Semantic Supervision: Enabling Generalization over Output Spaces

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Abstract

In this paper, we propose Semantic Supervision (SEMSUP) – a unified paradigm for training classifiers that generalize over output spaces. In contrast to standard classification, which treats classes as discrete symbols, SEMSUP represents them as dense vector features obtained from descriptions of classes (e.g., “The cat is a small carnivorous mammal”). This allows the output space to be unbounded (in the space of descriptions) and enables models to generalize both over unseen inputs and unseen outputs (e.g., “The aardvark is a nocturnal burrowing mammal with long ears”). Specifically, SEMSUP enables four types of generalization, to – (1) unseen class descriptions, (2) unseen classes, (3) unseen super-classes, and (4) unseen tasks. Through experiments on four classification datasets across two variants (multi-class and multi-label), two input modalities (text and images), and two output descriptions modalities (text and JSON), we show that our SEMSUP models significantly outperform standard supervised models and existing models that leverage word embeddings over class names. For instance, our model outperforms baselines by 40% and 20% precision points on unseen descriptions and classes, respectively, on a news categorization dataset (RCV1). SEMSUP can serve as a pathway for scaling neural models to large unbounded output spaces and enabling better generalization and model reuse for unseen tasks and domains.1

1 Introduction

Most approaches to supervised classification (SUP) have traditionally considered different output classes as abstract symbols devoid of meaning (e.g., 0, 1, 2). This pre-defines a rigid output space that inhibits models from learning semantic similarities between output classes or generalizing to unseen classes (e.g., “moth”), even if it is similar to a class seen during training (e.g., “butterfly”). Some prior works have aimed to tackle this problem by predicting classes based on semantic class attributes (Palatucci et al., 2009), word vectors of class names (Frome et al., 2013; Socher et al., 2013; Pappas and Henderson, 2019; Dauphin et al., 2014; Zhang et al., 2018), or textual class descriptions (Lei Ba et al., 2015; Zhang et al., 2017; Bujwid and Sullivan, 2021; Reed et al., 2016; Nam et al., 2016). These works provide specialized solutions with a specific capability in mind, such as zero-shot generalization to unseen classes or domain generalization.

In this paper, we develop a general unifying paradigm for supervised classification called semantic supervision (SEMSUP) to leverage rich semantic information about classes to enable better generalization over the output space. SEMSUP allows models to learn better representations of output classes using multiple “descriptions” that capture their semantics and neural output encoders to represent them in vector space. Figure 1 provides an example of SEMSUP models that predict classes based on descriptions.

Equal contribution – order decided over a game of snake.

1Code and data are available at https://github.com/princeton-nlp/semsup.
on textual descriptions collected in a semi-automatic fashion using web search or JSONs constructed programmatically from a knowledge base.

Intuitively, we can view SEMSUP as equivalent to providing models multiple-choice questions with informative choices that they must ‘read’ and understand before picking an answer. This is in contrast to the traditional classification setup where the choices are fixed and lack any interpretation on their own. Training models to predict over semantically informative choices has several advantages: (1) the number of choices can be varied at will during inference, (2) the choices can be described in several different ways (e.g., by different end-users), (3) new concepts can be provided as choices by describing them in known terms, and (4) the choices can span varying levels of granularity (e.g., classify between descriptions of vehicle, bus and wheel). In effect, SEMSUP allows the output space to be unbounded and defined on the fly using semantic descriptions, providing additional flexibility during model inference.

Operationally, SEMSUP uses input and output encoders to encode inputs and output descriptions onto a joint space. It utilizes this joint space by learning to push inputs and output descriptions corresponding to the same classes to be close to each other, which allows for generalization over unseen points in the output space. For instance, for a specific animal classification dataset (e.g., dog v.s. cat) seen during training, the model can generalize to new classes (e.g., classify wolf v.s. tiger), new high-level concepts (e.g. classify domestic v.s. wild), or new tasks (classify tree v.s. flower). SEMSUP models can be trained end-to-end with parameters of both encoders optimized jointly. We also improve generalization of SEMSUP in the output space by training it with multiple descriptions per class and data augmentation techniques to encourage order invariance in structured descriptions like JSONs – both of these help alleviate overfitting.

We demonstrate the general applicability of SEMSUP to any standard classification task by considering four existing benchmarks spanning text and image inputs, two different types of ‘descriptions’ (English text and structured JSON), and two paradigms – multi-class and multi-label classification. Our experiments showcase the ability of SEMSUP models to generalize over output spaces in various ways, including (1) new descriptions of seen classes, (2) unseen classes, (3) unseen high-level subclasses, and (4) unseen tasks (Figure 2). In all tasks and scenarios SEMSUP outperforms existing systems developed for zero-shot generalization to unseen classes while also remaining competitive with standard classifiers on seen classes. For instance, SEMSUP achieves absolute improvements of 40% on unseen descriptions in RCV1, 15% on unseen classes in CIFAR, and 10% on unseen superclasses in 20 Newsgroups. We analyze our SEMSUP models and recognize the importance of using multiple descriptions and pre-trained models for encoding semantic supervision (§ 6), which provides a recipe for users to adopt our work. We also release class descriptions for these datasets to aid future research.

2 Related Work
Several prior work can be treated as sub-cases of SEMSUP. These attempt to capture the semantic meaning of classes by using auxiliary information (like class names) to enable zero-shot learning (Table 1). SEMSUP unifies these works by using multiple rich descriptions, multiple input (e.g., image and text) and output (e.g., text and JSON) modalities, and exhibiting numerous generalization capabilities to – unseen descriptions, classes, superclasses, and tasks. We summarize SEMSUP’s capabilities and prior work in Table 1.

Zero-shot learning with auxiliary information The goal of zero-shot learning (Larochelle et al., 2008) is to predict novel classes not encountered at train time by using class specifications (auxiliary information) of some form, such as representative images (Larochelle et al., 2008) or knowledge base annotation (Palatucci et al., 2009). At their core, these works define a joint embedding space for inputs and auxiliary information that represents classes. Subsequent papers like DeVISE (Frome et al., 2013) and Socher et al. (2013) used averaged word embeddings (Mikolov et al., 2013) corresponding to class names. Several follow-up works have also implemented similar ideas (Pappas and Henderson, 2019; Dauphin et al., 2014; Mittal et al., 2021; Wang et al., 2018; Zhang et al., 2018), but in contrast to our model (SEMSUP), they use shallow bag-of-word features over class names which has its shortcomings (§ 5).
Table 1: Summary of related work. SEMSUP provides a unified framework to handle multiple and rich descriptions (referencing different attributes of the class), input modalities (image and text), and output modalities (text descriptions and JSON). Unlike prior work SEMSUP handles multiple modalities for representing the output (text and JSON) and exhibits several types of generalization (to unseen descriptions, classes, superclasses, and tasks).

Other papers have employed text descriptions of classes, either crowdsourced or scraped from Wikipedia. Some of these use simple bag-of-words features to encode them (Nam et al., 2016; Lei Ba et al., 2015; Qiao et al., 2016), which has the issue of ignoring word order and a portion of semantics, while others use deeper models (Reed et al., 2016; Bujwid and Sullivan, 2021). However, all these papers focus only on a single input modality (images), a single output modality (text), or a single generalization scenario (to unseen classes), whereas SEMSUP handles a variety of these attributes.

Concept bottleneck models (Koh et al., 2020) and other related works (Akata et al., 2015; Demirel et al., 2017; Lampert et al., 2009) use class attributes as auxiliary information, but these annotations are expensive to collect, harder to scale to large datasets, and are constrained to a limited number of preset attributes. Prototypical networks (Snell et al., 2017) and Matching networks (Vinyals et al., 2016) use a small set of images for each class as auxiliary information but have the downside that they cannot sufficiently capture a large number of class attributes or the variety of instances.

Prompting pre-trained models SEMSUP is partly related to a recent area of research which uses natural language to prompt large pre-trained models (Liu et al., 2021; Brown et al., 2020; Wei et al., 2021; Sanh et al., 2022; Radford et al.; Raffel et al., 2020; Schick and Schütze, 2021; Gao et al., 2021). Prompting generative models (e.g., BERT (Devlin et al., 2019), T5 (Raffel et al., 2020), and GPT-3 (Brown et al., 2020)) involves providing a rule-based template that is used to predict the class and can be viewed as auxiliary information (e.g., “The movie is [MASK] ”). These templates typically contain only class names, whereas SEMSUP uses diverse, freeform descriptions.

Prompting contrastive models like CLIP (Radford et al., 2021) involves providing class names at inference time (e.g., “Image of a dog”) and choosing the description with the highest similarity to the instance. CLIP requires pre-training on a large amount of paired image-caption data with captions serving as auxiliary information for specific instances. In contrast, SEMSUP can operate with smaller quantities of semantic supervision available for the task at hand.

Learning with natural language descriptions The body of work around natural language explanations (Srivastava et al., 2017, 2018; Murty et al., 2020; Hancock et al., 2018; Mu et al., 2020; Clarke et al., 2010; Fidler et al., 2017; Mitchell et al., 1986; DeJong and Mooney, 1986) aims to induce classifiers with the help of explanations that describe rationales for instances belonging to specific classes. Some weak supervision studies use class-specific auxiliary information (natural language descriptions or from knowledge bases) to generate labeling functions which are used to augment the training data by annotating unsupervised data (Hancock et al., 2018; Ratner et al., 2017; Lison et al., 2020; Safranchik et al., 2020; Varma and Ré, 2018; Mayhew et al., 2019). But unlike our paper, both these lines of work aim to improve few-shot learning on a bounded set of classes, whereas we enable even zero-shot learning on an unbounded set. Our work is also related to studies that learn classifiers (Andreas et al., 2018), reinforcement learning (RL) agents (Branavan et al., 2010, 2012; Denil et al., 2017; Andreas et al., 2018; Zhong et al., 2019; Narasimhan et al., 2018; Sharma et al., 2021; Hanjie et al., 2021), and programs (Acquaviva et al., 2021; Wong et al., 2021; Desai et al., 2016) by “reading” natural language descriptions of the task. In contrast to our work, these studies typically evaluate on synthetic domains and only consider descriptions in text.

3 Methodology

3.1 Background

Our paradigm (SEMSUP) is a modification of the standard supervised classification paradigm (SUP), which
involves using data to learn a model by minimizing a loss function. The training data can be represented as \( D_{\text{train}} = \{(x_1, y_1), \ldots, (x_n, y_n)\} \), where \( x_i \in \mathcal{X} \) and \( y_i \in \mathcal{Y} \) denote the input and the categorical output (\( \mathcal{Y} = \{1, \ldots, K\} \)) sampled from a hidden underlying distribution \( (x_i, y_i) \sim P_{\text{true}}(\mathcal{X}, \mathcal{Y}) \). We construct a model \( M_0 \) which can predict the conditional probability of outputs given the input – \( P_{\text{pred}}(y|x_i) \) and learn it by minimizing a loss function \( L(P_{\text{pred}}(y|x_i); y_i) \) like cross-entropy or max margin loss.

Without loss of generality, let us assume \( M_0 \) to be a neural network with a hidden representation of dimensionality \( d \) and the number of output classes to be \( K \). Then, we can factorize \( M_0 \) to consist of (1) an input encoder \( f(\cdot) \) which encodes the input as \( f(x_i) \in \mathbb{R}^d \) and an (2) output matrix \( O \in \mathbb{R}^{K \times d} \). This allows the model to represent the conditional distribution over output classes as:

\[
P_{\text{Sup}}(y|x_i) = \text{softmax} (O \times f(x_i)) \tag{1}
\]

Intuitively, the \( i^{th} \) row of the output matrix \( (O[i] \in \mathbb{R}^d) \) can be envisioned as a vector representing the \( i^{th} \) class, which is randomly initialized at the beginning of training (even if the encoder has been trained beforehand).

### 3.2 Semantic Supervision

Our semantic supervision (SEMSUP) paradigm uses the same data, loss functions, and input encoder \( f(\cdot) \) used in SUP, but changes the output matrix \( (O) \). Instead of representing the \( i^{th} \) class (say “cat”) using a randomly initialized vector, SEMSUP encodes semantic information about the class into \( O[i] \) (e.g., the sentence “The cat is a small carnivorous mammal”). Hereon, we will use the term “description” to refer to any kind of semantic information (text or JSON).

SEMSUP requires access to descriptions for each class \( \mathcal{C} = \{C_1, \ldots, C_K\} \), where the \( i^{th} \) element contains a set of descriptions corresponding to the \( i^{th} \) class: \( C_i = \{c_{1i}, \ldots, c_{Li}\} \). Our SEMSUP model independently samples a description for each class \( (c_{ij}) \) and employs an output encoder \( g(\cdot) \) to encode it as \( g(c_{ij}) \in \mathbb{R}^{d_{\text{out}}} \), which make up rows of the output matrix \( O_{\text{SEMSUP}}[i] = g(c_{ij}) \). Since the last dimension of \( O_{\text{SEMSUP}} \) doesn’t necessarily match the dimensionality of the input encoder \( f(x_i) \in \mathbb{R}^d \), we learn an intermediate projection matrix \( P \in \mathbb{R}^{d_{\text{out}} \times d} \). The final prediction is obtained as:

\[
P_{\text{SEMSUP}}(y|x_i) = \text{softmax} (O_{\text{SEMSUP}} \times P \times f(x_i)) \tag{2}
\]

#### Training and testing with SEMSUP

During training, we learn the input encoder \( f(\cdot) \), the output encoder \( g(\cdot) \), and the label projection matrix \( (P) \) together, and we refer to all of them together as the SEMSUP model. Descriptions are sampled uniformly at random for each class and for each batch, thus allowing the model to see different descriptions during training. During testing, we predict the class corresponding to the class description with the highest softmax probability. Generalizing to unseen classes is as simple as obtaining a description for it, encoding it using the output encoder, and adding it as a new row in the output matrix \( O_{\text{SEMSUP}} \). This is similar to simply changing the answer choices provided in a multiple-choice question.

#### Forms of semantic supervision

In the naivest form, classes can be represented by their class names (e.g., “This is a cat”) (Frome et al., 2013; Pappas and Henderson, 2019), which can be useful because the output encoders (such as Word2Vec, BERT) typically have some semantic information about words (e.g., cat is more similar to a dog than a banana). While using class names for descriptions is already an improvement over SUP which doesn’t contain any semantic information, SEMSUP uses multiple different descriptions referencing different attributes to improve the semantic understanding of classes. For example, a well-rounded representation of the class cat can be constructed by using the following descriptions:

(a) *High-level description* – “The cat is a small mammal”,

(b) *Types* – “Cat types include Persian and Sphinx.”,

(c) *Physical attributes* – “It has a strong flexible body, quick reflexes, and retractable claws”, and

(d) *Historical attributes* – “Cats were first domesticated in the Near East around 7500 BC.”

The SEMSUP framework allows for output supervision of various kinds, including (a) text, which describes different attributes, (b) structured representations, like JSONs or data structures that store attributes, (c) images, which visually represent defining aspects, (d) prototypes, which are representative inputs. In our experiments, we focus on text and structured representations. We collect descriptions for classes in a semi-automated fashion (§4.2).
How is semantic supervision useful? As mentioned before, semantic supervision allows models to make predictions over output choices by ‘reading’ their ‘description’ and deciding the best match for the input instance. This is akin to training models to answer informative multiple-choice questions, which provides several flexible use cases during model inference: (1) the number of choices can be changed, (2) choices can be described in different ways, (3) choices can contain new concepts described using known terminology, and (4) choices can even span varying level of granularity and are not restricted to the same level as the training set. Thus, semantic supervision (SEMSUP) allows the model to generalize to unseen outputs and have a potentially unbounded output space into which it can classify, providing various opportunities for model re-use.

Specifically, we investigate SEMSUP’s usefulness on the following four scenarios during model inference (Figure 2):

(S1) Generalization to unseen descriptions: We show the model unseen descriptions of classes it has previously seen during training. The goal is to evaluate the model’s ability to understand new descriptions.

(S2) Generalization to unseen classes: We test the model using descriptions of unseen classes – this is the most common zero-shot learning setup used in prior work (Akata et al., 2015; Zhang et al., 2017).

(S3) Generalization to unseen superclasses: We provide the model with choices of unseen superclasses, which are at a higher level of conceptual granularity than the classes seen during training. This tests the model’s capability at understanding class hierarchies and relationships between classes.

(S4) Generalization to unseen tasks: Finally, we also transfer a trained SEMSUP model to a new task with a similar input domain (e.g., news articles), but a new set of classes. This shows the ability of SEMSUP to enable model re-use across different datasets from similar domains.

4 Experimental Setup

4.1 Datasets

We evaluate SEMSUP on four diverse datasets chosen to test generalization on different scenarios (§3). Specifically, we choose three of them such that they have a hierarchical organization of classes and one which has annotated attributes (AWA2), and we describe them below. Unless mentioned otherwise, the datasets are multi-class classification datasets.

1. 20 Newsgroups (20NG) (Lang, 1995) consists of 20,000 newsgroup documents of correspondences between online users. The documents are divided roughly equally into 20 classes. We partition similar classes into 5 superclasses. We further partition the classes into 12 train, 4 validation and 4 test classes, and evaluate using accuracy.

2. CIFAR-100 (Krizhevsky et al., 2009) consists of 60K images from the Tiny Images dataset (Torralba et al., 2008) divided into 100 classes ranging from animals to household objects. Each class is assigned to one of 20 superclasses (e.g. aquatic mammals). We partition the dataset into 80 train, 10 validation, and 10 test classes, and evaluate using accuracy.

3. Animals with Attributes 2 (AWA2) (Xian et al., 2018) is an animal classification dataset with 37K images and 50 animal classes. The dataset also includes 85 animal attributes (e.g. fur, swims). Each class is annotated with binary values indicating whether the attribute is present in the class. We follow the split of classes into 27 train, 13 validation, and 10 test classes provided in the dataset.

4. RCV1 (Lewis et al., 2004) is a multi-label news classification dataset (multiple correct classes per instance) with over 800, 000 articles. It has 103 niche classes (e.g., bond markets and credit ratings) out of which we hold-out 25 of them to test unseen class generalization. The dataset also provides a hierarchy in which the classes are arranged, and we use 17 parent classes to test unseen superclass generalization. As is standard for multi-label datasets, we evaluate using the label ranking average precision (L.RAP) metric (Pappas and Henderson, 2019).

4.2 Collecting output supervision

Text output supervision We collect textual output descriptions for RCV1, 20NG, and CIFAR-100 by converting class names into queries: “what is a class” and issuing them to two popular search engines. We scrape the resulting preview snippets, automatically remove scraper artifacts and partial descriptions, and manually filter any remaining off-topic descriptions. We notice that there is variety in descriptions, including noisy descriptions.

JSON output supervision To construct JSON descriptions of an animal in AWA2, we use types of attributes as the keys (e.g. color) and the actual attribute lists as values (e.g. {color: [‘orange’, ‘black’]} for a tiger). To improve the robustness of the model, we automatically augment the descriptions by randomly removing attribute values and permuting the key and values.

5 We follow the division from: http://qwone.com/~jason/20Newsgroups/

3 We do not manually filter RCV1 descriptions due to a large number of descriptions and classes.
value list orders, and divide them into training, validation, and test sets. We provide examples of textual and JSON descriptions and details regarding their collection and filtering in Appendix A.

4.3 Models

For text datasets, we encode input features \((f(\cdot))\) using the \([\text{CLS}]\) representation from a pretrained BERT-small model (Turc et al., 2019). For image datasets, we use the activations of a ResNet-18 model (He et al., 2016) immediately preceding the fully-connected final layer. For each dataset, the input encoders are identical across our models and baselines, to ensure fair comparison. While the standard supervised baseline (SUP) uses an output matrix to output the logits, the other models use output encoders, which we describe below.

For our SEMSUP models, we encode output features \((g(\cdot))\) using the \([\text{CLS}]\) representations from a pretrained BERT-small model (Turc et al., 2019) for text descriptions and a pretrained CodeBERTa-small model for AWA2 JSONs. We propose three SEMSUP models:

1. **SEMSUP-ALL** samples from all available class descriptions during training.

2. **SEMSUP-SINGLE** uses a single fixed randomly selected description for each class during training.

3. **SEMSUP-NAMES** is a SEMSUP variant using class names instead of descriptions (e.g. “computer graphics”).

We consider two strong baselines from prior work.

1. **DEVISE** (Frome et al., 2013) uses the mean of the word vectors of the class names

2. **GILE** (Pappas and Henderson, 2019) is similar to DEVISE but introduces a tanh activation on top of the output embeddings.

For both the models, we use GloVe (Pennington et al., 2014) vectors which are fixed throughout training (Frome et al., 2013) to represent the class names.

**Training**  We train all models end-to-end and backpropagate gradients both through the input and output encoder. For all models, we use the cross-entropy loss for multi-class datasets and the binary cross-entropy loss for the multi-label dataset (best out of cross-entropy, hinge, and focal losses (Lin et al., 2017)). We perform hyperparameter tuning only on the validation set and report results on the test set. We provide additional details about training in Appendix C.

| Model       | RCV1 UN | RCV1 S  | CIFAR UN | CIFAR S  | AWA2 UN | AWA2 S  |
|-------------|---------|---------|----------|----------|---------|---------|
| SUP         | × 96    | × 92    | × 74     | × 94     |         |         |
| DEVISE      | 52 91   | 84 91   | 55 73    | 92 92    |         |         |
| GILE        | 53 91   | 85 92   | 53 73    | 93 93    |         |         |
| SEMSUP-SINGLE | 38 96 | 71 92   | 47 72    | 61 93    |         |         |
| SEMSUP-ALL  | 91 96   | 93 93   | 71 73    | 93 93    |         |         |

Table 2: (S1) Model performance on unseen descriptions (UN) and seen descriptions (S) at test time. SEMSUP-ALL drops ≤ 5 points across all datasets when switching from seen to unseen class descriptions whereas the next best model (GILE) loses almost 40 points on RCV1. We report performance on the test set (all classes included) for all datasets. RCV1 uses the LRAP metric and other datasets use ACCURACY. Decimal places removed for clarity.

5 Results

We now report results for four scenarios where SEMSUP improves over standard classification models and other strong baselines.

5.1 Generalizing to unseen descriptions (S1)

In this scenario, the input classes are identical between train and test time, but the model is given unseen descriptions at test time. For example, on CIFAR-100 one train-time description for flatfish is: “Flatfish is the common name for fish belonging to the order Pleuronectiformes”, and a test-time description not seen during training is: “A flatfish moves its fins up and down like a fan”. The ability to generalize to novel descriptions enables users to define classification problems over subsets of train classes simply by providing their own list of class descriptions. This can be particularly useful when there are a large number of classes (e.g., 1000) but a user wants to classify the instance into a small subset (e.g., 10 classes). The user can simply provide their own descriptions for the subset of 10 classes, thus eliminating the need to go through a long list of training classes or descriptions. For each dataset, we keep train and test descriptions consistent for our models and baselines. Notably, for DEVISE and GILE we use the same train and test descriptions as SEMSUP rather than class names in this scenario.

We present the results in Table 2. As expected, performance when using the training descriptions (S) at test time is similar for all models on all datasets and matches the standard supervised learning baseline (SUP). This shows that using the same descriptions at train and test time allows SEMSUP models to match the performance of a standard supervised learning model. However, for all models other than SEMSUP-ALL, there is a large gap between the performance when unseen descriptions (UN) and seen descriptions (S) are used, with similar trends on all datasets. For example, on RCV1, there is a 40 point drop when unseen descriptions are used

5.2 Filtering (SUP)

We now consider datasets where descriptions during training are different from those at test time. As expected, models trained on synthetic classes or descriptions (SUP) lose performance when using the training descriptions (S) at test time. For example, on RCV1, there is a large gap between the performance when unseen descriptions (UN) and seen descriptions (S) are used, with similar trends on all datasets. For example, on RCV1, there is a 40 point drop when unseen descriptions are used

5.3 Clipping (SUP)

We next examine results where we try to partially balance the performance when using training descriptions (S) and unseen descriptions (UN). We find that the results are very close to our baseline results where train and test descriptions are consistent.
Table 3: (S2) Mean performance on unseen test classes, which are a subset of classes not seen during training. The test classes are at the same level of hierarchy as train classes. SEMSUP models consistently outperform DEVISE and GILE. Bracketed numbers are standard deviation over 3 seeds and bolded numbers are statistically significantly higher than other numbers (p < .05).

| Model   | RCV1    | 20 NG  | CIFAR | AWA2 |
|---------|---------|--------|-------|------|
|         | LRAF    | Acc.   | Acc.  | Acc. |
| DEVISE  | 27.1 (±0.9) | 71.2 (±1.9) | 46.6 (±4.3) | 25.0 (±2.3) |
| GILE    | 27.5 (±3.3) | 71.5 (±0.9) | 45.6 (±0.1) | 28.2 (±0.2) |
| SEMSUP-NAMES | 44.6 (±0.9) | 74.0 (±4.1) | 58.5 (±2.3) | 27.6 (±1.9) |
| SEMSUP-SINGLE | 29.8 (±3.5) | 63.8 (±1.6) | 47.7 (±3.5) | 33.6 (±2.3) |
| SEMSUP-ALL | 48.0 (±2.4) | 72.5 (±0.9) | 61.0 (±1.7) | 40.0 (±1.3) |

Table 4: (S3) Mean performance of models on test superclasses, which consist of unseen supersets of train classes. SEMSUP-ALL outperforms all other models by significant margins on 20 NG and CIFAR and SEMSUP models and our SEMSUP models outperform baselines on all datasets. Bracketed numbers are standard deviation over 3 seeds and bolded numbers are statistically significantly higher than other numbers (p < .05).

| Model   | RCV1    | 20 NG  | CIFAR |
|---------|---------|--------|-------|
|         | LRAF    | Acc.   | Acc.  |
| DEVISE  | 47.0 (±4.1) | 76.1 (±2.7) | 43.1 (±2.6) |
| GILE    | 48.8 (±3.2) | 77.6 (±1.8) | 43.7 (±3.1) |
| SEMSUP-NAMES | 56.1 (±1.0) | 80.5 (±1.9) | 54.8 (±2.9) |
| SEMSUP-SINGLE | 44.6 (±2.4) | 80.4 (±2.4) | 53.2 (±2.5) |
| SEMSUP-ALL | 56.2 (±1.4) | 86.1 (±0.9) | 59.4 (±1.9) |

Table 5: (S4) Model transfer performance (Acc.) when trained on RCV1 and tested on 20NG. SEMSUP outperforms DEVISE and GILE by more than 2 ×. MAJORITY always predicts the majority class. Bracketed numbers are standard deviation over 3 seeds and bolded numbers are statistically significantly higher than other numbers (p < .05).

| Model   | RCV1—→20 NG |
|---------|-------------|
|         | MAJORITY    | 5.00 (±0.0) |
|         | DEVISE      | 7.93 (±1.2) |
|         | GILE        | 7.57 (±2.2) |
|         | SEMSUP-NAMES | 20.5 (±1.3) |
|         | SEMSUP-SINGLE | 14.8 (±0.9) |
|         | SEMSUP-ALL  | 19.5 (±1.0) |

5.2 Generalizing to unseen classes (S2)
In this case, classes are partitioned into training (Y_train) and test (Y_test) classes, where Y_train ∩ Y_test = ∅. The models generalize to unseen classes in Y_test by using corresponding class descriptions for the test classes. Our setup is similar to standard zero-shot (ZS) classification.

We present the results in Table 3. SEMSUP models significantly outperform DEVISE and GILE on three out of the four datasets, with performance improvements of 20 points on RCV1 and 15 points on CIFAR. Using a single description (SEMSUP-SINGLE) instead of all descriptions reduces performance by 10 points on average, and like in the previous scenario, highlights the importance of multiple training descriptions. Furthermore, SEMSUP-ALL outperforms SEMSUP-NAMES on two out of the four tasks, highlighting the advantage of using diverse descriptions of classes rather than class names alone. Interestingly, SEMSUP-ALL is also able to generalize better to unseen classes in AWA2 while using JSON attributes, beating DEVISE and GILE which use the class name, validating that our framework can use different kinds of output descriptions effectively.

5.3 Generalizing to unseen superclasses (S3)
In this scenario, the classes at test time are unseen superclasses of the classes from the training set. For example, if Y_train includes foxes, lions, and frogs, Y_test can consist of mammals and reptiles. This task is potentially more challenging because of the change in the granularity of classification. This scenario allows a user to interact with a model at a higher conceptual level than it was trained on and is enabled by the model generalizing to supersets of training classes.

We present the results in Table 4. Like in the previous scenarios, our SEMSUP models consistently outperform DEVISE and GILE, with improvements ranging from 10 points on 20 NG to 16 points on CIFAR-100. RCV1 is an especially challenging dataset for this scenario because the superclasses are niche topics, and SEMSUP-ALL is effectively able to generalize from training classes like Annual results and Forecasts to the superclass Accounts and earnings by leveraging appropriate superclass descriptions.

5.4 Generalizing to unseen tasks (S4)
In this final scenario, we evaluate models under the condition of task transfer by training on the source task RCV1 and evaluating on the target task 20NG.

Table 5 shows that SEMSUP achieves over 2 × the accuracy of DEVISE and GILE, demonstrating the strong transfer performance of our model even though RCV1 and 20NG are very different types of classification tasks (multi-label and multi-class respectively) and
We corroborate in the following sections that the reasons we evaluate on two scenarios – (a) unseen descriptions when we evaluate them on two different scenarios, unseen (§6.2). We also compare the effect of different output modalities (natural language text v.s. JSONs with attributes) on AWA2 (§6.3).

### 6 Analysis

We corroborate in the following sections that the reasons for strong performance of SESSUP are three-fold – multiple diverse descriptions of classes, pre-trained output encoders, and fine-tuning the output encoder. We use the RCV1 dataset for the following ablation experiments (§6.1,6.2). We also compare the effect of different input modalities (natural language text v.s. JSONs with attributes) on AWA2 (§6.3).

#### 6.1 The effect of number of descriptions

We study four variants of SESSUP which use $n = 1, 5, 10$ text descriptions at train time each. The models use the same set of descriptions at test time, and we evaluate them on two different scenarios, unseen descriptions and unseen classes, and report the results in Table 6.

Using a single description leads to poor performance for both scenarios, around 50 and 15 points lower than when 10 descriptions are used. This is likely because the output encoder learns spurious discriminative features from a single description that do not generalize. However, the likelihood of learning spurious features decreases as we increase the number of descriptions. Indeed, for both scenarios, we observe that the performance steadily increases as we increase the number of descriptions.

#### 6.2 The effect of the output encoder

The output encoder, which encodes the descriptions corresponding to classes, is crucial to the success of SESSUP, because it should learn discriminative yet generalizable features. We evaluate different encoders and report the results in Table 7. We use a 4 layer pre-trained model as our reference SESSUP ($L = 4$) and consider generalization to unseen classes (§5.2).

### Varying the encoder complexity

In the first segment of the table Table 7, we notice that using a linear model SESSUP (Linear), which computes a bag-of-vectors representation of the class descriptions, performs poorly when compared to non-linear models like SESSUP (L = 2). We experiment with three differently sized (non-linear) BERT (Devlin et al., 2019) models released by (Turc et al., 2019) which have 2, 4, and 8 layers, respectively, and notice no significant difference between their performance. While increasing the depth of the model typically leads to gains in performance, we speculate that the small number of class descriptions used (10 per class for 103, $10 \times 103 = 1030$) when compared to the number of instances (480, 000 for RCV1) means that a very deep model is unnecessary. Thus, we conclude that while it is extremely crucial to use a non-linear output encoder, its depth is less important.

| No. of desc. | Unseen descriptions | Unseen classes |
|--------------|---------------------|----------------|
| $n = 1$      | 38.3 ($\pm 2.6$)    | 35.6 ($\pm 1.2$) |
| $n = 5$      | 81.9 ($\pm 1.1$)    | 49.3 ($\pm 3.0$) |
| $n = 10$     | 90.5 ($\pm 3.0$)    | 50.5 ($\pm 2.4$) |

Table 6: Mean performance on RCV1 when we vary the number of descriptions used to train SESSUP models. We evaluate on two scenarios – (a) unseen descriptions and (b) unseen classes. Increasing the number of training descriptions significantly improve generalization performance, especially to unseen descriptions.

| Output encoder | Pre-trained | Fine-tuned | Unseen classes |
|----------------|-------------|------------|----------------|
| SESSUP (Linear) |             |            | 34.7 ($\pm 6.5$) |
| SESSUP (L = 2) | ✓           | ✓          | 47.2 ($\pm 5.6$) |
| SESSUP (L = 4) | ✓           | ✓          | 48.0 ($\pm 5.4$) |
| SESSUP (L = 8) |             |            | 45.4 ($\pm 2.9$) |
| SESSUP (R, L)  | ✓           | ✓          | 37.4 ($\pm 1.5$) |
| SESSUP (Frozen)| ✓           | X          | 36.0 ($\pm 1.0$) |

Table 7: Mean performance on RCV1 when we vary the output encoder and evaluate on unseen classes. L represents the number of layers, R, L means that the model is randomly initialized, and Frozen indicates that the output encoder’s weights are fixed. Jointly optimizing the input and output encoders and using pretrained output encoders are both important for strong performance.
We view SEMSUP as a generalization of the standard supervised learning setup currently prevalent in the field (since classes can always be ‘described’ as abstract numbers). Just as generalization over input spaces has been a significant point of effort in machine learning over the years, SEMSUP is a step towards providing the output space equal importance and more explicitly thinking about generalization in output spaces through semantic representations. This will enable better re-use of trained models for new tasks, new downstream applications, and by new end users, without requiring expensive re-training or fine-tuning procedures. We hope that SEMSUP can provide a valuable paradigm for developing new algorithms and model architectures for few-shot/zero-shot generalization, as well as enable more natural interaction between AI systems and humans.

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References

Samuel Acquaviva, Yewen Pu, Marta Kryven, Catherine Wong, Gabrielle E Ecanow, Maxwell Nye, Theodoros Sechopoulos, Michael Henry Tessler, and Joshua B Tenenbaum. 2021. Communicating natural programs to humans and machines. arXiv preprint arXiv:2106.07824.

Zeynep Akata, Florent Perronnin, Zaid Harchaoui, and Cordelia Schmid. 2015. Label-embedding for image classification. IEEE transactions on pattern analysis and machine intelligence, 38(7):1425–1438.

Jacob Andreas, Dan Klein, and Sergey Levine. 2018. Learning with latent language. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 2166–2179.

SRK Branavan, David Silver, and Regina Barzilay. 2012. Learning to win by reading manuals in a monte-carlo framework. Journal of Artificial Intelligence Research, 43:661–704.

SRK Branavan, Luke Zettlemoyer, and Regina Barzilay. 2010. Reading between the lines: Learning to map high-level instructions to commands. In Proceedings of the 48th annual meeting of the association for computational linguistics, pages 1268–1277.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss,
Andrea Frome, Greg S Corrado, Jonathon Shlens, Samy Bengio, Jeffrey Dean, Marc’Aurelio Ranzato, and Tomas Mikolov. 2013. Devise: a deep visual-semantic embedding model. In Proceedings of the 26th International Conference on Neural Information Processing Systems-Volume 2, pages 2121–2129.

Tianyu Gao, Adam Fisch, and Danqi Chen. 2021. Making pre-trained language models better few-shot learners. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 3816–3830.

Braden Hancock, Martin Bringmann, Paroma Varma, Percy Liang, Stephanie Wang, and Christopher Ré. 2018. Training classifiers with natural language explanations. In Proceedings of the conference. Association for Computational Linguistics. Meeting, volume 2018, page 1884. NIH Public Access.

Austin W. Hanjie, Victor Y Zhong, and Karthik Narasimhan. 2021. Grounding language to entities and dynamics for generalization in reinforcement learning. In Proceedings of the 38th International Conference on Machine Learning, volume 139 of Proceedings of Machine Learning Research, pages 4051–4062. PMLR.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778.

Pang Wei Koh, Thao Nguyen, Yew Siang Tang, Stephen Mussmann, Emma Pierson, Been Kim, and Percy Liang. 2020. Concept bottleneck models. In International Conference on Machine Learning, pages 5338–5348. PMLR.

Alex Krizhevsky, Geoffrey Hinton, et al. 2009. Learning multiple layers of features from tiny images. Christoph H Lampert, Hannes Nickisch, and Stefan Harmeling. 2009. Learning to detect unseen object classes by between-class attribute transfer. In 2009 IEEE conference on computer vision and pattern recognition, pages 951–958. IEEE.

Ken Lang. 1995. Newsweeder: Learning to filter news. In Machine Learning Proceedings 1995, pages 331–339. Elsevier.

Hugo Larochelle, Dumitru Erhan, and Yoshua Bengio. 2008. Zero-data learning of new tasks. In AAAI, volume 1, page 3.

Jimmy Lei Ba, Kevin Swersky, Sanja Fidler, et al. 2015. Predicting deep zero-shot convolutional neural networks using textual descriptions. In Proceedings of the IEEE International Conference on Computer Vision, pages 4247–4255.

David D Lewis, Yiming Yang, Tony Russell-Rose, and Fan Li. 2004. Rev1: A new benchmark collection for text categorization research. Journal of machine learning research, 5(Apr):361–397.
Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. 2017. Focal loss for dense object detection. In Proceedings of the IEEE international conference on computer vision, pages 2980–2988.

Pierre Lison, Jeremy Barnes, Aliaksandr Hubin, and Samia Touleb. 2020. Named entity recognition without labelled data: A weak supervision approach. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1518–1533.

Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2021. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. arXiv preprint arXiv:2107.13586.

Ilya Loshchilov and Frank Hutter. 2017. Decoupled weight decay regularization. arXiv preprint arXiv:1711.05101.

Stephen Mayhew, Snigdha Chaturvedi, Chen-Tse Tsai, and Dan Roth. 2019. Named entity recognition with partially annotated training data. In Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL), pages 645–655.

Tomás Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. In 1st International Conference on Learning Representations, ICLR 2013. Scottsdale, Arizona, USA, May 2–4, 2013. Workshop Track Proceedings.

Tom M Mitchell, Richard M Keller, and Smadar T Kedar-Cabelli. 1986. Explanation-based generalization: A unifying view. Machine learning, 1(1):47–80.

Anshul Mittal, Kunal Dahiya, Sheshansh Agrawal, Deepak Saini, Sumeet Agarwal, Purushottam Kar, and Manik Varma. 2021. Decaf: Deep extreme classification with label features. In Proceedings of the 14th ACM International Conference on Web Search and Data Mining, pages 49–57.

Jesse Mu, Percy Liang, and Noah Goodman. 2020. Shaping visual representations with language for few-shot classification. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4823–4830.

Shikhar Murty, Pang Wei Koh, and Percy Liang. 2020. Expert: Representation engineering with natural language explanations. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 2106–2113.

Jinseok Nam, Eneldo Loza Mencía, and Johannes Fünnkranz. 2016. All-in text: Learning document, label, and word representations jointly. In Thirtieth AAAI Conference on Artificial Intelligence.

Karthik Narasimhan, Regina Barzilay, and Tommi Jaakkola. 2018. Grounding language for transfer in deep reinforcement learning. Journal of Artificial Intelligence Research, 63:849–874.

Mark Palatucci, Dean Pomerleau, Geoffrey E Hinton, and Tom M Mitchell. 2009. Zero-shot learning with semantic output codes. In NIPS.

Nikolaos Pappas and James Henderson. 2019. Gile: A generalized input-label embedding for text classification. Transactions of the Association for Computational Linguistics, 7:139–155.

Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pages 1532–1543.

Ruizhi Qiao, Lingqiao Liu, Chunhua Shen, and Anton Van Den Hengel. 2016. Less is more: zero-shot learning from online textual documents with noise suppression. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2249–2257.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. 2021. Learning transferable visual models from natural language supervision. In Proceedings of the 38th International Conference on Machine Learning, ICML 2021, 18-24 July 2021, Virtual Event, volume 139 of Proceedings of Machine Learning Research, pages 8748–8763. PMLR.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. Journal of Machine Learning Research, 21:1–67.

Alexander Ratner, Stephen H Bach, Henry Ehrenberg, Jason Fries, Sen Wu, and Christopher Ré. 2017. Snorkel: Rapid training data creation with weak supervision. In Proceedings of the VLDB Endowment, International Conference on Very Large Data Bases, volume 11, page 269. NIH Public Access.

Scott Reed, Zeynep Akata, Honglak Lee, and Bernt Schiele. 2016. Learning deep representations of fine-grained visual descriptions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 49–58.

Esteban Safranchik, Shiyeng Luo, and Stephen Bach. 2020. Weakly supervised sequence tagging from noisy rules. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 5570–5578.

Victor Sanh, Albert Webson, Colin Raffel, Stephen Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegl, Teven Le Scao, Arun Raja,
et al. 2022. Multitask prompted training enables zero-shot task generalization. In The Tenth International Conference on Learning Representations.

Timo Schick and Hinrich Schütze. 2021. It’s not just size that matters: Small language models are also few-shot learners. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2339–2352.

Pratyusha Sharma, Antonio Torralba, and Jacob Andreas. 2021. Skill induction and planning with latent language. arXiv preprint arXiv:2110.01517.

Jake Snell, Kevin Swersky, and Richard Zemel. 2017. Prototypical networks for few-shot learning. In Proceedings of the 31st International Conference on Neural Information Processing Systems, pages 4080–4090.

Richard Socher, Milind Ganjoo, Christopher D Manning, and Andrew Ng. 2013. Zero-shot learning through cross-modal transfer. In Advances in Neural Information Processing Systems, pages 935–943.

Shashank Srivastava, Igor Labutov, and Tom Mitchell. 2017. Joint concept learning and semantic parsing from natural language explanations. In Proceedings of the 2017 conference on empirical methods in natural language processing, pages 1527–1536.

Shashank Srivastava, Igor Labutov, and Tom Mitchell. 2018. Zero-shot learning of classifiers from natural language quantification. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 306–316.

Antonio Torralba, Rob Fergus, and William T Freeman. 2008. 80 million tiny images: A large data set for nonparametric object and scene recognition. IEEE transactions on pattern analysis and machine intelligence, 30(11):1958–1970.

Iulia Turc, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Well-read students learn better: On the importance of pre-training compact models. arXiv preprint arXiv:1908.08962v2.

Paroma Varma and Christopher Ré. 2018. Snuba: Automating weak supervision to label training data. In Proceedings of the VLDB Endowment. International Conference on Very Large Data Bases, volume 12, page 223. NIH Public Access.

Oriol Vinyals, Charles Blundell, Timothy Lillicrap, Daan Wierstra, et al. 2016. Matching networks for one shot learning. Advances in neural information processing systems, 29:3630–3638.

Guoyin Wang, Chunyuan Li, Wenlin Wang, Yizhe Zhang, Dinghan Shen, Xinyuan Zhang, Ricardo Henao, and Lawrence Carin. 2018. Joint embedding of words and labels for text classification. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 2321–2331.

Jason Wei, Maarten Bosma, Vincent Y. Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. 2021. Finetuned language models are zero-shot learners. CoRR, abs/2109.01652.

Catherine Wong, Kevin M Ellis, Joshua Tenenbaum, and Jacob Andreas. 2021. Leveraging language to learn program abstractions and search heuristics. In International Conference on Machine Learning, pages 11193–11204. PMLR.

Yongqin Xian, Christoph H Lampert, Bernt Schiele, and Zeynep Akata. 2018. Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly. IEEE transactions on pattern analysis and machine intelligence, 41(9):2251–2265.

Honglun Zhang, Liqiang Xiao, Wening Chen, Yongkun Wang, and Yaohui Jin. 2018. Multi-task label embedding for text classification. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 4543–4553.

Li Zhang, Tao Xiang, and Shaogang Gong. 2017. Learning a deep embedding model for zero-shot learning. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2021–2030.

Victor Zhong, Tim Rocktäschel, and Edward Grefenstette. 2019. Rtfm: Generalising to new environment dynamics via reading. In International Conference on Learning Representations.
| Dataset (class) | Description |
|----------------|-------------|
| RCV1 (Consumer Prices) | A consumer price index is a price index, the price of a weighted average market basket of consumer goods and services purchased by households. |
| 20-NG (Cryptography) | Cryptography is the study and practice of sending secure, encrypted messages between two or more parties. |
| CIFAR-100 (Flatfish) | A category of fish that are characterized by their narrow bodies that are flat and oval-shaped. |
| AWA2 (Killer Whale) | \{appendages: \{flippers, tail\}, behavior: \{fierce, smart, group\}, color: \{black, white\}, diet: \{fish, meat, plankton, hunter\}, habitat: \{arctic, coastal, ocean, water\}, mobility: \{swims, fast, strong, active, agility\}, shape: \{big, bulbous, lean\}, skin: \{patches, spots, hairless, toughskin\}, teeth: \{meatteeth, strain-teeth\}\} |

Table 9: Randomly selected example class descriptions for RCV1, 20-NG, CIFAR-100, and AWA2 for a randomly selected class in each dataset.

A Output Supervision

We show example class descriptions for the datasets in table 9. The results were scraped from www.google.com and www.duckduckgo.com using a third-party scraping tool\(^6\). Data collection was conducted between September 2021 and January 2022. To reduce variability, personalized results were turned off and regions were fixed to United States. Safe search was enabled for www.google.com and set to moderate on www.duckduckgo.com. The number of search returns for www.google.com was varied between 10 and 50. While we obtained more descriptions using a higher number of search returns, we found that the quality and relevance was often lower.

[\text{h}]

An example scraping target is presented in Figure 4. We automatically filter the scraped preview blocks by removing any incomplete sentences. For multi-sentence descriptions, we only take the first sentence. Sentences that are less than 5 words are discarded. After automatic filtering, we manually inspect the descriptions and remove irrelevant descriptions. The mean number and lengths of the collected descriptions is presented in Table 10. On all datasets, we divide the class descriptions into a 60-20-20 train-val-test split.

B Dataset Details

B.1 RCV1

RCV1 contains 800,000 articles and we create a 60:20:20 split for train, validation, and test respectively.

\(^6\)www.webscraper.io

Table 10: Statistics of the collected class descriptions including mean number of descriptions per class and mean lengths per description. Note that on AWA2 we automatically augment the descriptions, so there is no variance in the number of descriptions between classes.

| Dataset   | Num Descriptions | Description Lengths |
|-----------|------------------|---------------------|
| RCV-1     | 17.9 ± 4.3       | 17.4 ± 9.7          |
| 20 NG     | 19.2 ± 3.8       | 17.7 ± 7.1          |
| CIFAR-100 | 20.3 ± 5.9       | 16.7 ± 7.1          |
| AWA2      | 1250 ± 0.0       | 30.6 ± 5.9          |
Table 11: Details for the 20 NG dataset. Training classes are the remaining 12 classes not in val classes or test classes.

| Val Classes | Test Classes | Val Superclasses | Test Superclasses |
|-------------|--------------|-----------------|-------------------|
| alt.atheism comp.sys.mac.hardware rec.motorcycles sci.electronics | comp.os.ms-windows.misc rec.sport.hockey sci.space talk.politics.guns | recreation religion | computer science politics |

Table 12: Details for CIFAR-100. Training classes are the remaining 80 classes not in val classes or test classes. The test superclasses are the remaining 10 superclasses not listed in the val superclasses above.

| Val Classes | Test Classes | Val Superclasses | Test Superclasses |
|-------------|--------------|-----------------|-------------------|
| streetcar, rabbit, man lamp, forest, otter crab, crocodile, house orchid | motorcycle, pine_tree, bottle trout, chair, butterfly chimpanzee, orange, leopard possum | large_omnivores_and_herbivores medium_mammals, people large_man-made_outdoor_things insects, household_electrical_devices food_containers, fish flowers, vehicles_2 |

It contains 103 classes.

### B.2 20NG

We use the 18828 variant for each newsgroup. Since the original dataset does not define train-test splits, we construct our own 80-20 train test split. We further divide the training set into training and validation sets with a proportion of 80-20.

We present details of the 20 NG dataset splits in table 11. When evaluating generalization to superclasses on 20 NG we remove the misc.forsale class since it is its own superclass.

### B.3 CIFAR-100

We use the provided train-test split, but divide the train set 80-20 into training and validation examples.

### B.4 AWA2

We use the predefined train-val-test splits of classes provided in the paper (Xian et al., 2018). We use only the second of the three train-val splits provided. We split the instances into train and test examples 80-20 and further divide the training set 80-20 into training and validation examples.

To construct the JSON, we first assign each attribute to a parent attribute. The final class-level JSON consists of the parent attributes as keys, and the values are attributes that are present in the class. We augment this dataset by first adding 50 samples per class of corrupted examples, by randomly deleting attributes independently with probability 0.15, and then further multiplying this by 25 permutations.

### C Model Training and Evaluation

All models are end-to-end differentiable and we train them using the AdamW optimizer (Loshchilov and Hutter, 2017). We use a constant learning rate of $1 \times 10^{-4}$ for all the vision experiments on AWA2 and CIFAR-100 and a constant learning rate of $2 \times 10^{-5}$ for all experiments on 20 NG. For efficiency, the class descriptions are encoded into the output matrix $O_{\text{SemStep}}$ at each mini-batch, so that all instances in the batch share the same output matrix. We use the validation set for early stopping, and test checkpoints saved at the point of highest validation accuracy. All implementation was done in PyTorch and PyTorch Lightning and experiments were run on either a single NVIDIA RTX2080 or a single NVIDIA RTX3090.