Penguins Don't Fly:
Reasoning about Generics through Instantiations and Exceptions

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Abstract

Generics express generalizations about the world (e.g., birds can fly) that are not universally true (e.g., newborn birds and penguins cannot fly). Commonsense knowledge bases, used extensively in NLP, encode some generic knowledge but rarely enumerate such exceptions and knowing when a generic statement holds or does not hold true is crucial for developing a comprehensive understanding of generics. We present a novel framework informed by linguistic theory to generate EXEMPLARS—specific cases when a generic holds true or false. We generate ~19k exemplars for ~650 generics and show that our framework outperforms a strong GPT-3 baseline by 12.8 precision points. Our analysis highlights the importance of linguistic theory-based controllability for generating exemplars, the insufficiency of knowledge bases as a source of exemplars, and the challenges exemplars pose for the task of natural language inference.

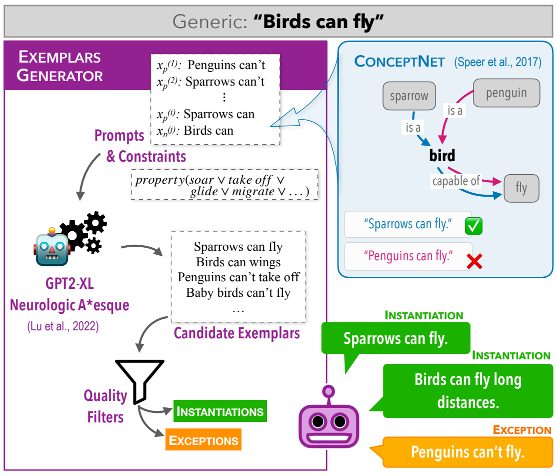


Figure 1: We present **EXEMPLARS generator**: given a generic like "Birds can fly" it generates truthful statements where the generic does (INSTANTIATIONS) and does not (EXCEPTIONS) hold. We extract commonsense knowledge (e.g., from ConceptNet (Speer et al., 2017)) in linguistically-informed prompts and constraints for constrained generation (Lu et al., 2022). We use trained discriminators to filter for quality.

1 Introduction

Generics express generalizations (e.g., birds can fly) that allow humans to reason and act with incomplete world knowledge (Asher and Morreau, 1995). Generics allow us to draw plausible inferences about individuals (e.g., Polly is a bird, so Polly can fly) *even when we know of counterexamples* (e.g., penguins cannot fly). Despite the utility of generalizations, knowledge of counterexamples is necessary for modeling generics and effectively reasoning with them in computational systems.

Recent studies of generics (e.g., Bhagavatula et al., 2022; Bhakthavatsalam et al., 2020) and commonsense KBs (e.g., Speer et al., 2017) provide repositories of generic knowledge. However, these resources rarely mention EXCEPTIONS (i.e., counterexamples) or INSTANTIATIONS (i.e., cases where the generic holds); collectively EXEMPLARS. For systems using these resources as a source of world knowledge, such incomplete information can lead to incorrect deductions (e.g., if Polly is a penguin, which is a bird, then inferring that Polly can fly because birds can fly is false[1]). Therefore, we propose a novel computational framework that operationalizes linguistic theories in order to automatically generate EXEMPLARS.

In our work, we unify two distinct linguistic theories and use linguistic theory-guided decoding to generate EXEMPLARS. Although large-scale neural language models such as GPT-3 (Brown et al., 2020) have been increasingly successful in few-shot text generation tasks, such generation is both expensive and not easily controllable. Therefore, we instead use the constrained generation algorithm Neurologic A*esque (Lu et al., 2022), which can be applied to any auto-regressive language model; we choose to use GPT-2 (Radford et al., 2019).

[1]penguin is a bird $\wedge$ birds can fly $\implies$ penguins can fly

In this manner, we generate 12562 INSTANTIATIONS and 6297 EXCEPTIONS for ∼650 generic statements from Bhagavatula et al. (2022). We conduct human evaluation of the generations and show that our system outperforms few-shot generation by GPT-3 by 12.8 precision points. Our analyses demonstrate not only the importance of linguistic modeling for generating EXEMPLARS and the insufficiency of KBs as a source of EXEMPLARS, but also the challenges EXEMPLARS pose for natural language reasoning.

Our contributions are as follows: **(1)** we present a novel framework grounded in linguistic theory for representing generics and their EXEMPLARS, **(2)** we present the first method to automatically generate generic EXEMPLARS and show it outperforms a competitive baseline based on GPT-3 and **(3)** we present analysis showing the importance of explicit linguistic modeling for this task and the insufficiency of current NLI methods for generics. Our system and data are publicly available[2].

2 Related Work

Theory Generics have been studied extensively in semantics, philosophy, and psychology to develop a single logical form for all generics (Lewis and Keenan, 1975; Carlson, 1977, 1989; Krifka, 1987) or a probabilistic definition (Cohen, 1996, 1999, 2004; Kochari et al., 2020), categorize generics (Leslie, 2007, 2008; Khemlani et al., 2009), and analyze specific types (Prasada and Dillingham, 2006, 2009; Haward et al., 2018; Mari et al., 2012; Krifka et al., 2012). Mechanisms to tolerate EXCEPTIONS have also been proposed (Kadmon and Landman, 1993; Greenberg, 2007; Lazaridou-Chatzigoga and Stockall, 2013) but these are primarily theoretical and use carefully chosen examples. In contrast, our work combines these EXCEPTION tolerance mechanisms with generic categorization and proposes a novel, large-scale, computational framework for EXEMPLARS.

Commonsense Knowledge While large-scale CKBs capture a range of commonsense knowledge (Speer et al., 2017; Sap et al., 2019; Forbes et al., 2020; Hwang et al., 2021), they contain necessarily incomplete (i.e., the open-world assumption (Reiter, 1978b)) *general* knowledge. Furthermore, although recent works have created KBs specifically of generics (Bhakthavatsalam et al., 2020; Bhagavatula et al., 2022) and proposed methods to identify generics in text (Friedrich et al., 2015, 2016), they do not identify or model EXEMPLARS. In our work, we focus directly on automatically generating EXEMPLARS, providing richer commonsense knowledge.

The application of generics to specific individuals is influenced by prototypicality (Rips, 1975; Osherson et al., 1990), with small sets of prototypical norms collected in cognitive science for a range of kinds (Devereux et al., 2014; McRae et al., 2005; Overschelde et al., 2004). However, recent work has shown that neural models have only moderate success at mimicking human prototypicality (Misra et al., 2021; Boratko et al., 2020) or producing commonsense facts without guidance (Petroni et al., 2019). Hence, we combine neural models with a KB of concepts, using linguistic-theory-guided decoding, to generate generics EXEMPLARS.

Reasoning Reasoning with generics is closely related to non-monotonic reasoning (Ginsberg, 1987b,a); specifically default inheritance reasoning (Brewka, 1987; Hanks and McDermott, 1986; Horty and Thomason, 1988; Imielinski, 1985; Poole, 1988; Reiter, 1978a, 1980). Contrary to the proposed solutions for linguistic tests on default inheritance reasoning (Lifschitz, 1989, e.g.,can a conclusion about inheritance be inferred based on provided evidence?), later works showed that the presence of generics EXEMPLARS in the evidence impacts what humans perceive as the correct answer (Elio and Pelletier, 1996; Pelletier and Elio, 2005; Pelletier, 2009). These results highlight the importance of identifying generics and accurately modeling their relationships in machine reasoning.

While natural language inference (NLI), a form of deductive reasoning well-studied in NLP (i.a., Dagan et al. (2013); Bowman et al. (2015)), captures notions of inference, studies on non-monotonic reasoning and NLI are limited (Wang et al., 2019; Cooper et al., 1994; Yanaka et al., 2019b,a; Rudinger et al., 2020) and do not include default inheritance reasoning. Therefore, in this work we analyze the interactions between generics EXEMPLARS and NLI and highlight the importance of modeling this relationship in machine reasoning.

3 Framework for EXEMPLARS

A generic statement describes a *relation* between a *concept* and a *property*. Usually, a **concept** $\boldsymbol{K}$ is a type or kind (e.g., bird) while a **property** $\boldsymbol{P}$

[2]https://github.com/emilyallaway/generics-exemplars

Category	Generic (G)	INSTANTIATION	EXCEPTION
(a) quasi-def	"Stars produce radiation"	"The sun produces radiation"	"Stars produce light"
	$K(x) \wedge r(x,y) \implies P(y)$	$K(x) \wedge r(x,y) \wedge P(y)$	$K(x) \wedge r(x,y) \wedge \nsim P(y)$
(b) principled	"Birds can fly"	"Owls can fly"	"Penguins can't fly"
	"Sharks attack swimmers"	"Threatened sharks attack swimmers"	"Sharks don't attack swimmers in the shallows"
	$K(x) \wedge P(y) \implies r(x,y)$	$K(x) \wedge r(x,y) \wedge P(y)$	$K(x) \wedge \neg r(x,y) \wedge P(y)$
(c) characterizing	"Cars have radios"	"2014 Prius model C has a radio "	"Cars have CD Players"
	L_G is ambiguous	$K(x) \wedge r(x,y) \wedge P(y)$	$K(x) \wedge r(x,y) \wedge \nsim P(y)$
			"Newer cars don't have radios"
			$K(x) \wedge \neg r(x,y) \wedge P(y)$

Table 1: We define three categories of generics with their EXEMPLARS. The logical forms for the generic (L_G) and its EXEMPLARS are also below the examples. Using these categories we formulate templates for generating EXEMPLARS (see Table 2). K is the concept (blue), P the property (pink). See §3.3 for exoproperty $\nsim P$.

is an ability (e.g., fly) or quality (e.g., feathered). Note that statements containing explicit quantification (e.g., "*Most* birds can fly") are generally *not* considered generics (Carlson, 1977; Krifka et al., 1995) and are therefore excluded from this study (see §A.1 for further discussion).

In our framework, we first categorize (§3.1) generics and derive their logical forms (§3.2). These logical forms for generics serve as our basis for formulating EXEMPLARS (§3.3) and designing templates suitable for generation (§3.4).

3.1 Generic Category Definitions

We categorize a generic based on the type of property it describes. In particular, by unifying theories from linguistics and philosophy[3], we split generics into three categories (see examples in Table 1). A generic has a particular category if:

(a) **Quasi-definitional**: the property is essential to a concept (Khemlani et al., 2009).

(b) **Principled**: the property has a strong association with the concept. This includes both properties with a principled association to a concept (e.g., flying is viewed as inherent to birds, although it is not essential in reality) (Prasada and Dillingham, 2006, 2009; Haward et al., 2018) and properties that are uncommon and often dangerous (Leslie, 2017).

(c) **Characterizing (char.)**: there is only a non-accidental relationship between the property and concept (e.g., based only on absolute or relative prevalence among concepts) (Leslie, 2007, 2008).

3.2 Logical Forms for Generics

We propose logical forms L_G that are used to represent an individual generic G. **Each generic category has a distinct logical form** (see Table 1). For quasi-definitional generics, since the property is defining we assert that the property is logically implied by the concept and relationship together (i.e., $K \wedge r \implies P$). In contrast, for principled generics we assert that the concept and property together logically imply the relationship (i.e., $K \wedge P \implies r$). Finally, for characterizing generics, the logical form depends on whether the generic is interpreted as quasi-definitional or principled. Logical forms with examples are shown in Table 1. Note that in a logical L_G, the concept K (property P) is satisfied by *both an individual or subtype* of K (P)[4].

3.3 Constructing EXEMPLARS

We now define generics EXEMPLARS, deriving them from the logical form of a generic.

INSTANTIATIONS For a generic, INSTANTIATIONS are contextually relevant **members of the concept with the desired property**. Formally,

Definition (INSTANTIATIONS)**.** *An* INSTANTIATION *satisfies* L'_G *(i.e.,* L_G *with implication replaced by conjunction*[5]*).*

For example, if we have

$$L_G\text{: }\textsc{Bird}(x) \wedge \textsc{Fly}(y) \implies \textit{can}(x,y)$$

$$\text{so, } L'_G\text{: }\textsc{Bird}(x) \wedge \textsc{Fly}(y) \wedge \textit{can}(x,y)$$

then (x,y) = ("owls", "fly") satisfies L'_G. Note that **INSTANTIATIONS all have the same logical form** regardless of the generic category (see Table 1).

[3]Description of the theories is provided in §A.2

[4]For example, $\textsc{Bird}(x)$ is true for x_1 ="my parrot", x_2 ="owls", and x_3 ="these birds" since all *are* birds.

[5]Replacing the implication with a conjunction excludes instances which satisfy L_G by satisfying *only* the right side of the implication (e.g., $\textsc{Bird}(x) \wedge \textsc{Fly}(y) \implies \textit{can}(x,y)$ is logically true for $(x,y) =$ (airplanes, fly) but this is not a valid INSTANTIATION).

Exceptions An EXCEPTION counters one of two interpretations of the generic (see §A.3 for an in-depth discussion). EXCEPTIONS are members of the concept either **(i)** ***without* the generic property** (Greenberg, 2007) or **(ii)** ***with* an alternative property** (i.e., **exoproperty**) when the generic property is essential to the concept. For example, "penguins can't fly" (for the generic "birds can fly") counters the interpretation that "*all* birds can fly". In contrast, "stars produce light" (for the generic "stars produce radiation") counters the interpretation that "stars produce *only* radiation". Note that in the latter case, there are no specific stars that do not produce radiation. More formally,

Definition (EXCEPTIONS)**.** *An* EXCEPTION *satisfies the logical form* $\sim L_G$ *(i.e.,* $\neg L_G$ *where* $\neg P$ *replaced by* $\sim P$ *when applicable). We define* $\sim \boldsymbol{P}$ *as* ***the exoproperty*** *of* P*: a property adjacent to* P *that is* ***not*** P *but* ***is*** *contextually relevant to* P*.*

For example, if the logical form L_G is

$$\textsc{Star}(x) \wedge \textit{produce}(x, y) \implies \textsc{Radiation}$$

then $\sim L_G$ is

$$\textsc{Star}(x) \wedge \textit{produce}(x, y) \wedge \sim\!\textsc{Radiation}(y)$$

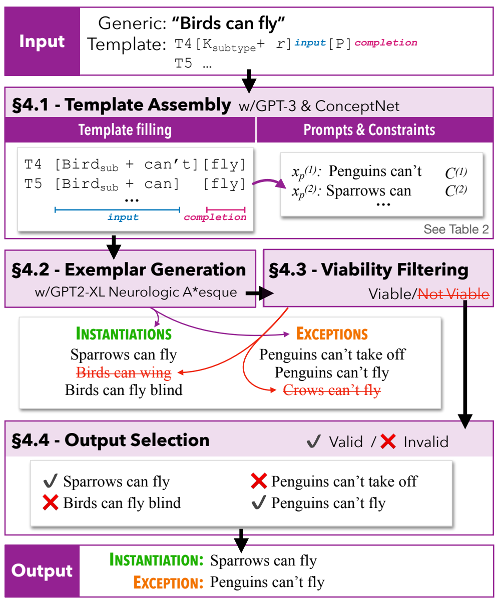
and so (x, y) = ("stars", "light") satisfies $\sim L_G$, while (x, y) = ("stars", "movies") does not. Notice that the latter pair is invalid because "movies" is not a relevant alternative to "radiation" since it is not informative about the generic.

Since a generic's EXCEPTIONS depend on its logical form L_G, they are also dependent on the generic's category (see Table 1). In particular, the EXCEPTIONS for quasi-defintional generics are individuals with alternative properties (since the property is viewed as essential) while for principled generics the EXCEPTIONS are individuals without the generic property. EXCEPTIONS for characterizing generics are, like the logical forms, dependent on the generic's interpretation (see §3.2)

3.4 Logical Forms to Templates

Based on our proposed formulae (Table 1) for EXEMPLARS we define seven templates for generation (Table 2). Each template expresses a set of instances that satisfy the logical form of an EXEMPLAR. Each template has two sets of content specifications: for the *input* and for the *completion* (i.e., the decoder output).

For **INSTANTIATIONS, we define three templates** with subtypes of the concept, property, or both. For **EXCEPTIONS we have four templates**,



Input
Generic: "Birds can fly"
Template: T4 [K_subtype + r] input [P] completion
T5 …
§4.1 - Template Assembly w/GPT-3 & ConceptNet
Template filling
Prompts & Constraints
T4 [Bird_sub + can't] [fly]
T5 [Bird_sub + can] [fly]
…
input
completion
x_p(1): Penguins can't C(1)
x_p(2): Sparrows can C(2)
…
See Table 2
§4.2 - Exemplar Generation
w/GPT2-XL Neurologic A*esque
§4.3 - Viability Filtering
Viable/~~Not Viable~~
INSTANTIATIONS
Sparrows can fly
~~Birds can wing~~
Birds can fly blind
EXCEPTIONS
Penguins can't take off
Penguins can't fly
~~Crows can't fly~~
§4.4 - Output Selection
✓ Valid / ✗ Invalid
✓ Sparrows can fly
✗ Birds can fly blind
✗ Penguins can't take off
✓ Penguins can't fly
Output
INSTANTIATION: Sparrows can fly
EXCEPTION: Penguins can't fly

Figure 2: Overview of our method for an input generic.

using subtypes of either the concept *or* property (but not both) in order to avoid irrelevant or uninformative instances. For example, for the generic "Birds can fly", the sentence "Penguins can't fly long distances" (which has subtypes of both the concept and property) is *uninformative* because it doesn't mean penguins can't fly *in general* (e.g., they might still be able to fly short distances).

4 Methodology

We propose a pipeline system to automatically generate generics EXEMPLARS. Our system takes as input a generic G and the templates derived from its category[6] (§3.4), and outputs a set of generated EXEMPLARS (Fig. 2). First, the system **assembles** and populates the templates according to the input generic (§4.1, Fig. 2). Then, the filled templates are converted into prompts and constraints that control the **generation** decoding process (§4.2). Finally, the output is **filtered** to remove non-viable (§4.3, Fig. 2) or irrelevant (§4.4, Fig. 2) EXEMPLARS.

4.1 Template Assembly

To populate our templates (defined in Table 2), we use a dependency parser[7] to identify the text spans of the concept, relation, and property in a generic. Then, **(i) we extract subtypes** for the concept and property and use these to construct the **(ii)** input i.e., generation prompts x_p) and **(iii)** completion (i.e., lexical constraints $\mathcal{C}$) specifications.

[6]We assume the generic's category is known.
[7]https://spacy.io/

	Categories	Template		Example			
		input	*comp.*	Generic	Prompt x_p	Constraints $\mathcal{C}$	
EXCEP.	quasi-def & char	K + r	$\not\sim$P	Stars produce radiation	"Stars *produce*"	¬radiation ∧¬ x-rays ∧ ...	t1
		K$_{sub}$ + r	$\not\sim$P		"Sun *produces*"	¬radiation ∧¬ x-rays ∧ ...	t2
	principled & char	K + ¬r	P$_{sub}$	Birds can fly	"Birds *can't*"	migrate ∨ soar ∨ glide ∨...	t3
		K$_{sub}$ + ¬r	P		"Penguins *can't*"	fly ∨ flying ∨...	t4
INST.	all	K$_{sub}$ + r	P	Birds can fly	"Sparrows *can*"	fly ∨ flying ∨...	t5
		K + r	P$_{sub}$		"Birds *can*"	migrate ∨ soar ∨ glide ∨...	t6
		K$_{sub}$ + r	P$_{sub}$		"Sparrows *can*"	migrate ∨ soar ∨ glide ∨...	t7

Table 2: Templates for generating EXEMPLARS, derived from their logical forms (§3.3). sub indicates a subtype, K the concept, P the property, $\not\sim$P its exoproperty (§3.2). *comp* is the completion.

(i) Subtype Extraction We extract subtypes using both ConceptNet (Speer et al., 2017)[8] and GPT-3 (Brown et al., 2020). GPT-3 increases the coverage and diversity of subtypes, since many natural and valid subtypes may be missing from ConceptNet (e.g., modifier phrases attached to a concept: "*young* Arctic fox"). We only use GPT-3 for subtypes of the concept, since by increasing the diversity in the prompt we may encourage diversity in the generated properties (see details Appendix D).

(ii) Input Specification We construct the input specifications by constructing generation prompts. Following the template, each prompt consists of either the concept (or a subtype) and the relationship (or its negation) (see Table 2). We prepend to each prompt the generic itself and a connective (e.g., "however"). We rank the prompts by perplexity and use the top k_p prompts for generation.

(iii) Completion Specification Following the templates, we constrain the generation output to describe the property (or a subtype) or its exoproperty (see Table 2). We construct a set of completion constraints (e.g., $\mathcal{C}^{(i)}$ in Fig. 2 specifies "fly" should be in the completion) using lexical items including subtypes, synonyms, and morphological forms.

4.2 Generation

In order to generate output that has a specific pragmatic relation to the input without requiring training, we use the NeuroLogic A*esque (NeuroLogic*) (Lu et al., 2022) decoding algorithm. NeuroLogic* is an unsupervised decoding algorithm that takes as input a prompt x_p and set of lexical constraints $\mathcal{C}$ and produces a completion of the prompt $\hat{y}$ which has high likelihood given the prompt *and* high satisfaction of the constraints (estimated throughout the decoding). A lexical constraint consists of a set of n-grams $w = (w_i^1, \ldots, w_i^m)$ and is satisfied when at least one $w_i \in w$ is in $\hat{y}$ (inclusion constraints) or is not in $\hat{y}$ (exclusion constraints).

By using the input prompts (as x_p) and completion constraints (as $\mathcal{C}$) derived from our templates (§4.1), we can control the output content, syntactic form, *and* pragmatic relevance. We note that since we cannot concretely define the set of relevant potential candidates for a property's exoproperty (§3.2), decoding constraints *must* be used to generate EXCEPTIONS.

Output Ranking We rank the outputs from NeuroLogic* by template and prompt and we take the top k_r outputs as potential EXEMPLARS. The outputs are ranked by perplexity (for fluency) and by the probability of a specific NLI label (for relevance) and we average the two ranks. For NLI labels, we hypothesize that a good EXCEPTION aligns with NLI's contradiction, as does a good INSTANTIATION with entailment (see Fig. 2). While this alignment is useful for ranking, the relationship between the EXEMPLARS and NLI labels is not this straightforward in reality, as we will discuss (§6.3).

4.3 Filtering For Viability

Since pre-trained language models have a tendency to hallucinate facts (Rohrbach et al., 2018) or produce non-specific output (e.g., "Birds can do things"), we apply a viability filter to the ranked output generations. Specifically, we train a discriminator to predict whether an output is viable (i.e., true *and* sufficiently specific that it could be an EXEMPLAR) or not, using human annotated examples (see Appendix B for details). Generations predicted not viable by the trained discriminator are removed from the dataset.

4.4 Output Selection

Our final task is to select the generations that are pragmatically relevant (i.e., **valid**; correctly follows a template) EXEMPLARS. To do this, we first collect gold labels from humans for whether an

[8]Relations: `IsA`, `InstanceOf`, `Synonym`

EXEMPLARS is valid. These annotations produce two sets of binary labels; one set each for INSTANTIATIONS and EXCEPTIONS.[9] Although this task is more complex than annotating for viability, removing non-viable generations helps reduce the complexity (i.e., we do not need to worry about false statements that adhere to the template). By annotating only viable generations we also reduce the required amount of annotation. Using the human annotations, we train two validity discriminators: one for EXCEPTIONS, one for INSTANTIATIONS. The trained validity discriminators are used to rank and select the best generations for each generic as our system output.

5 Experiment Details

We discuss our experimental setup and specify full hyperparameters in Appendix C.

5.1 Data Source

We use a subset of the generics dataset from Bhagavatula et al. (2022), a set of 30K generics built upon common everyday concepts (e.g., "hammers") and relations (e.g., "used for") sourced from resources such as GenericsKB (Bhakthavatsalam et al., 2020) and ConceptNet (Speer et al., 2017). The dataset includes a diverse variety of concepts, including general knowledge ("Dogs bark"), locative generics ("In a hotel, you will find a bed"), and comparative generics ("Cars are faster than people"). We use 653 generics from the test set, excluding human referents as the concept (e.g., nationalities, professions) due to social bias concerns.

5.2 Annotations

All annotations are done using Amazon Mechanical Turk with three annotators per HIT (paid at \$15/hour on average) and processed using MACE (Hovy et al., 2013) to filter annotators and determine the most likely label. We note that while all tasks achieve moderate inter-annotator agreement, the complex pragmatics of generics make these tasks difficult for human annotators.

For **generic type** (§3.1), we conduct two annotation passes to partition *all 653 generics* into the three groups in Table 1. The Fleiss' κ (Fleiss, 1971) is 0.41 and 0.58 for the first and second pass respectively. Our categorization results in 296 quasi-definitional, 125 principled, and 232 characterizing generics. For the **viability filter** (§4.3), we annotate a set of 7665 *system generations* from 150 generics. The Fleiss' κ is 0.53.

For **EXEMPLAR gold labels** (§4.4), we use separate annotation tasks for INSTANTIATIONS and EXCEPTIONS (see Appendix B for details) with Fleiss' κ of 0.40 and 0.45 respectively. For training each discriminator, we randomly sample and annotate $\sim 1k$ system generations from $\sim$300 generics. For human evaluation (§6.2), we annotate the *top* 5 discriminator-ranked generations for *all generics* from both our system and the baseline.

[9]Since a generation that is not an INSTANTIATION *in not necessarily* an EXCEPTION (and vise versa), these cannot be directly combined into a single multi-class labeling task.

		Subtype Source		
		G3	CN	G3+CN
Generated	Output (§4.2)	42272	10496	52768
	Viable (§4.3)	22865	5452	28317
Valid (§4.4)	EXCEP.	4375	1922	6297
	INST.	10983	1579	12562
	TOTAL	**15358**	**3501**	**18859**

Table 3: Statistics of the generated dataset, with GPT-3 (G3) and ConcepNet (CN) subtypes used.

5.3 Discriminators

For all discriminators, we fine-tune RoBERTa (Liu et al., 2019). All labeled data is split such that all generations for a particular generic are in the same data partition.

5.4 Few-Shot Baseline

As a baseline for generation, we use GPT-3 (Brown et al., 2020) with few-shot prompting. Since we do not have access to the decoding algorithm for GPT-3, we cannot use decoding constraints to control the output (as in our system). Therefore, we use few-shot prompting in order to control the output of GPT-3. Specifically, for each template (Table 2) we construct a few-shot prompt (Appendix D) that consists of three examples that illustrate the desired template. This setup is very similar to the prompts to our system, except our system is not provided examples and GPT-3 is not provided with subtypes (when appropriate to the template). Note, our goal is *not* to produce the best possible generations from GPT-3 but rather to show that constrained generation from GPT-2 (i.e., NeuroLogic*) outperforms (and is cheaper and more computationally feasible) than a natural use of GPT-3.

6 Evaluation

Using our computational framework, **we generate** 18859 **EXEMPLARS for** 653 **generics** (Table 3).

	Generic	INSTANTIATION	EXCEPTION
(a)	"Bleaches may be used to whiten the teeth."	"non-toxic bleaches can be used to remove discoloration" (t7)	"A bottle of liquid bleach should not be used to whiten the teeth" (t4)
(b)	"A chest pain has a physical cause."	"an angina pectoris has an underlying cause" (t5)	"a chest pain has an emotional or psychological origin" (t1)
(c)	"A gun are used for hunting."	"a shotgun is used for small game" (t7)	"semiautomatics can be used for target practice" (t2)

Table 4: Examples of generated INSTANTIATIONS and EXCEPTIONS. The template used in the prompt for generation is indicated in parentheses (see Table 2).

Example system generations are in Table 4.

To evaluate our approach, we first qualitatively investigate our system and outputs (§6.1) and then conduct a human evaluation (§6.2). We also conduct a detailed analysis of our system and the implications of our results.(§6.3). Our results show that our approach produces a large set of high quality generations for this difficult task. They also highlight current limitations in machine reasoning and potential directions for future work.

6.1 Qualitative Analysis

Observations We first observe that while close to half the output generations are untrue or not viable, the majority of viable generations are valid EXEMPLARS (Table 3). In addition, we see from system outputs (Table 4) that our system can successfully generate valid EXEMPLARS with subtypes of both the concept (e.g., "angina pectoris" vs. "a chest pain" in (b)) and the property (e.g., "small game" vs. "hunting" in (c)). Furthermore, it produces valid EXCEPTIONS with both the simpler relation-negation templates (i.e., templates t3/t4; see (a)) *and* with relevant exoproperties (i.e., templates t1/t2; see (b) and (c)). These highlight the success of our system in producing high-quality EXEMPLARS.

Discriminator Analysis On their respective annotated test sets, the accuracy of the viability discriminator (§4.3) is 75.2 and the accuracies of the trained validity discriminators are 77.4 for INSTANTIATIONS and 75.0 for EXCEPTIONS

In order to investigate the discriminator quality, we also conduct a manual analysis of the errors made by the *validity* discriminators. We observe that subtypes are particularly difficult for the discriminators to identify (e.g., that "freshwater lakes and rivers" are a type of "water"). Exoproperties can also be challenging for both the discriminators and humans (e.g., whether "able to land" is a subtype or alternative to "able to move").

We also observe that the discriminators identify a number of instances that were mislabeled by the human annotators. In particular, for 10 out of the 22 examples (5 out of the 14) where the EXCEPTION (INSTANTIATION) discriminator prediction disagrees with the human label, we judge the *discriminator* prediction to be correct. For example, "clocks are synchronized to the time zone" is labeled (incorrectly) by humans as an invalid EXCEPTION to the generic "clocks are synchronized to the second", despite "to the time zone" being a *relevant alternative* to "to the second". Counting the human-mislabeled instances as correct would increase the discriminator accuracies to 86% (85%) for the EXCEPTIONS (INSTANTIATIONS).

6.2 Human Evaluation

To quantitatively evaluate our system, we compute precision at k (for $k = 1$ and $k = 5$) using our human-annotated judgements (§5.2) (Table 5).

Our model outperforms the few-shot baseline (i.e., GPT-3) in all cases, and by a large gap (average 12.8 points). This is especially significant for EXCEPTIONS, which are more challenging to generate than INSTANTIATIONS, and where the baseline performance is close to random. Since generics are defaults, it follows that INSTANTIATIONS should be easier to produce than EXCEPTIONS. The fact that more generated INSTANTIATIONS are true (71% versus 40%) and more true INSTANTIATIONS are accepted by the discriminator (77% versus 50%), compared to the EXCEPTIONS, supports this intuition. Hence, the large improvements by our model over the baseline are significant towards generating these difficult EXCEPTIONS.

Additionally, we examine our model performance across templates. Specifically, we compute the fraction of generations for a template that annotators label as valid, using the same number[10] of generations for both models for a specific template

[10]The models produce similar numbers of generations on all templates except t5.

	EXCEPTIONS		INSTANTIATIONS	
	$P@1$	$P@5$	$P@1$	$P@5$
GPT-3	0.517	0.563	0.758	0.689
Ours	**0.632**	**0.616**	**0.911**	**0.882**

Table 5: Precision at k ($P@k$).

	EXCEPTIONS				INSTANTIATIONS		
	t1	t2	t3	t4	t5	t6	t7
#Gens	401	911	30	43	1147	4	862
GPT-3	0.65	0.53	**0.52**	**0.59**	0.78	0.75	0.50
Ours	**0.68**	**0.54**	0.30	0.47	**0.87**	**1.0**	**0.87**

Table 6: Precision by template. #Gens is per template and is the minimum of the models.

(Table 6). We see that not only does our model outperform the baseline for the majority of templates, these templates constitute the majority of the generations ('#Gens' in Table 6).

The performance comparison by template does not account for the fact that, while our system is constrained to follow the given template, with GPT-3 the template is only suggested by the prompt and so the model output may not adhere to it. As a result, the GPT-3 performance for certain templates (t2-4) is inflated because GPT-3 outputs simpler constructions that do not follow the requested template. Therefore, we conduct a manual analysis of the best 40 baseline (i.e., GPT-3) generations per template, ranked by perplexity. For EXCEPTIONS, the baseline produces on average only 2.5/40 generations that fit the desired templates for t2-t4. Additionally, for the one EXCEPTION template, t1, where most baseline generations fit the template (37/40), our model still outperforms the baseline. For INSTANTIATIONS, the baseline performs slightly better (average 10/40 fitting generations) but still poorly. From this we observe that not only is the baseline not controllable, our model outperforms the baseline in cases when it does adhere to output requirements.

6.3 Discussion

Does controllability matter? We ablate the decoding algorithm by removing the constraints (i.e., using beam search) (Table 7a). Although both systems condition their outputs on the same prompts, NeuroLogic*, with linguistic-theory-guided constraints, produces over seven times as many unique generations as unconstrained decoding (i.e., beam search). Additionally, the proportion of valid generations (i.e., accepted by our discriminators) is nearly twice as many for NeuroLogic*. This illus-

	Beam		NeuroLogic*	
	#Gens	%Val	#Gens	%Val
EXCEP.	5083	13.4	29962	21.0
INST.	2221	39.6	22806	55.3
ALL	7307	21.4	52768	35.7

(a) Decoding method ablation: beam search vs. NeuroLogic $\star$.

	MLM		CN		G3	
	#Gens	%Val	#Gens	%Val	#Gens	%Val
EXCEP.	10350	25.2	7521	25.5	22441	19.5
INST.	4459	50.7	2975	53.0	19831	55.4
ALL	14809	32.9	10496	33.3	42272	36.3

(b) Subtype ablation: MLM, ConceptNet (CN), GPT-3 (G3).

Table 7: Ablation results. #Gens: generations after ranking and filtering. %Val: percent accepted by the corresponding validity discriminator.

trates the importance of incorporating linguistic-theory-based control into decoding in order to generate a large set of unique, and valid, EXEMPLARS.

Do CKBs contain sufficiently rich information? We probe whether a CKB (i.e., ConceptNet) contains sufficiently rich type information to produce EXEMPLARS. Specifically, we vary the source of subtypes in the template-based prompts and constraints for our system, comparing ConceptNet (CN) to extracting commonsense knowledge from language models (i.e., from GPT-3 prompting (G3) and GPT-2 masked-language model (MLM) (Devlin et al., 2018; Taylor, 1953) infilling).

In fact, CN subtypes result in the fewest generations (Table 7b). In contrast, using GPT-3 for subtypes produces the most generations. Although using MLM for subtypes produces fewer generations than using GPT-3, the proportion of valid generations is comparable and hence MLM could be used as a substitute if using GPT-3 is not feasible. This shows that while CKBs such as ConceptNet are a good source of generics, producing EXEMPLARS requires knowledge that may not always be encoded within the CKB. Therefore, generating EXEMPLARS is important for accessing relevant knowledge beyond what is in CKBs and enabling tools that can effectively use CKBs in reasoning.

Does NLI impact EXEMPLARS? Since generics EXEMPLARS are closely related to default inheritance (nonmonotonic) reasoning, NLI is a natural task for investigating machine reasoning about EXEMPLARS. Thus, we examine whether controlling the NLI relation between generics and EXEMPLARS improves precision. Specifically, we compute the

	EXCEP.		INST.	
	$P@1$	$P@5$	$P@1$	$P@5$
Ours	0.632	0.616	0.911	0.882
+ NLI-neu	0.569	0.563	0.906	**0.891**
+ NLI-sim	**0.839**	**0.790**	0.864	0.862
+ NLI-neu-sim	0.638	0.618	**0.913**	**0.891**

Table 8: Precision at k with NLI label filtering. NLI-sim is contradiction for EXCEP., entailment for INST.

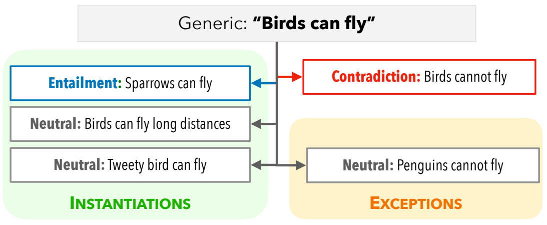

Generic: "Birds can fly"
Entailment: Sparrows can fly
Contradiction: Birds cannot fly
Neutral: Birds can fly long distances
Neutral: Tweety bird can fly
Neutral: Penguins cannot fly
INSTANTIATIONS
EXCEPTIONS

Figure 3: EXEMPLARS and correct NLI labels.

NLI label between the generic (premise) and EXEMPLAR (hypothesis) and exclude generations that do not have a specific predicted NLI label: 'contradiction' for EXCEPTIONS and 'entailment' for INSTANTIATIONS (NLI-sim), 'neutral' (NLI-neu), or NLI-sim and 'neutral' (NLI-neu-sim). We find that by controlling the NLI relation, we improve precision for EXCEPTIONS by 20.7 points (Table 8). However, for INSTANTIATIONS NLI label filtering has a negligible impact on precision. Therefore, we observe that controlling NLI relations can improve EXCEPTION quality but is less beneficial for INSTANTIATIONS. Additionally, note that the alignment with NLI labels is not actually as straightforward as observed, which we discuss next.

Can NLI sufficiently represent EXEMPLARS? Although we observe an alignment between *predicted* NLI labels and EXEMPLARS, this actually indicates systematic NLI-model errors, deriving from the insufficiency of NLI schema for capturing the nuances of generics EXEMPLARS.

Consider the sentences in Fig. 3, relating to the generic "Birds can fly". We see that *only false* statements (i.e., not EXCEPTIONS) are "unlikely to be true given the information in the premise [generic]" (Dagan et al., 2013) (i.e., NLI contradictions). Since the lack of explicit quantification in generics does not preclude the existence of exceptions, EXCEPTIONS *should actually be labeled neutral* by NLI. With INSTANTIATIONS, we observe that the NLI relationship may be *either* neutral or entailment. These theorized alignments, coupled with our prior observations about EXEMPLARS and predicted NLI labels, highlight the challenges of reasoning about EXEMPLARS with NLI.

The examples in Fig. 3 also highlight that the NLI neutral label does not distinguish between statements that are true but not entailed or contradictory (e.g., "Penguins cannot fly") and statements with unknown truth value (e.g., "Tweety bird can fly"). Our generics EXEMPLARS emphasize the need for a more fine-grained notion of NLI.

7 Conclusion

In this work, we draw on insights from linguistics to propose a novel computational framework to automatically generate valid EXEMPLARS for generics, as a step towards capturing the nuances of human reasoning for generics. Our system generates $\sim 19k$ EXEMPLARS for 653 generics and outperforms GPT-3 at generating viable examples, while remaining more controllable. We also demonstrate the limitations of CKBs and the importance of explicit linguistic modeling in generating EXEMPLARS. That is, the importance of linguistic-theory-based decoding and semantics-based filtering with NLI. Finally, we highlight the inability of current NLI models to reason about and represent the default-inheritance-reasoning relationship between generics and EXEMPLARS.

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Limitations and Risks

The generics we source (see §5.1) are exclusively in English. Therefore, our approach may not be suited to all possible generics in all languages. In particular, our system does not handle generics where valid INSTANTIATIONS include negating (§3.2) the concept. This is due to the restriction that most English generation is left-to-right and it is not possible to define a closed set of possible concept negations for the prompt.

In this work, we do not generate EXEMPLARS for generics involving human referents (e.g., professions, nationalities). We exclude generics involving human referents to mitigate the risk of generating socially biased EXEMPLARS or harmful stereotypes (e.g., "Black folks go to jail for crimes" for the generic "People go to jail for crimes"). Additionally, handling of human stereotypes require methods that are beyond the scope of this paper. For example, a socially-aware EXCEPTIONS to a generic like "Girls wear dresses" would be "Boys wear dresses, too". This would require the understanding of the possible subtext of such a statement (e.g. "Only girls wear dresses"), which is beyond the current capabilities of this study and worthy of future exploration.

Finally, we note that while it is not the intended purpose of our system, a malicious user could still use our system to generate EXEMPLARS for a generic involving a person and propagate potentially harmful social biases.

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A Generics

A.1 Generics and Quantifiers

Explicit quantification (e.g., "*Most* birds can fly", "Birds can *usually* fly") are excluded from this study because the quantifier implicitly accounts for all potential exceptions. That is, by saying "*Most* birds can fly" we implicitly indicate that a minority of the birds do not. This being the case, exceptions cannot be generated with statements with explicit quantification.

A.2 Generics Definitions

Categories of Generics We condense the five generic types proposed by Leslie (2007, 2008) and Khemlani et al. (2009) into our three categories (§3.1). The five types are:

- **Quasi-definitional**: generics concerning properties that are assumed to be universal among a concept. This is the same as our quasi-definitional category, see (a) Table 1. The property is considered a defining characteristic of the concept.
- **L-Principled**: generics concerning properties that are prevalent among a concept and are viewed as inherent, or connected in a principled way (Prasada and Dillingham, 2006, 2009; Haward et al., 2018). These generics are called principled in Leslie (2007, 2008). Note, these generics make up only one half of our "principled" category (§3.1). See first example for category (b) in Table 1; the second example there does *not* fit Leslie (2007, 2008)'s definition of principled (i.e., L-principled).
- **Striking**: generics describing properties that are uncommon and often dangerous, and members of the concept are *disposed* to possess them if given the chance (Leslie, 2017). For example, the striking generic "Sharks attack swimmers" assumes all sharks are capable of attacking swimmers. These generics constitute the second half of our "principled" category. See second example (not first) for category (b) in Table 1.
- **Majority characteristic**: generics concerning properties that are neither deeply connected to the concept nor striking but occur in the majority of members of the concept. These constitute one half of our "characterizing category". See example for (c) in Table 1.
- **Minority characteristic**: generics concerning properties that are neither deeply connected to the concept nor striking but occur in the minority of members of the concept. For example, "Lions have manes", since only adult male lions (the minority of the lion population) have manes. These constitute the second half of our "characterizing category".

Both L-principled and striking generics are true in-virtue-of a secondary factor and therefore we group these into one category (i.e., "principled"; see §3.1). For L-principled generics, this may be a factor that causes the property to occur in the concept (e.g., Birds can fly because they have wings). For striking generics, it is the assumed predisposition of the kind to possess the property if given the chance.

For quasi-definitional generics, because the property is considered defining to concept, there is no implied secondary factor in-virtue-of which the generic is true. Therefore, these generics are descriptive and we put them in a separate category from striking and L-principled generics.

Finally, majority and minority characteristic generics are ambiguous in their interpretation. For example, "Lions have manes" can be interpreted as being true in-virtue-of some secondary factor (e.g., as a signal of fitness) or as being a merely accidental relationship. If the interpretation is the former, then lions without manes are valid EXCEPTIONS (e.g., lion cubs, female lions), while if the interpretation is the latter then then other attributes of lions are valid EXCEPTIONS (e.g., claws, fur).

Focuses of Generics We note that a generic can focus on the presence of the property within the concept (e.g., "Birds can fly" is concerned with which birds can fly) **or** can focus on the presence of the concept within holders of the property (e.g., "Triangles have three sides" is more concerned with what concepts have three sides). We will say that the former kind of generic is *concept-oriented* and the latter is *property-oriented*. A generic can be both concept and property oriented if it is ambiguous between the two readings (e.g., "Aspirin relieves headaches").

In this work, we have discussed and used definitions only for concept-oriented generics.

A.3 EXEMPLARS Definitions

Interpretations As discussed (§3.3), EXCEPTIONS counter an interpretation of the generic. Importantly, these interpretations must contain *universal quantification* of either the concept or the property. In this way, the implied universality of the generic can be countered by an EXCEPTION.

We consider the four interpretations of a generic derived from attaching the universal quantifiers "all" (or "always") and "only" to either the concept or the property. For example, for the generic "Birds can fly", we have:

1. ***All* birds can fly.**
   ⇒ Concept-oriented:
   which birds (i.e., all) can fly.
2. ***Only* birds can fly.**
   ⇒Property-oriented:
   for being able to fly, how defining (i.e., entirely) are birds.
3. **Birds can fly *all ways*.**
   ⇒Property-oriented:
   for flight, which types (i.e., all of them) can birds do.
4. **Birds can *only* fly.**
   ⇒Concept-oriented:
   of the things birds can do, how defining (i.e., entirely) is flying.

For concept-oriented generics, interpretations 1 and 4 are salient. for property-oriented generics, interpretations 2 and 3 are salient.

The quantifier "only" specifies how *defining* the concept is for the property (for concept-oriented generics); for property-oriented generics it specifies how the concept is to the property. Hence, quasi-definitional generics (§3.1 correspond to the interpretations containing "only" quantifiers. Therefore, their EXCEPTIONS will counter the implicit assumption that the property is defining for the concept (or vise versa for property-oriented generics). That is, the EXCEPTIONS will be members of the concept with *other relevant* properties. For example, for the generic "Stars produce radiation", an exception is "The sun produces light".

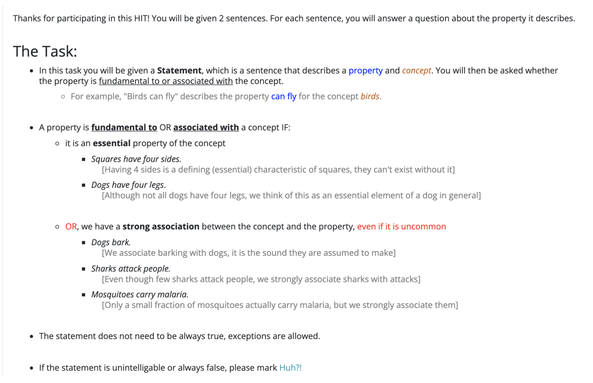
On the other hand, the quantifier "all" specifies the prevalence of the property among the concept (for concept-oriented generics). For property-oriented generics, "all" specifies the proportion of the property connected with the concept (e.g., how much of the property can members of the concept do). Hence, the "all" quantifier corresponds to principled generics (§3.1). Note, that even though striking generics (see §A.2) describe very low real-world prevalence, the *implication* is that prevalence is much higher, since individuals are disposed to possess the property (Leslie, 2017). Therefore, EXCEPTIONS to principled generics will be members of the concept (or types of the property) that do *not* possess the desired property (or are not present among the concept). For example, a bird that cannot fly (e.g., a penguin) or a type of movement humans cannot do (e.g., fly, for the generic "humans can move").

Logical Forms Although we only derived logical forms for concept-oriented generics in this work, similar definitions and logical forms can be derived for property-oriented generics. In particular, only the logical forms for quasi-definitional generics and their EXCEPTIONS will change if the generic is property-oriented. That is, the K and P in both logicals form for (a) in Table 1) can swapped to obtain the property-oriented versions. In this work, we do not deal with property-oriented generics and their EXEMPLARS due to the limitations of English generation (i.e., it is left-to-right).

B Annotation

For all annotation tasks, three annotators are used per HIT. When filtering annotators using MACE, we remove annotators with competence below 0.5 (or the median, if lower).

Generic Type Instructions for annotating generic types (§3.1) are shown Figure 4 (for the first pass) and Figure 5 (for the second pass). The first pass categorizes generics as either characterizing or not (either quasi-definitional or principled). The second pass categorizing non-characterizing generics as either quasi-definitional or principled.

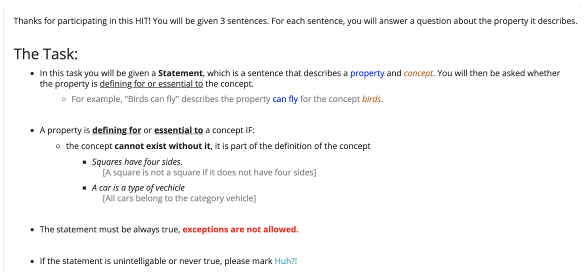


Thanks for participating in this HIT! You will be given 2 sentences. For each sentence, you will answer a question about the property it describes.

The Task:

- In this task you will be given a **Statement**, which is a sentence that describes a property and *concept*. You will then be asked whether the property is fundamental to or associated with the concept.
  - For example, "Birds can fly" describes the property can fly for the concept *birds*.
- A property is **fundamental to** OR **associated with** a concept IF:
  - it is an **essential** property of the concept
    - *Squares have four sides.*
      [Having 4 sides is a defining (essential) characteristic of squares, they can't exist without it]
    - *Dogs have four legs.*
      [Although not all dogs have four legs, we think of this as an essential element of a dog in general]
  - OR, we have a **strong association** between the concept and the property, even if it is uncommon
    - *Dogs bark.*
      [We associate barking with dogs, it is the sound they are assumed to make]
    - *Sharks attack people.*
      [Even though few sharks attack people, we strongly associate sharks with attacks]
    - *Mosquitoes carry malaria.*
      [Only a small fraction of mosquitoes actually carry malaria, but we strongly associate them]
- The statement does not need to be always true, exceptions are allowed.
- If the statement is unintelligable or always false, please mark Huh?!

Figure 4: Task instructions for first part of the generic type categorization annotation (§5.2).



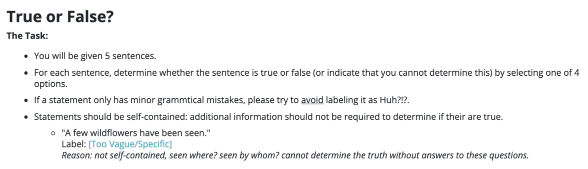
Thanks for participating in this HIT! You will be given 3 sentences. For each sentence, you will answer a question about the property it describes.

The Task:

- In this task you will be given a **Statement**, which is a sentence that describes a property and *concept*. You will then be asked whether the property is defining for or essential to the concept.
  - For example, "Birds can fly" describes the property can fly for the concept *birds*.
- A property is **defining for** or **essential to** a concept IF:
  - the concept **cannot exist without it**, it is part of the definition of the concept
    - *Squares have four sides.*
      [A square is not a square if it does not have four sides]
    - *A car is a type of vechicle*
      [All cars belong to the category vehicle]
- The statement must be always true, **exceptions are not allowed.**
- If the statement is unintelligable or never true, please mark Huh?!

Figure 5: Task instructions for second part of the generic type categorization annotation (§5.2).

Viability Task Instructions for annotating output generations for viability (§4.3) are shown in Figure 6.



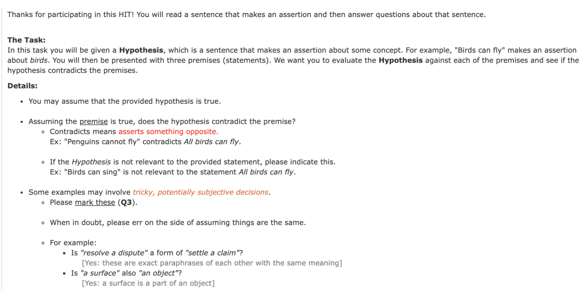
True or False?

The Task:

- You will be given 5 sentences.
- For each sentence, determine whether the sentence is true or false (or indicate that you cannot determine this) by selecting one of 4 options.
- If a statement only has minor grammtical mistakes, please try to avoid labeling it as Huh?!?.
- Statements should be self-contained: additional information should not be required to determine if their are true.
  - "A few wildflowers have been seen."
    Label: [Too Vague/Specific]
    Reason: not self-contained, seen where? seen by whom? cannot determine the truth without answers to these questions.

Figure 6: Task instructions for annotating truthfulness (§5.2).

EXEMPLARS Gold Labels For the INSTANTIATION template generations, annotators are asked whether the generation contradicts the original generic. Instructions are shown in Figure 8. However, for the exception template generations, an EXCEPTION is not a contradiction of the generic itself but of an associated logical form. For example, "Penguins cannot fly" does not actually contradict the generic itself ("Birds can fly") but a modified form of the generic involving quantification (i.e., "All birds can fly"). Therefore, we ask annotators whether the generation contradicts two modified forms of the generic. Instructions are shown in Figure 7.



Thanks for participating in this HIT! You will read a sentence that makes an assertion and then answer questions about that sentence.

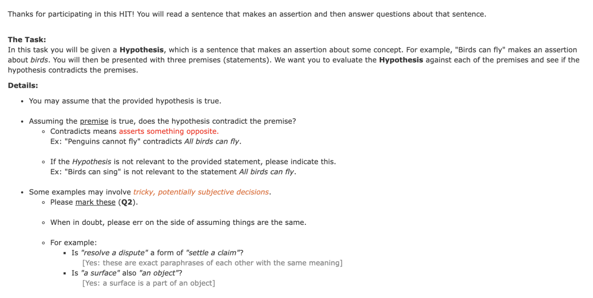
The Task:
In this task you will be given a **Hypothesis**, which is a sentence that makes an assertion about some concept. For example, "Birds can fly" makes an assertion about *birds*. You will then be presented with three premises (statements). We want you to evaluate the **Hypothesis** against each of the premises and see if the hypothesis contradicts the premises.

Details:

- You may assume that the provided hypothesis is true.
- Assuming the premise is true, does the hypothesis contradict the premise?
  - Contradicts means asserts something opposite.
    Ex: "Penguins cannot fly" contradicts *All birds can fly*.
  - If the *Hypothesis* is not relevant to the provided statement, please indicate this.
    Ex: "Birds can sing" is not relevant to the statement *All birds can fly*.
- Some examples may involve *tricky, potentially subjective decisions*.
  - Please mark these (**Q3**).
  - When in doubt, please err on the side of assuming things are the same.
  - For example:
    - Is *"resolve a dispute"* a form of *"settle a claim"*?
      [Yes: these are exact paraphrases of each other with the same meaning]
    - Is *"a surface"* also *"an object"*?
      [Yes: a surface is a part of an object]

Figure 7: Task instructions for annotating validity of EXCEPTIONS (§5.2).

We obtain modified forms of the generic by first converting the logical forms in Table 1 into a natural language templates by adding a universal quantifier. Then we apply the template to the generic itself. Specifically, from $K(x) \wedge r(x,y) \implies P(y)$ (e.g., for quasi-definitional generics) we derive "`[K] [REL]` *`ONLY`* `[P]`". For example, "mosquitoes drink *only* blood", which is contradicted by mosquitoes that drink something other than blood. Notice, that exceptions from templates 1 and 2 will contradict these statements. Similarly, for $K(x) \wedge P(y) \implies r(x,y)$ we derive "*`ALL`* `[K] [REL] [P]`". For example, "*All* birds can fly", which is contradicted by birds that cannot fly. Exceptions from templates 3 and 4 will contradict these statements.



Thanks for participating in this HIT! You will read a sentence that makes an assertion and then answer questions about that sentence.

The Task:
In this task you will be given a **Hypothesis**, which is a sentence that makes an assertion about some concept. For example, "Birds can fly" makes an assertion about *birds*. You will then be presented with three premises (statements). We want you to evaluate the **Hypothesis** against each of the premises and see if the hypothesis contradicts the premises.

Details:

- You may assume that the provided hypothesis is true.
- Assuming the premise is true, does the hypothesis contradict the premise?
  - Contradicts means asserts something opposite.
    Ex: "Penguins cannot fly" contradicts *All birds can fly*.
  - If the *Hypothesis* is not relevant to the provided statement, please indicate this.
    Ex: "Birds can sing" is not relevant to the statement *All birds can fly*.
- Some examples may involve *tricky, potentially subjective decisions*.
  - Please mark these (**Q2**).
  - When in doubt, please err on the side of assuming things are the same.
  - For example:
    - Is *"resolve a dispute"* a form of *"settle a claim"*?
      [Yes: these are exact paraphrases of each other with the same meaning]
    - Is *"a surface"* also *"an object"*?
      [Yes: a surface is a part of an object]

Figure 8: Task instructions for annotating validity of insts (§5.2).

C Implementation Details

C.1 Data

We use the generics data from Bhagavatula et al. (2022). For this study, we source from the subset of the test set found to be valid by the discriminator with probability at least 0.5 (768 generics). Of these, we exclude all mentions of human referents (e.g., kinship labels, nationalities, titles, professions) and actions (e.g., studying for a test) to arrive at a dataset of 653 generics. We remove human referents using a seed set of human referent terms compiled based on WordNet (Miller, 1995) and will be provided with the system code. We remove mentions of actions by excluding generics beginning with "In order to". The dataset is licensed under CC-BY and our usage aligns with the intended use of the data.

Preprocessing We remove adverbs of quantification (i.e., usually, typically, generally) from the generics and exclude generics with verbs of consideration (i.e., consider, posit, suppose, suspect, think). We also convert hedging statements to more explicit forms (e.g., "may have to be" to "must be").

	Train	Dev	Test	All
True	2831	412	433	3676
False/Non-salient	3180	367	442	3989
Total	6011	779	875	7665

Table 9: Data split statistics for truthfulness discriminator (§4.3).

		Train	Dev	Test	All
	Valid	342	35	35	412
EXCEPTION	Invalid	462	72	53	587
	Total	804	107	88	999
	Valid	374	38	29	441
INSTANTIATION	Invalid	466	38	33	537
	Total	840	76	62	978

Table 10: Data split statistics for validity discriminators (§4.4).

Partitions The data splits for training the viability discriminator and validity discriminators are shown in Table 9 and Table 10 respectively.

C.2 Tools

For extracting components of the generic data we use spacy[11] for dependency parsing. We use *inflect*[12] to obtain plural and singular word forms and *mlconjug3*[13] to conjugate verbs. We use *nltk*[14] for additional synonyms.

C.3 Hyperparameters

To obtain subtypes from GPT-3 we use the *davinci* model and top-p sampling with $p = 0.9$, temperature 0.8 and maximum length 100 tokens. We use the top 5 sequences to obtain subtypes. For NLI scores, we use RoBERTa fine-tuned on MNLI (Williams et al., 2018) available from AllenNLP[15]. For the GPT-3 baseline we use the davinci model and top-p sampling 1.0, temperature 0.8, maximum length 50 tokens and top 5 sequences. Prompts for GPT-3 are given in Appendix D. GPT2-XL has 1.5 billion parameters, GPT-3 has 175 billion parameters. Our experiments are done using Quadro RTX 8000 GPUs.

For generation with NeuroLogic*, we use GPT2-XL (Radford et al., 2019) with a maximum length of 50 tokens and a beam size of 10 with temperature 10000000. We set the constraint satisfaction tolerance to 3. This means that at each step, only candidates whose number of satisfied constraints is within three of the maximum so far are kept. The 'look ahead' is also set to 3; look ahead three generation steps during decoding to estimate future constraint satisfaction. During prompt construction, take the top $k_p = 10$ prompts. If the generic produced less than 10 prompts total, we take half so that low quality prompts are not used even if few are produced. After ranking the output, we keep the top $k_r = 10$ generations for a template, keeping at most 2 per prompt.

For the viability discriminator, we fine-tune the model for 5 epochs using a batch size of 16 and learning rate $1e-5$ and random seed 29725, selected by manual grid search with 27 trials (see bounds Table 11).

For the validity discriminators, we fine-tune *the viability discriminator* for 3 epochs with a batch size of 16 and learning rate $3e{-}5$. The instantiation discriminator uses a random seed of 4427 and the exception discriminator 4457. Hyperparameters are again selected by manual grid search with 36 trials (see bounds Table 12).

[11]https://spacy.io/
[12]https://pypi.org/project/inflect/
[13]https://pypi.org/project/mlconjug3/
[14]https://www.nltk.org/
[15]https://demo.allennlp.org/textual-entailment/roberta-mnli

Parameter	**Values**
Random seed	29725
Batch size	[64, 32, 16]
Learning rate	[3e-5, 1e-5, 3e-6]
Number of epochs	[1, 3, 5]

Table 11: Hyperparameter bounds for the viability discriminator.

Parameter	**Values**
Random seed	4427
Batch size	[64, 32, 16]
Learning rate	[1e-4, 3e-5, 1e-5, 3e-6, 1e-6, 3e-7]
Number of epochs	[1, 3]

Table 12: Hyperparameter bounds for the validity discriminators.

C.4 Validation Performance

We show the validation performance for the trained discriminators in Table 13.

D GPT-3 Prompts

D.1 Subtyping

To obtain subtypes from GPT-3, we first categorize the kinds into six categories: person, animal, other living (e.g., plants), location, temporal (e.g., Thursday), and other (e.g., candle, soup) (Table 14). For

Discriminator	**Val**			**Test**		
	Max	Mean	Var	Max	Mean	Var
Viability	0.771	0.685	4.3e-3	0.752	0.673	3.6e-3
Validity EXCEPTIONS	0.757	0.600	8.8e-3	0.750	0.557	4.4e-3
Validity INSTANTIATIONS	0.763	0.582	6.6e-3	0.774	0.577	7.1e-3

Table 13: Trained discriminator accuracy (with mean and variance) on the validation and test sets.

each category, we construct a separate prompt for GPT-3 containing one type and five example subtypes. Then, for each kind we use the prompt from its assigned category to obtain subtypes. Note that we exclude all generics where the kind is "person". This is to avoid producing or repeating stereotypes.

To determine the category, we use seed lists, for person, animal, other living, and locative, or the presence of prepositional beginnings ("On", "In", "At", "During"), for locative and temporal. The "other" category encompasses all kinds that do not fit into another category.

D.2 Few-shot Baseline

The prompts for our few-shot baseline are shown in Table 15. The three examples in the table are provided each on a separate line. Appended to the prompt is a fourth generic and the necessary connective. The same connective is used across all exception (instantiation) templates and is chosen through manual experimentation. We use "But also" for EXCEPTIONS and "For example" for INSTANTIATIONS.

Category	Prompt Concept	Prompt Subtypes
Animal	birds	sparrow, canary, large bird,bird of prey, sea bird
Other living	apple tree	small apple tree, flowering apple tree,apple tree with ripe apples, granny smith apple tree, young apple tree
Locative	hotels	beach hotel, boutique hotel, resort, bed and breakfast, five star hotel
Temporal	day	morning, hot day, short day, afternoon, evening
Other	candles	scented candle, advent candle, tealight, candle made from beeswax, candle that smells floral
	can of soup	can of tomato soup, can of mushroom bisque, expired can of soup, unopened can of soup, organic can of soup

Table 14: Prompts for generating subtypes with GPT-3.

	Template	Prompt Examples
(1)	`[KIND + REL]`^{p} `[NEG-PROP]`^{C}	Elephants are found in zoos. But also elephants are found in the wild in Africa. Viruses are spread through body fluids. But also viruses are spread in the air. A hair dryer is used to dry hair. But a hair dryer can also be used to dry clothes.
(2)	`[KIND`$_{sub}$ `+ REL]`^{p} `[NEG-PROP]`^{C}	Elephants are found in zoos. But also African elephants are found in the wild in Africa. Viruses are spread through body fluids. But also coronaviruses are spread in the air. A hair dryer is used to dry hair. But also an electric hair dryer can be used to dry clothes.
(3)	`[KIND + NEG-REL]`^{p} `[PROP`$_{sub}$`]`^{C}	Dogs protect buildings from intruders. But also dogs do not protect apartment buildings from intruders. Cowsheds are found on farms. But also cowsheds are not found in orchards. The sun produces radiation. But also the sun does not produce x-rays.
(4)	`[KIND`$_{sub}$ `+ NEG-REL]`^{p} `[PROP]`^{C}	Birds can fly. But also penguins cannot fly. Ducks lay eggs. But also male ducks do not lay eggs. Dogs protect buildings from intruders. But also very small dogs do not protect buildings from intruders.
(5)	`[KIND`$_{sub}$ `+ REL]`^{p} `[PROP]`^{C}	Birds can fly. For example, seagulls can fly. Dogs protect buildings from intruders. For example, pitbulls protect buildings from intruders. Ducks lay eggs. For example, female ducks lay eggs.
(6)	`[KIND + REL]`^{p} `[PROP`$_{sub}$`]`^{C}	Viruses are spread through body fluids. For example, viruses are spread through saliva. Dogs protect buildings from intruders. For example, dogs protect some private homes from intruders. Cowsheds are found on farms. For example, cowsheds are found on dairy farms.
(7)	`[KIND`$_{sub}$ `+ REL]`^{p} `[PROP`$_{sub}$`]`^{C}	Birds can fly. For example, Canadian geese fly long distances to migrate. Ostriches lay eggs. For example, female ostriches lay large spotted eggs. Elephants are found in zoos. For example, African elephants are found in most large zoos.

Table 15: Prompts for GPT-3 as Few-shot Baseline.