Cross-Domain Generalization Through Memorization: A Study of Nearest Neighbors in Neural Duplicate Question Detection

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Abstract
Duplicate question detection (DQD) is important to increase efficiency of community and automatic question answering systems. Unfortunately, gathering supervised data in a domain is time-consuming and expensive, and our ability to leverage annotations across domains is minimal. In this work, we leverage neural representations and study nearest neighbors for cross-domain generalization in DQD. We first encode question pairs of the source and target domain in a rich representation space and then using a k-nearest neighbour retrieval-based method, we aggregate the neighbors’ labels and distances to rank pairs. We observe robust performance of this method in different cross-domain scenarios of StackExchange, Spring and Quora datasets, outperforming cross-entropy classification in multiple cases. We will release our codes as part of the publication.

1 Introduction
Duplicate question detection (DQD) is an important application in information retrieval and NLP (Burke et al., 1997; Jeon et al., 2005; Lei et al., 2016; Nakov et al., 2016; Rücklé et al., 2019). It allows systems to recognize when two questions share an answer. This is significant for community forums, such as StackExchange1 (SE) to increase their effectiveness in avoiding redundant questions and displaying relevant answers to search questions. It is also important for FAQ retrieval question answering systems (Sakata et al., 2019).

To learn DQD models for SE, question pairs are usually annotated with duplication information that is extracted from community-provided meta-data. Such annotations are sparse for most domains, e.g., a new SE forum providing support for a new product. Therefore, leveraging other training signals either from unsupervised data or supervised data from other domains is important (Shah et al., 2018; Poerner and Schütze, 2019).

Pre-trained language models (PLMs) like BERT (Devlin et al., 2018) and RoBERTA (Liu et al., 2019) are great unsupervised textual representations. Several recent efforts adapt PLMs for the domains of interest by self-supervised fine-tuning on unsupervised domain data, which has shown to be promising in several scenarios (Lee et al., 2019; Beltagy et al., 2019; Han and Eisenstein, 2019; Gururangan et al., 2020). We follow that and tune BERT on SE domains to obtain richer representations for the task of DQD.

Recently, k-nearest neighbors (K−NNs) is applied on the PLM representations for language modeling (Khandelwal et al., 2019) and dialogue (Fan et al., 2020). We extend this line of study and apply $k$−NN for cross-domain generalization in DQD, where the models are trained on data from a source domain, and applied on data from a target domain. To do so, we represent pairs from source and target in a common representation space and then score target pairs using nearest neighbors in the source pairs. Figure 1 shows an illustration of this procedure.

Our study on AskUbuntu as target and source datasets of (Shah et al., 2018), which include several domains of SE and also Quora and Sprint, reveals that $k$−NN is more effective compared to cross-entropy classification if (i) the pair representation space from PLMs is rich for the target domain, i.e., adapted on the unsupervised data from target or similar domains; or (ii) source and target domains have large distributional shifts.

We make the following contributions: (i) We present the first study of combining strengths of $k$−NN and neural representations for cross-domain generalization in a sentence matching task, i.e., DQD. (ii) Our experimental results on cross-

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1https://stackexchange.com/
2 Related Work

Sparsity in DQD labeled examples in the SE domain is tackled by leveraging the unsupervised data (Poerner and Schütze, 2019), the supervised data from other domains, or both (Shah et al., 2018; Uva et al., 2018; Rücklé et al., 2019; Rochette et al., 2019). We follow these approaches and learn representations from unsupervised data and apply them for better generalization when external supervised data in other domains is used.

A combination of $k$–NN with neural representations is the subject of several earlier work, mostly in image classification (Papernot and McDaniel, 2018; Cohen et al., 2018) Papernot and McDaniel (2018) show that $k$–NN is more robust to out-of-distribution examples. More related to our work, Khandelwal et al. (2019) apply $k$–NN on neural representations computed from and applied on language modeling task and interpolates its scores with Softmax. They validate that this is effective in different scenarios, including domain adaptation. Here we do not compute representations for $k$–NN on the same task as the one we apply; the representations are computed by language modeling and applied on DQD.

3 Cross-Domain DQD

DQD is to identify pairs of questions answered by the same information. We address DQD for community forums like SE. In SE, several domains are built to address diverse user needs. We address DQD in a scenario where we perform on a Target domain with no task supervised data, by leveraging its unsupervised text if exists, and labeled examples from a Source domain.

3.1 Question Pair Representations

Our work leverages BERT (Devlin et al., 2018), a transformer-based language model, pre-trained on general text from Wikipedia and BookCorpus. We fine-tune BERT using its self-supervised objectives on unlabeled questions in SE formatted as (Title, Body). Specifically, we concatenate the Title and Body of the questions of a domain to form documents for BERT. We adopt the terminology of Gururangan et al. (2020) and call this process domain-adaptive pre-training (DAPT) and the resulting model BERT$_\text{DAPT}$. DAPT tailors the representation towards the particular vocabulary, syntax, and semantics of the problem space (DQD). It also adapts the representation to a specific domain (e.g. AskUbuntu). Therefore, we expect BERT$_\text{DAPT}$ to produce richer initial representations for our data.

To obtain a representation for a pair of questions $(q_1, q_2)$, we concatenate the text of both items and feed that as input to BERT$_\text{DAPT}$. The two items are separated by the [SEP] token. We regard the embedding of the first token ([CLS]) at the final layer as our pair representation. This representation is then utilized in two ways to produce DQD predictions, as described in the following.

3.2 Classification (CLF)

For CLF, we follow the standard BERT training for sequence classification starting from BERT$_\text{DAPT}$ as a better initial PLM for cross-domain DQD. In this setting, the CLS embedding is the input to a classification layer with a cross-entropy loss. The
gradients are back-propagated to the BERT\textsubscript{DAPT} parameters through CLS embedding and tuned for the DQD task.

3.3 \textit{k–Nearest Neighbors (k–NN)}

We leverage the self-supervised representation \( f_t \), corresponding to the CLS embedding in BERT\textsubscript{DAPT} and encode each pair \( q_i \), in the Source training set \( D_s \) using \( f_t \) and preserve its associated label \( y_i \in \{\text{duplicate}, \neg \text{duplicate}\} \), as illustrated in Figure 1. A distance function \( d \) between two vectors \( u \) and \( v \) is selected in order to establish the nearest neighbors. We use the cosine distance for this purpose: 
\[
d(u,v) = 1 - \cosine(u,v)
\]

One score for each potential label \( y \) of a test pair \( q_t \) is then computed using \( s \), representing the fraction of the mass of \( 1 - d_i \) in \( K \) of each.
\[
s(y) = \sum_{i=1}^{K} 1_{y_i = y} (1 - d(f_t(q_i), f_t(q_t))) / \sum_{i=1}^{K} 1 - d(f_t(q_i), f_t(q_t))
\]

4 Datasets

| Dataset         | Questions | Train | Dev | Test |
|-----------------|-----------|-------|-----|------|
| AskUbuntu       | 305,769   | 9,106 | 1,000 | 1,000 |
| SuperUser       | 390,378   | 9,106 | -   | -    |
| Sprint          | 31,768    | 9,106 | -   | -    |
| Quora           | 537,211   | 9,100 | -   | -    |

Table 1: The number of duplicates taken from Shah et al. (2018). For AskUbuntu, as our Target, Train, Dev and Test, and for others Train numbers are shown. Note that all AskUbuntu questions are considered for BERT\textsubscript{DAPT}.

We experiment on cross-domain DQD datasets of Shah et al. (2018)\(^2\) (See Table 1). For AskUbuntu and SuperUser, the positive examples are taken from the duplicate marks in SE. For Sprint, three paraphrases are generated by annotators for each question in a set of FAQ. In these three datasets, 100 negatives are sampled randomly per each positive. The annotation of Quora comes from the released Quora question pairs dataset (Kaggle, 2017).

We further extract all questions for SE domains from the dump files.\(^3\). These are integrated in our unsupervised adaptations. For our analysis in §5.2, we create two additional unsupervised corpora from SE. The first is from Academia consisting of around 27K questions. The second is from

\(^2\)github.com/darsh10/qra_code

\(^3\)archive.org/details/stackexchange

33 different SE domains (See Table 5 in Appendix), composed of around 1.5M questions.

4.1 Lexical Similarity Statistics

We select AskUbuntu as our only Target. In Table 2 (last column), we show the lexical similarity between each Source and the Target. Accordingly, Sprint and Quora hold low similarity with AskUbuntu, and SuperUser is the most similar domain.

We also present the similarity between paired questions in each class of duplicate and non-duplicate in Table 2. We observe that a duplicate pair in Sprint and Quora has higher word-overlap on average compared to SE datasets. Quora has another significant difference: its negative pairs are selected to have a high lexical overlap. This means that the labeling function in Quora is different from others.

5 Experiments

To obtain BERT\textsubscript{DAPT}, we fine-tune bert-base-cased (BERT\textsubscript{BASE}) using language modeling scripts in Transformers (Wolf et al., 2019) for 3 epochs using default hyperparameters. To clarify the effects of DAPT, we experiment with BERT\textsubscript{BASE} as well. For CLF, we fine-tune BERT on task training data for 10 epochs with a learning rate of 5e-5, early stopping on the Target dev set. All our \(k\)--NN experiments are done with with the \(k = 100\) using Faiss library (Johnson et al., 2017).

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|c|}
\hline
& dup & \neg dup & S(AskUbuntu) \\
\hline
AskUbuntu & 0.16 & 0.03 & 1.00 \\
SuperUser & 0.19 & 0.03 & 0.22 \\
Sprint & 0.37 & 0.04 & 0.03 \\
Quora & 0.47 & 0.30 & 0.12 \\
\hline
\end{tabular}
\caption{Lexical similarity (measured by Jaccard index) between question pairs within domains grouped by classes (first two columns) and between vocabulary of Sources and AskUbuntu.}
\end{table}

Evaluation metric Since the annotations are incomplete in SE, Shah et al. (2018) propose to use AUC as the metric for DQD performance. They report the normalized AUC(.05), which is the area under the curve of the true positive rate as function of the false positive rate \((fpr)\), from \(fpr = 0\) to \(fpr = .05\). We follow the same protocol and use
AUC(.05) metric.

5.1 Results

| Model          | AskUbuntu | SuperUser | Sprint | Quora |
|----------------|-----------|-----------|--------|-------|
| BERT\textsubscript{DAPT} |           |           |        |       |
| 1 CLF          | .923      | .870      | .749   | .609  |
| 2 \(k-\text{NN}\) | .936      | .908      | .753   | .800  |
| BERT\textsubscript{BASE} |           |           |        |       |
| 3 CLF          | .899      | .779      | .562   | .515  |
| 4 \(k-\text{NN}\) | .871      | .755      | .649   | .621  |
| 5 BiLSTM       | .858      | .796      | .615   | .446  |

From Shah et al. (2018)

Table 3: Comparing AUC(.05) results of our models and the baseline. Four Sources are evaluated for the Target, i.e., AskUbuntu. BERT\textsubscript{DAPT} is the adaptation of BERT\textsubscript{BASE} on AskUbuntu unsupervised data.

In Table 3, we present the performance of our models for AskUbuntu evaluation set given Source data from AskUbuntu, SuperUser, Sprint, or Quora. We add in-domain (AskUbuntu as Source) results for comparison. We include the results of Shah et al. (2018) obtained on the same data by learning domain-adversarial BiLSTM models in line 5.

The first block corresponds to BERT\textsubscript{DAPT}: the adapted BERT on AskUbuntu unsupervised data. We see that \(k-\text{NN}\) outperforms CLF in all cases (line 2 vs. 1), confirming that \(k-\text{NN}\) is more robust if the pair representation is rich. The most obvious improvement belongs to Quora as Source (.609 to .800), where the labeling function shifts significantly (See §4.1).

In the second block, BERT\textsubscript{BASE} results in consistently worse models (line 3-4) compared to BERT\textsubscript{DAPT}. Here for Sprint and Quora, \(k-\text{NN}\) again outperforms CLF, giving more evidence about robustness of \(k-\text{NN}\) in the case of domain shifts. However, for SuperUser, a closely related domain to AskUbuntu and also AskUbuntu itself, \(k-\text{NN}\) underperforms. Given that the input representations to \(k-\text{NN}\) are not tuned on SE in the case of BERT\textsubscript{BASE}, this is not surprising. CLF fine-tunes the representations as part of its task training on the Source data, which in this case is a related or same domain as the Target.

5.2 Domain of Unsupervised Data in BERT\textsubscript{DAPT}

Here we aim to understand more about the impact of the domain of unsupervised data on the quality of BERT\textsubscript{DAPT}. In Table 4, we report results for SuperUser as Source and AskUbuntu as Target, and vary the unsupervised corpus, starting from no data (i.e., BERT\textsubscript{BASE}).

We choose these domains (lines 2-5): Source (SuperUser), Target (AskUbuntu), Unrelated (Academia) as a lexically distant domain to Target, and a set of 33 SE domains including Source and Target (See Table 5 for full list).

Table 4 demonstrates that adaptation on Target data (line 3) is better than either of Source (line 2) or the unrelated domain (line 4). Adaptation on a large number of domains (line 5) is the best; the information across a diverse set of domains is complementary for the task. Notably, we observe that the representation is more critical for \(k-\text{NN}\) compared to CLF: the difference between the best representation (33 domains) and worst (BERT\textsubscript{BASE}) is much greater in \(k-\text{NN}\) compared to CLF. This behavior is understandable as CLF further updates the representation during its task training, while for \(k-\text{NN}\), it remains fixed.

6 Conclusion

In this work, we studied applying \(k-\text{NN}\) in DQD cross-domain generalization. We compared \(k-\text{NN}\) and a cross-entropy classifier when different question-pair representations are available. Our results showed that domain-adaptive pre-training on target data gives rich representations, and \(k-\text{NN}\) is more robust against distributional shifts compared to classification if question pairs are encoded by these rich representations.

We plan to extend our study to other tasks and understand better the strengths of memorization in learning robust models where rich PLM embeddings are utilized to represent examples. We believe concurrently that the promising results and
findings of this presented study could benefit other NLP research to explore this direction more.

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Table 5: The 33 StackExchange domains used in our unsupervised BERT adaptation analysis.

| unsupervised Data  | CLF | k−NN  |
|-------------------|-----|-------|
| 1     None        | .899| .871  |
| 3     Target      | .923| .936  |
| 4     Unrelated   | .899| .890  |
| 5     33 SE domains | .942| .942  |

Table 6: AUC(.05) of training on Source = AskUbuntu and evaluating on Target = AskUbuntu, as a function of the input corpus for BERT\textsubscript{DAPT}. None corresponds to BERT\textsubscript{BASE} and Unrelated to Academia.