Chasing the Tail with Domain Generalization: A Case Study on Frequency-Enriched Datasets

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Abstract
Natural language understanding (NLU) tasks are typically defined by creating an annotated dataset in which each utterance is encountered once. Such data does not resemble real-world natural language interactions in which certain utterances are encountered frequently, others rarely. For deployed NLU systems, this is a vital problem, since the underlying machine learning (ML) models are often fine-tuned on typical NLU data, in which utterance frequency is never factored in, and then applied to real-world data with a very different distribution. Such systems need to maintain interpretation consistency for the high-frequency (head) utterances, while also doing well on low-frequency (tail) utterances. We propose an alternative strategy that explicitly uses utterance frequency in training data to learn models that are more robust to unknown distributions. We present a methodology to simulate utterance usage in two public corpora and create two new corpora with head, body and tail segments. We evaluate several methods for joint intent classification and named entity recognition (referred to as IC-NER), and propose to use two domain generalization (DG) approaches that we adapt to sequence labeling task. The DG approaches demonstrate up to 7.02% relative improvement in semantic accuracy over baselines on the tail data. We provide insights as to why the proposed approaches work and show that the reasons for the observed improvements do not align with those reported in previous work.

1 Introduction
In academic research, natural language understanding (NLU) tasks are typically defined by creating annotated data, and then that data is used to train and evaluate machine learning models designed to solve that task. In such datasets, each utterance is typically encountered only once. But real-world natural language interactions do not look like that – in the real world, frequency matters. When people interact with each other “in the wild”, some things are said often (“Time to go to bed!”), others are infrequent to the point of being unique.

The same holds for how people interact with digital assistants such as Alexa, Siri, or Google Assistant, which we use as the case study in this paper. The backbone of such commercial systems is the task of joint intent classification and named entity recognition (IC-NER) (Su et al., 2018; Coucke et al., 2018; Anantha et al., 2021). The goal of this task is to identify the intended action (play music, open calendar, etc) and actionable slots (names, places, objects, etc) from a user utterance.

The underlying joint IC-NER models must correctly handle both the frequently occurring requests and a long tail of less common entities. But in the common IC-NER corpora such as SNIPS (Coucke et al., 2018), there is no way to distinguish between requests for generic entities (“play music from youtube”) and requests for a low-frequency entity (“help me locate a game called the master of ballantrae”). IC-NER models are fine-tuned on all training data, and then applied to real-world data with a very different distribution.

In order to mitigate this issue, this work proposes a method for creating annotated data which explicitly factors in utterance frequency. We divide an NLU dataset into three disjoint segments: head (most frequent utterances), tail (least frequent utterances) and body (all remaining utterances). In this work, we define a segment as a subset of the dataset with similar characteristics, for example the head segment contains utterances with high frequencies in the real world. We then develop learning strategies which benefit from the token and label distributions in the head, body, and tail segments of the resulting frequency-enriched datasets.

We simulate utterance usage patterns using two common public corpora for the IC-NER task: SNIPS (Coucke et al., 2018) which co-
Table 1: Selected examples from head and tail segments in the newly created corpora: SNIPSesv and TOPesv. Utterances from head segments include the repetition counts. Tokens with slot labels are boldfaced.

| SNIPSesv | TOPesv |
|----------|--------|
| **Head** | **Tail** |
| "play music off youtube": 76 | "is the weather causing traffic delays today": 65 |
| "play some google music": 36 | "where is macy's": 46 |
| "add outside the dream syndicate to millicent's fresh electronic playlist" | "what new movies start this weekend": 32 |
| "what is the weather in south punta gorda heights" | "what is the quickest route to get to valdosta from atlanta" |
| "add 9th inning to my bossa nova dinner playlist" | "how long does it take to drive from adair to chelsea" |

contains real-world utterances directed towards the SNIPS voice assistant, and the Facebook Dialog Corpus (TOP; Gupta et al. 2018) which is a crowdsourced collection of natural language queries related to navigation and event inquiries, creating two frequency-enriched datasets (SNIPSesv and TOPesv). Our methodology is based on entity search volumes, which allows us to emulate a realistic utterance frequency distribution in the data. Utterances are then upsampled according to their estimated frequency. SNIPSesv and TOPesv datasets separate test data for head, body and tail segments, enabling the comparison of model performance on each segment. The proposed methodology can be easily extended to other NLU tasks such as part-of-speech tagging, sentence generation, or question answering.

Using our frequency-enriched datasets, we compare IC-NER performance of several methods. We propose modifications to two domain generalization (DG; (Blanchard et al., 2011)) approaches: domain masks for generalization (DMG; Chattopadhyay et al. 2020) and optimal transport (OT; (Zhou et al., 2020a)). We adapt these methods for IC-NER and demonstrate up to 7.02% relative improvement in semantic accuracy on the tail data over strong baselines.

We provide insights as to why the proposed DG approaches work, showing that OT learns segment-invariant representations using segment classification analysis. Our analysis using random-valued masks reveals that performance improvements by DMG are rather likely due to the training process resembling an enhanced version of dropout, rather than learning segment-specific mask parameters, an observation which does not align with those reported in previous work. We corroborate our observations in NLU with similar findings on a related task from computer vision, for which DMG was originally proposed.

The main contributions of this work are thus as follows: (i) We simulate utterance usage frequency for two public NLU corpora. To the best of our knowledge, these frequency-enriched datasets are the first attempt to explicitly incorporate utterance usage information in NLU. (ii) We adapt two domain generalization approaches to the sequence labeling task in NLU and show improvement over strong baselines on the tail segment, using the frequency-enriched data. (iii) We demonstrate that the reasons for improved performance from DMG do not align with those reported in previous work.

2 Background

2.1 Improving tail recognition

Previous work on head to tail transfer learning has typically focused on assigning classes to either head or tail based on the number of examples present in each class (Xiao et al., 2021; Raunak et al., 2020). Our problem setting is different in that we divide the dataset into head, body and tail based on the estimated usage frequency of each utterance. For example, in our case, the utterances belonging to a common class (such as "play music" intent) may not all be assigned to the head segment, but rather may be split between head, body, and tail, depending on their frequencies.

Since our problem setting presumes a different definition of head and tail, many of the methods (Kang et al., 2020; Ouyang et al., 2016; Cao et al., 2019) developed for head-to-tail transfer are not directly applicable in our case.

2.2 Domain generalization approaches

Domain generalization techniques (Blanchard et al., 2011) are a subset of transfer learning approaches where multiple domains with different label distributions and class-conditional distributions are used for model building. As distinct from domain adaption, no data from the target domain(s) is assumed available for training/adaptation. We wanted to investigate DG methods for our scenario, since this would allow us to treat head, tail, and body segments as virtual domains, without making any
specific assumptions about the data and label distributions in each segment.

A variety of DG approaches have been proposed: kernel-based optimization methods (Blanchard et al., 2011, 2021; Muandet et al., 2013), augmenting with synthetic data perturbed using loss gradients (Shankar et al., 2018), learning a transformation to jointly classify domains and labels (Zhou et al., 2020b), learning a segment-invariant feature space by minimizing the optimal transport between domain pairs (Zhou et al., 2020a), etc. Broadly, these approaches learn to project datapoints from different segments into equivalent feature spaces for data representation, which improves performance. This paradigm closely resembles meta-learning, with the difference being that meta-learning assumes access to labeled samples from the target segment during the meta-testing phase (Ravi and Larochelle, 2017). An alternative set of approaches focuses on learning segment-specific knowledge, e.g., using outputs from a model trained on seen segments to train a model for unseen segments (Zhou et al., 2021) or selecting convolution activations to create segment-specific subnetworks in the model (Chattopadhyay et al., 2020; Mallya et al., 2018; Berriel et al., 2019).

DG has been relatively less explored in NLU when compared to computer vision. A handful of works have applied DG for semantic parsing: Wang et al. (2021) employed an adaptation of MAML (Finn et al., 2017) to simulate new segments, Marzinotto et al. (2019) used an adversarial domain classifier as a regularization technique. We adapt two categories of DG approaches: learning representations which are segment-specific (DMG; Chattopadhyay et al. 2020) and segment-invariant (optimal transport; (Zhou et al., 2020a)). We apply these approaches for generalizing IC-NER performance from head, body and tail segments.

3 Methods

3.1 Dataset preparation

Both SNIPS (Coucke et al., 2018) and TOP (Gupta et al., 2018) contain almost exclusively unique utterances, and SNIPS is purposefully designed to contain a balanced number of utterances per intent. Following Chen et al. (2019), IC-NER models are commonly evaluated on data that excludes nested intents, since BERT-based architectures make handling nested intents challenging. In order to enable fair comparison of model performance, we follow this strategy and remove nested intents from TOP. We also remove all utterances labeled with “Unsupported” intent.

3.1.1 Estimating usage frequency

In order to estimate usage frequency of each utterance, we use the internet search volumes of each labeled entity (defined as a token labeled with a slot, e.g., ArtistName). We hypothesize that the utterance’s usage frequency is influenced primarily by the mentioned entities (e.g., master of ballantrae in Section 1) and not the remaining tokens (e.g., stop words, play, order, etc).

We collect the monthly entity search volume (denoted $esv$) averaged over the last year using the Google AdWords API$^1$. We estimate the utterance search volume as mean $esv$ for all entities, assuming that each entity contributes equally to the utterance usage. For example, consider the following utterance in the SNIPS corpora: “Book reservations at a restaurant in Olton around supper time”. There are two labeled entities in it: Olton (city) and supper (time interval). Monthly search volumes in Google for each entity are 266 and 33.1K respectively. Hence, the estimated utterance usage $esv_u$ is 16.7K. In a similar manner, we estimate the usage frequency of all utterances in SNIPS and TOP.

Another option for estimating usage frequencies is to use utterance perplexity estimated by a high-quality pre-trained language model. In preliminary analysis, we used the perplexities from GPT-2 to approximate usage frequency. We did not find that this method produced good estimates of usage frequencies in spoken requests to digital assistants, likely due to the domain difference of the data used pre-training of GPT-2. Pre-training on in-domain data can be used to address this in the future, potentially enabling this alternative strategy for estimating utterance frequency.

3.1.2 Utterance sampling

We used the frequency estimate for each utterance to determine the upsampling factor for that utterance. Intuitively, an utterance with a higher $esv_u$ should be sampled more, and is more likely to be present in the head segment.

We normalize the obtained search volume to derive a probability distribution $p_u$ over utterances. However, we compared the resulting distribution

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1https://developers.google.com/adwords/api/
For each utterance from the original train, dev and test sets from SNIPS and TOP, we estimate the utterance frequency. The frequency is normalized to a probability distribution which is used to sample utterances.

against the utterance in a proprietary commercial dataset, and observed that while \( p_u \) gave reasonable estimates in many cases, it was not well calibrated. Specifically, it produced a heavy skew in favor of frequent utterances, possibly due to the fact that we were only able to approximate frequencies at the entity, rather than utterance level. Sampling directly from \( p_u \) would therefore have produced a corpus with a small number of unique utterances and many repetitions, while omitting most utterances from the original dataset.

To avoid this issue, we cap the maximum sampling probability \( p_{max} \) of an utterance. We define \( p_{max} \) to be the probability of the most common utterance, defined as follows:

\[
p_{max} = \frac{|u_{max}|}{\sum_i |u_i|} \tag{1}
\]

where \( u_i \) denotes a unique utterance and \( u_{max} \) denotes the most common unique utterance. We empirically determine \( p_{max} = 0.00245 \) using the proprietary corpus of user queries with semantically similar intent labels to SNIPS and TOP. Further details are provided in the Appendix.

3.1.3 Splitting into head, body and tail

We create frequency-enriched versions of the TOP and SNIPS datasets using the capped probability distribution to sample utterances with replacement. We fix the total number of utterances (\( N \)) in the new corpus and sample utterances using the capped distribution until we collect \( N \) utterances. We segment the upsampled corpus into head, body, and tail, where head and tail are designed to contain fewer utterances than body. The frequency of utterances in the head and tail segments is very high or very low, respectively. We assign 10% most frequent utterances to head, 10% least frequent utterances to tail and remaining utterances to body. We create the train and test partitions of SNIPSesv and TOPesv separately from the original train and test partitions, hence resulting in six segments (3 train + 3 test) for each corpus.

We report utterance and label statistics of the resulting datasets in Table 2. In both SNIPSesv and TOPesv, the head segment contains relatively fewer unique utterances than other segments, but each unique utterance is repeated multiple times. Note that the head segment does not contain the complete set of labels (intents and classes) found in the original corpora. Specifically, the head segment in SNIPSesv and TOPesv contain only 30.5% and 38.4% of all the slot labels in the original segment, respectively. Some intent labels are also missing in other segments in TOPesv, likely because the TOP corpus (Gupta et al., 2018), unlike SNIPS, has a non-uniform intent distribution. In Table 1, we provide representative examples from head and tail segments in the newly created corpora. Note that utterances with popular/generic entities (e.g., youtube, weather) are likely to end up in the head segment when compared to less widely used entities.

3.2 Domain Generalization Approaches

As the omitted intent statistics in Table 2 suggest, head, body and tail segments of both datasets have very different label distributions \( P(Y) \). At the same time, since utterances are sampled according to the entity search volume, each segment has a different distribution over tokens \( P(X) \) (Table 1). These differences in label and token distributions motivate our choice of DG approaches for improv-

\[\text{Utterance: } "can you play me some eighties music by adele"\]

\[\text{Google Adwords} \]

\["eighties": 12.4K \]

\["adele": 640K \]

\[\text{Mean: 327K} \]

\[\text{Normalize} \]

\[\text{Utt}1: p1 \]

\[\text{Utt}2: p2 \]

\[\ldots \]

\[\text{Utt}N: pN \]

\[\text{Sample} \]

\[\text{Split} \]

\[\text{Head} \]

\[\text{Body} \]

\[\text{Tail} \]
Table 2: Dataset statistics for head, body and tail segments in SNIPSesv and TOPesv, along with the respective original corpora (“Original” segment). Splits (train, dev and test) for each segment are created using the corresponding splits from the original corpora. For each split within a segment, the total utterance count (Utt), unique utterance count (Uniq Utt), average repetition of unique utterances (Rep), and missing labels are provided. The total number of intents and slot labels are provided against the respective column headers.

| Segment | Split | SNIPSesv | TOPesv |
|---------|-------|----------|--------|
|         |       | Utt | Uniq Utt | Rep | #Missing Intents(7) | #Missing Slots(72) | Utt | Uniq Utt | Rep | #Missing Intents(12) | #Missing Slots(26) |
| Original | Train | 13084 | 12860 | 1.02 | - | - | 20265 | 19764 | 1.03 | - | - |
|         | Dev | 700 | 695 | 1.01 | - | 2 | 2955 | 2937 | 1.01 | 5 | 1 |
|         | Test | 700 | 699 | 1.00 | 1.00 | 2 | 5884 | 5834 | 1.01 | 4 | 2 |
| Head | Train | 1323 | 34 | 38.91 | 2 | 44 | 1748 | 40 | 43.7 | 6 | 12 |
|         | Dev | 73 | 8 | 9.13 | 5 | 50 | 253 | 26 | 9.73 | 9 | 16 |
|         | Test | 74 | 11 | 6.73 | 1 | 48 | 515 | 40 | 12.88 | 7 | 15 |
| Body | Train | 10453 | 2537 | 4.12 | - | 2 | 13922 | 5668 | 2.46 | - | 1 |
|         | Dev | 558 | 230 | 2.43 | - | 11 | 2020 | 749 | 2.70 | 2 | 5 |
|         | Test | 557 | 267 | 2.09 | - | 3 | 4063 | 1634 | 2.49 | 2 | 5 |
| Tail | Train | 1308 | 1308 | 1.00 | - | 2 | 1740 | 1740 | 1.00 | 3 | 7 |
|         | Dev | 69 | 69 | 1.00 | - | 21 | 252 | 252 | 1.00 | 2 | 5 |
|         | Test | 69 | 69 | 1.00 | - | 14 | 508 | 508 | 1.00 | 3 | 5 |

Both DG approaches explored in this work, DMG (Chattopadhyay et al., 2020) and OT (Zhou et al., 2020a), assume that the model can be broken down into a feature extractor \( F \) and a task network \( T \). A typical feature extractor and task network for IC-NER are BERT-based pretrained model and sequence/slot classification network respectively (Chen et al., 2019).

3.2.1 Domain Masks for Generalization (DMG)

DMG encodes segment knowledge in masks \( \tilde{m}^d \), which are segment-specific parameters jointly learnt with \( F \) and \( T \). For segment \( d \), we extract binary activations \( m^d \) from masks as follows:

\[
m^d \sim \text{Bernoulli}(\sigma(\tilde{m}^d))
\]

where \( \sigma \) represents the sigmoid activation function. During forward pass, we multiply each activation by \( m^d \) to compute the effective activation passed to the next layer. Hence, masks serve as layer-wise “on”/“off” gates within \( T \). Masks are sampled during training, hence a different set of neurons are activated for different mini-batches within the same segment.

Similar to the original formulation of DMG (Chattopadhyay et al., 2020), we ensure that masks are incentivized to learn segment-specific information and avoid learning similar representations for all segments by using a soft overlap loss (sIoU; Rahman and Wang 2016). The soft-overlap loss is used in place of Jaccard Similarity Coefficient which is non-differentiable and hence cannot be optimized with gradient descent. Specifically, we compute:

\[
sIoU(\tilde{m}^d_i, \tilde{m}^d_j) = \frac{\tilde{m}^d_i \cdot \tilde{m}^d_j}{\sum (\tilde{m}^d_i + \tilde{m}^d_j - \tilde{m}^d_i \odot \tilde{m}^d_j)}
\]

At each mini-batch, we compute \( sIoU(\tilde{m}^d_i, \tilde{m}^d_j) \) for every segment pair and sum across all pairs. This soft-overlap loss is added to the classification loss and used as the overall objective for optimization.

\[
L_{DMG} = \frac{1}{n} \sum_i L_{class}(x_i, y_i) + \lambda_{DMG} \sum_{d_i, d_j \in d} sIoU(\tilde{m}^d_i, \tilde{m}^d_j)
\]

where \( n, d \) and \( L_{class} \) represent the mini-batch size, set of segments in the mini-batch, and the classification loss function. At test time, we do not have segment labels for a sample. We arrive at the predicted label by computing the mean prediction obtained with all segment-specific masks.

3.2.2 Optimal Transport

Optimal transport (Shen et al. (2018)) learns segment-invariant feature representations by ensuring feature compactness, i.e., samples from the same class across different segments are brought close to each other and vice versa. Assuming
Figure 2: Illustrating the different approaches used in this work: baselines Per-segment, aggregate and multihead, and DG approaches: DMG++ and Optimal Transport.

\[ c : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}^+ \] is the cost function for transporting an unit mass from \( x_i \) to \( x_j \), the \( p \)-th order Wasserstein distance between \( d_i \) and \( d_j \) is:

\[ W_p(d_i, d_j) = \inf_{\gamma \in \Pi(d_i, d_j)} \int_{\mathbb{R}^n \times \mathbb{R}^n} c(x_i, x_j) d\gamma(x_i, x_j) \tag{4} \]

where \( \Pi(d_i, d_j) \) is a collection of all joint probability measures on \( \mathbb{R}^n \times \mathbb{R}^n \) with marginals \( d_i \) and \( d_j \). Following Zhou et al. (2020a) and from the Kantorovich-Rubinstein theorem (Kantorovich and Rubinshtein, 1958), the first order Wasserstein distance can be given as:

\[ W_1(d_i, d_j) = \sup_{\|f\|_{L^1} < 1} E_{x \in d_i} f(x) - E_{x \in d_j} f(x) \tag{5} \]

3.3 Baselines

We compare DG approaches with three baselines: Per-segment, Aggregate and Multihead models. Among these three baselines, we experiment with shared and separate networks for the feature extractor \( F_\Psi \) and task networks \( T_\Theta \) (Figure 2). In the per-segment baseline, we construct a separate model for each segment, and train them using respective segment’s data. In the multihead baseline, \( F_\Psi \) is shared between segments while a different \( T_\Theta \) is trained for each segment. In the aggregate baseline, both \( F_\Psi \) and \( T_\Theta \) are shared between the segments. For the first two baselines where we have multiple task networks, we predict the intent and slot labels for a test sample by computing the mean prediction from all segment-specific models.

4 Experiments

4.1 Model Components

We use the pretrained BERT-base model (Devlin et al., 2019) as the feature extractor network \( F_\Psi \). The task network \( T_\Theta \) consists of two sub-networks: (i) The IC network is a linear feed-forward layer which predicts the intent given the CLS token embedding using a single feed-forward layer (ii) The NER network uses a similar feed-forward layer to predict the slot at each word given the hidden state from the last BERT layer. Similar to Chen et al. (2019), we use the hidden state of the first sub-word token of each word for slot prediction. We update
parameters of both IC and NER networks using a joint classification loss $L_{IC} + L_{NER}$ in order to benefit from any shared knowledge between IC and NER tasks.

### 4.2 Adapting DMG and OT for NER

Note that the DMG model learns a single mask parameter per segment, i.e. it learns one mask for IC ($\tilde{m}_d^{IC}$) and another mask for NER ($\tilde{m}_d^{NER}$). This implies that $\tilde{m}_d^{NER}$ is common across all tokens in the segment and the same activations in $F_{Q}$ are selected for all tokens. This constrains the learning process, since different tokens can benefit from selecting different activations when learning segment-specific representations. To support this, we propose formulating the mask parameters as a function of the segment and the token embedding:

$$\tilde{m}_d = w^d h_t + b^d \quad (8)$$

where $h_t$ represents activation from $F_{Q}$ for token $t$. We introduce a weight vector $w^d$ and bias $b^d$ for each segment. The masks are sampled using $\tilde{m}_d$ similar to Eq. 2. We refer to this modified version of DMG as DMG++. Similarly, we use two critic networks for OT: $C_{Q,IC}$ is a feed-forward linear layer which uses the CLS token embedding similar to the IC network, whereas $C_{Q,NER}$ applies a single long short-term memory (LSTM) layer to extract longitudinal information from the BERT hidden states at each token.

We also train a DG approach combining DMG and OT (referred to as Combined). We retain the critic networks from OT, and introduce masks at the input of critic networks in addition to masks at the inputs of IC and NER networks. The overall loss function to be optimized is a sum of classification losses, critic loss and the overlap penalty loss. We explore whether we can obtain any gains in task performance due to the complementary nature of these approaches.

We use AdamW (Loshchilov and Hutter, 2018) optimizer (initial LR: 5e-5, decay rate: 0.96, $(\beta_1, \beta_2) = (0.9, 0.999), \epsilon = 1e-8$) to minimize the respective loss objectives for each approach. We train the models for 10 epochs for SNIPSesv and 5 epochs for TOPesv. To improve training stability, we accumulate gradients from two mini-batches before back-propagation. We follow Chattopadhyay et al. (2020) and Zhou et al. (2020a) to fix approach-specific learning parameters: we set $\lambda_{DMG} = 0.1$ (Eq. 3) and set the critic coefficient as a function of the training progress $p$, $\lambda_{OT} = \frac{2}{1 + e^{-\delta p}} - 1$ where $\delta = 10$. We apply dropout with the rate of 0.1 at all layers in $F_{Q}$ and $T_{\Theta}$. Following Chen et al., 2019, we use two metrics to evaluate IC-NER performance: (1) slot-filling $F_1$ ($Slot F_1$), which is the weighted average of F1 scores across slot labels and (2) semantic accuracy rate ($Sem Acc$), which computes the exact match accuracy of ordered slot labels prefixed with the intent label.

### 5 Results

#### 5.1 Performance on Seen and Unseen Segments

We report IC-NER performance on the test sets from all four segments in Table 3. For each segment and method, we report mean $Slot F_1$ and $Sem Acc$ over 5 trials with different random seeds. We observe that for both datasets, performance on the head segment differs substantially.
between approaches. Note that in SNIPesv, different approaches produce the same evaluation figures, which we attribute to the limited number of unique utterances in the head segment (Table 2), even though it contains roughly the same utterance count as the tail. While DG approaches do not provide a boost in performance over baselines for the head segment, this is not necessarily a cause for concern. We believe that in a real-world scenario with digital assistants, very frequent requests can be easily recognized using non-statistical models such as rules and deterministic finite-state-transducers (Mohri, 1997).

Among the three segments, improvements with DG approaches (DMG++, OT & Combined) are more visible in tail: the best DG approach returns 7.02% and 1.27% relative improvement in semantic accuracy and slot \( F_1 \) on SNIPesv datasets over the best performing baseline. The original test set, which is not modified by our work and represents yet another segment demonstrates minor but consistent improvements in both metrics across SNIPesv and TOPesv. Further, we observe competitive performance by optimal transport-based approaches (OT and Combined) on the body segment: upto 2.25% relative improvement with the best performing baseline on SNIPesv and identical performance on TOPesv.

We observe that improvements in TOPesv are lesser than SNIPesv, specifically for Tail and Body segments. We believe that there exists a clearer variation between segments in case of SNIPesv due to a wider range of topics spanned by the utterances (music, books, events, weather) whereas TOPesv intents are generally confined to navigation. Hence, DG approaches are more likely to exhibit gains over baselines in SNIPesv vs TOPesv.

5.2 Analysis of DG performance gains

5.2.1 Segment Classification Model

Since OT attempts to learn segment-invariant representations, we validate this paradigm by building a segment classifier on the representations from the trained feature encoder. We extract CLS token embeddings for the above approaches and train a multi-class linear regression model using the segment as class information. We downsample the body segment by a factor of 8 to ensure a uniform class distribution. The per-segment approach trains a different \( F_q \) for each segment, hence we compute the mean embedding from all three models. We report segment accuracy (%) in Table 5.

We observe that the approaches which learn segment-specific network components such as per-segment (\( F_q \)) and multi-head (\( T_\Theta \)) yield relatively high classification accuracy, while the aggregate model which learns a single network across segments returns the lowest performance among baselines. Optimal transport performs the worst, suggesting that it learns the least segment-related information. However, the difference with the majority baseline (\( \approx 33\% \)) suggests that segment-invariant representations may not be completely achieved on the test set, also observed in Galstyan et al. (2022).

5.2.2 Random-valued Mask Analysis

In order to analyze the segment-specific masks learned by DMG++ approach, we compare the learned masks using three metrics: (i) M1: Mean pairwise cosine distance between \( \tilde{m}^d \), (ii) M2: Mean pairwise cosine distance between \( m^d \), and (iii) M3: Mean fraction of “off” (0) dimensions in \( m^d \). Since \( m^d \) is sampled from \( \tilde{m}^d \) (Eq. 2), we compute M2 and M3 over 5 trials and report their mean and standard deviation. Note that we only analyze \( \tilde{m}^d \) since \( \tilde{m}^d \) is dependent on token embeddings.

From Table 6, we notice that \( m^d \) are clearly different between segments in both SNIPesv and TOPesv. These differences extend to the sampled versions (which are used in forward-pass) are illustrated in M2 and M3, a result of the overlap penalty. Further, masks from all segments are “on” (= 1) for \( \approx 59\% \) and \( \approx 53\% \) dimensions for SNIPesv and TOPesv respectively. To ascertain if segment-specific information is learned by masks, we conduct a sanity check experiment where we replace the masks with a random parameter that encourages similar fraction of “on” dimensions to the learned masks.

Surprisingly, we notice that random masks return on-par performance on all metrics and segments with the learned masks on both SNIPesv and TOPesv corpora (Table 4). This result clearly indicates that the masks do not provide segment-specific information and the exact set of “on”/”off” dimensions which are controlled by the learned masks are not critical for performance on unseen segments. To further ascertain this finding, we repeated the random masks experiment on PACS corpora (Li et al., 2017) from computer vision, following (Chattopadhyay et al., 2020), with similar
results (see Appendix).

Instead of learning segment-specific information as suggested by Chattopadhyay et al. (2020), we believe that the improvements yielded by DMG approach can be attributed to learning generalizable parameters using masks. Masks are encouraged to be robust by the training process, since $m^d$ are stochastically determined at each mini-batch even for samples from the same segment. Further, our experiments with random masks resemble the training process in that a different set of masks are sampled, except that gradients are not back-propagated. Finally, we note that sampled masks operate similar to a segment-specific dropout (Srivastava et al., 2014) strategy. Hence, generalization improvements in deep learning which have been observed by dropout are likely to be enhanced with segment-specific mask parameters.

### 6 Limitations

Obtaining search volumes using the Google Adwords API cannot disambiguate between different context-based semantic interpretations of the same word, especially when there are no additional tokens to provide context. For instance, search volumes for apple will combine volumes related to the corporation and the fruit, while apple phone and apple juice will return only the relevant search volumes. Further, this work did not address availability concerns for tail utterances/entities which may be more expensive or labor intensive to collect and annotate.

### 7 Conclusions

We presented a methodology to estimate utterance frequency information in public datasets for IC-NER task. We create two new corpora: SNIPSesv and TOPesv which use the frequency information to segment the original corpora into head, body and tail segments. We adapt two DG approaches for IC-NER and compute performance on each segment as well as the original test set, which represents an unseen segment. Our experiments show improvement in tail entity recognition by each DG approach as well as their combination. Our follow-up analyses validate the segment-invariant representation learning by OT and suggest that DMG provides enhanced generalization using segment-specific masks. To assist future research in this direction, we will release the SNIPSesv and TOPesv datasets used in this work upon publication.

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A Determining Maximum Utterance Sampling Probability

We collected a real-world dataset of user-queries directed to our voice-controlled agent to determine the maximum utterance sampling probability $p_{max}$. We uniformly sample from all queries within a 10-day duration to preserve the frequency distribution. However, we retain only utterances which were identified as belonging to services similar to intents in SNIPS and TOP corpora: entertainment (music, books, video), weather, bookings and local search. This results in a total of 15M utterances. We compute repetition counts for each unique utterance and compute $p_{max}$ using the utterance with maximum repetition count following Eq. 1. This results in $p_{max}=0.00245$. We apply this estimated value for $F_{max}$ on SNIPSesv and TOPesv.

B Random-valued Masks for PACS

PACS corproa (Li et al., 2017) is a commonly used DG benchmark from computer vision and contains images from four different styles: sketch, cartoon, photo and art painting. Similar to previous evaluations (Li et al., 2017; Chattopadhyay et al., 2020; Zhou et al., 2020a), we compute the leave-one-domain-out accuracy, where one domain is treated as target and remaining three domains are treated as source. We build a DMG model following the same architecture as (Chattopadhyay et al., 2020) and repeat our evaluations by replacing the learned masks with random valued parameters. We observe identical performance with random masks, similar to SNIPSesv and TOPesv.

Table 7: Leave-one-domain-out accuracy (%) on PACS.

| Approach   | Sketch | Cartoon | Photo | Art  |
|------------|--------|---------|-------|------|
| DMG (rep)  | 71.42  | 69.88   | 87.31 | 64.65|
| DMG (ours) | 67.98  | 67.83   | 84.25 | 63.48|
| DMG (rand) | μ      | 67.24   | 67.71 | 83.75| 63.19|
|            | σ      | 0.32    | 0.06  | 0.13 | 0.24 |