Using Interventions to Improve Out-of-Distribution Generalization of Text-Matching Systems

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Abstract

Given a user's input text, *text-matching* recommender systems output relevant items by comparing the input text to available items' description. As users' interests and item inventory are expected to change, it is important for a text-matching system to generalize to out-of-distribution (OOD) data shifts. However, we find that the popular approach of fine-tuning a base language model on paired item relevance training data can be counter-productive. For a product recommendation task, fine-tuning obtains *worse* accuracy than the base model when recommending items in a new category or for a future time period. To explain this failure, we consider an *intervention-based* importance metric, which shows that a fine-tuned model fails to learn the causal features that determine the relevance between any two text inputs. Moreover, standard methods for causal regularization do not apply in this setting, because unlike in images, there exist no universally spurious features in a text-matching task (the same token may be spurious or causal depending on the text it is being matched to). For OOD generalization on text inputs, therefore, we highlight a different goal, avoiding high importance scores for certain features, and build an intervention-based regularizer. Results on Amazon product recommendation and other datasets show that our proposed regularizer improves OOD generalization. [1]

1 Introduction

In item-to-item recommendation [1], the goal is to output a list of relevant items given an input item. Many such recommender systems utilize the text content of an item, such as recommending relevant questions given a question in an online forum [19], suggesting relevant products given a product title [13], or predicting relevant ads given a search engine query [4]. A popular way for training these *text-matching* recommender systems is to fine-tune text embeddings from a *base* language model like BERT using supervised user feedback (such as clicks). For example, one may use a contrastive loss to ensure that given an input query, embedding of another user-labelled relevant item is closer [6, 23].

However, the generalizability of the fine-tuned embeddings to item distributions beyond the user-labelled data has received little attention. Distribution shifts are common in recommendation systems, such as when new product categories are added to an e-commerce platform, the list of recommendable items is modified, or the popularity of items changes over time. As a result, after a recommender model is deployed, it is likely to encounter out-of-distribution data compared to its training set. For such out-of-distribution data, we find that fine-tuned models using relevance labels can be worse than the pre-trained base model that they start from. On a product recommendations dataset from

[1] arxiv version : https://arxiv.org/pdf/2210.10636.pdf

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Amazon, while fine-tuning always increases in-distribution accuracy, the accuracy of the fine-tuned model on unseen product categories is lower than that of the base model. We find a similar result on question-to-question recommendation on online forums (*sentence matching* task [14, 18]).

To understand why, we characterize two common shifts in recommender systems: change in input query's distribution and change in candidate items' distribution. Even without any change in the relevance function, these distribution shifts lead to a change in association between relevance score and the input tokens of a model. As a result, even though standard fine-tuned models obtain high validation accuracy, they overfit to the training distribution by capturing spurious associations (e.g., between brand and a product category). We characterize model spuriousness through an intervention-based importance score for input tokens. Using the score, we find that the fine-tuned embedding on Amazon products learns a spuriously high importance for certain tokens while forgetting the rest.

To improve generalizability, we consider a causal graph for the relevance function's computation and highlight the difficulty of not having universally spurious tokens for the text-matching task. As a result, we argue that avoiding disproportionately high importance scores for tokens can be a viable way to regularize for OOD generalization. Specifically, we propose `ITVReg`, a method that constrains the importance of tokens to be similar to that in the base model, which has been trained on a larger and more diverse set and thus less likely to share the same spurious patterns. We evaluate `ITVReg` on OOD data for product title and question recommendation tasks and find that it improves OOD accuracy of naively finetuned models. Compared to a baseline of directly regularizing a model's predictions to the base model, `ITVReg` performs the best under reasonable OOD shifts, where exploiting training data is useful. Interestingly, `ITVReg` also helps accuracy on an IID test set: it increases accuracy over low-frequency, "tail" items while retaining high accuracy on others.

2 Distribution shifts in recommendation

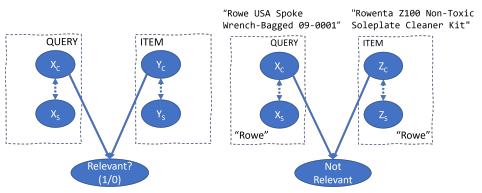
Let $\mathcal{X}$ be the set of input queries and $\mathcal{Z}$ be the set of candidate items. Let the train data be $(X_i, Z_i, R_i)_{1...N}$, where, X_i, Z_i correspond to the query and item text respectively and R_i is the relevance or similarity score between X_i, Z_i. For training, state-of-the-art methods [6, 23] embed both queries and items in a common space using a large, pre-trained base encoder like BERT, $f_{\theta_0} : \mathcal{X} \to \mathbb{R}^N$, that provides the initial embeddings. To obtain the trained encoder, f_θ, the embeddings are fine-tuned using a supervised loss on the paired relevance labels, $\mathcal{L} = \max(0, 1 + f_\theta(X)^\top f_\theta(Z^-) - f_\theta(X)^\top f_\theta(Z^+))$, where X, Z^+ and Z^- denote a query, relevant item, and a non-relevant item respectively. For a new input query, the model provides a *relevance score* with *j*th item, $r_j = f_\theta(X)^\top f_\theta(Z_j)$, and the task is to rank the "ground-truth" relevant items highest on the relevance score (e.g., metric may be precision at rank k).

Method	IID	OOD
Base Model	20.01	**30.61**
Fine-tuned Model	38.74	28.31.

Table 1: Precision@1 for recommending product titles on Amazon. OOD denotes queries from five categories not in train data. Fine-tuning results in lower precision than the base model.

Types of distribution shift. We study three shifts: change in queries $P(X)$, items $P(Z)$, and both queries and items $P(X, Z)$. **Change in P(X).** The distribution of queries changes but the set of candidate recommendations may remain the same. For example, the popularity of certain queries can shoot up due to external events, or the system may be expanded to new queries. **Change in P(Z).** The distribution of candidate items changes while the queries remain the same. For example, an e-commerce platform may alter the eligibility rules for an item to be recommended, or recommend items from a partner website. **Change in both P(X) and P(Z).** A final scenario is when the distribution of both queries and items changes. For example, introducing a new item category in an online store leads to new queries that can be accessed by user and also be recommended. While the criteria for relevance (i.e., user intent) can change over time, for simplicity, we assume that the *true* relevance function, $P(R|Z, X)$ remains constant.

Example: OOD failure on Amazon recommendation dataset. Consider the *Amazon Titles* dataset (see Supp. E) where both the input query and candidate items are titles of products on Amazon.com. We simulate a scenario where $P(X)$ is changed by removing queries from five categories from the train data and evaluate the model on those removed queries using precision@1 metric.Table 1 shows that fine-tuned model (that is initialized with the base model) improves significantly over the base model on IID test data, almost doubling the precision. However, on the queries from the unseen item categories, the finetuned model performs *worse* than the base model.



(a) General graph. (b) Example graph.

Figure 1: Graph for data-generating process for query, item and relevance score, (X, Z, R). Spurious tokens X_s or Z_s do not cause query-item relevance but are predictive of relevance score.

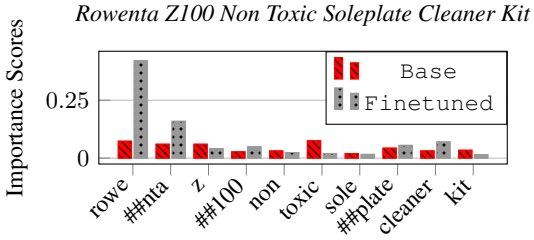


Figure 2: Token-wise importance scores. `Base` gives approximately equal importance scores to all tokens whereas `Finetuned` model gives disproportionately high weights to the token *"rowe"*.

Explaining the OOD generalization failure through causal graph. To understand the failure, consider the schematic causal diagram for the data-generating process of the training set. Figure 1 shows that each query can be broken down into its semantic (causal) component X_c and its spurious component X_s. Same for candidate items, denoted by Z_c and Z_s. The semantic components X_c and Z_c together cause the relevance label. An ideal encoder should only learn the semantic components. However, since the non-semantic components are correlated with the semantic component and can be easier to learn, a fine-tuned encoder may learn the non-semantic components too.

Specifically, when new queries are introduced, the correlation between X_c and X_s can be broken, even as $P(R|X, Z)$ remains the same. Hence, X_s is no longer a good predictor of relevance and any model relying on X_s will fail to generalize. For example, for certain queries in the Amazon data, X_s may correspond to the brand of a query product and X_c the rest of its title . In the training data, the brand (e.g., "samsung") may be correlated with a single product category (e.g., "smartphone") and thus an encoder may learn a non-zero weight for the brand to determine the relevance score. However, the correlation may be broken in the evaluation data where the same brand is associated with another product category (e.g., "refrigerator"). We can reason analogously for a change in $P(Z)$.

Explanation through intervention-based importance score. OOD generalization failure is more intuitively understood through intervention-based analysis [15], where we change parts of a query and inspect the model's prediction. To understand which tokens a model learns as important, we define an *importance score* s of each token, that corresponds to the causal effect of a token on the model's relevance score. To compute s for a token, we mask that token (intervention) and compute the dot product similarity (relevance) of the masked input's embedding with the original input's embedding. [2] $s_j = 1 - f_\theta(X)^\intercal f_\theta(X'_{-j})$ where X'_{-j} is X with its jth token masked.

Consider a candidate item in the Amazon dataset, "*Rowenta Z100 Non Toxic Soleplate Cleaner Kit*". As Figure 2 shows, the base encoder gives almost equal importance to each token, whereas the finetuned encoder is biased towards the token *rowe*, possibly because Rowenta products tend to be relevant to other Rowenta products. This token obtains such a disproportionately high importance score that the item's representation (average of all tokens' representation) is defined by it. Here *rowe* $\in Z_s$ is a spurious token since relevance may depend on the brand *rowenta*, but not on *rowe* alone. When we consider an OOD query having an actual brand called "Rowe", "*Rowe USA Spoke Wrench - Bagged 09-0001*", the model matches it to the Rowenta item and other products by Rowenta (see Suppl. Table 9), exposing the spurious correlation learnt by the encoder. Another example is the query, "*Soleus Air MS-09 Oscillating Reflective Heater*". The importance scores are in Suppl. Figure 4. Again, we see the finetuned encoder is biased towards the token *reflective* because *reflective* is a strong matching signal in the train set: products with this token are often marked as relevant to products that have it too. As a result, the top predicted item by the finetuned model is *3M Scotchlite Reflective Tape, Silver, 1-Inch by 36-Inch* (not a relevant item, see Suppl. Table 10).

3 Regularization for OOD generalization

The above analysis indicates that fine-tuning encourages a model to learn high importance for certain tokens while forgetting the rest, which is undesirable if the tokens are spuriously associated with the relevance label. However, it is non-trivial to identify the spurious versus causal/semantic tokens, since *spuriousness* depends on context. For instance, in our example with "samsung" products ("smartphone" and "refrigerator"), the brand was a spurious feature. However, when matching to

Fine-tuning Method	Temporal Shift		Categorical Shift	
	Amazon131K (IID)	**Amazon1.3M (OOD)**	**AmazonCatRemoved (IID)**	**AmazonCatOOD (OOD)**
`Base`	22.50	25.71	20.01	30.61
`Finetuned`	**39.71 ± 0.14**	26.02 ± 0.08	**38.74 ± 0.08**	28.31 ± 0.17
`MaskReg`	39.56 ± 0.01	26.65 ± 0.02	37.92 ± 0.11	29.09 ± 0.06
`SimCSE`	39.47 ± 0.11	26.05 ± 0.02	38.05 ± 0.56	28.52 ± 0.10
`OutReg`	38.03 ± 0.53	**27.60 ± 0.03**	37.66 ± 0.11	**31.21 ± 0.03**
`ITVReg`	**39.72 ± 0.10**	27.08 ± 0.01	**38.77 ± 0.02**	29.53 ± 0.04

Table 2: P@1 for Temporal and Categorical Shifts on *Amazon Titles*.

a smartphone accessory, the brand is no longer spurious (in fact, it is the causal feature). Thus, the subset X_c for a query may change based on the label, and similarly, the subset Z_c for a label may change based on different queries. Therefore, fully removing the influence of any token, as in OOD generalization for images that aims to remove spurious features [27], can be counter-productive. Instead, we propose that our goal should be to ensure that no token is under-weighted such that it is ignored for relevance prediction. Since finetuning models tends to assign very high weights to certain tokens, it implies: avoid learning large importance scores for tokens such that other tokens are ignored. To do so, we regularize the *importance scores* to be similar to the base model, since the base model has been trained on larger, diverse data and is unlikely to encode the same spurious patterns.

Intervention-based regularization. Generalizing the importance score from Section 2, given a text input, we define an *intervention* as an independent change to a *subset* of tokens without affecting the rest of the input. Further, we consider any intervention that removes information about the token subset, such as masking, deleting, replacing the token subset, etc. By definition, an intervention deviates from the original distribution $P(X)$ that generated the data, thus creating an out-of-distribution sample. For each input X, we construct an interventional input X' using a transformation on a random subset X_{sub} of the tokens. The key idea behind our regularizer is that for any subset of tokens X_{sub}, its importance score using the finetuned model should be the same as the importance score using the base model. This is a relaxation of the OOD generalization goal of ensuring that the accuracy of the finetuned model remains the same for X and X'. Using the equation for importance score from Section 2, the regularizer can be written as,

$$[(1 - f_\theta(X)^\intercal f_\theta(X')) - (1 - f_{\theta_0}(X)^\intercal f_{\theta_0}(X'))]^2 = (f_\theta(X)^\intercal f_\theta(X') - f_{\theta_0}(X)^\intercal f_{\theta_0}(X'))^2 \quad (1)$$

We call this the *Interventional* regularizer (`ITVReg`). The full training loss (where L_{ERM} can be the contrastive loss from Sec 2) is, $L_{ERM} + \lambda \mathbb{E}_X[(f_\theta(X)^\intercal f_\theta(X') - f_{\theta_0}(X)^\intercal f_{\theta_0}(X'))^2]$. As a baseline, we propose `OutReg` where the output prediction of the model is regularized to the base model.

4 Evaluation

We use two product-to-product recommendation datasets, namely *AmazonTitles131K* collected in 2013 and *AmazonTitles1.3M* [3] collected in 2014. We also simulate a categorical shift setting in *AmazonTitles131K*, with OOD evaluation set termed *AmazonCatOOD* and the in-distribution evaluation set termed *AmazonCatRemoved*. *Precision@1* is used for evaluation (details in Supp. E). For implementation details, see Supp. H. More evaluations can be found in Supp. D,F. **Baselines.** We compare `OutReg` and `ITVReg` to the `Base` model, standard `Finetuned` model, and two baselines from past work adapted to the OOD task, `SimCSE` [8] and `MaskReg` [21].

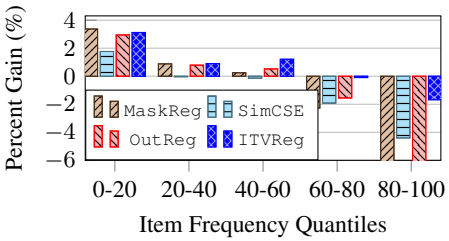


Figure 3: Percent gains in P@1 over `Finetuned` for different item quantiles.

Results. Table 2 shows the IID and OOD P@1 metrics for different methods . We first analyze the temporal distribution shift: train on *Amazon131K* and test on *Amazon1.3M*. On IID evaluation, `ITVReg` and `Finetuned` both obtain the highest P@1 while `OutReg` obtains the lowest P@1. On OOD evaluation, however, `OutReg` obtains the highest P@1 followed by `ITVReg`. Next, we consider categorical distribution shift from Table 2. We obtain similar results as the temporal shift: on the OOD evaluation, `OutReg` followed by `ITVReg` are the best performing models. Thus, `ITVReg` provides a balance between IID and OOD accuracy. This becomes evident as we consider a more realistic "temporal" shift where new items from *Amazon1.3M* are introduced gradually. As Suppl. Fig 5 shows, `ITVReg` is the only method that performs better than `Finetuned` (line $y = 0$) on P@1 on all such OOD datasets. Interestingly, the OOD regularization of `ITVReg` also helps in accuracy on low-frequency, "tail" items while retaining high accuracy on high-frequency, "head"

items. We bin the items according to their training set frequency in five quantiles i.e. 0-20%, ..., 80-100%, where lower quantiles denote low-frequency *tail*. Comparing the percentage gain in P@1 of methods wrt the `Finetuned` model (Figure 3), `OutReg` helps on the tail items but suffers a huge drop in P@1 on head items. In comparison, `ITVReg` achieves best of both worlds, with the same gains on tail and significantly lower drop on head items.

Importance Scores. Importance scores for the two examples in Sec. 2 after `ITVReg` regularisation are in Suppl. Fig 4. The problematic tokens *rowe* and *reflective* no longer have an extreme score.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [No]
   (c) Did you discuss any potential negative societal impacts of your work? [N/A]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No]

(b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]
(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]
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   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

A Related Work

Our work connects recommender systems, sentence matching, and OOD generalization literature.

Text-matching recommendation systems and Sentence matching. Among item-to-item recommendation systems, text-matching is a popular technique since many items can be characterized through their text, e.g., product-to-product recommendation on e-commerce websites or question-to-question recommendation on online forums. Given an input query (such as a product's title or description), the goal is to find the most relevant items. State-of-the-art models use dense text retrieval techniques [23, 11], based on a pre-trained *base model* like BERT [7] for the initial encoding. Then, either a bi-encoder or cross-encoder architecture [18, 11] is trained for learning the similarity between any two items. The former is computationally efficient while the latter is more accurate but inefficient [14]. Since recommender systems often deal with a large number of items, we restrict ourselves to bi-encoders. Contrastive loss with negative mining [26, 6, 10] is a popular way to train a bi-encoder model because recommender systems usually have one-sided feedback on the relevant pairs of items. Closer to our work, [18] tackled the problem of domain adaptation while our work focuses on the harder domain generalization problem [27].

OOD generalization and fine-tuning. Domain generalization in the vision literature [27] aims to identify spurious features in image data and remove them from a model's representation using data augmentation on the spurious feature [24] or through regularization [5]. While recent work has attempted using data augmentations from vision [22], such augmentations are not always useful in text data [25] since it is difficult to obtain universal augmentations. For instance, in the recommendation scenario, certain tokens (e.g., brand of a product) may be both spurious and causal depending on the user intent (e.g., substitute or accessory for a product). Given the prevalance of pre-trained base models, another direction is to utilize the base models for OOD generalization since they are trained on larger, diverse data [9]. Recent work proposes fine-tuning-based OOD generalization on image classification [12, 20, 5], but this direction has not been explored for text models or contrastive loss, especially in the recommendations context.

B Output-based regularization

We assume f outputs unit norm embeddings. Since both the fine-tuned model and the base model have the same architecture, a straightforward way to avoid very high importance scores is to make the

neural network output be the same as the base model. In a bi-encoder architecture for text-matching, we can implement this by enforcing that the finetuned and base encoders output exactly the same representation for an input. Given the finetuning $f_\theta(.)$ and base $f_{\theta_0}(.)$ encoders and an input query X, the output regularizer (`OutReg`) can be written as, $[f_\theta(X) - f_{\theta_0}(X)]^2$.

This simple regularizer is expected to do well for extreme distribution shifts where learning from IID data may not be that useful, since it constrains the encoder's representation to be closer to the base encoder. However, the same property is the biggest weakness of `OutReg`. As a regularization, it is too strong and discourages learning from train data: with a high enough penalty term, the final encoder may be exactly equal to the base encoder.

C Qualitative Analysis

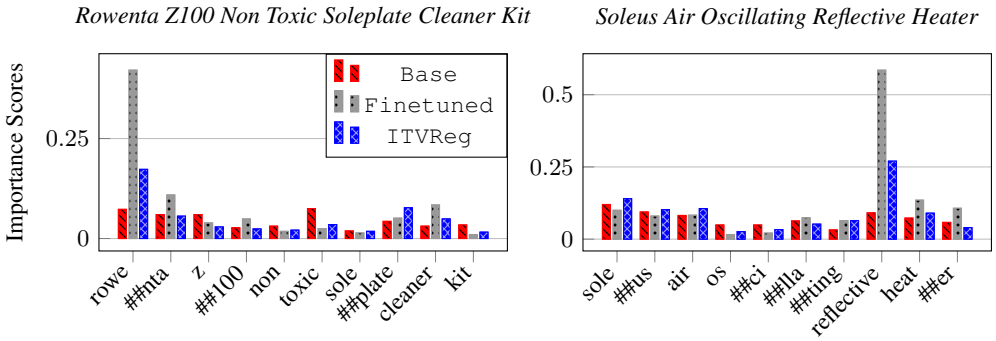

Figure 4: Token-wise importance scores for two example queries using the `Base`, `Finetuned` and `ITVReg`. `ITVReg` is able to normalise the importance scores for *"rowe"* (as in Fig. 2) and *"reflective"* tokens to be closer to `Base` model.

D Temporal Evolution

To understand the tradeoff between `ITVReg` and `OutReg`, we study how the accuracy of these models would vary as different amounts of OOD data (from 1.3M dataset) is mixed with IID data (131K validation) for evaluation. This simulates the real-world scenario where new items are progressively added. Specifically, we progressively add 40K new items and their relevant queries from 1.3M to create multiple OOD datasets. As Suppl. Figure 5 shows, `ITVReg` is the only method that performs better than `Finetuned` (line $y = 0$) on P@1 on all OOD datasets. As the distribution shift becomes more extreme, (around 24% of 1.3M OOD data) `OutReg` surpasses `ITVReg` indicating that `OutReg` is more suitable for large distribution shifts.

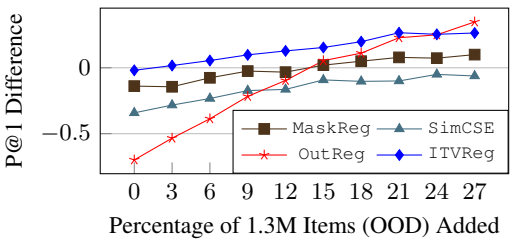

Figure 5: To simulate temporal evolution, we start with *Amazon131K* and add 39K new items from *Amazon1.3M* dataset at each tick. `ITVReg` is the only method that is consistently better than `Finetuned` on P@1.

E Amazon Titles Recommendations

Dataset. We use two product-to-product recommendation datasets, namely *AmazonTitles131K* and *AmazonTitles1.3M* [3]. These datasets contain titles of products that were recommended on a focal product's page. Only the product title can be used for recommendation. There is a time shift though: 131K is collected from the year 2013 and 1.3M is collected from 2014. As both new queries and labels are added while moving from 131K to 1.3M, this simulates the $P(X, Y)$ distribution shift setup. For each dataset, the same candidate items (131K and 1.3M items respectively) are shared across train and validation datasets. Each query in the train set has a labelled set of positive items with relevance 1. The validation set contains unseen queries and we need to recommend the most relevant items for them.

While going from 131K to 1.3M dataset represents a temporal shift where both queries and items' distributions change (and possibly other factors), we simulate a more controlled setup using category information.We exclude queries from the 5 most popular second-level categories from the train set, and use them to construct the OOD evaluation set (*AmazonCatOOD*). The in-distribution validation set also has the categories excluded (*AmazonCatRemoved*). Thus, the item distribution $P(Z)$ remains the same while the query distribution $P(X)$ changes across train and evaluation. Since X, Z have been treated symmetrically in our setup, this setups results can also be extrapolated to a case where the label distribution $P(Z)$ changes while the query distribution $P(X)$ remains the same.

Fine-tuning. We follow the modeling procedure used in a recent state-of-the-art work [6]. We initialize with MSMARCO-DistilBERT-v4 [16] and use contrastive loss with hard negative mining. Details are in Supp I.1.

All experiments are run for 3 random seeds and the mean and standard deviation are reported.

Evaluation metric. We use the $Precision@1$ metric for evaluation. Given predicted similarities $\hat{R} \in \mathbb{R}^M$ and ground truth similarities R (where r_i is 1 if its a relevant item, otherwise 0), $P@k$ is defined as $P@k = \frac{1}{k}\sum_{l \in rank_k(\hat{R})} R_l$.

F Question Recommendation Evaluation

Question Recommendations We also use the setup of [17] for numbers on question recommendations task. More details are in Supp. F

Datasets. We use the setup of [17] for our experiments. The *AskUbuntu* and *SuperUser* data comes from Stack Exchange, a family of technical community support forums. Both datasets contain around one million pairs of sentences, labeled either zero or one denoting a negative and a positive pair. Simulating a cold-start scenario with limited items, we present main results on 10% subsample of these datasets. Results on the complete datasets are in Suppl M. To study generalization under an extreme distribution shift, we additionally evaluate on a non-technical forum, *Quora-Question Pairs* dataset [19].

Fine-tuning. We adopt the same modeling procedure as [18], training with a MSE loss between the ground truth and the predicted relevance score. We initialize the models using two different `Base` models: NLI-DistilBERT [16] MSMARCO-DistilBERT-v4 [16] the latter having a substantially higher accuracy on our task. For more details on training, refer Supp I.2.

Evaluation metric. We use AUC(0.05) as the evaluation metric as in [17]. AUC(0.05) is the area under the ROC curve when the false positive rate (fpr) ranges from 0 to 0.05.

Results. Table 3 shows the IID and OOD performance of models trained on the two forum datasets. Let us first consider AUC on evaluation within the technical forums and using the less accurate NLI-DistilBERT `Base` model. On both IID and OOD evaluation, `ITVReg` obtains the highest AUC for both datasets. On OOD evaluation, `MaskReg` and `ITVAug` have the second-best AUC for SuperUser and AskUbuntu evaluation sets respectively. `OutReg` has comparatively lower AUC because the base model is not accurate: `ITVReg` obtains > 10 points higher AUC on both OOD datasets.

Base Model	Method	Train : AskUbuntu			Train : Superuser		
		AskUbuntu	**Superuser**	**Quora**	**AskUbuntu**	**Superuser**	**Quora**
NLI	Base	31.80	48.50	**14.00**	31.80	48.50	**14.00**
	Finetuned	65.68 ± 0.54	72.70 ± 0.73	12.74 ± 0.43	**47.98 ± 6.63**	75.70 ± 1.49	12.82 ± 0.49
	MaskReg	**71.51 ± 1.16**	77.55 ± 0.57	12.44 ± 0.48	33.83 ± 3.07	81.97 ± 0.33	13.13 ± 0.17
	SimCSE	67.31 ± 1.28	73.46 ± 2.24	12.87 ± 0.36	45.03 ± 4.22	76.80 ± 0.68	13.41 ± 0.20
	OutReg	56.86 ± 0.69	66.28 ± 0.66	**14.09 ± 0.18**	36.52 ± 1.53	71.11 ± 0.86	**14.44 ± 0.28**
	ITVAug	70.10 ± 0.80	76.98 ± 0.33	13.74 ± 0.12	45.86 ± 4.10	81.34 ± 0.11	14.22 ± 0.45
	ITVReg	**71.24 ± 0.62**	**78.89 ± 0.59**	13.57 ± 0.32	**47.00 ± 1.58**	**83.40 ± 0.54**	14.67 ± 0.18
MSMARCO	Base	54.01	80.73	**18.39**	54.01	80.73	**18.39**
	Finetuned	68.11 ± 1.09	75.33 ± 0.74	14.05 ± 0.19	59.27 ± 2.16	79.28 ± 0.94	14.35 ± 0.20
	MaskReg	72.59 ± 0.41	79.00 ± 0.08	12.63 ± 0.36	32.05 ± 6.53	83.53 ± 0.53	13.65 ± 0.20
	SimCSE	70.07 ± 0.32	76.54 ± 1.43	14.98 ± 0.08	48.97 ± 3.28	80.51 ± 0.70	14.70 ± 0.05
	OutReg	73.04 ± 0.77	**84.09 ± 0.28**	17.16 ± 0.13	**60.75 ± 0.84**	**86.24 ± 0.13**	17.64 ± 0.25
	ITVAug	73.17 ± 0.46	80.53 ± 0.23	15.36 ± 0.48	54.85 ± 3.94	84.29 ± 0.35	15.64 ± 0.32
	ITVReg	**74.64 ± 0.56**	82.86 ± 0.65	16.11 ± 0.36	**60.07 ± 2.42**	**86.24 ± 0.24**	16.39 ± 0.31

Table 3: AUC (0.05) using two different base models, NLI-DistilBERT-Base and MSMARCO-DistilBERT-Base. First three columns correspond to training on *AskUbuntu* and the last three training on *SuperUser*. When evaluated on technical forums with a weaker base model (NLI), ITVReg obtains the best AUC on both IID and OOD evaluation.

Using the more accurate MSMARCO-DistilBERT-v4, accuracy of both OutReg and ITVReg increases. P@1 on OOD data of OutReg is comparable to ITVReg on *AskUbuntu* evaluation and 1 point higher than ITVReg on *SuperUser* evaluation. In comparison, MaskReg and SimCSE fail to utilise the better Base model. When evaluated on an extreme distribution shift (*Quora*), Base model performs the best on OOD evaluation (Table 3) , followed by OutReg. Finetuning on *AskUbuntu* or *SuperUser* adds no information.

In OOD setup (training on AskUbuntu or Superuser) we can see that base model does the best and fine-tuning brings no gains.

Summary. Compared to other methods, ITVReg obtains high IID accuracy and OOD accuracy, thus exploiting the best of the Base model and the training data. However, under extreme distribution shifts, finetuning training data is not useful and thus OutReg or the Base model is more suitable.

G Dataset Details

Quora, SuperUser, AskUbuntu The ratio of positives to negatives in *SuperUser, AskUbuntu* is 1:100, while in *Quora* is 4:7.

Amazon131K In *Amazon131K* we have categorical information for 99K labels. The categorical shift experiments are conducted on this filtered data.

H Implementation Details

H.1 Baselines

1) SimCSE: We adapt SimCSE [8], an augmentation method for pretraining sentence matching models, for our fine-tuning task. During training, we use dropout (seeds s, s') to pass an input sentence twice through the model and obtain two embeddings, considered as a "relevant" pair. The regulariser is $(f(X,s)^\intercal f(X,s')-1)^2$. **2)** MaskReg: [21] propose deleting a span of words in the input as data augmentation. To adapt it for comparison to ITVReg, we mask a portion of tokens instead. The regulariser is $(f(X)^\intercal f(X')-1)^2$, where X' is masked input.

H.2 Hyper-parameter Tuning

For SimCSE the only choice of hyperparameter is the λ regularisation coefficient. We search over 3 values of λ i.e. 0.01,0.1,1.0 and select 0.1 as the best value. For other methods also we fix λ as 0.1. See Table 4

For MaskReg and ITVReg another hyperparameter choice is the masking fraction of the input. We search over 2 choices of masking namely masking 50% of input, or 15% of input. We find that 15%

Method	Quora	AskUbuntu	Superuser
SimCSE 0.01	54.98	73.70	84.91
SimCSE 0.1	55.40	74.34	86.38
SimCSE 1.0	54.89	74.07	85.41

Table 4: `SimCSE` IID numbers finetuned with base model as MSMARCO-DistilBERT-v4 on complete *Quora*,*AskUbuntu*,*SuperUser* datasets. This shows that 0.1 is the optimal hyperparameter for `SimCSE`

Base Model	Method	Train : AskUbuntu		Train : Superuser	
		AskUbuntu	**Superuser**	**AskUbuntu**	**Superuser**
NLI	`Base`	31.80	48.50	31.80	48.50
	`MaskReg` (0.15)	71.51 $\pm$ 1.16	77.55 $\pm$ 0.57	33.83 $\pm$ 3.07	81.97 $\pm$ 0.33
	`MaskReg` (0.50)	64.57 $\pm$ 0.68	69.87 $\pm$ 0.36	19.85 $\pm$ 4.14	77.17 $\pm$ 0.98
MSMARCO	`Base`	54.01	80.73	54.01	80.73
	`MaskReg` (0.15)	72.59 $\pm$ 0.41	79.00 $\pm$ 0.08	32.05 $\pm$ 6.53	83.53 $\pm$ 0.53
	`MaskReg` (0.50)	64.42 $\pm$ 1.44	71.56 $\pm$ 0.56	20.36 $\pm$ 5.69	77.64 $\pm$ 0.94

Table 5: AUC (0.05) for `MaskReg` with 15% and 50% input token masking. 15% is the optimal masking for `MaskReg`. The setup is same as in Table 3.

works best for `MaskReg` while 50% gives best results for `ITVReg`. We use these parameters for all experiments. For `MaskReg` results are reported in Table 5, while for `ITVReg` results can be seen in Table 11,13,12.

We also try running with lower learning rates but higher learning rate gives better numbers and hence we work with 1e-4. See Table 6 for reference.

Since we deal with short sentences, the max token length is fixed at 32 which allows for bigger batch sizes (900 for Amazon Titles, 250 for Question Recommendation).

For `ITVReg` and `OutReg` we report numbers for various values of hyperparameter λ in Table 7. We can see that for higher values of λ behaves more like the `Base` model but the numbers for both `ITVReg` and `OutReg` are stable across this wide range of λ.

I Training Details

I.1 AmazonTitle Recommendations Training Details

We follow the modeling procedure used in a recent state-of-the-art work [6]. For training, We use contrastive loss with hard negative mining. we initialise the model as MSMARCO-DistilBERT model, and fine-tune it for 200 epochs with a batch size of 900. The only difference from [6]'s setup is that we train only till 200 epochs instead of convergence (300-400 epochs) due to computational constraints. We use Adam optimizer with learning rate of 1e-4.

I.2 Question Recommendations Training Details

We train all the models for 5 epochs with a batch size of 250. We use learning rate of 1e-4 to fine-tune the model. We train the model with a MSE loss between the ground truth and the predicted similarities, as done in [18]. For *Quora* on the 10% subset, we train the model for 20 epochs with lr of 1e-4.

Learning Rate	2 Epochs	4 Epochs	10 Epochs
1e-5	39.15	45.05	53.40
5e-5	50.67	54.87	57.20
1e-4	52.14	55.54	57.80

Table 6: AUC(0.05) on IID complete *Quora* with `Finetuned` method on NLI-DistilBERT-Base model. Higher learning rate and more epochs help in training. For computational efficiency we hence take 4 epochs for complete setting and 20 epochs for 10% *Quora* subset.

Base Model	Method	Train : Quora		
		Quora	**AskUbuntu**	**Superuser**
MSMARCO-DistilBERT	`Base`	0.184 ± 0.000	0.540 ± 0.000	0.807 ± 0.000
	`ITVReg` 0.01	0.550 ± 0.031	0.165 ± 0.023	0.293 ± 0.018
	`ITVReg` 0.1	0.577 ± 0.002	0.175 ± 0.001	0.286 ± 0.011
	`ITVReg` 1.0	0.577 ± 0.002	0.175 ± 0.001	0.286 ± 0.011
	`OutReg` 0.01	0.570 ± 0.006	0.176 ± 0.023	0.278 ± 0.002
	`OutReg` 0.1	0.558 ± 0.005	0.297 ± 0.022	0.438 ± 0.006
	`OutReg` 1.0	0.491 ± 0.015	0.456 ± 0.001	0.646 ± 0.008

Table 7: AUC (0.05) for different values of the hyperparameter λ. We can see that both `ITVReg` and `OutReg` behave well in these reasonable range of λ. `OutReg` on higher values of hyperparameter imitates the `Base` model while `ITVReg` still learns useful information from the data

Fine-tuning Method	Automobiles	Kitchen and Dining	Health and Personal Care	Electronics	Tools and Home Imp.
No Finetune	32.66	30.68	30.42	32.07	31.67
Std Finetune	31.41 ± 0.28	29.70 ± 0.27	29.17 ± 0.25	30.60 ± 0.13	30.59 ± 0.25
`OutReg`	34.16 ± 0.04	32.25 ± 0.16	31.75 ± 0.11	33.14 ± 0.07	33.18 ± 0.10
`MaskReg`	32.16 ± 0.23	30.30 ± 0.18	29.85 ± 0.24	31.24 ± 0.11	31.22 ± 0.23
SimCSE	31.45 ± 0.12	29.84 ± 0.04	29.38 ± 0.06	30.70 ± 0.19	30.61 ± 0.16
`ITVReg`	32.61 ± 0.02	30.76 ± 0.10	30.26 ± 0.18	31.73 ± 0.14	31.59 ± 0.08

Table 8: Category wise numbers OOD numbers for *AmazonCatOOD* (Table 2). All categories have a similar trend as observed in Table 2. This shows that our results are agnostic to the choice of categories and hold true for any category in general.

J Category-wise P@1 for AmazonCatOOD

We report category wise numbers OOD numbers for AmazonCatOOD (Table 2). All categories have a similar trend. Results can be seen in Table 8.

K Evaluation Metrics

K.1 Precision@1

Given a query, the model outputs a vector $\hat{R} \in \mathbb{R}^M$, where M is the number of items and $\hat{r}_j$ denotes the similarity between the query and the j th item. We use the $Precision@1$ metric for evaluation, interpreted as the fraction of queries where the top-predicted item is in the query's ground-truth relevant items. Given predicted similarities $\hat{r}$ and ground truth similarities r (where r_i is 1 if its a relevant item, otherwise 0), $P@k$ is defined as $P@k = \frac{1}{k} \sum_{l \in rank_k(\hat{r})} r_l$.

L Qualitative Samples

We give top 5 predicted labels as qualitative samples for "*Soleus Air Oscillating Reflective Heater*" query in Table 10 and for query " *Rowenta Z100 Non Toxic Soleplate Cleaner*" in Table 9. Top-k predictions for all methods are in Suppl. L.

M Complete Dataset Results

For the complete dataset results, we follow the same setup as described before, with the only difference being number of epochs. We run *Quora* for 4 epochs and *SuperUser, Askubuntu* for 1 epoch. Results can be seen in Table 11,13,12.

N 10% Dataset Subset Results

Results on 10% subset of the data (most of them are redundant as they overlap with results in main paper) can be seen here: Table 14,16,15.

Method	Top 5 Predicted Items
Base	Ridgid 31105 24-Inch Aluminum Pipe **Wrench**
	Ridgid 31115 48-Inch Aluminum Pipe **Wrench**
	Ridgid 31110 36-Inch Aluminum Pipe **Wrench**
	Ridgid 31100 18-Inch Aluminum Pipe **Wrench**
	Craftsman 9-41796 Ratcheting Ready Bit Screwdriver
Finetuned	Rowenta ZD100 Non-Toxic Soleplate Cleaner Kit
	Rowenta DR5015 800 Watt Ultra Steam Brush with Travel Pouch
	Rowenta(R) Stainless Steel Soleplate Cleaning Kit ZD-110
	Rowenta DR6015 Ultrasteam Hand-Held Steam Brush with Travel Pouch, 800-watt
	Rowenta DR6050 Ultrasteam Hand-Held Steam Brush Dual-Voltage with Travel Pouch, 800-watt
OutReg	Rowenta DR6015 Ultrasteam Hand-Held Steam Brush with Travel Pouch, 800-watt
	Rowenta DW4060 Auto Steam Iron 1700W with Airglide Stainless Steel Soleplate Auto-off Anti-Scale, Blue
	Rowenta DR5015 800 Watt Ultra Steam Brush with Travel Pouch
	Rowenta VU2531 Turbo Silence 4-Speed Oscillating Desk Fan, 12-Inch, Bronze
	Rowenta(R) Stainless Steel Soleplate Cleaning Kit ZD-110
MaskReg	Rowenta(R) Stainless Steel Soleplate Cleaning Kit ZD-110
	Rowenta ZD100 Non-Toxic Soleplate Cleaner Kit
	Rowenta DG8430 Pro Precision Steam Station with 400 hole Stainless Steel soleplate 1800 Watt, Purple
	Rowenta DR5015 800 Watt Ultra Steam Brush with Travel Pouch
	Rowenta DR6015 Ultrasteam Hand-Held Steam Brush with Travel Pouch, 800-watt
SimCSE	Rowenta RH8559 Delta Force 18V Cordless Bagless Energy Star Rated Stick Vacuum Cleaner ...
	Rowenta ZD100 Non-Toxic Soleplate Cleaner Kit
	Rowenta(R) Stainless Steel Soleplate Cleaning Kit ZD-110
	Rowenta DR6015 Ultrasteam Hand-Held Steam Brush with Travel Pouch, 800-watt
	Rowenta DR6050 Ultrasteam Hand-Held Steam Brush Dual-Voltage with Travel Pouch, 800-watt
ITVReg	**Wrench** Set, Open End Metric 4mm-6mm - SCR-913.00
	Craftsman 6 pc. Universal **Wrench** Set - Metric
	Tusk Spoke **Wrench** Set
	Crescent RD12BK 3/8-Inch Ratcheting Socket **Wrench**
	Allen **Wrench** Set, 10 Pc. Heavy Duty, Extra Long 9 T-handle, Metric Sizes

Table 9: Top 5 predicted items for the query *Rowe USA Spoke Wrench - Bagged 09-0001* given by various methods sorted by relevance. Correct items should be about *wrench* and ITVReg and Base model both give the same. Other models rely on spurious feature i.e. *Rowe* for predicting items, which leads to wrong results

O Experimental Budget

Computing Infrastructure We use 16GB V100 GPUs for all our experiments

Training Time Our training time is around 1 hour for each run on Question Recommendation. Amazon dataset takes 8 hrs for training.

Parameters Of Model We use DistilBERT model for all our experiments.

Method	Top 5 Predicted Items
Base	Camco 57723 Dust Cover for Portable Wave 6 Olympian **Heater**
	Sylvania SA200 10 Amp Outdoor Timer with Light Sensor
	Scosche CRAB Chrysler/Jeep Antenna Adapter
	Lasko 6435 Designer Series Ceramic Oscillating **Heater** with Remote Control
	Reusable Angel Ice Sculpture Mold
Finetuned	3M Scotchlite Reflective Tape, Silver, 2-Inch by 36-Inch
	3M Scotchlite Reflective Tape, Red, 2-Inch by 36-Inch
	Reflective Band - Made With Genuine Reflexite in America - By Jogalite (Pair of Two)
	Sunlite 4 Piece Bicycle Reflector Set with Brackets
	Road ID - Reflective Shoe Laces
OutReg	3M Scotchlite Reflective Tape, Silver, 1-Inch by 36-Inch
	3M Scotchlite Reflective Tape, Red, 2-Inch by 36-Inch
	Reflective Band - Made With Genuine Reflexite in America - By Jogalite (Pair of Two)
	Casual Canine Reflective Jacket
	Aspects 264 Weather Dome
MaskReg	Reflective Band - Made With Genuine Reflexite in America - By Jogalite (Pair of Two)
	3M Scotchlite Reflective Tape, Red, 2-Inch by 36-Inch
	Lasko 6435 Designer Series Ceramic Oscillating Heater with Remote Control
	3M Scotchlite Reflective Tape, Silver, 1-Inch by 36-Inch
	Skylink PS-101 AAA+ Motion Sensor
SimCSE	3M Scotchlite Reflective Tape, Silver, 2-Inch by 36-Inch
	3M Scotchlite Reflective Tape, Red, 2-Inch by 36-Inch
	Reflective Band - Made With Genuine Reflexite in America - By Jogalite (Pair of Two)
	Gates T274 Timing Belt
	Bell Automotive 22-5-00106-8 Heavy Duty Tubeless Tire Repair Kit
ITVReg	Reflective Band - Made With Genuine Reflexite in America - By Jogalite (Pair of Two)
	Broan 679 Ventilation Fan and Light Combination
	3M Scotchlite Reflective Tape, Silver, 1-Inch by 36-Inch
	3M Scotchlite Reflective Tape, Red, 2-Inch by 36-Inch
	Roadpro 12V **Heater** and Fan with Swing-out Handle

Table 10: Top 5 predicted items for the query *Soleus Air Oscillating Reflective Heater* given by various methods sorted by relevance. Correct items should be about *Heater* and ITVReg and Base model both give the same. Other models rely on spurious feature i.e. *Reflective* for predicting items, which leads to wrong results

Pre-trained Model	**Fine-tuning Method**	**Quora**	**AskUbuntu**	**Superuser**
NLI-DistilBERT-Base	Base	14.00	31.80	48.50
	Finetuned	54.84 ± 0.82	17.50 ± 2.41	29.25 ± 1.10
	MaskReg	56.00 ± 1.15	19.79 ± 0.97	29.53 ± 1.59
	SimCSE	56.24 ± 0.55	21.05 ± 1.57	29.04 ± 2.01
	OutReg	52.69 ± 0.41	17.41 ± 1.16	27.33 ± 0.90
	ITVReg (0.15)	57.19 ± 0.57	19.70 ± 1.33	28.67 ± 0.26
	ITVReg (0.50)	56.64 ± 0.74	20.56 ± 1.07	28.57 ± 1.04
MSMARCO-DistilBERT-v4	Base	18.39	54.01	
	Finetuned	54.50 ± 0.31	19.79 ± 3.55	30.48 ± 1.33
	MaskReg	56.00 ± 0.60	19.55 ± 3.12	33.71 ± 0.62
	SimCSE	56.29 ± 1.62	19.57 ± 1.54	31.71 ± 0.93
	OutReg	54.41 ± 0.04	32.01 ± 1.72	46.80 ± 1.75
	ITVReg (0.15)	56.63 ± 0.65	20.09 ± 1.46	33.06 ± 1.65
	ITVReg (0.50)	55.98 ± 0.68	19.50 ± 1.77	33.51 ± 0.62

Table 11: Trained on Complete *Quora* for 4 epochs (same hyperparameters as in paper)

Pre-trained Model	Fine-tuning Method	Quora	AskUbuntu	Superuser
NLI-DistilBERT-Base	Base	14.00	31.80	48.50
	Finetuned	11.02 ± 0.43	71.09 ± 1.05	74.90 ± 0.27
	MaskReg	13.36 ± 0.38	77.62 ± 0.31	79.09 ± 0.21
	SimCSE	12.41 ± 0.34	74.73 ± 0.79	77.58 ± 0.11
	OutReg	14.75 ± 0.41	68.18 ± 0.64	72.88 ± 1.14
	ITVReg (0.15)	13.90 ± 0.51	77.54 ± 0.33	79.70 ± 0.31
	ITVReg (0.50)	13.77 ± 0.63	77.75 ± 0.49	81.06 ± 0.32
MSMARCO-DistilBERT-v4	Base	18.39	54.01	80.73
	Finetuned	12.01 ± 0.33	70.70 ± 1.16	74.94 ± 0.22
	MaskReg	13.66 ± 0.28	78.04 ± 0.44	79.94 ± 0.26
	SimCSE	13.89 ± 0.37	75.39 ± 0.99	78.53 ± 0.15
	OutReg	17.34 ± 0.26	78.84 ± 0.49	85.01 ± 1.41
	ITVReg (0.15)	14.84 ± 0.53	78.10 ± 0.55	81.19 ± 0.67
	ITVReg (0.50)	15.20 ± 0.41	78.47 ± 0.17	82.27 ± 0.36

Table 12: Trained on Complete *AskUbuntu* for 1 epoch (same hyperparameters as in paper)

Pre-trained Model	Fine-tuning Method	Quora	AskUbuntu	Superuser
NLI-DistilBERT-Base	Base	14.00	31.80	48.50
	Finetuned	12.68 ± 0.37	50.90 ± 2.95	83.50 ± 0.97
	MaskReg	13.65 ± 0.31	40.56 ± 2.66	87.79 ± 0.67
	SimCSE	14.39 ± 0.64	53.64 ± 1.67	85.85 ± 0.58
	OutReg	15.60 ± 0.13	35.41 ± 2.91	80.68 ± 0.73
	ITVReg (0.15)	15.19 ± 0.20	44.38 ± 1.10	88.31 ± 0.65
	ITVReg (0.50)	14.30 ± 0.18	45.83 ± 5.42	88.78 ± 0.39
MSMARCO-DistilBERT-v4	Base	18.39	54.01	80.73
	Finetuned	12.61 ± 0.46	52.32 ± 3.07	84.60 ± 0.77
	MaskReg	14.20 ± 0.22	38.32 ± 4.16	88.63 ± 0.44
	SimCSE	14.08 ± 0.39	49.04 ± 3.56	86.55 ± 0.32
	OutReg	17.42 ± 0.40	57.83 ± 1.31	89.94 ± 0.23
	ITVReg (0.15)	16.03 ± 0.66	52.77 ± 2.07	88.85 ± 0.43
	ITVReg (0.50)	16.24 ± 0.31	56.33 ± 1.91	89.90 ± 0.30

Table 13: Trained on Complete *SuperUser* for 1 epoch (same hyperparameters as in paper)

Pre-trained Model	Fine-tuning Method	Quora	AskUbuntu	Superuser
NLI-DistilBERT-Base	Base	14.00	31.80	48.50
	Finetuned	33.22 ± 0.82	10.95 ± 1.45	18.56 ± 1.53
	MaskReg	35.02 ± 0.85	12.94 ± 1.05	21.48 ± 1.65
	SimCSE	32.52 ± 0.29	10.82 ± 1.19	20.99 ± 1.13
	OutReg	33.41 ± 0.70	14.91 ± 1.26	25.63 ± 1.67
	ITVReg (0.15)	33.94 ± 1.47	13.73 ± 0.66	22.74 ± 0.59
	ITVReg (0.50)	32.93 ± 0.50	12.33 ± 0.89	20.91 ± 0.52
MSMARCO-DistilBERT-v4	Base	18.39	54.01	80.73
	Finetuned	34.15 ± 0.30	13.31 ± 1.29	23.73 ± 1.63
	MaskReg	36.49 ± 0.70	11.89 ± 1.70	25.88 ± 2.49
	SimCSE	34.85 ± 1.32	11.34 ± 1.99	25.63 ± 0.64
	OutReg	38.50 ± 0.29	31.96 ± 3.23	55.98 ± 1.49
	ITVReg (0.15)	38.41 ± 1.09	15.91 ± 2.22	30.95 ± 1.49
	ITVReg (0.50)	35.26 ± 1.09	12.28 ± 1.58	24.61 ± 0.95

Table 14: Trained on 10% *Quora*

Pre-trained Model	Fine-tuning Method	Quora	AskUbuntu	Superuser
NLI-DistilBERT-Base	Base	14.00	31.80	48.50
	Finetuned	12.74 ± 0.43	65.68 ± 0.54	72.70 ± 0.73
	MaskReg	12.44 ± 0.48	71.51 ± 1.16	77.55 ± 0.57
	SimCSE	12.87 ± 0.36	67.31 ± 1.28	73.46 ± 2.24
	OutReg	14.09 ± 0.18	56.86 ± 0.69	66.28 ± 0.66
	ITVReg (0.15)	13.62 ± 0.25	71.45 ± 1.17	78.32 ± 0.58
	ITVReg (0.50)	13.57 ± 0.32	71.24 ± 0.62	78.89 ± 0.59
MSMARCO-DistilBERT-v4	Base	18.39	54.01	80.73
	Finetuned	14.05 ± 0.19	68.11 ± 1.09	75.33 ± 0.74
	MaskReg	12.63 ± 0.36	72.59 ± 0.41	79.00 ± 0.08
	SimCSE	14.98 ± 0.08	70.07 ± 0.32	76.54 ± 1.43
	OutReg	17.16 ± 0.13	73.04 ± 0.77	84.09 ± 0.28
	ITVReg (0.15)	15.67 ± 0.22	74.11 ± 0.58	81.78 ± 0.28
	ITVReg (0.50)	16.11 ± 0.36	74.64 ± 0.56	82.86 ± 0.65

Table 15: Trained on 10 % *AskUbuntu*

Pre-trained Model	Fine-tuning Method	Quora	AskUbuntu	Superuser
NLI-DistilBERT-Base	Base	14.00	31.80	48.50
	Finetuned	12.82 ± 0.49	47.98 ± 6.63	75.70 ± 1.49
	MaskReg	13.13 ± 0.17	33.83 ± 3.07	81.97 ± 0.33
	SimCSE	13.41 ± 0.20	45.03 ± 4.22	76.80 ± 0.68
	OutReg	14.44 ± 0.28	36.52 ± 1.53	71.11 ± 0.86
	ITVReg (0.15)	14.35 ± 0.28	40.10 ± 3.68	82.27 ± 0.38
	ITVReg (0.50)	14.67 ± 0.18	47.00 ± 1.58	83.40 ± 0.54
MSMARCO-DistilBERT-v4	Base	18.39	54.01	
	Finetuned	14.35 ± 0.20	59.27 ± 2.16	79.28 ± 0.94
	MaskReg	13.65 ± 0.20	32.05 ± 6.53	83.53 ± 0.53
	SimCSE	14.70 ± 0.05	48.97 ± 3.28	80.51 ± 0.70
	OutReg	17.64 ± 0.25	60.75 ± 0.84	86.24 ± 0.13
	ITVReg (0.15)	15.94 ± 0.15	53.02 ± 5.42	85.44 ± 0.23
	ITVReg (0.50)	16.39 ± 0.31	60.07 ± 2.42	86.24 ± 0.24

Table 16: Trained on 10% *SuperUser*

Base Model	Method	Train : Quora			Train : AskUbuntu			Train : Superuser		
		Quora	AskUbuntu	Superuser	Quora	AskUbuntu	Superuser	Quora	AskUbuntu	Superuser
NLI	Base	0.140 ± 0.000	0.318 ± 0.000	0.486 ± 0.000	0.140 ± 0.000	0.318 ± 0.000	0.486 ± 0.000	0.140 ± 0.000	0.318 ± 0.000	0.486 ± 0.000
	Finetuned	0.559 ± 0.016	0.181 ± 0.018	0.257 ± 0.021	0.092 ± 0.001	0.775 ± 0.000	0.762 ± 0.002	0.122 ± 0.014	0.632 ± 0.029	0.863 ± 0.005
	MaskReg	0.529 ± 0.046	0.231 ± 0.014	0.331 ± 0.031	0.119 ± 0.010	0.810 ± 0.008	0.803 ± 0.010	0.132 ± 0.000	0.417 ± 0.057	0.901 ± 0.007
	SimCSE	0.571 ± 0.003	0.176 ± 0.023	0.259 ± 0.004	0.118 ± 0.012	0.792 ± 0.001	0.794 ± 0.012	0.137 ± 0.003	0.587 ± 0.024	0.876 ± 0.005
	OutReg	0.553 ± 0.002	0.149 ± 0.015	0.225 ± 0.005	0.146 ± 0.003	0.691 ± 0.009	0.737 ± 0.003	0.155 ± 0.000	0.383 ± 0.014	0.777 ± 0.019
	ITVReg	0.566 ± 0.013	0.186 ± 0.011	0.295 ± 0.018	0.136 ± 0.001	0.820 ± 0.001	0.815 ± 0.001	0.151 ± 0.000	0.563 ± 0.015	0.903 ± 0.005
MSMARCO	Base	0.184 ± 0.000	0.540 ± 0.000	0.807 ± 0.000	0.184 ± 0.000	0.540 ± 0.000	0.807 ± 0.000	0.184 ± 0.000	0.540 ± 0.000	0.807 ± 0.000
	Finetuned	0.564 ± 0.001	0.176 ± 0.005	0.265 ± 0.001	0.104 ± 0.007	0.776 ± 0.013	0.757 ± 0.011	0.144 ± 0.011	0.601 ± 0.020	0.862 ± 0.009
	MaskReg	0.526 ± 0.008	0.225 ± 0.011	0.363 ± 0.017	0.108 ± 0.004	0.813 ± 0.004	0.810 ± 0.000	0.131 ± 0.005	0.434 ± 0.007	0.908 ± 0.005
	SimCSE	0.574 ± 0.019	0.187 ± 0.006	0.301 ± 0.017	0.123 ± 0.004	0.797 ± 0.005	0.787 ± 0.007	0.125 ± 0.004	0.575 ± 0.050	0.887 ± 0.000
	OutReg	0.558 ± 0.005	0.297 ± 0.022	0.438 ± 0.006	0.166 ± 0.001	0.805 ± 0.002	0.851 ± 0.001	0.173 ± 0.004	0.614 ± 0.013	0.903 ± 0.001
	ITVReg	0.577 ± 0.002	0.175 ± 0.001	0.286 ± 0.011	0.134 ± 0.004	0.831 ± 0.004	0.826 ± 0.000	0.159 ± 0.002	0.575 ± 0.000	0.911 ± 0.008

Table 17: AUC (0.05) using two different base models, NLI-DistilBERT-Base and MSMARCO-DistilBERT-Base. First three columns correspond to training on *Quora*, middle three to *AskUbuntu* and the last three training on *SuperUser*. When evaluated on technical forums with a weaker base model (NLI), ITVReg obtains the best AUC on both IID and OOD evaluation. These are different from Table 3, they run with lower learning rate of 1e-5 and higher number of epochs with best model numbers reported