Non-Parametric Temporal Adaptation for Social Media Topic Classification

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Abstract
User-generated social media data is constantly changing as new trends influence online discussion, causing distribution shift in test data for social media NLP applications. In addition, training data is often subject to change as user data is deleted. Most current NLP systems are static and rely on fixed training data. As a result, they are unable to adapt to temporal change – both test distribution shift and deleted training data – without frequent, costly re-training. In this paper, we study temporal adaptation through the task of longitudinal hashtag prediction and propose a non-parametric technique as a simple but effective solution: non-parametric classifiers use datastores which can be updated, either to adapt to test distribution shift or training data deletion, without re-training. We release a new benchmark dataset comprised of 7.13M Tweets from 2021, along with their hashtags, broken into consecutive temporal buckets. We compare parametric neural hashtag classification and hashtag generation models, which need re-training for adaptation, with a non-parametric, training-free dense retrieval method that returns the nearest neighbor’s hashtags based on text embedding distance. In experiments on our longitudinal Twitter dataset we find that dense nearest neighbor retrieval has a relative performance gain of 64.12% over the best parametric baseline on test sets that exhibit distribution shift without requiring gradient-based re-training. Furthermore, we show that our datastore approach is particularly well-suited to dynamically deleted user data, with negligible computational cost and performance loss. Our novel benchmark dataset and empirical analysis can support future inquiry into the important challenges presented by temporality in the deployment of AI systems on real-world user data.

Introduction
Distribution shift presents a serious challenge for the deployment of NLP systems in real-world scenarios. The distribution of text data changes over time and most models quickly become stale without further re-training (Lazaridou et al. 2021; Dhingra et al. 2022; Luu et al. 2022). Social media data, in particular, are constantly changing over time, as they are heavily influenced by temporal trends which affect their themes and topics. Further, even training data may need to be deleted for a variety of reasons – for example, removing profanity and other harmful content, or capturing user-initiated deletions. These and other cases of data intervention necessitate retroactive data removal from deployed models.

Given the ever-shifting nature of user-generated data, deployed models need to have mechanisms that allow them to (1) adapt to the changes in the test distribution to prevent degradation in performance over time and (2) abide by the privacy policies that regulate users’ data usage by companies. Modern neural learning frameworks can achieve these goals, but at great computational cost. For example, some prior work adapts to test distribution shift by directly fine-tuning model parameters through gradient descent on new data at regular time intervals (Huang and Paul 2018; Jin et al. 2022). To address user deletion, some prior work has again relied on computationally expensive methods: deleted samples are simply removed from the training set and the entire model is re-trained from scratch. While several methods have been proposed to partially mitigate computational cost...
through techniques to speed up re-training, substantial compute is still required (Bourtoule et al. 2021; Wu, Dobriban, and Davidson 2020). Recently, more efficient methods for deletion with error guarantees have been proposed (Neel, Roth, and Sharifi-Malvajerdi 2021a); however, they are only applicable to convex models and cannot be applied to state-of-the-art neural systems.

Even with specialized mitigation strategies (e.g., efficient fine-tuning through adapters or prefixes, and efficient re-training techniques), these methods all rely on gradient descent in some form, which carries a high computational cost. Since the challenges of temporal shift are pervasive in a wide variety of real-world applications, in aggregate, gradient-based adaptation of actual production systems in industry may even have a non-negligible impact on carbon emissions (Strubell, Ganesh, and McCallum 2019).

In this paper, we make two main contributions: First, we introduce a novel benchmark dataset focused on hashtag prediction as a representative discriminative task in the social media domain. Hashtag prediction is a multi-label classification problem where a system attempts to predict the set of hashtags that will be included in a Tweet given the text contents of the input Tweet. We collected 7.13M Tweets, binned by week of creation, over the year of 2021. We explicitly organize this data into twelve non-overlapping time buckets spanning the entire year, each of which is subdivided into weeks, along with train/validation/test splits. This novel benchmark, depicted in Figure 1, is intended to facilitate the study of efficient methods for temporal adaptation and deletion on real-world user data. A simple measure of temporal change, overlap in the most frequent hashtags per time bucket, is depicted in Figure 2.

Our second contribution is an empirical analysis of a known, but understudied learning paradigm in the context of temporal adaptation: non-parametric classification through dense retrieval from a datastore. We demonstrate in experiments that by using a dense \( K \)-nearest neighbor classifier, with a static neural text encoder pre-trained on fixed historical training data, we can simply replace the datastore with more up-to-date training data (or with required deletions) to accommodate adaptation and deletion. This approach, which is also depicted in Figure 1, requires no gradient-based methods to achieve either goal – adaptation and retroactive deletion can be accomplished with minimal computational cost.

In addition to comparing several text encoding strategies and simple re-ranking methods, we compare against two state-of-the-art parametric baselines based on BART (Lewis et al. 2020): (1) a fine-tuned neural classifier based on BART’s pre-trained encoder, and (2) a fine-tuned neural sequence-to-sequence model which is fed the Tweet sequence as input and produces the set of hashtags as an output sequence. This latter baseline is not tied to a fixed label inventory and has the ability to generate unseen tags. Our results show that using the parametric classifier’s pre-trained encoder as the text encoder for the non-parametric classifier – effectively distilling a parametric model into a non-parametric one – leads to extremely high performance at low computational cost relative to baselines. More specifically, our best non-parametric approach outperforms static parametric models with an average relative gain of 64.12% recall when the test distribution shifts – and, even outperforms conventional gradient-based temporal adaptation of parametric baselines with an average relative gain of 11.58% recall. Together, our benchmark and empirical analysis highlight non-parametric techniques as a practical and promising direction for adaptation to distribution shift and user-deletion and may facilitate future work arising from temporality in real-world deployment of NLP systems.

**Related Work**

**Temporal Distribution Shift.** Early research models semantic shift of the same words as one type of temporal change (Wijaya and Yeniterzi 2011; Kulkarni et al. 2015; Hamilton, Leskovec, and Jurafsky 2016; Kutuzov et al. 2018). Separately, Blei and Lafferty (2006); Wang, Blei, and Heckerman (2012) add temporal information into topic models, and Huang and Paul (2018); He et al. (2018) analyze standard domain adaptation methods for temporal document classification. More recently, the temporal generalization problem has been re-emphasized in pretrained language models (Lazaridou et al. 2021; Dhingra et al. 2022; Luu et al. 2022; Jin et al. 2022) as their re-training cost continues to grow. The temporal distribution shift problem on Twitter has been studied in Preotiuc-Pietro and Cohn (2013); Rijhwani and Preotiuc-Pietro (2020); Luu et al. (2022). Most of these works explore traditional domain adaptation techniques that require re-training the model, the only exception is Preotiuc-Pietro and Cohn (2013) where they keep track of the latest hashtag frequencies as the prior to adapt a naive Bayes classifier. In this work, we study non-parametric methods that adapt models through dense retrieval without any retraining.

**User Data Deletion.** With a recent focus on providing users with control over when and how their data is used, many approaches have been proposed to address utilizing ML models when users have revoked the use of their data. Decremental learning (Cauwenberghs and Poggio 2000)

![Figure 2: Hashtag label set overlap, computed as recall, between Tweets from different time buckets in our benchmark dataset. Note: The scores are not symmetric because the hashtag sets for different time buckets have different sizes.](image-url)
Retrieval-Augmented Methods. Utilizing kNN retrieval on dense representations derived from parameterized models has seen recent success in natural language processing. In language modeling, nearest-neighbor language models (Khandelwal et al. 2020; He, Neubig, and Berg-Kirkpatrick 2021) extend a parametric pretrained language model by linearly interpolating probabilities over next-tokens with a k-nearest neighbors model. Similar techniques have been applied to machine translation as well (Khandelwal et al. 2021; Zheng et al. 2021). In particular, dense retrieval has achieved remarkable success in open-domain question answering (Chen et al. 2017; Guu et al. 2020; Izacard and Grave 2021). It has also been effectively applied to large-scale language model pretraining (Guu et al. 2020; Nakano et al. 2021; Borgeaud et al. 2022) as well as candidate retrieval in recommender systems (El-Kishky et al. 2022a,b).

Hashtag Prediction. Hashtag prediction was first studied in the context of predicting which hashtags will go viral in the future (Ma, Sun, and Cong 2012). We consider a related but different task of suggesting hashtags for a tweet. More related, methods were proposed that compute tf-idf vectors from extracted keywords and apply simple classifiers on these vectors for hashtag recommendation (Jeon, Jun, and Hwang 2014; Sedhai and Sun 2014). Later methods utilized deep learning architectures such as LSTMs (Li et al. 2016; Shen et al. 2019), CNNs (Gong and Zhang 2016), and other deep architectures (Ma et al. 2019) for hashtag recommendations. To the best of our knowledge, this is the first approach to apply dense retrieval for hashtag recommendation.

**Benchmark Dataset**

To evaluate a model’s ability to efficiently adapt to temporal change in social media topic classification, we need a benchmark dataset where examples are temporally annotated and temporally bucketed in a balanced and fine-grained manner. As far as we are aware, no such dataset is publicly available. Thus, we have curated a novel, public large-scale benchmark dataset for temporal hashtag prediction on Twitter data.

![Diagram](https://example.com/diagram.png)

**Figure 3:** Depiction of how time bucketing is done on the curated dataset. Each time bucket is made up of four weeks. For time bucket $i$, the first three weeks’ training data is used for training a model/building datastore, and the test set of the fourth week in the bucket is used for testing with temporal shift. The dataset has 12 time buckets.

We build our dataset by scraping Tweets over the course of the year 2021, with weekly granularity, which means that Tweets are grouped per the week in which they were published. For each week, we only keep Tweets that contain at least one hashtag from the top-10K most frequent hashtags that week. Further, we drop infrequent hashtags (i.e. hashtags not in the top-10K per week) from the label set. Thus, one very concrete form of distribution shift present in this dataset is that the label inventory of hashtags changes week-to-week across the dataset. Figure 2 visualizes the hashtag type overlap between different months in the dataset. Of course, temporal shift in the contents of the underlying Tweets and how Tweet contents correlates with hashtag choice is also present, though less visible in the dataset’s construction. We preprocess the data to partition each week into train/validation/test sections, and balance the number of train/validation/test Tweets across weeks. The main statistics of the dataset are shown in Table 1. We run evaluations on this dataset with three different temporal setups, explained in the Experimental Setup Section.

**Prediction Task.** Users very commonly add more than a single hashtag to a Tweet they are composing. In fact, in our dataset we find that on average users assign nearly three hashtags to each individual Tweet. Thus, we treat the hashtag prediction task as a multi-label classification problem. Each datum has two components: source and target, where source is the Tweet text, and target is the set of hashtags associated with that Tweet. Our models are required to produce a fixed number of output hashtags for a given input Tweet, and we will evaluate recall against the ground truth hashtags.

**Dataset Bucketing for Temporal Adaptation.** Figure 3 shows how the temporal bucketing of the curated dataset is

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1 Code and data is available at https://github.com/icebergnlp/twitter-temporal-adaptation
set up. To facilitate temporal evaluation, we bin the dataset into 12 buckets, each consisting of four weeks (near, but not exactly aligned with month boundaries). In each bucket, the first three weeks are intended to be used as a contemporaneous datastore for temporal adaptation (or as a re-training/fine-tuning set, depending on the method being employed). For static evaluation of models (i.e. without temporal shift) we further break each week into train, validation, and test sections with an 80/10/10% split. When evaluating in the temporal setting, the test section from the fourth week in each bucket is used as the test set. This ensures that the corresponding datastore / re-training dataset, while being nearly contemporary with the corresponding test set, is realistic in that it does not come from the future. Finally, some models require a frozen historical training corpus (e.g. to train an encoder to be used for dense retrieval). We reserve the first time bucket for this purpose.

KNN Model

We propose a simple but effective solution to distribution shift and user data deletion based around a non-parametric classifier. Unlike parametric models which need to be re-trained or fine-tuned when train or test data changes, non-parametric models can be quickly updated simply by replacing the datastore which contains the training data. We propose using a dense K-nearest neighbor (KNN) classifier with a neural text encoder [Altman 1992; Khandelwal et al. 2020], which retrieves the top $K$ nearest points from training data based on the neural encodings of the samples. The retrieval of the top-$K$ samples works as follows:

$$\mathcal{Y}_{K}(x) = \text{top-}K\text{-argmin}_{(x',y') \in \mathcal{D}} \| e(x) - e(x') \|_2, \tag{1}$$

where $e(x)$ is the neural encoding of the test Tweet $x$, and $x'$ represents training sample Tweets, stored in a datastore. $y'$ is the class label (hashtag) of $x'$. We use L2 as the distance metric. In our experiments, we found that re-ranking the top-$K$ tags, and returning only top $R$ of the re-ranked tweets (where $K \gg R$) yields higher recall, so we add a re-ranking step to the KNN retrieval:

$$\hat{\mathcal{Y}}_{R}(x, \mathcal{Y}_{K}(x)) = \text{top-}R\text{-rerk}(x, \mathcal{Y}_{K}(x)). \tag{2}$$

which re-ranks and returns the top $R$ tags. Based on this, the dense KNN models would have three main components: (1) A static neural encoder (static as in it is only trained once and doesn’t need to be updated) (2) a datastore that enables fast nearest neighbor search and (3) a re-ranker. Below we explain these components in more detail.

Encoder

We use representations generated by a transformer-based model (BART, Lewis et al. 2020) to encode the tweets for saving and retrieval. The encoding is very crucial, as it is the main tool that helps us find relevant hashtags, and we find that if the encoder model is not appropriately trained (on relevant data), it can adversely impact the performance of the model. We empirically ablate different transformer-based encoders with different training objectives in the Results Section. It is noteworthy that the encoder is only trained once, on historic training data (time bucket 1), and it is not temporally updated.

Datapoint and Search

For storing the Tweets and hashtags in the datastore as key-value pairs, we “unroll” Tweet/hashtag sets. This means that if the tweet is “Happy New Year #welcome2021 #growth #change #newyear”, we unroll it into four separate training samples, each with the Tweet text as source, but only a single hashtag as target, and then save each of these four separate pairs as a key-value pair.

The engine behind many modern non-parametric methods is an efficient indexing and search algorithm that allows for fast retrieval of approximate nearest neighbors [Khandelwal et al. 2020, 2021]. We follow prior work and use FAISS [Johnson, Douze, and Jégou 2019], which is a data structure that enables efficient similarity search and clustering of dense vectors based on product quantization. FAISS performs approximate nearest neighbor search over approximate distances due to vector quantization, which is faster than an exact search, but does not precisely correspond to exact L2 distance. We explain the implementation details of the datastore in the Experimental Setup Section.

Re-ranking

To re-rank the retrieved $K$ Tweets for better performance, we try the three methods below:

1. Default distance ranking: In this method, we use the L2 distances returned by FAISS, which are approximate as FAISS quantizes the vectors to speed up the search. We then rank the hashtags from nearest to furthest and return the “unique” top $R$, as there might be repetitions in the top retrieved hashtags.

2. Actual distance ranking: This is similar to the previous method, however, instead of using FAISS’s approximate distance, we find the actual distance between the encoding of the Tweet we want to do prediction for, and the retrieved neighbors. We then rank the neighbors based on this new distance and return the top $R$.

3. Frequency-based ranking: This method is similar to the conventional KNN classification, but with a multi-label twist, where we count the number of occurrences of each hashtag in the $K$ retrieved tags, and then rank them from most repeated to least, and return the top $R$ most common ones. This method prioritizes the $R$ hashtags that had the greatest support in the initial $K$ retrieval.

Experimental Setup

In this section, we discuss baseline model specification and training, and the metrics used for evaluation.

Evaluation Metrics and Temporal Setups

We report recall on top-5 and top-1 retrieved hashtags as our main metric. This means we collect the retrieved hashtags from each method, choose the top-5 or top-1, and then compare that against the gold target (i.e. hashtags that appear in the Tweet) and report the recall. We perform our evaluations with three different temporal setups:
1. **Non-temporal**: where there is *no* temporal distribution shift between train and test, as in the test set is from the same time interval that the training set is from (the test set is the aggregate of test sets from the first three weeks). i.e. it is conventional, non-temporal evaluation.

2. **W/o Adaptation**: a temporal evaluation setup where the model is trained on/dataset is created on data bucket 1 (weeks 1-3) and evaluated on the 12 test buckets (weeks 4 through 48).

3. **W/ Adaptation**: a temporal evaluation setup where the training and test data come from the same time bucket (e.g. for test week 8, the model is trained on weeks 5-7, and for test week 48, the model is trained on weeks 45-47, as shown in Figure 3).

Both W/ and W/o adaptation setups have temporal distribution shift between train and test. Non-temporal setup has no distribution shift.

**Baselines**

**Neural Classifier.** We use BART-large [Lewis et al. 2020] with a multi-label classification head as the neural, parametric classifier baseline. Our main baseline is the classifier trained on time bucket 1’s data, which we use for the ‘W/o Adaptation’ evaluation. This classifier has 16886 labels, which is equal to the training hashtag vocabulary size of time bucket 1. For the W/ adaptation setup, we train 12 classifiers, on the 12 time buckets (explained in the Experimental Setup Section). We train each classifier for 30 epochs, and choose the best checkpoint based on validation recall where the validation data overlaps in time with the training data. We use learning rate of 3e − 5 with a polynomial scheduler and training batch size of 36.

**Neural Sequence to Sequence Model.** To provide a baseline that is not restricted to a pre-set vocabulary (i.e. the neural classifier), we experiment with a sequence-to-sequence model, which is potentially capable of generating hashtags that has not been seen in the training set, as we want to show temporal degradation isn’t simply about the fixed label set. We use BART with a conditional generation head. The sequence-to-sequence model is trained on the Tweet text as input and the sequence of concatenated hashtags as the output. For decoding (generation), we run inference on the network, and make it generate 120 tokens, and then select the first 5 hashtags for calculating recall. The order of generated hashtags does not affect the score. Similar to the classifier baseline, we run training for 30 epochs, with learning rate of 3e − 5, polynomial scheduler and training batch size of 36.

**KNN Implementation Details**

**Encoder.** We explore multiple choices to obtain the tweet encodings for dense retrieval, and we found that the encodings from the BART classifier (the last hidden state that is fed to the classifier head) provides the best validation performance, and thus we use it in our main results, and we ablate the choice of the encoder model and K in the Results Section. The BART we use is fine-tuned on the hashtag classification task for time bucket 1’s data, but we use this same encoder for encoding *every* time bucket. In other words, we do not fine-tune a separate encoder for each time bucket.

**Datastore.** We encode all the Tweets into a float32 Numpy memory map for keys. The dimension of the keys memory map is $N \times E$, where $N$ is the number of Tweets in the training set. Given how we unroll Tweets (cf. Datastore Section), $N \geq |D|$, $|D|$ is the number of unique Tweets in the dataset (size of the dataset). $E$ is the dimension of the encoded vector, 1024 in our case with the classifier encoder. We also construct an unsigned int16 memory map for the hashtags, named values. We encode the hashtags by feeding them to the BART tokenizer and using the token ids (we do not embed the tags, we only tokenize and encode them using BART’s vocabulary) which has dimension $N \times V$, where $V$ is the length of the hashtag in tokens and is set at the upper bound 280, since a Tweet is maximum 280 characters long, and each token is at least a single character. We add padding to the hashtags that are shorter than 280 tokens.

We use the IndexFlatIP quantizer along with L2 distance as the FAISS metric. We also set the number of keys that are added at a time to be 500k. For retrieval, we use their search function as well, which retrieves the nearest $K$ neighbors but using the approximate (quantized) distances which means the retrieval and order is not exact. We also experimented with Cosine distance and found it to under-perform compared to L2 in our case.

**Results**

Our experimental results consist of: (1) Temporal performance of different methods, (2) user-deletion performance decay, and (3) ablation of $K$ in KNN, encoding models, and re-ranking methods.

**Temporal Adaptation Comparison with Baselines**

Table 2 summarizes the comparison of different methods averaged over the 12 time buckets, under three evaluation setups from the Experimental Setup Section. The results in the table are averaged over the 12 time buckets. Figure 4 shows the breakdown of the numbers in the table, over the 12 test weeks. The frequency-baseline just returns the top most common hashtag of the time bucket’s training data.
Figure 4: Comparison of the KNN classifier with the parametric neural sequence-to-sequence and classifier models, in terms of the recall on top 5 hashtags. The solid lines show evaluation results of a model trained/datstore created on the time bucket 1 (first 3 weeks) and tested on the test week. The dashed lines, however, show the performance of adapted models, as in models that are trained on the corresponding data bucket.

Figure 5: Results of the data deletion experiment, where we delete different proportions of the training data in a time bucket and observe how the performance degrades. Thickness of the line has correlation with amount of deleted data. The 1.7% is actually user deleted data, but the rest is randomly deleted. Evaluation follows the temporal W/o Adaptation setup, explained in the Experimental Setup Section.

Note that the results in the non-temporal column are strictly non-temporal, meaning that they use the train/test sets from the same time interval (3 first weeks of the time bucket). This is distinct from the leftmost point in Figure 4 where the fourth week in the time bucket is used for evaluation – which therefore includes a slightly larger degree of temporal change.

The first intuitive observation from Figure 4 is that for the solid line (W/o adaptation), as the test week gets temporally further and further from the train data. We can see that the KNN classifier outperforms both the baselines (BART Seq2seq and classifier), whether the evaluation setup is W/o adaptation or adapted. In terms of comparing the two parametric baselines, we can see that in the temporal setups (W/ and W/o adaptation) the seq2seq model outperforms the classifier, which could be due to how it is capable of generating unseen hashtags, unlike the classifier which is bound to a static pre-determined set. For non-temporal (conventional) evaluation, however, the neural classifier has the best performance. We hypothesize that this demonstrates the robustness of KNN to distribution shift (since both the W/o and W/ adaptation settings are temporal). However, for the non-temporal case where the train/test distribution matches the neural classifier is more accurate.

**User-Tweet Deletion**

As explained in the Introduction, efficient model adaptation facilitates selective deletion of training data, which can be an important feature for a variety of reasons. For instance, harmful training examples that may cause spurious outputs during inference can be removed, or fidelity to user-initiated
data deletions can be maintained. In this section, we study deletion in the parametric and non-parametric models. For the non-parametric KNN model, deletion involves removing the given tweet from the datastore – deleting the entry and re-indexing the datastore – an operation that takes minutes on CPU. The classifier, however, needs to be fully trained again, without the deleted tweets, which in our case (using a single A100 GPU and training for 40 epochs) takes about a week.

We use time bucket 3 for this experiment (i.e. weeks 9-11 are used for training) and we test on weeks 12 and later (16, 20, ..., 48). In terms of performance drop, we look at 4 different dataset deletion percentages: 1.7%, 20%, 50% and 80%. The 1.7% shows the scenario in which we re-scraped the Tweets 5 months after we originally collected them, and removed the Tweets that have become unavailable (through deletion or suspension), from the dataset. The other 3 percentages, however, are generated by taking i.i.d samples from the dataset, and dropping them. We compare the behavior of the KNN model with that of the parametric classifier w/o any deletion. Figure 5 shows the results for this experiment. We observe that the KNN model gracefully decays as more data is deleted, and even with the deletion, it still outperforms the upper bound classifier model.

Ablation Studies

In this section, we ablate the different components involved in deploying the KNN model: The encoding of the Tweets for building the datastore, the $K$ in KNN, and the re-ranking of the retrieved $K$ nearest neighbors. Finally, we breakdown the recall $@5$ results of the KNN over different time buckets, to see how well the updated datastore helps capture out of vocabulary tags that a datastore/model from the first time bucket wouldn’t have captured.

Ablating encoder for datastore. Apart from the classifier encoder used in all previous experiments, we also tried using the seq2seq model as the encoder, and also a generic encoder trained on Tweets, named Bertweet (Nguyen, Vu, and Tuan Nguyen 2020). We compare these encoders in Table 4. We can see that the classifier has the highest performance, then the Seq2Seq, followed by the Bertweet encoder which is the worst. We hypothesize that the poor performance of Bertweet is due to the outdatedness of its training set, which consists of Tweets from 2012 to 2019, creating a significant distribution mismatch. This hints that the encoder for the KNN also requires updates from time to time, however, it doesn’t need to be as frequent as updates for the neural classifier and sequence to sequence model, and one update per year might be enough (as the performance of the KNN on test week 48 is still acceptable in Figure 4).

Ablating $K$ and re-ranking methods. Table 3 shows the ablation studies, for re-ranking methods and different $K$ values for retrieval. The temporal setup here is W/ adaptation, and the recall $@5$ is averaged over the 12 test weeks and reported. Overall, the frequency-based method outperforms the distance-based methods by a large margin, which we hypothesize is due to the robustness added by the repetitions in hashtags. We can see that for the distance-based methods, the overall trend is that higher $K$ is better (1024 is on average the sweet spot), however, going even higher doesn’t degrade the performance meaningfully. The frequency-based re-ranking, however, degrades significantly if the number of retrieved neighbors is large (1024 and 2048), which is expected, as more irrelevant but common hashtags are suggested. We get closer to a random frequency-based classifier when $K$ approaches the datastore size.

Out of vocabulary tag prediction break down. Finally, we want to investigate how updating the datastore helps us capture out of vocabulary (new) hashtags, that would not be predicted if we kept using the datastore from time bucket 1. Figure 6 shows the results for this experiment, where the OOV refers to out of vocabulary with respect to bucket 1’s hashtag vocabulary. IV refers to in-vocabulary hashtags, which means the tags that appear both in the given test week, and the train data of time bucket 1. We report the recall over the IV and OOV tags separately. We can see that the updates in the datastores help predict 19% of the hashtags that would otherwise not be predicted, on average across the test weeks. We see that as we proceed with time buckets, the OOV recall grows, eventually overtaking the IV recall. It is worth noting that the number of IV tags is substantially smaller in later time buckets. Finally, we suspect the superior OOV performance on the later time buckets is related to content shift – i.e. the meanings of IV tags may have shifted by the later time buckets.

Conclusion

In this paper, we study the task of temporal adaptation for hashtag prediction, by introducing a new benchmark dataset consisting of Tweets and hashtags scraped over a year. We then evaluate two neural parametric models (classifier and sequence to sequence) and a non-parametric KNN model on the benchmark dataset. We show that a simple KNN model that retrieves hashtags from a datastore outperforms the sequence to sequence and classifier baselines when evaluated on test sets that have temporal distribution shift. We also demonstrate that the KNN model is more suitable for re-
moving deleted samples from the model, which is a common scenario in social media.

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