Do Transformers Encode a Foundational Ontology? Probing Abstract Classes in Natural Language

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Abstract

With the methodological support of probing (or diagnostic classification), recent studies have demonstrated that Transformers encode syntactic and semantic information to some extent. Following this line of research, this paper aims at taking semantic probing to an abstraction extreme with the goal of answering the following research question: can contemporary Transformer-based models reflect an underlying Foundational Ontology? To this end, we present a systematic Foundational Ontology (FO) probing methodology to investigate whether Transformers-based models encode abstract semantic information. Following different pre-training and fine-tuning regimes, we present an extensive evaluation of a diverse set of large-scale language models over three distinct and complementary FO tagging experiments. Specifically, we present and discuss the following conclusions: (1) The probing results indicate that Transformer-based models incidentally encode information related to Foundational Ontologies during the pre-training process; (2) Robust FO taggers (accuracy ≈ 90%) can be efficiently built leveraging on this knowledge.

1 Introduction

Large-scale neural language models have become the de-facto representational substrate for supporting language-based inference (Devlin et al., 2019; Liu et al., 2019). More recently, these models have been used and specialised to cope with abstract inference (Valentino et al., 2021; Thayaparan et al., 2021) and to support efficient generalisation (Zhou et al., 2021) in several downstream reasoning tasks.

As large-scale language models are gradually evolving towards more abstract inference, it is crucial to study and understand the underlying semantics encoded in their representation to identify biases and inconsistencies within the models (Elazar et al., 2021a), improve transparency (Thayaparan et al., 2020), and further investigate their generalisation and reasoning capabilities (Hu et al., 2020).

With the methodological support of probing (or diagnostic classification) (Elazar et al., 2021b; Ferreira et al., 2021), recent studies have demonstrated that transformers encode syntactic and semantic dependencies to some extent (Tenney et al., 2019a). The probing paradigm, in fact, has been recently employed to investigate whether abstract semantic information is encoded in large-scale language models, using auxiliary tasks such as Named Entity Recognition (NER) (Jin et al., 2019), Semantic Role Labeling (SRL) (Tenney et al., 2019b) and Semantic Annotation (SA) (Xu et al., 2020). This paper aims at taking semantic probing to an abstraction extreme with the goal of answering the following research question: can contemporary transformer-based models reflect an underlying Foundational Ontology?

Foundational ontologies provide logical axiomatisations for domain-agnostic top level categories, such as event, biological-object or geographical-object. Foundational Ontologies contain basic and universal concepts, which are either are meta, generic, or philosophical. to promote the integration of highly general information and expressiveness over a wide range of domains (Schmidt et al., 2020). Their general purpose is to map a concept to its most fundamental interpretation (Silva et al., 2016), e.g. “Inserted into the heart’s left ventricle”, the word “ventricle” is mapped to Biological-Object. Such a mapping is fundamental for enabling generalisation and reasoning since higher level categories can be adopted to deliver the required abstractive mechanisms without loss in meaning. Foundational ontologies and their ties to logics represent an important connection between natural language and reasoning (Silva et al., 2016). Additionally, Foundational ontology tagging presents a task requiring a unique level of abstraction, common-sense reasoning and a deep...
understanding of context and polysemy.

In this work, we link the formally grounded abstract categories of Foundational Ontologies (Gangemi et al., 2002; Guizzardi, 2005) to contextualised embeddings by exploring two distinct research hypotheses. The first hypothesis is semantic in nature: pre-trained transformer-based models incidentally encode FO categories, and this information can be inspected through the probing paradigm. The second research hypothesis is practical: based on these pre-encoded categories, a robust lexical semantic model (a term-level FO shallow parser) can be built.

We investigate these hypotheses with the support of a systematic FO probing methodology over a diverse set of reference models, following different pre-training and fine-tuning regimes. Specifically, we introduce three different FO tagging experiments using a mixture of probing and fine-tuning techniques defined on WordNet-DOLCE alignments (Silva et al., 2016), namely Basic Foundational Ontology Tagging, Binary Task, and Singular Contextualised Embedding Probe. Through the definition of distinct and complementary auxiliary tasks, we are able to conduct extensive experiments to investigate the encoding of Foundational Ontologies in a diverse set of large-scale language models, including BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) pre-trained on several downstream NLI datasets. The empirical evaluation resulted in the following conclusions:

- The probing results indicate that transformer-based models incidentally encode information related to Foundational Ontologies during the pre-training process, with Multi-Layer-Perceptron (MLP) probes being substantially more effective in all FO probing tasks.
- Robust FO taggers (accuracy $\approx 90\%$) can be efficiently built leveraging on this knowledge.
- There was no significant differences between the results of different architectures or different fine-tuning procedures.

The FO probing pipeline, dataset, and tagger are all available as open source projects at the following URL: anonymous-url.com.

2 Related Work

Semantic Annotation  Semantic annotation is a method of assigning an enumerable set of distinct classes to words, allowing for a more efficient encoding of generalisations, upon which algorithms could be applied (Silva et al., 2016). The most well-documented semantic annotation tasks include: Semantic Role Labelling (SRL) (Larionov et al., 2019), Sentiment annotation (SA) (Manning et al., 2014), Named Entity Recognition (NER) (Nadeau and Sekine, 2007) and Word Sense Disambiguation (Navigli, 2009). Transformer-based models and their word embeddings have been implemented to achieve state-of-the-art results on each of these tasks (Vial et al., 2019; Wang et al., 2021; Zhang et al., 2021; Jiang et al., 2019).

Ontology Tagging  Ontologies provide a machine-readable representation (class) of a concept in the real world (Neutel and de Boer, 2021a), drawing a connection between natural language and logical reasoning (Silva et al., 2016). Foundational Ontologies are a set of classes which map a concept to its most fundamental interpretation (Silva et al., 2016), see examples in Table 1. Currently, there is no existing Foundational Ontology (FO) tagging dataset large enough to support extensive analysis. The most closely related task to ontology tagging is ontology alignment, the task of generating correspondences between entities contained in a set of ontologies (Ardjani et al., 2015). Results from an automatic ontology alignment study indicated that BERT-based embeddings in isolation are not able to generate functional alignments (Neutel and de Boer, 2021b). However, this study is not concerned with ontologies at a foundational level, and does not offer probing analysis.

WordNet-DOLCE Mapping  The Descriptive Ontology for Linguistic and Cognitive Engineering (DOLCE) (Masolo et al., 2002) was created to encode categories which are inherently present within natural language and human reasoning (Silva et al., 2016). WordNet (Fellbaum, 2012) is an English lexical database containing approximately 155,000 words, organised into an acyclic graph with semantic relations as edges and words as vertices. An alignment between WordNet upper level nouns synsets and DOLCE was proposed (Gangemi et al., 2003), which was eventually expanded into fully classified verb and noun database (Silva et al., 2016). This alignment will form the basis of the FO tagging task presented in this paper. Silva et al. (2016) also presents Top Level Tagger (TLT), an
FO annotation tool. TLT applies a rigid mapping from WordNet to DOLCE classes, this causes issues for annotating large symbolic word spaces, as any words not explicitly mapped to a DOLCE class are assigned the null label.

Probing NLI Models Probing, also denoted as auxiliary prediction (Adi et al., 2017) or diagnostic classification (Hupkes et al., 2018), is designed to investigate the internal representations of a model, generally to explain what information is encoded and how it influences the output (Belinkov, 2021). This is done by training a basic probe model to predict a property of interest from the latent representations of the model (Elazar et al., 2021b). The probing paradigm has already been applied to NER (Jin et al., 2019), SRL (Tenney et al., 2019b) and SA (Xu et al., 2020) tasks. This paper will expand this discussion to FO categories. However, probing is not without its limitations: there is a lack of comparative baselines and there are questions about the choice of evaluation metrics, probe models and datasets, as well as the correlational nature of the method (Belinkov, 2021; Ravichander et al., 2021). To mitigate the impact of these issues this paper will employ the Probe-Ably framework (Ferreira et al., 2021) for all probing experiments, as it supports the current best practices for probing.

3 Foundational Ontology Tagging Dataset

The FO tagging dataset used in this paper was built by using the WordNet-DOLCE alignment (Silva et al., 2016). To construct this dataset, the FO annotation tool Top Level Tagger (Silva et al., 2016) was used to annotate the Brown corpus (Francis, 1965). The Brown corpus was used, as WordNet does not consistently provide example sentences for words. The Brown corpus is comprised of a variety of English texts concerning a range of topics, totalling approximately 1 million words. The data was tagged using a subset (6) of the Top Level Tagger Foundational classes: Socially-Constructed-Person, Cognitive-Event, Geographical-Role, Biological-Object, Non-Agentive-Functional-Object and Information-Object, to allow for more practical manual verification. For each sentence in the corpus one tagged word was extracted at random, resulting in a data set of 2760 unique samples (460 per class), with samples in the format seen in Table 1. The Biological-Object class was supplemented with 100 samples from the WordNet alignment to ensure a sufficiently large and equally distributed set of classes. All samples in the data set were manually verified.

4 Methodology

The evaluation of Transformer-based model performance on the FO tagging task is guided by the following research hypotheses:

• RH1: Pretrained Transformer-based models incidentally encode FO categories, and these can be extracted through the probing paradigm.

• RH2: Based on these pre-encoded categories, a robust lexical semantic model (a term-level FO shallowparser) can be built.

These hypotheses will be tested on a novel Foundational Ontology tagging dataset, using an array of Transformer-based models, consisting of pretrained BERT-base (Devlin et al., 2019), BERT-large, RoBERTa-base (Liu et al., 2019) and RoBERTa-large architectures. Additionally, we also test on BERT-base and RoBERTa-large models fine-tuned on four benchmark NLI datasets: Multi-Genre Natural Language Inference (MultiNLI) (Williams et al., 2018), Stanford Natural Language Inference (SNLI) (Bowman et al., 2015), Microsoft Research Paraphrase Corpus (MRPC) (Dolan and Brockett, 2005) and Quora Question Pairs1 (QQP) (see fine-tuning results in Table 2). This allows us to determine the impact of different fine-tuning tasks and architectures, as well as identifying possible correlations between model performance on the fine-tuned task and the auxiliary probe task. We define three different FO tagging experiments to test these research hypotheses:

• Basic Foundational Ontology tagging task: Probing and fine-tuning on a basic FO tagging task, consisting of classifying the concatenation of a given word with its respective example sentence on one of 6 FO classes.

• Binary task: Probing and fine-tuning on a Binary FO task, the classification of correct/incorrect on a concatenation of a given word with its respective example sentence and a given FO class.

1https://www.kaggle.com/c/quora-question-pairs/overview
Figure 1: Schematic representation of the three tasks adopted for the FO tagging probing and fine-tuning experiments.

| Ontology Class             | Word     | Example sentence                                      |
|----------------------------|----------|------------------------------------------------------|
| Cognitive-event            | Trusted  | Only people he liked and trusted got to see.         |
| Socially-constructed-person | Baby     | The baby began to cry again.                         |
| Non-agentive-functional-object | Car     | He needs a car to get to work.                       |
| Biological-Object          | Ventricle| Inserted into the heart’s left ventricle              |
| Information-Object         | Appendix | However, as noted in the Appendix                    |
| Geographical-Object        | Hemisphere| It was night on this hemisphere                     |

Table 1: Example of samples from the constructed FO tagging dataset.

- **Singular contextualised embedding Probe**
  Probing on a FO tagging task, classifying singular contextualised word embeddings on 6 FO classes.

These 3 tasks are designed to emulate a variety of different NLP tasks, the Basic task using the same format as POS tagging, the Binary task entailment classification, and the singular contextualised embedding probe aims to force the models to encode textual context. Using this we can evaluate if the format affects performance, and if so, which format is most effective.

4.1 Basic FO Tagging Probe
To extract the sentence embeddings, the [word][example] pairs are tokenized and input to a given model. Then the second to last hidden layer of each token is extracted from the output, the average of these layers is used as the sentence embeddings. This produces a single vector for each input data point, of size 768 for base models and 1024 for large models.

4.2 Basic FO Tagging Fine-tuning
The models are fine-tuned on the FO tagging dataset using a 60-20-20 train-validation-test split, for 10 epochs, after which the checkpoint with the minimum loss is then evaluated on the test set.

4.3 Binary Task
For the binary task each FO tagging dataset data point is duplicated, and the duplicate point is randomly assigned an incorrect FO class. The original point is given an additional Correct la-
bel and the duplicate is labelled Incorrect. The result is a binary data set containing 5520 samples with a 1 to 1 ratio of correct/incorrect FO labels. The premise hypothesis pairs for this task are constructed by introducing a new special token (TSEP) to the model’s tokenizer, to create the premise, [word][TSEP][example sentence], and the hypothesis, [FO class]. Passed to the model as [FO class][SEP][word][TSEP][example sentence], for binary classification. It should be noted that none of the models were pre-trained with this new token.

4.3.1 Binary Probe

The sentence embeddings for the binary samples are extracted using the same process as in the basic FO probe, as an average of the second to last hidden layer for each token.

4.3.2 Binary Fine-tuning

The models are fine-tuned on the binary dataset using a 60-20-20 train-validation-test split, for 10 epochs, after which the checkpoint with the minimum loss is then evaluated on the test set.

4.4 Singular Contextualised Embedding

The auxiliary task for this experiment is the classification of singular contextualised word embeddings on 6 FO classes. To generate a singular contextualised word embedding from a [word][example] pair, the example sentence is tokenized and input to a given model, and for each token generated from the target word (i.e. for the target word backboard, the resulting tokens are [back, ##board]) the last 4 hidden layers are concatenated together. These are then averaged out to form the singular contextualised word embedding. For base models these embeddings have a size of 3072, and for large models a size of 4096. The same precautions are applied here as in the basic FO tagging probe.

5 Empirical Evaluation

The two fine-tuning experiments were run on the same hyper-parameters, 10 epochs, using a training batch size of 16, an evaluation batch size of 64, 100 warm up steps, a weight decay of 0.01 and seed 42. The fine-tuned models are evaluated on their accuracy on the test set. For the probing experiments this paper will employ the Probe-Ably framework (Ferreira et al., 2021), an extendable probing framework designed to streamline the process of running probing experiments according to the best practices for probing. For each probe we record the maximum selectivity achieved, and the associated accuracy. The supplementary materials contains the Probe-Ably visualisations for all linear and MLP probes, as well as the source code for the probing pipeline.

5.1 Probing Configuration

For each individual probe we adopt both linear and MLP models. We test each architecture on 4 different transformer-based-models, BERT base, BERT large, RoBERTa base and RoBERTa large. Additionally, we test with BERT base and RoBERTa large models fine-tuned on MNLI, SNLI, QPP and MRPC. We train 50 probes of fluctuating complexities for 25 epochs on the Probe-Ably Framework, using the default train-validation-test split and a batch size of 128.

5.2 Probe Complexity

The Probe-Ably Framework initiates each probe model using an approximate complexity which is varied in a controlled manner across the 50 probe models (Ferreira et al., 2021). The variance in complexity is introduced as a means to alleviate the effect of overly expressive probes simply over fitting to the auxiliary task (Pimentel et al., 2020a).

Probe-Ably employs the same default hyperparameter ranges as (Pimentel et al., 2020b) for the MLP probes and MLP complexity is approximated using the hidden size of intermediate layers.

Probe-Ably follows the convention proposed in (Pimentel et al., 2020a) for approximating and controlling linear probe model complexity. That is for \( \hat{y} = Wx + b \), the nuclear norm (Equation 1) of the transformation matrix \( W \), is utilised to approximate linear model complexity. The theory behind this is that the nuclear norm is an approximation of \( \text{rank}(W) \).

\[
||W||_* = \sum_{i=1}^{\min(|T|,d)} \sigma_i(W).
\] (1)

The variance of the linear model complexity is regulated through the cross-entropy loss function used in the probe’s training loop, via a parameter \( \lambda \) (Equation 2).

\[
- \sum_{i=1}^{n} \log p(t^{(i)} | h^{(i)}) + \lambda \cdot ||W||_*
\] (2)

5.3 Metrics and Control Tasks

Probing models, particularly large MLP models can be susceptible to over-fitting to noise within data
Table 3: Results for Basic Foundational Ontology Tagging task and Binary task on the test set (fine-tuning).

| Model          | MLP probe Accuracy | Max selectivity | Linear probe Accuracy | Max selectivity |
|----------------|--------------------|-----------------|-----------------------|-----------------|
| Random baseline| 0.17               | -               | 0.17                  | -               |
| BERT base      | 0.54               | 0.27            | 0.44                  | 0.25            |
| BERT MNLI      | 0.55               | 0.18            | 0.36                  | 0.16            |
| BERT SNLI      | 0.53               | 0.20            | 0.36                  | 0.14            |
| BERT QQP       | 0.54               | 0.22            | 0.41                  | 0.22            |
| BERT MRPC      | 0.42               | 0.25            | 0.42                  | 0.21            |
| BERT Large     | 0.47               | 0.22            | 0.39                  | 0.22            |
| RoBERTa base   | 0.53               | 0.28            | 0.37                  | 0.16            |
| RoBERTa Large MNLI | 0.34           | 0.14            | 0.18                  | 0.04            |
| RoBERTa Large SNLI | 0.50         | 0.16            | 0.28                  | 0.10            |
| RoBERTa Large QQP | 0.28                | 0.06            | 0.26                  | 0.05            |
| RoBERTa Large MRPC | 0.41                | 0.21            | 0.37                  | 0.18            |
| RoBERTa Large  | 0.57               | 0.30            | 0.40                  | 0.20            |

Table 4: Basic FO tagging results (probing).

| Model          | MLP probe Accuracy | Max selectivity | Linear probe Accuracy | Max selectivity |
|----------------|--------------------|-----------------|-----------------------|-----------------|
| Random baseline| 0.5                | -               | 0.5                   | -               |
| BERT base      | 0.64               | 0.12            | 0.61                  | 0.09            |
| BERT MNLI      | 0.59               | 0.06            | 0.50                  | 0.03            |
| BERT SNLI      | 0.66               | 0.12            | 0.63                  | 0.10            |
| BERT QQP       | 0.59               | 0.06            | 0.57                  | 0.04            |
| BERT MRPC      | 0.65               | 0.12            | 0.61                  | 0.08            |
| BERT Large     | 0.64               | 0.14            | 0.61                  | 0.08            |
| RoBERTa base   | 0.62               | 0.05            | 0.59                  | 0.04            |
| RoBERTa Large MNLI | 0.66                | 0.10            | 0.57                  | 0.05            |
| RoBERTa Large SNLI | 0.63                | 0.08            | 0.59                  | 0.05            |
| RoBERTa Large QQP | 0.58                | 0.07            | 0.56                  | 0.05            |
| RoBERTa Large MRPC | 0.63                | 0.10            | 0.56                  | 0.01            |
| RoBERTa Large  | 0.64               | 0.14            | 0.56                  | 0.06            |

Table 5: Binary task results (probing).

Table 6: Roberta-large class-wise accuracy on the Foundational Ontology tagging test set (fine-tuning).

| Label                  | Accuracy |
|------------------------|----------|
| Socially-constructed-person | 0.946    |
| Non-agentive-functional-object | 0.878    |
| Cognitive-event        | 0.915    |
| Information-Object     | 0.863    |
| Geographical-Object    | 0.873    |
| Biological-Object      | 0.857    |

Table 7: BERT-base class-wise accuracy on the binary tagging test set (fine-tuning).

| Label | Accuracy |
|-------|----------|
| Incorrect | 0.864    |
| Correct   | 0.940    |

dimensional embeddings often require a higher probe complexity to achieve maximum accuracy than their lower dimension counterparts (Ferreira et al., 2021). This can potentially result in a superficially worse accuracy. This discrepancy has been accounted for in each task by ensuring that the probing hyper parameters allow larger models to reach, and pass a clear apex in selectivity. For each probe, we record the maximum selectivity achieved, and the accuracy produced at that same probe complexity. Additionally, we provide a graph of the results for each probe in the supplementary materials.

5.4 Basic FO Tagging Fine-tuning

All models effectively learned the task, with a minimum accuracy of 0.86 (RoBERTa base), results can be seen in Table 3. The maximum accuracy recorded was 0.90 by Bert large, RoBERTA large and RoBERTa QQP. Table 6 shows a class-wise error breakdown for RoBERTa large on the test set. This revealed an imbalanced model performance, with a maximum accuracy of 0.946 on the socially-constructed-person class, and a minimum of 0.857 on the biological object class (0.089 differential).
Figure 2: RoBERTa Large MLP results for the basic Foundational Ontology tagging task (probing).

| Model               | MLP probe | Linear probe |
|---------------------|-----------|--------------|
|                     | Accuracy  | Max selectivity | Accuracy  | Max selectivity |
| Random baseline     | 0.17      | -             | 0.17      | -              |
| BERT base           | 0.64      | 0.26          | 0.49      | 0.30           |
| BERT MNLI           | 0.64      | 0.25          | 0.54      | 0.22           |
| BERT SNLI           | 0.54      | 0.22          | 0.58      | 0.35           |
| BERT QQP            | 0.50      | 0.17          | 0.55      | 0.34           |
| BERT MRPC           | 0.55      | 0.25          | 0.56      | 0.35           |
| BERT Large          | 0.53      | 0.08          | 0.39      | 0.20           |
| RoBERTa base        | 0.55      | 0.24          | 0.50      | 0.20           |
| RoBERTa Large MNLI  | 0.34      | 0.10          | 0.27      | 0.08           |
| RoBERTa Large SNLI  | 0.66      | 0.27          | 0.47      | 0.18           |
| RoBERTa Large QQP   | 0.35      | 0.16          | 0.28      | 0.10           |
| RoBERTa Large MRPC  | 0.48      | 0.25          | 0.62      | 0.37           |
| RoBERTa Large       | 0.55      | 0.32          | 0.56      | 0.12           |

Table 8: Singular contextualised word embedding results (probing)

The large architectures each outperformed their base counterparts, with a +0.01 difference between the best large and base models. Additionally, the models fine-tuned on NLI tasks performed slightly worse on average, than the base versions, with a maximum -0.02 disparity.

5.5 Binary Fine-tuning
All models effectively learned the binary task, with a minimum accuracy of 0.89, and a maximum on 0.90, achieved by results can be seen in Table 3. Table 7 shows a class-wise error breakdown for BERT base on the test set, again a significant imbalance in performance can be observed as the model achieves a 0.940 accuracy on the Correct class and only 0.864 on the Incorrect class (-0.076 differential). There was very little difference in performance across model types and fine-tuning procedures.

5.6 Basic FO Tagging Probe
The Basic FO tagging dataset contains 2,760 samples, 460 per class. During probing this was split 552 - 552 - 1,656 as train-validation-test. The results from fine-tuning task on the basic FO tagging Probe can be found in Table 4. All of the probes, apart from the RoBERTa large MNLI linear probe, significantly outperform the random baseline accuracy (0.17 with 6 classes) at max selectivity. The RoBERTa large MNLI linear probe produces the lowest accuracy 0.18, as well as the lowest max selectivity, 0.04. The RoBERTa large MLP probe
generated the highest accuracy at max selectivity, +0.01 accuracy +0.03 max selectivity above next best probe, results seen in FIGURE 2. MLP probes also significantly outperformed the linear probes on this task, with a +0.13 accuracy +0.05 max selectivity difference between their best probes, RoBERTa large and BERT base respectively. The models fine-tuned on NLI benchmarks all performed worse than their base versions on both probe types. The most significant difference was recorded between RoBERTa large and RoBERTa large MNLI, with a +0.23 accuracy and +0.16 max selectivity differential. With regards to the results from the 4 architectures, the largest discrepancy in the base models was between RoBERTa large and BERT large with +0.10 accuracy and +0.08 max selectivity.

5.7 Binary Probe

The Basic FO tagging data set contains 5,520 samples, 2,760, per class. During probing this was split 1,104 - 1,104 - 3,312 train-validation-test. Table 5 shows the results of the binary probe. The graphs of the results for each probe are provided in the supplementary materials. All of the probe models, aside from BERT MNLI, outperform the random baseline accuracy (0.5 with two classes). The minimum accuracy at max selectivity was recorded on the BERT MNLI model, at 0.5, for the Linear probe type. The lowest accuracy at max selectivity for the MLP probe was produced by RoBERTa large QQP, at 0.58. The best performing models were BERT SNLI, RoBERTa large and BERT large, with BERT SNLI recording the highest accuracy, 0.66, and RoBERTa large and BERT Large generating the highest max selectivity, 0.14. As performance is evaluated on a combination of accuracy and maximum selectivity, it is difficult to make definitive claims about which of these probes was most effective. The MLP probes outperform each of their Linear counterparts, with the difference between their respective best results being +0.03 accuracy and +0.04 max selectivity. The most significant difference between a model and its NLI fine-tuned version occurs with the BERT base and BERT MNLI linear probes with +0.11 accuracy and +0.06 max selectivity. On the MLP probes BERT and RoBERTa large both achieve 0.64 accuracy and 0.14 max selectivity, in comparison, the weakest performing base model, RoBERTa base, records at 0.62 accuracy and 0.05 max selectivity.

5.8 Singular Contextualised Embedding Probe

The Singular contextualised embedding data set contains 2,760 samples, 460, per class. During probing this was split 552 - 552 - 1,656 train-validation-test. The results from singular contextualised embedding probe be found in Table 8. All probes significantly outperform the random baseline accuracy (0.17 with 6 classes). The highest accuracy, 0.66, was produced by the RoBERTa large SNLI MLP probe at 0.27 max selectivity. However, the highest max selectivity, 0.37, was generated by RoBERTa large MRPC linear probe, with a 0.62 accuracy. For this task several of the linear probes outperformed their MLP counterparts, BERT SNLI, QQP and MRPC, as well as RoBERTa MRPC and RoBERTa large. The difference between the best MLP and Linear probes was +0.04 accuracy and -0.10 Max selectivity. There was no significant difference between the base models and their best NLI fine-tuned equivalent. With regards to different architectures, the best base architecture was BERT base with 0.64 accuracy and 0.26 max selectivity, and the worst was BERT large with 0.53 accuracy and 0.08 selectivity.

6 Discussion

6.1 Fine-tuning Experiments

The results from the fine-tuning on both the binary and basic FO tagging tasks clearly show that transformer based models have a propensity for encoding FO information, achieving a maximum of 0.90 accuracy with several models, on both tasks. Class-wise error breakdown revealed a significant variation in accuracy across classes for both the binary task and the basic FO tagging task. Models fine-tuned on NLI benchmarks performed consistently worse than the base models. Additionally, RoBERTa large models outperformed BERT on the task, and the reverse was true on the binary task. However, as the test set for the basic FO task only contained 552 samples, and 1,104 for the binary task, the discrepancies are not significant enough to make any definitive statements with regards to either the effect of NLI fine-tuning or differing architectures.

6.2 Probing Experiments

For each of the probing experiments the majority of the probes achieved a significantly higher accuracy than the random baseline, indicating that
the transformer-based models which were tested incidentally encode some FO information during their pre-training. The MLP probes heavily outperformed the linear probes for the base and binary tasks, and were closely matched in the singular contextualised embedding task. However, the MLP probes generated the highest accuracy for all tasks. With regards to the 4 different base architectures and the NLI fine-tuned models, there was no significant differences in the results. The complete set of probe visualisations are available in the supplementary materials.

7 Conclusion

In this work, we aim to answer the question: can contemporary transformer-based models reflect an underlying Foundational Ontology? We present a novel FO tagging data set, and apply a systematic FO probing methodology on a range of transformer-based models with varied pre-training and fine-tuning protocols. An extensive evaluation of the probes demonstrated that transformer-based models incidentally encode information related to Foundational Ontologies during their pre-training. In particular, MLP probes are significantly more effective than linear probes in all probing tasks, and there was no significant differences between the results of different architectures or fine-tuning procedures. Additionally, it showed the effectiveness of training transformer based models on the FO dataset to produce Robust term-level FO taggers, opening the way for future research into sequence-to-sequence taggers for abstract ontology classes.

References

Yossi Adi, Einat Kermany, Yonatan Belinkov, Ofer Lavi, and Yoav Goldberg. 2017. Fine-grained analysis of sentence embeddings using auxiliary prediction tasks.

Fatima Ardjani, Djelloul Bouchiha, and Mimoun Malki. 2015. Ontology-alignment techniques: Survey and analysis. International Journal of Modern Education and Computer Science, 7:67–78.

Yonatan Belinkov. 2021. Probing classifiers: Promises, shortcomings, and advances.

Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015. A large annotated corpus for learning natural language inference. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 632–642, Lisbon, Portugal. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

William B. Dolan and Chris Brockett. 2005. Automatically constructing a corpus of sentential paraphrases. In Proceedings of the Third International Workshop on Paraphrasing (IWP2005).

Yanai Elazar, Nora Kassner, Shauli Ravfogel, Abhilasha Ravichander, Eduard H. Hovy, Hinrich Schütze, and Yoav Goldberg. 2021a. Measuring and improving consistency in pretrained language models. Transactions of the Association for Computational Linguistics, 9:1012–1031.

Yanai Elazar, Shauli Ravfogel, Alon Jacovi, and Yoav Goldberg. 2021b. Amnesic probing: Behavioral explanation with amnesic counterfactuals. Transactions of the Association for Computational Linguistics, 9:160–175.

Christiane Fellbaum. 2012. WordNet. In The Encyclopedia of Applied Linguistics. American Cancer Society.

Deborah Ferreira, Julia Rozanova, Mokanarangan Thayaparan, Marco Valentino, and André Freitas. 2021. Does my representation capture X? probeably. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing: System Demonstrations, pages 194–201, Online. Association for Computational Linguistics.

W. Nelson Francis. 1965. A standard corpus of edited present-day american english. College English, 26(4):267.

Aldo Gangemi, Nicola Guarino, Claudio Masolo, and Alessandro Oltramari. 2003. Sweetening wordnet with dolce. AI Mag., 24(3):13–24.

Aldo Gangemi, Nicola Guarino, Claudio Masolo, Alessandro Oltramari, and Luc Schneider. 2002. Sweetening ontologies with dolce. In International Conference on Knowledge Engineering and Knowledge Management, pages 166–181. Springer.

Giancarlo Guizzardi. 2005. Ontological foundations for structural conceptual models.

John Hewitt and Percy Liang. 2019. Designing and interpreting probes with control tasks. In Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics.
Jennifer Hu, Jon Gauthier, Peng Qian, Ethan Wilcox, and Roger Levy. 2020. A systematic assessment of syntactic generalization in neural language models. In Proceedings of the Association for Computational Linguistics.

Dieuwke Hupkes, Sara Veldhooien, and Willem Zuidema. 2018. Visualisation and ‘diagnostic classifiers’ reveal how recurrent and recursive neural networks process hierarchical structure.

Haoming Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Tuo. Zhao. 2019. Smart: Robust and efficient fine-tuning for pretrained natural language models through principled regularized optimization. Annual Meeting of the Association for Computational Linguistics.

Qiao Jin, Bhuwan Dhingra, William W. Cohen, and Xinghua Lu. 2019. Probing biomedical embeddings from language models.

Daniil Larionov, Artem Shelmanov, Elena Chistova, and Ivan Smirnov. 2019. Semantic role labeling with pretrained language models for known and unknown predicates. In Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2019), pages 619–628, Varna, Bulgaria. INCOMA Ltd.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. ArXiv, abs/1907.11692.

Christopher Manning, Mihai Surdeanu, John Bauer, Jenny Finkel, Steven Bethard, and David McClosky. 2014. The Stanford CoreNLP natural language processing toolkit. In Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations, pages 55–60, Baltimore, Maryland. Association for Computational Linguistics.

Claudio Masolo, Stefano Borgo, Aldo Gangemi, Nicola Guarino, Alessandro Oltramari, and Luc Schneider. 2002. Wonderweb deliverable d17. the wonderweb library of foundational ontologies and the dolce ontology.

David Nadeau and Satoshi Sekine. 2007. A survey of named entity recognition and classification. Linguisticae Investigationes, 30.

Roberto Navigli. 2009. Word sense disambiguation: A survey. ACM Comput. Surv., 41(2).

Sophie Neutel and Maaike HT de Boer. 2021a. Towards automatic ontology alignment using bert. In AAAI Spring Symposium: Combining Machine Learning with Knowledge Engineering.

Sophie Neutel and Maaike HT de Boer. 2021b. Towards automatic ontology alignment using bert. In AAAI Spring Symposium: Combining Machine Learning with Knowledge Engineering.

Tiago Pimentel, Naomi Saphra, Adina Williams, and Ryan Cotterell. 2020a. Pareto probing: Trading off accuracy for complexity. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 3138–3153, Online. Association for Computational Linguistics.

Tiago Pimentel, Josef Valvoda, Rowan Maudslay, Ran Zmigrod, Adina Williams, and Ryan Cotterell. 2020b. Information-theoretic probing for linguistic structure. pages 4609–4622.

Abhilasha Ravichander, Yonatan Belinkov, and Eduard Hovy. 2021. Probing the probing paradigm: Does probing accuracy entail task relevance?

Daniela Schmidt, Giancarlo Guizzardi, Adam Pease, Cassia Trojahn, and Renata Vieira. 2020. Foundational ontologies meet ontology matching: A survey. Semantic Web.

Vivian S. Silva, André Freitas, and Siegfried Handschuh. 2016. Word tagging with foundational ontology classes: Extending the wordnet-dolce mapping to verbs. In Knowledge Engineering and Knowledge Management, pages 593–605, Cham. Springer International Publishing.

Ian Tenney, Dipanjan Das, and Ellie Pavlick. 2019a. Bert rediscovers the classical nlp pipeline. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4593–4601.

Ian Tenney, Patrick Xia, Berlin Chen, Alex Wang, Adam Poliak, R Thomas McCoy, Najoung Kim, Benjamin Van Durme, Samuel R. Bowman, Dipanjan Das, and Ellie Pavlick. 2019b. What do you learn from context? probing for sentence structure in contextualized word representations.

Mokanarangan Thayaparan, Marco Valentino, and André Freitas. 2020. A survey on explainability in machine reading comprehension. arXiv preprint arXiv:2010.00389.

Mokanarangan Thayaparan, Marco Valentino, and André Freitas. 2021. Explainable inference over grounding-abstract chains for science questions. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 1–12.

Marco Valentino, Mokanarangan Thayaparan, and André Freitas. 2021. Unification-based reconstruction of multi-hop explanations for science questions. In Proceedings of the 10th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 200–211.

Loïc Vial, Benjamin Lecouteux, and Didier Schwab. 2019. Sense vocabulary compression through the semantic knowledge of WordNet for neural word sense disambiguation. In Proceedings of the 10th Global Wordnet Conference, pages 108–117, Wroclaw, Poland. Global Wordnet Association.
Xinyu Wang, Yong Jiang, Nguyen Bach, Tao Wang, Zhongqiang Huang, Fei Huang, and Kewei Tu. 2021. Automated Concatenation of Embeddings for Structured Prediction. Association for Computational Linguistics.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1112–1122, New Orleans, Louisiana. Association for Computational Linguistics.

Hu Xu, Lei Shu, Philip S. Yu, and Bing Liu. 2020. Understanding pre-trained bert for aspect-based sentiment analysis.

Kelly Zhang and Samuel Bowman. 2018. Language modeling teaches you more than translation does: Lessons learned through auxiliary syntactic task analysis. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 359–361, Brussels, Belgium. Association for Computational Linguistics.

Yu Zhang, Qingrong Xia, Shilin Zhou, Yong Jiang, Zhenghua Li, Guohong Fu, and Min Zhang. 2021. Semantic role labeling as dependency parsing: Exploring latent tree structures inside arguments.

Zili Zhou, Marco Valentino, Donal Landers, and André Freitas. 2021. Encoding explanatory knowledge for zero-shot science question answering. In Proceedings of the 14th International Conference on Computational Semantics (IWCS), pages 38–50, Groningen, The Netherlands (online). Association for Computational Linguistics.

A Supplementary Material

A.1 Data and code

All the models used in the paper can be found on URL: https://huggingface.co/. The full data set along with the graphs for all of the probe results and the code to reproduce the experiments described in the paper is available at the following URL: anonymous-url.com