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ScienceExamCER: A High-Density Fine-Grained Science-Domain Corpus for Common Entity Recognition

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Abstract

Named entity recognition identifies common classes of entities in text, but these entity labels are generally sparse, limiting utility to downstream tasks. In this work we present ScienceExamCER, a densely-labeled semantic classification corpus of 133k mentions in the science exam domain where nearly all (96%) of content words have been annotated with one or more fine-grained semantic class labels including taxonomic groups, meronym groups, verb/action groups, properties and values, and synonyms. Semantic class labels are drawn from a manually-constructed fine-grained typology of 601 classes generated through a data-driven analysis of 4,239 science exam questions. We show an off-the-shelf BERT-based named entity recognition model modified for multi-label classification achieves an accuracy of 0.85 F1 on this task, suggesting strong utility for downstream tasks in science domain question answering requiring densely-labeled semantic classification.

Keywords: named entity recognition, corpus, science

1. Introduction

Named entity recognition (NER) (Grishman and Sundheim, 1996) is a common natural language processing task that aims to abstract or categorize common classes of noun phrases in text, such as identifying "Arthur" as a *person* or "Montreal" as a *location*. This high-level categorization of important entities in text is a staple of most modern NLP pipelines, and has a variety of applications for higher-level tasks including information extraction (Valenzuela-Escárcega et al., 2016), knowledge base population (Dredze et al., 2010), and question answering (Abujabal et al., 2017).

Named entity recognition identifies common classes of entities in text, but these entity labels are generally sparse (typically occurring for between 10% to 20% of words in a corpus, see Section 3.4.), limiting utility to downstream tasks. In this work, we introduce the idea of common entity recognition (CER), which aims to tag all content words in text with an appropriate fine-grained semantic class. CER allows text to be automatically annotated with a much richer set of semantic labels, potentially providing greater utility for downstream applications such as question answering or automated inference. We explore CER in the context of scientific text, and present ScienceExamCER, a training corpus annotated with over 113k common entity annotations drawn from a fine-grained set of over 600 semantic categories, which include named entities, as well as verb groups, properties and quantities, thematic types, and synonyms for key terminology. We also release an off-the-shelf NER tagger modified to perform multilabel CER tagging. This BERT CER tagger achieves an accuracy of 0.85 F1 on this task, indicating that the tag ontology labels are well-defined and clearly identifiable. These two resources offer new opportunities to explore the impact of dense semantic annotation in downstream tasks.

We believe the notion of dense fine-grained semantic tagging to be potentially useful to any application domain, but explore common entity recognition here in the context of scientific text aimed at teaching and evaluating scientific knowledge. An example of this dense semantic classification in the context of standardized science exams is shown in Figure 1. While CoreNLP (Manning et al., 2014) does not locate any entities in the sentence *"Rolanda is growing tomato plants in her garden"*, our CER annotation and system abstracts this sentence to *"[Rolanda]$_{Human}$ [is]$_{StateOfBeing}$ [growing]$_{Growth/ActionsForAgriculture}$ [tomato]$_{Food}$ [plants]$_{Plant}$ [in]$_{RelativeLocation}$ her [garden]$_{ManmadeLocation}$"*.

We detail corpus and ontology/typology construction in Section 3, including a comparison of mention density with other common corpora. Automated evaluations of CER performance are shown in Section 4, including an analyses of the training data requirements of this fine-grained classification, as well as an error analysis.

2. Related Work

Common sets of entity labels (or *typologies*) have expanded from early experiments with a single label, *organization* (Rau, 1991), to the 7 common MUC-6 types (Grishman and Sundheim, 1996) typically used by NER systems, including named entities (*person, organization, location*), temporal mentions (*date, time*), and numeric categories (*money, percent*). Subsets of the MUC-6 types have been included in the typologies of benchmark NER corpora, including CoNLL-2003 (Sang and De Meulder, 2003), OntoNotes (Weischedel et al., 2013), and BBN (Weischedel and Brunstein, 2005).

Sekine et al. (2002) proposed an extended hierarchy of MUC-6 types expanded to include 150 open-domain category labels. While most of these category labels are named entities, Sekine et al. include 10 measurement categories (e.g. *weight, speed, temperature*) and 3 high-level natural object categories (*animal, vegetable, mineral*) that most closely relate to the 601 fine-grained science categories in this work. A subsequent version, the Extended Named Entity (ENE) Ontology (Sekine, 2008), expands the

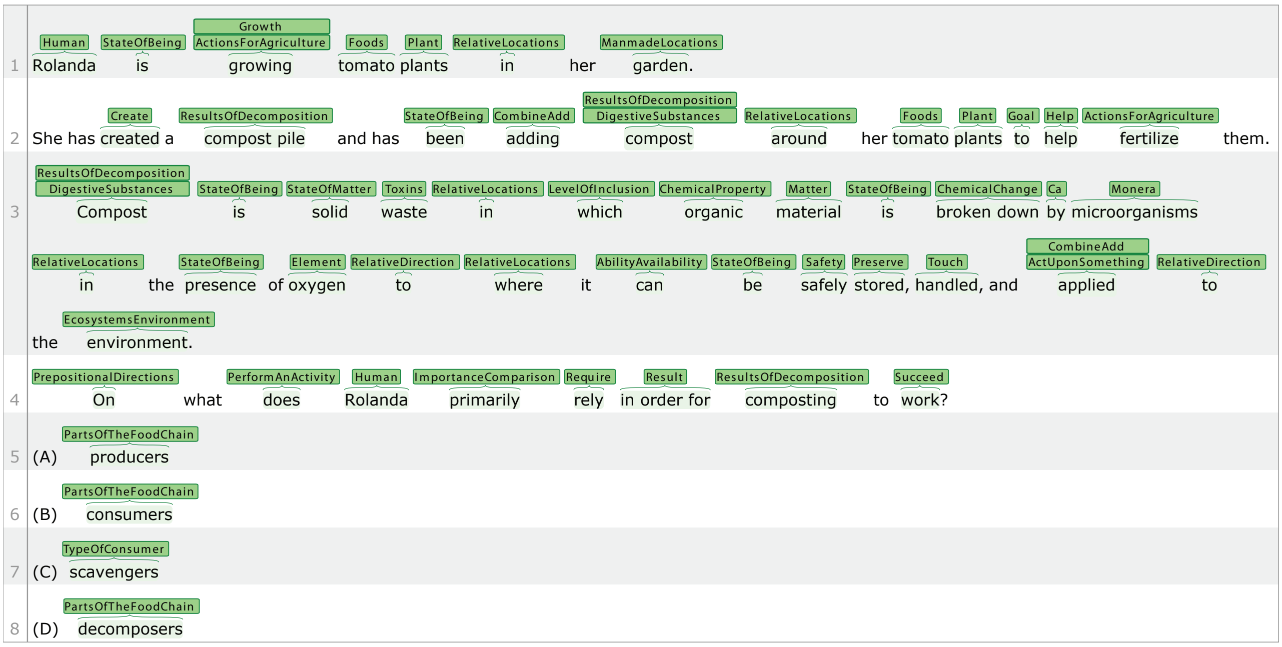

Figure 1: An example standardized science exam question densely annotated with one or more fine-grained semantic categories for nearly each word. This 4-choice multiple choice question (here, under the curriculum topic *"The Interdependence of Life >The Food Chain >Decomposers"*) is one of 4,239 drawn from the ARC corpus and densely annotated in this work.

typology to 200 classes, including 19 fine-grained expansions of the *natural_object* type, such as *bird* or *reptile*, as well as adding 5 meronym categories, such as *plant_part*, that further relax the working definition of named entities from proper names to include other categories (Nadeau and Sekine, 2007).

While open-domain typologies are common, domain-specific typologies and corpora are also popular, occasionally making use of existing domain ontologies to reduce the burden in manually generating fine-grained typologies, such as the manual creation of the fine-grained science-domain typology in this work. An extreme example of fine-grained NER is the MedMentions corpus (Murty et al., 2018), which contains 246k mentions labelled with Universal Medical Language System (UMLS) (Bodenreider, 2004) categories, a fine-grained ontology of over 3.5 million medical concepts. Similarly, large knowledge bases can be filtered to automatically produce fine-grained typologies (as in FIGER (Ling and Weld, 2012) and HYENA (Yosef et al., 2012)), or used to bootstrap the entity classification process in manually-generated typologies. Magnini et al. (2002) demonstrate combining WordNet predicates (Fellbaum, 1998) with approximately 200 handcoded rules can achieve an F1 score of 0.85 on recognizing 10 common entity types, while Ritter et al. (2011) use distantly supervised topic modeling over Freebase entities (Bollacker et al., 2008) to perform named entity recognition on social media posts, achieving an F1 score of 0.59 on 10 common entity types. With respect to larger typologies, Del Corro et al. (2015) perform super-fine grained entity typing using the 16k fine-grained WordNet types under the high-level taxonomic categories of *person, organization, and location*, achieving a manually-evaluated precision of 59.9% on the CoNLL corpus and 28.3% on New York Times news articles. For smaller manually-generated typologies, Mai et al. (2018) demonstrate a model combining LSTMs, CNNs, CRFs, and dictionary-based methods can achieve an F1 of 83.1 on an in-house corpus labeled with Sekine's (2008) 200-class ENE ontology.

NER has historically been approached using a wide variety of methods, including rules (Hanisch et al., 2005), feature-based machine learning systems (Mayfield et al., 2003), conditional random fields (Greenberg et al., 2018), contextualized embeddings (Peters et al., 2018), and combinations thereof. Qu et al. (2016) demonstrate that it is possible to use a conditional random field model to transfer NER performance between datasets, at least in part. Ma et al. (2016) show embedding models can transfer performance in zero-shot settings on fine-grained named entity classification. Expanding on this, recent transformer models (Peters et al., 2018; Devlin et al., 2018) have shown strong transfer performance on a variety of text classification tasks including named entity recognition using large pretrained contextualized embeddings that are fine-tuned on comparatively small in-domain corpora. In this work we make use of an off-the-shelf bidirectional transformer (BERT) NER system modified to support multi-label classification, and demonstrate strong performance on the fine-grained common entity recognition task.

3. Data and Annotation

3.1. Corpus

We annotate fine-grained semantic classes on standardized science exam questions drawn from the Aristo Reasoning Challenge (ARC) corpus (Clark et al., 2018), which contains 7,787 elementary and middle school (3^{rd} through

Label	Examples	Prop.
StateOfBeing	is, are, be	4.6%
LevelOfInclusion	which, each, only	4.0%
RelativeLocation	inside, under	3.0%
Comparison	identical, difference	1.9%
RelativeDirection	forward, upward	1.8%
ProbabilityAndCertainty	likely, possible	1.6%
Cause	because, due to	1.5%
AmountComparison	most, more, less	1.5%
RelativeTime	during, after	1.4%
Creation	produce, make, form	1.2%
PhasesOfWater	steam, ice	1.1%
CardinalNumber	one, 100	1.0%
ContainBeComposedOf	made of, contains	1.0%
IncreaseDecrease	increasing, decline	0.9%
Element	oxygen, carbon	0.9%
Plant	tree, crops, weeds	0.8%
Move	placed, motion, travel	0.8%
Use	with, apply	0.8%
AmountChangingActions	deplete, extend	0.8%
RelativeNumber	many, some, high	0.7%
Temperature	hot, warm, cold	0.7%
Energy	kinetic energy, power	0.7%
CombineAdd	add, absorb, mix	0.7%
LiquidMatter	water, oil, droplets	0.7%
Scientist	geologist, Galileo	0.6%
Quality	best, good, useful	0.6%
Size	large, thick, diameter	0.6%
AbilityAvailablity	potential, unable	0.6%
ManmadeObjects	ball, spoon, paper	0.6%
PrepDirections	on, through, along	0.6%
Human	person, astronaut	0.6%
ActionsForAnimals	eat, migrate, swim	0.6%
InnerPlanets	earth, mars, venus	0.6%
QualityComparison	advantage, benefit	0.6%
Mammal	dog, horse, bear	0.6%
Exemplar	including, such as	0.5%
PlantPart	leaves, flower, root	0.5%
PerformActivity	conduct, do	0.5%
Result	effect, impact	0.5%
Compound	carbon dioxide	0.5%
BodiesOfWater	ocean, lake, pond	0.5%
Help	benefit, support	0.5%
Require	need, must, takes	0.5%
Rock	bedrock, boulder	0.5%
TemporalProperty	first, over time	0.5%
EarthPartsGross	surface, equator	0.5%
WeatherPhenomena	wind, cloud, drought	0.5%
Communicate	explain, describe	0.5%
GeographicFormations	mountain, glacier	0.5%
ChangeInto	become, converted	0.5%
Soil	sand, ground, topsoil	0.4%
Color	green, blue, white	0.4%
Star	sun, proxima centauri	0.4%
PhaseChangingActions	melt, evaporation	0.4%
Nutrition	food, nutrient	0.4%
AnimalPart	body, organ, eye	0.4%
TimeUnit	day, second, year	0.4%
Method	process, procedure	0.4%
StateOfMatter	solid, liquid, gas	0.4%

Table 1: The most frequent subset of the 601 semantic classification labels used to annotate the ScienceExamCER corpus. Proportion refers to the proportion of mentions in the training set that are labeled with a given category. The full set of 601 classes is included in the supplementary material.

9^{th} grade) standardized exam questions drawn from 12 US states. Each question is a 4-way multiple choice question, ranging from short direct questions to detailed multi-step problems grounded in examples. An example question is shown in Figure 1. Question text contains an average of 21 words across 1.7 sentences, while answer candidate text averages 4 words, but can be as short as a single word (as in Figure 1). In this work we draw 4,239 questions from the ARC corpus, consisting of the full training and development folds, to use for our semantic labeling and prediction tasks.

3.2. Semantic Class Labels

We conducted a large data-driven analysis of the 4,239 science exam questions with the aim of identifying a set of high-level semantic categories that would provide near total coverage for classifying or grouping nearly all of the 156k words found across the question and answer text in this corpus. While named entity recognition typically focuses on proper names with specific referents (Nadeau and Sekine, 2007), in the end we arrived at creating 601 fine-grained categories spanning 6 classes of groups:

Taxonomic Groups: High-level categories expressing taxonomic membership, such as that a *hummingbird* is a kind of *bird*. This (or stricter interpretations) is the common form of entity classification in most named entity recognition corpora.

Meronym Groups: Categories expressing part-of relations, such as that a *fin* is a part of an *aquatic animal*, an *x-axis* is a part of a *graphical representation*, or that an *individual* is a part of a *group*.

Action Groups: Collections of action words that tend to describe similar ideas. For example, *decrease, increase, contract, expand, inflate, deflate, accelerate, decelerate, lower, raise* all describe a group of *actions that involve increasing or decreasing quantities*.

Thematic word groups: Groups of words that surround a particular topic. For example, *observe, conduct an experiment, compare, study, consider, test, collect, record, gather, examine,* and *research* are some of the words included in the *performing research using the scientific method* semantic class.

Properties and Values: Common science-domain properties of objects, such as *mass, size,* or *conductivity*, typically grouped with common values they might take, such as *soft, brittle, or hard* in the case of *hardness*.

Synonyms: Groups of words that tend to express similar ideas in the context of science exams. For example, *disease, infection, and sick* all convey the notion of *illness*.

To identify specific instances of these categories in the science exam domain, we first sorted questions into fine-grained curriculum topics using the 406 detailed science-domain question classification labels of Xu et al. (2019), noting that common categories of words tended to emerge upon detailed manual inspection when questions on similar topics were examined together. We proceeded through several iterations of this process, recording candidate high-level semantic classes, as well as seed words that belonged to those categories. After assembling a large list of candidate categories, we further enumerated the seed words with encyclopedic knowledge manually through web searches. For example, while the annotators may have only observed the words *Sun* and *Proxima Centauri* in the corpus for the *Star* category, we would manually expand this to also include other nearby stars such as *Vega*, *Polaris*, and *Wolf 359*.

As a final step, we automatically expanded the seed word list to include lexical variations of each manually added word by first using pretrained GLoVe embeddings (Pennington et al., 2014) to compute the top-N most similar words to a given seed word using cosine similarity, then using several low-precision high-recall heuristics to identify words that had the potential to be lexical variations of an existing word on the seed list. We then generated a frequency histogram of any word present in the corpus that did not yet belong to at least one semantic category, and either placed it in an existing category, or formed a new category for that word and repeated the expansion process for seed words. This detailed manual category development process required approximately three weeks of annotator time, ultimately arriving at a list of 601 high-level semantic categories, with an extensive list of both manually and automatically populated seed words for each category. The full list of semantic categories and seed words is included in the *supplementary material*.

3.3. Annotation Procedure

Annotating a large set of semantic classes onto more than one hundred thousand words presents challenges with annotation consistency and tractability. It would be challenging for crowdworkers to learn a detailed set of 601 fine-grained semantic categories, and extremely time consuming for research assistants to traditionally annotate a collection at this scale. To overcome these challenges, we modified the annotation task to automatically preannotate the entire corpus using the large set of bootstrapped seed words associated with each semantic class, effectively pre-annotating each word with a set of possible semantic category labels. These preannotated labels are effectively low-precision and high-recall, most often containing the correct label(s) for a given mention, but also containing other incorrect labels that must be manually removed by an annotator. A total of 226k preannotated mentions were generated (an average of 1.5 per word), which was reduced to 133k mentions (0.9 per word) after incorrect labels were removed by the annotator. We used the BRAT annotation tool (Stenetorp et al., 2012) for the label removal step. To ease the annotator's need for switching semantic contexts, questions were presented to the annotator sorted by curriculum topic using the question classification annotation of Xu et al. (2019). The annotation procedure took approximately 2.5 minutes per question, for a total of 200 hours. To maintain high consistency, all annotation was completed by a single trained annotator.

Overlapping or nested entity spans were infrequent in this corpus. The largest unit in an multi-word entity was generally kept, and if subsets of words were also relevant to a question, they were also be labeled. Occasionally, entities could be given different labels depending upon the context in which they appeared – for example, *ice* could be labeled as either *Solid* or *PhaseOfWater*, depending on whether the question focused on changes of states of matter generally, or phases of water in specific, such as during the water cycle. If the context in the question clearly indicated that only one of these properties was of use in answering the question, that label would be selected. Otherwise, the entity was given multiple labels.

A clear question with this "preannotate-then-filter" annotation protocol is how well this procedure is able to provide both coverage and accurate labels for the words in the corpus. Our analysis in Section 3.4. shows that after annotation, 96% of content words and 75% of all words have at least one gold semantic category label, suggesting this protocol allows for near-complete coverage of content words at a fraction of the time required to make accurate 601-class annotation judgements at scale. Both our interannotator agreement (included below) and automatic classification performance are high, suggesting adequate annotated label accuracy.

Label distribution: Named entity corpora often have many labels in their typologies, but the majority of mentions tend to cluster around a small set of possible labels (Choi et al., 2018). The distribution of most frequent labels after annotation is shown in Table 1. The usage of the 601 total semantic class labels in this corpus is well distributed, with the 356 most-frequent types covering 95% of the total mentions, while 479 types cover 99% of mentions. At the 99% level, categories (for example, *Geometric Qualities*, such as *angle, slope, or circumference*) still contain 16 mentions, highlighting the scale of the corpus.

Interannotator agreement: A single trained annotator annotated every question in the corpus. A second annotator was trained in the annotation procedure and re-annotated 50 questions totalling 1,756 tokens. Between both annotators, a total of 1,369 mentions were annotated with semantic class labels. Total percent agreement across both annotators was 76%.[1] Upon inspection, labeling multi-word sequences as either a single mention or multiple smaller mentions was a frequent source of disagreement. When these cases were removed, percent agreement rose to 83%.

[1] Because the bootstrapped preannotation procedure reduces the set of possible labels for a given mention from 601 to an average of approximately 2 (the average number of preannotated labels per annotated word), Cohen's Kappa (Cohen, 1960) would either be artificially inflated (if treating the annotation as a 601 class labeling problem) or reduced (if treating annotation as a 2 class problem). As such we report raw percent agreement, which (as critiqued by Cohen) has known problems when dealing with highly skewed frequency distributions of labels, particularly when few labels are present. Here, the number of label categories is high, and (as shown in Table 1) the frequency of labels is well distributed across the label set. As such, the inflation of the percent agreement statistic is likely to be minimal.

Measure	ScienceExamCER	OntoNotes 5	BBN	GUM	CoNLL 2003
Entity Categories	601	18	64	11	4
Total Mentions	133k*	162k	172k	11k	35k
Words	156k	2.44M	1.05M	55k	264k
Labeled Words	117k	284k	257k	33k	51k
Mention Density (overall)	**75%**	12%	25%	59%	19%
Content Words	104k	1.39M	677k	34k	190k
Labelled Content Words	100k	255k	243k	21k	50k
Mention Density (Content Words)	**96%**	18%	36%	62%	27%

Table 2: Summary statistics including *mention density* for the ScienceExamCER corpus, as well as four other common benchmark corpora. At 96%, the ScienceExamCER is significantly more densely labeled than the next-nearest corpus. (* denotes that approximately 16k spans have multiple labels, and as such the total mentions exceeds the total labeled words).

Fold	Science Questions	Words
Train	2,696	108,396
Development	674	27,560
Test	869	35,379

Table 3: Summary statistics for the training, evaluation, and test sets used for evaluating semantic category classification.

3.4. Mention density comparison

To increase the utility of our common entity corpus for downstream tasks, one of the design goals was to provide at least one high-level semantic category to nearly every word in the corpus. To measure this we define the notion of the *mention density* of a corpus as the proportion of words that contain at least one entity label.[2] We compare the mention density of this corpus with the English subsets of the four benchmark named entity recognition corpora listed below:

CoNLL (Sang and De Meulder, 2003): The CoNLL 2003 Named Entity Recognition Shared Task corpus, which includes 4 entity labels that are a subset of the MUC-6 typology: *person, location, organization* and *miscellaneous*.

OntoNotes 5.0 (Weischedel et al., 2013): A large multi-genre corpus of news media, blog, newsgroup, and conversational text, annotated with 18 entity labels, including the MUC-6 types.

BBN (Weischedel and Brunstein, 2005): A corpus of news text annotated with 21 course entity types, including 12 named entity types (e.g. *person, organization, product*) and 7 numeric types (e.g. *date, percent, cardinal number*). The full set of entity labels includes 64 fine-grained types.

GUM (Zeldes, 2017): An open-domain corpus annotated with a collapsed set of OntoNote entities reduced to 11 entity types, such as *person, organization,* or *place*. Two additional catch-all tags are added, *object* and *abstract*, which provide high-level but minimally informative categorical information for large noun phrases. Approximately 40.5% of the labelled words in this corpus are labelled as either *object* or *abstract*.

The analysis of mention density is shown in Table 2. Overall, the mention density of this science corpus is 75%, meaning that 75% of all words in the corpus are annotated with at least one high-level semantic category. When considering only content words (here, determined to be *nouns, verbs, adjectives, adverbs, and numbers*), this proportion increases to 96%. The mention density for the named entity corpora examined in Table 2 ranges between 12% and 59% for all words, and 18% to 62% when considering only content words. At 62%, the GUM corpus contains the next-nearest mention density to the ScienceExamCER corpus, however a large portion of those mentions (40.5%) of words) use the high-level *object* or *abstract* labels, and as such are of limited informativeness to downstream tasks. BBN, the corpus with the next-nearest mention density to GUM, has labels for only 36% of it content words, and 25% of all words.

4. Experimental Results

4.1. Model

Our semantic class labeling task is conceptually similar to named entity recognition or entity typing, only requiring a label for nearly every word in an input sentence. In light of this, here we use an off-the-shelf named entity recognition model, and show it also performs well on the densely-labeled common entity recognition task.

Recently, pretrained bidirectional encoder representation from transformer (BERT) models (Devlin et al., 2018) have shown state-of-the-art performance at both named entity recognition as well as a variety of other token-level classification tasks. In this work, we use an off-the-shelf implementation of a BERT-based named entity recognition system, BERT-NER[3]. Most approaches to named entity recognition model the task as a single-label prediction task, where each word has at most one label. We modify the BERT-NER implementation to allow for multi-label predictions using the following method.

[2]Specifically, the proportion of non-punctuation tokens in a BIO-formatted corpus that are labelled with either a B (beginning) or I (inside) tag.

[3]`https://github.com/kamalkraj/BERT-NER`

Given a sentence S consisting of L tokens, such that $S = (x_1, x_2, ..., x_L)$, the original BERT-based token classification model generates L respective M-dimensional encodings $(x_1, x_2, ..., x_L)$, one for each token. These encodings then pass through a *softmax* layer and make use of a multi-classes cross entropy loss function that generates a single class prediction per token. We adapt this system to multi-label classification by using a *sigmoid* function and binary cross entropy in place of the original loss function to allow the classifications for each token to return non-zero values for more than one class. More formally, our loss function becomes:

$$L_{multilabel} = -\frac{1}{M}\sum_{m=1}^{M}[\tilde{y}_l^m \cdot log\sigma(x_l^m) + (1-\tilde{y}_l^m)\cdot log(1-\sigma(x_l^m))] \quad (1)$$

$$\sigma(x_l^m) = \frac{1}{1+e^{-x_l^m}} \quad (2)$$

where M is the number of total classes, x_l is M-dimensional encoding for the l-th token in sentence, $\tilde{y}_l$ is the l-th token's gold label vector, and σ is the *sigmoid* activation function.

Folds: Because of the expense associated with annotating a large corpus, only the training and development subsets of the ARC corpus were manually annotated with semantic class labels. As such we repurpose the original development set for testing, and hold out 20% of the training corpus for development. Summary statistics on these folds are provided in Table 3.

Hyperparameters: We make use of the pre-trained English `BERT-Base-cased` model[4], with a maximum sequence length of 64. The threshold for the sigmoid activation layer was tuned on the development set, with a value of 0.4 found to provide good performance. The large number of possible class labels in our task compared with typical named entity recognition datasets, combined with the modified multi-label loss function, necessitated significantly longer training times for the model to converge. We empirically found that the model tended to converge by 140 epochs, which took approximately 5 hours to train using dual RTX2080Ti GPUs. Classification of the entire test dataset is comparatively fast, providing semantic class labels at a rate of approximately 900 questions (35,000 words) per minute, enabling the pre-trained model to be run on other science-domain corpora (for example, textbooks, study guides, Simple Wikipedia, or other grade-appropriate knowledge resources) at scale.

4.2. Evaluation

The results for our semantic classification task on the ScienceExamCER corpus using the 601-class fine-grained typology are shown in Table 4. We evaluate entity classification performance using the standard definitions of Precision, Recall, and F1. Overall classification performance is high, reaching 0.85 F1 on the held-out test set. This suggests the common entity recognition performance is sufficiently high to be useful for a variety of downstream tasks. To further characterize performance, we investigate how the availability of training data affects this fine-grained classification task, as well as common classes of prediction errors the BERT-NER model makes.

[4]`https://github.com/google-research/bert`

Model	Fold	Prec.	Recall	F1
BERT-NER	dev	0.84	0.85	0.84
BERT-NER	test	0.85	0.86	0.85

Table 4: Performance on the 601-category fine-grained semantic classification task on the development and test folds using the BERT-NER model.

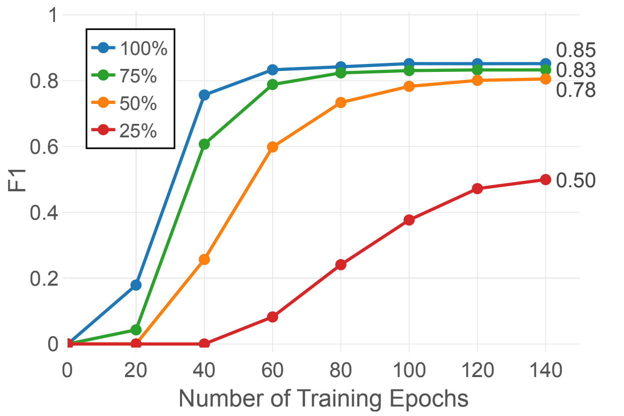

Figure 2: Classification performance (F1) versus the number of training epochs when training the model with less data. Series represent training the model with the entire training set, or randomly subsampled proportions of training data summing to 75%, 50%, and 25% of the original training set size. Each point represents the average of 5 randomly subsampled training sets.

4.3. Performance vs Training Data

Manually annotating fine-grained mentions in large corpora is expensive and time consuming. To investigate how classification performance varies with availability of training data, we randomly subsampled smaller training sets from our full training corpus that were 25%, 50%, or 75% as large, corresponding to spending approximately 50, 100, or 150 hours at the manual annotation task, respectively. The results are shown in Figure 2. With only 25% of training data available, F1 performance decreases dramatically from 0.85 to 0.50. 50% of training data decreases classification performance by 7 points, while 75% of available training data decreases classification performance by 2 points. This suggests that the scale of training data generated in this work provides near saturated performance using the BERT-NER model, and that annotating the remainder of available standardized science exam questions in the ARC corpus would likely result in only a minimal increase on classification performance.

Error Class	Prop.
Predicted label also good	24%
Model did not generate prediction	24%
Multiple gold labels, one found	21%
Predicted label semantically near gold label	17%
Gold label incorrect	7%
Multi-word Expression	6%
Predicted label using incorrect word sense	5%

Table 5: An analysis of common categories of model prediction errors, as a proportion of the first 100 errors on the test set. Note that a given errorful prediction may belong to more than one category, and as such the proportions do not sum to 100%.

4.4. Error Analysis

To better understand the sources of error in our model, we conducted an analysis of the first 100 errorful predictions on the test set, with the results shown in Table 5. Nearly one third of errors are due to issues with the annotation, such as a mention missing an additional label that is also good (24% of errors), or the manually annotated gold label being incorrect (7% of errors). For a substantial portion of errors (24%), no single semantic class rose to meet the activation threshold of the sigmoid layer and the model did not produce a prediction for that word, while, similarly, in 21% of cases only one label of a multi-label word was produced. The remaining errors broadly cluster around technical challenges in determining the semantics of each category, including word-sense disambiguation (5% of errors), locating multi-word expressions (6% of errors), or predicting a label whose category is semantically similar to the gold label (17% of errors).

5. Conclusion

We present ScienceExamCER, a densely annotated corpus of science exam questions for common entity recognition where nearly every word is annotated with fine-grained semantic classification labels drawn from a manually-constructed typology of 601 semantic classes. We demonstrate that BERT-NER, an off-the-shelf named entity recognition model, achieves 0.85 F1 on classifying these fine-grained semantic classes on unseen text in a multi-label setting. The data and code are released with the goal of supporting downstream tasks in question answering that are able to make use of this dense semantic category annotation.

6. Supplementary Material

The annotated corpora, fine-grained typology, and pretrained models for this work are available at `http://cognitiveai.org/explanationbank/`. A truncated version of the typology is included in the `Appendix` below.

7. Acknowledgements

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Appendix

The full list of semantic category labels is included in Table 6 below.

Label	Examples
Celestial Object	celestial object, astronomical body, celestial body, extrasolar-body
Asteroid	asteroid belt, Kuiper belt, asteroid, planetoid, Iris, Flora, Metis, Hygiea
Black Hole	super-massive black hole, black hole, Centaurus A, Sagittarius A*
Comet	Halley's comet, comet, Shoemaker-Levy, Great Comet of 1807
Constellation	constellation, Leo, Little Dipper, pattern of stars, star pattern, ursa Major
Galaxy	Andromeda galaxy, Milky Way, M87, galaxy, Large Magellanic Cloud
Galaxy Parts	galactic region, halo, spiral arm, spiral arms, nuclear bulge
Light	light, ray, beam, beam of light, ray of light, glow, radiance, corona, flash
Celestial Light on Earth	daylight, sunlight, starlight, moonlight, moonshine, sunshine, twilight
Meteor	meteor, meteoroid, meteorite, Perseids, Lyrids, Quadrantids, Geminids
Moon	moon, lunar, Deimos, Phobos, Europa, Ganymede, Rhea, Charon
Lunar Phases	new moon, waxing crescent, first quarter, waxing gibbous, full moon, last quarter
Nebula	nebula, Cat's Eye Nebula, Horseshoe Nebula, Orion Nebula
Particles	ice particle, dust, particle, particulate, cosmic dust, space dust, stardust
Planet	planet, planets, rouge planet, planetary
Dwarf Planets	Pluto, Ceres, Haumea, Makemake, Eris
Inner Planets	Earth, Venus, Mars, Mercury, terrestrial planets, inner planet, inner
Outer Planets	Saturn, Jupiter, Neptune, Uranus, gas giants, outer planet, outer
Planet Parts	core, crust, mantle, ring, surface, axis, magnetic pole, atmosphere, magnetosphere
Satellite	satellite, Sputnik, communications satellite, GOES 15, Oceansat-1, Astrosat
Solar System	solar system, multiplanetary system, planetary system, planetary systems
Space Probes	Mars Rover, exploratory robot, Viking I Lander, space probe, Luna 9, Voyager 1
Spacecraft (Human Rated)	lunar module, spacecraft, Soyuz, International Space Station, Apollo, Space Shuttle
Spacecraft Subsystem	guidance, propulsion, support, suspension, structure, attitude control
Star	star, Sun, Proxima Centauri, Polaris, Vega, VY Canis Majoris, Wolf 359
Star Types	giant, dwarf, main-sequence, supergiant, protostar, supernova, neutron, binary
Star Layers	core, radiative zone, convection zone, chromosphere, photosphere, corona
The Universe and Its Parts	universe, space, outer space, cosmos, observable universe, supercluster
Vacuum	vacuum, in vacuo, vacuity
Celestial Events	celestial event, solar flare, shooting star, meteor shower, transits, planetary
Eclipse Events	solar eclipse, lunar eclipse, annular eclipse, partial eclipse, partial lunar eclipse
Force	weak force, strong force, magnetic force, centripetal force, friction, centrifuge
Gravity	gravitational pull, gravitational acceleration, gravitational force, gravitation
Inertia	inertia
Magnetic Force	magnetism, magnetic force, magnetic pull, magnetic field, electromagnetic force
Pressure	atmospheric pressure, vapor pressure, air pressure, water pressure, barometric
"Pulling" Forces	air resistance, friction, traction, frictional force, sound barrier, drag, torsion
"Pulling" Actions	pull, slow down, stop, attract, pulling, draw in, wrench, twist, twisted, pull back
"Pushing" Forces	thrust, lift, compression, compressive force, compressive forces, normal force
"Pushing" Actions	push, throw, toss, fall, sink, accelerate, motion, repel, compress, swing, exert
Energy	energy, light energy, radiation, kinetic energy, thermal energy, mechanical energy
Absorb Energy	absorb, energy consumption, endothermic reaction, reabsorb, consume, uptake
Electrical Energy	electromagnetic energy, electrical charge, shock, electricity, electric current
Energy Waves	radio wave, wave, ripple, light wave, seismic wave, electromagnetic wave, sound
Parts of Waves	crest, trough, peak, amplitude, wavelength, frequency
Wave Perception	Doppler effect, interference, wave-particle duality, sound perception
Magnetic Energy	electromagnetic energy, magnetic field, magnetic moment, ferromagnetism, dipole
Produce Energy	fission, fusion, nuclear reaction, energy production, energy generation, create
Release Energy	burn, glow, transmit, heat, surface cooling, distribute, exothermic reaction
Sound Energy	sound, sound energy, noise, vibration, vibrations, pascal, decible, echo, echoes
Examples of Sounds	cluck, clucking, meow, meowing, humming, buzz, buzzing, shout, shouted, note, tune
Thermal Energy	conduction, convection, radiation, heat, solar radiation, thermal, latent heat
Transfer Energy	heat transfer, conduct, energy transfer, convection, convert, change into
Spectra	spectrum, electromagnetic spectrum, continuum, frequency spectrum
Electromagnetic Spectrum	visible light, radio waver, radio waves, microwave, x-ray, infrared
Living-thing	organism, creature, extra-terrestrial life, bacteria, living, biological, plankton
Animal	animal, worm, predator, sponge, Animalia, heterotroph, dinosaur, snail, creature
Aquatic	fish, sea star, anemone, shellfish, anglerfish, otter, walrus, stout beardfish

Aquatic Animal Part	scale, scales, gills, tentacle, outer casing, shell, fin, mouth, eye, eyes
Arachnid	spider, arachnid, arachnids, black widow, brown recluse
Insect	bee, wasp, cricket, insect, butterfly, ant, mosquito, fly, moth, caterpillar
Insect Animal Part	six legs, breathing tube, antennae, thorax, abdoment, feeler, wing, head, leg
Mammal	beaver, puppy, horse, mammal, mouse, monkey, bat, deer, lion, dog
Mammal Animal Part	teeth, fur, saliva, tail, paw, hoof, coat, brain, eye, prehensile tail, quill
Bird	chicken, bird, duck, eagle, parrot, yellow-throated longclaw, starling, hummingbird
Bird Animal Part	wing, feather, beak, crown, nape, tail feather, tail feathers, tarsus, hind toe
Reptile	lizard, reptile, crocodile, snake, turtle, rat snake, Elaphe obsoleta
Reptile Animal Part	scale, scales, venom, claw, tail, forked tongue, poison gland, venom canal
Amphibian	amphibian, tadpole, frog, newt, salamander
Amphibian Animal Part	tail, lungs, skin, eyes, feet, organs, mucus, toes, tympanum, forelimbs
Animal Additional Categories	invertebrate, mollusk, vertebrate, desert animal, desert animals, forest dweller
Animal Part	hind leg, hind legs, animal tissue, lung, lungs, brain, skin, eye, eyes, heart
Animal Classification Method	physical feature, physical features, skeletal structure, skeleton, paw, paws
Actions for Animals	swim, eat, hatch, lay egg, lay eggs, lays eggs, sit, tunnel, shed, hunt, hibernate
Human	human, students, Kevin, Michael, Andy, Jessica, Felicia, Martin, scientist
Human Part	mouth, liver, lung lungs, muscle, joint, body, eye, heart, tooth, teeth
Parts of the Eye	retina, pupil, iris, lens, cornea, conjunctiva, sclera, optic nerve, macula, fovea
Cell	skin cell, liver cell, chromatophore, muscle cell, cell, prokaryotic cell, stem
Animal Cell Part	cell membrane, mitochondrion, centriole, ribosome, chromosome
Plant Cell Part	mitochondrion, cell wall, cell membrane, choloroplast, ribosome
Cell Processes	osmosis, mitosis, cell division, meiosis, cellular respiration, differentiation
Cells and Genetics	haploid, diploid, aneuploid, ployploid, germ cell, zygote, triploid, tetraploid
Eukaryote	eukaryota, eukaryotic organism, amoeba, paramecium, yeast, euglena, dinoflagella
Fungi	fungi, mushroom, heterotroph, mold, sac fungi, eomycota, microsporidia
Genetics	DNA, hereditary material, genetic, chromosome, duplication, gene
Gene	gene, genetic information, recessive gene, genetic makeup, cistron, factor
Inheritance	incomplete dominance, polygenic inheritance, inherit, inherited, inheritance
Mutation	mutation, genetic mutation, chromosomal mutation, deletion, inversion
Genetic Processes	transcription, reverse transcription, translation, reverse translation, copy
Parts of a Chromosome	centromere, chromatid, short arm, long arm, p arm, q arm
Parts of Dna	adenine, cytosine, thymine, guanine, amino acid, nucleotide, phosphate group
Parts of Rna	uracil, nucleotide, guanine, adenine, cytosine, nucleobases, nitrogenous bases
Genetic Relations	ancestor, generation, inheritance, heredity, diversity, offspring, ancestor
Genetic Property	heterozygous, homozygous, dominant, recessive, genotype, phenotype, autosomal
Monera	monera, microbe, moneran, prokaryotic cell, prokaryotic organism, prokaryote
Archaea	archaea, euryachaeota, crenarchaeota, lokiarchaeota, acidilobus, pyrodictiaceae,
Bacteria	bacteria, eubacteria, E. coli, Escherichia coli, nitrogen-fixing bacteria, anaer
Bacteria Part	capsule, endospore, pili, flagella, nucleoid, cytoplasm, cell wall, cytoplasmic
Protist	algal colony, Protista, paramecium, protist, algae, volvox
Plant	vegetable, plant, plants, tree, Plantae, seedling, marsh willow herb,
Bryophyte	liverwort, moss, great scented liverword, silvery bryum, riccia fluitans
Seedless Vascular	fern, club moss, club mosses, horesetail, horsetails, psilotum, whisk fern
Gymnosperm	ginkgo, sequoia, thuja, Taxaceae, pine tree, Abies cilicica, Manchurian fir
Angiosperm	sunflower, grass, oak tree, aloe, Melaleuca, cacti, cactus, palm, apple tree
Plant Part	leaf, leaves, fruit, plant tissue, vascular tissue, chlorophyll, seed, root
Other Descriptions for Plants	grassy, leafy, biennial, annual, perennial, shrubby, flowering, deep-rooted
Taxonomy	kingdom, phylum, class, order, family, genus, species, domain, taxonomic group

Organic Processes	function, biological process, process, organic process, biological function
Organism Relationships	mutualism, parasitism, neutralism, commensalism, symbiotic relationship
Physical Activity	aerobic, anaerobic, aerobic activity, anaerobic activity, physical activity
Adaptation	adaptation, adaption, adjustment, alterations, changes, diachronic changes, accl
Behavioral Adaptation	behavior, experience, defense mechanism, behavioral adaptation, adaptation
Structural Adaptation	coloration, camouflage, layer of fat, blubber, mutations, body covering
Consumption	drink, eat, consume, feed, devour, absorbed, ingesting, take in, deplete
Cycles	cycle, water cycle, energy cycle, celestial cycle, rock cycle, nitrogen cycle
Carbon Cycle	carbon dioxide-oxygen cycle, carbon cycle, carbon sequestration, carbon sinks
Life Cycle	life cycle, stage of evolution, biological life cycle
Birth	infancy, origin, birth, born, nascency, nascence, nativity, fertilize, fetal
Words for Offspring	offspring, babies, baby, infants, infant, children, child, spawn, progeny
Growth	growth, regeneration, grow, growing, auxesis, cenogenesis, anthesis
Postnatal Organism Stages	adult, larva, nymph, pupa, young, cocoon, chrysalis, adolescent, youth, bot

Development	metamorphosis, differentiate, develop, development, stage of development
Reproduction	sex, sexual, asexual, reproduce, reproduction, interbreed, produce offspring
Prenatal Organism States	gamete, embryo, fertilized egg, egg, fetus, zygote, blastocyst
Death	collapse, dies, death, dead, decaying, died, expiry, expired, deceased, demise
Parts of Water Cycle	transpiration, precipitation, evaporation, infiltration, runoff, deposition
Evolution	evolve, sexual selection, disruptive selection, divergent evolution
Food Chain	food chain, food web, food pyramid, energy pyramid, food cycle
Parts of the Food Chain	consumer, decomposer, producer, apex predator, prey, autotroph, heterotroph
Type of Consumer	herbivore, omnivore, scavenger, carnivore, meat-eater, primary consumer
Results of Decomposition	compost, compost pile, proteoses, peptones, polypeptides, amino acids
Homeostasis	homeostasis, equilibrium, regulation, dynamic equilibrium
Living and Dying	live, survive, extinction, remains, lived, health, extinct, endangered, dead
Metabolism	metabolism, metabolic function, catabolic, anabolic, glycolysis
Toxins	waste, toxin, poisonous, poison, toxic waste, runoff, contaminant, pesticide
Plant Processes	photosynthesis, geotropism, production of oxygen, germination, pollination
Substances Produced by Plant Processes	hormone, auxin, alkaloids, terpenes, monterpenes, sesquiterpenese, diterpenese
Animal Systems/Processes	lymphatic system, organ system, chemosynthesis, visual system, auditory system
Digestive System	digestive system, digestive
Digestion Actions	chew, digestion, thirsty, digest, churn, absorb, ingestion, swallow, process
Parts of the Digestive System	large intestine, stomach, intestine, esophagus, mouth, small intestine, liver
Digestive Substances	compost, compost pile, proteoses, peptones, polypeptides, amino acids
Respiratory System	respiratory system, respiratory
Respiration Actions	breathe, respiration, exhale, gas exchange, inhale, respires, suspire
Parts of the Respiratory System	lungs, nose, mouth, diaphragm, trachea, bronchi, cilia, bronchial tube
Excretory System	extretory system
Excretory Actions	sweat, perspiration, perspire, excretion, remove, excrete, filter, defecate
Parts of the Excretory System	kidney, renal system, urinary system, ureter, urinary bladder, urethra, lungs
Circulatory System	circulatory system, circulatory, cardiovascular system, cardiovascular
Circulation Actions	heart beat, blood flow, pump blood, circulation, transportation, transport
Parts of the Circulatory System	arteries, blood vessels, heart, vein, pulse, capillaries, valve, liver
Blood	blood, white blood cells, red blood cells, platelets, plasma, erythrocytes, RBC
Immune System	immune system
Parts of the Immune System	immune cell, antibody, macrophage, white blood cell, innate immune system
Endocrine System	endocrine system
Endocrine Actions	secrete enzymes, secretion, hormone production, hormone secretion, stimulate
Parts of Endocrine System	insulin, pituitary gland, hypothalamous, thyroid, pancreas, lymphocyte
Nervous System	nervous system, nervous
Parts of the Nervous System	spinal cord, brain, nerve, neuron, dendrite, sensory neuron, motor neuron
Muscular System	muscular
Muscular System Actions	oxygenation, contract, push, pull, extend, relaxation, contract, relax, loosen
Parts of the Muscular System	muscle tissue, joint, muscle, muscle cell, actin, myosin, skeletal muscle
Integumentary System	integumentary system
Parts of the Integumentary System	skin, skin cell, pore, hair, scales, nails, epidermis, dermis
Skeletal System	skeletal, skeletal system
Parts of the Skeletal System	bone cell, bone, backbone, osteocyte, skull, skeleton, cranium, atlas, mandible
Reproductive System	reproductive system
Parts of the Reproductive System	testes, ovaries, scrotum, fallopian tube, umbilical cord, sperm, egg cell
Senses	sense, smell, touch, taste, hearing
Sensory Terms	smell, flavor, sound, echo, feel, touch, sense, hearing, taste, odor, scent
Sickness	disease, dehydration, infect, pathogen, virus, infected, infection, antigen
Parts of a Virus	protein shell, internal protein, tail sheath, end plate, nucleic acid genome
Types of Illness	athlete's foot, influenza, pneumonia, malaria, flu, communicable disease
Outbreak Classification	outbreak, pandemic, plague, epidemic, common source, continuous source
Properties of Sickness	fatal, contagious, symptoms, noninfectious, pain, asymptomatic, deadly, mild
Illness Prevention/Curing	vaccine, cure, sanitation, quarantine, hand sanitizer, immunity, health habit
Medicine	antibiotics, vitamins, antibody therapy, medicines, medicine, antivirals
Medical Terms	medical procedures, medical, dental hygiene, cavity, diagnosis, prognosis
Injuries	injury, cut, wound, hurt, harm, trauma, fracture, sprain, burn, bump, bruise
Nutrition	food, nutritional content, nutrition, nutrient, diet, nutritional requirement
Health	health, healthy, fertile, fertility, nourished, nurtured, sustained, nutrified
Poor Health	malnourished, injured, weakened, undernourished, starving, underfed, starved
Nutritive Substances	starch, sugar, glucose, glycogen, prebiotic, fat, enzyme, protein, carbohydrate
Meals	lunch, meals, dinner, breakfast, supper, tea

Foods	pizza, pepperoni, cheese, banana, corn, soybeans, wheat, tomatoes, apples
Plant Nutrients	humus, fertilizer, soil, carbon, hydrogen, oxygen, nitrogen, phosphorus
Actions for Nutrition	rehydration, dehydration, storage, overcook, pasteurization, cooking, absorb
Agriculture	crops, agriculture, agricultural, farming, food crops, farm land, livestock
Actions for Agriculture	growing, rotate, farming, harvest, irrigating, fertilization, grazing, raise

Measurements	measure, measured, measurement, measurements, gauge, quantitative comparison
Celestial Measurements	parallax, redshift, absolute magnitude, apparent magnitude, red shift
Geometric Measurements	angle, curvature, circumference, compactness, dimension, position, reach
Measures of Amount of Light	shadow, photoperiod, direct, indirect, darkness, half-light, shade, umbra
Measurements for Heat Change	specific heat, heat capacity, thermal capacity, specific heat capacity
Measuring Speed	slow, rate, speed, speed of light, constant, changing, fast, steady, increasing
Unit	unit of measurement, unit, SI unit, International System unit, metric system
Distance Unit	Astronomical Units, light year, A.U., AU, ly, Parsec, pc, light second
Acidity Unit	pH
Area Unit	hectare, square meters, m^2, square inches, in^2, square kilometers
Mass Unit	amu, atomic mass unit, gram, g, kg, cg, lb, ton, pounds, kilogram, tonne, t
Density Unit	g/mL, gram per milliliter, kilogram per cubic meter, kilogram per liter, kg/L
Pressure Unit	atmosphere, psi, pascal, Pa, newton per square meter, pounds per square inch
Temperature Unit	Â°C, Â°F, degrees Celsius, Â° Celsius, degree, K, Kelvin, Fahrenheit, Rankine
Time Unit	day, hour, season, year, period of daylight, month, week, century, minute
Volume Unit	mL, milliliters, milliliter, L, dL, deciliter, gallons, liter, fluid ounces
Geometric Unit	Â°, degree, degree of arc, arc degree, arcdegree, turns, radians, gradians
Speed Unit	meters per second, kilometer per second, speed of sound, m/s, km/h, mph
Electrical Unit	electromagnetic unit, A, ohm, volt, voltage, V
Force Unit	N, newton, dyne, dyn, kiogram-force, kilopond, kp, pound-force, lbf, poundal
Power Unit	W, kilowatts, kW, horsepower, watt, joule per second, ergs per second, erg/s
Energy Unit	J, joules, calorie, kilowatt-hour, foot-pound force, British thermal unit
Frequency Unit	Hz, megahertz, gigahertz, microhertz, terahertz, hertz, mHz, kHz, MHz, GHz
Percent Unit	percentage, percent
Hardness Unit	Mohs hardness, Vickers hardness number, Rockwell hardness, Shore hardnessl

Manmade Objects	golf ball, hammer, boots, solid, space suit, power lines, plate, balloon, box
Appliance	lawn mower, household appliance, solar panel, hand dryer, fan, drill
Heating Appliance	stove, Bunsen burner, heat source, open flame, candle, match, charcoal grill
Cooking Tools (Food)	gas grill, electric fry pan, microwave oven, solar cooker, electric stove
Cooling Appliance	freezer, refrigerator, cold pack, air conditioner, fan, ice box, air cooling
Cooling Tools (Food)	freezer, refrigerator, ice box, cooler
Electric Appliance	electric toothbrush, plug, sewing machine, telephone, electric stove
Liquid-holding Containers	pot, pan, graduated cylinder, jar, glass, container, reservoir, bucket
Circuits	electrical circuit, circuit, parallel circuit, electric circuit, series circuit
Device	cutting tool, heat engine, machine, device, radar, sonar, engine, outlet
Construction Tools	chisel, pliers, sander, saw, bandsaw, drill, sandpaper, needlenose pliers, axes
Magnetic Device	magnet, magnets, electromagnet, strong magnet, magnetic audiotape
Electricity and Circuits	battery, batteries, wire, wires, wiring, electrical conductor, conductor
Electricity Generation	photovoltaic cells, power generators; solar panel; solar-collection panels
Electrical Energy Source	battery, batteries, photovoltaic cells, power generators, solar panel
Scientific Tools	tool, piece of lab equipment, scientific equipment, instrument
Distance-measuring Tools	meter stick, ruler, compass, metric ruler, tape measure, yardstick, measure
Sound-measuring Tools	decibel meter, sound level meter, noise dosemeter
Angle-measuring Tools	protractor, kamal, astrolabe, octant
Time-measuring Tools	stopwatch, watch, sundial, clock, atomic clock
Temperature-measuring Tools	thermometer, thermostat, gas thermometer, glass thermometer, thermocouple
Viewing Tools	hand lens, microscope, binoculars, magnifying lens, optical tools, telescope
Mass-measuring Tool	balance, pan balance, triple beam balance
Volume-measuring Tool	measuring cup, beaker, eye dropper, graduated cylinder, measuring spoon, pipet
Weight-measuring Tool	scale, weighing scale, weight scale, weight balance, spring scale
Electricity-measuring Tool	voltmeter, ammeter, capacitance meter, curve tracer, cos phi meter
Magnetic Direction-measuring Tool	compass, magnetic compass, gyrocompass
Pressure-measuring Tool	barometer, pressure gauge, vacuum gauge, manometer, hydrostatic gauge, piston
Safety Equipment	safety goggles, goggles, nose plugs, gloves, breathing mask, rubber gloves
Light-examining Tool	photocell, prism, Triangular prism, Abbe prism, Pellin-Broca prism
Filtration Tool	filter, paper filter, coffee filter, sifter, surface filter, sieve

Computing Device	calculator, computer, laptop, personal computer, driver
Light-producing Object	light bulb, flashlight, incandescent light bulb, laser, penlight, lamp
Sound-producing Object	tuba, bassoon, viola, violin, guitar, drum, piano, flute, harp, recorder
Simple Machines	simple machine, wheel and axle, lever, inclined plane, screw, pulley, wedge
System of Communication	newspaper, Internet, telephone, radio, television, TV, walkie talkie
Technological Instrument	calculator, computer, tripod, test tube, camera, recorder, radio, robot
Technological Component	wire, power lines, attachment, filament, button, encoder, decoder, receiver
Chemical Product	cleaners, laundry detergent, dish soap, adhesives, sealants, polymers
Vehicle	mechanical system, vehicle, craft
Air Vehicle	jet plane, plane, helicopter, airplane, glider, airship, blimp, hot air balloon
Land Vehicle	car, automobile, bumper car, bus, bicycle, train, skateboard, motorcycle
Snow Vehicle	snowmobile, motor sled, motor sledge, skimobile, snow scooter, snowmachine
Space Vehicle	rocket, capsule, lunar lander, space shuttle, shuttle, spacecraft
Water Vehicle	boat, submarines, ocean liners, canoe, cable ferry, coble, cog, cutter, dugout
Water Vehicle Part	sails, propellers, bow, stern, port, starboard, gunwale, hull, propeller, mast
Vehicular Systems/Parts	guidance, propulsion, support, suspension, subsystem, gear, engine, speedometer
Traffic	traffic, congestion, air traffic, pedestrian traffic, foot traffic
Clothes/Textiles	biodegradable carpeting, clothes, shirt, skirt, pants, shorts, shoes, sock
Man-made Geographic Formations	oil wells, wells, dams, aeration pond, canal, port, harbor, wharf
Property	property, properties, characteristic, characteristics, nuclear property, trait
Age	old, young, new, ancient, mature, prehistoric, maturity, old-growth, aged
Chemical Property	chemical property, salinity, corrosive, nitrate levels, concentration
Ph (Acidity)	ph, acid, base, acidic, basic
Flammability	flammability, flammable, inflammable, conbust, combusts, combustible
Language	Latin, English, Spanish, Greek, Hawaiian, Italian, Chinese, Mandarin, Japanese
Nationality/Origin	American, North American, Hawaiian, foreign, Scottish, Chinese, European
Ability	ability, skill, aptitude, capability, capableness, potentiality
Other Organism Properties	alive, multicellular, DNA, unicellular, autotrophic, dormant, fossilized
Behaviors	behavior, conscious behavior, environmental behavior, conduct, comportment
Inherited Behavior	instinct, inherited behavior, heredity, inherit, inherited
Learned Behavior	routine, habit, learned behavior, acquired, modus operandi, habitual method
Other Animal Properties	fertile, adaptable, endothermic, ectothermic, hairy, slimy, warm-blooded
Gender	female, male, maleness, masculinity, androgyny, hermaphroditism, femaleness
Other Human Properties	blood type, humor, honesty, leadership, handedness, kindness, wisdom, duty
Physical Property	dense, density, height, surface area, weight, physical property, conductivity
Conductivity	conductivity; conducts heat, conducts electricity, conducts sound
Temperature	temperature, cool, hot, warm, cold, room temperature, unevenly heated
Composition	composition, chemical composition, metallic, rocky, icy, porous, concentration
Mass	mass, heavy, light, biomass, lightweight, hefty, massive, ponderous, weighty
Distance	distance, 100-meter
Shape	shape, long, elliptical, spiral, irregular, oval, circular, convex, concave
Size	size, big, small, large, size, diameter, radius, thin, thick, volume
Height	low, tall, short, high, elevation, altitude, high-altitude, highest, height
Depth	deep, shallow, deepest, depth, deepness, profundity, profoundness, shallowness
Width	wide, narrow, thin, thick, thickness, width, breadth, wideness, broadness
Length	long, short, length, longness, shortness, longer, shorter, longest
Wetness	wet, dry, damp, driest, wetter, moist, bedewed, dewy, besprent, boggy, marshy
Texture	texture, smooth, rough, waxy, rocky, slippery, porous, coarse, grainy, gritty
Material	material
Synthetic Material	plastic, glass, rubber, fiberglass, foam, Styrofoam, rayon, polyester, kevlar
Natural Material	clay, soil, wood, paper, natural material, cardboard, ceramic, cotton, wool
Rigidity	rigid, flexible, loose, brittle, rigidity, rigidness, inflexible, flexibility
Resistance/Strength	water-resistant, resistant, heat-resistant, insulator, strong, weak, insulated
Hardness	soft, brittle, hard, hardness, firmness, incompressibility, compressible
Permeability	permeable, impermeable, semi-permeable, porous, pervious, impervious, leaky
Magnetic	magnetic, nonmagnetic, ferromagnetic, magnetic field, magnetic flux, magnetize
Electrical Property	electrical property, charge, electrical conductivity, electrical resistivity
Properties of Food	fresh, shelf life, spoiled, rot, rotten, gone bad, unfermented, soured
Mineral Properties	cleavage, fracture, hardness, luster, streak, structure, composition, color
Quality	good, bad, useful, great, catastrophic, profound, adequate, best, crucial
Rarity	typical, rare, common, commonly, abnormal, unusual, conventional, common enough
Speed	fast, slow, quick, slowly, rapidly, rapid, immediate, gradual, faster, slower
Complexity	simple, complex, directly, raw , complicated, composite, decomposable

Visual Property	reflective, shiny, appearance, dull, opaque, polished, symmetrical, milky
Color	orange, color, red, blue, white, yellow, grey, green, violet, black, sepia
Brightness	brightness, luminosity, bright, dark, glowing, lighted, sunny, dimmest
Temporal Property	long, short, length, variance, spontaneous, rapid, relativly short, long-term
Property of Motion	speed, momentum, acceleration, velocity, rate, fast-flowing, movement, abrupt
Stability	fixed, moveable, constant, stable, stability, steady, static, unchanging
Position	position, horizontal, parallel, perpendicular, sitting, standing, lying down
Properties of Waves	wavelength, frequency, speed, amplitude
Safety	safe, safer, safest, harmful, dangerous, reliable, danger, vulnerable
Cost	expensive, inexpensively, affordable, efficiently, energy-saving
Property of Production	conventionally produced, organically produced, organic, coal-fired, manmade
Difficulty	easily, easy, difficult, average, normal, hard, simple, trivial, arduous
Other Properties	layered, covered, distinctive, diversity, amniotic, crowded, divergent
Numbers	number, amount, quantity, quantification, numerical, counting
Cardinal Number	one, two, three, four, 1, 12, 28, 7, 13, 130000, 2400, fifteen thousand
Arithmetic Measure	seven times, once, twice, 24 times, 365 times, ten times, millions, hundreds
Relative Number	several, abundance, fewer, lots, many, tankful, relative, too much, some, a few
Calculations	x, times, divide, average, multiply, add, subtract, $*$, $/$, $+$, $-$
Geography	geographical, geography, human geography, physical geography, spatial analysis
Earth Parts (Gross)	atmosphere, horizon, Northern Hemisphere, southern hemisphere, ocean, air
Layers of the Earth	crust, mantle, core, outer core, inner core, lithosphere, atmosphere
Parts of Earth Layers	tectonic plate, divergent boundries, convergent boundries, continental shelves
Tectonic Plates	oceanic, continental, crustal, Pacific Plate, North American Plate
Atmospheric Layers	stratosphere, exosphere, thermosphere, mesosphere, troposphere, ozone layer
Fossils	fossil, fossils, remains
Archeological Process/Technique	dated, technique, radioactive dating, road cut, Law of Superposition
Fossil Forming	fossil-forming conditions, permineralization, authigenic mineralization
Fossil Types	index fossils, marine fossils, transitional fossils, microfossils, resin, amber
Cast Fossil/mold Fossil	coral fossil, coral fossils, endocast, concretions, mold fossil, cast fossil
Trace Fossil	print, trace fossil, footprints, domichnia, fodinichnia, pascichnia
True Form Fossil	bone, bones, shell, shells, tooth, teeth, seashell, petrified wood, trilobite
Fossil Record/Timeline	fossil record, geologic history, timeline
Fossil Location	Appalachian Mountains, Grand Canyon, Ohio, wooded area, desert, mountains
Speciation	speciation
Extinction	extinct, mass extinction, mass extinctions
Geological Eons, Eras, Periods, Epochs	Mesozoic era, Cretaceous period, Precambrian, Paleozoic, Cenozoic, ice age
Natural Resources	resource, supply, natural resource, natural resources, biotic resource
Fossil Fuel	fossil fuel, oil, coal, petroleum, fuel, gas, natural gas, gasoline, crude oil
Other Energy Resources	solar, wind, water, solar energy, flowing water, sunlight, wind power
Changes to Resources	restriction, conservation, loss, preservation, depletion, overconsumption
Geographic Formations	valley, mountain, volcano, highland, crater, sea, glacier, cliff, lake, fault
Geographic Formation Parts	peaks, slope, foot, caldera, crater, sill, conduit, cone, vent, ledge, hump
Bodies of Water	pond, lake, puddle, ocean, spring, springs, groundwater, river, tributary
Specific Named Bodies of Water	Pacific Ocean, Atlantic Ocean, Mississippi River, Arctic ocean
Types of Water in Bodies of Water	freshwater, saltwater, groundwater, brackish
Parts of Bodies of Water	riverbeds, basin, mouth, floor, wave, waves, delta, deltas, shoreline
Currents	current, ocean current, wind current, wind currents, Great Ocean Conveyor
Tides	high tide, low tide, tides, tidal, intertidal, highest astronomical tide
Actions for Tides	rise, fall, tidal action, come in, go out
Geographic Formation Process	geologic process, geomorphology, petrifaction, petrification, permineralization
Change in Location	collide, collision, distance, distancing, impact, shift, shifting, strike
Change in Composition	chemical reactions, chemical reaction, burn, erupt, eruption, explode
Constructive/Destructive Forces	deposite, deposition, erode, erosion, weather, weathering, compress
Minerals	gold, silver, mineral, crystals, copper, phosphorus, abelsonite, abernathyite
Mineral Formations	vein deposite, vein deposits, mineral deposite, mineral deposits, stalactite
Rock	rock, pebbles, gravel, lava, boulder, boulders, slab, gravel deposite
Igneous	igneous, granite, igneous intrusion, basalt, volcanic, intrusive igneous
Metamorphic	marble, foliated, metamorphic, gneiss, anthracite, granulite, greenschist
Sedimentary	sedimentary, sediment, limestone, sandstone, shale, marine sediments
Soil	soil, sand, topsoil, mud, clay, ground, soil covering, earth, dirt
Properties of Soil	porous, fertility, nutrients, texture, structure, porosity, chemical makeup

Natural Phenomena	erode, flood, erupt, weathering, natural event, earthquake, glacial activity
Weather Phenomena	storm, wind, high tide, tide, trade winds, cloud, greenhouse effect, weather
Weather Descriptions	clear, cloudy, humid, stormy, sunny, snowy, windy, rainy, freezing, balmy, nice
Precipitation	snow, rain, precipitation, rainfall, snowfall, acid rain, sleet, fog, hail
Seasons	season, winter, summer, fall, spring
Environmental Phenomena	environmental pressure, environmental changes, habitat change
Ecosystems/Environment	ecosystem, environment, climate, world, biosphere, biome, environmental
Nonliving Parts of the Environment	abiotic element, abiotic factor, nonliving thing, inanimate objects
Habitat	habitat, shelter, territory, surroundings, landscape, home ground, habitation
Examples of Habitats	hive, hollow tree, dam, stream, nest, burrow, river bottom, forest floor, soil
Types of Terrestrial Ecosystems	desert, temperate, tropical, savanna, arctic, plain, tundra, grassland, prairie
Forests	rainforest, coniferous forest, deciduous forest, Alpine forest, wooded area
Sky	sky, night sky, ozone layer, greenhouse gas, air mass, blue sky, aerospace
Environmental Damage/Destruction	pollution, air pollution, chemical spills, logging, deforestation
Underwater Ecosystem	whale fall, black smoker, estuary, intertidal, reef, marine ecosystems
Other Geographic Words	volcanic, global, glacial, geological, oceanic, geologically, layers, buildup
Matter	matter, nonliving matter, agent, material, dark matter, antimatter, ylem, thing
Compound	carbon dioxide, chemical composition, ammonia, methane, greenhouse gas
Organic Compounds	organic, organic compound, hexane, ozone, formaldehyde, acetic acid, alcohol
Elemental Components	atom, molecules, polar molecule, ion, formula unit, biomolecules
Atom Components	proton, electron, nucleus, neutron, subatomic particles, particles
Atomic Properties	atomic mass, atomic radius, electrical charge, electric potential
Molecular Properties	covalent bond, cohesion, net charge, chemical bond, molecular speed, polarity
Chemical Processes	nitrification, denitrification, saturation, fixation, hydration, dehydration
Element	element, radioactive isotope, isotope, fluoride, ammonium, hydrogen, helium
Classes of Elements	alkali metal, nonmetal, metalloid, noble gas, halogen, alkaline earth metals
Mixtures	solution, mixture, suspension, colloid, alloy, blend, mix, azeotrope, air
Parts of a Solution	solute
Separating Mixtures	chromatography, distillation, evaporation
Phases of Water	water, frost, ice, steam, vapor, liquid water, ice crystals
State of Matter	solid, gas, liquid, plasma, state of matter, physical state
Solid Matter	ice, sulfur, flower, cloth, glass, wood paper, peanuts, match, top
Granular Solids	sugar, sand, table salt, salt, pepper, baking soda, powder, dust, pepper
Metal Solids	metal, nail, hammer, gold bar, magnesium, copper, car fender, wire, gold, iron
Liquid Matter	water, acid, carbonated water, milk, oil, vinegar, lemon juice
Capillary Action	capillary action, capillarity, capillary motion, caipllary effect
Gaseous Matter	oxygen, air, nonreactive gas, gases, bubble, vapor, greenhouse gas emissions
Phase Transition Point	boiling point, freezing point, transition point, evaporation point
Substances	substance, silver, magnesium, sulfur, aluminum, compounds, pure substance
Changes	electrical, thermal, change, conversion, transform, chemical reaction
Chemical Change	new/different substance be formed, chemical change, rust, light a candle, burn
Physical Change	physical change, change volume, change the shape, temperature change, diffusion
Phase Changes	phase change, change the state of matter, change to, change in the state of
Phase-changing Actions	melt, freeze, boil, evaporate, become steam, vaporize, condense, sublimate
Reactions	chemical reaction, nuclear reaction, thermonuclear reaction
Parts of Chemical Reactions	reactant, product, catalyst, inhibitor, positive feedback, negative feedback
Types of Chemical Reactions	endothermic, exothermic, combination, decomposition, single displacement
Actions	act on, apply, apply to, interact, interaction, transfer, operate, attract
Act Upon Something	act on, apply, apply to, interact, interaction, transfer, operate, attract
Alter	fix, affect, adapt, impact, shape, alter, modify, modified, regulate, recycle
Form-changing Actions	tie, cut, crush, break, shred, dissolve, saw, filter, mix, slice, spread, roll
Color-changing Actions	color, paint, polish, change color, stained, dyed, tinge, discoloring, colorize
Location-changing Actions	drop, blow, spin, float, sink, bury, burying, dump, dumping, pump, pumped
Amount-changing Actions	increase, decrease, reduce, add, take, put, lloss, extend, release, lost
Avoid/Reject	avoided, avoid, disregard, unattended, prevent, ignore, ignoring, evade, evaded
Believe	thought, believe, believed, conceived of, suspect, suspects, consider, hold
Buy	buy, purchase, buy back, bought back, buys up, repurchase, repurchases, owns
Change Into	change, converted, convert, become, replace, replacing, self-assemble, into
Classify	classify, label, call, called, categorize, classification, reclassify, identify

Choose	decide, decision, opt, option, choose, choice, prefer, vote, determine
Clean Up	clean, wipe up, cleaning, washing, wash, flush, wipe, dispose of, throw away
Collect	gather, gathering, congregate, collect, accumulate, amass, amassed, compile
Combine/Add	stir, stir into, mix, place in, shake, add, cover with, pour into, assemble
Communicate	communicate, imitate, mimic, mimicry, signal, discuss, discussing, message
Compete	compete, competition, vie, content, try for, race, rival, go for, challenge
Contain/Be Composed of	contain, compose, composed, together, consist, make up, accumulate, cover
Create	create, form, generate, produce, emit, replicate, formation, cause, make, grow
Differentiate	distinguish, specialize, differentiate, differ, differed, differentiation
Examine	compare, comparing, monitor, track, tracking, analyze, analyzing, study
Harm	destroy, damage, deplete, depletion, malfunction, contaminate, collapse, harm
Help	help, contribute, support, defend, benefit, helped, aid, beneficial, heal
Identify	detect, find, notice, found, discover, discovered, identify, identification
Increase/Decrease	decrease, increase, contract, expand, inflate, decline, accelerate, lower, thin
Indicate	mark, marked, indicate, indicates, list, listed, designate, show, give evidence
Move	pass through, carry through, deposit, travel, redistribute, move, migrate
Gaseous Movement	swirl, swirling, blowing, blow, rise, rose, airflow, sink, sinks, flight, float
Liquid Movement	flow, flows, flowing, drain, drained, flood, flooding, overflow, seep, seeps
Mechanical Movement	pull, push, pedal, roll, drop, locomotion, drive, drag, shove, cycle, cycling
Particle Movement	rise, fall, condense, expand, move faster, move slower, move upward, collide
Transportation	transport, deliver, ship, delivered, transporting, drive, driving, glide
Celestial Movement	revolve, rotate, orbit, tilt, move, turn, revolution, rotation, movement, spin
Apparent Celestial Movement	rise, set, apparent motion, disappear, become, appear, ascend, ascention
Light Movement	shine, refract, reflect, travel, block, transmit, strike, glow, produce, emit
Observe	appear, watch, observe, observation, seem, be seen, monitor, monitoring, view
Occur	happen, occur, experience, coincide, exist, present, undergo, take place
Permit	allow, letting, permit, accept, accepts, consent, consented, give permission
Perform an Activity	operate, dissect, express, expresses, repeat, coordinate, irradiate, perform
Preserve	sustain, storage, store, protect, recycle, preserve, continue, keep, conserve
Represent	represent, describe, represented, stand for, correspond, typify, symbolize
Require	require, requires, required, need, needs, needed, needing, rely on, depend upon
Separate	separate, break down, decompose, settle, sort, release, separation, escape
Release	discharge, discharging, release, emit, re-emit, spill, loosen, free, expel
Break	break, shatter, broken, crack, crumble, fracture, fall apart, come apart, burst
Divide	divide, differentiate, lose, loss, divide into, disperse, dissolve, split
Start	originate, begin, start, set out, commence, commenced, lead off, led off
Stop/Remove	block, prevent, eliminate, withstand, kill, stop, extinguish, dispose
Succeed	achieve, accomplish, flourish, complete, finish, succeed, succeeded, win, won
Surpass	outstrip, surpass, pass by, bypass, outmaneuver, overrule, exceed, outmatch
Touch	make contact with, connect, rub, tap, touch, stick together, reach, reached
Uptake	trap, take up, hold, pick up, obtain, colonization, process, capture, take
Use	use, deplete, using, burn, consume, consumption, used, utilized, overuse
Associate	associate, associated, match, link, linked, relate, related, lead to
Verify	make sure, ensure, verify, verified, verifying, validate, check, checking
Wait/Stay	wait, remain, stay, hold off, attend, continue, continued, expect, expecting

Scientific Method	scientific method, experimental method, methodology, method
Hypothesizing	hypothesize, predict, thought, estimate, suggested, topic , question, expected
Performing Research	observe, conduct an investigation, conduct an experiment, compare, study
Analyzing Research	inferring, classifying, generalizing, determine, calculate, analyze, discover
Concluding Research	conclusion, report, presentation, evidence, support, finding, share, shared
Replicating Research	reproduce, repeat, redo, replicate, duplicate, reproducible, reduplicate, copy
Question/Activity Type	question, activity, mission, report, research, work, fieldwork, project
Response Type	statement, explanation, fact, suggestion, term, theory, law, sentence
Experimentation	experimentation, experimental design, experiment, trials
Groups	control group
Variables and Controls	variable, independent variable, dependent variable, factor
Validity	valid, reliable, authoritative, validity, relevant, logical, legitimate
Performing Experiments Well	critically, critical, skeptical, cautiously, precaution, appraising, evaluative
Words for Data	data, information, metadata, raw data, data set, evidence, input, datum
Scientific Meetings	symposium, meeting, science fair, conventions, conference, seminar, colloquium
Audiences	audience, spectators, gallery, grandstand, house, gathering, assemblage
Guidelines and Rules	rule, laws, regulation, conventions, requirement, prescriptions, principle

Markers of Time	period, time zone, time, timing, era, epoch, biological time, cosmic time
Times of Day (Day/Night)	night, day, evening, nighttime, daytime, sunrise, noon, sunset, mid-afternoon
Relative Time	first, beginning, middle, end, never, during, throughout, between, past, span
Months	January, February, March, April, May, June, July, August, September, October
Day	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday
Year	year
Year Numerals	1971, 1953, 1990, 2020, 0, 45, 1266, 1496, 1692, 1777, 1787, 999, 1900, 1900s
Frequency	daily, constantly, monthly, yearly, times, every night, perpetual, continuously
Locations	location, land area, spot, place, region, position, setting, zone, point, site
Manmade Locations	house, street, garden, building, town, factory, airport, radio station tower
Parts of a Building	foundation, roof, floor, frame, walls, windows, window panes, beams, boards
Terrestrial Locations	beach, Equator, shoreline, field, underground, sea-floor, polar snowcaps
Northern Hemisphere Locations	Northern Hemisphere, Alaska, North Pole, New York State, Baltimore, Florida
Southern Hemisphere Locations	Southern Hemisphere, Australia, South Pole, South America, Chile, South Africa
Relative Locations	bottom, top, middle, between, surroundings, under, nearby, submerged, exposed
Directions	direction, path, route, trail, itinerary, way, via, course, trackway
Cardinal Directions	west, east, south
Relative Direction	upward, downhill, right, left, direct, clockwise, counterclockwise, western
Prepositional Directions	across, toward, around, through, away from, up, down, across from, along, among
Geopolitical Locations	county, Yellowstone National Park, Mojave Desert, Chesapeake Bay, Knight Island
Continents	Antarctica, North America, South America, Africa, Asia, Australia, Europe
Countries	nations, industrialized nations, country, Afghanistan, Albania, Algeria
Cities	Baltimore, Port Orange, city, Tucson, Yuma, Flagstaff, Winslow, Boston
States	Alabama, Alaska, Arizona, Arkansas, California, Colorado, Connecticut, Delaware
Verbs for Locate	located, placed, extend, transport, locate, navigate, circumnavigate, find
Comparisons	difference, in common, comparison, distinct, different, identical, similar
Visual Comparison	look like, resemble, looking similar, bear resemblance to, take after
Quality Comparison	better, best, good, poor, advantage, negative, benefit, improvements
Amount Comparison	fewer, less, more, quantity, a small amount, ratio, most, level, all, maximum
Importance Comparison	primary, primarily, main, dominant, of importance, of import, crucially
Distance Comparison	further, closest, closer, close, equal distances, nearer, farther
Scientific Theory, Experimentation, and History	science, scientific, scientific theories, scientific terms, topic area, history
Theory of Matter	law of conservation of mass, law of conservation of energy
Representing Elements and Molecules	orbitals, models, chemical formula, chemical equation
Astronomy/Aeronautics	astronomy, astronomical theory, aeornautics, Milankovitch cycles, Tusi couple
Space Agencies	NASA, National Aeronautics and Space Administration, Air Force Space Command
Space Missions	Kepler Mission, Apollo 14, manned space exploration, mission
Observation Places	Maryland Space Grant Observatory, observatory, Royal Observatory
Observation Instruments	Morris W. Offit telescope, telescope, Hubble space telescope
Parts of Observation Instruments	light filter, chronograph, electric drive, mirrors, lens, scope, eyepiece
Astronomical Distance Units	Astronomical Units, light year, A.U., AU, ly, Parsec, pc, light second
Cosmological Theories	Big Bang Theory, theory, Heliocentric Theory, Earth-centered universe theory
Cosmological Theory Thematic Words	contract, contracting, contracts. form, expand, expanding, expands, change
Theory of Physics	first law of motion, second law of motion, third law of motion, physics
Occupation	Professor, police, firefighter, teacher, doctor, nurse, baker, lumberjack
Scientists	Thomas Edison, Galileo, observer, student, Darwin, geologist, Jonas Salk
Groups of Scientists	students, scientists, observers, NASA, paleontologists, surveyors, researchers
Biology	selective breeding, cell theory, endosymbiotic theory, molecular biology
Natural Selection	natural selection, survival of the fittest, Darwin's Theory of evolution
Observation Techniques	color staining
Meteorology	weather forecasts, air-quality control, Saffir-Simpson scale, Coriolis effect
Meteorological Models	station model, atmospheric model, Mesoscale Model, NAM, Global Forecast System
Geologic Theories	Law of Superposition, law of crosscutting relationships, continental drift
Conservation Laws	The Water Quality Act of 1987, Clean Air Act, Clean Water Act
Discovery	discovery, invention, scientific advancement, advances, scientific discovery
Undiscovered	undiscovered, unknown, unidentified, undetected, unexplored, lost, hidden

Generic Terms	terms, terminology, generic, items, words, definitions, language, referents
Ability/Availability	unable, usable, useable, potential, room, able, available, unavailable
Relations	independent, together, homologous, relationship, imbalance, interaction
System and Functions	system, machine, subsystem, activity, function, network, practice, programs
Feedback Mechanism	feedback mechanism, positive feedback, negative feedback, regulatory feedback
System Parts	source, power source, structure, structural, boundary, functional, unit
System/Process Stages	step, sequence, stage, aspects, procedure, phase, degree, level, point
Representation	image, diagram, chart, sign, model, prototype, drawing, list, instructions
Parts of a Representation	x-axis, y-axis, axes, labels, title, bar, line, point, coordinates, key, grid
Belief/Knowledge	dogma, understanding, knowledge, learning, logical, attitude, belief, religion
Classification	classification, taxonomy, categorization, compartmentalization, assortment
Pattern	pattern, sequence, cycling, distribution, arrangement, trend, order, intervals
Gaps and Cracks	cracks, gap, crack, fractured, openings, grooves, pockets, diastema, hiatus
Exemplar	kind, example, type, breed, medium, nature, version, variant, variation
Emergency Services	911, emergency services, police, fire department, EMS
Method	method, way, fashion, strategy, technique, practice, plan, methodology
State of Being	condition, state, scenario, presence, role, lifestyle, format, formats
Event	phenomenon, episode, occurence, exhibit, event, practices, process, phenomena
Types of Event	race, party, test, class, explosion, club meeting, meeting, conference, match
Geometric/Spatial Objects	plane, sphere, incline, object, body, ramp, equilateral triangle
Object Part	end, center, core, surface, edge, rim, corner, middle, top, bottom, outside
Object Quantification	piece, sample, grain, component, whole, sheet, percent, group, chunk, layer
Negations	not, no, non, lacks, cannot, except, neither, nor, lack, never, nobody, none
Result	by-product, buildup, following, effect, outcome, product, impact, reward
Goal	goal, objective, solution, end, finish, destination, aim, target, object
Cause	stimulus, internal stimulus, external stimulus, reason, factor, demand
Source	source, reserve, supply, origin, root, beginning, rootage, head
Response	response, stress, reflex, symptom, reaction, answer, reply, aftereffect
Relevant	appropriate, applicable, germane, pertinent, relevant
Group	group, system, collection, cluster, list, combination, series,nature, council
Groups of Organisms	population, populations, community, residents, colony, the public, society
Parts of a Group	member, individual, leader, teams
Opportunities and Their Extent	opportunities, advancement, limitation, opportunity, limits
Probability and Certainty	approximately, exactly, about, correctly, likely, true, accurate, average
Level of Inclusion	complete, some, few, all, every, each, both, certain, part, partial, incomplete
Problem	flaw, disorder, danger, negative effect, defect, accident, issue, impurtities
Value	value, worth, cost, price, profit, rate, expense, appraisal, assessment, charge
Separation	barrier, separation, wall, membrane, divider, blockade, roadblock, block
Viewpoint	perspective, angle, attitude, mindset, viewpoint, headset, point of view
Business/Industry	supplier, companies, company, businesses, enterprise, movie studio, industry
Business Names	further, closest, closer, close, equal distances, nearer, farther
Scientific Associations/Administrations	American Dental Association, Food and Drug Administration, government agencies
Advertising	advertisement, commercial, advertise, ad, marketing, announcements, broadcast
Parts of a Business	distribution, mass marketing, public relations, research, quality control
Products	merchandise, goods, brands, products, services, commodities, stock, effects
Money Terms	funds, money, credited, funded, financial gain, shopping, lottery, income, fees
Patents	patented
Employment	unemployment, employment, full-time, part-time, temporary, seasonal
Media	mass media, media, medium, communication media, visual media, audio media
Academic Media	encyclopedia, world almanac, science textbooks, scientific journal, book
Popular Media	news report, music, public speaking, CDs, radio, radio show, website, blog
Written Media	wall poster, brochure, article, magazine, book, newspapers, printed media

Table 6: The full list of semantic categories used in the ScienceExamCER common entity recognition corpus, as well as example words for each category.