TransDrift: Modeling Word-Embedding Drift using Transformer

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Abstract

In modern NLP applications, word embeddings are a crucial backbone that can be readily shared across a number of tasks. However as the text distributions change and word semantics evolve over time, the downstream applications using the embeddings can suffer if the word representations do not conform to the data drift. Thus, maintaining word embeddings to be consistent with the underlying data distribution is a key problem. In this work, we tackle this problem and propose TransDrift, a transformer-based prediction model for word embeddings. Leveraging the flexibility of transformer, our model accurately learns the dynamics of the embedding drift and predicts the future embedding. In experiments, we compare with existing methods and show that our model makes significantly more accurate predictions of the word embedding than the baselines. Crucially, by applying the predicted embeddings as a backbone for downstream classification tasks, we show that our embeddings lead to superior performance compared to the previous methods. We will release the code and datasets at https://github.com/transdrift/

1 Introduction

Word embeddings play a major role in modern NLP applications providing a re-usable feature store that can be easily shared across multiple NLP tasks. This has led to their wide adoption in industry (Shiebler et al., 2018; Gordon, 2018; Sell and Pienaar, 2018; Derczynski et al., 2015; Fromreide et al., 2014). A crucial aspect of the real world is that data distributions change over time. In text, words can gradually acquire new semantics and usage over time. For instance in the summer months, the word vacation may be used more in relation to beach than to skiing and vice-versa in the winter months. A customer preference model relying on nearest neighbor lookup in the embedding space would thus suffer if the word embedding of vacation is closer to beach than to skiing during winter. Hence, a good embedding needs to be consistent with such underlying changes in data distribution to be useful for downstream NLP applications.

In addressing this problem, a key concern is that when temporal drift occurs, there is not enough data available from the drifted distribution. For instance, when the summer ends and winter begins, we may have a large dataset collected during the summer months but very little data for the winter. When the model is deployed, a naive solution that we can simply re-train the embeddings from the winter data is not possible as the data is too small or sometimes does not even exist. However, we still seek an updated set of word embeddings that are consistent with the underlying data drift.

At the intersection of word embedding and data drift, previous works have analyzed historical data to identify temporal drifts in word embeddings (Hamilton et al., 2016a,b; Dubossarsky et al., 2017; ...
Huang and Paul, 2018; Kutuzov et al., 2018; Garg et al., 2018). These works have shown not only that drift occurs but also identify the characteristics of the drift and their adverse effect on the performance of the downstream tasks. Instability of word embedding due to small data drifts has also been highlighted (Leszczynski et al., 2020; Chugh et al., 2018; Hellrich and Hahn, 2016; Antoniak and Mimno, 2018). However these approaches do not provide a way to learn the dynamics of drift for updating the word embeddings consistently with the data drift.

In this work, we propose TransDrift, a novel model that learns to predict the future word embeddings that are consistent with the drift in data. Our model combines the knowledge from the past word embedding with the knowledge of the drift dynamics and predicts accurate future word embedding. Our solution utilizes the flexibility of the transformer architecture to make the predictions. Our experiments demonstrate the effectiveness of using the predicted embeddings as backbone for downstream NLP tasks. Crucially, our method is simple and general can be used along with any word embedding algorithm.

Our main contributions can be summarized as: 1) We propose the first model, TransDrift, that leverages transformer to predict the future embeddings. 2) Our model can predict future embeddings. 3) Our results show that our model is effective in modeling the drift in the embeddings. 4) Lastly, we also show improvement in the accuracy on downstream NLP tasks when using our predicted embeddings.

2 Background

2.1 Word Embedding

Several commonly used methods such as word2vec generate rich application-agnostic embeddings for the words in the vocabulary (Mikolov et al., 2013; Bojanowski et al., 2017; Pennington et al., 2014). This process takes a text corpus \( D \) and returns embeddings \( E = \{ e_1, \ldots, e_N \} \) for \( N \) words in the vocabulary. Here, \( e_n \) represents \( n \)-th word in the vocabulary and it is a \( d \)-dimensional vector. In these methods, the main goal is to embed the words in a feature space while capturing their underlying semantic structure. For instance, the words having a similar usage such as apple and orange are embedded close together in the feature space. To learn such embedding, the common approach is to take each word in the given text corpus \( D \) and predict which words are present in its neighborhood. From this prediction objective, the gradient is backpropagated to the embedding of the input word which leads to learning of the word embeddings. Hence, the information about the neighborhood in which the word is commonly used becomes encoded in these embeddings.

2.2 Transformer

Transformer is an architecture for processing a set of vectors such that each vector is updated by flexibly interacting with all the other input vectors (Vaswani et al., 2017; Lee et al., 2019). Formally, given a set of \( N \) vectors, a transformer layer maps the input vectors to \( N \) output vectors. To enable interaction among the input vectors, a transformer layer first performs self-attention between the vectors (Vaswani et al., 2017). Following this self-attention step, each vector is then fed to an MLP to generate the output vectors which makes the model more expressive. Residual connections are added to both the self-attention and the MLP steps for improved gradient flow. In practice, multiple transformer blocks are stacked together to increase the modeling capacity of the Transformer. As transformers have been shown to be a powerful architecture showing impressive performance by modeling complex interactions, in this paper we seek to bring this idea to track the drift in the word embeddings over time.

3 Method

In this section, we propose a simple method to model the drift in word embeddings over time. Consider the text distribution at each time-step \( P_t \) which provides us a data sample \( D_t \sim P_t \). Crucially, this distribution undergoes change over time: \( P_t \rightarrow P_{t+1} \). Resulting from this distribution change, the word semantics and usage in the sampled datasets, \( D_t \) and \( D_{t+1} \), also change with time. We would like these changing semantics to be reflected in word embeddings of each time-step for them to be useful for the downstream tasks. That is, we desire word embeddings \( E_t \) at each time-step \( t \) such that they are consistent with the changing data distribution.

A key consideration is that while data at time \( t \) is large, the data \( D_{t+1} \) at time \( t + 1 \) is significantly smaller and might even be an empty set. Thus, while word embedding \( E_t \) can be learned accurately from \( D_t \) using standard methods such
as word2vec, however, directly learning $E_{t+1}$ from $D_{t+1}$ is likely to be ineffective and even impossible if $D_{t+1}$ is empty. Hence, during training, we seek to learn the drift dynamics that can be utilized at test time to predict $E_{t+1}$ directly from $E_t$ even when the data $D_{t+1}$ from the time-step $t + 1$ is small or empty.

For this, we first train the embedding at time $t$ using the large data set at time $t$ and then use a Transformer to map the word embeddings at time-step $t$ to the embeddings of the next time-step $t+1$. Formally,

$$E_t = \text{TrainWordEmbeddings}(D_t),$$
$$E_{t+1} = \text{Transformer}_\phi(E_t).$$

By using a Transformer model, the prediction of each word embedding can see the embeddings of all the other words via attention. This allows our model to learn complex dynamics of embedding drift, helping the model make better predictions.

Optionally, at inference time, if we have a small amount of data $D_{small}^{t+1}$ at timestep $t + 1$, we can use it to train the embeddings of a small number of words. The resulting embeddings $E_{t+1}^{small}$ can be provided as an additional context to our model during prediction. Taking these in addition to the embeddings of the previous time-step, our model predicts all the embeddings of time-step $t + 1$. This can be summarized as follows:

$$E_{t+1}^{small} = \text{TrainWordEmbeddings}(D_{small}^{t}),$$
$$E_{t+1} = \text{Transformer}_\phi(E_t, E_{t+1}^{small}).$$

In our experiments, we shall show that providing such additional context can lead to moderate improvements in the prediction accuracy. For downstream applications, providing such additional embeddings can therefore be beneficial.

**Training.** For training, we assume that our historical data provides large datasets for both time-steps $t$ and $t+1$ which we denote as $D_t$ and $D_{t+1}$. Taking these two datasets, we train the word embeddings as follows:

$$E_t = \text{TrainWordEmbeddings}(D_t),$$
$$E_{t+1} = \text{TrainWordEmbeddings}(D_{t+1}).$$

To train the Transformer, we minimize the following cosine embedding loss $L_{\text{predict}}(\phi)$ for predicting the embedding at time $t + 1$:

$$1 - \cos(E_{t+1}, \text{Transformer}_\phi(E_t, E_{t+1}^{small})).$$

where $\cos(\cdot, \cdot)$ denotes cosine similarity.

**Downstream Task.** As our end goal of modeling the embedding drift is to help downstream task, we now describe how we utilize our predicted word embedding to achieve this. We train a downstream task neural network on the predicted word embeddings as follows:

$$f_\theta(x; E_{t+1}).$$

Given embedding $E_{t+1}$, input $x$ and target label $y$, we learn the task-specific neural network at time-step $t + 1$ as:

$$L_{\text{task}}(\theta) = \text{CrossEntropy}(y, f_\theta(x; E_{t+1})).$$

### 4 Experiments

The goal of our experiments is to show how well our model can accurately predict the drifted word embeddings relying on little to no data from the drifted text distribution. Furthermore, we also show the benefits of our predicted word embedding in improving the performance of downstream classification tasks. As an instance to test our idea, we intentionally choose simplest and widely used embedding method word2vec so that our results can be interpreted more generally.

#### 4.1 Experiment Setup

**4.1.1 Datasets**

We evaluate our models on a synthetic dataset, Yelp Academic dataset (Crawford, 2018) and Amazon...
Customer Review dataset (McAuley, 2018). For each dataset, we consider drift instances with each instance consisting of \( D_1 \), \( D_2 \), and \( D_2^{\text{small}} \) during training. Here, the subscript 1 denotes the source time-step \( t = 1 \) and subscript 2 denotes the next time-step (i.e. \( t = 2 \)) in which the underlying text distribution has undergone a shift.

**Synthetic Dataset.** This datasets consists of several instances. For each instance, we generate a random sparse graph with each node in the graph representing a token in the vocabulary. In this graph, we randomly assign edge weights to denote the co-occurrence pattern among the tokens. Starting from a random node, we perform a random walk on the graph and collect the tokens encountered as text. During the random walk, the probability of transitioning to the next node is proportional to its edge weight. This results in a sample of dataset \( D_1 \). We then apply random modifications to edge weights of the graph. This modified graph is considered as the drifted data generating process. From this drifted graph, we again perform a random walk to sample a small dataset \( D_2^{\text{small}} \) and a large dataset \( D_2 \).

**Yelp Academic Dataset.** For Yelp Academic Dataset, we use the businesses, reviews, and user data. For this, we divide the dataset into two parts by timestamp – reviews before the year 2016 and reviews after the year 2016. We denote these two parts as: \( D_1 \) and \( D_2 \). We take smaller subsets of \( D_2 \) to obtain \( D_2^{\text{small}} \).

**Amazon Customer Review Dataset.** For Amazon Customer Review dataset, we separately consider the categories: Books, Electronics, DVD, and Kitchen. For this, we divide the dataset into two parts by timestamp – summer reviews and winter reviews. We call these two parts as: \( D_1 \) and \( D_2 \). We take smaller subsets of \( D_2 \) to be \( D_2^{\text{small}} \). For all the datasets we discussed above, more details can be found in Appendix A.

### 4.1.2 Metrics

To evaluate how well our predictions match the desired word embeddings of the drifted distribution, we compute cosine similarity between \( E_2 \) learned using full dataset \( D_2 \) and our predicted embeddings generated using the previous embeddings \( E_1 \) and \( E_2^{\text{small}} \). To measure the benefits of our predicted embedding on downstream task, we report the accuracy of the predictions of the downstream model.

![Table 1: Comparison of word embedding prediction between our model and the baselines.](image)

| Dataset       | No-Drift | Additive | TransDrift |
|---------------|----------|----------|------------|
| Synthetic     | 0.32     | 0.33     | 0.7724     |
| Yelp          | 0.19     | 0.7956   | 0.8910     |
| Amazon        | -0.004   | -0.0002  | 0.8170     |

Table 1: Comparison of word embedding prediction between our model and the baselines. We report the cosine similarity of the predicted embedding with the ground truth embedding trained using large amount of data from the drifted distribution. The predicted embeddings do not use any data from the drifted distribution. We note that our model, TransDrift, is significantly more accurate with respect to the baseline models.

### 4.1.3 Baselines

As no previous work directly tackles our problem setting, we develop the following baselines to show the efficacy of our model.

**No-Drift Model.** In this baseline for predicting the future embeddings, the modeling assumption is that the word embeddings do not undergo drift. That is, the model assumes that the embeddings learned at time-step 1 using \( D_1 \) can be naively reused time-step 2 even though the underlying data distribution has drifted between timesteps 1 and 2. The goal of this comparison is to justify the need for predicting the word embedding instead of simply re-using the previous outdated embeddings.

**Additive-Drift Model.** In this baseline for modeling the embedding drift, we assume that the drift can be modeled by adding a constant embedding vector to all the words in vocabulary as proposed by (Stowe and Greureych, 2021). That is, this model learns a vector \( \Delta \) such that the embedding at time-step 2 can be predicted as \( E_2 = E_1 + \Delta \). The goal of this comparison is to show that it is not enough to simply model the drift as a constant additive vector and it is required to model complex interaction and non-linear drift dynamics to predict the future embedding accurately.

### 4.2 Word-Embedding Prediction

We now evaluate the performance of word embedding prediction by the models.

#### 4.2.1 Quantitative Evaluation

We perform a quantitative evaluation by reporting the average cosine similarity under two prediction regimes: with and without the available data from the drifted distribution.
Figure 3: Qualitative Comparison of TransDrift with the Baselines on Yelp. We show the nearest neighbors of the word place using the word embedding predictions of various models. We visualize the embeddings on a 2D plane using t-SNE. For each model, we highlight the nearest neighbors that match the target nearest neighbors (top-left) using red boxes. We see that our model, TransDrift, has the most number of common nearest neighbors with respect to the target (bottom-right). In contrast, the baselines, No-Drift and Additive Drift, have significantly fewer common nearest neighbors.

### Table 2: Comparison of the word embedding prediction performance under varying percentages of $D_2$ data used. We report the average cosine similarity.

| Dataset | Size of $D_{2}^{\text{small}}$ as % of $D_2$ |
|---------|------------------------------------------|
|         | 30% | 20% | 0%   |
| Synthetic | 0.8067 | 0.7913 | 0.7724 |
| Yelp     | 0.9119 | 0.9075 | 0.8910 |
| Amazon   | 0.8829 | 0.8076 | 0.8170 |

### Prediction with Available Drifted Data

In Table 2, we show the effect of using increasingly larger amount of data $D_{2}^{\text{small}}$ from time-step 2 to inform the word embedding prediction in our model. We note that with increasing the size of this data, we see an increase in prediction accuracy across all datasets. In deployment settings, this property may be useful to continually improve the embeddings as increasingly more data is gradually collected. Interestingly, we note that even with no data from the time-step 2, our prediction accuracy already surpasses all our baselines reported in Table 1 across all datasets.

### 4.2.2 Qualitative Evaluation

To analyze our prediction results qualitatively, we take eight words: well, place, great, time, nice, customer, happy and people and visualize their nearest neighbors using the predicted embeddings of all the models. We also consider the word embedding trained using a large amount of data from time-step 2 to be the target embeddings. Hence, if a model is effective, then the number of words common nearest neighbors between the predicted and the target embeddings would be larger. We visualize...
Figure 4: Qualitative Comparison of TransDrift with the Baselines on Yelp. We show the nearest neighbors of the word happy (top) and time (bottom) using the word embedding predictions of various models. We visualize the embeddings on a 2D plane using t-SNE. For each model, we highlight the nearest neighbors that match the target nearest neighbors (top-left) using red boxes. We see that our model, TransDrift, has the most number of common nearest neighbors with respect to the target (bottom-right). In contrast, the baselines, No-Drift and Additive Drift, have significantly fewer common nearest neighbors.
Table 3: Qualitative analysis of nearest neighbors of the predicted word embeddings. For each prediction model, we find 30 nearest neighbors for each word shown in the first column. We then count the number of these nearest neighbors that are also the nearest neighbor in the target word embeddings. Thus, the higher number of nearest neighbors of our model TransDrift shows that our predicted embeddings agree significantly more with the target embeddings.

| Word   | No-Drift | Additive | TransDrift |
|--------|----------|----------|------------|
| well   | 7        | 4        | 7          |
| place  | 8        | 8        | 15         |
| great  | 10       | 11       | 13         |
| time   | 7        | 7        | 12         |
| nice   | 11       | 9        | 15         |
| customer | 8    | 9        | 10         |
| happy  | 3        | 1        | 7          |
| people | 9        | 8        | 12         |

Table 4: Downstream Prediction Results on Amazon Review (AR) and Yelp Datasets. Using embeddings from the evaluated methods, we train a downstream sentiment classifier and report its test accuracy. We note that the No-Drift model which re-uses the outdated embedding from the previous time-step suffers compared to TransDrift. TransDrift is significantly more accurate than the baseline models.

| Dataset   | No-Drift | Additive | TransDrift |
|-----------|----------|----------|------------|
| AR-Electro| 60.5%    | 60.56%   | 69.6%      |
| AR-Kitchen| 63.6%    | 63.52%   | 75.7%      |
| AR-DVD    | 59.0%    | 59.03%   | 63.5%      |
| Yelp      | 58%      | 60%      | 65.0%      |

We train a downstream classification model using the embedding from each of the evaluated methods and report the test accuracy in Table 4 for the Amazon Review dataset. We find that the No-Drift model which re-uses the outdated embedding from the previous time-step suffers with respect to our model. This suggests that embedding prediction is indeed useful. We further analyze the downstream performance by showing qualitative examples of text inputs from the drifted distribution that were misclassified by the No-Drift model but are correctly classified by our model TransDrift. We show these in Table 5.

4.3 Downstream Tasks

We now evaluate how well our predicted embeddings can enable better performance in downstream tasks. In particular, we seek to evaluate that as the data undergoes drift, can embedding prediction help the accuracy under the drifted distribution (at time-step 2) and if so then which prediction approach should be preferred. We consider the following approaches for obtaining word embedding under drift and compare with our model: i) No-Drift model: We compare with this approach as in deployment setting, this is often considered as the default approach. ii) Full Retraining. Another common approach is to retrain the embedding from scratch from the drifted distribution. However, note that in some cases, this can be an unfair comparison to our model as the data from the drifted distribution may be either too little or not available. For our model TransDrift, we also leverage embeddings from $D_{2, small}$ having 30% of the data of full $D_2$.  

4.4 Ablation Study

In this section, we ablate our model TransDrift. To better justify our choice of architecture for TransDrift, we perform additional experiments that we describe here. In terms of architectural components our model can be seen as Self-Attention + Feed Forward Network while our baseline MLP can be seen as Feed Forward Network. We analyze the effect of this choice in our experiments. We provide the results in Appendix A. The results show that the TransDrift outperforms the ablation model. This shows that the self-attention aspect of TransDrift plays a crucial role and not just MLP.

5 Related Work

Word Vectors. Learning word representations has seen significant interest in the past decade (Mikolov et al., 2013; Bojanowski et al., 2017; Barkan et al., 2021; Bojanowski* et al., 2017; Faruqui et al., 2015; Caciularu et al., 2021; Bollegala et al., 2016; Hu et al., 2019). The most common approach has been proposed by (Mikolov et al., 2013) pro-
First off, the iPod jiggles no matter what you do, secondly, it doesn’t stay straight on the power plug, it constantly tilts (the whole thing)... not worth $10  

I bought this amazing product and now it is easy to have high quality music. Just plug the iPod to your music equipment and you are done.

I just got my mouse today I was ecstatic about the performance I had initial problems installing the mouse but after I unplugged it and plugged it in again the problems went away. I have to agree with my other comrades from this site this is the best mouse for the price and I have no problems whatsoever except for the look which I thought was the result from damage from shipping but it was designed like that so I have no complaints.

| Review Text                                                                 | Ground Truth | TransDrift |
|----------------------------------------------------------------------------|--------------|------------|
| First off, the iPod jiggles no matter what you do, secondly, it doesn’t stay straight on the power plug, it constantly tilts (the whole thing)... not worth $10                  | Negative     | Negative   |
| I bought this amazing product and now it is easy to have high quality music. Just plug the iPod to your music equipment and you are done.          | Positive     | Positive   |
| I just got my mouse today I was ecstatic about the performance I had initial problems installing the mouse but after I unplugged it and plugged it in again the problems went away. I have to agree with my other comrades from this site this is the best mouse for the price and I have no problems whatsoever except for the look which I thought was the result from damage from shipping but it was designed like that so I have no complaints. | Positive | Positive |

Table 5: Text samples that were misclassified when using No-Drift model compared to our TransDrift model.

providing two architectures, CBOW and skip-gram, for learning high-quality word vectors from large text datasets. CBOW learns by predicting the current word based on the context words, whereas skip-gram predicts the nearby context words. (Bojanowski et al., 2017) discover a new method for learning word representation which incorporated character $n$-gram to the skipgram model. They ensure that the model takes sub-word information into account, improving embedding quality, and predicting the embeddings for unseen words.

Data Drift in Text. While analyzing the presence of drift in text has seen significant interest in recent years, efforts to model their drift are still in infancy. (Huang and Paul, 2018) examine the problem of drift and that show its adverse effects on the downstream performance if training and test sets are not the same distributions due to drift. (Leszczynski et al., 2020; Chugh et al., 2018) define task instability with respect to word embedding (and the task being done) and propose a metric to measure it. Using this metric, trade-off in stability with respect to precision and model dimension are identified. (Hellrich and Hahn, 2016) and (Antoniak and Mimno, 2018) identify instability in word neighbors between different training runs in word2vec and fasttext embeddings. (Wendlandt et al., 2018; Pierrejean and Tanguy, 2018) define stability as percent overlap among neighbors which, crucially, serves as a task independent definition. Analysis of various factors that affect word stability and their effects on downstream tasks was also performed. To address embedding instability, (Hellrich et al., 2018) propose a down-sampling based approach to make word embedding more stable. (Stowe and Gurevych, 2021) propose a reversal of drift in word embedding to make it stable over time while (He et al., 2018) propose an evolutionary approach. However, all these approaches only focus on making embedding more stable under the assumption that the downstream task should remain agnostic to the drift in the underlying data distribution. In contrast, our work seeks to improve the embedding and the task performance by taking drift and changing word semantics into account. (Xu et al., 2018) propose meta-learning approach to adapt word embedding from source to target domain. However unlike our method, this approach requires direct access to all the corpora of the previously seen domains and is thus orthogonal to our problem setting. Unlike our method, this approach cannot be applied if there is no available data from the target domain.

Contextual Embeddings. Contextual embeddings have also seen a rise alongside word2vec. However, word2vec is widely used in a lot of industrial applications (Shiebler et al., 2018; Gordon, 2018; Sell and Pienaar, 2018; Derczynski et al., 2015; Fromreide et al., 2014), the scope of our work is to deal with drift in regular word2vec embeddings.

6 Conclusion

In this paper, we proposed TransDrift, a framework to track embeddings under data drift. We showed that using a transformer model perform this task effectively with no data. Optionally, our model can also leverage small amount of data from drifted distribution to further improve its prediction. Finally, by performing downstream tasks using the predicted embeddings, we show a significant performance improvement compared to other options. One of the future work can be to study multi-step word embedding prediction.
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A Additional Experiment Details

A.1 Ablation Study

To better justify our choice of architecture for TransDrift, we perform additional experiments that we describe here. In terms of architectural components our model can be seen as Self-Attention + Feed Forward Network while our baseline MLP can be seen as Feed Forward Network. We analyze the effect of this choice in our experiments. We shown in Table 6 the cosine similarity of the predicted embedding with the ground truth embedding trained using large amount of data from the drifted distribution. We note that our model, TransDrift, is significantly more accurate with respect to the MLP model. Using embeddings from the evaluated methods, we train a downstream sentiment classifier and report its test accuracy in Table 7. We show a comparison between MLP and Transdrift. We note that the MLP model suffers compared to TransDrift. TransDrift is significantly more accurate than the baseline models.

| Dataset  | MLP    | TransDrift |
|----------|--------|------------|
| Synthetic| 0.785  | 0.773      |
| Yelp     | 0.89   | 0.89       |
| Amazon   | 0.231  | 0.8170     |

Table 6: Comparison of word embedding prediction between our model and the baselines. We report the cosine similarity of the predicted embedding with the ground truth embedding trained using large amount of data from the drifted distribution. The predicted embeddings do not use any data from the drifted distribution. We note that our model, TransDrift, is significantly more accurate with respect to the MLP model.

| Dataset     | Accuracy (in %) |
|-------------|----------------|
| AR-Electro  | 60.81%         |
| AR-Kitchen  | 55.72%         |
| AR-DVD      | 55.01%         |
| Yelp        | 59%            |

Table 7: Downstream Prediction Results on Amazon Review (AR) and Yelp Datasets. Using embeddings from the evaluated methods, we train a downstream sentiment classifier and report its test accuracy. We show a comparison between MLP and Transdrift. We note that the MLP model suffers compared to TransDrift. TransDrift is significantly more accurate than the baseline models.
A.2 Model Hyperparameters

MLP

- Model parameters = 20250
- Max-epochs = 50, model-dim = 50, warmup = 30, LR = 5e-4, Batch size = 100

B Synthetic Dataset

- Common words for the 1000 set of embeddings of:
  1. D1 = 100,
  2. D2 = 100,
  3. D2-small-50 = 50,
  4. D2-small-30 = 30,
  5. D2-small-20 = 20
- Dimension for D1, D2, D2-small-s and predicted embedding is 50.

TransDrift

- Model parameters = 504250
- Max-epochs = 100, num-heads = 1, model-dim = 100, num-layers = 4, LR = 5e-4, Batch size = 100

C Yelp Dataset

- Common words for the 1000 set of embeddings of:
  1. D1 = 1727,
  2. D2 = 1727,
  3. D2-small-50 = 1396,
  4. D2-small-30 = 901,
  5. D2-small-20 = 634
- Dimension for D1, D2, D2-small-s and predicted embedding is 50.

TransDrift Ran on CPU.

- Model parameters = 1833650
- Using word2vec, Max-epochs = 100, num-heads = 4, model-dim = 192, warmup = 30, num-layers = 4, LR = 5e-4, Batch size = 100

D Amazon Customer Review Dataset

- Common words for the 1000 set of embeddings of:
  1. D1 = 5018,
  2. D2 = 5018,
  3. D2-small-50 = 3323,
  4. D2-small-30 = 2235,
  5. D2-small-20 = 1603
- Dimension for D1, D2, D2-small-s and predicted embedding is 50.

TransDrift Ran on CPU.

- Model parameters = 1833650
- Using word2vec, Max-epochs = 100, num-heads = 4, model-dim = 192, warmup = 30, num-layers = 4, LR = 5e-4, Batch size = 100

E Downstream

- E1 and E2_small_30 are used to predict the embeddings using transformer. These predicted embeddings are used in the downstream tasks.

E.1 Synthetic Dataset

Not done

E.2 Yelp Dataset

Multi-label star classification

- 20k reviews: 10k from each time stamp t1 and t2
- 8:2 train-test split, epochs = 100, batch-size = 64

Model: "model"
Total params: 1,704,043 Trainable params: 92,293 Non-trainable params: 1,611,750

E.3 Amazon Customer Review Dataset

- Performed sentiment analysis task on electronics, kitchen, and dvd reviews
- Number of reviews used for sentiment analysis task:
  1. Electronics - 5682
  2. Kitchen - 5946
  3. DVD - 3587
Table 8: **Model architecture for multi-label classification task.** We present the layers contained in the LSTM-based model used to do classification on the Yelp dataset on star (rating).

| Layer (type)         | Output Shape      | Param #  |
|----------------------|-------------------|----------|
| input_1 (InputLayer) | (None, 150)       | 0        |
| embedding (Embedding)| (None, 150, 50)   | 1611750  |
| lstm (LSTM)          | (None, 128)       | 91648    |
| dense (Dense)        | (None, 5)         | 645      |

Table 9: **Model architecture for Sentiment Analysis task.** We report the layers present in the LSTM based model used to perform sentiment analysis on the Amazon dataset.

| Layer (type)         | Output Shape      | Param #  |
|----------------------|-------------------|----------|
| input_1 (InputLayer) | (None, 150)       | 0        |
| embedding (Embedding)| (None, 150, 50)   | 747250   |
| lstm (LSTM)          | (None, 150, 128)  | 91648    |
| dropout (Dropout)    | (None, 150, 128)  | 0        |
| lstm_1 (LSTM)        | (None, 150, 128)  | 131584   |
| dropout_1 (Dropout)  | (None, 150, 128)  | 0        |
| lstm_2 (LSTM)        | (None, 128)       | 131584   |
| dense (Dense)        | (None, 1)         | 129      |

- 8:2 train-test split, epochs = 100, batch-size = 64

Model: "model"

Total params: 1,102,195 Trainable params: 354,945 Non-trainable params: 747,250

**E.4 Qualitative Results**

We show the qualitative samples in Table 10 that were misclassified when using No-Drift model compared to our TransDrift model.
| Review Text                                                                 | Ground Truth | TransDrift |
|----------------------------------------------------------------------------|---------------|------------|
| First off, the ipod jiggles no matter what you do, secondly, it doesn’t stay straight on the power plug, it constantly tilts(the whole thing)...not worth $10 | Negative      | Negative   |
| I bought this amazing product and now it is easy to have high quality music. Just plug the iPod to your music equipment and you are done. | Positive      | Positive   |
| This printer was very easy to use. Just pop in the cartridge, paper, and plug in the camera. The camera has to be a certain type of Canon, but there is an available computer cable (I have not gotten it yet), to hook up other cameras. The benefit of using a Canon camera with this printer is you can travel without a computer, and still print out pictures. These pictures look beautiful, and the colors are true and bright. Printing couldn’t be easier and fast. I was able to get a print while my 2 year old was frantically trying to pull the plugs, press the buttons and all arms and legs struggling. It’s fun watching the three colors slide in and out in the three passes the printer makes to process the picture. Instant gratification | Positive      | Positive   |
| I just got my mouse today I was ecstatic about the performance I had initial problems installing the mouse but after I unplugged it and plugged it in again the problems went away. I have to agree with my other comrades from this site this is the best mouse for the price and I have no problems whatsoever except for the look which I thought was the result from damage from shipping but it was designed like that so I have no complaints | Positive      | Positive   |

Table 10: Text samples that were misclassified when using No-Drift model compared to our TransDrift model.