by a significant margin from the performance of the fully supervised learning methods trained with a large number of examples (for example ImageNet [41], or COCO [29]).

One important ingredient of human infant learning, which has only very recently found its way into the visual few-shot learning approaches, is the associated semantics that comes with the provided example. For example, it has been shown in the child development literature that infants' object recognition ability is linked to their language skills and it is hypothesized that it might be related to the ability to describe objects [30]. Indeed, when a parent points a finger at a new category to be learned ('look, here is a puppy', figure 1), it is commonly accompanied by additional semantic references or descriptions for that category (e.g., 'look at his nice fluffy ears', 'look at his nice silky fur', 'the puppy goes woof-woof'). This additional, and seldom rich, semantic information can be very useful to the learner, and has been exploited in the context of zero-shot learning [24, 25, 34] and visual-semantic embeddings [12, 45, 55]. Indeed, language as well as vision domains, both describe the same physical world in different ways, and in many cases contain useful complementary information that can be carried over to the learner in the other domain (visual to language and vice versa).

In the recent few-shot learning literature, the additional power of using semantics to facilitate few-shot learning was realized in only a handful of works. In [5] an embedding vector of either the category label or of the given set of category attributes is used to regularize the latent representation of an auto-encoder TriNet network by adding a loss for making the sample latent vector as close as possible to the corresponding semantic vector. In [56] the semantic representation of visual categories is learned on top of the GloVe [36] word embedding, jointly with a Proto-Net [46] based few-shot classifier, and jointly with the convex combination of both. The result of this joint training is a powerful few-shot and zero-shot (that is a semantic-based) ensemble that surpassed the performance of all other few-shot learning methods to-date on the challenging *mini*ImageNet few-shot learning benchmark [50]. In both of these cases, combining few-shot learning with some category semantics (labels or attributes) proved highly beneficial to the performance of the few-shot learner. Yet in both cases, only the simple one word embedding or a set of several prescribed numerical attributes were used to encode the semantics.

In this work, we show that more can be gained by exploring a more realistic human-like learning setting. This is done by providing the learner access to both richer 'description level' semantic information (a sentence, or a few sentences, in a natural language with a description of the category) instead of just a label, as well as multiple semantics - a set of several references or descriptions that are all related to the category being learned (e.g. both category label and category description used jointly).

We demonstrate how these richer descriptions and the multiple semantic setting can facilitate few-shot learning (leveraging the intuition of how human infants learn). We show that more complex semantics (description) alone is not sufficient for improving performance. Yet, when combined with the label semantics in a multiple semantic setting, it gets the desired performance, comparing favorably to the previous visual and visual + semantics state-of-the-art results on the challenging one-shot test of the *mini*ImageNet benchmark [50].

To summarize, the contributions of this work are three-fold. First, we propose the community to consider a new, perhaps closer to 'infant learning' setting of Few-Shot Learning with Multiple and Complex Semantics (FSL-MCS). Second, in this context we propose a new benchmark for FSL-MCS, and an associated training and evaluation protocol. Third, we propose a new multi-branch network

architecture that provides the first batch of encouraging results for the proposed FSL-MCS setting benchmark.

# 2 Related Work

The major approaches to few-shot learning include: metric learning, meta learning (or learning-to-learn), and generative (or augmentation) based methods.

Few-shot learning by metric learning: this type of methods [40, 47, 54] learn a non-linear embedding into a metric space where  $L_2$  nearest neighbor (or similar) approach is used to classify instances of new categories according to their proximity to the few labeled training examples embedded in the same space. Additional proposed variants include [15] that uses a metric learning method based on graph neural networks, that goes beyond the  $L_2$  metric. Similarly, [43, 49] introduce metric learning methods where the similarity is computed by an implicit learned function rather than via the  $L_2$  metric over an embedding space. The embedding space based metric-learning approaches are either posed as a general discriminative distance metric learning [6, 40], or optimized on the few-shot tasks [15, 33, 47, 54], via the meta-learning paradigm that will be described next. These approaches show a great promise, and in some cases are able to learn embedding spaces with quite meaningful semantics embedded in the metric [40]. The higher end of the performance spectrum for the metric learning based approaches has been achieved when combining these approaches with some additional semantic information. In [21] class conditioned embedding is used, and in [56] the visual prototypes are refined using a corresponding label embedding.

Few-shot meta-learning (learning-to-learn): These methods are trained on a set of few-shot tasks (also known as 'episodes') instead of a set of object instances, with the motivation to learn a learning strategy that will allow effective adaptation to new such (few-shot) tasks using one or few examples. An important sub-category of meta learning methods is metric-meta-learning, combining metric learning as explained above with task-based (episodic) training of meta-learning. In Matching Networks [50], a non-parametric k-NN classifier is meta-learned such that for each few-shot task the learned model generates an adaptive embedding space for which the task can be better solved. In [47] the metric (embedding) space is optimized such that in the resulting space different categories form compact and well separated uni-modal distributions around the category 'prototypes' (centers of the category modes). Another family of meta learning approaches is the so-called 'gradient based approaches', that try to maximize the 'adaptability', or speed of convergence, of the networks they train to new (few-shot) tasks (usually assuming an SGD optimizer). In other words, the meta-learned classifiers are optimized to be easily fine-tuned on new few-shot tasks using small training data. The first of these approaches is MAML [11] that due to its universality was later extended through many works such as, Meta-SGD [26], DEML+Meta-SGD [58], Meta-Learn LSTM [38], and Meta-Networks [32]. In LEO [42] a MAML like loss is applied not directly on the model parameters, but rather on a latent representation encoding them. This approach featured an encoder and a decoder to and from that latent space and achieved state-of-the-art results on miniImagenet few-shot benchmark among models relying on visual information alone.

Generative and augmentation-based few-shot approaches: This family of approaches refers to methods that (learn to) generate more samples from the one or a few examples available for training in a given few-shot learning task. These methods include synthesizing new data from few examples using a generative model, or using external data for obtaining additional examples that facilitate learning on a given few shot task. These approaches include: (i) semi-supervised approaches using additional unlabeled data [8, 13]; (ii) fine tuning from pre-trained models [27, 52, 53]; (iii) applying domain transfer by borrowing examples from relevant categories [28] or using semantic vocabularies [3, 14]; (iv) rendering synthetic examples [9, 35, 48]; (v) augmenting the training examples using geometric and photometric transformations [23] or learning adaptive augmentation strategies [17]; (vi) example synthesis using Generative Adversarial Networks (GANs) [2, 10, 16, 20, 22, 31, 37, 39, 59]. In [18, 44] additional examples are synthesized via extracting, encoding, and transferring to the novel category instances, of the intra-class relations between pairs of instances of reference categories. In [51], a generator sub-net is added to a classifier network and is trained to synthesize new examples on the fly in order to improve the classifier performance when being fine-tuned on a novel (few-shot) task. In [39], a few-shot class density estimation is performed with an auto-regressive model, augmented with an attention mechanism, where examples are synthesized by a sequential process. Notably,

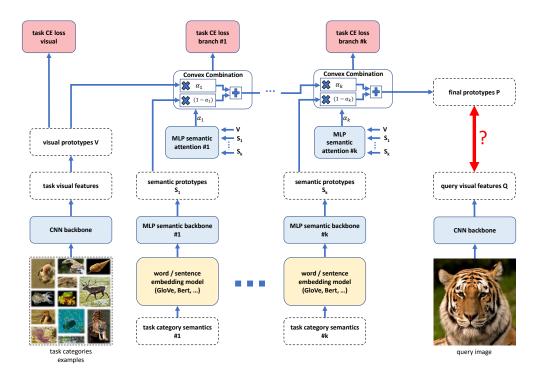


Figure 2: The proposed model, best viewed in color. Some connecting lines are excluded for brevity. Filled boxes represent neural nets and losses, bluish nets are jointly learned as part of our approach, yellowish ones are for word / sentence embedding and are pre-trained and fixed. Please see section 3 for details.

in [5, 57] label and attribute semantics are used as additional information for training an example synthesis network.

# 3 Method

Our approach builds upon the work of [56]. Our general model architecture is summarized in Figure 2. The model is trained using the episode-based meta-learning approach proposed by [50]. The training is performed on few-shot tasks (episodes) comprised of one or few image examples for each of the task categories (the so-called support set), as well as one or several query images belonging to these categories (the so-called query set). Each task is simulating a few-shot learning problem. In addition, for our multiple semantics approach, each task is accompanied by semantic information (label and description sentence(s)) on each of the task categories. For the labels we use the GloVe embedding [36] and for descriptions the BERT embedding [7], as we observed GloVe performs better for words and BERT for sentences.

The model is comprised of a visual information branch supported by a CNN backbone computing features both for the training images of the few-shot task and for the query images. As in Proto-Nets [46], the feature vectors for each set of the task category support examples are averaged to form a visual prototype feature vector V for that category. In addition, the model contains one or more "semantic branches" for learning to incorporate the additional semantic information. Each semantic branch starts with a pre-trained word or sentence embedding feature extractor, followed by an Multi Layer Perceptron (MLP) generating a "semantic prototypes"  $S_i$  to be combined with the corresponding (same category) visual prototype. For the sake of this combination, each semantic branch is equipped with an MLP calculating "semantic attention" - a coefficient  $\alpha_i$  of the semantic prototype of the branch in the overall convex combination of the category prototypes. For computing  $\alpha_i$ , the attention MLP for each branch can choose to receive as an input one of the task category prototypes generated by either the visual or the semantic branches. We examine the effect of different inputs to the attention MLP of different semantic branches in the ablation study section 4.3 below.

Optionally, our model also allows for adding into the convex combination additional branches with visual prototypes V attended by either of the  $S_i$  or V itself. Finally, our model features a task specific cross-entropy loss on the prototype resulting from each (semantic or visual) branch which allows for providing intermediate level supervision for each branch output using the ground truth labels associated to the few-shot tasks (episodes) used for meta-training. These losses admit the softmax normalized logits computed as negative distances between the task query samples and the prototypes produced by each respective semantic (or visual) branch.

To summarize, for each task category, each semantic branch is uniquely determined by its two inputs - the semantic information being processed into the semantic prototype  $S_i$  (category label, or one of the category descriptions), and the prototype (visual or semantic) being processed into the semantic attention coefficient  $\alpha_i$ . The final prototype P for a category in a given few shot task with an associated visual prototype V and semantic prototypes  $\{S_1, ..., S_k\}$  is computed as:

$$P = V \cdot \prod_{i=1}^{k} \alpha_i + \sum_{i=1}^{k} \left[ S_i \cdot (1 - \alpha_i) \cdot \prod_{j=i+1}^{k} \alpha_j \right]$$
 (1)

(please see Fig 2 for the intuitive visualization of eq. 1). The final category prototype P is then compared to the query visual feature vector Q (produced by the CNN backbone) for computing the category probability as  $prob(Q,P) = SM(-||P-Q||^2)$ , where SM stands for the softmax normalization operator.

Assuming the correct category for the query Q has visual prototype V and semantic prototypes  $\{S_1,...,S_k\}$ , than the final training loss incorporating the CE losses for all the visual and semantic branches can be written as:

$$Loss = -\log(prob(Q, V)) + \sum_{r=1}^{k} -\log(prob(Q, P_r))$$
 (2)

where  $P_r$  is the output of the partial computation of equation 1 up until the semantic branch #r:

$$P_r = V \cdot \prod_{i=1}^r \alpha_i + \sum_{i=1}^r \left[ S_i \cdot (1 - \alpha_i) \cdot \prod_{j=i+1}^r \alpha_j \right]$$
 (3)

#### 3.1 Implementation details

Our implementation is built on top and extends the code kindly provided by the authors of [56], also keeping their hyper-parameter setting (such as learning rate schedules, etc). Our code will be made available upon acceptance. Our experiments were conducted using K40 NVidia GPUs, taking about 1sec per batch while training.

In our experiments: we use the ResNet-12 backbone CNN [19] with 512-features (flattened output) for each image. For each semantic branch, the semantic backbone is a two-layer MLP with a 300-sized hidden layer, and 512-sized output layer. The semantic attention for each branch is a two-layer MLP with a 300-sized hidden layer and a scalar output layer followed by a sigmoid (to normalize the coefficients into a [0,1] range). All MLPs include a dropout layer with 0.7 rate between the hidden layer and the output layer.

The CNN backbone and all the semantic MLPs (backbones and attention) for the different branches are trained jointly using the per branch Cross Entropy losses (applied to the predicted logits after a softmax for each branch). We use 5 random few-shot episode in each training mini-batch. The training is performed using only the training subset of the categories of the few-shot dataset. All parameters are randomly initialized (random normal initialization for the weights and a constant zero for the biases). The category descriptions that are used for the more complex semantic branches are obtained automatically from WordNet. Please see Table 1 for some description examples.

# 4 Results

We have evaluated our approach on the challenging few-shot benchmark of *mini*ImageNet [50] used for evluation by most (if not all) the few-shot learning works.

Label	Description
Sorrel Consomme Bookshop	"A horse of a brownish orange to light brown color" "Clear soup usually of beef or veal or chicken" "A shop where books are sold"

Table 1: Some examples of descriptions for the miniImageNet categories we extracted from WordNet.

### 4.1 The miniImageNet benchamrk

The miniImageNet [50] is a subset of the ImageNet dataset [41]. It contains 100 randomly sampled categories, each with 600 images of size  $84 \times 84$ . We have used the standard evaluation protocol of [38] and evaluated the 1-shot and the 5-shot performance of our method in a 5-way scenario (that is having 1 or 5 training examples for each of the 5 categories in the support set), using 64 categories for training, 16 for validation, and 20 for test. For testing we used 1000 random test episodes (sampled from the test categories unseen during training). The same set of test episodes was used for all the experiments and repetitions. For each of the models evaluated by us, each experiment was repeated 5 times, each time with different random initialization of the network parameters, following which the obtained 5 accuracy measures (evaluated on the 1000 test episodes for each of the resulting 5 models) were averaged and confidence interval was computed. As explained in section 3, the description semantics for the miniImageNet categories were collected from the WordNet definitions associated with the category labels. We plan to make our proposed evaluation benchmark (and associated protocol) of few-shot with multiple semantics available for the community in order to encourage future work in this interesting direction.

Method	1-shot accuracy	5-shot accuracy		
Human performance				
4.5 years old	70.0	-		
Adult	99.0	-		
No semantics				
DEML+Meta-SGD [58]	$58.5 \pm 0.9$	$71.3 \pm 0.7$		
CAML [21]	$59.2 \pm 1.0$	$72.4 \pm 0.7$		
$\Delta$ -encoder [44]	$59.9 \pm 1.0$	$69.7 \pm 0.8$		
LEO [42]	$61.8 \pm 0.1$	$\textbf{77.6} \pm \textbf{0.1}$		
With semantics				
TriNet[3] [5]	$58.1 \pm 1.4$	$76.9 \pm 0.7$		
AM3 ProtoNets [56]	$65.0 \pm 0.4$	$74.5 \pm 0.2$		
Multiple semantics (ours)	$67.2 \pm 0.4$	$74.8 \pm 0.3$		

Table 2: Results on *mini*ImageNet benchmark. For 1-shot we observe that adding more semantics improve over a single semantics (AM3) by 2.2%. For 5-shot, as observed in previous works, since the visual information is more reliable, semantic information is not very helpful. For context we also report human performance of one of the authors and his daughter. The adult performance is very high mainly due to prior familiarity with the categories in question.

#### 4.2 Performance evaluation on the *mini*ImageNet

Table 2 summarizes the results of our approach applied to *mini*ImageNet and compares to the state-of-the-art results with and without using semantics. For brevity, only the highest results from the literature are reported in each category. As can be seen, in the most challenging 1-shot scenario, our multiple semantics based model improves the best previously reported result by 2.2%. The highest result is achieved using both multiple semantic branches, and more complex (than category labels)

<sup>&</sup>lt;sup>3</sup>TriNet [5] uses a deeper ResNet-18 feature extractor backbone than the ResNet-12 used in this work.

description based semantics. Please see section 4.3 for the description of the branches used to achieve the best result and for the examination of the different branch configurations alternatives.

As expected, the most significant gain from using multiple additional semantics comes when the fewest amount of training examples is available, that is in the 1-shot case. For the 5-shot scenario, when more image examples become available for the novel categories, the importance of semantic information diminishes, and we can observe better results from using deeper backbones (as in TriNet [5], and as pointed out in [4]) and advanced gradient based meta learning (LEO [42]). Yet, even in this case, multiple semantics provide small 0.3% improvement over using just the labels semantics (AM3-ProtoNet [56]).

The AM3 [56] implementation provided by the authors used a less-standard protocol for repeated evaluations. Instead of fixing the set of test episodes and training several times with random initialization of parameters for later averaging the results, in the AM3 original implementation the model was trained only once and the test set was randomized 5 times and not kept fixed between different tests. Therefore, in the spirit of the 'Reproducibility Checklist' adopted by the NeurIPS community, we report the AM3 results arising from re-running the AM3 original implementation code following exactly the same parameters setting as defined by the authors, while adhering to the more standard protocol of repeated evaluation as explained in the end of section 4.1. The original reported results for *mini*ImageNet evaluation of [56] using the less-standard protocol were 65.2 and 75.2 for the 1 and 5 shot evaluations respectively. The AM3 [56] paper featured also results of AM3 combined with TADAM [33]. However, we were not able to reproduce the reported results using the authors provided implementation and hyper-parameters, scoring significantly lower. Quoting the authors response to our email inquiry: "the AM3-TADAM is the most sensitive one to hyper-parameters and even random seeds". Hence we did not applied our method to AM3-TADAM the did not reported AM3+TADAM results 65.3 and 78.1 for 1 and 5 shot *mini*ImageNet are not included in the table.

## 4.3 Ablation study

The table 3 summarizes the performance of different (multiple) semantic branch configuration alternatives and other aspects of the proposed approach evaluated using the 1-shot *mini*ImageNet test.

Description	Branch 1	Branch 2	Branch 3	Branch 4	Branch losses	Accuracy
a. Only label (AM3 [56])	1/1	-	-	-	-	65.0
b. Switching to description	d/d	-	-	-	-	65.0
c. Cascade effect (same semantics)	1/1	1/1	-	-	-	65.3
d. Multiple semantics (2 branches)	1/1	d / v	-	-	-	65.8
e. Multiple semantics (2 branches)	1/1	d / v	-	-	$\checkmark$	66.4
f. Multiple semantics (2 branches)	1/1	d/d	-	-	$\checkmark$	66.4
g. Multiple semantics (3 branches)	1/1	d / v	d/d	-	$\checkmark$	67.1
h. Multiple semantics (3 branches)	1/1	d / v	d/1	-	$\checkmark$	67.2
i. Multiple semantics (4 branches)	1/1	d/v	d/1	v / 1	$\checkmark$	67.0

Table 3: Ablation study performed on 1-shot experiment on the miniImageNet benchmark. With l = category label, d = category description, v = visual prototype. x/y (e.g. l/l) means x is the branch input and the convex combination parameter is conditioned on y. The 'Branch losses' column marks models that utilize the internal supervision of per branch task CE losses. a. Is the AM3 baseline. b. Using only description semantics we observe similar results as when using only labels. c. The effect of 'ensemble', i.e. adding another branch with no extra semantic, is minor (+0.3). d. Adding a second branch with extra semantics adds 0.8% over the baseline. e-f. Utilizing branch losses with extra semantics adds another 0.6%. g-h. Third branch adds another 0.8%. i. Adding a forth branch does not help.

As can be seen from the table, using the more complex description semantics instead of the labels used in [56] does not by itself improve the performance (table 3b). Also, using multiple semantic branches relying only on the labels, without adding additional semantic information (descriptions), to test the effect of this so-called 'semantic ensemble' on its own, leads to only slight 0.3% improvement over the baseline (table 3c). More significant improvement of 0.8% over the baseline is attained by

incorporating additional semantic information (descriptions conditioned on the labels) in the second semantic branch (table 3d). Introducing intermediate supervision in the form of per branch task specific Cross Entropy losses brings even more significant improvement of 1.4% over the baseline (table 3e) underlining the importance of this component. In further tests, all using the branch losses, we see that conditioning the second (description) branch on itself does not bare improvements (table 3f), yet a substantial improvement of 2.1% over the baseline is obtained when adding the the self-attending description as the third semantic branch (table 3g). Changing the third semantic branch to use labels for attending to the added description semantics, and thus utilizing the most comprehensive conditioning strategy (attending using all prior inputs to the combination) leads to the maximal 2.2% improvement over the baseline (table 3h) and comprises our final method. Finally, in additional experiments we have observed that adding additional semantic branches, while re-using the same semantic information, does not help the performance (table 3i, as an example). This is intuitive as this likely leads to increased over-fitting due to adding more trainable network parameters.

# 5 Summary & conclusions

In this work, we have proposed an extended approach for few-shot learning with additional semantic information. We suggest making few-shot learning with semantics closer to the setting used by human infants: we build on multiple semantic explanations (e.g. name and description) that accompany the few image examples and utilize more complex natural language based semantics rather than just the name of the category. In our experiments, we only touch the tip of the iceberg of the possible approaches for using descriptive and multiple semantics for few-shot learning. Many other ways for combining multiple semantic information with visual inputs are possible and are very interesting topics for the follow-up works. In particular, we offer to investigate the following possible future work directions:

- Attending to visual and semantic branches combining information from all the task categories. In the current experiments, the coefficient of each category semantic prototype is computed from the attention MLP input of the corresponding category (either semantic or visual prototype of the same category). A future work may learn to attend based on the entire task jointly.
- Alternative non-linear (e.g. MLP) combination schemes for visual and semantic prototypes instead of the (linear) convex combination we use here.
- Learning alternative metrics, conditioned on the semantics, for comparing prototypes and query image features (e.g. learned Mahalanobis distance, with covariance matrix computed from semantic prototypes).
- Semantic ensembles: instead of combining prototypes, combine logits resulting from different semantic and visual branches.
- Further exploring different semantic sources and prototype / attention combinations. E.g. using the categories hierarchy [1] or investigating into multi-modal sources of semantics, such as audio / smell / touch / taste, to further approximate the human infant learning environment.

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