LexSym: Compositionality as Lexical Symmetry

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Abstract

In tasks like semantic parsing, instruction following, and question answering, standard deep networks fail to generalize compositionally from small datasets. Many existing approaches overcome this limitation with model architectures that enforce a compositional process of sentence interpretation. In this paper, we present a domain-general and model-agnostic formulation of compositionality as a constraint on *symmetries of data distributions* rather than models. Informally, we prove that whenever a task can be solved by a compositional model, there is a corresponding data augmentation scheme—a procedure for transforming examples into other well-formed examples—that imparts compositional inductive bias on *any* model trained to solve the same task. We describe a procedure called LexSym that discovers these transformations automatically, then applies them to training data for ordinary neural sequence models. Unlike existing compositional data augmentation procedures, LexSym can be deployed agnostically across text, structured data, and even images. It matches or surpasses state-of-the-art, task-specific models on COGS semantic parsing, SCAN and ALCHEMY instruction following, and CLEVR-CoGenT visual question answering datasets.

1 Introduction

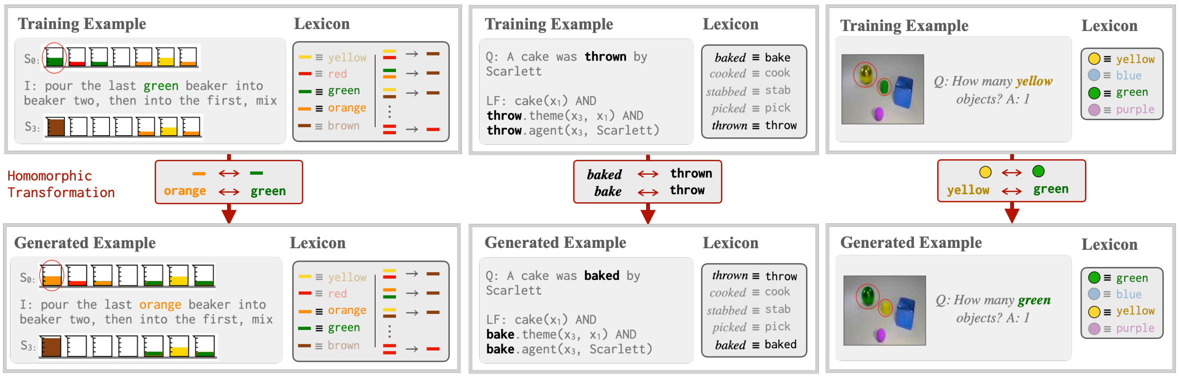
A central challenge in natural language processing is the design of models and learning algorithms that are simultaneously *flexible* enough to capture the variability of human language and *structured* enough to generalize in predictable and human-like ways. One important source of structure is the **principle of compositionality**, which (in one formulation) states that sentence meanings can be computed from a *lexicon* of word meanings and a set of *composition rules* governing how meanings combine (Montague, 1970b). A long line of language processing research has operationalized the principle of compositionality as a **constraint on model architectures**, via independence assumptions or parameter tying schemes that ensure a compositional process of sentence interpretation (Lewis and Stearns, 1968; Andreas et al., 2016). Compositional models enjoy sample-efficient learning and strong generalization in tasks from machine translation to question answering (McCoy et al., 2020).

But much of human language is not (or at least not straightforwardly) compositional. Idioms, disfluencies, and context-sensitive meanings present major challenges to models in which all predictions must derive from a sequence of local composition operations. In recent years, more generic model architectures such as recurrent neural networks (RNNs) and transformers, with no explicit compositional scaffolding, have consistently outperformed compositional models in language processing tasks with natural data (Wu et al., 2016). However, these models capture linguistic regularities only when trained on enormous amounts of data, and make surprising or problematic predictions when presented with novel word collocations or syntactic structures (Lake and Baroni, 2018).

How can we train unstructured neural sequence models that generalize compositionally? Recent work has introduced several *compositional data augmentation* schemes: rule-based procedures or learned models that synthesize artificial training examples to promote generalization (Andreas, 2020; Shaw et al., 2021; Akyürek et al., 2021; Zhang et al., 2022, *inter alia*). While often effective, existing methods are specialized to specific data modalities or datasets. The conditions under which they succeed, and their relationships to the formal principle of compositionality, have remained unclear.

This paper presents a framework for understanding and improving such data-centric approaches to compositional modeling. We first provide a mathematical characterization of the principle of compositionality as a **constraint on data distributions** rather than model architectures. Intuitively,

Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics
Volume 1: Long Papers, pages 639–657



(a) Alchemy: Instruction Following (b) COGS: Semantic Parsing (c) CLEVR-CoGenT: VQA

Figure 1: We extract a lexicon that relates words to their meanings in each dataset. We then find *homomorphic transformations* (Sec. 3) of this lexicon that, when applied to training examples, produce new, well-formed examples. (Note the changes in the generated examples)

we show that whenever a language understanding task can be solved compositionally, that task's data distribution is guaranteed to exhibit specific *symmetries*. These symmetries are functions that modify data points while preserving semantic acceptability. Fig. 1c gives an example of a symmetry in a visual question answering problem: in any well-formed (image, question, answer) triple, swapping the words *yellow* and *green* and their associated pixel values yields a valid new triple. Such symmetries exist even in complex tasks like instruction following (Fig. 1a), where they may depend not only on word-to-meaning mappings but relations *between* meanings (like the fact that red and green mix to produce brown).

Building on this formal link between compositionality and symmetry, we introduce a procedure called LEXSYM that discovers symmetries automatically, then uses them to synthesize new training examples guaranteed to be correct and informative. Crucially, LEXSYM does not require a complete compositional theory for a given problem domain—only a *lexicon* of word meanings. These lexicons may themselves be automatically derived for most tasks. This makes LEXSYM very flexible: it requires little or no task-specific engineering, can be combined with any predictor, and unlike other compositional data augmentation schemes does not require tree-structured or even sequential data.

Applied to ordinary neural sequence models, LEXSYM outperforms state-of-the-art models on the CLEVR COGENT visual question answering benchmark (Johnson et al., 2017) by a wide margin. LEXSYM is general, and matches or outperforms some specialized data augmentation schemes and models on the COGS semantic parsing task (Kim and Linzen, 2020; Kim et al., 2022), and the SCAN and ALCHEMY instruction following tasks (Lake and Baroni, 2018; Long et al., 2016).

This paper thus offers two contributions: a theoretical contribution, in the form of a new lens on the principle of compositionality via symmetries of data distributions; and an empirical contribution, in the form of a data augmentation scheme that improves generalization on diverse language understanding tasks. The recent success of data augmentation approaches highlight the fact that compositional inductive bias need not require compositional models. Our work formalizes and generalizes this "data-centric" account of compositionality.[1]

2 Background & Approach

We begin with a discussion on the more general role of *symmetry* in machine learning applications.

Definition 1. A **symmetry** of a set X is a function f satisfying:

$$\{f(\mathbf{x}) : \mathbf{x} \in X\} = X \tag{1}$$

That is, applying f to each element of X leaves X unchanged.

A familiar example from computer vision is *reflection symmetry*: in object recognition problems, image classes are generally invariant under reflection (a zebra seen in a mirror is still a zebra). The set of (image, class) pairs thus has as a symmetry the function $(\mathbf{x}, y) \mapsto (\texttt{reflect}(\mathbf{x}), y)$. In many domains, especially those (like computer vision and computational chemistry) that are constrained by physical laws, knowledge of the symmetries

[1]Code will be released after the anonymity period.

exhibited by a problem domain can dramatically reduce the difficulty of learning (Batzner et al., 2022; Simeonov et al., 2022).

Past work has incorporated symmetry into machine learning problems in two ways. **Invariant and equivariant modeling** approaches structurally enforce symmetries via specialized architectures (improving generalization by decreasing the size of the hypothesis class; Cohen and Welling, 2016). **Data augmentation** approaches generate new training examples by applying known symmetries like reflections directly to training data (improving generalization by increasing dataset size; Shorten and Khoshgoftaar, 2019). Data augmentation, the focus of this paper, is model-agnostic, and can be used in conjunction with pre-training while producing the same asymptotic effects as specialized model architectures (Chen et al., 2020).

The question this paper aims to answer is whether compositionality, like other domain-specific constraints, can be formalized in the language of symmetry. We are not the first to consider this question: Kiddon and Domingos (2015) define a theory of semantic equivalence in terms of symmetries of the set of natural language sentences, and Gordon et al. (2020) propose a model architecture for compositional semantic parsing via a symmetry that enforces *permutation invariance* of lexicon entries. LEXSYM also derives symmetries from lexicons. It builds on past work by (1) characterizing the algebraic relationship between compositionality and symmetry, explaining the effectiveness of both Gordon et al. (2020)'s approach as well as other data augmentation schemes based on token and phrase substitution (Andreas, 2020; Wang et al., 2018); (2) discovering symmetries automatically, and (3) showing how to leverage them in a model- and modality-agnostic way. Additional related work is discussed in Sec. 6.

3 Compositionality as Lexical Symmetry

Our main theoretical result, and the foundation of our modeling approach, can be stated as follows: *in any language understanding task that can be modeled compositionally, data for the task exhibits symmetries in the sense of Definition 1*. We explain, formalize, and prove this statement below.

We consider tasks defined by a space of possible examples $\mathcal{X}$, of which a subset of examples X are **well-formed**. We assume each example $\mathbf{x} \in \mathcal{X}$ is a discrete sequence $[x_1, \ldots, x_n]$, with x_i drawn from a vocabulary Σ. Finally, we assume that well-formedness can be computed by a a binary **interpretation function** $\mathcal{I} : \mathcal{X} \to \{0, 1\}$ with $\mathcal{I}(\mathbf{x}) = 1$ iff $\mathbf{x} \in X$. A wide variety of language understanding problems, from very simple to very complex, may be defined in this way:

Example 1a: *Arithmetic Language Modeling*. Examples $\mathbf{x}$ are true sentences of the form *a plus b is c*, where *a*, *b* and *c* are numbers: $\mathcal{I}$(*one plus two is three*) $= 1$ but $\mathcal{I}$(*two plus two is five*) $= 0$.

Example 1b: *Semantic Parsing*. Examples $\mathbf{x}$ are pairs $(\mathbf{x}_{\text{NL}}, \mathbf{x}_{\text{LF}})$, where $\mathbf{x}_{\text{NL}}$ is an sentence, $\mathbf{x}_{\text{LF}}$ is a logical form, and $\mathcal{I}(\mathbf{x}_{\text{NL}}, \mathbf{x}_{\text{LF}}) = 1$ iff $\mathbf{x}_{\text{LF}}$ represents a possible meaning of $\mathbf{x}_{\text{NL}}$ (Fig. 1b).

Example 1c: *Visual Question Answering*. Examples $\mathbf{x}$ are triples $(\mathbf{x}_{\text{Q}}, \mathbf{x}_{\text{I}}, \mathbf{x}_{\text{A}})$, where $\mathbf{x}_{\text{Q}}$ is a question, $\mathbf{x}_{\text{I}}$ is a (rasterized) image, $\mathbf{x}_{\text{A}}$ is an answer, and $\mathcal{I}(\mathbf{x}_{\text{Q}}, \mathbf{x}_{\text{I}}, \mathbf{x}_{\text{A}}) = 1$ iff $\mathbf{x}_{\text{A}}$ is the answer to $\mathbf{x}_{\text{Q}}$ in $\mathbf{x}_{\text{I}}$ (Fig. 1c).

Notice that the vocabulary Σ contains not just natural language words, but other kinds of data: logical symbols (1b) or even image patches (1c).

"Language understanding" in each of these tasks is encapsulated by the function $\mathcal{I}$. What does it mean for $\mathcal{I}$ to be *compositional*? Under most definitions, a compositional language understanding procedure should factorize into a lexicon, which captures meanings of words, and a composition procedure, which derives example-level interpretations from these meanings. We model word meanings in terms of *relations* between items in Σ. In arithmetic, to know the meaning of the word *five* is to know that it is a number, less than *seven*, the successor of *four*, etc. In semantic parsing, the meaning of the word *cat* is encapsulated by the fact that it is of the same type as *dog*, and translatable into the logical symbol `cat'`. We model this notion of word meaning by equipping Σ with extra structure describing these relations:

Definition 2. A **lexical algebra** is a collection of relations $r_1, \ldots, r_n$ between vocabulary items, where each $r : \Sigma^p \to \{0, 1\}$. A lexical algebra can represent type information, like "*dog* is a noun", as a unary relation; semantic correspondence, like "*sings* maps to `sing'`", as a binary relation; and richer semantic knowledge, like "*three* is the sum of *one* and *two*", with higher-order relations.

We may then represent individual examples in purely relational terms:

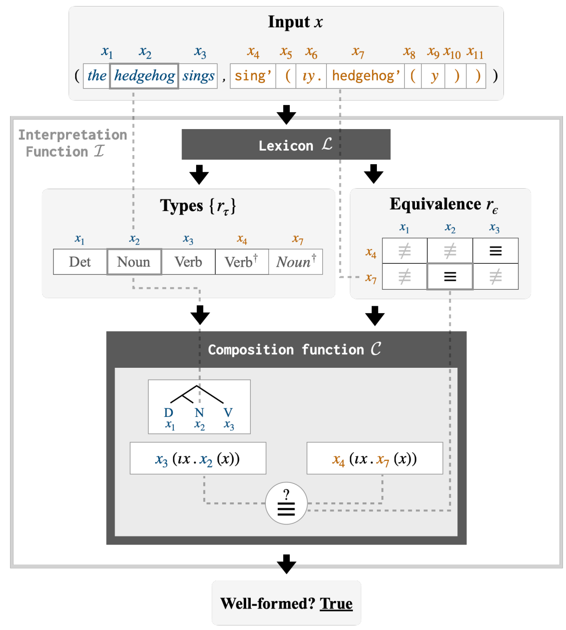


Figure 2: Idealized compositional semantic parser following Definition 3. A (sentence, logical form) pair is translated into a *lexical representation* containing information about each word's type and meaning. We then determine whether the sentence evaluates to the logical form using *only* the type and semantic correspondence matrices, using types to assign the sentence an abstract logical form, and correspondences to determine whether it matches the target.

Definition 3. Denote the **lexical representation** $\mathcal{L}(\mathbf{x}) = (R_1(\mathbf{x}), \dots, R_n(\mathbf{x}))$. $R(\mathbf{x})$ is an order-p tensor whose $(i, \dots, j)^{th}$ entry is equal to $r(x_i, \dots, x_j)$. (If r is a binary relation, $R(\mathbf{x})$ is an $|\mathbf{x}| \times |\mathbf{x}|$ matrix and $R(\mathbf{x})_{ij}$ specifies whether r holds between x_i and x_j.) See Fig. 2 for examples.

Finally, we use this relational representation to define compositionality of interpretation functions:

Definition 4. X is **$\mathcal{L}$-compositional** if $\mathcal{I}(\mathbf{x}) = \mathcal{C}(\mathcal{L}(\mathbf{x}))$ for some **composition procedure** $\mathcal{C}$. In other words, X is compositional if it compute the well-formedness of $\mathbf{x}$ from word-level meanings and a generic composition procedure.[2]

This definition makes no assumptions about $\mathcal{C}$ beyond the fact that it can be defined purely in terms of $\mathcal{L}(\mathbf{x})$. It can be applied to many tasks:

Example 2a: *Arithmetic Language Modeling*. Define r_1 to be the ternary relation $(a, b, c) \mapsto \mathbb{1}_{[a+b=c]}$. Then $\mathcal{C}$ takes an example and checks whether the index corresponding to its three number words is true in R_1.

Example 2b: *Semantic Parsing*. A sketch of a semantic parser factorizable into a lexicon and an abstract composition function is depicted in Fig. 2. As a real-world example, in the factored CCG semantic parser of Kwiatkowski et al. (2011), words are assigned types and logical forms via a lexicon. These logical fragments are then composed by a parsing algorithm that depends only their types.

Example 2c: *Natural Language Inference*. MacCartney and Manning (2014)'s Natural Logic framework provides a procedure for determining entailment relations between sentences via a set of sentence rewriting operations that use only word-level information about entailment relations.

Under Definition 4, a sentence interpretation procedure is compositional if the meaning of a sentence can be derived in a generic way ($\mathcal{C}$) from the meanings of its lexical items ($\mathcal{L}$).[3] We remark, finally, that the parsing procedure depicted in Fig. 2 is an idealization used to *motivate* our approach; our experiments use more flexible models.

We are now ready to describe how, for compositional $\mathcal{I}$, structure in $\mathcal{L}$ translates into structure in the set of well-formed examples X.

Definition 5. A function f is a **homomorphism of $(\Sigma, \mathcal{L})$** (an "$\mathcal{L}$-homomorphism") if:

$$\forall r \in \mathcal{L},\ \forall x_1 \dots x_p \in \Sigma : \\ r(x_1, \dots, x_p) = r(f(x_1), \dots, f(x_p)) \quad (2)$$

f "preserves the structure" of $\mathcal{L}$, ensuring that pairwise relationships are preserved among symbols. Fig. 1 shows examples: in (c), for instance, the words *yellow* and *green* and the corresponding colors must be *swapped* to satisfy Eq. 2.

Finally, we may state our main result:

Theorem 1. *If X is $\mathcal{L}$-compositional, f is an $\mathcal{L}$-homomorphism, and $\mathbf{x} \in X$, then $f(\mathbf{x}) = [f(x_1), \dots, f(x_n)] \in X$. Thus every homomorphism of $\mathcal{L}$ well-formed examples $\in X$.*

Proof. From Definition 3 and 5, $R_i(f(\mathbf{x})) = R_i(\mathbf{x})\ \forall i$. Then,

$$\begin{aligned} \mathbb{1}_{[f(\mathbf{x}) \in X]} &= \mathcal{I}(f(\mathbf{x})) \\ &= \mathcal{C}(\mathcal{L}(f(\mathbf{x}))) \\ &= \mathcal{C}(R_1(f(\mathbf{x})), \dots, R_n(f(\mathbf{x}))) \\ &= \mathcal{C}(R_1(\mathbf{x}), \dots, R_n(\mathbf{x})) \\ &= \mathcal{I}(\mathbf{x}) = \mathbb{1}_{[\mathbf{x} \in X]} \end{aligned}$$ ∎

[2] Every $\mathcal{I}$ is trivially $\mathcal{L}$-compositional with respect to an $\mathcal{L}$ that assigns every vocabulary item to a unique unary relation.

[3] As shown in Example 2b, it can be used to implement a language-to-logical form mapping, and thus generalizes the Montagovian definition of compositionality as a homomorphism from sentences to meanings (Montague, 1970a).

Corollary 1. *With the additional constraint that f is an $\mathcal{L}$-isomorphism (i.e., has an inverse), then f is a symmetry of X in the sense of Eq. 1.*

Here it suffices to show that the preimage of every $\mathbf{x} \in X$ is also in X; the proof is the same as Theorem 1 with f^{-1} in place of f.

Despite their simplicity, Theorem 1 and its corollary have an important consequence: if we can identify candidate entries in $\mathcal{L}$, *even if $\mathcal{C}$ is unknown*, we can construct new examples $\mathbf{x} \in X$ that respect, and provide evidence for, the compositional structure of X. There is an intriguing (if inexact) structural similarity between Corollary 1 and Noether's theorem (Noether, 1918), which establishes an equivalence between symmetries of physical systems and their conserved quantities. Here, such symmetries imply constraints not on conservation laws but interpretation functions.

4 LexSym: Data Augmentation with $\mathcal{L}$-homomorphisms

Given a lexicon describing symbols and their relations, we have shown how to turn homomorphisms of the lexicon into transformations of a dataset. Each such function f that takes an example $\mathbf{x}$ as input, replaces each token $x_i \in \mathbf{x}$ with a new one, and returns a well-formed example $\mathbf{x}'$ as output. Every $\mathcal{L}$-homomorphism may thus be viewed as a recipe for *synthesizing training examples* from a small initial training set (Japkowicz et al., 2000). However, to make this a practical modeling tool, we need some way of constucting $\mathcal{L}$-homomorphisms for a task of interest. Below, we describe how to do so automatically: first, starting with only a task-specific lexicon $\mathcal{L}$ (Sec. 4.1); next, starting with only a dataset and no initial lexicon (Sec. 4.2). We term the resulting approach **LexSym**.

4.1 Deriving Homomorphisms from Lexicons

Even in complex sequence modeling problems, useful lexicons are often simple enough that they can be specified by hand (Jones et al., 2012; Gordon et al., 2020). Given a pre-specified algebraic $\mathcal{L}$, there is a straightforward procedure for generating the associated symmetries by enumerating all functions $\Sigma \to \Sigma$ and testing which ones satisfy Eq. 2. (See Algorithm 1 in Appendix B.) This algorithm is inefficient, but simple and practical for small $|\mathcal{L}|$.

4.2 Deriving Lexicons from Datasets

For some tasks, it may be difficult to manually specify an algebraic lexicon. We next describe how to infer one automatically. We focus on an important and extremely common class of language understanding problems with special structure. In *semantic parsing* and *instruction following*, examples $\mathbf{x}$ consist of (input, output) pairs in which inputs are sentences, outputs are meaning representations, and word meaning is characterized by a lexicon with two components. First, a set of unary **type predicates** $\{r_\tau\}$ that assign words to types (like ENTITY in semantic parsing). Second, a **semantic correspondence relation** r_ϵ that specifies which actions or logical symbols can be derived from words (like *sings* $\to$ $\texttt{sing}'$). With n types, the lexicon required for these problems is $\mathcal{L} = (r_{\tau_1}, \ldots, r_{\tau_n}, r_\epsilon)$, which we abbreviate $(\{r_{\tau_k}\}, r_\epsilon)$ below. We now show how to improve upon the procedure in Sec. 4.1 by deriving $\mathcal{L}$ from data and sampling $\mathcal{L}$-homomorphisms in constant time.

Learning $\mathcal{L}$ We build on past work noting that dictionaries of semantic correspondences can be constructed using alignment algorithms (Brown et al., 1993). Given an input $\mathbf{x}$ consisting of a pair $(\mathbf{x}_{\text{text}}, \mathbf{x}_{\text{meaning}})$, we use existing algorithms to align tokens in individual training examples. Finally, we identify the most frequently occurring alignments and add these to the semantic correspondence relation. We may similarly use existing procedures to infer types by deriving them from part-of-speech tags or distributional patterns. See Appendix D for details of the alignment and type inference algorithms used in our experiments. These algorithms produce lexicons with three properties that are useful for the sampling scheme we describe next: types are *disjoint*, and semantic correspondences are *one-to-many* and *type-preserving* (if two words are of the same type, so are their translations).

Sampling $\mathcal{L}$-homomorphisms Once we have identified types and semantic correspondences, sampling $\mathcal{L}$-homomorphisms is straightforward:

Theorem 2. *Let x_i and $x_j \in \Sigma$ have the same type $r_\tau(x_i) = r_\tau(x_j) = 1$. For convenience, let $E_i = \{x : r_\epsilon(x_i, x) = 1\}$ denote possible translations of*

x_i. *The f is an $\mathcal{L}$-homomorphism:*

$$f(x) = \begin{cases} x_j & \textit{if } x = x_i \\ x_i & \textit{if } x = x_j \\ x' \in E_j & \textit{if } x \in E_i \\ x' \in E_i & \textit{if } x \in E_j \\ x & \textit{otherwise} \end{cases} \tag{3}$$

Proof is given in Appendix A. Theorem 2 yields an intuitive data augmentation procedure: select two (input, output) pairs of the same type, and *swap* them and any of their meanings wherever they occur. Fig. 1b shows an example. Eq. 3 is related to data augmentation schemes described by Andreas (2020) and Liu et al. (2021b), which synchronously *substitute* words or phrases (equivalent to removing cases 2 and 4). Unlike LEXSYM, these methods cannot guarantee correctness: in Fig. 1c, substituting *green* in place of *yellow* yields an image with two green objects and an incorrect answer.

5 Experiments

Our experiments aim to evaluate whether LEXSYM can improve compositional generalization in downstream models. The main goal of these experiments is to evaluate *generality* across tasks and data modalities. Evaluation focuses on three diverse classes of language understanding problems: complex, context-dependent computations (Sec. 5.1), large, automatically derived lexicons (Sec. 5.2), and multi-modal data (Sec. 5.3).

5.1 Complex computations

We first test LEXSYM on the ALCHEMY task from the SCONE benchmark (Long et al., 2016)—a problem involving a complex sentence interpretation procedure that makes it challenging to apply existing data augmentation schemes.

Data In ALCHEMY (Fig. 1a), models must execute a sequence of human-written English instructions $\boldsymbol{x}_{\text{ins}}^{1:\text{N}}$, on an initial state $\boldsymbol{x}_{\text{state}}^{0}$ consisting of beakers of colored liquids (textually represented as sequence of symbols "1: g g, 2: ..."), to predict the final state $\boldsymbol{x}_{\text{state}}^{N}$. Initial and final states are encoded as sequences of color tokens. Predicting final states requires both grounding colors in state variables (brown $\rightarrow$ b, red $\rightarrow$ g) and modeling what happens when colors are combined (e.g. mixing g and r yields b).

LEXSYM We manually construct a lexicon to showcase how to inject prior knowledge into LEXSYM. We encode word meaning in two relations: a semantic equivalence relation between color words and colors:

$$r_\epsilon(c_1, c_2) = \begin{cases} 1 & c_1 = \text{brown}, \quad c_2 = \text{b} \\ 1 & c_1 = \text{red}, \quad c_2 = \text{r} \\ 1 & c_1 = \text{green}, \quad c_2 = \text{g} \\ \vdots & \\ 0 & \text{otherwise} \end{cases}$$

and a ternary relation that encodes the result of mixing colors:[4]

$$r_{\texttt{mix}}(c_1, c_2, c_3) = \begin{cases} 1 & c_1 = c_2 = c_3 \\ 1 & c_1 \neq c_2 \wedge c_3 = \text{b} \\ 0 & \text{otherwise} \end{cases}$$

Together, $(r_\epsilon, r_{\texttt{mix}}, \{r_{\tau_k}\})$, where $\{r_{\tau_k}\}$ assigns different types to color words, colors, and remaining tokens. The homomorphic transformations of this lexicon exchange color words and colors but preserve mixing relations.

Models and Training We train an LSTM (Hochreiter and Schmidhuber, 1997) and fine-tune a T5 transformer (Raffel et al., 2020) on the sequence-to-sequence prediction problem $(\boldsymbol{x}_{\text{ins}}^{1:\text{N}}, \boldsymbol{x}_{\text{state}}^{0}) \rightarrow \boldsymbol{x}_{\text{state}}^{N}$ Training details may be found in Appendix C. We compare these baseline models to their LEXSYM-augmented versions as well as the existing compositional data augmentation scheme of Liu et al. (2021b).

Results See Table 1. LSTM+LEXSYM improves substantially over an LSTM. Preserving the homomorphism condition in Eq. 2 is extremely important: the procedure of Liu et al. (2021b), which naively substitutes aligned color pairs, actually *hurts* performance. Pre-trained models achieve strong initial results; combining pre-training with LEXSYM gives additional improvements.

5.2 Learned lexicons

We next show that for more conventional sequence-to-sequence problems, we may apply LEXSYM with automatically derived lexicons.

[4] In ALCHEMY, mixing non-identical colors produces b.

Model	ALCHEMY	SCAN (*jump*)	SCAN (*around right*)	COGS	COGS (nonce)
Previous Work on COGS & SCAN					
GECA (Andreas, 2020)	–	99.94 ± 0.10	98.50 ± 1.90	47.74 ± 4.52	–
LeAR (Liu et al., 2021a)	–	–	–	97.70 ± 0.70	–
LexLSTM (Akyurek and Andreas, 2021)	36.80 ± 1.96	99.14 ± 1.55	88.41 ± 7.35	82.17 ± 0.72	81.40 ± 0.40
No Pre-training					
LSTM	41.72 ± 1.15	0.41 ± 0.34	8.65 ± 4.52	61.13 ± 4.12	61.13 ± 4.12
+ Substitute (e.g. Liu et al., 2021b)	40.52 ± 0.84	99.95 ± 0.10	99.17 ± 0.93	81.99 ± 0.50	77.62 ± 0.78
+ LEXSYM	45.85 ± 2.00	100.00 ± 0	99.51 ± 0.48	81.86 ± 0.90	77.25 ± 0.34
Language Pre-training					
T5	84.95 ± 0.44	93.60 ± 0	38.40 ± 0.90	83.30 ± 0.10	64.20 ± 2.00
+CSL-Aug* (Qiu et al., 2022)	–	99.70 ± 0	–	99.50 ± 0	–
+LEXSYM	85.48 ± 0.16	99.96 ± 0.03	97.29 ± 2.16	83.62 ± 0.27	76.74 ± 2.23

Table 1: Results on semantic parsing and instruction following. We provide mean and standard deviations over 5 random seeds. LEXSYM improves significantly over baselines, with and without large-scale pretraining.
*Uses a customized formal representation.

	COGENT	CLEVR
Visual Pre-training		
Human (Johnson et al., 2017)	–	92.6
Film (Perez et al., 2018)	78.8	97.7
S-MAC (Marois et al., 2018)	78.7	98.9
NSVQA (Yi et al., 2018)	63.9	99.7
Seq2Seq Baselines		
T5	79.7	–
LexLSTM	62.1	–
No Pre-Praining		
VQATransformer	73.3 ± 1.0	93.6 ± 0.5
+ Substitute (e.g. Liu et al., 2021b)	84.4 ± 0.7	90.8 ± 0.3
+ LexSym	85.9 ± 0.9	92.0 ± 0.9

Table 2: Exact match accuries on the CLEVR and CLEVR-COGENT validation sets. Results are averaged over 4 seeds. We obtain state-of-the-art results after applying LEXSYM to a (non-pretrained) sequence model. LEXSYM also yields higher accuracies than synchronous token *substitution*. (A detailed breakdown by question category is presented in Table 4).

Data We study two standard compositional generalization benchmarks: the SCAN (Lake and Baroni, 2018) instruction following and COGS (Kim and Linzen, 2020, Fig. 1b) semantic parsing datasets. SCAN consists of simple instruction following tasks in which strings are translated into sequences of actions. We focus on the *jump* split, which measures models' ability to compose words that only appeared in isolation during training, and the *around right* split, which measures generalization to novel collocations. The COGS dataset tests compositional generalization in semantic parsing. The dataset includes English (sentence, logical form) pairs, with systematic differences between train and test set sentence structure. We include a variant containing nonce words (Kim et al., 2022) to disentangle general compositional skills from lexical knowledge acquired during pre-training. See Appendix G for dataset statistics.

LEXSYM We use automatic lexicon extraction to find semantic correspondence relations (r_ϵ) and types ($\{r_{\tau_k}\}$) as described in Appendix D. Next, we apply swap-based augmentation (Eq. 3).

Models We use the same models as Sec. 5.1, along with a strong semi-structured model, LeAR (Liu et al., 2021a) tailored for COGS, and another substitution based augmentation (Andreas, 2020) tailored for SCAN. Following Akyurek and Andreas (2021), we equip the LSTM for COGS with a copy mechanism as it achieves significantly better results than Kim and Linzen (2020)'s baseline.

Results On SCAN, LEXSYM obtains near-perfect accuracy in both *jump* and *around right* splits. On the original COGS datasets, LEXSYM substantially outperforms the LSTM model and GECA augmentation, and is comparable to a neural sequence model specialized for lexical generalization (LexLSTM). Stronger results can be achieved with models specifically tailored toward semantic parsing tasks (LeAR). In both tasks, LEXSYM also improves upon large-scale pre-training.

5.3 Multi-modal data

Finally, we combine learned lexicons with non-sequential data to advance the state of the art on a long-standing visual question answering challenge.

Data The CLEVR dataset (Johnson et al., 2017, Fig. 1c) contains English-language questions about generated 3D scenes containing multiple objects.

Questions involve complex computational operations including quantification, comparison, and spatial reasoning. CLEVR has been a popular testbed for evaluating composition in visual question answering models. Our main experiment uses the COGENT split of the dataset, which focuses on compositional generalization. In the CLEVR-COGENT training set (Split A), which contains roughly $700K$ (question, image, answer) triples, all cubes are gray, blue, brown or yellow, while all cylinders are red, green, purple or cyan. In the test set (validation set of Split B), these are reversed.

LEXSYM In VQA and other multi-modal tasks, part of the input is continuous (e.g. images and videos). Recent work has shown that it is possible to *learn* high-quality discrete representations of continuous input data. For example, in the VQ-VAE model of van den Oord et al. (2017), a continuous image is transformed into a grid of categorical codes, with individual codes representing color, and in some cases materials and illumination (examples in Table 3). We use this discretization procedure for our experiments (see Appendix C.1 for details). We use the same algorithm as previous section to extract lexical relations.

Models Most prior work on visual question answering has used pre-trained convolutional networks to encode images, and recurrent networks to encode questions and generate answers. For experiments on CLEVR, we use a simplified model in which both questions and images are mapped to answers by a transformer model, similarly to Ramesh et al. (2021). See Appendix C.2 for details.

Both LEXSYM augmentation and this VQA-Transformer model operate over sequences of discrete visual codes produced by a vector-quantized variational autoencoder. Once these discrete representations have been produced, we infer lexicons and perform data augmentation directly to these representations, without re-synthesizing images (though such synthesis is possible, as in Table 3, to interpret model behavior).

The COGENT task is very different from the sequence modeling tasks discussed above: inputs contain many tokens, and the training set is orders of magnitude larger. GECA and CSL-Aug, which have a high polynomial dependence on sequence length, could not be applied as they fail to terminate within a reasonable amount of time.

Results In Table 2, a transformer model with LEXSYM achieves state-of-the-art results on the CLEVR-COGENT dataset, reducing errors by roughly 33% relative to the best existing system. LEXSYM also outperforms substitution based-data augmentation (Liu et al., 2021b), particularly on semantically complex utterances involving quantification (App. Table 4). On the IID CLEVR split, LEXSYM's performance is comparable to humans, and somewhat behind pre-trained models.

6 Other Related Work

Lexicalized neural models Word-level alignments between input and output sequences were an essential feature of statistical phrase- and tree-based sequence models (Chiang et al., 2005; Koehn et al., 2003). Neural scoring functions were sometimes integrated into these models (Misra and Artzi, 2016). Neural models with attention (Bahdanau et al., 2015) do not require explicit alignment, though several pieces of past work have shown that incorporating explicit token-level correspondences improves generalization (Akyurek and Andreas, 2021; Prabhu and Kann, 2020; Pham et al., 2018). The semantic correspondence function in Sec. 4 plays the same role as the input–output dictionary in these methods, but LEXSYM as a whole is more general: it is not restricted to modeling sequence-to-sequence problems, and can infer and exploit correspondence relations between component of an example. To the best of our knowledge, this paper is also the first to make use of token-level alignments in joint neural models of text and images.

Compositionality in representation learning While we have focused on compositionality as a property of data distributions or interpretation functions, another line of work in machine learning and language evolution has studied compositionality as an emergent property of learned representations (Andreas, 2019; Resnick et al., 2019; Brighton and Kirby, 2006). In settings where representational compositionality is desirable (e.g. to train communication protocols that can generalize to new states), LEXSYM might provide a tool for promoting it.

Equivariant Sequence Models As mentioned in Sec. 2, our work builds on existing approaches that control generalization with specialized model architectures designed to be equivariant to permutations of a pre-specified lexicon (if $f(x_1 \cdots x_n) = y_1 \cdots y_m$ then

$f(\pi(x_1)\cdots\pi(x_n)) = \pi(y_1)\cdots\pi(y_m)$ for a permutation π) (Gordon et al., 2020; White and Cotterell, 2022). LEXSYM differs from these approaches in three ways. First, LEXSYM is model-agnostic and compatible with pre-training. Second, LEXSYM is compatible with (and automatically derives transformations for) more complicated relations than input–output correspondences, making it possible to apply to tasks like ALCHEMY where such relations are important. Finally, LEXSYM gracefully handles (possibly noisy) learned lexicons, making it applicable to tasks like COGENT with complex or uninterpretable token mappings.

Data Augmentation Data augmentation approaches are widely used across machine learning application domains featuring known invariances of the data distribution (Japkowicz et al., 2000; Jia and Liang, 2016; Shaw et al., 2021). Substitution-based schemes that replace words with synonyms, or synchronously replace words and their translations, are widely used for machine translation and general de-biasing (Liu et al., 2021b; Wang et al., 2018; Wei and Zou, 2019).

7 Limitations and Future Directions

While Sec. 3 characterizes the effect of general $\mathcal{L}$-homomorphisms, LEXSYM specifically produces single-token swaps. In images represented as discrete symbol sequences, if a single symbol simultaneously encodes multiple visual features (e.g. color and texture), these features will remain entangled in synthesized examples. It will not exchange substructures larger than a single token, and thus will not synthesize examples longer than those already present in the training set (Lake et al., 2019). This is because LEXSYM targets compositionality but not *recursion*, which is also required to model the full range of human-like generalizations in sequence learning problems.

LEXSYM is also sensitive to the nature of the tokenization scheme itself. In morphologically rich languages, for example, LEXSYM may need to be applied not on top of words or segments, but instead canonicalized morphemes produced by learned morphological analyzers (Narasimhan et al., 2015; Bergmanis and Goldwater, 2017; Cotterell and Schütze, 2018) (analogous to the use of learned image patch representations rather than pixels in our VQA experiments).

Finally, LEXSYM does not induce some of the generalizations obtained other methods for improving compositional generalization, especially those that exploit extra structure (e.g. tree-shaped inputs and outputs) in the semantic parsing domain (e.g. Liu et al., 2021a). It might serve as a platform for future versions of those methods that offer greater generality and formal guarantees.

8 Conclusion

We have presented LEXSYM, a new data augmentation method that improves compositional generalization of neural models in multiple domains. LEXSYM is derived from a characterization of the principle of compositionality as a constraint on the symmetries of data distributions, and a procedure for automatically identifying these symmetries using token-level alignments. Our results highlight the fact that many inductive biases targeted by specialized models in NLP can be alternatively, and often more flexibly, expressed as a hypothesis about the structure of the distribution to be modeled.

Acknowledgements

This work was supported by the Machine-LearningApplications initiative at MIT CSAIL, the MIT–IBM Watson AI lab, and the National Science Foundation under grant CCF-2217064. Computing resources were provided by a gift from NVIDIA through the NVAIL program and by the Lincoln Laboratory Supercloud.

Ethics Statement

We do not anticipate any ethical issues associated with the techniques decribed in this paper.

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A Proof of Theorem 2

Proof. The lexicons that we learn only unary type relations and a semantic correspondence relation $\mathcal{L} = (\{r_{\tau_k}\}, r_\epsilon)$. As noted there, we make the following additional assumptions (satisfied by our lexicon learning algorithms):

(i) *Types are disjoint*, i.e. every symbol belongs to a single type: $\forall_x \in \Sigma, |\tau_x| = |\{r_{\tau_k} \mid r_{\tau_k}(x) = 1\}| = 1$.

(ii) *Semantic correspondences are one-to-many from text to meaning*. This means that no two text symbols can translate into the same meaning symbol: $E_i \cap E_j = \mathbb{1}_{x_i = x_j}$ and all $r_\epsilon(x \notin \mathbf{x}_{\text{text}}, y) = r_\epsilon(y, x \notin \mathbf{x}_{\text{meaning}}) = 0$.

(iii) *Semantic correspondence is type preserving*: all symbols in a correspondence class have the same type $\tau_{e_i \in E_i} = \{r_{\tau_{E_i}}\}$.

To show that f is an $\mathcal{L}$-homomorphism, we want to show that $r_\epsilon(f(x_1), f(x_2)) = r_\epsilon(x_1, x_2)$ for any x_1, x_2. The transformation function and all the definitions are symmetric to indices i and j ($i - j$ symmetry), so it is sufficient to show the correspondence relations stay the same for below cases only:

(a) $x_1 = x_i, x_2 = x_i$:

$$r_\epsilon(f(x_i), f(x_i)) = r_\epsilon(x_j, x_j) = 0 = r_\epsilon(x_i, x_i)$$

(by ii)

(b) $x_1 = x_i, x_2 = x_j$:

$$r_\epsilon(f(x_i), f(x_j)) = r_\epsilon(x_j, x_i) = 0 = r_\epsilon(x_i, x_j)$$

(by ii)

(c) $x_1 = x_i, x_2 \in E_i$:

$$\begin{aligned} r_\epsilon(f(x_i), f(x_2)) &= r_\epsilon(x_j, x' \in E_j) \\ &= 1 = r_\epsilon(x_i, x_2) \end{aligned}$$

(by definition of E_i and E_j)

(d) $x_1 = x_i, x_2 \in E_j$:

$$\begin{aligned} r_\epsilon(f(x_i), f(x_2)) &= r_\epsilon(x_j, x' \in E_i) \\ &= \mathbb{1}_{x_i = x_j} = r_\epsilon(x_i, x_2) \end{aligned}$$

(by ii)

(e) $x_1 = x_i, x_2 \notin \{\{x_i\} \cup \{x_j\} \cup E_i, E_j\}$:

$$\begin{aligned} r_\epsilon(f(x_i), f(x_2)) &= r_\epsilon(x_j, x_2) \\ &= 0 = r_\epsilon(x_i, x_2) \end{aligned}$$

(f) $x_1 = x_i, x_2 \notin \{\{x_i\} \cup \{x_j\} \cup E_i, E_j\}$:

same steps as (e)

(g) $x_1 \in E_i, x_2 = x_i$:

$$\begin{aligned} r_\epsilon(f(x_1), f(x_i)) &= r_\epsilon(x' \in E_j, x_j) \\ &= 0 = r_\epsilon(x_1, x_i) \end{aligned}$$

(by ii)

(h) $x_1 \in E_i, x_2 = x_j$: *same steps as (g)*

(i) $x_1 \in E_i, x_2 \in \{\{x_i\} \cup \{x_j\} \cup E_i, E_j\}$:

$$\begin{aligned} r_\epsilon(f(x_1), f(x_2)) &= r_\epsilon(x' \in E_j, x_2) \\ &= 0 = r_\epsilon(x_1, x_2) \end{aligned}$$

(by ii)

Finally, we require $r_\tau(x) = r_\tau(f(x))$ for any x and τ. Since we assume all items in E_i belong to a type matching x_i (likewise for j), and types are disjoint, this follows immediately from the definition of f, which only swaps symbols of the same type. ∎

B Enumerating $\mathcal{L}$-homomorphisms

A simple algorithm is given below:

Algorithm 1 $\mathcal{L}$-homomorphism enumeration

```
input: Lexicon L = (Σ, r_1, ..., r_n)
for f ∈ Σ^Σ do
    h ← 1
    for i = 1..n, x_a..x_b ∈ Σ^p do
        if r(x_a, ..., x_b) ≠ r(f(x_a), ..., f(x_b)) then
            h ← 0
        end if
    end for
    if h then
        yield f
    end if
end for
```

C Implementation Details

C.1 VQVAE Details

We use a discrete variational auto-encoder (van den Oord et al., 2017) to encode the images 16×16 grids of discrete codes. We used a code-book with $n = 32$ tokens associated with $d = 64$ dimensional

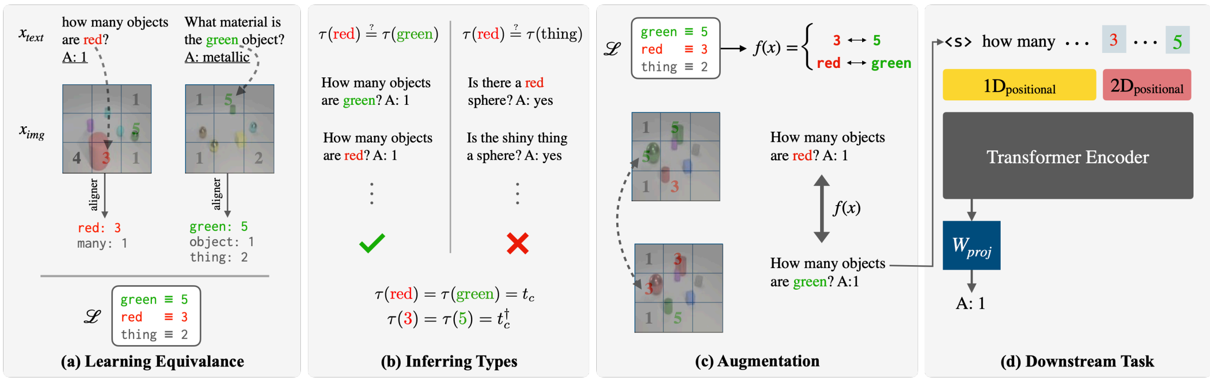


Figure 3: Overview of our approach in VQA. We discretize images using a VQVAE (van den Oord et al., 2017) learned from the training data. This discretization represents every image as a sequence of categorical codes. (a) We run a statistical aligner on ($\mathbf{x}_{\text{text}}$, $\mathbf{x}_{\text{img}}$) pairs to find word–visual token alignments within individual examples, then use these alignments to construct a global lexicon. (b) Each entry in the lexicon is assigned a type based on the context in which it occurs. (c) Next, we find *homomorphisms* of this lexicon, and use these as data augmentation functions to generate new training examples. (d) Finally, we train a neural sequence model on the augmented dataset.

learned latent vectors. The original image size $(480, 320)$ is cropped to $(440, 300)$ and resize our images into $(128, 128)$ pixels. The encoder convolutional neural network has three down-sampling layers which output $16 \times 16 \times d$ size hidden representations. For encoder and decoder CNN architectures, we follow the implementation provided in a public Pytorch implementation[5] by adding one more up-sampling and down-sampling layer to adjust our image size.

We use exponential moving average to update latent vectors as in official implementation[6] We train the model on the images of the same training data and did not use any external data.

We use batch size of 512, and learning rate 0.0003 with the Adam optimizer (Kingma and Ba, 2015). We clip the gradients to 5.0. Hyperparameters were selected by sweeping d over $\{64, 128\}$, image sizes over $\{128, 144\}$, and n over $\{24, 32, 48\}$ to maximize the the number of aligned tokens in the lexicon. For each experiments in Table 2, we run VQVAE for 4 random seeds and select the codebook that gives the largest IBM model likelihood for training data. Each experiment takes 10 hours in 4 NVIDIA V100 GPUs.

[5] https://github.com/ritheshkumar95/pytorch-vqvae

[6] https://github.com/deepmind/sonnet/blob/v2/sonnet/src/nets/vqvae.py

C.2 VQA Transformer Details

The Transformer takes tokenized images $\boldsymbol{x}_I$ and the question $\boldsymbol{x}_Q$ and outputs answers as follows:

$$
\begin{aligned}
c_{\mathbf{x}_I} &= \text{VQVAE}_{\text{enc}}(\mathbf{x}_I) \\
e_Q &= W_Q \mathbf{x}_Q + \text{1D}_{\text{positional}}(\mathbf{x}_Q) \\
e_{\mathbf{x}_I} &= W_c c_{\mathbf{x}_I} + \text{2D}_{\text{positional}}(c_{\mathbf{x}}) \\
h &= \text{Transformer}([e_Q \; e_{\mathbf{x}_I}]) \\
\boldsymbol{x}_A &= \operatorname{argmax} \operatorname{softmax}(W_{\text{proj}} h_{\text{start}})
\end{aligned} \tag{4}
$$

We follow the hyper-paramters provided in (Popel and Bojar, 2018). Transformers have 4 heads, 512-dimensional hidden vectors (same with embedding sizes) and 10 layers. We provide the dimensions in Eq. 4:

$$
\begin{aligned}
\mathbf{x}_I &: 3 \times 128 \times 128 \\
c_{\mathbf{x}_I} &: 32 \times 16 \times 16 \\
W_c &: 512 \times 32 \\
e_{\mathbf{x}_I} &: 512 \times (16 \times 16) \\
e_Q &: 512 \times |V_{text}| \\
W_Q &: 512 \times |\mathcal{V}_{\text{text}}| \\
h &: 512 \times (|Q| + 16 \times 16) \\
h_{\text{start}} &: 512 \times 1 \\
W_{\text{proj}} &: 512 \times |\mathcal{V}_{\text{text}}|
\end{aligned} \tag{5}
$$

Models are trained using the Adam optimizer with and Noam learning rate scheduler (Vaswani et al., 2017) with $lr = 1.0$ and $16k$ warming steps as provided in Popel and Bojar (2018). We use a batch size of 1024 and we train for $200k$ steps, which takes 48 hours on 8 NVIDIA V100 GPUs. In Fig. 3, we provide the sketch of overall pipeline.

C.3 Baselines: LSTM Details

We use the implementation provided by (Akyurek and Andreas, 2021), increasing the number of training iterations from $8k$ to $15k$ for augmented training runs in COGS, SCAN datasets. For the ALCHEMY dataset, we optimize iteration count over $\{8k, 15k, 25k, 50k\}$ based on validation accuracy, and found $25k$ to be optimal. For the CLEVR dataset, we optimize itreation count over $\{8k, 15k, 25k, 50k\}$ for CLEVR and CLEVR-COGENT dataset based on CLEVR's validation accuracy.

C.4 Baselines: T5 Details

We use the Huggingface (Wolf et al., 2019) implementation T5-base model. The difference between our T5 baselines results and the results in Qiu et al. (2022) due to their usage of different intermediate representation for the output in order to keep our evaluation consistent with other previous work. We try to optimize (learning rate, learning rate scheduler) and training parameters (iteration count) of Qiu et al. (2022) and (Akyurek and Andreas, 2021), use the best setting for the given dataset.

C.5 Alignment Model Details

In our experiments, we use the best alignment method reported in (Akyurek and Andreas, 2021), which is IBM Model 2 for all datasets except the SCAN dataset that uses their proposed algorithm, to obtain our initial alignments $\mathcal{A} = \{(x_i, x_j)$: set of tuples contains aligned tokens. We run alignment algorithms between $\mathbf{x}_{\text{text}}$ and $\mathbf{x}_{\text{meaning}}$. For SCAN and COGS, $\mathbf{x}_{\text{text}}$ is the actual inputs, $\mathbf{x}_{\text{meaning}}$ is the actual outputs. In ALCHEMY, $\mathbf{x}_{\text{text}}$ is instructions, $\mathbf{x}_{\text{meaning}}$ is beaker states. In VQA experiments, $\mathbf{x}_{\text{text}}$ question and answer words, $\mathbf{x}_{\text{meaning}}$ VQVAE codes. We disable *diagonalization* in FastAlign as it includes non-language structured VQVAE codes.

D Lexicons

D.1 Lexicon Learning

Extracting semantic correspondences $r_\epsilon(x_i, x_j)$ Given the initial alignments $\mathcal{A}$ in Appendix C.5, we remove every x_j that is not aligned to at least 1% of occurrences of x_i in the dataset. We then produce a *one-to-many* lexicon by deleting lexicon entries (x_i, x_j) and (x'_i, x_j) when both exist. With, these alignment creates entries in $r_\epsilon(x_i, x_j) = \mathbb{1}_{(x_i,x_j)\in\mathcal{A}}$

Extracting Types $\mathbf{r}_\tau(\mathbf{x})$ Given the partition of the data points $(\mathbf{x}_{\text{text}}, \mathbf{x}_{\text{meaning}})$, our type finding algorithm is essentially *unsupervised clustering* of the text symbols in $\mathbf{x}_{\text{text}}$. The types of matching $\mathbf{x}_{\text{meaning}}$ symbols are automatically determined by the correspondence relation, r_ϵ found above. In all our datasets $\mathbf{x}_{\text{text}}$ is English, so the symbols that goes into following clustering algorithm are actual words.

Following Clark and Eyraud (2007) and Andreas (2020), we assign types to individual words based on their environments. For each symbol, $x \in \Sigma$, that has at least one equivalent symbol in $\mathcal{A}$, we define the context $\kappa(x) = \{(\alpha, \beta) : \alpha x \beta \in X\}$: the set of strings (α, β) that appear surrounding x in the training set. (If the two examples in Fig. 1 formed the entire training set, we would have $\kappa(\textit{yellow}) = \kappa(\textit{green}) = \{(\textit{Q: How many}, \textit{objects? A: 1})\}$.).[7] We then represent Σ as a graph with an edge between each x_i and x_j where $\kappa(x_i) \cap \kappa(x_j) \neq \emptyset$ (Clark and Eyraud's *syntactic congruence* relation) and x_i and x_j has same part-of-speech tag according to spaCy pipeline with `en-core-web-lm` language model[8]. We assign each connected component of this graph a distinct type. This is only one possible approach to typing; alternatives might use clustering of distributed representations.

D.2 Extracted Lexicons

In this section, we present lexicon entries for symbols that we learned through our typing algorithm.

SCAN We present equivalance relations that we extracted from SCAN training dataset.

[7] The environment's window size $w = |\alpha| = |\beta|$ is a fixed hyper-parameter similar to Andreas (2020). We optimize it over $w \in \{1, 2, 5, 10, 15\}$ in ALCHEMY dataset (used $w = 10$) by using the validation set, in CLEVR and CLEVR-COGENT based on CLEVR's validation set (used $w = 10$). For COGS and SCAN datasets, we resort $w = 1$ to enable learning of extremely rare items.

[8] https://github.com/explosion/spacy-models/releases/tag/en_core_web_lg-3.5.0

Source symbol	Type	Target Symbol(s)
jump	t_1	I_JUMP
walk	t_1	I_WALK
run	t_1	I_RUN
look	t_1	I_LOOK
left	t_2	I_LEFT
right	t_2	I_RIGHT

COGS Since the extracted lexicon is large for semantic parsing, we present only some of the equivalance relations that we extracted from COGS training data for reference.

Source symbol	Type	Target Symbol(s)
baked	t_1	bake
noticed	t_1	notice
helped	t_1	help
dog	t_2	dog
boy	t_2	boy
sailor	t_2	sailor

COGENT We present equivalance relations that we extracted CLEVR-COGENT training data. The lexicon we found includes all the color symbols. The target symbols given here are learned VQVAE codes. In Appendix E, we show these codes on top of the images to qualitatively verify the alignments.

Source Symbol	Type	Target Symbols
red	t_1	9
purple	t_1	25, 29
cyan	t_1	28
blue	t_1	20
green	t_1	11
yellow	t_1	23, 18
gray	t_1	6
brown	t_1	2

E Samples & Statistics

We present examples generated by LEXSYM in Table 3. As we performed augmentation random and online during training, and we do not have a static augmented set to calculate statistics for. Instead, we run a single iteration of our augmentation function over all examples with our augmentation function and obtain following statistics:

Augmentation Statistics	COGS	CLEVR	SCAN	ALCHEMY
# Augmented samples	24155	699960	14670	18285
# Novel samples	23301	548277	7304	11786
# Unique novel samples	22617	548277	4851	11786
# Samples in test	121	0	7304	0
# Unique samples in test	109	0	4851	0

Note that, in CLEVR, we consider the novelty based on (question + answer) string since the generated image codes can be novel but the resulting image not. The following differences are significant under a paired t-test:

E.1 Statistical Significance Tests for Table 1

The following differences in Table 1 are significant under a paired t-test:

Alchemy:

- T5+LEXSYM > T5 ($p < 0.05$)
- LSTM+LEXSYM > LSTM+Substitute, LSTM, LexLSTM ($p < .00001$)

COGS:

- T5+LEXSYM > T5 ($p < .00001$)
- LSTM+LEXSYM > LSTM, ($p < .00001$)

F CLEVR-COGENT Detailed Results

COGENT results are presented in Table 4.

G Data

For CLEVR-COGENT (Johnson et al., 2017), we use training set for Split-A as our training set, validation set for Split-B as our validation set, and validation set of Split-B as our test set. The CLEVR and ALCHEMY datasets is released under the Creative Commons CC BY 4.0 license. The COGS datasets (Kim and Linzen, 2020; Kim et al., 2022) are released under MIT license. SCAN (Lake and Baroni, 2018) datasets are released under BSD license. The train, validation and test set sizes are given as below.

Generated Sentence	Generated Logical form	Original Sentence	Original Example Logical Form
A cake was baked by Scarlett .	`cake(`x_1`) AND bake.theme(`x_3`, `x_1`) AND bake.agent (`x_3`, Scarlett )`	*A cake was stabbed by Scarlett .*	`cake(`x_1`) AND stab.theme (`x_3`, `x_1`) AND stab.agent (`x_3`, Scarlett )`
The bunny needed to cook .	`*bunny(`x_1`); need.agent(`x_2`, `x_1`) AND need.xcomp (`x_2`, `x_4`) AND cook.agent(`x_4`, `x_1`)`	*The girl needed to cook .*	`*girl (`x_1`); need.agent (`x_2`, `x_1`) AND need.xcomp(`x_2`, `x_4`) AND cook.agent (`x_4`, `x_1`)`
The bun hunted Emma .	`*bun(`x_1`); hunt.agent(`x_2`, `x_1`) AND hunt.theme (`x_2`, Emma)`	*The teacher hunted Emma .*	`*teacher(`x_1`); hunt.agent(`x_2`, `x_1`) AND hunt.theme(`x_2`, Emma)`

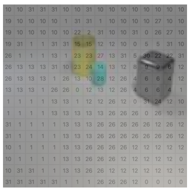
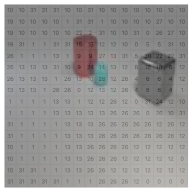
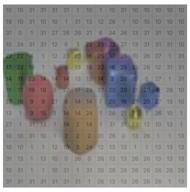
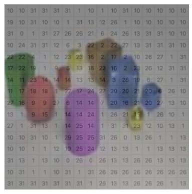
Generated Text	Generated Image	Original Text	Original Image
How many metallic objects are either tiny yellow things or blocks? *A: 1*		*How many metallic objects are either tiny red things or blocks?* *A: 1*	
What is the size of the other object that is the same material as the big brown thing *A: Large*		*What is the size of the other object that is the same material as the big purple thing?* *A: Large*	

Table 3: Generated samples for CLEVR-COGENT and COGS datasets. In CLEVR-COGENT, our method operate on displayed VQVAE symbols on top of the images and we can decode it to actual images as displayed here. The generated yellow cylinder in the first row is an unseen color+shape combination.

	CLEVR-COGENT					
VQATransformer (No Pre-Praining)						
Baseline	73.3 ±1.0	71.0 ±1.6	85.7 ±0.74	83.5 ±0.1	64.4 ±0.7	81.4 ±1.2
+ Substitute (e.g. Liu et al., 2021b)	84.4 ±0.7	76.7 ±1.1	89.5 ±0.3	88.8 ±0.3	**85.1** ±1.0	88.0 ±0.6
+ LexSym	**85.9** ±0.9	**80.1** ±0.9	**91.1** ±0.5	**91.0** ±0.7	**85.2** ±1.3	**88.9** ±0.7

Table 4: Breakdown of CLEVR-COGENT Results

Dataset	Train	Validation	Test
ALCHEMY	18285	1225	4495
SCAN			
(jump)	14670	–	7706
(around right)	15225	–	4476
COGS			
(original)	24155	3000	21000
(nonce)	24155	3000	21000
CLEVR			
(original)	699989	149991	
(CoGenT)	699960	–	150000

ACL 2023 Responsible NLP Checklist

A For every submission:

☑ A1. Did you describe the limitations of your work?
8 (Limitations)

☑ A2. Did you discuss any potential risks of your work?
9 (Impact Statement)

☑ A3. Do the abstract and introduction summarize the paper's main claims?
Left blank.

☒ A4. Have you used AI writing assistants when working on this paper?
Left blank.

B ☑ Did you use or create scientific artifacts?

Left blank.

☑ B1. Did you cite the creators of artifacts you used?
Left blank.

☑ B2. Did you discuss the license or terms for use and / or distribution of any artifacts?
Left blank.

☐ B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?
Not applicable. Left blank.

☐ B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?
Not applicable. Left blank.

☑ B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?
Left blank.

☑ B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.
Left blank.

C ☑ Did you run computational experiments?

Left blank.

☑ C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?
Left blank.

The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.

☑ C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
Left blank.

☑ C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
Left blank.

☑ C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
Left blank.

D ☒ Did you use human annotators (e.g., crowdworkers) or research with human participants?

Left blank.

☐ D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?
Not applicable. Left blank.

☐ D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants' demographic (e.g., country of residence)?
Not applicable. Left blank.

☐ D3. Did you discuss whether and how consent was obtained from people whose data you're using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
Not applicable. Left blank.

☐ D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
Not applicable. Left blank.

☐ D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
Not applicable. Left blank.