

Perturbed examples reveal invariances shared by language models

Ruchit Rawal *

MPI for Software Systems
Saarbrücken, Germany

Mariya Toneva

MPI for Software Systems
Saarbrücken, Germany

Abstract

The rapid growth in natural language processing (NLP) research has led to numerous new models, outpacing our understanding of how they compare to established ones. One major reason for this difficulty is saturating benchmarks, which may not well reflect differences in model performance in the wild. In this work, we introduce a novel framework to compare two NLP models by revealing their shared invariance to interpretable input perturbations targeting a specific linguistic capability. Via experiments on models from the same and different architecture families, this framework offers insights about how changes in models (e.g., distillation, size increase) affect linguistic capabilities. Furthermore, our framework enables evaluation of invariances between commercial black-box models (e.g., InstructGPT family) and models that are better understood (e.g., GPT-2). Across experiments, we observe that large language models share many invariances encoded by models of various sizes, whereas the invariances by large models are only shared by other large models. Possessing a wide variety of invariances may be key to the recent successes of large language models, and our framework can shed light on the types of invariances retained or emerging in new models. We make the code publicly available ¹.

1 Introduction

A key reason for the tremendous progress and adoption of natural language processing (NLP) models has been the ready availability of models that can be adapted to diverse downstream tasks and datasets (Wolf et al., 2019). However, with the increasing number of new models, it is difficult to know how new models compare to better-understood ones. This is complicated by the fact

*Correspondence: rawalruchit22@gmail.com

¹https://github.com/bridge-ai-neuro/shared_invariances_acl.

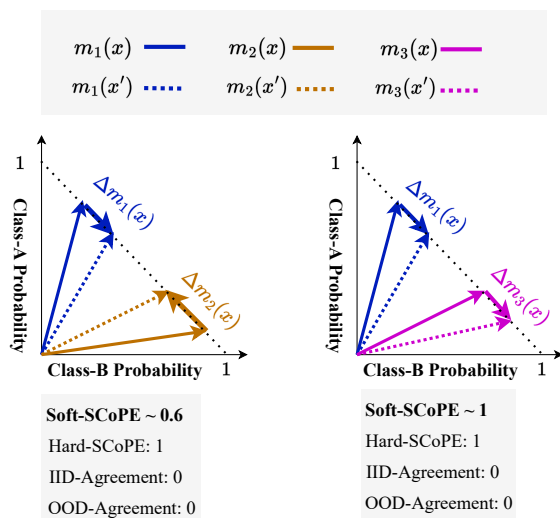


Figure 1: Proposed shared invariances metrics: Hard-SCoPE and Soft-SCoPE, for three binary-classifiers (m_1 , m_2 , and m_3). For perturbation $x \rightarrow x'$, both m_2 and m_3 satisfy the Hard-SCoPE criteria. However, the effect of the perturbation is more aligned for m_1 & m_3 compared to m_1 & m_2 .

that standard benchmark datasets are saturating (Dehghani et al., 2021; Owen, 2023), and small differences on these may in fact correspond to large differences in model performance in the wild (Tay et al., 2022; Zhang et al., 2022; Liu et al., 2023).

To enable more comprehensive model comparisons, we propose a novel framework for comparing two NLP models by investigating their shared invariance to specific input perturbations. We illustrate the idea of shared invariances with an example. Consider a scenario involving social media content moderation, in which a model is tasked with classifying whether a sentence is offensive. Now take two sentences that differ only by a synonym, e.g. “This game is a killer, totally blew my mind.” and “This game is a slayer, totally blew my mind.”. A well-understood model, m_1 , trained for general social media usage, classifies this pair

of sentences and other similarly perturbed pairs as non-offensive, and is thus invariant to synonym-based perturbations. We would now like to evaluate a new model, m_2 , which is specifically finetuned for children’s content moderation. Our framework allows us to determine to what degree m_2 maintains a similar synonym invariance to m_1 , despite possible differences in the predictions of m_1 and m_2 —such as m_1 classifying the sentences as non-offensive and m_2 as offensive.

To systematically measure these shared invariances across various perturbations, we introduce an invariant sample generation approach (see Section 3) and propose novel metrics: Hard-SCoPE and Soft-SCoPE (see Figure 1). These metrics assess shared invariances independently of the agreement between model predictions, i.e., Hard-SCoPE and Soft-SCoPE can be high even if two models consistently disagree in their predictions, as long as they remain invariant to the same perturbations. Such scenarios present an interesting opportunity for investigation, as they highlight how significant design changes, like finetuning, may not necessarily alter the features a model treats invariant (and irrelevant), despite changing its specific predictions.

While evaluating shared invariance is important, not all invariances are created equal: some may be desirable (e.g., invariance to synonym substitution for content moderation) while others may be undesirable (e.g., invariance to word order of image captioning). We enable the evaluation of specific shared invariances via interpretable input perturbations designed to target a specific linguistic capability (e.g., Synonym-Invariance, Typo-Invariance). A linguistic capability evaluates a model’s competence on a particular aspect of knowledge and understanding required to solve an NLP task by validating its input-output behavior under the corresponding scenario. For instance, the linguistic capability ‘Synonym-Invariance’ evaluates whether a sentiment analysis model changes its prediction if the positive verb is replaced by its synonym. Hence, the generated perturbations along specific linguistic capabilities enable us to measure shared model invariances along different linguistic capabilities.

We demonstrate our proposed framework’s utility in deriving novel insights on how changes in models such as distillation and increase/decrease in size affect shared invariances along multiple well-defined linguistic capabilities. We also show how our framework can be used to compare how invariances along different linguistic capabilities

evolve over the course of pre-training for a particular model. Additionally, we also demonstrate how our framework can enable evaluation of the invariances shared between models that are available as commercial black-box APIs (e.g., InstructGPT family) and models that are relatively better understood (e.g., GPT-2). Across several experiments, we find that while larger language models share many of the invariances encoded by models of varying scale, invariances encoded by large language models are only shared by other large models of similar sizes.

Our main contributions can be summarized as follows: (1) We propose a novel framework for defining linguistic capabilities w.r.t a reference NLP model to generate interpretable invariant perturbations. (2) We propose two novel measures: Hard-SCoPE and Soft-SCoPE to measure the degree of shared (behavioral) invariances between two models along a particular linguistic capability. (3) Through experiments on two NLP tasks—text classification and language modeling—we uncover several insights, such as: distilling BERT leads to loss of shared invariances along certain linguistic capabilities (such as Typo-Invariance) more than others (Synonym-Invariance); models (within an architecture family) tend to have a higher (or similar) degree of shared-invariances with models of larger sizes compared to other models of similar sizes—a pattern that also holds true for black-box InstructGPT models. We make our code publicly available so that other researchers can reproduce and build on our methodology and findings.

2 Related Works

Similarity measures between two neural networks usually operate at two levels of abstraction: output *behavior* and intermediate layer *representations*.

Behavior: Many works compare the behavioral similarity between two models (trained for a given task) by evaluating the difference between their average performances on the held-out “test-set” (e.g., IID accuracy, perplexity, etc). For example, previous work has used IID accuracy to evaluate the effect of well-defined design choices such as model architecture and training scheme (Ding et al., 2021), training time constraints (Geiping and Goldstein, 2022), and latency and memory (Sanh et al., 2019). However, recently many researchers have highlighted the limitations of IID test-sets in identifying different failure modes (Hooker et al., 2019, 2020) and have consequently proposed alter-

native approaches for rigorous evaluation (Rychalska et al., 2019; Prabhakaran et al., 2019; Ribeiro et al., 2020; Ribeiro and Lundberg, 2022). Most relevant to our work, Ribeiro et al. (2020) proposed CheckList—a methodology for evaluating the behavior of NLP models along general linguistic capabilities that are applicable for many NLP tasks. More recently, La Malfa and Kwiatkowska (2022) defined linguistic capabilities as symbolic perturbations of an input sentence for a particular task, and evaluated whether a model’s predictions for this sentence align with human annotators. While the above approaches can highlight differences between the two models’ ability to generalize under the perturbations introduced by a linguistic capability, they perform an indirect behavioral comparison via the human annotators. In this work, we provide a complementary approach that directly evaluates shared behavioral invariances between two models by defining linguistic capabilities with respect to an NLP model instead of a human annotator.

Representations: Numerous works have also proposed methods for analyzing and comparing NLP models based on their internal representations (Morcos et al., 2018; Saphra and Lopez, 2019; Liu et al., 2019; Durrani et al., 2021). Wu et al. (2020) investigate the representational similarity of NLP models at both neuron and layer-level output to quantify the effects of different design choices across models from both across and within architectural families. Phang et al. (2021) explore the effects of fine-tuning a neural language encoder by comparing representations of a fine-tuned language encoder with its pre-trained counterpart across layers. Nanda et al. (2022) proposed a novel measure (STIR) to quantify the similarity between representations of two models via measuring their shared invariances. They achieve this by first generating a set of perturbations that don’t change the representations of one model and consequently measuring the extent to which the other model’s representations are invariant on them. However, this setup is not directly applicable to NLP due to the discrete nature of language input, where representation inversion would lead to perturbations along arbitrary directions in the input space and consequently linguistically inconsistent samples (La Malfa and Kwiatkowska, 2022). We address this by generating invariant perturbations (for a particular model) along well-characterized and interpretable linguistic capabilities by using discrete optimization. Finally, while a central theme of our

work is also comparing the similarities and differences between two NLP models, we present an orthogonal approach that focuses on behavior.

3 Methodology

Measuring shared invariances along an interpretable linguistic capability necessitates the generation of controlled, meaningful perturbations to the input text. However, creating such perturbations end-to-end using gradient descent is impractical, due to the discrete nature of language inputs. To effectively generate these perturbations, one must first define a *transformation* class of broadly allowed perturbations (e.g., replacing words with their synonyms) based on the linguistic capability (e.g., Synonym-Invariance) under investigation, along with the constraints to outline specific exclusion criteria (e.g., ignoring stop words). Moreover, to automate the generation of these perturbations, we also need a *search method* to effectively traverse the space of all possible perturbations, and choose the one that maximizes a *goal function*. Therefore, each linguistic capability can be decomposed to four key components: transformation, constraints, goal function, and search method. This characterization is connected to insights in NLP adversarial robustness literature that explore generating perturbations that fools a particular model instead. Next, we discuss each component in detail.

3.1 Goal Function and Search Method

To effectively quantify measures such as shared invariances (defined in Sec. 3.3) between a reference and a target NLP model, we enforce that the reference model is invariant to the perturbation introduced by the linguistic capability. The behavioral invariance serves as the *goal function* while generating perturbations with respect to the *reference NLP model*, ensuring that the perturbation generation process interacts with the reference NLP model. This formulation is important as invariance-based measures are otherwise difficult to measure using purely observational data (Nanda et al., 2022). Additionally, this also lends directionality to our shared-invariance measures as the perturbations generated w.r.t two different reference models would be different, allowing us to delineate invariances unique to any model and measure their degree of overlap with others.

We define the goal of behavioral invariance at the level of the output softmax probabilities i.e., the

reference model m is behaviorally invariant if there is a negligible difference between the predicted probability distribution on the base and perturbed sample. More formally, consider an NLP model m that outputs probability distribution $m(x)$ for an input text x . A linguistic capability C perturbs $x \in X$ s.t. m is invariant to the perturbed text x'

$$C(x; m) = \underset{x'}{\operatorname{argmin}} \mathcal{L}(m(x), m(x')), \quad (1)$$

subject to $x \neq x'$

where \mathcal{L} is the goal function that guides the optimization process. Since x is a sequence of tokens, we use a greedy search algorithm for finding x' that minimizes $\mathcal{L}(m(x), m(x'))$ in the finitely large transformation space. In our experiments, we define $\mathcal{L}(m(x), m(x')) = \|m(x) - m(x')\|_1$. In practice, we observe that minimizing this objective leads to x' that are at least invariant in argmax predictions (refer supplementary Sec. E). As detailed in the supplementary Sec. J, the goal function can take other forms if it captures differences in both direction and magnitude between $m(x)$ and $m(x')$.

3.2 Transformations and Constraints

Next, we fully formalize different linguistic capabilities by specifying the corresponding transformations and constraints. In this work, we primarily focus on two such linguistic capabilities: *Synonym-Invariance* and *Typo-Invariance* that perform perturbations at multiple levels (i.e., character-level transformations to word-level substitutions). **Synonym-Invariance** perturbs words by replacing them with their synonyms. More specifically, we adopt the transformation strategy proposed by Ren et al. (2019) that determines candidate synonyms for a particular word based on WordNet (e.g., A man laughs out loud. \rightarrow A man laughs out loudly.). **Typo-Invariance** perturbs a word in the input text by swapping its middle characters (i.e., all characters in a word except the first and last one). Thus, while Synonym-Invariance perturbs input text at a word level, Typo-Invariance produces transformations at a character level (e.g., A man laughs out loud. \rightarrow A man laughs out luod.). For both linguistic capabilities, we disregard modifications of words that are stopwords, have lengths less than four, or are already perturbed. We focus on these two capabilities because there is a rich literature studying them, albeit from an adversarial robustness perspective as they concern the reliability of many real-world systems, such as spam detection,

toxicity classification (Lee and Ng, 2005; Pruthi et al., 2019). We perform experiments along an additional linguistic capability: Fairness and report our insights in the supplementary Sec. C due to space constraints. We would like to emphasize that the list of linguistic capabilities (e.g., negation, word order) can be easily expanded by defining the specific transformation and constraints.

3.3 Metrics for Quantifying Behavioral-Similarity

We perform experiments with a number of popular metrics (such as accuracy and agreement-rates) as well as propose novel ones (behavioral shared invariances). These metrics can be broadly categorized into three classes: performance-based (Gap in IID accuracy), agreement-based (IID and OOD (Out-of-Distribution) agreement), and invariance-based (Hard-SCoPE, Soft-SCoPE). The invariance-based metrics offer a complementary lens on the behavioral similarity between two NLP models as we empirically observe that the existing metrics often fail to adequately capture them for many kinds of models one would want to investigate. Due to space constraints, we present the correlation results between different metrics in supplementary Sec. I. Next, we discuss all the metrics in detail.

Notation: Consider a task T with an IID test set denoted as $(X_{\text{test}}, y_{\text{test}}) \sim D_{\text{test}}$. Models $\mathcal{M} = \{m_1, m_2\}$ are fine-tuned on training samples for this task, where each model m maps an input x to output a probability distribution $m(x) \in \mathbb{R}^n$ over n unique labels/vocabulary for T . The model’s prediction $y_m(x)$ is defined as: $y_m(x) = \underset{k \in [n]}{\operatorname{argmax}} m(x)_k$ where $m(x)_k$ denotes the probability score for k^{th} label. We aim to assess the behavioral similarity between m_1 and m_2 along a particular linguistic capability C . Perturbations are applied to a set of base samples X (typically X_{test}).

3.3.1 Performance-based Metrics

Comparing the gap between aggregate performance-based measures is one of the most common ways to characterize behavioral similarity between two models as models with lower performance gaps are generally thought of as more behaviorally similar (Ding et al., 2021; Klabunde et al., 2023). Specifically, the Gap in IID accuracy is the absolute difference in the accuracies of the reference and target models, i.e., **Gap in IID Accuracy:** $|acc(m_1) - acc(m_2)|$,

where accuracy of a model m is defined as $acc(m) = \mathbb{E}_{x,y \sim D_{test}} \mathbb{1}[y = y_m(x)]$.

3.3.2 Agreement-based Metrics

Instead of focusing on the average differences in performance, the agreement rates (between m_1 & m_2) explore the behavioral similarity directly at the instance level. We calculate model agreement rate on both base and perturbed samples.

IID Agreement:

$$\mathbb{E}_{x \in X} \mathbb{1}[y_{m_1}(x) = y_{m_2}(x)]$$

OOD Agreement:

$$\mathbb{E}_{x \in X} \mathbb{1}[y_{m_1}(C(x; m_1)) = y_{m_2}(C(x; m_1))]$$

Evaluating agreement rates is akin to comparing the similarity between their decision regions, especially for out-of-distribution (OOD) data, representing points sampled along linguistic capabilities in the data manifold (Somepalli et al., 2022).

3.3.3 Proposed Invariance-based Metrics

Shared invariances can reveal similarities and differences in the finer-grained instance properties used by two models for their predictions. For example, consider the example from the introduction section, "This game is a killer, totally blew my mind," perturbed to "This game is a slayer, totally blew my mind" through synonym swaps. Two models, differing in design choices such as finetuning, may predict differently depending on their intended use case (e.g., general social media vs. children’s social media moderation). However, if both models treat the perturbed sentence the same as the original, they demonstrate a shared invariance. This indicates a common underlying invariance mechanism between the models to certain types of perturbations, despite their differing individual decision outcomes (i.e., zero agreement rates). Thus, measuring shared invariances involves evaluating the effect of a perturbation within each model individually and then comparing if both models exhibit invariance. Consequently, this framework can also highlight if a model becomes sensitive to certain perturbations after a design choice or if it acquires new invariances not present in the original model. Agreement rates are inadequate for such investigations as they directly compare the behavior of two models on a particular set of samples, usually either original or perturbed, without accounting for within model invariances on a perturbation. Since behavior itself can be measured at different granularity

i.e., with respect to exact class prediction or predicted softmax probabilities, we propose two novel notions (Hard and Soft) of measuring behavioral shared-invariance: **SH**ared-Capabilities-thrOugh-Perturbed-Examples (**SCoPE**)

Hard-SCoPE: We want to measure to what degree target model m_2 ’s prediction remains invariant to a change in the input for which the reference model m_1 was invariant, i.e., $x \rightarrow x'$, where $x' = C(x; m_1)$. We define this quantity as Hard-SCoPE as it considers the ‘hard’ argmax predictions to determine behavioral shared-invariances.

$$\text{Hard-SCoPE}(m_2 | m_1) = \mathbb{E}_{x \in X} H(m_2 | m_1, x, C). \quad (2)$$

$H(m_2 | m_1, x, C)$, the hard shared-invariance for a particular sample, is defined as:

$$\mathbb{1}[y_{m_2}(x) = y_{m_2}(C(x; m_1)) | y_{m_1}(x) = y_{m_1}(C(x; m_1))]. \quad (3)$$

Note that the Hard-SCoPE is not calculated between two models (like agreement-rates), but rather between the base and perturbed samples for a particular target model m_2 . For a binary-classification setup, Hard-SCoPE can be seen as “agreement between agreement-rates” i.e., Hard-SCoPE would be 1 if either both IID and OOD agreement are 0 or both are 1 for a particular base-perturbed sample pair. We discuss the relationship between IID-, OOD-agreements and Hard-SCoPE in more detail in the supplementary Sec. E.

Soft-SCoPE: A softer notion of shared-invariances is to look beyond argmax predictions and investigate whether the perturbation in input space produces the same effect (change) in the output probability distributions of both models. The effect of the perturbation $x \rightarrow x'$, where $x' = C(x; m)$ is generated with reference model m , in the output probability distributions for a model m is denoted by $\Delta \vec{m}$ i.e., $\Delta \vec{m} = m(x') - m(x)$. We present an intuition of utility of soft shared invariance in Fig. 1 (left).

In Fig. 1 (left), we visualize the predicted probability distributions of three models m_1 , m_2 , and m_3 trained on a binary classification task on both base – $m_1(x)$, $m_2(x)$, $m_3(x)$ and perturbed samples – $m_1(x')$, $m_2(x')$, $m_3(x')$, where the perturbation x' is generated by a linguistic capability C and reference model m_1 i.e., $x' = C(x; m_1)$. While the input perturbation qualifies as a (hard) shared

invariance for both $(m_2 | m_1)$ and $(m_3 | m_1)$ since both m_2 and m_3 remain invariant in their argmax predictions; the effect (change in the predicted output probability distribution) of the perturbation is much more aligned for one pair (i.e., $\Delta\vec{m}_3$ and $\Delta\vec{m}_1$) than the other (i.e., $\Delta\vec{m}_2$ and $\Delta\vec{m}_1$). Thus, the reliance on (argmax) predictions to quantify shared-invariances by Hard-SCoPE could obscure key differences about the effect of the perturbation.

As motivated by this example, a desiderata for the soft shared-invariance metric is to obtain high values if the change in both models ($\Delta\vec{m}_1$, $\Delta\vec{m}_2$) is similar in both direction and magnitude and low values otherwise. Thus, we define Soft-SCoPE($m_2 | m_1$) as:

$$\mathbb{E}_{x \in X} \text{decay}(\text{dist}(\Delta\vec{m}_1, \Delta\vec{m}_2)) H(m_2 | m_1, x, C), \quad (4)$$

where $\text{decay}(\text{dist}(\Delta\vec{m}_1, \Delta\vec{m}_2))$ is an additional term that weighs the contribution of each pair of base and perturbed samples by a function of the corresponding changes in model probabilities $\Delta\vec{m}_1$ and $\Delta\vec{m}_2$. More specifically, the $\text{decay}(\text{dist}(\cdot))$ term is composed by two functions: a function dist that computes the difference between the changes in model probabilities, and a decay function decay , which has a range $[0, 1]$ i.e., $0 \leq \text{decay}(\text{dist}(\Delta\vec{m}_1, \Delta\vec{m}_2)) \leq 1$ and is monotonically decreasing to ensure lower dist values correspond to higher similarity as in all previous metrics. In our experiments, we chose $\text{dist}(\Delta\vec{m}_1, \Delta\vec{m}_2) = \|\Delta\vec{m}_1 - \Delta\vec{m}_2\|_1$ and decay as a linear function. Thus, Soft-SCoPE has an overall range of $[0, 1]$. We visualize how the Soft-SCoPE landscape varies for two different model pairs in the supplementary Sec. L.

4 Effect of Model Design Choices on Shared-Invariances

In this section, we investigate the effect of different design choices on the invariances shared by two models. Thus, we experiment with a range of NLP models varying in training objective (BERT (Devlin et al., 2019), DistilBERT (Sanh et al., 2019)), and size (BERT-Tiny, Mini, Small, Medium, Base). Unless otherwise stated, we finetune all architectures for 5 epochs on Stanford Sentiment Treebank (SST2 a binary sentiment classification dataset) (Socher et al., 2013). SST2 has a train/test split of 67.3k and 872, respectively. We present additional results for different datasets (AG-News) and tasks (language modeling) in the supplementary Sec. B

and Sec. G. We build upon the "textattack" library (Morris et al., 2020) to implement several linguistic capabilities based on our requirements. For each capability and reference-model pair we generate the perturbed examples three times and report the average results with standard errors.

4.1 Different Linguistic Capabilities

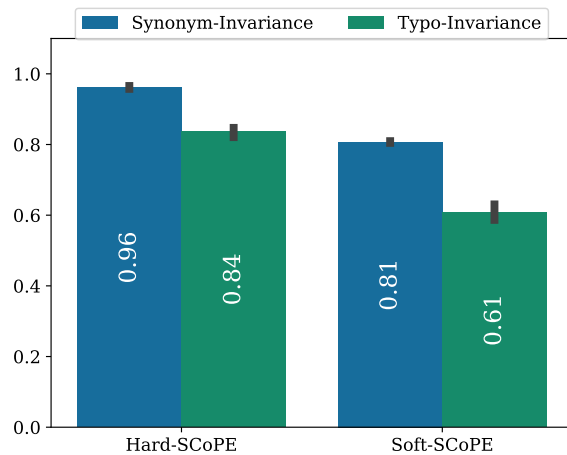


Figure 2: [Reference Model: BERT, Target Model: DistilBERT]. Comparing shared-invariances between DistilBERT and BERT on Synonym-Invariance and Typo-Invariance defined w.r.t BERT. Distillation hurts some capabilities (Typo-Invariance) substantially more than others (Synonym-Invariance).

In this section, we aim to investigate whether a design choice (i.e., distillation) that has a nominal impact on the IID accuracy, preserves shared invariances along different linguistic capabilities. Specifically, we fix BERT as the reference model & DistilBERT as the target model and compare shared capabilities along Synonym-Invariance and Typo-Invariance.

Gap in IID accuracy may overestimate the degree of shared invariances: Both BERT and DistilBERT achieve high accuracies on the SST2 test-set i.e., 93% and 89.49% respectively (3.51% Gap in IID accuracy). However, in Fig 2, we note that a low gap in generalization performance on the IID test-set doesn't necessarily ensure high shared invariances. For instance, DistilBERT is substantially less aligned to BERT along Typo-Invariance. Thus, Gap in IID accuracy may overestimate the degree of shared invariances between two models along a linguistic capability.

Distilling BERT affects some linguistic capabilities more than others: In Fig. 2, we also ob-

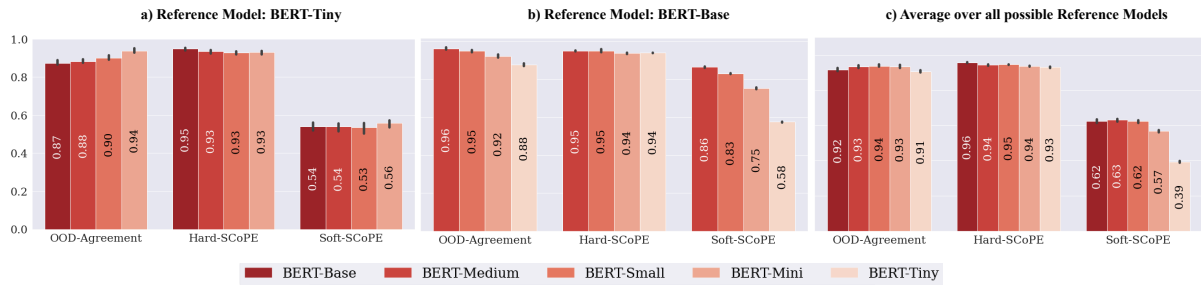


Figure 3: [Linguistic-Capability: **Synonym-Invariance**] Analyzing the effect of size on shared-invariances within the BERT architecture family. The OOD-agreement is higher for target models in similar size ranges as the reference model. However, shared-invariances are higher for target models of larger size irrespective of the reference model.

serve that DistilBERT is significantly more similar to BERT along Synonym-Invariance compared to Typo-Invariance. Thus not only is there a decrease in shared-invariances after distillation, but distillation also affects different linguistic capabilities to varying degrees. We posit that this trend can be attributed to the Masked Language Modelling (MLM) pre-training procedure that is common to both BERT and DistilBERT. As the MLM objective optimizes the model to predict masked words in a sentence correctly, it’s plausible that during pre-training a model develops invariances to diverse in-context word-substitutions. Since, both DistilBERT and BERT are pre-trained on the same corpus (i.e., concatenation of English Wikipedia and Toronto Book Corpus, (Sanh et al., 2019)), it’s highly likely that the learnt word-invariances are shared between them. Similarly, the lower values for Typo-Invariance may be explained by the lack of misspelled words in the training corpus.

4.2 Role of Inductive Biases

In this section, we explore the effect of changes in architectural inductive biases on a model’s behavior along a linguistic capability i.e., Synonym-Invariance. Specifically, we investigate the role of increasing/decreasing the depth and width of hidden-layers on the shared-invariances. To control for potential confounders we finetune a wide array of models (released by Turc et al. (2019)) belonging to the same architecture family (BERT) varying significantly in both number (L) and size (H) of the hidden layers. Specifically, we investigate BERT-Tiny (L=2, H=128), BERT-Mini (L=4, H=256), BERT-Small (L=4, H=512), BERT-Medium (L=8, H=512), and BERT-Base (L=12, H=768).

Different trends across different metrics: In Fig. 3-a, with BERT-Tiny (smallest model in our investigation) as the reference model, we observe

that the OOD agreement-rate indicate that models similar in size to BERT-Tiny (i.e., BERT-Mini, BERT-Small) have higher similarity with BERT-Tiny than other larger models (i.e., BERT-Medium, BERT-Base). In contrast, the shared-invariances metrics don’t follow the same trend as Hard-SCoPE values tend to increase for larger model sizes, and there isn’t a substantial difference between the Soft-SCoPE values across different target models.

Larger models share more invariances with models of any size: In Fig. 3-b, we repeat the same experiment with the largest model in our investigation—BERT-Base—as the reference model. Surprisingly, we observe that all metrics indicate that models become less similar to BERT-Base as their size decreases. This is in contrast to previous results with BERT-Tiny (smallest model) as the reference model where larger models had poor OOD-agreement and higher (or similar) shared-invariances. Thus, we hypothesize that even though larger models don’t agree with the behavior of smaller models from an agreement perspective, they still share the invariances generated by smaller models. Interestingly, the opposite is not true i.e., smaller models don’t necessarily share invariances generated w.r.t larger models as well as other larger models. To understand this more generally, we report the average results for all models (as target models) by marginalizing them over all the different reference models. We expect that metrics depending on model size (i.e., agreement rates) should have uniform values across different target models. In contrast, metrics that are tied to larger model sizes (i.e., shared-invariances) should peak for larger models even after averaging. We report the result in Fig. 3-c, which are consistent with our proposition. It’s especially interesting that larger models are able to share a more diverse set of invariances (both from other larger and smaller

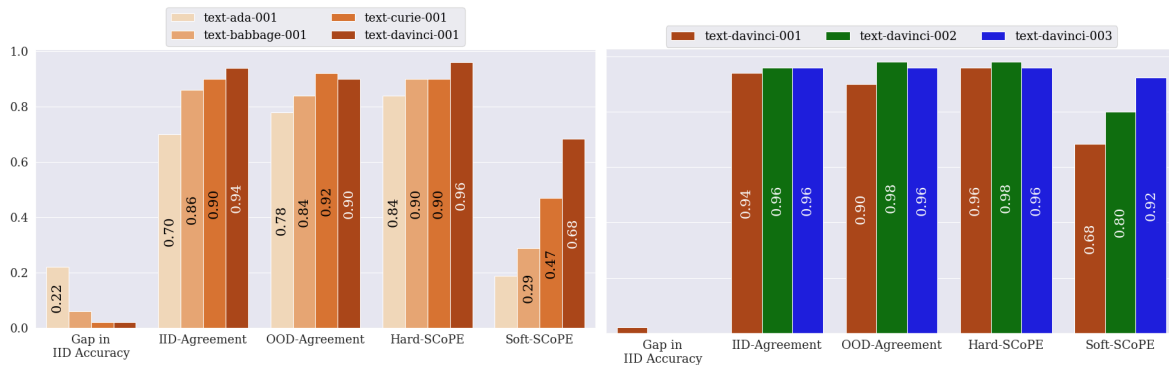


Figure 4: [Reference Model: **GPT-2**, Capability: **Synonym-Invariance**]. Comparing shared-invariances between GPT-2 and various OpenAI models differing in size and finetuning along Synonym-Invariance. Larger InstructGPT models share more invariances with GPT-2. Also, state-of-the-art models finetuned with reinforcement learning (text-davinci-003) share more invariances than their supervised finetuned counterparts (text-davinci-002).

models) even when they are pretrained/finetuned on the same corpus as the smaller models.

5 Relationship of Familiar Models with Black Box APIs

In the previous sections we discussed *specialist* models that are tuned to perform well on a specific task (e.g., sentiment analysis on SST2). However, in recent years the NLP community has shifted focus towards building more *generalist* models that can perform a diverse set of tasks when prompted with appropriate instructions and exemplars. However, the state-of-the-art of these models are primarily available in the form of black-box APIs, with little information available about their training. We explore how one can quantify the behavioral similarity between models released via black-box APIs (InstructGPT family) and models that are widely adopted in practice (e.g. GPT-2). We follow the methodology in Cheng et al. (2023) for estimating output probability distribution over the task-labels (positive and negative sentiment) from InstructGPT models. Specifically, we sample the output multiple times for each input and take the mode as the final prediction and its frequency as the probability score for that particular label. We perform all experiments in a zero-shot manner. To reduce costs, we perform experiments on 100 randomly selected samples from the SST2 test-set. The finetuned GPT-2 achieves 96% accuracy on this subset. It cost us \approx \$55 to compute all the results for this section.

Larger InstructGPT models share more invariances with GPT-2: We use InstructGPT models text-ada-001, text-babbage-001, text-curie-001,

text-davinci-001 that roughly correspond to model sizes: 350M, 1.3B, 6.7B, and 175B respectively (Gao et al., 2021). We note that there’s a substantial difference in IID performance between the smaller models (text-ada-001) and larger models (text-curie-001, text-davinci-001). Moreover, text-ada-001 is not only less agreeable to the GPT-2 model, but also seems to be substantially less invariant to perturbations that GPT-2 is invariant on i.e., low Hard-SCoPE and Soft-SCoPE. Interestingly, even though text-curie-001 and text-davinci-001 achieve similar IID accuracy (i.e., 94%) there’s substantial differences in their shared-invariances. Thus, even though both models seem equivalent based on IID performance, using text-davinci-001 would ensure higher behavioral similarity from the perspective of shared-invariances. Also, this result ties back to our previous observations in Sec. 4.2 about larger models sharing more invariances.

RL based finetuning may retain more invariances: We explore the effect of different finetuning methods for instruction following on shared-invariances in Fig. 4 (right). For this, we perform experiments on text-davinci-001, text-davinci-002, and text-davinci-003 models released by OpenAI. text-davinci-001 is finetuned using supervised learning on human and selected model written demonstrations. While, text-davinci-002 utilizes the same objective function, it’s pretrained on a mix of text and code. text-davinci-003 differs from text-davinci-002 by using reinforcement learning for finetuning instead of supervised learning. We note that both text-davinci-002 and text-davinci-003 have similar performances across IID accuracy, agreement rates, and Hard-SCoPE. Interestingly,

there’s a substantial gap in their Soft-SCoPE values, indicating that even though both models remain invariant on an equivalent number of samples (similar hard-scope), text-davinci-003’s output probability distribution is more invariant to perturbations generated along Synonym-Invariance.

6 Conclusion

We propose a framework for evaluating interpretable shared-invariances between two NLP models by evaluating the degree to which a target model shares behavioral similarity on a linguistic capability defined with respect to a reference model. We conduct extensive experiments to highlight the implications of different design choices (e.g. distillation) and find that shared-invariances tend to be affected more along certain linguistic capabilities than others. Furthermore, we also analyze models of different sizes and find that larger target models in general tend to share more invariances. Lastly, we demonstrate the use of our framework in analyzing relationships between black-box APIs and familiar models.

7 Limitations

In this section, we discuss key limitations of our work and potential for future improvements. One limitation of our current work is inefficient search methods as they need many queries to generate perturbations. Efficient search methods are necessary for generating perturbed samples with reference to a black box APIs. Additionally, we adopt the approach of (Cheng et al., 2023) for estimating predicted probabilities for instruction-tuned models. Since, evaluating semantic uncertainty over task-labels using language models is an open problem in itself, it would be interesting to evaluate whether our insights vary across different probability estimation methods.

8 Ethics and Broader Impact

In this work, we introduce a novel framework for comparing NLP models by assessing their invariances to interpretable input perturbations, aimed at better understanding their linguistic capabilities. Our framework sheds light on how various design choices influence a model’s sensitivity to specific perturbations, whether intentionally or unintentionally, offering deeper insights into the subtle effects of these choices on model behavior. This aids in

enhancing the overall comprehension of NLP models. Moreover, practitioners can use our framework to quantitatively assess whether the newer models they plan to integrate into their pipeline show significant differences in any linguistic capability of interest, compared to existing, well-understood models. Finally, we do not introduce any new classes of transformations, improved search methods, or optimization algorithms for generating perturbations. Therefore, we do not anticipate any increased risk of our work making deployed NLP models more vulnerable to attacks by malicious actors.

Acknowledgements

The authors would like to thank Camila Kolling, Vedant Nanda, Mathis Pink, Emin Çelik, Blerta Veseli, Cameron Braunstein, Gabriele Merlin, Subba Reddy Oota, Dota Dong, and Khai Loong Aw for their insightful comments and feedback on the project.

References

- Silei Cheng, Zhe Gan, Zhengyuan Yang, Shuohang Wang, Jianfeng Wang, Jordan Boyd-Graber, and Lijuan Wang. 2023. [Prompting gpt-3 to be reliable](#). In *International Conference on Learning Representations (ICLR 23)*.
- Mostafa Dehghani, Yi Tay, Alexey A Gritsenko, Zhe Zhao, Neil Houlsby, Fernando Diaz, Donald Metzler, and Oriol Vinyals. 2021. The benchmark lottery. *arXiv preprint arXiv:2107.07002*.
- 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, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers)*, pages 4171–4186. Association for Computational Linguistics.
- Frances Ding, Jean-Stanislas Denain, and Jacob Steinhardt. 2021. Grounding representation similarity through statistical testing. *Advances in Neural Information Processing Systems*, 34:1556–1568.
- Nadir Durrani, Hassan Sajjad, and Fahim Dalvi. 2021. [How transfer learning impacts linguistic knowledge in deep NLP models?](#) In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 4947–4957, Online. Association for Computational Linguistics.
- Leo Gao, Jonathan Tow, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding,

- Jeffrey Hsu, Kyle McDonell, Niklas Muennighoff, Jason Phang, Laria Reynolds, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. 2021. [A framework for few-shot language model evaluation](#).
- Jonas Geiping and Tom Goldstein. 2022. Cramming: Training a language model on a single gpu in one day. *arXiv preprint arXiv:2212.14034*.
- Sara Hooker, Aaron Courville, Gregory Clark, Yann Dauphin, and Andrea Frome. 2019. What do compressed deep neural networks forget? *arXiv preprint arXiv:1911.05248*.
- Sara Hooker, Nyalleng Moorosi, Gregory Clark, Samy Bengio, and Emily Denton. 2020. Characterising bias in compressed models. *arXiv preprint arXiv:2010.03058*.
- Max Klabunde, Tobias Schumacher, Markus Strohmaier, and Florian Lemmerich. 2023. Similarity of neural network models: A survey of functional and representational measures. *arXiv preprint arXiv:2305.06329*.
- Emanuele La Malfa and Marta Kwiatkowska. 2022. The king is naked: on the notion of robustness for natural language processing. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pages 11047–11057.
- Honglak Lee and Andrew Y Ng. 2005. Spam deobfuscation using a hidden markov model. In *CEAS*.
- Hong Liu, Sang Michael Xie, Zhiyuan Li, and Tengyu Ma. 2023. Same pre-training loss, better downstream: Implicit bias matters for language models. In *International Conference on Machine Learning*, pages 22188–22214. PMLR.
- Nelson F. Liu, Matt Gardner, Yonatan Belinkov, Matthew E. Peters, and Noah A. Smith. 2019. [Linguistic knowledge and transferability of contextual representations](#). 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 1073–1094, Minneapolis, Minnesota. Association for Computational Linguistics.
- Ari Morcos, Maithra Raghu, and Samy Bengio. 2018. Insights on representational similarity in neural networks with canonical correlation. *Advances in Neural Information Processing Systems*, 31.
- John Morris, Eli Lifland, Jin Yong Yoo, Jake Grigsby, Di Jin, and Yanjun Qi. 2020. Textattack: A framework for adversarial attacks, data augmentation, and adversarial training in nlp. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 119–126.
- Vedant Nanda, Till Speicher, Camila Kolling, John P Dickerson, Krishna Gummadi, and Adrian Weller. 2022. Measuring representational robustness of neural networks through shared invariances. In *International Conference on Machine Learning*, pages 16368–16382. PMLR.
- David Owen. 2023. Extrapolating performance in language modeling benchmarks.
- Jason Phang, Haokun Liu, and Samuel R. Bowman. 2021. [Fine-tuned transformers show clusters of similar representations across layers](#). In *Proceedings of the Fourth BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, pages 529–538, Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Vinodkumar Prabhakaran, Ben Hutchinson, and Margaret Mitchell. 2019. [Perturbation sensitivity analysis to detect unintended model biases](#). In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 5740–5745, Hong Kong, China. Association for Computational Linguistics.
- Danish Pruthi, Bhuwan Dhingra, and Zachary C. Lipton. 2019. [Combating adversarial misspellings with robust word recognition](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5582–5591, Florence, Italy. Association for Computational Linguistics.
- Shuhuai Ren, Yihe Deng, Kun He, and Wanxiang Che. 2019. [Generating natural language adversarial examples through probability weighted word saliency](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1085–1097, Florence, Italy. Association for Computational Linguistics.
- Marco Tulio Ribeiro and Scott Lundberg. 2022. Adaptive testing and debugging of nlp models. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3253–3267.
- Marco Tulio Ribeiro, Tongshuang Wu, Carlos Guestrin, and Sameer Singh. 2020. [Beyond accuracy: Behavioral testing of NLP models with CheckList](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4902–4912, Online. Association for Computational Linguistics.
- Barbara Rychalska, Dominika Basaj, Alicja Gosiewska, and Przemysław Biecek. 2019. Models in the wild: On corruption robustness of neural nlp systems. In *International Conference on Neural Information Processing*, pages 235–247. Springer.
- Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. *arXiv preprint arXiv:1910.01108*.

- Naomi Saphra and Adam Lopez. 2019. [Understanding learning dynamics of language models with SVCCA](#). 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 3257–3267, Minneapolis, Minnesota. Association for Computational Linguistics.
- Thibault Sellam, Steve Yadlowsky, Ian Tenney, Jason Wei, Naomi Saphra, Alexander D’Amour, Tal Linzen, Jasmijn Bastings, Iulia Raluca Turc, Jacob Eisenstein, Dipanjan Das, and Ellie Pavlick. 2022. [The multiberts: BERT reproductions for robustness analysis](#). In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net.
- Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Y Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 conference on empirical methods in natural language processing*, pages 1631–1642.
- Gowthami Somepalli, Liam Fowl, Arpit Bansal, Ping Yeh-Chiang, Yehuda Dar, Richard Baraniuk, Micah Goldblum, and Tom Goldstein. 2022. Can neural nets learn the same model twice? investigating reproducibility and double descent from the decision boundary perspective. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13699–13708.
- Anna Sotnikova, Yang Trista Cao, Hal Daumé III, and Rachel Rudinger. 2021. Analyzing stereotypes in generative text inference tasks. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 4052–4065.
- Yi Tay, Mostafa Dehghani, Jinfeng Rao, William Fedus, Samira Abnar, Hyung Won Chung, Sharan Narang, Dani Yogatama, Ashish Vaswani, and Donald Metzler. 2022. Scale efficiently: Insights from pre-training and fine-tuning transformers. In *International Conference on Learning Representations*.
- Iulia Turc, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Well-read students learn better: On the importance of pre-training compact models. *arXiv preprint arXiv:1908.08962*.
- Kevin Wang, Alexandre Variengien, Arthur Conmy, Buck Shlegeris, and Jacob Steinhardt. 2022. Interpretability in the wild: a circuit for indirect object identification in gpt-2 small. *arXiv preprint arXiv:2211.00593*.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. 2019. Huggingface’s transformers: State-of-the-art natural language processing. *arXiv preprint arXiv:1910.03771*.
- John Wu, Yonatan Belinkov, Hassan Sajjad, Nadir Durani, Fahim Dalvi, and James Glass. 2020. [Similarity analysis of contextual word representation models](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4638–4655, Online. Association for Computational Linguistics.
- Xiang Zhang, Junbo Jake Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. In *NIPS*.
- Yi Zhang, Arturs Backurs, Sébastien Bubeck, Ronen Eldan, Suriya Gunasekar, and Tal Wagner. 2022. Unveiling transformers with lego: a synthetic reasoning task. *arXiv preprint arXiv:2206.04301*.

A Additional Implementation Details

In this section, we provide an overview of our implementation details. For all our experiments, we use two NVIDIA A40 GPUs with 48GB of memory each. We use the standard model implementations provided by the Hugging Face transformers library (Wolf et al., 2019). We finetune all models for 5 epochs with a batch size of 64 using Adam optimizer and a linear-drop learning rate schedule with initial value of $2e-5$.

B Additional Dataset: AG’s News

In this section, we present results on an additional dataset – AG’s news topic classification dataset (Zhang et al., 2015). It’s a multi-class text classification task, where the goal is to classify text from an article into one of four categories i.e., World, Sports, Business, and Sci / Tech. It contains 120,000 training samples and 7,600 test samples. Due to compute and time constraints, we randomly sample a subset of 2,000 samples from the test-set and conduct our experiments on them as base samples. We train models using the same hyperparameters (learning rate, epochs, etc) as SST2 on the full training set. We repeat the experiments from the main paper and plot the results in Fig. 5 and Fig. 6. We note that the results are qualitatively similar across both the datasets.

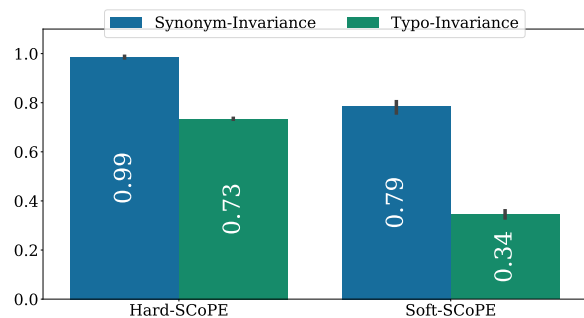


Figure 5: [Dataset: AG’s News, Reference Model: BERT, Target Model: DistilBERT]. Comparing shared-invariances between DistilBERT and BERT on Synonym-Invariance and Typo-Invariance defined w.r.t BERT trained on AG’s news dataset. Similar to our observations for SST2 in the main paper, we observe that distillation hurts some capabilities (Typo-Invariance) substantially more than others (Synonym-Invariance).

C Additional Linguistic Capability: Fairness

In the main paper, we performed experiments along two linguistic capabilities i.e., Synonym-Invariance

and Typo-Invariance. In this section, we explore an additional linguistic capability i.e., Fairness. Fairness perturbs the input text (“Men love sports.”) by substituting words corresponding to protected categories (such as men) with protected categories (e.g. ‘women’ \approx “Women love sports.”) from within the same stereotype domain (i.e. Gender). We use a greedy search approach for efficiently finding suitable transformations. We do not adopt any additional constraints on this linguistic capability.

Synonym-Invariance and Typo-Invariance are agnostic to the domain of base samples $x \in X$ i.e., they can be evaluated on any arbitrary set of base samples. In contrast, Fairness is only well defined if x contains words corresponding to different protected categories. Thus, we use the corpus released by Sotnikova et al. (2021) containing sentences with words corresponding to 71 protected categories from 6 different stereotype domains as base-samples X for experiments pertaining to evaluation of Fairness capability. Note, previous work on evaluating linguistic capabilities for a particular model (Ribeiro et al., 2020) also perform a change in base samples (i.e., use samples not necessarily from the test-split) for evaluating certain capabilities in order to decouple *testing* from *implementation*. Additionally, We control for the change in base samples (X) by conducting additional experiments on previously studied capabilities, such as Synonym-Invariance and Typo-Invariance, using the new set of base samples. We label them Synonym-Invariance* and Typo-Invariance* respectively. This allows us to draw meaningful comparisons across different capabilities.

In Fig. 7 (left), we first investigate the differences between different linguistic capabilities for a particular design choice. Thus, similar to Sec. 4.1 in the main paper, we fix BERT as the reference model and DistilBERT as the target model. We observe that while Fairness has lower OOD-agreement rate compared to Synonym-Invariance*, there isn’t a substantial difference between the shared-invariances (Hard-SCoPE & Soft-SCoPE). Thus, even though DistilBERT disagrees in its predictions with BERT for Fairness more (compared to Synonym-Invariance*), DistilBERT is invariant in its behavior on perturbations generated along Fairness to a similar degree as Synonym-Invariance. Additionally, we also note that Typo-Invariance* shares invariances to a lower degree compared to both Synonym-Invariance* and Fairness further

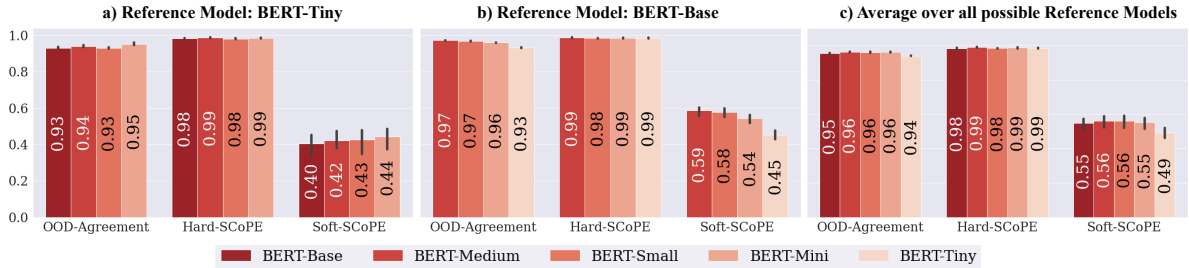


Figure 6: [Dataset: **AG’s News**, Linguistic-Capability: **Synonym-Invariance**] Analyzing the effect of size on shared-invariances within the BERT architecture family. Similar to results on the SST2 dataset in the main paper, we observe that larger target models tend to share higher invariances irrespective of the reference model.

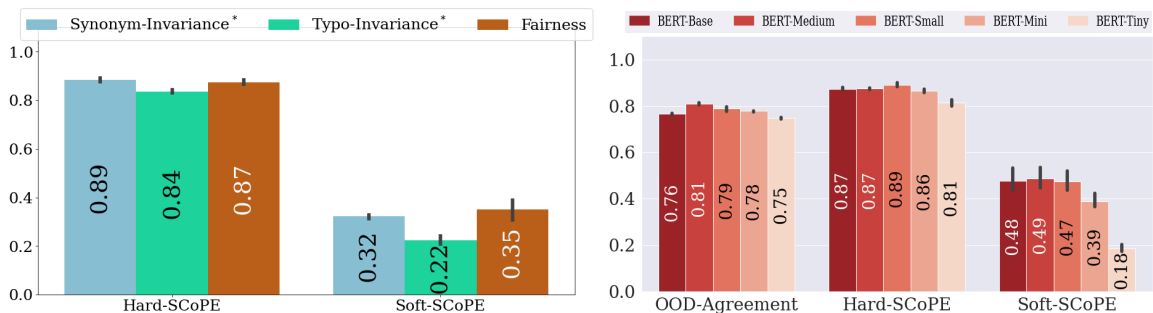


Figure 7: *Left*: [Reference Model: **BERT**, Target Model: **DistilBERT**]. Comparing shared-invariances between DistilBERT and BERT on Synonym-Invariance*, Typo-Invariance*, and Fairness defined w.r.t BERT. While there isn’t a substantial difference between shared-invariances along Synonym-Invariance* and Fairness, Typo-Invariance* is lower than both. *Right*: [Linguistic-Capability: **Fairness**] Analyzing the effect of size on shared-invariances within the BERT architecture family. Similar to results on Synonym-Invariance in the main paper, we observe that larger target models share more invariances irrespective of the reference model. Whereas OOD-agreement is higher for models in similar size ranges.

highlighting the role of MLM based training objective as word-substitution is a common perturbation in both Fairness and Synonym-Invariance*. In Fig. 7 (right), we report the shared-invariances between models across different sizes belonging to the same architecture family. Specifically, for each target model we report the averaged results over all possible reference models. Similar to our observations in Sec. 4.2 and Sec. 5 in the main paper for Synonym-Invariance, we observe that larger target models seem to share more invariances (with models of any size) on perturbations generated along Fairness.

D Pretraining Dynamics

In the main paper we focused on evaluating shared capabilities between two models differing in design choices along different linguistic capabilities. Additionally, we can also utilize our framework to empirically understand the dynamics of these linguistic capabilities over the course of pre-training of a language model. This line of analysis can help

us probe questions such as: Which linguistic capabilities are *learnt earlier* during pre-training?, How does a linguistic capability *evolve* over the course of pretraining?, etc. To probe such questions effectively, we utilize 21 (equally-spaced) intermediate pre-training checkpoints for BERT released by [Selam et al. \(2022\)](#). Since, we are primarily interested in quantifying the effect of pre-training (up to a particular checkpoint) in capturing different linguistic capabilities, we refrain from finetuning the full model (on SST2) and rather only train the linear probe layer on top of the frozen base network.

The curious case of 0% pretraining: In Fig. 8, we report values for all the checkpoints evaluated along Synonym-Invariance capability defined with the final-checkpoint (i.e., 100% pretraining) as the reference model (e.g. Soft-SCoPE ($m_t \mid m_{100\%}$ for t^{th} timestamp)). We note that the model corresponding to 0% pre-training (finetuned using random initialization) behaves as a random baseline ≈ 0.5 (or 50%) IID accuracy. We find that even though the network is akin to a random baseline, during predic-

tion it outputs only one label: ‘positive’ (in contrast to predicting both classes with equal probabilities) irrespective of the input. Surprisingly, this model has high IID and OOD agreement rates (≈ 0.8 or 80%) and the highest possible Hard-SCoPE value i.e. 1 with respect to the final-checkpoint. On a deeper look, we find that the prediction distribution for the final distribution is also biased towards the ‘positive’ label. In contrast, the Soft-SCoPE measure increases in a monotonically sublinear fashion over the course of pre-training, indicating that even though the predictions in both IID and OOD states might be similar (high IID/OOD-Agreement rates) and invariant (high Hard-SCoPE) the change in output probability vectors between the IID and OOD predictions varies significantly for the 0% and 100% (final) checkpoints. These observations further reinforce the importance of evaluating a wide range of metrics to gain a holistic understanding of the behavioral similarities between models as certain metrics can be especially deceptive in the low-accuracy regime due to larger possible variance in the underlying model structure.

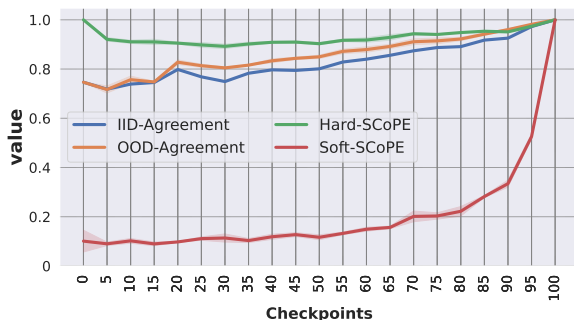


Figure 8: [Reference Model: **final-checkpoint i.e. 100% pre-training**, Target Model: m_t for $t\%$ pre-training, Linguistic-Capability: **Synonym-Invariance**] Comparing different metrics to analyze how intermediate-checkpoints share capabilities on Synonym-Invariance defined w.r.t the final-checkpoint. Even though the initial-checkpoint (0% pre-training) is not much better than a random-baseline, it shares a high-degree of Hard-SCoPE and IID/OOD-Agreements. Whereas Soft-SCoPE grows in a gradual manner over the course of pre-training.

Invariances for some capabilities are acquired earlier than others: Next in Fig. 9 we look at differences in evolution of different linguistic-capabilities over the course of pre-training. Firstly, in Fig. 9 (left), we observe that Soft-SCoPE (shared-invariances) along Synonym-Invariance is significantly higher compared to Typo-Invariance

for the major chunk of pre-training. Note, both of them converge to 1 at 100% pretraining as the Soft-SCoPE of a model with itself is 1 (irrespective of the linguistic-capability). Similar to our observations in Sec. 4.1, we posit that the shared pre-training objective (i.e. MLM) and training corpus leads to a higher degree of shared invariances much earlier in the pre-training for Synonym-Invariance compared to Typo-Invariance, which remains stagnant during most of the pretraining, with a sudden increase towards the end.

Retaining previously acquired invariances:

Till now our discussions have revolved around analyzing shared-invariances across different metrics (for a particular capability) and different capabilities (for a particular metric) with the final-checkpoint (i.e. 100% pre-training) as the reference-model. Thus, the central question for previous experiments has been: How (behaviorally) similar is an *intermediate checkpoint to the final checkpoint?* (w.r.t a particular metric along a particular linguistic capability). However, this setup provides little insight regarding whether the models retain their behavioral similarity w.r.t their previous counterparts as well (e.g. Soft-SCoPE ($m_t | m_{t-1}$ for $t\%$ pre-training)). Thus to probe questions such as: How (behaviorally) similar is an *intermediate checkpoint to its previous counterpart?*, we calculate values of Soft-SCoPE for each checkpoint with the previous checkpoint as the reference-model and report the results in Fig. 9 (right). A low value for a particular checkpoint indicates that the model has changed a lot w.r.t its predecessor while a high value would indicate that the model has retained the previously acquired behavioral invariances. We observe that the Soft-SCoPE values remain centered around mild values for most of the pre-training, indicating that while models are becoming more similar to the final-checkpoint they are only retaining a minor extent of their previously acquired behavioral shared invariances. We note that the shared invariances show a linear increase only towards the very end of the pre-training.

E Additional Explanation for Shared-Invariances

E.1 Generating Invariant Perturbations

In this section, we analyze properties of perturbations generated along different linguistic capabilities. While the primary goal of generated perturbations is to maintain behavioral invariance with

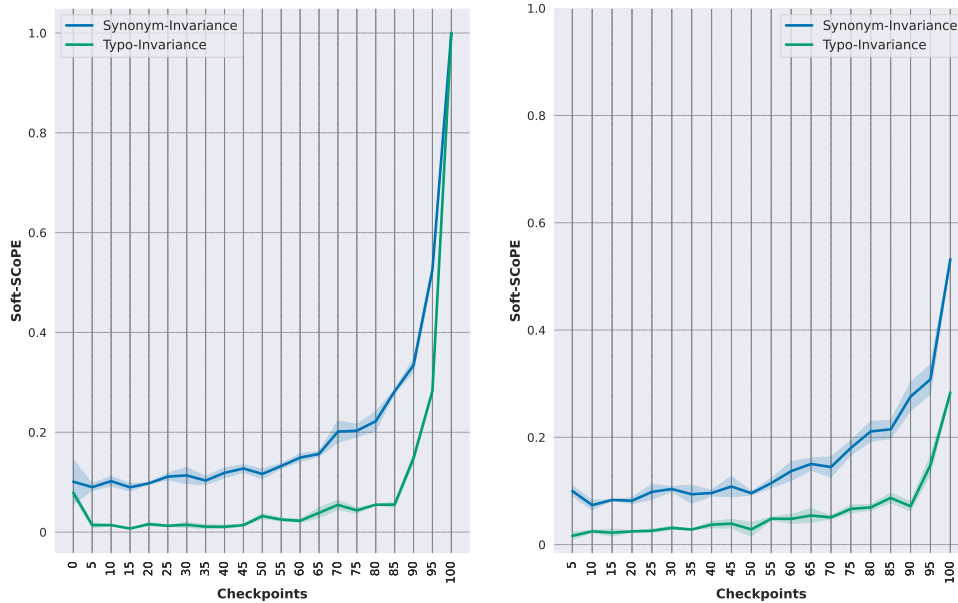


Figure 9: *Left*: [Reference Model: **final-checkpoint i.e. 100% pre-training**, Target Model: m_t for $t\%$ **pre-training**, Metric: **Soft-SCoPE**] Comparing the evolution of soft shared-invariances (i.e. Soft-SCoPE) for different linguistic-capabilities (i.e. Synonym-Invariance, Typo-Invariance) during pre-training. While all trends grow at a monotonically sub-linear pace, invariances for some are acquired earlier than others. *Right* [Reference Model: m_{t-1} for $t\%$ **pre-training**, Target Model: m_t for $t\%$ **pre-training**, **Soft-SCoPE**] Investigating the retention of previously acquired shared-invariances for different linguistic-capabilities (i.e. Synonym-Invariance, Typo-Invariance) during pre-training. Mild values indicate that many invariances are not retained during the first-half of pre-training, whereas checkpoints become more similar to the final-checkpoint as well as their previous counterparts during the end of pre-training.

respect to the reference model, it is possible that the search method is unable to find candidates that fulfill this criterion in the finitely large transformation space. Thus, in order to verify whether the generated perturbations are truly behaviorally invariant for the reference model we visualize the distribution of $\mathcal{L}(m(x), m(x'))$ – refer Fig. 10. Note, $\mathcal{L}(m(x), m(x')) = \|m(x) - m(x')\|_1$ is an objective function that penalizes the difference between reference model’s output softmax probabilities (behavior) on base and perturbed inputs i.e., lower $\mathcal{L}(m(x), m(x'))$ implies more behavioral invariance (refer Eq. 1).

In Fig. 10 (left) we note that for Synonym-Invariance, the distribution is highly skewed towards lower $\mathcal{L}(m(x), m(x'))$ values indicating that most generated perturbations have minimal difference between the predicted probability distribution on the base and perturbed samples for the reference model and all of them are argmax-invariant i.e., have same prediction on each base-perturbed sample pair. While, for Typo-Invariance (Fig. 10 right), the $\mathcal{L}(m(x), m(x'))$ values are higher and there are a few argmax-variant samples as well. Note, the argmax-variant samples would be ignored while

evaluating measures such as Hard-SCoPE and Soft-SCoPE (refer Eq. 2 & Eq. 4).

E.2 Relationship between Agreement-Rates and Shared-Invariances

In this section, we delve deeper into the relationship between agreement-based metrics i.e., IID-agreement & OOD-agreement and invariance-based measures i.e., Hard-SCoPE & Soft-SCoPE. While, Hard-SCoPE doesn’t solely depend on any one of IID-agreement or OOD-agreement, looking at both of them together can give indications about the Hard-SCoPE value. For instance, consider a binary classification setup with labels ‘Class-A’ and ‘Class-B’ and two models m_1 and m_2 that have predictions $y_{m_1}(x)$ & $y_{m_1}(x')$ and $y_{m_2}(x)$ & $y_{m_2}(x')$ for a particular base-perturbed sample pair (x, x') , where $x' = C(x; m_1)$.

In such a setup, the Hard-SCoPE can be seen as “agreement between agreement-rates” i.e., Hard-SCoPE is 1 only when both agreement-rates are either 0 or both are 1. Hard-SCoPE reaches a value of 1 when m_2 has consistent predictions for both IID and OOD inputs ($y_{m_2}(x) = y_{m_2}(x')$), on samples where m_1 ’s predictions are invariant

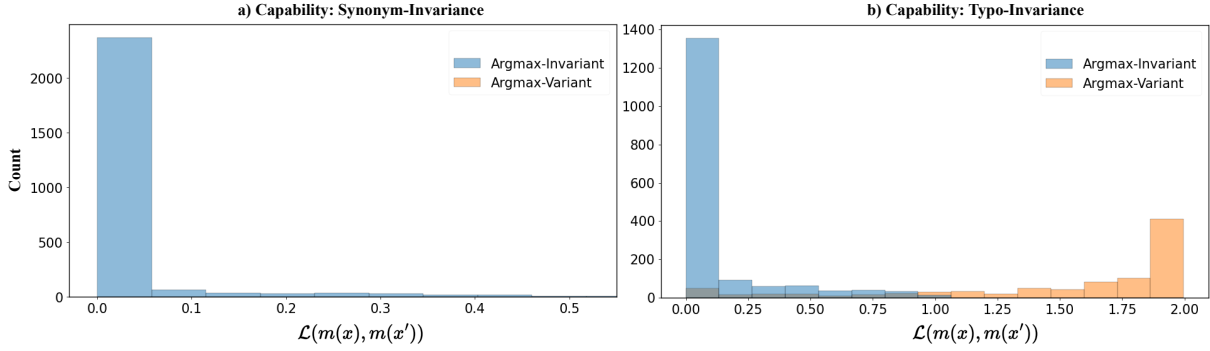


Figure 10: [Reference Model: **BERT**] Distribution of $\mathcal{L}(m(x), m(x'))$ for $x' = C(x; m_1)$ generated along Synonym-Invariance and Typo-Invariance. We note that the distribution is skewed towards lower $\mathcal{L}(m(x), m(x'))$ values and most samples generated are at least invariant in predictions (argmax-invariant).

Setup	m_1 's prediction		m_2 's prediction		IID-Agreement	OOD-Agreement	Hard-SCoPE
	$y_{m_1}(x)$	$y_{m_1}(x')$	$y_{m_2}(x)$	$y_{m_2}(x')$			
Binary Classification	Class-A	Class-A	Class-B	Class-B	0	0	1
	Class-A	Class-A	Class-B	Class-A	0	1	0
	Class-A	Class-A	Class-A	Class-B	1	0	0
	Class-A	Class-A	Class-A	Class-A	1	1	1
Multi-class Classification	Class-A	Class-A	Class-B	Class-B	0	0	1
	Class-A	Class-A	Class-B	Class-C	0	0	0

Table 1: Relationship between IID-agreement & OOD-agreement (agreement-rates) and Hard-SCoPE (shared-invariance). In a binary classification scenario, Hard-SCoPE can be seen as “agreement between agreement-rates” as it’s 1 when either IID- and OOD- agreement are both 0 or both 1. However, this relationship doesn’t hold for multi-class classification setup.

($y_{m_1}(x) = y_{m_1}(x')$). In a binary classification scenario where only two predictions are possible (Class-A or Class-B), achieving a Hard-SCoPE value of 1 requires either both m_1 and m_2 to predict the same label, resulting in IID-Agreement and OOD-Agreement both being 1, or they exhibit different predictions, leading to both IID-Agreement and OOD-Agreement being 0 (row 1 and 4 in Tab. 1). In cases where m_2 agrees with m_1 for IID(OOD) inputs but disagrees on OOD(IID) inputs, the Hard-SCoPE would be 0 as m_2 must have changed its prediction after the perturbation, given that m_1 is invariant to the perturbation by design (row 2 and 3 in Tab. 1). Importantly, this behavior does not hold for multi-class classification as it’s possible for m_2 to change its prediction even when both IID and OOD agreement are 0 (row-5 and 6 in Tab. 1).

We also discuss the relationship between Hard-SCoPE and Soft-SCoPE. Soft-SCoPE weighs the contribution of each base-perturbed pair by a function of similarity in their changes in the output soft-

max probability under a perturbation. Importantly, this weight lies between $[0, 1]$. Thus, Soft-SCoPE is upper-bounded by Hard-SCoPE i.e., $0 \leq \text{Soft-SCoPE} \leq \text{Hard-SCoPE}$.

F Shared-Invariances Across Architecture Families

In this section, we aim to investigate how differences in the architecture family of the reference and target models affect their shared-invariances. Intuitively, one would expect a higher degree of shared-invariances for models having similar architectures, courtesy of common inductive biases induced by the architectural family. Thus, to validate this intuition we fix the reference model as BERT and compare shared-invariances of target models both from the same architecture family (DistilBERT) and a different one (GPT-2). We report the results in Fig. 11.

Models from same architecture family share higher behavioral similarity & invariances:

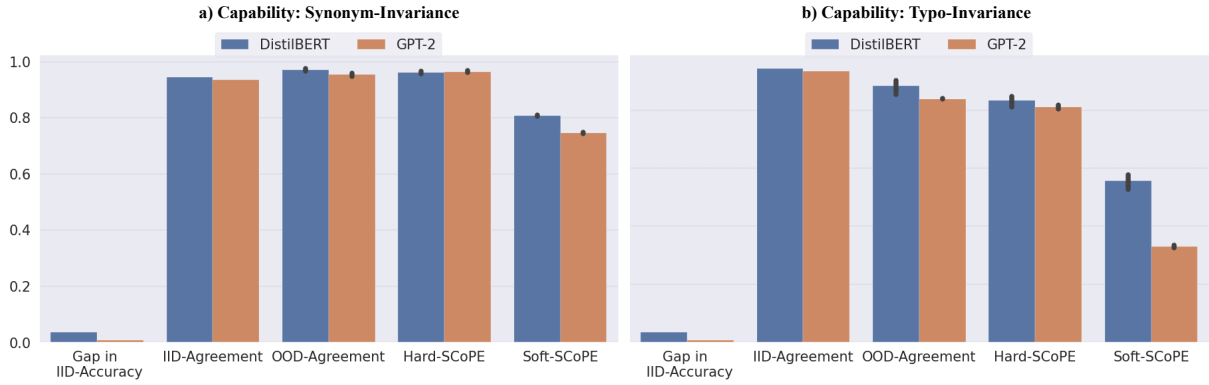


Figure 11: [Reference Model: **BERT**, Linguistic-Capability (left): **Synonym-Invariance**, Linguistic-Capability (right): **Typo-Invariance**] Even though the IID performance gap is smaller between GPT-2 & BERT compared to DistilBERT & BERT. For Synonym-Invariance & Typo-Invariance defined w.r.t BERT, DistilBERT (model from same architecture family) has a higher degree of shared capabilities than GPT-2 (model from different architecture family)

We observe that the difference between the IID-Accuracies (Gap in IID-Accuracy) is higher for DistilBERT compared to GPT-2 indicating that when evaluated conventionally, the gap between generalization ability of GPT-2 and BERT would be perceived to be smaller than DistilBERT and BERT. However across both linguistic capabilities i.e., Synonym-Invariance and Typo-Invariance, DistilBERT achieves higher IID and OOD agreement rates compared to GPT-2 highlighting when compared at an instance level DistilBERT behaves more similarly to BERT. Interestingly, even though DistilBERT only slightly edges GPT-2 in Hard-SCoPE, there is a substantial difference between their Soft-SCoPE values. This implies that DistilBERT is not only invariant on a large number of samples (that BERT is invariant on), but also the change in the output probability between base and perturbed predictions for DistilBERT is quite similar to that of BERT compared to GPT-2 and BERT.

G Additional Task: Language Modelling

In the main paper, we presented results across multiple linguistic-capabilities for different reference and target model combinations for one particular task i.e., sentiment classification. In this section, we present results on an additional task i.e., language modeling. More specifically, rather than fine-tuning the pre-trained language models on a downstream task and defining a linguistic-capability w.r.t them, we treat language modeling as a task in itself and define linguistic-capabilities w.r.t the pre-trained language models. We use cosine-similarity for computing agreements as language models have

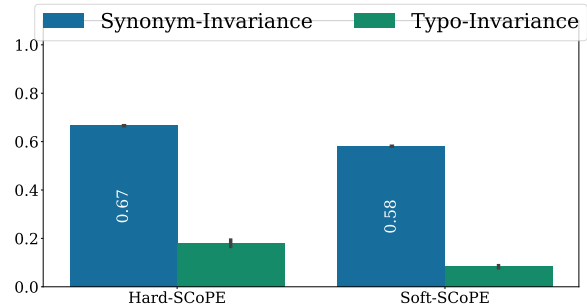


Figure 12: [Dataset: **SST-2**, Reference Model: **GPT-2**, Target Model: **DistilGPT-2**, Task: **Language Modelling**] Similar to results on sentiment-classification, we note that distillation affects shared-invariances across some linguistic-capabilities more than others.

a large vocabulary with many tokens repeating with minor variations. We repeat the experiments presented in the main paper with models from the GPT-2 language modeling architecture family on the SST-2 dataset and plot the results in Fig. 12 and Fig. 13. We note that the results are qualitatively similar to those observed with the BERT model in a classification setup in the main paper highlighting that the effects of design choices on linguistic-capabilities investigated in this paper are beyond task-specificities.

H Sample Complexity for Framework Effectiveness

In this section, we examine the impact of “number of base samples” on our proposed metrics and report the results in Fig. 14. Specifically, we report the mean metric values and the 95% confidence interval of this estimate computed over 100 trials

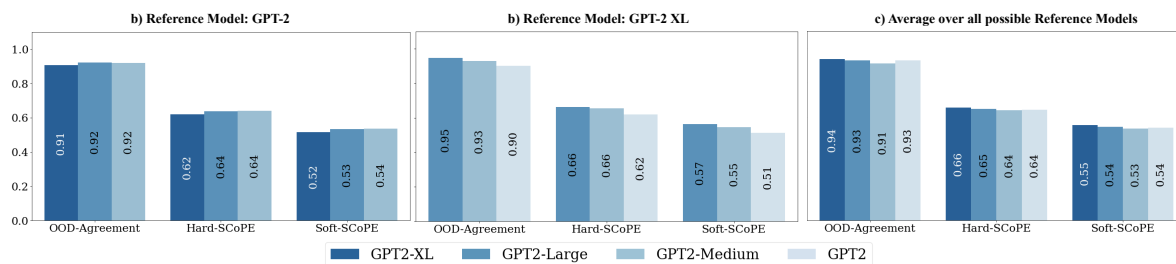


Figure 13: [Dataset: SST-2, Linguistic-Capability: **Synonym-Invariance**, Task: **Langug Modeling**] Similar to results on sentiment-classification, we find that larger target models tend to share higher invariances irrespective of the size of the reference model.

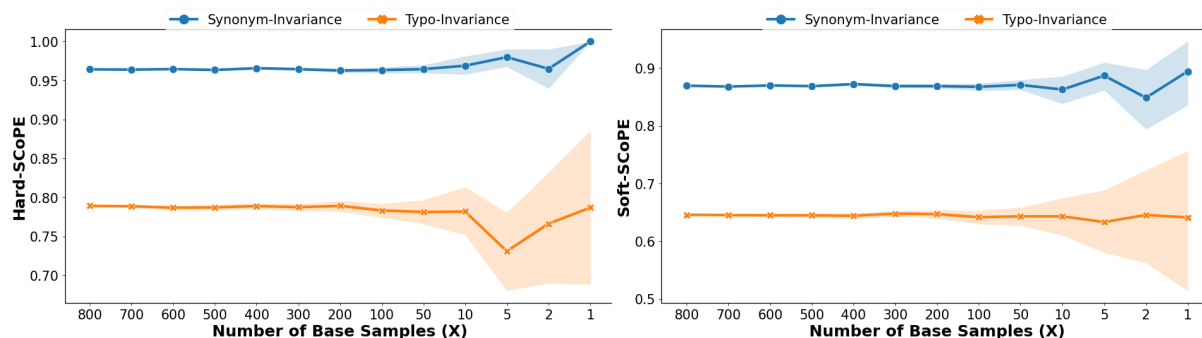


Figure 14: [Reference Model: **BERT**, Target Model: **DistilBERT**]. Examining the impact of base-samples / instances (X) count on the proposed metrics i.e., Hard-SCoPE (left) and Soft-SCoPE (right). We report an estimate of the mean metric values and the 95% confidence-interval (y-axis) around this estimate computed over 100 trials for each base-sample count (x-axis). We find that both the metrics are stable for as low as 50 base-samples with tight confidence-intervals.

for many values of base-samples count. We find that our metrics provide tight confidence intervals for as low as 50 base samples. Please note that for the previous experimental results in the main paper and the supplementary we utilize ≈ 1000 samples.

I Additional Correlation Results

Here, we explore whether the proposed invariance-based measures are tightly coupled with metrics previously explored in the literature such as agreement rates. We evaluate the Pearson correlation between OOD-agreement and Soft-SCoPE for different reference and target model pairs from the BERT architecture family and plot the results in Fig. 15. Each column consists of results for different target-reference model pairs for a particular reference model – BERT-Base or BERT-Tiny. We experiment with multiple different target models varying in size with BERT-Base being the largest and BERT-Tiny the smallest.

We find that OOD-agreement and Soft-SCoPE are poorly correlated when using comparatively smaller models as reference models i.e., $r=0.011$ for BERT-Tiny, whereas they are positively corre-

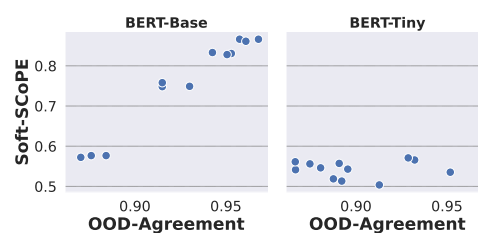


Figure 15: Correlation between proposed invariance-based metrics (Soft-SCoPE) and existing metrics (OOD-Agreement) for different reference and target model pairs. Existing metrics poorly correlate with invariance-based metrics as the size of the reference model is reduced.

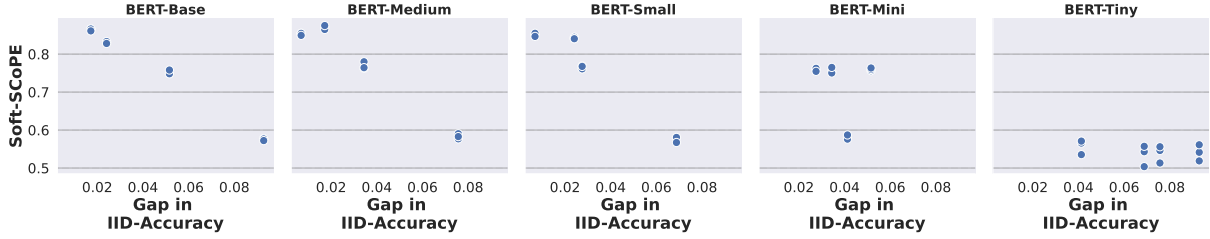


Figure 16: Correlation between proposed invariance-based metrics (Soft-SCoPE) and existing metrics (Gap in IID-Accuracy) for different reference and target model pairs. Similar to results noted in the main paper with OOD-Agreement, Gap in IID-Accuracy also poorly correlate with invariance-based metrics as the size of the reference model is reduced.

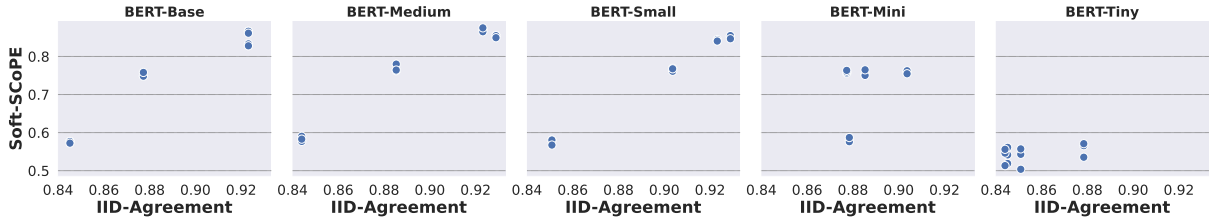


Figure 17: Correlation between proposed invariance-based metrics (Soft-SCoPE) and existing metrics (IID-Agreement) for different reference and target model pairs. Similar to results noted in the main paper with OOD-Agreement, IID-Agreement also poorly correlate with invariance-based metrics as the size of the reference model is reduced.

lated when using relatively larger models as reference models i.e., $r=0.97$ for BERT-Base. Thus, the invariances shared between two NLP models are not necessarily explained by existing metrics.

Importantly, the finding that existing metrics are especially poor at capturing shared invariance when the reference model is smaller than the target model further highlights the need for separately evaluating shared-invariances as smaller models are more amenable to controlled analysis (such as circuit analysis (Wang et al., 2022)) and hence likely to be used as reference models. We present results for correlations with other metrics such as IID-agreement and Gap in IID accuracy in the Fig. 16 and Fig. 17.

J Additional Goal Function Results

In the main paper we performed experiments with the L1 norm as the objective function described in Eq. 1. However, it can take other forms as well as long as it captures differences in both direction and magnitude between the reference model’s output on base and perturbed samples i.e., $m(x)$ and $m(x')$. In this section, we explore whether our insights are sensitive to the choice of the objective function by employing KL-divergence as the objective function instead. We report the results for one of the analyses in Fig. 18 and observe that there

are minimal effects on the overall takeaway when using different objective functions.

K Compute Costs

In this section, we discuss the computational costs of generating invariant samples for a reference model across different linguistic capabilities.

Linguistic Capability	Time (seconds per sample)
Synonym-Invariance	1.2
Typo-Invariance	0.48

Table 2: [Reference Model: BERT-Base, Dataset: SST2] Time taken in seconds, required to generate a perturbed sample on a NVIDIA-A100 GPU. The duration varies depending on distinct linguistic capabilities, as certain capabilities are more amenable to the search techniques in generating invariant perturbations than others.

L Soft-SCoPE Landscape Visualization

In this section, we visualize the the variation in Soft-SCoPE values between different model pairs i.e., $(m_2 | m_1)$ and $(m_3 | m_1)$. For this, we plot the 2-D plane spanned by vectors $\vec{v}_1 = \Delta\vec{m}_2 - \Delta\vec{m}_1$ and $\vec{v}_2 = \Delta\vec{m}_3 - \Delta\vec{m}_1$. Here, $\Delta\vec{m}_1$ corresponds to BERT (reference model), and $\Delta\vec{m}_2$ & $\Delta\vec{m}_3$

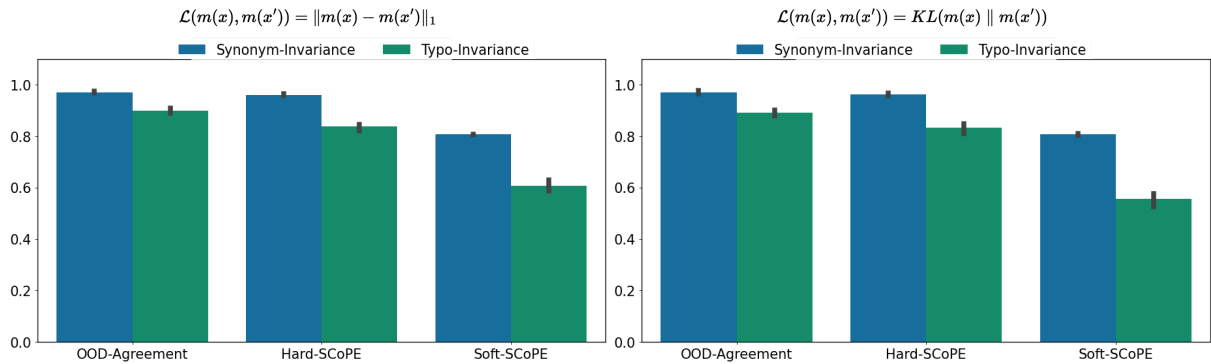


Figure 18: [Reference Model: **BERT**, Target Model: **DistilBERT**]. Analyzing the effect of different objective functions (\mathcal{L}) that guide the optimization process of the goal function while generating perturbations for a given reference model. We observe that different objective functions (L1 norm on the left, KL-divergence on the right) have minimal effect on the overall takeaway, i.e., distilling BERT affects some capabilities more than others.

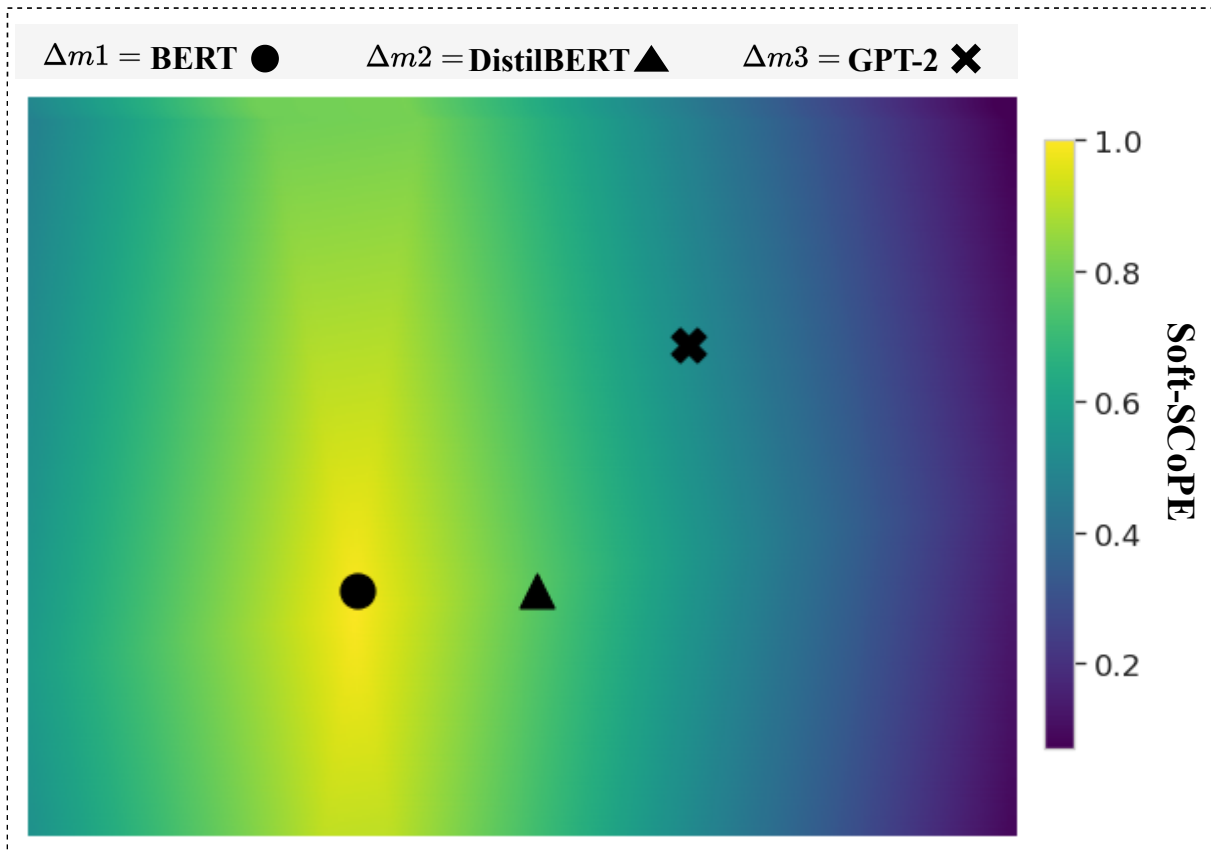


Figure 19: 2-D Soft-SCoPE surface for a pair of base and perturbed samples, where the reference model BERT is compared with DistilBERT and GPT-2.

refer to DistilBERT and GPT-2 respectively. In Fig. 19, we note that unlike Hard-SCoPE of two models that can only take binary values i.e., either 0 or 1 for a particular base-perturbed sample pair, Soft-SCoPE varies smoothly. We also observe that models from the same architectural family (BERT and DistilBERT) have higher Soft-SCoPE compared to models from different architectural fami-

lies (BERT and GPT-2).

Original Sample	Synonym-Invariance	Typo-Invariance
a fast, funny, highly enjoyable movie.	a fast, funny, highly enjoyable <u>film</u> .	a <u>fsat</u> , funny, highly enjoyable movie.
my reaction in a word: disappointment.	my <u>response</u> in a word: disappointment.	my reaction in a word: <u>disappointemnt</u> .
allows us to hope that nolan is poised to embark a major career as a commercial yet inventive filmmaker.	allows us to <u>trust</u> that nolan is poised to embark a major career as a commercial yet inventive filmmaker.	allows us to <u>hpoe</u> that nolan is poised to embark a major career as a commercial yet <u>inevntive</u> filmmaker.
too slow, too long, and too little happens.	too <u>tiresome</u> , too long, and too little happens.	too <u>solw</u> , too long, and too <u>lilte</u> happens.
a warm, funny, engaging film.	a warm, <u>comic</u> , engaging film.	a warm, <u>fnuny</u> , engaging film.

Table 3: [Reference Model: BERT-Base, Dataset: SST2] Examples of perturbed sentences that are invariant w.r.t the reference model BERT-Base for multiple linguistic capabilities i.e., Synonym-Invariance and Typo-Invariance.

M Perturbation Examples

In this section, we present a table with some original and perturbed examples from different linguistic capabilities.