MULTI-VIEW AND MULTI-SOURCE TRANSFERS IN NEURAL TOPIC MODELING WITH PRETRAINED TOPIC AND WORD EMBEDDINGS

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ABSTRACT

Though word embeddings and topics are complementary representations, several past works have only used pre-trained word embeddings in (neural) topic modeling to address data sparsity problem in short text or small collection of documents. However, no prior work has employed (pre-trained latent) topics in transfer learning paradigm. In this paper, we propose an approach to (1) perform knowledge transfer using latent topics obtained from a large source corpus, and (2) jointly transfer knowledge via the two representations (or views) in neural topic modeling to improve topic quality, better deal with polysemy and data sparsity issues in a target corpus. In doing so, we first accumulate topics and word representations from one or many source corpora to build a pool of topics and word vectors. Then, we identify one or multiple relevant source domain(s) and take advantage of corresponding topics and word features via the respective pools to guide meaningful learning in the sparse target domain. We quantify the quality of topic and document representations via generalization (perplexity), interpretability (topic coherence) and information retrieval (IR) using short-text, long-text, small and large document collections from news and medical domains. We have demonstrated the state-of-the-art results on topic modeling with the proposed framework.

1 INTRODUCTION

Probabilistic topic models, such as LDA (Blei et al., 2003), Replicated Softmax (RSM) (Salakhutdinov & Hinton, 2009) and Document Neural Autoregressive Distribution Estimator (DocNADE) (Larochelle & Lauly, 2012) are often used to extract topics from text collections and learn latent document representations to perform natural language processing tasks, such as information retrieval (IR). Though they have been shown to be powerful in modeling large text corpora, the topic modeling (TM) still remains challenging especially in the sparse-data setting, especially for the cases where word co-occurrence data is insufficient e.g., on short text or a corpus of few documents. To this end, several works (Das et al., 2015; Nguyen et al., 2015; Gupta et al., 2019) have introduced external knowledge in traditional topic models via word embeddings (Pennington et al., 2014). However, no prior work in topic modeling has employed topical embeddings (obtained from large document collection(s)), complementary to word embeddings.

Local vs Global Views: Though word embeddings (Pennington et al., 2014) and topics are complementary in how they represent the meaning, they are distinctive in how they learn from word occurrences observed in text corpora. Word embeddings have local context (view) in the sense that they are learned based on local collocation pattern in a text corpus, where the representation of each word either depends on a local context window (Mikolov et al., 2013) or is a function of its sentence(s) (Peters et al., 2018). Consequently, the word occurrences are modeled in a fine-granularity. On other hand, a topic (Blei et al., 2003) has a global word context (view): TM infers topic distributions across documents in the corpus and assigns a topic to each word occurrence, where the assignment is equally dependent on all other words appearing in the same document. Therefore, it learns from word occurrences across documents and encodes a coarse-granularity description. Un-
like topics, the word embeddings can not capture the thematic structures (topical semantics) in the underlying corpus.

Consider the following topics \((Z_1 \cdot Z_3)\), where \((Z_1 \cdot Z_3)\) are respectively obtained from different (high-resource) source \((S^1 \cdot S^3)\) domains whereas \(Z_4\) from the (low-resource) target domain \(T\) in the data-sparsity setting:

\[
\begin{align*}
Z_1 (S^1): & \text{ profit, growth, stocks, apple, fall, consumer, buy, billion, shares } \rightarrow \text{ Trading} \\
Z_2 (S^2): & \text{ smartphone, ipad, apple, app, iphone, devices, phone, tablet } \rightarrow \text{ Product Line} \\
Z_3 (S^3): & \text{ microsoft, mac, linux, ibm, ios, apple, xp, windows } \rightarrow \text{ Operating System/Company} \\
Z_4 (T): & \text{ apple, talk, computers, shares, disease, driver, electronics, profit, ios } \rightarrow \text{ ?}
\end{align*}
\]

Usually, top words associated with topics learned on a large corpus are semantically coherent, e.g., Trading, Product Line, etc. However in sparse-data setting, topics (e.g., \(Z_4\)) are incoherent (noisy) and therefore, it is difficult to infer meaningful semantics. Additionally, notice that the word apple is topically/thematically contextualized (topic-word association) in different semantics in \(S^1 \cdot S^3\) and referring to a company.

Unlike the topics, word embeddings encode syntactic and semantic relatedness in fine-granularity and therefore, do not capture thematic structures. For instance, the top-5 nearest neighbors (NN) of apple (below) in the embeddings [Mikolov et al., 2013] space suggest that it refers to a fruit; however, they do not express anything about its thematic context, e.g., Health.

\[
\begin{align*}
\text{apple} \Rightarrow & \text{ apples, pear, fruit, berry, pears, strawberry} \\
\text{fall} \Rightarrow & \text{ falling, falls, drop, tumble, rise, plummet, fell}
\end{align*}
\]

Similarly for the word fall, it is difficult to infer its coarse-grained description, e.g., Trading as expressed by the topic \(Z_1\).

**Motivation (1) Knowledge transfer via Complementary Representations (both word and topic representations):** Essentially, the application of TM aims to discover hidden thematic structures (i.e., topics) in text collection; however, it is challenging in data sparsity settings, e.g., in a short and/or small collection. This leads to suboptimal text representations and incoherent topics (e.g., topic \(Z_4\)).

To alleviate the data sparsity issues, recent works such as [Das et al., 2015], [Nguyen et al., 2015] and [Gupta et al., 2019] have shown that TM can be improved by introducing external knowledge, where they leverage pre-trained word embeddings (i.e., local view) only. However, the word embeddings ignore the thematically contextualized structures (i.e., document-level semantics), and can not deal with ambiguity. Given that the word and topic representations encode complementary information, no prior work has considered knowledge transfer via (pre-trained latent) topics (i.e., global view) from a large corpora.

**Motivation (2) Knowledge transfer via multiple sources of word and topic representations:** Knowledge transfer via word embeddings is vulnerable to negative transfer [Cao et al., 2010] on the target domain when domains are shifted and not handled properly. For instance, consider a short text document \(v\): [apple gained its US market shares] in the target domain \(T\). Here, the word apple refers to a company, and hence the word vector of apple (about fruit) is an irrelevant

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**Table 1: Description of the notations used in this work**

| Notation | Description | Notation | Description |
|----------|-------------|----------|-------------|
| LVT, GVT | Local-view Transfer, Global-view Transfer | \(A^T \in \mathbb{R}^{H \times H}\) | Topic-alignment in \(T\) and \(Z^L\) |
| MVT, MST | Multi-view Transfer, Multi-source Transfer | \(K, D\) | Vocabulary size, document size |
| \(T, S\) | A target domain, a set of source domains | \(E, H\) | Word embedding dimension, #topics |
| \(\lambda^k\) | Degree of relevance of \(E^k\) in \(T\) | \(b \in \mathbb{R}^K, c \in \mathbb{R}^E\) | Visible-bias, hidden-bias |
| \(\gamma^k\) | Degree of imitation of \(Z^k\) by \(W\) | \(v, k, \mathcal{L}\) | An input document, \(k\)th source, loss |
| \(E^k \in \mathbb{R}^{E \times K}\) | Word embeddings of \(k\)th source | \(W \in \mathbb{R}^{H \times K}\) | Encoding matrix of DocNADE in \(T\) |
| \(Z^k \in \mathbb{R}^{H \times K}\) | Topic embeddings of \(k\)th source | \(U \in \mathbb{R}^{K \times H}\) | Decoding matrix of DocNADE |
source of knowledge transfer for both \( v \) and the topic \( Z_4 \). In contrast, one can better model \( v \) and amend the noisy \( Z_4 \) for coherence, given the meaningful word and topic representations.

Often, there are several topic-word associations in different domains, e.g., in topics \( Z_1-Z_3 \). Given a noisy topic \( Z_4 \) in \( T \) and meaningful topics \( Z_1-Z_3 \) of \( S^1-S^3 \), we identify multiple relevant (source) domains and advantageously transfer their word and topic representations in order to facilitate meaningful learning in the sparse corpus, \( T \).

**Contribution (1)** To our knowledge, it is the first work in unsupervised topic modeling framework that introduces (external) knowledge transfer via (a) Global-view Transfer: latent topic representations (thematically contextualized) instead of using word embeddings exclusively, and (b) Multi-view Transfer: jointly using both the word and topic representations from a large source corpus in order to deal with polysemy and alleviate data sparsity issues in a small target corpus.

**Contribution (2)** Multi-source Transfer. Moreover, we first learn word and topic representations on multiple source domains and then perform multi-view and multi-source knowledge transfers within neural topic modeling by jointly using the complementary representations. In doing so, we guide the (unsupervised) generative process of learning hidden topics of the target domain by word and latent topic features from a source domain(s) such that the hidden topics on the target become meaningful.

We evaluate the effectiveness of our transfer learning approaches in neural topic modeling using 7 (5 low-resource and 2 high-resource) target and 5 (high-resource) source corpora from news and medical domains, consisting of short-text, long-text, small and large document collections. Particularly, we quantify the quality of text representations via generalization (perplexity), interpretability (topic coherence) and text retrieval. *The code is available in supplementary.*

## 2 Knowledge Transfer in Neural Topic Modeling

Consider a sparse target domain \( T \) and a set of \(|S| \) source domains \( S \), we first prepare two knowledge bases (KBs) of representations from each of the sources: (1) word embeddings matrices \( \{ E^1, ..., E^{|S|} \} \), where \( E^k \in \mathbb{R}^{E \times K} \) and (2) latent topic features \( \{ Z^1, ..., Z^{|S|} \} \), where \( Z^k \in \mathbb{R}^{H \times K} \) encodes a distribution over a vocabulary of \( K \) words. \( E \) and \( H \) are word embedding and latent topic dimensions, respectively. While topic modeling on \( T \), we introduce two types of knowledge transfers from one or several sources: Local (LVT) and Global (GVT) View Transfer using the two KBs of (pre-trained) latent word and topic representations, respectively. We employ a neural autoregressive topic model (i.e., DocNADE [Larochelle & Lauly 2012]) to prepare the KBs.

*Notice* that a superscript indicates a source. See Table 1 for the notations used in this work.
DocNADE \cite{Larochelle2012} is an unsupervised neural-network based topic model that is inspired by the benefits of NADE \cite{Larochelle2011} and RSM \cite{Salakhutdinov2009} architectures. RSM has difficulties due to intractability leading to approximate gradients of the negative log-likelihood, while NADE does not require such approximations. On other hand, RSM is a generative model of word count, while NADE is limited to binary data. Specifically, DocNADE factorizes the joint probability distribution of words in a document as a product of

\begin{equation}
\log p(v_1, ..., v_D) = \sum_{d=1}^{D} \log \prod_{i=1}^{K} (1 + \exp(b_w + U_{w,:} h_i(v_{<i})))
\end{equation}

where \( b_w \) and \( U_{w,:} \) are weight matrices, \( h_i \) encodes topic-proportion embedding. Importantly, the topic-word matrix \( W \) has a property that the column vector \( W_{:,v} \) corresponds to embedding of the word \( v \), whereas the row vector \( W_{j,:] \) encodes latent features for \( j \)th topic. We leverage this property to introduce external knowledge via latent word and topic features.

Additionally, DocNADE has shown to outperform traditional models such as LDA \cite{Blei2003} and RSM \cite{Salakhutdinov2009} in terms of both the log-probability on unseen documents and retrieval accuracy. Recently, \cite{Gupta2019} has improved topic modeling on short texts by introducing word embeddings \cite{Pennington2014} in DocNADE architecture. Thus, we adopt DocNADE to perform knowledge transfer within the neural topic modeling framework.

2.1 Neural Autoregressive Topic Models

DocNADE \cite{Larochelle2012} is an unsupervised neural-network based topic model that is inspired by the benefits of NADE \cite{Larochelle2011} and RSM \cite{Salakhutdinov2009} architectures. RSM has difficulties due to intractability leading to approximate gradients of the negative log-likelihood, while NADE does not require such approximations. On other hand, RSM is a generative model of word count, while NADE is limited to binary data. Specifically, DocNADE factorizes the joint probability distribution of words in a document as a product of conditional distributions and models each conditional via a feed-forward neural network to efficiently compute a document representation.

**DocNADE Formulation**: For a document \( v = (v_1, ..., v_D) \) of size \( D \), each word index \( v_i \) takes value in \( \{1, ..., K\} \) of vocabulary size \( K \). DocNADE learns topics in a language modeling fashion \cite{Bengio2003} and decomposes the joint distribution \( p(v_1, ..., v_D) = \prod_{i=1}^{D} p(v_i | v_{<i}) \) such that each autoregressive conditional \( p(v_i | v_{<i}) \) is modeled by a feed-forward neural network using preceding words \( v_{<i} \) in the sequence:

\[
\text{h}_i(v_{<i}) = g(c + \sum_{q<i} W_{:,v_q}) \quad \text{and} \quad p(v_i = w | v_{<i}) = \frac{\exp(b_w + U_{w,:} \text{h}_i(v_{<i}))}{\sum_{w'} \exp(b_{w'} + U_{w',:} \text{h}_i(v_{<i}))}
\]

for \( i \in \{1, ..., D\} \), where \( v_{<i} \) is the subvector consisting of all \( v_q \) such that \( q < i \) i.e., \( v_{<i} \in \{v_1, ..., v_{i-1}\} \), \( g(\cdot) \) is a non-linear activation function, \( W \in \mathbb{R}^{H \times K} \) and \( U \in \mathbb{R}^{K \times H} \) are weight matrices, \( c \in \mathbb{R}^H \) and \( b \in \mathbb{R}^K \) are bias parameter vectors. \( H \) is the number of hidden units (topics). Figure\[\text{[1]}\](left) (without “KB of word embeddings”) provides an illustration of the \( i \)th autoregressive step of the DocNADE architecture, where the parameter \( W \) is shared in the feed-forward networks and \( h_i \) encodes topic-proportion embedding. Importantly, the topic-word matrix \( W \) has a property that the column vector \( W_{:,v} \) corresponds to embedding of the word \( v \), whereas the row vector \( W_{j,:] \) encodes latent features for \( j \)th topic. We leverage this property to introduce external knowledge via latent word and topic features.

Additionally, DocNADE has shown to outperform traditional models such as LDA \cite{Blei2003} and RSM \cite{Salakhutdinov2009} in terms of both the log-probability on unseen documents and retrieval accuracy. Recently, \cite{Gupta2019} has improved topic modeling on short texts by introducing word embeddings \cite{Pennington2014} in DocNADE architecture. Thus, we adopt DocNADE to perform knowledge transfer within the neural topic modeling framework.
Algorithm 1 (for DocNADE, set LVT and GVT to False) demonstrates the computation of \( \log p(v) \) and negative log-likelihood \( \mathcal{L}(v) \) that is minimized using gradient descent. Moreover, computing \( h_i \) is efficient (linear complexity) due to the NADE architecture that leverages the pre-activation and negative log-likelihood. Furthermore, GVT+MST in DocNADE is given by:

\[
\mathcal{L}(v) = -\log p(v) + \sum_{k=1}^{\lvert S \rvert} \sum_{j=1}^{H} \gamma_j^k \sum_{q<i} \sum_{q<i} \lambda_q^k E_{i,q}^k
\]

Here, \( k \) refers to the \( k \)th source and \( \lambda_q^k \) is a weight for \( E_{i,q}^k \) that controls the amount of knowledge transferred in \( T \), based on domain overlap between target and source(s). Recently, DocNADE (Gupta et al., 2019) has incorporated word embeddings (Pennington et al., 2014) in extending DocNADE; however, it is based on a single source.

**2.2 Multi-View (MVT) and Multi-Source Transfers (MST) in Topic Modeling**

Here, we describe a topic modeling framework that jointly exploits the complementary knowledge using the two KBs of (pre-trained) latent word and topic representations (or embeddings), obtained from large document collections (DCs) from several sources. In doing so, we first apply the DocNADE to generate a topic-word matrix for each of the DCs, where its column-vector and row-vector generate \( E^k \) and \( Z^k \), respectively for the \( k \)th source.

**LVT+MST Formulation:** As illustrated in Figure 1 (left) and Algorithm 1 with LVT=\text{True}, we perform knowledge transfer to a target \( T \) using a KB of pre-trained word embeddings \( \{E^1, \ldots, E^{|S|}\} \) from several sources \( S \) (i.e., multi-source):

\[
h_i(v_{<i}) = g(c + \sum_{q<i} W_{i,q} + \sum_{q<i} \sum_{k=1}^{|S|} \lambda_w E_{i,q}^k)
\]

Here, \( k \) refers to the \( k \)th source and \( \lambda_w \) is a weight for \( E_{i,q}^k \) that controls the amount of knowledge transferred in \( T \), based on domain overlap between target and source(s). Recently, DocNADE (Gupta et al., 2019) has incorporated word embeddings (Pennington et al., 2014) in extending DocNADE; however, it is based on a single source.

**GVT+MST Formulation:** Next, we perform knowledge transfer exclusively using the KB of pre-trained latent topic features (e.g., \( Z^k \)) from one or several sources, \( S \). In doing so, we add a regularization term to the loss function \( \mathcal{L}(v) \) and require DocNADE to minimize the overall loss in a way that the (latent) topic features in \( W \) simultaneously inherit relevant topical features from each of the source domains \( S \), and generate meaningful representations for the target \( T \). The overall loss \( \mathcal{L}(v) \) due to GVT+MST in DocNADE is given by:

\[
\mathcal{L}(v) = -\log p(v) + \sum_{k=1}^{|S|} \sum_{j=1}^{H} \gamma_j^k || A_{i,j}^k W - Z_{i,j}^k ||_2
\]

Here, \( A_{i,j}^k \in \mathbb{R}^{H \times H} \) aligns latent topics in the target \( T \) and \( k \)th source, and \( \gamma_j^k \) governs the degree of imitation of topic features \( Z^k \) by \( W \) in \( T \). Consequently, the generative process of learning meaningful (latent) topic features in \( W \) is guided by relevant features in \( \{Z^k\}_{i=1}^{|S|} \) to address data-sparsity. Algorithm 1 describes the computation of the loss, when GVT = True and LVT = False.

Moreover, Figure 1 (right) illustrates the need for topic alignments between target and source(s). Here, \( j \) indicates the topic (i.e., row) index in a topic matrix, e.g., \( Z^k \). Observe that the first topic (gray curve), i.e., \( Z_{j=1}^k \in Z^k \) of the first source aligns with the first row-vector (i.e., topic) of \( W \) (of target). However, the other two topics \( Z_{j=2}^k, Z_{j=3}^k \in Z^k \) need alignment with the target topics.

**MVT+MST Formulation:** When LVT and GVT are True (Algorithm 1) for many sources, the two complementary representations are jointly used in knowledge transfer and therefore, the name multi-view and multi-source transfers.

### 3 Evaluation and Analysis

**Datasets:** Table 2 describes the datasets used in high-resource source and low-and high-resource target domains for our experiments. The target domain \( T \) consists of four short-text corpora (20NSshort, TMNtitle, R21578title and Ohsumedtitle), one small corpus (20NSsmall) and two large corpora (TMN and Ohsumed). However in source \( S \), we use five large corpora (20NS, R21578, TMN, AGnews and PubMed) in different label spaces (i.e., domains). Here, the corpora (\( T^3 \), \( T^6 \) and \( S^5 \)) belong to medical and others to news.
### Table 2: Data statistics: Short/long texts and/or small/large corpora in target and source domains. Symbols: $K$: vocabulary size, $L$: average text length (#words), $C$: number of classes and $k$: thousand. For short-text, $L<15$.

### Table 3: Domain overlap in source-target corpora. $\text{I}$: Identical, $\text{R}$: Related and $\text{D}$: Distant domains.

### Table 4: Baselines (related works) vs this work. Here, $\text{NTM}$ and $\text{AuR}$ refer to neural network-based TM and autoregressive assumption, respectively. DocNADEe → DocNADE+Glove embeddings.

Additionally, Table 3 suggests domain overlap (in terms of label match) in the target and source corpora, where we define three types of overlap: $\text{I}$ (identical) if all labels match, $\text{R}$ (related) if some labels match, and $\text{D}$ (distant) if a very few or no labels match. Note, our modeling approaches are completely unsupervised and do not use the data labels. See the data labels in supplementary.

### Baselines: As summarized in Table 3, we consider several baselines including (1) LDA-based and neural network-based topic models that use the target data, (2) topic models using pre-trained word embeddings (i.e., LVT) from Pennington et al. (2014) (Glove), (3) unsupervised document representation, where we employ doc2vec (Le & Mikolov, 2014) and EmbSum (to represent a document by summing the embedding vectors of its words using Glove) in order to quantify the quality of document representations, (4) zero-shot topic modeling, where we use all source corpora and no target corpus, and (5) data-augmentation, where we use all source corpora along with a target corpus for TM on $T$. Using DocNADE, we first prepare two KBs of word embeddings and latent topics from each of the source corpora, and then use them in knowledge transfer to $T$.

### Reproducibility: For evaluations in the following sections, we follow the experimental setup similar to DocNADE (Larochelle & Lauly, 2012) and DocNADEe (Gupta et al., 2019), where the number of topics ($H$) is set to 200. See supplementary for the experimental setup, hyperparameters, and optimal values of $\lambda^k \in [0.1, 0.5, 1.0]$ and $\gamma^k \in [0.1, 0.01, 0.001]$ (determined using development set) in different source-target configurations. In addition, we provide the code.

### 3.1 Generalization: Perplexity (PPL)

To evaluate the generative performance in TM, we estimate the log-probabilities for the test documents and compute the average held-out perplexity per word as, $PPL = \exp \left( - \frac{1}{\text{#words}} \sum_{t} - \log p(x_t | x_{<t}) \right)$. 

1 selected with grid search; suboptimal results (see supplementary) by learning $\lambda$ and $\gamma$ with backpropagation.
we also observe better generalization by MST+LVT on several target corpora, e.g., on TMN using PPL scores: (655 vs 680) and (663 vs 680) respectively in comparison to DocNADEe. Similarly using AGnews (as source) for LVT on TMN target, we observe improved scores: (564 vs 584) and (564 vs 572) compared to DocNADE and DocNADEe, respectively. It suggests a positive knowledge transfer and verifies domain relatedness in TMN-TMN title and AGnews-TMN (Table 5). Additionally, we also observe better generalization by MST+LVT on several target corpora, e.g., on TMN title: (663 vs 706) and (663 vs 680) compared to DocNADE and DocNADEe, respectively.

Table 5: State-of-the-art comparisons with topic models: Perplexity (PPL), topic coherence (COH) and precision (IR) at retrieval fraction 0.02. Scores are reported on each of the target, given KBs from one or several sources. Please read column-wise. Bold: best in column.

Table 6: State-of-the-art comparisons with word embeddings: PPL, COH and IR at retrieval fraction 0.02. Scores are reported on each of the target, given KBs from one or several sources. Here, MVT: LVT+GVT (Table 5). DocNADEe: DocNADE+Glove.

\[
\frac{1}{N} \sum_{i=1}^{N} \log p(v_i), \text{ where } N \text{ and } |v_i| \text{ are the number of documents and words in a document } v_i, \text{ respectively.}
\]
In Table 7 we demonstrate generalization performance via PPL on two medical target corpora: OhsumedTitle and Ohsumed by knowledge transfer from Agnews (news corpus) and PubMed (medical abstracts). We see that using PubMed for LVT on both the target corpora improves generalization: (1268 vs 1534) and (1535 vs 1637) compared to DocNADEe, respectively. Additionally, MST+GVT and MST+MVT lead to better generalization, compared to DocNADEe.

### 3.2 INTERPRETABILITY: TOPIC COHERENCE (COH)

Beyond perplexity, we compute topic coherence to estimate the meaningfulness of words in each of the topics captured. In doing so, we choose the coherence measure proposed by Röder et al. (2015) that identifies context features for each topic word using a sliding window over the reference corpus. We follow Gupta et al. (2019) and compute COH with the top 10 words in each topic. Essentially, higher scores imply more coherent topics.

Tables 5 and 6 (under COH column) demonstrate that our proposed knowledge transfer approaches show noticeable gains in COH, e.g., using Agnews as a source alone in GVT configuration for 20NSsmall dataset, we observe COH of (563 vs 455) compared to DocNADEe. In MVT+Glove and MST+MVT, it is increased to .573 and .600, respectively. Importantly, we find MVT>GVT>LVT in COH scores for both the single-source and multi-source transfers. Here, MST+MVT boosts COH for all the five target corpora compared to the baseline (i.e., DocNADE and DocNADEe) topic models. This suggests that there is a need for the two complementary (word and topics) representations and knowledge transfers from several domains in order to guide meaningful learning in \( T \). Table 7 also shows similar gains in COH due to GVT on OhsumedTitle and Ohsumed, using latent knowledge from PubMed. The results on both the low- and high-resource targets conclude that the proposed modeling scales.

### 3.3 APPLICABILITY: INFORMATION RETRIEVAL (IR)

To evaluate document representations, we perform a document retrieval task on the target datasets and use their label information to compute precision. We follow the experimental setup similar to Lauly et al. (2017), where all test documents are treated as queries to retrieve a fraction of the closest
Figure 2: (a, b, c, d) Retrieval performance (precision) on 20NSshort, 20NSsmall, TMNtitle and R21578title datasets. (e) Precision at recall fraction 0.02, each for a fraction (20%, 40%, 60%, 80%, 100%) of the training set of TMNtitle. (f) Zero-shot and data-augmentation (DA) experiments for topic coherence on TMNtitle and Ohsumed.

Tables 5 and 6 depict precision scores at retrieval fraction 0.02 (similar to Gupta et al. (2019)), where the configuration MST+GVT outperforms both the DocNADE and DocNADEe in retrieval performance on the four target (short-text) datasets, e.g., (.556 vs .521) and (.556 vs .541) for TMNtitle, respectively. A gain in IR performance is noticeable for highly overlapping domains, e.g., TMN-TMNtitle than the related, e.g., AGnews-TMNtitle. We also see a large gain (.326 vs .270) in DocNADE due to MST+GVT for 20NSsmall. Similarly, Table 7 shows improved precision on medical corpora, where MVT+BioEmb and GVT using PubMed report gains (.181 vs .160 and .192 vs .184) on Ohsumedtitle and Ohsumed, respectively. Additionally, Figures 2a, 2b, 2c and 2d illustrate the precision on 20NSshort, 20NSsmall, TMNtitle and R21578title, respectively, where the proposed approaches (MST+GVT and MST+MVT) consistently outperform the baselines at all fractions. The IR results on both the low- and high-resource targets imply that our approaches scale.

Moreover, we split the training data of TMNtitle into several sets: 20%, 40%, 60%, 80% of the training set and then retrain DocNADE, DocNADEe and DocNADE+MST+MVT. We demonstrate the impact of knowledge transfers via word and topic features in learning representations on the sparse target domain. Figure 2c plots precision at retrieval (recall) fraction 0.02 and demonstrates that the proposed modeling consistently reports a gain over DocNADE(e) at each of the splits.

3.4 ZERO-SHOT AND DATA-AUGMENTATION EVALUATIONS

Figures 2a, 2b, 2c and 2d show precision in the zero-shot (source-only training) and data-augmentation (source+target training) configurations. Observe that the latter helps in learning meaningful representations and performs better than zero-shot; however, it is outperformed by MST+MVT, suggesting that a naive (data space) augmentation does not add sufficient prior or relevant information to the sparse target. Thus, we find that it is beneficial to augment training data
in feature space (e.g., LVT, GVT and MVT) especially for unsupervised topic models using latent knowledge from one or several relevant sources.

Beyond IR, we further investigate computing topic coherence (COH) for zero-shot and data-augmentation baselines, where the COH scores (Figure 2f) suggest that MST+MVT outperforms DocNADEe, zero-shot and data-augmentation.

3.5 Qualitative Analysis: Topics and Nearest Neighbors (NN)

For topic level inspection, we first extract topics using the rows of \( W \) of source and target corpora. Table 8 demonstrates that topics in the target domains become more coherent due to GVT(+MST). Observe that we also show topics from source domain(s) that align with the topics from target.

For word level inspection, we extract word representations using the columns of \( W \). Table 9 shows nearest neighbors (NNs) of the word chip in 20NSshort (target) corpus, before and after GVT using three knowledge sources. Observe that the NNs in the target become more meaningful.

4 Conclusion

Within neural topic modeling, we have presented approaches to introduce (external) complementary knowledge: pre-trained word embeddings (i.e., local semantics) and latent topics (i.e., global semantics) exclusively or jointly from one or many sources (i.e., multi-view and multi-source) that better deal with data-sparsity issues, especially in a short-text and/or small document collection. We have shown learning meaningful topics and text representations on 7 (low- and high-resource) target corpora from news and medical domains.

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