Formal Specifications from Natural Language

Christopher Hahn[*]
Stanford University
Stanford, CA, USA
hahn@cs.stanford.edu

Frederik Schmitt[*]
CISPA Helmholtz Center for Information Security
Saarbrücken, Germany
frederik.schmitt@cispa.de

Julia J. Tillman[*]
Saarland University
Saarbrücken, Germany
s8jutill@stud.uni-saarland.de

Niklas Metzger
CISPA Helmholtz Center for Information Security
Saarbrücken, Germany
niklas.metzger@cispa.de

Julian Siber
CISPA Helmholtz Center for Information Security
Saarbrücken, Germany
julian.siber@cispa.de

Bernd Finkbeiner
CISPA Helmholtz Center for Information Security
Saarbrücken, Germany
finkbeiner@cispa.de

Abstract

We study the generalization abilities of language models when translating natural language into formal specifications with complex semantics. In particular, we fine-tune language models on three datasets consisting of English sentences and their corresponding formal representation: 1) regular expressions (regex), frequently used in programming and search; 2) First-order logic (FOL), commonly used in software verification and theorem proving; and 3) linear-time temporal logic (LTL), which forms the basis for industrial hardware specification languages. Our experiments show that, in these diverse domains, the language models maintain their generalization capabilities from pre-trained knowledge of natural language to generalize, e.g., to new variable names or operator descriptions. Additionally, they achieve competitive performance, and even outperform the state-of-the-art for translating into regular expressions, with the benefits of being easy to access, efficient to fine-tune, and without a particular need for domain-specific reasoning.

1 Introduction

Translating natural language into *formal* languages is a long-standing goal of artificial intelligence research dating back to the 1960s (e.g., Weizenbaum (1966); Winograd (1971)). Due to recent progress in deep learning (especially Vaswani et al. (2017)) and the development of language models (LMs), the field has seen significant improvements, for instance, in the translation from natural language into coding languages or formal mathematics (e.g., Lewkowycz et al. (2022); Chowdhery et al. (2022); Chen et al. (2021); Wu et al. (2022)). In this paper, we study the generalization abilities of a pre-trained LM when translating natural language into *formal specification languages*.

Formal specification languages are used in various computer science fields to describe a system's desired behavior, including fields such as systems design, requirements analysis, and automated reasoning. Examples include specification languages based on logics, such as Alloy (Jackson, 2002) and LTL (Pnueli, 1977), system specification languages based on state charts, such as SDL (Fonseca i Casas et al., 2013), or text processing specifications based on regular languages, omega-regular languages, and automata theory (Aho, 1991; Thomas, 1990). Compared to natural language, the benefit of a formal specification language is its unambiguous semantics making it accessible for algorithmic work that relies on a specification as input. Examples are high-performance SAT and SMT solvers (e.g., Sorensson & Een (2005); Biere et al. (2013); Audemard & Simon (2018); Moura & Bjørner (2008); Barrett et al. (2011)), planning tools LaValle (2006), model checkers (e.g., Cimatti

---

[*]Equal contribution. Alphabetical order.

natural language (ID)	lines having a character and the string 'dog' in them
regex prediction (correct)	((.)&(dog).*
natural language (OOD)	lines with words with a letter before the string 'eye' or the string 'time'
regex prediction (correct)	([A-Za-z]).*((eye) | (time)).*
natural language (ID)	Globally it is the case that if a holds then eventually a and b hold.
LTL prediction (correct)	$\square(a \rightarrow \diamondsuit(a \wedge b))$
natural language (OOD)	Whenever x does not hold , o9 will eventually hold.
LTL prediction (correct)	$\square(\neg x \rightarrow \diamondsuit o9)$

Figure 1: An ID example of a regex model trained solely on the noun "dog", tested OOD on new nouns "eye" and "time"; and an ID example of an LTL model trained on variables i_0 to i_4 and o_0 to o_4, tested OOD on new variables and operator descriptions (bottom). OOD fragments are highlighted.

et al. (2002); Holzmann (1997); Behrmann et al. (2006)), hardware synthesis tools (e.g., Bohy et al. (2012); Faymonville et al. (2017); Meyer et al. (2018)), or automatic theorem provers (e.g., Bertot & Castéran (2013); Nipkow et al. (2002)). Despite their benefits and various application areas, formal specification languages are still almost exclusively used by domain experts as their application requires significant domain-specific knowledge and extensive manual work. With the success of LMs, the goal of making the techniques mentioned above available to a broader user base to increase the correctness, trust, and assurance in computer systems is finally getting closer.

So far, efforts in utilizing deep learning to translate natural language into formal specifications have relied on training neural networks from scratch (e.g., Singh et al. (2020); He et al. (2022)). Such approaches are naturally limited in their generalization capabilities. The natural questions arise: 1) Can off-the-shelf LMs achieve competitive performance when fine-tuned on this challenging translation task? 2) How well will they generalize with their pre-trained knowledge of natural language? In this work, we initiate a study on this topic by fine-tuning the open-source transformer language model T5 (Raffel et al., 2020). The transformer architecture (Vaswani et al., 2017) has proven itself to be the most powerful general-purpose model at the moment of writing, setting new standards in many application domains such as computer vision (e.g., Dosovitskiy et al. (2020)), speech recognition (e.g., Dong et al. (2018)), and, especially, natural language processing (e.g., Brown et al. (2020)). Additionally, T5 is open-source and the trained models are easily accessible to a broad audience.

We have picked three common yet diverse formal representations used widely in software and hardware domains: 1) regular expressions, frequently used in programming and text manipulation, 2) First-order logic, which is a standard formalism used in software domains, such as theorem proving, and 3) Linear-time temporal logic, which is used in hardware domains, such as model checking of sequential circuits. Regular expressions (regex), introduced by Kleene et al. (1956), are sequences commonly used for text manipulation. For example, `(a|b)*` reads as "all sequences with no symbols other than a and b, including the empty string". First-order logic (FOL) extends propositional logic with predicates and quantification. With the foundations developed independently by Gottlob Frege and Charles Peirce (Peirce, 1933), FOL is a formal system of high importance in mathematics, computer science, and linguistics. For example, the formula $\forall x.\exists y.\neg(x = y)$ denotes that for every x, there is a y, which is not equal to x. Linear-time temporal logic (LTL) (Pnueli, 1977) is a hardware specification language widely used by the verification community. It forms the basis for industrial specification languages like the IEEE standard PSL (IEEE-Commission et al., 2005). LTL extends propositional logic with temporal operators, specifying behavior over time. For example, when considering a controller for a shared resource, the formula $\square(r \rightarrow \diamondsuit g)$ denotes that it is "always the case that a request r is eventually followed by a grant g".

Our experiments show that the fine-tuned LM achieves competitive performance on all tasks and even improves state-of-the-art performance in translating natural language to regex by 6 percentage points. Additionally, the models can utilize pre-trained knowledge of natural language. For example, Figure 1 shows hand-picked in-distribution (ID) and out-of-distribution (OOD) examples for models trained on translating natural language to regex and LTL, respectively. The regex model generalizes to new nouns that were not present during fine-tuning. The LTL model was fine-tuned on "globally" and "always" as the translation of the LTL operator $\square$, on "implies" and "if then" as the translation of

the implication $\rightarrow$, and on variables i_0 to i_4 and o_0 to o_4. It generalized to new variable names and operator descriptions, recognizing x and $o9$ as variables, "whenever" as a synonym for "globally", and a simple comma as a synonym for "implies". We provide detailed experiments in Section 4 showing, for example, that the regex model achieves the same accuracy on a held-out test set ($> 88\%$) when being trained on only four out of 16 occurring nouns in the test set (c.f., Figure 2 in Section 4).

In summary, we make the following contributions. We provide the first fine-tuned off-the-shelf language models for translating natural language into formal specifications, including a new state-of-the-art model for translating into regular expressions. We contribute two novel datasets for translating natural language into FOL and two for translating natural language into LTL. Furthermore, we analyze the generalization capabilities of the pre-trained language models by conducting generalization experiments on new variables, nouns, and operator descriptions, as well as out-of-distribution instances.

2 RELATED WORK

Natural language to regex. Similarly to FOL, there were early rule-based techniques for regex translation (Ranta, 1998). The regex datasets have been made more amenable to translation using semantic parsing for decomposition (Kushman & Barzilay, 2013). Training has been guided towards semantically equivalent (Zhong et al., 2018) or approximately equivalent regular expressions (Park et al., 2019); the natural language descriptions have been enriched by paraphrases generated by crowdsourcing (Locascio et al., 2016). The latter work is the most closely related to ours, as it also does not use domain-specific reasoning such as, e.g., semantic equivalence. Ye et al. (2020) have proposed to solely learn generation of regex sketches, and to relegate the construction of the final, correct regular expression to a program synthesis procedure; their dataset is not publically available.

Natural language to FOL. The task of translating natural language into logics, for example with rule-based (e.g., Johnson (1984); Woods (1973); Thompson et al. (1969); Waltz (1978); Hendrix et al. (1978); Templeton & Burger (1983)) or statistical approaches (Zelle & Mooney, 1996; Thompson, 2003; Zettlemoyer & Collins, 2007; 2012; Kwiatkowksi et al., 2010), and recently also neural methods (Kočiskỳ et al., 2016; Buys & Blunsom, 2017; Cheng et al., 2017; Liu et al., 2018; Li et al., 2018) has been studied extensively in the past in the area of semantic parsing Kamath & Das (2018). In this work, we rely on the FOL translation (Kamp & Reyle, 2013) of `boxer`'s output (Bos, 2015). Closest to our work on FOL translations is the first approach of translating natural language to FOL presented by Singh et al. (2020). They construct a dataset using semantic parsing, but clean up the representation of `boxer`'s FOL output, and train a highly specialized LSTM-based architecture. At the time of writing, no code or dataset are publically available for a direct comparison. Han et al. (2022) independently developed a few-shot learning approach using very large language models, achieving a similar accuracy on novel datasets.

Natural language to LTL. Other approaches to the problem of translating from natural language to LTL focus on the robotics domain, such as temporal aspects in grounded robotics (Wang et al., 2020) and planning (Patel et al., 2019). A survey of earlier research beyond neural approaches is provided by Brunello et al. (2019). Grammar-based approaches to translate LTL into structured natural language (Konrad & Cheng, 2005; Grunske, 2008) inspired the design of our grammar for constructing the dataset. Gavran et al. (2020) present an interactive method for translating into LTL specifications from example traces by combining SMT solving and semantic parsing. Cherukuri et al. (2022) consider the inverse direction: translating from LTL formulas to natural language.

Deep Learning in formal reasoning tasks. The term autoformalization (Wang et al., 2018; Szegedy, 2020; Wu et al., 2022) has been coined for tasks of translating between natural language and formal mathematics. Deep learning approaches were able to handle symbolic representations such as logical formulas in SAT-solving (Selsam et al., 2019; Selsam & Bjørner, 2019), expressions in mathematics (Lample & Charton, 2020), formalizations in theorem proving (Polu & Sutskever, 2020), specifications in hardware synthesis (Hahn et al., 2020; 2021), or even code in software generation (Li et al., 2022; Chen et al., 2021). Transformer models have successfully been trained on programming language translation (Roziere et al., 2020), on source code to learn representations of programs (Hellendoorn et al., 2020), and on code synthesis (Li et al., 2022; Chen et al., 2021; Nijkamp et al., 2022) all lacking a training for formal representation of their specifications. Saxton et al. (2019); Schlag et al. (2019) study to solve math problems given in natural language. Transformers were

also trained on symbolic integration and solving differential equations (Lample & Charton, 2020). Transformers have been applied to formal mathematics (Rabe et al., 2020).

3 DATA SETS

We consider three formal specification domains: 1) regular expressions (regex) frequently used in programming or search, 2) First-order logic (FOL), which is a standard formalism used in software domains, such as theorem proving, and 3) Linear-time Temporal Logic (LTL), which is used in verification, such as hardware model checking. We train on six datasets, two for each considered domain (see Table 2 in the appendix for an overview). For regular expressions, we used the existing benchmark sets `Regex-synthetic` and `Regex-turk`. The `FOL` and `LTL` datasets are new contributions. In the following, we give background on the respective domains and describe the existing datasets and our data generation methods in detail.

3.1 NATURAL LANGUAGE AND REGEX PAIRS

Regular expressions (regex) are sequences that describe a search pattern for natural language text. They are commonly used in programming, for example, for string-searching or find-and-replace operations. They have been introduced by Kleene et al. (1956) and are used extensively in text editors, and are even supported natively in many programming languages. For example, `(a|b)*` reads as "all sequences with no symbols other than a and b, including the empty string". We follow the regex representation defined in previous work (see Figure 5 in the appendix).

The `Regex-synthetic` dataset was synthetically generated by Locascio et al. (2016). They used a manually-crafted grammar based on the smaller dataset from Kushman & Barzilay (2013). Two randomly drawn samples from this dataset are "lines with a number or the string 'dog', zero or more times" paired with `((([0-9])|(dog))*` and "lines not starting with a character, 2 or more times" paired with `~(((.)(.*))2,)`. `Regex-turk` is a dataset that Locascio et al. (2016) generated based on paraphrases of the natural language descriptions in `Regex-synthetic`, collected through crowdsourcing at Amazon Mechanical Turk. Two randomly drawn samples from this dataset are "a letter appears before a number in the lines" paired with `.*([A-Za-z]).*([0-9]).*.*` and "lines do not start with the string 'dog' nor the string 'truck'" paired with `~(((dog)(.*))&(truck))`.

3.2 NATURAL LANGUAGE AND FOL FORMULA PAIRS

First-order logic (FOL) extends propositional logic with predicates and quantification. With the foundations being developed independently by Gottlob Frege and Charles Peirce (Peirce, 1933), FOL is a formal system of high importance in mathematics, computer science, and linguistics. First-order terms and formulas are defined relative to a given signature. A first-order signature is a pair of disjoint sets $\mathcal{F}$ and $\mathcal{P}$ of function and predicate symbols, respectively, as well as an arity function $\mathcal{F} \cup \mathcal{P} \rightarrow \mathbb{N}$. Given a signature, the FOL alphabet consists of the elements of $\mathcal{F}$ and $\mathcal{P}$ as well as standard logical connectives $(\neg, \vee, \wedge, \rightarrow, \top, \bot)$, quantifiers $\forall$ and $\exists$, the equality symbol $=$, and an infinite set of variables $\{x_1, x_2, \ldots\}$. The syntax of a well-defined formula is given as follows:

$$t ::= x \mid c \mid f(t_1, \ldots, t_n)$$
$$\alpha ::= Q \mid P(t_1, \ldots, t_n) \mid = (t_1, t_2) \mid \top \mid \bot \mid \neg \alpha \mid \alpha_1 \wedge \alpha_2 \mid \exists x. \alpha \ ,$$

where x is a variable, c is a constant, f is an n-ary function, Q is a nullary predicate and P an $1 \leq n$-ary predicate. The boolean connectives $\vee$, $\rightarrow$, and $\leftrightarrow$ as well as the quantifier $\forall$ can be derived. For example, the formula $\forall x. \exists y. \neg = (x, y)$ denotes that forall x, there is a y, which is not equal to x.

We generated FOL formulas from natural language sentences using the `candc` (Clark & Curran, 2004) and `boxer` (Bos, 2015) toolchain. `candc` is a wide-coverage Combinatory Categorial Grammar (CCG) parser. A CCG (Steedman, 2001) is a lexicalized grammar where every word in a sentence is assigned an elementary syntactic structure. A derivation of this CCG is then given to `boxer`, which provides a semantic framework to output various formal derivations of the input sentence, e.g., in first-order logic. Both datasets `FOL-mnli` and `FOL-codesc` are generated using this toolchain. The dataset `FOL-mnli` consists of small sentences taken from the hypothesis predictions of the glue/mnli dataset (Williams et al., 2018). Two randomly drawn examples are "The

fans do not bring any support." and "No one will ever understand how continental plates form.". The dataset `FOL-codesc` consists of pairs of natural language sentences of java code snippets and their first-order translations. We sampled the pairs from the recently published Codesc (Hasan et al., 2021) dataset consisting of 4.2M datapoints. We cut off the natural language descriptions after the first sentence and translated them into an FOL formula with the `candc-boxer` toolchain. This results in a highly challenging dataset, which we believe to be close to practical applications. For example, two randomly drawn instances are "deletes a certificate from a specified key vault" and "sets the base dir for the volume".

3.3 NATURAL LANGUAGE AND LTL FORMULA PAIRS

Linear-time temporal logic (LTL) (Pnueli, 1977) is a temporal logic for the verification of hardware systems. LTL extends propositional logic with temporal operators, specifying behavior over time. LTL formulas are defined over a set of variables AP called atomic propositions. The alphabet consists of elements of AP, standard logical connectives ($\neg, \vee, \wedge, \rightarrow, \top, \bot$), and temporal operators $\bigcirc$ (next) and $\mathcal{U}$ (until). The syntax of an LTL formula is given as follows:

$$\varphi ::= p \mid \neg\varphi \mid \varphi_1 \vee \varphi_2 \mid \bigcirc \varphi \mid \varphi_1 \mathcal{U} \varphi_2 \ ,$$

where $p \in AP$ is an atomic proposition and $\bigcirc \varphi$ means that the subformula φ holds in the next timestep or cycle and $\varphi_1 \mathcal{U} \varphi_2$ means that φ_1 holds until φ_2 holds. We additionally use the derived operaters *eventually* $\Diamond \varphi = \top \mathcal{U} \varphi$ and *globally* $\Box \varphi = \neg \Diamond \neg \varphi$. For example, when considering a controller for a shared resource, the formula $\Box(r \rightarrow \Diamond g)$ denotes that "it is always the case that a grant to the resource g eventually follows a process' request r".

We generated pairs of natural language sentences and LTL formulas with two different methods. In the first data generation method (`LTL-pattern`), we utilized these specification patterns commonly defined in the literature (Dwyer et al., 1998; Etessami & Holzmann, 2000; Holeček et al., 2004; Pelánek, 2007), which are provided by the `spot` library (Duret-Lutz et al., 2016). For example, the specification pattern $\Box(a \rightarrow b)$ states that at every timestep, whenever a holds, b has to hold as well and the specification pattern $\Box \Diamond a$ states that a has to hold infinitely often. Since an LTL specification typically consists of a conjunction of such patterns, we followed the approach in the literature and conjoined up to 4 patterns and their translations (Li et al., 2013). In the second dataset, we constructed pairs of natural language sentences and formulas using a straight-forward grammar with minimal domain-specific knowledge (Konrad & Cheng, 2005; Grunske, 2008) (see Appendix D in the appendix). The grammar restricts formulas to only contain negations directly in front of atomic propositions, which is dictated by the structure of the English language, as verbs follow a different conjugation depending on whether they are used in a positive or a negated case. For instance, $\Box a$ is translated to "Globally a holds" and $\Box \neg a$ is translated to "Globally a does not hold". To translate LTL formulas automatically, we used a natural language grammar that is structurally the same as the LTL grammar. The interested reader can find the grammar and a detailed explanation in Appendix D. The dataset `LTL-synthesis` consists of pairs of a natural language translation with our grammar (see Appendix D) and their LTL hardware synthesis specification. These hardware synthesis specifications are taken from a recently published dataset, where the authors trained a Transformer to predict hardware circuits directly from LTL specifications (Schmitt et al., 2021). The synthesis specifications consist of an LTL formula expressing the assumptions posed on the environment and an LTL formula expressing the desired guarantees of the system. They can be combined into a single LTL formula by implication.

4 EXPERIMENTS

We fine-tuned the `base` version of the open-source language model T5 Raffel et al. (2020) with 220 million parameters on an NVIDIA DGX A100 system for around 1 hour each run with a learning rate of 0.001. We needed to use the `small` version for our baseline experiments on an untrained T5 model to achieve stable training. We use PyTorch (Paszke et al., 2019) and the huggingface transformers library (Wolf et al., 2020) to fine-tune the models. We report accuracy of the best-performing models (see Appendix A for ablations). In general, achieving stable training for the baseline T5 model was challenging and required much more engineering effort compared to the pre-trained version of T5 (c.f Figure 3). We split the data into 90% training, 5% validation, and 5% test data. Table 1 summarizes

the test results. We used the following prompt, respectively: `"translate natural language to {FOL | LTL | a regular expression}:"`.

4.1 REGULAR EXPRESSIONS

New state-of-the-art by semantic generalization. The fine-tuned language model achieves a new state-of-the-art in translating natural language to regular expressions on both datasets. This even holds true when comparing against state-of-the-art reinforcement learning approaches (Zhong et al., 2018; Park et al., 2019); indicated in Table 1 by (RL). A natural language sentence has multiple correct translations into a regular expression. For example, the following prediction is correct, yet different from the training target:

natural language description	lines starting with a character followed by a vowel, 7 or more times
model prediction (correct)	((..*[AEIOUaeiou].*){7,})(.*)
training target	((..*[AEIOUaeiou].*)(.*)){7,}

To account for such predictions, the accuracy of the regex models is evaluated with an equivalence check, called semantic accuracy Locascio et al. (2016). On the synthetically generated dataset `Regex-synthetic`, the LM achieves 94.01% semantic accuracy; on the `Regex-turk` dataset, the language model achieves 64.20% semantic accuracy. Due to the model's generalization to the semantic, its performance increased from 90.62% to 94.01% and 47.00% to 64.20%, respectively, being the decisive factor in beating the state-of-the-art. This is exceptionally substantial on the `Regex-turk` dataset. Figure 3 (top left) depicts the accuracy per sequence of the best performing models during training. While the baseline model achieves the same accuracy (with longer training) on `Regex-synthetic`, the pre-trained model outperforms the baseline on `Regex-turk` by a significant margin. Note that we incorporate no additional training objective in contrast to previous work (Zhong et al., 2018; Park et al., 2019).

Generalization to new nouns. The high accuracy of the fine-tuned LM on this task poses the question if the model does "forget" its knowledge of the natural language during fine-tuning (see, e.g., He et al. (2021)). In this experiment, we tested the models generalization to English nouns that were not present during fine-tuning, but certainly during pre-training. Figure 2 shows the results of this experiment for the pre-trained T5 model (left) and the baseline T5 model (right). The first three nouns are the ones present in the datasets, i.e., "dog", "truck", and "ring". When fine-tuning on only four nouns, by adding another commonly used noun, namely "time", the model generalizes seamlessly to 16 nouns. The additional nouns were drawn from the 25 most common English nouns. Unsurprisingly, the baseline T5 model shows limited generalization capabilities to novel nouns and the pre-trained model consistently performs better, also for less nouns during training. Figure 3 (bottom right) shows the accuracies on the respective validation set. A similar observation can be made when testing on numbers that were not present during fine-tuning:

natural language description	lines with the string 'dog' or a letter, 9 or more times
model prediction (correct)	((dog)|([A-Za-z])){ 9 ,}

Table 1: Accuracy of the best runs for fine-tuned T5 language models on held-out test sets, where steps denote the number of training steps; accuracy is reported as the accuracy per sequence.

dataset	previous SOTA	baseline T5 (steps)	fine-tuned T5 (steps)
Regex-synthetic	88.7 / 91.6 (RL)	**94.01** (5K)	**94.01** (1K)
Regex-turk	58.2 / 62.8 (RL)	58.0 (5K)	**64.20** (1K)
FOL-mnli	**56.10** (estimated)	46.87 (10K)	53.91 (5K)
FOL-codesc	-	58.59 (10K)	**58.98** (3K)
LTL-pattern	-	**100.00** (5K)	**100.00** (1K)
LTL-synthesis	-	87.50 (5K)	**87.90** (1K)

	1	2	3	4	8	16
16	40.12	50.90	71.86	88.62	89.82	88.62
8	41.32	49.90	67.26	88.22	90.82	88.42
4	46.71	60.68	75.65	89.22	90.42	88.62
3	56.69	75.85	89.62	89.02	90.42	88.02
2	69.66	89.42	89.62	89.42	90.62	87.02
1	88.82	89.42	89.22	88.62	90.22	87.62

	1	2	3	4	8	16
16	37.92	40.32	43.31	45.91	60.48	89.02
8	39.12	44.51	50.30	56.09	89.22	87.42
4	43.91	55.29	70.46	87.22	89.02	88.42
3	53.29	69.66	88.62	88.82	89.62	88.22
2	61.68	88.02	88.82	88.62	88.82	88.42
1	88.62	88.02	89.02	88.42	88.62	88.62

(left) #nouns in test data / #nouns in training data — (right) #nouns in test data / #nouns in training data

Figure 2: Syntactic accuracy of pre-trained T5 regex models (left) and baseline T5 regex models (right) trained on variations of `Regex-synthetic` with proper subsets of nouns.

OOD-testing across datasets. As a final experiment in the regex domain, we cross-tested the models on the regex datasets. Such out-of-distribution (OOD) tests are known to be challenging for neural networks. It is especially interesting if a model trained on `Regex-synthetic`, which is purely synthetic, can translate instances of `Regex-turk`, which is constructed by humans. The model trained on the syntactic data achieved a semantic accuracy of 49.20%, which is only 15 percentage points behind the models accuracy that was trained on this dataset, and only 9 percentage points behind the previous state-of-the-art. Interestingly, the model can interpret ambiguous natural language sentences differently than its human counterpart and even corrects buggy targets, probably due to being trained on a slightly different dataset. For example:

natural language description	lines with a number that comes before a letter, and a vowel, and the string 'dog'
model prediction ("incorrect")	([0-9]).*(((([A-Za-z])&([AEIOUaeiou])&(dog)).*
training target	((([AEIOUaeiou])&(dog)&([0-9])).*([A-Za-z]).*

In the "easier" direction, the model trained on `Regex-turk` achieved an accuracy of 83.83% falling only 10 percentage points short behind the model trained on this dataset and 4 percentage points behind the previous state-of-the-art. However, it is only fair to note that T5 was trained on an internet corpus, making it likely that the model has seen regular expressions during pre-training, which probably contributes to the model's high accuracy. In the next sections, we will consider FOL and LTL, where it is much more unlikely that the network has seen many instances during pre-training.

4.2 First-order Logic (FOL)

Comparability to the state-of-the-art. Singh et al. (2020) achieved an estimated semantic accuracy of 56.10% on their 138K large dataset with a specialized architecture and an array of optimizations. Their dataset is similarly constructed as our 150K large dataset `FOL-mnli`, but they heuristically estimate their semantic accuracy with a matching algorithm. For best reproducibility, we thus only report on the syntactic accuracy of T5 in this paper as, at the time of writing, their dataset and code were not publically available. Their FOL formulas are represented as a reduced mapping of the `candc-boxer` output while we train on the raw output end-to-end in this work. On a held-out dataset, the fine-tuned LM achieved a syntactic accuracy of 53.91%, falling only 2 percentage points short of the semantically estimated state-of-the-art. On the `FOL-codesc` dataset, which was constructed to mimic code snippets, our best model achieved an accuracy of 58.98% (see Figure 3 top right). It will be interesting to see how specialized approaches perform on this new dataset. Since this is a newly contributed dataset, we provide two randomly sampled successful and failed translation attempts while evaluating the best model on a held-out test set of `FOL-codesc`:
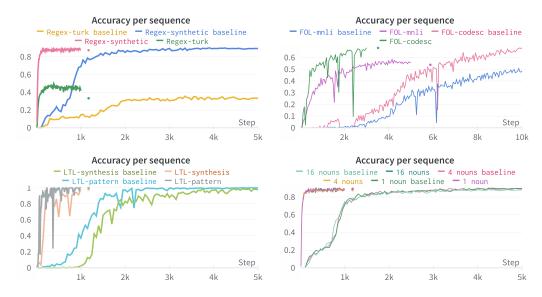
Figure 3: Respective accuracy per sequence on validation sets during training of the best performing models reported in Table 1: Regex (top left), FOL (top right), LTL (bottom left); and the accuracy per sequence for the new nouns experiment (bottom right).

natural language description model prediction (correct)	choose an available port fol(1,some(A,some(B,some(C,some(D,and(r1Theme(A,C), and(r1Actor(A,D),and(v1choose(A),and(n1port(C), and(a1available(B),and(r1Theme(B,C),n12thing(D)))))))))))).
natural language description model prediction (incorrect)	show start page fol(1,some(A,some(B,some(C,and(n1page(C),and(r1of(C,A), and(n1start(A),and(r1of(C,B),and(n1show(B),a1topic(C)))))))))).

OOD-testing across datasets. We experiment again with cross-testing in the FOL domain to report the performance of a model trained on everyday natural language (`FOL-mnli`) to the specialized domain of code (`FOL-codesc`). Note that, compared to the regex experiment, the domains considered in these datasets are much more different. A model trained on `FOL-mnli` achieved an accuracy of 31.25% when tested on the code comment examples from `FOL-codesc`. Vice versa, a model achieved an accuracy of 10.55%. This accuracy decreases drastically for the baseline model, achieving only 19.92% and 0%, respectively. Our experiments indicate that pre-trained language models used for code generation can translate its input into formal specifications, which formally represent their language understanding. They thus remove ambiguity and automatically formalize their input. Our long-term vision is that this additional output can be used to increase the trust in the code model's output. With the `FOL-codesc` dataset, we aim to make the first contribution toward this goal.

4.3 LINEAR-TIME TEMPORAL LOGIC (LTL)

New baseline and challenging datasets for LTL. The language model performed well on the task of translating natural language into LTL specifications as it seems to benefit from the models generalization capabilities from pre-trained knowledge on natural language (see Figure 3 bottom left). The `LTL-pattern` dataset serves as a baseline, where the language model achieves an accuracy of 100.00% by probably learning the underlying grammar. The `LTL-synthesis` dataset, however, is designed to be more challenging. It contains a combination of practical specifications to automatically synthesize hardware circuits Schmitt et al. (2021). For example:

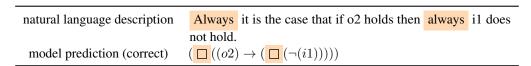|	
natural language description	Globally it is the case that if o4 holds and in the next step i0 does not hold then in the next step o4 holds and o1 does not hold until i1 does not hold or globally o1 does not hold and globally o3 holds.
model prediction (correct)	$((\Box(((o_4) \wedge (\bigcirc(\neg(i_0)))) \rightarrow (\bigcirc(o_4)))))$ $\wedge((((\neg(o_1))\mathcal{U}(\neg(i_1)))|(\Box(\neg(o_1)))))) \wedge ((\Box(o_3)))$

On these large instances, the language model achieves an accuracy of 87.50%. Failed translation attempts are, in general, due to the large size of the instances often overshooting the size limit of our language models. This experiment is especially interesting, since combining our approach with the approach of Schmitt et al. (2021) would enable the development of a tool that synthesizes sequential hardware circuits automatically out of natural language. Final circuit predictions can then be model-checked or tested against the intermediate LTL formalization of the natural language.

Generalization to new variable names. We observed that the models are also able to process new variable names. Although the models were fine-tuned on a fixed set of variables ($i_0, \ldots, i_4$ and $o_0, \ldots, o_4$ for `LTL-synthesis`, and $a, \ldots, e$ for `LTL-pattern`) using other variables also led to correct translations. A model trained on `LTL-pattern` achieved an accuracy of 95.00% when being tested on held-out instances where all variables were replaced with random letters from the alphabet. See Figure 1 in the introduction and the following example:

natural language (ID)	Globally it is the case that if a holds then eventually a and b hold.
model prediction (correct)	$\Box(a \rightarrow \Diamond(a \wedge b))$
natural language (OOD)	If x holds infinitely often then y holds infinitely often.
model prediction (correct)	$(\Box\Diamond x \rightarrow \Box\Diamond y)$

OOD-testing across datasets. We OOD cross-tested on the LTL datasets. Interestingly, only one of the directions showed generalization. We tested a model, trained on `LTL-pattern`, on large instances from the synthesis specifications in `LTL-synthesis`. A model trained and tested in this direction achieved an accuracy of 3.12%. However, in the other direction, i.e., a model trained on `LTL-synthesis` and tested on `LTL-pattern` achieved an accuracy of 37.11%. If we conduct the same experiment with the baseline model, the accuracy drops to 0% and 7.81%, respectively.

Generalization to new operator descriptions. Lastly, we quantitatively measured the generalization of LTL models to new operator descriptions, which were kindly provided by uninvolved experts, by adding them to our translation grammar. We build two grammars, one with the additional operator descriptions and one without them (see Appendix D). Translations are then randomly chosen. A model trained on the grammar only consisting of a single translation for each operator achieved an accuracy of 53% when being tested on instances generated with the enriched grammar. For example:

natural language description	Always it is the case that if o2 holds then always i1 does not hold.
model prediction (correct)	$(\Box((o2) \rightarrow (\Box(\neg(i1)))))$

An additional example is the test instance hand-crafted by an expert shown in Figure 1 in Section 1, where the model recognizes "whenever" as the $\Box$-operator and the comma as the very subtle representation of an implication, both of which are not even captured by our enriched grammar. A possible use-case in this domain is the automatic formalization of software and hardware requirements from natural language to formal LTL specifications.

5 LIMITATIONS AND CONCLUSION

A limiting factor is that our approach still requires a GPU with enough memory to fit the language model, which detracts from its general accessibility. We set out to demonstrate the applicability of language models to a wide variety of formal domains. Nevertheless, many interesting domains are out of this work's scope but still viable targets for our approach. These include theorem proving, SQL translations, logical programming, SAT, and SMT. Another limitation is the focus on one particular

class of language models. A possible further research direction is to explore the capabilities of decoder-only models such as the GPT-2 model family. Many datasets considered in this work are purely synthetic (which is only natural for the considered domains). Hence, a practical next step is encouraging experts to contribute open-source data in their respective domains. A final limitation is the unfeasibility of proper comparisons with existing works, e.g., due to unavailable datasets. With this work, we contribute to an open-source gathering of existing datasets to conduct further research.

To conclude, we conducted the first study on the generalization capabilities of fine-tuned language models to translate natural language into formal specifications, resulting in a new state-of-the-art for translating natural language into regular expressions. The benefits of fine-tuning an open-source language model are that they are easily accessible and cheap to train. We contributed two new datasets for translating natural language into First-order Logic and two new datasets for translating natural language into Linear-time Temporal Logic. We provided experiments on the generalization capabilities of the pre-trained language model T5, which serves as a baseline for further research. Our experimental results show that off-the-shelf language models can outperform approaches on existing datasets and perform well on new datasets. The language models prove themselves to be highly versatile. A unique selling point is their capability of generalizing from pre-trained knowledge of natural language, such as handling other variable names, new nouns, and new operator descriptions. We believe that the generalization capabilities of language models can be crucial in making real-world problems of translating natural language to formal specifications tractable.

ACKNOWLEDGEMENTS

REFERENCES

Alfred V Aho. Algorithms for finding patterns in strings, handbook of theoretical computer science (vol. a): algorithms and complexity, 1991.

Gilles Audemard and Laurent Simon. On the glucose sat solver. *International Journal on Artificial Intelligence Tools*, 27(01):1840001, 2018.

Clark Barrett, Christopher L Conway, Morgan Deters, Liana Hadarean, Dejan Jovanović, Tim King, Andrew Reynolds, and Cesare Tinelli. Cvc4. In *International Conference on Computer Aided Verification*, pp. 171–177. Springer, 2011.

Gerd Behrmann, Alexandre David, Kim Guldstrand Larsen, John Håkansson, Paul Pettersson, Wang Yi, and Martijn Hendriks. Uppaal 4.0. 2006.

Yves Bertot and Pierre Castéran. *Interactive theorem proving and program development: Coq'Art: the calculus of inductive constructions*. Springer Science & Business Media, 2013.

Armin Biere et al. Lingeling, plingeling and treengeling entering the sat competition 2013. *Proceedings of SAT competition*, 2013:1, 2013.

Aaron Bohy, Véronique Bruyere, Emmanuel Filiot, Naiyong Jin, and Jean-François Raskin. Acacia+, a tool for LTL synthesis. In *International Conference on Computer Aided Verification*, pp. 652–657. Springer, 2012.

Johan Bos. Open-domain semantic parsing with boxer. In *Proceedings of the 20th nordic conference of computational linguistics (NODALIDA 2015)*, pp. 301–304, 2015.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.

Andrea Brunello, Angelo Montanari, and Mark Reynolds. Synthesis of ltl formulas from natural language texts: State of the art and research directions. In *26th International Symposium on Temporal Representation and Reasoning (TIME 2019)*. Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, 2019.

Jan Buys and Phil Blunsom. Robust incremental neural semantic graph parsing. *arXiv preprint arXiv:1704.07092*, 2017.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*, 2021.

Jianpeng Cheng, Siva Reddy, Vijay Saraswat, and Mirella Lapata. Learning structured natural language representations for semantic parsing. *arXiv preprint arXiv:1704.08387*, 2017.

Himaja Cherukuri, Alessio Ferrari, and Paola Spoletini. Towards explainable formal methods: From ltl to natural language with neural machine translation. In *International Working Conference on Requirements Engineering: Foundation for Software Quality*, pp. 79–86. Springer, 2022.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*, 2022.

Alessandro Cimatti, Edmund Clarke, Enrico Giunchiglia, Fausto Giunchiglia, Marco Pistore, Marco Roveri, Roberto Sebastiani, and Armando Tacchella. Nusmv 2: An opensource tool for symbolic model checking. In *International conference on computer aided verification*, pp. 359–364. Springer, 2002.

Stephen Clark and James R Curran. Parsing the wsj using ccg and log-linear models. In *Proceedings of the 42nd Annual Meeting of the Association for Computational Linguistics (ACL-04)*, pp. 103–110, 2004.

Linhao Dong, Shuang Xu, and Bo Xu. Speech-transformer: a no-recurrence sequence-to-sequence model for speech recognition. In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 5884–5888. IEEE, 2018.

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020.

Alexandre Duret-Lutz, Alexandre Lewkowicz, Amaury Fauchille, Thibaud Michaud, Etienne Renault, and Laurent Xu. Spot 2.0 — a framework for LTL and ω-automata manipulation. In *Proceedings of the 14th International Symposium on Automated Technology for Verification and Analysis (ATVA'16)*, volume 9938 of *Lecture Notes in Computer Science*, pp. 122–129. Springer, October 2016. doi: 10.1007/978-3-319-46520-3_8.

Matthew B. Dwyer, George S. Avrunin, and James C. Corbett. Property specification patterns for finite-state verification. In *Proceedings of the Second Workshop on Formal Methods in Software Practice, March 4-5, 1998, Clearwater Beach, Florida, USA*, pp. 7–15. ACM, 1998. doi: 10.1145/298595.298598.

Kousha Etessami and Gerard J. Holzmann. Optimizing büchi automata. In Catuscia Palamidessi (ed.), *CONCUR 2000 - Concurrency Theory, 11th International Conference, University Park, PA, USA, August 22-25, 2000, Proceedings*, volume 1877 of *Lecture Notes in Computer Science*, pp. 153–167. Springer, 2000. doi: 10.1007/3-540-44618-4_13. URL https://doi.org/10.1007/3-540-44618-4_13.

Peter Faymonville, Bernd Finkbeiner, and Leander Tentrup. BoSy: An experimentation framework for bounded synthesis. In *International Conference on Computer Aided Verification*, pp. 325–332. Springer, 2017.

Pau Fonseca i Casas, Xavier Pi, Josep Casanovas, and Jordi Jové. Definition of virtual reality simulation models using specification and description language diagrams. In *International SDL Forum*, pp. 258–274. Springer, 2013.

Ivan Gavran, Eva Darulova, and Rupak Majumdar. Interactive synthesis of temporal specifications from examples and natural language. *Proceedings of the ACM on Programming Languages*, 4 (OOPSLA):1–26, 2020.

Lars Grunske. Specification patterns for probabilistic quality properties. In *2008 ACM/IEEE 30th International Conference on Software Engineering*, pp. 31–40. IEEE, 2008.

Christopher Hahn, Frederik Schmitt, Jens U. Kreber, Markus N. Rabe, and Bernd Finkbeiner. Deepltl, 2020. URL https://github.com/reactive-systems/deepltl.

Christopher Hahn, Frederik Schmitt, Jens U. Kreber, Markus N. Rabe, and Bernd Finkbeiner. Teaching temporal logics to neural networks. *International Conference on Learning Representations, ICLR*, 2021.

Simeng Han, Hailey Schoelkopf, Yilun Zhao, Zhenting Qi, Martin Riddell, Luke Benson, Lucy Sun, Ekaterina Zubova, Yujie Qiao, Matthew Burtell, et al. Folio: Natural language reasoning with first-order logic. *arXiv preprint arXiv:2209.00840*, 2022.

Masum Hasan, Tanveer Muttaqueen, Abdullah Al Ishtiaq, Kazi Sajeed Mehrab, Md. Mahim Anjum Haque, Tahmid Hasan, Wasi Ahmad, Anindya Iqbal, and Rifat Shahriyar. CoDesc: A large code–description parallel dataset. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pp. 210–218, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-acl.18. URL https://aclanthology.org/2021.findings-acl.18.

Jie He, Ezio Bartocci, Dejan Ničković, Haris Isakovic, and Radu Grosu. Deepstl-from english requirements to signal temporal logic. In *44th International Conference on Software Engineering (ICSE 2022)*, 2022.

Tianxing He, Jun Liu, Kyunghyun Cho, Myle Ott, Bing Liu, James Glass, and Fuchun Peng. Analyzing the forgetting problem in pretrain-finetuning of open-domain dialogue response models. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pp. 1121–1133, 2021.

Vincent J. Hellendoorn, Charles Sutton, Rishabh Singh, Petros Maniatis, and David Bieber. Global relational models of source code. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net, 2020. URL https://openreview.net/forum?id=B1lnbRNtwr.

Gary G Hendrix, Earl D Sacerdoti, Daniel Sagalowicz, and Jonathan Slocum. Developing a natural language interface to complex data. *ACM Transactions on Database Systems (TODS)*, 3(2): 105–147, 1978.

Jan Holeček, Tomáš Kratochvíla, Vojtěch Řehák, David Šafránek, Pavel Šimeček, et al. Verification results in Liberouter project, 2004.

Gerard J. Holzmann. The model checker spin. *IEEE Transactions on software engineering*, 23(5): 279–295, 1997.

IEEE-Commission et al. IEEE standard for property specification language (PSL). *IEEE Std 1850-2005*, 2005.

Daniel Jackson. Alloy: a lightweight object modelling notation. *ACM Transactions on software engineering and methodology (TOSEM)*, 11(2):256–290, 2002.

Tim Johnson. Natural language computing: the commercial applications. *The Knowledge Engineering Review*, 1(3):11–23, 1984.

Aishwarya Kamath and Rajarshi Das. A survey on semantic parsing. *arXiv preprint arXiv:1812.00978*, 2018.

Hans Kamp and Uwe Reyle. *From discourse to logic: Introduction to modeltheoretic semantics of natural language, formal logic and discourse representation theory*, volume 42. Springer Science & Business Media, 2013.

Stephen C Kleene et al. Representation of events in nerve nets and finite automata. *Automata studies*, 34:3–41, 1956.

Tomáš Kočiský, Gábor Melis, Edward Grefenstette, Chris Dyer, Wang Ling, Phil Blunsom, and Karl Moritz Hermann. Semantic parsing with semi-supervised sequential autoencoders. *arXiv preprint arXiv:1609.09315*, 2016.

Sascha Konrad and Betty HC Cheng. Real-time specification patterns. In *Proceedings of the 27th international conference on Software engineering*, pp. 372–381, 2005.

Nate Kushman and Regina Barzilay. Using semantic unification to generate regular expressions from natural language. In Lucy Vanderwende, Hal Daumé III, and Katrin Kirchhoff (eds.), *Human Language Technologies: Conference of the North American Chapter of the Association of Computational Linguistics, Proceedings, June 9-14, 2013, Westin Peachtree Plaza Hotel, Atlanta, Georgia, USA*, pp. 826–836. The Association for Computational Linguistics, 2013. URL https://aclanthology.org/N13-1103/.

Tom Kwiatkowksi, Luke Zettlemoyer, Sharon Goldwater, and Mark Steedman. Inducing probabilistic ccg grammars from logical form with higher-order unification. In *Proceedings of the 2010 conference on empirical methods in natural language processing*, pp. 1223–1233, 2010.

Guillaume Lample and François Charton. Deep learning for symbolic mathematics. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net, 2020.

Steven M LaValle. *Planning algorithms*. Cambridge university press, 2006.

Aitor Lewkowycz, Anders Andreassen, David Dohan, Ethan Dyer, Henryk Michalewski, Vinay Ramasesh, Ambrose Slone, Cem Anil, Imanol Schlag, Theo Gutman-Solo, et al. Solving quantitative reasoning problems with language models. *arXiv preprint arXiv:2206.14858*, 2022.

Jianwen Li, Lijun Zhang, Geguang Pu, Moshe Y. Vardi, and Jifeng He. LTL satisfiability checking revisited. In César Sánchez, Kristen Brent Venable, and Esteban Zimányi (eds.), *2013 20th International Symposium on Temporal Representation and Reasoning, Pensacola, FL, USA, September 26-28, 2013*, pp. 91–98. IEEE Computer Society, 2013. doi: 10.1109/TIME.2013.19. URL https://doi.org/10.1109/TIME.2013.19.

Yujia Li, David Choi, Junyoung Chung, Nate Kushman, Julian Schrittwieser, Rémi Leblond, Tom Eccles, James Keeling, Felix Gimeno, Agustin Dal Lago, et al. Competition-level code generation with alphacode. *arXiv preprint arXiv:2203.07814*, 2022.

Zuchao Li, Jiaxun Cai, Shexia He, and Hai Zhao. Seq2seq dependency parsing. In *Proceedings of the 27th International Conference on Computational Linguistics*, pp. 3203–3214, 2018.

Jiangming Liu, Shay B Cohen, and Mirella Lapata. Discourse representation structure parsing. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 429–439, 2018.

Nicholas Locascio, Karthik Narasimhan, Eduardo DeLeon, Nate Kushman, and Regina Barzilay. Neural generation of regular expressions from natural language with minimal domain knowledge. In Jian Su, Xavier Carreras, and Kevin Duh (eds.), *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, EMNLP 2016, Austin, Texas, USA, November 1-4, 2016*, pp. 1918–1923. The Association for Computational Linguistics, 2016. doi: 10.18653/v1/d16-1197. URL https://doi.org/10.18653/v1/d16-1197.

Philipp J. Meyer, Salomon Sickert, and Michael Luttenberger. Strix: Explicit reactive synthesis strikes back! In *Computer Aided Verification - 30th International Conference, CAV 2018, Held as Part of the Federated Logic Conference, FloC 2018, Oxford, UK, July 14-17, 2018, Proceedings, Part I*, volume 10981 of *Lecture Notes in Computer Science*, pp. 578–586. Springer, 2018. doi: 10.1007/978-3-319-96145-3_31.

Leonardo de Moura and Nikolaj Bjørner. Z3: An efficient smt solver. In *International conference on Tools and Algorithms for the Construction and Analysis of Systems*, pp. 337–340. Springer, 2008.

Erik Nijkamp, Bo Pang, Hiroaki Hayashi, Lifu Tu, Huan Wang, Yingbo Zhou, Silvio Savarese, and Caiming Xiong. A conversational paradigm for program synthesis. *arXiv preprint arXiv:2203.13474*, 2022.

Tobias Nipkow, Markus Wenzel, and Lawrence C Paulson. *Isabelle/HOL: a proof assistant for higher-order logic*. Springer, 2002.

Jun-U. Park, Sang-Ki Ko, Marco Cognetta, and Yo-Sub Han. Softregex: Generating regex from natural language descriptions using softened regex equivalence. In Kentaro Inui, Jing Jiang, Vincent Ng, and Xiaojun Wan (eds.), *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019*, pp. 6424–6430. Association for Computational Linguistics, 2019. doi: 10.18653/v1/D19-1677. URL `https://doi.org/10.18653/v1/D19-1677`.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett (eds.), *Advances in Neural Information Processing Systems 32*, pp. 8024–8035. Curran Associates, Inc., 2019.

Roma Patel, Roma Pavlick, and Stefanie Tellex. Learning to ground language to temporal logical form. NAACL, 2019.

Charles S. Peirce. *The Collected Papers of Charles Sanders Peirce, Vol. IV: The Simplest Mathematics*. Harvard University Press, Cambridge, 1933.

Radek Pelánek. BEEM: benchmarks for explicit model checkers. In Dragan Bosnacki and Stefan Edelkamp (eds.), *Model Checking Software, 14th International SPIN Workshop, Berlin, Germany, July 1-3, 2007, Proceedings*, volume 4595 of *Lecture Notes in Computer Science*, pp. 263–267. Springer, 2007. doi: 10.1007/978-3-540-73370-6_17. URL `https://doi.org/10.1007/978-3-540-73370-6_17`.

Amir Pnueli. The temporal logic of programs. In *18th Annual Symposium on Foundations of Computer Science, Providence, Rhode Island, USA, 31 October - 1 November 1977*, pp. 46–57. IEEE Computer Society, 1977. doi: 10.1109/SFCS.1977.32. URL `https://doi.org/10.1109/SFCS.1977.32`.

Stanislas Polu and Ilya Sutskever. Generative language modeling for automated theorem proving. *arXiv preprint arXiv:2009.03393*, 2020.

Markus N. Rabe, Dennis Lee, Kshitij Bansal, and Christian Szegedy. Mathematical reasoning via self-supervised skip-tree training. 2020.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.*, 21:140:1–140:67, 2020. URL `http://jmlr.org/papers/v21/20-074.html`.

Aarne Ranta. A multilingual natural-language interface to regular expressions. In *Finite State Methods in Natural Language Processing*, 1998. URL `https://aclanthology.org/W98-1308`.

Baptiste Roziere, Marie-Anne Lachaux, Lowik Chanussot, and Guillaume Lample. Unsupervised translation of programming languages. *Advances in Neural Information Processing Systems*, 33: 20601–20611, 2020.

David Saxton, Edward Grefenstette, Felix Hill, and Pushmeet Kohli. Analysing mathematical reasoning abilities of neural models. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*. OpenReview.net, 2019. URL `https://openreview.net/forum?id=H1gR5iR5FX`.

Imanol Schlag, Paul Smolensky, Roland Fernandez, Nebojsa Jojic, Jürgen Schmidhuber, and Jianfeng Gao. Enhancing the transformer with explicit relational encoding for math problem solving. *arXiv preprint arXiv:1910.06611*, 2019.

Frederik Schmitt, Christopher Hahn, Markus N. Rabe, and Bernd Finkbeiner. Neural circuit synthesis from specification patterns. In Marc'Aurelio Ranzato, Alina Beygelzimer, Yann N. Dauphin, Percy Liang, and Jennifer Wortman Vaughan (eds.), *Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2021, NeurIPS 2021, December 6-14, 2021, virtual*, pp. 15408–15420, 2021. URL `https://proceedings.neurips.cc/paper/2021/hash/8230bea7d54bcdf99cdfe85cb07313d5-Abstract.html`.

Daniel Selsam and Nikolaj Bjørner. Guiding high-performance SAT solvers with unsat-core predictions. In *Theory and Applications of Satisfiability Testing - SAT 2019 - 22nd International Conference, SAT 2019, Lisbon, Portugal, July 9-12, 2019, Proceedings*, volume 11628 of *Lecture Notes in Computer Science*, pp. 336–353. Springer, 2019. doi: 10.1007/978-3-030-24258-9_24.

Daniel Selsam, Matthew Lamm, Benedikt Bünz, Percy Liang, Leonardo de Moura, and David L. Dill. Learning a SAT solver from single-bit supervision. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*. OpenReview.net, 2019.

Hrituraj Singh, Milan Aggrawal, and Balaji Krishnamurthy. Exploring neural models for parsing natural language into first-order logic. *arXiv preprint arXiv:2002.06544*, 2020.

Niklas Sorensson and Niklas Een. Minisat v1. 13-a sat solver with conflict-clause minimization. *SAT*, 2005(53):1–2, 2005.

Mark Steedman. *The syntactic process*. MIT press, 2001.

Christian Szegedy. A promising path towards autoformalization and general artificial intelligence. In *International Conference on Intelligent Computer Mathematics*, pp. 3–20. Springer, 2020.

Marjorie Templeton and John F Burger. Problems in natural-language interface to dbms with examples from eufid. In *First Conference on Applied Natural Language Processing*, pp. 3–16, 1983.

Wolfgang Thomas. Automata on infinite objects. In *Formal Models and Semantics*, pp. 133–191. Elsevier, 1990.

Cynthia Thompson. Acquiring word-meaning mappings for natural language interfaces. *Journal of Artificial Intelligence Research*, 18:1–44, 2003.

Frederick B Thompson, Peter C Lockemann, B Dostert, and RS Deverill. Rel: A rapidly extensible language system. In *Proceedings of the 1969 24th national conference*, pp. 399–417, 1969.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Rob Fergus, S. V. N. Vishwanathan, and Roman Garnett (eds.), *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pp. 5998–6008, 2017. URL `https://proceedings.neurips.cc/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html`.

David L Waltz. An english language question answering system for a large relational database. *Communications of the ACM*, 21(7):526–539, 1978.

Christopher Wang, Candace Ross, Yen-Ling Kuo, Boris Katz, and Andrei Barbu. Learning a natural-language to ltl executable semantic parser for grounded robotics. *arXiv preprint arXiv:2008.03277*, 2020.

Qingxiang Wang, Cezary Kaliszyk, and Josef Urban. First experiments with neural translation of informal to formal mathematics. In *International Conference on Intelligent Computer Mathematics*, pp. 255–270. Springer, 2018.

Joseph Weizenbaum. Eliza—a computer program for the study of natural language communication between man and machine. *Communications of the ACM*, 9(1):36–45, 1966.

Adina Williams, Nikita Nangia, and Samuel R. Bowman. A broad-coverage challenge corpus for sentence understanding through inference. In Marilyn A. Walker, Heng Ji, and Amanda Stent (eds.), *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers)*, pp. 1112–1122. Association for Computational Linguistics, 2018. doi: 10.18653/v1/n18-1101. URL `https://doi.org/10.18653/v1/n18-1101`.

Terry Winograd. Procedures as a representation for data in a computer program for understanding natural language. Technical report, MASSACHUSETTS INST OF TECH CAMBRIDGE PROJECT MAC, 1971.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pp. 38–45, Online, October 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-demos.6. URL `https://aclanthology.org/2020.emnlp-demos.6`.

William A Woods. Progress in natural language understanding: an application to lunar geology. In *Proceedings of the June 4-8, 1973, national computer conference and exposition*, pp. 441–450, 1973.

Yuhuai Wu, Albert Q Jiang, Wenda Li, Markus N Rabe, Charles Staats, Mateja Jamnik, and Christian Szegedy. Autoformalization with large language models. *arXiv preprint arXiv:2205.12615*, 2022.

Xi Ye, Qiaochu Chen, Xinyu Wang, Isil Dillig, and Greg Durrett. Sketch-driven regular expression generation from natural language and examples. *Trans. Assoc. Comput. Linguistics*, 8:679–694, 2020. URL `https://transacl.org/ojs/index.php/tacl/article/view/2135`.

John M Zelle and Raymond J Mooney. Learning to parse database queries using inductive logic programming. In *Proceedings of the national conference on artificial intelligence*, pp. 1050–1055, 1996.

Luke Zettlemoyer and Michael Collins. Online learning of relaxed ccg grammars for parsing to logical form. In *Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL)*, pp. 678–687, 2007.

Luke S Zettlemoyer and Michael Collins. Learning to map sentences to logical form: Structured classification with probabilistic categorial grammars. *arXiv preprint arXiv:1207.1420*, 2012.

Zexuan Zhong, Jiaqi Guo, Wei Yang, Jian Peng, Tao Xie, Jian-Guang Lou, Ting Liu, and Dongmei Zhang. Semregex: A semantics-based approach for generating regular expressions from natural language specifications. In Ellen Riloff, David Chiang, Julia Hockenmaier, and Jun'ichi Tsujii (eds.), *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018*, pp. 1608–1618. Association for Computational Linguistics, 2018. doi: 10.18653/v1/d18-1189. URL `https://doi.org/10.18653/v1/d18-1189`.

A   ABLATIONS

We reported only a selected number of trained models and conducted experiments. We tried to avoid the report of duplications, where the model shows similar behavior across all domains (such as the generalization to new nouns), with the exception being the OOD cross-testing, which is an interesting insight for all considered domains. The models, code, and datasets will be available as part of the `ml2` Python library `https://github.com/reactive-systems/ml2`. We did several ablation studies while looking for the best performing models and performed a hyperparameter search for every reported model. The most influential hyperparameter for the baseline models is the learning rate. In Figure 4 we show the influence of different learning schedules on the accuracy per sequence for the `FOL-codesc` dataset. When fine-tuning T5 models we used a constant learning rate of 0.001. We also experimented with larger and smaller models, since pre-trained T5 models are available in different sizes. In general, the base model with 220 million parameters performed best when fine-tuning. Furthermore, we observed no significant increase in performance when fine-tuning for longer than a few thousand steps (depending on the size of the dataset between 1K to 3K steps), which takes around $1 - 3$ hours of training on an $A100$ for each run. Additionally, we experimented with prompting. We observed a significant (around $3\% - 5\%$) decrease in performance when omitting the prompt. Additional experiments with the prompt, for example prompting with "Translate the following *English* sentence to . . . ", lead to no significant increases or decreases in performance.
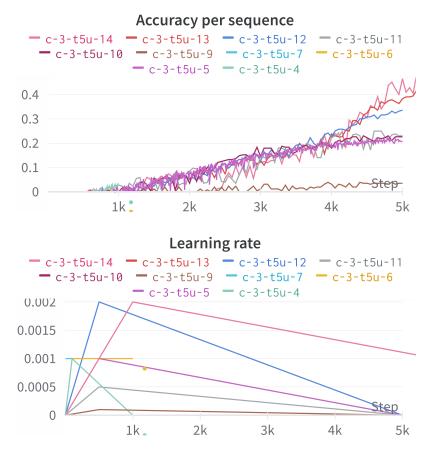

Figure 4: Sensitivity to learning rate schedule of baseline model on `FOL-codesc` dataset.

B DATASETS OVERVIEW

In Table 2 we give an overview of the datasets used in this work and their corresponding data source and size.

Table 2: The datasets used in this work for training and evaluation of the language models.

Dataset	Data source	Size
Regex-synthetic	synthesized regex Locascio et al. (2016)	10K
Regex-turk	regex using amazon turk Locascio et al. (2016)	10K
FOL-mnli	candc & boxer translation of mnli hypothesis	$\sim 150K$
FOL-codesc	candc & boxer translation of codesc	$\sim 600K$
LTL-pattern	grammar translation of specification patterns	$\sim 200K$
LTL-synthesis	grammar translation of synthesis specifications	$\sim 100K$

C REGEX DEFINITION

In Figure 5 we show the regex formalism used by Locascio et al. (2016) for creating datasets Regex-synthetic and Regex-synthetic.

Non-Terminals		
$x \,\&\, y \to$ x and y	$x \mid y \to$ x or y	$\sim (x) \to$ not x
$.*x.*y \to$ x followed by y	$.*x.* \to$ contains x	$x\{N, \} \to$ x, N or more times
$x \,\&\, y \,\&\, z \to$ x and y and z	$x \mid y \mid z \to$ x or y or z	$x\{1, N\} \to$ x, at most N times
$x.* \to$ starts with x	$.*x \to$ ends with x	\b x \b $\to$ words with x
$(x)+ \to$ x, at least once	$(x)* \to$ x, zero or more times	$x \to$ only x

Terminals		
[AEIOU] $\to$ a vowel	$[0-9] \to$ a number	word $\to$ the string 'word'
[A-Z] $\to$ an uppercase letter	[a- z] $\to$ a lowercase letter	$. \to$ a character

Figure 5: Regex syntax used in the considered datasets; taken from Locascio et al. (2016).

D NATURAL LANGUAGE GRAMMARS

In this section, we present the grammars that we used to construct the LTL datasets. On the highest level a formula can be, e.g., an implication, a conjunction, an equivalence or an atomic proposition. Atomic propositions as well as negated atomic propositions are represented by an e_p, which stands for "simple pattern". Every other subcomponent that is not an ap or a negated ap is represented by a c_p, which stands for "complex pattern". Binary operators like conjunction have operands that can be either easy or complex, represented by the e_or_c category. If the formula is complex, we need parentheses to clarify operator precedence. For instance $\square(a \wedge b)$ means that globally both a and b hold. However if we translate it directly and say "Globally a holds and b holds", we loose the meaning of the parentheses. This natural sentence could as well represent the formula $(\square a) \wedge b$. To avoid this ambiguity, we model parentheses by using the phrase "Globally it is the case that" followed by whatever the subformula is. This way it is clear that the scope of the operator extends to the entire translation of the subformula and not only to the very next part. The same principle is applied to the other unary operators such as finally and next, however not to negation as we only have negations followed by easy patterns.

The grammar with minimal domain-knowledge for a 1:1 translation between LTL formulas and natural language is the following:

```
formula         := highest_level
highest_level   := universality | existence | implication | equivalence
                   conjunction | disjunction | until | next | e_p
universality    := "□"e_p | "□("c_p")"
existence       := "◇"e_p | "◇("c_p")"
implication     := e_or_c"→"e_or_c
equivalence     := e_or_c"↔"e_or_c
conjunction     := e_or_c"∧"e_or_c
disjunction     := e_or_c"∨"e_or_c
until           := e_or_c"𝒰"e_or_c
release         := e_or_c"ℛ"e_or_c
next            := "○"e_p | "○""("c_p")"
c_p             := highest_level
e_or_c          := e_p | "("c_p")" | c_p
e_p             := ap | "!"ap
```

```
formula         := highest_level
highest_level   := universality | existence | implication | equivalence |
                   conjunction | disjunction | until | next | e_p
universality    := "Globally"e_p | "Globally it is the case that"c_p
existence       := "Eventually"e_p | "Eventually it is the case that"c_p
implication     := "if"e_or_c"then"e_or_c
equivalence     := e_or_c"if and only if"e_or_c
conjunction     := e_or_c"and"e_or_c
disjunction     := e_or_c"or"e_or_c
until           := e_or_c"until"e_or_c
release         := e_or_c"holds until"e_or_c"or forever"
next            := "in the next step"e_p | "in the next step it is the case that"c_p
c_p             := highest_level
e_or_c          := e_p | c_p
e_p             := ap"holds" | ap"does not hold"
```

In a second step, we replaced the operator descriptions with additional variations:

```
formula             := highest_level
highest_level       := universality | existence | implication | equivalence
                       conjunction | disjunction | until | next | e_p
infinitely_often    := "□(◇("e_or_c"))"
eventually_forever  := "◇(□("e_or_c"))"
universality        := "□"e_p | "□("c_p")"
existence           := "◇"e_p | "◇("c_p")"
implication         := e_or_c" → "e_or_c
equivalence         := e_or_c" ↔ "e_or_c
conjunction         := e_or_c" ∧ "e_or_c
disjunction         := e_or_c" ∨ "e_or_c
until               := e_or_c"𝒰"e_or_c
release             := e_or_c"ℛ"e_or_c
next                := "○"e_p | "○""("c_p")"
c_p                 := highest_level
e_or_c              := e_p | "("c_p")" | c_p
e_p                 := ap | "!"ap
```

```
formula             := highest_level
highest_level       := universality | existence | implication |
                       equivalence | conjunction | disjunction | until | next
                       e_p | infinitely_often | eventually_forever
infinitely_often    := "Infinitely often" e_p | "Infinitely often it is the case that" c_p
eventually_forever  := "Eventually forever" e_p |
                        "Eventually it is the case that forever" c_p
universality        := ("Globally" | "Always") e_p |
                       ("Globally it is the case that" | "Always it is the case that") c_p
existence           := ("Eventually" | "Finally") e_p |
                       ("Eventually it is the case that" | "Finally it is the case that") c_p
implication         := "if" e_or_c "then"e_or_c
equivalence         := e_or_c "if and only if" e_or_c
conjunction         := e_or_c "and" e_or_c
disjunction         := e_or_c "or" e_or_c
until               := e_or_c "until" e_or_c
release             := e_or_c "holds until" e_or_c "or forever"
next                := "in the next step" e_p | "in the next step it is the case that" c_p
c_p                 := highest_level
e_or_c              := e_p | c_p
e_p                 := ap "holds" | ap "does not hold"
```